Indian Ocean Tuna Commission
Commission des Thons de l'Ocean Indien

IOTC-2021-WPEB17(DP) -12

A review of the data availability, model configuration and catch estimation for the 2017 blue shark (Prionace Glauca) stock assessment in the Indian Ocean.

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Executive summary
This paper presents a review of the 2017 stock assessment of blue shark in the Indian Ocean using Stock Synthesis (version 3.24f http://nft.nefsc.noaa.gov/Download.html). This paper is largely based on the assessment document (IOTC–2017–WPEB13–33 Rev_1), as well as the catch estimation document (IOTC-2017-WPEB13-23). Herein the "assessment" refers The blue shark assessment model is an age structured (25 years), spatially aggregated (1 region) and two sex model. The catch, effort, and size composition of catch, are grouped into 8 fisheries covering the time period from 1950 through 2015. Seven indices of abundance, all from longline fisheries, were available as well as three alternative time series of total catch. The base case model is parameterized using indices of abundance from the Portugal (2000-2015), Reunion (2007-2015) and the Japanese late (1992-2015) series, along with estimates of catch generated via a generalized additive model. The estimated abundance trend is decreasing throughout the time frame of the model, and spawning stock abundance has decreased to approximately 1.503 times SSBMSY, (80% CI is 1.33-1.63). The fishing mortality has increased steadily over the model time frame with F2015/FMSY= 0.904 (80% CI =0.68 to 1.13).

Blue sharks are most often caught as bycatch in the Indian Ocean tuna fisheries, though some directed mixed species (sharks and tunas/billfish) fisheries do exist. Commercial reporting of landings has been minimal, as has information regarding the targeting and fate of blue sharks encountered in the fisheries. Useful data on catch and effort is mostly limited to recent years, and time series of historical catches have been estimated based on reported and observed catch rates, as well as observed ratios of blue shar to target species.

This analysis was developed as an assessment model that included the Portuguese, EU-France (Reunion) and Japanese late CPUE series, with the estimates of total catch based on generalized additive model based GAM series as the reference case, as it is referred to in the main text when presenting the model parametrization and diagnostics. The 13th meeting of the Indian Ocean Tuna Commission Working Party on Ecosystems and Bycatch (WPEB13) recommend this parameterization as a base case model for the provision of stock status. A grid of sensitivity runs using the alternative CPUE series is presented to characterize one of the major axes of

uncertainty. These models vary in their groupings of CPUE series for inclusion in the model, these groupings were determined by hierarchal cluster analysis and expert opinion during the WPEB13 meeting. Although the alternative catch series available were considered unreliable for use in the base case model, sensitivities using the nominal, EUPOA estimated catches and trade base catches were analysed to represent assumptions of higher and lower total catch. As such the estimated stock status differs between combinations of the catch datasets and CPUE series.

The results of the assessment are compared across different groupings of CPUE series and show the reference case parameterization resulting in estimates of SB_{2015}/SB_{MSY} =1.503% and F_{2015}/F_{MSY} = 0.904 though the range of uncertainty, based on alternative model runs considered covers 1.49-2.36 and 0.29-0.904 for SB_{2015}/SB_{MSY} and F_{2015}/F_{MSY} respectively. Stock status is reported in relation to MSY based reference points, however, the authors note that the IOTC has not yet adopted reference points for sharks. Due to the inherent unreliability of recruitment estimates in the terminal year this study defines 'current' as the average of the first four of the last five years (i.e. 2011-2014), and reports ratios of SB and F as current as well as with respect to 2015.

The main conclusions of this assessment are:

- The stock status is highly dependent on the CPUE series used to fit the model. Among the candidate CPUE models in this assessment no CPUE series runs through the entire time series.
- The estimates of catch are highly influential in the model, but mostly in terms of scale, as the current depletion and fishing mortality indicators are approximately equal across all catch estimates for a given CPUE series.
- The scale of the assessment is influenced by the CPUE series chosen, across these estimates the estimates of B0 range from approximately 1million mt to approximately 1.9 million mt.

When considering which model(s) to use for the provision of management advice, it is recommend that advice be based upon multiple model runs that consider the major axes of uncertainty.

1 Introduction

Blue shark (*Prionace glauca*) are a large pelagic species, broadly distributed throughout the Indian Ocean to a southern limit of ~50° S (Figure 1). Indian Ocean blue shark have been incidentally caught by the Japanese longline fleet since the early 1950s. The population was not heavily exploited before targeted fisheries (or bycatch rates increased) in the early 1990s. At this time the Taiwanese long line vessels began taking large numbers, initially in the SW region, followed by the other areas (Figure 1). The European longline fleet (predominantly Spanish vessels) started a targeted fishery in the 1990s, while only small numbers are reported in the driftnet fisheries, and purse seine catches are very rare.

2 Methods

Data

There are many different fleets catching blue shark in the Indian Ocean, with vastly different gear types and levels of data quality (Martin et. al. 2015). This model uses the same fishing fleet structure previously used (Rice and Sharma 2015), 8 fleets representing a wide variety of gears, some of which have been aggregated (e.g. F1 Miscellaneous). The number of CPUE series has increased from 4 to seven, all of which are based on longline fisheries. There is enough uncertainty about the selectivity assumptions with respect to time, and the low numbers of size composition data, that the size composition data are not expected to be very informative about year-class strength. Hence, in the assessment presented here, the length-composition data are down weighted so as to inform the selectivity but not alter the model fit to the abundance trend.

Total catch

Catch estimates by year and fishery are shown in Figure 2. In the previous assessment (Rice and Sharma 2015), it was assumed that the catch in mass figures provided by the IOTC members and cooperating non-contracting parties (CPCs) were the most reliable catch data available.

This assumption has been re-examined and additional estimates of total catch were produced based on generalized additive models (GAM) and the ratio of blue shark (BSH) to total target catch (Martin et al 2017 and Coelho 2017). While the total catch data are estimates, they are derived in large part from the industrial fleets in the Indian Ocean and are thought to be more reasonable for blue shark than for the other shark species.

Excerpts on the catch estimation from Martin et al. (2017) are available in

The major concern identified with respect to the catch time series are that catch-and-effort for BSH are highly incomplete. Reliable data are thought to be available for a limited number of years (i.e., from the late-1990s onwards) and for a very limited number of fisheries. In the previous assessment an alternative catch series was used based on trade based estimates using the proportion of tuna caught (Clarke, 2011). This series extends from 1981-2011, and was previously extended (both earlier and later) using a ratio based approach. This method used the average ratio of the nominal to trade based estimates from the years previous to 2011 to estimate the values for the years prior to 1981 and post 2011. Because of the uncertainty in the reported nominal catches introduced by using the average ratio, this method was not repeated for this analysis.

2.1 Relative abundance indices

The standardized CPUE series in 2017 were somewhat different from those previously submitted to the WPEB. Newly estimated CPUE series by Japan, Taiwan, Portugal, Spain, Indonesia and EU France (Reunion) were used in this analysis (Figure 2). All of these are based on bycatch in the longline fisheries. Excerpts from the working papers are presented here for an overview of the CPUE series. For further information consult the working papers. With the exception of S1 (Japanese Early CPUE series) all the CPUE series were presented to WPEB13.

S1 Japanese Early series (IOTC–2015–WPEB11–50)

This paper presents the estimates of catch-per-unit-of-effort (CPUE) and catch of the blue shark caught by Japanese longline fishery in the Indian Ocean during 1971-1993 with the *improvement of standardization methods. CPUE was standardized using zero-inflated negative binomial model after data filtering on the basis of more than 54 % reporting rate (RR; number of sets with “sharks” recorded/total number of sets). A stepwise approach is used to choose the preferred explanatory variables and the best model is selected based on the AIC. Annual changes in the CPUE suggested that the historical population trend of blue shark during 1971-1993 were relatively stable with annual fluctuations. Annual changes in total catch number had increased until mid 1980s and then decreased until 1990.*

S2 Japanese Late Series JPN_LT (IOTC–2017–WPEB13–29)

This paper presented revised standardized catch rates for blue shark from Japanese observer data in the Indian Ocean from 1992 to 2016, including the following abstract provided by the authors:

“We updated the standardized CPUE of blue shark (Prionace glauca) based on the Japanese observer data, collected in the Indian Ocean between 1992 and 2016. We also modified the area stratification as well as model structures in the CPUE standardization. We compared four candidate models and we selected the zero-inflated negative binomial model as the most parsimonious model using AIC. The trends in the CPUE was increased in 1990s and reached to the peak in 1999 followed by sharp decline in 2000. After that the trend in the CPUE has been constant or slightly increasing with a large fluctuation”.

S3 Portuguese Longline (IOTC–2017–WPEB13–24)

This paper presented catches and standardized CPUE of blue shark in the Indian Ocean from the Portuguese longline fleet from 2000 to 2016, including the following abstract provided by the authors:

“The Portuguese pelagic longline fishery in the Indian Ocean started in the late 1990’s, targeting mainly swordfish in the southwest region. This working document analyses catch, effort and standardized CPUE trends for blue shark captured by this fishery. Nominal annual CPUEs were calculated in biomass (kg/1000 hooks), and were standardized with Generalized Linear Mixed Models (GLMMs) using year, quarter, season and targeting as fixed effects, and vessel as

random effects. The standardized CPUE trends shows a general decrease in the initial years between 2000 and 2005, followed by an increase until 2008, and then another general decrease in the most recent years until 2016." (see paper for full abstract)

S4 Spanish Longline (IOTC–2017–WPEB13–25)

This paper presented standardized catch rates for blue shark from the Spanish surface longline fleet from 2001 to 2015, including the following abstract provided by the authors:

"*Based on 2,049 trips by vessels in the Spanish surface longline fleet in the Indian Ocean during the period 2001-2015, standardized CPUE catch rates were obtained for the blue shark (Prionace glauca) using General Linear Modelling. The main factors considered were year, quarter, area, ratio, gear and the interaction quarter*area. The basic significant model obtained explained 81% of CPUE variability observed and suggests a stable trend for this blue shark stock in the Indian Ocean. Most of the variability in CPUE was explained by the targeting factor, as represented by the ratio between catch levels for the two most valued and prevalent species landed: swordfish and blue shark*." (see paper for full abstract)

S5 Taiwanese Longline (IOTC–2017–WPEB13–INF08)

This paper provided an updated and revised standardized catch rate of blue sharks caught by the Taiwanese longline fishery in the Indian Ocean, including the following abstract provided by the authors:

"The blue shark catch and effort data from observers' records of Taiwanese large longline fishing vessels operating in the Indian Ocean from 2004-2016 were analyzed. To cope with the large percentage of zero shark catch, the catch per unit effort (CPUE) of blue shark, as the number of fish caught per 1,000 hooks, was standardized using a two-step delta-lognormal model that treats the proportion of positive sets and the CPUE of positive catches separately. Each model includes the main variables year, quarter, area, hooks per basket (HPB), and all two-way interactions between quarter, area and HPB. Standardized indices with 95% bootstrapping confidence intervals were reported. The standardized CPUE showed a stable trend for blue

sharks from 2004 to 2008 and increased steadily thereafter with peaks in 2014. The results obtained in this study can be improved if longer time series observers' data are available

S6 Indonesian Longline (IOTC–2017–WPEB13–26)

This paper presented standardized CPUE of blue shark from the Indonesian pelagic longline fishery in the Eastern Indian Ocean from 2005 to 2016, including the following abstract provided by the authors:

"Nominal annual CPUEs were calculated as number (N)/1000 hooks and were estimated with Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM). Using year, quarter, area, the environment variables (sea surface temperature, chlorophyll-a concentration, eddy kinetic energy, sea level anomaly, and absolute dynamic topography) and Operational characteristics of the gear. The results showed the factors that contributed most for the deviance were the Area, followed by Year, SST, NHBF and Quarter, followed by the other effects and the interactions. In general, there were no noticeable trends, with the series varying along the period." (see paper for full abstract)

S7 EU (France) Réunion Longline (IOTC–2017–WPEB13–27)

This paper presented standardized CPUE of blue shark from the French swordfish longline fishery in the southwest Indian Ocean from 2007 to 2016, including the following abstract provided by the authors:

"The blue shark (Prionace glauca) is the main bycatch of the French swordfish-targeting longline fishery operating in the south-west Indian Ocean. Using observer and self-reported data collected aboard commercial longliners between 2007 and 2016, we propose for the first time a standardized CPUE series for blue shark for this fishery estimated with a lognormal generalized linear mixed model (GLMM) to be used for stack assessment."

2.2 Size composition data

As with the previous analysis sex based length-composition data collected by observers and from logsheets for the main fleets (Japan, Taiwan and Portugal) were used (Coelho et al 2017) along with additional length composition data submitted to the IOTC in the last two years. In all, approximately twenty years of length composition data from the LL fleets were organized and used in the analysis. Some size and sex composition data of catch were available, but in many cases the data were in aggregated form covering several years, or size sampling was incomplete across fisheries. Many of the time series suffered from low sample sizes and inconsistencies across years. For this reason and because of the evidence that there was a conflict between the CPUE and the size data (see results below) lower weight was given to the size data in the model. This allowed the model to estimate selectivity, but did not allow the size data to dominate the estimates of abundance in the model. We assumed an annual effective sample size calculated as the overall (male and female) sample size divided by 40. The annual sample size was then weighted by the Francis (2011 and 2014) likelihood weighting method.

2.3 Software

The analysis was undertaken with Stock synthesis SS V3.234F, 64 bit version (Methot 2000, 2009, executable available from http://nft.nefsc.noaa.gov/SS3.html), running on MS Windows™ 10. Typical function minimization of the fully disaggregated model on a 3.0 GHz personal computer required about 10 minutes. Additional simplifications and aggregations could probably reduce the minimization time further, without significant loss to the stock status inferences.

2.4 Model Assumptions

The most important model assumptions are described in the following sections. Standard population dynamics and statistical terms are described verbally, while equations can be found in Methot (2000, 2009). Attachment 1 is the template specification file for all of the models, and includes additional information on secondary elements of model formulation which may be omitted in the description below. All of the specification files are archived with the IOTC Secretariat. Table 2 lists the assumptions for the sensitivity runs.

2.5 Time Period

The model was iterated from 1950-2015 using an annual time-step, however, further analysis of seasonal processes is encouraged. For a subset of the runs considered, the timeframe was shortened to 1971-2015, or 1981-2015 due to the contracted time series of catches.

2.6 Biological inputs and assumptions

Blue sharks have an Indian Ocean wide distribution, and genetic evidence of distinct population structure within other oceans (e.g. Pacific) has not been found (Taguchi and Yokawa 2013), and hence was assumed to be homogenous here as well. Conventional tagging studies need to be examined in the Indian Ocean, but currently limited data exist, though some tagging effort in the Pacific shows limited movement to the western Australian EEZ. In addition to assumptions regarding stock structure, the other critical information on the biology of blue shark necessary for the stock synthesis assessment relates to sex-specific growth, natural mortality, maturity and fecundity.

2.7 Growth

The standard assumptions made concerning age and growth in the SS model are (i) the lengths-at-age are assumed to be normally distributed for each age-class; (ii) the mean lengths-at-age are assumed to follow a von Bertalanffy growth curve. For any specific model, it is necessary to assume the number of significant age-classes in the exploited population, with the last age-class being defined as a “plus group”, i.e. all fish of the designated age and older. For the results presented here, 25 yearly age-classes have been assumed, as age 25 approximates to the age at the theoretical maximum length of an average fish.

No attempt was made to estimate growth within the model due to the uninformative nature of the size data to track cohorts through time. The previous assessment considered the growth curves from Hsu et al. (2011) as well as specific formulations based on data from the Indian Ocean. This assessment uses new sex specific growth curves based on data from the Indian

Ocean (Andrade et al 2017). A CV of 0.22 was used to model variation in length-at-age. All lengths reported from the assessment relate to fork length (FL).

2.8 Natural mortality

Sets of age and sex-specific natural mortality ogives were considered in the assessment based on the Peterson and Wroblewski (1984) method (Rice and Semba 2014) (Table 3).

2.9 Maturity and fecundity

For the purpose of computing the spawning biomass, we assume a logistic maturity schedule based on length with the age-at-50% maturity for females equal to 145cm (Nakano and Seki 2003). There is no information which indicates that sex ratio differs from parity throughout the lifecycle of blue shark. Fecundity was fixed to an average of 25 pups per annual gestation period.

2.10 Population and fishery dynamics

The model partitions the population into 25 yearly age-classes in one region (Figure 1). The last age-class comprises a “plus group” in which mortality and other characteristics are assumed to be constant. The population is “monitored” in the model at yearly time steps, extending through a time window of 1950-2015. The main population dynamics processes are as follows: In this model “recruitment” is the appearance of age-class 1 fish (i.e. fish averaging approximately 50 cm in the population). The results presented in this report were derived using one recruitment episode per year, which is assumed to occur at the start of each year. Annual recruitment deviates from the recruitment relationship were estimated, but constrained reflecting the limited scope for compensation given estimates of fecundity. Deviations from the SRR were estimated in two parts (i) the early recruitment deviates for the 5 years prior to the model period which has the bulk of the length composition information (1966 -1970) and (ii) the main recruitment deviates that covered the model period (1971 - 2015).

There is no information which indicates that sex ratio differs from parity throughout the lifecycle of blue shark. In this assessment the term spawning biomass (SB) is a relative measure of spawning potential (the mature female population) and is a dimensionless term. It is not comparable to total biomass.

2.11 Initial population state

In the previous model it was assumed that the blue shark population was at an unfished state of equilibrium at the start of the model (1950) with the beginning of longline fishing occurring in the following years (at least from the 1950s onwards).

The population age structure and overall size in the first year is determined as a function of the estimate of the first years recruitment (R_1) offset from virgin recruitment (R_0), the initial 'equilibrium' fishing mortality discussed above, and the initial recruitment deviations. As the size data were found to be uninformative about initial depletion and recruitment variation only a small number (five) of initial recruitment deviates were estimated.

2.12 Selectivity Curves

Selectivity is fishery-specific and was assumed to be time-invariant. A double-half normal functional form was assumed for all selectivity curves except the miscellaneous fishery which was set to a logistic. An offset on the peak and scale was estimated for sex-specific differences in selectivity that were evident in the data. The selectivity function location and scale were estimated for fleets 3, 4, 6, 7 and 8 and the ascending and descending functions were fixed to a best fit when estimated independently. Only the location parameter was estimated for fleet 5 as the model failed to converge if the scale was also estimated.

2.13 Parameter estimation and uncertainty

Model parameters were estimated by maximizing the log-likelihoods of the data plus the log of the probability density functions of the priors, and the normalized sum of the recruitment deviates estimated in the model. For the catch and the CPUE series we assumed lognormal likelihood functions while a multinomial was assumed for the size data. The maximization was performed by an efficient optimization using exact numerical derivatives with respect to the model parameters (Fournier et al. 2012). Estimation was conducted in a series of phases, the first of which used arbitrary starting values for most parameters. The Hessian matrix computed at the mode of the posterior distribution was used to obtain estimates of the covariance matrix.

This was used in combination with the Delta method to compute approximate confidence intervals for parameters of interest.

