Stock Assessment Update for the Main Hawaiian Islands Deep 7 Bottomfish Complex in 2021, with Catch Projections Through 2025

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ABSTRACT

A stock assessment update of the main Hawaiian Islands Deep 7 bottomfish complex was conducted in 2021. The assessment followed methods from the 2018 benchmark stock assessment and used a Bayesian surplus production model fit to bottomfish catch and effort data from commercial catch reports for fishing years 1949-2018 and a fishery-independent survey conducted in fishing years 2017-2020. Similar to the 2018 benchmark assessment, a single-species assessment model for opakapaka (*Pristipomoides filamentosus*) was also updated with corresponding data. 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 2021 through 2025. The projections included uncertainty in the posterior distribution of estimated bottomfish biomass in 2018 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 2018. The overfishing limit (OFL), defined as the future amount of reported catch that would yield a P*=50% probability of overfishing ranged from 556-618 thousand pounds depending on the future year. The smallest Deep 7 future catch that would lead to a roughly P*=40% chance of overfishing was 486 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 55%, which was intermediate between the ratio of opakapaka to Deep 7 biomass from the fishery-independent survey (46%), and the overall proportion of total of Deep 7 bottomfish composed of opakapaka (68%).

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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. 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 the 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

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

information on the expected life span of opakapaka (*Pristipomoides filamentosus*), a key bottomfish species (Andrews et al. 2012). 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. 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, the 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. 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 2018 benchmark assessment incorporated the recommendations made by participants at the data workshops.

1.3. 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 assessment provided stock status determinations for 2015, with projections through 2022. 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. Modifications to data and other improvements to the 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 (Neilson 2015). Improvements included using the results of data workshops to update catch and CPUE analyses (as described in depth in sections 2.4 and 2.5 of this document), evaluation of assumed prior values that provided greater support for chosen model parameters, and developing a single-species assessment for the dominant species in the catch, Opakapaka. 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. Additional details on these improvements can be found in the 2018 stock assessment report (Langseth et al. 2018).

1.4 Current Update Assessment in 2021

The 2021 assessment update is constrained to using the same data sources and methodology as the 2018 benchmark stock assessment under the framework of the Western Pacific Stock Assessment Review (available from https://www.fisheries.noaa.gov/pacific-islands/population-assessments/western-pacific-stock-assessment-review). The 2021 assessment includes an additional three years of data for each source, providing stock status determinations for 2018 and projections through 2025.

2. MATERIALS AND METHODS

In this section, basic information on data sources used in the 2021 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 2021 assessment update used the same annual time period for reporting bottomfish catch as in previous 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 2016-2019 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, 2019, 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, 2018, 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 2021 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 5.0 million DAR catch records submitted by fishers during fishing years 1949-2019 (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 (1,280) records of Deep 7 bottomfish catches were reported in unknown or invalid fishing areas, and the minor catch amount (55,429 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). The unreported catch included catch from fishers without CMLs as well as non-reported catch from CML holders and was included in the 2021 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 the base case scenario for the 2021 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 2019.

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 2014-2018 was $U = 1.11$ and the magnitude of the 2014-2018 average unreported catch was approximately 301 thousand pounds. The survey of bottomfish fishers conducted by Hospital and Beavers (2013) reported on the 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 the 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 1948-2018 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 and 2021 assessments to select data for standardizing indices of CPUE. In brief, Deep 7 bottomfish catch per effort data from 1948-2018 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 904,559 records from 1948-2018 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 847,958 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 and this 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 21,418 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 and 2021 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 the 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 159,096 records from these single-reporting days were removed from further analysis.

The Deep 7 bottomfish fishery was closed four times during 1948-2018. 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 4,180 records from the 1,887 fishing events that occurred when the Deep 7 bottomfish fishery was closed were removed, leaving a total of 663,174 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, 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 fisher 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 traveled:

Port landed and area fished should be reported for each record in the fisher reported data. Consequently, the distance traveled 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 traveled 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 513,144 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, the 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 86 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 23,256 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 7,743 records from 1,447 fishers who never reported a Deep 7 bottomfish, and the latter removed 191 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 1948-2018. 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, the 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 May 23, 2019. 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 311,769 records corresponding to 105,878 fishing events were assigned wind data for 1988-2018 out of the 365,544 possible records and 124,874 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 650,870 records from the 219,931 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 846 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 the 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 916 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 1,893 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 the number of days, while for fishing events that occurred since October 2002, the 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 214,846 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, 2002-2018, which corresponded to fishing years 1948-2003 and 2003-2018. 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 2003-2018

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 23% 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 22% from the null model (intercept only), 6% from the model with only fisher, and 5% 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). 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 4). 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 5) and for the recent time period (Figure 6). There remained some skewness towards smaller response values, as evident by the quantile-quantile plot (Figures 5 and 6). 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)

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

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 and 10.

2.6. Fishery-independent Survey

The PIFSC has developed a Bottomfish Fishery-Independent Survey in Hawaii to provide independent estimates 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. Surveys covered the entirety of the MHI including inside BRFAs. The first operational survey was conducted in calendar year 2016, and this assessment used biomass estimates from surveys conducted from 2016 through 2019 (Table 11). See Richards et al. (2016) for complete details on the fishery-independent survey and Ault et al. (2018a) 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 2018 are described. The same stock assessment modeling approach as used in the 2018 benchmark assessment was used in the 2021 assessment. In particular, a Bayesian generalized surplus production model was fit to standardized CPUE time series in fishing years 1949-2018, using catch data from 1949-2019. The assessment model used in 2018 and 2021 differed from the 2011 model structurally in that the model was also fit to a fishery-independent biomass estimates 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 and 2021 assessments also utilized new information on priors and error in unreported catches. A summary of assumed priors is found in Table 12.

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 7). 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 2003-2018). 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 and 10.

The second observation error model related to 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 in the calendar year 2016 (spring and fall), and early fall of calendar years 2017-2019, corresponding approximately to the beginning of fishing years 2017-2020. The observed relative fishery-independent biomass estimate (S_T) was subject to natural sampling variation which was assumed to be lognormally distributed. The observation equation for the survey was

$$(10) \qquad S_T = \frac{1}{q_S} P_T K \cdot \gamma_{S,T},$$

where q_S was a scalar to translate relative biomass to absolute biomass (see below), and $\gamma_{S,T}$ was a lognormal random variable with mean equal to 1.0 and variance ξ_T, which was the variance of the natural logarithm of the survey in year T. The value for ξ was calculated based on the CV of the survey on the original scale as $\xi_T = \ln[CV_{S,T}^2 + 1]$. 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 2019 (P_{2019}) and 2020 (P_{2020}) were calculated based on advancing the process equations with process error (Eq. 7) from 2018 to 2020. Although P_{2019} and P_{2020} were calculated to fit the available survey estimate for the beginning of fishing years 2019 and 2020 (early fall of calendar years 2018 and 2019), the terminal year for the model estimates remained at the fishing year 2018 because CPUE data were only available through 2018. 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. 2018a) 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 12.

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 2021 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 μR = 0.10. This mean value was chosen to reflect an expectation of low productivity for Deep 7 bottomfish. The specific choice of μR = 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*:

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

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., $C_U \sim \text{Uniform}[60, 140]$. 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 $\lambda>0$ 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 $\lambda = 0.1$ 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 $\lambda = 1$, 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, $p(PT{=}1)$, 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:

$$(16) \quad p(P_1) = \frac{1}{P_1 \sigma_P \sqrt{2\pi}} exp\left(-\frac{(lnP_1 - \mu_P)^2}{2\sigma_P^2}\right).$$

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 $\mu_P = 0.5$ (Figure 8). Second, the final prior mean for P1 was set to equal the posterior mean of P1 from the initial model with $\mu_P = 0.5$, which was $\mu_P = 0.53$. 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 8), 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:

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

The prior mean for *rad* was 27.6 m, based on the best estimate from Ault et al. (2018a). As in the 2018 benchmark assessment, a CV of 50% was used for the *rad* prior. The minimum and maximum values, respectively, for the effective radius of a single sample were assumed to be 7.5 m and 60.6 m (Ault et al. 2018a and b). As such, the prior distribution of *rad* was also constrained to be between 7.5 m and 60.6 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. The current stock assessment model included two time periods of CPUE observations, 1949-2003 and 2003-2018; two associated catchability parameters, q_1 and q_2, and observation error variances, τ_1^2 and τ_2^2; and estimates 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 sets (D):

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

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 $B/B_{MSY} < (1\text{-}natM)$. Time series of the relative harvest rate (e.g., in 2018 the relative harvest rate was the ratio H_{2018}/H_{MSY}) and relative biomass (e.g., the ratio B_{2018}/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 555,000 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 255,000 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

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

and for survey relative biomass, observation errors were

$$(20) \quad \varepsilon_{S,T} = \ln(S_T) - \ln\left(\frac{1}{q_S} K P_T\right).$$

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 four years, temporal model diagnostics were not evaluated.

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 2018 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 2021-2025

Estimated posterior distributions of assessment model parameters for 1949-2018 were projected forward for fishing years 2019-2025 to estimate probable stock status (i.e., the probability of overfishing, P*) in 2021-2025 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 2021-2025 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 2021-2025. Reported catch for 2020 was assumed to be equal to the average reported catch from 2017-2019 (i.e., 218,388 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 1949-2018. 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 2014-2018 (i.e., 1.11). 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 2021-2025 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., 2018) and excluding the fishery-independent survey. This was done because only two years of survey observations overlapped with the CPUE data and the estimated biomass time series. The retrospective analysis was conducted by successively deleting the catch and CPUE data for years 2018 through 2015 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):

$$\rho = \sum_y \left[X_{(y1:y),y} - X_{(y1:y2),y}\right] / X_{(y1:y2),y}, \qquad (21)$$

where y_1 = 1949 and y_2 = 2018 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 2014 to 2018).

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 13.

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 μK = 14.5 million pounds (50% decrease in baseline prior mean), μK = 21.75 million pounds (25% decrease in baseline prior mean), μK = 36.25 million pounds (25% increase in baseline prior mean), and μK = 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 the 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 μM = 0.5 to μM = 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 9). 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 2011 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 (2014-2018) 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 2000-2018. However, given that the preliminary analyses of HMRFS data suggested unreported catch ratios in 2004-2018 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 2000-2018 prior to taking 5-year averages. The average ratio of unreported catch to reported catch in the last five years (2014-2018) 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 (2014-2018) under alternative catch scenario III was 1.35, 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 the 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 ($\mu_{\ln qt} = \ln(q_{i,T-1})$) 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 2018 to 2020. Therefore, the sensitivity of model result to removing the survey was done with removing 2019 and 2020 from the model. 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.

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 by the fishery-independent survey (Table 11).

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. The 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 the 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 158 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 (0.53), 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 0.53 (59% 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 – 2018) 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 120,733 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 2.4% 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 20.9% from both the null model (intercept only), and 20.5% 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), 2.4% from the model with fisher only, and 1.7% 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-A4). 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 and A3). 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 46.4% based on the ratio of estimated opakapaka biomass to estimated Deep 7 biomass from the survey (Table 11). Consequently, the prior mean for carrying capacity was set to $\mu K = 13.5$. 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 A5), and the posterior estimate from this model was 0.62. The curvature of the RMSE curve across initial values for μP was similar to that from the Deep 7 model; therefore the CV for P_1 was kept at 20%. A total of 575,000 iterations were run for each of three chains. The first 275,000 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 14). 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. Autocorrelation was low for the majority of parameters. The highest lag1 autocorrelations were 0.77 for rad and 0.76 for *K*; however, the lag-5 values were reduced to 0.37 and 0.27, respectively. Visual inspection of trace plots for monitored parameters did not reveal convergence issues. Overall, the convergence diagnostics indicated convergence of the 2021 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 10 and 11) and 2003-2018 (Figures 12 and 13) 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 11) and a larger residuals in the second half of the 2003-2018 time period resulted in non-constant variance (Figure 13). For the 1949-2003 time period, residuals were normal ($p = 0.40$) when the three largest residuals were excluded from diagnostic tests. Visual inspection of the residuals also indicated a good fit to the fishery-independent survey (Figures 14 and 15); however, residual diagnostics were not conducted given the short time series.

Comparisons of assumed prior distributions and estimated posterior distributions showed that the priors were more informative for some model parameters than others (Table 12; Figure 16). The posterior mean (27.91) for the carrying capacity parameter was about 4% less than the prior mean (29; Table 12). The posterior mean (0.111) for intrinsic growth rate was 11% greater than the prior mean (0.10; Table 12). The posterior mean (0.56) for the initial proportion of carrying capacity was 5% greater than the prior mean (0.53; Table 12). 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 2018 (Figure 17) 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 217% (Table 12; Figure 16). Posterior distributions for catchability, process error, and observation errors were substantially different from the prior distributions, which were chosen to be uninformative (Table 12; Figure 16). The priors were less informative for estimating MSY and related parameters B_{MSY}, H_{MSY}, and P_{MSY} (Figure 18), 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 (1025 thousand pounds) and H_{MSY} (0.068) were 91% and 98% greater than the prior means. The posterior means for B_{MSY} (15.46 million pounds) and P_{MSY} (0.57) were 14% and 21% greater than the prior means, respectively (Figure 18). 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 15 and Figure 19). Correlations were highest (up to 0.80 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 0.34 in magnitude.

5.2. Stock Status

Production model estimates indicated that H_{MSY} was 6.8% and that B_{MSY} was 15.5 million pounds of exploitable Deep 7 bottomfish biomass with an associated MSY of 1.025 million pounds (Table 12).

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 = 473 thousand pounds (± 225 thousand pounds) for reported catch
2) H_{MSY} = 6.8% (± 2.6%)
3) B_{MSY} = 15.5 million pounds (± 5.0 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 16 and Figure 20). 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 2017 before declining in 2018 (Figure 20). 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 16 and Figure 21). 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 2018 (B_{2018}/B_{MSY}=1.43, Table 16; Figures 20 and 22) and that the stock complex was not experiencing overfishing (H_{2018}/H_{MSY}=0.37, Table 16; Figures 21 and 22). In fishing year 2018, there was a 13% probability that exploitable biomass exceeded the limit of 0.844*B_{MSY} and an 11% 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 2018.

5.3. Stock Projections

The constant 5-year catch projection scenarios showed the distribution of outcomes in the probability of overfishing, biomass, harvest rates, and the probability of depletion of Deep 7 bottomfish that would likely occur under alternative reported catch scenarios in the MHI during 2021-2025 (Tables 17 and 18; Figures 23-26). Projections indicated that the Deep 7 reported catch that would produce approximately 50% chance of overfishing for each year from 2021 through 2025 was between 556 to 618 thousand pounds (Table 17; Figure 23). For comparison, the smallest Deep 7 reported catch that would lead to a roughly 40% chance of overfishing was 530 thousand pounds through 2021, 518 thousand pounds through 2022, 504 thousand pounds through 2023, 496 thousand pounds through 2024 and 486 thousand pounds through 2025 (Table 17; Figure 23). The reported catch to achieve a lower risk of overfishing (P*=25%) from 2021 through 2025 varied across years from 372 to 384 thousand pounds (Tables 17 and 18).

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 27) or harvest rate (Figure 28). The retrospective pattern for estimates of biomass was slightly negative, with successive terminal biomass estimates underestimating by about 4% as new years of data were added (Mohn's rho = -0.211; Figure 27). The corresponding pattern for harvest rates was slightly positive, representing an underestimate in harvest rate by about 9% as new years of data were added (Mohn's rho = 0.449; Figure 28).

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. However, the status in 2018 relative to overfishing (H_{2018}/H_{MSY}) or overfished (B_{2018}/B_{MSY}) reference points did not change in any scenario. 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 19.

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

Model results were sensitive to the assumed prior mean for carrying capacity (Figures 29 and 30). The sensitivity analysis indicated that estimates of exploitable biomass were scaled with the prior mean for *K* (Figure 29). Assuming a higher prior mean for *K* resulted in greater estimates of biomass (Figure 29) and reduced harvest rate estimates (Figure 30). 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 19). The posterior estimates for intrinsic growth rate (*R*) were inversely related to estimates of *K* (Table 19). When the prior for *K* was reduced, estimates for H_{MSY} increased and estimates for B_{MSY} declined (Table 19). Subsequently, the probability of overfishing and the probability of being overfished in 2018 declined in scenarios when the prior mean for K was reduced and increased in scenarios when the prior for K was increased (Table 19).

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

Model results were sensitive to assumed mean prior values for intrinsic growth rate (Figures 31 and 32). Assuming a higher prior mean for R resulted in reduced estimates of biomass (Figure 31) and increased harvest rate estimates (Figure 32). 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 19). 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 2018 (Table 19). 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 2018 increased 253% and by 123%, respectively. However, the status relative to reference points remained unchanged from that of the base case scenario (Table 19).

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 33 and 34). As assumed prior mean for M increased, estimates of exploitable biomass declined (Figure 33), and estimates of harvest rate increased minimally (Figure 34). When the mean prior for M changed by 25%, the posterior estimate for the parameter M changed by about 10 to 15% (Table 19). Increasing the prior mean by 50% led to an increase in the posterior estimate of about 21%, whereas a 50% decrease in the prior mean resulted in about a 34% decrease in the posterior estimate (Table 19). Changing the prior mean by 25% and 50% resulted in relatively small changes to estimates of other model parameters (Table 19).

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 35 and 36). Estimates of K were inversely related to prior mean values for P_1 (Table 19). As the mean prior for P_1 changed by 25%, the posterior estimate for the parameter P_1 changed by about 20% (Table 19). 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 19). As the prior mean for P_1 increased, the estimated probabilities of overfishing and the stock being overfished in 2018 declined at most 43%. As the prior mean for P_1 decreased, the estimated probabilities of overfishing and the stock being overfished in 2018 increased by more than 125% (Table 19).

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 19; Figures 37 and 38). 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 19). Most of the effect of changing the prior for observation errors was in the probability of overfishing and the stock being overfished in 2018, which increased 223% and 242%, respectively, when the prior mean was increased 100-fold (Table 19). 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 19). Estimates of biomass increased by about 60% 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 37).

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 19; Figures 39 and 40). However, posterior estimates for some parameters were sensitive when the prior for σ^2 was increased by a factor of 100 (Table 19). Specifically, increasing the prior 100-fold resulted in a 45% reduction in the posterior mean estimate of M and a 259% increase in the estimated probability of overfishing in 2018. However, this did not cause a change in overfishing status compared to the base case model (Table 19). 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 39), and annual estimates of harvest rate towards the end of the time series were sensitive (Figure 40).

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 41 and 42). Estimates of R, K, M, and P_1 changed by 0-7% at most for Catch Scenarios II and III compared to 31% for scenarios I and IV (Table 19). 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 45% for scenario IV compared to no more than 11% 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 2018 changed comparably in magnitude among all Catch Scenarios. Estimates for the probability of being overfished and the probability of overfishing in 2018 were also similar in magnitude among all Catch Scenarios (Table 19).

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 19; Figures 43 and 44). 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 19). Similarly, parameter estimates were only marginally different after directional increases and decreases in average catch error of 25% (Table 19).

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 45), 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*; 30% increase), shape parameter (*M*; 32% decrease), and estimates of the probability of overfishing and being overfished in 2018 (123% and 83% increases, respectively) (Table 19). 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 $q_{2,T}$ 10% 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 points (Figures 45 and 46).

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 47) and estimated harvest (Figure 48) were similar to the base case. Changes in parameter estimates were generally less than 10%; however, the probability of overfishing in 2018 declined by 90% and the probability of the stock being overfished in 2018 declined by 98% (Table 19).

Sensitivity to exclusion of the fishery-independent survey

Model results were not very sensitive to the exclusion of the fishery-independent survey (Figures 49 and 50; Table 19). Estimates of biomass increased by about 4 to 6% when the survey was excluded (Figure 49; Table 19). The increase in biomass was accompanied by a slight increase in variation in the estimates. The CV for annual biomass estimates increased by 6-12% and the 95% credible interval width for biomass increased 10-15% for the model with the survey excluded (Figure 49). 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 50).

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 51 and 52; Table 19). Estimates of biomass decreased by 18-43% when the uncertainty in the survey radius was reduced, with the magnitude of the difference increasing through time (Figure 51). The decreases in biomass estimates resulted in increased estimates of mean harvest rate relative to the base case (Figure 52). Decreasing the uncertainty in the effective radius led to a decrease in the amount of variation in biomass estimates, with CVs decreasing relative to the base case by 6% at the beginning and 80% at the end of the time series (Figure 51). The width of 95% credible intervals decreased by 22 to 88% relative to the base case. The parameter *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 61% and 108% relative to the base case (Table 19).

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 MSY from a single chain, which was slightly greater than 2.0 (Table A3). 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 without trend (Figures A6-A11). As with the model for the Deep 7 complex, residuals did indicate non-constant variance (Figures A6-A9). Posterior means of model parameters were similar to those from the Deep 7 complex model (Table 19). 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 complex model by 50-60%. This reduction was intermediate between the ratio of the estimate of opakapaka biomass to Deep 7 biomass from the fishery-independent survey (46%; Table 11) and the average ratio for opakapaka to Deep 7 total catch by weight over all years (67%). Among other parameters and derived quantities, the absolute difference between posterior means for the opakapaka model and the Deep 7 model were greatest for the catchability parameters at 28% for q_1 and 31% for q_2 (Table 20), but only varied from 3 to 14% among remaining comparisons. Posterior means and 95% credible intervals for biomass scaled to 55% of the biomass for the Deep 7 bottomfish complex over all years (Figure 53). Posterior means of harvest rates for opakapaka averaged 21% greater than for the Deep 7 complex over all years (Figure 54). Given commensurate changes in the reference points BMSY and HMSY for the opakapaka model (Table 20), the relative status for opakapaka was similar to the status for Deep 7 bottomfish as a complex (Figure 55).

6. DISCUSSION

The Deep 7 bottomfish stock complex in the Main Hawaiian Islands was categorized as not being overfished and not experiencing overfishing in 2018. The 2021 assessment update produced estimates of biological reference points, biomasses, and harvest rates for Deep 7 bottomfish relatively similar to the 2018 benchmark assessment (Langseth et al. 2018). The terminal year for biomass estimation in the 2018 benchmark assessment was 2015. Biomass in 2015 was estimated at 22.56 million lb in the 2021 assessment update, an increase from the corresponding estimate of 20.03 million lb in 2015 from the 2018 benchmark assessment. The increase in the 2015 biomass estimate in the 2021 assessment update was caused by the increasing trend in CPUE from 2013 - 2016 and revising the 2016 survey biomass estimate upward from 10.15 to 15.1 million lb. The decline in estimated biomass from 2017 to 2018 was caused by declining CPUE and catch in the fishery-dependent data in addition to declining biomass estimated by the fishery-independent survey in fishing years 2017 through 2020.

Projections produced reported catch values corresponding to probabilities of overfishing that were similar to those in the 2018 benchmark assessment. The amount of reported catch that would yield a 50% probability of overfishing was 558-604 thousand pounds in the 2018 benchmark assessment compared to 556-618 thousand pounds in the 2021 assessment update.

The smallest Deep 7 projected reported catch that would lead to a roughly P*=40% chance of overfishing was about 486 thousand pounds in the 2021 assessment update compared to 490 thousand pounds in the 2018 benchmark assessment. Forty percent was approximately the risk of overfishing chosen by the WPRFMC for setting the annual catch limit (ACL) for fishing years 2018-2021 based on the 2018 benchmark assessment. The 486 thousand pound catch value is about 1.2% less than the ACL for the 2018-21 fishing season2 (492,000 lbs), based on the 2018 benchmark assessment. The similarity in the projected reported catches corresponding to a given probability of overfishing despite an increase in estimated terminal biomass in 2018 relative to 2015 is likely explained by two factors. First, the estimate of MSY in the assessment update decreased by 2% relative to the estimate from the 2018 benchmark assessment. Second, the average ratio of unreported to reported catch used in the projections was 1.11 in the 2021 assessment update, whereas the average ratio used in the 2018 benchmark assessment (2011-2015) was 1.06. Thus, a given level of projected reported catch resulted in an increase in the associated total catch used to calculate the probability of overfishing.

The main difference between the 2021 update and 2018 benchmark assessments involved methods related to inclusion of the fishery-independent survey. Additional years of survey implementation and refinements in methodology resulted in a new estimate for the effective radius of the camera gear (Ault et al. 2018a). Therefore, the prior mean for the radius increased from a value of 20.2 m used in the 2018 benchmark assessment (Ault et al. 2018b) to 27.6 m in the 2021 assessment update, with the upper bound of the radius prior increased from 41.6 m to 60 m (Ault et al. 2018a). The increased variation in the survey radius prior effectively down-weighted the survey data, causing this data source to serve more as an index rather than a scaling factor for absolute abundance.

The addition of three years of biomass estimates from the fishery-independent survey increased the uncertainty in the proper scaling factor for opakapaka biomass relative to the Deep 7 complex. Data used in the 2018 benchmark assessment indicated that opakapaka composed about 68% of Deep 7 biomass estimated from the survey and also composed about 67% of reported Deep 7 catch. Catch of opakapaka continued to compose about 67% of the total Deep 7 catch in the more recent years included in the 2021 assessment update; however, the proportion of total Deep7 biomass composed of opakapaka declined to an average of 46% when survey estimates from 2017 to 2019 were considered. The large estimate for opakapaka biomass in the survey in 2016 is now considered an artifact of two individuals caught in soft-bottom habitat, which composes a large portion of the survey domain (Richards et al. 2020). The differences in the proportion of opakapaka between the catch and the survey biomass estimates may be indicative of a fishery that predominately targets opakapaka. The analysis used to select opakapaka trips from the data set indicated that 59% of trips could be classified as targeting opakapaka, in which case the species would be expected to be over-represented in the catch in relation to true relative abundance in the complex. These findings highlight the importance of investigating species targeting when developing CPUE series for single species.

The 2018 and 2021 stock assessments represent the first attempt at a single-species assessment for a member of the Deep 7 bottomfish complex. There will likely be more attempts to develop single-species models in future assessments for Deep 7 species, which will rely on increasing the ability to determine species targeting, availability of life-history information, and flexibility in assessment approaches. For example, species with less data available may require length-based stock assessment methods that determine status based on SPR. In contrast, species with more information, such as opakapaka, may be assessed with integrated models, as was recently done for uku (*Aprion virescens*) in the main Hawaiian Islands (Nadon et al. 2020). 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 of opakapaka.

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 seven species can be caught on a given fishing event and 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	Deep7 species
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), 1949-2019.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1949	30.3	37.4	116.9	105.1	63.9	5.8	0.2	359.6
1950	18.8	30.0	113.8	75.5	61.3	4.6	0.7	304.7
1951	20.5	32.1	124.3	65.6	73.9	2.8	2.0	321.3
1952	27.8	45.3	118.8	52.0	44.5	9.5	2.7	300.6
1953	19.8	32.4	100.6	51.0	49.5	2.8	2.0	258.1
1954	16.7	40.2	102.3	40.8	65.6	3.9	1.9	271.3
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	69.7	3.8	3.7	281.4
1957	17.4	29.4	147.2	36.8	76.3	8.7	2.1	318.1
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	65.1	2.1	1.4	204.1
1960	12.4	18.9	70.6	19.3	39.0	1.6	1.2	163.0
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	0.7	167.6
1963	12.4	18.2	92.4	23.7	60.9	2.7	0.8	211.1
1964	11.6	23.5	92.4	24.7	47.1	1.0	2.3	202.6
1965	10.5	14.6	103.6	20.3	59.6	1.3	0.9	210.8
1966	12.7	13.6	71.4	18.1	64.1	2.0	0.8	182.7
1967	10.6	9.6	121.2	18.4	68.4	2.4	0.8	231.4
1968	11.3	6.9	85.1	19.9	69.5	2.2	0.8	195.6
1969	10.9	4.2	85.9	16.2	54.0	5.8	0.5	177.5
1970	20.1	5.1	69.7	15.9	44.0	2.7	1.4	158.8
1971	14.5	4.3	59.1	15.3	39.3	1.8	0.9	135.3
1972	17.5	8.1	117.9	21.3	58.8	4.4	1.2	229.2
1973	14.8	5.1	93.4	14.6	35.7	4.5	1.3	169.4
1974	14.6	5.2	135.3	21.1	43.6	4.9	1.5	226.2
1975	23.2	7.3	116.2	21.9	45.3	8.6	1.4	223.8
1976	22.4	14.8	105.4	31.3	80.3	10.4	1.2	265.7
1977	30.1	9.7	106.3	35.8	87.4	7.3	1.5	278.2
1978	28.7	12.4	154.6	35.7	66.6	9.8	2.6	310.3
1979	29.6	7.8	146.0	22.5	53.1	12.1	2.9	274.0
1980	17.7	7.1	151.1	17.0	31.4	17.8	2.4	244.6
1981	17.0	8.2	197.4	21.2	43.0	19.9	1.9	308.4
1982	21.7	8.1	177.7	24.5	66.0	30.0	1.6	329.5
1983	32.8	15.0	230.5	28.0	73.3	28.5	2.7	410.7

Table 2. Continued.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1984	27.1	13.4	158.7	37.6	86.7	16.8	3.5	343.9
1985	31.8	22.2	196.9	40.5	163.6	25.5	4.5	485.0
1986	24.1	24.9	173.3	61.1	195.1	27.7	3.5	509.8
1987	28.7	28.3	258.2	48.7	173.9	38.7	3.2	579.8
1988	10.3	18.1	300.7	41.2	156.4	38.2	2.0	567.0
1989	13.5	11.0	307.7	37.3	143.5	44.7	1.7	559.4
1990	14.2	15.5	209.9	37.4	142.2	34.9	2.8	456.7
1991	15.0	18.3	135.5	30.8	103.3	19.0	3.5	325.4
1992	15.0	27.6	171.3	31.8	92.1	17.1	5.0	359.8
1993	12.0	16.9	133.7	24.0	52.7	11.1	3.6	253.9
1994	10.3	17.3	173.4	23.3	68.2	11.6	3.7	307.8
1995	16.1	19.9	188.3	26.7	69.0	13.6	4.0	337.6
1996	9.8	18.7	139.8	28.1	65.4	9.7	2.9	274.3
1997	14.1	22.8	160.5	26.2	61.3	11.8	3.0	299.7
1998	12.7	24.5	149.7	26.4	70.8	9.4	3.4	296.8
1999	9.9	11.1	103.6	19.8	59.4	8.7	2.3	214.9
2000	13.1	15.9	166.1	27.0	72.3	11.1	3.2	308.7
2001	15.5	15.3	125.0	27.1	63.0	11.5	3.6	261.0
2002	9.0	10.3	103.6	17.0	59.8	10.8	2.4	212.8
2003	9.4	12.0	127.7	16.2	68.7	8.5	2.1	244.7
2004	7.9	8.0	88.1	19.2	75.7	4.9	2.1	206.0
2005	10.4	7.8	104.4	22.6	89.8	7.0	2.0	244.0
2006	7.2	5.5	76.0	18.9	74.4	6.3	1.6	190.0
2007	7.5	6.1	92.6	19.5	85.5	8.4	2.3	221.9
2008	6.6	5.5	96.2	18.5	55.9	11.0	2.8	196.5
2009	7.9	9.6	133.4	24.7	59.2	16.8	3.6	255.2
2010	8.3	8.2	105.5	24.4	57.2	6.0	2.8	212.3
2011	8.2	10.0	148.5	24.5	67.7	11.6	3.1	273.6
2012	9.9	11.3	105.2	25.8	53.2	7.9	3.7	216.8
2013	10.5	12.3	96.0	30.2	66.8	13.0	3.4	232.2
2014	10.6	18.8	160.8	31.3	75.7	8.4	3.8	309.4
2015	9.3	17.8	154.7	32.8	79.9	12.6	2.9	309.9
2016	10.2	13.1	137.3	31.9	62.1	7.7	1.9	264.3
2017	8.3	10.6	135.2	25.7	47.1	9.1	2.2	238.4
2018	9.5	12.4	118.7	21.7	66.2	8.6	2.6	239.8
2019	5.8	9.9	70.1	23.1	58.6	7.0	2.7	177.1

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), 1949-2019, 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

Table 3. Continued.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai
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
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	0.934	0.08	2.69	0.938	0.594	0.052	0.242
1999	0.848	0.13	2.51	0.766	0.458	0.064	0.334
2000	0.762	0.18	2.33	0.594	0.322	0.076	0.426
2001	0.676	0.23	2.15	0.422	0.186	0.088	0.518
2002	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2003	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2004	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2005	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2006	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2007	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2008	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2009	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2010	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2011	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2012	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2013	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2014	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2015	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2016	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2017	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2018	0.59	0.28	1.97	0.25	0.05	0.1	0.61
2019	0.59	0.28	1.97	0.25	0.05	0.1	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), 1949-2019, 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	116.6	46.6	0.2	0.0	531.0
1950	19.1	0.9	326.5	83.8	44.8	0.2	0.1	475.5
1951	20.9	1.0	356.8	72.8	54.0	0.1	0.3	505.9
1952	28.3	1.4	341.0	57.8	32.5	0.4	0.4	461.7
1953	20.2	1.0	288.6	56.6	36.2	0.1	0.3	402.9
1954	17.0	1.2	293.7	45.2	47.9	0.2	0.3	405.4
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	50.9	0.2	0.6	429.1
1957	17.8	0.9	422.6	40.8	55.7	0.3	0.3	538.5
1958	17.9	0.5	265.6	29.8	38.1	0.1	0.3	352.4
1959	16.0	0.6	223.3	25.3	47.5	0.1	0.2	313.0
1960	12.7	0.6	202.5	21.5	28.4	0.1	0.2	265.9
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	279.3
1963	12.7	0.5	265.2	26.3	44.5	0.1	0.1	349.4
1964	11.8	0.7	265.3	27.4	34.4	0.0	0.3	340.0
1965	10.7	0.4	297.2	22.5	43.5	0.1	0.1	374.6
1966	13.0	0.4	204.9	20.1	46.8	0.1	0.1	285.4
1967	10.8	0.3	347.8	20.4	50.0	0.1	0.1	429.5
1968	11.5	0.2	244.2	22.1	50.7	0.1	0.1	328.9
1969	11.1	0.1	246.7	18.0	39.4	0.2	0.1	315.6
1970	20.5	0.2	200.0	17.6	32.1	0.1	0.2	270.7
1971	14.8	0.1	169.7	17.0	28.7	0.1	0.1	230.5
1972	17.9	0.2	338.2	23.7	42.9	0.2	0.2	423.3
1973	15.1	0.2	267.9	16.2	26.1	0.2	0.2	325.8
1974	14.9	0.2	388.3	23.4	31.8	0.2	0.2	459.1
1975	23.7	0.2	333.4	24.3	33.1	0.3	0.2	415.3
1976	22.8	0.4	302.5	34.7	58.6	0.4	0.2	419.7
1977	30.7	0.3	305.2	39.8	63.8	0.3	0.2	440.3
1978	29.2	0.4	443.8	39.6	48.6	0.4	0.4	562.5
1979	30.1	0.2	419.1	25.0	38.7	0.5	0.4	514.1
1980	18.1	0.2	433.5	18.9	22.9	0.7	0.4	494.7
1981	17.3	0.2	566.4	23.5	31.4	0.8	0.3	639.9
1982	22.1	0.2	510.1	27.1	48.1	1.2	0.2	609.2
1983	33.4	0.4	661.5	31.1	53.5	1.1	0.4	781.5
1984	27.6	0.4	455.6	41.7	63.3	0.7	0.5	589.8
1985	32.4	0.7	565.0	44.9	119.4	1.0	0.7	764.2
1986	24.6	0.7	497.5	67.8	142.5	1.1	0.5	734.7

Table 4. Continued.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1987	29.3	0.8	741.0	54.1	127.0	1.5	0.5	954.2
1988	10.5	0.5	862.9	45.8	114.2	1.5	0.3	1035.8
1989	13.7	0.3	883.0	41.4	104.8	1.8	0.3	1045.3
1990	14.4	0.5	602.3	41.5	103.8	1.4	0.4	764.3
1991	15.3	0.5	388.9	34.2	75.4	0.8	0.5	515.6
1992	15.3	0.8	491.7	35.3	67.2	0.7	0.7	611.8
1993	12.2	0.5	383.6	26.7	38.5	0.4	0.5	462.4
1994	10.5	0.5	497.6	25.9	49.8	0.5	0.6	585.3
1995	16.4	0.6	540.4	29.6	50.4	0.5	0.6	638.6
1996	10.0	0.6	401.1	31.2	47.8	0.4	0.4	491.5
1997	14.3	0.7	460.6	29.0	44.8	0.5	0.5	550.4
1998	11.8	2.0	402.6	24.8	42.1	0.5	0.8	484.6
1999	8.4	1.4	260.1	15.2	27.2	0.6	0.8	313.7
2000	10.0	2.9	387.1	16.0	23.3	0.8	1.3	441.5
2001	10.5	3.5	268.8	11.4	11.7	1.0	1.9	308.8
2002	5.3	2.9	204.1	4.3	3.0	1.1	1.5	222.0
2003	5.6	3.4	251.5	4.1	3.4	0.9	1.3	270.1
2004	4.7	2.2	173.6	4.8	3.8	0.5	1.3	190.8
2005	6.1	2.2	205.7	5.6	4.5	0.7	1.2	226.1
2006	4.3	1.5	149.7	4.7	3.7	0.6	1.0	165.6
2007	4.4	1.7	182.4	4.9	4.3	0.8	1.4	199.9
2008	3.9	1.5	189.5	4.6	2.8	1.1	1.7	205.2
2009	4.7	2.7	262.7	6.2	3.0	1.7	2.2	283.1
2010	4.9	2.3	207.9	6.1	2.9	0.6	1.7	226.3
2011	4.9	2.8	292.5	6.1	3.4	1.2	1.9	312.7
2012	5.8	3.2	207.3	6.4	2.7	0.8	2.2	228.4
2013	6.2	3.4	189.2	7.5	3.3	1.3	2.0	213.1
2014	6.2	5.3	316.8	7.8	3.8	0.8	2.3	343.1
2015	5.5	5.0	304.7	8.2	4.0	1.3	1.7	330.4
2016	6.0	3.7	270.6	8.0	3.1	0.8	1.2	293.3
2017	4.9	3.0	266.3	6.4	2.4	0.9	1.3	285.3
2018	5.6	3.5	233.8	5.4	3.3	0.9	1.6	254.1
2019	3.4	2.8	138.0	5.8	2.9	0.7	1.6	155.2

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), 1949-2019, 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	110.5	6.0	0.2	890.6
1950	37.9	30.9	440.3	159.3	106.1	4.8	0.8	780.1
1951	41.5	33.1	481.1	138.4	127.9	2.9	2.2	827.1
1952	56.1	46.6	459.8	109.8	76.9	9.8	3.2	762.2
1953	40.0	33.4	389.2	107.6	85.7	2.9	2.2	661.0
1954	33.7	41.4	396.0	86.0	113.4	4.0	2.2	676.7
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	120.6	4.0	4.2	710.4
1957	35.2	30.3	569.8	77.6	132.1	9.1	2.5	856.5
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	112.6	2.2	1.7	517.1
1960	25.1	19.4	273.1	40.8	67.4	1.7	1.4	428.9
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	83.9	1.7	0.8	446.9
1963	25.1	18.8	357.7	50.0	105.4	2.8	0.9	560.5
1964	23.4	24.2	357.7	52.2	81.5	1.0	2.7	542.6
1965	21.3	15.1	400.8	42.8	103.2	1.3	1.1	585.5
1966	25.7	14.0	276.4	38.2	110.8	2.1	1.0	468.2
1967	21.5	9.9	469.0	38.7	118.4	2.5	0.9	660.8
1968	22.8	7.1	329.2	41.9	120.3	2.3	0.9	524.6
1969	22.1	4.3	332.6	34.2	93.4	6.0	0.5	493.1
1970	40.5	5.3	269.7	33.5	76.1	2.8	1.7	429.5
1971	29.3	4.5	228.8	32.3	68.0	1.9	1.0	365.8
1972	35.4	8.3	456.1	45.0	101.7	4.6	1.4	652.5
1973	30.0	5.3	361.3	30.7	61.8	4.7	1.5	495.2
1974	29.5	5.4	523.6	44.6	75.5	5.1	1.7	685.3
1975	46.9	7.5	449.6	46.2	78.4	8.9	1.6	639.1
1976	45.2	15.2	407.9	66.0	138.9	10.8	1.4	685.4
1977	60.8	10.0	411.5	75.6	151.2	7.6	1.8	718.5
1978	57.9	12.8	598.5	75.3	115.3	10.2	2.9	872.8
1979	59.7	8.1	565.1	47.5	91.8	12.6	3.3	788.1
1980	35.8	7.3	584.6	35.9	54.3	18.5	2.7	739.3
1981	34.3	8.4	763.8	44.6	74.3	20.7	2.1	948.3
1982	43.8	8.3	687.8	51.6	114.1	31.2	1.9	938.6
1983	66.2	15.4	892.0	59.1	126.8	29.6	3.1	1192.2
1984	54.7	13.8	614.3	79.3	150.0	17.5	4.1	933.6
1985	64.3	22.9	761.9	85.4	283.1	26.6	5.2	1249.2

Table 5. Continued.

