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Redefining risk in data-poor fisheries

Richard E. Grewelle[1,2] | Elizabeth Mansfield[1,2] | Fiorenza Micheli[1,2,3] | Giulio De Leo[1,2]

[1]Hopkins Marine Station, Stanford University, Pacific Grove, CA, USA

[2]Department of Biology, Stanford University, Stanford, CA, USA

[3]Center for Ocean Solutions, Stanford University, Stanford, CA, USA

Correspondence
Richard E. Grewelle, Hopkins Marine Station, Stanford University, Pacific Grove, CA 93950, USA.
Email: regrew@stanford.edu

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Abstract

The productivity susceptibility analysis (PSA) is a widely used method to rapidly assess species risk to fishing activities in data-poor fisheries. A step in ecological risk assessments and used in data-poor assessment for sustainable fisheries certification programmes (e.g. MSC) and recommendation lists (e.g. Seafood Watch), the PSA is semi-quantitative, yet little attention has been given to the theoretical basis of this analysis. Current thresholds designating low-, medium- and high-risk categories divide the PSA plot by equal area, assuming area corresponds to likelihood. We show that plot area does not correspond to likelihood, however, and existing thresholds need revision due to the non-uniform distribution of vulnerability scores on the PSA plot. The probability of medium risk assignment increases with the number of attributes used to characterize productivity and susceptibility. Here, we present a novel and statistically robust method to derive vulnerability, where threshold values between the risk categories are adjusted with the number of attributes used in the assessment. Our comprehensive framework accounts for all variations in the method, including logarithmic scaling of axes, weighting of attributes and scoring procedures. Simulated results across a range of conditions and comparative evaluation of 302 species in five studies show that one-third of species may be re-categorized with the new PSA approach. Importantly, the existing PSA approach underestimates risk by up to 35% when compared with the new method. These findings have strong implications for management of data-poor fisheries. We recommend adoption of this approach to the PSA to better resolve species' risk.

KEYWORDS

ecosystem-based management, productivity susceptibility analysis, stock assessments, vulnerability

1 | INTRODUCTION

The turn of the century saw a revolution in fisheries management. From the reinforcement of the Magnuson-Stevens Act in 1996 and 2006 in the US, to the introduction of the Australian Environment Protection and Biodiversity Conservation Act (EPBCA) in 1999, to the more recent reformation to the European Common Fisheries Policy in 2013, and adoption of a "Negative Growth" strategy by the Chinese Ministry of Agriculture in 2017, major countries are adjusting their approaches to managing shared marine resources (Day et al., 1999; Hsu & Wilen, 1997; Huang & He, 2019; Salomon et al., 2014). Inevitably, time and money to manage these resources is allocated disproportionately to species of great economic interest, neglecting many other species and habitats, especially in low-income countries and for small-scale fisheries. Due to the ecological value of non-target or by-catch species, some countries, including the US and Australia, mandated monitoring of these otherwise neglected species to minimize by-catch mortality (Dalton et al., 2018; Day et al., 1999; Hsu & Wilen, 1997). Without the capacity to perform full stock assessments on all species of conservation or commercial interest, government agencies and scientists have devised risk assessment frameworks to provide preliminary estimates of vulnerability for species or other managed resources (Hsu & Wilen, 1997; Pilling et al., 2009).

One of the most used risk assessment frameworks was initially devised by Stobutzki et al. (2001) to examine the sustainability of the Australian Northern Prawn Fishery. Since 1999, this framework has been expanded and incorporated into ecosystem-based fisheries management (EBFM) programmes (Hazen et al., 2016; Townsend et al., 2019). This framework is called the productivity susceptibility analysis (PSA). Developed by Hobday et al. (2007, 2011) as part of a hierarchical approach called the Ecological Risk Assessment for the Effects of Fishing (ERAEF), the PSA assigns low, medium or high vulnerability scores to species at risk to fishing activities. Assignment occurs via scoring of attributes in both productivity and susceptibility categories. In its most popular form, there are 7 productivity attributes, each related to the capacity of the species to increase its population size, and 4 susceptibility attributes, each corresponding to potential impact on the species by fishing activities (Hobday et al., 2007, 2011). Subsequent modifications of this approach change or add relevant attributes in the assessment (Fujita et al., 2014; Micheli et al., 2014; Patrick et al., 2010). Each productivity and susceptibility attribute is valued 1, 2 or 3 as low, medium or high, respectively. Calculating the mean of each set of values yields two overall scores, one for productivity and one for susceptibility. After adjusting P by subtracting from 4, vulnerability (V) is calculated as the Euclidean distance of the point ($4 - P$, S) from (0, 0) (Hobday et al., 2007):

$$V = \sqrt{(4 - P)^2 + S^2} \tag{1}$$

The adjustment for P occurs because high productivity is associated with low vulnerability. The PSA uses P and S to calculate vulnerability as an index of risk analogous to risk metrics otherwise

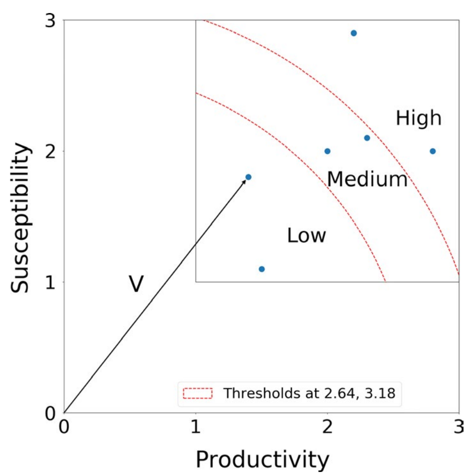


FIGURE 1 Vulnerability for each species is calculated as the distance of the plotted point from the origin (0,0). Productivity and susceptibility scores range from 1 to 3, and the 2×2 PSA plot is divided into thirds of equal area at $V = 2.64$ and $V = 3.18$

defined in the variety of existing risk assessment frameworks in ecology or other fields. Thresholds are given to divide the 2×2 P-S plane into three regions of equal area (Figure 1). Species with vulnerability scores <2.64 garner a low-risk designation, while species with scores above 3.18 are high risk (Hobday et al., 2007). Anything in between is medium risk (see Supporting Information for additional discussion on threshold derivation). These risk categories serve as rapid, easy-to-use indicators of management priority, and are often used as guidelines for downstream assessment. Those species interpreted as medium or high risk can be assessed in greater detail in the next step of the ERAEF framework or given higher priority in an agency's management plan. The vulnerability scores reflect relative risk and are not necessarily comparable across studies (Hobday et al., 2011).

