

Ecological Assessment of the Sustainable Impacts of Fisheries (EASI-Fish): a flexible vulnerability assessment approach to quantify the cumulative impacts of fishing in data-limited settings

Shane P. Griffiths^{1,*}, Kathleen Kesner-Reyes², Cristina Garilao³, Leanne M. Duffy¹,
Marlon H. Román¹

¹Inter-American Tropical Tuna Commission, 8901 La Jolla Shores Drive, La Jolla, CA 92037, USA

²Quantitative Aquatics, Inc., Khush Hall, International Rice Research Institute, Los Baños, 4031 Laguna, Philippines

³GEOMAR Helmholtz Centre for Ocean Research Kiel, 24148 Kiel, Germany

ABSTRACT: In fisheries, vulnerability assessments—also commonly known as ecological risk assessments (ERAs)—have been an increasingly popular alternative to stock assessments to evaluate the vulnerability of non-target species in resource- and data-limited settings. The widely-used productivity–susceptibility analysis (PSA) requires detailed species-specific biological information and fishery susceptibility for a large number of parameters to produce a relative vulnerability score. The two major disadvantages of PSA are that each species is assessed against an arbitrary reference point, and PSA cannot quantify cumulative impacts of multiple fisheries. This paper introduces an Ecological Assessment of the Sustainable Impacts of Fisheries (EASI-Fish), a flexible approach that quantifies the cumulative impacts of fisheries on data-limited bycatch species, demonstrated in eastern Pacific Ocean (EPO) tuna fisheries. The method first estimates fishing mortality (F) based on the ‘volumetric overlap’ of each fishery with the distribution of each species. F is then used in length-structured per-recruit models to assess population vulnerability status using conventional biological reference points. Model results were validated by comparison with stock assessments for bigeye and yellowfin tunas in the EPO for 2016. Application of the model to 24 species of epipelagic and mesopelagic teleosts, sharks, rays, sea turtles and cetaceans and identification of the most vulnerable species is demonstrated. With increasing demands on fisheries to demonstrate ecological sustainability, EASI-Fish allows fishery managers to more confidently identify vulnerable species to which resources can be directed to either implement mitigation measures or collect further data for more formal stock assessment.

KEY WORDS: Productivity–susceptibility analysis · Ecological risk assessment · Data-poor · Fisheries

Resale or republication not permitted without written consent of the publisher

1. INTRODUCTION

The traditional paradigm of fisheries management has typically aimed to ensure the sustainability of the populations of individual economically important target species. This has evolved significantly over the past 2 decades to include ecosystem-based approaches

to fisheries management in recognition of growing evidence that the direct and indirect impacts of fishing extend beyond those of the target species. Fishing can affect the populations of various species, from the inconspicuous to iconic megafauna (Lewison et al. 2004), the physical aquatic environment and habitats (Chuenpagdee et al. 2003), and can

*Corresponding author: sgriffiths@iattc.org

compromise the integrity of supporting ecosystems (Myers et al. 2007, Griffiths et al. 2019) and the quantity and quality of the services they provide not only to fisheries, but to human society in general (Worm et al. 2006).

Furthermore, the public perception of commercial fishing practices and their management has also been an increasingly important socio-political driver for fisheries to demonstrate their commitment to operating in an ecologically responsible manner (Hall et al. 2000, Mikalsen & Jentoft 2001, Jacquet & Pauly 2007). In recent years, this has manifested into eco-labelling of products produced by fisheries that have been certified, by organisations such as the Marine Stewardship Council, as being ecologically sustainable (Kirby et al. 2014).

Although a noble concept, ecological sustainability can be difficult and expensive to demonstrate in practice. This is due to the common paucity of reliable biological and catch information for non-target species, herein defined as a species that is not a primary target species but is either retained for economic reasons, consumed by crew members or used for bait ('byproduct'), or discarded at sea ('discard') (see Gilman et al. 2014). The challenge is exacerbated in fisheries that employ relatively unselective gears such as longline and purse seine used in tuna fisheries that interact with large numbers of taxa representing diverse life histories including teleosts, chondrichthyans, seabirds, sea turtles and marine mammals (Hall & Roman 2013). Therefore, assessing all affected species using traditional data-intensive stock assessment approaches is both cost-prohibitive and impractical.

A suite of simplified ecological assessment tools that have been developed since at least the late 1990s—in a research field commonly referred to in fisheries as ecological risk assessment (ERA)—has been increasingly used by fisheries worldwide as a rapid and cost-effective alternative for assessing the ecological effects of fishing, particularly in data-limited settings (Gallagher et al. 2012). However, as stated by Fletcher (2015), ERA is largely a misnomer, as the primary methods used in this field do not calculate the risk of a specific threat to a species manifesting under the formal International Organization for Standardization (ISO) risk definition as 'the effect of uncertainty on objectives' (ISO 2009). Instead, ERA, as commonly applied in fisheries, is a process to identify potentially vulnerable species for which specific management measures (e.g. gear modifications, time-area closures, etc.) can be implemented to reduce a species' vulnerability, or prioritise them for

further data collection, to subsequently facilitate more rigorous quantitative assessment.

Vulnerability assessment methods differ significantly in their data requirements and model complexity. The simplest method is the qualitative consequence-likelihood analysis that uses all available data types using a 'weight of evidence' approach driven by stakeholder involvement and expert opinion where justifying narratives are provided throughout the process (Fletcher 2005, 2015). This approach is also compliant with generic international and Australian risk assessment standards (IEC 2009, ISO 2009, Standards Australia 2012). In contrast, the more complex methods are quantitative, spatially explicit biomass-pool population models that require more detailed fishery and biological information for parameterisation (Zhou & Griffiths 2008, Pitcher et al. 2017). The semi-qualitative productivity-susceptibility analysis (PSA) (Stobutzki et al. 2001) of intermediate complexity has been a popular method applied to a vast array of species groups and fisheries worldwide (Milton 2001, Waugh et al. 2008, Cortés et al. 2010, Patrick et al. 2010, Lucena-Frédou et al. 2017). The popularity of PSA stems from its flexibility in data inputs and assessment attributes that can rapidly produce a relative measure of vulnerability of a large number of species that can be easily interpreted by fishery managers, policy makers and laypersons. For these reasons, PSA is the primary ecological assessment method recommended by the Marine Stewardship Council for fisheries seeking certification for eco-labelling purposes.

PSA assesses the relative vulnerability, rather than the absolute risk as defined by international risk standards (see IEC 2009, ISO 2009), of each affected species by scoring a number of attributes relating its susceptibility to being captured by a particular fishery or gear type, and the population's biological capacity to recover should it become depleted. Susceptibility (e.g. gear selectivity) and productivity (e.g. natural mortality rate, fecundity) attributes are developed for the species and fishery of interest, and the ranges of possible values for each attribute are divided into 3 categories, with cut-off values determined—often subjectively—by the practitioner.

For example, species comprising a bycatch assemblage may range in maximum age (t_{\max}) between 4 and 30 yr, resulting in scoring categories of <10, 10–20 and >20 yr. For each species, each attribute is then given a rank of 1 (least susceptible; least productive) to 3 (most susceptible; most productive). The susceptibility and productivity attribute scores for each species are averaged and then combined to produce a

vulnerability score (v). The species with a vulnerability score exceeding a pre-defined threshold value (e.g. >2.0) are deemed 'highly vulnerable' to becoming unsustainable under current levels of fishing.

Unfortunately, commonly adopted vulnerability threshold values are arbitrarily defined and have no biological significance, nor have they been statistically derived. This is because input data, even highly precise parameter estimates, are reduced to categorical scores. As a result, a PSA vulnerability score for a species provides only a measure of vulnerability relative to the other species included in the assessment for a single fishery. Furthermore, this scoring system does not allow the scores for multiple fisheries to simply be summed to assess the cumulative impacts of fishing, which is a growing need in many areas of the world, where target and associated bycatch species are shared between expanding and increasingly efficient fisheries (Martínez-Ortiz et al. 2015). However, a few authors have attempted to take into account the effects of multiple gears by applying various weighting methods to susceptibility scores (Ormseth & Spencer 2011, Micheli et al. 2014, Duffy et al. 2019).

These shortcomings present a conundrum for fishery managers, who may wish to establish formal PSA reference points (e.g. $v = 2.0$; see Cope et al. 2011) or relative risk boundaries (Hobday et al. 2006) to initiate a management response similar to the objectives of harvest control rules for commercially important species. Such arbitrary thresholds can therefore cost a fishery valuable resources by triggering mitigation measures for species that have only been classified as vulnerable due to artifacts of the assessment method. This highlights the need for improved assessment methods and biologically meaningful reference points to definitively determine the vulnerability of data-limited species.

In an attempt to address this issue, Zhou & Griffiths (2008) developed the quantitative Sustainability Assessment for Fishing Effects (SAFE) approach, which, like other vulnerability assessment methods, is comprised of a susceptibility and a productivity component. The proportion of each species' population that is vulnerable to capture, after accounting for various selectivity effects, is assessed against biological reference points (BRPs) developed from empirical equations that relate life history traits to natural mortality (M). These are (1) the maximum sustainable fishing mortality (F_{msm}) — a proxy for the fishing mortality at maximum sustainable yield (MSY) — and (2) the lowest fishing mortality that would render a species extinct (F_{crash}) (also see Zhou et al. 2012).

Although SAFE was designed to assess data-poor bycatch species, it is based upon high spatial resolution species distribution and fishing effort data derived from fishery-independent scientific surveys and vessel monitoring systems data. Unfortunately, for resource-limited or large-scale fisheries, fishery-independent faunal surveys are cost prohibitive. Fishery-dependent logbook and/or observer programmes are in place in many fisheries; however, the reporting level of low-value and rarely encountered bycatch species is generally poor, and at best would generally only provide presence-only data for most species. A data-limited approach is therefore needed to quantitatively measure the cumulative impacts of multiple fisheries in the absence of precise estimates of catch or abundance of bycatch species and to determine the vulnerability status of a species' population.

This paper introduces a spatially explicit quantitative vulnerability assessment approach, termed the Ecological Assessment of the Sustainable Impacts of Fisheries (EASI-Fish), that quantifies the cumulative impacts of multiple fisheries on data-limited species. The approach builds on PSA's flexibility in using a range of susceptibility and productivity data inputs — but as continuous rather than categorical values — coupled with the basic concept of quantifying population impact by the degree to which the distribution of fishing effort overlaps with a species' habitat. EASI-Fish first estimates the instantaneous fishing mortality rate from the 'volumetric overlap' of multiple fisheries on a species' 3-dimensional spatial distribution, in this case developed using a relative environmental suitability (RES) model based on presence-only data coupled with environmental data for the assessment region. The estimated fishing mortality is then used in length-structured per-recruit models to determine the vulnerability status of each species using conventional and precautionary fishing mortality- and spawning stock biomass-based BRPs commonly used in stock assessment. Using 'industrial' longline and purse-seine tuna fisheries in the eastern Pacific Ocean (EPO) as a case study, this paper aimed to (1) validate the approach by comparison with the results of fully integrated stock assessment results for yellowfin tuna *Thunnus albacares* and bigeye tuna *T. obesus* in the EPO, and (2) demonstrate the application of EASI-Fish to a representative subset of pelagic and mesopelagic teleost, shark, ray, turtle and dolphin species caught in these fisheries for the purpose of identifying and prioritising species for management, or for the collection of further information that will fill key data gaps and allow for more formal population assessments to be undertaken in the future.

2. MATERIALS AND METHODS

2.1. Assessment region and definition of included fisheries

EASI-Fish was designed for use in data-limited settings, but has sufficient flexibility to use a range of data types of varying quality. For demonstration purposes, the approach is used to assess the vulnerability of a representative assemblage of species (target, retained non-target and discarded non-target) caught in the 'industrial' longline and purse-seine fisheries in the EPO, and managed by the Inter-American Tropical Tuna Commission (IATTC). The IATTC Convention Area extends over an area of approximately 55 million km² from the west coast of the Americas to 150° W between latitudes 50° N and 50° S (Fig. 1).

The analyses presented in this paper draw upon fishing effort data for 2016 obtained from vessel log-books or collected by on-board scientific observers, or submitted to the IATTC by its members for longline vessels >24 m length overall (LOA) and purse-seine vessels (carrying capacity >363 t). The purse-seine fishery was disaggregated into 3 separate fisheries based on set type: (1) sets associated with floating objects (OBJ), (2) sets associated with dolphins (DEL) and (3) sets on unassociated schools of tuna (NOA). The spatial distribution of the 2016 effort for each fishery is shown in Fig. 1.

Although this paper presents a 'proof of concept' of the EASI-Fish approach using the aforementioned fisheries, it should be noted that several fisheries that catch the species included in this study were not included in our analyses since catch and/or effort data were not available. These mainly include domestic

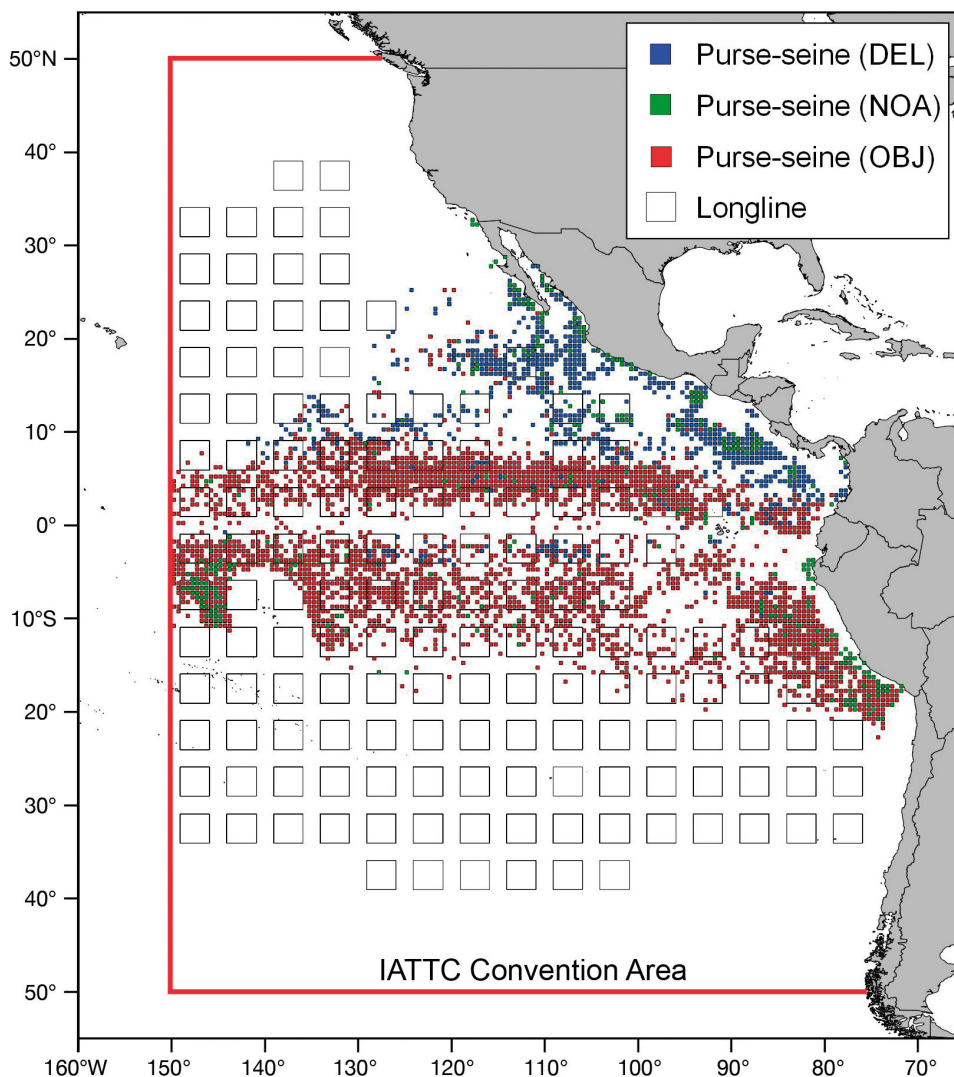


Fig. 1. Convention Area of the Inter-American Tropical Tuna Commission (IATTC) (red outline) with the distribution of fishing effort by the 'industrial' large-scale tuna longline fishery (5° × 5°, large open squares) and the 3 set types in the purse-seine fishery (DEL: dolphin sets; NOA: unassociated tuna school sets; OBJ: floating-object sets; 0.5° × 0.5°, smaller coloured squares) in 2016

small-scale commercial fisheries (e.g. gillnet, longline, troll, harpoon), the widespread artisanal fisheries (e.g. gillnet, longline) and sport fisheries that exist throughout South and Central America (see Alfaro-Shigueto et al. 2010, Cartamil et al. 2011, Southwick et al. 2013, Martínez-Ortiz et al. 2015).

