2018 Benchmark Stock Assessment of Main Hawaiian Islands Kona Crab

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Abstract

A stock assessment of the main Hawaiian Islands Kona crab fishery was conducted and finalized in 2019 using data from 1957 through 2016. This benchmark assessment improved upon filtering of data records by re-defining fishing effort as a single reported fishing day and exploring fisher effects (individual fisher effects and cumulative fishing experience) in catch-per-unit effort (CPUE) standardization. Additionally, this 2018 assessment addressed uncertainty previously unaccounted for, including unreported catch, incidental mortality of female crab catch following the prohibition of female crab harvest in 2006, and a Bayesian prior on the initial ratio of biomass to carrying capacity. The assessment used a state-space Bayesian surplus production model in a new user-friendly framework, Just Another Bayesian Biomass Assessment (JABBA). The model fit standardized CPUE data in a generalized Pella-Tomlinson surplus production model. Parameter distributions were estimated in a Bayesian framework, which estimates parameter posterior distributions starting from prior distributions and fitted to data. Annual harvest rates (H), harvest rate at maximum sustainable yield (H_{MSY}), annual biomass (B), and biomass at maximum sustainable yield (B_{MSY}) were estimated in JABBA, among other outputs. Results from this assessment conclude that in 2016, the Hawaii Kona crab fishery was not overfished (defined as $B/B_{MSY} < 0.7$) with a 0.01% probability of the status being overfished in 2016. In 2016, the stock was not experiencing overfishing (defined as $H/H_{MSY} > 1$), with 0% probability of overfishing occurring. The model converged and a retrospective analysis detected no strong retrospective pattern. Projections from 2020 to2026 quantified overfishing risks for various future catch levels, and concluded that a 50% risk of overfishing in 2026 corresponds to an annual reported catch of 33,989 lb.

1. Introduction

The Kona crab, *Ranina ranina* (Linnaeus, 1767), is a brachyuran crustacean in the Raninidae family. The species is fairly cosmopolitan throughout the tropical and sub-tropical Indo-Pacific region. Kona crabs are commonly referred to as spanner crabs (Australia) and the species is also known as the red frog crab, frog crab, papa'i kua loa, and krab ziraf. The southeast Queensland spanner crab fishery is the largest known fishery for the species, landing in excess of 1500 metric tons in annual catch records since the mid-1990s (Dichmont and Brown, 2010). Directed fisheries for the species also exist in Western Australia, New South Wales (Australia), the Philippines, Japan, Thailand, Mauritius, Reunion, and the Seychelles archipelago (Boulle, 1995; Cook, 1987; Krajangdara and Watanabe, 2005; Tahil, 1983). This benchmark assessment implements fishery data and biological information collected in the Main Hawaiian Islands (defined in Yau (2018); Fig. 1), with the exception of life history information borrowed from Australia to estimate natural mortality (explained in Section 1.1 Biology and Life History).

1.1 Biology and Life History

This section describes basic Kona crab biology and life history. When available, information specific to Kona crabs in Hawaii are provided. The information presented in this section is an overview, and the only value directly used in the stock assessment from this section was the natural mortality rate to define overfished criteria. Some basic biology is used to inform a prior on intrinsic growth rate.

Kona crabs possess a rigid and broad carapace that ranges in color from a pale whitish-red hue to bright orange-red. The boldness of color may correspond with age and size (Fielding and Haley, 1976). Small spines cover the carapace perimeter and saw-like spines cover the chelae, which grow and sharpen as the crab matures (Uchida and Uchiyama, 1986). Males and females are easily distinguishable by the size of the chelae (Minagawa, 1993) and more notably by the morphology of the abdomen (Fielding and Haley, 1976; Wiley, 2017).

Hawaii Kona crab habitat consists of moderately coarse sandy substrate 2–200 meters in depth, within areas with little change in relief, with exposure to currents, and in proximity to reef environments (Cook, 1987; Thomas et al., 2013; Vansant, 1978). Adult crabs share habitat preferences with juveniles and spend the majority of their time buried in the sand, typically only emerging for feeding or for mating (Brown et al., 2001; Skinner and Hill, 1986). Onizuka (1972) noted that young and smaller Kona crabs are frequently observed in high numbers in shallower sandy areas such as Waimea Bay on the island of Oʻahu. A high abundance and larger sizes of Kona crabs have been observed off Penguin Bank, a large sandy and deeper expanse protruding off southwest Molokai towards Oahu (Brown, 1985; Fielding and Haley, 1976; Thomas et al., 2013; Wiley, 2017).

Egg-bearing female Kona crabs are observed from May through September and larger females are thought to be observable in shallower areas immediately before and after this time (Onizuka, 1972), yet females seldom emerge from the sand during the egg-bearing period (Skinner and Hill, 1987). A closed season for Kona crab implemented by the state of Hawaii corresponds to spawning season, in which females are found to be egg bearing until the season ends (Fielding and Haley, 1976; Kennelly and Watkins, 1994).

Hawaii fishery catches were comprised of 55% male and 45% female in earlier studies (Fielding and Haley, 1976; Onizuka, 1972) and recent observations in 2018 have found sex composition in catches of Kona crabs to be slightly different, 49% male and 51% female (Wiley and Pardee, 2018). Male Kona crabs need to be large enough to move their female counterparts from the sand in order to successfully mate (Skinner and Hill, 1986). Males are mostly sexually mature by the time they reach 2.9 inches carapace length (Fielding, 1974; Fielding and Haley, 1976). Females are 87% sexually mature by the time they are 2.6 inches carapace length (Onizuka, 1972).

Kona crabs in Australia are hypothesized to have 'slow growth' (Brown, I.W., S. Kirkwood, C. Gaddes, 1999), confirmed through mark-recapture to estimate von Bertalanffy growth equation parameters: mean maximum length (L_∞) of 155.9 and 121.7 mm for males and females respectively; and Brody growth coefficient (k) of 0.29 and 0.24/yr for males and females respectively (Kirkwood et al., 2005). Chen and Kennelly (1999) used tagging data and found that these crabs grow stepwise and slowly with a von Bertalanffy Brody growth coefficient (k) of 0.216 and 0.08/yr for males and females, respectively. In comparison, Hawaii Kona crabs are assumed to grow larger based on age and growth studies (Brown, I.W., S. Kirkwood, C. Gaddes, 1999; Chen and Kennelly, 1999; Kirkwood et al., 2005) and have higher observed male growth rates in molt intervals (Onizuka, 1972). To reach a legal 4 inches (101.6 mm) rostral carapace length in Hawaii, it would take an average of 4.31 years for male crabs and 6.35 years for female crabs.

Kona crabs and their conspecifics in Australia are assumed to have a longevity of 10 to 16 years (Kirkwood et al., 2005) Natural mortality (*natM*) can be estimated using longevity, assuming a mortality rate under unfished conditions to reduce a population to 1%, such that $natM = \ln(0.01)/a_{max}$ (Hoenig, 1983). O'Neill et al. (2010) estimated *natM* to be 0.277/yr using the Hoenig (1983) approach with a_{max} = 17 years. Assuming a maximum age of 16 years from Kirkwood et al. (2005), natural mortality using the Hoenig approach would equal 0.29/yr. Then et al. (2015) recommend using maximum age but also offer an empirical estimation method using growth parameters such that $natM = 4.118k^{0.73} \times L_{\infty}^{-0.33}$. Using sex-averaged mean growth parameters (L_{∞} and k) from Kirkwood et al. (2005), natural mortality equals 0.31/yr when applying the Then et al. (2015) approach, which corroborates an estimate using longevity alone. For this stock assessment report, *natM* is assumed to be 0.30/yr.

Onizuka (1972) estimated comprehensive length-weight relationships for Hawaii Kona crabs. Weight for males (W, in grams) using length (L, in millimeters) is estimated as W=0.000273×$L^{2.9931}$. The female length-weight relationship is estimated as W=0.0001392×$L^{2.8345}$.

1.2 Fishery and Regulations

Kona crabs have been commercially fished in Hawaii since near the beginning of the 20th century. This is a targeted fishery that deploys hoop nets (also called 'tangle nets' or 'Kona crab nets,') which are circular frames (usually metal, but can be wooden) usually 24 to 30 inches in diameter, with 1-cm to 1-inch mesh (twine, polyester, or even metal). The hoop nets are baited and deployed in tethered daisy chains and set over sandy bottom, usually free of structure or rocky, hard substrate. When baited hoop nets are deployed, some Kona crabs will emerge from the sand and often quickly find the bait. The spiny appendages tangle the crab in the net.

The state of Hawaii has implemented several management regulations for the Kona crab fishery starting in 1938, when a minimum size of 4 inches rostral-carapace length went into effect for any crab sold or possessed in commercial fishing operations. Fishing of Kona crabs was also closed in summer months beginning June 1 through August 31 starting in 1938 to coincide with the spawning season. Spearing crabs and lobsters were prohibited beginning in 1958. In 1993, the Kona crab closed season was extended by starting earlier (May 1–August 31). In 1998, Kona crab gear was prohibited to be on a vessel in possession of bottomfish species gear. However, this regulation was repealed in 2010. In 2002, the 4-inch size limit provision was extended for any personal/non-commercial possession and consumption. Starting on September 1, 2006, the harvest of female Kona crabs was prohibited, and the fishery became male harvest only, with females still caught and released back into the water.

Kona crabs are consumed in social gatherings, graduations, weddings, holidays, and are even gifted. Kona crabs generally need to be consumed within a day of capture and can spoil quickly. They are eaten cooked and raw. In recent years, reported catch of this species has declined (Figure 2).

1.3 Previous Stock Assessment

The previous Kona crab stock assessment by Thomas et al. (2015) indicated that the Kona crab stock was experiencing overfishing and was overfished in 2007. The authors developed three time series of standardized catch-per-unit-effort (CPUE) indices for the stock. The first index was from 1948 to 1998 from the advent of data reporting in the Hawaii Kona crab fishery until the 1998 prohibition of possessing Kona crab gear with bottomfish gear. The second index ranged from 1998 to 2006 until the prohibition of female crab harvest, and the final series ranged from 2006 to 2009. In the assessment model, the earliest years of the first CPUE time series were not used and both catch and standardized CPUE time series began in 1970. The authors used A Surplus Production Incorporating Covariates (ASPIC; Prager, 1994) to deterministically estimate carrying capacity, intrinsic growth, biomass at maximum sustainable yield (MSY), fishing mortality at MSY, catchabilities, and other outputs. The ratio of initial year biomass to carrying capacity was fixed at 0.7 and a Schaefer production model was assumed.

This 2019 benchmark stock assessment addresses some of the concerns noted by an independent reviewer (Hall, 2015) regarding the assessment by Thomas et al. (2015). Notable improvements include:

1. Employment of a much longer time series of catch and CPUE.

2. Reconstruction of total catch by estimating incidental mortality from female discards based on recent studies and accounting for unreported catch.

3. Development of CPUE indices that include extensive data filtering to define a unit of fishing effort as single fishing day employing a specific gear, accounting for individual fisher effects through time, and exploration of the significance of habitat characteristics.

4. Adoption of a state-space Bayesian framework to allow for the use of informative priors in a Pella-Tomlinson production model using Just Another Bayesian Biomass Assessment (JABBA, Winker et al., (2018)) and estimation of posterior distributions for several parameters, including initial year ratio of biomass to carrying capacity, intrinsic growth rate, carrying capacity, shape parameter, catchabilities, and process error and observation error.

5. Sensitivity analyses on alternative parameter priors and catch scenarios, retrospective analyses, and overfishing risks in future catch scenarios.

2. Materials and Methods

2.1 Data

2.1.1 Data Sources

Data used in this Kona crab benchmark stock assessment originates from the state of Hawaii Department of Land and Natural Resources, Division of Aquatic Resources (DAR). DAR began collecting and recording official information on commercial fishing catch and effort in 1948 in the Fisher Reporting System (FRS). The state of Hawaii defines fishing as "commercial" if one fish/animal is sold. Commercial fishers must obtain a license and provide monthly reports on all fishing activity, regardless of what portion is ultimately sold. In this assessment and report, fishing year or simply year follows the state fiscal year such that fishing year 2016 refers to the period July 1, 2015 until June 30, 2016. Data used in this assessment were queried on June 30, 2017, and so only include final FRS data through fishing year 2016 because 2017 data were not yet finalized. Fields in each FRS data record of interest include fisher license (commercial marine license, hereafter referred to as CML number), date, DAR area fished (Figure 1), fishing gear, species caught, total weight caught by species in pounds (lb), and number of individuals caught by species. Not all fields were always filled out in each record. Since October 2002, more specific effort details were added to the form, including the number of fishing sets, hours fished, and number of gears deployed. These effort details are not used in this stock assessment because they are not consistently filled out.

Kona crabs are a targeted fishery when hoop nets are deployed. The hoop net gear was given a unique gear code in FRS records in 1954. Hoop nets were not a regularly reported fishing gear for Kona crabs until 1957, after which hoop net gear was consistently reported for Kona crab catch. As such, this stock assessment uses FRS records beginning in fishing year 1958 (starts July 1, 1957) to 2016 (ends June 30, 2016).

From fishing years 1958-2016 in the main Hawaiian Islands, Kona crabs were reported caught in 17 gear types in 12,237 FRS records, with 11,305 records indicating catch in Kona crab hoop nets (gear code 40), 442 records of catch in generic crab traps which can include deep sea traps (gear code 51), 209 records of catch in crab nets (gear code 26), and 160 records of catch in miscellaneous traps (gear code 11). There were a total of 12,446 FRS records that reported either Kona crabs caught or Kona crab hoop nets, which included catch records in 82 DAR fishing areas and landings in 72 unique port codes throughout the state of Hawaii from 1958 to 2016. Around 23% of records (2,916 of 12,446) were caught in Penguin Bank over time (Area 331, Figure 1).

Commercially reported weight data for Kona crabs was investigated. Each DAR FRS record contains fields for total pounds caught and total number caught; if nonzero values are reported in both fields, then the average weight of Kona crabs caught in a record can be calculated. However, the number caught is not commonly reported. Of the 12,237 records that reported pounds caught of Kona crab from 1958 to 2016 in the main Hawaiian Islands, 16 records report a pound value of zero. Of the remaining 12,221 records that report pounds of Kona crab greater than zero, only 5,557 (45%) also reported a number caught that is greater than zero. The remaining 54% of records report a number of zero Kona crabs caught even though they report a nonzero value for pounds of Kona crab caught. There are 196 records that report one Kona crab caught; of these, 147 report catching one Kona crab that weighed one pound. These few records are the only records that provide individual Kona crab weights, but the weight resolution is large given that weight is reported in 1-lb increments.

Given that the reporting incidence of Kona crab numbers caught is 45%, it is not known whether the resulting average weight calculations per record are representative of the fishery or not; therefore, average weight was not used for this assessment. For illustrative purposes, we calculate the average weight of Kona crabs for each of the 5,557 records that reported nonzero pounds and nonzero numbers and present the average annual weights in Figure 3 as boxplots without outliers plotted.

2.1.2 Annual Catch

Reported catches are calculated by summing up the pounds caught from all FRS records reporting within the main Hawaiian Island fishing areas (Figure 1). Annual reported catches $C_{reported,y}$ for each fishing year y are summed from 1958 to 2016. Catches reported in FRS data for Kona crab gradually increased from early years to the peak of the fishery in 1972 with reported catches nearly reaching 70,000 lb (Figure 2). Reported catches have not exceeded 40,000 lb since 1974, as the fishery had another peak of 36,714 lb reported in 1992. Reported catches declined in the last two decades to below 3,000 lb in 2015 and 2016, which are the last two years of data used in this benchmark stock assessment. Calculation of catch, nominal CPUE, and standardized CPUE were conducted using the R Statistical Computing Environment (R Foundation for Statistical Computing, Vienna, 2011).

Annual reported catch $C_{reported,y}$ is converted to estimated annual total catch C_y using a two-step process: 1) calculating adjusted reported catch $C_{adj\ reported,y}$ by adding discarded female mortality following the 2006 prohibition of possessing female Kona crabs, and 2) calculating total catch by adding unreported catch to adjusted reported catch.

Recent studies in Hawaii have shown that post-release mortality of female crabs is 10.77% (Wiley, 2017; Wiley and Pardee, 2018). This contrasts an earlier study that found discard mortality of crabs in Australia to be much higher, 70–100%, when dactyl or limbs were damaged or lost (Kennelly et al., 1990). The same recent studies also showed that 51% of crabs caught in Hawaii are female (Wiley, 2017; Wiley and Pardee, 2018).

Using the information from recent studies (Wiley, 2017; Wiley and Pardee, 2018), adjusted annual reported catch $C_{adj\ reported,y}$ is calculated per year y to account for female discard mortality starting in fishing year 2007 from reported catch $C_{reported,y}$ such that:

Equation 1
$$\boldsymbol{C_{adj.reported,y} = C_{reported,y} + \left[C_{reported,y} \times \frac{0.51}{0.49} \times 0.1077\right]}$$

In addition to female discards, unreported catch was addressed for all years. Unreported catch in Hawaii fisheries may be substantial and are a source of uncertainty in stock assessments (Courtney and Brodziak, 2011; Hamm and Lum, 1992; Hospital and Beavers, 2014; Zeller et al., 2008). We attempted to reconcile likely ratios of unreported catch to reported catches for Hawaii Deep-7 bottomfish by presenting scenarios of unreported catches based on empirical information from numerous studies. Most of the studies are based on intercept interviews and surveys of fishers or are based on recreational fishing catch and effort surveys from databases such as the Hawaii Marine Recreational Fishing Survey (HMRFS), also known as the Marine Recreational Information Program (MRIP). The aforementioned studies and surveys were targeted towards finfish with very little information on shellfish or crustacean catches. For example, a total of 12 Kona crabs were recorded in the entire HMRFS/MRIP survey database (H. Ma, *personal communication*).

Brodziak, et al. (2014) and Langseth et al. (2018) used annual, species-specific unreported catch ratios in Deep-7 bottomfish stock assessments from 1948 to 2016. The mean annual ratio of unreported to reported catch for the Deep-7 complex from 1948 to 2016 was 1.54:1 (Langseth et al., 2018). We refer to this number as the average ratio (*UCR* = 1.54) and use this number to estimate total catch as described next.

Total annual Kona crab catch (C_y) by year (y) is assumed to equal to adjusted reported catch by year ($C_{adj\ reported,y}$) plus unreported catch, which is adjusted reported catch by year scaled by the unreported catch ratio (*UCR*):

Equation 2

$$C_y = C_{adj.reported,y} + UCR \times C_{adj.reported,y}$$

This average unreported catch ratio (*UCR* = 1.54) was used due to a lack of thorough studies or available information to specifically estimate non-commercial unreported catch of Kona crab (or non-commercial fishing effort targeting Kona crab. There are some similarities between bottomfish and Kona crab operations (requires a small boat that can go far enough out to reach deeper depths, and deploy and retrieve gear from those depths). The resulting total catch for the base case is presented in Table 1. Alternative unreported catch scenarios are investigated as described in Section 2.3.6 Sensitivity Analyses and Section 3.5 Results of Sensitivity Analyses.

2.1.3 Nominal CPUE

DAR FRS records were used to calculate nominal catch-per-unit-effort (CPUE) for standardization. Only records reporting from areas within the main Hawaiian Islands (Figure 1) are used. Only records that report catching Kona crab using hoop net gear (code = 40) are used for CPUE calculation. Of all reported Kona crab pounds caught, 93% were caught by hoop net gear from 1958 to 2016.

Individual fishers were tracked through time using CML numbers (see Langseth et al., 2018). Before fishing year 1994, individuals were issued a different unique CML number every year. After 1994, individuals were issued the same CML number every year. In 2016, PIFSC scientists undertook an effort to link fishers back through time using names and as a result, individual fishers are tracked by CML number.

A 'single-reporting day' was used as the effort unit (Yau, 2018). Single-reporting day is defined as a unique combination of CML number and date. This definition is used because the FRS data do not have unique trip identifiers. Given that Kona crab catch is difficult to keep fresh, it is likely that Kona crab trips took place within a single day. This was confirmed through examination of FRS records since 2002 when more detailed effort fields became available on the reporting form. In FRS records since 2002 that did report more detailed effort information, there were no reported Kona crab fishing activities that took place longer than a 24 hour-period, and no reported gear deployments past 24 hours. These detailed effort fields are rarely completed for Kona crab reports and when they are completed, it is often unclear if total gear was deployed in multiple sets or was a multiplicative product of the number of reported sets. For these reasons, single-reporting day was used as the effort unit for the entire time series. There were 11,015 single-reporting days in which Kona crab was caught using hoop net gear in the main Hawaiian Islands from 1958 to 2016.

To calculate nominal CPUE in units of pounds per single-reporting day, the total pounds of Kona crab reported on a single-reporting day are summed up. Only 13 single-reporting days report 0 lb of Kona crab caught, and these single-reporting days were retained for nominal CPUE and CPUE standardization.

Single-reporting days with Kona crab catch were analyzed to determine whether other species are caught on the same day (Figure 4). Of the 11,214 single-reporting days with Kona crab caught in hoop net gear since 1958, the top three most commonly caught other species on Kona crab single-reporting days were yellowfin tuna (*Thunnes albacares*, 789 single-reporting days) followed by uku (*Aprion virescens*, 742 single-reporting days), then ono/wahoo (*Acanthocybium solandri*, 685 single-reporting days). These single-reporting days may not be mutually exclusive.

Bottomfish species were specifically analyzed because they exist at similar depths, have similar fishing vessel needs, and there was a regulation prohibiting the possession of Kona crab gear with bottomfishing gear on the same trip between 1998 and 2010. Of the 11,214 single-reporting days with Kona crab caught in hoop net gear since 1958, 742 reporting days also report catching uku (*Aprion virescens*), 317 also report catching opakapaka (*Pristipomoides filamentosus*), and 110 also report catching onaga (*Etelis coruscans*). Again, these single-reporting days may not be mutually exclusive. The frequency of bottomfish species associated with single-reporting days that caught Kona crab was not substantially different before and after the 1998 regulation prohibiting the possession of Kona crab gear with bottomfishing gear on the same trip, nor was it substantially different after the repeal of that regulation.

2.2 CPUE Standardization

2.2.1 Variables Used in CPUE Standardization

CPUE standardization was completed in an attempt to account for factors that affect CPUE other than changes in stock abundance. The following general categories of factors were considered for CPUE standardization, and described in more detail below: temporal, spatial, individual fisher effects, habitat, and oceanographic.

Temporal factors explored for CPUE standardization include fishing year, month, and season. All temporal factors are treated as categorical variables for the standardization model. Seasons are based on the female reproductive cycle (Minagawa, 1993) as used in Thomas et al. (2015), defined as September to October, November to December, January to February, March to April, and May through August which corresponds with the closed season. These seasons may explain activity rates of Kona crabs (Skinner and Hill, 1986).

Spatial factors explored include DAR grid area and island, both treated as categorical variables. For the purpose of using area as a factor for CPUE standardization, single-reporting days that report more than one area were assigned the area that yielded the highest pounds of Kona crab that day. Only 1% of single-reporting days reported more than one area. Islands are defined in Thomas et al. (2015) as Hawaii (Big) Island, Maui Nui (Molokai, Maui, Lanai, Kahoolawe), Oahu, and Kauai/Niihau. There were very few (0.32%) single-reporting days that reported from more than one island.

Individual fisher effects are explored using two different metrics: cumulative fisher experience, and CML number. Cumulative fisher experience for each single-reporting day by a given fisher is calculated as the cumulative number of other single-reporting days up to that date and tested in the CPUE standardization as a continuous variable in log-scale. CML numbers are categorical variables. For CML numbers, the names in 1976 were not available so records from 1976 could not be linked with the rest of the time series. For the purpose of CPUE standardization, fishers in 1976 were assumed to be a single-pooled fisher following the rationale of Langseth et al. (2018) and were all assigned a single dummy CML number for the purpose of CPUE standardization. Additionally, CML numbers that report five or fewer total Kona crab single-reporting days in the entire time series were also pooled under one of four dummy CML numbers unique to the four island areas (affecting 1,250 of 11,015 single reporting days). As a result, a total of 376 unique CMLs were used in the CPUE standardization from 1958 to 2016.

Habitat factors (Ault et al., 2018) explored include depth, slope, and bottom hardness of substrate in each fishing area. Oceanographic factors explored include the Pacific Decadal Oscillation (PDO) Index, and El Niño Southern Oscillation (ENSO) Index 3.4 on monthly time scales. These oceanographic indices were explored because of previously documented impacts such indices had on CPUE of Northwestern Hawaiian lobster fisheries (Polovina and Mitchum, 1992). All habitat factors and oceanographic factors are continuous variables.

2.2.2 CPUE Standardization Model Selection and Diagnostics

Kona crab CPUE series are standardized separately for 'Period 1' (1958–2006) and 'Period 2' (2007–2016) due to the recent prohibition of female catch beginning on September 1, 2006. There were 9,687 single-reporting days in Period 1 and 1,328 single-reporting days in Period 2.

CPUE was standardized using generalized linear mixed models (GLMMs) with a Gaussian error structure using the lme4 package (Bates et al., 2017) in R (R Foundation for Statistical Computing, Vienna, 2011). GLMMs estimate parameters using maximum likelihood. The response variable for each model was the natural logarithm of CPUE from positive catches of Kona crab; recorded catch values of zero were retained as zero rather than log-transformed. The natural log of catch (in pounds) per single reporting day as a response variable passes the Shapiro-Wilk test for normality ($p > 0.05$) when randomly sampled by year and in all years pooled. This confirms an underlying assumption of the standardization model subsequently applied.

All variables described in the previous Section 2.2.1 Variables Used in CPUE Standardization were explored as predictors for statistical inclusion in the standardization models for both time series. Interactive effects were considered between year and license, and year and area fished. All variables were modeled as fixed effects with the exception of CML number, which was modeled as a random effect.

The model selection procedure consisted of a forward selection routine with the variable fishing year, and CML number as a random effect, always included because CPUE by year is the required output of the model. Each and every remaining predictor was added one at a time, and the added predictor was retained if the resulting model met a minimum criteria of 2% reduction of Akaike's information criterion from the preceding model (Maunder and Punt, 2004). Model selection was complete when this criterion was not met with the addition of any additional predictor variable.

Model fit was assessed through visual comparison of Pearson residuals plotted against predicted values of the response variable and against values of the predictor variables. Residuals were examined visually for collinearity and normality.

2.2.3 Standardized CPUE Calculation

Estimated marginal means are popular for summarizing linear models of unbalanced data and were therefore used in our analysis, primarily accounting for area sampling imbalance over time. Estimated marginal means were calculated by year using the emmeans function in the package emmeans (Lenth et al., 2018) in R (R Foundation for Statistical Computing, Vienna, 2011) to generate standardized CPUE and residual variance for each year.

Standardized CPUE by year is given by these CPUE predictions ($U_{pred,y}$) back-transformed from the natural log scale and averaged using the bias correction technique of Brodziak and Walsh (2013). This correction is the sum of all linearized predictions ($e^{U_{pred,y}}$) for a given year added to one-half the residual variance; and this summation is then divided by the total number of observations in that year (n_y) used in that year's CPUE (U_y) standardization.

$$\widehat{U_y} = \frac{\sum e^{U_{pred,y}+\frac{\sigma^2}{2}}}{n_y}$$

Equation 3

A coefficient of variation (CV) of CPUE for each year is calculated by dividing the standard error from a given year by the mean predicted CPUE value for the corresponding year.

2.3 Assessment Model

2.3.1 Just Another Bayesian Biomass Assessment (JABBA)

This assessment implemented a modeling framework entitled Just Another Bayesian Biomass Assessment (JABBA), which is a tool for conducting state-space Bayesian surplus production models (Winker et al., 2018). It estimates both process error variance and observation error variance. JABBA uses R (R Foundation for Statistical Computing, Vienna, 2011) to set up the model and call up the software program JAGS (Just Another Gibbs Sampler, Plummer, (2003)) using the R package 'rjags' (Plummer, 2016). JABBA estimates Bayesian posterior distributions of model outputs by means of a Markov Chain Monte Carlo (MCMC) simulation.

JABBA provides a generalized Bayesian state-space estimation framework for surplus production models (SPMs) by building on previous formulations by Pella and Tomlinson (1969), (Gilbert, 1992; Wang et al., 2014), and Fletcher (Fletcher, 1978; Thorson et al., 2012). Surplus production models are frequently implemented to estimate sustainable levels of harvest (biomass removals) at corresponding levels of stock biomass. Maximum sustainable yield (*MSY*) is the maximum level of catch that can be removed from a stock over time while maintaining biomass at B_{MSY}, the biomass to produce *MSY*. JABBA formulates the surplus production function of the generalized three-parameter SPM by Pella and Tomlinson (1969, 'Pella-Tomlinson model'):

Equation 4

$$SP_t = \frac{r}{m-1} B_{t-1}\left(1 - \left(\frac{B_{t-1}}{K}\right)^{m-1}\right),$$

where *SP* is surplus production in a given time *t*, *r* is the intrinsic rate of population growth (yr^{-1}), *K* is the carrying capacity (lb), *B* is the biomass (lb), and *m* is a shape parameter that determines where maximum surplus production is attained.

The shape parameter *m* can be arithmetically translated into a ratio of B_{MSY} to carrying capacity (*K)* (Prager, 1994):

Equation 5

$$\frac{B_{MSY}}{K} = m^{\left(-\frac{1}{m-1}\right)}$$

Given a known *K* and *m*, B_{MSY} is solved:

Equation 6

$$B_{MSY} = Km^{\left(-\frac{1}{m-1}\right)}$$

Pella-Tomlinson surplus production models under varying values of the shape parameter, *m*, are depicted in Figure 5.

If the shape parameter $m = 2$, the model reduces to the Schaefer form, with the surplus production attaining maximum surplus production, or *MSY* at exactly a stock biomass level corresponding to $K/2$. If $0 < m < 2$, *MSY* occurs when biomass values are smaller than $K/2$; when $m > 2$, *MSY* occurs when biomass values are greater than $K/2$. The Pella-Tomlinson model reduces to a Fox model if *m* approaches 1 resulting in *MSY* at ~$0.37K$, but there is no solution for the exact Fox model with $m = 1$.

Per the Pella-Tomlinson formulation, the harvest rate at *MSY* (H_{MSY}) is:

Equation 7

$$H_{MSY} = \frac{r}{m-1}\left(1 - \frac{1}{m}\right)$$

where the harvest rate *H* is defined here as the ratio of:

Equation 8

$$H = \frac{C}{B},$$

where *C* denotes the total annual catch (lb).

2.3.2 Process and Observation Error

The surplus production model for Hawaii Kona crab was formulated as a Bayesian state-space production model using JABBA, as introduced above. It included explicit observation and process error terms that have been commonly used for fitting production models with relative abundance indices (Brodziak and Ishimura, 2012; McAllister et al., 2001; Meyer and Millar, 1999a; Punt, 2003). 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 (standardized CPUE). In particular, total observation error likelihood measured the discrepancy between observed and predicted CPUE. Prior distributions for input parameters are used to represent the relative degree of knowledge about the probable values of model parameters. Assumptions of this model included that production follows a specified functional form, the assessment is applicable to exploitable individuals, all exploitable individuals were mature and equally vulnerable to fishing, and that biomass was proportional to standardized CPUE.

JABBA is formulated on the Bayesian state-space estimation framework proposed by Meyer and Millar (Meyer and Millar, 1999b). The biomass *B* in year *y* is expressed as a proportion of *K* (i.e., $P_y = B_y / K$) to improve the efficiency of the estimation algorithm. The initial biomass in the first year of the time series was scaled by introducing model parameter ψ to estimate the ratio of the biomass in the first year to *K* (Carvalho et al., 2014). The stochastic form of the process equation is given by:

Equation 9

$$\boldsymbol{P_y = \begin{cases} \psi e^{\eta_y} & for\ y = 1 \\ \left(P_{y-1} + \frac{r}{(m-1)} P_{y-1}\left(1 - {P_{y-1}}^{m-1}\right) - \frac{\sum_i C_{i,y-1}}{K}\right) e^{\eta_y} & for\ y = 2, 3 \dots n \end{cases}}$$

where η_y is the annual process error deviation, with $\eta_y \sim N(0, \sigma_\eta^2)$ and σ_η^2 is the process error variance. In our modelling framework, the prior on process error is set on the square root of the variance (σ_η) and is referred to herein as "process error". $C_{i,y-1}$ is the catch in year *y*-1 by CPUE time series *i*, and *n* is the number of years in the model which corresponds to the number of years of catch and CPUE data. In the base-case JABBA model for Kona crab, process error was estimated jointly for the two CPUE time series (Period 1 and Period 2).

The corresponding biomass for year *y* is:

Equation 10

$$\boldsymbol{B_y = P_y K \qquad for\ y = 1, 2 \dots n}$$

The observation equation is given by:

Equation 11

$$\boldsymbol{I_{i,y} = q_i B_y e^{\tau_{y,i}} \qquad for\ y = 1, 2 \dots n}$$

where q_i is the estimable catchability coefficient associated with the CPUE time series *i*, $\tau_{y,i}$ is the observation error and $\tau_{y,i} \sim N(0, \sigma_{\tau_{y,i}}^2)$, where $\sigma_{\tau_{y,i}}^2$ is the total observation error variance in year *y* for CPUE time series *i*.

