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Executive Summary

Stock assessments of the bottomfish management unit species (BMUS) for Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa were conducted through 2018 and finalized in 2019. Bottomfish resources are managed as one multi-species complex around each territory. The BMUS identified within the archipelagic fishery ecosystem plans (FEPs) is comprised of 16 species for Guam and CNMI and 17 species for American Samoa. These species consist of snappers, groupers, emperors, and jacks. In 2019, the BMUS were reduced to 13 species for Guam and CNMI and 11 species for American Samoa. The species in the revised lists were assessed for this set of stock assessments after discussions with federal managers.

These 2019 assessments were conducted as a benchmark; therefore, all components of the assessment analyses (selection of data sets, data filtering, catch-per-unit-effort (CPUE) standardization, choice of model, and model fitting) were evaluated. Several changes relative to previous assessments of BMUS in Guam, CNMI, and American Samoa were incorporated into the 2019 benchmark assessments. These include using new species lists, calculating the percentage of catch reported at the family or species-group level and believed to contain BMUS, filtering CPUE based on gear, standardizing the CPUE for covariates that may affect the catch rate, removing independently-estimated maximum sustainable yield values from the model fitting process, and including a Pella-Tomlinson production model parameterization for Guam and American Samoa.

The assessments used a state-space Bayesian surplus production model within the modeling framework Just Another Bayesian Biomass Assessment (JABBA). Estimates of harvest rate (H), annual biomass (B), the harvest rate associated with overfishing as determined by the harvest control rule (H_{CR}), maximum sustainable yield (MSY), and the biomass at maximum sustainable yield (B_{MSY}) allowed for determination of stock status relative to reference points determining overfishing ($H/H_{CR} > 1$) and overfished ($B < 0.7 \times B_{MSY}$) status. Stock projections were conducted for 2020–2025 for a range of hypothetical 6-year catches, and the corresponding risk of overfishing was calculated.

Stock status of BMUS varied by territory. The current benchmark assessments determined that in 2017, Guam BMUS were in an overfished state but not undergoing overfishing, CNMI BMUS were not overfished nor were undergoing overfishing, and American Samoa BMUS were determined to be both undergoing overfishing and in an overfished state. The status determinations from the 2019 benchmark assessments differed from the previous assessments for Guam and American Samoa, which determined that these stocks were not overfished nor were undergoing overfishing as of 2015 (Yau et al. 2016).

Projections assumed that the same amount of catch was caught from 2020 to 2025. For Guam, the catch corresponding to a 50% probability of overfishing in 2025 was 36 thousand pounds. For CNMI, the catch that would produce a 50% probability of overfishing in 2025 was 95 thousand pounds. For American Samoa, the catch that would produce a 50% probability of overfishing in 2025 was 8 thousand pounds. The catch values associated with a 50% probability of overfishing were greater than the observed landings in 2017 for Guam (16 thousand pounds) and for CNMI (70 thousand pounds). For American Samoa, the observed landings in 2017 totaled 16 thousand pounds, which exceeded the catch that would produce a 50% probability of overfishing.

1. Introduction

Deep-slope finfish are found around all central and western Pacific islands and reefs where they support small vessel hook-and-line fisheries. The Western Pacific Regional Fishery Management Council (WPRFMC) manages these resources in federal waters surrounding Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa under the archipelagic fishery ecosystem plans (FEPs) for the Marianas (which includes both Guam and CNMI; WPRFMC 2009a) and American Samoa (WPRFMC 2009b). The set of bottomfish management unit species (BMUS) identified within the FEPs is comprised of 16 species for the Marianas and 17 species for American Samoa. These species consist of snappers, groupers, emperors, and jacks. As of March 11, 2019, the list of BMUS species in the FEPs was revised to 13 species for the Marinas and 11 species for American Samoa (NMFS 2019). The revised species lists were used for the stock assessments of Guam and CNMI (Table 1) and American Samoa (Table 2) after discussions with federal managers.

Bottomfish resources are managed as one multi-species complex around each territory. Amendment 6 of the FEPs established methods for determining fishing mortality and stock biomass reference values and, by a comparison of current conditions to the reference values, determining if the stock is being overfished and if overfishing is occurring. Overfished is defined as the stock biomass B falling below the Minimum Stock Size Threshold (MSST) of $(1 – M) \times B_{MSY}$, where M is the natural mortality rate of the complex and B_{MSY} is the biomass that produces the maximum sustainable yield. As was done in the previous assessment, M was set at 0.30, so the overfished definition is defined as $B < 0.7 \times B_{MSY}$. Overfishing is defined as a fishing/harvest rate H that exceeds the Maximum Fishing Mortality Threshold (MFMT) of H_{MSY}, the harvest rate that produces maximum sustainable yield. According to the FEPs, the MFMT varies depending on whether biomass is above or below the MSST (Figure 1; see WPRFMC 2009a, pages 127–128 for a description of the harvest control rule). If the stock biomass is above the MSST ($B > 0.7 \times B_{MSY}$), then the MFMT equals H_{MSY}, whereas if the stock biomass falls below the MSST ($B < 0.7 \times B_{MSY}$), then the MFMT declines from H_{MSY} in proportion to the ratio of biomass to the biomass reference point. Throughout this report, we refer to status in relation to H_{CR} instead of H_{MSY} to reflect the harvest control rule as stated in the FEPs.

1.1. Description of the Fisheries

Guam

Guam is the largest and southernmost of the Mariana Islands. Prior to European arrival, inhabitants possessed sailing canoes that allowed fishing of nearshore and offshore banks (Allen and Bartram 2008). Fishing in Guam continues to be important for contributing to the subsistence needs of the people, preserving history and identity, and maintaining cultural practices (Allen and Bartram 2008). Bottomfish are caught by a combination of recreational, subsistence, and small-scale commercial fishing operations utilizing vertical lines with electric or spin-casting reels depending on fishing depth. In 2017, a total of 841 fishers were estimated to have participated in bottomfishing activities (WPRFMC 2018). Most of the fleet consists of vessels less than 25 feet in length that target shallower BMUS species for recreational or subsistence purposes. Some recreational vessels (<25 ft) also target the deeper BMUS species at the offshore banks and other areas offshore of Guam where bottomfish habitat occurs. Larger vessels (>25 ft) fishing commercially target the deeper species at offshore banks (e.g., Galvez and Santa Rosa Banks to the south and Rota Bank to the north).

Commonwealth of the Northern Mariana Islands (CNMI)

The CNMI consists of a series of islands in the long Marianas Islands chain, which excluding Guam extends approximately 500 nm in a north-south direction, and is paralleled by a chain of seamounts about 150 nm to the west. Most of the fishing activity occurs around the population centers of Rota, Tinian, and Saipan and extends north to Zealandia Bank, approximately 120 nm north of Saipan. As in other territories, fishing has deep traditions and cultural significance (Hospital and Beavers 2014). In 2017, a total of 786 fishers were estimated to have participated in bottomfishing activities (WPRFMC 2018). The shallower BMUS component, dominated by *Lethrinus rubrioperculatus*, is fished both commercially and for subsistence with most fishing trips made by small vessels (<25 ft) using handlines or homemade hand or electric reels and lasting a single day (WPRFMC 2018). In contrast, the deeper BMUS component is fished primarily commercially using larger (>25 ft) vessels. In the late 1980s to early 1990s there were 12-15 large vessels (~70 ft) on Saipan that would fish around Saipan but also to the Northern Islands (Yau et al. 2016). The larger vessels can conduct multi-day trips and employ electric or hydraulic reels (WPRFMC 2018).

American Samoa

Prior to European contact, indigenous fishers of the Samoan Islands fished for subsistence from canoes using pearl shell hooks and sennit lines. They caught many fish species including some BMUS. By the 1950s, the Samoa fleet had adopted small boats equipped with outboard engines and fished with steel hooks and monofilament lines, but the fishery remained for subsistence only. Surveys conducted in the late 1960s by the American Samoa Office of Marine Resources revealed substantial deep bottomfish resources around the island of Tutuila, and by the early 1970s a small commercial fishery was established. In an attempt to develop local fisheries, two subsidized boat building programs, the dory program in the 1970s and the *alia* program in the 1980s, provided fishers with low cost vessels. The bottomfish fleet expanded in the mid-1980s with a government subsidized project aimed at exporting deep-water snappers to Hawaii (Itano 1996). At the fishery's peak in 1984, forty-eight vessels fished for bottomfish. Declines in participation in this fishery can be attributed to shifts in the importance of bottomfish fishing compared to trolling and longlining for pelagic species and to the periodic impact of hurricanes. In 1987, for example, hurricane Tusi damaged or destroyed a large segment of the small boat fishing fleet. In 2005, a total of 16 part-time vessels participated in the bottomfish fishery (WPRFMC 2006). Most vessels are small aluminum *alia* catamarans (<30 ft) with low-tech fishing practices (e.g., no depth sounders, electric or hydraulic reels, global positioning systems, or ice chilling capability) (WPRFMC 2006). In recent years, however, a number of larger (>35 ft) vessels with higher technological capability have been entering the fishery (WPRFMC 2006). As in Guam, during the period 1986–2005 fishing effort (in line hours) spent targeting the shallow bottomfish component was nearly double that spent on the deep component.

1.2. Previous Stock Assessments

Previous Benchmark Stock Assessments in 2007

The 2007 benchmark stock assessments improved upon earlier assessment approaches that used catch-per-unit-effort (CPUE) indices as proxies for MSY-based reference points (Moffitt et al. 2007). The base case model for the benchmark stock assessments was a Bayesian surplus production model, which directly estimated MSY-based reference points as well as trajectories of biomass and harvest rate from which stock status was determined. The Bayesian surplus production model explicitly accounted for both process and observation errors, and therefore captured parameter uncertainty for status determinations. Consequently, the 2007 benchmark assessments were the first to directly calculate reference points to use for status determination. The results from the 2007 benchmark assessments showed that for all territories, BMUS stocks were not overfished and overfishing was not occurring.

As with any modeling approach, the benchmark stock assessments made a number of assumptions on model structure and data treatment. In regards to model structure, a Schaefer surplus production function was assumed for all territories. To help inform parameter estimates, the models were fit to estimates of MSY calculated from independent studies. These estimates were based on research conducted in the Marianas (Polovina et al. 1985) and extended to include American Samoa, and were found in the Our Living Oceans (OLO) report by Humphreys and Moffitt (1999) and later Moffitt and Humphreys (2009). The methods used to estimate MSY were described in Polovina and Ralston (1986), and were a fishery-independent estimate that combined life history assumptions (von Bertalanffy growth, constant natural mortality, and constant recruitment) with data on length-frequency, CPUE, and an estimate of catchability from an intensive fishing experiment.

Assumptions around catch and CPUE data were also made. The 2007 benchmark assessment models used data through 2006. For CNMI, this limited the utility of relatively recent creel survey data that started in 2000, and so the model utilized commercial purchase data for CPUE and catch trends that extended back to 1983. Catch and CPUE data for Guam and American Samoa extended back to 1982 and 1986, respectively. Nominal CPUE data was exclusively used in the 2007 benchmark assessments, no standardizations were considered. The assessments also filtered the CPUE data to only include interviews with greater than 50% of BMUS by weight for Guam and American Samoa, and filtered to the data to only include interviews reporting bottomfishing gear for CNMI. Lastly, catch reported by families or species groups was assumed to be 75% BMUS for American Samoa, and because CNMI catch data were not filtered by species, all catch on bottomfishing gear for CNMI commercial purchase data were assumed to be BMUS.

Previous Stock Assessment Updates in 2012

The 2012 stock assessment updates used data through 2010 and used a similar treatment of data, analytical approach, and assessment methodology as the 2007 benchmark assessments (Brodziak et al. 2012). Five new years of data were added to the catch and CPUE time series from those used in the previous benchmark assessments. Results of the 2012 assessment updates were similar to the 2007 stock assessments, in that stocks for all territories were not overfished and overfishing was not occurring.

Previous Stock Assessment Updates in 2016

The 2016 stock assessment updates using data through 2013 also used a similar treatment of data, analytical approach, and assessment methodology as the 2012 assessment updates and 2007 benchmark assessments (Yau et al. 2016). Catch and CPUE for Guam and American Samoa were calculated using the offshore creel survey dataset, and catch and CPUE for CNMI were calculated using the Commercial Purchase Database program. Three new years of data were added to the catch and CPUE time series, with the exception of the CPUE time series for CNMI. The CNMI CPUE time series was truncated at 2006, which was the previous benchmark assessment's terminal year, because the updated data after 2006 differed substantially from the data used for the 2012 update assessment. Notwithstanding this small change in the length of the CPUE data time series for CNMI, results of the 2016 assessment updates were similar to the 2012 and 2007 stock assessments, in that stocks for all territories were not overfished and overfishing was not occurring.

The 2016 assessment updates were the first assessments to go through the Western Pacific Stock Assessment Review (WPSAR) process. This peer-review process produced a number of recommendations for improvements to the stock assessments (Franklin et al. 2015). Many of the improvements were incorporated for the current (2019) benchmark stock assessments, although not all could be addressed due to tractability and time constraints. The following section describes recommendations from the panel and responses to them in the current stock assessments.

Current Benchmark Stock Assessments

As done in previous assessments, the model for the 2019 benchmark stock assessments was a Bayesian surplus production model that explicitly accounted for both process and observation errors, and directly estimated MSY-based reference points as well as trajectories and projections of biomass and harvest rate to determine stock status of BMUS complexes for Guam, CNMI, and American Samoa. For these assessments, however, we used new modeling software to run the production model and estimate the trajectories and statuses of BMUS complexes for the three territories. In addition to updated modeling software, a number of changes from the previous update and benchmark stock assessments were made for the current benchmark stock assessments. The details of all of these changes are described throughout this report. The changes primarily followed from recommendations from the WPSAR panel of reviewers for the previous update assessments.

The WPSAR recommendations on future research, data collection, and changes in methods that may improve future iterations of territorial bottomfish assessments (Franklin et al. 2015, pg. 3–4) included, in order of priority:

1. *include all years of CNMI boat-based creel CPUE series into future assessments,*
2. *sufficiently verify and document the analysis and results for the* MSY *estimates (if these are included in future assessments),*
3. *investigate additional analysis that excludes the* MSY *prior values as a constraint to compare output with* MSY*-constrained models,*
4. *include a detailed explanation of the expansion algorithm used to generate catch data,*

5. *explore splitting the BMUS into shallow and deep species components for future assessments,*
6. *consider using standardized CPUE rather than nominal CPUE in future assessment,*
7. *explore macro-scale oceanographic effects on the process component of the model such as SST on productivity via the r parameter (make r a varying parameter as opposed to fixed),*
8. *explore local-scale oceanographic effects on the observation component of the model such as wind and current that influence fisher and fish behavior and catchability,*
9. *account for the varying BMUS species composition over time by either incorporating multilevel priors or in the CPUE data standardization process,*
10. *account for unreported landings by perhaps using a censored catch approach within the Bayesian stock assessment model,*
11. *investigate other prior distributions (e.g., uniforms) as well as document the various distributions used as well as show graphically how informative or uninformative they are,*
12. *integrate fishery area map designations into creel surveys to standardize reports of spatial fishing effort for American Samoa and CNMI, and*
13. *explore length-based data and life history-based approaches for the assessment process if sufficient data is available.*

All recommendations from the WPSAR process were considered, but only recommendations 1–3, 6, 8, and 11–12 were specifically completed for this set of benchmark stock assessments. In addition, recommendations 4 and 10 were partially addressed for this assessment. Other recommendations were not addressed because of time constraints, data availability, or jurisdiction (responsibility does not fall solely or primarily on the Pacific Islands Fisheries Science Center).

Recommendations 1, 6, 8, and 12 all dealt with CPUE processes. For this set of benchmark stock assessments, we standardized CPUE data from boat-based creel surveys for all territories, and therefore addressed recommendations 1 and 6. Factors within the standardizations included, among others, area and self-reported wind speed which addressed recommendations 8 and 12. Other environmental factors were not reported in the creel data and therefore could not be used. Recommendations 2 and 3 both dealt with treatment of the independent OLO MSY estimates used to inform model parameters in previous assessments. No further documentation about the data or methods used to generate these MSY estimates could be found. Therefore, the current benchmark stock assessments were not fit to the independent OLO MSY estimates. We did, however, use the independent OLO MSY estimates to inform the prior mean values for carrying capacity, as was done in previous stock assessments. For this set of assessments, we include extensive sensitivity analyses to understand the implications of prior assumptions on model results, which addressed recommendation 11.

We include a brief explanation of the expansion algorithm used to estimate catch, which partially addressed recommendation 4. Each territorial agency collects its own boat-based and shore-based creel survey data, and although sampling and estimates of expanded catch follow the same general methods, each territory differs slightly in the details. Guam's Division of Aquatic and Wildlife Resources creel survey manual provides more description of the methods for the data collection and estimation of expanded catch in Guam (Jasper et al. 2016). We have ongoing plans to work with territorial agency partners to document the expansion algorithms in detail for each territory, but such reports were not finalized before these 2019 stock assessments were completed. We also partially addressed recommendation 10 by allowing catch to be modelled with variability around the input values. Although not completely accounting for unreported catches (i.e., catches not captured in the creel surveys), this approach does acknowledge that catch values are derived estimates from a creel survey, and therefore by modifying the current assessment models to include variability in catch, we accounted for uncertainty from the catch expansion algorithm.

We did not incorporate recommendations 5, 7, 9, and 13 in the current stock assessment models due to time limitations after making the improvements already described. We considered splitting the BMUS complex into deep and shallow components, but did not do so. The current FEP specifies the BMUS complex as a single stock, and therefore we chose to maintain consistency with the FEPs' definition of the stock. Length measurements are collected by the biosampling program and are also collected during some creel survey interviews. The biosampling program also collects fish weight, and includes information on gear fished, hours fished, and area fished. Although a source of additional catch and effort information, we did not include the catch and effort data from the biosampling program in the current assessments because the earliest available data started in 2009 and represents a subset of the available catch. Length information from the biosampling program and creel survey interviews was also not included for this assessment given time constraints.

2. Methods for Assessment Model Including Values for Data Inputs

2.1. Data Sources

Three sources of catch or catch and effort data were used for each territory: the offshore (boat-based) creel survey data, nearshore (shore-based) creel survey data, and data from the Commercial Purchase Database program. Participation by fishers and dealers in all programs is voluntary. Creel surveys are conducted by territorial agencies to collect fishery data that are then passed to the Western Pacific Fisheries Information Network (WPacFIN). The creel surveys consist of fisher interviews, where species-specific catch and fishing effort information are recorded. The creel surveys also incorporate effort-based surveys, which consist of a participation survey for shore-based fishing, and a boating-log survey for boat-based fishing. For each territory, catch data from the surveyed (interviewed) subset of fishing trips are expanded using the effort surveys to estimate total (expanded) catch for the territory. The species composition from the surveyed subset of fishing trips was then applied to obtain total species-specific catches for each territory. Under the Commercial Purchase Database program, first-level purchasers of local fresh fish provided records of purchases by species categories. Species categories reported in the Commercial Purchase Database do not necessarily align with BMUS categories from the creel survey program, and are typically more aggregated. The commercial purchase dataset also includes an identifier of the seller for all territories, whether the sale is a resale and thus was previously reported in the dataset, information on method and location of fishing for the Guam and American Samoa datasets, information on effort for the Guam dataset, and information on whether the sale was of imported fish for the American Samoa dataset.

Survey coverage and quality of data collected vary by territory, location, and time period. Guam has been collecting voluntary fishery creel data since the late 1960s, although only shore-based creel data collected since 1985 and boat-based creel data collected since 1982 were used for analysis. Data collected prior to these years were not as extensive as required in order to apply the expansion algorithm for catch. Commercial purchase data were available starting in 1979. Collection of bottomfish catch data from the east side of the island is hampered by logistical problems and lack of voluntary reporting. The east side of the island is heavily fished for bottomfish species during the calmer summer months. The current statistical expansion of fishery data, however, adjusts for this to the extent possible. The CNMI creel survey is a more recent program, with available data starting in 2000 for the boat-based creel data and 2005 for the shore-based creel data. Prior to the creel survey, data were collected through the voluntary commercial purchase program, which started in 1983. The current American Samoa boat-based creel survey was initiated in October 1985 and recorded landings and effort of commercial, recreational, and subsistence fishers. Given that the data in 1985 started in October, and were therefore incomplete for the year, we used data starting in 1986. The shore-based creel survey was initiated in October 1987, but data from the participation survey and the resulting expanded catch estimates were not available until 1990. Commercial purchase data for American Samoa were available starting in 1990. All years referred to herein for this set of assessments are calendar years.

Other datasets of fishing information were available for consideration. These include the WPacFIN biosampling program and the federal permit logbook dataset of catch and effort for bottomfishing in federal waters. The biosampling program consisted of length and weight data on a subset of sampled catch, as well as information on where the fish was caught, what method was used to catch the fish, and the effort expended to catch the fish. Although this information could be used for length-based methods or even CPUE calculations, the data started in 2009 and so was of limited utility for determining the size of the stock compared to other data sources, and therefore ultimately the biosampling data were not used. As more and more years are added to the dataset in the future, the biosampling data could provide additional sources of information to inform the assessments. Investigation of the federal logbook dataset of catch and effort for bottomfishing in each of the territories revealed that the data are very sparse, starting in 2009 with only 0–5 permit holders reporting annually. Consequently, these data were not useful to include in the assessments. Until there is a higher reporting rate, the federal logbook dataset is likely not useful for future stock assessment purposes.

2.1. Methods of Calculating Catch and Resulting Catch Values

2.1.1. Total Catch

We explored all three data sources of catch data (expanded boat-based creel survey data, expanded shore-based creel survey data, and data from the Commercial Purchase Database program) when calculating total catch removals. For each data source, we calculated total catch by species for each year and then summed across species to obtain a total catch series. Data from American Samoa included information on the species *Pristipomoides rutilans*, which is not an actual species. Based on conversations with life history experts at PIFSC, we concluded that this species was likely *Aphareus rutilans*, and therefore replaced *P. rutilans* with *A. rutilans* when calculating catch (and also catch variance and CPUE) for the American Samoa assessment. In addition to species-specific codes in the data, valid species codes for species at the family level and for species categories were reported in the data. We included catch from these groupings by calculating the total catch of BMUS as the sum of catches of individual BMUS (Table 1 and Table 2) plus a percentage of catch from species groups believed to contain BMUS as explained in detail in the next paragraphs. A similar concept but using a fixed percentage (75%) was used in the previous benchmark and update assessments, and was applied solely to American Samoa creel-survey data. Prior to calculating commercial purchase catch, we excluded resale catches, which were catches already reported in the commercial purchase dataset, and imported catches, which were from sources outside the respective territory.

The percentage of catch of species groups believed to contain BMUS in each year was calculated based on the ratio of the catch of BMUS (Table 2) to the catch of non-BMUS within each species group for that year in each territory. If no BMUS within a group were caught, or no species-specific information other than that group was available, then the proportion of catch from that group applied to BMUS catch was zero. If no individual species of a group were caught within a year, but were caught in other years, then the overall average ratio of BMUS to non-BMUS across all years within that species group was used for that year. We assumed 10 species groups contained BMUS for Guam boat- and shore-based survey data, 7 for Guam commercial purchase data, 6 for CNMI boat- and shore-based survey data, 5 for CNMI commercial purchase data, and 9 for all three American Samoa data sources. Species groups for Guam survey data were Carangidae, *Caranx* i’e’ (juvenile *Caranx*), Lethrinidae, Lutjanidae, Serranidae, assorted bottomfish, shallow bottomfish, deep bottomfish, shallow snappers, and deep snappers. Species groups for Guam commercial purchase data were jacks, bottomfish, deep bottomfish, grouper, emperor, and two groupings of snapper (tagafi and snapper). Species groups for CNMI survey data were jacks, juvenile jacks, bottomfish, grouper, emperor, and snapper. Species groups for CNMI commercial purchase data were the same as for the survey data but did not include juvenile jacks. Species groups for American Samoa were trevallys, jacks, bottomfish, groupers, deepwater snappers, pristipomoides/etelis, emperors, inshore groupers, and inshore snappers.

General rules were applied to determine the non-BMUS species for each species group from the species lists provided by WPacFIN. For each territory, family-level groups included species within the family. Exceptions to this included Serranidae, where basslets and soapfish were not included, and Carangidae, where scads (i.e., genera *Decapterus*, *Selar*, and *Selaroides*) were not included. These exclusions were also applied to all rules described below. For the following sets of species groups, the same list of species was applied to all species groups within the set: juvenile and adult groups (Carangidae and Caranx i'e' in Guam survey data, and jacks and juvenile jacks in CNMI survey data), shallow and deep groups (shallow bottomfish and deep bottomfish, and shallow snappers and deep snappers in Guam data), deepwater and nearshore groups (groupers and inshore groupers, and inshore snappers and deepwater snappers in American Samoa data), and groups of similar categories (assorted bottomfish and shallow/deep bottomfish in Guam survey data, tagafi and snapper in Guam commercial purchase data, and trevallys and jacks in American Samoa data). Snappers were defined as species in the family Lutjanidae, emperors as species in the family Lethrinidae, groupers as species in the family Serranidae, jacks/trevallys as species in the family Carangidae, and pristipomoides/etelis as species in the genera *Etelis* or *Pristipomoides*. Bottomfish were defined as species in the families Lutjanidae, Lethrinidae, Serranidae, and Carangidae, and also included the large-headed scorpionfish (*Pontinus macrocephalus*), alfonsin (*Beryx decadactylus*), oilfish (*Ruvettus pretiosus*), species of the family Bramidae, and species of the family Priacanthidae. These additional species were added to "bottomfish" based on the assumption that these species were likely to be reported as bottomfish by fishers.

We compared catches across all three data sources, as well as compared how our choice to use a percentage of catch from species groups in our catch estimates influenced catch estimates. A comparison of BMUS catch and group species catch for all data sources are provided for Guam (Figure 2), CNMI (Figure 3), and American Samoa (Figure 4). These figures show that catch for all territories was primarily from individual BMUS and from the boat-based creel survey, and that catch of species groups in American Samoa was more prominent than for the other territories. Given that the majority of catch was from the boat-based survey, the start years of our models corresponded to the first year when boat-based creel survey data were available.

Once catch from non-BMUS groups was added to catch of individual BMUS for each data source, a single total catch time series was calculated for each source. The two creel surveys represent catch from different fishing sectors, so total expanded yearly catch from the boat-based and shore-based data were combined to obtain a total expanded creel survey catch estimate. The boat-based and shore-based creel data were added together in years when both were available. Boat-based data covered more years than shore-based data, so for years when shore-based data were not available but boat-based data were available, we assumed a value for shore-based catch equal to the average of shore-based catches across available years. This approach therefore assumed that shore based catch likely occurred during years when data were not collected. Commercial purchase data can overlap with catch from the creel surveys, and so represents a separate estimate of catch. Consequently, catch from the commercial purchase dataset was compared to the summed catch from the two creel surveys. To obtain a final catch time series, the maximum of the total expanded creel survey catch and the total catch from the commercial purchase data in each year was used as the final yearly catch value for use in the stock assessment models. Guam commercial purchase catch was always less than the sum of expanded catch from the creel surveys in overlapping years (Figure 2). CNMI commercial purchase data was greater than the sum of expanded catch from the creel surveys in only two of the overlapping years: 2003 and 2014 (Figure 3); while American Samoa commercial purchase data was greater than the sum of expanded catch from the creel surveys in six of the overlapping years: 1995, 1996, 1998, 2000, 2003, and 2006 (Figure 4). Resulting total catch values used for the assessments are provided in Table 3 and Figure 5.

Although we did not model individual species catch in the assessment models, for comparison among territories we report here the top five species or species groups recorded in the expanded boat-based survey catch (the data source reporting the most BMUS catch). For Guam, the dominant species was redgill emperor at 20% of the total catch over all years, followed by flame snapper (12%), goldflag snapper (11%), oblique-banded snapper (8%), and the species group shallow bottomfish (7%). For CNMI, the dominant species was also redgill emperor at 24% of the total catch over all years, followed by flame snapper (22%), ruby snapper (9%), pink snapper (9%), and Von Siebold's snapper (7%). For American Samoa, the dominant species was the species group bottomfish at 24% of the total catch over all years, followed by the species group emperors (11%), and then bluestripe snapper (11%), green jobfish (9%), and flame snapper (8%).

2.1.2. Catch Variance

Total catch of BMUS as reported in Table 3 was in part from expanded boat-based and shore-based interview data. Although total expanded creel survey catch had an associated variance estimate, variances of species-specific creel survey catch estimates did not have explicit variance formulations. To obtain variance estimates at a species level, the data were bootstrapped to generate uncertainty around species-specific catches. Initially, the bootstrap procedure was run separately for total expanded creel survey catch (in years with both shore-based and boat-based data), and for boat-based expanded catch. Given these two sets of variance estimates, we chose to use only the boat-based bootstrap estimates of variance. This choice assumed that the species-specific coefficients of variation for the boat-based data were the same as for the shore-based data. Given the much higher catch of BMUS in the boat-based survey, we felt this choice was better than the alternative option of using the combined shore-based and boat-based variance in overlapping years and applying an imputation algorithm to determine variance in years without bootstrap estimates but with catch estimates. Variance estimates were not available for commercial purchase data; therefore, in years where commercial purchase catch data were used (i.e., commercial purchase catch was greater than the sum of boat- and shore-based creel survey expanded catch), we applied the coefficient of variation from the boat-based data to the total catch value. In other words, we used variance estimates from the expanded boat-based creel survey catch estimates to represent total catch variance in every year. Given that the purpose was to capture general as opposed to exact variance, we believe the choice of using variance estimates from just the boat-based creel survey data was appropriate.

To generate the variance estimate, the value for expanded catch was drawn from a truncated (at 0) normal distribution with mean and standard deviation equal to the value and standard deviation of the original boat-based survey expanded catch estimate. Interview data were resampled with replacement, which were then used together with the redrawn expanded catch estimate to calculate species-specific expanded catch. This process was repeated 1,000 times and the variance around species-specific expanded catches for BMUS from the boat-based creel surveys were used as a measure of uncertainty around total BMUS catch.

We applied the same group proportions that were applied to catches of species groups for the boat-based data when calculating variance. Species-specific variance estimates for each BMUS within a year were summed to obtain total BMUS variance, which required an assumption of independence among species catches. The variance of each species group believed to contain BMUS was also added into the total variance for BMUS, and was scaled by the square of the percentage of BMUS to non-BMUS catch for each species group. Estimates of uncertainty applied to total catches, as reported using the coefficients of variation based on boat-based creel survey data, are provided for all territories in Table 4.

2.2. Methods of Calculating CPUE and Resulting CPUE Values

Estimation of standardized CPUE indices for each territory's BMUS complex was done as an improvement over methods used in previous stock assessments. The details of the standardization approach are described below, including selecting representative data from the fishery in section 2.2.1. Dataset Choice and Filtering, selecting covariates to include in the CPUE standardization in section 2.2.2. Covariates for Standardization, and details of the standardization procedure, including model choices and diagnostics, in section 2.2.3. CPUE Standardization.

2.2.1. Dataset Choice and Filtering

Dataset choice

Non-expanded interview data from the boat-based creel surveys were used as the basis for CPUE calculations. The interview data contained catch by species, measures of fishing activity that were used to determine fishing effort, and additional environmental and fishing related covariates that were used to account for changes in fishing conditions not related to changes in the underlying fish abundance. Two interview datasets were considered: boat-based interviews and shore-based interviews. Given that BMUS are primarily caught offshore and with boats, and that the expanded boat-based creel survey catch represented a greater proportion of total BMUS catch than the expanded shore-based creel survey catch (Figure 2–Figure 4), we restricted CPUE analyses to only the non-expanded boat-based interview dataset.

We considered using the commercial purchase dataset for CPUE standardization because it contained information that could be used to determine catch and effort of fishing activities. The commercial purchase dataset for Guam included information on the day of sale, the name of the seller, the method used, species name and corresponding catch, hours fished, and area fished. The dataset for CNMI had fewer fields, and only included day of sale, an identifier of the seller, and species name and corresponding catch weight. There was no information on method, effort, or area of fishing. The dataset for American Samoa was similar to Guam, with information on the day of sale, an identifier of the seller, the method used, species name and corresponding catch, and area fished, but lacked information on effort. Although many pertinent fields were available, not all values for each record were filled in, and information useful for standardizing CPUE was missing from roughly 10–50% of records, depending on the field and territory. Given the limited information in pertinent fields, in particular for effort for CNMI and American Samoa, as well as uncertainty around the proportion of catch that is sold or reported in the commercial purchase dataset, we did not use commercial purchase data for CPUE calculations.

Dataset filtering

Each interview in the boat-based survey data reflected the catch and fishing activity from a single fishing event. Consequently, interview was the basic unit of data. There were a total of 30,533 interviews in the boat-based dataset for Guam, 4,062 for CNMI, and 14,408 for American Samoa for all species/groups and gears. We applied a number of filtering steps to these base level datasets to come up with representative CPUE data for BMUS in each territory.

As was the case for the expanded catch datasets, non-expanded interview data contained both species-specific codes and aggregated family-level or species category codes. Consequently, catch of BMUS plus a portion of the catches from aggregated species codes within each interview were used to determine the catch of BMUS for CPUE. The same proportions used to determine catches of BMUS from aggregated groups in the expanded catch datasets were applied to determine the catch of BMUS from species groups in the non-expanded interview datasets. These proportions were calculated as the ratio of known (species-specific) catches of BMUS in a year to known catches of non-BMUS in a year. Within the interview datasets, Guam had 841 interviews (2.8% of total interviews) that included catch of species groups, CNMI had 964 interviews (24% of total interviews), and American Samoa had 2,196 interviews (15% of total interviews).

The interview data was filtered to reflect fishing activity expected to target BMUS. The reason for doing this was to avoid fishing activity unlikely to catch BMUS, the inclusion of which would inaccurately reflect CPUE patterns over time for BMUS. There is no indication in the interview data on the species or groups of species a fisher targets. Statistical methods exist for separating data into clusters which could be used to determine interviews targeting BMUS (e.g., Stephens and MacCall 2004). Such methods would rely on characteristics of either the catch composition or variables on fishing activity to differentiate among clusters. Our approach was to use gear as a simple and straightforward distinction for determining fishing that targeted BMUS. The vast majority of BMUS were caught on bottom-line gear (96% for Guam, 95% for CNMI, and 72% for American Samoa). The most significant other gears that caught BMUS were trolling for Guam, which accounted for 1.2% of BMUS catch; spear/snorkel for CNMI, which accounted for 2.3% of BMUS catch; and bottomfishing/trolling mix and spearfishing in boats without tanks for American Samoa, which accounted for 22% and 6% of BMUS catch, respectively. Although bottomfishing/trolling mix caught 22% of the BMUS for American Samoa, it was not ultimately used to maintain consistency with the Guam and CNMI filtering approaches and because it was not a dominant gear. After filtering by gear, there remained 5,423 interviews for Guam, 968 interviews for CNMI, and 2,437 interviews for American Samoa.

In addition to filtering the interview data by gear, we filtered data based on two additional criteria. First, we removed any interviews from vessels that never caught any BMUS. Catches of aggregated species codes were already adjusted to reflect expected catches of BMUS and were included when considering whether a vessel caught any BMUS. In total, this removed 314 vessels and 468 interviews from the Guam dataset, 51 vessels and 58 interviews from the CNMI dataset, and 2 vessels and 3 interviews from the American Samoa dataset. Second, we removed any interviews from charter fishing trips, which occurred in 726 interviews in the Guam dataset and 340 interviews in the CNMI dataset. Whether a vessel was a charter fishing event was reported in the interview form. These fishing events were most often designated in shallow water, and had much higher number of gears and slightly fewer hours of fishing, and therefore much lower CPUE values. The primary reason these fishing events were excluded was that they represented a different sector of fishing activity that did not target BMUS. As such, we assumed that this activity would not reflect BMUS fishing on the whole, and therefore interviews from charters were excluded. There was one interview in the American Samoa dataset that was reported as a charter fishing trip, but because this interview did not appear distinct from other non-charter interviews, we did not exclude it from the standardization.

The final step in filtering the CPUE data was to select interviews with complete information on the categories used within the standardization describing changes in the environment or patterns of fishing activity. These categories included temporal factors of month and year; spatial factors of area; fishing activity factors of type of day, depth, and vessel name; and categories used to calculate CPUE including catch, number of gears, and hours fished. In total, 409 interviews were removed based on incomplete field values in the Guam dataset, 4 interviews in the CNMI dataset, and 790 interviews in the American Samoa dataset. In addition, the 30 interviews from American Samoa’s initial survey year (1985) were excluded because they were from a partial calendar year. After all filtering steps were complete, the final number of interviews used for CPUE standardization of BMUS was 3,820 for Guam, 566 for CNMI, and 1,614 for American Samoa.

Once data filtering was complete, CPUE was calculated as catch divided by effort. Effort was calculated as the product of hours fished and number of gears, as was done in the previous benchmark stock assessments (Moffitt et al. 2007). We explored the influence of number of gears on the overall value of CPUE across years and found that the relative trend was similar regardless of whether number of gears was used in effort calculation.

2.2.2. Covariates for Standardization

Covariates explored in CPUE standardization included year, month, area, type of day, depth, wind speed, and vessel name, and are defined in more detail below. These covariates were considered to have a possible effect on BMUS CPUE other than changes in annual stock abundance. In other words, these factors may have caused CPUE to vary due to changes in the distribution of fish or the pattern and effectiveness of fishing effort. Only the Guam database included information on wind speed so wind speed was not explored for CNMI or American Samoa. Although the American Samoa database included the field for depth, there was no reported information on depth so depth was not used for that territory. All covariates were explored for inclusion in the standardization as categorical factors. Wind speed for Guam was reported in integers; however, it was apparent in the data that most fishers rounded to the nearest 5 knots. Therefore, we combined wind speed into groups of 0 knots, 1–5 knots, 6–10 knots, etc., up to 30 knots.

Year, month, and area are typical time and area covariates explored for CPUE standardization. Areas followed the grid numbering shown for Guam (Figure 6), CNMI (Figure 7), and American Samoa (Figure 8). Fishing grids as defined on interview sheets were not necessarily distinct because general cardinal directions were reported as well as ordinal directions for Guam and CNMI. Furthermore, individual areas such as banks or reefs within a general direction were also reported. We acknowledge that a lack of distinction among reported areas could mask any individual area effect, and thus we considered aggregating fishing grids into groups that were distinct from one another. Ultimately, we decided to keep reported fishing grids as they were reported without further adjustment to maintain as fine a scale as possible. When exploring the area designations for Guam, we removed an additional 17 interviews from grid 99 (northern Marianas) and the 9 interviews with invalid grid numbers (values less than 10; see Figure 6) prior to standardization. When exploring the area designations for CNMI, we removed an additional 8 interviews with invalid grid numbers (values equal to 0; see Figure 7) prior to standardization. We did not consider second order interactions between area-year for any territory because of the possibility of over-parameterizing the standardization models given the limited number of interview data points, and because there were no visual patterns of the most common fishing areas in each territory shifting over time.

Type of day, depth, wind speed, and vessel name were explored in the standardization because information on them was available in the datasets, and these covariates were believed to potentially influence CPUE independent of changes in BMUS abundance. Type of day was reported as either weekend or weekday interviews, and was explored in the standardization to capture potential differences between full-time fishers, which we assumed would fish on the weekday, and part-time fishers, which we assumed would fish on the weekends. Depth was reported in four categories: deep, mixed, shallow, and unknown; and all were explored within the standardization. Depth was included to account for differences among nearer shore versus farther offshore habitat and species within the BMUS complex. Lastly, vessel information was included in the standardization as an attempt to determine difference among individual fishers/vessels. Fisher-specific information such as fisher name was not reported in the creel-survey database, so vessel was used as a proxy to account for differences among vessels assuming vessel names are unique, and among fishers assuming fishers do not switch vessels.

2.2.3. CPUE Standardization

Catch-per-unit-effort data were standardized using generalized linear and generalized linear mixed models (McCulloch et al. 2008). Given our choices in filtering the data based on fishing gear, as described in section 2.2.1. Dataset Choice and Filtering, the data contained a number of records where CPUE of BMUS was zero. We considered it possible to catch zero pounds of BMUS when fishing. Consequently, instances of zero catches of BMUS were included in CPUE standardization for each assessment. Eighteen percent of the data for the Guam assessment, 14% for the CNMI assessment, and 6.6% for the American Samoa assessment had zero catches of BMUS. There are numerous ways to deal with zero catches when standardizing CPUE including ignoring them, adding a small constant, using count-based distributions that allow for zero catches such as Poisson or Negative Binomial, using continuous distributions that incorporate a zero component such as a Tweedie distribution, using zero-inflated models that account for greater than expected proportions of zeroes, and using delta-type models that separately model the zero-process (Maunder and Punt 2004).

A delta-type approach was used in the 2019 assessments wherein CPUE was modeled as the product of two processes: a Bernoulli process modeling the probability of positive catches, and a positive process modeling the distribution of CPUE given a positive catch. We tested both a gamma distribution and a lognormal distribution for the positive process by comparing fits of the nominal CPUE data to both distributions. The lognormal distribution fit the positive catch data better than the gamma for Guam and CNMI, and therefore was used for those assessments, whereas the gamma distribution fit the positive catch data better than the lognormal distribution for American Samoa, and therefore the gamma distribution was used for that assessment. The response variable for the Bernoulli process was a binomial variable that was added to the dataset, indicating whether a BMUS was captured (1 = captured, 0 = not captured). The relationship between the response variable and the predictor variables was modeled as a Binomial distribution using a logit link function. The response variable for the positive process for the Guam and CNMI assessment was the natural logarithm of CPUE from positive catches of BMUS and was modelled as a Gaussian distribution. The response variable for the positive gamma process for the American Samoa assessment was CPUE from positive catches of BMUS and was modeled as a Gamma distribution with inverse-link function.

2.2.3.1. CPUE Model Selection

Model selection techniques were used for each process (Bernoulli and positive) for each territory to select a set of predictors that most improved model fit from the suite of possible covariates. The covariates for each territory were described in section 2.2.2. Covariates for Standardization. All variables were modeled as fixed effects except for vessel name, which was modeled as a random effect. Selection among CPUE standardization models was performed using Akaike's information criterion (AIC = 2 × number of parameters – 2 × the natural logarithm of the likelihood evaluated at its maximum) to judge the relative goodness of fit (Burnham and Anderson 2002). Model selection was done using a backward-selection process with a threshold of 2 units above the previous model's AIC. Thus, if the AIC of a model after removing a predictor was less than or up to 2 units more than the previous model's AIC, the removed predictor was not considered significant and was removed from the standardization. The significance of the random effect of vessel name was tested first, and model selection using fixed effect terms was done thereafter. Year was required for the calculation of an annual index, so it was retained regardless of AIC score. Model selection was done using maximum likelihood for all models but estimation was done for generalized linear mixed models using restricted maximum likelihood once the best-fit model was determined. Restricted maximum likelihood accounts for degrees of freedom used in estimating fixed effects and estimates variance components of the random effects without influence from fixed-effect terms (Harville 1977; McCulloch et al. 2008). Statistical modeling was done with the lme4 package version 3.2 (Bates et al. 2015) within the R software package version 3.2.4 (R Core Team 2016).

Model selection for the vessel identifier was problematic for the Bernoulli process for all territories. A mix of convergence and memory errors were encountered when fitting using the vessel name covariate. Vessel name was therefore excluded as a covariate for model selection for the Bernoulli process for CNMI and Guam, but was retained as a covariate for model selection for the positive process.

The best-fit model for the Bernoulli process for Guam included only year, area, and depth. Wind speed, month, and type of day were not considered significant (Table 5). The best-fit model for the Bernoulli process reduced deviance by 22% from the null model (intercept only) and 17% from the year-effects only model. The best-fit model for the lognormal process for Guam included year, area, and depth, but also included vessel name. As for the Bernoulli process, wind speed, month, and type of day were not considered significant. The best-fit model for the lognormal process reduced deviance by 8.4% from the null model (intercept only), 4.4% from the model with only vessel name, and 2.9% from the model with only year and vessel name.

The best-fit model for the Bernoulli process for CNMI included only year, depth, and type of day. Area and month were not considered significant (Table 6). The best-fit model for the Bernoulli process reduced deviance by 23% from the null model (intercept only) and 16% from the year-effects only model. The best-fit model for the lognormal process for CNMI also included year, depth, and type of day, but also included vessel name and area. Only month was not considered significant. The best-fit model for the lognormal process reduced deviance by 14% from the null model (intercept only), 10% from the model with only vessel name, and 8.3% from the model with only year and vessel name.

The best-fit model for the Bernoulli process for American Samoa included year, area, and type of day. Only month was not considered significant (Table 7). The best-fit model for the Bernoulli process reduced deviance by 62% from the null model (intercept only) and 19% from the year-effects only model. The best-fit model for the gamma process included only year and vessel name. Month, type of day, and area were not considered significant. The best-fit model for the gamma process reduced deviance by 6% from the null model (intercept only) and 2.9% from the model with only fisher.

2.5.3.2. CPUE Model Diagnostics
Regression diagnostics were used to qualitatively check assumptions of the best-fit models for CPUE standardization. Model fit was assessed through visual comparison of residuals plotted against predicted values of the response variable and against values of the predictor variables. A histogram of the residuals was plotted to assess normality for both processes. Plots of the quantiles of the standardized residuals to the quantiles of a standard normal distribution were also used to assess assumptions of normality for models for the lognormal process. Pearson residuals were used for all models for the positive processes (lognormal for Guam and CNMI and gamma for American Samoa). Quantile residuals were used for all models for the Bernoulli process as recommended by Dunn and Smythe (1996).

Diagnostic residual plots showed that model assumptions were not violated for all processes and territories. Diagnostics for Guam indicated the model for each process was appropriate (Figure 9 and Figure 10). There was a slight reduction in the range of residuals at lower predicted probabilities for the Bernoulli process, and some patterning of residuals with area values, but we considered these minor (Figure 9). Diagnostics for the lognormal process indicated a slightly heavier lower tail of the residuals than expected for a normal distribution, but this too we considered minor (Figure 10). Diagnostics indicated the model for each process was also appropriate for CNMI (Figure 11 and Figure 12) and American Samoa (Figure 13 and Figure 14). For CNMI, there was a slight reduction in the range of the residuals at lower predicted probabilities and some variation in residuals by year for the Bernoulli process for CNMI (Figure 11), but we considered these minor. For American Samoa, although the few combinations of factors within the year, area, and type of day covariates with low probabilities aggregated predicted probabilities for the Bernoulli process, the ranges of residuals across predicted probabilities were similar (Figure 13). The quantile-quantile plot for the gamma distribution also indicated slightly heavier tails than expected for a gamma distribution, but we considered this to be minor (Figure 14).

2.5.3.3. CPUE Index Calculation

Once the set of factors that minimized AIC were selected and diagnostics indicated model assumptions were not violated, an index of CPUE as a proxy for biomass was generated using the best-fit models for each process within all territories. Predicted values of the response variable from each model were calculated using the predict function in R, and the mean and variance of the predictions within a year were calculated. The mean predicted values from the lognormal process for Guam and CNMI were multiplied by the exponential of one-half the residual variance to correct for bias when back-transforming from ln(CPUE) to CPUE, following Brodziak and Walsh (2013). The index I_t was then calculated as the product of the mean probability of catching BMUS in year t with the mean CPUE in year t calculated from positive catches of BMUS. The variance of the index in year t was calculated as the variance of the product of two independent random variables, the Bernoulli (Δ_t) and positive process (φ_t), following Brodziak and Walsh (2013):

Equation 1 $$Var\left(I_t\right) = Var\left(\Delta_t\right)Var\left(\varphi_t\right) + Var\left(\Delta_t\right)E\left[\varphi_t\right]^2 + Var\left(\varphi_t\right)E\left[\Delta_t\right]^2.$$

The variance of the index was then divided by the sample size in each year and used to obtain CVs around the mean index, which were then used for determining the yearly observation errors around the CPUE index in the assessment models. The assessment model requires the user to input variability around the CPUE index as the standard error of the mean index on the scale of the logarithm. Consequently, we calculated standard errors on the scale of the logarithm in each year from the CV in each year:

Equation 2 $$CV_t = \sqrt{e^{\sigma_t^2} - 1}.$$

The yearly indices and standard errors on the scale of the logarithm were used as input into the assessment models and are provided in Table 8 for all territories.

2.3. Assessment Model Methods

This section describes the production model assumptions and structure that were used to estimate biomass and fishing mortality for the territorial stock assessments. The current assessments use new modeling software from that of the previous benchmark and update assessments, yet still implements a Bayesian state-space surplus production modeling framework. The current assessment models do not fit to independent OLO MSY estimates that were included in the previous assessment models to inform model estimates.

2.3.1. Biomass Dynamics Model

This set of stock assessments used Just Another Bayesian Biomass Assessment (JABBA), which is an open-source modeling framework for conducting state-space Bayesian surplus production models (Winker et al. 2018). JABBA uses R to set up the model and call the software program JAGS (Just Another Gibbs Sampler, Plummer (2003)) using the R package “rjags” (Plummer

2016). JABBA explicitly estimates both process error variance and observation error variance that have been commonly used for fitting production models with biomass indices (Meyer and Millar 1999; McAllister et al. 2001; Punt 2003; Brodziak and Ishimura 2011), and estimates Bayesian posterior distributions of model outputs using Markov Chain Monte Carlo (MCMC) simulation (Gilks et al. 1996).

Surplus production models are frequently implemented to estimate sustainable levels of harvest (biomass removals) at corresponding levels of stock biomass. The exploitable biomass time series comprised the unobserved state variables, and was estimated by fitting model predictions to the observed biomass indices (i.e., CPUE) and catches using observation error likelihood functions and prior distributions for the model parameters. The observation error likelihood measured the discrepancy between observed and predicted CPUE, as well as between observed and predicted biomass indices, while the prior distributions represented the relative degree of belief about the probable values of model parameters. Assumptions of this model were that production followed a specified functional form, the assessments applied to exploitable individuals, all exploitable individuals were mature and equally vulnerable to fishing, and that biomass was proportional to CPUE.

The process dynamics represented the temporal fluctuations in exploitable bottomfish biomass due to density-dependent population processes (e.g., growth) and fishery catches. JABBA formulates the surplus production function as a generalized three-parameter equation following the formulation of Pella and Tomlinson (1969) and Fletcher (1978) (Gilbert 1992; Thorson et al. 2012). Under this three-parameter production function, exploitable biomass at the start of year t (B_t) depended only on the previous time period's exploitable biomass (B_{t-1}) and total catch (C_{t-1}), and on the intrinsic growth rate (r), carrying capacity (K), and production shape (m) parameters:

Equation 3 $$\boldsymbol{B_t = B_{t-1} + \frac{r}{m-1} B_{t-1}\left(1-\left(\frac{B_{t-1}}{K}\right)^{m-1}\right) - C_{t-1}}.$$

The production shape parameter m determined where surplus production peaked as biomass varied as a fraction of carrying capacity (Figure 15). If the shape parameter $m = 2$, the model reduces to the Schaefer form, with the surplus production function attaining a maximum at a biomass value equal to $K/2$. If $0 < m < 2$, MSY occurs when biomass values are smaller than $K/2$, and when $m > 2$, MSY occurs when biomass values are greater than $K/2$. The Pella-Tomlinson formulation reduces to a Fox form if m approaches 1, resulting in MSY at approximately $1/e \approx 0.368K$, but there is no exact solution for MSY when $m = 1$.

For computational purposes, the production model in Equation 3 was expressed in terms of the proportion of carrying capacity (P) in year t (i.e., setting $P_t = B_t/K$) to improve the efficiency of the MCMC algorithm for estimating parameters (e.g., Meyer and Millar 1999). As such, the process dynamics for the temporal changes in the proportion of carrying capacity were

Equation 4 $$\boldsymbol{P_t = P_{t-1} + \frac{r}{m-1} P_{t-1}\left(1-\left(P_{t-1}\right)^{m-1}\right) - \frac{C_{t-1}}{K}}.$$

The values of exploitable biomass and harvest rate that maximized biomass production were relevant as biological reference points for fishery management and for estimating the MSY of bottomfish stocks. Based on Equation 3, the exploitable biomass that was required to produce maximum sustainable yield (B_{MSY}) was

Equation 5 $$B_{MSY} = Km^{\frac{-1}{m-1}}.$$

It follows that the shape parameter m can be arithmetically translated into a ratio of B_{MSY} to K (Prager 1994), such that

Equation 6 $$\frac{B_{MSY}}{K} = m^{\left(-\frac{1}{m-1}\right)}.$$

Within JABBA, the user actually enters a value of B_{MSY}/K to assign the prior mean for m. The harvest rate that was required to produce maximum sustainable yield (H_{MSY}) was

Equation 7 $$H_{MSY} = \frac{r}{m-1}\left(1-\frac{1}{m}\right) = \frac{r}{m},$$

where the harvest rate H was defined as the ratio of catch over biomass. The estimate of MSY was

Equation 8 $$MSY = H_{MSY} B_{MSY} = \frac{r}{m-1}\left(1-\frac{1}{m}\right)Km^{\frac{-1}{m-1}}.$$

2.3.2. Process and Observation Error Models

2.3.2.1. Process Error Model

Process error was added to the deterministic process dynamics (Equation 4). The process error model related the dynamics of exploitable biomass to natural variability in demographic and environmental processes affecting populations of BMUS. The deterministic process dynamics were subject to natural variation due to fluctuations in life history parameters, trophic interactions, environmental conditions, and other factors. In this case, the process error represented the joint effects of many random multiplicative events which combined to form a multiplicative lognormal process under the Central Limit Theorem. As a result, the process error terms were set to be independent and lognormally distributed random variables.

The process error model defined the stochastic process dynamics by relating the unobserved biomass states to the observed catches and the estimated population dynamics parameters. Given the multiplicative lognormal process errors, the state equations for the initial year (t = 1) and subsequent years (t > 1) were

Equation 9 $$P_t = \begin{cases} \varphi e^{\eta_t} & \textit{for } t = 1 \\ \left(P_{t-1} + \frac{r}{(m-1)} P_{t-1}\left(1 - P_{t-1}{}^{m-1}\right) - \frac{C_{t-1}}{K}\right)e^{\eta_t} & \textit{for } t > 1 \end{cases},$$

where η_t were identically distributed normal random variables with mean 0 and constant process error variance σ_{η}^2. Separate process error variance was estimated for each territory. The coupled process dynamic equation set the prior distribution for the proportion of carrying capacity $p(P_t)$ in each year t > *1*, conditioned on the proportion of carrying capacity in the previous period. The proportion of carrying capacity in the initial year was assigned its own prior $p(\psi)$, which is described in section 2.3.3. Prior Distributions.

2.3.2.2. Observation Error Model

An observation error model for the CPUE index was applied for each territory. The observation error model related the observed fishery CPUE to the exploitable biomass of each bottomfish stock. We assumed that the standardized fishery CPUE index (I_t) in year t was proportional to biomass with catchability coefficient *q* as

Equation 10 $\boldsymbol{I_t = \mathrm{q}B_t = \mathrm{q}P_tK}$.

Observation error was added to the deterministic index equation (Equation 10). The observed CPUE dynamics were subject to natural sampling variation which was assumed to be lognormally distributed. Given the lognormal observation errors, the observation equations for the CPUE index for each year *t* were

Equation 11 $\boldsymbol{I_t = \mathrm{q}P_tKe^{\tau_t}}$,

where τ_t were identically distributed normal random variables with mean 0 and total observation error variance $\sigma_{\tau_t}^2$. This specifies the CPUE observation error likelihood function $p(I_t|\theta)$ for each territory given model parameters and unobservable states θ. Separate observation errors were estimated for each territory.

JABBA partitions the annual total observation error variance into three separate components following Francis et al. (2003). The three components were: 1) $\sigma_{\tau_{SE_t}}^2$, the inter-annual variability in observation error inputted as the standard error on the scale of the logarithm of standardized CPUE in year *t*; 2) $\sigma_{\tau_{fixed}}^2$, an optional user-provided component of observation error that is constant across all years, and 3) $\sigma_{\tau_{estimated}}^2$, an estimated observation error that is constant across all years. Consequently, total observation error variance for year *y* for each territory was

Equation 12 $\boldsymbol{\sigma_{\tau_t}^2 = \sigma_{\tau_{SE_t}}^2 + \sigma_{\tau_{fixed}}^2 + \sigma_{\tau_{estimated}}^2}$.

Total observation error typically ranges from 0.1 to 0.4 (Francis et al. 2003). For these assessments, we did not use the optional fixed component of observation error ($\sigma_{\tau_{fixed}}^2 = 0$), but rather allowed the model to estimate the total observation error variance.

The previous stock assessment updates (Brodziak et al. 2012; Yau et al. 2016) and benchmark (Moffitt et al. 2007) assessments included an observation error model on fits to independent MSY estimates for each territories. These estimates were based on research conducted in the

Marianas (Polovina et al. 1985), and extended to include American Samoa, and were found in the Our Living Oceans (OLO) report by Humphreys and Moffitt (1999) and later Moffitt and Humphreys (2009). The methods used to estimate MSY were described in Polovina and Ralston (1986), and are a fishery-independent estimate which combines life history assumptions (von Bertalanffy growth, constant natural mortality, and constant recruitment) with data on length-frequency, CPUE, and an estimate of catchability from an intensive fishing experiment. The results were extrapolated along pre-determined isobaths for each territory. The estimates of OLO MSY were 55,000 pounds, 172,000 pounds, and 75,000 pounds for Guam, CNMI, and American Samoa, respectively.

Despite the OLO MSY estimates representing fishery-independent values which could inform parameter estimates for this set of stock assessments, no further documentation about the data or methods used to generate these OLO MSY estimates could be found. As such, these OLO MSY estimates were not used for fitting to data in the base case model for the current stock assessments. As described in the section below, the independent OLO MSY estimates were used to inform the mean value for the prior distribution of carrying capacity. The effect of including the independent OLO MSY estimates in data fitting was addressed as a sensitivity analysis, and the observation error model for this sensitivity is described in section 2.3.8. Sensitivity Analysis.

2.3.3. Prior Distributions

A Bayesian estimation approach was used to estimate production model parameters. Prior distributions were used to represent existing knowledge and beliefs about the likely values of model parameters. The intrinsic growth rate parameter *r*, the production shape parameter *m*, the carrying capacity parameter *K*, the ratio of initial biomass to carrying capacity parameter ψ, the catchability parameter *q*, and the process error σ_{η}^2 and the estimable component of observation error $\sigma_{\tau_{estimated}}^2$ variance parameters had prior distributions. Unobserved biomass states expressed as the proportion of carrying capacity were included in the joint prior distribution and were conditioned on the parameter estimates and the previous biomass as a proportion of carrying capacity and catch. A summary of assumed priors is found in Table 9. The effect of the choice of prior assumptions on model results was assessed through sensitivity analyses as described in section 2.3.8. Sensitivity Analysis.

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 13 $$p(r)=\frac{1}{r\sigma_r\sqrt{2\pi}}exp\left(-\frac{(\ln r-\mu_r)^2}{2\sigma_r^2}\right).$$

As input for a lognormal prior on *r*, JABBA requires the user to enter the mean on the original scale, and the standard deviation on the scale of the natural logarithm. The value of the prior mean of the intrinsic growth rate parameter was set to $\mu_r = 0.46$ for each territory and the prior variance value was set such that the coefficient of variation was 50%. The prior mean and variance values were the same used in the last update assessment; however, that assessment assumed a beta distribution (Yau et al. 2016). JABBA does not use the beta distribution for *r* and so we used a lognormal distribution instead. A prior mean value of 0.46 is near the upper range of medium productivity species as suggested by Musick (1999), but is approximately the midpoint of the range (0.2–0.8) assumed by Froese et al. (2017) for medium resilient species. Medium categories were supported by values for age at maturity, maximum age, and the Brody growth coefficient for BMUS from an analysis of information available in FishBase (Froese and Pauly 2018) by Thorson et al. (2017), and from resiliency categories in FishBase for the majority of BMUS.

