CSIRO OCEANS & ATMOSPHERE
www.csiro.au

Ecological Risk Assessment Global Review

E.A. Fulton, C. Bulman, L. Thomas, M. Sporcic, J. Hartog

Dec 2019

Report for the Fisheries Research & Development Corporation

ISBN: 978-1-925994-02-5

Citation

Fulton EA, Bulman C, Thomas L, Sporcic M, Hartog J (2019) Ecological Risk Assessment Global Review. CSIRO, Australia.

Copyright

Important disclaimer

Contents

Figures

Tables

Acknowledgments

This work was funded by the Australian Fisheries Research and Development Corporation – Project # 2018-020 – and the CSIRO. We are grateful to all those researchers who shared materials or conversations with us in preparing this report.

Executive summary

The ecosystem approach to fisheries management necessitates consideration of the status and pressure on a broader set of species than the main target species. Extending traditional assessment approaches to the many hundreds of additional species is both prohibitive and impractical. This drove the development of the Ecological Risk Assessment for the Effects of Fishing (ERAEF) method developed by Hobday et al. (2007). This approach does not focus on estimating stock status, but on rapidly identifying potentially vulnerable species, prioritizing them for more rigorous assessment and management responses (e.g. time-area closures, gear modifications etc.) that can reduce this vulnerability. Over the past decade the ERAEF approach has been widely and variously adopted and modified. This report reviews those implementations and modifications with the intent of identifying advances that can be feasibly applied in Australia.

The useful extensions identified include re-consideration of biological traits and Level 2 analyses to capture sources or points of risk that may be missed with the standard set of attributes. For example: using taxon specific sets of attributes or SAFE-like assessment methods (easily picked up from the many modified ERAs that have already created taxon specific attribute lists); including exposure or sensitivity of individual life history stages (when strong ontogenetic changes exist); cryptic mortalities (e.g. for seabirds); habitat and trophic dependencies; climate and how that adds stress or modifies the attribute values of each species, or how it changes spatial distributions and thereby exposure to fishing, or even which species should be included in the assessment; "predictability" of stocks (i.e. the influence of environmental variability); for communities, review and update the indicators used. Many of these modifications (especially the use of taxon specific approaches) should be straightforward to do, without adding inconsistency or overhead, via the online assessment tool used in assessments for AFMA. Advances in computational capacity and statistical/computing methods (e.g. Artificial Intelligence and Machine Learning) mean that further automation of large parts of the workflow, beyond what is currently automated, may be possible in the not too distant future (likely lowering the resources needed and speeding up the assessment process).

Expanding the approach in these ways will also ease the extension of ERAEF (or methodologically similar assessments) to consider cumulative Impacts and to expand the temporal span of the ERAEF beyond looking into the past or present fishery interactions into proactive preparation for future effects and sustainability. This would involve moving from relative to absolute risk indices, which will facilitate creation of cumulative risk scores across fisheries, or to compare risk between fisheries or through time, or to look at risks from other stressors – such as other marine industries. It would also allow for more direct links to tactical multi-species management and allow for expansion of the ERAEF approach to ecosystem scales. This would however, require the replacement of the current relative risk thresholds to be replaced by more meaningful scoring thresholds.

On a longer time frame the following aspects should also be considered (i.e. they are not the highest priority for inclusion, but should receive consideration at some point): species interactions; indirect effects (e.g. trophic dependency, SURF index, hub score based on network indices);

system structure and function (this may become easier as ecosystem metrics get more consideration both in ERA and by EBFM science in general); inter-annual variability and regime shifts (which may change attribute scores, outcomes of residual risk analyses, or even the species considered).

Some of these options are more pressing or easy to implement and the modifications we recommend most strongly are to modify the ERAEF workflow so any target species (or habitats) with an existing Level 3 assessment potentially skip the Level 2 assessments (although if a substantial number of species continue to be assessed using PSA, then inclusion of target stocks in the PSA is a valuable means of facilitating interpretation of the vulnerability of non-target stocks). Moreover, the ERAEF workflow should be expanded to include a greater diversity of taxon-specific assessments in the Level-2 phase of the assessments. In addition, the attributes used and the scoring criteria should be periodically reviewed, as climate and exploitation can change susceptibility. The frequency of review should be tailored to the magnitude and rate of change of exploitation; with reviews occurring more frequently at higher rates of exploitation, where there is higher sensitivity to attribute mis-specification, or where exploitation rates are changing rapidly.

1 General Ecological Risk Assessment Approach

The move to an ecosystem approach to fisheries management has increased the pressure to show sustainability for a set of species far broader than the main target species that have been the focus of classical stock assessments. This can be challenging, however, given the lack of reliable information (catch or biological) for the majority of species that interact with fisheries, especially non-target or low value species. Extending traditional assessment approaches to these additional species is both prohibitive and impractical in terms of the level of resources required. Nevertheless, demand remains for some level of assessment to show sustainability against national (e.g. Ecologically Sustainable Development, Environment Protection & Biodiversity Conservation Act) and international requirements (e.g. for Marine Stewardship Council certification).

In response to this pressure the Ecological Risk Assessment for the Effects of Fishing (ERAEF) method was developed (Hobday et al. 2007). This approach does not attempt to precisely estimate stock status, but instead aims to rapidly identify potentially vulnerable species, prioritizing them for more rigorous assessment and management responses (e.g. time-area closures, gear modifications etc.) that can reduce this vulnerability. The intent of the ERAEF was to be precautionary and consequently absence of information automatically rated species as high risk. This was because it was decided by the original developers and AFMA managers involved that classifying a species as vulnerable when another classification was actually true (i.e. a false positive) was preferable to mis-classifying a truly vulnerable species (i.e. a false negative) (Pecl et al. 2011).

Another design feature was screening efficiency whereby the method could rapidly filter out low risk species, making more intensive assessments tractable as they were (i) for far fewer species and (ii) focused on those that actually needed assessing (i.e. avoiding needlessly expending resources on species that were at little to no risk). For example, in the 2019 assessment of the otter trawl component of the South East Shark and Scalefish Fishery (SESSF) (Sporcic et al 2019), 524 species spanning 19 key commercial, 402 byproduct/bycatch and 103 Threatened Endangered or Protected (TEP) species) were screened in the Level 1 Scale Intensity Consequence Analysis (SICA). Of those, 92 were further assessed at Level 2 using a Productivity Susceptibility Analysis (PSA) plus 303 using the Sustainability Assessment for Fishing Effects (SAFE) analyses (further details of this approach are given in a later section), resulting in 122 species at extremely high or high risk. Following a residual risk analysis this number was reduced to 45. A subsequent SAFE analysis, which incorporated fishing effort intensity, resulted in 12 species assessed at either extreme or high risk. These twelve species remained at either extreme or high risk following a residual risk analysis. Similarly, of the 25 habitat types at Level 1 during the assessment, only 7 were identified as a priority for further analysis or management response.

The ERAEF approach has been widely and variously adopted and modified over the last decade. In reviewing some of these studies, Holsman et al. (2017) attempted to map the complexity of the analysis needed to the complexity of the problem being assessed (single stressor or multiple, direct or indirect impact pathways). They stressed the value of qualitative network models, a type of dynamic conceptual model, as a means of structuring the analyses and identifying compensatory ecosystem dynamics and non-intuitive outcomes of management actions even when only considering fisheries interactions. They clearly identify that Level 1 and Level 2 stages of ERAs are governed by the need to rapidly provide information on potential risk to ecological components of exploited ecosystems, and to do this in a way that was not overly hampered by the divergent levels of available data across all the relevant species and habitats. Where management requires highly quantitative information on thresholds, and risk profiles then Level 3 risk assessments are required.

This review aims to build on the work of Holsman et al. (2017) and others and to synthesise the large number of publicly available documents (papers and reports) regarding the many ERA applications and modifications that now exist. The intent of this review is to see what methods advance the approach and ,of these, which are feasible for use in Australia. We do not attempt to review in detail the many Level 3 assessment models reviews already exist for different assessment methods (e.g. for single species, ecosystems and data poor) (Quinn 1999, Plagányi 2007, Travers et al 2008, Fulton 2010, ICES 2012, Fulton and Link 2014, Chrysafi and Kuparinen 2016, Dowling et al 2016, Carruthers and Hordyk 2018, Aeberhard et al 2018).

The approach taken in searching for documents to review was to perform searches in the Web of Science database, google scholar (https://scholar.google.com/), semantic scholar (https://www.semanticscholar.org/) as well as via google more generally. The search terms were "fisheries AND 'ecological risk assessment'" as well as "ecological AND risk AND assessment AND fisheries". The papers secured from this first search were reviewed and any relevant papers/reports referred to in those original with papers for additional rounds of review. A total of 221 documents were reviewed with respect to:

- geographic location
- objectives of the specific study being reported in the document
- ERA method used (including dimensions or criteria, if noted)
- Strengths and weaknesses of the specific approach
- Other relevant commentary on content or messages from the paper.

The majority of published marine risk assessments use a variant of the Ecological Risk Assessment of the Effects of Fishing (ERAEF) originally developed in Australia. These assessments (see tables in the Appendix) tend to focus on "Level 2" (the semi-quantitative step), often converting the approach to an absolute measure of risk rather than relative and adding in a more explicit consideration of uncertainty. This means they take the general hierarchical form outlined in Figure 1. This begins with a scoping phase and then general qualitative intensity-consequence rating, before escalating species of interest to a semi-quantitative level 2 scoring, with the species at greatest risk (or of greatest commercial interest) also then taken through a full quantitative level 3 assessment. This hierarchical approach is intended to be both conservative (so species with missing information are assumed to be rated immediately as higher risk) while also being tractable so that it can be applied to many hundreds of species encountered by fisheries without requiring a crippling level of resources.

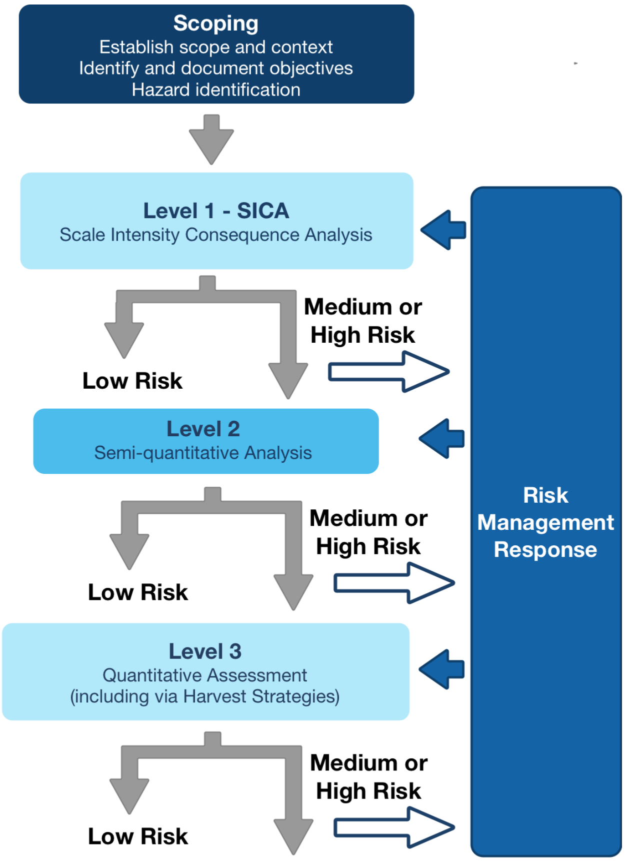


Figure 1: General form of the Ecological Risk Assessment approach (modified from Hobday et al. 2007).

This general structure has been largely maintained in all applications, though most published analyses either do not progress beyond level 1, or alternatively focus almost exclusively on the level 2 analyses (with the implication that very little is filtered out at level 1). Most of the modifications to the process to the ERA approach undertaken internationally have focused on alternative methods to use at the level 2 stage (this will be covered in more detail below). However, within Australia, where there has now been at least 1 iteration for each of the major fisheries, the process has been updated to leverage the broader assessment cycle whereby target species with existing quantitative assessments are excluded from the process rather than needlessly through the process (Figure 2). Moreover, this new approach also allows for a diversity of assessment methods to be used at the Level 2 stage to make best use of the available information and allow it to be attached to management responses as easily as possible. In Figure 2 we note that the "SAFE" methods used in the Australian context are in effect equivalent to some of the methods used at the Level 2 stage in other jurisdictions. This will be explored further in the section focused on the Level 2 analyses.

The value of the ERA approach as a key part of an ecosystem approach to fisheries is highlighted by its central role in packages such as the Environmental Defence Fund's *Framework for Integrated Stock and Habitat Evaluation (FISHE)* available at http://fishe.edf.org/

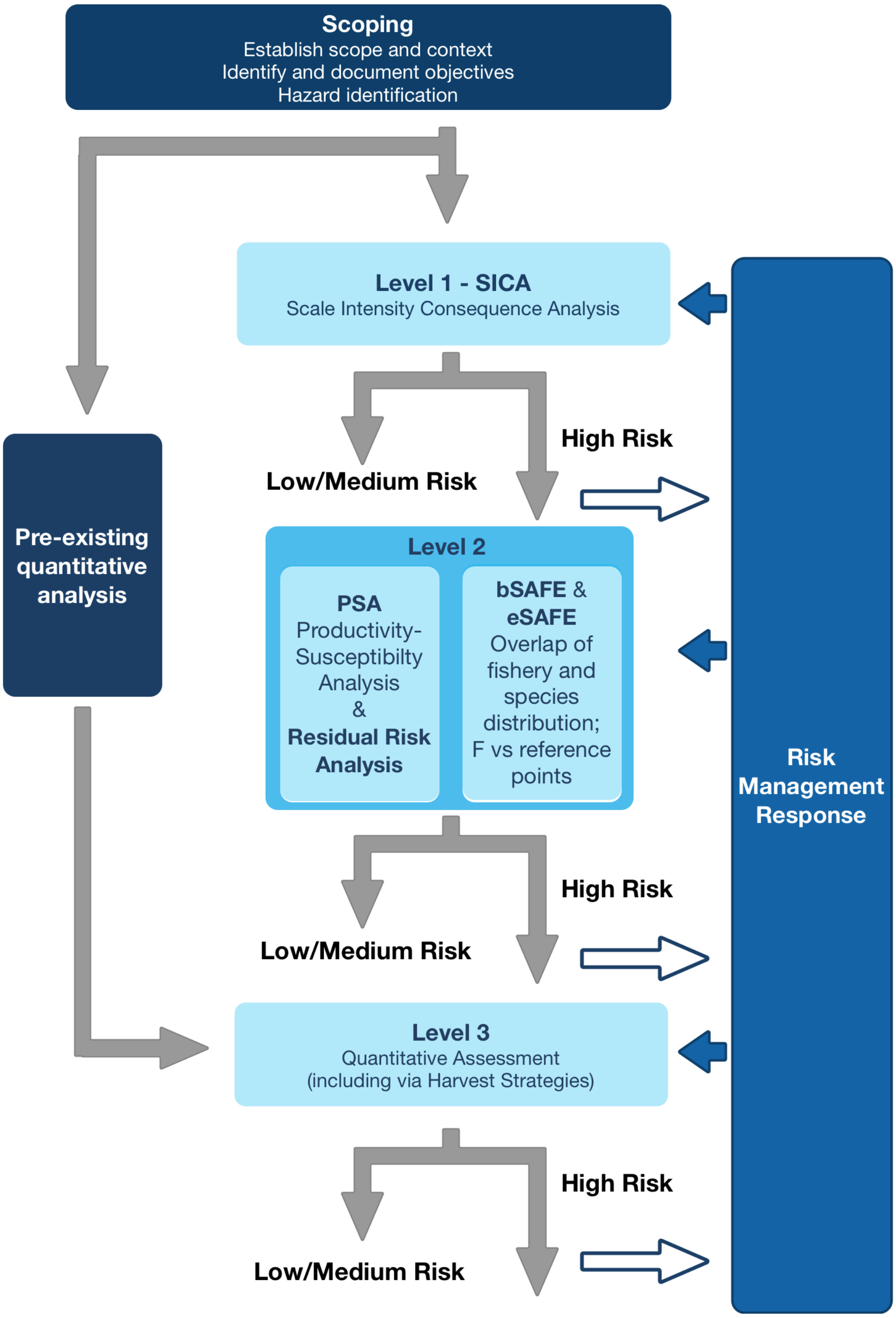


Figure 2: Current form of the hierarchical ERA approach as outlined in (AFMA 2017).

2 Scoping Step

This stage involves (i) identification of units of analysis (species, habitats and communities) potentially impacted by the fishery's activities; (ii) definition of objectives for the fishery (based on legislation or on generic sustainability operational objectives and indicators outlined in Hobday et al. 2007); (iii) selection of fisheries activities (taken from a generic and comprehensive activities/hazards checklist, Table 1). This scoping is usually initially undertaken with stakeholders and expert advice. In subsequent periodic reviews this consultation may be more limited (e.g. with the fishery's manager only).

Table 1: Hazard / Activity List

Class of Activity / Hazard	Activity / Hazard
Capture / removal	Bait collection
	Fishing
	Incidental behaviour (e.g. recreational fishing by the crew)
Direct impact without capture	Bait collection
	Fishing
	Incidental behaviour
	Gear loss
	Anchoring / mooring
	Navigation / steaming
Addition/ movement of biological material	Translocation of species
	On board processing
	Discarding catch
	Stock enhancement
	Provisioning
	Organic waste disposal
Addition of non-biological material	Debris
	Chemical pollution
	Exhaust
	Gear loss
	Navigation / steaming
	Activity/ presence on water
Disturb physical processes	Bait collection
	Fishing
	Boat launching
	Anchoring / mooring
	Navigation / steaming
External Hazards	Other capture fishery methods
	Aquaculture
	Coastal development
	Other extractive activities (e.g. offshore petroleum/gas exploration)
	Other non-extractive activities (e.g. shipping)
	Other anthropogenic activities (e.g. whale watching)
	Climate shifts and variability

3 Level 1: Scale Intensity Consequence Analysis (SICA)

This step evaluates the risk to the ecological components of interest (units of analysis) resulting from the stakeholder-agreed set of activities. This involves a researcher/analyst undertaking a preliminary evaluation (scoring) of the temporal and spatial scale, intensity, and credible scenario(s) of consequence for each activity on each ecological component (key and secondary commercial species, bycatch and byproduct species, protected (TEP) species, habitats and ecological communities). Scoring is done on a 1 to 6 (Table 2) using a “plausible worst case” approach (Smith et al. 2007). Any SICA element that scores 2 or less is documented, but not considered further for analysis or management response. Confidence in the scoring process is itself scored (on a scale of Low-High detailed further below). After the preliminary evaluation stakeholders are involved (via a workshop) to review the Level 1 assessment (including checking for oversights).

Table 2: Scoring criteria used in SICA

Score	Spatial	Temporal	Intensity	Consequence
1	<1 NM	Decadal	Negligible	Negligible (effectively undetectable)
2	1-10 NM	Every several years	Minor (rare)	Minor (minimal)
3	10-100 NM	Annual	Moderate (or localised)	Moderate (maximal sustainable rate)
4	100-500 NM	Quarterly	Major	Major (wide / long-term)
5	500-1000 NM	Weekly	Severe (or widespread)	Severe (serious impacts and long period to recovery)
6	> 1000 NM	Daily	Continual & widespread	Intolerable (widespread & irreversible)

Modifications to SICA

Internationally, less attention has been given to revising the SICA method as opposed to the Level 2 analyses. However there have been some developments that could be used to enrich the SICA approach if so desired. Cotter et al. (2014), for example, did not distinguish target, bycatch and protected species, but simply considered “units of assessment”, which may be species in some instances and individual stocks in others. In addition, they considered all “agents of change” not just fisheries and linked effects to policy goals. The most sensitive attribute of each unit was linked to the agent whose activities posed most threat to the achievement of the relevant policy goal (less threatening activities were ignored, as were cumulative effects). Relative impact scores (rather than “worst case” scores) were given for spatial scale, temporal scale, intensity of effect and duration of effect. These scores were also more quantitative than for the classical SICA (see Table 3), with the final score being the geometric mean of the four component scores. As with other ERA methods it focuses only on ecological and not economic aspects of the fished system.

Table 3: Cotter et al (2014) scoring criteria for their SICA equivalent

Score	Spatial	Temporal	Intensity	Duration
Definition	Spatial overlap of unit and activity within management zone (rescaled versus entire distribution)	Temporal overlap of unit and activity within management zone (rescaled versus species longevity)	Proportion of the unit affected when activity occurs	Duration of impact (~recovery time) once activity ceases
0	Negligible	Negligible	Negligible	Immediate
1	<10%	<10%	<10%	Several months
2	10-20%	10-20%	10-20%	Approximately 1 year
3	20-50%	20-50%	20-50%	1-3 years
4	50-90%	50-90%	50-90%	3-10 years
5	90-100%	90-100%	90-100%	> 10 years

Most of the focus has still gone to the species level, though sensitivity assessment tools that consider mutually exclusive pathways of impact (where A or B may occur) as well as dependent pathways (A and B must occur) and the implications for the final state of the system (Depestele et al. 2014) could form a useful basis for extending SICA easily to communities and ecosystems. Similarly, structured thinking using conceptual models to step through pathways of impact and risks to interactions and ecological functions rather than species per se (Gaichas et al. 2016, DePiper et al. 2017) could likewise be used to extend the SICA approach to communities and ecosystems. Work by Hare et al. (2016) introduces the notion of considering the direction of change (e.g. reduction in abundance) not just the chance of any change – this could be done in isolation or as a means of indicating how climate is modifying fisheries associated risks.

Handling Confidence and Uncertainty

As the information used in the SICA is qualitative and based on expert (fishers, managers, conservationists, scientists) judgment, a confidence score is generated for the analysis. The confidence for the scores (particularly the consequence score) per activity or component is rated as low or high confidence as shown in Table 4. These scores are then recorded and the rationale documented in the SICA Document. This confidence score reflects the levels of uncertainty for each scoring step – i.e. spatial, temporal, intensity and consequence (or duration).

Table 4: Confidence ratings (as per Hobday et al 2007).

Confidence	Score	Rationale
Low	1	Data exists, but is considered poor or conflicting
		No data exists
		Disagreement between experts
High	2	Data exists and is considered sound
		Consensus between experts
		Consequence is constrained by logical consideration

4 Level 2

Productivity-Susceptibility Analysis (PSA)

Where the Level 1 (SICA based) risk to a component is moderate or higher AND there is NO planned management intervention that would remove that risk, then a Level 2 assessment is undertaken[1]. In the original framework of Hobday et al. (2007) that assessment was undertaken solely using a Productivity-Susceptibility Analysis (PSA) adapted from Milton 2001 and Stobutzki et al. (2001), but later developments have added additional components (discussed further below).

The PSA approach typically only considers the direct impacts of fishing (not indirect effects such as gear loss, though it could). The core assumption of the PSA approach is that the risk to an ecological component depends on: (1) the extent of the impact due to the fishing activity (i.e. the **Susceptibility** of the component to the fishing activities); and (2) the **Productivity** of the component (as that is a determinant of its rate of recovery from any damage or depletion). The final ***P***roductivity and ***S***usceptibility scores are then given by:

$$P = \frac{\sum_i^n p_i}{n} \text{ and } S = \sqrt[k]{\prod_j^k s_j}$$

where p_i are the productivity attributes scores, *n* the number of productivity attributes used, s_j the susceptibility attribute scores and *k* is the number of susceptibility attribute used. Also note that the equation for ***S***usceptibility has changed. Originally ***S***usceptibility was calculated as

$$S = \frac{\left(\left(\prod_j^k s_j\right)-1\right)}{40} + 1$$

However due to bias introduced in intermediate scores this has more recently changed to the equation using the geometric mean shown above. The susceptibility score is multiplicative rather than additive because it is possible that a single susceptibility attribute (e.g., availability) can effectively make a stock invulnerable to fishing (i.e. it can never be accessed).

The **potential risk** (***R***) is then the Euclidean distance from the origin (1,1) of the (***P***roductivity, ***S***usceptibility) score in two dimensional space (Figure 3), i.e.:

$$R = \sqrt{(P-1)^2 + (S-1)^2}$$

This a relative potential measure of risk, not an absolute risk score, which requires some direct measure of abundance or mortality rate (and is often generally lacking for most components). Any components rated low risk in the PSA are screened out of further analyses.

The attributes used in the PSA are listed in Table 5. Prior to performing the PSA, if the assessment for a species that lacks stock information, a simple stock likelihood assessment (Table 6) is undertaken to make sure the PSA is suitably precautionary (i.e. where assessment for a stock rather than for the species is appropriate).

---

[1] Note that the ERA process in Australia does not attempt to undertake any management actions between Level 1 and 2 (with a Residual Risk Analysis coming after Level 2. However, action could in theory be taken before moving to Level 2.

Table 5: Attributes and risk scoring criteria used in a standard (Australian) PSA. Note that species with low productivity (e.g. a species that has fewer than <100 eggs per year) will be have a High risk score. Scores are: Low (1), Medium (2) and High (3).

	Attribute	Low	Medium	High
Productivity	Average age of maturity	< 5 years	5-15 years	> 15 years
	Average size at maturity	< 40 cm	40-200 cm	> 200 cm
	Average maximum age	< 10 years	10-25 years	> 25 years
	Average maximum size	< 100 cm	100-300 cm	> 300 cm
	Fecundity (eggs per year)	> 20,000	100-20,000	< 100
	Reproductive strategy	Broadcast Spawner, Asexual (some invertebrates)	Syngnathidae, Solenostomidae, Demersal egg layer	Live bearing, Brooder, Marine bird, Marine mammal or unknown,
	Trophic level	< 2.75	2.75-3.25	> 3.25
	Connectivity (for habitats)	High	Medium	Low
	Regeneration rate (for habitats)	Annual OR Encrusting	< Decadal OR Seagrass, Corals, Inner shelf non-encrusting filter feeders	Decadal+ OR Outer shelf or deeper non-encrusting filter feeders
	Natural disturbance level (habitats) – frequently disturbed species already adapted to recover	Regular OR Severe OR < 60m depth	Irregular OR Moderate OR 60-200m	None OR > 200m depth
	Diversity (species richness for communities)	High	Medium	Low
	Group membership (communities) • Proportion of fish groups with < 10 species • Proportion of fish groups > 30 species	Low	Medium	High
	Mean productivity score (communities, across all species in community)	High	Medium	Low
Susceptibility	Availability: overlap of fishing effort and the core of the stock/species/habitat/community distribution*,#	Default (stock level assessment):		
		Globally distributed	Restricted to same hemisphere/ocean basin as fishery	Restricted to same country as fishery
		Actual Distributions known:		
		Species: < 10% overlap Habitats: < 10% overlap	10-30% overlap 10-50% overlap	> 30% overlap > 50% overlap
	Community level component overlap (communities): proportion of species with > 50% overlap	Low	Medium	High
	Encounterability (species): likelihood of encounter given adult habitat† and depth distribution of gear‡ and species	Low overlap with fishing gear	Medium overlap with fishing gear	High overlap with fishing gear
	Encounterability (habitat): • depth	< 10% overlap	10-50% overlap	> 50% overlap
	• ruggedness	>1m relief, rugged structure, > 10 degree slope	<1m relief, rough surface, 1-10 degree slope	No relief, smooth, < 1 degree slope
	• level of disturbance (number encounters needed to cause impact)	Many (e.g. hand collection, traps and other lines (trot, set, drop, hand))	Several (e.g. Danish seine, longline, gillnets)	Single (e.g. trawl and dredge)

	Attribute	Low	Medium	High
	• gear type vs ruggedness	Dredge all but smooth Hand collection smooth Trawl rugged	Trap rugged Longline rugged Other lines rugged Trawl rough Prawn trawl other Gillnet rugged Danish seine other	Dredge smooth Hand collection other Trap other Long line other Other lines smooth Trawl smooth Prawn trawl smooth Gillnet other Danish seine smooth
	Selectivity (species): potential of gear to capture/retain species (values for nets given as an example)	< mesh size OR species >5m long	1-2x mesh size OR species is 4-5m long	> 2x mesh size OR
	Selectivity (habitat): • removability/mortality of fauna/flora	Low, robust or small (<5 cm), smooth or flexible, or deep burrowing	Erect or medium sized (but < 30 cm), moderately rugose or inflexible, or shallow burrowing	Tall, delicate or large (> 30 cm high), rugose or inflexible, or shallow burrowing
	• gear used vs removability	Hand collection Robust AND trap or demersal longline Auto longline other Robust AND trawl or Danish seine Robust AND gillnet	Trap or demersal longline other Erect AND trawl or Danish seine Erect AND gillnet	Dredge Delicate AND auto longline Delicate AND trawl or Danish seine Delicate AND gillnet
	• habitat areal extent	Common (>10%) in fishery area) OR on soft substratum	Moderately common (1-10%) in fishery area OR on gravel, or hard bottom <= 100m deep	Rare (<1%) in fishery area) OR on hard bottoms > 100m deep
	• removability of substratum	Immovable (bedrock and boulders >3 m) OR trap, line or gillnet OR hand collection other	< 6 cm (transferable) OR removable by hand collection	6 cm to 3 m (removable)
	• substratum hardness	Hard (igneous/ metamorphic rock)	Soft (sedimentary rock, cobble/ boulder/ slab, biogenic substrata)	Sediments (mud, fine sediments, coarse sediments, gravel/ pebble)
	• seabed slope	Plains and reefs	Terraces	Canyons and seamounts
	Post capture mortality rate	Evidence of post-capture release and survival	Released alive	Retained species, or majority dead when released
	Mean trophic level of the catch (communities)	Low mean trophic level	Medium mean trophic level	High mean trophic level
	Total catch percentage (communities): proportion of catch taken form the community / communities proportional cover (i.e. the proportion of the fished area made up by that community)	Low	Medium	High
	Functional groups fished by fishery (communities): proportion of the functional groups in the community that are fished	Low	Medium	High
	Proportion of functional groups with >50% of species fished (communities)	Low	Medium	High

	Attribute	Low	Medium	High
	Proportion of functional groups with >50% species rated at high risk in PSA	Low	Medium	High

* The core range is the geographic extent that contains 90% of the individuals (typically defined using bathymetric distributions). This method is used to account for the highly targeted nature of fisheries focusing on species with aggregated spatial extents (e.g. those mainly inhabiting the upper slope).

For TEP species expert observers can define the availability and override the criteria based score.

† Habitats considered are: air breathers (seabirds, mammals, reptiles), soft bottom demersal (sand and mud), hard bottom demersal (rocky or reefs), epipelagic (surface dwellers), benthopelagic (bottom and midwater), mesopelagic (midwater)

‡ Depth bands considered: 0-110, 110-250, 250-565, 565-820, 820-1100, 1100-3000, > 3000 (with demersal gears considered to reach up 100m from the bottom)

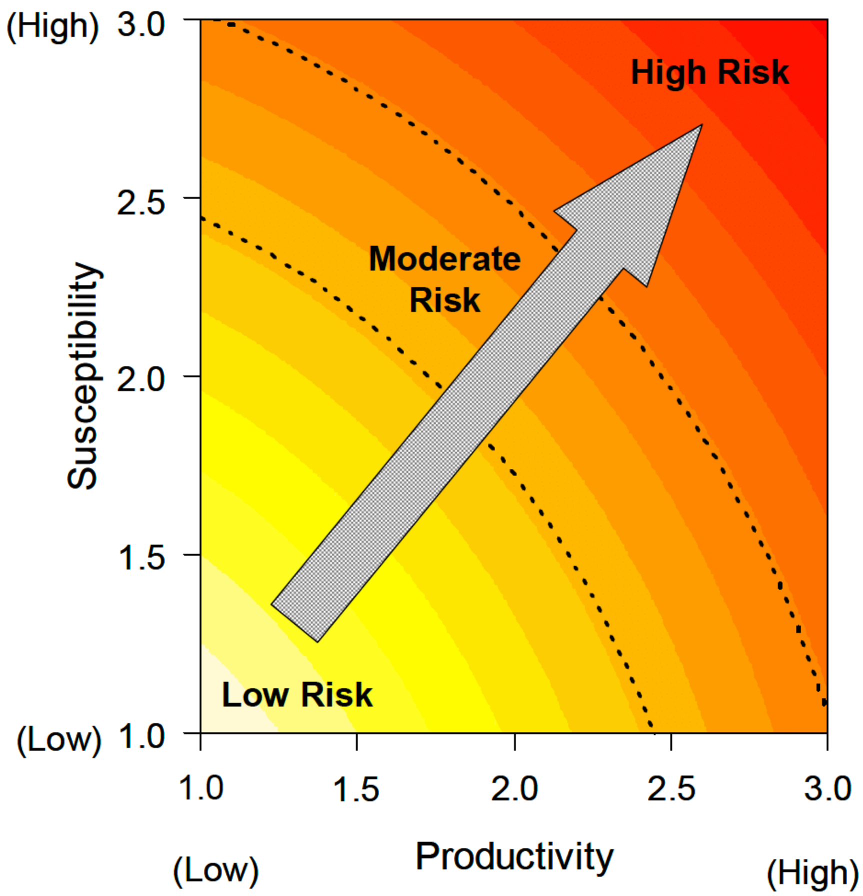


Figure 3: PSA plot (modified from Holt et al 2012) to match the risk scoring system of the standard PSA.

Table 6: Stock likelihood scores – rationale for reviewing availability risk scores for species without detailed distributional maps.

Rationale	Low risk of localised stocks	Medium risk of localised stocks	High risk of localised stocks
Geographic barriers	Few depth or geographic barriers (e.g. deep sea species; in semi-global water mass)	Some potential barriers (e.g. based on depth or water temperature for pelagic species)	Many barriers (e.g. restricted to estuaries or bays; strong temperature gradients)
Temporal barriers	No season phenology (spawning, feeding)	Some seasonal peaks, but activities not restricted to particular seasons.	Strong seasonality (e.g. spawning aggregations) AND fishing is adjacent to those seasonal aggregations.
Ecological barriers	Broadly dispersed habitats or no habitat dependency.	Strong habitat preferences but habitat is relatively widely distributed (>50% fished area); or habitat mis-match with targeted species.	Strong habitat preference and habitat is highly constrained (e.g. by food availability or bottom topography) AND fishing occurs in/near those habitats
Behavioural barriers	No behaviour	No social behaviour	Strong repeated behaviours (e.g. migration routes, breeding colony fidelity) AND fishing occurs near those behaviour hotspots.
Early life history	Pelagic larvae widely dispersed	Few restrictions to dispersal (e.g. pelagic larvae but constrained adult spawning sites)	Poor dispersal or inter-generational spawning site fidelity AND spawning area (or adjacent entries) are fished.

Residual Risk Analysis (RRA)

To make sure all relevant information (especially information on mitigating management measures not compatible with entry into the PSA criteria) is taken into consideration the final risk score can be adjusted based on a Residual Risk Analysis (RRA). This additional step is typically only undertaken for species assessed as high risk, but it has also been used to determine if some species have been incorrectly classified as low/medium risk. Additional information considered in the RRA are:

(i) whether the rating resulted from missing, incorrect or out of date information;
(ii) any external factors (cumulative risks);
(iii) whether there are actually negligible levels of susceptibility;
(iv) catch and effort management arrangements;
(v) bycatch mitigation;
(vi) any seasonal, spatial and depth closures;
(vii) any information on stock status and/or trends.

All of the information used in a RRA must be fully documented so any reasons for a modification of a final risk score are transparent (AFMA 2017).

Lack et al. (2014) took a classical approach (exposure-consequence) to assessing risk a management-extension that provided guidance to new assessors on the kind of questions to consider when looking at how management may mitigate risks due to fishing:

1. Is stock/species status tracked and known?
2. Is the stock managed under an Adaptive Management System?
    - Is information collected to inform the status of the stock?

- Have the available data been analysed to inform management decisions?
- How does the management unit manage the stock?
- Are the measures consistent with the species-specific advice for the stock?
- How comprehensive is the compliance regime in place to support these species-specific measures?
- What is the level of compliance with the reporting requirements for the stock?
- Is IUU fishing recognized as a problem for the stock (if it is a target) or for the fishery in which the stock is taken (if it is a bycatch)?

3. Generic Fisheries Management
    - Are the generic fisheries management measures in place likely to reduce the impact on the species / stock being assessed?
    - How comprehensive is the compliance regime in place to support the generic management measures that are relevant to the species/stock being assessed?

Under this system, a score of 1-4 is given to each question above, with the best management receiving a 4, the highest score (reflecting the lowest risk). Lack et al. (2014) then compared their intrinsic risk score with this management corrected "M-Risk" and the most pessimistic risk score used. This then allowed them to capture the situation where the current state may seem low risk, but due to management conditions has the potential to decline through time. Lack et al. (2014) then used the final risk score to prioritise species for management interventions.

A slightly different approach was taken by Gilman et al. (2014). While they did not undertake a residual risk analysis *per se* they did follow three criteria when estimating relative risks within and between taxonomic groups:

(i) the threat status assigned in the PSA versus global species-wide conservation status

(ii) phylogenetic uniqueness: phylogenetically distinct species were considered to be relatively more important given their distinct genetic diversity (few taxonomically close relatives so their loss potentially has evolutionary consequences); this was done by using PD_{50}, which is the expected phylogenetic diversity (PD) loss if the species is lost assuming all other species have a 50% (or greater) probability of persistence

(iii) relative importance of the role of the species in ecosystem structure and function (i.e. keystone and foundation species/guilds were considered relatively more important)

While, in theory, this approach could be used for any taxa, Gilman et al (2014) only used it for sea turtles and elasmobranchs in their study due to a paucity of data for seabirds and marine mammals interacting with the tuna longline fishery that was the focus of the study.

Modifications to PSA

Globally, the PSA has been a particularly popular ERA process and is the most broadly discussed in the literature, being applied to a wide range of taxa and fisheries worldwide. Some jurisdictions have expressed a dislike for a separate RRA and have instead chosen to modify the PSA instead. From the start Hobday et al. (2007) indicated that criteria could be more specifically tailored for individual taxa and life histories – such as dispersed, aggregating and migratory species. However, given available information and in an attempt to be precautionary, similar criteria were applied to all species in the original form of the ERA. In other jurisdictions which have modified the criteria used in the PSA it has primarily been to bring in attributes of productivity more relevant to taxa of specific interest (e.g. cetaceans; Brown et al. (2013)) or in modifying how the final productivity or susceptibility scores are calculated.

Cetaceans

Brown et al. (2013) opted to use the factors in Table 7 to define productivity for cetaceans, with the scoring thresholds determined by using a cluster analysis to distinguish different life history patterns and then assigning species to groups with similar life history parameters. Susceptibility was scored similarly to the original ERA approach, except for "post capture mortality", which was replaced by the potential (likelihood) for a lethal encounter and the final Susceptibility score calculated as:

$$S = \sqrt[6]{(av \cdot en^2 \cdot se^2 \cdot pl)}$$

where av is availability, en is encounterability, se is selectivity and pl is the potential for a lethal encounter. The alternative weighting for encounterability and selectivity was to ensure that species that had little real interaction[2] with a fishery could not generate moderate to high overall risk scores.

Table 7: Productivity and susceptibility attributes and risk scoring criteria for cetacean species from Brown et al (2013). Note the original referred only to availability in relation to the North Atlantic, it has been generalised here.

	Attribute	Low	Medium	High
Productivity	Average age of maturity	≤ 5 years	6-10 years	≥ 11 years
	Oldest reproducing female	≤ 44 years	45-60 years	≥ 61 years
	Calf survival (proportion)	≥ 0.9	0.77-0.89 years	≤ 0.76 years
	Inter-calving interval	≤ 2.5 years	2.6-3.5 years	> 3.5 years
Susceptibility	Availability	Globally (or multi ocean basin) distributed	Restricted to same hemisphere/ocean basin as fishery	Restricted to same region/country as fishery
	Encounterability	Spatial and temporal overlap but more than half of habitat range unaffected	Spatial and temporal overlap and less than half of habitat range unaffected	Total spatial or temporal overlap
	Selectivity	Low potential for capture	Moderate potential for capture	High potential for capture
	Potential for lethal encounter	Interaction with gear unlikely to result in injury or death	Interaction with gear likely to result in injury	Interaction with gear likely to result in death

Seabirds

PSAs have been explicitly updated for seabirds - e.g. by Filippi et al. (2010), Jiménez et al. (2012) and Waugh et al. (2012). Both Filippi et al. (2010) and Jiménez et al. (2012) defined productivity using the method developed by Waugh et al. (2009), which employs a "Demographic Invariant Method" (DIM). This method estimates r_{max}, the maximum rate of increase of a population with no resource limitation, predation or competition as:

[2] Where interaction was defined as spatial overlap or physical contact (such as capture) – it could be straightforwardly extended to consider ship strike, noise exposure or even indirect interactions mediated by diet, for instance.

$$r_{max} = 1 - \lambda_{max}$$

where λ_{max} is the rate of maximum population growth, the rate of annual growth of a population of a species without limiting factors and at low density, which is calculated using the age of first reproduction (α) and the survival of adults (*s*) using:

$$\lambda_{max} = \frac{(s\alpha - s + \alpha + 1) + \sqrt{(s + s\alpha - \alpha - 1)^2 - 4s\alpha^2}}{2\alpha}$$

This approximation assumes constant fecundity and constant survival of adults after first reproduction and produces values similar to those of matrix models and is particularly useful for long-lived birds. Filippi et al. (2010) intentionally only looked at Procellariiformes, even though other seabirds do interact with the fishery, as they chose to omit species that are data poor, but where experts said there is a low chance of interaction with the fishery anyway. In contrast, Jiménez et al. (2012) looked at many taxa and allowed the application across many species, which may be at differing levels of depletion, they used four combinations of survival and age at first breeding, based on the body size and breeding frequency (following Dillingham and Fletcher 2011):

(i) s = 0.93 and α = 6 for shearwaters (*Puffinus* spp.) and small petrels (e.g. *Daption* and *Fulmarus*)
(ii) s = 0.94 and α = 7 for medium sized petrels (*Procellaria*)
(iii) s = 0.95 and α = 8 for large petrels (*Macronectes*) and annually breeding albatrosses (*Thalassarche*)
(iv) s = 0.96 and α = 10 for biennially breeding albatrosses (*Diomedea* and *Phoebetria*).

This method was their preferred approach because it requires fewer biological attributes than other approaches and, notably, does not require estimates of maximum age or fecundity.

Jiménez et al. (2012) calculated susceptibility for species that consume discards, offal and bait, or are captured by the fishery, by using the criteria summarised in Table 8. Filippi et al. (2010) took a more quantitative approach to estimating susceptibility, creating a composite map of distributions that summed across a seasonal breeder layer and matching seasonal non-breeder layer. Hotspots were identified based on either species foraging radius or remote-tracking data. From these maps susceptibility was then calculated as the product of fishing effort and normalised species distributions (i.e. proportion of a species' range) weighted by the vulnerability (catchability) of the species (this appears to be the first instance of the use of a catchability term in a PSA assessment for birdlife).

Table 8: Attributes of the susceptibility used by Jiménez et al (2012) for seabirds. FO: is the relative frequency of occurrence (%) from observer counts of birds near vessels; Culmen is bill length; FL: is front length of the hook; and is the TL: total length of the hook.

Attribute (Probabilistic susceptibility score)	Low (0.33)	Medium (0.67)	High (1.00)
Availability or overlap with the fishery (as species distribution data patchy, used relative frequency of occurrence near fishing vessels as a proxy)			
Population size: > 100,000 breeding pairs	FO < 25%	FO 25-50%	FO > 50%
10,000-100,000 breeding pairs	FO < 10%	FO 10-25%	FO > 25%
< 10,000 breeding pairs	FO < 5%	FO 5-10%	FO > 10%
Access to bait (observed # attacks on bait / # birds present)	≤ 0.33	0.33 – 0.67	> 0.67
Hook selectivity	Culmen < FL	FL ≤ Culmen ≥ TL	Culmen > TL
Post-capture mortality	-	-	1.0*

* Considered to be 1 as the bait is taken as the line is set but the bird has drowned before being found when the gear is hauled.

While Jiménez et al. (2012) created PSA plots using susceptibility plotted against r_{max}, Filippi et al. (2010) used risk equal to the product of susceptibility and productivity. This meant that seabird species with high-productivity and low susceptibility were not always highly ranked, meaning their realistic vulnerability was captured in the outcome. The final risk scores were square-root transformed twice to normalize the distribution of the data and give values (0-1). In order to ease interpretation, five levels of risk based on the actual frequency distribution of the PSA scores were used where negligible levels of risk (0 – 0.001) were white; low (0.001 – 0.2) royal blue; low to Medium (0.2 – 0.4) pale blue; medium (0.4 – 0.6) green; medium to high (0.6 – 0.8): orange; and high (0.8 – 1.0) pink. Final aggregate risk maps per flag (nation) were created by summing scores over species per grid cell; and areas of high overall risk were identified by summing scores over fleet and species per grid cell.

Waugh et al. (2012) assessed risk to 70 species of albatrosses and petrels in New Zealand. They also used a modified PSA, employing explicit species distribution maps to determine susceptibility. In their case, for each season, a composite map was computed as the combination of a seasonal breeder layer that assumed exponential decline in foraging radius from breeding colonies, and matching seasonal non-breeder layers that assumed birds were distributed across their entire global distribution. The Susceptibility indicator was then calculated as the product of fishing effort and normalised species distributions (i.e. proportion of a species' range per grid cell), weighted by Vulnerability of the species to the fishing gear (longline). This Vulnerability was estimated for each species group by fitting a generalised linear model to observed captures and density data from the fishery.

Waugh et al. (2012) considered two productivity scores. The first was r_{max} which was related to λ_{max} in the same way as described above. However, in this instance λ_{max} was calculated using:

$$\lambda_{max} = e^{\left[\left(\alpha+\frac{s}{\lambda_{max}-s}\right)^{-1}\right]}$$

Where information was not available for a species (about a third of the species assessed) values were substituted from a closely-related species. The second approach used by Waugh et al. (2012) were Fecundity Factors Index (FFI), which is the product of normalised scores for life history strategy and median age of first reproduction (see Table 9 for definitions). For cases of missing data, average estimates for parameters were used rather than assuming such species are high risk.

Table 9: Life history definitions used for Seabirds in Waugh et al (2012).

Risk Score	Life history strategy	Median age of first reproduction
1	Annual breeding, multiple-egg clutches	< 5 years
2	Annual breeding, single-egg clutches	5-7.5 years
3	Biennial breeding, single-egg clutches	> 7.5 years

Both methods employed by Waugh et al. (2012) use age at first reproduction in their calculation, so it is unsurprising that a good correlation was found between the two productivity measures. However, they preferred FFI, as they felt it to be a simpler and more robust index and that r_{max} gave a false sense of precision.

Waugh et al. (2012) also wished to guard against the case where a species with low-productivity, but extremely low susceptibility could be highly ranked, despite very little exposure to fishing. This is an issue with distance-based measures on a standard PSA plot and so instead, risk was given as

$$Risk = \frac{Susceptibility}{Productivity}$$

These scores were then square-root transformed twice to normalise their distribution and divided evenly into five bins to get relative values form very low to very high risk (as for Filippi et al. 2010). Total risk per season and area was again given by the sum of species and fleets.

Sharks

In their review of ERAs for elasmobranchs Gallagher et al. (2012) points out the need to include measures of ecological specialization of elasmobranches in ERAs for these species. In that way their sensitivity to the degradation of suitable habitats can be captured as a second order effect of fishing. They suggested the inclusion of: ecophysiology (stress and post release mortality estimates); diet specificity; and a compound habitat dependency index determined using tracking data (where available) – this considers the distance moved and the mean difference in isotopes stored in different tissues (as this indicates how much foraging sites change through time); this movement can then be considered against the distribution of fishing pressure, much like the other overlap indices (e.g. in Table 5) or the approach used in SAFE assessments (see the dedicated section on this later in the report).

Chin et al. (2010) also assess risks to the sharks and rays (for the Great Barrier Reef ecosystem). While they used the conventional exposure, sensitivity and adaptive capacity approach, they did consider properties which might make useful PSA traits for chondrichthyans. Their approach to exposure was a straightforward overlap between the species distribution and depth range with footprint (observed and predicted) of the stressor. In assessing resulting risk, the vulnerability (sensitivity) of a species was judged based on its rarity and habitat specificity. Rarity was assumed to encompass the size and rebound potential of the species and so was thought to be a good proxy for other biological traits associated with vulnerability. Habitat specificity was chosen because it describes the extent of dependence of a species on particular habitat types and locations. Chin et al. (2010) point out that the adaptive capacity (robustness) of sharks and rays is dictated by their diet specificity, mobility, physical and chemical tolerances (with latitudinal range used as a proxy for temperature tolerance). In ranking these factors using the literature, unpublished data and expert knowledge, Chin et al. (2010) chose the most conservative ranking for each component, which meant that, as for the standard PSA, lack of information was ranked as high risk.

Turtles

Marine reptiles have not received the same level of tailored attention as some of the other large and charismatic groups. However Nel et al. (2013) have laid out clear criteria on which to base PSA for turtles. The modified set of criteria given in Table 10 drops some attributes not appropriate for turtles and instead add ones that capture the turtles reproductive traits, as adopted by Ormseth and Spencer (2011) and where attribute weightings were used in the final calculations. Nel et al. (2013) also went to great lengths to map the fisheries' footprints spatially and their potential overlap with turtle species. Ultimately, they found that the susceptibility scores were highly dependent on the size of the turtle population and the availability of information – smaller and data poor populations were rated at highest risk. The highly variable quality of the data, and its sparseness, highlighted to the IOTC that there was an urgent need to improve turtle bycatch data recording and reporting systems across all relevant fisheries. Nevertheless, it was still clear that longlining and gillnetting posed much greater threats to turtles than purse seines.

Table 10: Productivity and susceptibility attributes and risk scoring criteria for turtle species from Nel et al (2013). RMU = regional management unit. Scores are: Low (1), Medium (2) and High (3).

	Attribute	Low	Medium	High	Weight
Productivity	Recent (5-10 year) population trend	Uncertain OR Decline	Stable	Increase	20%
	RUM size/clades (number of nesting females)	Very small (1) Small (1.5)	Medium (2) Large (2.5)	Very Large (3)	30%
	Age at maturity	> 30 years	16-30 years	< 16 years	10%
	Maximum Age	Data deficient and not scored			
	Generation length (age of maturity + ½ maximum reproductive lifespan)	Data deficient and not scored			
	Natural survivorship – nest success	< 50%	50-75%	> 75%	5%
	Natural survivorship – hatching and emergence success (% nests producing eggs)	< 50%	50-75%	> 75%	5%
	Number of eggs per female	< 90 eggs	90-120 eggs	> 120 eggs	10%
	Number of clutches per individual per season	< 4 nests	4-6 nests	> 6 nests	10%
	Remigration Interval	> 4 years	2.6-4 years	< 2.6 years	10%
Susceptibility	Management Strategy/Recovery Plan	Threat score taken from Wallace et al (2011)			20%
	Spatial Overlap of RMU and Fishery Region (possible fished area)	< 30 spatial blocks	30 – 60 blocks	> 60 blocks	20%
	Confidence estimate in distribution data (number of tracks)	< 5	5 – 30	> 30	20%
	Geographic Concentration (overlap of high density turtle areas and high density fishing areas)	Data deficient and not scored			
	Vertical Overlap (% overlap of operational diving depths per fishery)	Data deficient and not scored			
	Bycatch estimate (relative to natural mortality for adults; or number of individuals caught; or estimated adult female abundance)	< 500 individuals OR < 30% of females	500 – 1500 individuals OR 100% of females	> 1500 individuals OR > 100% of females	20%
	Spawner Biomass (Number of breeding females per annum)	Very Large (1) Large (1.5)	Medium (2) Small (2.5)	Very Small (3)	20%
	Temporal Overlap between fisheries and turtle distribution	Data deficient and not scored			

PSA modifications used in the USA - ePSA

Patrick et al. (2009, 2010) made several modifications to the PSA, in order to meet the needs of US regulatory agencies. These modifications (referred to as ePSA by Hordyk and Carruthers (2018)) included: (i) redefining the scoring thresholds used by basing them on an ANOVA, rather than simply dividing each attribute into equal bins, or using a quantile method; (ii) increasing the number of productivity and susceptibility attributes considered; (iii) developing a data-quality index to allow for a comparison of uncertainty in risk scores across species; (iv) removing the requirement to assign a high risk score to any missing data; (v) using a weighted (additive) average score for both productivity and susceptibility rather than a multiplicative susceptibility score as in the standard PSA, that entailed employing an attribute weighting system to modify the weights assigned to each attribute for a given fishery analysis so that weights were based on relevance to that fishery as judged by local experts. The additive susceptibility score was used by Patrick et al. (2010) to minimise any chance that susceptibility would be underestimated. The weighting was used to filter down a much broader set of attributes than originally considered by Hobday et al. (2007). The broader set was initially considered given the very data poor status of some of the stocks under consideration and the desire to use any information available.

The modification of the scoring thresholds was based on the argument it was better suited to the distribution of life history characteristics observed in U.S. fish stocks (Patrick et al. 2010). The productivity attributes considered (Table 11) included all those of the standard PSA method, but also included the population intrinsic growth rate (*r*), von Bertalanffy growth parameter (*K*), and the natural mortality rate (*M*). Of the attributes considered, direct estimates of the intrinsic growth rate were preferred above all others. The reproductive strategy criterion of the standard PSA was also modified, replacing it with two attributes – breeding strategy (based on Winemiller's (1989) index of parental investment), and recruitment pattern (based on the expectation of successful recruitment events).

The ePSA includes a list of susceptibility attributes that expanded the standard PSA list by including: fish behaviour (and how that modifies interactions with gear); the value of the fishery management characteristics; stock status (F/M, relative depletion); and the impact of the fishery on the habitat. This means rather than using an RRA to account for management aspects and stock status implicitly, susceptibility is defined more broadly so, as to capture management and stock status and thereby include the susceptibility of a species to overfishing.

Patrick et al. (2010) indicated that a larger set of attributes would be useful given that a PSA would mainly be used to evaluate extremely data-poor stocks and thus more attributes would be beneficial to ensure that an adequate number of attributes were scored. However, as Hobday et al. (2007) had noted that more than six attributes for productivity or susceptibility did not markedly influence the accuracy of the assessment, Patrick et al. (2010) were reduced from an initial 75 down to the 22 listed in Table 11 by removing those attributes perceived as redundant or not directly related to vulnerability, suitability across scales and general data availability.

Where stock complexes rather than stocks are being managed, Patrick et al. (2010) advised that complexes exhibiting a wide range of vulnerabilities should be reorganised, or indicator stocks be chosen that represents the more vulnerable stock(s) within the complex – as done in the indicator species approach of Newman et al. (2018). Moreover, Patrick et al. (2010) agreed with Hobday et al. (2007) that given differences in how gears function and levels of post capture mortality, that the analyses should be cognisant of all (or a majority of) sectors interacting with a stock. However, while analyses per gear have been the typical approach taken in Australia, Patrick et al. (2010) preferred to do a separate analysis per sector and then calculate a final overall score by using a weighted average based on landings by sector over some predetermined time frame.

Ormseth and Spencer (2011) also used the same attributes and additive method of Patrick et al. (2010) but took the step of actively comparing the vulnerability of target and non-target stocks. In

Table 11: Attributes and risk scoring criteria used in an extended PSA (Patrick et al. 2010). Note that for consistency with Table 5, the scores have been put in terms of risk scores rather than pure productivity scores reported by Patrick et al (2010). Scores are: Low (1), Medium (2) and High (3). Intrinsic rate of increase is in bold as Patrick et al (201) holds to the view that this attribute "should take precedence over other productivity attributes because it combines many of the other attributes". Those attributes marked with [A] had scoring thresholds set by an ANOVA.

	Attribute	Low	Medium	High
Productivity	Average age of maturity [A]	< 2 years	2-4 years	> 4 years
	Average maximum age [A]	< 10 years	10-30 years	> 30 years
	Average maximum size [A]	< 60 cm	60-150 cm	> 150 cm
	Fecundity (eggs per spawning event)	> 10,000	100-10,000	< 100
	Intrinsic rate of population growth (r)	>0.5	0.16-0.5	<0.16
	Natural mortality rate (M) [A]	> 0.4	0.2-0.4	<0.2
	Recruitment pattern	Highly frequent recruitment success (>75% of year classes successful)	Moderately frequent recruitment success (10-75% of year classes successful)	Infrequent recruitment success (<19% of year classes successful)
	Reproductive (breeding) strategy index**	0	1-3	>3
	Trophic level	< 2.5	2.5-3.5	> 3.5
	von Bertalanffy growth coefficient (k) [A]	> 0.25	0.15-0.25	< 0.15
Susceptibility	Availability:		<u>Known distribution</u>:	
	• overlap of fishing effort and the core of the stock	< 25% overlap	25-50% overlap	> 50% overlap
	• geographic concentration (core distribution vs total range)	> 50%	25-50%	< 25%
	• overlay with any seasonal migrations	Seasonal migrations decrease overlap with the fishery	Seasonal migrations do not substantially affect the overlap.	Seasonal migrations increase overlap with the fishery.
	Catchability: • Behaviour (e.g. schooling or aggregations)	Decrease catchability of the gear.	No substantial effect on catchability of the gear.	Increase the catchability (hyperstability of CPUE with schooling)
	• Morphological influence on catchability (e.g. spines increase chance of capture)	Low	Moderate	High
	Encounterability: • depth (stock vs gear)	< 25% overlap	25-50% overlap	> 50% overlap
	Fishery Characteristics: • stock desirability or value (in USD)**	Not highly valued or desired (<$2.2 kg^{-1}; <$500,000 yr^{-1} landed; <33% retention).	Moderately valued or desired ($2.2–$5 kg^{-1}; $500,000–$10,000,000 yr^{-1} landed; 33–66% retention).	Highly valued or desired (>$5 kg^{-1}; >$10,000,000 yr^{-1} landed; >66% retention).
	• management strategy and	Target stocks have catch	Target stocks have catch	Target stocks do not have

	Attribute	Low	Medium	High
	effectiveness	limits & proactive accountability; non-target stocks closely monitored	limits and reactive accountability measures	catch limits or accountability measures; non-target stocks are not closely monitored.
	• impact on habitats	Adverse effects absent, minimal or temporary.	Adverse effects more than minimal or temporary but are mitigated	Adverse effects more than minimal or temporary and are not mitigated
	Stock characteristics: • Biomass status (e.g. Spawner stock biomass)	> 40% of B_0 (or maximum observed from time series of biomass estimates)	25-40% of B_0 (or maximum observed from time series of biomass estimates)	< 25% of B_0 (or maximum observed from time series of biomass estimates)
	• Fishing mortality (F) relative to M (F:M)	< 0.5	0.5-1	> 1
	Post capture mortality rate §	<33%	33-67%	>67%

* The breeding strategy of a stock provides an index of the level of larval and early juvenile mortality and was estimated using Winemiller's (1989) index of parental investment. The index values range from 0 to 14 and are a compound score based on: the placement of larvae or zygotes; length of time of parental protection of zygotes or larvae; length of gestation period or nutritional contribution.

** Converted to kg from lb

§ Expressed as a survival rate in Patrick et al (2010) but converted to a mortality rate here for consistency with other tables.

contrast to Patrick et al. (2010), Ormseth and Spencer (2011) weighted all attributes equally, except recruitment, which was down-weighted because there was little evidence for this being a useful attribute in Alaskan waters. Also instead of producing a final overall score using a weighted average across gears based on relative catch contributions, Ormseth and Spencer (2011) scored attributes based on the gear type with the highest proportion of the total catch in an area and producing a separate PSA for each management area. They found that productivity scores were similar between target and non-target stocks, but susceptibility scores were significantly higher for target stocks. Where multiple-gear analyses were undertaken, risk scores varied across gears and they noted that if a combined score was used, they often calculated a lower score than if the single most common gear was used instead. Ormseth and Spencer (2011) also concluded that while it may be a (marginal) computational saving not to run target species with an existing Level 3 assessment through a Level 2 assessment, the inclusion of target stocks in the PSA was valuable for interpreting the vulnerability of non-target stocks. This is particularly important if a fishery is operating under a policy where target and byproduct species or species included in stock complexes should have similar vulnerability scores (as is the case in the US). Inclusion of all relevant species in the PSA is a way of verifying that.

Holt et al. (2012) also adopted the approach of Patrick et al. (2010), providing a brief description of how the estimates of productivity parameters were obtained for each attribute and noting that consideration should be given to assigning natural mortality and growth coefficient attributes missing scores rather than using estimates derived from maximum length approximations, so as not to effectively put twice as much weight in the analysis on estimates of maximum length. They noted that extremely low productivity species have a high tendency to be progressed to a Level 3 analysis, regardless of their susceptibility score. Holt et al. (2012) also commented that (i) fecundity as an indicator of productivity has been discredited for teleost species due to lack of empirical support and data frustrations; and (ii) that F:M may not be as informative as originally thought for some species.

While Holt et al. (2012) used the measures of susceptibility of Patrick et al. (2010) by expanding the definition of susceptibility beyond early PSA applications by including information on fishery management, they still obtained false positive risk scores. Consequently, they decided a RRA step could still be required when a PSA is used to decide whether a species is progressed to a Level 3 assessment.

Use of empirical relationships to fill life history parameter gaps

There is significant pressure to fill as many biological attribute gaps as possible (as noted by Ormseth and Spencer (2011), see further detailed in the section on *Handling Confidence and Uncertainty* below). This has been done in many ways, from adopting values from similar species or other locations, but also via using empirical relationships. Lucena-Fredou et al. (2017) did just that when assessing species caught by the tuna longline fishery in the South Atlantic and the Indian Ocean, using the attributes in Table 12. As many studies have shown that life history parameters are correlated, Lucena-Fredou et al. (2017) replaced missing data with empirical relationships linking life history parameters to the desired biological attributes. For example, missing average size at maturity (L_{50}) and growth parameter (k) values were estimated from linear regressions against average maximum size (L_{max}). Final scores were weighted, with k. L_{max} and r weighed more heavily than other attributes due to a literature review which showed that differences between species and oceans were mainly explained by L_{max} and k; and r was a key indicator of resilience. Management strategy was down-weighted, given potential compliance issues.

Table 12: Attributes used by Lucena-Fredou et al. (2017). Scores are: Low (1), Medium (2) and High (3).

	Attribute	Low	Medium	High
Productivity	Average size of maturity (L_{50})	< 54 cm	54-105 cm	> 105 cm
	Average maximum age (T_{max})	< 8 years	8-14 years	> 14 years
	Average maximum size (L_{max})	< 110 cm	110-200 cm	> 200 cm
	Fecundity (eggs per spawning event)	> 2,880,000	1,030,000-2,880,000	< 1,030,000
	Intrinsic rate of population growth (r) [§]	>0.38	0.26-0.38	<0.26
	L_{50}/L_{max} (the relative investment into somatic and reproductive growth)	< 0.51	0.51-0.55	> 0.55
	von Bertalanffy growth coefficient (k) [A]	> 0.36	2.5-3.5	>= 3.5
Susceptibility	Availability: overlap of fishing effort and the core of the stock	Known distribution: < 25% overlap	25-50% overlap	> 50% overlap
	Encounterability: depth (stock vs gear)	< 25% overlap	25-50% overlap	> 50% overlap
	Fishery Characteristics: • % of catch with L > L_{50} (i.e. % of the catch that is adults)	> 95%	50-95%	< 50%
	• management strategy and effectiveness	Currently subject to a number of conservation and management measures	No specific regulations are in effect, but some indirect measures are in effect	No regulations are in effect
	Post capture mortality rate	<33%	33-67%	>67%
	Survivorship index - how the number of survivors deceases at	< 0.5	0.5-1	> 1

	Attribute	Low	Medium	High
	size (and age). Calculated as total mortality Z / k			

§ Which can be approximated by the maximum population growth that would occur in the absence of fishing when the population is at a small size

Small scale fisheries and Citizen science

Roux et al. (2019) show how the PSA framework can be strengthened by directly incorporating fisher knowledge (FK) data in the definition and scoring of susceptibility attributes (Table 13); and indirectly via the validation and weighing of productivity attributes based on correspondence between fisher knowledge and scientific observations. They then used a scenario-

Table 13: Attributes used by Roux et al. (2019) for anadromous Arctic char. Scores are: Low (1), Medium (2) and High (3). FK indicates an attribute was based solely on Fisher Knowledge.

	Attribute	Low	Medium	High
Productivity	Average maximum age	< 14 years	15-21 years	> 21 years
	Average maximum size	< 73.9 cm	73.9-84.7 cm	> 84.7 cm
	Average length at age 10	> 64.9 cm	51.8-64.9 cm	< 51.8 cm
	Instantaneous total mortality (estimated from catch curve analysis)	> 0.73	0.31-0.73	< 0.31
	Modal age of full recruitment to the fishery	< 10 years	10-14 years	> 14 years
FK-Productivity	Average fish size (relative to other stocks in the study area)	Small fish	Average fish size	Large fish
Susceptibility	Availability: Overlap between fishing activities and habitat type	Surrogate distribution for species incidence and distribution: Ocean and coastal	Lakes and Fjords (score 2) Lake/fjord and river mouth combinations (score 2.5) Coastal and fjord/lake combinations (score 1.5)	River mouth
	Encounterability: Straight line distance from nearest community	> 200 km	100-110 km (score 2) Intermediate scores (from 1.1 to 2.9) calculated assuming 0.1 increment for each 10 km distance interval.	< 10 km
	Selectivity: Ratio of mean length to commercial mesh size	< 4.3	4.3-4.8	> 4.8
FK-Susceptibility	Availability: • Overlap between fishing activities and habitat type	Ocean and coastal	Lakes and Fjords (or coastal areas and river mouth combinations)	River mouth
	• Seasonality: Annual recurrence of fishing as related to seasonal accessibility.	Fished once a year during either the ice-cover or open-water season	Fished more than once a year during either the open-water (summer and autumn) or ice-cover (winter and spring) season.	Fished during both the open-water and ice-cover seasons (accessible year-round).
	Catchability: Quality of fishing averaged across season	Poor	Good	Very good
	Desirability: Fish/waterbody preference and desirability as determined based on taste	Not so desirable (least favourite) fish	Desirable	Highly desirable (favourite) fish

	Attribute	Low	Medium	High
	and quality of the flesh, parasite loading, and other criteria.			
	Effort required to catch fish	Significant effort required (not so easy to catch fish)	Usual effort required (relatively easy to catch fish)	Little effort required (very easy to catch fish)
	Subsistence harvest levels: Relative importance as a food fishery to the community	Low	Moderate	High

based approach to compare outcomes between PSA assessments performed with and without the inclusion of Fisher Knowledge.