2.2. Assessing susceptibility to estimate fishing mortality

In data-rich situations, the instantaneous fishing mortality rate (F) of an assessed species is most commonly estimated using reliable species- and length-specific catch data. However, in resource-limited fisheries, or for low-value non-target species (e.g. discarded bycatch species), the length composition of the catch is often not available, and for many infrequently caught or taxonomically ambiguous species, catch is simply not recorded. Therefore, an alternative approach used in EASI-Fish is to estimate the proportion of the population that is susceptible to being captured and incur mortality, the finite mortality rate (f), which is converted to F .

A similar spatial approach was developed by Pitcher et al. (2007)—and later refined by Pitcher et al. (2017)—to estimate the impact of benthic trawling on epibenthos, and subsequently adapted to elasmobranchs (Zhou & Griffiths 2008) and teleosts (Zhou et al. 2009). However, these approaches assume the population to comprise a single biomass pool where selectivity components are independent of length or age. This becomes a limitation for researchers wishing to capture quite obvious length-related susceptibility effects for particular species (e.g. minimum or maximum size retention limits) and for fisheries managers wishing to rapidly consider the potential impact of easily implemented length-based management measures (e.g. gear modifications to reduce the length at first capture), before resorting to expensive species-specific monitoring and/or stock assessment.

To address such issues, EASI-Fish uses a length-based approach with various susceptibility parameters to estimate the proportion of a length class (j) of a species' population that is susceptible to incurring mortality by fishery x (S_{xj}) in a given year, which can be represented as:

$$S_{xj} = \frac{G_x}{G} (D_x A_{xj} N_{xj} C_{xj} P_{xj}) \quad (1)$$

where G is the total number of grid cells occupied by a species (i.e. the 'stock'); G_x is the number of occupied grid cells exposed to at least 1 unit of fishing

effort by fishery x ; duration of fishing season (D_x) is the proportion of the population that is available to fishery x given the proportion of a year when fishing is permitted; seasonal availability (A_{xj}) is the proportion of length class j that is available to capture by fishery x ; encounterability (N_{xj}) is the proportion of length class j that may potentially encounter the gear used by fishery x ; contact selectivity (C_{xj}) describes the proportion of length class j that is retained once it encounters the gear used by fishery x ; and post-release mortality (P_{xj}) is the proportion of length class j that is caught by fishery x and dies before, during or soon after release. Each of the parameters in Eq. (1) is described in detail in the following.

For the purposes of this study, the stock definition for each species, within which its distribution is estimated, was assumed to be defined by the boundaries of the IATTC Convention Area. Within these boundaries, G was estimated from RES models developed for each species at $0.5^\circ \times 0.5^\circ$ resolution based on presence-only data and environmental variables (depth, sea surface temperature, salinity and primary productivity) to develop an environmental envelope (see description of RES model development and Fig. S1 in Supplement 1 at www.int-res.com/articles/suppl/m625p089_supp1.pdf) using the method of Kaschner et al. (2006). These maps are publicly available, free of charge and customisable (www.aquamaps.org) and the presence (source and predicted) and environmental data are available for download should the user wish to use alternative habitat models (e.g. generalised additive models, maximum entropy models). A detailed description of the methodology and development of the RES models is provided in Text S1 in Supplement 1.

Although a knife-edge probability-of-occupancy (Ψ) threshold (e.g. 0.7) may be used for each cell to define the distribution of each species, the predicted distribution can differ substantially depending on the threshold value used (see example for *Mobula japonica* in Fig. S2 in Supplement 1). Since a defined species distribution can influence the proportion of the population exposed to fishing, we accounted for this uncertainty by running the EASI-Fish model using distribution maps based on Ψ values of 0.5–0.95 in 0.05 increments, with a preferred value determined after modelled distributions were reviewed by experts and cross referenced with catch data (if available) (see Section 2.6 below, and Table S1 in Supplement 1).

Fishing effort for each fishery in 2016 (Fig. 1) was overlaid on each species' distribution map—for each Ψ value—to calculate G_x , and the percentage overlap

of each fishery was calculated by dividing G_x by G . Effort data for purse-seine vessels (as the number of sets) were reported at $<0.5^\circ$ resolution, so each set location was allocated to the corresponding $0.5^\circ \times 0.5^\circ$ grid cell. In contrast, longline data (number of hooks) for 2016 were reported at $5^\circ \times 5^\circ$ resolution, conservatively assuming that there was at least 1 unit of effort in each occupied $0.5^\circ \times 0.5^\circ$ cell contained in a $5^\circ \times 5^\circ$ cell with effort. Certainly, there may be by-catch species for which data are too sparse to develop a reliable distribution map, or available effort data for a fishery is not spatially explicit, and so the precautionary approach would be to assume $G_x/G = 1$.

The first 4 parameters in the parentheses of Eq. (1) (D_x , A_{xj} , N_{xj} and C_{xj}) comprise what is generically regarded as 'selectivity' in stock assessment parlance, which combines — often implicitly — 'population availability' (the relative probability that a fish of length class j is located in the area at the time where the fishery is operating) and 'contact selectivity' (the relative probability that a fish of length class j will be retained once it comes in contact with the gear) (Millar & Fryer 1999). Because selectivity curves are unlikely to be available for data-limited bycatch species, it was considered important to disaggregate selectivity components as far as practicable. This also allows the individual components to be parameterised if information is available, or the default assumption of full selection to be implemented as a precautionary measure in the absence of reliable information.

Duration of fishing season (D_x) is the proportion of the population that is available to fishery x given the proportion of a year when fishing is permitted, expressed as the number of fishing days divided by 365. In the EPO, IATTC Resolution C-13-01 mandated a 62 d closure of the purse-seine fishery in 2016, meaning that the species was potentially exposed to purse-seine fishing for 0.83 $[(365 - 62)/365]$ of the year. Fishing effort is assumed to be evenly distributed throughout the year, since fishing mortality would be different in a fishery in which all the fish could be caught in 100 d, for example, rather than the full year. The default precautionary value is 1.0 for fishery x , to assume that the species is available to fishery x for the entire year.

Seasonal availability (A_{xj}) is the proportion of length class j that is available to capture by fishery x , given that some species may undertake extensive intra-annual migrations outside of the fishing boundaries, where they are unavailable for fishery interactions. This is expressed as the proportion of the year that the species is available to the fishery. In cases where migrations are known to occur, but are

not adequately quantified, broad categories may be used similar to the PSA approach (e.g. 1–3 mo = 0.25, 4–6 mo = 0.5, 7–9 mo = 0.75, 10–12 mo = 1.0), or a data range defined in a prior distribution to incorporate parameter uncertainty (see Section 2.6). The default precautionary value is 1.0 for fishery x , to assume that no seasonal movement outside of fishery x occurs for length class j .

Encounterability (N_{xj}) is the proportion of length class j that may potentially encounter the gear used by fishery x based on the species' distribution in the water column relative to the defined fishing depth range of the gear. In the EPO, we defined the effective fishing depth range for all purse-seine set types as 0–200 m (Hall & Roman 2013) and 0–300 m for 'deep sets' by longlines (Bigelow et al. 2006). Minimum and maximum depths of each species were defined using the results of published studies — generally independent of length or age — using electronic tags (e.g. Schaefer & Fuller 2010), longline fishing experiments using time–depth recorders (Boggs 1992) or relating catch to estimated maximum hook depths (Ward & Myers 2005, Zhu et al. 2012). The proportional vertical overlap between a species and fishery x is calculated using 1 of 5 equations (Eqs. 2a–2e), depending on the relationship between the defined maximum (Max) and minimum (Min) depth of length class j and the gear of fishery x :

$$N_{xj} = 0 \quad \text{for } \text{Min}_j \geq \text{Max}_x, \text{ or } \text{Max}_j \leq \text{Min}_x \quad (2a)$$

$$N_{xj} = 1.0 \quad \text{for } \text{Max}_j \leq \text{Max}_x \text{ and } \text{Min}_j \geq \text{Min}_x \quad (2b)$$

$$N_{xj} = \frac{(\text{Max}_j - \text{Min}_j) - (\text{Max}_j - \text{Min}_x)}{(\text{Max}_j - \text{Min}_j)} \quad \text{for } \text{Min}_j \leq \text{Min}_x \text{ and } \text{Max}_j \leq \text{Max}_x \quad (2c)$$

$$N_{xj} = \frac{(\text{Max}_j - \text{Min}_j) - (\text{Max}_x - \text{Min}_j)}{(\text{Max}_j - \text{Min}_j)} \quad \text{for } \text{Max}_j \geq \text{Max}_x \text{ and } \text{Min}_j \geq \text{Min}_x \quad (2d)$$

$$N_{xj} = \frac{(\text{Max}_j - \text{Min}_j) - (\text{Max}_x - \text{Min}_x)}{(\text{Max}_j - \text{Min}_j)} \quad \text{for } \text{Max}_j \geq \text{Max}_x \text{ and } \text{Min}_j \leq \text{Min}_x \quad (2e)$$

The default precautionary value is 1.0 for fishery x , thus assuming that all fish of length class j encounter the gear for fishery x . A graphical representation of the encounterability concept and its calculation is shown in Figs. S1 & S2 in Supplement 2 at www.int-res.com/articles/suppl/m625p089_suppl2.pdf.

Although a species may encounter the gear due to overlapping vertical and spatial distribution with the fishery, this does not mean all fish will be caught and

incur mortality. Contact selectivity (C_{xj}) describes the proportion of length class j that is retained once it encounters the gear used by fishery x . Typical gear selectivity curves can be used where available; for example, dome-shaped or logistic ogives can be used to represent net and longline fisheries, respectively. However, reliable gear selectivity curves are unlikely to be available for the majority of bycatch species. In such cases, knife-edge selectivity ($C_{xj} = 1.0$) may be assumed from the smallest length class fish observed in fishery x . However, the default precautionary value is 1.0 for fishery x , to assume full selectivity for all size classes in fishery x .

Although the volumetric overlap of fishery x with length class j of a species may be very high, the species may be discarded, either due to its low market value, or for conservation reasons. For example, the IATTC mandates the release of oceanic whitetip sharks *Carcharhinus longimanus* (Resolution C-11-10) and mobulid rays (Resolution C-15-04) in all fisheries, and the release of silky sharks *C. falciformis* in purse-seine fisheries (Resolution C-16-06). Therefore, fishing mortality would be overestimated unless the component of the catch that survives release is accounted for. This is introduced in the model as post-release mortality (P_{xj}), the proportion of length class j that is caught by fishery x and dies before, during or soon after release. Where species-specific data are not available, the default precautionary value is 1.0 for fishery x , to assume a post-release mortality rate of 100%.

Following the estimation of the overall susceptibility of length class j to incurring mortality from fishery x (S_{xj}), a proxy for F can be estimated from the annual finite fishing mortality rate (f) — or exploitation rate — for the species caught in one or more fisheries in a specified year as:

$$F = -\ln \left[1 - \sum_{x=1}^n q_x E_x \left(\frac{\sum_{j=1}^n S_{xj}}{n} \right) \right] \quad (3)$$

Here, n is the number of length classes defined for the species, which can theoretically be almost any number, but it is recommended that the length interval be relevant to the typical length range of the species and allow a reasonable growth interval between classes (Chen & Gordon 1997). For most species assessed in the present study, increments of 2 cm were used for j , whereas increments of 5 cm were used for some larger-growing species of billfish and sharks. In Eq. (3), E_x is the total effort of fishery x , scaled to a maximum of 1, applied in area G_x , while the catchability coefficient (q_x) is the fraction of the stock that is caught by 1 unit of effort (E_x) in fishery x . In many

data-limited fisheries, q and E will not be known, so a precautionary approach is to assume both are equal to 1 — as was assumed in the present study — which implies that 1 unit of fishing effort can catch all fish within each species-occupied grid where $S_{xj} = 1$.

The F value for the assessment year, in this case 2016, is then compared with values for F for the various BRPs derived from the per-recruit models (described in Section 2.3). However, it needs to be emphasised that, because of the assumptions and likely uncertainty in the parameters used in deriving the F estimate, it should only be considered a proxy of F (and probably a conservatively high one).

2.3. Modelling species productivity using per-recruit models

One of the major impediments for quantitative assessments of the population status of data-limited species is the lack of species-specific time series of catch data required for fully-integrated stock assessment models. However, yield-per-recruit (Y/R) models are widely used in developing or data-limited fisheries due to the relatively few parameters that need to be estimated (Gabriel & Mace 1999), most of which also need to be estimated for methods such as PSA. Y/R models are generally age-structured, which poses complications with most data-limited species and fisheries, since most biological and fishery processes are more precisely represented in terms of length rather than age (e.g. length-weight relationships, length-at-maturity, gear selectivity) (Chen & Gordon 1997). Many bycatch species also lack reliable biological studies that describe their growth or population dynamics in terms of age. Furthermore, many age-specific parameters are often estimated from length-based conversions, such as estimated length-at-age in the von Bertalanffy growth model. Therefore, it is more practical to construct per-recruit models based on length, rather than age.

