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Data-poor ecological risk assessment of multiple stressors

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ABSTRACT

Multiple stressors to species and ecosystems are pervasive and escalating. Effective management and mitigation of these pressures requires ecological risk assessment (ERA), but data are often lacking for detailed, quantitative risk assessment. Data-poor ERAs have been developed and widely applied to terrestrial, marine, and freshwater ecosystems. Current frameworks, such as the Productivity-Susceptibility Analysis (PSA), are limited to single stressors and were not developed on statistical grounds. Previous work has partly addressed these limitations by incorporating multiple stressors (e.g. Aggregated Susceptibility) and a statistical basis (rPSA). However, the more robust rPSA is more difficult to implement than the PSA. To overcome this barrier, here we develop EcoRAMS (Ecological Risk Assessment of Multiple Stressors), which provides statistically-robust ecological risk assessments of multiple stressors in data-poor contexts. The web app format of EcoRAMS.net lowers the barrier of use for practitioners and scientists at any level of statistical training.

1. Introduction

Gathering an accurate estimate of risk to multiple stressors is a fundamental challenge in ecological risk assessment. Quantification of threats to species and habitats is necessary to develop management policies, yet the magnitude of threats and their compounded effects are often obscured by data limitations. Because ecosystems affected by multiple stressors require broader assessment, data limitations render these analyses especially fraught. This includes systems of conservation and commercial significance, such as small scale fisheries that together support the livelihoods of over 117 million people and provide essential nutrition for many more (FAO, 2020). Data-poor risk assessments are critical to establish intervention priorities in these contexts. Therefore, a wide variety of qualitative and semi-quantitative approaches is deployed to measure risk of species to stressors, which are often human-mediated. Common stressors of wildlife result from harvesting, mining, recreational, or construction activities, and those chosen for analysis are relevant to the species affected and stakeholder interests (Hope, 2006).

Unlike contexts in which the effects of a stressor can be precisely quantified under controlled conditions – for instance when a physiological or behavioral response is measured for increasing concentration of a contaminant (Norton et al., 1992) – in data-poor contexts, the quantitative relationship between stressor and response is unknown or under-studied. Semi-quantitative methodologies developed to overcome these limitations assess risk via standardized scoring procedures. Scores are based on the life history traits of species of conservation and commercial interest and on stressors' magnitude, distribution, and effects on target species, sometimes supplemented by expert input (Pilling et al., 2009). This type of assessment is particularly common for species affected by harvesting or bycatch in small-scale fisheries, where data is often not collected systematically. The Productivity-Susceptibility Analysis (PSA) has become the most commonly used approach to conduct ecological risk assessments for data-poor fisheries and has been applied widely to freshwater and terrestrial ecosystems. The PSA calculates Vulnerability, a metric of risk that incorporates qualitative scores of life history characteristics of species (Productivity) and fishing activity that overlaps with each species (Susceptibility). It has been incorporated within the broader Ecological Risk Assessment for the Effects of Fishing (ERAEF) framework which uses Vulnerability estimates from the PSA to prioritize evaluation by managers, scientists, and

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stakeholders (Hobday et al., 2007; Hobday et al., 2011; Stobutzki et al., 2001). Ecosystem based management efforts can account for all species, guilds, and communities with this approach (Hazen et al., 2016; Townsend et al., 2019). For this reason, data-poor methodologies like the PSA have been widely adopted (Battista et al., 2017; Marine Stewardship Council, 2019; Pontón-Cevallos et al., 2020). Variations in input procedure and outcome of analysis, including the use of Exposure and Sensitivity as risk determinants, have made these approaches accessible to stakeholders with varied interests (Samhouri et al., 2019). However, we demonstrated in our previous work that the outcomes of these assessments introduce biases without statistical considerations (Grewelle et al., 2021). We presented a statistically-robust approach to derive Vulnerability from Productivity and Susceptibility scores that addresses several limitations with the original PSA. Productivity and Susceptibility are each scored as the mean of their respective set of several attributes. Attribute values are generally assigned by standardized biologically-relevant criteria. For example, a Productivity attribute, age at maturity, may receive values by percentiles derived from an expected range for the relevant managed species: 1 = 0–33%, 2 = 33–67%, 3 = 67–100%. A species with age at maturity in the 50th percentile receives an attribute score of 2. Risk associated to Productivity is then computed as 4 minus the mean of Productivity attributes, so that 1 = low Productivity is classified as 3 = high risk. (Grewelle et al., 2021; Hobday et al., 2011) further discuss scoring recommendations. Productivity and Susceptibility are then used to calculate Vulnerability. Vulnerability in the original PSA was calculated as the Euclidean distance from the origin.

$$V = \sqrt{P^2 + S^2} \tag{1}$$

The Euclidean distance of each species from the origin is not a suitable metric for Vulnerability because it does not account for the distribution of species on the PSA plot (Grewelle et al., 2021). Our revised PSA (rPSA) framework is able to incorporate commonly used variations of the analysis to assess Vulnerability by projecting the the two-dimensional distribution (e.g. P-S space) of species onto a one-dimensional risk axis, along which species' risk to fishing activity increases (Fig. 1).

While PSA-like approaches have been widely used in both marine and terrestrial ecosystems, these methods usually consider a single threat or pressure (e.g. susceptibility to a specific fishing gear), whereas populations are often subject to multiple stressors at the same time (Halpern et al., 2009; Van den Brink et al., 2016a). Thus it is crucial to have robust methods to assess Vulnerability to cumulative impacts of these stressors. Prior to our revised PSA, Micheli et al. addressed the limitations of single stressor analyses by computing an Aggregated Susceptibility (AS) that broadened the definition of Susceptibility to multiple fishing gears or stressors (Micheli et al., 2014). Susceptibility to each stressor was independently scored on the same scale between 1 and 3, and Aggregated Susceptibility reflected the combined contributions of all stressors to species' susceptibility to fishing activity. Aggregated Susceptibility was truncated at a maximum value of 3 and took a minimum value of 1 to remain within the scoring bounds of the PSA.

$$AS = min\left\{ 3, 1 + \sqrt{\sum_{i=1}^{n} (S_i - 1)^2} \right\} \tag{2}$$

When Susceptibility (S_i) to a stressor i is 1, this stressor does not increase AS. When $S_i > 1$ for two or more stressors, then AS is greater than or equal to Susceptibility from each stressor.

AS substituted S in Eq. (1) to calculate Vulnerability to multiple stressors. Though practical, the empirical formula to calculate AS was not derived on the basis of statistical principles. The aims of this work are two-fold: to create a statistical interpretation of AS to robustly measure Vulnerability to multiple stressors and to introduce a web application to enhance its use in data-poor ERAs. Because the dimensions of risk vary by study, we generalize this framework to evaluate any two-dimensional scoring procedure, including Sensitivity-Exposure (Rodier and Norton, 1992), Impact-Probability (Dumbravă and Iacob, 2013), or Severity-Likelihood based analyses (Woodruff, 2005). We

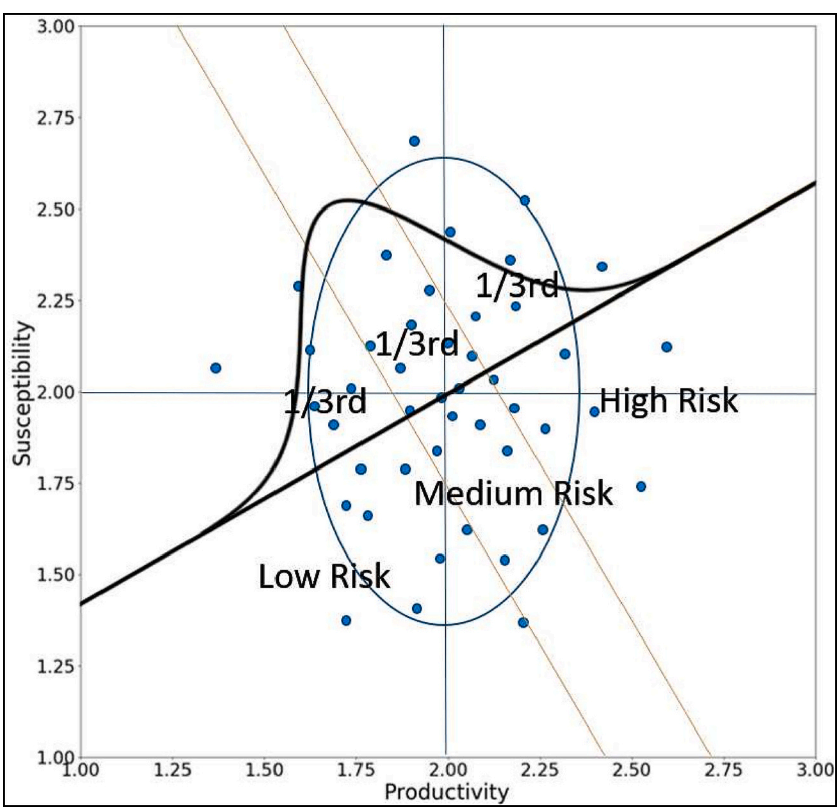

Fig. 1. In the scoring model used by the PSA, a bivariate normal distribution (blue ellipse) is produced along the Productivity and Susceptibility axes. This can be projected along a Risk Axis (black line, ascending left to right), which is defined by the likelihood properties of the analysis, to form an ordered set of points along a one dimensional normal distribution (black). This new distribution is used to score Vulnerability in the rPSA. Vulnerability scores fall into risk categories delineated by thresholds (light orange, descending left to right) which divide the distribution of points into equal partitions by probability. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

present this approach as a user-friendly web application, EcoRAMS, accessible to scientists and stakeholders at any level of statistical training.

