SCIENTIFIC COMMITTEE
FIFTEENTH REGULAR SESSION

Pohnpei, Federated States of Micronesia
12-20 August 2019

IDENTIFYING APPROPRIATE REFERENCE POINTS FOR ELASMOBRANCHS WITHIN THE WCPFC

WCPFC-SC15-2019/MI-IP-04

Zhou, S., Deng, R., Hoyle, S. and Dunn, M.

Identifying appropriate reference points for elasmobranchs within the WCPFC

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January 2019

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Citation

Zhou, S., Deng, A.R., Hoyle, S., and Dunn, M. 2019. Identifying appropriate reference points for elasmobranchs within the WCPFC. Report to Western and Central Pacific Fisheries Commission, Pohnpei, Federated States of Micronesia.

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Acknowledgments

We thank WCPFC Scientific Committee for their comments on the earlier draft and their feedback during the Fourteenth Regular Session. We are grateful to Dr S. Clarke and Mr T. Beeching for providing many documents and advices on the project. Dr F. Carvalho helped with gear selectivity issues. This project is co-funded by Western and Central Pacific Fisheries Commission and Australian Commonwealth Scientific and Industrial Research Organisation.

Executive summary

Elasmobranch species are bycatch in fisheries managed by the Western and Central Pacific Fisheries Commission (WCPFC). These species have limited fishery-dependent data and biological information. Traditional stock assessment cannot be performed for most of the stocks. Assessment using alternative approaches has become a priority research project. Recently, Clarke and Hoyle (2014) reviewed appropriate limit reference points (LRPs) for WCPFC elasmobranchs and provided a conceptual framework for selecting appropriate LRPs. In 2015 an expert panel held a workshop to identify the most appropriate life history data to be used in calculating the risk-based LRPs. The panel compiled and reviewed over 270 studies worldwide on 16 WCPFC elasmobranch stocks.

The current study continues the previous work. The report contains several components related to reference point development. In the first section, we apply a total of four methods and use the data in the expert panel report to estimate fishing mortality-based reference points (F_{RPs}). As natural mortality M is a key variable in three of the four methods, we start with M estimation by using six M estimators as well as adopting M values from the literature. Comparison among the seven M estimators shows that the estimator based on maximum life span t_{max} and the estimator based on the von Bertalanffy growth function (VBGF, K and L_{inf}) differ markedly from other estimators for most stocks. On average, M from t_{max} is 1.45 times higher than the mean value from all seven approaches. In contrast, M based on VBGF is only 0.73 times of the average.

The four methods for deriving F_{RPs} are: an empirical relationship between F_{RPs} and life history parameters, demographic analysis, the intrinsic population growth rate from literature, and the spawning potential ratio (SPR) approach. We provide three reference points, F_{msm}, F_{lim}, and F_{crash}. As expected, the estimated values are similar between multiple methods (i.e. 2 to 4 methods depending on available data) in some stocks but vary considerably in other stocks. Because of a lack of selectivity and maturity information, the SPR approach is applied to only three stocks. It is difficult to determine what percentage of SPR is appropriate for elasmobranchs and how it corresponds to the three F_{RPs}, so this approach has limited value. Since the WCPFC has adopted a benchmark 20%$SB_{dynamic10,\ unfished}$ as the limit biomass reference point for target species, we recommend using a similar RP—the combined F_{lim} (cF_{lim}, combined from the three methods) as LRP for elasmobranchs.

In the second section, we review some potential methods for estimating fishing mortality for data-poor species, including formal stock assessment, area-based ERA methods, age-based methods, and length-based methods. We focus on the area-based methods, as varying versions, tailored for varying data availability, have been developed and have been applied to two WCPFC species. This group of methods can be flexibly modified to suit the available data. To be consistent, this method is recommended for other data-poor WCPFC elasmobranch species.

In the third section, we briefly review other potential management procedures for WCPFC elasmobranchs. As a wide range of assessment methods and management procedures have been developed for data-poor fisheries, and several comprehensive reviews have already been completed, we only discuss three procedures that are potentially promising for WCPFC bycatch. These procedures include catch-rate approaches, length-based traffic-light approaches, and catch-only methods. We suggest that before adopting a particular approach, it is essential to check the data inventory against the key assumptions required by the method, and keep in mind the merit of consistent methodology across multiple species.

In the fourth section, we review the life history-based approach to estimating a stock recruitment relationship (SRR) for sharks, focusing in particular on the approach published by Kai and Fujinami (2018) in Fisheries Research. They modelled the SRR using the approach proposed by Mangel *et al.* (2010), based on maximum population growth rate at low population size and spawning biomass per-recruit at equilibrium without fishing. They used this approach to derive steepness parameter for both Beverton-Holt and Ricker's models, and argued for use of the estimate based on the Beverton-Holt stock recruitment relationship.

They suggested this steepness can be used as a prior for stock assessment. Their paper is, in general, well written and provides sufficient explanation to repeat the approach for other species. However, we have identified several weaknesses of the approach, including: underestimating uncertainty in input parameters and in the stock recruitment relationship, overlooking of the density-dependent effect on life-history parameters, and potentially unrepresentative coverage of the population. We conclude that the approach is an interesting theoretical idea, but requires further research before applying to sharks for estimating steepness priors for stock assessment.

1 Introduction

Fishing impact on elasmobranchs has become an increasing concern in fisheries management and biodiversity conservation (Dulvy *et al.*, 2014; Stein *et al.*, 2018). Lack of biological and fisheries data has hindered the use of traditional quantitative stock assessments (such as surplus production models, statistical catch-at-age models, stock-recruitment models, delay-difference models, and virtual population analysis models) and development of management advice based on the output of these assessments. Most elasmobranch species impacted by Western and Central Pacific Fisheries Commission (WCPFC) managed fisheries have very limited data. Traditional stock assessment has been attempted for only four of the 16 stocks of elasmobranchs in the Western and Central Pacific Ocean (WCPO) (Table 1). Developing management reference points using alternative approaches has been a priority research agenda for the Commission. In 2014, Clarke and Hoyle (2014) conducted a thorough review of appropriate limit reference points (LRPs) for WCPFC elasmobranchs. Based on the adopted WCPFC's framework for target species, they provided a conceptual framework for selecting potential LRPs for non-target elasmobranchs. Data needs were also identified as a priority issue and an expert panel was recommended to identify the most appropriate life history data to be used in calculating the risk-based LRPs. Consequentially, a workshop was held in 2015, which produced the "Report of the Pacific Shark Life History Expert Panel Workshop". The panel compiled and reviewed over 270 studies worldwide on 16 WCPFC elasmobranch stocks. Since then it has been endorsed by the Scientific Committee for the continued development of reference points for elasmobranchs based on previous findings and compiled data.

In April 2018, the Commission called for proposals for identifying appropriate reference points for elasmobranchs within the WCPFC. The terms of reference list six tasks:

1. For those elasmobranchs which have been evaluated using a stock assessment model, recalculate the risk-based limit reference points (LRPs, as described in Table 5, WCPFC-SC10-MI-WP-07 (Clarke and Hoyle, 2014)) using the updated life history information produced by the Shark Life History Expert Panel.

2. For those elasmobranchs which have not been evaluated using a stock assessment model advise on ways of developing an estimate of current fishing mortality (F), for example using catch curves, the method used in the bigeye thresher assessment (WCPFC-SC12-SA-IP-17, see updated version Fu *et al.*, 2018), or other suitable means. Risk-based LRPs (as described in WCPFC-SC10-MI-WP-07) should then be developed for all WCPFC key shark species.

3. Where the stock-recruitment relationship is highly uncertain, compare $F_{current}$ to SPR-based LRP such as $F_{60\%SPR,unfished}$ (or simply $F_{60\%}$) and discuss any new insights into the recommended estimated LRPs so that the WCPFC Scientific Committee can decided on a case-by-case basis which LRP is most appropriate.

4. Review the use or otherwise of other potential LRPs based on SPR, reduction of recruitment or empirical measures (e.g. catch rate or length values designed to signal unacceptable population states).

5. Advise on any changes or updates to the recommended LRPs in WCPFC-SC10-MI-WP-07 based on new developments, including any suggestions for further technical work before consideration of adoption of LRPs by fishery managers.

6. Review the work presently being undertaken by ISC on the development of stock-recruitment relationships and their parameter estimates, such as stock-recruitment steepness for North Pacific blue shark and assess the applicability of extending this work to other key shark species, especially South Pacific blue shark.

The report is organized in four sections: (1) Estimating F-based reference points; (2) Potential methods for estimating fishing mortality; (3) Other potential management procedures for WCPFC elasmobranchs, and (4) Review shark stock-recruitment relationships. Note that section (1) addresses tasks 1, 3, 5 and part of 2, because these tasks are all about developing reference points, whether the species have been evaluated or not, using risk-based or SPR-based estimators, and updating the existing estimates.

2 Estimating F-based reference points

2.1 Data sources

2.1.1 Life history parameters

An expert panel was convened in 2015 to review appropriate life history parameters for the fourteen WCPFC key shark species (16 stocks). The panel compiled and reviewed over 270 studies worldwide on blue, mako, silky, oceanic whitetip, thresher, porbeagle, hammerhead and whale shark species (Clarke *et al.*, 2015). Tables containing over a dozen of the most important life history parameters and their uncertainties and caveats were constructed for each species. We extracted all relevant numbers from the report. Some species and parameters had multiple studies, and we retained all individual values by sex. We primarily used "Pacific parameters", i.e., data from the Pacific Ocean. However, for certain parameters that were not available from the Pacific Ocean, "Alternative parameters" from other areas (e.g., Atlantic Ocean and Indian Ocean) were used instead (note that "Alternative parameters" are also provided in Clarke *et al*. (2015) report). We have provided a note in the results section when an alternative parameter was used for a particular stock. Specifically, we borrowed intrinsic rate of increase (*r*) from "alternative parameters" for two stocks, the Blue shark-North and the ocean Whitetip shark, and maximum age and age at maturity for smooth hammerhead shark. Different units, types of measurement (e.g. fork length, total length, pre-caudal length), and equations were used in different studies, and where necessary we converted measurements to consistent units and adjusted equations as appropriate, using relevant information from the original literature.

Since the Cairns workshop, updated life history parameters (LHPs) have become available for some stocks. However, in this study we did not have time to carry out a thorough review and find all the new estimates. We adopted updated estimates for three stocks that were readily known. Grant *et al.* (2018) recently examined the life history of silky sharks from Papua New Guinean waters. The newly estimated life history parameters differ significantly from those reported in the early literature (Clarke *et al.*, 2015). Fu *et al.* (2018) updated the maximum life span for the Bigeye thresher shark. Hoyle *et al.* (2017b) used the new maximum life span for the Porbeagle shark. We adopted the updated values for these three species.

2.1.2 Selectivity

Realised selectivity (i.e. relative catchability at size in all fisheries combined) is required by some methods for deriving reference points. However, this is a difficult relationship to estimate, and it may vary through time. Elasmobranchs are captured by various fishing gears in the WCPFC fisheries, including longline, purse seine, and some gillnet, each of which may have a different selectivity, and their effort levels vary through time. In addition, fish availability affects realised selectivity, since fishing effort varies spatially, and elasmobranch populations are usually spatially structured. Sexual segregation in space is a general characteristic of elasmobranchs (Wearmouth and Sims, 2008; Finucci *et al.*, 2018), and spatial segregation between juveniles and adults is also commonly observed (e.g. Finucci *et al.*, 2018; Gouraguine *et al.*, 2011; Semba *et al.*, 2013).

Moreover, selectivity has been estimated for very few elasmobranchs species. Most sharks are captured in longline fisheries (Shark Working Group, 2014), where two types of curves are often assumed (Hovgard and Lassen, 2000): dome-shaped and sigmoid (logistic). For example, Rice and Harley (2013) assumed the selectivity for the longline bycatch of Silky sharks to be dome shaped with a maximum at body length 172 cm. Selectivity for the target longline fishery (targeting the Silky sharks) was also assumed to be dome shaped but with maximum selectivity value that ranged from 168 cm to 204 cm. The selectivity for purse seine unassociated sets was assumed to be logistic with size at inflection of 64 cm. For oceanic whitetip sharks, Rice and Harley (2012) assumed that the longline bycatch fishery selectivity increased with age and remained at the maximum once attained. Selectivity for the target longline fishery was assumed to be dome shaped with a maximum selectivity value at 180 cm. Selectivity for purse seine associated sets were assumed to be logistic with size at inflection of 110 cm.

The logistic curve may be more typically assumed for longline for other species. For example, a study fitted the logistic size selectivity model to Blue shark catch-at-length data from 17 fleets operating in the North Pacific Ocean (Carvalho and Sippel, 2016). The majority of these fleets were longline. The selectivity at length *l* is modelled as

$$S_l = \frac{1}{1+e^{-S_a(L_l - S_{50})}} \qquad \text{(Eqn 1)}$$

Where S_a is the slope parameter, L_l is the pre-caudal length, and S_{50} is the length at which 50% of individuals encountered the gear are hooked. Across the 17 fleets, S_a ranges from 4.05 to 11.37 (mean = 7.46, sd = 2.29) and S_{50} ranges from 66.27 to 167.62 (mean = 126.02, sd = 28.44).

Based on these studies, we assume a logistic curve for Blue shark selectivity and use the means of the estimated S_a and S_l from Carvalho and Sippel (2016) study. Because the slope parameter was not provided for Silky shark and Whitetip shark in Rice and Harley (2012, 2013) reports, we assume a knife-edge selectivity at 64 cm and 110 cm for these two species respectively.

2.2 Estimating natural mortality rate

Natural mortality *M* is an essential parameter for Methods 1, 2, and 4 presented below. For most fish species (both teleosts and chondrichthyes), *M* is typically derived from other life history parameters. Although *M* is available from literature for most stocks (12 out of 16), we are unsure whether they are directly measured (e.g. from tagging studies, telemetry, or catch curve analysis) or indirectly estimated from other life-history parameters, and in particular whether these values are accurate. A range of indirect *M* estimators have been proposed for information-limited species. Kenchington (2014) reviewed 29 of these estimators and proposed a new alternative that requires an estimate of effective sample size in addition to other life-history parameters. He found that none of the 30 can provide accurate estimates for every species, while several perform so poorly as to have no practical utility.

Recently, Then *et al.* (2015) compared different approaches and recommended two basic equations, one based on the maximum life span, t_{max}, and the other one based on von Bertalanffy growth parameters, *K* and L_{inf}. These equations were modified or improved from similar equations that had been widely used, such as Hoenig (1983) and Pauly (1980) methods, and were not included in Kenchington (2014) review. Then *et al.* (2015) concluded that a t_{max} based estimator performed the best among all estimators evaluated. In our first version of this report, we used the two Then's equations with unequal weight using the inverse prediction error. However, the results from applying the two equations to the 15 WCPFC stocks indicated that the t_{max} based estimator often produced unrealistically large *M*. The problem may arise from both the estimator itself, and the input t_{max}, which may have been frequently underestimated. Furthermore, many of the indirect methods were developed almost entirely from teleosts. Elasmobranchs have lower fecundity, larger body size at birth, slower growth, later maturity, and longer life span than most teleosts, so many of these indirect methods largely based on teleosts may be inappropriate for elasmobranchs. A study from 29 elasmobranch species showed that the most common methods in elasmobranch literature appeared to be overestimating *M* by factors of 1.34 – 1.91 (Moe, 2015). It is well recognized that many popular estimators widely used for teleosts are less useful for elasmobranchs (Simpfendorfer *et al.*, 2005; Kenchington, 2014b; Moe, 2015).

In this updated version, we selected six estimators that were either recently developed or specifically formulated for elasmobranchs. Hence, including natural mortality adopted from literature, we have a total of seven methods for deriving *M*:

(1) $M = at_{max}^{b} = 4.899\ t_{max}^{-0.916}$ (Eqn 2a, Then1)

(2) $M = aK^{b}L_{inf}^{c} = 4.118\,K^{0.73}L_{inf}^{-0.33}$ (Eqn 2b, Then2)

(3) $\ln(M) = 0.42\ln(K) - 0.83$, or $M = 0.463K^{0.42}$ (Eqn 2c, Frisk1)

(4) $M = \frac{1}{0.44t_{mat}+1.87}$ (Eqn 2d, Frisk2)

(5) $M = \frac{1.65}{t_{mat}-t_0}$ (Eqn 2e, Hisano)

(6) $M = \begin{cases} \frac{K}{1-e^{-K(t-t_0)}}, & t < t_s \\ \frac{K}{a_0+a_1(t-t_s)+a_2(t-t_s)^2}, & t \geq t_s \end{cases}$ (Eqn 2f, Chen)

where $\begin{cases} a_0 = 1 - e^{-K(t_s-t_0)} \\ a_1 = Ke^{-K(t_s-t_0)} \\ a_2 = -\frac{1}{2}K^2e^{-K(t_s-t_0)} \end{cases}$

and $t_s = -\frac{1}{K}\ln|1 - e^{Kt_0}| + t_0$

(7) *M* from literature.

In these equations, t_{max} is the maximum life span, *K*, L_{inf}, and t_0 are von Bertalanffy growth parameters, t_{mat} is age at maturation, t_s is age when senescent growth phase begins.

Eqns 2a and 2b were proposed by Then et al. (2015) (we refer them as Then1 and Then2). Although their study focused on improving the estimation of *M* for both teleosts and elasmobranchs, only four elasmobranchs (all in order Carcharhiniformes) were included in the data of a total 230 species. The t_{max}-based equation had a mean prediction error = 0.32 (defined as the root-mean-square between the cross-validation predicted *M* and the true value), sd[*a*] = 0.11, and sd[*b*] = 0.02 across all species; the growth-based equation had a prediction error = 0.60, sd[*a*] = 0.80, sd[*b*] = 0.08, and sd[*c*] = 0.08 across all species (Then 2015).

Eqns 2c, 2d, and 2e were developed specifically for elasmobranchs. Frisk *et al.* (2001) obtained Eqns 2c and 2d (referred to as Frisk1 and Frisk2) through regression of data from 30 elasmobranchs species in nine families. Eqn 2e was modified from a widely used Jensen (1996) estimator, *M* =

1.65/t_{mat}. This estimator was extended from a theoretical work by Roff (1984). Roff established life history correlations for teleosts by incorporating the von Bertallanffy growth function where t_0, the age when an individual would have been of length 0, was set to 0. As length at birth is usually small for teleosts, assuming t_0 = 0 has little impact on other life history parameters. However, size at birth is much larger for elasmobranchs than teleosts. Hence, Hisano *et al.* (2011) modified Jensen's estimator by including t_0 (referred to as Hisano). For example, for the 16 WCPFC shark stocks the mean t_{mat} is 10.26 yrs while the mean t_0 is -3.46 yrs. Using Jensen's estimator would overestimate *M* by 34%. As no variance estimates were provided for the three equations in the original papers, we assumed a CV = 0.2 for the process error as in (Quiroz *et al.*, 2010).

Eqn 2f is an age-dependent estimator developed by Chen and Watanabe (1989) (referred to as Chen). This method was one of the five indirect estimators recommended for elasmobranchs (Moe, 2015) because it was relatively conservative than others while many estimators tended to produce upward biased estimation. To obtain a single *M* for the stock, we took the mean of the estimated *M* between age 1 and t_{max}. Again, we assumed a CV = 0.2 for the process error.

Uncertainty is an important factor affecting the reliability of the estimated natural mortality. Measurement error in life history parameters can be substantial due to factors such as ageing bias and error, fishing selectivity, and unrepresentative sampling across spatially separated life history stages. Process error can also be substantial and likely larger than the prediction error associated with each equation, since the values used to derive the equations are themselves uncertain but treated as known.

We took uncertainty into account at two levels: measurement error in each life-history parameter (i.e., t_{mat}, *K*, L_{inf}, t_0, as well as *M* from literature, except t_{max}), and the process error of the *M*~LHP(s) relationship in Eqns 2a to 2f. If t_{max} has multiple values from different studies, the maximum value was used. For other life history parameters, uncertainty was evaluated through Monte Carle simulation of 10,000 random samples at each level. At the parameter level, results from multiple studies were provided in two forms in the Clarke *et al.* (2015) report: a vector of single measurements and a range from low to high. For measurements in a vector we took 10,000 random samples (with replacement) from the vector. For range values we generated 10,000 samples by assuming a uniform distribution from low to high values. We used Pacific Ocean studies except when a particular parameter was not available from the Pacific, in which case the alternative estimate from another region (e.g. Atlantic Ocean or Indian Ocean) was used. These cases are noted in the results section. All study sources and all seven methods were given the same weight. For process error, estimated variances in the original studies (Then *et al.* 2015) or an assumed CV = 0.2 (Quiroz *et al.*, 2010), when variance was not available, were used to generate parameter distributions. Using multiple methods to avoid bias resulting from either life history parameters or *M* estimators concurs with the general recommendations of previous studies (Simpfendorfer *et al.*, 2005; Brodziak *et al.*, 2011; Zhou *et al.*, 2011; Kenchington, 2014a). Note that Eqn 2 differs from those used in Zhou et al. (2011) since the updated Eqn 2a and Eqn 2b were not available then, and their assessment did not focus on elasmobranchs.

After obtaining natural mortality estimates, we proceeded to the methods for deriving reference points.

2.3 Methods for estimating reference points

Ideally, reference points (RPs) should be defined for both biomass and fishing mortality. This is a common practice for target species. Examples of biomass-based (B-based) reference points include B_{msy}, B_{mey}, B_{lim}, B_{pa}, x%SSB_0, etc., while corresponding F-based RPs are F_{msy}, F_{mey}, F_{lim}, F_{pa}, and $F_{x\%}$. B-based RPs play a fundamental role in fisheries management because biomass and its composition (i.e., sex, size, and age structure) ultimately determine stock sustainability and fishery production. Unfortunately, B-based reference points are more difficult to estimate than F-based RPs and are typically obtained through stock assessment modelling using a range of data. Fishing mortality, on the other hand, is directly controlled by management. Long-term management of fishing mortality will shape the level and structure of population biomass. Theoretically, under stable environmental and biological conditions, applying fishing mortality rate at a fixed level, such as $F = F_{msy}$, year after year, will lead to $B = B_{msy}$ regardless the starting biomass level. The duration to reach this equilibrium state depends on the productivity of the stock and the level of its starting biomass. F-based RPs are relatively easier to estimate because alternative approaches can be used in addition to stock assessment models.

