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National Oceanic and Atmospheric Administration

National Marine Fisheries Service
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NOAA Technical Memorandum NMFS-PIFSC-69
https://doi.org/10.7289/V5/TM-PIFSC-69.

February 2018

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NOAA Technical Memorandum NMFS-PIFSC-69

February 2018

U.S. Department of Commerce
Wilbur L. Ross, Jr., Secretary

National Oceanic and Atmospheric Administration
Benjamin Friedman, Acting NOAA Administrator

National Marine Fisheries Service
Chris Oliver, Assistant Administrator for Fisheries

Recommended citation:

Langseth, B., J. Syslo, A. Yau, M. Kapur, and J. Brodziak. 2018.Stock Assessment for the Main Hawaiian Islands Deep 7 Bottomfish Complex in 2018, with Catch Projections Through 2022. NOAA Tech. Memo. NMFS-PIFSC-69, 217 p.

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ABSTRACT

A stock assessment of the main Hawaiian Islands Deep 7 bottomfish complex was conducted in 2018. The assessment used a Bayesian surplus production model fit to bottomfish catch and effort data from commercial catch reports for fishing years 1949-2015. Recommendations from the Center of Independent Experts panel concerning the initial 2014 assessment update were addressed, including improved data filtering and standardization techniques, readdressing assumptions for prior values, the inclusion of a fishery-independent estimate of abundance, and exploration of a single-species assessment model for opakapaka (*Pristipomoides filamentosus*). The surplus production model for the Deep 7 complex was used to evaluate the risk of overfishing as a function of alternative annual reported catches from fishing years 2018 through 2022. The projections included uncertainty in the posterior distribution of estimated bottomfish biomass in 2015 and population dynamics parameters estimated from the assessment model. The Deep 7 bottomfish stock complex in the Main Hawaiian Islands was categorized as not overfished (where overfished was defined as $B/B_{MSY} < 0.844$) and not experiencing overfishing (where overfishing was defined as $H/H_{MSY} > 1$) in 2015. The overfishing limit (OFL), defined as the future amount of reported catch that would yield a P*=50% probability of overfishing ranged from 558-604 thousand pounds depending on future year. The smallest Deep 7 future catch that would lead to a roughly P*=40% chance of overfishing was about 490 thousand pounds. The Bayesian surplus production model developed for opakapaka produced similar overall results to the model for the Deep 7 complex. Results were approximately proportional to the corresponding value in the Deep 7 bottomfish model with biomass over all years scaled by 68%, which was similar to the ratio of opakapaka to Deep 7 from two data sources: the estimate of opakapaka biomass to Deep 7 biomass from the fishery-independent survey (68%), and the overall proportion of total catch biomass of Deep 7 bottomfish comprised of opakapaka (67%).

Table of Contents

List of Tables

List of Figures

1. INTRODUCTION

The Hawaii bottomfish complex is a U.S. fishery management unit comprised of thirteen shallow- and deep-water species of snappers and jacks along with a single grouper species that inhabit waters of the Hawaiian Archipelago (Table 1). The ecological niches occupied by the shallow-water and deep-water components of the bottomfish complex differ (WPRFMC 2001). Deep-water bottomfish habitat in the Main Hawaiian Islands (MHI) includes waters of roughly 100-400 m depth (Parke 2007), although some species shoal to mid-water depths to feed. The bottomfish complex, along with three seamount groundfish species, is managed as bottomfish management unit species under the Fishery Ecosystem Plan for the Hawaii Archipelago (FEP) developed by the Western Pacific Regional Fishery Management Council (WPRFMC 2009). The federal fisheries management regime includes three fishing zones: MHI Zone, and two zones in the Northwestern Hawaiian Islands, the Mau Zone and the Ho'omalu Zone (Figure 1). All bottomfish fishing currently takes place in the MHI zone due to the closure of the Northwestern Hawaiian Islands under Presidential Proclamation 8031[1]. The Deep 7 bottomfish complex, the "Deep 7" (Table 1), comprises a subset of seven species from the bottomfish complex that have been a focus of fishery management measures including seasonal fishery closures and annual catch limits in the MHI since the larger bottomfish complex was determined to be experiencing overfishing on an archipelagic basis in 2005 (Moffitt et al. 2006). This benchmark stock assessment report assesses the Deep 7 bottomfish complex within the MHI zone.

Hawaii bottomfish were targeted by native Hawaiians using deep handlines from canoes for hundreds of years before the advent of the modern fishery after World War II. The modern fishery employs similar handline gear, albeit with braided synthetic line, along with power reels to haul back gear, fish finders to locate schools of fish, and GPS units and other navigational aids to find fishing grounds. Although the efficiency of the modern fishery has likely improved through time (Moffitt et al. 2011), the current Hawaii bottomfish fishery still uses traditional deep handline capture methods for commercial and recreational harvest. Bottomfish restricted fishing areas (BRFAs) were imposed in Hawaii state waters in 1998 and revised in 2006 to conserve fishery resources. Current BRFAs were placed with the intent to cover consequential areas of bottomfish habitat.

1.1. Previous Benchmark Stock Assessment in 2011

The 2011 benchmark stock assessment of the MHI Deep 7 bottomfish complex, using data through fishing year 2010, improved upon earlier assessments (Brodziak et al. 2011). The baseline model was a Bayesian surplus production model. Estimates of unreported fishery catch were incorporated into the model to account for all sources of Deep 7 bottomfish catch. Greater exploration of catch per unit effort (CPUE) standardization methods were incorporated to address concerns about potential influence of model structure and the treatment of CPUE data on model results. The treatment of the assessment data was modified to improve the approximation of bottomfish population dynamics based on recommendations from the Western Pacific Stock Assessment Review [WPSAR] report (Stokes 2009) as well as new research information on the

[1] http://www.papahanaumokuakea.gov/pdf/proclamation_8031.pdf

expected life span of opakapaka (*Pristipomoides filamentosus*), a key bottomfish species (Andrews et al. 2012).

The WPSAR recommendations for immediate consideration in the 2011 benchmark stock assessment were (Stokes 2009, see pp. 17-18):

1. *Comprehensively explore MHI CPUE data and qualitative information in close collaboration with HDAR and fishers throughout the process. Develop credible CPUE standardization, including if appropriate alternative indices.*
2. *Attempt to reconstruct noncommercial catch histories, possibly in the same collaborative process used for (1).*
3. *Consider using meta-data to develop informative prior on Rmax. Develop prior for Binit in collaborative process above (1).*
4. *Assess MHI as single stock to develop population benchmarks and management parameters. Ensure appropriate sensitivity testing to CPUE uncertainty.*

The 2011 benchmark stock assessment was developed to address each of the WPSAR review recommendations within the constraints of available data and the time required to generate the assessment for subsequent fishery management purposes. Details of these improvements can be found in the 2011 stock assessment report (Brodziak et al. 2011).

It should be noted that the 2011 stock assessment was the first assessment to estimate the biomass and harvest rates of the set of Deep 7 bottomfish species rather than all species within the bottomfish complex. The change to assess only the Deep 7 complex was made because the Deep 7 species have similar life histories, distribution, and are the focus of management efforts by the WPRFMC, using annual catch limit regulation and closed seasons (WPRFMC 2007). In contrast, in the bottomfish assessments prior to 2011, several productive shallow-water bottomfish species were included in the set of species modeled. In this context, it was judged that modeling Deep 7 species as a biologically and ecologically related complex would provide a much better approximation of their population dynamics, would be more consistent with the fishery management approach being applied, and would provide a more accurate estimate of the probable levels of intrinsic growth rate and associated levels of sustainable harvest rate. The 2011 stock assessment was also the first to assess the Deep 7 bottomfish in the MHI as a single unit stock without also considering stocks from the Northwestern Hawaiian Islands.

1.2. Previous Stock Assessment Update in 2014

The 2014 stock assessment update using data through fishing year 2013 used a similar analytical approach and assessment methodology as in the 2011 assessment, but incorporated a few changes (Brodziak et al. 2014). The 2014 update did not consider alternative fishing power scenarios for CPUE, but did include an improved CPUE standardization analysis from 1994 to 2013, when Hawaii state commercial logbooks included consistent commercial marine license (CML) information to estimate fisher effects. The inclusion of the fisher effects improved the explanatory power of the CPUE standardization by over 200% since 1994 and was included in the updated production model analysis of the Deep 7 bottomfish complex. Overall, results of the 2014 assessment were similar to the 2011 stock assessment and were not considered to be sensitive to the inclusion of improved CPUE standardization analyses.

The 2014 stock assessment was reviewed by a panel through the Center of Independent Experts (CIE). The panelists concluded that while the methods employed were generally appropriate, the quality of input data on catch and CPUE were questionable and thus did not recommend using the 2014 stock assessment results for management purposes despite the data having been used for all previous stock assessments (Neilson 2015). As a result, the Pacific Islands Fisheries Science Center (PIFSC) conducted a strict update of the 2011 stock assessment model using data through fishing year 2013, but following the same modeling procedures as for the 2011 assessment. The results from this strict update were the most recent set of results used for management purposes. When necessary to avoid confusion between the 2014 assessment sent to CIE review and the 2014 assessment used for management, the model sent to review is referenced herein as the "initial 2014 assessment update" whereas the model used for management is referenced herein as the "2014 assessment update used for management". To address the CIE panelists' concern about data quality, PIFSC conducted a series of workshops with the bottomfish fishery community to improve quality of input data for stock assessment purposes (Yau 2018). The current (2018) benchmark assessment described herein incorporates the recommendations made by participants at the data workshops.

1.3. Current Benchmark Stock Assessment in 2018

The 2018 benchmark Deep 7 bottomfish stock assessment for the MHI used a similar assessment methodology as in the 2011 benchmark assessment and 2014 assessment update used for management. The baseline assessment model was a Bayesian surplus production model that used updated information on CPUE data along with improved filtering procedures and data analyses. In addition, an absolute biomass estimate based on an estimated scalar and relative biomass estimate from the fishery-independent survey in the MHI was used to scale biomass estimates within the model. Modifications to data and other improvements to model structure were incorporated within the 2018 assessment to address both immediate and long-term recommendations raised by the CIE review of the initial 2014 assessment update.

Recommendation for immediate and long-term priorities from the CIE review of the initial 2014 assessment update (Neilson 2015, pg. 8-9) included:

Immediate

> *1. Strengthen the program of fishery monitoring to ensure that the collection of catch and effort data is complete and accurate.*
>
> *2. Investigate the development of a catch rate series using known "highliners" that have a history of good logbook completion.*
>
> *3. Do a catch curve analysis using length frequency information from biological sampling and published length-age relationships for approximate guidance on the estimate of total mortality.*
>
> *4. Readdress assumptions made for prior values and other model assumptions.*

Longer term

1. Develop alternative indices of abundance using fishery-independent information.

2. Develop a large-scale tagging program to provide independent estimates of harvest rates.

3. Move towards single species assessment as the needed data become available to support the evolution of the assessment.

All recommendations were considered, but only recommendations 1, 2, and 4 for immediate priorities, and recommendations 1 and 3 for long-term priorities were specifically addressed for this benchmark stock assessment.

The first two immediate recommendations of the CIE panel were related to data inputs for the assessment. Extensive collaboration with Hawaii Division of Aquatic Resources (DAR), fishermen, and the Council were done over a series of five workshops to address these data-specific recommendations (Yau, 2018). The results of these workshops were incorporated into updated catch and CPUE analyses for the assessment and are described in depth in sections 2.4 and 2.5 of this document. The updated CPUE analyses also addressed the fifth ranking priority for bottomfish research as discussed among the broader bottomfish research community at coordination workshops in 2013 and 2015 (Yau and Oram 2016). Within the workshops, inclusion of an index of specific highliners was discussed. Ultimately, workshop participants decided against such an index over concerns that using only highliners would bias the CPUE index towards higher CPUE values, and that the resulting index would be less responsive to underlying changes in the abundance of bottomfish stocks given the expectation that highliners would be better able to maintain their catch rates. Additional details about workshop decisions were provided in the workshop report (Yau 2018).

The fourth recommendation was incorporated through updated exploration of assumptions on prior values. These explorations resulted in greater support for the choice of parameters around the intrinsic growth rate and incorporation of life history parameters to inform estimates of natural mortality. New and not yet published data on unreported catch errors were also used for this stock assessment to adjust bounds for the prior on unreported catches.

Longer-term recommendations by the review panel were incorporated where applicable and as time allowed. The first longer-term recommendation by the review panel was addressed within the stock assessment by explicitly incorporating into the model fitting process an absolute biomass estimate based on an estimated scalar and relative biomass estimate from the first year of the Bottomfish Fishery-Independent Survey in Hawaii. Details on how the estimate of absolute biomass was obtained were provided elsewhere (Ault et al., 2018), but the description of how the survey estimate was included in the model is provided in sections 2.6 and 3.1.1 of this report. The third longer-term recommendation, for single-species assessment, was also explored. Catch, CPUE, and survey data were revised to focus solely on opakapaka and incorporated into a second Bayesian surplus production model. Opakapaka was chosen as the species to use for single species modeling because it is numerically the most abundant species in the complex and has historically made up the greatest proportion of the catch of the Deep 7 complex (an average of 67% of total annual catch by weight during 1949-2015). Results for the baseline opakapaka-only model were provided in this document and compared to those from the model of the Deep 7 bottomfish complex. A single species model for opakapaka using an alternative modelling framework to incorporate available weight data from DAR's Fisher Reporting System (FRS) database was also explored in Stock Synthesis. However, the Stock Synthesis model required further testing of model assumptions and exploration of parameterization and data fitting and, therefore, was not available for the 2018 stock assessment.

Other recommendations raised by the panel and further described in Neilson (2015) were not addressed given the current state of the data available and time constraints. These included the third immediate and second longer-term recommendations. Catch curve analyses using biological sampling data were not done because sampling was opportunistic and did not follow an experimental design; therefore, the data were not expected to be representative of the catch in the fishery. However, a new calculation of expected natural mortality rate was done using recent estimates of bottomfish longevity based on bomb radiocarbon ageing (Andrews et al. 2012). A PIFSC funded tagging program for bottomfish species was developed in 2007 and run through 2015. As of 2013, approximately 8,500 fish were tagged, but recapture information was insufficient to estimate mortality rates, even for opakapaka for which most recaptures occurred (O'Malley et al., 2015). An updated analysis of the tagging data incorporating new tagging events and continued recaptures since the end of 2013, as well as historical tagging data from the State of Hawaii data has not been undertaken at this time.

2. MATERIALS AND METHODS

In this section, basic information on data sources used in the 2018 MHI Deep 7 bottomfish assessment is described, including on biological information (section 2.3), fishery catch (section 2.4), fishery CPUE for standardization (section 2.5), and the fishery-independent survey (section 2.6).

2.1. Fishing Year

The 2018 benchmark assessment used the same annual time period for reporting bottomfish catch as in the 2014 update and 2011 benchmark assessments. Catch and CPUE data were reported annually from July 1st of the previous year through June 30th of the current year, which is defined as the fishing year. This fishing year coincides with the State of Hawaii's fiscal year and commercial marine license period but differs somewhat from the definition of fishing season in the bottomfish fishery management plan, which extends from September 1st of the previous year through August 31st of the current year. The fishing year beginning on July 1st corresponds to the annual biological cycle of the Deep 7 bottomfish complex which spawns in late spring to early summer (DeMartini 2016). Estimates of annual production biomass starting in July coincide with the settlement of juvenile bottomfish through midsummer (DeMartini et al. 1994). More importantly, the commercial fishery catch of Deep 7 bottomfish is typically highest during the winter months when there is strong market demand for red-colored fish during New Year holidays, and therefore is not operationally separated on a calendar year definition.

2.2. Data sources

Biological data, along with catch, CPUE, and survey biomass data were used to assess the MHI Deep 7 bottomfish complex stock. Catch and CPUE data were derived from Fisher Reporting

System (FRS) data collected by the State of Hawaii's Division of Aquatic Resources (DAR). Survey biomass data were derived from data collected during the 2016 Bottomfish Fishery-Independent Survey in Hawaii conducted by PIFSC in partnership with cooperative research fishers. Catch data were available from January 1, 1948 to June 30, 2016, but because catch data for 1948 covered only half the fishing year, catch data starting in fishing year 1949 were used in the assessment model. Catch and effort data were available from January 1, 1948 to June 30, 2015, and were used in CPUE standardization. However, the standardized index used in the assessment model excluded fishing year 1948 and instead started in fishing year 1949, to align with years having complete catch data. Details on each individual data component are described in the sections below.

2.3. Biological Data

There is limited quantitative information on the life history parameters of the Deep 7 bottomfish. In particular, the early life stages and juvenile characteristics of Hawaii bottomfish are not yet well-described. However, surplus production models have relatively few parameters, and there are studies for Deep 7 bottomfish that can be used to infer values for surplus production model parameters, particularly the intrinsic growth rate. Musick (1999) provides ranges of values for the intrinsic growth rate based on estimates of maximum age, age at maturity, and growth. Similarly, there are studies on maximum age for Deep 7 bottomfish that can be used to infer a value for natural mortality, which although not used explicitly within the surplus production model itself, was used to calculate the biomass reference point from which stock status is based.

Age determination for opakapaka, the most abundant Deep 7 species, has been challenging because their otoliths lack well-developed annual growth zones. Early growth has been well documented, and validated otolith growth rates were successfully developed for the first few years of growth using daily increments (Ralston and Miyamoto 1983; Radtke 1987). Previous research on the growth of opakapaka indicated substantial variation in growth and an estimated maximum age of 18 years (Ralston and Miyamoto 1983). However, more recent research on ageing of opakapaka based on bomb C-14 radiocarbon and lead radium dating of archival otolith samples showed that this species has a life span on the order of 40 years (Andrews et al. 2012) with a median age of maturity of about 3.5 years (Luers et al. 2017). This same study also found growth followed a von Bertalanffy growth curve with $k = 0.242$ (Andrews et al. 2012). Recent unpublished ageing research using bomb C-14 ageing of three other Deep 7 species indicates potential lifespans on the order of 53 years at 100 cm TL for hapuupuu (*Hyporthodus quernus*), with an age of maturity of 10 years; 54 years at 79 cm FL for onaga (*Etelis coruscans*); and 39 years at 43 cm FL for gindai (*Pristipomoides zonatus*) (A. Andrews, PIFSC, pers. comm.). Overall, information on maximal observed ages of Deep 7 bottomfish in MHI, along with information on growth, is consistent with biological assumptions made in previous assessments that the intrinsic growth rate reflects low productivity stock, following the categories described by Musick (1999).

Information on the expected natural mortality rate for the Deep 7 bottomfish complex for the current stock assessment differed from assumptions in previous assessments. In the initial 2014 stock assessment update, a natural mortality rate of 0.25 was used based on Martinez-Andrade (2003) (Brodziak et al. 2011). In the 2011 benchmark stock assessment, a value of 0.3 for natural mortality was used for the Deep 7 bottomfish complex, although it was acknowledged that the updated age information suggested a value closer to 0.1 (Brodziak et al. 2011). For the 2018 benchmark stock assessment, a value more consistent with expected longevity was used, as suggested by reviewers from the previous assessment update (Neilson 2015). Then et al. (2015) found that the best empirical relationship for predicting natural mortality was a relationship between natural mortality (*natM*) and maximum age (*tmax*), $natM = 4.899 * tmax^{-0.916}$. Based on the maximum longevity from Andrews et al. (2012) of 43 years for opakapaka, natural mortality was 0.156, and this value was used for the purposes of determining a minimum stock size threshold, which is defined as $B_{MSST} = (1\text{-natM}) * B_{MSY}$ for the bottomfish complex FEP, where B_{MSY} is exploitable biomass required to produce maximum sustainable yield (MSY).

2.4. Fishery Catch

Catch data for the 2018 assessment included a combination of reported catch data as well as estimates of unreported catch. Unreported catch based on estimates of unreported to reported catch ratios were calculated prior to use within the assessment model. Reported catch and unreported catch were added together to determine total catch for Deep 7 bottomfish in the MHI. Details on each component of catch are provided in sections 2.4.1-2.4.3.

2.4.1. Reported Catch of Deep 7 Bottomfish

Reported fishery catch data used in the model were based on Deep 7 bottomfish catch data extracted from approximately 4.8 million DAR catch records submitted by fishers during fishing years 1949-2016 (K. Lowe, PIFSC, pers. comm.). A subset of the records was used to calculate reported Deep 7 bottomfish catch in weight, based on methods agreed upon at the data workshops (Yau 2018). First, catch data for Deep 7 bottomfish species (Table 1) were separated from all other species based on species codes reported within the catch dataset. There were two species codes for ehu (*Etelis carbunculus*) in the dataset (Moffitt et al. 2011), so both were used and combined into a single code. Second, catch data of Deep 7 bottomfish species were assigned to the MHI and the Northwestern Hawaiian Islands fishing zones based on the reported DAR fishing areas in the dataset (Figure 2). Some (1,547) records of Deep 7 bottomfish catch were reported in unknown or invalid fishing areas, and the minor catch amount (79,632 lbs) from these records was prorated to the MHI fishing zone based on the percentage of Deep 7 bottomfish caught annually by species in known areas of the MHI compared to known areas of both the MHI and Northwestern Hawaiian Islands fishing zones. The final reported catch of Deep 7 bottomfish in the MHI was tabulated by fishing year and species during fishing years 1949-2016 (Table 2).

2.4.2. Estimates of Unreported Bottomfish Catch

Currently, there is no directed long-term monitoring program in place for quantifying the amount of unreported catches of bottomfish in the MHI. Therefore, estimates of unreported Deep 7 bottomfish catch were based on estimated ratios of unreported to reported catch as summarized by Courtney and Brodziak (2011), which were used in previous assessments (Brodziak et al. 2011; 2014). Unreported catch included catch from fishers without CMLs as well as non-reported catch from CML holders and was included in the 2018 stock assessment to account for the effects of total fishery removals on the Deep 7 bottomfish complex. Based on the estimated ratios (U) of unreported to reported bottomfish catch in the MHI, unreported bottomfish catch (C_U) was calculated from reported catch (C_R) as $C_U = U{*}C_R$ for each year.

The same unreported catch ratios used in the base case scenario for the previous benchmark stock assessment were also used in base case scenario for the 2018 assessment (Table 3). As in the 2011 and 2014 assessments, U was set for each Deep 7 species by fishing year to account for annual variation in the species composition of the reported Deep 7 bottomfish catch (Brodziak et al. 2011; 2014). Original estimates of U were only available up to 2010 (Courtney and Brodziak 2011). For the 2014 assessment, Brodziak et al. (2014) extended the species-specific estimates of U from 2010 through 2013, citing a recent survey to support the decision (Hospital and Beavers 2013). Following previous logic, and because further official updated estimates were not available for comparison, 2010 estimates of U were assumed to represent the best available information, and were extended from 2010 through 2016.

Estimates of the unreported catch ratio U (Table 3) indicated that unreported catch (Table 4) was slightly larger in magnitude than the reported commercial catch. Overall, the average unreported to reported catch ratio during 2011-2015 was $U = 1.06$ and the magnitude of the 2011-2015 average unreported catch was approximately 285 thousand pounds. The survey of bottomfish fishers conducted by Hospital and Beavers (2013) reported on disposition of the catch, and their data indicated that the ratio of not sold to sold was 1.33 for commercial fishers.

Uncertainty in estimates of unreported catch ratio was included as sensitivity analyses. Four alternative scenarios for unreported catch ratios were developed based on the available information presented in Courtney and Brodziak (2011) and based on recommendations from the review panel for the previous stock assessment update (Neilson 2015). Details on each of these alternative scenarios are provided in section 3.4.

2.4.3. Estimates of Total Bottomfish Catch

The total catch of Deep 7 bottomfish in the MHI was the sum of reported and unreported catch (Table 5). Uncertainty in the amount of unreported bottomfish catch was not directly estimable but was judged to be more substantial than that associated with reported commercial fishery catch. To account for uncertainty in estimates of unreported bottomfish catch, it was assumed that there was an independent error distribution for each annual estimate of unreported catch for fitting parameters of the production model used in the stock assessment. Therefore, the individual components of total catch were both used within the assessment model. The error distribution for underreported catch is described in further detail in section 3.1.2.

2.5. Standardized Fishery Catch Per Unit Effort

Estimation of standardized commercial fishery CPUE for Deep 7 bottomfish was improved over methods used for previous stock assessments. The review panel from the last stock assessment concluded that although the initial 2014 stock assessment was improved compared to the 2011 stock assessment, there were still concerns about the quality of the data used for CPUE indices of abundance (Neilson 2015). To address CIE reviews from the last assessment, as well as to improve the representativeness of the data used in the current stock assessment, PIFSC convened and completed five bottomfish data workshops with collaboration from the State of Hawaii, the fishing industry, and the Council. Discussions on commercial fishery CPUE for Deep 7 bottomfish were extensive, and improved approaches for selecting representative data were developed. The data are briefly described in section 2.5.1. Details on selecting representative data for use in CPUE standardization are described in section 2.5.2, with further details available in Yau (2018), and details on CPUE standardization methods are described in section 2.5.3.

2.5.1. Fishery Data for use in CPUE Analyses

As in previous assessments, fisher reported data were used for standardizing CPUE indices of abundance. Fisher reported catch and effort data from fishing years 1948-2015 were used in this stock assessment to calculate standardized indices of abundance. In the initial 2014 assessment update, the time series of fishery reported data was separated into two periods for CPUE standardization, 1949-1993 and 1994-2013 (Brodziak et al. 2014). The two time periods were used because 1) fisher-specific information on license number was obtainable from 1994-2013, whereas prior to 1994, license numbers were reassigned among fishers each year and therefore not traceable through time; and 2) different catchabilities could be assumed between the two time periods as a way to account for the possible effects of changes in gear technology. The review panel considered including fisher-specific information in the CPUE standardization an improvement over the 2011 benchmark stock assessment, which did not account for the effects of individual fishers. However, fisher-specific information was not used in the CPUE standardization for the 2014 assessment update used for management due to general concerns from the panel about the data quality.

The limitation of not being able to track individual fishers back through the entire time series was overcome for the 2018 assessment. With help from the State of Hawaii, yearly records of fisher reported data were cross-referenced with a separate and previously unused database of annual license holder names and license numbers. Names, when available, were then assigned to the corresponding license number for each year and added to the fisher reported dataset. This improvement added name information to approximately 3 million records, reflecting nearly all records back to 1977, and a majority of records in all but five years (1954-1958) between 1948-1975 (Table 6). Note however, that fisher name information for records in 1976 could not be located. The fisher reported data with fisher name information included formed the base dataset from which further data filtering steps were applied.

2.5.2. Fishery Data Filtering Steps for CPUE

Improved data filtering procedures were discussed at the data workshops (Yau 2018), and an agreed upon approach was used for the 2018 assessment to select data for standardizing indices of CPUE. In brief, Deep 7 bottomfish catch per effort data from 1948-2015 were summarized for directed deep-sea handline fishing in the MHI while accounting for potential multi-day trips. Multi-day trips were a large concern among reviewers from the last stock assessment. The efforts by workshop participants on improving and updating filtering procedures were significant and resulted in what the group considered the best available dataset for standardizing indices of CPUE.

Procedures for preparing fisher reported data for CPUE are described below in four steps, as outlined in the data workshop report (Yau 2018). The four steps included: 1) selecting records targeting Deep 7 bottomfish, 2) analyzing records to account for multi-day trips, 3) selecting records representative of the fishery, and 4) preparing the data to incorporate factors affecting CPUE. Each step is described below, and each was applied sequentially to the data.

2.5.2.1. Selecting targeted bottomfish records

The first step in preparing fisher reported data for CPUE analysis was to remove any records not targeting Deep 7 bottomfish. The FRS database did not indicate what records targeted Deep 7 bottomfish, so filtering procedures were used to select records considered to target Deep 7 bottomfish within the spatial and temporal range of the assessment.

Gear was identified as a critical determination for bottomfish fishing. Among records reporting Deep 7 bottomfish catch, 95% of the records and 98% of the fish weight summed over the records occurred with deep-sea handline gear. Fishers catching bottomfish primarily use and report this gear. Consequently, the 878,239 records from 1948-2015 that reported deep-sea handline gear were used exclusively for CPUE analysis, as in previous assessments. Given that this stock assessment was for the MHI population of Deep 7 bottomfish, only the 821,638 records reporting deep-sea handline gear within the MHI (Figure 2) were used. The definition of MHI areas for this stock assessment differed slightly from previous stock assessments, with the greatest change in number records caused by moving the western-most boundary one grid east to align with the boundary of the Northwestern Hawaiian Islands' Mau Zone (161°20' W) as stated in the federal registry (54 FR 29907, September 6, 1988). Overall, the current definition used in the 2018 assessment for the MHI removed 159 records that would have been included had the previous definition been used, which indicates that the change in boundary has a minor impact on data used.

After initial filtering procedures for gear and location, fisher reported data were next filtered to remove records not targeting Deep 7 bottomfish. Herein, the term 'fishing event' is used to describe a set of records for a unique commercial marine license (CML) number associated with a given unit of effort. That effort metric is a single day prior to October 2002, and a set of hours fished thereafter. Fishing events are referred to as 'single-reporting days' when referencing only data prior to October 2002. This terminology is used to avoid the use of the term 'trip' which is commonly defined by a fisher coming in and out of port. This definition of fishing event may result in overnight fishing being split into two fishing events for the purpose of CPUE calculation. Given the need for unique CML numbers, the 21,508 records with CML numbers that were zero were removed from further analyses. The definition of what constituted Deep 7 bottomfish fishing was discussed at length at the data workshops (Yau 2018). In the past, a cutoff point (17%) based on the weight of Deep 7 bottomfish caught in a single-reporting day was used to determine targeting of Deep 7 bottomfish (Brodziak et al. 2011). This removed all single-reporting days with less than 17% pounds of Deep 7 bottomfish. An alternative definition of targeted Deep 7 bottomfish fishing was used for the 2018 stock assessment to avoid using a weight-based criterion that could remove fishing events targeting bottomfish that caught low percentages based on total weight.

Filtering of non-bottomfish single-reporting days (and therefore defining bottomfish single-reporting days) was mostly done for records that occurred prior to October 2002, when the fish reporting form was less detailed. After October 2002, fishers could report on the hours fished, start and end times, and were given the option to record catches of 0 pounds, whereas prior to October 2002 this was not possible. Our definition of a targeted bottomfish single-reporting day for records prior to October 2002 was twofold. First, single-reporting days not targeting Deep 7 bottomfish were defined as single-reporting days that caught zero pounds of Deep 7 bottomfish and caught any Pelagic Management Unit Species (PMUS; WPRFMC 2009) listed in the DAR species code list, caught uku, or caught unknown species (species code=0). Workshop participants stated that it was possible to target Deep 7 bottomfish without catching any Deep 7, but that it would be unlikely that pelagic species would be caught if Deep 7 were truly targeted. Similarly, single-reporting days with catches of uku but without any catches of Deep 7 bottomfish were believed to be reflective of fishing specifically targeting uku.

Second, in waters around the southwestern shore of the Big Island (management grids 100-102, 108, 120-122, and 128 in Figure 2), and in years prior to and including 1985, single-reporting days with weight of Deep 7 bottomfish of less than 50 pounds as well as with catches of PMUS were considered to not be targeting bottomfish. This definition was restricted to the southwestern shore of the Big Island due to the uniqueness of the fishery there. The ocean bathymetry of this region drops off steeply very quickly, and fishers who catch pelagic species (in particular tuna) can easily also catch Deep 7 bottomfish and vice versa. Consequently, Deep 7 bottomfish can be caught when targeting pelagic species. In addition, the gears commonly used to target tuna were not given their own unique gear codes until 1981, before which these gears were recorded as deep-sea handline. Hence, it was difficult to determine whether single-reporting days using deep-sea handline off this region of the Big Island of Hawaii were actually targeting Deep 7 bottomfish or pelagic species. The choice to use 1985 instead of 1981, when pelagic gear codes were implemented, was based primarily on an analysis showing that for waters around the southwestern shore of the Big Island the percentage of bottomfish by weight within single-reporting days was more consistent and stable after 1985 (Figure 19 in Yau 2018), but also secondarily on the notion that it would take time for fishers to begin reporting the new gear codes consistently. Based on these two definitions of targeted bottomfish single-reporting days, 84,290 single-reporting days were not considered to be targeting Deep 7 bottomfish, and all 159,097 records from these single-reporting days were removed from further analysis.

The Deep 7 bottomfish fishery was closed four times during 1948-2015. These seasonal closures began on April 16, 2008, July 6, 2009, April 20, 2010, and March 12, 2011 and extended to the end of the fishing season (August 31) for each year. Directed bottomfish fishing was not allowed during this time; therefore, an additional 4,179 records from the 1,886 fishing events that occurred when the Deep 7 bottomfish fishery was closed were removed, leaving a total of 636,854 records remaining from fishing events considered to have targeted MHI Deep 7 bottomfish.

2.5.2.2. Accounting for multi-day trips

In the review of the previous stock assessment, the difficulty to determine whether catch reported on a single day represented catch from a single day or catch aggregated across many days was a major criticism (Neilson 2015). As such, the second step in preparing fisher reported data for CPUE analysis was to account for multi-day trips. In previous assessments, a cutoff of 1,500 pounds of Deep 7 bottomfish was used to determine the upper limit of what could be caught within a single-reporting day, and to remove single-reporting days above this threshold. However, as acknowledged by CIE reviewers, use of this cutoff failed to remove any multi-day trips that caught less than 1,500 lbs of Deep 7 bottomfish (Haist 2015), possibly leading to biased CPUE values. To remedy potential bias in using a weight-based criterion for the 2018 assessment, distance traveled was used as the primary determinant of whether single-reporting days occurred over multiple days, and a measure of how often an individual fishery reported was used as a secondary determinant. In both instances, the filtering step was done for data prior to October 2002. Details of each of these choices are described below.

Distance travelled:

Port landed and area fished should be reported for each record in the fisher reported data. Consequently, the distance travelled between the port and the center of the fishing area was used to determine whether a single-reporting day likely occurred over one or multiple days. The distance travelled between each port and area was determined based on an independent key table constructed for a separate and ongoing analysis of the fisher reported data (J. Ault and S. Smith, University of Miami, pers. comm.). To reduce the number of distances required to be calculated, all of which were done by hand, the key table provided distances from a common port rather than distances from all possible ports. The common port was centrally located among a group of ports in a similar geographic area on each island. In addition to saving time, a common port also allowed for the potential of landing a vessel there and driving to neighboring ports to sell the catch. Distances were calculated based on expected travel paths from the common port to the center of the fishing area while accounting for land barriers. Some records did not have a valid port recorded so a common port could not be assigned, while other records' port-area combinations were not calculated in the key table. Overall, only 5,819 of the 513,146 records prior to October 2002 could not be assigned a valid distance.

During initial analyses, it was noticed that a few single-reporting days reported multiple areas fished and multiple ports landed. Fishing in multiple areas and landing in multiple ports on a single-reporting day is possible, but for some combinations of areas and ports that are distant from one another this is highly improbable, and most likely represents records from multiple single-reporting days recorded together or represents a database error. To initially account for multi-day trips, information on the number and location of ports and areas recorded on a single-reporting day were first used to refine the records into separate single-reporting days where applicable. The criteria for splitting records within a single-reporting day differed based on the number of areas and common ports visited. There were multiple areas and a maximum of 2 common ports visited within any one single-reporting day. For single-reporting days with one area and one common port reported (1-1 single-reporting days), no further refinement was used. For single-reporting days with one area and two common ports reported (1-2 single-reporting days), records were separated into multiple single-reporting days only when the common ports were on two separate and nearby islands. If the common ports were on the same island, the single-reporting days were considered to accurately be a single-reporting day and were left unchanged. Similarly, if the common ports were at least two islands away (either Big Island-Oahu, or Kauai-Maui Nui), it was assumed to be a database error, and therefore the single-reporting day was left unchanged. Single-reporting days with multiple areas and a single common port (2^{+}-1 single-reporting days) were also considered accurate, and the distance for the single-reporting day was assigned as the greatest distance among each port-area distance. For single-reporting days with multiple areas and two common ports (2^{+}-2 single-reporting days), nearly all single-reporting days had areas uniquely associated with one common port or the other common port. Therefore, common port was used as a unique identifier to further separate among single-reporting days, and the distance assigned followed the same approach as for 2^{+}-1 single-reporting days. Accounting for multiple areas and common ports recorded for a single-reporting day added 57 new single-reporting days to the dataset.

Once distance was assigned to each single-reporting day based on the common ports and fishing areas visited, an expected number of days was assigned to each single-reporting day based on a selected distance cut-off value. The cut-off value was selected based on the frequency of distances in 10-year time blocks (Figure 21 in Yau 2018) and from conversations with participants at the data workshops. Based on these discussions, it was expected that the cutoff in the earlier part of the time series would be smaller than that in the later part of the time series due to the vessels participating in the fishery early on being larger and slower. However, a cutoff of 30 nm was applied to all years as it indicated a clear break in the number of single-reporting days occurring in years after 1960. The 30nm cutoff was also inclusive of possible single-reporting days in the 15nm-30nm range for years prior to 1960 where a clear breakpoint was slightly less obvious. Each single-reporting day was assumed to last a day for every multiple of its cutoff. Thus, a distance between 0-30 nm would reflect a single-reporting with one day of effort, 30.1-60 nm a single-reporting day with two days of effort, and so on. Based on this criterion, a total of 23,258 single-reporting days were adjusted to have more than one day of effort, with the longest timeframe being 11 days. Single-reporting days without distances were assumed to have one day of effort.

Timing of reporting:

The timing of reporting was also explored as a way to account for single reporting days occurring over multiple days. Prior to October 2002, the number of records that were reported on the first and last day of a month was higher than the number of records reported on other days (Figure 20 in Yau 2018), which suggested that some of the single-reporting days were likely reported together as monthly reports rather than as daily reports. As there was no way to determine the number of days fished that made up a monthly report, all 4,097 records from the 646 license-year combinations that only ever reported on the first or last day of a month in a year were removed from analyses. Although removing records from fishers that only ever reported on the first or last day of a month in a year may remove a valid single-reporting day that occurred during this time, such instances were expected to be inconsequential for CPUE calculation.

2.5.2.3. Selecting records that accurately represent trends in the fishery

The third step in preparing fisher reported data for CPUE analysis was to filter out records considered to be unrepresentative of the Deep 7 bottomfish fishery. Many options on how to do this were described in detail in the workshop report (Yau 2018). Ultimately, workshop participants agreed on two simple criteria: to filter out records from fishers who never reported catching a Deep 7 bottomfish, and to filter out records from fishers on days where they were participating in the fishery-independent bottomfish survey activities. The former criteria removed 7,851 records from 1,482 fishers who never reported a Deep 7 bottomfish, and the latter removed 97 records from fishers on days that they participated in the fishery-independent bottomfish survey. The logic for removing records from individuals who never reported Deep 7 bottomfish was that such individuals were unlikely targeting bottomfish even though they were fishing deep-sea handline gear. The logic for removing records from the fishery-independent survey was that the fishing method would be functionally different for the survey than for the fishery and therefore unrepresentative. In what fishers described as rare, some fishers participated in the survey but also fished on their own that same day. Records that were part of the survey were indistinguishable from other records fished on the same day; therefore, all records from days where the fisher participated in the survey were removed.

2.5.2.4. Preparing data to incorporate variables affecting CPUE

The final step in preparing the fisher reported data for CPUE analysis was to incorporate additional variables needed for the standardization and to prepare the data for CPUE analysis. Details on each step are described below.

Additional variables affecting CPUE:

Participants at the data workshops identified several variables they considered to influence bottomfish catch rates. Given time constraints, the top three were added to the dataset for use in the CPUE standardization process. They were: i) a measure of fisher experience, ii) the pounds of uku caught, and iii) wind speed and direction. The entire list of variables used in the standardization, including the three variables here, is stated in section 2.5.3.1. Other variables that workshop participants viewed as important (Table 8 in Yau 2018) were not incorporated into CPUE standardization due to time constraints but may be explored in future assessments.

Fisher experience was calculated for each fishing event as the cumulative number of fishing events taken previously. Including fisher experience was possible because individual fishers could be tracked from 1948-2015. Participants discussed and acknowledged that such a measure could not account for fishing done as crew members or experience gained through generational knowledge passed down by elders. Nonetheless, cumulative number of fishing events remained a way to account for differences between experienced and inexperienced fishers.

Pounds of uku caught in each fishing event was included as a variable due to gear competition with Deep 7 bottomfish and the potential for fishers targeting Deep 7 bottomfish to switch to uku (and therefore away from Deep 7 bottomfish) when uku were present. Uku can be found in large numbers and although are not always targeted, can be valuable when encountered, and therefore would alter the catch rates of Deep 7 bottomfish.

Wind data at scales similar to the fisher reported data were available starting July 9, 1987, yet had some gaps in coverage. Average wind speed and directional data on a daily basis for a 0.25 degree spatial grid were downloaded from https://www.ncdc.noaa.gov/data-access/marineocean-data/blended-global/blended-sea-winds on August 15, 2016. Midpoints of management grids calculated from the previous analysis from which grid to port distances were obtained (J. Ault, University of Miami, pers. comm.) were used and merged to each record in the CPUE dataset. Each record was then assigned the nearest wind data point for that day based on the location of the management grid where fishing took place. A total of 294,771 records corresponding to 99,005 fishing events were assigned wind data for 1988-2015 out of the 339,521 possible records and 115,074 fishing events starting on or after July 9, 1987. Fishing events without valid wind data were excluded when generating the final dataset.

Preparing data for standardization

The filtered record-based dataset for use in the CPUE standardization included 624,809 records from the 209,703 fishing events considered most representative of the Deep 7 bottomfish fishery. This dataset was a record-based dataset, which included fishing events containing records reporting different areas or separate hours. For CPUE standardization, only a single value of each dependent and independent variable can be included in the analysis. Consequently, the record-based dataset was summarized into an event-based dataset so that each data point used in the analysis contained information on a single unique fishing event.

Starting in October 2002, fishing events with multiple values of hours reported were divided into multiple fishing events so that each had only a single corresponding value of effort in hours. This was only possible for fishing events that occurred since October 2002 because effort for each record could be reported. A total of 782 fishing events that occurred since October 2002 had multiple hour values reported. Within each reported area for fishing events with multiple values of effort, records that had the same reported hours were treated as a single fishing event. Effort was equal to the reported value of hours, and catch was equal to the sum of reported weight of Deep 7 bottomfish. Records within each area that had different hours reported were treated as separate fishing events. This approach assumed that when the same effort was reported across many records, the value represented total hours fished on a fishing event, whereas when multiple hour values were reported, the values represented individual fishing events that occurred in either multiple parts of the same fishing area or in separate areas altogether. Although this assumption combines separate fishing events with the same reported effort, such cases could not be known for certain, so this approach at least accounted for unique fishing events with different effort values. Using this approach added 845 fishing events to the dataset. After accounting for fishing events with multiple hour values reported, there were 97 fishing events with all records having zero hours recorded. Because CPUE is undefined when the denominator is zero, these fishing events were removed from further analysis.

Multiple areas within a single fishing event were also reported for 1,877 fishing events, however, area-specific effort information for separating these into unique fishing events was not available. Consequently, the area with the greatest amount of Deep 7 bottomfish by weight was assigned to the fishing event for use in the standardization. In cases where the weight of Deep 7 bottomfish was the same across multiple areas, the smaller numbered management grid was selected, reflecting a general preference towards management grids nearer to land (Figure 2). This choice was somewhat arbitrary, but given the few occurrences (137 fishing events), the effect on the standardization was expected to be negligible. Since wind data were linked to the area reported, the wind data corresponding to the area selected for the fishing event was chosen when multiple areas were reported.

Once the dataset was summarized into individual fishing events, CPUE for each fishing event was calculated as the total weight in pounds of Deep 7 bottomfish caught across all records within a fishing event, divided by the unit of effort. For fishing events that occurred prior to October 2002, effort was number of days, while for fishing events that occurred since October 2002, effort was the number of hours. After accounting for multiple values of independent variables so that each fishing event had only one value for any independent variable and removing fishing events without valid wind data, the final filtered event-based dataset for use in the CPUE standardization consisted of 208,641 data points.

2.5.3. CPUE Standardization

2.5.3.1. Model Selection

Deep 7 bottomfish CPUE was standardized using generalized linear and generalized linear mixed models (McCulloch et al. 2008). It was acknowledged during the data workshops that catching zero pounds of Deep 7 bottomfish was possible when targeting Deep 7 bottomfish. Consequently, zero catches of Deep 7 bottomfish were included in CPUE standardization for the base case scenario for this assessment, which differed from choices made for CPUE data during the last two assessments. For this assessment, 17% of the total data points had zero catches of Deep 7 bottomfish. There are numerous ways to deal with zero catches when standardizing CPUE (Maunder and Punt 2004). A delta-lognormal approach was used in this assessment wherein CPUE was modeled as the product of two processes: a Bernoulli process modeling the probability of positive catches, and a positive process modeling the distribution of CPUE given a positive catch, which was assumed lognormal. The response variable for the Bernoulli process was a binomial variable that was added to the dataset, indicating whether a Deep 7 bottomfish was captured (1 = captured, 0 = not captured). The relationship between the response variable and the predictor variables was modeled as a Binomial distribution using a logit link function. The response variable for the positive process, hereafter referred to as the lognormal process, was the natural logarithm of CPUE from positive catches of Deep 7 bottomfish. A Poisson and negative binomial distribution were also considered in place of the delta-lognormal as alternative ways to include zero catches, but were ultimately not used. Models using the Poisson distribution had overdispersion constants of greater than 470, where values of greater than zero suggest overdispersion (Cameron and Trivedi 1990). Models using the negative binomial distribution had convergence issues.

Model selection techniques were used for each of the Bernoulli and lognormal processes to select from the suite of possible predictors those predictors that most improved model fit. Predictor variables for model selection included a mix of categorical and continuous variables, as well as fixed and random effects. Each variable was considered to have some effect on bottomfish CPUE that varied on an annual basis because of changes in the distribution of fish or the spatial pattern and effectiveness of fishing effort. Categorical variables included fishing year, management area, island region, quarter, cardinal and ordinal wind directions, and individual fisher as first-order variables, and area-fishing year and area-quarter as second-order interactions. Island region was defined as Big Island for management areas 100 to 299, Maui-Nui for management areas 300-399, Oahu for management areas 400 to 499, and Kauai-Niihau for management areas 500 and above. Quarter was separated along the definition of fishing year with July to September as quarter 1, October to December as quarter 2, January to March as quarter 3, and April to June as quarter 4. Continuous variables included a measure of the cumulative experience of an individual fisher, the pounds of uku caught, and the wind speed. Preliminary examination of the continuous variables showed some non-linearity in wind speed with positive CPUE; therefore, an additional term for the square of wind speed was included to allow a quadratic effect of wind speed. All variables were modeled as fixed effects except for fisher, which was modeled as a random effect.

Selection among CPUE standardization models was performed using Akaike's information criterion (AIC = 2*number of parameters – 2*ln(likelihood evaluated at its maximum)) to judge the relative goodness of fit (Burnham and Anderson 2002). Model selection was done using a forward-selection process with a threshold of 0.05% of the previous model's AIC. Thus, if the improvement in AIC of a model after adding a new predictor was greater than 0.05% of the previous model's AIC, the added predictor was considered significant, and kept for the best-fitting model. A percentage based threshold was used as opposed to a constant value due to large likelihood values caused by the high number of data points, following the suggestion by Maunder and Punt (2004). The significance of the random effect of fisher was tested first, and model selection using fixed effect terms was done thereafter. Fishing year was required for the index, so year was retained first among fixed effect terms in model selection regardless of AIC score. Model selection was done using maximum likelihood for all models. Estimation was done for generalized linear mixed models using restricted maximum likelihood once the best-fit model was determined. Restricted maximum likelihood accounts for degrees of freedom used in estimating fixed effects and estimates variance components of the random effects without influence from fixed-effect terms (Harville 1977; McCulloch et al. 2008). Statistical modeling was done with the lme4 package version 3.2 (Bates et al. 2015) within the R software package version 3.2 (R Core Team 2016).

As described previously in the data filtering section, CPUE was calculated with a different measure of fishing effort (single reporting days versus hours) in two different time periods. The time periods ranged from 1948 to September 30, 2002, and from October 1, 2002-2015, which corresponded to fishing years 1948-2003 and 2003-2015. This separation followed the change in reporting practices by the state of Hawaii starting in October 2002. Model selection was therefore done separately for data in each time period, resulting in two standardized indices of abundance. We describe the model selection for each index below.

Early time period: Fishing years 1948-2003

Not all predictors could be included in model selection for the early time period (Table 7). Single-reporting days in the early time period with catches of uku but no catches of Deep 7 bottomfish were previously excluded as part of the data filtering steps (see section 2.5.2.1). Consequently, pounds of uku caught was perfectly separated by the value of the Bernoulli response variable and therefore not included as a variable in model selection for the Bernoulli process. Pounds of uku was however included in model selection of the lognormal process. Wind data (wind speed and direction) were available starting in 1987, which covered only a portion of the early time period. Consequently, wind information was not included as a variable for model selection for either the Bernoulli or lognormal processes for the early time period. Lastly, model selection for ‘fisher’ was problematic for the Bernoulli process. A mix of convergence and memory errors were encountered when fitting using the fisher predictor. Fisher was therefore excluded as a variable for model selection for the Bernoulli process, but was retained as a variable for model selection for the lognormal process.

The best-fit model for the Bernoulli process included fishing year, area, quarter, an interaction term for area and quarter, and cumulative experience (Table 8). The best-fit model for the Bernoulli process reduced deviance by 17% from the null model (intercept only) and 11% from the year effect only model. The best-fit model for the lognormal process included fisher, as well as fishing year, area, quarter, pounds of uku, cumulative experience, and an interaction term for area and quarter (Table 8). The best-fit model for the lognormal process reduced deviance by 16% from the null model (intercept only), 2.5% from the model with only fisher, and only 2.2% from the model with only year and fisher. Including fisher in the model reduced total model deviance the most among predictors.

Recent time period: Fishing years 2003-2015

Not all predictors were included in model selection for the recent time period. Fisher was not included in model selection for the Bernoulli process in the recent time period due to convergence and memory errors. Wind data were available and were included in model selection. The best-fit model for the Bernoulli process included fishing year, area, quarter, wind speed, an interaction term for area and quarter, and pounds of uku (Table 8). The best-fit model for the Bernoulli process reduced deviance by 24% from the null model (intercept only) and 23% from a model with fishing year only. The best-fit model for the lognormal process included fisher, fishing year, area, quarter, pounds of uku, cumulative experience, and the linear term for wind speed. No interaction terms were selected, nor was the quadratic term for wind speed. The best-fit model for the lognormal process reduced deviance by 21% from the null model (intercept only), 5% from the model with only fisher, and 4.4% from the model with only year and fisher. The change in AIC, log-likelihood, and degrees of freedom for each predictor from both processes are provided in Table 8. As was the case in the early time period for the lognormal process, including fisher in the model reduced model deviance the most among predictors.

2.5.3.2. Model Diagnostics

Regression diagnostics were used to qualitatively check model assumptions. Model fit was assessed through visual comparison of residuals plotted against predicted values of the response variable and against values of the predictor variables. Pearson residuals were used for all models for the lognormal process. Quantile residuals were used for all models for the Bernoulli process as recommended by Dunn and Smythe (1996). Plots of the quantiles of the standardized residuals to the quantiles of a standard normal distribution were also used to assess assumptions of normality for models for the lognormal process.

Diagnostic residual plots and summary output of best-fit models show some deviation from assumptions about heteroscedasticity in models for the Bernoulli process but in general, models were appropriate. For the early time period, the histogram of quantile residuals indicated that distributional assumptions were not violated, and the plot of quantile residuals to the response variable showed some presence of heteroscedasticity (Figure 3.1). The smaller range in residuals at lower values of the response variable was attributed to fewer data points at these low probabilities. Plots of residuals against predictor variables indicated no patterning with individual variables. For the later time period, the histogram of quantile residuals did not indicate a violation of normality. With the exception of some patterning in pounds of uku, plots of quantile residuals against predictor variables showed no patterning (Figure 3.2). Altogether the diagnostic plots were not considered indicative of serious violations in model assumptions for the Bernoulli process.

Initial diagnostics of models for the lognormal process indicated skewed residuals for the predictors cumulative experience and pounds of uku, which was the reason the natural logarithm and square-root transformation on these parameters were used for both processes. The square root transformation was used for uku because there were instances with zero uku pounds. Residual plots with the transformed variables improved the patterning of the Pearson residuals for both overall predictions and parameter-specific residuals. These are shown for the early time period (Figure 3.3) and for the recent time period (Figure 3.4). There remained some skewness towards smaller response values as evident by the quantile-quantile plot (Figures 3.3 and 3.4). A Gamma distribution with log link was explored to determine if it would improve the residual patterns and add greater probability to the lower tails; however, the Gamma model was unable to converge with fisher as a random effect. Comparison between a fixed-effect only model (with fisher removed) under the Gamma distribution with an identical model under the lognormal distribution showed no improvement in residual patterns. Therefore, the lognormal distribution was kept for the best-fit models.

2.5.3.3. Index Calculation

Once the set of factors that minimized AIC were selected and diagnostics indicated model assumptions were not violated, an index of relative abundance was generated using the best-fit models for each time period. Predicted values of the response variable from each model were calculated using the predict function in R. The predicted values from the positive process were multiplied by the exponential of one-half the residual variance to correct for bias when back-transforming from ln(CPUE) to CPUE. The index I_T was then calculated as the product of the mean probability of catching a Deep 7 bottomfish in year T and the mean CPUE in year T calculated from positive catches of Deep 7 bottomfish. The variance of the index in year T was calculated as the variance of the product of two independent random variables, the Bernoulli (Δ_T) and lognormal process (φ_T), following Brodziak and Walsh (2013)

$$(1) \qquad \mathrm{Var}(I_T) = \mathrm{Var}(\Delta_T)\mathrm{Var}(\varphi_T) + \mathrm{Var}(\Delta_T)\mathrm{E}[\varphi_T]^2 + \mathrm{Var}(\varphi_T)\mathrm{E}[\Delta_T]^2.$$

The variance of the index was then divided by the sample size in each year for calculating the CVs around the mean index, which were then used in the calculation of relative CV for the stock assessment model. The yearly index and relative CV values are provided in Tables 9.1 and 9.2

2.6. Fishery-independent Survey

A new data source was used for this benchmark stock assessment. The PIFSC has developed a Bottomfish Fishery-Independent Survey in Hawaii to provide an independent estimate of Deep 7 biomass and worked with cooperative research fishers to conduct the survey (Richards et al. 2016). The survey consisted of two gears, research fishing and underwater stereo video cameras. Research fishing utilized fishing gears and techniques similar to those used in the Deep 7 fishery, so selectivity was expected to be similar. Fishing effort was identical among all fishing events, and the locations for fishing were pre-determined based on a stratified random sampling design. Underwater stereo video cameras were used to complement research fishing, and on occasion were used to focus sampling in sensitive areas and provide estimates on fish biomass that may be present in the water but not caught during research fishing. The first operational survey was conducted in the spring and fall of calendar year 2016, and covered the entirety of the MHI including inside BRFAs. An estimate for total biomass for Deep 7 bottomfish was calculated as the product of a relative biomass estimate and a scaling factor as 10.15 million pounds with a standard error of 1.96 million pounds. See Richards et al. (2016) for complete details on the fishery-independent survey and Ault et al. (2018) for the methods used to calculate the overall absolute biomass estimate.

3. ASSESSMENT MODEL

In this section, the production model assumptions and structure that were used to estimate biomass and fishing mortality for the Deep 7 bottomfish stock assessment for the MHI through 2015 are described. The same general stock assessment modeling approach as used in the 2011 benchmark assessment was used in the 2018 assessment. In particular, a Bayesian generalized surplus production model was fit to standardized CPUE time series in fishing years 1949-2015, using catch data from 1949-2016. The 2018 assessment model differed from the 2011 model structurally in that the 2018 assessment model also fit to a fishery-independent biomass estimate and included two time periods for the CPUE observation fitting. Both CPUE time periods were fit separately with different fishery catchabilities and observation error variances. The 2018 assessment also utilized new information on priors and error in unreported catches. A summary of assumed priors is found in Table 10.

3.1. Biomass Dynamics Model

The biomass dynamics model for the Deep 7 bottomfish complex in the MHI was formulated as a Bayesian state-space production model. It included explicit observation and process error terms that have been commonly used for fitting production models with relative abundance indices (Meyer and Millar 1999; McAllister et al. 2001; Punt 2003; Brodziak and Ishimura 2011). The exploitable biomass time series comprised the unobserved state variables. These annual biomasses were estimated by fitting model predictions to the observed relative abundance indices (i.e., CPUE), catches, and independent survey biomass estimate using observation error likelihood functions and prior distributions for the model parameters (θ). In particular, the observation error likelihood measured the discrepancy between observed and predicted CPUE, as well as between observed and predicted relative biomass, while the prior distributions represented the relative degree of belief about the probable values of model parameters. Assumption of this model included that production followed a specified functional form, the assessment applied to exploitable individuals, all exploitable individuals were mature and equally vulnerable to fishing, and that biomass was proportional to CPUE.

The process dynamics represented the temporal fluctuations in exploitable bottomfish biomass due to density-dependent population processes (e.g., growth) and fishery catches. The generalized production was a power function model with an annual time step. Under this 3-parameter model, exploitable biomass at the start of time period T (B_T) depended only on the previous time period's exploitable biomass (B_{T-1}), total catch (C_{T-1}), intrinsic growth rate (R), carrying capacity (K), and production shape parameter (M)

$$(2) \qquad B_T = B_{T-1} + R \cdot B_{T-1}\left(1 - \left(\frac{B_{T-1}}{K}\right)^M\right) - C_{T-1}.$$

The production shape parameter M determined where surplus production peaked as biomass varied as a fraction of carrying capacity (Figure 4). If M was less than unity ($0 < M < 1$), then surplus production peaked when biomass was below ½ of K (i.e., a right-skewed production curve). If M was greater than unity ($M > 1$), then biomass production was highest when biomass was above ½ of K (i.e., a left-skewed production curve). If M was identically unity ($M = 1$), then the production model was identical to a discrete-time Schaefer production model where maximum surplus production occurred when biomass was equal to ½ of K. In practice, estimates of M for Deep 7 biomass production in the MHI tended to be around $M = 2$ (Brodziak et al. 2011; 2014).

For computations, the production model in equation 2 was expressed in terms of the proportion (P) of carrying capacity in time period T (i.e., setting $P_T = B_T/K$) to improve the efficiency of the Markov Chain Monte Carlo (MCMC) algorithm to estimate parameters (e.g., Meyer and Millar 1999). Given this, the process dynamics for the temporal changes in the proportion of carrying capacity were

$$(3) \qquad P_T = P_{T-1} + RP_{T-1}\left(1 - P_{T-1}{}^M\right) - \frac{C_{T-1}}{K}$$

The values of exploitable biomass and harvest rate that maximized biomass production were relevant as biological reference points for fishery management and for estimating the MSY of the Deep 7 Hawaii bottomfish complex. Based on equation 3, the exploitable biomass that was required to produce MSY (B_{MSY}) was

$$(4) \qquad B_{MSY} = K(M+1)^{\frac{-1}{M}},$$

while the corresponding harvest rate that was required to produce MSY (H_{MSY}) was

$$(5) \qquad H_{MSY} = R\left(1 - \frac{1}{M+1}\right).$$

The estimate of MSY for the Deep 7 Hawaii bottomfish complex was

$$(6) \qquad MSY = R\left(1 - \frac{1}{M+1}\right) K(M+1)^{\frac{-1}{M}}.$$

As a result, the use of the production model led to direct estimates of MSY-based biological reference points for determining stock status of Deep 7 Hawaii bottomfish (WPRFMC, 2009). Note that the parameterization of the production function imposes a lower limit on the ratio of B_{MSY}/K, which approaches $1/e \approx 0.368$ as M approaches 0.

Process error was added to the deterministic process dynamics (Eq. 3). The process error model related the dynamics of exploitable biomass to natural variability in demographic and environmental processes affecting the bottomfish complex. The deterministic process dynamics were subject to natural variation due to fluctuations in life history parameters, trophic interactions, environmental conditions, and other factors. In this case, the process error represented the joint effects of many random multiplicative events which combined to form a multiplicative lognormal process under the Central Limit Theorem. As a result, the process error terms were set to be independent and lognormally distributed random variables.

Given the process errors, the state equations defined the stochastic process dynamics by relating the unobserved biomass states to the observed catches and the estimated population dynamics parameters. Given the multiplicative lognormal process errors, the state equations for the initial time period (T = 1) and subsequent periods (T > 1) were

$$(7) \qquad P_T = \begin{cases} P_1 & for\ T = 1 \\ \left(P_{T-1} + RP_{T-1}\left(1 - {P_{T-1}}^M\right) - \frac{C_{T-1}}{K}\right)\eta_T & for\ T > 1 \end{cases},$$

with $\eta_T = e^{\psi_T}$ where ψ_T were normal random variables with mean 0 and constant variance σ^2. These coupled equations set the prior distribution for the proportion of carrying capacity $p(P_T)$ in each time period $T > 1$, conditioned on the proportion in the previous period. The initial proportion of carrying capacity was assigned its own prior $p(P_1)$, which is described in section 3.1.2.