The PSA has been used for a wide variety of fisheries by many agencies, scientists and organizations across the globe in the past two decades. A vulnerability index calculated from 10 productivity and 12 susceptibility attributes is used by NOAA for risk assessment of 166 US fisheries (Patrick et al., 2009, 2010). The PSA has been used now in dozens of published studies and government reports to evaluate over 1,000 fished and by-catch species. It has established itself as a widespread and rapid tool to augment our understanding of data-poor fisheries (Dee et al., 2019; Duffy et al., 2019; Micheli et al., 2014; Stobutzki et al., 2001; Stobutzki et al., 2002). It is used to inform sustainable seafood practices for businesses and the public (Marine Stewardship Council, 2019; Monterey Bay Aquarium, 2020). Through the years, the PSA has been honed and modified to individual purposes, including the weighting of attributes by perceived importance, as in Patrick et al. (2009, 2010). The number of attributes used varies significantly with each study as does the use of the geometric or the arithmetic mean to calculate the susceptibility score.

Given the variety of ways the PSA is applied, the scientific community has scrutinized the degree to which the PSA is able to provide a robust and unbiased assessment of the vulnerability of species. Interpretation of the PSA and related ecological risk assessment results (e.g. CARE, SAFE, multiple stressor EBRA, cumulative impact assessment) requires attention to inputs and model assumptions (Battista et al., 2017; Dowling et al., 2019; Halpern et al., 2009; Samhouri et al., 2019; Zhou et al., 2016). Hordyk and Carruthers (2018) evaluated the consistency of the vulnerability scores across interpretations of the PSA and reliability of the PSA to conventional stock assessments. They found that the PSA performed unfavourably in a variety of conditions, particularly in its ability to accurately assign risk when vulnerability was not extremely high nor extremely low. The failure to rank species accordingly unless risk could be easily identified prior to analysis limits the power of the PSA as a semi-quantitative risk assessment method. The potential utility of the PSA has been limited by several factors. A few of these reasons are mentioned previously or explicitly tested, including correlation among attributes, use of uninformative attributes, use of ineffective weighting schemes, assignment of precautionary scores to species when data are unavailable, or even the quality of the data used to perform the analysis (Duffy & Griffiths, 2017; Hordyk & Carruthers, 2018). Other reasons that deserve attention include the type of mean used (geometric vs. arithmetic) for the susceptibility score and the number of attributes used; both factors warrant changing the thresholds used for risk categorization.

Here, we show that a major problem with the PSA is how vulnerability and the associated risk categories have been derived. As constructed, the three risk categories are divided by two vulnerability thresholds. According to Hobday et al. (2007), "The divisions between these risk categories are based on dividing the area of the PSA plots into equal thirds. If all productivity and susceptibility scores (scale 1–3) are assumed to be equally likely, then 1/3rd of the Euclidean overall risk values will be >3.18 (high risk), 1/3rd will be between 3.18 and 2.64 (medium risk), and 1/3rd will be lower than 2.64 (low risk)" (Hobday et al., 2007). This assumption is not true because area does not correspond to probability on the PSA plot. Due to the central limit theorem, productivity and susceptibility scores will cluster around the mean, and therefore plotted fisheries will cluster toward the centre of the PSA plot. Independent of the fishery analysed, the PSA will produce middling vulnerability scores with higher frequency than extremely low or high scores. This effect becomes more dramatic as the number of independent attributes increases (Figure 2). For these reasons, the existing risk categories do not represent the likelihood of a species receiving a vulnerability score and therefore are not capable of appropriately assigning risk. This fact may partially explain the inability of the PSA to appropriately discern risk in mid-range vulnerability scores as found by Hordyk and Carruthers (2018). To remedy this problem, it is crucial to adjust risk thresholds to reflect the statistical properties of the PSA plot defined by the central limit theorem as well as the assumptions used in each study for which the PSA is used. The number of independent attributes and the type of mean used to score productivity and susceptibility can have dramatic effects on risk categories.

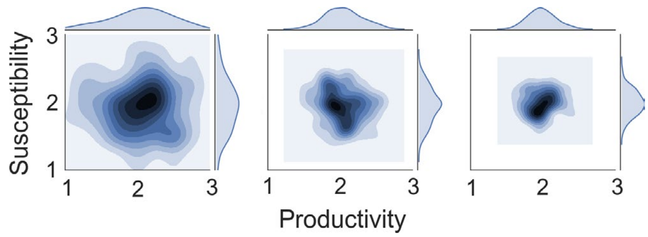


FIGURE 2 Kernel density plots showing the bivariate Gaussian distribution produced as a result of the scoring of productivity and susceptibility. More attributes used in scoring yields higher density plots. From left to right: 4 attributes each to calculate P and S, 10 attributes each, and 15 attributes each

The purpose of this paper is to make available a revised PSA with greater discriminatory power as the number of attributes increases and analysis assumptions change, so the PSA can be applied reliably across fisheries. We provide a statistically robust foundation to derive vulnerability values and thresholds for risk categories. This new approach addresses issues with correlation between attributes; handles any weighting scheme, axis scaling (multiplicative vs. additive) and number of attributes; and provides recommendations for scoring procedures. Provided in this paper and the supplement are theoretical and empirical examples of the use of this new method. To illustrate the different outcomes between the standard PSA (sPSA) and our newly proposed "revised PSA" (rPSA), we report the differences achieved between the two approaches when applied to NOAA's report in 2008 on 166 federally managed species (Patrick et al., 2009, 2010) and 4 other case studies, together representing 302 fisheries across 4 continents. Full functionality of this method is accessible via Excel, R and Python software packages accompanying this paper at https://github.com/grewelle/rPSA, though conversion tables are provided in the Supporting Information that allow the same procedures to be done manually.

2 | METHODS

In the PSA, productivity and susceptibility are each calculated as the mean of several attributes that take values 1, 2 or 3, corresponding to low, medium or high productivity/susceptibility, respectively. These three values correspond to biologically relevant cut-offs for each attribute that are consistent across fisheries (Hobday et al., 2007, 2011). The cut-offs serve to segregate the range of biological values for each attribute into bins standardized by percentile. When bins have equal size, namely 1 = 0%–33%, 2 = 33%–67% and 3 = 67%–100%, then the expected standard deviation for each attribute value is computed as follows:

$$\sigma = \frac{\sqrt{(1-2)^2 + (2-2)^2 + (3-2)^2}}{3} = \sqrt{\frac{2}{3}}$$

If scoring is distributed 1 = 0%–25%, 2 = 25%–75%, 3 = 75%–100%, the standard deviation would be

$$\sigma = \frac{\sqrt{(1-2)^2 + 2(2-2)^2 + (3-2)^2}}{4} = \sqrt{\frac{1}{2}}$$

Choosing productivity and susceptibility attributes is a key step in performing a robust analysis. This matter and the matter of weighting of influential attributes to produce a weighted mean are discussed but not statistically treated in previous works (Duffy & Griffiths, 2017; Hordyk & Carruthers, 2018; Patrick et al., 2009, 2010). The method presented here statistically treats both considerations as part of a flexible framework to compute vulnerability under a variety of conditions.