Fishing year	Hapuupuu	Kalekale	Opakapaka	Ehu	Onaga	Lehi	Gindai	Total
1986	48.6	25.7	670.9	128.9	337.6	28.8	4.0	1244.5
1987	58.1	29.1	999.2	102.8	300.9	40.2	3.7	1534.0
1988	20.8	18.6	1163.6	87.0	270.6	39.8	2.3	1602.8
1989	27.2	11.3	1190.6	78.7	248.3	46.5	1.9	1604.6
1990	28.6	16.0	812.2	78.8	245.9	36.3	3.2	1221.0
1991	30.2	18.8	524.3	65.1	178.8	19.7	4.0	841.0
1992	30.2	28.4	663.0	67.1	159.3	17.7	5.7	971.6
1993	24.2	17.4	517.2	50.7	91.2	11.5	4.1	716.3
1994	20.9	17.8	670.9	49.2	117.9	12.1	4.3	893.1
1995	32.6	20.5	728.8	56.3	119.4	14.1	4.6	976.3
1996	19.9	19.2	540.9	59.3	113.2	10.1	3.3	765.8
1997	28.4	23.5	621.1	55.2	106.1	12.3	3.5	850.1
1998	24.5	26.4	552.3	51.2	112.9	9.9	4.2	781.4
1999	18.3	12.5	363.8	35.0	86.6	9.3	3.1	528.5
2000	23.2	18.7	553.3	43.1	95.6	11.9	4.5	750.2
2001	25.9	18.8	393.8	38.5	74.7	12.5	5.5	569.9
2002	14.3	13.1	307.7	21.3	62.8	11.8	3.9	434.9
2003	15.0	15.4	379.2	20.3	72.2	9.4	3.4	514.8
2004	12.6	10.3	261.7	24.0	79.5	5.4	3.3	396.8
2005	16.5	10.0	310.1	28.2	94.3	7.7	3.2	470.0
2006	11.5	7.0	225.7	23.7	78.2	6.9	2.6	355.6
2007	12.0	7.9	275.0	24.3	89.8	9.2	3.7	421.9
2008	10.5	7.1	285.7	23.1	58.7	12.1	4.6	401.7
2009	12.6	12.3	396.1	30.9	62.2	18.5	5.8	538.4
2010	13.2	10.4	313.4	30.5	60.0	6.6	4.5	438.7
2011	13.1	12.8	441.0	30.6	71.1	12.8	5.0	586.3
2012	15.7	14.4	312.5	32.2	55.9	8.6	5.9	445.2
2013	16.8	15.8	285.3	37.7	70.1	14.3	5.4	445.4
2014	16.8	24.0	477.7	39.2	79.4	9.3	6.1	652.5
2015	14.9	22.8	459.4	41.0	83.9	13.8	4.6	640.4
2016	16.3	16.8	407.9	39.8	65.2	8.5	3.1	557.6
2017	13.2	13.6	401.5	32.2	49.5	10.1	3.5	523.6
2018	15.1	15.8	352.6	27.1	69.5	9.5	4.2	493.9
2019	9.2	12.7	208.1	28.8	61.5	7.7	4.3	332.3

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 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	0.7	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 6. Continued.

Fishing year	After names added	Before names added		Fishing year	After names added	Before names added
2016	1.0	1.0		2018	1.0	1.0
2017	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 (2003-2018) 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	2003-2018	1948-2003	2003-2018
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 (2003-2018) 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	delta	Log-Likelihood	Number of parameters
Bernoulli				
1948-2003	null	0	-73894.69	1
	+year	9552.9	-69063.2	56
	+area	13132.0	-62326.3	227
	+quarter	504.9	-62070.8	230
	+area:quarter	1033.0	-61237.3	547
	+ln(cumulative experience)	91.8	-61190.4	548
2003-2018	null	0	-25347.2	1
	+year	231.7	-25216.3	16
	+sqrt(lb uku)	5504.0	-22463.3	17
	+area	3907.8	-20405.4	121
	+qtr	703.0	-20050.9	124
	+area:qtr	311.5	-19629.2	390
	+speed	272.1	-19492.1	391
Lognormal				
1948-2003	null	0	-222522.0	2
	+fisher	63278.1	-190881.6	3
	+year	1190.2	-190231.5	58
	+area	3707.8	-188214.6	221
	+quarter	1448.3	-187487.5	224
	+sqrt(uku lbs)	1045.2	-186963.9	225
	+ln(cumulative experience)	594.3	-186665.7	226
	+area:quarter	418.2	-186149.6	533
2003-2018	Null	0	-56836.9	2
	+fisher	18703.9	-47483.9	3
	+year	955.2	-46991.3	18
	+area	870.3	-46460.2	114
	+sqrt(uku lbs)	594.5	-46162.0	115
	+speed	277.4	-46022.2	116
	+quarter	200.9	-45918.8	119
	+area:year	174.1	-44666.7	1284
	+ln(cumulative experience)	141.6	-44594.9	1285

Table 9. 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	88.21	2.70		1976	51.40	1.00
1949	56.49	2.23		1977	52.59	1.82
1950	51.55	2.00		1978	82.97	2.24
1951	72.06	2.16		1979	87.38	2.66
1952	95.55	2.60		1980	69.77	2.15
1953	87.76	2.94		1981	68.37	1.85
1954	95.69	3.36		1982	59.29	1.53
1955	154.47	3.55		1983	59.25	1.24
1956	91.70	3.65		1984	48.49	1.34
1957	114.40	3.03		1985	60.62	1.19
1958	64.56	2.93		1986	64.97	1.18
1959	55.65	3.69		1987	83.76	1.10
1960	102.78	2.44		1988	80.24	1.07
1961	115.00	3.44		1989	71.87	1.04
1962	177.18	3.17		1990	64.68	1.25
1963	125.86	3.44		1991	61.97	1.29
1964	114.17	3.49		1992	66.84	1.36
1965	120.53	3.31		1993	60.40	1.48
1966	120.69	3.19		1994	68.35	1.50
1967	108.37	2.38		1995	68.01	1.50
1968	99.22	2.76		1996	64.46	1.51
1969	94.75	2.79		1997	65.49	1.42
1970	81.02	3.09		1998	65.80	1.41
1971	75.14	2.75		1999	65.14	1.55
1972	88.44	2.48		2000	72.77	1.38
1973	75.04	2.47		2001	72.68	1.53
1974	81.96	1.94		2002	68.35	1.68
1975	76.91	2.01		2003	61.69	3.75

Table 10. Annual index of standardized CPUE (lbs/hour) for the late time period (2003-2018) with relative coefficient of variation (relCV) included. Relative CV was calculated as the ratio of CV/min(CV).

Year	Estimated CPUE	relCV
2003	8.25	1.24
2004	7.94	1.20
2005	8.84	1.19
2006	8.44	1.39
2007	8.56	1.34
2008	9.59	1.25
2009	9.05	1.05
2010	8.27	1.26
2011	9.41	1.22
2012	8.21	1.24
2013	8.10	1.12
2014	9.99	1.00
2015	12.59	1.04
2016	13.47	1.46
2017	11.07	1.56
2018	11.66	2.38

Table 11. Estimates of biomass and associated standard error (SE) for the Deep 7 complex and Opakapaka from the fishery-independent survey for calendar years 2016-2019 (fishing years 2017-2020).

Fishing year	Deep 7 Biomass (Million lb)	Deep 7 SE	Opakapaka Biomass (Million lb)	Opakapaka SE	Ratio of Opakapaka: Deep 7
2017	15.091	3.411	9.857	3.315	0.65
2018	12.903	1.526	5.105	0.938	0.40
2019	8.303	1.217	3.381	0.941	0.41
2020	8.587	1.171	3.447	0.815	0.40

Table 12. Prior distributions and parameter estimates for the 2021 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 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	0.027
K	lognormal	29 million lbs.	50%		27.91	10.18
M	gamma	1.0	140%		2.17	1.49
P_1	lognormal	0.53	20%		0.559	0.100
q_1	uniform			$[10^{-5},10^{5}]$	4.44	1.58
q_2	uniform			$[10^{-5},10^{5}]$	0.584	0.282
rad	lognormal	20.2	50%		22.35	5.77
τ_1^2	inverse gamma	0.83*			0.0536	0.012
τ_2^2	inverse gamma	0.83*			0.182	0.078
σ^2	inverse gamma	0.083*			0.031	0.012
C_U	uniform	$U \cdot C_R$		±40%		
MSY (total catch)					1.025	0.487
MSY (reported catch)					0.473	0.225
H_{MSY}					0.068	0.026
B_{MSY}					15.46	5.05
P_{MSY}					0.566	0.084

***Value is mode rather than mean.**

Table 13. 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 (*Survey*), 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	1	Data	Exclude survey from model
Survey (*rad*)	1	Distribution coefficient of variation (CV)	Prior CV reduced to 0.01

Table 14. 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}	1.001	1.78	0.21	Passed	0.62	0.21
F_{MSY}	1.001	1.62	0.07	Passed	0.37	0.17
H_{MSY}	1.001	1.62	0.07	Passed	0.37	0.17
MSY	1.002	1.50	0.18	Passed	0.30	0.13
P_{MSY}	1.001	1.63	0.08	Passed	0.31	0.16
R	1.000	0.79	0.14	Passed	0.08	0.04
K	1.000	1.87	0.14	Passed	0.76	0.27
M	1.001	1.45	0.16	Passed	0.24	0.12
q_1	1.003	1.97	0.15	Passed	0.71	0.23
q_2	1.004	1.45	0.20	Passed	0.69	0.34
rad	1.004	1.35	0.33	Passed	0.77	0.37
σ^2	1.001	0.26	0.05	Passed	0.09	0.01
τ_1^2	1.001	1.05	0.14	Passed	0.01	0.01
τ_2^2	1.000	0.65	0.38	Passed	0.02	0.01

Table 15. Correlation coefficients among parameter estimates. Parameters are carrying capacity (K), intrinsic growth rate (R), initial proportion of carrying capacity (P1), shape parameter (M), catchability in first (q1) and second (q2) 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	-0.21	-0.12	-0.34	-0.67	-0.42	-0.39	0.00	0.01	-0.03
R	-	0.01	-0.06	0.14	0.01	-0.02	0.01	-0.01	0.00
P_1	-	-	0.09	-0.16	-0.09	-0.07	0.01	0.00	-0.06
M	-	-	-	0.13	-0.02	-0.05	0.01	-0.01	-0.05
q_1	-	-	-	-	0.64	0.55	-0.01	-0.01	0.06
q_2	-	-	-	-	-	0.80	0.01	0.04	0.10
rad	-	-	-	-	-	-	0.02	0.06	0.12
τ_1^2	-	-	-	-	-			0.01	0.09
τ_2^2	-	-	-	-	-	-	-	-	0.06

Table 16. Estimates of mean exploitable biomass (B) in million lbs, mean relative exploitable biomass (B/BMSY), probability of being overfished (B/BMSY< 0.844), mean harvest rate (H), relative mean harvest rate (H/HMSY), and probability of overfishing (H/HMSY>1) for the Deep 7 Bottomfish complex in the main Hawaiian Islands from 1949 through 2018.

Year	B (million lbs)	B/B_{MSY}	Probability of Being Overfished	H	H/H_{MSY}	Probability of Overfishing
1949	15.49	1.01	0.25	0.07	0.96	0.46
1950	16.38	1.07	0.20	0.05	0.80	0.32
1951	17.95	1.17	0.13	0.05	0.78	0.31
1952	19.46	1.27	0.10	0.05	0.66	0.22
1953	20.61	1.34	0.08	0.04	0.55	0.14
1954	21.70	1.41	0.06	0.04	0.53	0.13
1955	22.62	1.47	0.05	0.03	0.42	0.08
1956	22.96	1.50	0.04	0.04	0.53	0.13
1957	23.09	1.50	0.04	0.04	0.63	0.20
1958	22.68	1.48	0.05	0.03	0.42	0.08
1959	23.13	1.51	0.04	0.03	0.38	0.06
1960	24.22	1.58	0.03	0.02	0.30	0.04
1961	25.30	1.65	0.02	0.02	0.23	0.03
1962	26.34	1.72	0.02	0.02	0.29	0.04
1963	26.35	1.72	0.02	0.03	0.36	0.05
1964	26.10	1.70	0.02	0.02	0.35	0.05
1965	25.88	1.69	0.02	0.03	0.38	0.06
1966	25.46	1.66	0.02	0.02	0.31	0.04
1967	24.97	1.63	0.02	0.03	0.45	0.09
1968	24.05	1.57	0.03	0.03	0.37	0.06
1969	23.24	1.52	0.04	0.03	0.36	0.06
1970	22.36	1.46	0.05	0.02	0.33	0.05
1971	21.65	1.41	0.06	0.02	0.29	0.04
1972	21.18	1.38	0.07	0.04	0.52	0.13
1973	20.14	1.31	0.10	0.03	0.42	0.08
1974	19.33	1.26	0.11	0.04	0.60	0.19
1975	17.98	1.17	0.16	0.04	0.61	0.19
1976	16.29	1.06	0.23	0.05	0.71	0.26
1977	16.71	1.09	0.22	0.05	0.73	0.28
1978	17.62	1.15	0.19	0.06	0.84	0.38
1979	17.83	1.16	0.18	0.05	0.76	0.31
1980	17.63	1.15	0.19	0.05	0.72	0.27
1981	17.29	1.13	0.19	0.06	0.93	0.45

Table 16. Continued.

Year	B (million lbs)	B/B_{MSY}	Probability of Being Overfished	H	H/H_{MSY}	Probability of Overfishing
1982	16.59	1.08	0.23	0.07	0.96	0.47
1983	16.19	1.06	0.24	0.09	1.24	0.66
1984	15.78	1.03	0.27	0.07	1.00	0.50
1985	16.76	1.09	0.20	0.09	1.25	0.67
1986	17.76	1.16	0.14	0.08	1.18	0.63
1987	19.21	1.25	0.09	0.09	1.35	0.72
1988	19.20	1.25	0.09	0.10	1.42	0.75
1989	18.32	1.19	0.12	0.10	1.49	0.78
1990	17.32	1.13	0.18	0.08	1.20	0.64
1991	16.88	1.10	0.21	0.06	0.85	0.38
1992	17.05	1.11	0.20	0.07	0.97	0.48
1993	16.92	1.10	0.21	0.05	0.72	0.28
1994	17.35	1.13	0.19	0.06	0.88	0.40
1995	17.41	1.14	0.18	0.07	0.95	0.46
1996	17.23	1.12	0.19	0.05	0.76	0.31
1997	17.34	1.13	0.19	0.06	0.83	0.37
1998	17.43	1.14	0.18	0.05	0.76	0.31
1999	17.60	1.15	0.18	0.04	0.51	0.12
2000	18.11	1.18	0.15	0.05	0.70	0.26
2001	18.08	1.18	0.16	0.04	0.54	0.14
2002	18.00	1.17	0.17	0.03	0.41	0.08
2003	18.08	1.18	0.18	0.03	0.48	0.13
2004	18.23	1.19	0.19	0.03	0.36	0.08
2005	18.61	1.21	0.19	0.03	0.42	0.12
2006	18.84	1.23	0.19	0.02	0.32	0.07
2007	19.16	1.25	0.18	0.03	0.37	0.09
2008	19.43	1.27	0.17	0.03	0.34	0.09
2009	19.53	1.27	0.17	0.03	0.46	0.15
2010	19.53	1.27	0.17	0.03	0.37	0.10
2011	19.82	1.29	0.16	0.04	0.49	0.17
2012	19.88	1.30	0.16	0.03	0.37	0.10
2013	20.39	1.33	0.14	0.03	0.36	0.10
2014	21.48	1.40	0.12	0.04	0.50	0.17
2015	22.56	1.47	0.10	0.04	0.46	0.15
2016	23.04	1.50	0.10	0.03	0.39	0.12
2017	23.42	1.53	0.10	0.03	0.36	0.11
2018	21.88	1.43	0.13	0.03	0.37	0.11

Table 17. Projection results for mean probability of overfishing (H/HMSY>1) and corresponding annual reported catch where the probability of overfishing is reached. The mean probability the stock is overfished (B/BMSY<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.), constant from 2021 through terminal year											
2021	0.000	0.126	0.210	0.274	0.330	0.384	0.434	0.484	0.530	0.576	0.618
2022	0.000	0.128	0.208	0.274	0.332	0.382	0.428	0.474	0.518	0.558	0.598
2023	0.000	0.130	0.210	0.272	0.330	0.378	0.424	0.466	0.504	0.542	0.582
2024	0.000	0.130	0.210	0.274	0.328	0.376	0.418	0.458	0.496	0.532	0.568
2025	0.000	0.130	0.212	0.274	0.326	0.372	0.414	0.454	0.486	0.524	0.556
Probability stock is overfished (B/B_{MSY}<0.844)											
2022	0.10	0.11	0.11	0.12	0.12	0.12	0.12	0.13	0.13	0.13	0.13
2023	0.09	0.10	0.11	0.11	0.12	0.12	0.13	0.13	0.14	0.14	0.15
2024	0.08	0.09	0.10	0.11	0.12	0.13	0.13	0.14	0.15	0.15	0.16
2025	0.06	0.08	0.10	0.11	0.12	0.13	0.14	0.15	0.16	0.16	0.17
Harvest rate											
2021	0.000	0.014	0.023	0.030	0.036	0.042	0.047	0.052	0.057	0.062	0.067
2022	0.000	0.014	0.022	0.030	0.036	0.042	0.047	0.052	0.058	0.062	0.067
2023	0.000	0.014	0.022	0.029	0.036	0.042	0.047	0.053	0.057	0.062	0.067
2024	0.000	0.014	0.022	0.030	0.036	0.042	0.047	0.052	0.058	0.062	0.067
2025	0.000	0.013	0.022	0.030	0.036	0.042	0.047	0.053	0.057	0.062	0.067
Biomass (millions of lbs.)											
2022	21.27	21.00	20.83	20.69	20.57	20.46	20.37	20.27	20.17	20.09	20.00
2023	21.71	21.21	20.89	20.65	20.42	20.23	20.04	19.87	19.72	19.57	19.41
2024	22.12	21.41	20.96	20.60	20.30	20.03	19.79	19.56	19.35	19.14	18.93
2025	22.49	21.59	21.02	20.58	20.21	19.88	19.57	19.28	19.05	18.77	18.53

Table 18. Probability of overfishing in terminal year (H/HMSY>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., 2021 to terminal year).

	Reported catch for a given year							Reported catch for a given year				
P(Overfishing)	2021	2022	2023	2024	2025		P(Overfishing)	2021	2022	2023	2024	2025
0.00	0	0	0	0	0		0.26	0.396	0.39	0.388	0.386	0.378
0.01	0.022	0.022	0.024	0.024	0.024		0.27	0.408	0.4	0.394	0.394	0.39
0.02	0.058	0.058	0.058	0.06	0.06		0.28	0.416	0.41	0.408	0.4	0.4
0.03	0.084	0.086	0.086	0.086	0.088		0.29	0.426	0.42	0.416	0.41	0.406
0.04	0.108	0.11	0.11	0.112	0.11		0.30	0.434	0.428	0.424	0.418	0.414
0.05	0.126	0.128	0.13	0.13	0.13		0.31	0.446	0.438	0.432	0.426	0.424
0.06	0.144	0.148	0.148	0.148	0.15		0.32	0.454	0.448	0.442	0.436	0.43
0.07	0.162	0.164	0.166	0.166	0.17		0.33	0.466	0.454	0.45	0.446	0.436
0.08	0.178	0.182	0.18	0.182	0.182		0.34	0.476	0.466	0.458	0.452	0.446
0.09	0.194	0.194	0.196	0.198	0.198		0.35	0.484	0.474	0.466	0.458	0.454
0.10	0.21	0.208	0.21	0.21	0.212		0.36	0.496	0.484	0.474	0.466	0.46
0.11	0.222	0.224	0.226	0.224	0.226		0.37	0.504	0.49	0.482	0.474	0.466
0.12	0.236	0.238	0.238	0.238	0.24		0.38	0.514	0.498	0.49	0.48	0.474
0.13	0.248	0.25	0.25	0.252	0.25		0.39	0.522	0.508	0.498	0.49	0.48
0.14	0.262	0.262	0.262	0.262	0.262		0.40	0.53	0.518	0.504	0.496	0.486
0.15	0.274	0.274	0.272	0.274	0.274		0.41	0.538	0.526	0.514	0.504	0.496
0.16	0.286	0.284	0.288	0.284	0.284		0.42	0.548	0.534	0.522	0.51	0.502
0.17	0.296	0.296	0.298	0.298	0.296		0.43	0.56	0.538	0.528	0.52	0.508
0.18	0.308	0.308	0.306	0.306	0.304		0.44	0.57	0.552	0.536	0.524	0.516
0.19	0.32	0.318	0.318	0.316	0.316		0.45	0.576	0.558	0.542	0.532	0.524
0.20	0.33	0.332	0.33	0.328	0.326		0.46	0.586	0.566	0.552	0.54	0.528
0.21	0.342	0.34	0.338	0.336	0.336		0.47	0.594	0.576	0.558	0.546	0.538
0.22	0.354	0.35	0.348	0.346	0.346		0.48	0.602	0.582	0.566	0.554	0.542
0.23	0.364	0.36	0.356	0.358	0.354		0.49	0.614	0.59	0.572	0.56	0.548
0.24	0.372	0.372	0.37	0.368	0.366		0.50	0.618	0.598	0.582	0.568	0.556
0.25	0.384	0.382	0.378	0.376	0.372							

Table 19. 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, 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 2018 (B_{2018}), harvest rate in 2018 (H_{2018}), probability of overfishing in 2018 (i.e., $H/H_{MSY}>1$; poflH$_{2018}$), probability of the stock being overfished in 2018 (i.e., $B/B_{MSY}<(1-natM)$; poflB$_{2018}$), harvest rate in 2018 relative to H_{MSY} (H_{2018}/H_{MSY}), and total exploitable biomass in 2018 relative to B_{MSY} (B_{2018}/B_{MSY}).

Scenario	R	K	M	P_1	MSY	B_{MSY}	H_{MSY}	B_{2018}	H_{2018}	poflH 2018	poflB 2018	H_{2018}/H_{MSY}	B_{2018}/B_{MSY}
K = 14.50	6.70	-27.02	22.97	1.57	-8.77	-22.51	17.87	-22.26	22.80	-28.47	-21.62	7.45	0.07
K = 21.75	2.71	-13.04	10.87	0.95	-2.83	-10.35	8.21	-9.28	7.93	-20.68	-16.04	1.97	0.84
K = 36.25	-1.99	12.22	-8.06	-0.88	3.90	9.96	-6.11	9.92	-8.14	5.23	0.92	-1.37	-0.28
K = 43.50	-3.26	25.98	-14.87	-1.23	7.90	20.76	-11.21	19.10	-14.14	20.92	14.06	-1.97	-1.33
R = 0.05	-50.36	22.07	1.01	-0.16	-40.07	21.15	-52.13	0.50	4.19	253.27	123.15	124.62	-15.35
R = 0.15	48.51	-11.43	-8.52	0.23	27.61	-12.35	45.92	-1.83	-2.53	-65.36	-60.63	-29.44	11.49
R = 0.25	141.00	-22.00	-25.74	0.00	63.02	-25.68	119.54	-6.31	1.04	-87.31	-87.86	-49.67	24.88
M=0.5	0.36	7.95	-34.39	-0.72	-16.05	-0.91	-15.07	-0.41	1.80	63.64	11.69	24.21	0.63
M=0.75	0.54	2.69	-15.10	-0.39	-5.95	-0.65	-5.38	-0.55	1.21	22.23	4.51	7.53	0.07
M=1.25	-0.27	-1.36	10.22	0.21	4.29	0.78	3.15	-0.09	-1.07	-16.02	-6.26	-2.55	-0.98
M=1.5	0.00	-3.44	21.27	0.66	7.90	0.71	6.85	0.91	-1.87	-28.37	-12.61	-7.01	0.07

Table 19. Continued.

Scenario	R	K	M	P_1	MSY	B_{MSY}	H_{MSY}	B_{2018}	H_{2018}	poflH 2018	poflB 2018	H_{2018}/H_{MSY}	B_{2018}/B_{MSY}
$P_I = 0.27$	-3.44	34.07	-33.47	-45.81	-5.17	21.99	-20.28	-13.53	21.83	125.89	217.65	59.99	-26.28
$P_I = 0.40$	-0.72	7.81	-9.76	-20.38	-0.98	5.05	-5.00	-1.33	2.46	17.52	35.98	9.26	-5.54
$P_I = 0.66$	0.09	-2.97	4.60	18.92	1.37	-1.62	2.00	2.51	-3.81	-16.05	-27.76	-3.50	3.92
$P_I = 0.80$	-0.09	-3.73	3.96	38.03	0.39	-2.46	1.18	4.98	-6.51	-15.35	-42.61	-4.76	7.36
τ_i^2 x 0.01	-0.27	-3.73	-10.04	-5.78	-4.84	-3.88	-0.87	6.12	-15.35	-78.22	-91.57	-4.24	9.67
τ_i^2 x 0.1	-0.81	-0.25	-7.37	-3.29	-2.79	-0.65	-1.64	9.14	-15.94	-66.68	-78.78	-5.89	9.11
τ_i^2 x 10	-1.72	4.34	-10.31	-1.82	-4.60	1.55	-7.41	-16.32	41.68	126.85	156.91	38.58	-16.12
τ_i^2 x 100	-3.35	10.64	-26.61	-3.20	-11.26	3.88	-16.99	-23.45	70.65	223.45	242.40	89.32	-21.72
σ^2 x 0.01	0.63	6.88	7.73	6.99	6.83	6.73	2.34	7.31	-15.87	-53.50	-60.43	-9.78	0.14
σ^2 x 0.1	0.36	3.51	6.31	4.02	4.49	3.82	2.03	5.12	-11.47	-39.43	-45.98	-7.78	0.84
σ^2 x 10	-1.27	-4.19	-15.65	-3.65	-10.44	-6.34	-7.39	-9.87	21.69	74.54	74.64	30.50	-0.98
σ^2 x 100	-5.25	-7.09	-45.44	-5.56	-35.67	-16.36	-28.71	-20.43	54.78	259.37	149.27	119.72	6.73
Catch I	2.71	15.37	11.46	0.84	28.88	18.95	8.25	10.37	54.57	65.48	27.43	43.67	-7.64
Catch II	-0.09	-1.00	-0.14	0.02	-0.49	-0.84	-0.13	5.76	-46.47	-60.53	-35.45	-44.80	7.01
Catch III	-1.36	-6.59	-4.83	-0.55	-10.82	-7.70	-3.64	-10.05	26.33	57.89	13.37	32.01	-2.87
Catch IV	-6.15	-22.93	-30.89	-2.09	-45.34	-29.62	-24.35	-24.63	-32.95	47.17	-13.83	-7.64	7.50
C_U 0.01	-0.09	-0.54	0.74	-0.11	0.68	-0.13	0.46	0.05	-0.90	-10.55	-7.79	0.52	-0.14
C_U 0.2	0.00	-0.18	0.00	-0.27	0.10	-0.13	0.07	-0.82	0.14	-3.40	0.31	1.75	-0.84
C_U 0.6	0.09	0.36	-0.41	-0.25	0.39	0.26	-0.10	0.27	-0.17	-0.26	-3.74	0.63	-0.14
C_U neg25	-0.45	-4.51	-2.53	-0.29	-6.61	-5.17	-1.85	-4.52	-3.88	-1.57	-6.49	-0.52	0.63
C_U pos25	1.09	3.51	4.01	0.41	8.20	4.72	3.16	5.16	0.73	-14.15	-10.08	-0.36	0.21
q	-5.34	30.20	-31.81	-2.70	-5.24	19.40	-23.85	19.70	4.05	123.19	83.42	23.14	4.27

Table 19. Continued.

Scenario	R	K	M	P_1	MSY	B_{MSY}	H_{MSY}	B_{2018}	H_{2018}	poflH 2018	poflB 2018	H_{2018}/H_{MSY}	B_{2018}/B_{MSY}
uniform	0.54	-2.08	-10.04	-5.22	-1.66	-1.94	0.69	10.56	-19.54	-89.27	-97.50	-9.53	11.56
No survey	0.18	5.70	2.44	-0.27	8.00	6.47	1.40	7.08	-3.92	-26.53	-8.33	-3.94	-0.70
Survey CV	0.36	-15.37	-5.11	-1.36	-22.23	-17.72	-2.56	-44.24	42.34	60.94	108.40	72.34	-28.03

Table 20. 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 lb) – average 2014-2018	0.420	0.732
Relative survey estimate (million lb)		
2017	2.23E-6	0.461
2018	1.866E-6	0.417
2019	1.583E-6	0.453
2020	1.509E-6	0.450
R	0.115	1.036
K (million lb)	14.39	0.516
M	2.567	1.183
q_1	5.798	1.310
q_2	0.748	1.281
rad	20.9	0.935
σ^2	0.032	1.032
τ_1^2	0.055	1.026
τ_2^2	0.191	1.049
P_1	0.635	1.136
MSY (million lb)	0.624	0.609
B_{MSY} (million lb)	8.343	0.540
H_{MSY}	0.076	1.118
P_{MSY}	0.590	1.042

9. FIGURES

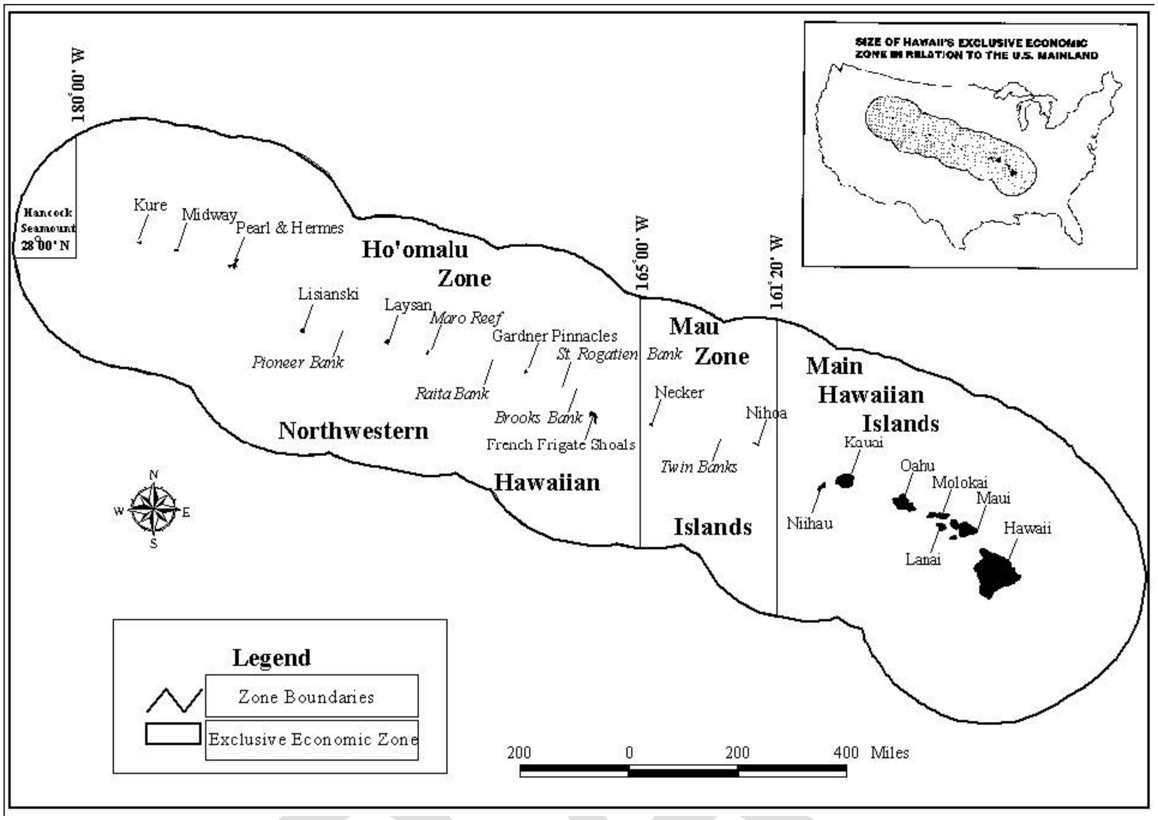
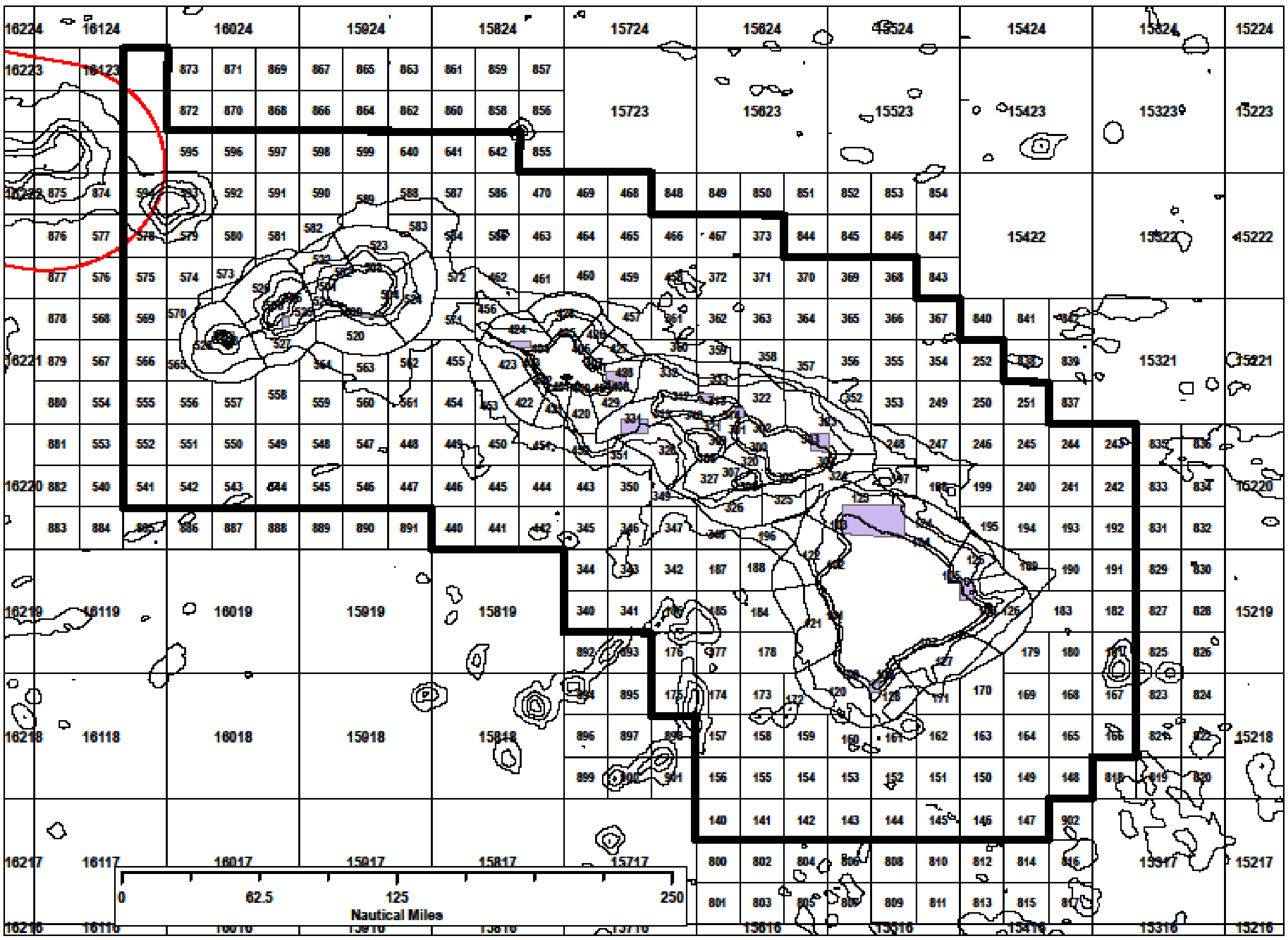


Figure 1. Location of the three Hawaiian bottomfish fishing zones: the main Hawaiian Islands (MHI) zone, the Mau Zone, and the Ho'omalu Zone. Together, the Mau and Ho'omalu Zones are known as the Northwestern Hawaiian Islands, which is now closed to fishing. The current stock assessment is for the Deep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

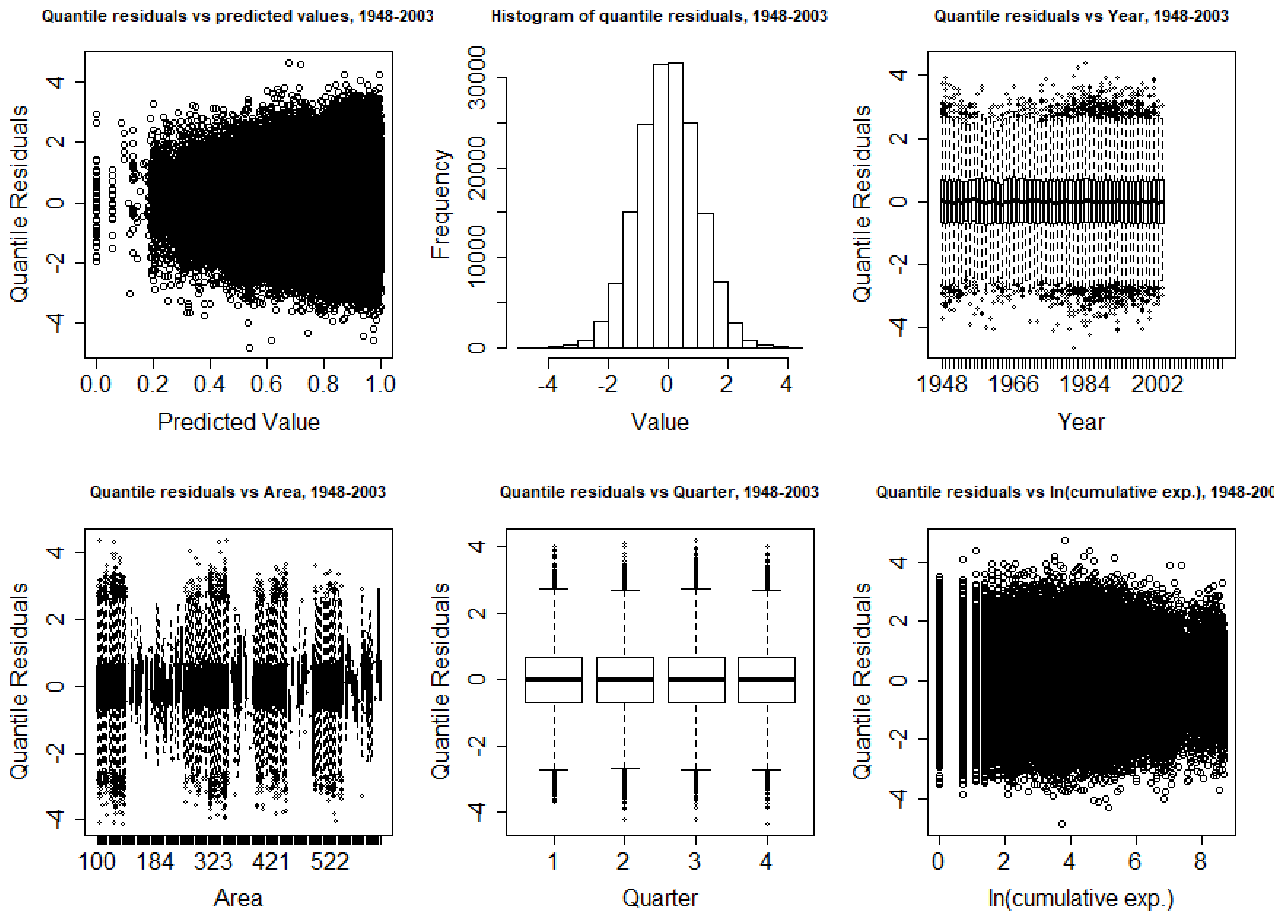


Figure 3. Model diagnostics for the best fit Bernoulli model for the early (1948-2003) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals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

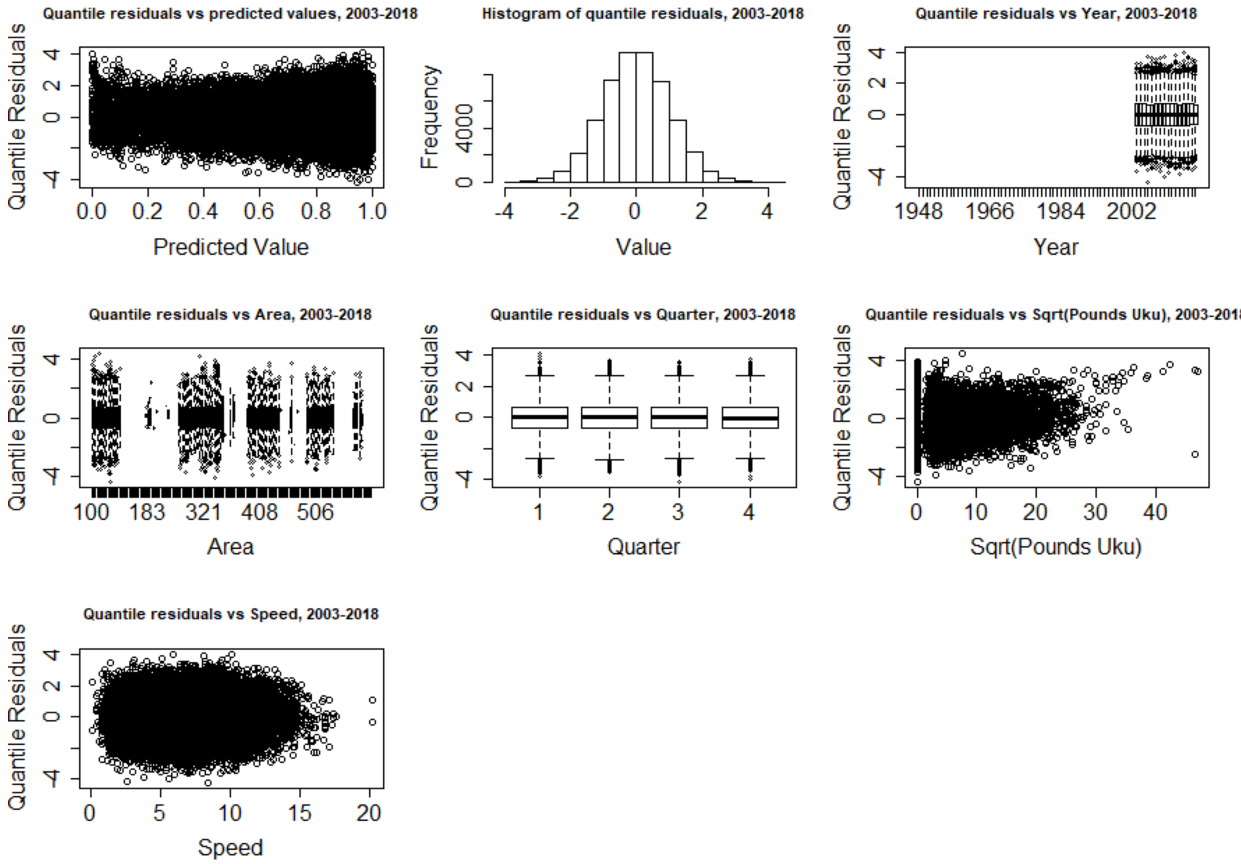


Figure 4. Model diagnostics for the best fit Bernoulli model for the recent (2003-2018) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