Y/R is used to characterise the biological dynamics of each species using the generic Ricker model (Ricker 1975), which Chen & Gordon (1997) adapted for lengths as:

$$\frac{Y}{R} = \sum_{j=1}^n \frac{W_j b_j F}{b_j F + M} [1 - e^{-(b_j F + M) \Delta T_j}] e^{-\sum_{k=1}^{j-1} (b_k F + M) \Delta T_k} \quad (4)$$

Here, j represents fully recruited length classes. W_j is the mean weight of a fish in length class j , the instantaneous natural mortality rate (M) is assumed to be constant across all length classes — but can be length-specific if sufficient data are available — while

selectivity (b_j) is the proportion of the population in length class j that is caught across all fisheries, represented as:

$$b_j = \sum_{x=1}^n S_{xj} \quad (5)$$

F is disaggregated into increments of 0.01, from 0 to a biologically realistic maximum for a species. The parameter ΔT represents the time taken for a fish to grow from one length class to the next, represented as:

$$\Delta T_j = \frac{1}{K} \ln \frac{L_\infty - L_j}{L_\infty - L_{j+1} - d_j} \quad (6)$$

where K and L_∞ are parameters from the von Bertalanffy growth function (VBGF), and d is the width of the length class, calculated as $L_{j+1} - L_j$. The VBGF was used to characterise growth for the 24 species, both for reasons of practicality, and because differences in predicted length-at-age, and thus ΔT , were negligible when alternative growth models were reparameterised as a VBGF (see Fig. S3 in Supplement 2). Nonetheless, Eq. (6) can be easily modified to estimate ΔT using alternative growth models (e.g. Richards, logistic, Laird-Gompertz), where L_∞ and K can be substituted for a relevant parameter characterising asymptotic length, and the rate at which this length is attained, respectively. In the absence of direct estimates of K and L_∞ , L_∞ may be estimated empirically from maximum recorded length (L_{\max}) (Froese & Binohlan 2000) and K values may be used from studies of closely related species (see Thorson et al. 2017).

The spawning stock biomass-per-recruit (SSB/ R) model of Quinn & Deriso (1999) is complementary to Y/R , and can be modified to suit the analysis of length rather than age classes and can be represented as:

$$\frac{\text{SSB}}{R} = \sum_{j=1}^n W_j m_j \prod_{k=1}^{j-1} e^{-(b_k F + M) \Delta T_k} \quad (7)$$

where W_j is the mean weight of fish in length class j , m_j is the proportion of mature females at the mean length of length class j , and the product operator describes the number of fish surviving from the length at recruitment (L_r) to L_j . Because the number of spawners is unlikely to be known for most bycatch species, and the model estimates the relative SSB/ R , the initial number of spawners is set to a value of 1. A range of maturity ogives may be used to parameterise m_j for a species, but in this study, it is derived from a female maturity ogive represented in the logistic form:

$$m_j = \frac{1}{1 + e^{[-r(L_j - L_{50})]}} \quad (8)$$

where L_j is the mean length of a fish in length class j , L_{50} is the length at which 50% of the population is

mature, and r is the curvature parameter. Alternatively, knife-edge maturity can be assumed from the length at first maturity (L_m). If a direct or reliable published estimate of L_{50} or L_m is unavailable, L_m can be estimated using the von Bertalanffy growth parameter L_∞ in the empirical equation of Froese & Binohlan (2000):

$$L_m = 10^{(0.898 \log_{10} L_\infty - 0.0781)} \quad (9)$$

2.4. Estimating natural mortality

The instantaneous natural mortality rate (M) is one of the most influential parameters in stock assessment models, but is notoriously difficult to estimate directly (Kenchington 2014, Then et al. 2015). Consequently, empirical equations based on life history traits, t_{\max} and VBGF parameters (L_∞ , K , t_0) are often used as an alternative. There are over 30 natural mortality estimators in existence, none of which has been proven to perform better than another for all species (Kenchington 2014). Therefore, it is commonplace to run stock assessment models using a range of M values derived from multiple estimators that the researchers deem most appropriate for the species in question. Therefore, M was calculated for each species using 6 estimators recommended by Kenchington (2014) and Then et al. (2015) (see Table S1 in Supplement 2). Priority was given to M values that were estimated directly (e.g. from tagging), followed by t_{\max} -based estimators (Hoenig_{nl} and Hoenig_{tmax}) for long-lived species such as elasmobranchs and cetaceans, and finally K -based estimators (Jensen, Pauly_{nl}, Pauly_{LKT} and Pauly_{KT}). Where species lacked information on longevity and L_∞ , L_∞ was estimated from maximum recorded length (L_{\max}), using the method of Froese & Binohlan (2000), and used in the Pauly_{LT} estimator with a mean annual water temperature of 25°C for the EPO (Fiedler & Talley 2006). A flow diagram showing the hierarchical approach to estimating M depending on the availability of data is shown in Fig. S4 in Supplement 2.

2.5. Biological reference points

BRPs are often used in stock assessment to define the status of a population relative to a fishing mortality rate. EASI-Fish uses a similar approach, but instead BRPs are used here to quantify relative vulnerability of species. The F value at MSY (F_{MSY}) is used, because it is a commonly-used BRP in stock

assessment. In Y/R models, it is, more specifically, the fishing mortality at which yield is maximised (F_{MAX}), since there is no stock-recruitment relationship (steepness = 1). However, F_{MSY} can be optimistic under certain conditions, and so $F_{0.1}$ was included as a precautionary BRP, as has been recommended for data-limited species or fisheries (Gabriel & Mace 1999). A second precautionary BRP used was $SSB_{40\%}$, which is the F value corresponding to 40% of the spawning potential ratio (SPR; the SSB/R at a given fishing mortality divided by the SSB/R where $F = 0$).

The assessment of the vulnerability of each species was determined using F and SSB expressed relative to the MSY or precautionary BRPs ($F_{0.1}$ and $SSB_{40\%}$). To aid in the interpretation of the results, BRP values are represented on the 4-quadrant phase (or Kobe) plot that is widely used to display the results of traditional stock assessments, and therefore easily interpreted by most fisheries managers and researchers. The traditional definitions of these quadrants relate to the degree to which the stock status is considered 'overfished' or 'undergoing overfishing'. In contrast, EASI-Fish uses generic definitions of vulnerability to define each quadrant, in order to reflect the uncertainty in model parameters for data-limited species. Fig. 2 shows the vulnerability definitions of each quadrant in the EASI-Fish phase plot, where the F and SSB index refers to one of the BRPs, MSY , 0.1 or 40% and denoted by x in the index definitions: (1) 'least vulnerable' (green; $F/F_x < 1$ and $SSB/SSB_x > 1$), (2) 'increasingly vulnerable' (orange; $F/F_x > 1$ and $SSB/SSB_x > 1$), (3) 'most vulnerable' (red; $F/F_x > 1$ and $SSB/SSB_x < 1$) and (4) 'decreasingly vulnerable' (yellow; $F/F_x < 1$ and $SSB/SSB_x < 1$).

The 2 simple alternative BRPs, F_{msm} and F_{crash} , proposed by Zhou et al. (2012) using life history traits to assess data-poor species, were also included in the results as a comparison of their performance, since the Y/R model used in EASI-Fish estimates F_{MAX} ($\approx F_{MSY}$) directly.

2.6. Implementation of the EASI-Fish model

Best available information from unpublished studies or the literature was used to derive biological parameter values for each species (see Tables S2 & S3 in Supplement 2). These parameters were fixed as point estimates in the EASI-Fish model, which is routine in stock assessment. Despite variability existing in these estimates, growth and reproductive parameters are highly correlated with natural mortality

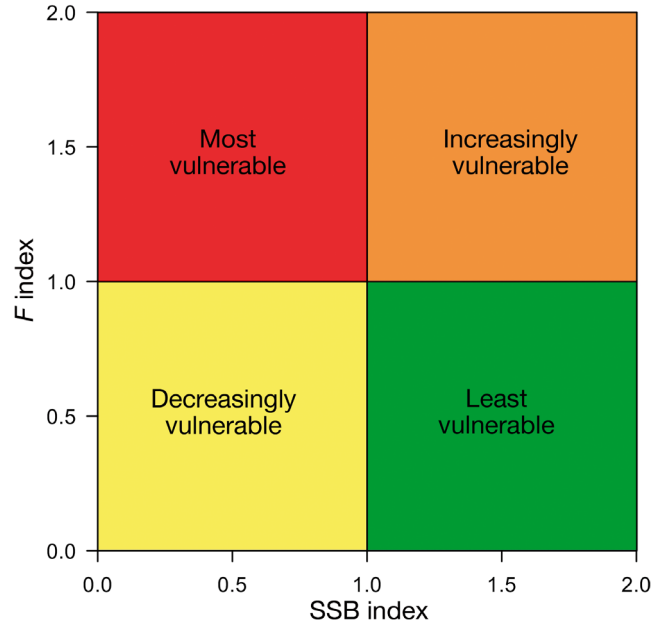


Fig. 2. Kobe plot illustrating how vulnerability status was defined for each species assessed using a desired fishing mortality (F) and spawning stock biomass (SSB) index from the EASI-Fish model as a reference point on the x - and y -axis, respectively. Using a maximum sustainable yield (MSY)-based index as an example, vulnerability of a species is defined by its position within 1 of 4 quadrants in the phase plot: 'least vulnerable' (green, $F/F_{MSY} < 1$ and $SSB/SSB_{MSY} > 1$), 'increasingly vulnerable' (orange, $F/F_{MSY} > 1$ and $SSB/SSB_{MSY} > 1$), 'most vulnerable' (red, $F/F_{MSY} > 1$ and $SSB/SSB_{MSY} < 1$), and 'decreasingly vulnerable' (yellow, $F/F_{MSY} < 1$ and $SSB/SSB_{MSY} < 1$). Maximum axis limits of 2.0 are for illustrative purposes only

(Thorson et al. 2017). Therefore, by simultaneously incorporating uncertainty in natural mortality and other biological parameters, the predicted variances in BRPs will be greatly overestimated. As a consequence, parameter uncertainty was incorporated only for M —and also for susceptibility parameter G , using values of 0.5–0.95 for Ψ . Monte Carlo simulations were used to generate uncertainty estimates for these parameters given a specified prior distribution (e.g. triangular, or uniform). For example, for G where several estimates were possible but one was considered more plausible by species experts (see Table S1 in Supplement 1), a triangular distribution was used with the most plausible parameter value as the mean and the extreme upper and lower estimates defining the bounds of the distribution. In contrast, for parameters where a range of values were equally plausible, a uniform distribution was used where values are selected at random between the minimum and maximum values defined.

Once the parameter distributions were defined, the Y/R and SSB/R models were run 10000 times using Monte Carlo simulations, each time using a random sample from the distribution of each parameter. The mean and 95 % confidence intervals (95 % CI) were estimated for the BRPs F_{MSY} , $F_{0.1}$, $F_{40\%}$, SSB_{MSY} , $SSB_{0.1}$ and $SSB_{40\%}$.

2.7. Qualitative scoring of input data relevance and quality

Although parameter uncertainty is incorporated into the EASI-Fish model, this does not necessarily indicate the precision, reliability, or relevance of the parameter value to the fishery in which it is applied. For example, the population dynamics of many fish species differ on various spatial scales (Williams et al. 2012), so the application of biological parameter values derived from one region, regardless of the quality of the study, may not be appropriate in a model of the same species in a different region. Of course, in the absence of local information, a common situation for bycatch species, the use of non-local studies may be required. Therefore, the reliability of parameter

values used plays an important role in identifying which species are truly vulnerable and deserve further management attention (i.e. true positives) and species that may be data-deficient and require further data collection and re-assessment (i.e. false positives). Therefore, a qualitative data quality index was developed to score the relevance of the data to the assessed fisheries and species by using a matrix of data quality, stratified by ocean basin and taxonomic resolution (Table 1).

For a hypothetical example in assigning a data quality index to growth parameters for black skipjack *Euthynnus lineatus* in the EPO, a study that statistically derived a growth curve for the species from thousands of precisely aged otoliths from fish collected from across the EPO, would be scored a 9–10, while an identical study of the species using the same sample size and methodology in the western Pacific Ocean would score 8–9. In contrast, a study of the closely related kawakawa *E. affinis* in the EPO that used only a few hundred length measurements to imprecisely estimate growth from cohort progressions would score 4–5. The use of empirical equations (e.g. Froese & Binohlan 2000) based on parameter values averaged across several species from

Table 1. Qualitative index used to rank the relative reliability of biological and ecological parameters used for each species in Ecological Assessment of the Sustainable Impacts of Fisheries (EASI-Fish) assessments with respect to the reliability of the methodology used to estimate the parameter and the precision of the parameter estimate, relative to the data source's relevance to the species and region being assessed. Colours correspond to indices (ranging from blue: 0 to red: 10). EPO: Eastern Pacific Ocean; WCPO: Western and Central Pacific Ocean

		High accuracy		Medium accuracy		Low accuracy		No data
		High precision	Low precision	High precision	Low precision	High precision	Low precision	
Species-specific	EPO	10	9	8	7	6	5	0
	WCPO	9	8	7	6	5	4	0
	Other	8	7	6	5	4	3	0
Related species	EPO	7	6	5	4	3	2	0
	WCPO	6	5	4	3	2	1	0
	Other	5	4	3	2	1	1	0

the same family (e.g. Scombridae) may score 1–2. Where no data are available for the species or any closely related species, a score of 0 would be assigned. Of course, these scores are subjective, so having multiple experts score the quality of the data source is desirable.

Once the data quality scores are finalised, they are represented in a single radar plot for each species, aiding in the easy interpretation of numerous model parameters and particularly to identify potential false positives.

2.8. Validation of EASI-Fish using fully integrated stock assessments

Although EASI-Fish is intended for data-limited species, it is first important to demonstrate that the model is capable of producing reliable results in moderately data-rich settings. As a model validation process, we replicated the data inputs, as far as possible, used in fully integrated statistical stock assessment models used for EPO stocks of *Thunnus albacares* (Minte-Vera et al. 2017) and *T. obesus* (Aires-da-Silva et al. 2017) in 2016. Although other stock assessments have been undertaken on a few other species in the EPO included in the present study, they were not suitable for direct comparison either because catch per unit effort (CPUE) indicators were used, the assessments were undertaken in other years or they incorporated only a fraction of the EPO stock as part of North Pacific assessments.

The values for the BRPs F/F_{MSY} and SSB/SSB_{MSY} produced by EASI-Fish for *T. albacares* and *T. obesus* were compared with those of the stock assessments. EASI-Fish was considered to produce acceptable results if the location of the plotted results on a conventional Kobe plot were located in the same vulnerability status quadrant or if the 95 % confidence intervals overlapped.

3. RESULTS

3.1. Estimates of susceptibility (S) and fishing mortality (F)

Habitat models developed for the 24 selected species are shown in Fig. 3, and the preferred probability of occupancy used to define each species' distribution is shown in Table S1 in Supplement 1. A prominent feature of many of these distributions is the low probability of occupancy in the central South Pacific

Subtropical Gyre at around 20–30°S, which is characterised by a deep (>200 m) pycnocline (Fiedler & Talley 2006) contributing to this region being the most oligotrophic zone in the world's oceans (Bonnet et al. 2008).