3.1.1. Observation Error Models

Two observation error models were applied to this current stock assessment: one for the CPUE indices and the other for the fishery-independent survey. The first observation error model related the observed fishery CPUE to the exploitable biomass of the bottomfish complex for each CPUE time series (i.e., 1949-2003 and 2003-2015). Although data from fishing year 1948 were used in CPUE standardization, the CPUE indices used within the stock assessment model started in fishing year 1949 to align with the starting year when complete catch data were available. It was assumed that the standardized fishery CPUE index ($I_{i,T}$) in year T in each time period i was proportional to biomass in year T with time period specific catchability coefficient q_i

$$(8) \qquad I_{i,T} = q_i B_T = q_i K P_T$$

Observation error was added to the deterministic index equation (Eq. 8). The observed CPUE dynamics were subject to natural sampling variation which was assumed to be lognormally distributed. Given the lognormal observation errors, the observation equations for the CPUE index for each year T in time period i were

$$(9) \qquad I_{i,T} = q_i K P_T \cdot \nu_{i,T}$$

with $\nu_{i,T} = e^{\varphi_{i,T}}$ where the $\varphi_{i,T}$ were identically distributed normal random variables with mean 0 and weighted variance $(W_{i,T} \cdot \tau_i)^2$ with standard deviation τ_i and weighting factor $W_{i,T}$. The weighting factors ($W_{i,T}$) reflected the relative uncertainty of the value of the CPUE index in year T for time period i and were scaled using the relative coefficient of variation (CV) of CPUE in each year (Brodziak and Ishimura 2011). Specifically, the annual weighting factors were calculated as the ratio of the CV of CPUE in each year T and the minimum observed CV of CPUE across years as $W_{i,T} = CV[CPUE_{i,T}]/\min(CV[CPUE_i])$. Minimum CVs were calculated separately for each CPUE index, and CVs were derived using the annual standard error of standardized CPUE and are provided in Tables 9.1 and 9.2.

The second observation error model related the relative biomass estimate from the fishery-independent survey to the estimated proportion of carrying capacity in the process equations (Eq. 3) scaled by survey catchability. The fishery-independent survey was estimated from two survey periods, spring and fall of calendar year 2016, which would correspond approximately to the beginning of fishery year 2017. The observed relative fishery-independent biomass estimate (S) was subject to natural sampling variation which was assumed to be lognormally distributed. The observation equation for the survey was

$$(10) \qquad S_{2017} = \frac{1}{q_S} P_{2017} K \cdot \gamma_s,$$

where q_S was a scalar to translate relative biomass to absolute biomass, and γ_S was a lognormal random variable with mean equal to 1.0 and variance ξ, which was the variance of the natural logarithm of the survey. The value for ξ was calculated based on the CV of the survey on the original scale as $\xi = \ln[CV_S^2 + 1]$. Attempts were made to use a prior distribution for the variance of the observation error model for the survey, as was done for observation errors for CPUE and for process error, but the estimate of the prior variance was highly uncertain. Therefore, a fixed value for the survey variance was used. The proportion of carrying capacity in 2017 (P_{2017}) was calculated based on advancing the process equations with process error (Eq. 7) from 2015 to 2017. Although P_{2017} was calculated to fit the available survey estimate for the beginning of fishing year 2017 (summer of calendar year 2016), the terminal year for the model estimates remained at fishing year 2015 because CPUE data was only available through 2015. Lastly, the scalar (q_S) was calculated based on the number of theoretical samples within a survey grid. This was calculated based on the estimated effective radius (*rad*) of a single sample scaled to the total area within a sampling grid (250,000 m^2), then multiplied by the number of sampling grids within the sampling domain (25,892) (see Ault et al. 2018) as

$$(11) \qquad q_S = \frac{250{,}000}{\pi \cdot rad^2} 25{,}892.$$

The effective radius of a single survey sample was assigned its own prior *p(rad)*, which is described in section 3.1.2.

The joint distribution of the error terms over the two CPUE standardization periods defined the observation error likelihood function $p(I_{i,T}|\theta)$ for the Deep 7 bottomfish CPUE indices through time. The distribution of the error term for the fishery-independent survey defined the observation error likelihood function $p(S|\theta)$ for the Deep 7 bottomfish biomass estimate.

3.1.2. Prior Distributions

A Bayesian estimation approach was used to estimate production model parameters. Prior distributions were employed to represent existing knowledge and beliefs about the likely values of model parameters. The carrying capacity parameter, the intrinsic growth rate parameter, the production shape parameter, the catchability parameters, the process and observation error variance parameters, the initial proportion of carrying capacity parameter, and the effective radius of a sample for the fishery-independent survey each had prior distributions. Unreported catch was also assigned a prior to account for uncertainty in its values. Unobserved biomass states expressed as the proportion of carrying capacity were included in the joint prior distribution and were conditioned on the parameter estimates and the previous proportion of carrying capacity and catch. A summary of assumed priors is found in Table 10.

Prior for Carrying Capacity

The prior distribution for carrying capacity *p(K)* was a moderately informative lognormal distribution with mean (μ_K) and variance (σ_K^2) parameters:

$$(12) \quad p(K) = \frac{1}{K\sigma_K\sqrt{2\pi}} exp\left(-\frac{(ln\ K-\mu_K)^2}{2\sigma_K{}^2}\right).$$

The prior mean for *K* was set based on the 2011 assessment benchmark in which the product of the *R* and *K* parameters was roughly 2.9 million pounds (Brodziak et al. 2011). Assuming that the product *R* and *K* would be similar for the 2018 assessment and observing that the mean of the intrinsic growth rate prior was μ_R = 0.1, the mean value of *K* was set to be μ_K = 2.9/0.1 = 29.0 million pounds. The variance parameter was set to achieve a CV for *K* of 50%. Overall, the prior mean of *K* was chosen to reflect the magnitude of exploitable biomass likely needed to support the estimated time series of fishery catches. The effect of the choice of prior mean on model results was assessed through sensitivity analyses.

Prior for Intrinsic Growth Rate

The prior distribution for intrinsic growth rate *p*(*R*) was a moderately informative lognormal distribution with mean (μ_R) and variance (σ_R^2) parameters:

$$(13) \quad p(R) = \frac{1}{R\sigma_R\sqrt{2\pi}} exp\left(-\frac{(ln\ R-\mu_R)^2}{2\sigma_R^2}\right).$$

The mean of the intrinsic growth rate parameter was set to be μ_R = 0.10. This mean value was chosen to reflect an expectation of low productivity for Deep 7 bottomfish. The specific choice of μ_R = 0.10 was based on the recommendations of Musick (1999), balancing a tradeoff between very low productivity (based on information about expected life span) and medium productivity (based on information about growth) for the primary Deep 7 species opakapaka (Andrews et al. 2012). The probable range of *R* values of 0.05-0.15 recommended by Musick (1999) was represented with a prior mean of *R* = 0.10 with a CV of 25%, which produces a 95% confidence interval that approximates the suggested range on the log scale. The effect of the choice of prior mean on model results was assessed through sensitivity analyses.

Prior for Production Shape Parameter

The prior distribution for the production function shape parameter *p(M)* was a moderately informative gamma distribution with rate parameter λ and shape parameter *k*:

$$p(M) = \frac{\lambda^k M^{k-1} exp\,(-\lambda M)}{\Gamma(k)}. \tag{14}$$

The values of the rate and shape parameters were set to $\lambda = k = 0.5$. This choice of parameters defined the mean of $p(M)$ to be $\mu_M = 1$, which corresponded to the value of *M* for the Schaefer production model. The choice of $k = 0.5$ also implied that the CV of the shape parameter prior was about 140%. In effect, the shape parameter prior was centered on the symmetric Schaefer production model as the default with sufficient flexibility to fit an asymmetrical production function. The effect of the choice of prior mean on model results was assessed through sensitivity analyses.

Prior for Catchability

The prior for bottomfish fishery catchability $p(q_i)$ in time period *i* was chosen to be an uninformative uniform distribution on the interval $[10^{-5}, 10^5]$. This diffuse prior was chosen to allow the data and model structure to completely determine the distribution of fishery catchability estimates. The effect of the choice of prior distribution on model results was assessed through sensitivity analyses.

Prior for Unreported Catch Error

An uninformative prior was used for the unreported catch error. The estimates of unreported catch each year were assumed to be observed with a prior error distribution $p(C_U)$ for fitting the production model to the observed fishery data. The catch error prior was chosen to propagate uncertainty in the estimation of unreported catch into the estimation of sustainable harvest rates and biomasses. It was assumed that the error in unreported catch was uniformly distributed about the point estimate with a ±40% error. For example, if the estimate of unreported catch was 100 thousand pounds in a given year, then the prior distribution of unreported catch error was uniformly distributed between 60 and 140 thousand pounds, i.e., $C_U \sim$ Uniform[60, 140]. The error value was taken from preliminary analyses of Hawaii Marine Recreational Fishery Survey (HMRFS) data (H. Ma, PIFSC, pers. comm.), and approximated the mean CV of yearly mean estimates of the percent of opakapaka, onaga, and ehu designated as not-sold from 2004-2016. The choice to use 40% also addressed reviewer comments from the past assessment that the value used (20%) was insufficient to characterize the expected variability in unreported catch estimates (Neilson 2015). The effect of the choice of prior interval on model results was assessed through sensitivity analyses.

Priors for Error Variances

Priors for the process error variance $p(\sigma^2)$ and observation error variance $p(\tau_i^2)$ for time period i were chosen to be moderately informative inverse-gamma distributions with rate parameter λ>0 and shape parameter k>0:

$$(15) \quad p(\sigma^2) = \frac{\lambda^k (\sigma^2)^{-k-1} exp\left(\frac{-\lambda}{\sigma^2}\right)}{\Gamma(k)}.$$

The inverse-gamma distribution is a useful choice for priors that describe model variances (Congdon, 2001). For the process error variance prior, the rate parameter was set to λ = 0.1 and the shape parameter was k = 0.2. For this choice of parameters, the expected value of the inverse-gamma distribution is not defined, and the mode for σ^2 denoted as MODE[σ^2] = 1/12 ≈ 0.083 provides an alternative measure of the central tendency of the distribution. For the observation error variance prior, the rate parameter was set to λ = 1, and the shape parameter was set to k = 0.2. The mode for τ_i^2 with this choice of parameters was MODE[τ_i^2] = 10/12 ≈ 0.83. The ratio of the modes of the observation error prior to the process error prior was MODE[τ_i^2]/MODE[σ^2] = 10. Thus, the central tendency of the observation error variance prior was assumed to be about tenfold greater than the process error variance prior. The choice of the process error prior matched the expected scaling of process errors for the state equation describing changes in the proportion of carrying capacity (Eq. 7), which was on the order of 0 to 1. Similarly, the choice of the observation error prior matched the expected scaling of observation errors for the observation equation (Eq. 9) describing the model fit to observed CPUE, which was on the order of 1 to 10. The effect of the choice of prior distribution on model results was assessed through sensitivity analyses.

Prior for Proportion of Carrying Capacity

A prior distribution for the initial (1949) biomass in proportion to carrying capacity, $p(P_{T=1})$, was determined through an empirical Bayes framework by examining the model fits to the CPUE data. The prior distribution for P_1 was a moderately informative lognormal distribution with mean (μ_P) and variance (σ_P^2) parameters:

$$(16) \quad p(P_1) = \frac{1}{P_1 \sigma_P \sqrt{2\pi}} exp\left(-\frac{(ln P_1 - \mu_P)^2}{2\sigma_P^2}\right).$$

The prior mean for P1 was determined in two steps. First, initial models were run with a prior mean for P1 ranging from 0.1 to 1, in increments of 0.1. The value of the prior mean for P1 that minimized the sum of the root-mean square error (RMSE) of the fit to the CPUE indices was determined to be μ_P = 0.5 (Figure 5). Second, the final prior mean for P1 was set to equal the posterior mean of P1 from the initial model with μ_P = 0.5, which was μ_P = 0.53. The coefficient of variation of the lognormal distribution of P1 was set to be 20% during initial exploration of P1. This choice of CV followed the approach from the last two stock assessments (Brodziak et al. 2011; 2014) and implied that probable values of P1 ranged from roughly 0.35 to 0.75. For the 2018 benchmark stock assessment, probable values for μ_P were within the range of 0.35-0.75 (Figure 5), so the CV of the lognormal distribution of P1 was kept at 20%. Prior mean values for the proportion of carrying capacity in other years T, where T > 1, were implicitly set following the prior values of PT-1, catch, and other parameters within the process equation (Eq. 3). The effect of the choice of prior mean on model results was assessed through sensitivity analyses.

Prior for effective radius of a single sample for the fishery-independent survey

Uncertainty in the scalar used to convert the relative biomass estimate from the fishery-independent survey to an absolute estimate (Eq. 11) was included in the model as a prior distribution on the effective radius of a single sample for the survey. The prior distribution for the radius $p(rad)$ was an informative lognormal distribution with mean (μ_{rad}) and variance (σ_{rad}^2) parameters:

$$(17) \quad p(rad) = \frac{1}{rad\,\sigma_{rad}\,\sqrt{2\pi}} exp\left(-\frac{(\ln rad - \mu_{rad})^2}{2\sigma_{rad}^2}\right).$$

The prior mean for *rad* was 20.2 m, based on the best estimate from Ault et al. (2018). A CV of 50% was selected so that the 95% confidence interval around the prior mean was approximately between 7.5 m to 41.6 m, which were the minimum and maximum values, respectively, for the effective radius of a single sample (Ault et al. 2018). As such, the prior distribution of *rad* was also constrained to be between 7.5 m and 41.6 m in the model.

3.1.3. Posterior Distribution

Independent samples from the joint posterior distribution of the production model parameters were numerically simulated to estimate model parameters and make inferences. In comparison to the 2011 benchmark stock assessment, the current stock assessment model included two time periods of CPUE observations, 1949-2003 and 2003-2015; two associated catchability parameters, q_1 and q_2, and observation error variances, τ_1^2 and τ_2^2; and an estimate of relative biomass from the fishery-independent survey. The joint posterior distribution of model parameters θ, $p(\theta|D)$, was proportional to the product of the priors of the unobservable states and the joint likelihood of the CPUE and survey data given catch, CPUE, and survey data (D):

$$(18) \quad \begin{aligned} p(\theta|D) \propto\ & p(K)p(R)p(M)p(q_1)p(q_2)p(\sigma^2)p(\tau_1^2)p(\tau_2^2)p(P_1)p\left(C_{U_T}\right)p(rad) \\ & \times\ p(S|\theta) \prod_{T=2}^{N+2} p(P_T|\theta) \prod_{T=1}^{N_1} p\left(I_{1,T}|\theta\right) \prod_{T=N_1}^{N} p\left(I_{2,T}|\theta\right), \end{aligned}$$

where N_1 was the number of data points in the first time period, and N was the number of data points over both time periods. We used a numerical MCMC simulation to generate sequences of estimates from the posterior distribution. Parameter estimation for multiparameter and nonlinear Bayesian models like the bottomfish production model is typically based on simulating a large number of independent samples from the posterior distribution (Gelman et al. 1995). In this case, MCMC simulation (Gilks et al. 1996) was applied to numerically generate samples from the posterior distribution. The WinBUGS software (Lunn et al. 2000; Spiegelhalter et al. 2003) and the R2WinBUGS package (Sturtz et al. 2005) in R version 3.2 (R Core Team 2016) were applied to program the production model, to set the initial conditions, to perform the MCMC calculations, to generate model diagnostics, to summarize the assessment model results, and to generate projections.

Production model results included the stock status of the Deep 7 bottomfish complex in the MHI relative to MSY-based reference points. The relevant Fishery Ecosystem Plan (WPRFMC 2009) indicates that the overfishing criterion is $F/F_{MSY} > 1$, and the overfished criterion is $B/B_{MSY} < (1-natM)$. Time series of the relative harvest rate (e.g., in 2015 the relative harvest rate was the ratio H_{2015}/H_{MSY}) and relative biomass (e.g., the ratio B_{2015}/B_{MSY}) were calculated for MHI Deep 7 bottomfish using the median (for harvest) and mean (for biomass) of the ratios from the joint posterior distribution of model parameters.

3.1.4. Convergence Diagnostics

MCMC simulations were conducted in an identical manner for the baseline assessment model as for all sensitivity analyses described below. Three chains of 500,000 samples were simulated from the posterior distribution in each model run. A range of initial conditions for R and K were used across the chains. The first 200,000 samples of each simulated chain were excluded from the estimation process to remove dependence of the MCMC chains on the initial conditions and to ensure stationarity of the remaining chain. Each chain was thinned by 20 to reduce autocorrelation, e.g., every twentieth sample from the posterior distribution was stored and used for inference. As a result, a total of 45,000 samples from the posterior distribution were available to summarize model results.

Convergence of the simulated MCMC chains to the posterior distribution was confirmed using the Geweke convergence diagnostic (Geweke 1992), the Gelman and Rubin diagnostic (Gelman and Rubin 1992; Brooks and Gelman 1998), and the Heidelberger and Welch stationarity and half-width diagnostics (Heidelberger and Welch 1992), as well as by monitoring the trace and assessing autocorrelation plots. These diagnostic tests were implemented in the R Language (R Core Team 2016) using the CODA software package (Best et al. 1996; Plummer et al. 2006). The set of convergence diagnostics were applied to key model parameters (intrinsic growth rate, carrying capacity, production function shape parameter, catchability coefficients, all MSY-parameters, error variances, and the effective sampling radius of a single sample for the fishery-independent survey) to verify convergence of the MCMC chains to the posterior distribution (e.g., Ntzoufras 2009).

3.1.5. Model Diagnostics

Residuals from the baseline model fit to CPUE by time period were used to measure the goodness of fit of the production model. These log-scale observation errors $\varepsilon_{i,T}$ of observed minus predicted Deep 7 bottomfish CPUE were

$$(19) \qquad \varepsilon_{i,T} = \ln\left(I_{i,T}\right) - \ln(q_i K P_T).$$

Nonrandom patterns in the CPUE residuals suggested that the observed CPUE may not have conformed to one or more model assumptions. The RMSE of the CPUE fit provided a simple diagnostic of the model goodness of fit with lower RMSE indicating a better fit. As the fishery-independent survey estimate was available for only one year, no time trend in model diagnostics could be done.

Comparisons of the prior distributions and estimated posterior distributions were made to show whether the observed catch and standardized CPUE data were informative for estimating model parameters. This comparison included the priors and posteriors for the following model parameters: carrying capacity, production shape, intrinsic growth rate, initial proportion of carrying capacity, observation error variances, process error variance, catchability, and effective radius of a sample for the fishery-independent survey. The posterior distributions for catch in 2015 and the derived quantities MSY, B_{MSY}, H_{MSY}, and P_{MSY} were also compared to the respective prior distributions.

3.2. Catch Projections for 2018-2022

Estimated posterior distributions of assessment model parameters for 1949-2015 were projected forward for fishing years 2016-2022 to estimate probable stock status (i.e., the probability of overfishing, P*) in 2018-2022 under alternative future reported catches. The projection results accounted for uncertainty in the distribution of estimates of model parameters, although process error in the biomass dynamics was not included. Projections were conducted for a set of alternative values of reported catches in 2018-2022 to estimate the probability of overfishing and other stock status measures as a function of catch.

The projections were conducted assuming each value for the future reported catch was constant through fishing years 2018-2022. Reported catch for 2017 was assumed to be equal to the average reported catch from 2014-2016 (i.e., 300,000 lbs.). Reported catch was scaled up to an estimate of total catch following the methods used in the estimation procedure for the surplus production model in 1949-2015. First, the unreported catch was calculated by multiplying reported catch by a non-reporting ratio generated from a uniform distribution with bounds equal to 0.6-1.4 multiplied by the average non-reporting ratio from 2011-2015 (i.e., 1.06). Second, the unreported catch was added to the reported catch for an estimate of total catch.

Projections were used to compute the 5-year constant commercial Deep 7 catch in the MHI for 2018-2022 that would produce probabilities of overfishing varying from 0% to 50% by 5% intervals. The effects of alternative annual reported catches were calculated using a numerical grid from 0 to 1000 thousand pounds of reported commercial catch of Deep 7 bottomfish over 5 years in steps of 2,000 pounds. The nearest grid value was used to approximate the catch corresponding to each 5% increment in probability.

3.3. Retrospective Analysis

A retrospective analysis was conducted to assess the effect of removing successive years of data off the end of the assessment time series on model estimates of biomass and harvest rate. The retrospective analysis was conducted starting with a model with the terminal year estimates (i.e., 2015) and excluding the fishery-independent survey. This was done because only a single year of data was available for the survey. Removing the survey would alter the structure of the model beyond simply removing data points from time series such as catch and CPUE. The retrospective analysis was conducted by successively deleting the catch and CPUE data for years 2015 through 2012 in one-year increments, refitting the assessment model, and summarizing the results. The degree of retrospective pattern compared to the base case was assessed using Mohn's rho (ρ; Mohn 1999):

$$\rho = \sum_y \left[X_{(y1:y),y} - X_{(y1:y2),y}\right] / X_{(y1:y),y}, \tag{20}$$

where y_1 = 1949 and y_2 = 2015 span the full data set, X indicates either exploitable biomass or harvest rate, and y indicates the terminal year for each retrospective refitting (i.e., y from 2011 to 2015).

3.4. Sensitivity Analyses

A suite of sensitivity analyses was conducted to evaluate how the baseline model results would be affected if different assumptions were made regarding unreported catch ratios, model structure, or prior distributions. Scenarios for sensitivity analyses are described below and in Table 11.

Sensitivity to alternative prior distribution for carrying capacity (*K*)

The sensitivity of baseline model results to the prior mean for carrying capacity was evaluated by fitting the model using different prior means for K. For these analyses, the prior mean for K was changed ±25% and ±50%, which corresponded to values μ_K = 14.5 million pounds (50% decrease in baseline prior mean), μ_K = 21.75 million pounds (25% decrease in baseline prior mean), μ_K = 36.25 million pounds (25% increase in baseline prior mean), and μ_K = 43.5 million pounds (50% increase in baseline prior mean). This sensitivity analysis addressed whether the choice of a prior mean had a strong influence on model estimated biomass and harvest rate.

Sensitivity to alternative prior distribution for intrinsic growth rate (*R*)

The sensitivity of baseline model results to the prior mean for intrinsic growth rate was also evaluated by fitting the model using different prior means for R. The prior mean for R was reduced by 50% to μ_R= 0.05, to represent the lower end of a low productivity stock (or upper end of a very low productivity stock), and was increased by 50% to μ_R= 0.15, to represent the higher end of a low productivity stock. Additionally, the prior mean for R was increased by 150% to μ_R= 0.25 to reflect a medium productivity classification as described by Musick (1999). This sensitivity analysis addressed whether the choice of a baseline prior mean for R (μ_R= 0.10) had a strong influence on model results.

Sensitivity to alternative prior distribution for production model shape parameter (*M*)

The sensitivity of baseline model results to the prior mean for the production model shape parameter M was evaluated. This sensitivity analysis showed the effects on biomass and harvest rate estimates by varying the rate parameter λ such that the prior mean for M, which equaled $\mu_M = k/\lambda$, was changed from μ_M = 0.5 to μ_M = 1.5, in increments of 0.25. This corresponded to a change in the mean of the distribution of ±25% and ±50%. The values of λ to achieve this were λ = 1, 2/3, 1, 2/5, and 1/3. Note that the value for the shape parameter k was 0.5.

Sensitivity to alternative prior distribution for proportion of carrying capacity (*P*$_1$)

The sensitivity of baseline model results to the prior mean for the initial proportion of carrying capacity in 1949 was evaluated by fitting the model using different prior means for P_1. As with the analyses for K, the prior mean for the initial proportion of carrying capacity was changed by ±25% and ±50% to μ_P = 0.265 (50% decrease), μ_P = 0.3975 (25% decrease), μ_P = 0.6625 (25%

increase), and μ_P = 0.795 (50% increase). This sensitivity analysis addressed whether the choice of a prior mean for P_1 had a strong influence on model results.

Sensitivity to alternative prior distribution for observation error variances (τ_i^2)

The sensitivity of baseline model results to the prior mode for the observation error variances was evaluated. This sensitivity analysis showed the effects on biomass and harvest rate estimates by changing the rate parameter λ such that the prior mode for τ_i^2, which equaled $\lambda/(k+1)$, ranged over five orders of magnitude from 0.00833 to 83.3, in multiples of 10. Note that the value for the shape parameter k was 0.2.

Sensitivity to alternative prior distribution for process error variance (σ^2)

The sensitivity of baseline model results to the prior mode for the observation error variance was evaluated. This sensitivity analysis showed the effects on biomass and harvest rate estimates by changing the rate parameter λ such that the prior mode for σ^2, which equaled $\lambda/(k+1)$, ranged over four orders of magnitude from 0.000833 to 8.3, in multiples of 10. Note that the value for the shape parameter k was 0.2.

Sensitivity to alternative unreported catch ratios (*U*)

The sensitivity of baseline model results to the assumed values of unreported catch ratios (U) was evaluated. This is separate from the previous sensitivity on unreported catch error. Four alternative scenarios for the ratio of unreported catch were considered (Figure 6). Total catch was calculated as the sum of reported catch (C_R) and unreported catch (C_U), which was calculated as $U*C_R$.

Alternative catch scenario I – The first alternative scenario for unreported catch ratios was identical to catch scenario I from the previous benchmark stock assessment (Brodziak et al. 2011), which was based on 5-year averages of the values reported in Zeller et al. (2008). Zeller et al. (2008) provided a single estimate and so under catch scenario I, the ratios of unreported catch were the same across all species. The average ratio of unreported catch to reported catch in the last five years (2011-2015) under alternative catch scenario I was 2.5, which represented an expectation of high unreported catch in all years consistent for all species.

Alternative catch scenario II – The second alternative scenario for unreported catch ratios was similar to the baseline catch scenario but differed in the value of the estimates beginning in 1998. The baseline catch scenario averaged the species-specific unreported catch ratios reported by Martell et al. (2011) for years 2004 and 2005, with the species-specific ratios reported by Lamson et al. (2007). The resulting value was applied to years 2000-2015. However, given that the preliminary analyses of HMRFS data suggested unreported catch ratios in 2004-2015 were more similar in magnitude to the ratios reported in 2005 by Lamson et al. (2007), ratios from only Lamson et al. (2007) were applied for 2000-2015 prior to taking 5-year averages. The average ratio of unreported catch to reported catch in the last five years (2011-2015) under alternative catch scenario II was 0.22, which represented an expectation of low unreported catch in recent years.

Alternative catch scenario III – The third alternative scenario for unreported catch ratios was based on the recommendation from the review panel for the 2014 stock assessment to maintain a constant unreported ratio through time (Nielsen 2015). Estimates from sources of species specific ratios were averaged within studies where applicable, then averaged across studies. Hence, we averaged the 2005 estimates from Lamson et al. (2007), the 1990 estimate from Hamm and Lumm (1992), and the average of the 2004 and 2005 estimates from Martell et al. (2011) to calculate an average unreported catch ratio by species over time. The average ratio of unreported catch to reported catch in the last five years (2011-2015) under alternative catch scenario III was 2.27, which represented an expectation of high unreported catch in all years. Note that this scenario was similar in value to alternative catch scenario I but incorporated additional information sources.

Alternative catch scenario IV – The fourth alternative scenario for unreported catch ratios represented an expectation of no unreported catch. The ratio of unreported catch for all species in all years was set to zero. This scenario evaluated the effect of removing unreported catch on baseline model results.

Sensitivity to alternative error distributions for unreported catch

The sensitivity of baseline model results to the assumed amount of error in the estimation of unreported catch was evaluated. The effects of removing unreported catch error and by decreasing and increasing the range of unreported catch error by 50% were evaluated by changing the width of the interval of the uniform distribution of catch errors to [0.9999, 1.0001], [0.80, 1.20], and [0.4, 1.6] from the baseline interval of [0.60, 1.40]. The sensitivity of model results to directional biases in the unreported catch error was also evaluated. The effects of a 25% decrease in average catch error was assessed by changing the interval of catch errors to [0.45, 1.25], while the effects of a 25% increase in average catch error were evaluated by setting the catch error interval to be [0.75, 1.55].

Sensitivity to alternative parameterization of catchability (q_i)

The sensitivity of baseline model results to the assumption of constant catchability was evaluated. Catchabilities ($q_{1,T1}$, $q_{2,T2}$) were assumed to follow a random-walk process where for $T1$=1949 and $T2$=2003, the natural logarithm of $q_{i,T}$ was an uninformative uniform distribution on the interval [$\ln(10^{-5})$, $\ln(10^{5})$]. For $T1 > 1949$ and $T2 > 2003$, the natural logarithm of $q_{i,T}$ was a moderately informative normal distribution with mean ($\mu_{lnqt} = \ln(q_{i,T-1})$) and variance set to produce a CV of 0.5. This analysis addressed whether baseline assumptions of the surplus production model that biomass was proportional to catchability had a strong influence on results.

Sensitivity to choice of uniform prior for observation and process error variances

The sensitivity of baseline model results to the choice of probability distribution for the prior of observation and process error variances was evaluated. This sensitivity analysis showed the effects of choosing a non-informative uniform prior on the interval [0,100] for the standard deviation of process and observation errors, as opposed to an inverse-gamma prior on the error variances, as recommended by Gelman (2006).

Sensitivity to inclusion of fishery-independent survey biomass estimate

The sensitivity of baseline model results to the inclusion of the fishery-independent survey biomass estimate was evaluated. Including the fishery-independent survey increased the time period for the process equations two years beyond the terminal year, from 2015 to 2017. Therefore, the sensitivity of model result to removing the survey was done for both removing 2017 and removing 2016 and 2017. The results for both sensitivities were very similar and so only results when excluding 2016 and 2017 were presented. This sensitivity analysis showed the effects of including the fishery-independent survey on the estimation of model parameters.

Sensitivity to uncertainty in the effective radius for the fishery-independent survey

The sensitivity of baseline model results to uncertainty in the absolute biomass estimate from the fishery-independent survey was also evaluated. Uncertainty for this sensitivity was evaluated by changing the CV for the prior distribution on the effective radius of a sample for the fishery-independent survey. The CV of the prior on *rad* was reduced to 0.01, effectively placing a point prior on the absolute biomass estimate as provided in Ault et al. (2018).

4. COMPARISON WITH A SINGLE SPECIES DATA AND MODEL

Data were available to produce a single species surplus-production model to compare to the assessment for the Deep 7 complex. Catch, CPUE, and survey data were revised to focus solely on opakapaka and used within the same modeling method as for the Deep 7 model described in this report. Opakapaka was chosen for modeling because it is numerically the most abundant species in the complex and has historically made up the greatest proportion of the catch of the Deep 7 complex. Results for data filtering and standardization for the opakapaka model are provided in the appendices. Surplus production model comparisons to the Deep 7 assessment model are presented in the results (section 5.6).

4.1. Catch, CPUE, and Survey Data for Single Species Modeling

Species-specific reported (Table 2) and unreported catch (Table 4) data for opakapaka were already calculated for the Deep 7 stock assessment model and were used for the single species model. Similarly, an estimate for total biomass as the product of a relative biomass estimate and a scaling constant for opakapaka was provided in Ault et al. (2018) and was 6.87 million pounds with a standard error of 3.14 million pounds.

Generating a CPUE index for opakapaka required additional analyses from what was done for the Deep 7 index. Fishers do not report targeted species when reporting catch data in the fisher reported database. Previous filtering, described in section 2.5, represented the best information available in determining targeted Deep 7 bottomfish fishing, but distinguishing targeting among the Deep 7 species required additional analysis. The method of Stephens and MacCall (2004) was used to subset fishing events that were likely targeting opakapaka from the final event-based dataset for Deep 7, which was used to calculate CPUE indices for opakapaka only. Stephens and MacCall (2004) used logistic regression of the catch composition (presence/absence) of non-target species to predict probability of catching the target species. In our application, opakapaka was defined as the target species, and species representing the highest 99% of cumulative catch were defined as non-target species. Of the 155 species in the final filtered dataset, only 38 represented the highest 99% of the cumulative catch, and thus used in the analysis.

Following the formulation in Stephens and MacCall (2004), Y_j was defined as the categorical variable describing the presence or absence of opakapaka in fishing event *j* such that $Y_j = 1$ if fishing event *j* caught any pounds of opakapaka, and $Y_j = 0$ if no opakapaka were caught. Similarly, X_{ij} were defined as categorical variables describing the presence or absence of non-target species *i* in fishing event *j*, such that $X_{ij} = 1$ if fishing event *j* caught any pounds of species *i*, and $X_{ij} = 0$ if fishing event *j* caught 0 pounds of species *i*. A logistic regression with a logit link function with dependent variable Y_j and independent variables X_{ij} was done using the glm function in the R statistical package, version 3.2 (R Core Team 2016) to predict the probability that each fishing event targeted opakapaka. Model selection of significant covariates was done using backward model selection. Five of the 38 species were insignificant and removed from the final model.

The approach used by Stephens and MacCall (2004) was applied to determine the critical value at which to consider fishing as targeting opakapaka. The value that minimized the number of incorrect predictions (0.51), both incorrectly assigning a fishing event to target opakapaka when it did not, and when incorrectly assigning a fishing event to not target opakapaka when it did, was chosen as the critical value. Every fishing event with predicted probability of catching opakapaka greater than or equal to 0.51 (58% of fishing events) was assumed to have targeted opakapaka and was used in the single species CPUE standardization. The total pounds of opakapaka caught in these fishing events was then calculated and divided by the corresponding amount of effort (days fished from 1948-September 2002, and hour fished from October 2002 – 2015) to calculate two CPUE time series, as was done with the dataset for the Deep 7 complex. The final event-based dataset for use in the opakapaka only CPUE standardization consisted of 120,650 data points.

4.2. CPUE Standardization for Single Species Modeling

The same methods used to calculate the standardized index of CPUE for the Deep 7 bottomfish complex described in section 2.5.3 were also used to calculate the standardized index of opakapaka CPUE. The change in AIC, log-likelihood, and degrees of freedom for each predictor from the Bernoulli and lognormal processes for both time periods are provided in the Appendix (Table A1).

The best-fit opakapaka model for the early time period varied slightly from the best-fit model for the Deep 7 bottomfish complex. The difference for the Bernoulli process was that pounds of uku was selected and the interaction term for area and quarter was not selected for the best fit opakapaka model. The difference for the lognormal process was that pounds of uku was not selected for the best fit opakapaka model. The best-fit opakapaka model for the Bernoulli process reduced deviance by 13% from the null model (intercept only) and 11% from a model with fishing year only. The best-fit model for the lognormal process reduced deviance by 14% from the null model (intercept only), 3% from the model with fisher only, and 2.3% from the model with year and fisher only.

The best-fit opakapaka model for the recent time period also varied slightly from the best-fit model for the Deep 7 bottomfish complex. Cumulative experience was not selected for the Bernoulli process in the opakapaka model but was for the Deep 7 model. The same variables were selected for the lognormal process in the opakapaka model as were selected for the Deep 7 model. The best-fit opakapaka model for the Bernoulli process reduced deviance by 19.9% from both the null model (intercept only), and 19.5% from a model with fishing year only. The best-fit model for the lognormal process reduced deviance by 17% from the null model (intercept only), 6% from the model with fisher only, and 5% from the model with year and fisher only.

Regression diagnostics for the best-fit opakapaka models were comparable to those for the best fit Deep 7 models (Figures A1.1-A1.4). The diagnostic plots were not considered to indicate serious violations in model assumptions for the Bernoulli and lognormal processes for either time period. The resulting index for the early and recent time periods was then calculated along with relative CV values (Tables A2.1 and A2.2). As with the Deep 7 complex surplus production model, data from fishing year 1948 were used in CPUE standardization. However, the CPUE index used in the stock assessment model started in fishing year 1949 to align with the starting year when complete catch data were available.

4.3. Assessment Model for Single Species Modeling

Parameter values were changed within the Bayesian surplus production model to reflect the species being assessed. Prior distributions for carrying capacity and for initial proportion of carrying capacity were modified to relate to values for opakapaka. The number of iterations and the length of the burn-in period were also reanalyzed. The prior mean for carrying capacity was reduced by 67.7% based on the ratio of estimated opakapaka biomass to estimated Deep 7 biomass from the survey (Ault et al. 2018). Consequently, the prior mean for carrying capacity was set to μ_K = 19.6. Similarly, the approach to estimate the prior mean for P_1 was redone using opakapaka data. The model with prior mean of P_1 equal to 0.6 minimized the RMSE of the CPUE indices (Figure A2), and the posterior estimate from this model was 0.61. The curvature of the RMSE curve across initial values for μ_P was similar to that from the Deep 7 model; therefore the CV for P_1 was kept at 20%. A total of 500,000 iterations were run for each of three chains. The first 200,000 samples were removed as a burn-in period in each chain, and every 20th sample was kept, resulting in a total of 45,000 samples for model inference.

5. RESULTS

In this section, production model outcomes for the Deep 7 complex are described. The results include: convergence and model diagnostics, exploitable biomass and fishing mortality estimates to assess stock status, retrospective analysis, sensitivity analyses, and projection analyses. A summary of the opakapaka production model results is also described.

5.1. Diagnostics

5.1.1. Convergence Diagnostics

Convergence diagnostics indicated that the MCMC simulation to estimate the posterior distribution of production model parameters converged (Table 12). In particular, none of the

Geweke diagnostics were greater than 2 standard deviations, indicating that the burn-in period removed any initial nonstationarity from the MCMC chains. The Gelman and Rubin potential scale reduction factors were equal to unity, confirming convergence to the posterior distribution. The Heidelberger and Welch stationarity and half-width diagnostic tests were also passed by all of the parameters at a confidence level of $\alpha = 0.05$ and ratio of halfwidth to sample mean of 0.1. The stationarity test passed for the intrinsic growth rate in the first chain only if the first 10% of samples was removed. This was not considered a serious violation and all samples were used for summarizing model results. Autocorrelation was low for the majority of parameters. The highest lag1 autocorrelation was 0.66 for *K*; however, the lag-5 value was reduced to 0.17. Visual inspection of trace plots for monitored parameters did not reveal convergence issues. Overall, the convergence diagnostics indicated convergence of the 2018 base case assessment model.

5.1.2. Model Diagnostics

Model residuals indicated that the production model provided a good fit to the standardized CPUE observations during both the 1949-2003 (Figures 7 and 8) and 2003-2015 (Figures 9 and 10) time periods. Model residuals did not exhibit significant trends in either time period, but did have non-constant variance for both time periods and were non-normal for the 1949-2003 time period. Large residuals toward the beginning of the 1949-2003 time period resulted in non-normality (Figure 8) and a large residual at the end of the 2003-2015 time period resulted in non-constant variance (Figures 10). For the 1949-2003 time period, residuals were normal ($p = 0.38$) when the three largest residuals were excluded from diagnostic tests. Variance in the residuals was constant ($p = 0.53$) for the 2003-2015 time period when the residual from 2015 was excluded from diagnostic tests.

Comparisons of assumed prior distributions and estimated posterior distributions showed that the priors were more informative for some model parameters than others (Table 10; Figure 11). The posterior mean (27.55) for the carrying capacity parameter was about 5% less than the prior mean (29; Table 10). The posterior mean (0.111) for intrinsic growth rate was 11% greater than the prior mean (0.10; Table 10). The posterior mean (0.56) for the initial proportion of carrying capacity was 5% greater than the prior mean (0.53; Table 10). The similarity between prior and posterior means for carrying capacity, intrinsic growth rate, and initial proportion of carrying capacity, all moderately informative priors, suggested that the priors were more informative for these parameters. The posteriors for catch matched the priors for all years. The results shown for 2015 (Figure 12) indicate uncertainty was accounted for while mean unreported catch was unchanged from input unreported catch.

The priors appeared to be slightly less informative when estimating other parameters, including the shape parameter, which varied from the prior mean by 226% (Table 10; Figure 11). Posterior distributions for catchability, process error, and observation errors were substantially different from the prior distributions, which were chosen to be uninformative (Table 10; Figure 11). The priors were less informative for estimating MSY and related parameters B_{MSY}, H_{MSY}, and P_{MSY} (Figure 13), although the prior distributions were not formally selected but instead were derived from the priors for *R*, *K*, and *M*. The posterior means for MSY (1048 thousand pounds) and H_{MSY} (0.069) were 94% and 103% greater than the prior means. The posterior means for B_{MSY} (15.42 million pounds) and P_{MSY} (0.57) were 13% and 5% greater than the prior means, respectively (Figure 13). Note that the posterior distribution for P_{MSY} had very little mass near 0.37, suggesting that the bounding on P_{MSY} at 1/*e*, as imposed by the parameterization of the production model (Eq. 3), was not an issue. Overall, the observed data appeared to contain enough information to adjust the implied prior estimates for MSY and related quantities.

Parameter correlations did not indicate a problem in model estimation (Table 13 and Figure 14). Correlations were highest (up to 0.68 in magnitude) among carrying capacity, parameters affecting the scaling of relative indices (q_1 and q_2), and the fishery-independent survey (*rad*). Other correlations were less than 0.35 in magnitude.

5.2. Stock Status

Production model estimates indicated that H_{MSY} was 6.9% and that B_{MSY} was 15.4 million pounds of exploitable Deep 7 bottomfish biomass with an associated MSY of 1.048 million pounds (Table 10).

Mean estimates of the MSY-based biological reference points of maximum sustainable yield for the reported catch (MSY ± one standard error, expressed in units of reported catch), the harvest rate to produce MSY (H_{MSY} ± one standard error), and the exploitable biomass to produce MSY (B_{MSY} ± one standard error) were:

1) MSY = 509 thousand pounds (± 233 thousand pounds) for reported catch
2) H_{MSY} = 6.9% (± 2.6%)
3) B_{MSY} = 15.4 million pounds (± 4.9 million pounds).

Deep 7 bottomfish biomass exhibited a long-term decline from high values in the 1960s to lower values around B_{MSY} in the mid-1970s (Table 14 and Figure 15). Exploitable biomass fluctuated just above B_{MSY} from the late 1970s through the early 1980s, exhibited a small peak during the late 1980s, and steadily increased from 1991 through 2015 (Figure 15). Harvest rates were relatively low from the mid-1950s through 1970, increased to a peak in 1989, steadily declined to the mid-2000s, and have increased slightly since (Table 14 and Figure 16). Harvest rates were greater than H_{MSY} in the late-1980s.

Baseline model results for the MHI Deep 7 bottomfish complex indicated that the stock was not overfished in 2015 (B_{2015}/B_{MSY}=1.31, Table 14; Figures 15 and 17) and that the stock complex was not experiencing overfishing (H_{2015}/H_{MSY}=0.51, Table 14; Figures 16 and 17). In fishing year 2015, there was a 16% probability that exploitable biomass exceeded the limit of 0.844*B_{MSY} and a 17% chance that the harvest rate exceeded H_{MSY}. As a result, the Deep 7 bottomfish stock complex was categorized as not overfished and not experiencing overfishing in 2015.

5.3. Stock Projections

The constant 5-year catch projection scenarios showed the distribution of outcomes in probability of overfishing, biomass, harvest rates, and probability of depletion of Deep 7 bottomfish that would likely occur under alternative reported catch scenarios in the MHI during 2018-2022 (Tables 15 and 16; Figures 18-21). Projections indicated that the Deep 7 reported catch in 2015 that would produce approximately 50% chance of overfishing for each year from 2018 through 2022 was between 558 to 604 thousand pounds (Table 15; Figure 18). For comparison, the smallest Deep 7 reported catch that would lead to a roughly 40% chance of overfishing was 518 thousand pounds through 2018, 508 thousand pounds through 2019, 500 thousand pounds through 2020, 492 thousand pounds through 2021 and 490 thousand pounds through 2022 (Table 15; Figure 18). The reported catch to achieve a lower risk of overfishing (P*=25%) from 2018 through 2022 varied across years from 378 to 382 thousand pounds (Tables 15 and 16).

5.4. Retrospective Analysis

Retrospective analysis of the estimated biomass and harvest rates from the assessment model indicated that model outputs did not exhibit substantial retrospective patterns in biomass (Figure 22.1) or harvest rate (Figure 22.2). The retrospective pattern for estimates of biomass was slightly positive, with successive terminal biomass estimates overestimating by about 7% as new years of data were added (Mohn's rho = 0.336; Figure 22.1). Excluding the biomass estimate from the fishery-independent survey for the retrospective analysis scaled biomass upward compared to the base case model. The corresponding pattern for harvest rates was slightly negative, representing an underestimate in harvest rate by about 4% as new years of data were added (Mohn's rho = 0.203; Figure 22.2).

5.5. Sensitivity Analyses

Sensitivity of model results varied depending on which parameters or model assumptions were being assessed, and which model result was being compared. Model results were sensitive to assumed prior distributions for the parameters R, K, M, P_1, *rad*, and prior modes for process and observation error; alterative unreported catch ratio scenarios; alternative uniform prior distributions for process and observation errors; and time-varying catchability. In particular, the status for the overfishing reference point (H_{2015}/H_{MSY}) changed compared to the base case model under sensitivities for low R and very high prior modes for process and observation error. Model results were not sensitive to changes in unreported catch error, nor were they very sensitive to the removal of the fishery-independent survey estimate. Details on each sensitivity are provided below and summarized in Table 17.

Sensitivity to alternative prior distribution for carrying capacity (*K*)

Model results were sensitive to the assumed prior mean for carrying capacity (Figures 23.1 and 23.2). The sensitivity analysis indicated that estimates of exploitable biomass were scaled with the prior mean for K (Figure 23.1). Assuming a higher prior mean for K resulted in greater estimates of biomass (Figure 23.1) and reduced harvest rate estimates (Figure 23.2). When the mean prior for K changed by 25% and 50%, the posterior estimate for the parameter K changed by about 13% and 27%, respectively (Table 17). The posterior estimates for intrinsic growth rate (R) were inversely related to estimates of K (Table 17). When the prior for K was reduced, estimates for H_{MSY} increased and estimates for B_{MSY} declined (Table 17). Subsequently, the probability of overfishing and the probability of being overfished in 2015 declined in scenarios when the prior mean for K was reduced and increased in scenarios when the prior for K was increased (Table 17).

Sensitivity to alternative prior distribution for intrinsic growth rate (*R*)

Model results were sensitive to assumed mean prior values for intrinsic growth rate (Figures 24.1 and 24.2). Assuming a higher prior mean for *R* resulted in reduced estimates of biomass (Figure 24.1) and increased harvest rate estimates (Figure 24.2). When the mean prior for *R* changed by -50%, 50%, and 150%, the posterior estimate for the parameter *R* also changed by about -50%, 50%, and 150%, respectively (Table 17). When the prior mean for *R* was increased, estimates for B_{MSY} declined and estimates for H_{MSY} increased, leading to reduced probabilities of overfishing and reduced probabilities of the stock being overfished in 2015 (Table 17). When the prior mean for R was decreased by 50%, which was the bound between the low and very low productivity categories presented in Musick (1999), the probability of overfishing and being overfished in 2015 increased 227% and by 109%, respectively, and the status for the overfishing reference point changed from that of the base case scenario (Table 17).

Sensitivity to alternative prior distribution for production model shape parameter (*M*)

Model results were less sensitive to the assumed mean prior for the shape parameter compared to the mean priors for other parameters (Figures 25.1 and 25.2). As assumed prior mean for *M* increased, estimates of exploitable biomass declined (Figure 25.1), and estimates of harvest rate increased minimally (Figure 25.2). When the mean prior for *M* changed by 25%, the posterior estimate for the parameter *M* changed by about 10 to 15% (Table 17). Increasing the prior mean by 50% led to an increase in the posterior estimate of about 20%, whereas a 50% decrease in the prior mean resulted in about a 35% decrease in the posterior estimate (Table 17). Changing the prior mean by 25% and 50% resulted in relatively small changes to estimates of other model parameters (Table 17).

Sensitivity to alternative prior distribution for initial proportion of carrying capacity (P_1)

Model results were sensitive to the assumed prior mean for initial proportion of carrying capacity. Estimates of biomass were positively related to the assumed prior mean for P_1, whereas harvest rates were inversely related to the assumed prior mean for P_1 (Figures 26.1 and 26.2). Estimates of *K* were inversely related to prior mean values for P_1 (Table 17). As the mean prior for P_1 changed by 25%, the posterior estimate for the parameter P_1 changed by about 20% (Table 17). Increasing the prior mean by 50% led to an increase in the posterior estimate increased by about 38%, whereas a 50% decrease in the prior mean resulted in about a 46% decrease in the posterior estimate (Table 17). As the prior mean for P_1 increased, the estimated probabilities of overfishing and the stock being overfished in 2015 declined at most 34%. As the prior mean for P_1 decreased, the estimated probabilities of overfishing and the stock being overfished in 2015 increased by more than 122% (Table 17).

Sensitivity to alternative prior distribution for observation error variances (τ_i^2)

Model results were sensitive to the assumed prior mode for observation error variances (Table 17; Figures 27.1 and 27.2). The prior mean for τ_i^2 varied nearly 100-fold; however, the largest change for model parameters *R*, *K*, and *M* was never greater than 27% (Table 17). Most of the effect of changing the prior for observation errors was in the probability of overfishing and the stock being overfishing in 2015, which increased 169% and 200%, respectively, when the prior mean was increased 100-fold (Table 17). Under a 100-fold increase to the mode of observation error, the status of the overfished reference point changed compared to the base case model (Table 17). Estimates of biomass increased by about 65% towards the center of the time series for the scenario with a 100-fold increase in τ_i^2 but were more similar towards the end of the time series (Figure 27.1).

Sensitivity to alternative prior distribution for process error variance (σ^2)

Model results were sensitive to changes in the assumed prior mean for σ^2 when varied by a factor of 0.01, 0.1, or 10 (Table 17; Figures 28.1 and 28.2). However, posterior estimates for some parameters were sensitive when the prior for σ^2 was increased by a factor of 100 (Table 17). Specifically, increasing the prior 100-fold resulted in a 48% reduction in the posterior mean estimate of M and a 232% increase in the estimated probability of overfishing in 2015. This resulted in a change in overfishing status compared to the base case model (Table 17). When increasing σ^2 100-fold, sensitivity of annual estimates of biomass to increases in σ^2 were most pronounced towards the early part of the time series (Figure 28.1), and annual estimates of harvest rate towards the end of the time series were sensitive (Figure 28.2).

Sensitivity to use of alternative unreported catch ratios (*U*)

Model results were sensitive to Catch Scenarios. Model parameters were more sensitive to Catch Scenarios I and IV than II and III (Figures 29.1 and 29.2). Estimates of R, K, M, and P_1 changed by 0-5% at most for Catch Scenarios II and III compared to 33% for scenarios I and IV (Table 17). Estimates of derived quantities (MSY, B_{MSY}, and H_{MSY}) changed more for Catch Scenarios I and IV than for scenarios II and III. Estimates changed by up to 29% for Catch Scenario I and 46% for scenario IV compared to no more than 10% for scenarios II and III. This appeared reasonable given that Catch Scenarios I (highest unreported catch) and IV (no unreported catch) were most extreme compared to the baseline scenario. However, estimates of biomass and harvest rate in 2015 changed comparably in magnitude among all Catch Scenarios. Estimates for the probability of being overfished and probability of overfishing in 2015 were also similar in magnitude among all Catch Scenarios, although for scenario II probabilities declined, but increased for other scenarios (Table 17).

Sensitivity to alternative error distributions for unreported catch ratio

Model results were not sensitive to the range of uncertainty in estimates of unreported catch (Table 17; Figures 30.1 and 30.2). Increasing the bounds on the uniform distribution to [0.4, 1.6] and decreasing them to [0.9999, 1.0001] had little effect on parameter estimates and derived quantities (Table 17). Similarly, parameter estimates were only marginally different after directional increases and decreases in average catch error of 25% (Table 17).

Sensitivity to alternative parameterization of catchability (q_i)

Model results were sensitive to the inclusion of time-varying catchability as a random walk. The temporal pattern in biomass estimates did not match the CPUE pattern as closely as for the base case model (Figure 31.1), but because of time-varying catchability, improved the fit to CPUE data. The greatest changes in parameter estimates occurred for estimates of carrying capacity (K;

29% increase), shape parameter (*M*; 26% decrease), and estimates of the probability of overfishing and being overfished in 2015 (71% and 65% increases, respectively) (Table 17). Estimates of random walk catchability were similar in scale to the corresponding constant catchability from the base case, with mean estimates over time of $q_{1,T}$ and $q_{2,T}$ 7% and 6% less than q_1 and q_2, respectively. Estimated biomass nearly doubled (and estimated harvest rate halved) towards the center of the time series when catchability was lowest. Estimates of biomass and harvest were more similar towards the end of the time series when catchability was increasing, likely as a consequence of the model fitting to the survey data point (Figures 31.1 and 31.2).

Sensitivity to use of uniform prior for observation and process error variances

Model results were sensitive to using a uniform prior for observation and process error rather than the default inverse gamma distribution, but less sensitive than other model parameters and structural assumptions. Time series of estimated biomass (Figure 32.1) and estimated harvest (Figure 32.2) were similar to the base case. Changes in parameter estimates were generally less than 10%; however, the probability of overfishing in 2015 declined by 90% and the probability of the stock being overfished in 2015 declined by 91% (Table 17).

Sensitivity to exclusion of the fishery-independent survey

Model results were not very sensitive to the exclusion of the fishery-independent survey (Figures 33.1 and 33.2; Table 17). Estimates of biomass increased by about 6 to 10% when the survey was excluded (Figure 33.1; Table 17). The increase in biomass was accompanied by a slight increase in variation in the estimates. The CV for annual biomass estimates increased by 7-17% and the 95% credible interval width for biomass increased 15-20% for the model with the survey excluded (Figure 33.1). The slight increases in biomass estimates resulted in decreased estimates of mean harvest rate for the scenario with the survey excluded and minimal changes to variation around harvest rates (Figure 33.2).

Sensitivity to uncertainty in the effective radius for the fishery-independent survey

Model results were sensitive to reducing the CV for the effective radius of the fishery-independent survey from 0.25 to 0.01 (Figure 34.1 and 34.2; Table 17). Estimates of biomass decreased by 16-37% when the uncertainty in the survey radius was reduced, with the magnitude of the difference increasing through time (Figure 34.1). The decreases in biomass estimates resulted in increased estimates of mean harvest rate relative to the base case (Figure 34.2). Decreasing the uncertainty in the effective radius led to a decrease in the amount of variation in biomass estimates, with CVs decreasing by 6 to 38% relative to the base case (Figure 34.1). The width of 95% credible intervals decreased by 21 to 61% relative to the base case. P*K* was most sensitive to the CV for the radius, decreasing by about 15% relative to the base case. Probabilities of overfishing and being overfished increased by 102% and 113% relative to the base case (Table 17).

5.6. Summary Attributes for Single Species Model

Diagnostics indicated that the MCMC simulation to estimate the posterior distribution of production model parameters for the opakapaka model converged, with the exception of the

Geweke diagnostic for process error from the third chain (Table A3). The stationarity test of process error for the third chain only passed if the first 10% of samples were removed. As was the case for the model of the Deep 7 complex, this was not considered a serious violation and all samples were used for summarizing model results for opakapaka. Residuals indicated that the production model provided a good fit to the standardized CPUE observations and that residuals were normal and untrending with constant variance for the at least the recent time period (Figures A3-A6). Residuals for the early time period were normal and untrending but had non-constant variance. Posterior means of model parameters were similar to those from the Deep 7 bottomfish model (Table 18). Parameters and model quantities related to the model scale, including K, B_{MSY} and MSY, were approximately proportional to the corresponding value in the Deep 7 bottomfish model by 65%. This was near the ratio of the estimate of opakapaka biomass to Deep 7 biomass from the fishery-independent survey (68%) and also the average ratio for opakapaka to Deep 7 total catch by weight over all years (67%). For other parameters and derived quantities, the absolute difference between posterior means for the opakapaka model and the Deep 7 model were no greater than 11%, and averaged only 3%. Posterior means and 95% credible intervals for biomass scaled to 68% of the biomass for the Deep 7 bottomfish complex over all years (Figure 35). Posterior means of harvest rates for opakapaka were similar to those for the Deep 7 complex (Figure 36). Given the slight changes in the posterior means of biomass and harvest rate from the Deep 7 model compared to reference points, the status for opakapaka was similar to the status for Deep 7 bottomfish as a complex (Figure 37).

6. DISCUSSION

The Deep 7 bottomfish stock complex in the Main Hawaiian Islands was categorized as not being overfished and not experiencing overfishing in 2015. The 2018 assessment produced estimates of biological references points, biomasses, and harvest rates through recent decades that were higher than previous assessments for Deep 7 bottomfish (Brodziak et al. 2011; 2014). The average estimated biomass from 1990 through 2013 for the 2014 assessment update used for management was 13.18 million pounds compared to 17.8 million pounds for the 2018 assessment. For the 2018 assessment, biomass in the late 2000s was even higher than for the 2014 assessment. The average estimated biomass from 2004 through 2013 for the 2014 assessment update used for management was 13.6 million pounds versus 18.4 for the 2018 assessment. As such, projections produced reported catch values corresponding to probabilities of overfishing that were higher than those in the 2014 assessment. The amount of reported catch that would yield a 50% probability of overfishing was 352 thousand pounds in the 2014 assessment update used for management compared to 558-604 thousand pounds in the 2018 benchmark assessment (a 65% increase). The smallest Deep 7 projected reported catch that would lead to a roughly P*=40% chance of overfishing was about 490 thousand pounds. Forty percent was approximately the risk of overfishing chosen by the WPRFMC for setting the annual catch limit (ACL) in 2015-2016 based on the 2014 assessment update used for management. The 490 thousand pound catch value is 50% greater than the ACL for the 2015-16 fishing season (326,000 lbs) and 54% greater than the ACL for the 2016-17 fishing season (318,000 lbs), which were based on the 2014 assessment update used for management. The large increase in the projected reported catches corresponding to probabilities of overfishing was mainly a function of greater biomass at the beginning of the projections. This greater biomass is likely influenced by several factors from the base case model (although it is difficult to pinpoint an exact cause), new methods for calculating nominal and standardized CPUE, and splitting CPUE into two time series each with unique catchabilities and observation error variances. Other contributing factors likely included an increase in the estimate of the production shape parameter (M) and intrinsic growth rate (R), reduced variation around estimates of biomass resulting from the inclusion of the fishery-independent survey. Another contributing factor is possibly the exclusion of process error from the projected biomass trajectory, although this exclusion is consisted with the 2014 assessment update used for management, and the directional effect of excluding process error is uncertain. An attempt was made to include process error in projections; however, this led to changes in the estimates of biomass for 1949-2015 from the base case, which was a consequence of the software used.

Several improvements relative to the previous benchmark assessment were incorporated into the 2018 benchmark assessment. The data filtering and standardization approaches were improved as a result of workshops held with the bottomfish fishery community (Yau 2018). These improvements included filtering out records not targeting Deep 7 bottomfish species, accounting for multi-day trips, and filtering out records unrepresentative of the fishery. Improvements to data standardization included a measure of fisher experience, pounds of uku caught, and wind speed and direction. Additionally, data were included on individual license holder for a majority of records back to 1949. Due to time constraints, no attempt was made to confirm whether similar names were actually the same name. For example, one name with a middle name or initial and another without the middle name or initial were treated as different individuals (John H. Smith versus John Henry Smith versus John Smith). This practice likely resulted in a higher number of fishers being tracked individually than may actually exist in the fishery. Confirming whether such names were from the same individual or not would result in an improvement for the next assessment, but it is not clear the extent to which this is possible, nor the time commitment required.

The 2018 benchmark assessment was the first assessment of Deep 7 bottomfish to be fitted to fishery-independent data. The bottomfish survey that was conducted during 2016 (Ault et al. 2018) produced an independent estimate for biomass that along with an estimated scaling factor was used to anchor the model estimates. Thus, the model was not entirely dependent on reported catch and effort and assumed unreporting ratios. The inclusion of the survey and scaling factor had a limited effect on changing the model results from a model without the survey information included. It did reduce the amount of variation for model estimates and scale biomass estimates downward. Using the exact value of the scaling factor applied in Ault et al. (2018) would reduce biomass estimates further.