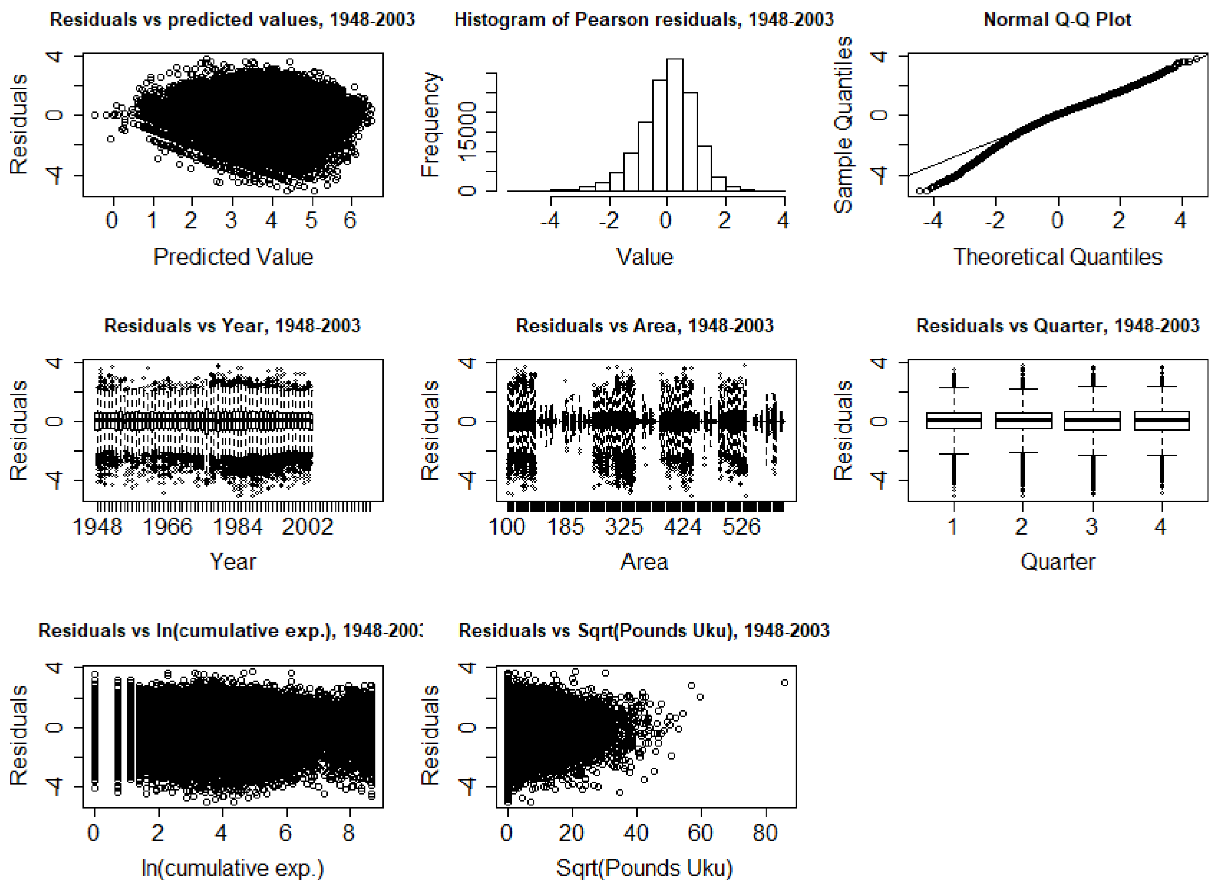


Figure 5. Model diagnostics for the best fit Lognormal model for the early (1948-2003) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

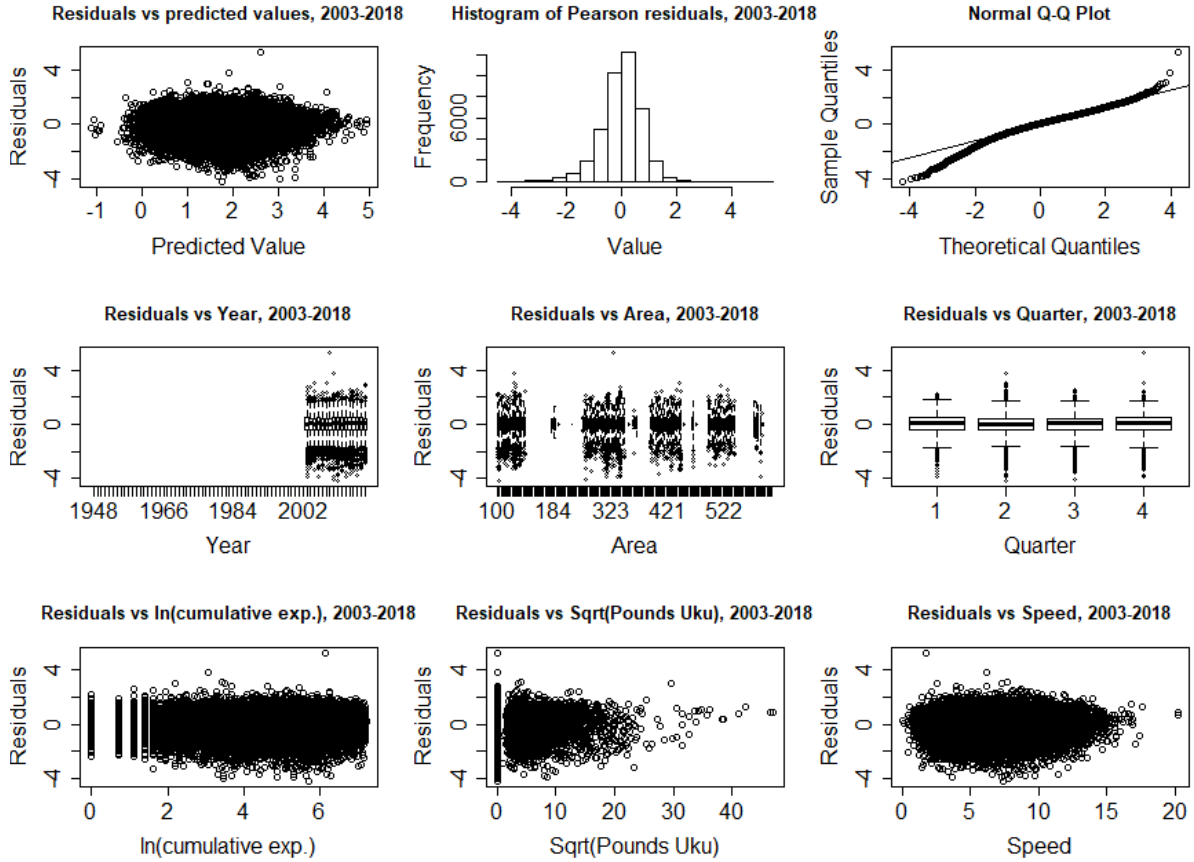


Figure 6. Model diagnostics for the best fit Lognormal model for the recent (2003-2018) time period. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

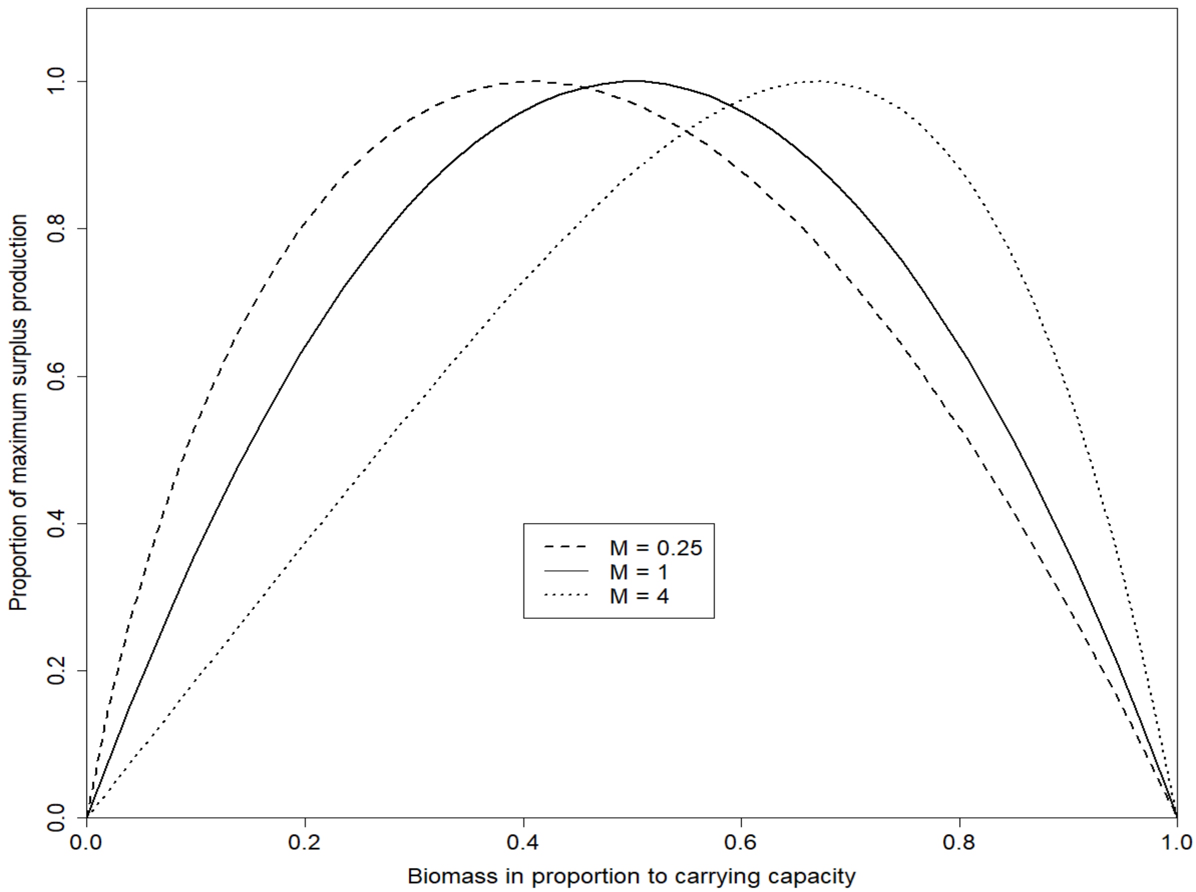


Figure 7. Effect of shape parameter M on the relationship between surplus production (expressed as proportion of maximum) and biomass (expressed as proportion of carrying capacity).

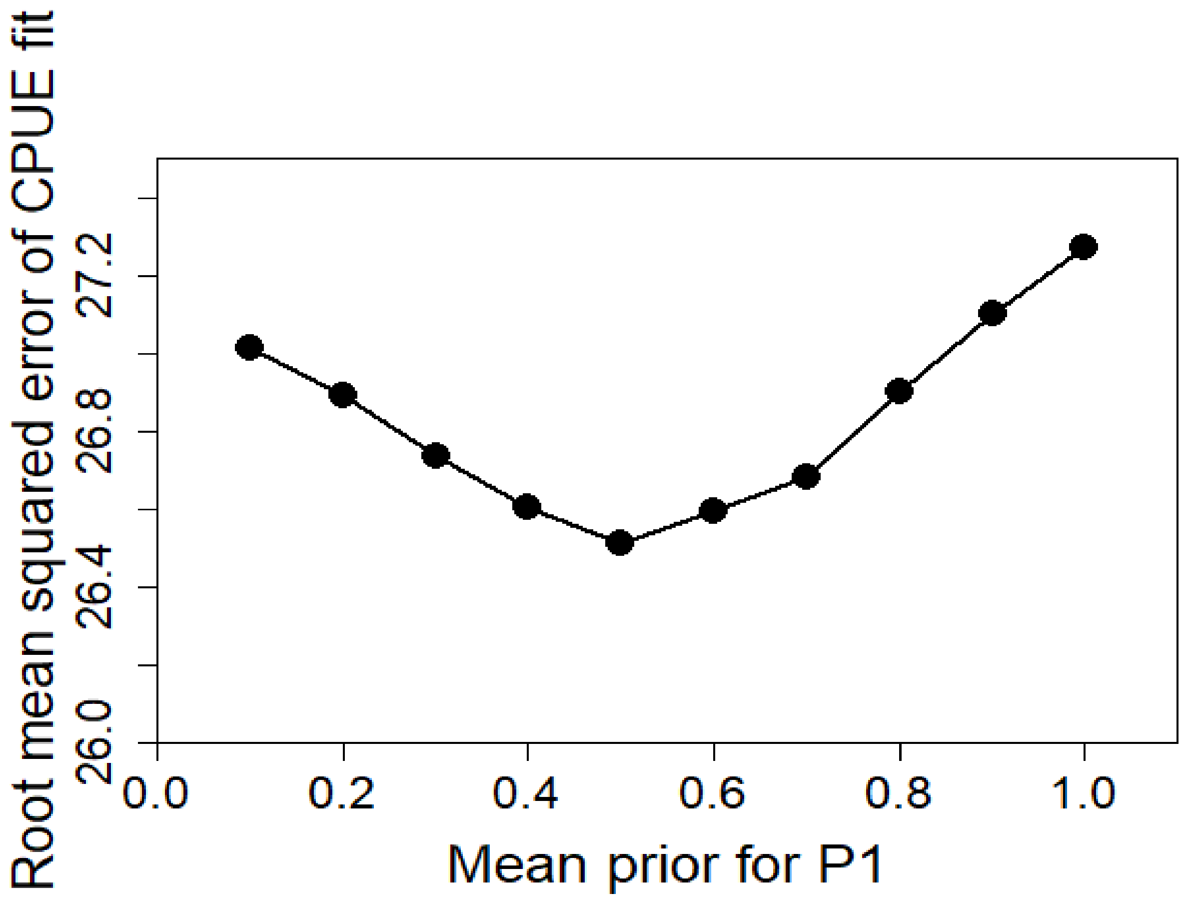


Figure 8. Goodness-of-fit values for alternative choices for the mean of the prior distribution of the initial proportion of carrying capacity (P1) for Deep 7 bottomfish in the main Hawaiian Islands.

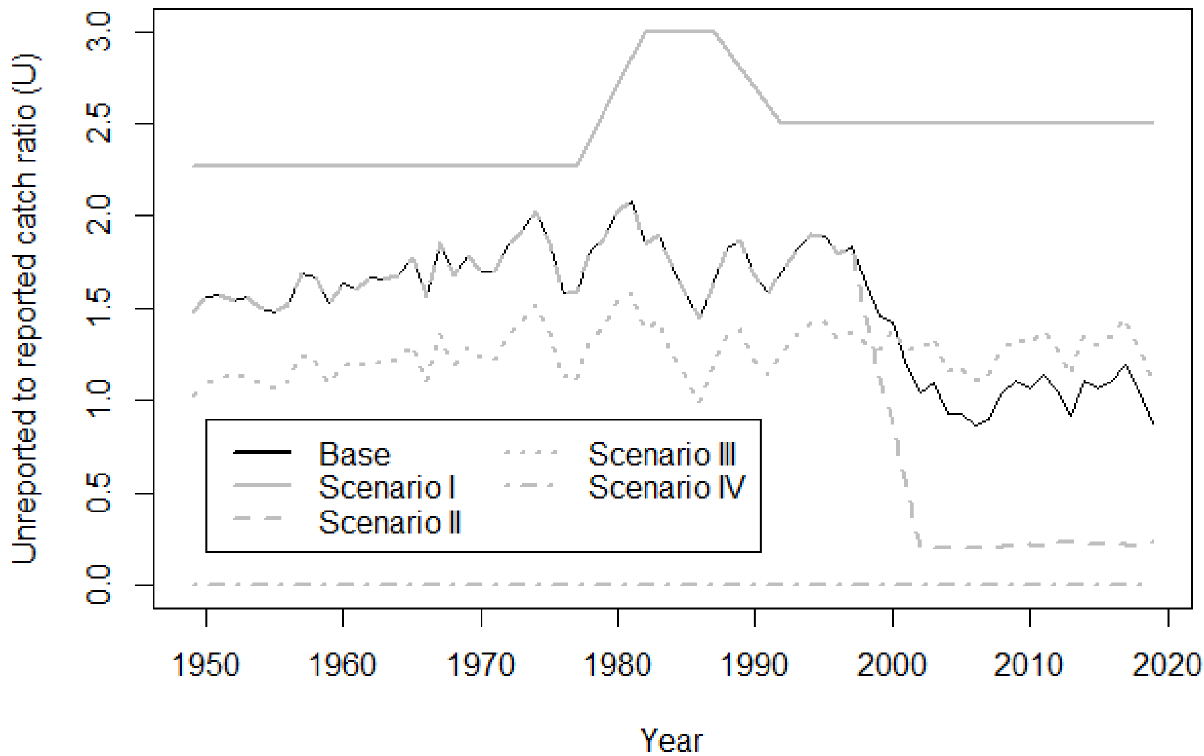


Figure 9. Unreported catch ratios (U) for the four sensitivities on alternative unreported catch (gray lines) compared to the ratios for the base model (black line). Ratios were assigned separately by species, but for ease of plotting, were averaged by catch weight across species here.

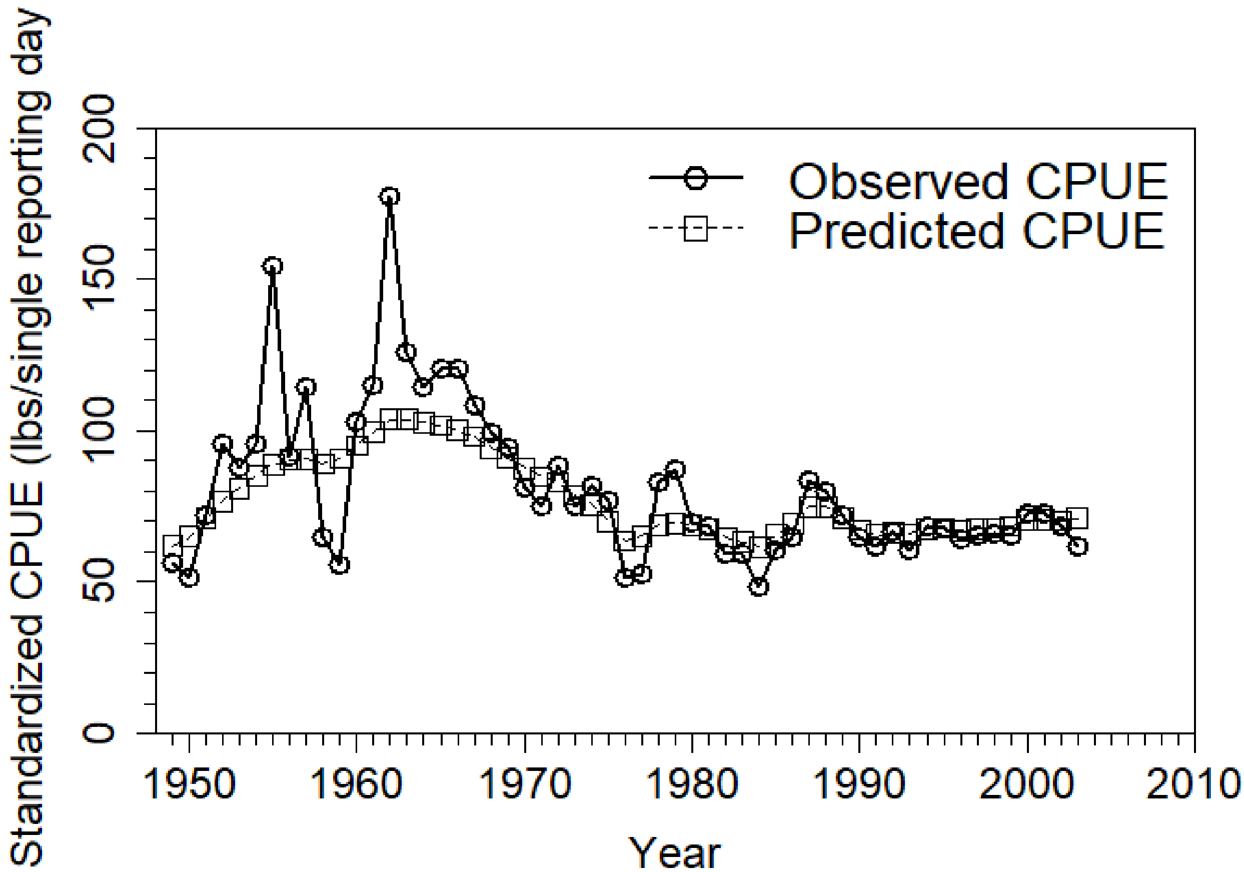


Figure 10. Observed and predicted CPUE for Deep7 bottomfish in the main Hawaiian Islands from 1949 through 2003.

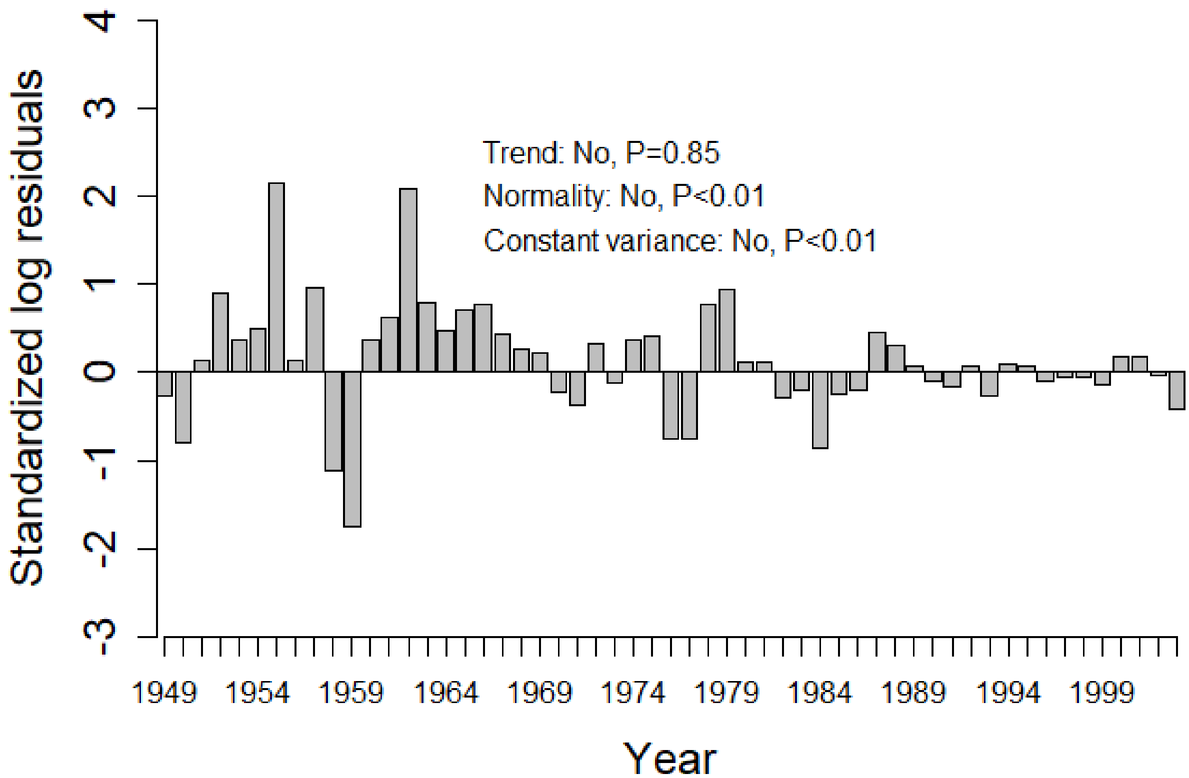


Figure 11. Standardized residuals of observed versus predicted CPUE for Deep 7 bottomfish CPUE in the main Hawaiian Islands by fishing year from 1949-2003 and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

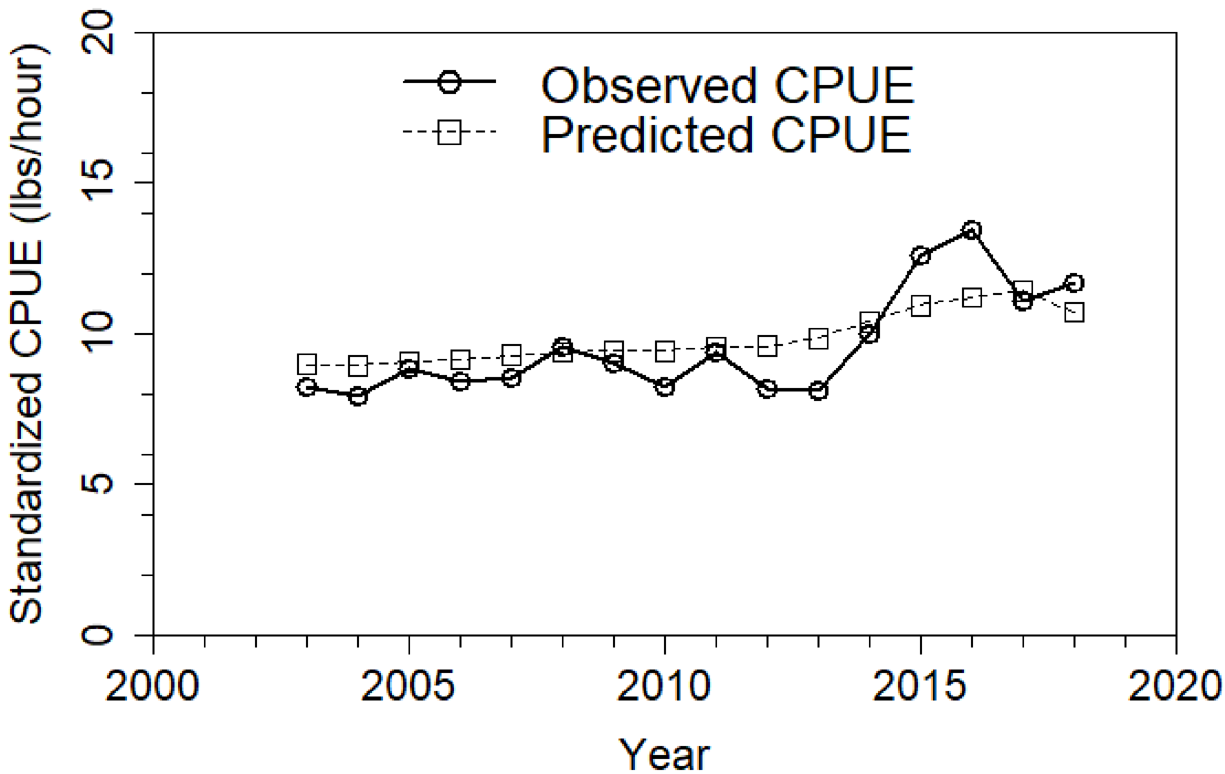


Figure 12. Observed and predicted CPUE for Deep 7 bottomfish in the main Hawaiian Islands from 2003 through 2018.

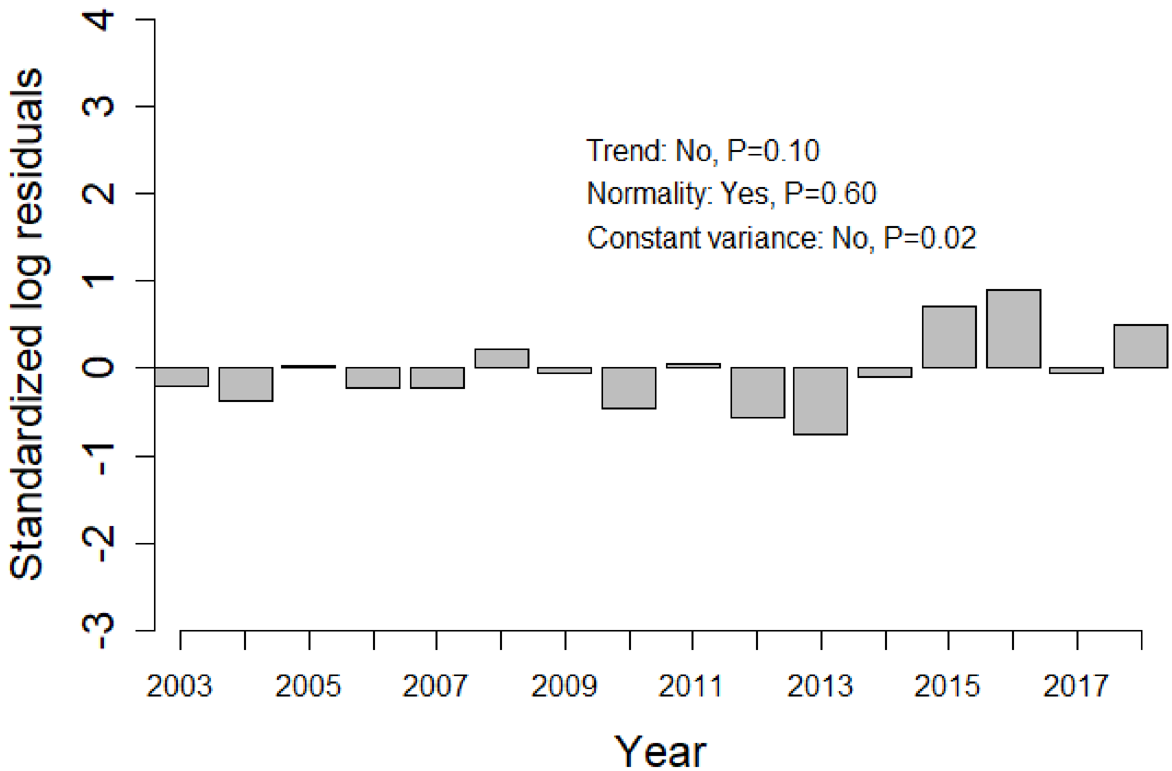


Figure 13. Standardized residuals of observed versus predicted CPUE for Deep 7 bottomfish CPUE in the main Hawaiian Islands by fishing year from 2003-2018, and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

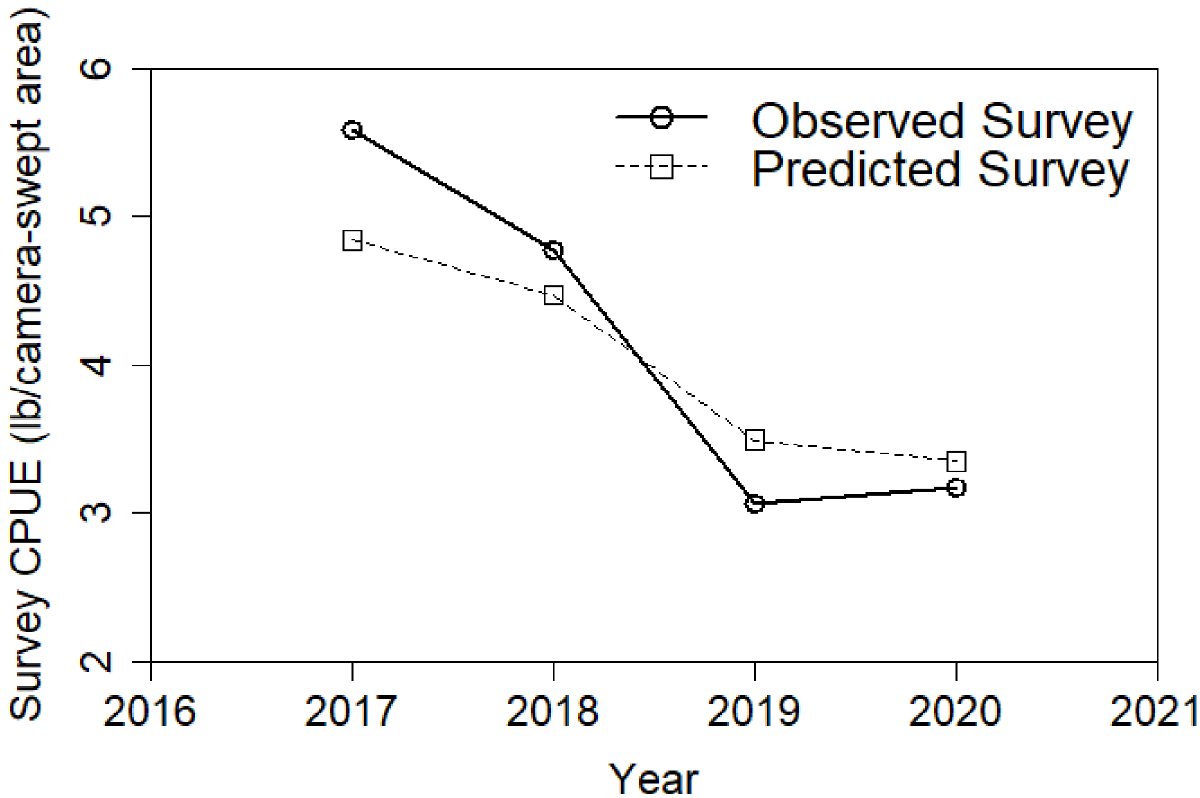


Figure 14. Observed and predicted CPUE for Deep 7 bottomfish in the fishery-independent survey around the main Hawaiian Islands from 2017 through 2020.

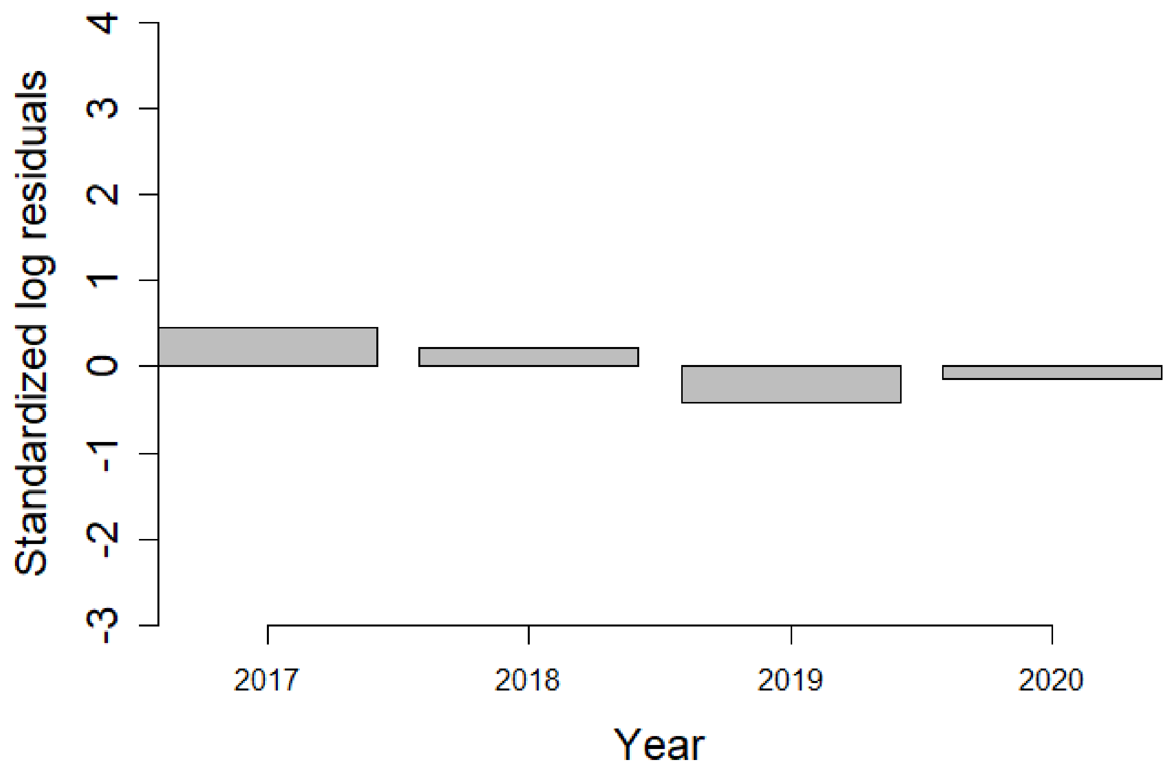


Figure 15. Standardized residuals of observed versus predicted CPUE for Deep 7 bottomfish CPUE in the fishery-independent survey around the main Hawaiian Islands around the main Hawaiian Islands by fishing year from 2017-2020.

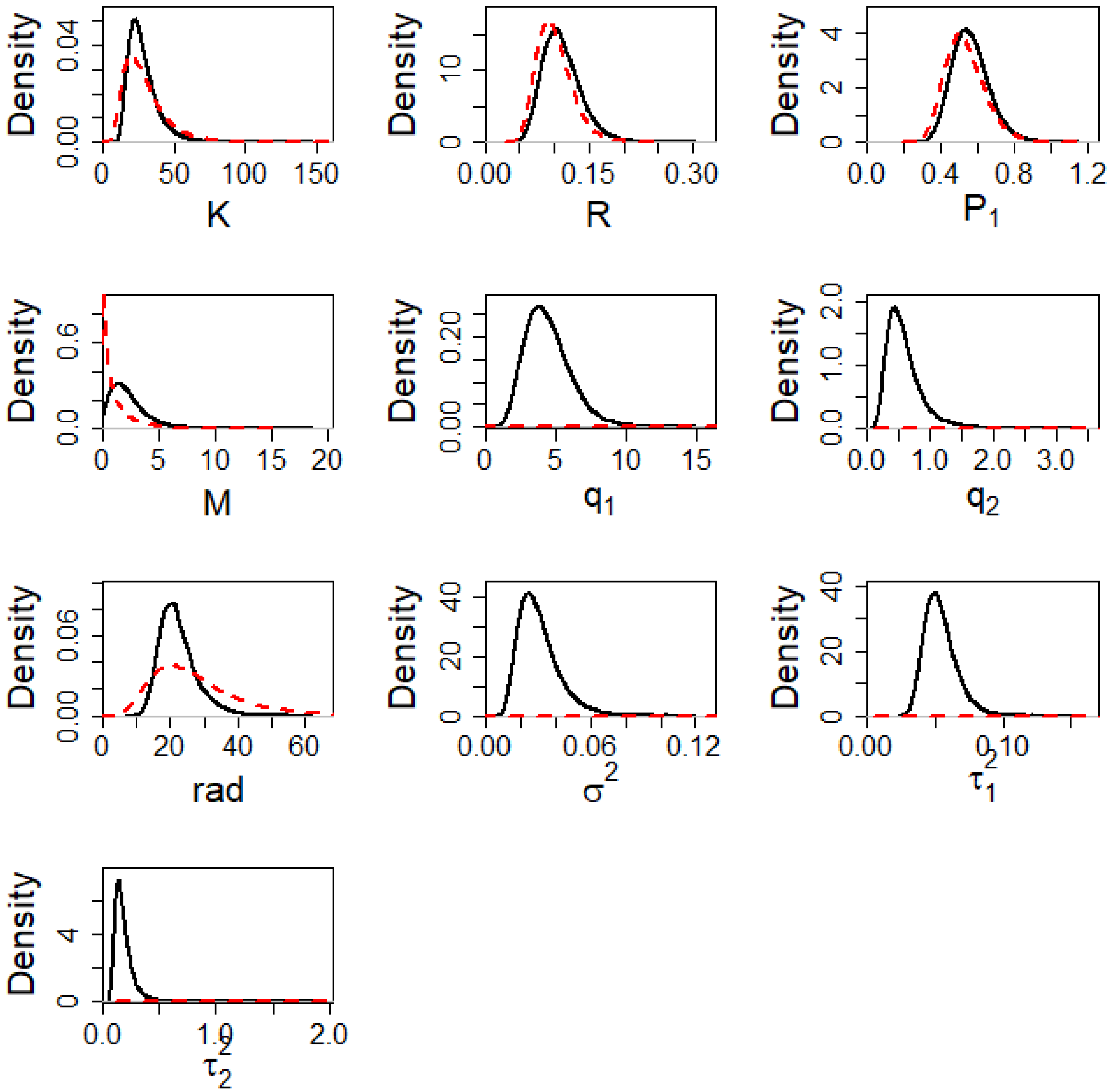


Figure 16. Prior distributions (dashed red line) and posterior densities (solid black line) for model parameters including carrying capacity (K), intrinsic growth rate (R), initial proportion of carrying capacity (P1), shape parameter (M), catchability in the early (*q_1*) and recent (*q_2*) time periods, 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.

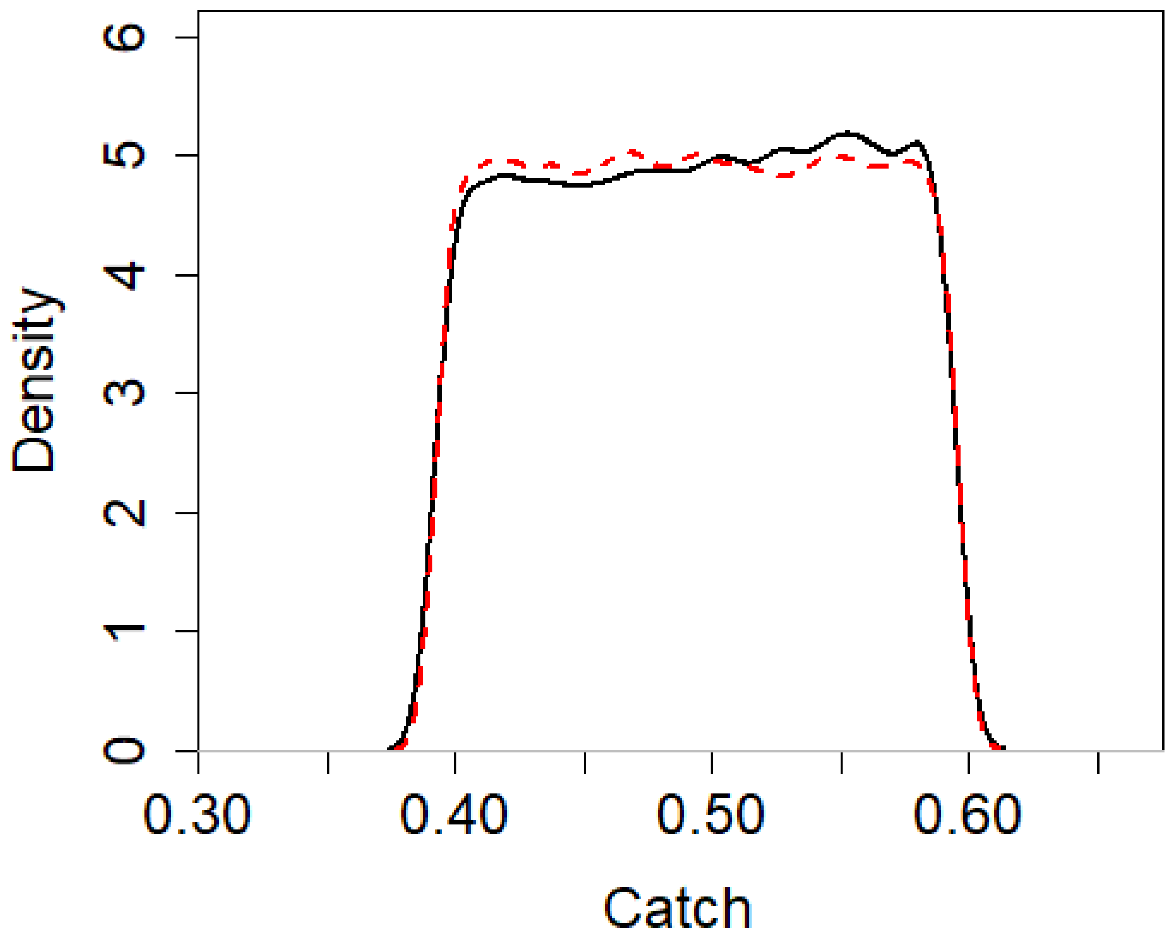


Figure 17. Uniform prior distribution (dashed red line) and posterior density (solid black line) for total Deep 7 bottomfish catch (million lb) in the main Hawaiian Islands in 2018.