When attributes are judged sufficiently independent, each attribute is an independent and identically distributed random variable. Let each attribute value for productivity be given as $p_i \in \{p_1, p_2 \ldots, p_N\}$, where N is the number of productivity attributes assessed in the PSA. Similarly, M susceptibility attribute values can be given as $s_j \in \{s_1, s_2, \ldots, s_M\}$. Each productivity attribute value p_i is calculated by subtracting the initial value from 4 to produce a plot with origin (1, 1). The productivity score is calculated as the arithmetic mean of productivity attribute values, while the susceptibility score is calculated either as the arithmetic (additive) or geometric (multiplicative) mean of susceptibility attribute values. To generalize, presented are methods for which the attributes of both productivity and susceptibility can be additive or multiplicative.

2.1 | Additive scoring

In the additive case, productivity and susceptibility scores for each species can be computed as the arithmetic mean of the corresponding attribute values, and according to the central limit theorem, the distribution of scores approaches Gaussian (normal). We can define random variables, P and S, $P \sim N(\mu_p, \sigma_p)$ for productivity and $S \sim N(\mu_s, \sigma_s)$ for susceptibility. σ_p is equivalent to the standard deviations shown above when productivity attributes are scored with the same bin sizes, and likewise for σ_s when the scoring procedure is standardized for all susceptibility attributes. As values for attributes can only take values 1, 2 or 3, each with equal probability, the arithmetic mean is:

$$\boxed{\mu_p = \mu_s = 2}$$

and associated standard error of the mean:

$$SE_p = \frac{\sigma_p}{\sqrt{N}} = \sqrt{\frac{2}{3N}} \quad SE_s = \frac{\sigma_s}{\sqrt{M}} = \sqrt{\frac{2}{3M}} \tag{2}$$

The standard error of the mean decreases with increasing number of attributes used to calculate P and S. Accordingly, P and S scores for a set of species naturally clump toward the middle of the PSA plot (Figure 2).

2.1.1 | Additive weighting

Where weighting of each attribute is needed, the mean does not change, but productivity and susceptibility for each species $k \in \{1, 2, \ldots, K\}$ are expressed as

$$P_k = \sum_{i=1}^{N} w_i p_{i,k} \quad S_k = \sum_{j=1}^{M} w_j s_{j,k} \tag{3}$$

where $0 \le w_i, w_j \le 1$ is the weight given to each attribute, and $\sum_{i=1}^{N} w_i = \sum_{j=1}^{M} w_j = 1$. When weighting has been applied in the PSA, values of weights took whole integers. To convert whole integer weights to w, simply divide the whole integers by the sum of all integer weights used for the each set of attributes. The standard error of the weighted mean is:

$$SE_p = \sigma_p \left(\sum_{i=1}^{N} w_i^2\right)^{1/2} = \left(\frac{2}{3}\sum_{i=1}^{N} w_i^2\right)^{1/2} \quad SE_s = \sigma_s \left(\sum_{j=1}^{M} w_j^2\right)^{1/2} = \left(\frac{2}{3}\sum_{j=1}^{M} w_j^2\right)^{1/2} \tag{4}$$

2.2 | Multiplicative scoring

In the multiplicative case, the mean is geometric and the distribution of values the attributes take is lognormal. This distribution can be transformed to Gaussian given the nature of logarithmic identities that the mean is:

$$\mathrm{GM}(S) = \left(\prod_{j=1}^{M} s_j\right)^{\frac{1}{M}} = e^{\frac{1}{M}\sum_{j=1}^{M} \log s_j} \tag{5}$$

Therefore by taking the natural logarithm of each attribute, the resulting distribution is normal around the arithmetic mean of the log-transformed values. This gives $\log P \sim N(\log \mathrm{GM}(P), \sigma_{\log P})$ and $\log S \sim N(\log GM(S), \sigma_{\log S})$. The log-transformation produces a symmetric distribution that allows direct comparison with distributions around an arithmetic mean in the case where one axis in a PSA plot is additive (often productivity) and the other axis is multiplicative (often susceptibility). Let $\mu_{\log P}$ and $\mu_{\log S}$ be the arithmetic means of the log-transformed attribute values.

$$\mu_{\log P} = \mu_{\log S} = \frac{\log(6)}{3}$$

Standard error of the mean is:

$$SE_{\log P} = \frac{\sigma_{\log P}}{\sqrt{N}} = \frac{0.4536}{\sqrt{N}} \quad SE_{\log S} = \frac{\sigma_{\log S}}{\sqrt{M}} = \frac{0.4536}{\sqrt{M}} \tag{6}$$

2.2.1 | Multiplicative weighting

Where weighting of each attribute is needed, the geometric mean is expressed as

$$\mathrm{GM}(P) = \left(\prod_{i=1}^{N} p_i^{w_i}\right)^{\frac{1}{N}} \quad \mathrm{GM}(S) = \left(\prod_{j=1}^{M} s_j^{w_j}\right)^{\frac{1}{M}} \tag{7}$$

Log-transforming yields

$$P_k = \sum_{i=1}^{N} w_i \log p_{i,k} \quad S_k = \sum_{j=1}^{M} w_j \log s_{j,k} \tag{8}$$

The mean of the data does not change with weighting. The corresponding standard error of the mean is:

$$\begin{aligned} SE_{\log P} &= \sigma_{\log P}\left(\sum_{i=1}^{N} w_i^2\right)^{1/2} = \left(0.2058\sum_{i=1}^{N} w_i^2\right)^{1/2} \\ SE_{\log S} &= \sigma_{\log S}\left(\sum_{j=1}^{M} w_j^2\right)^{1/2} = \left(0.2058\sum_{j=1}^{M} w_j^2\right)^{1/2} \end{aligned} \tag{9}$$

2.3 | The risk axis

With calculated mean and standard error or associated log-transformed values for productivity and susceptibility, we can define a bivariate Gaussian distribution $\mathbf{X} \sim N_2(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $\mathbf{X}$ is a random column vector. $\boldsymbol{\mu}$ is the mean column vector $[\hat{\mu}_p, \hat{\mu}_s]^T$ where $\hat{\mu}_p = \mu_p$ or $\mu_{\log P}$ and $\hat{\mu}_s = \mu_s$ or $\mu_{\log S}$. $\boldsymbol{\Sigma}$ is the covariance matrix. Let $\widehat{SE}_p = SE_p$ or $SE_{\log P}$ and $\widehat{SE}_s = SE_s$ or $SE_{\log S}$. The values of $\hat{\mu}$ and $\widehat{SE}$ are determined by whether attributes are treated as multiplicative or additive. Assuming productivity and susceptibility are statistically independent, the covariance matrix takes the form

$$\boldsymbol{\Sigma} = \begin{pmatrix} (\widehat{SE}_p)^2 & 0 \\ 0 & (\widehat{SE}_s)^2 \end{pmatrix} \tag{10}$$