Observation error was estimated independently for each CPUE series. Each observation error variance is partitioned into two components: the total observation variance, $\sigma_{\tau_{y,i}}^2$, typically ranges from 0.1 to 0.4 (Francis et al., 2003) and is comprised of 1) $\sigma_{\tau_{CV,y,i}}^2$, which is inter-annual variability in observation error input as the CV of standardized CPUE, and 2) $\sigma_{\tau_{estimated,i}}^2$, an estimated observation error. The two variance components are additive in their squared form (Francis et al., 2003), with the total observation variance for time series *i* and year *y* given by:

Equation 12

$$\sigma^2_{\tau_{y,i}} = \sigma^2_{\tau_{CV,y,i}} + \sigma^2_{\tau_{estimated,i}}$$

The full Bayesian state-space surplus production model model calculated over n years requires a joint probability distribution over all unobservable parameters $\boldsymbol{\theta}=\{K, r, \psi, m, \sigma^2_\eta, q_i, \sigma^2_{\tau_{y,i}}\}$ and the n process deviates relating to the vector of unobserved states $\boldsymbol{\eta} = \{\eta_1, \eta_2, \ldots \eta_n\}$, together with all observable data in the form of the relative abundance indices I for CPUE time series i, $I_i = \{I_{i,1}, I_{i,2} \ldots I_{i,n}\}$ (Meyer and Millar, 1999). According to Bayes' theorem, it follows that the joint posterior distribution over all unobservable parameters, given the data and unknown states, can be formulated as:

Equation 13

$$p(\boldsymbol{\theta}|\boldsymbol{\eta},\mathbf{I}) = p(K)p(r)p(\psi)p(m)p(\sigma^2_\eta)p(q_i)p(\sigma^2_{\tau_i}) \times p(P_1|\psi,\sigma^2_\eta)\prod_{y=1}^{n} p(P_y|P_y,K,r,m,\psi,\sigma^2_\eta)\prod_{y=1}^{n} p\left(I_{i,y}|P_y,q_i,\eta_y,\sigma^2_{\tau_{y,i}}\right)$$

2.3.3 Prior Distributions

A Bayesian estimation approach was used to estimate production model parameters. Prior distributions were employed to represent existing knowledge about the likely values of model parameters. The carrying capacity parameter K, the intrinsic growth rate parameter r, the production shape parameter m, the initial proportion of biomass to carrying capacity parameter ψ, the catchability parameters q_i, the process error σ_η, and the estimable component of observation error $\sigma_{\tau_{estimated,i}}$, each had prior distributions. For process error and the estimable component of observation error, priors were placed explicitly on the unsquared form of the prior (e.g., the standard deviation). A summary of assumed priors is found in Table 2. The effect of the choice of prior assumptions on model results was assessed through sensitivity analyses as described in Section 2.3.6 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:

Equation 14

$$p(r) = \frac{1}{r\sigma_r\sqrt{2\pi}}exp\left(-\frac{(\ln r-\mu_r)^2}{2\sigma_r^2}\right)$$

The mean of the intrinsic growth rate parameter was set to be $\mu_r = 0.2735$. This mean value was based on the recommendations of Musick (1999) which offered a likely 95% confidence interval of 0.16 to 0.5 for a moderately productive stock with life history characteristics commensurate to the Kona crab. The prior for r was set as a lognormal prior mean of $\mu_r = 0.2735$ with a CV of 30%, which produces a 95% confidence interval that approximates the suggested range on the lognormal scale.

Prior for Carrying Capacity

The prior distribution for carrying capacity *p(K)* was developed using considerations from Millar and Meyer (2000) and Froese et al. (2016). The method uses the maximum catch and the 10th and 90th quantiles of the *r* prior:

Equation 15

$$\boldsymbol{K_{low}} = \frac{\boldsymbol{max(catch)}}{\boldsymbol{r_{high}}}, \quad \boldsymbol{K_{high}} = \frac{\boldsymbol{4 \times max(catch)}}{\boldsymbol{r_{low}}}$$

where r_{low} = 0.184 and r_{high} = 0.397, given the *r* prior described above. The maximum total catch in the base case is 176,342 lb in year 1972. This results in K_{low} = 444,044 lb and K_{high} = 3,832,028 lb. Inputting this range into JABBA automatically converts this range into a lognormal prior, with mean (μ_K) given by the log of the midpoint between K_{low} and K_{high} and variance (σ_K^2) given by:

Equation 16

$$\boldsymbol{\sigma_K^2} = \sqrt{\mathbf{exp}\left(\frac{|\boldsymbol{\mu_K} - \mathbf{log}(\boldsymbol{K_{low}})|^2}{\mathbf{2}}\right) - \mathbf{1}}$$

The prior for *K* then becomes:

Equation 17

$$\boldsymbol{p(K)} = \frac{\mathbf{1}}{\mathbf{K\sigma_K\sqrt{2\pi}}}\mathbf{exp}\left(-\frac{(\mathbf{ln\,K} - \boldsymbol{\mu_K})^2}{\mathbf{2\sigma_K}^2}\right)$$

The resultant lognormal prior mean for mean μ_K =1,306,243 lb and CV = 53%.

Prior for Production Shape Parameter

The prior distribution for the production function shape parameter *p(m)* was a moderately informative lognormal distribution with mean (μ_m) and variance (σ_m^2):

Equation 18

$$\boldsymbol{p(m)} = \frac{\mathbf{1}}{\boldsymbol{m\sigma_m\sqrt{2\pi}}}\boldsymbol{exp}\left(-\frac{(\boldsymbol{ln\,m} - \boldsymbol{\mu_m})^2}{\mathbf{2}\boldsymbol{\sigma_m^2}}\right)$$

The value of the lognormal mean was set to μ_m = 1.188 with a CV of 35%. This mean value for *m* corresponds to the value of *m* for a model where B_{MSY}/K = 0.4. This value was chosen based on a meta-analyses from the RAM legacy database by Thorson et al. (2012) which concluded B_{MSY}/K = 0.404 was a conservative generalized estimate for most fishes. Punt et al. (2013) stated for crab and lobster stocks that a B_{MSY}/K range of 0.35 to 0.4 were often reliable estimates.

Prior for Catchability

The prior for Kona crab fishery catchability $p(q_i)$ in each of our two time periods *i* was an uninformative uniform distribution on the interval [10^{-30}, 3]. This diffuse prior was chosen to allow the data and model structure to completely determine the distribution of fishery catchability estimates.

Priors for Error Variances

In our modeling framework, the priors for error were placed on the standard error (square-root of the variance term), i.e., σ_η for process error, and $\sigma_{\tau_{estimated,i}}$ for observation error. When presenting results in figures, variances are presented.

The inverse-gamma distribution is uniform in log scale (Gelman, 2006; Winker et al., 2018) and is a commonly used distribution for error variances. The prior for the process error $p(\sigma_\eta)$ was chosen to be a moderately informative inverse-gamma distribution with rate parameter $\lambda > 0$ and shape parameter $k > 0$ for process error, σ_η:

$$\boldsymbol{p(\sigma_\eta) = \frac{\lambda^k (\sigma_\eta)^{-k-1} exp\left(\frac{-\lambda}{\sigma_\eta^2}\right)}{\Gamma(k)}}$$

Equation 19

The base case model includes an estimable process error term. For the process error variance prior, $k = 4$ and $\lambda = 0.01$. This matches the level of process error where state-space surplus production models are most likely to adequately perform, e.g., have lower model errors (Ono et al., 2012; Thorson et al., 2014). This distribution has a 95% confidence interval from 0.03 to 0.1 with a mean of 0.06 and a CV of 29%.

The prior for estimable observation error *$p(\sigma_{\tau_{estimated,i}})$*, for each CPUE series *i*, assumes an uninformative inverse-gamma distribution. The prior for the estimable component of observation error $\sigma^2_{\tau_{estimated,i}}$ is assigned identically for both time series *i* as:

$$\boldsymbol{p(\sigma_{\tau_{estimated,i}}) = \frac{\lambda^k (\sigma_{\tau_{estimated,i}})^{-k-1} exp\left(\frac{-\lambda}{\sigma_{\tau_{estimated,i}}}\right)}{\Gamma(k)}}$$

Equation 20

with gamma rate λ set to 0.004 and shape k parameters set to 0.001 (Gelman, 2006). The posterior for estimable observation error, and subsequently total observation error (which includes the squared form of $\sigma_{\tau_{estimated,i}}$, Equation 12) were estimated separately for each CPUE time series.

Prior for Initial Year Proportion of Carrying Capacity

The prior distribution for ψ was an uninformative lognormal distribution with mean (μ_ψ) and variance *(σ^2_ψ)* parameters:

$$\boldsymbol{p(\psi) = \frac{1}{\Psi\sigma_\psi\sqrt{2\pi}} exp\left(-\frac{(ln\psi - \mu_\psi)^2}{2\sigma^2_\psi}\right)}$$

Equation 21

The value of the prior mean for ψ was set at 0.83, equal to the ratio of the 95th percentile of the standardization-model initial year CPUE (1958) to the 95th percentile of all standardization model CPUE estimates for Period 1. A CV of 50% was chosen for this prior.

2.3.4 Convergence Diagnostics

Convergence of the MCMC samples to the posterior distribution is monitored via visual inspection of the trace, and Heidelberger and Welch (1992) and Geweke (1992) diagnostics as implemented in the coda R package (Plummer et al., 2006).

JABBA provides additional diagnostic plots to illustrate several components of model performance. JABBA also produces the Root-Mean-Squared-Error (RMSE) to quantitatively evaluate the relative accuracy of model predictions of the entire time series with respect to observed values, scaled as a percentage of deviation.

2.3.5 Retrospective Analysis

A retrospective analysis was conducted to assess whether there are consistent patterns in model-estimated outputs based on increasing periods of data (Mohn, 1999). A retrospective analysis is conducted by sequentially removing the terminal year of data and re-estimating model results. Each subsequent year removal is called a 'peel.' A retrospective analysis was conducted going back to 2011 by successively deleting the catch and CPUE data for years 2015 through 2011 in five 1-year 'peels,' refitting the assessment model, and comparing the results to the base case model with terminal data and estimates in 2016. The magnitude of retrospective pattern was assessed using Mohn's rho (ρ; Mohn, 1999), which computes relative patterns of deviations with respect to a base model:

$$\boldsymbol{\rho} = \sum_{y=2011}^{2015} \frac{\boldsymbol{X}_{(y1:y),y} - \boldsymbol{X}_{(y1:y2),y}}{\boldsymbol{X}_{(y1:y2),y}}$$

Equation 22

where y_1 = 1958 and y_2 = 2016, spanning the full data set of the base case model; X indicates either exploitable biomass or harvest rate, and y indicates the terminal year for each retrospective refitting (i.e., y from 2011 to 2015). Graphical interpretations of biomass and harvest rate are presented to visualize retrospective patterns.

2.3.6 Sensitivity Analyses

Sensitivity analyses examine the effect on model-estimated results of varying prior values relative to the base case values. They were conducted by altering input parameter values for priors in isolation and comparing results to base-case model results. Sensitivity analyses were conducted on the following input parameters: carrying capacity (K), intrinsic population growth rate (r), shape parameter (m), initial year proportion of biomass to carrying capacity (ψ), process error (σ_η), estimated observation error ($\sigma_{\tau_{estimated}}$), and unreported catch ratios. Early sensitivities on catchability (q_i) showed minimal impact on results and are not further presented here.

A table of sensitivity analyses tested is provided in Table 3. Carrying capacity (K, base case mean prior 1,306,243 lb with CV = 53%) had alternative prior means adjusted by 0.5, 0.75, 1.25, and 1.5 times base case prior means. Alternative intrinsic growth rate prior means (r, base case mean 0.27 with CV = 30%) were adjusted by factors of 0.5, 0.75, 1.25, and 1.5. Alternative prior means on shape parameter m (base case mean= 1.188, CV= 35%) were inspected by adjusting the base case m prior mean by 0.75, 1.25, and 1.5. Initial year proportion of biomass to carrying capacity ψ (base case mean 0.83, CV = 50%) had the prior mean adjusted by a factor of 0.5 and 0.75, and also fixed to equal 1. Sensitivity to process error (σ_{η}) was adjusted by adjusting rate parameters for the inverse gamma distribution so that the prior mean changed by a factor of 0.5, 0.75, or 2, and thus ranged from 50% to 100% changes in the prior mean with CV of 30% retained for each. For sensitivities on observation error, we adjusted the estimated component of observation error $\sigma_{\tau_{estimated}}$ by adjusting rate parameters for the inverse gamma distribution so that the prior mode changed by a factor of 0.5, 0.75, or 2. Given the parameterization of the estimated component of the observation error, the mean is undefined so changes in parameterization results in changes in the mode of the inverse gamma distribution.

Lastly, sensitivity runs for unreported catches include three scenarios: adjusted reported catch only (UCR = 0, no unreported catch), an annual ratio of UCR from Langseth et al. (2018) and a high ratio (UCR = 5) (Table 1, Table 3, Figure 2). The annual ratios varied from year to year and ranged from UCR = 0.9 to 2.06. The high ratio value comes from two sources. First, the United States Fish and Wildlife Service conducts state estimates of recreational and non-commercial consumptive fishing activity every 5 years starting in 1991 with the most recent survey in 2011, finding that the estimated frequency of total fishing trips in marine non-commercial consumptive and recreational fisheries in Hawaii (finfish, shellfish, and crustaceans combined) is on average 4.97 times that reported in the FRS system. This survey data primarily includes finfish, but does include shellfish and crustacean fishing in a few instances.[1] Second, another recent study estimated that unreported catch of nearshore reef-associated fishes is approximately five times that of reported catch and 84% of total removals for examined species in the region (McCoy et al., 2018).

2.3.7 Catch Projections

Estimated posterior distributions of base case assessment model parameters were used in forward projections for fishing years 2020–2026 to estimate the probability of overfishing, P^*, from 2020–2026 under alternative future catches. The projection results accounted for uncertainty in the distribution of estimates of model parameters from the posterior of the base case model.

In order to move the model forward to the starting year of projections, total catches from 2017 to 2019 were set equal to the total catch value from 2016, which is a total catch of 7,290 lb equivalent to a reported catch of 2,870 lb. Projections were conducted from 2020 to 2026 for a set of alternative values of total catches, which accounts for female discards and a UCR of 1.54. When results for projections are shown, total catches are converted back to reported catches only for management purposes. The projected total catch scenarios ranged from 10,000 to 160,000 lb in 1000-lb increments, corresponding to projected reported catches ranging from 3,937 to 66,992 lb. The projections were conducted assuming each value for the future total catch was constant for each fishing year 2020–2026. Projections were used to compute reported catches for 2020–2026 that would produce probabilities of overfishing varying from 0% to 50% at 1% intervals. The future catch corresponding to a 50% risk of overfishing can be considered the overfishing

[1] See https://wsfrprograms.fws.gov/subpages/nationalsurvey/NatSurveyIndex.htm for more information.

limit (OFL). Other quantities of interest including corresponding relative biomass (B/B_{MSY}), stock status, and risks of overfishing and overfished status were also calculated.

3. Results

3.1 CPUE Model Results and Diagnostics

The best-fit model for Period 1 included CML (as a random effect), year, and fishing area. The best-fit model for Period 1 reduced deviance by 6.7% from a null model with CML only and 5.1% from a model with CML and fishing year only. The best-fit model for Period 2 also included CML (as a random effect), year, and fishing area. No habitat or oceanographic factors were selected in either time period. The best-fit model for Period 2 reduced deviance by 6.5% from a null model with CML only, and 7.2% from the model with CML and fishing year only. The change in AIC, log-likelihood, and degrees of freedom for each predictor are provided in Table 4. Alternative models also explored the impact of removing "novice fishers" from the models. Results (not shown here) indicated that this group did not have a large influence in the overall standardized CPUE scale or trend.

Diagnostic residual plots and summary output of best-fit models show some minor deviation from assumptions about heteroscedasticity but in general, models did not appear to violate assumptions of normality. For Period 1, the histogram of quantile residuals indicated that distributional assumptions were reasonably satisfied (Figure 6). For both time periods, plots of residuals against predictor variables indicated no patterning with individual variables. For Period 2, the histogram of quantile residuals indicated that normality was reasonably satisfied. Plots of quantile residuals against predictor variables showed mild skew towards lower values of the response variable (Figure 7). This may be attributed to a preponderance of lower catch values in the dataset. Altogether, the diagnostic plots were considered indicative of model assumptions being reasonably satisfied. Bias-corrected standardized CPUE is presented in Figure 8. Table 5 provides standardized CPUE indices and CV for Periods 1 and 2, plus catch used in the base case stock assessment model.

3.2 Assessment Model Results and Diagnostics

All model-estimated posterior results from JABBA are reported as median values. Two hundred thousand iterations with a burn-in of 50,000 iterations and thinning increment of 25 were used for successful convergence. Visual inspection of trace plots for the base case model indicate steady convergence of parameters K, r, m, ψ, q_1, q_2, and σ_η^2. Estimated parameters all converge according to Geweke convergence criteria and values come from stable, stationary Markov chains according to Heidelberger and Welch diagnostics. Trace plots were satisfactory with no marked trends; the Heidelberger and Welch stationarity test indicated chains passed the half-width ratio test. Diagnostics confirm that convergence and stationarity criteria are satisfied. Predicted CPUE fits from the JABBA model provide a good fit to observed (standardized) CPUE series (Table 9). Table 10 depicts residuals from base case model fits to CPUE, which pass the Shapiro-Wilk normality test for both time periods (Period 1 $p = 0.32$, Period 2 $p = 0.28$). Resulting fit criteria included the Standard Deviation of Normalized Residuals (SDNR) = 0.70 and Root Mean Squared Error (RMSE) = 7.1 for the CPUE fits, which indicate fits are good. DIC for the base case model was 274.9.

Posteriors for model parameters including carrying capacity (K), intrinsic growth rate (r), shape parameter (m), initial proportion of carrying capacity (ψ), catchability in Period 1 (q_1) and Period 2 (q_2), process error variance (σ_η^2) for the base case Hawaii Kona crab assessment model are depicted as distributions in Figure 11.

The two observation error components (annual CV from standardized CPUE ($\sigma^2_{\tau_{CV,y,i}}$), , and estimable observation error ($\sigma^2_{\tau_{estimated,i}}$)), are additive in their squared forms (Equation 12) to yield total observation error variance $\sigma^2_{\tau_{y,i}}$ across years for Period 1 and Period 2, shown in Figure 12. Table 6 provides parameter estimates and confidence intervals; for process and observation error terms, the posterior estimates in Table 6 are presented in their unsquared form (i.e., $\sigma_\eta, \sigma^2_{\tau_{estimated,i}}$), which matches the format of the prior, and are the square root of the values depicted in Figure 11 and Figure 12.

The posterior median for carrying capacity K was estimated to be 1,445,595 lb. Posterior median intrinsic growth $r = 0.17$, and shape parameter $m = 1.50$. Initial year proportion of biomass to carrying capacity (ψ) was estimated to be 0.71. Maximum sustainable yield (MSY) for the base case model is estimated to be 73,069 lb total catch (25,870 lb reported catch). The posterior median estimate for biomass at maximum sustainable yield (B_{MSY}) is 640,489 lb. The posterior median estimate for harvest rate at MSY, H_{MSY}, is 0.114. Initial year biomass (B_{1958}) is 1,026,999 lb, while terminal year biomass (B_{2016}) is 885,057 lb (Table 7).

3.3 Stock Status of Kona Crab

Reference points for this assessment come from Table 23 of the Western Pacific Regional Fishery Management Council's (WPRFMC) Fishery Ecosystem Plan for the Hawaii Archipelago (*Fishery Ecosystem Plan for the Hawaii Archipelago*, 2009), for Northwest Hawaiian Islands lobster stocks. These reference points were borrowed based on discussions with staff from the Pacific Islands Regional Office and WPRFMC, since no reference points are specified for Hawaii Kona crab. The threshold for defining the Kona crab stock as overfished is $B/B_{MSY} < 0.7$. The value of 0.7 comes from the minimum stock size threshold defined as $(1\text{-}natM)\times B_{MSY}$, since $natM$ is assumed to be 0.3/yr in this assessment (see Section 1.1 Biology and Life History). The overfishing definition depends on biomass: overfishing occurs when $H/H_{MSY} > 1$ if $B > B_{MSY}$. Alternatively, overfishing occurs when $H/H_{MSY} > B/B_{MSY}$ when $B \leq B_{MSY}$. The risk of overfishing is calculated according to these conditions, but since B very rarely falls below B_{MSY} in model runs, the overfishing definition is often referred to as simply $H/H_{MSY} >1$ throughout the rest of this document. Table 7 provides details of biomass B, relative biomass B/B_{MSY}, harvest rates H, and relative harvest rates H/H_{MSY} from 1958 to 2016. Additionally, Table 7 provides probabilities that the stock was overfished, overfished while experiencing overfishing, and experiencing overfishing from 1958 to 2016. These probabilities were based on categorizing each annual resultant of overfished/overfishing status from each saved MCMC run, using the aforementioned reference point control rule.

Model results show that Hawaii Kona crabs have never been overfished (Table 7). Posterior median estimates of biomass relative to B_{MSY}(B/B_{MSY}) declined from a high of 2.14 in 1962 to 1.12 in 1986, increased to 1.48 in 1998, decreased again to 1.12 in 2006, and increased to 1.39 in the final year of the stock assessment (Figure 13). The stock experienced overfishing for 2 years in the early 1970s but has not been experiencing overfishing since (Figure 13). Posterior median estimates of harvest rates relative to H_{MSY}(H/H_{MSY}) are below 1.0 since 1973 and down to less than 0.1 since 2013, with an estimate of 0.07 in the final year of the stock assessment. There is a 0% chance of experiencing overfishing and a 0.01% chance of being overfished in 2016 (Table 7, Figure 14). There is uncertainty associated with model estimates.

3.4 Results of Retrospective Analysis

Retrospective analyses for median annual biomass and harvest rate showed no major or consistent retrospective pattern for five annual retrospective peels (Section 2.3.5 Retrospective Analysis, Figure 15). Mohn's ρ for median annual biomass estimates was 0.18. Mohn's ρ for harvest rate was 0.03.

3.5 Results of Sensitivity Analyses

Table 8 and Figure 16 through Figure 21 summarize analyses to test the model's sensitivity to varied priors of K, r, m, ψ, σ_η, and alternative unreported catch scenarios. The results are presented as proportional changes in posterior medians. Annual biomass and biomass relative to their reference points (B/B_{MSY}) sometimes exhibited some departure from base case trajectories in alternative scenarios, while harvest rates and harvest rates relative to their reference points (H/H_{MSY}) seldom showed departures from base case results. While results of sensitivities in Table 8 are given as proportional departures from the base case model, it should be noted that absolute departures from base case harvest rate in 2016 (H_{2016}) are often negligible in magnitude due to a small value for the base case *H2016* posterior.

For sensitivities to K, changes to terminal year biomass (B_{2016}) ranged from -15% to 9% compared to base case estimates from changes to the prior mean for K of ± 50%. The same changes to the prior mean on K resulted in changes in harvest rates (H_{2016}) ranging from a 17% increase to - 9% reduction, respectively. Posterior median estimates of K for the prior mean changes of + 50% and -50% ranged from - 14% to 22% difference from base case results. Results from sensitivity runs are depicted in Figure 16.

For sensitivities to r, halving the prior mean resulted in a 17% increase in B_{2016}, while increasing it by a factor of 1.5 resulted in a decrease in B_{2016} of 7%. Halving the prior mean for r decreased H_{2016} by 13%, while increasing it by a factor of 1.5 resulted in an increase in H_{2016} of 9%. The posterior median for r was sensitive to the prior, with a halving of the prior mean yielding a 35% decrease in the posterior, and with an increase by a factor of 1.5 for the r prior mean resulting in a 24% increase. Results from sensitivity runs for this variable are depicted in Figure 17.

For sensitivities to m, the model exhibited proportional changes in B_{MSY} ranging from -18% in response to changes in the prior mean by a reduction of 25%, to 22% in response to increasing the prior mean 50%. Increasing the prior mean for m by 50% also resulted in a 28% decrease in H_{MSY}. Results from sensitivity runs for this variable are depicted in Figure 18.

For sensitivities on ψ, when the prior mean was halved, B_{2016} decreased by 9% and H_{2016} increased by 10%. Changes in the prior mean of -25% resulted in a slight decrease in B_{2016} of 4% and an increase in H_{2016} of 6%. Setting the prior mean to 1 also produced changes of less than

5% in all model-estimated outputs. The model is not very sensitive to the prior mean ψ. Results for sensitivity runs for this variable are depicted in Figure 19.

For sensitivities on σ_η (estimated process error), reducing the prior mean by 50% resulted in a 14% increase in B_{MSY} and 8% decrease in $H_{MSY.}$ Doubling the prior mean did not have as pronounced an effect on these parameters and resulted in a decrease in B_{2016} of 13% and an increase in H_{2016} of 17%. Of the production model parameters, K was the most sensitive to σ_η, with an increase of 13% when the prior mean for σ_η was halved. Results for sensitivity runs for this variable are depicted in Figure 20.

For sensitivities on estimated (the estimated component of observation error), changes in the prior mode of -50% and -25% yielded minimal (<5%) proportional changes in all model-estimated outputs. Doubling the prior mode produced changes of less than 10% in all model-estimated outputs, except for B_{2016}, which showed an increase of 11%. Results for sensitivity runs for this variable are depicted in Figure 21.

The model was sensitive to alternative catch scenarios which include annual catch values that are both much greater and lower than the base case. UCR (unreported catch ratio) scenarios are discussed in Sections 2.1.2 Annual Catch and 2.3.6. Sensitivity Analyses. Scenarios of adjusted reported catch (UCR=0) and high unreported catch (UCR=5) are the scenarios with very different total catch values from the base case and showed the greatest departure from base case results. Using adjusted reported catch only (UCR=0) assumes that total catch is ~60% lower than in the base case model, and this decreased total catch *MSY*, B_{MSY}, and B_{2016} all by ~60%. However, the MSY from the UCR = 0 scenario is 28,628 lb which is similar to the reported catch MSY from the base case model of 25,870 lb. The H_{2016} was reduced by 11% in the adjusted reported catch scenario. Using the annual UCRs increased B_{MSY} by 15% and increased K by 14%. Assuming a high unreported catch ratio of 5 had the greatest impact: B_{MSY} increased by 131%, MSY increased by 135%, and B_{2016} increased by 137%. Figure 22 depicts sensitivity results for varying UCR scenarios.

3.6 Stock Projections 2020-2026

Projection analyses were executed using posterior distributions from the base case model for Hawaii Kona crab. Projections performed for this assessment produced overfishing risks associated with a range of catch values (in pounds), risks of overfishing or being overfished, biomass, and harvest rates, among other estimates. Projections projected total catch, but results are shown with corresponding reported catch numbers only for management purposes. A summary of overfishing risk by year, with associated reported catches in lb to reach those risks, associated risks of the stock being overfished, stock biomass levels, and harvest rates are provided in Table 9. Table 10 provides risk of overfishing from 1% to 50% in 1% intervals with associated reported catches to reach those risks for seven projection years, 2020–2026. Figure 23 shows the time series of biomass relative to biomass to produce MSY (B/B_{MSY}) by year for various future catches and indicates that stock biomass does not drop below the $B/B_{MSY} = 0.7$ overfished threshold in any year for any projected catch scenario from 2020 to 2026, though scenarios with high reported catches above ~10,000 pounds trend downwards through the projection period. Conversely, under the projection scenario using the lowest future catches which are also most similar to current reported catches (~3,496 lb, red increasing lines), B/B_{MSY}

continues to increase to closer to 2.0 (Figure 23). The reported catch amount corresponding to a 50% risk of overfishing in 2026 is 33,989 lb; this corresponds to a 0.08% chance of being overfished in 2026 (Table 9, Figure 24). In other words, if 33,989 lb of Kona crab are reported caught each year from 2020 to 2026, there is a 50% risk of overfishing in 2026 (with lower risk of overfishing in 2020–2025).

4. Discussion

The Hawaii Kona crab stock was not overfished or experiencing overfishing in 2016. There were an estimated 885,057 lb of Kona crab around Hawaii in 2016. The reported catch that corresponds to a 50% risk of overfishing in 2026 is 33,988 lb. Maximum sustainable yield in the base case model is 73,069 lb of total catch, corresponding to 25,869 lb of reported catch. Diagnostics, retrospective analyses, and sensitivity analyses of the JABBA surplus production model indicated the model has a relatively good fit to the data, the model converged, there was no retrospective pattern, and model results are not overly sensitive to prior distributions.

This benchmark assessment is an improvement over prior assessments of the Hawaii Kona crab in that it estimated parameters of a surplus production model using a Bayesian framework with no deterministic estimation and included process and observation error. It utilized CPUE from 1958 to 2016, which provides more information and contrast for estimation of posteriors in a production model. Furthermore, a posterior distribution of the proportion of initial biomass to carrying capacity was estimated using the framework of Meyer and Millar (1999a). This is the first application of the JABBA tool to a domestic US species, and on a crustacean fishery. This assessment also incorporated the addition of discard mortality as a result of a no-female take regulation, and also incorporated unreported catch estimates. The latter is especially important, since sensitivity analyses of unreported catch scenarios revealed that model results related to biomass and carrying capacity are sensitive to the total amount of catch included in the model because of the effect on the estimated scale of the model. However, relative estimates such as stock status in the various unreported catch scenarios did not significantly depart from base case estimates. Rudd and Branch (2017) asserted that unreported catches may not impede the assessment status of fisheries with significant unreported catches, as long as unreported catch ratios are consistent through time. However, in this model, the sensitivity that run annual ratios (*UCR*s that varied by year) did not lead to model estimates that were very different from the base case which used a constant average ratio (Table 8).

Two data categories, if available, could improve future Kona crab stock assessments. The first data source is life history information. More reliable life history information for Hawaii Kona crabs, notably age and growth information, would be useful if the goal is to implement more complex assessment approaches. Reliable life history information could benefit a stock assessment by empirical estimation of intrinsic growth rates. Terminal biomass displayed a moderate degree of sensitivity and annual harvest rates also displayed sensitivity in early years of the assessment with changes to the prior set for intrinsic growth rate, r (Figure 17). Base case posterior estimates of r for Kona crab (0.10 – 0.26, Table 6) would classify the stock as a low resilient stock per Froese et al. (2016) in contrast to the moderately resilient classification by Musick (1999) based on other life history characteristics. The only other production model on Kona crabs for Australian conspecifics showed r values slightly lower than this assessment in some scenarios (~ 0.1) but had much greater uncertainty (Brown et al., 1999). Other estimated r

values for other brachyuran crabs which may or may not be appropriate to compare to Kona crabs are all for blue crabs (*Callinectes sapidus*): ~0.25 in North Carolina (Eggleston and Johnson, 2004), 0.2 or 0.3 in the Chesapeake Bay (Miller and Houde, 1998), and 0.17 in the Chesapeake Bay in unfished conditions (Miller, 2001).

The second data category to improve future assessments is size or weight composition of individual crabs from the fishery. The DAR FRS data report total weight and total numbers of Kona crab caught per record, and thus individual crab weights are rare because it is rare to catch a single crab at a time. Computing average weight of individual crabs in each reporting day is possible in some records. However, weights are reported to the nearest pound, thus precision of average weight per crab is low particularly in smaller catches, and variability of weights per crab is unknown in each reporting day. Less than 45% of Kona crab single-reporting days report total numbers, so although an average Kona crab weight can be calculated and expanded, it is not clear how representative the resulting average weight would be. Individual crab weights and more life history information are needed if using a more complex model such as a structured model is eventually the goal.

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Literature Cited

Ault, J.S., Smith, S.G., Richards, B.L., Yau, A.J., Humphreys, R., 2018. Towards Fishery-independent Biomass Estimation for Hawaiian Deep 7 Bottomfish. NOAA Tech Memo. doi:10.7289/V5/TM-PIFSC-67

Bates, D., Bolker, B., Walker, S., Singmann, H., Dai, B., Scheipl, F., 2017. lme4: Linear Mixed-Effects Models using "Eigen" and S4 Contact. R package version 1.1-15. Keziamanlove.Com 1–23. doi:10.2307/2533043

Boulle, D.P., 1995. Seychelles krab ziraf (*Ranina ranina*) fishery: the status of the stock. Victoria: Seychelles Fishing Authority Tech Rep.

Brodziak, J., Ishimura, G., 2012. Development of Bayesian production models for assessing the North Pacific swordfish population. Fish. Sci. 77, 23–34. doi:10.1007/s12562-010-0300-0

Brodziak, J., Walsh, W.A., 2013. Model selection and multimodel inference for standardizing catch rates of bycatch species: a case study of oceanic whitetip shark in the Hawaii-based longline fishery. Can. J. Fish. Aquat. Sci. 70, 1723–1740. doi:10.1139/cjfas-2013-0111

Brodziak, J., Yau, A., O'Malley, J., Andrews, A., Humphreys, R., DeMartini, E., Pan, M., Parke, M., Fletcher, E., 2014. Stock assessment update for the main Hawaiian Islands Deep 7 bottomfish complex through 2013 with projected annual catch limits through 2016. (No. NOAA-TM-NMFS-PIFSC-42). doi:10.1017/CBO9781107415324.004

Brown, I.W., S. Kirkwood, C. Gaddes, C.M.D., and J.O., 1999. Population Dynamics and management of spanner crabs (*Ranina ranina*) in southern Queensland. FRDC Project Report Q099010. Deception Bay.

Brown, I.W., 1985. The Hawaiian Kona Crab Fishery. Queensland Department of Primary Industries, Brisbane.

Brown, I.W., Dunning, M., Hansford, S., Gwynne, L., 2001. Ecological Assessment of the Queensland Spanner Crab Fishery.

Carvalho, F., Ahrens, R., Murie, D., Ponciano, J.M., Aires-da-Silva, A., Maunder, M.N., Hazin, F., 2014. Incorporating specific change points in catchability in fisheries stock assessment models: An alternative approach applied to the blue shark (Prionace glauca) stock in the south Atlantic Ocean. Fish. Res. 154, 135–146. doi:10.1016/j.fishres.2014.01.022

Chen, Y., Kennelly, S.J., 1999. Growth of spanner crabs, Ranina ranina, off the east coast of Australia. Mar. Freshw. Res. 50, 319–325. doi:10.1071/MF00030

Cook, M., 1987. South Pacific Commission. Fish. Newsl. 12–14.

Courtney, D., Brodziak, J., 2011. A Review of Unreported to Reported Catch Ratios for Bottomfish Resources in the Main Hawaiian Islands. Pacific Islands Fisheries Science Center, PIFSC Internal Report, IR-11-017.

Dichmont, C.M., Brown, I.W., 2010. A Case Study in Successful Management of a Data-Poor Fishery Using Simple Decision Rules: The Queensland Spanner Crab Fishery. Mar. Coast. Fish. 2, 1–13. doi:10.1577/C08-034.1

Eggleston, D., Johnson, E., 2004. Population dynamics and stock assessment of the blue crab in

North Carolina Final Repo, 1–252.

Fielding, A., 1974. Aspects of the biology of the Hawaiian Kona crab, Ranina ranina (Linnaeus). University of Hawaii.

Fielding, A., Haley, S.R., 1976. Sex Ratio Size At Reproductive Maturity and Reproduction of the Hawaiian Kona Crab Ranina-Ranina Brachyura Gymnopleura Raninidae. Pacific Sci. 30, 131–146.

NOAA (National Oceanic and Atmospheric Administration) and WPRFMC (Western Pacific Regional Fishery Management Council). 2009. Fishery Ecosystem Plan for the Hawaii Archipelago. Honolulu, HI.

Fletcher, R.I., 1978. On the restructuring of the Pella–Tomlinson system. Fish. Bull. 76, 515–512.