Productivity attributes were estimated for each stock using fisheries-independent biological data collected in experimental surveys, while fisher knowledge was used to provide information on fish size and all the "FK" susceptibility attributes. For each FK attribute, individual fisher scores were combined using a weighted average, based on the fisher's number of years of experience fishing in the area. These scores were then considered via three separate PSA assessments: without any fisher knowledge; with fisher knowledge only; and combination of standard and FK attributes. Good agreement was found between the PSA based on empirical biological data and fisher knowledge. Roux et al. (2019) concluded that the productivity-susceptibility analysis provided a flexible tool for the incorporation of alternative information sources, such as fisher knowledge, which can be important where scientific information is scarce.

Criticism of the PSA approach

The PSA approach of Patrick et al. (2010) has been criticised by Hordyk and Carruthers (2018). Hordyk and Carruthers (2018) simulation tested both the standard PSA and ePSA and used the results to investigate the underlying assumptions of these qualitative risk-based approaches. They found that the assumption of a relatively linear and additive relationship between the productivity and susceptibility scores is not valid; the susceptibility score is typically of greater importance than productivity in determining overall risk to a stock. Overall the match between simulated risk and the PSA estimate could be as high as 66% but as low as 50% or worse depending on stock status and rates of exploitation. Although Hordyk and Carruthers (2018) conceded they could not simulate all facets of PSA and so that the test may be unfair and really requires additional consideration spanning all of its features before they would be completely comfortable with its efficacy. This caution is well-placed as it has been shown that classical models of the kind used to do the simulation testing are often poor predictors of fishery dynamics (Szuwalski and Thorson 2017). Nevertheless, Hordyk and Carruthers (2018) rightly point out that extensively testing the PSA (or ERA approach more generally) would give a clear indication of the theoretical consistency of the assumptions underlying the methods and its predictive capacity, while having the added benefit of resolving which is the most appropriate way of calculating the productivity, susceptibility, and overall vulnerability scores and providing insight into what uncertainties and caveats are introduced if those calculation methods are precluded, for example by missing data.

As the methods stand, the overall relative risk as presented in PSA plots is acceptable as a qualitative relative index of risk. For ePSA, the performance is most reliable at low exploitation rates, though it underestimates risk to high productivity species. By contast, for standard PSAs, performance is strongest with low initial stock size and high exploitation rates and risk tends to be underestimated. Reassuringly the simulation testing generally showed that the lowest and highest vulnerability scores correlate with a low and high biological risk respectively making it a useful measure of prioritising based on relative risk. Uncertainty regarding reliability enters for mid-range scores, as the approach shows high variability in its efficacy for such species.

Prediction error rates measured in the simulation testing also increased as more attributes were added to the scoring system. This indicates that keeping the most informative attributes rather than the entire list is a robust means of improving the veracity of the scoring for "medium" risk species. Hordyk and Carruthers (2018) caution, however, that more testing is needed to establish the best form of such a streamlined approach, with fewer or alternative productivity and susceptibility attributes. A meta-analysis of potential attributes (especially those in the many ERA studies) and other available life history and fishery attributes may also be advisable as it may provide an increased assurance that the PSA attributes do reflect system and species properties in the way(s) assumed. In terms of the existing simulation testing, selectivity (size of capture relative to the size of maturity) was the most reliable susceptibility attribute and that steepness of the stock-recruitment relationship (h), maximum age and the intrinsic rate of population growth (r) (where available) are the most reliable productivity attributes. Hordyk and Carruthers (2018) advise against the inclusion of management attributes in the PSA (*sensu* Patrick et al. (2010)) because it could nullify the impact of risk due to all other attributes (both productivity and susceptibility) combined and therefore potentially ill-inform managers about underlying risks in the system.

Hordyk and Carruthers (2018) also state that while the ePSA method provided the closest re-creation of (simulated) risk with respect to its productivity and susceptibility scores, the kinds and quality of data required mean that there is sufficient information to perform a Level 3 (full quantitative) assessment. Moreover, they argue that the affordability of high power computing and the capacity to create (semi-)automated analyses using open-source software and online databases means that barriers to doing Level 3 assessments for an increasing number of species have been significantly lowered. Noting the data availability issues around Australian taxa and the findings of Szuwalski and Thorson (2017) regarding the predictive capacity of existing classical assessment methods, a broad scale switch to automated Level 3 assessments for Australian taxa is not recommended and Level 2 assessments remain the most feasible means of assessing the hundreds of species that interact with Australian fisheries.

Handling Confidence and Uncertainty

As flagged by all uses of the ERA approach, there is significant uncertainty associated with the method. This can be due to imprecise, incorrect or missing data, where an average for a higher taxonomic unit was used (e.g. average genera value for species units), or because an inappropriate attribute was included (Sporcic et al. 2019). It can also be difficult to maintain consistency in scoring of attributes across a wide range of species (ICES 2013). The standard PSA method deals with all of this uncertainty by opting to assign any unknown or highly uncertain data as “high risk” and noting this in the documentation (Hobday et al. 2007, 2011). This is assumed to lead to a bias towards false positive (high risk ratings when that is not the case) and therefore is considered as a conservative approach. However, as shown in the simulation testing of Hordyk and Carruthers (2018), even this approach is not 100% proof against false negatives and some measure of uncertainty should be given when advising managers.

The influence of particular attributes on the final result for a unit of analysis can be quantified with an uncertainty analysis, using a Monte Carlo resampling technique (Sporcic et al. 2019). This involves removing one of the productivity (or susceptibility) attributes at a time and recalculating the productivity (or susceptibility) score for each unit; this is repeated until all attribute combinations have been used. The resulting variation (standard deviation) in the productivity and susceptibility scores is a measure of the uncertainty in the overall PSA score. While such analyses may be being undertaken in the automated tool now routinely used to do the Level 2 assessments for Australian ERAs no confidence bands are marked on the plots included in the final report.

Another means of checking the validity of the ranking is to compare the risk score for a species with completed stock assessments (for target species) or with time series of standardized catch-per-unit -efforts. These comparisons show whether the PSA ranking agrees with these other sources of information or more rigorous approaches (Sporcic et al. 2019). Again, in most cases such comparisons are not regularly reported currently in the main ERA reports in Australia, but are reported in associated RRAs and in comparisons with the SAFE methods, e.g., (Zhou et al. 2007, Zhou et al. 2009, Zhou et al. 2016), which is discussed further in the section dedicated to the SAFE methods.

Other research groups have used other approaches to more clearly quantify uncertainty. Patrick et al. (2009, 2010) and other US fisheries using the same method), for example, preferred not to assign missing data a High risk score, as they believed this confounded data quality with risk assessment. Instead a data quality index was calculated (using the criteria in Table 14) and reported along with the individual risk scores. They then intentionally weight the contribution of the individual attributes in the overall vulnerability score to reflect data quality; so the final index is then given as the weighted average across the data quality indices for the productivity and susceptibility scores. Holt et al. (2012) and ICES (2013) took the same approach of using a data quality index, but used equal weighting in order to maintain comparability, consistency and transparency across fisheries and though time. Duffy and Griffiths (2017) also use equal weighting as they found it made little difference to the overall risk score in their case. Either way, in all methods using a data quality index, the overall index was interpreted as the overall quality of the data or belief in the score rather than the actual type of data used in the analysis. Ormseth and Spencer (2011) and Lucena-Fredou et al. (2017) reflect this confidence in the PSA directly, by colouring points in the PSA plot by data quality index.

Table 14: Criteria used to calculate data quality by Patrick et al. (2010)

Data Quality Rating	Description
1	Best data. Information is based on collected data for the stock and area of interest that is established and substantial (e.g. from data-rich stock assessment; published literature for which multiple methods are used, etc)
2	Adequate data Information is based on limited coverage and corroboration, or for some other reason is deemed not as reliable as data quality rating 1. (e.g. limited temporal or spatial data, relatively old information, etc.)

3	Limited data. Estimates with high variation and limited confidence and may be based on studies of similar taxa or life history strategies (e.g. similar genus or family, etc)
4	Very limited data. Information based on expert opinion or on general literature reviews from a wide range of species, or outside of region (e.g. general and unreferenced data)
5	No data. In which case this attribute should be omitted from the calculation of the susceptibility or productivity index score (but the omission of the attribute should still be reflected in the overall data quality score).

Ormseth and Spencer (2011) also assessed implications of changing the number of attributes included in the calculations (i.e. the influence of missing, uninformative or incorrect scores) on the final risk score. They also checked on the implications of changing exploitation rates through time on the susceptibility scores (e.g. changing degrees of encounterability). Griffiths et al. (2006) have also assessed this for Australian elasmobranch fisheries. In both cases the PSAs were unable to capture important changes in susceptibility; this was found to be due to the limited number and range of the included attributes. Ormseth and Spencer (2011) also found that data quality was significantly higher for target stocks. Overall risk scores were found to increase with the number of individual attribute scores that were uninformative or incorrect, with the effect amplified if the original score was higher or if there were fewer attributes (as any one attribute makes a larger proportional contribution to the final score). This indicates that every effort should be made to make the PSA as complete as possible, even if data is poor, and if possible, attributes should not be omitted. These findings also show that there is sensitivity to susceptibility changes therefore the frequency of review of these attributes should also be tailored to the magnitude and rate of change of exploitation; reviews should occur more frequently at higher rates of exploitation, where there is higher sensitivity to attribute mis-specification, or where exploitation rates are changing rapidly.

As mentioned above, the analysis by Roux et al. (2019) considered the influence of the inclusion of fisher knowledge in the PSA via three separate PSA assessments: without any fisher knowledge; with fisher knowledge only; and combination of standard and fisher knowledge (FK) attributes (all plotted together using dots of different colours). They found good agreement between empirical biological data and information from fisher knowledge information. Inclusion of fisher knowledge served to enhance the PSA if directly included or at least validate available biological data if only considered indirectly. This indicates that when scientific observations are scarce, incomplete, or non-existent, traditional ecological fishers' knowledge is potentially a highly valuable source of information. Roux et al. (2019) also indicated the data quality index of their attributes on the PSA plot with dots whose size determined based on the data quality.

Cortés et al. (2010; 2015) considered minimising uncertainty in analyses. Cortés et al. (2010) provided a range of vulnerabilities (risk scores) for the most important pelagic shark species subject to ICCAT surface longline fisheries in the Atlantic Ocean. They used enough information in their PSA to give continuous probabilistic scores rather than simple discrete classifications (high, medium and low). They also clearly highlighted that the ERAEF approach will inevitably provide only a snapshot of a time- and space-dependent factors determining the vulnerability of stocks to the fishing gear in use. This realisation motivated Cortes et al. (2015) to give a more complete consideration of uncertainty. Firstly, fully quantitative estimates rather than semi-quantitative ranks were used wherever possible, by using metiers based on gear and depth fished, not just depth; by defining selectivity in terms of the overlap between the range of lengths of animals in the catch and their known length range in nature; and by using tagging data to provide better estimates of encounterability. Uncertainty in life history traits (i.e. age at maturity, maximum age, age-specific fecundity and age-specific survival) was then considered via Monte Carlo simulation, which randomly drew values from assumed statistical distributions for each of these variables and considered the outcome on the resulting PSA scores. Moreover, Cortes et al. (2015) computed three indices of vulnerability (risk): based on Euclidean distance (v1), multiplicative (v2), and arithmetic mean (v3). All scores were then ranked from highest (rank=1) to lowest (rank=20) risk and the results summarized using a modified Traffic Light procedure. They found that the way in which the final risk score is calculated is important i.e., vulnerability calculated as the arithmetic mean of the productivity and susceptibility ranks (v3) had similar correlations with productivity and susceptibility individually, indicating that neither of these two aspects affected the final score disproportionately, in contrast to the distance based and multiplicative metrics v1 and v2, where one or the other aspect could dominate the final outcome. Multiplicative forms of susceptibility are much lower than those obtained using additive measures.

Cumulative effects of multiple fisheries

While the list of evaluated stressors included in an ERA can be revised to include as many non-fishery impacts as can be identified by the assessment team the stressors considered in Level 2 and 3 have typically been fisheries only. While the occurrence of risks from non-fishery (external) activities is recognized within ERAEF (particularly in the SICA step), the assessment of potential risks from these activities is considered weak compared to the level of analysis afforded to fishery aspects. Holt et al. (2012) see the failure to address multiple activities in Level 2 analyses and the lack of consideration of socioeconomic benefits and risks as outstanding issues with regard ERAEF delivering information to managers that would support an ecosystem approach to management.

The Comprehensive Assessment of Risk to Ecosystems (CARE) approach by Battista et al. (2017) attempts to span multiple stressors and to allow for nonlinear cumulative effects and uncertainty scalars by conceptually collapsing all three levels of an ERA into Level 2. The CARE approach draws from other ERA methods, other cumulative effect assessments, ecosystem service assessments and research on ecosystem resilience (Link, 2005; Halpern et al. 2008; Barbier et al. 2011; Keith et al. 2013). CARE also takes a system perspective, using an expert based rating system of a comprehensive suite of attributes characterizing system health and functioning – including intrinsic system recovery potential (captured through regeneration time and connectivity), as well as the system's resistance to impact (as reflected by the removability of system components and functional redundancy and diversity). The final risk ratings are given as a matrix of scores across stressors against ecological components (whether target (valued) species; keystone species; habitat engineers; species of conservation concern; habitats; ecosystem services; or the ecosystem as a whole). The risk scoring is done a little different to both PSA and classical exposure-consequence scoring; considering the level of exposure, the potential effect of that exposure (based on spatial scale, frequency and intensity of the exposure in a "worst case scenario"), as well as the response score (based on factors influencing sensitivity, recovery time, diversity and functional redundancy).

Cormier et al. (2018) and Astles and Cormier (2018) take a different approach, using a graphical "Bow-tie analysis" to develop a qualitative model of how to reduce risk to valued system components caused by activities of fisheries (Astles and Cormier 2018) or multiple sectors (Cormier et al. 2018). A schematic of the structure is given in Figure 4, but the basic structure of the Bow-tie simultaneously identifies:

- sources of risk
- potential consequences
- preventive controls (intended to reduce the likelihood of an event)
- mitigation controls (intended to reduce the magnitude of the consequences of an event)
- recovery controls (used to recover from the consequences that could not be mitigated)
- escalation factors (external factors that can undermine the effectiveness of any of the controls) that may require their own targeted controls.

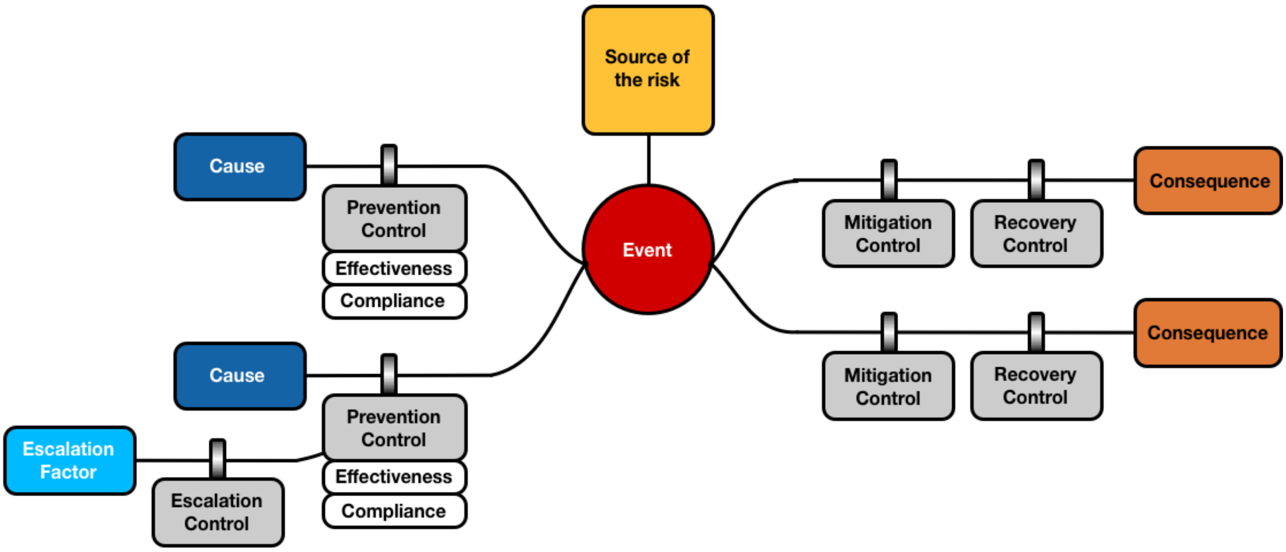


Figure 4: Example of the Bow-tie method conceptual model (modified from Cormier et al. 2018).

Some of the uncertainties of using the Bow-tie method include: the nature of the relationships between nodes in the diagram (e.g. between stressors and outcomes); the extent to which those relationships are correlative or causal; the contribution of the relationships to the actual capacity to respond; and potentially missing interactions between stressors and ecological components (Astles and Cormier 2018). Cormier et al. (2018) attempted to address some of this by building Bayesian belief network (BBN) models from the Bow-tie structures. They integrated information on the magnitude of the external factors and the effectiveness of each control in the system (including compliance) and then predicted the residual pressure, which can be used as a management indicator of the effectiveness of the overall management system. This BBN approach can convert qualitative Bow-tie analyses into quantitative risk assessments, but it can also be hampered by if there is insufficient data to define the respective probability distributions (transition matrices) for each node of the BBN.

Returning to more PSA-like approaches, in their analysis of the risks to the Great Barrier Reef, Chin et al. (2010) explicitly attempted to consider interactions between stressors (mainly to do with climate but similar approaches could be taken for fisheries). Knights et al. (2015) and Samhouri and Levin (2012) also described how to extend the ERA approach to stressors beyond fisheries. Knights et al. (2015) created an exhaustive sector–pressure–ecological component linkage matrix

—also known as an impact chain— across 17 sectors, 23 pressures and 5 broad types of ecological components. They then assessed risk in a PSA-like method where experts scored the extent (overlap), frequency, and degree of impact, the persistence of a pressure and the resilience (recovery time) of the stocks. Samhouri and Levin (2012) similarly considered exposure in terms of rating spatial extent and intensity of each pressure and their overlap with species distributions, both via direct and indirect impact pathways. They also considered management factors: the value of exploited species, existence value, current status and management effectiveness. The sensitivity of a species was rated by Samhouri and Levin (2012) using mortality and behavioural responses to the stressor, rates of natural disturbance, fecundity, age of maturity, life stages effected, reproductive strategy and population connectivity.

This approach could be used as a basis for extending ERAEF to cumulative fisheries effects. The majority of the original ERAEF applications consider individual sectors in isolation rather than as a set of cumulative effects. Patrick et al. (2010) recommended that an ERA should be performed for each (or at least a majority) of the sectors interacting with each stock so that in combination the majority of the catch of a stock is considered in some form; then an overall risk score can be calculated using a weighted average based on landings by sector over a pre-specified time. Patrick et al. (2010) thought this the best way of looking at both risk across stocks and prioritisation across sectors, which can then inform setting control rule buffers, identifying which sectors pose the greatest risk to a stock (e.g. in terms of susceptibility and intensity of pressure).

Micheli et al. (2014) proposed two extensions to the PSA approach – “fisheries with the greatest impact” (FGI) and the “aggregated susceptibility index” (AS). To calculate the FGI for a species (target or non-target) the susceptibility per fishery (fleet) is calculated as normal and then the greatest score (highest susceptibility) is used in calculating the final risk score:

$$FGI = \max_i(FSS_i)$$

where FSS_i is the fishery specific susceptibility score for fishery i. The aggregated susceptibility index (AS) is given by:

$$AS = \min\left(3{,}1 + \sqrt{\sum_i^n (FSS_i - 1)^2}\right)$$

The overall risk score is then calculated as normal but with susceptibility $S = AS$ such that

$$R = \sqrt{(P-1)^2 + (AS-1)^2}$$

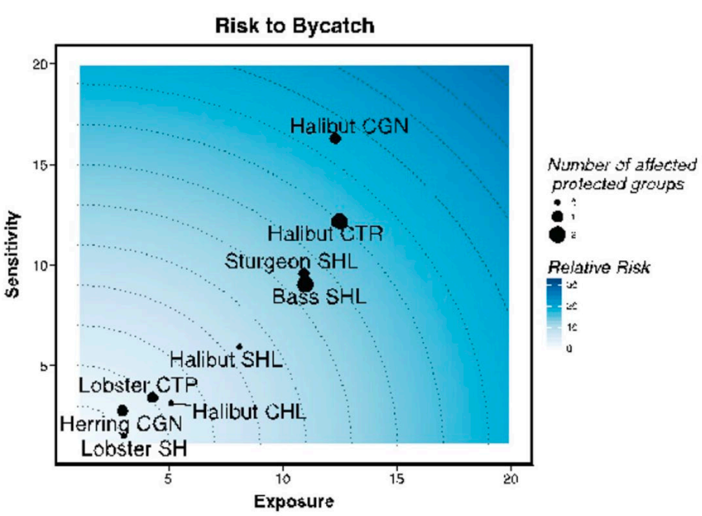
These formulations mean that AS increases with the number of fisheries included and whenever FSS is greater than 1 for two or more fisheries then $AS > FGI$ (i.e. AS can exceed the maximum value among the individual fishery scores). This means that if multiple fisheries are assessed to cause moderate or greater risk the combined risk of them simultaneously affecting a species can be quite high. This was an intentional decision because Micheli et al. (2014) found that while some species persistently show low risk, for many species, risk is underestimated if fisheries are not assessed in combination. The number of species assessed as low risk dropped substantially when using *FGI* rather than the susceptibility of individual fisheries in isolation, and dropped further still when aggregating the susceptibility scores of the different fisheries operating in the same area which also saw a notable increase in the number of species rated as high risk. Micheli et al. (2014)

concluded that both indices showed potential for significant cumulative impacts if multiple fisheries were actively interacting with several species in an area. However, they still found value in calculating results for individual fisheries because comparing those results with *FGI* provided insight into which fishery was the biggest contributor to the compound pressure on the stock. Building on this experience Micheli et al. (2014) recommend:

- that the aggregated susceptibility index (*AS*) be used for assessing cumulative risk, especially when catch and effort data are not available
- using as many independent scoring attributes as possible (where data exists)
- including other stressors beyond fishing (e.g. hypoxia) where feasible

Even then, Micheli et al. (2014) also stress that the PSA methodology as it is currently used does not account for possible synergistic effects of multiple, indirect impacts, and thus it may underestimate overall risk.

Samhouri et al. (2019) have also considered cumulative fisheries pressure, in their case using a variant of the PSA approach outlined in Samhouri and Levin (2012). The risk assessment for each fishery was based on the exposure and sensitivity of each target, bycatch, or habitat group using a tailored list of attributes (listed in Table 15).These attributes take into account direct and indirect impact pathways as given by the logic underlying the Integrated Ecosystem Assessment method of Samhouri et al., (2019) used as a basis for their fisheries extensions, and management considerations that remove the need for a RRA, as in Patrick et al. (2010). A set of ecosystem components were assessed using their updated scoring system for each fishery. These ecosystem components included target species, bycatch groups, and habitat groups; and were specifically highlighted in the US Marine Life Management Act. To keep the exercise tractable, relevant staff from the California Department of Fish and Wildlife (CDFW) selected ten representative bycatch and habitat groups (i.e. 20 in total) and then scored those species and all the target species with regard to the exposure and sensitivity attributes. The CDFW also assigned weightings to each attribute based on their perceived importance in affecting exposure and sensitivity, which were verified during broader stakeholder workshops. Final cumulative risk scores for each fishery were calculated by summing the risk scores across species (or ecosystem components), meaning cumulative risk was higher for fisheries interacting with many species groups. The final plots comparing cumulative risk across fisheries were then plotted in much the same way as for a standard PSA, except that the combined scores were plotted per fishery rather than per species, with the size of the dot proportional to the number of species affected by the stressor (especially the number of protected species) – see the example given in Figure 5. In communicating these results back to a broader stakeholder audience "risk thermometers" were used, which show the risk per target species, bycatch group and habitat, with specific scores for that species/ecosystem component per fishery component marked on the thermometer (see Figure 6). Samhouri et al. (2019) also recognised that in



future there will be the need to address climate in their assessment, as some species that had a low risk score in their initial assessment have actually been observed to be declining due to climate; and it was felt that it will be necessary in future to capture this to provide a complete perspective. Similarly, other pressures could also be included more explicitly into the approach.

Figure 5: Example of risk plots from Samhouri et al. (2019)

Table 15: Attributes used by Samhouri et al. (2019). Exposure is somewhat analogous to susceptibility, while sensitivity is somewhat analogous to productivity. Scores are: Low (1), Medium (2), High (3) and Very High (4).

	Attribute	Low	Medium	High	Very High
Sensitivity	Behavioural response	Behaviour reduces gear efficiency, or can escape gear	Behaviour does not change impact (e.g. sedentary)	Behaviour increases impact somewhat (e.g. schooling)	Behaviour significantly increases impact (attracted by gear, baits etc)
	Current status • Habitat:	No concern, negligible difference to historical levels	Low-moderate concern, some degradation but rebuilding	Highly degraded but is successfully managed (being restored) or has no official status	High concern (endangered, threatened), substantially degraded (or unrecognisable vs historical levels)
	• Bycatch species	Fish/invertebrates: Sustainable with FMP in place	Birds/mammals: Protected but not endangered/threatened Fish/invertebrates: Sustainable but no FMP in place	Threatened	Endangered
	Fishing mortality (target species)	≤ 0.2	0.21 – 0.30	0.31 – 0.40	> 0.4
	Probability of survival post release (of bycatch species)	> 75%	51 – 75%	26 – 50%	< 25%
	Age of maturity	< 2 years	2-5 years	6-10 years	> 10 years
	Breeding strategy	$\geq$ 4 (Internal fertilisation and parental care)	3 (Internal fertilisation OR parental care, but not both)	2 (External fertilisation and no parental care)	0-1 (External fertilisation and no parental care, with known low successful reproduction rates)
	Fecundity	$> 10^3$	$10^2 – 10^3$	$10^1 – 10^2$	< 10
	Population connectivity	No biogeographical boundary within the state; species has egg or larval dispersal period $\geq$ 1 month	No biogeographical boundary within the state; species has no egg or larval dispersal period or its dispersal period is < 1 month	Biogeographical boundary within the state; habitat/species NOT listed or protected; NOT considered an evolutionary unit	Biogeographical boundary within the state; habitat/species is listed or protected; considered an evolutionary unit
	Potential damage to habitat from fishing gear	No/insignificant potential modification to habitat structure caused by fishing gear	Potential modification to habitat structure by fishing gear (traps, hoop nets, hand collection) or anchor/chain damage	Potential modification to habitat structure by fishing gear (traps, weighted ground lines,	Potential modification to habitat structure by bottom or beam trawl (or gear has unstudied effects)

	Attribute	Low	Medium	High	Very High
			from vessels (not drifting)	gillnets, purse seine)	
	Recovery time	< 1 year	1-10 years	> 10 years	> 100 years
Exposure	Spatial intensity (areal and vertical overlap between species/habitat and fishery)	<10%	10-20%	20-40%	>40%
	Temporal intensity • Species: Temporal closures or migration out of the fishery • Habitat: Months fishery operates over a habitat per year	Closures or migrations for >6 months 0-3 months	Closures or migrations extend 3-6 months 4-6 months	Closures or migrations last < 3 months 7-9 months	None 9-12 months
	Target stock status and management strategy	Landings over past 5 years increasing, steady, or no trend. FMP in place	Landings over past 5 years increasing, steady, or no trend. No FMP in place	Overfishing may be occurring; landings in past 5 years declining or at historic lows. No FMP in place	Stock formally declared as overfished. No FMP in place
	Gear selectivity (for target species)	Very selective (gear captures only target species of legal or desirable size, which are sexually mature)	Selective (gear primarily captures target species of legal or desirable size, which mostly sexually mature)	Moderate selectivity (catches target species, but as many undersized as legal sized)	Low (catches more undersized than legal/desirable size individuals of the target species)
	Magnitude of bycatch	Absolute bycatch < 4.5 t OR Relative bycatch < 5% of total catch OR >50% target catch released alive (catch & release)	Absolute bycatch 4.5-18 t OR Relative bycatch 5-10% of total catch	Absolute bycatch 18-34 t OR Relative bycatch 11-25% of total catch	Absolute bycatch >34 t OR Relative bycatch >25% of total catch
	Management effectiveness (how target management measures benefit bycatch and habitat)	FMP addresses bycatch or habitat; management known to be very effective OR Fishery does not put direct stressor on indicator bycatch or habitat species	FMP addresses bycatch or habitat; management known to be effective OR Fishery is a controlled stressor on indicator bycatch or habitat species	No FMP that addresses bycatch or habitat; but management considered effective OR Fishery is a stressor on indicator bycatch or habitat species and management mitigates only some impacts	No FMP that addresses bycatch or habitat; management not considered effective OR Fishery is a poorly managed stressor on indicator bycatch or habitat species
	MPA and spatial closures (overlap of species range or habitat and MPAs);	20+% of species range or habitat; and beneficial	10-19% of range or habitat; provide some benefit	<10% of range or habitat; may provide some benefit	No overlap, no benefit provided, or no MPAs

	Attribute	Low	Medium	High	Very High
	MPAs benefit species (effort not displaced)				
	Value of exploited species	Stock not highly valued or desired < $2.2 USD / kg < $500,000 USD per yr landed < 25% retention	Stock moderately valued or desired $2.2-5 USD / kg $500,000 -$10,000,000 USD per yr landed 26-50% retention	Highly valued or desired < $5-11.1 USD / kg $10,000,000 - $99,000,000 USD per yr landed 51-75% retention	Highly valued or desired > 11.1 USD / kg > $99,000,000 per yr landed > 75% retention

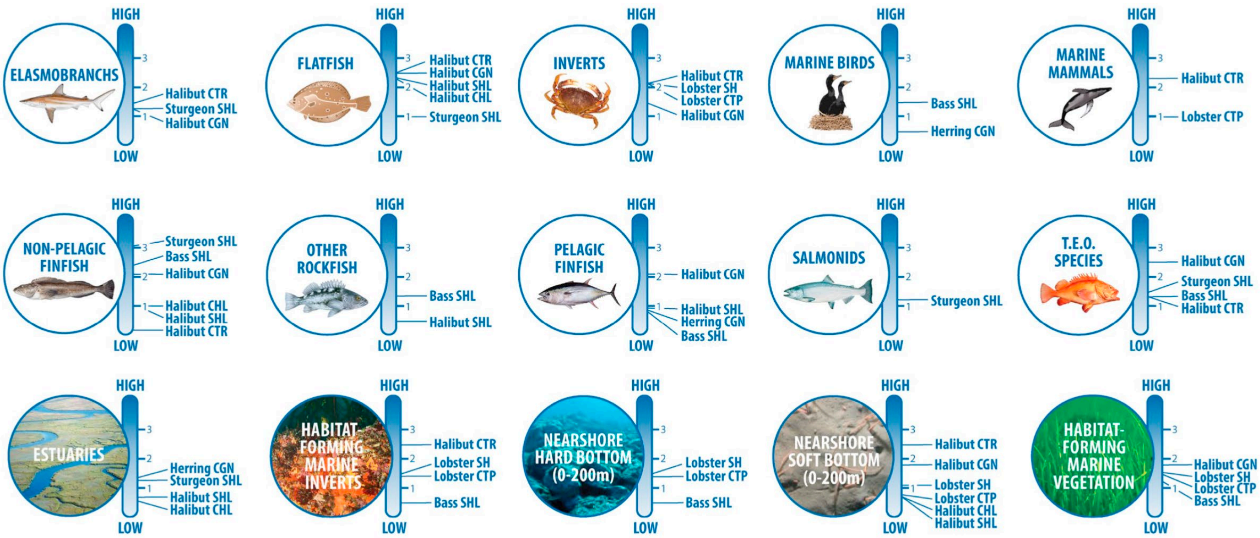


Figure 6: Example of risk thermometers used by Samhouri et al. (2019) to communicate risk to a broader audience.

Sustainability Assessment for Fishing Effects (SAFE)

The most common modification of Level 2 that departs from the PSA format is to introduce alternative means of assessing either relative or absolute risk while trying to avoid the degree of computation complexity and information required for a full Level 3 assessment. The earliest of these modifications (and one now formally included in the Australian framework) was the Sustainability Assessment for Fishing Effects (SAFE). This approach was originally developed for risk assessment of bycatch species in the Australian Northern Prawn Fishery (Brewer et al. 2006, Zhou and Griffiths 2008, Zhou et al. 2009) but was quickly extended to other fisheries (Zhou et al. 2011). It is now the standard method used for teleosts in the Australia ERA framework, with only data poor (typically invertebrate or TEP species) put through the PSA (AFMA 2017). While SAFE uses fewer attributes than the PSA method, it can be regarded as a quantitative equivalent to PSA. The SAFE method is also relatively easy to automate and is carried out in a batch process for the identified species in a fishery usually in the hundreds. As it requires limited data, it can be used for a wide variety of fishing gears and applied to many data-poor species. This can be demonstrated by its wider application since its initial application in northern Australian prawn fisheries to all major fisheries in Australia involving hundreds of target and bycatch species even including seasnakes (Milton et al. 2007; Zhou et al. 2007, 2009, 2011, 2012, 2013; Zhou and Fuller 2011; Bulman et al. 2017a,b; Sporcic et al. 2018a,b,c,d; Sporcic et al. 2019a,b,c,d,e).

The concepts underlying SAFE reflect those in traditional fishery management i.e. indicators (or performance measures) and reference points. SAFE focuses on fishing mortality rate (F) because there is often a lack of data for estimating biomass for most species, especially bycatch species or in particularly speciose multispecies fisheries. This reliance on F , however, is considered acceptable given that population reference points based on biomass and F based reference points (i.e. impact reference points) are inextricably linked (Moore et al. 2013) with F_{ref} being the fishing mortality rate that, under steady state conditions, would eventually enable the population to equilibrate at B_{ref}. To make the method applicable to as many species as possible, instead of using time series of catch data or age composition, the SAFE method derives fishing mortality rate via spatial overlap of the species distribution and the fishing effort distribution (Zhou et al. 2011) . This requires species distributions, fishing effort, fishing gear dimensions and some life history parameters as inputs. The explicit equations used are:

$$F = \kappa \cdot av \cdot en \cdot se \cdot pm$$

where F is a point estimate of fishing mortality, av is availability, en is encounterability, se is selectivity and pm is the post capture mortality. Noting that catch rate (which may be referred to as Q in some documentation) is given by $en \cdot se$. Availability is derived directly from the spatial overlap of species distribution and effort footprint, with κ set to 1.0 as a result. However, for longline this overlap is adjusted using κ, which is set to 1.48 for pelagic longline and 0.73 for demersal longline. If only qualitative information on general levels of en, se and pm are available then categorisations of low, medium and high equate to: low = 0.33, medium = 0.67 and high = 1.0. Variance on the F estimate (V_F) and 90% confidence intervals ($CI_{F,90\%}$) are also directly considered in this quantitative approach:

$$V_F = V_A \cdot (en \cdot se \cdot pm)^2 + V_Q \cdot (av \cdot pm)^2 + V_P \cdot (av \cdot en \cdot se)^2$$

$$CI_{F,90\%} = F \pm 1.64 \cdot \sqrt{V_F}$$

where V_A is the variance in availability calculated from the footprint database (set to 0 for any single year in insolation); and V_Q and V_P are given by:

$$V_Q = \frac{en \cdot se \cdot (1 - en \cdot se)}{9} \quad \text{and} \quad V_P = \frac{pm \cdot (1 - pm)}{9}$$

The resulting F estimates can be relatively uncertain, as the default basic SAFE (bSAFE) assessment assumes:

- fish densities are the same between fished and unfished areas within species distribution range and that fish are homogenously (or randomly) distributed in their habitat
- the probability of being caught by a specific gear (i.e. gear efficiency or catchability) is fixed at one of three levels (0.33, 0.67, and 1.0), which is determined by their body size perceived behaviour and morphology (versus gear specification).

These estimates can be refined using an enhanced SAFE (eSAFE) approach that relaxes these assumptions (Zhou et al. 2016) by making the encounterability (species-fishery overlap) dependent upon habitat, behaviour, fishing and size-dependent gear selectivity. Gear efficiency can be estimated from historical surveys or observer data, if available (Zhou et al. 2014). Similarly, heterogeneous species density can be recognised by stratifying distributional ranges and estimating density from historical surveys and observer data using General Additive Models (GAMs) (Zhou et al. 2013).

The SAFE approach allows for a brief assessment of the state of the stock via comparison of the estimate of F versus reference points derived from life-history parameters (Zhou et al 2012):

- F_{msm} (Fishing Maximum Sustainable Mortality) which is the mortality that in the long term would see stock biomass at B_{msm}.
- F_{lim} (Fishing mortality limit reference point), corresponding to the mortality rate that would see the stock biomass at B_{lim} (0.5 B_{msm}) in the long term; and
- F_{crash} – the minimum unsustainable instantaneous fishing mortality rate that (in theory) leads to population extinction in the long term.

The relative position of the estimate of F vs these reference points can be used to assign relative risk to a species – as shown in Figure 7.

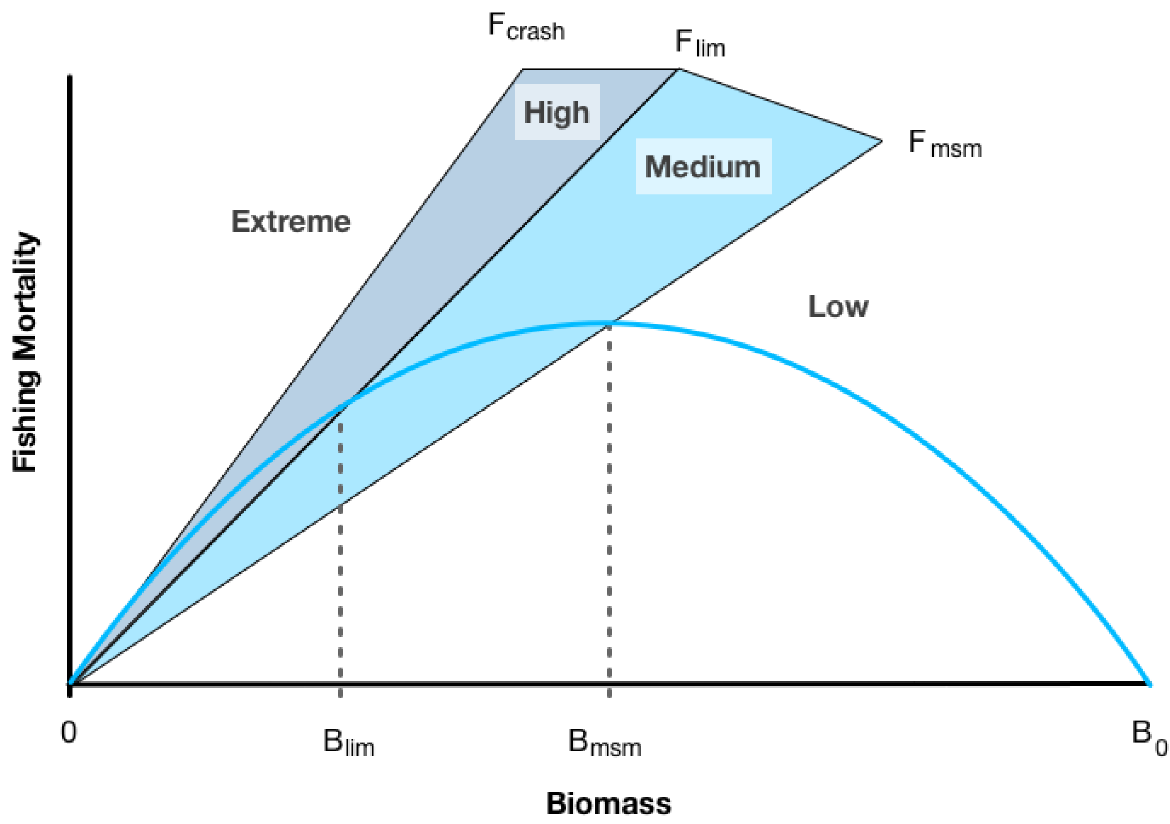


Figure 7: Reference points and risk levels used in the SAFE assessment method (as of Zhou et al 2011).

These F reference points can be calculated using six different methods:

(i) $F_{msm} = 0.5 \cdot \omega \cdot r$, $F_{lim} = 0.75 \cdot \omega \cdot r$ and $F_{crash} = \omega \cdot r$

(ii) $F_{msm} = \omega \cdot M$, $F_{lim} = 1.5 \cdot \omega \cdot M$ and $F_{crash} = 2 \cdot \omega \cdot M$

(iii) as for (ii) but with M given by the following empirical relationships from Pauly (1980) and Quinn and Deriso (1999):

$$\ln(M) = -0.0152 - 0.279 \cdot \ln(L_\infty) + 0.6543 \cdot \ln(k) + 0.4634 \cdot \ln(T)$$

(iv) as for (ii) but with M given by the empirical relationship of Hoenig (1983):

$$\ln(M) = 1.44 - 0.982 \cdot \ln(t_m)$$

(v) as for (ii) but with M given by the empirical relationship from Fishbase (provided in Zhou et al 2011): $M = 10^{0.566 - 0.718 \cdot \ln(L_\infty)} + 0.02 \cdot T$

(vi) as for (ii) but with M given by the relationship in Jensen (1996): $M = \frac{1.65}{t_{mat}}$

where ω is the coefficient linking fishing mortality based reference points to natural mortality, which is set to 0.87 for teleosts and 0.41 for elasmobranchs in the current software used by CSIRO (Zhou et al 2012; which differs slightly from the values of 0.91 and 0.43 stated in Zhou et al 2011); r is the intrinsic rate of population growth (natural increase); M is instantaneous natural mortality; T the average annual water temperature; t_m the maximum reproductive age (or maximum lifespan) in years; t_{mat} the average age at maturity in years; and k and L_∞ are the von Bertalanffy growth parameters. If L_∞ is unknown, then maximum length L_{max} (if known) can be used to provide an estimate of L_∞ using the relationship from Froese and Binohlan (2000):

$$L_\infty = 0.044 + 0.9841 \cdot \log(L_{max})$$

As data availability varies, one or more of the above methods can be applied and the uncertainty in the value of the reference points captured by using the mean and range given by the various methods used.

Moving from a bSAFE to an eSAFE assessment does add the requirement for shot-by-shot fishery or survey data to enable the estimates of gear efficiency and fish density. If the data is available, the step is worth taking as it quantitatively improves the risk estimate and in some cases, refines the estimate to the equivalent of a Level 3 assessment. Although, qualitatively the result does not differ for many species, improvement was made for the two species examined (Zhou et al. 2019) . Consequently, there is considerable merit in using bSAFE as a filter (in the same way that Level 2 of the ERA is supposed to filter for Level 3) to judge whether the qualitative risk level merits applying eSAFE.

The main challenges in using SAFE are that the estimated fishing mortality rates may have high uncertainty and may not be accurate for a range of species and that the relationship between sustainability and life history parameters may differ among taxonomic groups/species and so the reference points given above may not be appropriate for all species (thus the ω coefficient).

The advantage of SAFE and the other similar methods is that clear mathematical equations are used in each step, allowing for transparency and quantification of reference points and uncertainty. It achieves this while remaining cost effective in that reference points can be calculated from a small number of life history parameters; computational resource requirements and data demands are minimal; and it can be rapidly run for all fish species impacted by a fishery. By focusing on fishing mortality rate, the SAFE approach maintains flexibility because alternative methods of estimating *F* can easily be substituted. Moreover, as the framework is similar to the typical management regimes in that they use clear fishing mortality rate-based reference points, the results can also be easily incorporated into fishery management plans. Crucially, the risk index produced is easily converted into a measure of absolute risk and can be adapted to a measure of cumulative impact e.g. by summing over the absolute risk per fishery, as done in Zhou et al. (2013). When Zhou et al. (2013) trialled the approach they found that cumulative impact does not increase linearly with the number of fisheries, as typically the majority of the fishing mortality (impact) to a particular species is due to just a few fisheries, with the rest of the fisheries having only minor effects. This suggests that costs and analytical effort can be saved by identifying the major sources of impact (i.e. the main fisheries effecting the species based on targeting, susceptibility to the gear type and relative levels of fishing effort within the species' distribution) and focusing on those major fishing sectors.

Notably, AFMA (2017) clearly states that where the area of a stock overlaps two (or more) fisheries then a cumulative risk assessment is necessary and that SAFE is the appropriate tool. But they note that the Australian SAFE approach (bSAFE or eSAFE) is currently only developed for teleost species and is not applied to seabirds, mammals, reptiles and invertebrates. The PSA approach used for these latter species cannot yet deal with cumulative risk. However, it would be a relatively straight forward modification to the ERA process to substitute the taxa specific SAFE-like approaches discussed further below (developed for seabirds, cetaceans, sharks etc) for these other species, thereby enabling assessment of cumulative effects of fishing for many more species. This would be a much easier solution than attempting to redevelop PSA for cumulative risk assessment.

Comparing PSA and SAFE

Zhou et al. (2016) and Griffiths et al. (2018b) provide good summaries of the main differences between PSA and SAFE methods, an overview of which is given in Table 16.

Table 16: Summary of the main differences between PSA and SAFE methods

Feature	PSA	SAFE
Resolution	Aggregate	Spatially (and potentially) temporally resolved
Availability	Based on species presence/absence in fished grid cells	Estimates are based on actual area per grid cell affected by fishing (e.g. gear swept area); eSAFE accounts for heterogeneous fish density
Escapement		Optional (if information available)
Species distributions	Bioregional (range) maps	• Bioregional (range) maps • Species distribution models • Surveys and observer data • Habitat surrogate
Susceptibility	Ordinal	Continuous (ratio)
Productivity	Traits (there can be ad hoc inclusion)	F-based reference points
Low productivity species (F_{MSY} < 0.4)	Productivity score increases proportionally with F_{MSY}	
Moderate-High productivity species ($F_{MSY} \geq 0.4$)	Insensitive (i.e. productivity score remains effectively constant)	
Species under low fishing pressure (F < 0.1)	Susceptibility increases with F	

Species under moderate-high fishing pressure ($F \geq 0.1$)	Susceptibility score at maximum level at F = 0.1 and cannot increase further	
Risk misclassification vs status reports or Level 3 assessment	50-90% false positive (i.e. classified as high risk when more quantitative methods suggest a lower risk species)	~5% false negative; 3% false positive Can over-estimate F_{MSY} for less productive species, can slightly under-estimate F_{MSY} for highly productive species
Threshold/Reference points	No biological significance	Biologically relevant
Cumulative effects	Not straightforward	First approximation = additive

SAFE-like Methods

This quantitative and spatial approach to determining fishing mortalities or risk has been modified or paralleled by a number of similar approaches for other taxa – such as seabirds (Small et al. 2013, Abrahams et al. 2017, Walker and Abrahams 2017), marine mammals (Goldsworthy and Page 2007, Brown et al. 2015), sharks (Hoyle et al. 2017), and habitats (Penney and Guinotte 2013, Pitcher et al 2016b). All of these methods assume bycatch is proportional to the overlap between the animals' distributions and fishing effort, however, the different studies have put various emphasis on refined estimates of effort distributions or seasonal species distributions.

Goldsworthy and Page (2007) were one of the first to point out the value of spatial risk maps in support of spatial management for bycatch species (particularly seals). In the absence of quantitative data on bycatch rates and impacts (e.g. on population status) the approach taken was to:

(i) estimate the size of each (sub)population using species-specific life-tables and pup production estimates.
(ii) estimate the spatial distribution of foraging effort for each species per sex and age class;
(iii) compare these species distributions with the distribution of fishing effort in order to develop spatial estimates of the probability of interaction;
(iv) undertake population viability analyses, using Leslie matrices and calculating terminal extinction risk and the time for the median of the simulated population trajectory to drop to below 10 females
(v) from (iv) identify the levels of bycatch that would shift the species one species listing category higher e.g. threatened to endangered; and
(vi) examine different bycatch scenarios to identify (sub)populations, regions and fishing areas with the greatest bycatch risk.

Clarke et al. (2018) also took a spatial PSA approach, combining it with a spatial Hotspot Analysis to identify (i) which elasmobranch species are most vulnerable to the Costa Rican shrimp trawl fishery and (ii) the location and seasonal variation in spatial clustering of vulnerable elasmobranchs. The PSA approach used the **P**roductivity attributes of Hobday et al. (2011) and the **S**usceptibility attributes of Patrick et al. (2010). Hotspot analysis looked for statistically significant spatial clustering of those sharks, skates and rays that might interact with the shrimp trawl fishery. They used a Global Moran's I statistic (G_i*) to estimate spatial autocorrelation: a statistically significant positive G_i* statistic indicated the presence of a hotspot for highly vulnerable elasmobranchs and a statistically significant negative statistic indicated a coldspot of elasmobranchs with low vulnerability to the shrimp trawl fishery.

The approach taken by Brown et al. (2015) was closer to the original form of the ERA. They created a spatial and temporal version of the PSA rating by calculating risk quarterly to account for seasonal differences at two scales: (a) 0.25° x 0.25° spatial grid and (b) entire EEZ. The temporal aspects were accounted for by re-scoring availability and encounterability and a new attribute, exposure, quarterly. The new spatial considerations were reflected in updated susceptibility attributes – see Table 17 – which extend/modify the attributes of Brown et al. (2013) (summarised in Table 7) . This chiefly involved adding a new attribute exposure (*ex*), which represents the potential exposure of the population being assessed to fishing activity in that cell, based on species abundance and the extent of fishing activity. This meant at the EEZ scale Brown et al. (2015) followed the method of Brown et al. (2013), but switching in the new definition of availability and updating the calculation of the ***S***usceptibility score to ensure that moderate or high scores could not be generated when a species does not overlap with fishing, or if the gears has low potential to capture the species ,as follows:

$$\boldsymbol{S} = \sqrt[6]{(av^2 \cdot en \cdot se^2 \cdot pl)}$$

The spatial form was quite similar, except that it included the additional term, exposure (*ex*), – calculated as:

$$ex_{qrt} = \log_{10}\left(\frac{ex_{j,qrt}}{\overline{ex_J}}\right)$$

where j is the grid cell, qrt is the quarter of the year and the exposure per cell ($ex_{j,qrt}$) and mean exposure ($\overline{ex_J}$) are given by:

$$ex_{j,qrt} = \frac{N_{j,qrt} \cdot E_{j,qrt}}{N_{EEZ,qrt}} \qquad \text{and} \qquad \overline{ex_J} = \frac{\overline{N_J} \cdot \overline{E_J}}{N_{EEZ}}$$

respectively, with N the species abundance and E fishing effort (activity). The relative risk score per cell per quarter is then given by:

$$\boldsymbol{S}_{j,qrt} = \sqrt[8]{(av_{j,qrt}^2 \cdot en_{qrt} \cdot se^2 \cdot pl \cdot ex_{j,qrt}^2)}$$

Table 17: Availability and exposure attributes of the updated approach used by Brown et al. (2015) – refer to Table 7 for the other attributes used.

	Attribute	Low	Medium	High
Susceptibility	Availability (overlap between fishing activity and species distribution)	<10% overlap	10-30% overlap	> 30% overlap
	Exposure (only for gridded assessment; omitted from EEZ scale assessment)	≤ 0.1 of mean exposure (score of -1)	exposure in cell = mean exposure (score of 0)	exposure in cell ≥ 10 times mean exposure (score of 1)

In an assessment of ICCAT fishing operations Tuck et al. (2011) also took an approach that saw a PSA-like rating of seabird fisheries bycatch risk and a spatial mapping of where those risks were most likely to happen. The measure of productivity used was based on the seabird's life-history strategy, specifically the frequency of breeding and clutch size. The scoring attributes used are summarised in Table 18. The behavioural susceptibility attribute was based on the tendency of seabirds to follow fishing vessels and the relative incidence of bycatch in ICCAT (or other fisheries).

As for the standard Australian ERAEF, missing or uncertain information was assigned a high risk score. Spatial exposure to fishing was then calculated as an overlap (but note that this overlap did not consider susceptibility to capture). A bycatch estimate per grid cell was then calculated by taking the overlap and bycatch observations to determine bycatch rates and multiplying them by fishing effort in that grid cell. Total bycatch was finally summed across the entire ICCAT area. This semiquantitative method was preferred because it was readily updateable as new information becomes available. Of the 68 seabird populations considered, three were rated as being at such high risk that a full demographic population model (Level 3) assessment was undertaken, which used a sex-disaggregated, multi-life stage model to quantify at-sea distributions of seabirds at each life stage in each month of the year and the potential number caught per fleet.

Table 18: Attributes used in the assessment of Tuck et al (2011). Scores are: Low (1), Medium (2) and High (3).

	Attribute	Low	Medium	High
Productivity	Life history strategy	Annual breeder, multiple egg clutch	Annual breeder, single egg clutch	Single egg clutch
Susceptibility	Global IUCN status	Near Threatened (score of 1) or Least Concern (score of 0)	Vulnerable	Critically endangered or Endangered
	Breeding population status	Stable (score of 1) or Increase (score of 0)	Decline	Rapid decline (> 2% per year)
	Degree of overlap with ICCAT fishery	Low	Medium	High
	Behavioural susceptibility to capture	Low	-	High

Small et al. (2013) took a different approach and looked at a number of ERAEF-like studies across many jurisdictions - CCAMLR, WCPFC , MFish and ICCAT, most of which pre-screen for taxa known to be caught in their domain. They noted that while inclusivity would be more appropriate when species-specific bycatch data are sparse, one of the challenges is that it is impossible to determine the relative overlap of fisheries with specific seabird populations without independent information on the seabird's distribution (e.g. tracking data, ring recoveries etc.). A compromise, in their opinion, was to restrict the species considered to those most appropriate for the type of fishery/sector/fleet/gear type. For example, when considering a longline fishery a focus was on surface feeders, while for a gillnet fishery diving species were (would be) added etc. Susceptibility was calculated as the overlap of the species and the fishery, but there was a range of ways in which this was achieved from simplistic (imprecise) gross ranges through to complex calculations that could potentially provide a false perception of precision or was only possible for a small set of species with sufficient data. The best practice approach was to recognise seasonal differences in the overlap for breeders and non-breeders and by accounting for the behaviour of the seabirds and fleets. The method that most rigorously estimated susceptibility was the likelihood of capture (l_{cap}):

$$l_{cap} = N_{pop,mth,i} \cdot E_{mth,i}$$

where $N_{pop,mth,i}$ is the seasonal population density in spatial cell i and $E_{mth,I}$ is the fishing effort in that cell in that season. If population density isn't available, then seasonal species distributional ranges can be used and failing that, simpler gross species distributions. For example, when no specific information (e.g. tracking data) is available for each life stage then simple assumptions can be made such as a feeding radius from a rookery. However, when using such assumptions, it is important to have the distributions checked by experts and to check the sensitivity of the risk results to those assumed distributions (or the use of parameters taken from congeners); and not to use them to infer when bycatch is not occurring. While spatially resolved distributions (especially those using seasonal population density) are most helpful for informing targeted monitoring and bycatch mitigation, it is also important to recognise that there is no need to resolve the bird distributions to a finer resolution than that of the available effort maps. Where it is possible to put some faith in the risk maps, it is then possible to explore compound risk. For example, WPCFC not only produced risk maps per species quarter, but also summed across species-fishery risk scores to show (a) which species were most at risk and (b) which fleets posed the greatest risk across species (Small et al. 2013). There have been a number of similar risk mapping exercises and compound risk analyses undertaken for birds, including Abraham et al. (2017) and Walker and Abraham (2017) who employed the Spatially Explicit Risk Assessment Framework (SEFRA), which was originally developed for seabirds and has since been used for other wide ranging species. This approach produced risk maps using observer based effort data, observed bycatch, seabird distribution data, and fisheries effort data; obtaining seasonal species distributions by combining the distributions for non-breeders and breeders. Essentially, bycatch rates were created for the entire fleet by statistically extrapolating observer and fisheries data.

Kirby et al. (2009) took a more PSA-like approach, but spatialised the outcomes. They assessed areas in terms of absolute numbers of seabirds; areas frequented by more seabird species (which were identifying 'biodiversity hotspots'); the number of individuals potentially affected by fishing-induced mortality in any particular area (so areas where high levels of fisheries interactions with any seabird species could be identified); and areas where fisheries pose the most risk of population-level effects. In this instance susceptibility was given as:

$$S = N_i \cdot E_i$$

and productivity as r_{max}. To avoid the case where a seabird that had very little exposure to fishing (i.e. extremely low susceptibility) could still come out as high risk due to low-productivity, final risk score was calculated as:

$$R = \sqrt{\sqrt{\frac{S}{P}}}$$

and then evenly divided the scores into five bins so that each species was categorised with a relative risk level somewhere on the scale of negligible to high risk. Kirby et al. (2009) expressed the desire to include seasonality, inter-annual variation, estimates of catchability, and fisher behaviour (targeting) in future analyses.

Waugh et al. (2012) also followed this spatial PSA approach. Species distributions were calculated using an assumption of exponential decline to create a foraging radius and then for each season, computing a composite map from the combination of a seasonal breeder layer and seasonal non-breeder layer on a global scale, assuming 100% of the species population is distributed within the estimated range of the species. Similarly, to the other spatially resolved approaches, the **S**usceptibility indicator was then calculated as the product of fishing effort and normalised species distributions (i.e. proportion of a species' range), weighted by the **V**ulnerability of the different species to the focal (longline) fishing gear. In this case, using observer data, **V** was estimated for each species group by fitting a generalised linear model to captures and density data. The calculation was repeated both using an r_{max} estimate for **P**roductivity and using Fecundity Factors Index (FFI); given both are based on age at first reproduction it is not surprising that a good correlation was found between the results using the two **P**roductivity measures (they ultimately defaulted to FFI as they found it a simpler and more robust index). Risk was then calculated and binned as for Kirby et al. (2009). For missing data, Waugh et al. (2012) used best average estimates for parameters rather than making them high risk and no explicit reporting of uncertainty was given. Then, total risk per season and area was calculated as the sum over species and fleets. This mapping showed, risk is not evenly spread among the fishing nations participating in the fishery; that there are seasonal hotspots of seabird–fishery interactions; and that "risk is not simply proportional to the amount of fishing effort in the region, as differential vulnerability of species, and populations' ability to recover from occasional removals leads to effects being concentrated in some areas more than others" (Waugh et al. 2012).

Waugh et al. (2009) took a slightly different approach, combining their spatial mapping with explicit codification of the post capture mortality, to recognise that some fishing gears have a greater chance of causing mortality when interacting with a given species than others. Species also have different propensities for being caught and for recovering from injury. These additional considerations were accounted for in their analysis by fitting a generalized linear model to the captures and density data, for observed fishing events from each fishery. The resulting tables of likely captures were compared against species specific levels of "acceptable mortality" defined by the Potential Biological Removals (PBR) index:

$$PBR = 0.5 \cdot N_{min} \cdot r_{max} \cdot \zeta$$

where N_{min} is a conservative estimate of population size and ζ is set based on management goals (it is typically set to 0.5 for seabirds; see references provided in Waugh et al 2009). This then gave the final levels of risk, defined by the New Zealand Ministry of Fisheries as:

- Very High risk, where the likely captures exceeded the PBR index (risk score of >1.1);
- High risk (0.8 – 1.1);
- Moderate risk (0.4 – 0.79);
- and Low risk (< 0.4).

To be sure about how typical data issues might distort the outcomes, a sensitivity analysis of the method was undertaken to test for: the influence of 'unusual' survival inputs to the PBR index; the effect of using alternative sets of weightings on the distribution maps for species (especially cryptic kills); the implications of using vulnerability values from the extremes of the ranges generated (90% Confidence Limit (CL) on V); using cryptic kill values for trawl warp strike; and the size of the population size of sooty shearwaters (*Ardenna grisea*) (whether it is 20 million, 2 million, or 200,000 individuals).
All these issues were ultimately found to affect the risk scores for some species. Waugh et al. (2009) acknowledged that life-history parameter values for some species had to be inferred from other species and that fisheries with poor data were excluded. Moreover, the analysis did not address possible indirect fisheries-related impacts (e.g. trophic effects), other sources of mortality like invading predators, mortality external to New Zealand waters, or mortality due to non-fisheries sources – i.e. it only focused on mortality due to fisheries activities in New Zealand

waters. Waugh et al. (2009) would like to (i) update their analyses through time, as better biological information became available; (ii) acknowledge that effective management will change the vulnerability estimate and overlap through time; and (iii) to explore seasonality in future analyses.

Richard et al. (2017) took a very different approach to their Spatially Explicit Framework for Risk Assessment (SEFRA) in NZ waters, which they developed to address limitations identified in previous risk assessments. The SEFRA approach assumes a risk ratio calculated as annual potential fatalities divided by a Population Sustainability Threshold (PST), where PST was a generalisation of the Potential Biological Removal (PBR) index given by:

$$PST = 0.5 \cdot N_b \cdot r_{max} \cdot \zeta$$

where N_b is no longer the lower quartile (conservative population estimate) used previously in the PBR but is instead based on the total number of breeding pairs estimated using a simpler equilibrium survivorship model, explicitly including the uncertainty in all demographic parameters used, with the extra addition of a taxa-specific calibration factor to bias correct from the demographic model to observed breeding population estimates. The approach in calculating r_{max} was also updated by using of allometric modelling to reduce variability in the estimates of age at first reproduction and of adult survival, which are used in estimating r_{max} following the approach used in Waugh et al. (2012). The management coefficient was also intentionally set to 0.5 rather than just adopting the literature value of 0.5 under the clear management mandate of ensuring that the populations met the long-term goal of remaining above half their carrying capacity in the presence of environmental variability. With these updates, PST becomes the measure of seabird population productivity and differs from the PBR by explicitly including the uncertainty in population size rather than relying on a conservative point estimate of population size, and by not including a recovery factor.

In addition to these changes to the productivity calculation, the susceptibility approach was also updated. While annual potential fatalities is still estimated using spatial overlap, focussing on fatalities from the fisheries with sufficient observations, improvements to the estimation of potential fatalities included: the incorporation of cryptic mortalities i.e. seabirds that are killed by the fishing activity but not brought on-board the fishing vessel and not included in captures reported by fisheries observers; and for taxa with small populations, seabirds were aggregated into species groups with taxa within the same group assumed to have a similar vulnerability to capture in fisheries. These mortalities were estimated by using an integrated model consisting of a Poisson process fitted within a Bayesian statistical framework that allowed the joint estimation of the parameters e.g. vulnerabilities, proportion of captures released alive, from data on observed fishing effort and seabird captures. This approach prevented the estimates of mortality due to fishing exceeding the total annual mortality of the adult population, and to ensure that estimated mortalities, seabird population size and adult survival were mutually consistent.

Richard et al. (2017) then estimated vulnerability by fishery groups (métiers or fleets), where these groups were assigned based on, the target species, vessel size, and depth (specifically to identify trawling for middle-depth species) and whether there was on-board processing. Interactions between the seabirds and the fleet were assumed to be proportional to the overlap between the species distribution and the fishing activities with units of the overlap being birds km^{-2} effort^{-1} (where the unit of effort was defined as the number of tows for trawl fisheries, the number of lines set for bottom-and surface-longline fisheries, and the net length (metres) for set-net fisheries). In modelling the vulnerability, Richard et al. (2017) allowed for species to be differentially taken by different types of fisheries, to be differentially attracted to fishing vessels than others, or to behave in a way that makes them more likely to be caught when they are around fishing vessels and for fleet and gear technology creep/changes (specifically vulnerability was allowed to vary before and after 2010). Global species distributions were mapped seasonally using data from multiple sources and were scaled based on the proportion of the population in New Zealand waters in that season. For the breeding season, two distribution layers were created, one for the non-breeders and one for the breeders (where the relative density of decrease exponentially with the distance to colonies). Consequently, the risk bins of Waugh et al. (2009) were updated to:

- Very high risk: median risk ratio above 1 or an upper 95% bound of credible interval for the risk ratio above 2;
- High risk: median above 0.3 or an upper 95% credible limit above 1;
- Medium risk: median above 0.1 or an upper 95% credible limit above 0.3;
- Low risk: upper 95% credible limit above 0.1;
- Negligible risk: upper 95% credible limit less than 0.1.

As with any of the risk assessments discussed in this report, Richard et al. (2017) relied on some subjective decisions to address limitations due to paucity of data e.g. for at-sea distribution of seabirds, seabird demography and seabird captures. They tried to address this by exploring the impact of parametric uncertainty on the final uncertainty in the risk ratio. This was done by calculating the percentage reduction in the range of the 95% credible interval of the estimated risk ratios as each source of uncertainty was varied. The highest sensitivity to uncertainty in the majority of taxa came from the estimates of annual potential fatalities, especially those due to trawl fisheries. In addition to reducing this source of uncertainty (particularly the level of cryptic mortality), Richard et al. (2017) identified the need to include ontogenetic survival rates, estimation of the vulnerability and cumulative impacts due to the activities of other sectors in New Zealand waters and sectors beyond New Zealand for migratory species in future work.

Hoyle et al. (2017) (and Fu et al. (2017) who applied Hoyle et al.'s method) also chose a spatially-explicit risk assessment method that uses the spatial overlap of fishing and species distributions and density to derive a risk metric for the porbeagle shark (*Lamna nasus*) in the southern hemisphere. Hoyle et al. (2017) took a statistical delta lognormal approach, first modelling the probability of nonzero catch and then modelling the distribution of catch rates for non-zero catches. This approach required estimation of a catchability coefficient, which was achieved by fitting a logistic production model to available data in the most data-rich of the five assessment regions considered. This catchability scalar was then applied to effort overlap in all other regions to estimate spatially-explicit annual fishing mortality rates. The sum of these rates is finally used to calculate risk as shown in Figure 8, where the annual mortality rates are compared to a maximum impact sustainable threshold (MIST) – which is equivalent in definition to Zhou et al. (2013) F_{crash} – and is a limit reference point derived from the intrinsic rate of population growth.

