Received: 3 June 2017 | Accepted: 10 August 2017

DOI: 10.1111/gcb.13869

TECHNICAL ADVANCE

WILEY Global Change Biology

Using fuzzy logic to determine the vulnerability of marine species to climate change

Miranda C. Jones | **William W. L. Cheung**

Changing Ocean Research Unit, Institute for the Oceans and Fisheries, University of British Columbia, Vancouver, BC, Canada

Correspondence
William W. L. Cheung, Aquatic Ecosystems Research Laboratory, 2202 Main Mall, The University of British Columbia, Vancouver, BC, Canada.
Email: w.cheung@oceans.ubc.ca

Funding information
Nippon Foundation; Natural Sciences and Engineering Research Council of Canada

Abstract

Marine species are being impacted by climate change and ocean acidification, although their level of vulnerability varies due to differences in species' sensitivity, adaptive capacity and exposure to climate hazards. Due to limited data on the biological and ecological attributes of many marine species, as well as inherent uncertainties in the assessment process, climate change vulnerability assessments in the marine environment frequently focus on a limited number of taxa or geographic ranges. As climate change is already impacting marine biodiversity and fisheries, there is an urgent need to expand vulnerability assessment to cover a large number of species and areas. Here, we develop a modelling approach to synthesize data on species-specific estimates of exposure, and ecological and biological traits to undertake an assessment of vulnerability (sensitivity and adaptive capacity) and risk of impacts (combining exposure to hazards and vulnerability) of climate change (including ocean acidification) for global marine fishes and invertebrates. We use a fuzzy logic approach to accommodate the variability in data availability and uncertainties associated with inferring vulnerability levels from climate projections and species' traits. Applying the approach to estimate the relative vulnerability and risk of impacts of climate change in 1074 exploited marine species globally, we estimated their index of vulnerability and risk of impacts to be on average 52 ± 19 *SD* and 66 ± 11 *SD*, scaling from 1 to 100, with 100 being the most vulnerable and highest risk, respectively, under the 'business-as-usual' greenhouse gas emission scenario (Representative Concentration Pathway 8.5). We identified 157 species to be highly vulnerable while 294 species are identified as being at high risk of impacts. Species that are most vulnerable tend to be large-bodied endemic species. This study suggests that the fuzzy logic framework can help estimate climate vulnerabilities and risks of exploited marine species using publicly and readily available information.

KEYWORDS
climate change, fishes, fuzzy logic, invertebrates, marine, ocean acidification, risk of impacts, vulnerability

1 | INTRODUCTION

The oceans are getting warmer, less oxygenated and are increasing in acidity (Gattuso et al., 2015), causing large-scale changes in marine biodiversity (Cheung et al., 2009; Pörtner et al., 2014). For example, there is abundant evidence of climate change impacts in observed shifts in species' biogeography and phenology (Poloczanska et al. 2013; Pörtner et al., 2014). Moreover, ocean acidification impacts certain groups of marine organisms through its physiological effects on calcification, growth, larval mortality and behaviour (Kroeker et al., 2013; Pörtner et al., 2014). Such climate impacts are expected to continue to alter patterns of global marine biodiversity (Jones & Cheung, 2015), with consequences for the potential fish catch available to fisheries, economics and food security (Barange et al., 2014; Cheung, Reygondeau & Frölicher, 2016; Lam, Cheung, Reygondeau & Sumaila, 2016). However, variations in species' responses to climate change also depend partly on species-specific characteristics (Hare et al., 2016).

As studies have indicated that observed climate impacts are mediated by species' biological traits (Dawson, Jackson, House, Prentice & Mace, 2011), empirical and theoretical studies across taxonomic groups have begun to identify general attributes that predispose species to being vulnerable to the effects of climate change (e.g., Foden et al., 2013 Hare et al., 2016; Okey, Agbayani & Alidina, 2015; Pecl et al., 2014). Species with broad physiological tolerances, such as those accustomed to large climatic variations may be more likely to persist in their current habitat or range extent. Traits that influence a species ability to disperse, such as the mode of dispersal, duration of larval phase or fecundity, may further affect the capacity of a species to move away from prohibitively altered environments, into more suitable ones (Pöyry, Luoto, Heikkinen, Kuussaari & Saarinen, 2009).

Vulnerability assessment techniques have been applied that look at the extinction risk from a particular threat as a combination of a species' vulnerability and its exposure to that threat. While an in-depth understanding of population dynamics would be required for conventional assessments of extinction risk, the difficulty of obtaining these data for the majority of species (Dulvy, Sadovy & Reynolds, 2003) has necessitated that life history and ecological traits have been used as proxies to evaluate, for example, the intrinsic vulnerability of marine fishes to fishing (Cheung, Pitcher & Pauly, 2005; Reynolds, Dulvy, Goodwin & Hutchings, 2005). In a similar way, studies have started to combine proxy attributes with measures of exposure to changing environmental variables to assess the vulnerability of species to climate change (Foden et al., 2013; Garcia et al., 2014).

Such vulnerability assessments recognize that a species' vulnerability to climate change depends on an interaction between its intrinsic biological or ecological characteristics (sensitivity and adaptive capacity) and the extrinsic threats or stimuli (exposure and hazard) (Figure 1). In this study, we adopted the climate vulnerability and risk assessment framework used by the fifth assessment report of

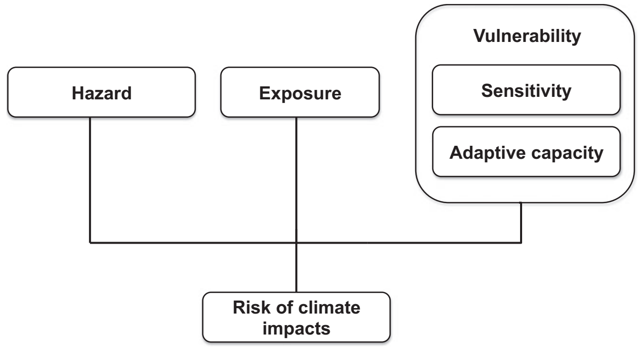

FIGURE 1 Framework for assessing climate change vulnerability and risk adopted by the fifth assessment report of the IPCC (Field et al., 2014)

the Intergovernmental Panel on Climate Change (IPCC) (Field et al., 2014). Sensitivity of a species, referred to here as the susceptibility to impacts from climate change, is affected by species' biological and ecological traits. Species' sensitivity may be moderated by their adaptive capacity, which reflects a species' ability to adapt and thus cope with, or avoid, the impacts of climate change. As the unit of assessment is an individual species, we consider a species' ability to shift in distribution to avoid or minimize negative impacts from changing habitat conditions on its viability as an adaptive response to climate change. Specifically, in this study, we focus on characteristics that determine a species ability to show this response, within its current distribution. Thus, the spatial response of a distribution shift may itself be influenced by adaptive characteristics included here. The combination of a species' sensitivity and (lack of) adaptive capacity determines its vulnerability to climate change. Ultimately, the risk of impacts of climate change on the species is determined by its vulnerability as well as the potential occurrence of climate-related ocean changes (i.e., hazards such as warming, ocean acidification) and the degree of exposure to such event (i.e., exposure) (Figure 1).

To help prioritize resources to focus on studying marine species that are most at risk to climate change in the world, a generalized approach that may be applied to a wide range of species with easily accessible information is needed. The development and applications of techniques to assess climate change vulnerability in the marine environment has so far focused on particular geographic regions and taxonomic groups (e.g., Foden et al., 2013; Graham et al., 2011; Hare et al., 2016; Okey et al., 2015). The generalization of such vulnerability assessments is limited by the paucity of data on marine species' traits, with knowledge on basic life history and biological traits frequently lacking, as well as the incomplete understanding about the linkages between these traits and vulnerability to climate change. It is thus desirable to have an approach that takes account of data gaps and inherent uncertainties in our understanding of inferred vulnerabilities from particular attribute levels, and is updatable following improvements in data and understanding.