Prior for Production Shape Parameter

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

Equation 14 $$p(m) = \frac{1}{m\sigma_m\sqrt{2\pi}} exp\left(-\frac{(ln\, m - \mu_m)^2}{2\sigma_m^2}\right).$$

JABBA parameterizes the *m* prior based on user input for B_{MSY}/K, where *m* is determined from B_{MSY}/K according to Equation 6. As input for the lognormal prior on *m*, JABBA requires the user to enter the mean of B_{MSY}/K on the original scale, and the standard deviation of *m* on the scale of the natural logarithm. The prior mean of the production shape parameter was set to $\mu_m = 2$ ($B_{MSY}/K = 0.5$) with a value of the variance for *m* set so that the coefficient of variation was 50%. This mean value for *m* corresponds to the value of *m* for a Schaefer production model, which was the assumed production function for the previous update assessment, and the choice of CV approximated a 95% confidence interval from 0.8 to 5. In effect, the production shape parameter prior was centered on the symmetric Schaefer production model as the default with flexibility to fit an asymmetrical production function.

The production shape parameter for CNMI was fixed at 2, and thus was set to follow the Schaefer production function. We fixed the surplus production function to be a Schaefer for CNMI because the catch and CPUE data showed little contrast in comparison to data for Guam and American Samoa, and therefore we assumed that the model for CNMI would have difficulty estimating *m*. We tested the effect of our choice of fixing *m* through a sensitivity analysis for CNMI by allowing the model to estimate *m* from the prior distribution described above. This sensitivity analysis is described in section 2.3.8. Sensitivity Analysis.

Prior for Carrying Capacity

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

Equation 15 $$p(K) = \frac{1}{\mathbf{K}\boldsymbol{\sigma}_{\mathbf{K}}\sqrt{2\pi}} \mathbf{exp}\left(-\frac{(\mathbf{ln\,K} - \boldsymbol{\mu}_{\mathbf{K}})^2}{2\boldsymbol{\sigma}_K^2}\right).$$

As input for a lognormal prior on *K*, JABBA requires the user to enter the mean and coefficient of variation on the original scale. The values of the prior means of carrying capacity were set to μ_K = 478,261, 1,495,652, and 652,174 pounds for Guam, CNMI, and American Samoa, respectively. The prior variance was set for all territories so that the coefficient of variation was 50%. The mean values were set following the same procedure as was used in the last benchmark assessment (Moffitt et al. 2007), which was to match the *MSY* calculated from the prior mean for intrinsic rate of growth, carrying capacity, and production shape parameter to the independent OLO MSY estimates for each territory as reported in Humphreys and Moffitt (1999). The independent OLO estimates of MSY were 55,000 pounds for Guam, 172,000 pounds for CNMI, and 75,000 pounds for American Samoa.

Prior for Ratio of Initial Biomass to Carrying Capacity

The prior distribution for the ratio of initial biomass to carrying capacity $p(\psi)$ was a moderately informative lognormal distribution with mean (μ_ψ) and variance (σ_ψ^2) parameters:

Equation 16 $$p(\psi) = \frac{1}{\boldsymbol{\psi\sigma_\psi}\sqrt{2\boldsymbol{\pi}}}\mathbf{exp}\left(-\frac{\left(\mathbf{ln}\,\boldsymbol{\psi}-\boldsymbol{\mu}_\psi\right)^2}{2\boldsymbol{\sigma}_\psi^2}\right).$$

As input for a lognormal prior on ψ, JABBA requires the user to enter the mean and coefficient of variation on the original scale. The values of the prior means of the ratio of initial biomass to carrying capacity were set to μ_ψ = 0.75, 0.45, and 0.8 for Guam, CNMI, and American Samoa, respectively. The prior variance was set for all territories so that the coefficient of variation was 50%. The mean values were identical to the values used in the previous update assessment, but the coefficient of variation was increased from 20% to 50%. The previous update assessment used the same values from the previous benchmark, which derived prior means from a grid search of a few K-ψ pairings. We did not do a similar grid search for the current assessment, but instead allowed greater flexibility in the prior distribution for both *K* and ψ by increasing CV to 50%.

Prior for Catchability

The prior distribution for fishery catchability *p(q)* was chosen to be an uninformative uniform distribution on the interval [10^{-10}, 10]. This diffuse prior was chosen to allow the data and model structure to completely determine the distribution of fishery catchability estimates.

Prior for Variability Around Catch

An informative prior was used to incorporate annual variability in catch in year *t* into model estimates. The prior distribution for catch uncertainty $p(C_t)$ was an informative lognormal distribution with mean (μ_{C_t}) and variance ($\sigma_{C_t}^2$) parameters:

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

The mean parameter was set to the value of catch in each year and variance was set to match the coefficient of variation in each year from the bootstrapped catch estimates, which were calculated as described in section 2.1.2. Catch Variance. The catch variation prior was chosen to propagate uncertainty inherent in the expansion of interview data to total catch into the estimation of sustainable harvest rates and biomasses. In effect, including in the model variation around catch estimates accounts for uncertainty in the data for total catch.

Priors for Error Variances

The prior distributions for the process error $p(\sigma_\eta^2)$ and the estimated component of the observation error $p(\sigma_{\tau_{estimated}}^2)$ were chosen to be moderately informative inverse-gamma distributions with rate parameter $\lambda > 0$ and shape parameter $k > 0$:

Equation 18 $$p\left(\sigma_x^2\right)=\frac{\lambda^k\left(\sigma^2\right)^{-k-1}exp\left(\frac{-\lambda}{\sigma^2}\right)}{\Gamma\left(k\right)},$$

where x represents either η or $\tau_{estimated}$. The inverse-gamma distribution is a useful choice for priors that describe model variances (Congdon 2001). For the process and estimated observation error variance priors, the rate parameter was set to $\lambda = 0.1$ and the shape parameter was $k = 0.2$. These values followed the same process for determining prior parameters values as was done in the last update assessment (Yau et al. 2016), and were identical to the values used for the process error prior. For this choice of parameters, the expected value of the inverse-gamma distribution is not defined, and the mode for σ_x^2 denoted as MODE[σ_x^2] = 1/12 ≈ 0.083 provides an alternative measure of the central tendency of the distribution. The choice of the process error prior matched the expected scaling of process errors for the state equations describing changes in the proportion of carrying capacity (Equation 9), which was on the order of 0 to 1. Similarly, the choice of the observation error prior matched the expected scaling of observation errors for the observation equation describing the model fit to observed CPUE (Equation 11). The observation error prior was based on CPUE and corresponding standard error values on the scale of the logarithm, which were on the order of 0 to 1. The central tendency of 0.083 for the process error is higher than the level of process error where state-space surplus production models are most likely to adequately perform, e.g., have lower model errors (Thorson et al. 2014), but is similar to or lower than the errors used in the last benchmark and update assessments.

2.3.4. Posterior Distribution

Independent samples from the joint posterior distribution of the surplus production model were numerically simulated to estimate model parameters and make inferences. The joint posterior distribution of model parameters and unobservable states θ given the data D, p(θ|D), was proportional to the product of the priors of the parameters and unobservable states, and the joint likelihood of the CPUE data across all *n* years:

Equation 19

$$p(\theta \mid D) = p(r)\,p(m)\,p(K)\,p(\varphi)\,p(q)\,p\left(\sigma_{\eta}^{2}\right)\prod_{t=1}^{n} p\left(\sigma_{\tau_t}^{2}\right)\prod_{t=1}^{n} p(C_t)$$
$$\times\, p\left(P_1 \mid \psi, K, \sigma_{\eta}^{2}\right)\prod_{t=2}^{n} p\left(P_t \mid P_{t-1}, r, m, K, \psi, \sigma_{\eta}^{2}\right)\prod_{t=1}^{n} p\left(I_t \mid P_t, q, K, \sigma_{\tau_t}^{2}\right)$$

Parameter estimation for multi-parameter and nonlinear Bayesian models, such as those used in this assessment, is typically based on simulating a large number of independent samples from the posterior distribution (Gelman et al. 1995). JABBA uses MCMC simulation (Gilks et al. 1996) to numerically generate samples from the posterior distribution.

MCMC simulations were done for each territory. Initial starting conditions of the MCMC chains were randomly drawn from their respective prior distributions. Two chains of 300,000 samples each were then simulated from the posterior distribution. The first 60,000 samples of each simulated chain for CNMI, and the first 75,000 samples of each simulated chain for Guam and American Samoa were excluded from the estimation process to remove dependence of the MCMC chain on the initial conditions and to ensure stationarity of the remaining samples in the chain. Each chain was then thinned by 5 to reduce autocorrelation (e.g., every fifth sample from the posterior distribution was stored and used for inference). As a result, a total of 96,000 samples for CNMI, and a total of 90,000 samples for Guam and American Samoa were available to summarize model results.

Prior distributions and estimated posterior distributions were compared to show whether the catch and standardized CPUE data were informative for estimating model parameters. This comparison included the priors and posteriors for the following model parameters: intrinsic growth rate, production shape, carrying capacity, ratio of initial biomass to carrying capacity, catchability, estimable observation error variance, and process error variance. Posteriors of the derived quantities MSY, B_{MSY}, and H_{MSY} were also compared to their respective derived prior distributions.

2.3.5. Convergence and Model Diagnostics

Convergence of the simulated MCMC samples to the posterior distribution was assessed via visual inspection of the trace and autocorrelation plots, and confirmed using the Geweke convergence diagnostic (Geweke 1992), and the Heidelberger and Welch stationarity and half-width diagnostics (Heidelberger and Welch 1992). The set of convergence diagnostics were applied to key model parameters (intrinsic growth rate, production function shape parameter, carrying capacity, ratio of initial biomass to carrying capacity, catchability coefficients, and error variances) to verify convergence of the MCMC chains to the posterior distribution.

Residuals from the base case model fit to CPUE were used to measure the goodness of fit of the production model. These log-scale observation errors $\varepsilon_{i,T}$ of observed minus predicted CPUE were

Equation 20 $\varepsilon_{i,T} = \ln\left(I_{i,T}\right) - \ln\left(q_i K P_T\right)$.

Nonrandom patterns in the CPUE residuals would suggest that the observed CPUE may not have conformed to one or more model assumptions. We tested normality of the log-scale residuals using the Shapiro-Wilk test, patterns in the sign of the residuals using a runs test, and trend in the residuals by assessing if the slope of a regression of the residuals over time was significantly different than zero. All residuals tests were done using a p-value of 0.05.

2.3.6. Retrospective Analysis

A retrospective analysis was conducted to assess whether there were consistent patterns in model-estimated outputs based on decreasing periods of data (Mohn 1999). The retrospective analysis was conducted by successively removing the catch and CPUE data for years 2017 to 2013 in one-year increments such that the terminal years of the model ranged from 2016 to 2012, re-estimating model parameters, and comparing the resulting biomass and harvest rate time series with the model with all data included. The magnitude of the retrospective pattern was assessed using Mohn's rho (ρ; Mohn 1999), which computes relative patterns of deviations with respect to a base case model:

Equation 21 $\rho = \sum_{y=2012}^{2016} \frac{X_{(y1:y),y} - X_{(y1:y2),y}}{X_{(y1:y2),y}}$,

where y_1 = the start year of data for each territory and y_2 = 2017, 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 2012 to 2016).

2.3.7. Catch Projections

Estimated posterior distributions of base case assessment model parameters were used in forward projections for 2020–2025 to estimate the probability of overfishing, P^*, from 2020 to 2025 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.

The projections were conducted assuming each value for the future catch was constant through all projection years. The projected total catch scenarios ranged from 0 to 200,000 lb in 1000-lb increments for Guam and American Samoa, and 0 to 500,000 lb in 1000-lb increments for CNMI. To move the model forward to the starting year of projections, total catches from 2018 to 2019 were set equal to the average catch value from 2015 to 2017. Projections were used to compute reported catches for 2020–2025 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 limit (OFL). Other quantities of interest were also calculated, including corresponding relative biomass (B/B_{MSY}), stock status, and risks of overfishing and overfished status.

2.3.8. Sensitivity Analysis

A suite of sensitivity analyses were conducted to evaluate how the base case model results would be affected if different assumptions were made regarding model structure, prior distributions, data sources, and initial conditions. The initial conditions and of the MCMC sampler for the sensitivities were kept the same as for the base case, except where otherwise noted. Scenarios for sensitivity analyses are described below and in Table 10.

Sensitivity to alternative prior distribution for intrinsic growth rate

The sensitivity of base case model results to the prior distribution for intrinsic growth rate was evaluated by fitting the model using four different prior distributions for *r*. The same sensitivities were done for each territory. In the first and second sensitivity, the prior mean for *r* was changed by ±50%, which corresponded to values $\mu_r = 0.23$ (50% decrease in base case prior mean) and $\mu_r = 0.69$ (50% increase in base case prior mean). In the third sensitivity, the prior mean for *r* was set to $\mu_r = 0.33$ and the prior variance value was set such that the coefficient of variation was 30%. A prior mean of 0.33 was the midpoint of the probable range of *r* (0.16–0.5) recommended by Musick (1999) for medium productivity stocks and a CV of 30% produced a 95% confidence interval that approximated the suggested range. In the fourth sensitivity, the prior distribution for *r* was set by supplying a lower and upper range for *r* values of 0.015 and 0.8, respectively. The model assumes a lognormal distribution with prior mean set to the geometric mean of the range values, and standard deviation set to approximate a 95% confidence interval at the range values (Winker et al. 2018). The resulting values from this sensitivity were a prior mean value of 0.15 and CV of 115%. The range of 0.015 and 0.8 reflected the range of *r* values for very low to medium resiliency categories provided in Froese et al. (2017) based on resiliency from FishBase across all BMUS. Altogether, the sensitivity analyses addressed whether the choice of the base case prior distribution for *r* had a strong influence on model results.

Sensitivity to alternative prior distribution for production model shape parameter

The sensitivity of base case model results to the prior distribution for the production model shape parameter *m* was evaluated by fitting the model using four different prior distributions for *m* for Guam and American Samoa, and fitting the model using a single different prior distribution for *m* for CNMI. In the first and second sensitivities for Guam and American Samoa, the prior mean for *m* was changed by ±50%, which corresponded to values $\mu_m = 1$ (50% decrease in base case prior mean) and $\mu_m = 3$ (50% increase in base case prior mean). In the third sensitivity for Guam and American Samoa, the prior mean for *m* was set to 0.92 with a CV of 80%. This prior mean was calculated from the average ratio of biomass at maximum sustainable yield to carrying capacity for Perciformes ($B_{MSY}/K = 0.353$) from an analysis of 147 stocks (Thorson et al. 2012). The production shape parameter prior mean was calculated from B_{MSY}/K following Equation 6 which yields $m = 0.92$ for $B_{MSY}/K = 0.353$. Thorson et al. (2012) present a coefficient of variation for B_{MSY}/K of 34%, but because JABBA requires a CV for *m*, the prior variance value for *m* was set such that the coefficient of variation was 80%, which approximates a CV of 34% for B_{MSY}/K. In the fourth sensitivity for Guam and American Samoa, a Schaefer surplus production curve was assumed, thereby fixing the prior mean for *m* at 2.

The sole sensitivity for CNMI assumed the base case assumptions from Guam and American Samoa, that is the prior mean was set to $m = 2$ and the variation was set so that the coefficient of variation was 50%. Essentially, the sensitivity was that instead of setting $m = 2$ and thereby assuming a Schaefer production function, a Pella-Tomlinson model was used with the prior distribution equivalent to the distribution assumed for the base case models for Guam and

American Samoa. Altogether, the sensitivity analyses addressed whether the choice of the base case prior distribution for m had a strong influence on model results.

Sensitivity to alternative prior distribution for carrying capacity

The sensitivity of base case model results to the prior distribution for carrying capacity was evaluated by fitting the model using four different prior distributions for K for each territory. In the first and second sensitivity, the prior mean for K was changed by ±50%, which corresponded to values μ_K = 239,130 pounds (50% decrease in base case prior mean) and μ_K = 717,391 pounds (50% increase in base case prior mean) for Guam; μ_K = 747,826 pounds (50% decrease in base case prior mean) and μ_K = 2,243,478 pounds (50% increase in base case prior mean) for CNMI, and μ_K = 326,087 pounds (50% decrease in base case prior mean) and μ_K = 978,261 pounds (50% increase in base case prior mean) for American Samoa. In the third sensitivity, the coefficient of variation for the prior distribution for K was decreased to 20%. In the fourth sensitivity, the prior distribution for K was set by supplying a lower and upper range for K values of

Equation 22 $$K_{low} = \frac{2 \times max(catch)}{r_{high}},\ K_{high} = \frac{12 \times max(catch)}{r_{low}},$$

where r_{high} = 1.16 and r_{low} = 0.18 were the upper and lower 95% confidence intervals from the base case prior distribution for intrinsic rate of growth. Equation 22 was based on recommendations from Froese et al. (2017) for lightly exploited populations, as suggested by the previous update assessment (Yau et al. 2016). The maximum total catch in the base case was 68,251 pounds for Guam, 176,129 pounds for CNMI, and 90,689 for American Samoa. Consequently, the range of K values in pounds was (117,674 and 4,550,067) for Guam, (303,671 and 11,741,933) for CNMI, and (156,360 and 6,045,933) for American Samoa. The model assumes a lognormal distribution with prior mean set to the geometric mean of the range values, and standard deviation set to approximate a 95% confidence interval at the range values (Winker et al. 2017). Altogether, the sensitivity analyses addressed whether the choice of the base case prior distribution had a strong influence on model results.

Sensitivity to alternative prior distribution for ratio of initial biomass to carrying capacity

The sensitivity of base case model results to the prior distribution for the ratio of initial biomass to carrying capacity was evaluated by fitting the model using six different prior distributions for ψ for each territory. In the first and second sensitivity, the prior mean for ψ was changed by ±50%, which corresponded to values μ_ψ = 0.375 (50% decrease in base case prior mean) and μ_ψ = 1.5 (50% increase in base case prior mean) for Guam; μ_ψ = 0.225 (50% decrease in base case prior mean) and μ_ψ = 0.9 (50% increase in base case prior mean) for CNMI, and μ_ψ = 0.4 pounds (50% decrease in base case prior mean) and μ_ψ = 1.6 (50% increase in base case prior mean) for American Samoa. In the third sensitivity, the coefficient of variation for ψ from the previous update assessment was used, which was 20%. In the fourth and fifth sensitivities, the prior distribution for ψ was set by supplying a lower and upper range for ψ values of 0.2–0.6 and 0.5–0.9, respectively. The model assumes a lognormal distribution with prior mean set to the geometric mean of the range values, and standard deviation set to approximate a 95% confidence interval at the range values (Winker et al. 2017). The resulting values for the lognormal distribution for ψ in the fourth and fifth sensitivity were 0.35 and 0.67 for the prior means, respectively, with variance values such that the CVs were 28% and 15%, respectively. The ranges 0.2–0.6 and 0.5–0.9 reflected the range of ψ values for species with medium and high prior biomasses, respectively, as assumed by Froese et al. (2017). Both ranges were used although Froese et al. (2017) suggest medium biomass be used for stocks such as ours where the catch data starts after 1960. In the sixth sensitivity, the prior distribution was changed to a beta distribution with shape parameters $\alpha = 1.5$ and $\beta = 1.5$. These values for the shape parameters corresponded to a beta distribution centered at 0.5 and spread across its domain with sufficient probability to cover the range from 0 to 1, and therefore reproduces a uniform distribution, for which JABBA currently does not have functionality. Initial conditions for the MCMC chains for the beta sensitivity were changed to come from the beta distribution. This was done to reflect the change in domain when going from a lognormal distribution to a beta distribution. Altogether, the sensitivity analyses addressed whether the choice of the base case prior distribution for ψ had a strong influence on model results.

Sensitivity to alternative prior distribution for observation and process error variance

The sensitivity of base case model results to the prior distributions for the estimated observation and process error variance was evaluated using three different prior distributions for σ_{η}^{2} and separately for $\sigma_{\tau_{estimated}}^{2}$ for each territory. Sensitivities were done for each error variance separately. In the first and second sensitivity, the rate parameter λ of the inverse-gamma distribution was changed such that the prior mode, which equaled $\lambda/(k+1)$, was decreased and increased an order of magnitude to 0.00833 and 0.833, respectively. Note that the value for the shape parameter k was 0.2. In the third sensitivity, a non-informative uniform prior distribution on the interval [0,10] was used for the standard deviation of process and estimated observation errors, as opposed to an inverse-gamma prior distribution on the error variances, as recommended by Gelman (2006). Initial conditions for the MCMC chains for the uniform sensitivity were changed to come from the uniform distribution. This was done to reflect the change in domain when going from an inverse-gamma distribution to a uniform distribution. Altogether, the sensitivity analyses addressed whether the choice of the base case prior distribution values and distribution for σ_{η}^{2} and $\sigma_{\tau_{estimated}}^{2}$ had a strong influence on model results.

Sensitivity to excluding variation around catch

The sensitivity of excluding variability around the catch estimates was assessed using a single sensitivity. For this sensitivity, the variation around catch was removed from the model. In effect, this sensitivity analyses addressed whether including additional uncertainty in the catch time series had a strong influence on model results.

Sensitivity to inclusion of OLO MSY estimates

The sensitivity of base case model results to fitting model-estimated *MSY* to the independent OLO MSY estimates was evaluated. Estimates of OLO MSY for each territory were 75,000 pounds for Guam, 172,000 for CNMI, and 55,000 pounds for American Samoa (Humphreys and Moffitt 1999). The independent estimates were added as an observation error model for model-estimated *MSY*. As such, this sensitivity explored the extent to which the independent estimates of OLO MSY affected the estimated model parameters and quantities.

Observation error was added to the equation for calculating *MSY* (Equation 8), which became

Equation 23 $$\boldsymbol{MSY} = \frac{\boldsymbol{r}}{\boldsymbol{m}-1}\left(1-\frac{1}{\boldsymbol{m}}\right)\boldsymbol{K}\boldsymbol{m}^{\frac{-1}{\boldsymbol{m}-1}} \cdot \xi ,$$

where ξ was a normally distributed random variable with mean 0 and error variance σ^2_{msy}. We assumed σ^2_{msy} was fixed such that the coefficient of variation of the OLO MSY estimate was 20%. The choice of 20% matches the assumptions made in the previous update and benchmark assessments for the independent OLO MSY estimates.

Sensitivity to initial conditions

The sensitivity of base case model results to the initial conditions used for the MCMC sampler was evaluated. In the base case, initial conditions were set using a single random draw from the prior distribution of each parameter. Consequently, for this sensitivity, the assessment model was rerun 10 times with different random seeds to allow for different initial conditions. The same random seeds were used for each chain.

3. Results for Assessment Model

3.1. Convergence Diagnostics

Convergence diagnostics indicated that the MCMC simulation to estimate the posterior distribution of production model parameters converged. The Geweke diagnostic test was passed for all parameters across all chains except for one chain of the ratio of initial biomass to carrying capacity for Guam. The Heidelberger and Welch stationarity and half-width diagnostic tests were passed by all of the parameters for both chains using all samples and using a ratio of half-width to sample mean of 0.1. Autocorrelation was low for all parameters. The highest lag-1 autocorrelation was less than 0.013 for all parameters in models for all territories. Visual inspection of trace plots of parameters did not reveal convergence issues. Overall, convergence diagnostics suggested that the MCMC sampler for the base case assessment models converged to a stationary distribution for each.

3.2. Assessment Model Diagnostics

The predicted CPUE from the base case model provided a good fit to the standardized CPUE observations for all three territories (Figure 16, Figure 17, and Figure 18). Residuals (Figure 19 – Figure 21) were normal (p = 0.81 for Guam, p = 0.95 for CNMI, and p = 0.20 for American Samoa), did not exhibit patterns in sign (p = 0.31 for Guam, p = 0.66 for CNMI, and p = 0.98 for American Samoa), and did not exhibit temporal trend (p = 0.51 for Guam, p = 0.60 for CNMI, and p = 0.77 for American Samoa).

Comparisons of assumed prior distributions and estimated posterior distributions showed that the priors were more informative or similarly informative relative to the information in the data for some model parameters and derived quantities than others, although the prior distributions for derived quantities MSY, B_{MSY}, H_{MSY}, and B_{MSY}/K were not formally set but instead derived from the priors for r, K, and m. For Guam, the median posterior estimate of K was 12% greater than the median of the prior distribution, the median estimate of the shape parameter m was 13% lower than the median of the prior distribution, and the median estimate for ψ was 10% greater than the median of the prior distribution (Table 9; Table 11; Figure 22). The derived quantities B_{MSY} and B_{MSY}/K were estimated to be 6% greater and 5% lower than the median of the prior distributions, respectively (Figure 23). The prior was less similar to the posterior for the parameter r, which was estimated to be 36% lower than the median of the prior distribution (Table 9; Table 11), and for the derived quantities MSY and H_{MSY}, which were estimated to be 24% and 28% lower than the median of the prior distribution, respectively (Figure 23). For CNMI, the prior was most similar to the posterior for the parameter ψ, which was estimated to be 6% greater than the median of the prior distribution (Table 9; Table 11; Figure 24). Prior distributions were less similar to the posterior for the parameters K and r, with estimates 24% and 27% lower than the median of the prior distribution, respectively (Table 9; Table 11; Figure 24); and for the estimate of the derived quantity MSY (46% lower than the median of the prior distribution), B_{MSY} (24% lower than the median of the prior distribution), and H_{MSY} (27% lower than the median of the prior distribution) (Figure 25). For American Samoa, the prior was most similar to the posterior for the parameter ψ, which was estimated to be 11% lower than the median of the prior distribution (Table 9; Table 11; Figure 26), and for B_{MSY} and B_{MSY}/K, which were estimated to be 16% lower and 11% higher than the median of the prior distributions, respectively (Figure 27). The priors were less similar to the posteriors for the shape parameter m

(posterior estimate 33% greater than the median of the prior distribution), *K* (posterior estimate 24% lower than the median of the prior distribution) and *r* (posterior estimate 39% lower than median of the prior distribution) (Table 9; Table 11; Figure 26). Priors were also less similar to the posteriors for the derived quantities *MSY* (posterior estimate 61% lower than prior median) and H_{MSY} (estimate 53% lower than the median of the prior distribution; Figure 27). Posterior distributions for catchability, process error, and the estimable component of observation error for all territories were substantially different from prior distributions, which were chosen to be uninformative (Table 9; Table 11; Figure 22, Figure 24, and Figure 26).

Parameter correlations aligned with expectations for a production model and therefore did not suggest problems with parameter estimation. For Guam, the greatest correlation (–0.73) occurred among carrying capacity *K* and catchability *q* (Figure 28) which both scale biomass to the relative CPUE index (Equation 10). Correlations among other parameters were less than 0.46 in magnitude. For CNMI, the highest correlation was –0.45 for the parameters *K* and *r*, with other correlations less than 0.40 in magnitude (Figure 29). For American Samoa, the greatest correlation was –0.60 for *K* and *q*, followed by *m* and *r* (0.47). Correlations among other parameters were less than 0.35 in magnitude (Figure 30). Total observation error (i.e., the sum of the uncertainty in the standardized CPUE estimates and the uncertainty estimated within the production model as described by Equation 12) averaged 0.084 and varied from 0.078 to 0.096 among years for Guam (Figure 31), averaged 0.51 and varied from 0.41 to 0.94 for CNMI (Figure 32), and averaged 0.17 and varied from 0.165 to 0.175 for American Samoa (Figure 33). Only the average total observation error for American Samoa was within the range of 0.1 to 0.4 suggested by Francis et al. (2003) as reasonable, with the estimate for Guam being slightly lower and the estimate for CNMI being higher. The larger observation error for the CNMI model was likely due to there being less contrast in the data compared to the models for Guam and American Samoa.

3.3. Parameter Estimates and Stock Status

Production model results included parameter estimates and stock status of bottomfish stocks for each territory relative to MSY-based reference points. Quantities of interest, including parameter estimates and time series of harvest rate and biomass were calculated from the median of their respective posterior distributions. Time series of the relative harvest rate (harvest rate in a given year compared to H_{CR}, e.g., in 2017 the relative harvest rate was the ratio H_{2017}/H_{CR}) and relative biomass (biomass in a given year compared to B_{MSY}, e.g., in 2017 the relative biomass was the ratio B_{2017}/B_{MSY}) were also calculated using the median of the posterior distributions of the ratios relative harvest rate and relative biomass to determine stock status.

3.3.1. Guam

Production model estimates indicated that H_{MSY} was 17% and that B_{MSY} was 248.8 thousand pounds of exploitable bottomfish with an associated *MSY* of 42.1 thousand pounds (Table 11). Median estimates of the MSY-based reference points of maximum sustainable yield for the catch (*MSY*) with 95% confidence interval, the harvest rate to produce maximum sustainable yield (H_{MSY}) with 95% confidence interval, and the exploitable biomass to produce maximum sustainable yield (B_{MSY}) with 95% confidence interval were

1) *MSY* = 42.1 thousand pounds (29.3 – 65.5 thousand pounds)

2) H_{MSY} = 17.0% (7.1% – 38.2%), and

3) B_{MSY} = 248.8 thousand pounds (107.1 – 636.8 thousand pounds).

Bottomfish biomass exhibited a decline from 443 thousand pounds in 1982 to values below 0.7 × B_{MSY} starting in the early 1990s, increased in the early 2000s, varied between 180 and 228 thousand pounds from 2004 through 2011, and declined to 143 thousand pounds in 2017 (Table 12, Figure 34). The estimated harvest rate increased from 6% in 1982 to a peak of 42% in 2000, declined to 15% in 2002 and varied from 8% to 24% from 2003 through 2016, and was 11% in 2017 (Table 12, Figure 34).

Base case model results indicated that the BMUS stock in Guam was overfished from 1995–2003, and in 2014–2017 which is the terminal year of these assessments (B_{2017}/B_{MSY} = 0.57; Table 12; Figure 34 and Figure 35). The BMUS stock in Guam was experiencing overfishing in 1985, 1988, 1992–2003, 2006, 2009, 2011, 2013, and 2016, but not in 2017 (H_{2017}/H_{CR} = 0.81; Table 12; Figure 34; Figure 35). In 2017, there was a 70% probability that biomass exceeded the limit of 0.7 × B_{MSY} and a 39% probability that the harvest rate exceeded H_{CR} (Table 12; Figure 35). As a result, BMUS in Guam was categorized as overfished but not experiencing overfishing in 2017.

3.3.2. Commonwealth of the Northern Mariana Islands

Production model estimates indicated that H_{MSY} was 16.7% and that B_{MSY} was 570.6 thousand pounds of exploitable bottomfish with an associated *MSY* of 93.6 thousand pounds (Table 11). Median estimates of the MSY-based reference points of maximum sustainable yield for the catch (*MSY*) with 95% confidence interval, the harvest rate to produce maximum sustainable yield (H_{MSY}) with 95% confidence interval, and the exploitable biomass to produce maximum sustainable yield (B_{MSY}) with 95% confidence interval were

1) *MSY* = 93.6 thousand pounds (48.8 – 205.3 thousand pounds)

2) H_{MSY} = 16.7% (8.4% – 31.5%), and

3) B_{MSY} = 570.6 thousand pounds (271.8 – 1,287.0 thousand pounds).

Bottomfish biomass exhibited a decline from 528 thousand pounds in 2000 to 311 thousand pounds in 2008, increased to 465 thousand pounds in 2012, and was 569 thousand pounds in 2017 (Table 13; Figure 36). The estimated harvest rate decreased from 36% in 2000 to 5% in 2003, varied from 8% to 31% from 2004 through 2013 before declining to 2% in 2015, and was 12% in 2017 (Table 13; Figure 36).

Base case model results indicated that the BMUS stock in CNMI was overfished from 2005 – 2009, but not in subsequent years, including 2017 (B_{2017}/B_{MSY} = 1.08; Table 13; Figure 36; Figure 37). The BMUS stock in CNMI was experiencing overfishing in 2000-2001, 2004-2005, 2007, 2009-2010, and 2012, but not in 2017 (H_{2017}/H_{CR} = 0.79; Table 13; Figure 36; Figure 37). In 2017, there was a 24% probability that biomass exceeded the limit of 0.7*B_{MSY} and a 41% probability that the harvest rate exceeded H_{CR} (Table 13; Figure 37). As a result, BMUS in CNMI was categorized as not overfished and not experiencing overfishing in 2017.

3.3.3. American Samoa

Production model estimates indicated that H_{MSY} was 10.7% and that B_{MSY} was 272.8 thousand pounds of exploitable bottomfish with an associated *MSY* of 28.8 thousand pounds (Table 11). Median estimates of the MSY-based reference points of maximum sustainable yield for the catch (*MSY*) with 95% confidence interval, the harvest rate to produce maximum sustainable yield (H_{MSY}) with 95% confidence interval, and the exploitable biomass to produce maximum sustainable yield (B_{MSY}) with 95% confidence interval were

1) *MSY* = 28.8 thousand pounds (16.4 – 55.9 thousand pounds)

2) H_{MSY} = 10.7% (4.4% – 22.8%), and

3) B_{MSY} = 272.8 thousand pounds (120.8 – 687.4 thousand pounds).

Bottomfish biomass exhibited a decline from 335.9 thousand pounds in 1986 to 229.7 thousand pounds in 1991, increased to about 285–300 thousand pounds in the late 1990s, and declined to a low of 102.6 thousand pounds in 2017 (Table 14; Figure 38). The estimated harvest rate decreased from 27% in 1986 to 5% in 1993, varied from 6% to 15% from 1994 through 2007, and varied from 7% to 24% from 2008 through 2016, and was 15% in 2017 (Table 14 ; Figure 38).

Base case model results indicated that the BMUS stock in American Samoa was overfished from 2006 – 2017 (B_{2017}/B_{MSY} = 0.38; Table 14; Figure 38; Figure 39). The BMUS stock in American Samoa was experiencing overfishing in 1986, 1988–1989, 1994-1995, 1997, 2001–2017 (H_{2017}/H_{CR} = 2.75; Table 14; Figure 38; Figure 39). In 2017, there was a 91% probability that biomass exceeded the limit of 0.7*B_{MSY} and an 85% probability that the harvest rate exceeded H_{CR} (Table 14; Figure 39). As a result, BMUS in American Samoa was categorized as overfished and experiencing overfishing in 2017.

3.4. Retrospective Analysis

3.4.1. Guam

Retrospective analysis of the estimated biomass and harvest rate from the assessment model for Guam indicated that the model outputs did not exhibit substantial retrospective patterns (Figure 40). The retrospective pattern for biomass in the most recent 5 years was positive (ρ = 0.3) with terminal biomass estimates overestimating biomass compared to the base case model by about 6% on average as each year of data was removed (Figure 40). In other words, adding additional years of data to the model resulted in lower terminal biomass estimates. The opposite is true for biomass estimates early in the time series; adding additional years of data resulted in higher biomass before 2012. The corresponding pattern for harvest rates was negative (ρ = –0.43), representing an underestimate of harvest rate by about 8.5% on average as each year of data was removed (Figure 40). In other words, adding additional years of data to the model resulted in slightly higher terminal year harvest rate estimates.

3.4.2. Commonwealth of the Northern Mariana Islands

Retrospective analysis of the estimated biomass and harvest rate from the assessment model for CNMI indicated that the model outputs did not exhibit substantial retrospective patterns (Figure

41). The retrospective pattern for biomass in the most recent 5 years was negative ($\rho = -0.25$), indicating that the terminal year biomass estimate increased by about 5% on average as each new year of data was added (Figure 41). The corresponding pattern for harvest rates was positive ($\rho = 0.21$), indicating that the terminal year harvest rate estimate decreased by about 4% on average as each new year of data was added (Figure 41).

3.4.3. American Samoa

Retrospective analysis of the estimated biomass and harvest rate from the assessment model for American Samoa indicated that the model outputs did not exhibit retrospective patterns (Figure 42). The retrospective pattern for biomass in the most recent 5 years was negative ($\rho = -0.014$) with an increase in terminal year biomass estimates by about 0.3% on average as each new year of data was added (Figure 42). The corresponding pattern for harvest rates was positive ($\rho = 0.080$), representing a decrease in terminal year harvest rate by about 1.6% on average as each new year of data was added (Figure 42).

3.5. Catch Projections

3.5.1. Guam

The constant 6-year catch projection scenarios showed the distribution of outcomes for probability of overfishing, biomass, harvest rates, and probability of being overfished that would likely occur under alternative catch levels in Guam during 2020–2025 (Table 15; Table 16; Figure 43; Figure 44). Projections indicated that the Guam bottomfish catch that would produce approximately a 50% chance of overfishing in any year from 2020 through 2025 was 36 thousand pounds when for each terminal projection year catch was constant in all projection years preceding it (Table 15; Figure 44). For comparison, the catch that would lead to roughly a 40% chance of overfishing in any given year from 2020 to 2025 was between 30 and 32 thousand pounds (Table 15; Figure 44). The reported catch to achieve a lower risk of overfishing (e.g., 25% chance of overfishing) in any year from 2020 through 2025 varied from 20 to 25 thousand pounds depending on the terminal projection year (Table 16).

3.5.2. Commonwealth of the Northern Mariana Islands

The constant 6-year catch projection scenarios showed the distribution of outcomes for probability of overfishing, biomass, harvest rates, and probability of being overfished that would likely occur under alternative catch levels in CNMI during 2020–2025 (Table 17; Table 18; Figure 45; Figure 46). Projections indicated that the CNMI bottomfish catch that would produce approximately a 50% chance of overfishing in any year from 2020 through 2025 was between 95 and 109 thousand pounds when for each terminal projection year catch was constant in all projection years preceding it (Table 17; Figure 46). For comparison, the smallest catch that would lead to roughly a 40% chance of overfishing in any given year from 2020-2025 was between 83 and 92 thousand pounds (Table 17; Figure 46). The reported catch to achieve a lower risk of overfishing (e.g., 25% chance of overfishing) in any year from 2020 through 2025 varied from 65 to 67 thousand pounds depending on the terminal projection year (Table 18).

3.5.3. American Samoa

The constant 6-year catch projection scenarios showed the distribution of outcomes for probability of overfishing, biomass, harvest rates, and probability of being overfished that would likely occur under alternative catch levels in American Samoa during 2020–2025 (Table 19; Table 20; Figure 47; Figure 48). Projections indicated that the American Samoa bottomfish catch that would produce approximately a 50% chance of overfishing in any year from 2020 through 2025 was between 4 and 8 thousand pounds when for each terminal projection year catch was constant in all projection years preceding it (Table 19; Figure 48). For comparison, the smallest catch that would lead to roughly a 40% chance of overfishing in any given year from 2020-2025 was between 2 and 5 thousand pounds (Table 19; Figure 48). The reported catch to achieve a lower risk of overfishing (e.g., 25% chance of overfishing) from 2020 through 2025 varied from 0 to 2 thousand pounds (Table 20).

3.6. Sensitivity Analyses

Sensitivity of model results varied depending on which parameters or model assumptions were assessed, and which model result was being compared. Model results for all three territories were sensitive to assumed prior distributions for the parameters r, K, m, ψ, and the inclusion of independent OLO MSY estimates to varying degrees. Results for CNMI exhibited greater sensitivity to starting conditions compared to Guam and American Samoa, while results for Guam and American Samoa exhibited greater sensitivity to the shape of the production curve compared to CNMI. Model results were less sensitive to assumed prior distributions for observation and process variances. None of the results was sensitive to exclusion of variation in catch estimates.

Several sensitivity scenarios resulted in changes in the status for H_{2017}/H_{CR} or B_{2017}/B_{MSY} for Guam and CNMI. These sensitivity scenarios included scenarios for m and ψ for Guam, and r and ψ for CNMI. Status for H_{2017}/H_{CR} or B_{2017}/B_{MSY} did not change for American Samoa in any scenario. Further details on sensitivity analyses are provided below and summarized for Guam (Table 21), CNMI (Table 22), and American Samoa (Table 23).

3.6.1. Sensitivity to Alternative Prior Distribution for Intrinsic Growth Rate

Model results for Guam were sensitive to assumed mean prior values for intrinsic growth rate (Table 21; Figure 49). Assuming a lower prior mean parameter for r resulted in increased estimates of biomass and reduced harvest rate estimates (Figure 49). When the prior mean parameter for r was changed by –50% and 50%, the posterior estimate for r changed by –30% and 23%, respectively (Table 21). The model compensated for changes in the mean prior for r with estimates of K that were inversely related and estimates of m that were directly related (Table 21). Reducing the prior mean parameter for r to 0.15 while increasing the CV to 115% resulted in a 48% reduction in the estimate of r, with the estimate of K increasing by 41% and m decreasing by 22% (Table 21). This scenario represented the most substantial changes to estimated biomass and harvest rate among the r sensitivity scenarios (Figure 49). None of the r-prior sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam (Table 21; Figure 49).

Model results for CNMI were highly sensitive to assumed mean prior values for intrinsic growth rate (Table 22; Figure 50). Assuming a lower prior mean for r resulted in increased estimates of biomass but lowered the relative biomass, and reduced harvest rate estimates but increased the relative harvest rate (Figure 50). When the prior mean parameter for r was changed by –50% and 50%, the posterior estimate for r changed by –32% and 21%, respectively (Table 22). The model compensated for changes in the mean prior for *r* with estimates of *K* that were inversely related (Table 22). Reducing the prior mean parameter for *r* to 0.15 while increasing the CV to 115% resulted in a 52% reduction in the estimate of *r*, with the estimate of *K* increasing by 41% (Table 22) and the most substantial changes to estimated biomass and harvest rate among the *r* sensitivity scenarios (Figure 50). The sensitivity scenarios with a large decrease in the prior mean parameter for *r* (decrease of 50% and decrease to 0.15) changed the status for H_{2017}/H_{CR} from not overfishing to overfishing for CNMI (Table 22; Figure 50).

Model results for American Samoa were sensitive to assumed mean prior values for intrinsic growth rate (Table 23; Figure 51). Assuming a lower prior mean for *r* resulted in increased estimates of biomass and reduced harvest rate estimates (Figure 51). When the prior mean parameter for *r* was changed by –50% and 50%, the posterior estimate for *r* changed by –36% and 28%, respectively (Table 23). The model compensated for changes in the mean prior for *r* with estimates of *K* that were inversely related and estimates of *m* that were directly related (Table 23). Reducing the prior mean parameter for *r* to 0.15 while increasing the CV to 115% resulted in a 64% reduction in the estimate of *r*, with the estimate of *K* increasing by 43% and the estimate of *m* decreasing by 28% (Table 23). This scenario represented the most substantial changes to estimated biomass and harvest rate among the *r* sensitivity scenarios (Figure 51). None of the *r*-prior sensitivity scenarios resulted in a change in status for $B_{2017}/\mathrm{B}_{MSY}$ or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 51).

3.6.2. Sensitivity to Alternative Prior Distribution for Production Model Shape Parameter

Model results for Guam were highly sensitive to the assumed prior for the shape parameter. When the prior mean parameter for *m* was changed by –50% and 50%, the posterior estimates changed by –46% and 48%, respectively (Table 21). Increasing the CV of the *m* prior from 50% to 100% resulted in a 17% decrease in the posterior estimate of *m* (Table 21). Estimates of biomass and relative harvest rate were directly related to the assumed prior mean for *m*, whereas harvest rates and relative biomass were inversely related to prior mean values for *m* (Figure 52). The use of a Schaefer surplus production model that assumes *m* was fixed at 2 resulted in similar estimates for biomass and harvest rate compared to the base case Pella-Tomlinson model (Figure 52). Scenarios in which the prior mean parameter for *m* was reduced by 50% and to 0.92 with an 80% CV resulted in changes in status for B_{2017}/B_{MSY} from overfished to not overfished for Guam (Table 21; Figure 52). The scenario in which the prior mean parameter for *m* was increased by 50% resulted in change in status for H_{2017}/H_{MSY} from not overfishing to overfishing (Table 21; Figure 52).

Model results for CNMI were not sensitive to the scenario that assumed a prior on *m* rather than setting $m = 2$. Although the estimate of *m* increased by 8% for this scenario (Table 22), estimates of biomass in 2017 increased slightly (3%) and estimates of harvest rate in 2017 decreased slightly (2%; Table 22; Figure 53). The *m*-prior sensitivity scenario did not result in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI (Table 22; Figure 53).

Model results for American Samoa were sensitive to the assumed prior for the shape parameter. When the prior mean parameter for *m* was changed by –50% and 50%, the posterior estimates changed by –40% and 46%, respectively (Table 23). Increasing the CV of the *m* prior from 50% to 100% resulted in a 44% increase in the posterior estimate of *m* (Table 23). Estimates of biomass were directly related to the assumed prior mean for *m*, whereas harvest rates were inversely related to prior mean values for *m* (Figure 54). The use of a Schaefer surplus production model that assumed *m* was fixed at 2 resulted in reduced estimates of biomass and increased estimates of harvest rate relative to the base case Pella-Tomlinson model (Figure 54). Estimates of H_{MSY} increased and B_{MSY} decreased when the prior mean parameter for *m* was reduced (Table 23). None of the *m*-prior sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 54).

3.6.3. Sensitivity to Alternative Prior Distribution for Carrying Capacity

Model results for Guam were sensitive to assumed mean prior values for carrying capacity (Table 21; Figure 55). The sensitivity analysis indicated that estimates of exploitable biomass were scaled with the prior mean for *K* (Figure 55). Assuming a higher prior mean parameter for *K* resulted in greater estimates of biomass and reduced harvest rate estimates (Figure 55). The posterior estimates for *r* were inversely related to estimates of *K* and the posterior estimates of *m* were directly related to estimates of *K* (Table 21). When the mean prior parameter for *K* was changed by –50% and 50%, the posterior estimates for *K* changed by –27% and 28%, respectively (Table 21). Decreasing the CV of the *K* prior resulted in a 9% decrease in the estimate of *K*, and modeling the *K* prior as a range from 118 to 4,550 thousand pounds resulted in a 24% increase in the posterior estimate for *K* (Table 21). None of the *K*-prior sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam (Table 21; Figure 55).

Model results for CNMI were sensitive to assumed mean prior values for carrying capacity (Table 22; Figure 56). The sensitivity analysis indicated that estimates of exploitable biomass were scaled with the prior mean for *K* (Figure 56). Assuming a higher prior mean parameter for *K* resulted in greater estimates of biomass and reduced harvest rate estimates (Figure 56). The posterior estimates for *r* were inversely related to estimates of *K* (Table 22). When the mean prior parameter for *K* was changed by –50% and 50%, the posterior estimates for *K* changed by –36% and 34%, respectively (Table 22). Decreasing the CV of the *K* prior resulted in a 23% increase in the estimate of *K*, and modeling the *K* prior as a range from 303 to 11,741 thousand pounds resulted in a 14% decrease in the posterior estimate for *K* (Table 22). None of the *K*-prior sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI (Table 22; Figure 56).

Model results for American Samoa were sensitive to assumed mean prior values for carrying capacity (Table 23; Figure 57). The sensitivity analysis indicated that estimates of exploitable biomass were scaled with the prior mean for *K* (Figure 57). Assuming a higher prior mean parameter for *K* resulted in greater estimates of biomass and reduced harvest rate estimates (Figure 57). The posterior estimates for *r* were inversely related to estimates of *K* and the posterior estimate of *m* were directly related to estimate of *K* (Table 23). When the mean prior parameter for *K* was changed by –50% and 50%, the posterior estimates for *K* changed by –30% and 32%, respectively (Table 23). Decreasing the CV of the *K* prior resulted in a 24% increase in the estimate of *K*, and modeling the *K* prior as a range from 156 to 6,046 thousand pounds resulted in a 4% decrease in the posterior estimate for *K* (Table 23). None of the *K*-prior sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 57).

3.6.4. Sensitivity to Alternative Prior Distribution for Ratio of Initial Biomass to Carrying Capacity

Model results for Guam were sensitive to the assumed prior mean for ratio of initial biomass to carrying capacity. Estimates of biomass and harvest rate were very similar to the base case estimates for all ψ scenarios but estimates of relative biomass and relative harvest differed from base case values (Table 21; Figure 58). The sensitivity analyses indicated that posterior estimates of ψ changed by 9% and –17% when prior mean parameter for ψ was changed by 50% and -50%, respectively (Table 21). The model assuming the prior mean parameter of ψ = 0.35 (95% CI of 0.2–0.6) had the largest effects on parameter estimates; the posterior estimate of *K* increased 16%, the posterior estimate of *MSY* decreased by 7%, H_{2017}/H_{CR} increased 48% and the status changed from not overfishing to overfishing for Guam (Table 21; Figure 58).

Model results for CNMI were highly sensitive to the assumed prior mean for ratio of initial biomass to carrying capacity. Estimates of biomass were directly related to the assumed prior mean for ψ, whereas harvest rates were inversely related to prior mean values for ψ (Figure 59). When the mean prior parameter for ψ was changed by –50% and 50%, the posterior estimates of ψ changed by –42% and 32%, respectively (Table 22). The scenarios assuming a 50% reduction in the prior mean parameter for ψ resulted in a change in the estimate of status for B_{2017}/B_{MSY} from not overfished to overfished for CNMI (Table 22; Figure 59). The scenario assuming a 50% reduction in the prior mean parameter for ψ along with the scenario assuming the prior mean parameter of ψ = 0.35 (50% CI of 0.2–0.6) resulted in a change in status for H_{2017}/H_{CR} from not overfishing to overfishing for CNMI (Table 22; Figure 59).

Model results for American Samoa were sensitive to the assumed prior mean for ratio of initial biomass to carrying capacity. Estimates of biomass were directly related to the assumed prior mean for ψ, whereas harvest rates were inversely related to prior mean values for ψ (Figure 60). When the mean prior parameter for ψ was changed by -50% and 50%, the posterior estimates changed by –31% and 13%, respectively (Table 23). None of the ψ-prior sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 60).

3.6.5. Sensitivity to Alternative Prior Distribution for Process Error Variance

Model results for Guam were not sensitive to the assumed prior for process error variance (Table 21; Figure 61). Estimates of biomass and harvest rate for the sensitivity analyses differed by at most 9% and –8%, respectively from the base model and parameter estimates were very similar (Table 21; Figure 61). None of the process error sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam (Table 21; Figure 61).

Model results for CNMI were not sensitive to the assumed prior for process error variance. Estimates of biomass increased and estimates of harvest rate decreased for the scenario with the scale parameter for σ^2 reduced by a factor of 10, with changes most noticeable in the middle of the data times series (i.e., the late 2000s; Figure 62). Neither scenario resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI (Table 22; Figure 62).

Model results for American Samoa were not sensitive to the assumed prior for process error variance. Estimates of biomass and harvest rate were very similar to the base case model, but estimates of relative harvest rate in 2017 increased 18% for the scenario with the scale parameter for σ^2 reduced by a factor of 10 (Table 23; Figure 63). Neither scenario resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 63).

3.6.6. Sensitivity to Alternative prior Distribution for Observation Error Variance

Model results for Guam were not sensitive to the assumed prior for observation error variance (Table 21; Figure 64). Estimates of biomass and harvest rate were similar between the base case model and the scenario when the prior mode of τ^2 decreased by a factor of 0.1 (Figure 64). None of the observation error sensitivity scenarios resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam (Table 21; Figure 64).

Model results for CNMI were not sensitive to the assumed prior for observation error variance. Changes in biomass and harvest rate were similar to those observed for the process error sensitivities; however, contrary to the process error sensitivities, biomass increased and harvest rate decreased when observation error was increased (Figure 65). Neither scenario resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI (Table 22; Figure 65).

Model results for American Samoa were not sensitive to the assumed prior for process error variance. Estimates of biomass and harvest rate were similar to the base case whether the prior mode for τ^2 was decreased or increased by a factor of 10 (Figure 66). Neither scenario resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 66).

3.6.7. Sensitivity to Uniform Prior for Observation and Process Error Standard Deviation

Model results for Guam were not sensitive to assuming a uniform prior distribution for both observation and process error variances. Estimated biomass increased slightly and the estimated harvest rate decreased slightly for the scenario assuming uniform prior distributions (Figure 67). This sensitivity did not result in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam (Table 21; Figure 67).

Model results for CNMI were sensitive to assuming a uniform prior distribution for both observation and process error variances. Estimates of biomass increased 10% and estimates of harvest rate decreased 10% for the scenario with the uniform prior distributions (Table 22; Figure 68). This sensitivity did not result in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI (Table 22; Figure 68).

Model results for American Samoa were not sensitive to assuming a uniform prior distribution for both observation and process error variances. Similar to the sensitivity when decreasing the prior mode for process error variance, estimates of biomass decreased slightly and estimates of harvest rate increased for the scenario using uniform prior distributions (Figure 69). Neither scenario resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 69).

3.6.8. Sensitivity to Excluding Variability around Catch

Model results for Guam were not sensitive to excluding variability around catch estimates. Estimates of model parameters K, r, m, and ψ from the model excluding catch variability were within 2% of the base case estimates (Table 21). Changes in model results did not cause changes in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam (Table 21; Figure 70).

Model results for CNMI were not sensitive to excluding variability around catch estimates based on median parameter estimates. Estimates of model parameters K, r, and ψ from the model excluding catch variability were within 3% of the base case estimates (Table 22). The greatest differences occurred for the estimates of the probability of overfishing and probability of being overfished, which changed by –15% and –5%, respectively (Table 22). Such decreases in the probability of being overfished or of overfishing indicate that removing variability around catch increased the certainty in estimating status, particularly given the small changes in relative biomass (1% increase) and relative harvest (2% decrease; Table 22). Plotting of the 95% CI also showed that variability in the estimate of harvest rate and H_{2017}/H_{CR} decreased when variability around catch was removed (Figure 71). Changes in model results did not cause changes in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI (Table 22; Figure 71).

Model results for American Samoa were not sensitive to excluding variability around catch estimates. Estimates of model parameters K, r, m, and ψ from the model excluding catch variability were within 2% of the base case estimates (Table 23). The greatest difference occurred for the estimate of H_{2017}/H_{CR}, which changed 5% (Table 23). Changes in model results did not cause changes in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa (Table 23; Figure 72).

3.6.9. Sensitivity to Inclusion of OLO MSY Estimates

Model results for Guam were not sensitive to including the independent OLO MSY estimate as a data point for the model to fit. Estimates of model parameters K, r, m, and ψ from the model with the OLO MSY estimate were within 6% of the base case estimates **(**Table 21). The estimate of MSY increased 9% from the base case model (Table 21). Estimates of biomass and harvest rate and status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} were similar to the base case results for Guam (Table 21; Figure 73).

Model results for CNMI were sensitive to including the independent OLO MSY estimate. Estimates of model parameters K, r, and ψ from the model with the OLO MSY estimate varied by 33%, 10%, and -14%, respectively from the estimates from the base case model (Table 22). The estimate of MSY increased by 50% from the base case model (Table 22). Estimates of biomass increased and estimates of harvest rate decreased when including the OLO MSY estimate (Figure 74). Status for B_{2017}/B_{MSY} and H_{2017}/H_{CR} did not change when including the OLO MSY estimate for CNMI (Table 22; Figure 74).

Model results for American Samoa were sensitive to including the independent OLO MSY estimate. Estimates of model parameters K, r, m, and ψ from the model with the OLO MSY estimate varied by 56%, 21%, 12%, and -15%, respectively from estimates from the base case model **(**Table 23). The estimate of *MSY* increased by 82% from the base case model (Table 23). Estimates of biomass increased and estimates of harvest rate decreased when including the OLO MSY estimate (Figure 75). Status for B_{2017}/B_{MSY} and H_{2017}/H_{CR} did not change when including the OLO MSY estimate for American Samoa (Table 23; Figure 75).

3.6.10. Sensitivity to Initial Conditions

Model results for Guam were not sensitive to initial conditions. Estimates of H_{2017}/H_{CR} varied from –2.6% to 1.6% relative to the base case results and estimates of B_{2017}/B_{MSY} varied from -0.9% to 1.6% relative to the base case results (Figure 76). None of the scenarios with different random seeds resulted in a change in status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for Guam.

Model results for CNMI were slightly sensitive to initial conditions. Estimates of H_{2017}/H_{CR} varied from –2.3% to 3.1% relative to the base case results and estimates of B_{2017}/B_{MSY} varied from –4.1% to 1.5% relative to the base case results (Figure 76). None of the scenarios with different random seeds resulted in a change status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for CNMI.

Model results for American Samoa were not sensitive to initial conditions. Estimates of H_{2017}/H_{CR} varied from –1.4% to 4.4% relative to the base case results and estimates of B_{2017}/B_{MSY} varied from –2.1% to 0.8% relative to the base case results (Figure 76). None of the scenarios with different random seeds resulted in a change status for B_{2017}/B_{MSY} or H_{2017}/H_{CR} for American Samoa.

4. Discussion

Several improvements relative to previous assessments for territorial bottomfish were incorporated into the 2019 benchmark assessments. The filtering procedure for CPUE data selected all creel survey interviews that reported using bottomfishing gear rather than selecting all interviews for which BMUS composed 50% or more of the catch, regardless of gear. This decision was made because we considered that it more accurately selected for bottomfish-directed trips and accounts for our understanding that bottomfishing does not specifically target only BMUS. Furthermore, CPUE data filtering methods used in the assessments included zero or low BMUS catch records which were previously excluded through a selection of records with 50% or more BMUS catch. For the 2019 benchmark stock assessments, we standardized CPUE data from non-expanded boat-based creel surveys for all territories, following the recommendation from the WPSAR review of the previous assessments (Franklin et al. 2015). The standardization included covariates likely to explain variation in CPUE that could reasonably be included for each territory.

The 2019 benchmark assessments for bottomfish management unit species in American Samoa, CNMI, and Guam represent what we consider an improvement in analyses and data consideration over previous assessments through detailed evaluation of previously used assumptions and methods for data preparation and production model fitting. The quality and coverage of the creel surveys remain a concern for these assessments, but they remain the primary source of data that are available. We acknowledge that the benchmark assessments represent substantial changes from previous assessments in the scale, status, and projected catches of these important stocks, yet we believe the updated methods and modeling approach are robust and represent an improvement in methods from previous assessments.

Stock status of BMUS for the territories of Guam, CNMI, and American Samoa was assessed based on reference points for overfishing ($H/H_{CR} > 1$) and for being overfished ($B/B_{MSY} < 0.7$). Guam was determined to be in an overfished state, and was not undergoing overfishing in 2017. CNMI was determined not to be undergoing overfishing, and was not in an overfished state in 2017. American Samoa was determined to be both undergoing overfishing and in an overfished state in 2017, and neither biomass nor harvest rate were particularly close to the reference points.

The status determinations from these 2019 benchmark assessments differed from the previous assessments for these territories, which determined that these stocks were not overfished nor were they undergoing overfishing as of 2015 (Yau et al. 2016). Not only did estimates of biomass and harvest rate change relative to the reference points, but the scaling of the absolute biomass estimates also changed in these 2019 benchmark assessments. In the 2016 assessments, estimated biomass exhibited no trend and fluctuated around 240 thousand pounds for Guam, 1,200 thousand pounds for CNMI, and 600 thousand pounds for American Samoa (Yau et al. 2016). For the 2019 benchmark assessments, estimated biomass exhibited more of a decline for Guam, but was scaled similarly to the 2016 assessment. Estimated biomass for CNMI in the 2019 benchmark assessment exhibited little temporal trend, but was scaled at about one-third as great as the biomass estimates from the previous assessment. For American Samoa, biomass in most years was scaled at about one-half as great as the estimates from the 2016 assessment and exhibited a decline through time that was not evident in the 2016 assessment. The estimates of *MSY* for the 2019 benchmark assessments were also reduced relative to the 2016 assessments.