2.14 Profile Likelihood

An investigation of the information content in the data components was undertaken via the use of profile likelihood on the global scaling parameter (R0) (Lee et al 2014). The negative log likelihood of a specific parameter or data component should, in theory, decline to an obvious minimum. In situations where this does not happen, at least from one side, there may be insufficient information within the data to estimate other parameters. Virgin recruitment (R0) is an ideal scaling parameter because it is proportional to the unfished biomass. Profiles were run with the natural log of virgin recruitment, ln(R0), fixed at various values above and below the model estimated value; the corresponding likelihood profile quantified how much loss of fit was contributed by each data source. One of the primary uses of the likelihood profile is to identify conflicting data and provide a rationale for down weighting or excluding any data.

2.15 Hierarchical cluster analysis

A hierarchical cluster analysis (HCA) was used to identify groupings of CPUE series that represented similar, or same states of nature. The goal of this analysis was to develop a framework for identifying groupings of CPUE series that were similar, so that the model did not include trends that implied conflicting states of nature (i.e. increasing and decreasing). The methods were adapted from those recently implemented in an Atlantic shortfin mako assessment conducted by the International Commission for the Conservation of Atlantic Tunas (ICCAT 2017). As noted in the Atlantic shortfin mako assessment (ICCAT 2017), “it is not uncommon for CPUE indices to contain conflicting information. However, when CPUE indices are conflicting, including them in a single assessment (either explicitly or after combining them into a single index) tends to result in parameter estimates intermediate to what would be obtained from the data sets individually. Schnute and Hilborn (1993) showed the most likely parameter values are usually not intermediate but occur at one of the apparent extremes. Including conflicting indices in a stock assessment scenario may also result in residuals not being identically and independently distributed (IID) and so procedures such as the bootstrap cannot be used to estimate parameter uncertainty. Consequently, when CPUEs with conflicting information are identified, an alternative is to assume that indices reflect hypotheses about states of nature and to run scenarios for single or sets of indices that represent a common hypothesis.”

The HCA used methods conducted in R using FLR (http://www.flr-project.org/). and the *diags* package. FLR provides a set of common methods for reading these data into R, plotting and summarizing them to assess the consistency in the CPUE trends. The CPUE time series along with a lowess smoother fitted to CPUE each year using a general additive model (GAM) to compare trends for the CPUEs. Hierarchical cluster analysis identified two groupings of time-series. The first group was characterized by time-series which were highly correlated with each other and which had some highly negative correlations with some time-series not included in the group. The second group was characterized by time-series which were less correlated with each other or were slightly negatively correlated with the CPUE series in other (positively correlated) group. Because CPUEs with conflicting information were identified, it may be reasonable to assume that the indices reflect alternative hypotheses about states of nature and to run separate scenarios for each group.

2.16 Selection of a base case

The WPEB NOTED that there are conflicting trends among some CPUE series and that the inclusion of conflicting data would result in a mis-specified model. A hierarchal cluster analysis showed that the most highly correlated CPUE series were EU, Portugal (PRT) and EU, France (La Reunion fleet - REU); these two series showed similar declining trends. These two CPUE series were therefore selected for the base case assessment run with the further inclusion of the late Japanese CPUE which was also slightly positively correlated with the PRT and REU series. Sensitivity trials were run using the other CPUE time series and combinations of CPUE. The WPEB noted that the early and late Japanese CPUE series would likely have been affected by the changes in market demand for fins and blue shark meat over time. Sensitivities to the base case CPUE series groupings were run for those groups identified in Table 3. Groupings of CPUE series were chosen by the WPEB and sought to use the results of the HCA as well as expert opinion to extend the spatial extent and the temporal coverage of the CPUE series groupings.

With respect to the estimated catch history the WPEB noted that the available nominal catch data currently held in the IOTC database is likely a gross underestimate of the true catch. Given that approximately one third of the total reported sharks in the IOTC database are non species specific reports (i.e. reported as “sharks”) it is reasonable to assume that some of these reports represent blue shark given that blue shark are the most commonly caught pelagic shark.

The estimates of blue shark catch presented to the WPEB were based on GAM and ratio based estimates of blue shark catch. The WPEB noted that the EUPOA ratio method estimates were lower than the reported catches for some fleets. The WPEB further noted the use of static catch ratios (blue sharks:target species by métier) which do not reflect the changes in species composition over time or changes within metiers which may be driving this trend. The ratio based method may perform well for the fleets for which observer information was available, it may not perform so well when expert knowledge has been based on logbooks recording only retained catches and therefore not accounting for discards. The WPEB agreed to use the GAM based catches in the base case model formulation and sensitivities.

Because the catch time series is a major source of uncertainty the WPEB chose to investigate the impact of using the nominal catch, EUPOA Catch, and the trade based catch on the estimated stock status. However, these were not considered to be optional catch series to be used in the blue shark stock assessment or the provision of estimated stock status. A sensitivity using the base case CPUE grouping and the trade based catches with the 2011 catch carried forward to 2015, was run to examine the effect of the trade base catch series. The chief utility of using the trade based estimates is that the other catch estimates are the result of using three separate methods on what is essentially the same data set, while the method employed by Clarke (2014) uses a separate, though highly aggregated, dataset.

For the scenarios in the sensitivity analysis that included catch estimates starting after the advent of large commercial, and especially distant water fishing operations (i.e. 1971 EUPOA catches and 1981 trade based catches) the model was parameterized to estimate an initial equilibrium fishing mortality, which would result in a stable age distribution, impacted by fishing, that would match the observed age distribution at the start of the time series. In this case the initial catch was set to approximately 50% of the first five year the estimated catch of the model to represent a plausible (though subjective) estimate for the initial depletion.

2.17 Benchmark and Reference Point Methods

Benchmarks included estimates of absolute population levels and fishing mortality for the terminal year, 2015 (F2015, SSB2015, B2015). These values are reported against reference points relative to MSY levels, and depletion estimates (relative to virgin levels).

2.18 Other Model Considerations

As explained above the length composition annual sample sizes were re-weighted by the Francis (2011) likelihood weighting method. The minimum average CV associated with the indices of abundance length likelihoods were re-weighting based on the Francis (2014) method. The life history and biology in the model are treated as constants, these parameters, along with the catch inputs influence the plausible range of population dynamics in the model. The likelihood components associated with the survey data were increased by a factor of 3 (i.e. lambdas for the CPUEs were changed from 1 to 3) to ensure that the model fit the CPUE as well as the length and catch data. This increase effectively allowed the model to fit the overall CPUE series and was applied equally across all CPUE series.

2.19 Projections

Projections were carried out using the forecast module internal to SS3 via MCMC analysis and as such used the uncertainty associated with the parameter estimates calculated internally to

SS3. Recruitment variability was not included in the projections, but given the reproductive biology of this species variability in recruitment is expected to be low, in comparison to teleosts. Projections were only carried out for the base case model configurations. Projections were run at fixed percentages (60% to 140% by 10% increments) of the 2015 estimated catch from the GAM estimates.

3 Results

In this section we focus on the results from the reference case model and the key results and diagnostics for this model. We then comment on any important differences in both outputs and model diagnostics for the sensitivity analyses, and present all results. The assessment model was implemented in Stock Synthesis version 3.24f (SS3 Methot 2013). A newer version of the model is available (version 3.3) but due to time constraints and the overall similarity of the model versions for the features implemented in this assessment, the SS3 model was not updated to version 3.3. Stock synthesis (v. 3.24f) was implemented here as a length-based age-structured stock assessment model (Methot and Wetzel 2013; e.g., Wetzel and Punt 2011a, 2011b). Stock synthesis utilizes an integrated modeling approach (Maunder and Punt 2013) to take advantage of the many data sources available for the Indian Ocean stock of blue shark (*Prionace glauca*). An advantage of the integrated modeling approach is that the development of statistical methods that combine several sources of information into a single analysis allows for consistency in assumptions and permits the uncertainty associated with each data source to be propagated to final model outputs (Maunder and Punt 2013).

3.1 Reference case model

The reference case model choice is described in section 2.16. The choice of model parameters and data inputs reflected the input of the WPEB 13 meeting and the available updated data for biology and life history.

Model Fits to Abundance Indices

The model was able to fit the general trends of the indices of abundance (Figure 10). Although the CPUE series S2 and S3 had periodic increases in the CPUE that the model was unable to fit (see in particular the years 1997-1999, 2001-2003, 2006-2008, 2010-2012 and 2013-2015 in S2 and 2005-2008 and 2008-2010 in S3, Figure 10). As a result, the model fitted the central tendency of each series, which for S2 the Japanese series was a slight increase in the early 1990 until 1999, after which a slight decline and levelling off is evident. The fits to S3 the Portuguese series and S7 Reunion show a modest and slight decline, respectively, throughout. The model interpreted these trends by predicting a decreasing total biomass through time. The spawning output was estimated to increase slightly in the late 1990s to the early 2000s followed by a period of decline coincident with the increase in catch (Figure 2) and decline in the CPUE series.

Fits to the Length composition

The differences estimated in the sex-specific selectivity curves for many of the fisheries reinforce the observations of biologists for areas of sex-segregation during the life history of blue sharks (Figure 12). With the exception of the Japanese longline fishery; all fisheries where sex specific selectivity could be estimated resulted in a lower peak selectivity (therefore catchability) for females.

The overall fit to the length data was generally good (Figure 13). Fleet specific annual length samples were often quite different, i.e. left skewed one year and bimodal the next, which accounts for the small amount of misfit in the aggregated samples. When attempting to estimate selectivity curves for fisheries with sex specific patterns the model often did not converge, therefore the sex specific offsets were fixed. Pearson residuals of the fit to the length compositions were small – on the order of 2 to -2 and did not show any temporal trend (Figures 14-16).

Stock-recruitment Parameters

The predicted virgin recruitment (R0; number of age 0 pups) was approximately 2,177,000 animals and the number of estimated pups was relatively constant from the early 1960 through the early 1980s, after which estimated recruitment slowly declined, and then experienced large fluctuations from 1990-2015 (Figure 17). The corresponding estimated stock recruitment relationship and annual deviations are also shown in Figure 18.

Fishing Mortality

Estimated F/F_{MSY} and fleet-specific instantaneous fishing mortality rates are presented in Figures 19 and 20 respectively. Fishing mortality was relatively low from the 1950 to the mid 1990s, which is in accordance with low catches and effort during that period. In the late 1990s fishing mortality increased with the advent of F1 the Miscellaneous fishery, this fishery is comprised mostly of coastal longline (>98%), with trolling, sport and artisanal fisheries contributing small percentages of the catch. Starting in the late-1990s overall fishing mortality began to increase sharply, with large fluctuations in the individual fisheries contribution to the overall fishing mortality. The overall fishing mortality has been below F_{MSY} (i.e. overfishing is not occurring) for the entire time series, however, in recent years the confidence intervals have included values greater than one.

Estimated stock status and other quantities

The estimated equilibrium yield curve for the reference case model is shown in Figure 21. The estimated MSY is approximately 33000 MT and this is predicted to occur at 34% of the unfished biomass (Figure 21), which is less than the standard Schaefer production model (0.5B0). The reference case model estimates that the total biomass of the stock was at approximately 100% of the unfished level at the start of the model period (Figure 11) and steadily decreased to an estimate of SB_{2015}/SB_{MSY} = 1.5 that corresponds with F_{2015}/F_{MSY} = 0.9. Recruitment is fairly well estimated throughout the model time period (Figure 8), with recent recruitment estimated to be lower than the implied stock recruitment curve due to deviations implied by the length data. The estimates of recruitment were quite tightly constrained to the stock recruitment curve for the initial period of the model when there was no length information to inform the model. The main trends in the population dynamics can be explained through the estimated fishing mortality which was greatly increased in the 1990s and early 2000s due to the increase in catch (Figures 19 and 20). These changes in fishing mortality correspond to an overall stock status that is headed from a virgin state to the direction of overfished and overfishing (Figure 22).

Stock status uncertainty was evaluated with MCMC analysis for the base case model. Figure 23 shows the estimated stock status based on the MCMC analysis for the base case model and figure 24 shows the estimated values from SS3 (the MLE) along with the 50th quantile and distribution of the MCMC analysis. The MLE estimates of SB2015/SBMSY and F2015/FMSY were 1.5 and 0.9, respectively, while the 50th quantiles of the MCMC analysis differ slightly at 1.53 and 0.87, respectively, for the same quantities, indicating a slight negative bias in SB2015/SBMSY and a slight positive bias in F2015/FMSY relative to the median MCMC output.

Stock synthesis provides estimates of the MSY-related quantities and these and other quantities of interest for management are provided in Table 4. We note that the IOTC has not yet adopted target or limit reference points for any shark species, so a suite of MSY-related quantities are presented.

Retrospective Analysis

As part of an analysis of model structure, retrospective analysis (sequentially deleting 1 year of data from the end of the model and re-running) was run using the base case formulation (the Portuguese, Japanese late and Reunion series and the GAM estimated catches). The estimates of spawning depletion remain very similar across all the retrospective model runs considered (Figure 25) indicating that the changes in estimates of virgin spawning biomass are based on the total catch (Figure 25 right panel). The last retrospective run (-5 years) estimated a more depleted stock that corresponds to a slightly smaller virgin recruitment (Figure 25 right panel), this is associated with higher estimated total fishing mortalities in the last 4 years. In general the retrospective analysis shows no large departures from the estimated scale, depletion, or overall trend based on the sequential deletion of the last 5 years of data.

3.2 Model Sensitivity Runs Representing Alternative State of Nature Scenarios

Model uncertainty was evaluated in this assessment with a set of sensitivity runs representing plausible alternative states of nature to the base case model. The main sensitivities considered in this assessment are the catch and CPUE series. Sensitivities to the base case CPUE series groupings were run for five alternative CPUE series which were chosen by the WPEB based on the results of the HCA, the extent of the spatial extent and the temporal coverage, as well as expert opinion. The CPUE series groupings considered were:

- The base case with the Japanese early CPUE series
- The Japanese early and late , Spanish and Indonesian CPUE series
- The Japanese late, the Spanish and Indonesian CPUE series
- The Japanese early, Portuguese and Reunion CPUE series
- The Portuguese and Reunion CPUE series.

The estimated spawning depletion was similar for all the runs that contained the Portuguese and Reunion CPUE series and separately (less depleted) for those that contained the Spanish and Indonesian CPUE series (Figure 26 top). The same separation of the CPUE groupings is also seen in the different scale of the total spawning output (Figure 26 bottom).

The WPEB was presented with multiple catch series only one of which (GAM estimated) was selected for completing sensitivity runs with the base case CPUE groupings. The alternative catch series along with the base case CPUE grouping are presented with the caveat that they are only considered to illustrate the range of different catch estimates and the commonalities of the resulting biomass trend over time. The model runs using the alternative catch series were not recommended for providing advice on stock status because they are thought to be subject to one or more of the following problems;

- underreporting,
- mis-reporting
- subjective assignment of catches to recent years
- lower than the reported catches in some years.

As the sensitivities to the base case model with alternative catch series (IOTC nominal, EUPOA ratio, and trade based Figure 29), were not evaluated for model consistency with respect to scale and trend the results are presented only in Figure 30 as stock status. The results of using the nominal reported catch series are similar to the base case results, though with a slightly higher SB/SB_{MSY} ratio and a slightly lower F/F_{MSY} ratio. The effects of using the EUPOA and Trade base catches on the analysis were quite similar with both models resulting in a stock status that has lower SB/SBMSY and higher F/FMSY ratios (Figure 30).

Current catches are estimated to be in excess of MSY for all models except for those with the Spanish and Indonesian CPUE series. (C2015/MSY in Table 4). The stock is declining due to an increase in F, with estimates of F_{2015}/F_{MSY} ranging from 0.29 to 0.904 depending on the CPUE and catch series selected. Based on estimates of 2015 conditions the spawning stock biomass is estimated to be SB_{2015}/S_{MSY} = 1.49-2.36 depending on the CPUE series grouping. By the standard terminology, this would indicate that the stock is not experiencing overfishing and is not overfished.

3.3 Projections

Projections were carried out using the forecast module internal to SS3 via MCMC analysis and as such used the uncertainty associated with the parameter estimates calculated internally to SS3. Recruitment variability was not included in the projections, but given the reproductive biology of this species variability in recruitment is expected to be low, in comparison to teleost species. Projections were only carried out for the base case model configurations. Projections were run at fixed percentages (60% to 140% by 10% increments) of the 2015 estimated catch from the GAM estimates. Projections are summarized by the Kobe II Strategy Matrix which shows the probability of reaching a reference point in a specified time frame (Table 5). These projections were carried out for periods of 3 and 10 years.

4 Conclusion

Although most pelagic sharks can be considered data poor when compared to targeted tuna and other teleosts, the information for blue shark in the Indian Ocean is relatively abundant because they are the most commonly caught pelagic shark. Although blue shark lack the traditional fisheries statistics such as landings and historic catch rates (CPUE series), blue shark have been caught in mixed target fisheries for at least the last two decades. The resulting CPUE series from these fisheries are concentrated in the most recent decade, and all come from fishery dependent longline sources. An issue of concern regarding the indices of relative abundance, is that many of them show inter-annual variability that does not seem to be compatible with the life history of the species, suggesting that the GLMs used to standardize the indices did not include all factors to help track relative abundance or that the spatial scope of sampling is too limited to allow for precise inference about stock-wide trends. The CPUE series that were used in the base case model came from on board observers and covered the majority of the southern Indian Ocean, however, the bulk of the observed effort was in the southwestern Indian Ocean in the waters from South Africa and Madagascar. In the future intersessional work to further develop the indices of abundance would be important.

Recent work has led to similar estimates with respect to age, growth, reproduction and the associated life history characteristics. As such the range of variation investigated in the previous assessment was not undertaken for this study. The parameterization of the model reflected the best available estimates. Changes to the biology and life history inputs were minor with respect to the last assessment. Changes were: the maximum age is now 25 (from 30); steepness is now 0.79 (from a range 0.3 – 0.5); the theoretical maximum length has changed a few centimeters. These changes affect the potential productivity/resiliency of the stock in different ways but the overall characteristics of shark with moderate productivity (fecundity) and an annual long gestation period have remained.

The results of the assessment are compared across different groupings of CPUE series and show the reference case parameterization resulting in estimates of SB_{2015} /SB_{MSY} =1.53 and F_{2015}/F_{MSY} = 0.94 though the range of uncertainty is covers 1.49-2.36 and 0.29-0.9 for SB_{2015} /SB_{MSY} and F_{2015}/F_{MSY} respectively. Stock status is reported in relation to MSY based reference points however the authors note that the IOTC has not yet adopted reference points for sharks. Due to the inherent unreliability of recruitment estimates in the terminal year this study defines ‘current’ as the average of the first four of the last five years (i.e. 2011-2014), and reports ratios of SB and F as current as well as with respect to 2015.

The main conclusions of this assessment are:

- The stock status is highly dependent on the CPUE series used to fit the model. Among the candidate CPUE models in this assessment no CPUE series runs through the entire time series.

- The estimates of catch are highly influential in the model, but mostly in terms of scale, as the current depletion and fishing mortality indicators are approximately equal across all alternative catch estimates for a given CPUE series.
- The scale of the assessment is influenced by the CPUE series chosen, across these estimates the estimates of B0 range from approximately 1million MT to approximately 1.9 million MT.