Fuzzy set theory (Zadeh, 1965) is particularly useful in dealing with high uncertainty in both input data and the relationship between species' traits and their vulnerability to climate change impacts. Rather than classifying membership to a category as "true" or "false", as under classical logic, fuzzy logic allows an element to belong to more than one category, or fuzzy set, with a gradation of membership defined by a fuzzy membership function. An expert system uses heuristic rules expressed in the form:

If *A* then *B*

where *A* is the premise and *B* is the conclusion. Actions defined by each rule are operated when a threshold value of membership is exceeded, thereby defining the minimum required membership of the premise that an expert would expect for a particular rule to be fired. Conclusions are then drawn from inferences of the expert rules. Fuzzy logic expert system approach has been applied in studying marine biodiversity and fisheries, such as to evaluate the vulnerability of marine fishes to fishing (Cheung et al., 2005).

In this paper, we developed a vulnerability assessment that drew on principles and approaches adopted by the IPCC (Field et al., 2014; Mach, Mastrandrea, Bilir & Field, 2016). We developed a fuzzy logic expert system adapted from the framework used by Cheung et al. (2005) that aimed to evaluate the intrinsic extinction vulnerability of marine fishes to fishing. We aimed to apply this expert system to undertake a large-scale, quantitative vulnerability assessment to evaluate potential climate change impacts, and identify species with the greatest vulnerability to climate change by incorporating variables determining species' sensitivity and adaptive capacity. We then combined species' vulnerability with exposure to projected climate hazards to examine the risk of impacts of climate change on each species. We use an ensemble projection of earth system models to improve the robustness of assessing exposure for species. Our approach uses biological and ecological data that are available for a wide range of species (those that are currently available through FishBase, Froese & Pauly, 2017, http://www.fishbase.org) so that we can assess the vulnerability of data-limited species.

2 | MATERIALS AND METHODS

We developed a fuzzy logic expert system to assess the level of exposure to hazard, sensitivity, adaptive capacity and the resulting overall vulnerability and risk of marine fishes and invertebrates to climate change and ocean acidification. The system is subdivided into three components: (i) fuzzification, (ii) fuzzy reasoning, and (iii) defuzzification (Cheung et al., 2005). Employing fuzzy set theory, or "fuzzy logic" allows the uncertainty surrounding our knowledge of fish biological and ecological characteristics as well as their linkages to vulnerability to be taken into account. Thus, rather than allocating a subject to one category, or set, overlapping fuzzy sets allow a subject to belong to one of more sets simultaneously, with the extent of membership to each being defined by a fuzzy membership function (Figure 2).

Input data for each variable enabled a species to be classified into linguistic categories of vulnerability using heuristic rules to define the classification of fuzzy sets for each component of vulnerability: exposure to hazard, sensitivity and adaptive capacity.

2.1 | Exposure to hazard

In the context of climate change, exposure describes the extent to which species would be subjected to climate hazards (predicted changes in physical environment). To calculate exposure to hazard across a species range, we obtained current range boundary for each species as predicted using the Sea Around Us method (see Jones, Dye, Pinnegar, Warren & Cheung, 2012 for details). The range boundary was defined based on latitudinal and depth ranges, as well as expert-delineated range boundaries such as those published in FAO species catalogues. The range boundary was then subsequently rasterized on a 0.5° latitude × 0.5° longitude grid.

Climate hazard was calculated from projected changes in key ocean ecosystem drivers that have shown to affect species population viability: temperature, oxygen and pH (Pörtner et al., 2014). Projected sea surface and bottom temperature, oxygen concentration and hydrogen ion concentration from three system models: the Geophysical Fluid Dynamics Laboratory's ESM 2G (GFDL-ESM-2G), Institut Pierre Simon Laplace's CM6-MR (IPSL-CM6-MR) and Max Planck Institute's ESM-MR (MPI-ESM-MR) for two time periods: 1951-2000 and 2041-2060 under the Representative Concentration Pathway 8.5 were extracted from the Coupled Models Intercomparison Project Phase 5. These model outputs were regridded and interpolated onto a 0.5° latitude × 0.5° longitude grid of the world ocean using the bilinear interpolation method. Climate hazard was indicated by the mean change in an environmental variable (*V*) between baseline (average between 1951 and 2000) and 2050 (average between 2041 and 2060) divided by the standard deviation (*SD*) over baseline period (1951–2000) (equation 1). This takes into account the interannual environmental variability a species would be accustomed to experiencing, thereby characterizing where the trend in the environmental variable becomes perceptible across each species' range.

$$\mathrm{ExV} = \frac{\mathrm{mean}(V_{2041-2060}) - \mathrm{mean}(V_{1951-2000})}{SD(V_{1951-2000})} \quad (1a)$$

$$ExV(\mathrm{Temperature}) = |ExV| \quad (1b)$$

$$Exv(\mathrm{Oxygen}) = |\min(ExV, 0)| \quad (1c)$$

$$ExV(\mathrm{Acidity}) = |\max(ExV, 0)| \quad (1d)$$

Exposure to climate hazard (ExV) was calculated for sea bottom temperature, oxygen concentration, and acidity for demersal species, and sea surface temperature, oxygen concentration, and acidity for pelagic species.

For each species, we categorized the level of exposure to each climate hazard into low, medium, high and very high (ExV, equation 1). These are fuzzy categorizes as the thresholds that delineate the categories overlap with one another. Specifically, exposure to climate hazard is low when changes in the ocean drivers are within historical variability, i.e., ExV $<$ 1. Intermediate exposure values of 0.5 $<$ ExV $<$ 2 and 1 $<$ ExV $<$ 3 are considered as moderate and high, respectively, while ExV $>$ 2 is also considered very high (Table 1). Thus, a spatial grid within a species' range can be categorized as two different level of exposure to climate hazard at the same time, with different levels of membership to each category.