Previous estimates of *MSY* were 56 thousand pounds for Guam, 173 thousand pounds for CNMI, and 76 thousand pounds for American Samoa (Yau et al. 2016). For the 2019 benchmark assessments, the estimates of *MSY* were 42 thousand pounds for Guam, 94 thousand pounds for CNMI, and 29 thousand pounds for American Samoa. Estimates of *MSY* from the previous stock assessments were close to the independent OLO MSY values used as fitted data points. As previously stated, the independent estimates were 75 thousand pounds for Guam, 172 thousand pounds for CNMI, and 55 thousand pounds for American Samoa.

For Guam, the catch that corresponded to 50% probability of overfishing through 6 years was 36 thousand pounds. For CNMI, the catch that would produce a 50% probability of overfishing was 95 thousand pounds. For American Samoa, the catch that would produce a 50% probability of overfishing was 8 thousand pounds. The catch values associated with a 50% probability of overfishing were greater than the observed landings in 2017 for Guam (16 thousand pounds) and for CNMI (70 thousand pounds). For American Samoa, the observed landings in 2017 totaled 16 thousand pounds, which exceeded the catch that would produce a 50% probability of overfishing.

The decreases in biomass and productivity found in these 2019 assessments relative to the 2016 assessments are likely a function of several factors that are new for these assessments, including different CPUE data filters, re-estimation of the proportion of species groups that were comprised of BMUS, the exclusion of the independent OLO MSY estimates from the likelihood estimation, the use of a Pella-Tomlinson model structure for Guam and American Samoa, and different data choices for CNMI. The filtering of CPUE data and application of new BMUS proportions for species groups resulted in temporal patterns for CPUE for Guam and American Samoa that were different from those found in the 2016 assessments. The production model attributed a decline in biomass resulting from these decreasing trends to lower stock production relative to the 2016 assessments. Thus, the different temporal trends that resulted from the CPUE filtering procedure are likely a dominant contributing factor to the decrease in the estimated biomass and *MSY* relative to the 2016 assessments.

The change in treatment of the independent estimates of MSY in the 2019 benchmark assessments, from use in the model estimation and informing the carrying capacity prior to only informing the carrying capacity prior, partially explained the difference in results between the 2019 benchmark and 2016 assessments. Given the limited contrast in the CPUE time series that were used in the 2016 assessments, the independent estimates of MSY were likely important for determining the scale of biomass estimates. Productivity was estimated to be high in order for the production model to produce *MSY* estimates that matched the independent OLO estimates, and the estimates of the intrinsic rate of increase (r) were greater for the 2016 assessments compared to the 2019 benchmark assessments. Sensitivity analyses indicated that excluding the independent OLO estimates of MSY from model estimation partially explained the decline in the estimates of *MSY* and biomass relative to the 2016 assessments for CNMI (Figure 74) and American Samoa (Figure 75), but not for Guam (Figure 73). However, the scenario in which the independent OLO MSY estimate was included for American Samoa did not cause results to change sufficiently to cause a change in status for B/B_{MSY} or H/H_{CR} in 2017. A possible reason why Guam *MSY* and biomass estimates were less affected by the inclusion of the independent OLO estimate of MSY was that the base case model *MSY* estimate was more similar to the independent OLO MSY estimate than for the other territories and therefore adding the OLO

MSY estimates offered very little new information compared to the assessments for the other territories.

The use of the Pella-Tomlinson model which includes a prior distribution and estimation of the shape parameter (m) for Guam and American Samoa also allowed for increased flexibility in the estimation of productivity for the 2019 benchmark assessments relative to the 2016 assessments. The 2016 assessments applied Schaefer models that forced maximum surplus production to occur at a biomass value one half of carrying capacity (K) by assuming the shape parameter was equal to 2. For Guam, the estimate of m was less than 2, indicating that maximum surplus production occurred at a biomass value less than $K/2$ and was greater than the production that would occur when $m = 2$ (Figure 15; Winker et al 2018). For American Samoa, the estimate of m was greater than 2, indicating that maximum surplus production occurred at a biomass value greater than $K/2$ and that estimated maximum surplus production was lower than the production that would occur when $m = 2$. However, sensitivity results indicated that the use of the Pella-Tomlinson model only did not explain the changes in results for Guam (Figure 52) and American Samoa (Figure 54) relative to the 2016 assessments.

The Pella-Tomlinson model was not applied to the CNMI model, primarily because of the limited amount of contrast in the catch and CPUE data over time for this territory. This lack of contrast remains a feature of the CNMI model, contributing both to high estimated observation error, and high uncertainty in the status of the stock. Given the use of the Schaefer model for CNMI, production model results were most sensitive to the assumed prior for the ratio of initial biomass to carrying capacity (ψ) rather than m, which was sensitive for the Pella-Tomlinson model results for Guam and American Samoa. The prior for ψ for the CNMI production model was influential in scaling the estimated biomass, and the sensitivity of base case model results to changes in ψ further suggest that the data for the CNMI model have limited information to inform model parameters related to model scale. In addition, variability around catch was higher for CNMI than for other territories, and influenced the certainty around estimates of harvest rate and relative harvest rate, suggesting variability around catch contributed in part to high uncertainty in overfishing status. All together, the overall certainty with which we could make conclusions about CNMI biomass and harvest rates was less than that for Guam and American Samoa.

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5. Literature Cited

Allen S, Bartram P. 2008. Guam as a fishing community. Pacific Islands Fisheries Science Center. Administrative Report H-08-01, 70 p.

Andrews KR, Williams AJ, Fernandez-Silva I, Newman SJ, Copus JM, Wakefield CB, Randall JE, Bowen BW. 2016. Phylogeny of deepwater snappers (Genus *Etelis*) reveals a cryptic species pair in the Indo-Pacific and Pleistocene invasion of the Atlantic. Mol Phylogenet Evol. 100:361–371.

Bates D., Machler M, Bolker B, Walker S. 2015. Fitting linear mixed-effects models using lme4. J Stat Softw. 67(1):1-48.

Brodziak J, O'Malley J, Richards B, DiNardo G. 2012. Stock assessment update of the status of the bottomfish resources of American Samoa, the Commonwealth of the Northern Mariana Islands, and Guam, 2012. Pacific Islands Fisheries Science Center. Administrative Report H-12-04, 124 p.

Brodziak J, Ishimura G. 2011. Development of Bayesian production models for assessing the North Pacific swordfish population. Fish Sci. 77(1):23-34.

Brodziak J, Walsh WA. 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(12):1723–1740. doi:10.1139/cjfas-2013-0111

Burnham K, Anderson D. 2002. Model selection and multimodel inference, 2nd Ed. New York (NY): Springer-Verlag.

Franklin EC, Chaloupka M, Kobayashi DR. 2015. WPSAR Tier 3 panel review of stock assessment updates of the bottomfish management unit species of American Samoa, the Commonwealth of the Northern Marina Islands, and Guam in 2015 using data through 2013. https://www.fisheries.noaa.gov/webdam/download/80809845

Congdon P. 2001. Bayesian statistical modeling. New York (NY): Wiley.

Dunn P, Smythe G. 1996. Randomized quantile residuals. J Comput Graph Stat. 5(3):236-244.

Fletcher RI. 1978. On the restructuring of the Pella–Tomlinson system. Fish Bull. 76:515–512.

Francis RICC, Hurst RJ, Renwick JA. 2003. Quantifying annual variation in catchability for commercial and research fishing. Fish Bull. 101(2):293–304.

Froese R, Demirel N, Coro G, Kleisner KM, Winker H. 2017. Estimating fisheries reference points from catch and resilience. Fish and Fish. 18(3):506–526. doi:10.1111/faf.12190

Froese R, PaulyD, editors. 2018. FishBase. World Wide Web electronic publication. [accessed September/October 2018] www.fishbase.org, version (06/2018).

Gelman A, Carlin J, Stern H, Rubin D. 1995. Bayesian data analysis. New York (NY):Chapman and Hall.

Gelman A. 2006. Prior distribution for variance parameters in hierarchical models. Bayesian Analysis 1:515–533. doi:10.1214/06-BA117A

Geweke J. 1992. Evaluating the accuracy of sampling-based approaches to calculating posterior moments. In: Bernardo J, Berger J, Dawid A, Smith A, editors. Bayesian Statistics. Vol. 4. Oxford (UK): Claredon Press. p. 169–194.

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

Gilks WR, Richardson S, Spiegelhalter DJ, editors. 1996. Markov Chain Monte Carlo in Practice. London (UK): Chapman and Hall.

Harville D. 1977. Maximum likelihood approaches to variance component estimation and related problems. J Am Stat Assoc. 72:320-338.

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

Hospital J, Beavers C. 2014. Economic and social characteristics of small boat fishing in the Commonwealth of the Northern Mariana Islands. Pacific Islands Fisheries Science Center, Administrative Report H-14-02, 58 p.

Humphreys R, Moffitt R. 1999. Unit 17 - Western Pacific bottomfish and armorhead fisheries. In: NMFS. Our Living Oceans – Report on the Status of U.S. Living Marine Resources. p. 189–192.

Itano D. 1996. The development of small-scale fisheries for bottomfish in American Samoa (1961-1987). SPC Fisheries Newsletters #76-77.

Jasper W, Matthews T, Gutierrez J, Flores T, Tibbatts B, Martin N, Bass J, Wusstig S, Franquez R, Manibusan F, Ducusin J, Regis A, Lowe MK, Quach M. 2016. DAWR Creel Survey Methodology. Division of Aquatic & Wildlife Resources (DAWR), Guam Department of Agriculture. Tech. Rept. 1, 110 p.

Maunder MN, Punt AE. 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, Babcock E, Pikitch E, Prager M. 2001. Application of a non-equilibrium generalized production model to South and North Atlantic swordfish: Combining Bayesian and demographic methods for parameter estimation. 2000. Col Vol Sci Pap. ICCAT 51(5):1523-1550.

McCulloch C, Searle S, Neuhaus J. 2008. Generalized, linear, and mixed models, 2nd Edition. Hoboken (NJ): John Wiley and Sons.

Meyer R, Millar R. 1999. BUGS in Bayesian stock assessments. Can J Fish Aquat Sci. 56:1078–1086.

[NMFS] National Marine Fisheries Service. 2019. Pacific Island Fisheries; Reclassifying Management Unit Species to Ecosystem Component Species. Fed Regist. 84:2767–2775.

Moffitt R, Brodziak J, Flores T. 2007. Status of the bottomfish resources of American Samoa, Guam, and Commonwealth of the Northern Mariana Islands, 2005. Pacific Islands Fisheries Science Center Administrative Report H-07-04, 52 p.

Moffitt R, Humphreys R. 2009. Unit 17 - Western Pacific Bottomfish and Groundfish Fisheries. In: NMFS. Our Living Oceans – Report on the Status of U.S. Living Marine Resources, 6th edition. U.S. Department of Commerce, NOAA Technical Memorandum NMFS-F/SPO-80, p. 231–236.

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 JA. 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

Pella JJ, Tomlinson PK. 1969. A generalized stock production model. Inter-American Trop Tuna Comm Bull. 13:421–458.

Plummer M. 2003. JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. Proceedings of the 3rd International Workshop on Distributed Statistical Computing (DSC 2003). Vienna, Austria.

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

Polovina JJ, Moffitt RB, Ralston S, Shiota PM, Williams HA. 1985. Fisheries Resource Assessment of the Mariana Archipelago, 1982-85. Mar Fish Rev 47(4):19–25.

Polovina J, Ralston S. 1986. An approach to yield assessment for unexploited resources with application to the deep slope fishes of the Marianas. Fish Bull. 84(4):759–770.

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

R Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org.

Stephens A, MacCall A. 2004. A multispecies approach to subsetting logbook data for purposes of estimating CPUE. Fish Res. 70:299-310.

Thorson JT, Cope HM, Branch TA, Jensen OP. 2012. Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. Can J Fish Aquat Sci. 69:1556-1568.

Thorson JT, Ono K, Munch SB. 2014. A Bayesian approach to identifying and compensating for model misspecification in population models. Ecology 95:329-341.

Thorson JT, Munch SB, Cope JM, Gao J. 2017. Predicting life history parameters for all fishes worldwide. Ecol Appl. 27(8):2262–2276.

[WPRFMC] Western Pacific Regional Fishery Management Council. 2006. Bottomfish and seamount groundfish fisheries of the Western Pacific Region. 2005 Annual Report. http://www.wpcouncil.org/bottomfish.htm

WPRFMC. 2009a. Fishery Ecosystem Plan for the Mariana Archipelago. Honolulu (HI). 231 p.

WPRFMC. 2009b. Fishery Ecosystem Plan for the American Samoa Archipelago. Honolulu (HI). 202 p.

WPRFMC. 2018. Annual stock assessment and fishery evaluation report for the Mariana Archipelago fishery ecosystem plan 2017. Sabater M, Ishizaki A, Remington T, Spalding S, editors. Honolulu (HI).

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, Nadon M, Richards B, Brodziak J, Fletcher E. 2016. Stock assessment updates of the bottomfish management unit species of American Samoa, the Commonwealth of the Northern Mariana Islands, and Guam in 2015 using data through 2013. U.S. Dept. of Commerce, NOAA Technical Memorandum, NOAA-TM-NMFS-PIFSC-51, 54 p. doi:10.7289/V5PR7T0G.

Yau A, editor. 2018. Report from Hawaii bottomfish commercial fishery data workshops, 2015–2016. U.S. Dept. of Commerce, NOAA Technical Memorandum, NOAA-TM-NMFS-PIFSC-68. 105 p.

6. Tables

Table 1: List of bottomfish management unit species (BMUS) that are identified in the relevant Fishery Ecosystem Plan and that are used for the bottomfish assessments for Guam and the Commonwealth of the Northern Mariana Islands.

Species name	**Common name**	**Chamorro/Carolinian name**
Aphareus rutilans	Rusty jobfish	lehi/maroobw
Caranx ignobilis	Giant trevally	mamulan/etam
Caranx lugubris	Black trevally	tarakiton attelong/orong
Etelis carbunculus	Ruby snapper	buninas agaga'/falaghal moroobw
Etelis coruscans	Flame snapper	buninas/taighulupegh
Lethrinus rubrioperculatus	Redgill emperor	mafute'/atigh
Lutjanus kasmira	Bluestripe snapper	funai/saas
Pristipomoides flavipinnis	Yelloweye snapper	buninas/falaghal-maroobw
Pristipomoides sieboldii	Von Siebold's snapper	buninas/-
Pristipomoides zonatus	Oblique-banded snapper	buninas rayao amiriyu /falaghal-maroobw
Pristipomoides auricilla	Goldflag snapper	buninas/falaghal-maroobw
Pristipomoides filamentosus	Pink snapper	buninas/falaghal-maroobw
Variola louti	Lyretail grouper	gadau matingon/bwele

Table 2: List of bottomfish management unit species (BMUS) that are identified in the relevant Fishery Ecosystem Plan and that are used for the bottomfish assessment for American Samoa.

Species name	Common name	Samoan name
Aphareus rutilans	Rusty jobfish	palu-gutusiliva
Aprion virescens	Green jobfish	asoama
Caranx lugubris	Black trevally	tafauli
Etelis carbunculus[1]	Ruby snapper	palu malau
Etelis coruscans	Flame snapper	palu-loa
Lethrinus rubrioperculatus	Redgill emperor	filoa-paomumu
Lutjanus kasmira	Bluestripe snapper	savane
Pristipomoides flavipinnis	Yelloweye snapper	palu-sina
Pristipomoides zonatus	Oblique-banded snapper	palu-ula, palu-sega
Pristipomoides filamentosus	Pink snapper	palu-‘ena‘ena
Variola louti	Lyretail grouper	papa, velo

[1] *E. carbunculus* is now known to be comprised of two distinct, non-interbreeding lineages (Andrews et al. 2016). Both species occur in the Samoa Archipelago and were likely both captured by fishermen in the 1980s but reported as one species.

Table 3: Annual total catch of bottomfish management unit species (BMUS) for Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa used as input into the stock assessments. Data are from the Western Pacific Fisheries Information Network, and are the greater of the sum of the boat-based and shore-based creel survey data, and the commercial purchase data. See section '2.1.1. Total Catch' in the text for the description for how catch was calculated.

Year	Guam BMUS catch (1000 lb)	CNMI BMUS catch (1000 lb)	American Samoa BMUS catch (1000 lb)
1982	27.357	-	-
1983	44.593	-	-
1984	52.018	-	-
1985	68.251	-	-
1986	29.560	-	90.689
1987	37.000	-	23.763
1988	50.455	-	44.718
1989	47.796	-	33.426
1990	37.223	-	14.885
1991	42.767	-	17.637
1992	46.714	-	12.559
1993	53.233	-	11.611
1994	54.128	-	28.817
1995	35.031	-	30.866
1996	51.242	-	28.713
1997	28.032	-	39.928
1998	29.480	-	22.593
1999	47.084	-	17.282
2000	66.447	176.129	23.913
2001	46.427	77.861	42.301
2002	21.727	34.006	31.657
2003	29.835	20.119	21.039
2004	25.236	76.132	17.622
2005	29.046	57.854	14.541
2006	34.917	35.294	15.569
2007	18.186	57.995	22.359
2008	34.249	22.908	32.965
2009	40.735	74.587	40.446
2010	26.544	67.944	11.978
2011	54.062	30.203	24.569
2012	19.714	140.631	7.688
2013	30.243	29.229	19.740
2014	20.554	13.889	20.352
2015	11.711	11.281	29.511
2016	30.192	59.774	20.181
2017	15.864	70.228	15.913

Table 4: Uncertainty in total catch for bottomfish management unit species in Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa. Uncertainty is reported as the coefficient of variation (CV).

Year	Guam catch CV	CNMI catch CV	American Samoa catch CV
1982	0.12	-	-
1983	0.16	-	-
1984	0.12	-	-
1985	0.10	-	-
1986	0.18	-	0.091
1987	0.14	-	0.162
1988	0.11	-	0.092
1989	0.11	-	0.078
1990	0.10	-	0.102
1991	0.12	-	0.106
1992	0.16	-	0.121
1993	0.22	-	0.111
1994	0.14	-	0.080
1995	0.17	-	0.090
1996	0.12	-	0.074
1997	0.17	-	0.061
1998	0.15	-	0.111
1999	0.24	-	0.089
2000	0.17	0.50	0.145
2001	0.17	0.15	0.110
2002	0.19	0.28	0.093
2003	0.31	0.50	0.087
2004	0.24	0.23	0.088
2005	0.32	0.20	0.116
2006	0.27	0.19	0.124
2007	0.43	0.21	0.093
2008	0.14	0.24	0.092
2009	0.16	0.22	0.076
2010	0.16	0.12	0.139
2011	0.18	0.23	0.121
2012	0.25	0.41	0.155
2013	0.19	0.47	0.115
2014	0.19	0.53	0.155
2015	0.28	0.59	0.081
2016	0.18	0.39	0.094
2017	0.22	0.83	0.095

Table 5: Summary of log likelihood values and reduction in AIC (ΔAIC = AIC proposed model – AIC previous model) during model selection for the best-fit model for the Bernoulli and lognormal processes for bottomfish management unit species in Guam. Each parameter removed was removed from the model with all previously removed parameters excluded. The year predictor was included in all models regardless of AIC value.

Process	Selected predictor	ΔAIC	AIC	Number of parameters
Bernoulli	Full (year+month+area+ depth+type of day+wind speed)		2952	87
	-wind speed	-6.01	2946	81
	-month	-2.00	2944	70
	-type of day	-1.81	2942	69
	Best = year+area+depth			
Lognormal	Full (year+vessel+month+ area+depth+type of day+ wind speed)		10254	89
	-month	-11.35	10243	78
	-wind speed	-1.07	10242	72
	-type of day	-0.29	10241	71
	Best = year+vessel+area+depth			

Table 6: Summary of log likelihood values and reduction in AIC (ΔAIC = AIC proposed model –AIC previous model) during model selection for the best-fit model for the Bernoulli and lognormal processes for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands. Each parameter removed was removed from the model with all previously removed parameters excluded. The year predictor was included in all models regardless of AIC value.

Process	Selected predictor	ΔAIC	AIC	Number of parameters
Bernoulli	Full (year+month+area+ depth+type of day)		433	56
	-area	-25.1	408	33
	-month	-14.0	394	22
	Best = year+depth+type of day			
Lognormal	Full (year+vessel+month +area+depth+type of day)		1776	58
	-month	-12.1	1764	47
	Best = year+vessel+area+depth+type of day			

Table 7: Summary of log likelihood values and reduction in AIC (∆AIC = AIC proposed model –AIC previous model) during model selection for the best-fit model for the Bernoulli and lognormal processes for bottomfish management unit species in American Samoa. Each parameter removed was removed from the model with all previously removed parameters excluded. The year predictor was included in all models regardless of AIC value.

Process	Selected predictor	∆AIC	AIC	Number of parameters
Bernoulli	Full (year+month+area+ type of day)		414	66
	-month	-10.3	403	55
	Best = year+area+type of day			
Gamma	Full (year+vessel+month +area+type of day)		5932	68
	-area	-20.4	5912	46
	-month	-13.5	5898	35
	-type of day	-1.6	5896	34
	Best = year+vessel			

Table 8: Annual index of standardized CPUE from boat-based creel survey data for bottomfish management unit species in Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa. Uncertainty around the standardized indices in the form of standard errors (SE) on the scale of the logarithm is also provided. Both the index and the measure of uncertainty were used as input into the assessment model for each territory.

Year	Guam CPUE (lb/line hr)	Guam SE	CNMI CPUE (lb/line hr)	CNMI SE	American Samoa CPUE (lb/line hr)	American Samoa SE
1982	3.22	0.047				
1983	2.17	0.050				
1984	3.73	0.033				
1985	1.82	0.037				
1986	1.80	0.064			3.66	0.052
1987	2.04	0.055			2.77	0.039
1988	1.26	0.044			4.62	0.074
1989	1.91	0.051			5.20	0.102
1990	1.50	0.056			2.50	0.065
1991	1.76	0.052			2.12	0.010
1992	1.10	0.055			3.01	0.025
1993	1.26	0.064			2.40	0.040
1994	1.12	0.078			2.01	0.014
1995	0.70	0.056			3.50	0.040
1996	1.16	0.073			4.56	0.064
1997	0.53	0.077			4.09	0.046
1998	0.60	0.058			4.00	0.076
1999	0.64	0.065			3.45	0.032
2000	0.71	0.071	5.36	0.206	4.54	0.086
2001	0.72	0.114	1.10	0.238	4.09	0.030
2002	0.80	0.113	2.62	0.339	2.20	0.016
2003	0.82	0.091	5.43	0.117	4.42	0.029
2004	1.27	0.074	3.98	0.141	1.81	0.022
2005	1.63	0.100	1.98	0.149	3.55	0.049
2006	1.35	0.124	0.98	0.155	0.90	0.042
2007	0.62	0.106	1.80	0.215	2.05	0.010
2008	1.28	0.100	0.54	0.116	2.32	0.018
2009	1.51	0.089	0.80	0.210	2.98	0.015
2010	0.68	0.074	2.69	0.170	1.77	0.025
2011	1.90	0.137	1.87	0.492	2.76	0.022
2012	1.49	0.105	6.32	0.320	0.60	0.070
2013	1.28	0.107	1.27	0.734	0.75	0.056
2014	0.77	0.102	1.39	0.741	1.67	0.018
2015	0.56	0.132	1.99	0.576	2.37	0.023
2016	0.82	0.115	4.32	0.171	1.05	0.010
2017	0.67	0.056	3.21	0.251	1.22	0.010

Table 9: Prior distributions for the 2019 base case assessment models for bottomfish management unit species in Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa (AmSam). Parameters are intrinsic growth rate (*r*), production shape parameter (*m*), carrying capacity (*K*), ratio of initial biomass to carrying capacity (ψ), catchability (*q*), process error (σ_{η}^2), and the estimable component of the observation error ($\sigma_{\tau estimated}^2$).

Parameter	Distribution	Prior mean parameter/bounds			CV
		Guam	CNMI	AmSam	
r	lognormal	0.46	0.46	0.46	0.50
K (lb)	lognormal	478,261	1,495,652	652,174	0.50
m	lognormal	2	fixed at 2	2	0.50
ψ	lognormal	0.75	0.45	0.8	0.50
q	uniform	$[10^{-10},10]$	$[10^{-10},10]$	$[10^{-10},10]$	-
σ_{η}^2	inverse gamma	0.083*	0.083*	0.083*	-
$\sigma_{\tau estimated}^2$	inverse gamma	0.083*	0.083*	0.083*	-

*Value is mode rather than mean parameter

Table 10. Summary of sensitivity scenarios evaluated for the territorial bottomfish assessments for Guam (G), the Commonwealth of the Northern Mariana Islands (C), and American Samoa (A) as described in detail in the sensitivity analyses section (2.3.8. Sensitivity Analysis). Sensitivities are for intrinsic growth rate (*r*), shape parameter (*m*), carrying capacity (*K*), ratio of initial biomass to carrying capacity (*ψ*), process error (σ_{η}^{2}), estimate component of observation error ($\sigma_{restimated}^{2}$), to include *MSY* estimates, to remove variability in catch, and to initial starting conditions of the Markov Chain Monte Carlo routine.

Sensitivity Scenario	Distribution	Mean Parameter /Value	CV/Value
r prior mean parameter increased 50%	lognormal	0.69	0.50
r prior mean parameter reduced 50%	lognormal	0.23	0.50
r prior based on medium productivity (Musick 1999)	lognormal	0.33	0.30
r prior based on range of very-low to medium resiliency (0.015-0.8; Froese et al. 2017)	lognormal	0.11	1.30
m prior mean parameter increased 50%	lognormal	3	0.50
m prior mean parameter decreased 50%	lognormal	1	0.50
m prior CV increased	lognormal	2	1.00
m prior based on B_{MSY}/K for teleosts (0.353; Thorson et al. 2012)	lognormal	0.92	0.80
m prior for alternative production function	fixed lognormal fixed	2 (G) 2 (C) 2 (A)	- 0.50 -
K prior mean parameter increased 50%	lognormal	717,391 lb (G) 2,242,478 lb (C) 978,261 lb (A)	0.50
K prior mean parameter reduced 50%	lognormal	239,130 lb (G) 747,826 lb (C) 326,087 lb (A)	0.50
K prior CV reduced	lognormal	478,261 lb (G) 1,495,652 lb (C) 652,174 lb (A)	0.20
K prior based on range for high biomass (Froese et al. 2017)	lognormal	731,727 lb (G) 1,888,302 lb (C) 1,038,791 lb (A)	1.14
ψ prior mean parameter increased 50%	lognormal	1.125 (G) 0.675 (C) 1.20 (A)	0.50
ψ prior mean parameter reduced 50%	lognormal	0.375 (G) 0.225 (C) 0.40 (A)	0.50
ψ prior CV reduced	lognormal	0.75 (G) 0.45 (C)	0.20

Sensitivity Scenario	Distribution	Mean Parameter /Value	CV/Value
		0.80 (A)	
beta ψ prior distribution	beta	α = 1.5	β = 1.5
ψ prior based on range for medium biomass (0.2-0.6; Froese et al. 2017)	lognormal	0.346	0.28
ψ prior based on range for high biomass (0.5-0.9; Froese et al. 2017)	lognormal	0.671	0.148
$\sigma_{\eta}{}^2$ prior mode increased 10x	inv-gamma	shape = 0.2	rate = 1
$\sigma_{\eta}{}^2$ prior mode decreased 10x	inv-gamma	shape = 0.2	rate = 0.01
$\sigma_{\tau estimated}{}^2$ prior mode increased 10x	inv-gamma	shape = 0.2	rate = 1
$\sigma_{\tau estimated}{}^2$ prior mode decreased 10x	inv-gamma	shape = 0.2	rate = 0.01
uniform σ_{η} and $\sigma_{\tau estimated}$ prior distributions	uniform	a = 10^{-10}	b = 10
Include independent OLO MSY estimates			
Exclude variability around catch			
Sensitivity of starting conditions for MCMC	priors	10 random draws	

Table 11. Parameter estimates for the 2019 base case assessment models for bottomfish management unit species in Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa. Parameters are intrinsic growth rate (*r*), carrying capacity (*K*), shape parameter (*m*), ratio of initial biomass to carrying capacity (*ψ*), catchability (*q*), process error (σ_{η}^{2}), and estimable component of observation error ($\sigma_{\tau estimated}^{2}$). Derived quantities are maximum sustainable yield (*MSY*), harvest rate at maximum sustainable yield (H_{MSY}), biomass at maximum sustainable yield (B_{MSY}), and proportion of carrying capacity at maximum sustainable yield (B_{MSY}/K). *K*, B_{MSY}, and *MSY* are reported in thousand pounds.

	Guam		CNMI		American Samoa	
Parameter	**Median**	**95% CI**	**Median**	**95% CI**	**Median**	**95% CI**
r	0.29	0.15–0.58	0.33	0.17–0.63	0.28	0.13–0.58
K	533.7	290.2–1104.6	1141.2	543.7–2574.0	495.8	262.0–1101.4
m	1.73	0.73–4.29	2.0	-	2.66	1.13–6.12
ψ	0.86	0.53–1.04	0.48	0.20–0.94	0.71	0.37–1.15
q	0.006	0.003–0.010	0.006	0.002–0.015	0.012	0.005–0.026
σ_{η}^{2}	0.035	0.019–0.044	0.035	0.019–0.045	0.034	0.018–0.044
$\sigma_{\tau estimated}^{2}$	0.077	0.039–0.157	0.394	0.168–0.896	0.159	0.090–0.301
MSY	42.1	29.3–65.5	93.6	48.8–205.3	28.8	16.4–55.9
H_{MSY}	0.170	0.071–0.382	0.167	0.084–0.315	0.107	0.044–0.228
B_{MSY}	248.8	107.1–636.8	570.6	271.8–1287.0	272.8	120.8–687.4
B_{MSY}/K	0.47	0.31-0.64	0.5	-	0.55	0.39–0.71

Table 12. Estimates of median exploitable biomass in thousand pounds, median relative exploitable biomass (B/B_{MSY}), probability of being overfished (B/B_{MSY}< 0.7), median harvest rate (H), median harvest rate relative to the control rule (H/H_{CR}), and probability of overfishing (H/H_{CR}>1) for bottomfish management unit species in Guam 1982-2017.

Year	Biomass	B/B_{MSY}	Probability of being Overfished	H	H/H_{CR}	Probability of Overfishing
1982	443.2	1.78	0.00	0.06	0.36	0.00
1983	425.2	1.71	0.00	0.10	0.61	0.06
1984	431.7	1.74	0.00	0.12	0.71	0.13
1985	368.3	1.48	0.01	0.19	1.09	0.62
1986	323.4	1.30	0.02	0.09	0.54	0.04
1987	323.2	1.30	0.03	0.12	0.68	0.12
1988	295.8	1.19	0.05	0.17	1.01	0.51
1989	293.5	1.18	0.05	0.16	0.97	0.46
1990	273.5	1.10	0.07	0.14	0.81	0.26
1991	266.3	1.07	0.09	0.16	0.96	0.45
1992	234.4	0.94	0.17	0.20	1.20	0.70
1993	216.7	0.87	0.23	0.25	1.51	0.86
1994	188.3	0.76	0.40	0.29	1.79	0.95
1995	157.0	0.63	0.65	0.22	1.52	0.82
1996	157.6	0.63	0.64	0.33	2.22	0.98
1997	127.0	0.50	0.87	0.22	1.84	0.86
1998	130.9	0.52	0.84	0.22	1.80	0.86
1999	143.1	0.57	0.75	0.30	2.23	0.96
2000	149.6	0.60	0.71	0.42	2.91	1.00
2001	137.3	0.55	0.81	0.33	2.50	0.97
2002	139.3	0.55	0.78	0.15	1.18	0.61
2003	164.5	0.66	0.58	0.17	1.14	0.60
2004	193.2	0.77	0.38	0.13	0.80	0.32
2005	215.4	0.86	0.26	0.14	0.85	0.37
2006	206.2	0.82	0.30	0.18	1.10	0.58
2007	180.1	0.72	0.47	0.10	0.64	0.23
2008	208.6	0.83	0.29	0.16	0.99	0.49
2009	214.4	0.86	0.26	0.19	1.16	0.66
2010	193.4	0.77	0.38	0.14	0.84	0.34
2011	228.0	0.91	0.20	0.24	1.43	0.83
2012	203.1	0.81	0.32	0.10	0.62	0.17
2013	189.0	0.75	0.41	0.17	1.04	0.53
2014	155.5	0.62	0.65	0.14	0.94	0.46
2015	140.3	0.56	0.75	0.08	0.64	0.25
2016	150.3	0.60	0.67	0.20	1.44	0.73
2017	143.0	0.57	0.70	0.11	0.81	0.39

Table 13. Estimates of median exploitable biomass in thousand pounds, median relative exploitable biomass (*B/B_{MSY}*), probability of being overfished (*B/B_{MSY}*< 0.7), median harvest rate (*H*), median harvest rate relative to the control rule (*H/H_{CR}*), and probability of overfishing (*H/H_{CR}*>1) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands 2000-2017.

Year	Biomass	B/B_{MSY}	Probability of being Overfished	H	H/H_{CR}	Probability of Overfishing
2000	528.3	0.96	0.24	0.36	2.30	0.89
2001	383.8	0.71	0.49	0.20	1.40	0.68
2002	382.6	0.71	0.49	0.09	0.63	0.32
2003	417.4	0.78	0.43	0.05	0.35	0.15
2004	427.8	0.80	0.41	0.18	1.26	0.61
2005	365.4	0.68	0.51	0.16	1.17	0.57
2006	329.3	0.61	0.59	0.11	0.83	0.43
2007	331.3	0.62	0.59	0.18	1.36	0.62
2008	310.8	0.58	0.63	0.07	0.59	0.32
2009	357.1	0.67	0.53	0.20	1.47	0.68
2010	379.5	0.71	0.49	0.18	1.23	0.60
2011	400.9	0.75	0.45	0.07	0.51	0.25
2012	464.7	0.88	0.35	0.31	2.04	0.82
2013	379.6	0.71	0.49	0.08	0.55	0.31
2014	416.8	0.79	0.43	0.03	0.23	0.12
2015	480.6	0.91	0.34	0.02	0.15	0.05
2016	558.1	1.06	0.25	0.11	0.67	0.31
2017	569.2	1.08	0.24	0.12	0.79	0.41

Table 14. Estimates of median exploitable biomass in thousand pounds, median relative exploitable biomass (*B/B_{MSY}*), probability of being overfished (*B/B_{MSY}*< 0.7), median harvest rate (*H*), median harvest rate relative to the control rule (*H/H_{CR}*), and probability of overfishing (*H/H_{CR}*>1) for bottomfish management unit species in American Samoa 1986-2017.

Year	Biomass	B/B_{MSY}	Probability of being Overfished	*H*	H/H_{CR}	Probability of Overfishing
1986	335.9	1.27	0.05	0.27	2.53	0.99
1987	270.9	1.02	0.15	0.09	0.84	0.34
1988	287.9	1.08	0.12	0.16	1.50	0.83
1989	266.9	1.00	0.18	0.13	1.22	0.67
1990	235.2	0.88	0.27	0.06	0.62	0.18
1991	229.7	0.86	0.29	0.08	0.76	0.29
1992	234.2	0.88	0.28	0.05	0.53	0.12
1993	239.1	0.90	0.26	0.05	0.47	0.08
1994	254.1	0.96	0.20	0.11	1.09	0.58
1995	274.7	1.04	0.15	0.11	1.07	0.57
1996	291.8	1.10	0.12	0.10	0.94	0.44
1997	298.2	1.13	0.11	0.13	1.28	0.72
1998	286.5	1.08	0.14	0.08	0.76	0.27
1999	286.0	1.08	0.14	0.06	0.58	0.12
2000	292.2	1.10	0.13	0.08	0.79	0.30
2001	277.6	1.05	0.15	0.15	1.48	0.81
2002	237.8	0.89	0.26	0.13	1.31	0.72
2003	224.2	0.84	0.32	0.09	0.93	0.45
2004	199.5	0.74	0.44	0.09	0.91	0.43
2005	191.5	0.71	0.48	0.08	0.79	0.35
2006	169.6	0.63	0.61	0.09	1.01	0.50
2007	177.7	0.66	0.56	0.13	1.34	0.71
2008	180.3	0.67	0.54	0.18	1.94	0.90
2009	168.6	0.63	0.62	0.24	2.66	0.96
2010	138.8	0.52	0.80	0.09	1.16	0.58
2011	134.4	0.50	0.83	0.19	2.54	0.91
2012	107.3	0.40	0.94	0.07	1.23	0.61
2013	113.4	0.42	0.93	0.17	2.76	0.92
2014	120.9	0.45	0.89	0.17	2.50	0.90
2015	123.9	0.46	0.87	0.24	3.49	0.96
2016	107.3	0.40	0.92	0.19	3.21	0.91
2017	102.6	0.38	0.91	0.15	2.75	0.85

Table 15. Projection results showing annual catch where the specified median probability of overfishing (H/H_{CR}>1) was reached for bottomfish management unit species in Guam. The median biomass, median harvest rate, and median probability the stock is overfished (B/B_{MSY}<0.7) are the values in each year that correspond to the specified catch values. Catch values for a given probability of overfishing in any terminal year were applied to all previous years from 2020 to the terminal year.

Probability of overfishing (H/H_{CR}>1) in terminal year	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
Terminal Year	Catch (1000 lb) Constant in all years from 2020-terminal year				
2020	9	16	24	30	36
2021	10	18	26	31	36
2022	12	19	26	31	36
2023	13	20	27	31	36
2024	13	21	27	32	36
2025	15	22	28	32	36
	Biomass (1000 lb)				
2020	212.4	213.8	211.4	211.8	212.2
2021	240.9	232.5	226.3	221.0	215.0
2022	268.0	254.5	238.6	227.4	217.6
2023	286.6	265.8	248.0	234.1	219.3
2024	307.6	282.7	259.1	235.2	220.5
2025	321.8	289.5	258.5	241.0	222.1
	Harvest rate				
2020	0.04	0.08	0.12	0.14	0.17
2021	0.04	0.08	0.12	0.14	0.17
2022	0.05	0.08	0.11	0.14	0.17
2023	0.05	0.08	0.12	0.14	0.17
2024	0.04	0.08	0.11	0.15	0.17
2025	0.05	0.08	0.12	0.14	0.17
	Probability stock is overfished (B/B_{MSY} < 0.7)				
2020	0.34	0.34	0.34	0.34	0.33
2021	0.28	0.29	0.31	0.33	0.34
2022	0.23	0.26	0.30	0.33	0.35
2023	0.21	0.25	0.29	0.32	0.35
2024	0.18	0.23	0.28	0.32	0.36
2025	0.17	0.22	0.28	0.33	0.37

Table 16. Projection results showing annual catch (1000 lb) applied across all years from 2020 to the terminal year where the specified median probability of overfishing (*$H/H_{CR}>1$*) was reached in the terminal year for bottomfish management unit species in Guam.

Probability of overfishing (H/H_{CR}>1) in terminal year	2020	2021	2022	2023	2024	2025	Probability of overfishing (H/H_{CR}>1) in terminal year	2020	2021	2022	2023	2024	2025
0.01	2	2	2	3	3	3	0.26	21	23	24	25	25	26
0.02	3	3	4	4	5	5	0.27	22	23	24	25	26	26
0.03	4	5	5	6	6	7	0.28	23	24	25	26	26	27
0.04	5	5	6	7	8	9	0.29	23	24	26	27	27	27
0.05	5	6	7	8	9	9	0.30	24	26	26	27	27	28
0.06	6	7	9	9	10	11	0.31	25	26	27	27	28	28
0.07	7	8	9	10	11	11	0.32	25	27	27	28	28	29
0.08	8	9	10	11	12	13	0.33	26	27	27	28	29	29
0.09	9	10	11	12	13	13	0.34	26	27	28	29	29	30
0.10	9	10	12	13	13	15	0.35	27	28	29	29	30	30
0.11	10	11	13	13	14	16	0.36	27	29	29	30	30	31
0.12	11	12	13	14	15	16	0.37	28	29	30	30	31	31
0.13	11	13	14	15	17	17	0.38	29	30	30	31	31	31
0.14	12	13	15	16	17	18	0.39	29	31	31	31	31	32
0.15	13	15	16	17	18	18	0.40	30	31	31	31	32	32
0.16	13	15	17	18	19	19	0.41	31	31	32	32	32	33
0.17	14	16	17	18	19	19	0.42	31	32	32	33	33	33
0.18	15	17	18	19	19	21	0.43	32	32	33	33	33	33
0.19	16	18	19	19	20	22	0.44	32	32	33	33	33	34
0.20	16	18	19	20	21	22	0.45	33	33	33	34	35	35
0.21	17	19	20	21	22	23	0.46	33	34	35	35	35	35
0.22	18	19	21	22	23	24	0.47	34	35	35	35	35	35
0.23	19	20	22	23	23	24	0.48	35	35	35	36	35	36
0.24	19	21	22	23	24	24	0.49	35	36	36	36	36	36
0.25	20	22	23	24	25	25	0.50	36	36	36	36	36	36

Table 17. Projection results showing annual catch where the specified median probability of overfishing (*H/H_{CR}>1*) was reached for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands. The median biomass, median harvest rate, and median probability the stock is overfished (*B/B_{MSY}<0.7*) are the values in each year that correspond to the specified catch values. Catch values for a given probability of overfishing in any terminal year were applied to all previous years from 2020 to the terminal year.

Probability of overfishing (*H/H_{CR}*>1) in terminal year	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
Terminal Year	Catch (1000 lb) Constant in all years from 2020-terminal year				
2020	32	57	75	92	109
2021	36	57	74	89	104
2022	38	58	74	87	101
2023	39	59	72	86	98
2024	40	59	72	84	96
2025	42	59	71	83	95
	Biomass (1000 lb)				
2020	699.2	689.4	695.5	696.3	701.2
2021	733.2	714.2	696.3	675.8	665.6
2022	770.4	724.5	688.7	665.1	639.5
2023	788.4	728.6	694.8	655.1	619.6
2024	809.7	742.3	698.9	644.7	606.2
2025	818.7	751.6	699.6	645.0	589.3
	Harvest rate				
2020	0.05	0.09	0.12	0.14	0.17
2021	0.05	0.09	0.11	0.14	0.17
2022	0.05	0.09	0.11	0.14	0.17
2023	0.05	0.09	0.11	0.14	0.17
2024	0.05	0.08	0.11	0.14	0.17
2025	0.05	0.08	0.11	0.14	0.17
	Probability stock is overfished (B/B*MSY* < 0.7)				
2020	0.18	0.18	0.18	0.18	0.18
2021	0.16	0.18	0.19	0.20	0.21
2022	0.14	0.17	0.20	0.21	0.24
2023	0.13	0.17	0.20	0.24	0.27
2024	0.12	0.17	0.20	0.25	0.29
2025	0.12	0.17	0.21	0.26	0.31

Table 18. Projection results showing annual catch (1000 lb) applied across all years from 2020 to the terminal year where the specified median probability of overfishing (*$H/H_{CR}>1$*) was reached in the terminal year for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands.

Probability of overfishing (H/H_{CR}>1) in terminal year	2020	2021	2022	2023	2024	2025	**Probability of overfishing (H/H_{CR}>1) in terminal year**	2020	2021	2022	2023	2024	2025
0.01	2	3	4	5	6	7	0.26	68	68	68	68	68	66
0.02	6	7	9	11	13	14	0.27	70	69	70	68	68	68
0.03	9	11	14	16	17	21	0.28	72	71	71	70	70	69
0.04	12	15	18	21	22	24	0.29	74	72	72	72	71	71
0.05	16	18	23	24	26	28	0.30	75	74	74	72	72	71
0.06	18	22	25	28	29	31	0.31	77	76	74	74	73	72
0.07	22	25	29	31	33	34	0.32	79	78	77	75	74	74
0.08	25	29	32	35	35	36	0.33	81	79	78	77	75	75
0.09	28	33	34	37	38	38	0.34	82	81	79	78	77	75
0.10	32	36	38	39	40	42	0.35	84	82	80	80	78	77
0.11	35	38	40	41	43	43	0.36	85	83	82	80	80	78
0.12	38	41	41	44	45	45	0.37	87	85	83	82	81	80
0.13	40	44	45	46	48	49	0.38	89	87	85	83	82	81
0.14	43	46	48	49	49	49	0.39	90	88	86	84	83	82
0.15	46	49	49	50	51	51	0.40	92	89	87	86	84	83
0.16	48	50	51	51	52	53	0.41	95	90	88	86	86	84
0.17	50	52	53	53	54	54	0.42	94	91	90	88	86	85
0.18	53	54	55	56	56	56	0.43	97	95	90	89	87	86
0.19	54	56	57	57	57	57	0.44	98	94	93	90	89	88
0.20	57	57	58	59	59	59	0.45	101	96	93	92	90	89
0.21	58	60	60	61	61	60	0.46	102	97	94	93	90	90
0.22	61	62	62	61	61	61	0.47	104	99	96	94	93	90
0.23	63	63	63	63	63	62	0.48	105	101	97	94	93	93
0.24	64	64	65	64	64	63	0.49	108	102	100	96	94	93
0.25	66	66	67	66	65	66	0.50	109	104	101	98	96	95

Table 19. Projection results showing annual catch where the specified median probability of overfishing (*$H/H_{CR}>1$*) was reached for bottomfish management unit species in American Samoa. The median biomass, median harvest rate, and median probability the stock is overfished (*$B/B_{MSY}<0.7$*) are the values in each year that correspond to the specified catch values. Catch values for a given probability of overfishing in any terminal year were applied to all previous years from 2020 to the terminal year.

Probability of overfishing (H/H_{CR}>1) in terminal year	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
Terminal Year	Catch (1000 lb) Constant in all years from 2020-terminal year				
2020	0	0	1	2	4
2021	0	0	1	3	5
2022	0	0	2	3	5
2023	0	1	2	4	6
2024	0	1	2	4	7
2025	0	1	3	5	8
	Biomass (1000 lb)				
2020	87.6	87.6	88.5	86.9	87.9
2021	102.4	102.4	101.5	98.4	95.8
2022	118.5	118.5	112.7	109.9	105.4
2023	136.1	132.4	128.2	120.4	114.0
2024	155.7	150.5	144.6	134.1	117.9
2025	175.6	168.3	155.1	139.8	122.4
	Harvest rate				
2020	0.00	0.00	0.01	0.02	0.05
2021	0.00	0.00	0.01	0.03	0.05
2022	0.00	0.00	0.02	0.03	0.05
2023	0.00	0.01	0.02	0.03	0.05
2024	0.00	0.01	0.01	0.03	0.06
2025	0.00	0.01	0.02	0.03	0.06
	Probability stock is overfished (*B/BMSY* < 0.7)				
2020	0.83	0.83	0.84	0.83	0.83
2021	0.77	0.77	0.77	0.78	0.78
2022	0.71	0.71	0.72	0.72	0.73
2023	0.65	0.65	0.66	0.67	0.70
2024	0.58	0.60	0.61	0.62	0.66
2025	0.53	0.54	0.58	0.61	0.64

Table 20. Projection results showing annual catch (1000 lb) applied across all years from 2020 to the terminal year where the specified median probability of overfishing (*$H/H_{CR}>1$*) was reached in the terminal year for bottomfish management unit species in American Samoa.

Probability of overfishing (H/H_{CR}>1) in terminal year	2020	2021	2022	2023	2024	2025	Probability of overfishing (H/H_{CR}>1) in terminal year	2020	2021	2022	2023	2024	2025
0.01	0	0	0	0	0	0	0.26	1	1	1	1	2	2
0.02	0	0	0	0	0	0	0.27	1	1	1	1	2	2
0.03	0	0	0	0	0	0	0.28	1	1	1	2	2	2
0.04	0	0	0	0	0	0	0.29	1	1	1	2	2	2
0.05	0	0	0	0	0	0	0.30	1	1	2	2	2	3
0.06	0	0	0	0	0	0	0.31	1	1	2	2	2	3
0.07	0	0	0	0	0	0	0.32	1	1	2	2	3	3
0.08	0	0	0	0	0	0	0.33	1	2	2	2	3	3
0.09	0	0	0	0	0	0	0.34	1	2	2	3	3	3
0.10	0	0	0	0	0	0	0.35	1	2	2	3	3	4
0.11	0	0	0	0	0	0	0.36	1	2	2	3	3	4
0.12	0	0	0	0	0	0	0.37	2	2	3	3	4	4
0.13	0	0	0	0	0	0	0.38	2	2	3	3	4	4
0.14	0	0	0	0	0	0	0.39	2	2	3	3	4	4
0.15	0	0	0	0	0	0	0.40	2	3	3	4	4	5
0.16	0	0	0	0	0	0	0.41	2	3	3	4	4	5
0.17	0	0	0	0	0	1	0.42	2	3	3	4	5	5
0.18	0	0	0	0	1	1	0.43	2	3	4	4	5	6
0.19	0	0	0	0	1	1	0.44	3	3	4	5	5	6
0.20	0	0	0	1	1	1	0.45	3	3	4	5	6	6
0.21	0	0	1	1	1	1	0.46	3	4	4	5	6	6
0.22	0	0	1	1	1	1	0.47	3	4	5	5	6	7
0.23	0	0	1	1	1	1	0.48	3	4	5	6	6	7
0.24	0	1	1	1	1	2	0.49	3	4	5	6	7	7
0.25	0	1	1	1	1	2	0.50	4	5	5	6	7	8

Table 21. Sensitivity of production model results for bottomfish management unit species in Guam to scenarios with different assumed prior distributions, different model structure (i.e., Schaefer), excluding variability in estimated catch, and fitting to an independent estimate of MSY (OLO MSY). Results are expressed as proportional change relative to base case model (first row) for *K*, *r*, *m*, *ψ*, maximum sustainable yield (*MSY*), biomass at maximum sustainable yield (B_{MSY}), harvest rate at maximum sustainable yield (H_{MSY}), total exploitable biomass in 2017 (B_{2017}), harvest rate in 2017 (H_{2017}), harvest rate in 2017 relative to the control rule (H_{2017}/H_{CR}), and total exploitable biomass in 2017 relative to B_{MSY} (B_{2017}/B_{MSY}), probability of overfishing in 2017 (i.e., H/H_{HCR}>1; poflH_{2017}), and probability of the stock being overfished in 2017 (i.e., B/B_{MSY}<0.7; poflB_{2017}). An asterisk (*) in cells of the pofl columns indicates a change in status for the sensitivity run compared to the base case.

Scenario	*K*	*r*	*m*	ψ	*MSY*	H_{MSY}	B_{MSY}	B_{2017}	H_{2017}	B_{2017}/B_{MSY}	H_{2017}/H_{CR}	poflH 2017	poflB 2017
Base case	533.7	0.29	1.73	0.82	42.15	0.17	248.8	142.97	0.11	0.57	0.81	0.39	0.70
r prior mean increased 50%	-0.08	0.23	0.15	0.00	0.04	0.07	-0.02	-0.05	0.05	-0.03	0.01	0.01	0.03
r prior mean reduced 50%	0.18	-0.30	-0.17	-0.02	-0.07	-0.15	0.10	0.11	-0.09	0.02	0.06	0.08	-0.01
r prior mean = 0.33, CV = 30%	0.01	-0.04	-0.03	0.00	-0.01	-0.01	0.00	0.01	-0.01	0.01	-0.01	-0.02	-0.01
r prior mean = 0.15, CV = 115%	0.41	-0.48	-0.22	-0.03	-0.14	-0.32	0.27	0.26	-0.18	0.00	0.23	0.28	0.01
K prior mean increased 50%	0.28	-0.08	0.17	-0.03	0.06	-0.22	0.36	0.18	-0.16	-0.13	0.22	0.27	0.14
K prior mean reduced 50%	-0.27	0.16	-0.16	0.02	-0.04	0.40	-0.32	-0.20	0.26	0.17	-0.20	-0.34	-0.22
K prior CV = 20%	-0.09	0.02	-0.07	0.01	-0.02	0.10	-0.10	-0.06	0.07	0.06	-0.07	-0.13	-0.05
K prior = range(118 – 4550)	0.24	-0.06	0.16	-0.03	0.06	-0.20	0.32	0.18	-0.17	-0.11	0.16	0.21	0.11
ψ prior mean increased 50%	-0.01	0.00	-0.01	0.09	-0.01	0.01	-0.02	0.01	-0.01	0.02	-0.03	-0.04	-0.02
ψ prior mean reduced 50%	0.05	-0.02	0.01	-0.17	0.03	-0.03	0.06	-0.02	0.02	-0.07	0.14	0.18	0.08
ψ prior CV = 20%	-0.01	0.00	-0.01	-0.04	0.00	0.01	-0.01	-0.01	0.01	0.00	0.00	-0.01	0.00

Scenario	K	r	m	ψ	MSY	H_{MSY}	B_{MSY}	B_{2017}	H_{2017}	B_{2017}/B_{MSY}	H_{2017}/H_{CR}	poflH 2017	poflB 2017
ψ prior = range(0.2,0.6)	0.16	-0.04	0.03	-0.39	0.08	-0.07	0.18	-0.07	0.08	-0.21	0.48	0.51*	0.20
ψ prior = range(0.5,0.9)	0.02	-0.01	0.00	-0.14	0.01	-0.01	0.02	-0.01	0.01	-0.04	0.06	0.08	0.05
ψ prior = beta(1.5,1.5)	0.01	0.00	0.01	-0.07	0.01	-0.01	0.01	-0.01	0.01	-0.02	0.04	0.06	0.03
m prior mean increased 50%	0.17	0.14	0.48	-0.01	0.04	-0.22	0.36	0.14	-0.11	-0.16	0.36	0.41*	0.21
m prior mean reduced 50%	-0.17	-0.17	-0.46	0.00	-0.04	0.52	-0.37	-0.14	0.17	0.37	-0.36	-0.58	-0.45*
m prior CV =100%	-0.05	-0.06	-0.17	0.00	-0.01	0.13	-0.13	-0.03	0.03	0.10	-0.15	-0.13	-0.16
m prior mean = 0.92, CV = 80%	-0.16	-0.20	-0.51	0.00	-0.03	0.62	-0.41	-0.13	0.15	0.45	-0.41	-0.60	-0.50*
Schaefer model	0.04	0.05	0.15	0.00	0.02	-0.09	0.12	0.04	-0.03	-0.07	0.14	0.16	0.16
σ_{η}^2 prior mode decreased 10x	-0.03	-0.03	-0.01	0.03	-0.05	-0.02	-0.03	0.09	-0.08	0.12	-0.14	-0.22	-0.16
σ_{η}^2 prior mode increased 10x	0.02	0.02	0.00	-0.02	0.04	0.02	0.02	-0.05	0.05	-0.06	0.10	0.12	0.09
$\sigma_{\tau estimated}^2$ prior mode decreased 10x	0.02	-0.01	0.00	0.00	0.01	-0.01	0.02	-0.02	0.02	-0.04	0.07	0.09	0.06
$\sigma_{\tau estimated}^2$ prior mode increased 10x	-0.05	0.06	0.01	-0.03	0.01	0.05	-0.05	0.15	-0.13	0.21	-0.28	-0.33	-0.28
Uniform σ_{η}^2 and $\sigma_{\tau estimated}^2$ priors	-0.03	-0.03	-0.01	0.03	-0.05	-0.02	-0.03	0.09	-0.07	0.11	-0.13	-0.19	-0.15
Exclude variability in catch	0.02	-0.01	0.02	0.00	0.00	-0.03	0.03	0.04	-0.04	0.02	-0.03	-0.04	-0.02
Fit to OLO MSY estimate	0.05	0.06	0.05	-0.01	0.09	0.02	0.07	0.05	-0.04	-0.02	-0.05	-0.05	0.02

Table 22. Sensitivity of production model results for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands to scenarios with different assumed prior distributions, different model structure (i.e., Pella), excluding variability in estimated catch, and fitting to an independent estimate of MSY (OLO MSY). Results are expressed as proportional change relative to base case model (first row) for *K*, *r*, *m*, *ψ*, maximum sustainable yield (*MSY*), biomass at maximum sustainable yield (B_{MSY}), harvest rate at maximum sustainable yield (H_{MSY}), total exploitable biomass in 2017 (B_{2017}), harvest rate in 2017 (H_{2017}), harvest rate in 2017 relative to the control rule (H_{2017}/H_{CR}), and total exploitable biomass in 2017 relative to B_{MSY} (B_{2017}/B_{MSY}), probability of overfishing in 2017 (i.e., H/H_{HCR}>1; poflH$_{2017}$), and probability of the stock being overfished in 2017 (i.e., B/B_{MSY}<0.7; poflB$_{2017}$). An asterisk (*) in cells of the pofl columns indicates a change in status for the sensitivity run compared to the base case.