The main drivers of this assessment are the trend in the catch and CPUE series. In particular the large increase in recent years of catch has different interpretations (within the model). based on whether the CPUE series is variable (Japanese late) or decreasing (Portuguese and Reunion Fleet). Recommended studies that would improve future analyses are:

- Develop appropriate length inputs for all fleet.
- Further investigation of CPUE series and their representativeness.
- Develop region specific biological inputs.
- Further work on developing catch histories.
- Undertake collaborative study of blue shark CPUE from multiple Indian Ocean longline fleets

5 Acknowledgements

The author would like to thank Sarah Martin, Fabio Fiorellato, and Rui Coelho for their help in preparing the data as well as all of the member countries that submitted data and analyses. This assessment benefited from the discussion and contribution of the WEPB13 attendees, including the invited expert Dr. Filipe Carvalho.

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7 Tables

Table 1. Fishery definitions for the Indian Ocean Assessment

Fleet/ Survey Number and Short Name	Gear(s)	Selectivity
F1 MISC	Costal longline, trolling, sport and artisanal fisheries	Fixed logistic
F2 GILL	Gillnet Fisheries	Fixed logistic
F3 OTHER_LL	All longline fishery other than Japan, TWN, China, Korea, Portugal and Spain.	Estimated double normal
F4 JPN_LL	Japanese longline fishery	Estimated double normal
F5 KOR_LL	Korean longline fishery	Estimated double normal
F6 PRT_LL	Taiwanese longline fishery	Estimated double normal
F7 TWN_LL	Portuguese longline fishery	Estimated double normal
F8 ESP_LL	Spanish longline fishery	Estimated double normal
S1 JPN_EARLY	Japan early years longline CPUE	NA
S2 JPN_LATE	Japan late years longline CPUE	NA
S3 POR	Portugal longline CPUE	NA
S4 ESP	Spain longline CPUE	NA
S5 TWN	Taiwanese longline CPUE	NA
S6 IND	Indonesian longline CPUE	NA
S7 REU	EU-Reunion longline CPUE	NA

Table 2: Estimates of age-specific natural mortality used in the assessment. The reference case used those based on the approach of Peterson and Wroblewski (1984) method and the Nakano data (Rice and Semba 2014).

	Natural Mortality	
Age	Male	Female
0	0.564	0.535
1	0.3	0.309
2	0.22	0.233
3	0.18	0.194
4	0.156	0.171
5	0.14	0.155
6	0.128	0.144
7	0.12	0.135
8	0.114	0.129
9	0.109	0.124
10	0.105	0.12
11	0.101	0.117
12	0.099	0.114
13	0.096	0.112
14	0.095	0.11
15	0.093	0.109
16	0.092	0.107
17	0.09	0.106
18	0.089	0.105
19	0.089	0.105
20	0.088	0.104
21	0.087	0.103
22	0.087	0.103
23	0.086	0.103
24	0.086	0.102
25	0.085	0.102
26	0.085	0.102
27	0.085	0.101
28	0.085	0.101
29	0.084	0.101
30	0.084	0.101

Table 3. Summary of SS3 specification options for the Indian Ocean blue shark assessment models. Other assumptions were constant for all models, a total 6 sensitivity runs were completed. The bold text indicates the base case configuration.

CPUE SERIES	Catch Series
PRT, REU, JPN Late (Base Case)	**GAM based estimates**
PRT, REU, JPN Late JPN Early	GAM based estimates
JPN Early JPN LT, ESPN, INDO	GAM based estimates
JPN LT, ESPN, INDO	GAM based estimates
JPN Early PRT REU	GAM based estimates
POR REU	GAM based estimates

Table 4: Estimates of key management quantities for the base case model (in bold text) and sensitivity runs. Stock status in 2015 is in the grey shaded rows.

CPUE used Catch	**PRT REU JPNL (Base Case) GAM estimates**	JPNE, PRT, REU GAM estimates	JPNE, JPN_L, ESPN, INDO GAM estimates	JPNL ESPN INDO GAM estimates	PRT REU GAM estimates	PRT REU JPNL JPNE GAM estimates
C2015/ MSY	**1.65**	1.61	0.91	0.93	1.62	1.66
Y_MSY	**33,152**	33,947	59,861	58,824	33,871	33,046
B_zero	**1,016,510**	1,051,610	1,899,520	1,860,230	1,048,070	1,016,380
B_msy	**348,257**	359,295	644,524	631,694	358,172	347,992
B_cur	**585,191**	609,601	1,572,776	1,497,688	602,193	601,271
SB_zero	**113,535**	117,456	212,159	207,771	117,060	113,521
SB_msy	**38,897**	40,130	71,987	70,555	40,005	38,868
SB_cur	**65,360**	68,087	175,665	167,279	67,260	67,157
SB_2015/SB_msy	**1.503**	1.512	2.367	2.299	1.497	1.548
SB_cur/SB_msy	**1.680**	1.697	2.440	2.371	1.681	1.728
SB_cur_init	**0.576**	0.580	0.828	0.805	0.575	0.592
Fcur	**0.241**	0.229	0.083	0.088	0.232	0.233
F_msy	**0.305**	0.303	0.299	0.299	0.304	0.304
F_2015/msy	**0.904**	0.867	0.290	0.304	0.880	0.875
F_cur/msy	**0.789**	0.754	0.279	0.293	0.764	0.766
SB_2015	**58447.3**	60678.9	170398	162170	59900.6	60152
F_2015	**0.276**	0.263	0.087	0.091	0.267	0.266
TotalBiomass_2015	**430,557**	454,145	1,388,070	1,313,550	447,145	445,870

Table 5. Blue shark stock syntheses assessment Kobe II Strategy Matrix. Probability (percentage) of violating the MSY based target reference point for constant catch projections (relative to catch level from 2015 (54,735 mt), projected for 3 and 10 years.

Reference point and projection time frame	Alternative catch projections (relative to the catch level from 2015) and probability (%) of violating MSY-based reference points (Btarg=Bmsy; Ftarg=Fmsy)								
Catch Relative to 2015	60%	70%	80%	90%	100%	110%	120%	130%	140%
Catch Amount	(32,841)	(38,315)	(43,788)	(49,262)	(54,735)	(60,209)	(65,682)	(71,156)	(76,629)
$\mathbf{B}_{2018} < B_{MSY}$	0%	0%	0%	0%	0%	0%	1%	1%	3%
$\mathbf{F}_{2018} > F_{MSY}$	0%	1%	7%	25%	49%	69%	83%	91%	95%
$\mathbf{B}_{2025} < B_{MSY}$	0%	1%	8%	25%	48%	68%	82%	89%	92%
$\mathbf{F}_{2025} > F_{MSY}$	0%	7%	35%	67%	87%	95%	97%	94%	90%

8 Figures

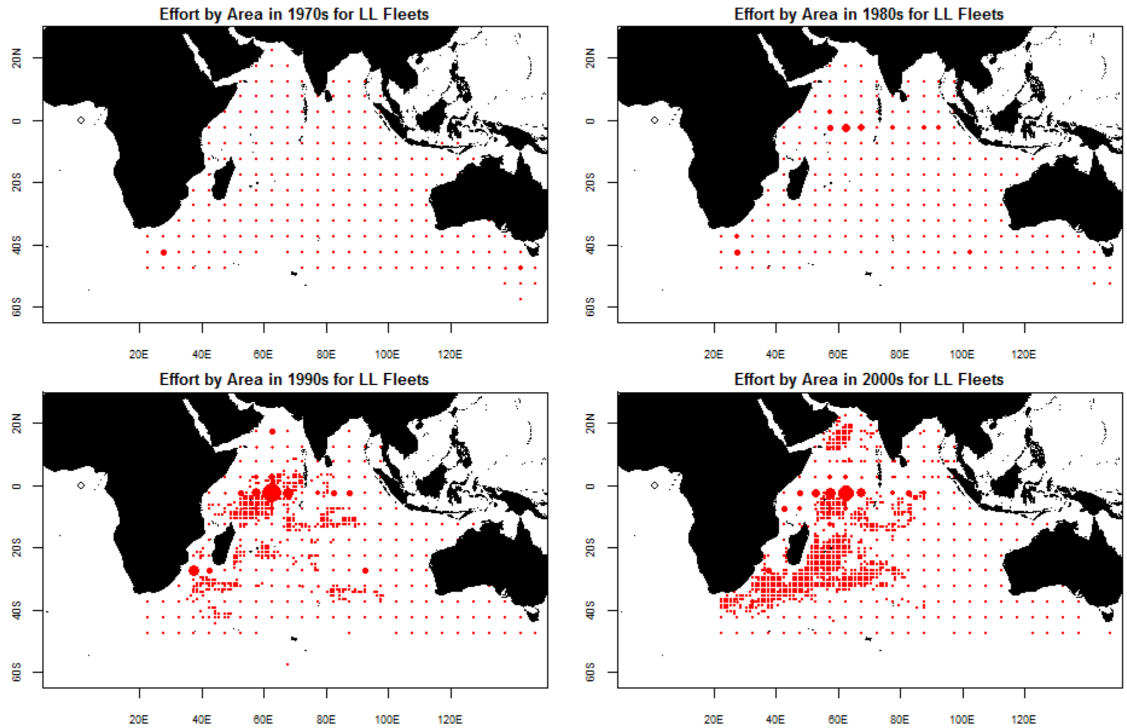

Figure 1. Study area and effort by decade. The red dots are proportional to the longline effort in each 5x5 degree cell.

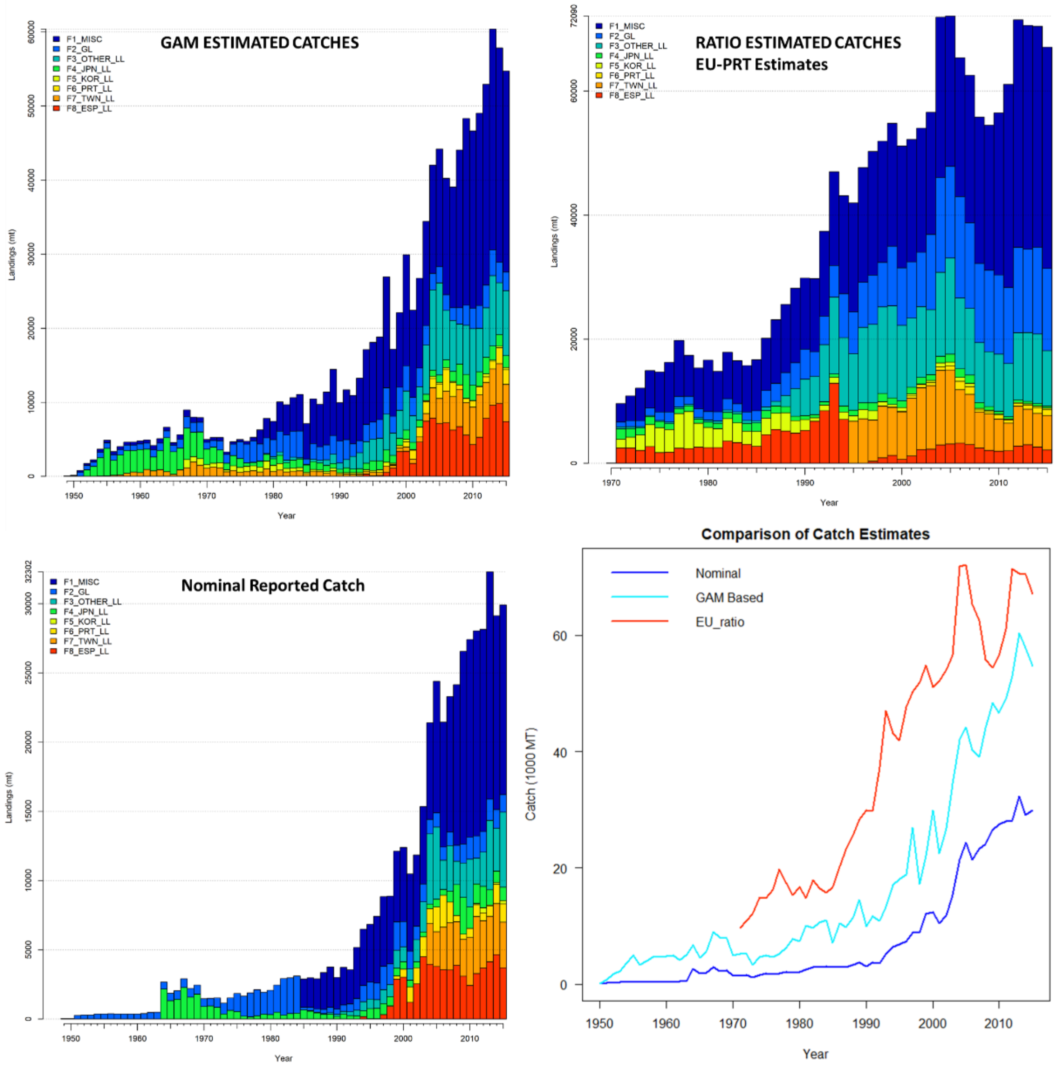

Figure 2 Estimated total blue shark catch in mass by fishery over time for the whole Indian Ocean based on the IOTC database (left hand panel) and based on trade based methods (right hand panel). Note the difference in scale on the y-axis.

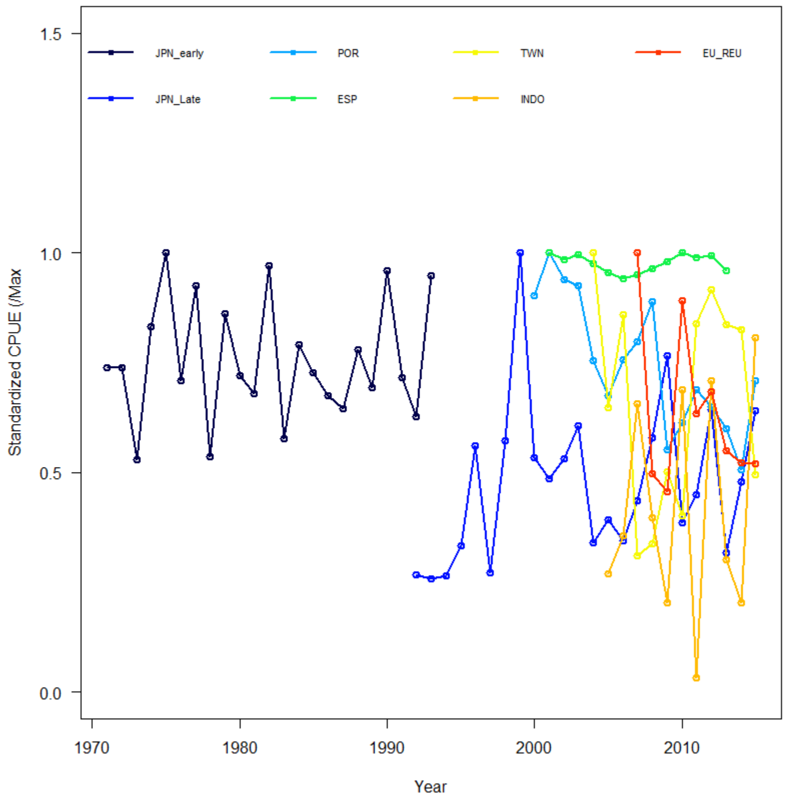

Figure 3. Standardized CPUE for Japanese(early and late), Portuguese, Taiwanese and Spanish , Indonesian, and EU Reunion longline fleets based on papers submitted to WPEB-13. All series have been rescaled by their max so that they are visually comparable for relevant periods of overlap.

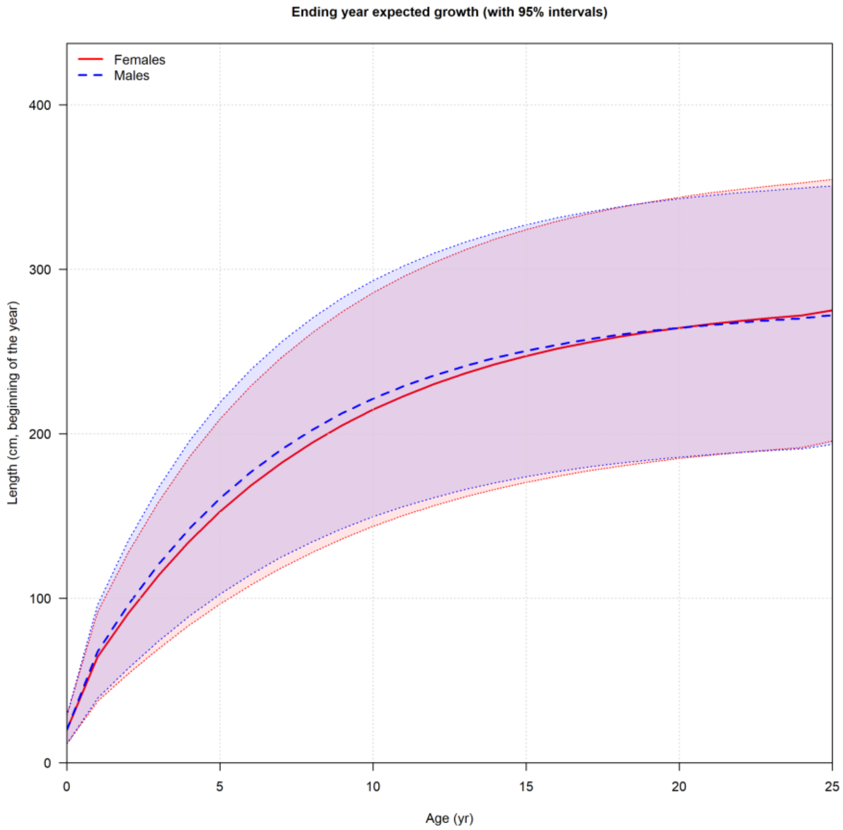

Figure 4. Sex-specific growth curves (from Coelho et al 2017) calculated based on blue sharks in the Indian Ocean.