2. Methods

2.1. Derivation of vulnerability

EcoRAMS ([data-poor] Ecological Risk Assessment of Multiple Stressors) measures Vulnerability from multiple stressor variables, standardized by the distance of each stressor score, x_u, from the theoretical mean, μ_u, set by the attribute scoring criteria and the chosen model (additive or multiplicative). Multiple stressor Vulnerability values provide unique resolution of risk across the low, medium, high-risk range not otherwise captured by evaluation of a single stressor. All ecological risk assessments which compute risk variable scores (e.g. Productivity, Susceptibility, Exposure, Likelihood, Probability, Sensitivity, Effect, Severity, Impact, etc.) from a mean of multiple attributes produce scores that are normally distributed along each variable's axis. The statistical properties of these assessments were derived in our previous work for a single stressor (Grewelle et al., 2021). To generalize the statistics for multiple stressors, we denote α as any response variable (e.g. Productivity, Sensitivity, Effect, Severity, Impact, etc.) determined by characteristics of the species or endpoints studied and β as any stressor variable (e.g. Susceptibility, Exposure, Likelihood, Probability, etc.) determined by the probability of contact with stressors. It is assumed that $\boldsymbol{\beta}$ is an n-dimensional variable with basis $\{\beta_1, \beta_2, \dots, \beta_n\}$ to represent n stressors, while α is a single variable. The formula for AS (Eq. (2)) does not yet form a statistical distribution. Below we create a suitable statistical metric for multiple stressors, $\boldsymbol{\beta}$, to be incorporated in the rPSA framework. Each stressor variable, β_i, forming the basis of β is Gaussian because they are scored by calculating the mean of several attributes, which were chosen to the reflect the interactions of species to one or more stressors (e.g. spatial overlap with stressor, post-contact mortality from stressor). Attributes are scored from low = 1 to high = 3 based on biologically relevant scoring criteria. Each stressor variable, β_i, can therefore be defined by a normal random variable, X:

$$X \sim N\left(\mu_X, \sigma_X^2\right) = f(x) = \frac{1}{\sigma_X\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2} \tag{3}$$

We further define Y as the distribution formed by the weighted sum of these stressor random variables.

$$Y = \mathbf{w}^T\mathbf{X} = \sum_{u=1}^{n} w_u X_u \tag{4}$$

Stressor random variables are weighted by importance by ω_u. By default, these weights should be equal across stressors. Differential contribution of each stressor to Vulnerability is incorporated in the low to high β_u scoring process. However, in some cases undo influence of one or more stressors may contribute to species' Vulnerability. In these instances, the importance of each stressor is different, and weighting should not be equal.

$$\mathbf{w} = \boldsymbol{\omega} diag^{-1}(\boldsymbol{\mu}_X) \tag{5}$$

The characteristic function for Y is

$$\phi_Y(t) = E\left[e^{itY}\right] = E\left[e^{it\mathbf{w}^T\mathbf{X}}\right] = \phi_X(t\mathbf{w}) \tag{6}$$

Expanded, this becomes

$$\phi_Y(t) = exp\left(it\sum_{u=1}^{n} w_u\mu_u - \frac{1}{2}t^2\sum_{u=1}^{n}\sum_{v=1}^{n} w_u w_v \boldsymbol{K}_{uv}\right) \tag{7}$$

where $\boldsymbol{K}_{XX}$ is the covariance matrix.

$$var(X_u) = \boldsymbol{K}_{uu} \tag{8}$$

$$cov(X_u, X_v) = \boldsymbol{K}_{uv} \tag{9}$$

The characteristic function for each stressor random variable is

$$\phi_X(t) = exp\left(it\mu_X - \frac{1}{2}t^2\sigma_X^2\right) \tag{10}$$

X and Y share the same form of characteristic function when

$$\mu_Y = \sum_{u=1}^{n} w_u\mu_u \tag{11}$$

$$\sigma_Y^2 = \sum_{u=1}^{n}\sum_{v=1}^{n} w_u w_v \boldsymbol{K}_{uv} \tag{12}$$

Therefore, Y is also normally distributed

$$Y \sim N\left(\mu_Y, \sigma_Y^2\right) \tag{13}$$

For β_u variables that are log-normally distributed due to the use of a multiplicative model in attribute scoring, log transformation produces a normal distribution. The transformation of mean and variance of these variables is presented in (Grewelle et al., 2021). Recalling from (Grewelle et al., 2021) any vector $\boldsymbol{x_k} = \left[\alpha_k - \widehat{\mu}_\alpha \ \ \beta_k - \widehat{\mu}_\beta\right]^T$ can be projected along the risk vector, $\boldsymbol{r}$, to map $\boldsymbol{X}$ to one dimension. $\boldsymbol{k}$ is the species index. After mapping all points to the risk vector, the distance of each point $x_k = (\alpha_k, \beta_k)$ from the mean is the magnitude of the projection:

$$D(\boldsymbol{x_k}) = \frac{\boldsymbol{r}\cdot\boldsymbol{x_k}}{|\boldsymbol{r}|} \tag{14}$$

The projection results in a linear transformation of $\boldsymbol{X}$ with standard error

$$\sigma_{\mathbf{r}} = \frac{\sqrt{2}\sigma_\alpha\sigma_\beta}{\sqrt{\sigma_\alpha^2 + \sigma_\beta^2}} \tag{15}$$

The cumulative distribution function that yields the probabilistic metric of Vulnerability is:

$$V_p = \frac{1}{2} + \frac{1}{\sqrt{\pi}}\int_0^{\frac{D(\boldsymbol{x_k})}{\sigma_r\sqrt{2}}} e^{-t^2}dt \tag{16}$$

This metric can be compared across all varieties of input conditions, including variable number and type of stressors and attributes. However, comparisons across studies are most explicable when conditions of the analyses are similar.

2.2. Covariance among stressors

By default, stressors are assumed independent. The covariance matrix, $\boldsymbol{K}_{XX}$, is the identity matrix. When stressors are expected to interact, covariance values are positive or negative, respectively. Variance can be calculated given known correlations between stressor variables.

$$var(\beta) = \left(\mathbf{w}\odot\boldsymbol{\sigma_\beta}\right)\boldsymbol{\rho}\left(\mathbf{w}\odot\boldsymbol{\sigma_\beta}\right)^T \tag{17}$$

$\boldsymbol{\sigma_\beta}$ is the row vector of standard errors for stressor variables, and $\boldsymbol{\rho}$ is the correlation matrix with entries between −1 and 1.

2.3. Treatment of stressors: Antagonistic, neutral, or compounding

For a single stressor, scoring criteria define the mean of the expected normal distribution for β. When additional stressors are included in the risk analysis, we provide flexibility in EcoRAMS to treat each of these stressors as an obligatory elevator of Vulnerability (compounding), neutrally with equal chance to decrease or increase Vulnerability, or antagonistically as an obligatory reducer of Vulnerability. In the neutral treatment, the above methods hold, and the definition of the distribution for β does not change. Generally, for all treatments, the mean is modified:

$$\mu_Y = \sum_{u=1}^{U} w_u \mu_u + \sum_{t=1}^{T} w_t max\left\{\beta_{U+t}\right\} + \sum_{v=1}^{V} w_v min\left\{\beta_{U+T+v}\right\} \tag{18}$$

U is the number of neutral stressors, T is the number of antagonistic stressors, and V is the number of compounding stressors. The minimum of β_{U+T+v} referenced is the minimum value an attribute used to score β_{U+T+v} could theoretically receive. In the case where attributes take values between 1 and 3, $min\{\beta_{U+T+v}\} = 1$. This treatment is analogous to the derivation of AS in Eq. (2). The maximum of β_{U+t} referenced is the maximum value an attribute used to score β_{U+t} could theoretically receive. In the case where attributes take values between 1 and 3, $max\{\beta_{U+t}\} = 3$.

2.4. Scoring practices

The EcoRAMS web app provides CSV (Comma Separated Values) templates for users to input scoring criteria, attribute scores for each stressor and species, and analysis conditions. Prior to submitting these templates to the web app and receiving results, EcoRAMS requires users to conduct several preparatory steps (Fig. 2). After the analysis conditions are setup, the α and β attributes must be chosen. Attributes should be approximately independent from each other. Biologically redundant attributes should not be used in the analysis to avoid double counting, and to account for highly collinear ones by estimating the effective number of attributes see the method outlined in the supplementary information of (Grewelle et al., 2021). Percentiles are then chosen for scoring each attribute, adhering to relevant expected ranges. For ease, we recommend equal bin sizes: 1 = 0–33%, 2 = 33–67%, 3 = 67–100%. When attributes are irrelevant or lack expert input or data for scoring, the attributes should not be scored. Leaving these cells and the corresponding weight cells blank in the CSV templates will adjust the number of attributes used for the species and broaden standard error estimates for calculating Vulnerability; scored attributes will be appropriately weighted. The α and β values are calculated as the weighted means of their respective attribute scores. Weights can be applied on the basis of importance or data quality, and efforts to justify weights via supporting mechanism or data should be made. The mean calculated depends on the model assumed for the attributes (geometric mean = multiplicative, arithmetic mean = additive). However, as a default, α variables are assumed to be additive, while β variables are assumed to be multiplicative. A multiplicative model should be used when the magnitude of risk associated with a variable depends on interactions of the attributes with each other. For instance, species mortality, often used as an attribute to score Susceptibility, depends on other attributes like spatial overlap between fishery activity and species distribution. Values of variables scored in this way act much like probabilities, and in fact, a geometric mean is an isotone (order-preserving) mapping of probability and is indistinguishable in the results of the EcoRAMS analysis. When β_1, $\beta_2, \ldots, \beta_n$ are scored with different sets of attributes, EcoRAMS supports the use of different models (additive or multiplicative) for each variable.

To demonstrate the use of EcoRAMS, we generated a hypothetical set of 100 species using a standard scoring procedure for the PSA used in the Ecological Risk Assessment for the Effects of Fishing. We adopted the same scoring procedure by which attributes of α and β variables are scored 1 (low-risk), 2 (medium-risk), or 3 (high-risk). Note that these scores reflected association with risk, not association with the α or β variables per se. For example, in a PSA high Productivity is associated with low-risk (Hobday et al., 2007), and therefore Productivity attribute scores were transformed by subtracting from 4 if originally scored as 1 = low Productivity, 2 = medium Productivity, 3 = high Productivity. For EcoRAMS users, this option can be chosen before analysis when applicable. In our simulated analysis, 7 α and 4 β attributes were scored randomly on a uniform distribution of integers between 1 and 3. The α score was calculated as the arithmetic mean assuming an additive model. The β score was calculated as the geometric mean assuming a multiplicative model. Attributes were weighted equally. We calculated the Vulnerability of 100 in silico species when three simulated stressors were treated both as neutral and compounding to compare the interpretations of Vulnerability. We also analyzed 81 fished species in Baja California, Mexico for which each of five fishing gear types represented a separate stressor. We used the same attributes and scoring procedure as the original study (Micheli et al., 2014). Species were analyzed for each single stressor, which produced results identical to the rPSA. Vulnerability was then computed for all five stressors (set gillnets, drift gillnets, lobster traps, fish traps, and dive fishing), treating each additional stressor as compounding on the stressor of greatest impact (set gillnets).

3. Results

3.1. Neutral treatment of stressors

When stressors (β variables) were treated neutrally and were instead standardized by the expected mean, additional stressors did not affect the distribution of risk categorization; approximately one-third of species fell into each category (Fig. 3). This procedure maximally discriminated Vulnerability of species within a study for downstream assessment.

