Discover Oceans

Research

Assessing vulnerability of Arctic fish species to climate change

K. J. Sora[1] · C. C. C. Wabnitz[1,2] · N. S. Steiner[3] · U. R. Sumaila[1,4] · C. Hoover[5,6,7] · A. Niemi[5] · L. Loseto[5] · E. V. Lea[5] · C. C. Breiter[5] · J. Palacios-Abrantes[1] · G. Reygondeau[1,8] · P. Farnole[9] · T. Sou[3] · W. W. L. Cheung[1]

Received: 10 January 2025 / Accepted: 11 May 2025
Published online: 31 July 2025

Abstract
Climate change is impacting Arctic marine ecosystems at faster rates than the global average, challenging the management and conservation of biodiversity and living marine resources. This study examined the climate risks and vulnerabilities of 21 Arctic fish species occurring in the western Canadian Arctic using a fuzzy logic approach. Identified climatic hazards to marine species and their habitats are increasing temperature, decreasing sea ice cover, freshening, decreasing oxygen concentration, and acidification. The nature of these hazards included changes in mean conditions by 2050 (2041–2060), compared to the historical period (1979–2015 average) simulated from a regional coupled ice-ocean biogeochemical model and two coupled Earth system models under low and high emissions scenarios. A spatially-explicit algorithm was used to assess the risk and vulnerability in the Beaufort Sea shelf and slope and Amundsen Gulf (BS–AG) based on the species' biological traits, biogeography and their exposure to climatic hazards. The results indicated high to very high exposure and risk of climate impacts across the ecosystem variables. Specifically, shallow areas were projected to be simultaneously exposed to more intense warming, reduced sea ice coverage, freshening, and acidification relative to the regional averages. In addition, for species occurring in the BS–AG, low adaptability and high sensitivity to climate hazards was identified. These applied tools and evaluations can inform marine spatial planning and climate adaptation efforts to help achieve conservation objectives and sustain ecosystem and community health in a changing Arctic climate.

Keywords Beaufort Sea · Amundsen Gulf · MPAs · Marine spatial planning · Multi-stressors · Climate adaptation · Risk of impacts

1 Introduction

Anthropogenic-driven changes in Arctic Ocean conditions have important implications for individual species' body size and long-term viability, as well as the biodiversity, structure, and function of sea ice and ocean ecosystems [32, 66, 81]. Climate-induced changes to the community structure within an ecosystem are dependent on the unique

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s44289-025-00056-7.

✉ K. J. Sora, k.sora@oceans.ubc.ca | [1]Institute for the Oceans and Fisheries, The University of British Columbia, Vancouver, BC V6T 1Z4, Canada. [2]Stanford Center for Ocean Solutions, Stanford University, Stanford, CA 94305, USA. [3]Institute of Ocean Sciences, Fisheries and Oceans Canada, Sidney, BC V8L 5T5, Canada. [4]School of Public Policy and Global Affairs, The University of British Columbia, Vancouver V6T 1Z2, Canada. [5]Freshwater Institute, Fisheries and Oceans Canada, Winnipeg, MB R3T 2N6, Canada. [6]Marine Affairs Program, Dalhousie University, Halifax, NS B3H 4R2, Canada. [7]Coastal First Nations/Great Bear Initiative, Vancouver, BC V6C 1T2, Canada. [8]Atmospheric & Earth Science, Rosenstiel School of Marine, University of Miami, Miami, FL 33149, USA. [9]School of Earth and Ocean Sciences, University of Victoria, Victoria, BC V8W 2Y2, Canada.

biological traits and biogeography of resident species [7, 47]. Information on physiological preferences, and tolerance ranges or thresholds (e.g., minimum, optimum, and maximum limits) of species to single and multiple ocean variables can help understand responses of predator–prey interactions, production and consumption rates, species distribution, and key life history processes to environmental changes. Quantitative indices have been developed and applied to understand the risk of marine species to climate change and other human stressors [17, 19, 44]. Most of these indices are grounded in the framework developed by the Intergovernmental Panel on Climate Change [34, 41], (Fig. 1). In this framework, the risk to species due to climate change is estimated by the probability of occurrence of hazardous conditions, and species' exposure and vulnerability to those hazards (a climate-induced physical event with potential negative impacts to species or ecosystems) [40]. Species' physiological tolerances and thresholds are important in determining the potential exposure level to climatic hazards, as well as species' vulnerability, adaptive capacity, and sensitivity to such hazards [79].

Some species tend to adapt to short-term environmental changes using phenotypic plasticity, which is of particular use in highly variable environments [68, 72], therefore differences in plasticity are common across populations [48, 61, 89]. Typically, Arctic species are stenothermic (specialized or narrow physiological ranges and thresholds), while mid-latitude, temperate species are generally more eurythermic (generalized or wide ranges) [1, 6, 38, 43, 73, 77, 84]. Stenotherms may be at a higher risk to climate change if they are near the limits of their thresholds [26, 39, 83, 88]. Species that cannot physiologically adapt to changes in environmental conditions may respond by a shift in their distributions to different depths or temperature zones (e.g., colder waters) to maintain metabolic performance [13]. Distribution shifts may lead to potential disturbances in community structure and ecosystem functions [57]. The extent of adaptation in populations due to climate change can be attributed to strength of selection or competition, fecundity (number of eggs), variation in phenology, or other biotic interactions [3]. The physiological tolerances (herein the "ecological niche") of a species and the environmental characteristics of its habitat can be included in a fuzzy logic framework to sort species' traits and climate hazards into levels of increasing exposure, sensitivity, and adaptability and relate these levels to the intensity of climatic risk and vulnerability through pre-defined rules [19, 44].

This study aims to understand the climatic risk of Arctic fish species in the Canadian Beaufort Sea shelf and slope and Amundsen Gulf (BS–AG) which can then inform climate-resilient conservation and management planning for the Western Arctic Bioregion [22]. For this study, we adapted and applied the fuzzy logic approach described in Cheung et al. [16], which includes analyzing climate-ocean modelling outputs with biogeographical data of Arctic fish species to assess their future vulnerability and risk to climate change in the Arctic Ocean. The outputs developed in this study offer valuable insights on climate change effects on Arctic marine ecosystems and may provide guidance on how existing and planned conservation measures such as protected areas, might support climate adaptation.

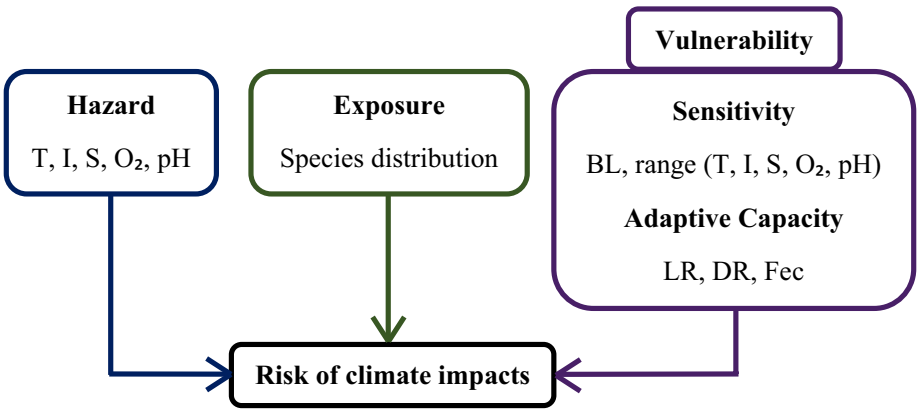


Fig. 1 Schematic of the risk of climate impacts for the 21 Arctic fish species calculated by the exposure to climate change (temperature (T), sea ice cover (I), salinity (S), dissolved oxygen concentration (O_2), and pH (pH)), and vulnerability. Vulnerability was calculated using the sensitivity (body length (BL), and physiological range (T, I, S, O_2, pH)), and adaptive capacity (latitudinal range (LR), depth range (DR), fecundity (Fec)). [16] Adapted from Cheung et al.

2 Methods

2.1 Study area

The BS–AG ecosystem includes distinct geographical regions including coastal, nearshore and offshore areas spanning the southern section of the Inuvialuit Settlement Region (ISR), Northwest Territories, and the western section of the Kitikmeot Region of Nunavut. The study area encompasses the TN and AN MPAs (Fig. 2). The AN MPA was Canada's first MPA with conservation objectives based on Indigenous traditional and local knowledge [25]. Both MPAs include the conservation objectives of protecting the ecosystem, habitat and harvest of key species, as well as cultural activities of the Inuvialuit [50]. Six Indigenous communities (Aklavik, Inuvik, Tuktoyaktuk, Paulatuk, Sachs Harbour, and Ulukhaktok reside within the ISR, and have traditional harvesting locations for whales, seals, birds/fowl, and fish within the BS–AG, including the TN and AN MPAs [22–24].

2.2 Species ecological and biological niches

We identified a subset of 21 Arctic fish species found within the BS–AG ecosystem, including those outlined in management plans, and harvest and fisheries assessment studies (e.g., Inuvialuit Harvest Study, Beaufort Regional Environmental Assessment Marine Fishes Project (BREA-MFP/CBS-MEA (2012–2014, 2017–2023), [54, 64]) (Table S1). The World Register of Marine Species (WoRMs), and FishBase [35] databases provided the ecological and biogeographic information, and adult life history characteristics of the selected species (Table 1). Some input parameters were not available for all species; however, the fuzzy logic methodology (see Fuzzy logic and reasoning subsection) allows for flexibility, where conclusions are drawn only from known values [44].

The Ocean Biodiversity Information System (OBIS), Global Biodiversity Information Facility (GBIF), and Nippon Foundation Nereus Program (NEREUS) databases provided species geo-referenced occurrence record data. All selected fish

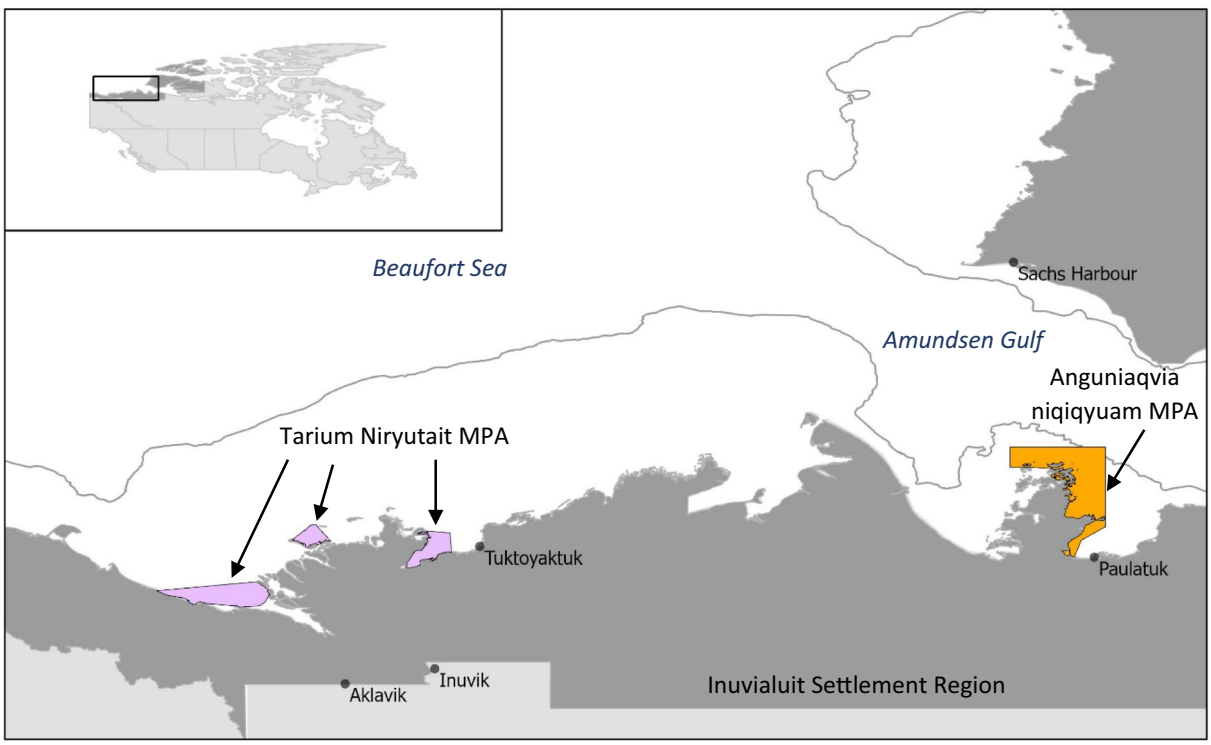


Fig. 2 Canadian Beaufort Sea shelf and slope and Amundsen Gulf ecosystem. The Tarium Niryutait (TN) Marine Protected Area (MPA) three sub-areas are shown in pink; Niaqunnaq, Okeevik, and Kittigaryuit (from west to east). The Anguniaqvia niqiqyuam (AN) MPA is shown in orange. The 200 m bathymetry line of the ecosystem is outlined. Both MPAs are located within the Inuvialuit Settlement Region (ISR, see map insert) of the Canadian Arctic in dark grey

Table 1 Trait value ranges of 21 Arctic fish species used for climate vulnerability modelling