For each species, the value for each parameter contributing to the overall susceptibility (S_x) estimate and a description of its derivation is given in Table S2 in Supplement 2. The horizontal overlap of the longline fishery with the distribution of the species assessed was high ($\geq 50\%$) for all species except *Lepidocybium flavobrunneum* (36%). However, this may be in part due to the longline fishery reporting effort at $5^\circ \times 5^\circ$ resolution, and potentially encapsulating more $0.5^\circ \times 0.5^\circ$ grids than would be the case if effort was reported at a finer resolution. The highest species overlap by the purse-seine fishery—mainly by OBJ sets—was *Mobula japanica*, (33%), *Alopias superciliosus* (28%; DEL), *Carcharhinus falciformis* (27%), *Makaira nigricans*, *Dermochelys coriacea* and *Lepidochelys olivacea* (26%) and *C. longimanus* (24%).

Encounterability of the gear by each of the 4 fisheries was high (>60%) for most species, given that most species spend the majority of their time at depths <300 m where they are vulnerable to capture by purse-seine (0–200 m) and longline (0–300 m) gears. Exceptions were *Thunnus obesus*, *A. superciliosus* and *L. flavobrunneum*, which spend a proportion of their time below the maximum fishing depths of the gears.

The range of contact selectivity, averaged across length classes, varied substantially between species due to the range of knife-edge, logistic- and dome-shape selectivity ogives assumed. Average selectivity-at-length was generally less than about 0.70 for most species, but as high as 1.0 for *Stenella attenuata*, *Delphinus delphis* and *A. superciliosus* in purse-seine fisheries where no species-specific selectivity information was available (see Fig. S5 in Supplement 2).

No reduction in fishing mortality was afforded by post-release survival of most species, since species were assumed to be retained as a target or marketable non-target species, or lacked sufficient data quantifying post-release survival. Exceptions were *C. falciformis*, *C. longimanus* and *L. olivacea* that were assumed to have a 95, 60 and 20 % post mortality rate in each fishery, respectively.

3.2. Vulnerability status of selected species in the EPO

Biological parameter values used in empirical equations, maturity ogives and the per-recruit and

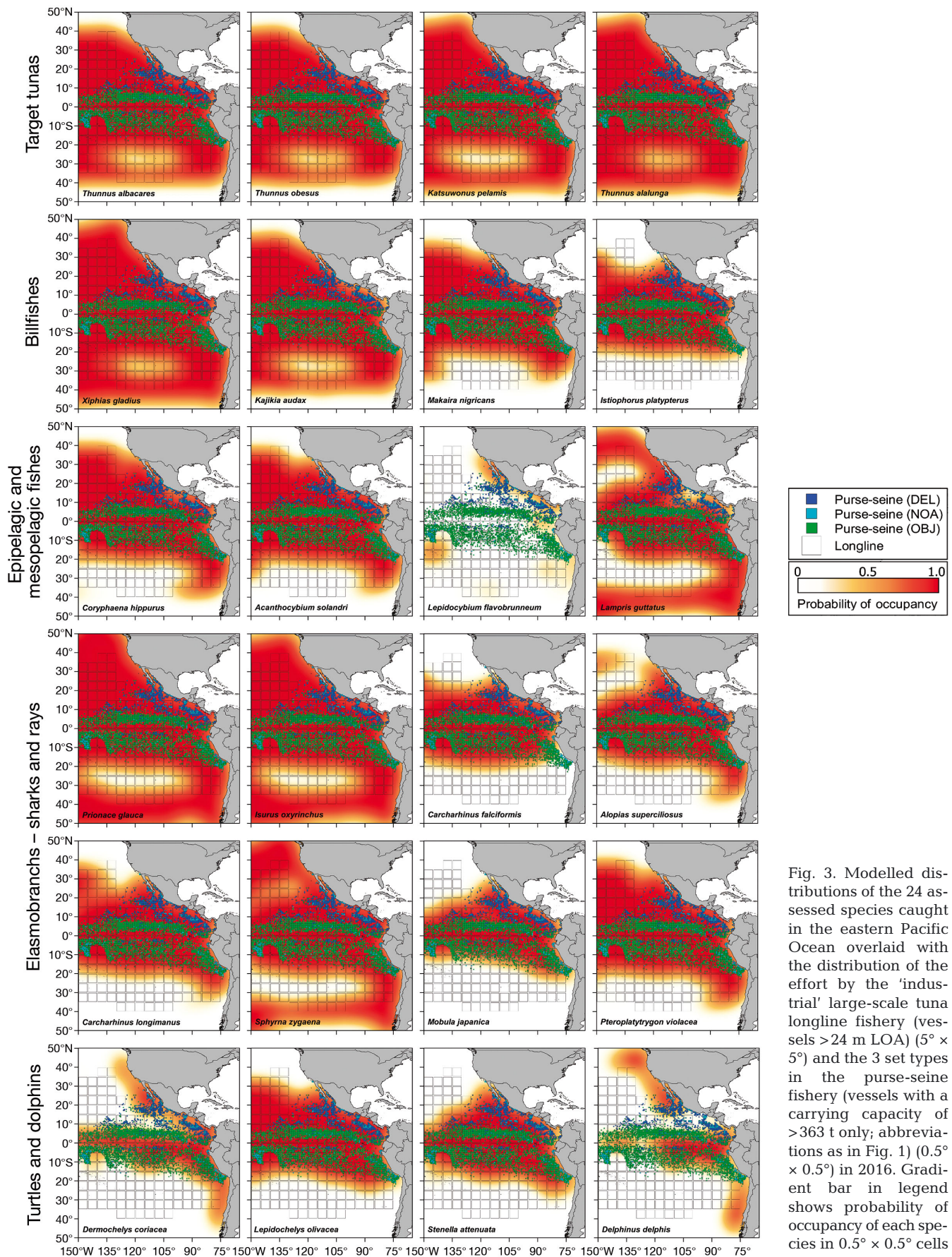


Fig. 3. Modelled distributions of the 24 assessed species caught in the eastern Pacific Ocean overlaid with the distribution of the effort by the 'industrial' large-scale tuna longline fishery (vessels >24 m LOA) ($5^\circ \times 5^\circ$) and the 3 set types in the purse-seine fishery (vessels with a carrying capacity of >363 t only; abbreviations as in Fig. 1) ($0.5^\circ \times 0.5^\circ$) in 2016. Gradient bar in legend shows probability of occupancy of each species in $0.5^\circ \times 0.5^\circ$ cells

growth models for the 24 species and their sources are shown in Tables S3 & S4 and Figs. S6 & S7 in Supplement 2. Estimates for fishing mortality, spawning stock biomass and BRPs are provided in Table 2.

Comparing the EASI-Fish results for *T. albacares* and *T. obesus* using integrated stock assessment models, as a form of validation, EASI-Fish produced a very similar value as the *T. albacares* stock assessment for the F_{MSY} BRP ($F/F_{MSY} = 0.92$ cf. 0.93) and a slightly more optimistic result for SSB_{MSY} BRP ($SSB/SSB_{MSY} = 1.04$ cf. 0.86). EASI-Fish allocated *T. obesus* to the same vulnerability status quadrant ('least vulnerable') as the stock assessment (Fig. 4) but was more optimistic for SSB ($SSB/SSB_{MSY} = 1.47$ cf. 1.23) and slightly more pessimistic in terms of fishing mortality ($F/F_{MSY} = 0.68$ cf. 0.89). Nonetheless, 95% confidence intervals for both species overlapped with the stock assessment results, indicating a reasonable corroboration between the 2 methods.

When assessing F and SSB for the 24 species against MSY BRPs, 10 species were classified as 'most vulnerable', with the sea turtles *D. coriacea* and *L. olivacea* having the highest vulnerability values, followed by sharks (*Sphyrna zygaena*, *C. longimanus*, *A. superciliosus*, *Isurus oxyrinchus* and *C. falciformis*), billfishes (*Kajikia audax* and *M. nigricans*), and the pelagic sting ray *Pteroplatytrygon vio-*

lacea (Fig. 5a). The remaining species were classified as 'least vulnerable', either due to their high productivity (e.g. *Acanthocybium solandri* and *Katsuwonus pelamis*), or low fishing mortality as a result of low areal overlap with fisheries (e.g. *S. attenuata* and *D. delphis*) or low encounterability and/or selectivity (e.g. *L. flavobrunneum* and *Lampris guttatus*).

When assessing the 24 species using the precautionary $F_{0.1}$ BRPs, the aforementioned 'most vulnerable' species retained this vulnerability classification, along with an additional 4 teleosts (*T. albacares*, *T. obesus*, *T. alalunga* and *Coryphaena hippurus*), and a billfish (*Istiophorus platypterus*) (Fig. 5b).

Using the precautionary SSB-based BRPs (F and SSB at $SPR_{40\%}$), the species classified as 'most vulnerable' using $F_{0.1}$ BRPs retained this vulnerability classification (with the exception of *T. albacares*), with an additional species, *M. japanica* (Fig. 5c). However, the magnitude and relative rank of the most vulnerable species differed between the $F_{0.1}$ and $SSB_{40\%}$, notably the sharks *A. superciliosus* and *I. oxyrinchus* that were ranked as highly as the sea turtles *D. coriacea* and *L. olivacea*.

In contrast to the results from conventional BRPs, F for only 3 species (*K. pelamis*, *C. hippurus* and *A. solandri*) and 5 species (*K. pelamis*, *C. hippurus*, *A. solandri*, *K. audax* and *I. platypterus*) did not exceed the F_{msm} and F_{crash} BRPs, respectively (Table 2).

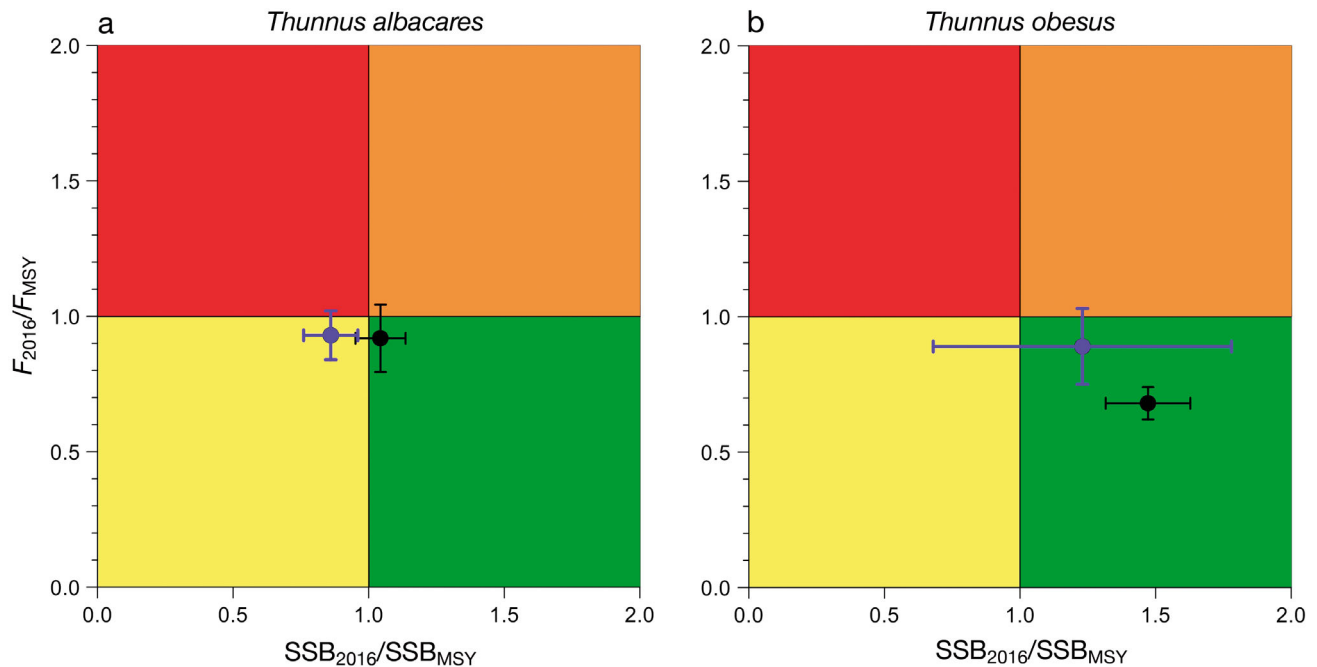


Fig. 4. Kobe plots (see Fig. 2) showing the mean ($\pm 95\%$ confidence intervals) estimates for biological reference points F/F_{MSY} and SSB/SSB_{MSY} for (a) yellowfin tuna *Thunnus albacares* and (b) bigeye tuna *T. obesus* from fully integrated stock assessments (purple) and EASI-Fish (black) in the eastern Pacific Ocean

Table 2. Values for fishing mortality (F) and spawning stock biomass per recruit (SSB) estimates for 2016 and biological reference point values derived from the EASI-Fish model for 24 species caught in purse-seine and longline tuna fisheries in the eastern Pacific Ocean. Data-poor reference points based on life history parameters (F_{msm} and F_{crash}) are also shown. See Section 2.5 for definitions of reference points. Colours indicate vulnerability status as 'most vulnerable' (red) or 'least vulnerable' (green) (see Fig. 2 for definitions)

