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Pacific-wide bigeye thresher shark (*Alopias superciliosus*) sustainability status assessment: introduction, datasets and methodology

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Dan Fu[1,2], Marie-Julie Roux[1], Shelley Clarke[3], Malcolm Francis[1], Alistair Dunn[1] and Simon Hoyle[4]

[1] National Institute of Water and Atmospheric Research, Wellington, New Zealand
[2] Address for correspondence: dan.fu@niwa.co.nz
[3] ABNJ Tuna Project (Common Oceans), Western and Central Pacific Fisheries Commission, Pohnpei, Federated States of Micronesia
[4] National Institute of Water and Atmospheric Research, Nelson, New Zealand

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[2] Address for correspondence: dan.fu@niwa.co.nz

[3] ABNJ Tuna Project (Common Oceans), Western and Central Pacific Fisheries Commission, Pohnpei, Federated States of Micronesia

[4] National Institute of Water and Atmospheric Research, Nelson, New Zealand

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Abstract

The bigeye thresher shark, *Alopias superciliosus*, has been identified as one of the least productive pelagic sharks and there is concern regarding its conservation status. Although it is one of three thresher sharks designated by WCPFC as key shark species, no stock assessment has been conducted due to information gaps and changes in reporting and observer coverage over time and space, which do not yet support a traditional approach to stock assessment. As an alternative to gain new insights into the sustainability status of bigeye thresher shark in relation to pelagic longline fisheries in the Pacific, this study applies a spatially explicit and quantitative sustainability risk assessment to available data. The analytical framework evaluates sustainability risk as the ratio of current impacts from fisheries (spatially-explicit and cumulative fishing mortality *F*) to a maximum impact sustainable threshold (MIST) reference point based on population productivity. This approach differs from traditional stock assessments, in which *F* is compared to estimates of population abundance. The risk assessment approach evaluates *F* in terms of whether the population's ability to withstand fishing pressure is exceeded, rather than evaluating biomass (B) and whether the population is overfished.

The assessment is constrained by the available data and by some aspects of the methodology which are currently being addressed. Key components (and analytical procedures) include: 1) estimation of the species distribution or relative abundance in space; 2) calibration of population and fishery groups catchability; and 3) estimation of the maximum intrinsic population growth rate *r* for the species, using available life history data. The first two are used in conjunction with commercial effort (logsheet) data to quantify fishing impact. The third is used to define the MIST reference point.

Observer data from the Pacific Community (SPC), United States (US) and Japan were standardized with two models, a zero-inflated negative binomial (ZINB) model and a geo-statistical delta-generalised linear mixed (delta-GLMM) model, which permitted derivation of spatial indices of relative abundance over different but overlapping areas.

Population catchability (*q*) is statistically calibrated using a Bayesian state-space biomass dynamics model (BDM) fitted to time series of relative abundance and annual catch estimates obtained using a representative subset of the observer data. This approach is under development and serves to estimate a plausible range of values for *q*, which are then adjusted spatially by fishing season and targeting strategy (i.e., 'fishery groups'). Relative *F* are calculated as the sum product of total effort and fishery-group specific catchability in 5x5 degree cells, weighted by the relative density of bigeye thresher shark in each cell, as obtained from the spatial standardization. Post-capture survival is not taken into account in the present assessment.

The strengths and value of a spatially-explicit, sustainability risk assessment framework reside in data integration from multiple sources and the ability to map relative fishing impact and sustainability risk spatially and among fishery sectors, with uncertainty.

List of acronyms

ABNJ	Areas Beyond National Jurisdiction (or Common Oceans)
AFFRC	Agriculture, Forestry and Fisheries Research Council, Japan
ALB	Albacore Tuna (*Thunnus alalunga*)
BET	Bigeye Tuna (*Thunnus obesus*)
BTH	Bigeye Thresher Shark (*Alopias superciliosus*)
CES	Tuna Fishery Catch and Effort Query System
HBF	number of hooks between floats
IATTC	Inter-American Tropical Tuna Commission
ICCAT	International Convention for the Conservation of Atlantic Tunas
IOTC	Indian Ocean Tuna Commission
JP	Japan
MIST	Maximum impact sustainable threshold
MLS	Striped marlin (*Kajikia audax*)
NOAA	National Oceanographic and Atmospheric Administration
ROP	Regional Observer Program
SPC	The Pacific Community
SST	Sea surface temperature
SWO	Broadbill Swordfish (*Xiphias gladius*)
TCSB	Tuna Project Technical Coordinator Sharks and Bycatch
TUBS	Tuna Fisheries Observer System
US	United States
YFT	Yellowfin Tuna (*Thunnus albacares*)
WCPFC	Western and Central Pacific Fisheries Commission
WCPO	Western and Central Pacific Ocean

1 INTRODUCTION

The Western and Central Pacific Fisheries Commission (WCPFC) is one of five tuna Regional Fisheries Management Organizations (t-RFMOs) responsible for the sustainable use, conservation and management of highly migratory species taken by tuna fisheries. Unlike some of the other t-RFMOs, the WCPFC has explicit responsibility for assessing and managing not only tuna species, but also dependent and associated species under Articles 5(d) and 10.1(c) of its Convention. Recognition by the WCPFC of sharks as dependent and associated species in need of conservation and management has resulted in a list of thirteen shark species found in the Western and Central Pacific Ocean (WCPO) for which both data provision and assessment are required (WCPFC 2012). The three thresher shark species of the family Alopiidae (*Alopias superciliosus*, bigeye thresher; *A. pelagicus*, pelagic thresher; and *A. vulpinus*, common thresher) have been included in this list since its original formulation in 2008. Thus far, the WCPFC has conducted stock assessments for three of the shark species on the key shark list: oceanic whitetip shark (*Carcharhinus longimanus*), silky shark (*Carcharhinus falciformis*) and North Pacific blue shark (*Prionace glauca*) (Rice & Harley 2012, 2013; Rice et al. 2014). A stock assessment for South Pacific blue shark is currently underway.

Indicator analyses for the thresher sharks were conducted by the WCPFC's Scientific Services Provider, the Pacific Community (SPC), in 2011 and 2015 (Clarke et al. 2011, Rice et al. 2015). In both cases, most of the analyses were performed at the family level due to presence of a substantial number of non-species specific observer records. The most recent of these analyses hinted at a declining index of abundance for the thresher group as a whole based on decreased catch rates in 2012-2014 and an overall decline since 2003 (Rice et al. 2015). On this basis, the WCPFC Scientific Committee in August 2015 recognized assessment of thresher sharks as a priority.

The WCPFC, along with the four t-RFMOs, is a partner in the Areas Beyond National Jurisdiction (ABNJ) – also referred to as Common Oceans – Tuna Project (www.commonoceans.org). The objective of the ABNJ Tuna Project is to achieve efficient and sustainable management of fisheries resources and biodiversity conservation in marine areas that do not fall under the responsibility of any one country. One set of activities of the GEF-funded ABNJ Tuna Project aims at reducing the impact of tuna fisheries on biodiversity by improving data and assessment methods for sharks and thereby promoting their sustainable management. Within this set of activities WCPFC has committed to leading four new stock status assessment studies for Pacific-wide shark stocks. The bigeye thresher shark was identified as the thresher species with the widest distribution and the greatest number of catch records from the WCPO (Matsunaga and Yokawa 2013, Rice et al. 2015), and it is likely to be the most vulnerable of the three threshers to longline fishing (WCPFC 2006, IOTC 2012, ICCAT 2015), so it was chosen as the best candidate for assessment. A bigeye thresher shark stock status assessment meets the criteria for ABNJ funding as this species has a Pacific-wide distribution, was identified as a priority assessment by at least one of the t-RFMOs, and provides an opportunity to further develop methods for data-poor species.

Biology and distribution

In the Pacific, the bigeye thresher shark primarily occurs in tropical waters, however its habitat ranges as far north as central Japan and Baja California and as far south as the North Island of New Zealand and the southern coast of Peru (Matsunaga & Yokawa 2013). This species is found near the surface at night and makes deep dives to experience temperatures of 6-11^{o}C (up to 500 m depth) during the day, perhaps aided by its *rete mirabile*, a structure within the orbital sinus believed to help stabilize brain and eye temperatures (Nakano et al. 2003, Weng & Block 2004). Studies from the Atlantic suggest that juveniles concentrate primarily in the tropical North Atlantic, and pregnant females are found at higher latitudes off West Africa and Brazil (Fernandez-Carvalho et al. 2015). Findings from the Pacific suggest a slightly different pattern: neonates and juveniles are clustered near 10^{o}N and S latitude, with pregnant females either also at 10^{o}N or at higher latitudes (20-30^{o}N) to the northeast. Few pregnant females have been found south of the equator in the Pacific (Matsunaga & Yokawa 2013).

There is limited information from which to draw any conclusions regarding stock structure for any of the thresher shark species. One unpublished study indicated no population structure across what it considered to be the Indo-Pacific (samples from California, Gulf of California, Ecuador, Hawaii, Taiwan and South Africa). However, the sample size was small (n=64) and it used only one type of DNA (mitochondrial control region) (Trejo 2005). Tagging studies of bigeye thresher sharks off Hawaii have reported movements in both northwesterly and easterly directions with a maximum linear displacement of nearly 3,500 km over 240 days (Weng & Block 2004, Musyl et al. 2011).

The bigeye thresher shark is characterized by high juvenile survival and year-round reproduction (i.e. there is no fixed mating or birthing season), but its low fecundity causes it to have low productivity compared to other pelagic sharks and to be highly vulnerable to fisheries which catch juveniles of this species. In the Pacific, age at maturity was estimated at 12.3-13.4 years for females and 9-10 years for males. The litter size is 2 pups per cycle with a 1:1 sex ratio and the reproductive cycle duration is unknown (Clarke et al. 2015). In a recent ecological risk assessment conducted for pelagic sharks caught by Atlantic longline tuna fisheries, the bigeye thresher was found to have the lowest intrinsic rate of increase (0.009, confidence interval 0.001-0.018), in other words to be the least productive, of the 16 species considered (ICCAT 2012).

Review of population trends

As introduced above, standardized catch rate indicators for *Alopias* spp. have been produced from SPC data holdings twice under the WCPFC's Shark Research Plan (Clarke et al. 2011a, Rice et al. 2015). Japanese longline logbook and research and training vessel data catch rate series for threshers as a group were also produced in the earlier round of analysis (Clarke et al. 2011b)[1]. In the 2011 analyses, no strong trends in standardized catch rates were found for thresher sharks analysed as a group, although the Japanese research and training vessel data indicated a slight increase in catch rates in the central Pacific from the early 2000s through 2008 (the last available data point; Clarke et al. 2011a,b). The Rice et al. (2015) update study, analyzing data through 2014 but excluding data from the US observer programmes, noted that most catches were observed in the longline fishery in an area from 10^{o}S to 20^{o}N and east of 170^{o}E, and the majority of observed individuals were immature. Catch rates rose from 1995-2001 but decreased slightly from 2003-2011 before falling more sharply in 2012-2014. That study thus concluded that the thresher shark complex appeared to be declining though it was noted that the last data point was based on relatively few data and may have exaggerated the trend in the final year (Rice et al. 2015).

[1] Note that while the Japanese research and training vessel data recorded the three thresher species separately, the Japanese logbook data do not, and so for the sake of comparison between the two Japanese datasets, as well between the Japanese datasets and the SPC datasets, threshers were analysed as a group.

All three studies also examined trends in median size as a potential measure of fishing pressure. The first SPC analysis considered threshers as a group and found statistically significant decreasing median sizes in the central Pacific (Clarke et al. 2011a). The analysis of Japanese research and training vessel data found declines in median size only for pelagic threshers and no trend for bigeye threshers (Clarke et al. 2011b) which suggests that the trends identified by Clarke et al. (2011a) may have been driven by pelagic thresher shark. The Rice et al. (2015) update study noted that thresher sharks as a group showed relatively stable size trends based on a sample of mostly immature females and immature and mature males in the central Pacific (Rice et al. 2015).