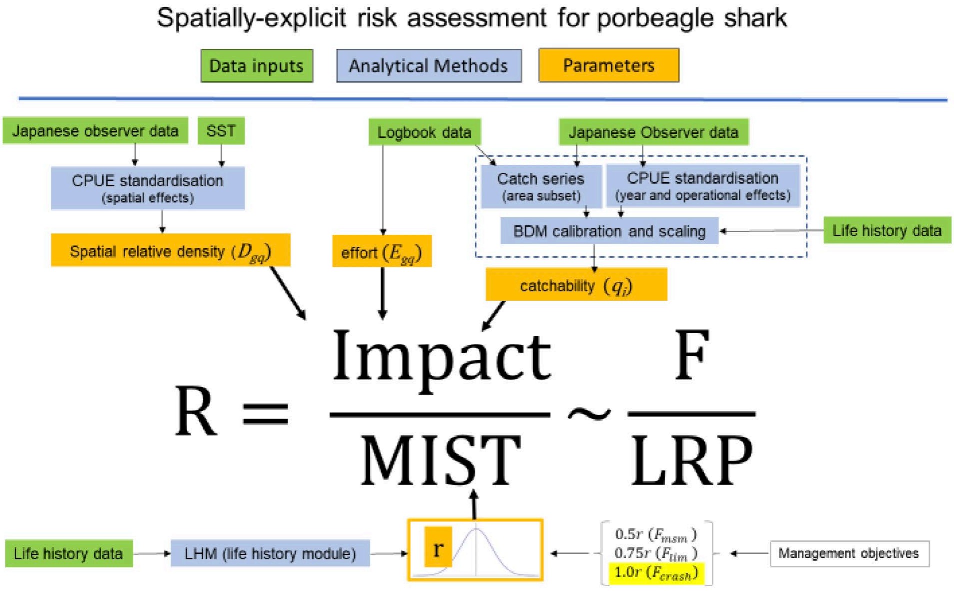


Figure 8: Conceptual diagram of steps used to calculate risk in Hoyle et al. (2017).

Abundance indices (relative population density across the spatial domain) through time were required as inputs into this risk assessment approach. These estimates were assumed to serve as indicators of population trend and condition and were estimated from commercial CPUE data. Trends in size and sex ratio based on biological data were used as a cross check on the abundance trends. While the abundance indicators were highly variable, they showed spatial patterns and relationships with environmental variables. However, it was noted that the assessment was sensitive to the catch rate indicators and their reliability determines the assessment's reliability. Nevertheless, the spatial nature of the assessment allowed for a prioritisation of fishery areas for monitoring and management and highlighted key biological information gaps to be filled.

EASI-Fish (Griffiths et al. 2018b) has perhaps taken this spatial risk assessment approach to cumulative estimates of combined fishing pressure the furthest, introducing a step where biological status versus reference points is calculated so that the species can be plotted on a Fishing mortality (F) vs Biomass (B) plot rather than a PSA risk plot. The susceptibility of species per fishery is calculated quite similarly to other approaches, except that it is calculated per length class, using the product (multiplication) of: (i) area overlap (the proportion of the species' distribution exposed to the fishery, based on GAMs or other methods such as species distribution models e.g. Maxent); (ii) duration of the fishing season (proportion of the year the fishery is open); (iii) seasonal availability (proportion of the year the species is available for capture in the fishery, to allow for migratory behaviour to be reflected in the estimate); (iv) encounterability (proportion of a species' vertical distribution in which it is exposed to the fishery); (v) selectivity (proportion of fish encountering the gear that are caught); and (vi) post-release mortality (the proportion of released fish that die). The total **S**usceptible proportion of the population caught by each fishery is then summed and converted to become a proxy for F (per grid cell) using:

$$F = -\ln\left[1 - \sum_x q_x E_x \left(\frac{\sum_j S_{j,x}}{n}\right)\right]$$

where n is the number of length classes defined for species j, E_x is relative effort in that grid cell, and q_x is catchability. These F and associated SSB-per-recruit estimates are then compared to reference points from simple per-recruit models (length-based yield per-recruit model) using standard F vs B phase plots (e.g. see

Figure 9) which are of a form similar to F vs SSB plots which many managers are already familiar with. The reference points used are typically $F_{0.4}$ and $F_{0.1}$.

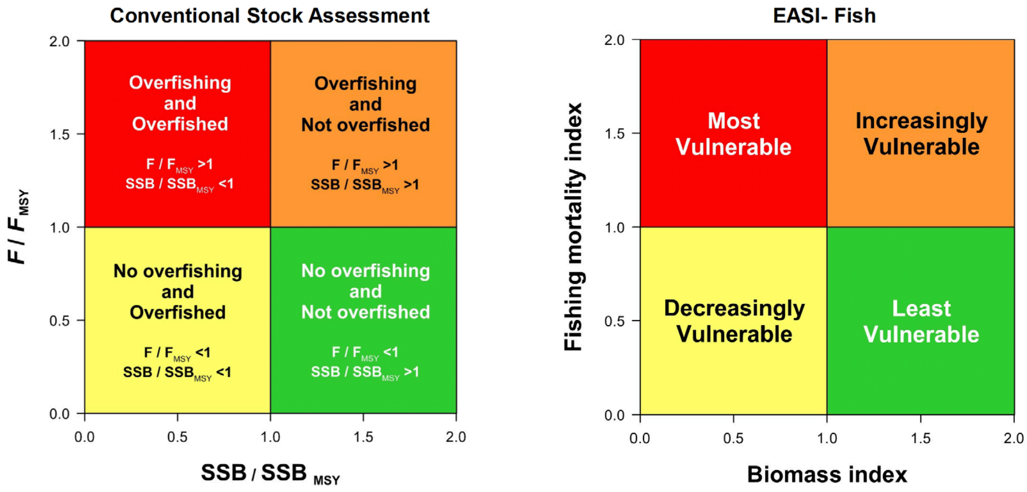


Figure 9: Example phase plot. Reproduced from Griffiths et al. (2018a).

Griffiths et al. (2018b) especially disaggregated selectivity components (as far as practicable) given selectivity curves are unlikely to be available for data-poor bycatch species, which was their focus. This also allows the individual components to be parameterized if information is available, or the default assumption of full selection can be used as a precautionary measure in the absence of reliable information. Monte Carlo simulations can also be used to generate uncertainty estimates for each model parameter given specified prior distributions. As with SAFE, EASI-Fish also produced far fewer false positive risk scores than a PSA, while remaining precautionary.

Griffiths et al. (2018b) also developed a qualitative data reliability index, which provided a measure of the quality/precision of parameters or data used in the analysis and the source of the information versus relevance to the study species and area (Figure 10). This gives some idea of the reliability of the model results. The parameter quality scores are represented in a radar plot for each species, to allow for easy interpretation of the analysis across a large number of model parameters (e.g. Figure 11).

		High reliability		Medium reliability		Low reliability		No data
Species	Region	High precision	Low precision	High precision	Low precision	High precision	Low precision	
Species-specific	Local	10	9	8	7	6	5	0
	Adjacent	9	8	7	6	5	4	0
	Other	8	7	6	5	4	3	0
Related species	Local	7	6	5	4	3	2	0
	Adjacent	6	5	4	3	2	1	0
	Other	5	4	3	2	1	1	0

Figure 10: Qualitative data reliability index (figure generalised based on Table 2 in Griffiths et al (2018b)).

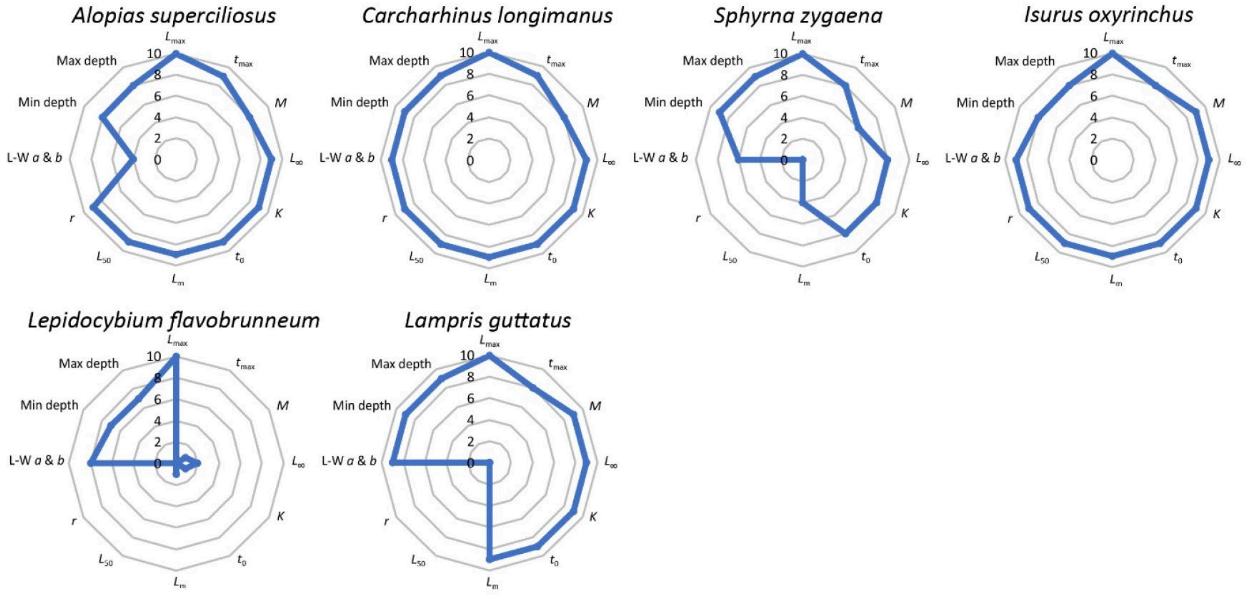


Figure 11: Example data reliability index scores per biological parameter per species (from Griffiths et al. 2018b).

Additional Means of Linking ERA Level-2 Results to Management

The EASI-Fish approach is not the only one where efforts have been made to directly connect the outputs of the ERA process to management. One of the first to take the ERA-like approach (indeed an ERA precursor) and translate the outcomes into management was Stobutzki et al. (2001). This involved applying an L2 like method to bycatch species in the NPF, defining risk in terms of susceptibility to capture and the population's capacity to recover which later became the productivity score; with the score per axis set by the weighted average of the attributes for that axis. Partial correlations were used to determine whether there was any redundancy in the attributes considered per axis. The link to management came through recognizing that some attributes on the recovery axis can be influenced, specifically removal (catch) rate, the probability of breeding before capture and the mortality index (which is related to whether turtle excluder devices or bycatch reduction devices are used; and to changes in closures or allowed effort levels). Stobutzki et al. (2001) stated that the idea behind using this approach was to maximise the utility of the (limited) available information and to provide a means of assisting researchers and managers to focus on (i) the species that are most likely to be unsustainable, or (ii) gaps in knowledge that affect the assessment of species' sustainability.

ERA L2-like rating were also used to define indicator species by Newman et al. (2018) who used those indicator species to guide and assess the overall management of a small (by volume, but very highly biodiverse) multispecies fishery in Western Australia. Tallman et al. (2019) also used an L2-like (PSA) rating approach to distinguish between regions where Arctic Charr populations may be more (or less) vulnerable to fishing; and to identify area-specific indicator stocks corresponding to the most vulnerable populations. They noted that with "limited information and data collection, PSA results may be used as a precautionary step for guiding management decisions in decision analysis or management strategy frameworks." Now that they have some idea of which are the indicator populations, Tallman et al. are asking local/traditional knowledge holders to help bring their knowledge into these data poor methods and to establish realistic monitoring and conservation plans.

5 Level 3

Level 3 species assessments are full quantitative assessments, typically taking the form of a population dynamics model or other formal estimation of abundance and mortality rates for the species in question. Many of these assessments are a standard part of Australian fisheries management for key target species. For habitat or community assessment, similar multispecies or ecosystem models may be used. There are a broad range of such models available to fisheries science, which have been reviewed in depth elsewhere with useful summaries including Plagányi 2007, Travers et al. 2008, Fulton 2010, ICES 2012, Punt et al. 2013, Fulton and Link 2014, Plagányi et al. 2014, Cadrin and Dickey-Collas 2015, Chrysafi and Kuparinen 2016, Aeberhard et al. 2018.

The diversity of approaches for single-species stock assessment models can be classified into a few broad classes based on modelling approach and data needs (Punt et al. 2013, Cadrin and Dickey-Collas 2015): (i) catch only models, (ii) time-series models, (iii) surplus production (or biomass dynamics) models, (iv) age- (or stage-) or size-structured models. All approaches have associated strengths and weaknesses (Maunder and Piner 2015). If the species to be assessed at Level 3 is "data limited" the process is more difficult, but even then, options exist for determining whether the stock is sits above a target reference point e.g. as shown in Cope and Punt (2009); Dowling et al. (2016) and Carruthers and Hordyk (2018) provide useful reviews.

While Level 3 assessment methods are standard practice for teleosts (forming the basis of much single species stock assessments), other taxa have fewer available examples. Within published ERAs, the exception is seabirds, where a few Level 3 assessments have been undertaken. These assessments typically use the Potential Biological Removals (PBR) or PBR-like approach, such as Jiménez et al. (2012).

6 Habitats and communities

While conceptual inclusion of habitats and communities into ERAEF began at an early stage they have received far less attention than the species and stock focused methods discussed in the previous sections. Indeed, Holt et al. (2012) developed a classification scheme for habitats and communities as one of the outstanding requirements for ERA approaches. Indeed it has really only been habitats that have received any real degree of attention and this section will focus on a review of those studies.

De Lange et al. (2010) lists a number of attributes that should be considered required aspects for a habitat or ecosystem level risk assessment: likelihood of exposure; community structure and function; sensitivity to stressors or toxicity; the role of sensitive species in community (e.g. whether they are ecosystem engineers); recovery or adaptive capacity; degree of degradation; existence ("naturalistic") value e.g. a protected area; and socioeconomic value. A Utility Index based on expert ranking of the attributes specifies the suitability of a species as a sentinel of exposure to a stressor, which is a means of selecting the appropriate species to use in biomonitoring. However, the same index could be used as an index of risk. Structured decision trees, as used by Depestele et al. (2014) in their assessment, could help repeatably extend the ERA approach to habitats, communities and ecosystems.

The Coastal Vulnerability and Habitat Risk Assessment (HRA) modules of the Integrated Valuation of Environmental Services and Tradeoffs (InVEST) version 3 software has been used in a number of places to provide cumulative risk maps for marine and coastal habitats (e.g. Eliff and Kikuchi 2017). These approaches either use additive overlaps, or geometric means of qualitative scores based on geomorphology, relief, bathymetry, biogenic habitat distribution, wind and wave exposure (etc) to determine the relative risk (or health) of the systems in question.

Williams et al. (2011) outlined the method applied to non-habitat taxa underlying AFMA's standard approach to the topic; using the same Level 1 and Level 2 screening logic, scoring habitats based on attributes describing the resistance of a habitat to specific fishing gears (its **S**usceptibility) and its resilience or ability to recover form damage (**P**roductivity). Seabed imagery was used to identify habitat units to assess, where habitats were defined based on physical seafloor structure and attached invertebrate fauna. Attributes used in the assessment are given in Table 5. While the attributes used for the habitat PSA are generic, the thresholds can be defined uniquely to a sub-fishery. This captures differences in taxa of interest (much like the taxonomic variants found for vertebrates), fishing methods, regions and depths fished. The standard equations are used to obtain the final Productivity (additive mean) and Susceptibility (geometric mean) scores. While there was no concern over the technical approach, Williams et al. (2011) expressed concern that the data for most habitats often constrained the analysis to two productivity attributes rather than the full suite identified in Table 5, which forced a heavy reliance on a residual risk analysis to reduce the number of false positives or negatives. They concluded that the attributes available for habitats cause the PSA for habitats to be scale-dependent when applied to fisheries that operate over large areas. Essentially, the larger the area assessed, the more the fixed scale of 1-3 must stretch: conditions that may rate as "most vulnerable" within a small area, might be considered only moderate at a larger scale where "even more vulnerable" examples can be found.

These concerns have been somewhat modified by newer more quantitative approaches that use habitat distribution models, which are effectively equivalent to eSAFE or even Level 3 assessments.

Penney and Guinotte (2013) used benthos distribution models (MAXENT) and mapped effort as a basis for plotting the likelihood of vulnerable marine ecosystem (VME) occurrence against the likelihood of fishery interaction (cumulative swept area) to quantify the risk of significant impacts on VMEs per management block. These plots were quite similar in form to a PSA (see Figure 12; A & B), but instead of each point representing a species or stock they represented a management area (spatial block). As the predictive habitat models simply predicted the likelihood of favourable habitat for VMEs using a wide variety of predictor variables and available data for ground truthing was incomplete, the scores were discounted for the assumed effects of historical fishing in each spatial cell. Penney and Guinotte (2013) recognise that ground truthing of the habitat models is critical for placing confidence in the assessment. They also indicated that integrating data on substratum type into the habitat models would improve the predictions.

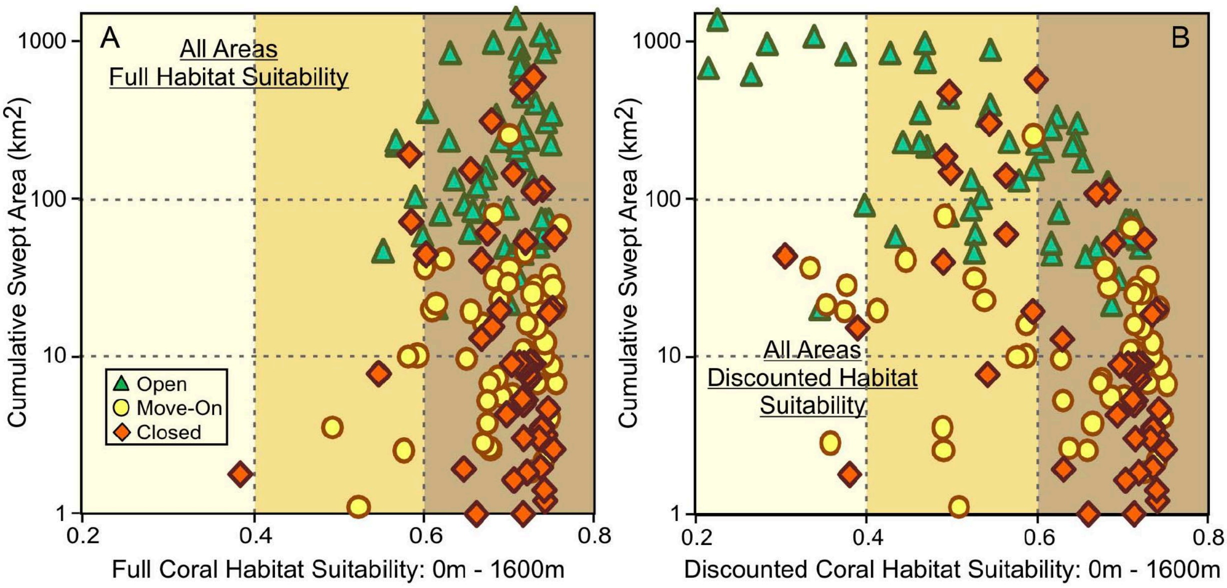


Figure 12: Example of the presentation of results by Penney and Guinotte (2013). A: Full Coral Habitat suitability; B: Discounted Coral Habitat Suitability.

More recently, Pitcher (2014), Pitcher et al. (2016a) and Pitcher et al. (2016b) have put considerable effort into developing and refining impact and risk assessment methods for habitats. Pitcher (2014) created general linear models (GLMs) predicting biomass distribution maps for around 850 benthic species (bycatch species and habitats) within Australia's Great Barrier Reef region. The overlap of these distribution maps was then compared with the fishery effort footprint of the fishery with final risk calculated using exposure indicators of increasing specificity – progressively accounting for management zoning, trawling footprint and intensity, relative catchability of species by trawls, and species productivity. A trawl exposure score (R) for species j in grid cell i was given as:

$$R_{i,j} = q_j \cdot \frac{A_{i,j}}{A_j} \cdot E_i$$

where q_j is the relative catch rate for species *j*.

These *R* values per grid cell were summed to provide the overall “percentage caught” index for the entire region, which was plotted against a recovery (productivity) axis to produce a PSA-like plot. The SAFE method was also applied, using exploitation rate (u) rather than F and employing more conservative reference points – so that ω (the coefficient linking fishing mortality based reference points to natural mortality) is 0.37 or 0.6 instead of the standard values used in SAFE. In comparing the relative risk as defined by the PSA-like method versus the SAFE method, they found different species were identified to be at risk by the different approaches i.e. there was a limited correspondence between the qualitative and quantitative methods, which contrasts with the general agreement between the two approaches found by Zhou et al. (2016).

Pitcher et al. (2016b) presented an assessment of habitat risk to trawling in Australia’s EEZ. It followed a similar approach to Pitcher (2014) but replaced the MAXENT models with assemblage maps estimated using the “Gradient Forest" method, which fitted an ensemble of bootstrapped regression tree between species abundance and environmental variables. The resulting cumulative turnover curves were transformed into a common biological scale and principal components analysis (PCA) run on the transformed information to identify assemblages by capturing the majority of compositional variation associated with environmental gradients in as few dimensions as possible. The PCA ordination was then mapped spatially to allow for visualisation of compositional patterns geographically, which was converted into an index of exposure by overlaying the trawl footprint to quantify percentage exposure; similarly, a percentage protection can be calculated by overlaying with spatial management zones. One of the recognised weaknesses of this approach is if there are insufficient data for the analyses of many species – typically more than half of species observed in biological surveys of an area. Moreover, of those with adequate occurrence data, up to a third show no statistical relationship with the environment, and even if a relationship is found, it may only explain a small percentage (<40%) of the variation in abundance. Furthermore, there is a lack of information on susceptible habitat components within the assemblages identified using the method.

Pitcher et al. (2017) undertook a Level3 assessment of the benthos in Exmouth Gulf (Australia) by calculating relative benthic status (RBS) per grid-cell based on trawl effort, depletion and recovery rates. The assessment model used was a Schaefer (1954)-type logistic population growth equation, that, when re-arranged, gives RBS as:

$$RBS = \frac{B}{K} = 1 - \frac{F \cdot D}{R}$$

where B is the biomass of the species of interest, K is the carrying capacity, F is swept-area ratio (the proportion of an area fished, which is a measure of fishing pressure or effort), D is the depletion rate and R is the recovery rate. Pitcher et al. (2017) noted that this representation was suitable for sedentary species but that cell-connectivity parameters could be added for mobile fauna (if available). This approach to estimating B/K requires relatively few parameters; habitat type, trawl effort, depletion rates and recovery rates. The fishery-wide status of habitats, accounting for their different sensitivity and exposure to trawling, was quantified by plotting the distribution of the RBS values against proportion of habitat area, or by the region-wide average RBS value.

7 Gaps & Extensions

This section discusses key gaps and extensions and provides recommendations for consideration in any future revision(s) of the ERAEF method.

Climate analysis

A remaining missing consideration in the PSA is the influence of climate change and variability. In its original form, the PSA (a) assumes biological characteristics are intrinsic and immutable and (b) is retrospective/instantaneous in terms of the interaction with fisheries. Climate induced shifts in life history or food web associated characteristics or trajectories of change in fishing practices are not currently considered in current Australian Level 2 analyses. Even if management bodies do not feel comfortable to project trends in fishing practices (e.g. fishing power) the influence of climate either directly or indirectly (e.g., Pecl et al. 2017, Barange et al. 2018) probably warrants special attention (Lucena-Fredou et al. 2017) especially where it (a) impacts upon productivity (e.g. via reducing survivorship or recruitment) or (b) influences susceptibility by changing species distribution (availability or encounterability). Given the overlap in traits between PSA and climate vulnerability analyses that consider influences on abundance, distribution and phenology (e.g. Pecl et al. 2011), it should be possible, with a little thought, to combine the approaches. Moreover, PSA scoring could be periodically updated with new observed values for the traits of species influenced by climate change. ERAs could also be made forward looking by not only looking at past observed species distributions in SAFE and similar assessments, but also by considering future projected species distributions.

Gaichas et al. (2014) was one of the first to bring an ERA-like approach to consider climate factors. They used literature and thought experiments to define physical mechanisms of action of climate change (Table 19) and the forms of potential biological impact and response (Table 20). For each climate attribute - biological response pair, they rated whether there was an expected change in that biological response as a result of that climate attribute (Yes, No, Maybe). If a response was predicted, the predicted general direction of change was recorded. Confidence in these ratings were scored on a scale of 1 (low confidence) – 5 (high confidence). Exposure vs sensitivity was then plotted in a PSA-like plot (Figure 13). Gaichas et al. (2014) undertook the analysis at the community level, rather than at the species level, as it was a preliminary analysis and rating each individual species and aggregating the results was too time-consuming for this proof of concept. However, Hare et al. (2016) showed that the approach can be straightforwardly completed at the species level. Expert scoring was used for climate exposure (based on projections synthesised for the scoring effort), directional effect of climate change, species sensitivity, expert certainty and data quality. The major difference between Gaichas et al. (2014) and Hare et al. (2016) was that a longer list of attributes was scored in Hare et al. (2016), but only as Low or High (Table 21), compared to 4 possible scores in Gaichas et al. (2014). Also, climate exposure did not just include environmental projections in this case, but also the estimated potential for a species/community distribution change.

Table 19: Anticipated climate change mechanisms and criteria for evaluating their probability of occurrence, severity, duration, spatial scale, trend and confidence of qualitative scores as defined in Gaichas et al. (2014). s.d.: standard deviation.

Climate change mechanism	Probability of occurrence	Degree (severity)	Duration	Trend	Spatial scale	Confidence
1. Temperature • Warmer surface water • Warmer bottom water	0 = None, no evidence from modelling or observations	*Only rated if probability of occurrence > 0*	*Only rated if probability of occurrence > 0*	*Only rated if probability of occurrence > 0*	*Only rated if probability of occurrence > 0*	0 = None, change has never been investigated
• Increased warm water • Thermal habitat volume (12-23°C)	1 = Low: no observations or not predicted by most models	1 = Low: change within 1 s.d. of baseline (or <33% above global average)	1 = Low: change present <33% of recent years	1 = Low: no trend or current trend returning toward baseline	1 = Low: change affects <33% of the area	1 = Low: little scientific information to support rating
2. Hydrography • Change in prevailing winds • Rising sea level • Shifts in major boundary currents	2 = Moderate: few observations or predicted in only some models	2 = Moderate: change > 1 s.d. of baseline (or 33-66% above global average)	2 = Moderate: change present 33-66% of recent years	2 = Moderate: Non-significant recent trend away from baseline	2 = Moderate: change affects 33-66% of the area	2 = Moderate: some scientific information to support rating, but conflicting
3. Salinity • Fresher surface water • Fresher bottom water	3 = High: observed or predicted by most models	3 = High: change > 2 s.d. of baseline (or >66% above global average)	3 = High: change present >66% of recent years	3 = High: Significant recent trend away from baseline	3 = High: change affects >66% of the area	3 = High: much information supports rating with few conflicts
4. Mixing • Impeded vertical mixing • Increased riverine water inputs	4 = Very High: observed in majority of past 5 years or in most models					4 = Very High: well observed phenomena, no conflicting scientific information
5. Lower dissolved oxygen **6. Increased acidity** **7. Mixing** • Increased storm frequency • Increased storm intensity **8. Cumulative** • Change in seasonal timing • Earlier spring	5 = Certain: commonly observed for past 10 years and is projected to continue by all models					

Table 20: Attributes for rating climate sensitivity in Gaichas et al (2014). Scores are: Low (1), Medium (2), High (3) and Very High (4).

Attribute	Low	Medium	High	Very High
Habitat specificity	Generalist	Particular preference	Specialist, abundant habitat	Restricted specialist
Prey specificity	Wide range	Limited number of prey types	Preferred single prey, switching detrimental	Specialist, no prey switching
Sensitivity to ocean acidification	Not reliant on shelled species	Somewhat reliant on shelled species	Reliant on shelled species	Shelled species
Sensitivity to temperature	Large range	Moderate range	Limited range	Very limited range (or depth band)
Reproductive strategy*	Simple	2 characteristics	3 characteristics	4+ characteristics
Annual spawning events	Continuous spawning throughout year	Several events	Confined time frame	Single narrow event
Early life history survival and settlement requirements	Minimal for larval	Minimal or unknown for larval	Specific larval requirements	Very specific larval requirements
Dispersal of early life stages (eggs and larvae)	Highly dispersed	Moderate	Low	Minimal

Attribute	Low	Medium	High	Very High
Adult mobility	Non-site dependent	Mobile, but site dependent	Limited mobility, size dependent	Non-mobile (sessile)
Stock size or status (B / B_{MSY})	> 1.5	0.8-1.5	0.5-0.8	< 0.5 or Unknown
Other stressors (pollution, disease, food web impacts etc.)	Fishing only	Limited (1)	Moderate (2)	High (>3)
Population growth rate (r_{max})	r selected, fast maturing, short lived, high M	More towards r selected	More towards K selected	K selected, late maturing, long lived, low M

* See Gaichas et al (2014) and references therein for further information on these characteristics.

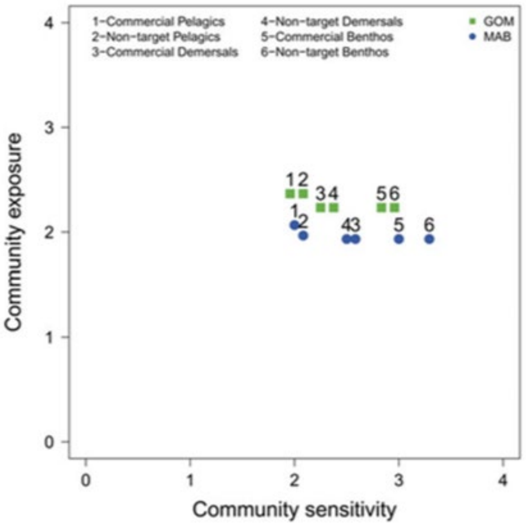


Figure 13: Example community climate sensitivity plot from Gaichas et al. (2014).

Table 21: Attributes used for rating climate sensitivity in Hare et al. (2016). Note Hare et al. (2016) based Low and High magnitude change on local expert opinion. It could also be based on tolerance levels of individual species.

	Attribute	Low	High
Climate factors	Mean ocean surface temperature	Determined by magnitude	Determined by magnitude
	Mean ocean surface salinity	Determined by magnitude	Determined by magnitude
	Mean air temperature	Determined by magnitude	Determined by magnitude
	Mean precipitation	Determined by magnitude	Determined by magnitude
	Mean ocean pH	Determined by magnitude	Determined by magnitude
	Variability ocean surface temperature	Determined by magnitude	Determined by magnitude
	Variability ocean surface salinity	Determined by magnitude	Determined by magnitude
	Variability air temperature	Determined by magnitude	Determined by magnitude
	Variability precipitation	Determined by magnitude	Determined by magnitude
	Variability ocean pH	Determined by magnitude	Determined by magnitude
	Sea level rise	Determined by magnitude	Determined by magnitude
	Ocean currents	Determined by magnitude	Determined by magnitude
Biological attributes	Prey specificity	Prey generalist	Prey specialist
	Habitat specificity	Habitat generalist	Habitat specialist
	Sensitivity to ocean acidification	Insensitive taxa	Sensitive taxa
	Sensitivity to temperature	Broad thermal limits	Narrow thermal limits
	Reproductive strategy	Low complexity; broadcast spawning	High complexity; aggregate spawning
	Early life history requirements	Generalist with few requirements	Specialist with specific requirements

Cheung et al. (2018) and Jones and Cheung (2018) also demonstrated a method similar to some of the Level-2 ERA methods, giving some indication of how climate might be included in the analyses, and also potential for automation of the methods. Cheung et al. (2018) focused on climate drivers (temperature), while Jones and Cheung (2018) also considered acidification. Climate hazard (exposure, ex) for each environmental variable (V) was given by

$$ex_V = \frac{\overline{V_{2041-2060}} - \overline{V_{1951-2000}}}{\sigma_{V,1951-2000}}$$

where $\overline{V_{2041-2060}}$ is the average value for the variable in projections for 2041 to 2060, $\overline{V_{1951-2000}}$ is the average of the variable over the baseline period 1951 to 2000, and $\sigma_{V,1951\text{-}2000}$ is the standard deviation over the baseline period (1951–2000). Other periods could be used for both the projection and baseline periods. This formulation accounts for the inter-annual environmental variability the species is accustomed to experiencing (an earlier baseline period maybe desired for species thought to already be under climate stress by the late 20th century), thereby identifying where the trend in the environmental variable becomes perceptible across the species' range. Like fishing, exposure to the climate variable was based on a species' geographic range (latitudinal and depth) versus the environmental conditions. The environmental variables considered included temperature (sea bottom or sea surface depending on whether a demersal or pelagic species was being assessed), oxygen concentration and acidity. Additional climate relevant biological attributes, specifically, temperature preference and habitat association, were also added to the typical set of productivity attributes which already included climate, acidification and adaptive capacity relevant attributes geographic range, latitudinal range, depth range, body size and fecundity. Categorisation (scoring) of the various attributes used (e.g. see Table 22) for exposure to fishing, exposure to climate change and species' sensitivity and adaptive capacity was done using fuzzy membership functions (see Figure 14). These scores were combined to determine species' risk score using pre-defined heuristic rules (fuzzy logic), with a final index of risk calculated from the average of the index values weighted by their accumulated membership. While expert input is needed in developing the fuzzy membership functions and heuristic rules, expert rating of individual attributes is not required and the entire process can be automated, allowing for a high (and rapid) throughput of species and areas. Furthermore, uncertainty can be explicitly considered because the fuzzy logic approach integrates and carries forward the uncertainties associated with the future climate projections and biological/ecological traits. It does this via the fuzzy membership functions, as the classification scheme does not allocate a species attribute to one category or another, but instead uses overlapping fuzzy sets to allow the species attribute to belong to one of more sets simultaneously, with the extent of membership to each being defined by a fuzzy membership function. By employing fuzzy set theory, or "fuzzy logic", the uncertainty surrounding our knowledge of fish biological and ecological characteristics as well as their linkages to vulnerability can be accounted for. Matrices matching exposure to vulnerability and sensitivity to adaptive capacity were used in the formalised rules (see Figure 15).

Table 22: Criteria used in the climate risk assessment of Jones and Cheung (2018). Note the boundaries between classes overlap due to the fuzzy logic approach used.

	Attribute	Low	Medium	High	Very High
Exposure	Exposure to climate variable (ex_V)	< 1	0.5 – 2	1 – 3	> 2
Sensitivity	Temperature tolerance	< 7	3 – 10	7 – 14	> 10
	Maximum body length	< 40 cm	20 – 60 cm	40 – 60 cm	60 – 80 cm
	Maximum body length and high coral association			20 – 60 cm and coral reef association > 1	> 40 cm and coral reef association > 1

	Attribute	Low	Medium	High	Very High
	Taxonomic group sensitivity to ocean acidification	Fishes, crustaceans, sea cucumbers	Fishes, crustaceans, sea cucumbers	Crustaceans, molluscs, sea urchins	Molluscs, sea urchins
Adaptive capacity	Latitudinal breadth	< 19	10 – 50	19 – 70	> 70
	Depth range	< 35	10 – 200	35 – 570	> 200
	Fecundity (eggs or pups per year)	< 500	500 – 10000	1000 – 100000	> 10000
	Habitat specificity	< 0.5	0.25 – 0.75	0.1 – 0.5	> 0.25

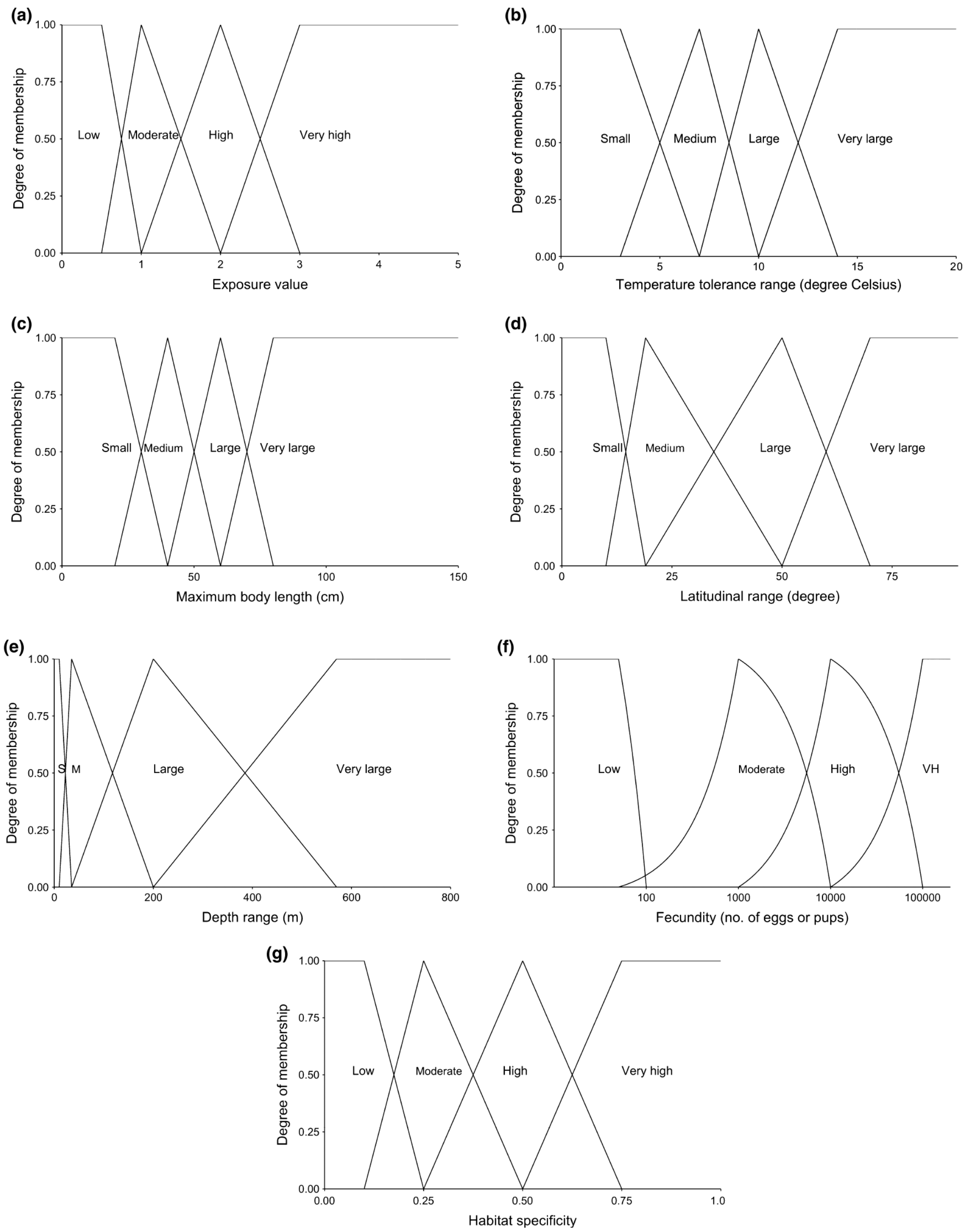


Figure 14: Fuzzy membership functions used to map to hazard, sensitivity and adaptive capacity categories by Jones and Cheung (2018): (a) exposure value; (b) temperature tolerance range; (c) maximum body length; (d) latitudinal range; (e) depth range; (f) fecundity; and (g) habitat specificity. S, Small; M, Medium; VH, Very high.

	Sensitivity			
Adaptive capacity	Low	Moderate	High	Very high
High	Low	Low	Moderate	High
Moderate	Low	Moderate	High	High
Low	Moderate	High	High	Very high
Very low	High	High	Very high	Very high

	Exposure to climate hazard			
Vulnerability	Low	Moderate	High	Very high
Low	Low	Low	Moderate	High
Moderate	Low	Moderate	High	High
High	Moderate	High	High	Very high
Very high	High	High	Very high	Very high

Figure 15: Decision rule mapping for sensitivity-adaptive capacity and climate hazard exposure - vulnerability used in Jones and Cheung (2018).

Habitats, Communities and Ecosystems

Few studies have considered entire communities or ecosystems – in those cases where such large ecological units are considered the researchers typically default to simply determining exposure to cumulative stressors rather than really assessing risk. Gilman et al. (2019) discusses some of the issues to be contended with when moving to larger ecological units (i.e. beyond stocks), expanding the discussion to genetic diversity and ecosystem aspects, pointing out that ERA methods that "comprehensively consider biodiversity across its hierarchical manifestations" are needed. The ecosystem-based rather than solely stock-based reference levels suggested by Gilman et al. (2019) could be useful as reference levels to help guide SAFE-like assessments. Gilman et al. (2019) also identified multispecies and ecosystem models as candidate Level 3 assessment methods for communities and ecosystems. In this context qualitative models of the kind used by Dambacher et al (2009), Treblico et al (in press) could have a useful role in Level-2 assessments.

Cumulative Impacts

As mentioned above, AFMA (2017) clearly states that cumulative impacts of fisheries on Australian stocks must be considered and that for teleosts SAFE is the appropriate tool – using the absolute risk values given to allow summing across sectors. As noted above, a simple means of extending this approach to other taxa of interest – such as seabirds, cetaceans, sharks etc. – is to adopt the taxa specific SAFE-like approaches developed by other jurisdictions. This would then leave only a small number of taxa for which cumulative effects assessments are either not possible, or for which a new, redeveloped, form of PSA that explicitly dealt with cumulative risk would be needed.

Zhou et al. (2019) pointed out that while current methods (i.e. ones discussed above such as eSAFE) have focused on fishing, different types of stressors such as habitat loss and marine transportation could be straightforwardly included if their impact in terms of mortality can be estimated. The multi-criteria component tree of Fletcher et al. (2010) could provide a useful basis, showing how to maintain relative weightings, but still group like-with-like and more easily reach consolidated risk scores that considers socioeconomic as well as ecological aspects. Alternatively, the methods of other research groups that have already begun extending PSAs into multi-stressor dimensions (e.g. Micheli et al. 2014) could be used for inspiration.

Even if multi-stressors (more than simply fishing activities) are not considered, the implications of near and far field effects, as well as local and dispersed effects, could be included (similar to consideration of noise pollution by Forney et al. 2017) to capture the true potential sensitivity to mobile species to the incremental additional of fishing activities in Australian waters.

Other Considerations

SICA modifications

Above we have concentrated on modification of the quantitative steps of the ERA to account for climate and cumulative impacts. This can (and should) also be considered for SICA too.

It is appreciated that a SICA is a non-trivial exercise to complete. Some resource savings can be made (i) in update ERAs (i.e. where a past ERA is being updated) by adopting the past SICA as a starting point and (ii) via some degree of automation. Nevertheless, it would be beneficial to define a protocol that identified (triggered) when a new SICA needed to be undertaken – i.e. a full SICA rather than a simple update. The same protocol could perhaps be used to trigger a new ERA (rather than waiting for a standard periodic update) due to a change in conditions – contextual (e.g. opening of a new industry which puts additional pressure on a stock), climate or other driver. While the process would necessarily need to be a low resource exercise (i.e. less intensive than an ERA itself) it should however address change at multiple levels – not just gross change, but capture sufficient proxies to identify situations where it was likely there had been underlying changes in finer resolution attributes, such as life history characteristics etc.

Even without such a trigger based process, the SICA itself may require some minor modifications to better resolve some of the external pressures being considered. Climate is a case in point. Rather than being included in aggregate amongst external hazards, it could instead be disaggregated to a small degree – perhaps either into primary drivers such as temperature, precipitation, acidification, sea-level rise, extreme events and oxygen levels (for example). Alternatively, and perhaps more usefully, it could be considered in terms of observed/anticipated changes in species distributions, abundance, phenology and “quality” (physiological health). This could include bulk change or changes in variability. This would bring it in-line with the climate adaptation framework that has been developed for Australian fisheries (van Putten in prep) and would also allow for the easy transfer of scores into the SICA, allowing for easy alignment of the two processes and a saving on resources. Given many of the same attributes are considered in the ERA (SICA and PSA) and the ecological base assessment of the adaptation framework it makes sense for the two to be seamlessly connected – the climate framework updating ERA relevant information and the ERA helping define the ecological risk component of the climate vulnerability assessments. In this way the two can cross support and be updated more easily (and at a saving in aggregate costs).

Considering past and future effects

DFO 2012 presents an Ecological Risk Assessment Framework (ERAF) for benthic communities that highlights the value of accounting for past, present and future effort footprints and conditions. Level 3 assessments already include such by-directional consideration by including hindcasts and forecasts/projections.

While this temporally expansive assessment requires more resources, as the assessment must at the very least be repeated looking backwards and forwards, it better positions management to understand whether current and planned management rules are addressed. Such considerations may not have been as necessary under more constant conditions, but with trending climate drivers (and the ways in which they may influence species productivity, distribution and exposure to fishing pressure) forward looking assessments will become more critical.

Just as future conditions could change the result of the risk assessment, consideration of legacy effects can clarify the effectiveness of current management approaches in reducing risk to acceptable levels. Past activities – particularly past fishing activities (intensity and footprints) and habitat degradation and recovery for habitat dependent species – can indicate the relative risk of a species population or stock already being in (or having been in) an overfished state.

Plots

A number of simple modifications of the PSA plots may improve communication of information relevant to management such as the representation of uncertainty in PSA plots through the use of error bars, or via the colour/size of the points could be used. This is possible within the online tools but should also be plotted in reports (even if only in an appendix if the plot is already crowded).

Another modification to the PSA plots that may be beneficial is to add another plot that reorders the attributes per axis to reflect those aspects that can and cannot be acted on. This approach has been used for a Chilean aquaculture example (Bravo and Bustamante 2018). Presenting results in this way more directly highlights the risk contributions that can be addressed and modified and those beyond influence.

The large-scale use of SAFE and SAFE-like approaches indicates a significant appetite for spatial maps of risk or at least relative risk. While sufficient information is not always available for such approaches, applying a spatial PSA as depicted in Brown et al. (2015), may still meet this desire for spatial representations. Although this may still prove too data-intense depending on the spatial resolution or if seasonal representations are attempted. It may also be too complicated to produce a combined product across species, so it may be advisable simply to do it for specific hotspots (like Clarke et al. 2018) or for the most at risk or representative species.

Meaningful scoring thresholds

If assessments move to absolute risk (e.g. as a consequence of more widely adopting SAFE-like approaches) defining risk thresholds will become moot. However, if PSAs remain the core of the approach then there may be value in moving away from the arbitrary “thirds” approach to meaningful thresholds. This would assist the inter-comparability of the assessments (between fisheries and through time). Patrick et al. (2010) suggest weighting of attributes can help, but that has its own issues (as discussed previously in the PSA section of this document). For example, using data quality as the weighting does not represent a time saving, as the Canadian assessments indicate that a residual risk assessment step is still required.

An approach that was found to be effective by Bravo and Bustamante (2018) was to use a distribution for each attribute, presented as a histogram so that sensible breakpoints can be identified – see Figure 16 for an example.

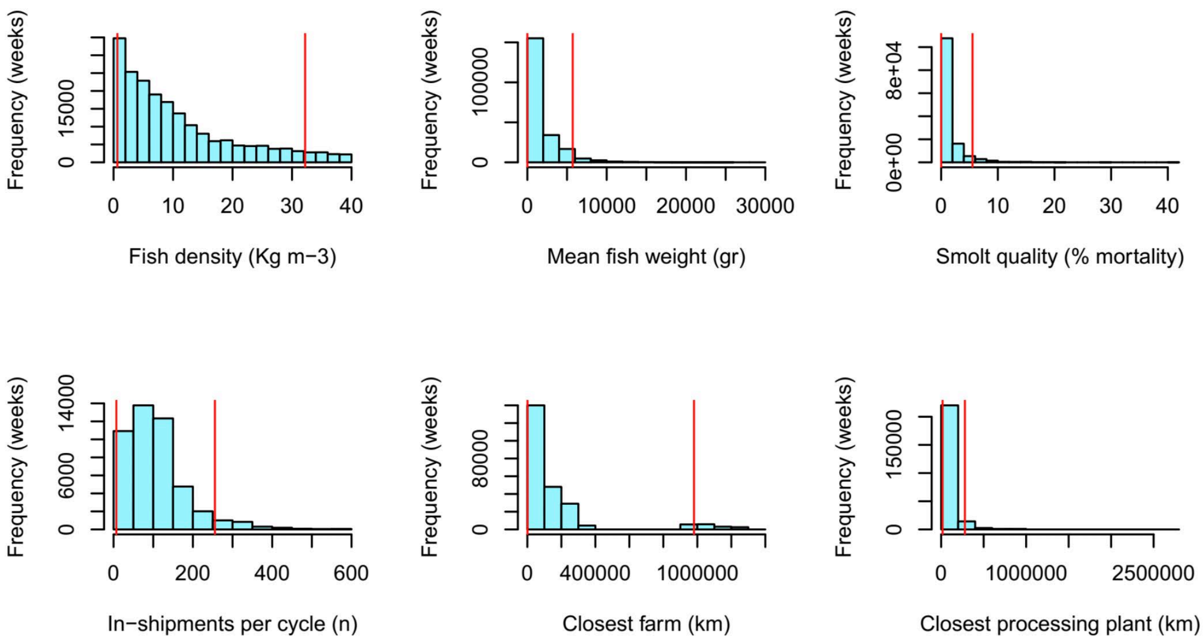


Figure 16: Example of the threshold determination approach used by Bravo and Bustamante (2018) - histograms of the distribution for risk attributes are used to define thresholds, such as the 5 and 95% percentiles (alternatively meaningful thresholds defined physiologically or by experts could be used; Bravo and Bustamante also took this approach).

Re-consideration of biological traits and Level 2 analyses

The number of variants of the basic ERA approaches show the versatility of the approach, but they also highlight that, where information is available, that it may be worth supplementing the traits considered to capture sources or points of risk that may be missed with the standard set of attributes. For example, the following are extra factors that may warrant inclusion:

- exposure or sensitivity of individual life history stages (when strong ontogenetic changes exist)
- cryptic mortalities (e.g. for seabirds; as done in Richard et al., 2017), including cryptic bycatch (such as warp strike in birds) and mortalities due to gear loss
- habitat and trophic dependencies
- climate and how that adds stress or modifies the attribute values of each species, or how it changes spatial distributions and thereby exposure to fishing, or even which species should be included in the assessment
- “predictability” of stocks (i.e. the influence of environmental variability)
- for communities, review and update the indicators used (e.g. mean trophic level has been shown not to be an informative indicator (Fulton et al. 2005; Shannon et al. 2014))

On a longer time frame the following aspects should also be considered (i.e. they are not the highest priority for inclusion, but should receive consideration at some point):

- species interactions (precedent exists for Level 1 assessment of these; Gaichas et al 2016)
- indirect effects (e.g. trophic dependency, SURF index, hub score based on network indices)

- system structure and function (this may become easier as ecosystem metrics get more consideration both in ERA and by EBFM science in general)
- inter-annual variability and regime shifts (which may change attribute scores, RRA outcomes, or even species considered)

It may also be wise to use different attributes for different sets of taxa, this would easily be facilitated if instead of using SAFE, the other existing SAFE-like methods (which have already been tailored to specific taxa) are substituted in the Level 2 assessment for seabirds or cetaceans. This should be straightforward to do, without adding inconsistency or overhead, in the online assessment tool used in assessments for AFMA, via using a taxon flag to trigger such alternative assessment pathways. However, in moving to more quantitative methods, it would be important to be conscious of any false impression of precision – such as when r_{max} estimates are used as the productivity attribute but the actual values used are substitutes (due to data gaps) from other species.

It may also be worth considering generally expanding the set of methods available for use in the Level 2 assessments in the same way that there is a wide range of available Level 3 methods. In a way SAFE (and the recommendation above of the adoption of taxon-specific SAFE-like alternatives) already does this, but it is worth noting that there are many data poor methods that have now been reviewed and packages are becoming available. “Traffic light” and Spawning Potential Ratio appear to be good options, for example (Geromont and Butterworth, 2015).

Relative vs absolute risk

Relative risk is a useful approach in data poor situations and where a simple prioritisation of species to consider per fishery is needed. However, it makes it quite difficult to create cumulative risk scores across fisheries or to compare risk between fisheries and through time. Reporting absolute risk rather than relative risk would help address these issues. It would also facilitate future connection to risks from other stressors – such as other marine industries.

If the decision is made to continue using relative risk, then the current PSA method doesn’t need a lot of adjustment beyond the considerations around thresholds, extra factors to consider, climate adjustment and/or inclusion of a measure of uncertainty on the plots. The work by Patrick et al. (2010), Abrahams et al. (2017) and Griffiths et al. (2018) may provide good starting spots for inspiration on how to achieve absolute risk scores.

Medium and longer terms extensions to consider

Links to tactical multi-species management

Multi-species harvest control rules are beginning to be developed for Australian multi-species fisheries. Whether as part of such a harvest control rule, or part of monitoring in support of EBFM, indicator or “sentinel” species will need to be identified. The use of clustering in PSA space can identify clusters of species with same biological traits, susceptibility, exposure and profiles. Representative species from these clusters can then be chosen as indicator “sentinel” species in the same way as the use of indicator species by Newman et al. 2018.

ERAEF at an ecosystem scale

Ecosystem level ERAEFs are an outstanding gap as risk approaches step up through ecological scales from single species, to communities to entire ecosystems. ERAEF at the ecosystem scale would need to include traits such as:

- natural variability
- functional diversity
- structural indices (such as the structural health index or exponential random graph models)
- guilds that summarise system structure and function – primary producers, habitats, fisheries resources, top predators
- environmental conditions – water quality/pollutants, physical environmental variables

Socioeconomic factors could also be included (perhaps as a 3rd dimension). Alternatively, these factors could be considered via social/economic assessments that mirror the ERA process for social/economic attributes of fisheries, or via linking with Life Cycle Assessments (Avadi 2013). It is likely if general cumulative impacts assessments became standard for marine industries then these cumulative assessments would subsume both biophysical and socioeconomic factors.

Other methodological considerations

If it is decided at some future point that management effectiveness should be directly incorporated in the assessment of risk, rather than using an RRA, then the "Bowtie method" (Cormier et al. 2018) presents a useful framework for making that connection and for clearly linking the components of the cause–effect pathway. This graphic-based approach includes the drivers leading to the focal activities, anticipatory prevention measures, including those limiting the severity of the focal activities, the consequences of the activities, as well as mitigation and compensation measures aimed at minimising those consequences. It is also possible that the Bowtie method could be utilised as a means of laying out available information in a way that facilitates validation of risk scores. The validation step is one very rarely undertaken globally, but is one that should be done (at least for a subset of fisheries) to have confidence in the veracity of the results.

An additional method modification might be maximisation of the automation of the method, so it can be run more efficiently or more often. The method already has some level of automation but advances in computational capacity and statistical/computing methods (e.g. Artificial Intelligence and Machine Learning) mean that there is the potential to automate large parts of the workflow, beyond what is currently automated. For example, fuzzy logic could be used to do the scoring, inherently allowing for uncertainty in the scoring, as done in Cheung et al. (2018) and Jones and Cheung (2018). Such an approach would allow for spatial assessments to be done rapidly for 100s-1000s of species – as Cheung et al. (2018) has done previously in global climate vulnerability assessments. Hordyk and Carruthers (2018) provided a critical review, which questions the validity of aspects of the PSA and makes the argument that as much of the same data is needed as used in Level-3 assessments that risk assessments should simply be automated using simple assessments. However, other authors have found more consistent and reliable performance of PSA (e.g. Zhou et al. 2016). Szuwalski and Thorson (2017) warn that for many species the assumptions in simple models are breached, which argues against jumping to automated Level 3 assessments. Furthermore, using current methods, there is much less chance for community/ecosystem scale efforts to be automated, as community indicators are hard to interpret in isolation.

Lastly, this document has focused on ecological risk assessment and thus ecological system components. However, as there is increasing demand for integaretd assessments and the even handling of ecological, economic, social, cultural (customary) and governance objectives around fisheries it makes sense to consider if/how the ERA style analysis could be straightforwardly extended to economic, social and cultural impacts. As a first step down that path, incorporation of fisher knowledge into the ERA process (as done by Roux et al. (2019) and as also advocated in the climate adaptation framework) may be a useful approach of broadening ecological knowledge in very data poor fisheries, but also as an entry point for including some market/economic or socially driven fishery behaviours that have implications for the susceptibility and exposure calculations undertaken in an ERA. It may also highlight, ahead of time, species that may be associated with situations such as the undercatch of TAC in the SESSF or species where climate change will be associated with strong social/economic/access issues that have rebound effects into the fishery and its associated risk envelope.

8 Recommendations

The extensions discussed in Section 7 are all worthy of consideration in reviewing and updating the ERAEF risk assessments adopted in Australia. However, some of these options are more pressing or easy to implement. The main modification we recommend is to modify the workflow to include a greater diversity of taxon-specific assessments as summarised in Figure 17. This would see SAFE and SAFE-like taxon specific variants for all but most data poor species – typically invertebrates, which would still go through PSA.

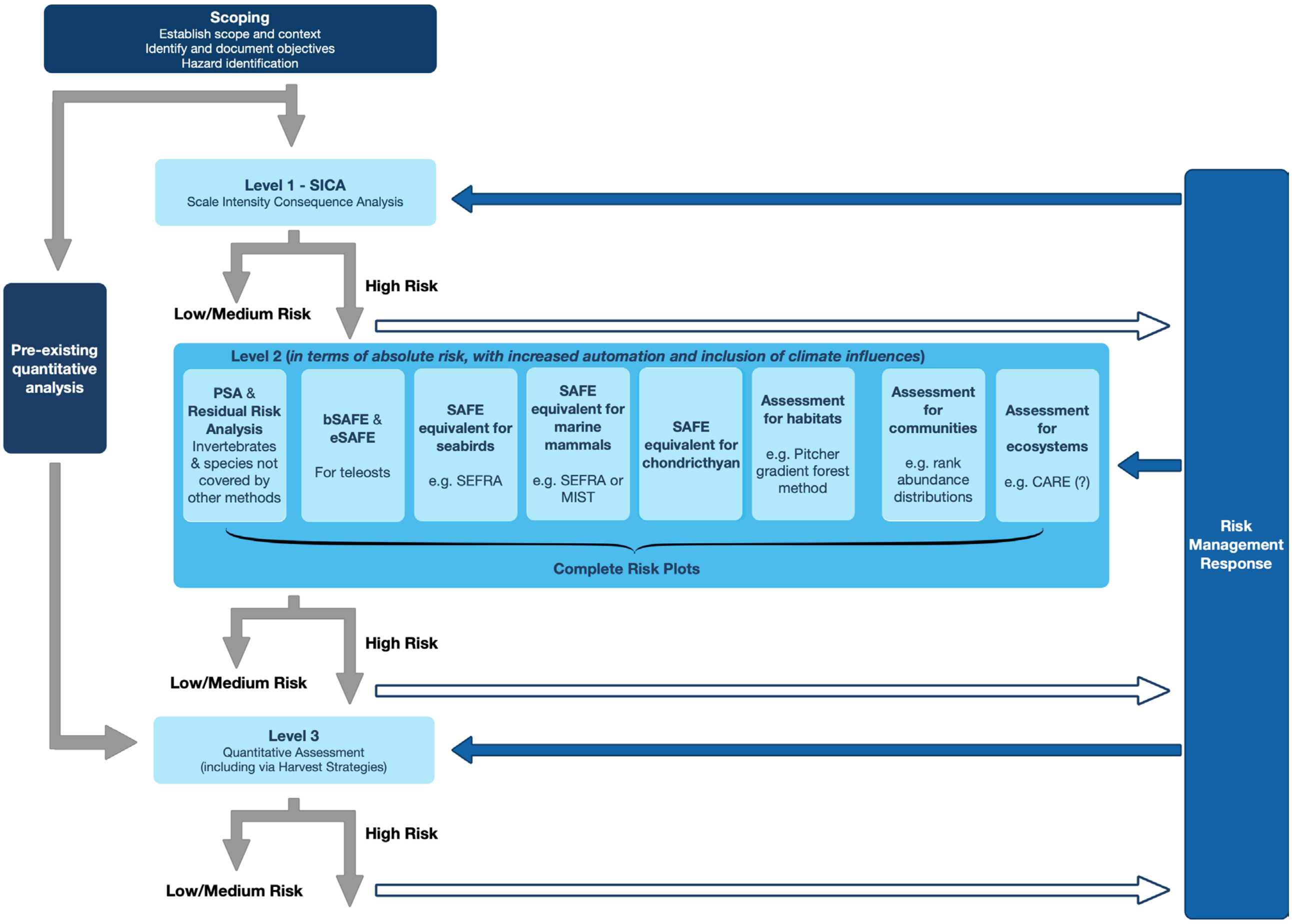


Figure 17: Recommended updated ERAEF workflow. Note that the use of absolute risk removes the need for RRA. Also note that if a substantial number of species continue to be assessed using PSA, then inclusion of target stocks in the PSA is a valuable means of facilitating interpretation of the vulnerability of non-target stocks.

In addition, the attributes used and the scoring criteria should be periodically reviewed, as climate and exploitation can change susceptibility and (Ormseth and Spencer 2011) found ERAs are sensitive to susceptibility changes. The frequency of review should be tailored to the magnitude and rate of change of exploitation; with reviews occurring more frequently at higher rates of exploitation, where there is higher sensitivity to attribute mis-specification, or where exploitation rates are changing rapidly.

References

Abraham, E., M. J. Roux, Y. Ricard, and N. Walker. 2017. Assessment of the risk of southern hemisphere surface longline fisheries to ACAP species. WCPFC.

Aeberhard, W.H., Flemming, J.M., Nielsen, A. (2018) Review of State-Space Models for Fisheries Science. Annual Review of Statistics and Its Application. 5:215-235

AFMA. 2008a. Ecological Risk Assessment: Residual Risk Assessment for Eastern Tuna and Billfish Fishery. Australian Fisheries Management Authority., Canberra, ACT.

AFMA 2008b. Residual Risk Assessment of the Level 2 Ecological Risk Assessment Species Results. Report for the Northern Prawn Fishery. Australian Fisheries Management Authority., Canberra, ACT.

AFMA 2012. Ecological Risk Management. Report for the Eastern Tuna and Billfish Fishery. Australian Fisheries Management Authority., Canberra, ACT.

AFMA. 2017. Guide to AFMA's Ecological Risk Management. Australian Fisheries Management Authority., Canberra, ACT.

Alexander K. A., A. J. Hobday, C. Cvitanovic, E. Ogier, K. L. Nash, R. S. Cottrell, A. Fleming, M. Fudge, E. A. Fulton, S. Frusher, R. Kelly, C. K. MacLeod, G. T. Pecl, I. van Putten, J. Vince, and R. A. Watson. 2019. Progress in integrating natural and social science in marine ecosystem-based management research. Marine and Freshwater Research 70:71–83.

Apel, A. M., R. Fujita, and K. Karr. (2013). Science-Based Management of Data-Limited Fisheries: A Supplement to the Catch Share Design Manual. Environmental Defense Fund.

Arechavala-Lopez P., K. Toledo-Guedes, D. Izquierdo-Gomez, T. Šegvić-Bubić, and P. Sanchez-Jerez. 2018. Implications of Sea Bream and Sea Bass escapes for sustainable aquaculture management: a review of interactions, risks and consequences. Reviews in Fisheries Science & Aquaculture 26:2: 214-234.

Arrizabalaga H., P. de Bruyn, G. A. Diaz, H. Murua, P. Chavance, A. Delgado de Molina, D. Gaertner, J. Ariz, J. Ruiz, and L. T. Kell. 2011. Productivity and susceptibility analysis for species caught in Atlantic tuna fisheries. Aquatic Living Resources 24:1–12

Astles, K., and R. Cormier. 2018. Implementing Sustainably Managed Fisheries Using Ecological Risk Assessment and Bowtie Analysis. 10:3659.

Astudillo V., B.G. Cané, D. Geymonat, A.B. Sathler, S. Garay Roman, P. Sutmoller, and E.J. Gimeno. 1997. Risk assessment and risk regionalisation, based on the surveillance system for foot and mouth disease in South America. Revue Scientifique et Technique-Office International Des Epizooties 16: 800-808

Avadi, A. 2013. Life cycle assessment of fisheries: A review for fisheries scientists and managers. Fisheries Research 143:21-38.

Ballesteros, M., R. Chapela, P. Ramirez-Monsalve, J. Raakjaer, T. J. Hegland, K. N. Nielsen, U. Laksa, and P. Degnbol. 2018. Do not shoot the messenger: ICES advice for an ecosystem approach to fisheries management in the European Union. Ices Journal of Marine Science 75:519-530.

Bao, M., G. J. Pierce, S. Pascual, M. Gonzalez-Munoz, S. Mattiucci, I. Mladineo, P. Cipriani, I. Buselic, and N. J. C. Strachan. 2017. Assessing the risk of an emerging zoonosis of worldwide concern: anisakiasis. Scientific Reports 7: 43699; doi: 10.1038/srep43699

Barbier, E.B., S. D. Hacker, C. Kennedy, E. W. Koch, A. C. Stier, and B. R. Silliman. 2011. The value of estuarine and coastal ecosystem services. Ecological Monographs 81:169–193

Barnett, A. J., and M. G. Wiber. 2019. What Scientists Say about the Changing Risk Calculation in the Marine Environment under the Harper Government of Canada (2006-2015). Science Technology & Human Values 44:29-51.

Barange, M., Bahri, T., Beveridge, M.C.M., Cochrane, K.L., Funge-Smith, S., Poulain, F. Ed's. 2018. Impacts of climate change on fisheries and aquaculture:Synthesis of current knowledge, adaptation and mitigation options. FAO: Rome. 628p

Barnthouse, L. W. 1994. Issues in Ecological Risk Assessment: The CRAM Perspective. 14:251-256.

Battista, W., K. Karr, N. Sarto, and R. Fujita. 2017. Comprehensive Assessment of Risk to Ecosystems (CARE): A cumulative ecosystem risk assessment tool. Fisheries Research 185:115-129.

Bell, J. D., and T. Bahri. 2018. A new climate change vulnerability assessment for fisheries and aquaculture. SPC Fisheries Newsletter. Secretariat of the Pacific Community (SPC).

Bellido, J. M., M. B. Santos, M. G. Pennino, X. Valeiras, and G. J. Pierce. 2011. Fishery discards and bycatch: solutions for an ecosystem approach to fisheries management? Hydrobiologia 670:317-333.

Ben-Hasan, A., C. Walters, R. Louton, V. Christensen, U. R. Sumaila, and H. Al-Foudari. 2018. Fishing-effort response dynamics in fisheries for short-lived invertebrates. Ocean & Coastal Management 165:33-38.

Bland, L. M., J. A. Rowland, T. J. Regan, D. A. Keith, N. J. Murray, R. E. Lester, M. Linn, J. P. Rodriguez, and E. Nicholson. 2018a. Developing a standardized definition of ecosystem collapse for risk assessment. Frontiers in Ecology and the Environment 16:29-36.

Bland, L. M., K. E. Watermeyer, D. A. Keith, E. Nicholson, T. J. Regan, and L. J. Shannon. 2018b. Assessing risks to marine ecosystems with indicators, ecosystem models and experts. Biological Conservation 227:19-28.