The probability density of such a bivariate distribution is elliptical, with elliptical isoclines representing standard deviations from the mean. The risk axis is the line whose slope is the reciprocal of the slope of the line that divides portion of the ellipse in the 1st and 3rd quadrants equally and passes through the mean $(\hat{\mu}_p, \hat{\mu}_s)$. Risk as a function of productivity and susceptibility of a species increases moving along the axis up and to the right. The equation for this axis can be expressed as

$$S - \hat{\mu}_s = \frac{\widehat{SE}_p}{\widehat{SE}_s}(P - \hat{\mu}_p) \tag{11}$$

Let $\mathbf{r}$ be the risk vector in the first quadrant of a coordinate plane with origin at the mean $(\hat{\mu}_p, \hat{\mu}_s)$ and defined by Equation 11. Any vector $\mathbf{x_k} = [P_k - \hat{\mu}_p \; S_k - \hat{\mu}_s]^T$ can be projected along this risk vector to map $\mathbf{X}$ to one dimension. After mapping all points to the risk vector, the distance of each point $x_k = (P_k, S_k)$ from the mean is the magnitude of the projection:

$$D(\mathbf{x_k}) = \frac{\mathbf{r} \cdot \mathbf{x_k}}{|\mathbf{r}|} \tag{12}$$

Projecting points along the risk axis does not change the mean, but the resulting distribution along the risk axis is Gaussian and has a univariate variance and standard error of the mean. The projection

$$\mathrm{proj}_{\mathbf{r}}(\mathbf{X}) = [\mathbf{r}(\mathbf{r}^T\mathbf{r})^{-1}\mathbf{r}^T]\mathbf{X} \tag{13}$$

results in a linear transformation of $\mathbf{X}$. It can be shown that linear transformation preserves the mean and the standard error is expressed as

$$\widehat{SE}_{\mathbf{r}} = \frac{\sqrt{2}\widehat{SE}_p\widehat{SE}_s}{\sqrt{\widehat{SE}_p^2 + \widehat{SE}_s^2}} \tag{14}$$

2.4 | Thresholds for risk categories

The cumulative distribution function for this Gaussian distribution is:

$$Pr(D(\mathbf{x_k}) \le T) = \frac{1}{2} + \frac{1}{\sqrt{\pi}}\int_0^{\frac{D(\mathbf{x_k})}{\widehat{SE}_{\mathbf{r}}\sqrt{2}}} e^{-t^2}\,dt \tag{15}$$

where T is the threshold of interest. One can define $Pr_1(\cdot) = \frac{1}{3}$ and $Pr_2(\cdot) = \frac{2}{3}$ to divide the set of points into 3 equal bins by probability. Solving the set of equations yields thresholds T_1 and T_2. Because $Z^{-1}\left(\frac{1}{3}\right) = -0.431$ and $Z^{-1}\left(\frac{2}{3}\right) = +0.431$, we can set $T_1 = -0.431(\widehat{SE}_r)$ and $T_2 = 0.431(\widehat{SE}_r)$ units from the mean along the risk axis to divide the possible set of values into equal thirds. A way to define thresholds in two dimensions is by constructing two lines L_1 and L_2 orthogonal to the risk axis that intersect the risk axis at T_1 and T_2, respectively:

$$L_1: S = -\frac{\widehat{SE}_s}{\widehat{SE}_p}P + \hat{\mu}_s + \frac{\widehat{SE}_s}{\widehat{SE}_p}\hat{\mu}_p - \frac{2(0.431)\widehat{SE}_s}{\sqrt{2}} \tag{16}$$

$$L_2: S = -\frac{\widehat{SE}_s}{\widehat{SE}_p}P + \hat{\mu}_s + \frac{\widehat{SE}_s}{\widehat{SE}_p}\hat{\mu}_p + \frac{2(0.431)\widehat{SE}_s}{\sqrt{2}} \tag{17}$$

Along these two lines and any line parallel to these, any given point has coordinates P_k and S_k that satisfy the equation

$$P_k\widehat{SE}_s + S_k\widehat{SE}_p = V \tag{18}$$

where V is a standardized risk score that represents vulnerability of a species to fishing activities. For L_1 and L_2, V is

$$L_1: V = -\sqrt{2}(0.431)\widehat{SE}_p\widehat{SE}_s + \hat{\mu}_p\widehat{SE}_s + \hat{\mu}_s\widehat{SE}_p \tag{19}$$

$$L_2: V = \sqrt{2}(0.431)\widehat{SE}_p\widehat{SE}_s + \hat{\mu}_p\widehat{SE}_s + \hat{\mu}_s\widehat{SE}_p \tag{20}$$

Grouping into low, medium or high risk is made simple by this relationship. After calculating the standard error and mean for each component, given any point (P_k, S_k), grouping is as follows:

$$\text{Low:}\; P_k\widehat{SE}_s + S_k\widehat{SE}_p \le -\sqrt{2}(0.431)\widehat{SE}_p\widehat{SE}_s + \hat{\mu}_p\widehat{SE}_s + \hat{\mu}_s\widehat{SE}_p$$

$$\text{Med:}\; -\sqrt{2}(0.431)\widehat{SE}_p\widehat{SE}_s + \hat{\mu}_p\widehat{SE}_s + \hat{\mu}_s\widehat{SE}_p < P_k\widehat{SE}_s + S_k\widehat{SE}_p < \sqrt{2}(0.431)\widehat{SE}_p\widehat{SE}_s + \hat{\mu}_p\widehat{SE}_s + \hat{\mu}_s\widehat{SE}_p$$

$$\text{High: } \sqrt{2}(0.431)\widehat{SE}_p\widehat{SE}_s + \hat{\mu}_p\widehat{SE}_s + \hat{\mu}_s\widehat{SE}_p \leq P_k\widehat{SE}_s + S_k\widehat{SE}_p$$

To make this categorization easier, a table is provided in the supplement with a list of values for V at L_1 and L_2 under various conditions. Those wanting to quickly categorize a set of points can use Equation S12 and the Table in Supporting Information. The supplement addresses extensions of these methods, including dependency among attributes and among axes. Vulnerability (V) is defined relative to the study conditions, and caution should be used to make cross-study comparisons when scoring procedures and input assumptions differ. However, cross-study comparisons can be made with the strict formulation of vulnerability as a probability:

$$V_p = Pr\,(D(\mathbf{x_k}) \leq T) \in (0, 1) \tag{21}$$

V and V_p are equally valid statistical metrics of vulnerability, with V holding an advantage in ease of calculation. V_p holds values between 0 and 1 and can be translated between studies and compared directly to probabilities corresponding to threshold values (e.g. 1/3 and 2/3).