Francis, R.I.C.C., Hurst, R.J., Renwick, J.A., 2003. Quantifying annual variation in catchability for commercial and research fishing. Fish. Bull. 101, 293–304.

Froese, R., Demirel, N., Coro, G., Kleisner, K.M., Winker, H., 2016. Estimating fisheries reference points from catch and resilience. Fish Fish. 506–526. doi:10.1111/faf.12190

Gelman, A., 2006. Prior Distribution for Variance Parameters in Hierarchical Models. Bayesian Anal. 1, 515–533. doi:10.1214/06-BA117A

Geweke, J., 1992. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments., in: Berger, J.O., Bernardo, J.M., Dawid, A.P., Smith, A.F.M. (Eds.), Bayesian Statistics 4: Proceedings of the Fourth Valencia International Meeting. Clarendon Press, Oxford, pp. 169–193.

Gilbert, D.J., 1992. A stock production modelling technique for fitting catch histories to stock index data., New Zealand Fisheries Assessment Research Document 92/15.

Hall, N.G., 2015. Center for Independent Experts (CIE) Independent Peer Review Report of the Kona Crab Benchmark Assessment 1–33.

Hamm, D.C., Lum, H., 1992. Preliminary results of the Hawaii small boat fisheries survey. Southwest Fisheries Science Center. Admin Rep. H-92-08.

Heidelberger, P., Welch, P., 1992. Simulation run length control in the presence of an initial transient. Oper. Res. 31, 1109–1144.

Hoenig, J.M., 1983. Empirical use of longevity data to estimate mortality-rates. Fish. Bull. doi:10.2307/1940298

Hospital, J., Beavers, C., 2014. Hawaii Retail Seafood Markets : Observations from Honolulu (2007-2011). Admin Rep. H-15-01. doi:10.7289/V53R0QSM

Kennelly, S.J., Watkins, D., 1994. Fecundity and reproductive period, and their relationship to catch rates of spanner crabs, *Ranina ranina*, off the East coast of Australia. J. Crustac. Biol. 14, 146–150.

Kennelly, S.J., Watkins, D., Craig, J.R.R., 1990. Mortality of discarded spanner crabs Ranina ranina (Linnaeus) in a tangle-net fishery - laboratory and field experiments. J. Exp. Mar. Bio. Ecol. 140, 39–48. doi:10.1016/0022-0981(90)90079-R

Kirkwood, J.M., Brown, I.W., Gaddes, S.W., Hoyle, S., 2005. Juvenile length-at-age data reveal that spanner crabs (Ranina ranina) grow slowly. Mar. Biol. 147, 331–339. doi:10.1007/s00227-005-1574-0

Krajangdara, T., Watanabe, S., 2005. Growth and reproduction of the red frog crab, *Ranina ranina* (Linnaeus, 1758), in the Andaman Sea off Thailand. Fish. Sci. 71, 20–28. doi:10.1111/j.1444-2906.2005.00926.x

Langseth, B., Syslo, J., Yau, A., Kapur, M., Brodziak, J., 2018. Stock assessment for the main Hawaiian Islands Deep 7 bottomfish complex in 2018, with catch projections through 2022. NOAA Tech. Memo. NMFS-PIFSC 69, 217.

Lenth, R., Love, J., Herve, M., 2018. Estimated Marginal Means, aka Least-Squares Means. April 1. doi:10.1080/00031305.1980.10483031>

Linnaeus, C. von, 1767. Systema naturae, per regna tria naturae : secundum classes, ordines, genera, species cum characteribus, differentiis, synonymis, locis. Vindobonae [Vienna] :Typis Ioannis Thomae.

Maunder, M.N., Punt, A.E., 2004. Standardizing catch and effort data: A review of recent approaches. Fish. Res. 70, 141–159. doi:10.1016/j.fishres.2004.08.002

McAllister, M.K., Pikitch, E.K., Babcock, E.A., 2001. Using demographic methods to construct Bayesian priors for the intrinsic rate of increase in the Schaefer model and implications for stock rebuilding. Can. J. Fish. Aquat. Sci. 58, 1871–1890. doi:10.1139/cjfas-58-9-1871

McCoy, K.S., Williams, I.D., Friedlander, A.M., Ma, H., Teneva, L., Kittinger, J.N., 2018. Estimating nearshore coral reef-associated fisheries production from the main Hawaiian Islands. PLoS One 13. doi:10.1371/journal.pone.0195840

Meyer, R., Millar, R.B., 1999a. BUGS in Bayesian stock assessments. Can. J. Fish. Aquat. Sci. 56, 1078–1087. doi:10.1139/cjfas-56-6-1078

Millar, R.B., Meyer, R., 2000. Non-linear state space modelling of fisheries biomass dynamics by using Metropolis-Hastings within Gibbs sampling. J. R. Stat. Soc. Ser. C (Applied Stat. 49, 327–342.

Miller, T.J., 2001. Matrix-Based Modeling of Blue Crab Population Dynamics with Applications to the Chesapeake Bay. Estuaries 24, 535. doi:10.2307/1353255

Miller, T.J., Houde., D.E., 1998. Blue crab target setting. Final report to the Living Resources Subcommittee. Chesapeake Bay. doi:[UMCES]CBL 98-129

Minagawa, M., 1993. Relative Growth and Sexual Dimorphism in the Red Frog Crab Ranina ranina (Decapoda: Raninidae). Nippon Suisan Gakkaishi 59, 2025–2030. doi:10.2331/suisan.59.2025

Mohn, R., 1999. The retrospective problem in sequential population analysis: An investigation using cod fishery and simulated data. ICES J. Mar. Sci. 56, 473–488. doi:10.1006/jmsc.1999.0481

Musick, J. A., 1999. Criteria to Define Extinction Risk in Marine Fishes: The American Fisheries Society Initiative. Fisheries 24, 6–14. doi:10.1577/1548-8446(1999)024<0006:CTDERI>2.0.CO;2

O'Neill, M.F., Campbell, A.B., Brown, I.W., Johnstone, R., 2010. Using catch rate data for simple cost-effective quota setting in the Australian spanner crab (*Ranina ranina*) fishery. ICES J. Mar. Sci. 67, 1538–1552. doi:10.1093/icesjms/fsq095

Onizuka, E.W., 1972. Management and Development Investigations of the Kona Crab, *Ranina ranina* (Linnaeus). Honolulu, HI.

Ono, K., Punt, A.E., Rivot, E., 2012. Model performance analysis for Bayesian biomass dynamics models using bias, precision and reliability metrics. Fish. Res. 125, 173–183. doi:10.1016/j.fishres.2012.02.022

Pella, J.J., Tomlinson, P.K., 1969. A generalized stock production model. Inter-American Trop. Tuna Comm. Bull. 13, 421–458.

Plummer, M., 2016. rjags: Bayesian graphical models using MCMC. R Packag. version 3-13. doi:http://cran.r-project.org/package=rjags

Plummer, M., 2003. JAGS: A Program for Analysis of Bayesian Graphical Models using Gibbs Sampling, 3rd International Workshop on Distributed Statistical Computing (DSC 2003); Vienna, Austria.

Plummer, M., Best, N., Cowles, K., Vines, K., 2006. CODA: convergence diagnosis and output analysis for MCMC. R News 6, 7–11. doi:10.1159/000323281

Polovina, J.J., Mitchum, G.T., 1992. Variability in spiny lobster *Panulirus marginatus* recruitment and sea level in the Northwestern Hawaiian Islands. Fish. Bull. 90, 483–493.

Prager, M.H., 1994. A suite of extensions to a nonequilibrium surplus-production model. Fish. Bull. 92, 374–389.

Punt, A.E., 2003. Extending production models to include process error in the population dynamics. Can. J. Fish. Aquat. Sci. 60, 1217–1228.

Punt, A.E., Huang, T., Maunder, M.N., 2013. Review of integrated size-structured models for stock assessment of hard-to-age crustacean and mollusc species. ICES J. Mar. Sci. 70, 352–361. doi:10.1093/icesjms/fst034

R Foundation for Statistical Computing, Vienna, A.I. 3-900051-07-0, 2011. R Development Core Team. R A Lang. Environ. Stat. Comput. 55, 275–286.

Rudd, M.B., Branch, T.A., 2017. Does unreported catch lead to overfishing? Fish Fish. 18, 313–323. doi:10.1111/faf.12181

Skinner, D.G., Hill, B.J., 1987. Feeding and reproductive behaviour and their effect on catchability of the spanner crab *Ranina ranina*. Mar. Biol. 94, 211–218. doi:10.1007/BF00392933

Skinner, D.G., Hill, B.J., 1986. Catch rate and emergence of male and female spanner crabs (*Ranina ranina*) in Australia. Mar. Biol. 91, 461–465. doi:10.1007/BF00392596

Tahil, A., 1983. Reproductive period and exploitation of the red frog crab, *Ranina ranina* (Linnaeus, 1758) in Central Tawi-Tawi, Philippines. Philipp. Sci.

Then, A.Y., Hoenig, J.M., Hall, N.G., Hewitt, D.A., 2015. Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. ICES J. Mar. Sci. 72, 82–92. doi:10.1093/icesjms/fsu136

Thomas, L.R., DiNardo, G.T., Lee, H.-H., Piner, K.R., Samuel E. Kahng, 2013. Factors influencing the distribution of Kona crabs *Ranina ranina* (Brachyura: Raninidae) catch rates in the Main Hawaiian Islands. J. Crustac. Biol. 33, 1–8. doi:10.1163/1937240X-00002171

Thomas, L.R., Lee, H.-H., Piner, K.R., 2015. Kona Crab Benchmark Assessment 4–5.

Thorson, J.T., Cope, J.M., Branch, T.A., Jensen, O.P., 2012. Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. Can. J. Fish. Aquat. Sci. 69, 1556–1568. doi:10.1139/f2012-077

Thorson, J.T., Cope, J.M., Branch, T.A., Jensen, O.P., 2012. Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. Can. J. Fish. Aquat. Sci. 69, 1556–1568. doi:10.1139/f2012-077

Thorson, J.T., Ono, K., Munch, S.B., 2014. A Bayesian approach to identifying and compensating for model misspecification in population models. Ecology 95, 329–341. doi:10.1890/13-0187.1

Uchida, R.N., Uchiyama, J.H., 1986. Fishery atlas of the Northwestern Hawaiian Islands. (No. 38), NOAA Technical Report.

Vansant, J.P., 1978. A Survey of the Hawaii Kona Crab Fishery. Univ. Hawaii.

Wang, S.-P., Maunder, M.N., Aires-da-Silva, A., 2014. Selectivity's distortion of the production function and its influence on management advice from surplus production models. Fish. Res. 158, 181–193. doi:10.1016/j.fishres.2014.01.017

Wiley, J., 2017. Specifying 2017 Annual Catch Limits and Accountability Measures for Kona Crab in Hawaii. Honolulu, HI 96813.

Wiley, J., Pardee, C., 2018. Post Release Mortality In The Hawaiian Kona Crab Fishery. Western Pacific Regional Fishery Management Council.

Winker, H., Carvalho, F., Kapur, M., 2018. JABBA: Just Another Bayesian Biomass Assessment. Fish. Res. 204, 275–288. doi:10.1016/j.fishres.2018.03.010

Yau, A., 2018. Report from Hawaii Bottomfish Commercial Fishery Data Workshops, 2015-2016. doi:https://doi.org/10.7289/V5/TM-PIFSC-68

Zeller, D., Darcy, M., Booth, S., Lowe, M.K., Martell, S., 2008. What about recreational catch?. Potential impact on stock assessment for Hawaii's bottomfish fisheries. Fish. Res. 91, 88–97. doi:10.1016/j.fishres.2007.11.010

Tables

Table 1. Hawaii Kona crab total catch data used in base case, and catches used for sensitivity analyses. All catch columns are in pounds. Total catches are calculated from adjusted reported catches using Equation 2.

	Base case	Sensitivities		
Year	Total catch using average ratio, *UCR* = 1.54	Adjusted reported catch, *UCR* = 0	Total catch using annual ratio, *UCR* varies by year	Total catch using high *UCR* = 5
1958	22284	8761	23461	52566
1959	10833	4259	11833	25554
1960	23985	9430	25520	56580
1961	38885	15288	41343	91728
1962	77345	30409	86503	182454
1963	53462	21019	61426	126114
1964	32272	12688	38475	76128
1965	29049	11421	32751	68526
1966	25519	10033	26297	60198
1967	44369	17444	45307	104664
1968	67197	26419	74644	158514
1969	91451	35955	103095	215730
1970	89129	35042	103987	210252
1971	110835	43576	133679	261456
1972	176343	69331	196553	415986
1973	159006	62515	181519	375090
1974	103144	40552	110210	243312
1975	62611	24616	63392	147696
1976	67598	26577	64852	159462
1977	58928	23168	61296	139008
1978	80565	31675	89542	190050
1979	73700	28976	83110	173856
1980	26427	10390	27791	62340
1981	45422	17858	46171	107148
1982	21938	8625	23301	51750
1983	28502	11206	31496	67236
1984	43789	17216	49957	103296
1985	55748	21918	63434	131508
1986	70195	27598	76922	165588
1987	56290	22131	62759	132786
1988	45147	17750	46714	106500
1989	33360	13116	32160	78696
1990	47843	18810	45704	112860
1991	60131	23641	51606	141846

	Base case	Sensitivities		
Year	Total catch using average ratio, *UCR* = 1.54	Adjusted reported catch, *UCR* = 0	Total catch using annual ratio, *UCR* varies by year	Total catch using high *UCR* = 5
1992	93382	36714	74845	220284
1993	65861	25894	53665	155364
1994	61146	24040	46165	144240
1995	58159	22866	44022	137196
1996	77818	30595	56505	183569
1997	73845	29033	55020	174198
1998	74295	29210	59683	175260
1999	64858	25500	53724	152997
2000	43417	17070	35251	102420
2001	25760	10128	21700	60768
2002	30298	11912	24445	71472
2003	32223	12669	24266	76013
2004	32518	12785	26928	76708
2005	30278	11904	24623	71425
2006	23906	9399	19467	56392
2007	16093	6327	16890	37964
2008	37681	14815	37499	88889
2009	22592	8882	23355	53293
2010	33398	13131	34257	78784
2011	30783	12103	32271	72616
2012	23772	9346	24822	56078
2013	27225	10704	28665	64222
2014	8676	3411	9455	20467
2015	6595	2593	6632	15558
2016	7290	2866	8160	17198

Table 2. Prior distributions and input assumptions used for the base-case Kona crab production model.

Parameter	Distribution	Mean	CV	Bounds	Source/Justification
K	Range, converted to lognormal	1,306,243 lb	53%	-	Empirical catch-growth method (Froese et al., 2016)
r	lognormal	0.2735	30%	-	Musick (1999): 0.15 to 0.50 95% C.I. for r for animals with lifespan 4-12 years, mature 2, "moderately resilient"
m	lognormal	1.188	35%	-	Uninformative prior on m shape, mean from Thorson et al. (2013), also default in JABBA using a $B_{MSY}/K = 0.4$
ψ	lognormal	0.83	50%	-	Ratio of 95th percentile 1958 CPUE to 95th percentile Period 1 CPUE
q_1	uniform	-	-	(10^{-30}, 3)	Uninformative prior
q_2	uniform	-	-	(10^{-30}, 3)	Uninformative prior
σ_η	inverse gamma	shape = 4	rate = 0.01	-	This is the square root of the process error variance term. Default in JABBA based on Ono et al. (2012), sets median sigma to 7%, range from 0% to 14.3%.
$\sigma_{\tau_{estimated,1}}$	inverse gamma	shape = 0.001	rate = 0.004	-	This is the square root of the estimated observation error variance term. Gelman (2006). 1/d gamma (0.001,0.004).
$\sigma_{\tau_{estimated,2}}$	inverse gamma	shape = 0.001	rate = 0.004	-	This is the square root of the estimated observation error variance term. Gelman (2006). 1/dgamma (0.001,0.004).
UCR	-	1.54	-	-	Average from annual ratios from Langseth et al. (2017) based on Courtney and Brodziak (2011)
Female post-release mortality	-	10.77%	-	-	Wiley and Pardee (2018)
Catch sex ratio, F:M	-	51:49	-	-	Wiley and Pardee (2018)

Table 3. Sensitivity analyses run for Kona crab surplus production model.

Sensitivity Scenario	Distribution	Mean/Value	CV
K prior mean reduced 50%	lognormal	653,121 lb	0.53
K prior mean reduced 25%	lognormal	979,682 lb	0.53
K prior mean increased 25%	lognormal	1,632,804 lb	0.53
K prior mean increased 50%	lognormal	1,959,365 lb	0.53
r prior mean reduced 50%	lognormal	0.13	0.3
r prior mean reduced 25%	lognormal	0.20	0.3
r prior mean increased 25%	lognormal	0.34	0.3
r prior mean increased 50%	lognormal	0.41	0.3
m prior mean reduced 25%	lognormal	0.9	0.35
m prior mean increased 25%	lognormal	1.5	0.35
m prior mean increased 50%	lognormal	1.8	0.35
ψ prior mean reduced 50%	lognormal	0.41	0.5
ψ prior mean reduced 25%	lognormal	0.62	0.5
ψ prior mean = 1	lognormal	1.0	0.5
σ_{η} prior mean reduced 50%	inverse gamma	shape = 4	rate = 0.0025
σ_{η} prior mean reduced 25%	inverse gamma	shape = 4	rate = 0.006
σ_{η} prior median increased 100%	inverse gamma	shape = 4	rate = 0.04
$\sigma_{\tau_{estimated}}$ prior mode reduced 50%	inverse gamma	shape = 0.001	rate = 0.008
$\sigma_{\tau_{estimated}}$ prior mode reduced 25%	inverse gamma	shape = 0.001	rate = 0.006
$\sigma_{\tau_{estimated}}$ prior mode increased 100%	inverse gamma	shape = 0.001	rate = 0.015
High ratio (*UCR* = 5)	-	-	-
Annual Ratio (*UCR* varies by year)	-	-	-
Adjusted Reported Catch (*UCR* = 0)	-	-	-

Table 4. CPUE standardization final models, showing log likelihood values and ΔAIC (AIC previous model – AIC proposed model) during model selection for the best-fit in the Period 1 (1958–2006) and Period 2 (2007–2016) time periods.

Time Period	Selected predictor	ΔAIC	ΔAIC%	AIC	Negative Log-Likelihood
1958–2006	License as random effect (null)			24579.85	-12286.92
	Year	321.34	1.31	24258.51	-12077.98
	Area	1077.49	4.38	23181.02	-11460.78
2007–2016	License as random effect (null)			3164.96	-1579.47
	Year	6.44	0.20	3158.52	-1567.14
	Area	103.72	3.28	3054.81	-1465.61

Table 5. Input data used in the base case surplus production model. CPUE is standardized CPUE.

Year	Total Catch (lb)	CPUE (lb/day) Period 1	CV Period 1	CPUE (lb/day) Period 2	CV Period 2
1958	22284	57.52	0.019	-	-
1959	10833	55.33	0.020	-	-
1960	23985	72.19	0.016	-	-
1961	38885	74.64	0.015	-	-
1962	77345	92.20	0.012	-	-
1963	53462	74.00	0.015	-	-
1964	32272	62.04	0.018	-	-
1965	29049	59.29	0.019	-	-
1966	25519	60.73	0.018	-	-
1967	44369	45.70	0.024	-	-
1968	67197	62.89	0.017	-	-
1969	91451	64.04	0.017	-	-
1970	89129	47.46	0.023	-	-
1971	110835	58.89	0.019	-	-
1972	176343	69.18	0.016	-	-
1973	159006	80.06	0.014	-	-
1974	103144	61.27	0.018	-	-
1975	62611	55.31	0.020	-	-
1976	67598	60.08	0.031	-	-
1977	58928	44.36	0.025	-	-
1978	80565	50.68	0.021	-	-
1979	73700	54.73	0.020	-	-
1980	26427	48.43	0.023	-	-
1981	45422	59.54	0.018	-	-
1982	21938	49.19	0.022	-	-
1983	28502	47.30	0.023	-	-
1984	43789	47.54	0.023	-	-
1985	55748	43.51	0.025	-	-
1986	70195	36.82	0.029	-	-
1987	56290	41.21	0.026	-	-
1988	45147	42.07	0.026	-	-
1989	33360	37.98	0.029	-	-
1990	47843	44.40	0.025	-	-
1991	60131	50.58	0.021	-	-
1992	93382	50.17	0.021	-	-
1993	65861	43.42	0.025	-	-
1994	61146	50.63	0.021	-	-
1995	58159	44.89	0.024	-	-

Year	Total Catch (lb)	CPUE (lb/day) Period 1	CV Period 1	CPUE (lb/day) Period 2	CV Period 2
1996	77818	48.95	0.022	-	-
1997	73845	50.99	0.021	-	-
1998	74295	57.52	0.019	-	-
1999	64858	56.16	0.019	-	-
2000	43417	50.00	0.022	-	-
2001	25760	41.68	0.026	-	-
2002	30298	46.66	0.023	-	-
2003	32223	45.76	0.024	-	-
2004	32518	40.69	0.027	-	-
2005	30278	39.17	0.028	-	-
2006	23906	37.29	0.029	-	-
2007	16093	-	-	26.93	0.043
2008	37681	-	-	30.62	0.038
2009	22592	-	-	31.86	0.036
2010	33398	-	-	32.89	0.035
2011	30783	-	-	34.01	0.034
2012	23772	-	-	32.50	0.036
2013	27225	-	-	39.91	0.029
2014	8676	-	-	29.27	0.040
2015	6595	-	-	31.84	0.037
2016	7290	-	-	27.51	0.043

Table 6. Posterior estimates of parameters and results from base case Kona crab production model. Median, lower 95% confidence interval (LCI), and upper 95% confidence interval are presented.

Parameter	Median	95% LCI	95% UCI
K (lb)	1,445,595	917,297	2,809,544
r (yr^{-1})	0.17	0.10	0.26
M	1.50	0.72	3.03
Ψ	0.71	0.50	0.95
q_1	0.00005	0.00002	0.00009
q_2	0.00003	0.00001	0.00006
σ_η	0.09	0.05	0.13
$\sigma_{\tau_{estimated,1}}$	0.09	0.05	0.13
$\sigma_{\tau_{estimated,2}}$	0.08	0.04	0.19
H_{MSY}	0.11	0.05	0.24
B_{MSY} (lb)	640,489	342,488	1,392,849
MSY (total lb)	73,069	48,045	127,364
MSY (reported lb)	25,869	17,010	45,092
P_{2016}	0.61	0.39	0.84
B/B_{MSY} *2016*	1.39	0.76	2.29
H/H_{MSY} *2016*	0.07	0.02	0.17

Table 7. Model-estimated exploitable biomass, relative biomass B/B_{MSY}, probability of being overfished (B/B_{MSY} < 0.7), harvest rate, relative harvest rate H/H_{MSY}, and probability of overfishing (H/H_{MSY} > 1.0), by year.

Year	Biomass (lb)	B/B_{MSY}	Probability Overfished	Harvest rate	H/H_{MSY}	Probability of Overfishing	Probability of Overfished and Overfishing
1958	1,026,999	1.6155	0.0002	0.0214	0.1890	0.0000	0.0000
1959	1,060,969	1.6652	0.0002	0.0100	0.0889	0.0000	0.0000
1960	1,207,884	1.8993	0.0000	0.0196	0.1727	0.0000	0.0000
1961	1,287,302	2.0214	0.0000	0.0298	0.2625	0.0000	0.0000
1962	1,366,677	2.1475	0.0000	0.0557	0.4907	0.0246	0.0000
1963	1,246,364	1.9558	0.0000	0.0424	0.3737	0.0020	0.0000
1964	1,123,829	1.7599	0.0000	0.0284	0.2510	0.0002	0.0000
1965	1,069,320	1.6752	0.0001	0.0269	0.2371	0.0000	0.0001
1966	1,038,091	1.6343	0.0002	0.0242	0.2139	0.0001	0.0000
1967	965,544	1.5105	0.0011	0.0457	0.4026	0.0152	0.0011
1968	1,057,149	1.6634	0.0001	0.0627	0.5530	0.0687	0.0001
1969	1,068,661	1.6797	0.0001	0.0844	0.7439	0.2693	0.0001
1970	988,391	1.5423	0.0004	0.0898	0.7912	0.3348	0.0004
1971	1,076,752	1.6869	0.0001	0.1023	0.9017	0.4690	0.0001
1972	1,184,651	1.8636	0.0000	0.1466	1.2916	0.8911	0.0000
1973	1,200,776	1.8958	0.0000	0.1302	1.1471	0.7600	0.0000
1974	1,059,301	1.6678	0.0000	0.0959	0.8453	0.4040	0.0000
1975	984,950	1.5510	0.0003	0.0629	0.5542	0.0696	0.0003
1976	973,579	1.5380	0.0006	0.0685	0.6043	0.1090	0.0006
1977	879,669	1.3786	0.0026	0.0664	0.5855	0.1062	0.0026
1978	903,071	1.4227	0.0017	0.0880	0.7758	0.3101	0.0017
1979	915,410	1.4427	0.0017	0.0795	0.7004	0.2134	0.0017
1980	884,446	1.3926	0.0031	0.0295	0.2603	0.0005	0.0017
1981	942,360	1.4843	0.0014	0.0474	0.4178	0.0172	0.0014
1982	878,231	1.3807	0.0031	0.0247	0.2180	0.0001	0.0003
1983	849,904	1.3323	0.0041	0.0333	0.2933	0.0021	0.0026
1984	829,925	1.3002	0.0054	0.0524	0.4616	0.0413	0.0054
1985	776,623	1.2175	0.0115	0.0714	0.6292	0.1564	0.0115
1986	720,708	1.1283	0.0222	0.0967	0.8521	0.4310	0.0222
1987	722,275	1.1351	0.0209	0.0767	0.6764	0.2345	0.0209
1988	726,749	1.1430	0.0195	0.0612	0.5395	0.1072	0.0195
1989	725,165	1.1383	0.0209	0.0455	0.4016	0.0287	0.0192
1990	792,975	1.2447	0.0090	0.0598	0.5269	0.0811	0.0090
1991	850,648	1.3405	0.0040	0.0698	0.6152	0.1265	0.0040
1992	859,675	1.3543	0.0033	0.1071	0.9444	0.5278	0.0033
1993	812,040	1.2770	0.0069	0.0802	0.7069	0.2300	0.0069
1994	843,969	1.3321	0.0036	0.0713	0.6290	0.1443	0.0036

Year	Biomass (lb)	B/B_{MSY}	Probability Overfished	Harvest rate	H/H_{MSY}	Probability of Overfishing	Probability of Overfished and Overfishing
1995	835,084	1.3082	0.0049	0.0689	0.6076	0.1269	0.0049
1996	873,406	1.3695	0.0027	0.0883	0.7779	0.3143	0.0027
1997	904,035	1.4159	0.0015	0.0810	0.7143	0.2309	0.0015
1998	947,288	1.4849	0.0008	0.0777	0.6853	0.1946	0.0008
1999	925,888	1.4609	0.0012	0.0692	0.6097	0.1162	0.0012
2000	855,806	1.3434	0.0040	0.0501	0.4418	0.0288	0.0040
2001	789,683	1.2409	0.0090	0.0322	0.2844	0.0019	0.0044
2002	804,941	1.2638	0.0078	0.0373	0.3287	0.0059	0.0061
2003	785,667	1.2347	0.0096	0.0404	0.3563	0.0106	0.0084
2004	743,424	1.1673	0.0183	0.0433	0.3816	0.0179	0.0162
2005	718,147	1.1280	0.0254	0.0416	0.3668	0.0163	0.0207
2006	718,963	1.1270	0.0317	0.0328	0.2898	0.0022	0.0146
2007	781,406	1.2327	0.0259	0.0202	0.1784	0.0000	0.0029
2008	859,880	1.3600	0.0163	0.0430	0.3791	0.0363	0.0160
2009	896,670	1.4218	0.0140	0.0246	0.2172	0.0005	0.0060
2010	934,985	1.4788	0.0099	0.0350	0.3083	0.0125	0.0094
2011	955,455	1.5131	0.0096	0.0315	0.2779	0.0073	0.0081
2012	960,947	1.5180	0.0091	0.0242	0.2136	0.0012	0.0041
2013	1,008,942	1.5972	0.0065	0.0263	0.2324	0.0018	0.0046
2014	910,446	1.4437	0.0151	0.0093	0.0823	0.0000	0.0000
2015	908,463	1.4382	0.0135	0.0071	0.0627	0.0000	0.0000
2016	885,057	1.3977	0.0166	0.0081	0.0714	0.0000	0.0000

Table 8. Results of sensitivity runs, showing proportional changes in posterior median values from base case. Priors for the base case are given in Table 3.

	K **(lb)**	***r***	***M***	***Ψ***	***MSY*** **(total lb)**	B_{MSY}	H_{MSY}	B_{2016}	H_{2016}
base case	1,445,594	0.171	1.501	0.720	73,069	640,488	0.114	885,056	0.008
K prior mean reduced 50%	-0.147	0.089	-0.044	-0.004	-0.051	-0.169	0.147	-0.151	0.178
K prior mean reduced 25%	-0.005	0.016	0.004	-0.005	-0.018	-0.014	0.020	-0.024	0.049
K prior mean increased 25%	0.006	-0.011	0.012	0.010	0.002	0.013	-0.018	0.006	-0.008
K prior mean increased 50%	0.223	-0.091	0.127	-0.044	0.030	0.274	-0.198	0.097	-0.095
r prior mean reduced 50%	0.262	-0.353	-0.137	-0.004	-0.114	0.184	-0.252	0.179	-0.138
r prior mean reduced 25%	0.093	-0.155	-0.068	0.015	-0.038	0.060	-0.087	0.082	-0.074
r prior mean increased 25%	-0.031	0.125	0.066	0.006	0.024	-0.018	0.059	-0.022	0.028
r prior mean increased 50%	-0.102	0.247	0.121	0.003	0.025	-0.065	0.113	-0.077	0.096
m prior mean reduced 25%	-0.048	-0.045	-0.278	0.005	0.064	-0.182	0.326	-0.044	0.068
m prior mean increased 25%	0.027	0.055	0.286	-0.019	-0.082	0.140	-0.186	-0.037	0.034
m prior mean increased 50%	0.032	0.088	0.525	-0.017	-0.115	0.225	-0.280	-0.027	0.039
Ψ prior mean reduced 50%	0.047	-0.029	0.080	-0.124	-0.045	0.072	-0.108	-0.093	0.100
Ψ prior mean reduced 25%	0.007	-0.021	0.038	-0.062	-0.038	0.022	-0.059	-0.040	0.063
Ψ prior mean = 1	-0.033	0.022	-0.024	0.031	-0.006	-0.044	0.047	-0.017	0.025
σ_{η} mean reduced 50%	0.133	-0.063	0.023	0.073	0.038	0.147	-0.085	0.214	-0.174
σ_{η} mean reduced 25%	0.074	-0.053	0.040	0.008	-0.008	0.090	-0.085	0.088	-0.061
σ_{η} mean increased 100%	-0.054	0.034	-0.018	-0.055	-0.022	-0.065	0.051	-0.139	0.171
$\sigma_{\tau_{estimated}}$ prior mode reduced 50%	0.026	-0.018	0.014	0.014	-0.012	0.029	-0.027	0.037	-0.024
$\sigma_{\tau_{estimated}}$ prior mode reduced 25%	-0.018	0.004	0.010	-0.011	-0.044	-0.024	-0.004	-0.036	0.047
$\sigma_{\tau_{estimated}}$ prior mode increased 100%	0.095	-0.040	0.031	0.017	0.022	0.094	-0.064	0.114	-0.083
Unreported Catch Ratio = 5	1.326	0.009	-0.018	0.014	1.357	1.311	0.029	1.371	-0.004
Annual Ratio Unreported Catch	0.141	-0.067	0.051	0.005	0.037	0.157	-0.108	0.142	-0.010
Adjusted Reported Catch	-0.597	-0.022	0.001	-0.003	-0.608	-0.599	-0.018	-0.597	-0.112

Table 9. Projection results showing various probabilities of overfishing (H/H_{MSY} > 1) and corresponding future annual reported catches, biomass, harvest rate, and probability the stock is overfished (B/B_{MSY} < 0.7) from 2020 to 2026.