Bravo, F. and R. H. Bustamante. 2018. Appendix J: Identification of risk attributes and breakpoint values for the risk analysis level 2 of SIMA Austral. In: Steven A. L., J. R. Andrewartha, P. A. Bernal, F. Bravo, R. H. Bustamante, S. A. Condie, M. St. J. Crane, J. M. Dambacher, S. Dowideit, E. A. Fulton, R. Gorton, M. Herzfeld, J. Hodge, E. Hoshino, E. Kenna, N. Margvelashvili, N. J. G. Moody, D. Ocampo, R. Pitcher, S. Richards, F. Rizwi, S. K. Aryal, J. H. Skerratt, A. Steven, L. Thomas, S. Tickell, I.E. van Putten, P. Vaquero, D. Wild, and K. Wild-Allen. 2018. SIMA-Austral FIE V008- Integrated Ecosystem-based Sanitary and Environmental Management System for Aquaculture. Final Report. CSIRO Chile.

Breen, P., S. Brown, D. Reid, and E. Rogan. 2017. Where is the risk? Integrating a spatial distribution model and a risk assessment to identify areas of cetacean interaction with fisheries in the northeast Atlantic. Ocean & Coastal Management 136:148-155.

Brewer, D. T., D. S. Heales, D. A. Milton, Q. Dell, W. Venables, and P. N. Jones. 2006. The impact of turtle excluder devices and bycatch reduction devices on diverse tropical marine communities in Australia's northern prawn trawl fishery. Fisheries Research 81:176–188.

Brown, S. L., D. Reid, and E. Rogan. 2013. A risk-based approach to rapidly screen vulnerability of cetaceans to impacts from fisheries bycatch. Biological Conservation 168:78-87.

Brown, S. L., D. Reid, and E. Rogan. 2015. Spatial and temporal assessment of potential risk to cetaceans from static fishing gears. Marine Policy 51:267-280.

Buckley, S. M., T. R. McClanahan, E. M. Quintana Morales, V. Mwakha, J. Nyanapah, L. M. Otwoma, and J. M. Pandolfi. 2019. Identifying species threatened with local extinction in tropical reef fisheries using historical reconstruction of species occurrence. Plos One 14.

Bulman, C., Sporcic, M., Fuller, M. and A. Hobday. 2017a. Ecological Risk Assessment for Effects of Fishing. Report for the Midwater Trawl Sub-fishery of the Small Pelagic Fishery. (CSIRO, Hobart

Bulman, C.M., Sporcic, M., Pethybridge, H. and A. Hobday. 2017b. Ecological Risk Assessment for Effects of Fishing. Final Report for the Demersal Longline Su b-fish ery of the Heard Island and McDonald Islands Fishery 2010/11-2015/16 (CSIRO/AFMA, Hobart). 126 pp.

Burdon, D., S. J. Boyes, M. Elliott, K. Smyth, J. P. Atkins, R. A. Barnes, and R. K. Wurzel. 2018. Integrating natural and social sciences to manage sustainably vectors of change in the marine environment: Dogger Bank transnational case study. Estuarine Coastal and Shelf Science 201:234-247.

Burgass, M. J., E. J. Milner-Gulland, J. S. S. Lowndes, C. O'Hara, J. C. Afflerbach, and B. S. Halpern. 2019. A pan-Arctic assessment of the status of marine social-ecological systems. Regional Environmental Change 19:293-308.

Burger, J., M. Gochfeld, L. Niles, N. Tsipoura, D. Mizrahi, A. Dey, C. Jeitner, and T. Pittfield. 2017. Stakeholder contributions to assessment, monitoring, and conservation of threatened species: black skimmer and red knot as case studies. Environmental Monitoring and Assessment 189.

Cadrin, S. X., and M. Dickey-Collas. 2015. Stock assessment methods for sustainable fisheries. ICES Journal of Marine Science 72: 1–6.

Campbell, M. J., M. F. McLennan, A. J. Courtney, and C. A. Simpfendorfer. 2018. Post-release survival of two elasmobranchs, the eastern shovelnose ray (Aptychotrema rostrata) and the common stingaree (Trygonoptera testacea), discarded from a prawn trawl fishery in southern Queensland, Australia. Marine and Freshwater Research 69:551-561.

Campbell, M. L., and C. Gallagher. 2007. Assessing the relative effects of fishing on the New Zealand marine environment through risk analysis. ICES Journal of Marine Science 64:256-270.

Cao, J., Y. Chen, and R. A. Richards. 2017. Improving assessment of Pandalus stocks using a seasonal, size-structured assessment model with environmental variables. Part II: Model evaluation and simulation. Canadian Journal of Fisheries and Aquatic Sciences 74:363-376.

Carruthers, T. R., and A. R. Hordyk. 2018. The Data-Limited Methods Toolkit (DLMtool): An R package for informing management of data-limited populations. Methods in Ecology and Evolution 9:2388–2395.

Chen, S., B. Chen, and B. D. Fath. 2013. Ecological risk assessment on the system scale: A review of state-of-the-art models and future perspectives. Ecological Modelling 250:25-33.

Cheung, W. W. L., M. C. Jones, G. Reygondeau, and T. L. Frolicher. 2018. Opportunities for climate-risk reduction through effective fisheries management. Global Change Biology 24:5149-5163.

Chin, A., P.M., Kyne, T. I. Walker, and R. B. McAuley. 2010. An integrated risk assessment for climate change: analysing the vulnerability of sharks and rays on Australia's Great Barrier Reef. 16:1936-1953.

Christian, R. R., M. M. Brinson, J. K. Dame, G. Johnson, C. H. Peterson, and D. Baird. 2009. Ecological network analyses and their use for establishing reference domain in functional assessment of an estuary. Ecological Modelling 220:3113-3122.

Chrysafi, A., and A. Kuparinen. 2016. Assessing abundance of populations with limited data: Lessons learned from data-poor fisheries stock assessment. Environmental Reviews 24: 25–38

Clark, M. R., T. A. Schlacher, A. A. Rowden, K. I. Stocks, and M. Consalvey. 2012. Science Priorities for Seamounts: Research Links to Conservation and Management. Plos One 7.

Clarke, T. M., M. Espinoza, R. R. Chaves, and I. S. Wehrtrnann. 2018. Assessing the vulnerability of demersal elasmobranchs to a data-poor shrimp trawl fishery in Costa Rica, Eastern Tropical Pacific. Biological Conservation 217:321-328.

Collie, J. S., R. M. Peterman, and B. M. Zuehlke. 2012. A fisheries risk-assessment framework to evaluate trade-offs among management options in the presence of time-varying productivity. Canadian Journal of Fisheries and Aquatic Sciences 69:209-223.

Cope, J. M. and A. E. Punt. 2009. Length-Based Reference Points for Data-Limited Situations: Applications and Restrictions. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science 1:169–186

Cormier, R., V. Stelzenmuller, I. F. Creed, J. Igras, H. Rambo, U. Callies, and L. B. Johnson. 2018. The science-policy interface of risk-based freshwater and marine management systems: From concepts to practical tools. Journal of Environmental Management 226:340-346.

Cortés, E., and E. N. Brooks. 2018. Stock status and reference points for sharks using data-limited methods and life history. Fish and Fisheries 19:1110-1129.

Cortés, E., F. Arocha, L. Beerkircher, F. Carvalho, A. Domingo, M. Heupel, H. Holtzhausen, M. N. Santos, M. Ribera, and C. Simpfendorfer. 2010. Ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. Aquatic Living Resources 23:25-34.

Cortes, E., A. Domingo, P. Miller, R. Forselledo, F. Mas, F. Arocha, S. Campana, R. Coelho, C. Da Silva, F. H. V. Hazin, H. Holtzhausen, K. Keene, F. Lucena, K. Ramirez, M. N. Santos, Y. Semba-Murakami, and K. Yokawa. 2015. Expanded ecological risk assessment of pelagic sharks caught in Atlantic pelagic longline fisheries. International Commission for the Conservation of Atlantic Tunas Collective Volume of Scientific Papers 71:2637-2708.

Cotter, A., W. Lart, N. de Rozarieux, A. Kingston, R. Caslake, W. Le Quesne, S. Jennings, A. Caveen, and M. Brown. 2014. A development of ecological risk screening with an application to fisheries off SW England.

Dambacher, J. M., D. J. Gaughan, M.-J. Rochet, P. A. Rossignol, and V. M. Trenkel. 2009. Qualitative modelling and indicators of exploited ecosystems. Fish and Fisheries 10:305–322.

De Anda-Montanez, J. A., S. Salas, and G. Galindo-Cortes. 2017. Dealing with dynamics and uncertainty of small pelagic fisheries: bioeconomic analysis of manager's responses to alternative management strategies. Revista De Biologia Marina Y Oceanografia 52:51-65.

de Chazal, J., F. Quétier, S. Lavorel, and A. Van Doorn. 2008. Including multiple differing stakeholder values into vulnerability assessments of socio-ecological systems. Global Environmental Change 18:508-520.

De Lange, H. J., S. Sala, M. Vighi, and J. H. Faber. 2010. Ecological vulnerability in risk assessment - A review and perspectives. Science of the Total Environment 408:3871-3879.

Department of Fisheries and Oceans Canada (DFO). 2012. Ecological Risk Assessment Framework (ERAF) for Coldwater Corals and Sponge Dominated Communities. Sustainable Fisheries Framework (SFF): Policy to Manage the Impacts of Fishing on Sensitive Benthic Areas. DFO Canada. 18 pg.

Depestele, J., W. Courtens, S. Degraer, J. Haelters, K. Hostens, M. Leopold, E. Pinn, B. Merckx, H. Polet, M. Rabaut, H. Reiss, E. Stienen, S. Vandendriessche, F. A. M. Volckaert, and M. Vincx. 2014. Sensitivity assessment as a tool for spatial and temporal gear-based fisheries management. Ocean & Coastal Management 102:149-160.

DePiper, G. S., S. K. Gaichas, S. M. Lucey, P. P. da Silva, M. R. Anderson, H. Breeze, A. Bundy, P. M. Clay, G. Fay, R. J. Gamble, R. S. Gregory, P. S. Fratantoni, C. L. Johnson, M. Koen-Alonso, K. M. Kleisner, J. Olson, C. T. Perretti, P. Pepin, F. Phelan, V. S. Saba, L. A. Smith, J. C. Tam, N. D. Templeman, and R. P. Wildermuth. 2017. Operationalizing integrated ecosystem assessments within a multidisciplinary team: lessons learned from a worked example. Ices Journal of Marine Science 74:2076-2086.

Dillingham P.W., and D. Fletcher. 2008. Estimating the ability of birds to sustain additional human-caused mortalities using a simple decision rule and allometric relationships. Biological Conservation 141: 1783−1792

Dowling, N.A., J. R. Wilson, M. B. Rudd, E. A. Babcock, M. Caillaux, J. Cope, D. Dougherty, R. Fujita, T. Gedamke, M. Gleason, N. Gutierrez, A. Hordyk, G. W. Maina, P. J. Mous, D. Ovando, A.M. Parma, J. Prince, C. Revenga, J. Rude, C. Szuwalski, S. Valencia, and S. Victor. 2016. FishPath: A Decision Support System for Assessing and Managing Data- and Capacity-Limited Fisheries. In: T.J. Quinn II, J.L. Armstrong, M.R. Baker, J. Heifetz, and D. Witherell (eds.), Assessing and Managing Data-Limited Fish Stocks. Alaska Sea Grant, University of Alaska Fairbanks. http://doi.org/10.4027/amdlfs.2016.03

Doyle, M. J., C. Debenham, S. J. Barbeaux, T. W. Buckley, J. L. Pirtle, I. B. Spies, W. T. Stockhausen, S. K. Shotwell, M. T. Wilson, and D. W. Cooper. 2018. A full life history synthesis of Arrowtooth Flounder ecology in the Gulf of Alaska: Exposure and sensitivity to potential ecosystem change. Journal of Sea Research 142:28-51.

Duffy L., and S. Griffiths. 2017. Resolving potential redundancy of productivity attributes to improve ecological risk assessments. La Jolla, California (USA).

Eliff, C. I. and R. K. P. Kikuchi. 2017. Ecosystem services provided by coral reefs in a Southwestern Atlantic Archipelago. Ocean & Coastal Management 136:49-55

Fairgrieve, W. T., and C. E. Nash. 2009. Ecological Risk Assessment of Marine Fish Aquaculture. NOAA.

FAO. 2010. Report of the first workshop on the assessment of fishery stock status in South and Southeast Asia. Bangkok, 16-19 June 2009. Rome.

Feitosa, C. V., B. P. Ferreira, and M. Elisabeth de Araújo. 2008. A rapid new method for assessing sustainability of ornamental fish by-catch from coral reefs. Marine and Freshwater Research 59:1092-1100.

Filippi, D., S. Waugh, and S. Nicol. 2010. Revised Spatial Risk Indicators for Seabird Interactions with Longline Fisheries in the Western and Central Pacific. Page 47, Western and Central Pacfic Fisheries Commission - Scientific Committee Sixth Regular Session.

Fletcher, W. J. R. 2012. National Application of Sustainability Indicators for Australian Fisheries-Part 2: Ecosystem based frameworks for aquaculture, multi-fishery and international applications. FRDC Report - Project 2000/145 Part 2., Western Australia.

Fletcher, W. J. 2015. Review and refinement of an existing qualitative risk assessment method for application within an ecosystem-based management framework. ICES Journal of Marine Science 72:1043-1056.

Fletcher, W. J., J. Chesson, Fisher M., K. J. Sainsbury, T. Hundloe, A. D. M. Smith, and B. Whitworth. 2002. National ESD Reporting Framework for Australian Fisheries: The 'How To' Guide for Wild Capture Fisheries. FRDC Project 2000/145, Canberra, Australia.

Fletcher, W. J., J. Chesson, K. J. Sainsbury, T. J. Hundloe, and M. Fisher. 2005. A flexible and practical framework for reporting on ecologically sustainable development for wild capture fisheries. Fisheries Research 71:175-183.

Fletcher, W. J., J. Shaw, S. J. Metcalf, and D. J. Gaughan. 2010. An ecosystem based fisheries management framework: the efficeient, regional-level planning toof for management agencies. Marine Policy 34:1226-1238.

Fock, H. 2011. Integrating Multiple Pressures at Different Spatial and Temporal Scales: A Concept for Relative Ecological Risk Assessment in the European Marine Environment. Human and Ecological Risk Assessment: An International Journal 17:187-211.

Ford, R. B., A. Galland, M. R. Clark, P. Crozier, C. A. J. Duffy, M. Dunn, M. P. Francis, and R. Wells. 2015. Qualitative (Level 1) Risk Assessment of the impact of commercial fishing on New Zealand Chondrichthyans., Ministry for Primary Industries, New Zealand.

Forney, K.A., B. L. Southall, E. Slooten, S. Dawson, A. J. Read, R. W. Baird, R. L. Brownell Jr. 2017. Nowhere to go: noise impact assessments for marine mammal populations with high site fidelity. Endangered Species Research 32:391–413.

Forrest, R. E., K. R. Holt, and A. R. Kronlund. 2018. Performance of alternative harvest control rules for two Pacific groundfish stocks with uncertain natural mortality: Bias, robustness and trade-offs. Fisheries Research 206:259-286.

Francis, R. I. C. 1992. Use of risk analysis to assess fishery management strategies - A case-study using Orange Roughy (*Hoplosetthus atlanticus*) on the Chatham Rise, New-Zealand. Canadian Journal of Fisheries and Aquatic Sciences 49:922-930.

Froese, R. and C. Binohlan. 2000. Empirical relationships to estimate asymptotic length, length at first maturity and length at maximum yield per recruit in fishers, with a simple method to evaluate length frequency data. Journal of Fish Biology 56:758–773.

Fu, D., M. J. Roux, S. Clarke, M. Francis, A. Dunn, and S. Hoyle. 2017. Pacific-wide sustainability risk assessment of bigeye thresher shark (Alopias superciliosus). NIWA.

Fulton, E.A. 2010. Approaches to end-to-end ecosystem models. Journal of Marine Systems 81:171-183.

Fulton, E. A. and J. S. Link. 2014. Modeling Approaches for Marine Ecosystem-based Management. In: M. J. Fogarty and J. J. McCarthy (Eds) Marine Ecosystem-Based Management. The Sea: Volume 16. Harvard University Press

Fulton, E.A., A. D. M. Smith, and A. E. Punt. 2005. Which ecological indicators can robustly detect effects of fishing? ICES Journal of Marine Science 62:540–551.

Fulton, E. A., A. E. Punt, C. M. Dichmont, C. J. Harvey, and R. Gorton. 2019. Ecosystems say good management pays off. Fish and Fisheries 20:66-96.

Furlong-Estrada, E., F. Galvan-Magana, and J. Tovar-Avila. 2017. Use of the productivity and susceptibility analysis and a rapid management-risk assessment to evaluate the vulnerability of sharks caught off the west coast of Baja California Sur, Mexico. Fisheries Research 194:197-208.

Furlong-Estrada, E., J. Tovar-Avila, and E. Rios-Jara. 2014. Ecological risk assessment of artisanal capture methods on sharks fished at the entrance of the Gulf of California. Hidrobiologica 24:83-97.

Gaichas, S. K., J. S. Link, and J. A. Hare. 2014. A risk-based approach to evaluating northeast US fish community vulnerability to climate change. ICES Journal of Marine Science 71:2323–2342.

Gaichas, S. K., R. J. Seagraves, J. M. Coakley, G. S. DePiper, V. G. Guida, J. A. Hare, P. J. Rego, and M. J. Wilberg. 2016. A Framework for Incorporating Species, Fleet, Habitat, and Climate Interactions into Fishery Management. Frontiers in Marine Science 3: 105. doi: 10.3389/fmars.2016.00105

Gaichas, S. K., G. S. DePiper, R. J. Seagraves, B. W. Muffley, M. G. Sabo, L. L. Colburn, and A. J. Loftus. 2018. Implementing Ecosystem Approaches to Fishery Management: Risk Assessment in the US Mid-Atlantic. 5:442. doi: 10.3389/fmars.2018.00442

Galindo-Cortes, G., L. Jiménez-Badillo, and C. Meiners. 2019. Moving from Stock Assessment to Fisheries Management in Mexico: The Finfish Fisheries from the Southern Gulf of Mexico and Caribbean Sea. Pages 243-263 in S. Salas, M. J. Barragán-Paladines, and R. Chuenpagdee, editors. Viability and Sustainability of Small-Scale Fisheries in Latin America and The Caribbean. Springer International Publishing, Cham.

Gallagher, A. J., P. M. Kyne, and N. Hammerschlag. 2012. Ecological risk assessment and its application to elasmobranch conservation and management. Journal of Fish Biology 80:1727-1748.

Geromont H. F., and D. S. Butterworth. 2015. A review of assessment methods and the development of management procedures for data-poor fisheries. Report for UN by Marine Resource Assessment and Management Group (MARAM), Department of Mathematics and Applied Mathematics, University of Cape Town. 218 pgs.

Gilman, E., M. Owens, and T. Kraft. 2014. Ecological risk assessment of the Marshall Islands longline tuna fishery. Marine Policy 44:239-255.

Gilman, E., M. Weijerman, and P. Suuronen. 2017. Ecological data from observer programmes underpin ecosystem-based fisheries management. Ices Journal of Marine Science 74:1481-1495.

Gilman, E., M. Chaloupka, L. Dagorn, M. Hall, A. Hobday, M. Musyl, T. Pitcher, F. Poisson, V. Restrepo, and P. Suuronen. 2019. Robbing Peter to pay Paul: replacing unintended cross-taxa conflicts with intentional tradeoffs by moving from piecemeal to integrated fisheries bycatch management. Reviews in Fish Biology and Fisheries 29:93-123.

Gimpel, A., V. Stelzenmuller, S. Topsch, I. Galparsoro, M. Gubbins, D. Miller, A. Murillas, A. G. Murray, K. Pinarbasi, G. Roca, and R. Watret. 2018. A GIS-based tool for an integrated assessment of spatial planning trade-offs with aquaculture. Science of the Total Environment 627:1644-1655.

Goetze, J. S., F. A. Januchowski-Hartley, J. Claudet, T. J. Langlois, S. K. Wilson, and S. D. Jupiter. 2017. Fish wariness is a more sensitive indicator to changes in fishing pressure than abundance, length or biomass. Ecological Applications 27:1178-1189.

Goldsworthy, S. D., and B. Page. 2007. A risk-assessment approach to evaluating the significance of seal bycatch in two Australian fisheries. Biological Conservation 139:269-285.

Government of Canada. 2012. Federal Contaminated Sites Action Plan (FCSAP) Ecological Risk Assessment Guidance. Canada. pgs 219.

Gray, S. A., M. C. Ives, J. P. Scandol, and R. C. Jordan. 2010. Categorising the risks in fisheries management. Fisheries Management and Ecology 17:501-512.

Griffiths, S. P., D. T. Brewer, D. S. Heales, D. A. Milton, and I. C. Stobutzki. 2006. Validating ecological risk assessments for fisheries: assessing the impacts of turtle excluder devices on elasmobranch bycatch populations in an Australian trawl fishery. Marine and Freshwater Research 57:395-401.

Griffiths, S., K. Kesner-Reyes, C. Garilao, K. Duffy, and M. Roman. 2018a. Development of a flexible Ecological Risk Assessment (ERA) approach for quantifying the cumulative impacts of fisheries on bycatch species in the eastern Pacific Ocean. Page 61, 9th Meeting of the Scientific Advisory Committee La Jolla, California USA, 14-18 May 2018.

Griffiths, S. P., K. Kesner-Reyes, C. V. Garilao, L. Duffy, and M. Roman. 2018b. Development of a flexible ecological risk assessment (ERA) approach for quantifying the cumulative impacts of fisheries on bycatch species in the Eastern Pacific Ocean. IOTTC.

Guo, X. H., S. H. Cui, T. Lin, and Y. Song. 2011. The ecological risk assessment of the Chinese White Dolphins in Xiamen coastal waters. Aquatic Ecosystem Health & Management 14:298-304.

Halpern, B.S., S. Walbridge, K. A. Selkoe, C. V. Kappel, F. Micheli, C. D'Agrosa, J. F. Bruno, K. S. Casey, C. Ebert, H. E. Fox, R. Fujita, D. Heinemann, H. S. Lenihan, E. M. P. Madin, M. T. Perry, E. R. Selig, M. Spalding, R. Steneck, R. Watson. 2008. A Global Map of Human Impact on Marine Ecosystems. Science 319:948-952

Hare, J. A., W. E. Morrison, M. W. Nelson, M. M. Stachura, E. J. Teeters, R. B. Griffis, M. A. Alexander, J. D. Scott, L. Alade, R. J. Bell, A. S. Chute, K. L. Curti, T. H. Curtis, D. Kircheis, J. F. Kocik, S. M. Lucey, C. T. McCandless, L. M. Milke, D. E. Richardson, E. Robillard, H. J. Walsh, M. C. McManus, K. E. Marancik, and C. A. Griswold. 2016. A Vulnerability Assessment of Fish and Invertebrates to Climate Change on the Northeast US Continental Shelf. PLoS ONE 11.

Harvey, C. J., C. R. Kelble, and F. B. Schwing. 2017. Implementing "the IEA": using integrated ecosystem assessment frameworks, programs, and applications in support of operationalizing ecosystem-based management. Ices Journal of Marine Science 74:398-405.

Hazen, E. L., K. L. Scales, S. M. Maxwell, D. K. Briscoe, H. Welch, S. J. Bograd, H. Bailey, S. R. Benson, T. Eguchi, H. Dewar, S. Kohin, D. P. Costa, L. B. Crowder, and R. L. Lewison. 2018. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. 4:eaar3001.

Hazen, L., E. Le Cornu, A. Zerbe, R. Martone, A. L. Erickson, and L. B. Crowder. 2016. Translating sustainable seafood frameworks to assess the implementation of ecosystem-based fisheries management. Fisheries Research 182:149-157.

Hiddink, J. G., S. Jennings, M. Sciberras, S. G. Bolam, G. Cambiè, R. A. McConnaughey, T. Mazor, R. Hilborn, J. S. Collie, C. R. Pitcher, A. M. Parma, P. Suuronen, M. J. Kaiser, and A. D. Rijnsdorp. 2019. Assessing bottom trawling impacts based on the longevity of benthic invertebrates. Journal of Applied Ecology 56: 1075-1084

Himes-Cornell, A., and S. Kasperski. 2015. Assessing climate change vulnerability in Alaska's fishing communities. Fisheries Research 162:1-11.

Himes-Cornell, A., and S. Kasperski. 2016. Using Socioeconomic and Fisheries Involvement Indices to Understand Alaska Fishing Community Well-Being. Coastal Management 44:36-70.

Himes-Cornell, A., C. Maguire, S. Kasperski, K. Hoelting, and R. Pollnac. 2016. Understanding vulnerability in Alaska fishing communities: A validation methodology for rapid assessment of indices related to well-being. Ocean & Coastal Management 124:53-65.

Hobday, D., A. E. Punt, and D. C. Smith. 2005. Modelling the effects of Marine Protected Areas (MPAs) on the southern rock lobster (Jasus edwardsii) fishery of Victoria, Australia. New Zealand Journal of Marine and Freshwater Research 39:675-686.

Hobday, A. J., A. D. M. Smith, H. Webb, R. Daley, S. Wayte, C. Bulman, J. Dowdney, A. Williams, M. Sporcic, J. M. Dambacher, M. Fuller, and W. T. 2007. Ecological Risk Assessment for the Effects of Fishing: Methodology. Report R04/1072 for the Australian Fisheries Management Authority., CSIRO Marine and Atmospheric Research, Hobart.

Hobday, A. J., A. D. M. Smith, I. C. Stobutzki, C. Bulman, R. Daley, J. M. Dambacher, R. A. Deng, J. Dowdney, M. Fuller, D. Furlani, S. P. Griffiths, D. Johnson, R. Kenyon, I. A. Knuckey, S. D. Ling, R. Pitcher, K. J. Sainsbury, M. Sporcic, T. Smith, C. Turnbull, T. I. Walker, S. E. Wayte, H. Webb, A. Williams, B. S. Wise, and S. Zhou. 2011a. Ecological risk assessment for the effects of fishing. Fisheries Research 108:372-384.

Hobday, A. J., C. M. Bulman, A. Williams, and M. Fuller. 2011b. Ecological risk assessment for effects of fishing on habitats and communities FRDC Report 2009/029. Fisheries Research and Development Corporation and CSIRO Marine and Atmospheric Research, Hobart, Australia.

Hoenig, J.M., 1983. Empirical use of longevity data to estimate mortality rates. Fisheries Bulletin 82:898–903.

Holsman, K., J. Samhouri, G. Cook, E. Hazen, E. Olsen, M. Dillard, S. Kasperski, S. Gaichas, C. R. Kelble, M. Fogarty, and K. Andrews. 2017. An ecosystem-based approach to marine risk assessment. Ecosystem Health and Sustainability 3:e01256.

Holt, K. R., B. Ackerman, R. Flemming, R. E. Forrest, A. R. Kronlund, L. Lacko, N. Olsen, K. Rutherford, R. D. Stanley, N. G. Taylor, and G. Workman. 2012. Ecological Risk Assessment for the Effects of Fishing: A Pilot Study for British Columbia Groundfish Fisheries. Fisheries an Oceans Canada, British Columbia, Canada.

Hordyk, A. R., and T. R. Carruthers. 2018. A quantitative evaluation of a qualitative risk assessment framework: Examining the assumptions and predictions of the Productivity Susceptibility Analysis (PSA). PLoS ONE 13:e0198298.

Hornborg, S., A. J. Hobday, F. Ziegler, A. D. M. Smith, and B. S. Green. 2018. Shaping sustainability of seafood from capture fisheries integrating the perspectives of supply chain stakeholders through combining systems analysis tools. Ices Journal of Marine Science 75:1965-1974.

Hoyle, S. D., C. T. T. Edwards, M.-J. Roux, S. C. Clarke, and M. P. Francis. 2017. Southern Hemisphere porbeagle shark stock status assessment. NIWA.

ICES. 2012. Report on the Classification of Stock Assessment Methods developed by SISAM. ICES CM 2012/ACOM/SCICOM:01. 15 pp.

ICES. 2013. ICES WKLIFE III REPORT. Report of the Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other key parameters for Data-limited Stocks; ICES CM 2013/ACOM.

Jensen, A.L., 1996. Beverton and Holt life history invariants result from optimal tradeoff of reproduction and survival. Canadian Journal of Fisheries and Aquatic Sciences 53:820–822.

Jepson, M. A., and L. L. Colburn. 2013. Development of social indicators of fishing community in the U.S. Southeast and Northeast regions.

Jiang, Z. G., N. Xu, B. X. Liu, L. Z. Zhou, J. Wang, C. Wang, B. G. Dai, and W. Xiong. 2018. Metal concentrations and risk assessment in water, sediment and economic fish species with various habitat preferences and trophic guilds from Lake Caizi, Southeast China. Ecotoxicology and Environmental Safety 157:1-8.

Jiménez, S., A. Domingo, M. Abreu, and A. Brazeiro. 2012. Risk assessment and relative impact of Uruguayan pelagic longliners on seabirds. Aquatic Living Resources 25:281-295.

Jin, D., G. DePiper, and P. Hoagland. 2016. Applying Portfolio Management to Implement Ecosystem-Based Fishery Management (EBFM). North American Journal of Fisheries Management 36:652-669.

Jones, B. L., L. C. Cullen-Unsworth, R. Howard, and R. K. F. Unsworth. 2018. Complex yet fauna-deficient seagrass ecosystems at risk in southern Myanmar. Botanica Marina 61:193-203.

Jones, M. C., and W. W. L. Cheung. 2018. Using fuzzy logic to determine the vulnerability of marine species to climate change. Global Change Biology 24:E719-E731.

Juan-Jordá M.J., A. H., Dulvy N., Cooper A. and Murua H. 2014. Preliminary review of ICCAT and IATTC progress in applying an ecosystem approach to fisheries management. SCRS/2014/126. International Commission for the Conservation of Atlantic Tunas Collective Volume of Scientific Papers 71.

Juan-Jorda, M. J., H. Murua, H. Arrizabalaga, N. K. Dulvy, and V. Restrepo. 2018. Report card on ecosystem-based fisheries management in tuna regional fisheries management organizations. Fish and Fisheries 19:321-339.

Kang, H. J., Y. I. Seo, and C. I. Zhang. 2018. A preliminary study on ABC estimation approach for ecosystem-based TAC management. Ocean & Coastal Management 157:9-22.

Karintseva, O. I. 2017. Scientific and methodical approaches to the environmental risk assessment for different types of economic activity. Marketing and Management of Innovations:377-387.

Karnauskas M., C. R. Kelble, S. Regan, C. Quenée, R. Allee, M. Jepson, A. Freitag, J. K. Craig, C. Carollo, L. Barbero, N. Trifonova, D. Hanisko, and G. Zapfe. 2017. 2017 Ecosystem status report update for the Gulf of Mexico. NOAA Technical Memorandum NMFS-SEFSC-706, 51 p.

Kell L.T., and L. B. 2018. Extending the indicator-based ecosystem report card to the whole ecosystem; a preliminary example based on the Sargasso Sea. International Commission for the Conservation of Atlantic Tunas Collective Volume of Scientific Papers 75:258-275.

Keith, D. A., J. P. Rodríguez, K. M. Rodríguez-Clark, E. Nicholson, K. Aapala, A. Alonso, M. Asmussen, S. Bachman, A. Basset, E. G. Barrow, J. S. Benson, M. J. Bishop, R. Bonifacio, T. M. Brooks, M. A. Burgman, P. Comer, F. A. Comín, F. Essl, D. Faber-Langendoen, P. G. Fairweather, R. J. Holdaway, M. Jennings, R. T. Kingsford, R. E. Lester, R. Mac Nally, M. A. McCarthy, J. Moat, M. A. Oliveira-Miranda, P. Pisanu, B. Poulin, T. J. Regan, U. Riecken, M. D. Spalding, S. Zambrano-Martínez. 2013. Scientific Foundations for an IUCN Red List of Ecosystems. PLoS ONE 8(5): e62111. doi:10.1371/journal.pone.0062111

Kenny, A. J., N. Campbell, M. Koen-Alonso, P. Pepin, and D. Diz. 2018. Delivering sustainable fisheries through adoption of a risk-based framework as part of an ecosystem approach to fisheries management. Marine Policy 93:232-240.

Kirby, D. S., S. M. Waugh, and D. P. Filippi. 2009. Spatial risk indicators for seabird interactions with longline fisheries in the western and central Pacific. Port Vila, Vanuatu.

Knights, A. M., G. J. Piet, R. H. Jongbloed, J. E. Tamis, L. White, E. Akoglu, L. Boicenco, T. Churilova, O. Kryvenko, V. Fleming-Lehtinen, J.-M. Leppanen, B. S. Galil, F. Goodsir, M. Goren, P. Margonski, S. Moncheva, T. Oguz, K. N. Papadopoulou, O. Setälä, C. J. Smith, K. Stefanova, F. Timofte, and L. A. Robinson. 2015. An exposure-effect approach for evaluating ecosystem-wide risks from human activities. ICES Journal of Marine Science 72:1105-1115.

Korpinen, S., and J. H. Andersen. 2016. A Global Review of Cumulative Pressure and Impact Assessments in Marine Environments. Frontiers in Marine Science 3.

Lack, M., G. Sant, M. Burgener, and N. Okes. 2014. Development of a Rapid Management-Risk Assessment Method for Fish Species through its Application to Sharks: Framework and Results. Report to the Department of Environment, Food and Rural Affairs. Defra Contract No. MB0123

Landis, W. G., J. L. Durda, M. L. Brooks, P. M. Chapman, C. A. Menzie, R. G. Stahl, and J. L. Stauber. 2013. Ecological risk assessment in the context of global climate change. Environmental Toxicology and Chemistry 32:79-92.

Leadbitter, D. 2013. A Risk Based Approach for Promoting Management Regimes for Trawl Fisheries in South East Asia. Asian Fisheries Science 26:65-78.

Levin, P. S., T. E. Essington, K. N. Marshall, L. E. Koehn, L. G. Anderson, A. Bundy, C. Carothers, F. Coleman, L. R. Gerber, J. H. Grabowski, E. Houde, O. P. Jensen, C. Möllmann, K. Rose, J. N. Sanchirico, and A. D. M. Smith. 2018. Building effective fishery ecosystem plans. Marine Policy 92:48-57.

Lillebo, A. I., H. Teixeira, M. Morgado, J. Martinez-Lopez, A. Marhubi, G. Delacamara, P. Strosser, and A. J. A. Nogueira. 2019. Ecosystem-based management planning across aquatic realms at the Ria de Aveiro Natura 2000 territory. Science of the Total Environment 650:1898-1912.

Link, J. S. 2005. Translating ecosystem indicators into decision criteria. ICES Journal of Marine Science 62:569-576.

Lucena-Fredou, F., L. Kell, T. Fredou, D. Gaertner, M. Potier, P. Bach, P. Travassos, F. Hazin, and F. Menard. 2017. Vulnerability of teleosts caught by the pelagic tuna longline fleets in South Atlantic and Western Indian Oceans. Deep-Sea Research Part Ii-Topical Studies in Oceanography 140:230-241.

Malakar, K., T. Mishra, and A. Patwardhan. 2019. Factors linked with adaptation in the Indian marine fishing community. Ocean & Coastal Management 171:37-46.

Marshall, K. N., I. C. Kaplan, E. E. Hodgson, A. Hermann, D. S. Busch, P. McElhany, T. E. Essington, C. J. Harvey, and E. A. Fulton. 2017. Risks of ocean acidification in the California Current food web and fisheries: ecosystem model projections. Global Change Biology 23:1525-1539.

Maunder, M. N., and K. R. Piner. 2015. Contemporary fisheries stock assessment: many issues still remain. ICES Journal of Marine Science 72: 7–18.

Mazaris, A. D., and B. Germond. 2018. Bridging the gap between climate change and maritime security: Towards a comprehensive framework for planning. Science of the Total Environment 635:1076-1080.

Mazor, T. K., C. R. Pitcher, N. Ellis, W. Rochester, S. Jennings, J. G. Hiddink, R. A. McConnaughey, M. J. Kaiser, A. M. Parma, P. Suuronen, M. Kangas, and R. Hilborn. 2017. Trawl exposure and protection of seabed fauna at large spatial scales. Diversity and Distributions 23:1280-1291.

McDonald, G., B. Harford, A. Arrivillaga, E. A. Babcock, R. Carcamo, J. Foley, R. Fujita, T. Gedamke, J. Gibson, K. Karr, J. Robinson, and J. Wilson. 2017. An indicator-based adaptive management framework and its development for data-limited fisheries in Belize. Marine Policy 76:28-37.

Meissa, B., and D. Gascuel. 2015. Overfishing of marine resources: some lessons from the assessment of demersal stocks off Mauritania. ICES Journal of Marine Science 72:414-427.

Micheli, F., G. De Leo, C. Butner, R. G. Martone, and G. Shester. 2014. A risk-based framework for assessing the cumulative impact of multiple fisheries. Biological Conservation 176:224-235.

Milton, D.A., 2001. Assessing the susceptibility to fishing of populations of rare trawl bycatch: sea snakes caught by Australia's Northern Prawn Fishery. Biological Conservation 101: 281–290.

Moore, J E., K. A. Curtis, R. L. Lewison, P. W. Dillingham, J. M. Copes, S. V. Fordham, S. S. Heppell, S. A. Pardo, C. A. Simpfendorf, G. N. Tuck, S. Zhou. 2013. Evaluating sustainability of fisheries bycatch mortality for marine megafauna: a review of conservation reference points for data-limited populations. Environmental Conservation 40: 329–344

Munoz, M., A. Reul, L. G. de Sola, R. A. M. Lauerburg, O. Tello, A. Gimpel, and V. Stelzenmuller. 2018. A spatial risk approach towards integrated marine spatial planning: A case study on European hake nursery areas in the North Alboran Sea. Marine Environmental Research 142:190-207.

Murua, H., R. Coelho, M. Santos, H. Arrizabalaga, K. Yokawa, E. Romanov, J. Zhu, Z. Kim, P. Bach, P. Chavance, A. Delgado de Monlina, and J. Ruiz. 2012. Preliminary Ecological Risk Assessment (ERA) for shark species caught in fisheries managed by the Indian Ocean Tuna Commission (IOTC). Page 17.

Nel, R., R. M. Wanless, A. Angel, B. Mellet, and L. Harris. 2013. Ecological Risk Assessment and Productivity - Susceptibility Analysis of sea turtles overlapping with fisheries in the IOTC region.

Newman, S. J., J. I. Brown, D. V. Fairclough, B. S. Wise, L. M. Bellchambers, B. W. Molony, R. C. J. Lenanton, G. Jackson, K. A. Smith, D. J. Gaughan, W. J. Fletcher, R. B. McAuley, and C. B. Wakefield. 2018. A risk assessment and prioritisation approach to the selection of indicator species for the assessment of multi-species, multi-gear, multi-sector fishery resources. Marine Policy 88:11-22.

O, M., R. Martone, L. Hannah, L. Greig, J. Boutillier, and S. Patton. 2015. An Ecological Risk Assessment Framework (ERAF) for Ecosystem-based Oceans Management in the Pacific Region. DFO Can. Sci. Advis. Sec. Res. Doc. 2014/072.vii + 59 p.

O'Laughlin, J. 2005. Conceptual model for comparative ecological risk assessment of wildfire effects on fish, with and without hazardous fuel treatment. Forest Ecology and Management 211:59-72.

Ormseth, O. A., and P. D. Spencer. 2011. An assessment of vulnerability in Alaska groundfish. Fisheries Research 112:127-133.

Parappurathu, S., C. Ramachandran, A. Gopalakrishnan, D. Kumar, M. K. Poddar, M. Choudhury, R. Geetha, K. M. Koya, R. N. Kumar, K. P. Salini, and P. V. Sunil. 2017. What ails fisheries insurance in India? An assessment of issues, challenges and future potential. Marine Policy 86:144-155.

Paterson, B., B. Neis, and R. L. Stephenson. 2018. A social-ecological study of stock structure and fleet dynamics in the Newfoundland herring fishery. Ices Journal of Marine Science 75:257-269.

Paterson, B., and S. L. Petersen. 2010. EAF implementation in Southern Africa: Lessons learnt. Marine Policy 34:276-292.

Patrick, W. S., P. Spencer, J. S. Link, J. Cope, J. Field, D. R. Kobayashi, P. Lawson, T. Gedamke, E. Cortes, O. Olav, K. Bigelow, and W. Overholtz. 2010. Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing. Fishery Bulletin 108:305-322.

Patrick, W., P. Spencer, O. Ormseth, J. Cope, J. Field, D.R. Kobayashi, T. Gedamke, E. Cortés, K. Bigelow, W. Overholtz, J. Link, and P. Lawson. 2009. Use of productivity and susceptibility indices to determine the vulnerability of a stock: with example applications to six US fisheries. NOAA Tech Memo.

Pauly, D., 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. Journal du Conseil International pour l'Exploration de la Mer 39:75–284.

Pecl, G. T., T. Ward, Z. Doubleday, S. Clarke, J. Day, C. Dixon, S. Frusher, P. Gibbs, A. Hobday, N. Hutchinson, S. Jennings, K. Jones, X. Li, D. Spooner, and R. Stoklosa. 2011. Risk Assessment of Impacts of Climate Change for Key Marine Species in South Eastern Australia. Part 1: Fisheries and Aquaculture Risk Assessment. Fisheries Research and Development Corporation, Project 2009/070.

Pecl, G. T., M. B. Araújo, J. D. Bell, J. Blanchard, T. C. Bonebrake, I.-C. Chen, T. D. Clark, R. K. Colwell, F. Danielsen, B. Evengård, L. Falconi, S. Ferrier, S. Frusher, R.A. Garcia, R.B. Griffis, A.J. Hobday, C. Janion-Scheepers, M.A. Jarzyna, S. Jennings, J. Lenoir, H.I. Linnetved, V.Y. Martin, P.C. McCormack, J. McDonald, N.J. Mitchell, T. Mustonen, J.M. Pandolfi, N. Pettorelli, E. Popova, S.A. Robinson, B.R. Scheffers, J.D. Shaw, C.J.B. Sorte, J.M. Strugnell, J.M. Sunday, M.N. Tuanmu, A. Vergés, C. Villanueva, T. Wernberg, E. Wapstra, and S.E. Williams. (2017) Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. Science 355: eaai9214

Pedreschi, D., P. Bouch, M. Moriarty, E. Nixon, A. M. Knights, and D. G. Reid. 2019. Integrated ecosystem analysis in Irish waters; Providing the context for ecosystem-based fisheries management. Fisheries Research 209:218-229.

Penney, A. J., and J. M. Guinotte. 2013. Evaluation of New Zealand's High-Seas Bottom Trawl Closures Using Predictive Habitat Models and Quantitative Risk Assessment. PLoS ONE 8:18.

Piet, G. J., R. H. Jongbloed, A. M. Knights, J. E. Tamis, A. J. Paijmans, M. T. v. d. Sluis, P. d. Vries, and L. A. Robinson. 2015. Evaluation of ecosystem-based marine management strategies based on risk assessment. Biological Conservation 186:158-166.

Piet, G. J., A. M. Knights, R. H. Jongbloed, J. E. Tamis, P. de Vries, and L. A. Robinson. 2017. Ecological risk assessments to guide decision-making: Methodology matters. Environmental Science & Policy 68:1-9.

Piet, G., F. Culhane, R. Jongbloed, L. Robinson, B. Rumes, and J. Tamis. 2019. An integrated risk-based assessment of the North Sea to guide ecosystem-based management. Science of the Total Environment 654:694-704.

Pitcher, C. R. 2014. Quantitative indicators of environmental sustainability risk for a tropical shelf trawl fishery. Fisheries Research 151:136-147.

Pitcher, C. R., N. Ellis, W. N. Venables, T. J. Wassenberg, C. Y. Burridge, G. P. Smith, M. Browne, F. Pantus, I. R. Poiner, P. J. Doherty, J. N. A. Hooper, and N. Gribble. 2016a. Effects of trawling on sessile megabenthos in the Great Barrier Reef and evaluation of the efficacy of management strategies. ICES Journal of Marine Science 73: 115-126.

Pitcher, R., N. Ellis, F. Althaus, A. Williams, I. McLeod, R. Bustamante, R. Kenyon, and M. Fuller. 2016b. Implications of current spatial management measures for AFMA ERAs for habitats. FRDC Project No 2014/204. Brisbane.

Pitcher, C.R., N. Ellis, S. Jennings, J.G. Hiddink, T. Mazor, M. J. Kaiser, M. I. Kangas, R. A. McConnaughey, A. M. Parma, A. D. Rijnsdorp, P. Suuronen, J. S. Collie, R. Amoroso, K. M. Hughes, and R. Hilborn. 2017. Estimating the sustainability of towed fishing-gear impacts on seabed habitats: a simple quantitative risk assessment method applicable to data-limited fisheries. Methods in Ecology and Evolution 8: 472–480.

Plagányi, É.E. 2007. Models for an ecosystem approach to fisheries. FAO Technical Paper 477.

Plagányi, É.E, A. E. Punt, R. Hillary, E. B. Morello, O. Thébaud, T. Hutton, R. D. Pillans, J. T. Thorson, E. A. Fulton, A. D. M. Smith, F. Smith, P. Bayliss, M. Haywood, V. Lyne, and P.C. Rothlisberg. 2014. Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries 15: 1-22.

Prince, J., A. Hordyk, N. Loneragan, S. R. Valencia, and K. Sainsbury. 2014. Revisiting the concept of Beverton-–Holt life-history invariants with the aim of informing data-poor fisheries assessment. ICES Journal of Marine Science 72:194-203.

Punt, A. E., T. Huang, and M. N. Maunder. 2013. Review of integrated size-structured models for stock assessment of hard-to-age crustacean and mollusc species. ICES Journal of Marine Science 70: 16–33.

Quinn, T. J. and R. B. Deriso. 1999. Quantitative Fish Dynamics. Oxford University Press, New York

Richard, Y., E. R. Abraham, and K. Berkenbusch. 2017. Assessment of the risk of commercial fisheries to New Zealand seabirds, 2006–07 to 2014–15.

Rico, A., Y. Geng, A. Focks, and P. J. van den Brink. 2012. ERA-AQUA version 2.0, technical description and manual : a decision support system for the Environmental Risk Assessment of veterinary medicines applied in pond AQUAculture. Alterra, Wageningen.

Rijnsdorp, A. D., S. G. Bolam, C. Garcia, J. G. Hiddink, N. T. Hintzen, P. D. van Denderen, and T. van Kooten. 2018. Estimating sensitivity of seabed habitats to disturbance by bottom trawling based on the longevity of benthic fauna. Ecological Applications 28:1302-1312.

Robinson, L. A., Culhane, F.E., Baulcomb, C., Bloomfield, H., Boehnke-Henrichs, A., Breen, P., Goodsir, F., Hussain, S.S., Knights, A.M., Piet, G.J., Raakjaer, J., van Tatenhove, J., Frid, C.L.J. 2014. Towards delivering ecosystem-based marine management: The ODEMM Approach. Deliverable 17, EC FP7 Project (244273) 'Options for Delivering Ecosystem-based Marine Management'. University of Liverpool., Liverpool.

Rosenberg, A., D. Agnew, E. Babcock, A. Cooper, C. Mogensen, R. O'Boyle, J. Powers, G. Stefánsson, and J. Swasey. 2009. Setting Annual Catch Limits for U.S. Fisheries: An Expert Working Group Report. Lenfest Ocean Program.

Roux, M. J., R. F. Tallman, and Z. A. Martin. 2019. Small-scale fisheries in Canada's Arctic: Combining science and fishers knowledge towards sustainable management. Marine Policy 101:177-186.

Rowland, J. A., E. Nicholson, N. J. Murray, D. A. Keith, R. E. Lester, and L. M. Bland. 2018. Selecting and applying indicators of ecosystem collapse for risk assessments. Conservation Biology 32:1233-1245.

Samhouri, J. F., and P. S. Levin. 2012. Linking land- and sea-based activities to risk in coastal ecosystems. Biological Conservation 145:118-129.

Samhouri, J. F., E. Ramanujam, J. J. Bizzarro, H. Carter, K. Sayce, and S. Shen. 2019. An ecosystem-based risk assessment for California fisheries co-developed by scientists, managers, and stakeholders. Biological Conservation 231:103-121.

Sanchirico, J. N., M. D. Smith, and D. W. Lipton. 2008. An empirical approach to ecosystem-based fishery management. Ecological economics: Journal of the International Society for Ecological Economics. 64:586-596.

Sara, J. R., S. M. Marr, N. M. Chabalala, W. J. Smit, L. J. C. Erasmus, and W. J. Luus-Powell. 2018. Human health risks of metalloids and metals in muscle tissue of silver carp Hypophthalmichthys molitrix (Valenciennes, 1844) from Lake Flag Boshielo, South Africa. African Journal of Aquatic Science 43:405-411.

Savenkoff, C., J. A. Gagne, M. Gilbert, M. Castonguay, D. Chabot, J. Chasse, S. Comtois, J. D. Dutil, P. S. Galbraith, J. F. Gosselin, F. Gregoire, R. Larocque, P. Larouche, D. Lavoie, M. Lebeuf, V. Lesage, F. Maps, I. H. McQuinn, A. Mosnier, C. Nozeres, P. Ouellet, S. Plourde, B. Sainte-Marie, L. Savard, M. Scarratt, and M. Starr. 2017. Le concept d'approche ecosystemique applique a l'estuaire maritime du Saint-Laurent (Canada). Environmental Reviews 25:26-96.

Schick, A., C. Sandig, A. Krause, P. R. Hobson, S. Porembski, and P. L. Ibisch. 2018. People-Centered and Ecosystem-Based Knowledge Co-Production to Promote Proactive Biodiversity Conservation and Sustainable Development in Namibia. Environmental Management 62:858-876.

Serveiss, V. B., J. L. Bowen, D. Dow, and I. Valiela. 2004. Using ecological risk assessment to identify the major anthropogenic stressor in the Waquoit Bay Watershed, Cape Cod, Massachusetts. Environmental Management 33:730-740.

Sethi, S. A. 2010. Risk management for fisheries. Fish and Fisheries 11:341-365.

Shannon, L., M. Coll, A. Bundy, D. Gascuel, J. J. Heymans, K. Kleisner, C. P. Lynam, C. Piroddi, J. Tam, M. Travers-Trolet, Y. Shin. 2014. Trophic level-based indicators to track fishing impacts across marine ecosystems. Marine Ecology Progress Series 512: 115–140.

Sharp, B. R., S. J. Parker, and N. Smith. 2009. An impact assessment framework for bottom fishing methods in the CAMLR Convention Area. CCAMLR Science 16:195-210.

Sherman, K. 2008. The Large Marine Ecosystem Approach to Marine Resources Assessment and Management. Pages 47-75 in Bergen Conference on Implementing the Ecosystem Approach to Fisheries organized by the Nordic Council of Ministers and the Governments of Iceland and Norway with technical support of the Food and Agriculture Organization (FAO) of the United Nations, Bergen, Norway, 26-28 September 2006. Cabi Publishing-C a B Int, Bergen.

Singh, G. G., J. Sinner, J. Ellis, M. Kandlikar, B. S. Halpern, T. Satterfield, and K. M. A. Chan. 2017. Mechanisms and risk of cumulative impacts to coastal ecosystem services: An expert elicitation approach. Journal of Environmental Management 199:229-241.

Singh-Renton, S., D. J. Die, and E. Mohammed. 2011. An Ecosystem Approach to Fisheries for Large Pelagic Fish Resources in theCaribbean Large Marine Ecosystem. Pages 197-212 in Lucia Fanning, Robin Mahon, and P. McConney, editors. Towards Marine Ecosystem-Based Management in the Wider Caribbean. Amsterdam University Press, Amsterdam.

Siple, M. C., T. E. Essington, and E. E. Plaganyi. 2019. Forage fish fisheries management requires a tailored approach to balance trade-offs. Fish and Fisheries 20:110-124.

Slooten, E., and N. Davies. 2012. Hector's dolphin risk assessments: old and new analyses show consistent results. Journal of the Royal Society of New Zealand 42:49-60.

Slooten, E., D. Fletcher, and B. L. Taylor. 2000. Accounting for uncertainty in risk assessment: Case study of Hector's dolphin mortality due to gillnet entanglement. Conservation Biology 14:1264-1270.

Small, C., S. M. Waugh, and R. A. Phillips. 2013. The justification, design and implementation of Ecological Risk Assessments of the effects of fishing on seabirds. Marine Policy 37:192-199.

Smith, A. D. M., E. J. Fulton, A. J. Hobday, D. C. Smith, and P. Shoulder. 2007. Scientific tools to support the practical implementation of ecosystem-based fisheries management. Ices Journal of Marine Science 64:633-639.

Soykan, O. 2018. Risk assessment in industrial fishing vessels by L type matrix method and its usability. Su Urunleri Dergisi 35:207-217.

Sporcic, M., Pethybridge, H., Bulman, C.M., Hobday, A., Fuller, M. (2018a). Ecological Risk Assessment for the Effects of Fishing. Final Report for the Heard Island and McDonald Islands Fishery: Demersal trawl sub-fishery 2010/11 to 2014/15. Report for the Australian Fisheries Management Authority. 142 pp.

Sporcic, M., Pethybridge, H., Bulman, C.M., Hobday, A., Fuller, M. (2018b). Ecological Risk Assessment for the Effects of Fishing. Final report for Heard Island and McDonald IslandsFishery: midwater trawl sub-fishery 2010/11 to 2014/15. Report for the Australian Fisheries Management Authority. 118pp.

Sporcic, M., Bulman, C.M., Fuller, M. 2018c. Ecological Risk Assessment for the Effects of Fishing. Draft report for Southern and Eastern Scalefish and Shark Fishery, Great Australian Bight Sector: Otter trawl sub-fishery 2012- 2016. Report for the Australian Fisheries Management Authority. 204 pp.

Sporcic, M., Bulman, C.M., Fuller, M. 2018d. Ecological Risk Assessment for the Effects of Fishing. Report for Southern and Eastern Scalefish and Shark Fishery (Commonwealth Trawl Sector): Gillnet sub-fishery 2012- 2016. Report for the Australian Fisheries Management Authority. 240 pp.

Sporcic, M., C. M. Bulman, and M. Fuller. 2019a. Ecological Risk Assessment for the Effects of Fishing. Report for Southern and Eastern Scalefish and Shark Fishery (Commonwealth Trawl Sector): Otter trawl Sub-fishery 2012- 2016. Report for the Australian Fisheries Management Authority. 296 p.

Sporcic, M., Bulman, C.M., Fuller, M. 2019b. Ecological Risk Assessment for the Effects of Fishing. Draft report for Southern and Eastern Scalefish and Shark Fishery (Commonwealth Trawl Sector):

Danish Seine Sub-fishery 2012- 2016. Report for the Australian Fisheries Management Authority. 196 p.

Sporcic, M., Hobday, A., Bulman, C., Fuller, M. 2019c. Ecological Risk Assessment for the Effects of Fishing: Eastern Tuna & Billfish Fishery: Longline Sub-fishery, data to 2015. Report for the Australian Fisheries Management Authority. 234 p.

Sporcic, M., Donovan, A., Van Der Velde, T., Fuller, M., Fry, G. 2019d. Ecological Risk Assessment for the Effects of Fishing. Draft report for Northern Prawn Fishery: Banana Prawn sub-fishery 2013- 2017. Report for the Australian Fisheries Management Authority. 221 p.

Sporcic, M., Donovan, A., Van Der Velde, T., Fuller, M., Fry, G. 2019e. Ecological Risk Assessment for the Effects of Fishing. Draft report for Northern Prawn Fishery: Tiger Prawn sub-fishery 2013-2017. Report for the Australian Fisheries Management Authority. 274 p.

Stelzenmuller, V., M. Coll, A. D. Mazaris, S. Giakoumi, S. Katsanevakis, M. E. Portman, R. Degen, P. Mackelworth, A. Gimpel, P. G. Albano, V. Almpanidou, J. Claudet, F. Essl, T. Evagelopoulos, J. J. Heymans, T. Genov, S. Kark, F. Micheli, M. G. Pennino, G. Rilov, B. Rumes, J. Steenbeek, and H. Ojaveer. 2018. A risk-based approach to cumulative effect assessments for marine management. Science of the Total Environment 612:1132-1140.

Stepanuk, J. E. F., A. J. Read, R. W. Baird, D. L. Webster, and L. H. Thorne. 2018. Spatiotemporal patterns of overlap between short-finned pilot whales and the US pelagic longline fishery in the Mid-Atlantic Bight: An assessment to inform the management of fisheries bycatch. Fisheries Research 208:309-320.

Stewart, K. R., E. L. LaCasella, M. P. Jensen, S. P. Epperly, H. L. Haas, L. W. Stokes, and P. H. Dutton. 2019. Using mixed stock analysis to assess source populations for at-sea bycaught juvenile and adult loggerhead turtles (*Caretta caretta*) in the north-west Atlantic. Fish and Fisheries 20:239-254.

Stewart, T. J., A. Joubert, R. Janssen 2010. MCDA Framework for Fishing Rights Allocation in South Africa. 19:247-265.

Stobutzki, I., M. Miller, and D. Brewer. 2001. Sustainability of fishery bycatch: a process for assessing highly diverse and numerous bycatch. Environmental Conservation 28:167-181.

Suter, G. W. 2008. Ecological risk assessment in the United States environmental protection agency: a historical overview. Integrated Environmental Assessment and Management 4:285-289.

Szuwalski, C. S., and J. T. Thorson. 2017. Global fishery dynamics are poorly predicted by classical models. Fish and Fisheries. 18:1085–1095.

Tallman, R. F., M. J. Roux, and Z. A. Martin. 2019. Governance and assessment of small-scale data-limited Arctic Charr fisheries using productivity-susceptibility analysis coupled with life history invariant models. Marine Policy 101:187-197.

Thorpe, R. B., P. J. Dolder, S. Reeves, P. Robinson, and S. Jennings. 2016. Assessing fishery and ecological consequences of alternate management options for multispecies fisheries. ICES Journal of Marine Science 73:1503-1512.

Travers, M., Y.-J. Shin, S. Jennings, and P. Cury. 2008. Towards end-to-end models for investigating the effects of climate and fishing in marine ecosystems. Progress in Oceanography 75:751–770

Trebilco, R., J. Melbourne-Thomas, and A. Constable. in press. The policy relevance of Southern Ocean food web structure: implications of food web change for fisheries, conservation and carbon sequestration. Journal of Marine Policy

Trenkel, V. M. 2018. How to provide scientific advice for ecosystem-based management now. Fish and Fisheries 19:390-398.

Tuck, G. N., and C. Wilcox. 2009. Assessing the impacts of fishing and habitat loss on the Lord Howe Island population of flesh-footed shearwaters. Proceedings 18th World IMACS / MODSIM Congress, Cairns, Australia 13-17 July 2009. http://mssanz.org.au/modsim09

Tuck, G. N., R. A. Phillips, C. Small, R. B. Thomson, N. L. Klaer, F. Taylor, R. M. Wanless, and H. Arrizabalaga. 2011. An assessment of seabird–fishery interactions in the Atlantic Ocean. ICES Journal of Marine Science 68:1628-1637.

Utizi, K., E. Notti, A. Sala, A. Buzzi, I. Rodella, U. Simeoni, and C. Corbau. 2018. Impact assessment of EMFF measures on Good Environmental Status (GES) as defined by Italy. Marine Policy 88:248-260.

Valsecchi, S., D. Conti, R. Crebelli, S. Polesello, M. Rusconi, M. Mazzoni, E. Preziosi, M. Carere, L. Lucentini, E. Ferretti, S. Balzamo, M. G. Simeone, and F. Aste. 2017. Deriving environmental quality standards for perfluorooctanoic acid (PFOA) and related short chain perfluorinated alkyl acids. Journal of Hazardous Materials 323:84-98.

Walker, N., and E. Abraham. 2017. Updating New Zealand's bycatch estimations and risk assessment. Eighth Meeting of the Seabird Bycatch Working Group Proceedings:16.

Waugh, S. M., D. P. Filippi, and E. Abraham. 2009. Ecological Risk Assessment for Seabirds in New Zealand fisheries. Sextant Technology.

Waugh, S. M., D. P. Filippi, D. S. Kirby, E. Abraham, and N. Walker. 2012. Ecological Risk Assessment for seabird interactions in Western and Central Pacific longline fisheries. Marine Policy 36:933-946.

Wetzel, C. R., and A. Punt. 2017. The performance and trade-offs of alternative harvest control rules to meet management goals for US west coast flatfish stocks. Fisheries Research 187:139-149.

Wiedenmann, J., M. Wilberg, A. Sylvia, and T. Miller. 2017. An evaluation of acceptable biological catch (ABC) harvest control rules designed to limit overfishing. Canadian Journal of Fisheries and Aquatic Sciences 74:1028-1040.

Williams, Dowdney, smith, A. Hobday, and M. Fuller. 2011. Evaluating impacts of fishing on benthic habitats: A risk assessment framework applied to Australian fisheries. Fisheries Research 112: 154– 167

Williams, A., P. Hamer, M. Haddon, S. Robertson, F. Althaus, M. Green, and J. Kool. 2017. Determining Blue-eye Trevalla stock structure and improving methods for stock assessment Final Report FRDC Project no 2013/015. CSIRO.

Winemiller, K. O. 1989. Patterns of variation in life history among South American fishes in seasonal environments. Oecologia 81:225–241.

Wyatt, K. H., R. Griffin, A. D. Guerry, M. Ruckelshaus, M. Fogarty, and K. K. Arkema. 2017. Habitat risk assessment for regional ocean planning in the US Northeast and Mid-Atlantic. Plos One 12.

Zhang, C., and S. Kim. 2011. A pragmatic approach for ecosystem-based fisheries assessment and management: A Korean marine ranch ecosystem. Presentation to the OECD, available from https://businessdocbox.com/Green_Solutions/77189326-Assessing-impacts-of-climate-changes-on-fisheries-an-eaf-perspective.html

Zhang, C. I., A. B. Hollowed, J.-B. Lee, and D.-H. Kim. 2011a. An IFRAME approach for assessing impacts of climate change on fisheries. ICES Journal of Marine Science 68:1318-1328.

Zhou, S., and Fuller, M. 2011. Sustainability assessment for fishing effect on fish bycatch species in the Macquarie Island Toothfish Longline Fishery: 2007-2010. Report to the Australian Fisheries Management Authority, Canberra, Australia. June 2011.

Zhou, S., and S. P. Griffiths. 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. Fisheries Research 91:56-68.

Zhou, S., A. D. M. Smith, and M. Fuller. 2007. Rapid quantitative risk assessment for fish species in selected Commonwealth fisheries. Report to AFMA. CSIRO, Cleveland, Qld.

Zhou, S., A. D. M. Smith, and M. Fuller. 2009. Rapid quantitative risk assessment for fish species in additional seven Commonwealth fisheries. CSIRO, Hobart.

Zhou, S., A. D. M. Smith, and M. Fuller. 2011. Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. Fisheries Research 112:168-178.

Zhou, S., D. A., Milton, and G. C. Fry. 2012. Integrated risk analysis for rare marinespecies impacted by fishing: sustainability asssessment and population trendmodelling. ICES Journal of Marine Science 69, 271–280

Zhou S., S. Yin, J. T. Thorson, A. D. M. Smith and M. Fuller. 2012. Linking fishing mortality reference points to life history traits: an empirical study. Canadian Journal of Fisheries and Aquatic Sciences 69: 1292–1301

Zhou, S. R. Daley, M. Fuller, C. M. Bulman, A. J. Hobday, T. Courtney, P. Ryan, and D. Ferrel. 2013. ERA extension to assess cumulative effects of fishing on species. Final Report on FRDC Project 2011/029. Canberra, Australia

Zhou, S., N. L. Klaer, R. M. Daley, Z. Zhu, M. Fuller, and A. D. M. Smith. 2014. Modelling multiple fishing gear efficiencies and abundance for aggregated populations using fishery or survey data. ICES Journal of Marine Science, 71: 2436–2447.

Zhou, S., A. J. Hobday, C. M. Dichmont, and A. D. M. Smith. 2016. Ecological risk assessments for the effects of fishing: A comparisonand validation of PSA and SAFE. Fisheries Research 183: 518-529

Zhou, S., R. M. Daley, M. Fuller, C. M. Bulman, A. J. Hobday, and H. E. E. Jardim. 2019. A data-limited method for assessing cumulative fishing risk on bycatch. ICES Journal of Marine Science 76: 837-847

Appendix A Table of Reviewed Literature

Table A.1: Table of material (academic papers and grey literature reports) reviewed. Notes on method, positive features and weaknesses and includes observations on the material and relevant direct quotations from the materials.

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Abraham et al 2017	* PSA replacement (seabird method could be generalised)	Pacific		Follows the Spatially Explicit Risk Assessment Framework (SEFRA) - originally for seabirds - where risk ratio = annual potential fatalities / population sustainability threshold. Uncertainty is carried through all parameters in the calculation, so there is uncertainty in the resulting risk ratio. The APFs are estimated from a combination of observer effort data, observed bycatch, seabird distribution data, and fisheries effort data. Essentially, they are a statistical extrapolation of bycatch rates from observer data to all fishing, on the assumption that seabird bycatch is proportional to the overlap between seabird distributions and fishing effort. The PST is an estimate of the productivity of seabird populations and is closely related to Potential Biological Removals. PST = 0.5 *v*rmax*N (as NZ goal is population of seabirds can't be < 50% of K after 200 yrs with 95% certainty). rmax was calculated using the demographic invariants method of Niel & Lebreton (2005) - the standard one that relates it to age of first breeding etc (allometric model). The total number of incidental captures of seabirds was estimated by assuming that, for similar species, and for similar fisheries, the number of incidental captures of protected species is proportional to the overlap between the density of the populations and the fishing. Standard data used = effort, observer data, species distribution, forage radius (exponential decline from nesting sites) etc (demographic parameters from literature). The distributions from all colonies of each species were combined and were then normalised to integrate to one. A distribution was derived by combining the distributions for the non-breeders and the breeders.	It has the advantage of being fully quantitative. When only a point estimate was available, an uncertainty was assigned using a set of rules that was based on the quality of the information, as described in Richard & Abraham (2015). An advantage of the risk assessment method is that the APFs may be estimated spatially (Figure 3), at the same resolution as the fishing effort data.	PBR related so will this cause an issue for Aussie law?