The level of stock depletion, B_{cur}/B_0, is an important concept in fisheries management. A pre-defined depletion (x%B_0), expressed as a ratio with values from 0 to 1, is technically a B-based RP. Depletion may be estimated without traditional stock assessment modelling. For example, a simple catch trend analysis was developed for determining stock status by comparing annual catch to the historical maximum catch (Froese and Kesner-reyes, 2002; Pauly, 2008). This method has received widespread criticism (Branch *et al.*, 2011; Daan *et al.*, 2011). Additional research on this method has been undertaken (Anderson *et al.*, 2012; Carruthers *et al.*, 2012), but using catch data alone to classify fisheries status continues to be debatable (Froese *et al.*, 2012; Cook, 2013; Pauly *et al.*, 2013). Recently, Zhou *et al.* (2017) used the RAM Legacy database and developed a boosted regression tree (BRT) model to correlate depletion with a range of easily available predictors. However, this method may have a low prediction accuracy for some stocks and requires time series of catch data that are not available for most WCPFC elasmobranchs. Due to these limitations, this report focuses on F-based RPs.

Two main types of reference point are used for commercial species, and considered in relation to both pressure (fishing mortality) and state (biomass level). The target reference point (TRP) is typically an MSY-related quantity, and the limit reference point (LRP) is defined as the level of biomass or fishing mortality at which the risk to the stock (in terms of recruitment impairment) is regarded as unacceptably high. A proxy value for the LRP of 20% of the unfished spawning biomass is often used for productive stocks such as tuna (for example in Australia and New Zealand). The WCPFC adopted a benchmark 20%$SB_{dynamic10,\ unfished}$ as the limit biomass reference point for target species (20% of the average theoretical level of spawning biomass that would be present during recent 10 years with no fishing) (Clarke and Hoyle, 2014). If B_{MSY} can be reliably estimated and is above $B_{40\%}$, then 0.5B_{MSY} may be an appropriate alternative LRP (Dowling *et al.*, 2008; Sainsbury, 2008). For less productive stocks (such as some sharks), more conservative biomass LRPs may be adopted—$B_{30\%}$ and associated fishing mortality $F_{30\%}$ being advocated as best practice in some cases (see Sainsbury, 2008). Because available information varies between stocks, and the reliability of stock assessments, if available, also varies, the following tiered framework has been recommended (Clarke and Hoyle, 2014):

(1) For those elasmobranchs evaluated using a stock assessment model for which there is confidence that the stock-recruitment relationship is appropriately specified, use a fishing mortality-based LRP of F_{msy};

(2) In cases where a stock assessment model was used but the stock-recruitment relationship is highly uncertain, also consider SPR-based LRP such as $F_{60\%SPR}$;

(3) When stock assessments are not available, or when the results are not considered robust, use risk-based fishing mortality LRP benchmarks (F_{msm}, F_{lim} and F_{crash}), as used in Australia (Zhou et al. 2011).

The method we used for deriving risk-based reference points assumed that the population dynamics could be described by a Graham-Schaefer production model where $F_{msm} = F_{msy}$, $F_{lim} = 1.5\ F_{msm}$, and $F_{crash} = 2F_{msm} = r_{\max}$ (Zhou *et al.*, 2011). These three reference points were adopted in this report. The acronym "msm" stands for "maximum sustainable mortality" for non-retained bycatch, but it is equivalent to MSY for commercial species. Hence F_{msm} is identical to F_{msy}. In addition to the recommendation and the requirement set out in the terms of reference, we used four methods to estimate reference points. Method 1 was based on the empirical relationship between F_{msy} and life history parameters, which corresponded to Methods ii to vi in Zhou *et al*. (2011), except that we used M estimators that have been recently updated or tailored for elasmobranchs. Method 2 used a demographic model, the Euler-Lotka equation, to derive the intrinsic population growth rate r, and assumed $F_{msm} = 0.5\ r$. Method 3 used r from the literature, which was identical to Method i in Zhou et al. (2011). Method 4 was based on the spawning potential ratio approach and did not directly refer to msm or msy, which distinguished it from Methods 1 to 3.

2.3.1 Method 1: empirical relationship

An empirical relationship between biological reference points based on fishing mortality (F_{BRP}) and life-history parameters (LHPs) was developed from a meta-analysis of 245 data-rich fish species worldwide (Zhou *et al.*, 2012). It was found that natural mortality M was the most important LHP affecting F_{BRP}. The relationship may vary among taxonomic groups. For example,

(1) $F_{msm1} = 0.87M$ (SD = 0.05) for teleosts

(2) $F_{msm1} = 0.41M$ (SD = 0.09) for chondrichthyans (Eqn 3)

In addition to the two-level uncertainty in M as described in "Estimating natural mortality rate", Eqn 3 involves a third level of uncertainty: process error between $F_{BRP} \sim M$. Again, we derived statistics of F_{msm1} from simulation of 10,000 random samples. The empirical relationship approach corresponded to methods ii to vi for sustainability reference points in the SAFE (Zhou *et al*., 2011). Eqn 3 is comparable to recent study by Cortés and Brooks (2018) who recommended that for low productivity species, such as many shark stocks, the F_{msy}/M ratio should not exceed $\approx$ 0.4.

2.3.2 Method 2: Euler-Lotka equation (or demographic model)

The ability of a species to withstand fishing mortality is determined by its intrinsic ability to increase its population. The intrinsic population growth rate, denoted as r_m, r_{max}, or simply r, can be estimated by different methods. This is a growth parameter r in the Graham-Schaefer production model. However, for sharks it is more commonly derived from the Euler-Lotka equation because life-history parameters are relatively easier to obtain than time series of population and fisheries data. The original Euler-Lotka equation has been modified in various ways and has been incorrectly used in some studies (see discussion in Cortés, 2016; Pardo *et al.*, 2016). The following (correct) equation is commonly used for sharks (Skalski *et al.*, 2008; Cortés, 2016; Pardo *et al.*, 2018):

$$e^{rt_{mat}} - e^{-M}(e^{r})^{t_{mat}-1} - fl_{mat} = 0 \qquad \text{(Eqn 4)}$$

Where t_{mat} is age at first breeding, f is constant annual fecundity, l_{mat} the cumulative survival from age 0 to age at maturity. Assuming constant natural mortality leads to $l_{mat} = e^{-Mt_{mat}}$. Equation (4) is equivalent to a model for estimating the limits of fishery exploitation (Myers and Mertz, 1998) when it assumes vulnerable age to fishing gear is 1. Age at recruitment is available for 5 out of the 16 WCPFC stocks reported in Clarke *et al*. (2015): BSH-N, SMA-N, SMA-S, LMA, and POR. All are suggested to be vulnerable to fishing at ages between 0 and 1 (however, see selectivity study for BSH below).

Solving equation (4) for r requires t_{mat}, M, f, as well as the reproduction cycle Rc because f is annual fecundity which consists of the mean reported litter size (ls) and reproductive frequency, such that $f = ls/Rc/2$ to account for female pups only. In this equation, r increases as t_{mat} reduces, or M reduces, or f increases, or Rc reduces. Both Methods 1 and 2 depend on M, but the effect of M is opposite in the two methods.

We treated the parameter uncertainty in the same way as in Method 1, i.e., using Monte Carlo resampling for point values and assuming uniform distribution for range values, and giving the same weight to each study. The final distribution was based on 10,000 random samples, whether the value was positive or negative. Again, according to a logistic production model

$$F_{msm2} = r/2 \qquad \text{(Eqn 5)}$$

2.3.3 Method 3: Intrinsic population growth rate from literature

Three types of population growth rates were reported in the literature assembled in Shark Life History Expert Panel Workshop (Clarke *et al.*, 2015): r, λ, and $r_{Z(msy)}$ (= $r_{1.5M}$). Unlike some basic life history parameters, fish population growth rates are always model estimates. By adopting these estimates we assumed that the original modelling in the literature was reasonable. We converted λ and $r_{Z(msy)}$ to r by $r = \log(\lambda)$ and $r = 2r_{Z(msy)}$ (Cortés, 2016). Again, parameter uncertainty was handled in the same way as in Method 1. The primary reference point is $F_{msm3} = r/2$ as in Eqn 5.

2.3.4 Method 4: Spawning potential ratio (SPR)

Reference points based on spawning stock biomass per recruit (or spawning potential ratio, SPR) have been used or suggested for data-limited fisheries (Pope, 2000; Le Quesne *et al.*, 2012; Clarke and Hoyle, 2014; Prince *et al.*, 2015; Hordyk *et al.*, 2016). Spawning potential ratio is estimated as (Goodyear, 1993):

$$SPR = \frac{SSBR_{fished}}{SSBR_{unfished}} \qquad \text{(Eqn 6)}$$

Where SSBR is the spawning stock biomass per recruit. SPR is similar to yield per recruit (YPR) and estimated for only a single cohort, so does not consider a stock-recruitment relationship. Assuming a constant year class, SSBR can be obtained by following a cohort through their entire life from growth, maturation, natural and fishing mortality rates, to the end of their maximum life span. The required information includes: growth parameters (i.e., K, L_{inf}, and t_0), length at maturity L_{mat} or maturity ogive m_o, maximum age t_{max}, length-weight relationship (power function parameters *a* and *b*), and fishing gear selectivity curve. Other data may also be used, including the proportion of fishing mortality that occurs before spawning, and the proportion of natural mortality that occurs before spawning. Clearly, the SPR approach requires more inputs than the other three methods. In particular, selectivity and maturity ogives are typically unavailable for data-poor elasmobranchs. Amongst the 16 stocks in the WCPFC region, only four stocks have maturity ogive information (i.e., BSH-N, SMA-N, FAL, and SPL). Furthermore, we only found one study on gear selectivity for Blue Shark (Carvalho and Sippel, 2016) and assumed selectivity and its function form for Silky shark and oceanic Whitetip shark. Therefore, this method was applied to these three stocks only (we assumed OCS had the same m_o as BSH-N as they had similar L_{mat} (values for both species largely overlapped each other, with a mean L_{mat} = 192 cm for BSH-N and mean 196 cm for OCS, respectively).

Unlike MSY-related reference points, the benchmark for SPR is the depletion level of spawning biomass per recruit, typically set as $F_{35\%}$ to $F_{40\%}$ as a proxy for F_{msy}, that is, fishing mortality that depletes spawning biomass per recruit down to 35% - 40% of unfished level (Gabriel and Mace 1999). It is worth to point out that although SPR refers to spawning biomass, this biomass is not the biomass of the population but a relative value, in terms of “per recruit”. Any arbitrarily number, such as 1 or 1000 fish, can be used as the initial population size to derive SPR. Reference points derived from SPR, generally expressed as $F_{x\%}$, are also F-based rather than B-based reference points. They refer to the fishing mortality that corresponds to the percentage of depletion in spawning biomass from an unfished level on a “per recruit” basis.

SPR requires a link between $F_{x\%}$ and F_{msy} and there has been extensive research on the particular x% as proxy for F_{msy}. For example in a review of biological reference points for precautionary approaches, Gabriel and Mace (1999) recommended that fishing mortality rates in the range $F_{30\%}$ to $F_{40\%}$ be used as general default proxies for F_{msy}, in cases where the latter cannot be reliably estimated. In the absence of data and analyses that can be used to justify alternative approaches, they recommended that $F_{30\%}$ be used for stocks believed to have relatively high resilience, $F_{40\%}$ for stocks believed to have low to moderate resilience, and $F_{35\%SPR}$ for stocks with “average” resilience. It is becoming increasingly difficult to justify MSY-compatible targets less than 30-40% B_0, so $F_{45\%}$ is recommended for low productivity stocks in New Zealand (Ministry of Fisheries, 2011). Here we provided three reference points: $F_{60\%}$, $F_{40\%}$, and $F_{10\%}$. We were unable to investigate what fraction of F_{msy} the SPR-based $F_{60\%}$, $F_{40\%}$ and $F_{10\%}$ may correspond to as this requires a stock-recruitment relationship and may differ from species to species. To integrate multiple methods, we tentatively treated $F_{60\%}$ as F_{msm}, $F_{40\%}$ as F_{lim}, and $F_{10\%}$ as F_{crash}.

2.3.5 Joint reference points

The results from multiple methods were combined to give a more balanced estimation. Depending on the available information, two to four methods were applied to each stock and each method was given the same weight. The combined reference points are cF_{msm}, cF_{lim}, and cF_{crash}. Similar to the dilemma encountered in *M* estimation, using the combined RPs from multiple methods rather than choosing a single method is more likely to minimize bias (Simpfendorfer *et al.*, 2005; Brodziak *et al.*, 2011; Kenchington, 2014c; Moe, 2015). However, the SPR approach concerns a single cohort and disregards the stock-recruitment relationship, and is only applied to three stocks. As the development of SPR strategy mainly concerned obtaining a large fraction of the MSY in the long term and biomass levels were not considered important (Clark, 2002), we recommend using joint RPs from Methods 1 to 3 only for the WCPFC stocks.

2.4 Results of natural mortality estimation

Comparison among the seven estimators of natural mortality (the last estimator adopts values from literature) indicated that the first two estimators, Then1 and Then2, differed markedly from other estimators for most stocks (Figure 1). Eqn 2a (Then1) based on t_{max} yielded larger M than the average for all stocks except Porbeagle shark (Table 2). On average, M from Then1 was 1.23 times higher than the mean value of all seven approaches. In contrast, Eqn 2b (Then2) based on growth parameters yielded smaller M than the average for all stocks except Porbeagle shark (Table 2). On average, M from Then2 was only 71% of the mean value of all seven approaches. The deviations in opposite directions from these two estimators may be seen as fortunate, as they offset each other.

It was interesting to see this stark disparity between the first two methods and other estimators. Then *et al*. (2015) is the most recent development in natural mortality estimation and was considered to have improved existing research.

2.5 Results of estimated reference points

(1) BSH-N: the Blue shark (*Prionace glauca*), North Pacific stock

This stock may be considered “data-rich” amongst the 16 shark stocks because there was sufficient information to apply all four methods. The posterior distributions of F_{msm} from the four methods largely overlapped each other (Figure 2), and the summary statistics were similar between methods. For example, the mean F_{msm} was 0.10, 0.19, 0.15, and 0.14 for Methods 1 to 4, respectively (Table 3). The r values from the literature (Method 3) were typically derived from demographic approaches so the results between Methods 2 and 3 should be close. We recognize that if the same life history parameters and the same form of Euler-Lotka equation were used in the literature (Method 3), then Method 2 would have simply duplicated Method 3.

It was interesting to see that $F_{60\%}$ falls within the range of F_{msm} estimated by Methods 1 to 3. However, this does not imply that $F_{60\%}$ is a proper proxy for F_{msm} for this stock because these methods may have used different age composition data. For example, the SPR method involved larger and older fish than Method 2. The mean S_{50} from 16 fleets catching Blue shark (Carvalho and Sippel, 2016) was 126.0 cm. This translated into a mean age of 2.77 (sd = 1.16, ranging from 1.01 to 5.73 yrs) based on various von Bertalanffy growth parameters estimated for this stock. The demographic method implicitly assumed that recruitment age was 1 yr. If we used a knife-edge selectivity at age 2.77, the Euler-Lotka equation yielded a mean F_{msm2} = 0.258 (sd = 0.127), similar to $F_{40\%}$.

Other reference points, i.e., F_{lim} and F_{crash}, exhibited similar distribution patterns to F_{msm} (Figure 2) because they were essentially calculated from F_{msm}, except for the SPR method. Because it was difficult to determine which one of Methods 1 to 3 was most reliable, we recommended using the combined results from all three methods, i.e., cF_{msm}, cF_{lim}, and cF_{crash} in Table 4.

(2) BSH-S: the Blue shark (*Prionace glauca*), South Pacific stock

This stock had fewer life-history data available than the same species in the North Pacific. There was a lack of maturity ogive and gear selectivity information, so the SPR method cannot be applied. The reproductive cycle was also unknown. To use Method 2, we assumed that the reproductive frequency was the same for the North and South stocks, i.e., 1 or 2 yrs (values from two studies, Clarke *et al.*, 2015). There was no intrinsic rate of increase (r or λ) available for BSH-S in the Pacific and we used the alternative value of r = 0.34 from the Clarke et al. (2015) report. With this borrowed information, the analysis resulted in mean F_{msm} 0.08, 0.13, and 0.17 for Methods 1 to 3, respectively (Figure 3 and Table 4).

(3) SMA-N: the Shortfin mako shark (*Isurus oxyrinchus*), North Pacific stock

The estimated reference points differed considerably between methods (Figure 4), perhaps due to large variations in life history parameters from different studies. The mean F_{msm2} was about 1/3 of F_{msm1} (Table 4). Reproductive cycle was one of the most uncertain parameters used in Method 2. Two studies found Rc = 3 yrs (Clarke *et al.*, 2015), but a more recent study indicated a time shorter than 3 yr (Semba *et al.*, 2011). Instead of using Rc = 3 yr, we tested Rc = 2 and 1 yr with all other parameters remaining unchanged. The test led to a mean F_{msm2} = 0.03 when Rc = 2 yr (same as F_{msm3}) and 0.05 for Rc = 1 yr, which were closer to F_{msm1}.

(4) SMA-S: the Shortfin mako shark (*Isurus oxyrinchus*), South Pacific stock

Life-history parameters were very limited for the South Pacific stock compared to the North Pacific stock. There were no growth parameters (K, L_{inf}, and t_0), fecundity, reproductive cycle, and intrinsic population growth rate available. Another important life history parameter was maximum age t_{max}. This parameter had not been determined for SMA-S but was considered to be greater than 29 yrs for males and greater than 28 yrs for females (Clarke *et al.*, 2015). We used t_{max} = 29 for both sexes and assumed that growth parameters, reproductive parameters, and intrinsic population growth rate were the same as SMA-N. Such information borrowing resulted in a wide distribution of F_{msm2} (Figure 5) and a very small mean F_{msm2} (0.002 rounded to 0.00 in Table 4). The inputs may have led to overestimation of M and consequentially overestimating F_{msm1} but underestimation of F_{msm2}.

(5) LMA: the Longfin mako shark (*Isurus paucus*)

Longfin mako shark had very few life-history parameters available, i.e., no other information except length at birth, length at maturity, and litter size. There were also no alternative parameters available from other regions. The limited information was insufficient to apply any method.

(6) FAL: the Silky shark (*Carcharhinus falciformis*)

The early studies reported that Silky shark longevity ranged from 8 to 16 yrs (mean =12.67) (Clarke *et al.*, 2015). This range differed markedly from alternative t_{max} in other regions (30, 32, 19, and 20 yrs, mean=25.25). Using the smaller t_{max} from the Pacific resulted in large F_{msm1} by Method 1 (likely overestimation) and small F_{msm2} by Method 2 (likely underestimation). So for this stock we used the newly estimated life history parameters, including t_{max} (28 yr), t_{mat}, L_{inf}, K, t_0, L_{mat} (Grant *et al.*, 2018). These new values and a knife-edge selectivity at 64 cm total length led to reasonably similar reference points from the four methods (Table 3, Figure 6). For example, F_{msm} (or $F_{60\%}$) was 0.06, 0.07, 0.07, and 0.03 for Methods 1 to 4, respectively.

However, as discussed in BSH-N, we recommended using the combined RPs from Methods 1 to 3 (Table 4). The combined mean cF_{msm} was 0.06 and mean cF_{lim} was 0.09.

(7) OCS: the oceanic whitetip shark (*Carcharhinus longimanus*)

No estimate of the intrinsic rate of increase was available for the Pacific for OCS so we borrowed estimated *r* from Atlantic and Indian Oceans (Clarke et al. 2015). Similar to FAL, a knife-edge selectivity at 175 cm total length was assumed for OCS. The longevity estimates came from two studies and differed markedly: 11 yrs and 36 yrs. We used t_{max} = 36. The estimated reference points were not too far apart (Figure 7). The mean F_{msm} was 0.07, 0.12, 0.06, and 0.05 from Methods 1 to 4 (Table 3). Again, we recommended using Methods 1 to 3 where the combined mean cF_{msm} was 0.08 and the mean cF_{lim} was 0.12 (Table 4).

(8) BTH: the Bigeye thresher shark (*Alopias superciliosus*)

The estimated intrinsic rate of increase λ by demographic analysis from the literature was 0.996 (ranging between 0.0978 and 1.014)(Cortés, 2002; Clarke *et al.*, 2015). This suggests that the Bigeye thresher shark in the Pacific would suffer a negative population growth rate even with no fishing. Longevities of 21 yrs for females and 20 yrs for males were based on the largest observed sizes. There was no reproductive cycle information available for BTH so we assume *Rc* = 1 yr.

Recently, Fu *et al.* (2018) used the longevity of 22 yrs for females in the Atlantic in their demographic analysis. If we used t_{max} = 22 yrs for both males and females (all other parameters from the Clarke *et al*. (2015) report), the estimated mean F_{msm} was 0.07, -0.01, and 0.004 (rounded to 0.00) for Methods 1 and 3, respective, and the combined result of cF_{msm} was 0.02 (Figure 8, Table 4).

(9) PTH: the Pelagic thresher shark (*Alopias pelagicus*)

There was also no reproductive cycle information available for PTH so we again assumed *Rc* = 1 yr. The estimated reference points varied between the three methods, with mean F_{msm} of 0.06, 0.02, and 0.03 for Methods 1 to 3 (Table 4, Figure 9). The longevity from literature ranged from 14 to 28.5 and we again used the maximum value. The estimated natural mortality may have played a role in causing the disparity between Methods 1 and 2. The method based on t_{max} (Eqn 2a) yielded a larger *M* (mean = 0.23) than the method based on growth (Eqn 2b) (mean = 0.13) and *M* from other estimators. It was unclear whether the maximum t_{max} was still biased low. Conventional techniques to resolve growth rings in older shark can be very unreliable. The revision of longevity in white sharks would seem to be a good example of the potential underestimation of longevity (Hamady *et al.*, 2014).

(10) ALV: the Common thresher shark (*Alopias vulpinus*)

The t_{max} came from two studies: 25 yrs and 15 yrs. Using the larger value 0f 25 yielded mean *M* = 0.26 and 0.12 from Then1 and Then2 estimators. The former is the largest and the latter the smallest amongst the seven estimators (Figure 1). All three methods produced moderately similar reference points for ALV (Table 4, Figure 10). Again, the combined mean cF_{msm} of 0.07 was more balanced estimate than the individual estimate from Methods 1 to 3 (mean F_{msm} = 0.08, 0.07, and 0.05, respectively).

(11) POR: the Porbeagle shark (*Lamna nasus*)

Only two methods were applied to Porbeagle shark, as there was no estimated intrinsic population growth rate in literature (Table 4). The estimated M was more similar between the seven methods than many other species (Figure 1). Recently, Hoyle *et al.* (2017b) conducted a stock-assessment for the southern hemisphere porbeagle shark and used updated LHPs since the Clarke *et al*. (2015) report. We used their data (in their Table 2, e.g., t_{max} = 75, t_m = 14.5, L_{inf} = 211, K = 0.086, and M = 0.09). The estimated mean F_{msm} was 0.05 and 0.03 for Methods 1 and 2, respectively (Figure 11).