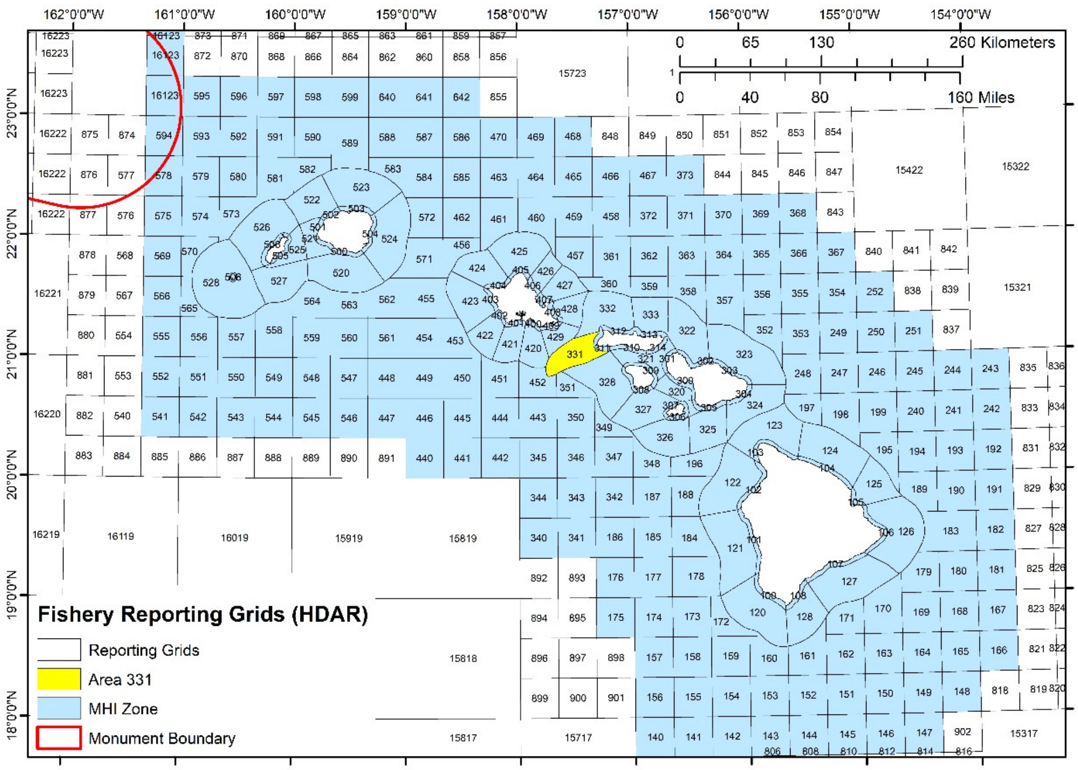
Prob. of overfishing (H/H_{MSY} > 1)	**0.01**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
Year	Reported Catch (lb)					
2020	12,392	24,429	30,094	35,051	39,299	44,256
2021	12,392	23,721	29,032	33,280	37,175	41,070
2022	12,038	23,013	27,970	31,864	35,405	39,299
2023	11,684	22,659	27,262	30,802	33,989	37,529
2024	12,038	21,951	26,554	29,740	32,926	36,113
2025	12,038	21,597	25,845	29,386	31,864	35,051
2026	12,038	21,243	25,491	28,324	31,156	33,989
Year	Biomass (lb)					
2020	1,101,480	1,095,540	1,099707	1,098893	1,100,925	1,100,427
2021	1,108,561	1,078,820	1,059655	1,051517	1,038,860	1,026,565
2022	1,116,579	1,062,823	1,033262	1,014613	993,008	975,851
2023	1,128,754	1,046,237	1,010532	986,044	960,529	928,009
2024	1,136,618	1,037,401	998,899.6	964,458	932,273	901,930
2025	1,145,818	1,033,322	984,765.4	940,619	915,054	870,447
2026	1,153,881	1,028,821	974,959.4	931,710	892,995	852,259
Year	Harvest rate					
2020	0.032	0.062	0.077	0.089	0.100	0.112
2021	0.031	0.062	0.077	0.089	0.100	0.112
2022	0.030	0.061	0.076	0.088	0.100	0.113
2023	0.029	0.061	0.076	0.087	0.099	0.113
2024	0.030	0.059	0.075	0.086	0.099	0.112
2025	0.029	0.058	0.074	0.088	0.098	0.113
2026	0.029	0.058	0.073	0.086	0.098	0.112
Year	Probability stock is overfished (B/B_{MSY} < 0.7)					
2020	0.004	0.005	0.004	0.005	0.005	0.005
2021	0.005	0.007	0.008	0.009	0.009	0.010
2022	0.005	0.009	0.011	0.013	0.016	0.019
2023	0.005	0.012	0.016	0.020	0.027	0.033
2024	0.005	0.014	0.020	0.025	0.034	0.045
2025	0.005	0.015	0.026	0.036	0.044	0.063
2026	0.005	0.017	0.032	0.041	0.058	0.082

Table 10. Probability of overfishing (H/H_{MSY} > 1) from 0.01 to 0.50 and corresponding projected reported catch (lb) by year. Catch values for a given probability of overfishing in a given year were applied in all previous projection years.

P(Overfishing)	2020	2021	2022	2023	2024	2025	2026
0.01	12,392	12,392	12,038	11,684	12,038	12,038	12,038
0.02	15,224	15,224	14,870	14,516	14,516	14,516	14,516
0.03	17,348	16,994	16,640	16,640	16,286	16,286	15,932
0.04	19,119	18,765	18,056	17,702	17,348	17,348	16,994
0.05	19,827	19,827	19,119	19,119	18,765	18,410	18,056
0.06	21,243	20,889	19,827	19,827	19,473	19,119	18,410
0.07	22,305	21,597	20,889	20,889	20,181	19,827	19,827
0.08	23,013	22,305	21,951	21,243	20,889	20,889	20,181
0.09	23,367	23,013	22,305	21,951	21,597	21,243	20,889
0.10	24,429	23,721	23,013	22,659	21,951	21,597	21,243
0.11	25,137	24,429	23,367	23,367	22,659	22,305	21,951
0.12	25,845	24,783	24,429	23,367	23,367	22,659	22,305
0.13	26,200	25,137	24,783	24,075	23,367	23,367	23,013
0.14	26,908	25,845	25,137	24,783	24,075	23,721	23,013
0.15	27,262	26,554	25,845	25,137	24,429	24,075	23,367
0.16	27,970	27,262	26,200	25,491	25,137	24,429	24,075
0.17	28,324	27,262	26,908	25,845	25,491	24,783	24,429
0.18	29,386	27,970	27,262	26,554	25,845	25,137	24,783
0.19	29,386	28,324	27,262	26,908	26,200	25,491	25,137
0.20	30,094	29,032	27,970	27,262	26,554	25,845	25,491
0.21	30,802	29,386	28,324	27,262	26,908	26,200	25,845
0.22	31,156	29,740	28,678	27,970	27,262	26,554	26,200
0.23	31,864	30,094	29,032	28,324	27,262	26,908	26200
0.24	31,864	30,448	29,386	28,324	27,970	27,262	26,554
0.25	32,572	30,802	30,094	29,032	28,324	27,616	26,908
0.26	32,926	31,510	30,094	29,386	28,324	27,970	27,262
0.27	33,635	31,864	30,802	29,740	29,032	28,324	27,616
0.28	33,989	32,218	31,156	30,094	29,386	28,324	27,970
0.29	34,343	32,926	31,510	30,094	29,386	29,032	28,324
0.30	35,051	33,280	31,864	30,802	29,740	29,386	28,324
0.31	35,405	33,635	32,218	31,156	30,094	29,386	28,678
0.32	35,759	33,989	32,218	31,510	30,448	29,740	29,032
0.33	36,113	34,343	32,572	31,864	30,802	30,094	29,386
0.34	36,467	34,697	33,280	31,864	31,156	30,094	29,386
0.35	37,175	35,051	33,635	32,218	31,510	30,448	29,740
0.36	37,883	35,405	33,989	32,926	31,864	30,802	30,094
0.37	38,237	36,113	34,697	32,926	31,864	31,156	30,094
0.38	38,591	36,467	34,697	33,280	32,218	31,510	30,802

P(Overfishing)	2020	2021	2022	2023	2024	2025	2026
0.39	39,299	37,175	35,051	33,635	32,572	31,864	31,156
0.40	39,299	37,175	35,405	33,989	32,926	31,864	31,156
0.41	40,007	37,529	35,759	34,697	33,280	32,218	31,510
0.42	40,715	37,883	36,113	34,697	33,635	32,572	31,864
0.43	41,070	38,237	36,467	35,051	33,989	32,926	32,218
0.44	41,424	38,591	36,821	35,405	34,343	33,280	32,572
0.45	41,778	38,945	37,529	35,759	34,697	33,635	32,572
0.46	42,132	39,653	37,883	36,113	34,697	33,989	32,926
0.47	42,840	40,007	37,883	36,467	35,051	34,343	33,280
0.48	43,194	40,361	38,237	36,821	35,405	34,697	33,280
0.49	43,902	41,070	38,591	37,175	35,759	34,697	33,635
0.50	44,256	41,070	39,299	37,529	36,113	35,051	33,989

Figures



Author: benjamin.richards@noaa.gov

Date Saved: 8/20/2018 9:33:47 AM

Figure 1. Boundary of the main Hawaiian Islands (blue shaded cells) as defined in (Yau, 2018). The portion circled in red is the Papahānaumokuākea Marine National Monument as of August 25, 2016 prior to subsequent expansion. Yellow shaded area is Penguin Banks, Area = 331.

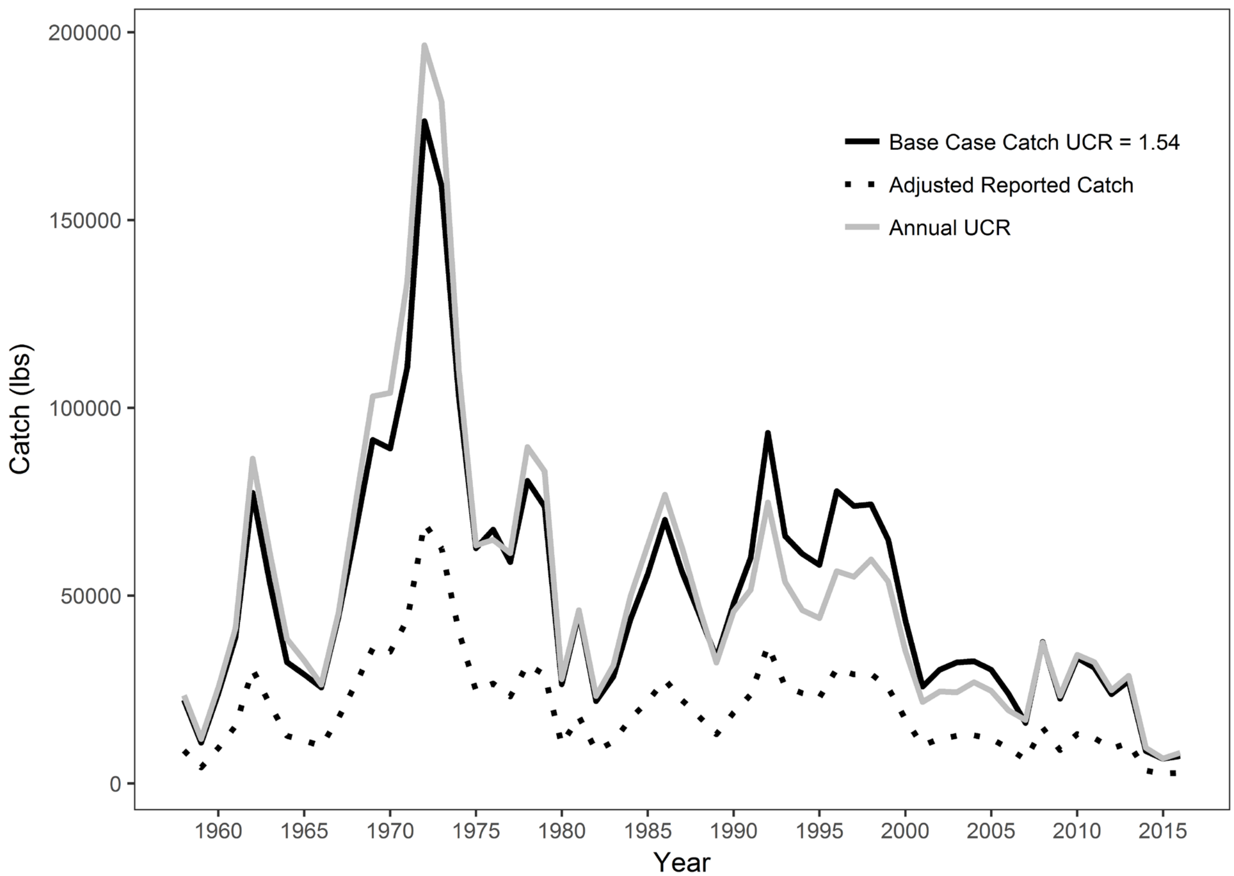


Figure 2. Scenarios of total catch for Hawaii Kona crabs by year, 1958–2016. Solid black line represents total catch from the base case (average ratio of *UCR* = 1.54). Dashed line represents adjusted reported catch (*UCR* = 0). Solid grey line represents total catch using an annual ratio (*UCR* varies by year from Langseth et al., 2018). Scenario of high *UCR* = 5 not shown because of y-axis scaling.

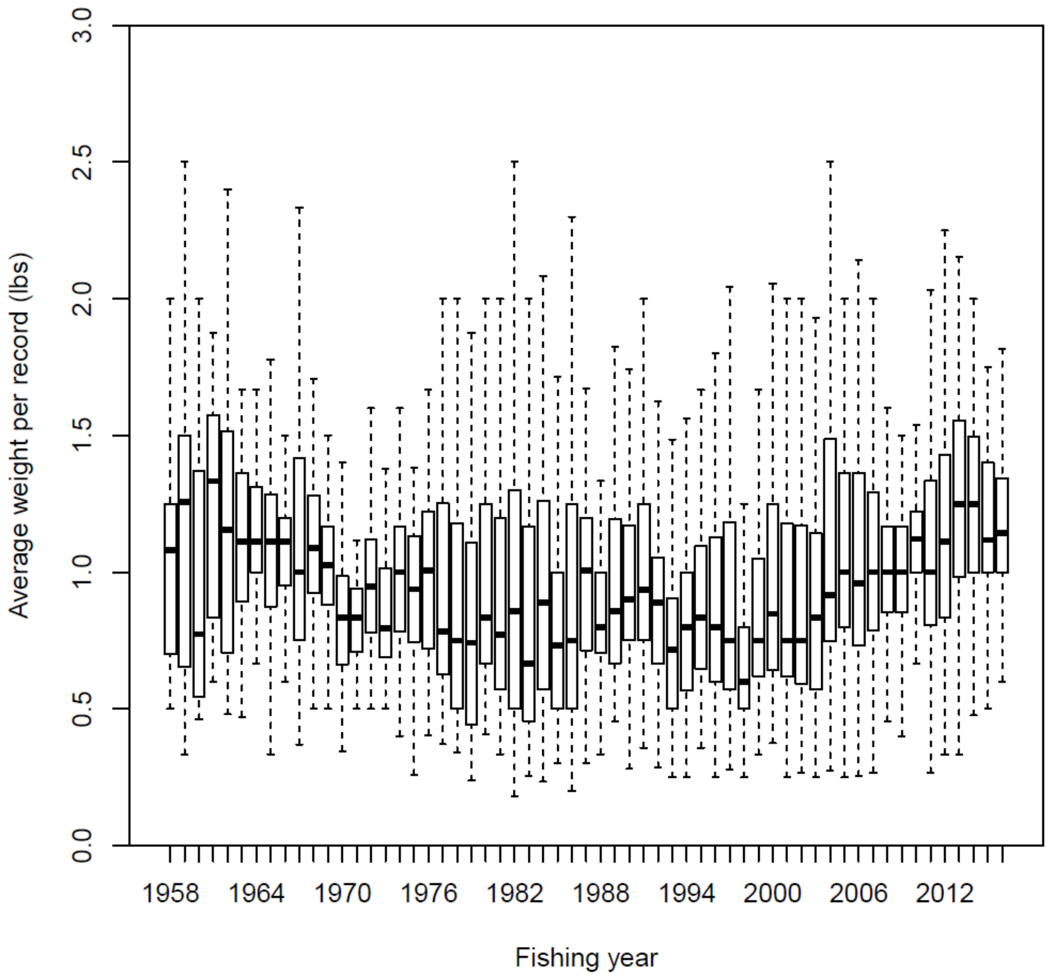


Figure 3. Boxplot illustrating the average weight per record for the 45% of Kona crab records that report both a nonzero number and weight from 1958 to 2016. The horizontal lines inside each box represent the median, the lower and upper box edges are the 25th and 75th percentiles respectively, and the whiskers extend to 1.5 times the interquartile ranges. Outliers have been omitted to maintain confidentiality.

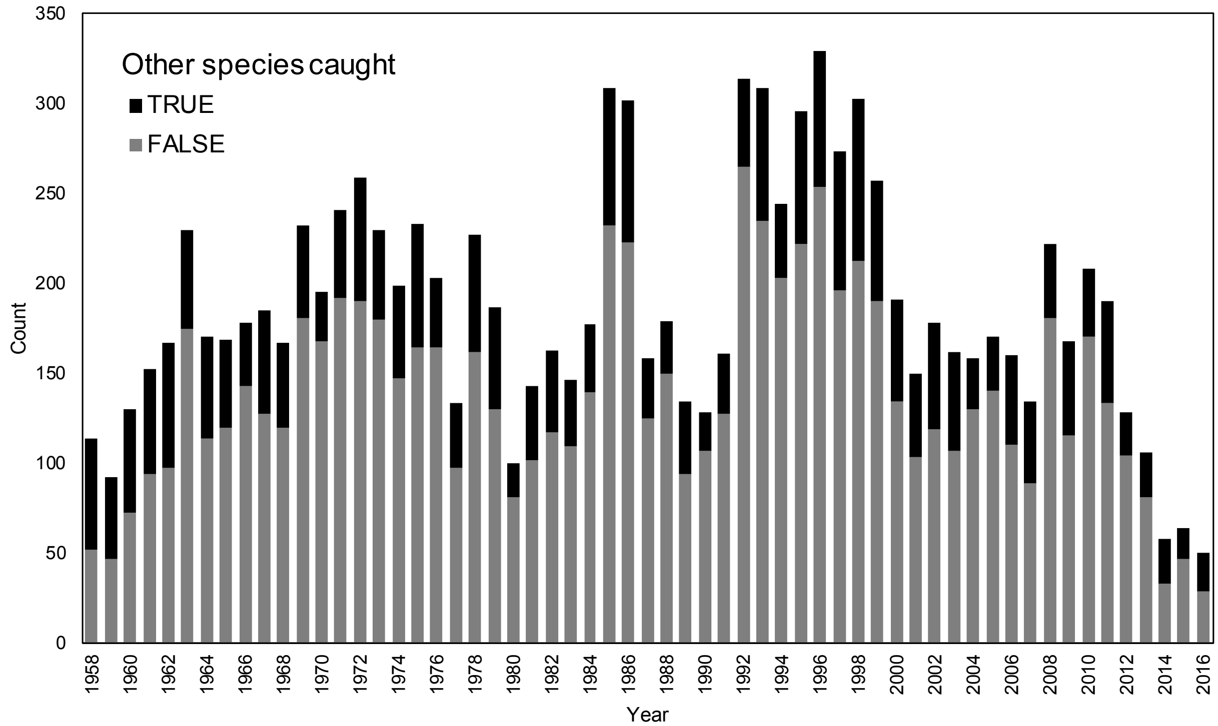


Figure 4. Number of single-reporting days with Kona crab catch in which other species were caught (True) or not (False). Total number of single-reporting days is shown as the sum of both bars in each year.

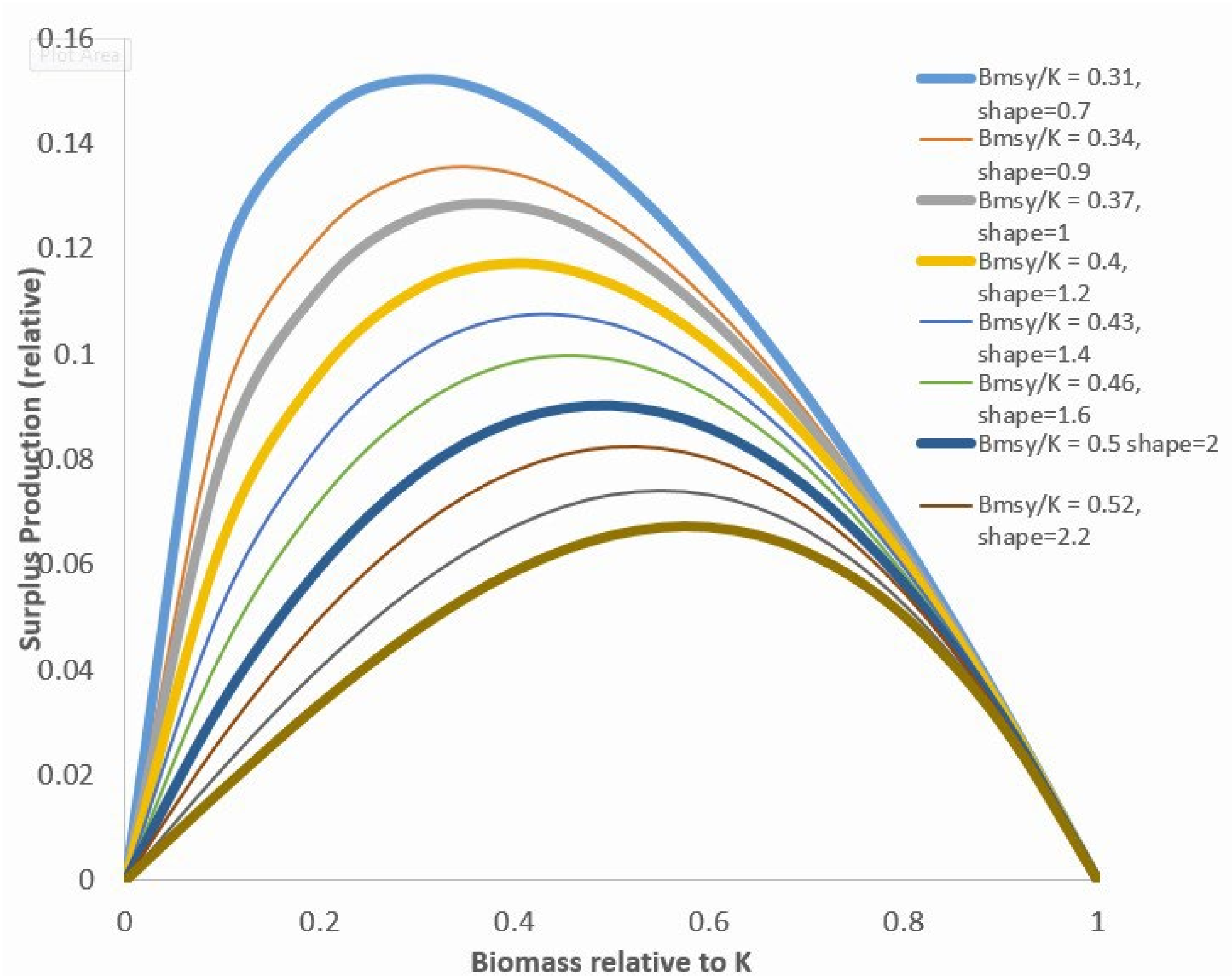


Figure 5. Illustration of Pella-Tomlinson (1969) generalized relative surplus production curves as a function of biomass relative to carrying capacity (*K*) for various shape (*m*) values. In this example, *K* = 1, and intrinsic growth rate (*r*) = 0.5.

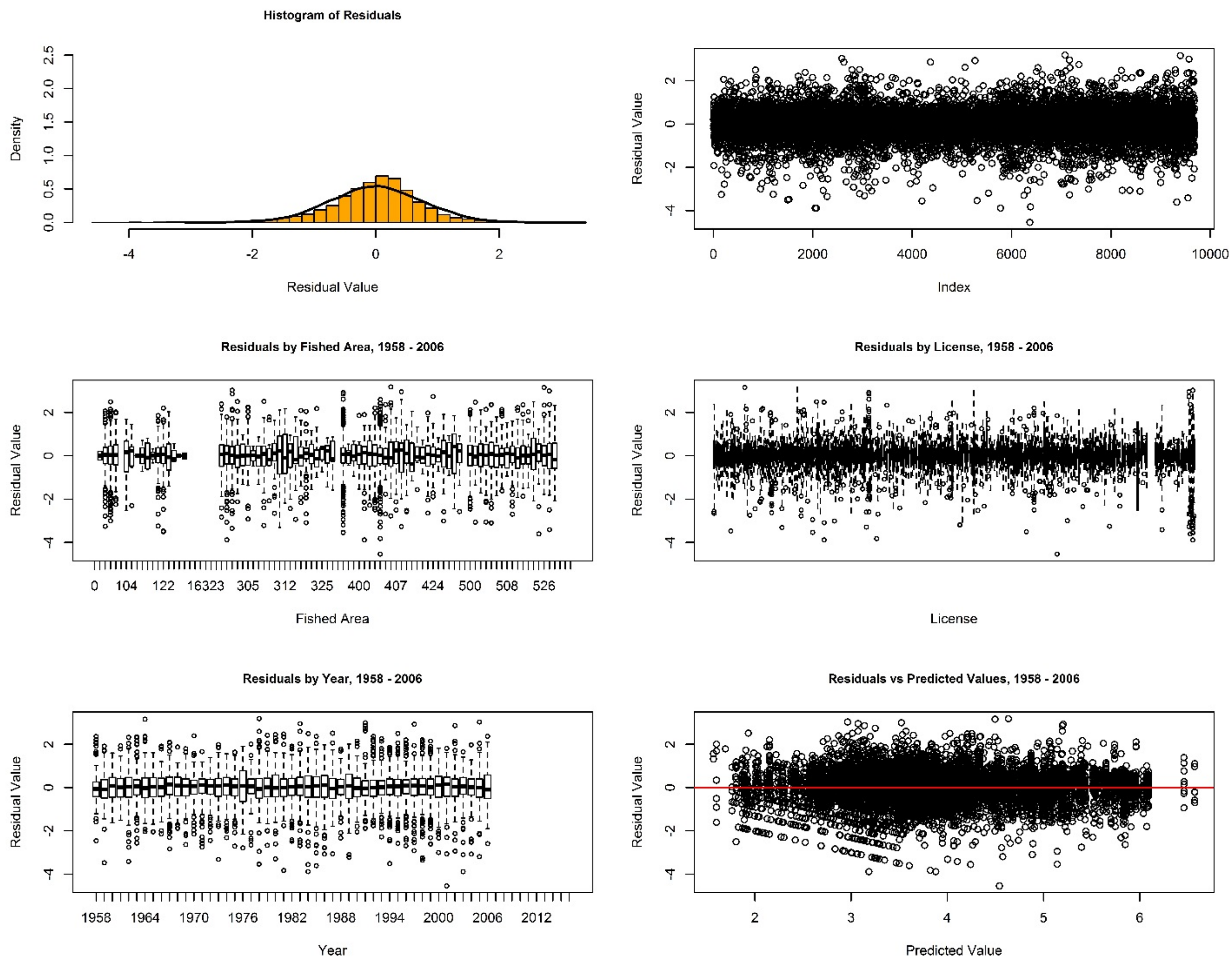


Figure 6. Model diagnostics for the Period 1 (1958–2006) CPUE standardization model. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).

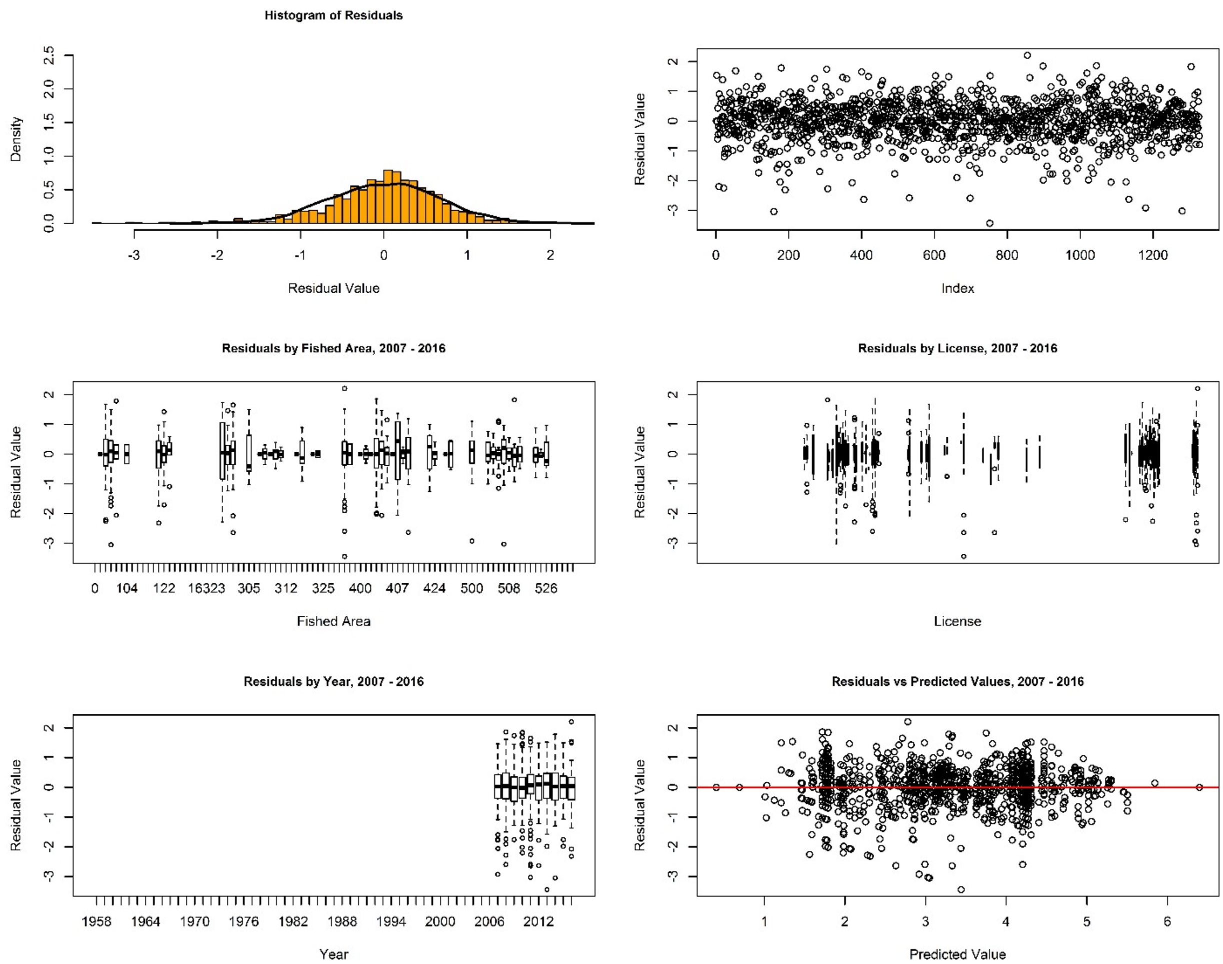
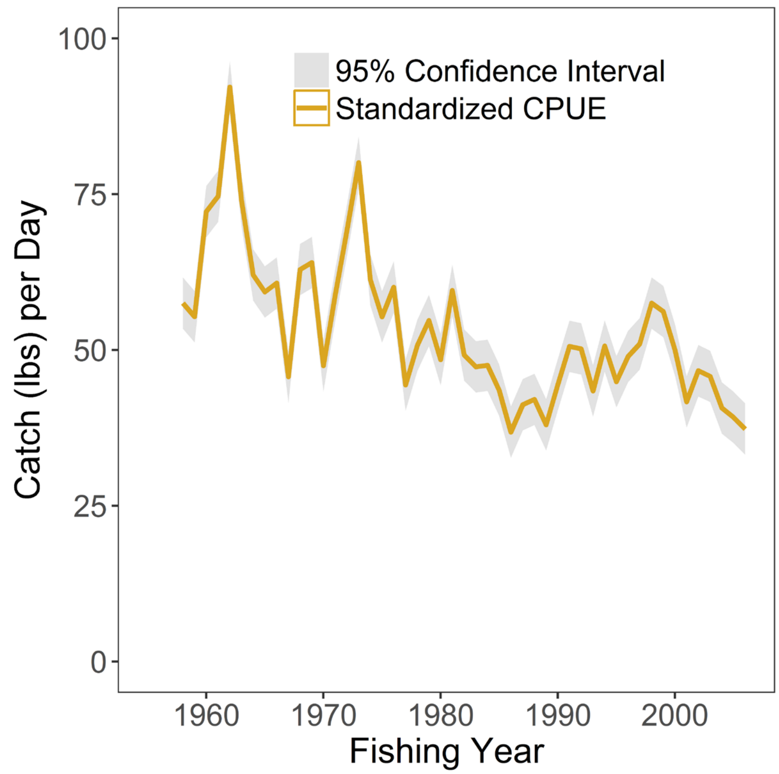


Figure 7. Model diagnostics for the Period 2 (2007–2016) CPUE standardization model. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each predictor variable (to assess patterning in the predictor variables).



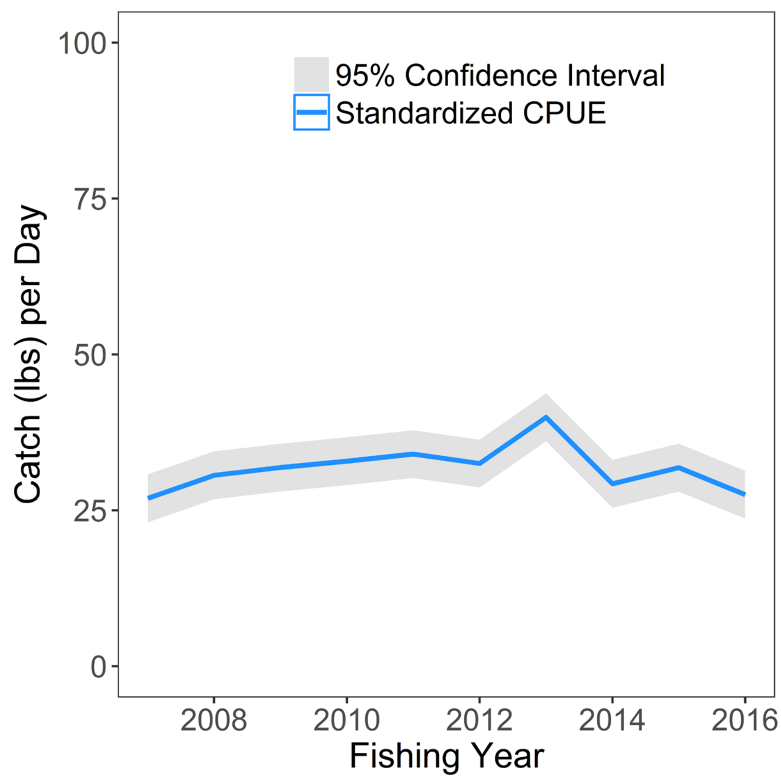


Figure 8. Standardized (solid line, with gray shaded 95% confidence intervals) for Period 1 (top, 1958–2006) and Period 2 (bottom, 2007–2016).