Scenario	*K*	*r*	*m*	ψ	*MSY*	H_{MSY}	B_{MSY}	B_{2017}	H_{2017}	B_{2017}/B_{MSY}	H_{2017}/H_{CR}	poflH 2017	poflB 2017
Base	1141.2	0.33	2.00	0.48	93.64	0.17	570.6	569.23	0.13	1.08	0.79	0.41	0.24
r prior mean increased 50%	-0.11	0.21	-	0.02	0.06	0.21	-0.11	-0.08	0.08	0.06	-0.11	-0.11	-0.09
r prior mean reduced 50%	0.25	-0.32	-	-0.02	-0.14	-0.32	0.25	0.13	-0.11	-0.12	0.33	0.27*	0.26
r prior mean = 0.33, CV = 30%	0.06	-0.09	-	-0.01	-0.03	-0.09	0.06	0.03	-0.04	-0.04	0.06	0.06	0.05
r prior mean = 0.15, CV = 115%	0.41	-0.52	-	0.03	-0.32	-0.52	0.41	0.22	-0.13	-0.16	0.88	0.54*	0.36
K prior mean increased 50%	0.34	-0.11	-	-0.07	0.19	-0.11	0.34	0.31	-0.23	-0.02	-0.13	-0.10	0.11
K prior mean reduced 50%	-0.36	0.26	-	0.17	-0.19	0.26	-0.36	-0.29	0.40	0.09	0.08	0.06	-0.37
K prior CV = 20%	0.23	-0.10	-	-0.09	0.12	-0.10	0.23	0.20	-0.12	-0.09	0.00	0.00	0.24
K prior = range(303 – 11741)	-0.14	0.08	-	0.05	-0.07	0.08	-0.14	-0.13	0.11	0.03	0.02	0.01	-0.11
ψ prior mean increased 50%	-0.07	0.01	-	0.32	-0.06	0.01	-0.07	0.08	-0.08	0.15	-0.12	-0.13	-0.45
ψ prior mean reduced 50%	0.23	0.00	-	-0.42	0.23	0.00	0.23	-0.17	0.20	-0.36	0.39	0.30*	1.12*

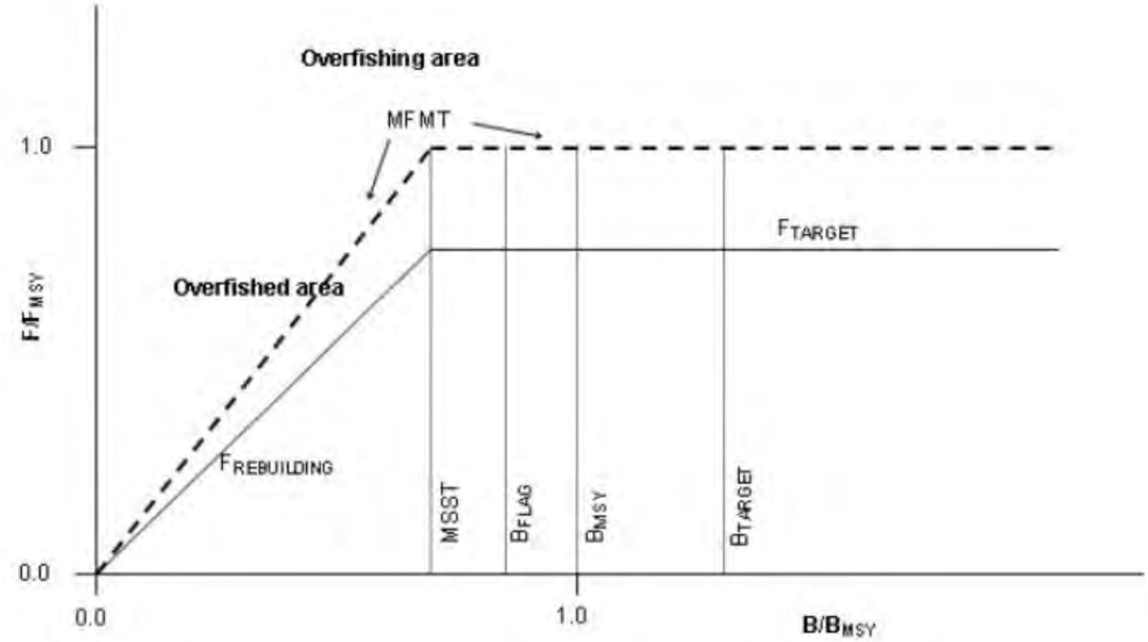
Scenario	***K***	***r***	***m***	**ψ**	***MSY***	H_{MSY}	B_{MSY}	B_{2017}	H_{2017}	B_{2017}/B_{MSY}	H_{2017}/H_{CR}	**poflH 2017**	**poflB 2017**
ψ prior CV = 20%	-0.01	-0.02	-	-0.04	-0.02	-0.02	-0.01	0.00	0.00	-0.02	0.01	0.00	-0.07
ψ prior = range(0.2,0.6)	0.08	-0.01	-	-0.23	0.07	-0.01	0.08	-0.07	0.08	-0.17	0.14	0.12	0.43
ψ prior = range(0.5,0.9)	-0.11	0.02	-	0.40	-0.10	0.02	-0.11	0.10	-0.09	0.19	-0.14	-0.17	-0.62
ψ prior = beta(1.5,1.5)	-0.03	0.01	-	0.20	-0.02	0.01	-0.03	0.03	-0.02	0.07	-0.04	-0.04	-0.15
Pella model	0.04	0.03	0.08	0.00	0.00	-0.04	0.06	0.03	-0.02	-0.04	0.03	0.04	0.12
σ_{η}^{2} prior mode decreased 10x	-0.02	-0.02	-	0.02	-0.04	-0.02	-0.02	0.00	-0.01	0.03	0.01	0.01	-0.03
σ_{η}^{2} prior mode increased 10x	0.02	0.01	-	0.00	0.03	0.01	0.02	0.02	-0.02	-0.01	-0.03	-0.03	-0.03
$\sigma_{\tau estimated}^{2}$ prior mode decreased 10x	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.02
$\sigma_{\tau estimated}^{2}$ prior mode increased 10x	0.02	0.00	-	-0.01	0.01	-0.01	0.02	0.03	-0.02	0.02	-0.02	-0.01	0.00
Uniform σ_{η}^{2} and $\sigma_{\tau estimated}^{2}$ priors	-0.02	-0.01	-	0.06	-0.03	-0.01	-0.02	0.10	-0.10	0.15	-0.11	-0.10	-0.22
Exclude variability in catch	-0.03	-0.01	-	-0.02	-0.04	-0.01	-0.03	-0.02	0.01	0.01	-0.02	-0.15	-0.05
Fit to OLO MS*Y* estimate	0.33	0.10	-	-0.14	0.50	0.10	0.33	0.38	-0.24	0.04	-0.30	-0.27	0.19

Table 23. Sensitivity of production model results for bottomfish management unit species in American Samoa to scenarios with different assumed prior distributions, different model structure (i.e., Schaefer), excluding variability in estimated catch, and fitting to an independent estimate of MSY (OLO MSY). Results are expressed as proportional change relative to base case model (first row) for *K*, *r*, *m*, *ψ*, maximum sustainable yield (*MSY*), biomass at maximum sustainable yield (B_{MSY}), harvest rate at maximum sustainable yield (H_{MSY}), total exploitable biomass in 2017 (B_{2017}), harvest rate in 2017 (H_{2017}), harvest rate in 2017 relative to the control rule (H_{2017}/H_{CR}), and total exploitable biomass in 2017 relative to B_{MSY} (B_{2017}/B_{MSY}), probability of overfishing in 2017 (i.e., H/H_{HCR}>1; poflH$_{2017}$), and probability of the stock being overfished in 2017 (i.e., B/B_{MSY}<0.7; poflB$_{2017}$). An asterisk (*) in cells of the pofl columns indicates a change in status for the sensitivity run compared to the base case.

Scenario	*K*	*r*	*m*	ψ	*MSY*	H_{MSY}	B_{MSY}	B_{2017}	H_{2017}	B_{2017}/B_{MSY}	H_{2017}/H_{CR}	poflH 2017	poflB 2017
Base case	495.8	0.28	2.66	0.71	28.8	0.11	272.8	102.6	0.15	0.38	2.75	0.85	0.91
r prior mean increased 50%	-0.06	0.28	0.16	-0.01	0.09	0.12	-0.02	-0.09	0.11	-0.07	0.07	0.02	0.02
r prior mean reduced 50%	0.17	-0.36	-0.19	-0.03	-0.13	-0.21	0.09	0.13	-0.11	0.03	0.09	0.03	-0.01
r prior mean = 0.33, CV = 30%	0.00	-0.02	-0.03	-0.01	0.00	0.00	0.00	-0.01	0.02	-0.01	0.03	0.00	0.00
r prior mean = 0.15, CV = 115%	0.43	-0.64	-0.28	-0.02	-0.35	-0.50	0.26	0.37	-0.26	0.08	0.41	0.09	-0.03
K prior mean increased 50%	0.32	-0.07	0.11	-0.07	0.14	-0.16	0.37	0.23	-0.19	-0.08	0.06	-0.02	0.01
K prior mean reduced 50%	-0.30	0.16	-0.14	0.08	-0.09	0.35	-0.33	-0.26	0.36	0.08	-0.08	0.01	-0.02
K prior CV = 20%	0.24	-0.08	0.09	-0.07	0.09	-0.14	0.28	0.20	-0.13	-0.08	0.11	0.01	0.02
K prior = range (156 – 6046)	-0.04	0.03	-0.01	0.01	0.00	0.05	-0.05	-0.05	0.03	0.00	-0.02	-0.01	0.00
ψ prior mean increased 50%	-0.05	0.01	-0.02	0.13	-0.03	0.03	-0.05	0.01	-0.01	0.06	-0.10	-0.03	-0.02
ψ prior mean reduced 50%	0.19	0.00	0.03	-0.31	0.15	-0.02	0.21	-0.14	0.17	-0.29	0.71	0.11	0.07
ψ prior CV = 20%	-0.04	0.00	-0.01	0.09	-0.04	0.02	-0.05	0.04	-0.04	0.08	-0.13	-0.04	-0.03

Scenario	K	r	m	ψ	MSY	H_{MSY}	B_{MSY}	B_{2017}	H_{2017}	B_{2017}/B_{MSY}	H_{2017}/H_{CR}	poflH 2017	poflB 2017
ψ prior = range(0.2,0.6)	0.36	0.02	0.06	-0.46	0.31	-0.03	0.39	-0.23	0.30	-0.46	1.48	0.17	0.10
ψ prior = range(0.5,0.9)	0.00	-0.01	0.00	-0.05	-0.01	0.00	0.00	0.01	-0.01	0.00	0.00	0.01	0.01
ψ prior = beta(1.5,1.5)	0.08	0.00	0.02	-0.12	0.06	-0.01	0.09	-0.07	0.08	-0.13	0.26	0.05	0.04
m prior mean increased 50%	0.12	0.14	0.40	-0.02	0.02	-0.18	0.26	0.09	-0.09	-0.12	0.27	0.08	0.07
m prior mean reduced 50%	-0.13	-0.20	-0.46	0.03	-0.01	0.47	-0.32	-0.07	0.09	0.37	-0.46	-0.27	-0.25
m prior CV =100%	0.13	0.14	0.44	-0.02	0.01	-0.19	0.27	0.10	-0.07	-0.14	0.34	0.06	0.04
m prior mean = 0.92, CV = 80%	-0.08	-0.12	-0.29	0.02	0.00	0.25	-0.20	-0.01	0.04	0.20	-0.31	-0.18	-0.17
Schaefer model	-0.09	-0.10	-0.25	0.00	-0.02	0.19	-0.18	-0.10	0.10	0.11	-0.17	-0.05	-0.03
σ_{η}^2 prior mode decreased 10x	0.00	-0.04	0.08	0.01	-0.09	-0.10	0.03	0.00	0.02	-0.03	0.18	0.05	0.00
σ_{η}^2 prior mode increased 10x	0.02	0.02	-0.04	-0.03	0.07	0.07	0.01	-0.02	0.02	-0.03	-0.02	-0.01	0.01
$\sigma_{\tau estimated}^2$ prior mode decreased 10x	0.01	0.00	0.01	0.00	0.00	-0.01	0.01	0.00	0.00	-0.01	0.01	0.02	0.02
$\sigma_{\tau estimated}^2$ prior mode increased 10x	0.01	0.01	-0.03	0.00	0.03	0.05	-0.01	0.07	-0.06	0.07	-0.15	-0.10	-0.09
Uniform $\sigma_{\eta}^2$and $\sigma_{\tau estimated}^2$ priors	0.01	-0.02	0.12	-0.05	-0.10	-0.12	0.05	-0.09	0.11	-0.13	0.47	0.13	0.06
Exclude variability in catch	0.02	0.00	0.01	-0.01	0.01	-0.01	0.02	-0.01	0.01	-0.03	0.05	0.01	0.01
Fit to OLO MSY estimate	0.56	0.21	0.12	-0.15	0.82	0.09	0.62	0.46	-0.29	-0.08	-0.29	-0.23	-0.07

7. Figures



MFMT	MSST	B_{FLAG}
$F(B) = \frac{F_{MSY} B}{c\, B_{MSY}}$ for $B \le c\, B_{MSY}$ $F(B) = F_{MSY}$ for $B > c\, B_{MSY}$	$c\, B_{MSY}$	B_{MSY}
where $c = \max(1\text{-M}, 0.5)$		

Figure 1: Harvest control rule for Guam, the Commonwealth of the Northern Mariana Islands, and American Samoa (reproduced from WPRFMC 2009a). *F* and F_{MSY} in the figure are equivalent to harvest rate (*H*) and harvest rate that produces maximum sustainable yield (MSY; H_{MSY}) in the 2019 benchmark assessments. The harvest control rule determines the threshold for overfishing (defined as H_{CR} in the 2019 assessments) as a function of H_{MSY}, biomass (*B*), the biomass that produces maximum sustainable yield (B_{MSY}), and 1 minus the rate of natural mortality (*M*; assumed to be 0.3).

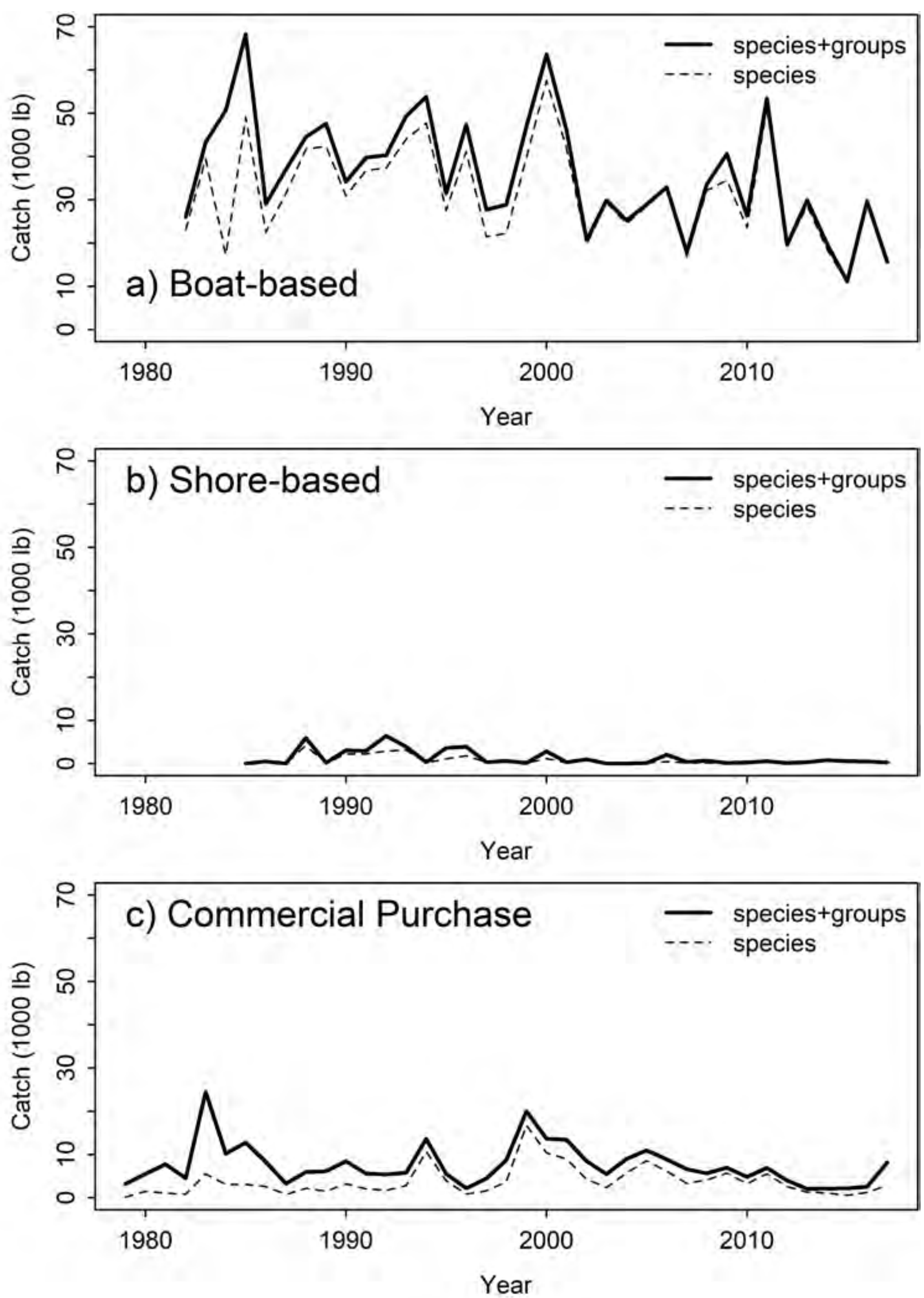


Figure 2: Catch in Guam of individual bottomfish management unit species (BMUS; dashed line) and catch of individual species with added portion from species groups believed to contain BMUS (solid line) for the a) boat-based survey, b) shore-based survey, and c) commercial purchase data in years where data were available. Subpanels are plotted on the same axes to allow comparison.

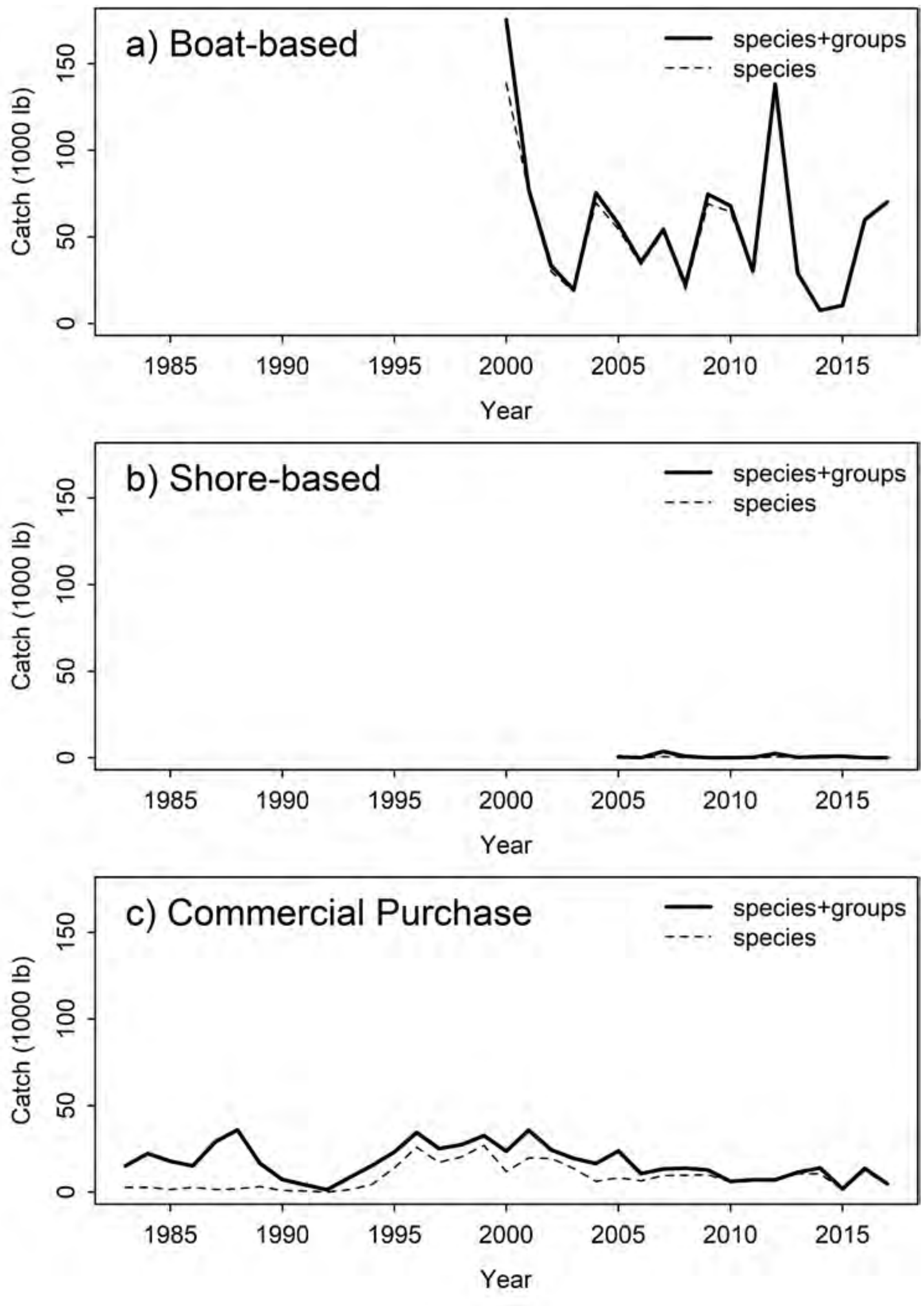


Figure 3: Catch in the Commonwealth of the Northern Mariana Islands of individual bottomfish management unit species (BMUS; dashed line) and catch of individual species with added portion from species groups believed to contain BMUS (solid line) for the a) boat-based survey, b) shore-based survey, and c) commercial purchase data in years where data were available. Subpanels are plotted on the same axes to allow comparison.

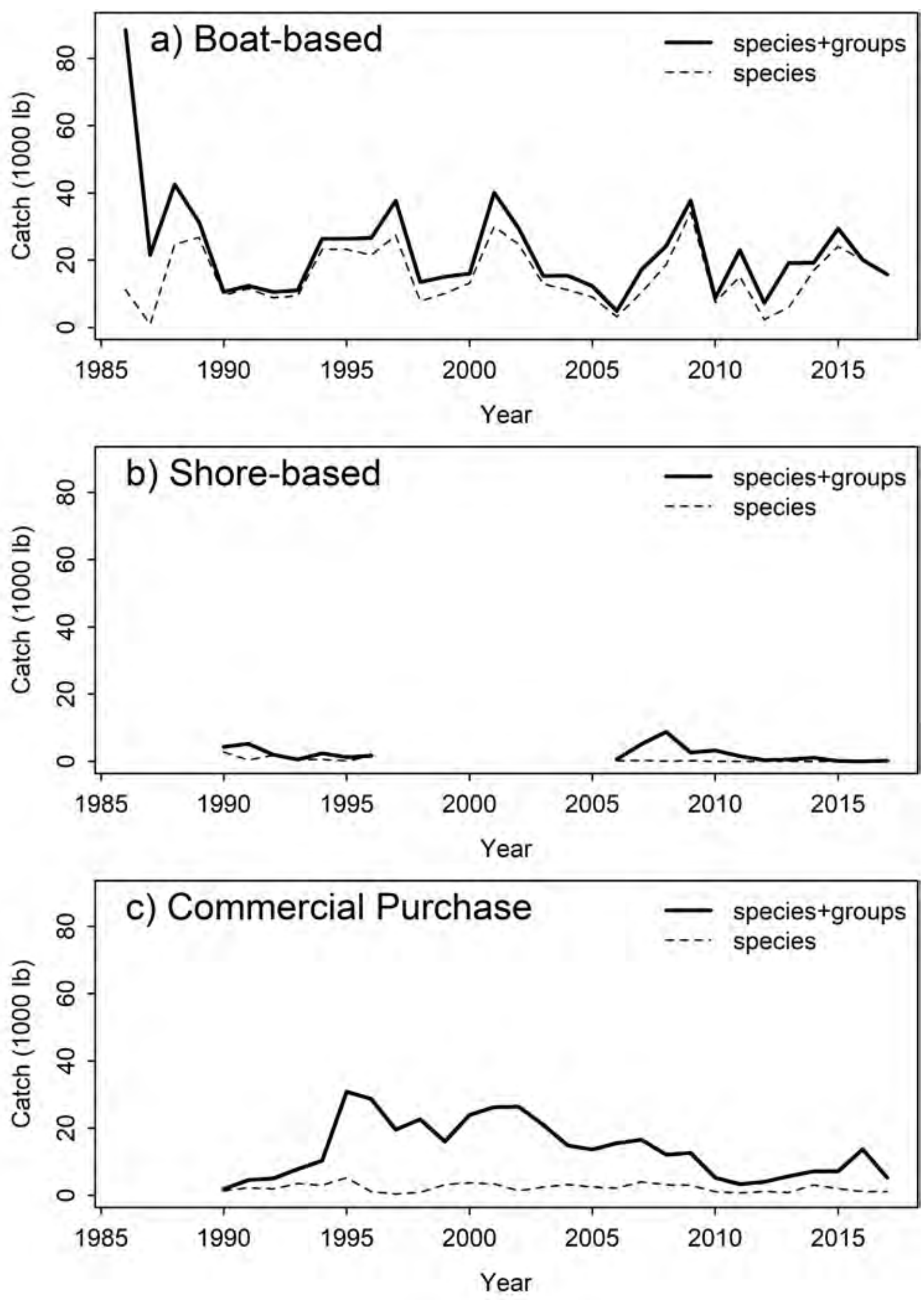


Figure 4: Catch in American Samoa of individual bottomfish management unit species (BMUS; dashed line) and catch of individual species with added portion from species groups believed to contain BMUS (solid line) for the (a) boat-based survey, (b) shore-based survey, and (c) commercial purchase data in years where data were available. Subpanels are plotted on the same axes to allow comparison.

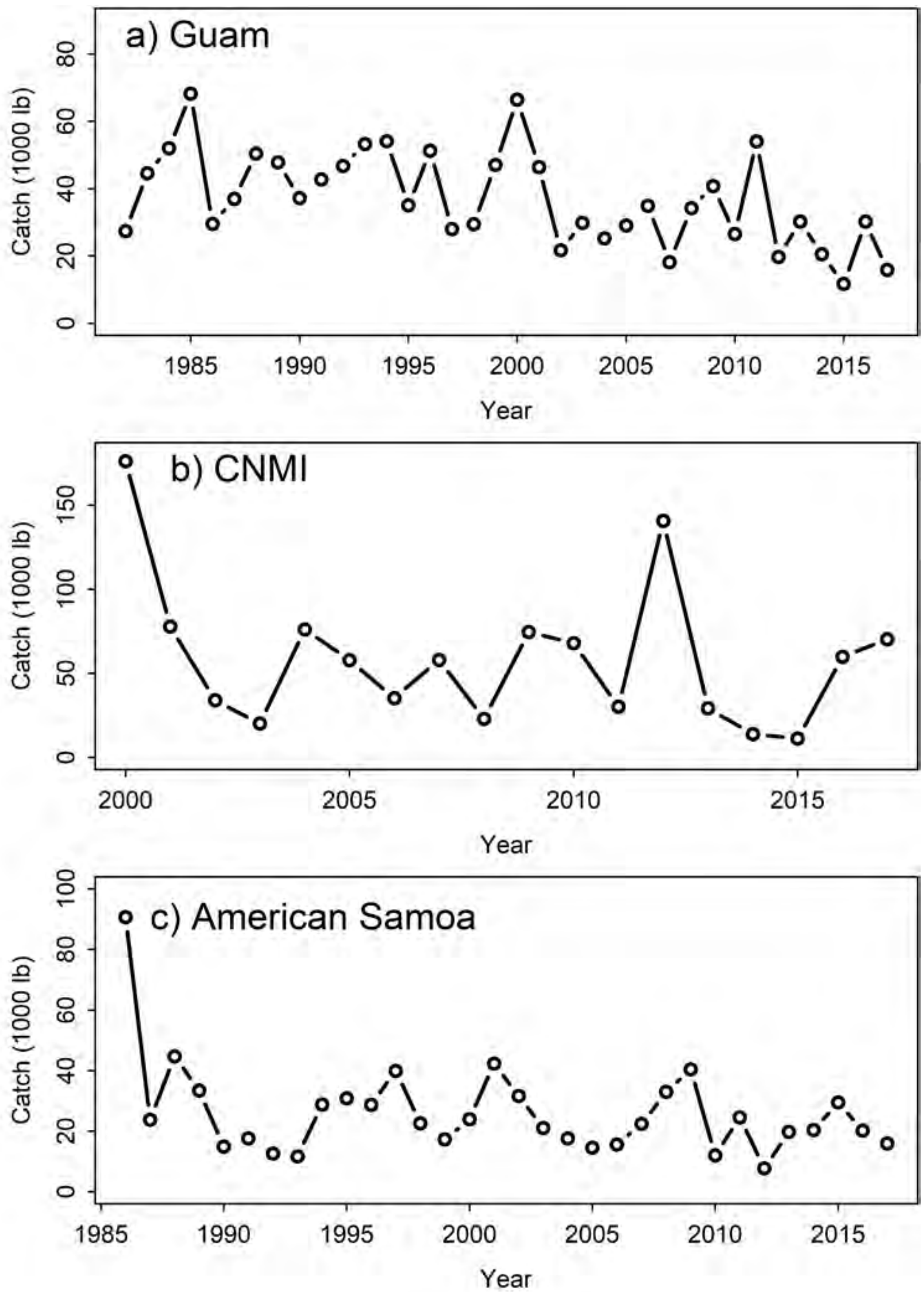


Figure 5: Total catch used as input into the 2019 benchmark stock assessment models for (a) Guam, (b) the Commonwealth of the Northern Mariana Islands (CNMI), and (c) American Samoa.

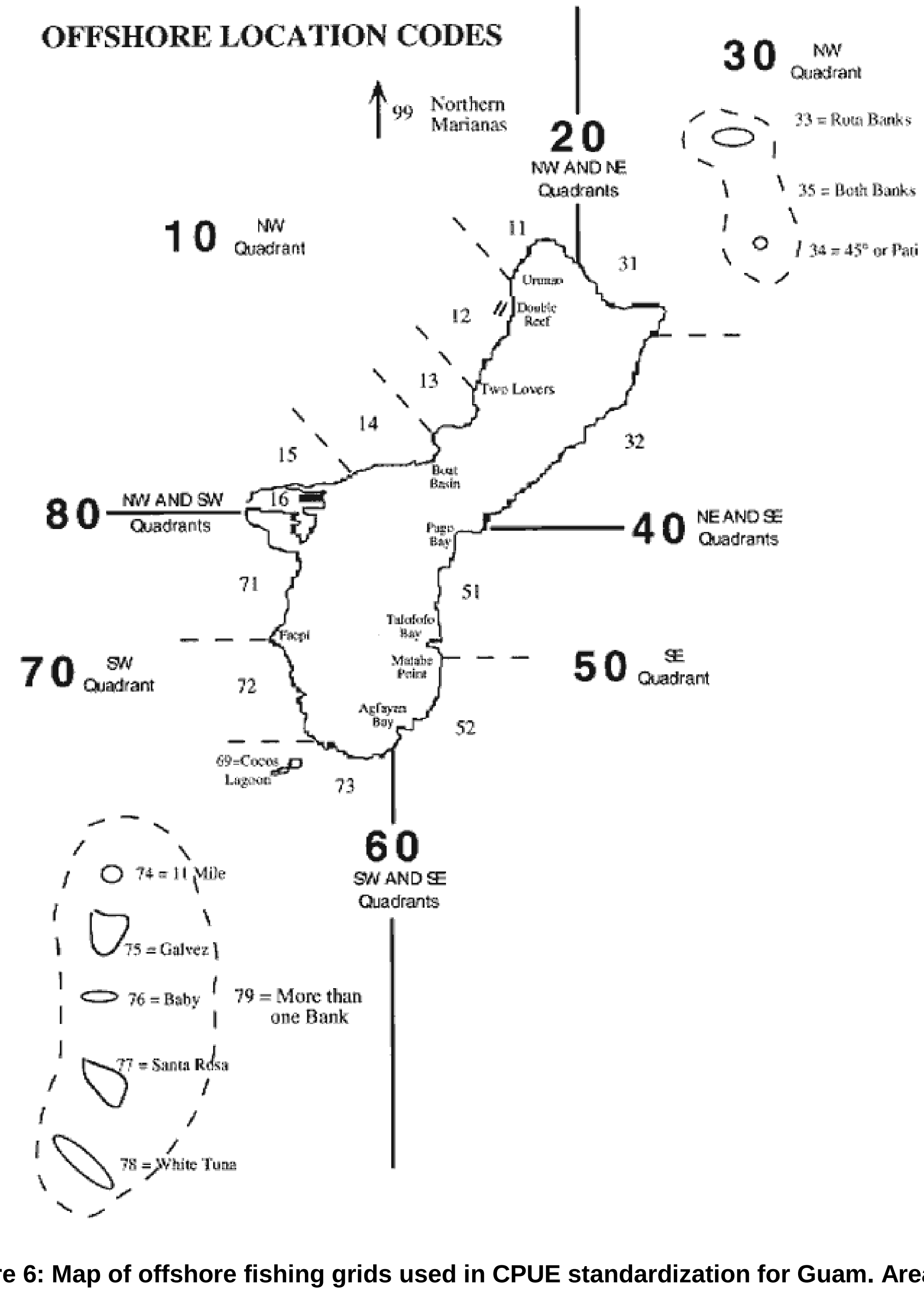


Figure 6: Map of offshore fishing grids used in CPUE standardization for Guam. Areas 10, 30, 50, and 70 represent ordinal directions, while areas 20, 40, 60, and 80 represent cardinal directions. Cardinal directions overlap with two of the ordinal directions. Map provided by Western Pacific Fisheries Information Network (WPacFIN).

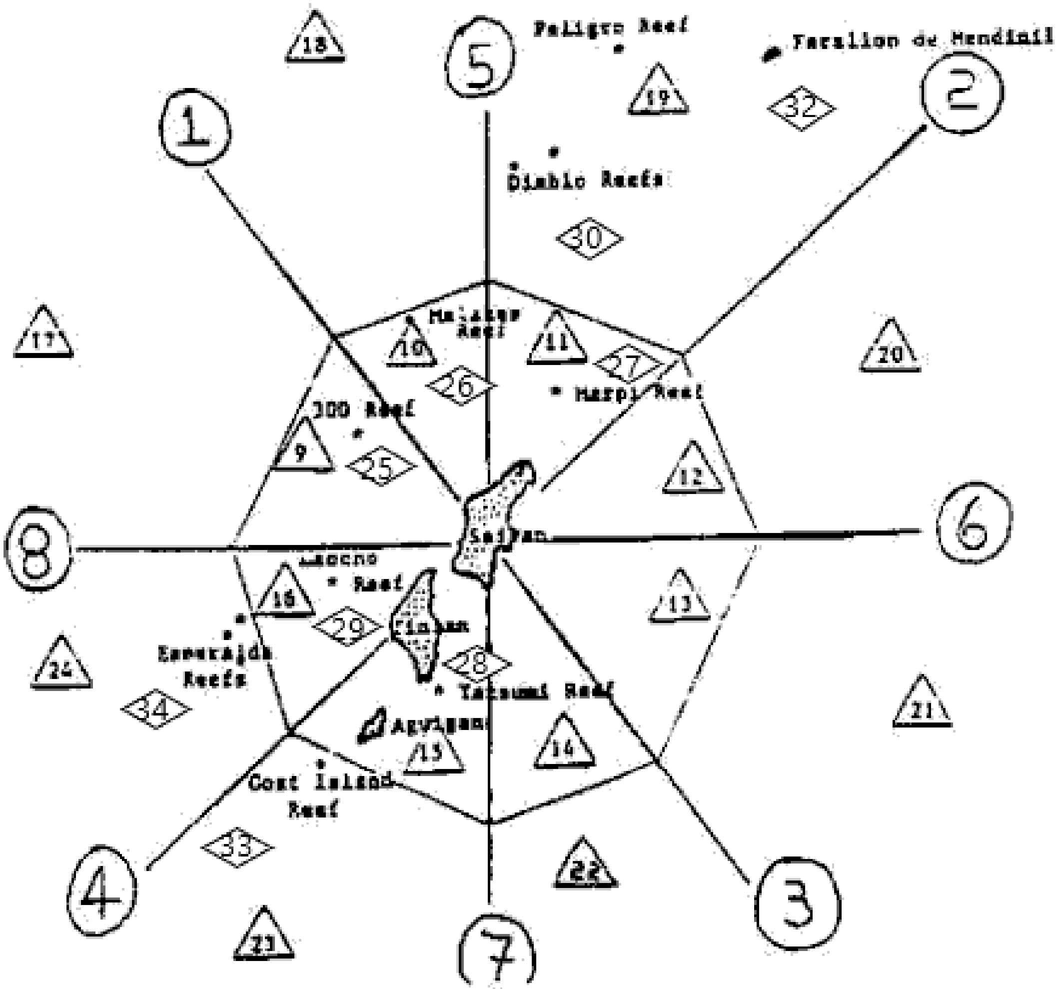


Figure 7: Map of offshore fishing grids used in CPUE standardization for the Commonwealth of the Northern Mariana Islands. Circles (1-8) represent large general fishing areas by cardinal and ordinal quadrants, triangles (9-24) represent inshore and offshore areas within the quadrants, and diamonds (25-34) represent specific reefs. Map provided by Western Pacific Fisheries Information Network (WPacFIN).

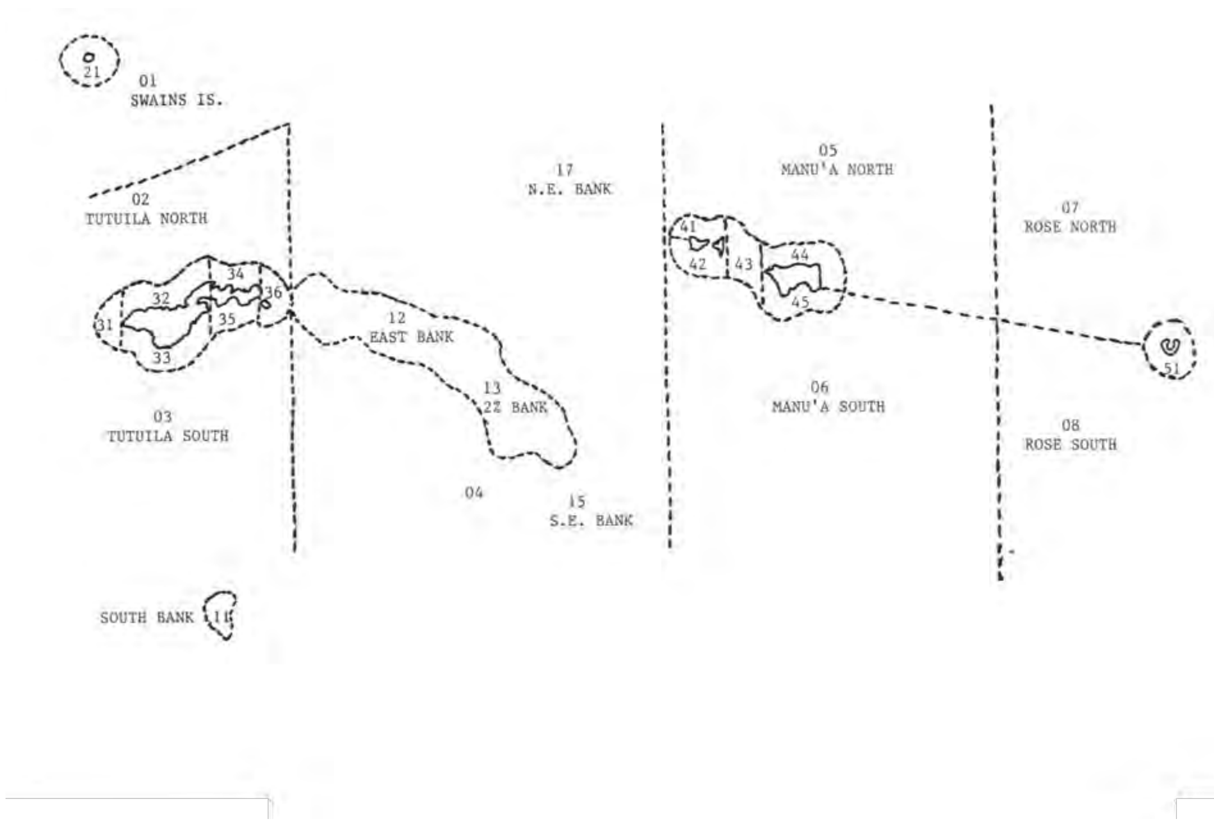


Figure 8: Map of offshore fishing grids used in CPUE standardization for American Samoa. Map provided by Western Pacific Fisheries Information Network (WPacFIN).

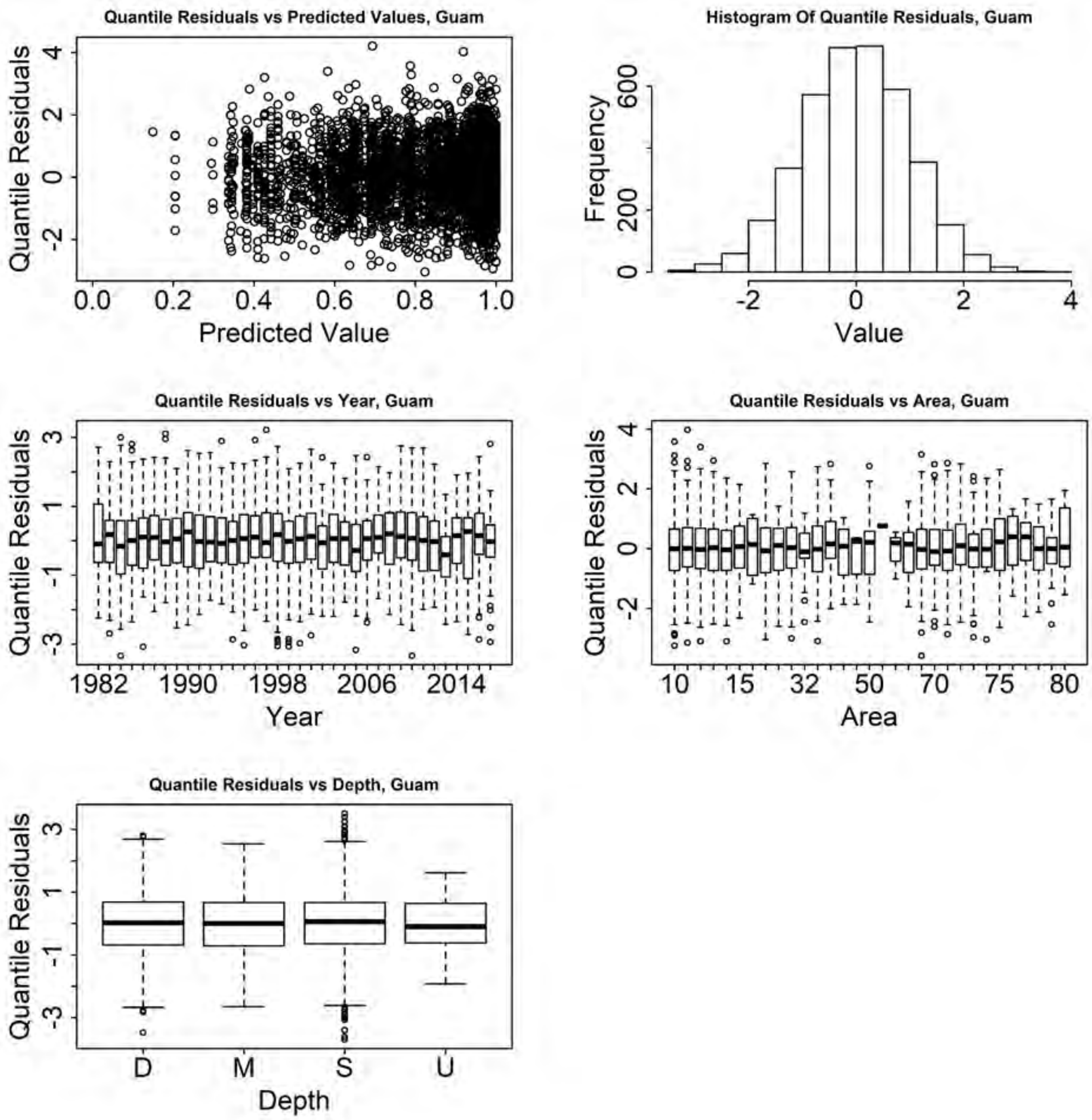


Figure 9: Model diagnostics for the best fit Bernoulli model for bottomfish management unit species in Guam. Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each selected covariate (to assess patterning in the covariates).

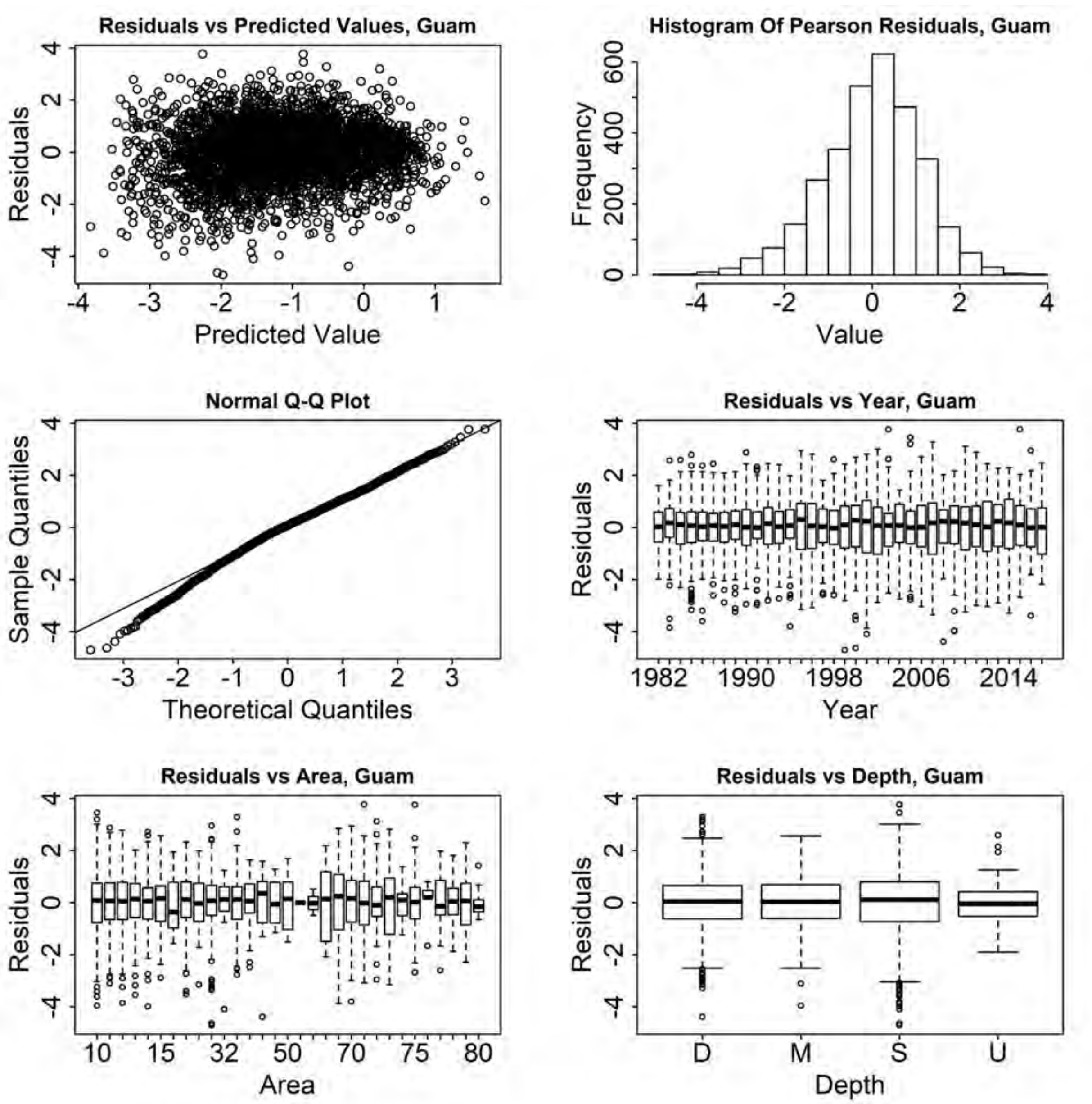


Figure 10: Model diagnostics for the best fit lognormal model for bottomfish management unit species in Guam. Diagnostic plots include plots of residuals against model predicted values (to assess heteroscedasticity), histogram of residuals and the quantile-quantile plot (to assess normality), and plots of residuals against values of each covariate (to assess patterning in the covariates).

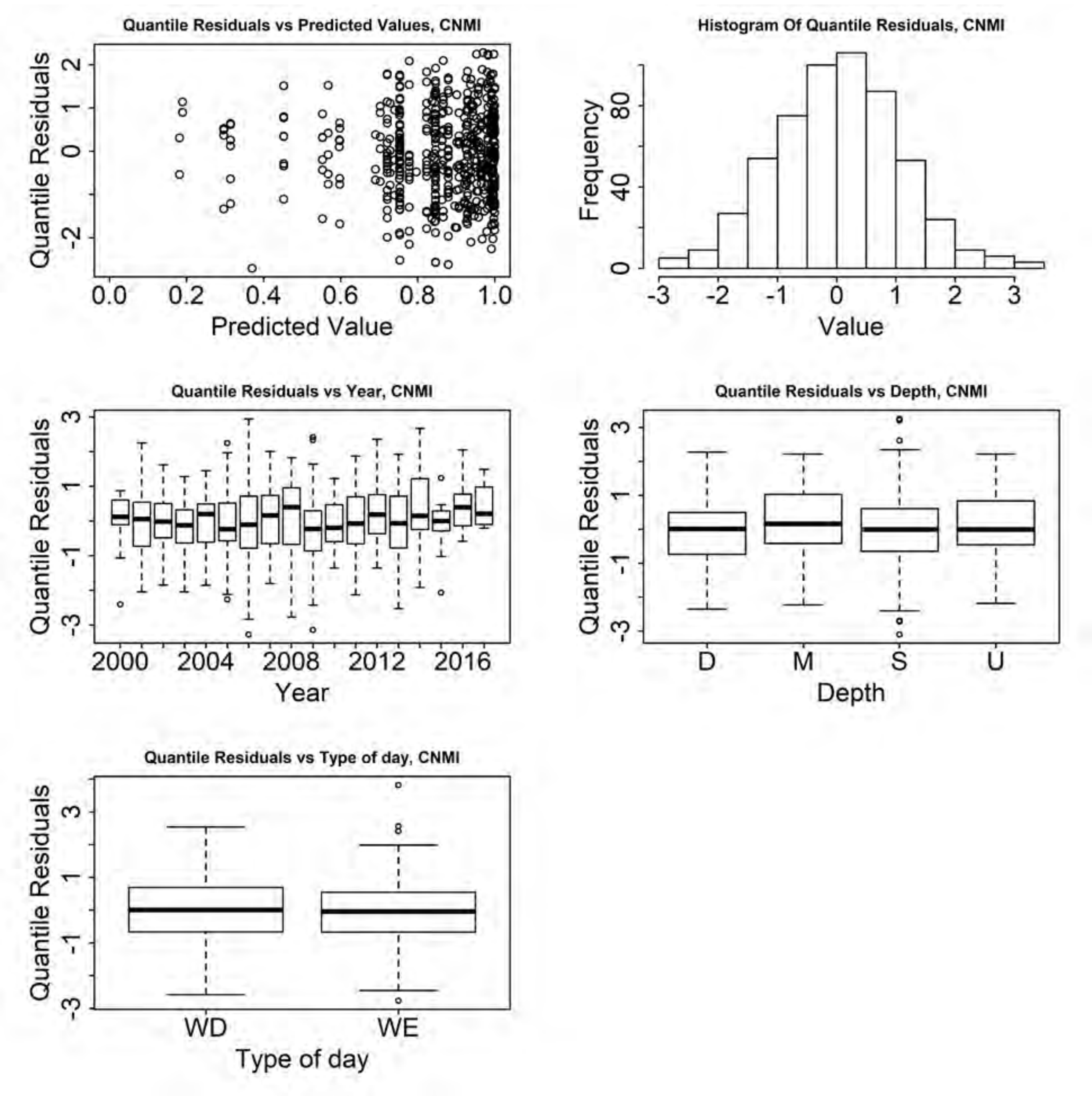


Figure 11: Model diagnostics for the best fit Bernoulli model for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands (CNMI). Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each selected covariate (to assess patterning in the covariates).

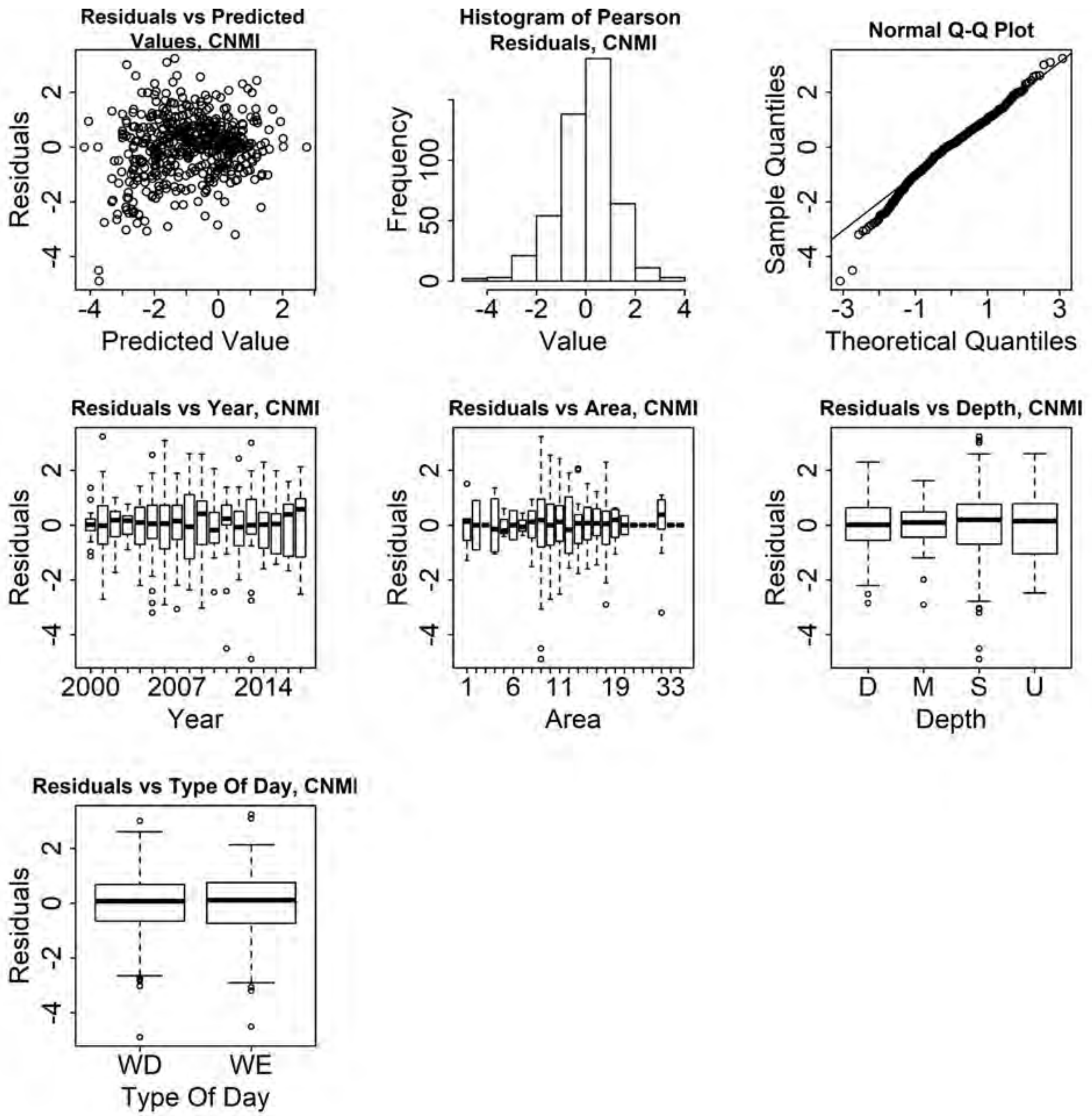


Figure 12: Model diagnostics for the best fit lognormal model for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands (CNMI). Diagnostic plots include plots of residuals against model predicted values (to assess heteroscedasticity), histogram of residuals and the quantile-quantile plot (to assess normality), and plots of residuals against values of each covariate (to assess patterning in the covariates).

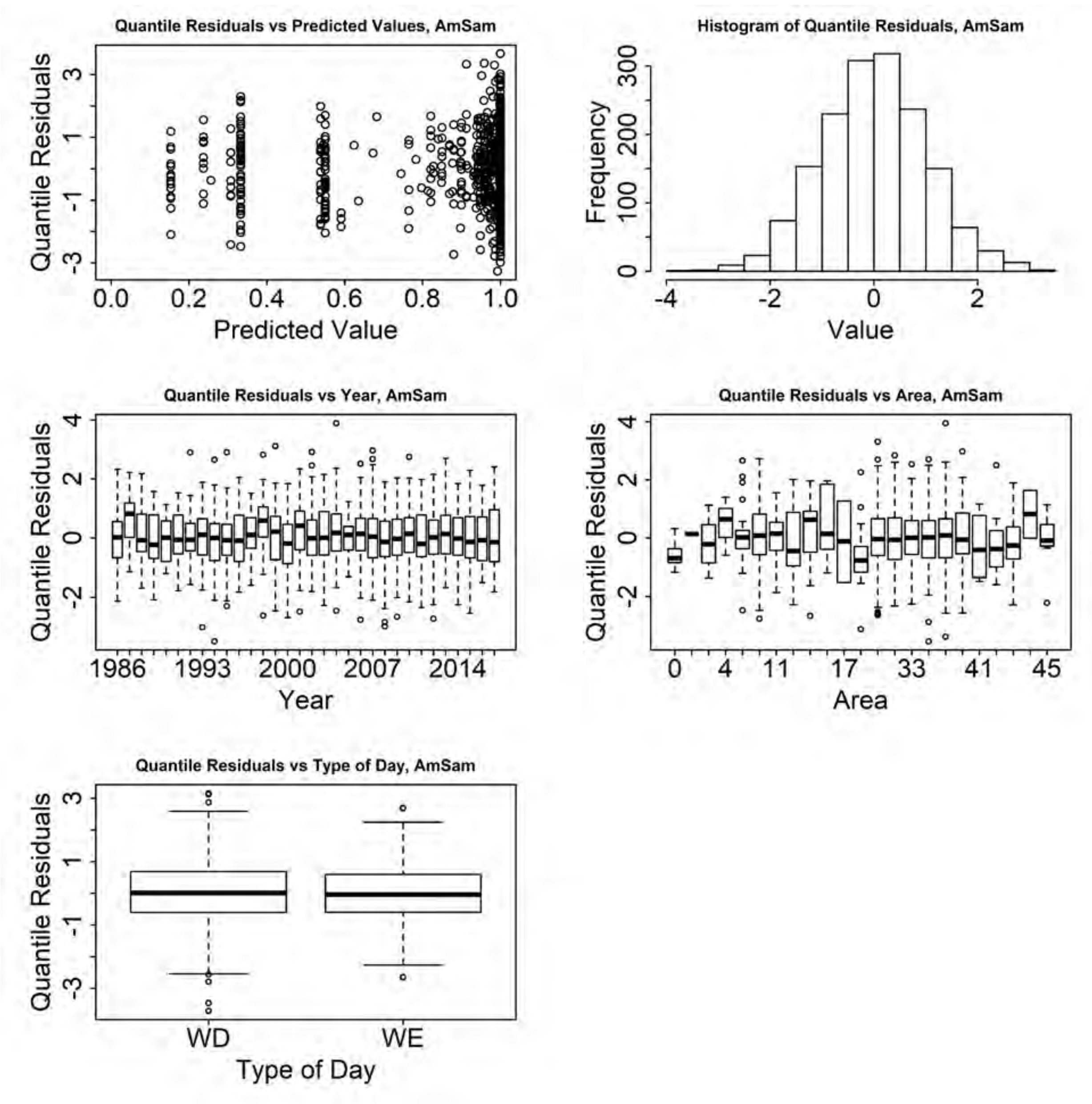


Figure 13: Model diagnostics for the best fit Bernoulli model for bottomfish management unit species in American Samoa (AmSam). Diagnostic plots include plots of quantile residuals against model predicted values (to assess heteroscedasticity), histogram of quantile residuals (to assess normality), and plots of quantile residuals against values of each selected covariate (to assess patterning in the covariates).