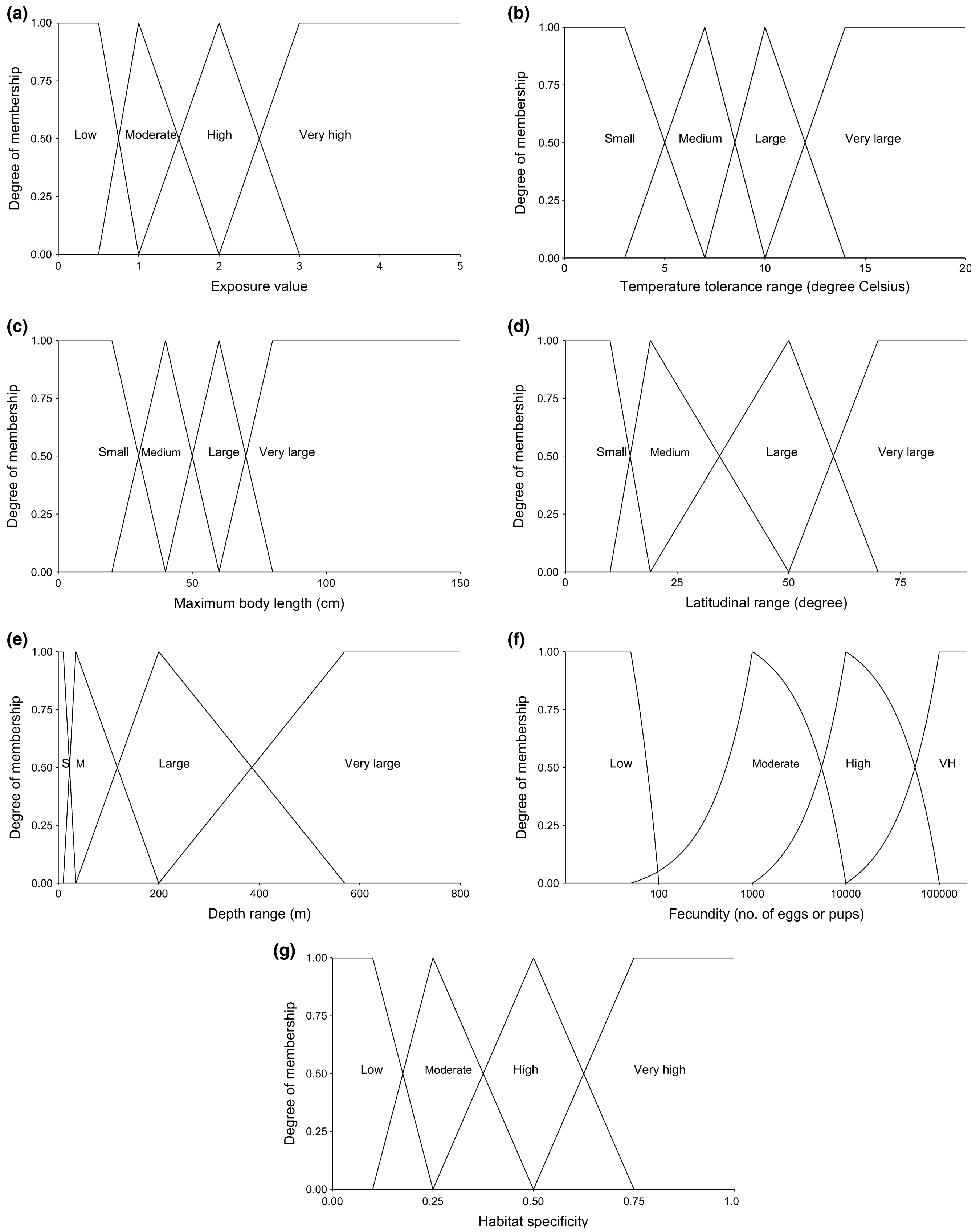

FIGURE 2 Fuzzy membership functions for different input variables for exposure to hazard, sensitivity and adaptive capacity categories. (a) Exposure value, (b) temperature tolerance range, (c) maximum body length, (d) latitudinal range, (e) depth range, (f) fecundity and (g) habitat specificity. The apparent nonlinear shape of the fecundity membership function is a result of the use of log-transformed scale for fecundity in the figure. S, Small; M, Medium; VH, Very high

TABLE 1 The definition of rules used to classify into different categories to calculate an overall index of exposure to climate hazard (*ExV*) and the levels of attributes used to define categories of sensitivity and adaptive capacity

Categories and their resulting linguistic level				
Exposure	Low	Moderate	High	Very high
Exposure value (*ExV*)	1 > *ExV*	0.5 < *ExV* < 2	1 < *ExV* < 3	2 < *ExV*
Sensitivity	Low	Moderate	High	Very high
Temperature tolerance (TT, °C)	7 > *TT*	3 < *TT* < 10	7 < *TT* < 14	10 < *TT*
Maximum body length (BS, cm)	40 > BS	20 < *BS* < 60	40 < *BS* < 80	60 < *BS* < 80
Maximum body length & high coral reef association			20 < *BS* < 60 and coral reef association >1	40 > BS and coral reef association >1
Taxonomic group (ocean acidification)[1]	Fishes, crustaceans, sea cucumbers	Fishes, crustaceans, sea cucumbers	Crustaceans, molluscs, sea urchins	Molluscs, sea urchins
Adaptive Capacity	Low	Moderate	High	Very high
Latitudinal breadth (LB, degree)	19 > *LB*	10 < *LB* < 50	19 < *LB* < 70	70 < *LB*
Depth range (DR, m)	35 > *DR*	10 < *DR* < 200	35 < *DR* < 570	200 < *DR*
Fecundity (Fec, eggs or pups per year)	500 > *Fec*	500 < *Fec* < 10000	1000 < *Fec* < 100000	10000 < *Fec*
Habitat specificity (HS)	0.5 < *HS*	0.25 < *HS* < 0.75	0.1 < *HS* < 0.5	0.25 > *HS*

[1]Taxonomic groups and their corresponding linguistic categories of the sensitivity to ocean acidification.

The membership is defined by the fuzzy membership functions (Figure 2). Following Cheung et al. (2005), we assumed trapezoid functions for the upper and lower categories (low and very high) and triangular functions for the intermediate categories (moderate and high). The fuzziness of the categories (as indicated by the degree of overlap between the fuzzy sets) represents our uncertainty in deciding the exposure level. Using projected ocean variables from each of the three earth system models, the exposure categories and their membership were calculated for each spatial grid within each species' distribution range.

2.2 | Sensitivity

Attributes that are related to the sensitivity of marine fishes and invertebrates to climate change are identified based on published literature. For temperature related effects, sensitivity was based on species' temperature tolerance ranges and maximum body size. Temperature tolerance data were obtained from published calculations of each species' temperature preference profile (the relative suitability of particular temperatures), inferred from the mean temperature of fisheries catches (Cheung, Watson & Pauly, 2013). Fuzzy sets for temperature tolerance range (small, medium, large, very large) were defined based on the minimum, 10th percentile, 25th percentile, median, 75th percentile, 90th percentile and maximum values across the set of species studied, respectively (Table 1). These temperature tolerance range categories then correspond to very high, high, moderate and low sensitivity, respectively. As species with large body size are suggested to be metabolically more sensitive to warming and ocean deoxygenation (Cheung, Sarmiento, et al., 2013; Pörtner et al., 2014; Simpson et al., 2011), species were also categorized into small, medium, large and very large body size (thus low, medium, high and very high sensitivity, respectively) (see Table 1).

In addition, when coral reef is degraded by exposure to climate stressors such as warming, small-bodied coral reef fishes are suggested to be particularly sensitive to such impacts on their associated habitats (Graham et al., 2011). Species' degree of membership of association with coral reef was assigned based on description of the species' habitat requirement in FishBase and SeaLifeBase (0 to 1, with 0 = no association and 1 = obligatory association) (see http://www.seaaroundus.org/catch-reconstruction-and-allocation-methods/). Species with small and medium body size and is associated to coral reef have very high and high sensitivity. It is noted that the rule that links large body size and high sensitivity remains valid for coral reef fishes as suggested by empirical evidence (Messmer et al., 2017).

We categorized species sensitivity to ocean acidification based on published meta-analysis (Kroeker et al., 2013; Wittmann & Pörtner, 2013). We ranked the order of sensitivity of the main groups of exploited marine species (negative impacts on growth, calcification, survivorship or reproduction for similar level increase in acidity): molluscs, echinoderms, crustaceans and fishes (including chondrichthyes). For molluscs, we assumed a high to very high sensitivity to ocean acidification (membership = 0.25 and 0.75, respectively). For echinoderms and crustaceans, we assumed a moderate sensitivity (membership = 0.25, 0.50 and 0.75 from low, moderate and very high sensitivity, respectively), and for fishes, we assumed a low to moderate sensitivity (membership = 0.75 and 0.25, respectively) (Table 1).

2.3 | Adaptive capacity

Adaptive capacity incorporated information on latitudinal breadth, depth range, association with specific habitats, and fecundity.

Species with larger latitudinal breadth and depth range as well as less demand for specific habitats (coral reef, seagrass, estuary or seamount) are considered to be more flexible in their environmental preferences and thus have larger scope to adapt to environmental changes through physiological (e.g., acclimation) and biogeographical (e.g., range shift) responses. Moreover, species with higher fecundity have larger number of larvae or juveniles that are exposed to the changing environment, thus potentially result in a higher rate of selection and adaptation from these changes (Aitken, Yeaman, Holliday, Wang & Curtis-McLane, 2008).