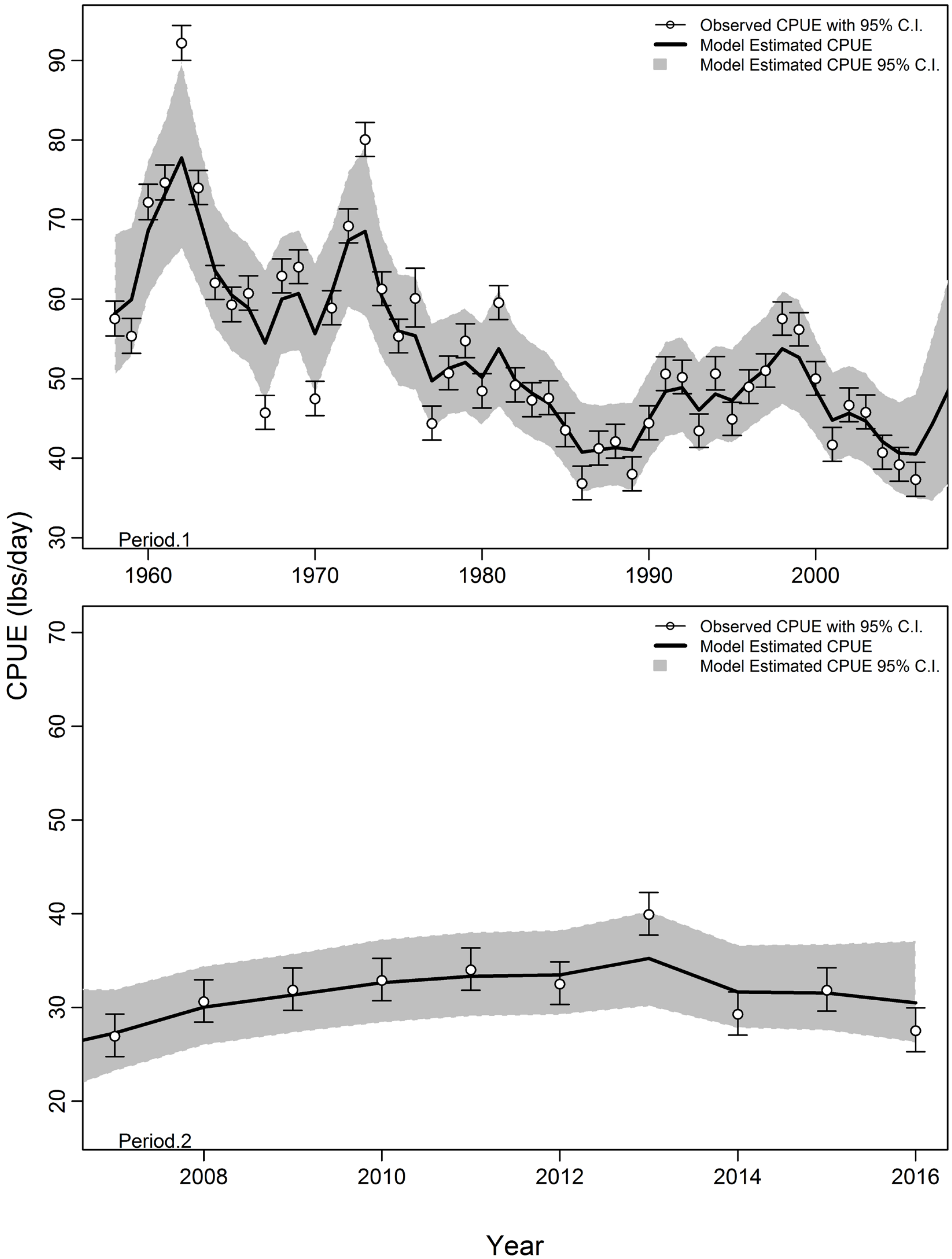


Figure 9. Observed (standardized CPUE) and production model estimated CPUE series for Period 1 (1958–2006) and Period 2 (2007–2016).

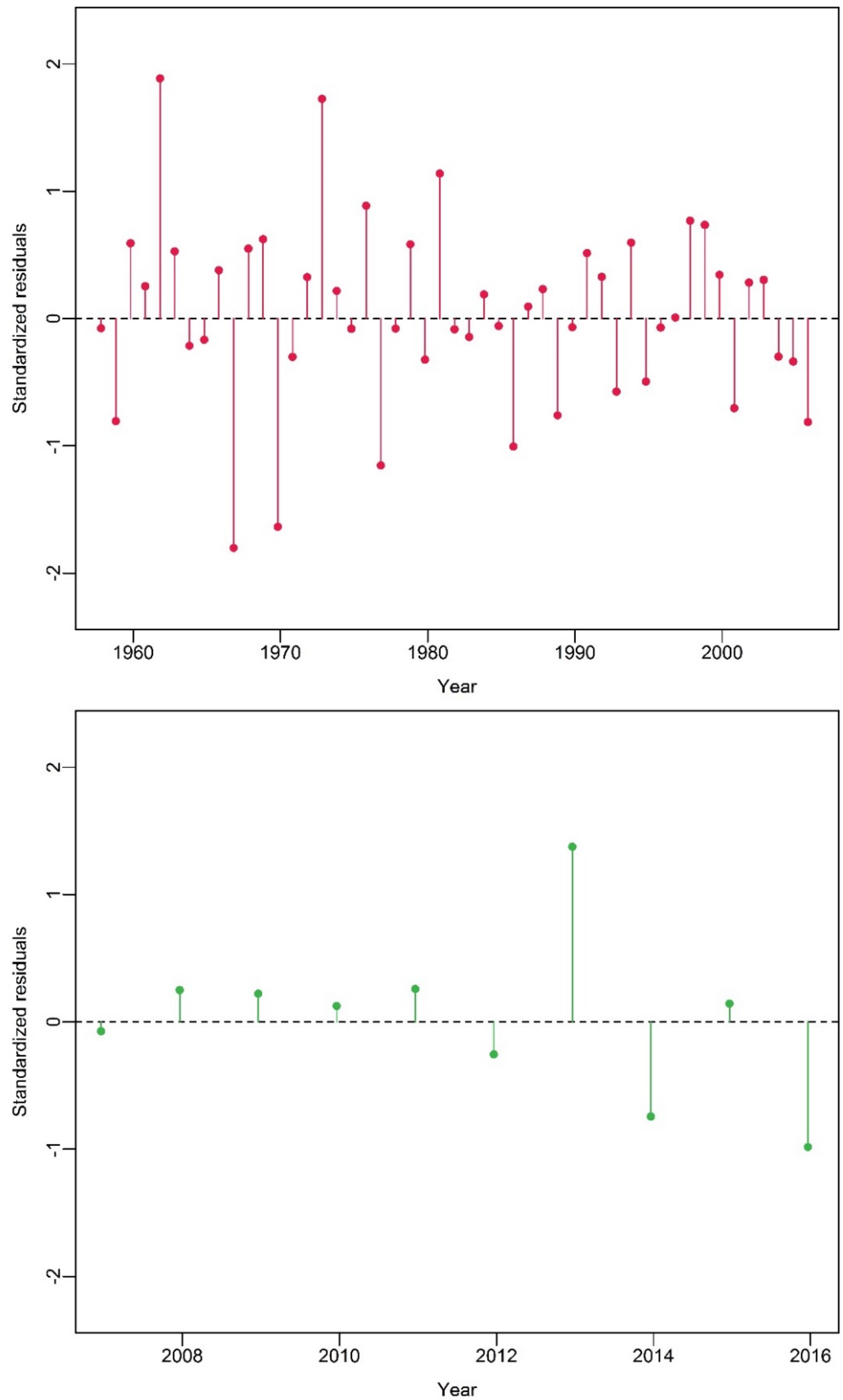


Figure 10. Standardized residuals of observed (standardized) minus production model estimated CPUE for (top) Period 1 (1958–2006) and (bottom) Period 2 (2007–2016).

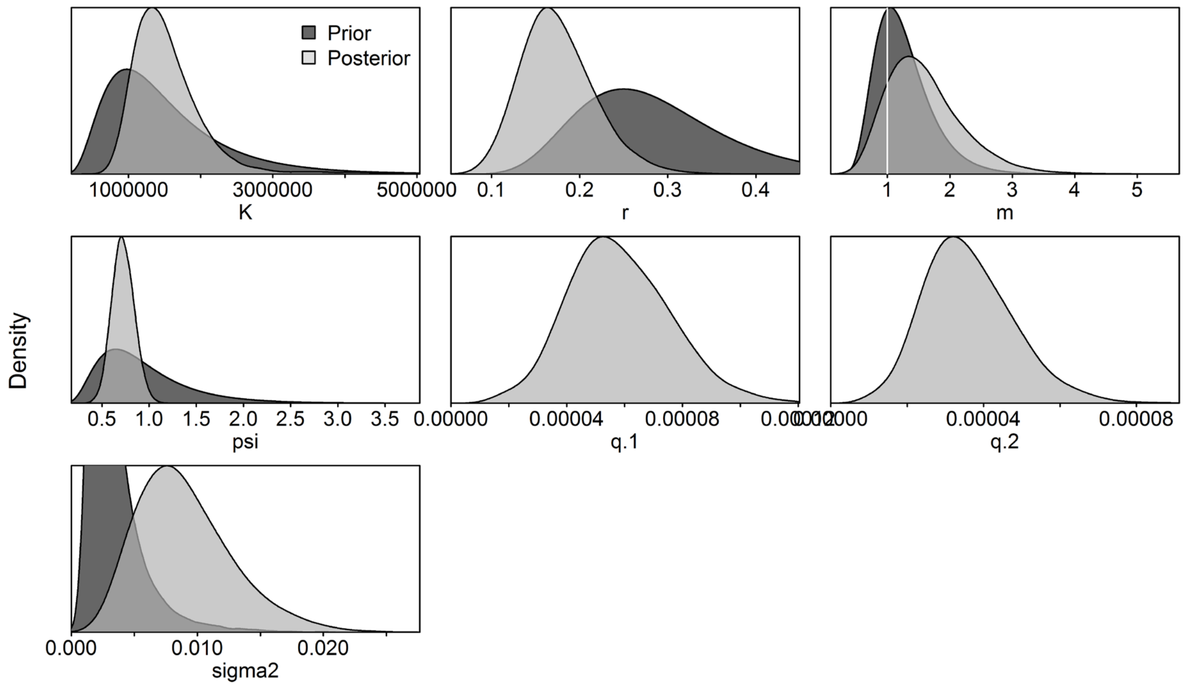


Figure 11. Prior (dark gray) and posterior (light gray) distributions for model parameters including carrying capacity (*K*), intrinsic growth rate (*r*), shape parameter (*m*), initial proportion of biomass to carrying capacity (psi, ψ), catchability in Period 1 (*q.1,* q_1) and Period 2 (*q.2,* q_2), process error variance (*sigma2,* σ_η^2) for the base case Hawaii Kona crab assessment model.

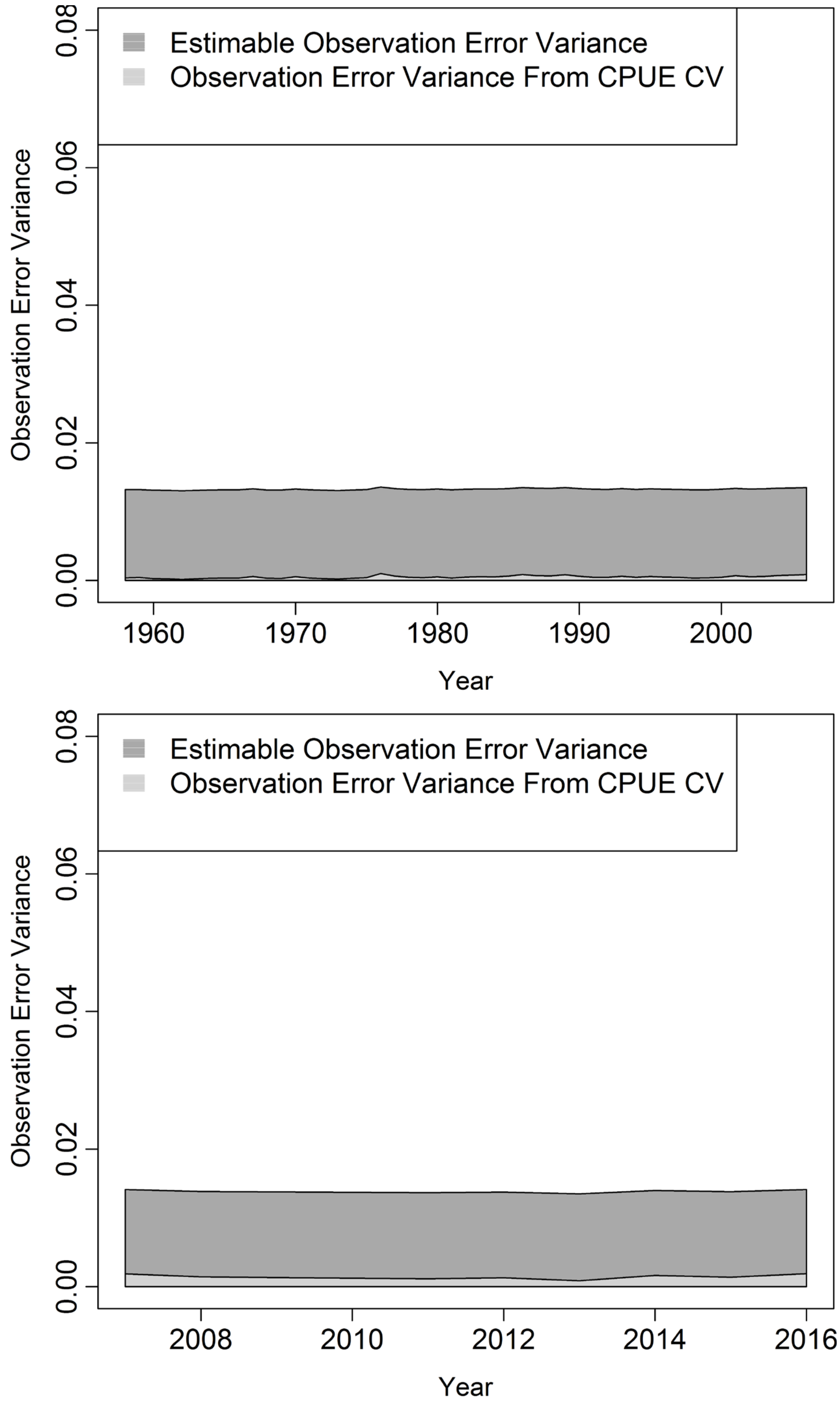
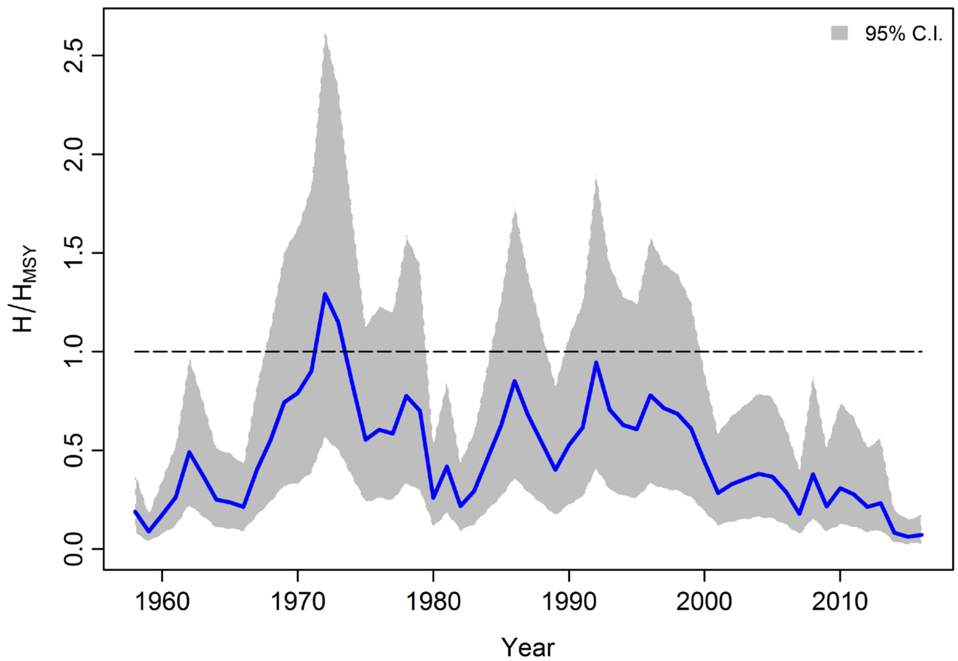


Figure 12. Total observation error variance, $\sigma^2_{\tau_{y,i}}$, by year for Period 1 (1958–2006, top) and Period 2 (2007–2016, bottom), partitioned into the sum of 1) observation error from CPUE CV $\sigma^2_{\tau_{CV,y,i}}$ (light gray), and 2) estimable observation error $\sigma^2_{\tau_{estimated,i}}$ (dark gray).



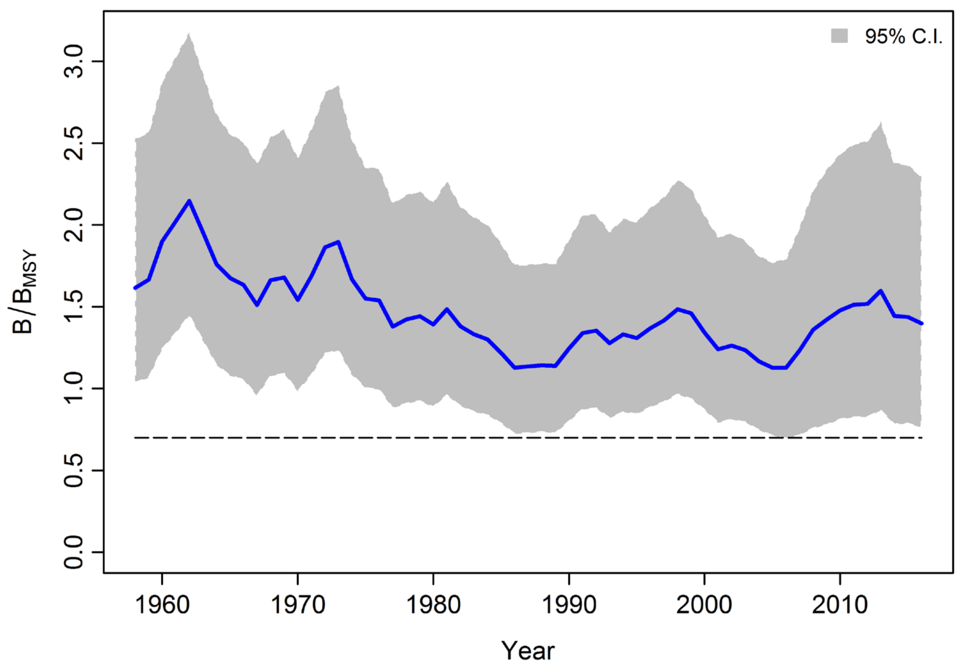


Figure 13. Estimated ratio of harvest rate to harvest rate at maximum sustainable yield (H/H$_{MSY}$, top) and estimated ratio of biomass to biomass at maximum sustainable yield (B/B$_{MSY}$, bottom) for Hawaii Kona crabs from 1958 through 2016 (solid blue line). Solid grey area indicates 95% confidence intervals. Horizontal dashed lines indicates overfishing limit (*H/H$_{MSY}$* > 1.0) and overfished limit (*B/B$_{MSY}$* < 0.7).

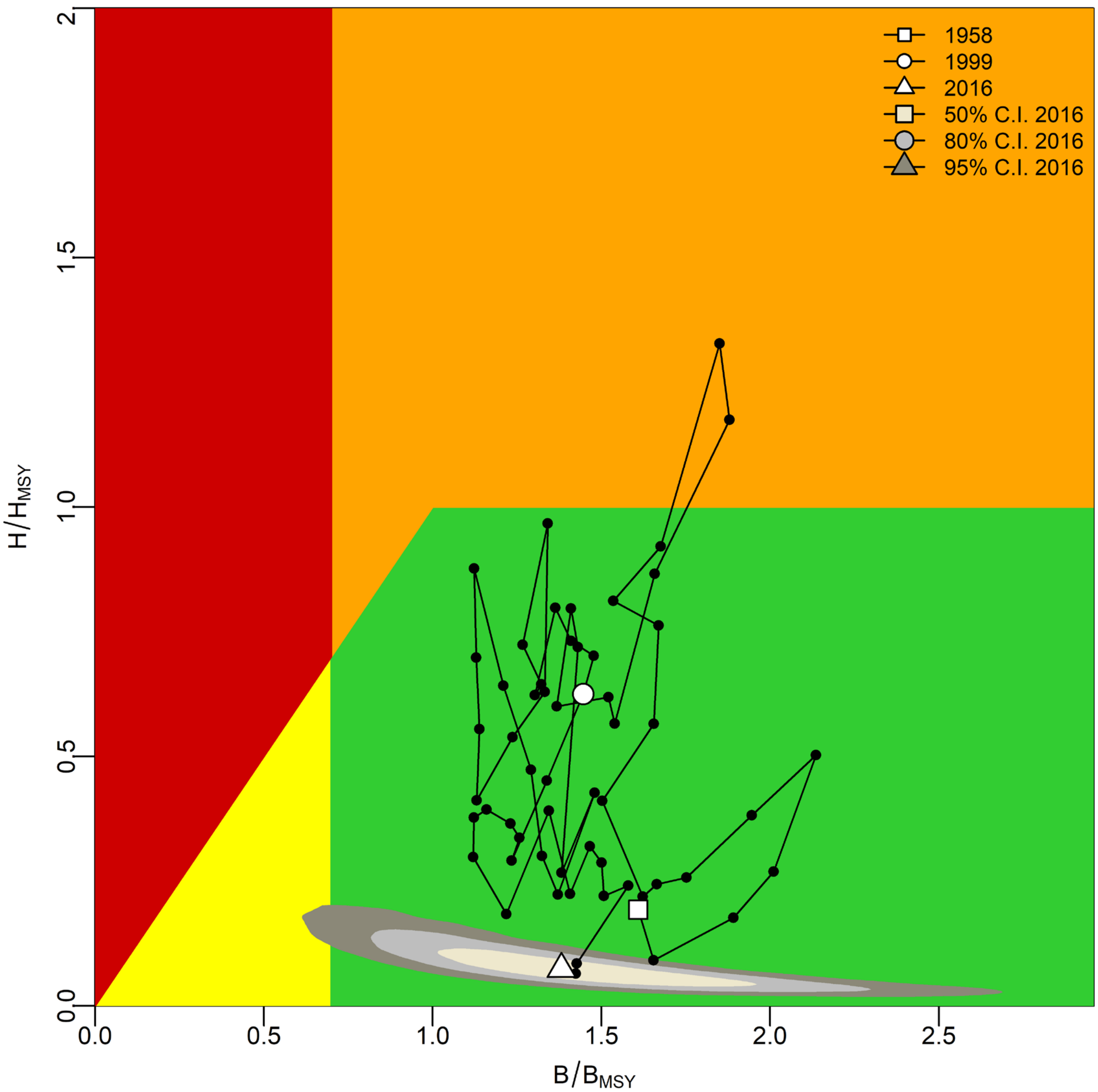
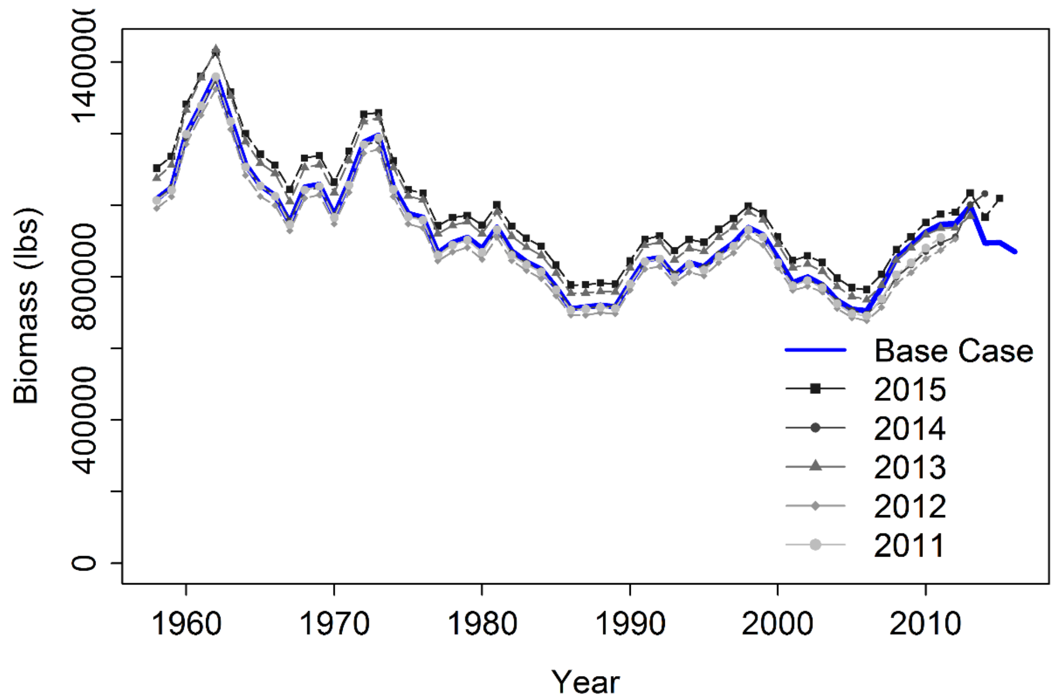


Figure 14. Kobe plot of the estimated stock status for Hawaii Kona crab from 1958 through 2016. Square denotes start year (1958), circle denotes 40-year mark (1999), and triangle denotes end year (2016). Outer bounds of grey shading area indicate 95% confidence interval for final year 2016 with 0% chance of overfished (B/B_{MSY} < 0.7) and 0% chance of overfishing. Overfishing occurs when H/H_{MSY} > 1 if $B > B_{MSY}$. Alternatively, overfishing occurs when $H/H_{MSY} > B/B_{MSY}$ when $B \leq B_{MSY}$. Colored boxes indicate various stock statuses: red = overfished and overfishing, yellow = overfished but no overfishing, orange = not overfished and overfishing, and green = not overfished, no overfishing.



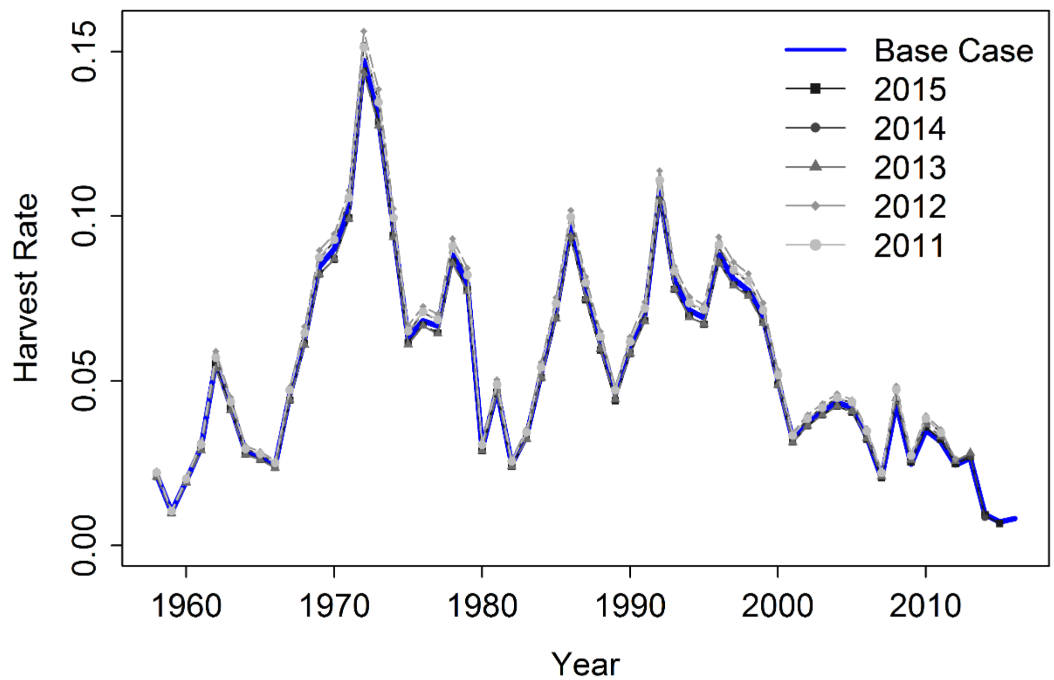


Figure 15. Retrospective analysis for annual biomass (top) and annual harvest rate (bottom) with base case model ending in 2016 as reference (base case) and with retrospective peels from 2011–2015.

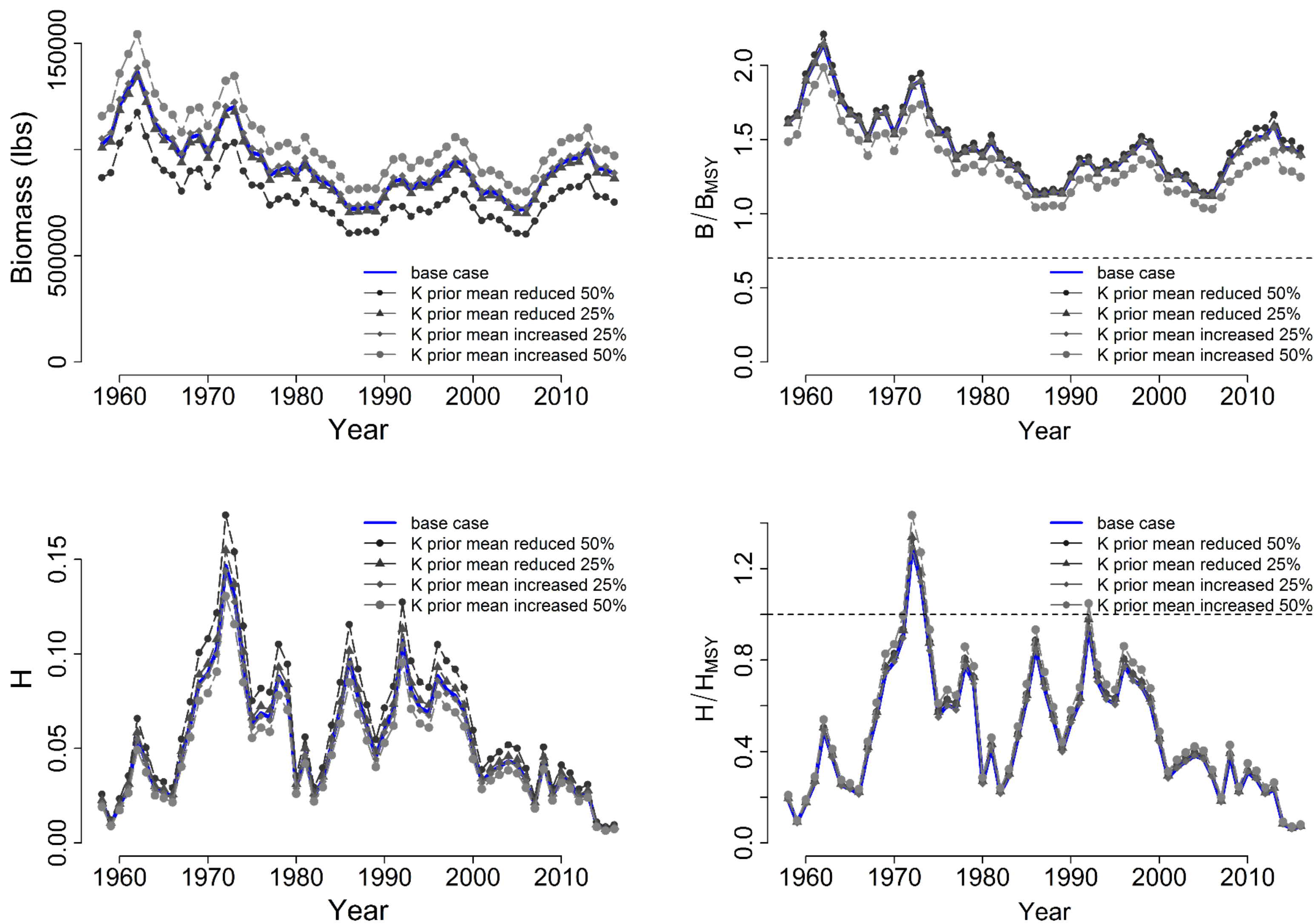


Figure 16. Results of sensitivity analyses for carrying capacity, K: Estimated annual biomass (top left), harvest rate (bottom left), *B/B_{MSY}* (top right), and *H/H_{MSY}* (bottom right).

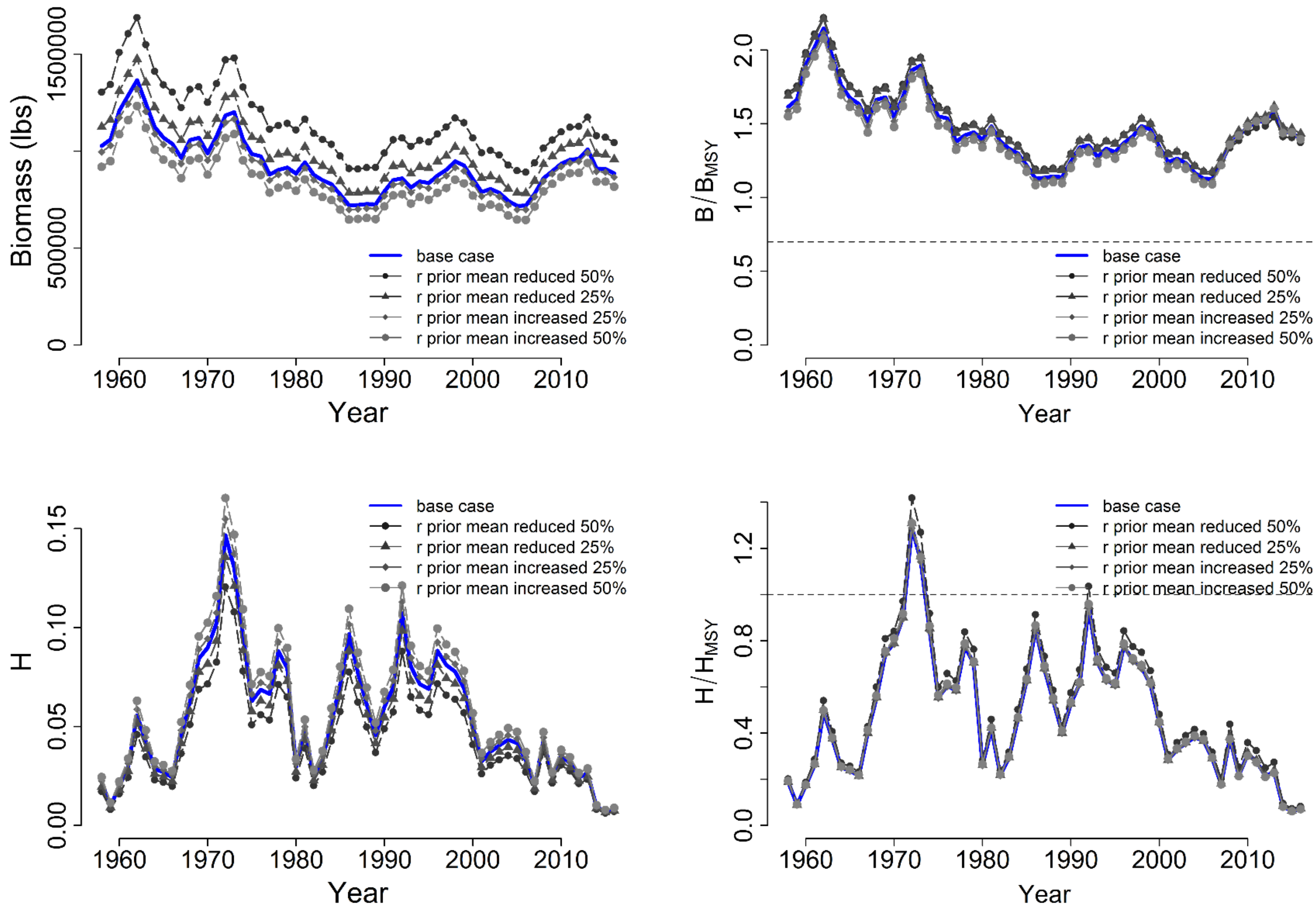


Figure 17. Results of sensitivity analyses for intrinsic growth, *r*: Estimated annual biomass (top left), harvest rate (bottom left), B/B_{MSY} (top right), and H/H_{MSY} (bottom right).