3.2. Compounded stressors

When stressors were compounded on the first, the distribution of Vulnerability scores shifted upward (Fig. 4). Fewer species remained in

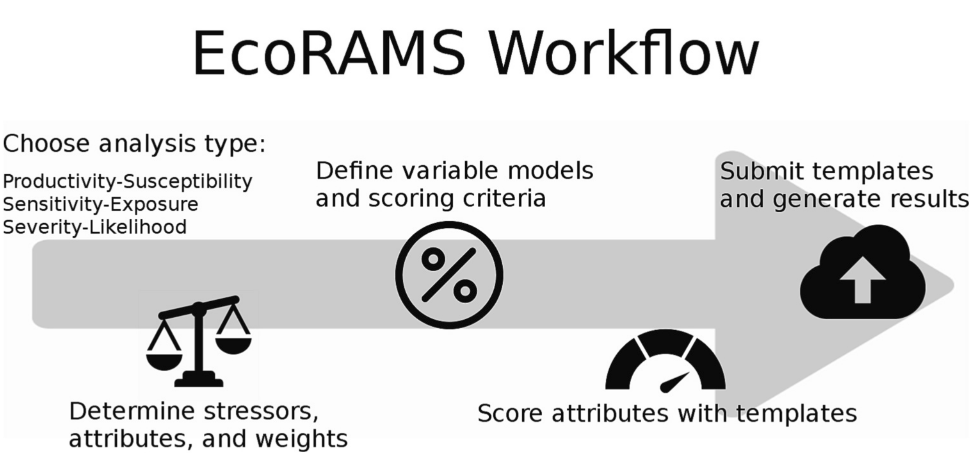

Fig. 2. Workflow diagram for EcoRAMS analysis. The analysis type chosen determines which of the pairs of variables is used in the risk assessment, which will constrain the types of attributes used for scoring. Included stressors, attribute weights, and their associated models and scoring criteria will define the scope and structure of the analysis. After attributes are scored using provided templates, users submit templates simultaneously on the EcoRAMS web app at EcoRAMS.net and results are automatically generated.

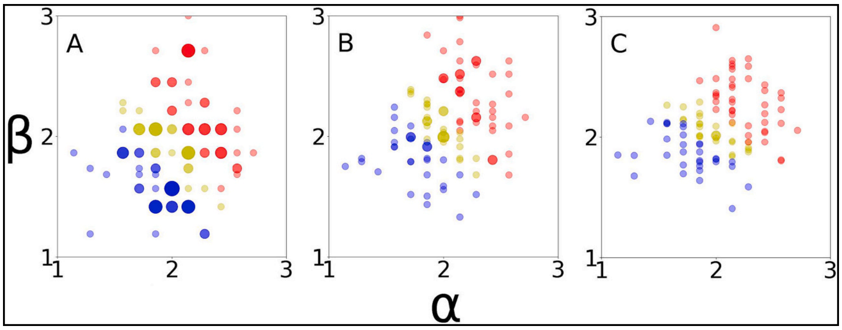

Fig. 3. Risk classification of 100 simulated species by Vulnerability scores in which stressors were treated neutrally. The horizontal axis (α) measures Productivity, Sensitivity, Effect, Severity, Impact, etc., while the vertical axis (β) measures Susceptibility, Exposure, Likelihood, Probability, etc. Low-risk species are in blue, medium-risk in yellow, high-risk in red. The size of a dot corresponds to the number of species sharing overlapping positions in the plot. (A) A single stressor (β_1) was used in the analysis. (B) Two stressors were used in the analysis; the second (β_2) was treated neutrally with the first shown in panel A. (C) Three stressors ($\beta_1, \beta_2, \beta_3$) treated neutrally were used in an analysis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

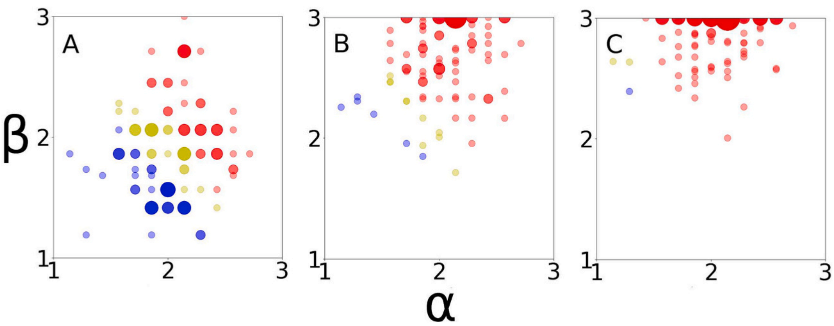

Fig. 4. Risk classification of 100 simulated species by Vulnerability scores in which stressors compounded. The horizontal axis (α) measures Productivity, Sensitivity, Effect, Severity, Impact, etc., while the vertical axis (β) measures Susceptibility, Exposure, Likelihood, Probability, etc. Low-risk species are in blue, medium-risk in yellow, high-risk in red. The size of a dot corresponds to the number of species sharing overlapping positions in the plot. (A) A single stressor (β variable) was used in the analysis. (B) Two stressors were used in the analysis, the second (β_2) compounded on the first shown in panel A. (C) Three stressors ($\beta_1, \beta_2, \beta_3$) were used in the analysis, the second and third compounded on the first. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the low- or medium-risk categories; this effect became more pronounced as the number of stressors increased. Visualized β scores were truncated at 3, resulting in a collection of species at this upper limit when more stressors are included.

3.3. Correlated stressors

In some cases, stressors analyzed cannot be assumed to independently influence species' Vulnerability. Using the same 100 simulated species previously analyzed, we visualized the effects on risk categorization thresholds of positive and negative correlation between stressors in a two-stressor analysis (Fig. 5). Positive correlations widen the medium-risk thresholds, while negative correlations narrow them. For these simulated species, fewer are categorized as medium-risk when stressors are negatively correlated, which is expected when β scores were derived independently (no correlation) in the simulation. Simulating dependent stressors would recapitulate equal partitioning of species across risk categories observed in Figs. 3 and 4.

3.4. Baja California case study

Figs. 3, 4, and 5 represent uniform attribute scoring for all stressors; however, for empirical multiple stressor analyses not all stressors equivalently impact the group of species analyzed. Across the 81 species, set gillnets was the stressor of highest impact measured by mean Susceptibility score. Despite the majority of species being classified in the low-risk category if each stressor is assessed individually (Fig. 6 A-E), the cumulative impacts of each of the five stressors produced a higher Susceptibility score, and therefore, a higher Vulnerability score when compounded (Fig. 6 F). Compared with the single stressor of highest impact (set gillnets), accounting for multiple stressors resulted in 46% higher net risk overall (37/81 species shifted to higher risk categories). Of the 81 species assessed, the Vulnerability breakdown was 14% low, 17% medium, 69% high for multiple stressors compared to 49% low, 10% medium, 41% high for set gillnets.

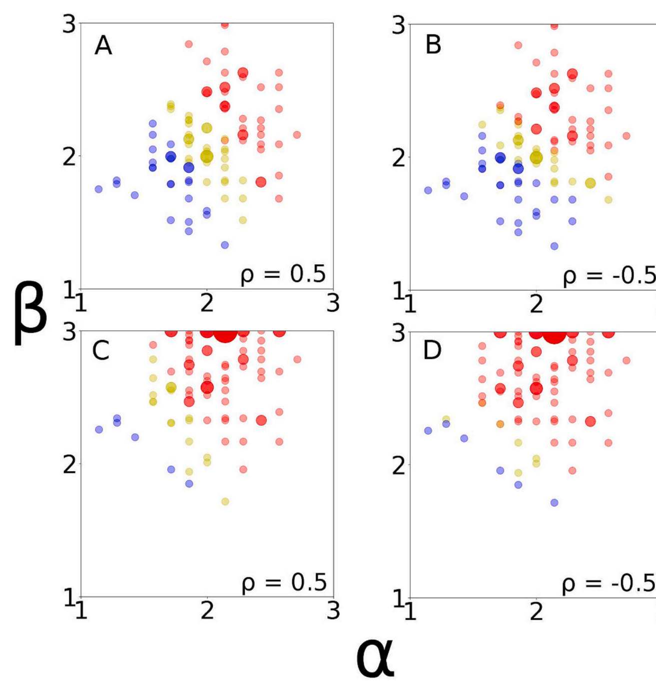

Fig. 5. Risk classification of 100 simulated species by Vulnerability scores in which the two stressors analyzed are correlated. The horizontal axis (α) measures Productivity, Sensitivity, Effect, Severity, Impact, etc., while the vertical axis (β) measures Susceptibility, Exposure, Likelihood, Probability, etc. Low-risk species are in blue, medium-risk in yellow, high-risk in red. The size of a dot corresponds to the number of species sharing overlapping positions in the plot. (A) Two neutral stressors (β variables) were positively correlated. (B) Two neutral stressors were negatively correlated. (C) A second, positively correlated stressor compounds on the first. (D) A second, negatively correlated stressor compounds on the first. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

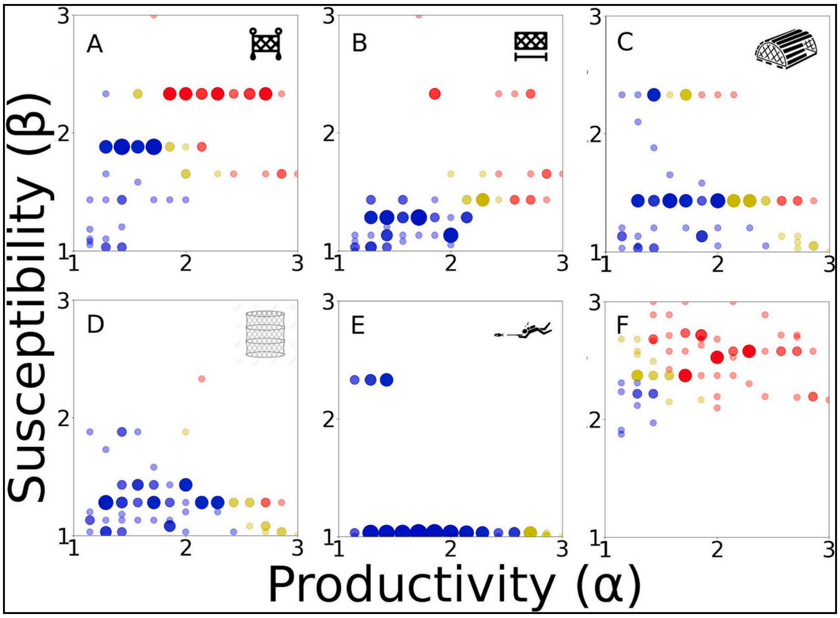

Fig. 6. Risk classification of 81 marine species in Baja California, Mexico analyzed by Micheli et al. Low-risk species are in blue, medium-risk in yellow, high-risk in red. The size of a dot corresponds to the number of species sharing overlapping positions in the plot. $\alpha =$ Productivity and $\beta =$ Susceptibility. (A) Analysis of stressor of highest impact, set gillnets, followed by analyses of four other fishing stressors in descending order of impact: (B) drift gillnets, (C) lobster traps, (D) fish traps, (E) dive fishing. (F) These stressors are analyzed together in the EcoRAMS framework assuming stressors compound, revealing higher Vulnerability scores due to increased Susceptibility than for any stressor alone. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