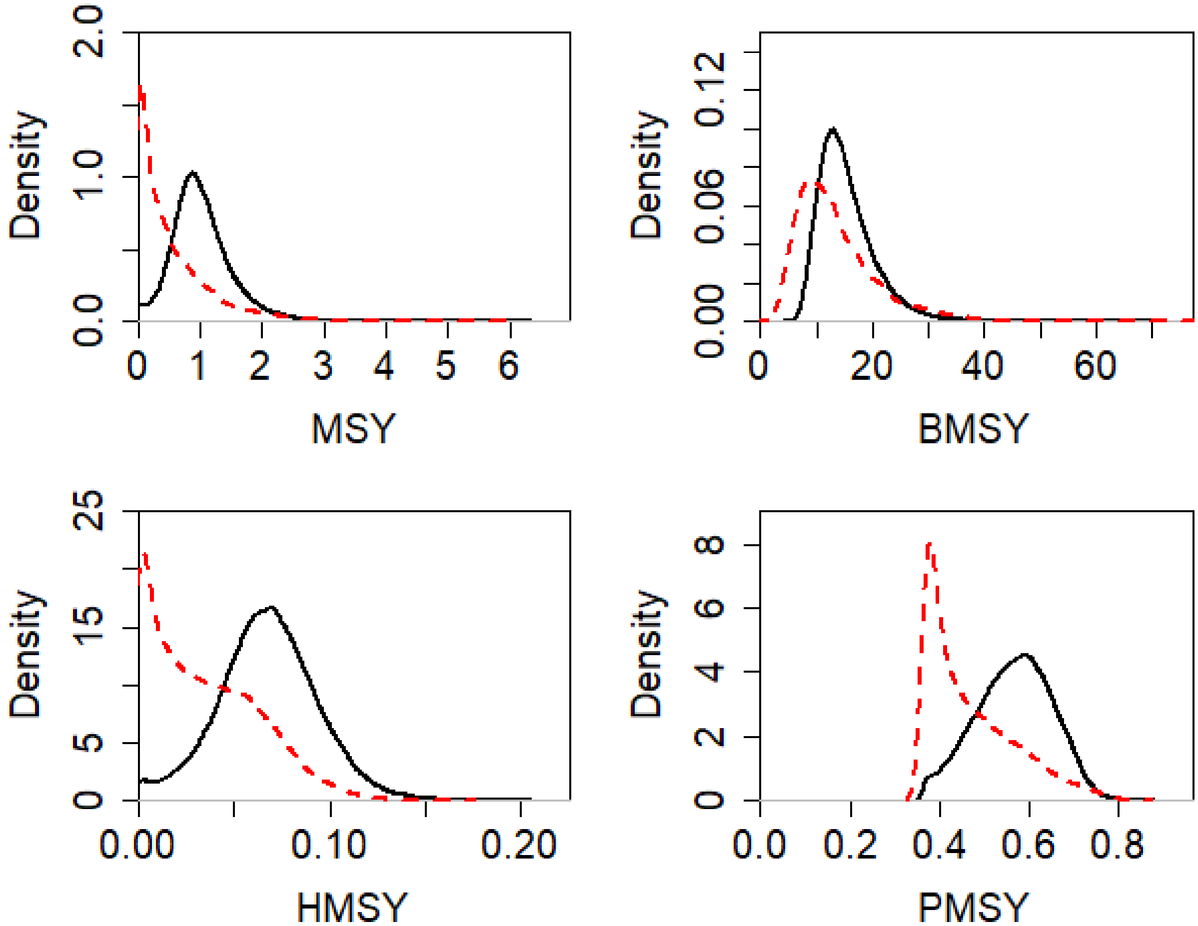


Figure 18. Calculated prior distributions (dashed red lines) and posterior densities (solid lines) for model estimates of maximum sustainable yield (MSY), biomass to produce MSY (BMSY), harvest rate to produce MSY (HMSY), and proportion of carrying capacity to produce MSY (P_{MSY}) for Deep 7 bottomfish in the main Hawaiian Islands.

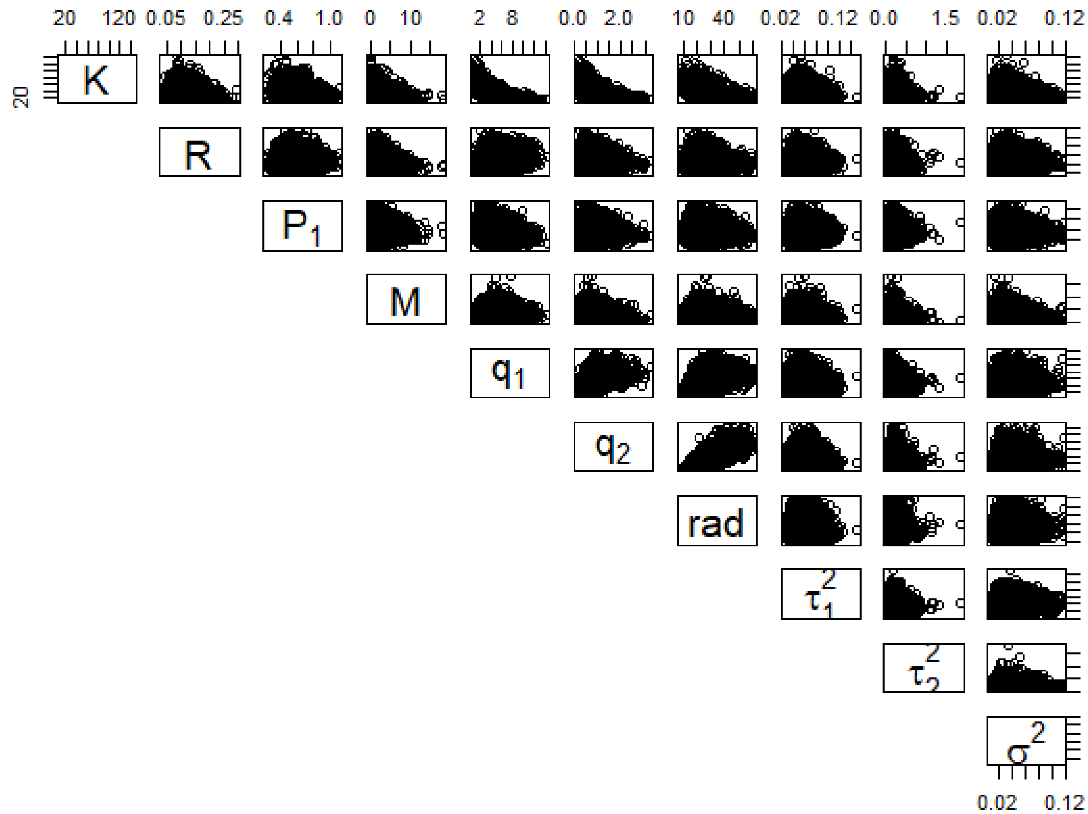


Figure 19. Pairwise scatterplots of parameter estimates. Parameters are carrying capacity (K), intrinsic growth rate (R), initial proportion of carrying capacity (P1), shape parameter (M), catchability in first (q1) and second (q2) time periods, survey sample radius (*rad*), observation error in first (τ_1^2) and second (τ_2^2) time periods, and process error (σ^2).

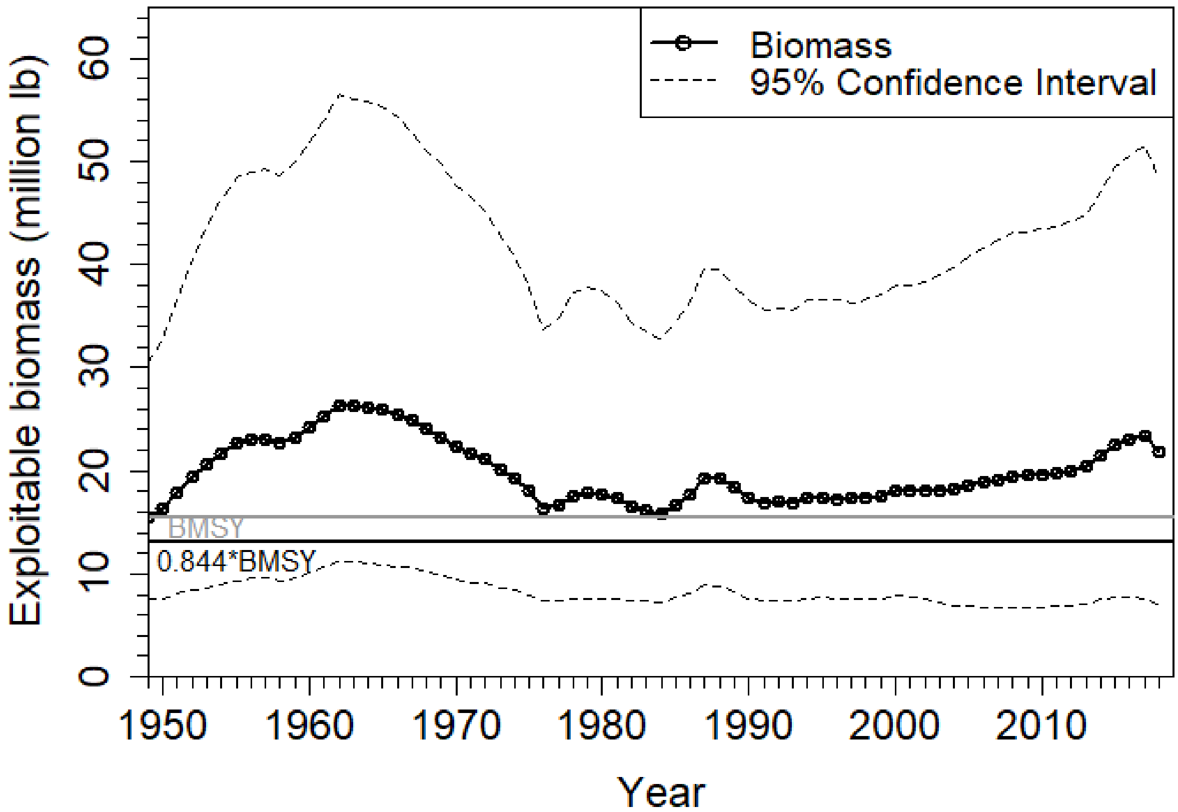


Figure 20. Estimated exploitable biomass (solid line) with 95% credible interval (dashed lines) for Deep 7 bottomfish in the main Hawaiian Islands from 1949 through 2018. Horizontal gray line depicts BMSY, and black line depicts the 0.844*BMSY reference point.

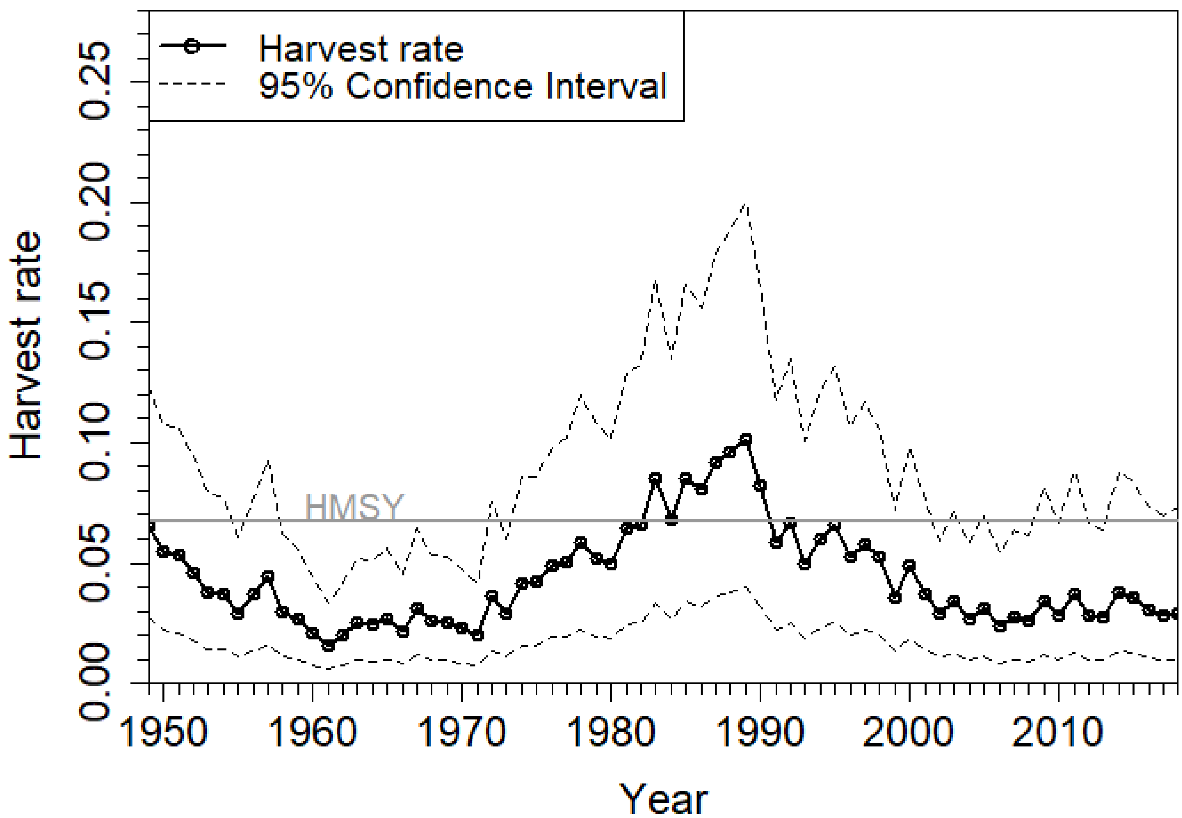


Figure 21. Estimated harvest rate (solid line) with 95% credible interval (dashed lines) for Deep 7 bottomfish in the main Hawaiian Islands from 1949 through 2018. Horizontal gray line depicts HMSY reference point.

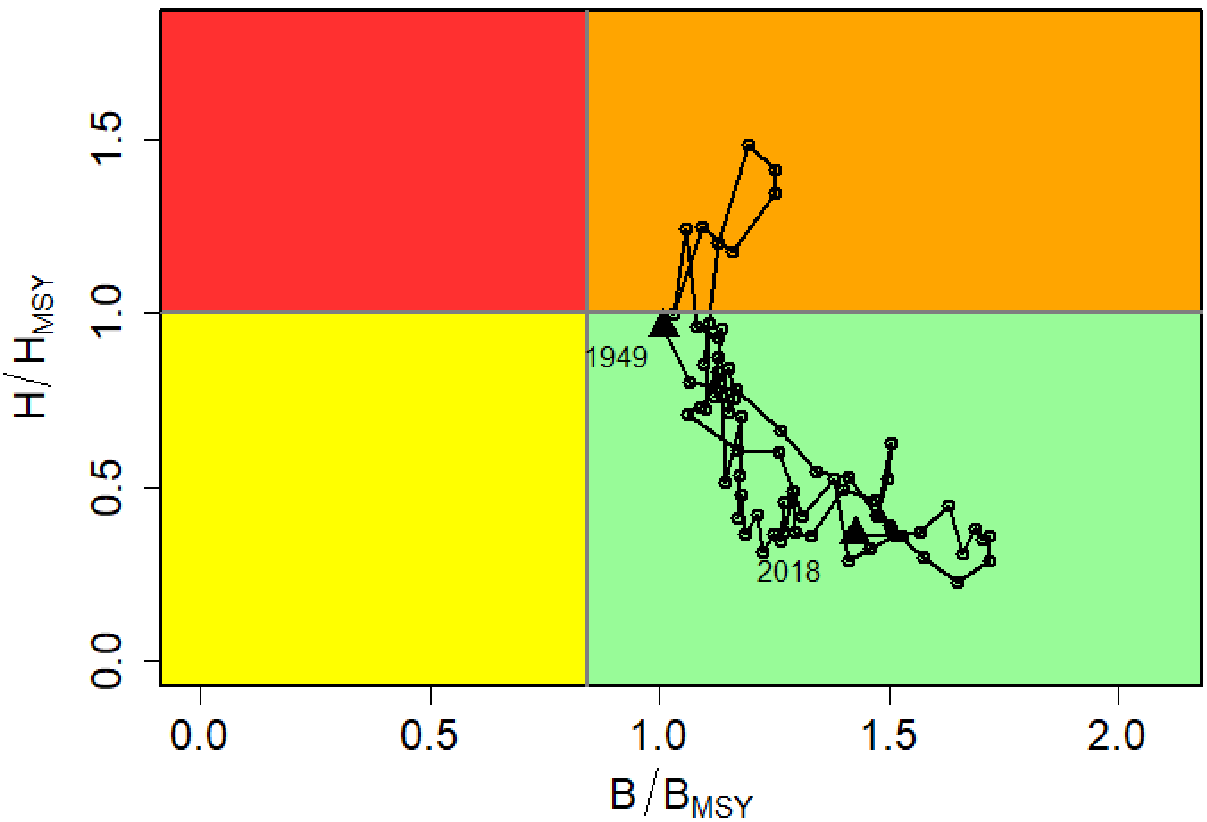


Figure 22. Estimated status for Deep 7 Bottomfish in the main Hawaiian Islands from 1949 through 2018. Triangles delineate start and end years. Horizontal and vertical lines delineate reference points for overfishing (i.e., H/HMSY>1) and overfished status (i.e., B/B_{MSY}< 0.844).

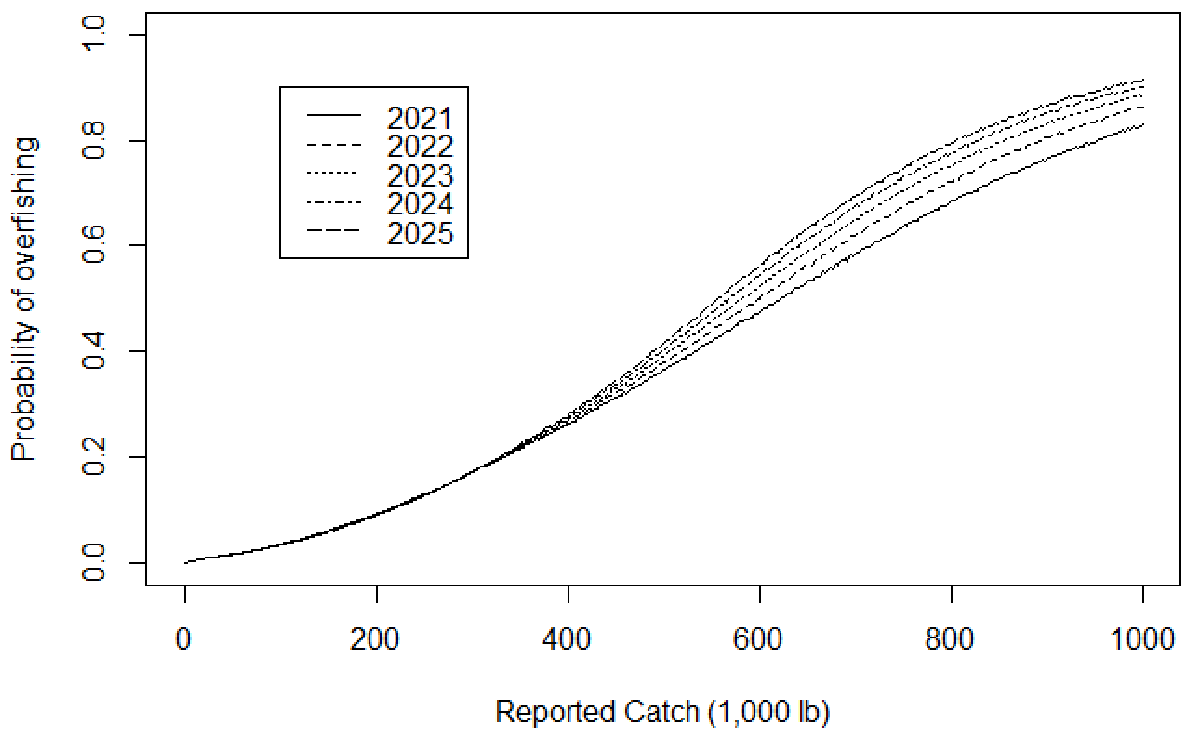


Figure 23. Probability of overfishing (i.e., H/HMSY>1) Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2021 through 2025 as a function of projected reported catch varying from 0 to 1 million pounds.

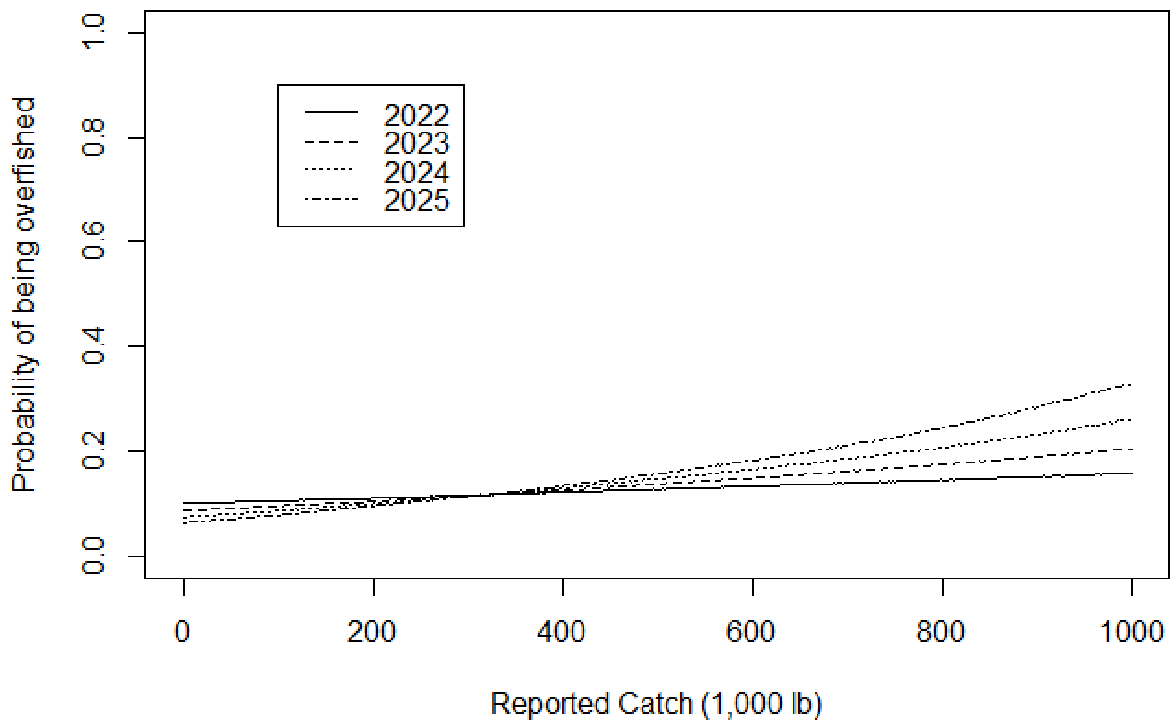


Figure 24. Probability of the stock being overfished (i.e., B/BMSY<0.844) for Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2022 through 2025 as a function of projected reported catch varying from 0 to 1 million pounds (2021 was not shown because it was not a function of simulated alternative catch values).

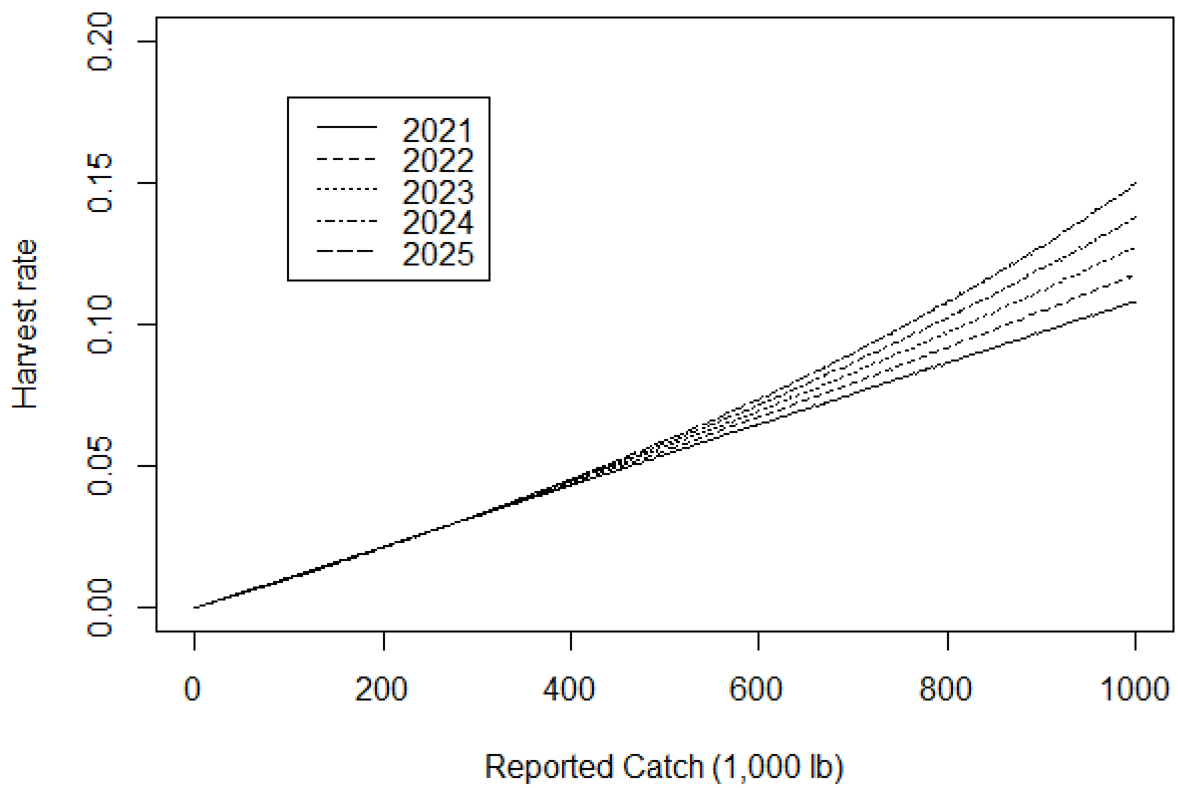


Figure 25. Median harvest rate for Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2021 through 2025 as a function of projected reported catch varying from 0 to 1 million pounds.

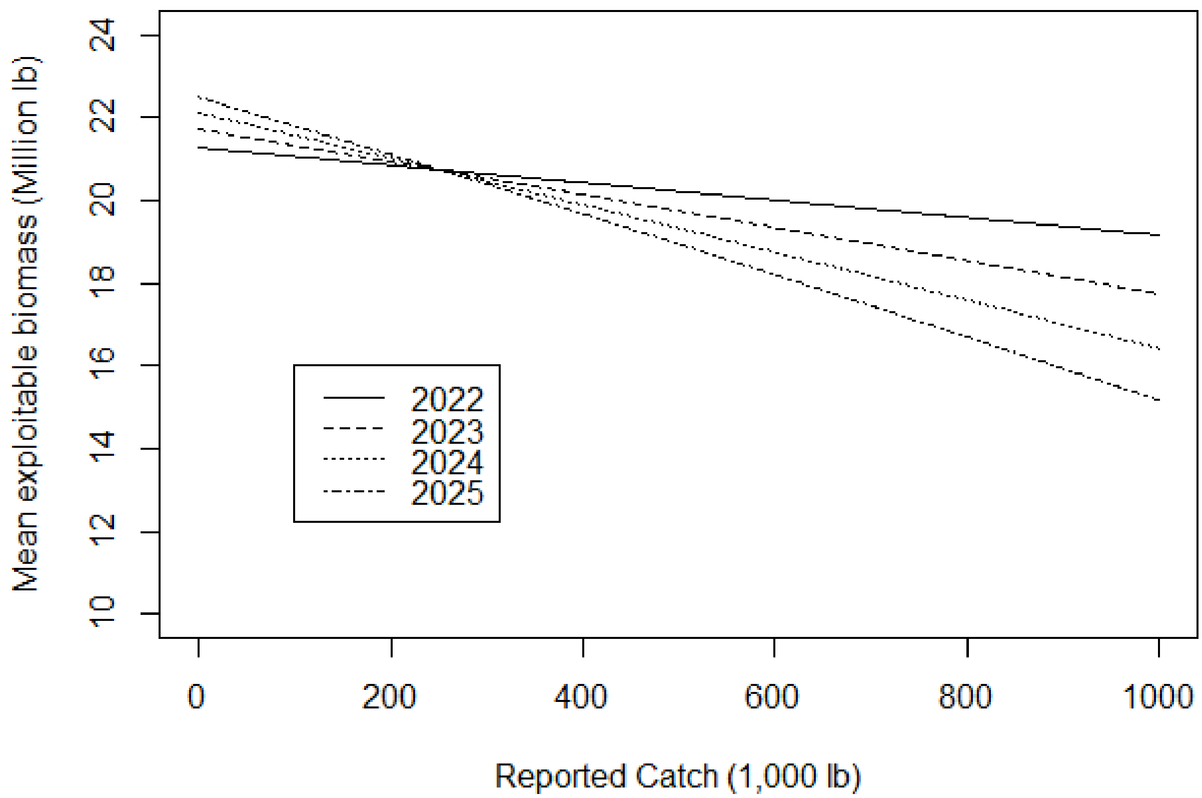


Figure 26. Mean exploitable biomass for Deep 7 bottomfish in the main Hawaiian Islands in fishing years 2022 through 2025 as a function of projected reported catch varying from 0 to 1 million pounds (biomass in 2021 is not shown because it was not a function of simulated alternative catch values).

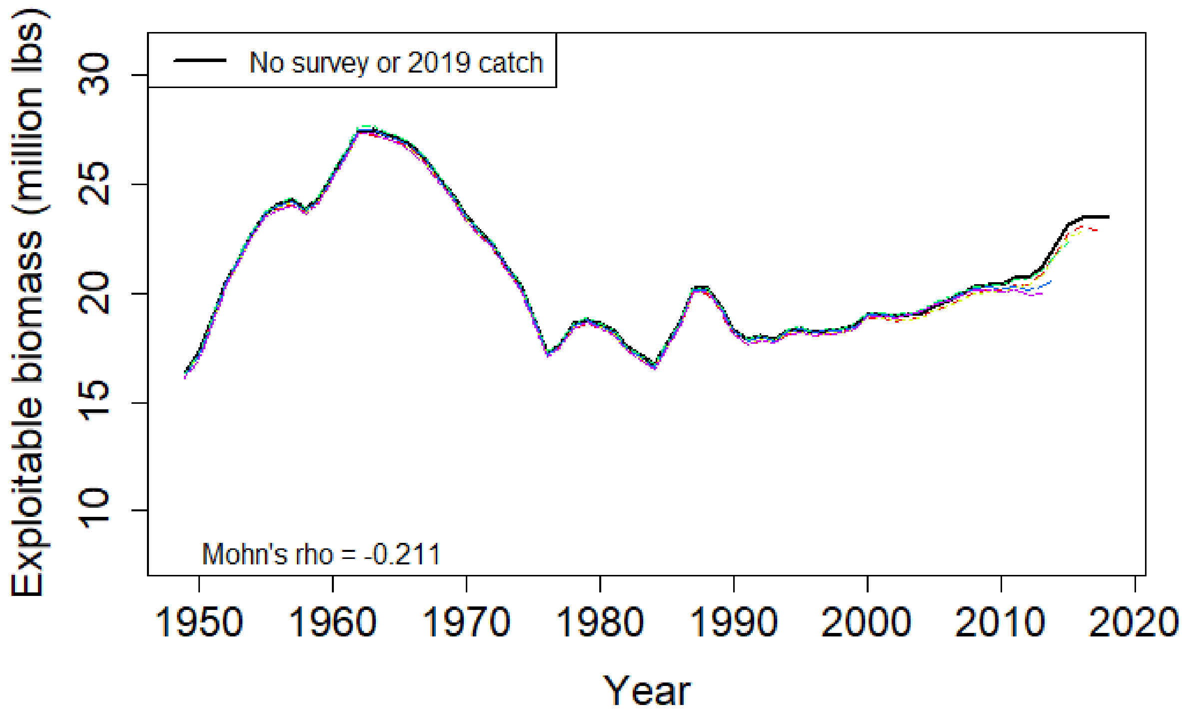


Figure 27. Retrospective analysis for estimated mean exploitable biomass from a model excluding the fishery-independent survey and with terminal year set as fishing year 2018 through 2014.

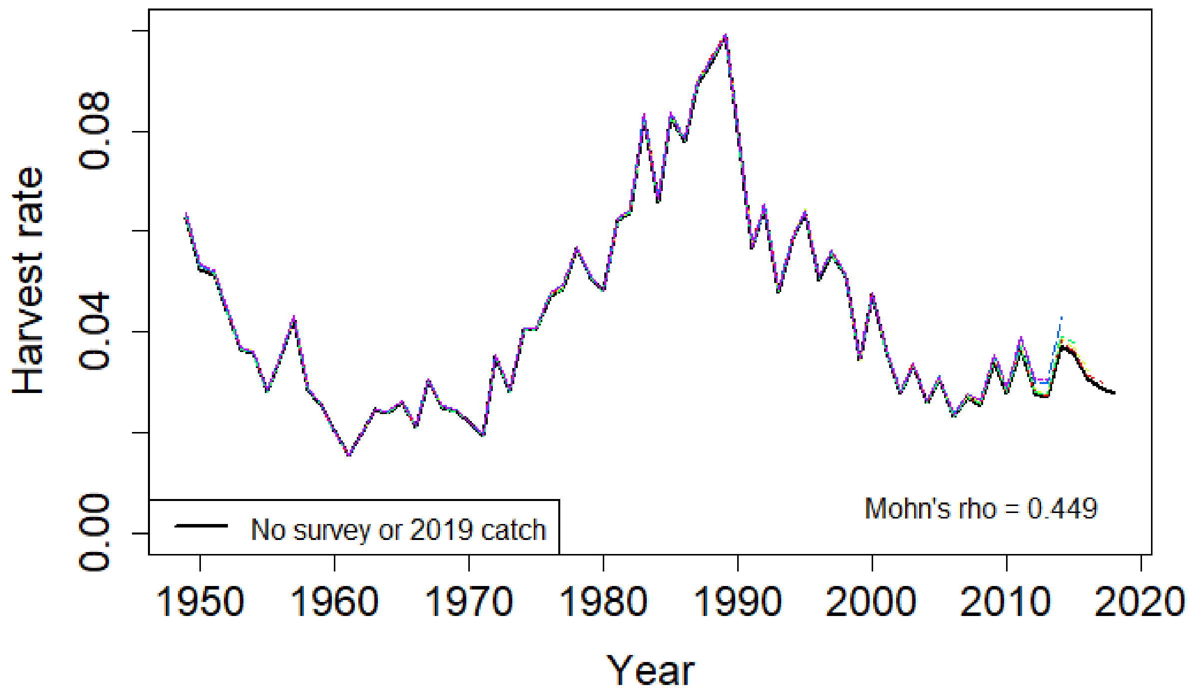


Figure 28. Retrospective analysis for estimated mean harvest rate from a model excluding the fishery-independent survey and with terminal year set as 2018 through 2014.

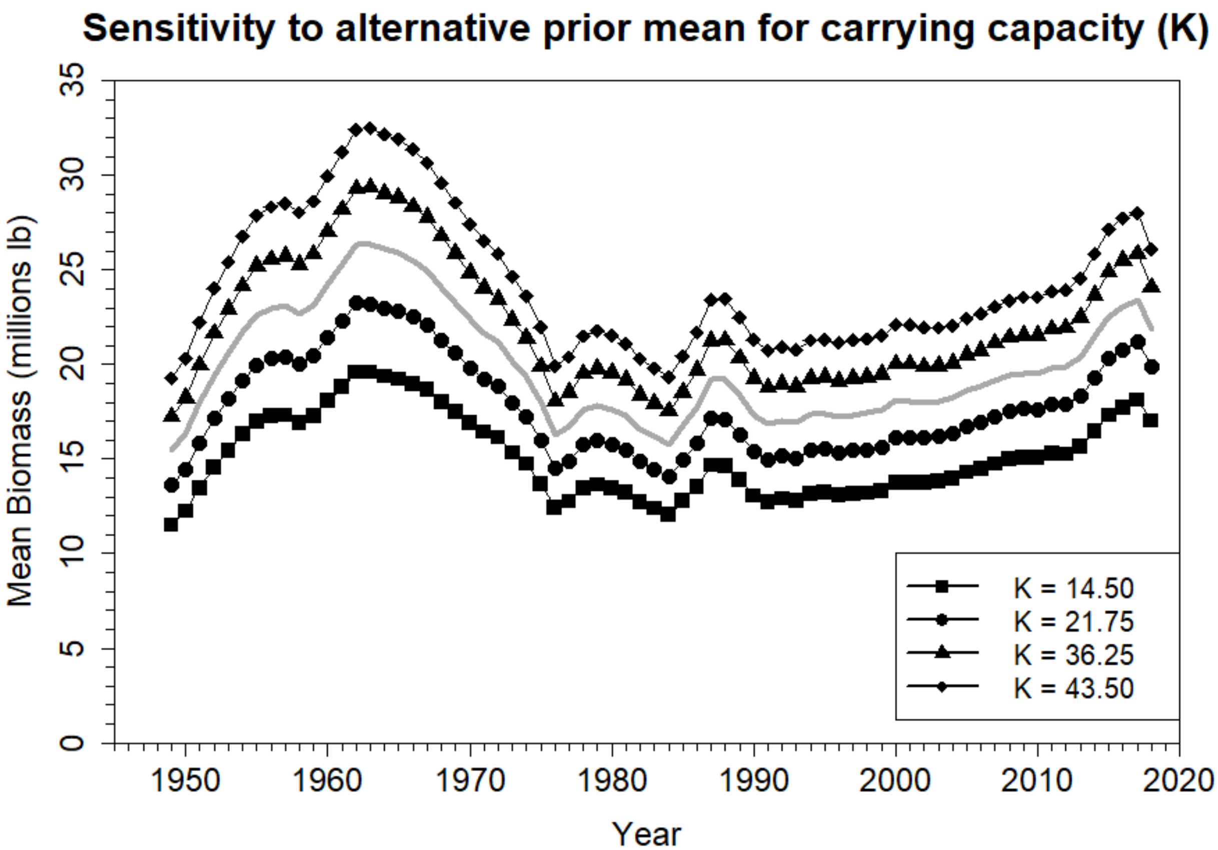


Figure 29. Estimated mean exploitable biomass as a function of different prior means for carrying capacity (K). Values of K were calculated as +/-25% and +/-50% of the mean value used for the base case (µK = 29 million lbs.; gray line).

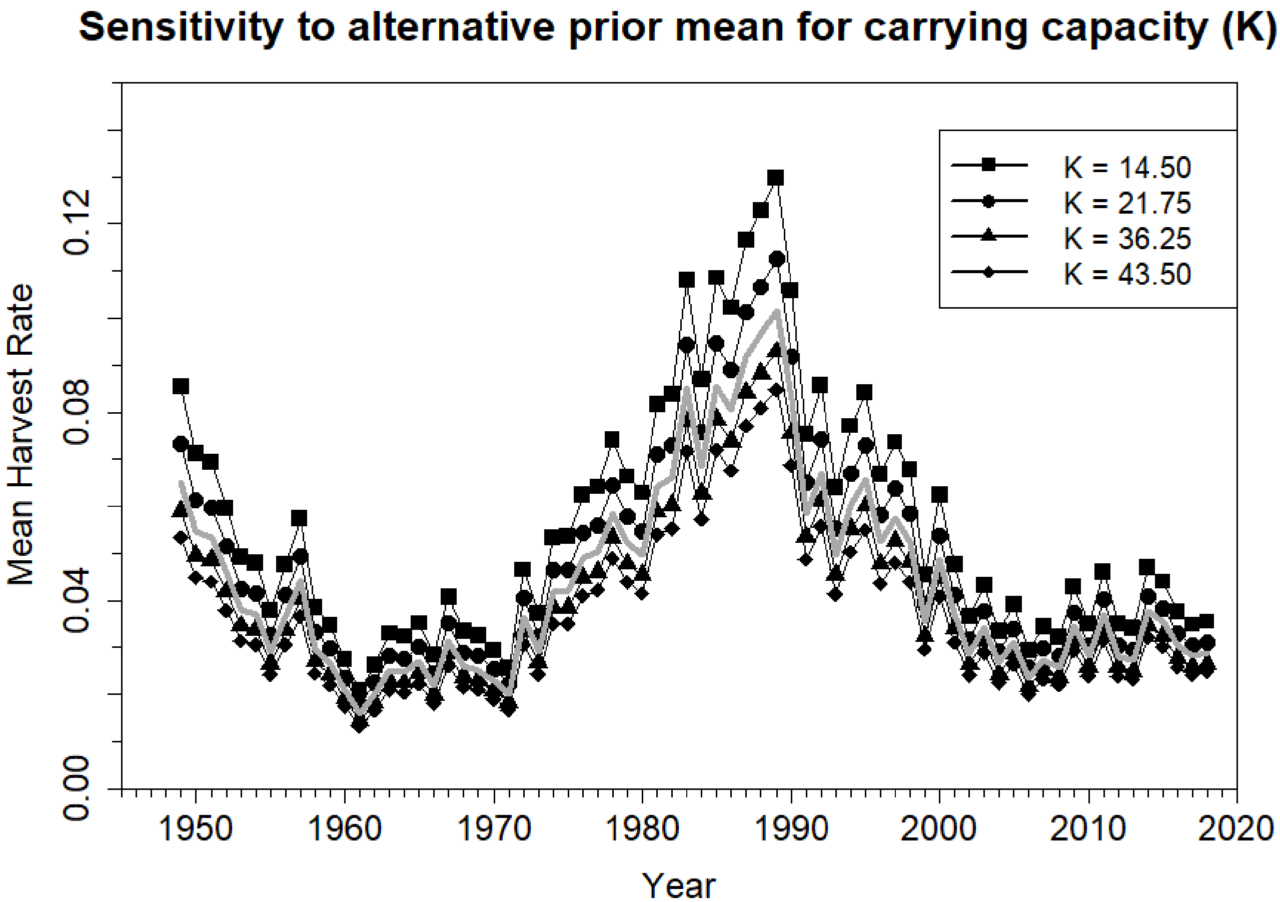


Figure 30. Estimated mean harvest rate as a function of different prior means for carrying capacity (K). Values of K were calculated as +/-25% and +/-50% of the mean value used for the base case (μK = 29 million lbs.; gray line).