(12) SPZ: the Smooth hammerhead shark (*Sphyrna zygaena*)

Only two methods were applied to the Smooth hammerhead shark, as there was no estimated intrinsic population growth rate in literature (Table 4, Figure 12). Moreover, there was also no age at maturity t_m and longevity t_{max} from the Pacific Ocean, no reproductive cycle Rc and estimated natural mortality rate M from the Pacific or other regions. To apply Method 2, we used alternative parameters t_m and t_{max}, and again assume Rc = 1 yr. These treatments led to a mean F_{msm} of 0.07 and 0.03 for Methods 1 and 2, respectively, with a mean cF_{msm} 0.05.

(13) SPL: the Scalloped hammerhead shark (*Sphyrna lewini*)

The t_{max} significantly differ between males (21 yrs) and females (35 yrs) and we used 35 yrs for both sexes. The estimated reference points (e.g., mean F_{msm} = 0.06, 0.06, and 0.03) from the three methods were relatively comparable (Table 4, Figures 13) when compared with other species.

(14) SPK: the Great hammerhead shark (*Sphyrna mokarran*)

There was no estimated intrinsic population growth rate available for the Great hammerhead, so we used only two methods to derive reference points. Interestingly, this was one of a few stocks where Method 2 yielded a higher reference point (mean F_{msm2} = 0.09) than Method 1 (mean F_{msm1} = 0.06, Table 4, Figure 14). Although Eqn 2a still gave a larger M (mean 0.15) than Eqn 2b (mean 0.10), the difference was smaller than for many other species.

(15) EUB: the Winghead shark (*Eusphyra blochii*)

There was no estimated natural mortality or intrinsic population growth rate available for the Winghead shark in the literature so only Methods 1 and 2 were used. The reproductive cycle was "seasonal", which we assumed to mean annual. The estimated M based on t_{max} (Eqn 2a) was again higher than the estimate based on growth parameters (Eqn 2b), i.e., mean M of 0.30 vs 0.18. Compared with other stocks, the estimated reference points were relatively similar (Table 4, Figure 15). The mean F_{msm} was 0.08 and 0.11 for Methods 1 and 2, respectively, with a mean cF_{msm} 0.09.

(16) RHN: the Whale shark (*Rhincodon typus*)

There was no estimated intrinsic population growth rate, natural mortality nor reproductive cycle in the literature. Some parameters (e.g., longevity, maximum length, age at maturity) were observed values (e.g. t_{max} includes maximum observed number of growth band pairs), or estimated from very small samples. To apply Method 2, we assumed *Rc* = 1 yr. The estimated *M* based on growth parameters was very small compared to *M* based on other estimators (mean 0.03 vs 0.08), but the average of 0.08 was smaller than for other species. The low natural mortality contributed to a low F_{msm1} (mean 0.03) and a high F_{msm2} (mean F_{msm2} = 0.11) (Table 4, Figure 16).

2.6 Discussions on F-based reference points

2.6.1 Comparison between methods

Method 1 based on empirical relationships were applied to all 15 stocks (except Longfin mako shark). Although we also applied Method 2 (demographic analysis) to all 15 stocks, we had to borrow some life history parameters from other regions for some stocks and make assumption about the reproductive cycles for several stocks. Comparison of these two methods shows that they provide similar mean RPs (Figure 17). For example, the mean RPs across the 15 stocks are nearly identical between the two methods: 0.06 vs 0.07 for F_{msm}, 0.10 vs 0.10 for F_{lim}, and 0.13 vs 0.14 for F_{crash}, respectively. Both methods have the same number of stocks with a higher RP value than the other method (seven stocks plus one stock (SPL) in a tie). However, the estimated RP values can be different between the two methods and their correlation is low (Figure 18). The empirical method is less likely to yield extreme estimates than the Euler-Lotka equation (e.g., for SMA-S, BTH, and RHN). Method 1 also tends to produce smaller uncertainty than Method2, with an overall SD[F_{msm1}] = 0.03 compared to SD[F_{msm}2] = 0.04.

Method 3 based on intrinsic population growth rate from the literature was applied to 10 stocks. The result from this method is similar to Method 2. The correlation between Methods 2 and 3 (0.85) is much higher than correlation between Methods 1 and 2 (Figure 18).

Method 4 based on SPR was applied to three stocks. For the Blue shark in the North Pacific $F_{60\%}$ appears to be a proper proxy for F_{msm} as the mean $F_{60\%}$ = 0.14 is within the F_{msm} range estimated by Methods 1 to 3 (Table 3). Similarly, $F_{40\%}$ is within the range of F_{lim} estimated by Methods 1 to 3. However, $F_{10\%}$ is too high compared to F_{crash} from other methods.

For the Silky shark $F_{60\%}$ appears to be a more conservative proxy for F_{msm} as the mean $F_{60\%}$ = 0.03 is lower than the F_{msm} range estimated by Methods 1 to 3 (i.e. 0.06, 0.07, and 0.07). Instead, $F_{40\%}$ (= 0.05) or slightly lower (e.g. $F_{35\%}$) would be comparable to F_{msm}, while $F_{10\%}$ is close to F_{crash} from other methods. The low values for these $F_{x\%}$ may be mainly caused by the knife-edge selectivity set at a low 64 cm.

Similar to BSH-N, for the Ocean whitetip shark it seems appropriate to use $F_{60\%}$ as a proxy for F_{msm}, $F_{40\%}$ as a proxy for F_{lim}, but $F_{10\%}$ is too large for F_{crash}.

Overall it is difficult to conclude which method is the best across all species. Besides the effect of alternative methods, available life-history parameters and their quality have marked impact on the quality of the estimated reference points. Table 5 summarizes available data for each stock and the relative reliability of the derived reference points.

2.6.2 Uncertainty in life-history parameters

A close examination of the life-history parameters fed into the four methods reveals high uncertainty in life-history parameters. In particular, maximum age may have been underestimated for most stocks because this parameter is either the observed or estimated maximum age from a population that has been fished for many years so fish at maximum age are no longer included in the sample. Sample sizes may also be inadequate (since the maximum of a distribution tends to increase at larger sample sizes), and sampling fisheries may have selected smaller, younger fish, either through gear selectivity or because they fish in areas where older sharks are not present. Moreover, recent studies show that the common method of ageing sharks and rays, counting growth zones on calcified structures, can substantially underestimate true age (Francis *et al.*, 2007; Hamady *et al.*, 2014; Harry, 2018). Underestimation of t_{max} leads to overestimation of natural mortality rate. Different studies were often found to produce a wide range of estimates for the same life history parameters (including t_{max}). Large uncertainty in life history parameters leads to a wide spread of the estimated reference points, as evidenced in Figures 2 to 16. Greater precision in reference points cannot be achieved without greater precision in life-history parameter estimates.

We note that Method 2 is more likely to produce extreme estimates and even negative F_{msm2}. The reason behind this may be due to its use of more life history parameters and more assumptions. In addition to natural mortality which is used in Method 1, the Euler-Lotka equation requires age at maturity, annual fecundity, and reproduction cycle. It also requires the assumptions that survival from age 0 to the age at maturity is constant, and that knife-edge selectivity occurs at age 1.

Mean negative F_{msm2} results from the estimated negative mean r (or $\lambda < 1$). Although some of the LHPs are certainly problematic and are the most likely causes of the negative estimates, the negative values are theoretically valid, since it is possible for a population to suffer a period of negative growth even without fishing, perhaps due to adverse environmental conditions.

The bias in t_{max} and M has an opposite effect on Methods 1 and 2 (Figure 19, Figure 20). Interestingly, Method 2 exhibits counter-intuitive behaviour: the longer life span or lower natural mortality leads to higher sustainability. Hence, if the methods are used independently (not combined), we recommend using Method 1 as it shows an intuitive behaviour and is less likely to produce extreme values. Overall, it is recommended to use the combined estimates, i.e., cF_{msm}, cF_{lim}, and cF_{crash} from Methods 1 to 3 for risk-based reference points, instead of adopting a particular method, so the bias in the different methods can at least partially offset each other.

2.6.3 Effect of gear selectivity

Selectivity plays a significant role in all methods, because MSY-related RPs vary with the age/size composition of the fish used to derive the RPs. Method 1 is based on empirical relationships between F_{msy} and life-history parameters from formal stock assessments of data-rich stocks. The data used in formal stock assessment are gear-specific, meaning that catches by certain gear types are used for the assessment. Similarly, applying Method 1 implicitly involves an assumption that the estimated reference points go with the catches assuming the same selectivity. However, when a stock is impacted by multiple sub-fisheries with different selectivity, it is impractical to set different RPs for different sub-fisheries. In such cases, we need to assume that the selectivity in the data-rich stocks used to build the empirical relationship is similar to the overall selectivity in the multiple sub-fisheries.

On the other hand, the widely adopted demographic approach (Method 2) implicitly assumes that fish are vulnerable to the fishery at age 1 and equally vulnerable at all older ages. If the majority of fish are not captured until older ages, this method will underestimate RPs, regardless of whether other life-history parameters are accurate or not. It appears that the intrinsic population growth rates in literature are often estimated from demographic analysis, suggesting that they are also likely underestimated if vulnerable age is greater than 1.

F-based reference points are both stock-specific and age-specific. The significance of age-specific F_{BRPs} are often overlooked. The classic fisheries sciences focus on single stock assessments. A stock's capability to withstand fishing mortality depends on their age/size at recruitment, relative to maturity. For example, selectively harvesting only large fish that have spawned in their earlier life has a low impact on their population sustainability (if we ignore their potential disproportionate contribution to reproductive output (Barneche *et al.*, 2018), fishing induced evolution (Law, 2000; Heino *et al.*, 2015), and changes in ecosystem structure (Zhou *et al.*, 2010; Garcia *et al.*, 2012)). On the other hand, when fish enter fisheries at young ages, fishing mortality rate must be lower to allow a sufficient fraction of the population to reach maturity (noting that low *F* does not necessary translate to a low catch as catch also depends on biomass). Method 1 does not require selectivity (it assumes that selectivity is the same as those data-rich stocks used to derive the empirical relationship between F_{BRPs} and LHPs), but an estimated or assumed selectivity is needed for Methods 2 to 4.

2.6.4 Spawning stock biomass per recruit approach

We have only applied the SPR approach to three stocks as required LHPs are not available for the other 13 stocks. Besides the concerns about uncertainty of input life history parameters and a lack of selectivity information, this "per recruit" approach fundamentally differs from other methods. A species' intrinsic productivity determines its ability to sustain fishing impact but the SPR approach basically ignores this critical trait. Extensive studies have examined the appropriate $F_{x\%}$ proxy for F_{msy}, and a range from $F_{20\%}$ to $F_{70\%}$ have been suggested (see discussion in Brooks et al. 2010). It has been well recognized that SPR levels are related to the slope at the origin of stock–recruit curves, and that life history is an important consideration. However, the analytical relationship between SPR and the underlying stock–recruit curve had not been explicitly explored until the work of Brooks et al. (2010). They investigated the relationship between the slope of a stock–recruit function and the maximum excess recruitment (MER) in number of individuals. MER differs from MSY in two respects. First, MER is derived by solving for a maximum in numbers, whereas MSY is the maximum in weight. Second, MER is a property of the stock–recruit function, whereas MSY considers the combined effect of a given fishing mortality on YPR and the extent of excess recruitment (Brooks et al. 2010). For the Beverton-Holt SRR, the spawning potential ratio (SPR) at MER is $SPR_{MER} = \frac{1}{\sqrt{\hat{\alpha}}}$, where $\hat{\alpha}$ is the maximum lifetime reproductive rate at low density, a property of the slope *b* of SRR: $\hat{\alpha} = b\frac{S_0}{R_0}$, where R_0 and S_0 are recruits and spawners when the stock is unexploited. F_{MER} (corresponding to SPR_{MER}) is generally greater than F_{msy}, but both are comparable when steepness and natural mortality are relatively low (commonly the case for elasmobranchs). This study demonstrated that SPRx% is a function of the stock productivity quantified as life time reproduction rate, which is a product of the slope at the origin of a stock-recruitment function and SPR when no fishing (Figure 21). In other words, to maintain stock biomass at certain x% of unfished level or of a reference point (i.e., 20%B_0 or 10%B_{msy}) requires varying SPRx% from species to species. Therefore, it is inappropriate to use a common x% such as $F_{40\%}$ for all stocks unless they have the same productivity. Indeed, Brooks et al. (2010) showed that SPR_{MER} varied among 11 elasmobranchs, ranging from 0.26 to 0.89.

The level of risk to sustainability varies between stocks due to their varying productivity and compensation (measured by r or the steepness parameter in the stock-recruitment relationship). Because SPR does not take the stock-recruitment relationship or population growth rate into account, choosing a particular x% for a particular stock is more or less arbitrary. For example, $F_{40\%}$ can maintain 40% spawning biomass relative to the unfished condition for *a single cohort*, but it may lead SSB_{cur}/SSB_0 (depletion level of actual spawning biomass) above or below this level depending on the stock's productivity or compensation. In other words, $F_{40\%}$ can be very conservative for a productive stock but may be too risky for unproductive elasmobranchs. Unlike Methods 1 to 3, a pre-defined $F_{x\%}$ value lacks a theoretical basis. Note that a similar reference point based on maximum excess recruitment, SPR_{MER}, can be defined for each species if the steepness parameter is known (Brooks *et al.*, 2010).

2.6.5 Approaches based on population growth rate

In contrast to the SPR approach, Methods 1 to 3 are based on population growth rate r, where F_{msm} corresponds to reducing stock biomass to $0.5B_0$ in the Graham-Schaeffer production model if fishing mortality is maintained at this level for a long term. Amongst the three methods in this group, Method 1 may deserve some additional discussions. This method is based on established empirical relationship between F_{BRP} and LHPs. In the established relationship, F_{BRP} are estimated from stock assessment models for data-rich species, so it has taken into account the stock-recruitment relationship. Seeking a reliable correlation between F_{msy} ~ M has attracted extensive research. Because natural mortality is often derived from other life-history parameters, this relationship involves uncertainty at three levels: measurement error in LHPs used to derive M (e.g. t_{max}, K, L_{inf}), process error in M ~ LHP(s) relationship, and process error in F_{msy} ~ M (or r_m ~ M) relationship. The first two levels uncertainty also occurs in Method 2 (Euler-Lokta equation) and Method 4 (SPR approach) as M is also needed for these methods, but the last level uncertainty is unique to Method 1 (but other methods also have their own unique uncertainties). Eqn 3 is for class Chondrichthyes in general, and the estimated coefficient can be different between orders in the same class (for example, Carcharhinifores has a smaller coefficient than Lamniformes) (Zhou *et al*. 2012). Cortes and Brooks (2018) suggest that the F_{msy}/M ratio should not exceed 0.4 for shark species. They further suggest that if the stock is harvested before reaching maturity, as a rule of thumb the F_{msy}/M ratio should not exceed 0.2, 0.5, and 0.8 for low, medium and high productivity stocks, respectively.

To validate the results from these studies, we examined the relationship between intrinsic population growth rate r_m and M using Euler-Lotka equation. Assuming litter size = 13.3 (mean of the 14 stocks in this report, except very uncertain whale shark), and reproductive cycle of one year, we simulated maturation age from 5 to 40 years in Eqn (4) to obtain both r_m and M. Figure 22 shows a clear linear relationship between r_m and M when M is smaller than 0.17, (i.e. $r_m \approx M \approx 2F_{msy}$) but r_m increases more quickly than M when $M > 0.17$ ($F_{msy} > 0.5M$). Because the change is less dramatic comparing to SPR in Figure 21, Method 1 based on natural mortality is more reliable than Method 4 based on SPR approach, although it may be slightly too conservative for many stocks.

Method 2 requires more LHPs than Method 1, which could be an advantage if these LHPs exist and are reasonable accurate. On the other hand, our results indicate this method is more likely to produce extreme estimates and even negative F_{msm2}. Using more life history parameters may absorb more uncertainty and more assumptions. For example, age at maturity, annual fecundity, and reproduction cycle required by Euler-Lotka equation may be difficult to obtain or highly uncertain.

The assumptions of constant M from age 0 and knife-edge selectivity at age 1 are also difficult to hold.

2.6.6 Theoretical basis for Methods 1 to 3

It is worthwhile to recall that the biomass dynamics model provides the technical foundation for the three RPs (F_{msm}, F_{lim}, and F_{crash}) estimated by Methods 1 to 3. Each RP has a corresponding equilibrium biomass: $B_{msm} = 0.5B_0$, $B_{lim} = 0.25B_0$, and $B_{crash} = 0$. In classical single-stock dynamics theory, if fishing mortality is maintained at one of the three F levels for a long time, the stock biomass will tend towards the corresponding B level regardless of the initial biomass level and the stock's productivity. However, these reference points do not directly relate to spawning biomass. It is more likely that B_{lim} is closer to 20% or 30%$SB_{dynamic10,unfished}$ than B_{msm} so F_{lim} is recommended as the limit reference point for WCPFC bycatch, given the fact that the WCPFC has adopted a benchmark 20%$SB_{dynamic10, unfished}$ as the limit biomass reference point (F_{lim}) for target species.

The Schaefer production model is a symmetrical curve, which assumes that the maximum yield occurs at $B_{msy} = B_0/2$. This model is widely accepted for teleosts, but there is a concern that the curve may not be symmetric for elasmobranchs. If this is the case, a general surplus production (Pella-Tomlinson) model (Pella and Tomlinson, 1969) may be more appropriate. However, the shape parameter is rarely available for most groups of animals, including sharks.

2.6.7 Management objectives and reference points for non-target species

The Convention on the Conservation and Management of Highly Migratory Fish Stocks in the Western and Central Pacific Ocean (CCMWCPO) stipulates management objective for target species to "maintain or restore stocks at levels capable of producing maximum sustainable yield, as qualified by relevant environmental and economic factors" (Article 5). This is simply MSY-based target and mirrors the objective in FAO Code of Conduct for Responsible Fisheries (CCRF) and UN Convention on the Law of the Sea (UNCLOS). In addition to a target, fisheries management often specifies limit reference points. Limit reference points are set primarily on biological grounds to protect the stock from serious, slowly reversible or irreversible fishing impacts, which include recruitment overfishing and genetic modification. The distinction between retained and by-catch species is a result of human values and utilisation, rather than one of biology or ecology. In that limit reference points are set to so as to prevent slowly reversible or irreversible biological impacts there is no biological basis for by-catch and retained species having different limit reference points (Sainsbury 2008). As such, for non-target species, the CCMWCPO adopts "a view to maintaining or restoring populations of such species above levels at which their reproduction may become seriously threatened" (Article 10). Apparently, this view matches the limit reference point for target species. Hence, setting aside ecological interaction among species, the biological objective is consistent between target and non-target species.

In the present report, we developed three reference points (F_{msm}, F_{lim} and F_{crash}) rather than a single LRP. Providing multiple reference points is helpful as they explicitly link to the level of ecological risk as described in

Table 6 (Zhou *et al*. 2011). For this reason, we removed the word "limit" from the original title. These are the same reference points adopted for Bigeye thresher shark (Fu et al. 2018) and Porbeagle shark (Hoyle et al. 2017) where the three RPs are termed as maximum impact sustainable threshold (MIST) limit reference points (LRP). However, a particular stock cannot have three different "limit reference points". We must choose one out of these three as the LRP. For commercial species, F_{msy} is often a target reference point (TRP) and F_{lim} a LRP (Sainsbury, 2008), although defining a TRP or LRP is not purely a scientific question but also a management and societal choice. Similarly, for bycatch species a limit reference point is essentially the acceptable level of risk to sustainability. From the scientific point of view, if we wish to reduce fishing impact on ecosystem structure and function (a key goal in Ecosystem-based fisheries management), it is more sensible to adopt a common and impartial benchmark for all competitive species in the same ecosystem, whether it is commercial species or bycatch species, than to treat them differently. From the management point of view, this is also a simpler procedure. This is similar to the previous recommendation for WCPFC elasmobranchs (Clarke and Hoyle, 2014). WCPFC has adopted 20%$SB_{dynamic10,unfished}$ as a LRP for target species. The notation $SB_{dynamic10,unfished}$ is adapted from SB_0, the virgin spawning biomass when there was no fishing. This biomass is fundamentally different from $SB_{SPR,unfished}$, and is difficult to estimate without time series data and traditional stock assessment. Out of the three RPs (F_{msm}, F_{lim} and F_{crash}), F_{lim} corresponds to B_{lim} that is 25% of fishable virgin biomass B_0 and is closer to 20%$SB_{dynamic10,unfished}$ than the other two RPs. Therefore, in this study F_{lim} corresponds most closely to the requirements of Article 10 of the CCMWCPO.

For the sake of discussion, the analysis in this report deals with each stock or species independently without taking ecological interactions into account. Because most elasmobranchs are typically high trophic level predators, the abundances of their prey species may have declined due to fishing, which may have already led to a proportional decline of these elasmobranchs from their unfished population size (Zhou and Smith, 2017). In addition to this bottom-up effect, any additional fishing mortality on predators will further reduce their biomass. Hence, accepting $F = F_{lim}$ will eventually drive population lower than B_{lim} for top predatory sharks so adopting LRP $F = F_{msy}$ (corresponding to B_{msy} = 50% B_0) is more precautionary for elasmobranchs.

Incorporating reference points into management of non-target species has been adopted in some countries. In New Zealand, Ministry for Primary Industries has developed Spatially Explicit Fisheries Risk Assessment method (Ministry for Primary Industries, 2016), which is designed to estimate fisheries impact and reference points spatially for non-target species, and to inform risk management responses for these species. In Australia, a comprehensive Guide to AFMA's Ecological Risk Management has been developed for management of non-target species (AFMA, 2017). The area-based risk assessment method is used for ecological risk assessment in which reference points are an essential component. The WCPFC may consider these existing examples and adopt constructive elements for the risk management of these shark bycatch.

2.7 Recommended reference points and further research for WCPFC elasmobranchs

Our analyses and discussions support the previous recommendations of Clarke and Hoyle (2014). Considering the current and previous studies, we provide the following recommendations:

(1) Reference points should adopt a tiered (based on availability of information) framework. For those elasmobranchs evaluated using a stock assessment model, reference points estimated in the

same stock-assessment should be adopted. This will avoid the potential inconsistency of demographic composition used to estimate F_{cur} and F_{BPR} when they are derived separately.

(2) When stock assessments are not available, or when the results are not considered robust by the WCPFC Scientific Committee, risk-based fishing mortality benchmarks (F_{msm}, F_{lim} and F_{crash}) developed in the present report are recommended.