Common name	Scientific name	Environment	Habitat	Climate Zone	LR		DR		Fec	BL
					Min	Max	Min	Max		
Ammodytidae (Sand lances)										
Pacific sand lance	*Ammodytes hexapterus*	Marine/brackish	Benthopelagic	Temperate	64	72.48	0	275	16,081	30
Cottidae (Sculpins)										
Fourhorn sculpin	*Myoxocephalus quadricornis*	Marine/freshwater/brackish	Demersal	Temperate	64	83.11	0	100	18,000	60
Bigeye sculpin	*Triglops nybelini*	Marine	Demersal	Polar	64	81.5	71	1270	NA	17
Gadidae (Cods and haddocks)										
Polar cod	*Arctogadus glacialis*	Marine	Bathypelagic	Deep-water	64	88.46	0	1000	NA	32.5
Arctic cod	*Boreogadus saida*	Marine/brackish	Demersal	Polar	64	89.36	0	1383	69,700	40
Cisco	*Coregonus artedi*	Anadromous	Pelagic	Polar	-82.63	76.18	0	64	24,549	57
Saffron cod	*Eleginus gracilis*	Amphidromous	Demersal	Polar	64	71.95	0	300	680,000	55
Walleye pollock	*Gadus chalcogrammus*	Marine/brackish	Benthopelagic	Deep-water	64	80.61	30	1280	15,000,000	91
Liparidae (Snailfishes)										
Gelatinous snailfish	*Liparis fabricii*	Marine	Bathydemersal	Polar	64	82.48	6	1880	735	20
Osmeridae (Smelts)										
Capelin	*Mallotus villosus*	Marine/inshore	Pelagic	Temperate	28.52	80.3	0	725	53,200	25.2
Rainbow smelt	*Osmerus dentex*	Anadromous	Pelagic	Boreal	35.29	73	0	290	70,000	34
Pleuronectidae (Righteye flounders)										
Yellowfin sole	*Limanda aspera*	Marine	Demersal	Polar	64	71.5	0	700	3,300,000	49
Longhead dab	*Myzopsetta proboscidea*	Marine	Demersal	Polar	64	71.68	0	160	NA	40
Starry flounder	*Platichthys stellatus*	Marine/freshwater/brackish	Demersal	Polar	64	70.96	0	375	5,955,245	91
Salmonidae (Salmonids)										
Arctic cisco	*Coregonus autumnalis*	Anadromous	Pelagic	Temperate	49.75	73.2	NA	NA	90,000	65
Lake whitefish	*Coregonus clupeaformis*	Anadromous	Benthopelagic	Polar	-81.88	71.99	8	128	121,700	100
Least cisco	*Coregonus sardinella*	Anadromous	Pelagic	Polar	51.73	74.2	0	25	93,500	47
Chum salmon	*Oncorhynchus keta*	Anadromous	Benthopelagic	Temperate	64	71.32	0	250	3,100	100
Arctic char	*Salvelinus alpinus*	Anadromous	Benthopelagic	Polar/ Temperate	64	83.11	0	70	8,065	107
Dolly Varden	*Salvelinus malma*	Anadromous	Benthopelagic	Temperate	64	76.32	0	200	10,000	127
Inconnu	*Stenodus leucichthys*	Anadromous	Demersal	Deep-water	64	73.02	0	50	420,000	150

species had ≥ 50 unique occurrence records within the Arctic region. The R Statistical Software (v2022.02.3 + 494; [71]) packages worrms [14], rfishbase [10], robis [69], and rgbif [15] were used to determine the occurrence data of the selected fish species in the study area. Latitudinal range, depth range, fecundity, and body length values were gleaned from the public databases OBIS, GBIF, NEREUS, WoRMs, and FishBase. Species' latitudinal ranges were calculated from the difference between the most northern and southern occurrence points, and depth ranges between the maximum and minimum depths.

The species' ecological, biological, and geo-referenced occurrence data were overlaid with the mean historical environmental conditions obtained from a regional coupled ice-ocean biogeochemical model (North Atlantic Arctic (NAA) Canadian ocean ecosystem (CanOE) and Canadian sea ice biogeochemistry (CSIB) model, herein "NCC", [36, 37, 62]). Species ecological niches (represented by the 1st, 10th, 90th, and 99th percentiles) were calculated for pelagic and demersal species using sea surface values, and sea bottom values for benthic species. The optimum range values were estimated by averaging the 10th and 90th percentiles. Simulations from the NCC model provide potential changes to future biogeochemical or environmental variables to assess climatic risk and vulnerability [80], and to calculate each Arctic fish species' ecological niche with respect to temperature, sea ice cover, salinity, oxygen concentration, and pH (surface and bottom values) as described in Sora et al. [78].

Values represent environment, habitat, climate zone, latitudinal range (LR, Min/Max in degrees), depth range (DR, Min/Max in m), fecundity (Fec, maximum number of eggs), maximum body length (BL, cm) from the NCC model, OBIS, GBIF, NEREUS, WoRMs, and FishBase databases [35]. "NA" indicates no data available for the species' trait and was not included in the calculations.

2.3 Fuzzy logic and reasoning

Fuzzy logic methodology was first developed by Zadeh [95], and since then fuzzy risk and vulnerability approaches have been applied to study exploited marine species globally [44] and to deep sea fish assemblages [19]. The fuzzy logic expert system developed by Cheung et al. [17, 19] and Jones and Cheung [44] include three components: (i) fuzzification (identifying associations between climate variables by the IF–THEN rules for degree of memberships to the "fuzzy sets" or categories), (ii) fuzzy reasoning (rule evaluation and aggregation) and,(iii) defuzzification (calculating a precise value from the membership functions). Species are categorized into the fuzzy sets of low, medium, high, or very high climate exposure categories, where memberships to these categories overlaps (fuzziness) [19, 44]. Following Cheung et al. [17, 19], trapezoid shapes were assumed for low and very high fuzzy membership category scales, and triangular shapes for medium and high membership category scales of the fuzzy logic functions (Fig. 3). In this approach, species can have a gradation of membership (or truth) to each category, where conclusions are "possibilities" of fuzzy set associations [17]. Therefore, a species can simultaneously belong to more than one category, with the amount of membership to each category defined by the fuzzy membership function [44]. For example, based on the fuzzy membership functions in Fig. 3(b), a fish with a temperature tolerance spanning across a range of 2.5 °C, simultaneously belongs in the low (trapezoid shape in blue) and medium (triangle shape in orange) categories with a membership of 0.3 and 0.7, respectively. The relationships between Arctic fish species' biological and ecological characteristics, and the physical and biogeochemical ocean conditions were incorporated into the calculated risk levels using the fuzzy logic methodology [16]. This approach combines the climate indices with the biogeography of the species', allowing for identification of vulnerable Arctic fish.

2.4 Species exposure to climate hazards

Climate hazards were quantified by subtracting the historical average (1979–2015) from the mid-century future average (2041–2060) for each environmental condition generated by the NCC model (Eq. 1, adapted from [44]). Scenario values were obtained from the Representative Concentration Pathways (RCP4.5 and RCP8.5) for the NCC model [36]. RCP4.5 is considered as an intermediate climate change scenario representing future greenhouse gas concentrations as recognized by the IPCC and associated with global sea surface temperature increasing between 2–3 °C. RCP8.5 is the "extreme worst-case" trajectory during which emissions continue to rise throughout the twenty-first century, and with warming reaching 3.5 °C by 2100 [11, 12, 80]. It is unlikely that global temperatures will remain below 1.5 °C or surpass 3.0 °C warming [91]. The moderate RCP4.5 is now the most-likely future projection, while RCP8.5 is deemed unlikely but not impossible. RCP8.5 is used to provide the upper bound for emission scenarios and emphasizes model differences or specific areas of concern [91]. RCP4.5 and RCP8.5 scenarios are herein referred to as the "low" and "high" scenarios, respectively. Climate variables representing the hazards include sea water temperature, sea ice concentration (% cover),

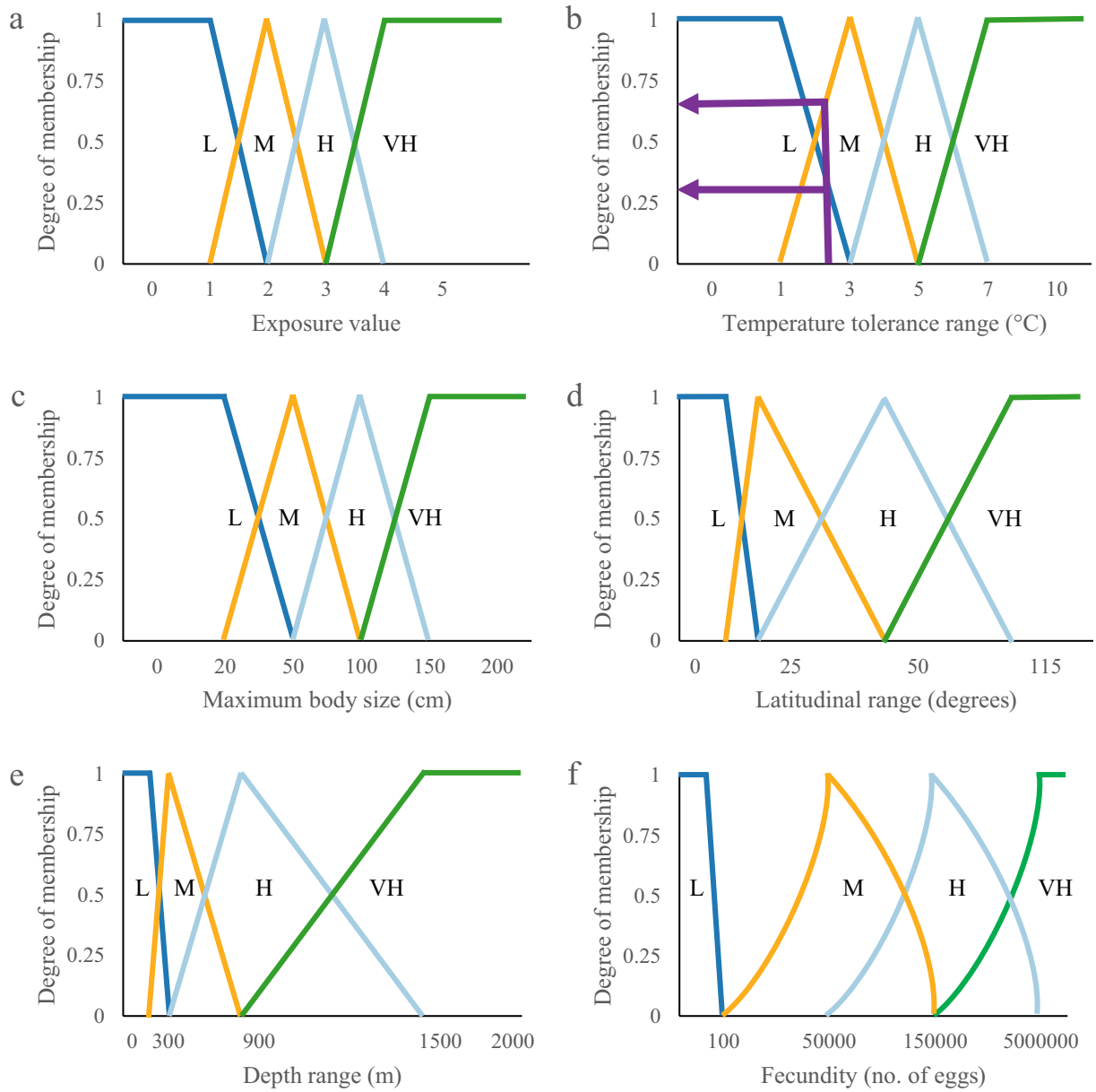


Fig. 3 Fuzzy membership functions for input variables for exposure to hazard, sensitivity and adaptive capacity categories. **a** Exposure value, **b** temperature tolerance range, **c** maximum body length, **d** latitudinal range, **e** depth range, and **f** fecundity. The apparent nonlinear shape of the fecundity membership function is a result of the use of log-transformed scale for fecundity in the figure. Values represent L, low (blue); M, medium (orange); H, high (light blue); VH, very high (green) categories. A fish with a temperature tolerance range of 2.5 °C corresponds to the L and M categories with 0.3 and 0.7 degrees of membership (purple). [44] Adapted from Jones and Cheung,

salinity, oxygen concentration, and pH (sea surface for pelagic species, and sea bottom for demersal or benthic species), with projected changes to these variables in the future considered here.

The impact of projected climate hazards onto Arctic fish species was developed in Jones and Cheung [44]. The species' exposure to climate change hazard (*ExV*, exposure (*Ex*) to climate variable (*V*)) or the extent to which modeled changes to the environment are impacting Arctic fish species was estimated by the amplitude (difference between the mean values of future and historical climate variables) of the hazard relative to its historical variability. We modified the Jones and Cheung [44] algorithm for calculating *ExV* by including the Arctic fish species ecological niche for species' exposure, sensitivity, adaptive capacity (and vulnerability) to climate change. The formulation of climatic hazard in Jones and Cheung [44] does not account for the baseline conditions relative to the environmental preferences of the species. For example, projected warming may be favorable to a warm-adapted species but would be considered a climatic hazard

using the original Jones and Cheung [44] algorithm. The importance of this addition is particularly pertinent for the Arctic as sub-polar and temperate eurytherms are expected to become more abundant under climate change [26, 39, 83, 88]. Thus, in the modified algorithm, we expressed climate variable (*V*) as a hazard index (*H*) calculated from a trapezoid function defined by the 1st, 10th, 90th, 99th percentiles of the ecological niche of the specific variable for a given species as estimated from their occurrence records and baseline environmental conditions (Eq. 1):

$$ExV_i = \frac{\overline{H}_{future,i} - \overline{H}_{historical,i}}{\partial H_{historical,i}} \quad (1)$$

where *H* is the mean hazard index of the future ($\overline{H}_{future}$), historical ($\overline{H}_{historical}$), and standard deviation ($\overline{\partial H}_{historical}$) per climate variable (*V*) for each gridded pixel of the study area (*i*).