In this assessment, the uncertainty in the scalar is an important uncertainty in fitting to the survey data. The scalar used for the total estimate was based on the assumption that the camera had a certain effective radius, based on a combination of technology specifications and scalars from other surveys using similar sampling gear, and validated against fishery-dependent data (20.2 m; Ault et al. 2018). If the assumed effective radius was smaller, total biomass estimates would be higher. Conversely, an assumed radius that was larger would result in a lower total estimate of biomass. As described in Ault et al. (2018), the choice of the scalar had support from available information, but the exact value remains an uncertainty. This uncertainty was treated explicitly in the model by assigning a prior to the radius of a sample from the survey. Nonetheless, there remains uncertainty in the conversion factors between gears that was not explicitly accounted for within the model. Improving the estimate of the scalar from relative to absolute abundance/biomass in the survey as well as calculating uncertainty in the conversion factors between survey gears would improve the next stock assessment. In the future, as a longer time series of survey data is used in the model, the survey is expected to have a greater influence on model results as the time series of survey data becomes more informative. The certainty around the scaling factor is expected to increase, and consequently, the uncertainty around the posterior for the radius of a sample (scalar) will likely be reduced.

The 2018 assessment also included improved assumptions about prior distributions. The assessment used a more realistic value for natural mortality that incorporated information on longevity for species in the Deep 7 bottomfish complex. This updated estimate of natural mortality resulted in a more realistic definition of minimum stock size threshold for biomass, although it should be noted that using the previous value does not alter stock status. The assessment also used unpublished data from HMRFS on the disposition of catch to inform a higher value of uncertainty around unreported catch, although this was not found to be a significant uncertainty that affected model results.

The surplus production model developed for opakapaka produced similar overall results to the model for the Deep 7 complex. Results were approximately proportional to the corresponding value in the Deep 7 bottomfish model with biomass over all years scaled by 68%.This was similar to the ratio of opakapaka to Deep 7 from two data sources: the estimate of opakapaka biomass to Deep 7 biomass from the fishery-independent survey (68%) and the proportion of total catch of Deep 7 bottomfish comprised of opakapaka (67%). The estimation of a single-species model is an advancement that addresses recommendations made during the review of the initial 2014 assessment update. There was an attempt to incorporate available commercial weight data into a structure Stock Synthesis model for opakapaka, but there were challenges with incorporating a weight time series that included average rather than individual weights. The Stock Synthesis model was therefore not finalized in time for inclusion in this stock assessment. Incorporation of commercial weight data into a structured model is a research area that can be explored in future benchmark assessments. It remains uncertain whether life history data for the other species will be sufficiently informative and available to develop single-species models, particularly those that represent a small proportion of the overall catch and are not targeted to the extent that opakapaka is. Furthermore, a shift towards single-species assessments would necessitate consideration about how to manage on a species-specific level or how to manage a complex using only single-species indicators. Several or all 7 species can be caught on a given fishing event plus not all fishers are skilled in targeting certain species. Some work on exploring management approaches for aggregate and single-species models for Hawaiian bottomfish has been done (Bryan 2012), and similar approaches could be used to further inform the management process for Deep 7 bottomfish.

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8. TABLES

Table 1. List of bottomfish species in the Hawaiian bottomfish management unit species complex. The current stock assessment provides an assessment of the status of the set of Deep 7 bottomfish species.

Common name	Local name	Scientific name	Deep7species
Pink snapper	Opakapaka	*Pristipomoides filamentosus*	X
Longtail snapper	Onaga	*Etelis coruscans*	X
Squirrelfish snapper	Ehu	*Etelis carbunculus*	X
Sea bass	Hapuupuu	*Hyporthodus quernus*	X
Grey jobfish	Uku	*Aprion virescens*	-
Snapper	Gindai	*Pristipomoides zonatus*	X
Snapper	Kalekale	*Pristipomoides sieboldii*	X
Blue stripe snapper	Taape	*Lutjanus kasmira*	-
Yellowtail snapper	Yellowtail kalekale	*Pristipomoides auricilla*	-
Silver jaw jobfish	Lehi	*Aphareus rutilans*	X
Amberjack	Kahala	*Seriola dumerili*	-
Thick lipped trevally	Butaguchi	*Pseudocaranx dentex*	-
Giant trevally	White ulua	*Caranx ignobilis*	-
Black jack	Black ulua	*Caranx lugubris*	-

Table 2. Reported catch (units are 1000 pounds) of Deep 7 bottomfish by species in the main Hawaiian Islands as reported in the Division of Aquatic Resources Fishery Reporting System by fishing year (July 1st – June 30th), 1949-2016.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1949	30.3	37.4	116.9	105.1	63.4	5.8	0.2	359.1
1950	18.8	30.0	113.8	75.7	60.4	4.6	0.7	304.0
1951	20.5	32.1	124.3	65.6	72.3	2.8	2.0	319.6
1952	27.8	45.3	118.8	52.0	44.7	9.5	2.7	300.8
1953	19.8	32.4	100.6	51.0	49.7	2.8	2.0	258.3
1954	16.7	40.2	102.5	40.8	65.5	3.9	1.9	271.5
1955	18.4	28.5	80.8	30.1	61.7	1.1	2.6	223.4
1956	23.4	33.1	107.2	40.5	69.4	3.8	3.7	281.0
1957	17.4	29.4	147.2	36.8	76.2	8.7	2.1	317.9
1958	17.5	17.5	92.6	26.8	52.3	2.4	2.0	211.1
1959	15.7	19.2	77.8	22.8	65.7	2.1	1.4	204.7
1960	12.4	18.9	70.6	19.3	39.4	1.6	1.2	163.4
1961	6.2	19.6	57.1	12.9	32.9	1.0	0.4	130.0
1962	9.8	16.3	75.4	15.3	48.5	1.6	0.8	167.6
1963	12.4	18.2	92.4	23.7	60.8	2.7	0.8	211.0
1964	11.6	23.5	92.5	24.7	47.2	1.0	2.3	202.8
1965	10.6	15.0	103.6	20.3	60.0	1.3	0.9	211.7
1966	12.7	13.6	71.4	18.1	65.0	2.0	0.8	183.7
1967	10.6	9.7	121.2	18.4	70.3	2.4	0.8	233.3
1968	11.3	7.3	85.1	19.9	69.5	2.2	0.8	196.0
1969	10.9	4.2	85.9	16.2	53.9	5.8	0.5	177.5
1970	20.1	5.1	69.7	15.9	43.6	2.7	1.4	158.5
1971	14.5	4.3	59.1	15.3	39.3	1.8	0.9	135.2
1972	17.6	8.1	117.9	21.3	59.1	4.4	1.2	229.7
1973	14.9	5.1	93.4	14.6	35.9	4.5	1.3	169.6
1974	14.6	4.9	135.3	21.1	43.6	4.9	1.5	225.9
1975	23.2	6.0	116.2	21.9	45.1	8.5	1.4	222.3
1976	22.4	7.9	105.4	31.3	80.2	10.3	1.2	258.7
1977	30.1	8.6	106.3	35.7	84.8	7.3	1.5	274.3
1978	28.7	10.2	154.6	35.7	66.5	9.8	2.6	308.1
1979	29.6	9.1	146.0	22.5	53.3	12.1	2.9	275.4
1980	17.7	14.2	151.1	17.0	31.4	17.8	2.4	251.5
1981	17.0	9.3	197.4	21.2	42.9	19.9	1.9	309.5
1982	21.7	10.6	177.7	24.4	66.0	30.0	1.6	332.0
1983	32.8	15.1	230.5	28.0	72.8	28.5	2.7	410.4
1984	27.1	13.5	158.7	35.9	86.8	16.8	3.5	342.3
1985	31.8	22.2	196.9	40.4	163.8	25.5	4.5	485.2
1986	24.1	24.9	173.3	60.6	196.1	27.7	3.5	510.3

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1987	28.7	28.3	258.2	48.5	174.2	38.7	3.2	579.8
1988	10.3	18.1	300.7	41.2	156.5	38.2	2.0	567.0
1989	13.5	11.0	307.7	37.4	143.7	44.7	1.7	559.6
1990	14.2	15.5	209.9	37.3	141.6	34.9	2.8	456.1
1991	15.0	18.3	135.5	30.8	103.1	19.0	3.5	325.1
1992	15.0	27.6	171.3	31.6	91.7	17.1	5.0	359.2
1993	12.0	16.9	133.7	23.7	55.4	11.1	3.6	256.3
1994	10.3	17.3	173.4	22.9	68.3	11.6	3.7	307.5
1995	16.1	19.7	188.3	25.8	69.0	13.7	4.0	336.6
1996	9.8	18.6	139.8	29.7	65.5	9.7	2.9	276.1
1997	14.1	22.8	160.5	26.2	61.4	11.9	3.0	299.8
1998	12.7	24.4	149.7	26.8	70.9	9.4	3.4	297.2
1999	9.9	12.1	103.7	19.8	59.8	8.7	2.3	216.3
2000	13.1	16.0	166.1	26.8	72.5	11.1	3.2	308.7
2001	15.5	15.6	125.0	26.5	63.2	11.5	3.6	261.0
2002	9.0	11.3	103.6	16.9	60.0	10.8	2.4	214.1
2003	9.4	21.5	127.7	16.3	68.7	8.6	2.1	254.3
2004	7.9	8.0	87.3	19.5	75.9	5.0	2.1	205.6
2005	10.4	7.9	104.4	23.1	89.8	6.9	2.0	244.4
2006	7.2	5.3	72.1	19.3	74.7	6.3	1.6	186.6
2007	7.5	6.1	92.4	20.7	85.9	8.4	2.3	223.3
2008	6.6	5.5	96.2	18.2	56.2	11.0	2.8	196.6
2009	7.9	9.6	132.6	24.6	59.5	16.6	3.6	254.3
2010	8.2	8.2	105.4	24.4	57.2	6.0	2.8	212.2
2011	8.2	9.9	148.4	24.8	67.6	11.6	3.1	273.6
2012	9.1	11.2	105.2	27.2	52.6	7.9	3.7	216.9
2013	10.5	12.3	96.0	30.8	66.9	13.0	3.4	232.9
2014	10.6	18.8	160.8	32.2	75.7	8.4	3.8	310.2
2015	9.3	17.7	154.6	32.1	79.9	12.5	2.8	308.9
2016	10.5	13.6	140.7	32.7	73.7	7.8	2.0	281.1

Table 3. Ratios of unreported catch to reported catch of Deep 7 bottomfish in the main Hawaiian Islands by fishing year (July 1st – June 30th), 1949-2016, for the base case model scenario.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai
1949	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1950	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1951	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1952	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1953	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1954	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1955	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1956	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1957	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1958	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1959	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1960	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1961	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1962	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1963	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1964	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1965	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1966	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1967	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1968	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1969	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1970	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1971	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1972	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1973	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1974	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1975	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1976	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1977	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1978	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1979	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1980	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1981	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1982	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1983	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1984	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1985	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1986	1.02	0.03	2.87	1.11	0.73	0.04	0.15

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai
1987	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1988	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1989	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1990	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1991	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1992	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1993	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1994	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1995	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1996	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1997	1.02	0.03	2.87	1.11	0.73	0.04	0.15
1998	0.93	0.08	2.69	0.94	0.59	0.05	0.24
1999	0.85	0.13	2.51	0.77	0.46	0.06	0.33
2000	0.76	0.18	2.33	0.59	0.32	0.08	0.43
2001	0.68	0.23	2.15	0.42	0.19	0.09	0.52
2002	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2003	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2004	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2005	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2006	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2007	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2008	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2009	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2010	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2011	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2012	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2013	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2014	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2015	0.59	0.28	1.97	0.25	0.05	0.10	0.61
2016	0.59	0.28	1.97	0.25	0.05	0.10	0.61

Table 4. Unreported catch (units are 1000 pounds) of Deep 7 bottomfish by species in the main Hawaiian Islands by fishing year (July 1st – June 30th), 1949-2016, as calculated from reported catch (Table 2) and unreported:reported catch ratios (Table 3).

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1949	30.9	1.1	335.4	116.7	46.3	0.2	0.0	530.7
1950	19.1	0.9	326.5	84.0	44.1	0.2	0.1	475.0
1951	20.9	1.0	356.8	72.8	52.7	0.1	0.3	504.7
1952	28.3	1.4	341.0	57.8	32.6	0.4	0.4	461.8
1953	20.2	1.0	288.6	56.6	36.3	0.1	0.3	403.1
1954	17.0	1.2	294.2	45.3	47.8	0.2	0.3	406.0
1955	18.8	0.9	232.0	33.5	45.0	0.0	0.4	330.5
1956	23.9	1.0	307.7	44.9	50.6	0.2	0.6	428.8
1957	17.8	0.9	422.6	40.8	55.6	0.3	0.3	538.3
1958	17.9	0.5	265.6	29.8	38.2	0.1	0.3	352.4
1959	16.0	0.6	223.3	25.3	47.9	0.1	0.2	313.4
1960	12.7	0.6	202.5	21.5	28.8	0.1	0.2	266.2
1961	6.3	0.6	163.8	14.4	24.0	0.0	0.1	209.2
1962	10.0	0.5	216.3	17.0	35.4	0.1	0.1	279.4
1963	12.7	0.5	265.2	26.3	44.4	0.1	0.1	349.3
1964	11.8	0.7	265.6	27.4	34.4	0.0	0.3	340.4
1965	10.8	0.4	297.2	22.5	43.8	0.1	0.1	375.0
1966	13.0	0.4	204.9	20.1	47.5	0.1	0.1	286.1
1967	10.8	0.3	347.8	20.4	51.3	0.1	0.1	430.9
1968	11.5	0.2	244.2	22.1	50.8	0.1	0.1	328.9
1969	11.2	0.1	246.7	18.0	39.4	0.2	0.1	315.6
1970	20.5	0.2	200.0	17.6	31.8	0.1	0.2	270.4
1971	14.8	0.1	169.7	17.0	28.7	0.1	0.1	230.5
1972	18.0	0.2	338.2	23.7	43.2	0.2	0.2	423.6
1973	15.2	0.2	267.9	16.2	26.2	0.2	0.2	326.0
1974	14.9	0.1	388.3	23.4	31.8	0.2	0.2	459.1
1975	23.7	0.2	333.4	24.3	33.0	0.3	0.2	415.1
1976	22.8	0.2	302.5	34.7	58.6	0.4	0.2	419.4
1977	30.7	0.3	305.2	39.7	61.9	0.3	0.2	438.2
1978	29.2	0.3	443.8	39.6	48.6	0.4	0.4	562.3
1979	30.1	0.3	419.1	25.0	38.9	0.5	0.4	514.2
1980	18.1	0.4	433.5	18.9	22.9	0.7	0.4	494.9
1981	17.3	0.3	566.4	23.5	31.3	0.8	0.3	639.9
1982	22.1	0.3	510.1	27.1	48.2	1.2	0.2	609.2
1983	33.4	0.5	661.5	31.1	53.2	1.1	0.4	781.2
1984	27.6	0.4	455.6	39.9	63.4	0.7	0.5	588.0
1985	32.4	0.7	565.0	44.9	119.6	1.0	0.7	764.3
1986	24.6	0.7	497.5	67.3	143.2	1.1	0.5	734.9

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1987	29.3	0.8	741.0	53.8	127.2	1.5	0.5	954.2
1988	10.5	0.5	862.9	45.7	114.2	1.5	0.3	1035.8
1989	13.7	0.3	883.0	41.5	104.9	1.8	0.3	1045.4
1990	14.4	0.5	602.3	41.4	103.4	1.4	0.4	763.9
1991	15.3	0.5	388.9	34.2	75.3	0.8	0.5	515.4
1992	15.3	0.8	491.7	35.0	66.9	0.7	0.7	611.2
1993	12.2	0.5	383.6	26.3	40.5	0.4	0.5	464.0
1994	10.5	0.5	497.6	25.4	49.9	0.5	0.6	584.9
1995	16.4	0.6	540.4	28.6	50.4	0.5	0.6	637.7
1996	10.0	0.6	401.1	33.0	47.8	0.4	0.4	493.4
1997	14.3	0.7	460.6	29.0	44.9	0.5	0.5	550.4
1998	11.8	2.0	402.6	25.2	42.1	0.5	0.8	485.0
1999	8.4	1.6	260.2	15.1	27.4	0.6	0.8	314.1
2000	10.0	2.9	387.1	15.9	23.3	0.8	1.3	441.4
2001	10.5	3.6	268.8	11.2	11.8	1.0	1.9	308.7
2002	5.3	3.2	204.1	4.2	3.0	1.1	1.5	222.3
2003	5.6	6.0	251.5	4.1	3.4	0.9	1.3	272.8
2004	4.7	2.2	171.9	4.9	3.8	0.5	1.3	189.2
2005	6.1	2.2	205.6	5.8	4.5	0.7	1.2	226.2
2006	4.2	1.5	142.1	4.8	3.7	0.6	1.0	158.0
2007	4.4	1.7	182.0	5.2	4.3	0.8	1.4	199.9
2008	3.9	1.5	189.5	4.6	2.8	1.1	1.7	205.1
2009	4.7	2.7	261.2	6.1	3.0	1.7	2.2	281.5
2010	4.9	2.3	207.6	6.1	2.9	0.6	1.7	226.0
2011	4.8	2.8	292.4	6.2	3.4	1.2	1.9	312.6
2012	5.4	3.1	207.3	6.8	2.6	0.8	2.2	228.2
2013	6.2	3.4	189.2	7.7	3.3	1.3	2.0	213.2
2014	6.2	5.3	316.7	8.1	3.8	0.8	2.3	343.2
2015	5.5	4.9	304.6	8.0	4.0	1.2	1.7	330.0
2016	6.2	3.8	277.2	8.2	3.7	0.8	1.2	301.1

Table 5. Total catch (units are 1000 pounds) of Deep 7 bottomfish by species in the main Hawaiian Islands by fishing year (July 1st – June 30th), 1949-2016, as calculated from the sum of reported catch (Table 2) and unreported catch (Table 4).

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1949	61.2	38.6	452.3	221.7	109.7	6.0	0.3	889.8
1950	37.9	30.9	440.3	159.6	104.6	4.8	0.8	778.9
1951	41.5	33.1	481.1	138.4	125.0	2.9	2.2	824.3
1952	56.1	46.6	459.8	109.8	77.3	9.8	3.2	762.6
1953	40.0	33.4	389.2	107.6	86.0	2.9	2.2	661.4
1954	33.7	41.4	396.7	86.1	113.4	4.0	2.2	677.4
1955	37.1	29.4	312.8	63.6	106.8	1.2	3.0	553.9
1956	47.2	34.1	415.0	85.4	120.0	4.0	4.2	709.8
1957	35.2	30.3	569.8	77.6	131.8	9.1	2.5	856.3
1958	35.4	18.0	358.2	56.6	90.4	2.5	2.3	563.4
1959	31.7	19.7	301.1	48.1	113.6	2.2	1.7	518.1
1960	25.1	19.4	273.1	40.8	68.2	1.7	1.4	429.6
1961	12.5	20.1	220.9	27.3	56.9	1.0	0.5	339.2
1962	19.8	16.8	291.7	32.2	84.0	1.7	0.9	447.0
1963	25.1	18.8	357.7	50.0	105.1	2.8	0.9	560.3
1964	23.4	24.2	358.1	52.2	81.6	1.0	2.7	543.2
1965	21.5	15.4	400.8	42.8	103.9	1.3	1.1	586.7
1966	25.7	14.0	276.4	38.2	112.5	2.1	1.0	469.8
1967	21.5	9.9	469.0	38.7	121.7	2.5	0.9	664.1
1968	22.8	7.5	329.2	41.9	120.3	2.3	0.9	525.0
1969	22.1	4.3	332.6	34.2	93.3	6.0	0.5	493.1
1970	40.5	5.3	269.7	33.5	75.4	2.8	1.7	428.9
1971	29.3	4.5	228.8	32.3	67.9	1.9	1.0	365.7
1972	35.6	8.3	456.1	45.0	102.3	4.6	1.4	653.3
1973	30.1	5.3	361.3	30.7	62.0	4.7	1.5	495.6
1974	29.5	5.0	523.6	44.6	75.5	5.1	1.7	684.9
1975	46.9	6.1	449.6	46.2	78.1	8.8	1.6	637.4
1976	45.2	8.1	407.9	66.0	138.8	10.7	1.4	678.2
1977	60.8	8.9	411.5	75.4	146.6	7.6	1.8	712.6
1978	57.9	10.5	598.5	75.3	115.1	10.2	2.9	870.4
1979	59.7	9.3	565.1	47.5	92.1	12.6	3.3	789.6
1980	35.8	14.6	584.6	35.9	54.3	18.5	2.7	746.4
1981	34.3	9.6	763.8	44.6	74.3	20.7	2.1	949.4
1982	43.8	10.9	687.8	51.6	114.1	31.2	1.9	941.2
1983	66.2	15.6	892.0	59.1	126.0	29.6	3.1	1191.6
1984	54.7	13.9	614.3	75.8	150.1	17.4	4.1	930.3
1985	64.3	22.9	761.9	85.3	283.4	26.6	5.2	1249.4
1986	48.6	25.7	670.9	128.0	339.3	28.8	4.0	1245.2

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1987	58.1	29.1	999.2	102.3	301.4	40.2	3.7	1534.0
1988	20.8	18.6	1163.6	86.9	270.7	39.8	2.3	1602.7
1989	27.2	11.3	1190.6	78.8	248.6	46.5	1.9	1605.0
1990	28.6	16.0	812.2	78.8	245.0	36.3	3.2	1220.0
1991	30.2	18.8	524.3	65.0	178.4	19.7	4.0	840.5
1992	30.3	28.4	663.0	66.6	158.7	17.7	5.7	970.5
1993	24.2	17.4	517.2	50.0	95.9	11.5	4.1	720.3
1994	20.9	17.8	670.9	48.3	118.1	12.1	4.3	892.4
1995	32.6	20.3	728.8	54.4	119.4	14.2	4.6	974.3
1996	19.9	19.2	540.9	62.7	113.3	10.1	3.3	769.4
1997	28.4	23.5	621.1	55.2	106.3	12.3	3.5	850.3
1998	24.5	26.4	552.3	52.0	112.9	9.9	4.2	782.2
1999	18.3	13.7	363.9	34.9	87.3	9.2	3.1	530.4
2000	23.2	18.8	553.3	42.7	95.8	11.9	4.5	750.2
2001	25.9	19.1	393.8	37.7	75.0	12.5	5.5	569.6
2002	14.3	14.5	307.7	21.1	63.1	11.8	3.9	436.4
2003	15.0	27.6	379.2	20.4	72.2	9.4	3.4	527.1
2004	12.6	10.2	259.1	24.4	79.7	5.5	3.3	394.8
2005	16.5	10.1	310.0	28.9	94.3	7.6	3.2	470.6
2006	11.4	6.8	214.2	24.1	78.5	6.9	2.6	344.5
2007	12.0	7.8	274.4	25.9	90.2	9.2	3.7	423.2
2008	10.5	7.1	285.7	22.8	59.0	12.1	4.6	401.8
2009	12.6	12.3	393.8	30.7	62.5	18.2	5.8	535.9
2010	13.1	10.4	313.0	30.5	60.1	6.6	4.5	438.2
2011	13.0	12.7	440.8	31.0	71.0	12.7	5.0	586.2
2012	14.5	14.4	312.5	34.0	55.3	8.6	5.9	445.2
2013	16.8	15.8	285.2	38.5	70.2	14.3	5.4	446.1
2014	16.8	24.0	477.4	40.3	79.4	9.3	6.1	653.4
2015	14.8	22.6	459.2	40.1	83.9	13.7	4.5	638.9
2016	16.8	17.4	417.9	40.9	77.4	8.6	3.2	582.2

Table 6. Proportion of records with individual name information before and after using the new database to link names and license numbers. The dataset used for CPUE analysis in this 2018 assessment included the new name information.

Fishing year	After names added	Before names added		Fishing year	After names added	Before names added
1948	0.7	0.0		1982	0.9	0.0
1949	0.8	0.0		1983	1.0	0.0
1950	0.7	0.0		1984	0.9	0.0
1951	0.7	0.0		1985	0.9	0.0
1952	0.8	0.0		1986	1.0	0.0
1953	0.6	0.0		1987	1.0	0.0
1954	0.3	0.0		1988	1.0	0.0
1955	0.3	0.0		1989	1.0	0.0
1956	0.3	0.0		1990	1.0	0.0
1957	0.3	0.0		1991	1.0	0.0
1958	0.3	0.0		1992	1.0	0.0
1959	0.5	0.0		1993	1.0	0.0
1960	0.6	0.0		1994	1.0	0.0
1961	0.7	0.0		1995	1.0	0.0
1962	0.6	0.0		1996	1.0	0.0
1963	0.6	0.0		1997	1.0	0.0
1964	0.7	0.0		1998	1.0	0.0
1965	0.6	0.0		1999	1.0	0.0
1966	0.6	0.0		2000	1.0	0.0
1967	0.6	0.0		2001	1.0	0.0
1968	0.6	0.0		2002	1.0	0.0
1969	0.6	0.0		2003	1.0	0.7
1970	0.7	0.0		2004	1.0	1.0
1971	0.6	0.0		2005	1.0	1.0
1972	0.7	0.0		2006	1.0	1.0
1973	0.6	0.0		2007	1.0	1.0
1974	0.7	0.0		2008	1.0	1.0
1975	0.6	0.0		2009	1.0	1.0
1976	0.0	0.0		2010	1.0	1.0
1977	1.0	0.0		2011	1.0	1.0
1978	1.0	0.0		2012	1.0	1.0
1979	1.0	0.0		2013	1.0	1.0
1980	1.0	0.0		2014	1.0	1.0
1981	1.0	0.0		2015	1.0	1.0

Table 7. List of predictors that were considered in model selection for the Bernoulli and Lognormal processes in the early (1948-2003) and recent (2003-2015) time periods. Dashes (-) represent variables that were not available, while "Errors" represents variables that resulted in convergence errors when included during model selection.

Model	Bernoulli	Bernoulli	Lognormal	Lognormal
Time period	1948-2003	2003-2015	1948-2003	2003-2015
Predictor				
Year	Y	Y	Y	Y
Fisher	Errors	Errors	Y	Y
Area	Y	Y	Y	Y
Region	Y	Y	Y	Y
Quarter	Y	Y	Y	Y
Ln(Cumulative experience)	Y	Y	Y	Y
Sqrt(Pounds of uku)	-	Y	Y	Y
Wind speed	-	Y	-	Y
Wind speed squared	-	Y	-	Y
Wind direction	-	Y	-	Y
Area:Quarter	Y	Y	Y	Y
Year:Area	Errors	Errors	Errors	Y

Table 8. Summary of log likelihood values and reduction in AIC (ΔAIC = AIC previous model – AIC proposed model) during model selection for the best-fit model for the Bernoulli and Lognormal processes in the early (1948-2003) and recent (2003-2015) time periods using maximum likelihood. Each parameter added is added to the model with all previously selected parameters included. The year predictor was included in all baseline models and was added first among fixed effects in model selection.

Time Period	Selected predictor	ΔAIC	Log-Likelihood	Number of parameters
Bernoulli process				
1948-2003	Null	0	-73917	1
	+year	9602	-69061	56
	+area	19137.9	-62321	227
	+quarter	506.8	-62065	230
	+area:quarter	1034.4	-61231	547
	+ln(cumulative experience)	147.0	-61156	548
2003-2015	Null	0	-21636	1
	+year	173	-21538	13
	+sqrt(pounds of uku)	5029.36	-19022	14
	+area	3209.4	-17321	111
	+quarter	584.87	-17025	114
	+area:quarter	264.75	-16632	375
	+speed	221.33	-16520	376
Lognormal process				
1948-2003	Null	0	-222512	2
	+fisher	63392	-190175	3
	+year	1171	-224504	58
	+area	3669	-188177	221
	+quarter	1463	-187442	224
	+sqrt(pounds of uku)	1081	-186901	225
	+ln(cumulative experience)	608	-186596	226
	+Area:quarter	424	-186076	533
2003-2015	Null	0	-50085	2
	+fisher	16866	-41367	3
	+year	544	-49776	15
	+area	763	-40894	107
	+sqrt(pounds of uku)	465	-40660	108
	+speed	237	-40541	109
	+quarter	168	-40454	112
	+Area:year	96	-39460	1058
	+ln(cumulative experience)	88	-39415	1059

Table 9.1. Annual index of standardized CPUE (lbs/single reporting day) for the early time period (1948-2003) with relative coefficient of variation (relCV) included. Relative CV was calculated as the ratio of CV/min(CV). Data from fishing year 1948 were used in CPUE standardization, with index values presented here, but the CPUE index used within the stock assessment model started in fishing year 1949 to align with the starting year when complete catch data were available.

Year	Estimated CPUE	relCV		Year	Estimated CPUE	relCV
1948	88.23	2.71		1976	51.38	1.00
1949	56.47	2.24		1977	52.76	1.83
1950	51.51	2.00		1978	83.24	2.25
1951	72.03	2.16		1979	88.21	2.68
1952	95.54	2.60		1980	69.94	2.14
1953	87.77	2.95		1981	68.00	1.85
1954	95.66	3.36		1982	59.21	1.53
1955	154.42	3.56		1983	59.13	1.23
1956	91.88	3.69		1984	48.53	1.35
1957	114.42	3.04		1985	60.75	1.19
1958	64.64	2.93		1986	64.74	1.18
1959	55.61	3.69		1987	83.96	1.11
1960	102.88	2.45		1988	80.23	1.07
1961	115.02	3.45		1989	71.53	1.03
1962	177.22	3.17		1990	64.68	1.26
1963	126.06	3.45		1991	62.08	1.27
1964	114.24	3.50		1992	67.47	1.38
1965	120.58	3.33		1993	60.56	1.47
1966	120.63	3.19		1994	67.78	1.49
1967	108.25	2.38		1995	67.45	1.51
1968	99.17	2.76		1996	64.43	1.53
1969	94.77	2.80		1997	66.01	1.47
1970	81.03	3.10		1998	65.86	1.44
1971	75.17	2.76		1999	65.46	1.60
1972	88.55	2.49		2000	72.59	1.41
1973	75.18	2.48		2001	72.51	1.56
1974	82.07	1.95		2002	68.71	1.74
1975	77.19	2.05		2003	62.03	3.95

Table 9.2. Annual index of standardized CPUE (lbs/hour) for the late time period (2003-2015) with relative coefficient of variation (relCV) included. Relative CV was calculated as the ratio of CV/min(CV).

Year	Estimated CPUE	relCV
2003	8.22	1.24
2004	7.97	1.25
2005	9.01	1.22
2006	8.41	1.43
2007	8.53	1.33
2008	9.54	1.26
2009	9.07	1.07
2010	8.22	1.27
2011	9.38	1.24
2012	8.17	1.24
2013	8.10	1.12
2014	10.00	1.00
2015	12.56	1.03

Table 10. Prior distributions and parameter estimates for the 2018 base case assessment model for the main Hawaiian Islands Deep 7 bottomfish stock complex. Parameters are intrinsic growth rate (R), carrying capacity (K), shape parameter (M), initial proportion of carrying capacity (*P_1*), catchability in first (*q_1*) and second (*q_2*) time periods, effective radius of a sample for the fishery-independent survey (*rad*), observation error in first (τ_1^2) and second (τ_2^2) time periods, process error (σ^2), and annual unreported catch (*C_U*). Derived quantities are relative biomass in 2017 ($relB_{2017}$; for fitting to the observed relative fishery-independent survey estimate), maximum sustainable yield (MSY) for total and reported catch, harvest rate at MSY (H_{MSY}), biomass at MSY (B_{MSY}), and proportion of carrying capacity at MSY (P_{MSY}). Biomass and MSY are reported in millions of pounds.

	Prior distributions				Parameter estimates	
Parameter	Distribution	Mean	CV	Bounds	Mean	SD
R	lognormal	0.10	25%		0.111	0.028
K	lognormal	29 million lbs.	50%		27.55	9.69
M	gamma	1.0	140%		2.26	1.54
P_1	lognormal	0.53	20%		0.558	0.100
q_1	uniform			$[10^{-5},10^{5}]$	4.52	1.60
q_2	uniform			$[10^{-5},10^{5}]$	0.616	0.301
rad	lognormal	20.2	50%		16.00	4.11
τ_1^2	inverse gamma	0.83*			0.0534	0.012
τ_2^2	inverse gamma	0.83*			0.231	0.116
σ^2	inverse gamma	0.083*			0.030	0.012
C_U	uniform	$U \cdot C_R$		±40%		
$relB_{2017}$					2.08×10^{-6}	3.97×10^{-7}
MSY (total catch)					1.048	0.481
MSY (reported catch)					0.509	0.233
H_{MSY}					0.069	0.026
B_{MSY}					15.42	4.91
P_{MSY}					0.571	0.083

*Value is mode rather than mean.

Table 11. Summary of sensitivity scenarios evaluated for the Deep 7 bottomfish surplus production model as described in detail in the sensitivity analyses section (section 3.4). Values are for carrying capacity (K), intrinsic growth rate (R), shape parameter (M), initial proportion of carrying capacity (P_1), process error (σ^2), observation errors (τ_i^2) in time period *i*, catch scenarios for unreported to reported ratios (*U*), error bounds in estimating unreported catch (C_U), random-walk catchability (q_i) in time period *i*, uniform prior for process and observation errors (uniform), removal of the fishery-independent survey (S_{2017}), and effective radius of a sample for the fishery-independent survey (*rad*).

Value	Number of scenarios	Type of change	Description
K	4	Distribution mean	Prior mean adjusted by ± 25% and 50%
R	3	Distribution mean	Prior mean adjusted by ± 50% and +150%
M	4	Distribution mean	Scale parameter adjusted to produce ± 25% and 50% changes in prior mean
P_1	4	Distribution mean	Prior mean adjusted by ± 25% and 50%
τ_i^2	4	Distribution mode	Prior mode adjusted by multiplicative factors of ± 10 and ± 100
σ^2	4	Distribution mode	Prior mode adjusted by multiplicative factors of ± 10 and ± 100
Unreported catch ratio (U)	4	Data	Catch data adjusted using different non-reporting ratios
Error around unreported catch (C_U)	3	Distribution bounds	Prior uniform distribution bounds adjusted by ± 50% and set near zero
Directional error around unreported catch (C_U)	2	Distribution bounds	Adjusting prior uniform distribution bounds directionally by ± 25%
q_i	1	Model parameterization	Random walk q incorporated
σ^2, τ_i^2 prior distributions	1	Distribution type	Uniform prior for process and observation errors
Survey (S_{2017})	1	Data	Exclude survey from model
Survey (rad)	1	Distribution coefficient of variation (CV)	Prior CV reduced to 0.01

Table 12. Convergence diagnostics for the Gelman Rubin, Geweke, and Heidelberger and Welch (HW) tests, along with autocorrelation at lags 1 and 5. Values shown are the upper confidence interval for the Gelman Rubin diagnostic, which when near 1 indicates convergence; the absolute value of the Z-score for the Geweke diagnostic, which when < 2 indicates convergence; and p values from the Heidelberger and Welch stationarity diagnostic for the full chain, which when > 0.05 indicates convergence. For the criteria based on individual chains (Geweke and Heidelberger and Welch diagnostics, and autocorrelation), the values shown are from the most extreme chain for each parameter.

Parameters	Gelman and Rubin	Geweke	HW stationarity	HW half-width	Lag1 auto-correlation	Lag5 auto-correlation
B_{MSY}	1.002	0.97	0.25	Passed	0.53	0.11
F_{MSY}	1.001	1.26	0.07	Passed	0.33	0.14
H_{MSY}	1.001	1.24	0.07	Passed	0.33	0.14
MSY	1.001	0.34	0.70	Passed	0.25	0.09
P_{MSY}	1.001	1.28	0.13	Passed	0.28	0.12
R	1.000	1.83	0.10	Passed	0.07	0.03
K	1.003	1.15	0.10	Passed	0.66	0.17
M	1.001	1.69	0.10	Passed	0.23	0.09
q_1	1.003	0.26	0.51	Passed	0.65	0.17
q_2	1.001	0.67	0.30	Passed	0.58	0.18
rad	1.000	0.89	0.15	Passed	0.45	0.12
σ^2	1.000	1.17	0.16	Passed	0.12	0.01
τ_1^2	1.000	1.49	0.47	Passed	0.01	0.01
τ_2^2	1.000	1.23	0.32	Passed	0.01	0.01

Table 13. Correlation coefficients among parameter estimates. Parameters are carrying capacity (K), intrinsic growth rate (R), initial proportion of carrying capacity (P_1), shape parameter (M), catchability in first (q_1) and second (q_2) time periods, survey sample radius (*rad*), observation error in first (τ_1^2) and second (τ_2^2) time periods, and process error (σ^2).

	R	P_1	M	q_1	q_2	*rad*	τ_1^2	τ_2^2	σ^2
K	-0.23	-0.12	-0.34	-0.67	-0.43	-0.39	0.01	0.01	-0.04
R	-	0.01	-0.06	0.16	0.04	0.03	0.00	-0.01	0.00
P_1	-	-	0.09	-0.17	-0.09	-0.05	0.01	0.00	-0.07
M	-	-	-	0.12	-0.02	-0.03	0.02	-0.01	-0.03
q_1	-	-	-	-	0.63	0.51	-0.01	0.00	0.06
q_2	-	-	-	-	-	0.68	0.02	0.06	0.12
rad	-	-	-	-	-	-	0.01	0.05	0.10
τ_1^2	-	-	-	-	-	-	-	0.00	0.10
τ_2^2	-	-	-	-	-	-	-	-	0.06

Table 14. Estimates of mean exploitable biomass (B) in million lbs, mean relative exploitable biomass (B/B_{MSY}), probability of being overfished (B/B_{MSY}< 0.844), mean harvest rate (H), relative mean harvest rate (H/H_{MSY}), and probability of overfishing (H/H_{MSY}>1) for the Deep 7 Bottomfish complex in the main Hawaiian Islands from 1949 through 2015.

Year	B (million lbs)	B/B_{MSY}	Probability of Being Overfished	H	H/H_{MSY}	Probability of Overfishing
1949	15.25	1	0.27	0.07	0.95	0.45
1950	16.1	1.05	0.22	0.06	0.79	0.3
1951	17.62	1.15	0.15	0.05	0.77	0.29
1952	19.05	1.24	0.11	0.05	0.66	0.21
1953	20.13	1.31	0.08	0.04	0.54	0.12
1954	21.22	1.38	0.07	0.04	0.53	0.12
1955	22.11	1.44	0.05	0.03	0.42	0.06
1956	22.43	1.47	0.05	0.04	0.52	0.12
1957	22.55	1.47	0.05	0.04	0.62	0.19
1958	22.14	1.44	0.05	0.03	0.42	0.06
1959	22.64	1.48	0.05	0.03	0.38	0.05
1960	23.68	1.55	0.03	0.02	0.3	0.03
1961	24.64	1.61	0.03	0.02	0.23	0.02
1962	25.64	1.68	0.02	0.02	0.29	0.03
1963	25.66	1.68	0.02	0.03	0.36	0.04
1964	25.42	1.66	0.02	0.03	0.35	0.04
1965	25.19	1.65	0.02	0.03	0.38	0.05
1966	24.8	1.62	0.02	0.02	0.31	0.03
1967	24.37	1.59	0.03	0.03	0.45	0.08
1968	23.51	1.54	0.04	0.03	0.37	0.05
1969	22.74	1.49	0.05	0.03	0.36	0.04
1970	21.89	1.43	0.06	0.02	0.32	0.04
1971	21.19	1.39	0.07	0.02	0.28	0.03
1972	20.74	1.36	0.08	0.04	0.52	0.12
1973	19.78	1.29	0.1	0.03	0.42	0.07
1974	18.96	1.24	0.12	0.04	0.6	0.17
1975	17.64	1.15	0.17	0.04	0.6	0.17
1976	16.02	1.05	0.25	0.05	0.7	0.24
1977	16.44	1.07	0.24	0.05	0.72	0.27
1978	17.32	1.13	0.2	0.06	0.84	0.37
1979	17.54	1.15	0.2	0.05	0.75	0.3
1980	17.29	1.13	0.2	0.05	0.72	0.27
1981	16.98	1.11	0.21	0.07	0.93	0.45

Year	B (million lbs)	B/B_{MSY}	Probability of Being Overfished	H	H/H_{MSY}	Probability of Overfishing
1982	16.29	1.06	0.24	0.07	0.96	0.47
1983	15.89	1.04	0.26	0.09	1.24	0.66
1984	15.54	1.02	0.29	0.07	0.99	0.49
1985	16.45	1.08	0.21	0.09	1.25	0.67
1986	17.42	1.14	0.16	0.08	1.17	0.62
1987	18.81	1.23	0.1	0.09	1.34	0.72
1988	18.79	1.23	0.1	0.1	1.41	0.75
1989	17.93	1.17	0.14	0.1	1.48	0.78
1990	16.96	1.11	0.2	0.08	1.2	0.64
1991	16.57	1.08	0.23	0.06	0.84	0.37
1992	16.76	1.09	0.22	0.07	0.97	0.47
1993	16.61	1.08	0.23	0.05	0.72	0.27
1994	17	1.11	0.2	0.06	0.87	0.4
1995	17.05	1.11	0.2	0.07	0.95	0.46
1996	16.92	1.1	0.21	0.05	0.76	0.3
1997	17.04	1.11	0.2	0.06	0.83	0.36
1998	17.09	1.11	0.2	0.05	0.76	0.3
1999	17.23	1.12	0.2	0.04	0.51	0.11
2000	17.72	1.16	0.17	0.05	0.71	0.26
2001	17.68	1.15	0.17	0.04	0.54	0.13
2002	17.56	1.14	0.18	0.03	0.41	0.07
2003	17.59	1.15	0.2	0.04	0.5	0.12
2004	17.66	1.15	0.22	0.03	0.37	0.07
2005	17.98	1.17	0.21	0.03	0.43	0.1
2006	18.09	1.18	0.22	0.02	0.32	0.06
2007	18.33	1.2	0.21	0.03	0.38	0.08
2008	18.55	1.21	0.21	0.03	0.36	0.08
2009	18.62	1.22	0.21	0.04	0.47	0.14
2010	18.57	1.21	0.21	0.03	0.39	0.09
2011	18.74	1.22	0.2	0.04	0.51	0.17
2012	18.68	1.22	0.2	0.03	0.39	0.1
2013	18.99	1.24	0.19	0.03	0.38	0.09
2014	19.62	1.28	0.17	0.04	0.54	0.18
2015	20.03	1.31	0.16	0.04	0.51	0.17

Table 15. Projection results for mean probability of overfishing ($H/H_{MSY}>1$) and corresponding annual reported catch where the probability of overfishing is reached. The mean probability the stock is overfished ($B/B_{MSY}<0.844$), median harvest rate, and mean biomass are the values in each year that correspond to the specified reported catch values.

Probability of overfishing ($H/H_{MSY}>1$)	0.00	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
Reported catch (millions of lbs.)											
2018	0	0.146	0.222	0.282	0.336	0.382	0.43	0.474	0.518	0.562	0.604
2019	0	0.148	0.224	0.284	0.336	0.382	0.426	0.468	0.508	0.550	0.588
2020	0	0.150	0.226	0.284	0.334	0.38	0.422	0.462	0.500	0.538	0.578
2021	0	0.152	0.228	0.286	0.336	0.378	0.420	0.458	0.492	0.528	0.566
2022	0	0.152	0.228	0.286	0.334	0.378	0.418	0.452	0.490	0.522	0.558
Probability stock is overfished ($B/B_{MSY}<0.844$)											
2019	0.12	0.13	0.13	0.14	0.14	0.14	0.15	0.15	0.15	0.16	0.16
2020	0.10	0.12	0.12	0.13	0.14	0.14	0.15	0.16	0.16	0.17	0.17
2021	0.08	0.10	0.12	0.13	0.14	0.15	0.15	0.16	0.17	0.18	0.19
2022	0.07	0.10	0.11	0.12	0.14	0.15	0.16	0.17	0.18	0.19	0.20
Harvest rate											
2018	0.000	0.016	0.025	0.032	0.038	0.043	0.048	0.053	0.058	0.063	0.068
2019	0.000	0.016	0.025	0.032	0.038	0.043	0.048	0.053	0.058	0.064	0.068
2020	0.000	0.016	0.025	0.032	0.037	0.043	0.048	0.053	0.058	0.063	0.068
2021	0.000	0.016	0.025	0.032	0.038	0.043	0.048	0.053	0.058	0.063	0.068
2022	0.000	0.016	0.025	0.031	0.037	0.043	0.048	0.053	0.058	0.063	0.069
Biomass (millions of lbs.)											
2019	20.22	19.91	19.76	19.63	19.52	19.43	19.34	19.25	19.17	19.08	19.01
2020	20.79	20.21	19.92	19.69	19.50	19.32	19.15	19.00	18.85	18.70	18.54
2021	21.31	20.48	20.07	19.75	19.47	19.23	19.00	18.78	18.59	18.39	18.17
2022	21.78	20.74	20.21	19.80	19.46	19.15	18.86	18.61	18.34	18.10	17.83

Table 16. Probability of overfishing (H/H_{MSY}>1) and projected reported catch (millions of lbs) by year. Catch values for a given probability of overfishing in a given year were applied in all previous years (i.e., 2018 to year of interest).

	Reported catch for a given year							Reported catch for a given year				
P(Overfishing)	2018	2019	2020	2021	2022		P(Overfishing)	2018	2019	2020	2021	2022
0.00	0	0	0	0	0		0.26	0.392	0.39	0.39	0.386	0.386
0.01	0.034	0.036	0.036	0.036	0.036		0.27	0.4	0.4	0.398	0.396	0.392
0.02	0.072	0.074	0.076	0.076	0.078		0.28	0.412	0.408	0.406	0.404	0.402
0.03	0.102	0.102	0.106	0.106	0.106		0.29	0.42	0.418	0.414	0.412	0.408
0.04	0.126	0.128	0.128	0.132	0.132		0.30	0.43	0.426	0.422	0.42	0.418
0.05	0.146	0.148	0.15	0.152	0.152		0.31	0.438	0.434	0.432	0.426	0.424
0.06	0.164	0.164	0.166	0.168	0.168		0.32	0.448	0.444	0.438	0.434	0.43
0.07	0.18	0.182	0.184	0.184	0.186		0.33	0.456	0.452	0.448	0.444	0.438
0.08	0.194	0.196	0.198	0.198	0.202		0.34	0.466	0.458	0.454	0.452	0.446
0.09	0.208	0.212	0.212	0.214	0.216		0.35	0.474	0.468	0.462	0.458	0.452
0.10	0.222	0.224	0.226	0.228	0.228		0.36	0.484	0.476	0.472	0.464	0.46
0.11	0.234	0.238	0.238	0.242	0.242		0.37	0.492	0.484	0.478	0.472	0.468
0.12	0.246	0.25	0.252	0.254	0.254		0.38	0.5	0.49	0.486	0.48	0.474
0.13	0.262	0.262	0.262	0.264	0.266		0.39	0.51	0.502	0.492	0.486	0.482
0.14	0.272	0.272	0.274	0.274	0.276		0.40	0.518	0.508	0.5	0.492	0.49
0.15	0.282	0.284	0.284	0.286	0.286		0.41	0.528	0.516	0.51	0.502	0.494
0.16	0.294	0.296	0.294	0.296	0.298		0.42	0.536	0.526	0.514	0.508	0.502
0.17	0.304	0.304	0.306	0.306	0.308		0.43	0.544	0.532	0.524	0.516	0.508
0.18	0.314	0.314	0.316	0.316	0.318		0.44	0.552	0.54	0.532	0.522	0.516
0.19	0.324	0.326	0.326	0.326	0.326		0.45	0.562	0.55	0.538	0.528	0.522
0.20	0.336	0.336	0.334	0.336	0.334		0.46	0.57	0.556	0.548	0.538	0.528
0.21	0.346	0.346	0.344	0.344	0.344		0.47	0.58	0.564	0.552	0.546	0.536
0.22	0.356	0.354	0.354	0.352	0.352		0.48	0.588	0.574	0.56	0.552	0.544
0.23	0.364	0.364	0.362	0.362	0.36		0.49	0.596	0.58	0.57	0.56	0.55
0.24	0.376	0.374	0.372	0.37	0.37		0.50	0.604	0.588	0.578	0.566	0.558
0.25	0.382	0.382	0.38	0.378	0.378							

Table 17. Sensitivity of production model results to 25% and 50% increases and decreases to prior means for carrying capacity (*K*), shape parameter (*M*), initial proportion of carrying capacity (P_1); 50% increase and decreases and 150% increase to prior means for intrinsic growth rate (*R*); 10 and 100-fold increases and decreases in prior values for process error (σ^2) and observation errors in both time periods i (τ_i^2); alternative error bounds for estimating unreported catch (C_U 0.01- C_U pos25; see section 3.4), alternative catch scenarios (Catch I-Catch IV; see section 3.4), random-walk catchability (*q*), uniform prior for process and observation error (uniform), removal of the fishery-independent survey (S_{2017}), and reduction in prior CV of survey sample radius (Survey CV). Results are expressed as percent change relative to base case model for *R*, *K*, *M*, P_1, maximum sustainable yield (MSY), biomass at MSY (B_{MSY}), harvest rate at MSY (H_{MSY}), total exploitable biomass in 2015 (B_{2015}), harvest rate in 2015 (H_{2015}), probability of overfishing in 2015 (i.e., H/H_{MSY}>1; poflH$_{2015}$), probability of the stock being overfished in 2015 (i.e., B/B_{MSY}<(1-natM); poflB$_{2015}$), harvest rate in 2015 relative to H_{MSY} (H_{2015}/H_{MSY}), and total exploitable biomass in 2015 relative to B_{MSY} (B_{2015}/B_{MSY}). An asterisk (*) in cells of the pofl columns indicates a change in status for the sensitivity run compared to the base case.

Scenario	R	K	M	P_1	MSY	B_{MSY}	H_{MSY}	B_{2015}	H_{2015}	poflH 2015	poflB 2015	H_{2015}/H_{MSY}	B_{2015}/B_{MSY}
K = 14.50	7.28	-26.50	23.69	1.85	-8.15	-22.05	18.20	-21.72	23.69	-12.30	-16.52	4.64	0.43
K = 21.75	2.70	-12.23	9.24	0.59	-4.10	-10.18	7.11	-10.43	10.21	-4.00	-6.57	2.90	-0.28
K = 36.25	-2.07	13.43	-9.63	-1.15	2.39	10.18	-7.04	7.59	-5.71	15.58	16.26	1.42	-2.35
K = 43.50	-3.68	26.61	-16.35	-1.69	5.44	20.49	-12.33	16.28	-11.50	23.88	24.62	0.94	-3.50
R = 0.05	-50.31	24.57	0.09	-0.22	-39.21	23.28	-52.10	3.00	0.13	227.10*	109.25	109.03	-16.45
R = 0.15	48.61	-11.91	-7.42	0.59	27.00	-12.91	46.11	-2.65	1.01	-60.32	-53.95	-30.87	11.78
R = 0.25	140.52	-22.29	-25.23	-0.04	60.88	-26.20	118.66	-8.84	7.21	-82.25	-79.67	-50.97	23.53
M=0.5	0.45	9.04	-35.40	-1.17	-15.84	-0.26	-15.17	0.20	0.99	58.33	12.50	19.05	0.46
M=0.75	0.09	3.81	-15.47	-0.50	-5.83	0.13	-5.78	0.75	-0.13	19.46	3.70	6.00	0.62
M=1.25	-0.54	-0.69	9.94	-0.11	3.53	1.10	2.35	-0.45	0.53	-4.06	1.79	-1.78	-1.53
M=1.5	-0.63	-1.96	19.18	-0.13	6.11	1.36	4.69	-0.75	0.30	-12.06	1.91	-4.19	-2.08
P_1 = 0.215	-3.32	36.01	-33.67	-46.18	-2.86	23.87	-19.83	-14.13	20.61	122.93	212.05	50.44	-30.67
P_1 = 0.323	-0.99	9.62	-12.68	-21.46	-2.58	5.71	-6.72	-4.44	6.30	36.66	56.12	13.96	-9.60
P_1 = 0.538	0.09	-2.36	4.11	19.25	0.76	-1.36	1.51	2.90	-3.39	-11.22	-24.74	-4.83	4.32
P_1= 0.645	-0.09	-3.67	4.46	37.63	0.00	-2.46	1.25	4.79	-5.01	-11.58	-34.69	-6.18	7.44

Scenario	R	K	M	P_1	MSY	B_{MSY}	H_{MSY}	B_{2015}	H_{2015}	poflH 2015	poflB 2015	H_{2015}/ H_{MSY}	B_{2015}/B_{MSY}
τ_i^2 x 0.01	-0.18	-4.25	-9.01	-7.48	-5.29	-4.41	-0.65	14.68	-19.95	-77.81	-93.95	-19.43	19.97
τ_i^2 x 0.1	-0.99	-0.18	-8.26	-3.89	-3.91	-1.04	-2.42	11.13	-15.78	-55.52	-74.59	-13.69	12.30
τ_i^2 x 10	-1.26	5.48	-7.87	-1.85	-1.53	3.18	-5.57	-13.33	33.75	95.64	135.59	41.64	-16.00
τ_i^2 x 100	-2.79	11.80	-26.47	-3.10	-8.71	5.06	-15.66	-18.27	58.43	168.78*	200.38	87.86	-22.21
σ^2 x 0.01	0.18	9.07	2.96	8.14	4.01	7.26	-0.09	10.88	-18.08	-52.53	-66.75	-18.01	3.38
σ^2 x 0.1	0.00	5.59	1.55	4.34	2.39	4.60	-0.23	5.94	-11.25	-30.99	-41.52	-11.05	1.28
σ^2 x 10	-1.53	-3.16	-17.41	-3.80	-11.20	-5.97	-8.39	-7.09	22.12	83.16	76.72	33.32	-1.19
σ^2 x 100	-5.66	-5.81	-47.46	-5.83	-36.75	-16.02	-30.04	-11.18	69.10	231.88*	144.39	141.73	5.76
Catch I	2.70	17.21	10.30	0.99	29.39	20.36	7.56	13.33	48.87	77.25	23.47	38.41	-5.84
Catch II	-0.63	0.00	-1.99	-0.25	-2.48	-0.71	-1.88	3.39	-43.46	-62.59	-18.11	-42.38	4.14
Catch III	-1.17	-5.34	-4.77	-0.47	-10.17	-6.68	-3.66	-8.44	23.77	65.07	11.03	28.47	-1.88
Catch IV	-6.74	-22.00	-32.52	-2.44	-46.43	-29.44	-25.72	-25.41	-31.00	38.63	-5.04	-7.11	5.71
C_U 0.01	-0.18	0.76	-0.35	-0.11	-0.10	0.52	-0.48	0.25	-0.03	0.42	-0.77	0.45	-0.27
C_U 0.2	0.27	-0.11	-0.09	0.00	0.00	-0.19	0.26	-1.20	1.26	3.76	3.44	1.00	-1.01
C_U 0.6	-0.18	1.45	-1.59	-0.32	-0.48	0.84	-1.04	-0.20	0.81	8.42	6.95	1.87	-1.03
C_U neg25	-0.90	-3.23	-5.61	-0.38	-8.25	-4.73	-3.55	-5.29	-1.80	9.13	4.15	1.82	-0.59
C_U pos25	0.72	4.61	1.77	0.00	6.20	4.86	1.53	2.90	4.93	7.76	8.23	3.35	-1.88
q	-4.58	28.82	-26.20	-3.03	0.29	20.00	-19.04	20.67	-1.95	70.99	64.60	21.11	0.52
uniform	0.54	-3.23	-9.28	-7.74	-3.34	-3.18	0.61	19.12	-24.12	-90.25	-98.43	-24.58	23.03
No survey	-0.63	5.88	-2.39	0.23	3.72	5.25	-1.70	10.18	-1.87	0.00	0.00	-0.17	4.69
Survey CV	0.72	-14.77	-2.56	-1.15	-18.72	-16.28	-0.66	-37.24	39.39	102.03	113.90	40.32	-25.04

Table 18. Posterior mean of select model parameters and derived quantities from the opakapaka production model. The ratio of these values to corresponding values from the production model for the Deep 7 bottomfish complex are also shown. The total catch and survey estimates, which were data inputs, are provided for comparison.

Parameters or quantities	Opakapaka model	Ratio of opakapaka:Deep7
Total catch (million lbs) – average 2011-2015	0.395	0.709
2016 relative survey estimate (million lbs)	1.36×10^{-6}	0.677
R	0.111	1.000
K (million lbs)	17.77	0.645
M	2.311	1.021
q_1	4.861	1.074
q_2	0.637	1.033
rad	16.69	1.043
σ^2	0.029	0.992
τ_1^2	0.056	1.042
τ_2^2	0.238	1.035
P_1	0.620	1.112
MSY (million lbs)	0.687	0.655
B_{MSY} (million lbs)	10.00	0.648
H_{MSY}	0.070	1.009
P_{MSY}	0.574	1.005

9. FIGURES

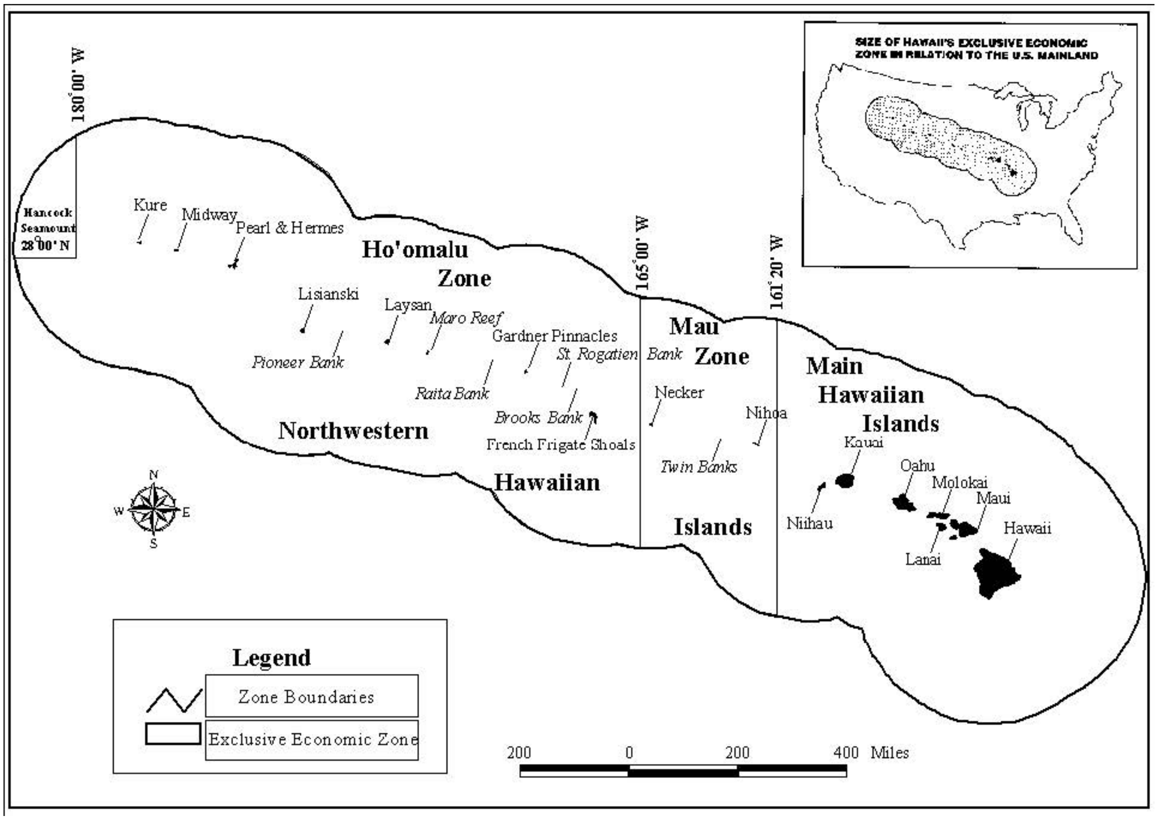
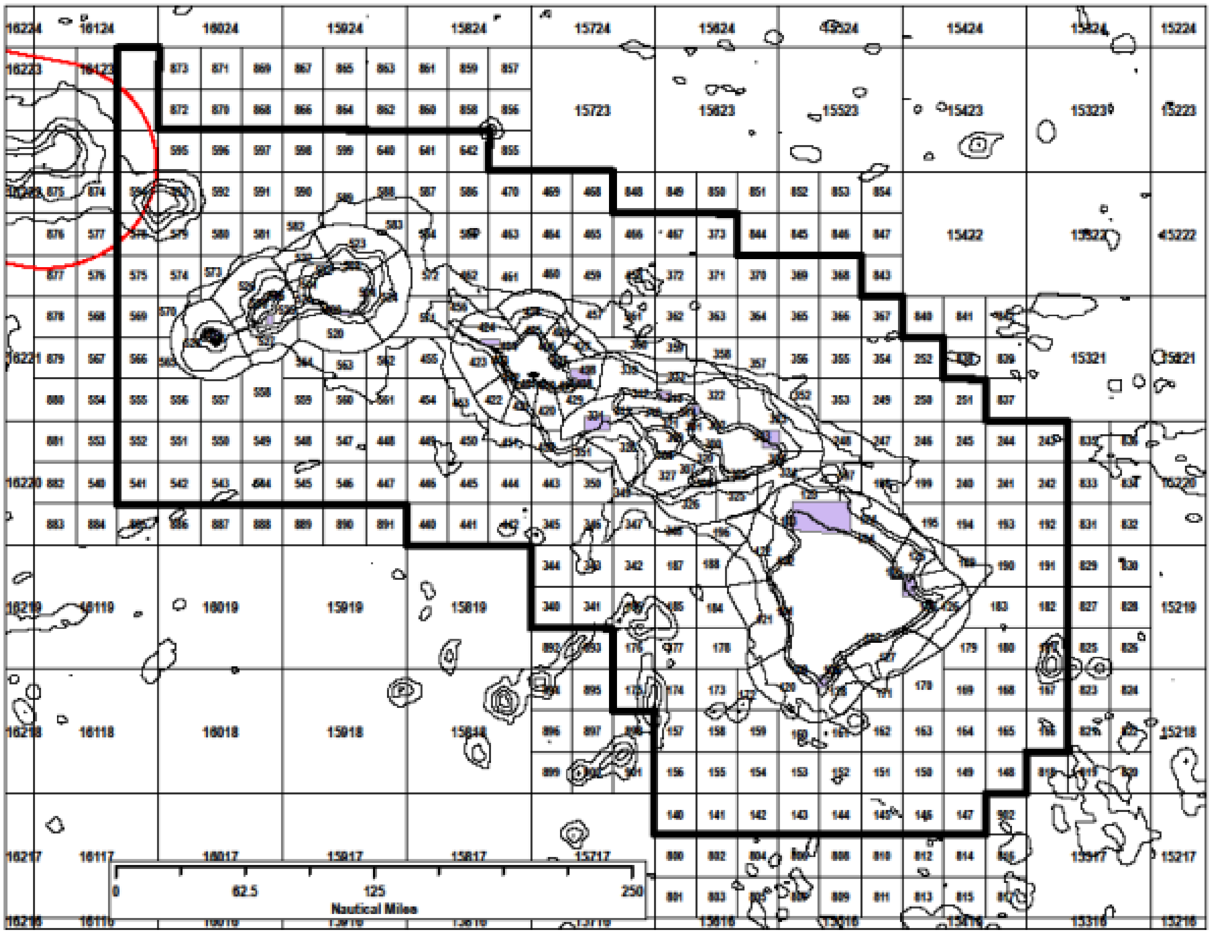


Figure 1. Location of the three Hawaiian bottomfish fishing zones: the main Hawaiian Islands (MHI) zone, the Mau Zone, and the Ho'omalu Zone. Together, the Mau and Ho'omalu Zones are known as the Northwestern Hawaiian Islands, which is now closed to fishing. The current stock assessment is for the Deep 7 bottomfish complex in the main Hawaiian Islands.