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
AFMA 2017	* Original	Australia	Ensuring populations are maintained at biomass levels above which recruitment failure is likely. Avoid negative consequences, for species/populations/foodweb components. Avoid reduction in the amount and quality of the environment. Avoid negative impacts on the composition/ function/ distribution/ structure of the community.	ERAEF standard - Scoping (hazard analysis), SICA (Scale Intensity Consequence Analysis = exposure-effects risk assessment... to save resources, done only for plausible worst case, if that passes all pass as its worst case), PSA (Productivity-Susceptibility Analysis; including management axis; for species unsuitable for SAFE… data poor), SAFE (Sustainability Assessment for Fishing Effects; base bSAFE, extended eSAFE), residual risk analysis (RRA... so can recognise whether there is management in place to avoid/mitigate the risk), L3 quantitative. based on the Potential Biological Removal (PBR) of Wade (1998). The PBR is numerically equivalent to the PST, with the exception that the PBR uses a minimum point estimate of the population size, and a point estimate of the maximum growth rate, whereas the PST includes uncertainty in all the parameters.	Comprehensive, Consistent (evidence not subjective based), Resource and cost efficient (hierarchical), Identify high-risk activities (for immediate remedial action), Precautionary (no info = at risk). Has reassessment triggers.	Need to differentiate data deficient species from true assessed high risk species.
AFMA 2008a	* Residual risk assessment example	Australia		Clear decision rules that can be applied to a species (if relevant) to calculate Level 2 PSA residual risk - applied species-by-species. Broadly the application processes involved the following steps: • Sorting the ERA result by high risk, then grouping the high risk species by role within the fishery, then by taxonomic group; • Creating a list of all management arrangements not included in the Level 2 PSA results for reference when applying the guidelines; • Considering each management arrangement to relevant high risk species; • Collating spatial information from experts, observer and logbook data for all high risk species for reference when applying the guidelines; • Deciding if and what guideline applies to each of the high risk species by conducting a species-by-species application; • Making changes to the necessary attributes, productivity and susceptibility scores to calculate the Level 2 PSA residual risk score; • Recording all workings, guidelines used, how they have been applied and a justification for the Level 2 PSA residual risk score; • Providing preliminary Level 2 PSA residual risk results to		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				MACs for feedback; • Finalising the Level 2 PSA residual risk results for release.		
AFMA 2008b	* Shows early use and motivation for RRA	Australia		ERAEF Standard with addition of RRA (not originally included but now standard)	Due to the semi-quantitative nature of the risk assessment, the Level 2 results do not directly account for all management measures, resulting in an over-estimation of the actual risk for some species. To account for this and to bring the results of the ERA up-to-date, the Level 2 analysis has undergone further assessment for residual risk. Residual risk is what remains after consideration is given to mitigation measures that may modify risk.... Short cut the process if better than L2 analysis already exists for a species/feature	TEP species are included within the assessment on the basis that they occur in the area of the fishery, whether or not there has been a recorded interaction with the fishery. The Level 2 analysis utilises a precautionary approach when calculating susceptibility by assuming species distribution is only within the jurisdictional boundary of the fishery. While this is appropriate for species that form discrete populations or stocks, the risk score for species that do not have this spatial arrangement such as pelagic and migratory species, the susceptibility scoring is not appropriately represented. Some species have a low to negligible level of interaction or capture. They may however still be scored high to high-medium risk irrespective of their low susceptibility, because they have a low productivity score (which raises the risk score). Considering the likelihood of the impact is low, there is little additional management that a fishery can introduce. Therefore, the level of interaction or capture should be included as part of the residual risk process.
AFMA 2012		Australia		ERAEF Standard with The priority list for the ETBF was developed using: • Level 2 PSA assessment for all other non protected species identified as high risk • Level 2 PSA Residual Risk (completed in December 2008)		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				• The Level 3 Sustainability Assessment of Fishing Effects (SAFE) methodology for any teleost or chondrichthyan species identified as precautionary high risk or higher risk category .		
Alexander et al 2019		Australia	Looking at research needed to operationalise adaptive EBM rather than do an ERA per se… does say "Goals and targets should be based on societal values of marine ecosystem functions and services" (but acknowledges can be contentious and in conflict)	This research has involved working with stakeholders to identify ecological, economic and social objectives for management of the marine environment and then matching these to indicators identified from the literature (Trenkel et al. 2015) or system models (Hayes et al. 2015), as well as soliciting preferences for the types of indicators used (Marre et al. 2016). The involvement of stakeholders in the co-production of holistic assessment frameworks and suites of management objectives has entailed a form of boundary work between the domains of science, public policy and non-science interests, as well as between natural and social sciences.		
Apel et al 2013	* Gives stock depletion estimation methods and management targets	General	Guidance document on the method	SICA and PSA as of standard ERAEF, may have some SAFE alternatives	Provides list of data-limited assessment methods to determine depletion of target stocks (to use in conjunction with PSA results to prioritize stocks for further assessment in order to set catch limits and other management measures) and management targets	
Arechavala-Lopez et al 2018		NE Atlantic	Highlight potential negative effects of escaped fish (almost as a summary document)	Audit procedure (hazard analysis from previous work). Expert based ranking of potential severity and likelihood of event - ranked intensity, probability and uncertainty	Rapid	Expert based so new info needed to reduce uncertainties. Meta-pop level scale assessment could miss localised effects
Arrizabalaga et al 2011	* Bias correction	Atlantic (ICCAT)		Productivity and susceptibility analysis - using Kirby (2006) method. Also calculated the average intrinsic vulnerability per IUCN category and the relative contribution of each gear to the bycatch of each species. Risk scores were ranked in order to highlight the species and species groups most at risk of being negatively impacted by the fisheries. Risk index = Euclidean distance in the PSA. To remove abundance bias in the susceptibility scores, multiplied the S score by catch:abundance ratio (Rc)	PSA has proved to be a useful methodology to simultaneously compare large numbers of species and identify those most at risk, further methodological development is needed to address analyses that include species groups of a significantly different nature. The use of Rc helps. Common risk metric for fish, birds, turtles and mammals	Rc needs more data... usually L3 like analysis so bit self-defeating?

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Astles and Cormier 2018		Australia	Review of ERA and add in management context	Bowtie method tied to ERA and has six elements—source of the risk (or hazard), undesirable event, causes of the undesirable event, impacts of the event, management controls and escalating factors. These elements are then assessed using classic exposure-consequence style scoring system	Integrates science and management into a single process, whilst respecting their different inputs and roles in the system. This streamlines the assessment process…. The risk of not achieving the fisheries management objectives for a fishery is determined by incorporating all relevant components into the ERA. Stressors, management controls (preventative and mitigative) and impacts are all included in the ERA to assess the risk. This is in contrast to most ERA methods in fisheries in which only stressors and impacts are used in the assessment...	
Astudillo et al 1997		South America	Evaluate the risk of disease transmission by embryo transfer	Scenario pathway identification and calculation of probabilities of failure at each of the three fines of defence (so can see where to prioritise action) - so assumed probability of event is p1 * p2 * p3		
Avila et al 2018		Global	Identification of location and type of threats to marine mammals globally (to aid with conservation actions)	1) the definition of threat types, 2) the compilation of information about species-specific threats documented in the scientific literature (including location), and 3) the standardized spatial allocation of threats using available geo-political, oceanographic and ecological map layers.... expanded the existing Threats Classification Scheme of IUCN - identifying the threat category (proximate origin), threat source (defined as the ultimate origin of the threat). Spatial allocation based on core distributions of the species.	Maximum in flexibility and accuracy when encoding information from the literature, while at the same time ensuring that encoded data can be mapped back easily to the IUCN Threat Classification Scheme. Performed statistical analysis to conform that literature review "coverage far exceeded the required number of papers to identify all threats to any group of marine mammals"	Species core habitat maps fail to show the actual species distribution during crucial life stages and transient migration routes between summer and winter ranges. In addition, did not take population size of different species into consideration but implicitly assumed a homogenous density of species throughout the core habitat. Incorporation of more detailed spatial and temporal variation in species occurrence as well as densities would further improve the specificity of conservation measurements
Ballesteros et al 2018		Europe	EAFM	The fisheries overviews (e.g. ICES, 2017c), of which first examples were released in 2017, include: a summary of the activities and impacts of the fleets fishing in the ICES area; a regional assessment of the performance of fisheries		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				management regarding targets, as well as an assessment of GES for MSFD descriptor 3 (ICES, 2012a); a description of the fleets and their interactions with the ecosystem; a description of the consequences and options for management of mixed fisheries; maps of the distributions of fishing by gear type and maps of the impact on the seabed of trawled fishing gear; and a risk assessment by gear of the impact of bycatch on endangered, protected, or threatened species.		
Bao et al 2017		Spain	Estimate the probability and severity of an adverse event - probability of disease due to eating anchovies in the home (e.g. health risk to individuals or populations due to exposure of zoonotic parasites through ingestion of contaminated fish meals).	(1) Hazard identification: identifies the pathogen (e.g. Anisakis spp.) of concern, determines whether it is actually a hazard, and identifies the vehicle of transmission (e.g. raw and marinated anchovies). (2) Exposure assessment: determines the number of Anisakis spp. ingested per meal (i.e. the dose). (3) Hazard characterization: gives a quantitative or qualitative assessment of the adverse effects of the pathogen on humans; more specifically a dose-response model can be implemented, which mathematically models the response (i.e. the impact and its variability) following exposure to different doses. (4) Risk characterization: gives a probability of occurrence of the disease (e.g. anisakiasis) and estimates the disease burden in a given population.	Used biological data (directly sampled), with social/economic data coming from a survey	
Barange et al 2018	* Mentions role for ERA in climate work	Global				
Barnett & Wiber 2018		Canada				
Barnthouse 1994		General		Integrated risk assessment framework consisting of the four components: Hazard Identification, Exposure Assessment, Exposure-Response Assessment, and Risk Characterization		
Battista et al 2017	* Collapses L1-L3 into L2 but tries to allow for nonlinear cumulative effects and uncertainty scalars	General	Ecosystem assessment	The CARE model draws from other ERA methods, and from recent research on cumulative impact assessment, ecosystem resilience, and ecosystem service assessment (Barbier et al., 2011; Halpern et al., 2008; Keith et al., 2013; Link, 2005) to add value to the existing ecosystem risk assessment tools in a number of important ways. First, CARE can be used to assess risk from any number of threats to a given ecosystem. Second, CARE allows the analyst to assess the inter-actions (synergistic	CARE can be used to evaluate risks facing a single site, to compare multiple sites for the suitability or necessity of different management options, or to evaluate the effects of a proposed management action aimed at reducing one or more risks. This method can help users identify which threats are the most important at a given	The more factors scored the more likely a false positive. Users can decrease this possibility by applying ATM Factors only when they are reasonably confident about the existence of that interaction effect.

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				or antagonistic) of multiple threats with each other. Third, CARE assesses risk to the entire ecosystem through use of a more comprehensive suite of attributes that characterize system health and functioning as described by intrinsic system recovery potential (e.g., "regeneration time" and "connectivity") and resistance to impact (e.g., "removability of system components" and "functional redundancy and diversity"). Fourth, CARE includes a module designed to quantify risk to the production of ecosystem services in both data-rich and data-limited settings. Finally, CARE can be implemented in the field, relying largely on local and expert knowledge when data are limited, and completion of a CARE analysis by system experts can take as little as 1–2 h. CARE generates risk values for each threat as it impacts each "target" (valued components of the system selected for analysis), ecosystem service production, and the ecosystem as a whole. Risk in CARE is calculated as the product of an Exposure score (the extent to which the target is exposed to a threat, and the potential effect of that exposure, based on considerations such as spatial scale, frequency, and intensity of the threat, given the "worst case scenario") and a Response score (the likely response of the target to the impact, based on factors thought to contribute to system vulnerability and to recovery time, such as species diversity and functional redundancy), following the methods of Miriam et al. The multiplicative approach is therefore more appropriate than the Euclidean distance approach for our purposes because it results in similar risk scores for threats with different intensity and impact characteristics, but that would result in the same potential consequences. CARE also includes a way to score the interactions of multiple system threats, to estimate the degree of synergy between hem and thus characterize the cumulative impact of threats more accurately. The first step when applying CARE is to select a site, and identify a target or targets within that site that users value. **Targets can include any valued species, including fisheries targets, keystone species, engineer species, charismatic species, or any other species users wish to assess, and all ecosystem types, identified by the dominant habitat type** (e.g., coral reef, seagrass, mangrove), within the site.	site and for a given target, and therefore where limited management resources should be targeted. It can also help to identify where different management approaches might be most appropriate.... ***While calling it an ecosystem assessment they are doing it via species and habitats as a proxy for ecosystem structure and function***.... **The effects of other threats present in the system on the "focal threat" (the threat for which a Base Risk Score has just been calculated) are assessed.** Here our method differs from the ERAEF, the ERAF, and all other similar existing risk assessments. Other ERAs include methods to calculate cumulative threat impact scores after individual scores have been determined. However, because many threats do in fact interact C**ARE allows users to evaluate the potential synergistic or antagonistic effects of the other present threats in the system and use them to modify individual threat impact scores before they are combined into a cumulative score. Expert judgment is used** because data are generally lacking on the effects of threats on each other. To quantify these potential synergistic or antagonistic inter-action effects, CARE includes guidance for scoring an "Additional Threat Modification (ATM) Factor" for each of the five vulnerability criteria in each threat-target pair analysis. The ATM Factor is a value falling between –1 and 1, by increments of 0.25. This value is a numerical representation of the degree to which the impact of the focal threat, and the target's response to that impact, maybe changed by other threats in the system. This modification value must be considered separately foreach of the five vulnerability criteria, as the interaction	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
					effects on each may not be to the same degree, or in the same direction.... Uncertainty of each attribute score is itself scored and these qualitative scores are normalised and combined into a single uncertainty factor between 0 and 1. This uncertainty factor is multiplied by the adjusted risk score, and then this value is added to the adjusted risk score to determine a final adjusted risk score that has been proportionally increased relative to the amount of uncertainty present.	
Bell and Bahri 2018		General		Scoping (Identify risks, vulnerabilities, and objectives; Establish decision-making criteria). Analysis (Identify options; Assess risk; Evaluate trade-offs). Implementation (Implement decision; Monitor; Review and learn)		
Bellido et al 2011		EU and global	Minimising/reducing discards	Stock assessments with discards as separate data stream (and updated equations)		
Ben-Hasan et al 2018		Various	Recognizing fishing-effort responses for short lived invertebrates	Seasonal age-structured model using monthly catch and effort data. If fishing effort pattern mirrors biomass then in "healthy" bionomic equilibrium; if effort flat (and presumably high) across seasons then independent of stock size and therefore "bad" as overexploiting		
Bland et al 2018		General	Define ecosystem collapse method	1. Describe initial or baseline states that reflect the natural range of spatial and temporal variability in ecosystem; 2. Identify potential pathways of collapse and symptoms of degradation (ecological models can be used as proxies for risk); 3. collapsed states should be defined with quantitative decision thresholds - using key indicators, which can be informed by observation, experimentation, modelling, or expert elicitation (and with uncertainty bounds clearly shown)		
Bland et al 2018	* Could help extend community/ ecosystem aspect	South Africa	Assess ecosystem collapse Benguela	1. Use conceptual models and sister ecosystems to define 'conditions of collapsed ecosystem state'. 2. Estimate declines in spatial distribution (using maps of extent. occupancy, threats), environmental degradation (using Relative severity describes the proportional change in an indicator scaled	Precautionary as the indicator returning the highest risk category defines the overall category for the criterion. Used	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				between two values: a value describing the state of the ecosystem at the beginning of the assessment timeframe (0%) and one describing a collapsed state (100%)) and biotic disruption (taken from: i) survey-based indicators derived from fisheries-independent surveys, ii) catch-based indicators, and iii) model-based indicators derived from Ecopath models and then combined to quantify biotic change (a) over the period of the time series with generalized linear models and (b) comparing now state with reconstructed historical state). To derive collapse thresholds, we conducted structured expert elicitation with the "Investigate, Discuss, Estimate, and Aggregate" protocol - including their estimate of the upper/lower bound of the threshold and estimate of likelihood true value within the bound	multiple lines of evidence to assess risks to a complex marine ecosystem	
Bravo & Bustamante 2018	* Aquaculture with modified PSA plot in terms of risk can/can't do something about	Chile		Instead of productivity and susceptibility = intrinsic risk (farming practices) vs extrinsic (environmental factors) …. In fisheries terms productivity axis ~ extrinsic (can't do anything to modify it) and susceptibility ~ intrinsic (as cold potentially do something about it)	Provided a histogram of distribution for risk attributes so could see sensible thresholds/breakpoints	
Breen et al 2017	* Guide on how to take it spatial * Uses weights in PSA *Marine mammal example	Europe (Ireland)	Cetacean ERA - highlight potential areas where cetaceans are at high risk to bycatch in certain fisheries	1. Maxent quarterly species distribution models (conditioned on depth, distance from shore, chl, temperature etc). 2. species-gear PSA, but included availability (the spatial overlap (co-occurrence) between cetacean distribution and fishing activity). A percentage overlap of >30% was considered high susceptibility and thus scored (3), percentage overlap between 30% and 10% was considered moderate susceptibility and scored (2) and overlap of <10% was considered low susceptibility and scored (1). Encounterability is defined as the seasonal overlap between the fishery and the species outside the assessment period. Using the maps generated for availability a species whose distribution overlapped in all seasons was considered more susceptible (therefore scored high (3)), than a species whose distribution only overlapped during one season (low susceptibility (1)). Exposure is a factor of the likelihood of observing the species in a cell and the amount of fishing activity in that cell compared to the mean of cells in the entire survey area = log10 * (exposure_cell / exposure_mean) where exposure_cell	Allows for easy comparison between gears, and is therefore useful when developing a bycatch mitigation plan for the area	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				= likelihood_in_cell_from_maxent * hrs_fished_in_cell / pp_eez. Final susceptibility = (a^2 * e * ex^2 * s^2 * ple)^(1/8)		
Brown et al 2013	* Guide on how to take it spatial * Uses weights in PSA	Europe (Ireland)	Assess the potential risk posed to cetaceans by fisheries	PSA - productivity: age at female sexual maturity; oldest reproducing female (as can have reproductive senescence); calf survival; inter-calving interval. The overall species productivity score was an arithmetic (additive) mean of the four attribute scores. Values taken from literature. Cluster analysis, using Ward's method (Ward, 1963), was applied to define attribute scoring thresholds by assigning species to groups with similar life history parameters. Susceptibility scored based on availability; encounterability; selectivity; potential for a lethal encounter, with susceptibility = (avail * encounterability ^ 2 * selectivity ^ 2 * potential_lethal) ^ 1/6. Weighting Encounterability and Selectivity in this is what ensured that species which did not overlap with the fishery and could not be captured by the gear, generating low scores for both attributes, could not generate moderate or high risk scores. Availability was scored on the basis of global distribution and the presence of subpopulations, or stocks, within the area of interest (globally distributed species with no stock structure would be considered at less risk than a species with distribution restricted to the location of the fishery, or with distinct subpopulations present in the location of the fishery). Modified encounterability scoring to reflect potential overlap between habitat use and seasonal movements of cetaceans and the seasonal nature of fisheries. Scoring reflected the degree of potential overlap (Table 1) on the basis that a species whose habitat overlapped completely with a fishery would be at greater risk than a species whose habitat included areas not utilized by that fishery. Nil scores were given if a fishery did not occur within the habitat of the cetacean species, or if the species and fishery did not overlap temporally		
Brown et al 2015	* Guide on how to take it spatial * Uses weights in PSA	Europe (Ireland)		A spatially and temporally explicit extension of PSA, incorporating data on fishing activity and species distribution to assess and map the potential risk posed by fisheries. The susceptibility of each species to each fishery was assessed in two stages, at two spatial scales and stratified by quarter. Overall susceptibility and risk scores were generated for each	Including the uncertainty (data quality) approach outlined by Brown et al 2013	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				fishery, for the EEZ as a whole. At the level of the EEZ the spatial aspect of the assessment was based on the extent of overlap between the distribution of the species and the distribution of fishing activity. VMS and species distribution models used to generate grids of activity which were then translated to corresponding grids of presence/absence, stratified by quarter. The presence/absence fishing activity grids for each gear type were overlain with presence/absence for cetaceans, to produce an overall matrix of spatial overlap, or co-occurrence. Availability was scored as high (score3) if fishing activity and cetacean species co-occurred across more than 30% of the species distribution in the EEZ, moderate (score2) if between 10 and 30% and low (score1) if less than 10%. For finer scale assessment of risk (at grid cell size), in addition to the four attributes used to score susceptibility for the EEZ as a whole (the values of which remained constant), a fifth attribute, Exposure, was included, which estimated the potential exposure of the population to fishing activity in that cell and was based on the abundance of the species and the extent of fishing activity (as for Breen seabird example).		
Buckley et al 2019		Kenya	Investigated historically-exploited coral reef fish species in Kenya to determine taxa likely to be threatened by local extinction.	Used archaeological records (750–1500... stratified into 50 yr layers), naturalists' species lists (1759–2003), catch assessment surveys (1995–2013), and underwater surveys (1991–2013) to get presence of species through time. The first step compares across data sources to identify which reef species are absent or rare in current records compared to the past. The second step is to leverage across data sources to determine the probability that those species identified in step 1 may be locally extinct while accounting for uncertainties in disparate data sources (did this using Bayesian extinction analysis). Compared this against Vulnerability to fishing which uses a fuzzy logic expert system that takes into account eight life-history and ecological characteristics (body size, longevity, age at maturity, von Bertalanffy growth parameter, natural mortality, fecundity, spatial behaviour, geographic range) that makes species vulnerable to fisheries exploitation. Species were placed into categorical groups based on level of vulnerability to fishing from the estimate produced from the fuzzy logic system	The framework used should be of value to conservation management efforts. The assessment of local extinction was carried out at a species level at a local scale which will allow easier application into species management policies and regulations. Furthermore, the framework proved an inexpensive and effective for identifying threatened species when historical data, particularly archaeological records, were available. Such assessments are especially critical for data- poor areas where inexpensive management advice is needed the most. Combining these data and applying Bayesian extinction risk methods can strengthen other species assessment efforts. The Bayesian extinction analysis proved an effective model by explicitly accounting for several sources of uncertainty.	Only considering captured species and not the full assemblage of fish (so unfished species could have gone extinct and wouldn't know). Factors affecting extinction risk, such as fishing intensity and climate are among influential factors not accounted for in this method.

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Burdon et al 2018		Europe (North Sea)	Risk assessment for wind and fishing on Digger Bank	Bowtie method (uses qual info, but can extend with quant modelling). By linking this method to the DAPSI(W) R(M) framework, it enables scoping, identification and analysis of: i) the drivers leading to the main events; ii) anticipatory prevention measures, including those limiting the severity of the main event; iii) the consequences of the events; and iv) mitigation and compensation measures aimed at minimising those consequences. The role of future scenarios assessments is complimentary to modelling as a way of informing Bow-tie development.	Bowtie method is a highly graphical approach that can be clearly understood by personnel of all levels of an organisation and encompassing detailed information and quantitative aspects.	
Burgass et al 2019		Arctic	OHI application to Arctic area	OHI (Halpern) application - The OHI is calculated by combining individual indicators via a structured framework designed to measure progress towards optimal sustainable delivery of each of the goals - including: food provision, mariculture, coastal livelihoods and economies, sense of place, coastal protection, marine mammal harvest, tourism & recreation, artisanal needs, biodiversity (habitats & species)		
Burger et al 2017		USA				
Campbell & Gallagher 2007		NZ		Strong stakeholder engagement push. Data from observer and catch-effort database. Create hazard/pathways for non-target species, i.e. species of commercial value captured, but which are not target species; biodiversity, i.e. all species of non-commercial value captured but not protected or habitat-forming; habitat, i.e. habitats that influence fisheries or are impacted by fisheries; trophic interactions, i.e. indirect impacts of fishing attributable to flow-on effects on the food chain; protected species, i.e. species protected under New Zealand legislation, specifically coral species, marine mammals, and seabirds. Then for each hazard/pathway (i) Determine likelihood; (2) Determine consequence (using consequence matrix.... based on expert opinion, with the threshold values derived from legislative and policy obligations in the first instance and subsequently adjusted through stakeholder consultation); (3) Determine risk (likelihood * consequence); (4) Assess and state uncertainties; (5) Treat and/or mitigate the risk	A precautionary approach is emphasized, in which a lack of information results in a designation of significant consequence.	Other environmental EoF categories, such as an alteration in the chemical processes are not included because within New Zealand the data for such evaluations are limited.

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Campbell et al 2018		Australia (Qld)	Assess the short term (~3 days) post-trawl survival and to examine factors affecting the survival of the two most common elasmobranchs found in the catch	Collect rays from commercial and sample trawls, monitor for few days and see mortality rate; create a generalised linear modelling (GLM) via a binomial distribution with a logit link function for survival		
Cao et al 2017		USA	Size-structured model for pandalid stocks	A seasonal, size-structured assessment model - Monte Carlo simulations were used to evaluate the performance of the size-structured model under various misspecifications regarding temporal fishing pattern, growth, recruitment, and natural mortality (estimation methods;	Seasonal time step that accounts for seasonal variations in biological processes and fishing patterns and incorporates submodels for changes in length at sex change and environmental effects on recruitment dynamics.	
Carruthers et al 2016	* Testing control rules but shows off methods that could be used as L2.5 - L3 methods		Aim to use recent observations of absolute biomass B, and total annual catches C, to infer surplus production S, and therefore stock level relative to a productive stock size	Tested harvest control rules where target cpue index varied over time rather being fixed at a historical average cpue. Used surplus production based model (though using relative productivity so could have time varying productivity and just looking at state relative to that) - so more appropriate to data rich/moderate stocks		
Chen et al 2013	* Could help extend community/ ecosystem aspect		This paper reviews state-of-the-art models developed for ecological risk assessment and presents a system-oriented perspective for holistic risk evaluation and management	Concerned with models to inform USEPA risk assessments (mainly around chemical pollutants, but being expanded to more stressors given nonlinear interactions). Model types include: food web models which were developed to evaluate the exposure to specific pollutants; ecosystem scale models (often network analyses) are not only focused on the changes of predator–prey relationships within organisms, but also the altered interactions among organisms and environmental factors (e.g., sunlight, temperature, soil and water) associated with a certain hazard; also chemical EPA-ERA equivalent of MICE models. Net benefit analysis (originally used in predicting risks and benefits of invasive plants) useful cross-cutting approach to linking uncertainty analysis and risk management decisions in the context of the eco-economic system. However, it needs to be further developed to provide mechanisms for conducting risk assessments regarding the balance between economic and ecological benefits in risk reduction.		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Cheung et al 2018	* How to automate the process * How to include climate * Include index of uncertainty	Global	Examine the combined contributions of climate change and fishing to the risk of impacts of exploited fishes, and the scope for climate-risk reduction from fisheries management.	Indicators of exposure to fishing and climate change and species' biological and ecological traits were categorized into one or more levels simultaneously, with the degree of membership to the levels being defined by fuzzy membership functions (Table S1). For fishing hazard, we used the fisheries components of the Ocean Health Index (OHI-fisheries) to represent the fishing hazards to fishes' population viability. Climate hazards are indicated by the changes in annual average physical and biogeochemical ocean conditions by the mid-21st century. We determined exposure to climate or fishing hazards for each species based on its geographic range (latitudinal and depth). Life history and biological characteristics that represented species' sensitivity and adaptive capacity included: maximum body size, von Bertalanffy growth parameter K, age-at-maturity, longevity, fecundity, an index of spatial aggregation behaviour, temperature preferences, geographic range, latitudinal range, depth range, taxonomic group, and association to specific habitats. The levels of fishing and climate change as well as species' biological and ecological traits were classified into levels of exposure to hazards, sensitivity, and adaptive capacity. Consequently, these levels were combined to determine species' vulnerability and risk of impacts based on pre-defined heuristic rules (fuzzy logic) - the final index of risk of impacts or vulnerability was calculated from the average of the index values weighted by their accumulated membership. D**eveloped and applied an index of certainty**.	An advantage of the fuzzy logic framework as it is adaptive to new knowledge that can be incorporated and updated easily	
Chin et al 2010		GBR	A simple and transparent mechanism to assess the vulnerability of individual species to climate change even when there are few data available.	Described numerous linkages between climate change factors and the species, habitats, physical and ecological processes of the GBR ecosystem, and further information was collated - through expert info & literature review. Species were assigned to ecological groups defined by habitat types and associated biological and physical processes. Risk then assessed using exposure, sensitivity and adaptive capacity. Overlapped species distribution and depth range with predicted effect footprint. Vulnerability = rarity and habitat specificity (as rarity encompasses the size and rebound potential so good proxy for other biological traits associated with vulnerability; habitat specificity describes the extent of dependence on particular habitat types and locations). Highly adaptable sharks and rays can alter their behaviour or physical state to accommodate changing conditions and exploit new opportunities - based on	Integrating multiple variables provides a more comprehensive account of the vulnerability of a system to climate change. Identifies the species at highest relative risk, which will help to prioritize management responses. This approach also reduces potential errors arising from grouped assessments that use aggregated data which may mask significant impacts. While some species groups are too numerous or diverse to assess as individual species, the IRACC can be scaled to an appropriate taxonomic level by selecting	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				diet specificity, mobility, physical or chemical tolerance (ranges of conditions it will tolerate or acclimate to), latitudinal range was used as a proxy for temperature intolerance. All factors were ranked using literature, unpublished data and expert knowledge. Most conservative ranking of the attributes determined the overall rank of that component. No information available to rank attributes of sensitivity or rigidity, the attribute was ranked as high. Then used component integration matrix to determine species vulnerability rating from component rankings. Interactions between climate change factors, vulnerability components and nonclimate related variables were considered.	appropriate ecological groups and attributes to use in the assessment.	
Christain et al 2009		Europe	Show how ecological network analysis can be applied to functional assessment in support of ecosystem based management	Constructed four reference networks to analyse food web structure (multiple networks to cover seasonal and interannual differences). Species were grouped into compartments based on extensive empirical data, literature, and best professional judgment of similarities in diet and habitat use.		
Clark et al 2012		Global	Review seamount research and management needs			
Clarke et al 2018	* Guide on how to take it spatial and inform spatial management	Costa Rica	Use the best available scientific information to propose management measures for elasmobranch bycatch in the Costa Rican shrimp trawl fishery	Productivity Susceptibility Analysis (PSA, a semi-quantitative Ecological Risk Assessment commonly used in data-deficient fisheries) combined with a spatial Hotspot Analysis to identify (i) which elasmobranch species are most vulnerable to the Costa Rican shrimp trawl fishery, (ii) the location and seasonal variation in spatial clustering of vulnerable elasmobranchs. Data uses in PSA = based on short–term scientific survey data (2008–2012), scientific literature and FishBase - Productivity (Hobday et al., 2011) and susceptibility (Patrick et al., 2010) attributes. Hotspot analysis = statistically significant spatial clustering (“hotspots”) of sharks, skates and rays with a high vulnerability to the shrimp trawl fishery (data from fishery dependent catch info and independent surveys); Hotspot Analysis to identify aggregations of highly vulnerable species, or hotspots, and aggregations of low vulnerability species, or coldspots (inputs = 2113 presence records from the 346 analysed tows for 25 species, which were represented by their PSA vulnerability index)... 2113 entries were converted into two spatial point layers, one for the dry season another for the rainy, used Global Moran's I statistic to look at spatial autocorrelation (whether clustered, dispersed, random), with	Spatial analysis of PSA results can be useful in the design of potential spatial fishing closures	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				a positive Gi* statistic associated with a p–value smaller than 0.1 indicates the presence of a hotspot for highly vulnerable elasmobranchs, while a negative Gi* statistic associated with a p–value smaller than 0.1 indicates the presence of a coldspot for elasmobranchs with low vulnerability to the shrimp trawl fishery . Hotspots were then categorized by their distance from a Marine Protected Area (MPA) (inside, 0–5, 5–10 or> 10 km) and depth (< 50 m, 50–100 m or> 100 m).		
Collie et al 2012		USA (Alaska)		Empirically based stochastic simulation model (see Materials and methods) for each of the four chum salmon populations. Then used this model to evaluate the potential effectiveness of various harvesting–escapement goal policies at meeting management objectives. The model included not only salmon population dynamics and environmental influences on them, but also uncertainty in implementation of harvesting decisions, which caused realized escapements to differ stochastically from targets.		
Cope et al 2011	* Show how can use weighting to reflect confidence in usefulness of an attribute as informative measure for that taxa * Uncertainty handling	USA	Uses the vulnerability scores to revisit current stock complexes.	Standard PSA with the overall productivity and susceptibility scores calculated as the weighted average across all scored attributes. The definitions for the bins of the first susceptibility attribute (“management strategy”) were updated from Patrick et al. (2009) to reflect specific qualities of U.S. west coast groundfish management. Maximum length and fecundity productivity attributes were down weighted by half in two species groups because these attributes are inconsistently indicative of productivity within those species groups. Maximum length becomes inconsistently related to productivity when comparing elasmobranchs and rockfishes outside of their taxonomic families, while fecundity is a misleading measure for rockfishes, which often demonstrate low productivity despite large numbers of inconsistently spawned offspring.... Chose to decouple vulnerability and data quality by not scoring attributes for which had no information, vulnerability scores are “best estimates” while the data quality score measures the information content in that best estimate.... To create complexes (1) clustering stocks based on ecological distribution (e.g., depth and latitude), (2) grouping within ecological distributional clusters based on vulnerability scores, and (3) evaluating the final groups in terms of fishery	Confidence in each attribute bin score is obtained by scoring data quality on a five-point scale, weakly scored stocks to be flagged as either needing revised scoring (in the case a more knowledgeable scorer can be found) or indicating information is generally lacking for that stock. Identified an "overfished score' - for currently recovering species did a retrospective PSA reflecting susceptibility/exposure at peak fishing and also estimated the probability of overfishing occurring among several data-limited stocks using the depletion-based stock reduction analysis. Combining these two sources of information (the retrospective PSA and comparisons with DB-SRA), a minimum vulnerability of 2.2 was used to indicate stocks with high probabilities of being overfished or in the midst of overfishing.... $V \geq 2.2$ indicates stocks of major concern; $2.0 \leq V < 2.2$ indicates stocks of high concern; $1.8 \leq V <$	Maintaining a consistency in scoring these attributes when there are multiple scorers proved challenging and should be a focus when applying the PSA. Having all scorers clarify how each bin definition is treated during the first scoring iteration encouraged consistency. Data quality scoring was particularly useful in identifying such troublesome attributes in need of further consideration. Using the retrospective susceptibility scores to help define these reference points demonstrates a main attribute of interpreting vulnerabilities; management has the greatest influence in altering susceptibility when trying to reduce a stock’s vulnerability. Productivity scores (Figure 1, horizontal axis) are usually static in the short term, thus are

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				interactions (i.e., separating groups further by associations in particular fisheries, if needed)	2.0 indicates stocks of medium concern; and V < 1.8 indicates stocks of low concern.... Resulting stock complexes offer managers focused attention on stocks that co-occur and exhibit similar responses to current fishing conditions.	unlikely to change unless improvements in the data quality alter scoring. Most reduction in vulnerability via management will thus be realized on the susceptibility axis (Figure 1, vertical axis). Scoring should be updated on a regular basis to reflect any changes in susceptibility or increased knowledge of productivity attributes.
Cormier et al 2018	* How to do residual risk straight up * How to get relative attribution across sectors and prioritise management action * Importance of considering exacerbation factors (cumulative effects)	Europe (North Sea)		Bow-tie analysis to develop a qualitative model of the controls implemented to reduce a pressure generated from the activities of multiple sectors. We then use a Bayesian belief network model to predict the residual pressure based on the integration of the effectiveness of each control, the implementation compliance of the controls and external factors that could undermine the effectiveness of the controls. Here, we are using the predicted residual pressure as an indicator of the effectiveness of the management system of controls implemented to reduce an initial pressure instead of predicting the ecosystem effects..... The basic structure of the Bow-tie (which is a graphical method) identifies the causes of an event in the presence of a source of risk and the consequences of that event \when it occurs. Prevention controls are intended to reduce the likelihood of an event; mitigation controls are intended to reduce the magnitude of the consequences of an event and recovery controls are used to recover from the consequences that could not be mitigated. Escalation factors are external factors that can undermine the effectiveness of any of the prevention, mitigation or recovery controls. They require additional escalation controls to reduce the effects of the escalation factor on their effectiveness. This technique is a qualitative assessment of the prevention controls to prevent the event, the mitigation and recovery controls to reduce the consequences and the escalation controls to reduce the effect of escalation factors on controls. Conceptually, the left side of the Bow-tie represents the management system and the right side of the Bow-tie represents the ecosystem. BowTieXP (v 9.0.10.0W; CGE Risk Management Solutions) is the software	Bowtie+BBN can be used to analyse the effectiveness of different management systems of prevention controls regardless of the ecosystem setting. Bayesian belief networks are used to provide a quantitative approach to the Bow-tie analysis - uncover the complex conditional dependencies between the cause-event-consequence pathways, and to assess the effectiveness and compliance of the controls (can either be developed by experts, based on the understanding of the system being modelled or can be learned by empirical observation). Analysis was able to single out compliance as the key factor that is potentially undermining the effectiveness of the fisheries restriction areas....**The Bow-tie/Bayesian belief network analysis identified the different abrasion loads generated by each activity and their contribution to the residual abrasion load in the restricted areas. This demonstrates the usefulness of the Bow-tie/ Bayesian belief network approach to identify the activities that need the most attention from an enforcement perspective.**	BBN can't include feedbacks. The approach was limited by the data availability needed to define the respective probability distribution for each node of the Bayesian belief network. Managers and stakeholders must be able to identify the right pressure source to improve the prevention control of the right activity which may not be located at the same time and place as the effects

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				that is used to develop Bow-tie diagrams. The Bayesian belief network replicates the left side of the Bow-tie diagram of prevention controls for each activity.		
Cortés et al 2010		Atlantic (ICCAT)	Provide a range vulnerabilities for the most important pelagic shark species subject to ICCAT surface longline fisheries in the Atlantic Ocean.	PSA but with sufficient information to give continuous probabilistic scores rather than simple classification of high/medium/low		Highlights that the approach will inevitably provide only a snapshot of a combination of time- and space-dependent factors determining the vulnerability of a stock to the fishing gear
Cortés and Brooks 2018	* Supplementary method for data poor chondricthyans (alternative to SAFE?)	Global	Test the ability of data-limited approaches to replicate results obtained in shark stock assessments worldwide			
Cortés et al 2015	* Include uncertainty handling * Done by stock not species	Atlantic (ICCAT)	Expand/update and increase resolution of the previous ICCAT shark PSA/ERA	PSA with updated info and resolving stocks. Uncertainty in life history variables (age at maturity, maximum age, age-specific fecundity and age-specific survival) was incorporated through Monte Carlo simulation by randomly drawing values from assumed statistical distributions for each of these variables. Fleets broken up further by depth fished. Selectivity = catch size distribution vs observation size distribution so get a "true" measure of selectivity. Computed three indices of vulnerability: based on Euclidean distance (v1), multiplicative (v2), and arithmetic mean (v3). All scores were ranked from highest (rank=1) to lowest (rank=20) risk. We summarized results by using a modified Traffic Light procedure.	Tagging data gives better estimate of encounterability. Selectivity was now calculated in a more intuitive way, as the overlap between the length range of animals caught and their known length range in nature. Post-capture mortality includes an estimate of post-release mortality	
Cotter et al 2014	* Alternative form of SICA - L1.5?	Europe (UK)	The primary aim was to prioritize systematically and consistently the main ecological risks posed by fishing in the SW and, if possible, by other agents operating there, taking into account any adjusting factors such as existing management measures. The SG and other stakeholders would then be better informed to discuss with fish retailers which risks	SICA. Didn't break into target/bycatch/habitat etc just "unit of assessment" which could be species or stock ("In this way, our lists were independent of varying fishery practices and conservation priorities"). Background materials also included information on "other agents of change". Effects of activities were classified and named with the aim of creating mutually exclusive categories that were generally applicable, not just to fishing. The most sensitive attribute of each unit was paired with the activity of the agent thought most likely to prevent achievement of the policy goal most likely to be impacted (Other, lesser impacts were ignored, as were cumulative impacts). Scored all pairings, not just the "worst case" and did		A danger, though, with this hierarchical approach is that the different levels utilize many of the same data and information and therefore are not independent, implying that poorly determined RISs could be erroneously confirmed automatically by the more specialized studies. A better strategy is to seek new sources of

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
			needed action and which were relatively unimportant. A secondary aim was that risk-scoring should link compatibly across neighbouring marine regions, thus leaving the way open to apply ERS elsewhere around Britain.	not always assign a high score when information was lacking. Scoring = relative impact score = geometric mean (fourth root of the product) of scores for spatial scale, temporal scale, intensity-of-effect, and duration-of-effect, each ranging from 0 to 5 and intended to contribute independent, nonoverlapping information to the RIS. Spatial and temporal scores were scaled in relation to the geographic domains and lifespans of the units. The two scores were thus based on measures with biological relevance not possessed by the absolute units (nautical miles, days) employed by SICA, the intention was to improve the comparability of scores across different units. The intensity score was defined as the proportion of the members of the unit of analysis affected by an activity where and when it occurs. Duration score = measure or recovery capacity (~ productivity in PSA)		information for new studies to confirm or explore high risks.
De Anda-Montañez et al 2017	* Provide a method for L3 to take management risk aversion into account	Mexico	MSE of sardine fishery in BCS Mexico	Bioeconomic model (simulations/MSE)	Performed a sensitivity analysis (parametric)	
de Lange et al 2010	* Could help extend community/ ecosystem aspect	General	Review of ecological vulnerability assessments (coming from EPA perspective)	All ranked based methods (expert judgement driven) - may call on multi-criteria analysis tool	Lists off the required aspects for an ecosystem level risk/vulnerability assessment: likelihood of exposure; community structure & function; sensitivity (including role of sensitive species in community, e.g. bad if ecosystem engineer effected); habitat vulnerability; recovery/adaptive capacity; actual & potential quality of the ecosystem; naturalistic value; socioeconomic value. **The Utility Index ranks the suitability of a species as a sentinel of exposure to a stressor** (aid for selecting the appropriate species to use in biomonitoring). LS = landscape species selects the appropriate species in a landscape for conservation purposes, it uses expert judgment to score preselected vertebrate species on area requirement,	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
					heterogeneity, ecological function, vulnerability, and socioeconomic function	
de Chazal et al 2008	* Alternative/ complement to SICA to show why get mismatch between AFMA and stakeholder perceptions id that becomes an issue in the future	General		Five matrices provide a transparent and flexible means for classifying and linking social and ecological information to enable their integration. The assessment is implemented through a multiplication of the initial projected changes with the matrices - Exposure is represented by a range of prospective use scenarios; habitat/species functional traits were selected as they provide general relationships between environmental change, composition and ecosystem properties; sensitivity = pathway from change in use -> change in traits -> change in ecosystem services. Acceptability is then calculated by multiplying projected changes in the delivery of ecosystem services with stakeholder preferences for ecosystem services obtained through social surveys. Vulnerability is assessed for selected groups of stakeholders within a site or across sites by comparing acceptability scores. Data collection = by surveys and workshops	Do it by matrix so can trace back the stakeholder group logic - so can see differences in acceptability based on perceptions from different groups (and perhaps compare against "pure science" much like the adaptation ranking that Al Hobday work led for seabirds)	
Dellinger et al 2018		USA				
Depestele et al 2014	* Could help extend community/ ecosystem aspect or spatial management * Using SDTs to help strengthen SICA?	General (Europe case study - Belgium)		SAGE combines: (1) ERA scoping, (2) assessment of ecosystem's intolerance to disturbance by each type of fishing gear is combined with the recovery capacity of each component of the ecosystem to create a sensitivity index and (3) mapping. Includes evaluating their associated uncertainties. When doing scoring can give one general score per effect or partition by effect pathway (e.g. trawl vs line) or even finer into the relationship between the gear and the pressure, and the effect of the pressure on the ecosystem component. The combination of individual partition scores depends on their mutual exclusivity. If two parts are indispensable in causing an impact, then their effect is multiplicative (not mutually exclusive). The resultant impact score is given by the geometric mean. If two parts contribute separately to the resultant impact score, their effect is additive and given by the arithmetic mean (mutually exclusive). The geometric mean of the demographic aspect and the state of the ecosystem component results in the final recoverability score	The mean score of the pedigree criteria is the pedigree index of recoverability attributes and individual pressures. SAGE method is transparent, repeatable and can differentiate between the sensitivities of ecosystem components and the fishing metiers affecting the components.	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
de Piper et al 2017	* Role of qualitative model & MSE even at SICA/PSA level * Can go beyond just fisheries	North Atlantic	IEA	Conceptual models drawn up as qualitative models. MSE done on risk scores by scaling effects aspects.	The use of support tables standardized the work in a manner that bolstered this trust in the process	
Doyle et al 2018		USA (Alaska)	1) decipher mechanisms of early life history interaction with the pelagic environment, 2) assess habitat utilization and ecological patterns from settlement through adult life, and 3) evaluate the synthesized patterns in terms of sensitivity and potential response of the ATF population in the GOA to climate- induced variability in the ecosystem.	Data work up; larval/juvenile IBM; age structured populations model; habitat suitability model; climate vulnerability analysis based on 12 "sensitivity attributes"		
DFO 2012	* Brings in past/present/ future impact thinking	Canada	Ecological Risk Assessment Framework (ERAF) to be used as a decision making process under Canada's Policy to Manage the Impacts of Fishing on Sensitive Benthic Areas	**Accounting for past/present/future effort footprints.** Estimate consequence, likelihood, score risk (using risk matrix based on consequence &likelihood), categorise risk	Gives some management response guidance	
Eliff & Kikuchi 2017	* Could help extend community/ ecosystem aspect or spatial management? InVEST is becoming a standard approach	Brazil	Estimate ecosystems services provided by Reefs and probability of adverse human impacts impairing the capacity of the coral reefs to supply ecosystem services	Coastal Vulnerability model and Habitat Risk Assessment (HRA) model of the Integrated Valuation of Environmental Services and Tradeoffs (InVEST 3 software used). Cumulative risk is considered to be additive - maps produced		
Fairgrieve & Nash 2009	* Additional system level considerations to highlight (beyond direct biological effects)			WHO framework for ecological risk assessment. (1) Problem formulation (scoping domain/focus and defining the biological or ecological end points and their attributes that are the concern for protection; creation of a conceptual model or diagram of how the system being assessed is thought to be organized) (2) Problem analysis = when all available scientific information relevant to the issue is collected and applied (exposure = predictions or measures of spatial and temporal distribution of a stressor and a point of concern;		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				effects/exposure response, which identifies and quantifies any adverse effects caused by a stressor); (3) Risk characterization = bring together analyses of exposure and effects		
FAO 2010		SE Asia	Summarise available assessment methods for multispecies fisheries			
Feitsa et al 2008	* Example for ornamental fish, makes point of selecting species wise/sensible attributes to rank. * Talking points to why qualitative/ subjective can be ok	Brazil	Is the original Stobutzki method appropriate for ornamental reef fish? (2) Is the capture of ornamental reef fish as by-catch sustainable?	Attributes used for susceptibility (assuming trap ornamentals): Water column position, Preferred habitat, Day/night catchability, Diet (attracted to area/bait in traps), Depth range; attributes for resilience: Maturity, Maximum size, Removal rate, Reproductive strategy, Hermaphroditism, Mortality index (size based). Score = sum of ranks for susceptibility (or resilience) / sum of weights of the attributes		
Filippi et al 2010	* Provides modifications for PSA when dealing with seabirds	Pacific	Use a spatially explicit version of a Productivity-Susceptibility Analysis (PSA) to determine the probability of seabird-fisheries interactions and the potential for adverse effects of fisheries mortality on populations of seabirds	Updated PSA for seabirds - especially susceptibility. Step through the development of the Susceptibility axis, mapping the results at each stage. Omitted species that are data poor but where experts said low chance of interaction with fishery anyway. Intentionally only looked at Procellariiformes (even though other seabirds do interact with the fishery). Combined various layers to compute a composite map which is the addition of the seasonal breeder layer and the seasonal non-breeder layer. To find hotspots used either species foraging radius or remote-tracking data. Susceptibility indicator is calculated as the product of fishing effort and normalised species distributions (i.e. proportion of a species' range) weighted with the vulnerability of the species which relates to the catchability of birds at a certain density exposed to an equal amount of fishing effort (this vulnerability/catchability term is a new addition vs previous bird PSA). For productivity, where all study species are within a single taxonomic order, able to use a more harmonious set of life-history parameters to approximate Rmax, the maximum rate of increase of a population with no resource limitation, predation or competition. constant relationship between generation length and population growth rate. They established that maximum annual growth rate λmax can be estimated for long-lived species using estimates of age at first reproduction α and		Excluded species for which there was no information about their distribution at sea

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				adult annual survival s. Instead of using standard PSA risk score calculation, used risk = susceptibility * productivity so that seabirds species with high-productivity and low susceptibility aren't just always highly ranked shadowing the importance of their vulnerability. Also normalised the final score (0-1) We normalized outputs of the overall seasonal PSA, combining both Susceptibility and Productivity indicators, so that values fell between 0 and 1. Values plotted were square-root transformed twice to normalize the distribution of the data. Five levels were attributed to the outputs based on the actual frequency distribution of the PSA scores, in order to ease interpretation. Negligible levels of risk (0 – 0.001): white; Low (0.001 – 0,2): royal blue; Low to Medium (0.2 – 0.4): pale blue; Medium (0.4 – 0.6): green; Medium to High (0.6 – 0.8): orange; High (0.8 – 1.0): pink. Final risk maps = sum of scores over flag-fleet and sum over species		
Fletcher et al 2002	* Could help extend community/ ecosystem aspect (by providing component tree to work from?)	General	How to do ESD reporting	1. Scope using generic component tree tailored to specific fishery; 2. Assess risk by assigning a level of consequence (from negligible to catastrophic) and the likelihood of this consequence occurring (from remote to likely) for each issue in the tree. 3. Provide management response details. 4. Provide background/other relevant materials used in the ESD assessment in appendix	Using trees provides the mechanism for the structured assessments of fisheries to be completed in a consistent manner. The system also requires the explicit determination of whether an issue is relevant for a fishery. Thus, in many cases it requires both the specification that each of the potential sub-components present on the generic component trees are NOT issues as much as determining what are issues. This should result in less issues being omitted purely because no one thought of them at the time when they were being generated. Risk assessment approach based on based on the Australian standard AS/NZS 4360 1999	
Fletcher et al 2005	As for Fletcher et al 2002	General	How to do ESD reporting	As for Fletcher et al 2002 (as is paper version of the report)		
Fletcher et al 2010	* Could help extend community/ ecosystem aspect (by providing component tree	General		Looked at risks to individual components in the tree and then (to avoid targeted fisheries management worried about stock level issues, as wanted an EBFM vision level approach to complement the stock work) got consolidated risk scores: For ecological assets, specific indicator species or components	The simple multi-criteria system integrated the various ecological, economic and social scores into a single Departmental priority score that was used to compare priorities across the 24 regional level	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	to work from and example of how to get consolidated higher order risk scores?)			were identified with the risk value assigned to the entire 'suite' of species or functional group using the highest risk value of any of the indicator species. For the non-ecological issues, the consolidated risk value was the average of the risk ratings for each of the components in the subbranch and, where relevant, each sub-branch within a branch.	assets/categories. The structure of the priority matrix, whereby each of the ecological assets are integrated with their associated economic and social issues and risks, provides both conservation and fisher based stakeholder groups with the holistic management system they have been seeking	
Fletcher 2012		Australia				
Fletcher 2015	* Potentially useful ideas on uncertainty handling	General	Update of 2005 paper	Use Fletcher 2005 method but with multiple lines of evidence and sphere of plausibility to comment on level of consequence		
Fock 2011		Europe (North Sea)		Account for frequency, pressure intensity, recovery potential, and group results by ecosystem function. Likelihood is determined by an exposure function for spatial and temporal overlap. Risk score based on ratio of negative/positive consequences of the activity - assumes additivity to go across scales and stressors		
Ford et al 2015	* L1 application (minor tweaks)	NZ	The risk assessment was designed to help prioritise actions to sharks taxa, noting that protected species are also given priority	Standard SICA L1. As this was not a preliminary screening exercise, the panel attempted to take a "realistic case" approach (as opposed to the usual "worst case" approach where the most "at risk" subcomponents are selected). This "realistic case" approach involved examining all subcomponents for all taxa. Fishing intensity was first scored for both temporal and spatial subcomponents (on a categorical scale of increasing risk from 1 to 6). Spatial and temporal scale were scored in a manner consistent with MSC requirements (Marine Stewardship Council 2013). Spatial and temporal intensity were estimated after examining catch quantities, maps of catch and range, and assessing the temporal nature of the fishery. Overall intensity was then scored using the criteria in Table 2, and notes were taken for each taxon to substantiate scores and justify any deviations of the overall intensity score from the score class definition. Consequence was then scored, again in a manner consistent with MSC guidelines (Marine Stewardship Council 2013). This was based on discussion and consideration of the	In addition to the overall risk score, the quantity and quality of data used and the extent of expert consensus were also rated for each taxon according to the ERAEF methodology	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				subcomponents of consequence and any abundance index/indices for that taxon. In the absence of trawl survey indices trends in the bycatch rates were examined for deepwater taxa. The overall scores for intensity (1-6) and consequence (1-6) were then multiplied together to get an overall risk score for the taxa across all commercial fisheries (potential range = 1–36).		
Forney et al 2017	* Potentially useful thoughts for TEPs - local/dispersed effects	USA		Comprehensive paradigm for assessing impacts of anthropogenic noise (or other activities) on marine mammals needs to include explicit consideration of all potential pathways of harm, including adverse impacts resulting from both close-range exposure and displacement away from the sound source (See figure 6.... might be of use for structuring some of the TEP ERA risk criteria/questions?).		
Forrest et al 2018		Canada		MSE		
Francis 1992		NZ		Simulation assessment model based approach		
Fu et al 2017 - with covering note by Clark	* L2.5 variant (MIST)	Pacific	Explore whether the current rates of fishing mortality on Pacific bigeye thresher, likely to be the most vulnerable of the three thresher species, are sustainable. This was undertaken by evaluating whether current impacts from fisheries exceed a maximum impact sustainable threshold (MIST) defined based on population productivity.	Used SST and observer data. The analytical framework is risk-based and spatially-explicit. Sustainability status S is assessed relative to current impacts from fisheries (or relative fishing mortality F) and a maximum impact sustainable threshold (MIST) limit reference point (LRP): S= Impact / MIST which ~ F / LRP. In this context, sustainability risk R is the probability p, given the uncertainty, that the total Impact exceeds the MIST. Uncertainty in all parameters is quantified and propagated through the assessment framework. Fishing impact is estimated as the average of fishing mortality F weighted by species relative abundance in each cell. F is calculated as the product of fishing effort E and catchability q (fraction of the total population in each cell that is available for capture by each unit of effort, adjusted for capture efficiency) distinguished among (and summed across) fishery groups. MIST is the sustainable reference threshold for the species. The MIST is defined based on population productivity inferred from life history data. Life history parameters are used to estimate a maximum intrinsic population growth rate r, with uncertainty. In turn, r is used to derive sustainable impact thresholds similar to the fishing mortality-based sustainability		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				reference points (Fcrash, Fmsm, Flim) described by Zhou et al. (2011) - i.e. like SAFE. Fishery groups were defined as the combination of catch groups and fishing season. Catch groups were determined by performing clustering analyses on logsheet data using the "k-means" algorithm (see Hoyle et al. (2015) for details). Logsheet data (rather than observer data) were used as they contain complete and reliable information on catch composition by species for the main target species.		
Fulton et al 2019	* Could help extend community/ ecosystem aspect (at L3 level?)	Australia		Atlantis MSE		
Furlong-Estrada et al 2014	* Makes a good point re differential risks with ontogeny	Mexico		Standard ERA		Suggests doing for different onto genetic steps where there is strong change over the life of a species
Furlong-Estrada et al 2017	* Nice clustering of vulnerabilities so had classes (traits) of different groups at risk	Mexico		Standard ERA with A cluster analysis (Euclidean distance between objects as a measure of similarity and Ward's method as clustering method) was applied to the vulnerabilities to identify possible associations among species. Also do an "M-Risk" residual risk assessment step	M-Risk assessment also has the capacity to identify those stocks where improvements in specific aspects of management are required	
Gaichas et al 2018	* Alternative approach if want to go beyond ecological components	USA		Risk Elements were organized into five categories: Ecological (including stock biology, habitat, and ecosystem interactions), Economic, Social, **Food Production, Management**. Analysts assembled indicators for each element from available sources, including the indicators from the State of the Ecosystem report, an estuarine habitat assessment, a climate vulnerability analysis, existing social vulnerability analyses, additional information came from literature searches and from expert opinion for some elements.	Assessment to differentiate risks between sectors. Risk criteria given for each element. All the work was done within 6 months and included stakeholder elicitation	
Gaichas et al 2014	* Ideas on how to bring climate into compound risk / residual risk considerations	USA	Assess the risk posed by climate-related changes (including both climate change and climate variability) on Northeast US marine communities, specifically to inform fisheries management.	Use literature and thought experiments to define physical mechanisms of climate change and then forms of potential biological impact/response. Then examined each pair of climate attributes and biological responses and asked first whether we expected a change in that biological response as a result of that climate attribute (Y—yes, N—no, or M—maybe), and if a response was predicted, whether we could predict a		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				general direction of change. We expressed our confidence in these ratings on a scale of 1–5, with 1 being low confidence and 5 being high. Plotted exposure vs sensitivity (due to differential response/importance of different physical properties per fish community type included importance weighting)		
Gaichas et al 2016	* SICA but for interactions	USA	Assessments and management frameworks that incorporate, (1) environmental drivers, (2) habitat and climate change, (3) species interactions, and (4) fleet interactions, into fisheries management.	Mentions a L1 assessment of risks to interactions (for Aleutians)	A conceptual model linking climate, habitat, species, fleet, and regulatory interactions can be constructed for the set of species using a multi-disciplinary team with expertise appropriate to identify key interactions	
Galindo-Cortes et al 2019		Caribbean				
Gallagher et al 2012	* Points out need to bring interactions and habitat dependency into ERA for sharks		Review existing elasmobranch ERA methods			
Gasalla et al 2016		Brazil	Undertake an ecological risk assessment based on key commercial marine species of South-eastern Brazil, exploring an evaluation of their sensitivity to climate change impacts ultimately aiming to rank them to assist natural resource management			
Geromont & Butterworth 2015	* GO over this one and snip out stuff that could supplement way ERA is done	General				
Gilman et al 2014	* Includes role in ecosystem function as one of the criteria to judge * Also includes PD50 so have	Pacific	Study aims were to identify:(i) relative risks to population viability of associated and dependent species; (ii) opportunities to mitigate identified problematic bycatch through gear technology	Standard ERA categorization scheme, L1 employing qualitative information from surveys of participants in the capture sector, and a partial Level2 ERA through assessing susceptibility through a combination of available quantitative (gear inventory, amalgamated observer data, conservation status of affected vulnerable stocks and populations, relative	Criteria for including species in the analysis included the importance of their role in ecosystem functioning - so prevent fishery removing populations critical to maintain broad community/ecosystem-level integrity (i.e. keystone or foundation	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	some genetic diversity consideration		methods, involving changes in fishing gear and methods; and (iii)opportunities to improve vessel fuel efficiency, lowering fuel costs and greenhouse gas emissions.	phylogenetic uniqueness, relative role in ecosystem regulation) and qualitative (survey of captains and crew) data sources. Susceptibility was assessed through a combination of: (i) an inventory of fishing gear and assessment of the risk to vulnerable species based on knowledge of the effects of different gear designs on species-specific catch rates; (ii) interviews with vessel operators and crew; and (iii) information from studies that analysed observer program data and summary statistics from amalgamated observer program data from the fishery, documenting catch rates, levels and disposition of vulnerable species upon release. Given the high uncertainty in estimates of bycatch levels and rates and lack of age-or length- specific data, the poor data quality did not support assessing population-level effects. However, the conservation status of affected stocks of shark species and populations of sea turtles captured in the fishery are identified and discussed to support understanding the relative risks posed by the fishery.	species). Used capture records from observer data not overlap of species and fishery distribution to judge susceptibility as this will likely avoid more false positives.	
Gilman et al 2017	* Useful context on how to cost effectively increase data streams from observers (value of observer data, if end up recommending more data types needed)	General				
Gilman et al 2019	* Identifies need for both the genetic diversity and ecosystem end to be included in ERAs and gives suggestions on how	General				
Gimpel et al 2018	* In discussion terms, useful reference to point to in terms of spatial	Europe (North Sea)		GIS based layering of environmental fields and other uses to highlight suitability of alternative aquaculture sites based on environmental conditions (vs species optima), potential conflicts (defined using a conflict matrix indicating conflicts or		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	planning tools starting to be picked up by other sectors when considering cumulative impacts (on and by a sector)			synergies with other human uses), cumulative pressure, economic and potential to have a footprint that effects conservation/cultural/social etc values		
Goetze et al 2017	* Highlights discussion point of potential addition of new indices with new data types coming on line * Also that the PSA needs to be made climate/ cumulative impacts aware	Pacific				
Goldsworthy & Page 2007	* Alternative method for L2 * Points out need for spatialised risk maps to help spatial management	Australia	Risk assessment of seal bycatch	In the absence of quantitative data on bycatch rates and impacts on species and subpopulations, the approach taken here was to: (1) estimate the spatial distribution of foraging effort for different sex and age classes within each species; (2) compare these with the spatial distribution of fishing effort in order to develop spatial estimates of seal-fishery interaction probabilities; (3) undertake population viability analyses to identify the levels of bycatch that would place subpopulations into different risk categories; and (4) examine different bycatch scenarios and identify subpopulations, regions and marine fishing areas with the greatest bycatch risk, based upon interaction probabilities and population viability analyses. The size of each subpopulation was estimated utilising species-specific life-tables and pup production estimates. The RAMAS Metapopulation software was used to model female populations of each species. Leslie matrices developed for each species were used to undertake population viability analyses on the subpopulations. Two measures of risk were calculated, terminal extinction risk (the probability that a population will go extinct during a specified time period) and quasiextinction time (Qt, the time for the median of the simulated population trajectory replicates to go quasi-		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				extinct.... < 10 females in the sub-population). Population viability analysis was undertaken to investigate the potential implication of additional (anthropogenic) mortality on the conservation status of each subpopulation. This was achieved by applying virtual bycatch mortalities of female seals to each subpopulation, and determining the level of additional mortality required to increase the risk of extinction (and effects of mortality directed at different stages).... so basically how much mortality from bycatch was needed to shift the species a category (.g. threatened to endangered) in the viability analysis		
Govt of Canada 2012	* Potentially useful ideas on uncertainty handling	Canada	Steps through sequence of assessments for contaminated sites	Condition assessment - to detect impairment; Causal pathway assessment - to determine proximate causes; **Predictive assessment** – purpose is to estimate environmental, economic, and societal risks, and benefits associated with different management alternatives. Acceptability of actions may be determined through evaluating the risks in light of social, economic, and legal considerations; Outcome assessment – purpose is to evaluate the results of a past management action, through estimation and/or direct measurement	Provide guidance on types of receptors and example surrogates for aquatic ecosystems and for selecting indicator species (ecological role, degree of exposure, sensitivity, conservation value, social/economic/cultural value, availability of relevant life history data, availability of reference points). "Line of evidence" pedigree	
Gray et al 2010	* Useful in discussion for highlighting which risks ERA servicing	Australia & US	Attempt to categorise the risks to fisheries as reported by fishery scientists and managers	Surveys		
Griffiths et al 2006	* Example of PSA weakness - now sorted?	Australia	(i) examine the change in sustainability of individual species after the introduction of TEDs in the NPF by incorporating new data on elasmobranch exclusion and (ii) validate the SRA method and assess its sensitivity to changes in catchability resulting from the introduction of TEDs in the NPF.	Standard PSA (early version when still known as susceptibility-recovery analysis). Updated the analysis (ranking of recovery characteristics) for effect of TED and how that reduced exposure	The SRA method clearly does not reflect changes in risk due to changes in size selectivity, but may be suitable for once-off assessments of species where there are few data, and to help guide management and research where the relative risk of species is desired. The SRA model provides a critical first step in the process for assessing ecological sustainability, especially for speciose assemblages with limited data.	The re-implementation of this method described here suggests that the introduction of TEDs had a negligible or negative impact on the sustainability status of 15 elasmobranch species in the NPF, despite large reductions in the number and mean size of animals caught in nets using TEDs. In fact, we found ten species to have a lower recovery rank after the introduction of TEDs, and thus be considered less sustainable. This was mainly attributed to the

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
						exclusion of large animals from the catch, which resulted in a lower mean length at capture. Owing to this reduction in mean length at capture, ranks for two recovery criteria that rely on length data (probability of breeding before capture and mortality index) were reduced. This falsely indicates that the fishery is increasing its impact on pre-breeding animals, thus reducing the recovery potential of the species.
Griffiths et al 2018a	* PSA alternative that is easier and more reliable and closer to what single species managers used to looking at	Pacific	More reliable method than PSA	EASI-Fish = Update on PSA and L3. Susceptibility comprised of 6 components: (i) Areal overlap (G) -proportion of the species' distribution exposed to fishery; (ii) Duration of the fishing season (D) –proportion of the year exposed to a fishery; (iii) Seasonal availability (A) –proportion of the year available for capture in a fishery; (iv) Encounterability (N) -proportion of species' vertical habitat exposed to a fishery; (v) Contact selectivity (C) -proportion of fish encountering the gear that is caught; (vi) Post-release mortality (P) -proportion of released fish that die. Susceptibility is estimated by fishery (x) by length class (j). Total proportion of the population (S) caught by each fishery is summed and converted to become a proxy for F. F is compared to reference points from simple per-recruit models (length-based yield per-recruit model). In stock assessment BRPs define stock status (e.g. F/FMSY) and equivalently relative vulnerability.	Developed a qualitative data reliability index - Quality/precision of source study vs. relevance to species/area. Spatially-explicit, so vulnerability assessed under spatial and temporal scenarios. Uses reference points and result display format (Kobe plot) familiar to managers. Requires less data than PSA. EASI-Fish is precautionary and results in fewer false positives.	Determine most appropriate method for species distribution basemaps (GAMs, Maxent)
Griffiths et al 2018b	* PSA alternative that is easier and more reliable and closer to what single species managers used to looking at	Pacific	More reliable method than PSA so can prioritize bycatch species management	EASI-Fish - The method first produces a proxy of the instantaneous fishing mortality rate (F) of each species based on the 'volumetric overlap' of each fishery with the stock's distribution. F is then used in length-structured per-recruit models to assess the vulnerability of each species using conventional biological reference points. Classification of the vulnerability status of each species using a phase plot. Using reference points of F0.1, F0.4 (compared the performance of their chosen reference points vs SAFE reference points).	Because selectivity curves are unlikely to be available for data-poor bycatch species, it was considered important to disaggregate selectivity components as far as practicable. This also allows the individual components to be parameterized if information is available, or the default assumption of full selection to be implemented as a precautionary measure in the absence of reliable	Assumptions to be wary of = homogeneous distribution within stock boundary; stock boundaries known (dodgy assumption so might want to split to oceanographic features rather than assuming universal widely spread pelagic species); encounterability parameter (E) assumed that the efficiency of a specific fishing gear