(3) Caution is needed when key life-history parameters are copied from literature, such as t_{max}. It is important to continue research to provide or improve estimates of life-history parameters. A meta-analysis should be considered to integrate studies on growth, maturity, and other LHPs from sampling across the whole population in the WCPO.

(4) Selectivity should be estimated for all elasmobranchs in the WCPFC jurisdiction. If selectivity cannot be modelled, a knife-edge size of entry may be determined by length samples of the observed catch.

(5) Further examination and research on spawning potential ratio approach is needed. Until the particular $F_{SPRx\%}$ that ensures low risk to population sustainability can be determined for each stock, we do not recommend SPR approach for setting a limit reference point for elasmobranchs using one generic value for all species.

(6) Adopt the combined LRP (cF_{lim}) derived in this study as tentative limit reference point for elasmobranchs managed by WCPFC. These estimates should be reviewed and updated in three to five years when new methods or additional data become available.

(7) In the future if the Commission deems that ecological interactions among species and ecosystem structure conservation are essential elements in the management of shark species, a relative lower fishing mortality benchmark such as F_{msm} should be considered as a limit reference point for these top predators.

3 Potential methods for estimating fishing mortality

3.1 Traditional stock assessment

This is the ideal approach for estimating both reference points and current fishing mortality. Traditional stock assessment models include surplus production models (biomass dynamics models), statistical catch-at-age models, delay-difference models, and virtual population analysis models. Traditional stock assessment models require various data, including at least a time series of catch and biomass index (often CPUE) records. The models produce biological and management quantities that quantify biological status, fishing impact, and at the same time produce corresponding reference points (i.e., there is no need to calculate reference points separately using additional models). This cohesive approach avoids possible inconsistency between reference points and biological status because both refer to the same type of fish in terms of their age/size/sex composition.

3.2 Area-based ERA methods

Unfortunately, the types of data required for traditional stock assessment models are generally unavailable for lower-value or bycatch species. Alternative data-poor techniques are needed for these species. In the last two decades, an area-based ecological risk assessment approach has become increasingly popular. The assessment involves two separate components: (1) deriving reference points based on biological and life-history traits as we have described in the previous section; (2) estimating fishing impact using fishery and ecological data.

The sustainability assessment for fishing effect (SAFE) (Zhou and Griffiths, 2008; Zhou *et al.*, 2009a, 2011) is an area-base ERA method to estimate the annual instantaneous fishing mortality for a species in defined period (i.e. one year):

$$F = \frac{C}{\bar{N}} \approx \frac{\sum_t a_{s|A_J,t}}{A_J} q_h q_\lambda (1 - S) \quad \text{(Eqn 7)}$$

Where C is catch, $\bar{N}$ is average abundance over the period, A_J is the species distribution range within the jurisdiction, $a_{s|AJ,t}$ is gear affected area by one unit of fishing effort when fishing site s is within A_J at time t, (a combination of habitat-dependent encounterability q_h and size- and behaviour-dependent selectivity q_λ), and S is the discard survival rate or escapement rate in some gear types (e.g. gear fitted with bycatch reduction device). This equation assumes that fish density is constant within its distribution range, and encounterability and selectivity can be predefined by fish size and behaviour. It implies that fishing mortality is the fraction of overlap between fished area and the species distribution area within the jurisdiction (availability), adjusted by catchability and post-capture mortality. This simple approach has been referred to as base SAFE (or bSAFE, AFMA, 2017).

If catch data are available in some years, fish density and gear efficiency may be estimated so bSAFE can be enhanced:

$$F = \frac{C}{\bar{N}} = \frac{\sum_t (d_s a_{s|A_J,t})}{\sum_s (d_s A_{s,J})} Q(1 - S) \quad \text{(Eqn 8)}$$

where d_s is fish density at site *s*, *Q* is catch efficiency. This version has been referred to as enhanced SAFE (or eSAFE, AFMA, 2017).

Eqns (7 and 8) assume no local depletion effects from repeated fishing at the same location, i.e., populations rapidly mix between fished and unfished areas. The fishing mortality will likely be overestimated if this assumption is not satisfied.

These basic equations have been modified in various ways depending on available data. Modification can be made to each of the input variables in the equations. In particular, if there is sufficient information to estimate CPUE trends, biomass and fishing mortality can be estimated using biomass dynamic models. This approach was used in the WCPFC stock assessments for bigeye thresher and porbeagle sharks (Fu et al 2018; Hoyle et al 2017).

3.2.1 Species distribution

Species distribution can be obtained from survey data (Zhou and Griffiths, 2008; Zhou *et al.*, 2009b; Ministry for Primary Industries, 2016; Grüss *et al.*, 2018), existing distribution maps based on habitat and other information (Zhou *et al.*, 2009a; Ministry for Primary Industries, 2016), and fishery data (Zhou *et al.*, 2009c, 2015; Hoyle *et al.*, 2017c; Fu *et al.*, 2018). Relative fish density is an important feature of species distribution. Depending on available information, homogeneous or random distribution may be assumed for data-poor species. If catch at location or presence-absence are available, heterogeneous density can be estimated and predicted through various statistical models as such GLMM, GAM, N-mixture, and geostatistical models (Zhou and Griffiths, 2007, 2008; Zhou *et al.*, 2013; Hoyle *et al.*, 2017c; Fu *et al.*, 2018; Grüss *et al.*, 2018). Models that include environmental data can be used to extend predicted distributions into areas with insufficient fishery data (Hoyle et al 2017).

3.2.2 Area affected by fishing

The simplest method is to divide the management area into many small equal-sized cells and count the number of cells with fishing effort greater than a threshold (e.g., 3 boat-days or 1 unit of fishing effort) (Zhou and Griffiths, 2008; Griffiths *et al.*, 2018). It may be preferable to calculate actual gear affected area from gear dimension (i.e., length of longline, gillnet, and seine, or trawl opening width) and soak time (Zhou *et al.*, 2011, 2013; Ministry for Primary Industries, 2016). The total area affected by fishing is a function of the total fishing effort and the gear-affected area per set.

3.2.3 Gear efficiency

This term is sometime called catch efficiency, fishing power, or catchability. Unlike catchability parameter *q* in stock assessment model, *Q* is the probability of catching a particular fish in one gear setting (deployment) when that fish is within the gear affect area. It may be considered as the combined effect of encounterability and selectivity (Zhou *et al.*, 2011, 2016). For data-poor species, a constant value may be assumed and assigned to encounterability and selectivity for each gear type based on fish size and behaviour (e.g. low 0.33, medium 0.67, high 1.0). If sufficient set-by-set catch data are available, gear efficiency can be estimated by abundance and detectability (referred to as N-mixture) models (Zhou and Griffiths, 2007; Zhou *et al.*, 2013, 2014; Campbell *et al.*, 2017).

Gear efficiency Q is directly related to catchability q in stock assessment models. When individuals are assumed to be randomly or evenly distributed in stock distribution area A, the relationship between these two quantities is $q = Qa/A$, where a is the average gear affected area by one unit of fishing effort. Hoyle *et al*. (2017) and Fu *et al*. (2018) took a different approach to derive catchability for Porbeagle shark and Bigeye thresher shark. They used a subset of the observer data within a subsection of the assessment area A_{Ω} where the data are believed to have good quality. They fitted a Bayesian state-space biomass dynamic model to an index of relative abundance in the selected sub-area. Catchability q_{Ω} is one of the three parameters (the other two parameters are carrying capacity K and intrinsic population growth rate r) in the biomass dynamics model. This q_{Ω} is then adjusted by area and used to estimate fishing mortality. This approach may be compared with the N-mixture model for estimating gear efficiency.

3.2.4 Discard survival rate and escapement

Bycatch species are often returned to the sea and some of these fish may survive. When there is no data available, survival rate may be assumed, for example $S = 0$ as the most conservative option. Results from field studies are available for some elasmobranchs (Campbell *et al.*, 2017; Ellis *et al.*, 2017). Fu et al. (2018) derive this variable for Bigeye thresher shark using a uniform distribution with bounds [0.3, 0.7] based on the calculated proportion of BTH released alive in the SPC and US observer datasets.

Modification of fishing gear can facilitate escapement of some bycatch species. For example, prawn trawl rigged with turtle excluder devices (TEDs) and bycatch reduction devices (BRDs) can reduce a range of species groups caught in tropical Australia (Brewer *et al.*, 2006). Nets with a combination of a turtle excluder device and bycatch reduction device reduced the catches of turtles by 99%, sharks by 17.7%, and rays by 36.3%. Similarly, a study on the demersal fish-trawl fishery found that BRDs significantly improved the escape proportions for most chondrichthyans by 20–30% (Wakefield *et al.*, 2017). The results of these and other studies may be used as the escapement rate in calculation of fishing mortality for similar gear types.

3.3 Age-based methods—catch curve

Statistical catch-at-age methods are considered the state-of-the-art in modern stock assessment. Catch curves represent the simplest catch-at-age methods. If catch-at-age data are available, catch curve analysis may be carried out to estimate total mortality Z and fishing mortality F if natural mortality M is known. There are alternative methods for estimating Z from catch curve data, including regression-based methods, the Chapman-Robson estimator, and the Heincke estimator. These methods generally require that vulnerability to fishing gear is constant above the age when maximum catch occurs, and that the population has a stable age structure. For example, a dome-shaped selectivity curve may distort the linear relationship between log(catch) and age. Catch curve analysis can be applied to catches taken in the same year so the fish are composed of cohorts born in different years. In this case catch curve analysis has to assume (1) a constant recruitment for these cohorts; (2) similar survival history for these cohorts (Quinn and Deriso, 1999).

In additional to potential violations of assumptions, non-random sampling, and inaccurate ageing data, stochastic error in the true mortality rate, recruitment, and ageing affect the accurate of the estimated mortality. Comparison between the Chapman-Robson and regression estimators found the Chapman-Robson estimator to be more accurate than regression methods (Dunn *et al.*, 2002). Another comparison study comparing three catch-curve methods (the Chapman–Robson, regression, and Heincke estimators) also showed that the Chapman-Robson estimator generally out-performed the other two methods (Smith *et al.*, 2012) and was recommended, after correction for over-dispersion, for estimating total mortality.

3.4 Length-based methods

The most common length-based model is the Beverton-Holt "per-recruit" estimator (BHE) based on von Bertalanffy growth model with an assumption that total mortality *Z* is constant beyond the age of recruitment (Quinn and Deriso, 1999). Z is calculated as

$$Z = \frac{K(L_{inf} - \bar{L})}{\bar{L} - L_c} \qquad \text{(Eqn 9)}$$

where *K* and L_{inf} are VB growth parameters, $\bar{L}$ is the mean length in the catch, and L_c is the length at recruitment age. The BHE (Eqn 9) assumes steady-state conditions, deterministic vB growth function, a constant mortality rate of all fully recruited fish, and continuous and constant recruitment to the fishery.

As length is a function of age, length frequency data can be converted to age under the assumption of deterministic growth following a vB growth model. Hence, the length converted catch curve (LCCC) method was developed. It has been shown that the standard LCCC overestimates *Z*, but by explicitly considering seasonal growth oscillations LCCC can produce unbiased estimates (Pauly *et al.*, 1995).

Recently, Hordyk *et al.* (2014, 2016) have developed the length-based spawning potential ratio (LB-SPR) mortality estimator. This is an equilibrium age-structured model that converts the predicted age distribution of the catch to a length distribution. Given known *M*/*K*, the LB-SPR estimates the parameters *F*/*M* from the standardized length composition of the catch.

Huynh *et al.* (2018) compared these three length-based methods used Monte Carlo simulations across a range of scenarios with varying mortality and life history characteristics. They showed that neither the LCCC nor the BHE was uniformly superior in terms of bias or root mean square error across simulations, but these estimators performed better than LB-SPR, which had the largest bias in most cases. Generally, if the ratio of natural mortality (*M*) to the von Bertalanffy growth rate parameter (*M*) is low, then the BHE is preferred, although there is likely to be high bias and low precision. If *M*/*M* is high, then the LCCC and BHE performed better and similarly to each other.

The requirement of constant fishing mortality and recruitment over time has been relaxed by a recent developed length-based method. Rudd and Thorson (2017) extended the length-only approaches to account for time-varying recruitment and fishing mortality using a Length-based Integrated Mixed Effects (LIME) method. LIME requires a single year of length data and basic biological information and can fit to multiple years of length data, catch, and an abundance index if available.

The most recent development in this area is length-based Bayesian biomass estimation method (LBB) (Froese *et al.*, 2018). The method estimates asymptotic length, length at first capture, relative natural mortality, and relative fishing mortality using length frequency data. Standard fisheries equations can then be used to approximate current exploited biomass relative to unexploited biomass.

3.5 Discussion on estimating fishing mortality

Clearly, the traditional stock assessment is the first choice for estimating current fishing mortality (and reference points) if required data are available. When using data-limited approaches, their assumptions and caveats should be kept in mind.

Area-based methods involve a series of assumptions regarding species distribution pattern and range, gear efficiency, discards survival rate and escapement rate. Accuracy can be improved with more data and better estimators, but uncertainly may still be high for some species.

Age and length-based methods generally require constant recruitment, growth, natural mortality, and fishing mortality, in addition to the requirement that the age composition and length frequency data in the sample truly represent those of the exploited age/size range of the stock. In addition, as discussed in the previous section, ageing sharks and rays can have high errors (Francis et al., 2007; Hamady et al., 2014; Harry, 2018). Moreover, age data are expensive to obtain and the samples often come from selected sub-populations.

Similarly, real fisheries data may violate many assumptions required by length-based methods. In a review of data-poor methods, Edwards (2015) recommended that pending further testing by proponents of these approaches, they were not considered suitable for immediate application in New Zealand.

Amongst the four categories of potential methods, the area-based ERA method has been widely applied to bycatch risk assessment. Conceptually, the method is analogous to formal stock assessment as both indicator (F_{cur}) and reference points (F_{RPs}) are equivalent to those in formal stock assessment. This group of methods can be flexibly modified to suit the existing data. Indeed, varying versions have been developed according to available data. Furthermore, this method has been applied to two WCPFC elasmobranch species (Bigeye thresher and Porbeagle shark). We recommend this method to be the first choice for data-poor elasmobranch species in WCPO.

The most important piece of information required by area-based method is fishing effort data. A recent analysis of data for sharks caught in longline and purse seine fisheries in the WCPO reveals fishing effort data exist for several shark species (Rice, 2018). In addition to the two species that have already been assessed, these species include Silky shark, Blue shark, Pelagic thresher, Common thresher, Oceanic Whitetip, Shortfin mako, and Whale shark. It is possible that similar analysis can be carried out for these species.

4 Other potential management procedures for WCPFC elasmobranchs

A wide range of assessment methods and management procedures have been developed for data-poor fisheries in the past two decades. The methods vary from life-history-based to catch-only, from qualitative to quantitative, and from traditional to simple rules. These research also prompt several reviews of the methods and procedures (e.g., Edwards, 2015; Geromont and Butterworth, 2015; Oliveira *et al.*, 2017). It is unnecessary and unrealistic to repeat the review, but a few methods show potential merit for testing of WCPFC stocks.

4.1 Catch-rate (CPUE) approach

The New Zealand Ministry for Primary industries has accepted a method where an F-proxy is estimated as catch/CPUE, where CPUE is derived from a standardisation model (generalised linear model). This model assumes CPUE is analogous to biomass (i.e., the F-proxy is a relative exploitation rate). If the catch and CPUE are the same data set then effectively catch/CPUE = effort, but in practice the CPUE dataset is a subset of the catch. For example, the Assessment Plenary for Rig shark (*Mustelus lenticulatus*) agreed to use the average CPUE during the period 2005–2015, a period of relatively stable CPUE and catches, as a proxy for B_{msy}. Reference points may then follow, usually an F_{msy} proxy based on the average F during the same period. This is done from consideration of fishery (catch) history, and expert opinion. This method has been used for both rig and school sharks (e.g., https://fs.fish.govt.nz/Page.aspx?pk=113&dk=24365). This approach may only work when there is a long and reliable time series of catch and CPUE.

4.2 Traffic-light framework

Caddy (1999, 2002) developed a series of limit reference points based on measures or proxies for fishing mortality rate or stock size, relating to the biology, economic, and social aspects of a fishery. Many of these LRPs may be difficult to apply to WCPFC bycatch due to lack of data, but a length-based LRP may be useful. The total mortality limit reference point is derived by replacing the mean length in the catch in Eqn (9) by length at maturity:

$$Z_{LRP} = \frac{K(L_{inf} - L_{mat})}{L_{mat} - L_c} \qquad \text{Eqn (10)}$$

This LRP implies that mean length in the catch must be greater than the mean size at maturity.

Alternative length-based approaches have been developed (see Geromont and Butterworth, 2015; Oliveira *et al.*, 2017; Froese *et al*. 2018). These methods require assumptions that the stock is equilibrium, recruitment and mortality are time-invariant, and selectivity is knife-edged above the age at first capture. Length-based indicators have previously been developed for WCPFC elasmobranchs using standardized length data (Francis *et al.*, 2014; Cortés *et al.*, 2017; Hoyle *et al.*, 2017a, 2017b). However, simulations suggest that they may be relatively insensitive indicators of population status (Clarke & Hoyle 2014).

4.3 Catch-only methods

There has in recent years been an increasing interest in developing catch-only methods. These methods require only time series of catch data and perhaps some life history parameters, so they can be applied to many fisheries where catch records are available. These methods typically require information about stock depletion. Model performance will be affected by the depletion level chosen so methods that assume a common depletion have limited application. Amongst the catch-only methods, Catch-MSY (Martell and Froese, 2013; Froese *et al.*, 2017) and OCOM (Zhou *et al.*, 2017b) attempt to come up a depletion prior based on catch history. Hence, they are more promising than other catch-only methods. Catch-MSY and OCOM produce time series of biomass, fishing mortality, and both F-based and B-based reference points such as B_{msy} and F_{msy}. The main disadvantage of catch-only methods is their potentially inaccurate results for some stocks, particularly for unproductive, lightly fished, or highly depleted stocks.

Before deciding which category of approaches may be tested for WCPFC elasmobranchs, a few factors should be taken into consideration. It is essential to examine the data inventory, including the types of data available and their quality and quantity. The key assumptions required by each potential method should be examined. As the WCPFC is concerned with multiple species, applying consistent methodology across multiple species could facilitate both assessment and management.

5 Review of Shark Stock-Recruitment Relationship

5.1 Introduction

Stock recruitment relationships are very influential in stock assessments and can substantially affect MSY-related parameters. They are also considered very difficult to estimate from fishery data (Lee *et al.*, 2012). Current practice in many WCPFC stock assessments is to consider a range of plausible values of steepness, giving equal weight to each of them (e.g., Tremblay-Boyer *et al.*, 2018; Vincent *et al.*, 2018), but determining plausibility also requires some information, and the chosen values imply a prior. It would be very useful to be able to infer prior distributions for stock recruitment relationships from another data source, such as life history parameters.

ISC scientists have been involved in developing and applying models to predict stock recruitment relationships based on early life history, with applications to Pacific bluefin tuna (Mangel *et al.*, 2010, 2013), billfish (Brodziak and Mangel, 2011; Brodziak *et al.*, 2015), and recently also sharks (Kai and Fujinami, 2018).

Task 6 in the term of reference requests a review of the work presently being undertaken by ISC on the development of stock-recruitment relationships and their parameter estimates. Stock-recruitment steepness for North Pacific blue shark has been estimated recently using life-history parameters. Task 6 also requests an assessment of the applicability of extending this work to other key shark species, especially South Pacific blue shark.

Here we review the life history-based approach to estimating a stock recruitment relationship for sharks, focusing in particular on the approach published by Kai and Fujinami (2018) in Fisheries Research.

5.2 Overview

In Kai and Fujinami (2018) (KF) the authors consider the relationship between blue shark spawning stock size and recruitment to the age 1 year-class. They model this relationship using the approach proposed by Mangel *et al.* (2010) (referred to as Mangel hereafter), based on maximum population growth rate at low population size and spawning biomass per-recruit at equilibrium without fishing (i.e., virgin population). They use this relationship to infer the proportion of maximum recruitment that occurs at 20% B_0 (steepness), under several different stock recruitment relationships. They argue for use of the estimate based on the Beverton-Holt stock recruitment relationship, and provide an estimate of steepness with a form of uncertainty that they suggest can be used as a prior.

The adaptation of the method to sharks has been performed effectively. The paper is, in general, well written and provides sufficient explanation to repeat the approach for other species. The implementation for blue sharks is competently performed and well justified, although when repeating the analysis we obtained a different result (0.71 rather than 0.58).

However, for the reasons identified below we consider the approach implemented here for sharks, and proposed by Mangel, to be an interesting theoretical idea, but doubt its practical utility in its present form. We have reservations about using Mangel's method, or its application here to sharks, to provide priors for stock assessment.

5.3 Method in general, including Mangel et al. (2010)

Estimation error. When developing a prior distribution, estimation error is the key issue. The prior should describe the distribution of relative probabilities for all potential parameter values. KF and Mangel simulated process uncertainty in a small population, and their resulting distribution described the estimates one might obtain by sampling a small population. The process error approach was, as described by Mangel, an *ad hoc* approach for assigning a probability distribution, and did not contain the information about the relative probabilities of different steepness values implied by a prior. To explore estimation error, one could implement a Monte Carlo procedure to recalculate steepness given resampled plausible values of all the important input parameters, such as alternative ogives or estimates for *M*, the shape of the SRR, maturity, the growth curve, length-weight relationship, etc. We demonstrate below that using such an approach to generate a more realistic uncertainty distribution would result in a much less informative prior for north Pacific blue shark.

Uncertainty in natural mortality. The method of KF, like the approach of Mangel, relies strongly on estimates of age-dependent mortality and pre-recruit mortality. Mangel (page 99) say "Perhaps most importantly, Equations 20 and 26 show that as soon as we are able to develop a demographic model for the survival of a cohort, we are close to being able to obtain a point estimate for steepness."

This also implies that the functional form of density dependence in recruitment is determined entirely by age-dependent mortality and reproductive rates averaged across the population. However, the true *M* at age is unknown, and various alternative assumptions could be made. The appendix in KF presented a range of possibilities and finally selected an approach based on the (Lorenzen, 2005) method, which assumed that natural mortality was inversely proportional to body length. However, there is little evidence to support the Lorenzen method over the others for blue sharks, and the true uncertainty would be better represented by sampling from approaches at random. Moreover, as noted by KF, Peterson and Wroblewski (1984) advised (with respect to their own method) that "the relationship between mortality rate and size can only be viewed as a central tendency for organisms in an ecosystem as a whole and may not be applicable to individual species" and cautioned against its use as an estimator for a specific species. This excellent advice is equally applicable to the Lorenzen (2005) method.