The only consistent catch rate time series specific to bigeye thresher shark prior to the current study was an analysis by the United States National Oceanic and Atmospheric Administration (NOAA) in support of a decision regarding whether to list bigeye thresher sharks on the United States Endangered Species Act. The analysis standardized catch rates based on the extensive Hawaii-based longline observer data for 1995-2014. The catch rate in the final year of the series (2014) was nearly double that of the previous year and was the highest on record. As a result, NOAA conducted a sensitivity test by excluding the 2014 data point but concluded that the influence of the 2014 data point was negligible and that abundance was relatively stable (Young et al. 2016).

At present there are no known stock status assessments for the bigeye thresher shark in any ocean, but two studies of pelagic thresher in Taiwanese waters concluded that the stock was slightly over-exploited (Liu et al. 2006, Tsai et al. 2010). NOAA also recently completed a stock assessment for the common thresher shark (*Alopias vulpinus*) based primarily on data from California and Mexico. That assessment found that fishing mortality for this primarily coastal stock was relatively low (0.08), well below the overfishing threshold, and the stock was at 94% of its unexploited level and so substantially larger than the minimum stock size threshold. Therefore, the assessment concluded that the common thresher shark was unlikely to be in an overfished condition nor to be experiencing overfishing (Teo et al. 2016).

Finally, there have been a number of studies of thresher sharks in the Atlantic Ocean in recent years, but most analyses have been conducted for *Alopias* species, i.e. at the family level. In this region, the most consistent, comprehensive data sources are logbook and observer records from the United States' longline fishery in the northwest Atlantic. Selecting the observer data as the more reliable dataset, Young et al. (2016) re-analysed the time series from 1992-2013 for bigeye thresher shark *per se*. They found no obvious change in the population trend over time and thus concluded that the northwest Atlantic population had stabilized. One older analysis from the southwest Atlantic, quoted in Amorim et al. (2009), indicated increasing catch rates from 1971-1989 and a gradual decrease from 1990-2001. However, the authors noted that during this period a change in the depth of fishing operations also occurred and this may have affected the time series (Amorim et al. 2009). There are no known available catch rate time series for bigeye thresher sharks from the Indian Ocean.

Current conservation and management designations and measures

The IUCN Red List classifies all three thresher species as "Vulnerable" (IUCN 2015). The Red List assessment for the bigeye thresher shark dates from 2007 and is supplemented by regional assessments of "Vulnerable" in the eastern central Pacific, "Endangered" in the northwest and western central Atlantic, "Near Threatened" in the southwest Atlantic, "Data Deficient" in the Mediterranean Sea; and "Vulnerable" in the Indo-West Pacific (Amorim et al. 2009).

Two of the five t-RFMOs have adopted conservation and management measures which pertain to bigeye thresher sharks. In 2009, ICCAT adopted a measure requiring all members to prohibit retention of bigeye thresher sharks with the exception of Mexican small-scale coastal fisheries with catches of less than 110 fish (ICCAT Resolution 09-07). IOTC's measure requires all members to prohibit retention of all species of thresher shark (IOTC Resolution 13/06). In addition to these species-specific measures, starting with ICCAT in 2004 (Recommendation 04-10), and followed by IATTC (Resolution C-05-03) and IOTC (Resolution 05/05) in 2005, WCPFC in 2006 (CMM 2006-05) and CCSBT in 2008, all of the t-RFMOs have adopted a 5% fins-to-carcass ratio as a means of controlling shark finning for all species including thresher sharks (Clarke et al. 2014a).

All three species of thresher sharks were listed on Appendix II of the Convention on the Conservation of Migratory Species of Wild Animals (CMS) in November 2014. CMS Appendix II listing encourages international cooperation towards conservation of shared species. Subsequently, the three thresher species were added to the Convention on Migratory Species (CMS) Memorandum of Understanding (MOU) for Sharks in February 2016. The function of the MOU is to develop a Conservation Plan to guide cooperation between the signatories to CMS Convention as well as other interested stakeholders.

A proposal to list the bigeye thresher shark, along with the pelagic and common threshers as look-alike species, on Appendix II of the Convention on International Trade in Endangered Species of Wild Flora and Fauna (CITES) was first posted on 2 May 2016 and revised on 1 June 2016. The proponents for the proposal include Sri Lanka, the Bahamas, Bangladesh, Benin, Brazil, Burkina Faso, the Comoros, the Dominican Republic, Egypt, the European Union, Fiji, Gabon, Ghana, Guinea, Guinea-Bissau, Kenya, the Maldives, Mauritania, Palau, Panama, Samoa, Senegal, Seychelles and Ukraine. The proposal will be considered at the 17th Conference of the Parties (COP) in Johannesburg, South Africa from 24 September-05 October 2016. If listed, all exports of thresher sharks, including landings in non-flag State ports will require permits to be issued by the flag State CITES Management Authority. Export permits are contingent upon legal acquisition and non-detriment findings (NDFs), the latter of which represents a certification by an authorized CITES Scientific Authority that the proposed export is not detrimental to the survival of the species (Clarke et al. 2014b).

Sustainability status evaluation

This report presents the preliminary results of a Pacific-wide, spatially-explicit sustainability risk assessment of bigeye thresher shark. Risk assessment tools have been developed in response to data limitation problems in the evaluation of fishing effects on non-target species, including sharks and other elasmobranch species (Stobutski et al. 2002, Griffiths et al. 2006, Braccini et al. 2006, Zhou & Griffiths 2008, Cortés et al. 2010, Gallagher et al. 2012). Recent applications have used semi-quantitative approaches (namely productivity-susceptibility analysis) and demographic methods to estimate population productivity, without quantifying total impacts from fisheries or fishing-induced mortality. Such risk assessments applied to pelagic sharks caught in Atlantic pelagic longline fisheries identified bigeye thresher as one of the most vulnerable species to exploitation (Cortés et al. 2008, 2010, 2012).

Herein, we develop and apply a quantitative framework for estimating spatially-explicit fishing mortality and derive a sustainability status for the species as the ratio of total impact to a maximum impact sustainable threshold (MIST) reference point. Rather than following a traditional stock assessment approach, which relies heavily on population processes that for sharks are often poorly understood, this spatially-explicit approach is based on species productivity, inferred distribution and data on the occurrence, characteristics and intensity of fishing. The quantitative framework allows uncertainty to be quantified and propagated throughout the assessment process. An important outcome is that impact, sustainability risk and uncertainty can be partitioned spatially and/or among fishery sectors, allowing more focused management.

2 DATASETS

Review of the potential sources of catch, effort and size data for *A. superciliosus* in the Pacific identified the following as key data sets:

- Non-public domain longline catch and effort data for the entire Pacific maintained in the SPC CES database and accessible to the ABNJ TCSB via the WCPFC Secretariat ("CES longline logsheet data");
- Non-public domain longline observer data maintained by SPC as part of the ROP and on behalf of Australia, the Cook Islands, the Federated States of Micronesia, Fiji, French Polynesia, the Republic of the Marshall Islands, New Caledonia, New Zealand, Samoa, Solomon Islands, Tonga and Vanuatu and accessible to the ABNJ TCSB through data confidentiality agreements with each country for use in the ABNJ Tuna Project ("SPC observer data");
- Non-public domain United States longline observer data provided directly to the ABNJ TCSB for use in the ABNJ Tuna Project under a data confidentiality agreement ("US observer data");
- Non-public domain Japan longline observer data provided to the ABNJ TCSB and to NIWA under a data confidentiality agreement specific to this BTH assessment ("Japan observer data").

Each of these datasets is described separately below. Data confidentiality agreements necessary to obtain access to the data required for this study have precluded the provision of the majority of datasets described in this report to NIWA. As a result, the ABNJ (Common Oceans) Tuna Project Technical Coordinator-Sharks and Bycatch (ABNJ TCSB) has taken on the role of data manager and has served as an intermediary between NIWA and the raw datasets.

2.1 CES longline logsheet (commercial effort) data

The data were downloaded by the ABNJ TCSB from CES on 11 March 2016 and again on 14 April 2016 as there was an update to the data by SPC. The downloaded data consisted of 269,702 records aggregated by year (1950-2014), month (1-12), flag[2], and 5 degree latitude by 5 degree longitude (5x5) cell (ranges: -82.5 to 62.5 latitude; 7.5 to 362.5 longitude). The coordinates for each grid represent the southwest corner of each 5x5 cell. Catch data were provided for albacore (ALB), bigeye (BET), Pacific bluefin, skipjack (SKJ), southern bluefin, and yellowfin tunas (YFT); black, blue and striped marlin; Indo-Pacific sailfish; shortbilled spearfish; broadbill swordfish (SWO); blue, "mako", silky, oceanic whitetip, "thresher" and "other" sharks; and "other".

Annual effort totalled 1.3-1.4 billion hooks in 2011-2013, with lower effort recorded for 2014 likely as a result of incomplete reporting at the time of writing (Figure 1). Overall trends in effort and target species catch in the WCPO longline fishery through 2014 were reviewed by Williams & Terawasi (2015).

[2] Flags (countries and fishing entities) include AU, BZ, CK, CN, ES, FJ, FM, GU, ID, JP, KI, KR, MH, NC, NU, NZ, PF, PG, PH, PT, PW, SB, SN, TO, TV, TW, US, VN, VU and WS (see http://www.nationsonline.org/oneworld/country_code_list.htm for code and country name matching)

Catch was downloaded in number of sharks as that is the unit used in the observer datasets and is likely to be more accurate than weight-based measures. The total number of “thresher” sharks in the dataset was 129,933 with an annual high of 28,991 in 2014 (data for 2015 were likely incomplete at the time of writing). The first “thresher” shark to be recorded on a logsheet was by Papua New Guinea in 1997; other flags’ first reporting was in 1998 (Samoa), 2000 (US), 2002 (Fiji), 2006 (Spain), 2007 (Australia and New Zealand), 2008 (Japan and Taiwan), 2010 (Korea and New Caledonia), 2011 (Cook Islands), 2013 (FSM and Vanuatu), 2014 (Kiribati) and 2015 (China). These dates probably reflect the year in which the logsheets first provided a space for recording thresher sharks rather than the actual first encounter of a thresher shark by each flag’s fishing vessels.

The CES longline logsheet data were aggregated by year, month, 5x5 cell and flag to obtain the total effort in hooks fished per strata.

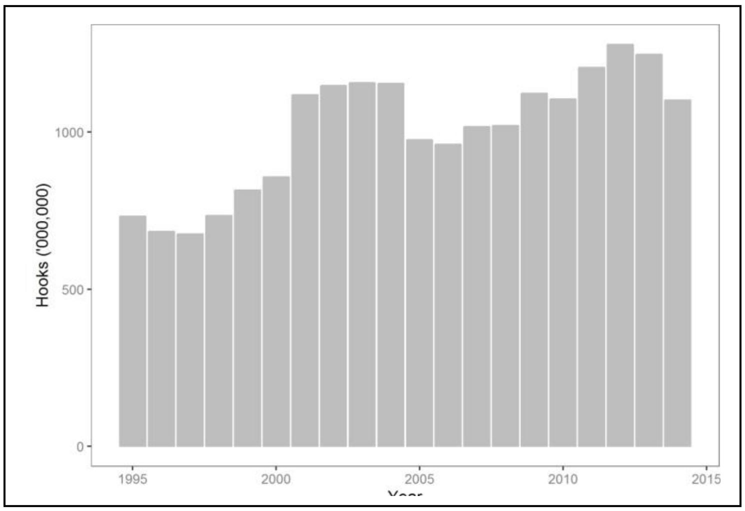


Figure 1. Total longline effort for the Pacific Ocean, 1995-2014 as downloaded from the SPC Catch Effort Query System (CES as of April 2016).