We categorized species' latitudinal breadths, depth ranges, habitat specificities and fecundities based on information available from public databases of marine fishes and invertebrates (FishBase and SeaLifeBase) (see Table 1). Latitudinal breadth and depth range were based on the difference between the northern and southern range limits and the maximum and minimum occurrence depth of each species. The specificity of species to particular key habitats was based on an index of association with key habitats: seamounts, coral reefs, seagrass and estuaries that scale between 0 and 1 (0 = no specific association and 1 = obligatory association) (see http://www.seaaroundus.org/catch-reconstruction-and-allocation-methods/). A species' adaptive capacity to climate change is low when habitat specificity is high because of the possible restriction of a species to respond to climate change induced increase in sea temperature by range shift. All in all, small latitudinal or depth range, low fecundity or very high habitat specificity corresponds to low adaptive capacity, and *vice versa* (see Table 1).

2.4 | Calculation of index of vulnerability and risk of climate impacts

Indices of vulnerability and risk of climate impacts were calculated using the framework presented in Figure 1. Firstly, we concluded the level of vulnerability based on the sensitivity and adaptive capacity categories determined from the input variables and fuzzy membership functions (Table 1, Figure 2). The conclusion was determined based on a set of IF-THEN rules (Table 2). The level of vulnerability was expressed as four linguistic categories: (i) low; (ii) moderate; (iii) high; (iv) very high. For example:

IF *sensitivity* is *Low* (degree of membership = 0.5) AND *adaptive capacity* is *High* (degree of membership = 0.3) THEN *Potential impact* is *Low* (degree of membership = 0.3).

As the conditional categories are joined by *AND*, the conclusion degree of membership is the minimum of the degrees of membership of the conditional categories. Conclusions are operated when the degree of membership of the conditions exceeds a threshold value, which defines the minimum required membership on the condition needed for a particular rule to be fired. Here, the minimum threshold membership value was assumed to be 0.2 to omit conclusions with very low degrees of membership (Cheung et al., 2005). The set of rules determining the potential impact of a species is described in Tables 2 and 3. Specifically, ocean acidification related exposure and sensitivity were based on a different set of rules than temperature and oxygen related inputs. The calculated levels of vulnerability and risk of impacts were then combined with the level of exposure to climate hazard to draw conclusions on the level of risk of climate impacts.

The algorithm calculated the final degree of membership associated with each level of conclusions based on all the available input variables. The algorithm explicitly carried all the uncertainties from the inputs to the final conclusion. For example, different hazard exposure levels calculated from different earth system model outputs could initiate different set of rules and draw different conclusions. Simultaneously, different input variables would initiate different sets of rules that could arrive at the same conclusions, with different degrees of membership. Thus, the degrees of membership for the final conclusion were accumulated using an algorithm called MYCIN (see Cheung et al., 2005), where:

$$\text{AccMem}_{(i+1)} = \text{AccMem}_{(i)} + \text{Membership}_{(i+1)} \times (1 - \text{AccMem}_{(i)}) \tag{2}$$

where AccMem is the accumulated membership of a particular conclusion (e.g., high vulnerability) and *i* denote one of the rules that has lead to this conclusion.

Following the accumulation of knowledge from all input attributes, a defuzzification process was applied to calculate a vulnerability index. Vulnerability was expressed on a scale from 1 to 100, 100 being the most vulnerable. Index values (Indval) correspond to each linguistic vulnerability category (x) were Low (x = 1) = 1, Medium (x = 2) = 25, High (x = 3) = 75 and Very high (x = 4) = 100. The final index of vulnerability (Vul) of each species was calculated from the average of the index values weighted by their accumulated membership (Cheung et al. 2005):

TABLE 2 Matrix of rules that determine the level of vulnerability based on species' sensitivity and adaptive capacity to climate change

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

TABLE 3 Matrix of rules that determine the risk of climate impacts based on species' vulnerability and exposure to climate hazard

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

$$\mathrm{Vul} = \frac{\sum_{x=1}^{4} \mathrm{AccMem}_x \cdot \mathrm{Indval}_x}{\sum_{x=1}^{4} \mathrm{AccMem}_x} \quad (3)$$

Similarly, we calculate an index of sensitivity, adaptive capacity, hazard exposure and risk of climate impacts for each species using equation 3, where the AccMem represents each level of risk inferred from the rule matrix (Table 3).

We calculated the vulnerability and risk of climate impacts of 1,074 species of marine fishes and invertebrates that were reported at the species level in the Sea Around Us fisheries catches database (www.seaaroundus.org). The input biological and ecological traits were based on information available from FishBase (www.fishbase.org) and SeaLifeBase (www.sealifebase.org). Although not every species had all the available input parameters, the fuzzy algorithm described here is flexible in the available information, with conclusions being drawn based on known input attributes values only. For each species, a risk of climate impact index was calculated for each 0.5° × 0.5° spatial grid based on the combination of hazard exposure in each cell where the species may occur now (within their range boundary), and the overall index value was subsequently calculated from the average index values of these cells.

To illustrate the operation of the framework, we described, step-by-step, the calculation of the vulnerability and risk of impacts for Atlantic cod (*Gadus morhua*) as an illustrative example. We then calculated the distributions of the indices for sensitivity, adaptive capacity, vulnerability, exposure and risk of impacts for all the 1,074 studied species, all together and by taxonomic groups. We also specifically examined the vulnerability and risk of impacts of the ten taxa that contributed most to global fisheries catches in 2010 (amongst taxa that were reported at the species level).

2.5 | Sensitivity analysis

The sensitivity of the algorithm to the input parameters and rules in determining the vulnerability and risk of impacts of a species was examined by a jack-knife analysis. Firstly, we subset 50 species with all available input parameters for the sensitivity analysis. Secondly, we calculated the vulnerabilities based on the full set of input variables (n), then with one (n – 1), two (n -2), three (n – 3), four (n – 4) and five (n – 5) variable(s) (and thus their associated rules) removed. Finally, we compared the vulnerability and risk of impacts index following removal of each variable and evaluated the sensitivity of the index to different level of data availability.

3 | RESULTS

3.1 | An illustrative example: Atlantic cod

Globally, Atlantic cod was predicted to have a moderate vulnerability (index value = 39) and moderate to high risk of impacts (index value

TABLE 4 Calculation of vulnerability and risk of climate impacts for Atlantic cod

Attributes	Values	Input categories	Sensitivity/Adaptive capacity/Exposure	Vulnerability and risk of impacts
Width of temperature preference	12°C	Large (0.50), Very large (0.50)	Sensitivity = low (0.5), moderate (0.5), very high (1.0)	Vulnerability = low (0.58), moderate (0.25), high (0.70). Vulnerability index = 39
Maximum body size	200 cm	Very large (1.00)		
Coral reef association	No	(0.00)		
Taxonomic group	Fishes	NA	Sensitivity to acidification = low (0.75), moderate (0.25)	
Latitudinal range	54°	Large (0.80), very large (0.20)	Adaptive capacity = high (0.8), very high (1.0)	
Depth range	599 m	Very large (1.00)		
Fecundity (million)	~1.6 eggs	Very large (1.00)		
Habitat restriction	No	Low (1.00)		
Sea bottom temperature	GFDL = 2.60 ± 1.74 *SD* IPSL = 6.78 ± 4.30 *SD* MPI = 3.17 ± 1.51 *SD*	Low (0.14), moderate (0.23), high (0.50), very high (0.99)	Exposure (excluding acidification) = low (0.69), moderate (0.48), high (0.67), very high (0.99)	Risk of impacts (average across range) = low (0.41), moderate (0.53), high (0.81), very high (0.35). Impact index = 53
Sea bottom oxygen	GFDL = 2.22 ± 1.83 *SD* IPSL = 2.03 ± 3.16 *SD* MPI = 2.85 ± 1.39 *SD*	Low (0.63), moderate (0.38), high (0.5), very high (0.78)	Exposure (acidification) = very high (1.00)	
Sea bottom acidity	GFDL = 12.82 ± 1.75 *SD* IPSL = 10.07 ± 4.60 *SD* MPI = 12.27 ± 1.66 *SD*	Low (0.05), moderate (0.01), high (0.03), very high (1.00)		

Degree of membership is noted in parenthesis.
The table includes the calculated membership associated with categories of input variables, sensitivity, adaptive capacity, exposure, vulnerability and risk of climate impacts and their index values. Exposure values are reported here as the mean and standard deviation across the species' distribution range for each earth system model.