4.1. The future of ecological risk assessment

The evolution of ecological risk assessments has occurred in independent scientific fields, such as toxicology and fisheries research. An increasing focus on ecosystem-level analysis, rather than species-specific impacts, highlights the importance of the interactions between species and the effects of multiple stressors (Hines and Landis, 2014; Van den Brink et al., 2016b). The inclusion of multiple stressors at the problem formulation stage promises to protect the values of stakeholders and ecosystems through integrated research design. Building conceptual models of cause and effect to improve the selection of relevant risk attributes is a crucial step in ecological risk assessments (Jackson et al., 2016), and although data-rich analyses have incorporated probabilistic interpretations of risk for decades, data-poor analyses have done so only recently (Grewelle et al., 2021; Ofungwu, 2014). Probabilistic approaches are far more accurate in that they provide a quantitative description of risk that can be used to rank vulnerable species for conservation priority. These rankings can be used to inform practitioners, stakeholders, and the public of routes to protection of species threatened by one or more stressors. Movement toward ecosystem-wide assessments requires evaluating ecosystem function (McMahon et al., 2012), not only species preservation. Management priorities informed by the role of species and their interactions within ecosystems will lead to more resilient communities. Ultimately, modern approaches to ecological risk assessment, such as EcoRAMS, will lead to more capable adaptive management strategies that are crucial in rapidly changing environments (Walters, 1986).

4.2. The role of EcoRAMS for evaluating multiple stressors

Although these analyses highlighted the application of EcoRAMS to multiple sources of fishing pressure, EcoRAMS is fully flexible to analyze any system for which multiple independent sources of stress introduce risk to subjects of the analysis. For example, the PSA has been used to evaluate terrestrial ecosystems, subsequent to its use for data-poor fisheries. Similar risk-based frameworks that use Exposure and Sensitivity (or Effect) or Severity and Likelihood as variables have been applied to marine and terrestrial systems and have also been extensively developed for data-rich ecological risk assessments (N. R. Council, 2009; Samhouri et al., 2019). These applications extend beyond ecology and include analysis of risk in business (Koller, 2005), human health (Ravindra and Mor, 2019; World Health Organization, 2020), engineering (Zio, 2018), and others. We provided a cohesive statistical framework, associated software, and web application to easily and robustly analyze risk in any data-poor context for one or more stressors. EcoRAMS requires no prior statistical or programming knowledge, as full functionality of this software is deployed as a web app that only requires users to fill template CSV files with their data. We view wide and reliable access to robust statistical methods as imperative to the progress of ecosystem-based management and risk analysis. Because 90 + % of marine species are considered data-poor (FAO, 2020; Mora et al., 2011), EcoRAMS has the opportunity to be widely adopted to improve analyses marine sciences, and we anticipate EcoRAMS to have similar value to other ecological risk assessments of terrestrial and freshwater systems when data is sparse. The best use of EcoRAMS is with input from scientists, managers, practitioners, and stakeholders to allocate time and resources to species for which conservation provides mutual benefits to the ecosystem and the people within it (Finkbeiner et al., 2017; Oestreich et al., 2019).

4.3. Considerations

EcoRAMS is a highly flexible tool that may be leveraged in different ways to fit the needs of diverse analyses. Attributes and scoring practices often differ between PSA studies, and the EcoRAMS framework provides opportunities for further diversification as multiple stressors are incorporated. In each study where EcoRAMS is applied, it is crucial to carefully consider the assumptions made and provide justifications for choices such as scoring models, chosen attributes, chosen stressors, weighting schemes, and the interactions stressors have with each other. External data regarding correlations between stressors, for example, can provide a more ecologically relevant analysis. Prior studies have focused on the cumulative impacts of multiple stressors, assuming that more stressors equals proportionately greater risk to affected species and habitats (Halpern et al., 2009). However, when stressors interact with one another, these assumptions break down. Accounting for these complexities as well as providing a cohesive statistical framework multi-stress risk analyses were key goals for the design of EcoRAMS. Even when a stressor is treated neutrally (i.e. incorporating it into the analysis does not inherently imply increase or decreased risk), information about the impacts of the stressor on species improves resolution of Vulnerability scores by reducing standard errors of measurements along the β axis. Greater confidence of relative risk between species in the analysis is useful for initiating prioritization of actions to reduce risk.

Statistical (probabilistic) methods have been deployed for ecological risk assessments where data is available (Ofungwu, 2014). EcoRAMS makes multi-stressor, multi-species risk assessment broadly accessible, without requiring advanced statistical skills and in data poor contexts. Even in data-rich contexts, the use of statistical risk assessments is not universally accepted practice. Challenges like increased complexity, greater data needs, and difficulty in communicating results to stakeholders slow widespread uptake (Hope, 2006). Conventional non-statistical methods like hazard quotients or guidelines set to fixed thresholds without regard to uncertainty in data or mechanistic interpretation of the underlying model are often simple and convenient interpretations of risk and are used by decision-makers (Tannenbaum et al., 2003), but these benefits become less tenable when statistical practices are highly accessible. Changing convention will take time, and ecological risk assessments will benefit from the transition to statistical methods, as they provide more reliable insights into risk management. Adoption of statistical methods for data-poor ecological risk assessments may similarly require time, and the key to improving the state of the field in the shortest time is to make methods accessible. EcoRAMS represents a sophisticated statistical software with easy inputs and easily understood results for any audience. Engagement with stakeholders and downstream efforts to prioritize management is crucial for any risk assessment, and EcoRAMS can facilitate these synergies.

CRediT authorship contribution statement

Richard E. Grewelle: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Elizabeth Mansfield:** Formal analysis, Writing – review & editing. **Fiorenza Micheli:** Writing – review & editing, Funding acquisition. **Giulio De Leo:** Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Software associated with this study is available for download and use at https://github.com/grewelle/EcoRAMS. Empirical data evaluated is publicly available in referenced works. The web app is deployed at EcoRAMS.net.

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Appendix A. EcoRAMS Instructions

Downloadable templates and instructions for EcoRAMS, also found at https://github.com/grewelle/EcoRAMS/blob/main/README.md.

EcoRAMS is software used to perform ecological risk assessments in data-poor contexts. It provides a statistical interpretation of risk for each species or endpoint analyzed. This metric is probabilistic Vulnerability (Vp). Inputs are attribute scores and weights for two variables: response (e.g. Productivity, Effect, Sensitivity, Severity) and stressor (e.g. Susceptibility, Exposure, Likelihood). EcoRAMS is designed to incorporate multiple stressors that when aggregated can have compound impacts on risk or not. Below is a guide to using EcoRAMS. After downloading and completing templates, analysis occurs within a few seconds of upload. If your data is well organized to be input into templates, a full analysis from template download to results can occur within a few minutes. The instructions are divided into three sections: pre-download of templates, template completion, and EcoRAMS analysis.

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1. Pre-download of templates

- Determine the types of response and stressor variables used in analysis (e.g. Productivity-Susceptibility, Exposure-Effect/Sensitivity, Severity-Likelihood)
- Generate a set of one or more stressor variables that independently contribute to risk
- Decide which set of attributes will be used to assess each of the variables. If more than one stressor is included, different attributes may be used for different types of stressors, though care should be taken to interpret results appropriately given the added complexity of the analysis. Chosen attributes should be approximately independent from each other. Highly correlated/redundant attributes should not be included in the analysis. If moderately-highly correlated attributes are used, refer to the supplement of Grewelle et al. 2021, *Redefining Risk in Data-Poor Fisheries* to estimate the effective number of attributes used for each variable.
- Classify each variable as additive or multiplicative in nature. When an additive model is used for a variable, it is assumed that each attribute contributes to a fraction of risk proportional to its weight (see following instruction on weighting). Therefore, adding all attribute contributions to risk gives the full risk associated with the variable. When a multiplicative model is used for a variable, it is assumed that each attribute's contribution is affected by the contributions of other attributes. Simply, if risk from one or more attributes is absent, overall risk associated with the variable would be absent as well even when high risk is associated with other attributes. This model is often used when attributes measured operate in a sequence or are probabilistic (e.g. Likelihood). By default, response variables are additive and stressor variables are multiplicative in the templates. Different models can be used for each stressor, though care should be taken to interpret results appropriately given the added complexity of the analysis.
- Set criteria for low-, medium-, and high-risk for each variable. This consists of two percentile cut-offs, below the first is low-, above the second is high-, and between them is medium-risk. These cut-offs can be chosen as any percentile provided they are symmetric (i.e. low and high categories are of equal range). The template defaults assume equally sized categories.

- Assign weights to each attribute. Weights can take any numerical value and are only important relative to weights of other attributes for a single species or endpoint. Weights can differ within an attribute but across species. The template defaults to equal weighting.
- Score attributes for all species. Attribute scores should take values between 1 and 3. These values should fall within intended categories based on the percentile cut-offs assigned above. Defaults correspond to 1 = low-risk, 2 = medium-risk, 3 = high-risk.