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				Monte Carlo simulations to generate uncertainty estimates for each model parameter given specified prior distributions.	information. Used the data reliability index because the application of biological parameters 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. However, a measure of the relevance and quality of parameter values is required to quickly determine the reliability of the model results, which will be important in situations where ERAs may contain a large number of species that are classified as “most vulnerable”. The parameter quality scores are represented in a single radar plot for each species, aiding in the easy interpretation of a large number of model parameters.	was constant over its specified depth range, which is often not the case for longlines due to environmental factors such as currents and wind, and differences in gear configuration; selectivity known (otherwise = 1 or at least knife-edge at smallest size taken); cumulative fisheries = additive (when fisheries are combined, they should be evaluated to ensure that they do not substantially overlap in the fish that they catch, given the information available. If they do, then some adjustments should be made. For example, the spatial overlap could be calculated by combining the data for the fisheries that overlap); appropriate reference points (less-productive species such as sharks and turtles may be best assessed using biomass-based RPs, while fishing mortality-based RPs may be more appropriate for more productive species)
Guo et al 2011	* Alternative method but does show that it could track the score through time if had enough info	China	-1.- to analyse the stressors of Chinese White Dolphins in Xiamen coastal waters, especially from human activities; 2. to assess the ecological risk for dolphins during the period of 1996-2007; .3. to analyse the relationship between human activities and the ecological risk.	Divided the DPSIR framework into six steps: 1. Describe the driving forces (including the economic development, the population, and the tourism industry); 2. Identify the ecological pressure–the stresses of the ecological risk which is originated from the anthropogenic system and will affect the water environment; 3. State description–figuring out the environment conditions of the waters; 4. Analyse the impacts–the measure of the effects resulting from the pressures and the states; 5. Discuss responses–management strategies for solving the marine environmental problems; 6. Evaluate the ecological risk for the Chinese White Dolphins based upon the above results.Indicators were selected according to their relevance and priority to the ecological risk. They were composed of eleven indicators, including two		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				driving, four pressure, two state, one impacts and two response indicators (Table 1). The weighting factor of each indicator was calculated by means of Analytic Hierarchy Process (AHP) - a method providing an effective framework to input judgements and measurements to derive ratio scale priorities. This method has been used to develop weights to measure the importance of elements in management processes. The AHP software package known as Super Decisions is what we used here: 1. Develop a hierarchy of interrelated decision elements describing the risk; 2. Perform criteria for pairwise comparison using the nine-point weighting scale; 3. Compute the individual relative weights of each decision element. Final score = weighted sum of the individual normalised risk scores (i.e. one normalised score per indicator). This final score was plotted through time to show change in risk through time (trending up)		
Hare et al 2016	* Climate but implications for how to modify PSA	USA	Conduct a climate vulnerability assessment for fish and invertebrate species in the Northeast U.S. Continental Shelf Large Marine Ecosystem	Define vulnerability as a change in a species' productivity and or abundance associated with a changing climate, including both climate change and decadal climate variability. We also evaluate the potential for a change in distribution. Used (NMFS) Climate Vulnerability Assessment Methodology - steps are: 1. scoping and planning the assessment including i) identifying the spatial region, ii) the species to include, iii) the climate variables to include as exposure factors, iv) the biological and ecological traits to include as sensitivity attributes, and v) recruiting experts to participate in the assessment; 2. preparation of materials for the assessment including i) consolidating available information on each species, ii) obtaining information on the future state of exposure factors, and iii) providing the spatial overlap between climate exposure and species distributions in the region; 3. expert scoring of the different components of the assessment including i) climate exposure scoring, ii) sensitivity attribute scoring, iii) quantifying expert certainty in scoring, iv) scoring the directional effect of climate change on a species in		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				the region, and v) scoring the quality of data used in the assessment; and 4. analyses of the scores including i) estimating overall climate vulnerability, ii) estimating the potential for a distribution change using a subset of sensitivity attributes, iii) estimating certainty in overall climate vulnerability, potential for a distribution change, and the directional effect of climate change using bootstrapping; iv) identifying the importance of each exposure factor and sensitivity attribute to the overall climate vulnerability using a leave-one out sensitivity analysis, v) evaluating the results on a functional group basis, and vi) developing species specific narratives that summarize the results for each species.		
Harvey et al 2017	* Remember to define scope of review (i.e. not spanning into IEA yet)	USA		IEA and discussing how tailored system to system		
Hazen et al 2017		General	Evaluate and compare four of the best-known frameworks available to assess fishery sustainability and consider their potential applicability to fisheries management in California: the Marine Stewardship Council's 2013 certification requirements for fisheries, Friend of the Sea's 2011 certification criteria for wild-caught fisheries, the Seafood Watch program's current criteria for fisheries, and an FAO sustainability checklist combined with the FAO's International Guidelines on Bycatch Management and Reduction of Discards. We assessed the alignment between the indicators used in these frameworks and the goals and requirements of the Marine Life Management Act			

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Hazen et al 2018	* Takes into account distributions in different years (conditions)	USA		Data-driven, multispecies predictive habitat modelling framework termed EcoCast to create daily predictive surfaces that quantify relative target catch-bycatch probabilities over the domain of the fishery: (i) determine habitat preferences for species of interest (target and bycatch); (ii) use tracking data and other distribution data sets to determine the species' presence and absence and to sample contemporaneous environmental conditions (used some stats methods around tracks to show potential habitat use, with track as on stochastic realisation); (iii) presence and absence data sets were used to sample remotely sensed environmental variables using date, location, and mean position error; (iv) Presence and absence data sets were used to sample remotely sensed environmental variables using date, location, and mean position error as a function of combined environmental covariates, with resultant models then were used to predict relative habitat suitability for each of the focal species at daily time steps; (v) To create an integrated multispecies predictive surface, we weighted each layer by the relative management risk of the focal species before averaging across layers. Species risk weightings were determined on the basis of management concern, discussion with fishers and managers, and fishery bycatch rates such that critically endangered leatherback turtles were given values twice the weighting of blue sharks and over 10 times that of sea lions. Prediction layers for each species were combined into a single surface by multiplying the layer by the species weighting, summing the layers, and then normalizing the range of values in the final predictive surface from −1 (low catch and high bycatch) to 1 (high catch and low bycatch).	Plotted in time to illustrate how they changed throughout the season for a normal and anomalously warm year… as using historical species distribution data to designate static or seasonal closures puts these areas at the risk of losing ecological relevance as species' distributions shift with a changing climate	Assessed a suite of potential species weightings based on management concern (fig. S6) to illustrate how they influence the EcoCast predictions. Given that the weightings are arithmetically determined, increasing bycatch risk for a species by a factor of 2 would also increase risk in the integrated surface proportionally, albeit with different spatial patterns.
Hiddink et al 2019	* Shows that longevity based characteristic useful for benthos ERA	Europe (North Sea)	Examine the relationship between the longevity of benthic invertebrates (Tmax) and their response to trawling, both in terms of the mortality induced by the passage of a trawl and their recovery following trawling			
Himes-Cornell & Kaperski 2016	* Socioeconomic	USA (Alaska)	Social wellbeing/vulnerability index creation and vulnerability analysis	Created 14 indices of community well-being along several different dimensions of well-being to undertake a national analysis of community vulnerability and well-being - Each		Important to examine the appropriateness of the input variables selected for each index for

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				index of community well-being is created through a separate principal components factor analysis (PCFA) of factors that are thought to contribute to (or detract from) community well-being, each index can then be interpreted as increasing or decreasing community well-being based on the signs of the factor loadings on each of the included variables. The quantitative indices of community socioeconomic well-being and fishing involvement for each of the indices are created using the regression method by summing the standardized coefficient score multiplied by the included variables		every new geographical region or set of communities that are being assessed.
Himes-Cornell et al 2016	* Socioeconomic * Example of ground truthing a compound index	USA (Alaska)	Social wellbeing/vulnerability index validation	Gather ethnographic data that can be used to “groundtruth” - comparing qualitative, ethnographic data for a representative sub-set of communities to their respective quantitative index rankings allows the researcher to test for convergence. If the two measures are highly correlated, it provides evidence that the quantitative well-being indices possess a sufficient level of construct validity to justify their use in policy and planning processes	Example of rapid method to double check compound index capturing the right kind of features	
Himes-Cornell & Kaperski 2015	* Socioeconomic	USA (Alaska)	Social wellbeing/vulnerability index creation and vulnerability analysis	We present a framework of indicators to assess three basic constituents of community vulnerability:exposure to the bio-physical effects of climate change, dependence on resources that will be affected by climate change, and a community’s adaptive capacity to offset negative impacts of climate change. We conduct three principal components analyses, one for each vulnerability constituent, for 315 Alaskan communities to assess each community’s overall vulnerability to climate change.		
Holsman et al 2017	* Reflects way of thinking about complexity of pressure(s) to consider vs tools available (hierarchical L1-L3)… place ERAEF in context of future extensions like cumulative impact assessment		Review ERA - categorizing ERAs in terms of analytical approach (Levels 1–3), and extend it to include assessments of risk due to any natural or anthropogenic pressure(s) by classifying studies based on the complexity of the coupled human-nature system under consideration	In addition to ERAEF hierarchy have hierarchy of system complexity - direct impact of a single pressure on a given social or ecological subject (e.g., single species or social component; Class 1), to the direct and indirect effects of a pressure on multiple interacting subjects (e.g. fishing impacts on ecosystems) or multiple pressures on a single subject (i.e., Class 2), to the direct and indirect effects of multiple interacting pressures on multiple interacting subjects (i.e., Class 3; e.g. multiple industries impacting an ecosystem). Appropriate model selection driven by class of problem; selection of the class of system complexity should be based on		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				the urgency, research capacity, and most importantly, management need to evaluate cumulative (minimally Class 2) and indirect (Class 3) impacts and/or multi-sector tradeoffs (Class 3). **For all classes of system complexity, Level 1 analyses act as a screening or scoping step** to flag potential high-risk interactions for more quantitative analyses (i.e., Levels 2 and 3), for Class 1 assessments at this initial level—where a single pressure creates risk for a single component only direct impacts would be considered vs for Level 1-Classes 2 and 3, both direct and indirect impacts (via changes to food-web structure, for example) would be considered by expert opinion. For Level 2 analyses when indirect impacts are also of interest (Level 2-Class 3 ERAs), qualitative network models, a type of dynamic conceptual model, are useful as they can identify compensatory ecosystem dynamics and non-intuitive outcomes of management actions. We suggest that Level 2 assessments such as this one are ideal for vetting potential interventions to be evaluated more specifically and quantitatively with scenario analyses (i.e., Level 3 ERAs). Level 1 and Level 2 ERAs are governed by the need to rapidly provide information on potential risk to an ecological component of the ecosystem, computational or other resource limitations, as well as differences in data quality and availability for a broad range of focal ecosystem components. Yet, frequently ecosystem management requires maximizing socio-economic extractive or utilization needs while minimizing risk to ecological components in order to enhance sustainability. In these cases, specific thresholds, based on acceptable probabilities of risk, are required and risk analyses are designed to characterize risk profiles under alternative management strategies. Level 3 risk assessments produce this level of quantitative information based on a mechanistic understanding and assessment of the system and focal component		
Hobday et al 2005	* Original	Australia		ERAEF standard = on species (target, bycatch, TEP), habitats (pelagic or benthic) or communities; direct and indirect interactions are considered. In defining habitats - classification enables three relevant attributes of benthic habitat to be scored for substratum (sediment type), geomorphology (seafloor topography) and fauna (dominant faunal group), the resulting combination generates a list of habitat units or	Should be done at stock level. For availability (overlap of core ranges of species and fishery) step of PSA In the longer term it may be possible to establish different cutoffs for dispersed, aggregating and migratory species [was this done?]. Uses core ranges so take into account	Encounterability only based on adult habitat. Cumulative effects on species from all fisheries have not been addressed in these assessments, but remain an important risk for a community - whilst we do not address this

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				‘types’ per fishery area (where no image data for this then us combo of geomorphology and depth). Community = species assemblage that occupy the large-scale provinces and biomes generally identified by the bio-regionalisation projects (biota included are classified as all mobile fauna, vertebrate or invertebrate, but not including sessile organisms such as coral that are largely structural and therefore classified as habitat). Objectives must be defined for each subfishery with Core objectives (also called endpoints) identify what you are trying to achieve and operational objectives (or measurement endpoints) are objectives stated in ways that can be measured.... Hazards analysis identifies activities undertaken in the process of fishing, and any external activities, which have the potential to lead to harm. The effects of fishery/sub-fishery specific hazards are identified under the following categories: capture, direct impact without capture, addition/movement of biological material, addition of non biological material, disturbance of physical processes, external hazards (identify those activities/hazards that are present/absent). Level 1 Scale, Intensity and Consequence Analysis (SICA) aims to identify which hazards lead to a significant impact on any species, habitat or community; a “worst case” approach is used to ensure that elements screened out as low risk (either activities or components) are genuinely low risk. When the risk of an activity at Level 1 (SICA) on a component is moderate or higher and no planned management interventions that would remove this risk are identified, an assessment is required at Level 2 (originally only measure risk from direct impacts of fishing only, was to be expanded to indirect effects - ***has that happened?***) - susceptibility = potential level of impact, productivity = potential for recovery (but as no actual mortality estimate then not an absolute risk measure, only relative). Table 1 has important list of PSA factors for communities [could add SURF etc?]	preferred conditions/depths not just all conditions. Do bathymetry-regulation check to make sure gear can recall encounter the species given regulations on where gear can be used (vs theoretical limits). As most species don't reach max size the selectivity scoring is done vs size at maturity. For habitats, depth is regarded as a proxy for productivity. Use look up table for influence of ruggedness (rugosity and seabed slope) on habitat susceptibility; connectivity = the recruitment analogue/proxy. For **communities uses dominator trees and key player analysis too look for the "hub nodes" to check status off for ecosystem/typological health** (species/functional groups in community, especially hub species, scored using standard PSA even if do not directly link to fishery)... If an additional scientific assessment for a species has been published that provides a more quantitative analysis than the Level 2 assessment, then the risk score from the additional assessment may be adopted [basically shortcut by leaping straight to L3 and don't waste time needlessly]	problem in this stage, we developed several fishery-specific spatial metrics, such as the % overlap of the fishery with the community assessed and the proportion of the total catch per species caught by sub-fishery within that community to derive proxy susceptibility attributes for the community [***might be integral to determining cumulative effects in the future.?***]. Topological analyses and diversity measures, rankings have not been determined or are arbitrary until we have results from more community analyses to determine an appropriate range. Invertebrates were restricted to those which were primarily of fishery interest and those which were mobile. Sessile or attached invertebrates (including infauna) are dealt with in the Habitat analyses.
Hobday et al 2011a	* Original methods paper for ERAEF	Australia		Original ERA paper. Five components are: Target species; By-product and by-catch species; Threatened, endangered and protected species (TEP species); Habitats; Ecological communities. Because a single widely accepted operational definition of an ecosystem is lacking, we define these five components in such a way that “elements of an ecosystem” are covered. The first step in the ERAEF is the scoping stage,	Precautionary at all stages - even scoping where default objectives provided are generally of the form “impact is within acceptable bounds” and these bounds are selected to be precautionary; and comprehensive activity checklist forces	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				and it is here that a description of the fishery is completed, management objectives recorded, activities/hazards listed, and units of analyses identified. Only those activities that are scored as present in a fishery are then carried forward for analysis in subsequent levels. Several desirable attributes of an ERA: • Comprehensive (identify and analyse all potential hazards). • Flexible (applicable to all types of fishery, irrespective of size, fishing method, species). • Transparent and repeatable (be clear about the methods, data and assumptions used in the analyses). • Understandable (easy for stakeholders to grasp). • Cost effective (make use of existing knowledge, information and data within realistic limits of time and resources). • Scientifically defensible (be able to withstand independent scientific peer review). • Useful for management (inform appropriate risk management responses), and • Take a precautionary approach to uncertainty.	consideration of a broad range of potential hazards, which is precautionary in nature compared to considering only expert-selected subsets of activities.	
Hobday et al 2011b	* Original (for communities and habitats, including some discussion of "next steps")	Australia		One community attribute = functional group attributes. Another community attribute = mean TL of catch - can ***we please use something else!!!*** Unlike at species level (where susceptibility is multiplicative). Both productivity and susceptibility factors are treated as additive - the attributes are scored and averaged to generate the overall productivity (or susceptibility) score for each community.		The methodology we present here is simple conceptually, but the development was operationally complex. The definition of reference points for community indicators remains a pressing issue [actually still not done really in literature]. The PSA community assessment as implemented here reflects the impact of fishing from one fishery only, in this case the Commonwealth otter trawl fishery. There may also be impact on the community from other fisheries, and even other activities (e.g. pollution, oil and gas, pipeline dredging). These other impacts in the same communities may increase the risk (i.e. cumulative) to communities which should also be explored in future work [***and thus need for truly cumulative impacts assessment!***]. Lack of detailed data

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
						on invertebrates might be a serious shortcoming in other fisheries that focus on invertebrates such as scallop, squid or prawn fisheries. The method can certainly be applied if data exists. If there is insufficient data, then management decisions may need to be made based on level 1 assessment results
Hobday et al 2005		Australia				
Holt et al 2012	* Discusses adjustments to PSA used in Canada and some remaining holes	Canada	1) To evaluate the ability of ERAEF to provide timely advice on the impacts of BC fisheries on marine ecosystems using a risk-based triage approach 2) To evaluate the ability of ERAEF to provide timely advice on the impacts of non-fishing activities in BC on marine ecosystems using a risk-based triage approach 3) To determine whether risk-based outputs from ERAEF could help prioritize scheduling of science advice related to groundfish species and fisheries 4) To demonstrate a potential format for science input to an Ecosystem Approach to Management.	Adopt Patrick version of the attribute scoring thresholds of Patrick et al. (2010). We also adopt the data quality index because it matches well with the types of data sources we used to parameterize our analysis (Table 4-3). We do not apply the attribute weighting option suggested by Patrick et al. (2010). Rather, we allow for equal weighting in order to maintain consistency and transparency among different fishery applications and though time. Productivity attributes: maximum age, maximum size, VBGF K, natural mortality estimate, fecundity, breeding strategy, recruitment pattern, age maturity, trophic level. Susceptibility attributes: areal overlap, geographic concentration, vertical overlap, seasonal migration, schooling/aggregation/behavioural responses, morphological characteristics affecting capture, desirability/value, management strategy, F vs M, SSB, survival post capture/release. Five tiers of data quality - best, adequate, limited, very limited and none.		Extremely low productivity species have a high tendency to be moved forward to a Level 3 analysis, regardless of their susceptibility score. Fecundity as an indicator of productivity has been discredited for teleost species in recent years due to lack of empirical support (and fact hard to get good data). F:M may also not be as informative as originally thought for some species. Should consider assigning natural mortality and growth coefficient attributes missing scores rather than using estimates derived from max length approximations so that twice as much weight is not assigned to estimates of maximum length. **The occurrence of risks from non-fishery (external) activities is recognized within ERAEF. However, the assessment of potential risks from these activities is weak compared to the level of analysis afforded to fishery impacts.**
Hordyk & Carruthers 2018	* KEY discussion of limitations of PSA		Quantitatively evaluate the PSA as a tool for determining the risk of over-exploitation of fish stocks.	PSA attributes mapped to parameters for population dynamic model (*not always easy so maybe some apples vs oranges happening*) then look at performance of simulated population		Under the most favourable conditions best performance was accurately predicting risk rating 66%

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	* Good argument for automation			under F vs risk score from PSA - to check on whether score is good index of sustainability (and thus trustworthy for management advice). The bounds given in PSA for scoring -> bounds on parameter for species of different risk classes; so calculated all possible P vs S classifications based on these parameters (>500000 so picked a subset of 640, 10 each from the 64 possible rough P vs S classes (where P and S each broken into 8 sub-classes very low, low, low-med, med etc and then get P sub-class x S sub-class combo)) and then ran 10 sims each to look at % time B < Blim. Empirical relationship used to exclude implausible parameter combinations. Start sim at unfished level do 1 of 3 historical fishing patterns for 50 years (to get different levels of 'current' depletion) and then for next 50 yrs run under 1 of 3 exploitation rates - 0.2, 0.4 and 0.6.		of the time (drops to ~50% or less under other conditions... ***AND NOT ALWAYS FALSE POSITIVE, UNDER LOTS OF ATTRIBUTES WAS THROWING UP A LOT OF FALSE NEGATIVES***). Overall prediction error rate increases as more attributes were added to the scoring system, with the highest prediction accuracy occurring when only one productivity and two susceptibility attributes were used (Rate of Increase, Selectivity, and Discard Mortality respectively) and the lowest accuracy when all 12 attributes were used. Testing suggests fewer attributes (keeping most informative ones) helps in the correct scoring of "medium" risk species - **though more extensive testing over a wider range of conditions should be carried out before establishing a modified version of the scoring system with fewer or alternative productivity and susceptibility** attributes. Omitting potentially critical features of PSA this was an unfair test of the approach? *Need more work but does suggest need meta-anal to make sure PSA attributes doing what say they are reflecting.*
Hornborg et al 2018	* Marries ERA and LCA so get human dimension aspects of most interest to industry added (e.g. fuel efficiency tradeoffs of	Australia (Southern Ocean)	Examine the influence of management measures and industry initiatives on seafood sustainability indicators based on both ERAEF and LCA over time.	ERA standard + LCA (where the environmental pressures from each production phase, such as fishing or transportation, are quantified for a range of environmental concerns, such as global warming potential and eutrophication potential). LCA involves: goal and scope, inventory, impact assessment, interpretation steps. Focused on fishing phase GHG (as post landing GHG marginal in comparison). Other ecologically relevant inventory results used in seafood LCA as proxies for		LCA perspectives currently time-consuming and struggle to get data so need to start collecting the right info automatically (e.g. fuel use)

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	management actions etc)			fisheries-specific impacts were also quantified per FU, such as bycatch quantity and seafloor pressure.		
Hoyle et al 2017 - cover not by Clarke for IOTC	* L2.5 variant (MIST)	Southern hemisph ere		The spatially-explicit risk assessment methodology uses the spatial overlap of fishing e Analyses used a delta lognormal approach, first modelling the probability of nonzero catch, and then modelling the distribution of catch rates in the nonzero catches. Effort and population density to derive a risk metric. This requires estimation of relative population density over the spatial domain of the assessment. Analyses used a delta lognormal approach, first modelling the probability of nonzero catch, and then modelling the distribution of catch rates in the nonzero catches. Abundance indices through time were required as inputs into the risk assessment, and to serve as indicators of population trend and condition. The abundance indicators reported here are based fisheries that operated within each of the five areas, and were taken to be representative of temporal trends in abundance. The risk assessment methodology uses the spatial overlap of fishing effort and population density to derive a risk metric. This requires estimation of a catchability coefficient, which is achieved by fitting a logistic production model to available data in the most data-rich of the assessment regions. The catchability scalar is then applied to effort overlap in the other regions to estimate a fishing mortality. The sum of spatially-explicit, annual fishing mortality (annual impact) is compared to a maximum impact sustainable threshold (MIST), which is a limit reference point derived from the intrinsic rate of population growth. Risk is estimated from the ratio of annual impact to the MIST, and expresses the probability, given the uncertainty, that total impacts exceed the MIST.	Broke distribution up into 5 stocks	
Jepson & Colburn 2013	* Flags useful attributes should ERA be extended to social aspects	USA	Identify indicators to monitor sustainability and other measures of well-being	Surveys/workshops to elicit ideas and then factor analysis to determine what works		
Jiang et al 2018	* Generic ecotox ERA (in case need reference for discussion etc)	China		Brought together samples from different media (water, mud, fish etc) and then calculated the human health risk assessment of heavy metals from fish consumption as: $EDI = (C \times DC)/(1000 \times BW)$ (1) $THQ = EDI/RfD$ (2) where C is the mean concentration of heavy elements in fish		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				(mg/kg); DC is the daily fish consumption (71 g/day/person) as recorded by the Food and Agricultural Organization (2008); BW is the average Chinese adult body weight (58.1 kg) (Gu et al., 2006); RfD is the oral reference dose (μg/kg/day), which is an estimate of a daily dose of contaminants that is likely to be without appreciable risk or deleterious effects on human health (IRIS, 2015; USEPA, 2013).		
Jiménez et al 2012	* Provides modifications for PSA when dealing with seabirds	Uruguay	Measure the relative impact that the Uruguayan pelagic longline fleet has on different populations of Procellariiformes.	Waugh bird PSA version - using "Demographic Invariant Method" (DIM), where productivity is estimated as the rate of maximum population growth (λmax), which is the rate of annual growth of a population of a species without limiting factors and at low density, works for long lived birds and uses the age of first reproduction (α) and the survival of adults (s). Came up with four combinations of survival and age at first breeding, based on the body size (and breeding frequency), are as follows: 1) s = 0.93 and α = 6 for shearwater Puffinus spp.) and small petrels (Daption and Fulmarus in our case), 2) s = 0.94 and α = 7 for medium sized petrels Procellaria), 3) s = 0.95 and α = 8 for large petrel Macronectes) and annually breeding albatrosses (Thalassarche), 4) s = 0.96 and α = 10 for biennially breeding albatrosses (Diomedea and Phoebetria). In the current study, for species that consume discards, offal, bait and/or are captured by the fishery, we estimated the susceptibility to incidental capture considering the availability, encounterability or access to bait and probability of remaining captured or selectivity, and the probability of post-capture mortality, considered to be 1 (as take bait on set but drown before found on haul). L3 method used = PBR	Main argument in favour of using Rmax obtained from the DIM as a measure of productivity for each population in the PSA and also for estimating PBR since this method requires fewer biological attributes compared to other approaches, notably it does not require estimates of maximum age or fecundity. Since current estimates of adult survival come from populations subject to different levels of depletion, we used assumed values based in the body mass and breeding frequency (following Dillingham and Fletcher 2011) in order to make valid interspecific comparisons. Also used conservative PBR parametrisation as looking at a subset of global footprint and conservation concern species.	Had to use to qualitative info to estimate some parameters for susceptibility (i.e. availability and selectivity).
Jin et al 2016	* Portfolio analysis as a contrasting approach			Portfolio analysis = alternative method of looking at risk–return trade-offs. Can include sustainability constraints		
Jones et al 2018		Myanmar	Baseline assessment of the seagrass meadows and their associated fish assemblages			
Jones & Cheung 2018	* Shows how to handle uncertainty in classification (fuzzy logic and	General		We developed a fuzzy logic expert system to assess the level of exposure to hazard, sensitivity, adaptive capacity and the resulting overall vulnerability and risk of marine fishes and invertebrates to climate change and ocean acidification. Employing fuzzy set theory, or "fuzzy logic" allows the		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	automation of classification) * Combine with PSA to bring in climate aspect to cumulative impacts			uncertainty surrounding our knowledge of fish biological and ecological characteristics as well as their linkages to vulnerability to be taken into account. Thus, rather than allocating a subject to one category, or set, overlapping fuzzy sets allow a subject to belong to one of more sets simultaneously, with the extent of membership to each being defined by a fuzzy membership function. Climate hazard was indicated by the mean change in an environmental variable (V) between baseline (average between 1951 and 2000) and 2050 (average between 2041 and 2060) divided by the standard deviation (SD) over baseline period (1951–2000) (equation 1). This takes into account the interannual environmental variability a species would be accustomed to experiencing, thereby characterizing where the trend in the environmental variable becomes perceptible across each species' range. Exposure to climate hazard (ExV) was calculated for sea bottom temperature, oxygen concentration, and acidity for demersal species, and sea surface temperature, oxygen concentration, and acidity for pelagic species. For each species, we categorized the level of exposure to each climate hazard into low, medium, high and very high (ExV, equation 1). These are fuzzy categorizes as the thresholds that delineate the categories overlap with one another. Rules for classification included. Sensitivity based on known temperature tolerance range and body size and other sensitivity = whether acidification = known issue or that taxa. Adaptive capacity incorporated information on latitudinal breadth, depth range, association with specific habitats, and fecundity. Matrices or rules that determine the level of vulnerability off species' sensitivity, adaptive capacity and exposure		
Juan-Jorda et al 2014	* Evidence of how used globally to inform management	Global				
Juan-Jorda et al 2018	* Evidence of how used globally to inform management (but not all smooth sailing)	Global				

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Kang et al 2018	* How could like PSA L2 and L3 as a method of multispecies management	Korea	Integrate the ecosystem-based fisheries assessment (EBFA) approach into Korea's acceptable biological catch (ABC) for total allowable catch (TAC) management system			
Karnauskas et al. 2017		USA		Ecosystem status report - could be used as input for a formal assessment, but really just a cataloguing of current state and recent trends with no formal assessment step		
Karintseva 2017		Ukraine				
Kell & Luckhurst 2018	* Alternative approach at system level			Used DPSIR framework to identify indicators to track to form basis of a report card at an ecosystem level		
Kenny et al 2018	* Provides a comment on UN impact assessment requirements - how many does ERAEF meet? Even need an explicit ecosystem level?					
Kirby et al 2009	* Seabird L2 example	Pacific	Assess the risk of interactions between longline fisheries and seabirds	Spatial PSA. Additional indicators are then developed for the number of species and the number of individuals potentially affected by fishing-induced mortality in any particular area. This allows consideration of 'biodiversity hotspots' as well as areas where the potential for fisheries interactions with seabirds of any species is highest. Finally, we determine areas where fisheries pose the most risk of population-level effects. To assess the risk of population-level effects we carry out an analysis including a measure of the population growth rate for each species and re-define 'risk' as the anticipated consequences at a population level of the probable fishing-induced mortality incurred. This therefore includes the Productivity axis of the PSA in addition to the Susceptibility as derived from the spatial overlap. Used tracking data and range maps to get species distribution then susceptibility = bird density * effort of that fleet. Productivity = rmax. Did the		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				double square root transformation and binning to get class of risk (summing over fleets and species to get total risk in a cell).		
Knights et al 2015	* Shows extension into cumulative impacts thinking	Europe	Proof of concept of regional cumulative impacts assessment	Proof of concept so included (i) up to 17 sectors (the number of sectors included in a regional assessment was dependent on whether it is currently operational in the region), (ii) 23 pressure types, and (iii) 5 broad ecological components. Using literature made exhaustive sector–pressure–ecological component linkage matrix where each cell in the matrix describes the potential for impact on an ecological component from a sector, wherein a pressure is the mechanism through which an impact occurs = impact chain (>4300 identified). Threat from each chain was assessed by way of a pressure assessment (sensu exposure-effect) approach (using expert judgement). Built off PSA idea - used combinations of the assessment criteria to describe two axes of information: “impact risk (IR)” and “recovery lag (RL)”. IR was constructed using a combination of exposure (2) and sensitivity (1) criteria, which describe the spatial extent and temporal (frequency) overlap of a sector–pressure within an ecological component, and the severity of the interaction where overlap occurs (degree of impact). These criteria were combined into the aggregate criterion, we refer to as IR, where the greater the IR score, the greater the threat to a component (Figure 2). It is important to note that each assessment criterion was evaluated independently before being combined into an aggregate score. This was intentional such that the effect of each criterion on the combined risk score could be evaluated separately, but which can lead to equivalent scores from different combinations, e.g. “Acute-Occasional-Widespread” and “Acute-Persistent-Low”. RL was described using the combination of pressure persistence (the number of years before the pressure impact ceases following cessation of the sector introducing it) and ecological component resilience (recovery time) following the cessation of the pressure impact. This aggregate criterion gives an indication of the time required for potential improvement in ecosystem state to be seen following the management of a specific impact chain, where the greater the RL value, the longer period required for an ecological component to recovery back to its pre-impacted state. IR and RL scores were calculated for each impact chain	RL score turned into a value in years and IR and RL (years) were then grouped, either by sector, pressure type, or ecological component and the distribution of values presented using boxplots.	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				as the product (multiplication) of the assigned categorical scores.		
Korpinen & Andersen 2016	* Review of IEA but makes some points important for ERA too		Review marine CPIAs (IEAs). This review has specific objectives: (1) Compare and find similarities in methods; (2) evaluate selection of ecosystem components included; (3) evaluate links between human activities, pressures and associated impacts considered; (4) compare methods of estimating potential impacts; (5) find good practices in validating CPIAs.			
Lack et al 2014	* Supplement/ complement to RRA?	Global		Standard vulnerability (exposure, consequence thinking) but with M-Risk extension: Basically management and compliance risk: the following six factors were suitable for the assessment of M-Risk: The indicators used to assess each of these elements are: Stock Status a) What is the status of each stock OR the status of the species in each management unit if stocks are not well-defined? Adaptive Management System b) Is information collected to inform the status of the stock? c) Have the available data been analysed to inform management decisions? d) How does the management unit manage the stock? e) Are the measures consistent with the species-specific advice for the stock? f) How comprehensive is the compliance regime in place to support these species-specific measures? g) What is the level of compliance with the reporting requirements for the stock? h) Is IUU fishing recognized as a problem for the stock (if it is a target) or for the fishery in which the stock is taken (if it is a bycatch)? Generic Fisheries Management i) Are the generic fisheries management measures in place likely to reduce the impact on the species / stock being assessed?	M-Risk assessment also has the capacity to identify those stocks where improvements in specific aspects of management are required	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				j) How comprehensive is the compliance regime in place to support the generic management measures that are relevant to the species/stock being assessed? Scores of 1-4 are attributed to each indicator, with the highest score reflecting the better management and the lowest risk. This approach was dictated by the need to weight the elements of M-Risk. Compare intrinsic and M-Risk and if M-Risk actually worse go with that as suggest intrinsic will get worse with time (or not realise it is already bad) - see Table 7 (Intrinsic risk has been used as the mechanism for identifying the shark species to be subjected to M-Risk assessment. Given that the purpose of the M- Risk assessment is to identify those species where intervention through MEAs or other management mechanisms can reduce the risk posed by fishing mortality it is considered appropriate that, where the intrinsic and M-Risk ratings diverge, the default overall risk rating is the M-Risk rating.)		
Landis et al 2012	* Explanation of why need to bring in climate context					
Leadbetter 2013	* Example of how useful to multispecies fisheries in developing nations * Discusses the caveats	SE Asia		Checked value of using PSA in SE Asia by doing hypothetical using example low/high productivity species (based on life history characteristics and 12 different fisheries/management scenarios (to check susceptibility ratings)		
Levin et al 2018	* Role of ERA in EBFM/EBM * Hype cycle					
Lillebø et al 2019	* Alternative method used in Europe for cumulative impacts / conservation	Europe	Characterise Natura 2000 site	GIS maps put through AquaLinks Tool to assess the causality links in a linkage chain relating activities, pressures and habitats/highly mobile biotic groups and ecosystem services, to assess the vulnerability of ecosystem components regarding the provisioning of ecosystem services (ES). Aqualinks Tool brings together the data sets for the demand and supply sides of the linkage chain, demand side of the linkage chain allows the calculation of an impact score. Both scores are used by AquaLinks Tool to produce a Vulnerability		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				Quotient (VQ) for each unique chain of activity pressure-habitat-ES (analogous to a hazard quotient). Produced ecosystem service prioritisation and allowed for discussion of different management options across stakeholder groups (spatial multi-criteria analysis)		
Lucena-Frédou et al 2017	** Points out adding climate - a must * Adjusted PSA factors	Global	Do a PSA to (a) the vulnerability of the species in the study areas was evaluated; (b) the vulnerability of target and non-target species by ocean was compared; (c) the sensitivity of the results to data quality was analysed; and (d) the results of the PSA were compared to other more quantitative assessments methods.	PSA with productivity attributes (1) Maximum size (Lmax, cm), (2) Fecundity, (3) r: the intrinsic rate of population growth or maximum population growth that would occur in the absence of fishing at a small size, calculated from life history parameters for each stock using the approach of Fortuna et al. (2014), (4) von Bertalanffy growth coefficient (k, cm.k−1): measures how rapidly a fish reaches its maximum size, (5) Size at first maturity (L50, cm), (6) Maximum age (Tmax, years), (7) L50/Lmax: a ratio that describes the relative investment into somatic and reproductive growth. Many studies have shown that life history parameters are correlated so when data were missing, we used empirical relationships between life history parameters to estimate biological attributes. For instance, missing L50 and k were estimated from linear regressions against maximum size. The boundaries between the three risk categories (low, medium, high) were established using the quantiles of the distribution of the vulnerability scores for the 60 stocks. Susceptibility attributes: (1) Availability or horizontal overlap, (1) Availability or horizontal overlap, (3) Z/k: the ratio of total mortality (Z) to the von Bertalanffy growth rate (k), (4) Percentage of adults in catches (% > L50), (5) Post-capture mortality, (6) Management strategy (Stocks subjected to a number of conservation and management measures were assumed to be less susceptible to be overfished and/or subjected to overfishing, while stocks with no effective regulation were considered more susceptible). Weights were adjusted within a scale from 1 to 3 (default weight of 2). Literature showed that differences between species and oceans were mainly explained by Lmax and k so these two attributes, plus r (a key to resilience) were thus given weight 3. A default weight of 2 was used for all other susceptibility attributes except for Management Strategy for which a weight of 1 was assigned, given that, although there are often a large amount of regulations in	Tracked a data reliability index too. Used Z/k as an indicator of mortality in order to replace Z/M, which can be highly influenced by the uncertainty in estimating natural mortality (M), which remains as one of the most difficult parameters to estimate in fish stock assessments	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				force, it is difficult to guarantee compliance with these by each flag state.		
Malakar et al 2019		India		Fractional logit regression is utilized to investigate the significant factors associated with adaptation in the (human) fishing community (factors could be used in future "social ERA").		
Marshall et al 2017		USA		Atlantis as L3 model for looking at acidification impacts		
Mazaris & Germond 2018	* Further commentary from security perspective on why need cumulative impact assessments					
Mazor et al 2017		Australia		Random Forests to predict spatial abundance distributions of benthos groups from environmental variables - mapped against trawl footprint to look at exposure.		
McDonald et al 2017	* Possible link ERA to indicator based HCR	Belize		11-step process for designing and implementing an adaptive management framework (AMF) that relies upon model-free indicators and harvest control rules (HCRs) that are used to adjust fishery management tactics: (1) Compile existing information; (2) Define social, ecological, and economic objectives; (3) Identify the fisheries of key species for management; (4) Identify indicators of stock trajectory; (5) Identify target and limit reference points for indicators; (6) Define HCRs; (7) Evaluate the expected efficacy of the management process (i.e. MSE test); (8) Collect and manage data necessary to inform indicators and reference points; (9) Undertake data analysis; (10) Interpret results; (11) Adjust fishery management tactics as specified by the harvest control rule.		
Meissa & Gascuel 2015	* Discuss relationships between F, abundance and life history	Mauritania	(i) to establish the very first diagnosis of the health of demersal resources in Mauritania, (ii) to identify sentinel species which should	Collate ecobiological parameters for species making up majority of the catch; calculate survey index, do Bayesian fox production model. Many exploitation indicators, derived from estimates of abundance indices and results of exploited-stock		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	characteristics; highlight which ones may/may no work and suggest new ones (including at system level)		be considered in priority for fisheries management, due to their intrinsic vulnerability, and (iii) to characterize the fishing impact not only at the stock level but also at the scale of the demersal community.	assessments, were considered: the slope of abundance over time (Slope, in percentage of interannual variation), obtained by adjusting an exponential model to the series of abundance intervals available; the parameters q, B0/K, r, and K of the biomass-production model (median posterior estimates); fishing mortality at MSY (Fmsy); current fishing mortality (Fcur); multiplier of fishing effort for any year t (mEt ¼ Ft/Fref), with a value set to 1 for the mean effort of the last 3 years; a multiplier of fishing effort at MSY (mEmsy ¼ Fmsy/Fref); the ratio of current biomass observed to that at the beginning of the study period (Bcur/Bstart); and the current level of stock depletion, equal to the ratio of current biomass at equilibrium to that of virgin biomass (i.e. without fishing mortality; Becur/K). In addition, taxa were classified by fishing effort at MSY (mEmsy), defining stocks that were overexploited (mEmsy ≤ 0.9), fully exploited (0.9, mEmsy , 1.1), or underexploited (mEmsy ≥ 1.1). Also, 12 life history traits were selected: the von Bertalanffy growth coefficient (Kvb), asymptotic length (Linf), maximum length (Lmax), maximum age (Tmax), age at first maturity (Tm), trophic level (TL), intrinsic growth rate (r, estimated with the method presented above), natural mortality (M), consumption rate (Q/B), production rate (P/B), asymptotic weight (Winf), and the intrinsic vulnerability to fishing (V). Principal component analysis (PCA) was used to study relations between exploitation indicators and parameters representing life history traits		
Micheli et al 2014	* Shows simple extension to cumulative impacts (e.g. multiple fisheries)	Mexico	Extend PSA to allow risk-based assessments of the cumulative effects of multiple fisheries operating within the same geographic region	Two extensions to PSA - fisheries with the greatest impact (FGI) and aggregated susceptibility index (AS). For FGI find susceptibility per fishery/fleet and then use the greatest score (highest susceptibility) as what plug into the final risk calc. For AS = min (3, 1 + sqrt(sum((FSSi-1)^2))), so as AS increases with the number of fisheries that are accounted for, as long as their FSS is greater than 1. If two or more fisheries have FSS larger than 1, AS is larger than FGI, the maximum value among the FSS scores - this AS score is then what plug into final risk calc. Thus, multiple fisheries, each assessed to cause moderate risk, could result in high risk when combined, i.e. when simultaneously affecting the same species.	The extended PSA approach presented here also allows for an evaluation of how possible management changes may influence multiple species within the ecosystem (by dropping individual fisheries out of the compound indices and see how risk rating changes).	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Milton et al 2008	* SAFE application to snakes	Australia		Use SAFE as sharks ~ sharks in life history characteristics so didn't change assumptions. Used a fish method to estimate natural mortality. F calculated doing % overlap and effort-based versions		To better improve the link between life history traits and sustainability, we need direct measurements of natural mortality for sea snake species.
Muñoz et al 2018	* Alternative spatial habitat/ life history stage vulnerability assessment method	Europe	a) identifying areas of high risk and conflict potential between human activities and ecosystem services (European hake nursery, as an example for a key area of provisioning services), b) identifying areas with potential conflicts among human activities in the future and c) prioritizing areas in the Spanish contiguous zone of the Alboran sea where MSP is necessary.	The workflow adopts the risk assessment concept outlined in Gimpel et al. (2013) and described in more detail in Stelzenmüller et al. (2015, 2018). First, for risk identification of ecosystem services such as habitat (supporting service) and nursery area (food supply), a General Additive Model (GAM) analysis for determining hake nursery areas was carried out. Then, human activities, driver, footprint and pressure categories were determined. For risk analysis, the habitat-specific sensitivity, the modelled nursery areas have been overlaid with EUNIS habitats. Subsequently, by combining pressure and sensitivity maps the vulnerability of the EUNIS habitats and therefore the hake nursery grounds were assessed during risk assessment. Present and future conflicts among activities were estimated applying a conflict matrix. Based on the results of the risk analysis (conflict maps, vulnerability maps and Spr index) the risk evaluation was carried out and priority areas for MSP approaches were identified in the Spanish contiguous zone. GAM was used to predict the potential location of hake nursery areas, considering bathymetry, geology, sediment type, EUNIS habitat types, surface chlorophyll a, surface temperature and bottom salinity. Got GIS layers and then corresponding to the activity-pressure relationship, spatial footprint and frequency, spatial maps of each pressure (Pi) (i=Extraction, Siltation, Smothering, Obstruction, Alteration, and Enrichment) were elaborated following formulae (II). $Pi = \Sigma pij*fj$ Combining the pressure maps (Pi) and the sensitivity of the habitat to the pressure categories (Sih) a vulnerability (likelihood of impact) assessment for the habitats (Vh) was carried out following formulae: $Vh = \Sigma Pi*Sih$		
Murua et al 2012		Indian Ocean		Standard PSA		Lack of biological parameters specific to Indian Ocean for most of the sharks as well as limited length frequency and

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
						post-capture mortality data from observes may affect the results of this analysis.
Nel et al 2013	* Turtle example (also calls for cumulative assessment)	Indian Ocean		Ormseth and Spencer PSA method - as had few data so had to drop some productivity and susceptibility attributes. Productivity: **recent population trend, RMU clades, age at maturity**, max age, generation length, **nest success, hatchling/emergence success, number of eggs per female, clutches per individual per season, remigration survival**. Susceptibility: **management/recovery plan, spatial overlap, confidence estimate in distribution data**, geographic concentration, vertical overlap, **bycatch estimate, number breeding females**, temporal overlap. Used weights against attributes, those in bold had weights > 0	Looked at it per gear type and per species	The susceptibility scores were highly dependent on the size of the population and the availability of information.
Newman et al 2018	*PSA used to find indicator species (representing classes of species with similar attributes) for "indicator species based management approach"			Indicator species-based management. In adopting an indicator species approach to assess and manage entire suites, indicator species are intended to be in some way representative or typical of a suite, but they may also represent some extreme; e.g. they may be the most vulnerable, least resilient or have a restricted range. The selection of indicator species is based on the scoring of attributes within three broad categories: inherent vulnerability, current risk to sustainability of the stock and management importance (the contribution of the species to commercial and recreational catches, and their cultural and/or community importance). Within a suite, the species with the highest total scores are selected as the indicator species for that suite. The number of indicator species within a suite may vary spatially to accommodate multiple fishing sectors that use different gears to target and retain a different range of species. Use PSA to get to the inherent vulnerability (~productivity) and current risk (~susceptibility) scores.		
O et al 2015	* Modified form bringing in cumulative risk and ecosystem risk options	Canada	The goal of developing this ecological risk assessment framework (ERAF) is to provide managers with science advice on the ecological risk consequences of anthropogenic stressors on	The scoping phase consists of the following steps: 1. Identifying Valued Ecosystem Components (VECs) for the area of interest (Structure the ecosystem into components and subcomponents of species, habitats, and community/ecosystem properties and then have criteria to select ones care about); and	Provide tables of guidelines/criteria for species sections; habitat type definitions; community/ecosystem components of interest (recognise not much guidance available on these later ones). Gives uncertainty categories and scoring	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
			ecosystem components, together with the processes and tools that can be used in the development of conservation objectives and management measures in PNCIMA and MPA initiatives in Pacific Region.	2. Identifying activities, associated stressors, and generic pathways of effects models. For species cared about: Number of individuals, Population density, Biomass per unit area, Organism condition, Age/size structure, Genetic diversity and structure, Spatial distribution of population, Reproductive capacity, Behaviour / Movement; For Habitats: Spatial distribution of habitat (aerial extent, % cover), Condition of habitats, Habitat structure (patchiness, morphology), Substrate Quality, Water quality, Air quality; Community properties: Species diversity, Species composition, Species evenness, Functional group / guild composition, Spatial distribution of the community, Trophic diversity; Ecosystem processes: Primary production, Nutrient cycling, Oceanographic processes, Flows of organic and inorganic matter. To select human activities use Pathways of Effects models (PoEs) = a representation of cause-and-effect relationships between human activities, their associated stressors, and their impacts. In the absence of a PoE model, the best available information should be used and other methods or models should be explored, such as the Driver-Pressure- State-Impact-Response (DPSIR) and Bayesian models.		
O'Laughlin 2005	* Describing approach used in other field (fire management)	General		1. A diagram of the conceptual model visualizes the hazard pathway. 2. Sketched plot visualises a risk hypothesis - connecting action to outcome		
Orsmeth & Spencer 2011	* Checks implications of score incorrectness and frequency of review	USA (Alaska)	(1) Evaluate the vulnerability of all groundfish stocks included in the FMPs. (2) Compare the vulnerability of target and non-target stocks. (3) Compare methods for analysing fisheries caught using different gear types. (4) Analyse the sensitivity of the PSA to changes in attribute scores.	NMFS (Patrick et al) PSA variant - All additive. No data quality index built in (like Patrick did), Productivity attributes: r, Maximum age, Maximum size, Growth rate (k), Natural mortality, Age at maturity, Mean trophic level, Measured fecundity, Breeding strategy, Recruitment pattern. Susceptibility attributes: Management strategy, Areal overlap, Geographic concentration, Vertical overlap, Fishing rate relative to natural mortality (F/M), Biomass of spawners (SSB) or other proxies, Seasonal migrations, Schooling/aggregation and other behaviours, Gear selectivity, Survival after capture and release, Desirability/value of the fishery, Fishery impact to habitat. All attributes were weighted equally, except recruitment as little evidence for this in Alaska so got half weight. PSA plot coloured by data quality index. The original	Looked at implications of # attributes with changed susceptibility score (i.e. how does vulnerability change if 1, 2…. 12 attribute scores were wrong; what is the implications if only have 4 or 8 attributes in total to calculate susceptibility score…. *Getting back to the criticism from the sim test paper and checking on implication of changing exploitation rates through time*)	Like in Australia, PSAs were unable to capture important changes in susceptibility due to the limited number and range of the included attributes

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				working group document recommended that a separate PSA be performed for each gear type and the results combined according to the proportion represented by each gear type in the total catch. In contrast, the analysis presented here scored attributes conservatively according to the fishery and gear type with the highest proportion of the total catch (though did actually calculate both methods and compare)		
Parappurathu et al 2007		India		Survey based info collection and then "constraints analysis" on what is stopping insurance up take and "risk management" of economic risks in fisheries		
Park et al 2010		Canada		Application of Canadian VEC risk framework - work out "Magnitude of Interaction" (extent, direction, intensity) * sensitivity (acute and chronic)	Takes ecosystem implications into account by looking at dependency of ecosystem in that component	
Paterson & Peterson 2010	* Comment on value of ERA to EAF	South Africa				
Paterson et al 2018		Canada		Socioecogical approach to collecting the kind of info you can then use to calculate PSA/SAFE values		
Patrick et al 2010	* Discusses tweaks to PSA (brought management into PSA instead of RRA)	USA		Productivity attribute - use direct estimate r OR other proxies (can use the lot but really via weighting r to dominate really just using one or the other as proxies are trying to capture r anyways). Attribute weighting scheme was used in which higher weights were applied to the more important attributes. The scoring for the productivity attributes in ePSA was the reverse of sPSA, such that high values of productivity (i.e., 3) correspond with low risk and low productive attributes were scored 1 - so had to change formula for calculating final risk index. The ePSA differs from the sPSA in several ways, revised the productivity and susceptibility criteria, which resulted in 10 productivity attributes, including many of those in standard PSA (sPSA) and some additional attributes: population growth rate (r), von Bertalanffy growth parameter (K), and the natural mortality rate (M). They also modified the reproductive strategy criterion of sPSA to include two attributes: breeding strategy, based on Winemiller's [21] index of parental investment, and recruitment pattern, based on the expectation of successful recruitment events. The ePSA	Rather than requiring separate RRA, define susceptibility more broadly as the susceptibility of a species to overfishing, which is also dependent on the current status of a species and the management measures in place	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				includes 12 susceptibility attributes, separated into two sub-categories: catchability and management. The 7 catchability attributes were based on sPSA but with the addition of criteria on the value of the fishery and fish behaviour including seasonal migration. The 5 management criteria included estimates of current fishing mortality relative to natural mortality (F/M), management strategy, estimate of spawning biomass relative to reference points (e.g., depletion), survival of released fish, and the impact of the fishery on the habitat.		
Pedreschi et al 2019	* IEA example using an alternative method	Europe (Ireland)	Perform IEA for Irish Waters	Used a risk assessment framework, based on the ODEMM approach (as the best available means of rapidly and efficiently assimilating expert input into an integrated assessment for the purposes of determining the key pressures acting on the Irish ecosystems and their components). Consensus scoring by expert panels. The linkage framework was built by identifying 'links' between elements of the framework, e.g. between a sector and a pressure, and between a pressure and an ecological characteristic. 'Linkage chains' consist of pathways between multiple elements of the framework (i.e. tracing a potential impact from a sector and the pressure it creates to the ecological characteristic affected). Each one of these linkage chains was assessed by the expert panels to assign broad qualitative categories to each of 5 assessment criteria; overlap (spatial), frequency of occurrence, degree of impact, persistence (of the pressure), and resilience (of the ecological characteristic). Final scores are 'Proportional Connectance', 'Impact Risk' (product of the 'overlap', 'frequency' and 'degree of impact' scores) and 'Recovery Lag' (product of 'resilience' and 'persistence' scores) -shown as boxplots and estimates produced in R. Bias was further mitigated by selecting the highest impacting individual linkage chains to recommend foci for action to decision-makers. These highest risk chains were identified by ranking the risk scores (Total Risk, Impact Risk and Recovery Lag). Irish assessment was further related to the MSFD descriptors. Pressure pathways were also traced through to ecosystem services, by linking the ecological characteristics to ecosystem services		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Penney & Guinotte 2013	* Variant to look at habitats - changed meaning of axes so like L2.5 or L3 version		The ERAEF productivity–susceptibility analysis approach was further adapted in this study to directly address the two main questions arising out of y UNGA resolution 61/105: where are VMEs likely to occur? and what is the risk of fisheries interaction with these VMEs?	Mapped out effort and did habitat models (for benthos distribution). Likelihood of VME Occurrence was plotted against Likelihood of Fishery Interaction to quantify the risk of significant impacts on VMEs in each footprint block. predictive habitat models (MAXENT) predict the likelihood of favourable habitat for VMEs, in this case deep-sea corals, using a wide variety of predictor variables. These models therefore provide multi-factorial, integrated measures of the likelihood of favourable habitat that can be directly used as indices of likelihood of occurrence of the VMEs concerned. Habitat suitability values from model were used as indices of the VME Likelihood (x-axis) values per footprint block (only considering fishable depths)-. Predicted fishable-depth VME likelihood values were then discounted for the effects of historical fishing in each block. Cumulative swept area values for each footprint block were therefore used for the Fishery-Interaction axis in risk assessment plots. Produced risk maps but also PSA-like plot (with updated axes) and blocks have been classified by their current management status (open, move-on or closed).		
Pitcher 2014	* Spatial PSA update for benthos (include SAFE-like step)	Australia		Spatial PSA. Created GLM models predicting biomass distribution maps for ~850 benthic species. The approach to this ecological risk assessment was to examine overlap of habitats, assemblages and species distributions with the footprint of the QECTF, using a series of exposure indicators of increasing specificity – progressively accounting for management zoning, actual distribution of trawling, and intensity of trawl effort, relative catchability of species in trawls and species productivity potential was taken into account, providing more specific indications of relative risk and sustainability. The series of trawl exposure estimates were based on mapped area for habitat types and seabed assemblages and on mapped biomass distributions for individual species. This series included: 1. Estimates of the percentage of the distribution of each habitat, assemblage, and individual species, located in areas open to trawling under spatial management arrangements – without accounting for the distribution or intensity of trawl effort.		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				2. Estimates of the percentage of the distribution of each habitat, assemblage, and individual species, located in areas where trawl effort is present – without accounting for the intensity of trawleffort. 3. Estimates of the percentage of the distribution of each habitat, assemblage, and individual species, located in areas where trawl effort is present taking into account the intensity of trawl effort. A given grid cell's contribution to the overall index was the estimated proportion by area or biomass of the respective biological attribute, multiplied by the estimated effort coverage. These estimates for grid cells were summed to provide the overall index for the GBR region. Used data from previous work on relative catch rate information of species in a prawn trawl vs fish trawl vs an epibenthic sled. If evidence from literature demonstrated that TEDs and/or BRDs further reduce catchability, this information reduced the estimated percentage of the biomass of a species exposed in indicator #3. For productivity (recovery) axis used mean recovery attributes from Stobutzki's NPF SRA analyses. Also adapted SAFE method - using more conservative reference points and estimated exploitation rate (u) divided by natural mortality (i.e., u/M) - instead of F/M.		
Pitcher et al 2016a	* Habitat ERA			Australia wide habitat ERA vs trawl effort. Each mapped assemblage provided the basic unit of assessment and after the assemblage maps and trawl effort & closures datasets were produced for each Commonwealth fishery jurisdiction, the quantitative overlap assessments comprised relatively straightforward spatial analyses. First, the various types of spatial management, including Commonwealth marine reserves, other marine protected areas, and fishery closures (Figure 1) were overlaid on the assemblage maps and the area of each mapped assemblage represented in each category of spatial management was quantified by area and as a percentage. As an indicator of trawl effort intensity, the total swept area in each assemblage was also quantified by area and as a percentage. This information was tabulated for each assemblage in each fishery. The level of exposure of each assemblage to trawling, and protection in spatial management, was also plotted for each fishery in a format analogous to previous ERA presentations.	Plot of percentage of area of each assemblage open to potential trawling against exposure to actual effort as trawl footprint and swept intensity - done per jurisdictional (fishery) area	not all variation in demersal species composition is explained by relationships with environmental variables. Typically, more than half the species present in a biological survey dataset are too rare for analysis, and of those having adequate occurrence perhaps a third show no statistical relationship with the environment — and further, of those that have a relationship, on average 10–40% of their variation in abundance could be successfully predicted by environmental variables. True number of assemblages unknown. Lack of information on susceptible

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
						habitat components within assemblages
Pitcher et al 2016b		Australia	Summarise 15 years of related GBR research	Observational and experimental effects of trawling and recovery; surveys; habitat models; impact models; habitat PSA; L3 model for MSE of trawl impacts		
Pitcher et al 2017	* L3 benthos assessment method	Australia	Develop a simple, widely applicable quantitative level-3 ERAEF method for assessing relative benthic status (RBS) in areas fished with towed bottom-contact gears	The dynamics of the abundance of seabed communities are assumed to be described by a Schaefer (1954)-type logistic population growth equation, with an additional term to describe the direct impacts of trawling on the seabed, consistent with previous ERAEF approaches. rate of change of benthic abundance = recovery rate * abundance * (1- abundance / K) - trawl depletion rate * trawl effort * abundance. Cell-connectivity parameters could be added for mobile fauna (if available). RBS index is then RBS = B/K = 1 - FD / R. Estimating B/k requires relatively few parameters: habitat type, trawl effort, depletion rates and recovery rates. Then RBS is estimated for each grid-cell based on trawl effort and appropriate depletion and recovery rates for the gear and habitat. The average RBS and distribution of RBS values over grid cells, by habitat, indicate the landscape scale status of habitats. The Gulf-wide status of habitats, accounting for their different sensitivity and exposure to trawling, was quantified by plotting the distribution of RBS values against proportion of habitat area, by mapping their spatial distribution and by the region-wide average RBS value.		
Piet et al 2015	* IEA application using EU method and quasi MSE	Europe	Integrated assessment and want to link to policy (for impact consideration)	Risk is determined based on scores given to five criteria. These are: (1) the spatial (Extent), and (2) temporal (Frequency) overlap of a sector-pressure and ecological characteristic, which together describe the exposure of the ecological component to a sector-pressure combination in terms of their spatio-temporal overlap; (3) the Degree of Impact (DoI) of the sector- pressure on that characteristic describing the severity of the impact where interactions occur; whilst the potential for recovery after the impact has occurred is described by (4) the Persistence of the pressure (the number of years before the pressure impact ceases following cessation of the activity introducing it), and (5) the Resilience of the ecological		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				characteristic (recovery time in years); then allocated scores and considered two aspects of risk: Impact Risk (IR) = the likelihood of an adverse ecological impact following a sector-pressure introduction = Extent ⁄ Frequency ⁄ DoI; Recovery Lag (RL) = a relative indication of the time it takes for an impacted ecological component to return to pre-impacted condition after the implementation of a measure = Persistence ⁄ Resilience. Responding management measures involve the ''Focus'' and the ''Type'' of measure - the ''Focus'' is determined by the element(s) of the impact chain (i.e. Driver–Pressure–State) that the measure targets and type mitigate or counteract the impact of the human activity. Look at change in risk and recovery once measure in place (assuming 100% effectiveness).		
Piet et al 2017	* Looks at implications of different score aggregation methods in IEA			IEA approach. The ERA framework evaluated here was based on a sector- pressure-ecosystem component linkage matrix broadly consistent with the interactions possible in European regional seas Each of these interactions (herein referred to as impact chains) had earlier been categorised following the methods outlined in Robinson et al. (2013) using five assessment criteria ((criteria: (1) spatial exposure, (2) temporal exposure, (3) impact/ severity where exposure occurs, (4) resilience of affected ecosystem components, and (5) persistence of the pressure in the ecosystem). Each impact chain was given a categorical valuation for each of the five assessment criteria; the value derived using expert judgement underpinned by a combination of qualitative and quantitative data through a series of expert workshops. Did an analysis to explore how altering the method of score aggregation (sum, average, median, max; ordinal (all equal) or weighted) can affect the outcomes of an ERA.	Nice impact chain plot	
Piet et al 2019	* Application of Pier IEA to deliver EBM	Europe (North Sea)		Piet IEA method with impact risk (IR) scores were aggregated (additively) for each human activity and its pressures, as well as for each ecosystem component (consisting of specific mobile biotic groups and habitats), to indicate which ecosystem components are most at risk and which human activities and pressures contribute to that risk. The outcome of this risk assessment, in terms of the relative contribution of the different human activities and their pressures to the risk of		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				not achieving the societal goals (this phase II), as well as the evaluation of the potential performance of the management measures (phase III), should then be the basis to develop and apply one or more dedicated quantitative risk assessments covering only one or more specific impact chains. These impact chains emerge from the semi-quantitative risk assessment as the main threats.		
Prince et al 2015	* Potential L2.5 or L3 assessment (could automate to apply to many species?)	General				
Richard et al 2017	* More quantitative L2 method (and updated for issues found in Waugh version) * Identifies persistent weaknesses (further update)	NZ	This report presents an update of the previous assessment of the risk of commercial fisheries in New Zealand	Spatially Explicit Framework for Risk Assessment - **Risk ratio = annual potential fatalities / Population Sustainability Threshold**. A Population Sustainability Threshold (PST) was used for seabird population productivity, a generalisation of the Potential Biological Removal (PBR) index, based on the total number of breeding pairs, and including the uncertainty in all demographic parameters explicitly. Fishery groups (metiers) were assigned on the basis of the target species of each fishing event, the size of the vessel, and, for trawl fishing targeting middle-depth species, whether the vessel was processing fish on-board or not, as reported by fishers. Fishery groups were used to constrain the estimation of vulnerability. Interactions seabird-fleet assumed to be proportional to the overlap (units of the overlap are bird km−2 effort−1), model of vulnerability allowed for species have a tendency to be more attracted to fishing vessels than others, or to behave in a way that makes them more likely to be caught when they are around fishing vessels, and some fisheries are more likely than others to catch birds. Spatial used global distribution map extractions from multiple sources; for the breeding season, two distribution layers were created, one for the non-breeders (as above) and one for the breeders (where relative density of breeders within these discs was assumed to decrease exponentially with the distance to colonies). For migratory species had a scalar representing the number of birds in New Zealand waters during that season vs other seasons	The annual potential fatalities includes cryptic mortalities, i.e., birds that are killed by the fishing activity but not brought on-board the fishing vessel and not included in captures reported by fisheries observers. An overall correction factor φ was included in the PST calculation to achieve the long-term management goal of populations remaining above half their carrying capacity, in the presence of environmental variability. To improve the estimation of potential fatalities for taxa with small populations, seabirds were aggregated into species groups; taxa within the same group are assumed to have a similar vulnerability to capture in fisheries. Looked at parametric uncertainty- impact of each uncertainty on the final uncertainty in the risk ratio was measured by calculating the percentage of reduction in the range of the 95% credible interval of the estimated risk ratios when fixing the parameter to its mean. Like any risk assessment, the chosen methodology relied on some subjective decisions to address limitations imposed through the paucity of data on the at-sea distribution of seabirds, their demography and also on fishing and seabird captures. To assess the	The annual potential fatalities are estimated using spatial overlap, and include all fatalities from the fisheries with sufficient observations

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
					impact of some of the specific choices in the methods, the current study tested alternative approaches, including different data. There was a close relationship between estimated and observed data, indicating a close model fit	
Rico et al 2012	* Example of method used in aquaculture (where now have standardised software for vets to do the calculations)	General	Aquaculture risk assessment manual	ERA-AQUA Decision Support System was developed to estimate risks posed by the use of veterinary medicines in pond aquaculture production systems for the targeted produce, non-target aquatic organisms (acute and chronic), consumers, and the trade of the aquaculture produce. For all risk assessments an exposure as well as an effect assessment is performed following a conservative approach. In the exposure assessment, concentrations of the aquaculture drug are calculated in the pond water, in the targeted produce and in the effluent discharge point of the adjacent aquatic ecosystems by mass balance equations. The effect assessment consists of determining safe concentrations for the different compartments, and is based on the use of safety factors applied to toxicity data or food safety standards. The risk assessment is then performed by following a risk quotient approach, by dividing the predicted exposure concentration by the predicted no effect concentration in the compartment under study. When the predicted exposure concentration exceeds the predicted no effect concentration it is indicated by the DSS.		
Rijnsdorp et al 2018		Europe (North Sea)	Examine how the longevity composition of benthic communities varies across benthic habitats in relation to natural disturbance, sediment composition, and trawling intensity.			
Robinson et al 2014	* IEA approach	Europe				
Rosenberg et al 2009	* Use of PSA to inform management precaution for annual TAC setting	USA		PSA		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Roux et al 2019	* How to use fisher info (citizen sci) in PSA	Canada	The PSA framework is used to directly incorporate Fisher Knowledge (FK) data in the definition and scoring of a set of FK susceptibility attributes; and indirectly via the validation and weighing of productivity attributes based on correspondence between FK and scientific observations. A scenario-based approach is used to compare outcomes between PSA assessments performed with and without the inclusion of FK.	PSA. Productivity attributes: Maximum length (mm (fork length)), Maximum age (years), Mean length at Age (mm (fork length)), Modal age (years), Instantaneous mortality (estimated from catch curve analysis). Productivity attributes were estimated for each stock using fisheries-independent biological data collected in experimental surveys. Susceptibility attributes for Arctic char were estimated and scored based on availability, encounterability and selectivity proxies. FK data were used to estimate a set of FK attributes for use in productivity-susceptibility analysis. These included one attribute related to stock productivity (FK-Fish size) and six attributes related to fishery susceptibility: FK-Overlap, FK-Catchability, FK-Seasonality, FK Subsistence Harvest, FK-Effort and FK-Desirability. For each FK attribute, individual fisher scores were combined using weighted average, whereby each fisher's score was weighted based on the fisher's number of years of experience fishing in the Cumberland Sound Area. Three separate PSA assessments were performed: a standard estimation (PSA conducted without FK); and two PSAs with FK, including FK-weighted productivity scores and susceptibility scores estimated using FK susceptibility attributes (PSA with FK susceptibility) or a combination of standard and FK susceptibility attributes (combined PSA). PSA plot with circles size determined based on the data quality index for productivity attributes		
Rowland et al 2018	* Selecting useful indicators (e.g. for ecosystem health)		Guide on how to pick ecosystem health/collapse indicators			
Sara et al 2018	* Ecotox example	South Africa	Look at human health risks	Used the standard Hazard Quotient (HQ) to estimate the human health risk		
Savenkoff et al 2017		Canada	Description of how ecosystem research initiatives (ERI) was described for St Lawrence estuary			
Schick et al 2018		Namibia				
Samhouri & Levin 2012	* Demonstration of modified PSA for doing IEA	USA		Generalised from PSA - The first axis was related to the exposure E of a population to stressors associated with	Exposure factors included both direct and indirect effects as well as management	Only relative not absolute measures