2.2 SPC observer data

These data were downloaded by the ABNJ TCSB on 3 March 2016 through a special TUBS interface for SPC and WCPFC Secretariat staff. Some issues with large files sizes were encountered which prevented remote downloading of all necessary files at that time; the remaining large data files were received on 8 March 2016. Downloaded data consisted of two files for each fleet and year: one file that contained set-level information with one row per set and one file that contained catch records for individual sharks with one row per shark or ray caught.

Length data were provided in some datasets (i.e. SPC and Japan data), but were not formatted for use[3]. Length data can be used to distinguish life stages of the species, potentially allowing for fishing impacts to be evaluated for different life stage groups, but this requires further development of the

[3] Length data presumably exist in the US observer programme data but were not included in the extract provided by the US for this study.

methodology in this assessment which has not been undertaken. Fate and condition data were provided and used to distinguish between BTH which were and were not alive upon release. This was accomplished by first removing all BTH which were recorded as unknown either at landing or upon release. Then those with fate codes beginning with R (retained) or DFR (discarded, fins retained), or condition codes A3 (alive but dying) or D (dead) were considered dead and all others were considered to be alive at release. These data could be used to examine the trend in the post-capture survival. Data on BTH sex exist in the SPC observer dataset (Clarke et al. 2011, Rice et al. 2015) but were not included in the subset of data downloadable through the TUBS interface.

To link each catch record to its set characteristics, a unique identifier was created by combining set identifiers and trip identifiers in the set database. At this step, 522 set records shared identifiers with another set. As it was impossible to know which, if any, of these set records were correct, all 522 were removed. From the remaining number of sets (n=41,048), containing 3,388 BTH, the following number of sets (and BTH records) were removed sequentially:

- Removed due to missing lat/long information (1,947 sets and 180 BTH);
- Removed due to not being within the year range 1995-2014 (4,791 sets and 51 BTH);
- Removed due to missing hooks fished values (715 sets and no BTH);
- Removed due to missing hooks between floats (68 sets and no BTH);
- Removed due to too many or too few hooks (965 sets and 34 BTH);
- Removed due to too many or too few hooks between baskets (220 sets and 7 BTH); and
- Removed due to being outside the spatial boundaries of the assessment (4,226 sets and 4 BTH) (see Section 3.1 for the spatial range criteria applied).

Removals related to missing values (hooks between floats, latitude, longitude and number of hooks fished) were necessary because these values are likely to be very important in the standardizations and missing values may interfere with coefficient estimation. Extreme values of hooks fished (i.e. <500 or >4000) were considered to represent abnormal fishing operations and were also thus removed. Similarly, sets recording fewer than four, or more than 45 hooks between baskets were considered dubious and were removed. Finally, sets before 1995 (the year when the SPC regional observer program began in earnest) were removed due to expected poorer data quality in the initial years, and sets after 2014 were removed to avoid biases associated with incomplete reporting.

A number of other filters applied or discussed in Rice et al. (2015) were considered but not applied as follows:

- sets from fisheries known to be targeting sharks (e.g. Papua New Guinea) and those sets for which the set header field target_shk_yn=yes (Table 3), were not removed *a priori* as it was considered that any shark targeting effect could be addressed through the catch rate standardization;
- removing sets from small national observer programs with < 100 sets each was not considered necessary as this analysis will not be using the observer program identifier in lieu of actual (lat/long) location;

- removing records considered to be outside the sea surface temperature (SST) range of species was not done due to doubts about the certainty of bigeye thresher species' SST range and a preference to address habitat issues through a lat/long exclusion criterion; and

- removing records where the catch rate of BTH was greater than the 97.5th percentile of nominal mean CPUE for the dataset as a whole was not done because BTH may exhibit schooling behaviour and thus we might expect to see rare large catches.

In total 12,932 sets were removed from the analysis, containing 276 BTH, leaving 28,116 sets and 3,112 BTH[4]. The annual number of sets observed and number of BTH caught per year in the SPC observer dataset are shown in Table 1.

Table 1. Summary of BTH catch and effort information by year available in the SPC observer dataset.

Year	**Sets**	**BTH Catch Records**
1995	469	3
1996	485	4
1997	621	9
1998	581	38
1999	456	39
2000	507	61
2001	634	62
2002	1 576	136
2003	1 536	87
2004	1 428	86
2005	1 834	247
2006	2 497	876
2007	1 960	698
2008	1 540	111
2009	1 581	150
2010	1 284	23
2011	1 346	63
2012	1 566	187
2013	3 328	131
2014	2 887	101

The SPC observer dataset is distributed with low coverage over a wide area from 1993-2015. Detailed analysis of thresher shark data in the SPC observer set was conducted by Clarke et al. (2011) and Rice et al. (2015) but it should be noted that most of those analyses were conducted for *Alopias* spp (see section 1). The spatial distribution of the SPC observer dataset is shown in Figure 2.

[4] There were n=2,001 sets with 183 BTH that had date or time errors (missing values, or Haul Start before Set Start) but these were retained pending a decision about whether time of day, soak time, hours of set during night, or other time-related variables would be used in the standardization model.

2.3 US observer data

Data from the US longline observer programme were prepared by NOAA on 11 March 2015 and sent by post to the ABNJ TCSB in the Federated States of Micronesia. When the ABNJ TCSB began using the data for this study in March 2016 it was discovered that all Hawaiian longline fleet data for 2002 were missing from the provided dataset. Upon request, the missing 2002 data were provided by NOAA via a secure download facility on 24 March 2016. Table 2 shows the number of sets observed, total catch, and the number of BTH caught per year, for the observed sets in the Hawaii-permitted and American Samo-permitteda longline fleets.

Table 2. Number of sets observed, total number of fish (etc.) caught, and BTH caught by year in the observed sets of the two fleets covered by the US observer programme and used in this study.

Year	Sets	Total Catch Records	BTH Catch Records	Sets	Total Catch Records	BTH Catch Records
	Hawaii-permitted Longline Fishery			American Samoa-permitted Longline Fishery		
1995	519	26,422	75	0	0	0
1996	587	28,560	208	0	0	0
1997	443	30,507	140	0	0	0
1998	556	31,511	229	0	0	0
1999	421	24,794	83	0	0	0
2000	1,370	69,393	399	0	0	0
2001	2,699	132,214	692	0	0	0
2002	3,296	152,505	1,271	0	0	0
2003	3,078	160,255	765	0	0	0
2004	3,855	186,788	1,789	0	0	0
2005	5,829	274,322	1,158	0	0	0
2006	4,120	180,912	1,521	235	27,100	20
2007	4,762	223,752	1,293	327	40,497	19
2008	4,968	226,722	1,075	266	29,254	19
2009	4,683	199,899	1,660	237	26,167	24
2010	4,958	246,262	1,381	890	100,052	61
2011	4,572	236,003	1,319	1,017	90,357	67
2012	4,639	224,117	1,708	592	57,427	28
2013	4,389	262,919	1,645	584	44,863	49
2014	4,857	279,463	3,828	515	40,115	43
Total	64,601	3,197,320	22,239	4,663	455,832	330

Length and sex data may exist in the US observer dataset but were not included in the subset provided for this study. Regarding fate and condition classification, the US observer programme only records shark condition at retrieval as alive or dead, and at release as alive, dead or kept. This simplified distinguishing between BTH which did and did not survive until release.

As for the SPC observer data, a number of filters were considered to clean and format the US observer data (see section 2.3). Of these, six filters were applied with the following results:

- Removed due to missing lat/long information (9 sets and 1 BTH);
- Removed due to missing hooks fished values (6 sets and no BTH);
- Removed due to missing hooks between floats (22 sets and 8 BTH);

- Removed due to too many or too few hooks (293 sets and 17 BTH);
- Removed due to too many or too few hooks between baskets (186 sets and 9 BTH); and
- Removed due to being outside the spatial boundaries of the assessment (551 sets and 11 BTH) (see section 3.1 for the spatial range criteria applied).

In total 1,067 sets were removed from the analysis, containing 46 BTH, leaving 69,264 sets and 22,523 BTH.

The US observer dataset is a rich source of BTH data with considerably more records for this species than the SPC dataset (22,523 BTH in 69,264 sets versus 3,112 BTH in 28,116 sets). The spatial distribution of the US observer dataset is shown in Figure 2.

2.4 Japanese observer data

Japan's longline observer program has been operating since 2007 but has only been fully implemented since 2011. A data confidentiality agreement was negotiated between the Japan Fisheries Agency, NIWA and the ABNJ (Common Oceans) Tuna Project on 24 March 2016. Data were provided using a secure internet file sharing system on the same day and re-provided on 25 March 2016 to correct minor formatting errors. The number of sets observed, total number of thresher sharks caught and the number of BTH caught per year for the observed Japanese longline sets as received are shown in Table 3.

Table 3. Number of sets observed, total number of threshers caught, and BTH caught by year in the observed sets of the Japanese longline fleet as provided by Japan. Note that Japan did not provide catch records for species other than thresher sharks (bigeye, pelagic, common and unknown).

Year	Sets	Total Catch of Threshers	Catch of BTH
2007	13	4	4
2008	143	27	20
2009	89	4	2
2010	162	183	28
2011	638	275	152
2012	908	357	57
2013	1,756	972	376
2014	1,877	788	513
2015	1,371	355	171
Total	6,957	2965	1323

Length data were provided for 949 BTH and sex data for 939 BTH. These data have not yet been formatted for use. Fate and condition data were not provided.

Filters were considered and applied as for the other observer data (see section 2.3). Of these, six filters were applied with the following results:

- Removed due to missing lat/long information (317 sets and 28 BTH);
- Removed due to missing hooks fished values (1 set and 3 BTH);
- Removed due to missing hooks between floats (33 sets and 20 BTH);

- Removed due to being outside the spatial boundaries of the assessment (218 sets and 6 BTH) (see section 3.1 for the spatial range criteria applied).

In total 569 sets were removed from the analysis, containing 57 BTH, leaving 6,405 sets and 1,266 BTH.

The Japan observer dataset contains 1,266 BTH from 6,405 sets. The number of BTH per set in the Japan observer dataset (0.20) is intermediate between that of the SPC observer dataset (0.11) and the US observer dataset (0.33). The spatial distribution of the Japanese observer dataset is shown in Figure 2.

2.5 Composite dataset

A composite dataset composed of the SPC, US and Japanese observer data consisting of 104,320 sets and 26,917 BTH was compiled on 25 March 2016. The distribution of BTH captures by 5x5 grid and source dataset is shown in Figure 2. The annual observed effort and annual observed catch by source dataset are shown in Figure 3.

Fields such as the number of hooks between floats (*HBF*), *bait_type*, *hook_type* and *wire_trace* that were recorded for some sets were retained for analyses. *HBF* was used as a proxy for the fishing depth of pelagic longline sets. Information on the time of set start and hauling start was used to estimate fishing duration at night (number of hours fishing in dark conditions) for each set. This was done by relating the reported setting and hauling times with the expected sunrise and sunset times at each location and date.

A standardised measure of SST was assigned to each set, corresponding to monthly average SSTs recorded from 1995 to 2014, available from NOAA Extended Reconstructed Sea Surface Temperature (ERSST) database (http://www1.ncdc.noaa.gov/pub/data/cmb/ersst/v4/netcdf/). Other, finer scale datasets were sought but could not be accessed in a workable format within the timeframe of this study.