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2. Template completion

- Download one alpha template, one beta csv template, and one correlation template.
- Open the alpha template. The top four rows have six sets of values to input.
  a) Additive or Multiplicative attributes? Acceptable inputs: Additive, Multiplicative.
  b) Low and high percentile cut-offs for attribute scoring. Acceptable inputs: any two fractions that as cut-offs produce a symmetric distribution of score ranges. Numerators and denominators must include a decimal. Values must remain in fraction form (i.e. do not give the decimal equivalent of the fraction).
  c) Number of attributes. Acceptable input: a whole number corresponding to the number of attribute columns.
  d) Low and high thresholds. Acceptable inputs: The second value must be larger than the first. Numerators and denominators must include a decimal. Values must remain in fraction form (i.e. do not give the decimal equivalent of the fraction). These thresholds determine the risk categories following Vulnerability scoring.
  e) Scoring in reversed risk order? Acceptable inputs: Y, N. In some cases (e.g. Productivity) the attributes of the alpha variable may be scored such that high values represent low risk. If scores input in the template were scored in this way, assign Y to this field. If high values correspond to high-risk, assign N to this field.
  f) Axis label. Acceptable inputs: any x-axis label for the resulting plot, preferably the name of the alpha variable.
  g) Weight. Acceptable inputs: any numerical value. The weight of each stressor relative to the others determines the contribution of each stressor to the β score. Higher input values indicate greater weight.
- Row 5 must be left empty. Row 6 is the dataset header, and values in these cells can be changed without affecting the analysis.
- Columns must be organized accordingly: column 1 is for higher level organization of species and will not be output in results. Column 2 is the list of species and will be reported in results alongside Vulnerability scores and risk categories. Input your list of species in column 2. No input is required for column 1 unless it is helpful for your organization. Blank rows can be included in between species or chunks of species for aesthetics without affecting the analysis provided the blank rows are placed consistently for all templates so that species fall on the same row.
- Columns 3+ are for attribute scores and weights. Add or remove columns to rows 6+ to add or subtract attributes. Two empty columns must be kept between attribute scores and attribute weights. Attribute weight columns must be in the same order, left to right, as the attribute columns. For example, for 5 attributes, columns 1 and 2 would report group (optional) and species (or endpoint generally). Columns 3–7 would report attribute scores. Columns 8–9 would be blank. Columns 10–14 would report attribute weights. When an attribute is unscored due to lack of data or irrelevance for the species, both the attribute score and weight cells should be left blank. Default attribute scores are randomly chosen between 1 and 3. Default weights are equal.
- Save the alpha template as alpha_xxx.csv where xxx is any string you choose. The file must be saved in UTF-8 format. Note: Microsoft Office for Mac incorrectly encodes the UTF-8 format, so upload errors may be a result of incorrect encoding. Use LibreOffice, Google Sheets, or Numbers on a Mac. Microsoft Office works correctly on a PC for csv encoding.
- Open the beta template. Like the alpha template, the top four rows have six sets of values to input. These sets of values can be entered according to the guidelines for the alpha template above except for (e). Here the entry differs: Compound model? Acceptable inputs: A, N, C. This entry refers to whether the stressor is statistically standardized by the expected mean (N), the expected minimum (C), or the expected maximum (A). By default, this value should be N for the first beta template to yield an identical analysis to the rPSA for a single stressor. Subsequent stressors can be treated as compounding (increasing risk with more stressors – C), neutral (N), or antagonistic (A) by completing additional beta templates for each stressor.
- The same rules apply for column and row formatting and data entry for both beta and alpha templates. It is recommended to rank stressors in order of impact, with the highest impact stressor entered in the first beta template, and the lowest impact stressor entered in the last beta template. All values can differ between stressors except for (d) low and high thresholds. These thresholds will be the same across all templates, including the alpha template, as the thresholds are applied to Vulnerability scores at the end of the analysis. The software is setup to take the threshold values from the alpha template, so modifying the thresholds in the beta templates will not change results.
- Save each beta template as beta1_xxx.csv, beta2_xxx.csv, beta3_xxx.csv, etc. in the same folder as you saved the completed alpha template. Ordering of these completed templates matters in the upload stage, as all files are selected simultaneously. Therefore, in the folder, files must appear in the following order: alpha_xxx.csv, beta1_xxx.csv, beta2_xxx.csv, beta3_xxx.csv, etc.
- Open the correlation matrix template. Starting in cell A1, input a symmetric matrix describing the expected correlations between stressor variables. Acceptable values in each cell are numbers between −1 and 1. By default, the identity matrix for three variables is given. Save the matrix template as corrMatrix.csv so that this file appears after the alpha and beta templates in the same folder.

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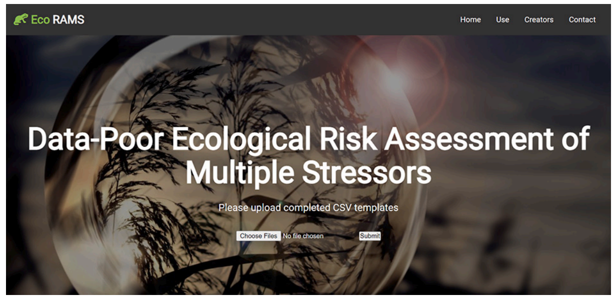
3. EcoRAMS analysis

- Navigate to the main page of EcoRAMS.net.
- Click on the'Choose Files' button after which a file browser window will appear. Navigate to the folder hosting your completed templates. The order the files appear is the order they will be uploaded and should be in the order described above. Use ctrl (or cmd) + select or shift select to select all files to be analyzed.
- After opening these files, the homepage will read the number of files selected. Click'Submit' to analyze your data.

- After a few seconds, a display page will appear with results. Results will appear in order of the stressors uploaded with stressor 1 corresponding to beta1_xxx.csv. These are single stressor results for each stressor standardized by the expected mean. Each plot will precede a list of all species and their associated α, β, probabilistic Vulnerability scores between 0 (lowest) and 1 (highest), and their associated risk category determined by the thresholds set. The final result is the multiple stressor result.
- All figures can be downloaded by saving the image with a right click, and the data tables can be copied and pasted directly into any format like a csv file.

Appendix B. EcoRAMS home page



Appendix C. Empirical case study tables of results

Scores in the following tables are truncated to a single decimal place.

Appendix C.1
Set gillnets.

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Cynoscion parvipinnis	1.7	3.0	0.82	high
Gymnothorax mordax	2.1	2.3	0.86	high
Mycteroperca jordani	2.3	2.3	0.92	high
Paralichthys californicus	2.1	2.3	0.86	high
Sarda chiliensis var. chiliensis	1.9	2.3	0.67	high
Sphyraena argentea	1.9	2.3	0.67	high
Stereolepis gigas	2.4	2.3	0.96	high
Synodus lucioceps	1.4	1.9	0.11	low
Torpedo californica	2.6	2.3	0.98	high
Pteroplatytrygon violacea	2.4	1.6	0.75	high
Squalus acanthias	2.9	1.6	0.95	high
Kathetostoma averruncus	1.4	1.9	0.11	low
Squatina californica	2.7	2.3	0.99	high
Sphyrna lewini	2.9	1.6	0.95	high
Seriola lalandi	2.0	1.6	0.38	medium
Porichthys notatus	1.7	1.9	0.29	low
Pristigenys serrula	1.3	1.9	0.06	low
Antennarius avalonis	1.3	1.9	0.06	low
Phalacrocorax pelagicus	2.3	1.6	0.64	medium
Phoca vitulina	2.7	1.6	0.91	high
Tursiops truncatus	3.0	1.6	0.98	high
Zalophus californianus	2.7	2.3	0.99	high
Gymnura marmorata	2.6	2.3	0.98	high
Caulolatilus princeps	1.9	2.3	0.67	high
Heterostichus rostratus	1.7	1.9	0.29	low
Paralabrax clathratus	1.7	1.9	0.29	low
Cephaloscyllium ventriosum	2.6	2.3	0.98	high
Raja rhina	2.7	2.3	0.99	high
Scorpaena guttata	1.9	1.9	0.41	medium
Rhacochilus vacca	2.1	1.9	0.67	high
Triakis semifasciata	2.9	2.3	1.0	high
Scorpaenichthys marmoratus	1.7	1.9	0.29	low
Semicossyphus pulcher	2.1	1.9	0.67	high
Cheilotrema saturnum	1.7	1.9	0.29	low
Microlepidotus inornatus	1.6	2.3	0.42	medium
Rhinobatos productus	2.7	2.3	0.99	high
Zapteryx exasperata	2.3	2.3	0.92	high
Anisotremus davidsoni	1.6	1.9	0.19	low
Paralabrax nebulifer	1.7	1.9	0.29	low
Calamus brachysomus	1.6	2.3	0.42	medium

(*continued on next page*)

Appendix C.1 (*continued*)

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Sebastes paucispinis	2.1	2.3	0.86	high
Anisotremus interruptus	1.4	1.9	0.11	low
Brachyistius frenatus	1.7	1.4	0.08	low
Platyrhinoidis triseriata	2.3	2.3	0.92	high
Rhacochilus toxotes	2.0	1.9	0.54	medium
Balistes polylepis	1.6	1.9	0.19	low
Hypsurus caryi	1.9	1.9	0.41	medium
Halichoeres semicinctus	1.3	1.9	0.06	low
Embiotoca jacksoni	1.4	1.4	0.02	low
Atractoscion nobilis	1.9	2.3	0.67	high
Heterodontus francisci	2.3	2.3	0.92	high
Urolophus halleri	2.0	1.4	0.23	low
Hypsypops rubicundus	1.6	1.9	0.19	low
Myliobatis californica	2.4	2.3	0.96	high
Oxyjulis californica	1.1	1.4	0.0	low
Scomber japonicus	1.3	1.6	0.03	low
Sphoeroides annulatus	1.4	1.9	0.11	low
Callinectes bellicosus	1.1	1.0	0.0	low
Cancer anthonyi	1.6	1.6	0.08	low
Eugorgia ampla	2.0	2.3	0.78	high
Eugorgia daniana	2.0	2.3	0.78	high
Leptogorgia diffusa	2.0	2.3	0.78	high
Muricea californica	2.0	2.3	0.78	high
Octopus rubescens	1.4	1.9	0.11	low
Pacifigorgia	2.0	1.6	0.38	medium
Panulirus interruptus	1.9	1.4	0.14	low
Chromis punctipinnis	1.3	1.4	0.01	low
Medialuna californiensis	1.4	1.9	0.11	low
Parastichopus parvimensis	1.3	1.1	0.0	low
Sardinops sagax	1.4	1.2	0.0	low
Girella nigricans	1.3	2.3	0.19	low
Eucidaris thourasii	1.1	1.2	0.0	low
Haliotis corrugata	1.3	1.0	0.0	low
Haliotis fulgens	1.4	1.0	0.0	low
Kyphosus analogus	1.3	1.9	0.06	low
Megastraea undosa	1.1	1.1	0.0	low
Megathura crenulata	1.1	1.1	0.0	low
Strongylocentrotus franciscanus	1.3	1.0	0.0	low
Strongylocentrotus purpuratus	1.4	1.0	0.0	low
Eisenia arborea	1.6	1.9	0.19	low
Gelidium robustum	1.4	1.4	0.02	low

Appendix C.2
Drift gillnets.