The exposure of the 21 Arctic fish species to each climatic hazard was expressed as the sum of the gridded pixels overlapping with levels of climatic hazards and species occurrence data. The frequency distribution of species richness-pixels was compared to climatic hazard exposure levels of temperature, sea ice cover, salinity, oxygen concentration, and pH [19], where a higher richness-pixel indicates more species occurring in areas with specific hazard levels.

Uncertainty in the climate exposure level in fuzzy logic is represented by the degree of overlap (or fuzziness) of the fuzzy set categories [44]. On the spatial grid, the exposure to climate hazard categories can represent multiple types simultaneously, where belonging to each category is defined by the fuzzy logic membership [19]. For instance, if X (premise) then Y (conclusion), where membership to a category isn't "True" or "False", rather the fuzzy logic rules (Table 2) define when a threshold is passed, indicating the amount of membership to each fuzzy set category [44]. Conclusions are then inferred from these fuzzy logic memberships [44].

2.5 Climate sensitivity

The climate sensitivities of the 21 Arctic fish species were categorized based on the calculated ecological niche for each climate variable, and the species' body length (Table 2). The exposure value of each species was categorized by the exposure level to each climate hazard (Eq. 1) with their ecological niche categorized into four fuzzy sets representing low ($ExV < 1$, within historical ranges), medium ($0.5 < ExV < 2$), high ($1 < ExV < 3$), and very high ($ExV > 2$) categories [19]. Species' sensitivity to individual climate variables was categorized as low (25th percentile), medium (50th percentile), high (75th percentile), and very high (90th percentile) categories, based on the breadth of the ecological niche (e.g., temperature preferences, salinity tolerance ranges, etc.) across all Arctic fish species included in this study [44]. Acidification (pH, surface and bottom) sensitivity was categorized in fuzzy sets based on meta-analyses from Kroeker et al. [46] and Wittmann and Pörtner [94]. Fishes were categorized as low sensitivity (0.25) to medium sensitivity (0.50) to acidification, based on negative impacts on species' growth, survival, or calcification (e.g., mollusks were categorized as very high sensitivity

Table 2 Fuzzy logic rules to determine the climate hazard exposure (ExV), sensitivity, and adaptive capacity of the 21 Arctic fish species under conditions simulated with the NCC model

Exposure	Low	Medium	High	Very High
Exposure value (*ExV*)	1 > *ExV*	0.5 < *ExV* < 2	1 < *ExV* < 3	2 < *ExV*
Sensitivity	Low	Medium	High	Very High
Sea Surface Temperature (SST)	0.95 > SST tolerance	0.93 < SST tolerance < 1.02	0.95 < SST tolerance < 4.96	1.02 < SST tolerance
Sea Bottom Temperature (SBT)	1.55 > SBT tolerance	1.12 < SBT tolerance < 3.6	1.55 < SBT tolerance < 5.92	3.6 < SBT tolerance
Sea Ice Cover (ICE)	48 > ICE	35 < ICE < 60	48 < ICE < 65	60 < ICE
Sea Surface Salinity (SSS)	13.62 < SSS	13.06 < SSS < 13.68	13.62 < SSS < 14.69	13.68 < SSS
Sea Bottom Salinity (SBS)	12.56 < SBS	8.73 < SBS < 15.89	12.56 < SBS < 17.31	15.89 < SBS
Acidification (SpH/BpH)	< 0.25 pH	< 0.25 pH < 0.5	NA	NA
Maximum body length (BL)	55 > BL	34 < BL < 91	55 < BL < 107	91 < BL
Adaptive Capacity	Low	Medium	High	Very High
Latitudinal range (LR)	18 > LR	8 < LR < 25	18 < LR < 95	25 < LR
Depth range (DR)	282 > DR	115 < DR < 794	282 < DR < 1263	794 < DR
Fecundity (Fec)	69,850 > Fec	16,561 < Fec < 345,425	69,850 < Fec < 4,096,573	345,425 < Fec

(0.75) in Jones and Cheung [44]. Species' maximum body length was categorized as small, medium, large, and very large. As large-bodied ectotherms are more metabolically sensitive to temperature and deoxygenation (surface and bottom values, these membership categories increased with body length (small = low, medium = medium, large = high, and very large = very high sensitivity [18, 67, 76] (Table 2).

Values represent sea surface temperature (SST, °C), sea bottom temperature (SBT, °C), sea ice cover (ICE, %), sea surface salinity (SSS, no units), sea bottom salinity (SBS, no units), sea surface pH (SpH, no units), sea bottom pH (BpH, no units), maximum body length (BL, cm), latitudinal range (LR, degrees), depth range (DR, m), and fecundity (Fec, maximum number of eggs). "NA" indicates category was not included in the calculations. Thresholds recreated from methods of Jones and Cheung [44].

2.6 Species vulnerability

Species vulnerability was calculated based on fuzzy membership functions for the categories of climate sensitivity and adaptive capacity. Species' adaptive capacity was calculated based on latitudinal range, depth range, and fecundity (Tables 2 and 3). Larger latitudinal and depth ranges, and higher fecundity indicated higher adaptive capacity via acclimation, range shift, or selection [3, 44]. Low adaptive capacity was defined as fish species with narrow latitudinal or depth ranges. The rules were adapted from Cheung et al. [16], which describe the relationship between species' ecological niches, latitudinal range, depth range, fecundity, and body length,and the species' sensitivity, adaptive capacity, and vulnerability.

Species vulnerability was calculated based on IF–THEN rules joined by AND (e.g., IF the fish species has low sensitivity AND high adaptive capacity, THEN potential vulnerability is low), therefore the resulting vulnerability is the minimum value on the spectrum [44] (Tables 2 and 3; Fig. 3). The conclusions from the rules were divided into four categories: (i) low, (ii) medium, (iii) high, and (iv) very high vulnerability. As the IF–THEN rules are joined by AND, the resulting vulnerability must exceed the minimum threshold value of 0.2 (minimum membership required for the rule to be applied) to meet the requirements of each category [17, 44].

The same rules are applied to species' climate risk determined by the combination of a species' exposure to hazard and its vulnerability. Recreated from Jones and Cheung [44].

The fuzzy logic algorithm rules used all available input variables to calculate the degree of membership to each of the fuzzy categories for vulnerability (Table 2, Fig. 3). Vulnerabilities and risk of climate hazards were combined with climate exposure to determine the overall risk of climate impacts. Uncertainties of the input variables are included in this analysis, as the set of rules and exposure hazard level categories are specified for each model (see Sensitivity analysis subsection). This allows for the simultaneous possibilities of different rules drawing different or similar conclusions with variability and the degrees of memberships [44]. Therefore, the algorithm (MYCIN) accumulated the degrees of memberships in Eq. 2 [17]:

$$AccMem_{i+1} = AccMem_i + Membership_{i+1} * (1 - AccMem_i) \quad (2)$$

where *AccMem* is the accumulated membership (e.g., high vulnerability) and *i* indicates a rule of the accumulated membership.

Defuzzification was then used to determine the vulnerability, sensitivity, adaptive capacity, hazard exposure, and climate impact risk indices. A scale from 1 (lowest) to 100 (most at risk or vulnerable) was used to quantify the indices, which were then divided into the categories: (i) low = 1, (ii) medium = 25, (iii) high = 75, and (iv) very high = 100 [19].

Table 3 Matrix rules for Arctic fish species' vulnerability determined by its sensitivity and adaptive capacity

	Sensitivity | Exposure to hazard			
Adaptive capacity | Vulnerability	Low	Medium	High	Very High
High	Low	Low	Medium	High
Medium	Low	Medium	High	High
Low	Medium	High	High	Very high
Very low	High	High	Very high	Very high

Vulnerability values here represent the fuzzy membership function centroids, where the final vulnerability index (*Vul*) was calculated by weighting the index values (*Indval*) average by the accumulated membership, Eq. 3 [17]:

$$Vul = \frac{\sum_{x=1}^{4} AccMem_x \bullet Indval_x}{\sum_{x=1}^{4} AccMem_x} \quad (3)$$

where *x* indicates a category (low = 1, medium = 25, high = 75, and very high = 100). The climate vulnerability and risk indices for the 21 Arctic fish species were calculated using the fuzzy logic membership algorithms (Eq. 2 described above). Index values which scored above 75 represented a species assessed to be at high risk to climate hazards and of highest conservation concern. The estimated climatic risk was compared to the species' climate vulnerabilities.

2.7 Sensitivity analysis

The sensitivity of the climatic hazards for Arctic fish species to uncertainties associated with the ocean-climate models were tested using projections of ocean conditions from two Earth system models (ESMs) participating in the Coupled Models Intercomparison Project Phase 6 (CMIP6): (i) the Geophysical Fluid Dynamics Laboratory (GFDL)-ESM4, and; (ii) the Institut Pierre-Simon Laplace (IPSL)-CM6A-LR. These ESMs were chosen as the climate sensitivities encompass a wide range, where IPSL and GFDL SSP1-2.6 are one standard deviation higher/lower respectively than the CMIP6 model mean [56]. Climate hazards for each model were quantified by subtracting the historical average (1951–2000) from the future average (2041–2060), with future values obtained from Shared Socio-economic Pathway (SSP) SSP1-2.6 and SSP5-8.5 scenarios. Temperature, sea ice cover, salinity, oxygen, and pH ranges of the Arctic fish species based on the ESMs are provided in Tables S2–S3, and respective fuzzy logic rules in Table S4.

3 Results

Here, we present the results based on the higher-resolution regional NCC model for both RCP4.5 and RCP8.5. Results based on the GFDL and IPSL ESMs can be found in the SI (Figs. S1–S6) and are discussed as part of the sensitivity analysis subsections.

3.1 Ecological niche of Arctic fish species

In the NCC model, many Arctic fish species had narrow ecological niches for multiple environmental variables. Namely, Arctic char (*Salvelinus alpinus*), Capelin (*Mallotus villosus*), and Arctic cod had narrow salinity, oxygen, and pH ranges (Table 4). Furthermore, Pacific sand lance (*Ammodytes hexapterus*), Longhead dab (*Myzopsetta proboscidea*), and Inconnu (*Stenodus leucichthys*) had some of the narrowest ice, salinity, oxygen, and pH ranges. The anadromous cisco species (*Coregonus sardinella*, *Coregonus artedi*, *Coregonus autumnalis*), Fourhorn sculpin (*Myoxocephalus quadricornis*), and Chum salmon (*Oncorhynchus keta*) had narrow temperature ranges. Temperature ranges were available on FishBase for nearly all species and showed a larger breadth of temperatures for two thirds of the species evaluated compared to all modelled niches.

Values represent the preferred minimum (10th percentile, Min), and preferred maximum (90th percentile, Max) quantile ranges calculated from the NCC model or from FishBase [35]. Ranges for pelagic species include sea surface temperature (SST, °C), sea surface pH (SpH, no units), sea surface salinity (SSS, no units), and sea surface dissolved oxygen (SO2, µmol/kg). Ranges for benthic species include sea bottom temperature (SBT, °C), sea bottom pH (BpH, no units), sea bottom salinity (SBS, no units), and sea bottom dissolved oxygen (BO2, µmol/kg). Ranges for sea ice cover (ICE, % cover) were calculated for all species. "NA" indicates temperature ranges were not available on FishBase and were not included in the comparison.

Table 4 Ecological niche of the 21 Arctic fish species separated by pelagic and benthic species

Pelagic Species													
		SST				SpH		SSS		SO2		ICE	
		NCC		FishBase		NCC		NCC		NCC		NCC	
Common name	Species name	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Cisco	*Coregonus artedi*	− 0.48	0.04	0	26	7.82	8.28	11.98	25.05	165.46	364.21	0	63
Arctic cisco	*Coregonus autumnalis*	− 0.71	0.24	− 1.7	3.4	7.88	8.27	13.45	28.81	175.29	363.15	0	65
Least cisco	*Coregonus sardinella*	− 0.66	0.27	− 1.8	2.7	7.90	8.26	13.31	26.93	176.92	360.82	2	62
Capelin	*Mallotus villosus*	− 0.10	7.48	0.3	7.1	8.08	8.22	22.90	34.90	233.85	356.82	0	34
Rainbow smelt	*Osmerus dentex*	− 0.54	0.48	− 1.6	4.8	7.90	8.17	15.13	28.81	209.60	365.85	3	62
Benthic species													
Pacific sand lance	*Ammodytes hexapterus*	− 1.08	0.34	0.5	8.9	7.94	7.98	30.29	32.13	348.12	358.82	40	71
Polar cod	*Arctogadus glacialis*	− 0.73	5.15	− 1.3	1.6	7.74	8.16	18.98	34.77	189.41	312.52	12	78
Arctic cod	*Boreogadus saida*	− 0.61	2.10	− 1.3	4	7.78	7.99	22.70	32.17	229.13	360.34	19	66
Lake whitefish	*Coregonus clupeaformis*	− 0.50	1.04	8	14	7.82	8.23	9.22	27.90	116.11	324.18	0	35
Saffron cod	*Eleginus gracilis*	− 0.10	1.04	− 1.5	5.9	7.82	8.14	10.38	27.90	171.72	324.18	3	35
Walleye pollock	*Gadus chalcogrammus*	− 0.31	0.69	0.4	5.6	7.78	8.21	14.54	26.89	168.91	352.08	0	48
Yellowfin sole	*Limanda aspera*	− 0.70	4.87	0.2	6.1	7.70	8.32	14.12	31.22	140.32	310.61	0	60
Gelatinous snailfish	*Liparis fabricii*	− 0.69	0.86	− 0.9	4.6	7.82	8.23	12.60	28.66	167.96	357.35	0	63
Fourhorn sculpin	*Myoxocephalus quadricornis*	− 0.08	0.46	− 1.8	4.3	7.82	8.17	13.89	26.48	180.91	355.96	3	48
Longhead dab	*Myzopsetta proboscidea*	− 0.28	5.97	− 1.1	6.6	7.78	7.97	30.27	34.74	226.68	301.38	46	67
Chum salmon	*Oncorhynchus keta*	− 0.46	0.45	1.1	8.3	7.78	8.23	9.84	22.37	163.38	298.32	3	43
Starry flounder	*Platichthys stellatus*	− 0.43	0.92	0.2	8.3	7.92	8.20	17.14	31.93	203.32	362.93	10	58
Arctic char	*Salvelinus alpinus*	− 0.93	1.26	0.1	9.7	7.95	8.01	31.07	34.57	311.62	355.05	29	82
Dolly Varden	*Salvelinus malma*	− 0.30	2.64	0.2	8	7.77	8.01	23.76	32.04	284.37	359.04	18	54
Inconnu	*Stenodus leucichthys*	− 0.77	5.19	NA	NA	7.79	7.98	25.86	34.73	203.53	314.70	46	74
Bigeye sculpin	*Triglops nybelini*	− 0.72	0.34	− 0.1	4.5	7.85	8.24	14.46	30.29	177.17	359.24	0	66