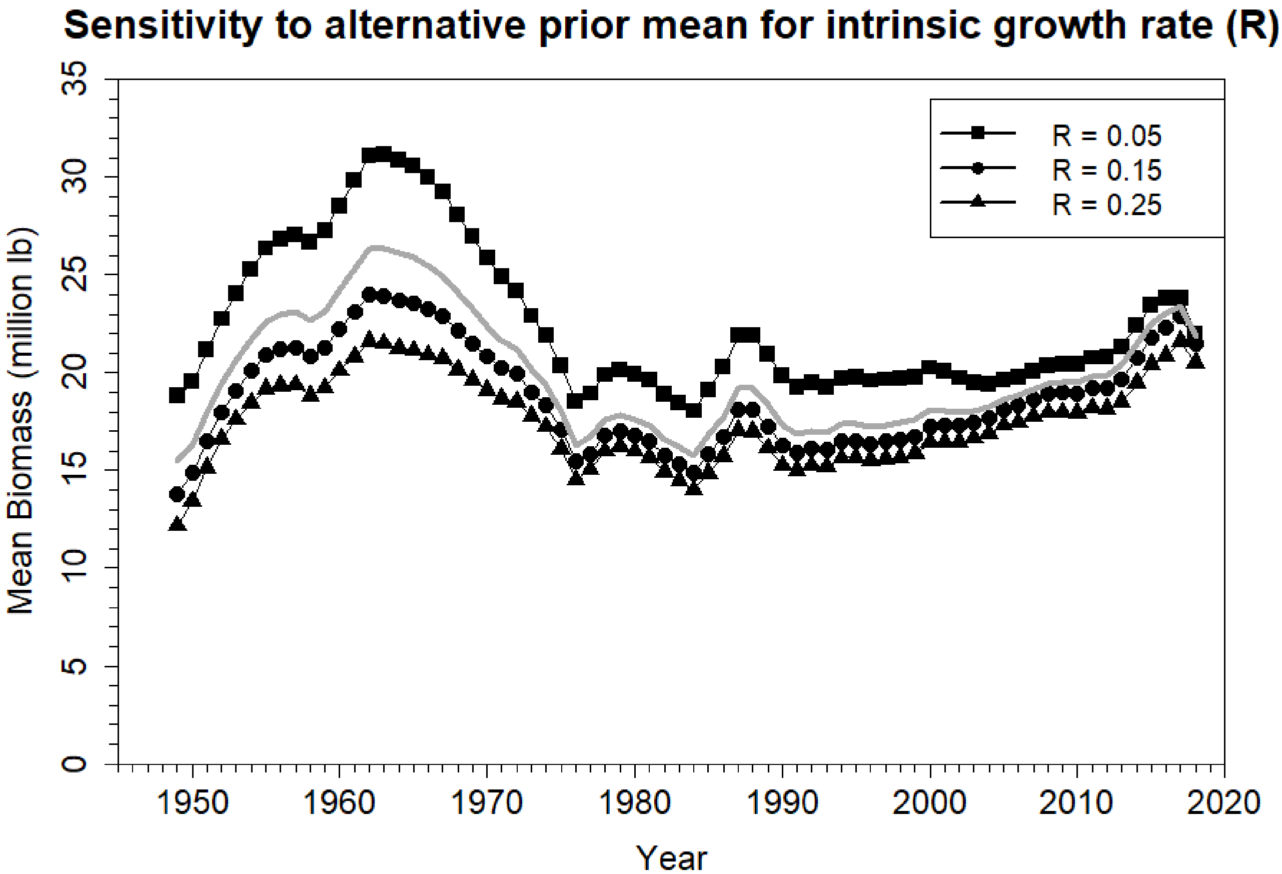


Figure 31. Estimated mean exploitable biomass as a function of different prior means for intrinsic growth rate (R). Values of R were calculated as +/- 50% and +150% of the mean value used for the base case (μR = 0.10.; gray line).

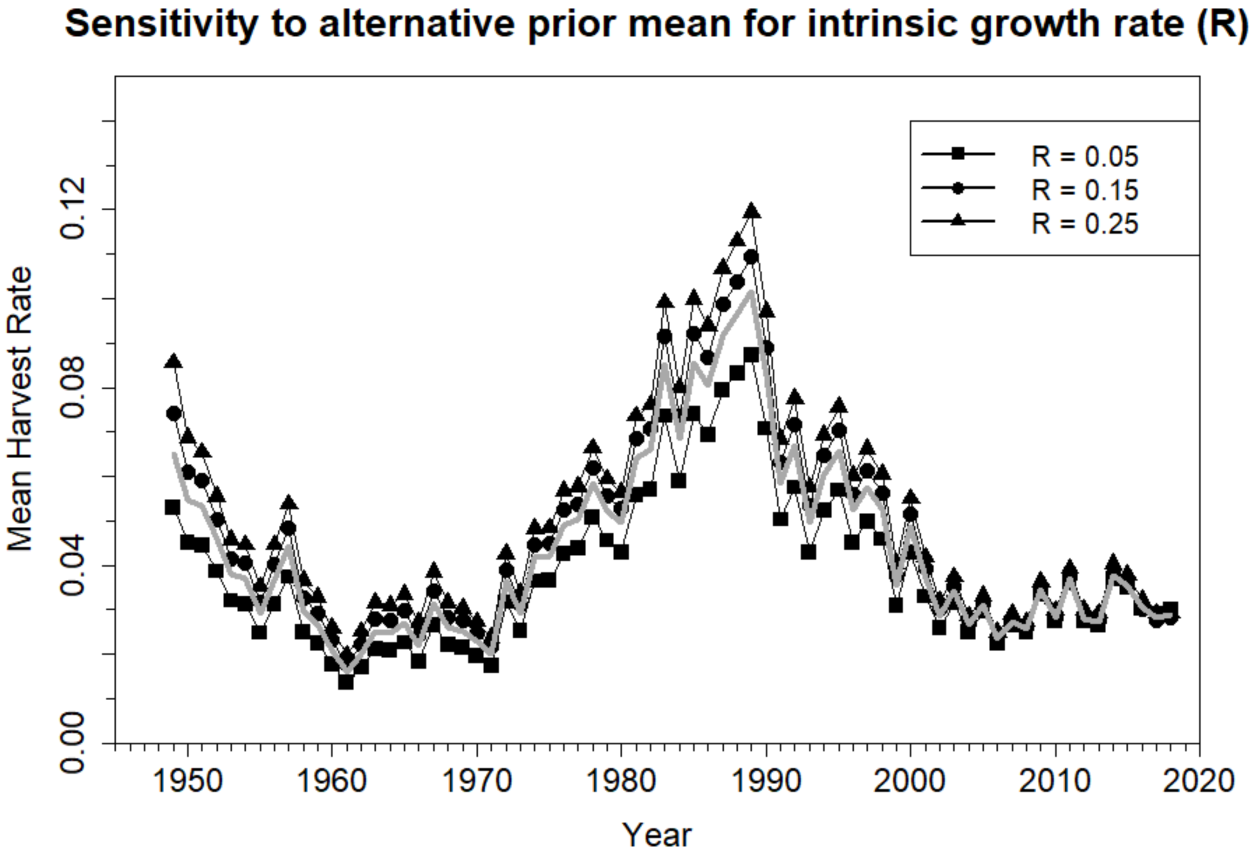


Figure 32. Estimated mean harvest rate as a function of different prior means for intrinsic growth rate (R). Values of R were calculated as +/- 50% and +150% of the mean value used for the base case (µR = 0.10.; gray line).

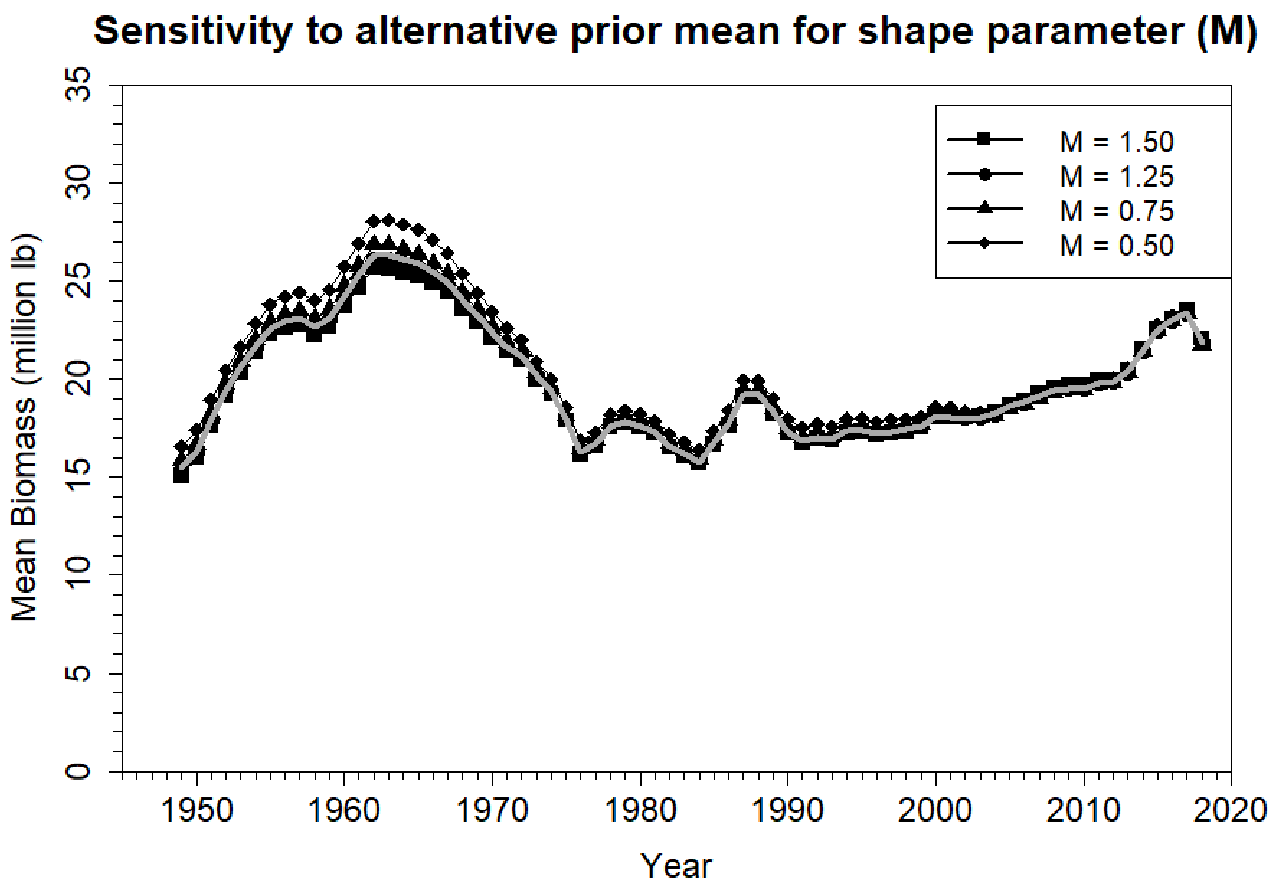


Figure 33. Estimated mean exploitable biomass as a function of different prior means for the shape parameter (M). Values of M were calculated as +/- 25% and +/- 50% of the mean value used for the base case (µM = 1.00.; gray line).

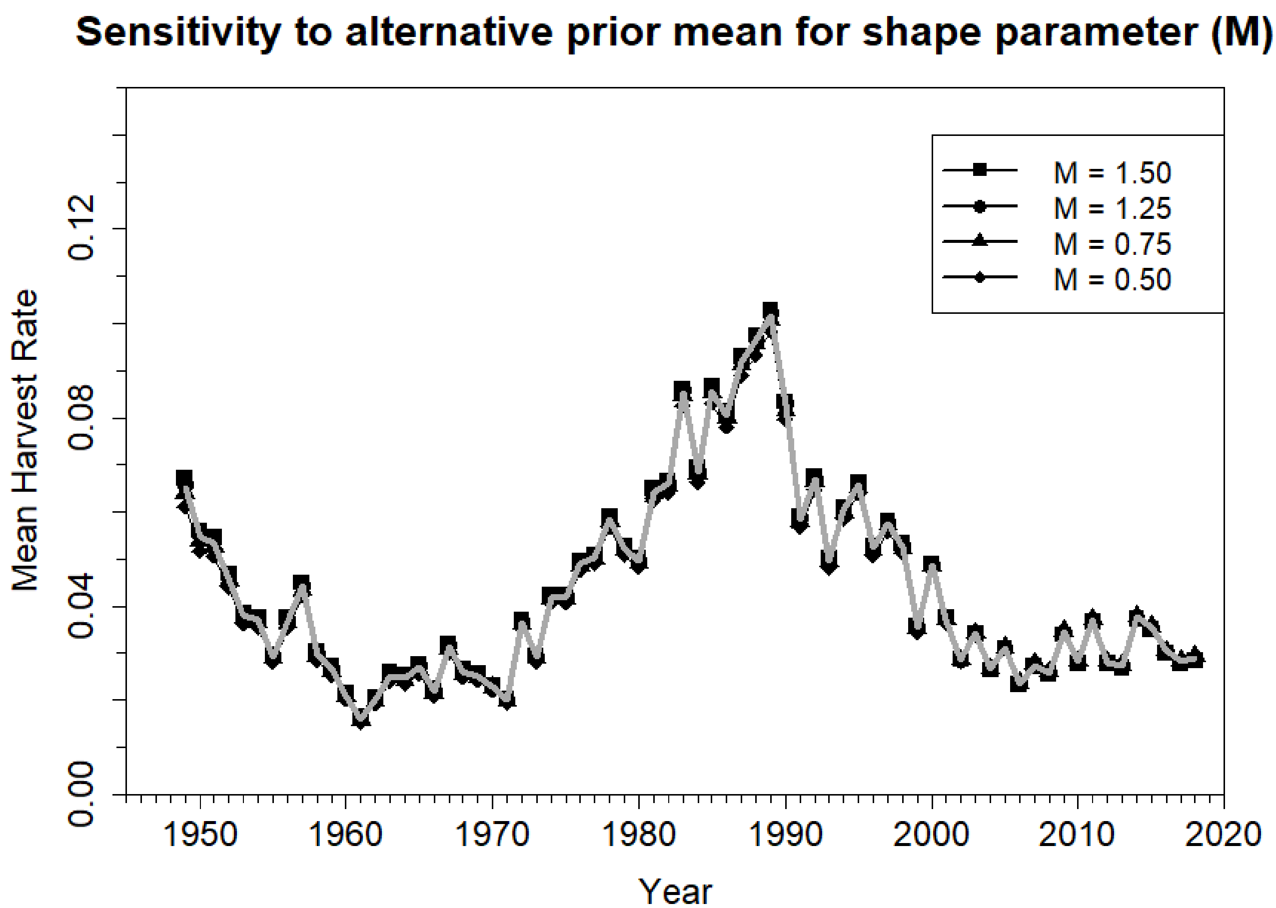


Figure 34. Estimated mean harvest rate as a function of different prior means for the shape parameter (M). Values of M were calculated as +/- 25% and +/- 50% of the mean value used for the base case (μM = 1.00.; gray line).

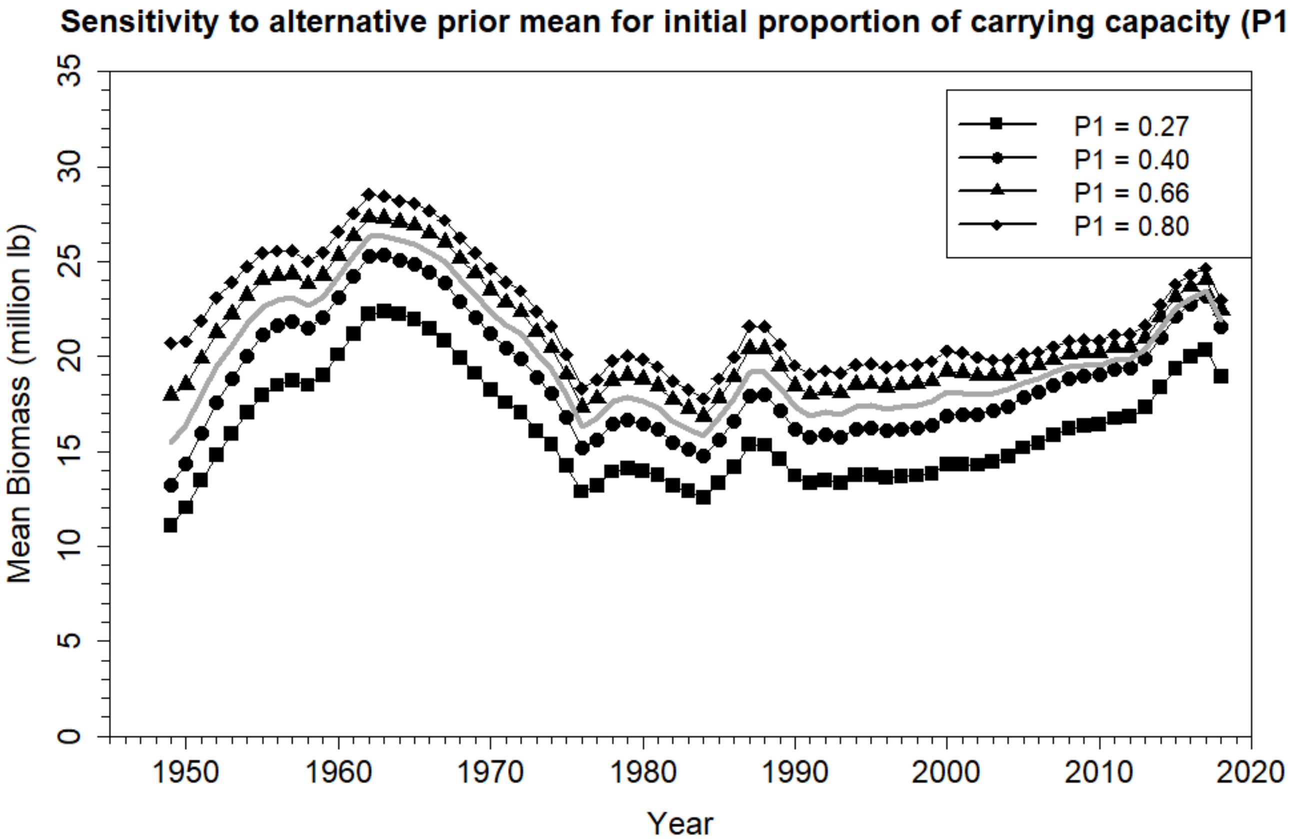


Figure 35. Estimated mean exploitable biomass as a function of different prior means for the initial proportion of carrying capacity (P1). Values of P1 were calculated as +/- 25% and +/- 50% of the mean value used for the base case (µP = 0.53.; gray line).

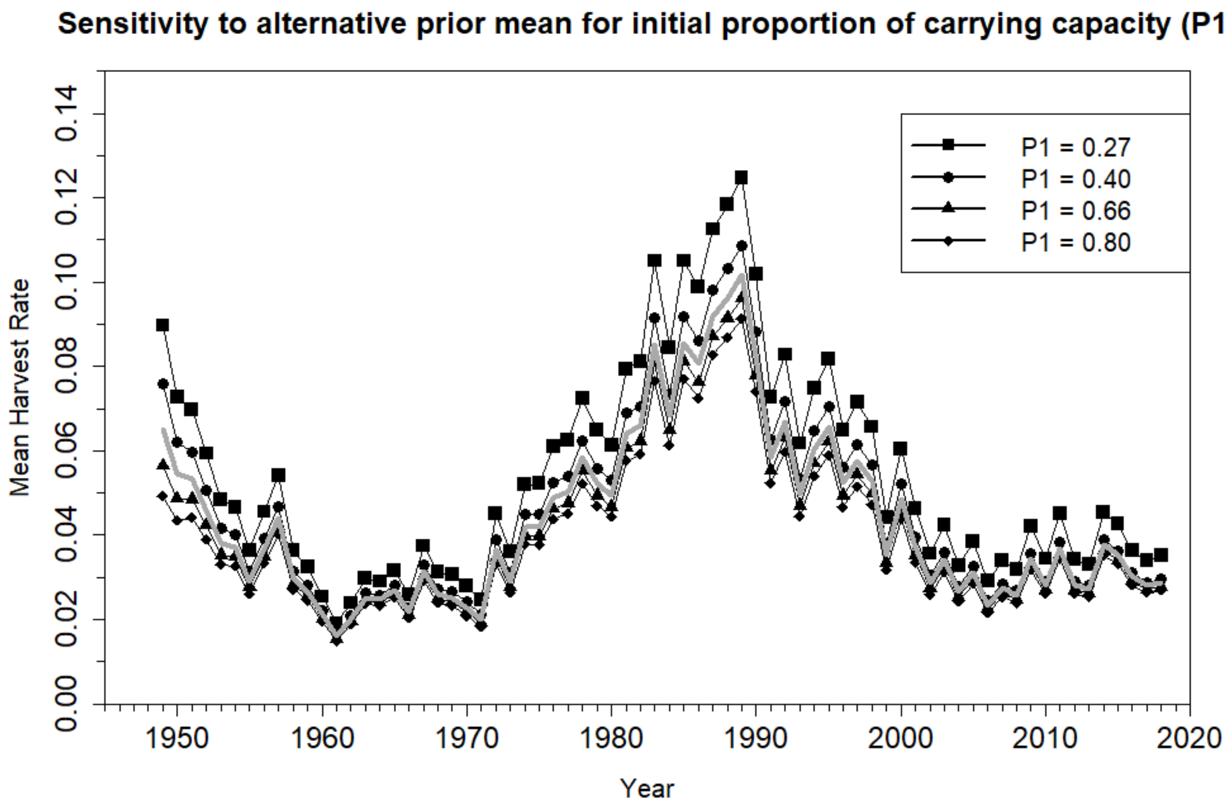


Figure 36. Estimated mean harvest rate as a function of different prior means for the initial proportion of carrying capacity (P1). Values of P1 were calculated as +/- 25% and +/- 50% of the mean value used for the base case (µP = 0.53.; gray line).

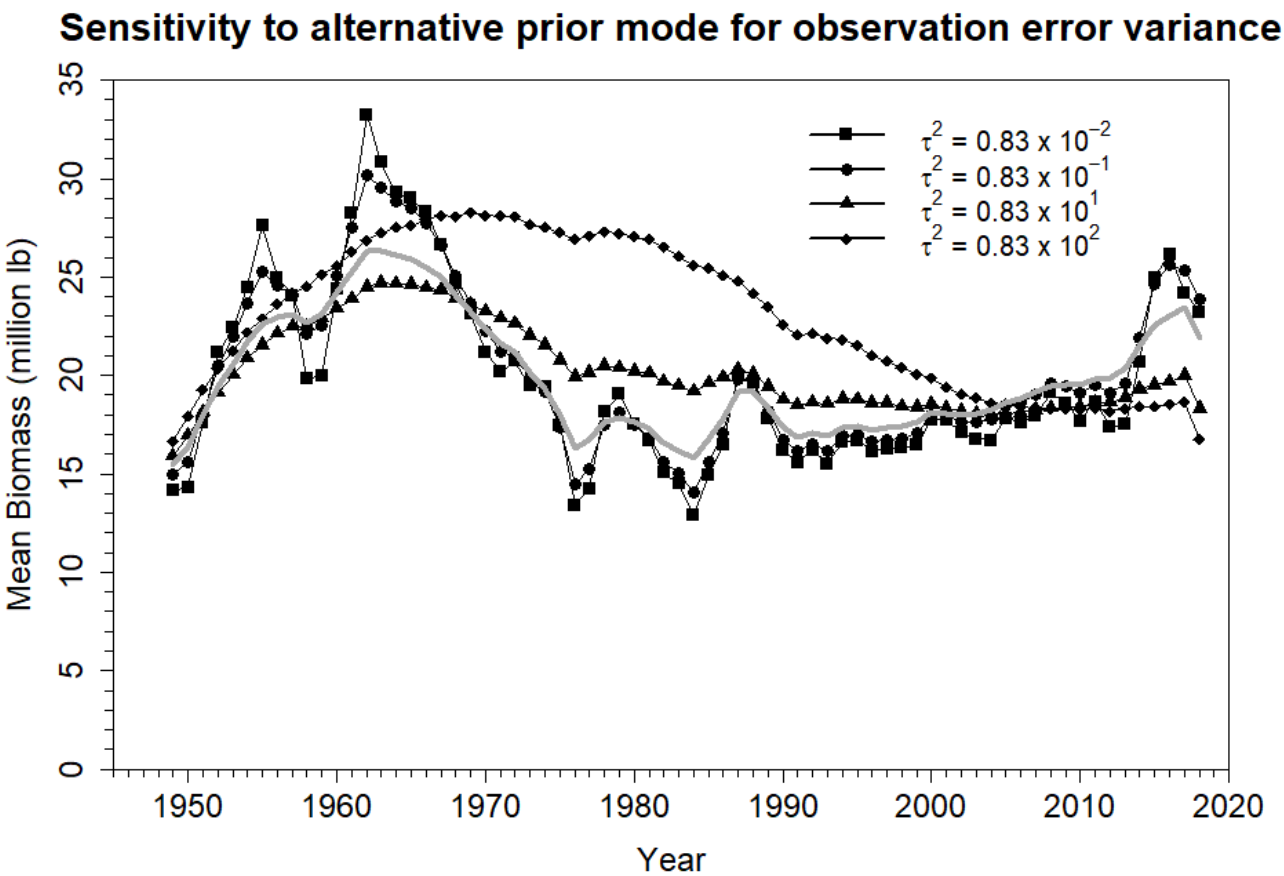


Figure 37. Estimated mean exploitable biomass as a function of different prior modes for observation error variance for both time periods i (τi2). The base-case value (MODE[τi2] = 0.83; gray line) was multiplied by 10^{-2}, 10^{-1}, 101, and 10^{2}

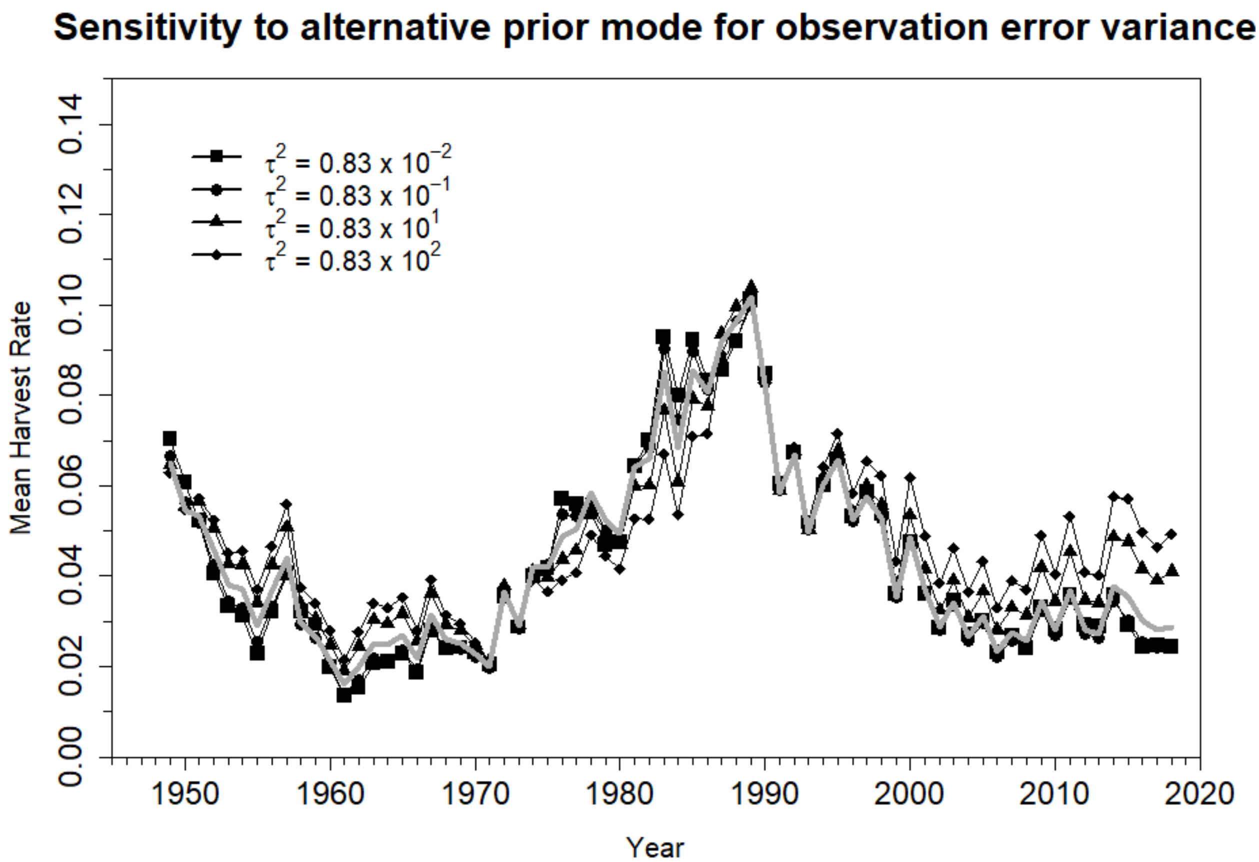


Figure 38. Estimated mean harvest rate as a function of different prior modes for observation error variance for both time periods i (τi2). The base-case value (MODE[τi2] = 0.83; gray line) was multiplied by 10^{-2}, 10^{-1}, 101, and 10^{2}.

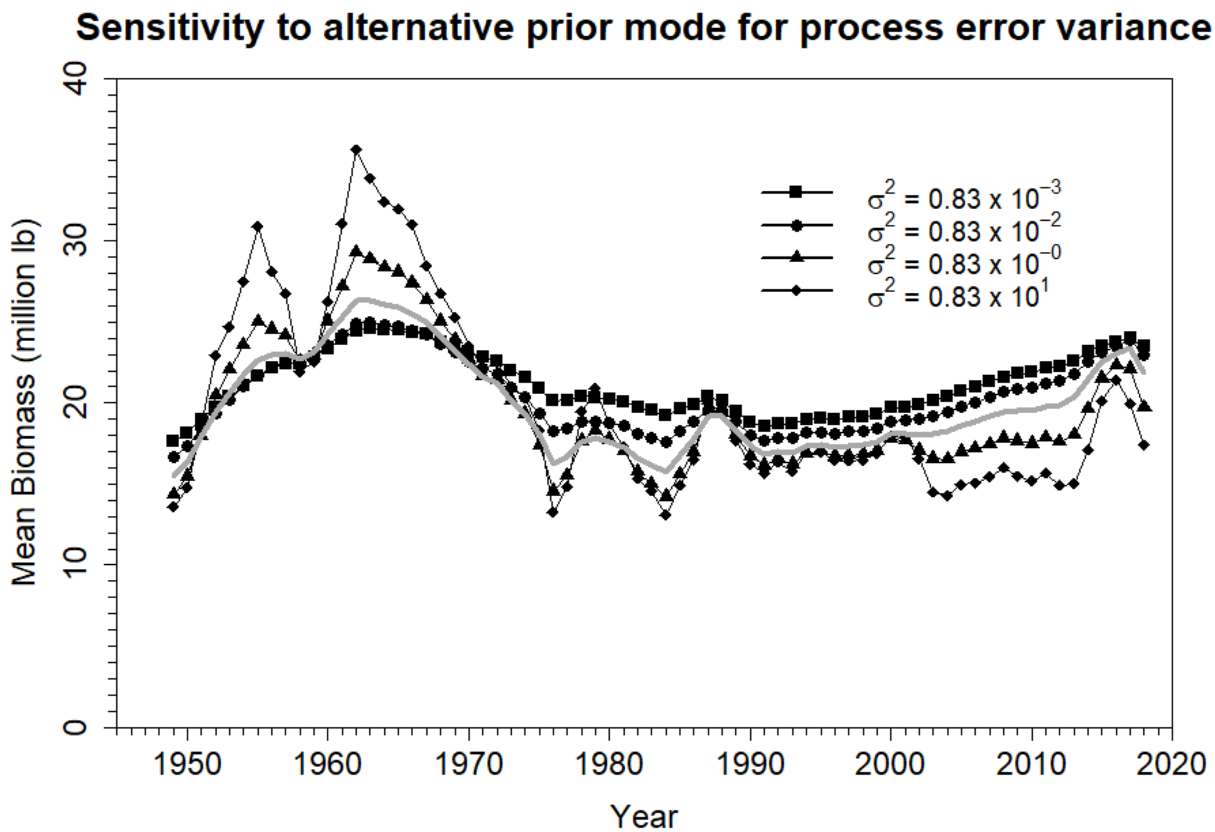


Figure 39. Estimated mean exploitable biomass as a function of different prior modes for process error variance (σ2). The base-case value (MODE[σ2] = 0.83 x 10-1; gray line) was multiplied by 10^{-2}, 10^{-1}, 101, and 10^{2}.

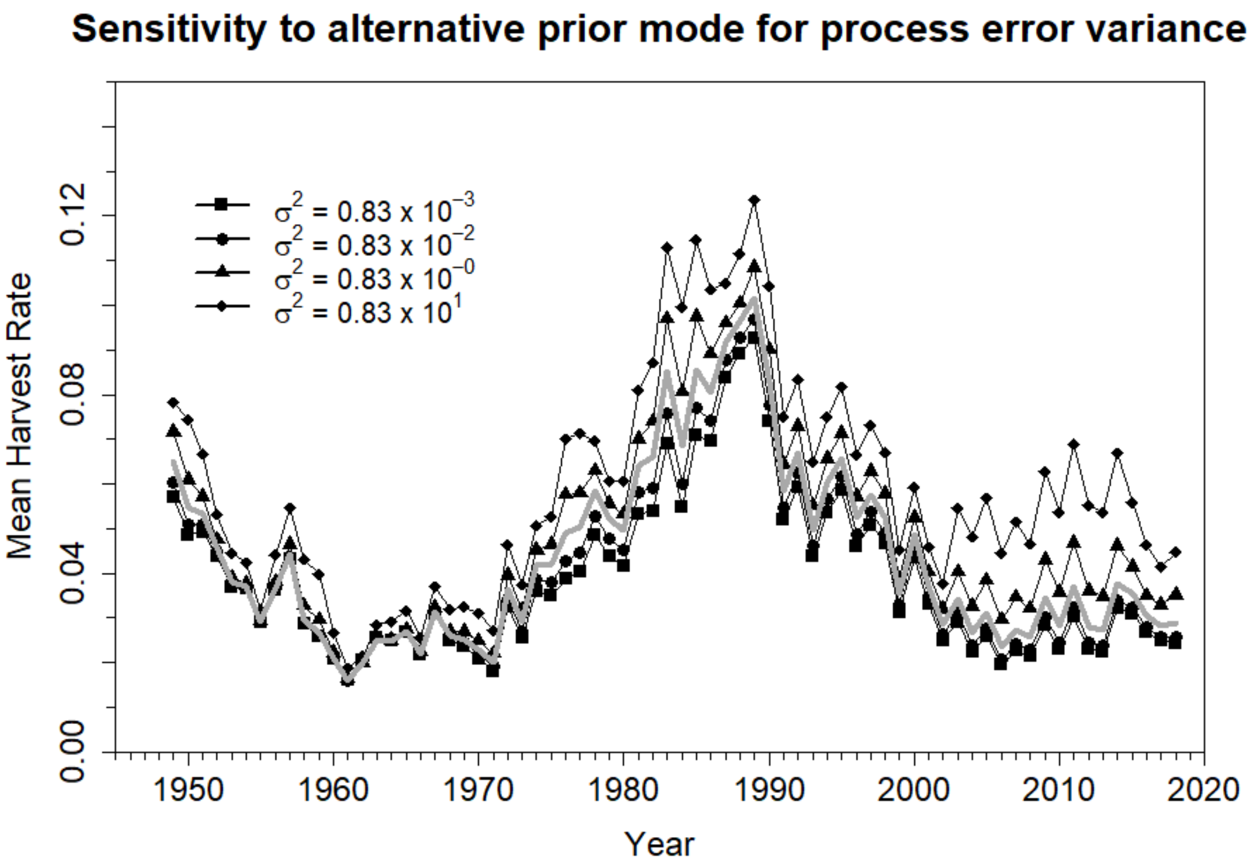


Figure 40. Estimated mean harvest rate as a function of different prior modes for process error variance (σ2). The base-case value (MODE[σ2] = 0.83; gray line) was multiplied by 10^{-2}, 10^{-1}, 101, and 10^{2}.

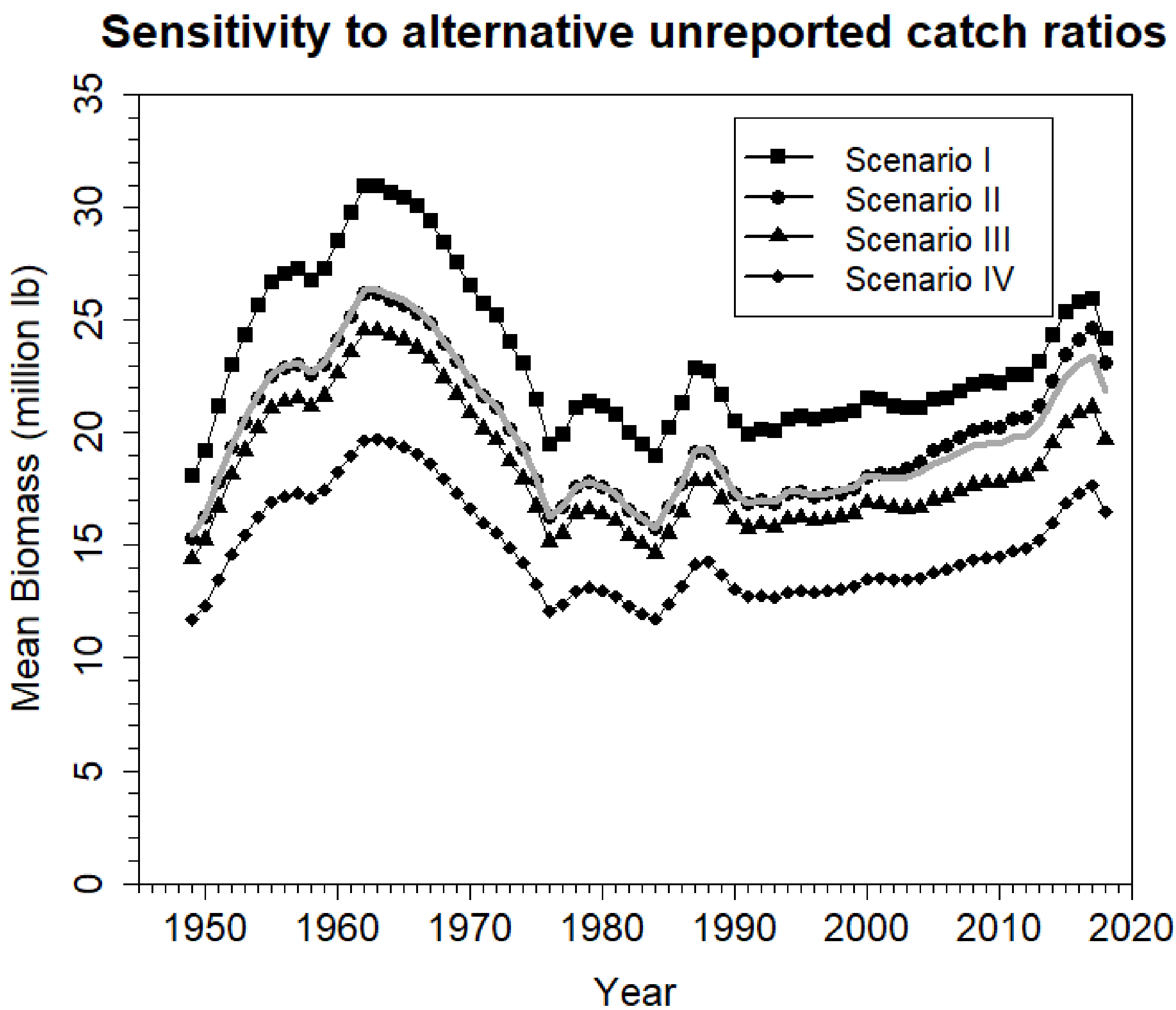


Figure 41. Estimated mean exploitable biomass as a function of different scenarios for modeling unreported catch ratios (see text for scenario descriptions).