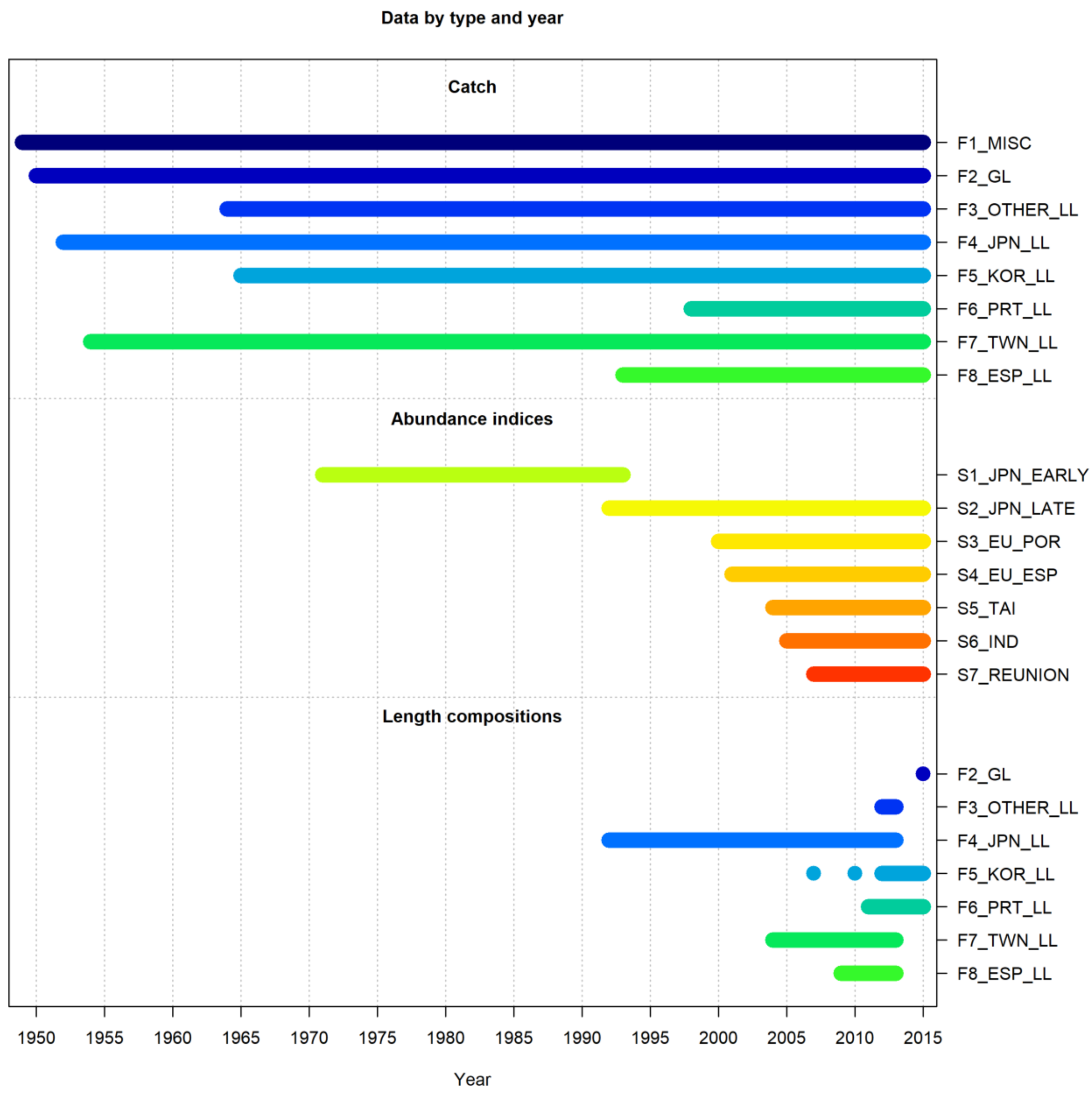

Figure 5: Temporal data coverage for the reference case model for the assessment of blue sharks in the north Pacific.

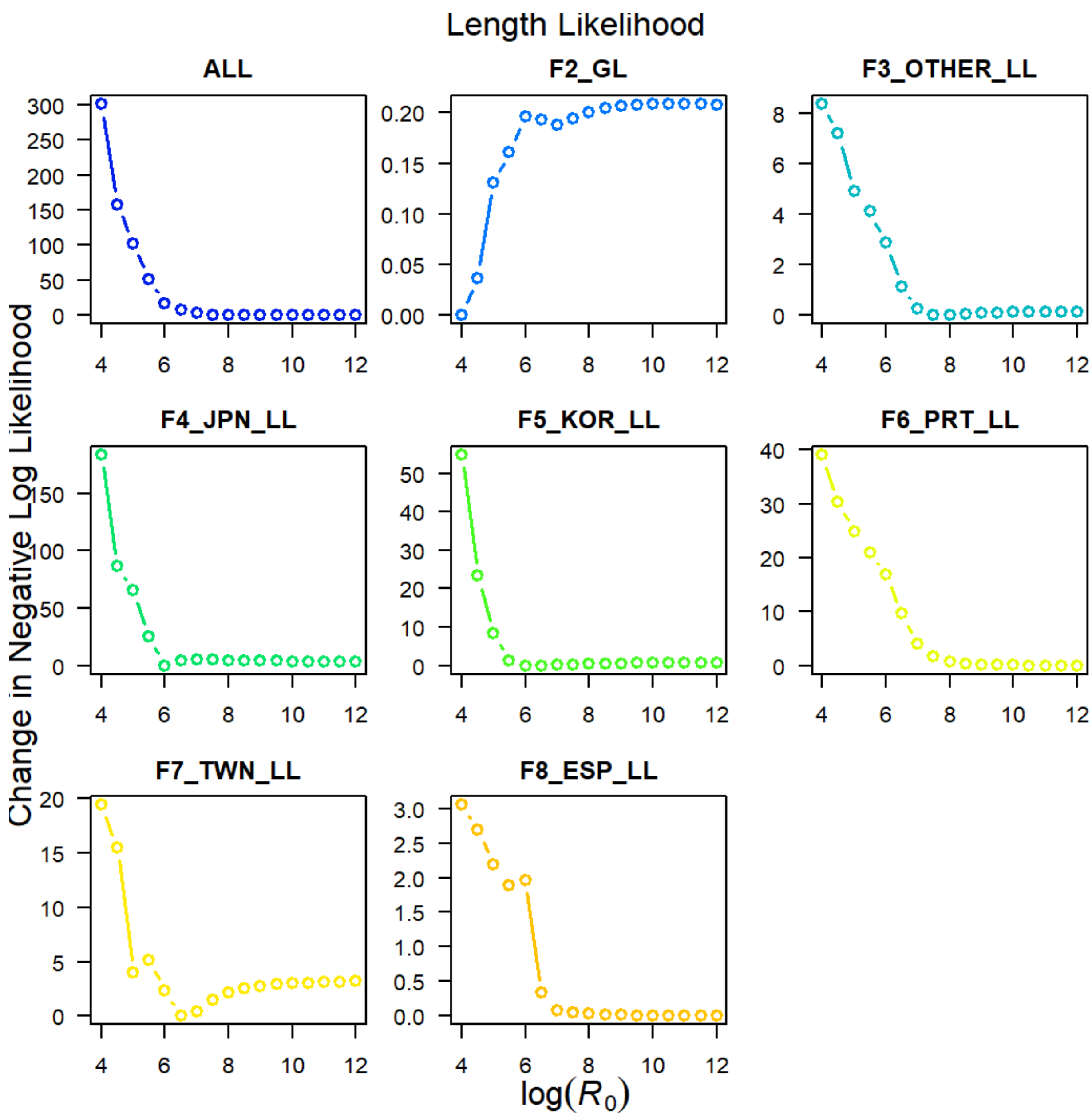

Figure 6: Likelihood profiles for length composition.

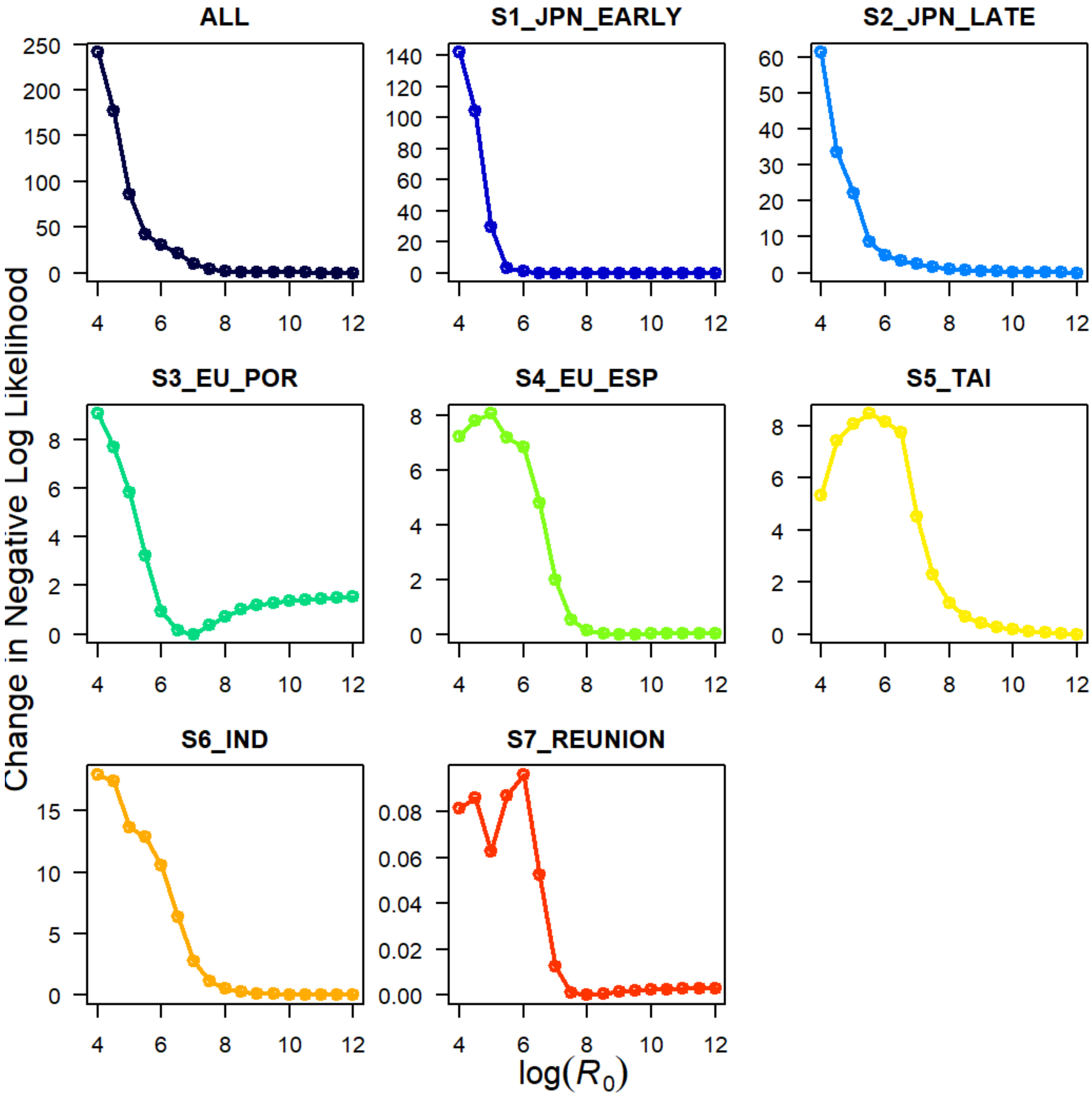

Figure 7: Likelihood profiles for the CPUE components.

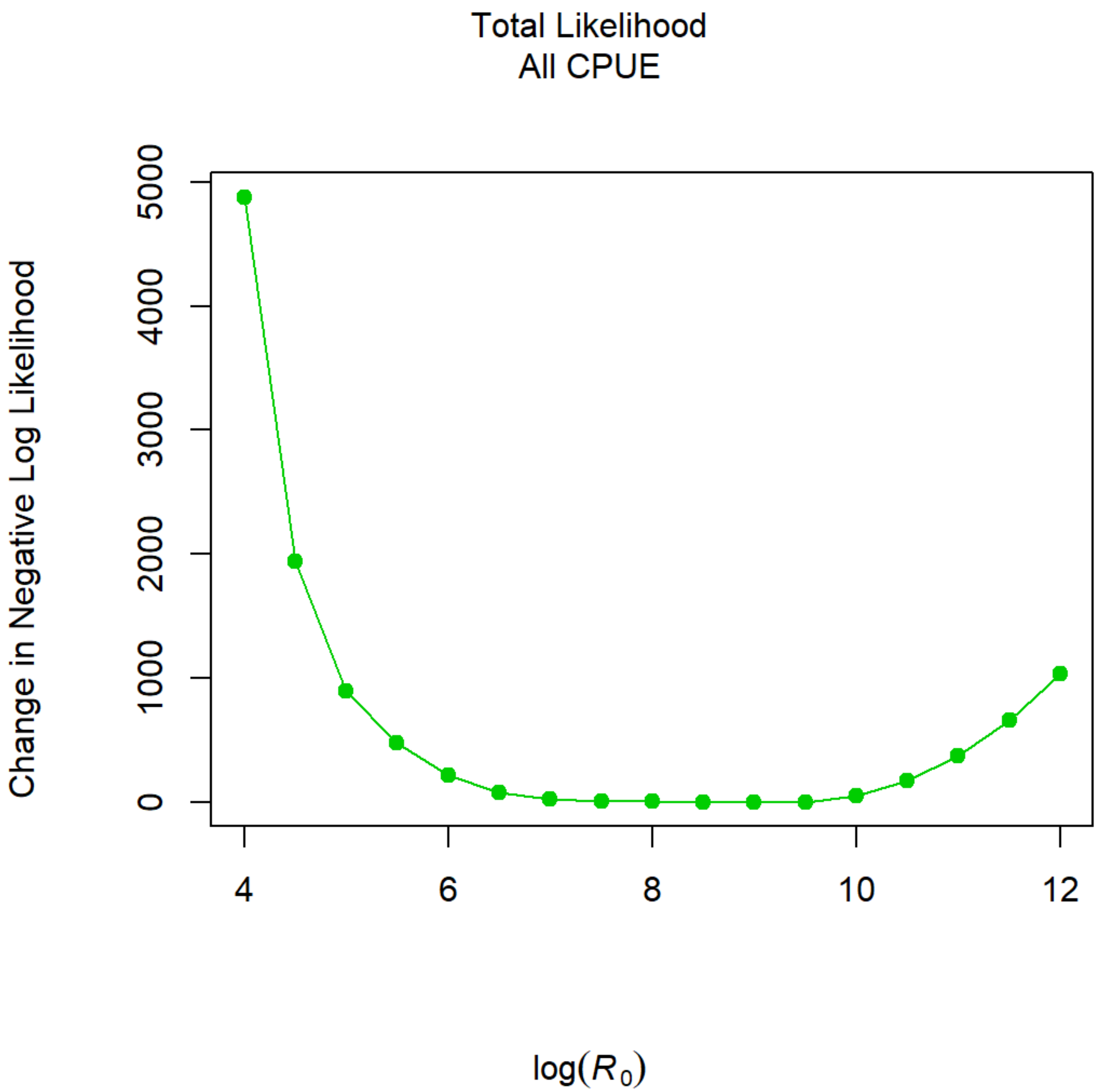

Figure 8 Likelihood profile for the total likelihood.

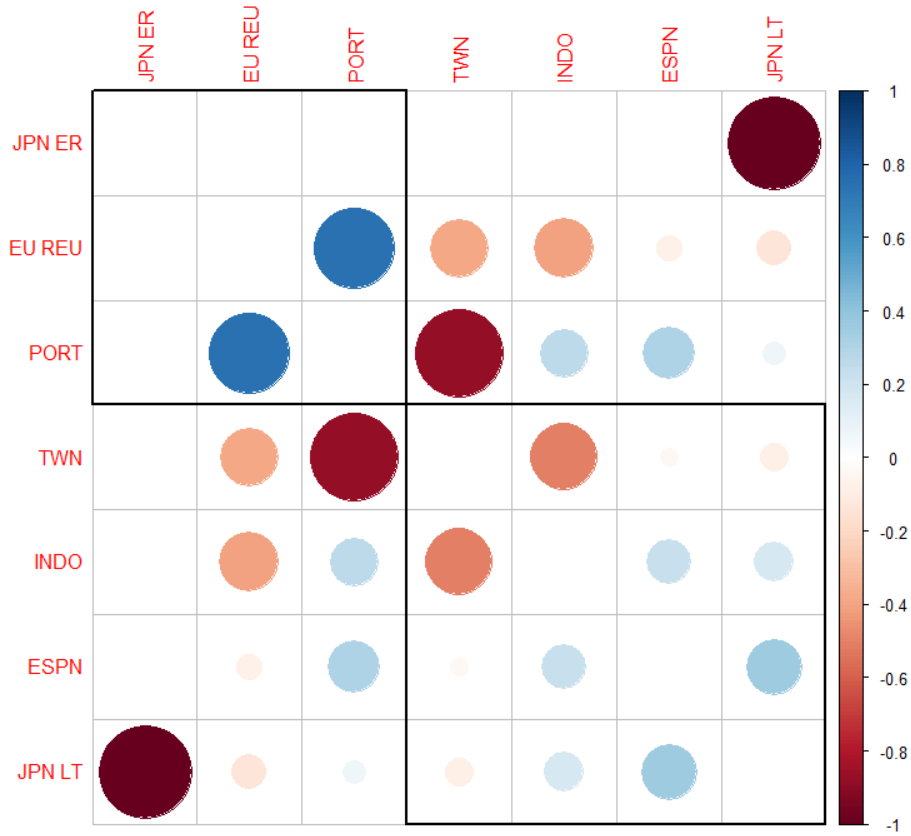

Figure 9. Correlation matrix for CPUE indices available for the Indian Ocean blue shark. Blue indicates positive and red negative correlations. The order of the indices and the rectangular boxes are chosen based on a hierarchical cluster analysis using a set of dissimilarities.

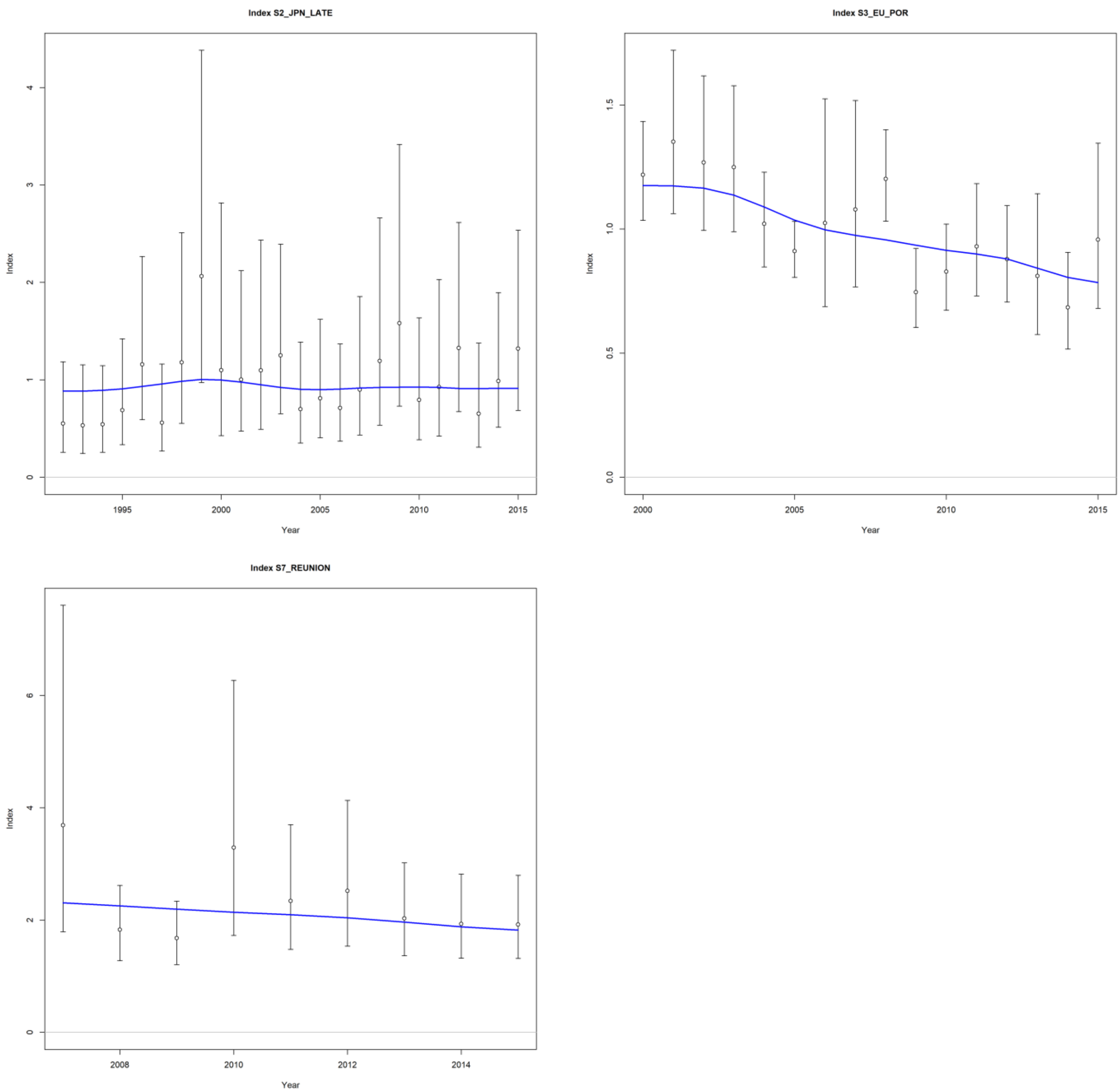

Figure 10: Reference case fit to the CPUE series, presented on a log scale. The top left panel is the Japanese late series (S2) the top right is the Portuguese series (S3) and the bottom right is S7 Reunion.