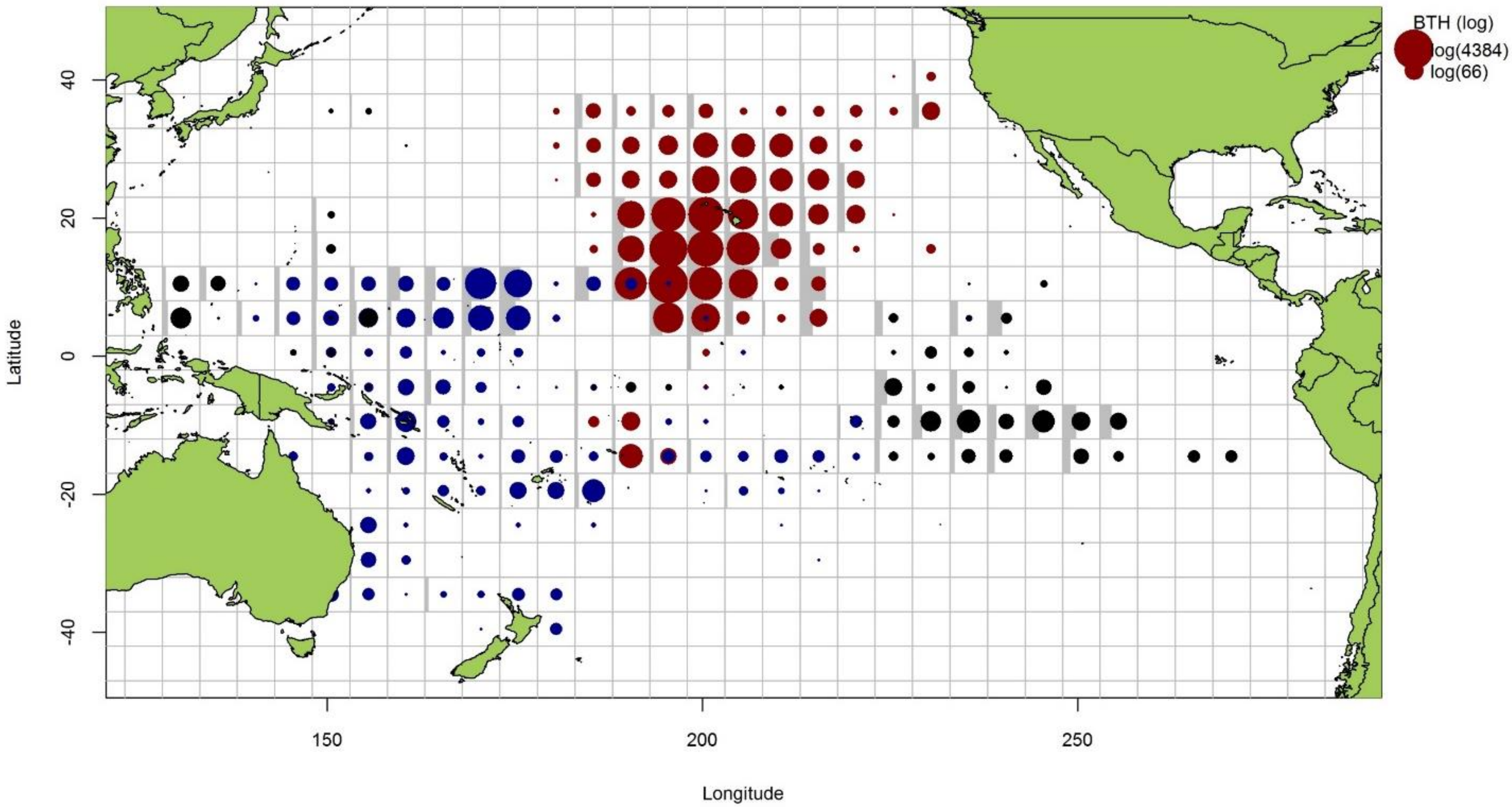
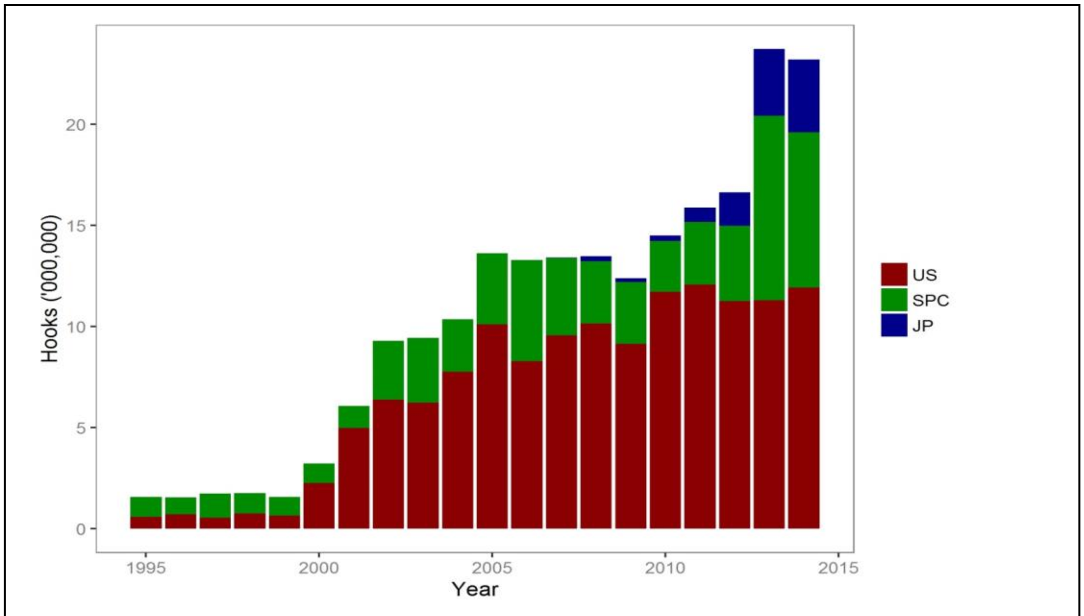


Figure 2.Distribution of BTH caught in observed sets in the Pacific, 1995-2014. Catches from the SPC dataset are in blue, the US dataset in red and the Japanese dataset in black. The size of the circle is proportional to log(catch) as shown in the legend. The grey-shaded portion in each grid square represents the proportion of sets with positive catches of BTH. Catches from grids where fewer than three vessels caught BTH are not shown. The numbers in parentheses are numbers of BTH caught.



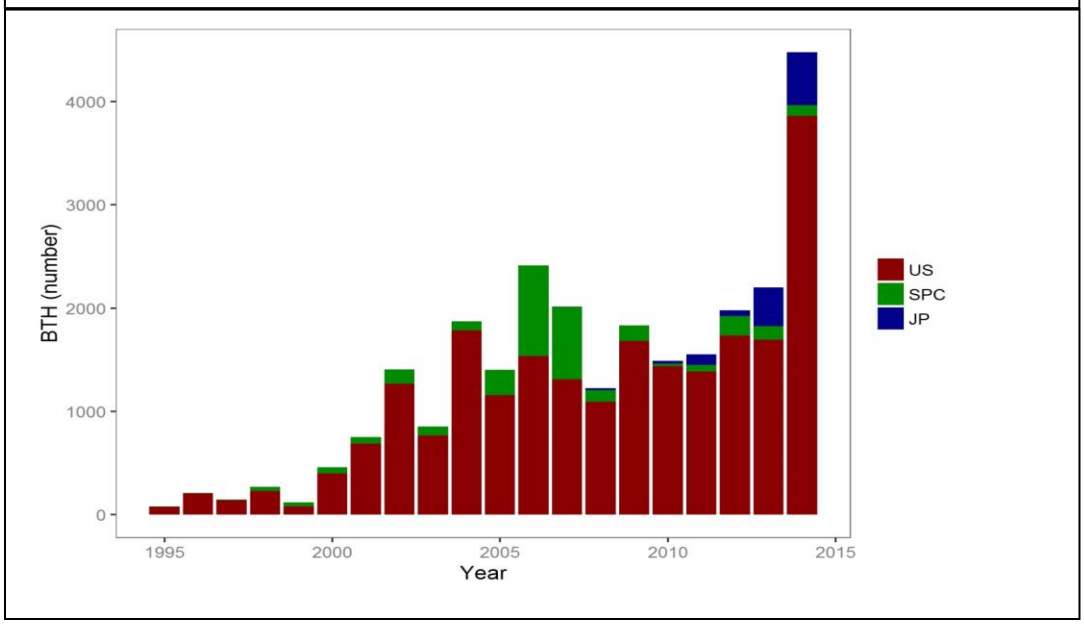


Figure 3. Total observed effort (in million hooks) by data source (top panel) and total number of BTH observed by data source (bottom panel), 1995-2014.

3 APPROACH AND METHODS

3.1 Analytical approach

The analytical framework is risk-based and spatially-explicit. Sustainability status S is assessed relative to current impacts from fisheries (or relative fishing mortality F) and a maximum impact sustainable threshold (MIST) limit reference point (LRP):

$$S = \frac{\text{Impact}}{\text{MIST}} \approx \frac{\text{F}}{\text{LRP}}$$

Uncertainty in all parameters is quantified and propagated through the assessment framework. In this context, sustainability risk R is the probability p, given the uncertainty, that the total impact exceeds the MIST:

$$R = \text{p}[\text{Impact} \; > \text{MIST}]$$

The assessment is conducted over a spatial grid of 5 by 5 degree latitude and longitude cells (section 3.2). Fishing impact is estimated as the average of fishing mortality F_i weighted by species relative abundance n_i in each cell:

$$\text{Impact} = \frac{\sum_i F_i n_i}{\sum_i n_i}$$

Cell-specific F_i is calculated as the product of fishing effort E and catchability q distinguished among (and summed across) fishery groups j :

$$F_i = \sum_j E_{i,j} q_j$$

where q_j expresses the fraction of the total population in each cell that is available for capture by each unit of effort, adjusted for capture efficiency in fishery group j .

Effort differentiation into fishery groups serves to handle the effects of different fishing operations and operational practices on total impact. Impacts are assumed to be cumulative across fishery groups and over the spatial domain of the assessment. As a result, sustainability risk, fishing impact and uncertainty can be disaggregated in space and among fishery sectors.

MIST is the sustainable reference threshold for the species. The MIST is defined based on population productivity inferred from life history data. Life history parameters are used to estimate a maximum intrinsic population growth rate *r*, with uncertainty. In turn, *r* is used to derive sustainable impact thresholds similar to the fishing mortality-based sustainability reference points (F_{crash}, F_{msm}, F_{lim}) described by Zhou *et al.* (2011).

The assessment is implemented in a flexible framework allowing incremental improvements and fine-tuning as data are augmented and/or better information becomes available.

A summary of data inputs, analytical methods and key parameters is presented in Figure 4. Details on all components are presented in the following sections.

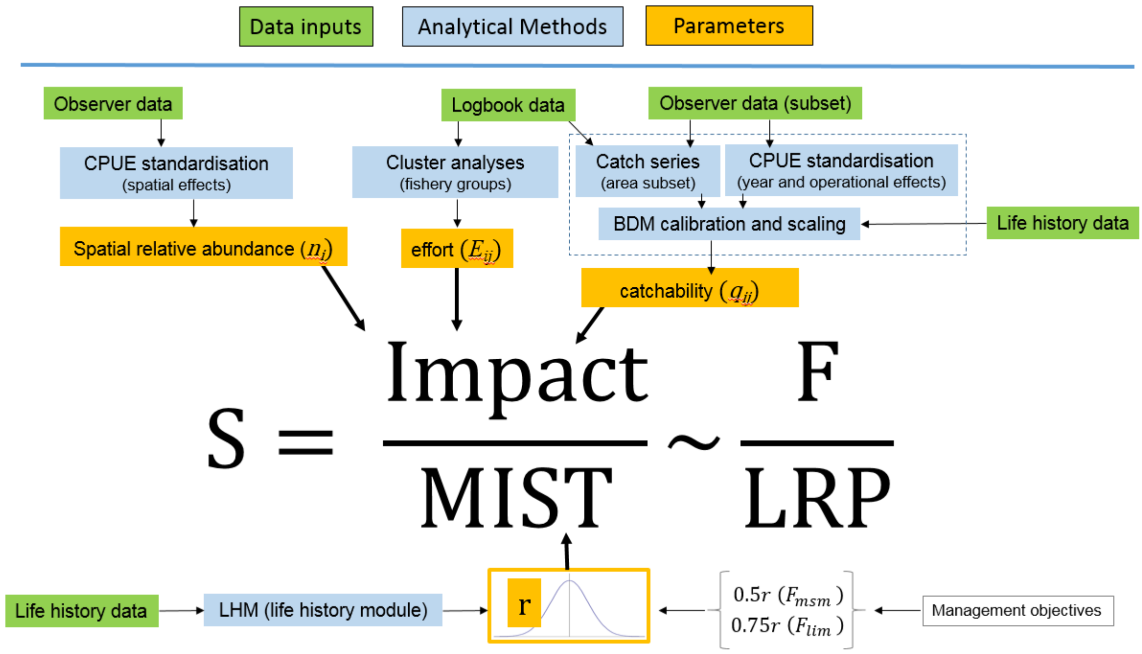


Figure 4. Conceptual representation of data inputs, analytical methods and key parameters used in Pacific-wide spatially-explicit sustainability assessment of bigeye thresher shark. BDM = Bayesian state-space biomass dynamics model. The dashed outline box represents analytical methods applied to an area subset of the available data.