3.2 Exposure to main climatic hazards by 2050 (2041–2060 average)

The exposure to climate change hazards (*ExV*, Eq. 1) was higher for RCP8.5 compared to RCP4.5 (Fig. 4, red areas). The highest intensity or largest difference between the mean future and historical climate hazards of bottom temperature, and surface and bottom salinity, oxygen, and pH were found for the deep waters of the slope, and offshore areas of the BS–AG ecosystem for RCP8.5. The degree of surface temperature and sea ice hazards increased across the BS–AG ecosystem (Fig. 5 a–b, c–f). Surface salinity and pH hazards were highest in nearshore areas adjacent to the TN and AN MPAs for both scenarios (Fig. 5 g–h, o–p). Oxygen concentration (Fig. 5 k–n) was the only climate exposure variable that remained relatively constant in exposure between scenarios.

3.3 Species-richness exposure to main climate hazards

The exposure to climatic hazards across the BS–AG ecosystem varied among fish species groups (pelagic vs benthic). A total of 98% of species-richness pixels were projected to experience very low exposure (0–0.5) to temperature, sea ice, salinity, and oxygen hazards by the 2041–2060 average for both RCP4.5 and RCP8.5 relative to historical variabilities (Fig. 5a–h). More species-richness pixels were projected to overlap with very low exposures in RCP4.5 (blue) than RCP8.5 (red). The majority of species-richness pixels (44–76%) overlapped with very high pH exposure (> 3.0) for RCP4.5 and RCP8.5 (Fig. 5 i–j). 20–30% of benthic species-richness pixels overlapped with very high exposure (> 3.0) to temperature and oxygen (Fig. 5 b, h), indicating a large proportion of Arctic fish species occurring in high hazard (acidification, warming, deoxygenation) areas.

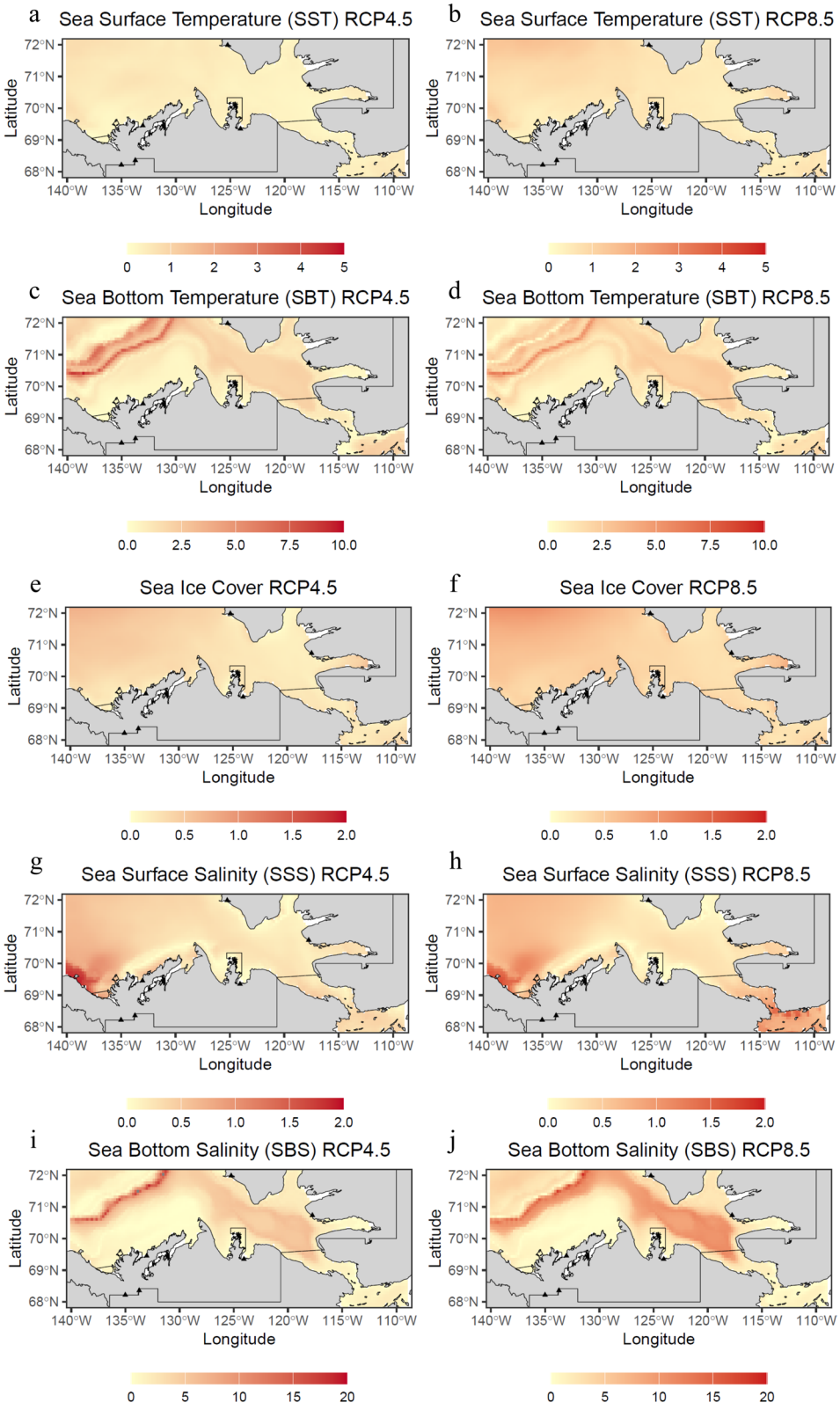
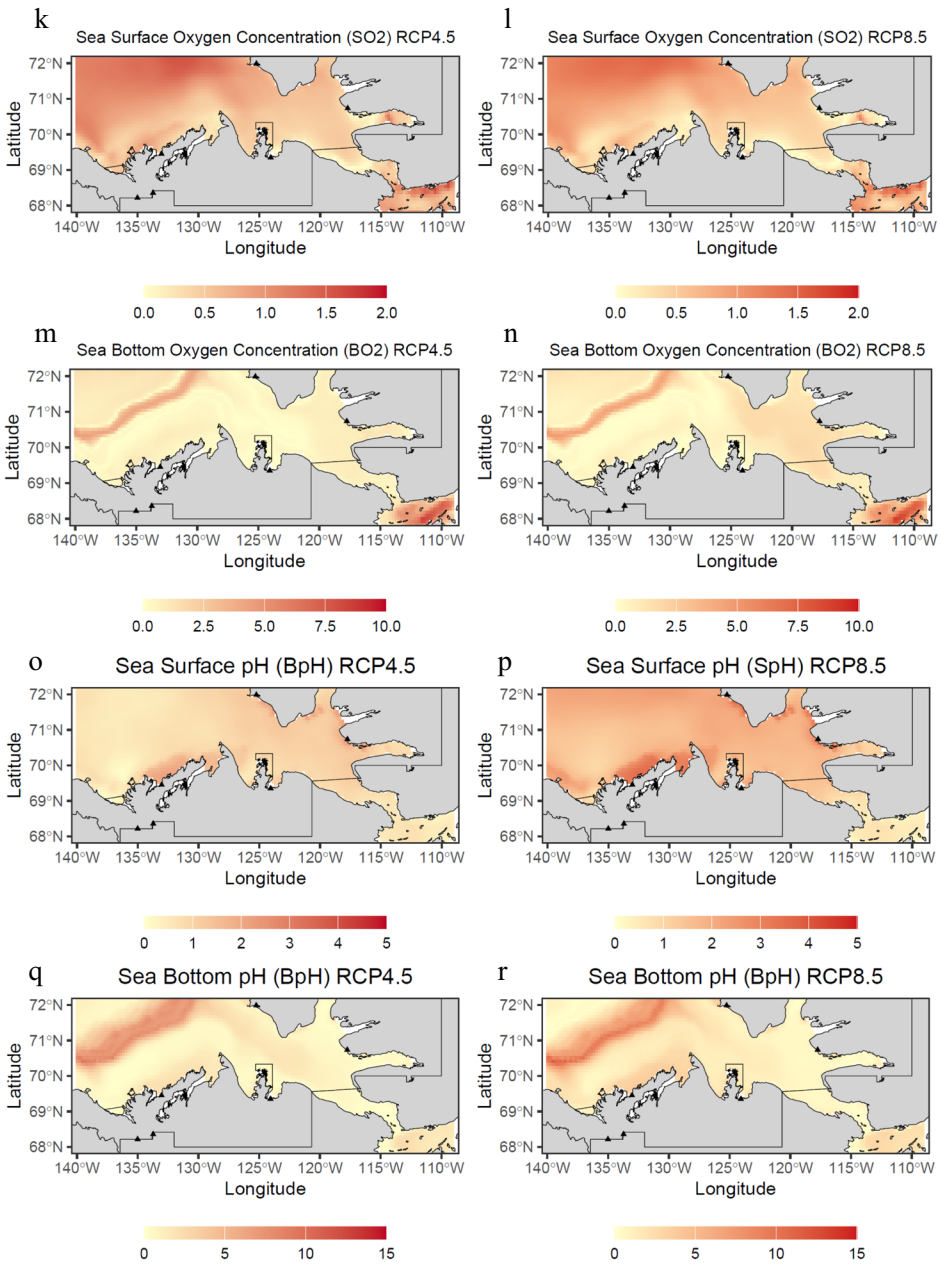


Fig. 4 Projected average exposure to climate hazards (defined as the amplitude: difference between the mean values of future and historical climate variables) for Arctic fish species arising from changing ocean variables by 2050 (2041–2060 average). Projections of changes in ocean variables were obtained from the NCC model. The climate hazards include: temperature (**a**–**d**), sea ice cover (**e**, **f**), salinity (**g**–**j**), oxygen concentration (**k**–**n**), and pH (**o**–**r**). Hazards are projected for RCP4.5 (**a**, **c**, **e**, **g**, **i**, **k**, **m**, **o**, **q**) and RCP8.5 (**b**, **d**, **f**, **h**, **j**, **l**, **n**, **p**, **r**) for surface (**a**, **b**, **e**, **g**, **h**, **k**, **l**, **o**, **p**) and bottom (**c**, **d**, **f**, **i**, **j**, **m**, **n**, **q**, **r**) variables. Colour scale from low (yellow) to high (red) hazardous changes

Fig. 4 (continued)



3.4 Species' sensitivity, adaptive capacity, vulnerability and risk to climate hazards

The fuzzy logic algorithm computed indices of cumulated level of exposure to hazards and risk of climate impacts across the evaluated ocean variables for each species with values ranging from 0 (low) to 100 (most exposed to hazards or at risk). The median values for the exposure index of climate hazards across the Arctic fish species were 31 (range = 10–47) and 38 (19–58), for RCP4.5 and RCP8.5 respectively, by 2050 (2041–2060) (Fig. 6a). The median values for the climate risk index were 55 (24–68) for RCP4.5, and 56 (27–70) for RCP8.5 by 2050 (Fig. 6b). A higher proportion of Arctic fish species above 50 (shaded areas) indicates more species at high or very high climate risk. Species that are among the most exposed to climate hazards include Polar cod (*Arctogadus glacialis*), Yellowfin sole, and Arctic cisco (*C. autumnalis*).