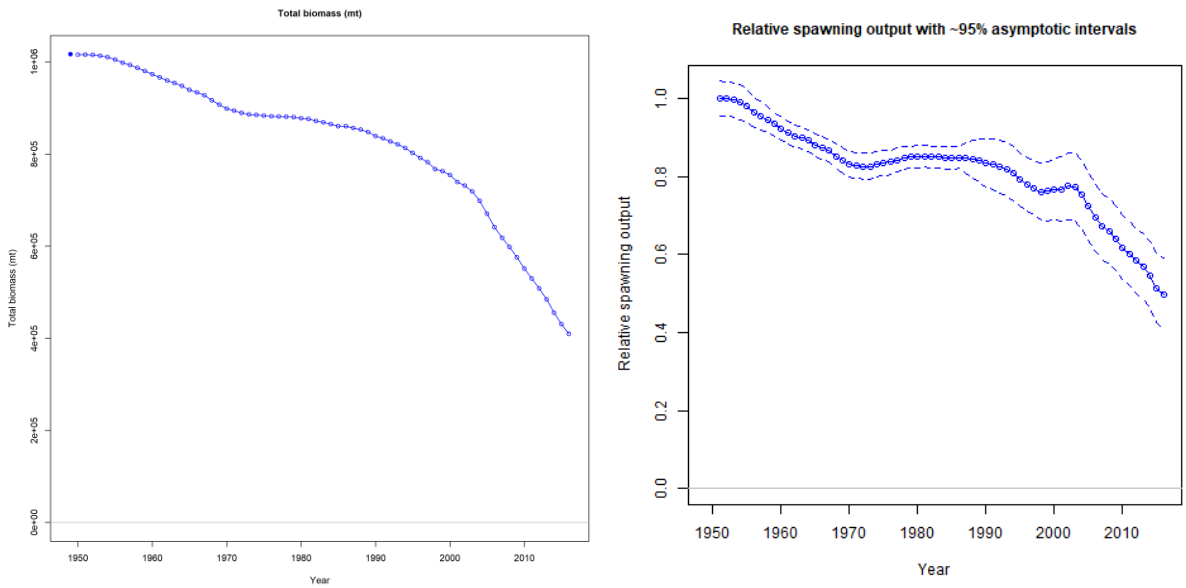

Figure 11: Total biomass (left) and spawning potential (output) for the reference case parameterization model. The filled dot represents the pre-model estimate of unfished biomass.

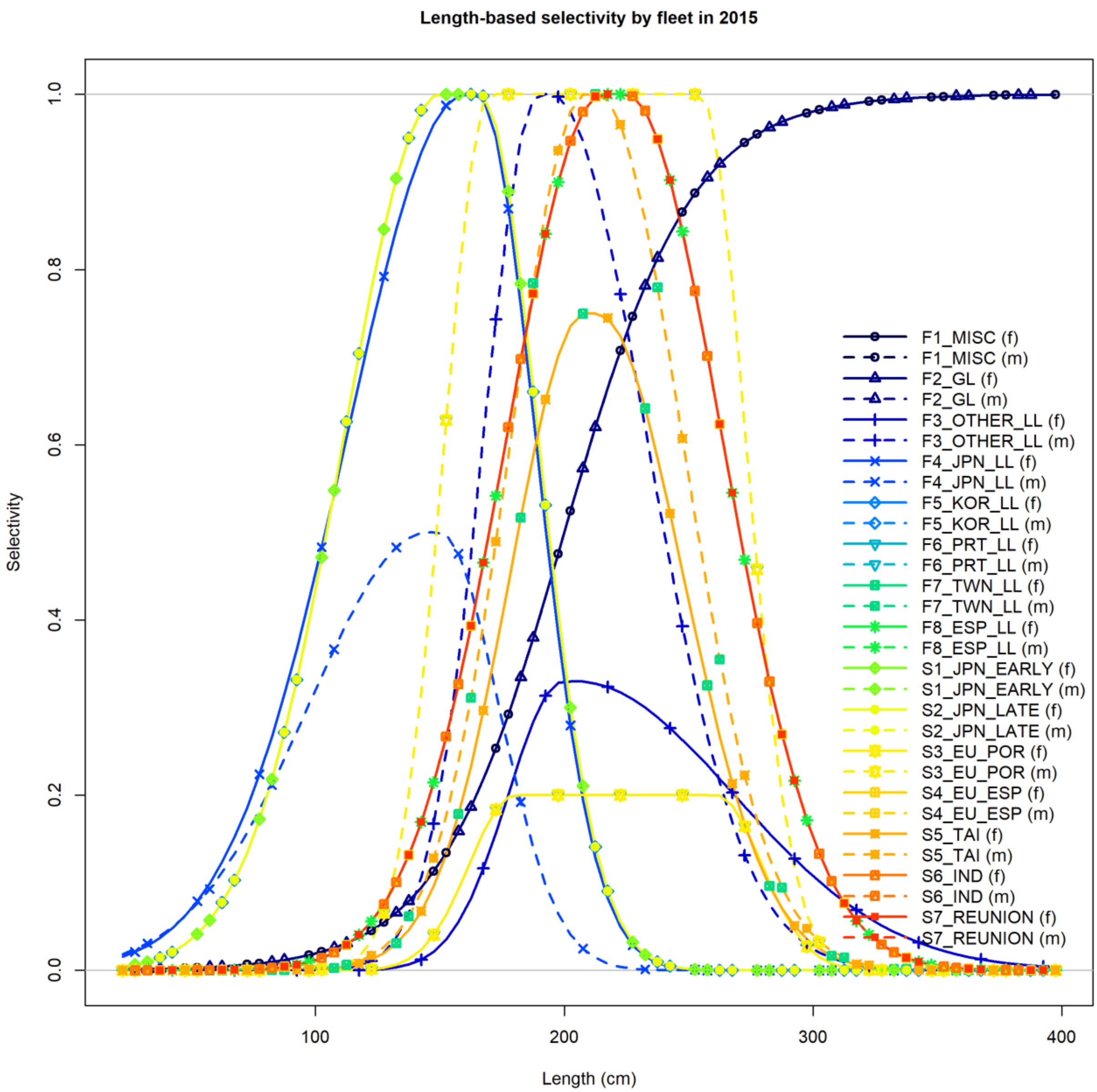

Figure 12: Selectivity curves estimated for female and male from the reference case model for the assessment of blue sharks in the Indian Ocean.

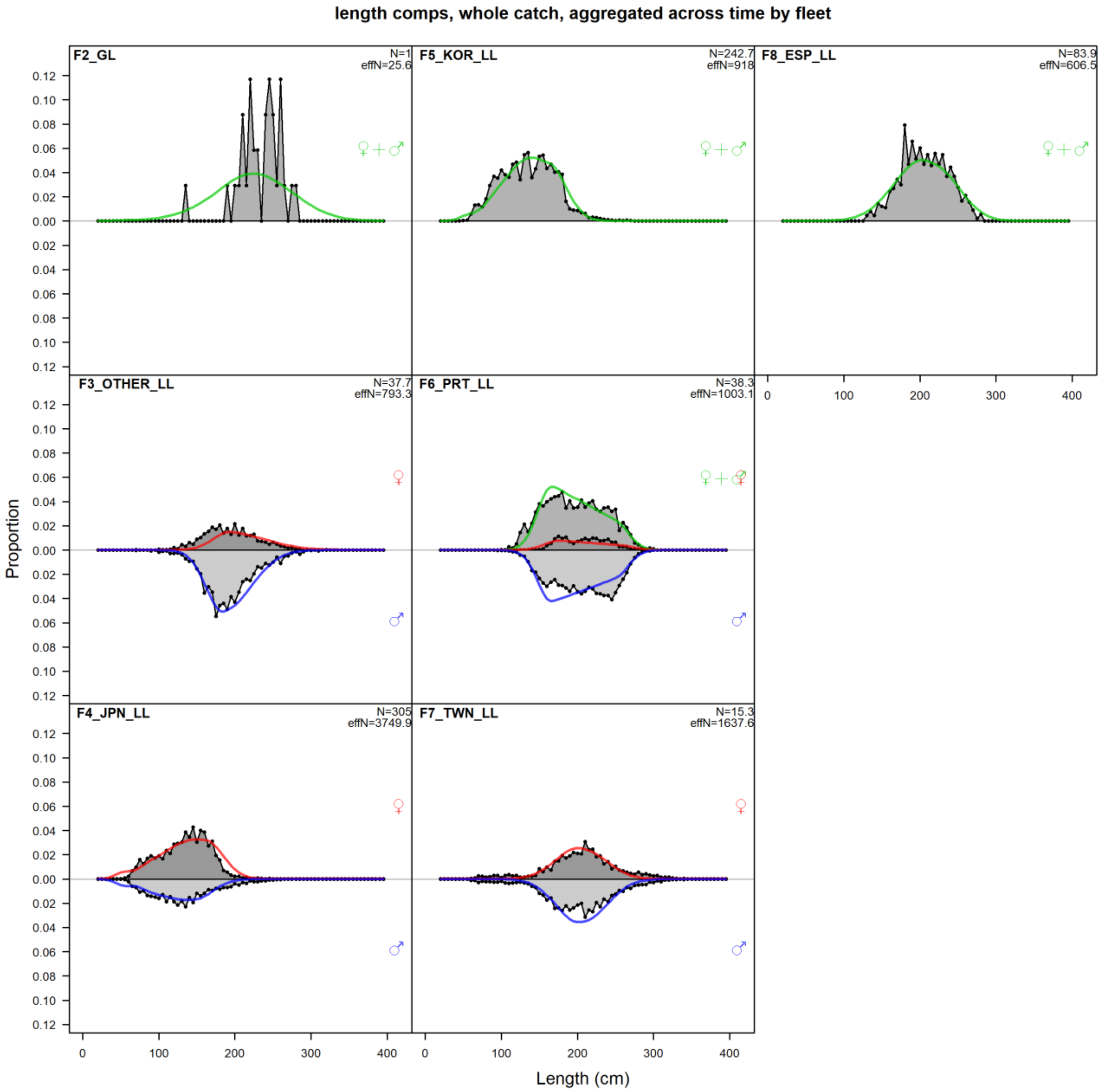

Figure 13 Fit to the female length frequency data for the reference case model for the assessment of blue sharks in the Indian Ocean.

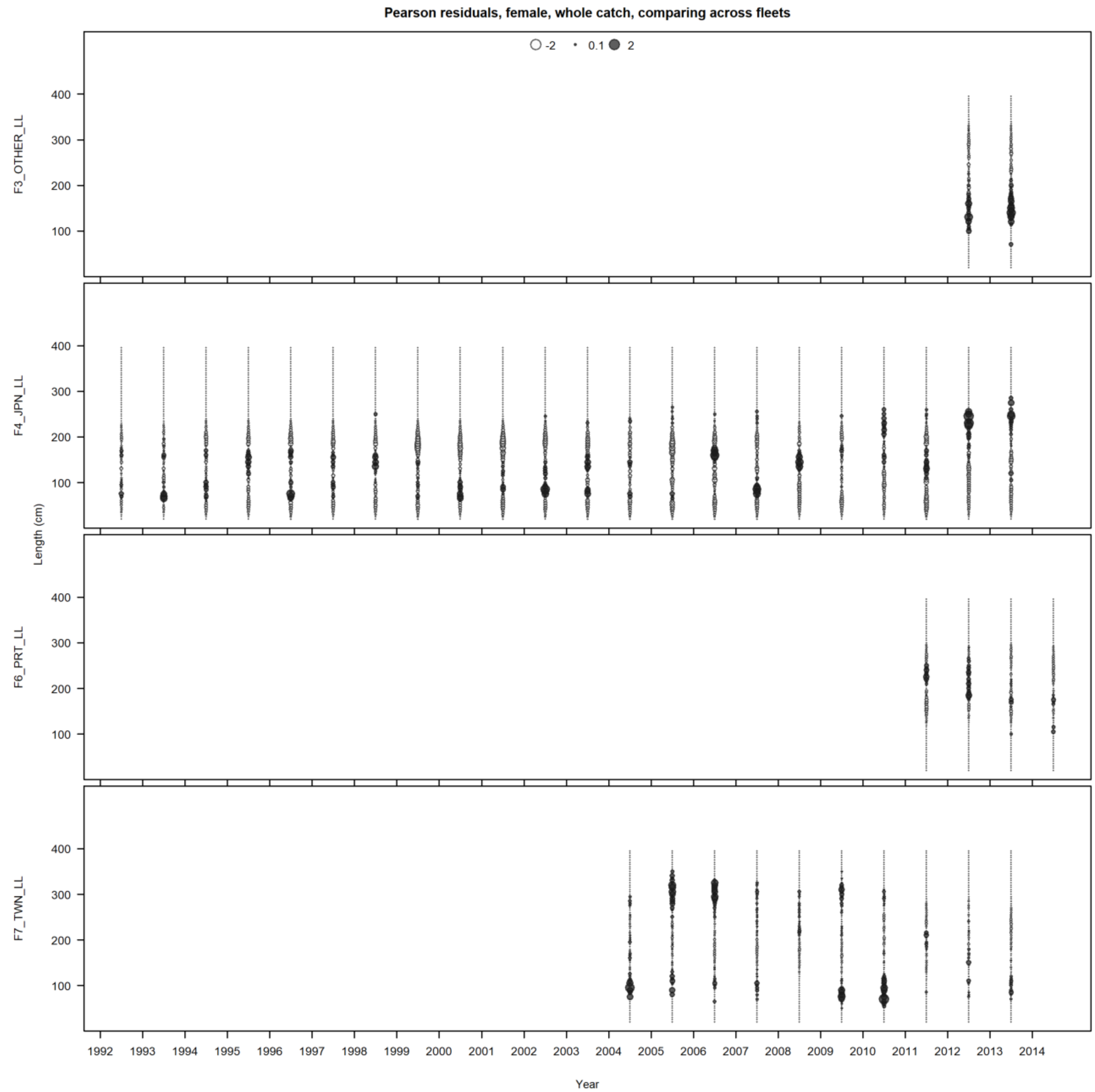

Figure 14 Residuals from the fit to the female length frequency data for the reference case model for the assessment of blue sharks in the Indian Ocean.

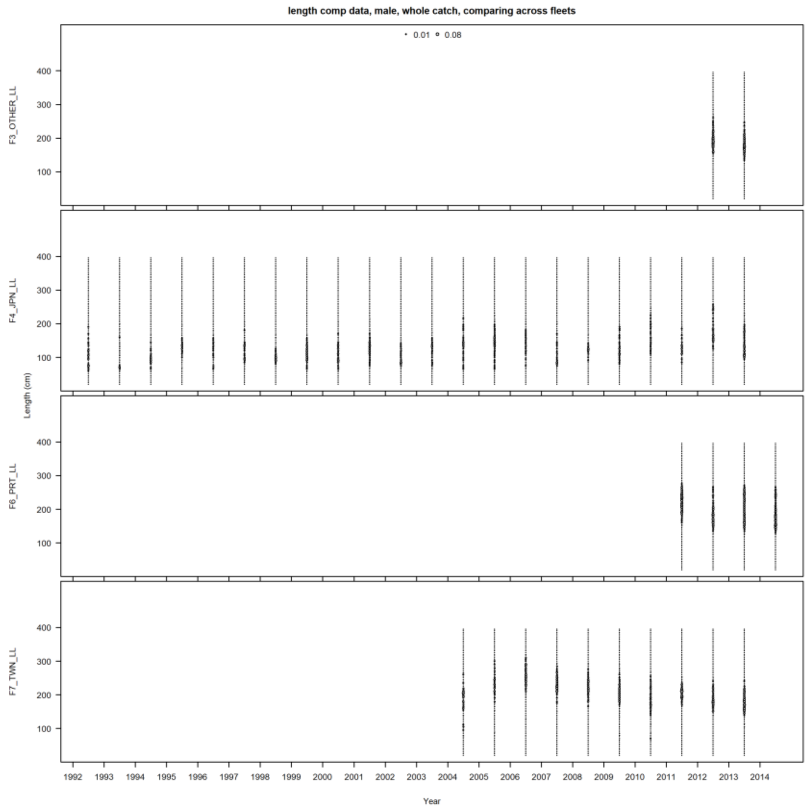

Figure 15 Pearson residuals, comparing across fleets (males). Closed bubbles are positive residuals and open bubbles are negative residuals, bubble sizes are scaled to maximum within each panel.

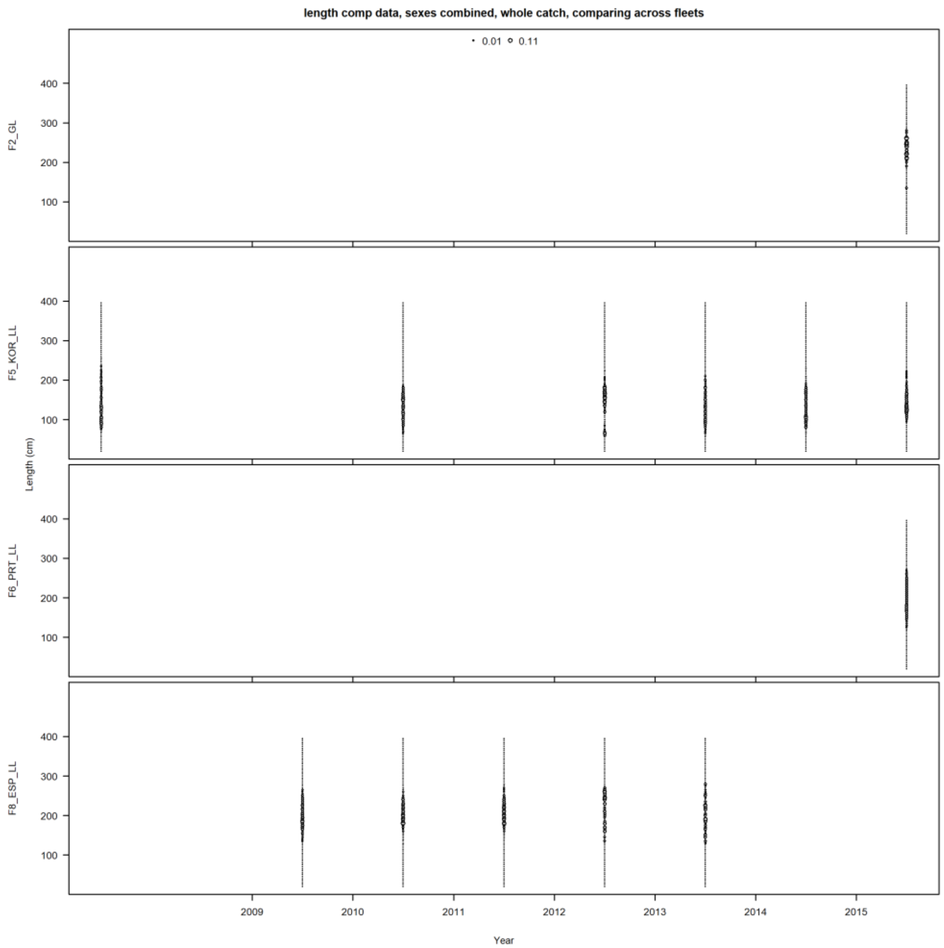

Figure 16. Pearson residuals, comparing across fleets (sexes combined). Closed bubbles are positive residuals and open bubbles are negative residuals, bubble sizes are scaled to maximum within each panel. Thus, comparisons across panels should focus on patterns, not bubble sizes.