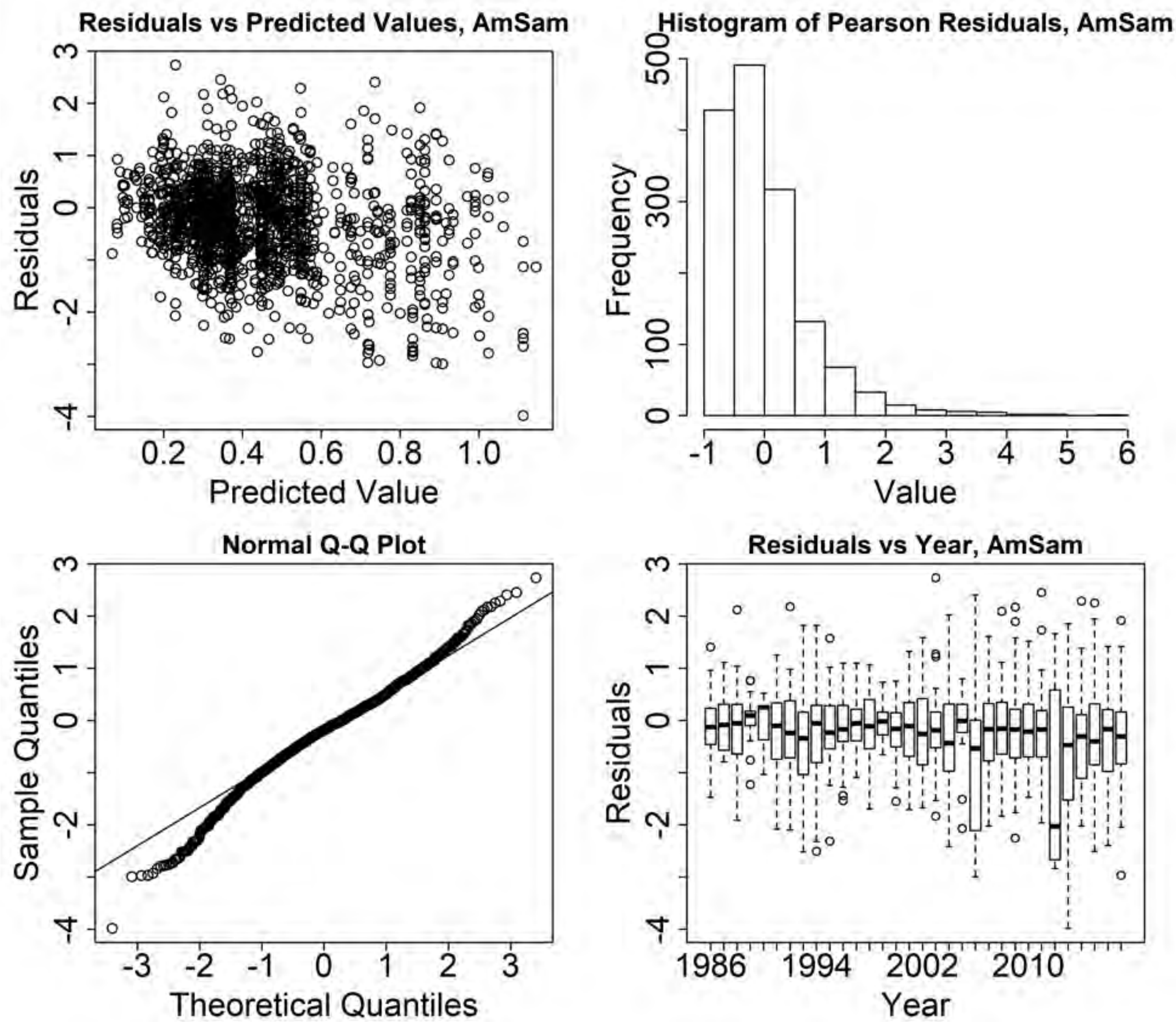


Figure 14: Model diagnostics for the best fit gamma model for bottomfish management unit species in American Samoa (AmSam). Diagnostic plots include plots of residuals against model predicted values (to assess heteroscedasticity), histogram of residuals and the quantile-quantile plot (to assess normality), and plots of residuals against values of each covariate (to assess patterning in the covariates).

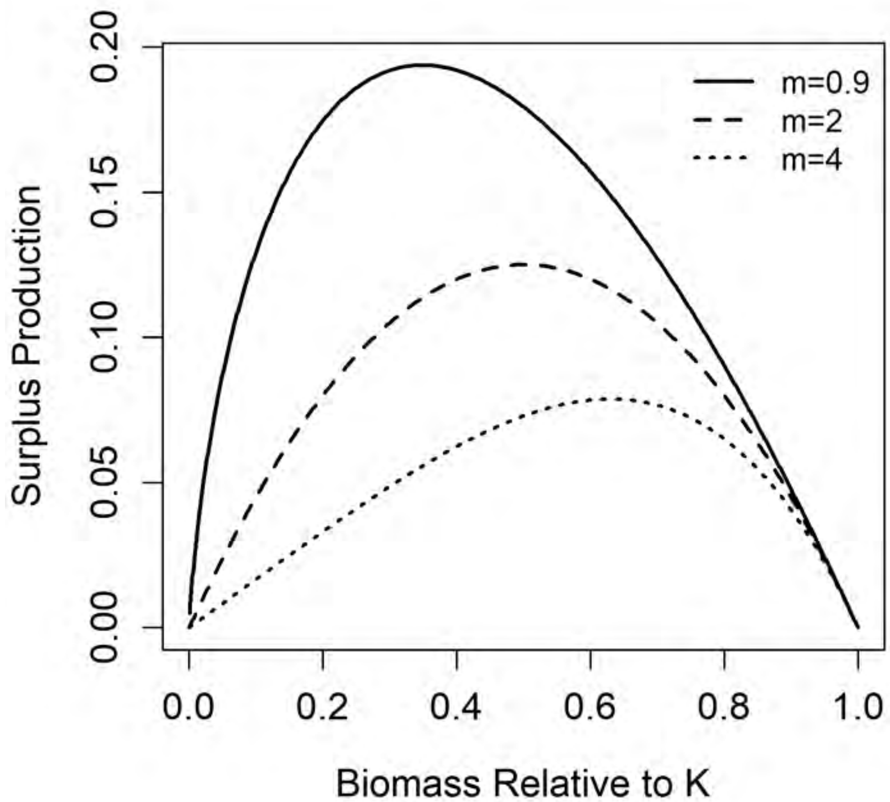


Figure 15: Pella-Tomlinson (1969) generalized surplus production curves as a function of biomass relative to carrying capacity (*K*) for various production shape parameter (*m*) values. In this example, *K* = 1, and intrinsic growth rate (*r*) = 0.5.

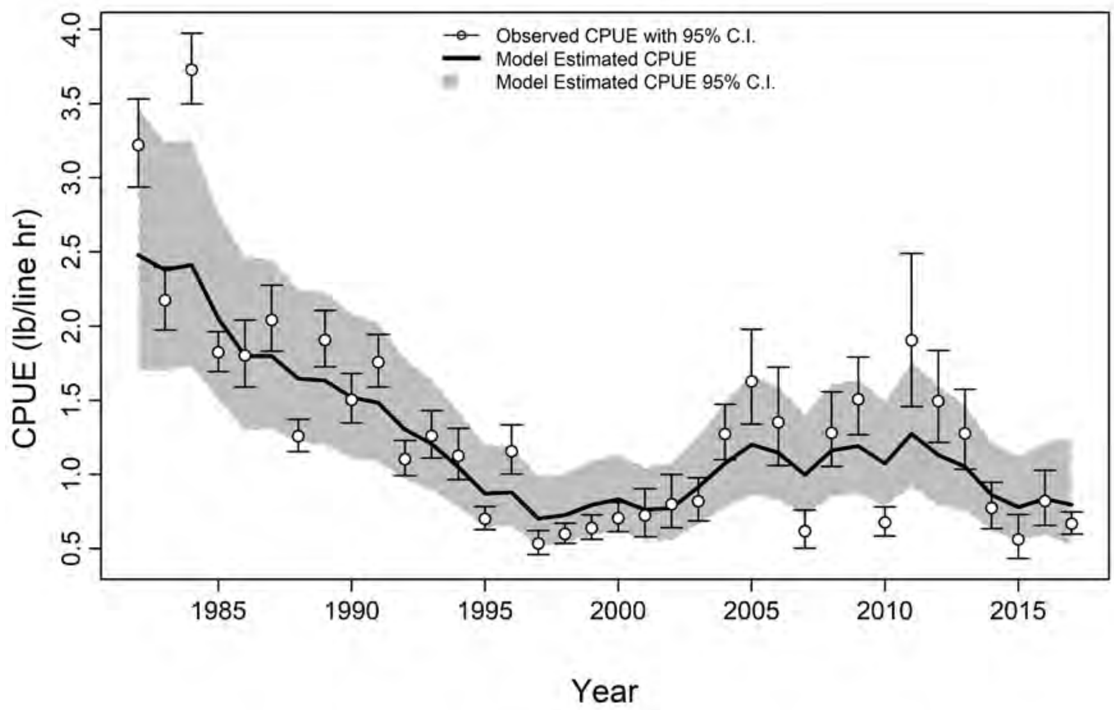


Figure 16. Observed (standardized CPUE) and the CPUE series estimated from the production model for bottomfish management unit species in Guam from 1982 through 2017.

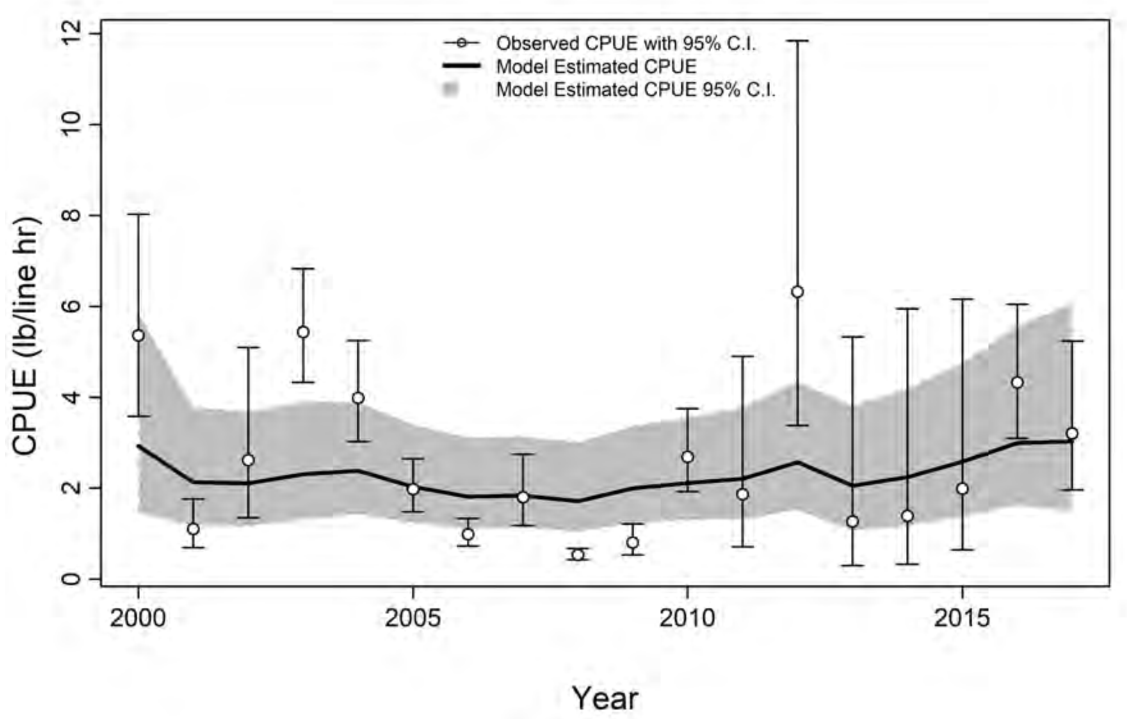


Figure 17. Observed (standardized CPUE) and the CPUE series estimated from the production model for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands from 2000 through 2017.

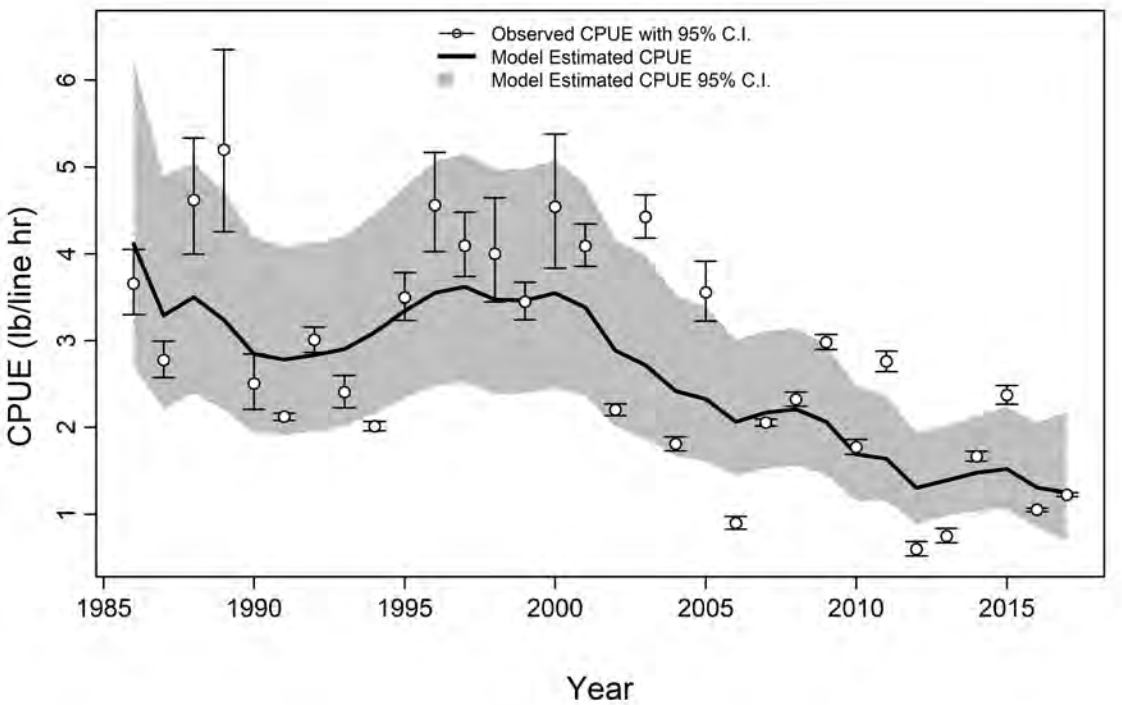


Figure 18. Observed (standardized CPUE) and the CPUE series estimated from the production model for bottomfish management unit species in American Samoa from 1986 through 2017.

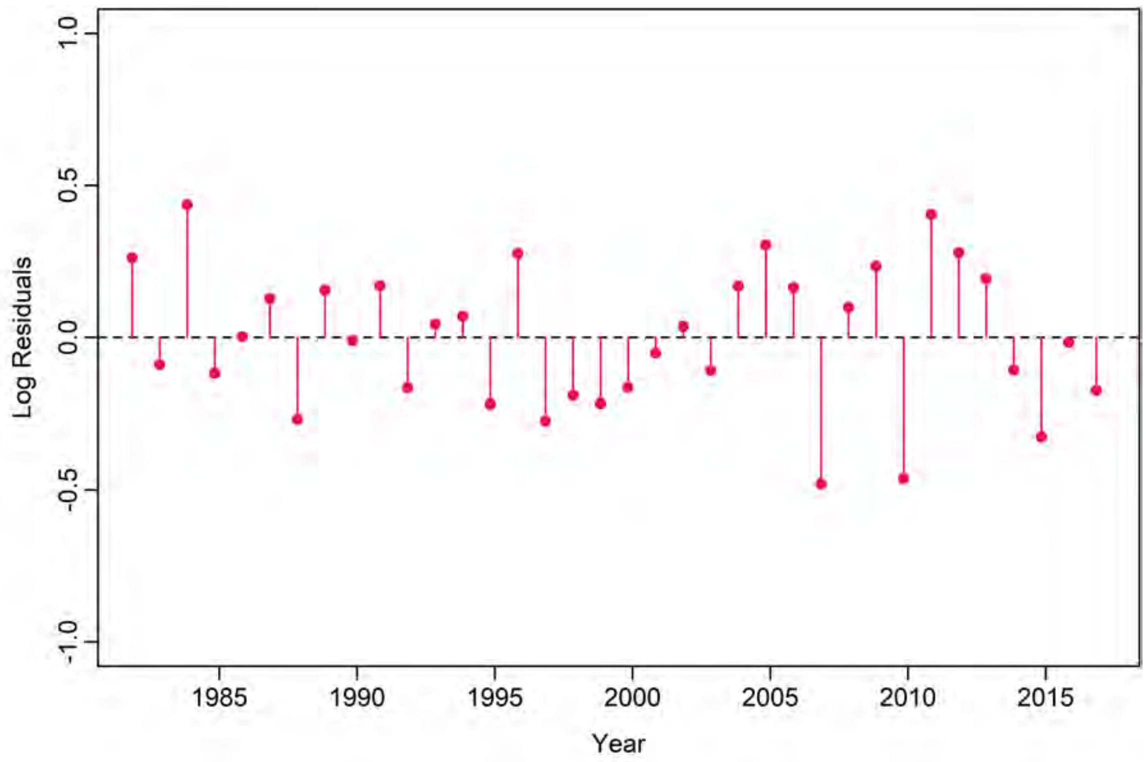


Figure 19. Residuals of production model fit to standardized CPUE for bottomfish management unit species in Guam from 1982-2017.

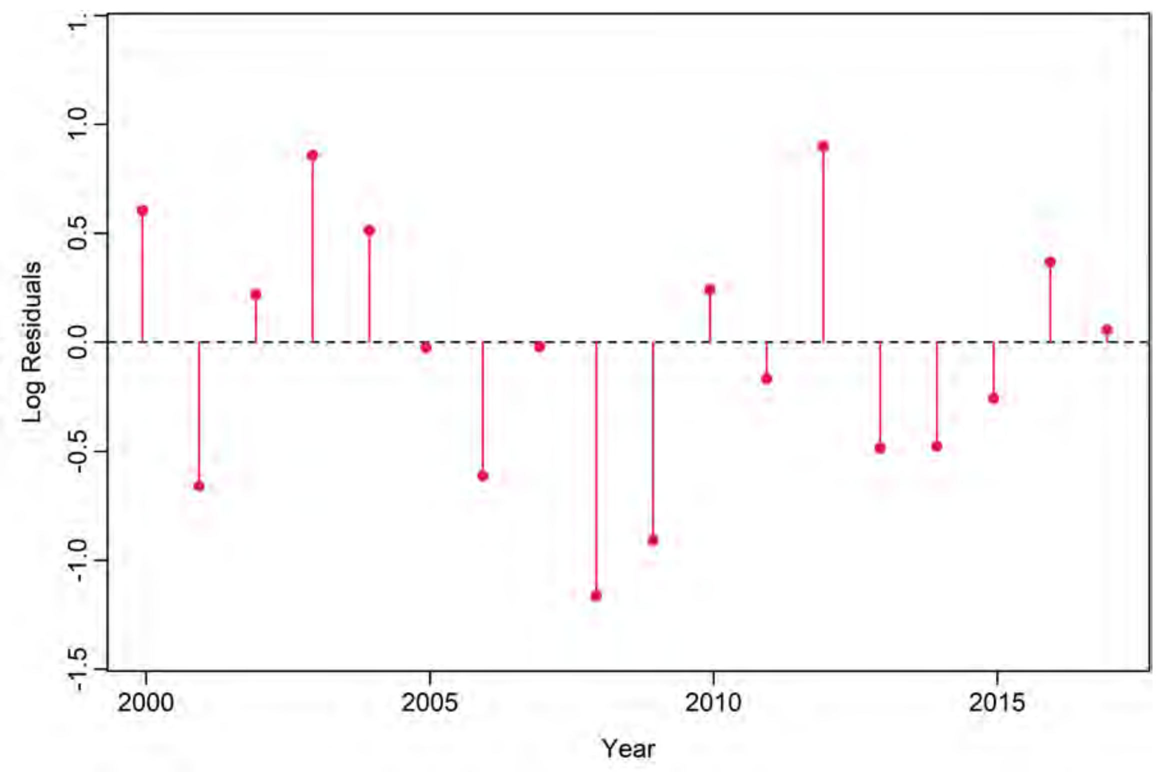


Figure 20. Residuals of production model fit to standardized CPUE for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands from 2000-2017.

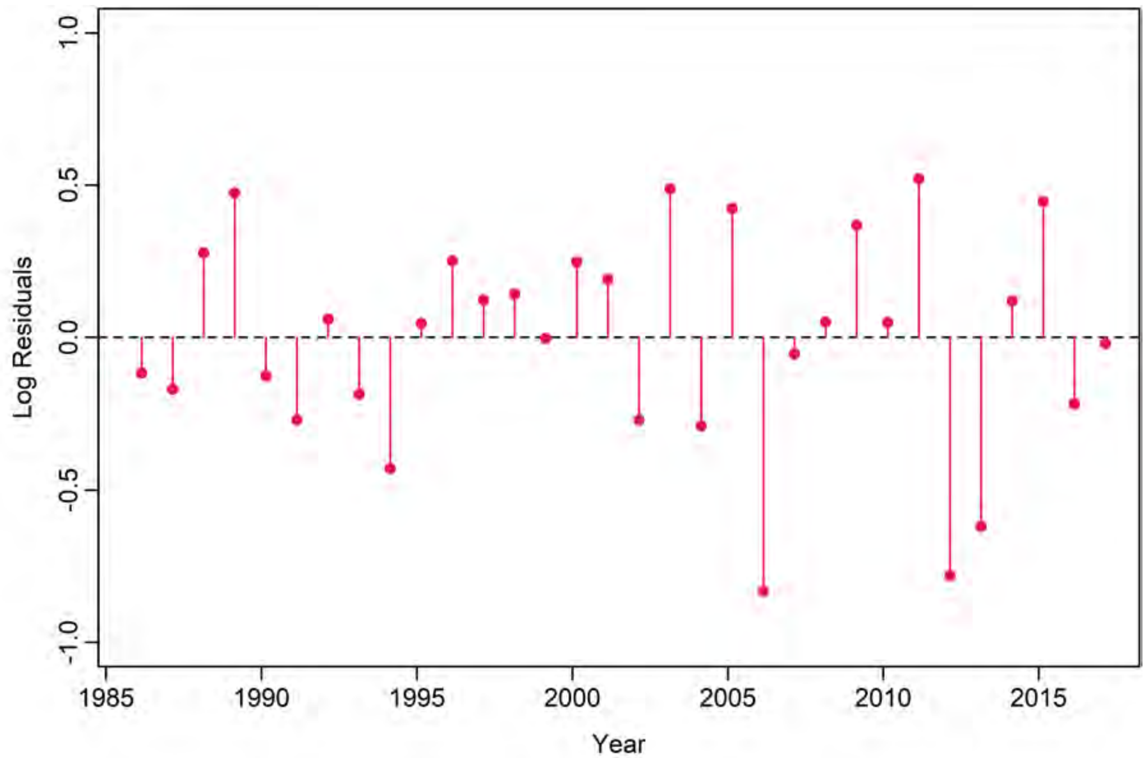


Figure 21. Residuals of production model fit to standardized CPUE for bottomfish management unit species in American Samoa from 1986 to 2017.

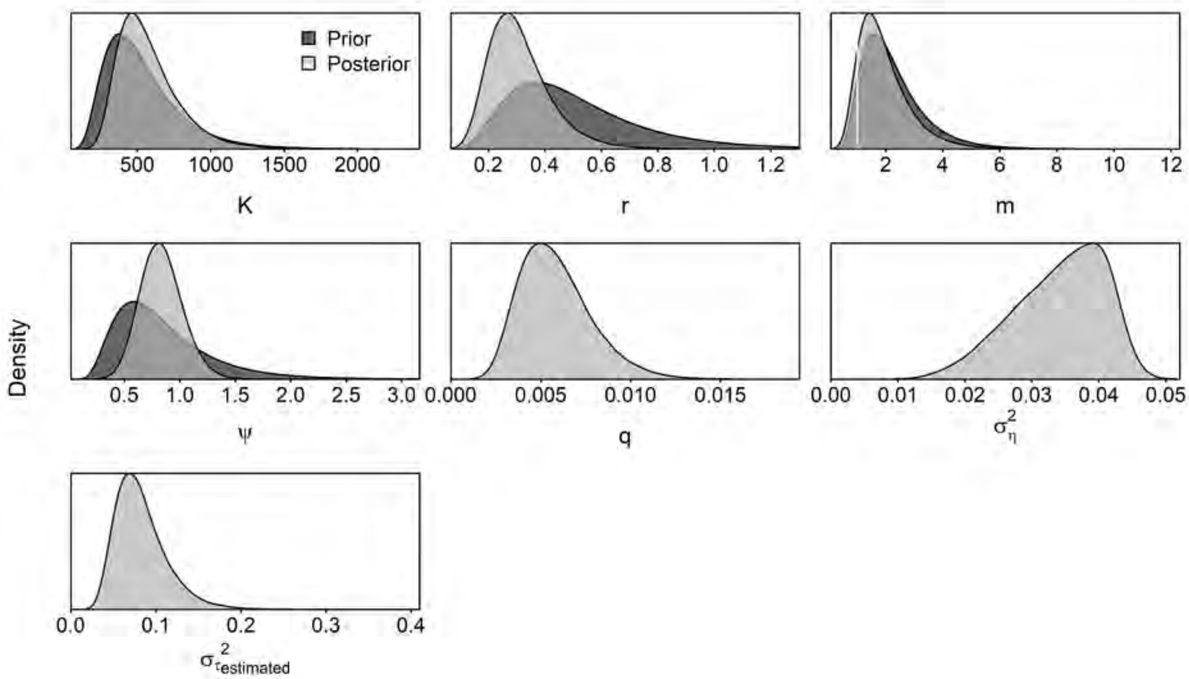


Figure 22. Prior distributions (dark gray) and posterior densities (light gray) for model parameters for bottomfish management unit species in Guam including carrying capacity (*K*), intrinsic growth rate (*r*), shape parameter (*m*), ratio of initial biomass to carrying capacity (ψ), catchability (*q*), process error variance ($\sigma_\eta{}^2$), and the estimable component of observation error variance ($\sigma_{\tau estimated}{}^2$). The vertical white line in the shape parameter panel indicates that the Pella-Tomlinson production function is undefined at *m*=1.

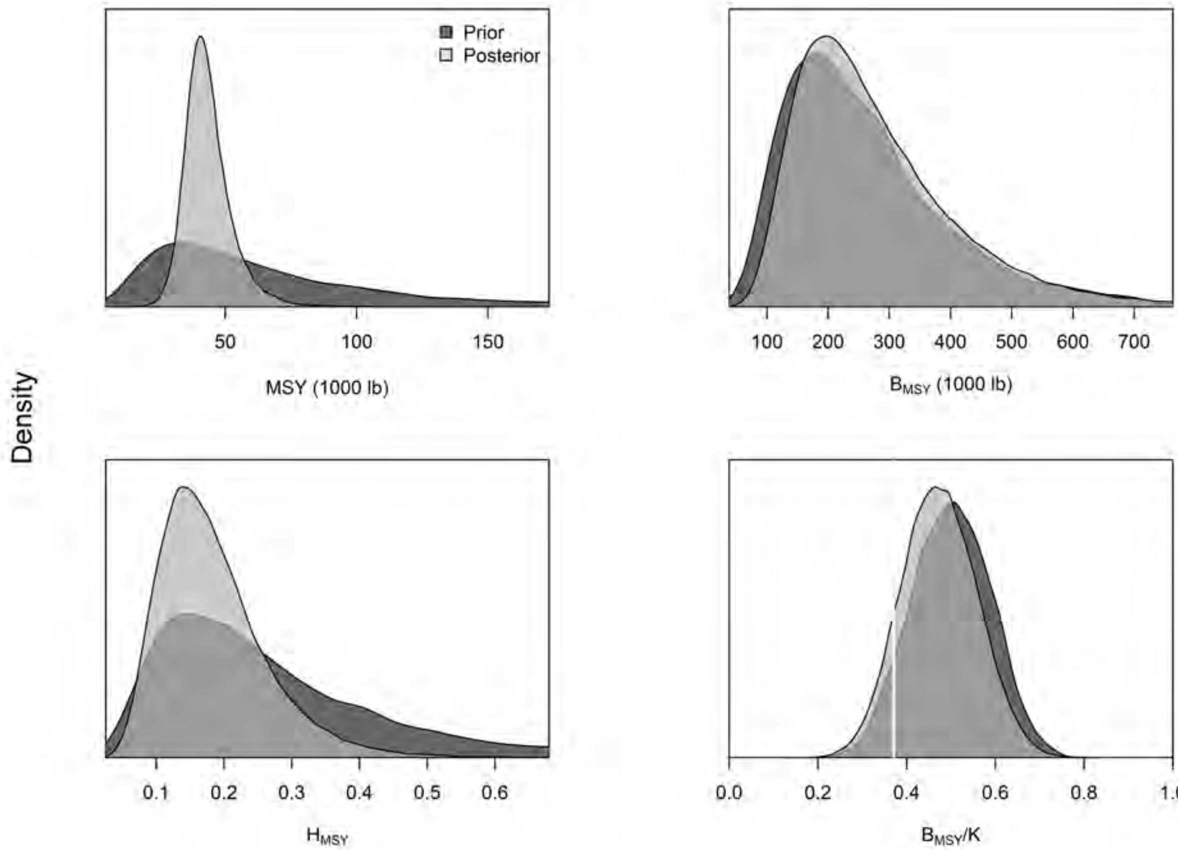


Figure 23. Calculated prior distributions (dark gray) and posterior densities (light gray) for model estimates of derived quantities maximum sustainable yield (*MSY*), biomass to produce maximum sustainable yield (B_{MSY}), harvest rate to produce maximum sustainable yield (H_{MSY}), and proportion of carrying capacity to produce maximum sustainable yield (B_{MSY}/K) for bottomfish management unit species in Guam. The vertical white line in the B_{MSY}/K panel indicates where the Pella-Tomlinson production function is undefined at *m*=1.

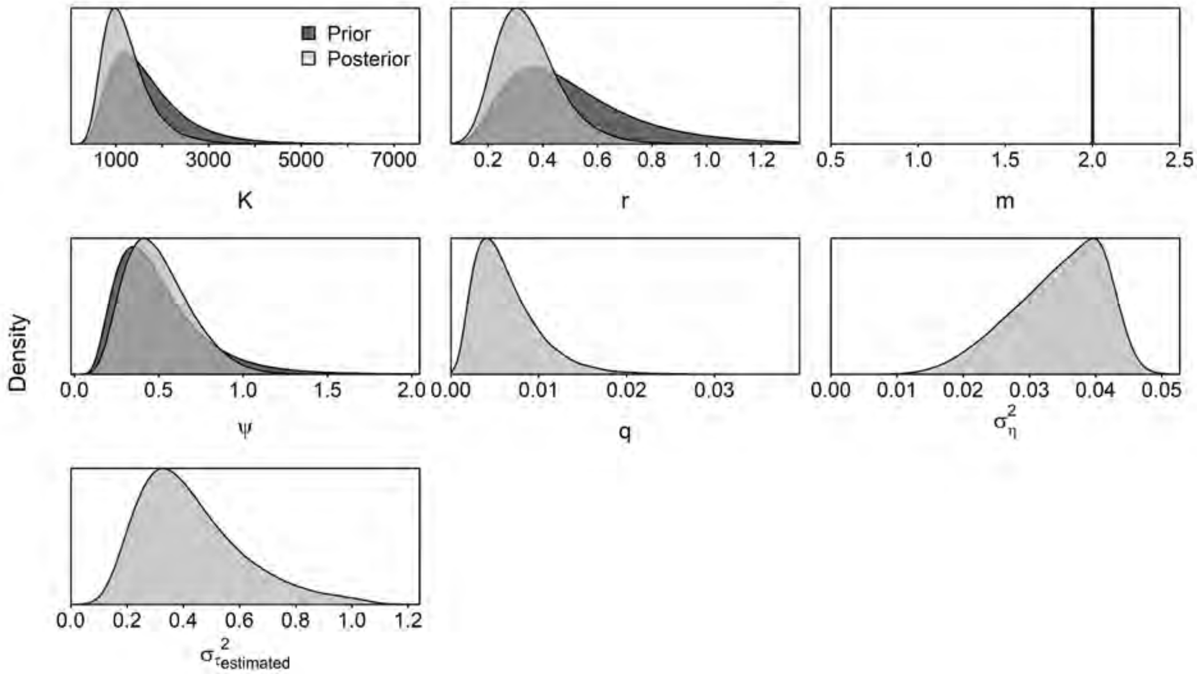


Figure 24. Prior distributions (dark gray) and posterior densities (light gray) for model parameters for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands including carrying capacity (*K*), intrinsic growth rate (*r*), shape parameter (*m*), ratio of initial biomass to carrying capacity (ψ), catchability (*q*), process error variance ($\sigma_\eta{}^2$), and the estimable component of observation error variance ($\sigma_{\tau estimated}{}^2$). The value for *m* was fixed at 2 to represent a Schaefer production function.

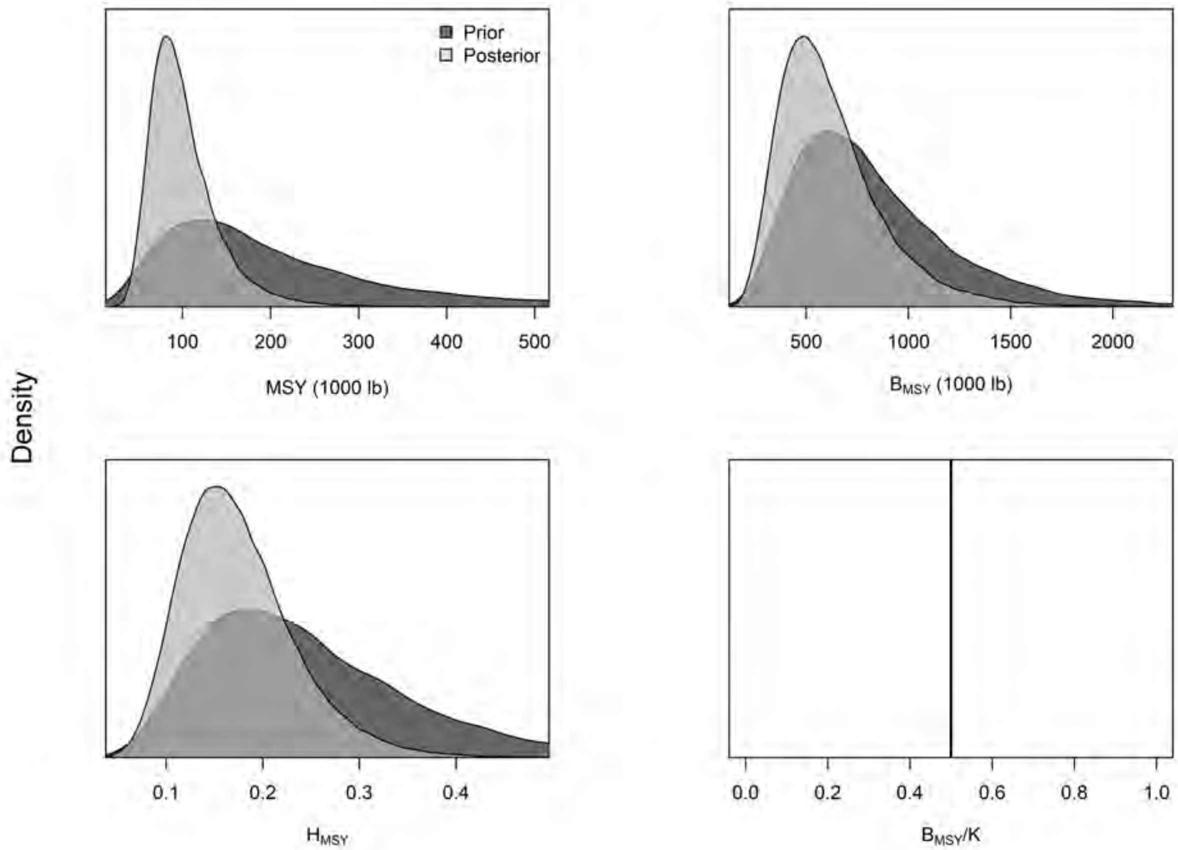


Figure 25. Calculated prior distributions (dark gray) and posterior densities (light gray) for model estimates of derived quantities maximum sustainable yield (*MSY*), biomass to produce maximum sustainable yield (B_{MSY}), harvest rate to produce maximum sustainable yield (H_{MSY}), and proportion of carrying capacity to produce maximum sustainable yield (B_{MSY}/K) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands.

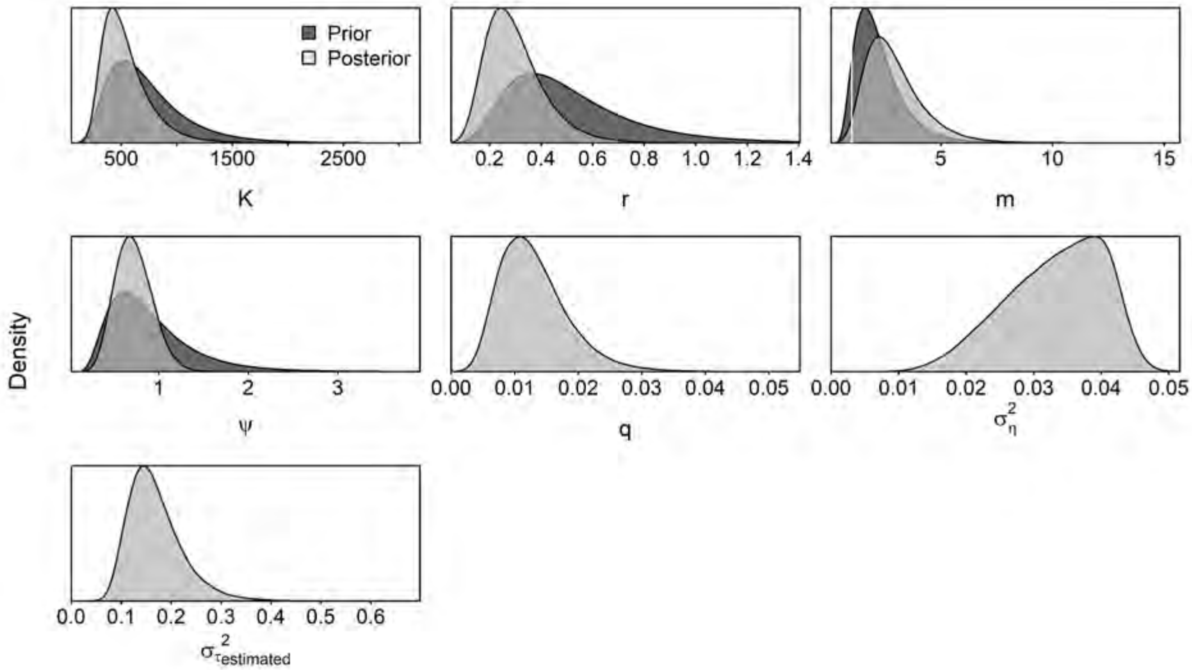


Figure 26. Prior distributions (dark gray) and posterior densities (light gray) for model parameters for bottomfish management unit species in American Samoa including carrying capacity (*K*), intrinsic growth rate (*r*), shape parameter (*m*), ratio of initial biomass to carrying capacity (ψ), catchability (*q*), process error variance (σ_η^2), and the estimable component of observation error variance ($\sigma_{\tau estimated}^2$). The vertical white line in the shape parameter panel indicates that the Pella-Tomlinson production function is undefined at *m*=1.

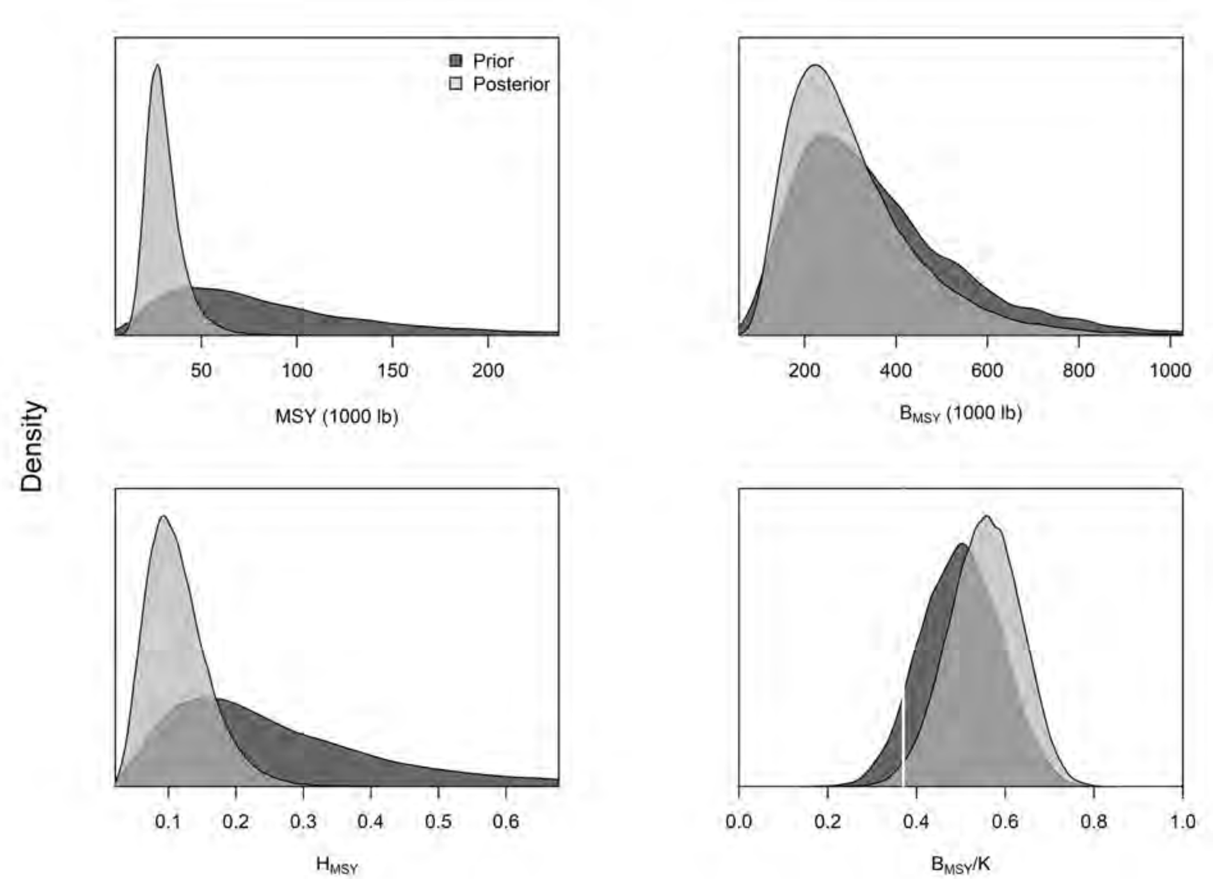


Figure 27. Calculated prior distributions (dark gray) and posterior densities (light gray) for model estimates of derived quantities maximum sustainable yield (*MSY*), biomass to produce maximum sustainable yield (B_{MSY}), harvest rate to produce maximum sustainable yield (H_{MSY}), and proportion of carrying capacity to produce maximum sustainable yield (B_{MSY}/K) for bottomfish management unit species in American Samoa. The vertical white line in the B_{MSY}/K panel indicates where the Pella-Tomlinson production function is undefined at *m*=1.

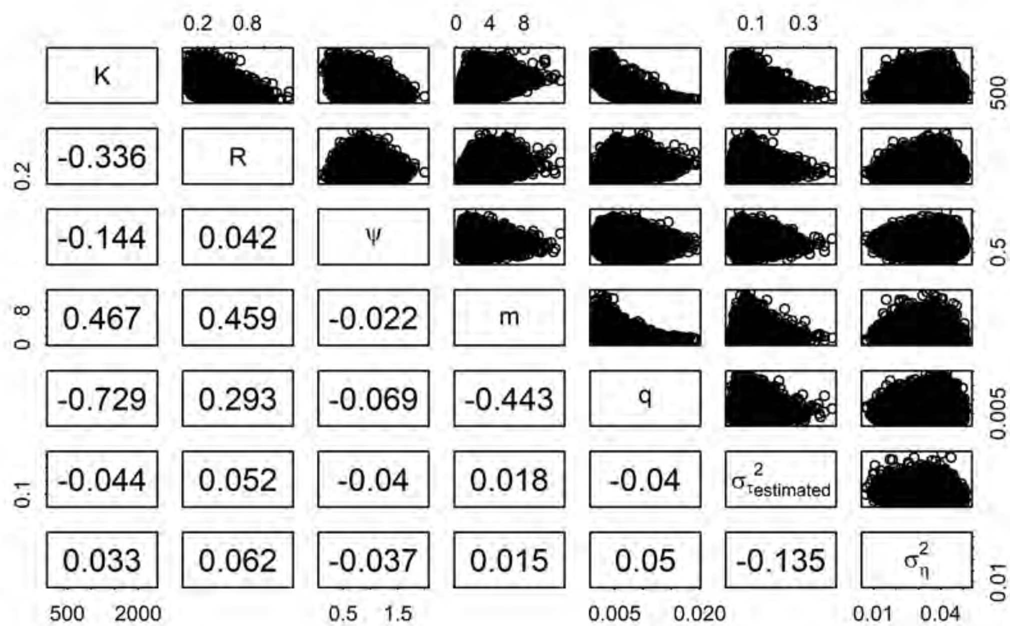


Figure 28. Pairwise scatterplots and correlations for parameter estimates for bottomfish management unit species in Guam. Parameters are carrying capacity (*K*), intrinsic rate of increase (*r*), ratio of initial biomass to carrying capacity (ψ), shape parameter (*m*), catchability (*q*), observation error variance (σ_{η}^2), and the estimable component of observation error variance ($\sigma_{\tau estimated}^2$).

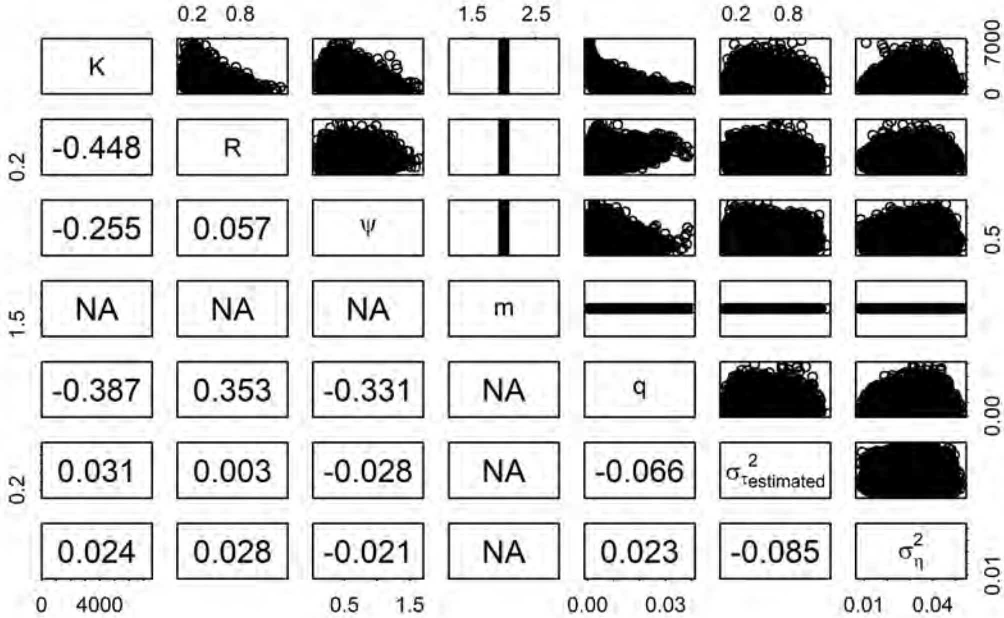


Figure 29. Pairwise scatterplots and correlations for parameter estimates for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands. Parameters are carrying capacity (*K*), intrinsic rate of increase (*r*), ratio of initial biomass to carrying capacity (ψ), shape parameter (*m*) set to 2, catchability (*q*), observation error variance (σ_η^2), and the estimable component of observation error variance ($\sigma_{\tau estimated}^2$).

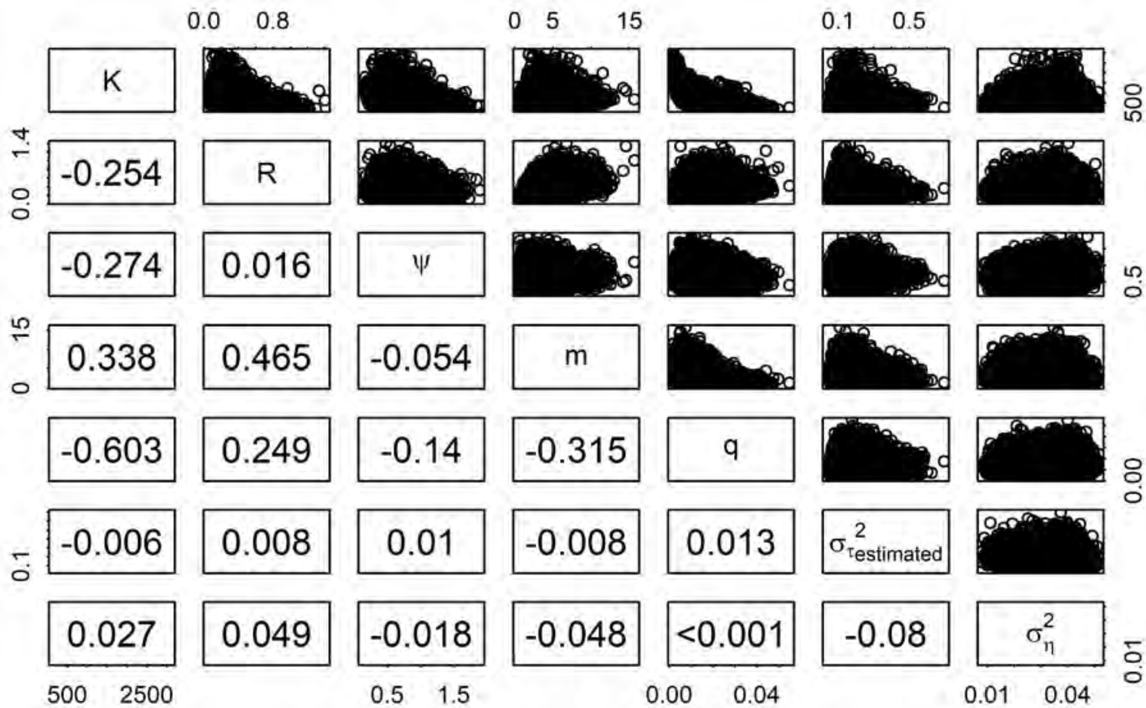


Figure 30. Pairwise scatterplots and correlations for parameter estimates for bottomfish management unit species in American Samoa. Parameters are carrying capacity (*K*), intrinsic rate of increase (*r*), ratio of initial biomass to carrying capacity (ψ), shape parameter (*m*), catchability (*q*), observation error variance ($\sigma_\eta{}^2$), and the estimable component of observation error variance ($\sigma_{\tau estimated}{}^2$).

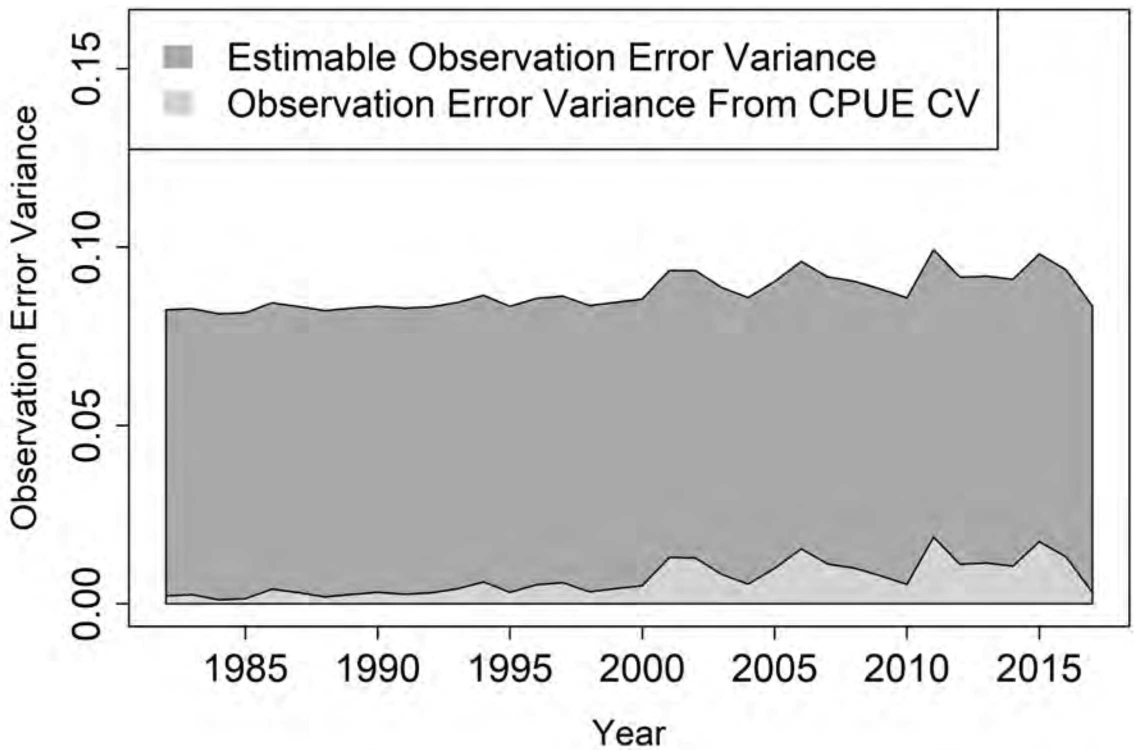


Figure 31. Total observation error variance by year for bottomfish management unit species in Guam from 1982 through 2017, partitioned into minimum observation error (set to 0), observation error from CPUE (light gray) and estimable observation error (dark gray).

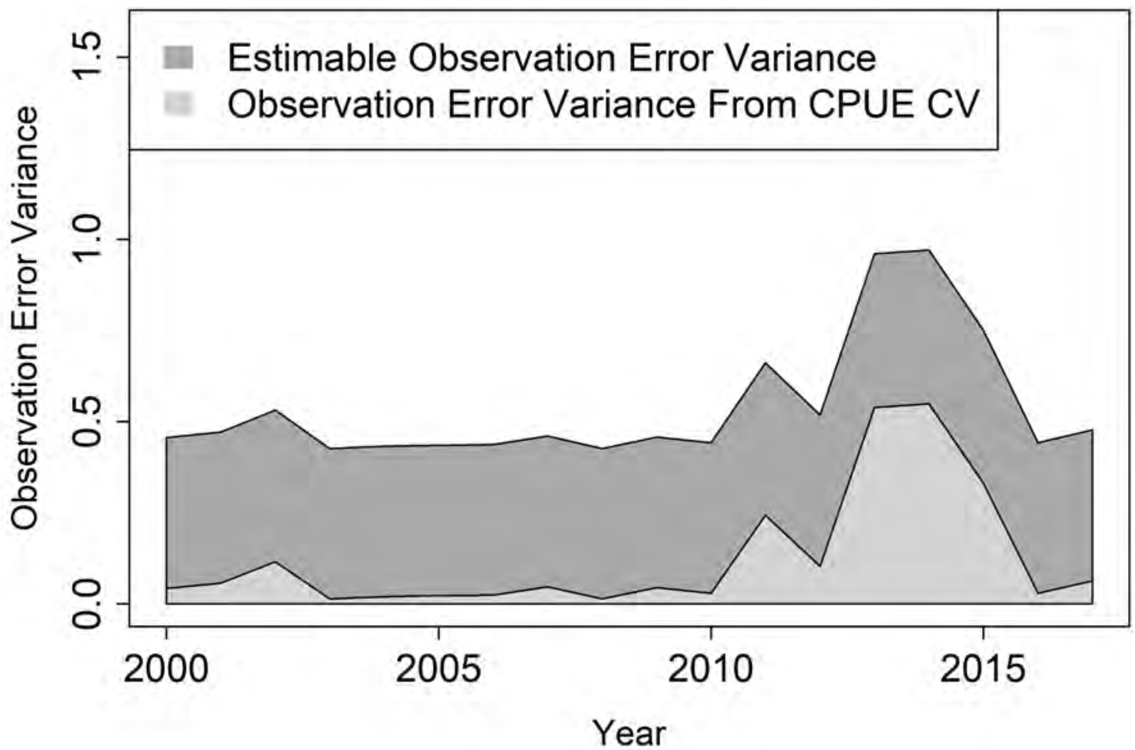


Figure 32. Total observation error variance by year for the Commonwealth of the Northern Mariana Islands from 2000 through 2017, partitioned into minimum observation error (set to 0), observation error from CPUE (light gray) and estimable observation error (dark gray).

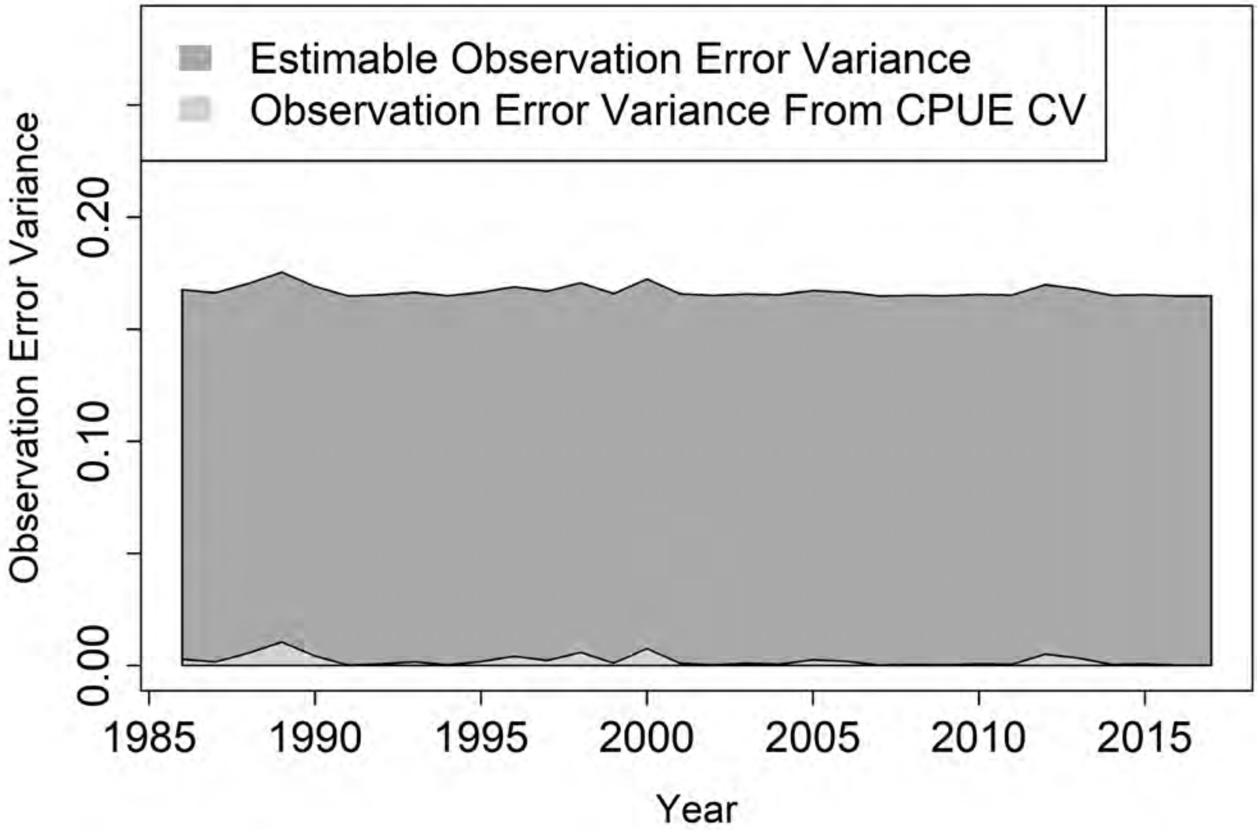


Figure 33. Total observation error variance by year for American Samoa from 1986 through 2017, partitioned into minimum observation error (set to 0), observation error from CPUE (light gray) and estimable observation error (dark gray).