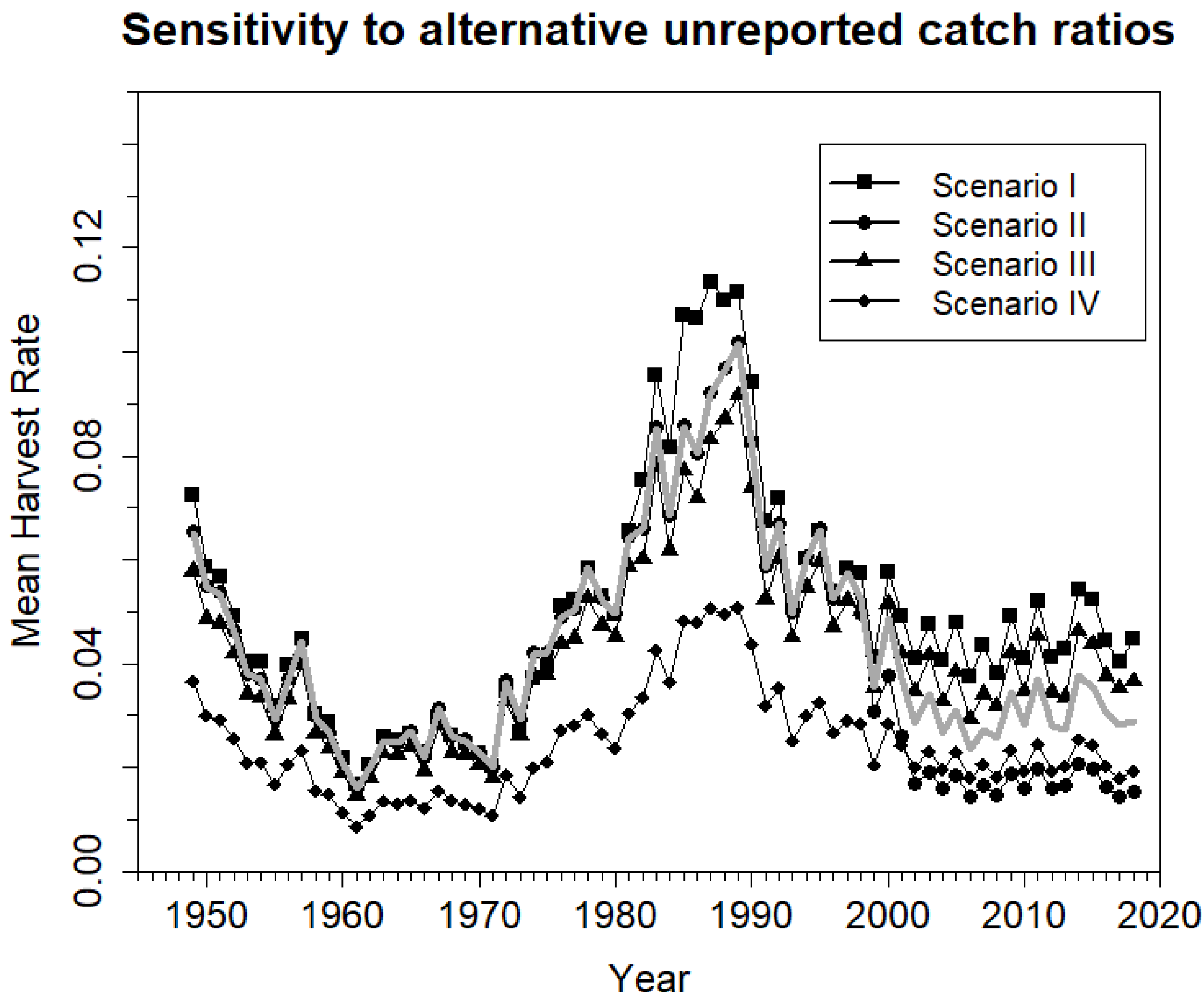


Figure 42. Estimated mean harvest rate as a function of different scenarios for modeling unreported catch ratios (see text for scenario descriptions).

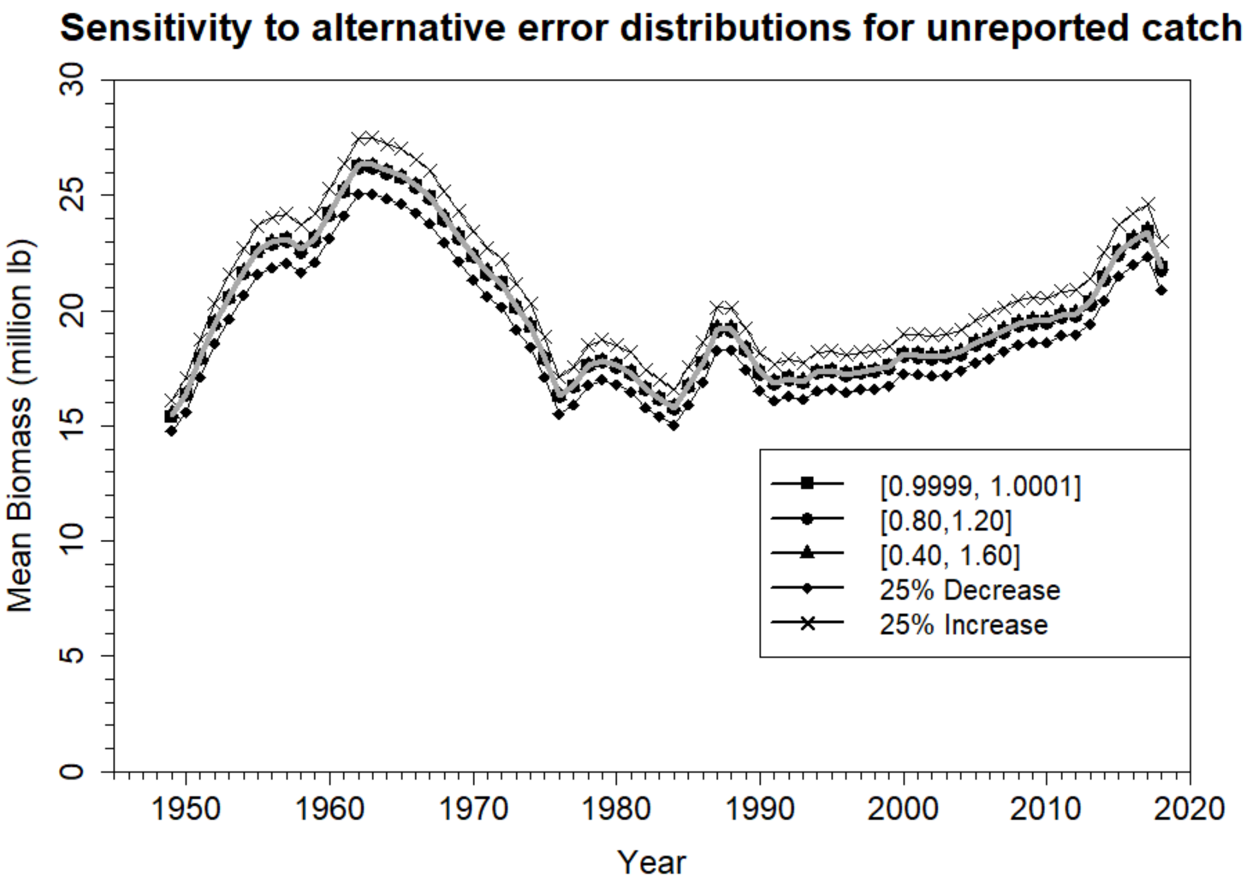


Figure 43. Estimated mean exploitable biomass given alternative bounds on uniform distribution used to estimate unreported catch. Directional biases in the unreported catch error were evaluated by adjusting the base-case bounds (gray line, [0.60,1.40]) downward and upward by 25%.

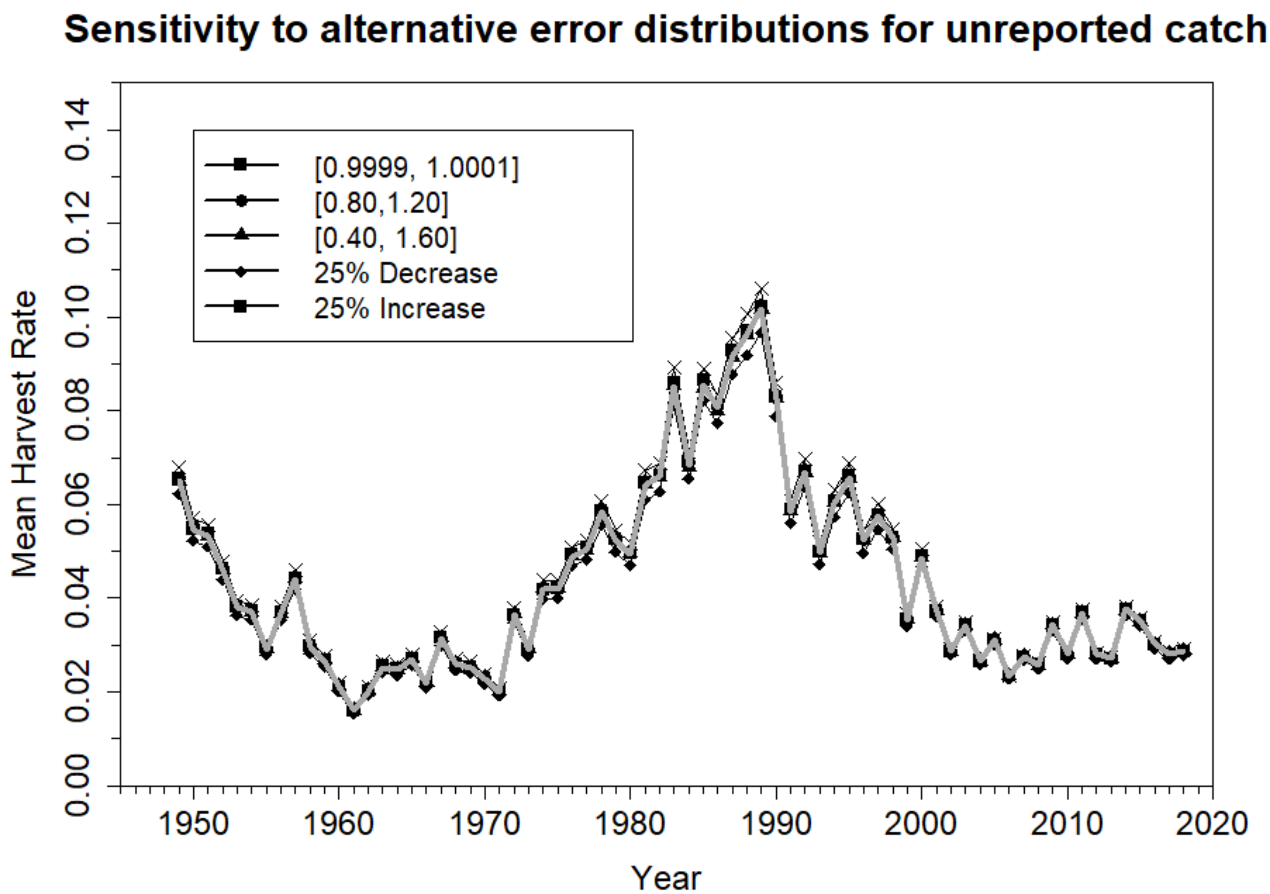


Figure 44. Estimated mean harvest rate given alternative bounds on uniform distribution used to estimate unreported catch. Directional biases in the unreported catch error were evaluated by adjusting the base-case bounds (gray line, [0.60,1.40]) downward and upward by 25%.

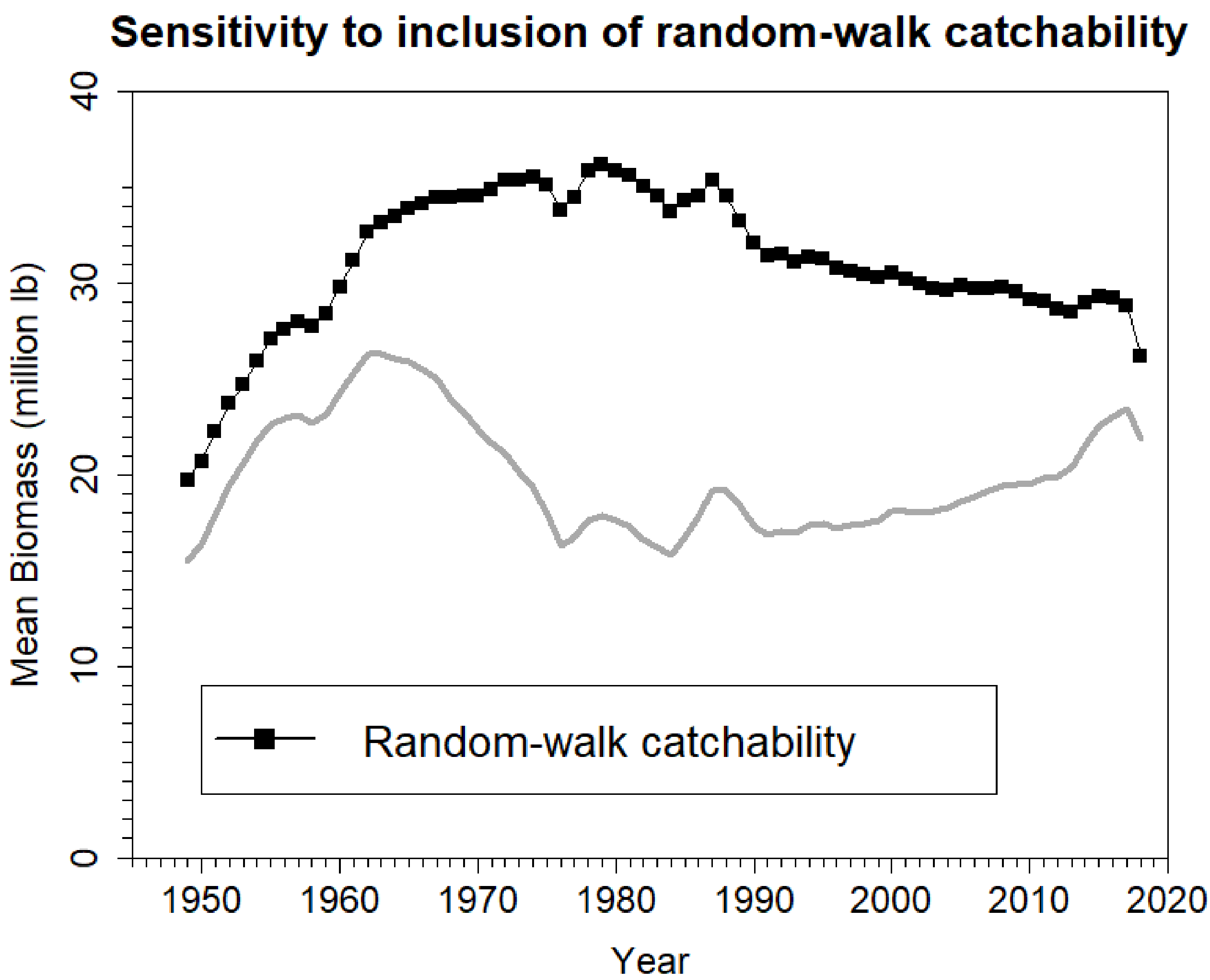


Figure 45. Estimated mean exploitable biomass when incorporating time-varying catchability, as a random walk (black line) versus constant catchability (base case; gray line).

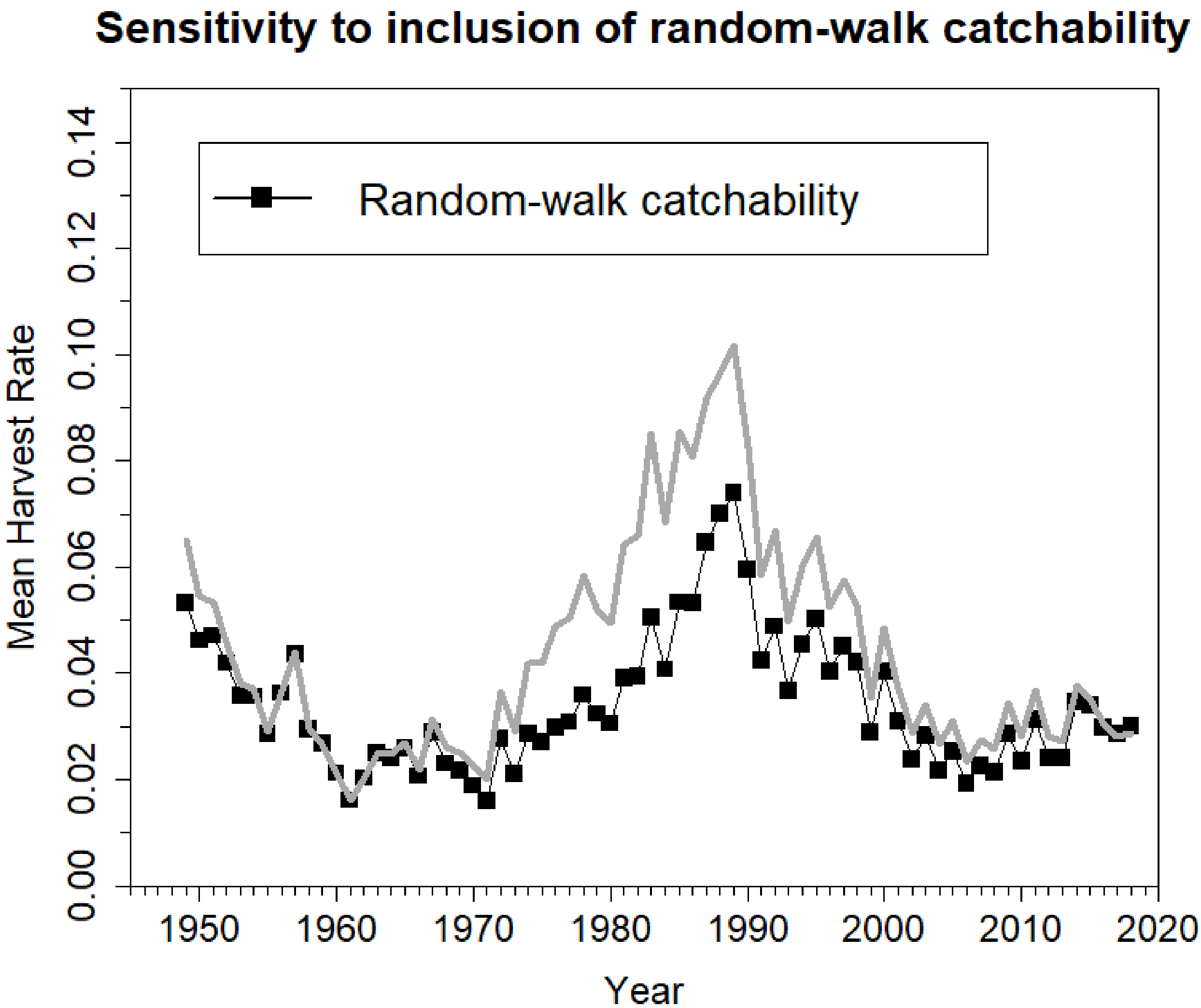


Figure 46. Estimated mean harvest rate when incorporating time-varying catchability as a random walk (black line) versus constant catchability (base case; gray line).

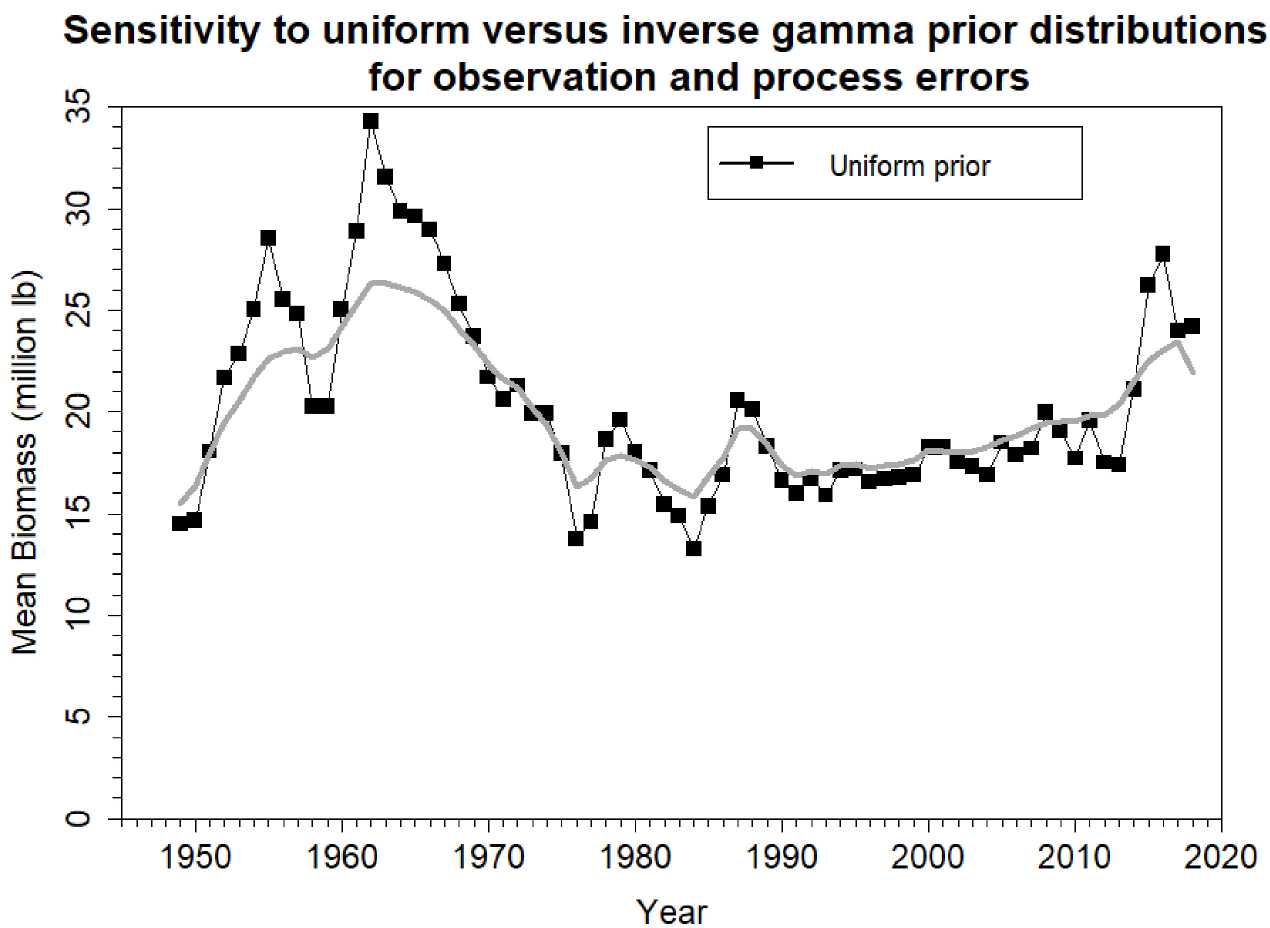


Figure 47. Estimated mean exploitable biomass using uniform prior distributions for the standard deviation of observation and process errors (black line) versus using the inverse gamma distribution for the variance of observation and process errors (base case; gray line).

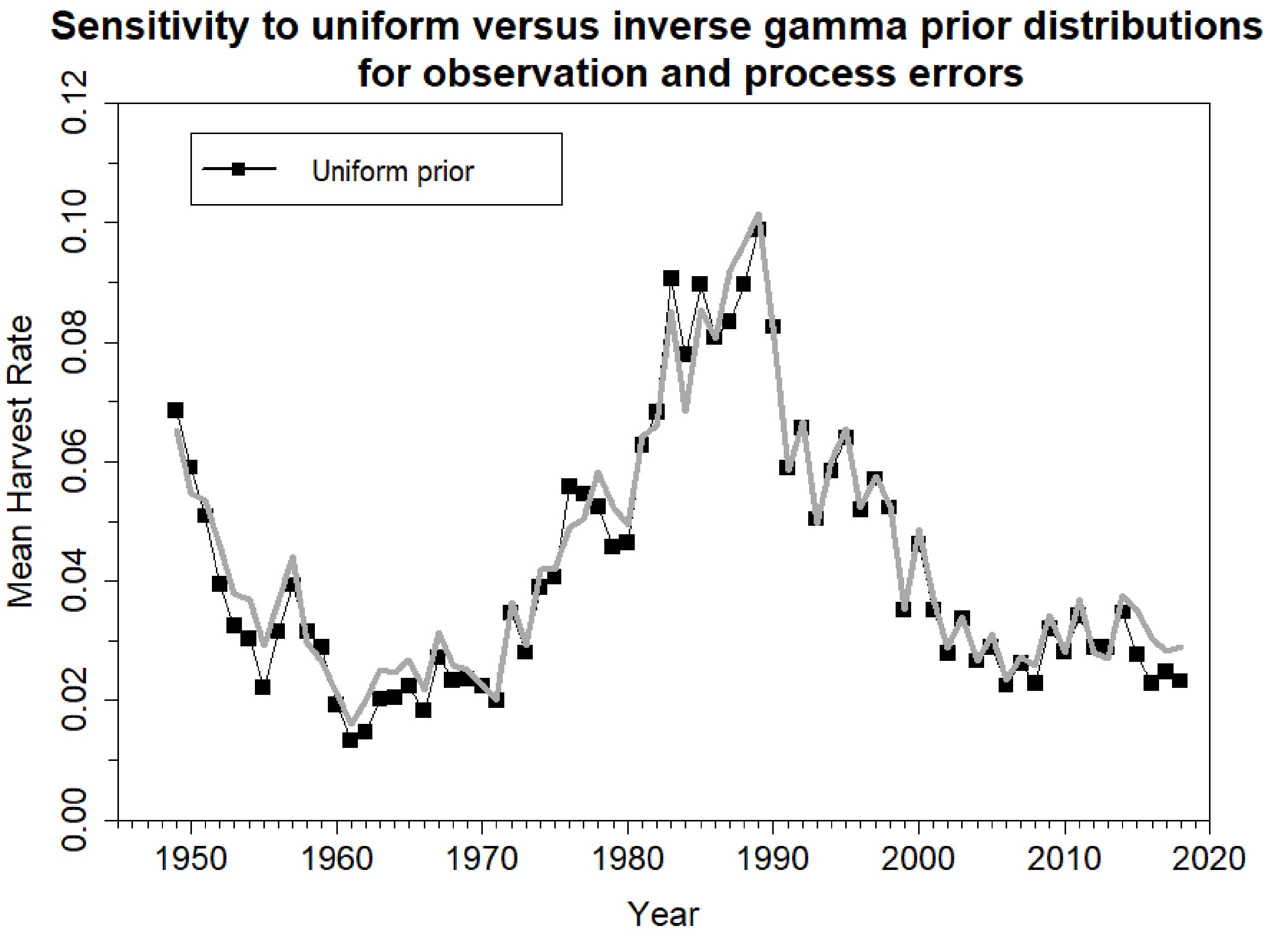


Figure 48. Estimated mean harvest rate using uniform prior for the standard deviation of observation and process errors (black line) versus using the inverse gamma distribution for the variance of observation and process errors (base case; gray line).

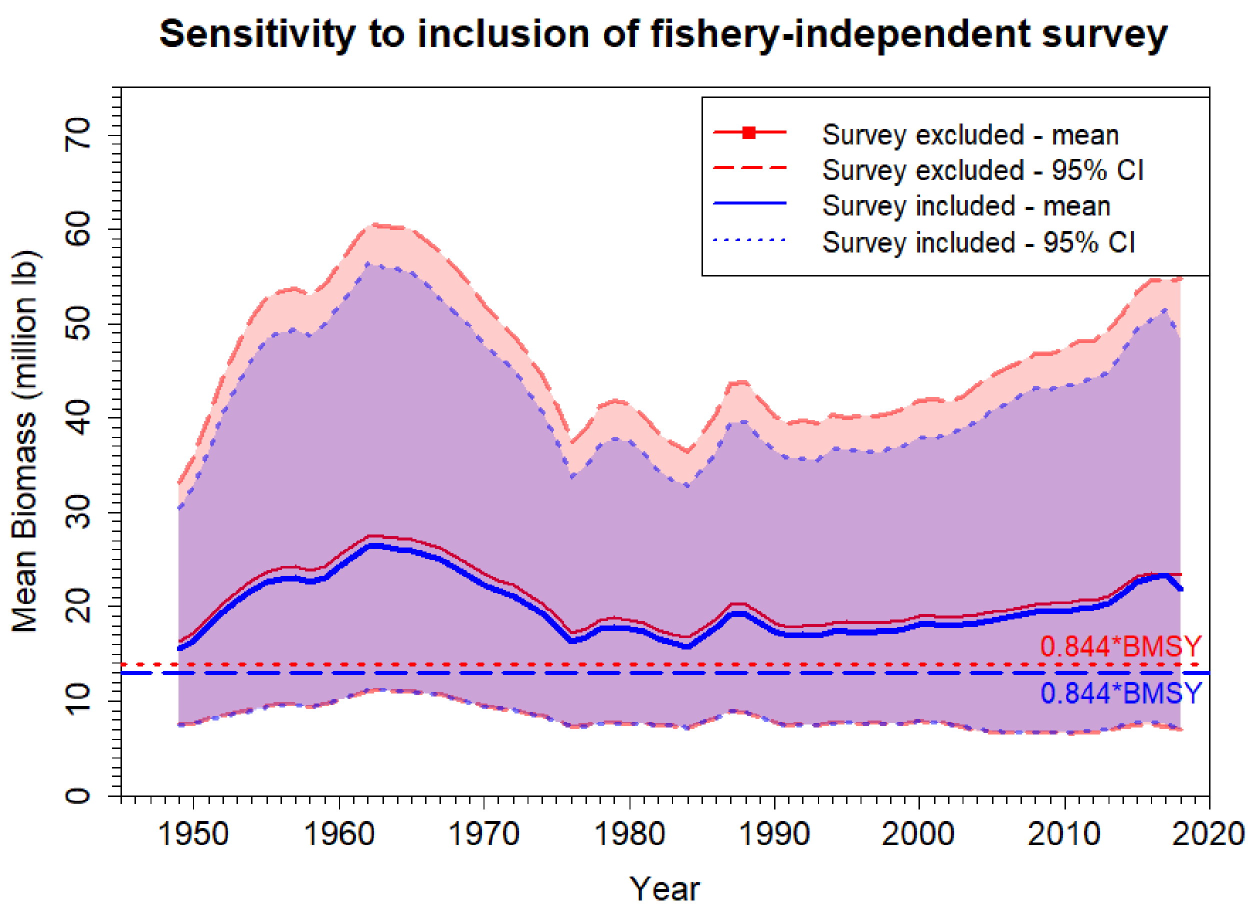


Figure 49. Estimated mean exploitable biomass for the base case (blue lines and shading) and with the fishery-independent survey excluded (red lines and shading). Horizontal lines delineate 0.844*BMSY reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

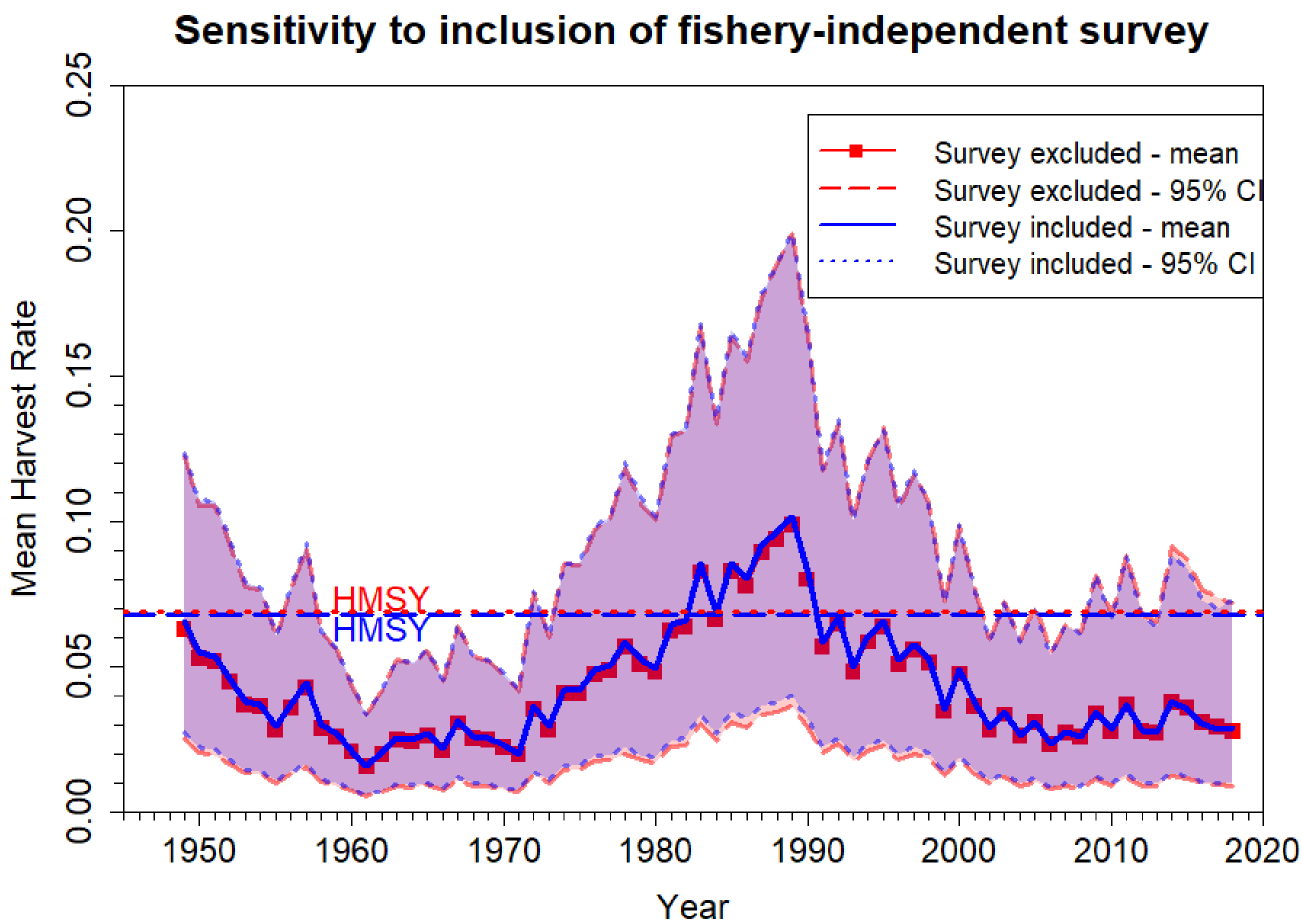


Figure 50. Estimated mean harvest rate for the base case (blue lines and shading) and with the fishery-independent survey excluded (red lines and shading). Horizontal line delineates the HMSY reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

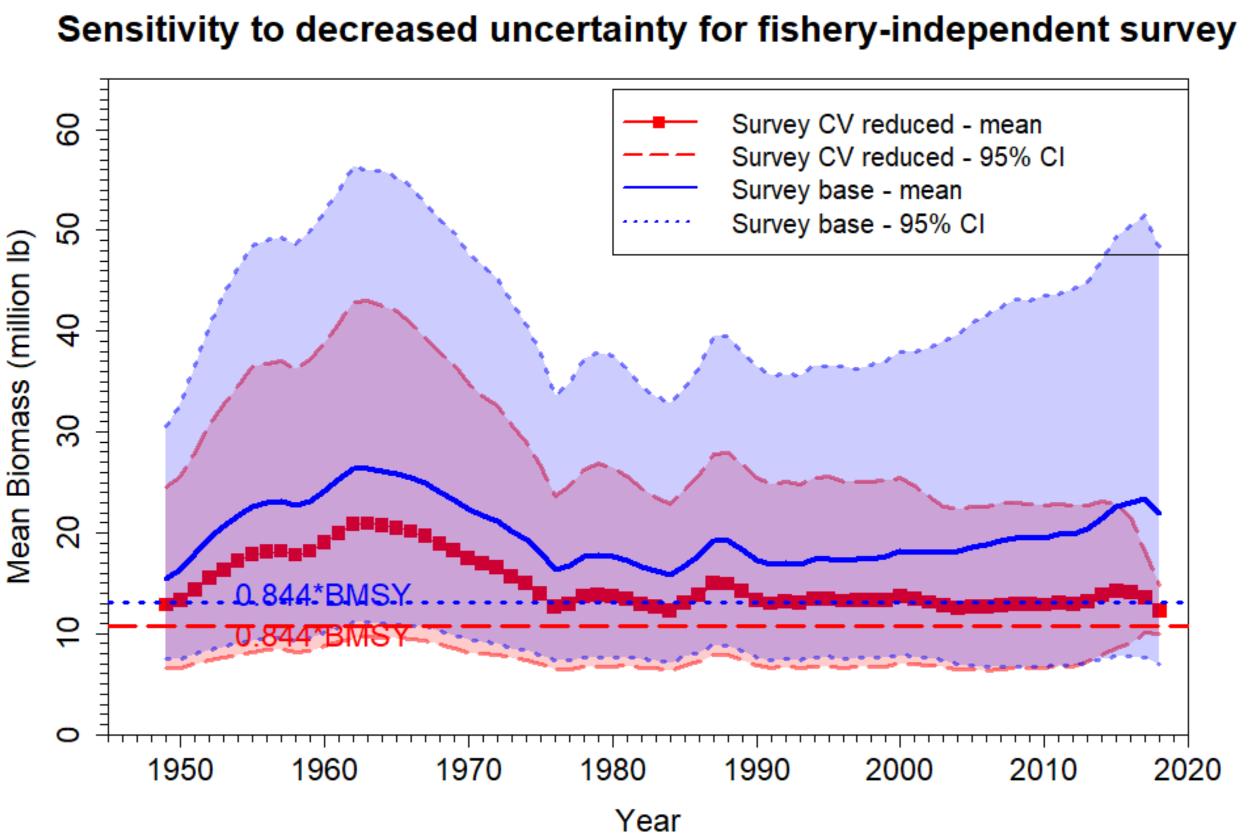


Figure 51. Estimated mean exploitable biomass for the base case (blue lines and shading) and with decreased CV of the prior on the effective radius of a single sample for the fishery-independent survey (red lines and shading). Horizontal lines delineate 0.844*B_{MSY} reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

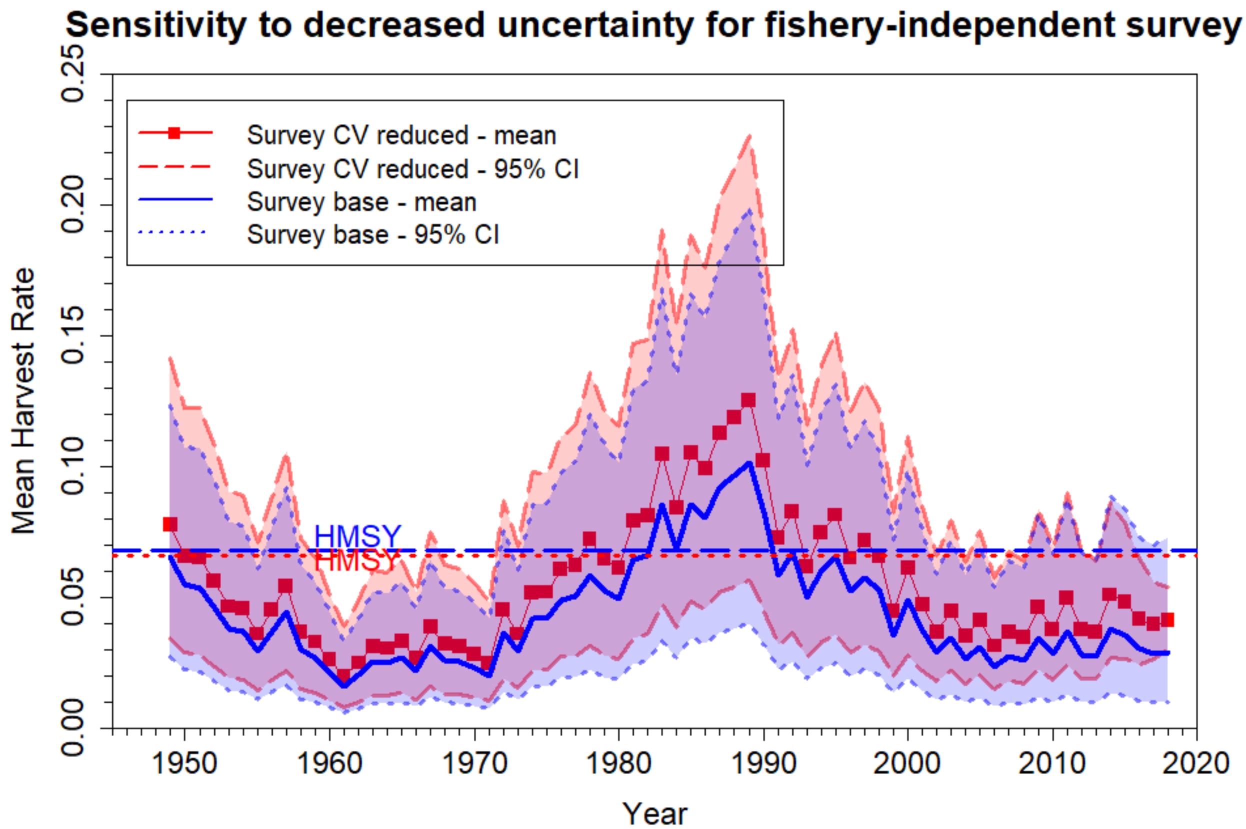


Figure 52. Estimated mean harvest rate for the base case (blue lines and shading) and with decreased CV of the prior on the effective radius of a single sample for the fishery-independent survey (red lines and shading). Horizontal line delineates the HMSY reference points for the base case (dotted blue line) and the scenario with the survey excluded (dashed red line).