Source: NOAA PIFSC IFMP (MKL 11/1/2016)

Figure 2. Boundary of the main Hawaiian Islands (thick solid black outline) used for the 2018 benchmark stock assessment using defined area codes. The portion outlined in red is the definition for the Papahānaumokuākea Marine National Monument as of August 25, 2016 prior to subsequent expansion. Purple shading reflects locations of bottomfish restricted fishing areas (BRFAs).

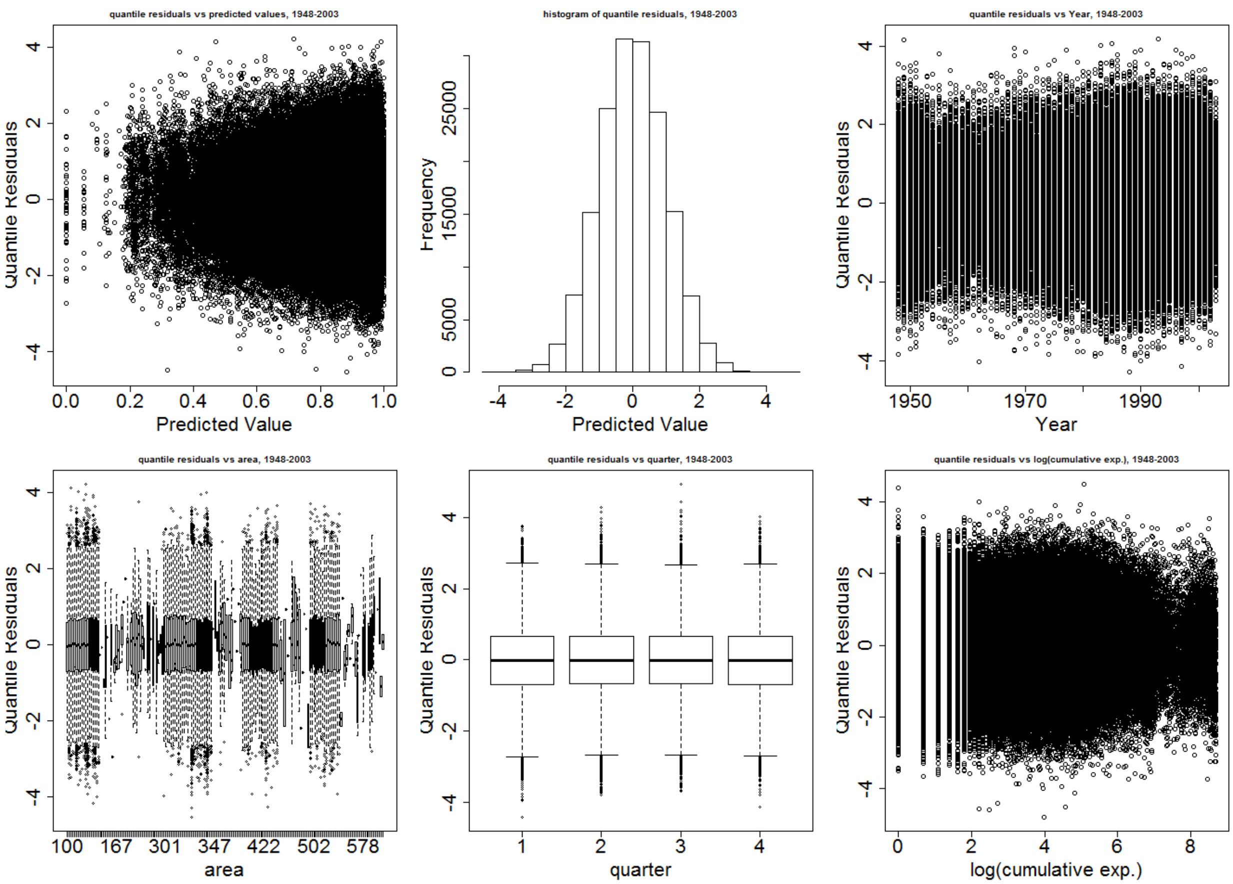


Figure 3.1 Model diagnostics for the best fit Bernoulli model for the early (1948-2003) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

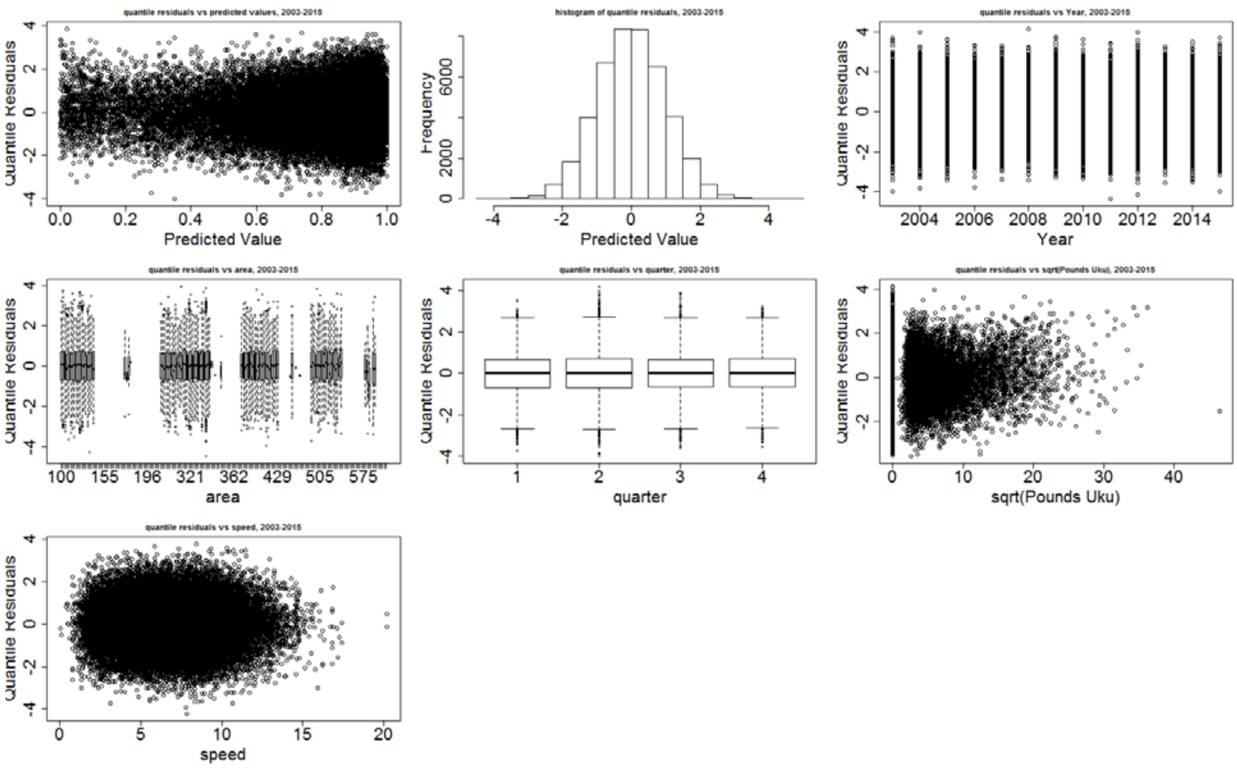


Figure 3.2. Model diagnostics for the best fit Bernoulli model for the recent (2003-2015) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

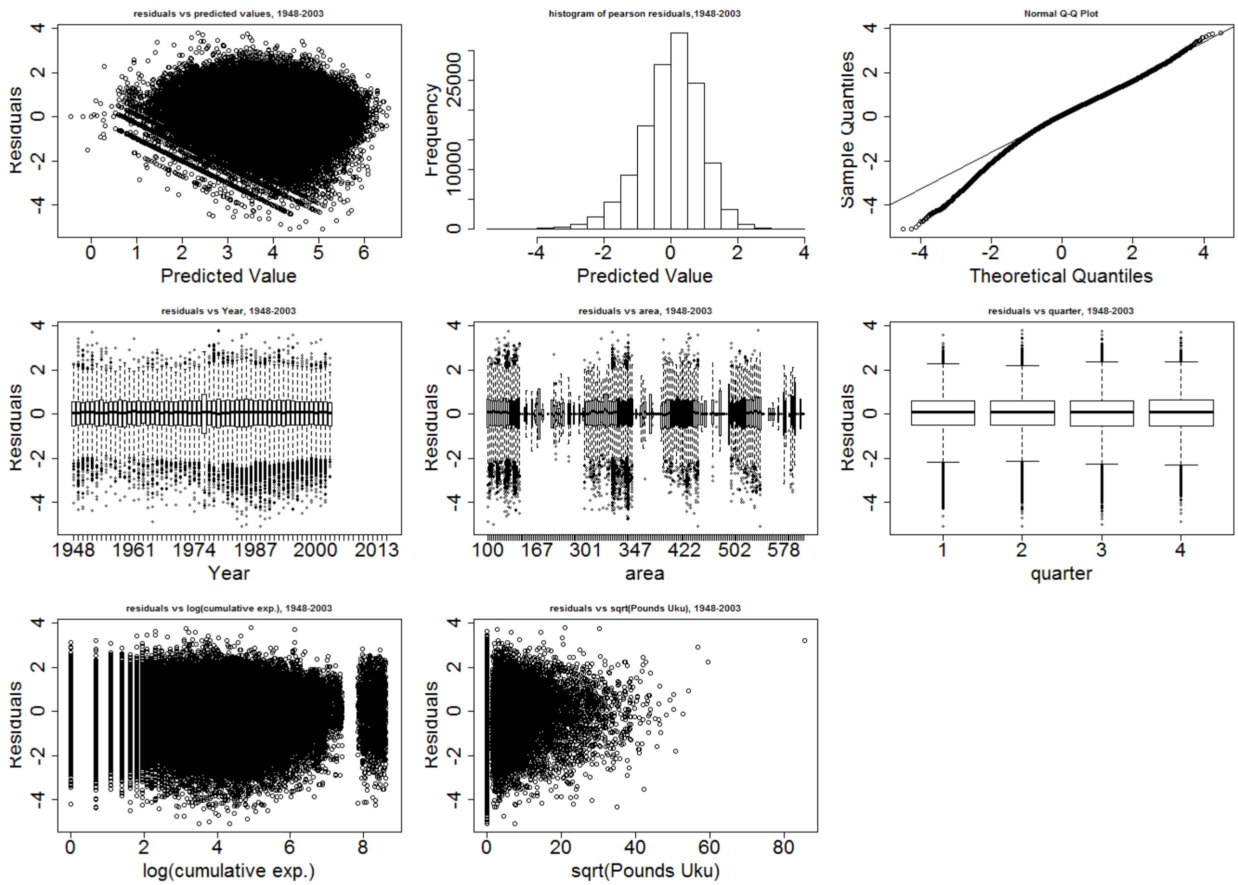


Figure 3.3. Model diagnostics for the best fit Lognormal model for the early (1948-2003) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

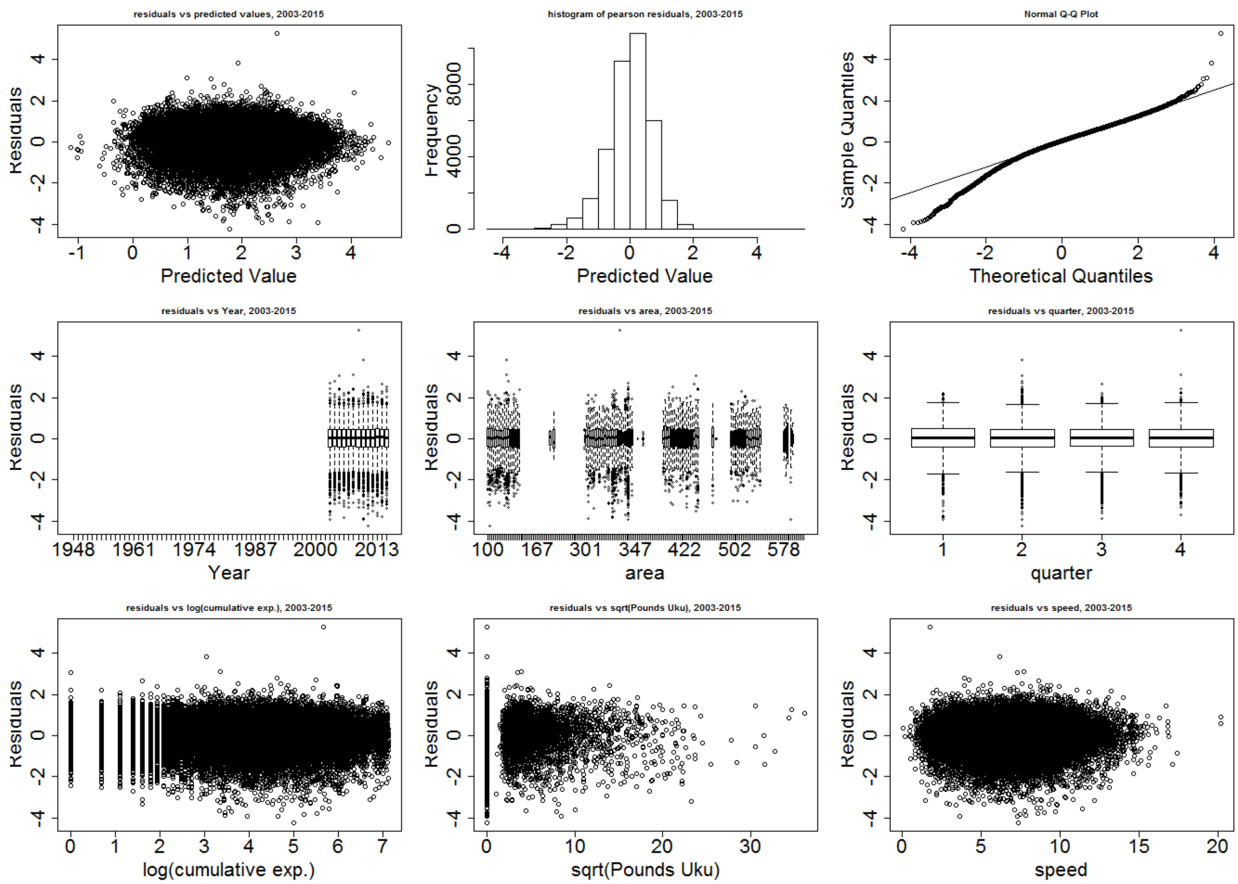


Figure 3.4. Model diagnostics for the best fit Lognormal model for the recent (2003-2015) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

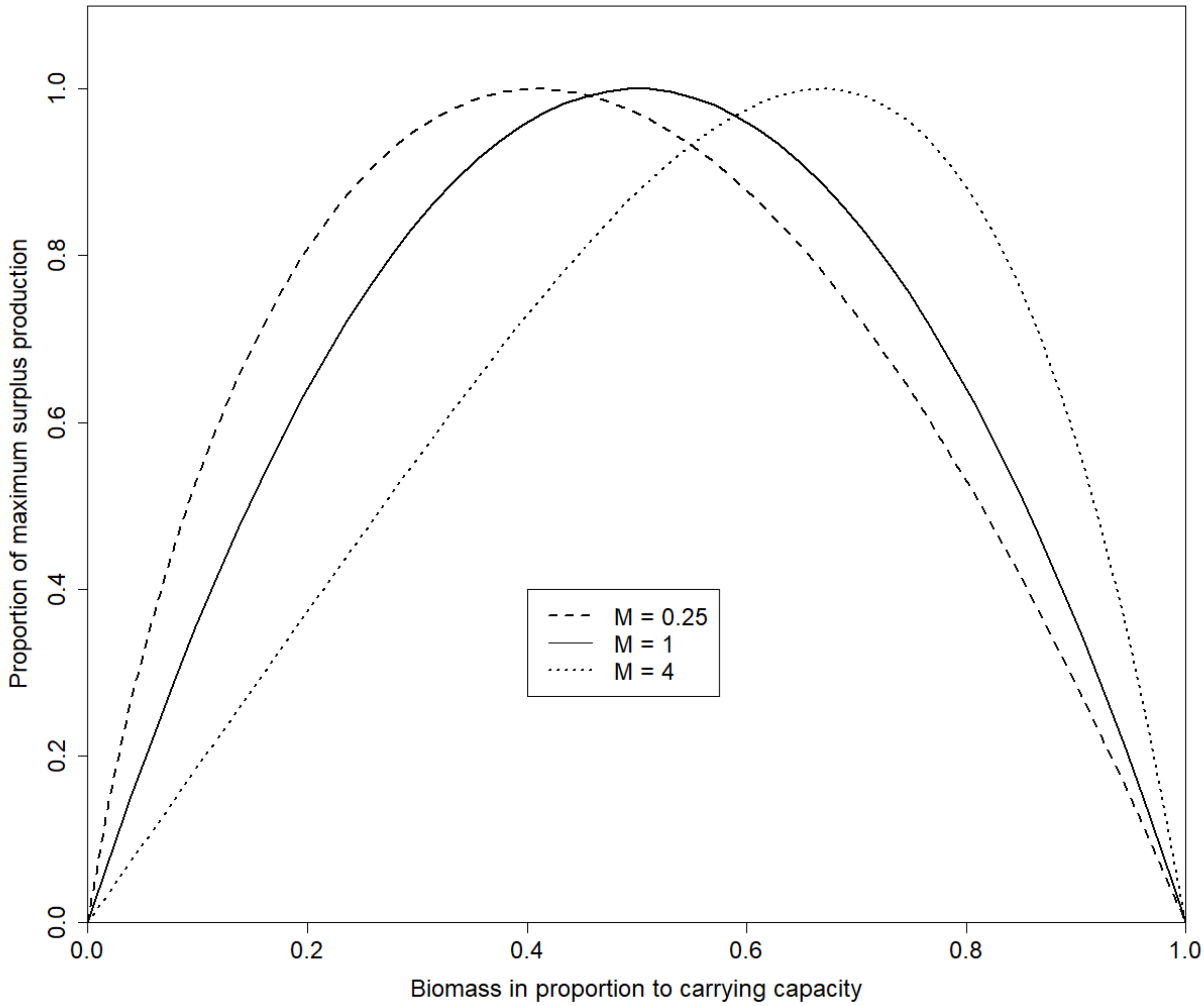


Figure 4. Effect of shape parameter M on the relationship between surplus production (expressed as proportion of maximum) and biomass (expressed as proportion of carrying capacity).

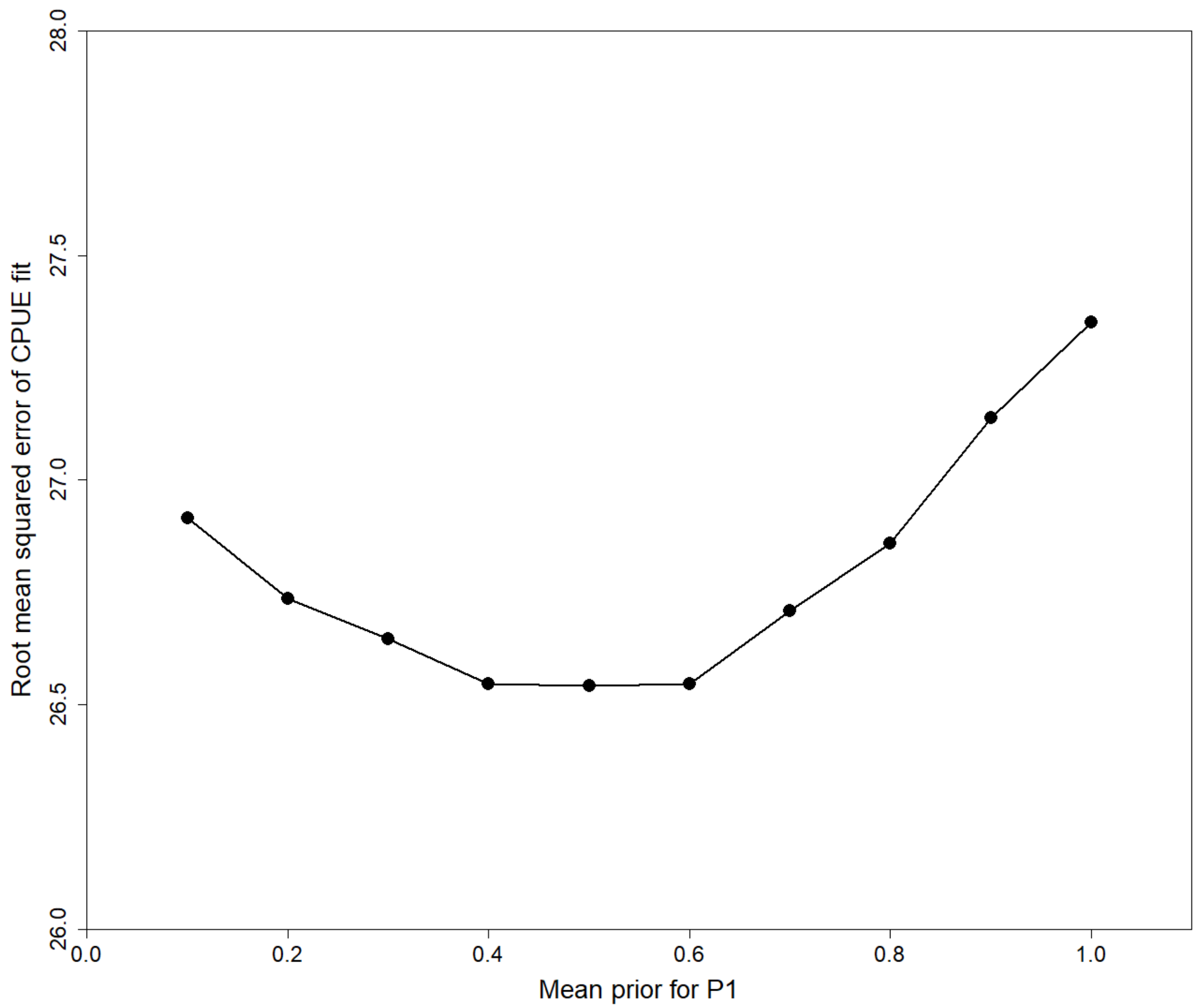


Figure 5. Goodness-of-fit values for alternative choices for the mean of the prior distribution of the initial proportion of carrying capacity (P_1) for Deep 7 bottomfish in the main Hawaiian Islands.

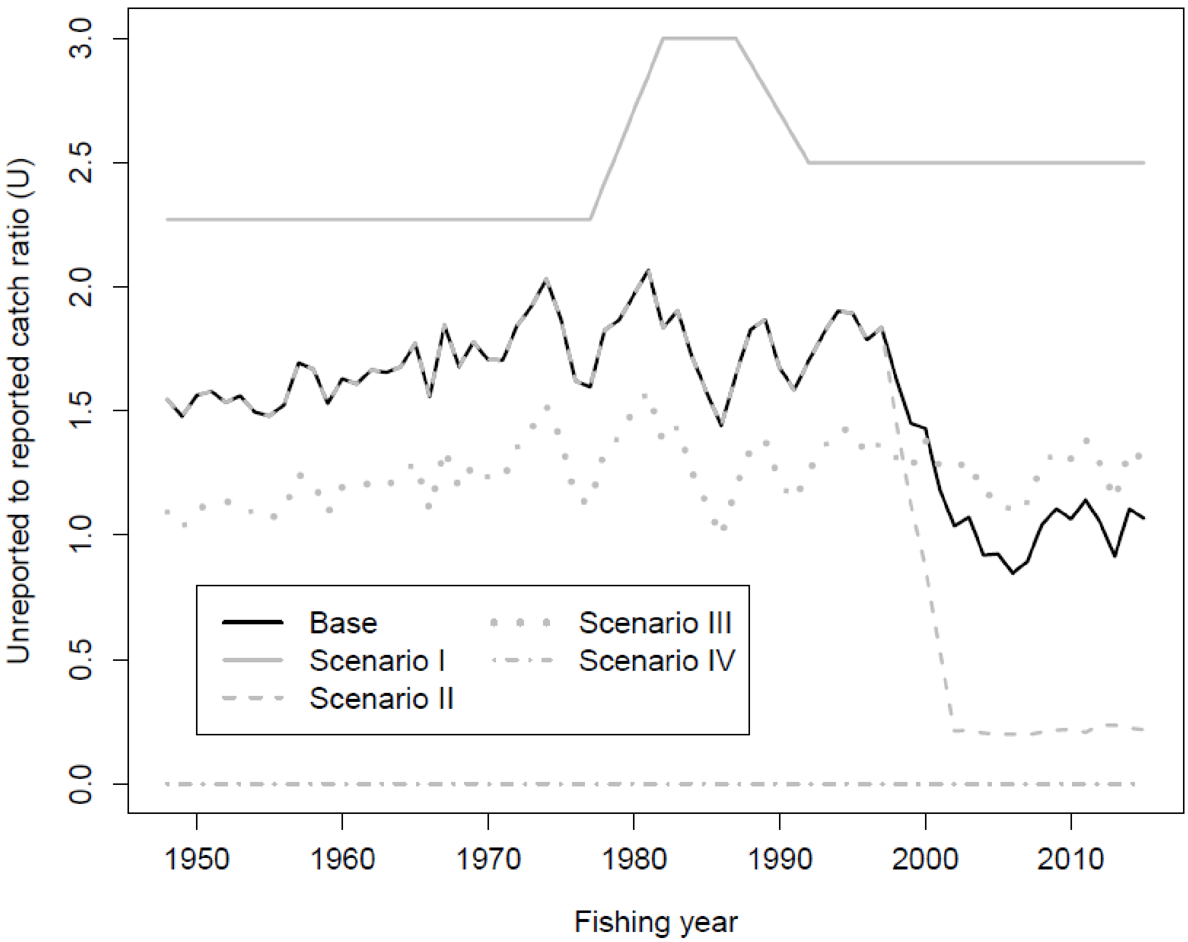


Figure 6. Unreported catch ratios (U) for the four sensitivities on alternative unreported catch (gray lines) compared to the ratios for the base model (black line). Ratios were assigned separately by species, but for ease of plotting, were averaged by catch weight across species here.

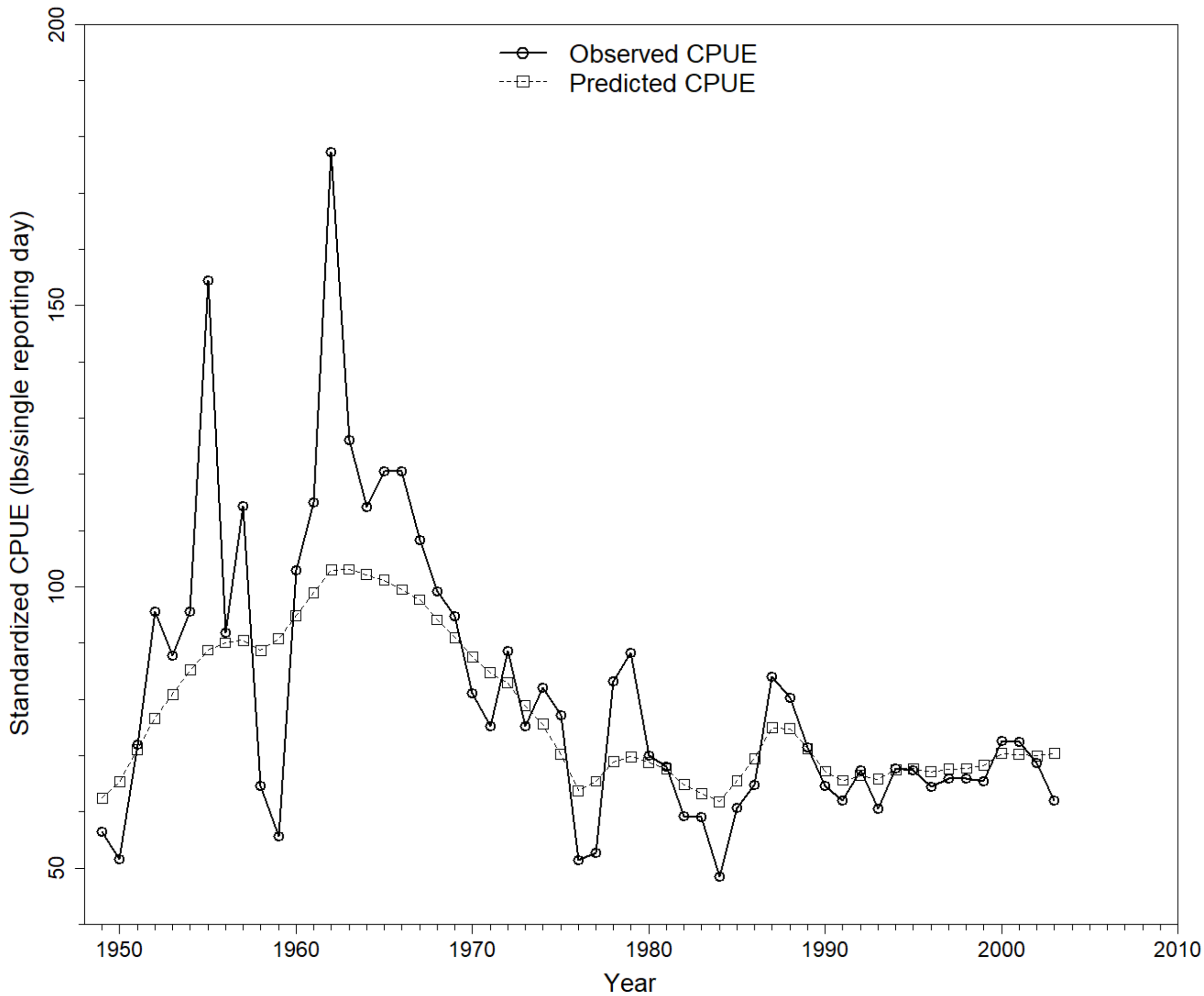


Figure 7. Observed and predicted CPUE for Deep7 bottomfish in the main Hawaiian Islands from 1949 through 2003.

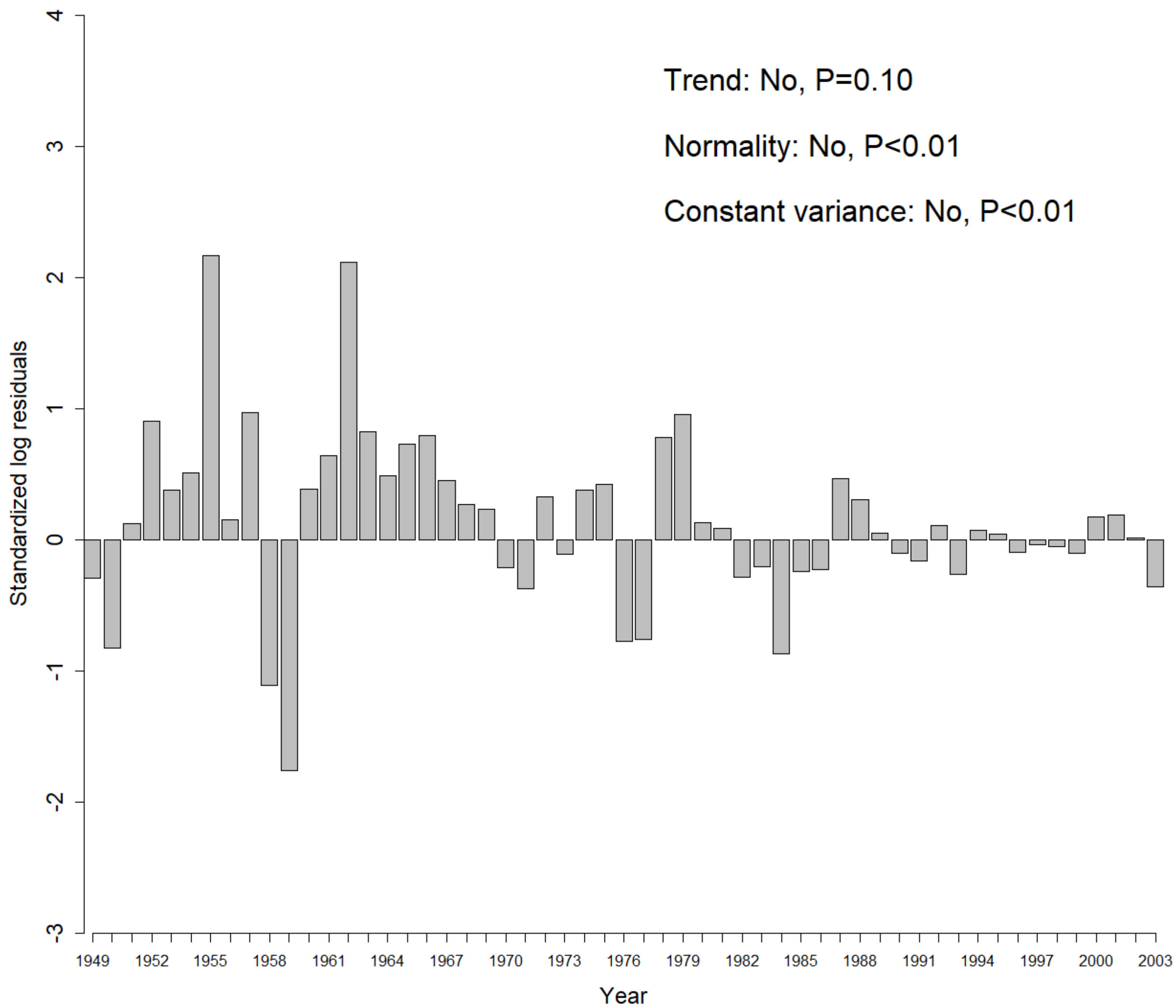


Figure 8. Standardized residuals of observed versus predicted CPUE for Deep 7 bottomfish CPUE in the main Hawaiian Islands by fishing year from 1949-2003 and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

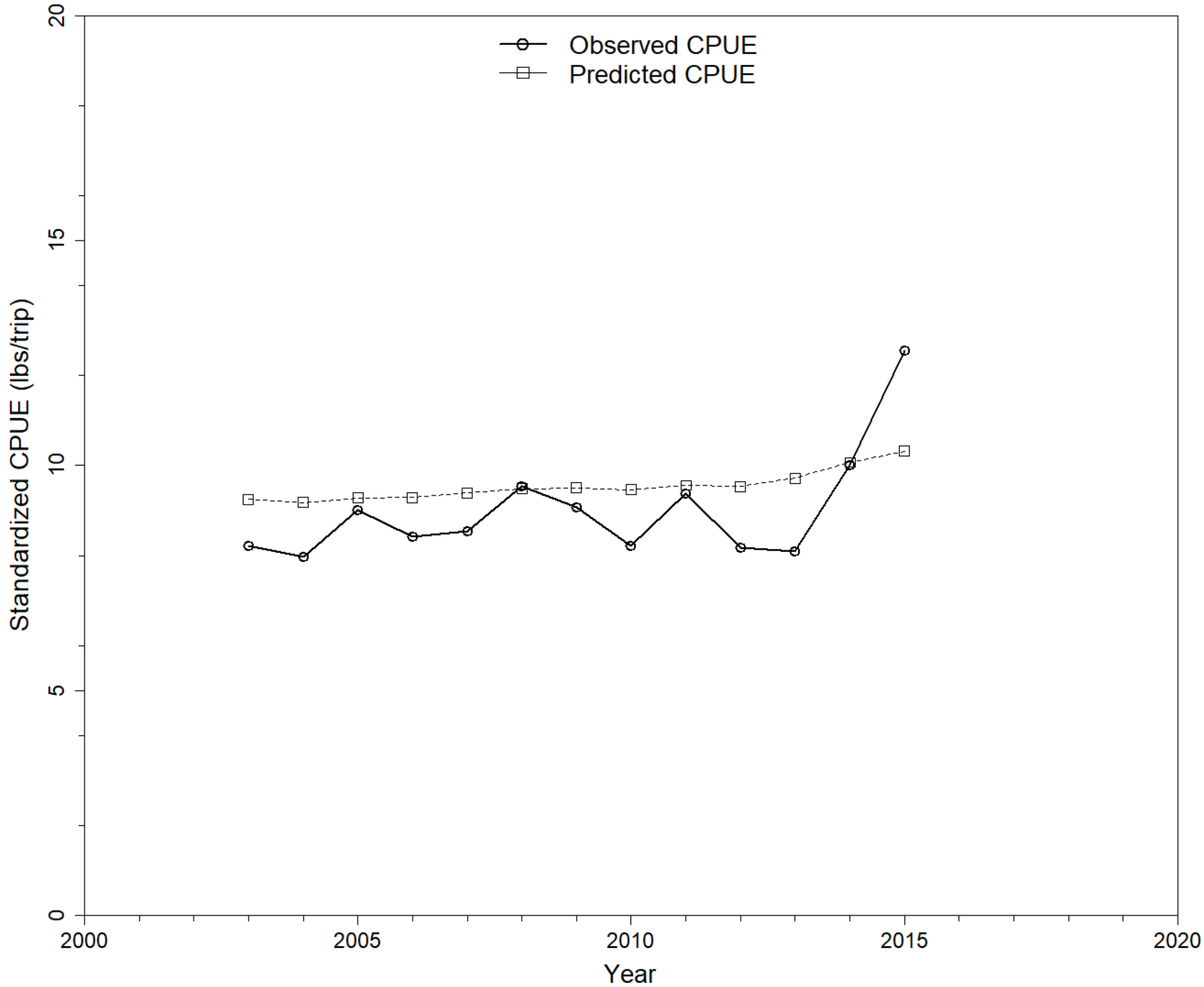


Figure 9. Observed and predicted CPUE for Deep 7 bottomfish in the main Hawaiian Islands from 2003 through 2015.

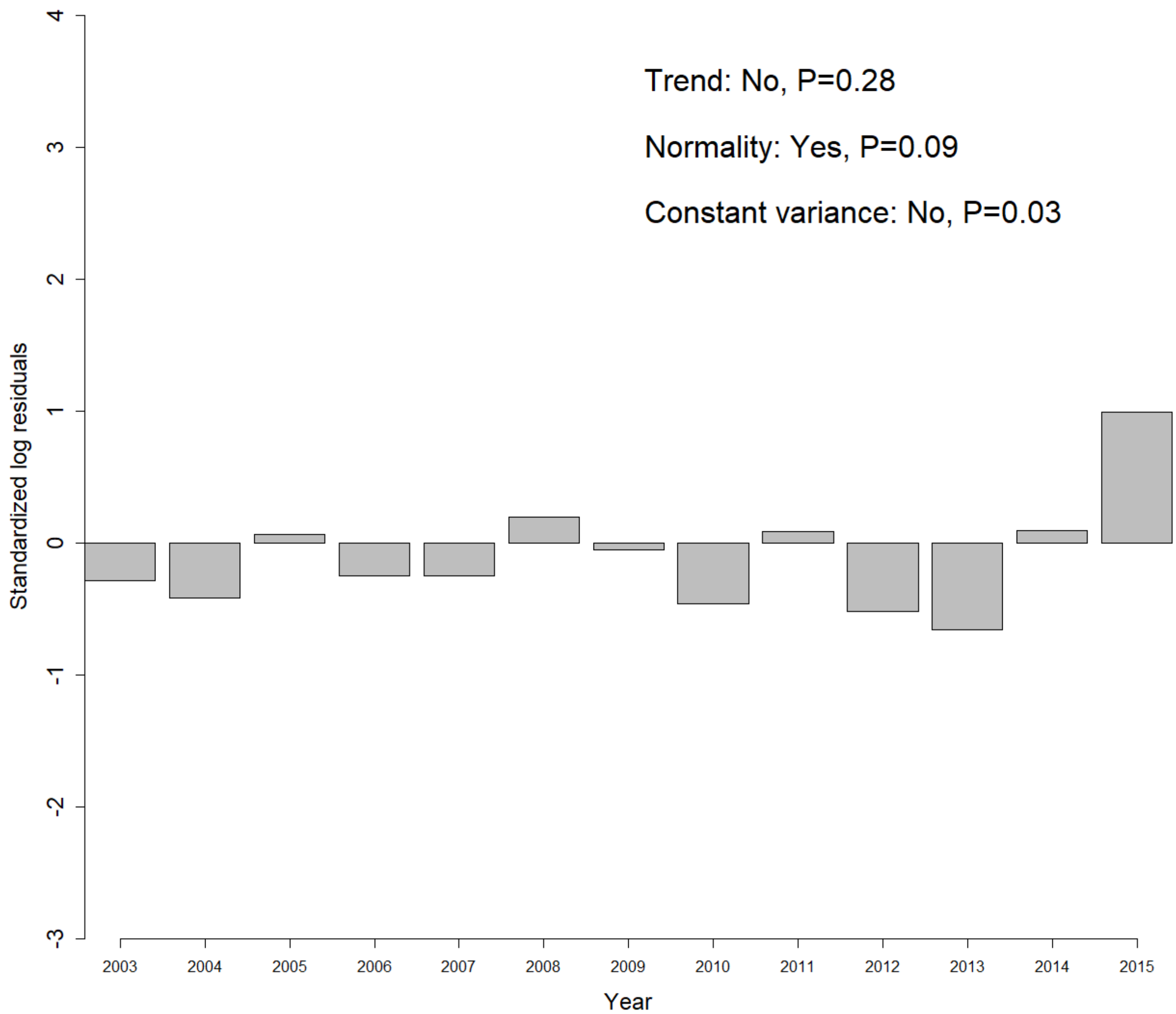


Figure 10. Standardized residuals of observed versus predicted CPUE for Deep 7 bottomfish CPUE in the main Hawaiian Islands by fishing year from 2003-2015, and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

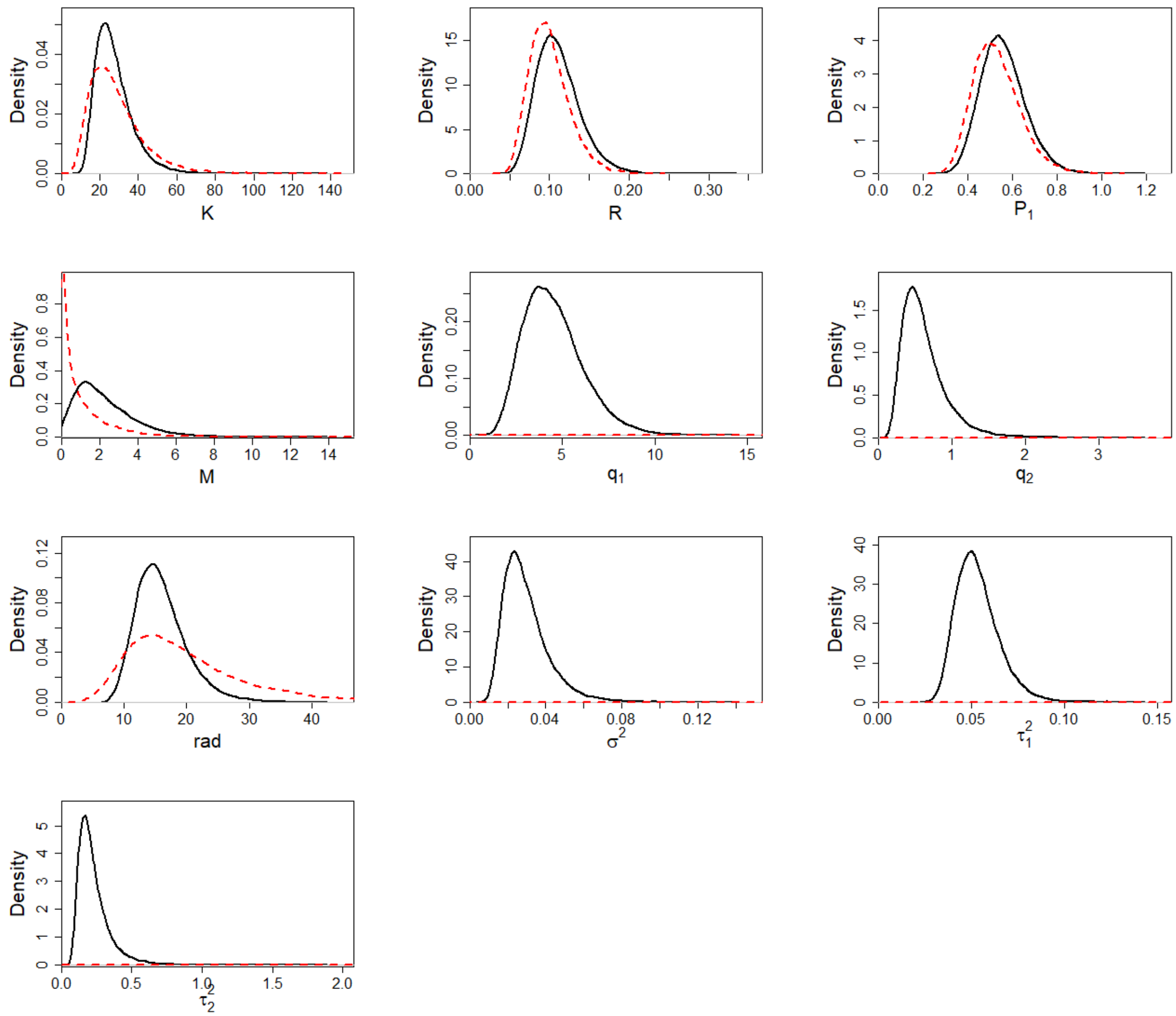


Figure 11. Prior distributions (dashed red line) and posterior densities (solid black line) for model parameters including carrying capacity (K), intrinsic growth rate (R), initial proportion of carrying capacity (P_1), shape parameter (M), catchability in the early (q_1) and recent (q_2) time periods, effective radius of a sample from the fishery-independent survey (*rad*), process error (σ^2), and observation error for the early (τ_1^2) and recent (τ_2^2) time periods for Deep 7 bottomfish in the main Hawaiian Islands. See Section 3.1.2 for descriptions of prior distributions.

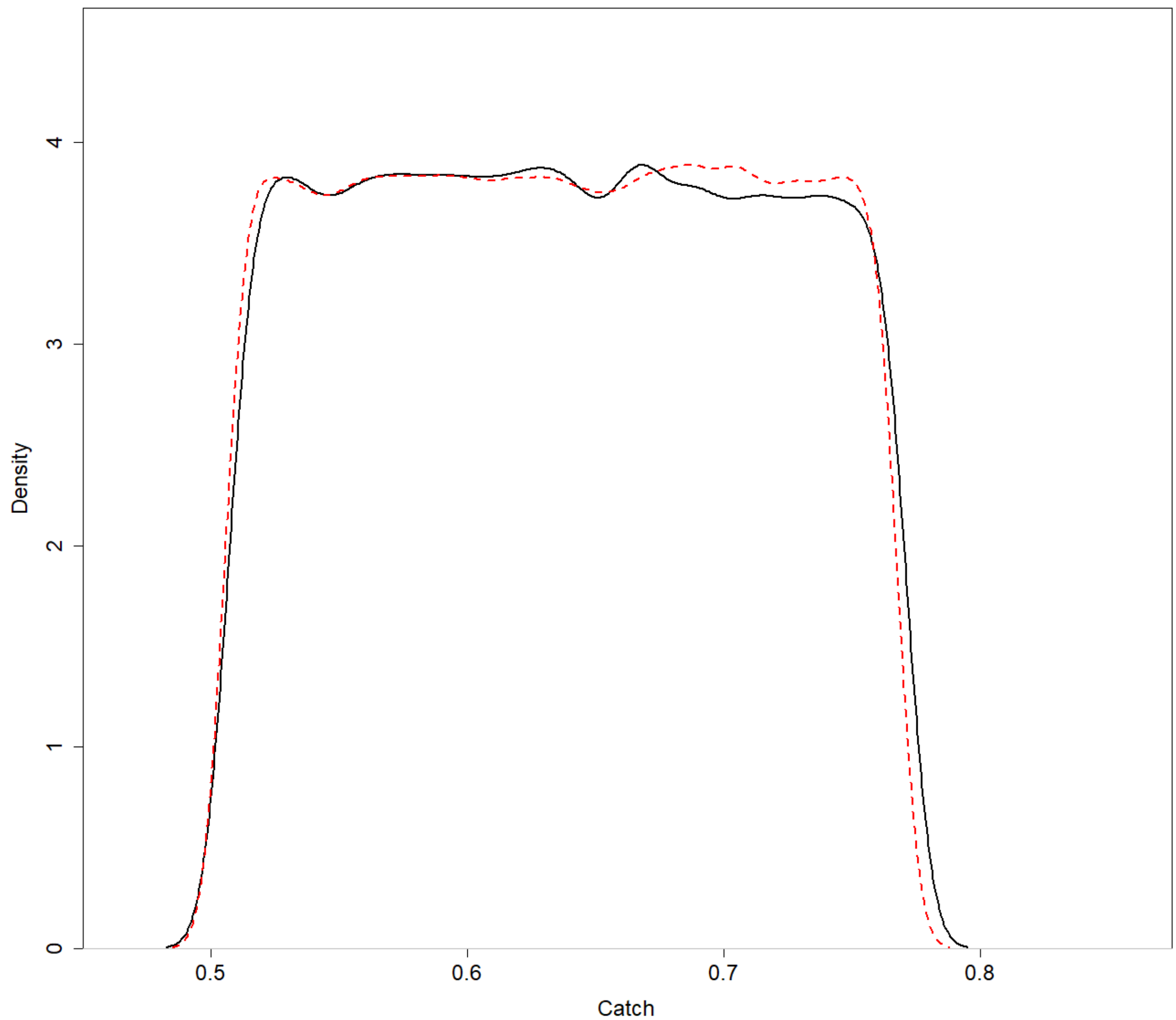


Figure 12. Uniform prior distribution (dashed red line) and posterior density (solid black line) for total Deep 7 bottomfish catch in the main Hawaiian Islands in 2015.

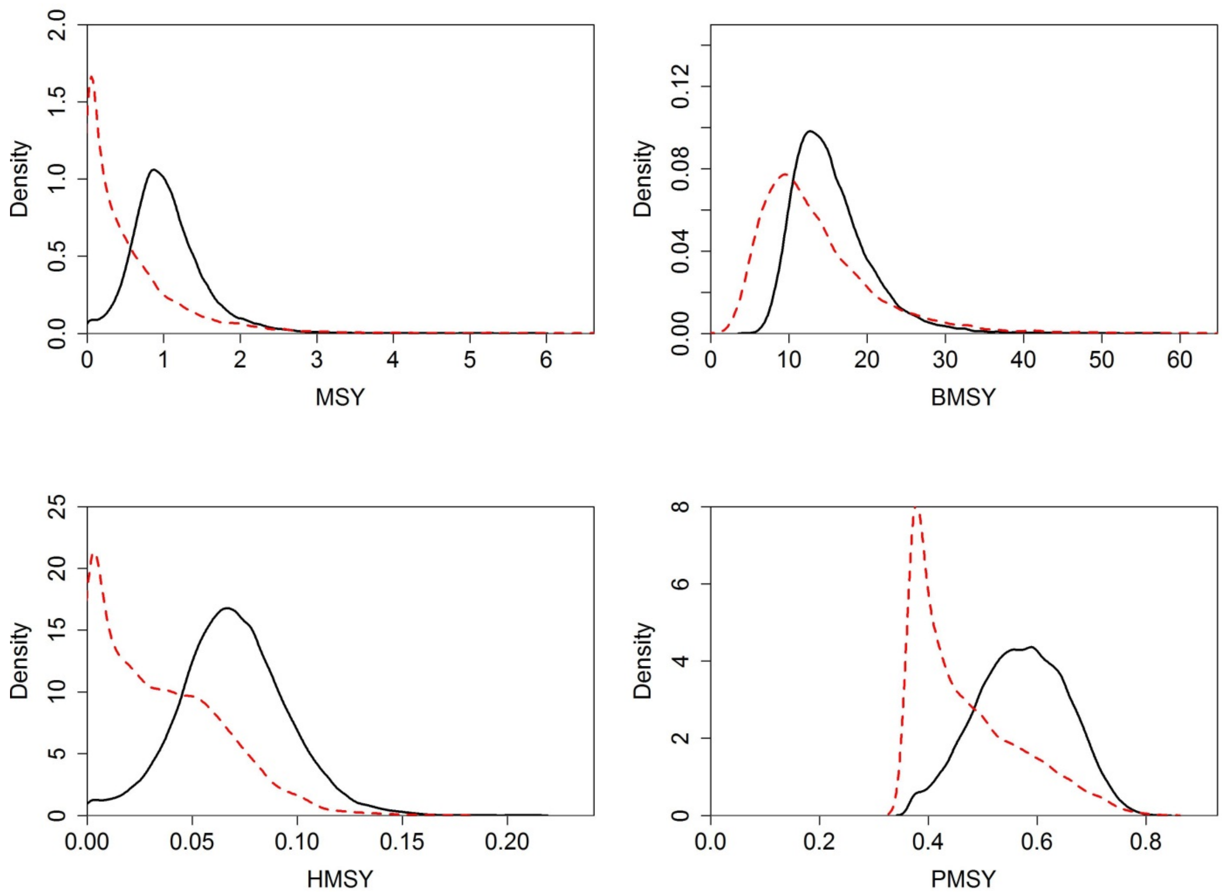


Figure 13. Calculated prior distributions (dashed red lines) and posterior densities (solid lines) for model estimates of maximum sustainable yield (MSY), biomass to produce MSY (B_{MSY}), harvest rate to produce MSY (H_{MSY}), and proportion of carrying capacity to produce MSY (P_{MSY}) for Deep 7 bottomfish in the main Hawaiian Islands.

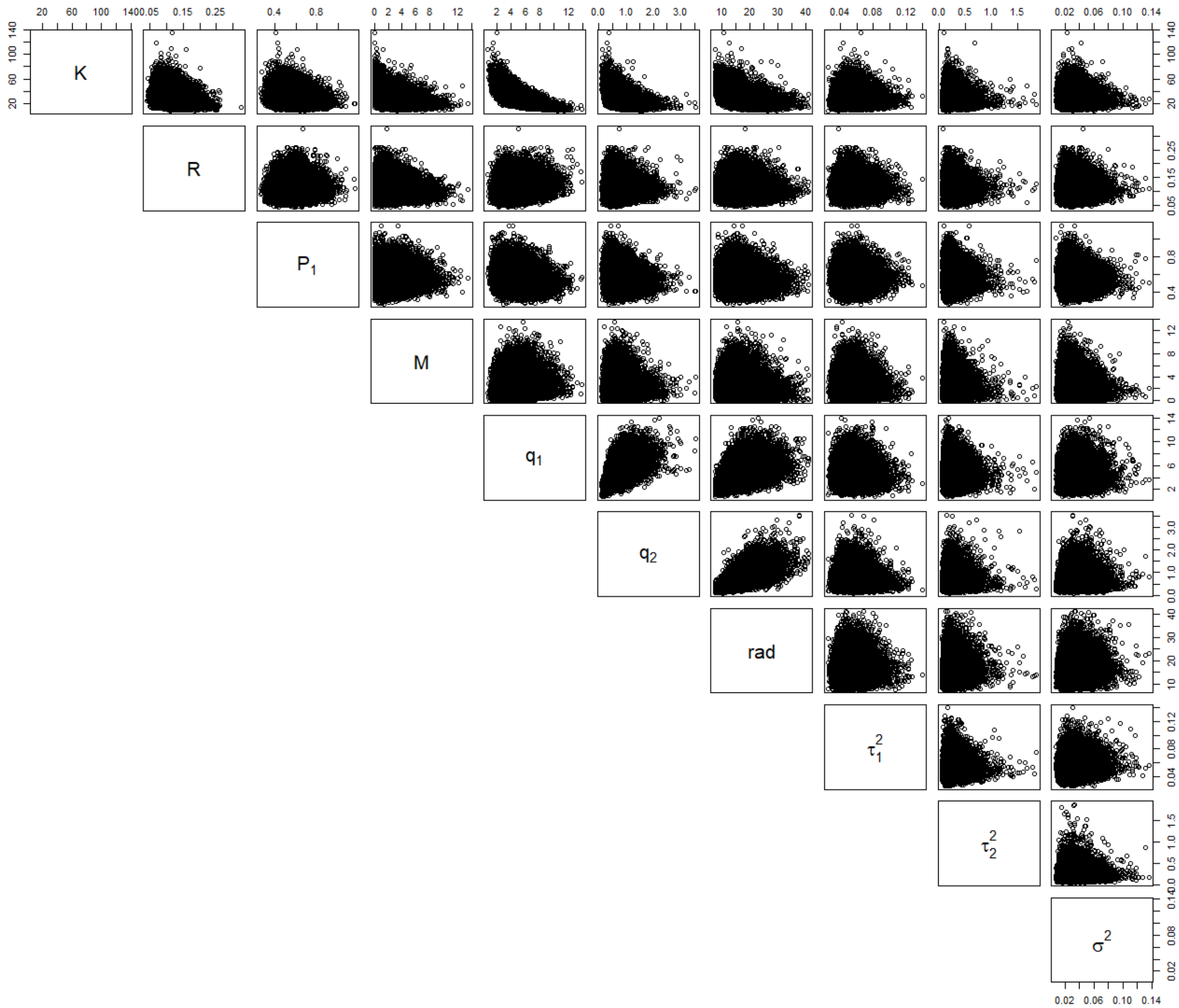


Figure 14. Pairwise scatterplots of parameter estimates. Parameters are carrying capacity (K), intrinsic growth rate (R), initial proportion of carrying capacity (P_1), shape parameter (M), catchability in first (q_1) and second (q_2) time periods, survey sample radius (*rad*), observation error in first (τ_1^2) and second (τ_2^2) time periods, and process error (σ^2).