Species	Code	F	SSB	F_{MSY}	SSB_{MSY}	$F_{0.1}$	$SSB_{0.1}$	$F_{40\%}$	$SSB_{40\%}$	F/F_{MSY}	SSB/SSB_{MSY}	$F/F_{0.1}$	$SSB/SSB_{0.1}$	$F/F_{40\%}$	$SSB/SSB_{40\%}$	F_{msm}	F_{crash}
<i>Thunnus albacares</i>	YFT	0.81	215.99	0.88	206.96	0.46	288.58	0.93	198.60	0.92	1.04	1.75	0.75	0.86	1.09	0.39	0.78
<i>Thunnus obesus</i>	BET	0.55	292.80	0.81	198.92	0.49	319.55	0.55	292.10	0.68	1.47	1.12	0.92	1.00	1.00	0.30	0.61
<i>Katsuwonus pelamis</i>	SKJ	0.58	3.77	4.94	1.78	1.99	2.71	4.70	1.83	0.12	2.12	0.29	1.39	0.12	2.06	1.31	2.61
<i>Thunnus alalunga</i>	ALB	0.47	4.18	1.28	1.11	0.47	4.17	0.42	4.60	0.37	3.75	1.01	1.01	1.13	0.91	0.26	0.52
<i>Xiphias gladius</i>	SWO	0.24	227.57	1.12	74.44	0.61	130.85	0.54	142.77	0.22	3.06	0.40	1.74	0.45	1.59	0.22	0.44
<i>Kajikia audax</i>	MLS	1.35	143.49	0.85	333.58	0.49	650.02	0.42	739.87	1.59	0.43	2.76	0.22	3.20	0.19	0.44	0.87
<i>Makaira nigricans</i>	BUM	0.90	8.37	0.79	12.85	0.28	53.57	0.21	69.23	1.14	0.65	3.16	0.16	4.25	0.12	0.23	0.46
<i>Istiophorus platypterus</i>	SFA	0.95	0.53	1.21	0.28	0.62	1.27	0.33	2.85	0.78	1.89	1.53	0.42	2.91	0.19	0.41	0.82
<i>Coryphaena hippurus</i>	DOL	1.10	3.83	1.51	3.14	0.84	4.83	1.04	4.13	0.73	1.22	1.31	0.79	1.06	0.93	0.85	1.71
<i>Acanthocybium solandri</i>	WAH	1.12	29.89	2.55	19.79	1.35	27.87	2.11	22.38	0.44	1.51	0.83	1.07	0.53	1.34	0.87	1.74
<i>Lepidocybium flavobrunneum</i>	LEC	0.08	50.91	1.18	16.13	0.77	24.16	0.84	22.20	0.07	3.16	0.10	2.11	0.10	2.29	0.13	0.26
<i>Lampris guttatus</i>	LAG	0.30	22.18	0.93	8.34	0.48	16.21	0.52	15.13	0.32	2.66	0.62	1.37	0.57	1.47	0.20	0.39
<i>Prionace glauca</i>	BSH	0.52	18.29	0.53	19.40	0.29	35.05	0.29	33.46	0.98	0.94	1.81	0.52	1.77	0.55	0.09	0.19
<i>Isurus oxyrinchus</i>	SMA	0.49	0.04	0.34	0.20	0.22	0.64	0.10	2.12	1.44	0.22	2.25	0.07	5.14	0.02	0.08	0.15
<i>Carcharhinus falciformis</i>	FAL	0.84	8.24	0.58	15.23	0.26	32.57	0.27	31.04	1.45	0.54	3.18	0.25	3.05	0.27	0.09	0.18
<i>Alopias superciliosus</i>	BTH	0.58	0.08	0.39	0.55	0.23	1.47	0.11	3.15	1.49	0.15	2.48	0.06	5.15	0.03	0.08	0.16
<i>Carcharhinus longimanus</i>	OCS	0.65	4.02	0.39	13.86	0.23	25.60	0.19	28.24	1.67	0.29	2.88	0.16	3.46	0.14	0.07	0.15
<i>Sphyrna zygaena</i>	SPZ	0.91	4.68	0.45	13.15	0.26	21.32	0.31	18.71	2.01	0.36	3.48	0.22	2.97	0.25	0.11	0.22
<i>Mobula japanica</i>	RMJ	0.38	42.82	0.71	18.83	0.48	33.62	0.35	46.81	0.54	2.27	0.80	1.27	1.11	0.91	0.15	0.30
<i>Pteroplatytrigon violacea</i>	PLS	0.70	7.11	0.55	9.48	0.31	13.56	0.46	10.26	1.26	0.75	2.27	0.52	1.51	0.69	0.12	0.24
<i>Dermochelys coriacea</i>	DKK	0.70	0.64	0.25	2.55	0.17	4.05	0.15	4.41	2.78	0.25	4.14	0.16	4.56	0.15	0.05	0.09
<i>Lepidochelys olivacea</i>	LKV	1.15	0.00	0.44	0.00	0.23	0.01	0.19	0.01	2.62	0.08	4.93	0.03	6.14	0.03	0.09	0.18
<i>Stenella attenuata</i>	DPN	0.13	9.05	1.94	1.85	1.37	3.03	1.03	4.07	0.07	4.89	0.10	2.99	0.13	2.23	0.12	0.24
<i>Delphinus delphis</i>	DCO	0.05	53.02	5.00	13.03	4.35	15.64	3.21	21.49	0.01	4.07	0.01	3.39	0.02	2.47	0.09	0.18

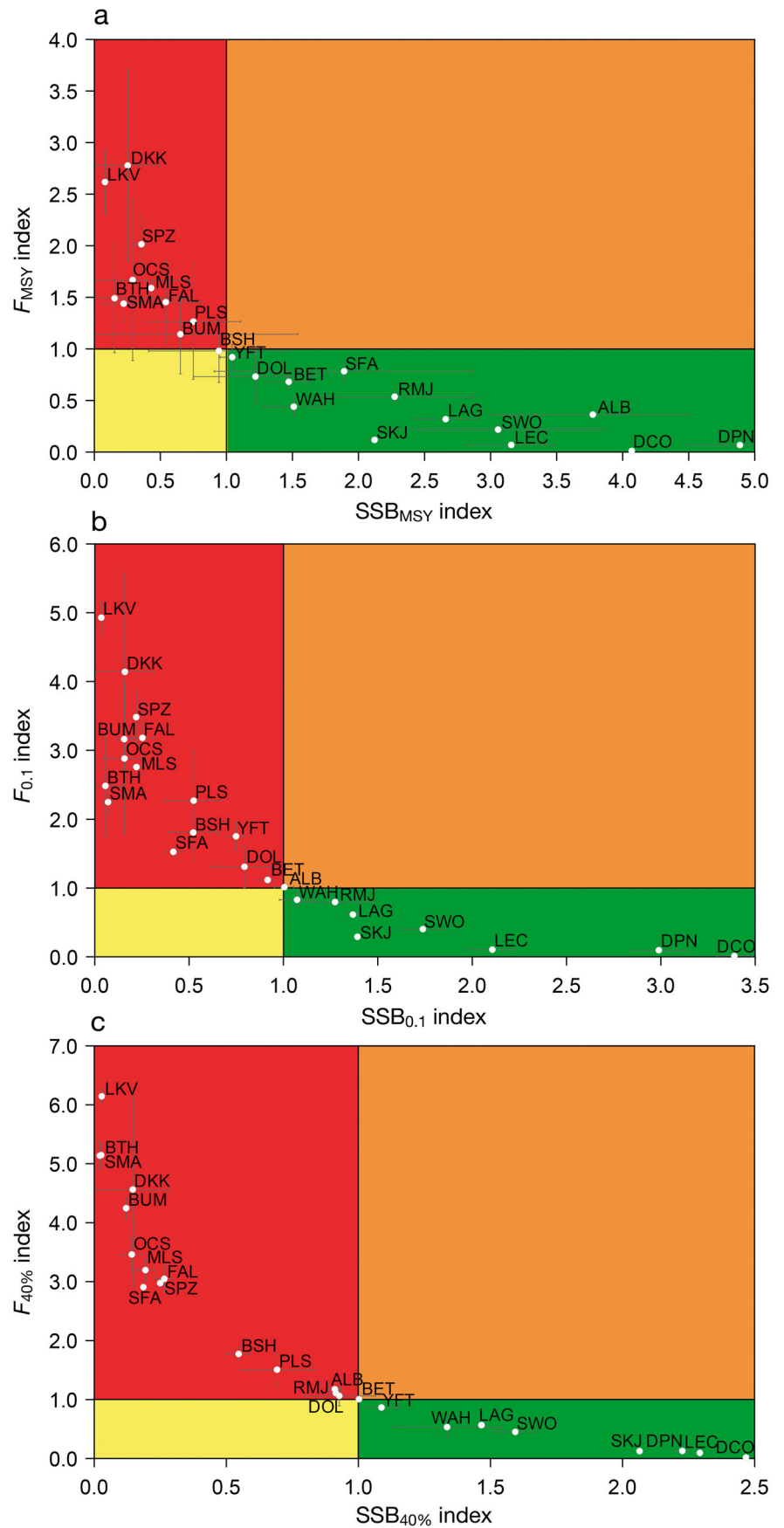


Fig. 5. Kobe plots (see Fig. 2) showing the vulnerability status of 24 species caught in eastern Pacific Ocean tuna fisheries assessed by EASI-Fish represented by mean ($\pm 95\%$ confidence intervals) estimates for 3 pairs of biological reference points: (a) F/F_{MSY} and SSB/SSB_{MSY} , (b) $F/F_{0.1}$ and $SSB/SSB_{0.1}$ and (c) $F/F_{40\%}$ and $SSB/SSB_{40\%}$. Note the differences in axis scales between plots. Species codes shown in Table 2

In assessing the data reliability for species modeling, the radar plots in Fig. 6 show that of the 10 most vulnerable species with respect to the MSY BRPs (Fig. 5a), 8 have data reliability scores of ≥ 8 for each parameter, and may therefore be regarded as legitimately vulnerable species. The 2 exceptions, *S. zygaena* and *P. violacea*, both had low scores for L_{50} and natural mortality, while *P. violacea* also had very low scores for minimum and maximum depth (5) and VBGF parameters (6). Together, these low data quality scores may have overestimated the vulnerability of this species.

In contrast, it is also important to consider the least vulnerable species with the data reliability scores to identify potential false negatives. For example, *L. flavobrunneum* and *L. guttatus* were among the least vulnerable species *prima facie* (Fig. 5a), but the former species lacked reliable data for all growth and reproductive parameters. The latter species lacked a reliable length-at-maturity ogive to estimate L_{50} (Fig. 6), which would likely increase the length-at-maturity, and reduce the SSB/SSB_{MSY} value, and thus increase its relative vulnerability.

4. DISCUSSION

Our results comparing the vulnerability of 24 species caught in EPO tuna fisheries demonstrated the usefulness of EASI-Fish as a tool to quantitatively assess the vulnerability of affected assemblages of species representing a wide range of life history strategies—from fast-growing fecund teleosts to slow-growing and reproductively limited cetaceans—to the cumulative impacts of multiple fisheries within a single assessment framework using conventional and scientifically defensible fishing mortality and spawning biomass BRPs that are familiar to most fisheries researchers and managers. Although the method is designed to be applied in the future to data-limited bycatch species, a range of species caught in ‘industrial’ EPO fisheries were included, from data-rich target species (e.g. *Thunnus obesus*, *Xiphias gladius*), moderately data-rich retained non-target species (e.g. *Kajikia audax*, *Coryphaena hippurus*) and data-poor, discarded non-target species (e.g. *Lepidocybium flavobrunneum*, *Mobula japanica*) in order to better ‘ground truth’ the model results for species that were expected *a priori* to span a wide spectrum of vulnerability to fishing impacts. It is also important to note that this ‘proof of concept’ assessment included only 4 ‘industrial’ fisheries in the EPO and did not include several smaller commercial, recreational and artisanal

fisheries that are known to impact many of the species assessed, to varying degrees, throughout the high seas and national exclusive economic zones (EEZs) within the EPO (Cartamil et al. 2011, Dapp et al. 2013, Martínez-Ortiz et al. 2015). Therefore, the fishing mortality rates reported for the species assessed in this paper are considered minimum estimates.

The model produced intuitive results, classifying the least productive species with the highest volumetric overlap with fisheries as ‘most vulnerable’. The most vulnerable species were the sea turtles *Dermochelys coriacea* and *Lepidochelys olivacea*. Although *D. coriacea* has been listed by the IUCN as Critically Endangered in the EPO, our analysis suggests that *L. olivacea* has higher vulnerability, in spite of surveys showing an increasing population size in the EPO between 1992 and 2006 (Eguchi et al. 2007). This higher vulnerability is because *L. olivacea* was predicted by the model to experience higher fishing mortality than *D. coriacea* (1.15 yr^{-1} cf. 0.70 yr^{-1}) since it has high spatial overlap and selectivity in all 3 purse-seine set types, additional to the longline fishery in which *D. coriacea* is caught almost exclusively. The fishing mortality is likely overestimated for both species given the extensive conservation initiatives currently implemented the EPO, particularly by the USA, to reduce incidences of capture through modifications in gear (e.g. use of circle hooks) and fishing techniques (e.g. minimising shallow sets), and handling practices to improve post-release survival of captured sea turtles (Swimmer et al. 2017; IATTC Resolutions C-04-05 and C-07-03). Although EASI-Fish allows the incorporation of data relating to post-release survival, we precautionarily assumed no post-release survival for sea turtles in the EPO longline fishery in the absence of substantive quantitative post-release survival data. However, if high post-release survival rates in EPO fisheries were assumed based on anecdotal information and limited tagging experiments (see Swimmer et al. 2017), the fishing mortality and the subsequent vulnerability status would be greatly reduced.

The majority of elasmobranch species assessed were also classified as ‘most vulnerable’, with *Alopias superciliosus*, *Isurus oxyrinchus*, *Sphyrna zygaena*, *Carcharhinus longimanus* and *C. falciformis* having the highest vulnerability ranks using the $F_{40\%}/SSB_{40\%}$ BRPs. The fact that all of these species are classified as Vulnerable by the IUCN provides a strong indication that the model is correctly ranking the true vulnerability of assessed species. Similar to sea turtles, the aforementioned species were vulnerable due to a combination of high volumetric overlap with fisheries,

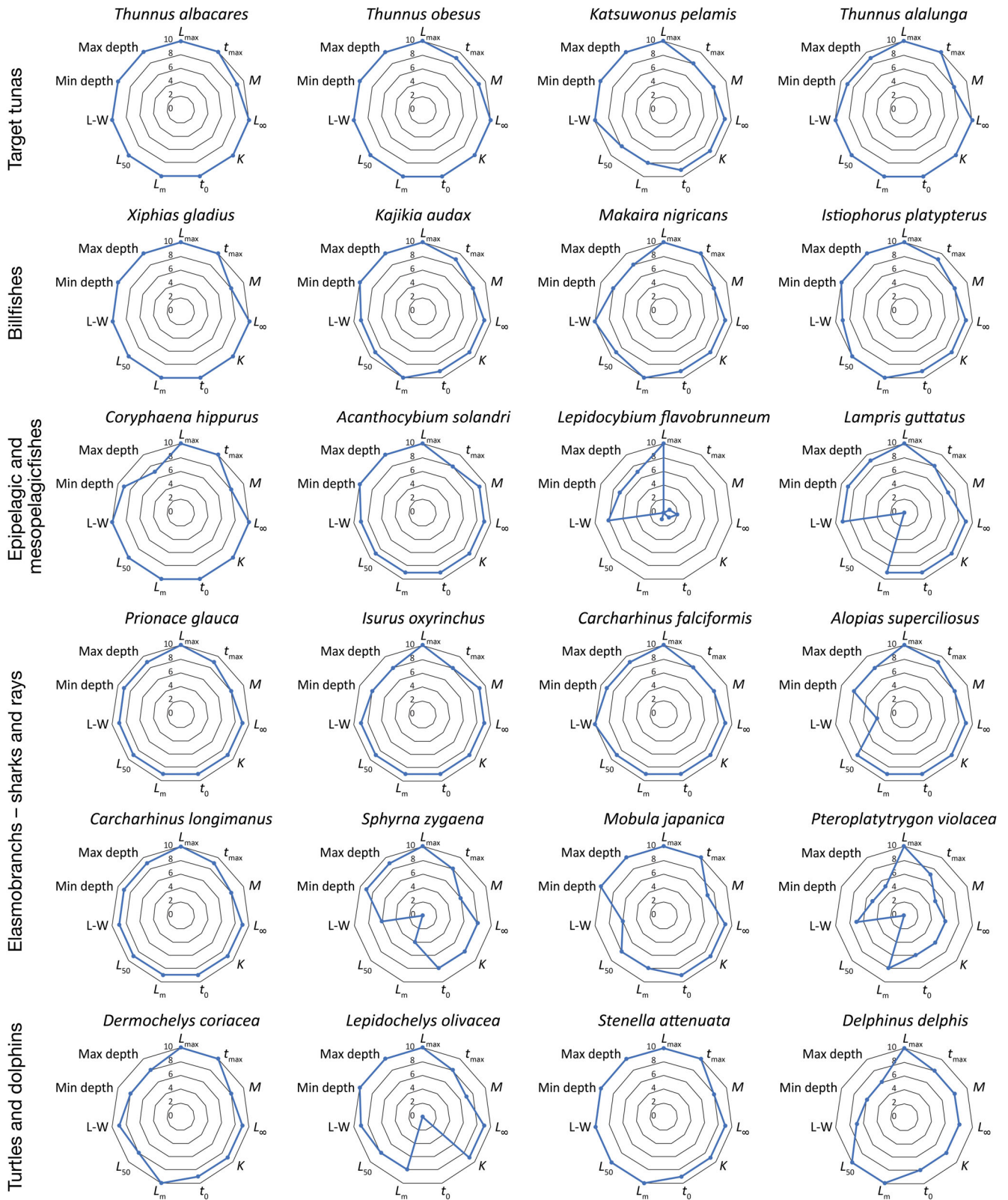


Fig. 6. Relative quality of 11 biological and ecological parameters (L_{max} , t_{max} , M , L_{∞} , K , t_0 , L_m , L_{50} , length-weight parameters a and b , minimum and maximum depth; see Section 2 for definitions) used in EASI-Fish models of 24 species caught in eastern Pacific Ocean (EPO) tuna fisheries. Scale ranges from 0 (data absent for the species and its closely related species) to 10 (high quality species-specific data derived from the EPO)