3 | ANALYSIS

The extent to which the results of the rPSA differ from results of the sPSA depends on how dramatically the risk thresholds change. Management priorities are shaped by risk categorization of species, so below we compute vulnerability scores and associated risk categorization using both PSA approaches on (a) synthetic data representing 100 simulated species evaluated across 3–15 productivity and susceptibility attributes and (b) 5 empirical cases studies, including the 2008 NOAA report on 166 commercial stocks by Patrick et al. (2009, 2010). We evaluate the proportion of species that change risk category when the new approach is applied as well as the net shift in average risk. Net shift in average risk is defined as the difference between the proportion of species moved into a higher-risk category and the proportion of species moved into a lower-risk category with the new approach.

3.1 | Sensitivity analysis of a synthetic dataset

One hundred simulated species were randomly (uniformly) assigned attribute values for every permutation of number of attributes from 3 to 15 for productivity and susceptibility. Attributes were equally weighted, and both productivity scores were arithmetic means of the associated attribute values. Susceptibility scores were arithmetic means or geometric means, reflecting the use of both additive and multiplicative models for susceptibility scores in PSA studies. Vulnerability scores were calculated for each species for both the sPSA and rPSA. We categorized species according to the respective thresholds for both methods and, for each permutation, computed the mean fraction of species that change categorization under the new method averaged from 1,000 bootstrap replicates (standard error < 0.01 for each value). We demonstrate that the number of attributes has a strong effect on categorization as expected from clumping of species toward the centre of the plot. Up to 52 percent of species are reassigned to another risk category when the new method is applied (Figure 3), with up to 35 percent net increase in risk observed (Figure 4). Universally, the rPSA is expected to recategorize species and do so in a way that favours higher-risk assignment than previously recognized through the sPSA. These effects are largely due to lumping of many species in the medium-risk category and the curvature of the thresholds in the sPSA. When the geometric mean is used for susceptibility (Figure 3a), higher-risk assignment occurs more frequently than when the arithmetic mean is used (Figure 3b).

3.2 | Empirical case studies

To illustrate the use of this method on an empirical data set, we applied the existing and new PSA methods to the 2008 NOAA report by Patrick et al. This study includes 166 species in managed North American fisheries. In this study, screening methods were used to remove redundant attributes in the analysis. This resulted in 10 attributes for productivity and 12 for susceptibility (Section 3 in Supporting Information). When attributes were not applicable or informative for a species, these attributes were not scored, resulting in fewer attributes used to yield productivity and susceptibility scores. Attributes in this study are weighted according to perceived importance, and the productivity score is given as the arithmetic mean of corresponding attribute values. The susceptibility score is given as the arithmetic mean (Figure 5a) and the geometric mean (Figure 5b) of corresponding attribute values. Scoring of attributes is partitioned in 3 equal-sized categories, whereby assignment of values 1, 2 or 3 could occur uniformly. We analysed the data set using both the standard PSA approach and the new, revised form. Figure 5 shows the results of the analysis. Size and shading of dots corresponds to the number of species sharing the same coordinates on the PSA plot. Blue species are categorized as lower risk with the new method, red species are now higher risk than previously assessed, and grey species were assigned in the same risk category between methods. When P and S were additive, 10% ($n = 16$) of species were assigned to a lower-risk category with the new method, 25% ($n = 42$) of species were assigned to a higher-risk category with the new method, and 65% (n = 108) of species retained their risk categorization. An overall reassignment of 35% (n = 58) of species and a net increase in risk of 16% with the new method reveal striking changes in the conclusions of the PSA study of these fisheries. These percentages align well with the simulation results, which predict reassignment of 39% of species and net increase in risk of 13% for a PSA study using 10 productivity and 12 susceptibility attributes. When P was additive and S was multiplicative, 1% (n = 2) of species were assigned to a lower-risk category with the new

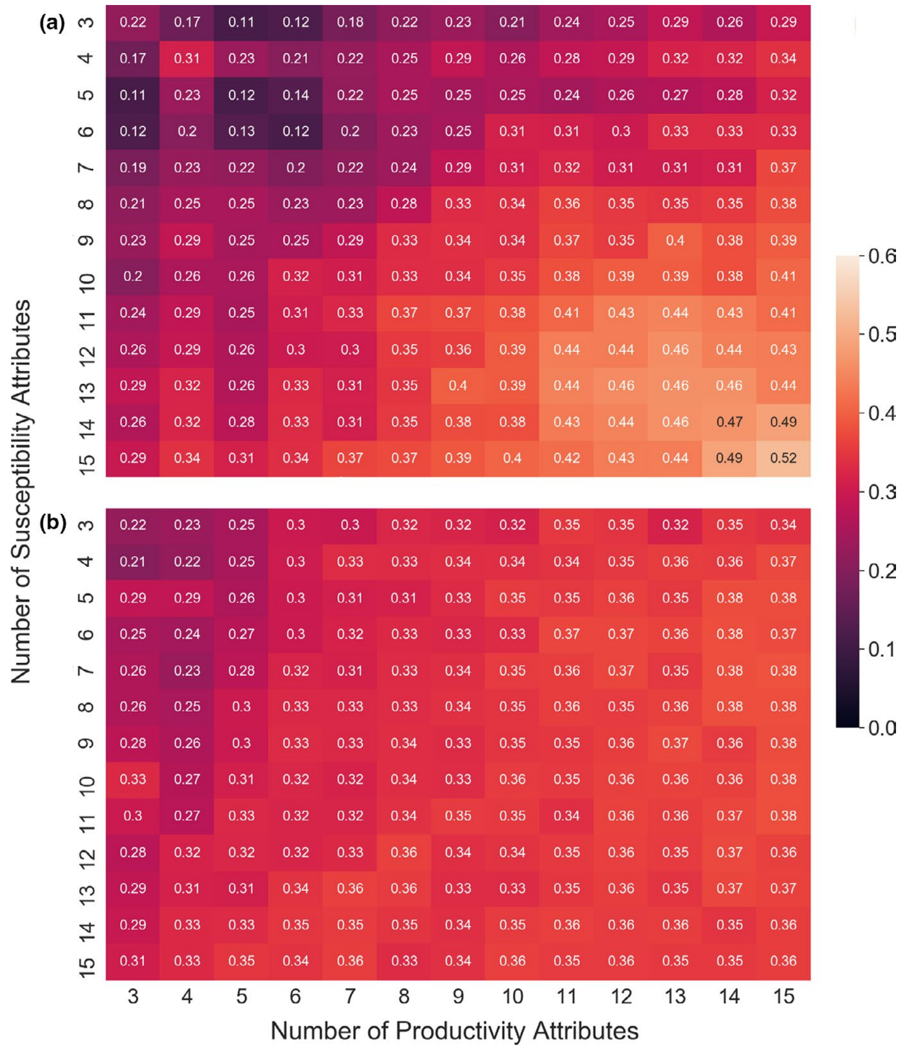


FIGURE 3 Heat map representing the proportion of species that change risk category when applying the new PSA approach to 100 simulated species. Values are the average of 1,000 bootstrap replicates. (a) *P* and *S* are arithmetic means (additive model) of 3–15 attribute values. Re-categorization is more pronounced as more attributes are used in the analysis. (b) *P* is the arithmetic mean and *S* is the geometric mean (multiplicative model) of 3–15 attribute values. Re-categorization is pronounced as more P attributes are used, though this trend is weaker as more *S* attributes are used, reflecting the differing results between the multiplicative and additive models