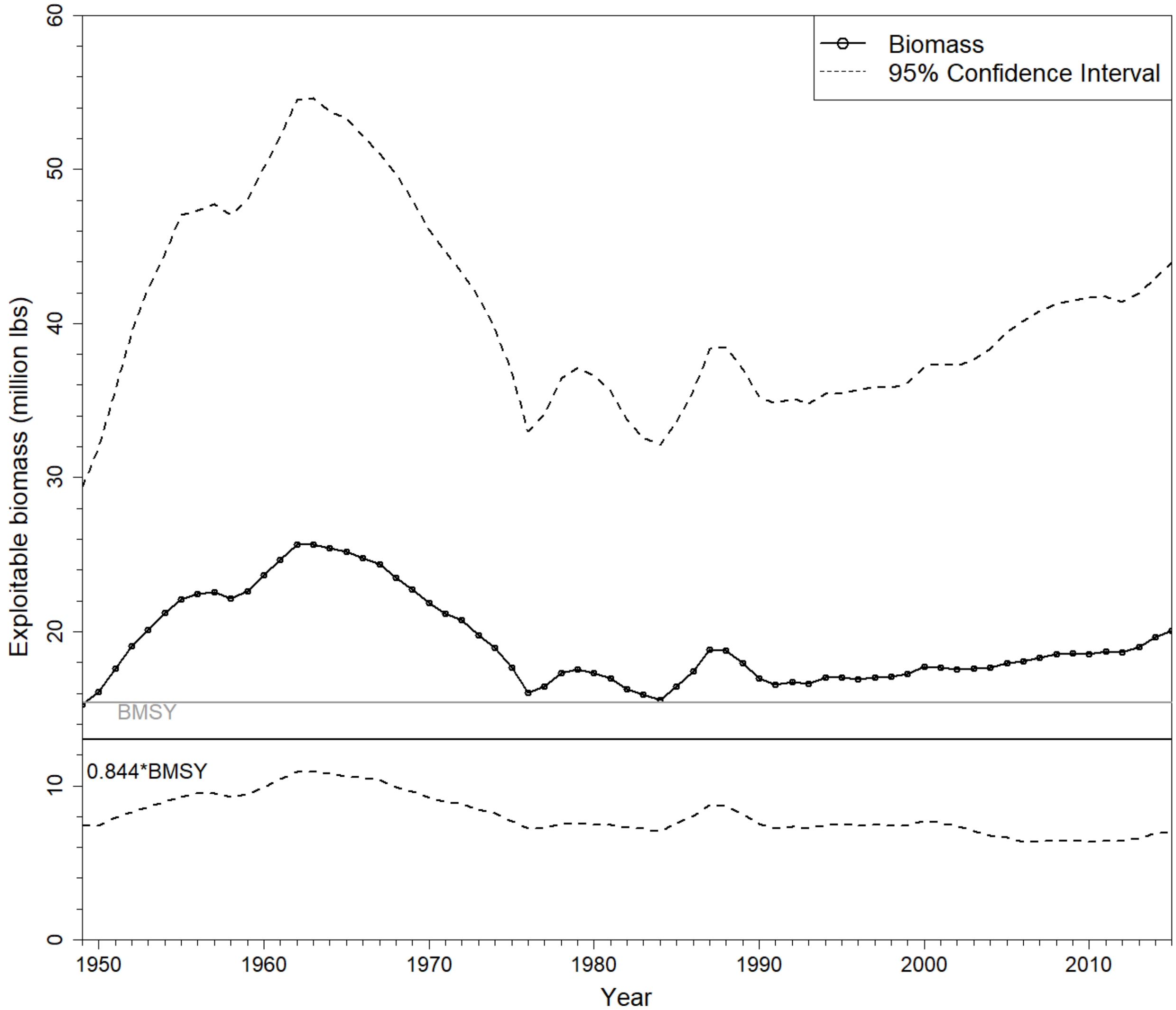


Figure 15. Estimated exploitable biomass (solid line) with 95% credible interval (dashed lines) for Deep 7 bottomfish in the main Hawaiian Islands from 1949 through 2015. Horizontal gray line depicts BMSY, and black line depicts the 0.844*B_{MSY} reference point.

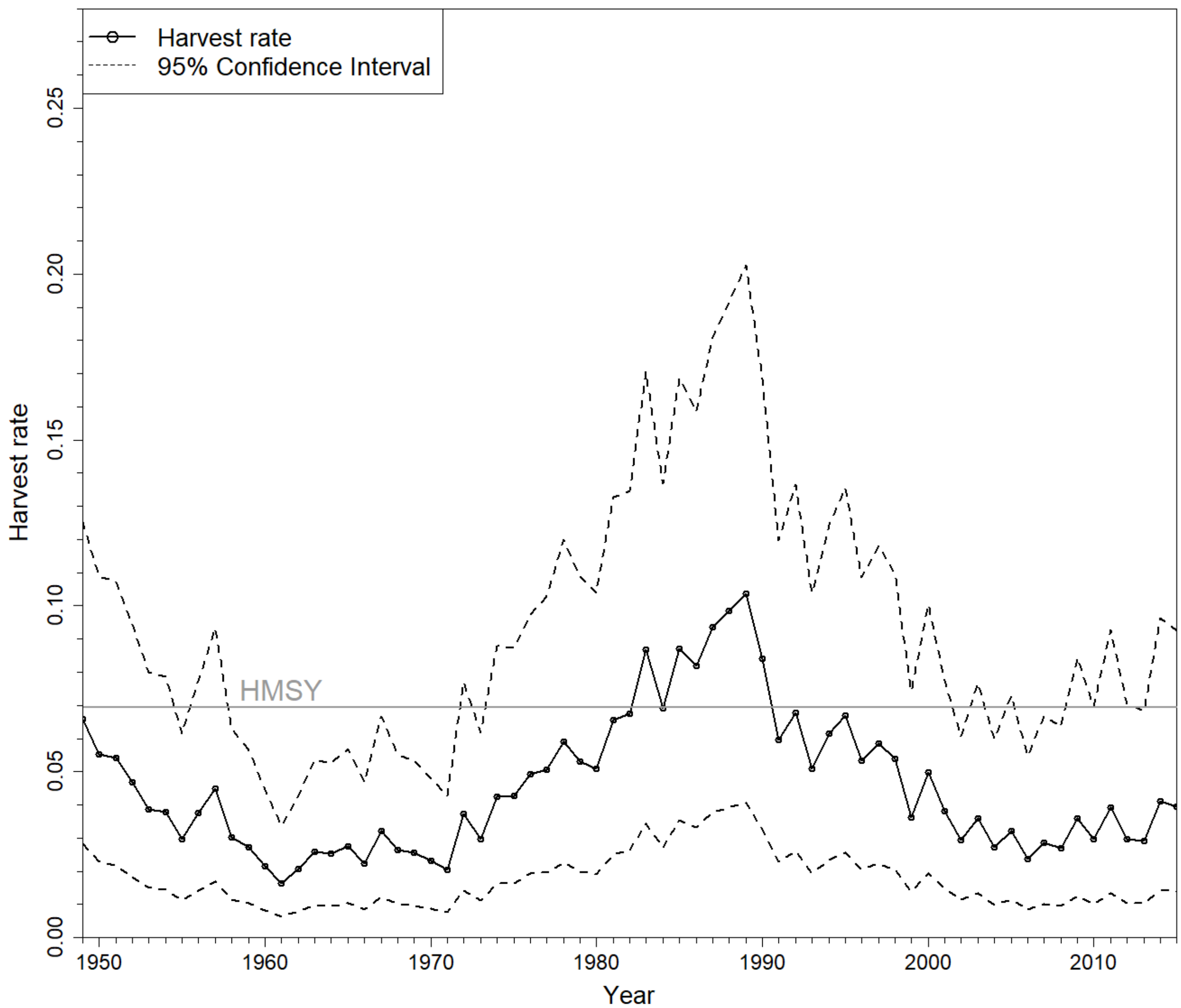


Figure 16. Estimated harvest rate (solid line) with 95% credible interval (dashed lines) for Deep 7 bottomfish in the main Hawaiian Islands from 1949 through 2015. Horizontal gray line depicts H_{MSY} reference point.

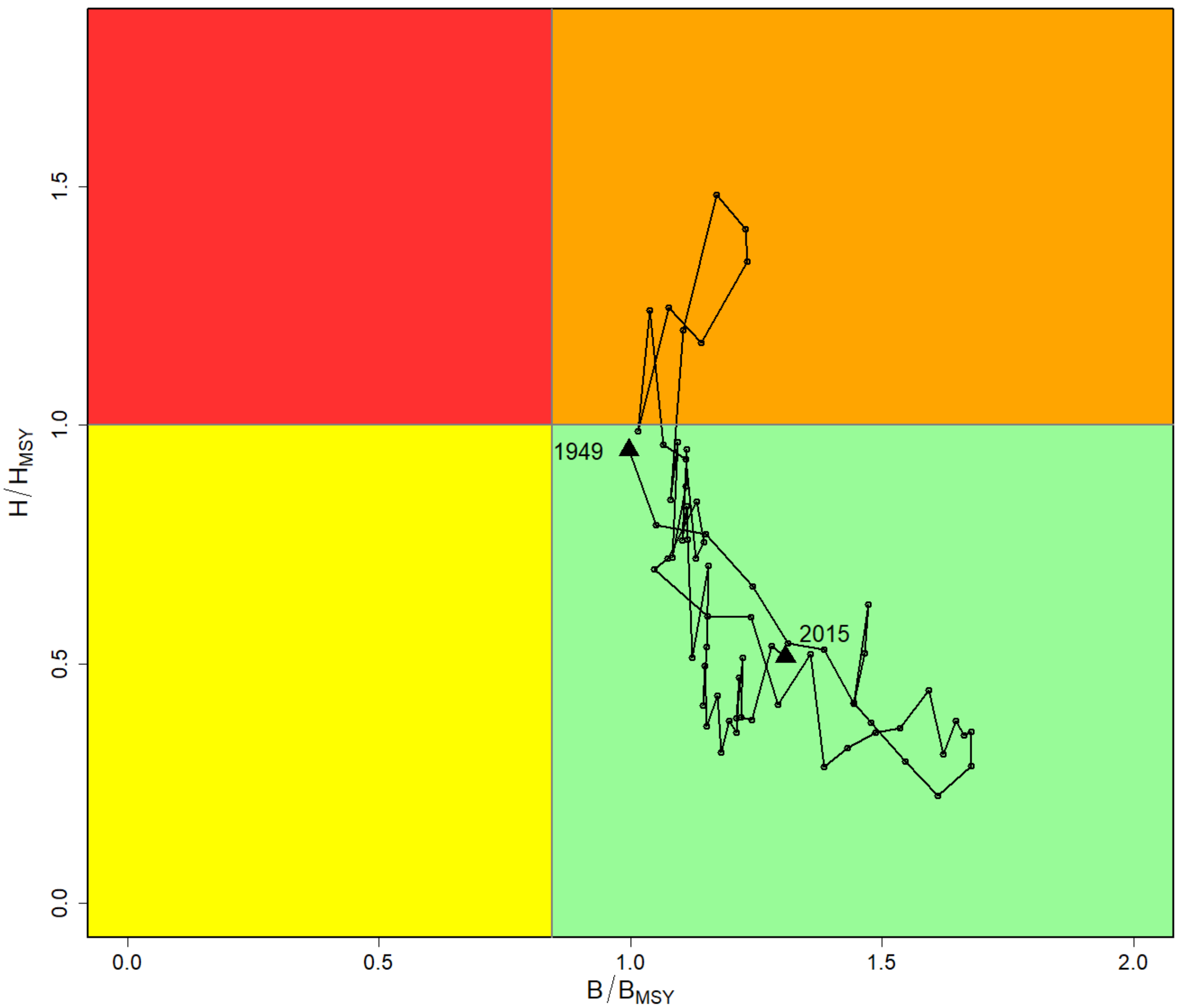


Figure 17. Estimated status for Deep 7 Bottomfish in the main Hawaiian Islands from 1949 through 2015. Triangles delineate start and end years. Horizontal and vertical lines delineate reference points for overfishing (i.e., $H/H_{MSY}>1$) and overfished status (i.e., $B/B_{MSY}< 0.844$).

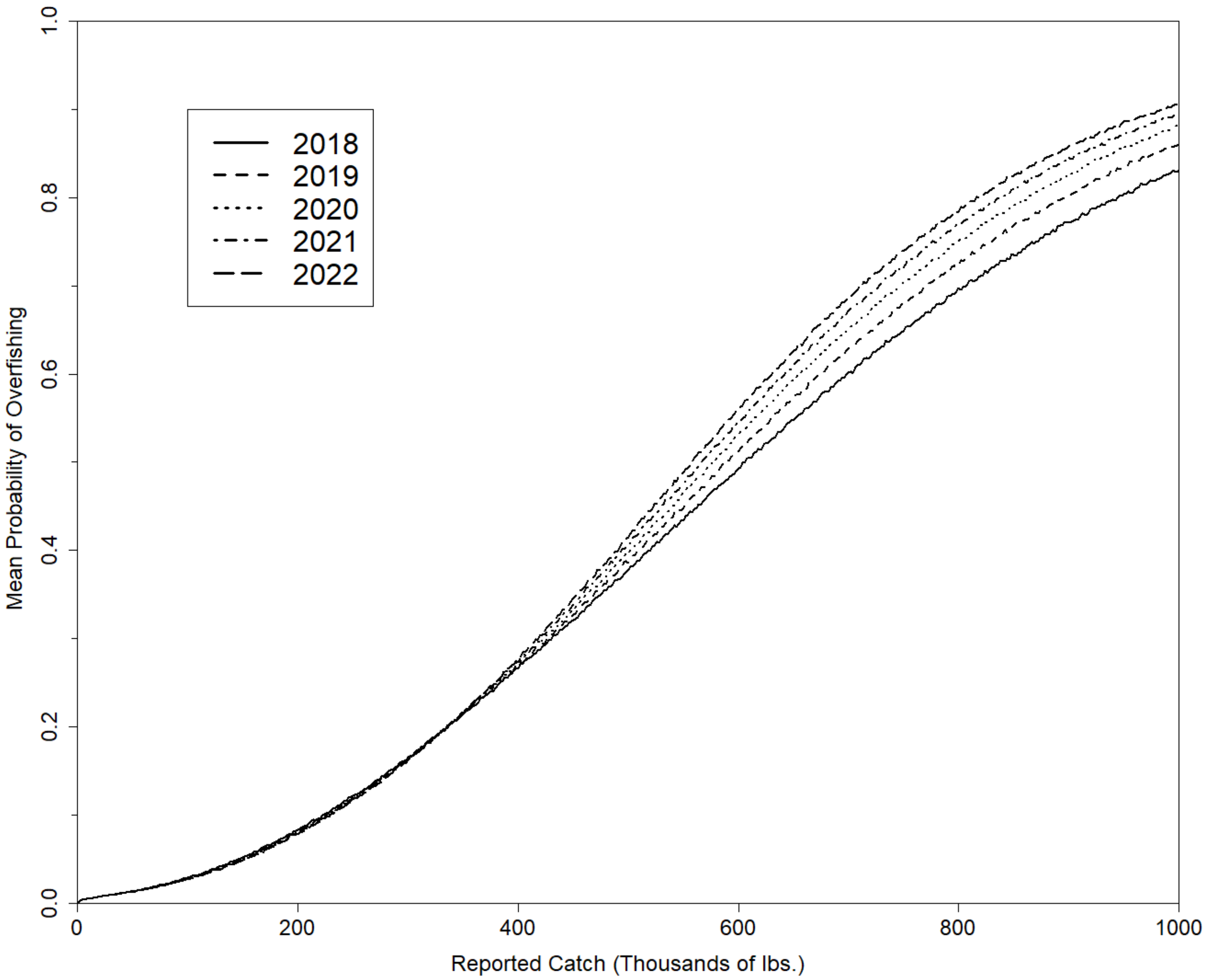


Figure 18. Probability of overfishing (i.e., $H/H_{MSY}>1$) Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2018 through 2022 as a function of projected reported catch varying from 0 to 1 million pounds.

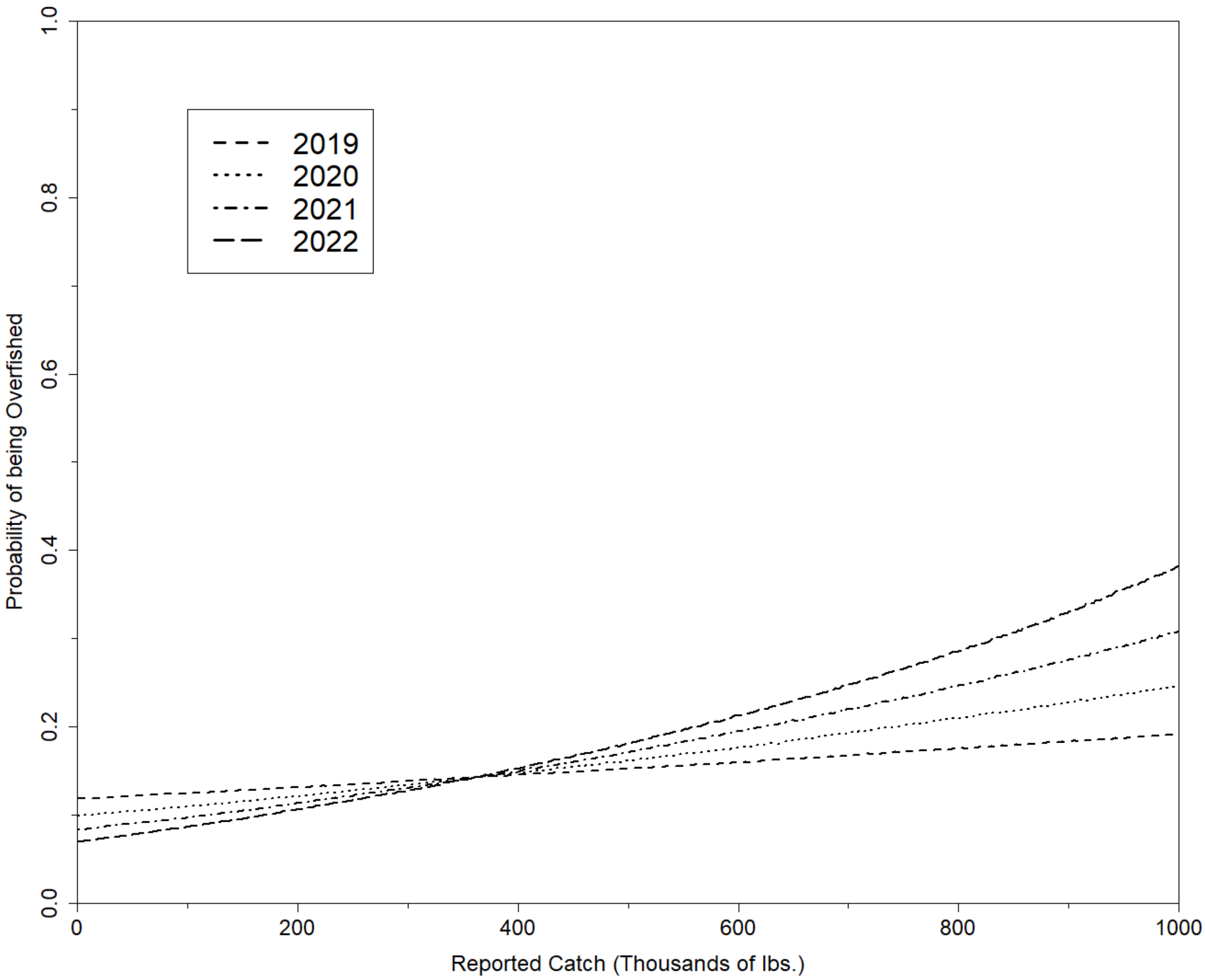


Figure 19. Probability of the stock being overfished (i.e., B/B_{MSY}<0.844) for Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2019 through 2022 as a function of projected reported catch varying from 0 to 1 million pounds (2018 was not shown because it was not a function of simulated alternative catch values).

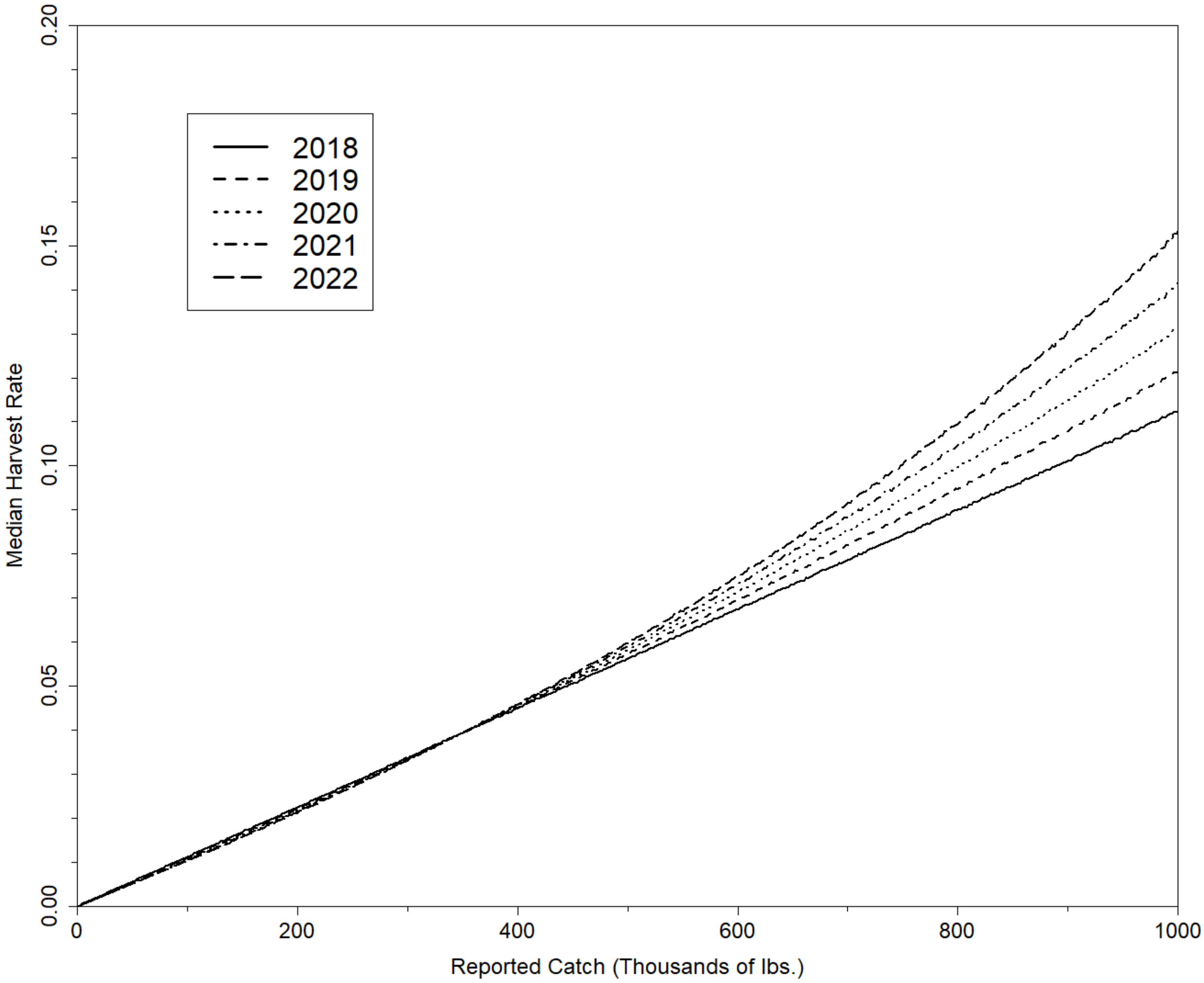


Figure.20. Median harvest rate for Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2018 through 2022 as a function of projected reported catch varying from 0 to 1 million pounds.

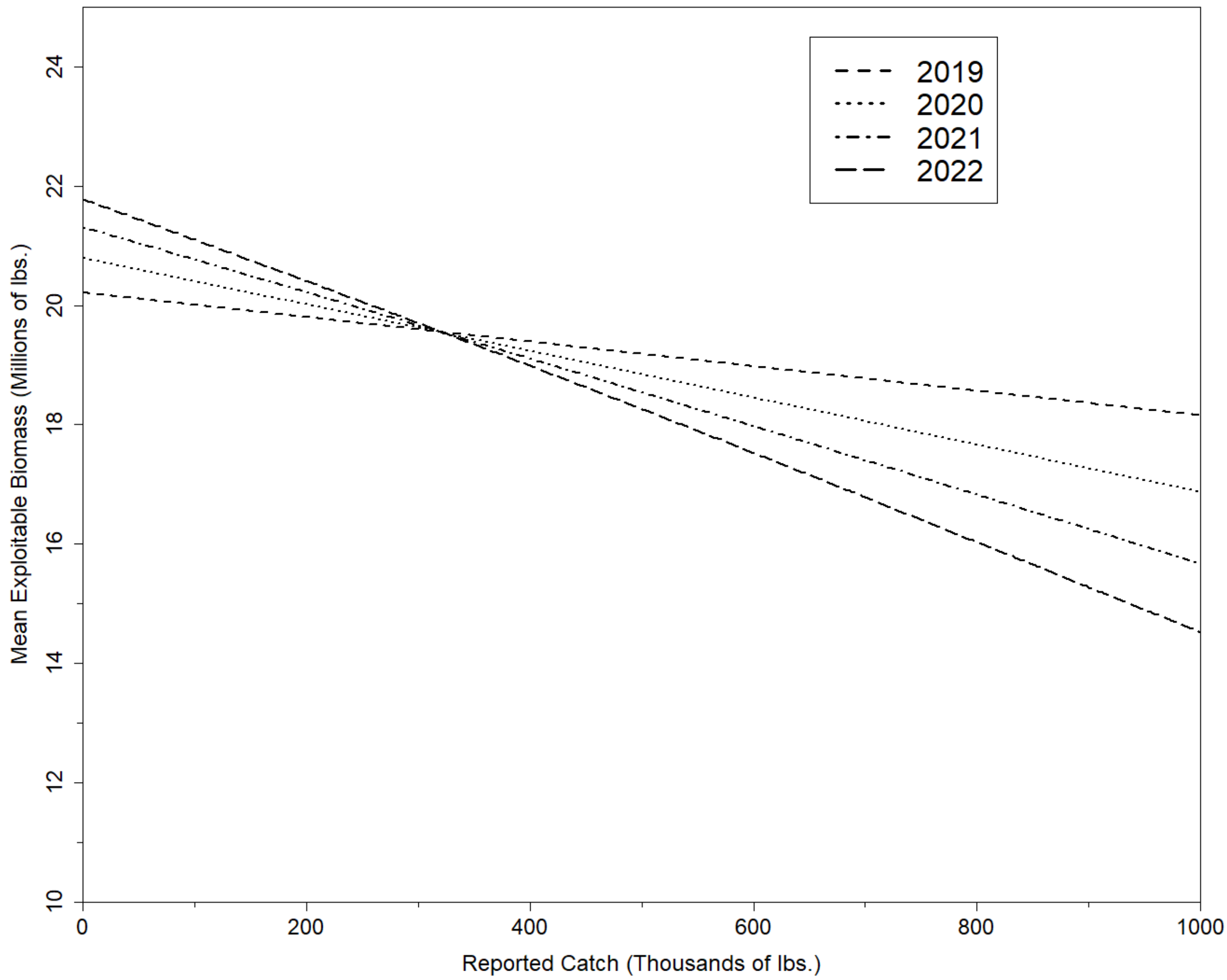


Figure 21. Mean exploitable biomass for Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2019 through 2022 as a function of projected reported catch varying from 0 to 1 million pounds (biomass in 2018 is not shown because it was not a function of simulated alternative catch values).

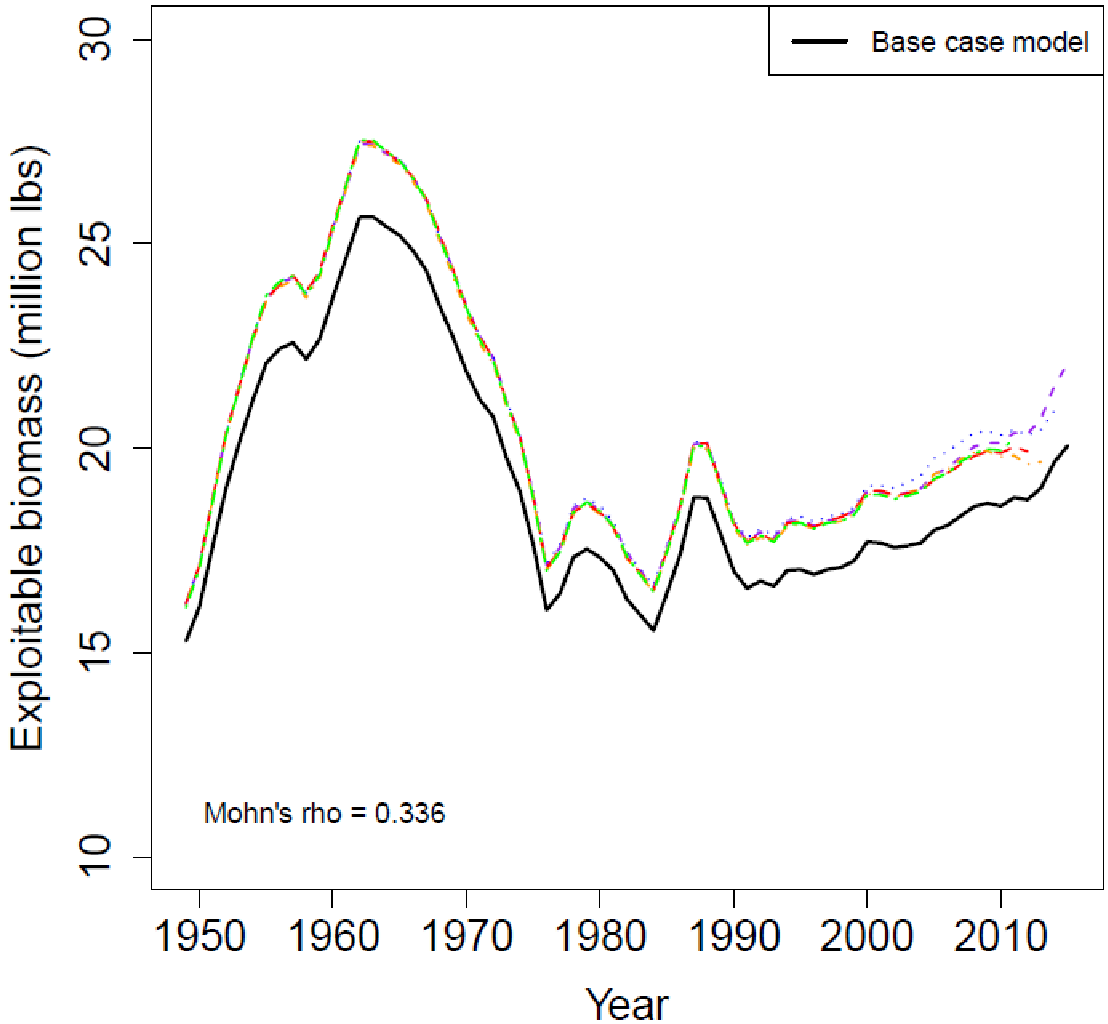


Figure 22.1. Retrospective analysis for estimated mean exploitable biomass from a model excluding the fishery-independent survey and with terminal year set as fishing year 2015 through 2011 (non-solid lines) compared to the base case model (solid line).

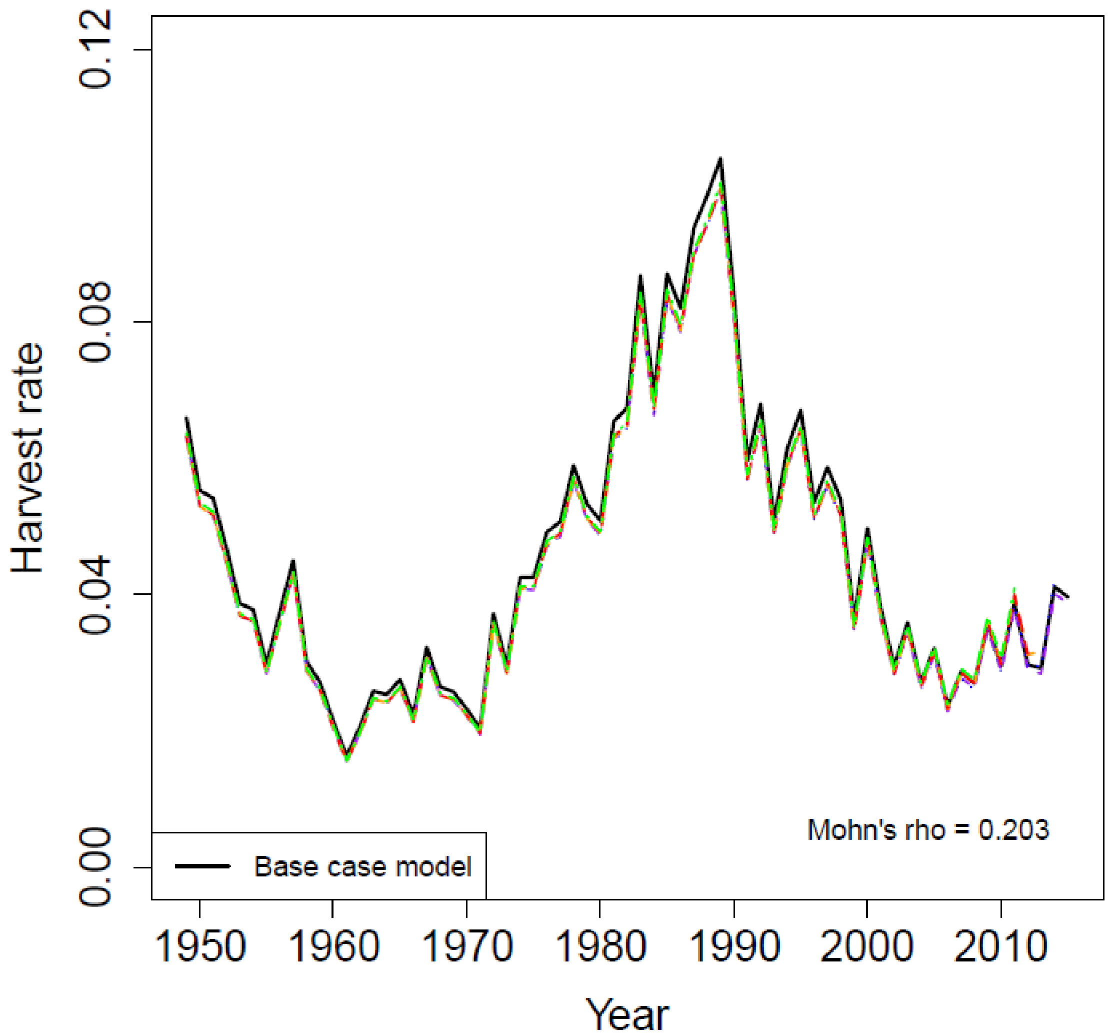


Figure 22.2. Retrospective analysis for estimated mean harvest rate from a model excluding the fishery-independent survey and with terminal year set as 2015 through 2011 (non-solid lines) compared to the base case model (solid line).

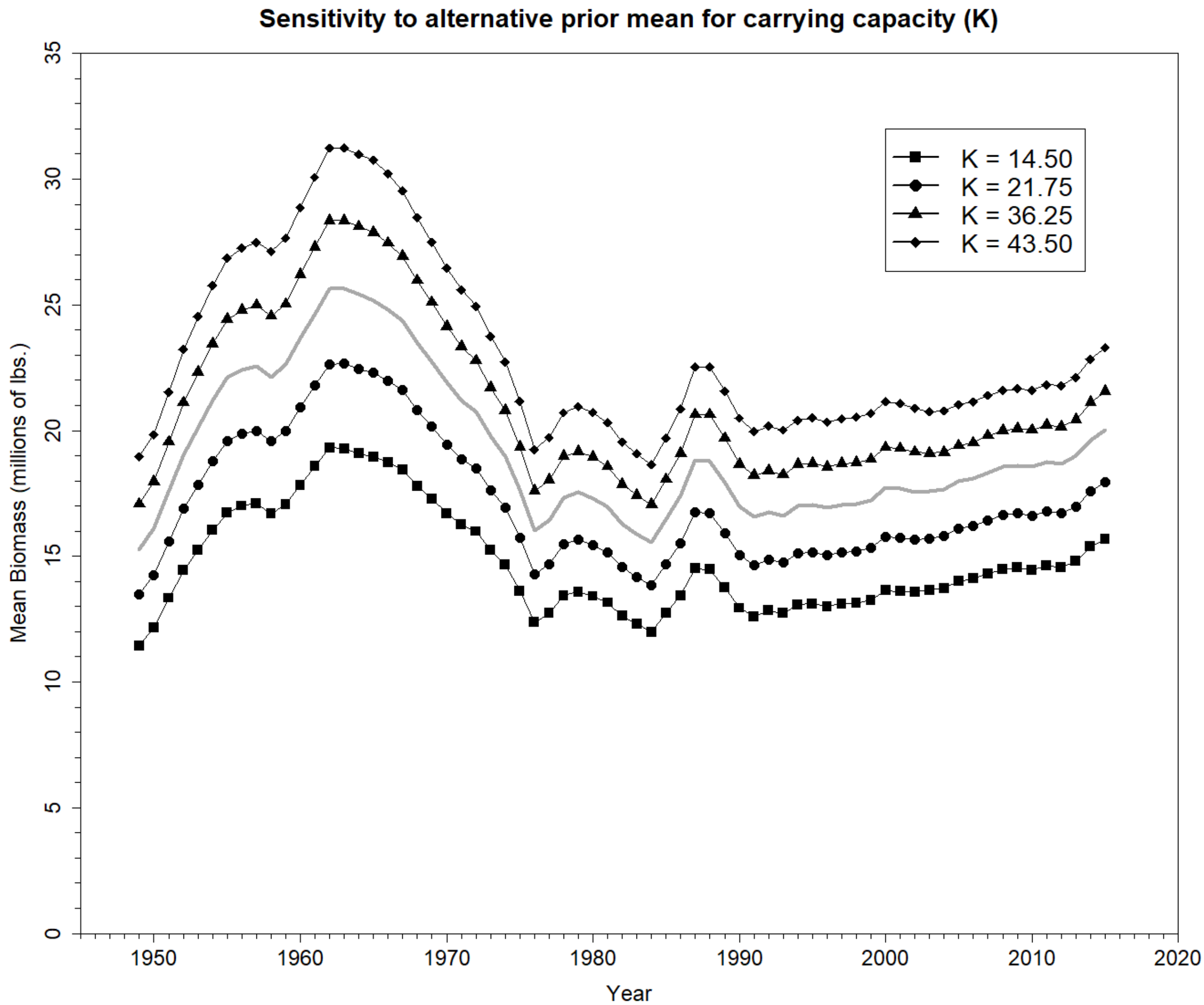


Figure 23.1. Estimated mean exploitable biomass as a function of different prior means for carrying capacity (K). Values of K were calculated as +/-25% and +/-50% of the mean value used for the base case (μ_K = 29 million lbs.; gray line).

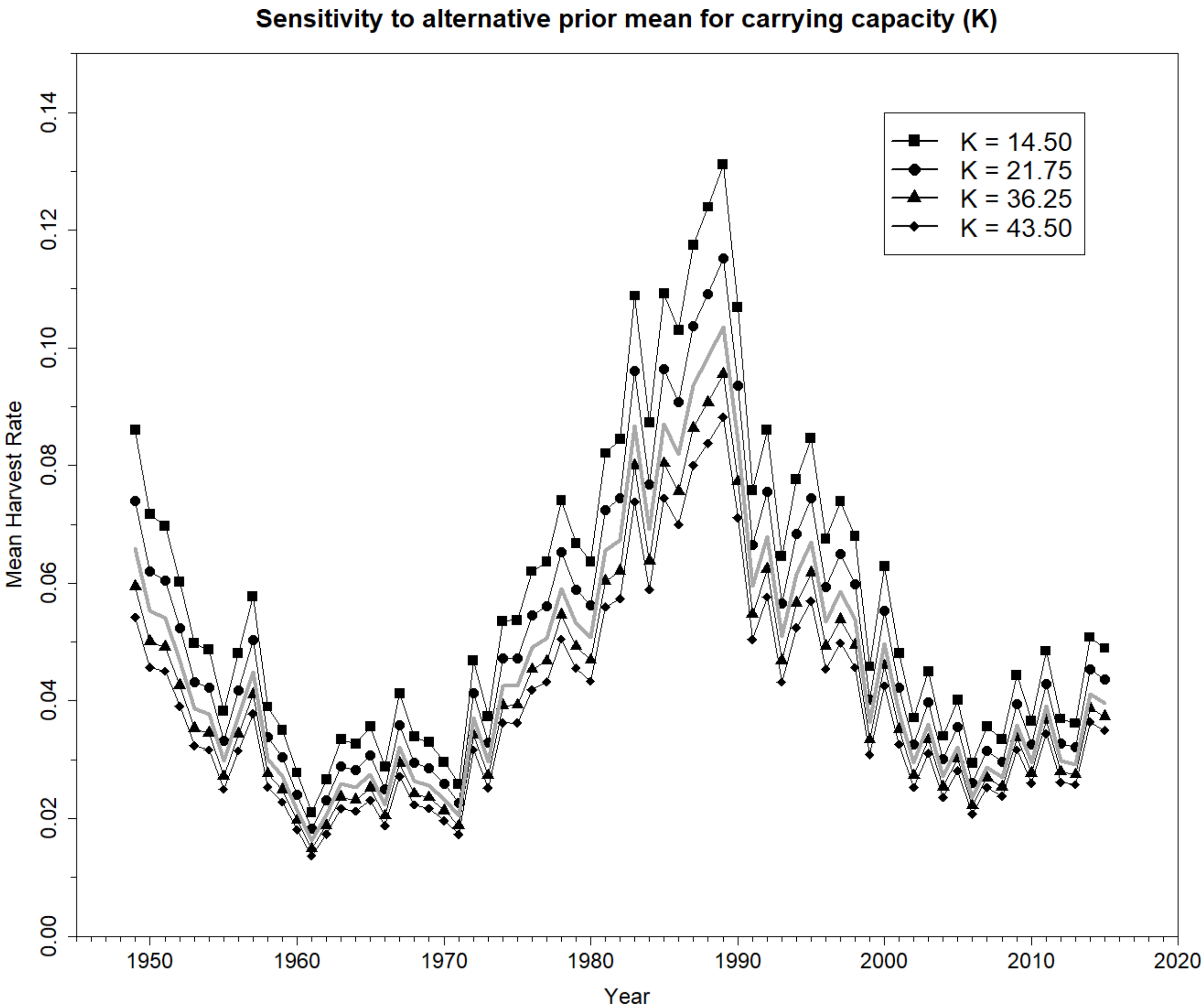


Figure 23.2. Estimated mean harvest rate as a function of different prior means for carrying capacity (K). Values of K were calculated as +/-25% and +/-50% of the mean value used for the base case (μ_K = 29 million lbs.; gray line).

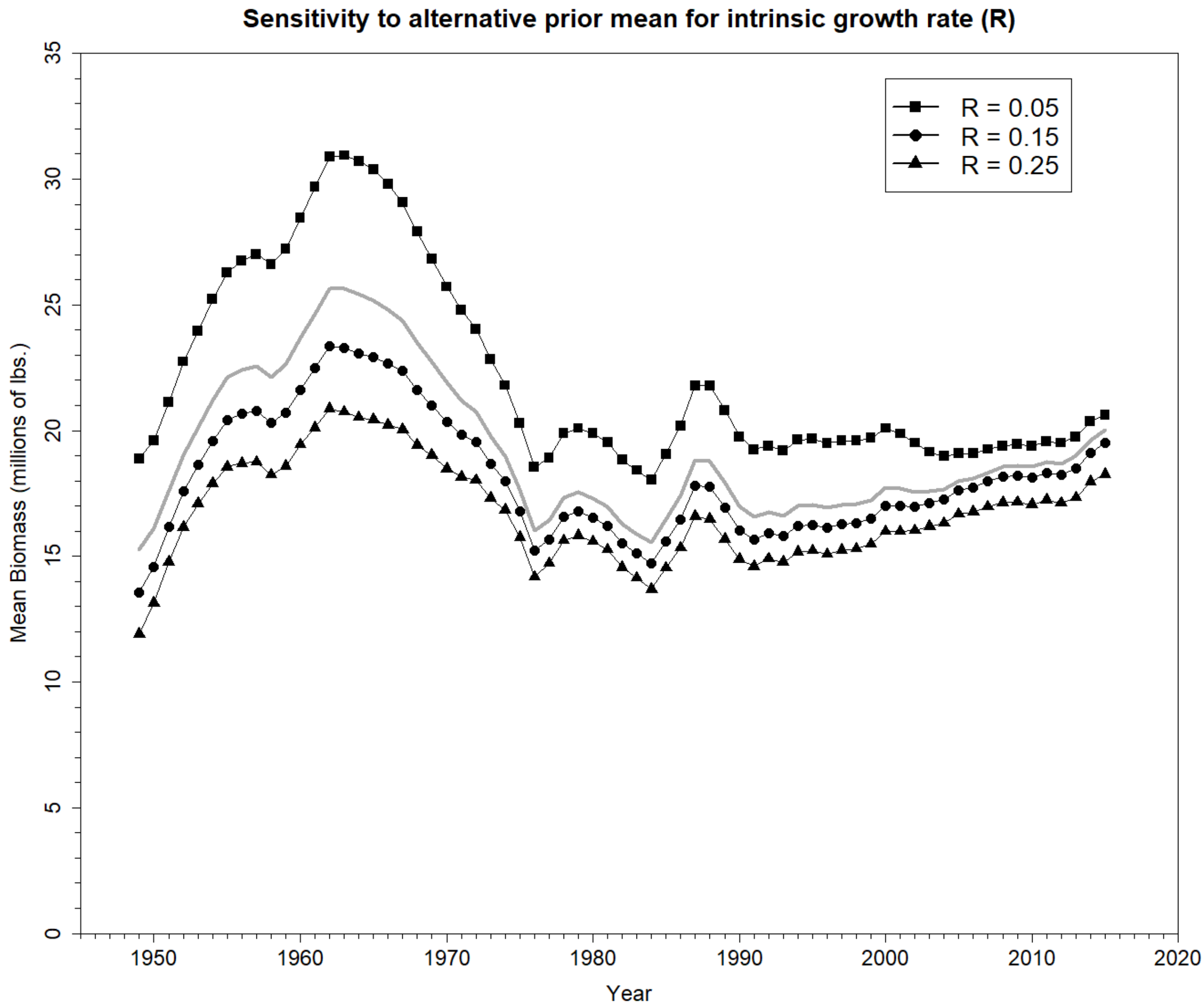


Figure 24.1. Estimated mean exploitable biomass as a function of different prior means for intrinsic growth rate (R). Values of R were calculated as +/- 50% and +150% of the mean value used for the base case (μ_R = 0.10.; gray line).

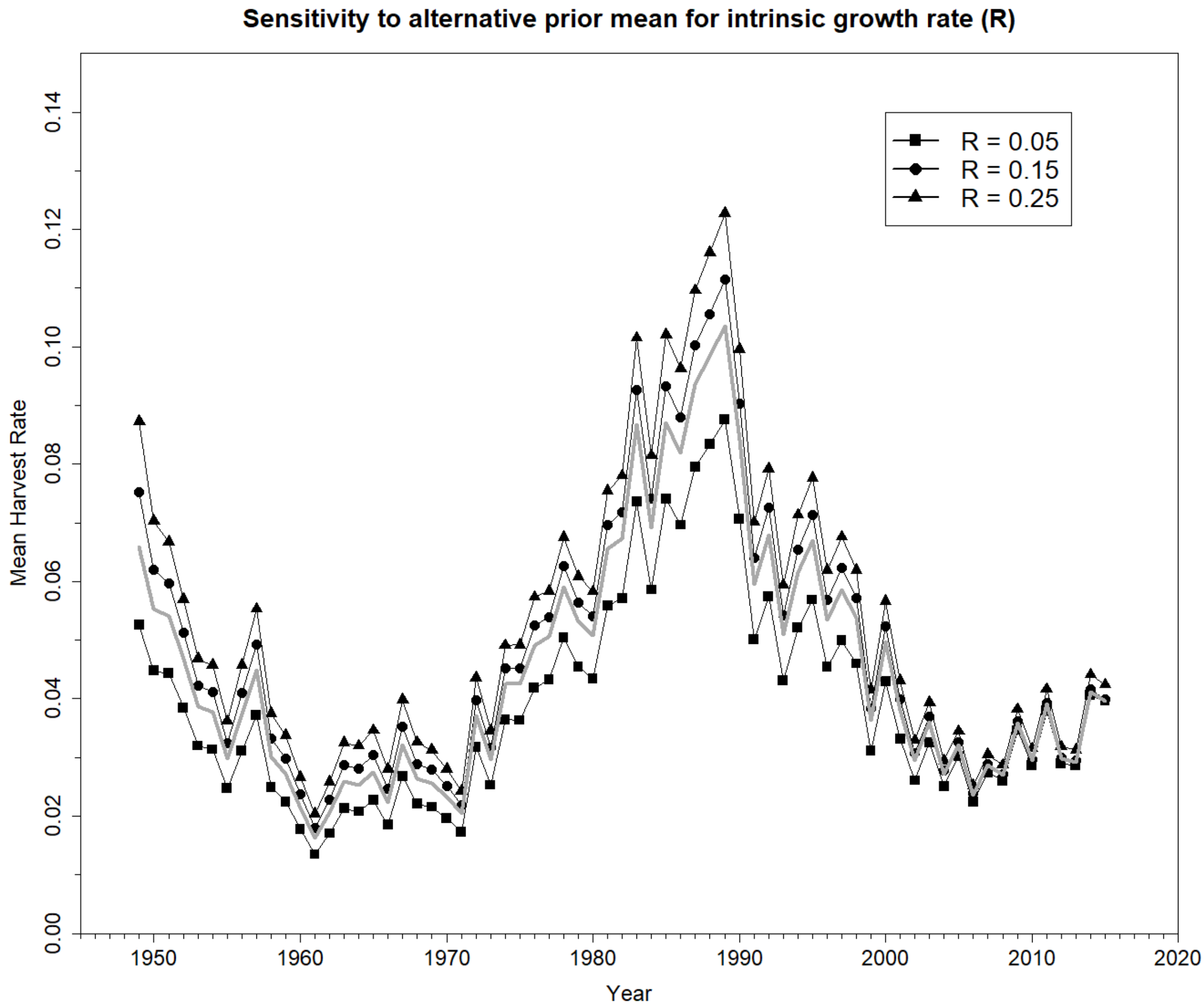


Figure 24.2. Estimated mean harvest rate as a function of different prior means for intrinsic growth rate (R). Values of R were calculated as +/- 50% and +150% of the mean value used for the base case (μ_R = 0.10.; gray line).

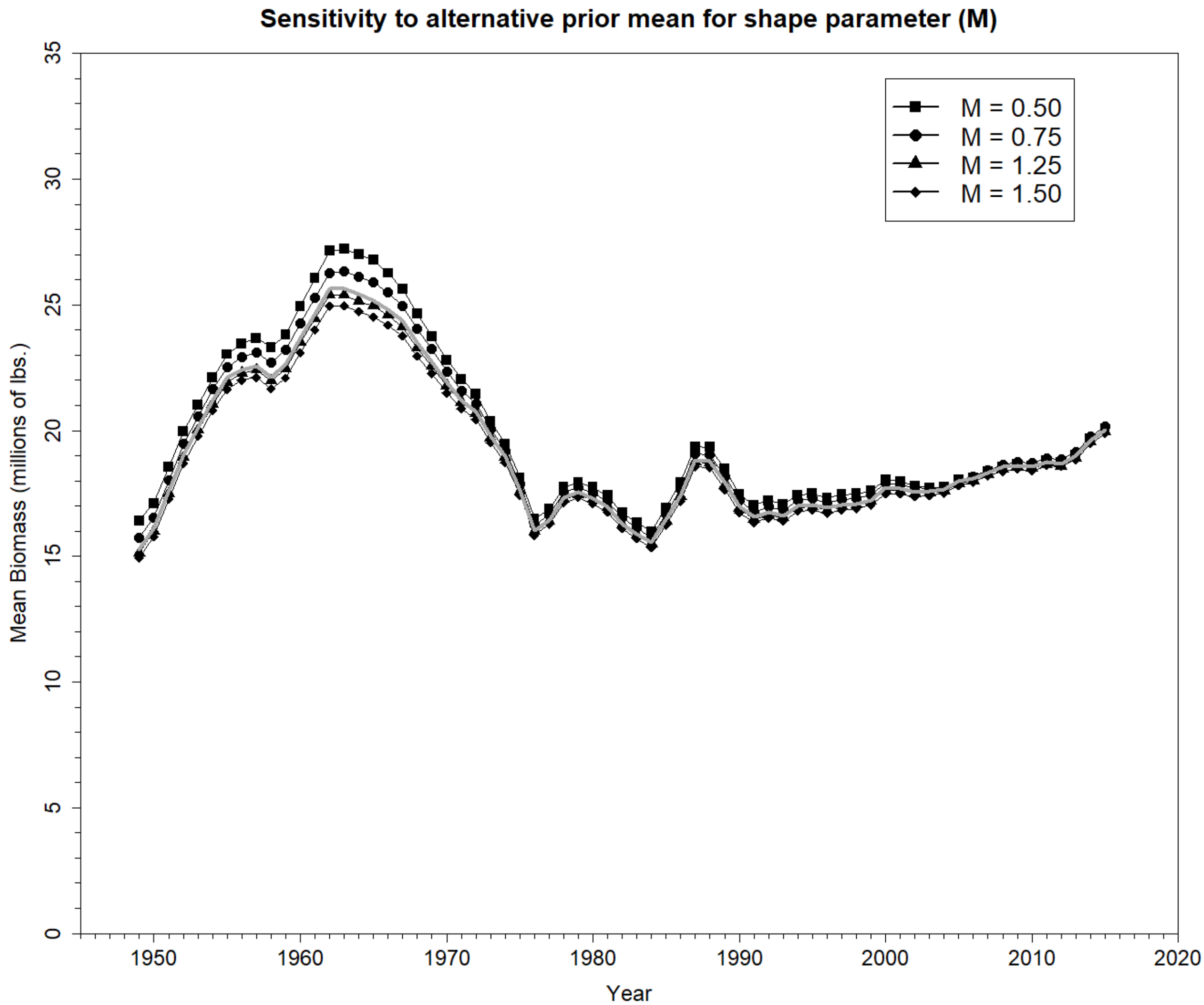


Figure 25.1. Estimated mean exploitable biomass as a function of different prior means for the shape parameter (M). Values of M were calculated as +/- 25% and +/- 50% of the mean value used for the base case (μ_M = 1.00.; gray line).

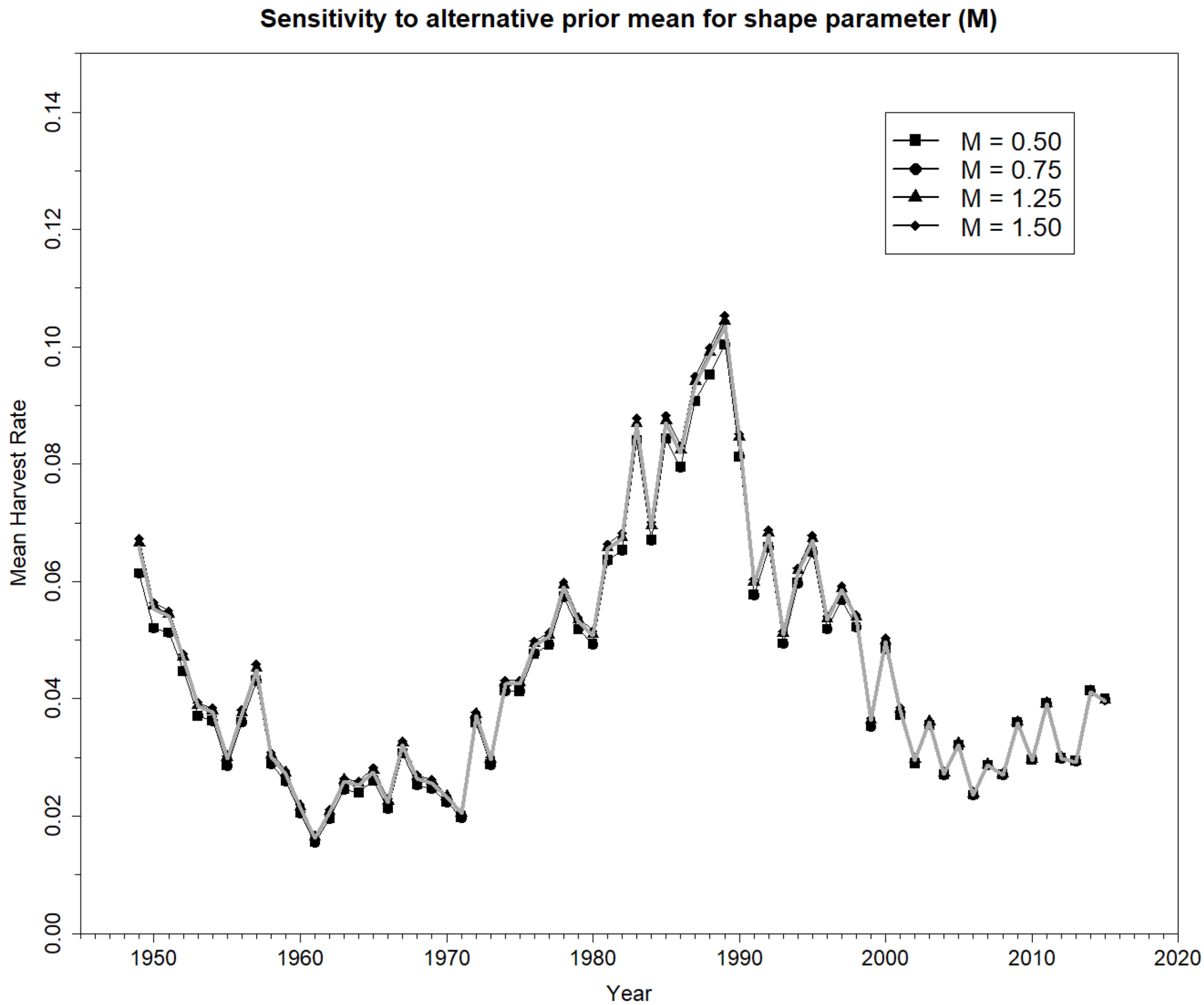


Figure 25.2. Estimated mean harvest rate as a function of different prior means for the shape parameter (M). Values of M were calculated as +/- 25% and +/- 50% of the mean value used for the base case (μ_M = 1.00.; gray line).

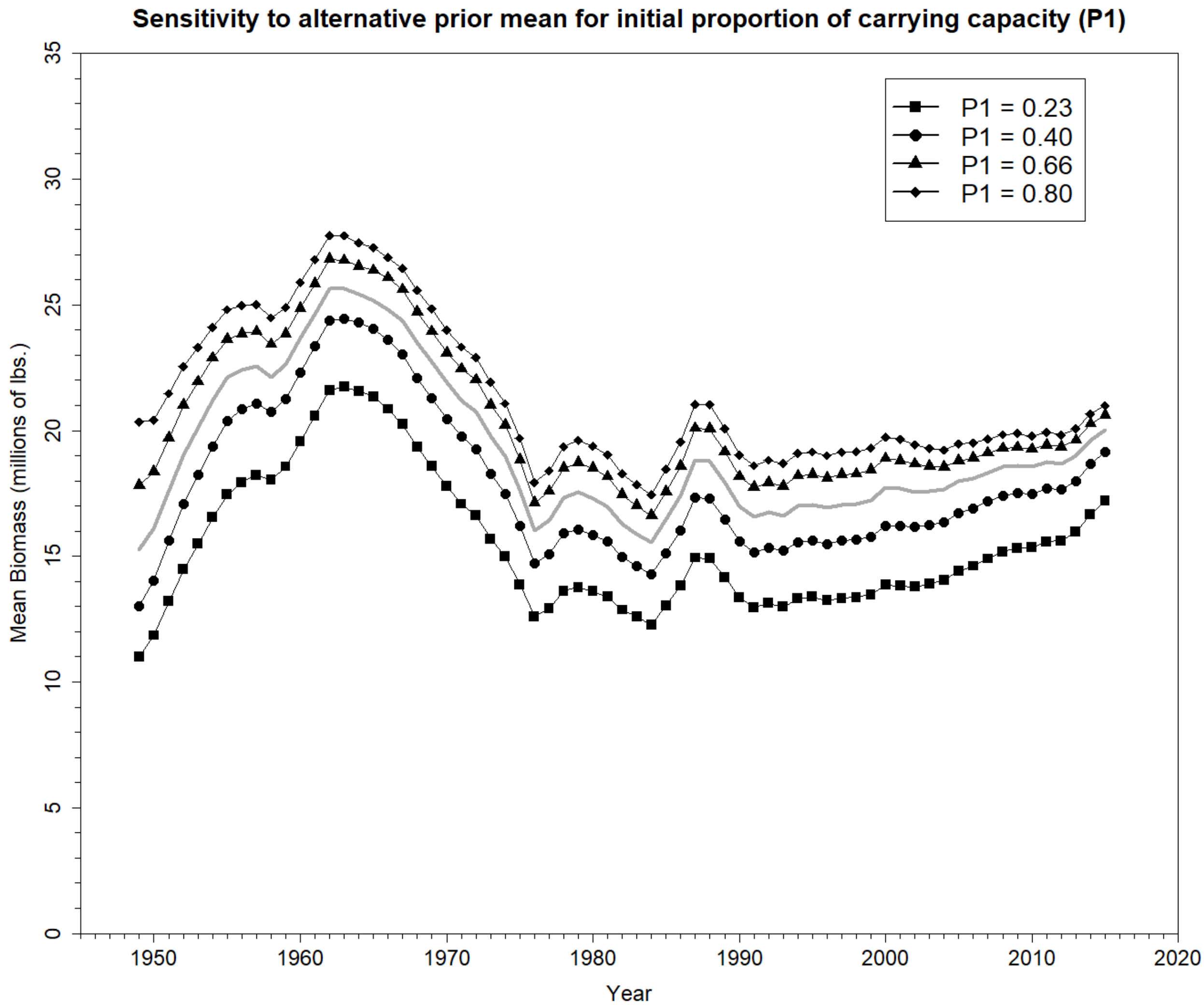


Figure 26.1. Estimated mean exploitable biomass as a function of different prior means for the initial proportion of carrying capacity (P_1). Values of P_1 were calculated as +/- 25% and +/- 50% of the mean value used for the base case (μ_P = 0.53.; gray line).