Assumptions about natural mortality of pre-recruits are likely to be more accurate and precise for sharks than they are for broadcast spawning fish, which is one advantage when estimating demographic models of cohort survival. Pre-recruit mortality rates for pelagic fish, which Mangel based on estimates reported by (McGurk, 1986), are highly uncertain. In fact (McGurk, 1987) later recalculated his size to mortality relationship using fish data only and changed the size exponent from -0.25 to -0.39, which may have significant implications for predicted mortality rates. This highlights the degree of variability among species and taxonomic groups, and the potential for error when applying a general principle to a specific case without fully considering uncertainty.

The choice of stock-recruitment function. Steepness is typically estimated from sufficiently contrasting and reliable pairs of stock-recruitment data. Rather than using data on stock and recruitment, the method reviewed here uses the maximum population growth rate α_s at low population size and spawning biomass per-recruit $\overline{W}_f$ at no fishing (i.e., virgin population) to predict steepness. The prediction strongly depends on the shape of the spawner recruit curve. This sensitivity is shown by the very different steepness estimates of 0.584 based on the Beverton-Holt curve, and 0.851 based on the Ricker curve.

In choosing a value of steepness for blue shark, KF argue that the Ricker curve is not appropriate "because there is little scientific evidence of cannibalism by adult blue sharks on juvenile blue sharks" which by elimination leaves the BH model.

However, these two curves are far from the only options – they are simply two mathematically convenient ways of summarising possible stock recruitment curves. They have little inferential value in estimating the appropriate value of steepness to use for a stock. If a species truly has a consistent SRR, there is no reason to assume *a priori* that its shape matches BH or any other simple and convenient curve. As acknowledged by Mangel *et al.* (2013) Punt *et al.* (2005) stated "other (more complicated) forms may provide better representations of the existing data". For example, the low fecundity stock recruitment relationship (Taylor *et al.*, 2013), which is often used for sharks, has a very flexible shape. With this curve, as KF note, a single value for maximum reproductive rate can be associated with various steepness estimates. Accordingly, even precisely-estimated values of �s at low population size and $\overline{W}_f$ at no fishing cannot be assumed to imply a precise value of steepness.

Effect of density-dependence on life history parameters and estimated h. Stock-recruitment functions (including Beverton-Holt and Ricker models) are density-dependent, meaning that the stock is more productive at low density than at high density. Such density-dependent mechanisms manifest through life-history traits, including natural mortality rate and reproductive rate, as well as other parameters such as growth rate, maturation age and size, fecundity, egg size, etc. (Rochet, 2000). Traditionally, SRR is estimated from time series of stock-recruitment data at varying density (a wide range of data points). In KF and Mangel, *h* is defined as a function of both population growth rate at low population size α_s, and spawning biomass per-recruit at unfished virgin biomass $\overline{W}_f$. These two variables should have been calculated from life history parameters (LHPs, including fecundity, litter size, survival rate, weight at age, etc.) obtained from the two very different population densities. However, both KF and Mangel used the same LHPs to calculate the two variables, meaning that this approach is essentially using one data point (one set of LHPs) to derive a SR curve, even though the LHPs at virgin biomass and low population size are very different. The same LHPs cannot be used for two completely different statuses.

Population coverage. The estimated life history parameters are assumed to apply to the whole population, but this assumption may not be valid. The parameters have actually been estimated from a subset of the population in space and time, with particular environmental conditions and history. This is of course a general criticism that can be applied to all population model parameters but must also be considered here. It may be particularly difficult to estimate population-level parameters for sharks, because sexual segregation in space is a general characteristic of elasmobranchs (Wearmouth and Sims, 2008; Finucci *et al.*, 2018), and spatial segregation between juveniles and adults is also commonly observed (e.g., Gouraguine *et al.*, 2011; Semba *et al.*, 2013; Finucci *et al.*, 2018). Blue shark populations are known to be spatially segregated by size and sex (Clarke et al. 2015). Estimates of population parameters vary widely among studies, with (for example) female longevity estimates varying from 12 in a study off the northwest coast of Mexico

(Blanco-Parra *et al.*, 2008) to 28.6 in a Taiwanese northwest Pacific study (Hsu *et al.*, 2011). Accurate estimates of population-level parameters require understanding of both parameter variation and stock distribution. These factors add uncertainty to the estimates and may, depending on the stock structure, add bias. Longevity estimates, for example, can often be biased low by surveying a subset of the population.

5.4 Simulation

We repeated the analyses of Kai and Fujinami (2018) incorporating some of the suggestions above.

5.4.1 Methods

Parameter values are reported in Table 7.

$$a = 0 : a_{max}$$

Growth was modelled using the von Bertalanffy growth equation.

$$L_a = L_\infty\left(1 - e^{-k(a-a_0)}\right)$$

Mortality at age was defined in the same way as KF, with *MT* defined across the ages of 0 (i.e. ac was set to 0) to a_{max}.

$$L_c = L_{a=ac}$$

$$M_a = \frac{MT(a_{max} - a_c)}{log\left(\frac{L_c}{L_c + L_\infty\left(exp\left(k(a_{max} - a_c)\right) - 1\right)}\right)} log\left(\frac{L_a}{L_a + L_\infty(exp(k) - 1)}\right)$$

Probability of maturity, weight at age, and fecundity at age were calculated as follows.

$$pmat_a = \frac{1}{1 + exp(c3 + c4 \,.\, L_a)}$$

$$w_a = c1 \,.\, {L_a}^{c2}$$

$$litter_a = c5 + c6 \,.\, L_a$$

We could not determine the value used by KF for pre-recruit survival at stage 3 (juveniles), and chose to set it to the estimated annual survival rate at age 0. Since this is an annual survival rate, it implies full recruitment at age 1.

$$S_{pre} = S0. S1. S2. S3$$

Survivors per recruit were calculated from age 1.

$$S_a = \prod_{i=1}^{a-1} exp\left(-M(i)\right)$$

Female spawning biomass per female recruit was calculated as follows.

$$W_f = \sum_{a=1}^{amax} S_a W_f(a) p_{f,m}(a)$$

We modified equation (9) in Kai and Fujinami (2018) for calculation of α_s, individuals per spawning biomass, to adjust for relative productivity at age, following equation 41 in Mangel et al 2010. This modification is needed since a summation appears to be omitted in KF's equation (9), probably because the summation is carried out as part of their simulation. The sex ratio is applied to both the individuals spawned and the spawning biomass, so cancels out.

$$\alpha_s = S_{pre} S_{cycle} \frac{\sum_{a=1}^{amax} S_a . p_{f,m}(a). litter_a}{W_f}$$

Steepness was calculated as follows:

$$h = \frac{\alpha_s (1 - sr) W_f}{4 + \alpha_s (1 - sr) W_f}$$

5.4.2 Parameter values

We tested only two of the many sources of uncertainty. Potential values of MT were obtained from Campana *et al.* (2005), Table 14, the mean of which (0.23) was used by KF as their estimate. Based on the values reported by Campana *et al*. (2005), we estimated mean as 0.23 and standard deviation as 0.08, and sampled random values of MT from this distribution.

Maximum age values were reported for blue shark (both north and south) by Clarke et al. (2015) of 12, 15, 20-24 (set to 22), 29, 21, and 20. These values were resampled randomly with replacement, with n = 200,000.

The model was implemented in R, and all code is provided in Appendix 1.

5.4.3 Results and Discussion

With the base values, Beverton-Holt steepness was estimated to be 0.71. This is higher than the estimate of 0.58 provided by KF. The explanation of this difference is unclear and should be explored further. The R code provided in Appendix 1 can be used for this purpose. The main differences between the analyses are our use of 1 year rather than age 0 as the age of recruitment, and our use of the point estimate of steepness with the base parameter values rather than the mean of 200 simulations.

Including two sources of estimation uncertainty resulted in a much wider uncertainty distribution (Figure 23) for Beverton-Holt steepness *h* than proposed by Kai and Fujinami (2018) based on process error. The distribution included estimates below 0.2. These represent unrealistic scenarios in which the assumed mortality was above replacement level. A more thorough exploration of uncertainty should address this by selecting scenarios that include plausible combinations of life history parameters, with growth rate greater than zero.

5.5 Conclusions – applicability of method to species in general

Given the above, it seems premature to use steepness distributions based on the methods proposed by Kai and Fujinami (2018) and Mangel et al. (2010) as prior distributions in stock assessments. Consideration of estimation uncertainty in just a few of the input parameters considerably broadens the uncertainty distribution. Considering uncertainty in other parameters is likely to add considerably more variability.

The method may be useful for comparing reproductive strategies among shark species, or for identifying factors that are particularly influential and therefore warrant further research.

To use the method for these purposes, it will be important to perform the analyses with appropriate consideration of estimation error in all input parameters, and in the shape of the SRR curve. This would demonstrate how much uncertainty there is in the estimates of steepness, and which factors are most important in determining it. It is also necessary to use LHPs appropriate for populations at a) very low population size, and b) virgin biomass.

Finally, we would like to recommend: (1) modelling estimation error for h, rather than using the numerical simulation method. An estimation error approach is likely to provide a much wider distribution of plausible values for steepness than the distribution presented here. (2) Using multiple alternative models to characterise the plausible distribution of natural mortality. A single model can considerably underestimate the uncertainty in this key parameter. Reproductive output per spawner, and hence the steepness estimate, is likely to be highly sensitive to the selected particular *M* estimator. Potential bias in natural mortality due to underestimation of longevity, and uncertainty about the natural mortality of pre-recruits should also be considered. (3) Conducting sensitivity tests to examine the effect of density-dependent mechanisms on LHPs and resulting h. (4) Where whole-population estimates are unavailable, considering uncertainty by using alternative estimates of life history parameters.

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Table 1. WCPFC key elasmobranchs species reviewed by the Pacific Shark Life History Expert Panel Workshop (2015, WCPFC-SC11-2015/EB-IP-13)

ID	Stock	Code	Recent assessment	Method	Result
1	Blue shark – North Pacific	BSH-N	2017	SS3	F_{msy} = 0.35 $F_{12\text{-}14}$ = 0.13
2	Blue shark – South Pacific	BSH-S	2016	Multifan-CL	Results inconclusive
3	Shortfin mako North Pacific	SMA-N	2015	Indicators	Results inconclusive
4	Shortfin mako (South Pacific	SMA-S			
5	Longfin mako	LMA			
6	Silky shark (WCPO)	FAL	2013	SS3	F_{msy} = 0.08 F_{cur} = 0.358
7	Oceanic whitetip (WCPO)	OWT/OCS	2012	SS3	F_{msy} = 0.07 F_{cur} = 0.469
8	Bigeye thresher (Pacific)	BTH	2017	Quantitative ERA	$F_{00\text{-}14}/F_{lim}$ = 0.33 $F_{00\text{-}14}/F_{msm}$ = 0.54
9	Pelagic thresher shark	PTH			
10	Common thresher shark	ALV			
11	Porbeagle shark (Southern hemisphere)	POR	2017	Quantitative ERA	$F_{06\text{-}14}/F_{lim}$ = 0.002 $F_{06\text{-}14}/F_{msm}$ = 0.007
12	Smooth hammerhead	SPZ			
13	Scalloped hammerhead	SPL			
14	Great hammerhead	SPK			
15	Winghead	EUB			
16	Whale shark (Pacific)	RHN	2018	Quantitative ERA	Not see

Table 2. Comparison of mean *M* estimated from Eqns 2a (M.1) and 2b (M.2) with all estimators (M.all) for the 15 elasmobranch stocks. On average, *M* from both Eqns 2a and 2b is 1.11 times higher than *M* from all estimators.

ID	Stock	M.1/M.all	M.2/M.all
1	BSH-N	0.98	0.73
2	BSH-S	1.26	0.78
3	SMA-N	1.09	0.88
4	SMA-S	1.57	0.85
5	LMA	0.00	0.00
6	FAL	1.73	0.47
7	OCS	1.09	0.69
8	BTH	1.71	0.66
9	PTH	1.50	0.83
10	ALV	1.30	0.63
11	POR	0.78	1.09
12	SPZ	1.60	0.87
13	SPL	1.36	0.84
14	SPK	1.06	0.72
15	EUB	1.50	0.88
16	RHN	1.15	0.44
	Mean	1.23	0.71

Table 3. Comparison of estimated reference points by four methods for three shark stocks in the WCPFC managed areas. cF_{msm}, cF_{lim}, and cF_{crash} are combined from 1 Methods 1 to 4. L10% and H90% are 10% and 90% percentiles.

ID	Stock	Quantit	F_{msm1}	F_{msm2}	F_{msm3}	$F_{60\%}$	cF_{msm}	F_{lim1}	F_{lim2}	F_{lim3}	$F_{40\%}$	cF_{lim}	F_{crash1}	F_{crash2}	F_{crash3}	$F_{10\%}$	cF_{crash}
1	BSH-N	mean	0.10	0.19	0.15	0.14	0.14	0.14	0.28	0.22	0.27	0.23	0.19	0.37	0.29	0.77	0.40
1	BSH-N	sd	0.04	0.08	0.07	0.04	0.07	0.06	0.11	0.11	0.07	0.11	0.08	0.15	0.14	0.14	0.25
1	BSH-N	cv	0.42	0.41	0.49	0.27	0.48	0.42	0.40	0.49	0.27	0.46	0.42	0.40	0.49	0.19	0.63
1	BSH-N	median	0.09	0.19	0.15	0.14	0.13	0.14	0.28	0.23	0.26	0.23	0.18	0.38	0.30	0.79	0.34
1	BSH-N	L10%	0.05	0.09	0.04	0.10	0.06	0.08	0.14	0.05	0.19	0.09	0.10	0.18	0.07	0.57	0.13
1	BSH-N	H90%	0.15	0.28	0.24	0.18	0.24	0.22	0.43	0.36	0.35	0.37	0.29	0.57	0.49	0.94	0.83
6	FAL	mean	0.06	0.07	0.07	0.03	0.05	0.08	0.10	0.10	0.05	0.08	0.11	0.13	0.13	0.13	0.13
6	FAL	sd	0.03	0.05	0.02	0.01	0.03	0.05	0.07	0.02	0.01	0.05	0.06	0.09	0.03	0.04	0.06
6	FAL	cv	0.56	0.70	0.25	0.27	0.61	0.56	0.67	0.25	0.28	0.58	0.56	0.66	0.25	0.34	0.48
6	FAL	median	0.05	0.07	0.07	0.03	0.04	0.07	0.10	0.11	0.05	0.07	0.09	0.13	0.14	0.12	0.12
6	FAL	L10%	0.02	0.01	0.04	0.02	0.02	0.03	0.01	0.06	0.04	0.04	0.04	0.01	0.09	0.10	0.06
6	FAL	H90%	0.10	0.13	0.08	0.04	0.09	0.15	0.19	0.12	0.07	0.14	0.20	0.25	0.16	0.17	0.20
7	OCS	mean	0.07	0.12	0.06	0.05	0.07	0.10	0.18	0.09	0.09	0.12	0.14	0.24	0.12	0.25	0.19
7	OCS	sd	0.03	0.06	0.02	0.02	0.04	0.04	0.09	0.03	0.03	0.06	0.06	0.12	0.04	0.08	0.10
7	OCS	cv	0.40	0.51	0.30	0.29	0.59	0.40	0.50	0.30	0.30	0.56	0.40	0.50	0.30	0.33	0.53
7	OCS	median	0.07	0.11	0.06	0.05	0.06	0.10	0.17	0.08	0.09	0.10	0.13	0.22	0.11	0.23	0.16
7	OCS	L10%	0.04	0.05	0.03	0.03	0.03	0.06	0.07	0.05	0.06	0.05	0.07	0.09	0.07	0.15	0.08
7	OCS	H90%	0.10	0.20	0.08	0.07	0.14	0.16	0.30	0.12	0.13	0.21	0.21	0.40	0.16	0.37	0.34

Table 4. Comparison of estimated reference points by three methods for the 15 shark stocks in the WCPFC managed areas. cF_{msm}, cF_{lim}, and cF_{crash} are combined from 1 Methods 1 to 4. L10% and H90% are 10% and 90% percentiles.

ID	Stock	Quantity	F_{msm1}	F_{msm2}	F_{msm3}	**cF_{msm}**	F_{lim1}	F_{lim2}	F_{lim3}	**cF_{lim}**	F_{crash1}	F_{crash2}	F_{crash3}	cF_{crash}
1	BSH-N	mean	0.10	0.19	0.14	0.14	0.14	0.28	0.22	0.21	0.19	0.38	0.29	0.29
1	BSH-N	sd	0.04	0.08	0.07	0.08	0.06	0.11	0.11	0.11	0.08	0.15	0.14	0.15
1	BSH-N	cv	0.43	0.40	0.49	0.52	0.43	0.40	0.49	0.52	0.43	0.40	0.49	0.52
1	BSH-N	median	0.09	0.19	0.15	0.13	0.14	0.28	0.23	0.20	0.18	0.38	0.30	0.27
1	BSH-N	L10%	0.05	0.09	0.04	0.05	0.07	0.14	0.05	0.08	0.10	0.19	0.07	0.11
1	BSH-N	H90%	0.15	0.29	0.24	0.25	0.22	0.43	0.35	0.37	0.30	0.57	0.47	0.50
2	BSH-S	mean	0.08	0.13	0.17	0.13	0.12	0.19	0.26	0.19	0.16	0.25	0.34	0.25
2	BSH-S	sd	0.03	0.04	0.00	0.05	0.04	0.06	0.00	0.07	0.05	0.07	0.00	0.09
2	BSH-S	cv	0.35	0.29	0.00	0.37	0.35	0.29	0.00	0.37	0.35	0.29	0.00	0.37
2	BSH-S	median	0.08	0.13	0.17	0.13	0.12	0.19	0.26	0.19	0.16	0.25	0.34	0.26
2	BSH-S	L10%	0.05	0.08	0.17	0.06	0.07	0.12	0.26	0.09	0.09	0.16	0.34	0.12
2	BSH-S	H90%	0.11	0.17	0.17	0.17	0.17	0.26	0.26	0.26	0.22	0.34	0.34	0.34
3	SMA-N	mean	0.06	0.02	0.03	0.04	0.09	0.04	0.05	0.06	0.12	0.05	0.06	0.08
3	SMA-N	sd	0.03	0.04	0.01	0.03	0.04	0.05	0.01	0.04	0.06	0.07	0.01	0.06
3	SMA-N	cv	0.48	1.73	0.21	0.87	0.48	1.42	0.21	0.78	0.48	1.30	0.21	0.75
3	SMA-N	median	0.05	0.02	0.03	0.04	0.08	0.03	0.05	0.05	0.11	0.05	0.06	0.07
3	SMA-N	L10%	0.03	-0.02	0.02	0.01	0.04	-0.02	0.03	0.01	0.06	-0.02	0.05	0.01
3	SMA-N	H90%	0.09	0.07	0.04	0.07	0.14	0.11	0.06	0.11	0.19	0.14	0.08	0.15
4	SMA-S	mean	0.06	0.00	0.03	0.03	0.09	0.01	0.05	0.05	0.12	0.02	0.06	0.07
4	SMA-S	sd	0.03	0.03	0.01	0.04	0.05	0.04	0.01	0.05	0.06	0.05	0.01	0.06
4	SMA-S	cv	0.51	15.69	0.21	1.14	0.51	4.25	0.21	0.98	0.51	2.80	0.21	0.93
4	SMA-S	median	0.05	0.01	0.03	0.03	0.08	0.02	0.05	0.05	0.11	0.02	0.06	0.06
4	SMA-S	L10%	0.03	-0.05	0.02	-0.01	0.04	-0.05	0.03	0.00	0.05	-0.05	0.05	-0.01
4	SMA-S	H90%	0.10	0.04	0.04	0.07	0.15	0.06	0.06	0.11	0.20	0.08	0.08	0.14

Table 4 continues

ID	Stock	Quantity	F_{msm1}	F_{msm2}	F_{msm3}	**cF_{msm}**	F_{lim1}	F_{lim2}	F_{lim3}	**cF_{lim}**	F_{crash1}	F_{crash2}	F_{crash3}	cF_{crash}
6	FAL	mean	0.06	0.07	0.07	0.06	0.08	0.10	0.10	0.09	0.11	0.13	0.13	0.12
6	FAL	sd	0.03	0.05	0.02	0.03	0.05	0.07	0.02	0.05	0.06	0.09	0.03	0.07
6	FAL	cv	0.56	0.69	0.25	0.54	0.56	0.67	0.25	0.53	0.56	0.66	0.25	0.53
6	FAL	median	0.05	0.07	0.07	0.07	0.07	0.10	0.11	0.10	0.10	0.13	0.14	0.13
6	FAL	L10%	0.02	0.01	0.04	0.02	0.03	0.01	0.06	0.04	0.04	0.01	0.09	0.05
6	FAL	H90%	0.10	0.13	0.08	0.10	0.15	0.19	0.12	0.15	0.21	0.25	0.16	0.21
7	OCS	mean	0.07	0.12	0.06	0.08	0.10	0.18	0.09	0.12	0.14	0.24	0.12	0.16
7	OCS	sd	0.03	0.06	0.02	0.05	0.04	0.09	0.03	0.07	0.06	0.12	0.04	0.09
7	OCS	cv	0.41	0.51	0.30	0.58	0.41	0.50	0.30	0.58	0.41	0.50	0.30	0.57
7	OCS	median	0.07	0.11	0.06	0.08	0.10	0.17	0.08	0.11	0.13	0.23	0.11	0.15
7	OCS	L10%	0.04	0.05	0.03	0.03	0.06	0.07	0.05	0.05	0.07	0.09	0.07	0.07
7	OCS	H90%	0.11	0.20	0.08	0.16	0.16	0.30	0.12	0.24	0.21	0.40	0.16	0.31
8	BTH	mean	0.07	-0.01	0.00	0.02	0.10	0.00	0.01	0.04	0.14	0.00	0.01	0.05
8	BTH	sd	0.03	0.04	0.01	0.04	0.05	0.04	0.01	0.06	0.07	0.05	0.02	0.08
8	BTH	cv	0.47	-5.31	2.40	1.97	0.47	-35.45	1.83	1.63	0.47	11.06	1.61	1.53
8	BTH	median	0.06	0.01	0.00	0.02	0.09	0.01	0.00	0.02	0.13	0.01	0.01	0.03
8	BTH	L10%	0.03	-0.06	-0.01	-0.03	0.05	-0.06	-0.01	-0.03	0.06	-0.06	-0.01	-0.03
8	BTH	H90%	0.12	0.03	0.02	0.08	0.17	0.05	0.02	0.12	0.23	0.07	0.03	0.16
9	PTH	mean	0.06	0.02	0.03	0.04	0.09	0.04	0.04	0.06	0.13	0.05	0.05	0.08
9	PTH	sd	0.03	0.03	0.01	0.03	0.05	0.04	0.01	0.04	0.07	0.05	0.02	0.06
9	PTH	cv	0.53	1.07	0.34	0.82	0.53	0.96	0.34	0.78	0.53	0.91	0.34	0.78
9	PTH	median	0.06	0.03	0.02	0.03	0.09	0.04	0.04	0.05	0.13	0.06	0.05	0.06
9	PTH	L10%	0.03	-0.01	0.02	0.01	0.05	-0.01	0.02	0.01	0.06	-0.01	0.03	0.02
9	PTH	H90%	0.10	0.06	0.04	0.08	0.15	0.09	0.06	0.12	0.20	0.11	0.08	0.16

Table 4 continues.