= 53) under RCP 8.5 (Table 4). Atlantic cod has a large to very large temperature tolerance window implying lower sensitivity to climate change. However, it is also large-bodied which corresponded to high sensitivity. As the fuzzy logic expert system explicitly represents conflicting conclusions, Atlantic cod thus has low, moderate and very high sensitivity with different levels of membership simultaneously. Combined with its low sensitivity to ocean acidification and high adaptive capacity, vulnerability of cod to climate change is on average moderate. However, substantial areas of the cod's range were projected to be exposed to high level of temperature changes, deoxygenation and acidification; thus the overall risk of impacts of cod to climate change increased to moderate to high (Table 4).

3.2 | Vulnerability and risk of impacts across species

The median sensitivity, adaptive capacity and vulnerability across the studied marine species are moderate while the risk of impact under the RCP 8.5 scenario by 2050 (average between 2041 and 2060) is moderate to high (mean index value = 65) (Figure 3a). A weak positive correlation (Pearson correlation test, $p = 0.03$, correlation coefficient = 0.07) between sensitivity and the lack of adaptive capacity was found, suggesting that species with high sensitivity may likely to be lacking adaptive capacity (Fig. S1). In contrast, vulnerability correlated with risk of impacts significantly (Pearson correlation test, $p < 0.001$, correlation coefficient = 0.78) (Fig. S2). Fishes and molluscs were predicted to have higher median vulnerability, followed by crustaceans and then other exploited taxonomic groups (Figure 3b). Overall, fishes were predicted to have a higher median risk of impacts with a wider range of index values. The predicted risk of impacts was similar across other taxonomic groups (Figure 3c).

The vulnerability of the ten species with the highest global capture production in 2010 (www.seaaroundus.org) range from low e.g., Japanese anchovy (*Engraulis japonicas*) to high e.g., largehead hairtail (*Trichiurus lepturus*) while their risks of climate impacts range from moderate e.g., Atlantic herring (*Clupea harengus*) to high e.g., skipjack tuna (*Katsuwonus pelamis*) (Table 5). For example, skipjack tuna was found to have an average vulnerability of 39, as a result of a moderate level of sensitivity (index value = 45), due to its moderate breath of temperature tolerance and large body size, and high adaptive capacity (index value = 11) due to its high fecundity and wide geographic distribution. However, because of the high to very high level of exposure to climate hazard (index value = 87), the risk of climate impacts of skipjack tuna was predicted to be high (average = 71).

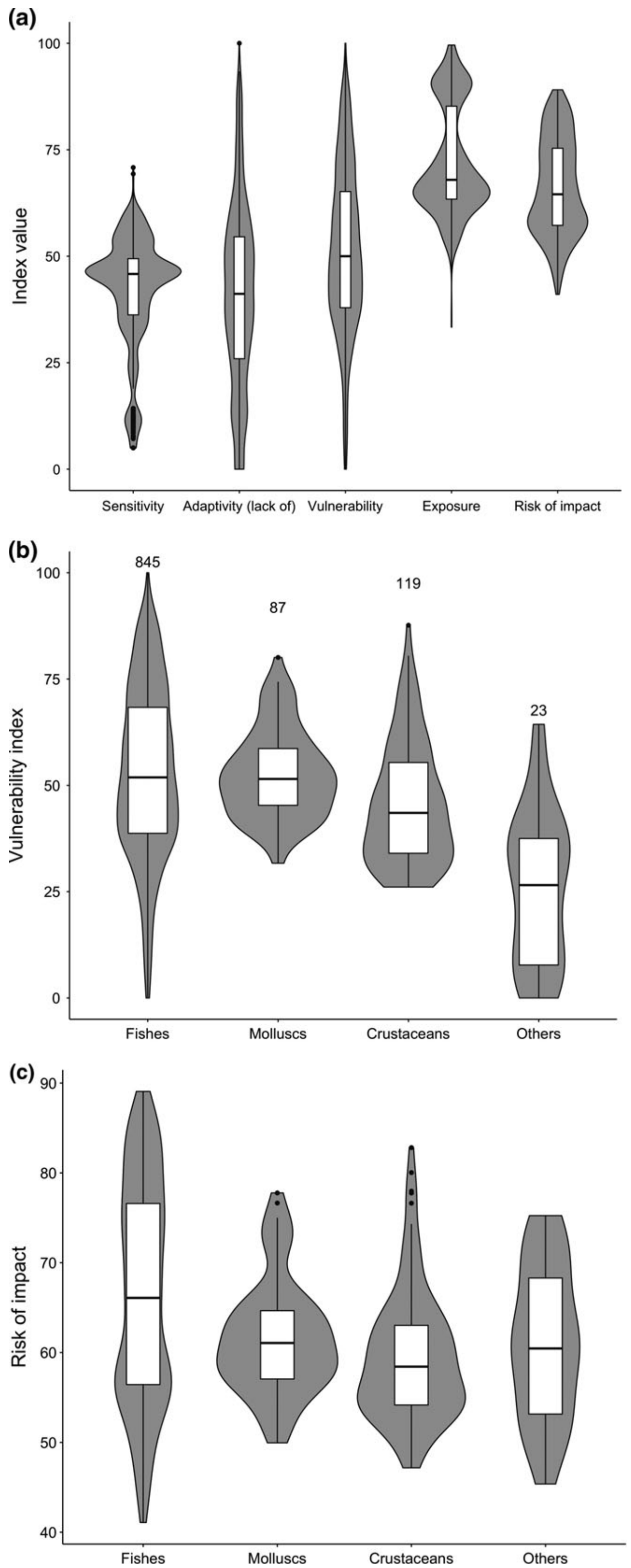

FIGURE 3 Predicted indices of sensitivity, adaptive capacity (lack of), vulnerability exposure to climate hazards and risk of impacts for the 1074 exploited marine species using the fuzzy logic expert system developed in this study: (a) distribution of each index across all species, (b) vulnerability and (c) risk of impacts subdivided by major taxonomic groups. The boxplot represents the median (thick black line in the middle of each box), 25th and 75th quartiles (lower and upper boundary of each boxy) and the minimum and maximum values (the lower and upper ends of the vertical lines). The shaded areas represent the frequency distribution (in proportion). The number on top of each box in (b) indicates the number of species. The others group include invertebrates, mostly echinoderms, cephalopods and polychaetes

TABLE 5 Index of sensitivity, adaptive capacity, exposure to hazard, vulnerability and risk of impacts for the 10 species with the highest catches reported at the species level in 2010 (www.seaaroundus.org)

Scientific name	Common name	Sensitivity	Adaptive Capacity	Vulnerability	Exposure to hazard	Risk of impacts
Clupea harengus	Atlantic herring	32	17	28	65	53
Engraulis japonicus	Japanese anchovy	5	14	1	91	65
Engraulis ringens	Anchoveta	30	52	41	74	60
Katsuwonus pelamis	Skipjack tuna	45	11	39	87	71
Sardina pilchardus	European pilchard	10	28	23	70	53
Sardinops sagax	Pacific sardine	23	12	18	84	60
Scomber japonicus	Chub mackerel	38	11	30	86	67
Theragra chalcogramma	Alaska Pollack	46	25	48	63	58
Thunnus albacares	Yellowfin tuna	45	13	39	84	69
Trichiurus lepturus	Largehead hairtail	47	50	61	63	65

Species that are most vulnerable and have the highest risk of impacts to climate change (index value > 90) generally have restricted distribution and is large-bodied. For example, the most vulnerable species predicted in this study is whiteleg skate (*Amblyraja taaf*) (vulnerability = 100, risk of impact = 85), which is known to occur only in French southern territories (Crozet Island and Kerguelen) (Endicott 2009). Some of the large-bodied croakers with restricted range were also predicted to be highly vulnerable, such as totoaba (*Totoaba macdonaldi*) (vulnerability = 92, risk of impact = 82), mi-iuy croaker (*Miichthys miiuy*) (vulnerability = 96, risk of impact = 83) and honnibe croaker (*Nibea mitsukurii*) (vulnerability = 90, risk of impact = 82). Other highly vulnerable species are endemics, for example, Australian ruff (*Arripis georgianus*) (vulnerability = 94, endemic to southern coast of Australia). In contrast, species that are least vulnerable include wide-ranging species that have large thermal tolerance, small-bodied and fast-turnover, such as common cuttlefish (*Sepia officinalis*) (vulnerability = 5) and round sardinella (*Sardinella aurita*) (vulnerability = 8). However, the high exposure to climate stressors still made these least vulnerable species to have moderate to high risk of climate impacts (59 and 68 for common cuttlefish and round sardinella, respectively).