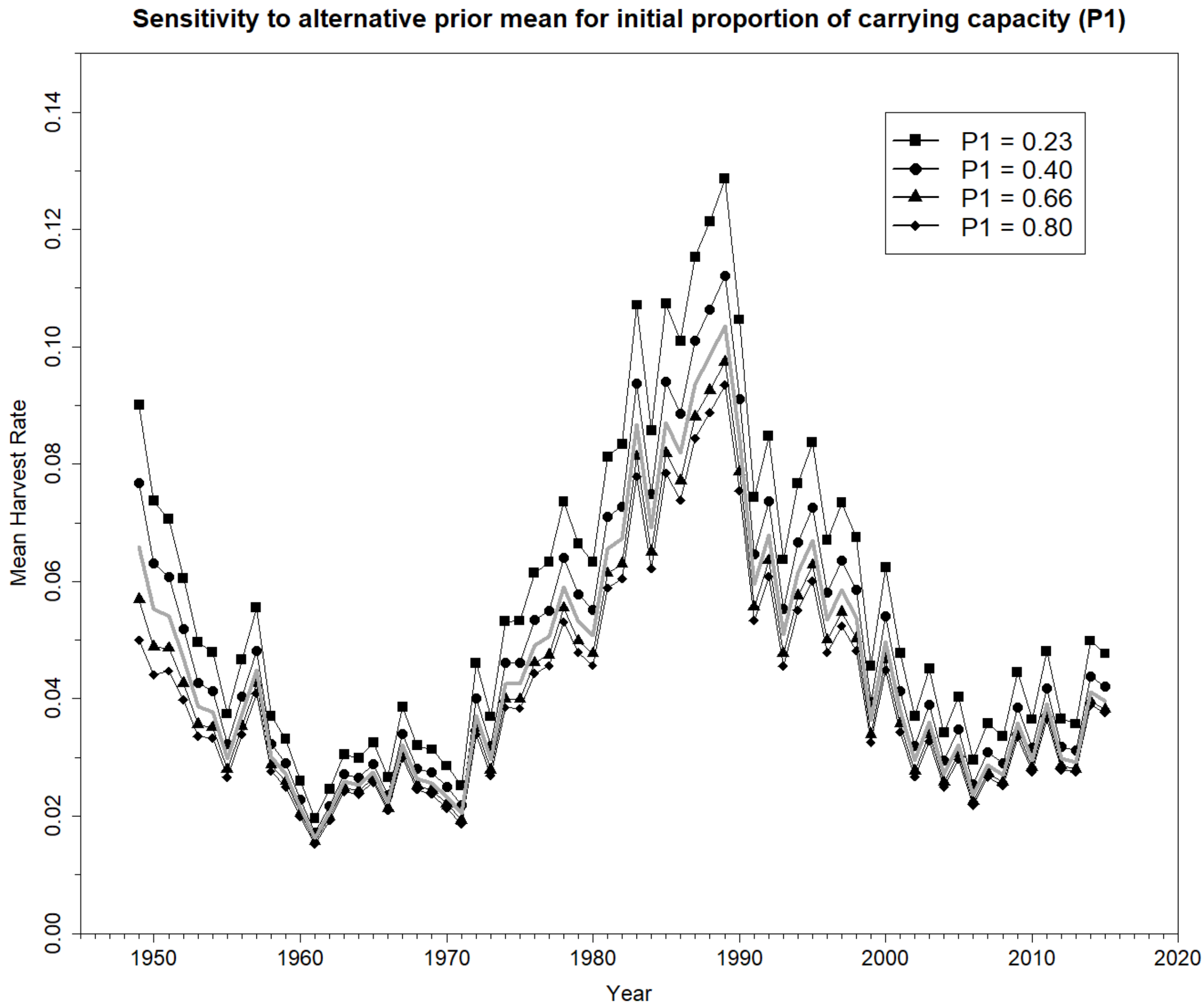


Figure 26.2. Estimated mean harvest rate as a function of different prior means for the initial proportion of carrying capacity (P_1). Values of P_1 were calculated as +/- 25% and +/- 50% of the mean value used for the base case (μ_P = 0.53.; gray line).

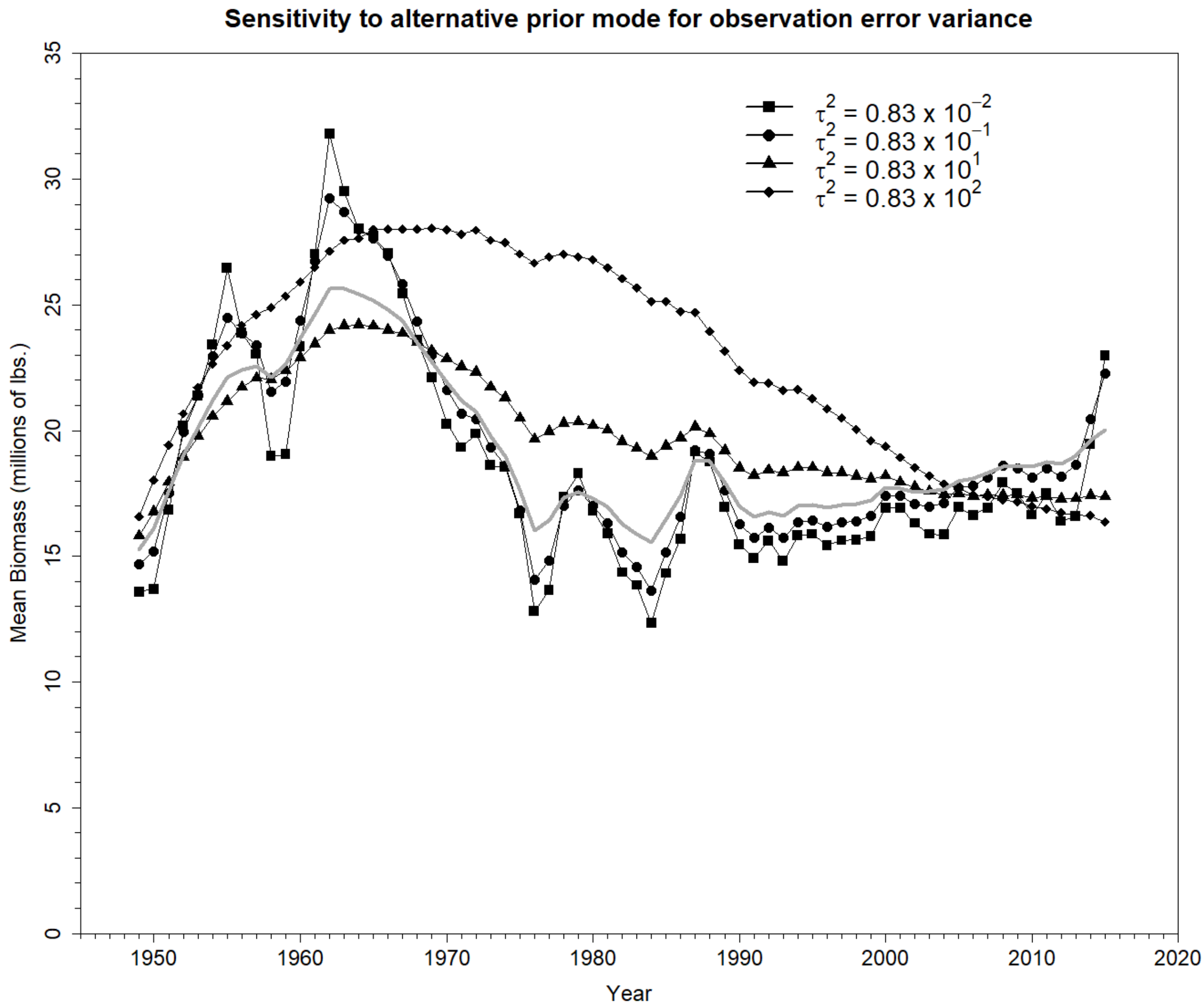


Figure 27.1. Estimated mean exploitable biomass as a function of different prior modes for observation error variance for both time periods i (τ_i^2). The base-case value (MODE[τ_i^2] = 0.83; gray line) was multiplied by 10^{-2}, 10^{-1}, 10^{1}, and 10^{2}

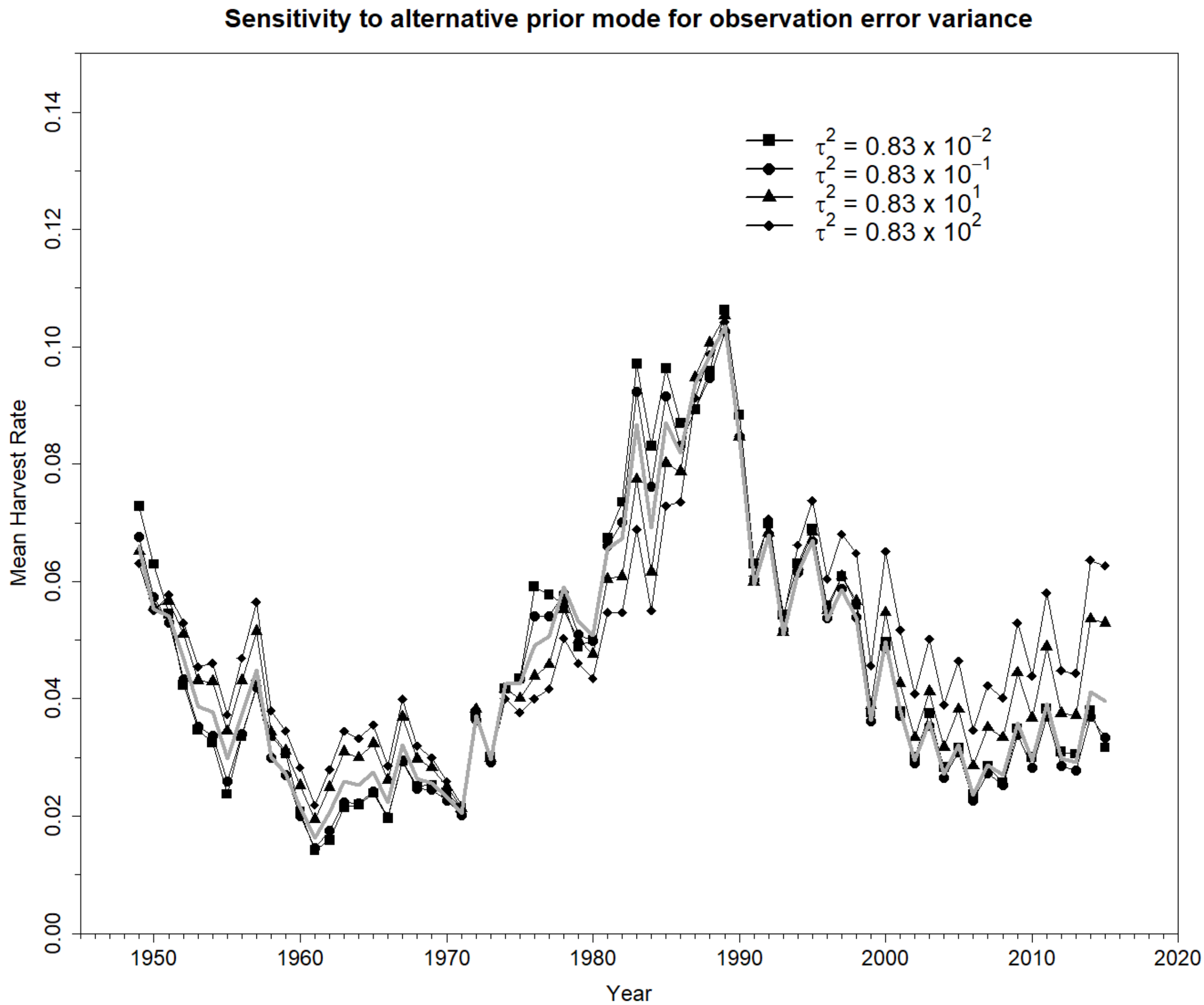


Figure 27.2. Estimated mean harvest rate as a function of different prior modes for observation error variance for both time periods i (τ_i^2). The base-case value (MODE[τ_i^2] = 0.83; gray line) was multiplied by 10^{-2}, 10^{-1}, 10^{1}, and 10^{2}.

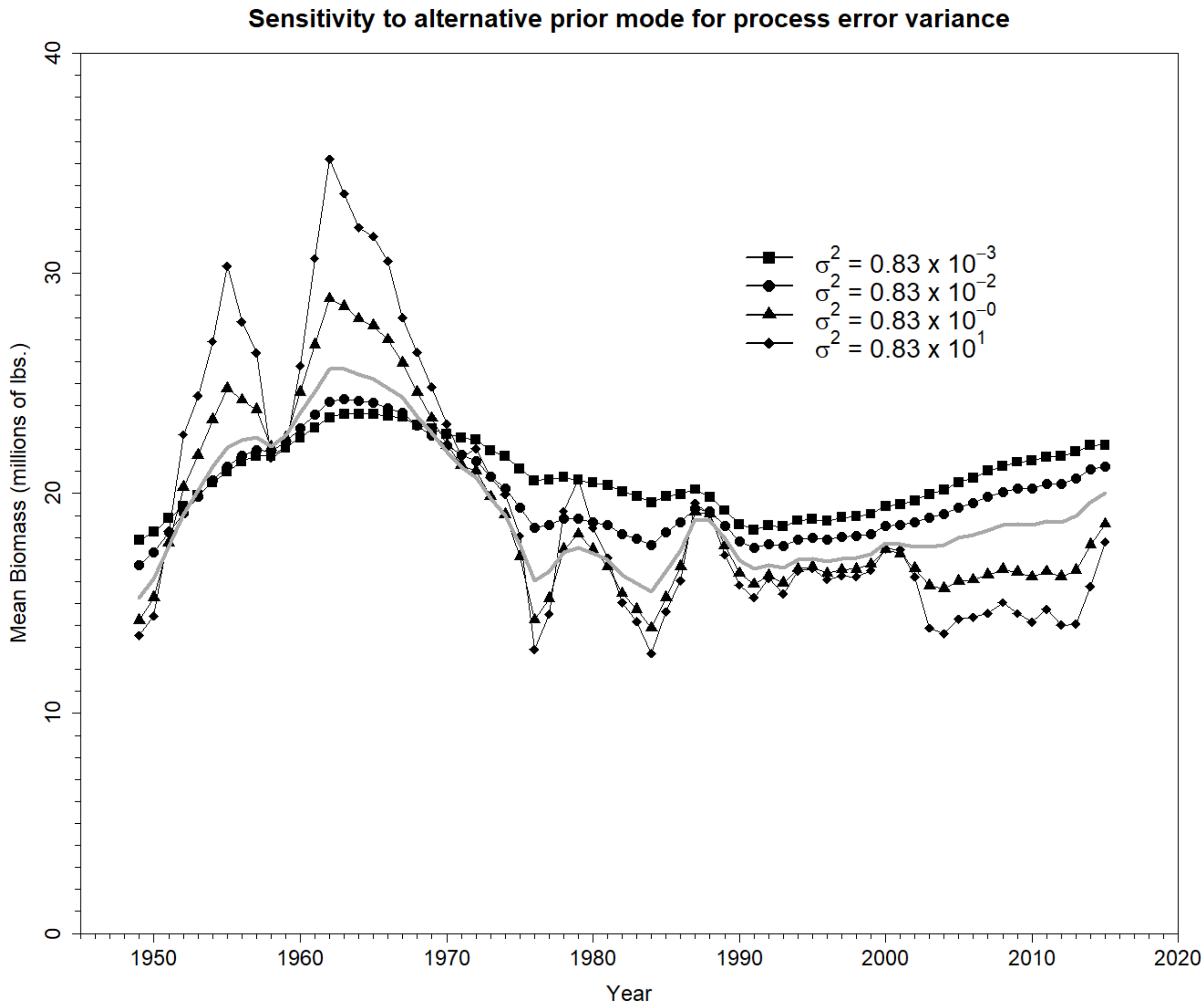


Figure 28.1. Estimated mean exploitable biomass as a function of different prior modes for process error variance (σ^2). The base-case value (MODE[σ^2] = 0.83 x 10^{-1}; gray line) was multiplied by 10^{-2}, 10^{-1}, 10^1, and10^2

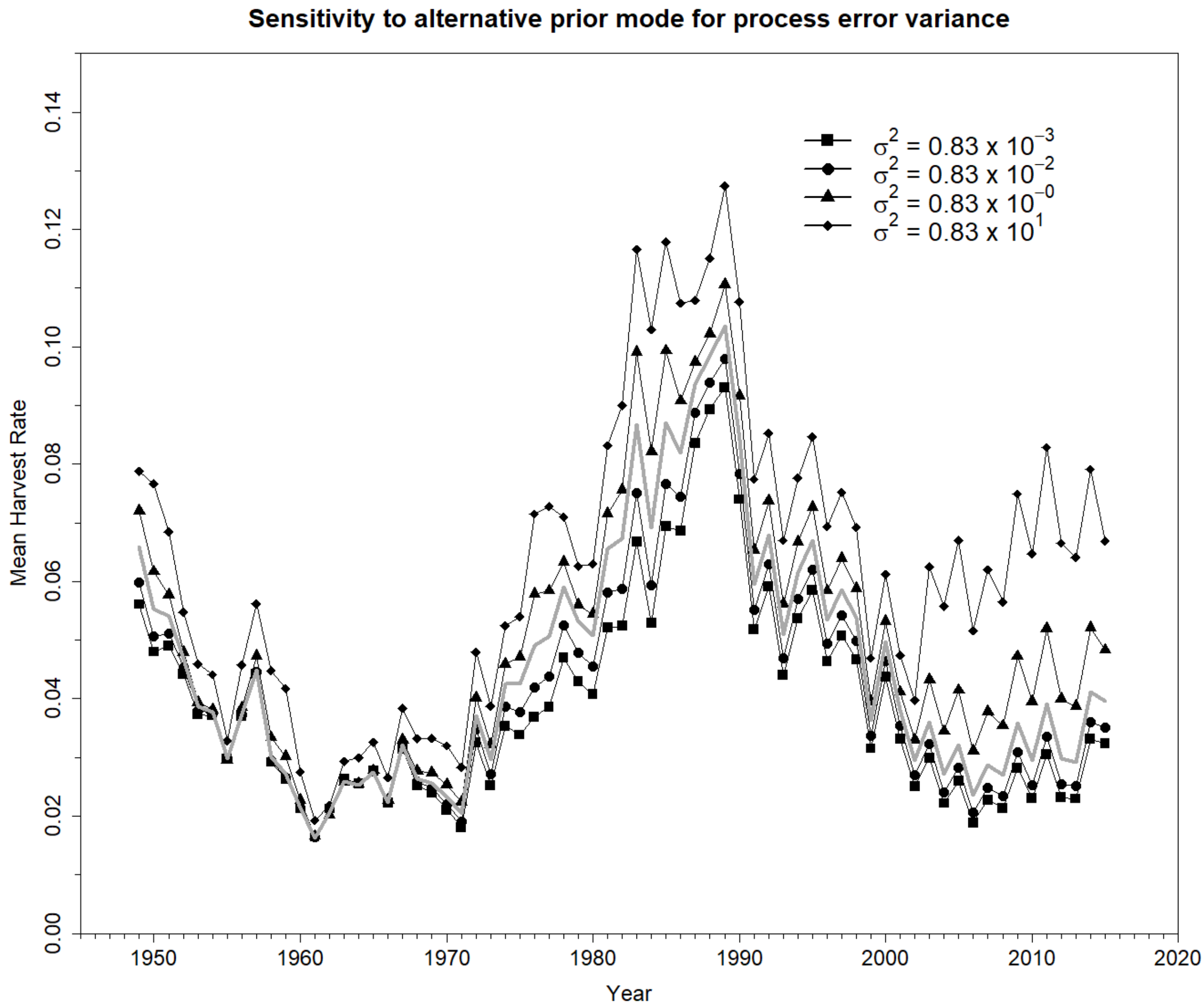


Figure 28.2. Estimated mean harvest rate as a function of different prior modes for process error variance (σ^2). The base-case value (MODE[σ^2] = 0.83; gray line) was multiplied by 10^{-2}, 10^{-1}, 10^{1}, and 10^{2}.

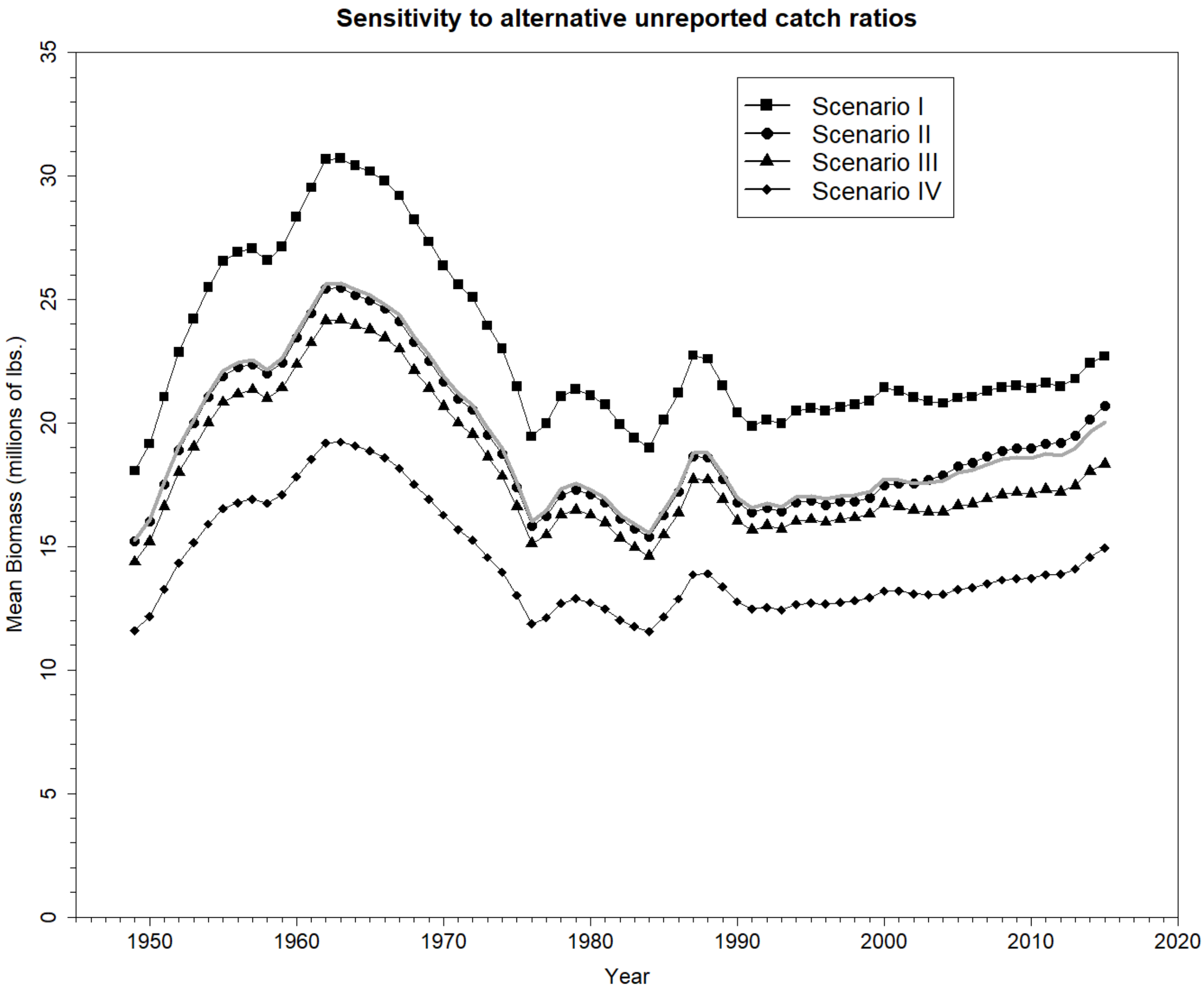


Figure 29.1. Estimated mean exploitable biomass as a function of different scenarios for modeling unreported catch ratios (see text for scenario descriptions).

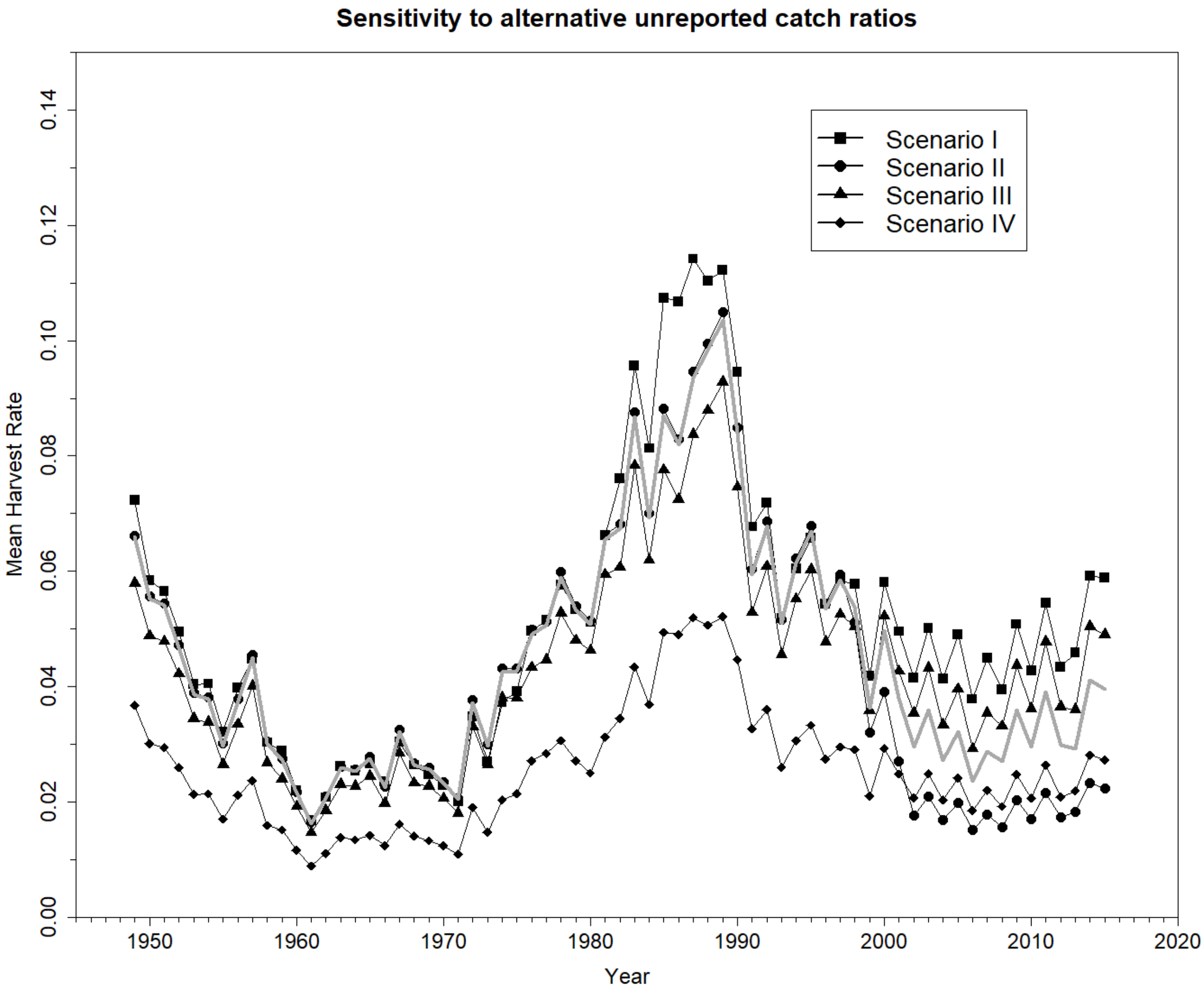


Figure 29.2. Estimated mean harvest rate as a function of different scenarios for modeling unreported catch ratios (see text for scenario descriptions).

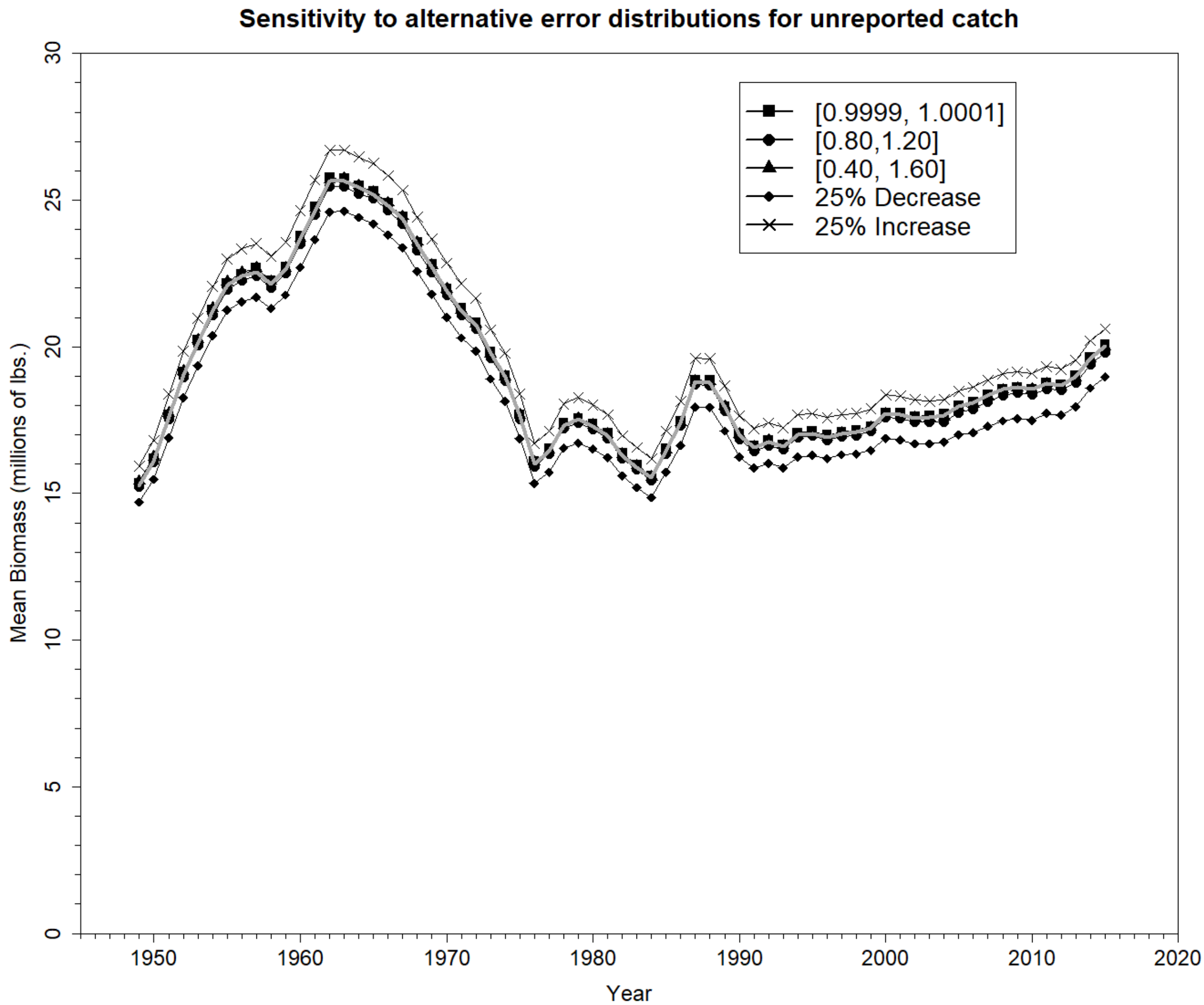


Figure 30.1. Estimated mean exploitable biomass given alternative bounds on uniform distribution used to estimate unreported catch. Directional biases in the unreported catch error were evaluated by adjusting the base-case bounds (gray line, [0.60,1.40]) downward and upward by 25%.

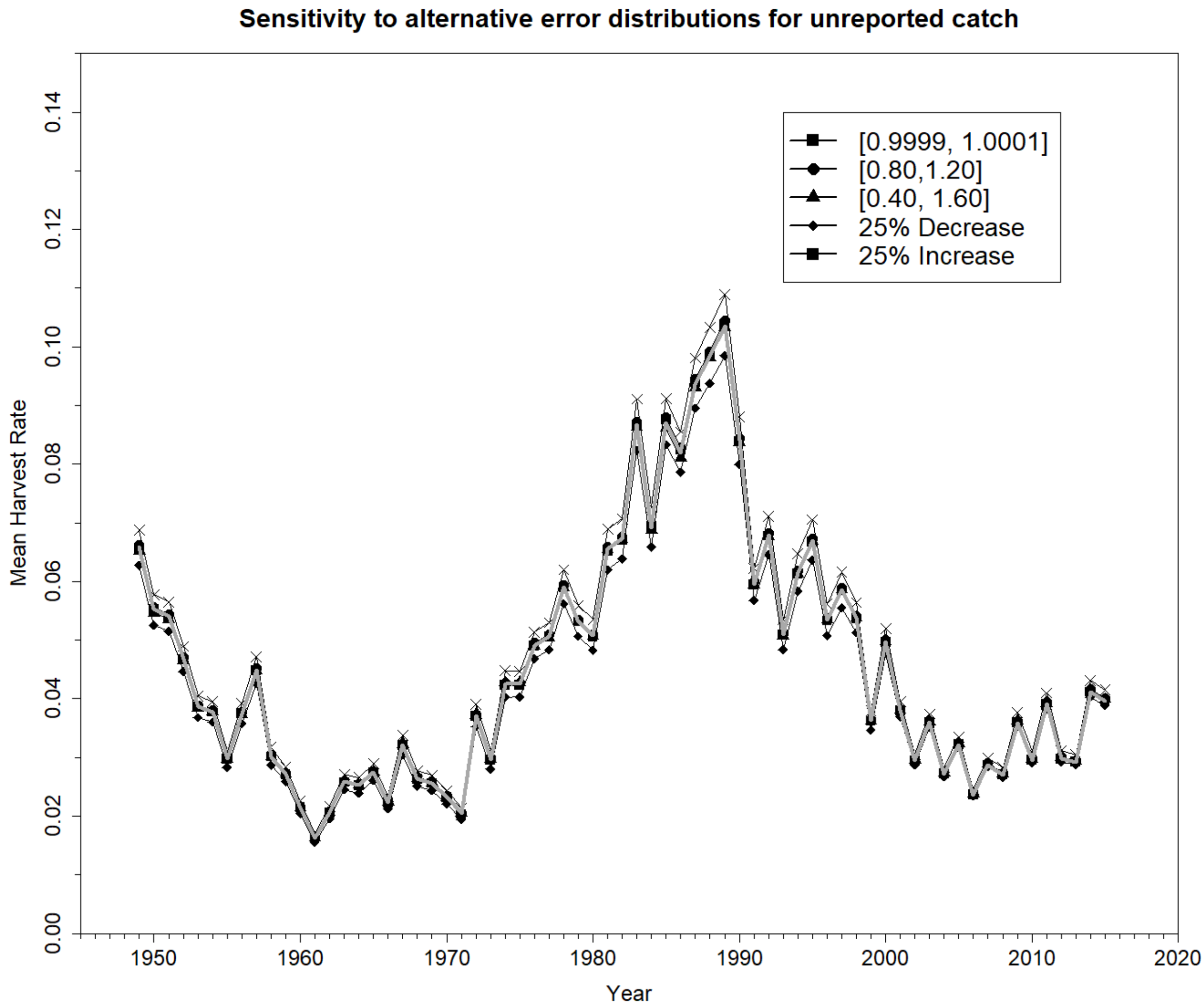


Figure 30.2. Estimated mean harvest rate given alternative bounds on uniform distribution used to estimate unreported catch. Directional biases in the unreported catch error were evaluated by adjusting the base-case bounds (gray line, [0.60,1.40]) downward and upward by 25%.

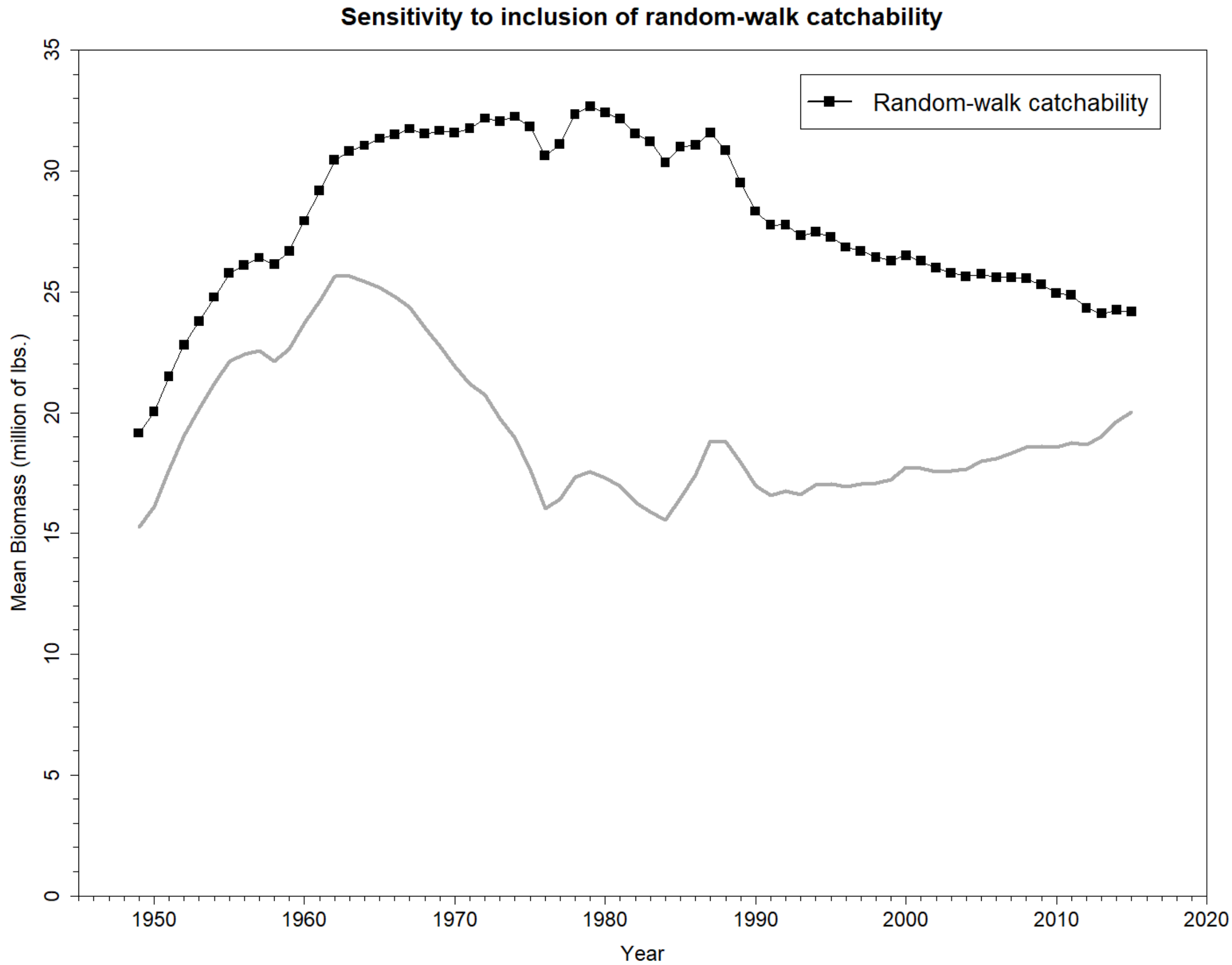


Figure 31.1. Estimated mean exploitable biomass when incorporating time-varying catchability, as a random walk (black line) versus constant catchability (base case; gray line).

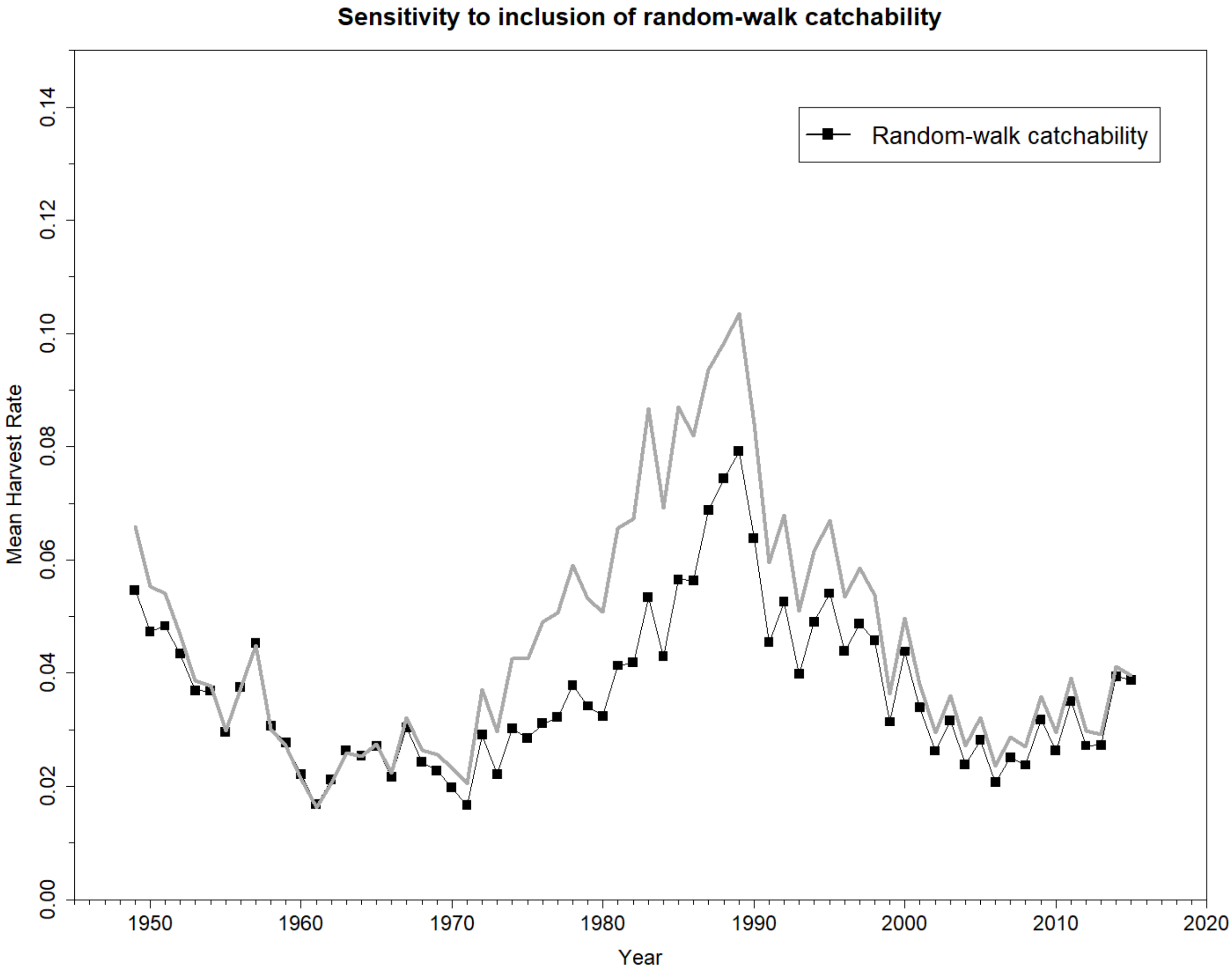


Figure 31.2. Estimated mean harvest rate when incorporating time-varying catchability as a random walk (black line) versus constant catchability (base case; gray line).

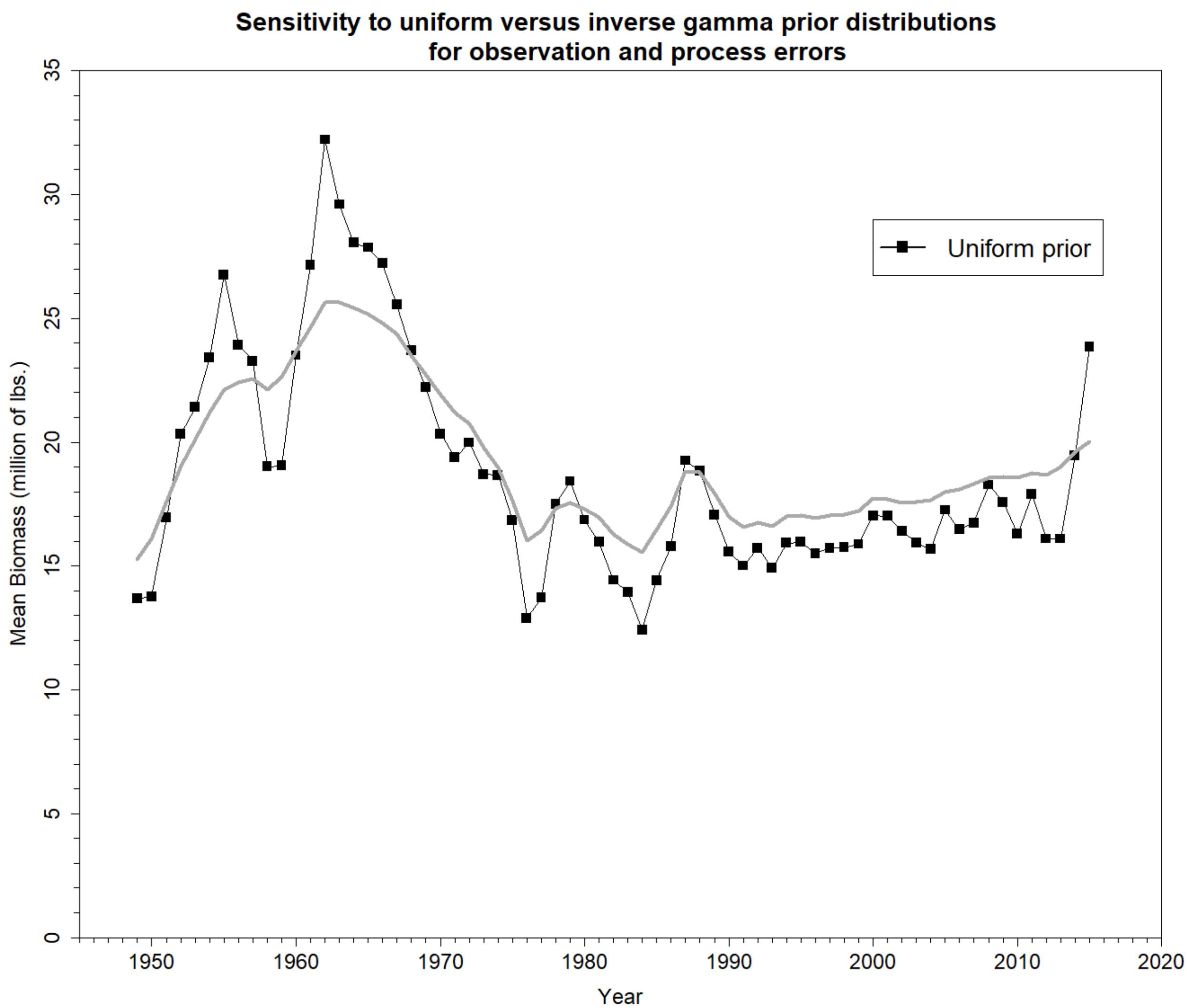


Figure 32.1. Estimated mean exploitable biomass using uniform prior distributions for the standard deviation of observation and process errors (black line) versus using the inverse gamma distribution for the variance of observation and process errors (base case; gray line).

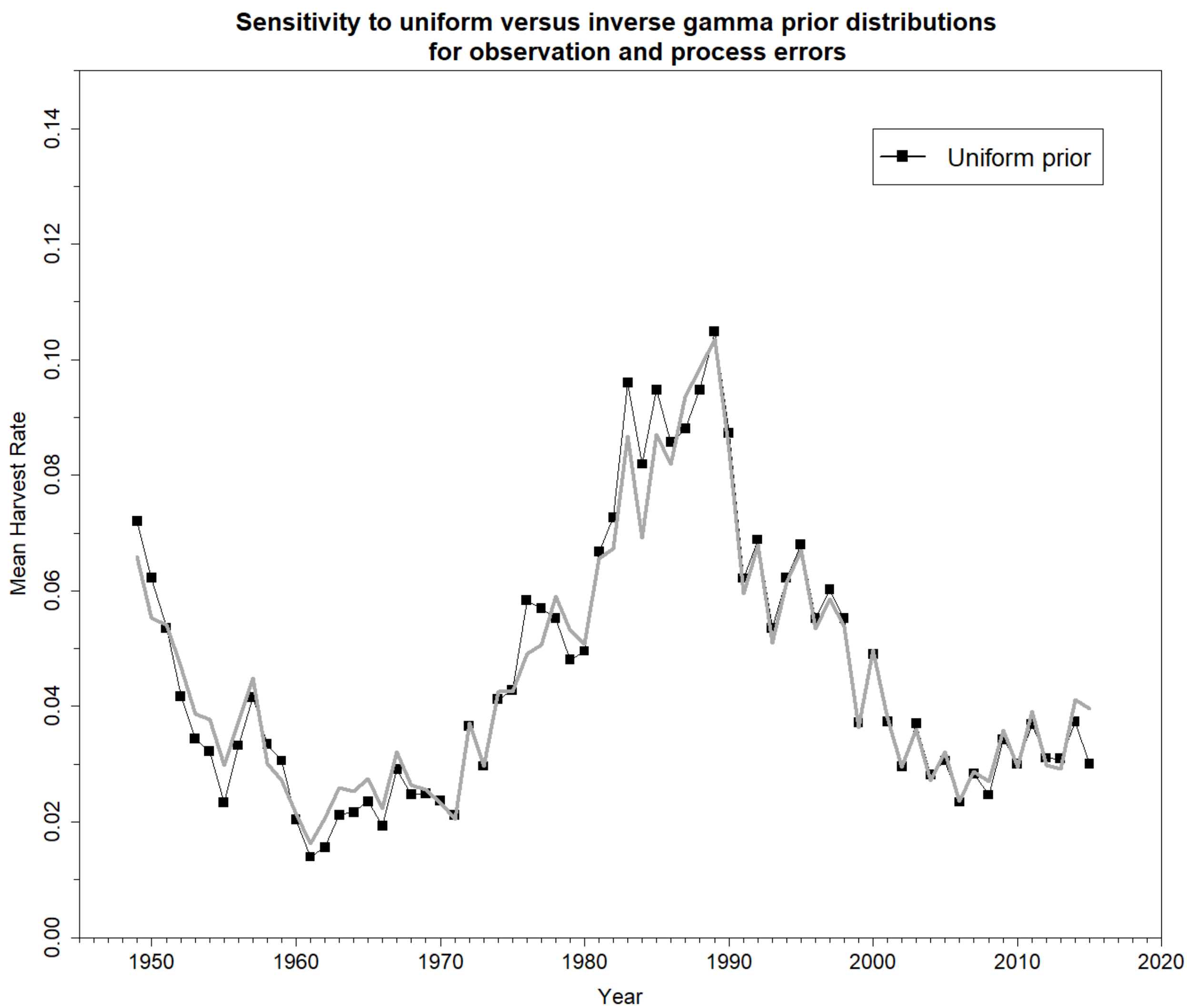


Figure 32.2. Estimated mean harvest rate using uniform prior for the standard deviation of observation and process errors (black line) versus using the inverse gamma distribution for the variance of observation and process errors (base case; gray line).