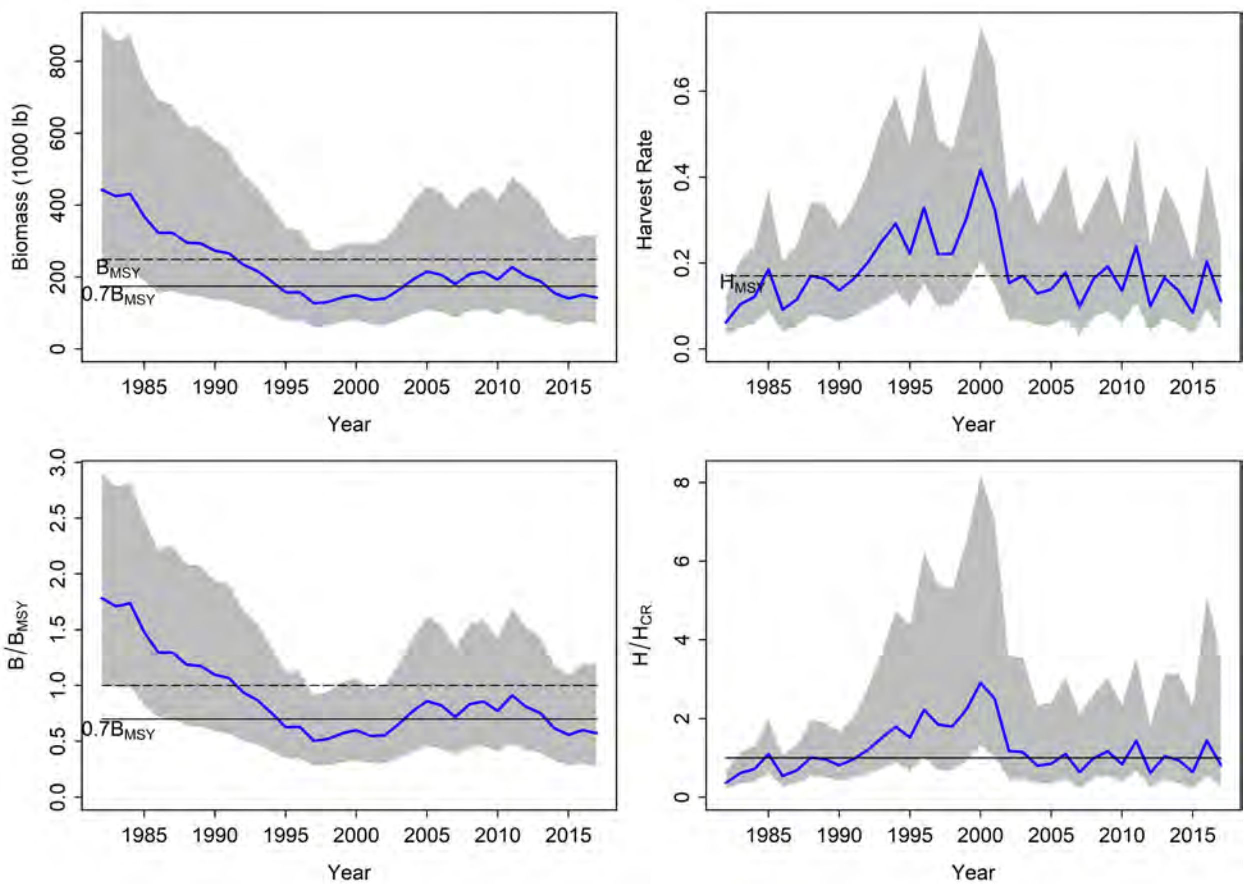


Figure 34. Estimated biomass, harvest rate, relative biomass (B/B_{MSY}), and relative harvest rate (H/H_{CR}) for bottomfish management unit species in Guam from 1982 through 2017 with 95% credible intervals (shaded area). Solid horizontal lines delineate reference points for biomass ($0.7{*}B_{MSY}$) and harvest rate (H/H_{CR}). Dashed horizontal lines delineate B_{MSY} and H_{MSY}.

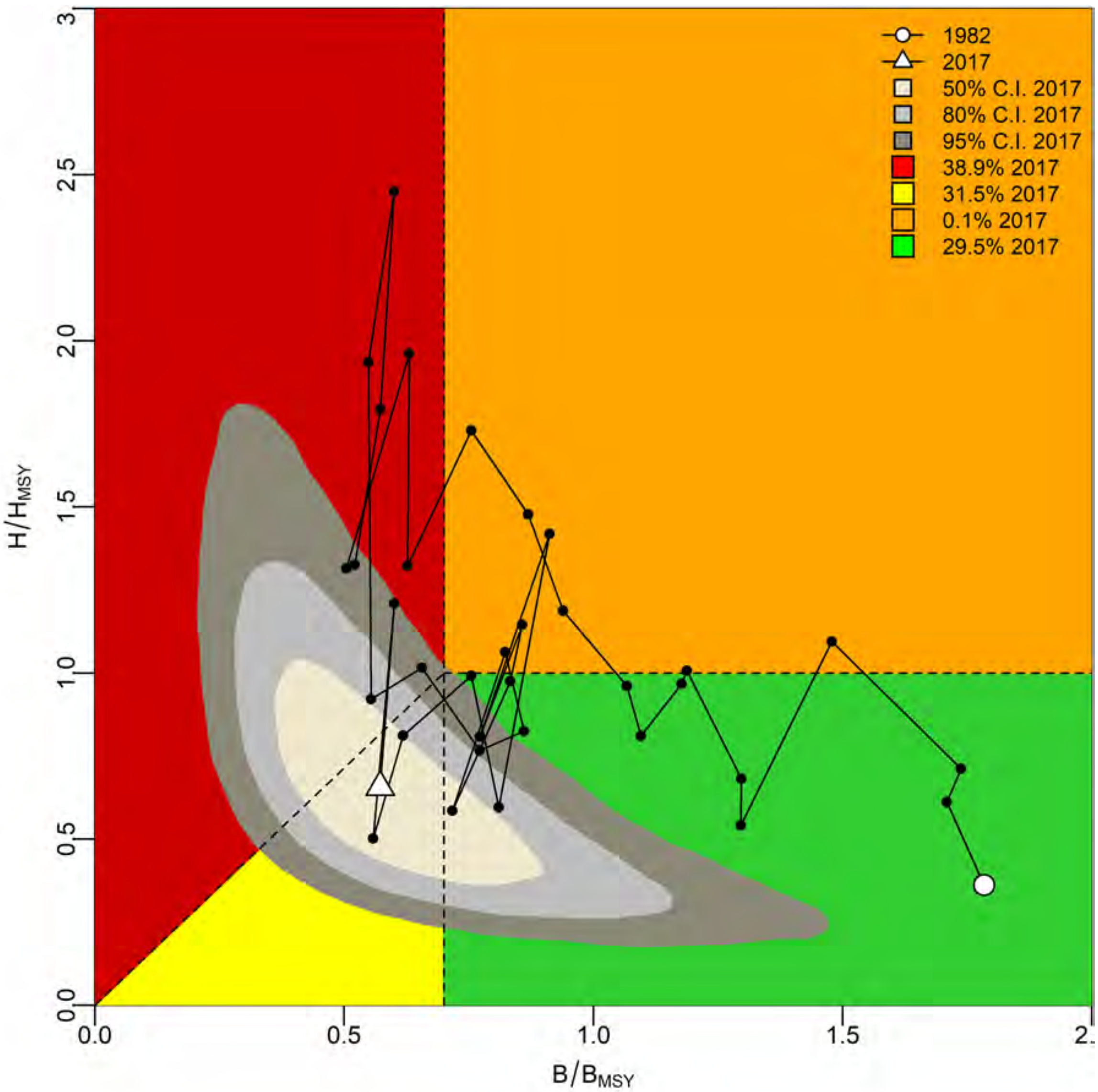


Figure 35. Estimated stock status for bottomfish management unit species in Guam from 1982 through 2017. The circle denotes the start year and the triangle denotes the final year. Outer bounds of gray shaded area delineate the 95% credible interval for 2017. Colored areas delineate stock statuses (red = overfished and overfishing, yellow = overfished but not overfishing, orange = overfishing but not overfished, and green = not overfished and no overfishing). The probability of stock status in 2017 occurring in each area is displayed in the legend.

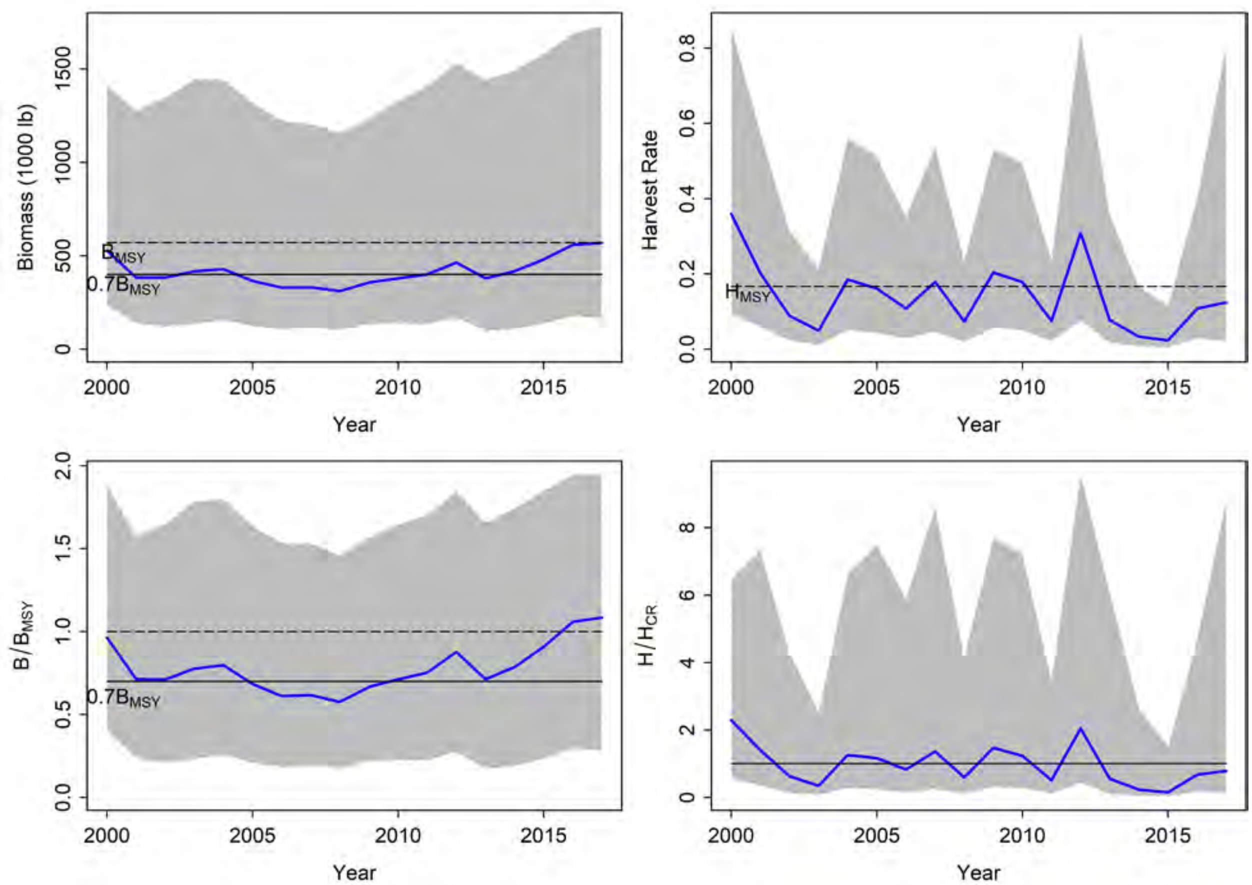


Figure 36. Estimated biomass, harvest rate, relative biomass (*B/B_{MSY}*), and relative harvest rate (*H/H_{CR}*) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands from 2000 through 2017 with 95% credible intervals (shaded area). Solid horizontal lines delineate reference points for biomass (0.7B_{MSY}*) and harvest rate (*H/H_{CR}*). Dashed horizontal lines delineate *B_{MSY}* and *H_{MSY}*.**

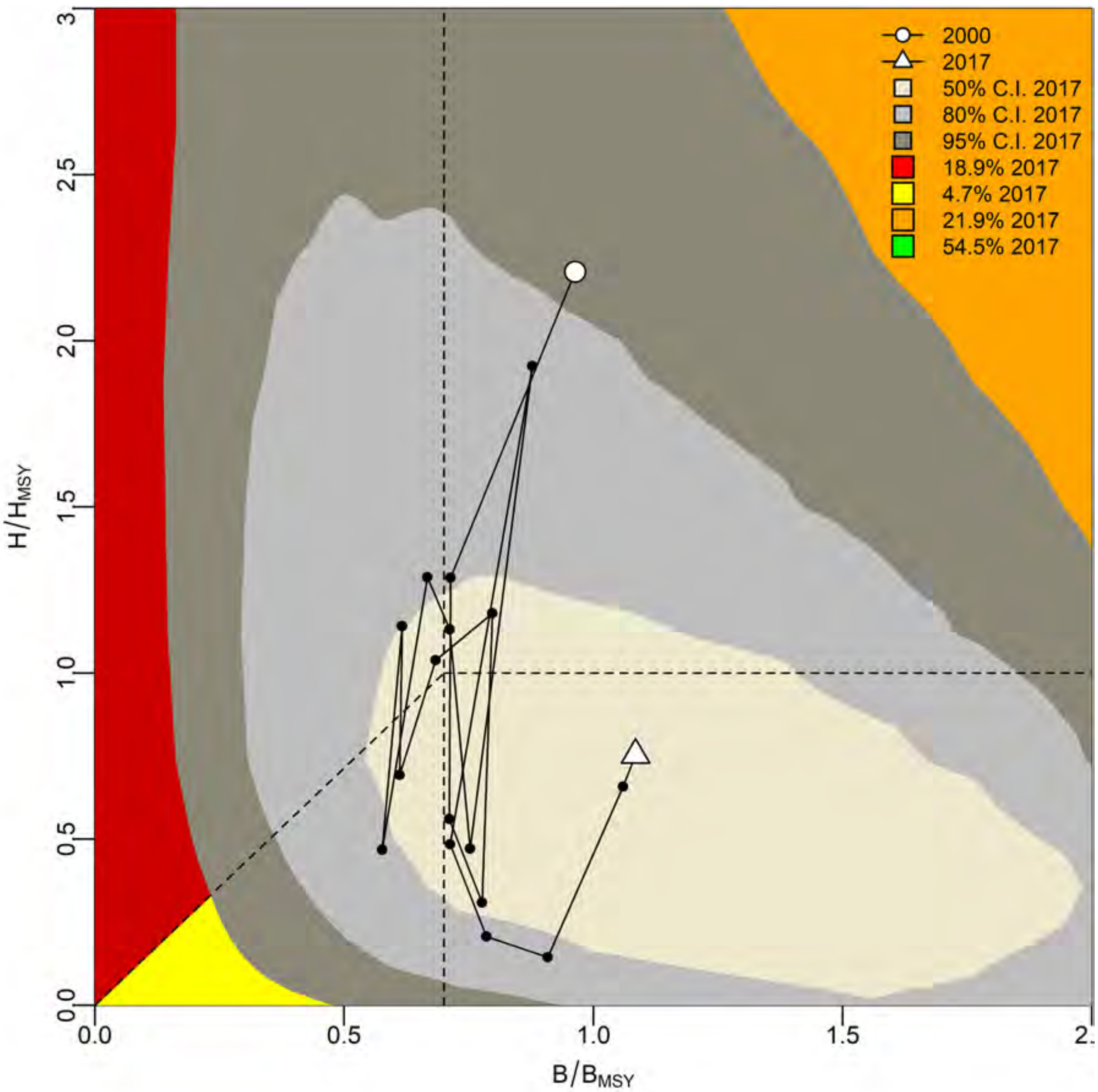


Figure 37. Estimated stock status for bottomfish management unit species the Commonwealth of the Northern Mariana Islands from 2000 through 2017. The circle denotes the start year and the triangle denotes the final year. Outer bounds of gray shaded area delineate the 95% credible interval for 2017. Colored areas delineate stock statuses (red = overfished and overfishing, yellow = overfished but not overfishing, orange = overfishing but not overfished, and green = not overfished and no overfishing). The probability of stock status in 2017 occurring in each area is displayed in the legend. Bounds of the credibility intervals are cut off on both axes for illustrative purposes.

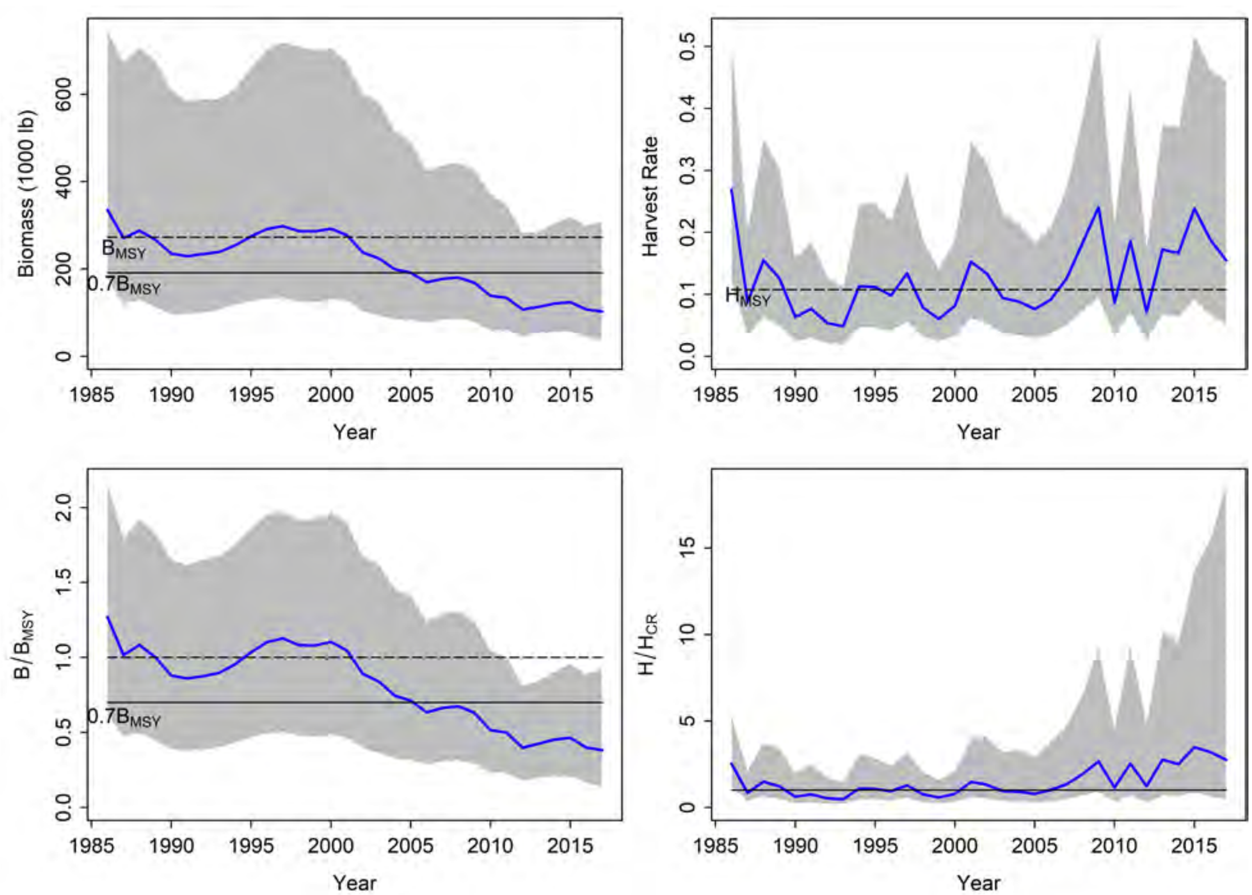


Figure 38. Estimated biomass, harvest rate, relative biomass (*B/B_{MSY}*), and relative harvest rate (*H/H_{CR}*) for bottomfish management unit species in American Samoa from 1986 through 2017 with 95% credible intervals (shaded area). Solid horizontal lines delineate reference points for biomass (0.7B_{MSY}*) and harvest rate (*H/H_{CR}*). Dashed horizontal lines delineate *B_{MSY}* and *H_{MSY}*.**

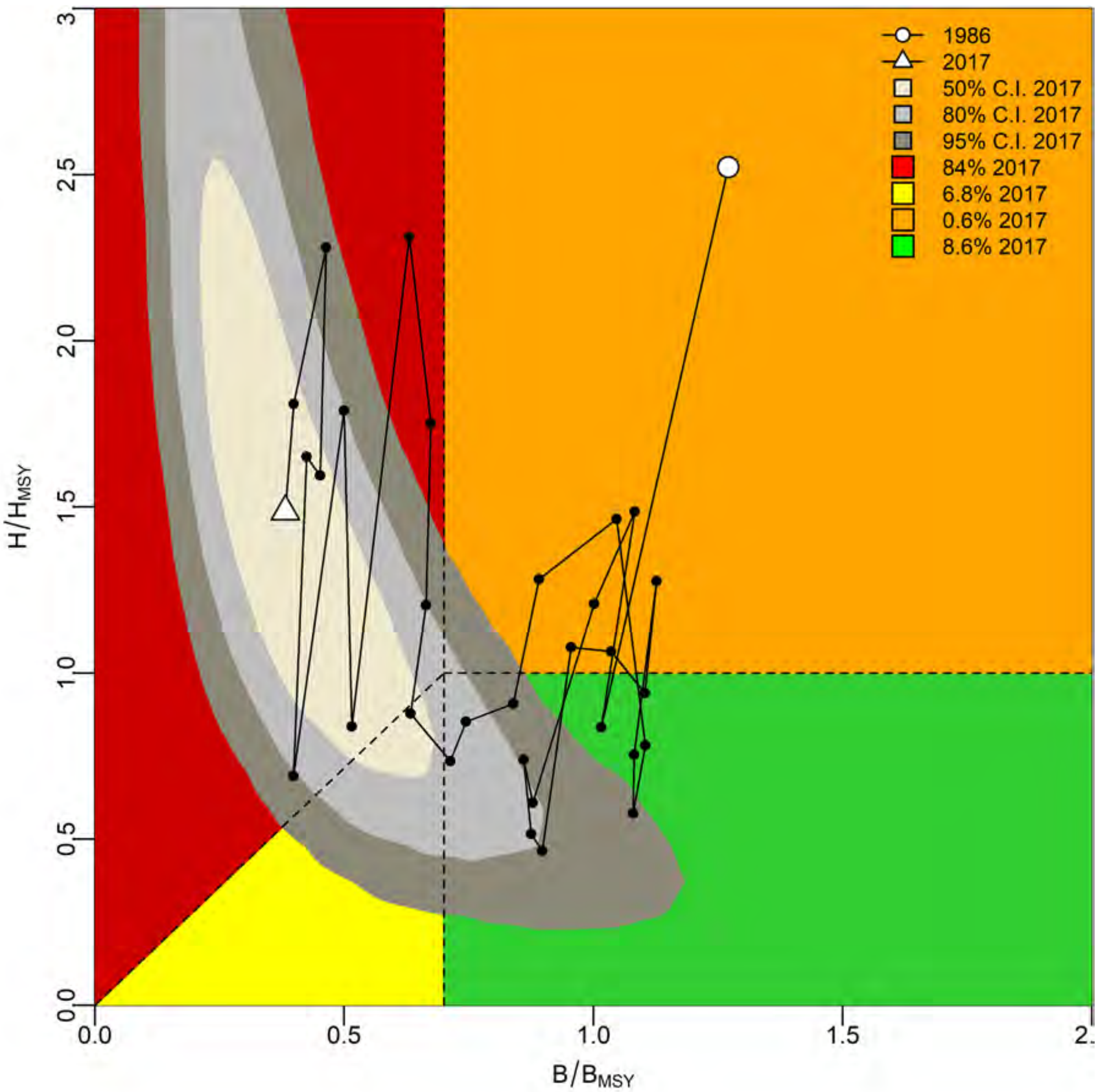


Figure 39. Estimated stock status for bottomfish management unit species in American Samoa from 1986 through 2017. The circle denotes the start year and the triangle denotes the final year. Outer bounds of gray shaded area delineate the 95% credible interval for 2017. Colored areas delineate stock statuses (red = overfished and overfishing, yellow = overfished but not overfishing, orange = overfishing but not overfished, and green = not overfished and no overfishing). The probability of stock status in 2017 occurring in each area is displayed in the legend. Bounds of the credibility intervals are cut off on the y-axis for illustrative purposes.

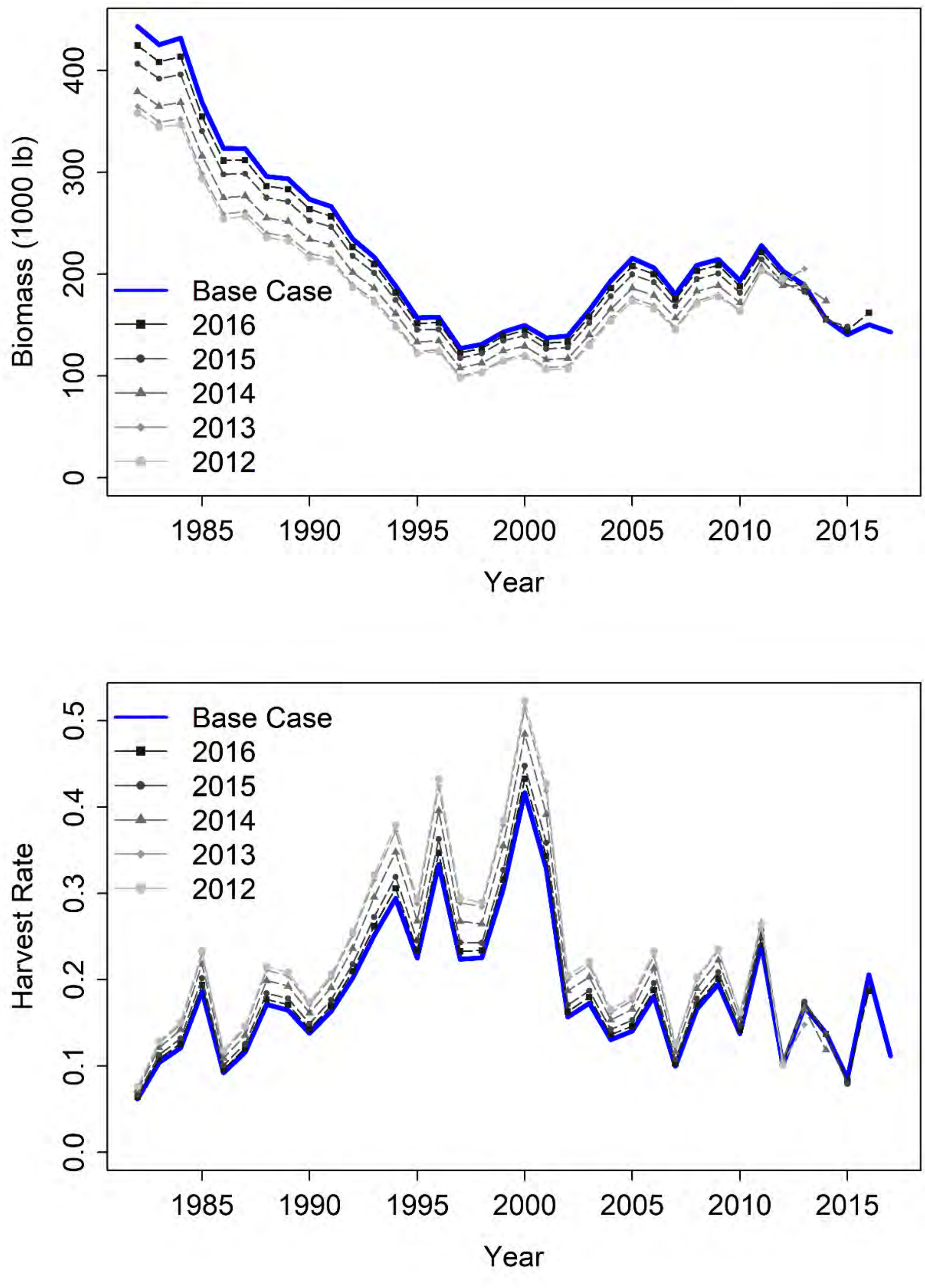


Figure 40. Retrospective analysis for biomass (top) and harvest rate (bottom) with the base case model ending in 2017 as a reference (blue line) and with terminal year set as 2016 through 2012 (gray lines) for bottomfish management unit species in Guam.

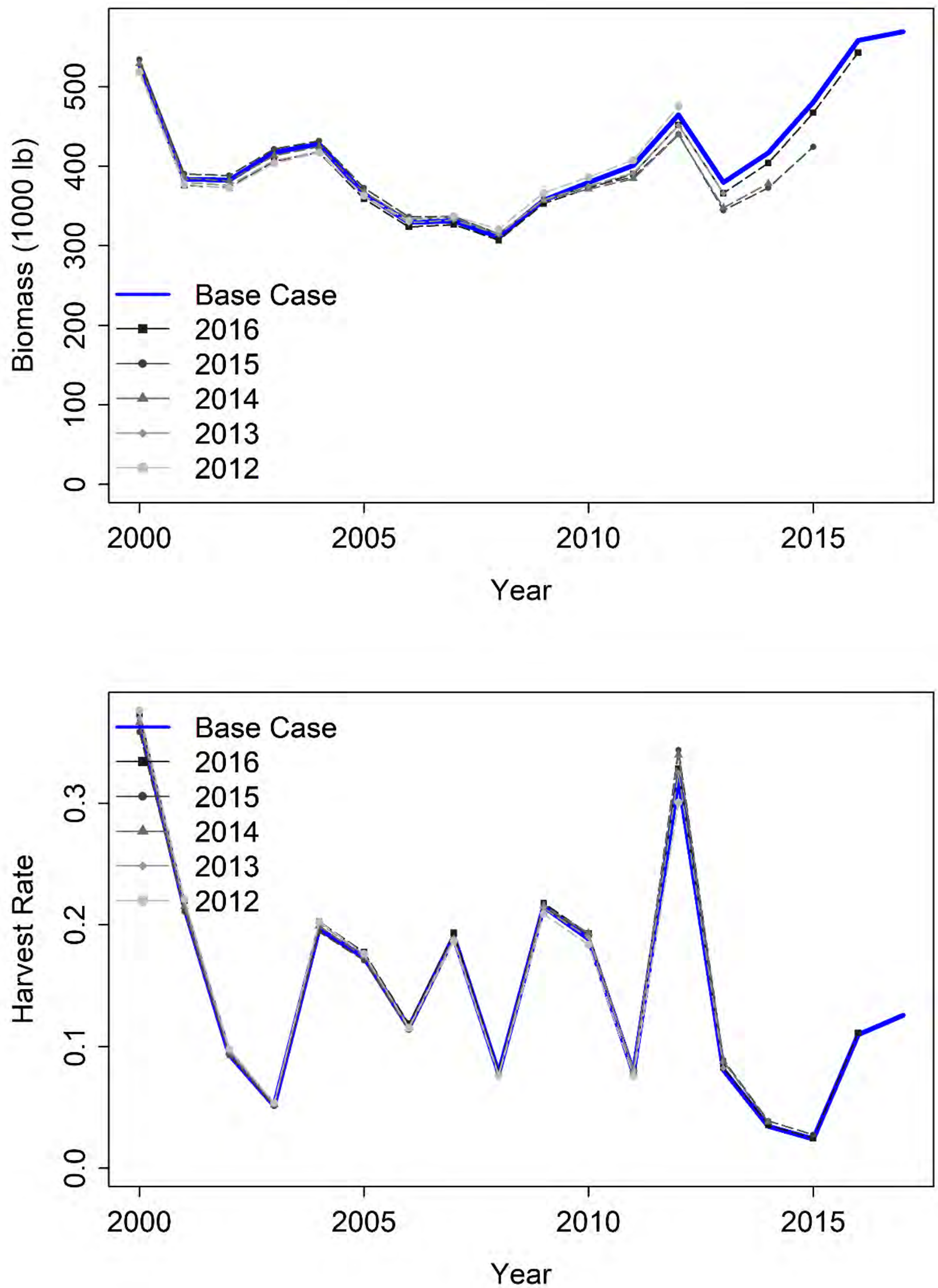
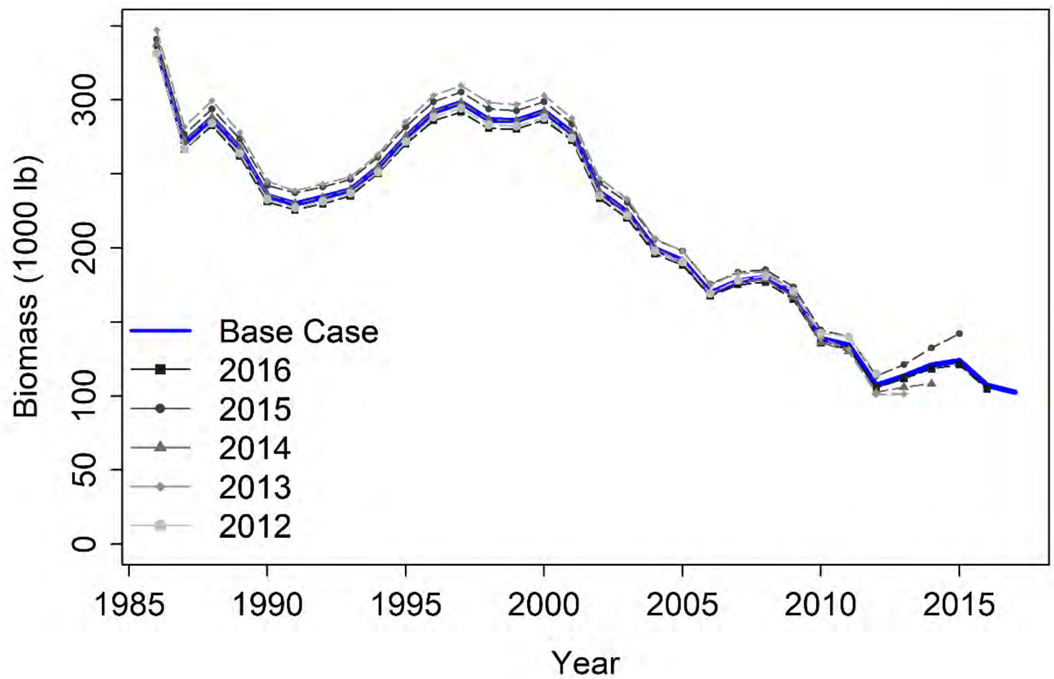


Figure 41. Retrospective analysis for biomass (top) and harvest rate (bottom) with the base case model ending in 2017 as a reference (blue line) and with terminal year set as 2016 through 2012 (gray lines) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands.



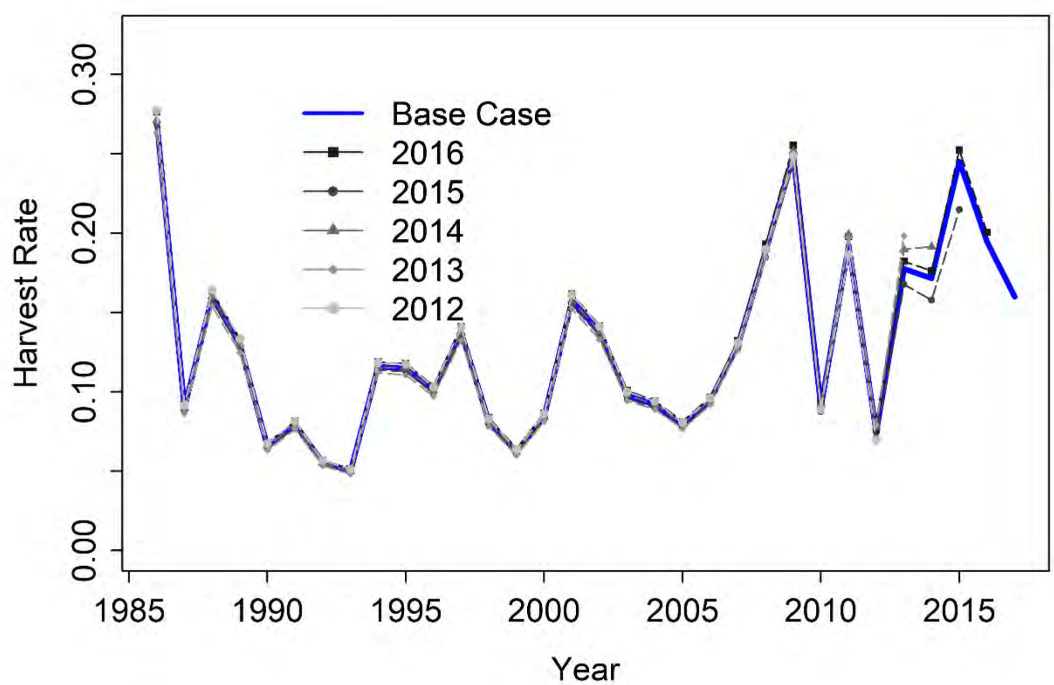


Figure 42. Retrospective analysis for biomass (top) and harvest rate (bottom) with the base case model ending in 2017 as a reference (blue line) and with terminal year set as 2016 through 2012 (gray lines) for bottomfish management unit species in American Samoa.

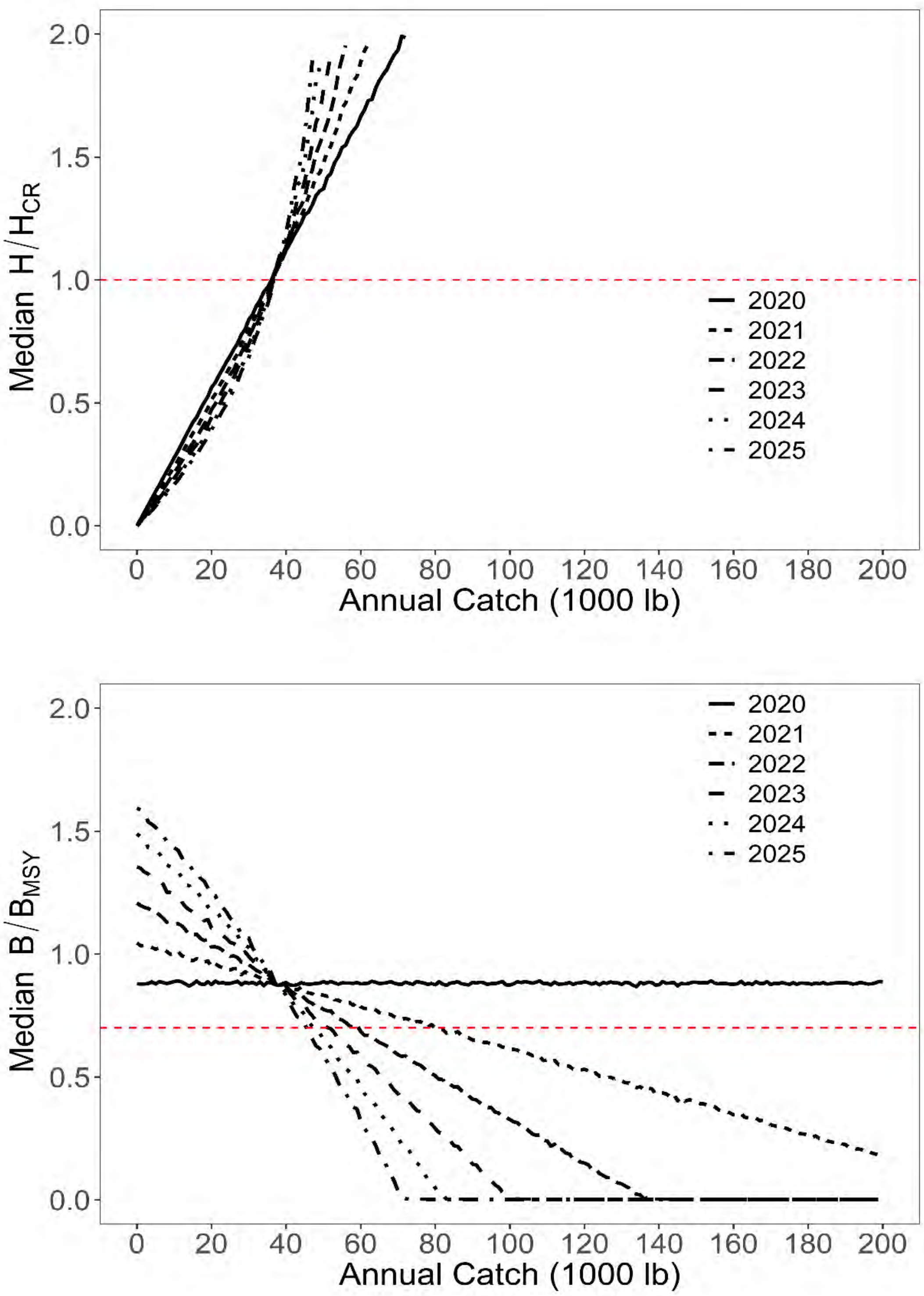


Figure 43. Relative harvest rate H/H_{CR} (top) and relative biomass B/B_{MSY} (bottom) for bottomfish management unit species in Guam from 2020 through 2025 as a function of catch varying from 0 to 200 thousand pounds.

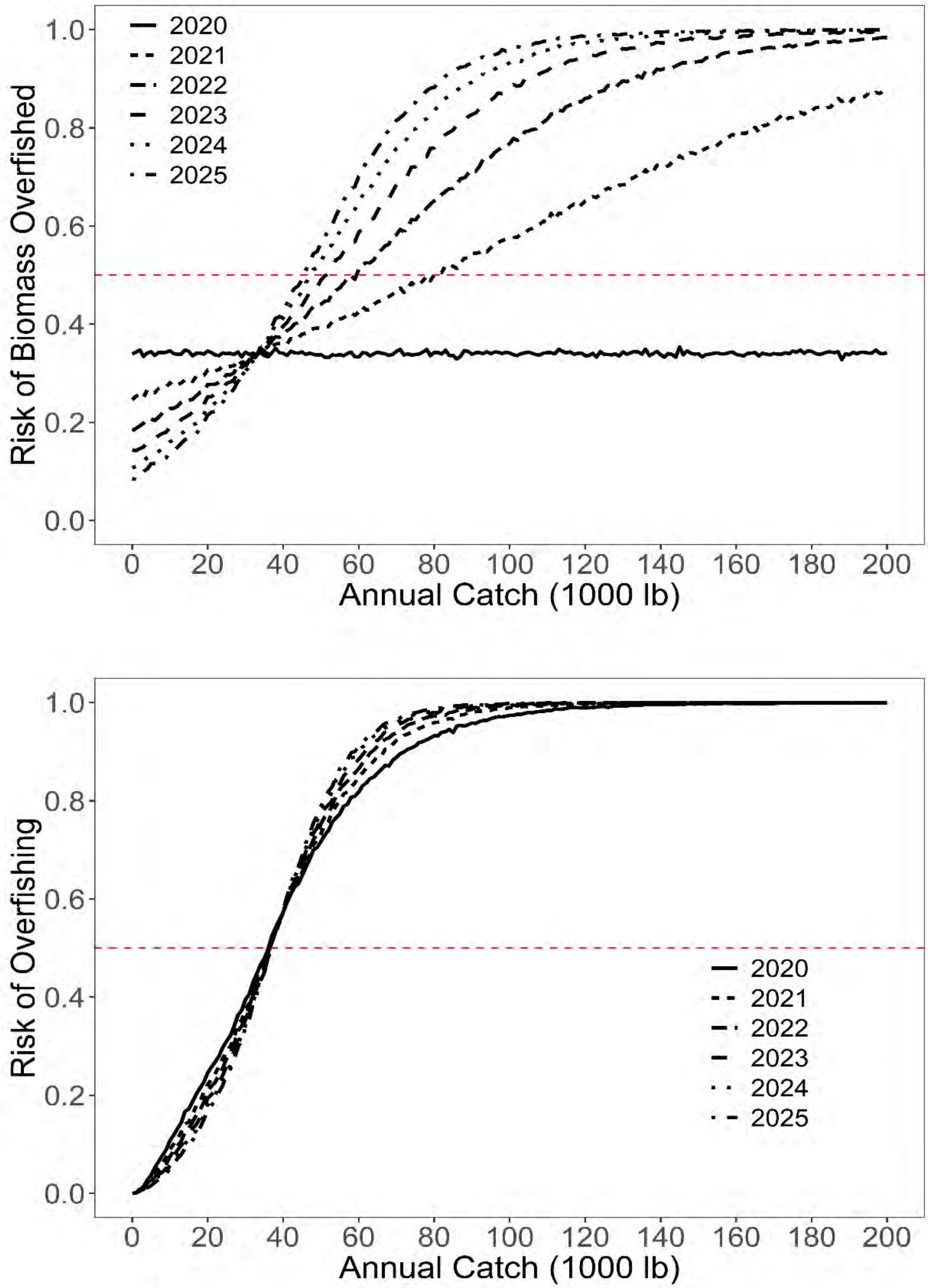


Figure 44. Risk of Guam bottomfish management unit species becoming overfished (B/B_{MSY} < 0.7) and risk of overfishing (H/H_{CR} > 1.0) from 2020 through 2025 as a function of catch varying from 0 to 200 thousand pounds.

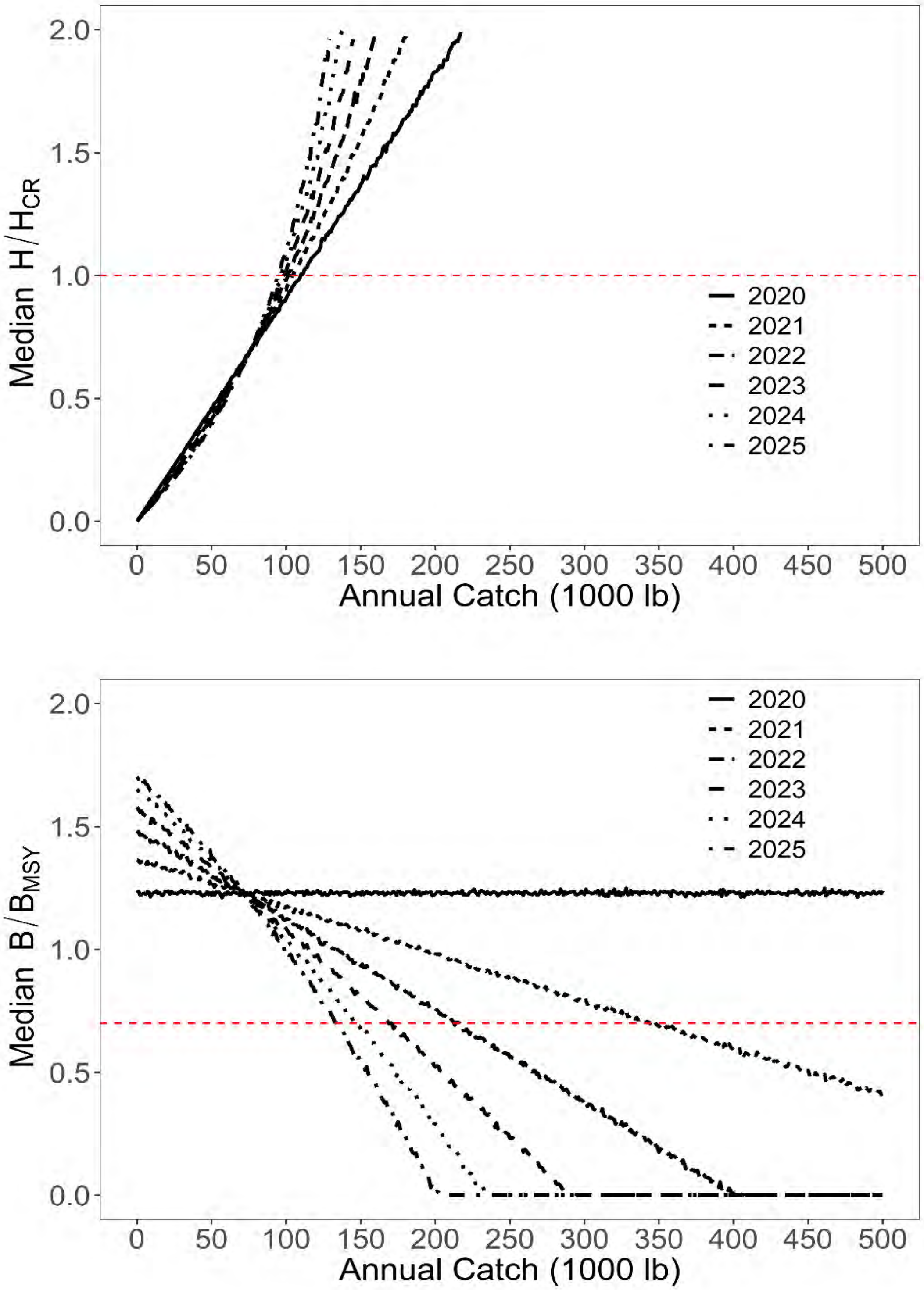


Figure 45. Relative harvest rate *H/H_{CR}* (top) and relative biomass *B/B_{MSY}* (bottom) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands from 2020 through 2025 as a function of catch varying from 0 to 500 thousand pounds.

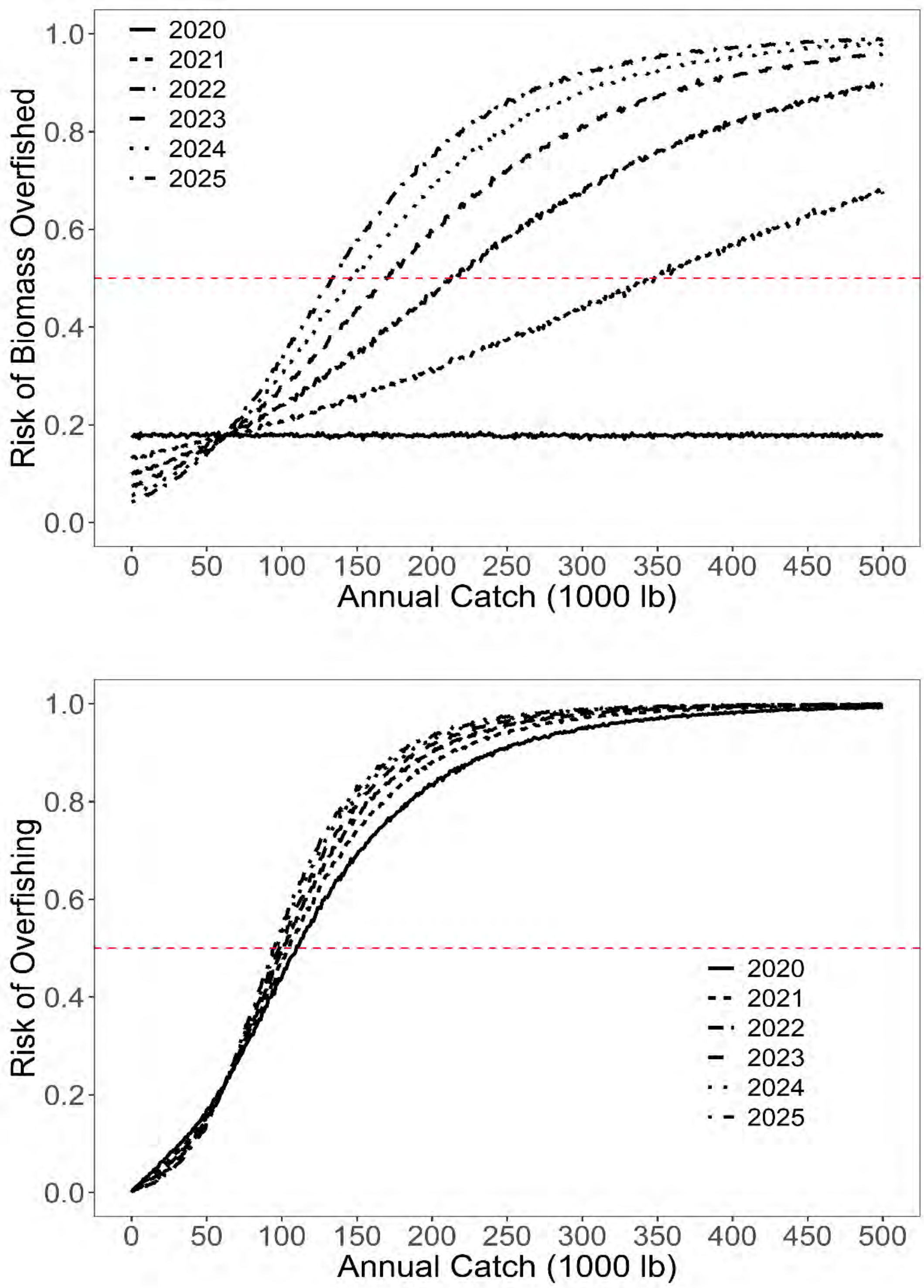


Figure 46. Risk of the Commonwealth of the Northern Mariana Islands bottomfish management unit species becoming overfished (B/B_{MSY} < 0.7) and risk of overfishing (H/H_{CR} > 1.0) from 2020 through 2025 as a function of catch varying from 0 to 500 thousand pounds.

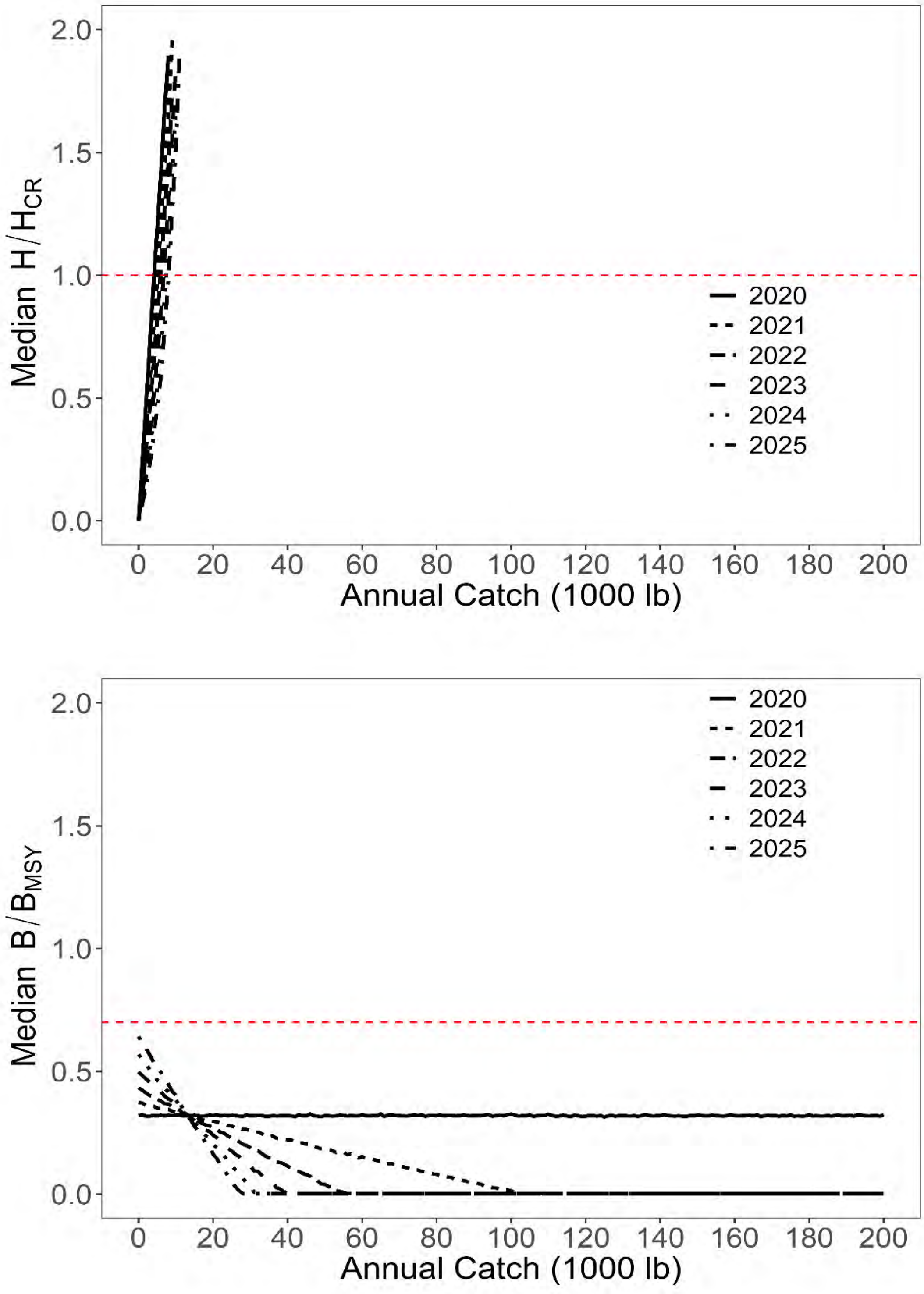


Figure 47. Relative harvest rate *H/H_{CR}* (top) and relative biomass *B/B_{MSY}* (bottom) for bottomfish management unit species in American Samoa from 2020 through 2025 as a function of catch varying from 0 to 200 thousand pounds.

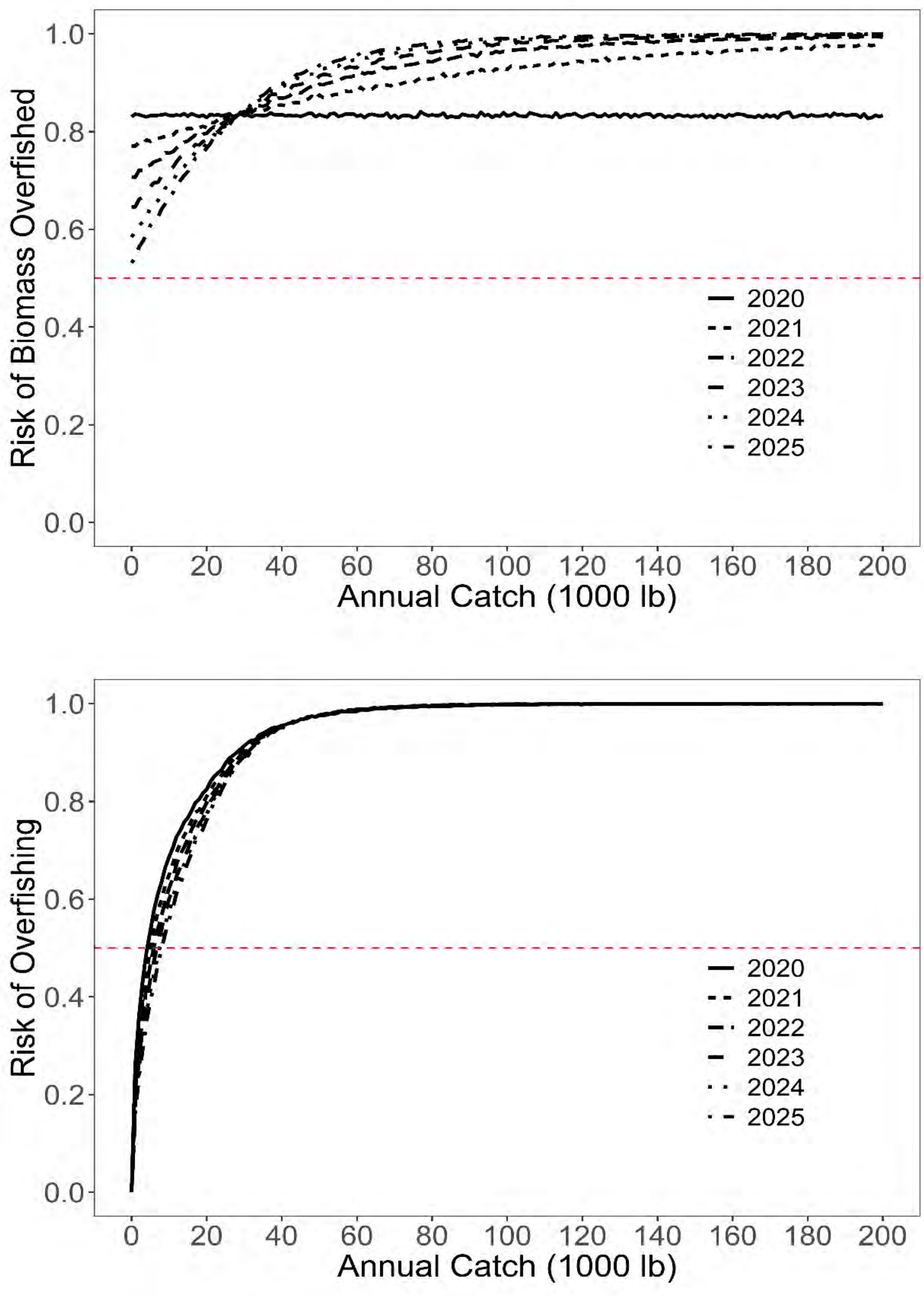


Figure 48. Risk of the American Samoa bottomfish management unit species becoming overfished (*B/B_{MSY}* < 0.7) and risk of overfishing (*H/H_{CR}* > 1.0) from 2020 through 2025 as a function of catch varying from 0 to 200 thousand pounds.