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Cynoscion parvipinnis	1.7	3.0	0.82	high
Gymnothorax mordax	2.1	1.4	0.34	medium
Mycteroperca jordani	2.3	1.4	0.46	medium
Paralichthys californicus	2.1	1.3	0.22	low
Sarda chiliensis var. chiliensis	1.9	2.3	0.67	high
Sphyraena argentea	1.9	2.3	0.67	high
Stereolepis gigas	2.4	2.3	0.96	high
Synodus lucioceps	1.4	1.3	0.01	low
Torpedo californica	2.6	2.3	0.98	high
Pteroplatytrygon violacea	2.4	1.6	0.75	high
Squalus acanthias	2.9	1.6	0.95	high
Kathetostoma averruncus	1.4	1.3	0.01	low
Squatina californica	2.7	2.3	0.99	high
Sphyrna lewini	2.9	1.6	0.95	high
Seriola lalandi	2.0	1.6	0.38	medium
Porichthys notatus	1.7	1.3	0.04	low
Pristigenys serrula	1.3	1.3	0.0	low
Antennarius avalonis	1.3	1.3	0.0	low
Phalacrocorax pelagicus	2.3	1.6	0.64	medium
Phoca vitulina	2.7	1.6	0.91	high
Tursiops truncatus	3.0	1.6	0.98	high
Zalophus californianus	2.7	2.3	0.99	high
Gymnura marmorata	2.6	1.4	0.71	high
Caulolatilus princeps	1.9	1.4	0.14	low
Heterostichus rostratus	1.7	1.3	0.04	low
Paralabrax clathratus	1.7	1.3	0.04	low

(*continued on next page*)

Appendix C.2 (*continued*)

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Cephaloscyllium ventriosum	2.6	1.4	0.71	high
Raja rhina	2.7	1.4	0.81	high
Scorpaena guttata	1.9	1.3	0.08	low
Rhacochilus vacca	2.1	1.3	0.22	low
Triakis semifasciata	2.9	1.4	0.89	high
Scorpaenichthys marmoratus	1.7	1.3	0.04	low
Semicossyphus pulcher	2.1	1.3	0.22	low
Cheilotrema saturnum	1.7	1.3	0.04	low
Microlepidotus inornatus	1.6	1.4	0.04	low
Rhinobatos productus	2.7	1.4	0.81	high
Zapteryx exasperata	2.3	1.4	0.46	medium
Anisotremus davidsoni	1.6	1.3	0.02	low
Paralabrax nebulifer	1.7	1.3	0.04	low
Calamus brachysomus	1.6	1.4	0.04	low
Sebastes paucispinis	2.1	1.4	0.34	medium
Anisotremus interruptus	1.4	1.3	0.01	low
Brachyistius frenatus	1.7	1.1	0.02	low
Platyrhinoidis triseriata	2.3	1.4	0.46	medium
Rhacochilus toxotes	2.0	1.3	0.14	low
Balistes polylepis	1.6	1.3	0.02	low
Hypsurus caryi	1.9	1.3	0.08	low
Halichoeres semicinctus	1.3	1.3	0.0	low
Embiotoca jacksoni	1.4	1.1	0.0	low
Atractoscion nobilis	1.9	2.3	0.67	high
Heterodontus francisci	2.3	1.4	0.46	medium
Urolophus halleri	2.0	1.1	0.07	low
Hypsypops rubicundus	1.6	1.3	0.02	low
Myliobatis californica	2.4	1.4	0.59	medium
Oxyjulis californica	1.1	1.1	0.0	low
Scomber japonicus	1.3	1.4	0.01	low
Sphoeroides annulatus	1.4	1.3	0.01	low
Callinectes bellicosus	1.1	1.0	0.0	low
Cancer anthonyi	1.6	1.1	0.0	low
Eugorgia ampla	2.0	1.1	0.07	low
Eugorgia daniana	2.0	1.1	0.07	low
Leptogorgia diffusa	2.0	1.1	0.07	low
Muricea californica	2.0	1.1	0.07	low
Octopus rubescens	1.4	1.1	0.0	low
Pacifigorgia	2.0	1.0	0.04	low
Panulirus interruptus	1.9	1.1	0.04	low
Chromis punctipinnis	1.3	1.1	0.0	low
Medialuna californiensis	1.4	1.3	0.01	low
Parastichopus parvimensis	1.3	1.0	0.0	low
Sardinops sagax	1.4	1.2	0.0	low
Girella nigricans	1.3	1.4	0.01	low
Eucidaris thourasii	1.1	1.1	0.0	low
Haliotis corrugata	1.3	1.0	0.0	low
Haliotis fulgens	1.4	1.0	0.0	low
Kyphosus analogus	1.3	1.3	0.0	low
Megastraea undosa	1.1	1.0	0.0	low
Megathura crenulata	1.1	1.0	0.0	low
Strongylocentrotus franciscanus	1.3	1.0	0.0	low
Strongylocentrotus purpuratus	1.4	1.0	0.0	low
Eisenia arborea	1.6	1.1	0.01	low
Gelidium robustum	1.4	1.1	0.0	low

Appendix C.3
Lobster traps.

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Cynoscion parvipinnis	1.7	1.2	0.03	low
Gymnothorax mordax	2.1	1.4	0.34	medium
Mycteroperca jordani	2.3	1.4	0.46	medium
Paralichthys californicus	2.1	1.4	0.34	medium
Sarda chiliensis var. chiliensis	1.9	1.1	0.04	low
Sphyraena argentea	1.9	1.1	0.04	low
Stereolepis gigas	2.4	1.4	0.59	medium
Synodus lucioceps	1.4	1.4	0.02	low
Torpedo californica	2.6	1.1	0.43	medium
Pteroplatytrygon violacea	2.4	1.0	0.23	low
Squalus acanthias	2.9	1.0	0.6	medium
Kathetostoma averruncus	1.4	1.9	0.11	low

(*continued on next page*)

Appendix C.3 (*continued*)

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Squatina californica	2.7	1.1	0.56	medium
Sphyrna lewini	2.9	1.0	0.6	medium
Seriola lalandi	2.0	1.0	0.04	low
Porichthys notatus	1.7	1.4	0.08	low
Pristigenys serrula	1.3	1.4	0.01	low
Antennarius avalonis	1.3	2.3	0.19	low
Phalacrocorax pelagicus	2.3	1.2	0.26	low
Phoca vitulina	2.7	1.0	0.45	medium
Tursiops truncatus	3.0	1.0	0.67	medium
Zalophus californianus	2.7	1.1	0.51	medium
Gymnura marmorata	2.6	1.4	0.71	high
Caulolatilus princeps	1.9	1.4	0.14	low
Heterostichus rostratus	1.7	1.4	0.08	low
Paralabrax clathratus	1.7	2.3	0.55	medium
Cephaloscyllium ventriosum	2.6	1.4	0.71	high
Raja rhina	2.7	1.4	0.81	high
Scorpaena guttata	1.9	1.4	0.14	low
Rhacochilus vacca	2.1	1.4	0.34	medium
Triakis semifasciata	2.9	1.4	0.89	high
Scorpaenichthys marmoratus	1.7	1.4	0.08	low
Semicossyphus pulcher	2.1	2.3	0.86	high
Cheilotrema saturnum	1.7	1.4	0.08	low
Microlepidotus inornatus	1.6	1.6	0.1	low
Rhinobatos productus	2.7	1.4	0.81	high
Zapteryx exasperata	2.3	1.4	0.46	medium
Anisotremus davidsoni	1.6	2.3	0.42	medium
Paralabrax nebulifer	1.7	2.3	0.55	medium
Calamus brachysomus	1.6	1.4	0.04	low
Sebastes paucispinis	2.1	1.4	0.34	medium
Anisotremus interruptus	1.4	1.4	0.02	low
Brachyistius frenatus	1.7	2.3	0.55	medium
Platyrhinoidis triseriata	2.3	1.4	0.46	medium
Rhacochilus toxotes	2.0	1.4	0.23	low
Balistes polylepis	1.6	1.4	0.04	low
Hypsurus caryi	1.9	2.3	0.67	high
Halichoeres semicinctus	1.3	1.4	0.01	low
Embiotoca jacksoni	1.4	2.3	0.3	low
Atractoscion nobilis	1.9	1.1	0.04	low
Heterodontus francisci	2.3	1.4	0.46	medium
Urolophus halleri	2.0	2.3	0.78	high
Hypsypops rubicundus	1.6	1.4	0.04	low
Myliobatis californica	2.4	1.4	0.59	medium
Oxyjulis californica	1.1	2.3	0.12	low
Scomber japonicus	1.3	1.0	0.0	low
Sphoeroides annulatus	1.4	2.3	0.3	low
Callinectes bellicosus	1.1	1.2	0.0	low
Cancer anthonyi	1.6	1.4	0.04	low
Eugorgia ampla	2.0	1.4	0.23	low
Eugorgia daniana	2.0	1.4	0.23	low
Leptogorgia diffusa	2.0	1.4	0.23	low
Muricea californica	2.0	1.4	0.23	low
Octopus rubescens	1.4	2.3	0.3	low
Pacifigorgia	2.0	1.2	0.1	low
Panulirus interruptus	1.9	1.6	0.22	low
Chromis punctipinnis	1.3	2.1	0.12	low
Medialuna californiensis	1.4	2.3	0.3	low
Parastichopus parvimensis	1.3	1.1	0.0	low
Sardinops sagax	1.4	1.2	0.0	low
Girella nigricans	1.3	1.4	0.01	low
Eucidaris thourasii	1.1	1.1	0.0	low
Haliotis corrugata	1.3	1.0	0.0	low
Haliotis fulgens	1.4	1.0	0.0	low
Kyphosus analogus	1.3	1.4	0.01	low
Megastraea undosa	1.1	1.1	0.0	low
Megathura crenulata	1.1	1.0	0.0	low
Strongylocentrotus franciscanus	1.3	1.0	0.0	low
Strongylocentrotus purpuratus	1.4	1.0	0.0	low
Eisenia arborea	1.6	1.4	0.04	low
Gelidium robustum	1.4	1.4	0.02	low

Appendix C.4
Fish traps.