3.3 | Sensitivity analysis

Recalculating vulnerability and risk of impacts values following the individual removal of each input variable related to sensitivity and adaptive capacity showed that the results are most sensitive to species' temperature preference ranges and maximum body size and relatively less sensitive to other species' traits (Figure 4a,b). Removal of temperature preference ranges and maximum body size results in a median of around 10 index points increase and decrease in vulnerability, and around 5 index points for risk of impacts. The deviations in these indices from the removal of these two species' traits can be as large as 38 and 20 index points for vulnerability and risk of impacts, respectively. Removal of increasing number of input attributes corresponded to increases in deviation in vulnerability and risk of impacts index values (Figure 4c,d). Considerable number of outliers occurred when one to two input variables were removed, which were caused by the removal of temperature preference ranges and maximum body size.

4 | DISCUSSION

The global nature of climate change, and its impacts of shifting fish stocks and changes in potential fish catch that cross-jurisdictional and geographic boundaries mean that approaches are required that enable assessments of the vulnerability to climate change for marine species covering a range of taxonomic groups and geographic locations. Although the majority of ecological studies exploring climate change impacts use predominantly exposure-based measures to infer, for example, shifts in species' distributions or extinction risk based on loss of suitable habitat, it was found here that the magnitude of exposure experienced by a species across its range does not correspond to characteristic levels of sensitivity and adaptive capacity, and a relationship therefore cannot be inferred. This highlights the importance of considering additional factors on biological and ecological characteristics to increase the realism of impact assessments and further inform assessments of likely responses to climate change in the marine environment.

The high sensitivity of the results to species' temperature preference range and maximum body size corroborates with empirical evidence that the rate of species' responses to climate change (particularly ocean warming), such as range shift and decrease in body size, is strongly related to these attributes (Cheung, Watson & Pauly, 2013; Cheung, Sarmiento, et al., 2013; Pörtner et al., 2014; Simpson et al., 2011). Maximum body size is readily available for most marine fishes from FishBase (www.fishbase.org). However, physiological tolerance limits of marine species have only been empirically estimated for a small number of species. On the other hand, inferred temperature preferences, like those used in this study, have been estimated for thousands of marine fishes and invertebrates with sufficient occurrence records using species distribution models (Cheung, Watson & Pauly, 2013). In addition to temperature and body size, our study also highlights that more available information could substantially increase the robustness of the estimation of

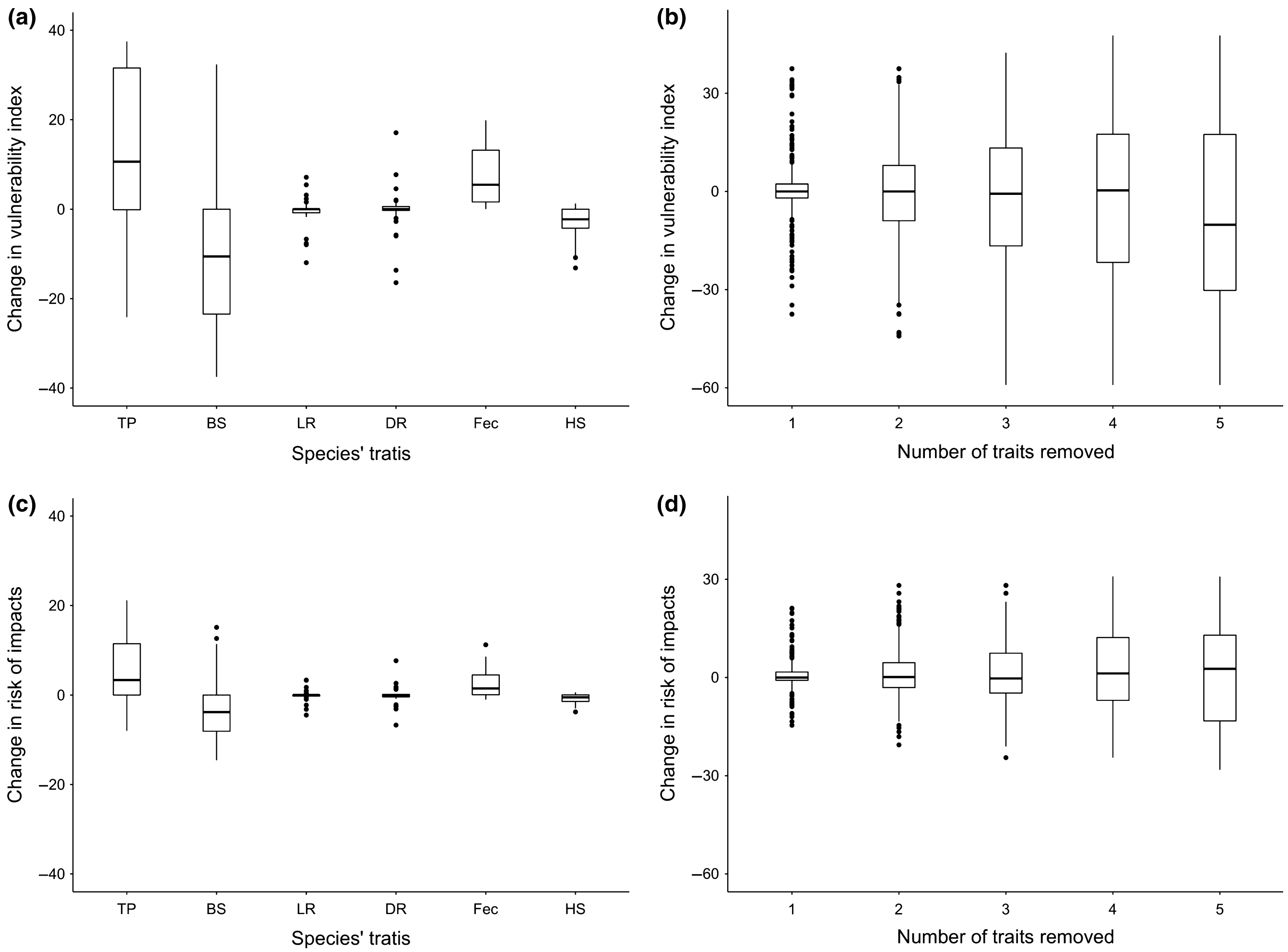

FIGURE 4 Deviations in the index values (relative to the estimation with full set of attributes) of climate vulnerability (a,b) and risk of impacts (c,d) of the 30 selected species following the selective removal of input variable to the fuzzy logic expert system: (a,c) removal of information on temperature preferences (TP), maximum body size (BS), latitudinal range (LR), depth range (DR), annual fecundity (Fec) and habitat specificity (HS); (b,d) removal of increasing number of input variables from 1 variable to 5 variables. Thick horizontal line: median, lower and upper boundary of each box: 25th and 75th quartiles, lower and upper end of vertical lines: minimum and maximum values) and black dots: outliers

vulnerability and risk of impacts. Therefore, future studies could use our framework to identify species with the least available information but are predicted to be vulnerable to climate change, and subsequently fill in the information gap to improve the estimation of their vulnerability and risks to climate change impacts.