The estimated median adaptability index (defined by species' latitudinal range, depth range, fecundity) was 57 (range = 17–100), the median sensitivity index (defined by species' body length and ecological niche) value was 48

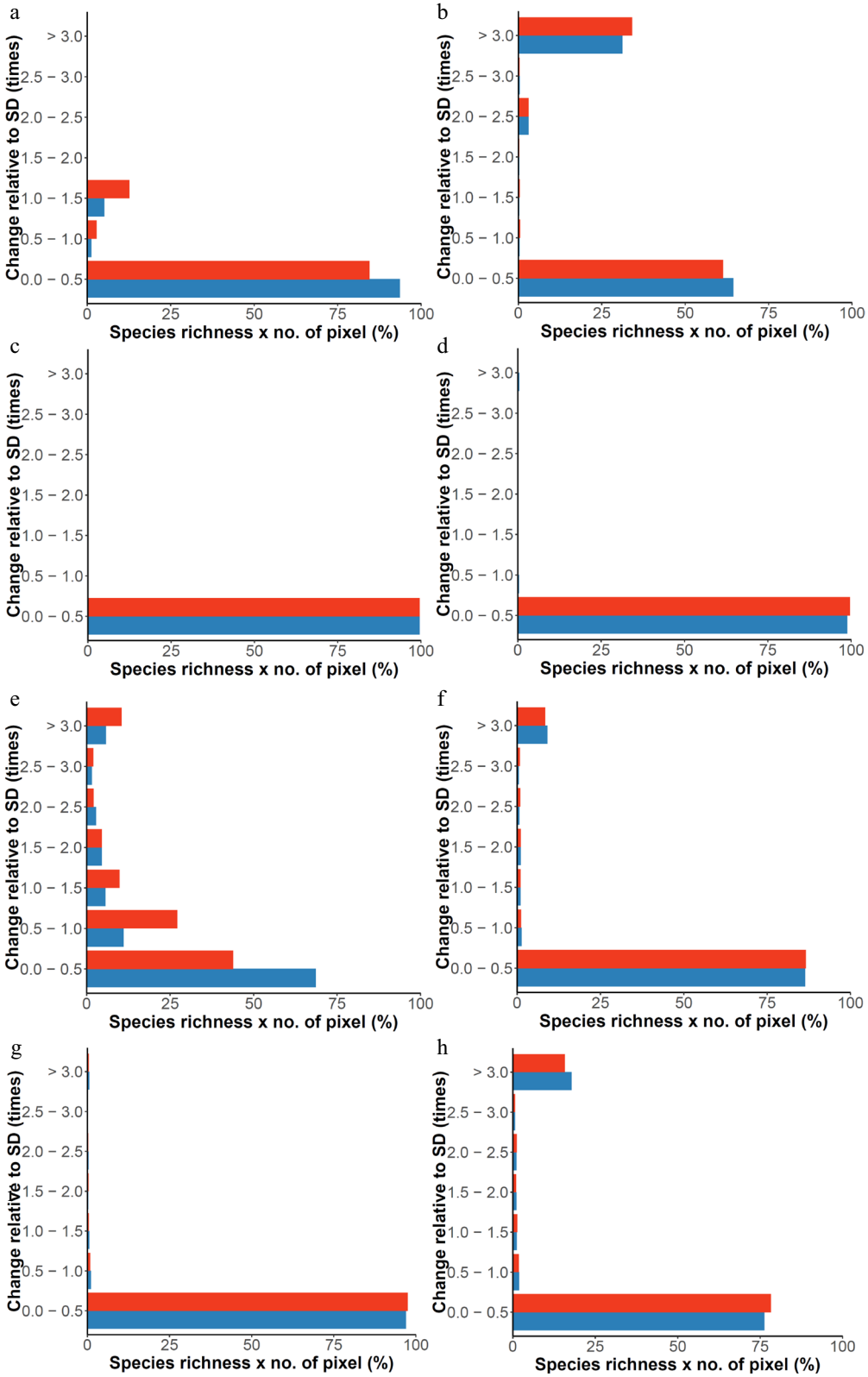


Fig. 5 Exposure to main climatic hazards (defined as the amplitude: difference between the mean values of future and historical climate variables) for 21 Arctic fish species by 2050 (2041–2060 average) calculated using projections from the NCC model (see text for details). Exposure was assessed for the following key climate hazards: temperature (**a**, **b**), sea ice cover (**c**, **d**), salinity (**e**, **f**), oxygen concentration (**g**, **h**), and pH (**i**, j). Surface values were applied to pelagic species (left column, **a**, **c**, **e**, **g**, **i**), and bottom values applied to benthic species (right column, **b**, **d**, **f**, **h**, **j**). The blue and red bars represent RCP4.5 and RCP8.5, respectively

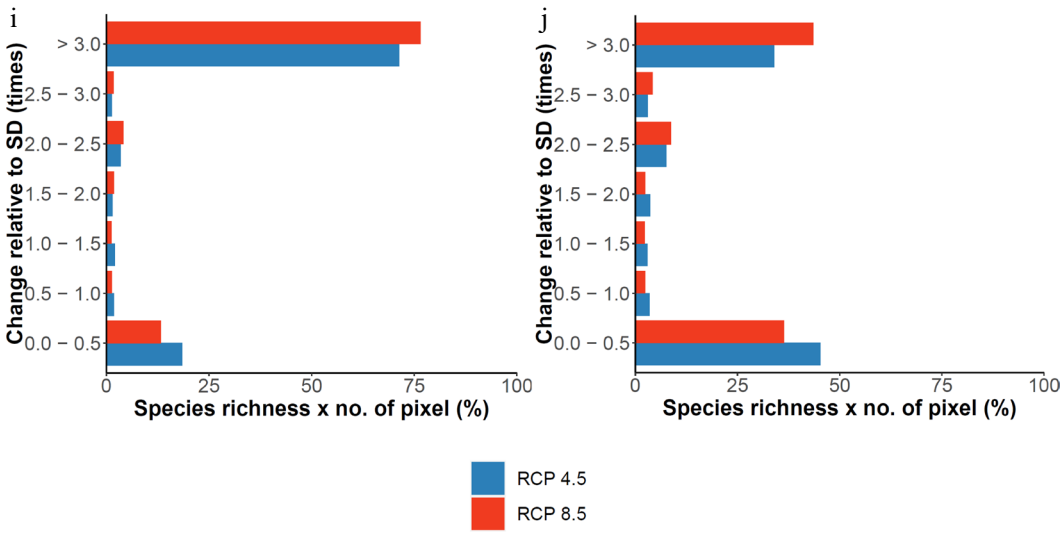


Fig. 5 (continued)

(26–58), and the median vulnerability index (defined by IF–THEN rules joined by AND for the categories of climate sensitivity and adaptive capacity) was 68 (23–86) (Fig. 6c). Arctic fishes emerging among the most adaptable include Longhead dab, Dolly Varden (*Salvelinus malma*), and Chum salmon; while the least adaptable include Polar cod, Capelin, and Arctic cod (Table S6). Species that are among the most sensitive include Starry flounder, Least cisco (*C. sardinella*), and Lake whitefish (*Coregonus clupeaformis*), while the least sensitive include Capelin, Arctic cod, and Longhead dab (Table S6). Species that are among the most vulnerable include Fourhorn sculpin, Chum salmon, and Least cisco, while the least vulnerable include Capelin, Arctic cod, and Polar cod (Table S6).

3.5 Comparison of exposure to hazard index and vulnerability

Most fish species had low (1 < index value < 25) to medium (25 < index value < 50) climate risk and high (50 < index value < 75) to very high (index value > 75) vulnerability (Fig. 7). Polar cod and Yellowfin sole were the only species with high climate risk (50 < index value < 75) under the RCP8.5 scenario. Five species had very high vulnerability (index value > 75) with medium (25 < index value < 50) climate risk, including Chum salmon, Dolly Varden, Arctic char, Lake whitefish, and Longhead dab.

Eight of the studied Arctic fish species were projected to have high (50 < index value < 75) vulnerability and medium risk of climate impacts hazards (25 < index value < 75) by 2051–2060 under low and high emission scenarios (Fig. 7). Capelin, Arctic cod, and Rainbow smelt were the species with low (index value < 25) or medium (25 < index value < 50) exposure to climate hazards and vulnerability, suggesting that they are species that may be more resilient to climate change.

3.6 Sensitivity analysis

The sensitivity analysis revealed that species-richness projections for the ESMs followed similar trends to the NCC model, with most pixels experiencing low exposure (0–0.5) to temperature, sea ice, salinity, and oxygen concentration hazards by 2041–2060 under both low (SSP1-2.6) and high (SSP5-8.5) emission scenarios for GFDL and IPSL models (Figs. S4–S5). However, the IPSL model projected fewer benthic species in very high pH exposure (> 3.0), with most species-richness pixels remaining in low exposure (Fig. S4 j). Comparisons of exposure, risk, sensitivity, and vulnerability indices showed that median exposure and risk were higher for GFDL and IPSL than for the NCC model, whereas median adaptability and vulnerability were similar across all models, and median sensitivity was lower for GFDL and IPSL (Fig. S5). Species with high exposure, risk, sensitivity, and vulnerability included Gelatinous snailfish, Fourhorn sculpin, Walleye pollock, Yellowfin sole, and anadromous cisco species (*C. sardinella*, *C. artedi*, *C. autumnalis*), along with Longhead dab. Notably, six Arctic fish species (Arctic cisco, Dolly Varden, least cisco, longhead dab, fourhorn sculpin, chum salmon, and rainbow smelt) were identified as having very high climate risk and vulnerability (index > 75) under GFDL and IPSL models. Additionally, ten

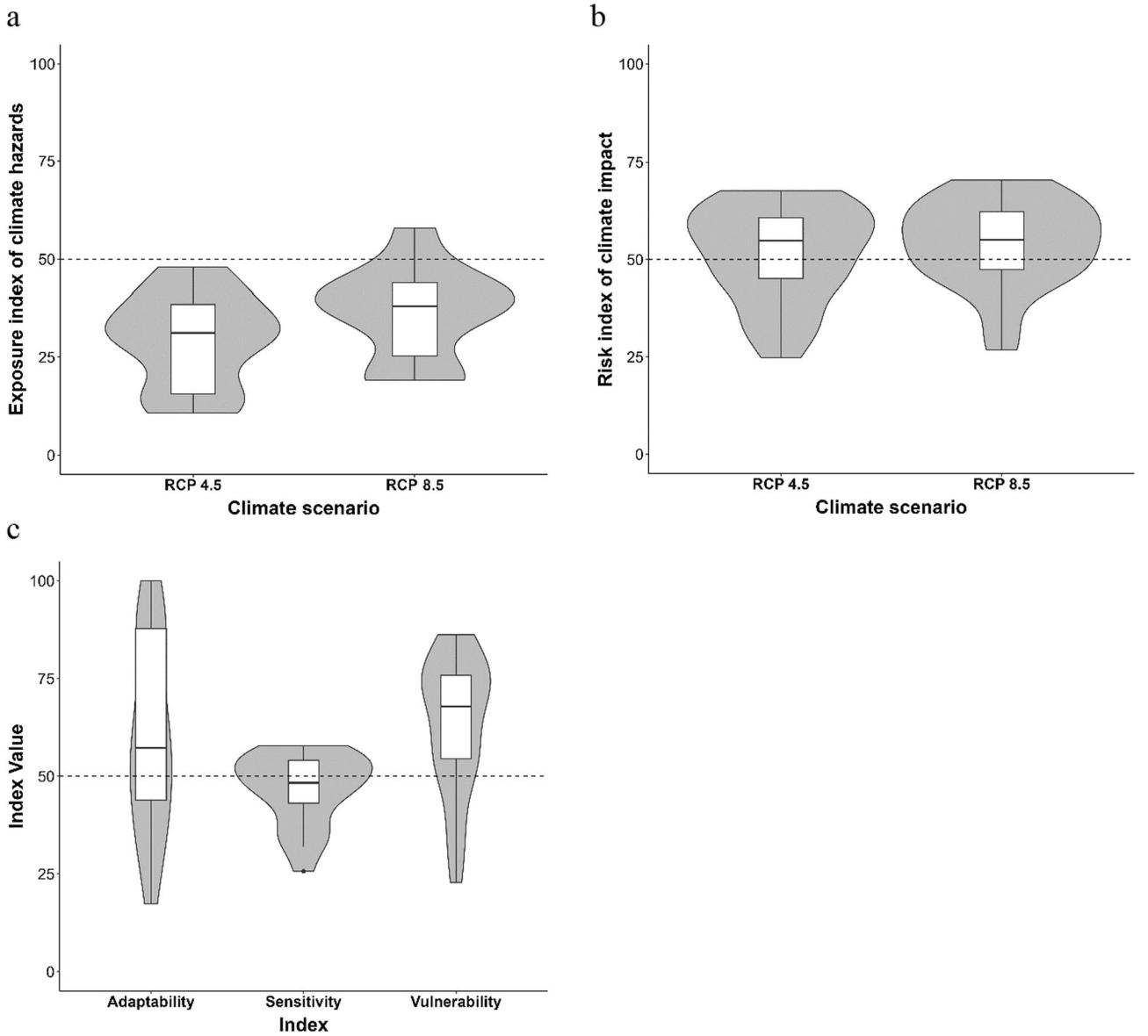


Fig. 6 Calculated (**a**) exposure index of climate hazards, **b** risk index of climate impacts, and **c** adaptive capacity, sensitivity, and vulnerability (see text for details) of the 21 Arctic fish species under the NCC model RCP4.5 and RCP8.5 by 2050 (2041–2060 average) relative to the historical reference period (1979–2015). Index values range from 1 to 100, with 100 indicating maximum climate impact risk. Index values above 50 (dashed lines) indicate high or very high climate impact risk. The boxplot represents the median, 25th and 75th quartiles, and the minimum and maximum values, see Table S6. The shaded areas represent the proportion of the frequency distribution

Arctic fish species showed very high exposure to climate hazards (index > 75) and medium to high vulnerability (index 25–75), overlapping with many species identified in the NCC model (Figs. S5–S6, Tables S5–S6).