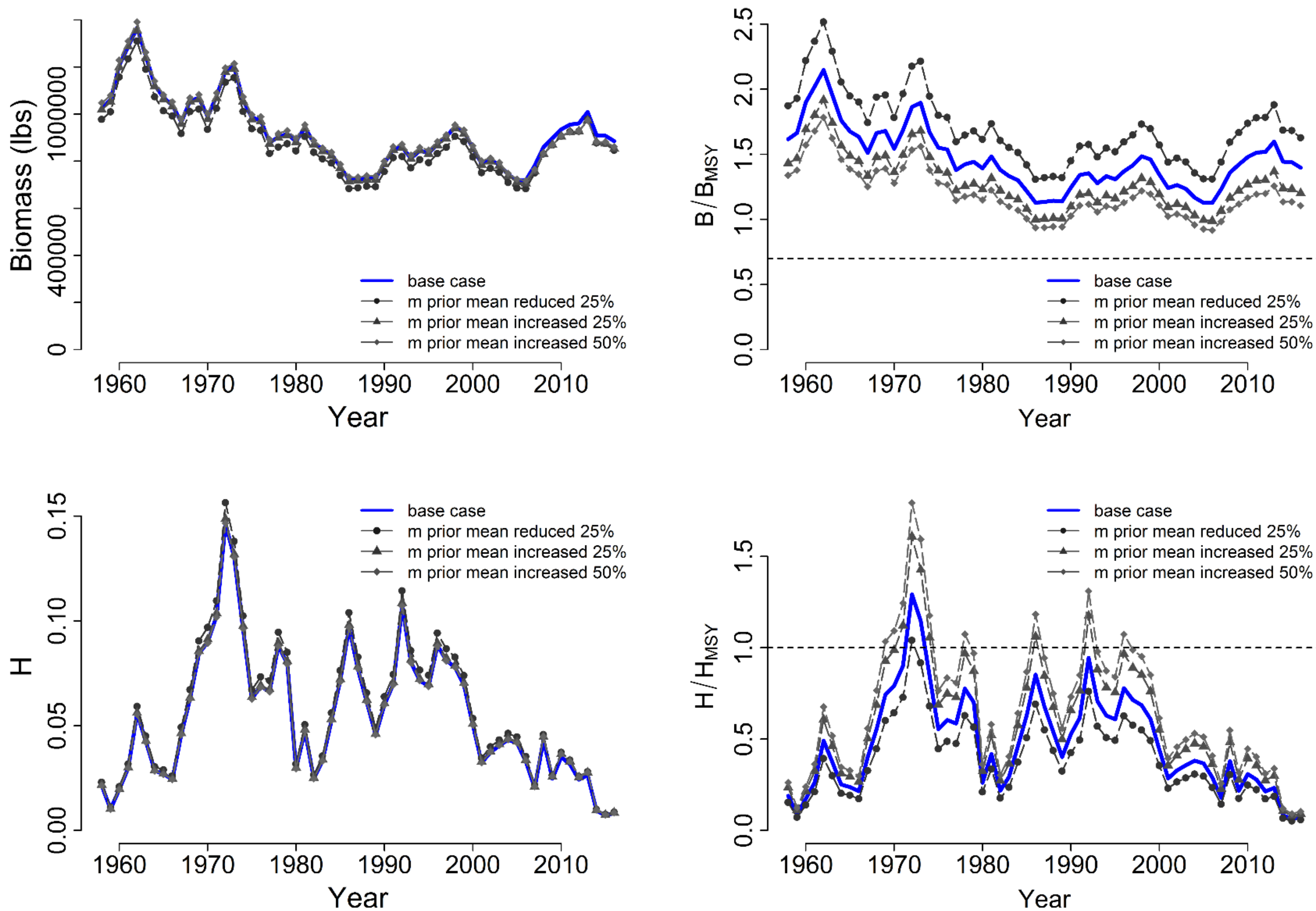


Figure 18. Results of sensitivity analyses for shape parameter, *m*: Estimated annual biomass (top left), harvest rate (bottom left), B/B_{MSY} (top right), and H/H_{MSY} (bottom right).

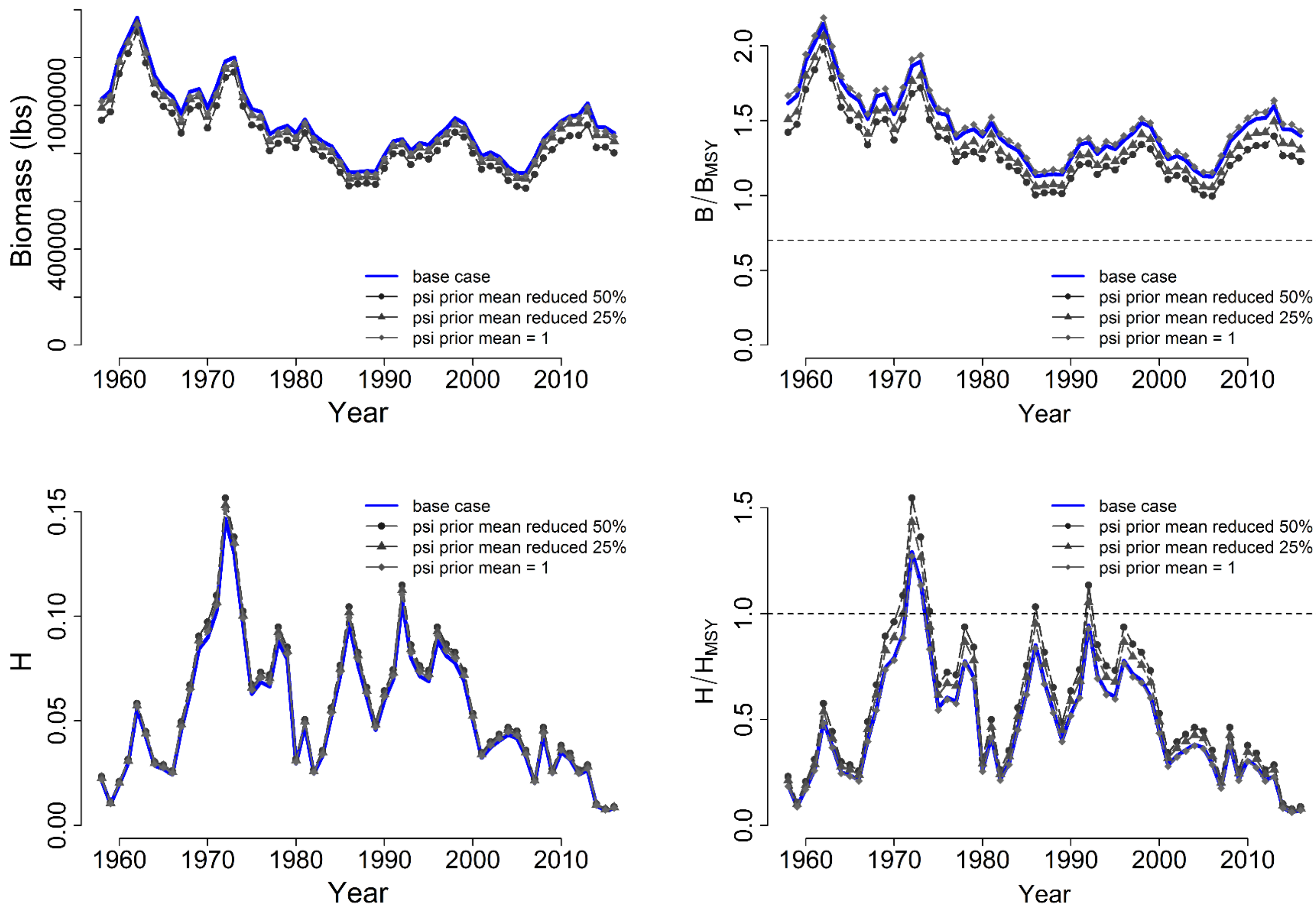


Figure 19. Results of sensitivity analyses for initial ratio of biomass to carrying capacity, ψ: Estimated annual biomass (top left), harvest rate (bottom left), *B/B_{MSY}* (top right), and *H/H_{MSY}* (bottom right).

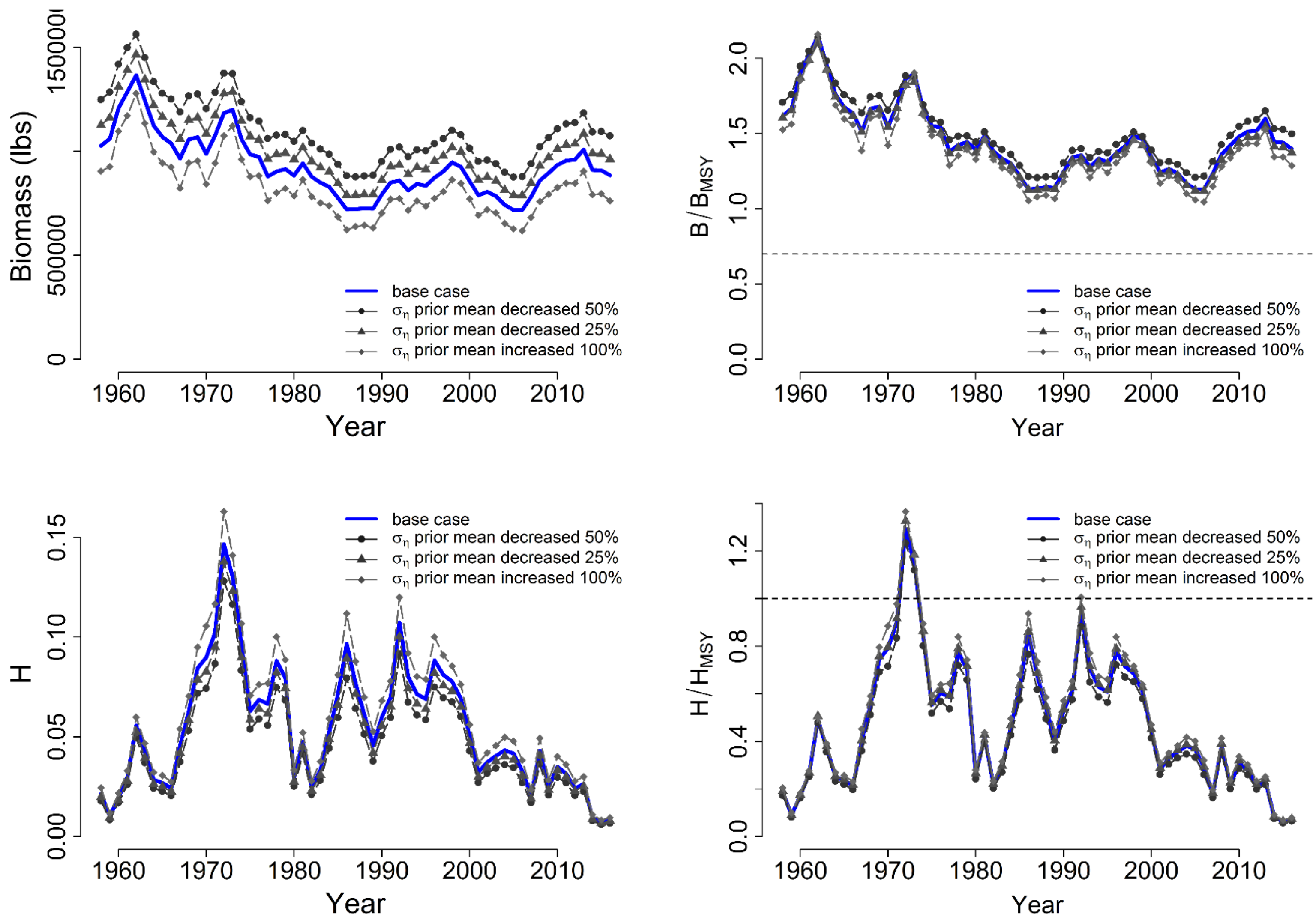


Figure 20. Results of sensitivity analyses for process error, σ_η: Estimated annual biomass (top left), harvest rate (bottom left), B/B_{MSY} (top right), and H/H_{MSY} (bottom right).

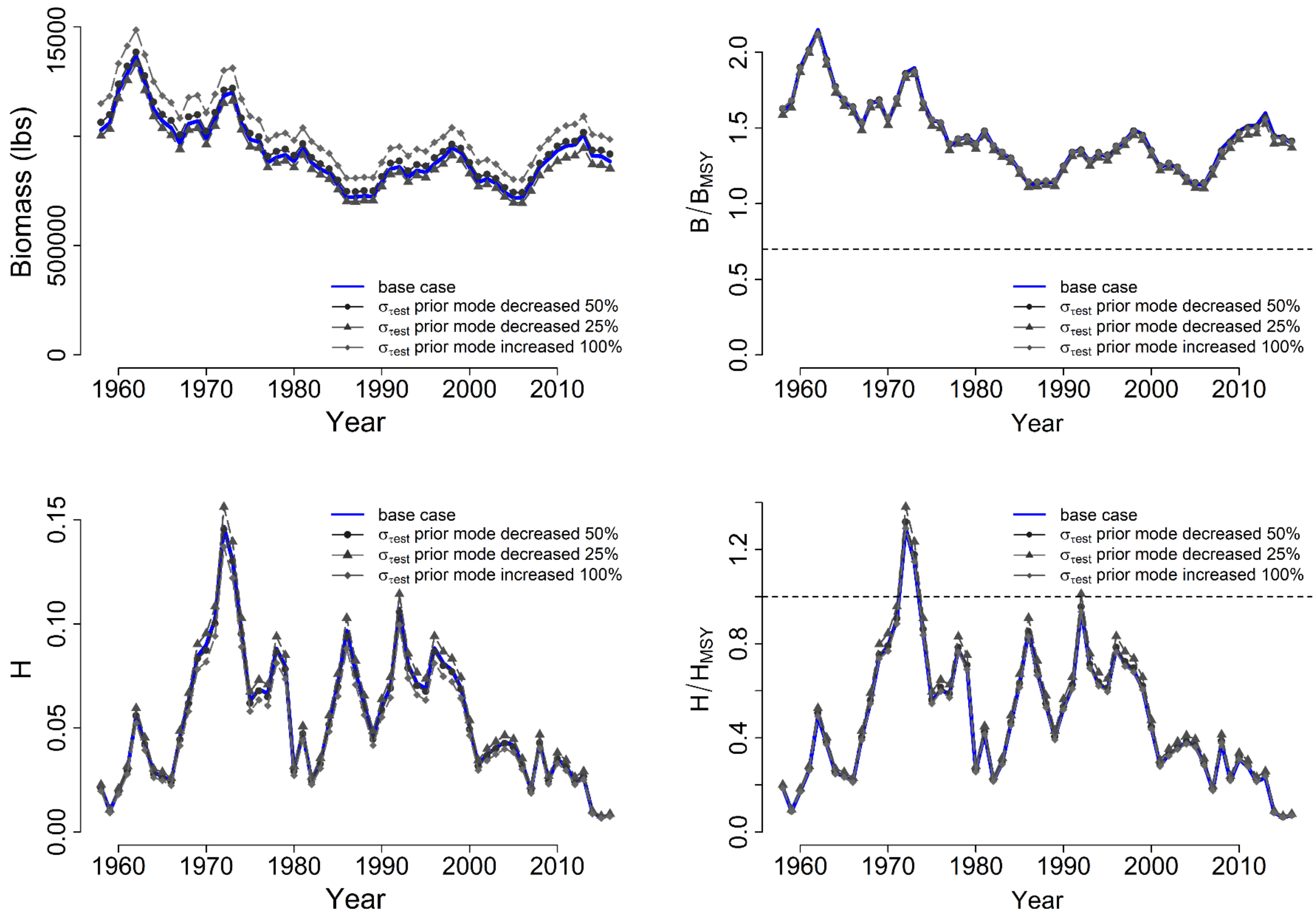


Figure 21. Results of sensitivity analyses for estimated observation error, $\sigma_{\tau_{estimated}}$: Estimated annual biomass (top left), harvest rate (bottom left), *B/B_{MSY}* (top right), and *H/H_{MSY}* (bottom right).

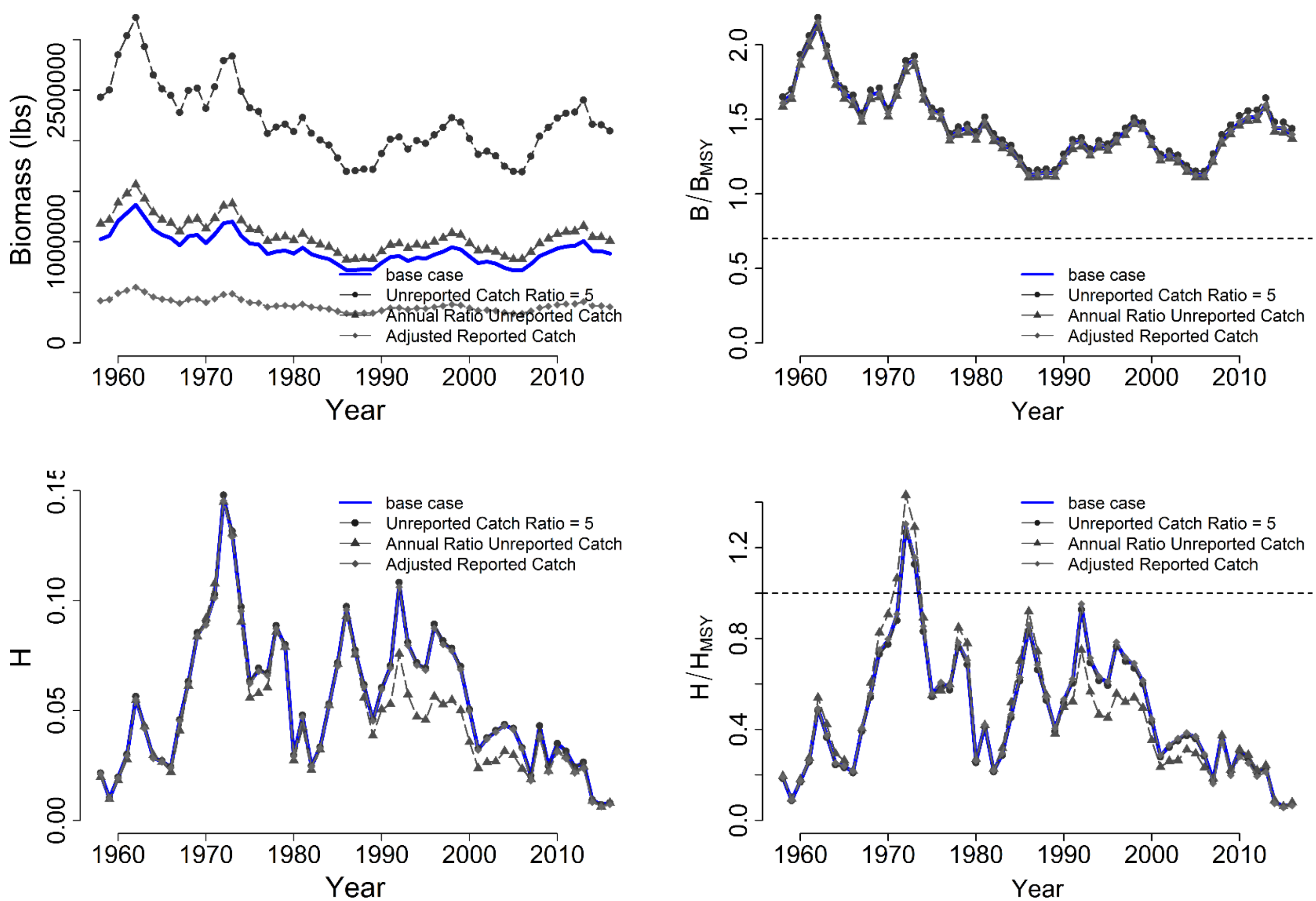


Figure 22. Results of sensitivity analyses for various assumptions on unreported catch: Estimated annual biomass (top left), harvest rate (bottom left), *B/B$_{MSY}$* (top right), and *H/H$_{MSY}$* (bottom right).

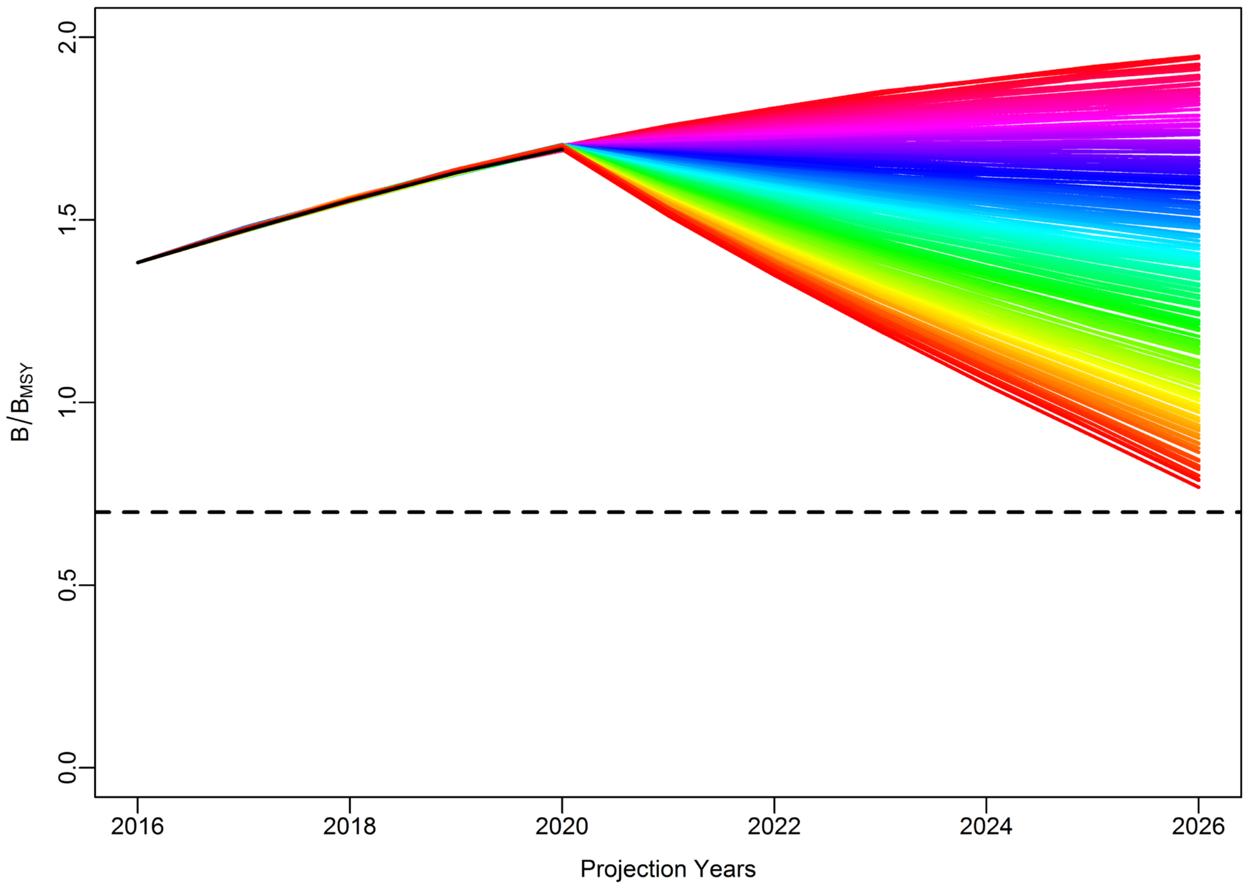


Figure 23. Projections of relative biomass, *B/B_{MSY}*, for years 2020–2026 based on Kona crab base case model projected with various future total catch scenarios (10,000 to 160,000 lb, in 1000-lb increments), equivalent to reported future catches of 3,496 to 55,931 lb. Scenarios with low reported future catches are typically higher in *B/B_{MSY}* over time; the top red trajectories are reported catches <10,000 lb; blue lines are for reported catches approximately 20,000 to 30,000 lb; green from 30,000 to 40,000 lb; yellow, orange to bottom red trajectories are >40,000 lb. Horizontal dashed line indicates the overfished limit of 0.7 *B_{MSY}*.

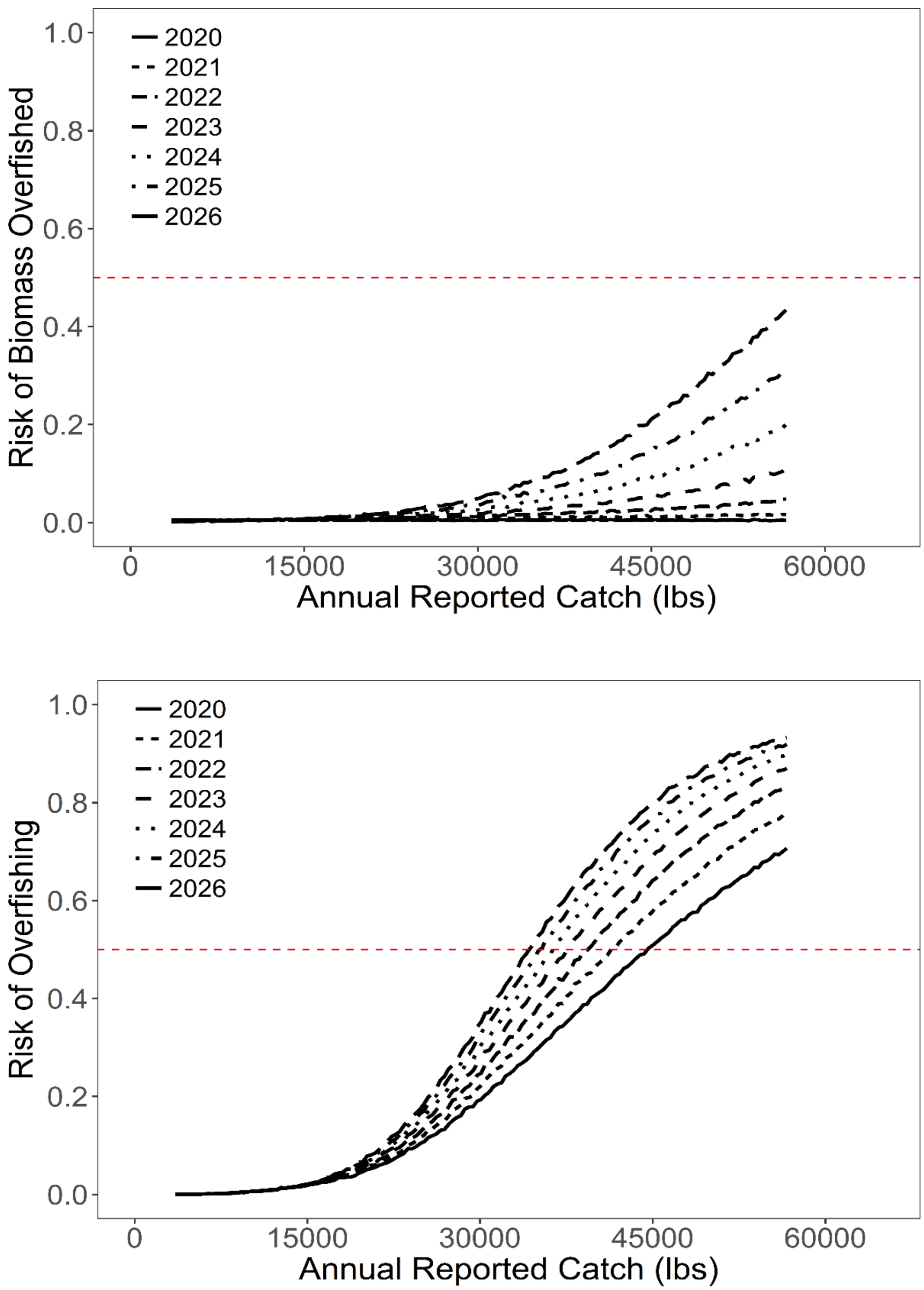


Figure 24. Risk of Hawaii Kona crab stock becoming overfished (*B/B$_{MSY}$* < 0.7) (top) and risk of overfishing (*H/H$_{MSY}$* > 1.0) (bottom) for fishing years 2020 through 2026, presented as a function of projected reported catch.

Appendices

Appendix I. R Code for Calculating Catch Scenarios

```r
require(dplyr)
require(lubridate)
require(reshape2)
require(ggplot2)

## raw DAR data ----
catch <- read.csv("catch_raw_30JUN.csv")

## ratios for unreported catch
UCR <- read.csv("UCR.csv")
kc_only <- subset(catch, SPECIES_FK == 701)


kc_only$FYEAR <-
  ifelse(kc_only$REPORT_MONTH > 6,
         kc_only$REPORT_YEAR + 1,
         kc_only$REPORT_YEAR)


## From Wiley and Pardee (2018)
sexratio <- 0.51 #female sex ratio %
survive.rate <- 0.8923 # survival rate of released crabs


catch_kc <- kc_only %>%
  group_by(FYEAR) %>%
  dplyr::summarise(
    raw_observed = sum(LBS_KEPT),
    ## apply post-release sex ratio with estimated mortality after 2006
    sex_adjusted = if (FYEAR > 2006)
      raw_observed + raw_observed * (sexratio / (1 - sexratio))* (1 - survive
.rate)
    else
      raw_observed
  ) %>%
  mutate(
    ## apply 1.54 scaling (mean(UCR$Annual_Ratio ~ 1.54))
    base_case = sex_adjusted + sex_adjusted * mean(UCR$Annual_Ratio),
    ## UCR = 5x sex-adjusted catch throughout
    UCR5 = sex_adjusted * 6,
    ## apply annualized scaling
    annual_ratio = sex_adjusted +  sex_adjusted * UCR$Annual_Ratio
  ) %>%
  filter(FYEAR > 1957 & FYEAR < 2017) %>%
  select(FYEAR, raw_observed, base_case,sex_adjusted,annual_ratio,UCR5)
```

```
## write CSVs ----
catch_kc %>%
  write.csv("Table1_scenarios_for_catch.csv",row.names = F)

catch_kc %>%
  select(FYEAR, base_case) %>%
  write.csv("base_catch.csv",row.names = F)

catch_kc %>%
  select(FYEAR, annual_ratio) %>%
  write.csv("catch_AnnualR.csv",row.names = F)

catch_kc %>%
  select(FYEAR, UCR5) %>%
  write.csv("catch_5.csv",row.names = F)

catch_kc %>% select(FYEAR, raw_observed) %>%
  write.csv("catch_rept.csv",row.names = F)
```