This approach applied here was developed to provide a mean of assessing a broad range of species, across marine taxa, for which data and knowledge are frequently unavailable. It is hoped that as more data become available, not only on biological and ecological traits for more species, but also data that further the understanding of which traits are likely to affect a species' sensitivity and ability to adapt, these results may be updated and refined. However, by explicitly incorporating uncertainties at several stages of the modelling approach, we aimed to bracket the range of likely vulnerabilities and risk of impacts for each species, based on plausible and justifiable data. Furthermore, inferred vulnerability levels from particular exposure or ecological/biological characteristic levels may vary across species due to other traits or factors not included in the model. Using a set of earth system models to calculate exposure, and a fuzzy logic approach to infer vulnerability and risk of impacts thus allows uncertainties to be explicitly represented in the calculation. There are, however, additional uncertainties associated with this approach, discussed as follows:

First of all, the assessment undertaken here may omit attributes or environmental variables of importance in determining a species' vulnerability. Although many of these depend on data that is not currently available for a wide range of species, others require a more in-depth exploration of possible environmental changes. In particular, the relative importance of any omitted variables may vary for different species or those occupying particular habitats or geographic locations. For example, warming waters are predicted to decrease upper ocean biomass (Bopp et al., 2013; Steinacher et al., 2010) due to increased stratification and slowed mixing reducing the nutrient supply for primary productivity at the ocean's surface. As this is in turn expected to reduce the flux of particulate organic carbon (POC) from the surface to benthic communities, the impact of this reduction on food-limited deep sea communities might be particularly severe (Jones et al., 2014). A more in-depth assessment of the relative importance of variables such as primary productivity may therefore be beneficial in improving the vulnerability assessment to climate change for particular communities. Additional variables that might be included given more comprehensive data include diet specializartion (Chin, Kyne, Walker & McAuley, 2010; Graham et al., 2011; Laidre et al., 2008), rarity (IUCN 2012; Davies, Margules & Lawrence, 2004; Chin et al., 2010) and dispersal (Chin et al., 2010; Foden et al., 2013). For example, Fernandes et al. (2013) calculated that predicted latitudinal shifts would decrease by about 20% when species interactions were included, with implications for species' ability to adapt, shifting in response to high climate change exposure. Furthermore, other metrics of the oceanographic variables, such as kurtosis and skewness, can be considered in representing the climate hazards to marine species (Ateweberhan & McClanahan, 2010).

In addition to climate change, other anthropogenic stressors are impacting on marine species, with the potential to act synergistically, influencing a species' resilience and adaptability to climate change and thereby increasing its potential vulnerability. Most notable is the impact of overfishing. For example, a reduction in age and maximum body length of commercially targeted fish species due to overfishing is likely to influence the overall reproductive success of a population, reducing its adaptive capacity and increasing its susceptibility to both long- and short-term perturbations. The impact of multiple threats may further be exacerbated if traits that increase a populations' vulnerability to climate change are closely linked to those that confer low resilience to fishing pressure. For example, large body size is frequently found to confer lower resilience to fishing pressure on species as they are likely to be more commercially valuable and thus suffer greater mortality (Dulvy et al., 2003, 2004). Large size is also frequently correlated with other factors, such as low intrinsic population growth rate and late maturity (Dulvy et al., 2003; Reynolds et al., 2005) that might reduce fecundity and a species' adaptive capacity. On the other hand, larger species may more likely be wide ranging, with broad latitudinal breaths and temperature tolerance limits that reduce their potential vulnerability to climate change. In addition, habitat disturbance and degradation may slow the recovery of overfished populations and reduce their resilience to climate change. Combing this vulnerability index with information on habitat degradation and fishing pressure may thus enable geographic hotspots of vulnerability to three key anthropogenic threats to be identified, potentially enabling future prioritizartion for conservation.

Fuzzy sets are thus frequently defined by subjective criteria, and although intrinsic vulnerability values for each species would vary depending on the definition of fuzzy sets, the overall vulnerability value, or linguistic category of risk is relative to that calculated for other species and scenarios of climate change, irrespective of changes in the threshold values for the delineation of fuzzy sets. It therefore cannot be used to infer risk of extinction as this would require a more in-depth knowledge of population abundances and their likely responses to climate change. However, as all fuzzy membership functions assume a high degree of overlap between fuzzy sets, this approach allows for flexibility, reflecting our uncertainty on the exact relationship between biological and ecological characteristics, exposure to a threat, and the conclusion of degree of vulnerability.

This study applied a climate change vulnerability assessment to a set of globally distributed marine species covering several taxa. The generalized approach developed allows inferences to be made based on the available data while incorporating uncertainty concerning key aspects of the likely responses to climate change. This approach facilitates the identification of species that are particularly vulnerable to climate change, and highlights the importance of enhancing exposure-based measures of impact with data on species attributes. It may therefore promote the targeting of species-specific management plans and assessments of potential risks to fisheries and fishing communities from climate change. Furthermore, an updatable index provides a means of validating or refining findings, and assessing the relative importance of different attributes and exposures as observation data and new understanding about climate vulnerability become increasingly available.

ACKNOWLEDGEMENT

This is a contribution from the Nippon Foundation-the University of British Columbia Nereus Program. We also acknowledge funding support from the Natural Sciences and Engineering Research Council of Canada. We are grateful for Thomas Frölicher for providing us with the Earth System Model outputs from the Coupled Models Intercomparison Project Phase 5. The calculated vulnerability and risk of impacts indices reported in this paper can be found in the online data repository: http://datadryad.org with https://doi.org/10.5061/dryad.9dc21.

ORCID

William W. L. Cheung http://orcid.org/0000-0001-9998-0384

REFERENCES

Aitken, S. N., Yeaman, S., Holliday, J. A., Wang, T., & Curtis-McLane, S. (2008). Adaptation, migration or extirpation: Climate change outcomes for tree populations. *Evolutionary Applications*, *1*(1), 95–111.

Ateweberhan, M., & McClanahan, T. R. (2010). Relationship between historical sea-surface temperature variability and climate change-induced coral mortality in the western Indian Ocean. *Marine Pollution Bulletin*, *60*(7), 964–970.

Barange, M., Merino, G., Blanchard, J. L., Scholtens, J., Harle, J., Allison, E. H., . . . Jennings, S. (2014). Impacts of climate change on marine ecosystem production in societies dependent on fisheries. *Nature Climate Change*, *4*(3), 211–216.

Bopp, L., Resplandy, L., Orr, J. C., Doney, S. C., Dunne, J. P., Gehlen, M., . . . Tjiputra, J. (2013). Multiple stressors of ocean ecosystems in the

21st century: Projections with CMIP5 models. *Biogeosciences*, *10*, 6225–6245.

Cheung, W. W. L., Lam, V. W., Sarmiento, J. L., Kearney, K., Watson, R., & Pauly, D. (2009). Projecting global marine biodiversity impacts under climate change scenarios. *Fish and Fisheries*, *10*(3), 235–251.

Cheung, W. W. L., Pitcher, T. J., & Pauly, D. (2005). A fuzzy logic expert system to estimate intrinsic extinction vulnerabilities of marine fishes to fishing. *Biological Conservation*, *124*(1), 97–111.

Cheung, W. W. L., Reygondeau, G., & Frölicher, T. L. (2016). Large benefits to marine fisheries of meeting the 1.5°C global warming target. *Science*, *354*(6319), 1591–1594.

Cheung, W. W. L., Sarmiento, J. L., Dunne, J., Frölicher, T. L., Lam, V. W., Palomares, M. D., … Pauly, D. (2013). Shrinking of fishes exacerbates impacts of global ocean changes on marine ecosystems. *Nature Climate Change*, *3*(3), 254–258.

Cheung, W. W. L., Watson, R., & Pauly, D. (2013). Signature of ocean warming in global fisheries catch. *Nature*, *497*(7449), 365–368.