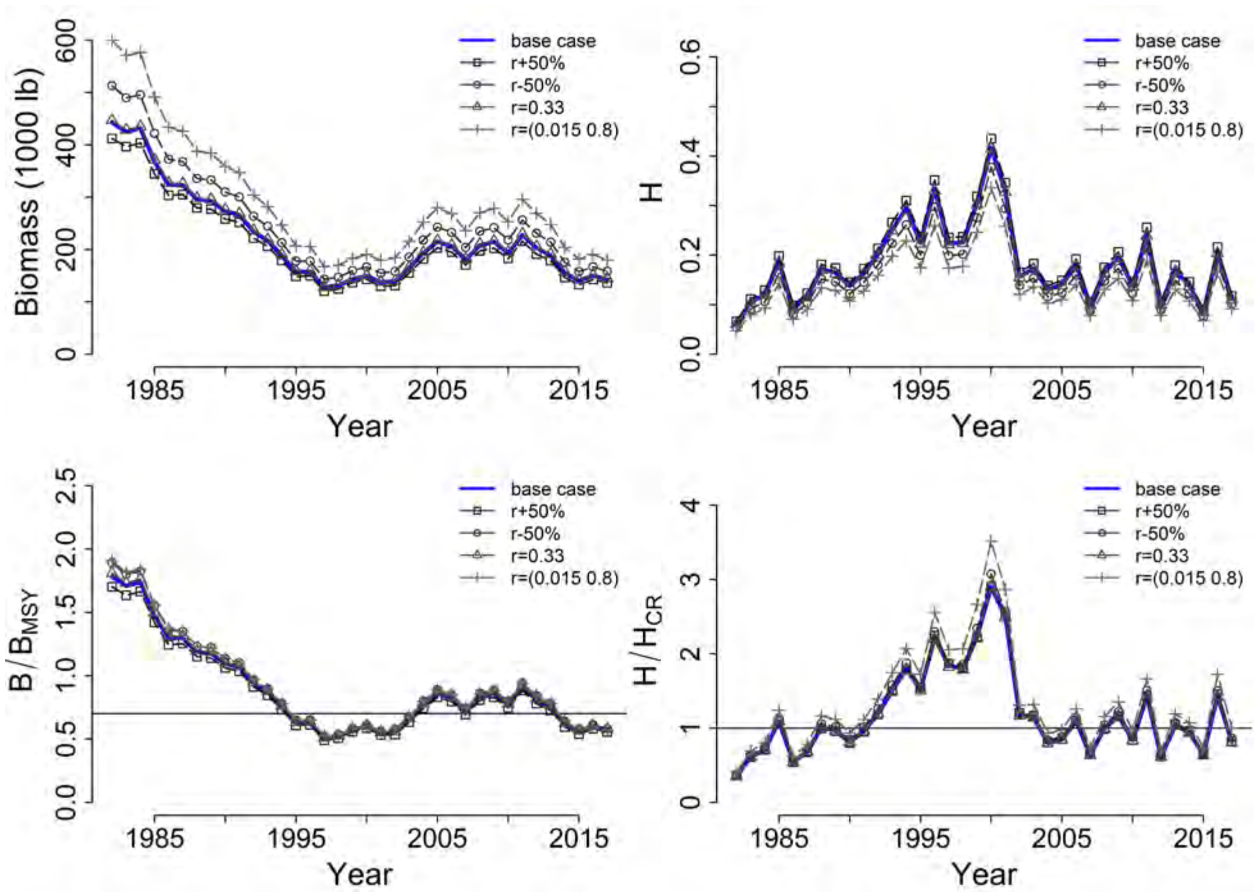


Figure 49. Results of sensitivity analyses for the prior distribution of intrinsic growth rate (*r*) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *r* were calculated as ± 50% of the mean prior, the mean prior for *r* = 0.33, and the mean prior for *r* = 0.15 with CV of 115% (inputted as a range for *r* from 0.015 to 0.8).

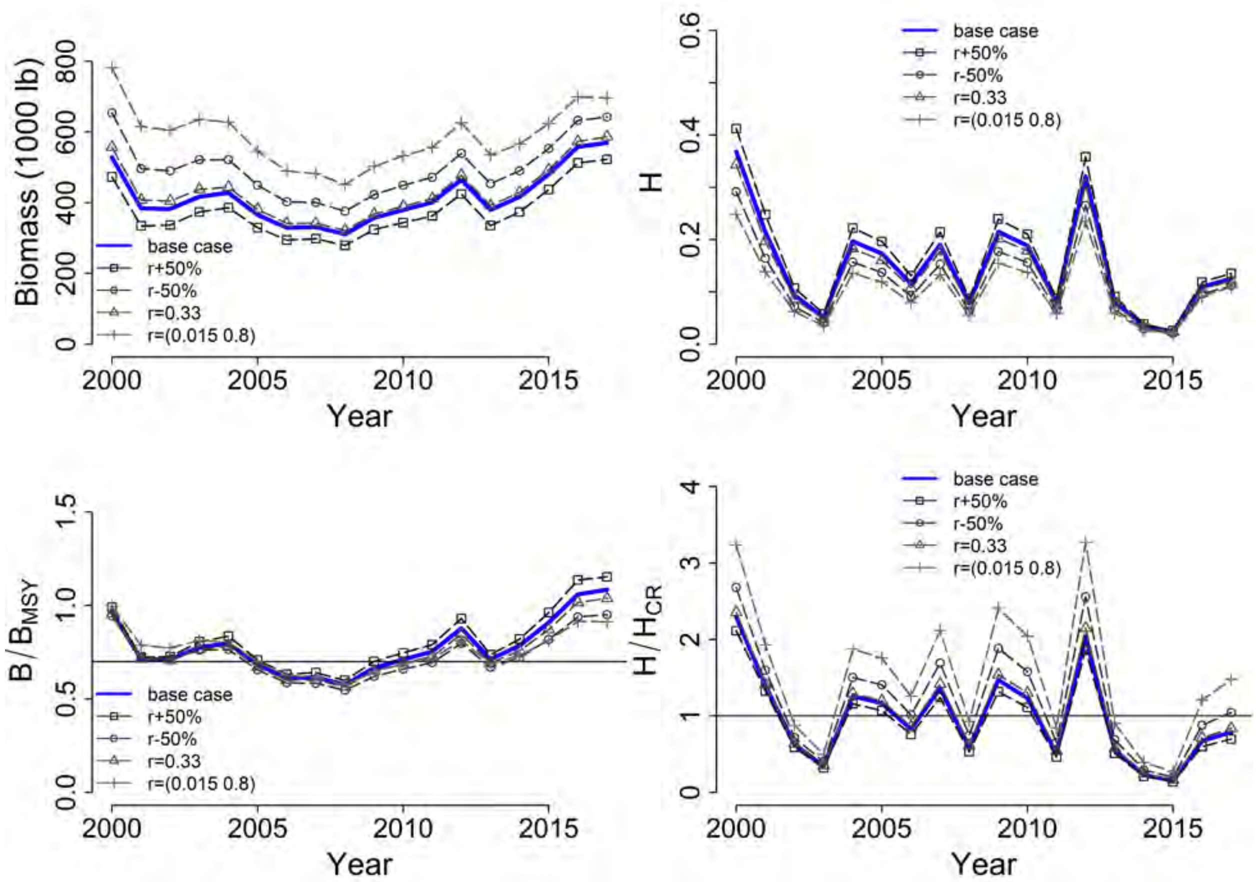


Figure 50. Results of sensitivity analyses for the prior distribution of intrinsic growth rate (*r*) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *r* were calculated as ± 50% of the mean prior, the mean prior for *r* = 0.33, the mean prior for *r* = 0.15 with CV of 115% (inputted as a range for *r* from 0.015 to 0.8).

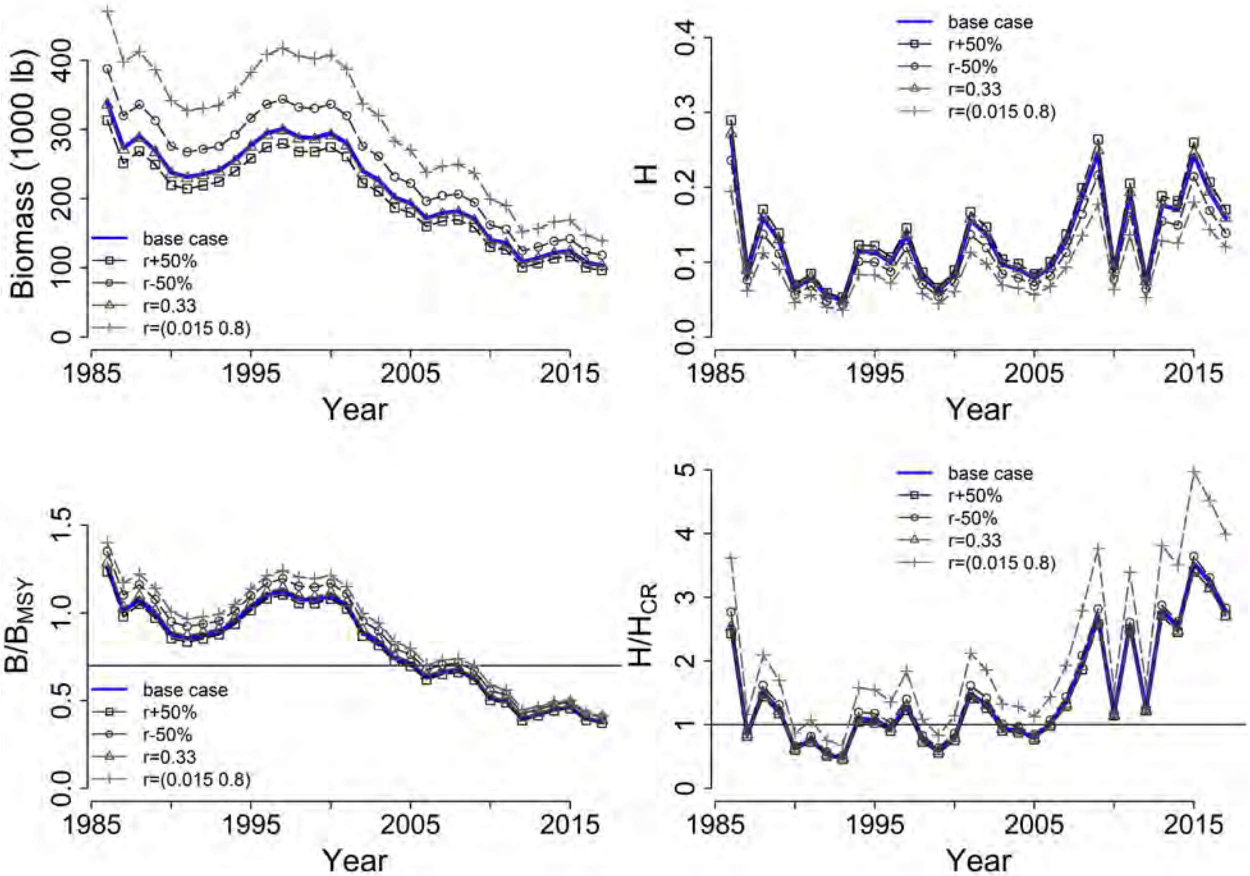


Figure 51. Results of sensitivity analyses for the prior distribution of intrinsic growth rate (*r*) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *r* were calculated as ± 50% of the mean prior, the mean prior for *r* = 0.33, the mean prior for *r* = 0.15 with CV of 115% (inputted as a range for *r* from 0.015 to 0.8).

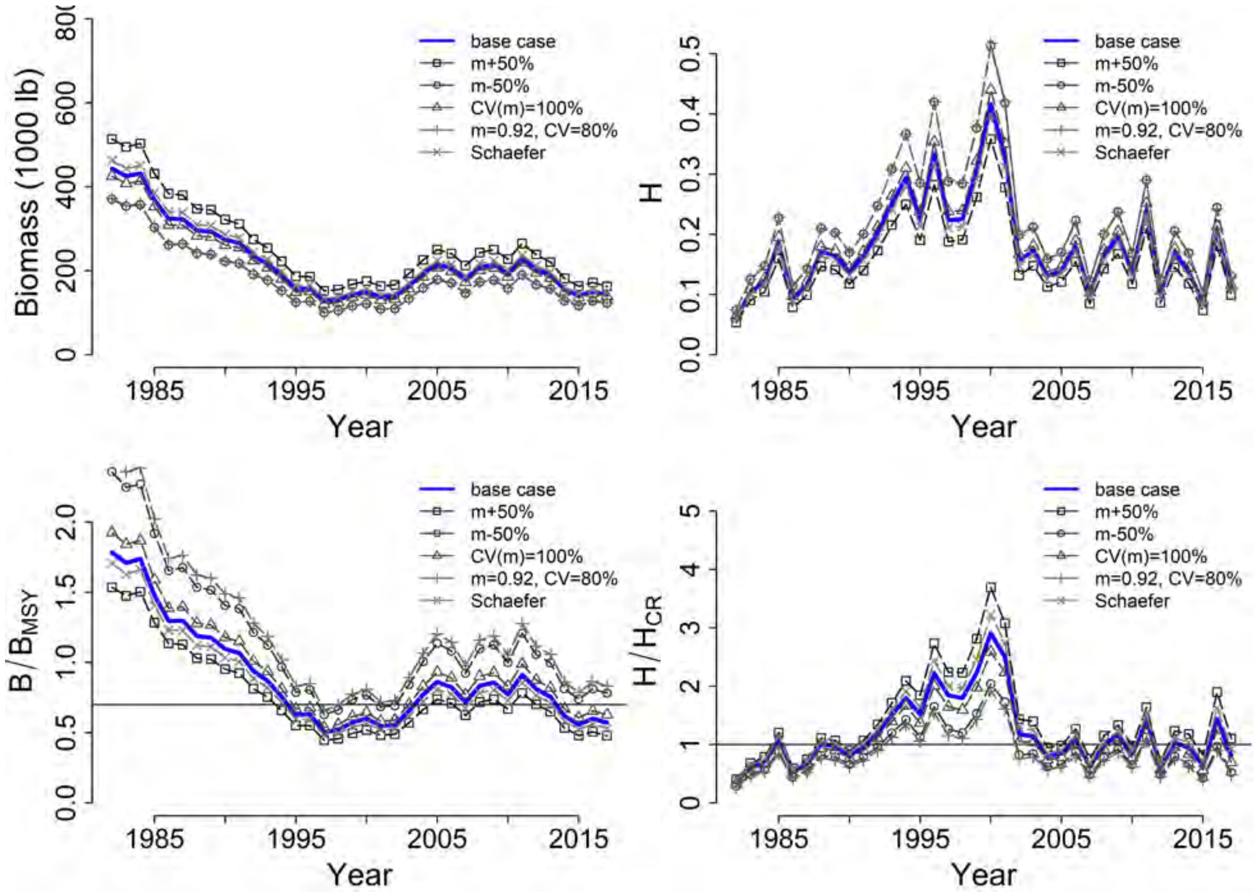


Figure 52. Results of sensitivity analyses for the shape parameter (*m*) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *m* were calculated as ± 50% of the mean prior, the CV for the *m* prior increased to 100%, mean of prior *m* = 0.92 with 80% CV, and *m* fixed at 2.0 (i.e., a Schaefer model).

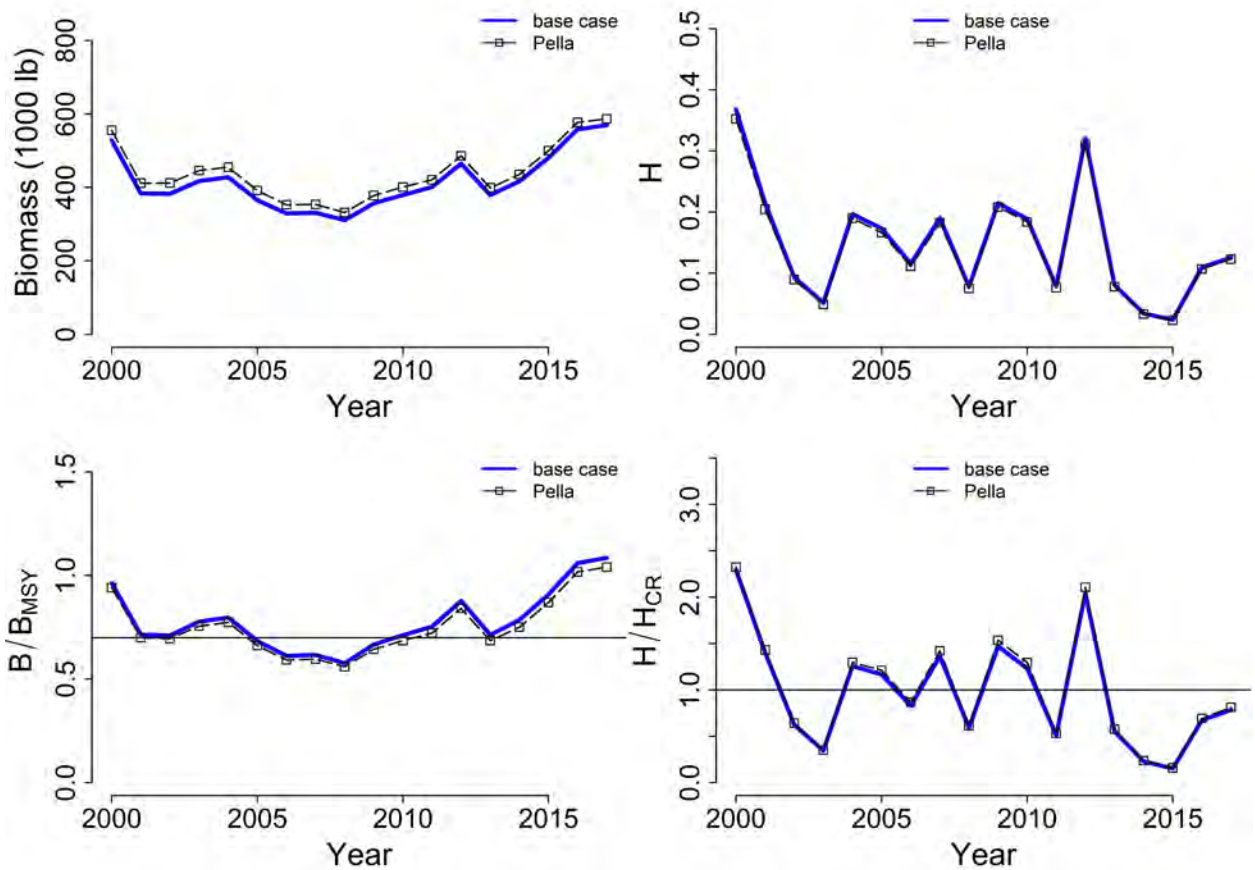


Figure 53. Results of sensitivity analyses for the shape parameter (*m*) for the bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). A model estimating *m* (i.e., a Pella-Tomlinson model) was fit as an alternative to the base case model where *m* was fixed at 2.

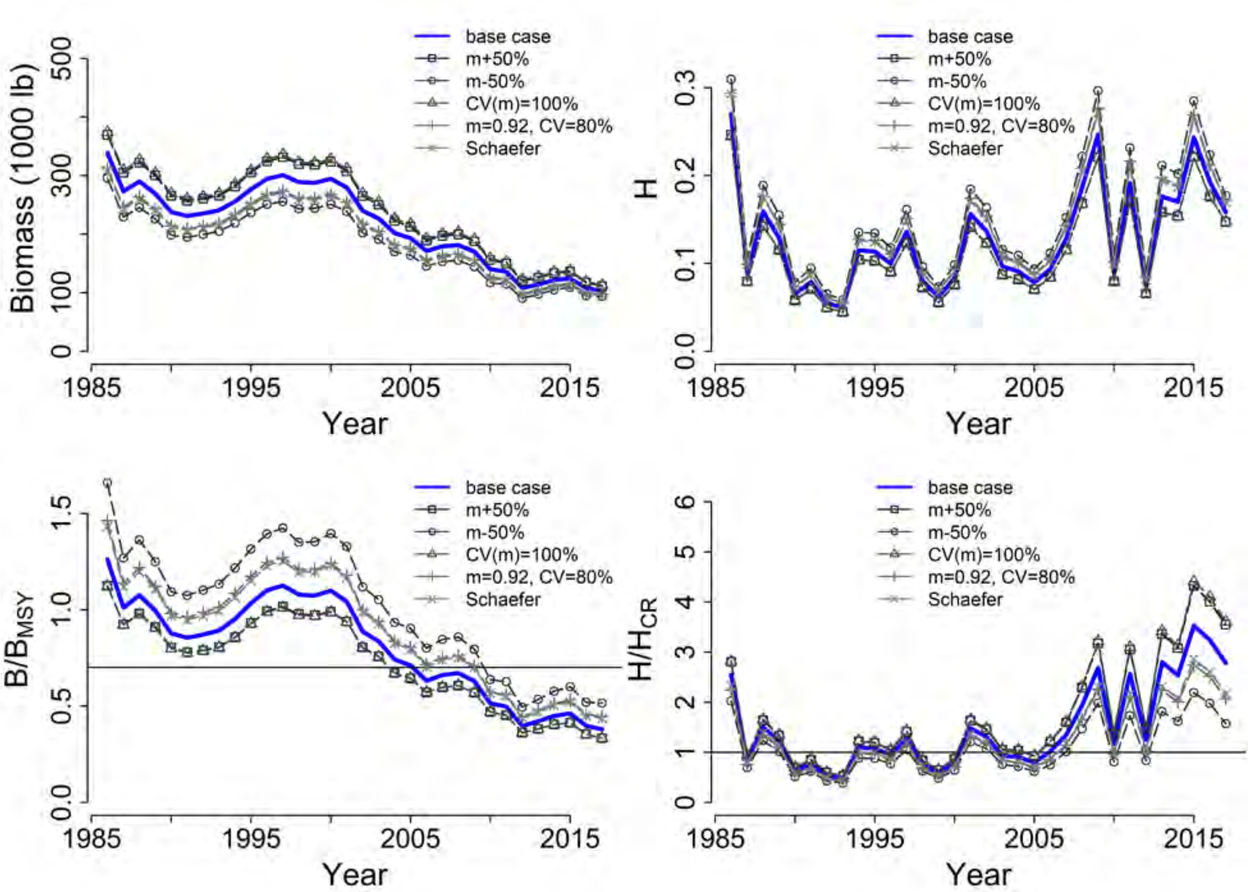


Figure 54. Results of sensitivity analyses for the shape parameter (*m*) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *m* were calculated as ± 50% of the mean prior, the CV for the *m* prior increased to 100%, mean of prior *m* = 0.92 with 80% CV, and *m* fixed at 2.0 (i.e., a Schaefer model).

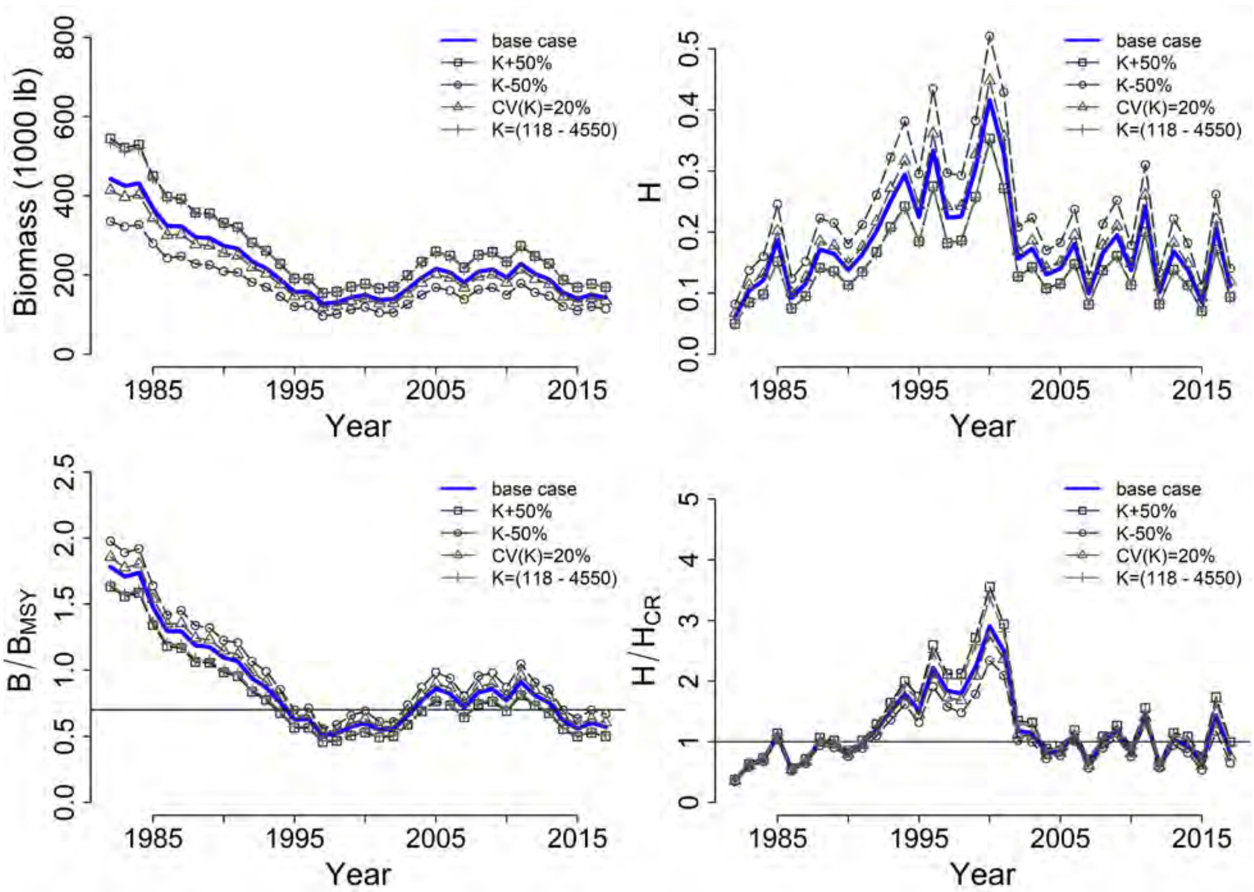


Figure 55. Results of sensitivity analyses for the prior distribution of carrying capacity (*K*) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *K* were calculated as ± 50% of the mean prior, the CV for the *K* prior decreased to 20%, and *K* with 95% confidence interval from 118 to 4550 thousand pounds.

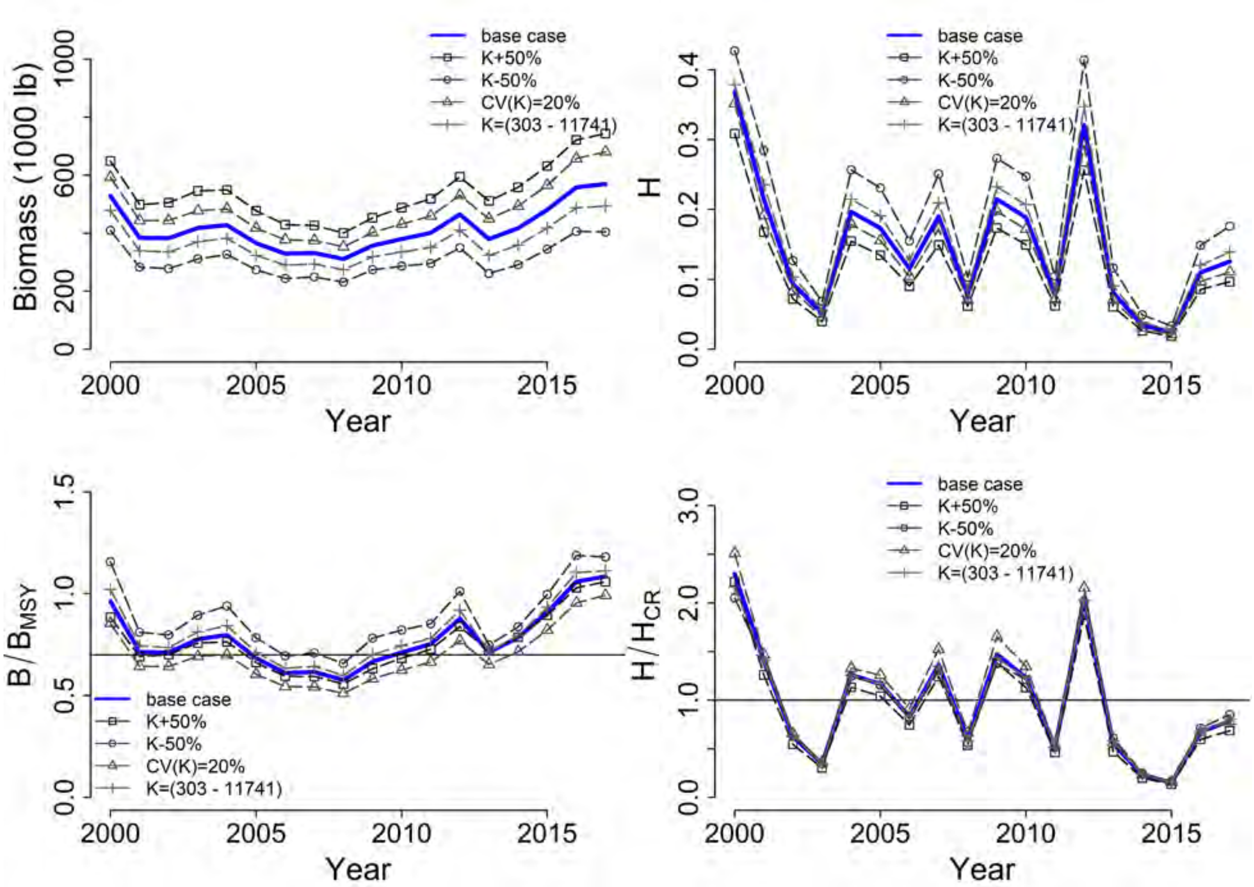


Figure 56. Results of sensitivity analyses for the prior distribution of carrying capacity (*K*) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *K* were calculated as ± 50% of the mean prior, the CV for the *K* prior decreased to 20%, and *K* with 95% confidence interval from 303 to 11741 thousand pounds.

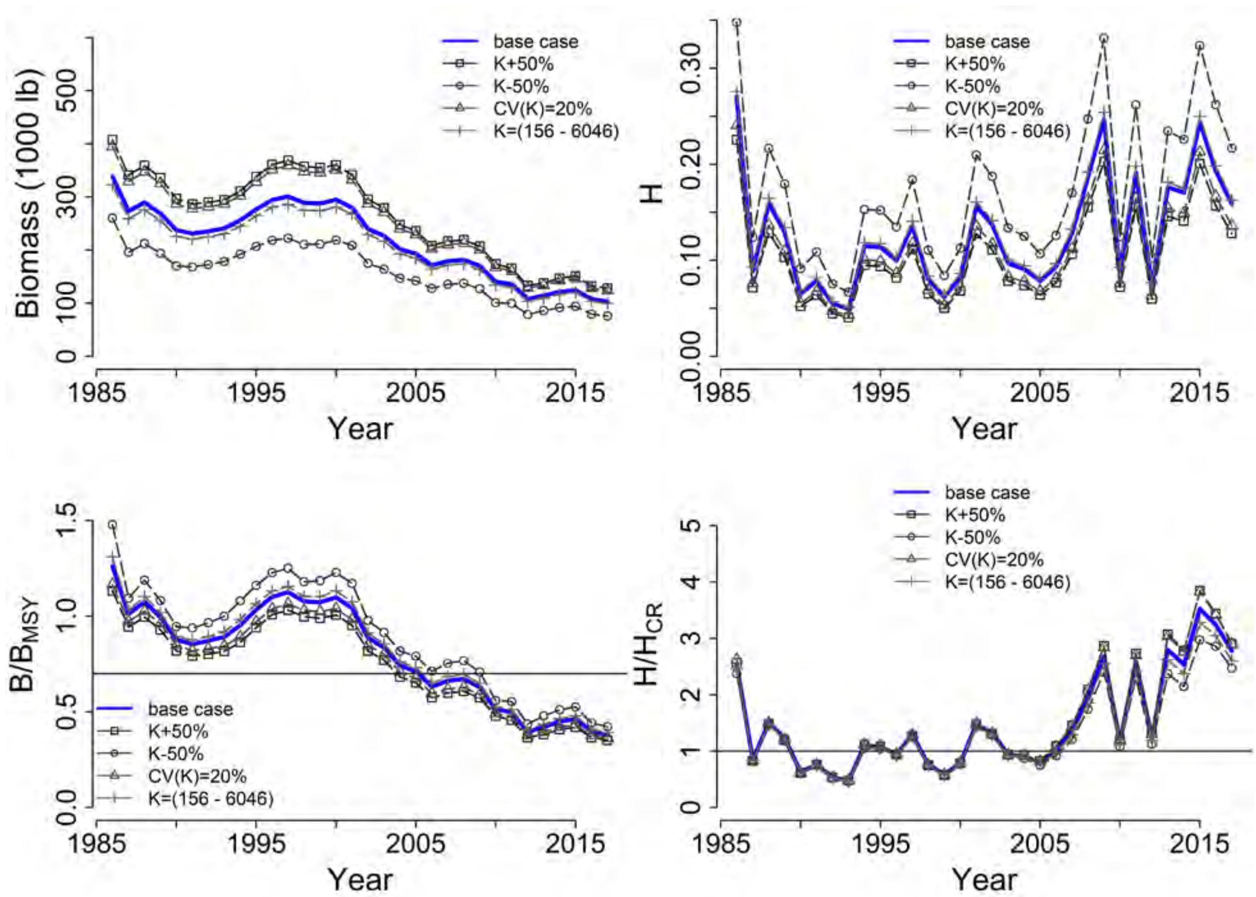


Figure 57. Results of sensitivity analyses for the prior distribution of carrying capacity (*K*) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for *K* were calculated as ± 50% of the mean prior, the CV for the *K* prior decreased to 20%, and *K* with a 95% confidence interval from 156 to 6046 thousand pounds.

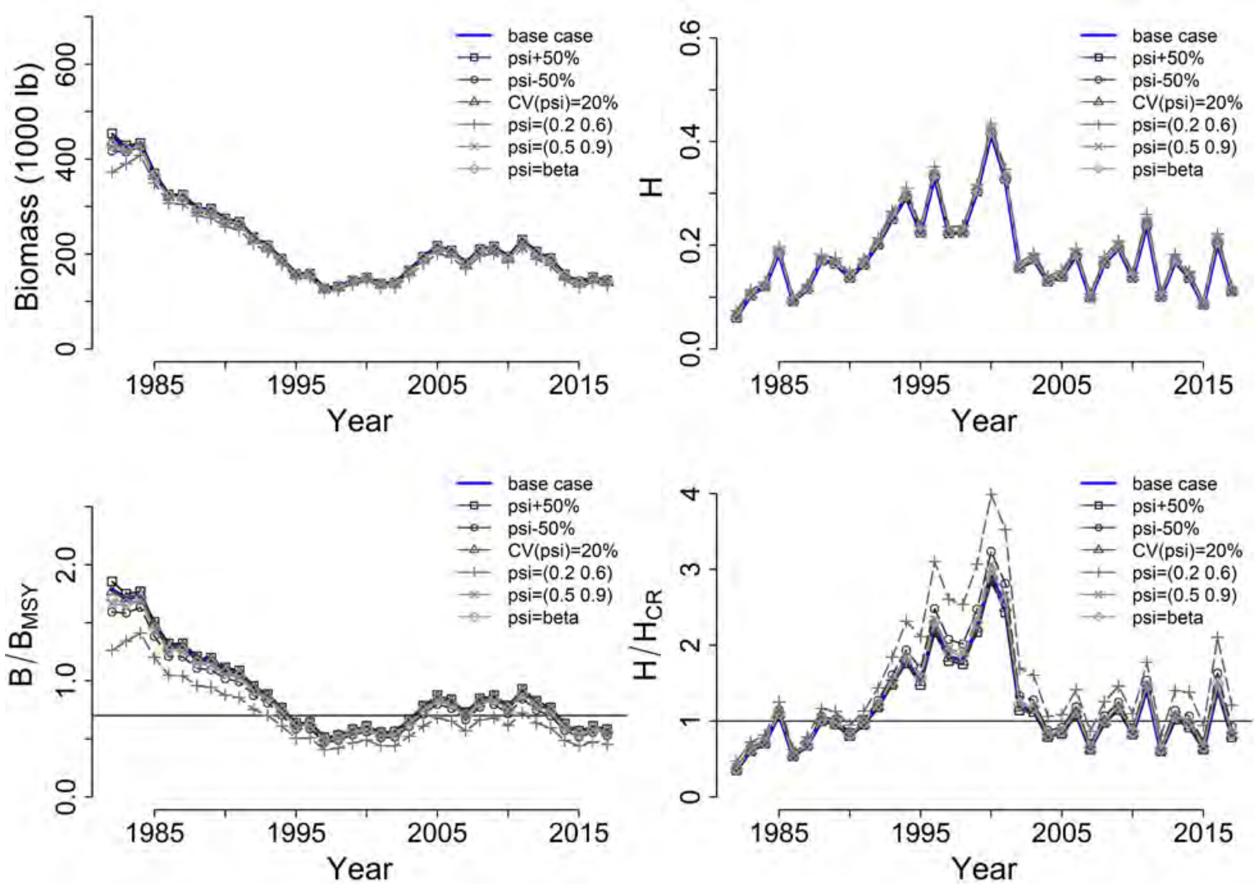


Figure 58. Results of sensitivity analyses for the prior distribution of ratio of initial biomass to carrying capacity (ψ) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), *B/B_{MSY}* (bottom left), and *H/H_{CR}* (bottom right). Priors for ψ were calculated as ± 50% of the mean prior, the CV for the ψ prior decreased to 20%, ψ with a 95% confidence interval from 0.2 to 0.6 and 0.5 to 0.9, and ψ as a beta distribution with mean and CV equal to 0.5.

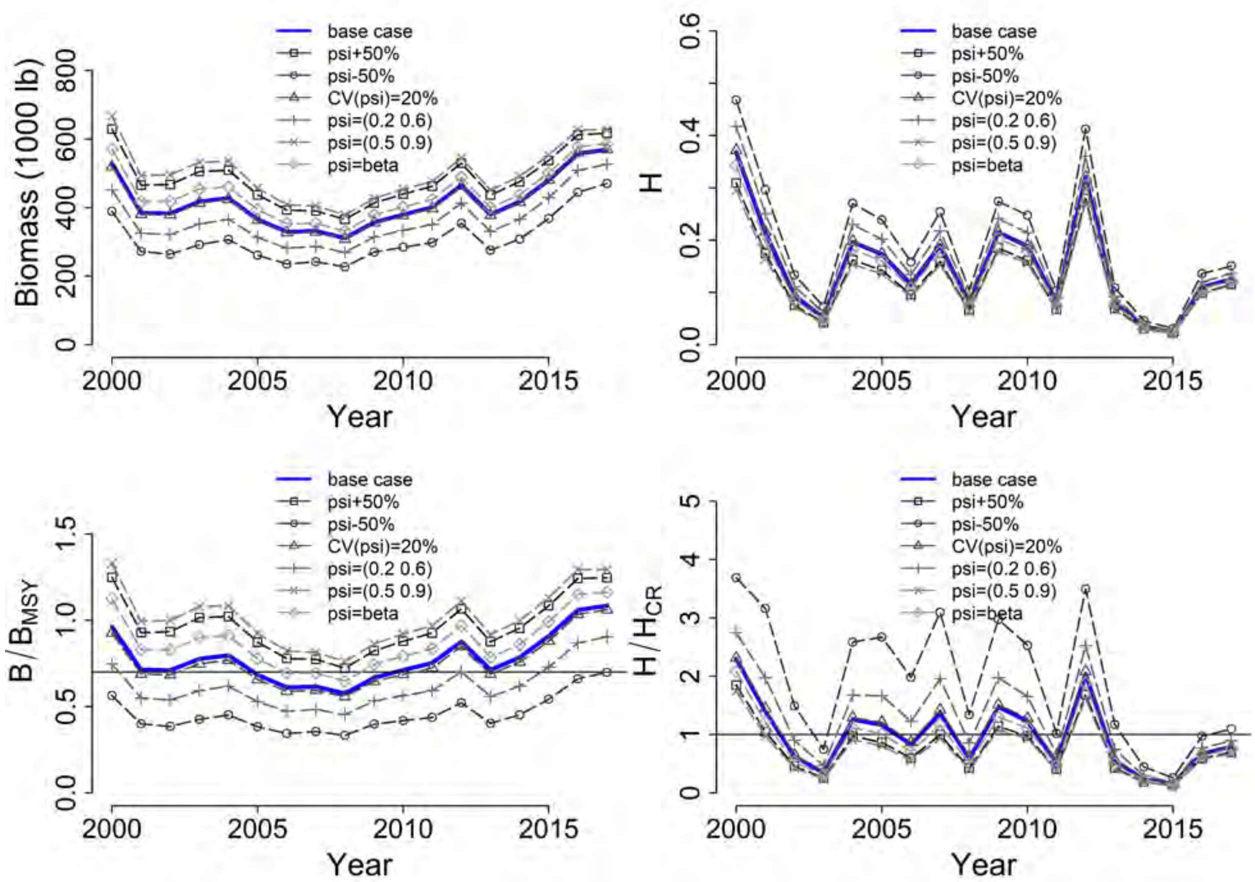


Figure 59. Results of sensitivity analyses for the prior distribution of ratio of initial biomass to carrying capacity (ψ) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for ψ were calculated as ± 50% of the mean prior, the CV for the ψ prior decreased to 20%, ψ with a 95% confidence interval from 0.2 to 0.6 and 0.5 to 0.9, and ψ as a beta distribution with mean and CV equal to 0.5.

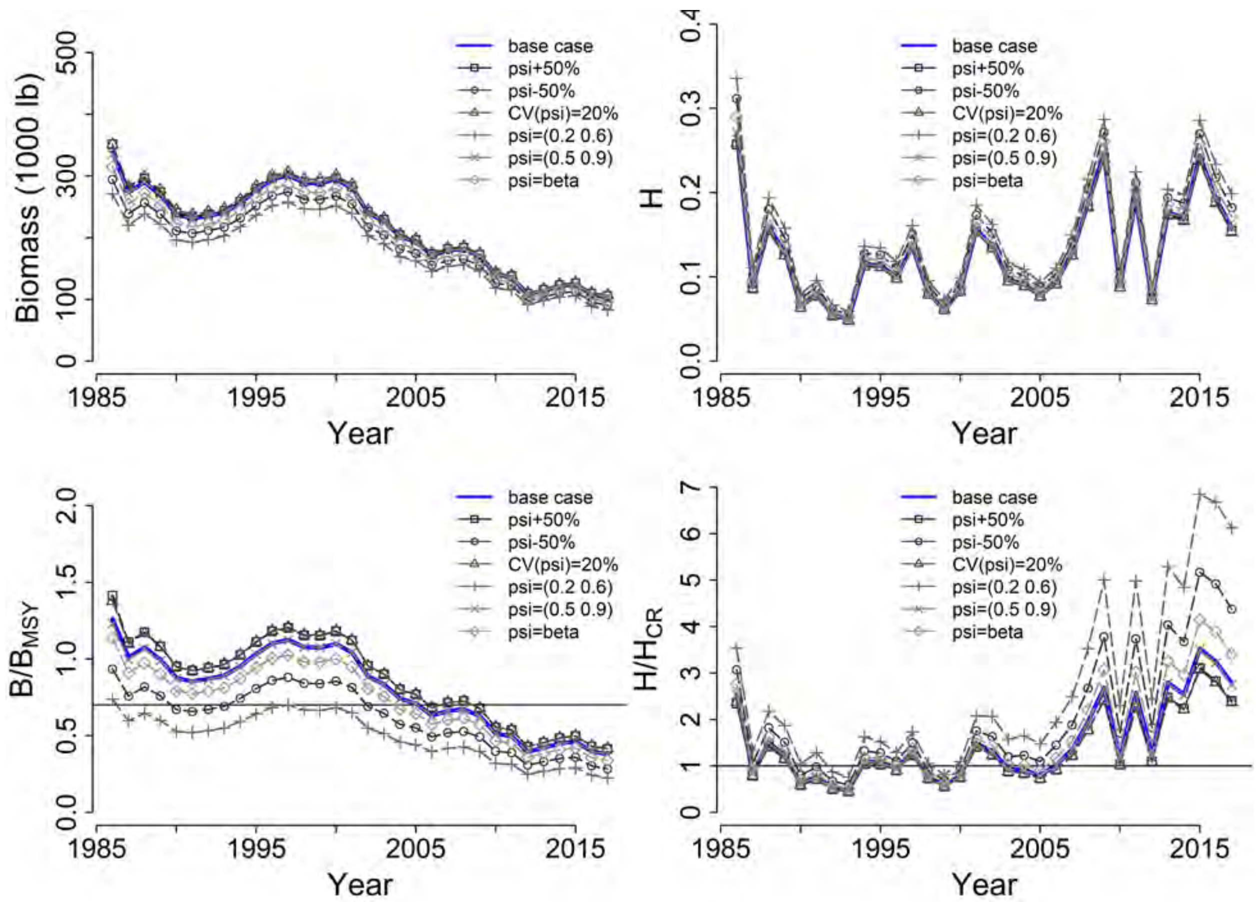


Figure 60. Results of sensitivity analyses for the prior distribution of ratio of initial biomass to carrying capacity (ψ) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Priors for ψ were calculated as ± 50% of the mean prior, the CV for the ψ prior decreased to 20%, ψ with a 95% confidence interval from 0.2 to 0.6 and 0.5 to 0.9, and ψ as a beta distribution with mean and CV equal to 0.5.

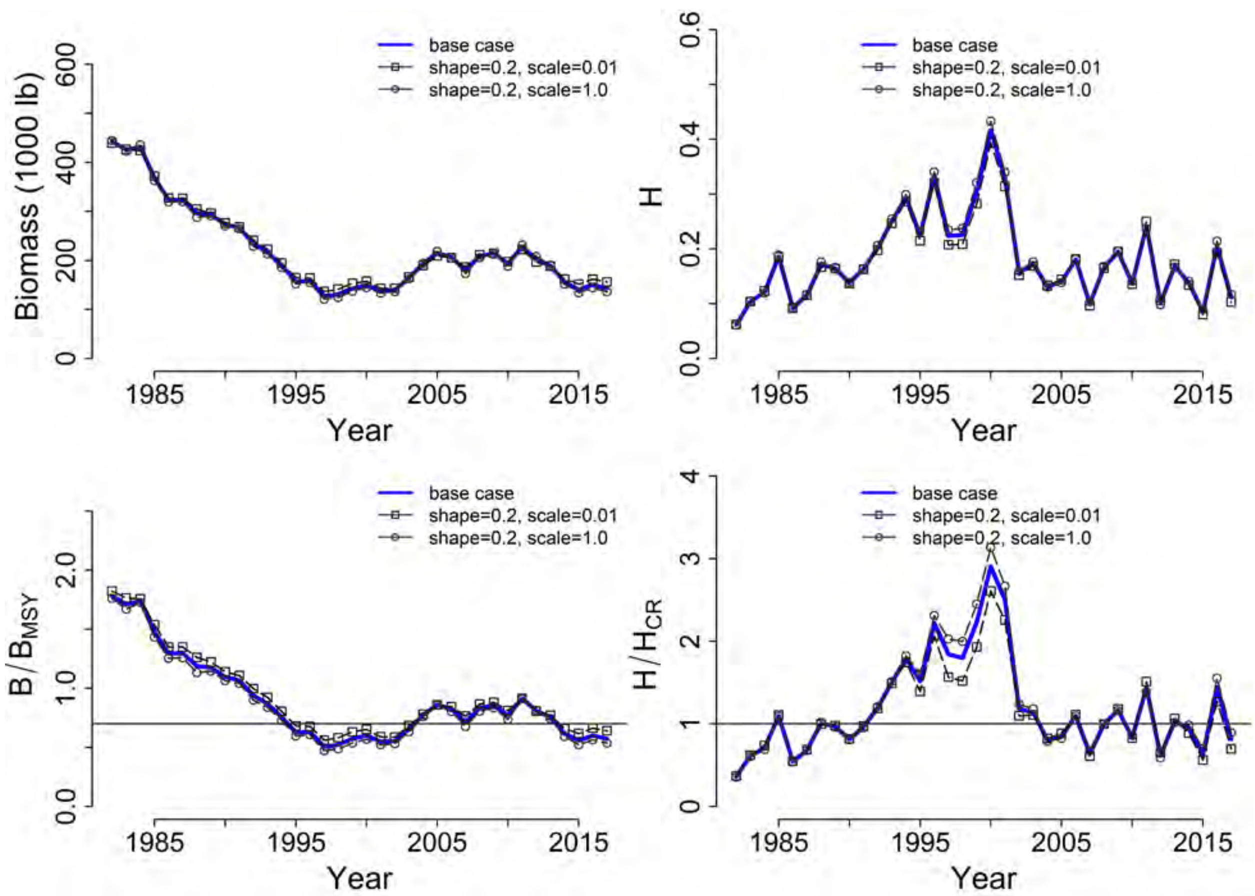


Figure 61. Results of sensitivity analyses for the prior mode of process error (σ_η^2) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), *B/B_{MSY}* (bottom left), and *H/H_{CR}* (bottom right). Prior mode for σ_η^2 was decreased by a factor of 10 by reducing the scale parameter to 0.01 and increased by a factor of 10 by increasing the scale parameter to 1.0.

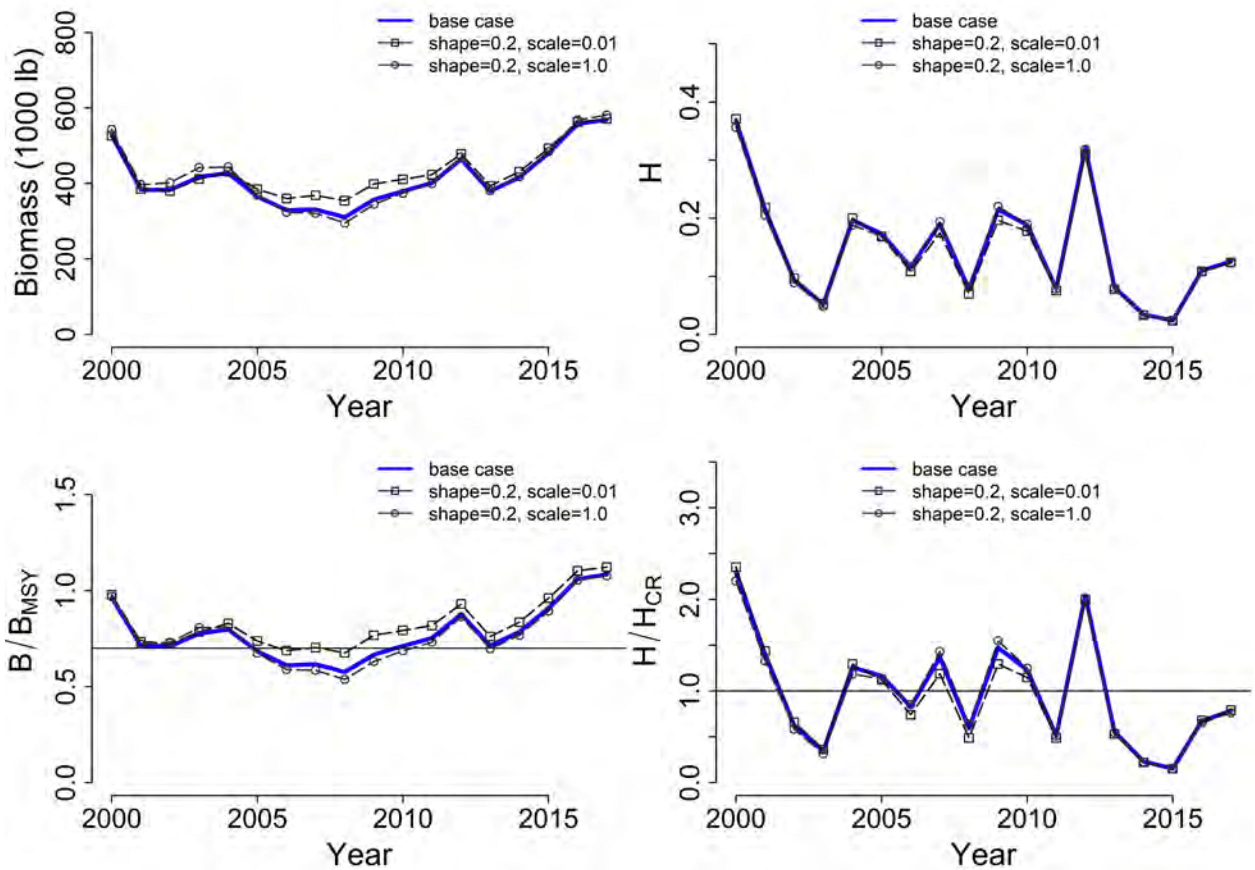


Figure 62. Results of sensitivity analyses for the prior mode of process error (σ_η^2) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), *B/B*$_{MSY}$ (bottom left), and *H/H*$_{CR}$ (bottom right). Prior mode for σ_η^2 was decreased by a factor of 10 by reducing the scale parameter to 0.01 and increased by a factor of 10 by increasing the scale parameter to 1.0.

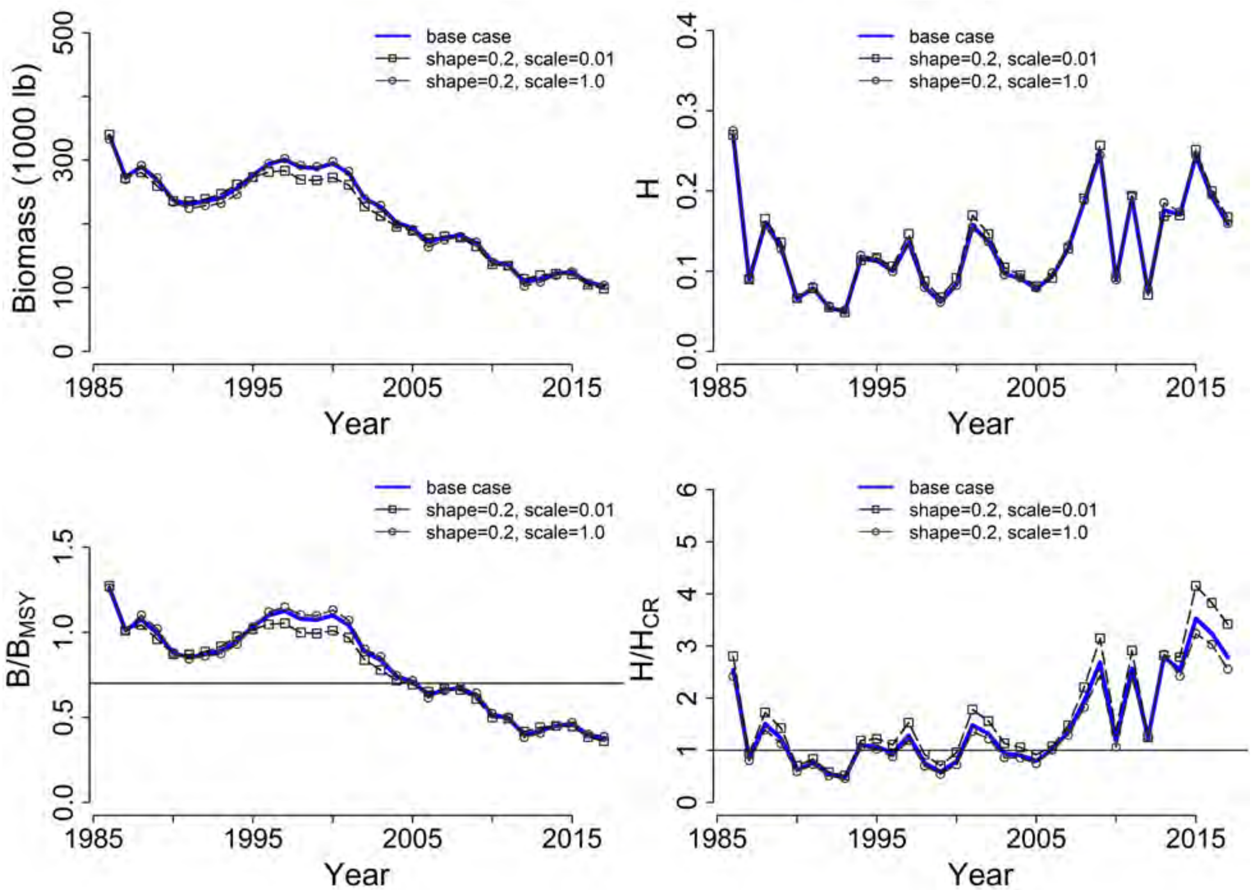


Figure 63. Results of sensitivity analyses for the prior mode of process error (σ_η^2) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Prior mode for σ_η^2 was decreased by a factor of 10 by reducing the scale parameter to 0.01 and increased by a factor of 10 by increasing the scale parameter to 1.0.