especially longline, and life history traits that are not conducive to withstanding high fishing mortality. For example, the longline fishing effort had a 71 and 59 % spatial overlap with the modelled distributions of *A. superciliosus* and *I. oxyrinchus*, as well as high (≥ 62 %) encounterability and contact selectivity, leading to high fishing mortality rates of 0.58 and 0.49 yr⁻¹, respectively. Considering that these 2 species live for at least 20 yr (Liu et al. 1998, Bishop et al. 2006) and reach maturity at >80 % of L_{∞} (Liu et al. 1998, Semba et al. 2011), their populations are vulnerable to decline under existing fishing mortality regimes. *C. longimanus* and *C. falciformis* are more productive than *A. superciliosus* and *I. oxyrinchus*, by being slightly shorter lived ($t_{\max} = 13$ –25 yr) and reaching maturity at 57–68 % of L_{∞} (Seki et al. 1998, Oshitani et al. 2003), but are still considered vulnerable. The vulnerability status of these 4 species determined by EASI-Fish corroborates well with quantitative stock assessments of these species that indicate they are considered overfished in the northern and western Pacific Ocean (Liu et al. 2006, Rice & Harley 2012, 2013, Fu et al. 2016). EASI-Fish results also complement the results of qualitative vulnerability assessments of elasmobranchs using PSA in the Pacific, Indian and Atlantic Oceans. For example, Murua et al. (2018) determined that species with the highest relative vulnerability in the Indian Ocean longline fishery were also *I. oxyrinchus*, *C. falciformis* and *A. superciliosus*. Similarly, Cortés et al. (2015) used various relative vulnerability measures within PSA to conclude that *A. superciliosus*, *I. paucus* and *I. oxyrinchus* were the 3 most vulnerable species caught by longline fisheries in the Atlantic Ocean.

Interestingly, the 2 species of cetaceans assessed, *Stenella attenuata* and *Delphinus delphis*, were among the least vulnerable species, despite their low reproductive capacity and the conservation concerns that have existed in the EPO for several decades regarding the impacts of purse-seine fishing for yellowfin tuna on sympatric populations of dolphins (Joseph 1994). This result is due to only the purse-seine (DEL) fishery interacting with these 2 species, overlapping with 18 and 6 % of their predicted distributions, respectively. Although the number of fishery related dolphin mortalities has continued to decline from over 133 000 in 1986 to 688 in 2017 in the EPO (Hall 1998, IATTC 2017), Gerrodette & Forcada (2005) warned that populations of *S. attenuata* had not recovered to pre-fishery levels based on a survey conducted in 2000. Consequently, we ensured precautionary parameterisation of the models of both species, with encounterability and selectivity para-

meters being fully realised. Furthermore, we assumed 100 % post-release mortality in spite of the actual post-release mortality now probably being negligible due to the widespread use of effective release strategies, including net 'backdown' procedures, finer mesh nets to reduce entanglement and manual rescue of encircled dolphins (Hall et al. 2000).

4.1. Model assumptions

As in all ecological assessment approaches, assumptions must be made to overcome deficiencies in knowledge about the species and fisheries being analysed. EASI-Fish makes several assumptions related to the derivation of susceptibility parameter values (e.g. encounterability) additional to those of per-recruit models, and these should be carefully considered when interpreting the results. For example, both length-structured per-recruit models and simple surplus production models used in single-species stock assessments (Chen & Gordon 1997, Ye 1998) assume that the density of the species within the defined stock boundaries is homogeneously distributed in space and time. This is a simplistic assumption that ignores the typical heterogeneity in fish densities, even for wide-ranging pelagic fishes whose local abundances are often influenced by a range of physical and oceanographic features (Musyl et al. 2003, Royer et al. 2004). However, in an equilibrium state (which assumes no immigration or emigration, and that the biomass of a species is pooled over the year), such variability in local abundance may be tempered at the stock level.

The definition of stock boundaries is a particularly important consideration in the assessment of any species affected by fishing (Cadrin & Secor 2009). Unfortunately, stock boundaries can be difficult to determine, even for species of high commercial and conservation importance such as Atlantic bluefin tuna *T. thynnus* that has been the subject of extensive tagging studies (Block et al. 2005) and genetic analyses (Carlsson et al. 2007). Therefore, it can be assumed that the stock boundaries of most bycatch species will be poorly understood, and so a precautionary approach is to define the smallest feasible stock boundary relative to the fishery being assessed. Pelagic species may have an assumed stock boundary at least at the spatial scale of the smallest management unit. For example, for a country assessing a wide-ranging species within its EEZ, a precautionary stock boundary would be the EEZ. However, for large management areas such as the EPO, it may be precautionary to as-

sume multiple smaller stocks based on, for example, prominent oceanographic features or the movements of well-studied species. For example, a tagging study of bigeye tuna in the EPO indicated that there may be little mixing across the Equator, suggesting separate northern and southern stocks (Schaefer et al. 2015).

One of the most important assumptions of the susceptibility component of EASI-Fish is that the presence of any level of fishing by any gear in a $0.5^\circ \times 0.5^\circ$ grid cell where a species is predicted to be present is evenly distributed and has the potential to remove all fish within that cell, providing all other susceptibility attributes (e.g. encounterability, selectivity) are fully realised. This assumption is required to estimate fishing mortality independent of catch data, since catch data are often unavailable, or unreliable, for many bycatch species that are often of low commercial value, infrequently encountered and taxonomically ambiguous. Obviously, this is a conservative assumption. However, since the goal of the analysis is to quantitatively determine species' vulnerability status to prioritise species for data collection, further analysis and/or management, it can be considered reasonable, and it does take the lack of information into consideration to easily identify false positives. However, even if all susceptibility parameters were fully realised, and all fisheries impacting a species were represented, EASI-Fish would likely overestimate fishing mortality, and thus represent a precautionary 'worst case' estimate of fishing impacts. It should be emphasised that, because of this assumption, the analysis should not be used in place of stock assessment for determining the status of a stock (e.g. 'overfished'; 'subjected to overfishing') and is the reason generic definitions of vulnerability were used to define each quadrant in the EASI-Fish Kobe plot.

A similar precautionary approach was also exercised for other susceptibility parameters. For example, an assumption when deriving the encounterability parameter (N) is that a specific fishing gear fished equally as efficiently over its specified depth range. The effective fishing depth has been reasonably well estimated for tuna purse-seine nets at around 200 m (Hall & Roman 2013), although longlines can fish as little as 54% of the intended fishing depth (Boggs 1992). This is due to numerous environmental (e.g. currents, wind) factors and gear configuration (e.g. number of branchlines between floats) that affect the extent of shoaling of the gear and its ultimate fishing depth (Bigelow et al. 2006). Therefore, our assumed maximum longline fishing depth of 300 m—derived from various experiments using time-depth recorders on branchlines during 'deep' sets targeting bigeye

tuna and swordfish during the day (e.g. Bigelow et al. 2006)—may have slightly overestimated the encounterability of the gear by species with depth ranges that extend beyond this depth (e.g. *L. flavobrunneum*, *T. obesus*). Furthermore, depending on the gear configuration, the minimum effective fishing depth is determined by the length of the floatlines—used to suspend the mainline—that can be up to 50 m in length, meaning the top 50 m of the water column may not be fished. This may be an important consideration for refining the fishing mortality of sea turtles—the most vulnerable species in the present assessment—that are most vulnerable to longline capture in depths <40 m (Gilman et al. 2006).

Considering encounterability in a temporal context, it was assumed that fish were available for capture throughout their specified depth range at all times of day and night, despite documented nocturnal vertical migrations to epipelagic waters by some species included in this study (e.g. Polovina et al. 2008, Schaefer & Fuller 2010, Hoolihan et al. 2011). Again, this was a precautionary approach to account for the lack of differentiation between deep and shallow sets in reported longline effort data (see Griffiths et al. 2017) that would allow the definition of 2 'fleets' in the model, as was done for the 3 purse-seine set types. This would in turn allow a better approximation of the potential for each longline 'fleet' to interact with animals while they occupied different depth ranges by day and by night. However, such precautionary assumptions are justified, and recommended, in the absence of more informative data.

Of the susceptibility components, contact selectivity is one of the most important parameters influencing the outcomes of stock assessments and the subsequent management advice (Maunder et al. 2014), and therefore needs careful consideration for data-limited bycatch species. Selectivity-at-length ogives were available for some economically important species from stock assessments that included fleets or gear types that were the same as, or comparable to, the purse-seine and longline fleets specified in the EASI-Fish models. However, selectivity ogives are unlikely to be available for bycatch species. The most precautionary approach for these species is to assume that selectivity is fully realised for all length classes, as was done for *A. superciliosus* in the 3 purse-seine fisheries. However, if limited length-frequency or reliable anecdotal information is available (from scientific observers or fishers, for instance) to determine the smallest length caught by a particular gear (L_c), knife-edge selectivity can be assumed where selectivity is fully realised for all length classes

greater than L_c , thereby removing any unrealistic fishing mortality on smaller length classes.

Post-release mortality is an important parameter when assessing a fishery. Handling and release practices that allow a significant proportion of captured fish to survive the sub-lethal effects of capture and release are much simpler management measures to implement for reducing fishing mortality than measures such as gear modifications or spatial and temporal closures to reduce the capture of a particular non-target species. In the present study, post-release mortality was assumed to be 100% for the majority of species assessed, since many species were either marketable non-target species and unlikely to be released, or data on post-release mortality were insufficient. However, a small number of tagging experiments pertaining to post-release mortality of purse-seine-caught *C. falci-formis*, *C. longimanus* and *M. japonica* (Hutchinson et al. 2015, Francis & Jones 2017)—albeit with small sample sizes—allowed this information to be integrated into the assessment. A precautionary approach was used in these cases, assuming slightly higher post-release mortality rate than the highest recorded rate from these studies.

4.2. Assessing the cumulative impacts of multiple fisheries

A key feature of EASI-Fish is that it allows the cumulative impacts of multiple fisheries on each species to be assessed. Summing fisheries impacts implies that each fleet does not catch the same fish. The assumption that all fish in a grid can be caught—where fisheries happen to overlap exactly and have fully realised selectivity—can obviously violate the additive assumption. However, this assumption can be relaxed since fisheries rarely exactly overlap temporally. For example, in the EPO, purse-seine sets are rarely made in the vicinity of longlines, both to avoid gear interactions, but also because each fishery tends to fish in different habitats to target different species.

Therefore, by each fishery not impacting all fish in a grid cell instantaneously, fishing is considered to occur ‘with replacement’ from adjacent unfished cells under the assumption that the stock is homogeneously distributed throughout its defined range. However, in settings where multiple fisheries exactly overlap in space and time, some adjustments should be made. For example, the spatial overlap could be calculated by combining the data for the fisheries that overlap, or assuming the precautionary value of

1.0 until improved data become available on selectivity components that can better separate the fisheries.

4.3. Biological reference points

Selecting appropriate BRPs to assess fish stocks is an ongoing topic of debate among stock assessment modelers, fisheries managers and policy makers, especially for data-limited species. Whilst many modern stock assessments use F_{MSY} as a target reference point for economically important species (Smith & Punt 2001), it has been suggested that F_{MSY} should be regarded as an upper limit reference point, because the difficulty of estimating it with precision means that overfishing can occur before fishing mortality reaches the F_{MSY} level (Caddy & McGarvey 1996). Given the likely uncertainty in the input data used for deriving both susceptibility and productivity estimates for data-limited bycatch species, F_{MSY} may therefore not be an appropriate target reference point on the simple basis that a fishery manager's objective is not to optimise yield, but instead to ensure that a buffer exists between fishing mortality and a BRP sufficient to respond with appropriate management intervention should bycatch populations begin to show signs of becoming unsustainable.

For these reasons, Walters et al. (2005) argued that MSY has the potential to deteriorate the structure of ecosystems supporting fisheries, and advocated for the use of alternative, more conservative BRPs for target species. For instance, Dichmont et al. (2010) demonstrated that using maximum economic yield (F_{MEY}) can optimise fishery profits whilst simultaneously satisfying biological conservation objectives, since F_{MEY} is generally attained at fishing mortalities less than F_{MSY} . Other authors recommended the use of $F_{0.1}$ as a precautionary BRP for data-limited species or fisheries (Gabriel & Mace 1999), although subsequent work has suggested that low-productivity species, such as elasmobranchs and long-lived teleosts, may be overexploited before $F_{0.1}$ is reached (Punt 2000). The problem is exacerbated for these less-productive species and for data-limited species whose biological parameter estimates have large uncertainties, because F -based reference points (F_{MSY} and $F_{0.1}$) can be too sensitive to provide reliable estimates of vulnerability (Tsai et al. 2011), and are therefore liable to incur false negatives.

Interestingly, the opposite was true in the present study when applying F -based BRPs (F_{msm} and F_{crash}) based on life history traits—ultimately M —developed specifically for data-poor species (Zhou et al.

2012) that overestimated fishing impacts for most teleosts, in most cases by more than a factor of 2. This may be attributed to the meta-analysis of Zhou et al. (2012) including a wide range of elasmobranch and demersal teleost species, but a comparatively small number of high-performance pelagic fishes. These species have unique metabolic and growth processes in that their gill surface area does not grow isometrically with their body mass, with higher weight exponents of around 0.95 compared to 0.66 assumed for most fishes (Temming 1994), thereby allowing them to extract proportionally more oxygen from the water to facilitate anabolic processes (Pauly 2010). This may have resulted in the growth parameters for these species bearing a different relationship to M as modelled by Zhou et al. (2012), and thus, the BRPs may not have been well predicted by their model.