Appendix II. R Code for CPUE Standardization

Nominal CPUE Calculation

```
require(dplyr)
require(lubridate)
require(foreign)
require(ggplot2)

## raw DAR data ----
df0 <- read.csv(" catch_raw_30JUN.csv")

## filter on gear code 40 AND species code 701 & save ----
df1 <- df0 %>% filter(GEAR_FK == 40 & SPECIES_FK == 701)
write.csv(df1, "kona_crab_catch_raw.csv")
df1 <- read.csv("kona_crab_catch_raw.csv")

dim(df1)
length(unique(df1$AREA_FK))
length(unique(df1$LANDING_PORT_FK))

## drop areas outside MHI_SAP Definition grids ----
mhiareas <- read.csv("MHI_SAPdefinition.csv")
df1.1 <- df1[which(df1$AREA_FK %in% mhiareas$area),]

## add FYEAR ----
df2 <- df1.1 %>%
  mutate(FYEAR = ifelse(REPORT_MONTH>6, REPORT_YEAR+1,REPORT_YEAR))

## match on fisher names ----
namesdf <- read.csv("filtered_names.csv") %>%
  select( FISHED, AREA, LICENSE, RELEASE, FNAME)

## check if we lose data by only using names tracker thru 2016
df2temp <- subset(df2, FYEAR == 2016)
df2temp[!(df2temp$FISHER_LIC_FK %in% namesdf$LICENSE),]
## there is literally one unmatched record, with LBS_KEPT of 0

## perform match where FISHER_LIC_FK == LICENSE and FISHED == FISHED_DATE
## create unique license ID
## coerce FNAME to numeric; if no FNAME available, this is retained as FISHER
_LIC_FK

df3 <-
  merge(
    df2,
    namesdf,
    by.x = c("FISHED_DATE", "FISHER_LIC_FK"),
    by.y = c('FISHED', 'LICENSE'),
    all = T
```

```
  ) %>%
  mutate(LICENSE =  ifelse(!is.na(FNAME), as.numeric(factor(FNAME, levels=uni
que(FNAME))),FISHER_LIC_FK))
dim(df3)

length(unique(namesdf$FNAME)) == length(unique(df3$FNAME)) ## now all unique
fnames are in there
length(unique(df3$LICENSE)) < length(unique(df3$FISHER_LIC_FK)) ## should be
fewer licenses than unique LIC_FKs
subset(df3, LICENSE == 611) ## this license straddles FYEAR 1994-1998, note t
hat FISHER_LIC_FK changed but LICENSE is stable

## create LBS variable ----
df3$LBS <- df3$LBS_KEPT

## group & collapse by single fishing day
df4 <- df3  %>%
  group_by(LICENSE,FISHED_DATE,AREA_FK) %>%
  summarise(LBS = sum(LBS)) %>%
  group_by(LICENSE,FISHED_DATE) %>%
  top_n(1) %>%
  mutate(  MONTH = month(FISHED_DATE),
           R_YEAR = year(FISHED_DATE),
           FYEAR = ifelse(MONTH>6, R_YEAR+1,R_YEAR))


## Apply 'Novice' labels ----
for (i in 1:nrow(df4)) {
  fisherx <-
    which(df4$LICENSE == df4$LICENSE[i]) ## find all matched occurences
  ## assign dummy to novice fishers & year 1976, else retain
  df4$lic.correct[i] <-
    ifelse(length(fisherx) < 6, 99999, df4$LICENSE[i])
  df4$lic.correct[i] <-
    ifelse(df4$FYEAR[i] == 1976, 197600, df4$lic.correct[i])
}

## generate island labels ----
df4$island <- cut(as.numeric(as.character(df4$AREA_FK)), breaks = c(99,299,39
9,499,20000), labels =   c("big","mauinui","oahu",'kauai'))

## apply area-based variation into novice records (99999 = maui nui)
df4$lic.correct <- ifelse(df4$lic.correct==99999 & df4$island =='big', 88888,
df4$lic.correct)
df4$lic.correct <-ifelse(df4$lic.correct==99999 & df4$island =='kauai', 77777
, df4$lic.correct)
df4$lic.correct <-ifelse(df4$lic.correct==99999 & df4$island =='oahu', 66666,
df4$lic.correct)
df4$lic.correct <-ifelse(df4$lic.correct==99999 & df4$island =='NA', 77777, d
f4$lic.correct)
```

```
## add season ----
df5 <- df4 %>% mutate(
  MONTH = month(FISHED_DATE),
  R_YEAR = year(FISHED_DATE),
  FYEAR = ifelse(MONTH>6, R_YEAR+1,R_YEAR),
  island = cut(
    as.numeric(as.character(AREA_FK)),
    breaks = c(99, 299, 399, 499, 20000),
    labels =   c("big", "mauinui", "oahu", 'kauai')
  ),
  season = ifelse(MONTH == 9  |
                    MONTH == 10, 1, ifelse(
                      MONTH == 11  | MONTH == 12, 2, ifelse(MONTH == 1  | MON
TH == 2, 3,
                                                            ifelse(MONTH ==
                                                                    3  | MON
TH == 4, 4, 5))
                    ))
)

## cumulative experience ----
df6 <- df5 %>% ungroup() %>% mutate(FISHED_DATE = as.Date(FISHED_DATE)) %>%
  filter(FISHED_DATE >= as.Date("1957-07-01")  & FISHED_DATE < as.Date("2016-
06-30") )

df6$cumexp <- ave(df6$lic.correct == df6$lic.correct, df6$lic.correct, FUN =
cumsum)


## env data ----
## match on environmental data; make sure to use raw year (R_YEAR)
EnvData <- read.csv(" Monthly_Environment_Data.csv")
df7 <- merge(df6, EnvData, by.x = c("MONTH", "R_YEAR"), by.y = c("Month", "Ye
ar"), all.x = T)

## habitat information ----
habitat <- read.csv( " Kona_Crab_Hab_stats_by_DAR_grid.csv")
df8 <- merge(df7, habitat, by.x = "AREA_FK", by.y = 'AREA_ID', all.y = F)

## reformatting and factors ----
## rename and coerce to factors.
df9 <- df8 %>%
  plyr::rename(c(
    'Hardness..mean.' = 'hardness',
                 'Depth..mean.' = 'depth',
                 'Slope..mean.' = 'slope',
                 'PDO' = 'pdo',
                 'ENSOAnom' = 'enso',
                 'cumexp' = 'experience')) %>%
```

```
  mutate(lnlbs = ifelse(LBS > 0, log(LBS),0),
         FYEAR = as.factor(FYEAR),
         season = as.factor(season),
         license = as.factor(lic.correct),
         MONTH = as.factor(MONTH),
         AREA = as.factor(AREA_FK)) %>%
  select(FYEAR,FISHED_DATE, MONTH, AREA, license, LBS, lnlbs, experience, sea
son, island, pdo, enso, hardness, depth, slope)

early <- df9 %>% filter(FISHED_DATE >= as.Date("1957-07-01")  & FISHED_DATE <
as.Date("2006-06-30") )
late <- df9 %>%   filter(FISHED_DATE >= as.Date("2006-06-30") )

save(early, "early.Rdata")

save(late, "late.Rdata")
```

Standardization - Period 1

```
require(MuMIn)
require(dplyr)
require(ggplot2)
require(lubridate)
require(lme4)

early <- readRDS("early.Rdata")
late <- readRDS("late.Rdata")


## early Series(TP1) ----
## STEP 1 ----
p = proc.time()
TP1.rmod0 = lmer(lnlbs ~ (1|license),  data = early, REML = FALSE, na.action
= na.omit)
TP1.rmod1 = lmer(lnlbs ~ (1|license) + FYEAR, data = early, REML = FALSE, na.
action = na.omit)
TP1.rmod2 = lmer(lnlbs ~ (1|license) + FYEAR + season, data = early, REML = F
ALSE, na.action = na.omit)
TP1.rmod3 = lmer(lnlbs ~ (1|license) + FYEAR + MONTH, data = early, REML = FA
LSE, na.action = na.omit)
TP1.rmod4 = lmer(lnlbs ~ (1|license) + FYEAR + island, data = early, REML = F
ALSE, na.action = na.omit)
TP1.rmod5 = lmer(lnlbs ~ (1|license) + FYEAR + AREA,  data = early, REML = FA
LSE, na.action = na.omit)
TP1.rmod6 = lmer(lnlbs ~ (1|license) + FYEAR + log(experience), data = early,
REML = FALSE, na.action = na.omit)
TP1.rmod7 = lmer(lnlbs ~ (1|license) + FYEAR + depth, data = early, REML = FA
LSE, na.action = na.omit)
TP1.rmod8 = lmer(lnlbs ~ (1|license) + FYEAR + hardness,data = early, REML =
```

```
FALSE, na.action = na.omit)
TP1.rmod9 = lmer(lnlbs ~ (1|license) + FYEAR + pdo, data = early, REML = FALS
E, na.action = na.omit)
TP1.rmod10 = lmer(lnlbs ~ (1|license) + FYEAR + enso,  data = early, REML = F
ALSE, na.action = na.omit)
model.sel(TP1.rmod0, TP1.rmod1, TP1.rmod2,TP1.rmod3,TP1.rmod4,TP1.rmod5,TP1.r
mod6,TP1.rmod7,TP1.rmod8,TP1.rmod9,TP1.rmod10, rank = AICc)
proc.time() - p
## AREA provided most improvement [TP1.rmod5]

## STEP 2 ----
## cutoff failed
p = proc.time() ## 30 seconds
TP1.rmoda = lmer(lnlbs ~ (1|license) + FYEAR + AREA + season, data = early, R
EML = FALSE, na.action = na.omit)
TP1.rmodb = lmer(lnlbs ~ (1|license) + FYEAR + AREA + MONTH,  data = early, R
EML = FALSE, na.action = na.omit)
TP1.rmodc = lmer(lnlbs ~ (1|license) + FYEAR + AREA + island, data = early, R
EML = FALSE, na.action = na.omit)
TP1.rmodd = lmer(lnlbs ~ (1|license) + FYEAR + AREA + log(experience),  data
= early, REML = FALSE, na.action = na.omit)
TP1.rmode = lmer(lnlbs ~ (1|license) + FYEAR + AREA + depth, data = early, RE
ML = FALSE, na.action = na.omit)
TP1.rmodf = lmer(lnlbs ~ (1|license) + FYEAR + AREA + hardness,  data = early
, REML = FALSE, na.action = na.omit)
TP1.rmodg = lmer(lnlbs ~ (1|license) + FYEAR + AREA + pdo, data = early, REML
= FALSE, na.action = na.omit)
TP1.rmodh = lmer(lnlbs ~ (1|license) + FYEAR + AREA + enso, data = early, REM
L = FALSE, na.action = na.omit)
# model.sel(TP1.rmod5, TP1.rmoda, TP1.rmodb, TP1.rmodc,TP1.rmodd,TP1.rmode,TP
1.rmodf,TP1.rmodg,TP1.rmodh, rank = AICc)
proc.time() - p
# interaction (slow)
TP1.rmodIA1 = lmer(lnlbs ~ (1|license) + FYEAR + AREA + FYEAR:AREA, data = ea
rly, REML = FALSE, na.action = na.omit)
model.sel(TP1.rmod5, TP1.rmoda, TP1.rmodb, TP1.rmodc,TP1.rmodd,TP1.rmode,TP1.
rmodf,TP1.rmodg,TP1.rmodh,TP1.rmodIA1, rank = AICc)

## check %dAIC (prev-current)/previous > 2%
(AICc(TP1.rmodIA1)-AICc(TP1.rmod5))/AICc(TP1.rmodIA1)*100 >= 2 ## cuttoff fai
led
(deviance(TP1.rmod1) - deviance(TP1.rmod5))/deviance(TP1.rmod1)*100 (deviance
(TP1.rmod0) - deviance(TP1.rmod5))/deviance(TP1.rmod0)*100 ## SAVE MODEL & TA
BLES ----
## re run best mod w reml = T
TP1.rmod5T <- lmer(lnlbs ~ (1|license) + FYEAR + AREA,  data = early, REML =
TRUE, na.action = na.omit)
saveRDS(TP1.rmod5T, file = "TP1_r_best.rds")
mst.all <-
  model.sel(
```

```
    TP1.rmod0,
    TP1.rmod1,
    TP1.rmod2,
    TP1.rmod3,
    TP1.rmod4,
    TP1.rmod5,
    TP1.rmod6,
    TP1.rmod7,
    TP1.rmod8,
    TP1.rmod9,
    TP1.rmod10,
    TP1.rmoda,
    TP1.rmodb,
    TP1.rmodc,
    TP1.rmodd,
    TP1.rmode,
    TP1.rmodf,
    TP1.rmodg,
    TP1.rmodh,
    TP1.rmodIA1,
    rank = AICc
  ) %>% mutate(
    Deviance = get.models(., subset = T) %>% lapply(., deviance) %>% as.data.
frame() %>% t(),
    modname = rownames(.),
    'Formula' = get.models(.,subset = T) %>% lapply(FUN = formula) %>% as.cha
racter()
  )
mst.fwd <-
  model.sel(TP1.rmod0, TP1.rmod1, TP1.rmod5, rank = AICc) %>% mutate(
    pdAIC = NA,
    Deviance = get.models(., subset = T) %>% lapply(., deviance) %>% as.data.
frame() %>% t(),
    pdDeviance = NA,
    modname = rownames(.),
    'Formula' = get.models(.,subset = T) %>% lapply(FUN = formula) %>% as.cha
racter()
  )

## loop to input % changes to forward list
for(i in rev(1:(nrow(mst.fwd)-1))){
  mst.fwd[nrow(mst.fwd),c("pdDeviance","pdAIC")] <- 0 ## first model (last ro
w) is zero
  mst.fwd[i,"pdAICc"] <- round((mst.fwd[i+1,"AICc"] - mst.fwd[i,"AICc"])/mst.
fwd[i+1,"AICc"] *100,digits = 2)
  mst.fwd[i,"pdDeviance"] <- round((mst.fwd[i+1,"Deviance"] - mst.fwd[i,"Devi
ance"])/mst.fwd[i+1,"Deviance"] *100,digits = 2)
}
```

```
write.csv(mst.all, "TP1_MST_r_all.csv", row.names = F)
write.csv(mst.fwd, "TP1_MST_r_fwd.csv", row.names = F)
```

Standardization - Period 2

```
## LATE Series(TP2) ----
## STEP 1 ----
p = proc.time() ## 4 seconds
TP2.rmod0 = lmer(lnlbs ~ (1|license),  data = late, REML = FALSE, na.action =
na.omit)
TP2.rmod1 = lmer(lnlbs ~ (1|license) + FYEAR, data = late, REML = FALSE, na.a
ction = na.omit)
TP2.rmod2 = lmer(lnlbs ~ (1|license) + FYEAR + season, data = late, REML = FA
LSE, na.action = na.omit)
TP2.rmod3 = lmer(lnlbs ~ (1|license) + FYEAR + MONTH, data = late, REML = FAL
SE, na.action = na.omit)
TP2.rmod4 = lmer(lnlbs ~ (1|license) + FYEAR + island, data = late, REML = FA
LSE, na.action = na.omit)
TP2.rmod5 = lmer(lnlbs ~ (1|license) + FYEAR + AREA,  data = late, REML = FAL
SE, na.action = na.omit)
TP2.rmod6 = lmer(lnlbs ~ (1|license) + FYEAR + log(experience), data = late,
REML = FALSE, na.action = na.omit)
TP2.rmod7 = lmer(lnlbs ~ (1|license) + FYEAR + depth, data = late, REML = FAL
SE, na.action = na.omit)
TP2.rmod8 = lmer(lnlbs ~ (1|license) + FYEAR + hardness,data = late, REML = F
ALSE, na.action = na.omit)
TP2.rmod9 = lmer(lnlbs ~ (1|license) + FYEAR + pdo, data = late, REML = FALSE
, na.action = na.omit)
TP2.rmod10 = lmer(lnlbs ~ (1|license) + FYEAR + enso,  data = late, REML = FA
LSE, na.action = na.omit)
model.sel(TP2.rmod0, TP2.rmod1, TP2.rmod2,TP2.rmod3,TP2.rmod4,TP2.rmod5,TP2.r
mod6,TP2.rmod7,TP2.rmod8,TP2.rmod9,TP2.rmod10, rank = AICc)
proc.time() - p
## AREA provided most improvement [TP2.rmod5]

## STEP 2 ----
## cuttof failed
p = proc.time() ## 30 seconds
TP2.rmoda = lmer(lnlbs ~ (1|license) + FYEAR + AREA + season, data = late, RE
ML = FALSE, na.action = na.omit)
TP2.rmodb = lmer(lnlbs ~ (1|license) + FYEAR + AREA + MONTH,  data = late, RE
ML = FALSE, na.action = na.omit)
TP2.rmodc = lmer(lnlbs ~ (1|license) + FYEAR + AREA + island, data = late, RE
ML = FALSE, na.action = na.omit)
TP2.rmodd = lmer(lnlbs ~ (1|license) + FYEAR + AREA + log(experience),  data
= late, REML = FALSE, na.action = na.omit)
TP2.rmode = lmer(lnlbs ~ (1|license) + FYEAR + AREA + depth, data = late, REM
L = FALSE, na.action = na.omit)
TP2.rmodf = lmer(lnlbs ~ (1|license) + FYEAR + AREA + hardness,  data = late,
REML = FALSE, na.action = na.omit)
```

```
TP2.rmodg = lmer(lnlbs ~ (1|license) + FYEAR + AREA + pdo, data = late, REML
= FALSE, na.action = na.omit)
TP2.rmodh = lmer(lnlbs ~ (1|license) + FYEAR + AREA + enso, data = late, REML
= FALSE, na.action = na.omit)
# interaction (slow)
TP2.rmodIA1 = lmer(lnlbs ~ (1|license) + FYEAR + AREA + FYEAR:AREA, data = la
te, REML = FALSE, na.action = na.omit)
model.sel(TP2.rmod5, TP2.rmoda, TP2.rmodb, TP2.rmodc,TP2.rmodd,TP2.rmode,TP2.
rmodf,TP2.rmodg,TP2.rmodh,TP2.rmodIA1, rank = AICc)

model.sel(TP2.rmod5, TP2.rmoda, TP2.rmodb, TP2.rmodc,TP2.rmodd,TP2.rmode,TP2.
rmodf,TP2.rmodg,TP2.rmodh,TP2.rmodIA1, rank = AICc)
proc.time() - p
## AREA provided most improvement [TP2.rmodb]

## check %dAIC (prev-current)/previous > 2%
(AICc(TP2.rmoda)-AICc(TP2.rmod5))/AICc(TP2.rmoda)*100 >= 2 ## cuttoff failed
(deviance(TP2.rmod1) - deviance(TP2.rmod5))/deviance(TP2.rmod1)*100 (deviance
(TP2.rmod0) - deviance(TP2.rmod5))/deviance(TP2.rmod0)*100 ## SAVE MODEL & TA
BLES ----
## re run best mod w reml = T
TP2.rmod5T <- lmer(lnlbs ~ (1|license) + FYEAR + AREA,  data = late,  REML =
TRUE, na.action = na.omit)
saveRDS(TP2.rmod5T, file = "TP2_r_best.rds")
mst.all <-
  model.sel(
    TP2.rmod0,
    TP2.rmod1,
    TP2.rmod2,
    TP2.rmod3,
    TP2.rmod4,
    TP2.rmod5,
    TP2.rmod6,
    TP2.rmod7,
    TP2.rmod8,
    TP2.rmod9,
    TP2.rmod10,
    TP2.rmoda,
    TP2.rmodb,
    TP2.rmodc,
    TP2.rmodd,
    TP2.rmode,
    TP2.rmodf,
    TP2.rmodg,
    TP2.rmodh,
    TP2.rmodIA1,
    rank = AICc
  ) %>% mutate(
    Deviance = get.models(., subset = T) %>% lapply(., deviance) %>% as.data.
frame() %>% t(),
```

```
    modname = rownames(.),
    'Formula' = get.models(.,subset = T) %>% lapply(FUN = formula) %>% as.cha
racter()
  )
mst.fwd <-
  model.sel(TP2.rmod0, TP2.rmod1, TP2.rmod5, rank = AICc) %>% mutate(
    pdAIC = NA,
    Deviance = get.models(., subset = T) %>% lapply(., deviance) %>% as.data.
frame() %>% t(),
    pdDeviance = NA,
    modname = rownames(.),
    'Formula' = get.models(.,subset = T) %>% lapply(FUN = formula) %>% as.cha
racter()
  )

## loop to input % changes to forward list
for(i in rev(1:(nrow(mst.fwd)-1))){
  mst.fwd[nrow(mst.fwd),c("pdDeviance","pdAIC")] <- 0 ## first model (last ro
w) is zero
  mst.fwd[i,"pdAIC"] <- round((mst.fwd[i+1,"AICc"] - mst.fwd[i,"AICc"])/mst.f
wd[i+1,"AICc"] *100,digits = 2)
  mst.fwd[i,"pdDeviance"] <- round((mst.fwd[i+1,"Deviance"] - mst.fwd[i,"Devi
ance"])/mst.fwd[i+1,"Deviance"] *100,digits = 2)
}

write.csv(mst.all, "TP2_MST_r_all.csv", row.names = F)
write.csv(mst.fwd, "TP2_MST_r_fwd.csv", row.names = F)
```

Prediction

```
## em-means predictions on random effects models
require(emmeans)
require(dplyr)
require(ggplot2)

early <- readRDS("early.Rdata")
late <- readRDS("late.Rdata")

## load best models
TP1.best <- readRDS("TP1_r_best.rds")
TP2.best <- readRDS("TP2_r_best.rds")

raw.emmeans1 <- emmeans(TP1.best, ~ FYEAR, data = early ) %>% data.frame()
saveRDS(raw.emmeans1, "rawemmeans1_r.rds")
raw.emmeans1 <- readRDS("rawemmeans1_r.rds")

raw.emmeans2 <- emmeans(TP2.best, ~ FYEAR) %>% data.frame()
saveRDS(raw.emmeans2, "rawemmeans2_r.rds")
raw.emmeans2 <- readRDS("rawemmeans2_r.rds")
```

```r
emdf <- bind_rows(na.omit(raw.emmeans1) %>%
                    group_by(FYEAR) %>%
                    dplyr::summarise(
                      raw.mean = mean(emmean),
                      total.sigma = sd(resid(TP1.best)),
                      cor.mean = raw.mean + (total.sigma ^ 2) / 2,
                      trans.mean = exp(cor.mean),
                      lci =  exp(cor.mean) -  exp(total.sigma) * 1.96,
                      uci =  exp(cor.mean) +   exp(total.sigma) * 1.96,
                      CV = exp(mean(SE)) / trans.mean,
                      meanlbs = trans.mean
                    ) %>% mutate(SOURCE = 'Ranef Standardization P1'),
                  na.omit(raw.emmeans2) %>%
                    group_by(FYEAR) %>%
                    dplyr::summarise(
                      raw.mean = mean(emmean),
                      total.sigma = sd(resid(TP2.best)),
                      cor.mean = raw.mean + (total.sigma ^ 2) / 2,
                      trans.mean = exp(cor.mean),
                      lci =  exp(cor.mean) -  exp(total.sigma) * 1.96,
                      uci =  exp(cor.mean) +  exp(total.sigma) * 1.96,
                      CV = exp(mean(SE)) / trans.mean,
                      meanlbs = trans.mean
                    ) %>% mutate(SOURCE = 'Ranef Standardization P2')

)
emdf$FYEAR  <- as.numeric(as.character(emdf$FYEAR))

write.csv(emdf,"emmeans_ranef_10Jul.csv", row.names = F)
```

Appendix III. R Code for JABBA Prime File to Execute Model in JABBA

```
# required packages
library(gplots); library(coda); library(rjags); library(R2jags); library(fitd
istrplus); library(reshape)

# Set Working directory file, where assessments are stored
File = "FILEA"
# Set working directory for JABBA R source code
JABBA.file = "JABBAFILE"
# JABBA version
version = "v1.2"
# Set Assessment file: assessment folder within File that includes .csv input
files
assessment = "pex_base_em"
# add specifier for assessment (File names of outputs)


#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
# Graphic, Output, Saving (.RData) settings
#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
KOBE.plot = TRUE # Produces JABBA Kobe plot
KOBE.type = c("ICCAT","IOTC")[2] # ICCAT uses 3 colors; IOTC 4 (incl. orange)
Biplot= TRUE # Produces a "post-modern" biplot with buffer and target zones (
Quinn & Collie 2005)
SP.plot = c("standard","phase")[2] # Produces standard or 'Kobe phase' SP plo
t
save.trajectories =TRUE # saves posteriors of P=B/K, B/Bmsy and H/Hmsy as .RD
ata object
harvest.label = c("Hmsy","Fmsy")[1] # choose label preference H/Hmsy versus F
msy
CPUE.plot= TRUE # Runs state-tool to produce "aligned" multi-CPUE plot
meanCPUE = FALSE # Uses averaged CPUE from state-space tool instead of indivi
dual indices
Projection = TRUE # Use Projections: requires to define TACs vectors
save.projections = TRUE # saves projection posteriors as .RData object
catch.metric = "(lb)" # Define catch input metric e.g. (tons) "000 t" etc
Reproduce.seed = TRUE # If FALSE a random seed assigned to each run, if TRUE
set.seed(123)
# P_bound = c(0.02,1.2)  # Soft penalty bounds for P
# Save entire posterior as .RData object
save.all = TRUE # (if TRUE, a very large R object of entire posterior is save
d)
#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>

#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
# Optional: Note Scenarios
#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
# Specify Scenario name for output file names
Scenarios = c("base-case",NA,NA,NA)
```

```
for(s in 1:1){

 Scenario = Scenarios[s]

  Model = c(4,4,4,4)[s]
  Mod.names = c("Schaefer","Fox","Pella","Pella_m")[4]

  # Depensation option:
  # Set Plim = Blim/K where recruitment may become impaired (e.g. Plim = 0.25
)
  # Choose Plim = 0 to reduce to conventional Schaefer, Fox, Pella models
  Plim = 0

  # Required specification for Pella-Tomlinson (Model = 3/4)
  BmsyK = 0.4 # Set Surplus Production curve inflection point
  shape.CV = 0.35 # Must be defined if Model = 4!
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>

  #--------------------------------------------------
  # Read csv files
  #--------------------------------------------------

  # Use errors (SEs, CVs, any other form) from csv file for abundance indices
(TRUE/FALSE)
  SE.I = TRUE
  # Load assessment data
  catch = read.csv(paste0(File,"/",assessment,"/catch",assessment,".csv"))
  cpue = read.csv(paste0(File,"/",assessment,"/cpue",assessment,".csv"))

  if(SE.I ==TRUE){
    se =  read.csv(paste0(File,"/",assessment,"/se",assessment,".csv"))
  }
  indices2 = names(cpue)[-1]
  wink.colors = data.frame(idx = indices2,
                           cols = c('#e6194b', "#3cb44b", "#ffe119",
                                    "#0082c8","#f58231", "#911eb4",
                                    "#46f0f0", "#f032e6", "#d2f53c",
                                    "#fabebe", "#008080","#e6beff", "#aa6e28"
)[1:length(indices2)])


  #------------------------------------------------------
  # Option use mean CPUE from state-space cpue averaging
  #-----------------------------------------------------
  meanCPUE = FALSE

  #-----------------------------------------------------
  # Starting value option for r and K
  #-----------------------------------------------------
```

```
#-------------------------------------------------
# Prior for unfished biomass K
#-------------------------------------------------
# The option are:
# a) Specify as a lognormal prior with mean and CV
# b) Specify as range to be converted into lognormal prior

# ><> new objective K prior
K.dist <- c("lnorm","range")[2] # ><> to range
# Get low and upper r quantile 10th and 90th
qrs <- qlnorm(c(0.1,0.9),log(0.27),0.3)

#Apply CMSY Eq 3 by Froese et al, (2017)
Klow <- max(catch[,2])/qrs[2]
Khigh <- 4*max(catch[,2])/qrs[1]
K.prior <- c(Klow,Khigh)


#------------------------------------------------------------
# mean and CV and sd for Initial depletion level P1= SB/SB0
#------------------------------------------------------------
# Set the initial depletion prior B1/K
# To be converted into a lognormal prior (with upper bound at 1.1)

psi.dist = c("lnorm","beta")[1]
# specify as mean and CV
psi.prior.mean <- signif(as.numeric(61.674/quantile(cpue[,2], na.rm = TRUE,
                                                    probs = 0.95)), digits =
2) ## uci over 95th
psi.prior = c(psi.prior.mean,0.5)

#---------------------------------------------------------------
# Determine estimation for catchability q and observation error
#---------------------------------------------------------------
# Assign q to CPUE
sets.q = 1:(ncol(cpue)-1)

#-----------------------------------------------------
# Determine r prior
#-----------------------------------------------------
# The option are:
# a) Specifying a lognormal prior
# b) Specifying a resiliance category after Froese et al. (2017; CMSY)
# Resilience: "Very low", "Low", "Medium", High" (requires r.range = TRUE)

# use [1] lognormal(mean,stdev) or [2] range (min,max) or
r.dist = c("lnorm","range")[1]
r.prior = c(0.2735,0.3)

#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
```

```
  # Observation Error
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
  
  #To Estimate additional observation variance set sigma.add = TRUE
  sigma.est = TRUE
  
  # Series
  sets.var = 1:(ncol(cpue)-1) # estimate individual additional variance
  
  # As option for data-weighing
  # minimum fixed observation error for each variance set (optional choose 1
value for both)
  fixed.obsE = c(0.0) # Important if SE.I is not available
  
  # Total observation error: TOE = sqrt(SE^2+sigma.est^2+fixed.obsE^2)
  
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
  # Process Error
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
  #Estimate set sigma.proc == True
  sigma.proc = TRUE
  # Determines if process error deviation are estimated for all years (TRUE)
  # or only from the point the first abundance index becomes available (FALSE
)
  proc.dev.all = TRUE
  #------------------------------------------
  if(sigma.proc == TRUE){
    igamma = c(4,0.01) #specify inv-gamma parameters
    
    # Process error check
    gamma.check = 1/rgamma(1000,igamma[1],igamma[2])
    # check mean process error + CV
    # mu.proc = sqrt(mean(gamma.check)); CV.proc = sd(sqrt(gamma.check))/mean
(sqrt(gamma.check))
    
    # check CV
    # round(c(mu.proc,CV.proc),3)
    # quantile(sqrt(gamma.check),c(0.1,0.9))
  }else{
    sigma.proc = 0.05 #IF Fixed: typicallly 0.05-0.15 (see Ono et al. 2012)
  }
  #--------------------------------------------
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
  # Optional: Do TAC Projections
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
  Projection = TRUE# Switch on by Projection = TRUE
  
  # Set range for alternative TAC projections
  TACs = seq(10000,160000,1000)
```

```
  TACint <- catch[nrow(catch),2] ## Catch 2016 is initial

  # Set number of years out from 2016
  pyrs = 10

  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
  # Execute model and produce output
  #><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>

  # MCMC settings
  ni <- 200000 # Number of iterations
  nt <- 25 # Steps saved
  nb <- 50000 # Burn-in
  nc <- 2 # number of chains
  nsaved = (ni-nb)/nt*nc

  source(paste0(JABBA.file,"/JABBA",version,".R"))

}# THE END
```