4 Discussion

A multivariate fuzzy logic approach was used in this study to identify Arctic fishes individual and cumulative risks to multiple climate variables. New to this study, species' ecological niche (temperature, sea ice cover, salinity, oxygen concentration, and pH) were included in the fuzzy logic system adapted from Jones and Cheung [44]. Species' ecological niche to single and multiple ocean variables were critical to analyzing vulnerability, risk, exposure to hazards, and adaptability

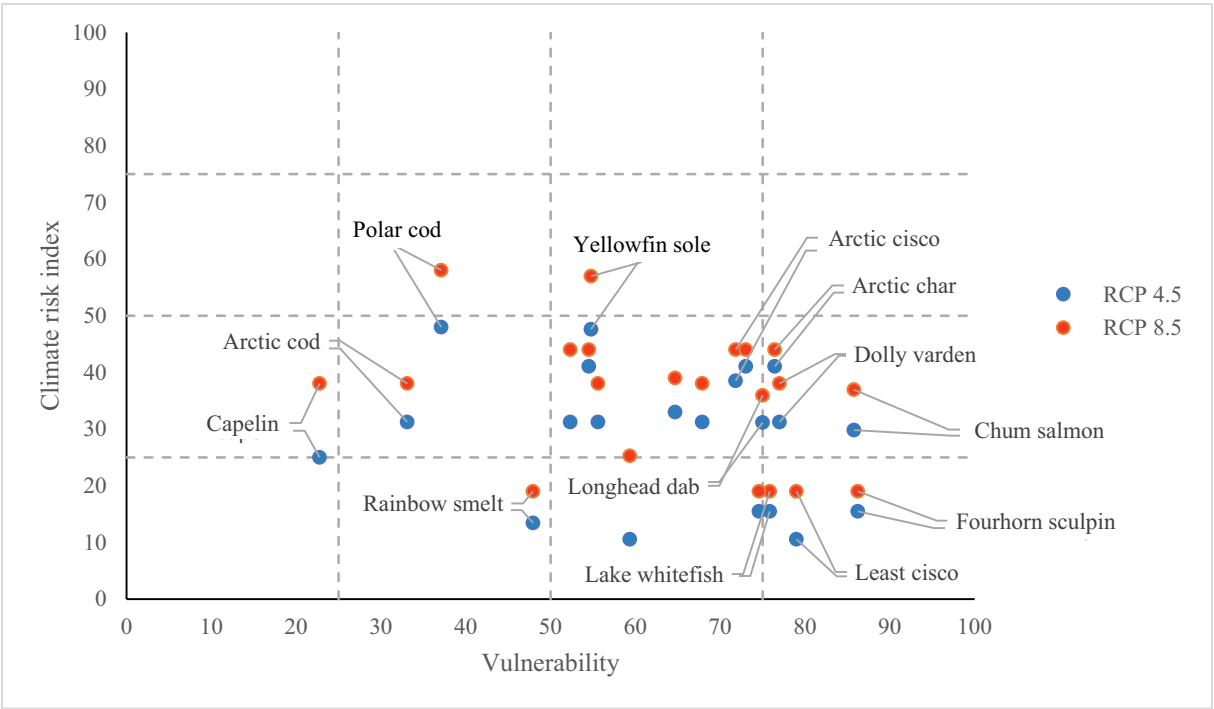


Fig. 7 Comparison of exposure to hazard index and vulnerability under the NCC model RCP4.5 and RCP8.5 by 2050 (2041–2060 average) relative to the historical reference period (1979–2015). Index values (dashed lines) indicate low (25), medium (50), high (75), and very high (100) hazard risk or vulnerability

to projected climate changes and helped understand potential climate change impacts on Arctic fishes, biodiversity and the food web.

This study showed that approximately 25% of the studied Arctic fish species were projected to face medium exposure to climate hazards and high vulnerability towards the mid-century in the marine environment under the NCC model. Under GFDL and IPSL ESMs, more species were projected to face similar or higher levels of hazards, including ocean warming, sea ice loss, changing salinity, deoxygenation, and acidification towards the mid-century compared to the NCC model. These differences can be attributed to differences in the ecological niche derived from the ocean parameters of each model. Differences in ocean models are due to both model parameterizations and spatial resolution. The NCC model implicitly represents ecological niche for fish subpopulations (stenothermic) that are adapted to the Arctic region. In contrast, estimated ecological niche from the global ESMs represent the full ecological breadth of the species. The calculated ecological niche for the Arctic fish species here and estimated in FishBase [35] were narrower than indicated in the Aquatic Species Physiological Limits Database [79]. Differences in estimates may be due to the applied methods, i.e., laboratory studies of various life history stages compared to presence/absence species distributions of adult fish (as used in this study). Presence/absence studies may be limited due to incomplete area coverage of the observations supporting these databases, while laboratory studies are often limited to few individuals and may not represent the range within populations. The narrower ecological niches calculated from the NCC model with more detailed spatial resolution indicate species' higher sensitivity to climate change and suggests that coarser resolution models may underestimate the species sensitivity to climate change.

The addition of ecological niches in the fuzzy logic methodology accounted for the baseline conditions for each species or subpopulation, which in turn allowed to identify that projected warming may be favourable to warm-adapted (eurythermic) species. Arctic fish species have been previously found to acclimate to higher temperatures. For example, Arctic cod were shown to increase their critical upper temperature limit from 14.9 °C to 17.1 °C, depending on exposure time and temperature in laboratory studies [28]. This acclimation potential of Arctic fish species has only been limitedly explored and needs further study to help fully understand the cumulative impacts of multiple stressors. Furthermore, anadromous species such as Arctic char, also face additional climate risks in their freshwater environments used seasonally for spawning and overwintering. The mid-century projections (average from the years 2041–2060) may have smoothed any outliers from extreme event years into an annual average applied here, along with the model uncertainty and errors.

However, given the extreme seasonal variations in the Arctic, including habitat use or characteristics (e.g., summering habitat, spring migration), the adaptability of species to these seasonal extremes may be underestimated due to such averaging. Understanding variations in subpopulation traits can provide insights into the population dynamics, ecological strategies, species interactions, and adaptive capacity to climate change [4, 74, 75, 90, 92].

The number of pelagic species-pixels exposed to very high exposure (> 3.0) level of pH increased to over half of the species (44–76%) in the high emission scenarios (RCP8.5 of the NCC model, and SSP5-8.5 of the GFDL and IPSL models), suggesting that pH may significantly influence Arctic fish species. Additionally, pH exposure was highest in nearshore areas adjacent to the TN and AN MPAs. However, recent testing of the NCC model has indicated a pH bias, which may cause acidification exposures to be overestimated. This is apparent when NCC modeled outputs are compared to projected lower pH exposure trends of the ESMs for the majority of the species-richness pixels. Compared to most other Arctic regions (except for the East Siberian Sea), the BS–AG ecosystem has particularly low $CaCO_3$ concentrations [82]. This is due a combination of factors, including reduced sea ice extent, as open water areas allow for positive feedback of the uptake of atmospheric CO_2 via ocean-air gas exchanges, cold temperatures, and water circulation patterns, including the inflow and upwelling of low pH Pacific halocline waters to the shelf [5, 20, 33, 53, 58, 59, 70]. *Limacina helicina* is a planktonic sea snail that is abundant in the BS–AG ecosystem and can be used as an indicator species for low pH [8, 9, 21, 63, 93]. For example, observations from Niemi et al. [63] support our modeled climate risks of acidification in the region, which was considered a hotspot of *L. helicina* with severe physical damage (e.g., shell dissolution) due to low pH.

4.1 Uncertainties

Fuzzy logic methodology has embedded uncertainty from multiple sources. These include (i) definitions, clarity, or precision of wording for rules or fuzzy sets (categories), (ii) differing knowledge base or bias of expert opinions on data (uncertain advice), (iii) ambiguous data or measurements, and (iv) subjective weighting or aggregating criteria [65, 86]. Species' sensitivity was refined within the fuzzy logic methodology, which allowed for the differentiation in sensitivity between large-bodied and small-bodies ectotherms. i.e., as large-bodies ectotherms are more metabolically sensitive, a larger body length increased a species' sensitivity. Uncertainty of language exists when defining the biological and ecological characteristics and the vulnerability categories. For example, if a large fish has a higher climate risk, what is considered a "small" or "large" fish [17] is unclear. Furthermore, other characteristics may contribute to the example of "low" or "high" climate risk unrelated to body length [17]. Therefore, as other characteristics may contribute to climate risk despite body length, a key issue within the fuzzy logic system is how to design the analysis of these uncertainties to allow "defuzzification" to provide accurate outputs and conclusions from the membership functions for expert interpretation [17]. These uncertainties can be partially modeled in the fuzzy sets as memberships are "fuzzy" (degree of overlap) to disentangle incomplete or uncertain data with multiple known possibilities [55]. Furthermore, the expert rule definitions can be altered based on numerical data, which can add uncertainty to the membership functions [45].

An ensemble of three models in this study provided more robust results that accounts for differences in the structural composition and uncertainties of each model. Two contrasting emission scenarios (RCP4.5 and RCP8.5 (NCC), or SSP1-2.6 and SSP5-8.5 (GFDL and IPSL)) allowed for estimates in scenario uncertainty as there is ambiguity in societal decisions regarding policies that address future climate change. By comparing three models, we estimated the model structural uncertainties. The NCC model has a higher resolution (rotated $0.25° \times 0.25°$ spatial grid, representing 11–15 km resolution), compared to a $0.5° \times 0.5°$ spatial grid for GFDL and IPSL models. The lower resolution of the ESM models was not able to resolve detailed exposure changes to the Beaufort Sea shelf or slope, the Amundsen Gulf, nor did they resolve specific exposure changes for the MPAs. Instead, the ESMs projected the general nearshore area (including the TN and AN MPAs) exposure bias to higher temperature, reduced sea ice, salinity and pH changes. The coarse resolution of the ESMs may not accurately project coastal species abundance or distribution, where ESM accuracy and precision errors are higher for benthic species than pelagic species [60, 80]. Lastly, ESMs create their own internal variability which limits their ability to reproduce observed interannual or decadal variability. These limitations can enhance or mask trends over the long-term [49, 80, 85, 87]. The NCC model, while improved from the ESMs, still only limitedly resolves Arctic coastline and bathymetry features. Future studies with higher model resolutions, shorter timestep averages, focused analyses by season to understand species' movement patterns during seasonal extremes, and including a focus on river flow and mixing, can address more detailed exposure changes to the environmental variables including salinity changes (freshwater input) in nearshore areas, including the MPAs.

Limitations to this study include the availability of regionally-specific physiological, demographic, and ecological parameters, updated and complete occurrence data of all these species within this area, and the ability of the fuzzy logic

framework to capture complex ecological dynamics, e.g., competition, trophic interactions affecting species vulnerabilities or responses to climate change. Other modelling frameworks such as ecosystem modelling are better suited to represent these complex dynamics [31, 78]. Furthermore, the environmental and geographic features of an ecosystem can impact the biodiversity and abundance of species, including seasonal variability of habitats, seasonal extremes, vulnerability of freshwater habitats, or species' migratory patterns, especially for anadromous fishes has not been assessed here and is critical for many of these species. For example, temperature and coral reef habitat was highly correlated in Edgar et al. [30], which contributed to the species' richness at the site-level. A Pearson's correlation threshold can be used in future studies to determine the collinearity of the environmental variables [27]. A habitat suitability index for the BS–AG ecosystem for Arctic fish species can be normalized to allow for model comparisons, and correlation plots across modelled outputs. Understanding the habitat suitability for Arctic fish species into the future can be pertinent for informing the management and monitoring of the MPAs through regional-scale environmental processes.

5 Future studies

The fuzzy logic algorithm was generalized in this study to provide a comprehensive assessment of risks and vulnerabilities of Arctic fish species across the BS–AG ecosystem. The fuzzy logic algorithm allows for more qualitative comparisons of risks, where future studies may include additional species, such as marine mammal (e.g., [2]) or bird (e.g., [42]) data into the fuzzy logic methodology. However, it should be noted that some of the indicators for sensitivity and adaptive capacity between ectotherms and endotherms may not be precisely comparable. Due to limited Arctic data, the complexity and interactions of the models are subject to uncertainty [51]. Fish species in particular have limited data, as large-scale assessments have only been conducted in recent years (BREA-MFP/CBS-MEA (2012–2014, 2017–2023), [52, 64]), indicating high uncertainty in observational data (e.g., lack of temporal coverage, biological parameters, abundance, diet). To bridge this uncertainty, further research colleting and applying scientific and Indigenous and local knowledge of species with this fuzzy logic approach should be considered. For example, Inuit traditional knowledge on the historical abundances and population statistics of Arctic char has been recently incorporated into fuzzy logic to assess suitable spawning habitat in Nunavik, Québec, Canada [29]. In the fuzzy logic method, the local ecological knowledge and catch per unit effort data were transformed into membership functions with low, medium, medium–high and high categories to determine the species' vulnerability to fishing, and suitable habitat [2, 42]. Future studies with a focus on the development of endotherm specific indicators, and addition of Inuvialuit ecological knowledge can be compared to the results of this current assessment.

6 Conclusions

Our results highlight multiple climatic stressors' compounding effects, where vast areas of the BS–AG are projected to be at a high exposure and risk level for identified Arctic fish species by mid-century. Changes in the Arctic Ocean are chiefly due to warming temperatures, sea ice loss, deoxygenation, freshening, and acidification, along with the subsequent habitat loss. Analyses between NCC, GFDL, and IPSL models, with projections under two emissions scenarios by mid-century indicate similar future trends. The largest differences between the mean future and historical climate hazards were found for the deep waters of the slope, and offshore areas of the BS–AG ecosystem under the higher emission scenarios. We found that species with narrow ecological niches (stenothermic species) were found to be at significant risk and vulnerability to climate change. Many species-richness pixels overlapped with very high climate exposures, indicating a large proportion of Arctic fish species occurring in high hazard areas, specifically acidification, warming, and deoxygenation. Some of these species at high risk to climate hazards included culturally significant species such as Arctic and polar cods, and Arctic char. There is a need to integrate climate change research and assessments, resource management, and conservation efforts and planning, as highlighted by the IPCC report on Biodiversity and Ecosystem Services in future studies.