ID	Stock	Quantity	F_{msm1}	F_{msm2}	F_{msm3}	**cF_{msm}**	F_{lim1}	F_{lim2}	F_{lim3}	**cF_{lim}**	F_{crash1}	F_{crash2}	F_{crash3}	cF_{crash}
10	ALV	mean	0.08	0.07	0.05	0.07	0.12	0.11	0.08	0.10	0.16	0.14	0.10	0.14
10	ALV	sd	0.03	0.03	0.02	0.03	0.05	0.05	0.02	0.05	0.07	0.07	0.03	0.06
10	ALV	cv	0.40	0.48	0.29	0.46	0.40	0.47	0.29	0.45	0.40	0.47	0.29	0.45
10	ALV	median	0.08	0.07	0.05	0.07	0.12	0.10	0.07	0.10	0.16	0.14	0.10	0.13
10	ALV	L10%	0.04	0.03	0.04	0.04	0.06	0.04	0.06	0.06	0.09	0.05	0.07	0.07
10	ALV	H90%	0.12	0.11	0.08	0.11	0.19	0.17	0.11	0.16	0.25	0.22	0.15	0.21
11	POR	mean	0.05	0.03		0.04	0.08	0.04		0.06	0.10	0.06		0.08
11	POR	sd	0.03	0.03		0.03	0.04	0.04		0.04	0.05	0.06		0.06
11	POR	cv	0.50	1.14		0.78	0.50	1.01		0.73	0.50	0.95		0.72
11	POR	median	0.05	0.03		0.04	0.07	0.04		0.06	0.09	0.06		0.08
11	POR	L10%	0.03	-0.01		0.01	0.04	-0.01		0.01	0.05	-0.01		0.01
11	POR	H90%	0.08	0.06		0.07	0.12	0.09		0.11	0.16	0.12		0.15
12	SPZ	mean	0.07	0.03		0.05	0.10	0.04		0.07	0.13	0.06		0.10
12	SPZ	sd	0.03	0.04		0.04	0.05	0.05		0.06	0.07	0.06		0.08
12	SPZ	cv	0.50	1.42		0.89	0.50	1.20		0.81	0.50	1.11		0.79
12	SPZ	median	0.06	0.02		0.05	0.09	0.03		0.08	0.12	0.04		0.10
12	SPZ	L10%	0.03	-0.03		-0.01	0.04	-0.03		-0.01	0.06	-0.03		-0.01
12	SPZ	H90%	0.11	0.07		0.10	0.17	0.11		0.14	0.22	0.14		0.19
13	SPL	mean	0.06	0.06	0.03	0.05	0.09	0.09	0.05	0.07	0.11	0.12	0.07	0.10
13	SPL	sd	0.02	0.02	0.01	0.02	0.03	0.03	0.02	0.03	0.05	0.05	0.02	0.05
13	SPL	cv	0.39	0.41	0.31	0.47	0.39	0.40	0.31	0.46	0.39	0.40	0.31	0.46
13	SPL	median	0.05	0.06	0.02	0.04	0.08	0.09	0.03	0.06	0.11	0.12	0.05	0.09
13	SPL	L10%	0.03	0.03	0.02	0.02	0.05	0.04	0.03	0.03	0.06	0.06	0.05	0.05
13	SPL	H90%	0.09	0.08	0.04	0.08	0.13	0.13	0.06	0.12	0.18	0.17	0.09	0.16

Table 4 continues

ID	Stock	Quantity	F_{msm1}	F_{msm2}	F_{msm3}	$\boldsymbol{cF_{msm}}$	F_{lim1}	F_{lim2}	F_{lim3}	$\boldsymbol{cF_{lim}}$	F_{crash1}	F_{crash2}	F_{crash3}	cF_{crash}
14	SPK	mean	0.06	0.09		0.07	0.09	0.14		0.11	0.12	0.18		0.15
14	SPK	sd	0.02	0.03		0.03	0.03	0.04		0.05	0.05	0.06		0.06
14	SPK	cv	0.39	0.31		0.40	0.39	0.31		0.41	0.39	0.31		0.41
14	SPK	median	0.06	0.09		0.07	0.08	0.14		0.11	0.11	0.18		0.14
14	SPK	L10%	0.03	0.06		0.04	0.05	0.08		0.06	0.06	0.11		0.08
14	SPK	H90%	0.09	0.13		0.11	0.13	0.19		0.17	0.17	0.25		0.23
15	EUB	mean	0.08	0.11		0.09	0.13	0.16		0.14	0.17	0.21		0.19
15	EUB	sd	0.03	0.04		0.04	0.05	0.06		0.06	0.07	0.07		0.08
15	EUB	cv	0.40	0.36		0.39	0.40	0.35		0.40	0.40	0.35		0.40
15	EUB	median	0.08	0.11		0.09	0.12	0.17		0.14	0.16	0.22		0.19
15	EUB	L10%	0.05	0.05		0.05	0.07	0.08		0.07	0.09	0.11		0.10
15	EUB	H90%	0.13	0.15		0.14	0.19	0.23		0.22	0.26	0.30		0.29
16	RHN	mean	0.03	0.11		0.07	0.05	0.17		0.11	0.06	0.22		0.14
16	RHN	sd	0.01	0.02		0.04	0.02	0.02		0.06	0.03	0.03		0.09
16	RHN	cv	0.44	0.14		0.60	0.44	0.14		0.60	0.44	0.14		0.59
16	RHN	median	0.03	0.11		0.08	0.05	0.17		0.10	0.06	0.22		0.15
16	RHN	L10%	0.01	0.10		0.02	0.02	0.14		0.03	0.03	0.19		0.04
16	RHN	H90%	0.05	0.13		0.13	0.07	0.20		0.19	0.10	0.27		0.25

Table 5. Available data from WCPFC-SC11-2015/EB-IP-13 (number of studies in parenthesis) and relative quality of the estimated reference points for WCPFC key elasmobranchs species. Alternative *r* is adopted from regions outside Western and Central Pacific Ocean. New data are used for three stocks.

ID	Code	LHP			*RP quality*
1	BSH-N	t_0 (5) L_0 (3) T_{mat} (2) K(5) L_{inf} (6)	T_{max} (3) L_{50} (3) Gp (2) Rc (2) Ls (2)	$W.b$ (1) M (2) λ (2) r (1) $r_{1.5M}$ (1)	High
2	BSH-S	t_0 (2) L_0 (0) T_{mat} (1) K (2) L_{inf} (2)	T_{max} (2) L_{50} (2) Gp (1) Rc (0) Ls (1)	$W.b$ (1) M (1) λ (0) r (0) Alt $r_{1.5M}$ (0)	Low Alternative *r*
3	SMA-N	t_0 (5) L_0 (6) T_{mat} (6) K (6) L_{inf} (6)	T_{max} (3) L_{50} (5) Gp (4) Rc (2) Ls (5)	$W.b$ (2) M (4) λ (4) r (0) $r_{1.5M}$ (0)	High
4	SMA-S	t_0 (0) L_0 (1) T_{mat} (1) K (0) L_{inf} (0)	T_{max} (1) L_{50} (51 Gp (0) Rc (0) Ls (0)	$W.b$ (1) M (1) λ (0) r (0) $r_{1.5M}$ (0)	Low
5	LMA	t_0 (0) L_0 (1) T_{mat} (0) K (0) L_{inf} (0)	T_{max} (0) L_{50} (1) Gp (0) Rc (0) Ls (1)	$W.b$ (0) M (0) λ (0) r (0) $r_{1.5M}$ (0)	NA
6	FAL	t_0 (3) L_0 (5) T_{mat} (2) K (3) L_{inf} (2)	T_{max} (3) L_{50} (5) Gp (2) Rc (1) Ls (4)	$W.b$ (1) M (2) λ (0) r (2) $r_{1.5M}$ (1)	High (L_0, T_{mat}, K, L_{inf}, T_{max} from Grant et al. 2018)
7	OWT/OCS	t_0 (1) L_0 (3) T_{mat} (2) K (2) L_{inf} (2)	T_{max} (2) L_{50} (3) Gp (2) Rc (1) Ls (5)	$W.b$ (1) M (1) λ (0) r (0) Alt $r_{1.5M}$ (1)	Medium Alternative *r*
8	BTH	t_0 (1) L_0 (2) T_{mat} (1) K (1) L_{inf} (1)	T_{max} (1) L_{50} (1) Gp (0) Rc (0) Ls (1)	$W.b$ (2) M (1) λ (1) r (0) $r_{1.5M}$ (1)	Medium (T_{max} from Fu et al. 2018)

Table 5 continues

ID	Code	LHP			RP quality
9	PTH	t_0 (1)	T_{max} (2)	$W.b$ (2)	Medium
		L_0 (1)	L_{50} (2)	M (2)	
		T_{mat} (1)	Gp (1)	λ (1)	
		K (1)	Rc (0)	r (0)	
		L_{inf} (1)	Ls (1)	$r_{1.5M}$ (1)	
10	ALV	t_0 (1)	T_{max} (2)	$W.b$ (0)	Medium
		L_0 (2)	L_{50} (2)	M (1)	
		T_{mat} (2)	Gp (0)	λ (1)	
		K (2)	Rc (0)	r (0)	
		L_{inf} (2)	Ls (1)	$r_{1.5M}$ (1)	
11	POR	t_0 (1)	T_{max} (1)	$W.b$ (1)	Low
		L_0 (1)	L_{50} (1)	M (1)	(T_{max}, K, M from Hoyle et al. 2017)
		T_{mat} (1)	Gp (1)	λ (0)	
		K (1)	Rc (1)	r (0)	
		L_{inf} (1)	Ls (1)	$r_{1.5M}$ (0)	
12	SPZ	t_0 (1)	T_{max} (1)	$W.b$ (1)	Low
		L_0 (2)	L_{50} (1)	M (0)	
		T_{mat} (1)	Gp (1)	λ (0)	
		K (1)	Rc (0)	r (0)	
		L_{inf} (1)	Ls (1)	$r_{1.5M}$ (0)	
13	SPL	t_0 (0)	T_{max} (1)	$W.b$ (1)	Medium
		L_0 (3)	L_{50} (1)	M (1)	
		T_{mat} (1)	Gp (1)	λ (0)	
		K (1)	Rc (1)	r (1)	
		L_{inf} (1)	Ls (1)	$r_{1.5M}$ (1)	
14	SPK	t_0 (0)	T_{max} (1)	$W.b$ (1)	Low
		L_0 (1)	L_{50} (1)	M (0)	
		T_{mat} (1)	Gp (1)	λ (0)	
		K (1)	Rc (1)	r (0)	
		L_{inf} (1)	Ls (1)	$r_{1.5M}$ (0)	
15	EUB	t_0 (0)	T_{max} (1)	$W.b$ (1)	Low
		L_0 (2)	L_{50} (1)	M (0)	
		T_{mat} (1)	Gp (1)	λ (0)	
		K (1)	Rc (1)	r (0)	
		L_{inf} (1)	Ls (1)	$r_{1.5M}$ (0)	
16	RHN	t_0 (0)	T_{max} (1)	$W.b$ (0)	Low
		L_0 (3)	L_{50} (6)	M (1)	
		T_{mat} (2)	Gp (0)	λ (0)	
		K (2)	Rc (0)	r (0)	
		L_{inf} (2)	Ls (1)	$r_{1.5M}$ (0)	

Table 6. Biological reference points, proposed ecological risk assessment categories, and ecological consequences for WCPFC bycatch species.

	$F < F_{msm}$	$F_{lim} > F \geq F_{msm}$	$F_{crash} > F \geq F_{lim}$	$F \geq F_{crash}$
Risk	Low	Medium	High	Extreme high
Ecological consequence	Overfishing not occurring. May keep population above 50% of virgin level	Overfishing is occurring but population can be sustainable	May drive population to very low levels in longer term	Population is unsustainable in long term – possibility of extinction

Table 7: Parameter values used in estimation of stock recruitment relationship.

Parameter	Value
L_{inf}	243.3 cm
K	0.144 yr^{-1}
a_0	-0.849 yr
a_c	0 yr
$c1$	5.859 x 10^{-6}
$c2$	3.093
$c3$	24.52
$c4$	-0.16
$c5$	-45.54
$c6$	0.455
MT	0.23 yr^{-1}
sr	0.5
$S0$	0.965 yr^{-1}
$S1$	1 yr^{-1}
$S2$	0.993 yr^{-1}
$S3$	$e^{-M(age=0)}$
S_{cycle}	1 yr
age_{max}	20 yr

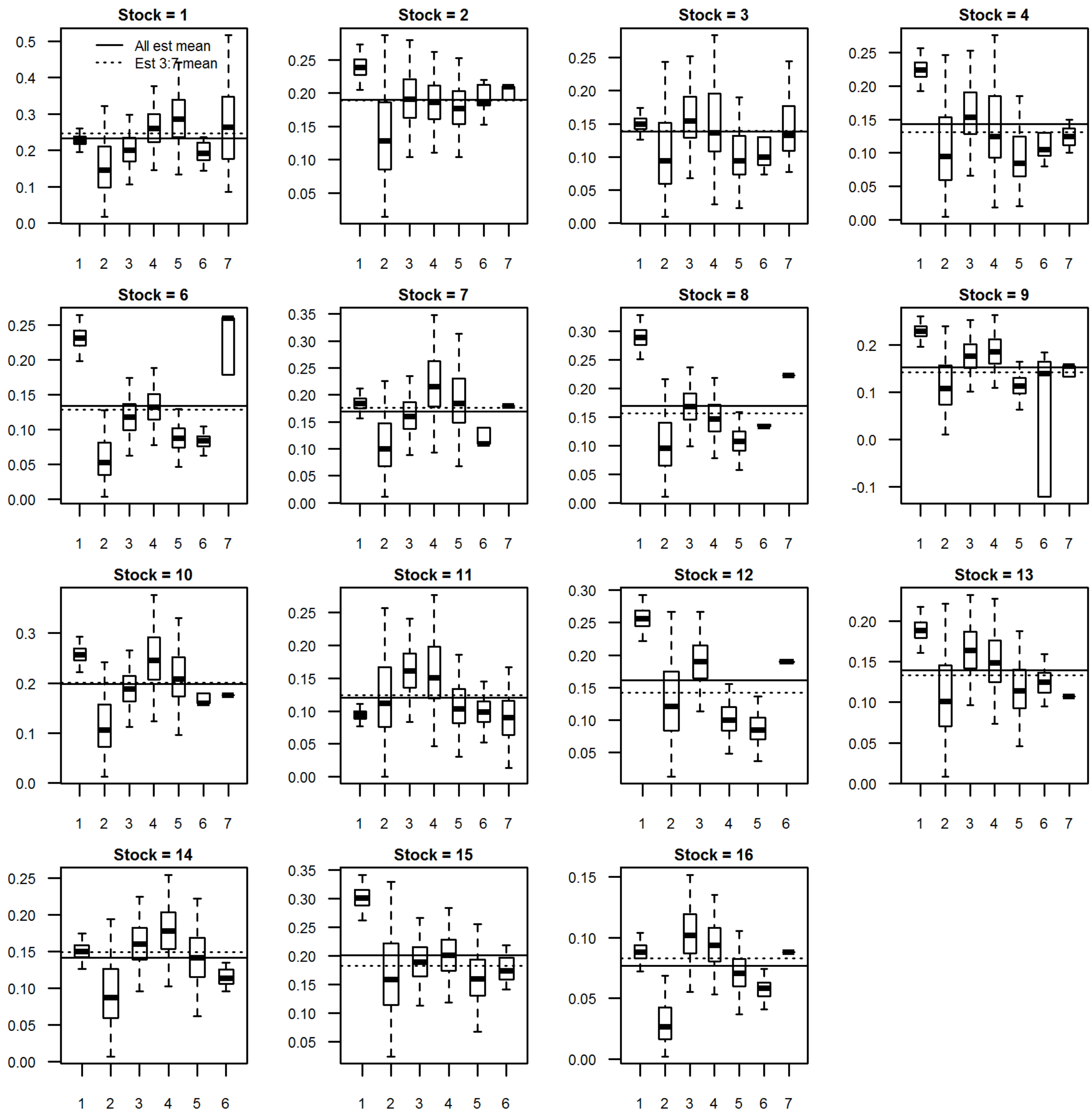

Figure 1. Comparison of estimated *M* from seven estimators for the 15 elasmobranch stocks. Estimator 7 is based on values from the literature.

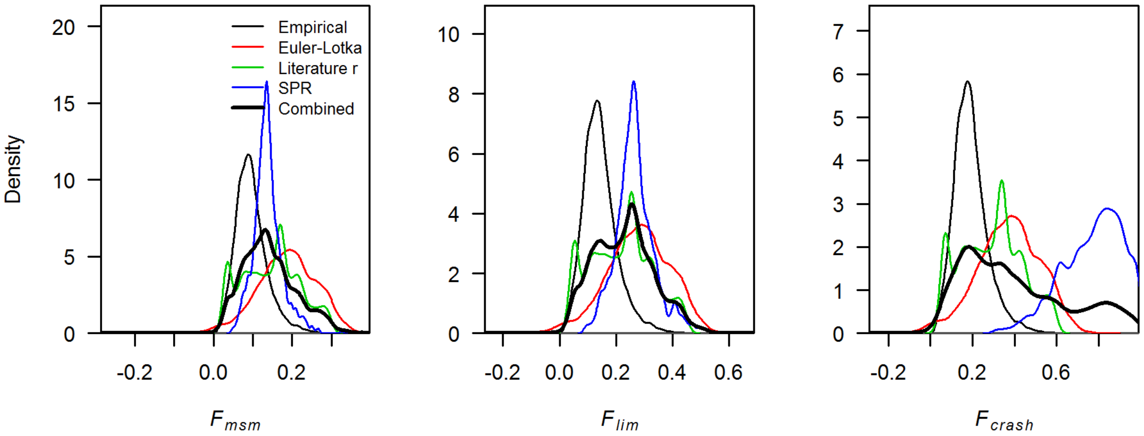

Figure 2. Density distributions of estimated reference points for Blue shark in the North Pacific Ocean (BSH-N) from four alternative methods. For the SPR method, $F_{40\%}$ is used as F_{msm}, $F_{40\%}$ as F_{lim}, and $F_{10\%}$ as F_{crash}.

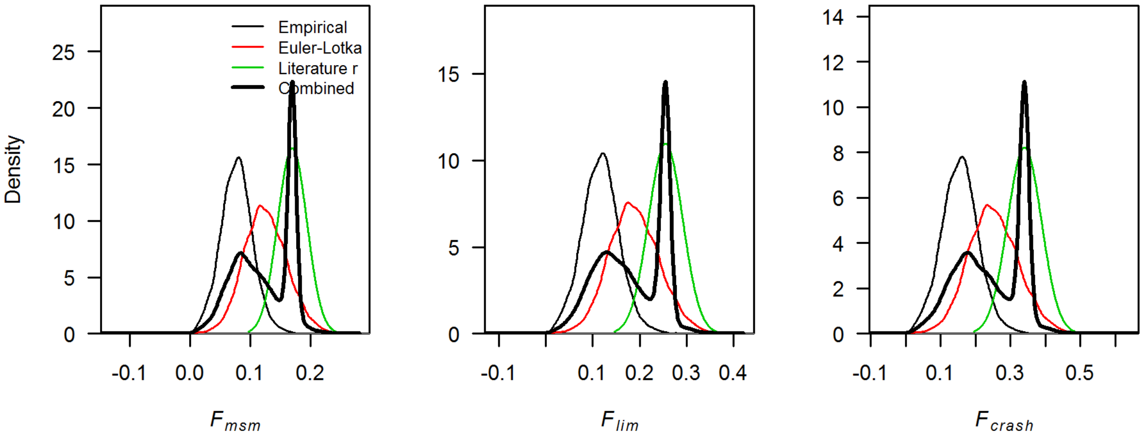

Figure 3. Density distributions of estimated reference points for Blue shark in the South Pacific Ocean (BSH-S) from three alternative methods.

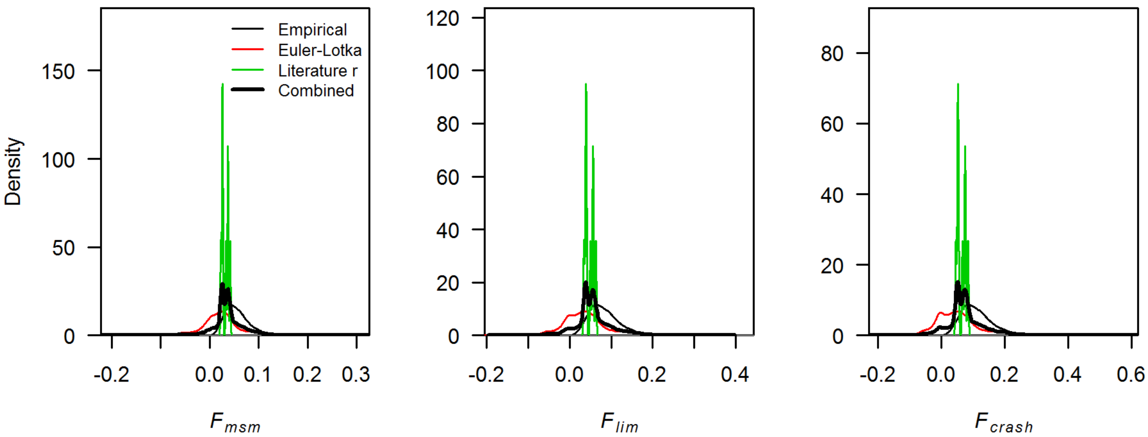

Figure 4. Density distributions of estimated reference points for Shortfin mako shark in the North Pacific Ocean (SMA-N) from three alternative methods.