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	*** Shows that simple qualitative approach works / is reliable**			particular human activities, and the other axis was a conditional probability related to the sensitivity S of the population to the activities, given its exposure. Mapped risk scores spatially. For community risk used non-metric multidimensional scaling (MDS) analysis (with a Spearman rank correlation distance matrix) to investigate associations between risk scores for the indicator species, or risk to the community.	aspects. Sensitivity factors included connectivity. Data quality boiled into the exposure and sensitivity scores as a weighting). Efficient because it can be conducted quickly, with limited resources, using existing information.	
Samhouri et al 2019	* IEA method used to look at cumulative fisheries pressure * Nice visualisation approach	USA		Used variant of Samhouri & Levin PSA approach. The risk assessment for each fishery was based on the exposure and sensitivity of each target, bycatch, or habitat group. Tailored list of attributes (bit different to other PSA as keep direct/indirect thinking of IEA method). CDFW staff quantified exposure and sensitivity based on sets of attributes. Individual attributes were assigned weightings based on their perceived importance in affecting exposure and sensitivity. Perceived importance emerged from discussions with CDFW staff and via conversations at the stakeholder workshops - so weightings based on perceived importance. For habitats had additional weighting of relative amount of fishing effort occurring within that habitat	Standard "PSA" plot + aggregate scores per fleet + risk thermometers per bycatch group/habitat (with component species specific score marked on the thermometer).	Need to add climate as some species coming out as low risk are actually declining due to climate
Sanchirico et al 2008		USA		Portfolio approach to EBFM - does catch allocations and estimates expected revenue - should lead to less variation in catch and improved sustainability (i.e. reduce economic risk)		
Serveiss et al 2004		USA		IEA considering ● Chemical pollution from pesticides, herbicides, emissions, industrial point sources, and boating activities ● Altered freshwater flow from new construction and wastewater treatment ● Nutrient enrichment/eutrophication from fertilization of agriculture, lawns and gardens, wastewater treatment, industrial point sources, and atmospheric deposition ● Physical alteration of habitat from dredging and boating activities ● Fishing and shellfishing resulting from commercial and recreational harvest pressure ● Pathogens from industrial point sources, impervious surface runoff, and waste discharges....... Indicators chosen were ● Estuarine eelgrass percent cover ● Finfish diversity and abundance ● Scallop abundance ● Anadromous fish reproduction ● Wetland bird habitat		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				distribution and abundance ● Piping plover distribution and abundance ● Tissue contamination of fish and shellfish. Thinking around objective vs indicator supported by watershed conceptual model. L1: each stressor endpoint pair was given a score ranging from minimal effect (1) to severe effect (5). Scores were summed across endpoints to develop a cumulative ranking for each stressor. For highest rank stressors then created exposure-response curves for each relevant indicator (these then help identify remediation actions to prioritise)		
Sethi 2010		General	Summarize risk management practices in use in fisheries and to present strategies that are currently not taken advantages of but may be appropriate for fisheries management.	Much broader discussion of all kinds of risk associated with fishing operations. Gives a nod to multicriteria decision analysis and MSE in decisions aspects but then goes on to talk about mechanisms for minimising economic risk and doing resource allocation (portfolio approach etc).		
Sharp et al 2009	* Fairly simplistic approach but along similar conceptual lines to standard ERA L1-L2	Antarctic a		Step 1: Description of fishing gear (including weight, sinking rate etc); Step 2: Description of fishing activity, and definition of spatial footprint for a typical fishing gear deployment event (for effort reporting); Step 3: Description of non-standard gear deployment scenarios, and associated footprints including how often these freak events occur (Expressing nonstandard impacts relative to the standard set is necessary to avoid double-counting of impacts); Step 4: Vulnerability assessment of VME taxa (consequence/impact rated by experts). Step 5: Description of total historical fishing effort Step 6: Calculation of total cumulative impact...... Upon completion of Steps 1–5, above, it was possible to calculate the total cumulative impact for each VME taxonomic group, utilising the following formula: 6.1 Multiply the size of the standard set gear deployment footprints per unit effort (Step 2) by total historical effort (Step 5) to yield total historical footprint per gear component for standard sets. 6.2 Multiply the frequency of occurrence of nonstandard gear deployment events (Step 3) by total historical effort (Step 5) to yield a cumulative numerical occurrence estimate for each non-standard scenario.] 6.3 Multiply the size of the non-standard gear deployment footprints per event (Step 3) by total non-standard event occurrence (Step 6.2) to yield total historical footprint per		Update in future with better species distribution maps. 'Slow recovery time' as a criterion for the selection of VME taxa; however, temporal recovery dynamics were not included in the subsequent impact assessment - it was just exposure * 'sensitivity index'

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				non-standard gear deployment scenario. 6.4 Divide the total historical footprint for each gear component and gear deployment scenario (Steps 6.1 and 6.3) by the size of the fishable area (or specific area of interest; Step 5) to yield a cumulative total historical footprint per gear component/scenario expressed as a proportion of the total area. 6.5 Multiply the results of Step 6.4 by the impact matrix (Step 4) to yield the total historical lethal and non-lethal impact of each gear component or scenario on each vulnerable taxa. 6.6 Sum across all gear components and scenarios (Step 6.5) to yield cumulative total historical impact for each VME taxa, expressed as a percentage (e.g. x% of taxa A in the fishable area has been lethally impacted at the scale of the fishery, y% of taxa B in the fishable area has been sub-lethally impacted at the scale of the fishery etc.).		
Sherman 2008 (in Bianchi et al 2008)	* Example of how to bring in other factors?	General		Use quantitative condition indicators for five modules of spatial and temporal indicators of ecosystem: (i) productivity; (ii) fish and fisheries; (iii) pollution and ecosystem health; (iv) socio-economics; and (v) governance. Modelling = EwE, statistical estimate or nitrogen loading (eutrophication) and particle spectra pattern analysis	True system perspective	Requires lots of data - possible to get some of it from other agencies (e.g. EPA)
Singh et al 2017	* An alternative purely qualitative approach to IEA * Includes cap on cumulative risk so have some sense of what the score means in absolute terms	NZ	Expert elicitation to identify which ecosystem services are at risk by what human activities in what ways.	Survey instrument to provide a ranked list of drivers and stressors acting upon each service. Interviewed each expert individually to derive impact scores and pathways for each designated activity or stressor, characterizing uncertainty parameters for each resulting in 'impact profiles'. After interviews all done had a workshop so experts could discuss and revise impact profiles. Scoring was digitized & data were combined to create density histograms of the impact scores for every driver and stressor on every= ecosystem service across all experts. To maintain the impact scale and its associated meaning, we aggregated impact scores in a way that maintained a cumulative score of 1 as the upper limit (i.e., 100% loss of service). To do this we calculated the extent to which each ES is not impacted by each stressor and multiplied these scores together to calculate how much of each ES is free from all impact. We then subtracted this product from 1 to generate the total impact score.	A second innovation of this method is that it includes an upper bound of impact. Almost all studies of regional cumulative impacts use an additive model for accumulating impact, with no upper limit of impact scores and no absolute sense of what impact levels mean	Resulting cumulative impact curves from all experts are very high, approaching (and often butting up to) the upper boundary of impact. This indicates that experts think that the ecosystem services are largely unavailable for human benefit. On its face this result is spurious, as fishing, aquaculture, and tourism are among the key industries in Tasman district. Perhaps experts provided impact curves that are too high for individual stressors, or the cumulative impact equation does not properly capture the way that experts conceive of interactions between impacts. Additionally,

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
						asking experts to score impacts individually rather than collectively may lead to overestimates of cumulative impacts as people are poor at assigning fractional scores. Model of impact accumulation may not have captured the degree to which some impacts are antagonistic.
Singh-Renton 2013		Caribbean				
Singh-Renton et al 2011	* Comment on role of ERA in EBFM	Caribbean				
Siple et al 2019	* L3 example - forage fish	USA		L3 model for forage fish - showing influence of life history characteristics of performance of different harvest control rules. Used MSE		
Slooten & Davies 2012	* L3 example - dolphins	NZ		L3 models for dolphins: Leslie matrix, Schafer models, Bayesian age-structured, temporally and spatially stratified population model, Potential Biological Removal (PBR), statistical (data-based) catch mimic models (using binomial function (rbinom), bootstrapped uniform random selection without replacement). From all these estimate fishing mortality rates and exposure to being caught rates of different management options - compare against PBR to comment on risk to the population		
Slooten et al 2000	* L3 example - dolphins (why need to track uncertainty)	NZ		Age structured Leslie matrix, propagating error for parameters - both drawing from distribution and holding constant over run and also drawing fresh with each year of simulation; added in demographic stochasticity. Evaluated the main effects and two-way interactions for all eight input parameters to see attribution of each uncertain parameter to model trajectories/overall uncertainty		
Small et al 2013	* Review of ERAs for birds but has some good general conclusions	General	Review ERAs for seabirds			

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
SIOFA 2017				PSA standard + SAFE for deepwater chonricthyans in (Southern) Indian Ocean		
Soykan 2018	* Worker risk on vessel example	Turkey	Risk assessment (OH&S) of working on fishing vessels	Risk = exposure * consequence approach		
Stelzenmüller et al 2018	* Comments on treatment of uncertainty in ERA/IEA (and general form of IEAs to date)	General	Review uncertainty handling in cumulative effects assessments			
Stepanuk et al 2018	* Example spatial overlap model	Atlantic	1) assess spatial overlap between pilot whales and longlines along the north-eastern coast of the United States; and 2) examine temporal patterns and environmental drivers of both overlap and observations of pilot whale bycatch.	Density grids, which include all longline effort (logbook sets and observer data) and pilot whale tag transmissions in the study period, were used as inputs for the spatial overlap analysis - also mapped on enviro layers like SST so could estimate bycatch relationship with depth, SST etc		
Stewart et al 2019	* Example of use of DNA for bycatch-population attribution	Atlantic	Use available ocean-caught loggerhead samples to determine nesting population contributions to by-catch by geographical area	Use DNA samples from bycatch to attribute home population of individuals caught by different fleets		
Stewart et al 2010	* Social/cultural method	South Africa		Multiple criteria decision analysis		
Stobutzki et al 2001	* L2 update for bycatch species, including how to translate to management actions	Australia	Develop a broad-brush method to examine the likely impact of trawling on the sustainability of teleost bycatch species. Identify species least likely to be sustainable in the bycatch, so that these could be the focus of research and management.	Applied in NPF. Two overriding characteristics were deemed to determine the sustainability of bycatch species to trawling, namely their susceptibility to capture and fishing mortality, and the population's capacity to recover. These characteristics are organized into a matrix in Figure 1. By marking the position of each species on the two characteristics we can assess all of bycatch of a fishery. Consistently apply the systematic approach to all the teleost bycatch species, to examine their status and highlight potential problems. Biological and ecological information was collated from the literature for each species encountered in research surveys and observers' records. This information was then used to rank the species along two axes that described the overriding characteristics that would determine the sustainability of the species in bycatch, axis 1 indicating the susceptibility of a		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				species to capture and mortality due to prawn trawling (Susceptibility), and axis 2 the capacity of species to recover after the population is depleted (Recovery). Each characteristic (or axis) was derived from several criteria that summarized aspects of the biology and ecology of the species. Axis 1 (susceptibility): Depth range (vs trawlable depths), Water column position (vs encountering demersal trawl), Preferred habitat (vs trawlable grounds), Survival (post capture), Range (geographic), Day/night catchability (vs night fishery), Diet (and whether this means will be attracted to trawl grounds given what's there). Axis 2 (Recovery): Probability of breeding (size first capture > size maturity), Maximum size (relative recovery rate index), Removal rate (as determines & pop remaining to reproduce and support recovery), Reproductive strategy, Hermaphroditism (as slower to recover), Fishing mortality index. Partial correlations were used to determine whether there was any redundancy in the criteria. A rank of 1 suggested the species is highly susceptible to capture or has a low capacity to recover; a rank of 3 suggested the species has a low susceptibility to capture or a high capacity to recover. Depending on the criterion these ranks were based on categorical or continuous data (criteria and rank definitions listed in Table 2). Where continuous data were used, as no information was available to assign the divisions between the ranks, the range of the data was divided into thirds to create the categories. Where species-specific information was not available, a species was given the same rank as other species within its family for the criteria water column position, diet and day/night catchability. For other criteria where it was not logical that family members would be similar, or where family information was not available, the rank of 1 was given as a precautionary approach. Final susceptibility and recovery scores = weighted average of components (weightings given by NFPRAG). Final sustainability contours given by 16(y 0.75) (x 0.75) 4, 9, 16, 25, 36, 49		
Suter 2008	* Nice background context to structural (hierarchical form) of ERA	USA	Discussion of history of EPA risk assessment			

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Szuwalski & Thorson 2016	* Discusses whether stocks match L3 assumptions (not so much, so automatically jumping to L3 may not be wise)	Global		Characterize the fishery dynamics for 173 stocks from the RAM Legacy Stock Assessment Database by fitting generalized additive models to estimates of SB and F. Using these fitted models, we ask, “If today’s SB and F are known, can changes in SB and F next year be predicted based on the past responses of the fishery?” We then link stock characteristics to a measure of predictability and identify stocks with expected fishery dynamics given common assumptions of density dependence, stationary dynamics, active management and/or cost-based constraints on fishing effort.... Did a simulation based round so had "perfect knowledge case to compare real world data to.... "Conduct a post hoc analysis of predictability based on biological and fishery characteristic using random forest as boast high classification accuracy, can model non-linear relationships between predictor and response variables, can model complex interactions among predictor variables, and provide a method for determining variable importance. Characteristics considered include: Maximum weight, maximum length, maximum age and habitat type, large marine ecosystem, managing body, phylogenetic order, average F, minimum observed spawning biomass, and length of time series		
Tallman et al 2019	* L2 example as part of larger management effort	Canada	Outline new methodologies for quantitative stock assessment	High priority stocks are assessed using conventional sampling and sophisticated modelling techniques such as statistical catch-at-age and Bayesian modelling; regional priority stocks as assessed using intermediate to data-limited modelling approaches such as productivity susceptibility- analysis (PSA), life history invariant and catch based modelling such as depletion corrected average catch for stocks where data is limited; and the remainder are assessed using a simple conservation rule for sustainable harvest when time series data is too limited for modelling. For data poor stocks, the percentage of over-fishing or under-fishing was calculated using "Maximum Sustainable Productivity" (MSP., a data poor assessment method) and the equation: fishing pattern = (MSP – Average Yield)/ MSP. The stock status in the precautionary approach framework was predicted by combining vulnerability and the relative over or under-harvesting value by normalizing the fishing pattern values and dividing by the vulnerability scores. These were partitioned into the Critical, Cautious and	Checked the data poor approaches (e.g. A 5% percent precautionary harvest rate applied where data is insufficient for conventional stock assessment) to data rich stocks	

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				Healthy Zones by arbitrary limit cut-offs of below 0.2 = Critical, 0.2–0.5 = Cautious, greater than 0.5 = Healthy.		
Thorpe et al 2016	* L3 multispecies example * Shows community indicators hard to interpret in isolation (so less chance of automation)		Here, we use a size-based fish community model to investigate the effects of technical interactions among North Sea fleets on (i) on stock sizes, yield and value; (ii) trade-offs between the quantity and value of sustainable yield; (iii) risks to biodiversity (depletion of the most sensitive species); and (iv) risks of not achieving targets for foodweb indicators. We also assess whether fish community indicators can guide assessment and management of multispecies fisheries given uncertainty. Our approach is based on a simplified fleet categorization and on those species that currently dominate catches.	**L3 model** - length-based multispecies model with 4 fleets (technical interactions only). **Stocks were deemed to be at risk of collapse if their biomass fell to <10% of unfished biomass. The ensemble mean number of stocks at risk was taken to represent the overall level of risk associated with a given scenario.** Also calculated (output) biomass fraction <40 cm (dubbed the LFI) and the slope of the size-spectrum (slope of relationship between log numbers in each log size class and log size, SSS). Looked at relations between mean number stocks at risk and LFI, SSS	Checked parametric uncertainty	
Trenkel 2017	* While more MMSY relevant does highlight facets to consider for ecosystem analyses	Europe				
Tuck & Wilcox 2009	* L3 bird model	Australia		A discrete age-, sex- and colony-structured model is developed that accounts for natural and fishing mortality, together with potential consequences from the loss of nesting habitat on Lord Howe Island. Fit to tracking data, observed bycatch and island colony surveys. The model includes two general linear models (GLMs) and a fit to on-land survey data, all built within a single likelihood framework. These GLMs predict the influence of various factors (such as SST, longitude) on the probability of a bird being in a particular region (its availability), and the probability of a bird being caught if it is available. The second GLM has factors that include shot type (e.g. swordfish or albacore shot), time of day and trial type (e.g. chute-trial or a ‘typical’ tuna shot). It also allows the		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				population model to use the GLM factors to predict bycatch and population trends well beyond the scope of the observed data		
Tuck et al 2011	* Example of L1-L3 for seabirds	Atlantic (ICCAT)	(1) identify the seabird species most at risk from fishing in the ICCAT Convention Area; (2) collate the available data on at-sea distributions of these species; (3) analyse the spatial and temporal overlap between species distribution and longline fishing effort (ICCAT longlining); (4) review the existing estimates of bycatch rates for ICCAT longline fisheries; (5) estimate the total annual seabird bycatch in the ICCAT Convention Area; (6) assess the likely impact of this bycatch on seabird populations.	The measure of productivity was based on life-history strategy, specifically the frequency of breeding and clutch size. Although other measures of productivity were considered, such as age-at-first-breeding and adult survival, the selected life-history features were believed to be sufficient for purpose. The productivity measure and scores were (a) life-history strategy: biennial breeder, single-egg clutch ¼ 3, annual breeder, single-egg clutch ¼ 2, annual breeder, multiple-egg clutch ¼ 1. The measures of susceptibility and their scores were (b) global International Union for the Conservation of Nature (IUCN) status: Critically endangered/Endangered ¼ 3, Vulnerable ¼ 2, Near Threatened ¼ 1, and Least Concern ¼ 0; (c) breeding population status: rapid decline (.2% per year) ¼ 3, decline ¼ 2, stable ¼ 1, increase ¼ 0; (d) degree of overlap with ICCAT fisheries: high ¼ 3, medium ¼ 2, low ¼ 1; (e) behavioural susceptibility to capture: high ¼ 3, low ¼ 1. The last was based on the tendency of seabirds to follow fishing vessels and the relative incidence of bycatch in ICCAT or other fisheries. A precautionary approach was taken where data were lacking or were uncertain, the highest (risk) score being assigned in those cases. Calculated various species distributions and overlap indices (noting the overlap indices do not consider susceptibility to capture). This meta-analysis took bycatch-rate information, where available, raised by fishing effort to provide an ocean-wide estimate of bycatch. Species-specific bycatch totals were also calculated when the relevant data were available. For regions where bycatch data were unavailable, assumptions were made to fill these gaps. Pelagic-longline bycatch rates, by population if possible, from individual studies were then mapped as appropriate onto this region, given knowledge of the spatial distribution of each fishery. Where bycatch-rate data were missing for particular grid squares, values were substituted from the nearest and most appropriate cells. These rates were multiplied by the reported effort to produce bycatch estimates for each grid square, which were then summed across the entire ICCAT area. Small		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				number of most vulnerable species that had sufficient data got an L3 model		
Utizi et al 2018	* Legal (policy) risk assessment	Europe	Examine the impact and interaction of a number of EMFF measures on the GES of Italian seas, to identify any conflict with MSFD provisions and to establish whether it has the potential to undermine the achievement of GES.	Expert judgement-based approach to evaluate the synergies and/or inconsistencies among the policies regulating the marine environmental status		
Valsecchi et al 2017				Creation of ecotox water quality standards. When the data were sufficient, the QSs were derived by probabilistic approach adopting Species Sensitivity Distribution (SSD)modelling		
Walker & Abraham 2017	* Seabird example L2 (NZ)	NZ		Updated time series and used the risk assessment followed the Spatially Explicit Framework for Risk Assessment (SEFRA) PSA variant		
Waugh et al 2009	* Seabird example L2	NZ	To provide an assessment of the risk posed by different fisheries to the viability of New Zealand seabirds species, and to assign a risk category to all New Zealand fishing operations.	'Exposure effects' method of assessing ecological risk to describe the relative risk to seabirds from longline fishing was chosen as bycatch events occur with low frequency, but the cumulative effect of infrequent events can result in important impacts at population levels (original version of this method produced relative risk score as exposure was assessed via the spatial overlap of species ranges and fishing effort, where the exposure was assumed to be proportional to the rate of potential interaction). Challenge of the current study was to explore the effects of very different fishing methods within the same analysis, and define the relative contribution mortality of each to species risk. This required that the outcome of interactions be codified, so that population effects could be examined. Some fishing methods have a greater chance of causing mortality when interacting with a given species than others, and species have different propensities to be caught and to recover from occasional mortalities, as a result different behaviours and differential inherent population growth rates, respectively. The vulnerability (~selectivity), V, was then estimated for each species group and fishing group, by fitting a generalized linear model to the captures and density data, for observed fishing events from	Sensitivity analysis tested: 1. The influence of some 'unusual' survival inputs to the PBR index 2. Using alternative sets of weightings on the distribution maps for species (especially cryptic kills) 3. Using vulnerability values at the extremes of the ranges generated (90% Confidence Limit (CL) on V) 4. Using cryptic kill values for trawl warp strike. 5. The population size of sooty shearwaters (20 million, 2 million, or 200,000 individuals) All found to effect risk ratings for some species	Does not address possible indirect fisheries-related impacts, e.g. trophic effects; or other sources of mortality like invading predators; or mortality due to non-fisheries sources or if outside NZ (only the consequences of NZ fisheries mortality). Life-history parameter value inferred from other species. Fisheries with poor data excluded

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				that fishery. We generated tables of the likely captures for each species, and compared these with the PBR index (we refer to the ratio of the likely captures over the PBR index as the risk score). Four levels of risk were described by the Ministry of Fisheries: Very High risk, where the likely captures exceeded the PBR index (risk score of >1.1); High risk (0.8 – 1.1); Moderate risk (0.4 – 0.79); and Low risk (< 0.4).		
Waugh et al 2012	* Seabird example L2	Pacific		Seabird PSA, exponential decline used in foraging radius mapping. For each season, computed composite map = combination of seasonal breeder layer and seasonal non-breeder layers on global scale, assuming 100% of population of the species is distributed within estimated range of the species. The Susceptibility indicator was calculated as the product of fishing effort and normalised species distributions (i.e. Proportion of a species' range). This was weighted with the Vulnerability of the different species to longline fishing gear. V was estimated for each species group by fitting a generalised linear model to captures and density data, for observed fishing events from the surface longline fishery. Two productivity methods, rmax estimate; Fecundity Factors Index (FFI) (normalised score for life history strategy * median age of first reproduction). As both use age at first reproduction in calculation not surprisingly found a good correlation between the two productivity measures (**used FFI as rmax gave false sense of precision and simpler more robust index**). If use standard risk (as distance measure on PSA plot) calculation in some extreme cases, seabird species with low-productivity, but extremely low susceptibility could be highly ranked, despite very little exposure to fishing events, so used sqrt(sqrt(risk = Susceptibility/Productivity)) and then evenly divided scores into 5 bins to get form very low to very high risk - so only relative. Total risk per season and area = sum of species and fleets. For missing data used best average estimates for parameters rather than making them high risk.		Doesn't consider uncertainty
Wetzel & Punt 2017	* L3 model example	USA	This MSE aims to address the ability of each harvest control rule to maintain stocks at or near the target level, the potential risks of each approach, and the trade-offs	L3 model (MSE) based on an age- and sex-structured population dynamics model. The outcomes of the simulations for each harvest control rule were summarized using the following five metrics:1 The probability that the spawning biomass was below a minimum stock size threshold level		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
			between potential catches and target stock sizes.	(0.5BPROXYfor each harvest control rule) during the last 25 years of the management period for each simulation to evaluate the probability of each harvest control rule preventing a stock from becoming overfished;2 The median probability of being within 10% of the BPROXY over the last 25 years of the management period (abbreviation "P ± 0.10BPROXY)" which evaluated the performance of the harvest control rule in maintaining the relative biomass near theBPROXY;3 The median of the average catch over the last 25 years of the management period to evaluate the average long-term yield of the harvest control rule;4 The distribution of the relative biomass over the last 25 years of the management period to evaluate the variance in the relative biomass under each harvest control rule;5 The median annual average variability of the catches (abbreviation AAV) over the last 25 years of the management period.		
Weidenmann et al 2017	* L3 model example	USA		L3 model - To test the performance of alternative ABC control rules, we conducted a management strategy evaluation (MSE) over a range of scenarios encompassing different life histories (in age-structured model), exploitation histories, and levels of assessment quality. Primary performance measures we used to assess control rule performance were population size, fishery yield, variability in fishery yield, frequency of overfishing, magnitude of overfishing when it occurs, proportion of years below the stock size threshold (S < 0.5Starg; calculated using all runs and also excluding runs where biomass started below the threshold), and years required to rebuild the population (calculated as the number of years for a population starting with below 0.5Starg to increase to a level at or above Starg). For most performance measures, we used the mean over a portion of the management period, such as the first 5 years or final 20 years, or over the entire management period. The probability of overfishing was calculated as the proportion of years during the management period in which F exceeded Flim. Summarized year-to-year variability in fishery yield by calculating the average of the absolute value (AAV; Punt 2003) of difference in yield from one year to the next across the management period.		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
Williams et al 2011	* Habitat ERA	Australia		L1-L2 with set of quantifiable attributes to describe the resistance of a habitat to specific fishing gears as its potential 'susceptibility' (ability to avoid damage by the gear) and its resilience is generalised as its inherent 'productivity' (ability to recover from damage). Used seabed imagery to identify habitat units to assess - habitat' includes both physical seafloor structure and its attached invertebrate fauna. Three characteristics were used to classify habitat type at the fine scales recorded by cameras: substrate type (S) – 7 categories; geomorphology (G) – 10 categories; and dominant fauna (F) – 10 categories. At the scoping stage, distributions of habitat types were defined simply by their presence or absence in depth zones ('bathomes') and association with particular geomorphic seabed features. Productivity attributes: regeneration (growth rates). natural disturbance rate. Susceptibility - availability = overlap; encounterability = depth zone and feature type overlap, ruggedness, level of disturbance (frequency and intensity fishery footprint); selectivity = removability/mortality (fauna or substrate), areal extent, substrate hardness, seabed slope. The attributes used for the habitat PSA are generic but thresholds are unique to a sub-fishery to capture differences in fishing methods, regions and depths fished. Productivity attributes averaged; Susceptibility = cube_root(attributes multiplied (sub-attributes averaged to give attribute score first)). No weighting is applied to individual attributes. Selection of the attribute set was constrained both by the information available for benthic habitats, and by the timelines and scope of the risk assessment being undertaken - had to rely on RRA to undo # false positives due to only having 2 productivity attributes		A potential weakness in the results, was the low number of shallow (inner continental shelf) habitats in high-risk lists, especially sediment habitats. In most instances the finding of low fishing risk to inner shelf habitats was driven by a range of susceptibility attributes: relatively large habitat areas, low proportional overlap of fishing effort, large areas of relatively invulnerable habitat (dynamic, naturally disturbed sediment plains with little emergent fauna), and a relatively high proportion of inaccessible habitat (e.g. hard, high relief rocky outcrop to bottom trawl). However, false negatives could be generated by the two productivity attributes that assume higher productivity in shallow waters compared to deep, i.e. faster regeneration time of fauna, and adaptation of fauna to a greater degree of natural disturbance. Trawl impacts on shallow fauna vary greatly between major taxonomic groups (Kaiser et al., 2006), and may be long-lasting (years to decades) for large structural fauna (e.g. Pitcher et al., 2008) and those associated with biogenic habitat.
Williams et al 2017	* Stock identification - implications for ERA?	Australia				
Wyatt et al 2017	* Discusses an alternative method (some similarities to PSA and how	USA		Apply the InVEST Habitat Risk Assessment (HRA) model. The HRA model is a quantitative approach to evaluating the cumulative influence of stressors associated with human activities on habitats - risk = exposure * consequence.	Ecosystem risk maps, which incorporate habitat locations as well as the exposure and consequence of each stressor on each habitat, go beyond simple un-weighted	Additive approach, offers a snapshot in time and **does not explicitly account for the historical impacts or ecological legacies**,

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	extended to cumulative impacts)			Exposure = extent, intensity, frequency, level of impact. Consequence criteria include change in biomass, trophic impact, and expected recovery time. For scores on relative recovery time after impact from different activities used the scores developed through the Massachusetts cumulative impact assessment (based on expert elicitation). Risk = calculated as for PSA but with one axis = exposure and other = consequence. **Cumulative risk to each habitat is the sum of the risk scores related the human activities cooccurring in each location containing that habitat**. **Ecosystem risk for each grid cell is the sum of habitat risk scores in that cell**.	overlays of human activities - notes interaction/close proximity of activities in hotspots nearshore and relative importance of fewer, higher consequence stressors in the offshore area. Can decompose source of risk	subjective scores, pre-filtered out some habitats
Zhang & Kinm 2011	* Alternative method (aimed at ecosystem level)	Korea	Ecosystem assessment to meet the objectives of: sustainability, biodiversity, and habitat quality.	IFRAME assessment. Ecosystem indicators, along with target and limit reference points, are identified for each selected objective. Indicators were identified for both data-rich (Tier 1) and data-poor (Tier 2) situations. Relative weights for each indicator were obtained by conducting a series of expert workshops (weights = 1-3), considering: (1) the importance for achieving the objectives, (2) scientific basis for estimating indicators and reference points, and (3) availability of data and information. The same indicators across Tier 1 and Tier 2 assessments can be weighted differently, depending on the situation. Indicators selected: Biomass (or CPUE), fishing intensity (catch or mortality), size at first capture, habitat size, community structure, reproductive potential, productivity, life history (max age, age of maturity, adult/juvenile spatial overlap), management (legal and IUU), recovery, genetic structure, bycatch and discard rates, mean trophic level of community, diversity, functional group ratios , gear restrictions, habitat damage, levels of pollution, lost gear, litter, habitat protection, habitat recovery. Status vs target reference point was scored and then these scores combined as a weighted average to give the objectives risk index (ORI), species risk index (SRI), fishery risk index (FRI), and ecosystem risk index (ERI). ORI nest within SRI which nest in FRI which nest in ERI. Scores plotted on risk-assessment quadrant plot (with planes for sustainability–biodiversity, habitat quality–sustainability plane, biodiversity–habitat quality plane.		
Zhang et al 2011	* Alternative method (aimed at ecosystem level),	General		Species groups can be identified using the self-organizing mapping (SOM) analysis based on nine ecological		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
	bringing in climate considerations			characteristics (these = groups to put into EwE). Do predictions under F and RCPs scenarios using NEMURO (forced by (i) daily sea surface temperature, (ii) daily solar radiation, and (iii) daily MLD) output to force EwE. Calculate IFRAME indices off model output to look at future of management strategies		
Zhou & Griffith 2008	* SAFE method	Australia		Species-specific fishing-induced mortality was derived from a number of variables: the proportion of the entire management area trawled; the relative abundance of individual bycatch species in trawled areas compared to the total area; the probability of a fish on a trawl track entering the net; and the probability of a fish escaping after it has entered the net. exploitation rate= prop_in_fished_area * catchability * (1 − escapement). Reference points Fmsm = max_productivity / biomass_at_max_sustainable_F. Other reference point is for Fcrash. Proxies Fmsm ~ 0.8M, Fcrash = 2xFmsm.	Evaluated uncertainty	
Zhou et al 2007	* SAFE method	Australia	Main objective of this project is to evaluate fishing impact on sustainability of fish species in selected Commonwealth fisheries	SAFE - the mean fishing mortality rate u is derived from fishing activity overlapping with species core distribution area within the fishery jurisdictional boundary, adjusted by the probability of being caught by the trawl. Area fished uses swept area method. Made assumptions re q and E. Assumes that there would be no local depletion effects from repeat trawls and that there is rapid mixing between trawled and untrawled areas. For encircling methods base area of fishery on a circle not a rectangle shot. For gillnet affected fishing area (i.e., the maximum area within which a fish could encounter the net), is a function of gillnet length, soak time, and swimming speed of fish (so species specific). Because of shape of area of influence of nets had to calculate 4 different encounter probabilities and piece them together to get entire net coverage. For longline had two qs - one for habitat encounterability and one for size-based catchability. Fishing impacts by multiple fisheries can be added together to derive cumulative impacts (sum over fleet specific exploitation rates to get total rate). Means of estimating fishing impacts can differ per gear but all methods involve similar steps and include similar components: fishery distribution, fishing gear affected area, species distribution, habitat dependent encounterability, size-dependent	Table of Biological reference points, proposed ecological risk assessment category, ecological consequence, and provisional management rules for bycatch species. We defined confident risk as follows and used the following method for categorising the cumulative impact only. Confident medium risk (1): E[u] ≥ max[umsm] or E[u] - 90%CI ≥ E[umsm]; Confident high risk (2): E[u] ≥ max[ulim] or E[u] - 90%CI ≥ E[ulim]; Confident extreme high risk (3): E[u] ≥ max[ucrash] or E[u] - 90%CI ≥ E[ucrash]. Major advantages include: * Less data demanding: this approach does not require fishery time-series data. Only one or a few life history parameters will be sufficient for establishing sustainability reference points. By making some key simplifying assumptions, it circumvents the need for full stock assessments on large numbers of impacted species by using	The main cons and challenges are: * Estimated fishing mortality rate may have high uncertainty and may not be accurate for a range of species. * Relationship between sustainability and life history parameters may differ among taxonomic groups/species (Setting Fmsm = M may not be appropriate for every species). By using area overlap of species distribution with fishing effort, we assume that individuals of fish randomly or homogeneously distribute within their distribution range, and fish densities are the same between fished and unfished areas within species distribution range. We believe it would be more accurate if we have data on relative

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
				catchability, and post-capture mortality. **Area overlap of fishing effort with species distribution, is critical for estimating fishing impact**.	limited information. * Flexible: it focuses on one single indictor – fishing mortality rate. This allows alternative methods to be used to estimate fishing impact depending on available data while the measurements are in the "same currency" for easy comparison and possible assessment of cumulative impact. * Scientific: the concept and method are based on existing fishery knowledge. * Comprehensive: it can assess all species including target and non-target species in a batch process. * Precautionary: the method is more scientifically rigorous as uncertainty in both indicator and reference points can be quantified. * Cost effective: resource requirements on data and analytical time are minimal. It is a onestep process to assess all fish species impacted by a fishery. * Transparent: all processes in estimating fishing mortality rate and reference points are quantitatively formulated. * Impacts additive: assessing cumulative fisheries impacts is straightforward. * Management application: results can be easily incorporated into fishery management plan, because this framework is similar to the typical management regimes used for target species.	abundance or density between fished and unfished area
Zhou et al 2013	* eSAFE and cumulative impacts	Australia	1. Scope the range of applications and review existing methods for measuring cumulative effects of capture fishing on species that are caught across a number of different fisheries or sub-fisheries. 2. Scope the different data	eSAFE: Reliable estimates of gear efficiency enable fish density to be calculated from catch data. Developed statistical methods to estimate gear efficiency for multiple gear types catching a population with either random or aggregated distribution patterns. The methods can simultaneously estimate population density or abundance. A general additive model is then developed for smoothing density across the distributional range in each year. Distributional ranges are		

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
			sources that are currently available and those that may be required to include assessment of cumulative effects under future ERAs. 3. Develop methods for assessing cumulative risk from multiple fisheries or sub-fisheries including recreational and international fisheries, where feasible, on each individual fish species and stock, especially methods that can be applied to data poor fisheries. 4. Apply the method to selected Commonwealth fisheries that operate in the same area with high levels of effort and multiple gear types, e.g., in the southeast region, with further consultation with AFMA. 5. Describe the trade-off between the costs of collecting data for ERA as compared to the benefit returned to the industry/management of the approach.	stratified (by Core area, Bioregional area, eastern region, and western region) to better capture heterogeneous density patterns. These results, combined with actual fishing effort and distribution or actual catch data, allow fishing mortality to be derived for each gear type or fishery. Consequently, cumulative fishing mortality is readily estimated. This F can then be compared with reference points. Here we develop reference points based on basic life history parameters (as natural mortality is often calculated from other more easily obtainable parameters and Fref often related to M, this means that these more easily available parameters can be reliable predictors for biological reference points), this is based on the theory of life history invariant: growth coefficient, maximum length, and maximum age. Three reference points based on these alternative methods were developed: Fmsy from stock assessment, Fproxy from per-recruit analysis, and F0.5r from demographic analysis. The best model is to include all of these three parameters, but a model with growth coefficient as a single predictor can be adequate if maximum length and age are not available. The results show that the importance of a particular LHP depends on whether the fish is a chondrichthyan or a teleost, and the former exhibits a lower sustainability for the same LHPs values. Our assessments show that cumulative impact does not increase linearly as the number of fisheries increases. Typically, only a few fisheries cause the majority of the fishing mortality to particular species while many fisheries have very minor effects.		
Zhou et al 2019	* ESAFE and cumulative impacts	Australia		eSAFE		For each species the current map is a deterministic distribution, which prevents including uncertainty in the estimated fishing mortality. A model-based map may be more realistic (which may be produced if some catch data and habitat information are available)
Zhou et al 2016	* PSA vs SAFE	Australia	(1) a comparison of PSA and SAFE methods by examining their basic assumptions, input data, and risk computation; (2) a comparison of PSA and SAFE using actual fisheries data; (3)			

Reference	Relevance	Location	Objective of study	Assessment Method Summary	Positive Features	Weaknesses
			a comparison of PSA and SAFE with stock status determination in the Fishery Status Report (FSR); and (4) a comparison of PSA and SAFE with classic stock assessment using real fisheries data.			
Zhou et al 2011	* eSAFE and cumulative impacts (across fisheries)	Australia	SESSF eSAFE	Extend the SAFE methodology, develop new methods to estimate fishing mortalities by four types of fishing gears (trawl, Danish seine, gillnet, and longline) and assess their cumulative impacts. We also extend the SAFE method by quantifying uncertainty in both fishing impacts and reference points		
Zhou et al 2009	* SAFE method	Australia		SAFE original method - for 7 fisheries		

Table A.2: Table of other commentary on the reviewed material – this includes relevant direct quotations from the materials on points regarding the method, barriers to implementation and general findings that has a bearing on the use of risk assessment methods. For completeness, all materials reviewed are included here, even if there was no comment made, so that the entries in this table aline with Table A.1.

Reference	Other relevant commentary
Abraham et al 2017	The strength of the PBR type approaches is that seabird captures are estimated and compared to population sustainability thresholds, and the results can be disaggregated or aggregated readily to the desired scale. It has the advantage of being fully quantitative: the ratio is a direct comparison between birds killed and the number of birds that can be produced by the population.
AFMA 2017	Original and updated method. Within the scoping process, the use of species-accumulation-curves may now be used as a tool for developing the species list (it's a method to inform on whether existing sampling has provided an adequate species list). If it is deemed adequate (has plateaued), species lists will be compiled using only the species included in the curve. Where the curve is not considered to be mature, the species list must be based on all species with a range and depth overlap with the fishery. Skip to L3 if already have quant assessment (e.g. for harvest strategy). Skip L1 if all species like to need L2 anyway (due to interactions with target species). Whether manage at current L risk assessment or progress up hierarchy depends on: risk rating (low not progressed); available data (and whether assessed high as data missing; or if enough data to go further); required management responses at current level; risk-cost-catch (is it cheaper to use precautionary management at current level or do next level to reduce uncertainty?) Provides productivity and susceptibility threshold scores for risk rating. High/medium L2 scores see species divided into 5 categories with respect to why rated high (so have guidance on appropriate management response): missing data, spatial overlap, low productivity (even if low susceptibility), spatial uncertainty, other. Response to high risk species: management to reduce risk, gap-fill missing info, do L3. **AFMA and CSIRO will need to give consideration to the development of Level 2 methods that might be able to indicate the relative risk of a species population or stock having been or already being in an overfished state**. Can have high false positive (SAFE has some chance of false negative and assumes no local depletion effects). Good summary of data types used in Table 7 (need a matching table for collection method).
AFMA 2008a	Due to the semi-quantitative nature of the risk assessment, the Level 2 PSA results do not directly account for all management measures, resulting in an over-estimation of the actual risk for some species. To better encompass this, the Level 2 PSA analysis has undergone further refinement by applying a set of residual risk guidelines. The management arrangements that are not accounted for in the Level 2 assessment include: Limits to fishing effort; Catch limits (such as Total Allowable Catches - TACs); and Other controls such as seasonal closures. Management arrangements that are accounted for in the assessment include: Spatial management that limits the range of the fishery (affecting availability); Gear limits that affect the size of animals that are captured (selectivity); and Handling practices that may affect the survival of species after capture (post capture mortality. In addition, TEP species are included within the assessment on the basis that they occur in the area of the fishery, whether or not there has been a recorded interaction with the fishery. For this reason there may be a higher proportion of false positives for high risk TEP species, unless there is a robust observer program that can verify that species do not interact with the fishing gear. Guideline 1. Risk rating due to missing/incorrect information. Considers if susceptibility and/or productivity attribute data for a species is missing or incorrect for the fishery assessment, and is corrected using data from a trusted source or another fishery. Guideline 2. Additional scientific assessment. Considers any additional rigorous scientific assessment (i.e. rapid Level 3 risk assessment, population viability analysis) that calculates the species level of risk from fishing, or considers any other scientific published assessments or results. Guideline 3. At risk due to missing attributes. When there are three or more missing productivity attributes, considers closely related species within a fishery that have those productivity attributes known. Guideline 4. At risk with spatial assumptions. Uses additional information on spatial distribution of species populations to better represent the species distribution overlap with the fishery. Guideline 5. At risk in regards to level of interaction/capture with a zero or negligible level of susceptibility. Considers observer or expert information to better calculate susceptibility for those species known to have a low likelihood or no record of interaction or capture with the fishery. Guideline 6. Effort and catch management arrangements for target and byproduct species. Considers current management arrangements based on effort and catch limits set using a scientific assessment for key species. Guideline 7. Management arrangements to mitigate against the level of bycatch. Considers management arrangements in place that mitigate against bycatch by the use of gear modifications, mitigation devices and catch limits. Guideline 8. Limits on associated species through other management arrangements. Considers

Reference	Other relevant commentary
	the implications of management arrangements for a particular species on other associated species. Guideline 9. Management arrangements relating to seasonal, spatial and depth closures. Considers management arrangements based on seasonal, spatial and/or depth closures.
AFMA 2008b	The management strategies that are not accounted for in the Level 2 assessment include: • Limits to fishing effort; • Catch limits (such as TACs); and • Other controls such as seasonal closures. Management actions or strategies that are accounted for in the assessment include: • Spatial management that limits the range of the fishery (affecting availability); • Gear limits that affect the size of animals that are captured (selectivity); and • Handling practices that may affect the survival of species after capture (post capture mortality). Risk score was reduced under Guideline 7 because the fishery is compliant with the statutory Threat Abatement Plan (TAP) which reduces the encounterability of birds to hooks through line weighting, tori lines, use of thawed bait and prohibition on offal discharge for all vessels. Seven species' risk scores were reduced under Guideline 5 where there were minimal to zero observed interactions with that species since 2001 in the fishery. Guideline 6 was used once to reduce risk score for Broadbill Swordfish where the implementation of a competitive TAC of 1,400t with attached trigger limits has addressed concerns of localised depletion. Guidelines 1 and 3 were used five times and twice respectively, to complete productivity attributes for species that were missing or had incorrect values. In total the guidelines were employed 42 times across 32 species.
AFMA 2012	
Alexander et al 2019	
Apel et al 2013	
Arechavala-Lopez et al 2018	
Arrizabalaga et al 2011	
Astles and Cormier 2018	State that "ERAs, as they are currently used in fisheries, on the whole do not include management effectiveness in the assessment of risk nor do they clearly link the components of the cause–effect pathway" (thus need for RRA in ERAEF). Worth flagging this effort but not sure it adds much beyond what the RRA does - though if an easy tweak to do perhaps makes it easier than RRA on the end?
Astudillo et al 1997	Showed the necessity of considering the whole chain of events, from the origins to the destination (and flags that each link in chain may not realise individual importance)… certain steps in the chain of events are much more important than others, and that a risk assessment highlights the points at which risk reduction measures might be most cost-effective.
Avila et al 2018	
Ballesteros et al 2018	General discussion of EAFM rather than a specific application
Bao et al 2017	implemented in Microsoft Excel™ using @RISK software

Reference	Other relevant commentary
Barange et al 2018	Recommends use of risk assessment (of various forms) to identify climate pressure points and assist in shaping management/adaptation decisions
Barnett & Wiber 2018	Examines how the Harper Government of Canada (2006-2015) shut down both debate about threats and research into environmental risk
Barnthouse 1994	
Battista et al 2017	The Canadian the ERAF calculates risk doesn't use productivity-susceptibility but instead calculates risk as the product of the exposure to a threat, and the likely response to that exposure. Because of this change, the resulting risk scores more accurately represent the potential impact of a given threat on a system, making them more appropriate for comparison with risk scores from other threats, or at other sites. Existing ERA tools represent remarkable progress in ecosystem risk assessment. However they all have certain limitations that will be important to overcome to fully characterize risk and thus provide good guidance for risk management. Specifically: most of these tools model only the impacts of fishing without quantitatively considering other threats that may face a marine system; none of these tools assess the synergistic or antagonistic effects that different threats acting on a system may have on each other; ecosystem productivity and functioning are substantially simplified to just a handful of representative factors, such as key population abundance or spatial habitat extent, and do not incorporate new findings on attributes of ecosystems associated with recovery or resilience; there are currently no tools designed to evaluate risk in relation to differential ecosystem service provision in data-limited systems, which will be especially important when considering siting of spatial management measures such as exclusive fishing territories and marine protected areas; all existing ecosystem risk assessment tools require significant time (several days) and capacity (expert knowledge and access to primary literature) to complete, limiting their feasibility where capacity is low......A CARE worksheet must be completed for each target identified in the Scoping phase, and thus the goal should be to identify the smallest number of targets that can be considered representative of the system under analysis, as determined by expert opinion. Ata minimum, the predominant ecosystem, or the most vulnerable ecosystem within the focal site should be selected as a target for evaluation. Threats can include any natural or anthropogenic processes or activity that system experts suspect might pose a risk to any of the valued targets - expert opinion based as to what to include. Scoring = modified form of Halpern's "vulnerability criteria": (1)the spatial scale at which the threat acts within the site (including both direct and indirect impacts), (2) the frequency with which it acts, (3) the intensity (based on number of trophic levels impacted),(4) the resistance of the target to impact, and (5) the recovery time needed to transition to a desired state after impact. CARE adapts this method by combining the first three of these vulnerability criteria (scale, frequency, and intensity) into an Exposure score, and the latter two (resistance and recovery) into a Response score. These two values are multiplied to result in a Base Threat Risk Score for a given target (c) from a given threat (t). BaseRisk = BaseResponse × BaseExposure. to generate a Base Response score, which represents the tar-get ecosystem's or species' intrinsic productivity and vulnerability. This calculation is done once for each target being assessed. Recovery attributes measure the intrinsic productivity of the given target as it presents in the site under evaluation. Resistance attributes describe the target's intrinsic vulnerability and capacity to resist or avoid harm. **Specific life history attributes used can be added or subtracted (i.e. selected) to better match the assessment to the specific characteristics of any given site.** Exposure or vulnerability is scored on (1) the spatial scale at which the threat acts within the site, (2) the frequency with which it acts, (3) and the intensity, or number of trophic levels impacted
Bell and Bahri 2018	Iterative risk management (and adaptation) framework
Bellido et al 2011	
Ben-Hasan et al 2018	Might be a useful L3 method if required
Bland et al 2018	Points out need baselines so can judge of change is beyond natural variability and constituent 'collapse', noting the IUCN protocol specifies three temporal baselines: historic, current and future

Reference	Other relevant commentary
Bland et al 2018	Information from analogous but collapsed ecosystems is key to informing definitions of collapse, selecting meaningful indicators and setting quantitative thresholds for risk assessment
Bravo & Bustamante 2018	Plotted up attributes against how map on PSA space
Breen et al 2017	Further work to integrate gears and/or species to develop a multi-species/gear risk assessment for bycatch in general would provide valuable information on where and how to target bycatch mitigation
Brown et al 2013	An attribute data quality index (Patrick et al., 2010) was used to assign Data Quality Scores (DQS) to each attribute to indicate the degree of confidence in the attribute value (Table 2). Scoring considered the age of the data; the population and species the data were drawn from; and whether the original source was cited and accessible for verification. Sensitivity analysis was conducted to test the appropriateness of the attributes used to generate the risk scores. PSA scores were generated for each species by dropping each attribute in turn until all attribute combinations had been used. The standard deviation of the resulting PSA scores was a measure of the uncertainty of the score attributed to each species. The mean PSA score and upper and lower confidence intervals were calculated, compared with the risk score generated by the full attribute set and discrepancies noted. Documenting the quality of data used to produce the productivity score allows research efforts to focus on areas were data are lacking, or of poor quality, and allows future iterations of the PSA process to incorporate higher quality data as it becomes available.
Brown et al 2015	The results demonstrate that although a fishery might pose high risk to a species, low or moderate risk areas can exist within the range of the fishery, enabling management measures to focus on areas of greatest risk. Incorporating accurate estimates of fishing effort in calculating potential exposure to a fishery is important extension
Buckley et al 2019	
Burdon et al 2018	The Bow-tie methodology is an appropriate methodology to assess risks in the marine environment, but it requires further development to account for combined pressures and cumulative impact assessments.
Burgass et al 2019	
Burger et al 2017	Not on assessment so much as the kinds of stakeholders to include in monitoring and ecosystem assessment - types of stakeholders involved in research and conservation… regardless of agency or personal goals, the stakeholders worked together toward a goal, and toward a goal that was time-dependent (i.e. time critical so being able to call on stakeholders to help deliver info quickly was important)
Campbell & Gallagher 2007	Fairly standard risk approach - not incompatible with ERA, but not materially an extension of it
Campbell et al 2018	Not an ERA method but could be input into an ERA
Cao et al 2017	Useful L3 quantitative assessment model (if needed for specific invertebrate species). The idea of MSE testing performance is a good one for the method, especially L2/L3.
Carruthers et al 2016	

Reference	Other relevant commentary
Chen et al 2013	“probability” and “severity” are two central elements contributing to the characterization of risk - with impacts/risks being reflected at different organizational scales…. Mathematical models developed to deal with these undesired ecological risks include cross-validated multiple regression, holographic neural networks, Bayesian networks, comprehensive aquatic systems models, environmental contaminant dispersion models, and food web models, organisms and sub-organisms models.... as assessments are typically constrained to things of interest (often directly affected by the stressor/hazard), components indirectly related to the cause–effect reaction are not taken into consideration even though they are actually part of the resilience or response process of the disturbed system..... **NEXT STEPS** The multi-dimensional risk assessment from the ecosystem safety, improvement lies in developing all-sided science-oriented metrics and objective indices based on structural and functional evaluation of ecosystems <<NOTE: Not actually good for science to dictate and other stakeholders don't get a word in edgewise.>...... Although some pragmatic techniques to assess ecological conditions and identify impaired ecosystems are advancing, establishing diagnostic capabilities to determine cause–effect relationships within impaired systems remains a significant challenge for risk management activities. In this context, the application and integration of system-based models, which addresses interactions within risk processes on different organization levels is an important evolutionary step in advancing the scientific development of ERA as a useful environmental management tool.
Cheung et al 2018	
Chin et al 2010	Species-specific attribute rankings and vulnerability rankings were also examined to determine whether any patterns of vulnerability emerged amongst species, their attributes, climate change factors and vulnerability components. There are no data on the potential long-term effects of physiological changes resulting from climate change factors.
Christain et al 2009	Indices to reflect the condition of systems and their growth and development - these indices could be brought into community/system assessments (especially as indices of structure and function come on line)
Clark et al 2012	Calls for more ERAs on seamounts, summarises existing knowledge and highlights future research needs
Clarke et al 2018	
Collie et al 2012	L3 model contender - uses closed loop (MSE) to do the risk assessment/objective trade-off work
Cope et al 2011	
Cormier et al 2018	Without the capability of estimating the level of the residual pressures, we are unlikely to reconcile the root causes of disturbances to ecosystems with the management practices for addressing those disturbances and ultimately, the performance of their management systems in achieving environmental objectives. Based on the elements of the Bow-tie diagram, a node is used to represent the activity that generates the initial pressure load and the residual pressure of each prevention control combined into the total residual pressure load. The residual pressure of each prevention control is based on a performance node that integrates the effectiveness of the control with the compliance and escalation factor nodes. The output of the total residual pressure load becomes an input into a node to predict ecosystem effects. Nodes are also assigned for the natural processes that are contributing natural pressures to the total residual pressure load. Netica is the software that is used to develop Bayesian belief network. The Bow-tie/Bayesian belief network models must capture the inherent spatial and temporal properties of the pressure-effect pathways. There may be significant separation between where and when the initial pressure load is occurring, the prevention controls are being implemented, the total residual pressure load is being released and the resulting ecosystem effects. Each side of the Bow-tie demarks two spatial and temporal pathways of risk. The left side of the Bow-tie represents the boundary of the sources of the pressures while the right side of the Bow-tie represents the ecological boundary of the ecosystem effects. Each application of the Bow-tie/Bayesian belief network models will be constrained by a unique set of spatial and temporal scales that will determine the appropriate data inputs for the analysis. In some cases, the pressure and the effect will be co-located and contemporaneous (e.g., fishing restriction areas example), while in other cases, the pressure is remote from the effect and the time lags may be significant.... learning from the petroleum and other industries, **all**

Reference	Other relevant commentary
	human activities that contribute to a pressure within the spatial boundary of the ecosystem effects have to be accounted for... In addition to accounting for all the operational sources of the pressure, natural pressures also need to be accounted for to avoid underestimating the total residual pressure loads. Ecosystem effects can be exacerbated by natural processes as well as the effects of climate change despite the implementation of effective prevention controls. Based on a better understanding of the pressures generated by natural processes, managers and stakeholders would be informed of the need for mitigation strategies to address ecosystem effects instead of pursuing futile improvements to prevention controls used in the daily operations of industry sectors. Prevention controls can only reduce the pressures generated by operational activities. They cannot control the pressures generated by natural processes or the effects of climate change.
Cortés et al 2010	
Cortés and Brooks 2018	Also explored through simulation how the ratios of FMSY and M vary across a range of life histories, given different relationships between fishery selectivity and maturity (median age and slope of the ogives) and shape of fishery selectivity (flat-topped or dome-shaped). Conclude by proposing a triage approach that provides a roadmap on how these data-limited methods can be applied to chondrichthyan stocks to provide an initial assessment of stock status and sustainability. Could inform the assessments- via giving reference points or providing a supplement/alternative to SAFE for the chondricthyans
Cortés et al 2015	Because the susceptibility aspect we used was calculated as the product of four attributes, susceptibility values obtained here are much lower than those that would be obtained in semi-quantitative analyses that use additive measures for computation of susceptibility. Way in which calculate final risk score is important - vulnerability calculated as the arithmetic mean of the productivity and susceptibility ranks (v3) had similar correlations with productivity and susceptibility, indicating that neither of these two aspects affected it disproportionately, in contrast to vulnerability metrics v1 and v2.
Cotter et al 2014	Suggested expanding to other sectors and socioeconomic factors too
De Anda-Montañez et al 2017	Looked at performance measures per management strategy but from the perspective of three different types of managers - classified depending on different levels of risk aversion: (1) A highly cautious manager adverse to risk that is willing to lose the least; (2) A moderately cautious manager that will try to minimize the maximum regret from the maximum loss of opportunities of each management strategy; and (3) A broadly optimistic manager that would select the strategy that maximizes his benefits - so gives decision tables, using the Maximin, Minimax, and Maximax criteria to capture different risk attitudes. The results from these analyses show that management strategies chosen by a particular manager will vary according to their personal preferences at that time, the information at hand and the legislation in place, which can restrict or facilitate the implementation of the selected strategy. The advantage of incorporating risk and uncertainty in fisheries assessment is that decision makers in charge of management can have an idea of the potential effect of such decisions
de Lange et al 2010	Three factors to consider: effects of the stressor, exposure conditions, and biotic and abiotic characteristics of the systems potentially exposed. These three factors together determine the overall in situ ecosystem effect, and each component of the assessment needs to be described with suitable indicators. Generic version of risk assessment shows a yes/no risk exists answer, but extension = site-specific assessment, for which the characteristics of the endangered biological community (structure, function, sensitivity, vulnerability, naturalistic value, etc.) are needed...may include probabilistic methods in which likelihood of exposure and effects is considered... shift from sensitivity at the individual organism level to vulnerability at the higher organization levels (e.g. via use of trait-based ecological risk assessment). Assessments of higher hierarchical levels show that not only system components are important, but also the relations between them
de Chazal et al 2008	Ecosystem Services matrix scores represent how stakeholder groups currently value each ecosystem service. Descriptors matrix links biophysical and land-use descriptors to the ecosystem services (as defined by stakeholders); The Ecosystem Properties matrix links the biophysical descriptors used by stakeholders to ecosystem properties identified by ecologists as contributing to ecosystem service delivery. The Land-use Attributes matrix links land-use descriptors to land-use attributes (the distinction between descriptors related

Reference	Other relevant commentary
	to land-use attributes and those related to ecosystem properties is made on the basis that only the latter require ecological understanding of underlying processes). Trait matrix links plant functional traits to ecosystem properties.
Dellinger et al 2018	App using dose-response relationships to tell consumers how much fish is safe to eat given local contaminant levels and dietary/traditional habits
Depestele et al 2014	Requires investigation of all potential interactions between the gears and the ecosystem components under study. Using a structured process for scoring guidelines B1 and B2. Qualitative inferences are guided by Structured Decision Trees (SDTs). Expert judgement is structured using the Delphi Technique. The intolerance-recoverability approach was preferred, because recoverability attributes are intrinsic to the ecosystem component, and intolerance clearly relates to the fishing metier. Separating intolerance and recoverability allows the user to disentangle the associated uncertainties. SAGE compares the relative sensitivity of the ecosystem effects of fishing metiers, and provides a basis for spatial and temporal redistributing of fisheries to reduce overall ecosystem impacts
de Piper et al 2017	**In trying to permute these changes into the larger set of attributes, the group determined that impacts of changes in community structure or predator-prey interactions would need to be evaluated through modelling exercises to understand even the direction of change; an expert opinion approach is not sufficient for this level of assessment**. Did MSE to help think through options.... Sort advice on reducing complexity in the analysis to achieve consistent and timely results across a large matrix of ecosystem components ranging from individual species to economies and both biological and human communities. The breadth of the undertaking necessitated the sacrifice of complexity across all disciplines and led to the current modelling approach.
Doyle et al 2018	Species specific and rather effort intensive - data would be input to ERA but not really a replacement for ERAEF methods
DFO 2012	Desirable from an ecological perspective to examine all gear types being utilized in a given area through a single risk assessment process (i.e. cumulative impacts)
Eliff & Kikuchi 2017	
Fairgrieve & Nash 2009	Points out need for consideration of physical or chemical modification of the system - does ERAEF do that or just direct biological interactions? Also discusses near field and far field effects (at present ERAEF confined to the immediate domain of the fishery not how it influences beyond its boundaries). Points out that it is important to include the uncertainty with any risk assessment.
FAO 2010	Summary of available methods - mentions ERA and list of potential L3 assessment options
Feitsa et al 2008	Specific biological information is optimised when well defined criteria are applied - Although the analysis presented is subjective, this may be the only one available to evaluate and monitor multi-specific fisheries. The method employed in the present study (susceptibility and resilience criteria) is efficient for evaluating the impact of newly formed fisheries with few available data that occur in areas with high species richness - so get action without delay waiting for data in situations where fast depletion possible.
Filippi et al 2010	
Fletcher et al 2002	ESD has been divided into eight major components (within three main categories) relevant to fisheries: *Contributions of the fishery to ecological well-being*: 1. Retained species 2. Non-retained species 3. General Ecosystem; *Contributions of the fishery to human well-being* 4. Indigenous well-being 5. Community and regional well-being 6. National social and economic well-being; *Factors affecting the ability of the fishery to contribute to ESD* 7 Impact of the environment on the fishery 8. Governance Arrangements. Reporting unit may

Reference	Other relevant commentary
	well be the fishery but "**If the fishery only covers one method/sector, this does not mean that the impacts of other methods or sectors would be ignored in the generation of the report if they affected the same stocks or habitats.**"
Fletcher et al 2005	As for Fletcher et al 2002
Fletcher et al 2010	Step-wise, hierarchical, risk-based approach, was tested on the West Coast Bioregion of Western Australia. With structured stakeholder input, over 600 ecological, social, economic and governance issues were initially identified for the region. This complexity was reduced to a level useful for management by consolidating the individual risks into 60 regional-level risks, with a multi-criteria analysis used to integrate the ecological, social and economic risks into just 24 Departmental-level priorities, which ranged from very low to urgent. Given this success, EBFM-based priorities now form the basis for the Department's budget planning process, plus the framework is providing a critical link between fishery level issues and the broader processes undertaken by other marine based agencies.......Had done risk assessment based prioritisation processes at stock level but most have yet to fully incorporate the assessment and integration of the social and economic aspects of fisheries; to address these deficiencies, senior fisheries managers in Australia recognised the need to have a higher, regional level assessment and management planning system - also aligns fisheries management with regional marine planning process and is same scale as region encompassing climate impacts
Fletcher 2012	Application of EBFM and ESD frameworks from Fletcher et al 2010 across fisheries and aquaculture examples. Framework figure might be useful.
Fletcher 2015	
Fock 2011	An alternative risk scoring approach
Ford et al 2015	
Forney et al 2017	
Forrest et al 2018	
Francis 1992	Potential L3 method
Fu et al 2017 - with covering note by Clark	Spatial mapping used Delta-GLMM standardisation
Fulton et al 2019	Ecosystem scale L3 method
Furlong-Estrada et al 2014	
Furlong-Estrada et al 2017	
Gaichas et al 2018	

Reference	Other relevant commentary
Gaichas et al 2014	
Gaichas et al 2016	Also mentioned IEA and climate vulnerability/risk assessments
Galindo-Cortes et al 2019	Summary of status of Gulf of Mexico stocks - calls for a risk assessment
Gallagher et al 2012	Review failed to identify any ERAs for elasmobranchs assessing their vulnerability to habitat degradation. Also points out the need to include measures of ecological specialization - around: ecophysiology (stress ad post release mortality estimates); diet habits (diet specificity like in Chin.... can get compound habitat dependency index via tracking distance moved and mean difference in isotopes stored in different tissues as then shows how much foraging sites change through time); movement (like SAFE overlap idea)
Gasalla et al 2016	
Geromont & Butterworth 2015	Review of alternative L2 and L3 assessment methods - Traffic light and Spawning Potential Ratio look good robust potential methods that are not as subjective as a PSA can be
Gilman et al 2014	Argue that next step = standardized catch rates L3 method
Gilman et al 2017	Describes how observer data can feed ERA L2, L3 (including ecosystem models) and how to easily extend observed based monitoring (cost effectively) to get more EBFM data
Gilman et al 2019	Brings up the idea of making sure cover genetic diversity and ecosystem aspects. Also flags use of ecosystem based rather than sully stock based reference levels - ***could such reference levels then be used to help guide SAFE assessment rates***? Gives pointers to different L3 models and also points out methods for ERAs of the effects of bycatch fishing mortality that comprehensively consider biodiversity across its hierarchical manifestations are needed. Multispecies and ecosystem models are additional examples of quantitative ERAs (L3) that can be designed to determine ecosystem changes in response to pressures, including from bycatch removals, and simulate ecosystem effects of alternative bycatch management approaches. Dambacher style qualitative models could be an L2 for ecosystem ERA? Similarly, evaluation of effects of bycatch management options on genetic diversity among species should also be conducted (suggests L3 assessment steps for that too)
Gimpel et al 2018	
Goetze et al 2017	Rapid increase in the wariness of fishes but inconsistent impacts across the other metrics, results suggest that fish wariness is the most sensitive indicator of fishing pressure, followed by biomass, length, and abundance (also noting that biomass may change under climate due to condition effects even if don't get abundance change so will need to start to bring climate impact thinking into PSA scoring, in own right as may undermine straight scoring but also because of addition effects where older score components need supplementing). Won't necessarily be feasible everywhere for everything but useful in some contexts as stereo-DOVs can rapidly provide large amounts of behavioural data from monitoring programs historically focused on estimating abundance and length of fishes, which is not feasible with visual methods (opening up discussion point that what include in the ERA data/metrics will should be reviewed every few years to make the most of new technology data streams... so can build collection/calculation of the metrics into the data collection by AI etc).
Goldsworthy & Page 2007	This could be alternative L2.5 for bycatch species. Points out that enhanced spatial tools for risk assessment will be required if spatial management of fishing effort is to become a management strategy for mitigating Australian sea lion bycatch in the demersal gillnet fishery. Such tools would provide a simple mechanism for policy makers and managers to