method, 37% (n = 61) of species were assigned to a higher-risk category with the new method, and 62% (n = 103) of species retained their risk categorization. 38% of species were reassigned with a net increase in risk of 36% with the new method, matching well to the 34% predicted via simulation for both values. Additionally, the sPSA assigns 34 species low risk, 91 species medium risk and 41 species high risk. There is a disproportionate number of medium-risk species due to clumping of species toward the centre of the PSA plot as previously discussed. No species are found in lower extremes of the plot, and some species are found in upper extremes of the plot due in part to a precautionary approach to scoring of attributes without sufficient data. With the new method, 34 species are low risk, 32 are medium risk, and 100 are high risk. Species are more evenly distributed in low and medium categories, with a larger bulk of species in the high-risk category, representative of the precautionary scoring approach used.

The PSA is used widely to assess data-poor fisheries with different needs and contexts. Its use across six continents demonstrates the flexibility of the approach, and the differences in species risk categorization between the sPSA and the rPSA are not equal between studies. The set of attributes used, model assumptions, as well as the species assessed play roles to determine the magnitude of the change observed when applying the rPSA. We compare five previously published studies, conducted across 4 continents and 302 species: Sri Lanka (12 species, 11 attributes) (Cotter & Lart, 2011), aquarium trade (61 species, 22 attributes) (Dee et al., 2019), Taiwan (52 species, 12 attributes) (Lin et al., 2020), North America (166 species, 22 attributes) (Patrick et al., 2009) and Galapagos (11 species, 11 attributes) (Pontón-Cevallos et al., 2020). Figure 6 demonstrates that despite the range of inputs to the PSA, a significant proportion of species is re-categorized with the rPSA. Moreover, in all five case studies, there is an observed net increase in risk assessed with the rPSA. Differences in each study tend to be highest when (a) a wide range of species is analysed, (b) more attributes are used, and (c) a multiplicative model is used for susceptibility (Section 3 in Supporting Information). These observations are expected given simulated results in Figure 4 and empirical results in Figure 5 and Figure S4 for the Patrick et al. study, which satisfies all 3 criteria.

4 | DISCUSSION

Given here is a new approach to the PSA that is broad in scope to account for weighting of attributes, any number of attributes used

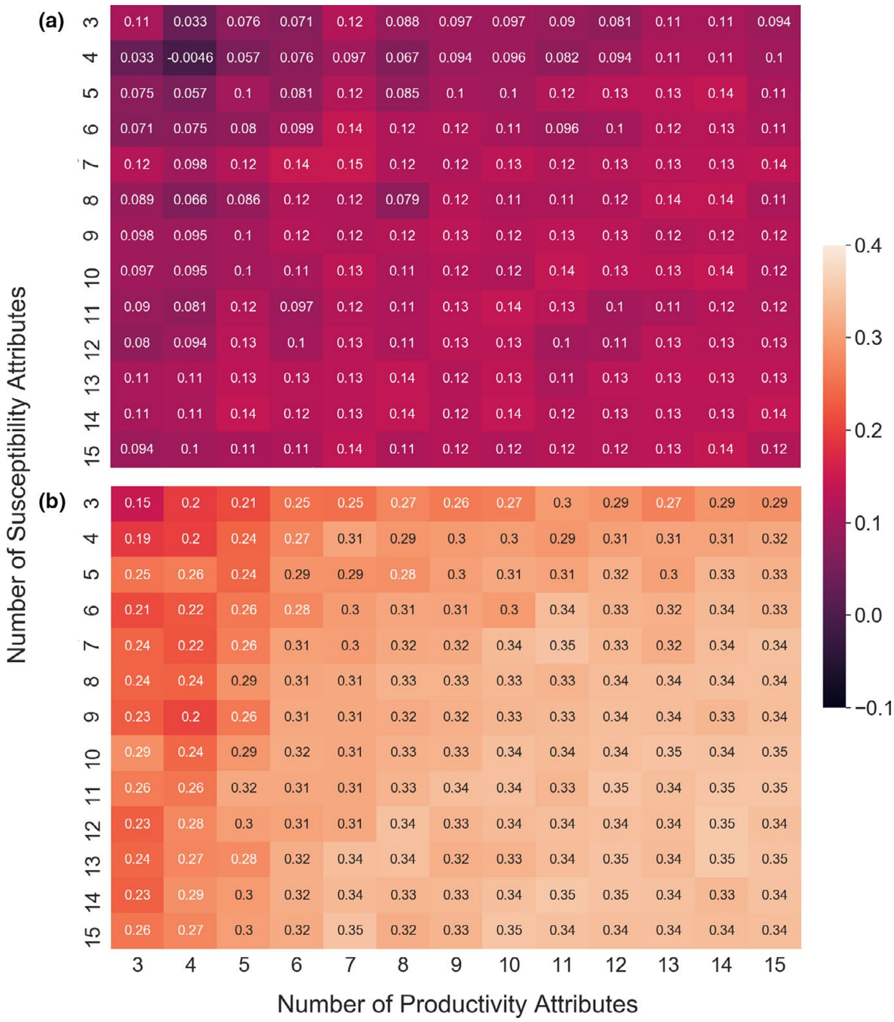


FIGURE 4 Heat map representing the net proportional change in risk when applying the new PSA approach to 100 simulated species. Values are the average of 1,000 bootstrap replicates. (a) *P* and *S* are arithmetic means (additive model) of 3–15 attribute values. In all but one permutation, the new method assessed risk higher than the existing PSA. (b) *P* is the arithmetic mean and *S* is the geometric mean (multiplicative model) of 3–15 attribute values. Net proportional change in risk is higher when the multiplicative model is used for *S* because the lower mean ($S = 1.8$ rather than 2) and shape of the resulting thresholds in the rPSA strongly favours higher risk assignment compared to the sPSA

to calculate productivity and susceptibility, and use of additive or multiplicative models for productivity and susceptibility. Quality of information can be easily incorporated without loss of application as components of the weights given to each attribute. This revised method is adaptable to any level of mathematical training. Modifications are possible for large analyses with complex assumptions. Those variations are outlined in the methods and supplement, and software packages in Excel, R and Python accompany this publication. Vulnerability calculations and risk categorization can also be performed manually via the conversion tables provided in the supplement. The tables have simplified the analysis to four values, such that results are achieved rapidly. Vulnerability values (V_p) in this method are standardized, so comparisons can be made across studies with shared attributes, and species can be ranked accordingly.