Acknowledgements This comparative analysis was conducted as part of a thesis dissertation. The authors wish to thank Kiyo Campbell, Claire Hornby, Shannon MacPhee, Andrew Majewski, Isabella Morgante, Jim Reist, Ambre Soszynski, Wojciech Walkusz, and Krystal Woodard for their advice and technical assistance.

Author contributions K.J.S, J.P.-A., G.R., and W.W.L.C. contributed to the conceptualization, data curation, methodology, and writing of the manuscript. K.J.S.and W.W.L.C conducted the modeling work and analyzed the data. K.J.S, C.C.C.W, N.S.S, U.R.S, C.H, A.N, L.L, E.V.L, C.C.B, J.P.-A, G.R, P.F, T.S, and W.W.L.C contributed to the reviewing, validation, and editing of the manuscript.

Funding Funding was provided by the Natural Sciences and Engineering Research Council of Canada [Discovery Grant: RGPIN-2018–03864] through the Changing Ocean Research Unit (CORU) of the University of British Columbia (UBC), as well as funding provided through Fisheries and Oceans Canada's Aquatic Climate Change Adaptation Services Program (ACCASP).

Data availability The data underlying this article are available in the article and in its online supplementary material.

Code availability Not applicable.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests William W.L. Cheung is a co-author of this manuscript and the Editor-in-Chief of Discover Oceans.

References

1. Addo-Bediako A, Chown SL, Gaston KJ. Thermal tolerance, climatic variability and latitude. Proc R Soc B Biol Sci. 2000;267(1445):739–45. https://doi.org/10.1098/rspb.2000.1065.
2. Ainsworth CH, Samhouri JF, Busch DS, Cheung WWL, Dunne J, Okey TA. Potential impacts of climate change on Northeast Pacific marine foodwebs and fisheries. ICES J Marine Sci. 2011;68:1217–29. https://doi.org/10.1093/icesjms/fsr043.
3. Aitken SN, Yeaman S, Holliday JA, Wang T, Curtis-McLane S. Adaptation, migration or extirpation: climate change outcomes for tree populations. Evol Appl. 2008;1(1):95–111. https://doi.org/10.1111/j.1752-4571.2007.00013.x.
4. Albert CH, Thuiller W, Yoccoz NG, Douzet R, Aubert S, Lavorel S. Multi-trait approach reveals the structure and the relative importance of intra- vs. interspecific variability in plant traits. Funct Ecol. 2010;24(6):1192–201. https://doi.org/10.1111/j.1365-2435.2010.01727.x.
5. AMAP. AMAP assessment 2018: Arctic Ocean Acidification. Tromsø: Arctic Monitoring and Assessment Programme (AMAP), vi+187. 2018.
6. Angilletta MJ. Thermal adaptation: a theoretical and empirical synthesis. Oxford Univ Press. 2009. https://doi.org/10.1093/acprof:oso/9780198570875.001.1.
7. Barton MB, Vollenweider JJ, Heintz RA, Norcross BL, Boswell KM. Spatiotemporal variation of environmental conditions and prey availability that drive arctic nearshore fish community structure in the point barrow, Alaska, region. Can J Fish Aquat Sci. 2020;77(10):1612–24. https://doi.org/10.1139/cjfas-2019-0068.
8. Bednaršek N, Mozina J, Vogt M, O'Brien C, Tarling GA. The global distribution of pteropods and their contribution to carbonate and carbon biomass in the modern ocean. Earth Syst Sci Data. 2012;4(1):167–86. https://doi.org/10.5194/essd-4-167-2012.
9. Bednaršek N, Tarling GA, Bakker DC, Fielding S, Cohen A, Kuzirian A, McCorkle D, Lézé B, Montagna R. Description and quantification of pteropod shell dissolution: a sensitive bioindicator of ocean acidification. Glob Change Biol. 2012;18(7):2378–88. https://doi.org/10.1111/j.1365-2486.2012.02668.x.
10. Boettiger C, Chamberlain S, Lang DT, Wainwright P, Cazelles K. rfishbase. R package version 4.1.2. 2023. https://CRAN.R-project.org/package=rfishbase
11. Burgess MG, Pielke R, Ritchie J. Catastrophic climate risks should be neither understated nor overstated. PNAS. 2022;119(42):e2214347119–e2214347119. https://doi.org/10.1073/pnas.2214347119.
12. Burgess MG, Becker SL, Langendorf RE, Fredston A, Brooks CM. Climate change scenarios in fisheries and aquatic conservation research. ICES J Mar Sci. 2023;80(5):1163–78. https://doi.org/10.1093/icesjms/fsad045.
13. Chaikin S, Dubiner S, Belmaker J, MacNeil A. Cold-water species deepen to escape warm water temperatures. Glob Ecol Biogeogr. 2022;31(1):75–88. https://doi.org/10.1111/geb.13414.
14. Chamberlain S, Vanhoorne C. worrms. R package version 0.4.3. 2023. https://CRAN.R-project.org/package=worrms
15. Chamberlain S, Oldoni D, Barve V, Desmet P, Geffert L, Mcglinn D, Ram K, Waller J. rgbif. R package version 3.7.8. 2023. https://CRAN.R-project.org/package=rgbif
16. Cheung WWL, Jones MC, Reygondeau G, Frölicher TL. Opportunities for climate-risk reduction through effective fisheries management. Glob Change Biol. 2018;24(11):5149–63. https://doi.org/10.1111/gcb.14390.

17. Cheung WWL, Pitcher TJ, Pauly D. A fuzzy logic expert system to estimate intrinsic extinction vulnerabilities of marine fishes to fishing. Biol Cons. 2005;124(1):97–111. https://doi.org/10.1016/j.biocon.2005.01.017.
18. Cheung WWL, Sarmiento JL, Dunne J, Frölicher TL, Lam VWY, Palomares MLD, Watson R, Pauly D. Shrinking of fishes exacerbates impacts of global ocean changes on marine ecosystems. Nat Clim Chang. 2013;3(3):254–8. https://doi.org/10.1038/nclimate1691.
19. Cheung WWL, Wei C, Levin LA. Vulnerability of exploited deep-sea demersal species to ocean warming, deoxygenation, and acidification. Environ Biol Fishes. 2022;105(10):1301–15. https://doi.org/10.1007/s10641-022-01321-w.
20. Cross JN, Mathis JT, Pickart RS, Bates NR. Formation and transport of corrosive water in the pacific arctic region. Deep-Sea Res Part II. 2018;152:67–81. https://doi.org/10.1016/j.dsr2.2018.05.020.
21. Darnis G, Barber DG, Fortier L. Sea ice and the onshore-offshore gradient in pre-winter zooplankton assemblages in southeastern Beaufort Sea. J Mar Syst. 2008;74:994–1011. https://doi.org/10.1016/j.jmarsys.2007.09.003.
22. DFO (Department of Fisheries and Oceans). National Capital Region, & Canadian Science Advisory Secretariat. Development of a framework and principles for the biogeographic classification of Canadian marine areas. (No. 2010-02701.;2009/056;2009/056). Ottawa: Fisheries and Oceans Canada, Science, National Capital Region. 2009.
23. DFO (Fisheries and Oceans Canada). Monitoring Indicators for the Tarium Niryutait Marine Protected Area (TNMPA). [pdf] Winnipeg: Fisheries and Oceans Canada. 2010. https://waves-vagues.dfo-mpo.gc.ca/Library/342106.pdf. Accessed 1 Feb 2020.
24. DFO (Fisheries and Oceans Canada). Anguniaqvia niqiqyuam Marine Protected Area (MPA). 2019. https://www.dfo-mpo.gc.ca/oceans/mpa-zpm/anguniaqvia-niqiqyuam/index-eng.html
25. DFO (Fisheries and Oceans Canada). Central and Arctic Region, Canadian Government EBook Collection, & Canadian Science Advisory Secretariat. Science advice to assist in the development of an ecological monitoring plan for the Anguniaqvia niqiqyuam marine protected area. Canadian Science Advisory Secretariat. 2022.
26. Dillon ME, Wang G, Huey RB. Global metabolic impacts of recent climate warming. Nature (London). 2010;467(7316):704–6. https://doi.org/10.1038/nature09407.
27. Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, Marquéz JRG, Gruber B, Lafourcade B, Leitão PJ, Münkemüller T, McClean C, Osborne PE, Reineking B, Schröder B, Skidmore AK, Zurell D, Lautenbach S. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography. 2013;36(1):27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x.
28. Drost HE, Lo M, Carmack EC, Farrell AP. Acclimation potential of Arctic cod (*Boreogadus saida*) from the rapidly warming Arctic Ocean. J Exp Biol. 2016;219(19):3114–25. https://doi.org/10.1242/jeb.140194.
29. Dubos V, St-Hilaire A, Bergeron NE. Fuzzy logic modelling of anadromous arctic char spawning habitat from Nunavik Inuit knowledge. Ecol Model. 2023;477: 110262. https://doi.org/10.1016/j.ecolmodel.2022.110262.
30. Edgar GJ, Alexander TJ, Lefcheck JS, Bates AE, Kininmonth SJ, Thomson RJ, Duffy JE, Costello MJ, Stuart-Smith RD. Abundance and local-scale processes contribute to multi-phyla gradients in global marine diversity. Sci Adv. 2017;3(10):e1700419–e1700419. https://doi.org/10.1126/sciadv.1700419.
31. Eddy TD, Heneghan RF, Bryndum-Buchholz A, Fulton EA, Harrison CS, Tittensor DP, Lotze HK, Ortega-Cisneros K, Novaglio C, Bianchi D, Büchner M. Global and regional marine ecosystem models reveal key uncertainties in climate change projections. Earth's Future. 2025;13(3):e2024EF005537.
32. Ehrenfeld JG. Ecosystem consequences of biological invasions. Annu Rev Ecol Evol Syst. 2010;41(1):59–80. https://doi.org/10.1146/annurev-ecolsys-102209-144650.
33. Fabry VJ, McClintock JB, Mathis JT, Grehmeier JM, et al. Ocean acidification at high latitudes; the bellwether. Oceanography. 2009;22(4):160–71. https://doi.org/10.5670/oceanog.2009.105.
34. Field CB, Barros V, Stocker TF, Dahe Q. In: Field C. B., Field C. B., Barros V., Stocker T. F. and Dahe Q. (Eds.), Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change (1st ed.). Cambridge University Press. 2012. https://doi.org/10.1017/CBO9781139177245
35. Froese R, Pauly D, eds. 2023. FishBase. World Wide Web electronic publication. www.fishbase.org, version (06/2023).
36. Haddon A, Farnole P, Monahan AH, Sou T, Steiner N. Environmental controls and phenology of sea ice algal growth in a future Arctic. Elementa. 2024;12(1):00129. https://doi.org/10.1525/elementa.2023.00129.
37. Hayashida H, Christian JR, Holdsworth AM, Hu X, Monahan AH, Mortenson E, Myers PG, Riche OGJ, Sou T, Steiner NS. CSIB v1 (Canadian sea-ice biogeochemistry): a sea-ice biogeochemical model for the NEMO community ocean modelling framework. Geosci Model Dev. 2019;12(5):1965–90. https://doi.org/10.5194/gmd-12-1965-2019.
38. Hochachka PW, Somero GN. Biochemical adaptation: mechanism and process in physiological evolution. Oxford Univ Press. 2002. https://doi.org/10.1093/oso/9780195117028.001.0001.
39. Huey RB, Kearney MR, Krockenberger A, Holtum JAM, Jess M, Williams SE. Predicting organismal vulnerability to climate warming: roles of behaviour, physiology and adaptation. Phil Trans R Soc B. 2012;367(1596):1665–79. https://doi.org/10.1098/rstb.2012.0005.
40. IPCC (Intergovernmental Panel on Climate Change). (2014a): Summary for policymakers. In: 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 [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1–32.
41. IPCC (Intergovernmental Panel on Climate Change). (2014b). Climate change 2014 – impacts, adaptation and vulnerability: Part B: Regional aspects: Working group II contribution to the IPCC fifth assessment report. https://doi.org/10.1017/CBO9781107415386
42. Jakubas D, Wojczulanis-Jakubas K, Iliszko LM, Strøm H, Stempniewicz L. Habitat foraging niche of a high arctic zooplanktivorous seabird in a changing environment. Sci Rep. 2017;7(1):16203–14. https://doi.org/10.1038/s41598-017-16589-7.
43. Janzen DH. Why mountain passes are higher in the tropics. Am Nat. 1967;101(919):233–49. https://doi.org/10.1086/282487.
44. Jones MC, Cheung WWL. Using fuzzy logic to determine the vulnerability of marine species to climate change. Glob Change Biol. 2018;24(2):e719–31. https://doi.org/10.1111/gcb.13869.
45. Karnik N, Mendel J. Operations on type-2 fuzzy sets. Fuzzy Sets Syst. 2001;122(2):327–48. https://doi.org/10.1016/S0165-0114(00)00079-8.