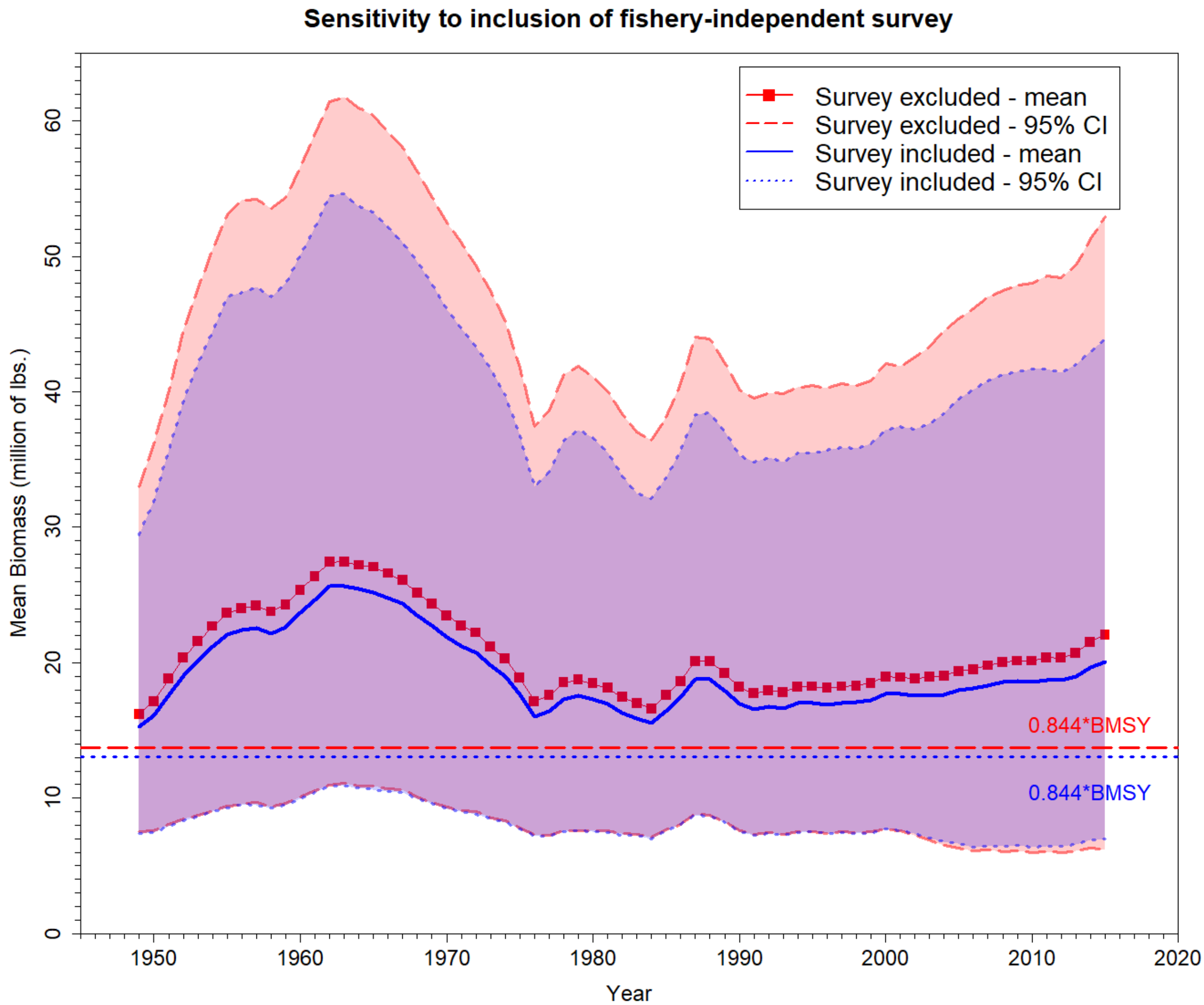


Figure 33.1. Estimated mean exploitable biomass for the base case (blue lines and shading) and with the fishery-independent survey excluded (red lines and shading). Horizontal lines delineate 0.844*B_{MSY} reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

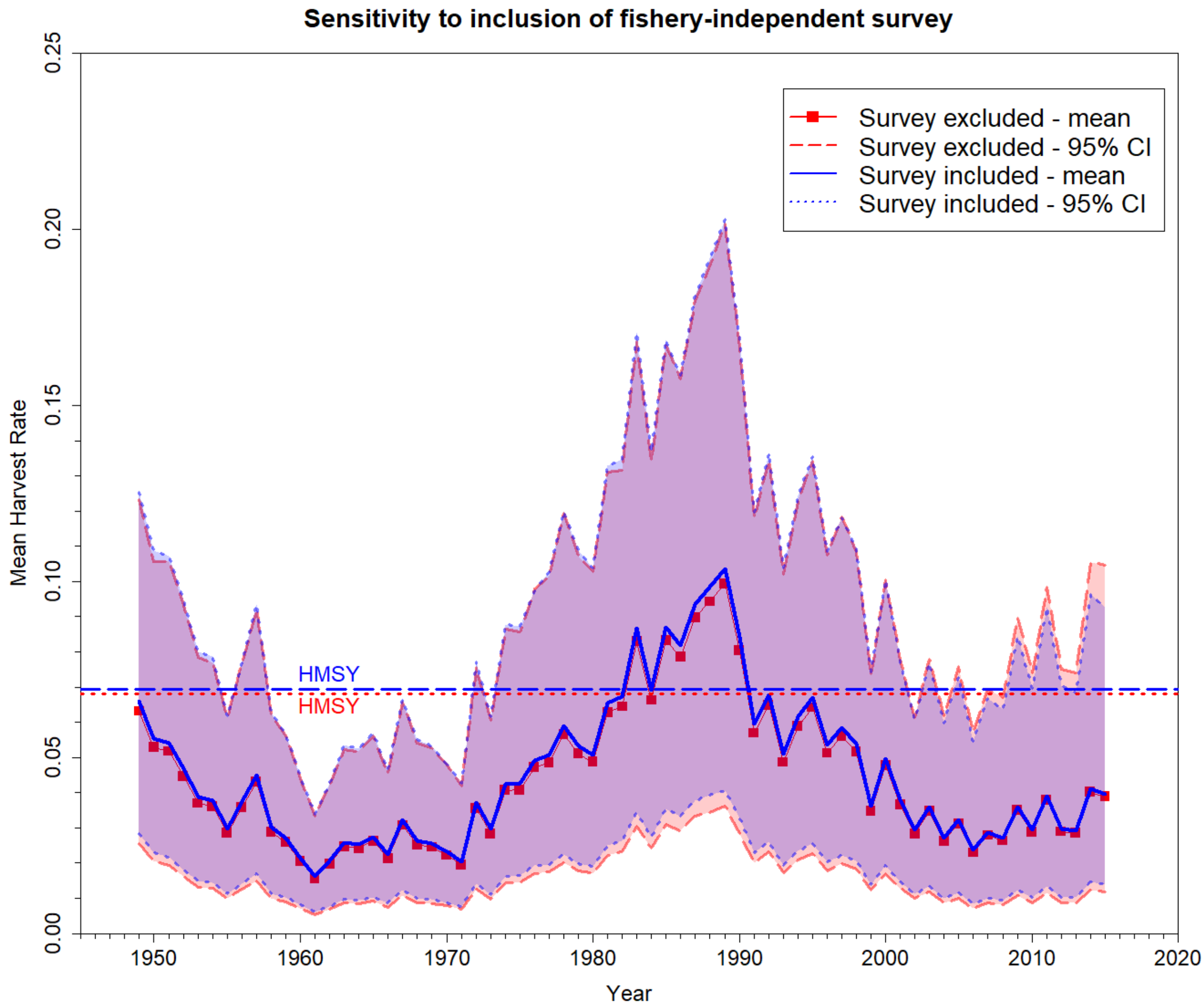


Figure 33.2. Estimated mean harvest rate for the base case (blue lines and shading) and with the fishery-independent survey excluded (red lines and shading). Horizontal line delineates the H_{MSY} reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

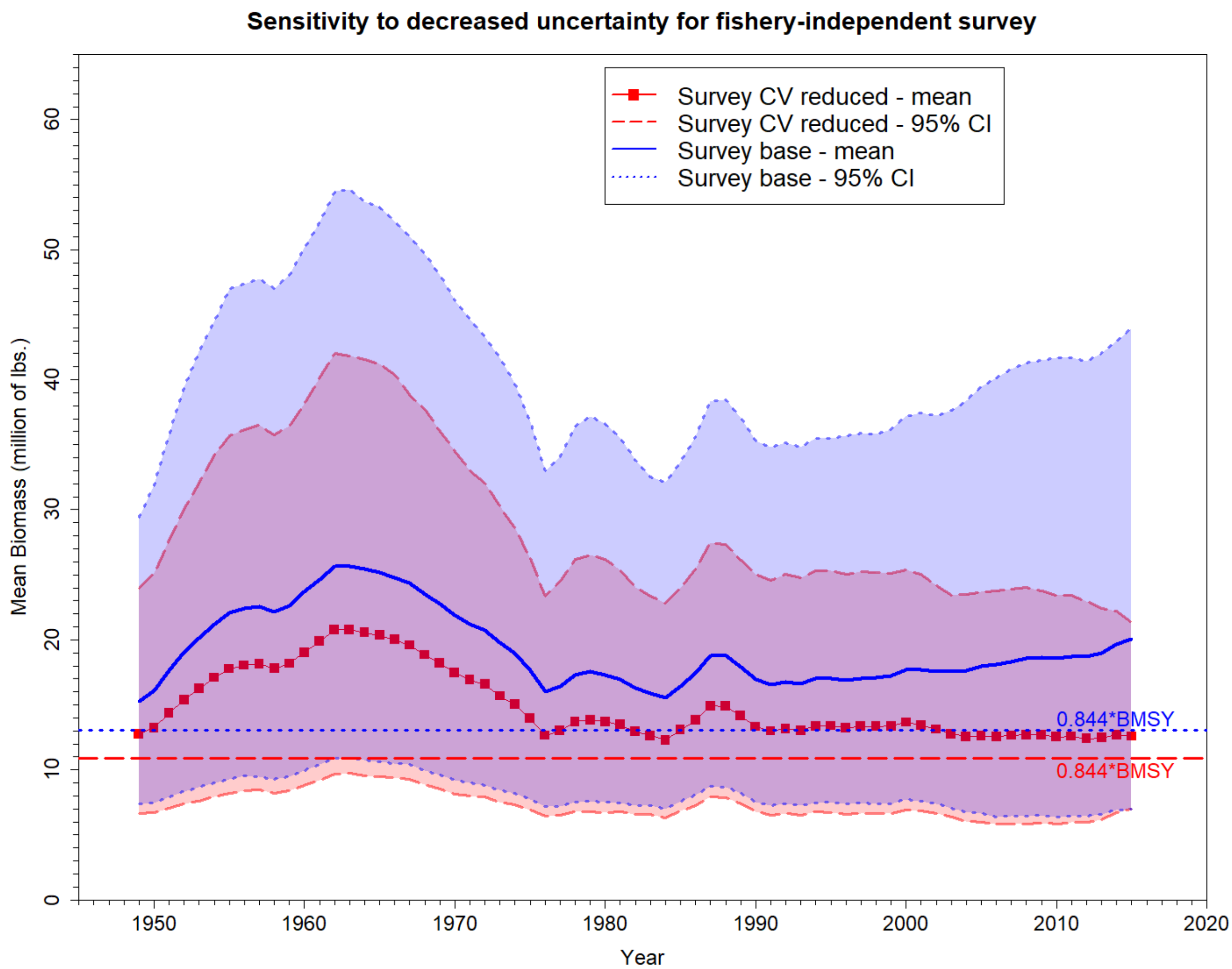


Figure 34.1. Estimated mean exploitable biomass for the base case (blue lines and shading) and with decreased CV of the prior on the effective radius of a single sample for the fishery-independent survey (red lines and shading). Horizontal lines delineate 0.844*B_{MSY} reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

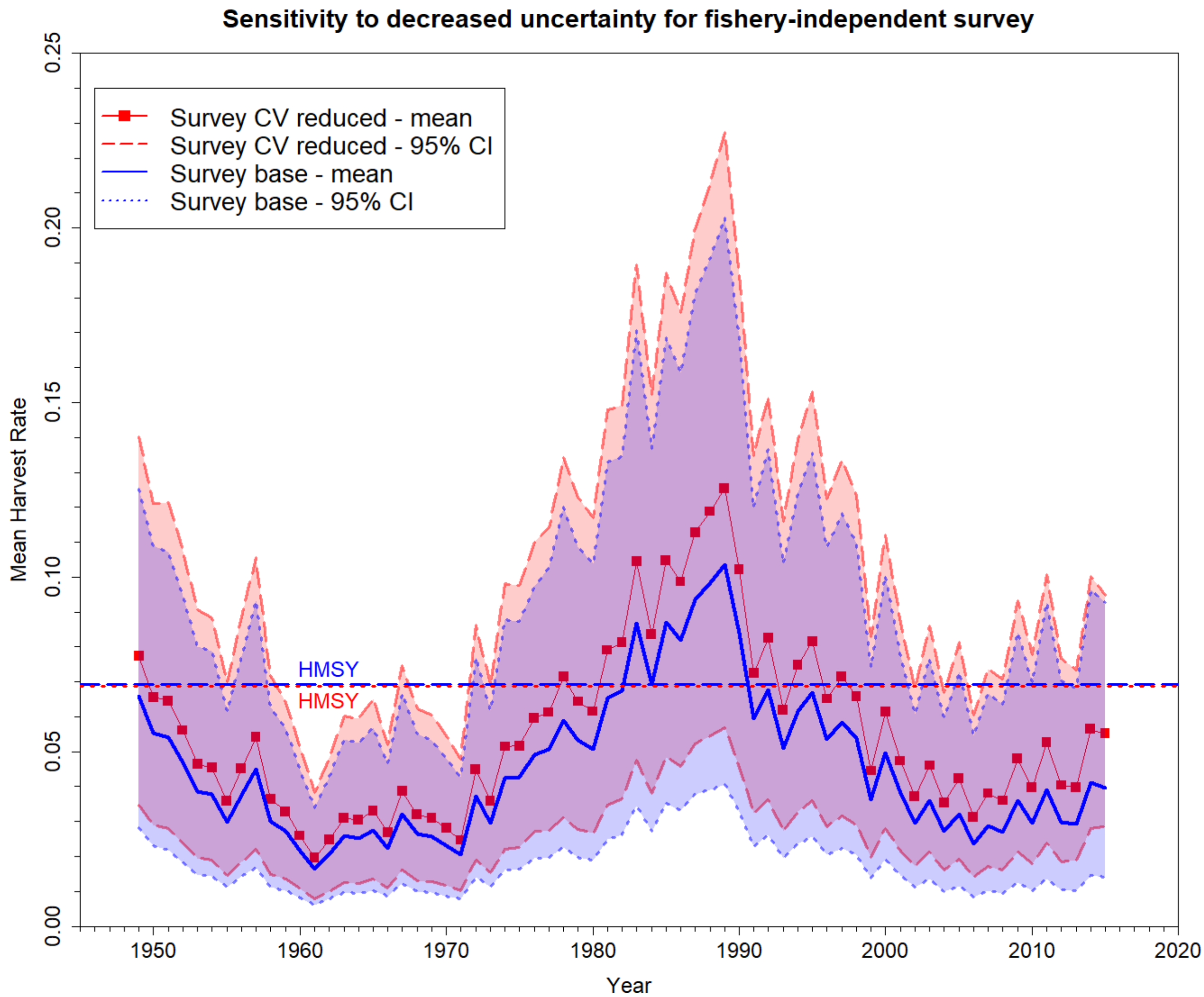


Figure 34.2. Estimated mean harvest rate for the base case (blue lines and shading) and with decreased CV of the prior on the effective radius of a single sample for the fishery-independent survey (red lines and shading). Horizontal line delineates the H_{MSY} reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

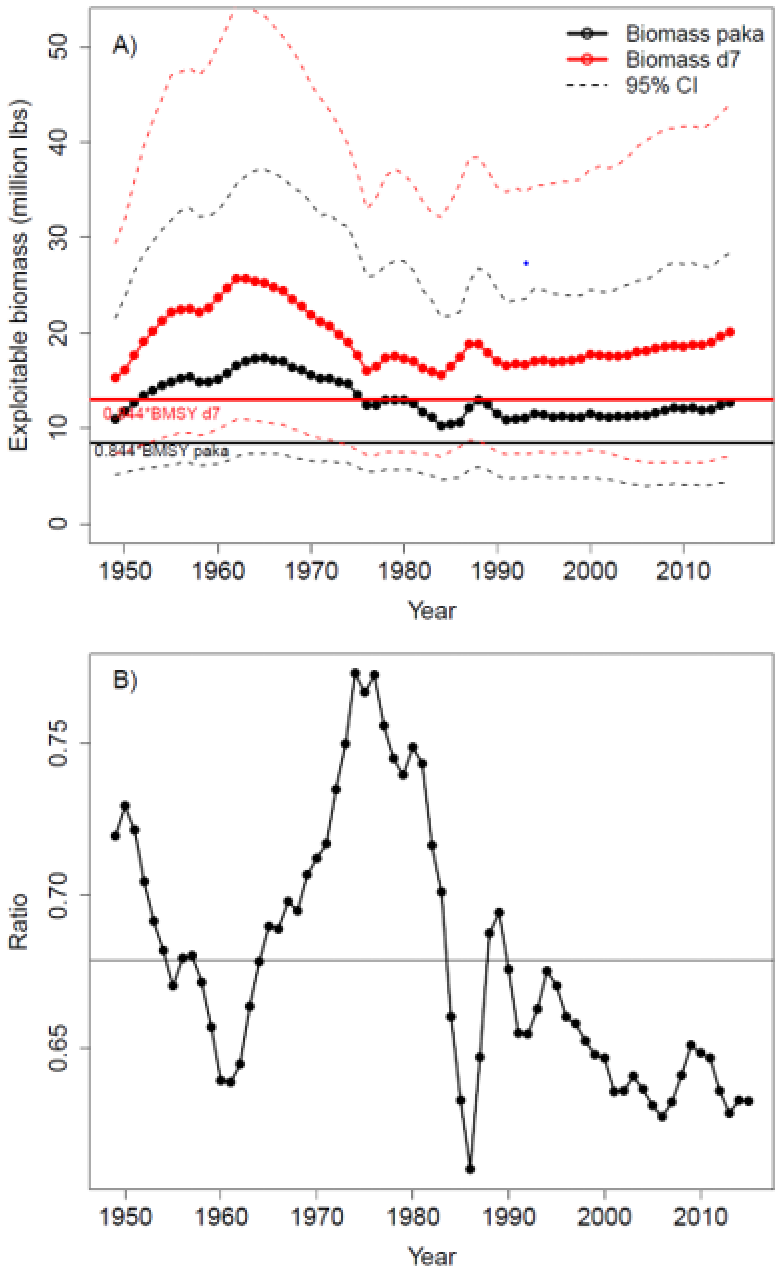


Figure 35. Biomass comparison between the opakapaka production model (paka) and the Deep 7 production model (d7) for the main Hawaiian Islands. Panel A: Posterior mean exploitable biomass estimates and 95% credible intervals for the opakapaka production model (black) and the Deep 7 complex production model (red). Panel B: Ratio (black line with circles) and average ratio (0.679; horizontal solid line) of the posterior mean exploitable biomass from the opakapaka production model to the posterior mean biomass from the Deep 7 production model.

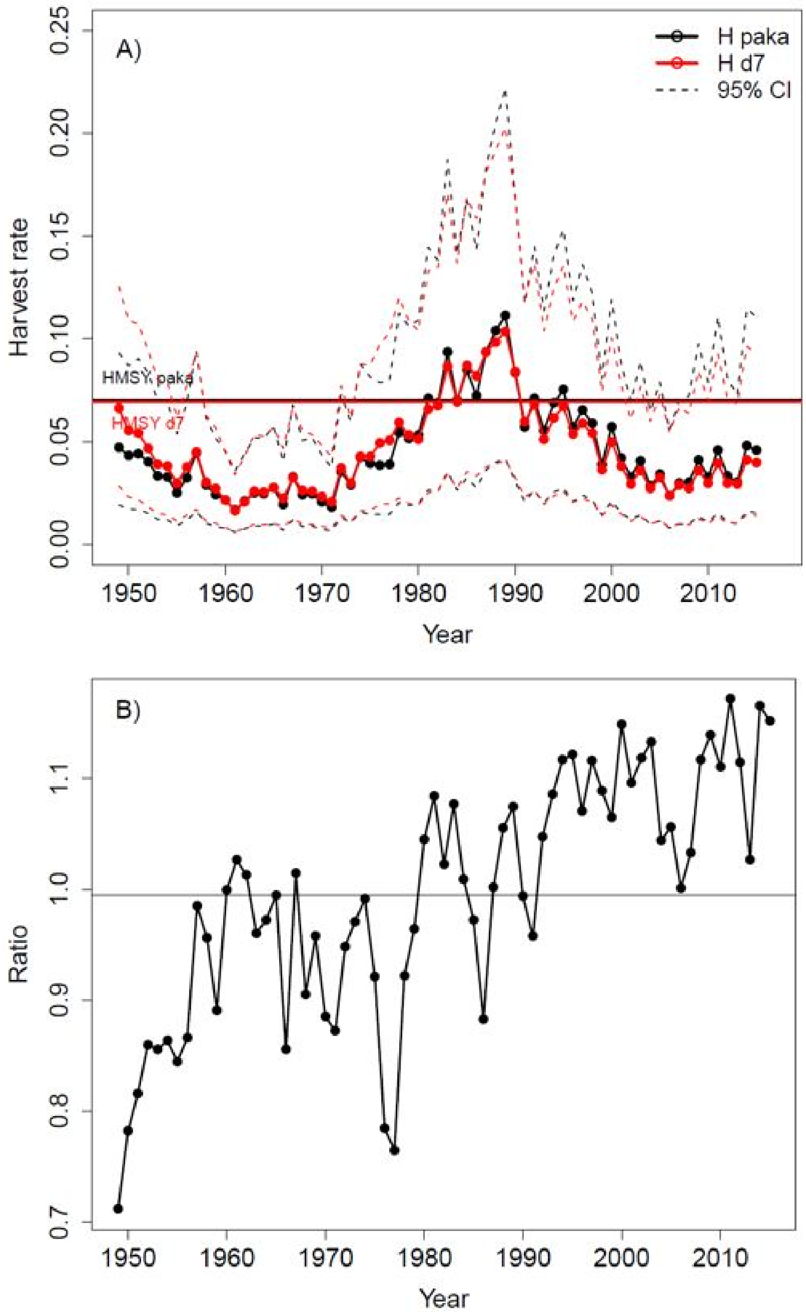


Figure 36. Harvest rate comparison between the opakapaka production model (paka) and the Deep 7 production model (d7) for the main Hawaiian Islands. Panel A: Posterior mean harvest ratio estimates and 95% credible intervals for the opakapaka production model (black) and the Deep 7 production model (red). Panel B: Ratio (black line with circles) and average ratio (0.995; horizontal solid line) of the posterior mean of opakapaka harvest rate to the posterior mean of Deep 7 harvest rate.

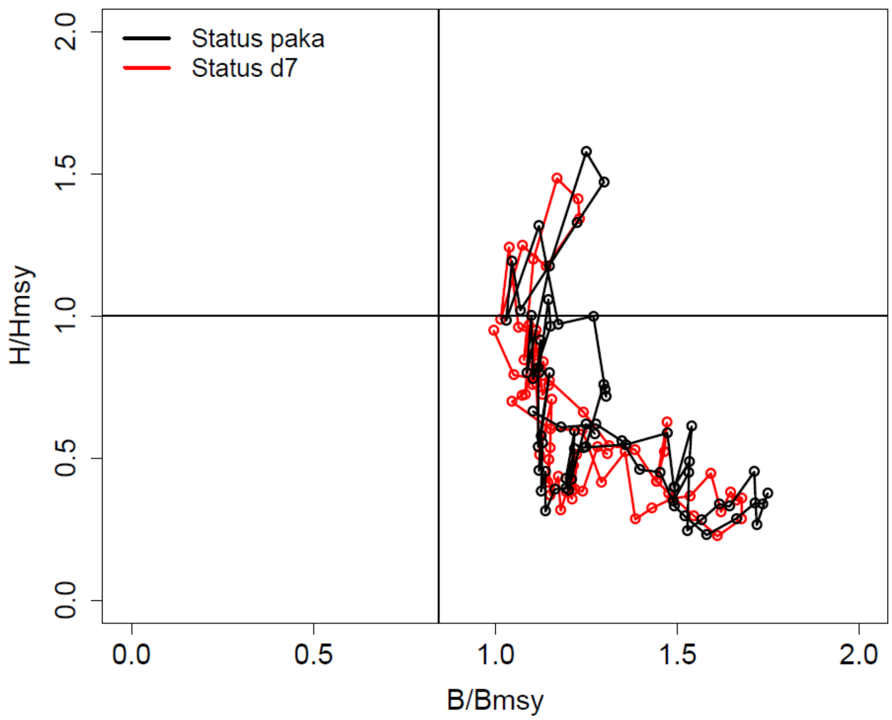


Figure 37. Status of opakapaka, as based on the opakapaka only model (paka; black line), compared to the status estimated from the model of the Deep 7 bottomfish complex (d7; red line) for the main Hawaiian Islands.

10. APPENDICES

Appendix A. Supplementary methods and results for opakapaka production model.

Appendix B. R code that calls WinBUGS used to fit base case assessment and projection model for the Deep 7 bottomfish complex in the main Hawaiian Islands from 1949-2015.

Appendix C. R code that calls WinBUGS used to fit assessment model for opakapaka in the main Hawaiian Islands from 1949-2015.

Appendix D. R code that calculates the standardized CPUE index from the final event-based dataset for Deep 7 in the main Hawaiian Islands during the early (1948-2003) and recent (2003-2015) time periods.

Appendix A. Supplementary methods and results for opakapaka production model.

Table A1. Summary of log likelihood values and reduction in AIC (ΔAIC = AIC previous model – AIC proposed model) during model selection for the best-fit opakapaka only model for the Bernoulli and Lognormal processes in the early (1948-2003) and recent (2003-2015) time periods using maximum likelihood. Each parameter added is added to the model with all previously selected parameters included. The year predictor was included in all baseline models and was added first among fixed effects in model selection.

Time Period	Selected predictor	ΔAIC	Log-Likelihood	Number of parameters
Bernoulli process				
1948:2003	Null	0	-53795	1
	+year	1770	-52855	56
	+area	10296	-47553	210
	+sqrt(pounds of uku)	1037	-47034	211
	+ln(cumulative experience)	273	-46896	212
	+quarter	232	-46777	215
2003:2015	Null	0	-16312	1
	+year	109	-16246	13
	+area	3240	-14542	106
	+sqrt(pounds of uku)	1662	-13700	107
	+quarter	343	-13525	110
	+ln(cumulative experience)	147	-13451	111
	+area:quarter	138	-13118	370
	+speed	94	-13070	371
Lognormal process				
1948:2003	Null	0	-115996	2
	+fisher	26045	-102972	3
	+year	1105	-102365	58
	+area	2479	-100980	195
	+quarter	906	-100532	198
	+area:quarter	311	-100085	490
	+ln(cumulative experience)	245	-99962	491
2003:2015	Null	0	-24566	2
	+fisher	5896	-21617	3
	+year	217	-21497	15
	+area	343	-21234	106
	+sqrt(pounds of uku)	75	-21196	107
	+quarter	62	-21162	110
	+speed	27	-21148	111
	+ln(cumulative experience)	24	-21135	112

Table A2.1. Annual index of standardized CPUE (lbs/single reporting day) for opakapaka for the early time period (1948-2003), with relative coefficient of variation (relCV) included. Relative CV was calculated as the ratio of CV/min(CV). Data from fishing year 1948 were used in CPUE standardization, with index value presented here, but the CPUE index used within the stock assessment model started in fishing year 1949 to align with the starting year when complete catch data were available.

Year	Estimated opakapaka CPUE	relCV		Year	Estimated opakapaka CPUE	relCV
1948	56.73	2.90		1980	59.76	1.92
1949	34.56	2.21		1981	62.43	1.64
1950	41.96	2.45		1982	45.49	1.26
1951	62.04	2.28		1983	48.12	1.14
1952	68.96	2.73		1984	32.95	1.37
1953	59.43	3.24		1984	32.95	1.37
1954	76.23	3.43		1985	40.21	1.23
1955	67.20	5.18		1986	34.26	1.15
1956	85.51	3.63		1987	56.17	1.12
1957	97.72	3.17		1988	63.28	1.00
1958	54.20	2.75		1989	57.00	1.03
1959	45.42	3.35		1990	48.58	1.22
1960	54.64	2.36		1991	39.96	1.31
1961	54.11	3.73		1992	44.31	1.34
1962	92.04	3.25		1993	41.43	1.51
1963	91.27	2.62		1994	53.72	1.53
1964	85.90	2.71		1995	49.44	1.43
1965	100.68	2.68		1996	44.32	1.65
1966	78.63	2.80		1997	46.63	1.43
1967	90.34	2.37		1998	45.87	1.56
1968	66.01	2.69		1999	43.99	1.61
1969	77.48	2.43		2000	52.51	1.42
1970	62.06	3.59		2001	47.21	1.77
1971	50.38	2.50		2002	44.81	1.76
1972	71.28	2.40		2003	44.42	4.26
1973	60.15	2.12				
1974	77.48	1.69				
1975	60.85	1.82				
1976	42.03	1.19				
1977	43.68	1.57				
1978	58.80	2.01				
1979	57.88	2.40				

Table A2.2. Annual index of standardized CPUE (lbs/hour) for opakapaka for the late time period (2003-2015), with relative coefficient of variation (relCV) included. Relative CV was calculated as the ratio of CV/min(CV).

Year	Estimated opakapaka CPUE	relCV
2003	5.93	1.32
2004	5.16	1.32
2005	5.69	1.31
2006	4.78	1.33
2007	5.21	1.18
2008	6.15	1.11
2009	6.60	1.03
2010	5.77	1.21
2011	6.63	1.06
2012	5.19	1.19
2013	4.68	1.10
2014	6.54	1.00
2015	8.08	1.03

Table A3. Convergence diagnostics for the Gelman Rubin, Geweke, and Heidelberger and Welch (HW) tests, along with autocorrelation at lags 1 and 5 for the opakapaka production model. Values shown are the upper confidence interval for the Gelman Rubin diagnostic, which when near 1 indicates convergence; the absolute value of the Z-score for the Geweke diagnostic, which when < 2 indicates convergence; and p values from the Heidelberger and Welch stationarity diagnostic for the full chain, which when > 0.05 indicates convergence. For the criteria based on individual chains (Geweke and Heidelberger and Welch diagnostics, and autocorrelation), the values shown are from the most extreme chain for each parameter.

Parameters	Gelman and Rubin	Geweke	HW stationarity	HW half-width	Lag1 auto-correlation	Lag5 auto-correlation
B_{MSY}	1.00063	1.60	0.14	Passed	0.52	0.11
F_{MSY}	1.00311	1.21	0.18	Passed	0.31	0.11
H_{MSY}	1.00313	1.20	0.17	Passed	0.31	0.11
MSY	1.00104	1.63	0.15	Passed	0.24	0.08
P_{MSY}	1.00333	1.56	0.09	Passed	0.26	0.09
R	1.00059	1.46	0.53	Passed	0.07	0.03
K	1.00218	1.89	0.20	Passed	0.66	0.15
M	1.00294	1.21	0.22	Passed	0.21	0.07
q_1	1.00175	1.33	0.34	Passed	0.65	0.16
q_2	1.00036	1.92	0.08	Passed	0.60	0.19
rad	1.00019	1.95	0.05	Passed	0.38	0.10
σ^2	1.00014	1.82	0.06	Passed	0.41	0.11
τ_1^2	1.00000	2.91	0.06	Passed	0.11	0.01
τ_2^2	1.00006	0.98	0.40	Passed	0.01	0.01

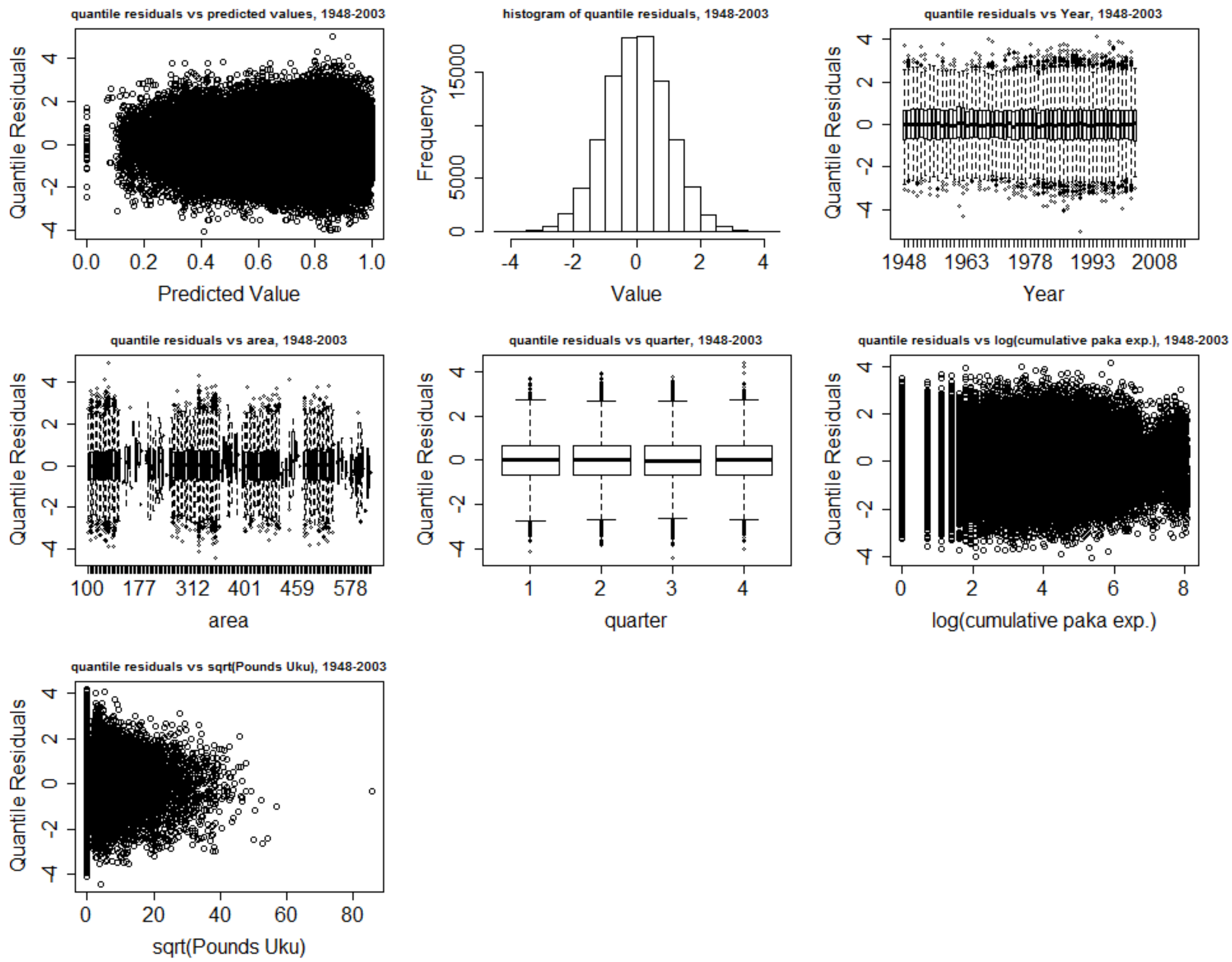


Figure A1.1. Model diagnostics for the best fit Bernoulli model for the early (1948-2003) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictors variables).

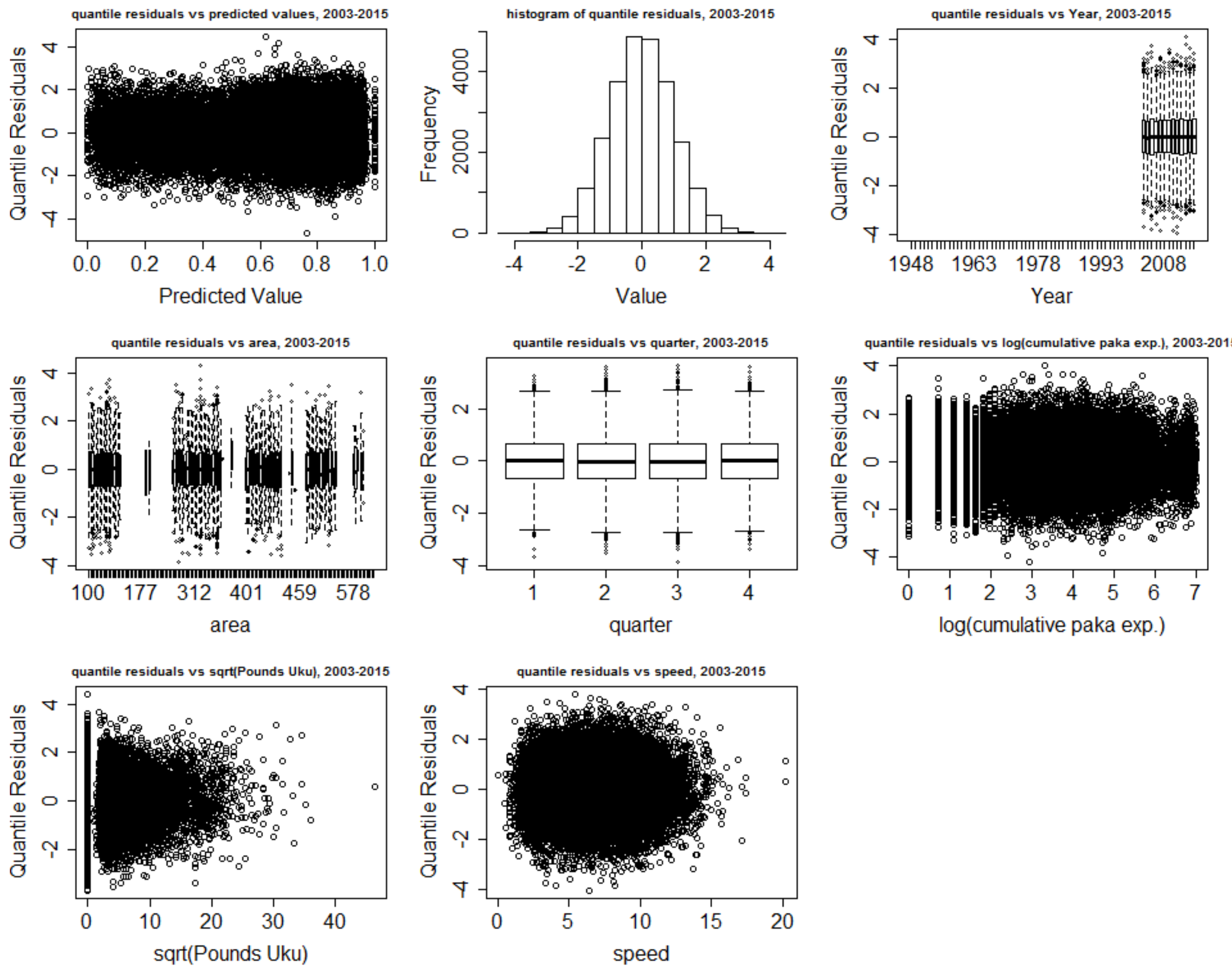


Figure A1.2. Model diagnostics for the best fit Bernoulli model for the recent (2003-2015) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictors variables).

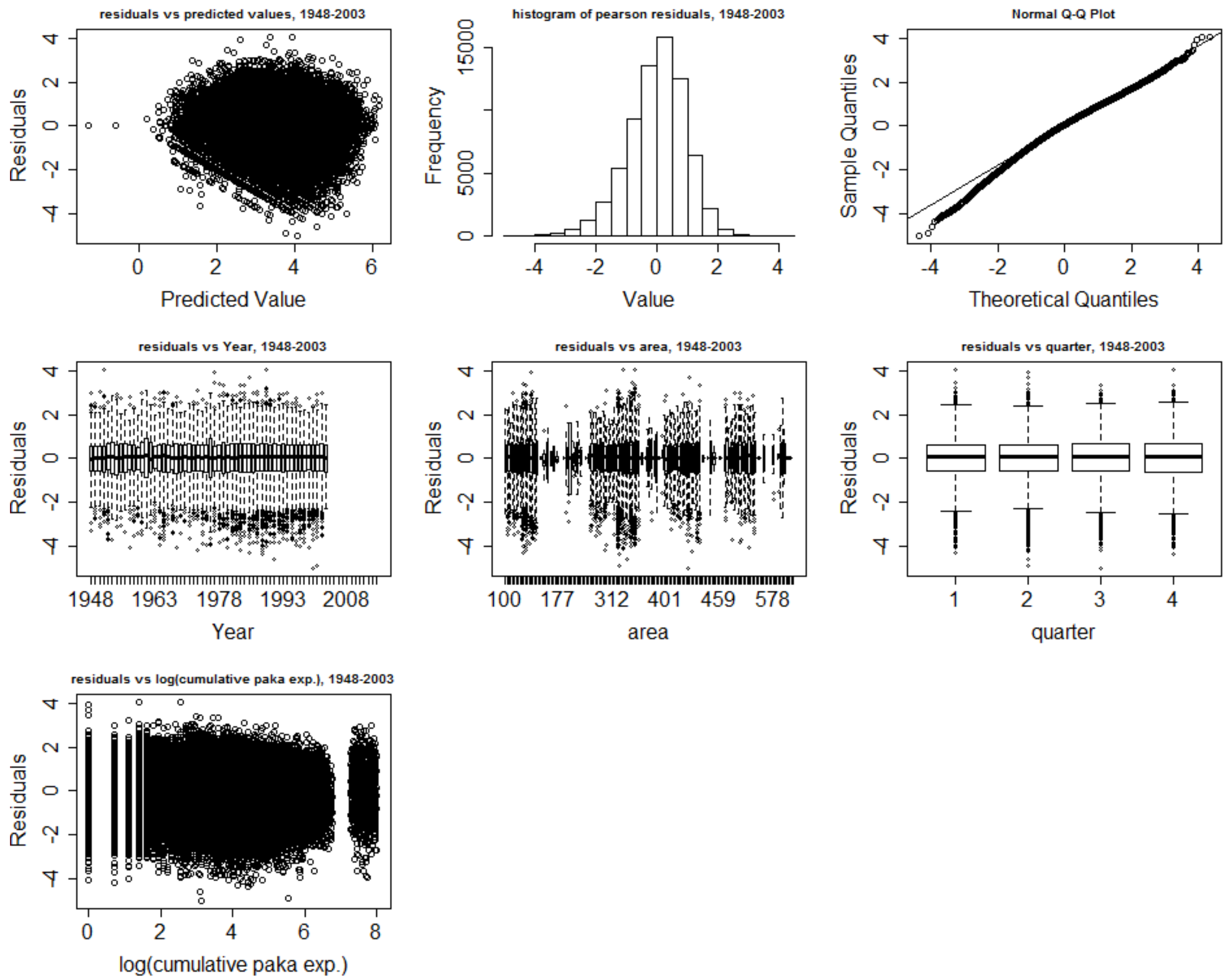


Figure A1.3. Model diagnostics for the best fit Lognormal model for the early (1948-2003) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictors variables).

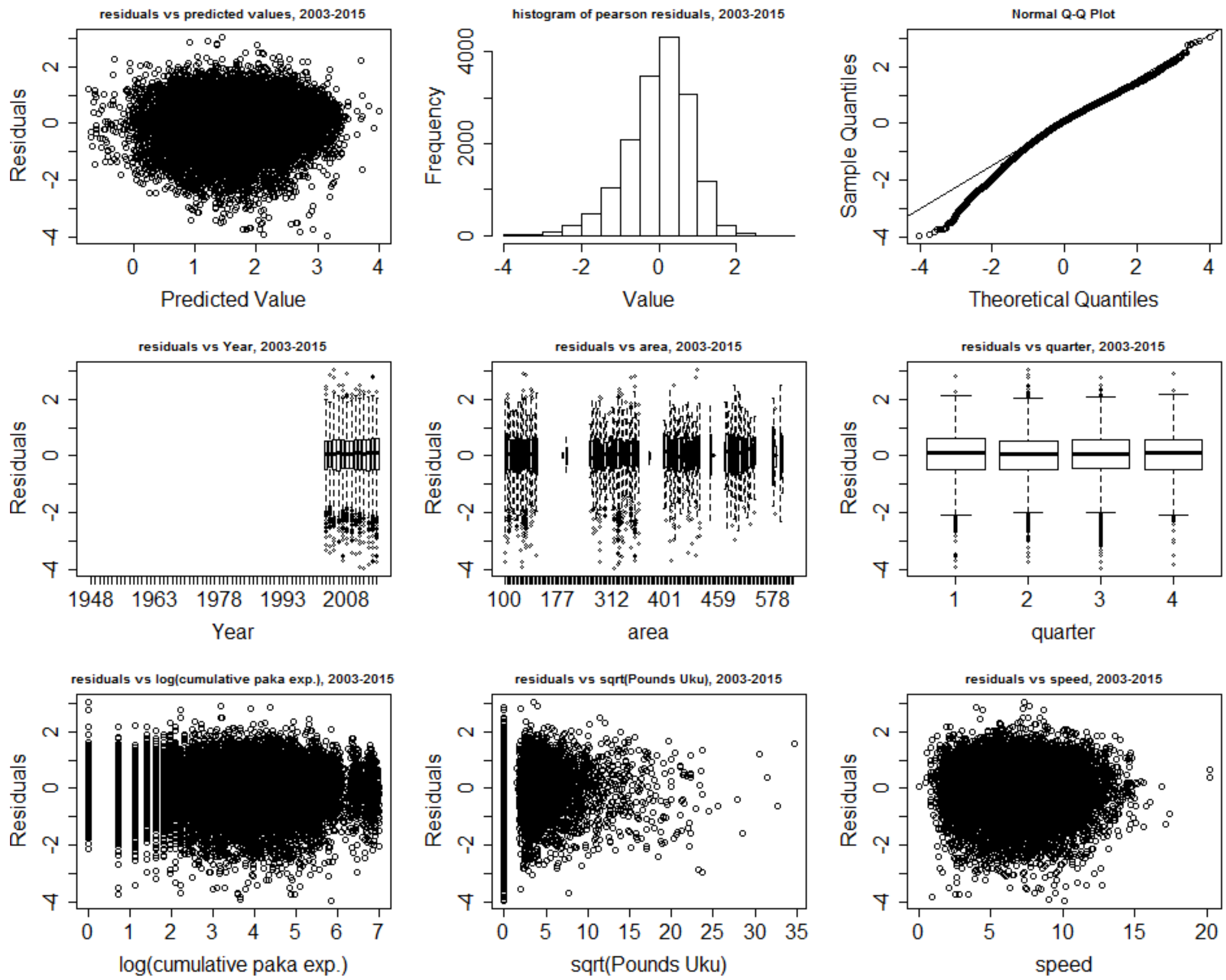


Figure A1.4. Model diagnostics for the best fit Lognormal model for the recent (2003-2015) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictors variables).

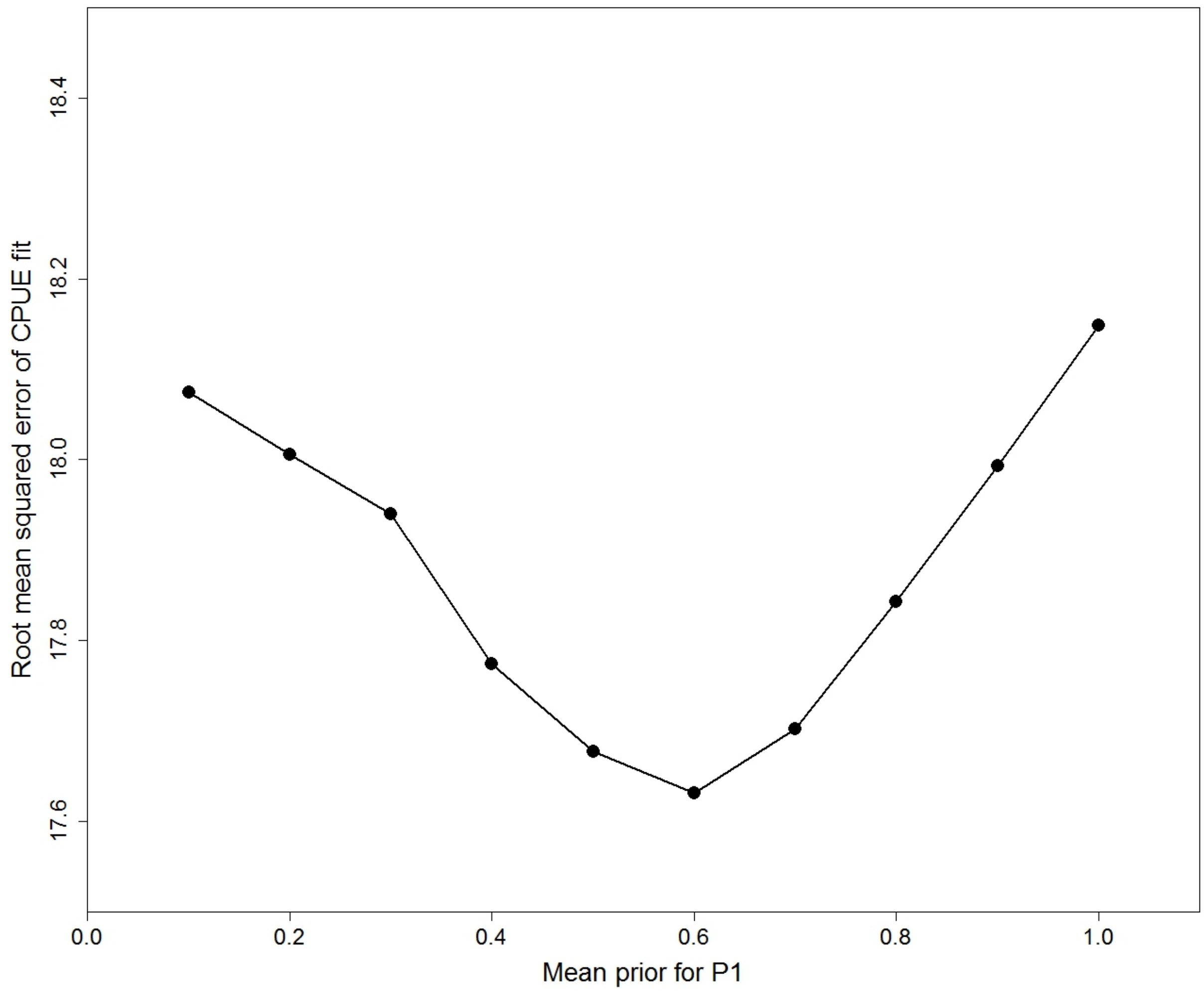


Figure A2. Goodness-of-fit values for alternative choices for the mean of the prior distribution of the initial proportion of carrying capacity (P_1) for the opakapaka production model for the main Hawaiian Islands.

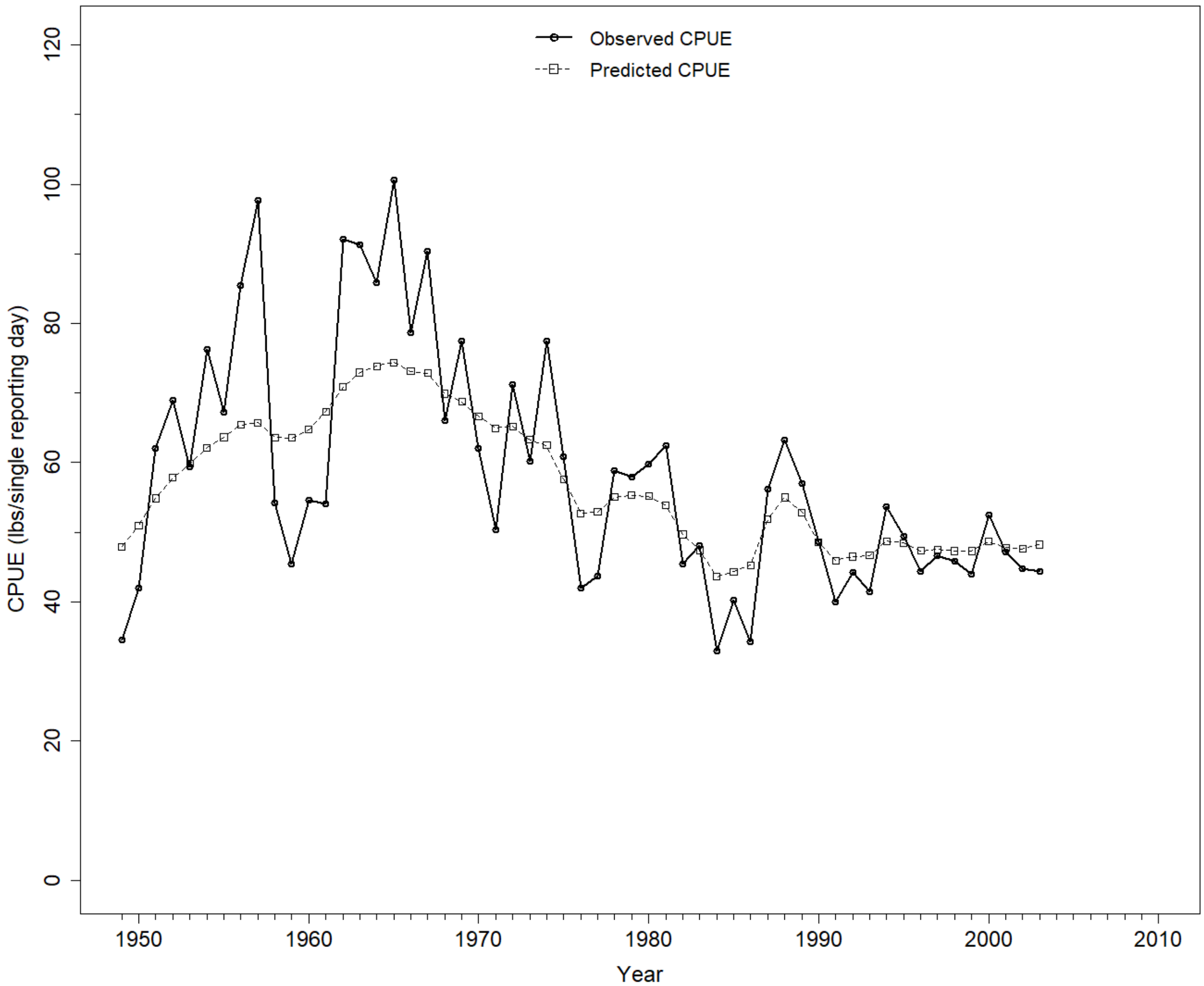


Figure A3. Observed and predicted CPUE for opakapaka in the main Hawaiian Islands from 1949 through 2003.

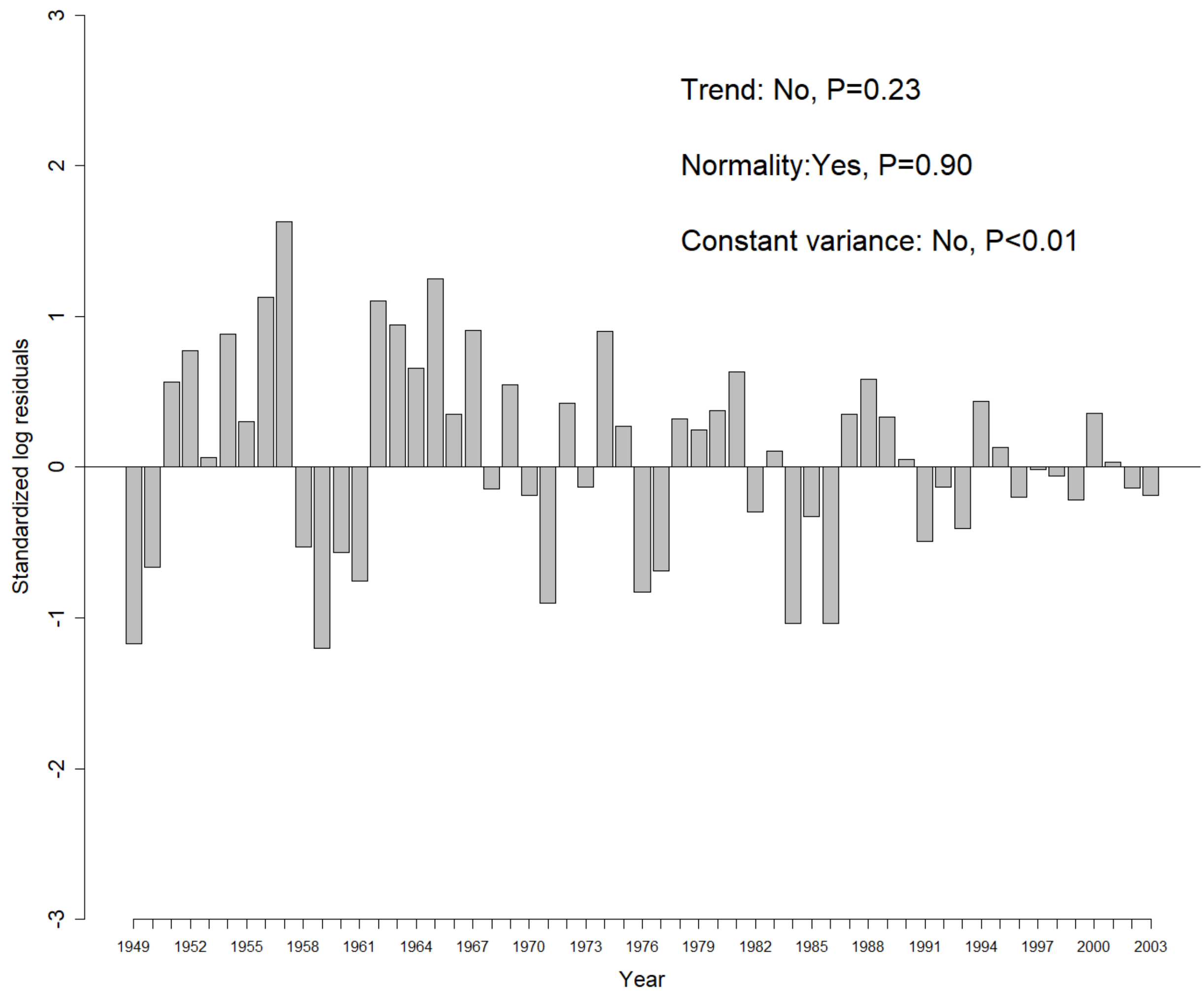


Figure A4. Standardized residuals of observed versus predicted CPUE for opakapaka CPUE in the main Hawaiian Islands by fishing year from 1949-2003 and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

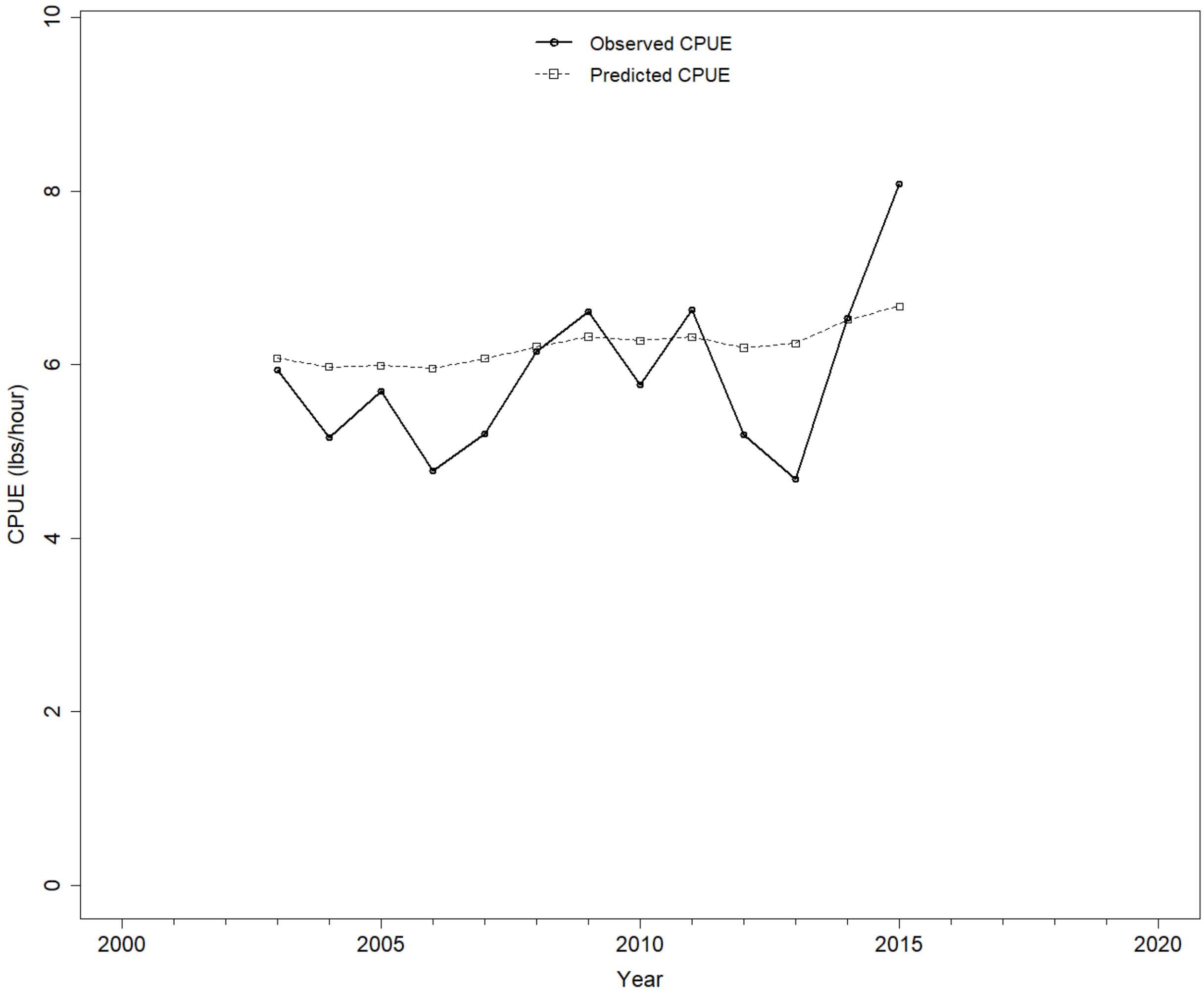


Figure A5. Observed and predicted CPUE for opakapaka in the main Hawaiian Islands from 2003 through 2015.