Reference	Other relevant commentary
	evaluate the benefits and costs of different spatial allocations of fishing effort, in terms of increasing or decreasing (1) risk to sea lion subpopulations and (2) fishery catches. While data hungry there is enough data now in 2018 (vs 2007 time of paper) from tags and VMS that could conceivably do it.
Govt of Canada 2012	
Gray et al 2010	Showed that ERA covers "II. Managed risk" category A. Species/stock-level The risk of a decline to a species/population B. Ecosystem-level The risk of loss to ecosystem-function C. Economic or individual The risk of loss to the economic or cultural systems (both to the individual and community) Where the species risk is highest (rank 1)... then there are concerns over data/method used to service that before come back to working about ecosystem/economic underperformance (other 2 listed here) before concern over communications/institutional issues [perhaps because objectives still couched in single species terms?]
Griffiths et al 2006	Points out that species with high exclusion rates by TEDs need to receive lower ranks in order for such an effective bycatch management strategy to be correctly reflected in the risk analysis…… Also warned that if do u spatial distributions as a criterion and ranked species susceptibility based on how many of the 11 high-effort fishing regions it occurs in, from most susceptible (<3 regions) to least susceptible (>6 regions). However, this criterion does not take into account whether the species is also distributed outside the fished region. This is a potentially dangerous assumption if the entire natural geographic distribution of a species is largely within high-effort regions. In this scenario the species is assigned a low susceptibility to capture using the definition of, but it may potentially be at far greater risk of overfishing than a species found in only one high-effort area but distributed further into unfished regions.
Griffiths et al 2018	
Griffiths et al 2018	PSA requires detailed fishery susceptibility and biological information for a large number of parameters, and cannot definitely determine species vulnerability or quantify cumulative impacts from multiple fisheries. In PSA the scores for susceptibility and productivity attributes for each species are averaged, and then combined to produce an overall vulnerability (v) score from 1 (least vulnerable) to 3 (most vulnerable). An arbitrary threshold score (e.g. v > 2.0) is then used to classify species as “high risk”. Unfortunately, these thresholds have no biological significance and scores for separate fisheries cannot be summed to assess the cumulative impacts of multiple fisheries. Conundrum for fisheries managers, who may wish to establish formal PSA reference points (e.g. v = 2.0) to initiate a management response (especially as get a lot of false positives).... The SAFE RP Fmsm—a proxy for FMSY—was generally less than half that of the estimates of FMSY from EASI-Fish..... Viewing the EASI-Fish results as a catch assemblage on a phase plot for the MSY RPs it is immediately obvious which species are classified as “most vulnerable" and should be management priorities. The radar plots of data quality show that of the five most vulnerable species with respect to the FMSY/SSBMSY RPs the four most vulnerable species have data reliability scores of 8 or more for each parameter, and can therefore be regarded as legitimate “most vulnerable” species. In contrast, the fifth most vulnerable species has scores of 0-4 for reproductive parameters and a low-quality estimate of natural mortality, which together may have overestimated the vulnerability of this species..... PSA attributes are often added or removed, and scores weighted, in an ad hoc manner, with little statistical demonstration of the impacts on overall vulnerability scores due to biases from autocorrelated attributes; do not allow the cumulative effects of multiple fisheries impacts to be quantified, thereby underestimating a species’ vulnerability. EASI-Fish overcomes these significant shortcomings, while using fewer data inputs than the widely-used PSA method, and quantifies the cumulative impacts of fisheries using conventional and scientifically defensible fishing mortality and spawning biomass RPs that are familiar to most fisheries researchers and managers. Include a comparison of productivity attributes used by the Sustainability Assessment of Impacts by Fisheries on Vulnerable Species (EASI-Fish) and a version of Productivity-Susceptibility Analysis (PSA).
Guo et al 2011	Adapted accepted chemical approach to ecological risks with many aspects

Reference	Other relevant commentary
Hare et al 2016	Gave direction of change assessment not just whether any change likely - this could be folded in/combined with SICA/PSA step to get compound risk given climate is the new reality so can't ignore its influence on fisheries
Harvey et al 2017	Make it clear that focusing on **ERA** not IEA or socioeconomic aspects
Hazen et al 2017	
Hazen et al 2018	
Hiddink et al 2019	Information for input into ERA - magnitude of depletion was not related to benthos longevity, except for Tmax <1 year, where abundance increased immediately after trawling (!!). However, the abundance of benthic macroinvertebrates in trawled locations was lower than in reference locations for all organisms with Tmax >1 year. Whilst the effect of fishing was to reduce abundance of biota, the response did not differ significantly among biota with different Tmax. Tmax did effect rate of recovery with increasing F and the relationship between 1/Tmax and r is consistent with the linear relationship predicted by theory
Himes-Cornell & Kaperski 2016	
Himes-Cornell et al 2016	Also did a creation of a community typology using cluster analysis of the vulnerability index
Himes-Cornell & Kaperski 2015	
Holsman et al 2017	ERAs increasingly quantify the direct and indirect cumulative impacts of a pressure on multiple ecosystem components - need system models of some form (EwE, BSS, Atlantis etc) to look at non-stationarity… Perhaps the key ingredient to integrating social and ecological risk assessments is to level the playing field by addressing both human and natural system endpoints within a single analysis and similar, or at least comparable, units of measure. One approach to making the analysis of risk due to CNH interactions tractable is to conduct social and ecological risk assessments sequentially, and then consider the individual and joint risk to the human and natural components of the system - while these analyses represent strong advances toward CNH risk assessment, they do not capture dynamic feedbacks between social and ecological components of the system..... **adaptation occurs rapidly, is non-uniform, and is worth considering in future vulnerability assessments**
Hobday et al 2005	Can habitats be updated based on Pitcher/Dunstan work? For communities' use (depending on the level of knowledge of trophodynamics): topological analyses, qualitative models, and quantitative models [***assume non-trophic interactions covered by habitat analysis?***]. PSA intentionally does not account is taken of the level of catch (intentionally potential not actual risk), the size of the population, or the likely exploitation rate. The PSA analyses do not fully take account of management actions already in place in the fishery that may mitigate for high risk species. In PSA, the overall risk value for each unit is the Euclidean distance from the origin to the location of the species on the PSA plot. The units are then divided into three risk categories, high, medium and low, according to the risk values; the cutoffs for each category are thirds of the total distribution of all possible risk values. RRA can only decrease risk rating.
Hobday et al 2011a	The ecological risk is the expression of the influence of the fishery activities on the rate of change of the unit. Compare PSA and SAFE (shows the scoring of attributes in the PSA, there is a bias to false positives). The development of new tools that can be "plugged" into the hierarchy is also a feature of the ERAEF: each level is defined by the complexity and focus of the analysis and by the data requirements, rather than as a tool per-se. This flexibility has allowed application to all types of fishery, irrespective of size, method, or species. The ERAEF is, however, only an ecological risk assessment, and does not cover the economic, social and governance components of management that are important in many fisheries. A single level system used in Australia for state-based fisheries (Fletcher et al., 2002; Fletcher, 2005) does allow this holistic treatment, but at a more qualitative level

Reference	Other relevant commentary
	(Scandol et al., 2009). needed". Explicit inclusion of management actions in the PSA is possible. Extending the ERAEF to include two further stages: (i) risk categorisation for species that provides more information about the reasons why certain species have been identified as high risk; and (ii) an assessment of residual risk, which is the level of risk remaining after current management arrangements are fully taken into account
Hobday et al 2011b	In general, correlation (r) above 0.9 would be reason to discard one of the attributes before calculating the overall score. FRRA likely important for habitats. Also think about scale of analysis - too blocky = not informative, too fine = too dependent on interpolation. No real update on habitat reference points presented (from Sainbury 2008 report) - ***though do a quick check (perhaps call on Aichi targets?***)
Hobday et al 2005	L3 model, though info on MPA effect could help inform RRA
Holt et al 2012	Outstanding issues that are necessary for EAM but that are not addressed by ERAEF at Levels 1 and 2 include the assessment of cumulative impacts over multiple activities and the consideration of socioeconomic benefits and risks when making management decisions. Directed = target, non-directed = bycatch species. Gives definitions and a brief description of how the estimates of productivity parameters were obtained for each attribute. Measure susceptibility in the same way as Patrick et al. (2010), which expands the definition of susceptibility beyond early PSA applications by including information on fishery management... **however as still got a false positive decided a Residual Risk Analysis step could still be needed when PSA is applied to decide whether to move species forward to Level 3**. **New or alternative tools can be "plugged-in" at any level. Similarly, the list of evaluated stressors can be revised to include as many non-fishery impacts as can be identified by the assessment team**. Work on habitats and communities requires development of a classification scheme.
Hordyk & Carruthers 2018	Simulation test PSA and show results demonstrate that the underlying assumptions of these qualitative risk-based approaches are inappropriate, and the expected performance is poor for a wide range of conditions. Argue that to do PSA well need all the info for L3 anyways, so why not just do that (especially since affordability of high power computing, open-source software, and online data-bases have substantially lowered the barriers to developing operating models and evaluating risk with simulation modelling... ***so could do automated MSE and still get fast results, so pressure to go qual route might be dropping away***). Points to literature questioning assumption that highly fecund species are more robust to over exploitation. Took most exception to differing ways PSA done so judged as too subjective and linear when complex systems are non-linear. Sees the inclusion of management attributes in PSA as a highly questionable attribute of the fishery management attribute in the ePSA that could nullify the impact on risk of all other attributes (productivity and susceptibility) combined. Some combinations of risk categories are not possible. For example, species in the low risk category for maximum age (maximum age < 10 years) cannot be scored as high risk for the age of maturity criterion (age of maturity > 15 years). Other less obvious **correlations also exist among the risk categories - *should be remembered when doing PSA*** *(like when some groups only use r OR other attributes of ePSA not both)*. **Found susceptibility score is of greater importance compared to the productivity score in determining the overall risk to the stock (especially the selectivity parameter; size at maturity least informative)**. PSA plot inference ~ ok if additive ePSA with low exploitation rate; slightly underestimating risk to high productivity species b otherwise okish if multiplicative sPSA with low initial stock size and high exploitation rate; and definitely underestimating risk for all but least susceptible if multiplicative sPSA with high initial stock size, high exploitation rate. Only 100% confident PSA right if say risk is low-low or high-high. In general, ePSA was closest to the underlying assumptions of PSA and provided the closest re-creation of risk with respect to its productivity and susceptibility scores. **Attributes do not contribute equally to risk, the most important productivity attributes are, in the case of the ePSA, the intrinsic rate of increase and the steepness of the stock-recruitment relationship, and for the sPSA, steepness and maximum age**. These results **demonstrate that there is a complex non-linear relationship between the individual productivity and susceptibility attributes** and their relationship with overall risk (see fig 7). Applications that use the PSA to evaluate a range of species and rank them according to risk assume that the PSA vulnerability score is a reliable indicator of biological risk. **The results from this study demonstrate that, in general, the lowest and highest vulnerability scores correlate with a low and high biological risk respectively. However, while the risk generally increased with increasing vulnerability score, there was high variability among the individual simulations, particularly for vulnerability scores between 2.5 and 3.5 where the probability of B < 0.5BMSY was found to range from 0 to 1 (Figs 8 and 9 for additive sPSA and ePSA respectively). This finding is particularly important as both the theory (Fig 1) and applications of the PSA (shaded regions in Figs 8 and 9) reveal that most stocks evaluated with the PSA result in mid-range vulnerability scores, where the vulnerability score is a very poor predictor of risk**.

Reference	Other relevant commentary
Hornborg et al 2018	Results suggest that LCA and ERAEF may provide contrasting and complementary perspectives on sustainability and reveal trade-offs when used in combination. From an ERA perspective, management has been effective in reducing local ecological risks from the Patagonian toothfish fishery at HIMI over time. Present fishing mortality and stock biomass are assessed as ecologically sustainable, and no IUU detected inside the HIMI EEZ since 2005. However management. actions had GHG cost (steaming away to dispose of offal). ERAEF provides important decision-support for place-based EBFM, identifying when a management system is maladapted in terms of fishing economy (fuel use) and off-site impacts (GHG) through low CPUE is a starting point to discuss improvement potentials (Figure 6). Furthermore, as LCA has a strong connection to supply chain stakeholders (based on industry and societal interest in results), routine LCA inclusion in assessing sustainability of seafood may provide further progress towards including the human dimension of EBFM. By studying the performance of a fisheries production system (i.e. “pressures per quantity of product”), insights may be provided on how a stock is best utilized from a societal perspective.
Hoyle et al 2017 - cover not by Clarke for IOTC	
Jepson & Colburn 2013	
Jiang et al 2018	Detected significantly different metal accumulations in fish species among various trophic guilds and habitat preferences. Our results demonstrated that metal concentrations in fishes are simultaneously influenced by the habitat and bio-accumulation through the food chain.
Jiménez et al 2012	
Jin et al 2016	
Jones et al 2018	
Jones & Cheung 2018	
Juan-Jorda et al 2014	Shows tuna RFMOs are trying - the ecological risk assessments conducted for several taxonomic groups of target and bycatch species have been decisive to establish research priorities and put in place management measures for by-catch species generally lacking quality data to conduct quantitative stock assessments
Juan-Jorda et al 2018	The development of qualitative and semi-quantitative ecological risk assessments for incidentally caught species of billfishes, sharks, seabirds, sea turtles, marine mammals and other finfishes have been pivotal in all tRFMOs to set priorities and take management actions to mitigate the impacts of fisheries on these species following the precautionary approach in the absence of quantitative stock assessments. Yet, these assessment and derived indicators are not enough as they are not regularly updated or monitored over time by the Scientific Committee and at this stage they cannot be used to provide robust management advice (e.g. establish level of exploitation status, set impact or catch limits or evaluate the efficacy of current adopted mitigation measures). Furthermore, the establishment of limit reference points for vulnerable and threatened bycatch species and the incorporation of limits in the development of harvest control rules for target species that account for bycatch issues remains a pressing task in all the tRFMOs
Kang et al 2018	How take standard single species RBC estimation process as input data, along with info on habitat, socioeconomics et to get ecosystem adjusted RBC. Combines TAC setting and "EBFA" is a pragmatic ecosystem-based approach for assessing fishery resources in Korean waters involving four management objectives: sustainability, biodiversity, habitat quality, and socio-economic benefit. Reproductive potential and mean total length were used as indicators for the sustainability objective, and they denote indices of recruitment overfishing and growth overfishing, respectively. Bycatch rate and discard rate were used as indicators for the biodiversity objective, and they present indices of trophic level

Reference	Other relevant commentary
	reduction in catch that come from bycatch and discard activity. Oil pollution and discarded wastes were used as indicators for the habitat quality objective, and they show indices of habitat damage that occur from oil accidents and discarded wastes from fishery activities. Maximum economic yield and ratio of landing to total supply were used as indicators for the socio-economic benefit objective. For each one got a risk index curve that is a value as a function of F. **Finally came up with an estimated RBC adjustment curve by SRI (risk index) - so how to rescale single species RBC given ecosystem level risk score**
Karnauskas et al. 2017	
Karintseva 2017	Discusses method for multi-sector especially energy sector risk assessment - in Russian so too hard to follow
Kell & Luckhurst 2018	
Kenny et al 2018	UNGA resolution 61/105 (2006) identifies significant adverse impacts (SAIs) as those impacts that compromise ecosystem integrity (i.e. ecosystem structure or function) in a manner that: i. impairs the ability of affected populations to replace themselves; ii. degrades the long-term natural productivity of habitats; or iii. causes, on more than a temporary basis, significant loss of species richness, habitat or community types. In addition, the following six factors or criteria should be considered when determining the scale and significance of an impact. i. the intensity or severity of the impact at the specific site being affected; ii. the spatial extent of the impact relative to the availability of the habitat type affected; iii. the sensitivity/vulnerability of the ecosystem to the impact; iv. the ability of an ecosystem to recover from harm, and the rate of such recovery; v. the extent to which ecosystem functions may be altered by the impact; and vi. the timing and duration of the impact relative to the period in which a species needs the habitat during one or more of its life history stages.
Kirby et al 2009	In future include seasonality/inter-annual variation; estimate catchability, fisher behaviour (targeting)
Knights et al 2015	Risk assessment is gaining momentum as a decision-support tool that allows managers and policymakers to prioritize human drivers of environmental change. This is a structured way of doing it that can cope with current level of available data
Korpinen & Andersen 2016	Impacts (risk) estimated numerically on the basis of spatial damage or loss of individuals or categorically on the basis of literature reviews and expert panels. General method = layer up pressures, layer up distribution of ecosystem component(s), risk/impact = sum (pressure layer * component layer * pressure-component-weighting). Most IEAs done in Europe/Nth America; mostly additive and assume linearly increasing impact with pressure level. Typically benthic or pelagic (or on limited number/kind of species) but not both. Few studies compared current with max possible, just normalised across current to compare across multiple uses, none of the studies had benchmarked the pressures in order to estimate the impacts in a comparable way. Impact estimates were most often categorical expressions of the sensitivity of the ecosystem components to the pressures or severity of the pressures on ecosystem components (especially if across multiple taxa types), a few studies used ecosystem models. <20% of studies validated the IEA results. One innovation = use fuzzy logic for impact occurrence. Important question = how to deal with legacy effects, the question of how to assess extinct species or significantly reduced habitat coverage was not addressed by any of the reviewed studies. Say particular focus has to go on habitats and keystone species (how does AFMA ERA do that?)
Lack et al 2014	The approach should identify the problems with existing management and compliance arrangements and logically draw attention to what management and compliance solutions may be used to reduce risk for a species through risk management. · The M-Risk assessment results could be used for the purposes of identifying where specific management improvements are required in addition to informing potential MEA listing decisions.

Reference	Other relevant commentary
	· For the purposes of developing the M-Risk framework it was appropriate that only medium to high risk sharks are assessed but this does not imply that low intrinsic risk species should not be subject to M-Risk assessment, since even those species can be overfished if not managed appropriately. · M-Risk should encompass management of all anthropogenic sources of mortality (commercial, recreational, subsistence and artisanal). · Given that species tend to be managed as stocks, or at least as management units, it would be more informative for M-Risk assessment to be conducted at stock / management unit level rather than species level. · M-Risk should be assessed on the basis of stock status, adaptive management and generic management. · An indication of the level of confidence in the scores should be provided. · The M-Risk assessment framework should provide for ‘override’ of the assessment where strict application of the method does not reflect what is actually known. While such overrides should be exceptions, failure to allow for them leave the framework open to criticism and reduce its credibility.
Landis et al 2012	Argument for updating classic ecotox ERA in context of climate change - ERA must consider interactions among contaminant and noncontaminant stressors. With new regimes of temperature and precipitation at specific geographic sites, novel ecosystems with novel hydrologic processes will be created that will trigger novel responses (interactions, responses to variability/spikes). Simplistic assumptions of static conditions and unidirectional change are no longer appropriate. 7 ERA principles to consider: (1) Consider the importance of GCC-related factors in the ERA process and subsequent management decisions; (2) Assessment end points should be expressed as ecosystem services (3) Responses of ecosystem services (end points) can be positive or negative (4) The ERA process requires a multiple-stressor approach, and responses may be nonlinear (Analyses dealing with spatial and temporal scales and nonlinear dynamics may benefit from the use of Bayesian networks, which incorporate probabilistic relationships and explicitly deal with uncertainty). (5) Develop conceptual cause–effect diagrams that consider relevant management decisions as well as appropriate spatial and temporal scales to allow consideration of both direct and indirect effects of climate change (6) Determine the major drivers of uncertainty, estimating and bounding stochastic uncertainty spatially and temporally, and continue the process as management activities are implemented (7) Plan for adaptive management to account for changing environmental conditions and consequent changes to ecosystem services
Leadbetter 2013	Post capture survival not applicable attribute so would need to substitute something else. Method does mean stakeholders could explore scenarios and what the consequences could be for fishing activities. Be careful of bias, end pt. where have species "sustainably" (i.e. persistently) overfished and where degree of gear interaction changes (fisher behavioural change). Attractive to multispecies fisheries as can cover a lot quickly and at least get some action going. If did pick it up would have to put thought into known issues such as the possibility of excessive subjectivity (which could lead to interpretations of available information that are either too lenient or too strict), the need to ensure that interactions with other fisheries are taken into account, the need to incorporate non fishery influences on vulnerability risk minimisation).
Levin et al 2018	Describes Fisheries Ecosystem Plan process and role of ERA/IEA and MSE in that… brings in idea of hype cycle (where is ERA on that?)
Lillebø et al 2019	
Lucena-Frédou et al 2017	Found in this instance that there were significant differences were observed for productivity and vulnerability scores between the catch fate categories; target species (T) showed lower scores of productivity than all the other categories and were also more vulnerable than non-commercialized species (BY/D and BY/KA). Results correlated well with what would have got if applied IUCN methods..... Extension of PSA may provide a tool for evaluating risk posed by overlapping fisheries within an ecosystem-based management framework that accounts for the full suite of extractive activities and their possible interactions. The PSA approach could also take into account additional possible stressors due climate change in the future, particularly where changes are mainly related to life history and marine species distribution. **It is expected that climate changes could affect the results of PSA model in future and the inclusion of this aspect into assessment models is encouraged**.
Malakar et al 2019	

Reference	Other relevant commentary
Marshall et al 2017	
Mazaris & Germond 2018	Cumulative Effect Assessment (CEA) allow identifying causalities of multiple pressures operating at various temporal and spatial scales, offering the means for systematic, spatially explicit action planning. Cumulative Effect Assessment (CEA) allow identifying causalities of multiple pressures operating at various temporal and spatial scales, offering the means for systematic, spatially explicit action planning. Basic rationale behind CEA is to spatially overlay multiple pressures and assess their impact on ecosystem components (e.g. species, communities, ecosystem functions). The impact of a pressure upon the target ecosystem's features is assessed either through numeric evidence (e.g. spatial extent of degradation, species population reduction) or categorically as the outputs of expert consultations. Once impacts of climate change and interactions with other pressures are conceptualized, they become part of the assessment process.
Mazor et al 2017	Could be input into ERA
McDonald et al 2017	If used similar indicators could link PSA to indicator based HCR - i.e. be consistent
Meissa & Gascuel 2015	Given the PCA results, three indicators of life history traits (the vulnerability index V, maximum length Lmax, and trophic level TL) were targeted for specific analyses: (i) Calculation of correlations between indicators and the three main exploitation parameters: mortality at MSY Fmsy (defining a potential of exploitation intensity), the effort multiplier mEmsy (indicating the current state of over- or underexploitation), and the current level of stock depletion Becur/K. (ii) Calculation of ecosystem indicators of the mean vulnerability index (MV), the mean maximum length (MML), and the mean trophic level (MTL) within catches and within the ecosystem (represented by the biomass of the 22 taxa) and analysis of their change from 1990 to 2010. (iii) Use predictions of the surplus production models to express these indicators (MV, MML, and MTL) either as a function of the fishing effort multiplier (i.e. compared with the current effort) or as a function of fishing mortality (i.e. for the same fishing pressure applied to all stocks). .... In “stock PCA”, the axis 1 is highly correlated with the multiplier of fishing effort at MSY (mEmsy), separating overexploited taxa (negative values on the axis representing low mEmsy) from underexploited taxa (positive values). The variable mEmsy is correlated with the indicators of biomass depletion Slope, Becur/K, and Bcur/Bstart, which increasing as fishing impact decreases (underexploited stocks), and mortality at MSY (Fmsy), which is highest for species able to withstand high fishing pressure and which are currently underexploited. Axis 2 is built from mortality atMSY (Fmsy) and mortality from current fishing (Fcur). The factorial plot of individuals separated the taxa most impacted by fishing from those less impacted (axis 1) and taxa heavily fished from those less targeted (axis 2). Axis 2 can thus be interpreted as an axis of taxon sensitivity that is independent of its current state of exploitation. It is correlated with life-history-trait parameters and separates, in particular, taxa with rapid turnover (variables r, M, Kvb, and P/B) from taxa with high vulnerability index (V) and high longevity (Tmax, Tm). In contrast, axis 1 is more directly related to the current level of overexploitation, which seems a characteristic of taxa with large individuals (Linf, Lmax, Winf) and of high trophic level (TL). The “ecology PCA” confirms this interpretation, with high correlations between Fmsy and rapid turnover and between trophic level and the current level of stock depletion. The exploitation indicators Fmsy and mEmsy are significantly correlated with the eco-biological factors maximum length (Lmax) and vulnerability index (V). mean V and mean Lmax did respond clearly to fishing pressure, mean TL did not (though some value in mean TL index found).
Micheli et al 2014	Number at low risk drop under FGI - indicating that risk is underestimated if fisheries are not assessed in combination (looking at individual fisheries results vs FGI case could also see which fishery was biggest contributor to this compound problem). Aggregating the susceptibility scores of the different fisheries operating in the same area results in a remarkable increase in number of species at high risk and drop in numbers at low risk - even compared to FGI. Both indices show there is a potential for significant cumulative impacts of multiple fisheries on several species. Recommend that the aggregated susceptibility index (AS) be used for assessing cumulative risk, especially when catch and effort data are not available..... Did identify some species to low vulnerability even to cumulative pressure......Advocate using more attributes to do scoring if data exists..... Recent hypoxia mort emphasizes the need for risk- and impact-based assessments that take multiple stressors, beyond fishing, into consideration..... The PSA methodology does not account for possible synergistic effects of multiple, indirect impacts, and thus it may underestimate risk.

Reference	Other relevant commentary
Milton et al 2008	Thinks method ok as assumed no escapement when in fact can and used reference points that were half those for fish
Muñoz et al 2018	
Murua et al 2012	
Nel et al 2013	To evaluate the impact of fisheries on these turtles it should be conducted across multiple fisheries, assessing a variety of gears. The highly variable quality, and general lack of data in many instances, highlight the need to improve turtle bycatch data recording and reporting systems across all IOTC fisheries. Data on gillnet effort and interactions with turtles are completely lacking, although this method of fishing, and the areas in which they occur (inshore, and therefore often close to nesting beaches) are likely to pose the greatest risk to turtle conservation. Improving data collection and reporting for the coastal gillnet fisheries of the Indian Ocean is the highest priority recommendation. Improving the quality of data in National Reports and standardising the reporting into tables with bycatch numbers (dead and released alive) and effort data, and compliance to specific components of conservation measures. This is critical to improve both quality and quantity of turtle bycatch data.
Newman et al 2018	Should be noted that the inherent vulnerability of a given species is essentially a fixed score as it is a function of a species biological traits and life history attributes. As such, these traits are unlikely to change in the short to medium term (e.g. 5–10 years). In contrast, the current risk to the wild stock represents a range of current threats, such as the level of fishing effort/catch, or environmental factors that may affect recruitment levels adversely. These threats may change within a short time frame (i.e.<5 years) and therefore the current risk to the wild stock should be reviewed on a regular basis (annually) with the periodicity of review needing to be cognisant of the level of inherent vulnerability.
O et al 2015	If the focus is on cumulative effects and if more quantitative data is available, then the framework should be applied modularly, proceeding directly into a Level 2 or 3 assessment and bypassing the lower levels. Discusses simplistic approach to tackling non-additive interactions. Did a yes/no screening of which activities effect species/habitat/community/ecosystem - then for those that are screened in score exposure and consequence (risk = exposure * consequence) and then final risk score marks whether progress to L2 or not. L2 = estimate score multiple attributes of exposure and consequence to calculate indices and then risk = exposure score * consequence score, cumulative risk then = sum over risk from single stressors. Exposure = % exposed * intensity of activity (where % exposed = overlap in space * overlap of depth * overlap in time). Consequence = (acute + chronic) * recovery indices. AcuteChangeC is measured as the percent change in population-wide average mortality rate of a species when exposed to a given stressor, ChronicChangeC is measured as the percent change in condition, fitness, genetic diversity, of a population, RecoveryC represents the recovery time. **Ecosystem risk** either calculate directly for ecosystem properties (like in IEA ecosystem indices) in same way done for species or communities or ecosystem risk = cum_risk_per_unit (e.g. species) * sensitivity_loss_that_unit
O'Laughlin 2005	
Orsmeth & Spencer 2011	Target stocks produced different results from non-target stocks. In both areas mean P scores were similar between target and non-target stocks but S scores for target stocks were significantly higher. .... Vulnerability scores were not significantly different, but data quality was significantly higher for target stocks. Multiple-gear analysis produced slightly different vulnerability scores than the approach using a single fishery (though lower rather than higher final scores actually). Vulnerability scores increased with the number of individual attribute scores that were changed, with effect amplified if had higher starting score; effect also bigger if fewer attributes (as larger proportional change in score contribution... ***so try to make PSA as complete as possible even if data poor, don't omit attributes if can avoid it***). **Shows that there is sensitivity to susceptibility changes and so period of review should also be tailored to level of exploitation (more frequent the higher the exploitation as more sensitive to mis-specification).**....... All stocks included in the PSA are listed as managed species in the FMPs, indicating that there was at least some level of conservation concern for those stocks when the FMPs were created. Because of this, all stocks should display some susceptibility to commercial fishing. Conversely, the lack of high susceptibility scores may be indicative of successful management practices. The

Reference	Other relevant commentary
	inclusion of target stocks in the PSA was valuable for interpreting the vulnerability of non-target stocks. Under the new federal guidelines, species included in stock complexes should have similar vulnerability scores and PSA = way of checking that.
Parappurathu et al 2007	
Park et al 2010	
Paterson & Peterson 2010	Lessons come from doing 10 ERAs in South Africa. Thought about putting in a generic approach as found many cross cutting issues, but a disadvantage of a generic approach is the potential loss of fishery specific detail. This potential disadvantage highlights the importance of conducting a fishery specific ERA as a first step (and making sure include scoping and L1).
Paterson et al 2018	
Patrick et al 2010	Several modifications made to the PSA to better meet the needs of US regulatory agencies. These modifications included: (i) redefining the scoring thresholds used to calculate productivity to be more representative of life history traits of US fish species; (ii) increasing the number of productivity and susceptibility attributes to include more data-intensive measures; (iii) developing a data-quality index that allowed a comparison of uncertainty in risk scores among species; (iv) eliminating the requirement that missing data be assigned a precautionary score of high risk; and (v) developing an attribute weighting system that allows users to modify the weights assigned to each attribute for a given fishery analysis. Recognised that recognized that the PSA would mainly be used to evaluate extremely data-poor stocks; thus, a larger set of attributes would be useful to ensure that an adequate number of attributes were scored....managers should consider reorganizing complexes that exhibit a wide range of vulnerabilities, or at least consider choosing an indicator stock that represents the more vulnerable stock(s) within the complex... Given differences in how gars function and levels of post capture mortality, it is recommended that a vulnerability evaluation be performed for all or a majority of sectors interacting with the stock when the overall vulnerability of stock is needed... An overarching vulnerability evaluation score could then be calculated by using a weighting system based on average landings by sector over some predetermined time frame.....
Pedreschi et al 2019	
Penney & Guinotte 2013	To improve need to ground truth the habitat models. Integration of substratum type data into the habitat models would improve the predictions and enable better discrimination of suitable habitat within the fishable depth range.
Pitcher 2014	Did SAFE plot and % caught vs SRA rank plot. Did look at implications of uncertainty - did raise u/M but little effect in the end, with only 2 species went from low to higher risk based on passing a reference point. Area-based trawl swept exposure indicators showed which species, habitats and assemblages were the most exposed habitats (and then could check their characteristics to see how much recovery potential/robustness they have). Found most of species ranked highest by the exploitation: SRA-recovery approach did not appear to be at risk by the quantitative u/M method and, conversely, most of the species identified as most at risk by the u/M method did not coincide with the species ranked highest when qualitative SRA-recovery scores were used (despite both approaches using the same quantitative exploitation axis), suggesting that there is limited correspondence between the qualitative and quantitative methods – a result that contrasts with Hobday et al. (2011). The latter authors found a positive relationship between qualitative PSA and the more quantitative SAFE method, albeit not entirely independent with respect to underlying data and showing many false positives for PSA.
Pitcher et al 2016a	Across all fisheries, there were relatively few assemblages that had both high exposures to trawling and low protection by closed areas. Updated survey databases and environmental variable layers. 26 environmental variables were collated and mapped at 0.01° for the Australian EEZ. All effort converted to swept-area per grid-area ratio, to standardise for different gear sizes and tow speeds. Did swept area estimates with differing assumptions on clumping within grid cell. The estimated annual footprints range from <1% to ~8% of the managed area of each fishery within the specified depth range, whereas the multi-year footprints typically are about 25% larger. Both estimates account for the

Reference	Other relevant commentary
	aggregated nature of trawling at ~1–10 km scales. Distribution of benthos done via the approach for producing the assemblage maps is now established; it involves quantifying the magnitude of change in species composition along environmental gradients (predictors) and using this information to predict distribution patterns of demersal biodiversity. The method, called "Gradient Forest" (Ellis et al. 2012), is an extension of Random Forest (Breiman 2001), which fits an ensemble of bootstrapped regression tree models (a 'forest' — of 500 trees in our case) between each individual species abundance and environmental variables. The many branches (or 'splits') in the tree models are fitted recursively along the environmental gradients at locations on variables where the most deviance in species response is explained (fit 'improvement'). Each tree is fitted to a different random sample of ~⅔ of the data (in-bag) and fit performance is tested on the ~⅓ of data held out-of-bag (OOB). The influence of each variable was assessed by randomly permuting each variable in turn and quantifying the degradation in prediction performance on the OOB data ('predictor importance'). Models were fitted for every species with adequate occurrence in every available biological survey dataset. Cumulative distributions of the splits on each predictor represent overall changes in the whole community, or compositional turnover, in standardised units of R^2 along the gradient of each predictor. These turnover curves are accumulated for the fishery region to provide empirical functions for transforming the multi-dimensional environmental gradients to common biologically-scaled axes that can be used to estimate the spatial pattern of species composition — or assemblages — associated with the environment and mapping in geographic space. After the multiple environmental gradients have all been transformed to a common biological scale, principal components analysis (PCA) is used to capture the majority of compositional variation associated with environmental gradients in as few dimensions as possible. A colour ramp is applied to the PCA ordination (e.g. red-green-blue in three dimensions, or a colour wheel around the first two dimensions) to allow visualisation of compositional patterns in 2-D PCA-space and in mapped geographic space. The visualisation in PCA-space may be called 'biological-space' — it is a 'bi-plot', with vectors showing the direction of the major environmental drivers and provides a colour key for the corresponding geographic map to facilitate interpretation.
Pitcher et al 2016b	
Pitcher et al 2017	
Piet et al 2015	
Piet et al 2017	In the risk assessment, all impact chains are individually scored. Impact chains can then be aggregated depending on interest and context. For example, chains can be grouped by sector (thereby aggregating all pressures introduced by that sector and all ecosystem components those sector-pressure combinations interact with), pressure (aggregating all sectors introducing the pressure type and all ecosystem components those sector-pressure combinations interact with), or ecosystem component (aggregating all sector(s)/pressure(s) combinations affecting a specific ecosystem component) thereby allowing an estimate of total IR to be determined for each combination. Cool way of plotting impact pathways. Weighting and aggregation methods influenced relative ranking of pressure and components. Averaging scores in aggregation step was found to be more sensitive to the number of impact chains and the choice and definition of risk factors. MAX performs poorly in prioritising between the risk factors based on these aggregated risk scores and is therefore not a useful aggregation method. Alternatively, if summation of risk scores is the preferred method, risk factors should be identified in relation to the specific issue the risk assessment is expected to address at the initial stage through e.g. a stakeholder consultation process. If a risk assessment is devised for general application, such as to inform decision-makers on issues related to different policy frameworks for which different risk factors may apply, it is advisable to initially use the most detailed basic elements, i.e. least aggregated risk factors, allowing best available evidence to be clearly linked to specific impact chains and thus, increase transparency of the decision-making process. Best practice would be to start with those risk factors and include only the most relevant impact chains such that the impact chains are more or less evenly distributed among the risk facto
Piet et al 2019	This EBM approach distinguishes four phases, some with multiple steps, each described in more detail below: I. Societal goals: define what is to be achieved II. Integrated Ecosystem Assessment: establish the knowledge base and identify the main threats to the achievement of the societal goals • Scoping • Risk Assessment III. Planning of EBM: select management options likely to perform best at achieving the societal goals

Reference	Other relevant commentary
	• Design • Evaluation IV. Implementation, monitoring and evaluation: this occurs outside the science domain and is therefore not considered further in this study.
Prince et al 2015	Beverton–Holt life-history invariants (BH-LHI; Lm/L1, M/k, M × Agem) actually vary together in relation to life-history strategy, determining the relationship between size, age, and reproductive potential for each species. Considerable but predictable natural variation in the BH-LHI ratios and the relationships between size, age, and reproductive potential that they determine. We believe that this reconceptualization of the BH-LHI has potential to provide a theoretical framework for “borrowing” knowledge from well-studied species to apply to related, unstudied species and populations, and when applied together with the SPR assessment technique described by Hordyk et al. (2015b), could make simple forms of size-based assessment possible for many currently unassessable fish stocks.
Richard et al 2017	Significant changes were made to the methodology to address limitations identified in previous risk assessments. Updates to the methodology included the use of a Population Sustainability Threshold (PST) for seabird population productivity, based on the total number of breeding pairs (rather than the lower quartile used previously in the PBR). This update included changes in the correction factors to meet the long-term goal of populations remaining above half their carrying capacity, in the presence of environmental variability. Other changes from the preceding risk assessment included the use of allometric modelling to reduce variability in the estimates of age at first reproduction and of adult survival. Both parameters were used in calculating the population growth rate under optimal conditions (rmax). Updates from the preceding risk assessment also included the use of an integrated model for estimating fisheries mortalities, to prevent them from exceeding the total annual mortality of the adult population, and to ensure that estimated mortalities, seabird population size, and adult survival were mutually consistent. In addition, the proportion of captures released alive was estimated from the data, and half of the live releases were assumed to survive on average; the cryptic multiplier, used to estimate the total number of fatalities from the number of observable captures, was disaggregated between fishery groups in trawl fisheries; vulnerability to capture was estimated in a single model across all fishing methods; for selected fisheries, the vulnerability was allowed to vary between the period before and after 2010. The PST differs from the PBR by explicitly including the uncertainty in population size, instead of considering a conservative point estimate of population size, and by not including a recovery factor. The highest sensitivity to the uncertainty in the annual potential fatalities was in trawl fisheries; this parameter was the most influential parameter for most taxa (other parameters important to specific species). **Areas for improvement:** In the current risk assessment framework, **cryptic mortality** had a considerable influence on the estimated risk ratio, but poorly know; need to i**nclude ontogenetic survival rates**; **estimation of the vulnerability**; **cumulative impacts** (other sectors in NZ and sectors beyond NZ for migratory).
Rico et al 2012	
Rijnsdorp et al 2018	Information that can be used as input to productivity scoring for habitat ERA
Robinson et al 2014	Describes an IEA approach
Rosenberg et al 2009	Recommend doing a PSA as basis for an annual catch level setting procedure for US fished stocks. More vulnerable stocks should be managed such that there is lower probability of overfishing occurring because the consequences for that fishery are greater (e.g., recovery times are longer or depletion more severe). The measure of relative vulnerability should be used by managers to determine the acceptable level of risk of overfishing in step 3 of the ACL setting process
Roux et al 2019	Found good agreement between empirical biological data and FK information. Traditional ecological fishers’ knowledge on Arctic char populations is available where scientific observations are scarce, incomplete, or inexistent. This calls for the incorporation of FK in stock status and management strategies evaluation for the species in Arctic regions. The productivity-susceptibility analysis provides a flexible tool for the incorporation of alternative information sources and the evaluation of risk from fishing activities. Inclusion of FK served to enhance susceptibility evaluation (direct inclusion) and validate the available biological data (indirect inclusion).

Reference	Other relevant commentary
Rowland et al 2018	Shortlist of candidate indicators: ecological relevance informed by conceptual models ecosystem dynamics; relative sensitivity to threats; temporal (and spatial quality) of data; lack of redundancy among candidate indicators; and ability to set a justifiable collapse threshold. Sensitivity to threats can be quantified by examining exposure–response relationships between indicators and threats. A range of empirical and model-simulation approaches may be used to test the performance of indicators to ensure they are reliable measures of ecosystem risk status. After suitable candidates are identified, assessors should select a set of indicators that capture the effects of contrasting threats on the ecosystem (Supporting Information). Where time and resources permit, multiple indicators within an indicator category should be assessed to produce a more robust assessment. Data availability is one way of screening out excess indicators, but better way is use of quantitative approaches, such as cluster analysis, multivariate linear regressions, principle component analyses, and correlations to identify complementary indicators.
Sara et al 2018	
Savenkoff et al 2017	
Schick et al 2018	Description of participatory process to look at development (multiple use) land planning & conservation - MARISCO = adaptive management approach including a structured approach for practitioners to document both knowledge and “nonknowledge” related to biodiversity, threats and drivers of change, as well as the (previous) conservation management for a given site in a systematic fashion
Samhouri & Levin 2012	Present an efficient, transparent, scalable, and repeatable framework for conducting an ecosystem risk assessment that links the status of marine populations to coastal activities. Building from emerging research related to ecosystem-based fisheries management, risk is estimated based on the exposure and sensitivity to a diversity of human activities influencing regional populations of species. This quantitative analysis produces a qualitative understanding of risk to populations of species and, because the species can serve as ecosystem indicators, to attributes of ecosystem structure and function. In so doing, the framework uses the best available science to provide important context for choosing among management actions that influence individual populations as well as EBM goals. There are six types of risk germane to our framework: absolute, relative, baseline, community, spatial, and ecosystem risk. Absolute risk describes the chance that a species will experience population decline on an absolute scale ranging from completely improbable to certain (needs ground truthing).Relative risk describes the chance that a species will experience population decline due to a particular activity in terms of higher or lower exposure and sensitivity scores, without reference to an absolute scale defining the probability associated with high or low scores. Relative risk allows direct comparison of risk scores among species but not among different types of activities. Baseline risk describes the chance that a species will experience population decline based on biological traits and current status alone. This type of risk is invariant across human activities. Community risk describes risk due to coastal activities that is shared among species. Associations between relative risk scores for a community of species allows grouping of species with similar relative risk scores across activities. Spatial risk describes relative risk in a spatially explicit manner on a subregional scale. Ecosystem risk is a reinterpretation of a species' relative risk based on the species perceived ability to convey information about ecosystem structure and function, i.e., its indicator properties..... Comparison of baseline risk to activity-specific relative risk suggests that even an extremely coarse form of ecosystem risk assessment, based solely on ecological traits, status, and existing management regulations, can be sufficient to distinguish higher from lower risk species
Samhouri et al 2019	
Sanchirico et al 2008	
Serveiss et al 2004	Selected assessment endpoints (indicators) based on three criteria: 1) their ecological relevance, 2) their susceptibility to stressors of concern, and 3) their relationship to previously defined management objectives
Sethi 2010	

Reference	Other relevant commentary
Sharp et al 2009	No peer-reviewed studies based on actual observations of the effects of bottom longline gear on benthic organisms, in contrast to a multitude of comparable studies of the effects of trawl gear. Assessments that itemise impacts separately for different gear components and different fishing scenarios are a valuable tool to help focus mitigation efforts in areas where they are most needed or are likely to yield the greatest reduction in impact.
Sherman 2008 (in Bianchi et al 2008)	A method for economic valuations of LME goods and services, has been developed using framework matrices for ecological states and economic consequences of change
Singh et al 2017	
Singh-Renton 2013	Just noted they looked at ERAEF
Singh-Renton et al 2011	Ecological risk assessment for the effects of fishing (ERAEF) help form solid understanding basis for EBFM via examining ecosystem component interactions and can identify those species and habitats at most risk from fishing as well as from other human/human-induced activities. Also of direct relevance are evaluations of fishery-fishery interactions and fishery bycatches (biological interactions), as well as fishing gear-species interactions (technical interactions).
Siple et al 2019	
Slooten & Davies 2012	
Slooten et al 2000	Uncertainty has delayed management decisions, authors argue that if analyses routinely incorporated un- certainty into risk assessments, it would be clear that many decisions could be made without further delay. Found degree to which the conclusions are robust to uncertainty has now been quantified. No longer is uncertainty a reason to delay action (generally a high risk of decline across all scenarios). Results also indicate which re- search will contribute most effectively to reducing un- certainty in management decisions. Performing this type of analysis can therefore reduce delays in decision making and ensure that future research addresses areas of most relevance to management.
Small et al 2013	ERAEF envisages management responses at each level, and a precautionary approach exemplified by assignment of high-risk scores where data are unavailable. CCAMLR = L1, WCPFC and MFish = L2, ICCAT = L1-L3 (4 breeding populations at L3), other L3 equivalent studies (models) done for individual species. Noted that CCAMLR, ICCAT pre-screened to specific taxa or species known to be caught; but i**nclusive approach may be necessary in situations in which species-specific bycatch data are sparse (if that would be overwhelming then keep inclusive but for most appropriate species for the type of fishery** - longlines = surface feeders, gillnets add in divers etc). Given differential population exposure to pressure population scale analyses make sense, but disadvantages = impossible to assign bycatch/determine relative overlap with fisheries with specific population without independent information on bird distribution (e.g. tracking data, ring recoveries etc), thus ERAs usually at species level. **Ideally, ERA should be flexible enough to allow inclusion of both species and populations (if data available even incorporate different parameter values for different populations)**. True expert opinion should guide ERA resolution. ICCAT/WCFPC had equally populated risk categories (double checked with experts about cut-off pts between bins). MFISH got a quantitative impact estimate (Impact Ratio = Fcurr / PBR) - attractive as can then be used directly in management as performance metric, but VERY data intensive (also UN code of conduct says need to minimise bycatch mort regardless). L3 attractive but data hungry and people argue about the models so **L1 and L2 should be the focus** (so get risk ranking of most/all species/populations of interest) then **L3 can provide useful** case studies that **support** results from L2 (where data available). **Productivity trait**: quantitative Rmax estimate typically requires many parameter assumptions/substitutions so maybe unreliable/misleading but give false confidence as quantitative (vs scored life history characteristics - really just n**eed a measure that discriminates among species in relation to their capacity to buffer impacts of fisheries and reflects current availability/quality of data**). **Susceptibility**: largely calculated as overlap so need to find a balance between a simplistic approach (too imprecise to help) and more complex calculations (false confidence of precision or for only some species where sufficient data available). Lists off the different ways of estimating overlap, all ERAs face too few tracking data, species range maps = too coarse, feeding radius = "gross" assumption. Best practice = seasonal (given bird and fleet behaviour), test sensitivity, laugh check distributions used and remember only need to match resolution of effort (going

Reference	Other relevant commentary
	finer doesn't help). **If can go further than straight overlap by (i) xEffort per cell and (ii) xEffort per cell x pop density per cell (especially if can do this seasonally) then most helpful for targeting of monitoring and bycatch mitigation**. Can estimate a "vulnerability" (likelihood of capture) for seabirds but given poor quality of bycatch data it would be unwise to use it to infer bycatch isn't occurring. If not treating data gap as "high risk" but substituting value from analogous species or leaving species out then sensitivity test to make sure not underestimating risk. MFish estimate tried to go for absolute risk score as working across fisheries so trying to figure out attribution. WCPFC risk index = Susceptibility/Productivity scores. WPCFC did species-fleet maps per quarter but also summed species-fishery risk scores to show which species most at risk, also summed risk scores across all species per fleet to determine which fleets posed the greatest risk across species.
SIOFA 2017	
Soykan 2018	
Stelzenmüller et al 2018	All recognise uncertainty, but only a limited number of studies actually assess uncertainty related to generated output and there is a clear gap between the sources of uncertainty recognized and the types of uncertainty assessed. CEA (ERA) results should reveal the probability of occurrence and intensity of cumulative effects of multiple human activities and natural disturbances on defined ecosystem components; and should evaluate management procedures regarding potential failure to meet such management objectives (e.g. conservation targets for certain species or habitats). In other words, when following the standardized CEA, results should describe the risk of failing on the management objective to manage cumulative pressures in such a way that cumulative effects do not exceed accepted thresholds. A key task to risk identification is the establishment of the cause-effect relationships or pathways of risks to describe the vulnerability of ecosystem components to pressures. Disentangling cause-effect pathways is supported by a number of conceptual frameworks (e.g. Driver Pressure State Impact Response (DPSIR)) which provide guidance on how to link 'driving forces' to generic 'pressures' and to physical, chemical and biological attributes, and then translate the impacts into policy responses. Fundamental for the proximate assessment is the common understanding that the vulnerability of an ecosystem component is defined by the degree of exposure to a pressure, its sensitivity and recovery potential. As opposed to single ecosystem components, defining the vulnerabilities of ecosystem functions or services has received less attention in current CEAs. Functional trait approaches are promising especially as trait databases are growing. Online spatial time series is helping move from qualitative scoring to quantitative due to recent advances in developing of models that directly implement risk criteria and thresholds (e.g. mortality rate is equal, larger or smaller as recoverability rate) using quantitative data to map the vulnerability of ecosystem components to specific pressures (e.g. Roland Pitcher work). Risk analysis comprises the comprehension of the nature of risk and the determination of the level of risk (ISO Guide 73, 2009). This consists of determining the probabilities of identified risk events, taking into account the presence and effectiveness of control measures and requires also a performance assessment of new measures.
Stepanuk et al 2018	L3 model or input info for L2
Stewart et al 2019	This work plays a critical role in evaluating stock specific threats from fisheries and identifies which fishing areas have the potential to affect those stocks (now need to repeat in other locations and for other stocks). L3 statistical method/model or input info for L2
Stewart et al 2010	Could be used to generate ideas on how to fold economic/social aspects into a cumulative risk assessment or to supplement ERAEF
Stobutzki et al 2001	The use of criteria maximizes what can be determined from the limited information available on individual species. The criteria include characteristics that are thought to influence the sensitivity of species to overfishing and the probability of extinction. The ranking is aimed at assisting researchers and managers to focus on the species that are most likely to be unsustainable or gaps in knowledge that affect the assessment of species' sustainability (fine-scale distribution of species vs overlap with commercial fishing; estimates of the removal rate; indirect impacts of trawling on species as current approach is all about direct effects). The criteria we have employed can be used to examine how management actions change the ranking of a species, and therefore its likely sustainability. The criteria on the recovery axis that can be influenced are the removal rate, the probability of breeding before capture and the mortality index. - e.g. via use of Turtle excluder devices (TEDs), bycatch reduction devices (BRDs), changes in closures or allowed effort levels. Sustainability plot shape.

Reference	Other relevant commentary
Suter 2008	Risk assessment in this context includes a variety of techniques: Statistical analysis of past frequencies of events, trend analysis, mechanistic modelling, and professional judgment to estimate how proposed actions, individual events, and poorly defined trends will affect the future. From the insurance context, risk assessment spread to the assessment of risks to the safety of people and property, health risk assessment (e.g., drugs, devices, and chemicals) and engineering risk assessment (e.g., reactor and aircraft safety). Red book laid out - provides a framework for human health risk assessment that included hazard identification, dose– response assessment, exposure assessment, and risk characterization. Hazard assessment paradigm (1979 workshops): This paradigm focused on the aquatic environment and emphasized 3 concepts. First, the hazard posed by a chemical is a function of the magnitude of the exposure concentration relative to the toxicologically effective concentration. Second, toxicity tests and studies of environmental transport and fate properties should be performed in tiers, beginning with simple and inexpensive studies. Third, as more tiers of testing are performed, uncertainty will decline, and the relative magnitudes of exposure and effective concentrations will become clear. 1990s updated added scoping & conceptual model step.
Szuwalski & Thorson 2016	Did see density dependent dynamics in ~75% of stocks and SSB dropped as F increases in about 50% of stocks. < 25% stocks did what most assessment models assume. The predictability of changes in F and SB based on these fitted models varied significantly across large marine ecosystem (LME), recruitment variability, maximum weight of the species fished and the ratio of minimum and maximum observed SB; predictability of changes in SB also varied across maximum length of the species fished, while predictability of changes in F also varied among habitat types. Counter-intuitive responses to fishing were common, corroborating evidence that population dynamics for many exploited species are influenced more strongly by the factors other than SB over the range of observed stock sizes. If stock productivity is influenced by factors other than SB and large environmental changes occur, past observations of catch and estimates of abundance will be less informative about expected future productivity. Longer maximum lengths and higher maximum weights (which both are related to older maximum ages) buffer against large interannual changes in SB and therefore improve predictability of changes in SB. Higher CVs of recruitment can make predicting F and SB more difficult, particularly if recruitment comprises a relatively large fraction of exploitable biomass. The influence of habitat on predictability of changes in F may stem from differential selectivity of gear types used in different habitats and differences in management (consider the targeting ability of a demersal trawl fishery and a pelagic purse seine fishery). LME was important for both changes in F and SB, perhaps due to differences in fisheries management or environmental forcing by geographic area. Higher minimum observed SB improved predictability in F and SB, perhaps because relatively low SB is correlated with increased variability in recruitment and hence less-predictable biomass dynamics. **Show "classical" production models do not effectively predict the dynamics of a large fraction of global fisheries (*perhaps warning against idea of only doing L3!!!*)**. Additional biological information may improve predictability (so use more sophisticated models then). Method does identify relatively unpredictable stocks, which could then be managed with greater precaution (***is this built in to L2 criteria?***)
Tallman et al 2019	PSA has indicated that the method is useful for distinguishing between regions where Charr populations may be more vulnerable to fishing compared to those less vulnerable, and for identifying area specific indicator stocks (corresponding to most vulnerable populations). With limited information and data collection, PSA results may be used as a precautionary step for guiding management decisions in decision analysis or management strategy frameworks. Knowledge of indicator populations will be highly valuable. Now calling on local/traditional knowledge to build into data poor methods. for establishing realistic monitoring and conservation plans
Thorpe et al 2016	The strong differential sensitivity of the LFI (and SSS) to fleet effort suggests that there is no simple relation between these indicators and average fishing mortality in a multi-fleet world. Past work found SSS provided greater power than the LFI to detect changes in community-wide F. However, for the wider range of fishing scenarios in the present analysis, the two indicators perform similarly with both showing differential sensitivity to the various fishing fleets. **Basic community indicators will not be interpretable without supporting information**. This outcome supports the conclusions of Fay et al. (2013), who emphasized the importance of expert knowledge of the fishery when interpreting community indicator values.
Trenkel 2017	Aiming for MMSY combined with MSY for individual stocks (or at least some upper exploitation limit preventing extinction of bycaught species) could be a way to achieve this ecological objective at the same time as the economic objective of maximum yield. Set cap to MTAC (1) t+1 =0.9ΔPPtMMSY. In allocating MMSY to species, consider life history (less to long lived), technical interactions etc, but make sure no F would see B < B0.2 for any species.

Reference	Other relevant commentary
Tuck & Wilcox 2009	
Tuck et al 2011	Although each population could have been ranked according to the degree of risk based on expert knowledge of their biology, behaviour, and bycatch rates, a semiquantitative method was preferred that could formalize this in a repeatable and impartial manner and be subsequently verified using expert opinion. Succinctly, it identified gaps in both fishery and seabird data (e.g. in spatio-temporal distributions and observer coverage), identified the species most at risk from fishing using a semiquantitative framework that is readily updateable as new information becomes available, identified fisheries, seasons, and areas of high bycatch, and provided a unified and focused study that enabled issues to be discussed and addressed with fishery managers in a more systematic manner than would have been possible otherwise. A key need in future ERA applications is an explicit link between the outcomes of the assessment and agreed management.
Utizi et al 2018	
Valsecchi et al 2017	
Walker & Abraham 2017	
Waugh et al 2009	Update through time as better biological information available. Management will change vulnerability estimate and overlap. Explore seasonality in future analyses
Waugh et al 2012	Assumes that sets by all fishing fleets have equal likelihood of capturing birds. This is unlikely to be true. However, information is lacking to provide finer definition of the relevant parameters. Need better data to improve this. Risk is not evenly spread among the fishing nations participating in the fishery. Risk is not simply proportional to the amount of fishing effort in the region, as differential vulnerability of species, and populations' ability to recover from occasional removals leads to effects being concentrated in some areas more than others. Specific hotspots of seabird–fishery interaction varied seasonally.
Wetzel & Punt 2017	The performance of alternative harvest control rules determined here could be expanded upon by future simulation studies to evaluate the impact of varying assumptions or dynamics. For example, within a single-stock framework additional explorations of alternative relationships between stock size and recruitment should be explored to identify the robustness of each strategy. Incorporating more complex population dynamics that vary over time may offer deeper insight about the potential performance of each of the harvest control rule across a range of changing environmental conditions. Additionally, extending this work to evaluate multi-stock fisheries would provide added context to the trade-offs among metrics and alternative harvest control rules. The exploitation of flatfish stocks as part of a mixed-stock fishery justifies the development of a multi-species operating model which could be used to evaluate the performance of alternative harvest control rules to maximize catches while limiting the risk of overfishing when applied across a complex of stocks with varying life histories.
Weidenmann et al 2017	In future add implementation error. Another potential modification to the current model might be to add changes in stock productivity associated with a regime shift.
Williams et al 2011	It is important to note that the PSA analysis measures potential for risk (hereafter referred to as 'risk'). A fully quantitative estimate of risk requires some direct measure of abundance or mortality rate for the unit in question, and this information is generally lacking for habitats. If that information were available, then an ERAEF Level 3 assessment could be conducted. Additional productivity attributes were considered, but they were not easily quantified and/or were not supported by sufficient information in most fishery areas. They included Habitat connectivity (source-sink recruitment dynamics of structural fauna); Chain of habitats (habitat fragmentation); Naturalness (historical level of fishing impact); and Export Production (flux of organic material to benthos). These kinds of additional attributes, some identified at finer resolution, could be used during Level 3 (fully quantitative) analyses, or in a Level 2 framework where concerns are focussed on particular habitats, species or smaller fishery areas. The overall result of the PSA for benthic habitat identified a degree of scale-dependence and relativity when applied to fisheries that operate over large areas, or in the Australian case, when applied at a national scale. As

Reference	Other relevant commentary
	habitat heterogeneity increases as a result of increasing the geographical area of assessment, the scope of individual attributes also increases while the options for ranking remain static (3 categories of high, medium and low risk). This can have the effect of reducing the sensitivity of rank scores. Depth is the obvious example because several attributes are strongly influenced by or correlated with it. Thus, sensitivity may be increased if one or a few fathoms (depth ranges characterised by fauna or physical habitat structures) are included within a single assessment. There is the need to assess 'residual risk' for habitats – establishing whether current management measures already mitigate habitat interactions identified as high potential risk at Level 2, will need to consider the variety of existing management measures that may be effective for habitat protection: spatial closures, gear restrictions, changing fishing patterns including effort reduction, bycatch limits, move-on rules and restoration initiatives. **For all areas, irrespective of data density, there is a need to account for cumulative impacts of different sub-fisheries (as well as other human pressures), and their combined impacts through time**. ***Does Roland method now mean just go straight to L3? What about for pelagic habitats?***
Williams et al 2017	Each of our three primary analyses provided evidence for stock structure within the broad southern Australian distribution of Blue-eye Trevalla: spatial differences in age and growth (phenotypic variation) and otolith chemistry of the adult life stage implied there was local and regional residency by adults. Dispersal potential indicated a broader scale connectivity amongst regional populations was likely during early life. By overlaying these spatial patterns, we identified four broad Blue-eye 'stock areas': West, South, East and Seamounts-Lord Howe. Each of these stock areas represents an interconnected 'metapopulation', i.e. a group of discrete adult sub-populations resident on the continental slope and seamounts without extensive migration between them. Stock areas do not reflect truly separated biological stocks because there is some exchange between them during pelagic early life history, and some of the adult subpopulations act as larger 'sinks' than others, i.e. benefiting more from recruitment derived from 'upstream' spawning areas. Recognise stock areas in management work - ***what about ERAs?***
Wyatt et al 2017	**The risk assessment approach provides spatially explicit information that highlights variation in in risk at multiple scales**. Each of these spatial scales - comparable to regional, state, and bay-wide planning processes - reveals areas of particular concern and adds detail to our general understanding of coastlines at risk. Across all habitats, our results indicate that rising sea surface temperatures, commercial fishing, and shipping consistently and disproportionally contribute to risk.
Zhang & Kinm 2011	When selecting indicators four considerations are used in the indicator selection process: (1) ease of understanding by users, (2) susceptibility to influence through management of human activities , and (3) measurability, using existing data or currently monitored information.
Zhang et al 2011	
Zhou & Griffith 2008	Walters and Martell (2002) suggested that any assessment that results in Fopt > 0.5M must be carefully justified. However, their populations could potentially be at risk from the cumulative impacts of both the state-regulated, and the illegal gillnet fisheries in the region. As a result, there is an urgent need to assess the cumulative impacts of fisheries on elasmobranch populations. The estimated fishing impacts in the present study are additive, so our SAFE method has the potential to study the cumulative impacts from fisheries and possibly other anthropogenic activities
Zhou et al 2007	It is essentially the same as the Tier 3 harvest control rule and similar to PBR. Reference points: umsm = fishing mortality rates corresponding to the maximum sustainable fishing mortality (MSM) at Bmsm (biomass that supports MSM); ulim = fishing mortality rate corresponding to limit biomass Blim, where Blim is defined as half of the biomass that supports a maximum sustainable fishing mortality (0.5Bmsm); and ucrash = minimum unsustainable fishing mortality rate that, in theory, will lead to population extinction in the longer term. Trialled various forms linking them to the intrinsic population growth rate r and instantaneous natural mortality M: Fmsm = r/2, Flim = 0.75 r, and Fcrash = r; Fmsm = M, Flim = 1.5 M, and Fcrash = 2M;

Reference	Other relevant commentary
Zhou et al 2013	Addressing assumptions of SAFE: First, for many data-poor species, the method assumed that the distribution of the species has a random or uniform distribution with their distribution range. A method to capture their heterogeneous distribution patterns could be more appropriate for many species. Second, a three-level gear efficiency was typically assumed for data-poor species, i.e., Q = 0.33, 0.66, and 1.0. This quantity directly affects the estimated fishing impact. For a rigorous assessment, an estimation based on data is preferred over assumed values. Furthermore, other fisheries have different geographic coverages, stock boundaries, species compositions, and data availability. Even for the SESSF, the cumulative impacts only included impacts from five Commonwealth sub-fisheries and none from overlapping state, international, or recreational fisheries. It is necessary to extend the existing methods, and develop new methods for these fisheries. The goal is to apply advanced statistical and mathematical techniques to limited existing data to quantify cumulative fishing effects from various sources. The techniques include parametric statistical distributions, Bayesian theory, as well as general mathematical calculations.... Can't just add SICA as subjective. In theory can add susceptibility in PSA. The Ranked Risk Assessment of Multiple Fisheries (RRAMF) method has made integrating qualitative risks possible by using relative catch as weighting when summing scores. WA does use consequence-likelihood scores in cumulative sense by using the branch structure of the component trees to combine multiple risk categories and treat like-with-like. Quantitative methods have the capacity to straightforwardly deal with cumulative effects in an ecological process.
Zhou et al 2019	The two major enhancements are the derivation of a more realistic gear efficiency and the estimation of fishing mortality from the heterogeneous density distribution. The data requirement of this method, beyond that required by the bSAFE method, is the need for shot-by-shot fishery or survey data to enable the estimates of gear efficiency and fish density. The comparison between bSAFE and eSAFE revealed quantitative but not qualitative improvement for the two species examined. The enhanced method can yield reasonably accurate estimates, which was demonstrated by a comparison with age structured fully quantitative stock assessments for four commercial species (<15% different). The comparison also showed the merit of first conducting a bSAFE analysis as it provides a useful indication of qualitative risk level (Zhou et al., 2016), and a decision can then be made regarding the merit of applying more intensive methods, such as eSAFE..... Hence, we suggest identifying major sources of impact e.g. by examining gear type and fishing effort and its distribution, and devoting analytical effort to a few major fishing sectors. This can significantly reduce the costs and effort in risk assessment of bycatch species. Many minor fishing sectors can be either ignored or given a small estimated fishing mortality consistent with a precautionary approach. The cumulative impact can then be assessed for the main fisheries, rather than all fisheries. While this is a single sector (fishing) cumulative impact approach, different types of stressors such as habitat loss and marine transportation could also be included if their impact in terms of mortality can be estimated—this cross-sectoral element is the next challenge for cumulative assessment.
Zhou et al 2016	The main difference between PSA and bSAFE is that the former derives availability based on presence in spatial grids that are fished whereas SAFE uses estimated actual area affected by fishing within grids (e.g. gear swept area).The eSAFE method does not require this assumption as it estimates fish density at different locations. SAFE can include escapement from gear as an additional parameter when the information is available, such as in the case of turtle excluder devises or bycatch reduction devises. The major difference between PSA and SAFE is that they use susceptibility attributes at different measurement scales, i.e. ordinal scales in PSA and a continuous ratio scale in SAFE. SAFE more flexible in how calculate overlap. Corresponding to productivity, SAFE uses sustainability reference points. PSA productivity score is insensitive for species with moderate or high productivity. The PSA risk score quickly increases to High as the SAFE F/Fmsy ratio only moderately increases. Although both methods classify most species at low risk, PSA has more species in its Medium and High risk categories than SAFE. PSA misclassifies (as high risk when not) ~50% of classically assessed species, but all false positive. SAFE gets <5-1% wrong, but about evenly split between false positive and false negative. Compared to classical assessments PSA way too conservative, SAFE tends to over-estimate Fmsy when the species is less productive, but slightly under-estimates Fmsy when the species is highly productive, but its F/Fmsy values are about right ~90% of the time. SAFE method outperforms PSA in nearly all cases for assessing fishing mortality risk. **For PSA to perform better need more informative scoring thresholds and attribute weighting (like Patrick does)**. Efforts to improve and validate the input data, particularly life-history parameters, will yield reductions in error rates. Both PSA and SAFE rely heavily on basic life-history parameters, but different values have been used in ERA and stock assessments. Cross-checking these data and applying the most reliable ones may improve the accuracy and facilitate further comparison between alternative approaches.
Zhou et al 2011	
Zhou et al 2009	

CONTACT US

t 1300 363 400
+61 3 9545 2176
e csiroenquiries@csiro.au
w www.csiro.au

AT CSIRO, WE DO THE EXTRAORDINARY EVERY DAY

We innovate for tomorrow and help improve today – for our customers, all Australians and the world.

Our innovations contribute billions of dollars to the Australian economy every year. As the largest patent holder in the nation, our vast wealth of intellectual property has led to more than 150 spin-off companies.

With more than 5,000 experts and a burning desire to get things done, we are Australia's catalyst for innovation.

CSIRO. WE IMAGINE. WE COLLABORATE. WE INNOVATE.

FOR FURTHER INFORMATION

CSIRO Oceans & Atmosphere
Beth Fulton
t +61 3 6232 5018
e **be**th.fulton@csiro.au
w www.csiro.au