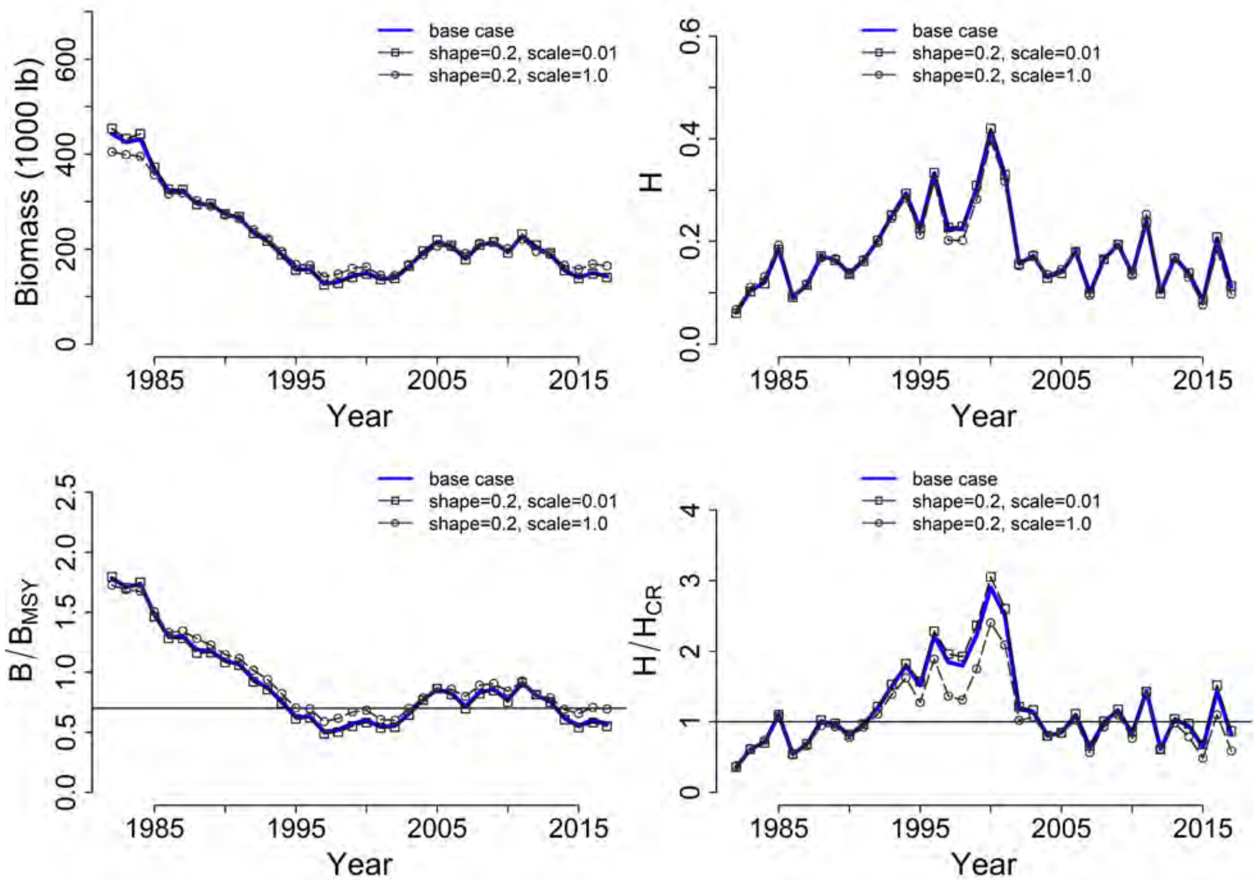


Figure 64. Results of sensitivity analyses for the prior mode of observation error ($\sigma_{\tau estimated}^2$) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), *B/B$_{MSY}$* (bottom left), and *H/H$_{CR}$* (bottom right). Prior mode for $\sigma_{\tau estimated}^2$ was decreased by a factor of 10 by reducing the scale parameter to 0.01 and increased by a factor of 10 by increasing the scale parameter to 1.0.

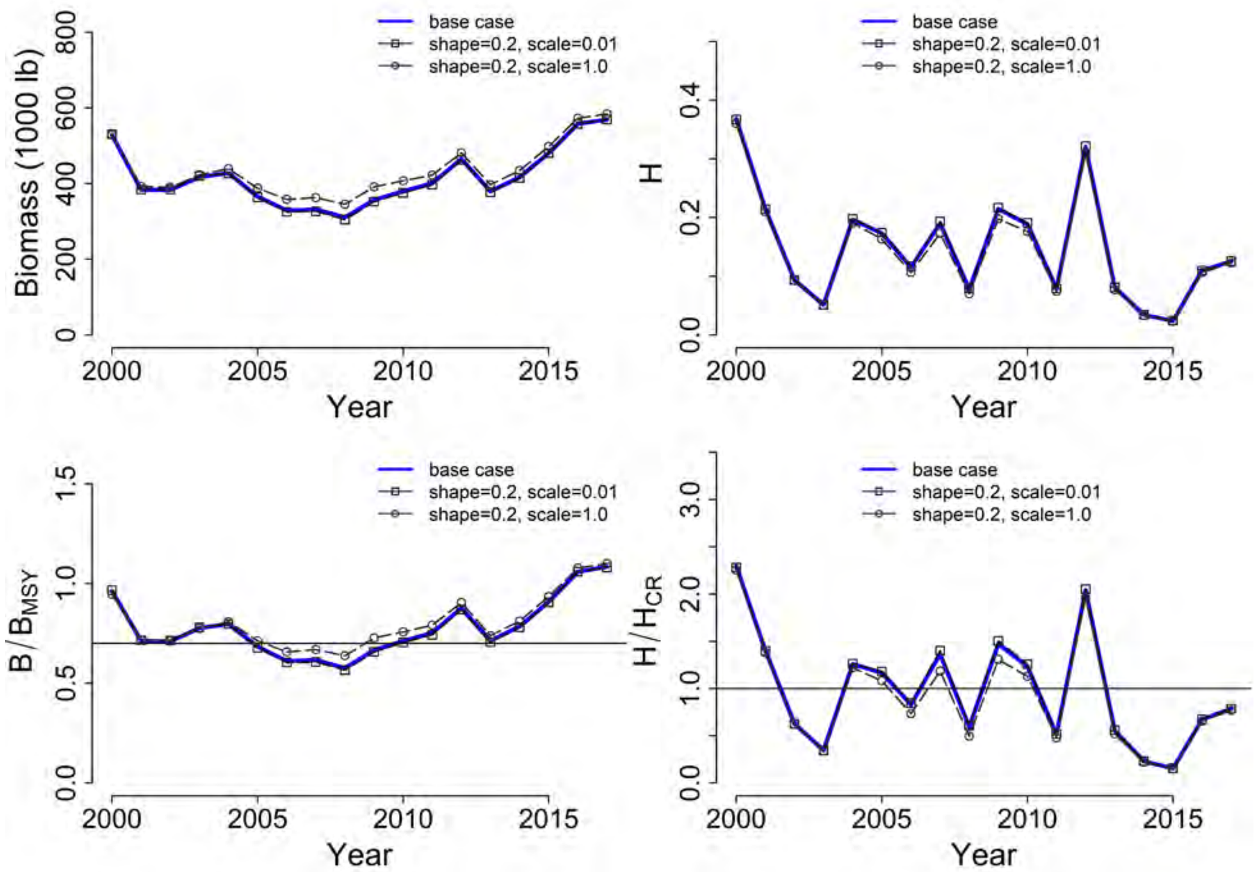


Figure 65. Results of sensitivity analyses for the prior mode of observation error ($\sigma_{\tau estimated}^2$) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Prior mode for $\sigma_{\tau estimated}^2$ was decreased by a factor of 10 by reducing the scale parameter to 0.01 and increased by a factor of 10 by increasing the scale parameter to 1.0.

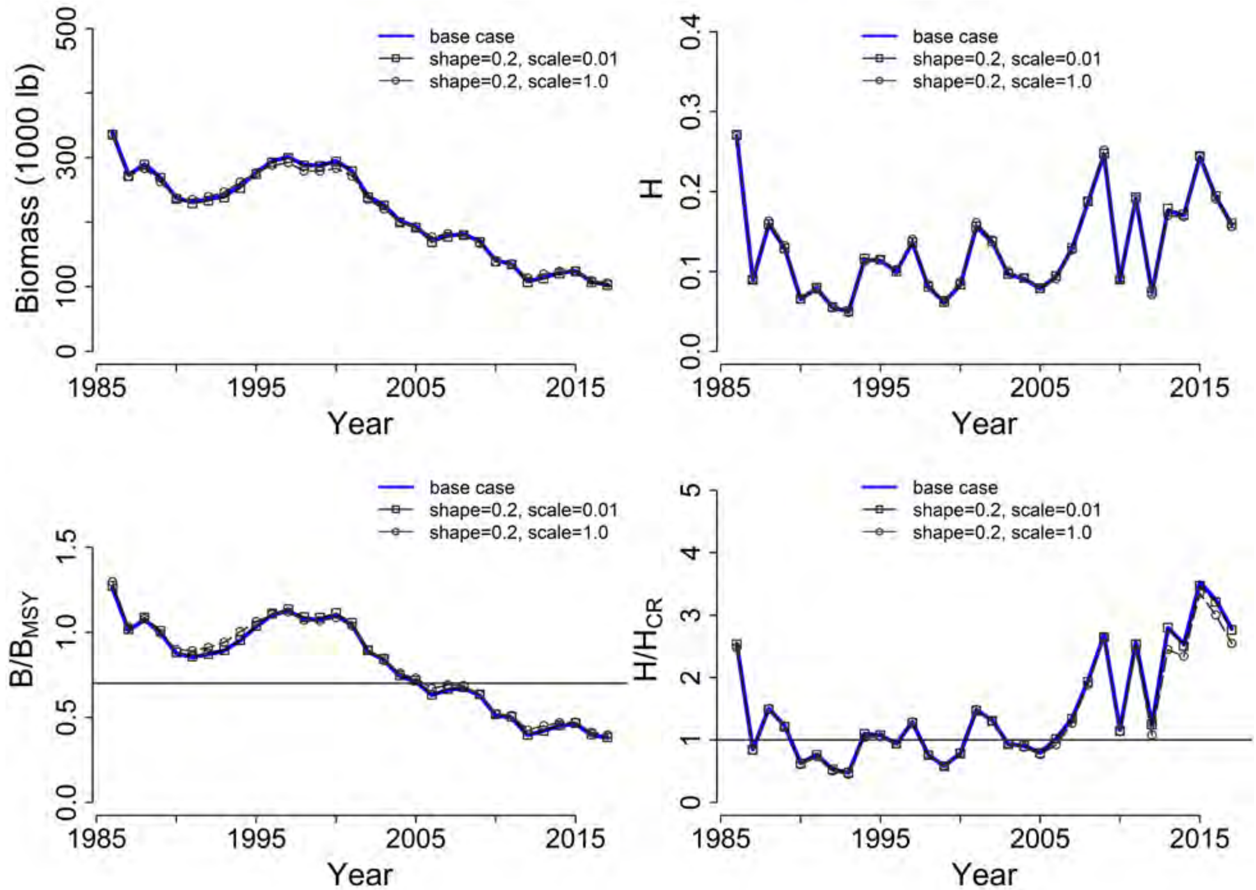


Figure 66. Results of sensitivity analyses for the prior mode of observation error ($\sigma_{\tau estimated}^2$) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Prior mode for $\sigma_{\tau estimated}^2$ was decreased by a factor of 10 by reducing the scale parameter to 0.01 and increased by a factor of 10 by increasing the scale parameter to 1.0.

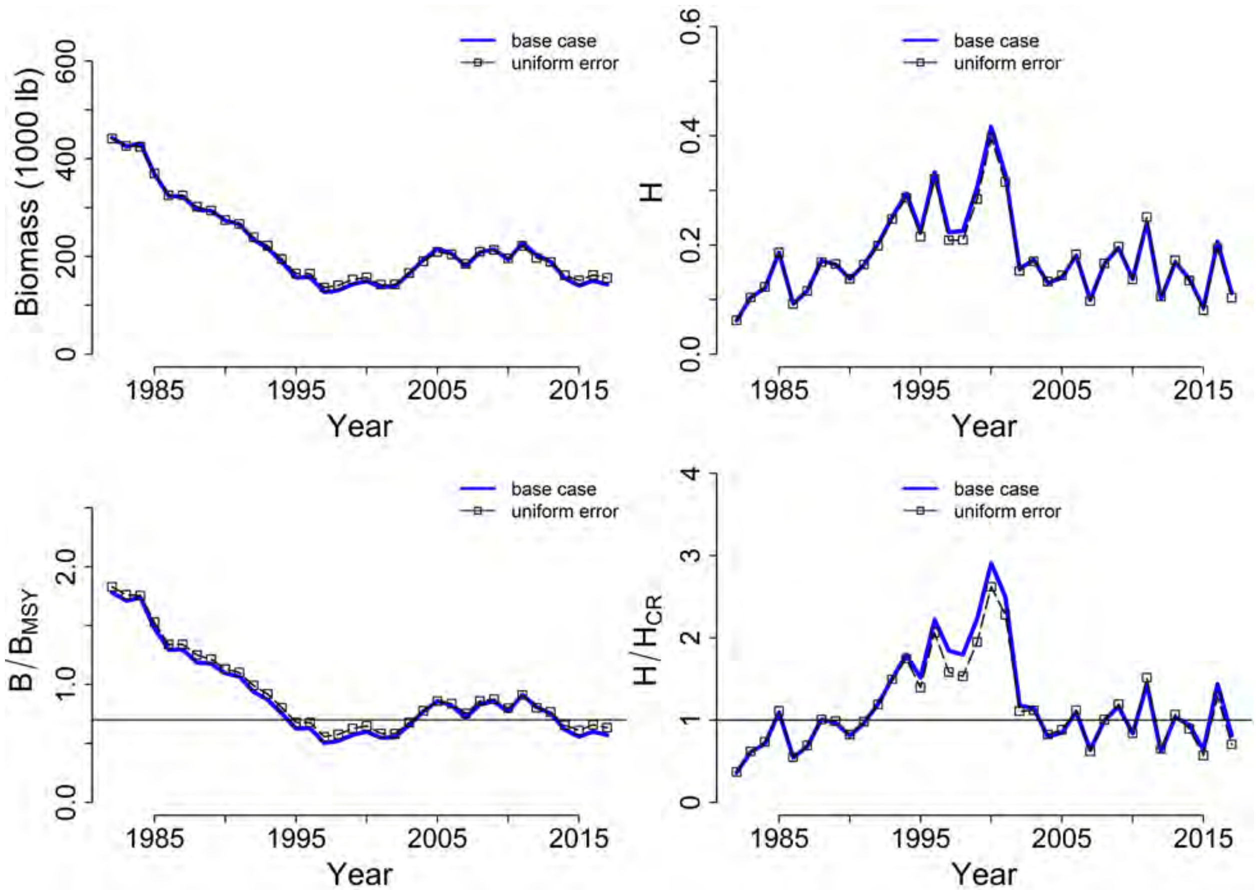


Figure 67. Results of sensitivity analyses for uniform prior distributions for the standard deviation of both the estimable component of observation error ($\sigma_{\varepsilon estimated}$) and process error ($\sigma_{\eta}$) for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right).

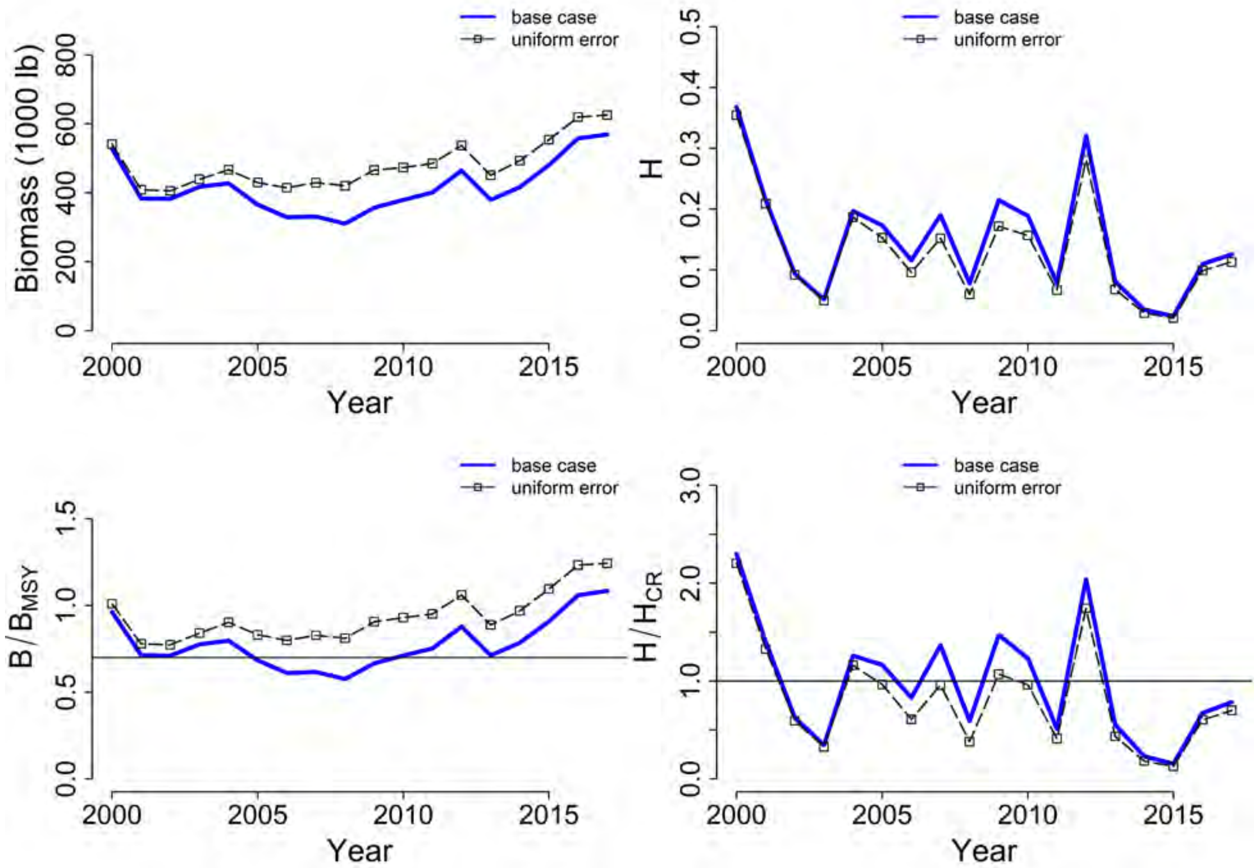


Figure 68. Results of sensitivity analyses for uniform prior distributions for the standard deviation of both the estimable component of observation error ($\sigma_{\varepsilon estimated}$) and process error ($\sigma_{\eta}$) for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), *B/B$_{MSY}$* (bottom left), and *H/H$_{CR}$* (bottom right).

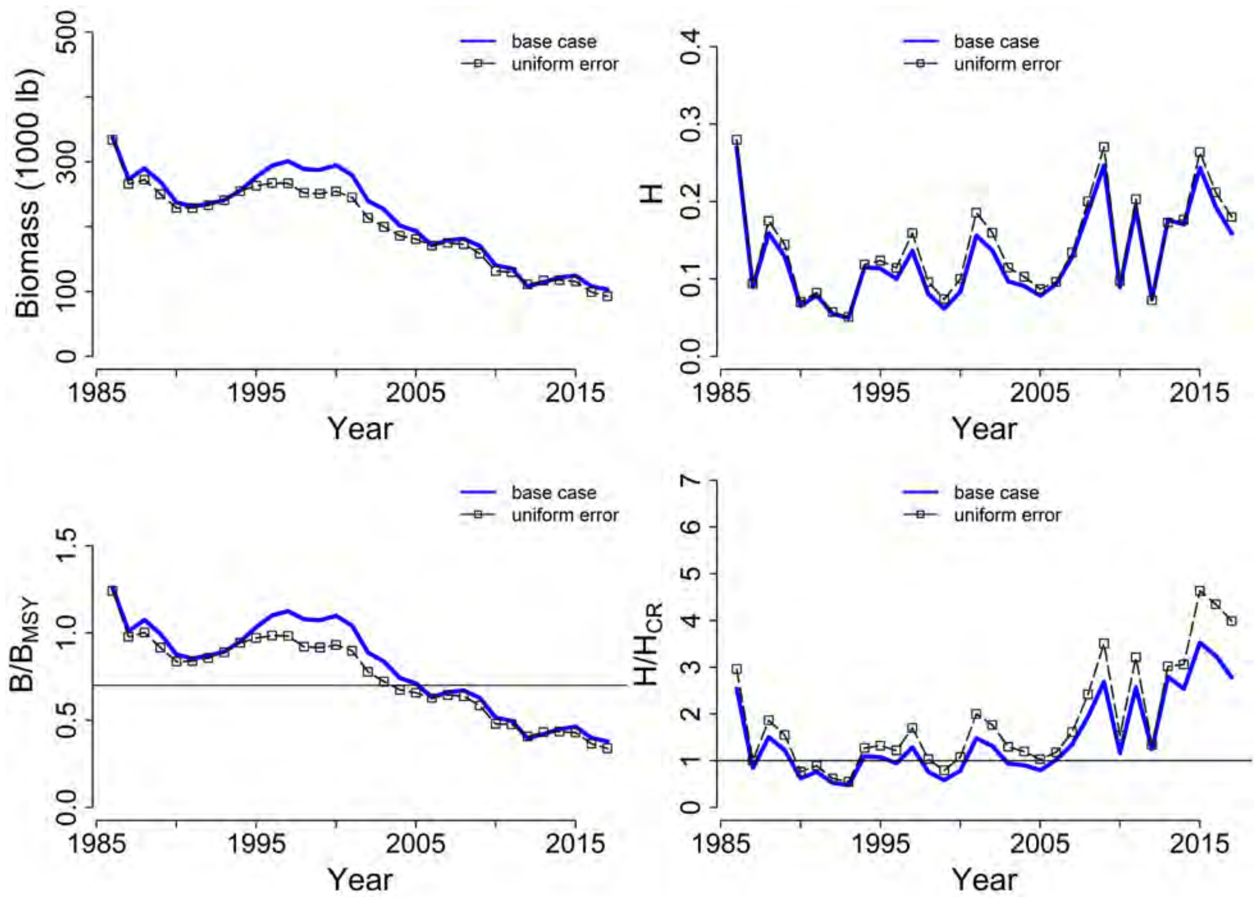


Figure 69. Results of sensitivity analyses for uniform prior distributions for the standard deviation of both the estimable component of observation error ($\sigma_{\tau estimated}$) and process error (σ_η) for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right).

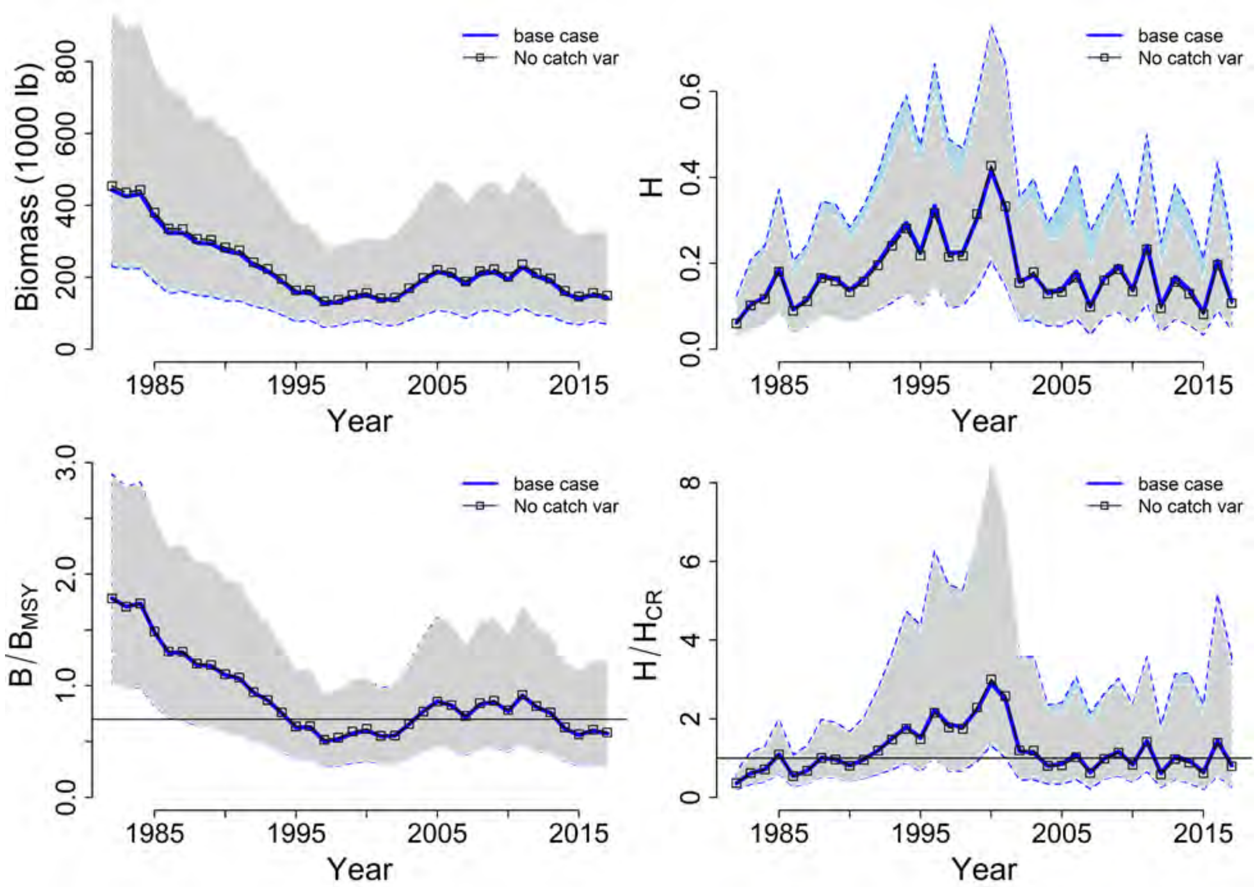


Figure 70. Results of sensitivity analyses for excluding variation in bottomfish management unit species catch for Guam: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Shaded areas are the 95% credible intervals for the base case (blue shading) and for the sensitivity when excluding variation in catch (grey shading).

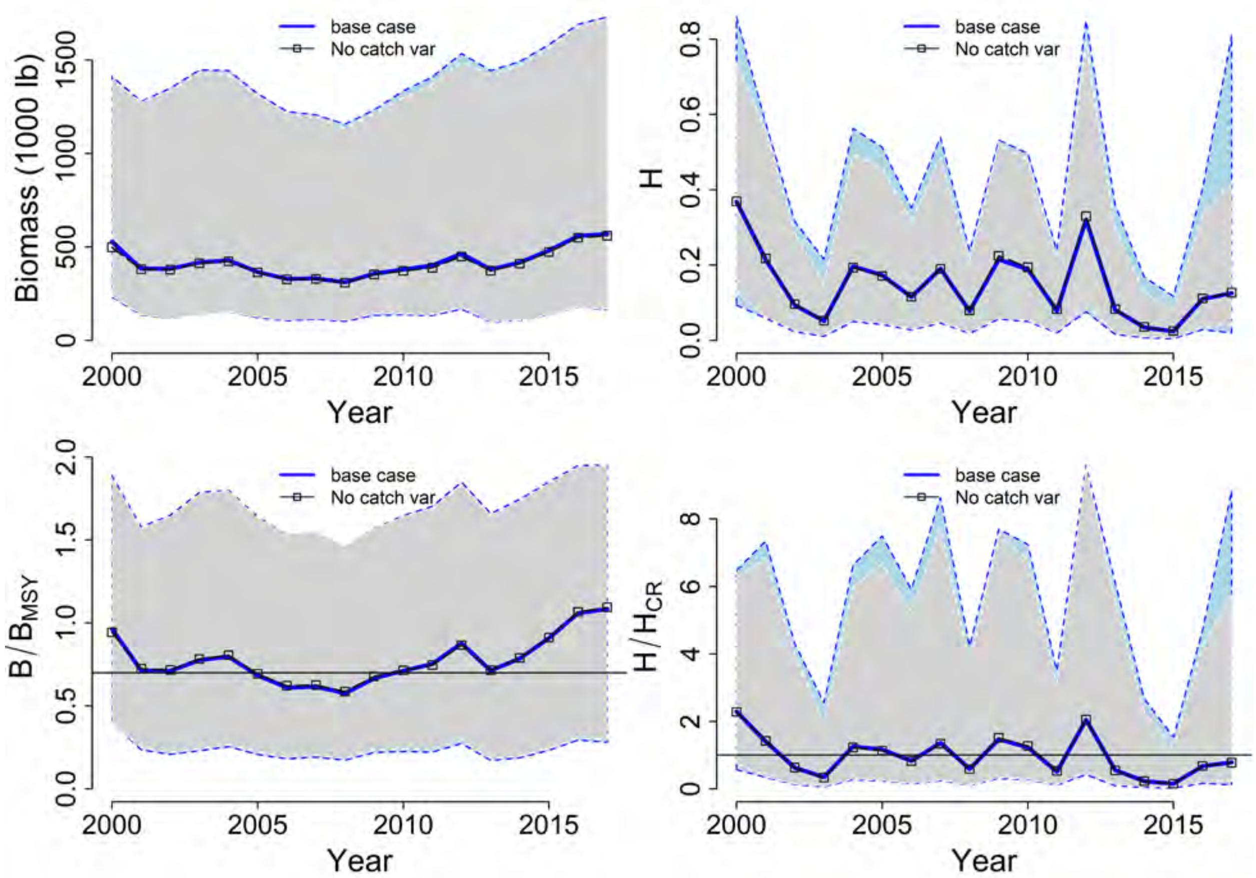


Figure 71. Results of sensitivity analyses for excluding variation in bottomfish management unit species catch for the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), *B*/*B*$_{MSY}$ (bottom left), and *H*/*H*$_{CR}$ (bottom right). Shaded areas are the 95% credible intervals for the base case (blue shading) and for the sensitivity when excluding variation in catch (grey shading).

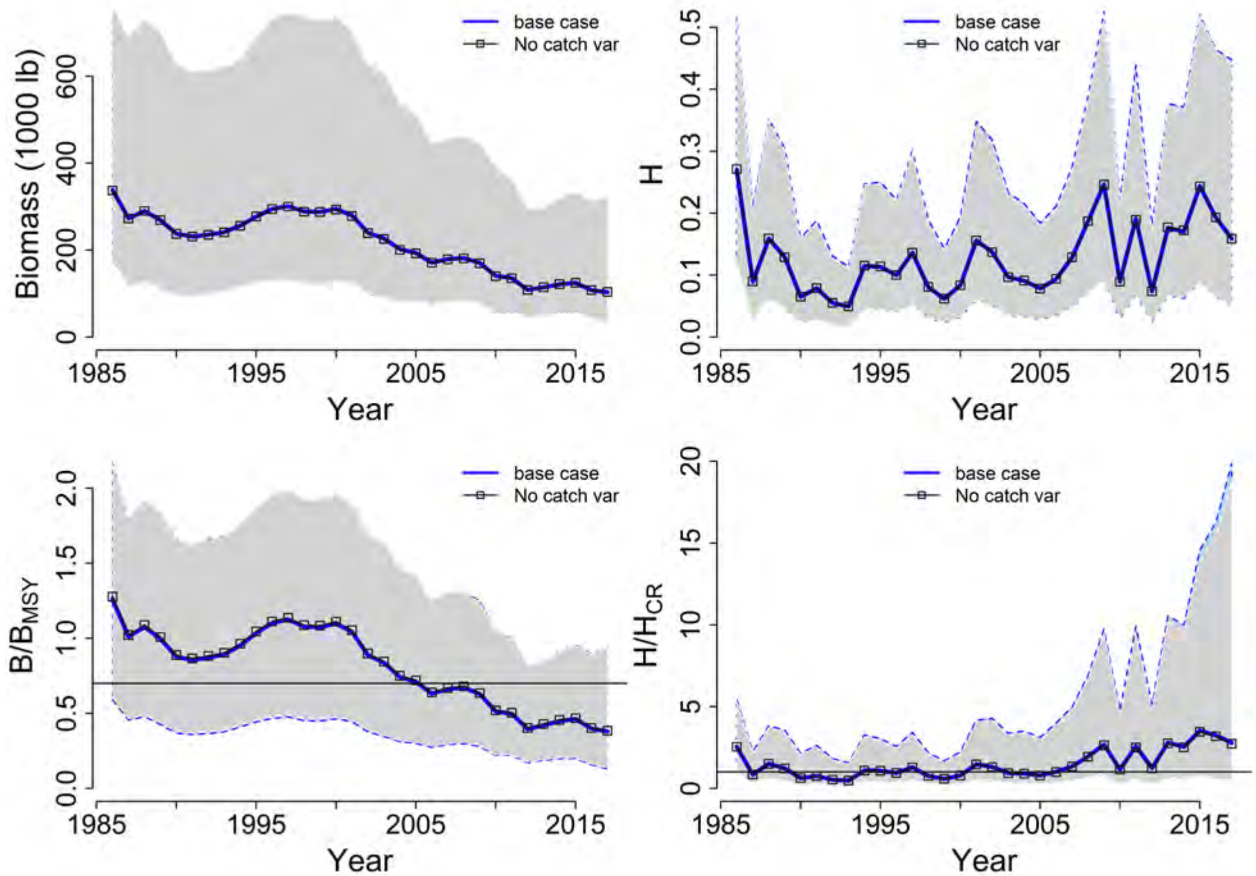


Figure 72. Results of sensitivity analyses for excluding variation in bottomfish management unit species catch for American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right). Shaded areas are the 95% credible intervals for the base case (blue shading) and for the sensitivity when excluding variation in catch (grey shading).

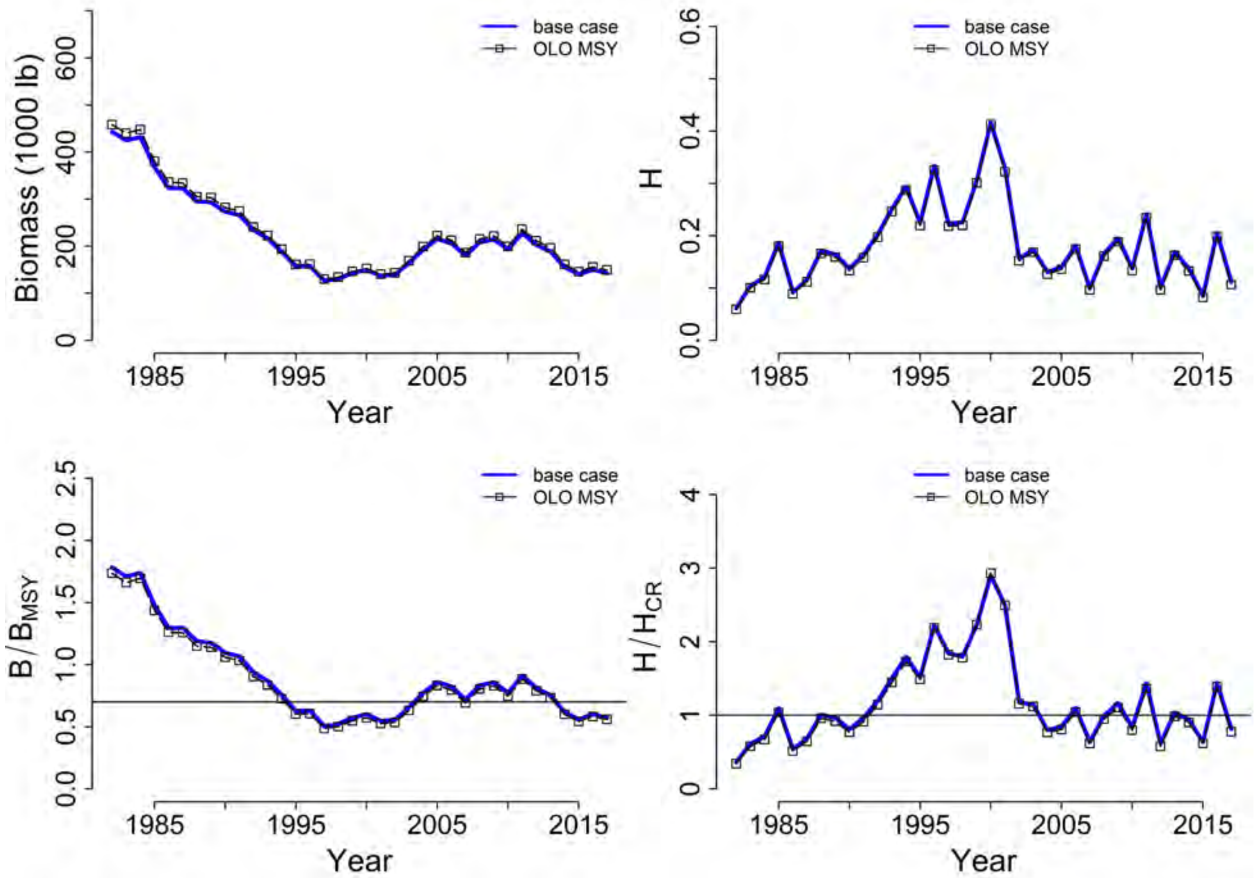


Figure 73. Results of sensitivity analyses for fitting to independent estimate of MSY for bottomfish management unit species in Guam: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right).

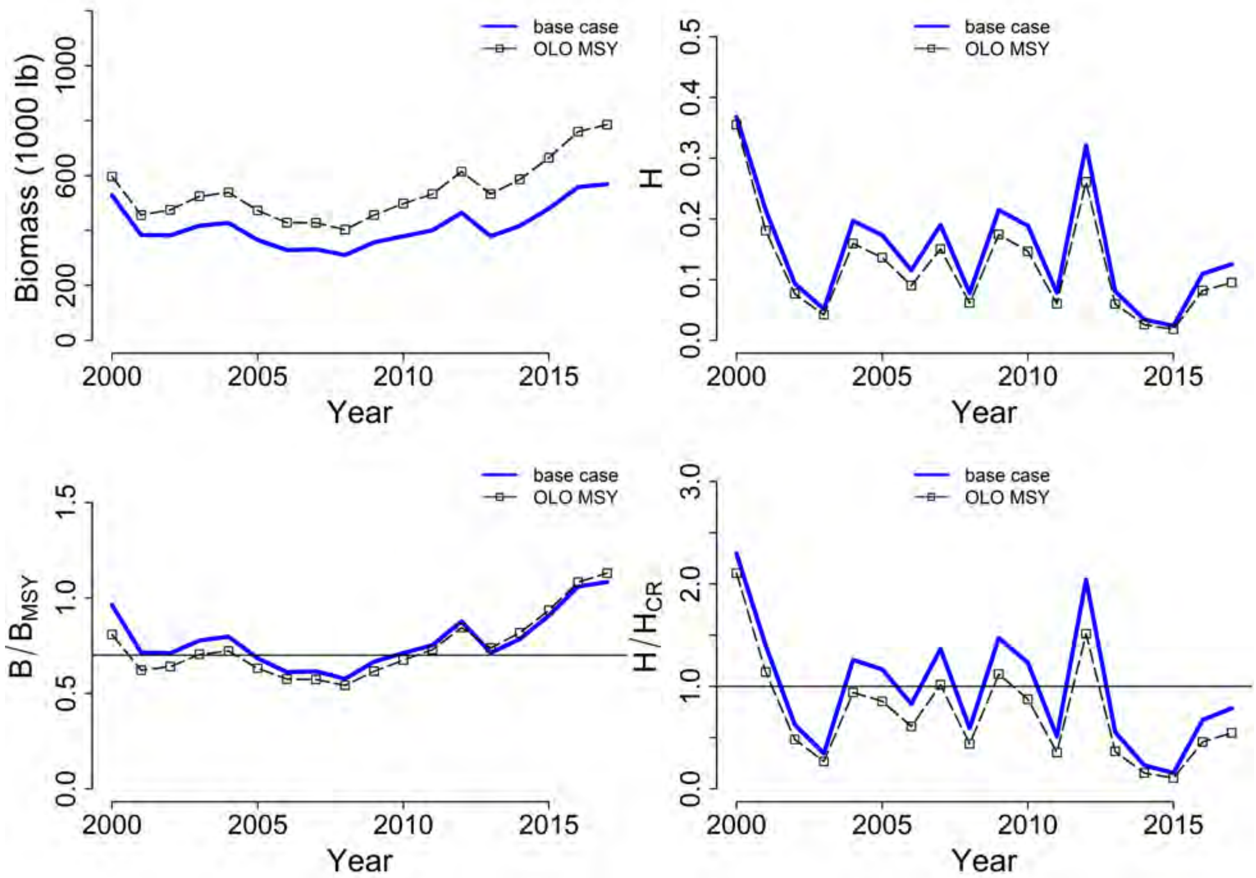


Figure 74. Results of sensitivity analyses for fitting to independent estimate of MSY for bottomfish management unit species in the Commonwealth of the Northern Mariana Islands: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right).

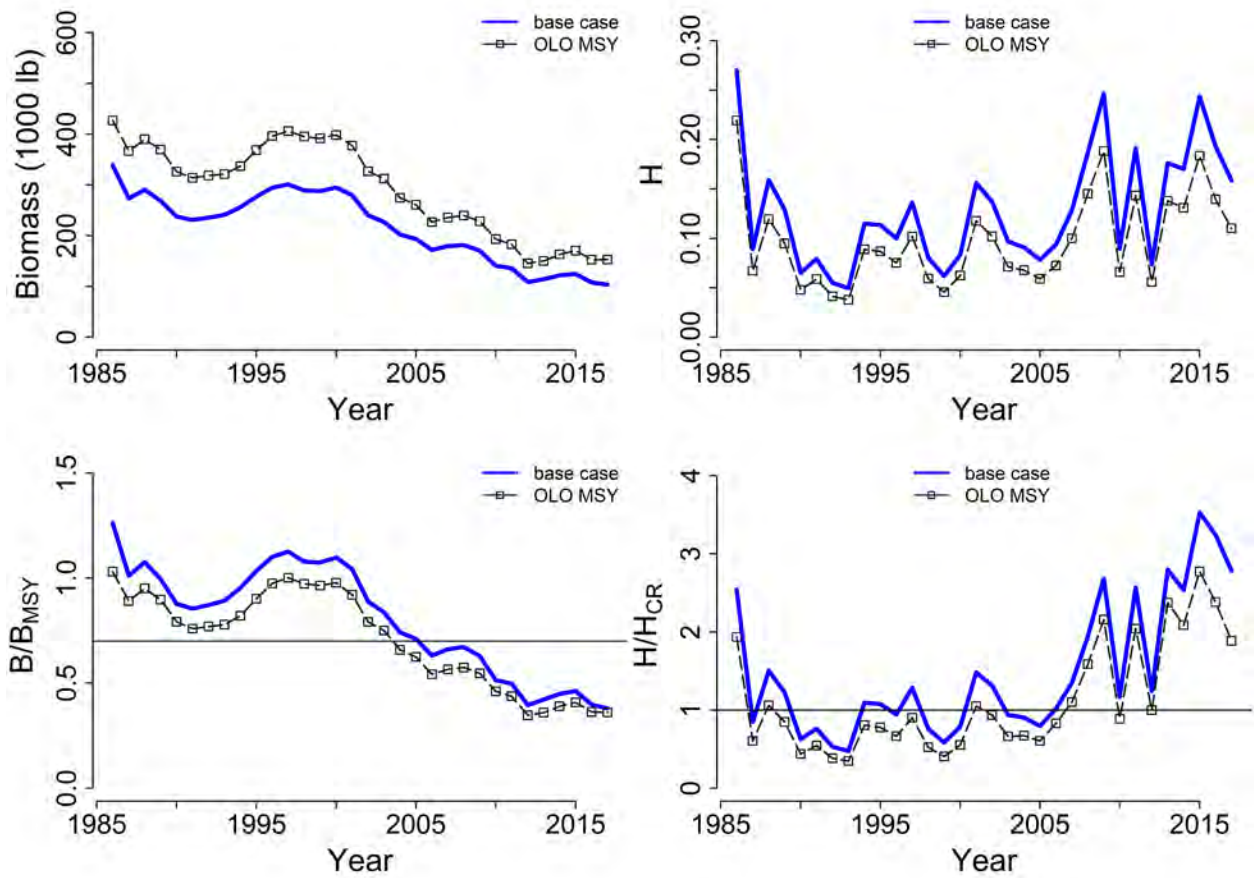


Figure 75. Results of sensitivity analyses for fitting to independent estimate of MSY for bottomfish management unit species in American Samoa: estimated biomass (top left), harvest rate (*H*; top right), B/B_{MSY} (bottom left), and H/H_{CR} (bottom right).

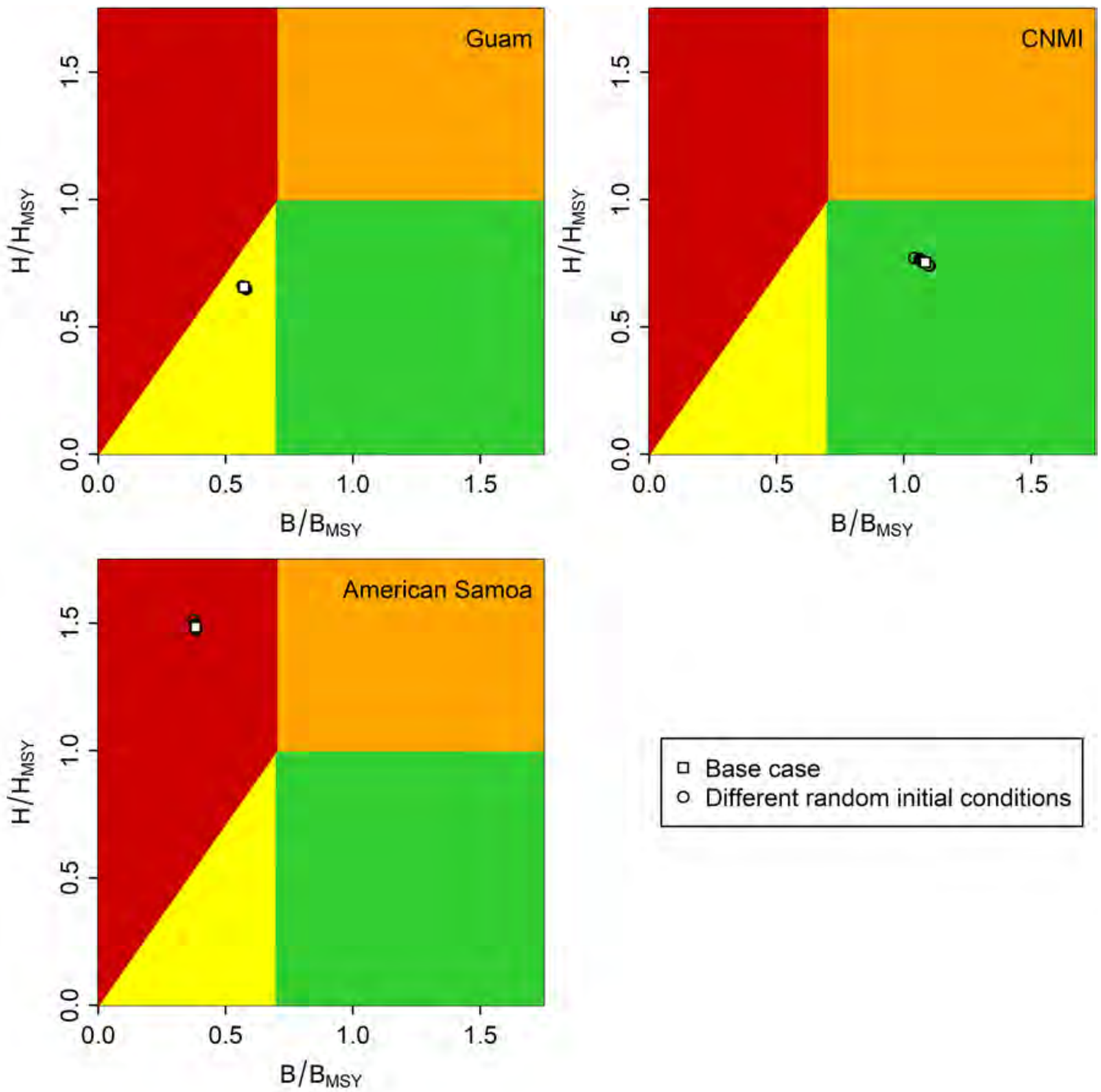


Figure 76. Results of sensitivity analyses for initial conditions of the Markov Chain Monte Carlo routine for Guam, the Commonwealth of the Northern Mariana Islands (CNMI), and American Samoa. The open black circles are the estimated stock status in 2017 for the ten models with random initial conditions, and the closed white square is the estimated stock status in 2017 of the base case model.

Appendix A: Effects of data preparation procedures on nominal CPUE.

Methods

At the request of the WPSAR panel at the conclusion of the 2019 review, we prepared nominal catch per unit effort (CPUE) time series for Guam and American Samoa resulting from each of four procedural steps in data preparation for the 2019 assessments and compared these trends to the CPUE time series from the 2016 assessments. The intent of this appendix is to show how the data preparation choices made for the 2019 assessments result in differences with the 2016 update assessments for Guam and American Samoa. We did not prepare time series for the Commonwealth of the Northern Mariana Islands (CNMI) because the dataset used for the 2019 assessment was different from the dataset used for the 2016 assessment, and therefore comparing data preparation procedures would not be applicable. The 2016 assessments for Guam and American Samoa used data that ended in 2013, had a different species list than the 2019 assessments, assumed that species reported at the family- or species-group level either contained no BMUS (for Guam) or 75% BMUS (for American Samoa) for all years, and only selected interviews where 50% or more of the catch by weight was BMUS regardless of fishing gear. The first series we prepared was the nominal CPUE series reported in Yau et al. (2016). The second series used the 2016 procedure with the 2019 data, which ended in 2017. For this series, nominal CPUE was calculated after applying the 2016 species list, using species-group proportions from the 2016 assessments, and selecting all interviews where at least 50% of the catch by weight was composed of BMUS. The third series used the 2019 data and 2019 species list but assumed species group proportions from the 2016 assessments and selected all interviews where at least 50% of the catch by weight was of BMUS. The fourth series used the 2019 data, 2019 species list and 2019 species group proportions, and selected all interviews where at least 50% of the catch by weight was of BMUS. The fifth series used the 2019 data, 2019 species list and 2019 species group proportions, and selected all interviews that reported using bottomfishing gear, regardless of the proportion of the catch that was BMUS. The fifth series was the same as used for CPUE standardization for the 2019 benchmark stock assessments. For each series, we also excluded interviews with incomplete information on factors used in the standardization of nominal CPUE. The order of data preparation steps presented herein were done for ease of presentation in meeting the intent of this appendix and are not meant to reflect a preferred order for steps done within the assessments.

Results

Guam

Nominal CPUE series using the data preparation procedure from the 2019 assessments were generally similar to nominal CPUE from the 2016 assessment with the exception of filtering based on bottomfishing gear and the value in 1984 (Figure A1). The choice to use bottomfishing gear, and thereby the choice not to filter based on a percentage of BMUS catch within an interview, changed nominal CPUE the most among all procedural differences. Although the decline in CPUE compared to previous approaches appears consistent across years in Figure A1, CPUE declined more in the later part of the time series than in the earlier part after filtering based on bottomfishing gear. Nominal CPUE for the 2019 assessment was approximately 80%

the value prior to applying the bottomfishing gear filter in the early part of the time series, declined to 40% the value in 1997, and then averaged 47% thereafter. The other large change in CPUE when applying the data preparation procedure for the 2019 assessment occurred for 1984. Given that no procedural steps for the 2019 assessment showed the same large spike in 1984 that was present in the 2016 assessment, the difference was not due to data preparation but instead was due to underlying differences in the data.

American Samoa

Nominal CPUE calculated using the 2019 data with the 2016 data preparation procedure (Series 2) was similar to CPUE from the 2016 report in most years (Figure A2). The single largest differences occurred in 1989 and 2000, when CPUE using the 2019 data was 65% and 43% greater, respectively, relative to using the 2019 data. Nominal CPUE using the 2019 data varied from -21% to +33% relative to the 2016 data among all other years. The use of the 2019 species list (Series 3) resulted in similar CPUE to Series 1 and 2 in most years, with the exception of 2012, when the use of the 2019 species list accounted for a 52% increase in CPUE for the new data. The use of the estimated group proportions (Series 4) reduced nominal CPUE in several years starting with 2000. The selection of interviews reporting bottomfishing gear (Series 5) resulted in a reduction in nominal CPUE in most years, particularly after 2005. Selecting interviews based on bottomfishing gear resulted in the inclusion of interviews reporting zero BMUS catch in the data set, whereas using a 50% BMUS threshold excluded any interviews reporting zero catch.

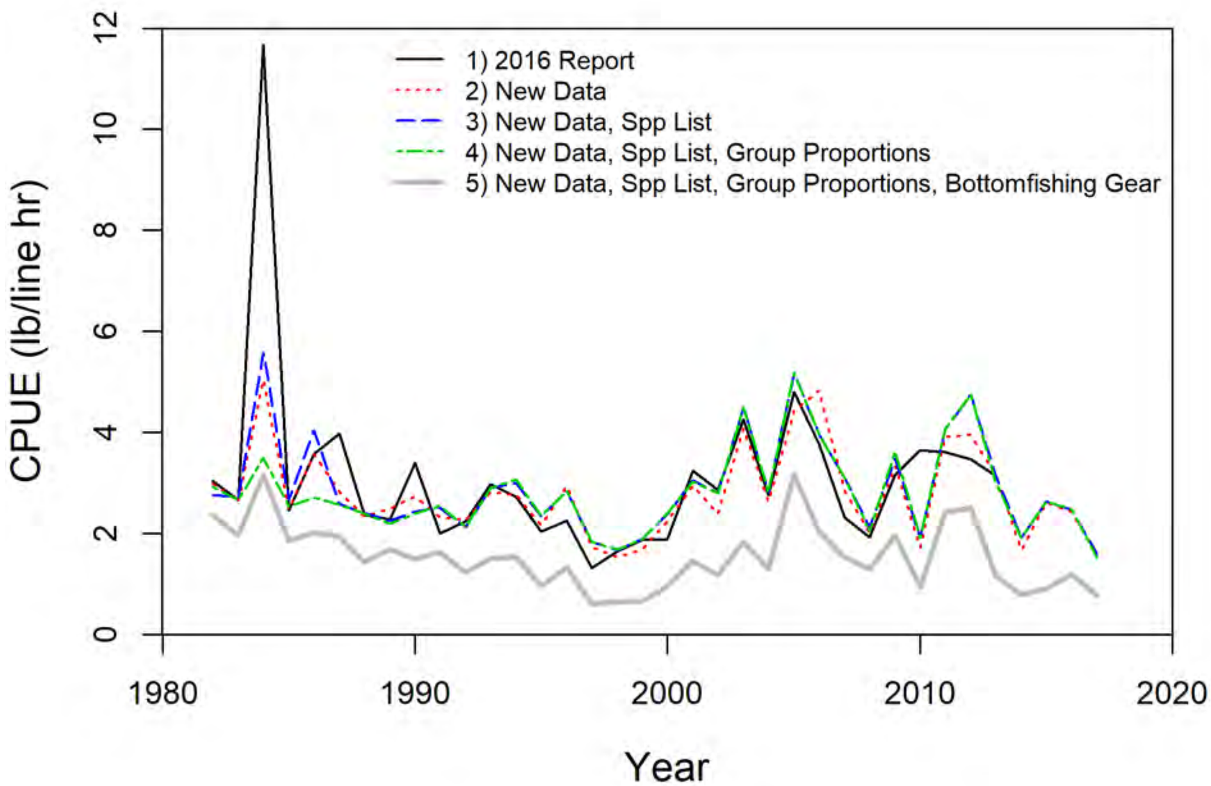


Figure A1: Nominal catch per unit effort (CPUE) following a sequence of data preparation steps from the 2016 update assessment to the 2019 benchmark assessment for Guam. The series are from 1) the 2016 assessment report; 2) the data for the 2019 assessment but applying the 2016 species list, the 2016 species group proportions (assumed 0% of species groups are BMUS), and the 2016 filtering approach (only selecting interviews with at least 50% BMUS catch); 3) the data for the 2019 assessment, applying the 2019 species list, but applying the 2016 species group proportions, and the 2016 filtering approach; 4) the data for the 2019 assessment, applying the 2019 species list and the 2019 species group proportions, but using the 2016 filtering approach; and 5) the data for the 2019 assessment and applying the 2019 species list, 2019 species group proportions, and 2019 filtering (i.e., selecting interviews that reported bottomfishing gear). Series 5 was used for standardization in the 2019 benchmark assessment.

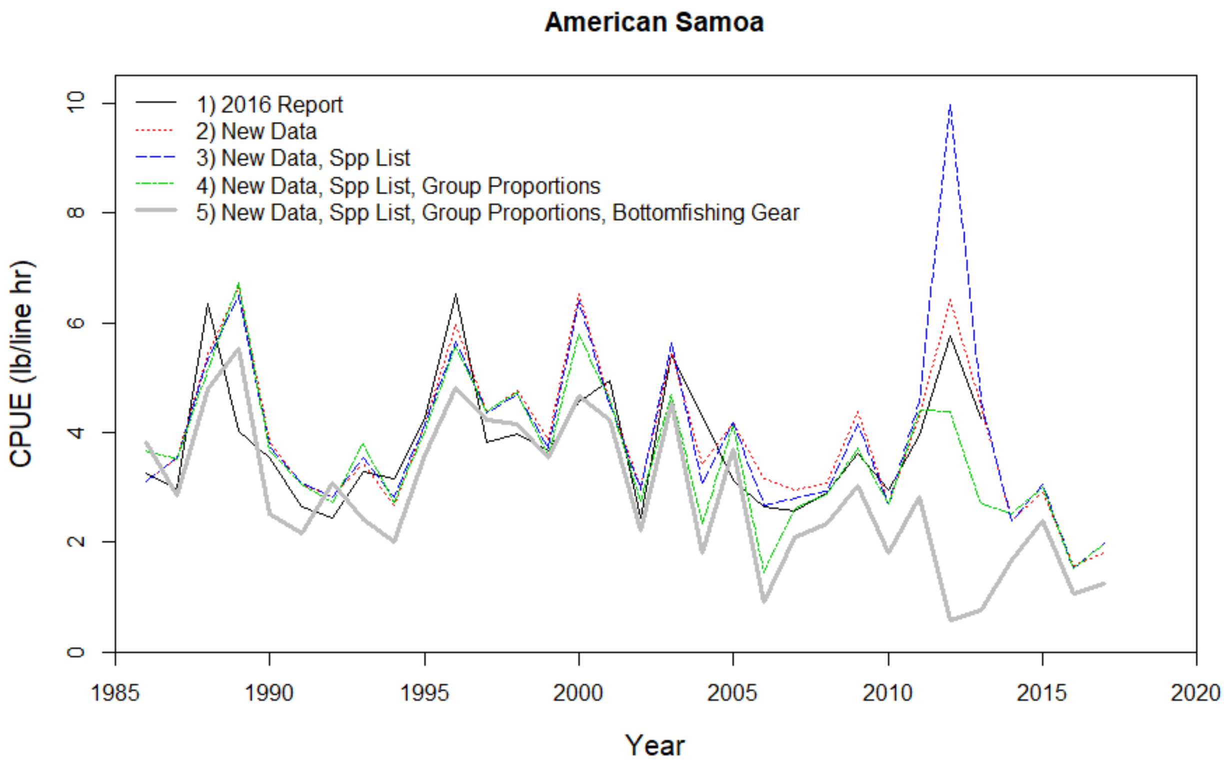


Figure A2: Nominal catch per unit effort (CPUE) following a sequence of data preparation steps from the 2016 update assessment to the 2019 benchmark assessment for American Samoa. The series are from 1) the 2016 assessment report; 2) the data for the 2019 assessment but applying the 2016 species list, the 2016 species group proportions (assumed 75% of species groups are BMUS), and the 2016 filtering approach (only selecting interviews with at least 50% BMUS catch); 3) the data for the 2019 assessment, applying the 2019 species list, but applying the 2016 species group proportions, and the 2016 filtering approach; 4) the data for the 2019 assessment, applying the 2019 species list and the 2019 species group proportions, but using the 2016 filtering approach; and 5) the data for the 2019 assessment and applying the 2019 species list, 2019 species group proportions, and 2019 filtering (i.e., selecting interviews that reported bottomfishing gear). Series 5 was used for standardization in the 2019 benchmark assessment.

Supplementary material

Supplementary material on model code and data scripts for each territorial assessment are provided in a separate document connected to this assessment report, and can be found at https://doi.org/10.25923/bz8b-ng72.