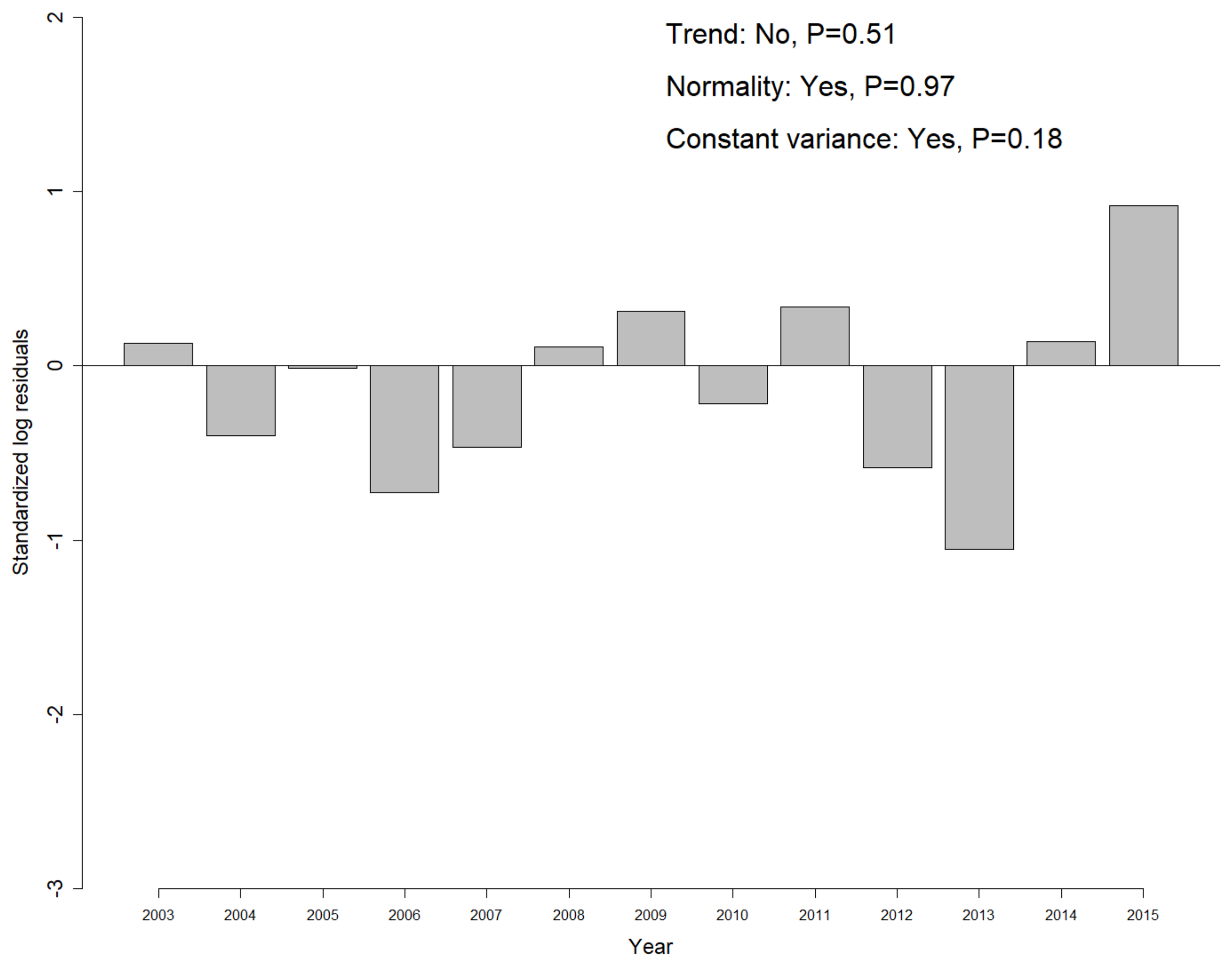


Figure A6. Standardized residuals of observed versus predicted CPUE for opakapaka CPUE in the main Hawaiian Islands by fishing year from 2003-2015 and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

Appendix B. R code that calls WinBUGS used to fit base case assessment and projection model for the Deep 7 bottomfish complex in the main Hawaiian Islands from 1949-2015.

```
##############################################################

# d7_2018_baseWPSAR

# Jon Brodziak, PIFSC, December 2010, updated by Annie Yau, May 2014

# to two-CPUE time series. Updated further by Brian Langseth, April 2017


# Catch is in million pounds

# CPUE is in lbs/single-reporting day up before 10/1/2002, and lbs/hr thereafter


# Time period for two-CPUE indices, 1949-2002 and 2002-2015 (calendar year)

# and so use revised data entry structure.

# The CVs for years where CPUE is not used must still be entered, so

# that the code runs properly.


# Single catchability value per index

# Include fitting to survey biomass


# Updated the survey to reflect a prior around the survey catchability

# based on min and max effective radius, corresponding to min and max

# scalar of 7.5-41.6, centered at 20.2


# Updated November 14, 2017

##############################################################
```

```
rm(list=ls())

DATA = read.csv("C:\\PathfilenameToInputData\\Datafile.csv",header=T)


head(DATA)


addname <- 'd7_2018_base_proj'   ##<--------name of model---------- # change accordingly

src.dir<-paste('C:\\PathfilenameOfSourceDirectory')

dir.create(src.dir)

dest.dir <- src.dir # where you want files copied to

setwd(src.dir)


library(R2WinBUGS)            # Load the R2WinBUGS library

library(coda)


##################################################################################

#Reported catches in 2016, 2017 to be used in projections


RC_2016 = 0.281   #reported catch from 2016 (millions of lbs.) used in projections


RC_2017 = 0.300   #2017 catch is mean of last 3 years empirical data - used in projections

##################################################################################



#MCMC sampling

nt <- 20 # Thinning rate
```

```
ni <- 500000 # Number of iterations per chain

nb <- 200000 #round(ni*(1/10)) # Number of draws to discard as burn in



##########################################################################

# DATA

# model variable set-up

##########################################################################

###obs_CPUE_1 = na.rm(DATA$CPUE_1_1)

# In this case, there is one CPUE set split at 2003 into two

# Vector Catch() is total catch weight in thousand metric tons 1949-2015

# Vector S1() is the Main Hawaiian Islands CPUE index 1949-2003

# Vector S2() is the Main Hawaiian Islands CPUE index 2003-2015


# sigma2 is process error

# tau2 is observation error by survey


NTIME <- length(DATA$Catch)

Reported_Catch <- DATA$Catch


UnrepCatch <- DATA$UnrepCatch


#CPUE and relCV of CPUE

CPUE_S1 <- DATA$CPUE_1

CPUE_S2 <- DATA$CPUE_2
```

```
CPUE_S1_REL_CV <- DATA$CPUE_1_rel_CV[!is.na(DATA$CPUE_1_rel_CV)] #exclude NAs

CPUE_S2_REL_CV <- DATA$CPUE_2_rel_CV[!is.na(DATA$CPUE_2_rel_CV)] #exclude NAs


#Accounting of time series length and dealing with NAs

NCPUE_S1_1=0

NCPUE_S1_MISS=0

NCPUE_S1_2 <- max(which(!is.na(DATA$CPUE_1))) #end year of first time series

if (match(NA, CPUE_S1)>0 & match(NA,CPUE_S1)!=(NCPUE_S1_2+1)){ #if there is an NA in first time period, prior to when the first time period ends

  NCPUE_S1_1 <- match(NA, CPUE_S1)-1 #last year prior to first NA

  NCPUE_S1_MISS <- length(DATA$CPUE_1[is.na(DATA$CPUE_1)]) + max(which(!is.na(DATA$CPUE_1)))-length(CPUE_S1) # Total missing values within time series (last positive + total NAs - total length)

}

NCPUE_S1_2 <- max(which(!is.na(DATA$CPUE_1))) #end year of first time series

NCPUE_S1_3 <- length(DATA$CPUE_1) #end year of all time series


#Survey biomass and SE estimate for 2016 calendar year. From Ault et al Tech Memo.

#Convert from kg to million lbs

Bio2017 <- 4604640/1000000*2.20462 /(25892*194.89)

s_eta2 <- (891127.6/1000000*2.20462 /(25892*194.89))^2

s_CV <- sqrt(s_eta2)/Bio2017

s_eta2log <- log(s_CV*s_CV+1)


#########################
```

```
# model parameters
#########################

Target_K_Prior_avg <- 29
CV_K <- 0.5

Target_r_Prior_avg <- 0.10
CV_r <- 0.25

Target_P1_Prior_avg <- 0.53
CV_P1 <- 0.2

M_shape <- 0.5
M_scale <- 0.5

process_shape <- 0.2
process_scale <- 0.1

observation_shape <- 0.2
observation_scale <- 1.0

q_lo <- 0.00001
q_hi <- 100000

Target_rad_Prior_avg <-20.2
```

```
CV_rad <- 0.5


LB <- 0.6

UB <- 1.4


proj_LB <- 0.6

proj_UB <- 1.4


pLIM_B <- 0.844


UC_ratio <-1.06


start_TAC <- 0.000  #Values for setting up catches for projections 0-1 million lbs. by 0.002*1 million

mesh_TAC <- 0.002

NTAC <- 501



##################################################################

# Bundle Data

##################################################################


win.data <- list(


  NTIME = NTIME,

  Reported_Catch = Reported_Catch,
```

UnrepCatch = UnrepCatch,

CPUE_S1 = CPUE_S1,

CPUE_S2 = CPUE_S2,

CPUE_S1_REL_CV = CPUE_S1_REL_CV,

CPUE_S2_REL_CV = CPUE_S2_REL_CV,

NCPUE_S1_1 = NCPUE_S1_1,

NCPUE_S1_MISS = NCPUE_S1_MISS,

NCPUE_S1_2 = NCPUE_S1_2,

NCPUE_S1_3 = NCPUE_S1_3,

Target_K_Prior_avg = Target_K_Prior_avg,

CV_K = CV_K,

Target_r_Prior_avg = Target_r_Prior_avg,

CV_r = CV_r,

Target_P1_Prior_avg = Target_P1_Prior_avg,

CV_P1 = CV_P1,

M_shape = M_shape,

M_scale = M_scale,

process_shape = process_shape,

process_scale = process_scale,

```
observation_shape = observation_shape,
observation_scale = observation_scale,

q_lo = q_lo,
q_hi = q_hi,

Target_rad_Prior_avg = Target_rad_Prior_avg,
CV_rad = CV_rad,
LB = LB,
UB = UB,

pLIM_B = pLIM_B,

Bio2017 = Bio2017,

s_eta2log = s_eta2log,

proj_LB = proj_LB,
proj_UB = proj_UB,

RC_2016 = RC_2016,

RC_2017 = RC_2017,
```

```
  UC_ratio = UC_ratio,


  start_TAC = start_TAC,
  mesh_TAC = mesh_TAC,
  NTAC = NTAC

) # end data list

## END DATA
#######################################################################

# Define model written in WinBUGS code ------
model_code=paste0("model ",addname,".txt")
sink(model_code)  # sink diverts R output to a connection.
cat("

   model
   {

   ##################################################################
   # PRIOR DISTRIBUTIONS
   ##################################################################

   # Lognormal prior for carrying capacity parameter, K
   #(P1)##############################################################
```

```
K_Prior_Precision <- 1.0/log(1.0+CV_K*CV_K)
K_Prior_avg <- log(Target_K_Prior_avg) - (0.5/K_Prior_Precision)
K ~ dlnorm(K_Prior_avg,K_Prior_Precision)I(0.001,200.0)

# Lognormal prior for intrinsic growth rate parameter, r
#(P2)############################################################
r_Prior_Precision <- 1.0/log(1.0+CV_r*CV_r)
r_Prior_avg <- log(Target_r_Prior_avg) - (0.5/r_Prior_Precision)
r ~ dlnorm(r_Prior_avg,r_Prior_Precision)I(0.01,1.00)

# Gamma prior for production shape parameter, M
#(P3)############################################################
M ~ dgamma(M_shape, M_scale)

# Uniform prior for CPUE catchability coefficients
# in the interval (0.0001,10000), q1 and q2
#(P4)############################################################
q1 ~ dunif(q_lo, q_hi)
q2 ~ dunif(q_lo, q_hi)

# Lognormal prior for effective radius for survey
#(P4.b)############################################################
rad_Prior_Precision <- 1.0/log(1.0+CV_rad*CV_rad)
rad_Prior_avg <- log(Target_rad_Prior_avg) - (0.5/rad_Prior_Precision)
rad ~ dlnorm(rad_Prior_avg,rad_Prior_Precision)I(7.5,41.6)
```

```
q3 <- 250000/(rad*rad*3.14159)

# Inverse gamma prior for process error variance, sigma2
#(P5)############################################################
isigma2 ~ dgamma(process_shape,process_scale)I(0.000001,1000000)
sigma2 <- 1/isigma2

# Inverse gamma prior for observation error variance, tau2
#(P6)############################################################
itau2_1   ~ dgamma(observation_shape,observation_scale)I(0.000001,1000000)
tau2_1  <- 1/itau2_1

itau2_2   ~ dgamma(observation_shape,observation_scale)I(0.000001,1000000)
tau2_2   <- 1/itau2_2

# Lognormal priors for unobserved states, the time series of proportions of K, P[]
# MHI time catch series starts in FY1949 and ends in FY2015, n=67
#(P7)############################################################
P1_Prior_Precision <- 1.0/log(1.0+CV_P1*CV_P1)
P1_Prior_avg <-log(Target_P1_Prior_avg) - (0.5/P1_Prior_Precision)
P[1] ~ dlnorm(P1_Prior_avg,P1_Prior_Precision) I(0.0001,10000)

# Catch is uniformly distributed on the interval [lower, upper]
#(P8)############################################################
lower[1] <- LB*UnrepCatch[1] + Reported_Catch[1]
```

```
upper[1] <- UB*UnrepCatch[1] + Reported_Catch[1]

Catch[1] ~ dunif(lower[1],upper[1])


#################################################################

# PROCESS DYNAMICS

#################################################################

for (i in 2:NTIME) {

Pmean[i] <- log(max(P[i-1] + r*P[i-1]*(1-pow(P[i-1],M)) - Catch[i-1]/K,0.0001))

P[i]  ~ dlnorm(Pmean[i],isigma2)I(0.0001,10000)

lower[i] <- LB*UnrepCatch[i] + Reported_Catch[i]

upper[i] <- UB*UnrepCatch[i] + Reported_Catch[i]

Catch[i] ~ dunif(lower[i],upper[i])

}


Pmean2016 <- log(max(P[NTIME] + r*P[NTIME]*(1-pow(P[NTIME],M)) -
Catch[NTIME]/K,0.0001))

P2016 ~ dlnorm(Pmean2016,isigma2)I(0.0001,10000)

C2016lo <- LB*0.301106 + 0.281079

C2016hi <- UB*0.301106 + 0.281079

Catch2016 ~ dunif(C2016lo,C2016hi)

Pmean2017 <- log(max(P2016 + r*P2016*(1-pow(P2016,M)) - Catch2016/K,0.0001))

P2017 ~ dlnorm(Pmean2017,isigma2)I(0.0001,10000)



#################################################################

# LIKELIHOOD OF OBSERVED CPUE
```

```
#################################################################

# Deep 7 bottomfish CPUE lLIKELIHOOD, 1949-2003
P[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2]

#(L1)############################################################

for (i in (NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2) {

CPUE_mean[i] <- log(q1*K*P[i])

Precision_CPUE[i] <- itau2_1/(CPUE_S1_REL_CV[i]*CPUE_S1_REL_CV[i])

CPUE_S1[i] ~ dlnorm(CPUE_mean[i],Precision_CPUE[i])

LOG_RESID1[i] <- log(CPUE_S1[i]) - log(q1*K*P[i])

}


# Deep 7 bottomfish CPUE lLIKELIHOOD, 2003-2015 P[(NCPUE_S1_2+1):NCPUE_S1_3]

#(L2)############################################################

for (i in (NCPUE_S1_2):NCPUE_S1_3) {

CPUE_mean2[i] <- log(q2*K*P[i])

Precision_CPUE2[i] <- itau2_2/(CPUE_S2_REL_CV[i]*CPUE_S2_REL_CV[i])

CPUE_S2[i] ~ dlnorm(CPUE_mean2[i],Precision_CPUE2[i])

LOG_RESID2[i] <- log(CPUE_S2[i]) - log(q2*K*P[i])

}


# survey likelihood, for 2017 estimate

#(L3)############################################################

survey_mean <- log(P2017*K /(q3*25892))

Precision_survey <- 1/s_eta2log

Bio2017 ~ dlnorm(survey_mean,Precision_survey)
```

```
LOG_RESID3 <- log(Bio2017) - log(P2017*K /(q3*25892))



# Compute LOG_RSS and LOG_RMSE
################################################################
# LOG_RSS1 <- inprod(LOG_RESID1[1:NCPUE_S1_1], LOG_RESID1[1:NCPUE_S1_1])
+
LOG_RSS1 <- inprod(LOG_RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2],
LOG_RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2])


LOG_RSS2 <- inprod(LOG_RESID2[(NCPUE_S1_2):NCPUE_S1_3],
LOG_RESID2[(NCPUE_S1_2):NCPUE_S1_3])


LOG_RSS3 <- inprod(LOG_RESID3, LOG_RESID3)


LOG_RMSE1 <- sqrt(LOG_RSS1/(NCPUE_S1_2-NCPUE_S1_MISS))


LOG_RMSE2 <- sqrt(LOG_RSS2/(NCPUE_S1_3-(NCPUE_S1_2-1)))


LOG_RMSE3 <- sqrt(LOG_RSS3)



# Compute standardized log-scale residuals, predicted CPUE, and unscaled residuals
################################################################
# for (i in 1:NCPUE_S1_1) {
# STD_LOG_RESID1[i] <- LOG_RESID1[i]/LOG_RMSE1
```

```
# PRED_CPUE[i] <- exp(CPUE_mean[i]) ## PRED_CPUE[i] <- exp(log(CPUE_mean[i]))
# RESID1[i] <- CPUE_S1[i] - PRED_CPUE[i]
# }

for (i in (NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2) {
STD_LOG_RESID1[i] <- LOG_RESID1[i]/LOG_RMSE1
PRED_CPUE[i] <- exp(CPUE_mean[i]) ## PRED_CPUE[i] <- exp(log(CPUE_mean[i]))
RESID1[i] <- CPUE_S1[i] - PRED_CPUE[i]
}

for (i in (NCPUE_S1_2):NCPUE_S1_3) {
STD_LOG_RESID2[i] <- LOG_RESID2[i]/LOG_RMSE2
PRED_CPUE2[i] <- exp(CPUE_mean2[i])
RESID2[i] <- CPUE_S2[i] - PRED_CPUE2[i]
}

STD_LOG_RESID3 <- LOG_RESID3/LOG_RMSE2
PRED_Bio2017 <- exp(survey_mean)
RESID3 <- Bio2017 - PRED_Bio2017



# Compute RSS and RMSE for MHI CPUE
###########################################################
#RSS1 <- inprod(RESID1[1:NCPUE_S1_1], RESID1[1:NCPUE_S1_1]) +
RSS1 <- inprod(RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2],
RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2])
```

```
RSS2 <- inprod(RESID2[(NCPUE_S1_2):NCPUE_S1_3],
RESID2[(NCPUE_S1_2):NCPUE_S1_3])

RSS3 <- inprod(RESID3,RESID3)

RMSE1 <- sqrt(RSS1/(NCPUE_S1_2-NCPUE_S1_MISS))

RMSE2 <- sqrt(RSS2/(NCPUE_S1_3-(NCPUE_S1_2-1)))

RMSE3 <- sqrt(RSS3)

##################################################################
# STOCK ASSESSMENT QUANTITIES OF INTEREST
##################################################################

# Compute exploitation rate and biomass time series
#(QOI1)############################################################
# MHI 1949-2015 P[1:NTIME]
for (i in 1:NTIME) {
B[i] <- P[i]*K
H[i] <- min(Catch[i]/B[i],0.999)
F[i] <- -log(1-H[i])
}

# Compute MSY reference points
```

```
#(QOI2)############################################################
BMSY <- K*pow(M+1.0,(-1.0/M))
MSY <- r*BMSY*(1.0-(1.0/(M+1.0)))
HMSY <- min(r*(1.0-(1.0/(M+1.0))),0.999)
PMSY <- BMSY/K
FMSY <- -log(1-HMSY)
CPUE_MSY <- q2*BMSY

# Compute relative biomass and harvest, BSTATUS and HSTATUS
#(QOI3)############################################################
for (i in 1:NTIME) {
BSTATUS[i] <- B[i]/BMSY
HSTATUS[i] <- H[i]/HMSY
production[i] <- r*B[i]*(1-pow(P[i],M))
}

# Compute probabilities of H[i] > HMSY, B[i] < BMSY,
# and B[i] < pLIM_B*BMSY, a minimum biomass limit
#(QOI4)############################################################
for (i in 1:NTIME) {
pOFL_H[i] <- step(HSTATUS[i] - 1.0)
pBMSY_B[i] <- step(1.0 - BSTATUS[i])
pOFL_B[i] <- step(pLIM_B - BSTATUS[i])
}
```

```
##################################################################
 #####   PROJECTIONS
   ##################################################################
   # Fishing Year 2016 Projection
   proj_Pmean2016 <- (max(P[NTIME] + r*P[NTIME]*(1-pow(P[NTIME],M)) -
Catch[NTIME]/K,0.0001))

   B[NTIME+1] <- proj_Pmean2016*K

   UC[1] <- UC_ratio*RC_2016

   lower[NTIME+1] <- proj_LB*UC[1] + RC_2016
   upper[NTIME+1] <- proj_UB*UC[1] + RC_2016

   proj_C2016 ~ dunif(lower[NTIME+1],upper[NTIME+1])

   H[NTIME+1] <- min(proj_C2016/B[NTIME+1],0.999)

   BSTATUS[NTIME+1] <- B[NTIME+1]/BMSY
   HSTATUS[NTIME+1] <- H[NTIME+1]/HMSY
   production[NTIME+1] <- r*B[NTIME+1]*(1-pow(proj_Pmean2016,M))

   pOFL_H[NTIME+1] <- step(HSTATUS[NTIME+1] - 1.0)
   pBMSY_B[NTIME+1] <- step(1.0 - BSTATUS[NTIME+1])
   pOFL_B[NTIME+1] <- step(pLIM_B - BSTATUS[NTIME+1])
```

```
# Fishing Year 2017 Projection

#####################################################################

proj_Pmean2017 <- (max(proj_Pmean2016 + r*proj_Pmean2016*(1-pow(proj_Pmean2016,M)) - proj_C2016/K,0.0001))


B[NTIME+2] <- proj_Pmean2017*K


UC[2] <- UC_ratio*RC_2017


lower[NTIME+2] <- proj_LB*UC[2] + RC_2017

upper[NTIME+2] <- proj_UB*UC[2] + RC_2017


proj_C2017 ~ dunif(lower[NTIME+2],upper[NTIME+2])


H[NTIME+2] <- min(proj_C2017/B[NTIME+2],0.999)


BSTATUS[NTIME+2] <- B[NTIME+2]/BMSY

HSTATUS[NTIME+2] <- H[NTIME+2]/HMSY

production[NTIME+2] <- r*B[NTIME+2]*(1-pow(proj_Pmean2017,M))


pOFL_H[NTIME+2] <- step(HSTATUS[NTIME+2] - 1.0)

pBMSY_B[NTIME+2] <- step(1.0 - BSTATUS[NTIME+2])

pOFL_B[NTIME+2] <- step(pLIM_B - BSTATUS[NTIME+2])
```

```
    # Fishing Year 2018-2019 Projection
###################################################################

    proj_lower <- proj_LB*UC_ratio

    proj_upper <- proj_UB*UC_ratio


    proj_Pmean <- (max(proj_Pmean2017 + r*proj_Pmean2017*(1-pow(proj_Pmean2017,M)) - 
proj_C2017/K,0.0001))

    B[NTIME+3] <- proj_Pmean*K  #2018 biomass


    BSTATUS[NTIME+3] <- B[NTIME+3]/BMSY

    production[NTIME+3] <- r*B[NTIME+3]*(1-pow(proj_Pmean,M))

    pBMSY_B[NTIME+3] <- step(1.0 - BSTATUS[NTIME+3])

    pOFL_B[NTIME+3] <- step(pLIM_B - BSTATUS[NTIME+3])


    for (j in 1:NTAC)

    {

#2018-2019

    proj_TAC[j] <- start_TAC+mesh_TAC*(j-1)


    proj_UC_ratio1[j] ~ dunif(proj_lower,proj_upper)

    proj_UC1[j] <- proj_UC_ratio1[j]*proj_TAC[j]

    proj_C1[j] <- proj_TAC[j] + proj_UC1[j]

    proj_H1[j] <- min(proj_C1[j]/B[NTIME+3],0.999)

    proj_HSTATUS1[j] <- proj_H1[j]/HMSY

    proj_pOFL_H1[j] <- step(proj_HSTATUS1[j] - 1.0)
```

```
    proj_P2019[j] <- max(proj_Pmean + r*proj_Pmean*(1-pow(proj_Pmean,M)) -
proj_C1[j]/K,0.0001)

    proj_B2019[j] <- proj_P2019[j]*K



    proj_BSTATUS[j] <- proj_B2019[j]/BMSY

    proj_pOFL_B[j] <- step(pLIM_B - proj_BSTATUS[j])

    proj_UC_ratio2[j] ~ dunif(proj_lower,proj_upper)

    proj_UC2[j] <- proj_UC_ratio2[j]*proj_TAC[j]

    proj_C2[j] <- proj_TAC[j] + proj_UC2[j]

    proj_H2[j] <- min(proj_C2[j]/proj_B2019[j],0.999)

    proj_HSTATUS2[j] <- proj_H2[j]/HMSY

    proj_pOFL_H2[j] <- step(proj_HSTATUS2[j] - 1.0




    proj_P2020[j] <- max(proj_P2019[j] + r*proj_P2019[j]*(1-pow(proj_P2019[j],M)) -
proj_C2[j]/K,0.0001)

    proj_B2020[j]<- proj_P2020[j]*K



    proj_UC_ratio3[j] ~ dunif(proj_lower,proj_upper)

    proj_UC3[j] <- proj_UC_ratio3[j]*proj_TAC[j]

    proj_C3[j] <- proj_TAC[j] + proj_UC3[j]

    proj_H3[j] <- min(proj_C3[j]/proj_B2020[j],0.999)

    proj_HSTATUS3[j] <- proj_H3[j]/HMSY

    proj_pOFL_H3[j] <- step(proj_HSTATUS3[j] - 1.0)

    proj_BSTATUS3[j]<- proj_B2020[j]/BMSY

    proj_pOFL_B3[j] <- step(pLIM_B - proj_BSTATUS3[j])
```

```
    proj_P2021[j] <- max(proj_P2020[j] + r*proj_P2020[j]*(1-pow(proj_P2020[j],M)) -
proj_C3[j]/K,0.0001)

    proj_B2021[j] <-proj_P2021[j]*K



    proj_UC_ratio4[j] ~ dunif(proj_lower,proj_upper)

    proj_UC4[j] <- proj_UC_ratio4[j]*proj_TAC[j]

    proj_C4[j] <- proj_TAC[j] + proj_UC4[j]

    proj_H4[j] <- min(proj_C4[j]/proj_B2021[j],0.999)

    proj_HSTATUS4[j] <- proj_H4[j]/HMSY

    proj_pOFL_H4[j] <- step(proj_HSTATUS4[j] - 1.0)

    proj_BSTATUS4[j]<- proj_B2021[j]/BMSY

    proj_pOFL_B4[j] <- step(pLIM_B - proj_BSTATUS4[j])



    proj_P2022[j] <- max(proj_P2021[j] + r*proj_P2021[j]*(1-pow(proj_P2021[j],M)) -
proj_C4[j]/K,0.0001)

    proj_B2022[j] <- proj_P2022[j]*K



    proj_UC_ratio5[j] ~ dunif(proj_lower,proj_upper)

    proj_UC5[j] <- proj_UC_ratio5[j]*proj_TAC[j]

    proj_C5[j] <- proj_TAC[j] + proj_UC5[j]

    proj_H5[j] <- min(proj_C5[j]/proj_B2022[j], 0.999)

    proj_HSTATUS5[j] <- proj_H5[j]/HMSY

    proj_pOFL_H5[j] <- step(proj_HSTATUS5[j] - 1.0)
```

```
   proj_BSTATUS5[j] <- proj_B2022[j]/BMSY
   proj_pOFL_B5[j] <- step(pLIM_B - proj_BSTATUS5[j])

   }

   ########################
   } ## END OF WinBUGS MODEL

   ",fill=TRUE)
sink()      # ends the last diversion

###################################################################
# END OF CODE/MODEL
###################################################################

#######################################################################  ------
############ Create list of inits for WinBUGS use #####################
#######################################################################

inits <- list(    # create inits list of functions

  ## Initial Condition 1

  list(
```

```
Catch=c(0.889846783,0.778941737,0.824254018,0.762620337,
    0.661370999,0.677419931,0.553893321,0.709836464,0.856255301,
    0.563444848,0.518085637,0.429625612,0.33919519,0.446999966,
    0.560303076,0.543231463,0.586733137,0.469831635,0.664149948,
    0.524969584,0.493058543,0.42888162,0.3657332,0.653303227,
    0.49559336,0.684927867,0.637403776,0.67817695,0.712558533,
    0.870372753,0.789619688,0.746366372,0.94938799,0.941233443,
    1.191552026,0.930339634,1.24944603,1.245210744,1.53397504,
    1.602716019,1.60503175,1.219962022,0.840492747,0.970455548,
    0.720273837,0.892439097,0.974311859,0.769418048,0.850288559,
    0.782225449,0.530352097,0.750185256,0.56962955,0.436408415,
    0.527079244,0.394814741,0.470591447,0.344546487,0.423234016,
    0.401774757,0.535873576,0.438224507,0.586167313,0.445163771,
    0.446142896,0.653405446,0.638883526),

Catch2016 = 0.58,

r=0.05,

P=c(rep(0.5,32), rep(0.5, NTIME-32)),

P2016=0.5,
P2017=0.5,

K=45.0,
```

```
M=1.0,

q1=10.0,
q2=10.0,
rad=20.2,

isigma2=100,

itau2_1=100,
itau2_2=100,

proj_C2016= 0.579,

proj_C2017=0.618,

proj_UC_ratio1=rep(1.06, 501),

proj_UC_ratio2=rep(1.06, 501),

proj_UC_ratio3=rep(1.06, 501),

proj_UC_ratio4=rep(1.06, 501),

proj_UC_ratio5=rep(1.06, 501)
```

```
) ##END init 1

## Initial Condition 2

,list(

  Catch=c(0.889846783,0.778941737,0.824254018,0.762620337,
          0.661370999,0.677419931,0.553893321,0.709836464,0.856255301,
          0.563444848,0.518085637,0.429625612,0.33919519,0.446999966,
          0.560303076,0.543231463,0.586733137,0.469831635,0.664149948,
          0.524969584,0.493058543,0.42888162,0.3657332,0.653303227,
          0.49559336,0.684927867,0.637403776,0.67817695,0.712558533,
          0.870372753,0.789619688,0.746366372,0.94938799,0.941233443,
          1.191552026,0.930339634,1.24944603,1.245210744,1.53397504,
          1.602716019,1.60503175,1.219962022,0.840492747,0.970455548,
          0.720273837,0.892439097,0.974311859,0.769418048,0.850288559,
          0.782225449,0.530352097,0.750185256,0.56962955,0.436408415,
          0.527079244,0.394814741,0.470591447,0.344546487,0.423234016,
          0.401774757,0.535873576,0.438224507,0.586167313,0.445163771,
          0.446142896,0.653405446,0.638883526),

  Catch2016 = 0.58,

  r=0.15,
```

```
P=c(rep(0.5,32), rep(0.5, NTIME-32)),

P2016=0.5,
P2017=0.5,

K=15.0,

M=1.0,

q1=10.0,
q2=10.0,
rad=20.2,

isigma2=100,

itau2_1=100,
itau2_2=100,

proj_C2016= 0.579,

proj_C2017=0.618,

proj_UC_ratio1=rep(1.06, 501),
```

```
  proj_UC_ratio2=rep(1.06, 501),

  proj_UC_ratio3=rep(1.06, 501),

  proj_UC_ratio4=rep(1.06, 501),

  proj_UC_ratio5=rep(1.06, 501)


)  ##END init 2

## Initial Condition 3

,list(

  Catch=c(0.889846783,0.778941737,0.824254018,0.762620337,
        0.661370999,0.677419931,0.553893321,0.709836464,0.856255301,
        0.563444848,0.518085637,0.429625612,0.33919519,0.446999966,
        0.560303076,0.543231463,0.586733137,0.469831635,0.664149948,
        0.524969584,0.493058543,0.42888162,0.3657332,0.653303227,
        0.49559336,0.684927867,0.637403776,0.67817695,0.712558533,
        0.870372753,0.789619688,0.746366372,0.94938799,0.941233443,
        1.191552026,0.930339634,1.24944603,1.245210744,1.53397504,
        1.602716019,1.60503175,1.219962022,0.840492747,0.970455548,
        0.720273837,0.892439097,0.974311859,0.769418048,0.850288559,
```

```
    0.782225449,0.530352097,0.750185256,0.56962955,0.436408415,
    0.527079244,0.394814741,0.470591447,0.344546487,0.423234016,
    0.401774757,0.535873576,0.438224507,0.586167313,0.445163771,
    0.446142896,0.653405446,0.638883526),

Catch2016 = 0.58,

r=0.10,

P=c(rep(0.5,32), rep(0.5, NTIME-32)),

P2016=0.5,
P2017=0.5,

K=30.0,

M=1.0,

q1=10.0,
q2=10.0,
rad=20.2,

isigma2=100,

itau2_1=100,
```

```
    itau2_2=100,

    proj_C2016= 0.579,

    proj_C2017=0.618,

    proj_UC_ratio1=rep(1.06, 501),

    proj_UC_ratio2=rep(1.06, 501),

    proj_UC_ratio3=rep(1.06, 501),

    proj_UC_ratio4=rep(1.06, 501),

    proj_UC_ratio5=rep(1.06, 501)

  )##END init 3
)  ## close list of functions

##### end initials function ############################################
########################################################################

## Parameters to estimate
########################################################################
```

```
params <- c(

  ## model parameters ##
  "K","r","M", "q1","q2","sigma2", "tau2_1","tau2_2",”q3”,”rad”,

  ## time-series derived variables ##
  "P","B","H","PRED_CPUE","PRED_CPUE2","PRED_Bio2017",

  ## management metrics ##
  "MSY","BMSY","HMSY",

  "MSY","PMSY","BMSY","HMSY","BSTATUS","HSTATUS","FMSY",
  "pOFL_H","pOFL_B","pBMSY_B",

  ## statistics and diagnoses ##
  "STD_LOG_RESID1", "STD_LOG_RESID2", "STD_LOG_RESID3",
  "LOG_RESID1", "LOG_RESID2", "LOG_RESID3","RESID1", "RESID2", "RESID3",
  "LOG_RSS1", "LOG_RSS2", "LOG_RSS3", "LOG_RMSE1", "LOG_RMSE2",
  "LOG_RMSE3","RSS1", "RSS2", "RSS3", "RMSE1", "RMSE2", "RMSE3",

  ## projection quantities to monitor ##

  "B", "proj_B2019", "proj_B2020", "proj_B2021", "proj_B2022", "proj_H1",
  "proj_H2", "proj_H3", "proj_H4", "proj_H5", "proj_pOFL_H1", "proj_pOFL_H2",
  "proj_pOFL_H3", "proj_pOFL_H4", "proj_pOFL_H5", "pOFL_B", "proj_pOFL_B",
```

```
  "proj_pOFL_B3", "proj_pOFL_B4", "proj_pOFL_B5"

)

begin_time = proc.time()[3]
nc <- length(inits)    # Number of Markov chains, default is 3
####################################################################
# Start Gibbs sampling, cycle through the initials

bugs(win.data,inits,params,model_code,n.chains=nc,n.iter=ni,n.burnin=nb,n.thin=nt,
    debug=FALSEFALSE,codaPkg=TRUE,bugs.directory="c:/WinBUGS/",
    working.directory=src.dir)

####################################################################

end_time = proc.time()[3]
print(paste("RUN_COST = ",(end_time-begin_time)/60," mins",sep=""))

########################################################################
```

Appendix C. R code that calls WinBUGS used to fit assessment model for opakapaka in the main Hawaiian Islands from 1949-2015.

```
###########################################################

# paka_2018_baseWPSAR

# Jon Brodziak, PIFSC, December 2010, updated by Annie Yau, May 2014

# to two-CPUE time series. Updated further by Brian Langseth, April 2017


# Catch is in million pounds

# CPUE is in lbs/single-reporting day up before 10/1/2002 (calendar year), and lbs/hr thereafter


# Time period for two-CPUE indices, 1949-2002 and 2002-2015 (calendar year)

# and so use revised data entry structure.

# The CVs for years where CPUE is not used must still be entered, so

# that the code runs properly.


# Single catchability value per index

# Include fitting to survey biomass, with sd of survey on scale of log of data

# Use actual 2016 catch to set catch for that year

# Use natural mortality of 0.156


# Data changed for paka only model. prior on K changed based on ratio

# of paka to total in the survey estimate.


# Updated the survey to reflect a prior around the survey catchability

# based on min and max effective radiuas, corresponding to min and max

# scalar of 7.5-41.6, centered at 20.2
```

```
# Updated December 18, 2017
#####################################################################


rm(list=ls())
DATA = read.csv("C:\\PathfilenameToInputData\\Datafile.csv",header=T)
head(DATA)


addname <- 'paka_2018_baseWPSAR'  ##<--------name of model---------- # change accordingly
src.dir <- paste('C:\\PathfilenameOfSourceDirectory') # Change accordingly
dir.create(src.dir)
dest.dir <- src.dir # where you want files copied to
setwd(src.dir)


library(R2WinBUGS)            # Load the R2WinBUGS library
library(coda)


nt <- 20     # Thinning rate
ni <- 500000 # Number of total iterations per chain, including burn-in
nb <- 200000 #round(ni*(1/10)) # Number of draws to discard as burn in




###############################################################################
# DATA
# model variable set-up
```

```
#############################################################################

###obs_CPUE_1 = na.rm(DATA$CPUE_1_1)

# In this case, there is one CPUE set split at 2003 (fishing year) into two

# Vector Catch() is total catch weight in thousand metric tons 1949-2015

# Vector S1() is the Main Hawaiian Islands CPUE index 1949-2003

# Vector S2() is the Main Hawaiian Islands CPUE index 2003-2015


# sigma2 is process error

# tau2 is observation error


NTIME <- length(DATA$Catch)

Reported_Catch <- DATA$Catch


UnrepCatch <- DATA$UnrepCatch


#CPUE and relCV of CPUE

CPUE_S1 <- DATA$CPUE_1

CPUE_S2 <- DATA$CPUE_2

CPUE_S1_REL_CV <- DATA$CPUE_1_rel_CV[!is.na(DATA$CPUE_1_rel_CV)] #exclude
NAs

CPUE_S2_REL_CV <- DATA$CPUE_2_rel_CV[!is.na(DATA$CPUE_2_rel_CV)] #exclude
NAs


#Accounting of time series length and dealing with NAs

NCPUE_S1_1=0

NCPUE_S1_MISS=0
```

```
NCPUE_S1_2 <- max(which(!is.na(DATA$CPUE_1))) #end year of first time series

if (match(NA, CPUE_S1)>0 & match(NA,CPUE_S1)!=(NCPUE_S1_2+1)){ #if there is an NA in first time period, prior to when the first time period ends

  NCPUE_S1_1 <- match(NA, CPUE_S1)-1 #last year prior to first NA

  NCPUE_S1_MISS <- length(DATA$CPUE_1[is.na(DATA$CPUE_1)]) + max(which(!is.na(DATA$CPUE_1)))-length(CPUE_S1) # Total missing values within time series (last positive + total NAs - total length)

}

NCPUE_S1_2 <- max(which(!is.na(DATA$CPUE_1))) #end year of first time series

NCPUE_S1_3 <- length(DATA$CPUE_1) #end year of all time series


#Survey biomass and SE estimate for 2016 calendar year. From Ault et al Tech Memo.

#Convert from kg to million lbs

Bio2017 <- 3118160.5/1000000*2.20462 /(25892*194.89)

s_eta2 <- (803815.3/1000000*2.20462 /(25892*194.89))^2

s_CV <- sqrt(s_eta2)/Bio2017

s_eta2log <- log(s_CV*s_CV+1)


########################

# model parameters

########################


Target_K_Prior_avg <- 19.6

CV_K <- 0.5


Target_r_Prior_avg <- 0.10
```

```
CV_r <- 0.25

Target_P1_Prior_avg <- 0.52
CV_P1 <- 0.2

M_shape <- 0.5
M_scale <- 0.5

process_shape <- 0.2
process_scale <- 0.1

observation_shape <- 0.2
observation_scale <- 1.0

q_lo <- 0.00001
q_hi <- 100000

Target_rad_Prior_avg <-20.2
CV_rad <- 0.5

LB <- 0.6
UB <- 1.4

pLIM_B <- 0.844
```

```
#################################################################
# Bundle Data
#################################################################

win.data <- list(

  NTIME = NTIME,
  Reported_Catch = Reported_Catch,
  UnrepCatch = UnrepCatch,

  CPUE_S1 = CPUE_S1,
  CPUE_S2 = CPUE_S2,
  CPUE_S1_REL_CV = CPUE_S1_REL_CV,
  CPUE_S2_REL_CV = CPUE_S2_REL_CV,
  NCPUE_S1_1 = NCPUE_S1_1,
  NCPUE_S1_MISS = NCPUE_S1_MISS,
  NCPUE_S1_2 = NCPUE_S1_2,
  NCPUE_S1_3 = NCPUE_S1_3,

  Target_K_Prior_avg = Target_K_Prior_avg,
  CV_K = CV_K,

  Target_r_Prior_avg = Target_r_Prior_avg,
  CV_r = CV_r,
```

```
Target_P1_Prior_avg = Target_P1_Prior_avg,
CV_P1 = CV_P1,

M_shape = M_shape,
M_scale = M_scale,

process_shape = process_shape,
process_scale = process_scale,

observation_shape = observation_shape,
observation_scale = observation_scale,

q_lo = q_lo,
q_hi = q_hi,

Target_rad_Prior_avg = Target_rad_Prior_avg,
CV_rad = CV_rad,

LB = LB,
UB = UB,

pLIM_B = pLIM_B,

Bio2017 = Bio2017,
```

```
  s_eta2log = s_eta2log

) # end data list

## END DATA
####################################################################

# Define model written in WinBUGS code ------
model_code=paste0("model ",addname,".txt")
sink(model_code)  # sink diverts R output to a connection.
cat("

   model
   {

   ###############################################################
   # PRIOR DISTRIBUTIONS
   ###############################################################

   # Lognormal prior for carrying capacity parameter, K
   #(P1)###########################################################
   K_Prior_Precision <- 1.0/log(1.0+CV_K*CV_K)
   K_Prior_avg <- log(Target_K_Prior_avg) - (0.5/K_Prior_Precision)
   K ~ dlnorm(K_Prior_avg,K_Prior_Precision)I(0.001,200.0)
```

```
# Lognormal prior for intrinsic growth rate parameter, r
#(P2)############################################################
r_Prior_Precision <- 1.0/log(1.0+CV_r*CV_r)
r_Prior_avg <- log(Target_r_Prior_avg) - (0.5/r_Prior_Precision)
r ~ dlnorm(r_Prior_avg,r_Prior_Precision)I(0.01,1.00)

# Gamma prior for production shape parameter, M
#(P3)############################################################
M ~ dgamma(M_shape, M_scale)

# Uniform prior for CPUE catchability coefficients, q1 and q2
#(P4)############################################################
q1 ~ dunif(q_lo, q_hi)
q2 ~ dunif(q_lo, q_hi)

# Lognormal prior for effective radius for survey
#(P4.b)############################################################
rad_Prior_Precision <- 1.0/log(1.0+CV_rad*CV_rad)
rad_Prior_avg <- log(Target_rad_Prior_avg) - (0.5/rad_Prior_Precision)
rad ~ dlnorm(rad_Prior_avg,rad_Prior_Precision)I(7.5,41.6)
q3 <- 250000/(rad*rad*3.14159)

# Inverse gamma prior for process error variance, sigma2
#(P5)############################################################
isigma2 ~ dgamma(process_shape,process_scale)I(0.000001,1000000)
```

```
sigma2 <- 1/isigma2


# Inverse gamma prior for observation error variance, tau2
#(P6)##############################################################
itau2_1   ~ dgamma(observation_shape,observation_scale)I(0.000001,1000000)
tau2_1  <- 1/itau2_1


itau2_2   ~ dgamma(observation_shape,observation_scale)I(0.000001,1000000)
tau2_2   <- 1/itau2_2


# Lognormal priors for unobserved states, the time series of proportions of K, P[]
# MHI time catch series starts in FY1949 and ends in FY2015, n=67
#(P7)##############################################################
P1_Prior_Precision <- 1.0/log(1.0+CV_P1*CV_P1)
P1_Prior_avg <-log(Target_P1_Prior_avg) - (0.5/P1_Prior_Precision)
P[1] ~ dlnorm(P1_Prior_avg,P1_Prior_Precision) I(0.0001,10000)


# Catch is uninformly distributed on the interval [lower, upper]
#(P8)##############################################################
lower[1] <- LB*UnrepCatch[1] + Reported_Catch[1]
upper[1] <- UB*UnrepCatch[1] + Reported_Catch[1]
Catch[1] ~ dunif(lower[1],upper[1])


##################################################################
# PROCESS DYNAMICS
```

```
################################################################
for (i in 2:NTIME) {
Pmean[i] <- log(max(P[i-1] + r*P[i-1]*(1-pow(P[i-1],M)) - Catch[i-1]/K,0.0001))
P[i]  ~ dlnorm(Pmean[i],isigma2)I(0.0001,10000)
lower[i] <- LB*UnrepCatch[i] + Reported_Catch[i]
upper[i] <- UB*UnrepCatch[i] + Reported_Catch[i]
Catch[i] ~ dunif(lower[i],upper[i])
}

Pmean2016 <- log(max(P[NTIME] + r*P[NTIME]*(1-pow(P[NTIME],M)) -
Catch[NTIME]/K,0.0001))
P2016 ~ dlnorm(Pmean2016,isigma2)I(0.0001,10000)
C2016lo <- LB*0.277223 + 0.140722
C2016hi <- UB*0.277223 + 0.140722
Catch2016 ~ dunif(C2016lo,C2016hi)
Pmean2017 <- log(max(P2016 + r*P2016*(1-pow(P2016,M)) - Catch2016/K,0.0001))
P2017 ~ dlnorm(Pmean2017,isigma2)I(0.0001,10000)


################################################################
# LIKELIHOOD OF OBSERVED CPUE
################################################################

# Deep 7 bottomfish CPUE LIKELIHOOD, 1949-2003
P[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2]
#(L1)############################################################
```

```
for (i in (NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2) {

CPUE_mean[i] <- log(q1*K*P[i])

Precision_CPUE[i] <- itau2_1/(CPUE_S1_REL_CV[i]*CPUE_S1_REL_CV[i])

CPUE_S1[i] ~ dlnorm(CPUE_mean[i],Precision_CPUE[i])

LOG_RESID1[i] <- log(CPUE_S1[i]) - log(q1*K*P[i])

}


# Deep 7 bottomfish CPUE LIKELIHOOD, 2003-2015 P[(NCPUE_S1_2+1):NCPUE_S1_3]

#(L2)##########################################################

for (i in (NCPUE_S1_2):NCPUE_S1_3) {

CPUE_mean2[i] <- log(q2*K*P[i])

Precision_CPUE2[i] <- itau2_2/(CPUE_S2_REL_CV[i]*CPUE_S2_REL_CV[i])

CPUE_S2[i] ~ dlnorm(CPUE_mean2[i],Precision_CPUE2[i])

LOG_RESID2[i] <- log(CPUE_S2[i]) - log(q2*K*P[i])

}


# survey likelihood, for 2017 estimate

#(L3)##########################################################

survey_mean <- log(P2017*K /(q3*25892))

Precision_survey <- 1/s_eta2log

Bio2017 ~ dlnorm(survey_mean,Precision_survey)

LOG_RESID3 <- log(Bio2017) - log(P2017*K/(q3*25892))



# Compute LOG_RSS and LOG_RMSE
```

```
################################################################

# LOG_RSS1 <- inprod(LOG_RESID1[1:NCPUE_S1_1], LOG_RESID1[1:NCPUE_S1_1])
+

LOG_RSS1 <- inprod(LOG_RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2],
LOG_RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2])

LOG_RSS2 <- inprod(LOG_RESID2[(NCPUE_S1_2):NCPUE_S1_3],
LOG_RESID2[(NCPUE_S1_2):NCPUE_S1_3])

LOG_RSS3 <- inprod(LOG_RESID3, LOG_RESID3)

LOG_RMSE1 <- sqrt(LOG_RSS1/(NCPUE_S1_2-NCPUE_S1_MISS))

LOG_RMSE2 <- sqrt(LOG_RSS2/(NCPUE_S1_3-(NCPUE_S1_2-1)))

LOG_RMSE3 <- sqrt(LOG_RSS3)

# Compute standardized log-scale residuals, predicted CPUE, and unscaled residuals

################################################################

for (i in (NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2) {

STD_LOG_RESID1[i] <- LOG_RESID1[i]/LOG_RMSE1

PRED_CPUE[i] <- exp(CPUE_mean[i]) ## PRED_CPUE[i] <- exp(log(CPUE_mean[i]))

RESID1[i] <- CPUE_S1[i] - PRED_CPUE[i]

}
```

```
for (i in (NCPUE_S1_2):NCPUE_S1_3) {

STD_LOG_RESID2[i] <- LOG_RESID2[i]/LOG_RMSE2

PRED_CPUE2[i] <- exp(CPUE_mean2[i])

RESID2[i] <- CPUE_S2[i] - PRED_CPUE2[i]

}


STD_LOG_RESID3 <- LOG_RESID3/LOG_RMSE2

PRED_Bio2017 <- exp(survey_mean)

RESID3 <- Bio2017 - PRED_Bio2017




# Compute RSS and RMSE for MHI CPUE

################################################################

#RSS1 <- inprod(RESID1[1:NCPUE_S1_1], RESID1[1:NCPUE_S1_1]) +

RSS1 <- inprod(RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2],
RESID1[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2])


RSS2 <- inprod(RESID2[(NCPUE_S1_2):NCPUE_S1_3],
RESID2[(NCPUE_S1_2):NCPUE_S1_3])


RSS3 <- inprod(RESID3,RESID3)


RMSE1 <- sqrt(RSS1/(NCPUE_S1_2-NCPUE_S1_MISS))


RMSE2 <- sqrt(RSS2/(NCPUE_S1_3-(NCPUE_S1_2-1)))
```

```
RMSE3 <- sqrt(RSS3)

#################################################################
# STOCK ASSESSMENT QUANTITIES OF INTEREST
#################################################################

# Compute exploitation rate and biomass time series
#(QOI1)##########################################################
# MHI 1949-2015 P[1:NTIME]
for (i in 1:NTIME) {
B[i] <- P[i]*K
H[i] <- min(Catch[i]/B[i],0.999)
F[i] <- -log(1-H[i])
}

# Compute MSY reference points
#(QOI2)##########################################################
BMSY <- K*pow(M+1.0,(-1.0/M))
MSY <- r*BMSY*(1.0-(1.0/(M+1.0)))
HMSY <- min(r*(1.0-(1.0/(M+1.0))),0.999)
PMSY <- BMSY/K
FMSY <- -log(1-HMSY)
CPUE_MSY <- q2*BMSY

# Compute relative biomass and harvest, BSTATUS and HSTATUS
```

```
    #(QOI3)############################################################
    for (i in 1:NTIME) {
    BSTATUS[i] <- B[i]/BMSY
    HSTATUS[i] <- H[i]/HMSY
    production[i] <- r*B[i]*(1-pow(P[i],M))
    }

    # Compute probabilities of H[i] > HMSY, B[i] < BMSY,
    # and B[i] < pLIM_B*BMSY, a minimum biomass limit
    #(QOI4)#############################################################
    for (i in 1:NTIME) {
    pOFL_H[i] <- step(HSTATUS[i] - 1.0)
    pBMSY_B[i] <- step(1.0 - BSTATUS[i])
    pOFL_B[i] <- step(pLIM_B - BSTATUS[i])
    }

    #########################
    } ## END OF WinBUGS MODEL

    ",fill=TRUE)
sink()      # ends the last diversion




######################################################################
```

```
# END OF CODE/MODEL
###################################################################



#######################################################################  ------
############ Create list of inits for WinBUGS use #####################
#######################################################################

inits <- list(    # create inits list of functions

  ## Initial Condition 1

  list(

    Catch=c(0.45229851,0.44030925,0.48110292,0.45978309,
            0.38915946,0.396672678,0.31280049,0.41497623,
            0.56982267,0.35820333,0.30107439,0.27311751,
            0.22088799,0.29168964,0.35766153,0.35814915,
            0.40078881,0.27636057,0.46898982,0.32923251,
            0.33260328,0.2697003,0.22880988,0.45609498,
            0.36128772,0.52358391,0.44963208,0.40785543,
            0.41149323,0.59846454,0.56506257,0.58459059,
            0.76381029,0.68780736,0.89200791,0.61428897,
            0.76187142,0.67085289,0.99916047,1.16362773,
            1.19060937,0.8121969,0.52433856,0.66302775,
```

```
    0.51723711,0.67092642,0.7287597,0.540900573,
    0.621104737,0.552321266,0.363870819,0.553269843,
    0.393816339,0.307659835,0.379168109,0.259142954,
    0.310034053,0.214235901,0.274423218,0.285705387,
    0.393775074,0.313008597,0.440775918,0.312457811,
    0.285182311,0.477448617,0.459193066),

Catch2016 = 0.42,

r=0.05,

P=c(rep(0.5,32), rep(0.5, NTIME-32)),

P2016=0.5,
P2017=0.5,

K=30.0,

M=1.0,

q1=10.0,
q2=10.0,
rad=20.2,

isigma2=100,
```

```
  itau2_1=100,
  itau2_2=100

)##END init 1

## Initial Condition 2

,list(

  Catch=c(0.45229851,0.44030925,0.48110292,0.45978309,
          0.38915946,0.396672678,0.31280049,0.41497623,
          0.56982267,0.35820333,0.30107439,0.27311751,
          0.22088799,0.29168964,0.35766153,0.35814915,
          0.40078881,0.27636057,0.46898982,0.32923251,
          0.33260328,0.2697003,0.22880988,0.45609498,
          0.36128772,0.52358391,0.44963208,0.40785543,
          0.41149323,0.59846454,0.56506257,0.58459059,
          0.76381029,0.68780736,0.89200791,0.61428897,
          0.76187142,0.67085289,0.99916047,1.16362773,
          1.19060937,0.8121969,0.52433856,0.66302775,
          0.51723711,0.67092642,0.7287597,0.540900573,
          0.621104737,0.552321266,0.363870819,0.553269843,
          0.393816339,0.307659835,0.379168109,0.259142954,
          0.310034053,0.214235901,0.274423218,0.285705387,
```

```
    0.393775074,0.313008597,0.440775918,0.312457811,
    0.285182311,0.477448617,0.459193066),

Catch2016 = 0.42,

r=0.15,

P=c(rep(0.5,32), rep(0.5, NTIME-32)),

P2016=0.5,
P2017=0.5,

K=10.0,

M=1.0,

q1=10.0,
q2=10.0,
rad=20.2,

isigma2=100,

itau2_1=100,
itau2_2=100
```

```
)##END init 2

## Initial Condition 3

,list(

  Catch=c(0.45229851,0.44030925,0.48110292,0.45978309,
        0.38915946,0.396672678,0.31280049,0.41497623,
        0.56982267,0.35820333,0.30107439,0.27311751,
        0.22088799,0.29168964,0.35766153,0.35814915,
        0.40078881,0.27636057,0.46898982,0.32923251,
        0.33260328,0.2697003,0.22880988,0.45609498,
        0.36128772,0.52358391,0.44963208,0.40785543,
        0.41149323,0.59846454,0.56506257,0.58459059,
        0.76381029,0.68780736,0.89200791,0.61428897,
        0.76187142,0.67085289,0.99916047,1.16362773,
        1.19060937,0.8121969,0.52433856,0.66302775,
        0.51723711,0.67092642,0.7287597,0.540900573,
        0.621104737,0.552321266,0.363870819,0.553269843,
        0.393816339,0.307659835,0.379168109,0.259142954,
        0.310034053,0.214235901,0.274423218,0.285705387,
        0.393775074,0.313008597,0.440775918,0.312457811,
        0.285182311,0.477448617,0.459193066),

  Catch2016 = 0.42,
```

```
  r=0.10,

  P=c(rep(0.5,32), rep(0.5, NTIME-32)),

  P2016=0.5,
  P2017=0.5,

  K=20.0,

  M=1.0,

  q1=10.0,
  q2=10.0,
  rad=20.2,

  isigma2=100,

  itau2_1=100,
  itau2_2=100

 )##END init 3
)  ## close list of functions

##### end initials function ############################################
```

```
################################################################################

## Parameters to estimate
################################################################################

params <- c(

  ## model parameters ##
  "K","r","M", "q1","q2","sigma2","tau2_1","tau2_2",”q3”,”rad”,

  ## time-series derived variables ##
  "P","B","H","PRED_CPUE","PRED_CPUE2","PRED_Bio2017",

  ## management metrics ##
  "MSY","PMSY","BMSY","HMSY","BSTATUS","HSTATUS","FMSY",
  "pOFL_H","pOFL_B","pBMSY_B",

  ## statistics and diagnoses ##
  "STD_LOG_RESID1", "STD_LOG_RESID2", "STD_LOG_RESID3",
  "LOG_RESID1", "LOG_RESID2", "LOG_RESID3","RESID1", "RESID2", "RESID3",
  "LOG_RSS1", "LOG_RSS2", "LOG_RSS3", "LOG_RMSE1", "LOG_RMSE2",
  "LOG_RMSE3","RSS1", "RSS2", "RSS3", "RMSE1", "RMSE2", "RMSE3"

)
```

```
begin_time = proc.time()[3]
nc <- length(inits)    # Number of Markov chains, default is 3
######################################################################
# Start Gibbs sampling, cycle through the initials

bugs(win.data,inits,params,model_code,n.chains=nc,n.iter=ni,n.burnin=nb,n.thin=nt,
    debug=FALSE,codaPkg=FALSE,bugs.directory="c:/Program Files/WinBUGS14/",
    working.directory=src.dir)

######################################################################
end_time = proc.time()[3]
print(paste("RUN_COST = ",(end_time-begin_time)/60," mins",sep=""))
##########################################################################
```

Appendix D. R code that calculates the standardized CPUE index from the final event-based dataset for Deep 7 in the main Hawaiian Islands during the early (1948-2003) and recent (2003-2015) time periods.

```
##################################################################

#Code to take event-based dataset and standardize based on best-fit model selection for the

#early and late time periods.

#M Kapur & B Langseth "17 Feb - 01 Mar 2017"

#################################################################


library(ggplot2)

library(GGally)

library(lubridate)

library(Rmisc)


raw.data = read.csv("D:\\File
path\\Finalized_tripCPUE_dataset_forStandardization.csv",header=T)


## Fix up wind parameters

## convert to 360-degree circle, arctan in radians

windrad = with(raw.data,atan2(ydir,xdir))

## convert to degrees

raw.data$winddeg = (windrad*180)/pi

## assign negatives

raw.data$winddeg = ifelse(raw.data$winddeg < 0, raw.data$winddeg + 360, raw.data$winddeg)

## change to compass directions; 0 corresponds to the positive X axis which would be wind
blowing FROM the west
```

```
raw.data$winddir = cut(raw.data$winddeg, breaks = seq(0,360,45), labels =
c("W","NW","N","NE","E","SE","S","SW"))


## Cut Area Polygons

raw.data$region = cut(raw.data$area, breaks = c(99,300,400,500,20000), labels = c("BIG
ISLAND","MAUI NUI","OAHU",'KAUAI-NIIHAU'))


## save the new one with special variables

write.csv(raw.data, "D:\\File path\\tripCPUE_reformat_noscale.csv", row.names = F)



##################################################################

## A script to centralize data cleanup & time periods for use in D7 CPUE standardization

## and to take best-fit models, and  generate CPUE index for use in assessment model for both
#time periods.

#################################################################


rm(list=ls())

library(lubridate)

library(plyr)

library(dplyr)

library(ggplot2)

library(lme4)

require(Rmisc)


df = read.csv("D:\\File path\\tripCPUE_reformat_noscale.csv",header=T)
```

```
df$FYEAR = as.factor(df$FYEAR)

df$qtr = as.factor(df$qtr)

df$area = as.factor(df$area)

df$log_cum_exp = log(df$cum_exp)

df$sqrt_uku_lbs = sqrt(df$uku_lbs)

print('reformatted predictors')

df$fisher = as.character(df$fisher)

df$fisher[df$FYEAR == '1976'] <-'1976FISHER'

print('made dummy variable for 1976 FISHER')


#' for binomial -- change positive catches into zeros.

#' be sure to classify as a factor otherwise it may interpret as proportion

df$bin.catch = as.factor(ifelse(df$d7catch > 0, 1, 0))


## Manipulate time periods

#' Assuming FYEAR has been properly assigned (based on Fishing, not Calendar year).

#' The main splits are designated tp1 and tp2

df.tp1 = subset(df, FYEAR %in% c(1948:2003))

df.tp2 = subset(df, FYEAR %in% c(2003:2015))


## use this to drop Jul - Oct 2002 from latter time periodstr

## first convert FISHED to date format

df.tp2$FISHED = lubridate::ymd(df.tp2$FISHED)

## extract month
```

```
df.tp2$FISHEDMONTH = month(df.tp2$FISHED)

## id and drop Jul - Oct (7 - 10) of year 2002

df.tp2.0 = subset(df.tp2, !(FISHEDMONTH %in% 7:9 & FYEAR == 2003))


## use this to drop Oct-Jun of FYEAR 2003 from first time period

df.tp1$FISHEDMONTH = month(df.tp1$FISHED)

df.tp1.0 = subset(df.tp1, !(FYEAR == 2003 & FISHEDMONTH %in% c(10:12,1:6)))


## FINAL TIME PERIODS FOR MODELING PURPOSES

TP1 = df.tp1.0

TP2 = df.tp2.0

print('split time periods ')

TP2 = TP2[complete.cases(TP2[,c(13:17)]),]

print('selected complete cases only')


#Load the best-fit models

TP1.B.best = glm(bin.catch~FYEAR + area + qtr + log_cum_exp + area:qtr, family = binomial,
data = TP1, na.action = na.exclude)

TP1.RLN.best = lmer(log(cpue) ~ (1|fisher) + FYEAR + area + qtr + sqrt_uku_lbs +
log_cum_exp + area:qtr, data = TP1[TP1$cpue>0,], REML=T, na.action = na.exclude)

TP2.B.best = glm(bin.catch ~ FYEAR + sqrt_uku_lbs + area + qtr + area:qtr + speed, family =
binomial, data = TP2, na.action = na.exclude)
TP2.RLN.best = lmer(log(cpue) ~ (1|fisher) + FYEAR + area + sqrt_uku_lbs + speed + qtr +
area:FYEAR + log_cum_exp, data =TP2[TP2$cpue>0,], REML=T, na.action = na.exclude)


# Positive Process

## Extract predicted values for Positive process ("p") and bind to YEAR (for aggregating)
```

TP1p = data.frame('LOGCPUE' = predict(TP1.RLN.best), 'FYEAR' = TP1[TP1$cpue>0,][,'FYEAR'])

TP2p = data.frame('LOGCPUE' = predict(TP2.RLN.best),'FYEAR' =TP2[TP2$cpue>0,][,'FYEAR'])

Backtransform positive process using dispersion from each model following Brian's STM #standardization and that from Brodziak and Walsh (2013)

TP1p$trans=exp(TP1p$LOGCPUE + ((summary(TP1.RLN.best)$sigma^2)/2))

TP2p$trans=exp(TP2p$LOGCPUE + ((summary(TP2.RLN.best)$sigma^2)/2))

Bernoulli process

Extract predicted values for Bernoulli process ("b")- be sure to use type = 'response' which #provides the probability of having a non zero tow (Stefansson 1996)

TP1b = data.frame('BIN.CATCH' = predict(TP1.B.best, type = 'response'),'FYEAR' = TP1[,'FYEAR'])

TP2b = data.frame('BIN.CATCH' = predict(TP2.B.best, type = 'response'),'FYEAR' = TP2[,'FYEAR'])

Use aggregate ('a') to get means and sd for each yearfor the positive process (remember sd2 is #var)

TP1pa = aggregate(trans ~ FYEAR, TP1p, function(x) c(mean = mean(x), sd = sd(x), var = var(x)))

TP2pa = aggregate(trans ~ FYEAR, TP2p, function(x) c(mean = mean(x), sd = sd(x), var = var(x)))

Use aggregate ('a') to get means, sd and variance for each year for the bernoulli process. Var #for bernoulli is not standard. Don't transform after this.

TP1ba = aggregate(BIN.CATCH ~ FYEAR, data = TP1b, FUN = function(x) c(mean = mean(x), sd = sd(x), var = var(x)))

TP2ba = aggregate(BIN.CATCH ~ FYEAR, data = TP2b, FUN = function(x) c(mean = mean(x), sd = sd(x), var = var(x)))

```
# Index generation

## Multiply each estimate together and calculate the variance according to Brodziak and Walsh
#(2013) but ultimately following Goodman (1960)- no bother with the covariance as it is set to 0.

varI=function(pmean,pvar,bmean,bvar){

  index_totvar = bvar*pvar + bvar*(pmean^2) + pvar*(bmean^2)  }



TP1I = data.frame('FYEAR' = TP1ba[,'FYEAR'], 'INDEX.EST' = TP1ba$BIN.CATCH[,'mean']
* TP1pa$trans[,'mean'],'VARIANCE.FORM' =
varI(TP1pa$trans[,'mean'],TP1pa$trans[,'var'],TP1ba$BIN.CATCH[,'mean'],TP1ba$BIN.CATC
H[,'var']),'VARIANCE.ADDITIVE'=TP1pa$trans[,'var']+TP1ba$BIN.CATCH[,'var'])

TP1I$MODEL = 'TP1'



TP2I = data.frame('FYEAR' = TP2ba[,'FYEAR'], 'INDEX.EST' = TP2ba$BIN.CATCH[,'mean']
* TP2pa$trans[,'mean'], 'VARIANCE.FORM' =
varI(TP2pa$trans[,'mean'],TP2pa$trans[,'var'],TP2ba$BIN.CATCH[,'mean'],TP2ba$BIN.CATC
H[,'var']),'VARIANCE.ADDITIVE'=TP2pa$trans[,'var']+TP2ba$BIN.CATCH[,'var'])

TP2I$MODEL = 'TP2'

##set up full df

full.df = rbind(TP1I,TP2I)

full.df$SD = sqrt(full.df$VARIANCE.FORM)

full.df$N=c(table(TP1$FYEAR)[-c(57:68)],table(TP2$FYEAR)[-c(1:55)])

full.df$SE=full.df$SD/sqrt(full.df$N)

full.df$CV_mean=full.df$SE/full.df$INDEX.EST

full.df$relCV=c(full.df$CV_mean[-c(57:69)]/min(full.df$CV_mean)[-
c(57:69)],full.df$CV_mean[-c(1:56)]/min(full.df$CV_mean[-c(1:56)]))

head(full.df)

write.csv(full.df,'D:\\File name\\Finalized_stdindex_0822_REMLF.csv', row.names = F)
```