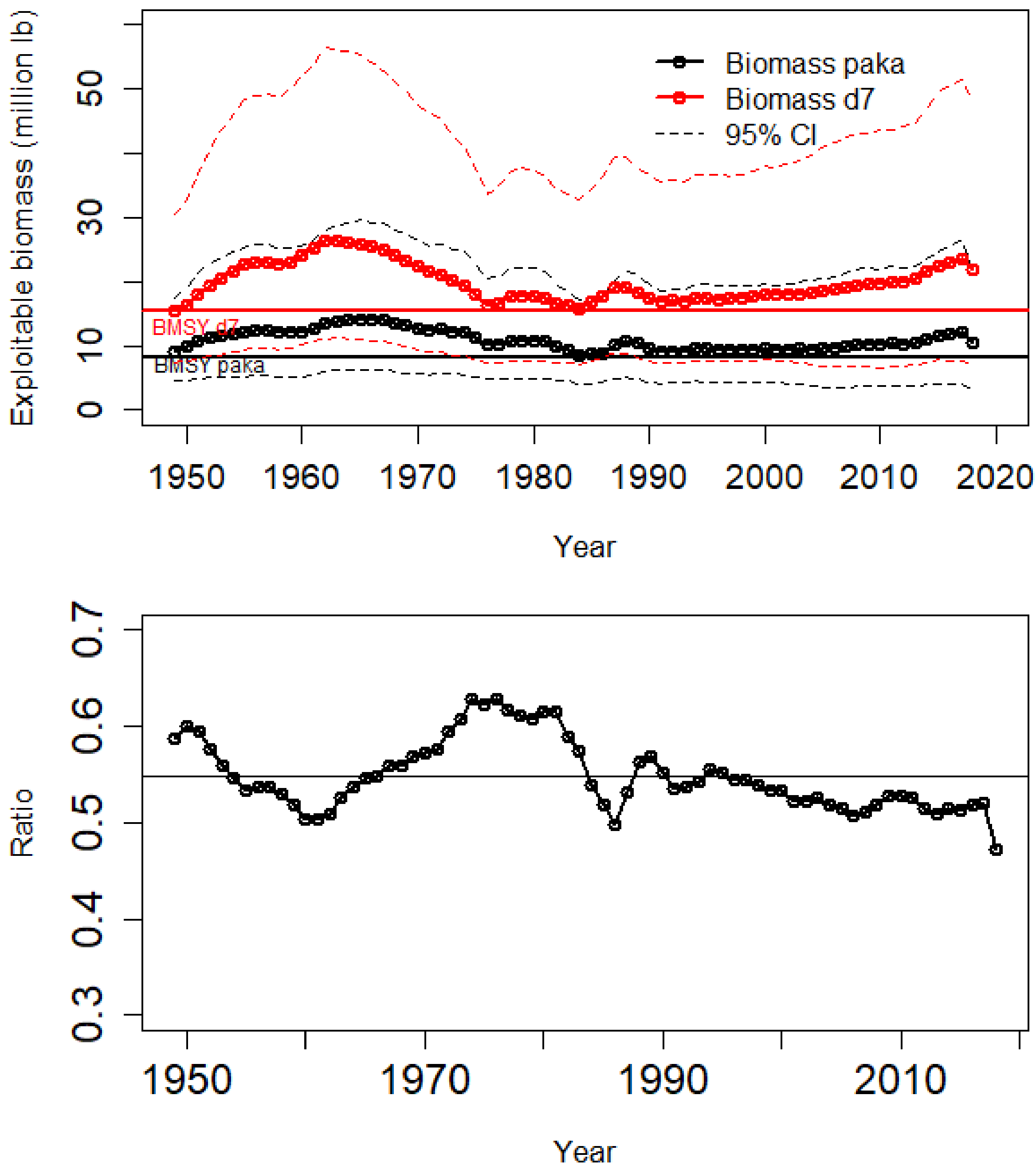


Figure 53. Biomass comparison between the opakapaka production model (paka) and the Deep 7 production model (d7) for the main Hawaiian Islands. Top panel: Posterior mean exploitable biomass estimates and 95% credible intervals for the opakapaka production model (black) and the Deep 7 complex production model (red). Bottom panel: Ratio (black line with circles) and average ratio (0.55; 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.

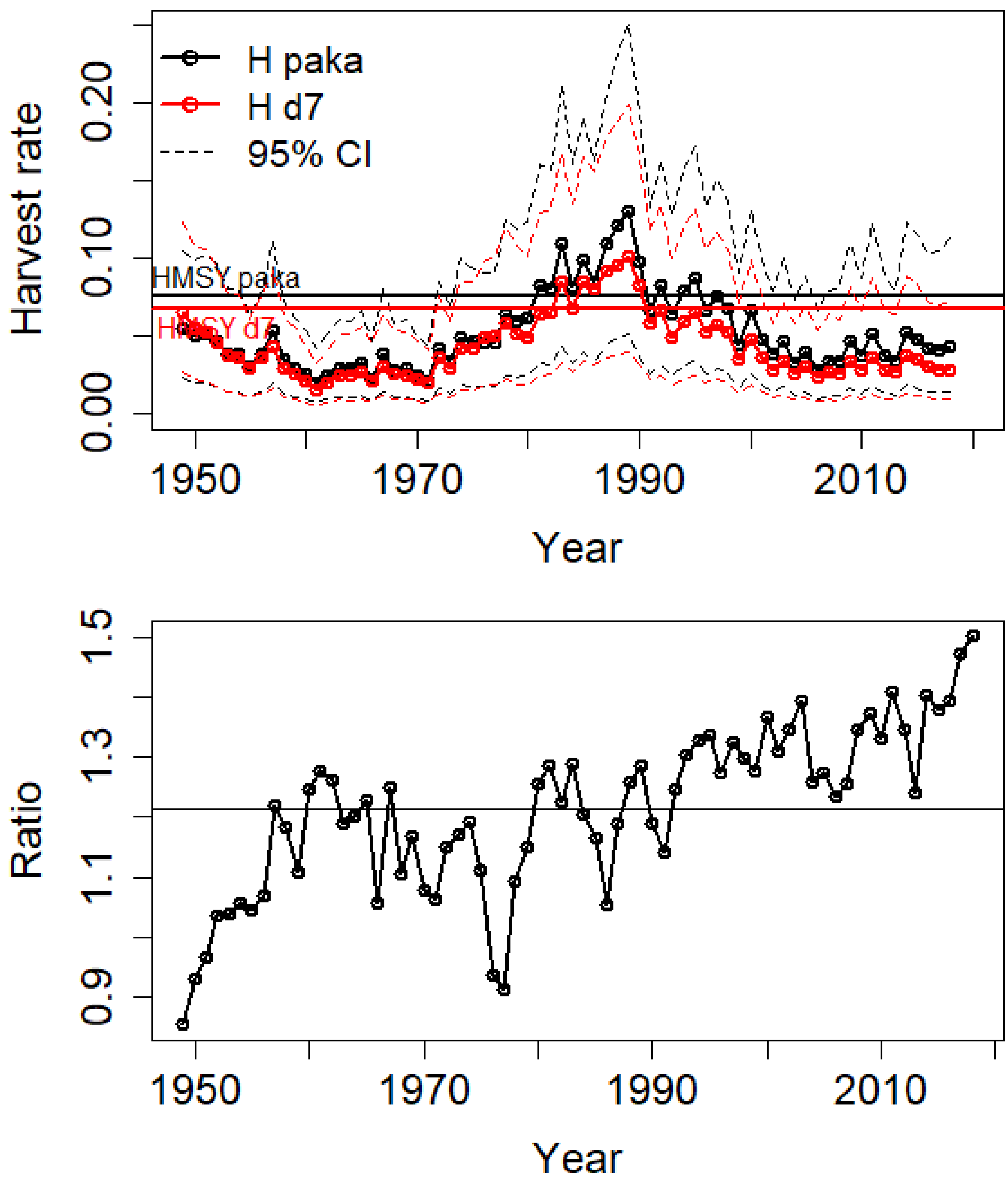


Figure 54. Harvest rate comparison between the opakapaka production model (paka) and the Deep 7 production model (d7) for the main Hawaiian Islands. Top panel: Posterior mean harvest ratio estimates and 95% credible intervals for the opakapaka production model (black) and the Deep 7 production model (red). Bottom panel: Ratio (black line with circles) and average ratio (1.21; horizontal solid line) of the posterior mean of opakapaka harvest rate to the posterior mean of Deep 7 harvest rate.

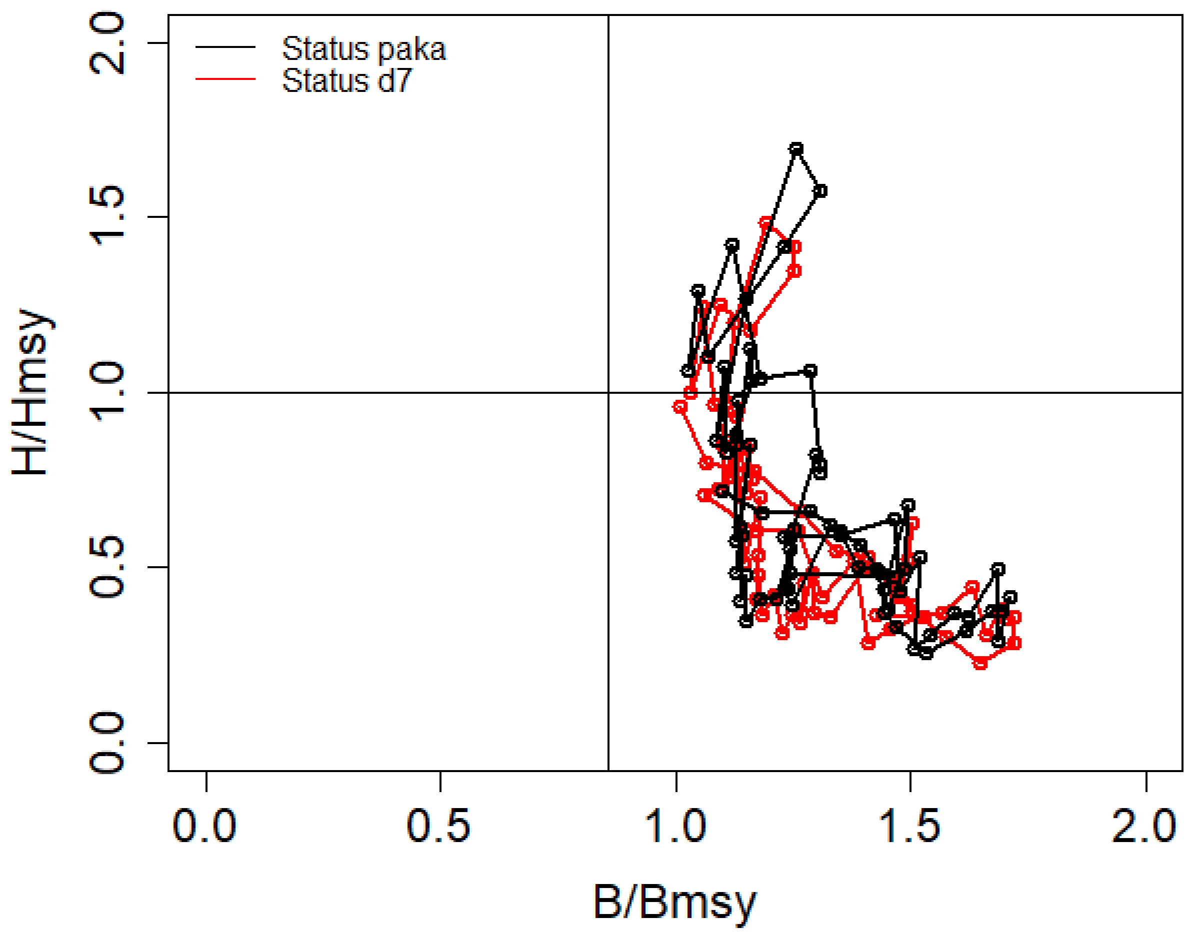


Figure 55. Status of opakapaka, as based on the opakapaka only model (paka; black line), compared to the status estimated from the model of the Deep 7 bottomfish complex (d7; red line) for the main Hawaiian Islands.

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 1949-2018.

Appendix C. R code that calls WinBUGS used to fit assessment model for opakapaka in the main Hawaiian Islands from 1949-2018.

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 (2003-2018) time periods.

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

Table A 1. 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 (2003-2018) 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	-51448	1
	+year	1650	-50568	56
	+area	10259	-45283	210
	+sqrt(pounds of uku)	916	-44824	211
	+ln(cumulative experience)	275	-44686	212
	+quarter	237	-44564	215
2003:2018	Null	0	-18017.15	1
	+year	126	-17939	16
	+area	3799	-15941	114
	+sqrt(pounds of uku)	1949	-14966	115
	+quarter	362	-14782	118
	+ln(cumulative experience)	228	-14667	119
	+area:quarter	159	-14319	383
	+speed	123	-14256	384
Lognormal process				
1948:2003	Null	0	-115440	2
	+fisher	25563	-102658	3
	+year	1074	-102066	58
	+area	2620	-100619	195
	+quarter	873	-100179	198
	+area:quarter	314	-99728	492
	+ln(cumulative experience)	230	-99612	493

Table A 1. Continued.

Time Period		Selected predictor	ΔAIC	Log-Likelihood	Number of parameters
2003:2018	Null		0	-27405	2
		+fisher	6621	-24093	3
		+year	349	-23904	18
		+area	398	-23611	112
		+sqrt(pounds of uku)	99	-23560	113
		+quarter	75	-23520	116
		+speed	39	-23499	117

Table A 2. 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	57.41	2.94		1980	60.55	1.96
1949	34.56	2.26		1981	64.57	1.64
1950	45.56	2.53		1982	45.91	1.30
1951	65.32	2.34		1983	48.67	1.14
1952	71.86	2.75		1984	33.41	1.39
1953	62.54	3.35		1985	40.82	1.26
1954	68.67	3.48		1986	34.65	1.17
1955	67.48	5.23		1987	56.56	1.10
1956	73.44	3.57		1988	63.75	1.00
1957	89.13	3.19		1989	58.90	1.25
1958	54.31	2.86		1990	49.76	1.26
1959	46.30	3.44		1991	40.42	1.36
1960	50.80	2.49		1992	45.00	1.37
1961	57.71	3.53		1993	41.65	1.51
1962	85.33	3.34		1994	55.05	1.57
1963	91.64	2.65		1995	50.46	1.46
1964	82.72	2.78		1996	45.94	1.75
1965	99.97	2.73		1997	47.54	1.46
1966	79.61	2.94		1998	47.22	1.61
1967	92.45	2.44		1999	45.20	1.65
1968	68.63	2.78		2000	53.57	1.45
1969	76.41	2.49		2001	48.16	1.81
1970	63.10	3.66		2002	45.60	1.81
1971	49.99	2.54		2003	46.32	4.56
1972	71.73	2.43				
1973	60.54	2.16				
1974	78.08	1.73				
1975	60.90	1.85				
1976	42.16	1.21				
1977	43.98	1.59				
1978	59.23	2.00				
1979	57.61	2.47				

Table A 3. Annual index of standardized CPUE (lbs/hour) for opakapaka for the late time period (2003-2018), with relative coefficient of variation (relCV) included. Relative CV was calculated as the ratio of CV/min(CV).

Year	Estimated opakapaka CPUE	relCV
2003	5.95	1.21
2004	5.45	1.29
2005	5.70	1.28
2006	5.01	1.30
2007	5.33	1.18
2008	6.27	1.11
2009	6.66	1.01
2010	6.00	1.22
2011	6.77	1.03
2012	5.34	1.18
2013	4.81	1.10
2014	6.69	1.00
2015	8.28	1.03
2016	9.47	1.27
2017	7.70	1.38
2018	6.63	1.53

Table A 4. 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}	1.00028	0.97	0.59	Passed	0.52	0.10
F_{MSY}	1.00053	1.33	0.15	Passed	0.33	0.11
H_{MSY}	1.00055	1.32	0.14	Passed	0.33	0.11
MSY	1.00107	2.06	0.24	Passed	0.23	0.09
P_{MSY}	1.00009	1.21	0.11	Passed	0.27	0.10
R	1.00046	1.26	0.12	Passed	0.10	0.03
K	1.00014	0.91	0.41	Passed	0.66	0.15
M	1.00005	1.50	0.26	Passed	0.20	0.07
q_1	1.00054	1.19	0.43	Passed	0.64	0.14
q_2	1.00295	0.94	0.49	Passed	0.66	0.26
rad	1.00344	1.04	0.53	Passed	0.65	0.25
σ^2	1.00013	0.81	0.36	Passed	0.12	0.01
τ_1^2	1.00035	0.33	0.81	Passed	0.01	0.00
τ_2^2	1.00009	1.51	0.49	Passed	0.01	0.00

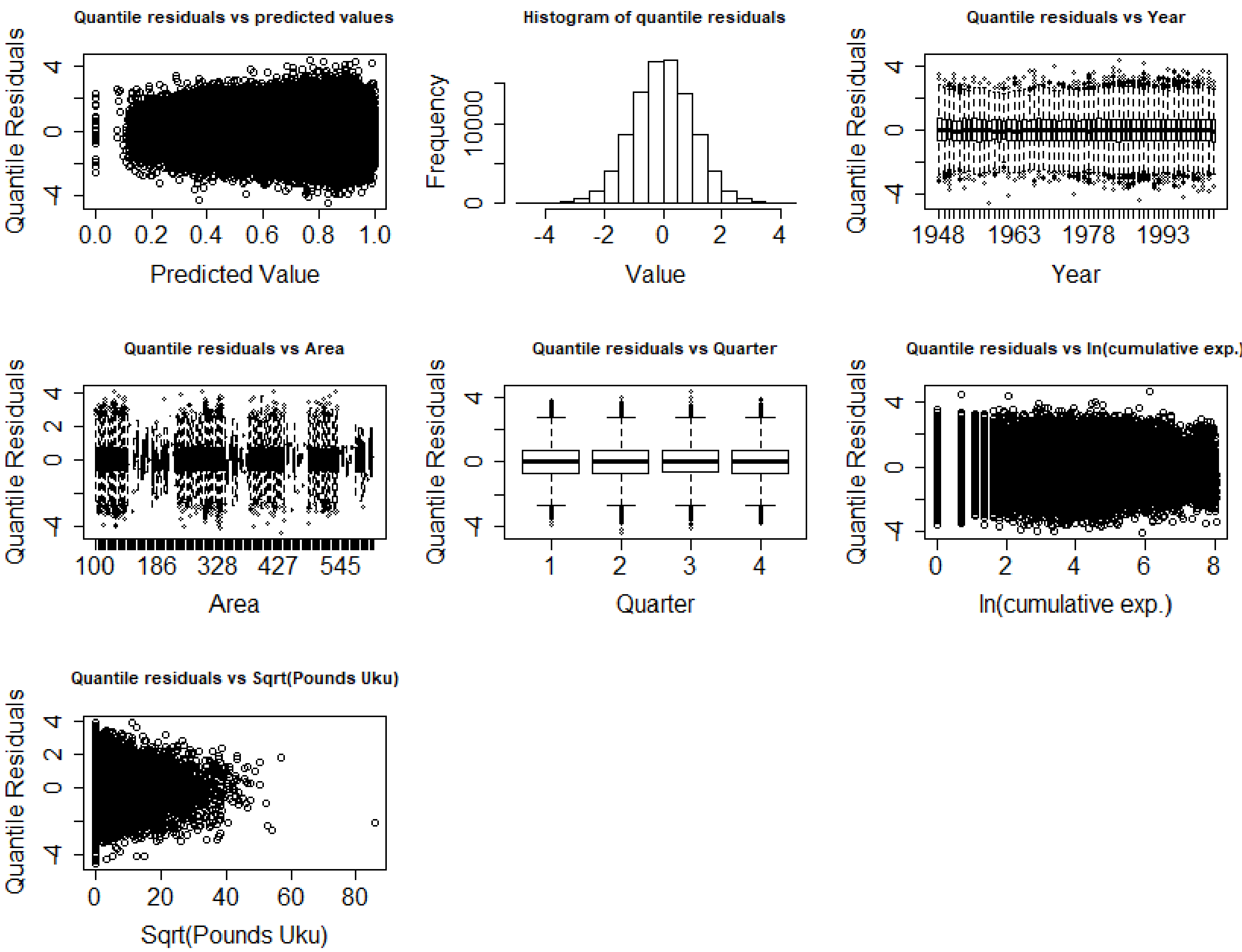


Figure A 1. Model diagnostics for the best fit Bernoulli model for the early (1948-2003) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals against model predicted 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).

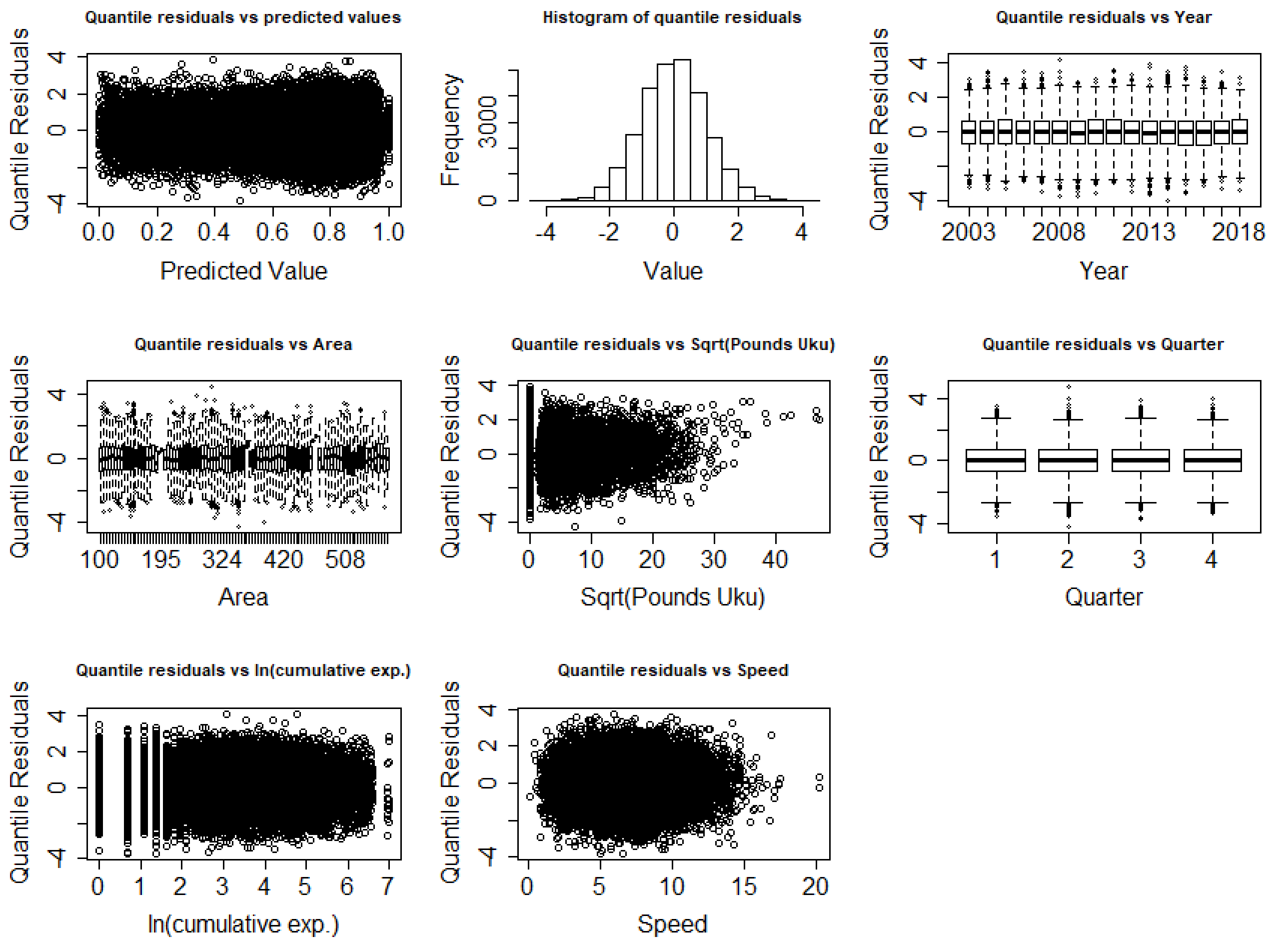


Figure A 2. Model diagnostics for the best fit Bernoulli model for the recent (2003-2018) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictors variables).

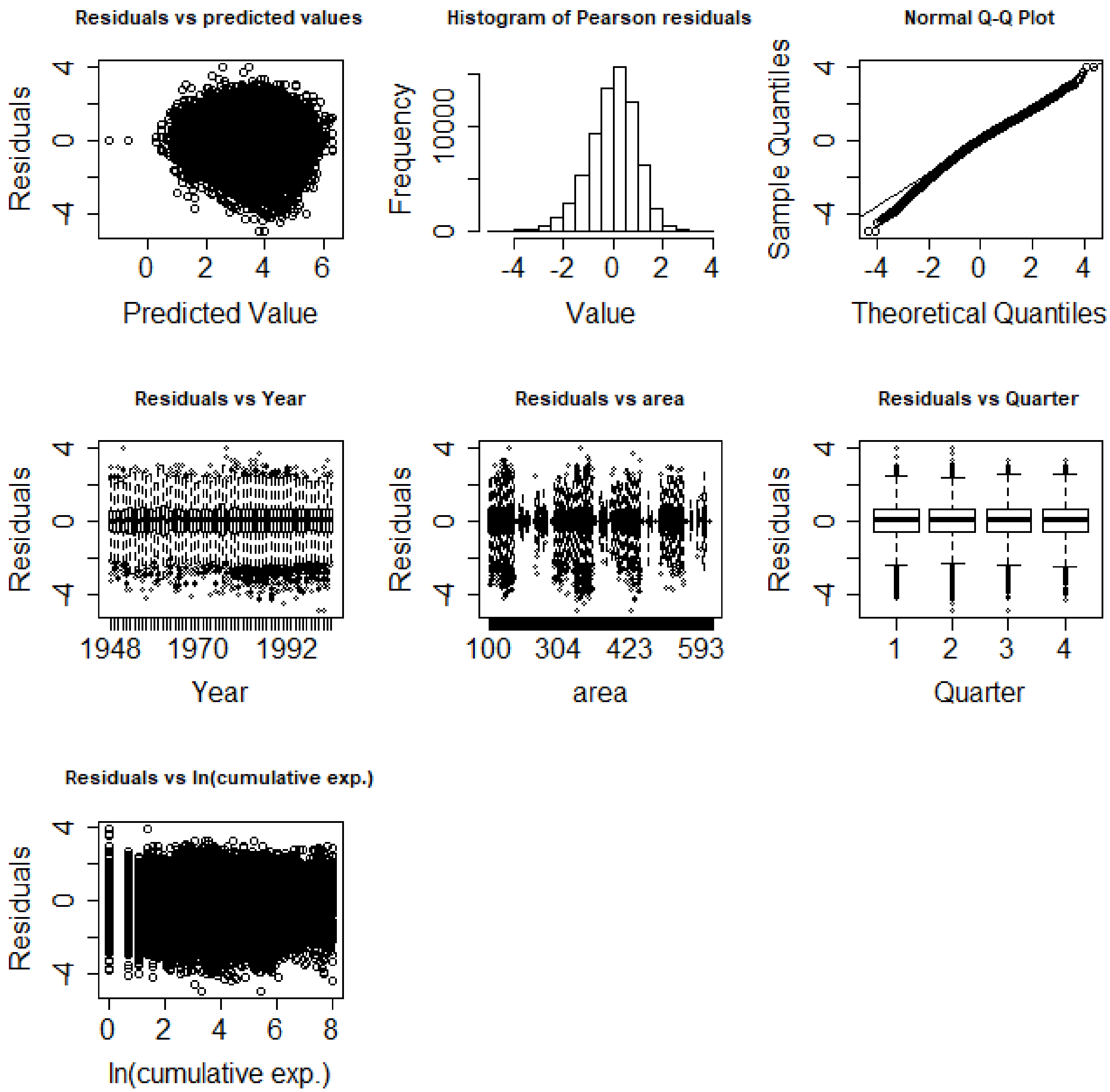


Figure A 3. Model diagnostics for the best fit Lognormal model for the early (1948-2003) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile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

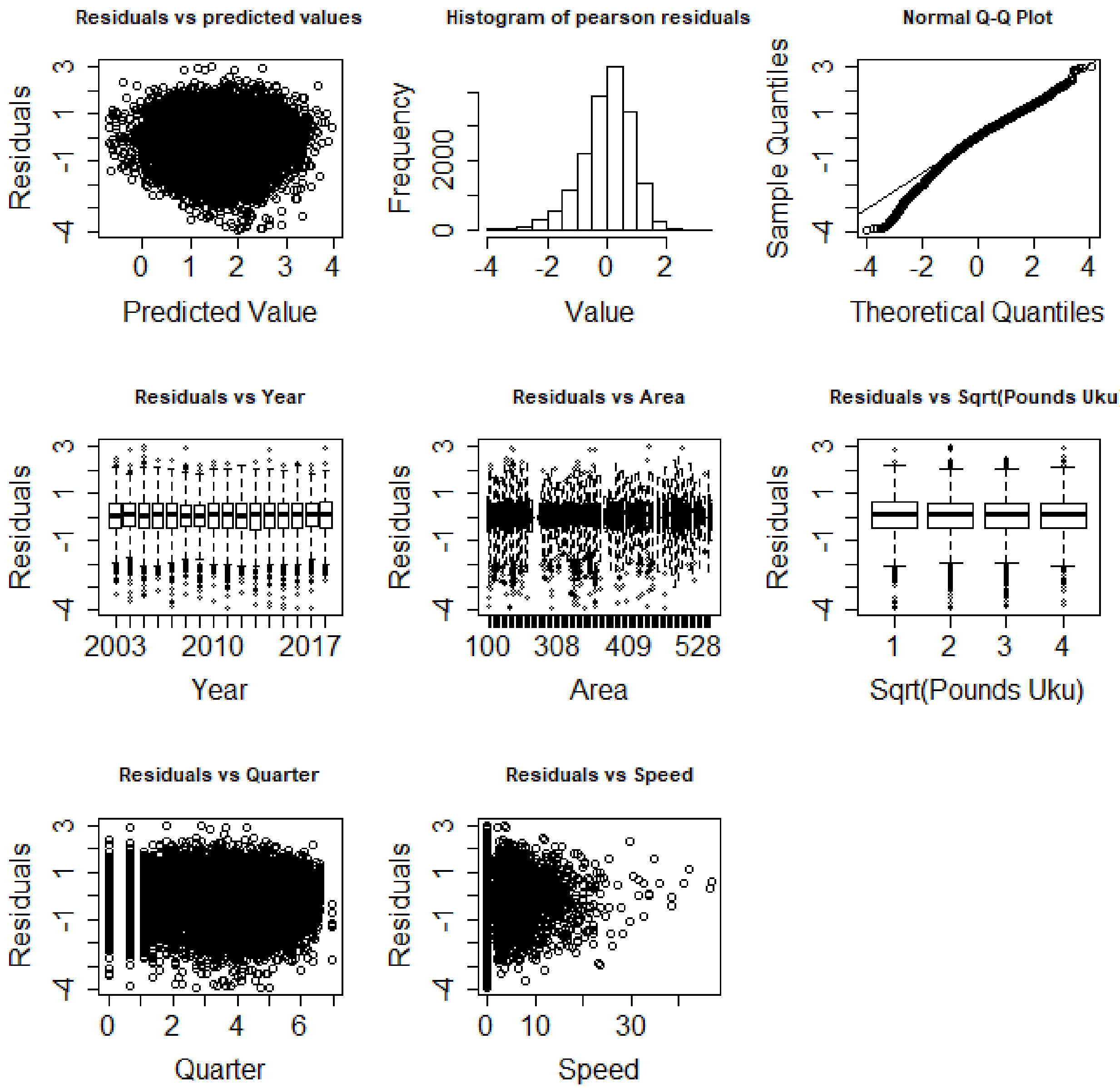


Figure A 4. Model diagnostics for the best fit Lognormal model for the recent (2003-2018) time period based on opakapaka data only. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals and the quantile-quantile plot (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictors variables).

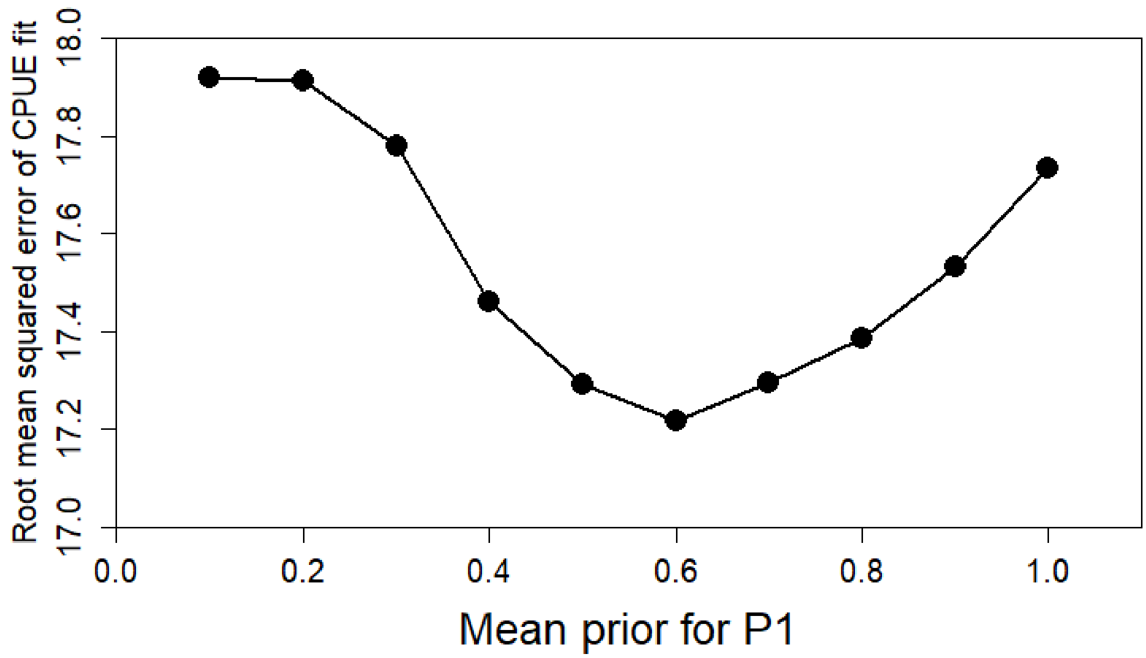


Figure A 5. Goodness-of-fit values for alternative choices for the mean of the prior distribution of the initial proportion of carrying capacity (P1) for the opakapaka production model for the main Hawaiian Islands.

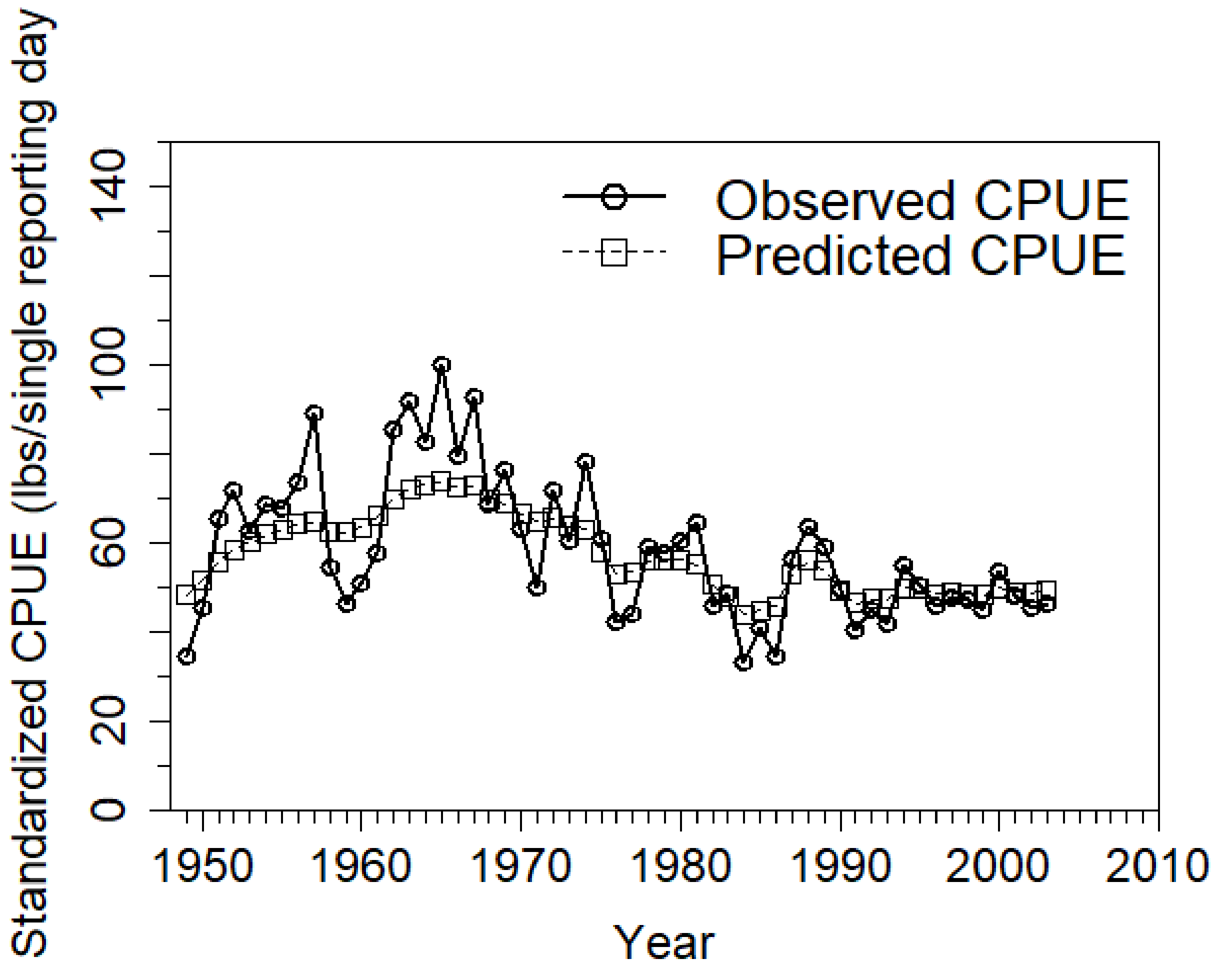


Figure A 6. Observed and predicted CPUE for opakapaka in the main Hawaiian Islands from 1949 through 2003.

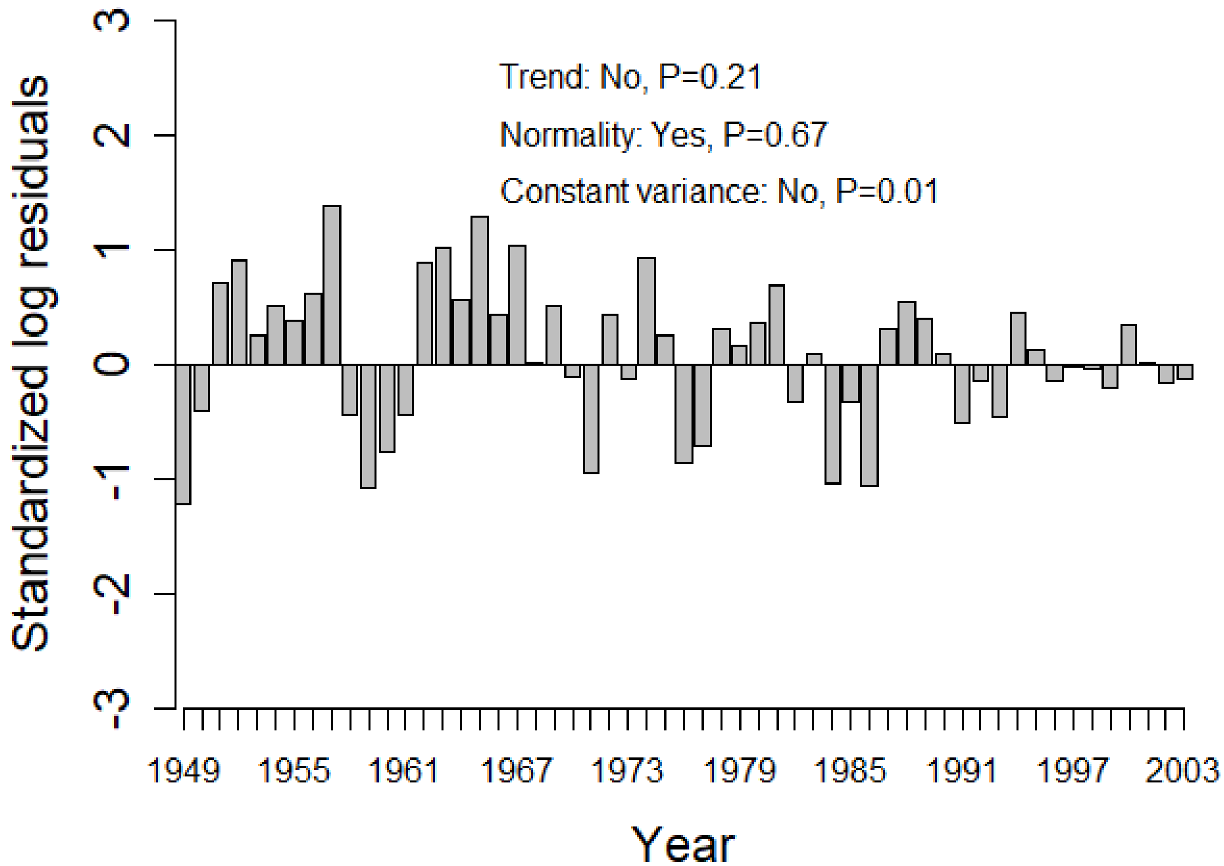


Figure A 7. Standardized residuals of observed versus predicted CPUE for opakapaka CPUE in the main Hawaiian Islands by fishing year from 1949-2003 and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

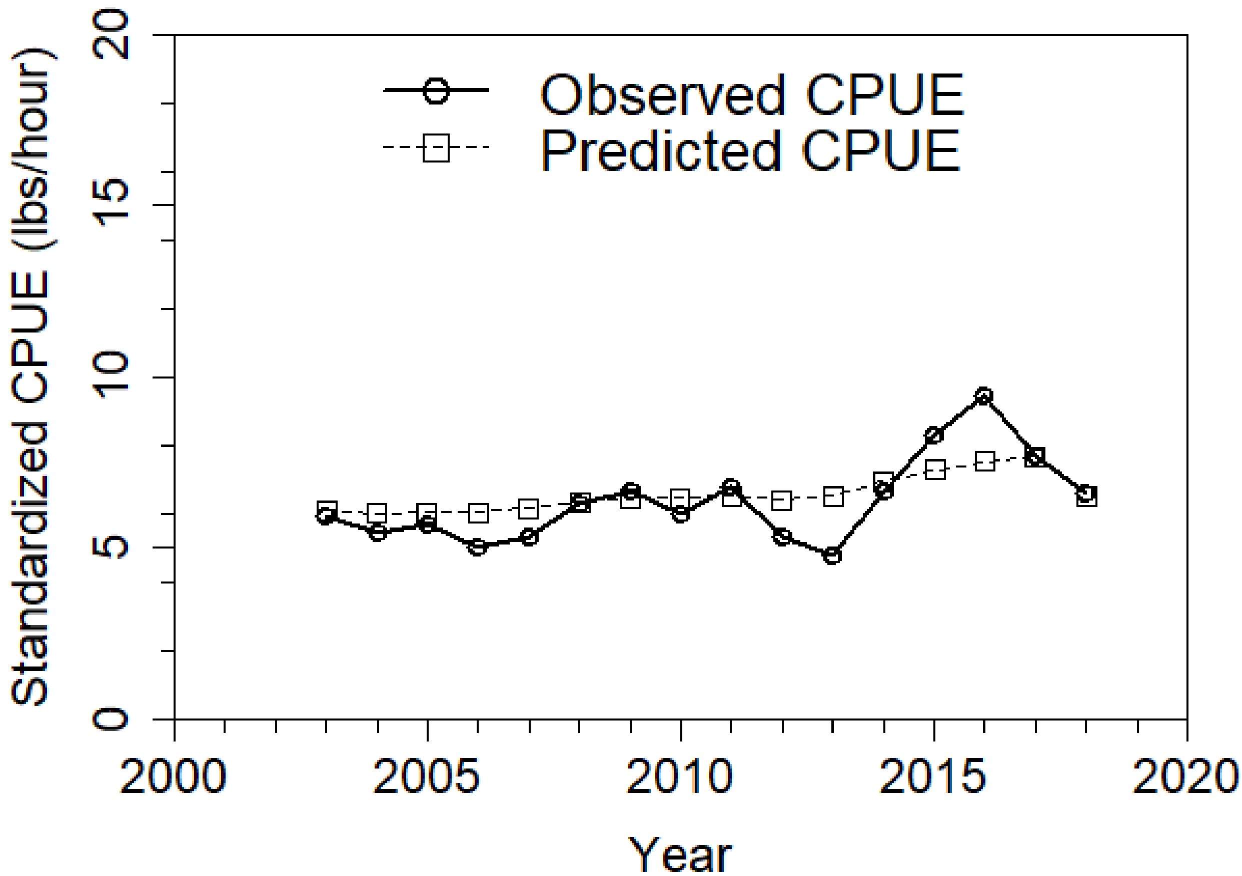


Figure A 8. Observed and predicted CPUE for opakapaka in the main Hawaiian Islands from 2003 through 2018.