3.2 Spatial and temporal domains of the assessment

The spatial domain of the assessment was defined as the region between 38°N and 42°S latitude and 120°E and 70°W (290°E on map) longitude. The latitudinal range is based on published information on the geographic distribution of bigeye thresher in the Pacific Ocean (Compagno 2001, Matsunaga & Yokawa 2013). The longitudinal range is arbitrarily defined, with the eastern limit set to encompass the full eastern extent of the Pacific (i.e., area offshore of the boundary between Peru and Chile) and the western limit set near the Makassar Strait between Borneo and Sulawesi.

The assessment is conducted over a spatial grid of 5 by 5 degree latitude and longitude cells, corresponding to the spatial resolution of the catch and effort data available for assessment. Three area subsets were distinguished for analyses within the spatial domain of the assessment (Figure 5):

1) Assessment Area - corresponding to all grid cells in which at least one specimen of *A. superciliosus* was caught between 2000 and 2014 (n=219 cells);
2) Core Area – corresponding to those grid cells that together contributed 95% of *A. superciliosus* captures between 2000 and 2014 (n=62 cells).
3) Calibration Area – subset of grid cells from the Core Area (above) corresponding to the area covered by the US Hawaii observer data (n=33 cells).

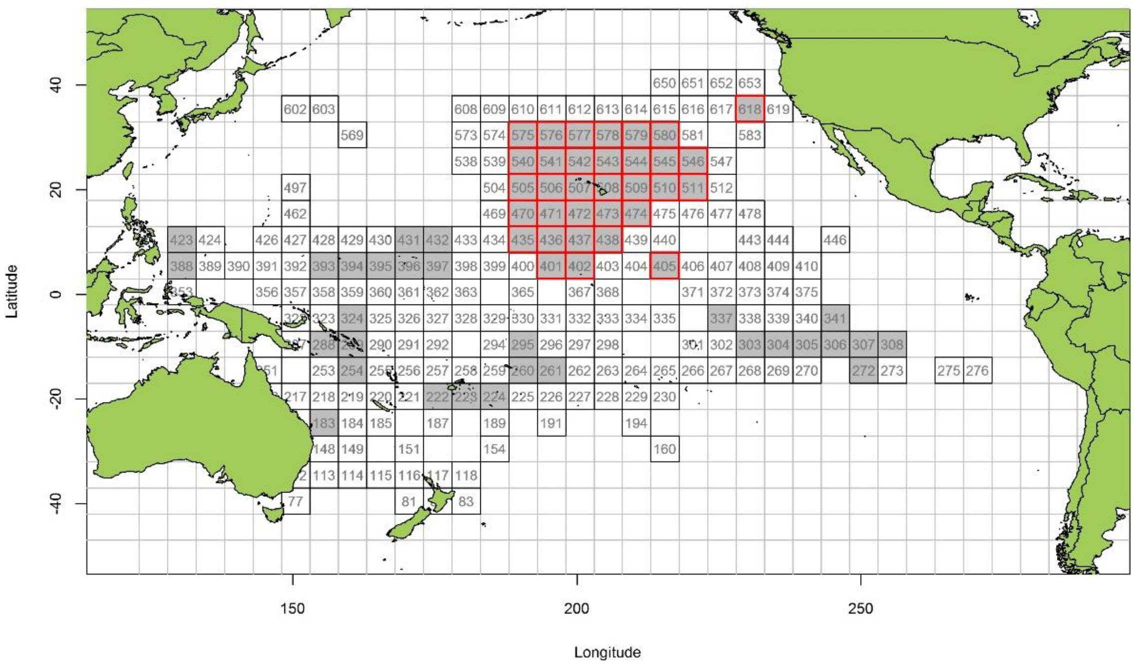


Figure 5.Spatial domain of the assessment as defined in 5x5 degrees of latitude and longitude grid cells, showing the three area subsets considered for analyses: Assessment Area (cells with numbers); Core Area (shaded grey cells), and Calibration Area (cells with red borders). Cell numbers were assigned sequentially from west to east and from south to north and are used to identify each cell in the datasets.

The timeframe of the assessment was set to include all commercial effort (logsheet) and observer data from 1995 to 2014 in preliminary analyses. The start of this period corresponds to the full-scale implementation of the SPC and US observer programmes. Species distribution was estimated using the composite observer dataset including data from 2000 to 2014 (section 3.4). The start year of 2000 reflects the small amount of observer data in previous years (Figure 3). The catchability (*q*) parameter calibration was performed using observer and commercial effort data for the period 1995-2014. A longer time period was considered in this process to better inform the catch series and abundance index required by the calibration. Impact was estimated using the total commercial pelagic longline fishing effort from the last fifteen years (2000-2014).

3.3 Targeting strategies and fishery groups definition

Fishery groups or targeting strategies were determined by performing hierarchical clustering analyses on logsheet data using the "k-means" algorithm (see Hoyle *et al.* (2015) for details). Logsheet data (rather than observer data) were used as they contain complete and reliable information on catch composition by species for the main target species.

Catch data for albacore tuna, southern bluefin and yellowfin tuna, bigeye tuna, broadbill swordfish and striped marlin were clustered over two periods (1995–2004 and 2005–2014) to account for potential changes in fishing operations over time. The optimal number of clusters was determined based on the maximum reduction of mean square error (Figure 6).

For both time periods, the analyses produced four clusters corresponding to a predominance of BET, ALB, YFT or SWO in the catch, as well as an additional cluster ('others') in which none of the main five target species (above) were caught. The five clusters were used to distinguish targeting strategies in the assessment.

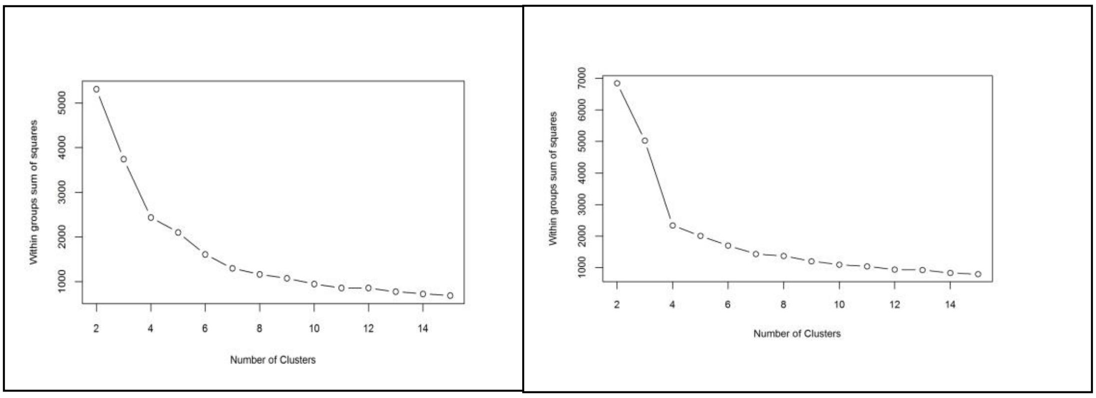


Figure 6. **Diagnostics from kmeans cluster analysis showing the optimal number of targeting strategies based on the species composition of the longline catch for 1995-2004 (left) and 2005-2015 (right).**

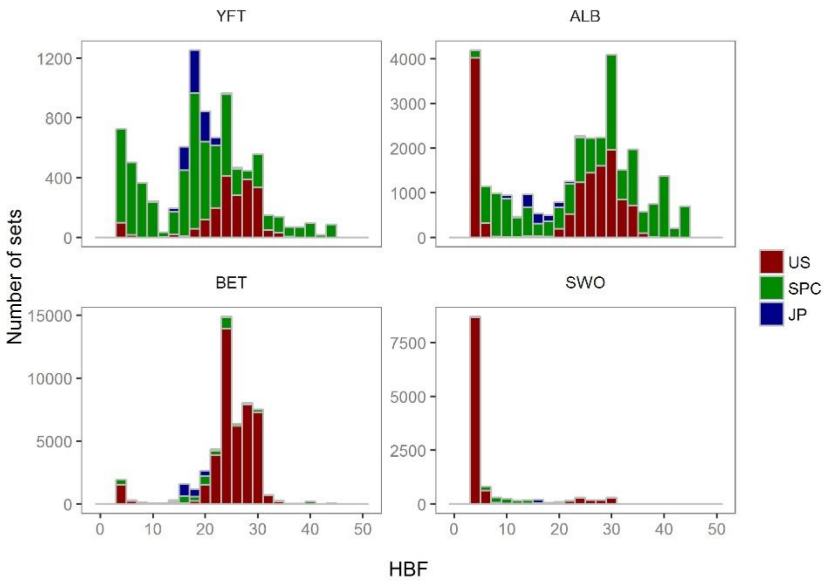
Observer sets were then assigned a targeting strategy based on the results of the clustering analysis performed on the logsheet data. A target species was assigned to each combination of grid cell, year, and month in the logsheet data, and then all the observer records were assigned a targeting strategy based on year, month, and set location. This approach was used because there appears to be little reliable information on the targeting strategy for all observer programmes (especially SPC). We aimed to "assign" a targeting strategy based on location (5x5 grid cell) and time (year/month) of the observed set using the assumption that the ALB, BET, YFT and SWO fisheries would be separated in space and/or time. It has been suggested that the targeting strategies for the Japan and US fleets are more straightforward, and could be determined using prior information such as Hooks between Floats (HBF) or recorded targeted species. This has not been considered for two reasons: first, it is difficult to relate the observer data to the logsheet data due to differences in the resolution of the datasets (5x5 vs 1x1 (or finer)) and the lack of operational characteristics in the latter. Additionally, target strategy directly inferred from other effort variables (such as HBF) may lead to double counting of information if it is also included as an explanatory variable in a standardisation analysis. Our approach permitted us to account for differences in targeting strategies in the observer data (and spatial and year effects standardisations), despite incomplete and/or unreliable information.

Variations in the number of hooks between floats (HBF) and fishing duration at night among targeting strategies are shown in Figure 7. Sets targeting BET generally fished deeper (HBFs mostly ranging between 20 and 30) and operated during daylight hours, right before sunset. Sets targeting SWO were mostly shallow and fished during the night. Other targeting strategies (YFT and ALB) covered a broad range of HBF values (with some differences among datasets) and mainly fished during daylight hours.

Agreement between targeting strategies inferred from cluster analyses and recorded target species was assessed using the Japanese observer data (not including SBT effort). Recorded target species in the Japanese observer data are believed to be representative of targeting strategies (Y. Semba, AFFRC, pers. comm.). Proportions of matching sets (i.e. agreement between inferred vs recorded target species) were 62% for ALB, 59% for YFT, 94% for BET and only 5% for SWO.