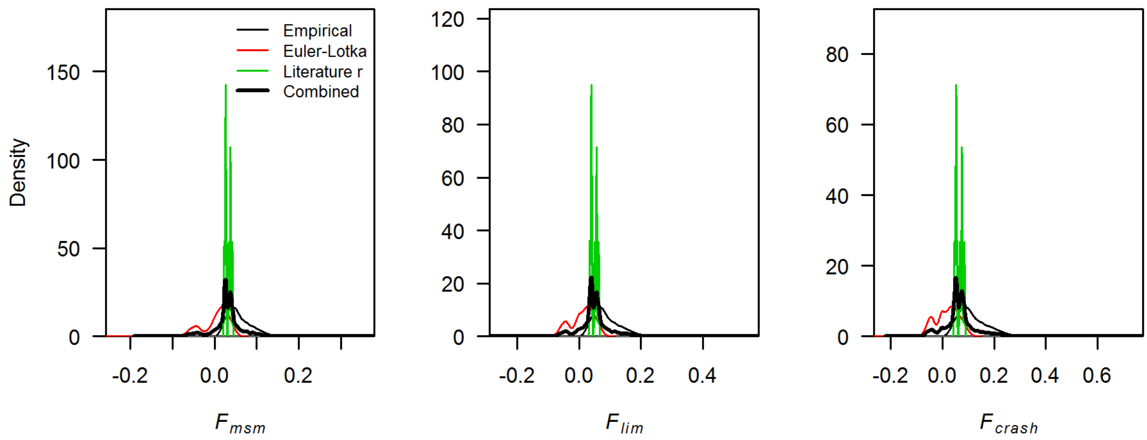

Figure 5. Density distributions of estimated reference points for Shortfin mako shark in the South Pacific Ocean (SMA-S) from three alternative methods.

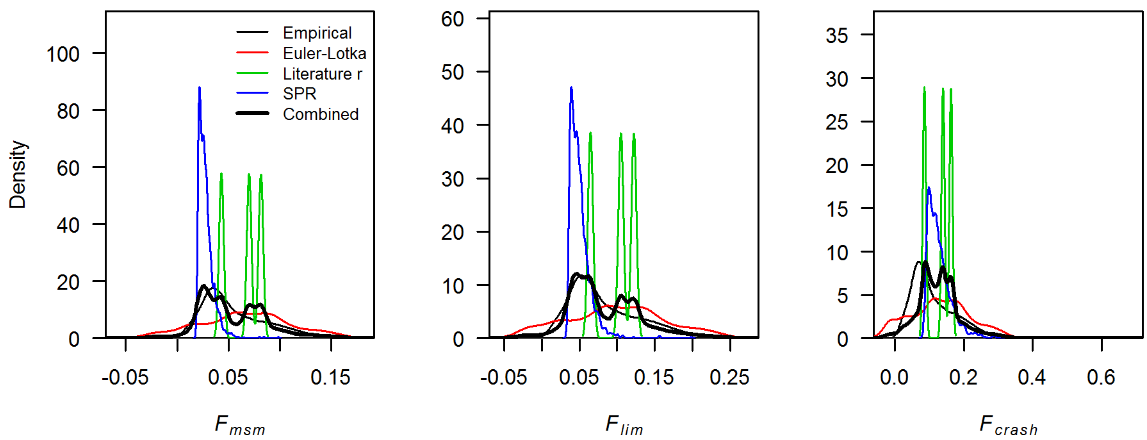

Figure 6. Density distributions of estimated reference points for Silky shark in the Pacific Ocean (FAL) from four alternative methods using newly estimated life-history parameters (Grant et al. 2018).

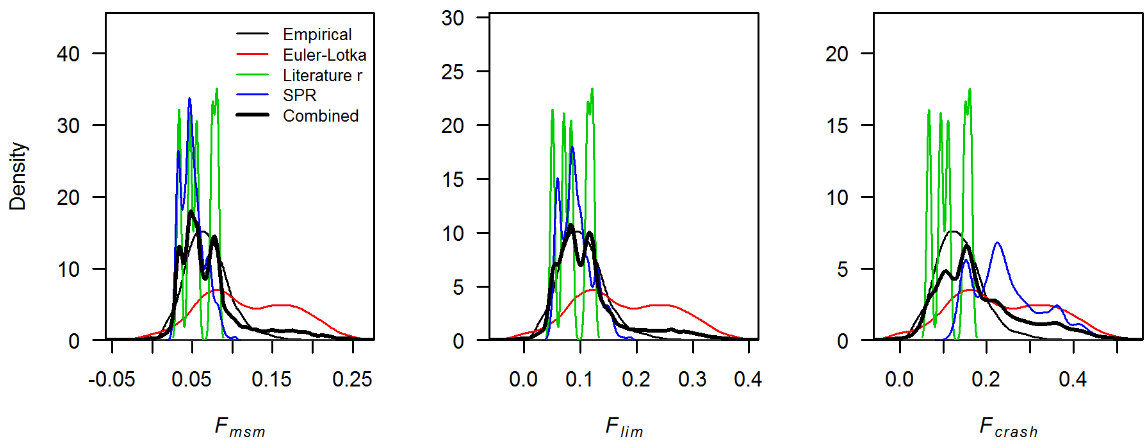

Figure 7. Density distributions of estimated reference points for Oceanic whitetip shark in the Pacific Ocean (OCS) from four alternative methods.

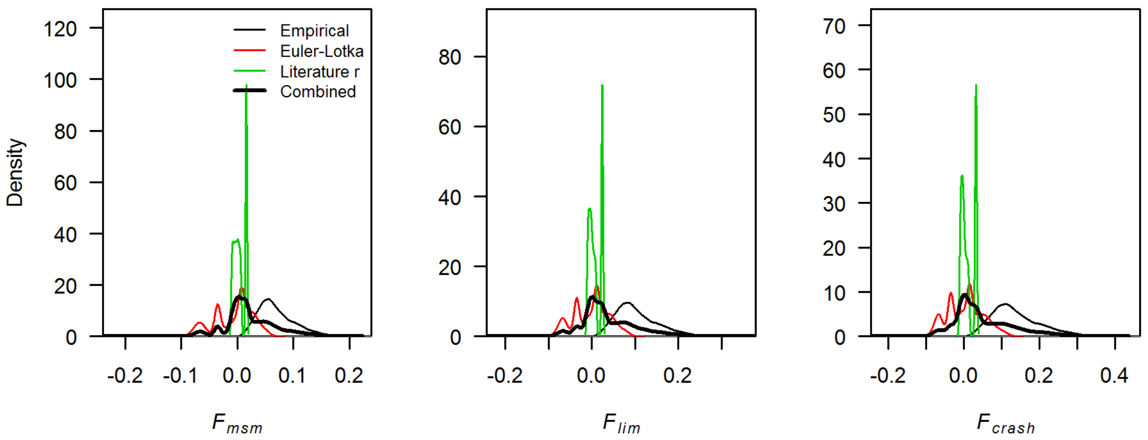

Figure 8. Density distributions of estimated reference points for Bigeye thresher shark in the Pacific Ocean (BTH) from three alternative methods.

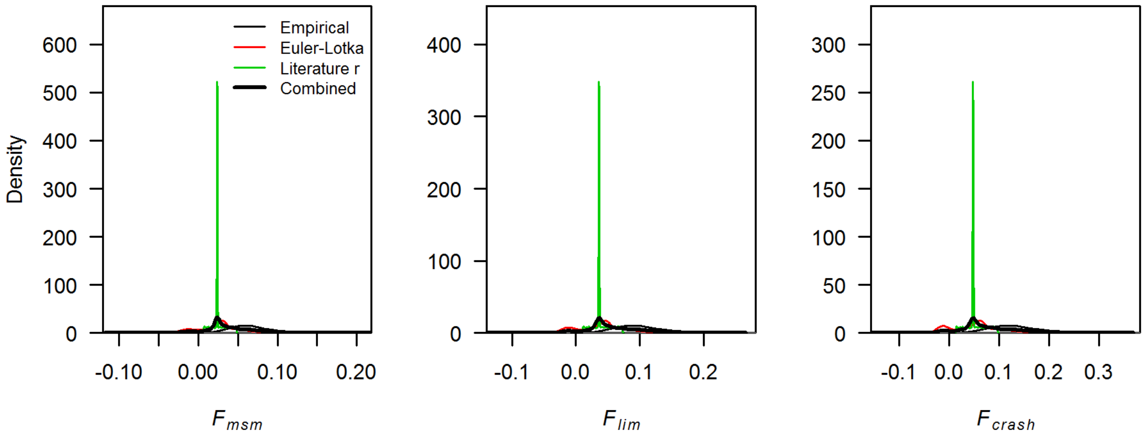

Figure 9. Density distributions of estimated reference points for Pelagic thresher shark in the Pacific Ocean (PTH) from three alternative methods.

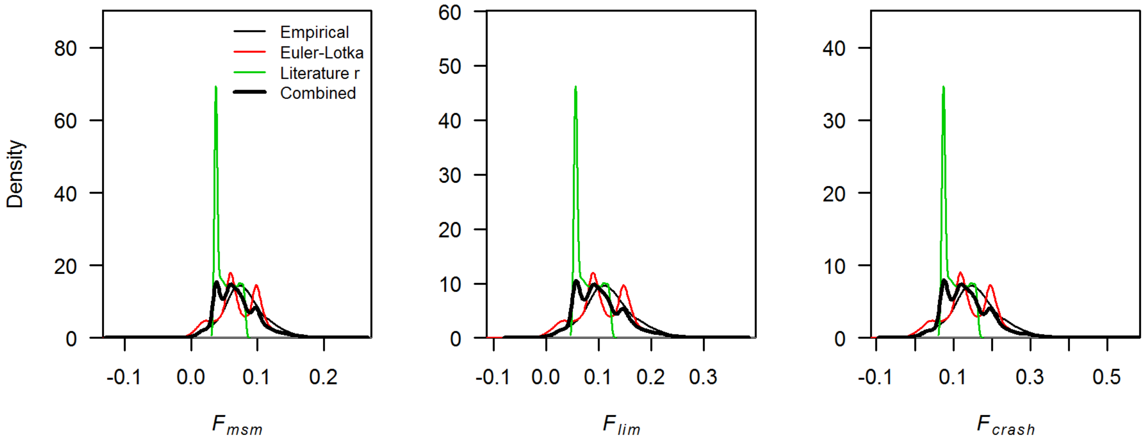

Figure 10. Density distributions of estimated reference points for Common thresher shark in the Pacific Ocean (ALV) from three alternative methods.

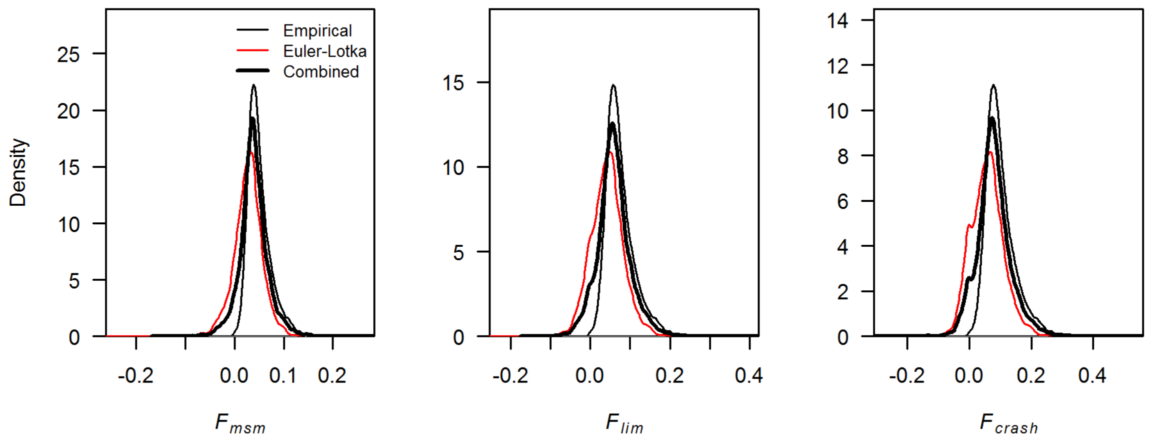

Figure 11. Density distributions of estimated reference points for Porbeagle shark in the Pacific Ocean (POR) from three alternative methods.

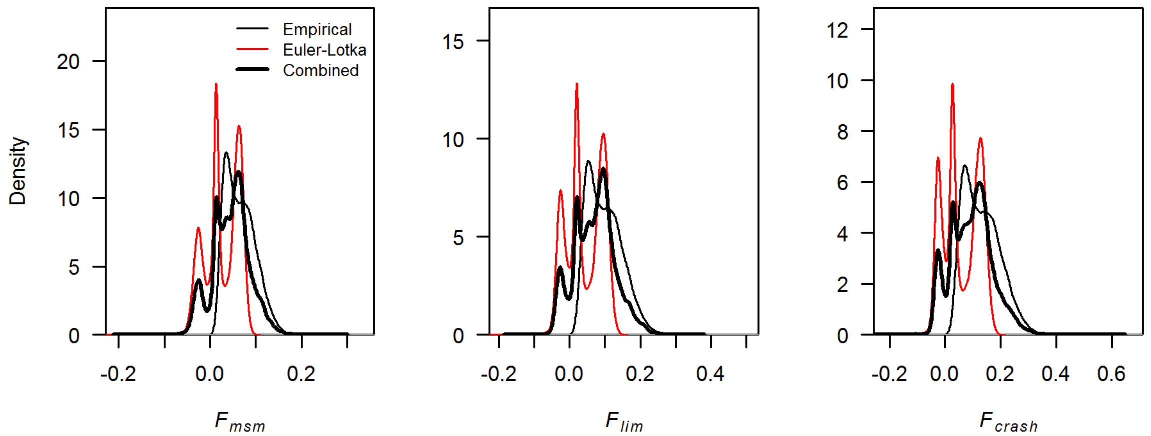

Figure 12. Density distributions of estimated reference points for Smooth hammerhead shark in the Pacific Ocean (SPZ) from three alternative methods.

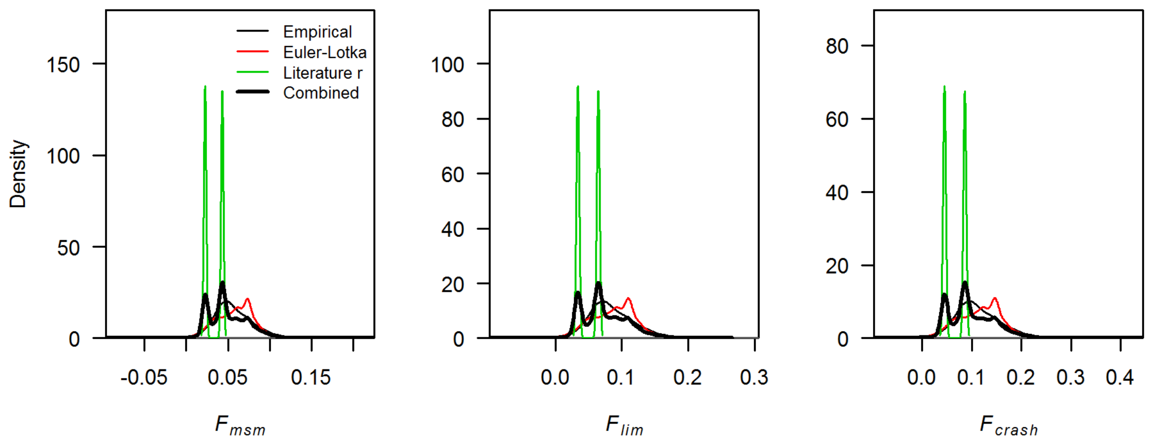

Figure 13. Density distributions of estimated reference points for Scalloped hammerhead shark in the Pacific Ocean (SPL) from three alternative methods.

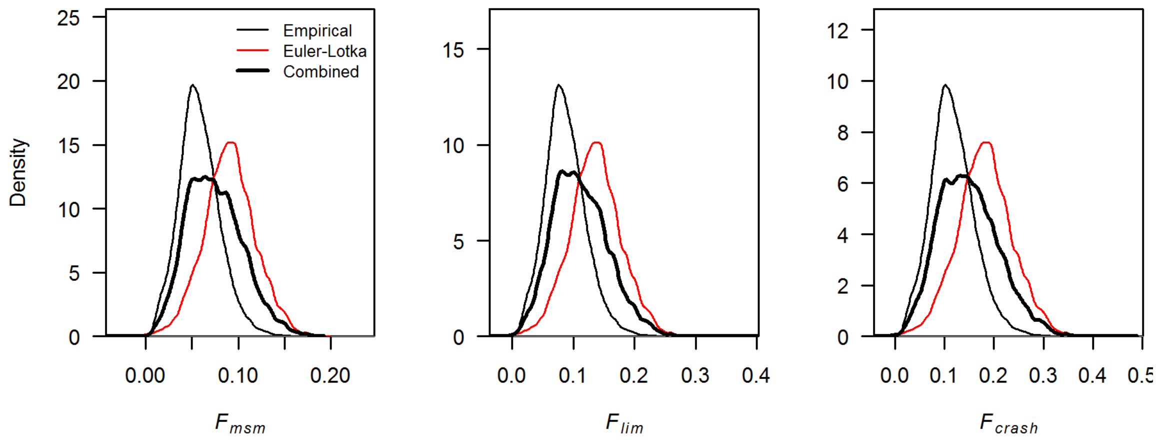

Figure 14. Density distributions of estimated reference points for Great hammerhead shark in the Pacific Ocean (SPK) from three alternative methods.

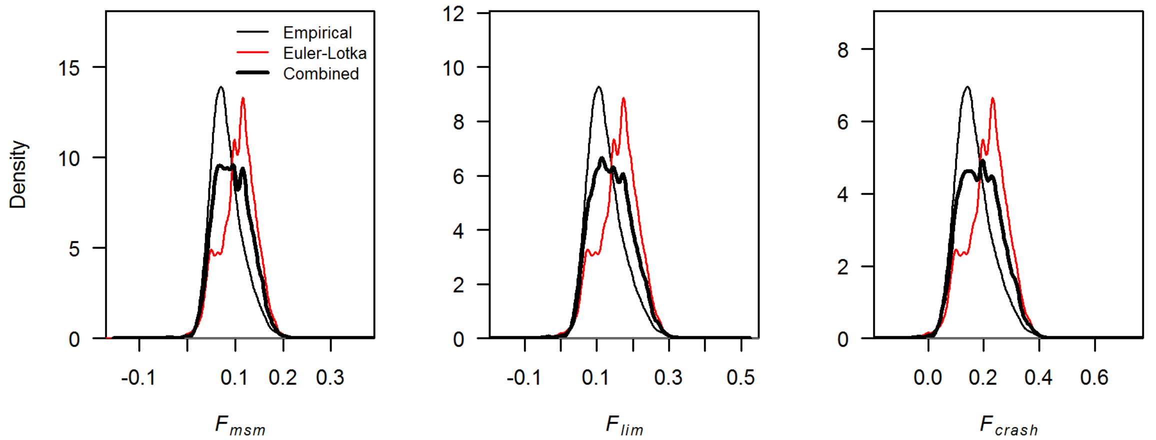

Figure 15. Density distributions of estimated reference points for Winghead shark in the Pacific Ocean (EUB) from three alternative methods.

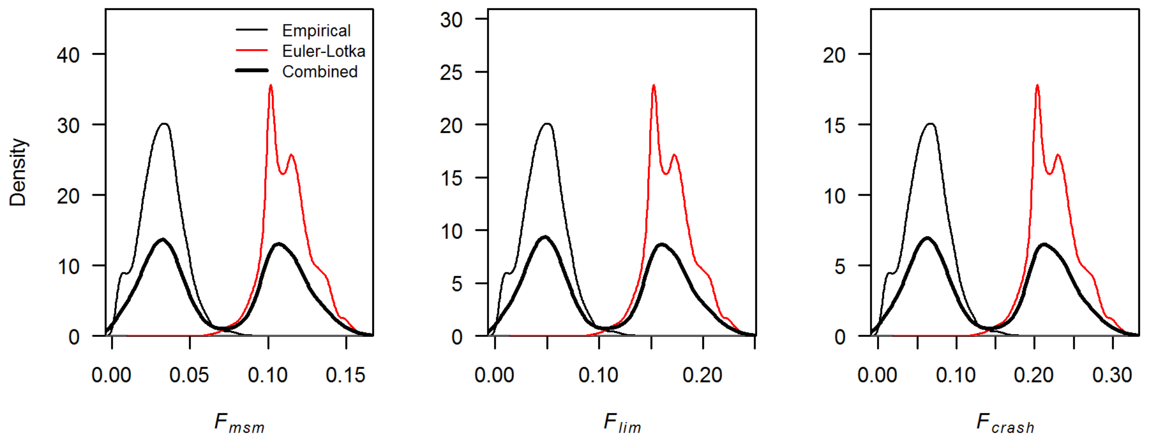

Figure 16. Density distributions of estimated reference points for Whale shark in the Pacific Ocean (RHN) from three alternative methods.