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk category
Cynoscion parvipinnis	1.7	1.1	0.02	low
Gymnothorax mordax	2.1	1.3	0.22	low
Mycteroperca jordani	2.3	1.3	0.33	low
Paralichthys californicus	2.1	1.3	0.22	low
Sarda chiliensis var. chiliensis	1.9	1.1	0.03	low
Sphyraena argentea	1.9	1.1	0.03	low
Stereolepis gigas	2.4	1.3	0.46	medium
Synodus lucioceps	1.4	1.3	0.01	low
Torpedo californica	2.6	1.1	0.38	medium
Pteroplatytrygon violacea	2.4	1.0	0.22	low
Squalus acanthias	2.9	1.0	0.58	medium
Kathetostoma averruncus	1.4	1.2	0.0	low
Squatina californica	2.7	1.1	0.51	medium
Sphyrna lewini	2.9	1.0	0.58	medium
Seriola lalandi	2.0	1.0	0.04	low
Porichthys notatus	1.7	1.3	0.04	low
Pristigenys serrula	1.3	1.3	0.0	low
Antennarius avalonis	1.3	1.3	0.0	low
Phalacrocorax pelagicus	2.3	1.2	0.26	low
Phoca vitulina	2.7	1.0	0.45	medium
Tursiops truncatus	3.0	1.0	0.67	medium
Zalophus californianus	2.7	1.1	0.51	medium
Gymnura marmorata	2.6	1.3	0.59	medium
Caulolatilus princeps	1.9	1.4	0.14	low
Heterostichus rostratus	1.7	1.3	0.04	low
Paralabrax clathratus	1.7	1.4	0.08	low
Cephaloscyllium ventriosum	2.6	1.3	0.59	medium
Raja rhina	2.7	1.3	0.71	high
Scorpaena guttata	1.9	1.3	0.08	low
Rhacochilus vacca	2.1	1.3	0.22	low
Triakis semifasciata	2.9	1.3	0.81	high
Scorpaenichthys marmoratus	1.7	1.3	0.04	low
Semicossyphus pulcher	2.1	2.3	0.86	high
Cheilotrema saturnum	1.7	1.3	0.04	low
Microlepidotus inornatus	1.6	1.4	0.04	low
Rhinobatos productus	2.7	1.3	0.71	high
Zapteryx exasperata	2.3	1.3	0.33	low
Anisotremus davidsoni	1.6	1.9	0.19	low
Paralabrax nebulifer	1.7	1.4	0.08	low
Calamus brachysomus	1.6	1.3	0.02	low
Sebastes paucispinis	2.1	1.3	0.22	low
Anisotremus interruptus	1.4	1.3	0.01	low
Brachyistius frenatus	1.7	1.6	0.14	low
Platyrhinoidis triseriata	2.3	1.3	0.33	low
Rhacochilus toxotes	2.0	1.3	0.14	low
Balistes polylepis	1.6	1.3	0.02	low
Hypsurus caryi	1.9	1.3	0.08	low
Halichoeres semicinctus	1.3	1.3	0.0	low
Embiotoca jacksoni	1.4	1.9	0.11	low
Atractoscion nobilis	1.9	1.1	0.03	low
Heterodontus francisci	2.3	1.3	0.33	low
Urolophus halleri	2.0	1.9	0.54	medium
Hypsypops rubicundus	1.6	1.4	0.04	low
Myliobatis californica	2.4	1.3	0.46	medium
Oxyjulis californica	1.1	1.9	0.03	low
Scomber japonicus	1.3	1.0	0.0	low
Sphoeroides annulatus	1.4	1.9	0.11	low
Callinectes bellicosus	1.1	1.2	0.0	low
Cancer anthonyi	1.6	1.1	0.01	low
Eugorgia ampla	2.0	1.4	0.23	low
Eugorgia daniana	2.0	1.4	0.23	low
Leptogorgia diffusa	2.0	1.4	0.23	low
Muricea californica	2.0	1.4	0.23	low
Octopus rubescens	1.4	1.4	0.02	low
Pacifigorgia	2.0	1.2	0.1	low
Panulirus interruptus	1.9	1.1	0.04	low
Chromis punctipinnis	1.3	1.7	0.04	low
Medialuna californiensis	1.4	1.3	0.01	low
Parastichopus parvimensis	1.3	1.1	0.0	low
Sardinops sagax	1.4	1.1	0.0	low
Girella nigricans	1.3	1.3	0.0	low
Eucidaris thourasii	1.1	1.1	0.0	low
Haliotis corrugata	1.3	1.0	0.0	low
Haliotis fulgens	1.4	1.0	0.0	low

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Appendix C.4 (*continued*)

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk category
Kyphosus analogus	1.3	1.3	0.0	low
Megastraea undosa	1.1	1.1	0.0	low
Megathura crenulata	1.1	1.0	0.0	low
Strongylocentrotus franciscanus	1.3	1.0	0.0	low
Strongylocentrotus purpuratus	1.4	1.0	0.0	low
Eisenia arborea	1.6	1.4	0.04	low
Gelidium robustum	1.4	1.4	0.02	low

Appendix C.5
Dive fishing.

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Cynoscion parvipinnis	1.7	1.0	0.01	low
Gymnothorax mordax	2.1	1.0	0.07	low
Mycteroperca jordani	2.3	1.0	0.13	low
Paralichthys californicus	2.1	1.0	0.07	low
Sarda chiliensis var. chiliensis	1.9	1.0	0.02	low
Sphyraena argentea	1.9	1.0	0.02	low
Stereolepis gigas	2.4	1.0	0.22	low
Synodus lucioceps	1.4	1.0	0.0	low
Torpedo californica	2.6	1.0	0.32	low
Pteroplatytrygon violacea	2.4	1.0	0.19	low
Squalus acanthias	2.9	1.0	0.54	medium
Kathetostoma averruncus	1.4	1.0	0.0	low
Squatina californica	2.7	1.0	0.45	medium
Sphyrna lewini	2.9	1.0	0.54	medium
Seriola lalandi	2.0	1.0	0.03	low
Porichthys notatus	1.7	1.0	0.01	low
Pristigenys serrula	1.3	1.0	0.0	low
Antennarius avalonis	1.3	1.0	0.0	low
Phalacrocorax pelagicus	2.3	1.0	0.11	low
Phoca vitulina	2.7	1.0	0.41	medium
Tursiops truncatus	3.0	1.0	0.67	medium
Zalophus californianus	2.7	1.0	0.45	medium
Gymnura marmorata	2.6	1.0	0.32	low
Caulolatilus princeps	1.9	1.0	0.02	low
Heterostichus rostratus	1.7	1.0	0.01	low
Paralabrax clathratus	1.7	1.0	0.01	low
Cephaloscyllium ventriosum	2.6	1.0	0.32	low
Raja rhina	2.7	1.0	0.45	medium
Scorpaena guttata	1.9	1.0	0.02	low
Rhacochilus vacca	2.1	1.0	0.07	low
Triakis semifasciata	2.9	1.0	0.58	medium
Scorpaenichthys marmoratus	1.7	1.0	0.01	low
Semicossyphus pulcher	2.1	1.0	0.07	low
Cheilotrema saturnum	1.7	1.0	0.01	low
Microlepidotus inornatus	1.6	1.0	0.0	low
Rhinobatos productus	2.7	1.0	0.45	medium
Zapteryx exasperata	2.3	1.0	0.13	low
Anisotremus davidsoni	1.6	1.0	0.0	low
Paralabrax nebulifer	1.7	1.0	0.01	low
Calamus brachysomus	1.6	1.0	0.0	low
Sebastes paucispinis	2.1	1.0	0.07	low
Anisotremus interruptus	1.4	1.0	0.0	low
Brachyistius frenatus	1.7	1.0	0.01	low
Platyrhinoidis triseriata	2.3	1.0	0.13	low
Rhacochilus toxotes	2.0	1.0	0.04	low
Balistes polylepis	1.6	1.0	0.0	low
Hypsurus caryi	1.9	1.0	0.02	low
Halichoeres semicinctus	1.3	1.0	0.0	low
Embiotoca jacksoni	1.4	1.0	0.0	low
Atractoscion nobilis	1.9	1.0	0.02	low
Heterodontus francisci	2.3	1.0	0.13	low
Urolophus halleri	2.0	1.0	0.04	low
Hypsypops rubicundus	1.6	1.0	0.0	low
Myliobatis californica	2.4	1.0	0.22	low
Oxyjulis californica	1.1	1.0	0.0	low
Scomber japonicus	1.3	1.0	0.0	low
Sphoeroides annulatus	1.4	1.0	0.0	low
Callinectes bellicosus	1.1	1.0	0.0	low
Cancer anthonyi	1.6	1.0	0.0	low
Eugorgia ampla	2.0	1.0	0.04	low

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Appendix C.5 (*continued*)

Species	Productivity	Susceptibility	Vulnerability (Vp)	Risk Category
Eugorgia daniana	2.0	1.0	0.04	low
Leptogorgia diffusa	2.0	1.0	0.04	low
Muricea californica	2.0	1.0	0.04	low
Octopus rubescens	1.4	2.3	0.3	low
Pacifigorgia	2.0	1.0	0.03	low
Panulirus interruptus	1.9	1.0	0.02	low
Chromis punctipinnis	1.3	1.0	0.0	low
Medialuna californiensis	1.4	1.0	0.0	low
Parastichopus parvimensis	1.3	2.3	0.19	low
Sardinops sagax	1.4	1.0	0.0	low
Girella nigricans	1.3	1.0	0.0	low
Eucidaris thourasii	1.1	1.0	0.0	low
Haliotis corrugata	1.3	2.3	0.19	low
Haliotis fulgens	1.4	2.3	0.3	low
Kyphosus analogus	1.3	1.0	0.0	low
Megastraea undosa	1.1	2.3	0.12	low
Megathura crenulata	1.1	2.3	0.12	low
Strongylocentrotus franciscanus	1.3	2.3	0.19	low
Strongylocentrotus purpuratus	1.4	2.3	0.3	low
Eisenia arborea	1.6	1.0	0.0	low
Gelidium robustum	1.4	2.3	0.3	low

Appendix C.6
All stressors.

Species	Productivity	Susceptibility*	Vulnerability (Vp)	Risk Category
Cynoscion parvipinnis	1.7	3	0.98	high
Gymnothorax mordax	2.1	2.6	0.98	high
Mycteroperca jordani	2.3	2.6	0.99	high
Paralichthys californicus	2.1	2.5	0.97	high
Sarda chiliensis var. chiliensis	1.9	2.7	0.94	high
Sphyraena argentea	1.9	2.7	0.94	high
Stereolepis gigas	2.4	2.9	1.0	high
Synodus lucioceps	1.4	2.4	0.49	medium
Torpedo californica	2.6	2.7	1.0	high
Pteroplatytrygon violacea	2.4	2.2	0.95	high
Squalus acanthias	2.9	2.2	1.0	high
Kathetostoma averruncus	1.4	2.5	0.59	medium
Squatina californica	2.7	2.7	1.0	high
Sphyrna lewini	2.9	2.2	1.0	high
Seriola lalandi	2.0	2.2	0.75	high
Porichthys notatus	1.7	2.4	0.73	high
Pristigenys serrula	1.3	2.4	0.36	medium
Antennarius avalonis	1.3	2.7	0.63	medium
Phalacrocorax pelagicus	2.3	2.3	0.96	high
Phoca vitulina	2.7	2.2	0.99	high
Tursiops truncatus	3.0	2.2	1.0	high
Zalophus californianus	2.7	2.7	1.0	high
Gymnura marmorata	2.6	2.6	1.0	high
Caulolatilus princeps	1.9	2.6	0.94	high
Heterostichus rostratus	1.7	2.4	0.73	high
Paralabrax clathratus	1.7	2.7	0.93	high
Cephaloscyllium ventriosum	2.6	2.6	1.0	high
Raja rhina	2.7	2.6	1.0	high
Scorpaena guttata	1.9	2.4	0.83	high
Rhacochilus vacca	2.1	2.4	0.95	high
Triakis semifasciata	2.9	2.6	1.0	high
Scorpaenichthys marmoratus	1.7	2.4	0.73	high
Semicossyphus pulcher	2.1	3	1.0	high
Cheilotrema saturnum	1.7	2.4	0.73	high
Microlepidotus inornatus	1.6	2.7	0.87	high
Rhinobatos productus	2.7	2.6	1.0	high
Zapteryx exasperata	2.3	2.6	0.99	high
Anisotremus davidsoni	1.6	2.9	0.93	high
Paralabrax nebulifer	1.7	2.7	0.93	high
Calamus brachysomus	1.6	2.6	0.77	high
Sebastes paucispinis	2.1	2.6	0.98	high
Anisotremus interruptus	1.4	2.4	0.49	medium
Brachyistius frenatus	1.7	2.6	0.85	high
Platyrhinoidis triseriata	2.3	2.6	0.99	high
Rhacochilus toxotes	2.0	2.4	0.9	high
Balistes polylepis	1.6	2.4	0.62	medium