Appendix IV. R Source Code for JABBA Model and Projections

```
cat(paste0("\n","><>><>><>><>><>><>><>><>"))
cat(paste0("\n","><> Run Model ",Mod.names,"<><"))
cat(paste0("\n","><>><>><>><>><>><>><>><>","\n","\n"))
# setwd(paste(File))
dir.create(paste0(File,"/",assessment),showWarnings = FALSE)
dir.create(paste0(File,"/",assessment,"/",Scenario,"_",Mod.names),showWarning
s = FALSE)
dir.create(paste0(File,"/",assessment,"/",Scenario,"_",Mod.names,"/Input"),sh
owWarnings = FALSE)
input.dir = paste0(File,"/",assessment,"/",Scenario,"_",Mod.names,"/Input")

#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
# Define objects to make sure they exist if not included in Prime file
#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>
if(exists("igamma")==FALSE) igamma = c(4,0.01)  # Generic process error prior
if(exists("BmsyK")==FALSE) BmsyK = 0.4  # JABBA default for Pella model
if(exists("Model")==FALSE){ model = 1; Mod.names = c("Schaefer")} # Run Schae
fer if model is not specified
if(exists("proc.dev.all")==FALSE) proc.dev.all = FALSE # process error deviat
ion if only catch is available
if(exists("Plim")==FALSE) Plim = 0  # Standard non-compound model
if(exists("P_bound")==FALSE) P_bound = c(0.02,1)  # Soft penalty bounds for P
if(exists("KOBE.plot")==FALSE) KOBE.plot = TRUE # Produces JABBA Kobe plot
if(exists("KOBE.type")==FALSE) KOBE.type = c("ICCAT","IOTC")[2] # ICCAT uses
3 colors; IOTC 4 (incl. orange)
if(exists("SP.plot")==FALSE) SP.plot = c("standard","phase")[2] # Produces st
andard or 'Kobe phase' SP plot
if(exists("Biplot")==FALSE) Biplot= TRUE # Produces a "post-modern" biplot wi
th buffer and target zones (Quinn & Collie 2005)
if(exists("save.trajectories")==FALSE) save.trajectories =FALSE # saves poste
riors of P=B/K, B/Bmsy and H/Hmsy as .RData object
if(exists("harvest.label")==FALSE) harvest.label = c("Hmsy","Fmsy")[2] # choo
se label preference H/Hmsy versus Fmsy
if(exists("CPUE.plot")==FALSE) CPUE.plot= TRUE # Runs state-tool to produce "
alligned" multi-CPUE plot
if(exists("catch.metric")==FALSE) catch.metric = "(t)" # Runs state-tool to p
roduce "alligned" multi-CPUE plot
if(exists("meanCPUE")==FALSE) meanCPUE = FALSE # Uses averaged CPUE from stat
e-space tool instead of individual indices
if(exists("Projection")==FALSE) Projection = FALSE # Use Projections: require
s to define TACs vectors
if(exists("save.projections")==FALSE) save.projections = FALSE# saves project
ion posteriors as .RData object
if(exists("Reproduce.seed")==FALSE) Reproduce.seed = FALSE # If FALSE a rando
m seed assigned to each run (default)
if(exists("TACint")==FALSE) TACint = mean(catch[nrow(catch)-3,2]:catch[nrow(c
atch),2]) # use mean catch from last years
if(exists("imp.yr")==FALSE) imp.yr = as.numeric(format(Sys.Date(), "%Y"))+1 #
```

```
use next year from now
if(exists("init.values")==FALSE) init.values =FALSE # Allows to add manual st
arting values for K, r, q
if(exists("sigmaobs_bound")==FALSE) sigmaobs_bound = 1 # Adds an upper bound
to the observation variance
if(exists("sigmaproc_bound")==FALSE) sigmaproc_bound = 0.2 # Adds an upper bo
und to the process variance
if(exists("q_bounds")==FALSE) q_bounds= c(10^-30,100) # Defines lower and upp
er bounds for q
if(exists("K_bounds")==FALSE) K_bounds= c(10,10^8) # Defines lower and upper
bounds for q
# Save entire posterior as .RData object
if(exists("save.all")==FALSE) save.all = FALSE #
#><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>><>

## Prepare input data ----

cat(paste0("\n","><> Prepare input data <><","\n"))
indices = names(cpue)[2:ncol(cpue)]
n.indices = max(length(indices),1)
catches = names(catch)[2:ncol(catch)]
n.catches = length(catches)

years=catch[,1]
styr = min(years)
endyr = max(years)
n.years = length(years)
styr.cpue = min(cpue[,1])
styr.I = styr.cpue-styr+1


# Convert input data to matrices for JAGS input
conv.cpue = as.numeric(rbind(matrix(rep(NA,(styr.I-1)*n.indices),styr.I-1,n.i
ndices),as.matrix(cpue[,-1])))
CPUE=matrix(conv.cpue,nrow=n.years,ncol=n.indices)


if(SE.I==FALSE){
  se = cpue
  conv.se = as.numeric(rbind(matrix(rep(NA,(styr.I-1)*n.indices),styr.I-1,n.i
ndices),as.matrix(cpue[,-1])))
  se2 = matrix(ifelse(fixed.obsE>0,fixed.obsE^2,10^-10),n.years,n.indices)#/2
} else{
  conv.se = as.numeric(rbind(matrix(rep(NA,(styr.I-1)*n.indices),styr.I-1,n.i
ndices),as.matrix(se[,-1])))
  #conv.se = sqrt(conv.se^2+fixed.obsE^2)
  se2 = matrix(ifelse(is.na(conv.se),0.3^2,conv.se)^2,n.years,n.indices)+fixe
d.obsE^2#/2
}
```

```
conv.catch = as.numeric(rbind(matrix(rep(NA,(styr.I-1)*n.catches),styr.I-1,n.
catches),as.matrix(catch[,-1])))
Catch=matrix(conv.catch,nrow=n.years,ncol=n.catches)
Catch[is.na(Catch)] = 0 # Replace any NA by zero

# Total Catch
TC = apply(Catch,1,sum)

# Plot Catch

cat(paste0("\n","><> Plot Catch in Input subfolder <><","\n"))

Par = list(mfrow=c(1,1),mar = c(5, 5, 1, 1), mgp =c(3,1,0), tck = -0.02,cex=0
.8)
png(file = paste0(input.dir,"/Catches_",assessment,".png"), width = 7, height
= 5,
    res = 200, units = "in")
par(Par)
plot(catch[,1],catch[,1],ylim=c(0,max(catch[,2:ncol(catch)],na.rm=TRUE)),ylab
=paste0("Catch ",catch.metric),xlab="Year",type="n")
for(i in 2:ncol(catch)) lines(catch[,1],catch[,i],lty=(i-1),lwd=2)
legend("topright",paste(names(catch)[2:ncol(catch)]),lty=1:(ncol(catch)-1),bt
y="n")
dev.off()

#---------------------
# Index color palette
#---------------------
jabba.colors = as.character(rep(c('#e6194b', "#3cb44b", "#ffe119",
                                  "#0082c8","#f58231", "#911eb4",
                                  "#46f0f0", "#f032e6", "#d2f53c",
                                  "#fabebe", "#008080","#e6beff", "#aa6e28"),
2))
#--------------------
# Set seed
#--------------------
if(Reproduce.seed==FALSE){ set.seed(ceiling(runif(1,min=0,max=1e6))) } else {
set.seed(123)}

#----------------------------------------------------------------------------
# CPUE run State-Space model for averaging CPUE
#----------------------------------------------------------------------------
if(CPUE.plot==TRUE){
  cat(paste0("\n","><> Run State-Space CPUE averaging tool","\n"))
  #find first time-series with first CPUE
  q1.y = c(1:n.years)[is.na(apply(CPUE,1,mean,na.rm=TRUE))==FALSE][1] #first
year with CPUE
  q1.I = which.max(CPUE[q1.y,])

  qs = c(q1.I,c(1:(ncol(cpue)-1))[-q1.I])
```

```
sink("cpueAVG.jags")
cat("
    model {

    # Prior specifications
    eps <- 0.0000000000001 # small constant

    iq[1] ~ dgamma(1000,1000)
    q[1] <-  pow(iq[1],-1)
    logq[1] <- log(1)
    for(i in 2:nI){
    iq[i] ~ dgamma(0.001,0.001)
    q[i] <- pow(iq[i],-1)
    logq[i] <-  log(q[i])
    }


    ")

if(sigma.proc==TRUE){
  cat("
      # Process variance
      isigma2 <- isigma2.est
      sigma2 <- pow(isigma2,-1)
      sigma <- sqrt(sigma2)
      fakesigma.fixed <- sigma.fixed # Prevent unused variable error msg
      ",append=TRUE)
}else{ cat("
    isigma2 <- pow(sigma.fixed+eps,-2)
           sigma2 <- pow(isigma2,-1)
           sigma <- sqrt(sigma2)

           ",append=TRUE)}

if(sigma.est==TRUE){
  cat("
      # Obsevation variance
      # Observation error
      itau2~ dgamma(0.001,0.001)
      tau2 <- 1/itau2


      for(i in 1:nI)
      {
      for(t in 1:N)
      {
      var.obs[t,i] <- SE2[t,i]+tau2
      ivar.obs[t,i] <- 1/var.obs[t,i]
```

```
      # note total observation error (TOE)
      TOE[t,i] <- sqrt(var.obs[t,i])

      }}
      ",append=TRUE)
}else{ cat("
    # Obsevation variance
           # Observation error
           itau2~ dgamma(2,2)
           tau2 <- 1/itau2


           for(i in 1:nI)
           {
           for(t in 1:N)
           {
           var.obs[t,i] <- SE2[t,i] # drop tau2
           fake.tau[t,i] <- tau2

           ivar.obs[t,i] <- 1/var.obs[t,i]
           # note total observation error (TOE)
           TOE[t,i] <- sqrt(var.obs[t,i])

           }}

           ",append=TRUE)}

# Run rest of code
cat("
    # Process variance prior
    isigma2.est ~ dgamma(0.001,0.001)


    # Priors and constraints
    logY.est[1] ~ dnorm(logY1, 1)       # Prior for initial population size

    mean.r ~ dnorm(1, 0.001)             # Prior for mean growth rate

    # Likelihood
    # State process
    for (t in 1:(N-1)){
    r[t] ~ dnorm(mean.r, isigma2)
    logY.est[t+1] <- logY.est[t] + r[t] }

    # Observation process
    for (t in 1:N) {
    for(i in 1:nI){
    y[t,i] ~ dnorm(logY.est[t]+logq[i], ivar.obs[t,i])
    }}
```

```
      # Population sizes on real scale
      for (t in 1:N) {
      Y.est[t] <- exp(logY.est[t])
      }

  }
      ",fill = TRUE)
  sink()



  q.init = 1
  mCPUE = as.matrix(CPUE[q1.y:n.years,qs])
  mSE2 = as.matrix(se2[q1.y:n.years,qs])
  if(n.indices>1) for(i in 2:n.indices){q.init[i] = mean(mCPUE[,i],na.rm=TRUE
)/mean(mCPUE[,1],na.rm=TRUE)}
  # Bundle data
  jags.data <- list(y = log(mCPUE),SE2=mSE2, logY1 = log(mCPUE[1,1]), N = len
gth(q1.y:n.years),nI=n.indices,sigma.fixed=ifelse(sigma.proc==TRUE,0,sigma.pr
oc))

  # Initial values
  inits <- function(){list(isigma2.est=runif(1,20,100), itau2=runif(1,80,200)
, mean.r = rnorm(1),iq = 1/q.init)}

  # Parameters monitored
  parameters <- c("mean.r", "sigma","r", "Y.est","q")


  # Call JAGS from R (BRT 3 min)
  mod.cpue <- jags(jags.data, inits, parameters, "cpueAVG.jags", n.chains = n
c, n.thin = max(nt,2), n.iter = max(ni/5,10000), n.burnin = nb/10)


  cat(paste0("\n","><> Plot State-Space CPUE fits in Input subfolder <><","\n
"))
  # get individual trends
  fitted <- lower <- upper <- NULL
  cpue.yrs = years[q1.y:n.years]

  for (t in 1:nrow(mCPUE)){
    fitted[t] <- median(mod.cpue$BUGSoutput$sims.list$Y.est[,t])
    lower[t] <- quantile(mod.cpue$BUGSoutput$sims.list$Y.est[,t], 0.025)
    upper[t] <- quantile(mod.cpue$BUGSoutput$sims.list$Y.est[,t], 0.975)}


  q.adj = apply(mod.cpue$BUGSoutput$sims.list$q,2,median)


  Par = list(mfrow=c(1,1),mar = c(3.5, 3.5, 0.1, 0.1), mgp =c(2.,0.5,0), tck
```

```
= -0.02,cex=0.8)
  png(file = paste0(input.dir,"/CPUE_",assessment,"_",Scenario,".png"), width
= 5, height = 3.5,
      res = 200, units = "in")
  par(Par)
  u.ylim = NULL
  for(i in 1:n.indices){ u.ylim = c(u.ylim,exp(log(mCPUE[,i]/q.adj[i])+1.96*s
qrt(mSE2[,i])))}
  ylim = c(0,max(u.ylim,na.rm=TRUE))
  plot(0, 0, ylim = ylim, xlim = range(cpue.yrs), ylab = "Expected CPUE", xla
b = "Year", col = "black", type = "n")
  legend("topright",paste(indices),lwd=2,col=(jabba.colors)[1:n.indices],bty=
"n")
  polygon(x = c(cpue.yrs,rev(cpue.yrs)), y = c(lower,rev(upper)), col = "gray
", border = "gray90")

  for(i in 1:n.indices)
  {
    shift = runif(1,-0.1,0.1)
    cols=jabba.colors[qs[i]]
    plotCI(cpue.yrs+shift,mCPUE[,i]/q.adj[i],ui=exp(log(mCPUE[,i]/q.adj[i])+1
.96*sqrt(mSE2[,i])),li=exp(log(mCPUE[,i]/q.adj[i])-1.96*sqrt(mSE2[,i])),add=T
RUE,col= cols,pt.bg = cols,pch=21,gap=0)
    lines(cpue.yrs+shift,mCPUE[,i]/q.adj[i], col = cols,lwd=2)
    points(cpue.yrs+shift,mCPUE[,i]/q.adj[i], bg = cols,pch=21)
  }
  lines(cpue.yrs,fitted,lwd=2)

  dev.off()

  logSE = apply(log(mod.cpue$BUGSoutput$sims.list$Y.est),2,sd)


  if(nrow(mCPUE)<n.years) {
    fitted = c(rep(NA,q1.y-1),fitted)
    logSE = c(rep(0.2,q1.y-1),logSE)
  }
  avgCPUE = data.frame(Year=years,CPUE= fitted,logSE=logSE)

  write.csv(avgCPUE,paste0(input.dir,"/avgCPUE_",assessment,"_",Scenario,".cs
v"))

  if(meanCPUE==TRUE){
    cat(paste0("\n","><> Use average CPUE as input for JABBA <><","\n"))

    CPUE = as.matrix(avgCPUE[,2])
    cpue.check = cpue[,-1]
    cpue.check[is.na(cpue[,-1])]=0
    CPUE[,1] = ifelse(apply(cpue.check,1,sum)==0,rep(NA,length(CPUE[,1])),CPU
E[,1])
```

```
    se2 =  as.matrix(avgCPUE[,3]^2)
    n.indices=1
    indices = "All"
    sets.q =1
    sets.var =1
  }

  }

#---------------------------------------------------------------------------
# END of CPUE State-Space tool
#---------------------------------------------------------------------------

#-----------
# FUNCTIONS
#-----------
cat(paste0("\n","><> Prepare JABBA prior inputs <><","\n"))

#-----------------------------------------------
# Function to get beta prior parameters
#-----------------------------------------------
get_beta <- function(mu,CV,Min=0,Prior="x"){
  a = seq(0.0001,1000,0.001)
  b= (a-mu*a)/mu
  s2 = a*b/((a+b)^2*(a+b+1))
  sdev = sqrt(s2)
  # find beta )parameter a
  CV.check = (sdev/mu-CV)^2
  a = a[CV.check==min(CV.check)]
  #find beta parameter b
  b = (a-mu*a)/mu
  x = seq(Min,1,0.001)
  pdf = dbeta(x,a,b)
  plot(x,pdf,type="l",xlim=range(x[pdf>0.01]),xlab=paste(Prior),ylab="",yaxt=
"n")
  polygon(c(x,rev(x)),c(rep(0,length(x)),rev(ifelse(pdf==Inf,100000,pdf))),co
l="grey")
  return(c(a,b))
}

#-----------------------------------------------
# Function to get gamma prior parameters
#-----------------------------------------------

get_gamma <- function(mu,CV,Prior="x"){
  a = seq(0.0001,1000,0.0001)
  b = a/mu
  s2 = (a/b^2)
  sdev = sqrt(s2)
  # find beta )parameter a
```

```
  CV.check = (sdev/mu-CV)^2
  a = a[CV.check==min(CV.check)]
  #find beta parameter b
  b = a/mu
  x = sort(rgamma(1000,a,b))
  pdf = dgamma(x,a,b)
  plot(x,pdf,type="l",xlim=range(x[pdf>0.01]),xlab=paste(Prior),ylab="",yaxt=
"n")
  polygon(c(x,rev(x)),c(rep(0,length(x)),rev(ifelse(pdf==Inf,100000,pdf))),co
l="grey")
  return(c(a,b))
}


#--------------------------------------------------
# Function to get lognormal prior parameters
#--------------------------------------------------
plot_lnorm <- function(mu,CV,Prior="x"){
  sdev= sqrt(log(CV^2+1))
  rand.pr = rlnorm(1000,log(mu),sdev)
  x = seq(min(rand.pr),quantile(rand.pr,0.995),max(rand.pr/500))
  pdf = dlnorm(x,log(mu),sdev)
  plot(x,pdf,type="l",xlim=range(x),xlab=paste(Prior),ylab="",yaxt="n")
  polygon(c(x,rev(x)),c(rep(0,length(x)),rev(ifelse(pdf==Inf,100000,pdf))),co
l="grey")
  return(c(mu,sdev))
}

#------------------------------------
# Function kobeJabba for FLR
#------------------------------------
kobeJabba<-function(x,minyear=1){

  out=cbind(melt(x[,,2]),c(x[,,3]))
  names(out)=c("iter","year","stock","harvest")
  out$year=out$year+minyear-1
  out}

#-------------------------------------------------
# Function kobeJabbaProj for projections with FLR
#-------------------------------------------------
kobeJabbaProj<-function(x,minyear=1,tac=NULL){

  out=cbind(melt(x[,,,2]),c(x[,,,3]))
  names(out)=c("iter","year","tac","stock","harvest")
  out$year=out$year+minyear-1

  out}

#---------------------------------------------------
```

```r
# Determine initial ranges for r
#-----------------------------------------------------
if(r.dist=="range"){
  # initial range of r based on resilience (FishBase.org)
  if(length(r.prior)>1){ start.r = r.prior} else
    if(r.prior == "High") {
      start.r <- c(0.6,1.5)} else if(r.prior == "Medium") {
        start.r <- c(0.2,0.8)}    else if(r.prior == "Low") {
          start.r <- c(0.05,0.5)}  else { # i.e. res== "Very low"
            start.r <- c(0.015,0.1)}

  log.r = mean(log(start.r))
  sd.r = abs(log.r - log(start.r[1]))/2
  r.prior = c(exp(log.r),sd.r)
  CV.r = sqrt(exp(sd.r^2)-1)
} else {
  log.r = log(r.prior[1])
  sd.r = r.prior[2]
  CV.r = sqrt(exp(sd.r^2)-1)
}

#-----------------------------------------------------
# Prepare K prior
#-----------------------------------------------------
if(K.dist=="range"){
  log.K = mean(log(K.prior))
  sd.K= abs(log.K - log(K.prior[1]))/2
  CV.K = sqrt(exp(sd.K^2)-1)
} else {

  log.K = log(K.prior[1])
  CV.K = K.prior[2]
  sd.K=sqrt(log(CV.K^2+1))
}


#-----------------------------------------------------------
# Get JABBA parameterization and surplus production function
#-----------------------------------------------------------
# For Pella-Tomlinson
if (Model == 3 | Model == 4) {
  ## run thru sensitivities if given shape
  # find inflection point
  ishape = NULL
  # Find shape for  SBmsytoK
  ishape = seq(0.1, 10, 0.001)
  check.shape = ((ishape) ^ (-1 / (ishape - 1)) - BmsyK) ^ 2
  #  Set shape (> 0, with 1.001 ~ Fox and 2 = Schaefer)
  shape =  ishape[check.shape == min(check.shape)]
```

```
  if (exists("sensname")) {
    if (sensname == 'M') {
      m = shape = sensmean[s] ## becomes m.mu
      shape.CV = sensvar[s]
      cat(paste0(shape, " ", shape.CV), "\n")
    } ## end sensname == M
  } ## end sensname exists
} else {shape = FALSE}


#-------------------------------------------------


# Set shape m for Fox and Schaefer: Fox m ~1; Schaefer m =2
if(shape==FALSE){
  if(Model == 1){m=2} else {m = 1.001}}else{m=shape}

cat(paste0("\n","><> Plot Prior distributions in Input subfolder  <><","\n"))

Par = list(mfrow=c(1,3),mai=c(0.5,0.1,0,.1),omi = c(0.1,0.2,0.1,0) + 0.1,mgp=
c(2,1,0), tck = -0.02,cex=0.8)
png(file = paste0(input.dir,"/Priors_",assessment,"_",Scenario,".png"), width
= 9, height = 3,
    res = 200, units = "in")
par(Par)
K.pr = plot_lnorm(exp(log.K),CV.K,Prior="K")

if(psi.dist=="beta"){
  psi.pr = get_beta(mu=psi.prior[1],CV=psi.prior[2],Min=0,Prior=paste0("Prior
B(",years[1],")/K"))} else {
    psi.pr = plot_lnorm(mu=psi.prior[1],CV=psi.prior[2],Prior=paste0("Prior B
(",years[1],")/K"))
  }


r.pr = plot_lnorm(mu=exp(log.r),CV=CV.r,Prior="r")
mtext(paste("Density"), side=2, outer=TRUE, at=0.5,line=1,cex=0.9)
dev.off()


cat(paste0("\n","><> Plot assumed Surplus Production shape in Input subfolder
<><","\n"))


# Plot MSY
Par = list(mfrow=c(1,1),mai=c(0.6,0.3,0,.15),omi = c(0.1,0.2,0.2,0) + 0.1,mgp
=c(2,1,0), tck = -0.02,cex=0.8)
png(file = paste0(input.dir,"/Production",assessment,"_",Scenario,".png"), wi
dth = 6, height = 5,
    res = 200, units = "in")
```

```
par(Par)

# Get Bmsy/B0 as a function of M
Bmsy=(m)^(-1/(m-1))
P = seq(0.0001,1,0.001)
SP = ifelse(P>Plim,r.pr[1]/(m-1)*P*(1-P^(m-1)),r.pr[1]/(m-1)*P*(1-P^(m-1))*4*
P)
#if(is.null(refBmsy)==TRUE) refBmsy = Bmsy
plot(P,SP/max(SP),type="l",ylab="Relative Yield",xlab="B/B0",lwd=2)
mtext(paste("Relative Yield"), side=2, outer=TRUE, at=0.6,line=1,cex=0.9)
legend("topright",c("SPM"),col=c(1),lwd=2,bty="n")


if(Model==4){
  # shape density
  #dm = dgamma(seq(0.001,5,0.1),5,5)*m
  dm = dlnorm((seq(0.001,5,0.1)),log(m),shape.CV)
  dm = dm/max(dm)
  bmsyk  = (seq(0.001,5,0.1))^(-1/(seq(0.001,5,0.1)-1))

  polygon(c(bmsyk,rev(bmsyk)),c(dm,rep(0,length(dm))),col="grey",border=0)
}
abline(v=Bmsy,lty=2)
mtext(paste("Relative Yield"), side=2, outer=TRUE, at=0.6,line=1,cex=0.9)
legend("topright",c("SPM"),col=c(1),lwd=2,bty="n")
abline(v=Bmsy,lty=2)
dev.off()


# Note PRIORS and save input subfolder
Priors =rbind(K.pr,psi.prior,c(r.pr[1],CV.r))
row.names(Priors) = c("K","Psi","r")
colnames(Priors) = c("Mean","CV")
write.csv(Priors,paste0(input.dir,"/Priors",assessment,"_",Scenario,".csv"))


#-----------------------------------------------------------
# Set up JABBA
#-----------------------------------------------------------
cat(paste0("\n","><> Set up JAGS input <><","\n"))
# Plot MSY
# remove scientific numbers
options(scipen=999)
#-----------------------------------------------------------


# starting values
nq = length(unique(sets.q))
nvar = length(unique(sets.var))
```

```
## TAC setup
#-----------------------------------------------------------
# Setup TAC projection
#----------------------------------------------------------
if(Projection==TRUE) {
  nTAC = length(TACs)
  TAC = mat.or.vec(pyrs, nTAC)
  yr.now = as.numeric(format(Sys.Date(), "%Y")) + 1
  yr.last = max(years) # assessment year

  for (i in 1:nTAC) {
    TAC[, i] = c(rep(TC[n.years], yr.now - yr.last), rep(TACs[i], pyrs - (yr.
now -yr.last)))
  }

} else if(Projection == FALSE){
  nTAC = 1
  TAC = TC[n.years]
  pyrs = 1
}

#---------------------------------------------------------------
# JABBA Schaefer/Fox Models 1-2, Pella 3
#---------------------------------------------------------------

# Slope of hockey-stick
slope.HS = ifelse(Plim==0,1/10^-10,1/Plim)


nSel = 1 # setup for JABBA-SELECT version (in prep)
nI = ncol(CPUE) # number of CPUE series
stI = ifelse(proc.dev.all==TRUE,1, c(1:n.years)[is.na(apply(CPUE,1,mean,na.rm
=TRUE))==FALSE][1]) #first year with CPUE


# Initial starting values
inits <- function(){list(K= rlnorm(1,log.K,0.3),q = runif(nq,0.005,0.5), isig
ma2.est=runif(1,20,100), itau2=runif(nvar,80,200))}
# starting value option
if(init.values==TRUE){
inits <- function(){list(K= K.init,r=r.init,q = q.init, isigma2.est=runif(1,2
0,100), itau2=runif(nvar,80,200))}
}

# JABBA input data
surplus.dat = list(N=n.years, TC = TC,I=CPUE,SE2=se2,mu.m=m,r.pr=r.pr,psi.pr=
psi.pr,K.pr = K.pr,
                   nq=nq,nI = nI,nvar=nvar,sigma.fixed=ifelse(sigma.proc==TRU
E,0,sigma.proc),
                   sets.var=sets.var, sets.q=sets.q,pen.bk = rep(0,n.years),P
```

```
lim=Plim,slope.HS=slope.HS,
                          nTAC=nTAC,pyrs=pyrs,TAC=TAC,igamma = igamma,stI=stI,TACint
=TACint,P_bound=P_bound,proc.pen=0,K.pen = 0,
                          obs.pen = rep(0,nvar),q_bounds=q_bounds,sigmaobs_bound=sig
maobs_bound,sigmaproc_bound=sigmaproc_bound,K_bounds=K_bounds)
# If shape parameter is estimated (Model =4)
if(Model==4){
  surplus.dat$m.CV = shape.CV }


# JAGS model file
JABBA = "JABBA.jags"


# PARAMETERS TO MONITOR
params <- c("K","r", "q", "psi","sigma2", "tau2","m","Hmsy","SBmsy", "MSY", "
BtoBmsy","HtoHmsy","CPUE","Proc.Dev","P","SB","prP","prBtoBmsy","prHtoHmsy","
TOE")


cat(paste0("\n","><> RUN ",Mod.names," model for ",assessment," ",Scenario,"
in JAGS <><","\n","\n"))

# JAGS MODEL Standard
sink("JABBA.jags")
cat("

    model {

    # Prior specifications
    eps <- 0.0000000000000000000000000000000001 # small constant

    #Catchability coefficients
    for(i in 1:nq)
    {
    q[i] ~ dunif(q_bounds[1],q_bounds[2])
    }


    ")

if(Model==4){
  cat("
      # Shape m prior
      m ~ dlnorm(log(mu.m),pow(m.CV,-2))
      ",append=TRUE)
  }else{ cat("
      m <- mu.m
    ",append=TRUE)}
```

```
if(psi.dist =="beta"){
  cat("
      # Beta Prior for Biomass depletion at the start (deteministic)
      psi ~ dbeta(psi.pr[1],psi.pr[2])
      ",append=TRUE)
} else {
  cat("
      # Lognormal for Biomass depletion at the start (deteministic)
      psi ~ dlnorm(log(psi.pr[1]),pow(psi.pr[2],-2)) #I(0.1,1.1)
      ",append=TRUE)
}

if(sigma.proc==TRUE){
  cat("
      # Process variance
      isigma2 <- isigma2.est
      sigma2 <- pow(isigma2,-1)
      sigma <- sqrt(sigma2)
      fakesigma.fixed <- sigma.fixed # Prevent unused variable error msg
      ",append=TRUE)
}else{ cat("
      isigma2 <- pow(sigma.fixed+eps,-2)
           sigma2 <- pow(isigma2,-1)
           sigma <- sqrt(sigma2)

           ",append=TRUE)}

if(sigma.est==TRUE){
  cat("
      # Obsevation variance
      for(i in 1:nvar)
      {
      # Observation error
      itau2[i]~ dgamma(0.001,0.004)
      tau2[i] <- 1/itau2[i]
      }

      for(i in 1:nI)
      {
      for(t in 1:N)
      {
      var.obs[t,i] <- SE2[t,i]+tau2[sets.var[i]]
      ivar.obs[t,i] <- 1/var.obs[t,i]
      # note total observation error (TOE)
      TOE[t,i] <- sqrt(var.obs[t,i]) # Total observation variance

      }}
      ",append=TRUE)
}else{ cat("
      # Obsevation variance
```

```
            for(i in 1:nvar)
            {
            # Observation error
            itau2[i]~ dgamma(4,0.01)
            tau2[i] <- 1/itau2[i]
            }

            for(i in 1:nI)
            {
            for(t in 1:N)
            {
            var.obs[t,i] <- SE2[t,i] # drop tau2
            fake.tau[t,i] <- tau2[sets.var[i]]

            ivar.obs[t,i] <- 1/var.obs[t,i]
            # note total observation error (TOE)
            TOE[t,i] <- sqrt(var.obs[t,i])

            }}

            ",append=TRUE)}

# Run rest of code
cat("
    # Process variance prior
    isigma2.est ~ dgamma(igamma[1],igamma[2])

    # Carrying Capacity SB0
    K ~ dlnorm(log(K.pr[1]),pow(K.pr[2], -2))

    # informative priors for Hmsy as a function of r
    r ~ dlnorm(log(r.pr[1]),pow(r.pr[2],-2))


    #Process equation
    Pmean[1] <- log(psi)
    iPV[1] <- ifelse(1<(stI),10000,isigma2) # inverse process variance
    P[1] ~ dlnorm(Pmean[1],iPV[1]) # set to small noise instead of isigma2
    penB[1]  <- ifelse(P[1]<P_bound[1],log(K*P[1])-log(K*P_bound[1]),ifelse(P
[1]>P_bound[2],log(K*P[1])-log(K*P_bound[2]),0)) # penalty if Pmean is outsid
e viable biomass

    # Process equation
    for (t in 2:N)
    {
    Pmean[t] <- ifelse(P[t-1] > Plim,
    log(max(P[t-1] +  r/(m-1)*P[t-1]*(1-pow(P[t-1],m-1)) - TC[t-1]/K,0.005)),
    log(max(P[t-1] +  r/(m-1)*P[t-1]*(1-pow(P[t-1],m-1))*P[t-1]*slope.HS - TC
[t-1]/K,0.005)))
    iPV[t] <- ifelse(t<(stI),10000,isigma2) # inverse process variance
```

```
    P[t] ~ dlnorm(Pmean[t],iPV[t])
    penB[t]  <- ifelse(P[t]<(P_bound[1]),log(K*P[t])-log(K*(P_bound[1])),ifel
se(P[t]>P_bound[2],log(K*P[t])-log(K*(P_bound[2])),0)) # penalty if Pmean is
outside viable biomass
    }

    # Process error deviation
    for(t in 1:N){
    Proc.Dev[t] <- P[t]-exp(Pmean[t])}

    # Enforce soft penalties on bounds for P
    for(t in 1:N){
    pen.bk[t] ~ dnorm(penB[t],1000) # enforce penalty with CV = 0.1
    }

    Hmsy <- r*pow(m-1,-1)*(1-1/m)

    for (t in 1:N)
    {
    SB[t] <- K*P[t]
    H[t] <- TC[t]/SB[t]
    }

    # Observation equation in related to EB

    for(i in 1:nI)
    {
    for (t in 1:N)
    {
    Imean[t,i] <- log(q[sets.q[i]]*P[t]*K);
    I[t,i] ~ dlnorm(Imean[t,i],(ivar.obs[t,i]));
    CPUE[t,i] <- q[sets.q[i]]*P[t]*K
    }}


    #Management quantities
    SBmsy_K <- (m)^(-1/(m-1))
    SBmsy <- SBmsy_K*K

    MSY <- SBmsy*Hmsy
    for (t in 1:N)
    {
    # use x y to put them towards the end of the alphabetically sorted  mcmc
object
    #SP[t] <- pow(r.pella,-(m-1))*SB[t]*(1-pow(P[t],m-1))
    BtoBmsy[t] <- SB[t]/SBmsy
    HtoHmsy[t] <- H[t]/(Hmsy)
    }
```

```
    # Enforce soft penalty on K if < K_bounds >
    K.pen ~ dnorm(penK,1000) # enforce penalty
    penK  <- ifelse(K<(K_bounds[1]),log(K)-log(K_bounds[1]),ifelse(K>K_bounds
[2],log(K)-log(K_bounds[2]),0)) # penalty if Pmean is outside viable biomass


    # Enforce soft penalty on process deviance if sigma.proc > 0.2
    proc.pen ~ dnorm(penProc,1000) # enforce penalty
    penProc  <- ifelse(sigma>sigmaproc_bound,log(sigma)-log(sigmaproc_bound),
0)


    # Enforce soft penalty on observation error if sigma.obs > sigma_bound
    for(i in 1:nvar){
    obs.pen[i] ~ dnorm(penObs[i],1000) # enforce penalty
    penObs[i]  <- ifelse(pow(tau2[i],0.5)>sigmaobs_bound,log(pow(tau2[i],0.5)
)-log(sigmaobs_bound),0)
    }

    ", append=TRUE)

# PROJECTION
if(Projection==TRUE){
  cat("
      for(i in 1:nTAC){
      # Project first year into the future
      prPmean[1,i] <- ifelse(P[N] > Plim,
      log(max(P[N] +  Hmsy/(1-1/m)*P[N]*(1-pow(P[N],m-1)) - TACint/K,0.005)),
      log(max(P[N] +  Hmsy/(1-1/m)*P[N]*(1-pow(P[N],m-1))*4*P[N] - TACint/K,0
.005)))
      prP[1,i] ~ dlnorm(prPmean[1,i],isigma2)
      # Project all following years
      for(t in 2:pyrs){
      prPmean[t,i] <- ifelse(prP[t-1,i] > Plim,
      log(max(prP[t-1,i] +  Hmsy/(1-1/m)*prP[t-1,i]*(1-pow(prP[t-1,i],m-1)) -
TAC[t-1,i]/K,0.001)),
      log(max(prP[t-1,i] +  Hmsy/(1-1/m)*prP[t-1,i]*(1-pow(prP[t-1,i],m-1))*s
lope.HS*prP[t-1,i] - TAC[t-1,i]/K,0.005)))
      # process error (as monte-carlo simular)
      prP[t,i] ~ dlnorm(prPmean[t,i],isigma2)}
      for(t in 1:pyrs){
      prB[t,i] <- prP[t,i]*K
      prH[t,i] <- TAC[t,i]/prB[t,i]
      prHtoHmsy[t,i] <- prH[t,i]/Hmsy
      prBtoBmsy[t,i] <- prB[t,i]/SBmsy
      }}
      ",append=TRUE)} else {
        cat("
            #Prevent error for unused input
            fakeTAC <-  TAC
```

```
            fakepyrs <- pyrs
            fakenTAC <- nTAC
            fakeTACint <- TACint
            prHtoHmsy <- 1
            prP <- 1
            prBtoBmsy <- 1
            ", append=TRUE)}

cat("

} # END OF MODEL
    ",append=TRUE,fill = TRUE)
sink()


ptm <- proc.time()

mod <- jags(surplus.dat, inits,params,paste(JABBA), n.chains = nc, n.thin = n
t, n.iter = ni, n.burnin = nb)  # adapt is burn-in

proc.time() - ptm
save.time = proc.time() - ptm

cat(paste0("\n",paste0("><> Scenario ",Scenario,"_",Mod.names," completed in
",as.integer(save.time[3]/60)," min and ",round((save.time[3]/60-as.integer(s
ave.time[3]/60))*100)," sec <><","\n")))

cat(paste0("\n","><> Produce results output of ",Mod.names," model for ",asse
ssment," ",Scenario," <><","\n"))

# if run with library(rjags)
posteriors = mod$BUGSoutput$sims.list



#-----------------------------------------------------------
# <><<><<><<><<><<><<>< Outputs ><>><>><>><>><>><>><>><>><>
#-----------------------------------------------------------
output.dir = paste0(File,"/",assessment,"/",Scenario,"_",Mod.names,"/Output")
dir.create(output.dir, showWarnings = FALSE)

# run some mcmc convergence tests
par.dat= data.frame(posteriors[params[c(1:7)]])
geweke = geweke.diag(data.frame(par.dat))
pvalues <- 2*pnorm(-abs(geweke$z))

heidle = heidel.diag(data.frame(par.dat))

# postrior means + 95% BCIs
#Model  parameter
```

```
apply(par.dat,2,quantile,c(0.025,0.5,0.975))

man.dat = data.frame(posteriors[params[8:10]])
#Management quantaties
apply(man.dat,2,quantile,c(0.025,0.5,0.975))

# Depletion
Depletion = posteriors$P[,c(1,n.years)]
colnames(Depletion) = c(paste0("P",years[1]),paste0("P",years[n.years]))

# Current stock status (Kobe posterior)
H_Hmsy.cur = posteriors$HtoHmsy[,c(n.years)]
B_Bmsy.cur = posteriors$BtoBmsy[,c(n.years)]


# Prepare posterior quantaties
man.dat = data.frame(man.dat,Depletion,B_Bmsy.cur,H_Hmsy.cur)

results = round(t(cbind(apply(par.dat,2,quantile,c(0.025,0.5,0.975)))),6)

results = data.frame(Median = results[,2],LCI=results[,1],UCI=results[,3],Gew
eke.p=round(pvalues,3),Heidel.p = round(heidle[,3],3))

ref.points = round(t(cbind(apply(man.dat,2,quantile,c(0.025,0.5,0.975)))),3)

ref.points = data.frame(Median = ref.points[,2],LCI=ref.points[,1],UCI=ref.po
ints[,3])

# get number of parameters
npar = length(par.dat)
# number of years
N=n.years

# Save posteriors (Produces large object!)
if(save.all==TRUE) save(posteriors,file=paste0(output.dir,"/",Scenario,"_post
eriors"))

#-----------------------------------------------------------------------
# Save parameters, results table and current status posterior in csv files
#-----------------------------------------------------------------------

# Save model estimates and convergence p-values
write.csv(data.frame(results),paste0(output.dir,"/Estimates_",assessment,"_",
Scenario,".csv"))

# Make standard results table with parameter estimates and reference points
Table = rbind(data.frame(results)[,1:3],data.frame(ref.points))
Table[4,] = round(sqrt((Table[4,])),3)
rownames(Table)[4] = "sigma.proc"
write.csv(Table,paste0(output.dir,"/Results_",assessment,"_",Scenario,".csv")
```

```
)
#Save posterior of recent assessment year (KOBE posterior)


write.csv(data.frame(BtoBmsy=B_Bmsy.cur,FtoFmsy=H_Hmsy.cur),paste0(output.dir
,"/Status_posterior",assessment,".csv"))

## source all plotting scripts
#source(paste0(JABBA.file,'/plot_JABBA.R'))


if(save.trajectories==TRUE){
  cat(paste0("\n","><> Saving Posteriors of FRP trajectories <><","\n"))

  # FRP trajectories
  trajectories = array(NA,c(nsaved,n.years,3))
  trajectories[,,1] = posteriors$P
  trajectories[,,2] = posteriors$BtoBmsy
  trajectories[,,3] = posteriors$HtoHmsy


  kb=kobeJabba(trajectories,years[1])
  save(kb,file=paste0(output.dir,"/",Scenario,"_trajectories"))

}

cat(paste0("\n","><> Scenario ",Mod.names,"_",Scenario," for ",assessment," -
DONE! <><","\n"))
```