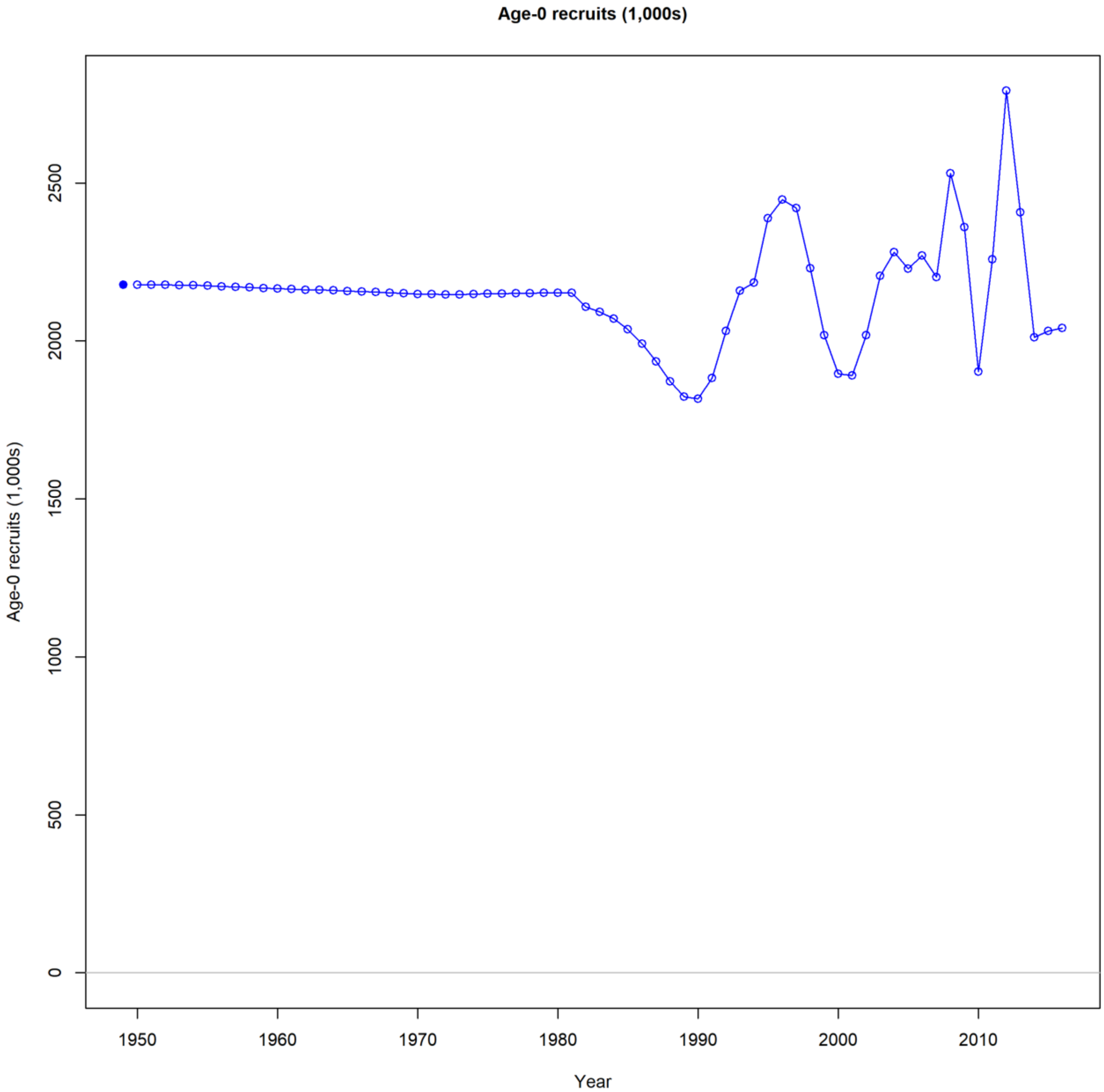

Figure 17 .Estimated recruitment including the estimate of virgin recruitment (filled circle at the start of the time series) for the reference case model for the assessment of blue sharks in the Indian Ocean.

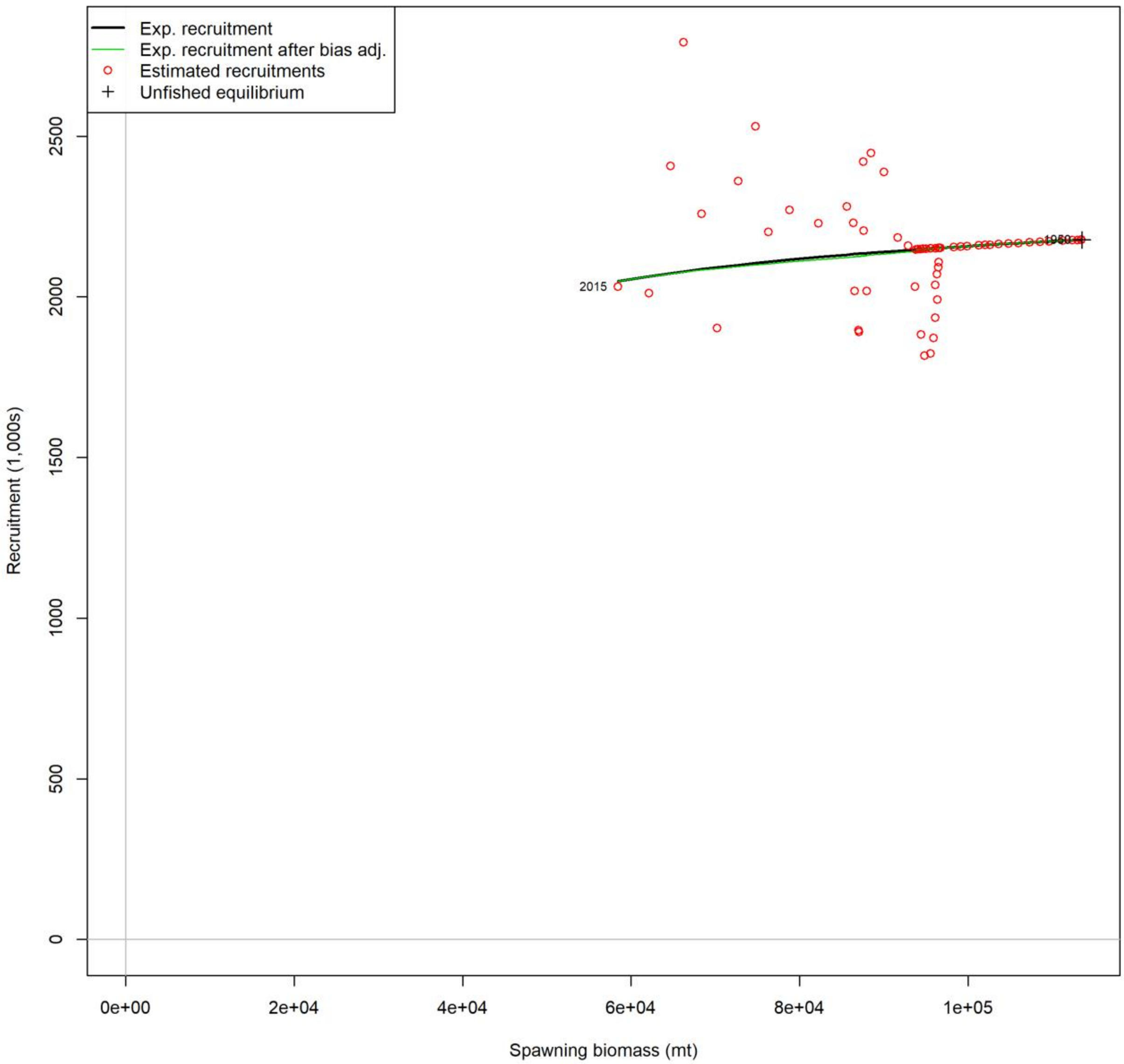

Figure 18 Stock recruitment curve used in the assessment and time series of estimates of recruitment deviations (red points).

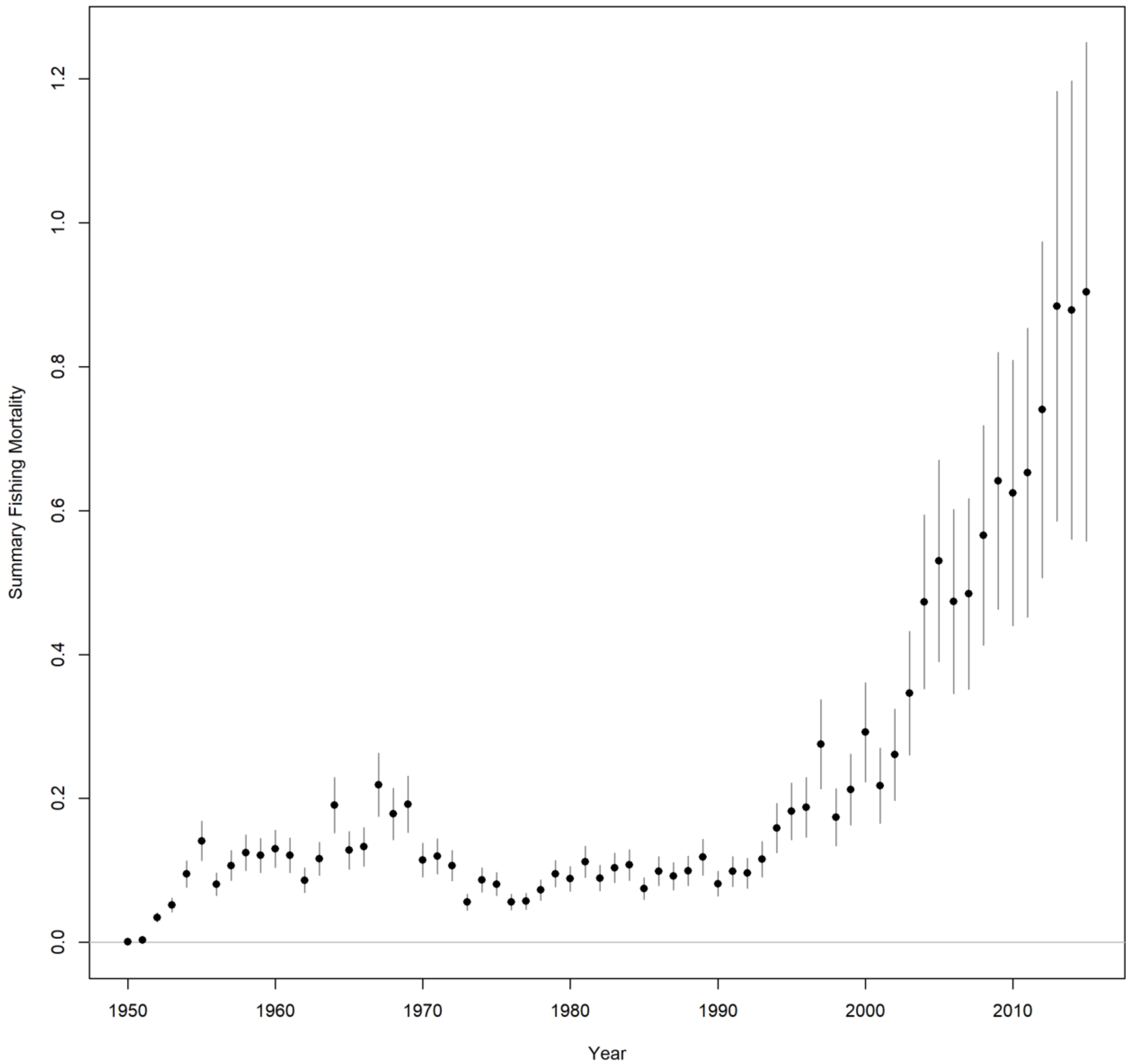

Figure 19 Estimated total fishing mortality/FMSY.

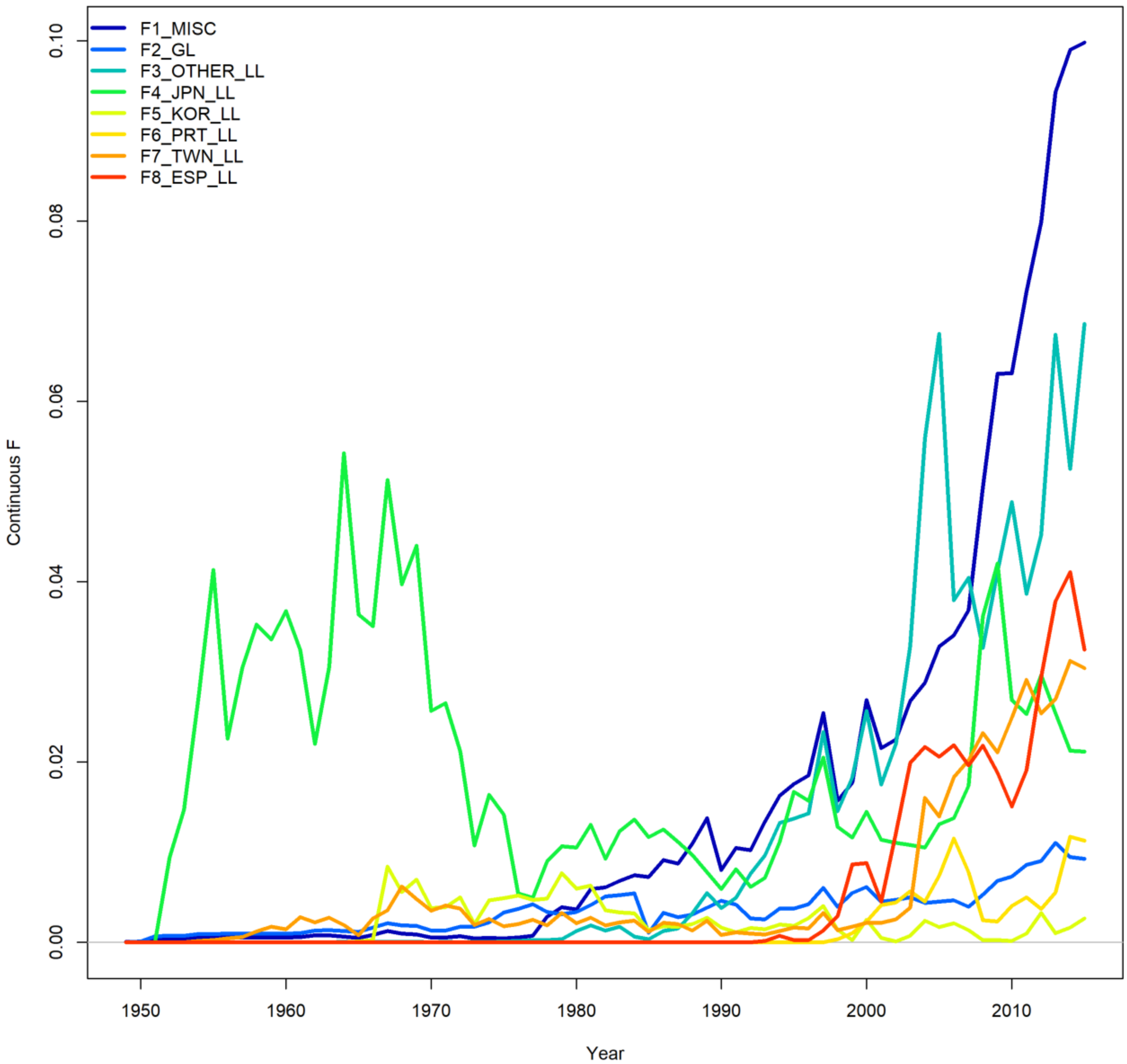

Figure 20. Estimated fleet specific fishing mortality by year for the base case model configuration.

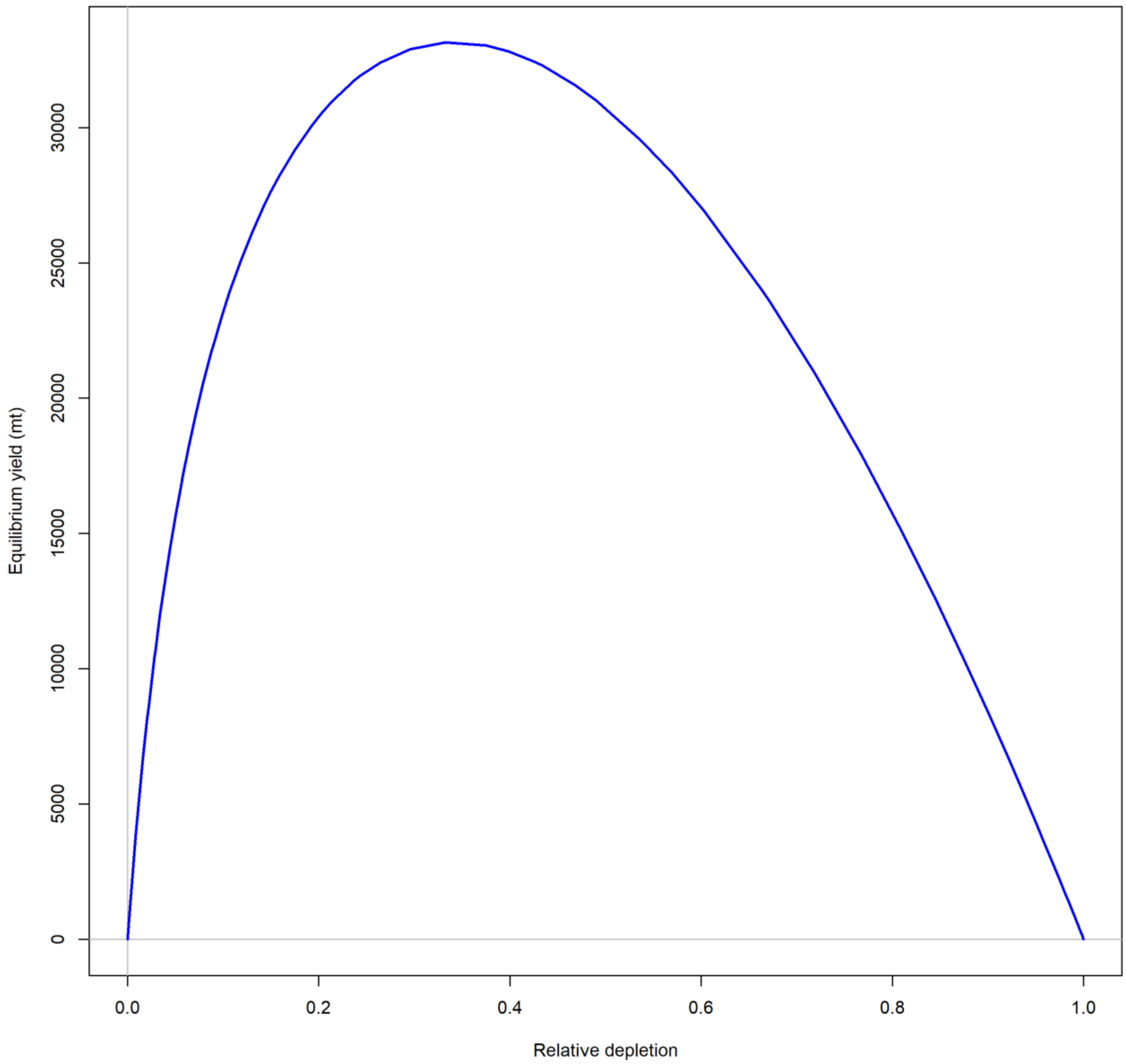

Figure 21. Equilibrium yield curve for the reference case model for the assessment of blue sharks in the Indian Ocean.