(*continued on next page*)

Appendix C.6 (*continued*)

Species	Productivity	Susceptibility*	Vulnerability (Vp)	Risk Category
Hypsurus caryi	1.9	2.7	0.95	high
Halichoeres semicinctus	1.3	2.4	0.36	medium
Embiotoca jacksoni	1.4	2.7	0.73	high
Atractoscion nobilis	1.9	2.7	0.94	high
Heterodontus francisci	2.3	2.6	0.99	high
Urolophus halleri	2.0	2.7	0.97	high
Hypsypops rubicundus	1.6	2.4	0.67	high
Myliobatis californica	2.4	2.6	1.0	high
Oxyjulis californica	1.1	2.7	0.49	medium
Scomber japonicus	1.3	2.1	0.12	low
Sphoeroides annulatus	1.4	2.9	0.88	high
Callinectes bellicosus	1.1	1.9	0.01	low
Cancer anthonyi	1.6	2.1	0.36	medium
Eugorgia ampla	2.0	2.5	0.94	high
Eugorgia daniana	2.0	2.5	0.94	high
Leptogorgia diffusa	2.0	2.5	0.94	high
Muricea californica	2.0	2.5	0.94	high
Octopus rubescens	1.4	3	0.96	high
Pacifigorgia	2.0	2.1	0.67	high
Panulirus interruptus	1.9	2.2	0.64	medium
Chromis punctipinnis	1.3	2.6	0.52	medium
Medialuna californiensis	1.4	2.7	0.74	high
Parastichopus parvimensis	1.3	2.3	0.22	low
Sardinops sagax	1.4	2.0	0.11	low
Girella nigricans	1.3	2.6	0.54	medium
Eucidaris thourasii	1.1	1.9	0.02	low
Haliotis corrugata	1.3	2.2	0.13	low
Haliotis fulgens	1.4	2.2	0.21	low
Kyphosus analogus	1.3	2.4	0.36	medium
Megastraea undosa	1.1	2.3	0.14	low
Megathura crenulata	1.1	2.2	0.08	low
Strongylocentrotus franciscanus	1.3	2.2	0.13	low
Strongylocentrotus purpuratus	1.4	2.2	0.21	low
Eisenia arborea	1.6	2.4	0.61	medium
Gelidium robustum	1.4	2.7	0.76	high

* Multi-stressor Susceptibility values are used for plot visualization and are not always equivalent to single stressor Susceptibility values, though they are an order-preserving metric of single stressor Susceptibility values.

References

Battista, W., Karr, K., Sarto, N., Fujita, R., 2017. Comprehensive assessment of risk to ecosystems (care): a cumulative ecosystem risk assessment tool. Fish. Res. 185, 115–129.

Dumbravă, V., Iacob, V.-S., 2013. Using Probability–Impact Matrix in Analysis and Risk Assessment Projects, Descrierea CIP/Description of CIP–Biblioteca Naţională a României Conferinţa Internaţională Educaţie şi Creativitate Pentru O Societate Bazată Pe Cunoaştere–ŞTIINŢE ECONOMICE 42.

FAO, 2020. The State of World Fisheries and Aquaculture (Sofia), 2020.

Finkbeiner, E.M., Bennett, N.J., Frawley, T.H., Mason, J.G., Briscoe, D.K., Brooks, C.M., Ng, C.A., Ourens, R., Seto, K., Switzer Swanson, S., et al., 2017. Reconstructing overfishing: moving beyond malthus for effective and equitable solutions. Fish Fish. 18 (6), 1180–1191.

Grewelle, R.E., Mansfield, E., Micheli, F., De Leo, G., 2021. Redefining risk in data-poor fisheries. Fish 22 (5), 929–940.

Halpern, B.S., Kappel, C.V., Selkoe, K.A., Micheli, F., Ebert, C.M., Kontgis, C., Crain, C. M., Martone, R.G., Shearer, C., Teck, S.J., 2009. Mapping cumulative human impacts to California current marine ecosystems. Conserv. Lett. 2 (3), 138–148.

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

Hines, E.E., Landis, W.G., 2014. Regional risk assessment of the Puyallup river watershed and the evaluation of low impact development in meeting management goals. Integr. Environ. Assess. Manag. 10 (2), 269–278.

Hobday, A., Smith, A., Webb, H., Daley, R., Wayte, S., Bulman, C., Dowdney, J., Williams, A., Sporcic, M., Dambacher, J., et al., 2007. Ecological Risk Assessment for the Effects of Fishing: Methodology. Report r04/1072 for the Australian Fisheries Management Authority.

Hobday, A., Smith, A., Stobutzki, I., Bulman, C., Daley, R., Dambacher, J., Deng, R., Dowdney, J., Fuller, M., Furlani, D., et al., 2011. Ecological risk assessment for the effects of fishing. Fish. Res. 108 (2–3), 372–384.

Hope, B.K., 2006. An examination of ecological risk assessment and management practices. Environ. Int. 32 (8), 983–995.

Jackson, M.C., Loewen, C.J., Vinebrooke, R.D., Chimimba, C.T., 2016. Net effects of multiple stressors in freshwater ecosystems: a meta-analysis. Glob. Chang. Biol. 22 (1), 180–189.

Koller, G., 2005. Risk Assessment and Decision Making in Business and Industry: A Practical Guide. CRC Press.

Marine Stewardship Council, 2019. The MSC Annual Report 2018-2019.

McMahon, T.A., Halstead, N.T., Johnson, S., Raffel, T.R., Romansic, J.M., Crumrine, P. W., Rohr, J.R., 2012. Fungicide-induced declines of freshwater biodiversity modify ecosystem functions and services. Ecol. Lett. 15 (7), 714–722.

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

Mora, C., Tittensor, D.P., Adl, S., Simpson, A.G., Worm, B., 2011. How many species are there on earth and in the ocean? PLoS Biol. 9 (8), e1001127.

N. R. Council, 2009. et al. Science and Decisions: Advancing Risk Assessment.

Norton, S.B., Rodier, D.J., van der Schalie, W.H., Wood, W.P., Slimak, M.W., Gentile, J. H., 1992. A framework for ecological risk assessment at the epa. Environ. Toxicol. Chem. 11 (12), 1663–1672.

Oestreich, W.K., Frawley, T.H., Mansfield, E.J., Green, K.M., Green, S.J., Naggea, J., Selgrath, J.C., Swanson, S.S., Urteaga, J., White, T.D., et al., 2019. The Impact of Environmental Change on Small-Scale Fishing Communities: Moving beyond Adaptive Capacity to Community Response. Predicting Future Oceans, Elsevier, pp. 271–282.

Ofungwu, J., 2014. Statistical Applications for Environmental Analysis and Risk Assessment. John Wiley & Sons.

Pilling, G.M., Apostolaki, P., Failler, P., Floros, C., Large, P.A., Morales-Nin, B., Reglero, P., Stergiou, K.I., Tsikliras, A.C., 2009. Assessment and management of data-poor fisheries. Adv. Fish. Sci. 50, 280–305.

Pontón-Cevallos, J.F., Bruneel, S., Marn Jarrn, J.R., Ramrez-González, J., Bermúdez-Monsalve, J.R., Goethals, P.L., 2020. Vulnerability and decision-making in multispecies fisheries: a risk assessment of bacalao (*mycteroperca olfax*) and related species in the galapagos' handline fishery. Sustainability 12 (17), 6931.

Ravindra, K., Mor, S., 2019. Distribution and health risk assessment of arsenic and selected heavy metals in groundwater of Chandigarh, India. Environ. Pollut. 250, 820–830.

Rodier, D., Norton, S., 1992. Framework for Ecological Risk Assessment. Environmental Protection Agency, Washington, DC (United States). Risk ….

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

Stobutzki, I., Miller, M., Brewer, D., 2001. Sustainability of fishery bycatch: a process for assessing highly diverse and numerous bycatch. Environ. Conserv. 28 (2), 167–181.

Tannenbaum, L.V., Johnson, M.S., Bazar, M., 2003. Application of the hazard quotient method in remedial decisions: a comparison of human and ecological risk assessments. Hum. Ecol. Risk. Assess. 9 (1), 387–401.

Townsend, H., Harvey, C.J., deReynier, Y., Davis, D., Zador, S., Gaichas, S., Weijerman, M., Hazen, E.L., Kaplan, I.C., 2019. Progress on implementing ecosystem-based fisheries management in the us through the use of ecosystem models and analysis. Front. Mar. Sci. 6, 641.

Van den Brink, P.J., Choung, C.B., Landis, W., Mayer-Pinto, M., Pettigrove, V., Scanes, P., Smith, R., Stauber, J., 2016a. New approaches to the ecological risk assessment of multiple stressors. Mar. Freshw. Res. 67 (4), 429–439.

Van den Brink, P.J., Choung, C.B., Landis, W., Mayer-Pinto, M., Pettigrove, V., Scanes, P., Smith, R., Stauber, J., 2016b. New approaches to the ecological risk assessment of multiple stressors. Mar. Freshw. Res. 67 (4), 429–439.

Walters, C.J., 1986. Adaptive Management of Renewable Resources. Macmillan Publishers Ltd.

Woodruff, J.M., 2005. Consequence and likelihood in risk estimation: a matter of balance in UK health and safety risk assessment practice. Saf. Sci. 43 (5–6), 345–353.

World Health Organization, et al., 2020. Risk Assessment.

Zio, E., 2018. The future of risk assessment. Reliab. Eng. Syst. Saf. 177, 176–190.