Analyses examining the differences between the results of the sPSA and the new approach proposed (rPSA) here show significantly improved resolution of risk for the species in the middle of the PSA plot. Because there is an increasing probability for species to fall in the middle region of the PSA plot as more attributes are used in the analysis, we derive a statistically robust method to compute vulnerability and define risk categories according to the expected distribution of vulnerability scores rather than dividing the plot into three regions of equal area. With the new method, fewer species are now categorized as medium risk. Re-analysis of the Patrick et al. study of 166 North American species demonstrates this phenomenon with the medium-risk category downsizing from 91 species to 32. The magnitude of the shift of species to new risk categories with the new method can be large. In some case studies, more than one-third of species shifted to new risk categories. This aligned well with the expected percent of re-categorization as predicted with simulation, and for a reasonable range of attributes used in a PSA, this can vary from 11% to 52%. The majority of re-categorized species are mid-risk species that are categorized low or high risk with the rPSA. Due to the difference in curvature of the thresholds between the sPSA and rPSA, other species shift categorization, with a net shift to higher-risk categories using the rPSA. Compared to the rPSA, the sPSA underestimates overall risk by 0%–35% across a range of simulated scenarios and does so by 36% specifically for the 166 species in the NOAA vulnerability assessment presented by Patrick et al. Applying the rPSA to four other case studies demonstrated similar patterns, with the magnitude of re-categorization depending on study assumptions and analysed species, and net increase in assessed vulnerability in all studies (Figure 6 and Figure S5).

Together our analysis shows that the existing framework to assess vulnerability through the PSA incompletely resolves and under-evaluates risk of species to fishing pressure, and may therefore jeopardize the utility of the precautionary approach used by most to assign higher risk to species when data are limited for certain attributes (Hobday et al., 2007, 2011). Improper resolution paired with incomplete data clouds prioritization of vulnerable species for downstream analysis or management. We recommend attention be given to the practice of high-risk assignment in the absence of data as the field moves toward a more refined means to assess data-poor fisheries. If limited in use, this type 1 error in risk assignment serves to benefit the few species that would have been missed due to lack of data in a vulnerability analysis. However, if applied to many species, this practice may dilute directives and resources to serve species in most critical need. Future work is needed to determine whether agnostic assignment of risk (with medium scores) rather than precautionary assignment of risk (with high scores) leads to improved efficiency in downstream evaluation proceeding the rPSA.

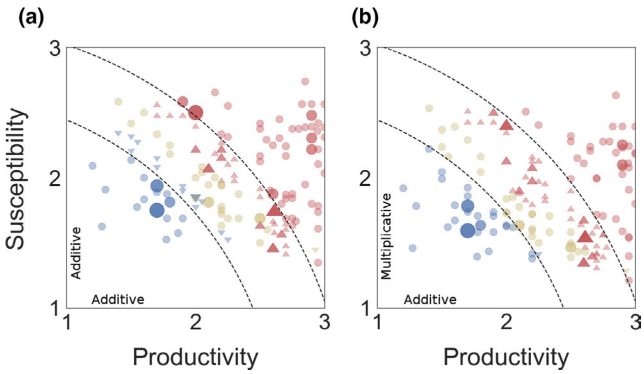
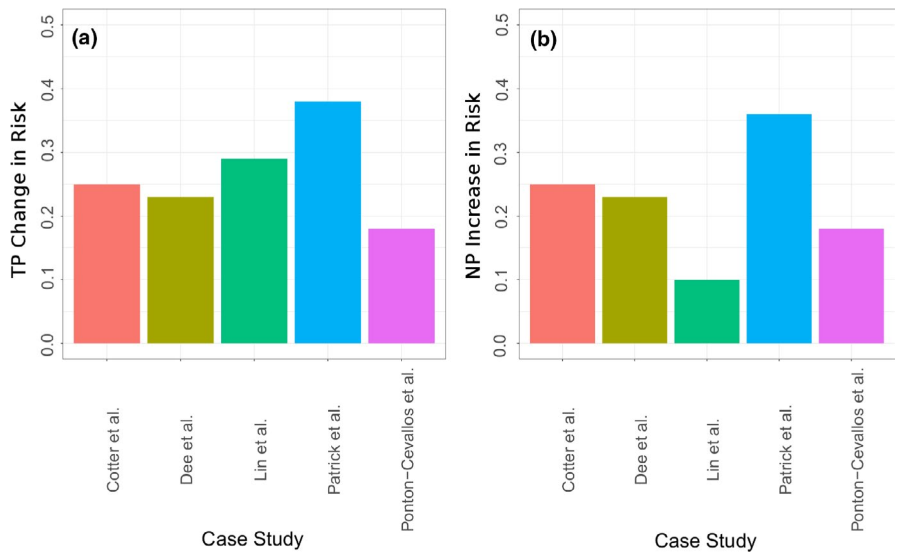


FIGURE 5 One hundred and sixty-six North American species from Patrick et al. plotted on a PSA plot. Shade and area of the points correspond to the number of species at each coordinate. Down facing arrows represent species that are designated a lower risk categorization with the new PSA method compared to the existing method. Species with up facing arrows are those designated a higher risk categorization. Circles represent species that are designated the same risk categorization. Colours give the risk categorization assigned by the rPSA (blue = low, yellow = medium, red = high). The dotted lines are given to show thresholds of the existing method at $V = 2.64, 3.18$. New thresholds vary with each species in this study because not all species received values for all attributes. Therefore, these thresholds are not plotted. (a) P and S are arithmetic means (additive model) of attribute values. (b) P and S are arithmetic and geometric (multiplicative model) means, respectively, of attribute values

Application of the rPSA in many cases will yield substantially different results than the standard PSA. Better resolution of species' risk will both streamline the next step of the ERAEF and shift management priorities for many marine species. With greater pressure to determine the impact of fisheries, this new framework is a step toward creating a robust, reliable method to assess small-scale or data-deficient systems. Alone this new method represents only a small piece of efforts to assess these fisheries. Efforts to improve scoring through standardization, use of independent and informative attributes, and broad acquisition of available data is key to improving accuracy. Even still, when using the ERAEF framework, analyses only provide recommendations to be used in downstream evaluation. Decisions on mitigation strategies rely on integration of vulnerability analyses with the needs of the communities that rely on the managed fishery. Corroborating vulnerability assessment provided by the PSA with local knowledge, trend analyses and extrapolation techniques can give a more complete picture of how to best prioritize research and management efforts (Finkbeiner et al., 2017; Frawley et al., 2019; Mason et al., 2019; Oestreich et al., 2019; Schall et al., 2018). Previous studies employing the existing PSA could benefit from re-analysis to discover whether management priorities require shifts. Realistically, this method provides an opportunity to gain insight in the risk of fished species in later analyses and gives a framework that allows more reliable comparison across similar studies. Comparison of this method to sensitivity analyses of traditional stock assessments will inform our confidence in the reliability of the approach and is a recommended future step. Although we compare the standard form of the PSA (sPSA) devised by

FIGURE 6 Compared changes in risk categorization between the sPSA and rPSA applied to five previously published studies. From left to right: Cotter et al. (Sri Lanka), Dee et al. (Aquarium), Lin et al. (Taiwan), Patrick et al. (North America), Ponton-Cevallos et al. (Galapagos). The two panels representing (a) the total proportion of species that changed categories between the methods and (b) the net increase in risk assessed with the rPSA show that across studies of disparate systems, re-categorization is significant and leads to an increased assessed risk to species



Hobday et al. to our revised form (rPSA), other variants of ecological risk assessments exist that share properties with the sPSA. One such variation calculates vulnerability as the distance from (1,1) rather than the origin at (0,0) (Equation S5). Other studies which use attributes to highlight different components of risk like exposure and sensitivity (Samhouri et al., 2019) can similarly benefit from the methods outlined in this work. The choice of the Euclidean norm by many of these studies (rather than other metrics, such as other members of the p-norms family) implies the improvements we show will be similar in magnitude for these related methods.