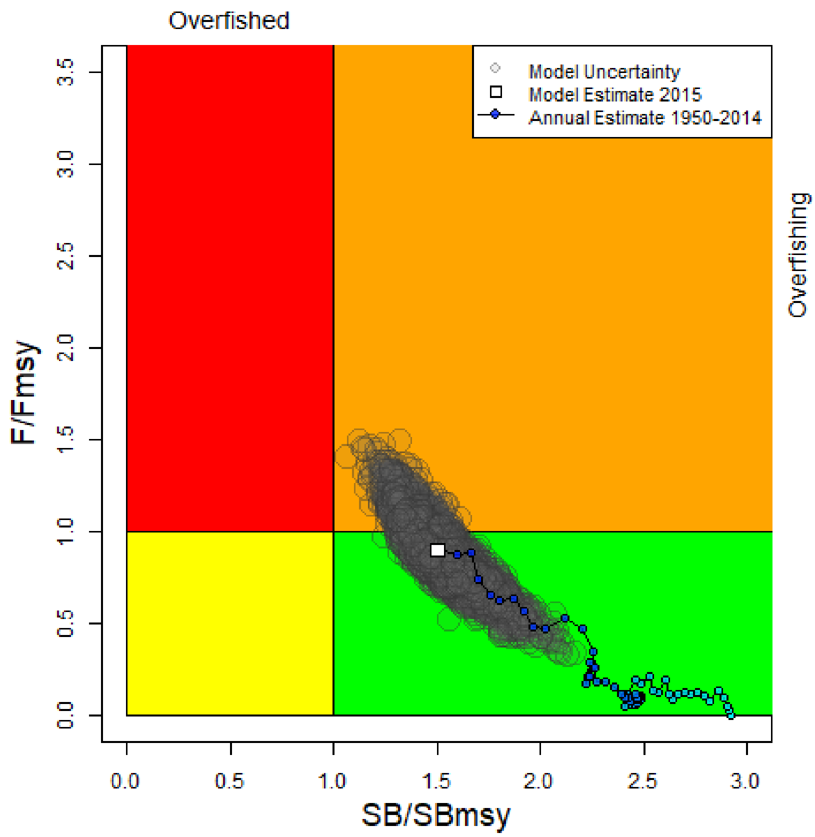

Figure 22. Kobe plot of the annual stock status

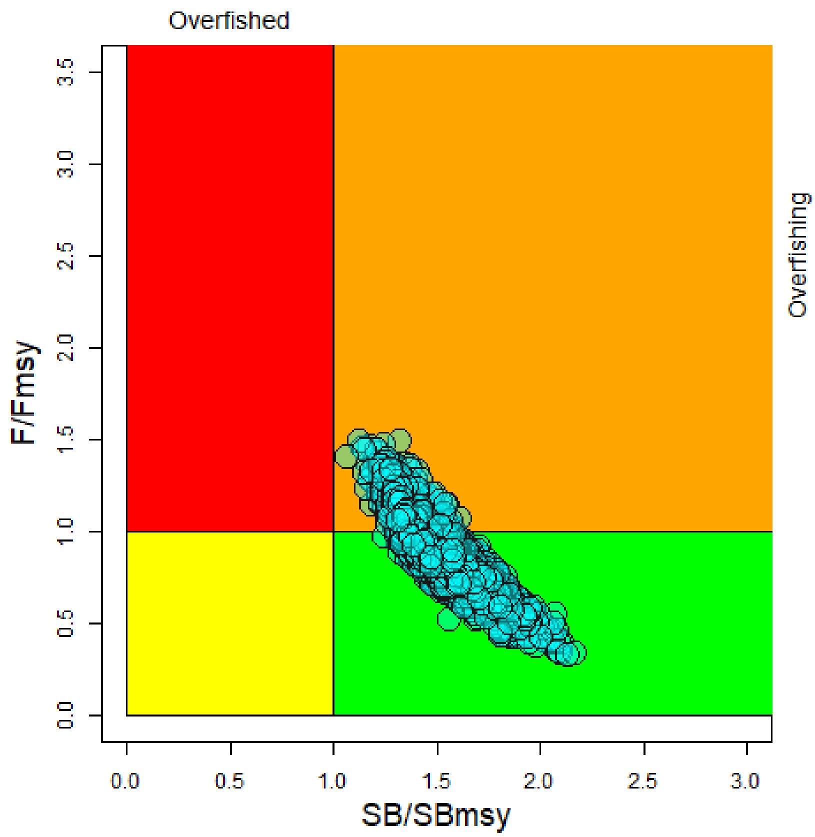

Figure 23. Estimated stock status based on MCMC analysis for the base case model

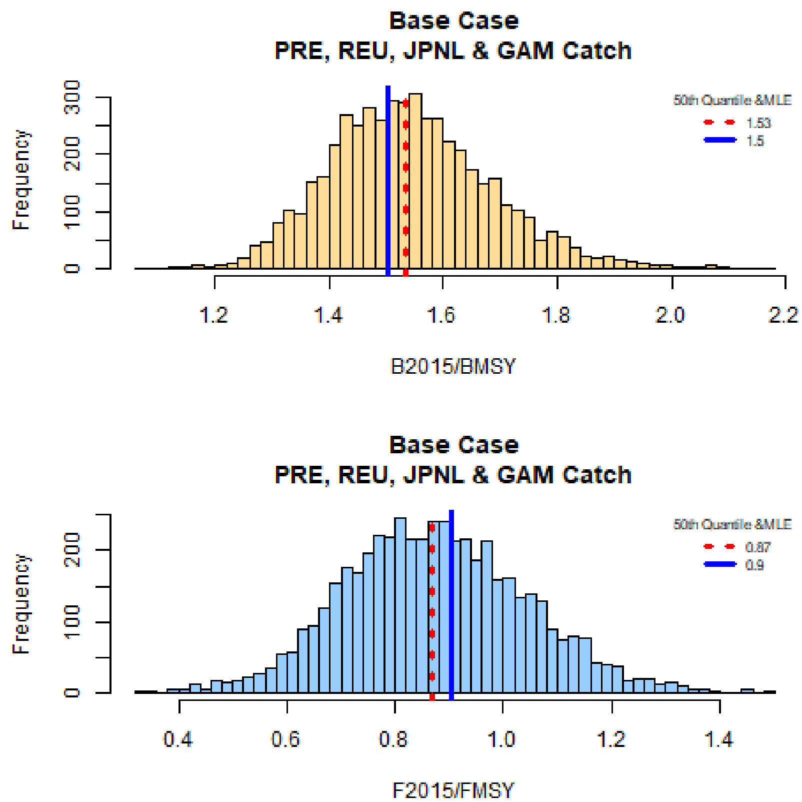

Figure 24. Estimated spawning biomass in 2015 relative to MSY (SSB2015/SSBMSY, top panel) and estimated total fishing mortality in 2015 relative to MSY (F2015/FMSY, bottom panel) for the base case model configuration, comparing the maximum likelihood estimate (MLE blue line in both panels) obtained from Stock Synthesis and the 50th quantile (stippled line in both panels) obtained from MCMC analysis (histograms in both panels).

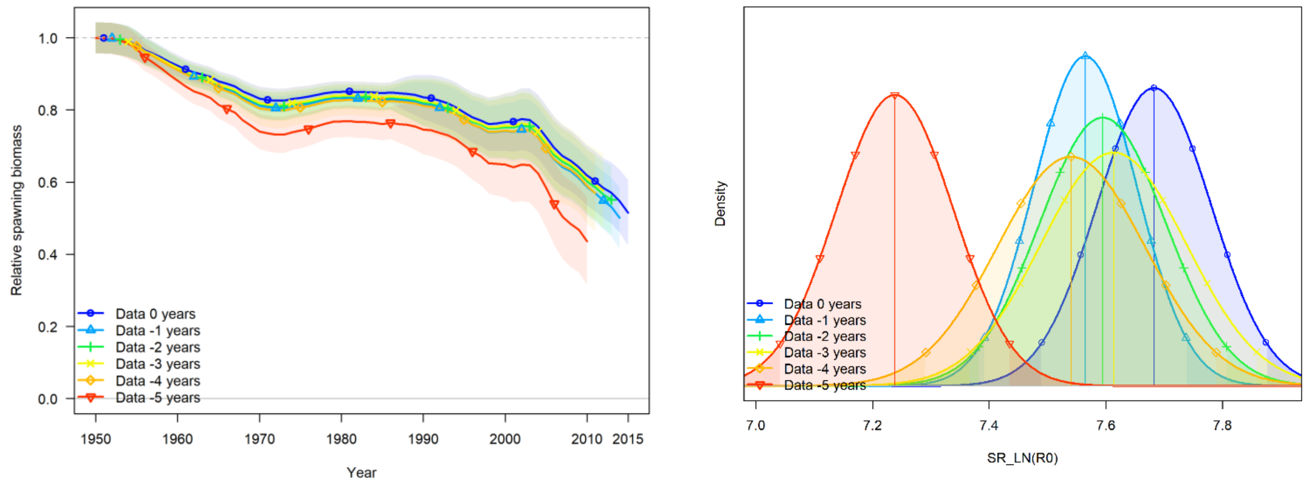

Figure 25. Estimated spawning biomass relative to virgin (SB/SB_0, left panel) by year along with 95% asymptotic uncertainty (shaded areas) and the maximum likelihood estimate (MLE, vertical lines) and asymptotic uncertainty (bell shaped curves) of the natural log of virgin recruitment size (right panel) for each of the retrospective model runs conducted for the base case model configuration.

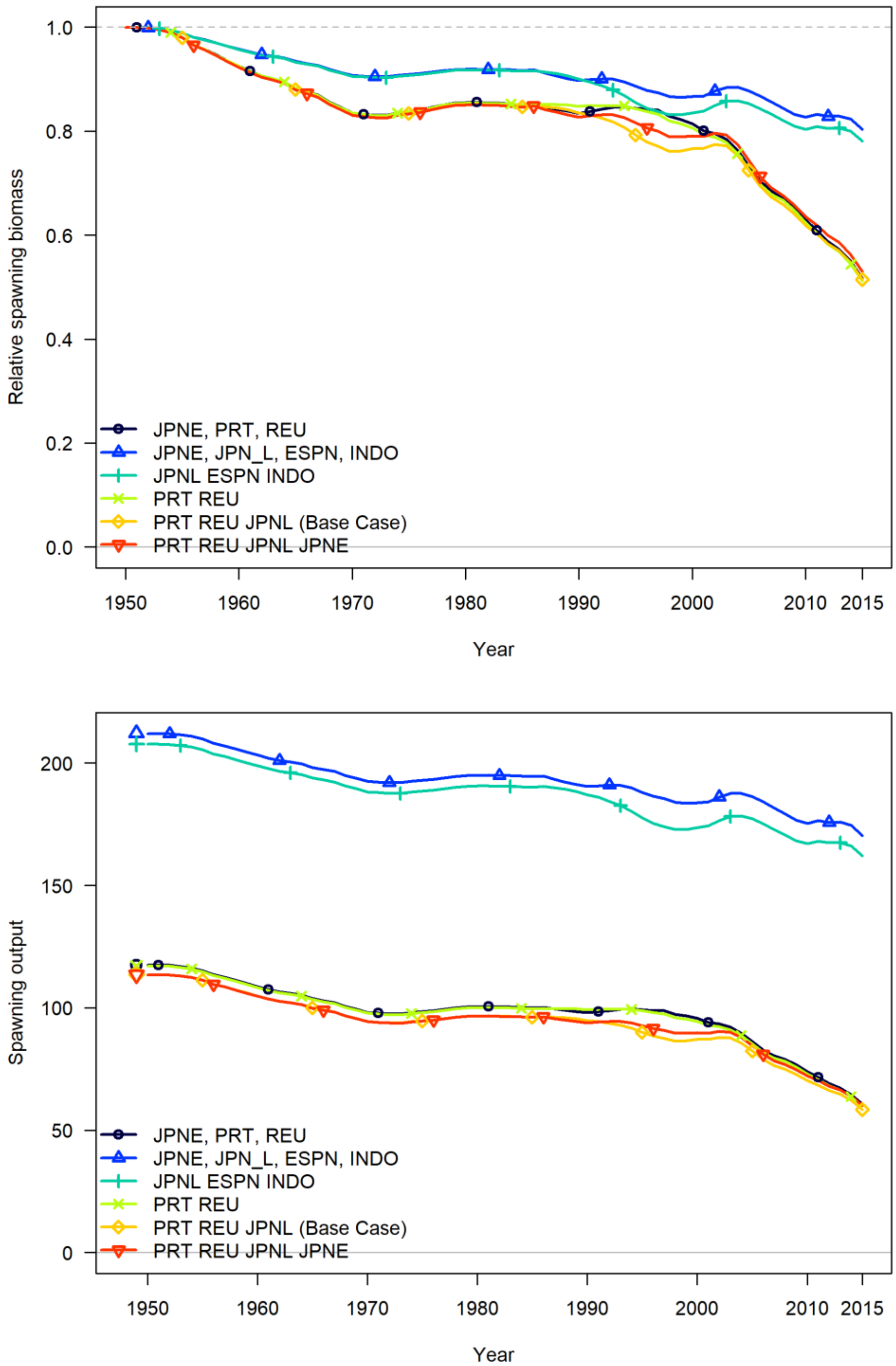

Figure 26 Spawning biomass depletion for all runs in the grid of sensitivities. The top panel shows the depletion based on the different CPUE series used and the bottom panel shows the estimated spawning output.

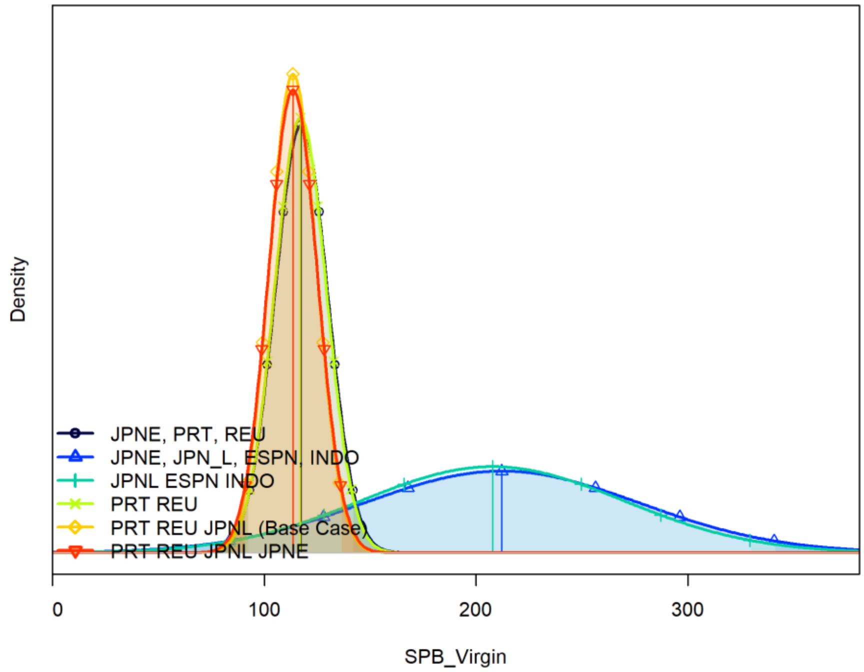

Figure 27 Density estimates for the virgin spawning biomass from sensitivities using different CPUE series.

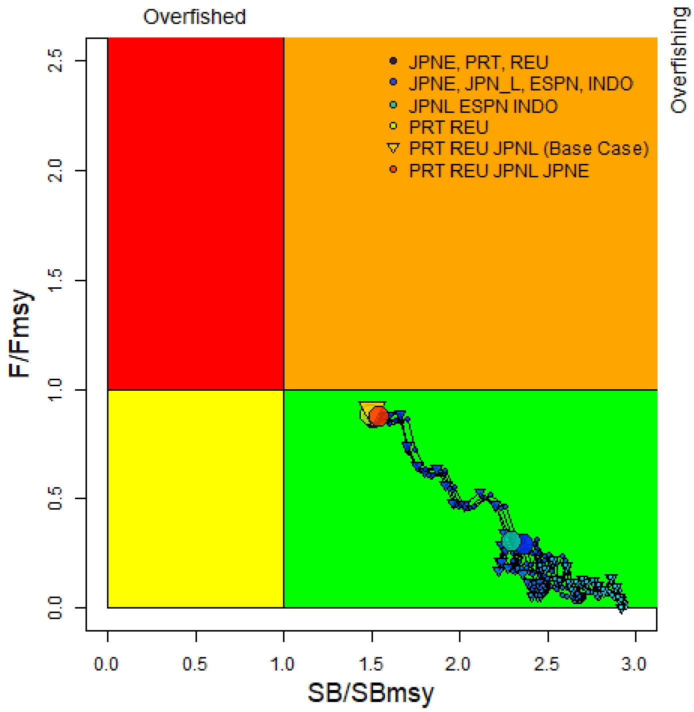

Figure 28. Kobe plot showing the results the estimation of SB/SB$_{MSY}$ and F/F$_{MSY}$, for the terminal year of the model (2015).