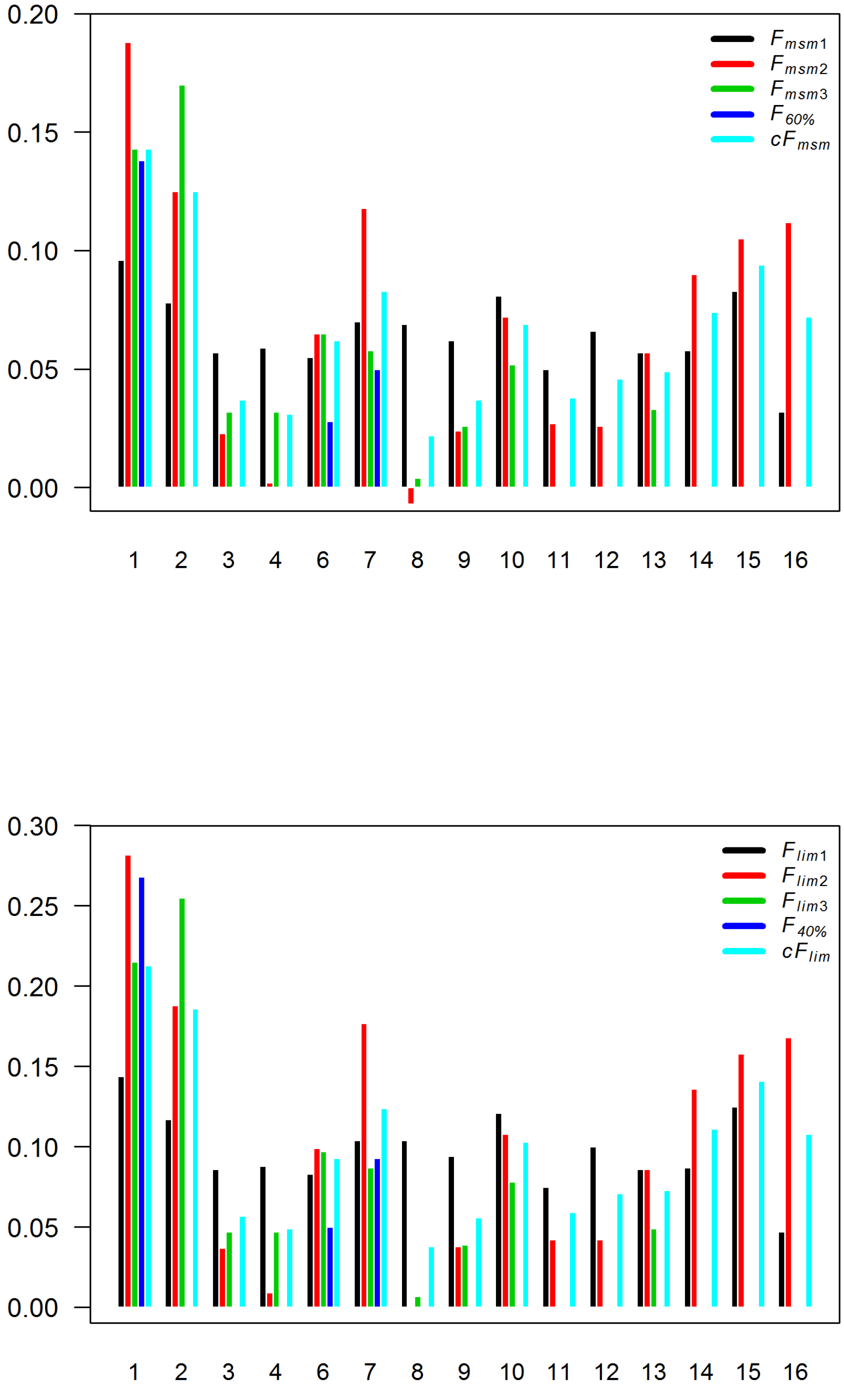

Figure 17. Comparison of estimated F_{msm} and F_{lim} between Methods 1 to 4 for the 16 shark stocks (RP cannot be estimated for stock #5 LMA).

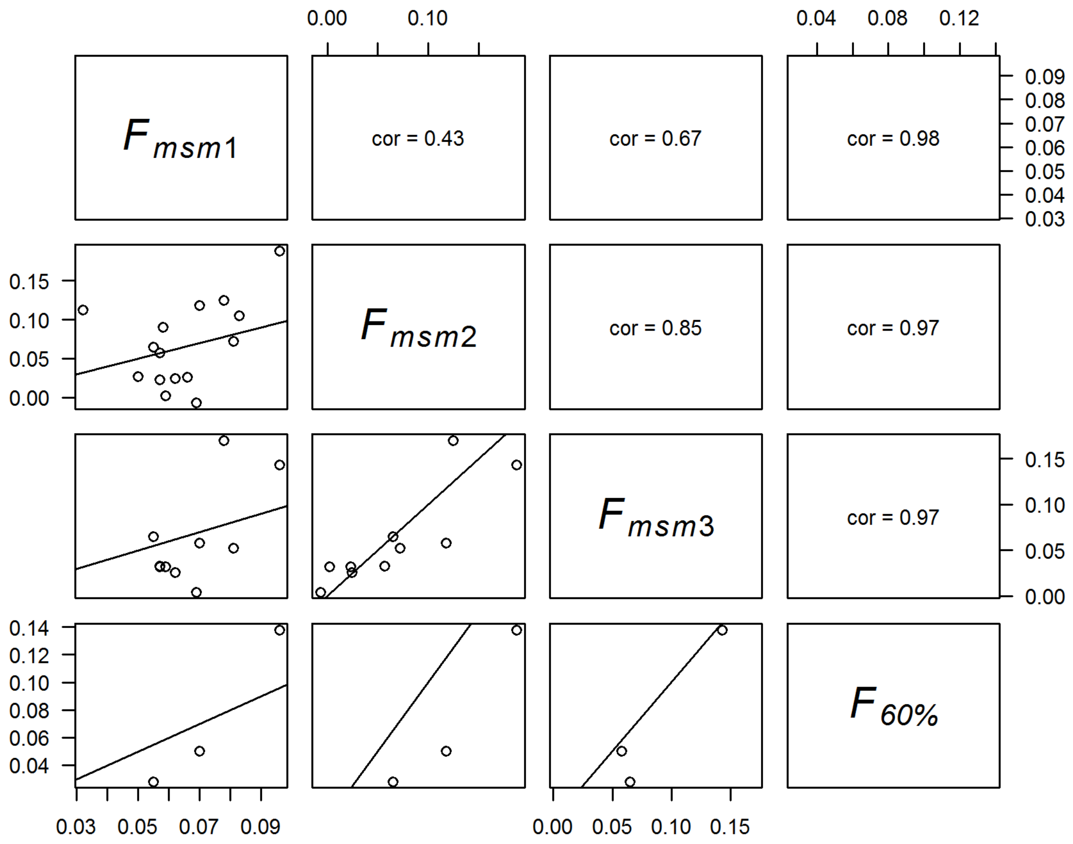

Figure 18. Comparison of estimated F_{msm} between four alternative methods for the 16 shark stocks (RP cannot be estimated for stock #5 LMA). The line indicates where $F_x = F_y$.

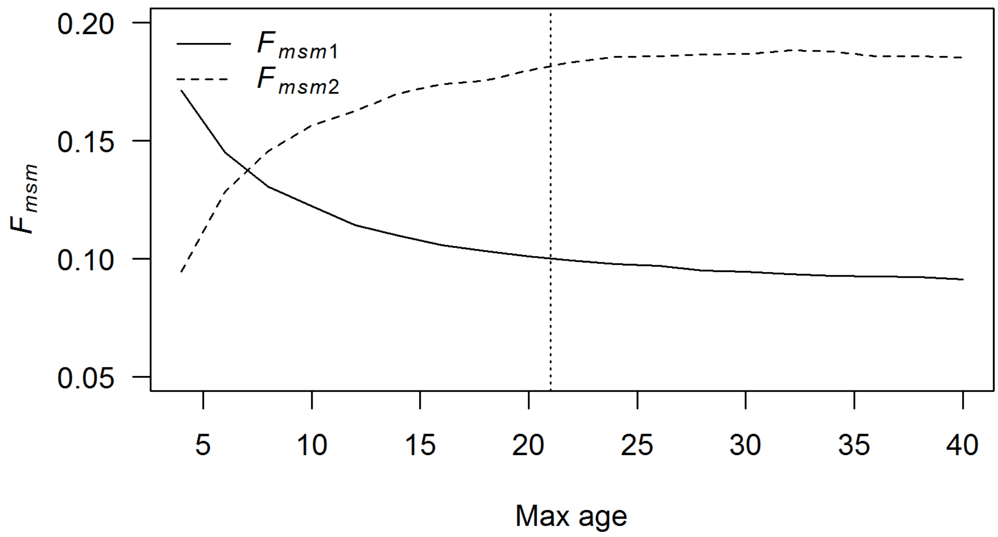

Figure 19. Methods 1 and 2 sensitivity to estimated maximum age. The example is F_{msm} for Blue shark in the Northern Pacific with all other life history parameters remaining unchanged. The vertical line is the estimated t_{max}.

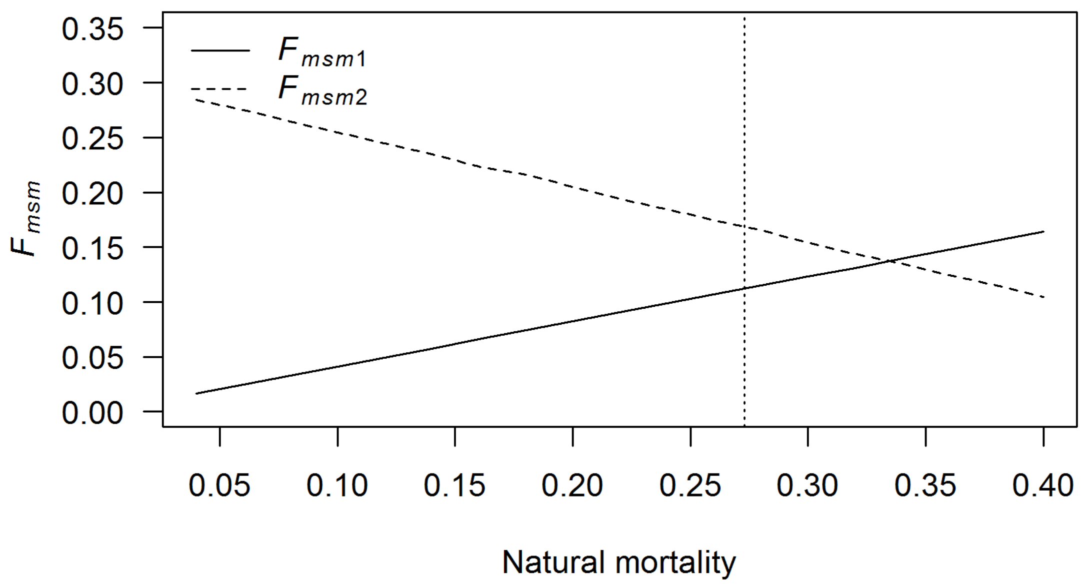

Figure 20. Methods 1 and 2 sensitivity to estimated natural mortality. The example is F_{msm} for Blue shark in the Northern Pacific. The vertical line is the estimated M.

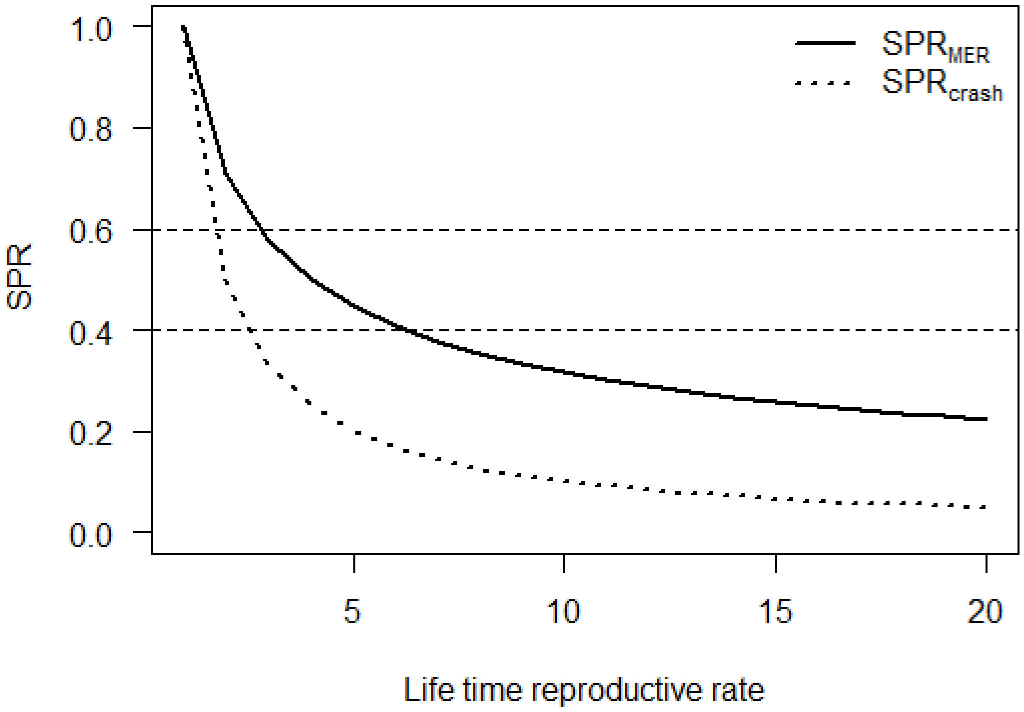

Figure 21. Relationship between reference points based on spawning potential ratio (SPR) and stock productivity measured as life time reproductive rate (x-axis). SPR_{MER} is the spawning potential ratio at maximum excess recruitment in number, and SPR_{crash} below which the stock will become extinct.

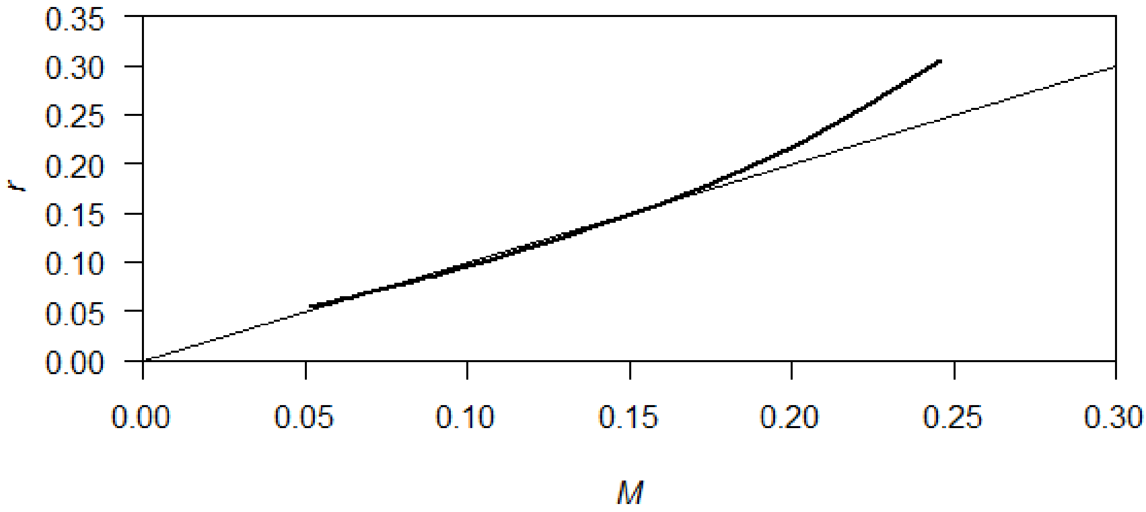

Figure 22. Intrinsic population growth rate *r* as a function of natural mortality *M* based on Euler-Lotka equation and mean fecundity of sharks species in the WCPFC. The thin line is *r* = *M*.

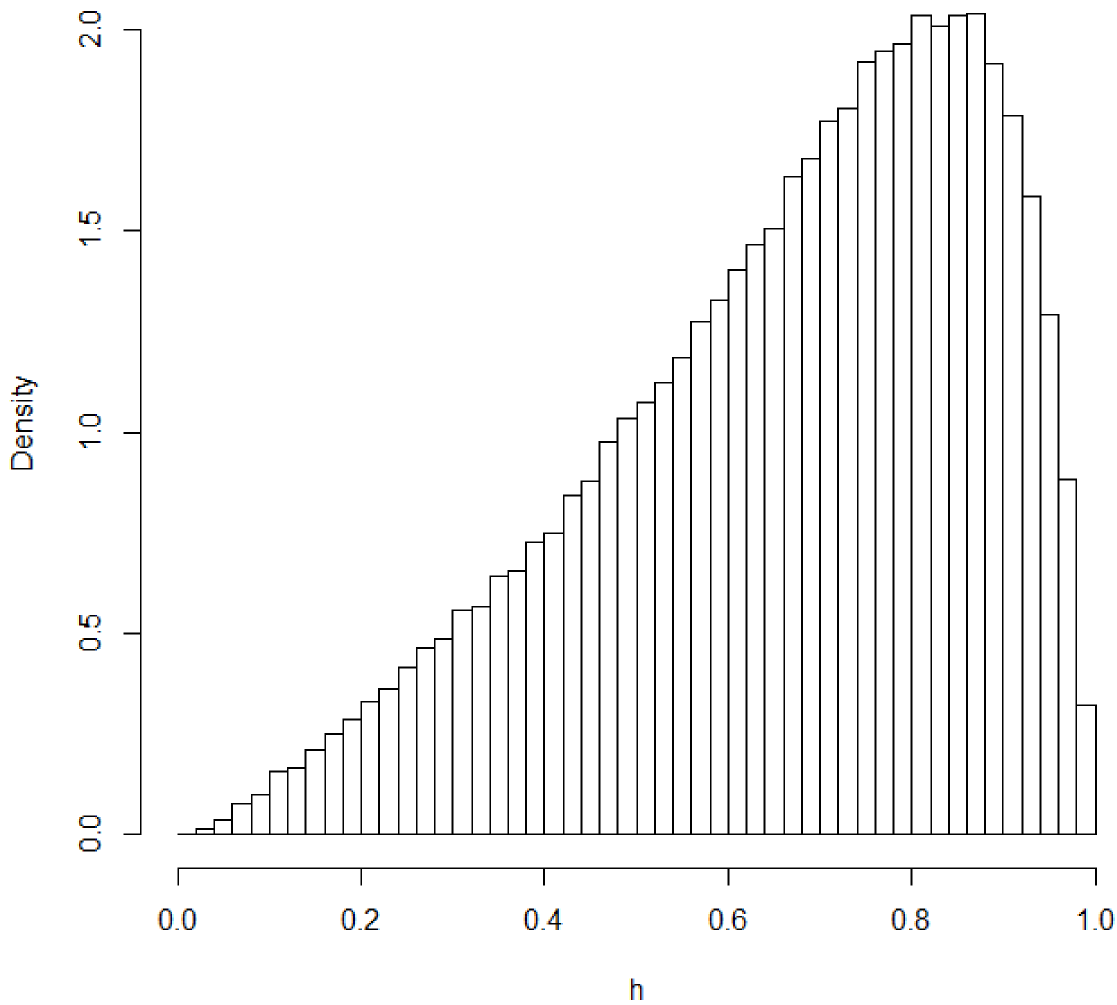

Figure 23: Probability density distribution for von Bertalanffy steepness *h*, including uncertainties associated with maximum age and mean natural mortality.

7 Appendix 1: R code for testing stock-recruitment steepness

```
#--------------------
# Parameter values
#--------------------

# Age and growth
amax <- 20
Linf <- 243.3
k <- 0.144
a0 <- -0.849
ac <- 0 # First age, used in Lorenzen.

# Length-weight
c1 <- 5.859E-6
c2 <- 3.093
c1m <- 1.21E-5
c2m <- 2.94

# Maturity
c3 <- 24.52
c4 <- -0.16

# Littersize-length
c5 <- -45.54
c6 <- 0.455

# Natural mortality
MT <- 0.23  # Target natural mortality
sr <- 0.5

S0 <- 0.965 # Occurrence rate of embryos from fertilised eggs, beta distributed
S1 <- 1 # Assumed, though max may actually be survival rate of pregnant females
S2 <- 0.993 # Neonates: proportion of abnormal embryos, beta distributed

# Reproduction
y <- 1 # Reproductive period
Scycle <- 1/y

#--------------------
# Functions
#--------------------

# vonB function
vb <- function(a, Linf, k, a0) Linf * (1-exp(-k * (a - a0)))

# M function
calcM <- function(amax, Linf, k, a0, MT, ac) {
  LL <- vb(seq(0, amax, 1), Linf, k, a0)
  Lc <- vb(ac, Linf, k, a0)
  (MT * (amax - ac) / log(Lc / (Lc + Linf * (exp(k * (amax - ac))- 1)))) * log(LL / (LL +
Linf * (exp(k) - 1)))
}

# am=20
# Mtest <- calcM(amax=am, Linf, k, a0, MT=0.23, ac=0)
# plot(0:am, Mtest, type="l", xlab = "Age")
# mean(Mtest)
# exp(-Mtest[2])
# L <- vb(0:am, Linf, k, a0)
# p_mat <- 1 / (1 + exp(c3 + c4 * L))
# plot(0:am, p_mat, type = "l")
```

```
# Combined function
calc_h <- function(a_s, sr, Wf) {
  h <- a_s * (1 - sr) * Wf / (4 + a_s * (1 - sr) * Wf)
  return(h)
}

# Steepness function
est_steepness <- function(amaxx=amax, Linfx=Linf, kx=k, a0x=a0, MTx=MT,
       acx=ac, c1x=c1, c2x=c2, c3x=c3, c4x=c4, c5x=c5, c6x=c6, srx=sr, S0x=S0,
       S1x=S1, S2x=S2, Scyclex=Scycle, rec_age=1) {
  a <- 0:amaxx
  L <- vb(a, Linfx, kx, a0x)          # Length at age
  Lc <- vb(acx, Linfx, kx, a0x)       # Length of minimum age for estimating mean M
  p_mat <- 1 / (1 + exp(c3x + c4x * L)) # Maturity
  W <- c1x * (L)^c2x                  # Length-weight relationship
  litter <- c5x + c6x * L             # Fecundity
  litter[litter < 0] <- 0
  M <- calcM(amaxx, Linfx, kx, a0x, MTx, acx) # Natural mortality
  S3 <- exp(-M[1])                    # Juvenile mortality. How old is S3? Assume 0
  Spre <- S0x * S1x * S2x * S3        # Total pre-recruit mortality
  Sac <- Sa <- vector("double", length = length(a))
  recind <- rec_age + 1
  Sac[recind] <- 1                    # Recruitment at age rec_age (should be 1)
  Sa <- exp(-M)
  for (i in recind:amaxx) {
    Sac[i + 1] <- Sac[i] * Sa[i]
  }
  Wfa <- Sac * W * p_mat              # Female spawning biomass at age
  Wf <- sum(Wfa)
  # new individuals per spawning biomass, weighted by abundance at age
  alpha_s <- Spre * Scyclex * sum(Sac * p_mat * litter) / sum(Sac * p_mat * W)
  #  alpha_s <- sum(litter) * Spre * Scyclex / sum(W)

  h <- calc_h(a_s=alpha_s, sr = srx, Wf = Wf)
  return(h)
}

#--------------------
# Results
#--------------------
est_steepness()
est_steepness(rec_age = 0)

est_steepness(amax=12)
est_steepness(amax=24)

est_steepness(MT=0.2)
est_steepness(MT=0.3)

est_steepness(ac = 0)
est_steepness(ac = 0.1)
est_steepness(ac = 1)

# Randomization
nsamp = 200000
MT_r <- rnorm(nsamp, mean = 0.23, sd=0.08)
amax_r <- sample(x=c(12, 15, 22, 29, 21, 20), nsamp, replace = TRUE)

stpp <- rep(0, nsamp)
for (i in 1:nsamp) {
  stpp[i] <- est_steepness(amaxx = amax_r[i], MTx = MT_r[i])
}
windows()
hist(stpp, xlim = c(0,1), nclass = 50, freq = FALSE, main = "Uncertainty distribution for
h", xlab = "h")
savePlot("steep_prior_MT_amax.png", type = "png")
```

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