Fishery groups were defined as the combination of targeting strategies and fishing season (Jan-Mar, Apr-Jun, Jul-Sep and Oct-Dec). Commercial effort (logsheet) data were then categorised into fishery groups for impact estimation. Each group is assumed to represent different operational characteristics of the effort, as this is likely to affect capture efficiency for *A. superciliosus*.

(a)



(b)

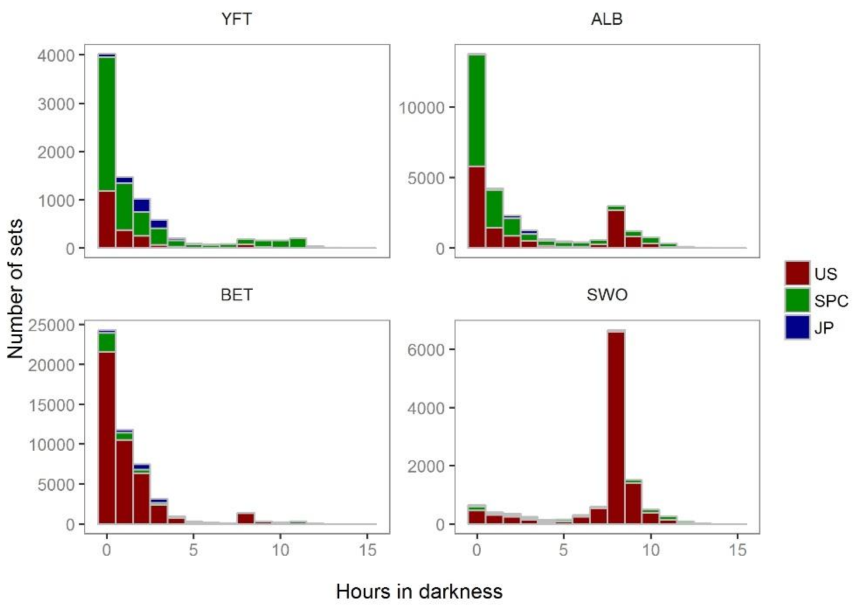


Figure 7: Total observed effort (no. of sets) as related to (a) hooks between floats (HBF) and (b) nighttime fishing duration (hours in darkness) among targeting strategies (YFT, ALB, BET and SWO) and observer datasets (US, JP and SPC) in the Assessment Area, 2000-2014.

3.4 Species distribution estimation

3.4.1 Approach and input data

Standardisation analyses performed on observer catch and effort data were used to infer the spatial distribution of *A. superciliosus*. The composite observer dataset for the period 2000-2014 was used. Data from 1995-1999 were excluded owing to comparatively limited spatial and numerical coverage.

Two standardisation models were applied for comparison: a zero-inflated negative binomial model (ZINB) (Zuur et al. 2009) and a geo-statistical delta-generalised linear mixed model (delta-GLMM) (Thorson et al. 2015). Both were used to standardise catch rates of *A. superciliosus* in 5x5 degree cells. The standardised catch rates or relative densities are assumed to be representative of spatial abundance distribution for the species.

Data from all observed longline sets were included in the spatial standardisations (i.e., no representative 'fishery subset' was defined for the species). Outputs from both models as well as strengths and limitations are compared and discussed in the context of spatially-explicit sustainability risk assessment for pelagic shark species.

3.4.2 ZINB standardisation

ZINB models serve to handle overdispersed count data with excessive number of zeros (Zuur *et al.* 2009). The relationship between the response variable (in this case, the number of *A. superciliosus* caught per set) and a set of explanatory variables is modelled as a mixture of an encounter probability (binomial process) and a negative binomial count process (that allows for overdispersion and zero occurrences).

The estimation of spatial effects in each grid cell requires a large number of coefficients to be estimated. To reduce the number of parameters and improve estimation, the fitting of the ZINB model was restricted to observer catch and effort data from the Core Area (Figure 5, section 3.2). This was required to ensure successful model convergence. Likewise, convergence problems caused by the estimation of a large number of coefficients precluded the inclusion of vessel effects in the ZINB model. The implication of this is that the abundance outside the Core Area is assumed to be very low so that its contribution to the overall fishing impact on the whole population is negligible.

Explanatory variables considered in spatial standardisations are listed in Table 4. A number of variables including *bait_type*, *hook_type*, *wire_trace*, *sst* and *night_fishing* were included in preliminary analyses but excluded from the final models due to missing or ambiguous values (*wire_trace* and *hook_type*); too many values (too many coefficients to be estimated and no clear basis for grouping) (*bait_type*); confounding effects with other covariates (*night_fishing*) and dubious relationships to the response variable (*sst*). Other variables were offered sequentially, producing a series of nested models. The same sets of variables were offered simultaneously to both the zero and count components of ZINB models. Likelihood ratio tests with AIC (performed using function *lrtest* in R package *lmtest* (R core development team 2016)) were used to assess the effect of each additional variable on model fit and explanatory power. Alternative models were also compared using AIC (Akaike Information Criterion).

Table 4. Summary of explanatory variables offered to ZINB models for spatial standardisation of catch rates of *A. superciliosus* in observed pelagic longline fisheries in the Pacific Ocean. Continuous variables were modelled as natural splines with 3 degrees of freedom.

Variable	Type	Description
year	Categorical	Calendar year (2000-2014)
cell	Categorical	5x5 degree grid cells in the Core Area
month	Continuous	Calendar month (1-12)
Target	Categorical	Targeting strategy
log(effort)	Offset	No. of hooks per set
HBF	Continuous	Hooks between floats
bait_type	Categorical	Types of bait used
hook_type	Categorical	Types of hooks used
wire_trace	Categorical	Presence/Absence (retention effect)
night_fishing	Continuous	Fishing duration at night (hours)
SST	Continuous	Sea surface temperature

Spatial indices of relative abundance were derived as the predicted catch rate (no. of *A. superciliosus* caught per 1000 hooks) for each grid cell in the Core Area, with other covariates fixed to a reference value corresponding to the coefficient calculated for the intercept term (categorical variables) or the median observed value multiplied by the coefficient (continuous variables).

Model fit was assessed using a number of diagnostics plots, including observed versus fitted catch rates, plots of Pearson residuals versus fitted values and Pearson residuals by year and grid cell.

3.4.3 Delta-GLMM standardisation

The delta-GLMM model developed by Thorson et al (2015) allows for extrapolation to nearby cells (i.e., density estimation in cells with no observations) by assuming spatially correlated spatial variation. Similar to the ZINB, the delta-GLMM includes a binomial process that models the probability of encounter (i.e., proportion of sets that catch *A. superciliosus*) and a count process (positive catch rates) that follows a gamma distribution. Additional complexity relates to the integration and differentiation of fixed and random effects.

Random spatial variation and spatiotemporal variation are approximated using Gaussian Markov random fields over a number of 'knots'. The location of each knot is determined by applying the *k-means* clustering algorithm to the positional information in the available data (i.e., latitude and longitude data from all sets converted to eastings and northings). This results in a distribution of 'knots' with density proportional to sampling intensity (or in this case, fishing intensity as related to observer coverage). The knots define the model's 'predictive framework' and allow for piecewise-constant random fields approximation. This approach has a number of computational advantages and assumes that density at any location is equal to the density value estimated at the nearest knot. The number of knots can be specified within the model framework, allowing control over the accuracy of random effects estimation. This can also be used to achieve a balance of accuracy and computational speed (Thorson et al. 2015). Both the encounter probability and catch process are modelled using a link function and a combination of linear predictors including the random fields. Fixed effects are estimated using maximum marginal likelihood (approximated using the Laplace approximation), while integrating across all random effects. The model is implemented in template model builder (Kristensen et al. 2014).

For application to *A. superciliosus*, *year* was included as a fixed effect and *vessel* was included as a random effect in all models. Other variables considered and included as potential linear predictors were *fishery groups*, *HBF* and *month* (see Table 4, section 3.4.2 for details). The number of knots was fixed at 1000 in all runs. The estimation of spatial abundance indices (number of *A. superciliosus* caught per 1000 hooks) involved a two-step process: 1) fine-scale extrapolation; and 2) density estimation at the spatial scale of the assessment (5x5 degree cells).

The Assessment Area (Figure 5, section 3.2) was subdivided into a fine-scale (10x10 km cells) extrapolation grid. Density extrapolation was restricted to cells with observations (i.e., in which there was a recorded longline set start position) and to cells with no observations but a recorded longline set start position within a maximum distance of 50 km. The resulting predictive framework was composed of 296 045 square grids of 100 km^2 each and an extrapolation layer of 1000 knots. Relative abundance at the scale of 5x5 degree cells was calculated as the average density estimated in 10x10km cells in the predictive framework. Three separate delta-GLMM models were fitted and compared: 1) a spatial model (assuming constant spatial variation over time); 2) a spatiotemporal model (allowing spatial variation to differ among years); and 3) a core vessels model (like the spatial model in 1) but including only vessels that caught at least one specimen of *A. superciliosus*).

Spatial correlation was assessed using geometric anisotropy plots. Estimated vessel effects on encounter probability and positive catch rates were plotted (with 95% confidence intervals) and differentiated among contributing observer datasets.

3.4.4 Uncertainty estimation

Uncertainty in species distribution inferred from the final ZINB model was estimated using a bootstrap (resampling) procedure that resampled data from all sets within each grid cell (with replacement) and refitted the standardisation model to predict spatial indices (300 iterations).

Uncertainty in species distribution inferred from the delta-GLMM model was reported as the marginal standard deviations estimated for the spatial effects and spatiotemporal effects on encounter probabilities and positive catch rates. Details on the computation of marginal standard deviation for random fields are available in Thorson et al. (2015). However, uncertainty estimation and summarization for the delta-GLMM model still require further research (Thorson et al. 2015). Additional complications also arise when extrapolating spatial effects to obtain spatial indices on 5x5 cells. For these reasons, uncertainty for the spatial indices inferred from the delta-GLMM model is not formally quantified.

3.4.5 Key assumptions

The estimation of a species distribution layer using available data from observed fishing events assumes that the aggregated data from observer programmes from 2000 to 2014 are representative of the species distribution in the Pacific. The estimated spatial distribution for *A. superciliosus* is assumed to have remained constant over the timeframe of the assessment (2000-2014; see Section 5.2 for discussion of this assumption).

The delta-GLMM model applied in this study was designed to estimate population abundance from survey (fishery-independent) data and area-swept by trawl gear. Its application to estimate spatial indices of abundance for *A. superciliosus* using fishery-dependent catch and effort data from pelagic longlines assumes that all observed longline sets have a comparable area of impact. Constant gear-affected area has been assumed in the catchability studies for passive fishing methods including longline by Zhou et al. (2014).

3.5 Catchability estimation

3.5.1 Approach and input data

The approach to catchability estimation was developed based on the assumption that the available data were insufficient to estimate absolute catchability, but could be used to calibrate a relative catchability parameter for use in relative impact estimation. Plausible values for the population catchability scalar q were derived in a calibration exercise using available life history information for *A. superciliosus* and a representative subset of the observer data within a subsection of the Assessment Area (the Calibration Area (A_Ω) - see Figure 5, section 3.2). The Calibration Area accounted for 82% of all captures in the observer datasets and is assumed to be representative of population dynamics for the species.