The stock-recruitment relationship is a highly influential component of the productivity of a stock and can differ substantially among species and is therefore important to consider when selecting BRPs. Given the diversity of species groups in which fisheries like the EPO tuna fisheries interact, a single BRP may therefore not be appropriate to assess vulnerability, so careful consideration needs to be given to life history traits, as well as the assumptions of the underlying population model. There is the potential for overestimating the vulnerability of a stock when using Y/R models, since the stock-recruitment relationship is assumed to be time-invariant and recruitment is independent of stock size — equivalent to a steepness (h) value of 1 (Gabriel & Mace 1999). In an ecological vulnerability assessment context, this is favourable since it is precautionary. Therefore, it would be reasonable to propose $F_{0.1}$ as a target reference point and F_{MSY} as a limit reference point for teleosts, based on the validation results comparing EASI-Fish and the stock assessments of *T. albacares* and *T. obesus*, which showed close corroboration of the models using these reference points.

Conversely, a Y/R assessment for species that have a strong stock-recruitment relationship (i.e. $h < 1$), such as elasmobranchs and cetaceans (Punt 2017), would probably be optimistic. In these cases, there are 3 primary options. The first option is to improve the precision of the Y/R analysis to include the stock-recruitment relationship to directly estimate MSY -based reference points, rather than relying on F_{MAX} or other proxies. Unfortunately, the stock-recruitment relationship is difficult to estimate (Lee et al. 2012), especially for data-limited species, and so the alternative options are to use species or taxonomic group-based proxies that may be obtained from meta-analyses (see Myers et al. 1999), or employ pre-

cautionary BRPs that take into account the stock-recruitment relationship. For example, in the USA, the Pacific Management Council used $F_{40\%}$ as a proxy for all species of *Sebastes*, and $F_{35\%}$ for all other stocks (Ralston 2002), while Tsai et al. (2011) explored a range of BRPs as target reference points for shortfin mako shark and recommended BRPs that relate to the spawning stock size in data-limited settings, namely a spawning potential ratio of 35% ($SPR_{35\%}$). Our results showed that $SSB_{40\%}$ (equivalent to $SPR_{40\%}$) is the most precautionary of the 3 BRPs implemented for longer-lived and less productive species, including elasmobranchs, turtles and dolphins, that tend to have a strong stock-recruitment relationship, and therefore may be an appropriate BRP for these species groups.

5. CONCLUSIONS

The primary objective of ecological assessments in fisheries is to identify, rapidly and cost-effectively, species that are most vulnerable to fishing impacts, in order to guide the development of mitigation measures to reduce or eliminate those impacts, or to collect further information to facilitate more formal stock assessment (Hobday et al. 2011). Therefore, incurring false positives is preferable to incurring false negatives. As such, outcomes from vulnerability assessment models — including EASI-Fish — do not need to be precise, but the models need to be (1) reasonably accurate at defining the vulnerability of species to all mortality sources relative to some scientifically defensible benchmark(s), (2) transferable between species with different life histories (e.g. teleosts to cetaceans), although the choice of BRP may vary, (3) transparent in their assumptions and repeatable and (4) transferable between fisheries and gear types. The first 2 points are a major advantage of the EASI-Fish approach over most other vulnerability assessment methods, while using significantly fewer data inputs than the widely used PSA method (see Table S5 in Supplement 2), in that species groups with different life histories that are affected by multiple fisheries can be assessed with the same model using an appropriate BRP — and even presented on the same Kobe plot.

By comparison, most attribute-based vulnerability assessment methods such as PSA fall short of these desirable model characteristics, producing only a relative indicator of risk based on categorical values for attributes describing a species' susceptibility and productivity, without biologically meaningful reference

points with which to definitively determine the vulnerability of a population. Such attributes are often added or removed, input data category ranges are manipulated and scores are weighted, often in an ad hoc manner, depending on the species group assessed, with little statistical demonstration of the impacts on overall vulnerability scores due to biases from correlated attributes (Duffy & Griffiths 2019). This is because productivity and susceptibility attributes used in methods such as PSA ideally need to be adapted to particular species groups (see Milton 2001, Stobutzki et al. 2001, 2002) given the differences in the magnitude of their productivity parameter values. For example, the reproductive biology of elasmobranchs and marine mammals differs significantly from that of teleosts, particularly in that they generally produce numbers of offspring that are many orders of magnitude smaller and exhibit some degree of parental care (Walker 1998). Therefore, when assessed together with teleosts, it is not surprising, or informative for managers, that elasmobranchs and marine mammals are often identified as the most vulnerable species (see Kirby 2006, Arrizabalaga et al. 2011), but only because of the magnitude of the biological attribute scales required to accommodate all species. This increases the potential for creating false negatives for more productive species that may in fact be vulnerable, which would be apparent if productivity scales were used that are relevant to these species.

Furthermore, separating species groups for analysis using PSA also creates other issues for determining which species are vulnerable, owing to the adoption of arbitrary vulnerability threshold values derived from categorical attribute scores. For instance, a vulnerability score of 2.3 for teleosts does not necessarily have the same biological meaning as a score of 2.3 for marine mammals or sea turtles, and this creates difficulties in objectively determining which species are truly vulnerable to fishing.

Although the approach for implementing EASI-Fish described in this paper, using EPO tuna fisheries as a case study, marks an important 'proof of concept', there is scope for further development of the model and its application to other fisheries, such as demersal fisheries that may have unique issues to consider in the estimation of susceptibility parameter values. In view of the growing worldwide demand for fisheries to demonstrate that they are ecologically responsible, through both formal avenues (e.g. legislation and policies) and the influence of the public perception of commercial fishing (Jacquet & Pauly 2007), EASI-Fish was designed with the end-user in mind to assist fisheries stakeholders to meet these demands cost-effec-

tively. The flexibility of the EASI-Fish approach allows researchers and managers, independently or in a workshop setting, to quickly and easily explore the potential outcomes of the implementation of specific management measures such as spatial and/or temporal closures, improved post-release survival of discarded species due to improved handling practices, minimum retention lengths, changes in gear selectivity or the potential effects of climate change, such as a species' distribution moving relative to fishing grounds or political boundaries (e.g. marine protected areas or EEZs). Variations in such factors can be implemented independently or in unison, and the change in a species' status can be easily assessed using the conventional BRPs recommended in this paper, or specific BRPs considered by the user to be appropriate for a particular species group.

The EASI-Fish model presents a significant evolutionary step in the development of rapid and cost-effective ecological assessment approaches that are capable of quantitatively assessing the vulnerability of data-limited bycatch species to the cumulative impacts of multiple fisheries by using conventional BRPs that have been validated in data-rich settings and are widely understood by fisheries researchers and managers. As a result, EASI-Fish may afford fisheries managers more confidence in identifying the most vulnerable species, in order to direct resources to either implementing mitigation measures, or prioritising research or data collection that can fill key data gaps and subsequently allow more formal and precise stock assessments.

Acknowledgements. We thank Mark Maunder, Rick Deriso, Alexandre Aires-da-Silva and Cleridy Lennert-Cody for providing valuable advice on the model development and critically reviewing drafts of the manuscript; Carolina Minte-Vera for providing data inputs for EPO yellowfin and bigeye tuna stock assessment models; Michael Scott for advice on cetacean biology and habitat in the EPO; and Nick Webb for editorial comments that greatly improved the manuscript.

LITERATURE CITED

- Aires-da-Silva A, Minte-Vera C, Maunder MN (2017) Status of bigeye tuna in the Eastern Pacific Ocean in 2016 and outlook for the future. 8th Meeting of the Scientific Advisory Committee of the IATTC, 8-12 May 2017, La Jolla, California. Document SAC-08-04a. Inter-American Tropical Tuna Commission, La Jolla, CA
- ✦ Alfaro-Shigueto J, Mangel JC, Pajuelo M, Dutton PH, Seminoff JA, Godley BJ (2010) Where small can have a large impact: structure and characterization of small-scale fisheries in Peru. *Fish Res* 106:8–17
- ✦ Arrizabalaga H, de Bruyn P, Diaz GA, Murua H and others

- (2011) Productivity and susceptibility analysis for species caught in Atlantic tuna fisheries. *Aquat Living Resour* 24: 1–12
- Bigelow K, Musyl MK, Poisson F, Kleiber P (2006) Pelagic longline gear depth and shoaling. *Fish Res* 77:173–183
- Bishop SDH, Francis MP, Duffy C, Montgomery JC (2006) Age, growth, maturity, longevity and natural mortality of the shortfin mako shark (*Isurus oxyrinchus*) in New Zealand waters. *Mar Freshw Res* 57:143–154
- Block BA, Teo SLH, Walli A, Boustany AM and others (2005) Electronic tagging and population structure of Atlantic bluefin tuna. *Nature* 434:1121–1127
- Boggs CH (1992) Depth, capture time, and hooked longevity of longline-caught pelagic fish: timing bites of fish with chips. *Fish Bull* 90:642–658
- Bonnet S, Guieu C, Bruyant F, Prášil O and others (2008) Nutrient limitation of primary productivity in the South-east Pacific (BIOSCOPE cruise). *Biogeosciences* 5:215–225
- Caddy JF, McGarvey R (1996) Targets or limits for management of fisheries? *N Am J Fish Manag* 16:479–487
- Cadrin SX, Secor DH (2009) Accounting for spatial population structure in stock assessment: past, present, and future. In: Beamish RJ, Rothschild BJ (eds) *The future of fisheries science in North America*. Springer, Dordrecht, p 405–426
- Carlsson J, McDowell JR, Carlsson JEL, Graves JE (2007) Genetic identity of YOY bluefin tuna from the eastern and western Atlantic spawning areas. *J Hered* 98:23–28
- Cartamil D, Santana-Morales O, Escobedo-Olvera M, Kacev D and others (2011) The artisanal elasmobranch fishery of the Pacific coast of Baja California, Mexico. *Fish Res* 108:393–403
- Chen Y, Gordon GNG (1997) Assessing discarding at sea using a length-structured yield-per-recruit model. *Fish Res* 30:43–55
- Chuenpagdee R, Morgan LE, Maxwell SM, Norse EA, Pauly D (2003) Shifting gears: assessing collateral impacts of fishing methods in US waters. *Front Ecol Environ* 1:517–524
- Cope JM, DeVore J, Dick EJ, Ames K and others (2011) An approach to defining stock complexes for U.S. west coast groundfishes using vulnerabilities and ecological distributions. *N Am J Fish Manag* 31:589–604
- Cortés E, Arocha F, Beerkircher L, Carvalho F and others (2010) Ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. *Aquat Living Resour* 23:25–34
- Cortés E, Domingo A, Miller P, Forselledo R and others (2015) Expanded ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. *Collect Vol Sci Pap ICCAT* 71:2637–2688
- Dapp D, Arauz R, Spotila JR, O'Connor MP (2013) Impact of Costa Rican longline fishery on its bycatch of sharks, stingrays, bony fish and olive ridley turtles (*Lepidochelys olivacea*). *J Exp Mar Biol Ecol* 448:228–239
- Dichmont CM, Pascoe S, Kompas T, Punt AE, Deng R (2010) On implementing maximum economic yield in commercial fisheries. *Proc Natl Acad Sci USA* 107:16–21
- Duffy LM, Griffiths SP (2019) Assessing attribute redundancy in the application of productivity-susceptibility analysis to data-limited fisheries. *Aquat Living Resour* 32:20
- Duffy LM, Lennert-Cody CE, Olson RJ, Minte-Vera CV, Griffiths SP (2019) Assessing vulnerability of bycatch species in the tuna purse-seine fisheries of the eastern Pacific Ocean. *Fish Res* 219 (in press), <https://doi.org/10.1016/j.fishres.2019.105316>
- Eguchi T, Gerrodette T, Pitman RL, Seminoff JA, Dutton PH (2007) At-sea density and abundance estimates of the olive ridley turtle *Lepidochelys olivacea* in the eastern tropical Pacific. *Endang Species Res* 3:191–203
- Fiedler PC, Talley LD (2006) Hydrography of the eastern tropical Pacific: a review. *Prog Oceanogr* 69:143–180
- Fletcher WJ (2005) The application of qualitative risk assessment methodology to prioritize issues for fisheries management. *ICES J Mar Sci* 62:1576–1587
- Fletcher WJ (2015) Review and refinement of an existing qualitative risk assessment method for application within an ecosystem-based management framework. *ICES J Mar Sci* 72:1043–1056
- Francis MP, Jones EG (2017) Movement, depth distribution and survival of spinetail devilrays (*Mobula japanica*) tagged and released from purse-seine catches in New Zealand. *Aquat Conserv* 27:219–236
- Froese R, Binohlan C (2000) Empirical relationships to estimate asymptotic length, length at first maturity, and length at maximum yield per recruit in fishes, with a simple method to evaluate length frequency data. *J Fish Biol* 56:758–773
- Fu D, Roux MJ, Clarke S, Francis M, Dunn A, Hoyle S (2016) Pacific-wide sustainability risk assessment of bigeye thresher shark (*Alopias superciliosus*). National Institute of Water and Atmospheric Research, Wellington
- Gabriel WL, Mace PM (1999) A review of biological reference points in the context of the precautionary approach. In: Restrepo VR (ed) *Proceedings of the Fifth National NMFS Stock Assessment Workshop: Providing Scientific Advice to Implement the Precautionary Approach Under the Magnuson-Stevens Fishery Conservation and Management Act*. Tech Memo NMFS-F/SPO-40. US Department of Commerce, NOAA, Silver Spring, MD, p 34–45
- Gallagher AJ, Kyne PM, Hammerschlag N (2012) Ecological risk assessment and its application to elasmobranch conservation and management. *J Fish Biol* 80:1727–1748
- Gerrodette T, Forcada J (2005) Non-recovery of two spotted and spinner dolphin populations in the eastern tropical Pacific Ocean. *Mar Ecol Prog Ser* 291:1–21
- Gilman E, Zollett E, Beverly S, Nakano H and others (2006) Reducing sea turtle by-catch in pelagic longline fisheries. *Fish Fish* 7:2–23
- Gilman E, Passfield K, Nakamura K (2014) Performance of regional fisheries management organizations: ecosystem based governance of bycatch and discards. *Fish Fish* 15:327–351
- Griffiths S, Duffy L, Aires-da-Silva A (2017) A preliminary ecological risk assessment of the largescale tuna longline fishery in the eastern Pacific Ocean using productivity-susceptibility analysis. 8th Meeting of the Scientific Advisory Committee of the IATTC, 8–12 May 2017, La Jolla, California, USA. Document SAC-08-07d:1–21. Inter-American Tropical Tuna Commission, La Jolla, CA
- Griffiths SP, Allain V, Hoyle SD, Lawson TA, Nicol SJ (2019) Just a FAD? Ecosystem impacts of tuna purse-seine fishing associated with fish aggregating devices in the western Pacific Warm Pool Province. *Fish Oceanogr* 28:94–112
- Hall MA (1998) An ecological view of the tuna-dolphin problem: impacts and trade-offs. *Rev Fish Biol Fish* 8:1–34
- Hall M, Roman M (2013) Bycatch and non-tuna catch in the tropical tuna purse seine fisheries of the world. *FAO Fish Aquac Tech Pap* 568. FAO, Rome
- Hall MA, Alverson DL, Metuzals KI (2000) By-catch: problems and solutions. *Mar Pollut Bull* 41:204–219
- Hobday A, Smith A, Webb H, Daley R and others (2006) Eco-