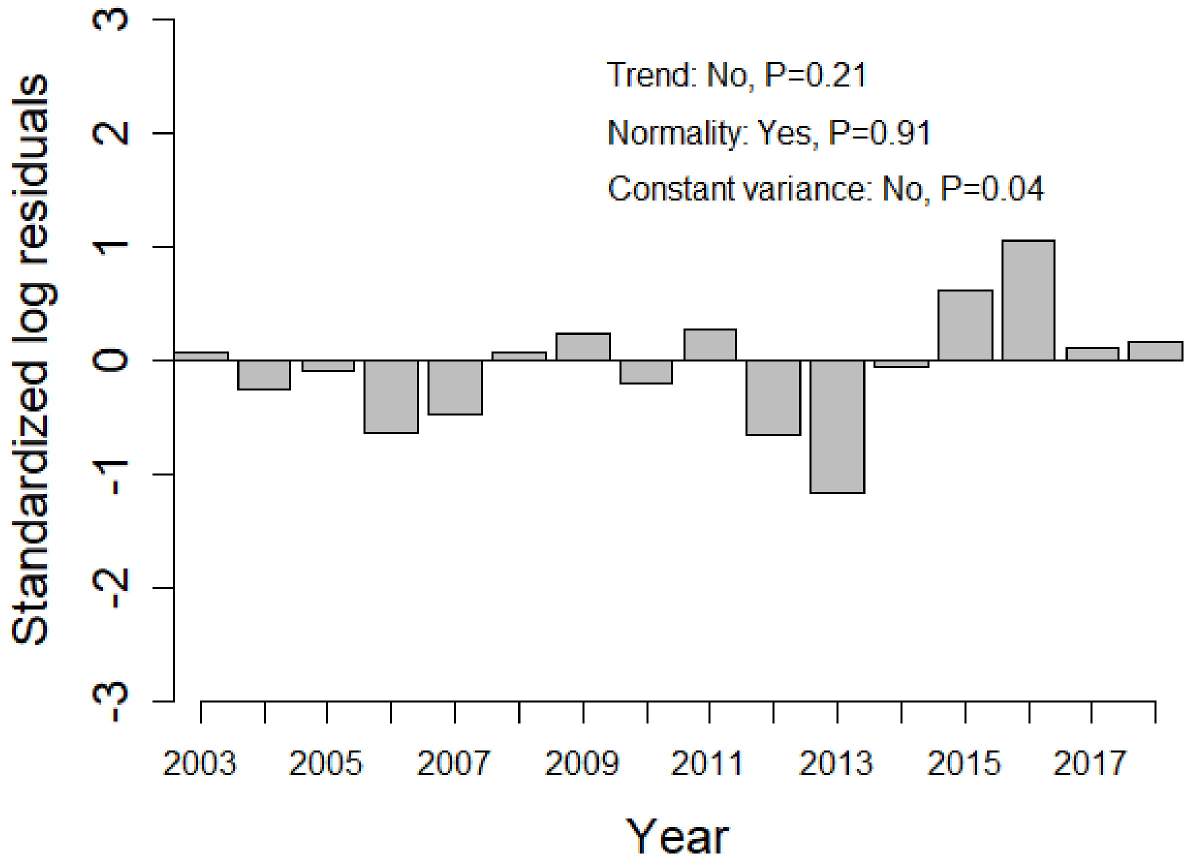


Figure A 9. Standardized residuals of observed versus predicted CPUE for opakapaka CPUE in the main Hawaiian Islands by fishing year from 2003-2018 and p values for linear regression hypothesis tests of whether standardized residuals had a temporal trend, were normally distributed, and had constant variance.

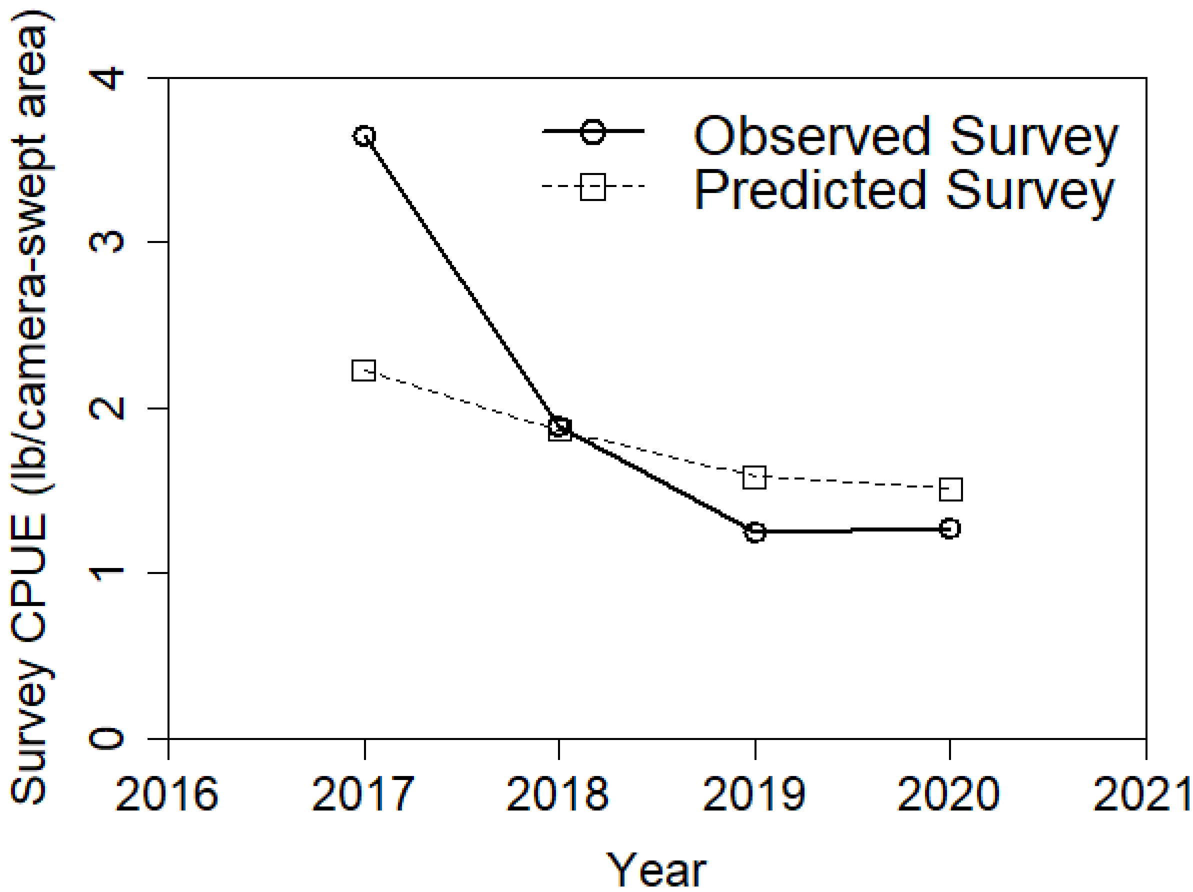


Figure A 10. Observed and predicted CPUE for opakapaka in the fishery-independent survey around the main Hawaiian Islands from 2017 through 2020.

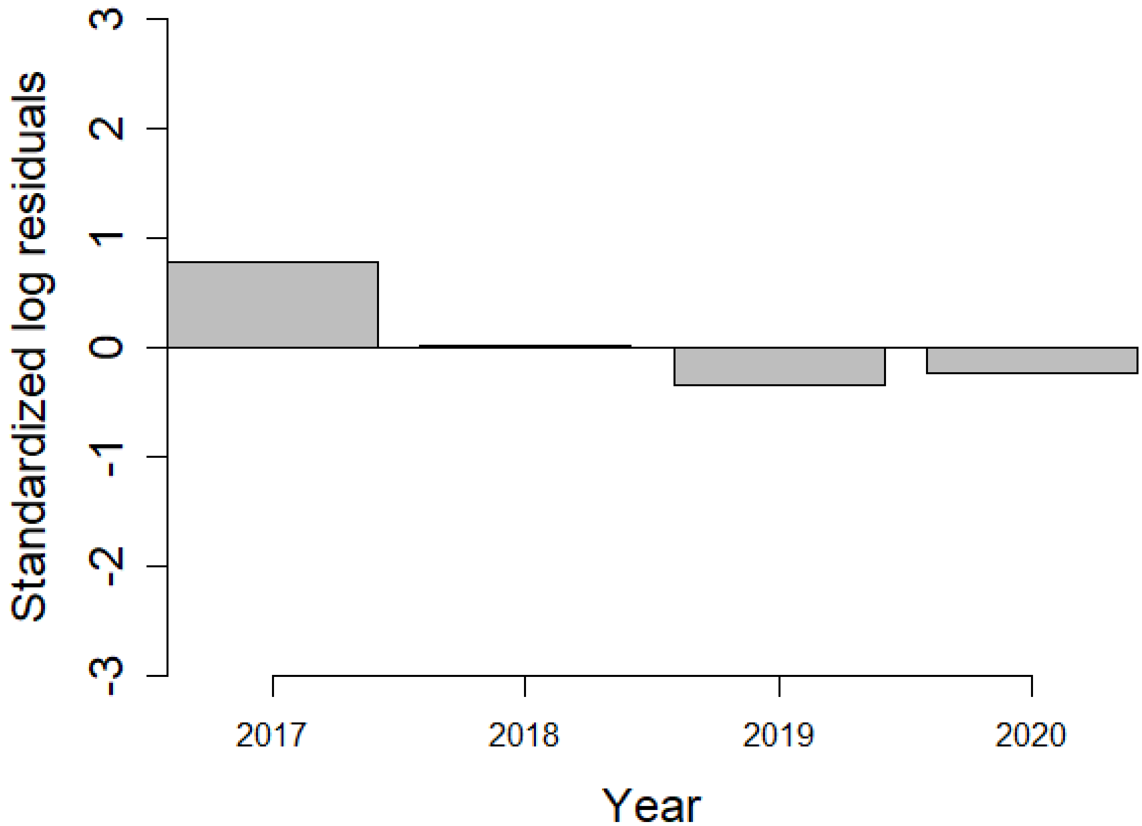


Figure A 11. Standardized residuals of observed versus predicted CPUE for opakapaka CPUE in the fishery-independent survey around the main Hawaiian Islands 2020 around the main Hawaiian Islands by fishing year from 2017-2020.

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 1949-2018.

```
##############################################################
# d7_2020_baseFINAL
# Jon Brodziak, PIFSC, December 2010, updated by Annie Yau, May 2014
# to two-CPUE time series. Updated further by Brian Langseth, April 2017, for 2018 benchmark
#John Syslo updated June 2020 for 2021 update assessment

# Catch is in million pounds
# CPUE is in lbs/trip up before 10/1/2002, and lbs/hr thereafter

# Time period for two-CPUE indices, 1948-2002 and 2002-2018 (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
# Includes capacity to set a weight to the survey std dev to fit the survey
# better (downeight survey sd)
# Exclude 1948 and use actual 2019 catch to set catch for that year
# Use natural mortality of 0.156

# Updated the survey to reflect a prior around the survey catchability
# based on min and max effective radius, corresponding to min and max

# Updated November 14, 2017

#Updated June 2020

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

rm(list=ls())
DATA = read.csv("C:\\File path\\2020_Deep_7\\Complex BSP\\data_NA.csv",header=T)
head(DATA)
DATA=DATA[-1,]

Survey_data = read.csv("C:\\File path\\Survey_data.csv",header=T)

addname <- 'd7_2020_base'  ##<--------name of model---------- # change accordingly
src.dir <- paste('C:\\File path\\2020_Deep_7\\',addname,"\\",sep="")# 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)


################################################################################
#These represent the previous measures:
RC_2019 = 0.177051     #reported catch in 2019

RC_2020 = 0.218388    #Assumed reported catch in 2020
################################################################################


nt <- 20     # Thinning rate
ni <- 555000 # Number of total iterations per chain, including burn-in = multiply # of iterations desired
nb <- 255000 # 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 1994 into two
# Vector Catch() is total catch weight in thousand metric tons 1949-2015
# Vector S1() is the Main Hawaiian Islands CPUE index 1949-1993
# Vector S1() is the Main Hawaiian Islands CPUE index 1993-2015

# 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

#Biomass and SE of survey
BIOSV<- Survey_data$Biomass_kg
SE_SV<- Survey_data$SE_Biomass_kg


#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

NSV_1<- length(DATA$CPUE_1)-1 #account for 4 years of survey data: 2016 - 2019 (Fishing years 2017-
2020)
NSV_2<- length(DATA$CPUE_1)   #FY 17 and 18 will be within a loop

#set up other survey index bounds to avoid errors within BUGS
NSVa<-NSV_1-1
NSVb<-NSV_2+1
NSVc<-((NSV_2+1)-(NSV_1-1))
NSVd<-NSV_2+2
NSVe<-((NSV_2+2)-(NSV_1-1))

#Survey biomass and SE estimate for 2016-19 calendar years (millions of pounds)
#From B. Richards 27.6 m radius Convert to million lbs
                              #27.6^2*pi*104.4653 gives psu area
BioYR <- BIOSV/1000000*2.20462/(25892*104.4653)
s_eta2 <- (SE_SV/1000000*2.20462/(25892*104.4653))^2
s_CV <- sqrt(s_eta2)/BioYR
s_eta2log <- log(s_CV*s_CV+1)
s_lambda <- 1 #initial weighting on sd of survey estimate


#########################
# 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 <-27.6
CV_rad <- 0.5

LB <- 0.6
UB <- 1.4

proj_LB <- 0.6
proj_UB <- 1.4


pLIM_B <- 0.844

UC_ratio <-1.11  # average of 2014-2018

start_TAC <- 0.000
mesh_TAC <- 0.002
#mesh_TAC <- 0.005
NTAC <- 501
#NTAC <- 201


#################################################################
# 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,
  NSV_1 = NSV_1,
```

```
NSV_2 = NSV_2,
NSVa = NSVa,
NSVb = NSVb,
NSVc = NSVc,
NSVd = NSVd,
NSVe = NSVe,


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,

BioYR = BioYR,
s_eta2log = s_eta2log,
s_lambda = s_lambda,

proj_LB = proj_LB,
proj_UB = proj_UB,

RC_2019 = RC_2019,

RC_2020 = RC_2020,
```

```
  UC_ratio = UC_ratio,


  start_TAC = start_TAC,
  mesh_TAC = mesh_TAC,
  NTAC = NTAC

) # end data list

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

# Analysis using WinBUGS - not used at the momment. Instead read separate BUGS file
# 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 the survey radius
```

```
#(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(7.5,60.6)
q3 <- 250000/(rad*rad*3.14159)

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

# 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 FY2018, n=70
#(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])
}

Pmean2019 <- log(max(P[NTIME] + r*P[NTIME]*(1-pow(P[NTIME],M)) - Catch[NTIME]/K,0.0001))
P2019 ~ dlnorm(Pmean2019,isigma2)I(0.0001,10000)
C2019lo <- LB*0.15521783 + 0.177051  #last quantity is reported
C2019hi <- UB*0.15521783 + 0.177051  #last quantity is reported
Catch2019 ~ dunif(C2019lo,C2019hi)
```

```
Pmean2020 <- log(max(P2019 + r*P2019*(1-pow(P2019,M)) - Catch2019/K,0.0001))
P2020 ~ dlnorm(Pmean2020,isigma2)I(0.0001,10000)


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

# deep7 bottomfish CPUE lLIKELIHOOD, NOT USED P[1:NCPUE_S1_1]
#(L1)########################################################
# for (i in 1:NCPUE_S1_1) {
# 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])
# }

# deep7 bottomfish CPUE lLIKELIHOOD, 1948-2003
P[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2]
#(L2)########################################################
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])
}

# deep7 bottomfish CPUE lLIKELIHOOD, 2003-2019 P[(NCPUE_S1_2+1):NCPUE_S1_3]
#(L3)########################################################
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 2017-18 estimates  #P2019 and P2020 aren't in this
#(L4)########################################################
for (i in (NSV_1):NSV_2){
survey_mean[i] <- log(P[i]*K/(q3*25892))
Precision_survey[i] <- (s_lambda*s_lambda)/s_eta2log[i-NSVa]
BioYR[i-NSVa] ~ dlnorm(survey_mean[i],Precision_survey[i])
LOG_RESID3[i] <- log(BioYR[i-NSVa]) - log(P[i]*K/(q3*25892))
}


# survey likelihood, for 2019 and 2020 estimates
#(L4)########################################################
```

```
survey_mean[NSVb] <- log(P2019*K/(q3*25892))
Precision_survey19 <- (s_lambda*s_lambda)/s_eta2log[NSVc]
BioYR[NSVc] ~ dlnorm(survey_mean[NSVb],Precision_survey19)
LOG_RESID3[NSVb] <- log(BioYR[NSVc]) - log(P2019*K/(q3*25892))



survey_mean[NSVd] <- log(P2020*K/(q3*25892))
Precision_survey20 <- (s_lambda*s_lambda)/s_eta2log[NSVe]
BioYR[NSVe] ~ dlnorm(survey_mean[NSVd] ,Precision_survey20)
LOG_RESID3[NSVd] <- log(BioYR[NSVe]) - log(P2020*K/(q3*25892))



# Compute LOG_RSS and LOG_RMSE
#################################################################
  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[NSV_1:NSVd], LOG_RESID3[NSV_1:NSVd])

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]
}


for (i in (NSV_1):NSVd){
```

```
STD_LOG_RESID3[i] <- LOG_RESID3[i]/LOG_RMSE3
PRED_Bio[i] <- exp(survey_mean[i])
RESID3[i] <- BioYR[i-(NSV_1-1)] - PRED_Bio[i]
}



# Compute RSS and RMSE for MHI CPUE
###################################################################
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[NSV_1:NSVd],RESID3[NSV_1:NSVd])

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

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

RMSE3 <- sqrt(RSS3/(NSV_2+2-NSV_1))

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

# Compute exploitation rate and biomass time series
#(QOI1)##############################################################
# MHI 1948-2015 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 2019 Projection
   proj_Pmean2019<- (max(P[NTIME] + r*P[NTIME]*(1-pow(P[NTIME],M)) - Catch[NTIME]/K,0.0001))
   B[NTIME+1] <- proj_Pmean2019*K


   UC[1] <- UC_ratio*RC_2019

   lower[NTIME+1] <- proj_LB*UC[1] + RC_2019
   upper[NTIME+1] <- proj_UB*UC[1] + RC_2019


   proj_C2019 ~ dunif(lower[NTIME+1],upper[NTIME+1])

   H[NTIME+1] <- min(proj_C2019/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_Pmean2019,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 2020 Projection
   #################################################################
   proj_Pmean2020 <- (max(proj_Pmean2019 + r*proj_Pmean2019*(1-pow(proj_Pmean2019,M)) -
proj_C2019/K,0.0001))

   B[NTIME+2] <- proj_Pmean2020*K
```

```
   UC[2] <- UC_ratio*RC_2020

   lower[NTIME+2] <- proj_LB*UC[2] + RC_2020
   upper[NTIME+2] <- proj_UB*UC[2] + RC_2020

   proj_C2020 ~ dunif(lower[NTIME+2],upper[NTIME+2])

   H[NTIME+2] <- min(proj_C2020/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_Pmean2020,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 2021-2022 Projection
###################################################################
   proj_lower <- proj_LB*UC_ratio
   proj_upper <- proj_UB*UC_ratio

   proj_Pmean <- (max(proj_Pmean2020 + r*proj_Pmean2020*(1-pow(proj_Pmean2020,M)) -
proj_C2020/K,0.0001))

   B[NTIME+3] <- proj_Pmean*K  #2021 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)
   {
   #2021-2022
   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_P2022[j] <- max(proj_Pmean + r*proj_Pmean*(1-pow(proj_Pmean,M)) - proj_C1[j]/K,0.0001)
   proj_B2022[j] <- proj_P2022[j]*K
```

```
proj_BSTATUS[j] <- proj_B2022[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_B2022[j],0.999)
#    proj_H2[j] <- min(proj_C2[j]/proj_B[j],0.999)
proj_HSTATUS2[j] <- proj_H2[j]/HMSY
proj_pOFL_H2[j] <- step(proj_HSTATUS2[j] - 1.0)



#2023-2025  projection



proj_P2023[j] <- max(proj_P2022[j] + r*proj_P2022[j]*(1-pow(proj_P2022[j],M)) - proj_C2[j]/K,0.0001)
proj_B2023[j]<- proj_P2023[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_B2023[j],0.999)
proj_HSTATUS3[j] <- proj_H3[j]/HMSY
proj_pOFL_H3[j] <- step(proj_HSTATUS3[j] - 1.0)
proj_BSTATUS3[j]<- proj_B2023[j]/BMSY
proj_pOFL_B3[j] <- step(pLIM_B - proj_BSTATUS3[j])

proj_P2024[j] <- max(proj_P2023[j] + r*proj_P2023[j]*(1-pow(proj_P2023[j],M)) - proj_C3[j]/K,0.0001)
proj_B2024[j] <-proj_P2024[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_B2024[j],0.999)
proj_HSTATUS4[j] <- proj_H4[j]/HMSY
proj_pOFL_H4[j] <- step(proj_HSTATUS4[j] - 1.0)
proj_BSTATUS4[j]<- proj_B2024[j]/BMSY
proj_pOFL_B4[j] <- step(pLIM_B - proj_BSTATUS4[j])

proj_P2025[j] <- max(proj_P2024[j] + r*proj_P2024[j]*(1-pow(proj_P2024[j],M)) - proj_C4[j]/K,0.0001)
proj_B2025[j] <- proj_P2025[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_B2025[j], 0.999)
   proj_HSTATUS5[j] <- proj_H5[j]/HMSY
   proj_pOFL_H5[j] <- step(proj_HSTATUS5[j] - 1.0)

   proj_BSTATUS5[j] <- proj_B2025[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(0.890568408,0.780141322,0.827136735,0.76223799,0.661001365,
       0.676712544,0.55389128,0.710439819,0.856515787,0.563433499,
       0.517070196,0.42887519,0.339205311,0.4469463,0.560498174,
       0.542606506,0.585471579,0.468168603,0.660834647,0.524553112,
       0.493078085,0.429513477,0.365754118,0.652472663,0.49518941,
       0.68527923,0.639130203,0.685372642,0.718483749,0.872808368,
       0.788074103,0.739263202,0.948284067,0.93863966,1.192176718,
```

```
    0.933642904,1.249188416,1.244535433,1.534016004,1.60281839,
    1.604606184,1.220957021,0.840975704,0.971630742,0.716315491,
    0.893114185,0.976257722,0.765849379,0.850127531,0.781433882,
    0.528538985,0.750220277,0.569860369,0.43489043,0.514820142,
    0.396826878,0.470045616,0.355597079,0.421877928,0.40172532,
    0.538372806,0.438659038,0.586252204,0.445221546,0.445352322,
    0.652537384,0.640379572,0.557556757,0.523622913,0.493875921),

Catch2019 = 0.332268904,

r=0.05,

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

P2019=0.5,
P2020=0.5,

K=45.0,

M=1.0,

q1=10.0,
q2=10.0,
rad=27.6,

isigma2=100,

itau2_1=100,
itau2_2=100,

proj_C2019= 0.332268904,

proj_C2020= 0.449923,

proj_UC_ratio1=rep(1.11, 501),

proj_UC_ratio2=rep(1.11, 501),

proj_UC_ratio3=rep(1.11, 501),

proj_UC_ratio4=rep(1.11, 501),

proj_UC_ratio5=rep(1.11, 501)
```

```
)##END init 1

## Initial Condition 2

,list(

  Catch=c(0.890568408,0.780141322,0.827136735,0.76223799,0.661001365,
        0.676712544,0.55389128,0.710439819,0.856515787,0.563433499,
        0.517070196,0.42887519,0.339205311,0.4469463,0.560498174,
        0.542606506,0.585471579,0.468168603,0.660834647,0.524553112,
        0.493078085,0.429513477,0.365754118,0.652472663,0.49518941,
        0.68527923,0.639130203,0.685372642,0.718483749,0.872808368,
        0.788074103,0.739263202,0.948284067,0.93863966,1.192176718,
        0.933642904,1.249188416,1.244535433,1.534016004,1.60281839,
        1.604606184,1.220957021,0.840975704,0.971630742,0.716315491,
        0.893114185,0.976257722,0.765849379,0.850127531,0.781433882,
        0.528538985,0.750220277,0.569860369,0.43489043,0.514820142,
        0.396826878,0.470045616,0.355597079,0.421877928,0.40172532,
        0.538372806,0.438659038,0.586252204,0.445221546,0.445352322,
        0.652537384,0.640379572,0.557556757,0.523622913,0.493875921),

  Catch2019 = 0.332268904,

  r=0.15,

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

  P2019=0.5,
  P2020=0.5,

  K=15.0,

  M=1.0,

  q1=10.0,
  q2=10.0,
  rad=27.6,

  isigma2=100,

  itau2_1=100,
  itau2_2=100,

  proj_C2019= 0.332268904,
  proj_C2020= 0.449923,

  proj_UC_ratio1=rep(1.11, 501),
```

```
  proj_UC_ratio2=rep(1.11, 501),

  proj_UC_ratio3=rep(1.11, 501),

  proj_UC_ratio4=rep(1.11, 501),

  proj_UC_ratio5=rep(1.11, 501)

)##END init 2

## Initial Condition 3

,list(

  Catch=c(0.890568408,0.780141322,0.827136735,0.76223799,0.661001365,
        0.676712544,0.55389128,0.710439819,0.856515787,0.563433499,
        0.517070196,0.42887519,0.339205311,0.4469463,0.560498174,
        0.542606506,0.585471579,0.468168603,0.660834647,0.524553112,
        0.493078085,0.429513477,0.365754118,0.652472663,0.49518941,
        0.68527923,0.639130203,0.685372642,0.718483749,0.872808368,
        0.788074103,0.739263202,0.948284067,0.93863966,1.192176718,
        0.933642904,1.249188416,1.244535433,1.534016004,1.60281839,
        1.604606184,1.220957021,0.840975704,0.971630742,0.716315491,
        0.893114185,0.976257722,0.765849379,0.850127531,0.781433882,
        0.528538985,0.750220277,0.569860369,0.43489043,0.514820142,
        0.396826878,0.470045616,0.355597079,0.421877928,0.40172532,
        0.538372806,0.438659038,0.586252204,0.445221546,0.445352322,
        0.652537384,0.640379572,0.557556757,0.523622913,0.493875921),

  Catch2019 = 0.332268904,

  r=0.10,

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

  P2019=0.5,
  P2020=0.5,

  K=30.0,

  M=1.0,

  q1=10.0,
  q2=10.0,
  rad=27.6,

  isigma2=100,
```

```
    itau2_1=100,
    itau2_2=100,

    proj_C2019= 0.332268904,
    proj_C2020= 0.449923,

    proj_UC_ratio1=rep(1.11, 501),

    proj_UC_ratio2=rep(1.11, 501),

    proj_UC_ratio3=rep(1.11, 501),

    proj_UC_ratio4=rep(1.11, 501),

    proj_UC_ratio5=rep(1.11, 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_Bio",

  ## 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_RESID3", "RESID3",
  "LOG_RSS1", "LOG_RSS2", "LOG_RSS3", "LOG_RMSE1", "LOG_RMSE2", "LOG_RMSE3",   "RSS1",
"RSS2","RSS3",  "RMSE1", "RMSE2" ,"RMSE3"



#Nodes to monitor if projecting#################
```

#Need to divide out due to number of nodes being monitored, do
#B and H for one, and rerun with poflB and poflH as the other]

"B", #always monitor B as a check

"proj_B2022",

"proj_B2023",

"proj_B2024",

"proj_B2025",

"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"

"proj_C1", "proj_H1", "proj_HSTATUS1", "proj_P", "proj_P2017",
"proj_BSTATUS", "proj_C2", "proj_pOFL_B",

```
    "proj_H2", "proj_HSTATUS2", "proj_pOFL_H2"#,

)

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=TRUE,codaPkg=FALSE,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 1949-2018.

```
#################################################################
# paka_2020_baseFINAL
# Jon Brodziak, PIFSC, December 2010, updated by Annie Yau, May 2014
# to two-CPUE time series. Updated further by Brian Langseth, April 2017, for 2018 benchmark
#John Syslo updated June 2020 for 2021 update assessment


# Catch is in million pounds
# CPUE is in lbs/trip up before 10/1/2002, and lbs/hr thereafter

# Time period for two-CPUE indices, 1948-2002 and 2002-2018 (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
# Includes capacity to set a weight to the survey std dev to fit the survey
# better (downeight survey sd)
# Exclude 1948 and use actual 2019 catch to set catch for that year
# Use natural mortality of 0.156

# Updated the survey to reflect a prior around the survey catchability
# based on min and max effective radius, corresponding to min and max

# Updated July 30, 2020
################################################################

rm(list=ls())
DATA = read.csv("C:\\File path\\2020_data_paka.csv",header=T)

head(DATA)
DATA=DATA[-1,]

Survey_data = read.csv("C:\\File path\\Survey_data_paka.csv",header=T)

addname <- 'Paka_2020_575'  ##<--------name of model---------- # change accordingly
src.dir <- paste('C:\\File path\\Paka BSP\\',addname,"\\",sep="")

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 <- 575000 # Number of total iterations per chain, including burn-in = multiply # of iterations desired
by nt
nb <- 275000 #round(ni*(1/10)) # Number of draws to discard as burn in; discard 10,000


#########################################################################
# DATA
# model variable set-up
#########################################################################
###obs_CPUE_1 = na.rm(DATA$CPUE_1_1)
# In this case, there is one CPUE set split at 1994 into two
# Vector Catch() is total catch weight in thousand metric tons 1949-2018
# Vector S1() is the Main Hawaiian Islands CPUE index 1949-1993
# Vector S1() is the Main Hawaiian Islands CPUE index 1993-2018

# 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

#Biomass and SE of survey  #will probably need to remove last 2 years from this data frame
BIOSV<- Survey_data$Biomass_kg
SE_SV<- Survey_data$SE_Biomass_kg


#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

NSV_1<- length(DATA$CPUE_1)-1 #account for 4 years of survey data: 2016 - 2019 (Fishing years 2017-
2020)
NSV_2<- length(DATA$CPUE_1)   #17 and 18 will be within a loop

#set up other survey index bounds to avoid errors within BUGS
NSVa<-NSV_1-1
NSVb<-NSV_2+1
NSVc<-((NSV_2+1)-(NSV_1-1))
NSVd<-NSV_2+2
NSVe<-((NSV_2+2)-(NSV_1-1))

#Survey biomass and SE estimate for 2016-19 calendar years (millions of pounds)
#From B. Richards 27.6 m radius Convert to million lbs
                                #27.6^2*pi*104.4653 gives psu area
BioYR <- BIOSV/1000000*2.20462/(25892*104.4653)

s_eta2 <- (SE_SV/1000000*2.20462/(25892*104.4653))^2
s_CV <- sqrt(s_eta2)/BioYR
s_eta2log <- log(s_CV*s_CV+1)
s_lambda <- 1 #initial weighting on sd of survey estimate


#########################
# model parameters
#########################

Target_K_Prior_avg <- 13.5
CV_K <- 0.5

Target_r_Prior_avg <- 0.10
CV_r <- 0.25

Target_P1_Prior_avg <- 0.62
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 <-27.6
CV_rad <- 0.5

LB <- 0.6
UB <- 1.4

pLIM_B <- 0.844


#  NPROJ <- 4


##################################################################
# 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,
  NSV_1 = NSV_1,
  NSV_2 = NSV_2,
  NSVa = NSVa,
  NSVb = NSVb,
  NSVc = NSVc,
  NSVd = NSVd,
  NSVe = NSVe,



  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,

  BioYR = BioYR,
  s_eta2log = s_eta2log,
  s_lambda = s_lambda



) # end data list

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

# Analysis using WinBUGS - not used at the momment. Instead read separate BUGS file
# 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 the survey radius
#(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(7.5,60.6)
q3 <- 250000/(rad*rad*3.14159)

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

# 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 FY2018, n=70
#(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])
}

Pmean2019 <- log(max(P[NTIME] + r*P[NTIME]*(1-pow(P[NTIME],M)) - Catch[NTIME]/K,0.0001))
P2019 ~ dlnorm(Pmean2019,isigma2)I(0.0001,10000)
C2019lo <- LB*0.138017 + 0.070660  #last quantity is reported
C2019hi <- UB*0.138017 + 0.070660  #last quantity is reported
Catch2019 ~ dunif(C2019lo,C2019hi)
Pmean2020 <- log(max(P2019 + r*P2019*(1-pow(P2019,M)) - Catch2019/K,0.0001))
P2020 ~ dlnorm(Pmean2020,isigma2)I(0.0001,10000)


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

  # deep7 bottomfish CPUE lLIKELIHOOD, 1948-2003
P[(NCPUE_S1_1+NCPUE_S1_MISS+1):NCPUE_S1_2]
#(L2)############################################################
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])
}

# deep7 bottomfish CPUE lLIKELIHOOD, 2003-2018 P[(NCPUE_S1_2+1):NCPUE_S1_3]
#(L3)############################################################
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 2017-18 estimates  ##P2019 and P2020 aren't in this
#(L4)############################################################
for (i in (NSV_1):NSV_2){
survey_mean[i] <- log(P[i]*K/(q3*25892))
Precision_survey[i] <- (s_lambda*s_lambda)/s_eta2log[i-NSVa]
BioYR[i-NSVa] ~ dlnorm(survey_mean[i],Precision_survey[i])
LOG_RESID3[i] <- log(BioYR[i-NSVa]) - log(P[i]*K/(q3*25892))
}


# survey likelihood, for 2019 and 2020 estimates
#(L4)############################################################
survey_mean[NSVb] <- log(P2019*K/(q3*25892))
Precision_survey19 <- (s_lambda*s_lambda)/s_eta2log[NSVc]
BioYR[NSVc] ~ dlnorm(survey_mean[NSVb],Precision_survey19)
LOG_RESID3[NSVb] <- log(BioYR[NSVc]) - log(P2019*K/(q3*25892))


survey_mean[NSVd] <- log(P2020*K/(q3*25892))
Precision_survey20 <- (s_lambda*s_lambda)/s_eta2log[NSVe]
BioYR[NSVe] ~ dlnorm(survey_mean[NSVd] ,Precision_survey20)
LOG_RESID3[NSVd] <- log(BioYR[NSVe]) - log(P2020*K/(q3*25892))



# Compute LOG_RSS and LOG_RMSE
################################################################
  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[NSV_1:NSVd], LOG_RESID3[NSV_1:NSVd])

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]
}


for (i in (NSV_1):NSVd){
STD_LOG_RESID3[i] <- LOG_RESID3[i]/LOG_RMSE3
PRED_Bio[i] <- exp(survey_mean[i])
RESID3[i] <- BioYR[i-(NSV_1-1)] - PRED_Bio[i]
}



# Compute RSS and RMSE for MHI CPUE
################################################################
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[NSV_1:NSVd],RESID3[NSV_1:NSVd])

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

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

RMSE3 <- sqrt(RSS3/(NSV_2+2-NSV_1))

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

# Compute exploitation rate and biomass time series
#(QOI1)###########################################################
# MHI 1948-2018 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,
       0.45978309,0.38915946,0.39598227,0.31280049,
       0.41497623,0.56982267,0.35820333,0.30107439,
       0.27311751,0.22088799,0.29168964,0.35766153,
       0.35770797,0.40078881,0.27636057,0.46898982,
       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,
       0.540903089,0.621108878,0.55232444,0.363770012,
       0.55327001,0.393816906,0.307659983,0.379168317,
       0.261657149,0.310099779,0.225664461,0.274954106,
       0.285705387,0.396121938,0.31343206,0.440957088,
       0.312547059,0.285265976,0.477684375,0.459445041,
       0.407928609,0.401534793,0.352552365
),


Catch2019 = 0.208077,

r=0.05,

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

P2019=0.5,
P2020=0.5,

K=21.0,

M=1.0,

q1=10.0,
q2=10.0,
rad=27.6,

isigma2=100,

itau2_1=100,
itau2_2=100

)##END init 1

## Initial Condition 2
```

```
,list(

  Catch=c(0.45229851,0.44030925,0.48110292,
        0.45978309,0.38915946,0.39598227,0.31280049,
        0.41497623,0.56982267,0.35820333,0.30107439,
        0.27311751,0.22088799,0.29168964,0.35766153,
        0.35770797,0.40078881,0.27636057,0.46898982,
        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,
        0.540903089,0.621108878,0.55232444,0.363770012,
        0.55327001,0.393816906,0.307659983,0.379168317,
        0.261657149,0.310099779,0.225664461,0.274954106,
        0.285705387,0.396121938,0.31343206,0.440957088,
        0.312547059,0.285265976,0.477684375,0.459445041,
        0.407928609,0.401534793,0.352552365),

  Catch2019 = 0.208077,

  r=0.15,

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

  P2019=0.5,
  P2020=0.5,

  K=7.0,

  M=1.0,

  q1=10.0,
  q2=10.0,
  rad=27.6,

  isigma2=100,

  itau2_1=100,
  itau2_2=100

)##END init 2

## Initial Condition 3

,list(
```

```
  Catch=c(0.45229851,0.44030925,0.48110292,
        0.45978309,0.38915946,0.39598227,0.31280049,
        0.41497623,0.56982267,0.35820333,0.30107439,
        0.27311751,0.22088799,0.29168964,0.35766153,
        0.35770797,0.40078881,0.27636057,0.46898982,
        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,
        0.540903089,0.621108878,0.55232444,0.363770012,
        0.55327001,0.393816906,0.307659983,0.379168317,
        0.261657149,0.310099779,0.225664461,0.274954106,
        0.285705387,0.396121938,0.31343206,0.440957088,
        0.312547059,0.285265976,0.477684375,0.459445041,
        0.407928609,0.401534793,0.352552365),

  Catch2019 = 0.208077,

  r=0.10,

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

  P2019=0.5,
  P2020=0.5,

  K=14.0,

  M=1.0,

  q1=10.0,
  q2=10.0,
  rad=27.6,

  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_Bio",

  ## 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",   "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:/WinBUGS,
    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 (2003-2018) 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"

#Update by J Syslo May 2020

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


library(ggplot2)

library(GGally)

library(lubridate)

library(Rmisc)

raw.data = read.csv("C:\\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'))
```

```
## Output new dataset

write.csv(raw.data, "C:\\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("C:\\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; those with suspect periods dropped are tpX.0.

```
df.tp1 = subset(df, FYEAR %in% c(1948:2003))
df.tp2 = subset(df, FYEAR %in% c(2003:2018))

## 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 + area:qtr+ log_cum_exp , 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)


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.
```

```
bernvar = function(x) mean(x)*(1-mean(x))

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

TP2ba = aggregate(BIN.CATCH ~ FYEAR, data = TP2b,  FUN = function(x) c(mean = mean(x), sd = sd(x), var = var(x),bernvar=bernvar(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.CATCH[,'var']),'VARIANCE.ADDITIVE'=TP1pa$trans[,'var']+TP1ba$BIN.CATCH[,'var'],'BERNVARIANCE.FORM' = varI(TP1pa$trans[,'mean'],TP1pa$trans[,'var'],TP1ba$BIN.CATCH[,'mean'],TP1ba$BIN.CATCH[,'bernvar'])
)

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.CATCH[,'var']),'VARIANCE.ADDITIVE'=TP2pa$trans[,'var']+TP2ba$BIN.CATCH[,'var'],'BERNVARIANCE.FORM' = varI(TP2pa$trans[,'mean'],TP2pa$trans[,'var'],TP2ba$BIN.CATCH[,'mean'],TP2ba$BIN.CATCH[,'bernvar'])
)

TP2I$MODEL = 'TP2'

#set up full df


full.df = rbind(TP1I,TP2I)  #removed TP10I,TP1WI,
```

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

full.df$CV = full.df$SD/full.df$INDEX.EST

full.df$N=c(table(TP1$FYEAR)[1:56],table(TP2$FYEAR)[56:71])

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

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

head(full.df)

write.csv(full.df,'C:\\File path\\Finalized_stdindex_0715_REMLF_NA.csv', row.names = F)
```