Chin, A., Kyne, P. M., Walker, T. I., & McAuley, R. O. R. Y. (2010). An integrated risk assessment for climate change: Analysing the vulnerability of sharks and rays on Australia's Great Barrier Reef. *Global Change Biology*, *16*(7), 1936–1953.

Davies, K. F., Margules, C. R., & Lawrence, J. F. (2004). A synergistic effect puts rare, specialized species at greater risk of extinction. *Ecology*, *85*(1), 265–271.

Dawson, T. P., Jackson, S. T., House, J. I., Prentice, I. C., & Mace, G. M. (2011). Beyond predictions: Biodiversity conservation in a changing climate. *Science*, *332*(6025), 53–58.

Dulvy, N. K., Ellis, J. R., Goodwin, N. B., Grant, A., Reynolds, J. D., & Jennings, S. (2004). Methods of assessing extinction risk in marine fishes. *Fish and Fisheries*, *5*(3), 255–276.

Dulvy, N. K., Sadovy, Y., & Reynolds, J. D. (2003). Extinction vulnerability in marine populations. *Fish and Fisheries*, *4*(1), 25–64.

Fernandes, J. A., Cheung, W. W. L., Jennings, S., Butenschön, M., Mora, L., Frölicher, T. L., … Grant, A. (2013). Modelling the effects of climate change on the distribution and production of marine fishes: Accounting for trophic interactions in a dynamic bioclimate envelope model. *Global Change Biology*, *19*(8), 2596–2607.

Field, C. B., Barros, V. R., Mastrandrea, M. D., Mach, K. J., Abdrabo, M. K., Adger, N., … Burkett, V. R. (2014). Summary for policymakers. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, … L. L. White, (Eds.) *Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1–32). Cambridge, UK: Cambridge University Press.

Foden, W. B., Butchart, S. H., Stuart, S. N., Vié, J. C., Akçakaya, H. R., Angulo, A., … Donner, S. D. (2013). Identifying the world's most climate change vulnerable species: A systematic trait-based assessment of all birds, amphibians and corals. *PLoS ONE*, *8*(6), e65427.

Froese R., & Pauly D (Eds.) (2017). *FishBase. World Wide Web electronic publication*, Retrieved from http://www.fishbase.org, version.

Garcia, R. A., Araújo, M. B., Burgess, N. D., Foden, W. B., Gutsche, A., Rahbek, C., & Cabeza, M. (2014). Matching species traits to projected threats and opportunities from climate change. *Journal of Biogeography*, *41*(4), 724–735.

Gattuso, J. P., Magnan, A., Billé, R., Cheung, W. W. L., Howes, E. L., Joos, F., … Turley, C. (2015). Contrasting futures for ocean and society from different anthropogenic CO_2 emissions scenarios. *Science*, *349* (6243), aac4722.

Graham, N. A., Chabanet, P., Evans, R. D., Jennings, S., Letourneur, Y., Aaron MacNeil, M., … Wilson, S. K. (2011). Extinction vulnerability of coral reef fishes. *Ecology Letters*, *14*(4), 341–348.

Hare, J. A., Morrison, W. E., Nelson, M. W., Stachura, M. M., Teeters, E. J., Griffis, R. B., … Chute, A. S. (2016). A vulnerability assessment of fish and invertebrates to climate change on the Northeast US continental shelf. *PLoS ONE*, *11*(2), e0146756.

IUCN (2012). *IUCN red list categories and criteria: Version 3.1*. (2nd edn). Gland, Switzerland: IUCN, iv + 32 pp.

Jones, M. C., & Cheung, W. W. L. (2015). Multi-model ensemble projections of climate change effects on global marine biodiversity. *ICES Journal of Marine Science*, *72*(3), 741–752.

Jones, M. C., Dye, S. R., Pinnegar, J. K., Warren, R., & Cheung, W. W. L. (2012). Modelling commercial fish distributions: Prediction and assessment using different approaches. *Ecological Modelling*, *225*, 133–145.

Jones, D. O., Yool, A., Wei, C. L., Henson, S. A., Ruhl, H. A., Watson, R. A., & Gehlen, M. (2014). Global reductions in seafloor biomass in response to climate change. *Global Change Biology*, *20*(6), 1861–1872.

Kroeker, K. J., Kordas, R. L., Crim, R., Hendriks, I. E., Ramajo, L., Singh, G. S., … Gattuso, J. P. (2013). Impacts of ocean acidification on marine organisms: Quantifying sensitivities and interaction with warming. *Global Change Biology*, *19*(6), 1884–1896.

Laidre, K. L., Stirling, I., Lowry, L. F., Wiig, Ø., Heide-Jørgensen, M. P., & Ferguson, S. H. (2008). Quantifying the sensitivity of Arctic marine mammals to climate-induced habitat change. *Ecological Applications*, *18*(sp2), S97–S125.

Lam, V. W., Cheung, W. W. L., Reygondeau, G., & Sumaila, U. R. (2016). Projected change in global fisheries revenues under climate change. *Scientific Reports*, *6*, https://doi.org/10.1038/srep32607.

Mach, K. J., Mastrandrea, M. D., Bilir, T. E., & Field, C. B. (2016). Understanding and responding to danger from climate change: The role of key risks in the IPCC AR5. *Climatic Change*, *136*(3–4), 427–444.

Messmer, V., Pratchett, M. S., Hoey, A. S., Tobin, A. J., Coker, D. J., Cooke, S. J., & Clark, T. D. (2017). Global warming may disproportionately affect larger adults in a predatory coral reef fish. *Global Change Biology*, *23*(6), 2230–2240.

Okey, T. A., Agbayani, S., & Alidina, H. M. (2015). Mapping ecological vulnerability to recent climate change in Canada's Pacific marine ecosystems. *Ocean & Coastal Management*, *106*, 35–48.

Pecl, G. T., Ward, T. M., Doubleday, Z. A., Clarke, S., Day, J., Dixon, C., … Jennings, S. (2014). Rapid assessment of fisheries species sensitivity to climate change. *Climatic Change*, *127*(3–4), 505–520.

Poloczanska, E. S., Brown, C. J., Sydeman, W. J., Kiessling, W., Schoeman, D. S., Moore, P. J., … Duarte, C. M. (2013) Global imprint of climate change on marine life. *Nature Climate Change*, *3* (10), 919–925.

Pörtner, H. O., Karl, D. M., Boyd, P. W., Cheung, W., Lluch-Cota, S. E., Nojiri, Y., … Armstrong, C. (2014). Ocean systems. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, … L. L. White, (Eds.), *Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change* (pp. 411–484). Cambridge, UK: Cambridge University Press.

Pöyry, J., Luoto, M., Heikkinen, R. K., Kuussaari, M., & Saarinen, K. (2009). Species traits explain recent range shifts of Finnish butterflies. *Global Change Biology*, *15*(3), 732–743.

Reynolds, J. D., Dulvy, N. K., Goodwin, N. B., & Hutchings, J. A. (2005). Biology of extinction risk in marine fishes. *Proceedings of the Royal Society of London B: Biological Sciences*, *272*(1579), 2337–2344.

Simpson, S. D., Jennings, S., Johnson, M. P., Blanchard, J. L., Schön, P. J., Sims, D. W., & Genner, M. J. (2011). Continental shelf-wide response of a fish assemblage to rapid warming of the sea. *Current Biology*, *21* (18), 1565–1570.

Steinacher, M., Joos, F., Frolicher, T. L., Bopp, L., Cadule, P., Cocco, V., … Schneider, B. (2010). Projected 21st century decrease in marine productivity: A multi-model analysis. *Biogeosciences*, *7*(3), 979–1005.

Wittmann, A. C., & Pörtner, H. O. (2013). Sensitivities of extant animal taxa to ocean acidification. *Nature Climate Change*, *3*(11), 95–1001.
Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

How to cite this article: Jones MC, Cheung WWL. Using fuzzy logic to determine the vulnerability of marine species to climate change. *Glob Change Biol*. 2017;00:1–13. https://doi.org/10.1111/gcb.13869