- logical risk assessment for the effects of fishing: methodology. Final report for AFMA project R04/1072. CSIRO Marine and Atmospheric Research, Hobart
- Hobday AJ, Smith ADM, Stobutzki IC, Bulman C and others (2011) Ecological risk assessment for the effects of fishing. *Fish Res* 108:372–384
- Hoolihan JP, Luo J, Goodyear CP, Orbesen ES, Prince ED (2011) Vertical habitat use of sailfin (*Istiophorus platypterus*) in the Atlantic and eastern Pacific, derived from pop-up satellite archival tag data. *Fish Oceanogr* 20: 192–205
- Hutchinson MR, Itano DG, Muir JA, Holland KN (2015) Post-release survival of juvenile silky sharks captured in a tropical tuna purse seine fishery. *Mar Ecol Prog Ser* 521:143–154
- IATTC (Inter-American Tropical Tuna Commission) (2017) Ecosystem considerations. 8th Meeting of the Scientific Advisory Committee of the IATTC, 8–12 May 2017, La Jolla, California, USA. Document SAC-08-07a. Inter-American Tropical Tuna Commission, La Jolla, CA
- IEC (International Electrotechno Commission) (2009) IEC 31010. International Standard. Risk management—risk assessment techniques. International Electrotechno Commission, Geneva
- ISO (International Organization for Standardization) (2009) ISO 31000. Risk management—principles and guidelines. International Organization for Standardization, Geneva
- Jacquet JL, Pauly D (2007) The rise of seafood awareness campaigns in an era of collapsing fisheries. *Mar Policy* 31:308–313
- Joseph J (1994) The tuna-dolphin controversy in the eastern Pacific Ocean: biological, economic, and political impacts. *Ocean Dev Int Law* 25:1–30
- Kaschner K, Watson R, Trites AW, Pauly D (2006) Mapping world-wide distributions of marine mammal species using a relative environmental suitability (RES) model. *Mar Ecol Prog Ser* 316:285–310
- Kenchington TJ (2014) Natural mortality estimators for information-limited fisheries. *Fish Fish* 15:533–562
- Kirby DS (2006) Ecological risk assessment for species caught in WCPO tuna fisheries: inherent risk as determined by productivity-susceptibility analysis. 2nd Regular Session of the Scientific Committee of the Western and Central Pacific Fisheries Commission, Manila, Philippines, 7–18 August 2006. Document WCPFC-SC2–2006/EB WP–1. Western and Central Pacific Fisheries Commission, Kolonia
- Kirby DS, Visser C, Hanich Q (2014) Assessment of eco-labelling schemes for Pacific tuna fisheries. *Mar Policy* 43:132–142
- Lee HH, Maunder MN, Piner KR, Methot RD (2012) Can steepness of the stock-recruitment relationship be estimated in fishery stock assessment models? *Fish Res* 125:254–261
- Lewison RL, Crowder LB, Read AJ, Freeman SA (2004) Understanding impacts of fisheries bycatch on marine megafauna. *Trends Ecol Evol* 19:598–604
- Liu KM, Chiang PJ, Chen CT (1998) Age and growth estimates of the bigeye thresher shark, *Alopias superciliosus*, in northeastern Taiwan waters. *Fish Bull* 96:482–491
- Liu KM, Chang YT, Ni IH, Jin CB (2006) Spawning per recruit analysis of the pelagic thresher shark, *Alopias pelagicus*, in the eastern Taiwan waters. *Fish Res* 82:56–64
- Lucena-Frédou F, Kell LT, Frédou T, Gaertner D and others (2017) Vulnerability of teleosts caught by the pelagic tuna longline fleets in South Atlantic and Western Indian Oceans. *Deep Sea Res II* 140:230–241
- Martínez-Ortiz J, Aires-da-Silva AM, Lennert-Cody CE, Maunder MN (2015) The Ecuadorian artisanal fishery for large pelagics: species composition and spatio-temporal dynamics. *PLOS ONE* 10:e0135136
- Maunder MN, Crone PR, Valero JL, Semmens BX (2014) Selectivity: theory, estimation, and application in fishery stock assessment models. *Fish Res* 158:1–4
- Micheli F, De Leo G, Butner C, Martone RG, Shester G (2014) A risk-based framework for assessing the cumulative impact of multiple fisheries. *Biol Conserv* 176:224–235
- Mikalsen KH, Jentoft S (2001) From user-groups to stakeholders? The public interest in fisheries management. *Mar Policy* 25:281–292
- Millar RB, Fryer RJ (1999) Estimating the size-selection curves of towed gears, traps, nets and hooks. *Rev Fish Biol Fish* 9:89–116
- Milton DA (2001) Assessing the susceptibility to fishing of populations of rare trawl bycatch: sea snakes caught by Australia's Northern Prawn Fishery. *Biol Conserv* 101: 281–290
- Minte-Vera CV, Aires-da-Silva A, Maunder MN (2017) Status of yellowfin tuna in the Eastern Pacific Ocean in 2016 and outlook for the future. 8th Meeting of the Scientific Advisory Committee of the IATTC, 8–12 May 2017, La Jolla, California. Document SAC-08-04b. Inter-American Tropical Tuna Commission, La Jolla, CA
- Murua H, Santiago J, Coelho R, Zudaire I and others (2018) Updated Ecological Risk Assessment (ERA) for shark species caught in fisheries managed by the Indian Ocean Tuna Commission (IOTC). 21st Meeting of the Scientific Committee of the IOTC, 3–7 December 2018, Mahé, Seychelles. Document IOTC-2018-SC21-14_Rev1:16. Indian Ocean Tuna Commission, Mahé
- Musyl MK, Brill RW, Boggs CH, Curran DS, Kazama TK, Seki MP (2003) Vertical movements of bigeye tuna (*Thunnus obesus*) associated with islands, buoys, and seamounts near the main Hawaiian Islands from archival tagging data. *Fish Oceanogr* 12:152–169
- Myers RA, Bowen KG, Barrowman NJ (1999) Maximum reproductive rate of fish at low population sizes. *Can J Fish Aquat Sci* 56:2404–2419
- Myers RA, Baum JK, Shepherd TD, Powers SP, Peterson CH (2007) Cascading effects of the loss of apex predatory sharks from a coastal ocean. *Science* 315:1846–1850
- Ormseth OA, Spencer PD (2011) An assessment of vulnerability in Alaska groundfish. *Fish Res* 112:127–133
- Oshitani S, Nakano H, Tanaka SHO (2003) Age and growth of the silky shark *Carcharhinus falciformis* from the Pacific Ocean. *Fish Sci* 69:456–464
- Patrick WS, Spencer P, Link J, Cope J and others (2010) Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing. *Fish Bull* 108:305–322
- Pauly D (2010) Gasping fish and panting squids: oxygen, temperature and the growth of water-breathing animals. *Excellence in ecology*, Vol 22. International Ecology Institute, Oldendorf/Luhe
- Pitcher CR, Doherty P, Arnold P, Hooper J and others (2007) Seabed biodiversity on the continental shelf of the Great Barrier Reef World Heritage Area. Final report to the Cooperative Research Centre for the Great Barrier Reef World Heritage Area. CSIRO, Cleveland
- Pitcher CR, Ellis N, Jennings S, Hiddink JG and others (2017) Estimating the sustainability of towed fishing-

- gear impacts on seabed habitats: a simple quantitative risk assessment method applicable to data-limited fisheries. *Methods Ecol Evol* 8:472–480
- ✦ Polovina JJ, Hawn D, Abecassis M (2008) Vertical movement and habitat of opah (*Lampris guttatus*) in the central North Pacific recorded with pop-up archival tags. *Mar Biol* 153:257–267
- ✦ Punt AE (2000) Extinction of marine renewable resources: a demographic analysis. *Popul Ecol* 42:19–27
- Punt AE (2017) Review of contemporary cetacean stock assessment models. *J Cetacean Res Manag* 17:35–56
- Quinn TJ, Deriso RB (1999) Quantitative fish dynamics. Oxford University Press, New York, NY
- ✦ Ralston S (2002) West coast groundfish harvest policy. *N Am J Fish Manag* 22:249–250
- Rice J, Harley S (2012) Stock assessment of oceanic whitetip sharks in the western and central Pacific Ocean. 8th Regular Session of the Scientific Committee of the Western and Central Pacific Fisheries Commission, 7–15 August 2012, Busan, Republic of Korea. Document WCPFC-SC8-2012/SA-WP-06 Rev1. Western and Central Pacific Fisheries Commission, Kolonia
- Rice J, Harley S (2013) Updated stock assessment of silky sharks in the western and central Pacific Ocean. 9th Regular Session of the Scientific Committee of the Western and Central Pacific Fisheries Commission, 6–14 August 2011, Pohnpei, Federated States of Micronesia. WCPFC-SC9-2013/SA-WP-03. Western and Central Pacific Fisheries Commission, Kolonia
- Ricker WE (1975) Computation and interpretation of biological statistics of fish populations. *Bull Fish Res Board Can* 191:1–382
- ✦ Royer F, Fromentin JM, Gaspar P (2004) Association between bluefin tuna schools and oceanic features in the western Mediterranean. *Mar Ecol Prog Ser* 269:249–263
- ✦ Schaefer KM, Fuller DW (2010) Vertical movements, behavior, and habitat of bigeye tuna (*Thunnus obesus*) in the equatorial eastern Pacific Ocean, ascertained from archival tag data. *Mar Biol* 157:2625–2642
- ✦ Schaefer K, Fuller D, Hampton J, Caillot S, Leroy B, Itano D (2015) Movements, dispersion, and mixing of bigeye tuna (*Thunnus obesus*) tagged and released in the equatorial Central Pacific Ocean, with conventional and archival tags. *Fish Res* 161:336–355
- ✦ Seki T, Taniuchi T, Nakano H, Shimizu M (1998) Age, growth and reproduction of the oceanic whitetip shark from the Pacific Ocean. *Fish Sci* 64:14–20
- ✦ Semba Y, Aoki I, Yokawa K (2011) Size at maturity and reproductive traits of shortfin mako, *Isurus oxyrinchus*, in the western and central North Pacific. *Mar Freshw Res* 62:20–29
- Smith T, Punt AE (2001) The gospel of maximum sustainable yield in fisheries management: birth, crucifixion and reincarnation. In: Reynolds JD, Mace GM, Redford KH, Robinson JG (eds) Conservation of exploited species. Cambridge University Press, Cambridge, p 41–66
- Southwick R, Nelson R, Lachman R, Dreyfus J (2013) Sport-fishing in Panama: size, economic impacts and market potential. The Billfish Foundation, Fort Lauderdale, FL
- Standards Australia (2012) Risk management—guidelines on risk assessment techniques. HB 89. Standards Australia Limited, Sydney
- ✦ Stobutzki IC, Miller MJ, Brewer DT (2001) Sustainability of fishery bycatch: a process for assessing highly diverse and numerous bycatch. *Environ Conserv* 28:167–181
- Stobutzki IC, Miller MJ, Heales DS, Brewer DT (2002) Sustainability of elasmobranchs caught as bycatch in a tropical prawn (shrimp) trawl fishery. *Fish Bull* 100:800–821
- ✦ Swimmer Y, Gutierrez A, Bigelow K, Barceló C and others (2017) Sea turtle bycatch mitigation in US longline fisheries. *Front Mar Sci* 4:260
- Temming A (1994) Food conversion efficiency and the von Bertalanffy growth function. Part II and conclusion: extension of the new model to the generalized von Bertalanffy growth function. *Naga* 17:41–45
- ✦ Then AY, Hoenig JM, Hall NG, Hewitt DA (2015) Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. *ICES J Mar Sci* 72:82–92
- ✦ Thorson JT, Munch SB, Cope JM, Gao J (2017) Predicting life history parameters for all fishes worldwide. *Ecol Appl* 27:2262–2276
- ✦ Tsai WP, Sun CL, Wang SP, Liu KM (2011) Evaluating the impacts of uncertainty on the estimation of biological reference points for the shortfin mako shark, *Isurus oxyrinchus*, in the north-western Pacific Ocean. *Mar Freshw Res* 62:1383–1394
- ✦ Walker TI (1998) Can shark resources be harvested sustainably? A question revisited with a review of shark fisheries. *Mar Freshw Res* 49:553–572
- ✦ Walters CJ, Christensen V, Martell SJ, Kitchell JF (2005) Possible ecosystem impacts of applying MSY policies from single-species assessment. *ICES J Mar Sci* 62:558–568
- ✦ Ward P, Myers RA (2005) Inferring the depth distribution of catchability for pelagic fishes and correcting for variations in the depth of longline fishing gear. *Can J Fish Aquat Sci* 62:1130–1142
- Waugh S, Filippi D, Walker N, Kirby DS (2008) Preliminary results of an Ecological Risk Assessment for New Zealand fisheries interactions with seabirds and marine mammals. 4th Regular Session of the Scientific Committee of the Western and Central Pacific Fisheries Commission, 11–22 August 2008, Port Moresby, Papua New Guinea. Document WCPFC-SC4-2008/EB-WP2. Western and Central Pacific Fisheries Commission, Kolonia
- ✦ Williams AJ, Farley JH, Hoyle SD, Davies CR, Nicol SJ (2012) Spatial and sex-specific variation in growth of albacore tuna (*Thunnus alalunga*) across the South Pacific Ocean. *PLOS ONE* 7:e39318
- ✦ Worm B, Barbier EB, Beaumont N, Duffy JE and others (2006) Impacts of biodiversity loss on ocean ecosystem services. *Science* 314:787–790
- ✦ Ye Y (1998) Assessing effects of closed seasons in tropical and subtropical penaeid shrimp fisheries using a length-based yield-per-recruit model. *ICES J Mar Sci* 55:1112–1124
- ✦ Zhou S, Griffiths SP (2008) Sustainability Assessment for Fishing Effects (SAFE): a new quantitative ecological risk assessment method and its application to elasmobranch bycatch in an Australian trawl fishery. *Fish Res* 91:56–68
- ✦ Zhou S, Griffiths SP, Miller M (2009) Sustainability assessment for fishing effects (SAFE) on highly diverse and data-limited fish bycatch in a tropical prawn trawl fishery. *Mar Freshw Res* 60:563–570
- ✦ Zhou S, Yin S, Thorson JT, Smith ADM, Fuller M (2012) Linking fishing mortality reference points to life history traits: an empirical study. *Can J Fish Aquat Sci* 69:1292–1301
- ✦ Zhu J, Xu L, Dai X, Chen X, Chen Y (2012) Comparative analysis of depth distribution for seventeen large pelagic fish species captured in a longline fishery in the central-eastern Pacific Ocean. *Sci Mar* 76:149–157