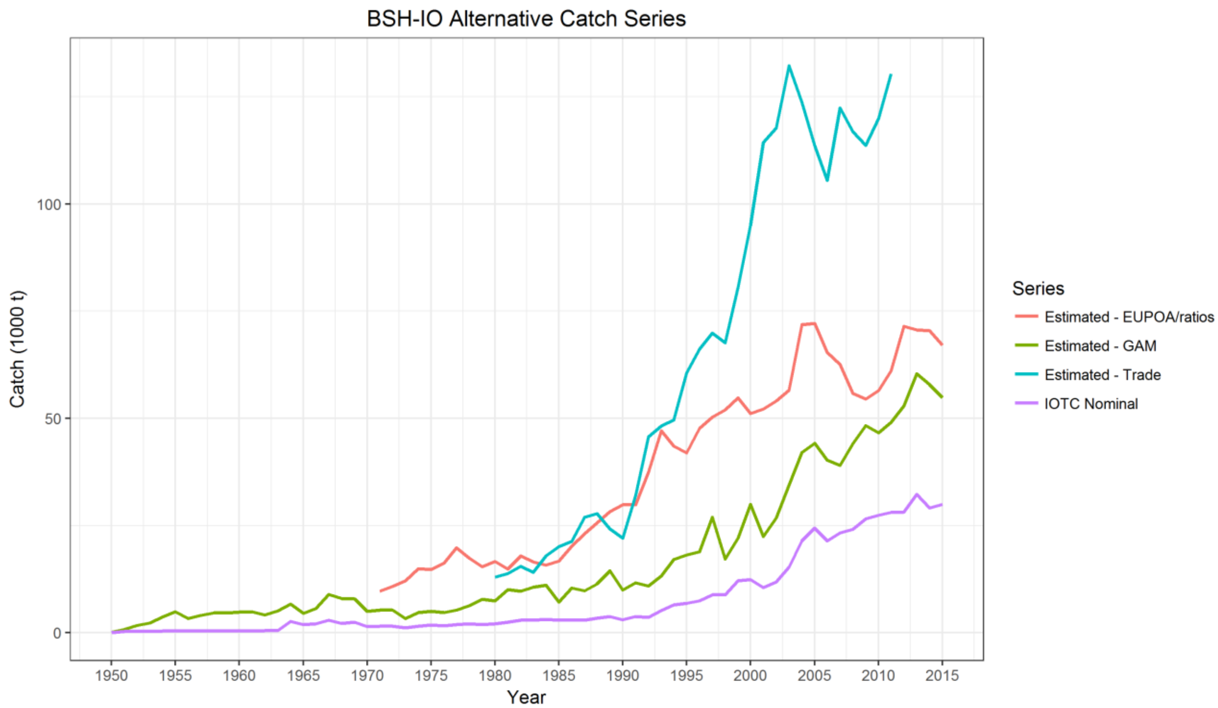

Figure 29 Nominal and estimated catch trends that are used in the sensitivities using base case grouping of CPUE series and alternative catch estimates.

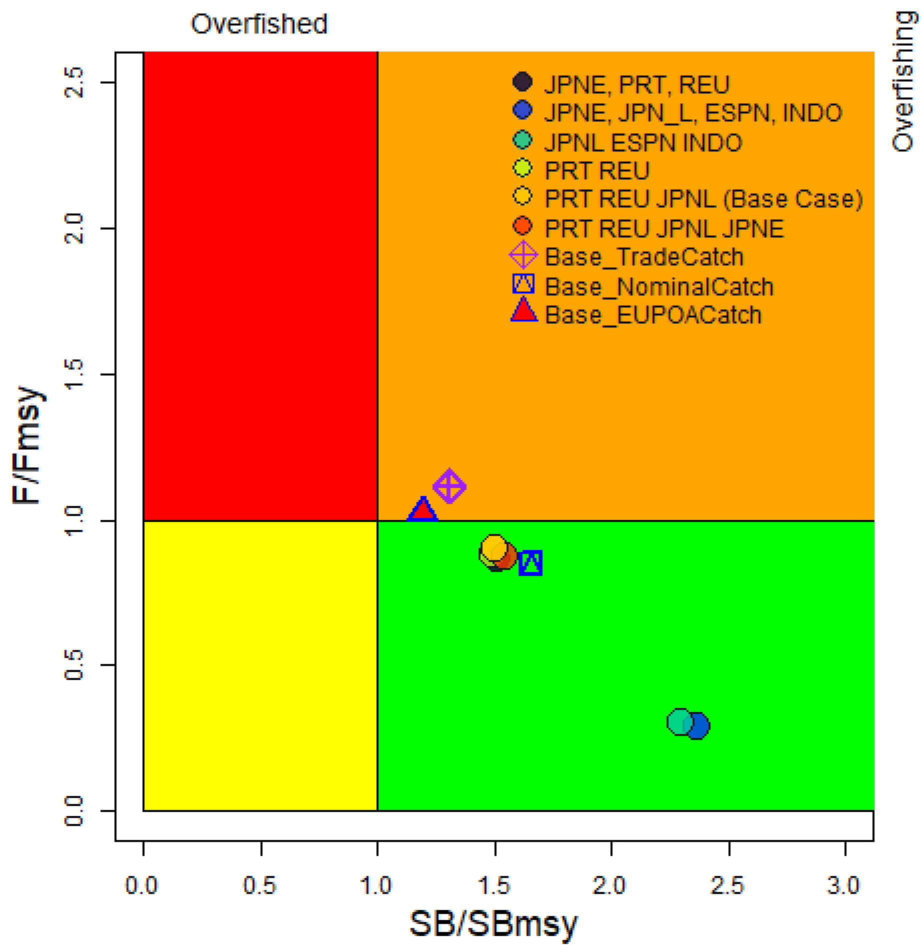

Figure 30. Kobe plot showing the results the estimation of SB/SB$_{MSY}$ and F/F$_{MSY}$, for the terminal year of the model (2015) for the sensitivities using alternative groupings of CPUE series and catch estimates.

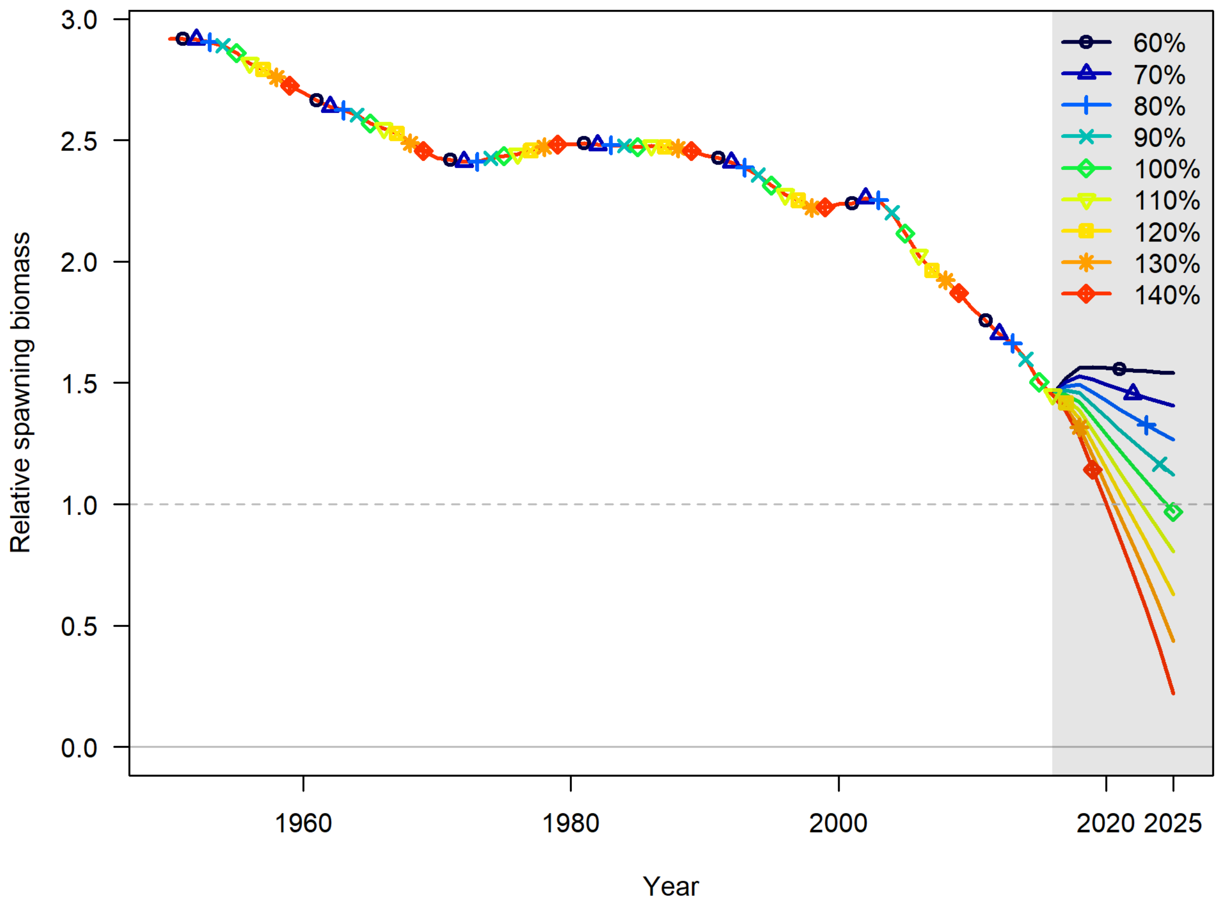

Figure 31. Projections from the base case model configuration with constant catch based on percentages (60%-140%) of the 2015 catch based on the GAM estimates of total catch.

9 ANNEX A. Excerpts on Catch estimation from Martin et al. 2017.

This annex contains the introduction, methods that pertain to the GAM estimated BSH catches and relevant figures and tables from the paper catch estimation paper (IOTC-2017-WPEB13-23).

9.1 Introduction

Catch histories form an important component of stock assessments and so having a reliable and believable catch series is a key part in developing a good estimate of the level of stock depletion. In data-limited situations, reported nominal catches are often not considered reliable and so reconstruction of catch histories plays an important role. This is particularly important for bycatch species where data are often sparse and of varying quality. Nominal catches of blue sharks in the Indian Ocean held by the IOTC[2] are considered to be highly uncertain, and are likely to be 'severe underestimates' of the actual catches taken as concluded by the Working Party on Ecosystem and Bycatch in 2015.

The first Indian Ocean stock assessment of blue shark took place in 2015, however, due to the amount of uncertainty in the assessments, the conclusion regarding stock status remained as uncertain[3]. The historic catch series was considered to be one of the key sources of uncertainty and so the Working Party requested that participants develop new approaches to reconstructing historic catches to be used as alternate series for assessment. There a number of approaches that may be used to produce catch history reconstructions. One method that has been used previously for Indian Ocean blue shark was based on information obtained from the shark fin trade, providing estimates used in the 2015 assessment[4] that were approximately four times higher than the IOTC nominal catches[5]. Another method has been developed which is based on expert knowledge of Indian Ocean fisheries to determine catch rates of sharks to target species and separating out the different shark species using a proportioning method[6]. Yet another approach that has been applied for southern bluefin tuna in the southern Ocean involved the use of random forests to predict CPUE of non-members based on the reported CPUE of members[7].

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[2] IOTC Nominal catches: IOTC-2017-WPEB13-DATA03. www.iotc.org/meetings/13th-working-party-ecosystems-and-bycatch-wpeb13

[3] IOTC, 2015. Report of the 11th Session of the IOTC Working Party on Ecosystems and Bycatch. Olhão, Portugal, 7-11 September 2015.

[4] Rice J and Sharma R., 2015. Stock assessment blue shark (*Prionace glauca*) in the Indian Ocean using Stock Synthesis. IOTC-2015-WPEB11-28 Rev_1.

[5] Clarke, S., 2015. Historical Catch Estimate Reconstruction for the Indian Ocean based on Shark Fin Trade Data. IOTC–2015–WPEB11–24

[6] Murua H., Santos, M.N., Chavance, P., Amande, J., Seret, B., Poisson, F., Ariz, J., Abascal, F.J., Bach, P., Coelho, R., Korta, M. 2013b. EU project for the Provision of Scientific Advice for the Purpose of the implementation of the EUPOA sharks: a brief overview of the results for Indian Ocean. 9th Working Party on Ecosystems and Bycatch, 12-16 September, La Reunion, French Overseas Territories. (IOTC Doc: IOTC–2013–WPEB09–19).

[7] Chambers, M. and Hoyle, S. 2015. Proposed approach to estimate non-member catch of SBT using ransom forests to model CPUE. CCSBT/CPUE2015/04

This paper uses the available nominal catch data currently held in the IOTC database and explores the use of a ratio based method and a GAM statistical approach to reconstructing historic blue shark catches in the Indian Ocean.

GAM approach to estimate unreported blue shark catches

A second method was used to attempt to estimate blue shark catches based on the nominal catches in the IOTC database. A statistical modelling approach based on generalized additive models (GAMs) was used to predict unreported catches. The model was set up incorporating a number of explanatory variables thought to be influential in determining whether a fleet catches blue sharks. The model was parameterised based on the records where reported blue shark and the selected covariates were available and the model was run on the remaining dataset where zero blue shark catches were reported, and where sufficient levels of the covariates were available for prediction. Records with levels outside the model, and so for which prediction was not possible, were dropped.

The log transformed nominal blue shark catches were used as the response variable. A filter was applied to remove extremely high catch rates by selecting only those records where catches of blue shark were less than 80% of the total catches of non-shark species. This was performed to remove those high values where the fishery is likely to be targeting blue sharks and therefore more likely to be accurately reporting those sharks. Outliers were not well predicted by the model so the dataset on which to predict the unreported blue shark catches was also filtered to remove extreme values (records where target catches >80,000 t) which had a disproportionately large effect on the results. This resulted in the removal of 77 outliers which was 1.06% of the data set.

The explanatory variables year, target species catch, gear, area (E/W) and fishing ground (coastal, pelagic or all). Different classifications of non-blue shark species were also explored including separate covariates for temperate tuna species, tropical tunas, other shark species and all other species, added using splines. To avoid over-parameterisation, models were run sequentially starting from the simplest model and incorporating covariates and interactions, where they made sense theoretically (e.g. area-gear interactions) in an iterative manner. Models were evaluated based on AIC values.

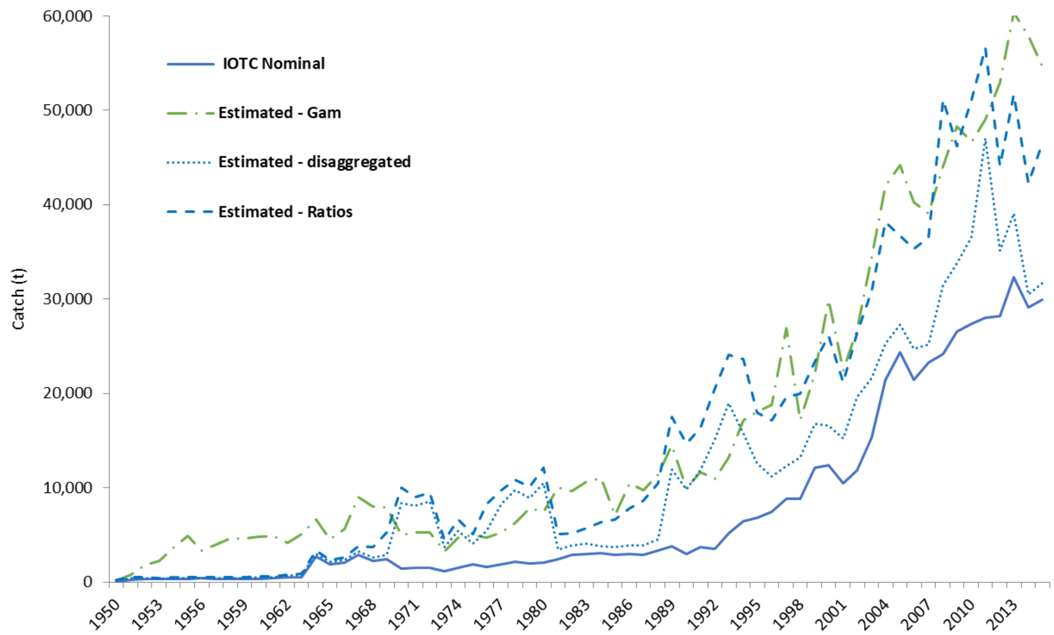

Figure A1. Reported, disaggregated, ratio based and GAM estimates of Indian Ocean blue shark catches.

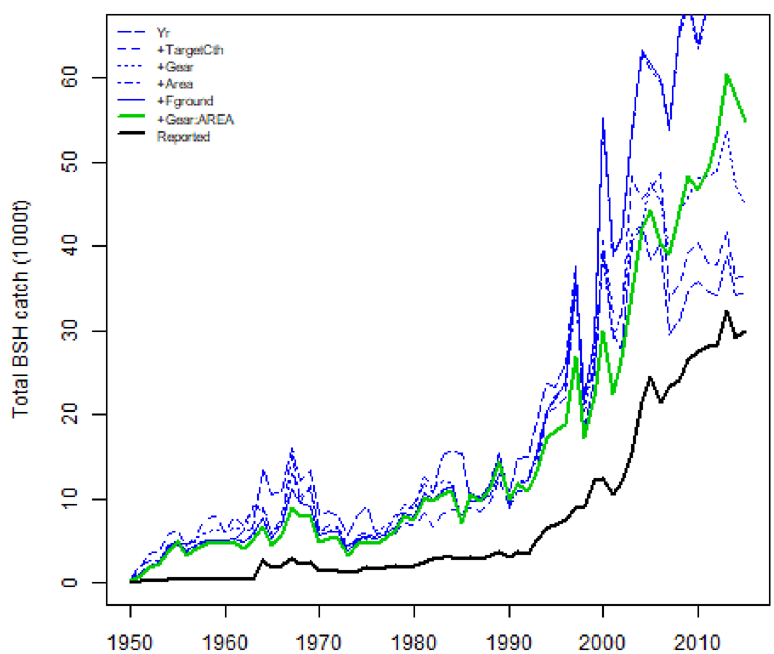

Figure A2. Stepwise results of predicted catch via GAM on the nominal catch data set (selected model = green line).

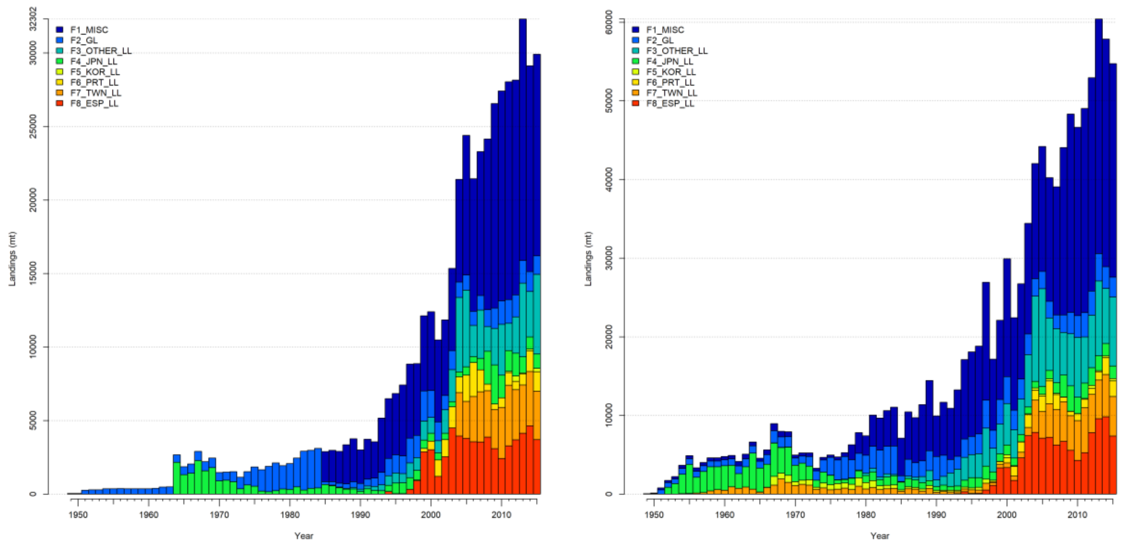

Figure A3. Nominal catch by fleet (left panel) and estimated catch by fleet based on the GAM model (right panel). Note the difference in scale of the y axis.