The calibration fits a Bayesian state-space biomass dynamics model (BDM, Edwards 2016) to an index of relative abundance with year effects ($CPUE_\Omega$) (section 3.5.3) and a catch series (C_Ω) (section 3.5.2) (Figure 4). The model assumes a uniform prior on *log(K)* (the biomass at unexploited equilibrium) and an informed prior on *r* (the maximum intrinsic population growth rate) estimated using life history data (section 3.8). The maximum plausible values for *q* (i.e., values corresponding to lower *K* estimates) were derived from the posterior samples distribution. Thus, q_Ω is the maximum population catchability assumed to be constant over the Calibration Area A_Ω. The catchability scalar q_Ω is then adjusted by fishery group and scaled to the spatial resolution (5x5 degree cells) used to estimate fishing impact in the assessment.

3.5.2 Catch history

A catch history (C_Ω) for *A. superciliosus* in the Calibration Area A_Ω was constructed by scaling the number of observed captures by the ratio of total effort to total observed effort. Data from all observer sets in the Calibration Area for the period 1995-2014 and commercial effort (logsheet) data aggregated in 5x5 degree cells for the period 1952-2014 (which covers the time span of extracted logsheet data), were used.

Catch estimation was stratified by year, year and fishery group, or year and season (Jan–Mar, Apr–Jun, Jul-Sep, and Oct–Dec). The number of observed captures was multiplied by the ratio of the total number of hooks (logsheet data) and the number of observed hooks within each stratum, summed over all strata to obtain the annual catch from 1995 to 2014. Historical (pre-1995) catches were calculated by scaling the average observed catch for the period 1995–2014, by the ratio of the annual (logsheet) effort to the average annual observed effort (1995-2014) in each year from 1952 to 1994. The catch history calculated for the pre-1995 period is highly uncertain and is provided only as an indication (i.e., only the 1995-2014 catch history is included in BDM runs for q_Ω calibration).

3.5.3 Abundance index

Year effects standardisations of observer catch and effort (CPUE) data were used to estimate annual indices of relative abundance ($CPUE_\Omega$) for *A. superciliosus* in the Calibration Area A_Ω.

Standardisations were performed by fitting a ZINB model to the US Hawaii observer data in A_Ω from 1995 to 2014. These data accounted for the majority (82%) of observed BTH captures in the composite observer dataset (see sections 2.3 and 2.5) and provided a relatively long and spatially consistent time series of catch and effort information over a region with generally high observer coverage (10% or higher since 2000). Pre-2000 data were included to estimate a more informative index of abundance for the BDM process, but were characterized by comparatively limited observer coverage.

Explanatory variables included in year effects standardisations were *month*, *HBF*, *targeting strategy*, *effort* (log no. of hooks) and *subarea*. Variables were offered sequentially and nested models were compared using the likelihood ratio test and AIC.

Subarea was used to include spatial effects on a coarser scale than the 5x5 degree cells used to estimate species relative densities (section 3.4) and fishing impact (section 3.7). This was done to ensure that spatial effects on annual indices of relative abundance are estimated at a scale that reflects differences in fishing intensity (as opposed to an arbitrarily defined geometric grid). The data were partitioned into 12 knots (*subareas*) by applying the *k-means* clustering algorithm (similar to that used in the geostatistical delta-GLMM model (see section 3.4.3)) to position (latitude-longitude) data from all sets in the Calibration Area. The number of *knots* was based on the maximum reduction of mean square error from the clustering (as shown in section 3.3).

The aim of this analysis is to derive an annual CPUE index for use in q_Ω calibration. This requires the CPUE index to measure the average catch rate of BTH (numbers per 1000 hooks) with respect to the Calibration Area (not a specific subarea). Therefore spatial effects (coefficients for subareas), which are assumed to represent differences in abundance among subareas, need to be excluded when predicting the annual index (but spatial effects must be accounted for in the standardisation process). To this end, the following procedure was carried out:

The annual CPUE index for a “reference” subarea was predicted using the final ZINB model by fixing the value of all covariates (intercept term for categorical variables including *subarea* or a median value for continuous variables). A ‘non-spatial’ model (final ZINB model without spatial effects) was fitted to estimate the effort-weighted average annual CPUE over all subareas (Appendix A). Annual indices predicted by the final ZINB model for the reference subarea were then scaled to have the same mean as the annual CPUE predicted by the ‘non-spatial’ model:

$$CPUE_{\Omega}^{y} = CPUE_{leffort}^{y} \frac{\sum_i CPUE_{non-spatial}^{i}}{\sum_i CPUE_{leffort}^{i}}$$

Where $CPUE_{\Omega}^{y}$ is index of $CPUE_{\Omega}$ in year y; $CPUE_{non-spatial}^{i}$ is the CPUE index from non-spatial model in year i; and $CPUE_{leffort}^{i}$ is the CPUE index from the final model “leffort” in year i.

Sensitivity testing of year effects standardisation was performed by fitting a number of geostatistical delta-GLMM models (n=4) and a delta lognormal model to the same dataset and using the same explanatory variables as the final ZINB model.

3.5.4 BDM calibration

The index of relative abundance ($CPUE_\Omega$) (section 3.5.3) and catch history (C_Ω) (section 3.5.2) for *A. superciliosus* in the Calibration Area A_Ω are inputted into the BDM to estimate a range of plausible values for q_Ω.

A detailed description of the BDM model is presented in Appendix B. The model describes changes in biomass in response to a particular harvest regime and according to the generalised (hybrid) production function described by McAllister et al. (2000). The catchability scalar relates the abundance index and estimated biomass trajectory and is calculated as a set of most likely values relative to the values of other parameters, assuming a uniform prior on the natural scale.

For q calibration runs, the shape parameter value is arbitrarily fixed at 0.4 ($\varphi = 0.4K$) and both the observation errors and process errors are fixed at 0.05. BDMs are fitted to the catch history and abundance index for *A. superciliosus* in the Calibration Area, and to an informed prior on the maximum intrinsic population growth rate *r* for the species (lognormal with mean 0.03 and standard deviation 0.02) (section 3.7) (see Figure 4 for conceptual representation).

The population was unlikely to be in an unfished equilibrium state at the start of our time series in 1995 (i.e., initial biomass (depletion) level u<1). Initial depletion could not be estimated by the model and values u were randomly sampled from three normal distributions with means 0.3 (low initial biomass), 0.5 (medium initial biomass) and 0.7 (high initial biomass) and a standard deviation of 0.05. Each was sampled 300 times, for a total sample of 900 *u* values ranging from 0.15 to 0.84 (Figure 8). A BDM was fitted to obtain 1000 posterior samples of *q* for each *u*. Calibration runs are currently focused on the medium initial biomass level (i.e., depletion state ranging from 0.35 to 0.63 with a median of 0.5) and the assumptions of low (0.3) and high (0.7) initial biomass (depletion state) levels are examined in sensitivity tests.

A plausible range of *q* values corresponding to *K* distributions bounded by multiples of the lowest *K,* are retained from each of the 1000 BDM runs. *K* distributions are selected so as to represent the most precautionary signal (1x to 2x minimum *K*) and less precautionary signals (2x to 5x minimum *K* and 5x to 10x minimum *K*, respectively). This is done because the available data are generally uninformative for the biomass estimation process. The lack of contrast in the abundance index and potentially incomplete catch series do not permit us to constrain the upper range of the unfished biomass *K* (corresponding to the lower range for *q*), but allow successful estimation of the lower range (corresponding to maximum *q* values). The combined samples therefore, constitute the plausible range of q values across a probable range of *K* levels defined based on minimum *K* values. This approach does not fully capture the uncertainty in the catchability scalar, which is restricted to a statistically estimated distribution of minimum *K* values and a subjective but plausible set of *K* multipliers. Another way to achieve this is through the definition of an informed prior on *K* (i.e., making an informed guess as to what the maximum and most likely biomass values may be for the species in the Calibration Area). These, and potentially other options, will be explored in the Final Report.

The estimation process involves process error specification and inclusion. At present, process error standard deviation values ranging from 0.01 to 0.1 are being explored. Process error allows the model to account for inter-annual variability in stock biomass caused by temporal changes in biological processes that are not observed or modelled (Edwards 2016). In this case, this includes potential immigration/emigration of bigeye thresher to/from the Calibration Area. The effect of process error inclusion on *q* estimation is being tested in sensitivity analyses.

Sensitivity testing of the BDM calibration process is also being conducted by varying input assumptions and/or data and refitting the model to examine and compare outputs.

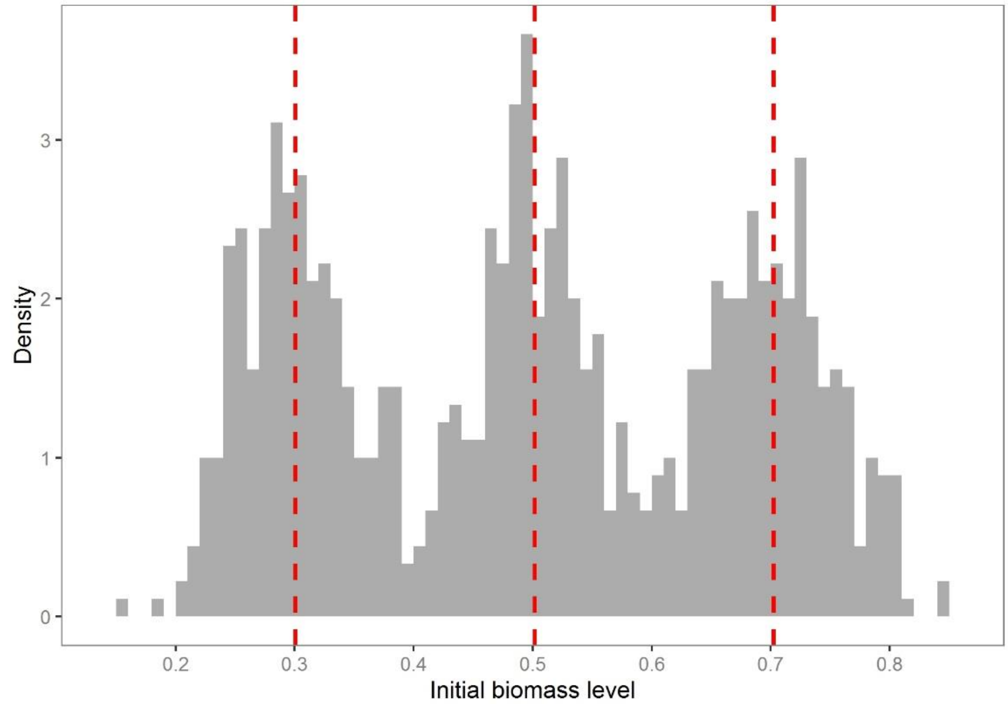


Figure 8:Initial biomass (depletion) level μ was sampled from three normal distributions (n=300 from each), with means of 0.3, 0.5, and 0.7 (vertical dashed lines), respectively, and a standard deviation of 0.05.

3.5.5 Spatial scaling and adjustments by fishery groups

The catchability scalar is adjusted by fishery groups to account for differences in operational practices and associated capture efficiency for *A. superciliosus* among fishery sectors.

Fishery group-specific catchability q_j is estimated as:

$$q_j = qf_j$$

where q is the average catchability (q_Ω) scaled to the spatial resolution of the assessment (5x5 degree cells) and f_j is the adjustment factor for fishery group j (see Appendix C for complete derivation).

The adjustment factor f_j is calculated as the predicted catch rate for each fishery group relative to a reference group (defined as the 'BET' targeting strategy and 'Jan-Mar' season) using the final (spatial standardisation) ZINB model fitted to all observer data within the Core Area. Since month was modelled as a continuous variable, seasonal predictions are based on the intermediate month within each season (i.e., February for Jan-Mar).

Uncertainty in f_j can be estimated using a bootstrap procedure (similar to that used for the spatial abundance indices) but will not be performed in this assessment.

3.5.6 Key assumptions

Our q estimation method assumes that the Calibration Area and US Hawaii observer data are representative of population dynamics for bigeye thresher sharks at the scale of the Pacific Ocean.