There are scenarios when caution is appropriate before applying the revised PSA approach proposed here. Firstly, if some attributes are highly correlated, redundant attributes should be excluded or the number of effectively independent attributes should be estimated as described in the methods presented in the supplement. Secondly, when attributes are weighted, if one of the attributes is weighted far more than others, this method will be less accurate. The more attributes used, the less this is a problem, as this heavily weighted attribute will contribute less overall to productivity or susceptibility (see Lindeberg's condition for central limit theorems). Often attributes are not scored for all species due to insufficient data or because some attributes are not applicable for all species. This new PSA approach should be applied specific to each species when the weighting structure or number of attributes varies by species within the same study. For example, some species are assessed with 10 attributes while others are assessed with 5, threshold lines must be re-evaluated on a species-by-species basis. Calculated vulnerability values (V_p) are directly comparable in this way, and either V or V_p can be used for risk categorization. Because the PSA is used to assess data-poor species, attribute scoring is often qualitative. Efforts to standardize this procedure by establishing specific bins for scoring based on percentiles in a biologically realistic range of values is key to making the PSA more robust. There is little use in applying statistics to non-statistical data. This makes for overly precise but inaccurate conclusions. The bins established can be in any chosen percentile range as long as calculations for standard deviation are adjusted as shown above. However, the percentile ranges must be consistent across attributes. For ease, we recommend bins be treated equally so each score (1, 2, or 3) captures one-third of potential values. This standardization process should be considered an essential component of the rPSA. Ecological modelling or, when available, empirical data can inform the choice of bin thresholds, as is commonplace in ecosystem-based management analyses (Samhouri et al., 2010). Choice of model (additive vs. multiplicative) depends on the expected nature of the contributions of attributes to productivity or susceptibility. Generally, a multiplicative model gives greater importance to extremely low values than an additive model. Therefore, its use as a model for susceptibility implies, for example, that a small number of low scoring attributes outweigh the same small number of high scoring attributes. This assumption may not be supported in practice if instead a few high scoring attributes should have a larger than additive effect on the susceptibility of a species. In the most common use of susceptibility, the four attributes (Availability, Encounterability, Selectivity, and Post-capture Mortality) are presumed to interact in a multiplicative fashion because low scoring of any of these attributes reduces the risk associated with the other attributes. From Hobday et al. (2011): "For example, if a species is available in a fishing area, encounters the fishing gear, is selected by the gear, but is returned to the water unharmed (post-capture mortality low), then the overall susceptibility should be recognized as low." In contrast, an additive model assumes the magnitude of the effect of each attribute is not contingent on the magnitude of other attributes. Choice of model is distinct from effects that correlation among attributes may have on the representation of the analysis.

Use of the rPSA, as with the sPSA, is best conducted in a risk assessment framework like ERAEF because results are meant to be used as a relative measure of vulnerability of fished or by-catch species to fishing. Adaptation of the rPSA in each local context requires input from scientists, managers, and stakeholders to determine how to appropriately assess the present risks to fisheries. The framework presented allows flexible choice of attributes while providing the statistical rigor needed to move the PSA and similar risk assessments to a quantitative format. Moreover, the method can be scaled by level of expertise and complexity of assumptions, making practical use widely accessible. The degree to which results of the rPSA and adaptations of this method will change existing management will depend on the downstream evaluation practices of each management community. For communities that rely on unrelated methods to assess data-poor fisheries, adoption of the rPSA could provide a robust alternative, though the practical choice depends on context. Unlike quantitative stock assessments, which rely on empirical data, the PSA is qualitative, and relies on associations between the attributes used and Productivity or Susceptibility. Chosen attributes should, therefore, demonstrate a sufficiently strong and causal relationship to either Productivity or Susceptibility, which are assumed directly related to Vulnerability. Weighting is designed to quantify the strength of these relationships, and efforts should be made to justify weight values with the most applicable empirical data. Future exploration is needed to optimize weighting of attributes in a way that leverages the improvements introduced with the rPSA. Vulnerability as an index of risk is not an absolute indication of stock decline or potential for stock decline and depends on the attributes used in the analysis. Because risk categorization of species using the PSA is best interpreted relative to other species for which the same set of attributes can be applied, caution should be taken to over-interpret results of broad studies where evaluated attributes differ among species. In these cases it is imperative to conduct further assessment comparing vulnerable species as outlined by frameworks like ERAEF. Nevertheless, the rPSA improves upon an accessible method to assess risk in 90+% of fisheries which are considered data-poor. Without a cohesive framework to garner crucial information about these species, the vast majority of non-commercially fished species would be neglected when establishing management priorities.

5 | CONCLUSION

The PSA provides a standardized means to determine the vulnerability of marine species affected by fisheries. Its structure and simplicity enable its use by broad interest groups, scientists and stakeholders. Great strides have been made to improve the way we assess data-deficient species, and the work presented in this study is intended to be a step in that direction. This new approach to the PSA allows incorporation of all existing modifications that have accumulated over the years and gives a statistically robust means of determining relative risk of species. Light is shed on why the standard PSA needs improvement and how resolution can be gained, especially for mid-risk species, with the new index of vulnerability provided by the new method. Because of its robustness across any variety of conditions and study types, we consider this new approach a revised PSA. We encourage incorporation of the rPSA into the existing ERAEF framework to improve validity of its results.

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CONFLICT OF INTEREST

The authors declare no competing interests.

AUTHOR CONTRIBUTIONS

Conceptualization, REG; Methodology, REG; Software, REG; Analysis, REG & EM; Visualization, REG; Writing – Original Draft, REG; Writing – Review & Editing, REG, EM, FM, GDL; Funding Acquisition, REG, FM, GDL.

DATA AVAILABILITY STATEMENT

Software associated with this study is available for download and use at https://github.com/grewelle/rPSA. Empirical data evaluated is publicly available in referenced works.

ORCID

Richard E. Grewelle https://orcid.org/0000-0002-6432-1423

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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