46. Kroeker KJ, Kordas RL, Crim R, Hendriks IE, Ramajo L, Singh GS, Duarte CM, Gattuso J. Impacts of ocean acidification on marine organisms: quantifying sensitivities and interaction with warming. Glob Change Biol. 2013;19(6):1884–96. https://doi.org/10.1111/gcb.12179.
47. Legendre P, Gauthier O. Statistical methods for temporal and space–time analysis of community composition data. Proc R Soc B Biol Sci. 2014;281(1778):20132728–20132728. https://doi.org/10.1098/rspb.2013.2728.
48. Liefting M, Hoffmann AA, Ellers J. Plasticity versus environmental canalization: population differences in thermal responses along a latitudinal gradient in drosophila serrata. Evolution. 2009;63(8):1954–63. https://doi.org/10.1111/j.1558-5646.2009.00683.x.
49. Loder J, van der Baaren A. Climate Change Projections for the Northwest Atlantic From Six CMIP5 Earth System Models. Canadian Technical Report of Hydrography and Ocean Sciences 286; Fisheries and Oceans Canada. 2013.
50. Loseto LL, Hoover C, Ostertag S, Whalen D, Pearce T, Paulic J, Iacozza J, MacPhee S. Beluga whales (*Delphinapterus leucas*), environmental change and marine protected areas in the western Canadian arctic. Estuar Coast Shelf Sci. 2018;212:128–37. https://doi.org/10.1016/j.ecss.2018.05.026.
51. Loucks D, Van Beek E, Stedinger J, Dijkman J, Villars M. Model sensitivity and uncertainty analysis. In: Water Resources Systems Planning and Management, 2005, pp. 255–290
52. Majewski AR, Walkusz W, Lynn BR, Atchison S, Eert J, Reist JD. Distribution and diet of demersal Arctic Cod, Boreogadus saida, in relation to habitat characteristics in the Canadian Beaufort Sea. Polar Biol. 2016;39:1087–98. https://doi.org/10.1007/s00300-015-1857-y.
53. Mathis JT, Cross JN, Evans W, Doney SC, NOAA. Ocean acidification in the surface waters of the pacific-arctic boundary regions. Oceanography. 2015;28(2):122–35. https://doi.org/10.5670/oceanog.2015.36.
54. McNicholl DG, Christie LR, Dunmall KM, Illasiak S, Ruben N, Illasiak D, Green B, Green T, Green N, Ruben R, Illasiak J, Ruben BS, Ruben R, et al. Anguniaqvia niqiqyuam marine protected area coastal monitoring: synthesis of 2017–2021 summer and winter field programs. Can Tech Rep Fish Aquat Sci. 2024;3595:103.
55. Mendel JM, John RIB. Type-2 fuzzy sets made simple. IEEE Trans Fuzzy Syst. 2002;10(2):117–27. https://doi.org/10.1109/91.995115.
56. Meehl GA, et al. Context for interpreting equilibrium climate sensitivity and transient climate response from the CMIP6 earth system models. Sci Adv. 2020;6(26):eaba1981. https://doi.org/10.1126/sciadv.aba1981.
57. Meredith, M., M. Sommerkorn, S. Cassotta, C. Derksen, A. Ekaykin, A. Hollowed, G. Kofinas, A. Mackintosh, J. Melbourne-Thomas, M.M.C. Muelbert, G. Ottersen, H. Pritchard, and E.A.G. Schuur, 2019. Polar Regions. In: H.O. Pörtner, D.C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer, eds. 2019. Intergovernmental Panel on Climate Change (IPCC) Special Report on the Ocean and Cryosphere in a Changing Climate (SROCC). Ch.3. In press. <https://www.ipcc.ch/srocc/chapter/chapter-3-2/> [Accessed 1 March 2020].
58. Miller LA, Macdonald RW, McLaughlin F, Mucci A, Yamamoto-Kawai M, Giesbrecht KE, Williams WJ. Changes in the marine carbonate system of the western arctic: patterns in a rescued data set. Polar Res. 2014;33(1):20577–615. https://doi.org/10.3402/polar.v33.20577.
59. Mol J, Thomas H, Myers PG, Hu X, Mucci A. Inorganic carbon fluxes on the Mackenzie shelf of the Beaufort Sea. Biogeosciences. 2018;15(4):1011–27. https://doi.org/10.5194/bg-15-1011-2018.
60. Mora C, Wei CL, Rollo A, Amaro T, Baco AR, Billett D, Bopp L, Chen Q, Collier M, Danovaro R, Gooday AJ, Grupe BM, Halloran PR, Ingels J, Jones DOB, Levin LA, Nakano H, Norling K, Ramirez-Llodra E, Yasuhara M. Biotic and human vulnerability to projected changes in ocean biogeochemistry over the 21st century. PLoS Biol. 2013;11(10):e1001682. https://doi.org/10.1371/journal.pbio.1001682.
61. Morin JP, Moreteau B, Pétavy G, David JR. Divergence of reaction norms of size characters between tropical and temperate populations of drosophila melanogaster and *D. simulans*. J Evol Biol. 1999;12(2):329–39. https://doi.org/10.1046/j.1420-9101.1999.00038.x.
62. Mortenson E, Steiner N, Monahan AH, Hayashida H, Sou T, Shao A. Modeled impacts of sea ice exchange processes on arctic ocean carbon uptake and acidification (1980–2015). J Geophys Res Oceans. 2020. https://doi.org/10.1029/2019JC015782.
63. Niemi A, Bednaršek N, Michel C, Feely RA, Williams W, Azetsu-Scott K, Walkusz W, Reist JD. Biological impact of ocean acidification in the Canadian arctic: Widespread severe pteropod shell dissolution in Amundsen Gulf. Front Mar Sci. 2021. https://doi.org/10.3389/fmars.2021.600184.
64. Niemi A, Majewski A, Eert J, Ehrman A, Michel C, Archambault P, Atchison S, Cypihot V, Dempsey M, de Montety L, Dunn M, Geoffroy M, Hussherr R, MacPhee S, Mehdipour N, Power M, Swanson H, Treau de Coeli L, Walkusz W, Williams W, Woodard K, Zimmerman S, Reist J. Data from the BREA-MFP and CBS-MEA research programs describing the *Anguniaqvia niqiqyuam* Marine Protected Area (ANMPA) ecosystem. Can Data Rep Fish Aquat Sci. 2020;1316:90.
65. Ozkaya G, Erdin C. Evaluation of smart and sustainable cities through a hybrid MCDM approach based on ANP and TOPSIS technique. Heliyon. 2020;6(10):e05052–e05052. https://doi.org/10.1016/j.heliyon.2020.e05052.
66. Pimentel D, Zuniga R, Morrison D. Update on the environmental and economic costs associated with alien-invasive species in the United States. Ecol Econ. 2005;52(3):273–88. https://doi.org/10.1016/j.ecolecon.2004.10.002.
67. Pörtner HO, Karl D, Boyd PW, Cheung WWL, Lluch-Cota SE, Nojiri Y, Change IPC. IPCC Fifth assessment report working group II: Ocean systems. 2014, 138 pp.
68. Price TD, Qvarnström A, Irwin DE. Review paper. The role of phenotypic plasticity in driving genetic evolution. Proc R Soc B Biol Sci. 2003;270(1523):1433–40.
69. Provoost P, Bosch S, Appeltans W. robis. R package version 2.11.3. 2022. https://CRAN.R-project.org/package=robis
70. Qi D, Chen L, Chen B, Gao Z, Zhong W, Feely RA, Anderson LG, Sun H, Chen J, Chen M, Zhan L, Zhang Y, Cai WJ. Increase in acidifying water in the western arctic ocean. Nat Clim Chang. 2017;7(3):195–9. https://doi.org/10.1038/nclimate3228.
71. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2022. https://www.R-project.org/.
72. Scheiner SM. Selection experiments and the study of phenotypic plasticity. J Evol Biol. 2002;15(6):889–98. https://doi.org/10.1046/j.1420-9101.2002.00468.x.
73. Schlichting CD, Pigliucci M. Phenotypic Plasticity: A Reaction Norm Perspective. Sinauer Associates 1998
74. Schoener TW. Newest synthesis: Understanding the interplay of evolutionary and ecological dynamics. Science (American Association for the Advancement of Science). 2011;331(6016):426–9. https://doi.org/10.1126/science.1193954.

75. Siefert A, Violle C, Chalmandrier L, Albert CH, Taudiere A, Fajardo A, Aarssen LW, Baraloto C, Carlucci MB, Cianciaruso MV, Dantas L, et al. global meta-analysis of the relative extent of intraspecific trait variation in plant communities. Ecol Lett. 2015;18(12):1406–19. https://doi.org/10.1111/ele.12508.
76. Simpson S, Jennings S, Johnson M, Blanchard J, Schön P, Sims D, Genner M. Continental shelf-wide response of a fish assemblage to rapid warming of the sea. Curr Biol. 2011;21(18):1565–70. https://doi.org/10.1016/j.cub.2011.08.016.
77. Somero GN, Dahlhoff E, Lin JJ. Stenotherms and eurytherms: Mechanisms establishing thermal optima and tolerance ranges. Animals and temperature (pp. 53–78). Cambridge University Press. 1996. https://doi.org/10.1017/CBO9780511721854.004
78. Sora KJ, Wabnitz CCC, Steiner NS, Sumaila UR, Hoover C, Niemi A, Loseto LL, Li M, Giang A, Gillies E, Cheung WWL. Historical climate drivers and species' ecological niche in the Beaufort Sea food web. ICES J Mar Sci. 2025. https://doi.org/10.1093/icesjms/fsae062.
79. Steiner N, Drost HE, Hunter K. A physiological limits database for arctic and subarctic aquatic species. Can Tech Rep Fish Aquat Sci. 2018;3256:56.
80. Steiner NS, Cheung WWL, Cisneros-Montemayor AM, Drost H, Hayashida H, Hoover C, Lam J, Sou T, Sumaila UR, Suprenand P, Tai TC, VanderZwaag DL. Impacts of the changing ocean-sea ice system on the key forage fish Arctic cod (Boreogadus saida) and subsistence fisheries in the western Canadian arctic-evaluating linked climate, ecosystem and economic (CEE) models. Front Mar Sci. 2019. https://doi.org/10.3389/fmars.2019.00179.
81. Steiner NS, Bowman J, Campbell K, Chierici M, Eronen-Rasimus E, Falardeau M, Flores H, Fransson A, Herr H, Insley SJ, Kauko HM, Lannuzel D, Loseto L, Lynnes A, Majewski A, Meiners KM, Miller LA, Michel LN, Moreau S, Wongpan P. Climate change impacts on sea-ice ecosystems and associated ecosystem services. Elementa. 2021. https://doi.org/10.1525/elementa.2021.00007.
82. Steiner NS, Bryndum-Buchholz A, Cheung WWL, Holdsworth AM, Lotze HK, et al. Large changes in Canada's oceans and their impacts on ecosystems and fisheries. In U. R. Sumaila, D. Armitage, M. Bailey & W. Cheung (Eds.), Sea change (pp. 61–77). University of British Columbia Press. 2024. https://doi.org/10.59962/9780774869058-008
83. Stillman JH. Acclimation capacity underlies susceptibility to climate change. Science. 2003;301(5629):65–65. https://doi.org/10.1126/science.1083073.
84. Sunday JM, Bates AE, Dulvy NK. Global analysis of thermal tolerance and latitude in ectotherms. Proc R Soc B Biol Sci. 2011;278(1713):1823–30. https://doi.org/10.1098/rspb.2010.1295.
85. Swart NC, Fyfe JC, Hawkins E, Kay JE, Jahn A. Influence of internal variability on arctic sea-ice trends. Nat Clim Chang. 2015;5(2):86–9. https://doi.org/10.1038/nclimate2483.
86. Tavana M, Hajipour V. A practical review and taxonomy of fuzzy expert systems: methods and applications. Benchmarking. 2020;27(1):81–136. https://doi.org/10.1108/BIJ-04-2019-0178.
87. Taylor KE, Stouffer RJ, Meehl GA. an overview of cmip5 and the experiment design. Bull Am Meteor Soc. 2012;93(4):485–98. https://doi.org/10.1175/BAMS-D-11-00094.1.
88. Tewksbury JJ, Huey RB, Deutsch CA. Ecology: putting the heat on tropical animals. Science. 2008;320(5881):1296–7. https://doi.org/10.1126/science.1159328.
89. Trotta V, Calboli FCF, Ziosi M, Guerra D, Pezzoli MC, David JR, Cavicchi S. Thermal plasticity in drosophila melanogaster: a comparison of geographic populations. BMC Evol Biol. 2006;6(1):67–67. https://doi.org/10.1186/1471-2148-6-67.
90. Turcotte MM, Reznick DN, Hare JD. The impact of rapid evolution on population dynamics in the wild: experimental test of eco-evolutionary dynamics. Ecol Lett. 2011;14(11):1084–92. https://doi.org/10.1111/j.1461-0248.2011.01676.x.
91. Venmans F, Carr B. Literature-informed likelihoods of future emissions and temperatures. Clim Risk Manag. 2024;44: 100605. https://doi.org/10.1016/j.crm.2024.100605.
92. Violle C, Enquist BJ, McGill BJ, Jiang L, Albert CH, Hulshof C, Jung V, Messier J. The return of the variance: Intraspecific variability in community ecology. Trends Ecol Evol (Amsterdam). 2012;27(4):244–52. https://doi.org/10.1016/j.tree.2011.11.014.
93. Walkusz W, Williams WJ, Kwasniewski S. Vertical distribution of mesozooplankton in the coastal Canadian Beaufort Sea in summer. J Mar Syst. 2013;127:26–35. https://doi.org/10.1016/j.jmarsys.2012.01.001.
94. Wittmann AC, Pörtner HO. Sensitivities of extant animal taxa to ocean acidification. Nat Clim Chang. 2013;3(11):995–1001. https://doi.org/10.1038/nclimate1982.
95. Zadeh LA. Fuzzy sets. Inf Control. 1965;8(3):338–53.