This means we assume that on average the fishing power of longline sets on bigeye thresher is the same across the Pacific region, but differences in relative catchability (targeting strategy and seasonal effects) and population density explain the differences in catch rates. This is unlikely to be the case but was a necessary assumption in the absence of informative data indicating otherwise. The assumptions made on the initial biomass level for the population are arbitrary and intended to improve estimation and ensure realistic outcomes in *q* estimation. Indirectly, initial biomass level assumptions also serve to deal with uncertainty in post-capture survival of *A. superciliosus* in pelagic longline fisheries (e.g., a high post-capture survival scenario would correspond to a high initial biomass level for the stock, and vice-versa). As in most age-structured stock assessment models, values of *q* are assumed to remain constant over the time frame of the assessment (2000-2014).

3.6 Impact estimation (fishing mortality)

Impact was estimated relative to the total (commercial) pelagic longline effort available in the CES Longline Logsheet dataset, from 2000 to 2014.

Spatially-explicit impact is the average annual fishing mortality in 5x5 degree cells calculated using commercial effort data (split by fishery groups), species relative density and fishery group catchability. We assumed cumulative fishing mortality as contributed from different fishery groups in each cell, and cumulative impact over the spatial domain of the assessment.

Fishing mortality in each cell is calculated as the product of effort and fishery group catchability and contrasted across a range of scenarios.

Impacts are estimated and compared for the Core Area (using species relative density estimates derived from the ZINB model); and for the Assessment Area (using density estimates from the delta-GLMM model). Uncertainty in species distribution information is incorporated in impact estimation by resampling density indices from bootstrapped estimates.

3.7 Population productivity and MIST estimation

3.7.1 Maximum intrinsic growth rate r

The life history module (LHM) for BDM developed by Edwards (2016) was used to estimate a distribution for the maximum intrinsic population growth rate r for *A. superciliosus.* The model implements Monte Carlo sampling of life history parameter distributions, with iterated solving of the Euler-Lotka equation (McAllister *et al.* 2001). The Euler-Lotka equation defines maximum intrinsic growth r as the net balance of survivorship s and unconstrained fecundity f, integrated over all age classes a:

$$\sum_{a=0}^{\infty} s_a f_a e^{-ar} = 1$$

$$s_a = e^{-aM}$$

$$f_a = \alpha\, m_a w_a$$

Survivorship (s) is a function of the natural mortality M, assumed constant across ages. Fecundity (f) is the product of female maturity m, weight w and the maximum recruits per spawner α (in the absence of density dependent effects). The relevant functional forms are the maturity-at-age m_a, length-at-age l_a (modelled as per von Bertalanffy growth), weight-at-age w_a and recruits per spawner α:

$$m_a = \left(1 + exp((a_{50} - a)/\delta)\right)^{-1}$$

$$l_a = l_\infty \left(1 - exp\left(-k(a - t_0)\right)\right)$$

$$w_a = a l_a^{\ b}$$

$$\alpha = \frac{4h}{\rho(1-h)}$$

Recruits per spawner is related to steepness h and the female spawning biomass per recruit *ρ,* assuming a Beverton-Holt stock recruitment relationship.

The model incorporates uncertainty in all parameters, which can be fixed on input. Life history data used to estimate a distribution for r are summarized in Table 5. Parameter values calculated for females of *A. superciliosus* were used whenever possible. Parameters that were poorly-informed or unobserved (i.e., those relating to maturation and recruitment) were given a higher cv (0.2) in the estimation process, and others that were estimated based on observations with sample sizes >100 specimens (growth and longevity) were given a cv of 0.10. We assumed that females have a litter size of two (Chen et al. 1997) and an annual reproductive cycle.

The maximum observed age for female *A. superciliosus* in the Atlantic was 22 yr (Fernandez-Carvalho et al. 2011), and the maximum observed age in the Pacific was 21 yr (Liu et al. 1998). True longevity in an unfished population probably exceeds both these values, so we used the larger value in the Euler-Lotka equation. Natural mortality estimates were available from Smith *et al.* (2008) (M=0.223) and Chen and Yuan (2006) (M=0.147). Additional M estimates were derived using four empirical equations summarised in Tsai et al. (2010), including the Hoenig (1983) and Campana et al. (2001) approximations based on maximum age; and the Jensen (1996) approximations based on age at maturity and the growth parameter of the von Bertalanffy equation. The value in the table represents the mean value for *M* (and calculated cv) obtained using the four empirical relationships.

A number of sensitivities were performed on selected input parameters, including h, M and parameters of the maturity ogive. A thousand (x1000) iterations were performed in each run.

3.7.2 Maximum Impact Sustainable Threshold (MIST)

In preliminary analyses, the MIST was set at 1.0r = F_{crash} (the instantaneous fishing mortality rate corresponding to the minimum unsustainable instantaneous fishing mortality rate) (Zhou *et al.* 2011). The MIST was used to compute sustainability status and sustainability risk for the species in the Pacific.

3.7.3 Key assumptions

The intrinsic growth rate r is assumed to represent population productivity (and thus resilience and recovery potential) for *A. superciliosus*. Productivity is assumed to have remained constant over the spatial domain of the assessment, from 2000 to 2014. This implies a stable environment and stable state (equilibrium) population dynamics for the species.

Table 5: Input life history information used to develop a prior for the maximum intrinsic population growth rate of *A. superciliosus* in the Pacific. Maturation, Growth and Recruitment parameters are based on available information for females only.

Process	Parameter	Value	cv	Reference(s)
Longevity				
	A_{max} (yr)	22		Fernandez-Carvalho et al. 2011
Maturation				
	A_{50} (yr)	13.4	0.20	Liu et al. 1998
	delta δ	0.6	0.20	estimated
Growth				
	L_{inf} (cm, PCL)	224.6	0.10	Liu et al. 1998
	k	0.092	0.10	Liu et al. 1998
	t_0	-4.21	0.10	Liu et al. 1998
	a	6.87×10^{-5}	0.10	Liu et al. 1998
	b	2.769	0.10	Liu et al. 1998
Recruitment				
	α	2		Liu et al. 1998
	h	0.30	0.20	estimated
Mortality	M	0.171	0.17	See text

3.8 Sustainability risk calculations

Sustainability status is determined relative to fishing impact from pelagic longline fisheries in the Pacific over the period 2000-2014, and computed relative to a MIST=1.0r= F_{crash}. A sustainability risk metric, corresponding to the ratio of total impact to the species MIST, was computed and compared between impact estimated at the scale of the Core Area (ZINB model species distribution) and impact estimated at the scale of the Assessment Area (delta-GLMM model species distribution).

The probability that current impacts exceed the MIST (Pr(Impact/MIST>1)) is calculated by re-sampling across the uncertainty range estimated for all parameters. Additional sustainability risk thresholds were defined *a posteriori* based on the distribution of annual sustainability status and uncertainty.

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Appendix A – $CPUE_{\Omega}$ estimation and derivation

In this section we derive $CPUE_{\Omega}$ (the CPUE index for the Calibration Area A_{Ω}) from $CPUE_a$ (CPUE in subarea a within A_{Ω}).

$CPUE_{\Omega}$ is used to estimate a range of plausible values for q_{Ω} in the BDM calibration.

$CPUE_a$ is the predicted catch rate for subarea a from the final ZINB standardisation model.

Firstly,

$$q_{\Omega}\sum_i E_i = \sum_i\left(qE_i\frac{n_i}{n_{\Omega}}\right)$$

where q_{Ω} is the catchability scalar over A_{Ω}, and q is the average catchability in each subarea. E_a and n_a are the total effort and abundance in subarea a respectively, and n_{Ω} is total abundance in A_{Ω}.

Assuming that CPUE index is proportional to abundance implies that:

$$CPUE_{\Omega} = q_{\Omega}n_{\Omega}$$

$$CPUE_a = qn_a$$

Therefore,

$$CPUE_{\Omega} = \frac{n_{\Omega}}{\sum_i E_i}\sum_i\left(qE_i\frac{n_i}{n_{\Omega}}\right) = \frac{1}{E_{\Omega}}\sum_i E_i CPUE_i$$

Appendix B – BDM description

The Biomass dynamic model (BDM) developed by Edwards (2016) implements the Fletcher-Schaefer hybrid model proposed by McAllister et al. (2000) in a state-space modelling framework that describes changes in stock depletion in response to fishing,:

$$x_0 = \mu\varepsilon_0 \qquad \text{for } t = 0 \tag{1}$$

$$x_t = \left(x_{t-1} + r x_{t-1}\left(1 - \frac{x_{x-1}}{2\varphi}\right) - H_{t-1} \right)\exp(\varepsilon_t - \frac{1}{2}\sigma_p^2) \qquad \text{for } t > 0 \text{ and } x_t < \varphi \tag{2}$$

$$x_t = \left(x_{t-1} + \frac{1}{2} g r \varphi x_{t-1}\left(1 - \left(x_{t-1}\right)^{n-1}\right) - H_{t-1} \right)\exp(\varepsilon_t - \frac{1}{2}\sigma_p^2) \qquad \text{for } t > 0 \text{ and } x_t \geq \varphi \tag{3}$$

where x_t is the depletion in year t (abundance as a percent of unfished equilibrium abundance); u is the initial biomass; φ is the depletion level at which Maximum Sustainable Yield occurs, which is controlled by a shape parameter n, and

$$\varphi = \left(\frac{1}{n}\right)^{\frac{1}{n-1}} \tag{4}$$

$$g = \frac{n^{\frac{n}{n-1}}}{n-1} \tag{5}$$

r is the intrinsic growth rate. H_t is the harvest rate in year t, and

$$H_t = \frac{C_t}{K} \tag{6}$$

where C_t is the catch is year t and K is the unfished equilibrium abundance, ε_t is the process error in year t following a normal distribution:

$$\varepsilon_t \sim \text{normal}\left(0, \sigma_p^2\right) \tag{7}$$

σ_p is the standard deviation for the process error. The expected abundance index in year t, $\hat{I}_t$ is calculated as,

$$\hat{I}_t = qKx_t \exp(\xi_t - \frac{1}{2}\sigma_o^2) \tag{8}$$

Where q is the catchability coefficient and ξ_t is the observation error in year t, and

$$\varsigma_t \sim \text{normal } (0, \sigma_o^2) \tag{9}$$

Where σ_o is the standard deviation for observation errors.

The hybrid model allows $\varphi < 0.5K$ whilst maintaining an ecologically consistent interpretation of r. Using a Bayesian framework, BDM estimates the marginal posterior distribution of underlying parameters including K, r, and q, by incorporating time series of catches and observed abundance indices.

Appendix C – *q* adjustment by fishery groups and spatial scaling

In this section, we derive q_j, the catchability for fishery group *j* at the level of 5x5 degree cells used in the assessment. Firstly,

$$q_j = qf_j \tag{1}$$

where q is the average catchability on the grid cell (constant across spatial domain) and f_j is the adjustment factor for fishery group j, calculated as the predicted CPUE for each fishery group (averaged over space and time) relative to a reference fishery group (i.e., targeting strategy of "BET" in February).

To obtain the q_j, we first write the fishing mortality in the Calibration Area, F_Ω, as

$$F_\Omega = q_\Omega \sum_{i,j} E_{ij} \tag{2}$$

where q_Ω is the catchability over A_Ω, $E_{i,j}$ is the fishing effort for fishery group j in grid cell i. Using a spatially-explicit approach:

$$F_\Omega = \sum_i \frac{n_i}{n_\Omega} \left(\sum_j \left(q_j E_{i,j} \right) \right) \tag{3}$$

Where n_i is the abundance (relative density) in cell i and n_Ω is the total relative abundance in the Calibration Area A_Ω

Combining (1), (2), and (3) we obtain:

$$q_j = \frac{q_\Omega \sum_{i,j} E_{ij}}{\sum_i \frac{n_i}{n_\Omega} \left(\sum_j \left(f_j E_{i,j} \right) \right)} f_j \tag{4}$$