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Trait-based climate vulnerability assessments in data-rich systems: An application to eastern Bering Sea fish and invertebrate stocks

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Abstract

Trait-based climate vulnerability assessments based on expert evaluation have emerged as a rapid tool to assess biological vulnerability when detailed correlative or mechanistic studies are not feasible. Trait-based assessments typically view vulnerability as a combination of sensitivity and exposure to climate change. However, in some locations, a substantial amount of information may exist on system productivity and environmental conditions (both current and projected), with potential disparities in the information available for data-rich and data-poor stocks. Incorporating this level of detailed information poses challenges when conducting, and communicating uncertainty from, rapid vulnerability assessments. We applied a trait-based vulnerability assessment to 36 fish and invertebrate stocks in the eastern Bering Sea (EBS), a data-rich ecosystem. In recent years, the living marine resources of the EBS and Aleutian Islands have supported fisheries worth more than US $1 billion of annual ex-vessel value. Our vulnerability assessment uses projections (to 2039) from three downscaled climate models, and graphically characterizes the variation in climate projections between climate models and between seasons. Bootstrapping was used to characterize uncertainty in specific biological traits and environmental variables, and in the scores for sensitivity, exposure, and vulnerability. The sensitivity of EBS stocks to climate change ranged from "low" to "high," but vulnerability ranged between "low" and "moderate" due to limited exposure to climate change. Comparison with more detailed studies reveals that water temperature is an important variable for projecting climate impacts on stocks such as walleye pollock (*Gadus chalcogrammus*), and sensitivity analyses revealed that modifying the rule for determining vulnerability increased the vulnerability scores. This study demonstrates the importance of considering several uncertainties (e.g., climate projections, biological, and model structure) when conducting climate vulnerability assessments, and can be extended in future research to consider the vulnerability of user groups dependent on these stocks.

KEYWORDS
climate change, climate projections, eastern Bering Sea, exposure, sensitivity, trait-based vulnerability, uncertainty

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1 | INTRODUCTION

Analyses of the vulnerability of natural and social systems to climate change have substantially increased in recent years, reflecting the wide variety of contexts in which this concept has been applied. In marine environments, vulnerability has been examined for regional marine ecosystems (Gaichas, Link, & Hare, 2014), particularly for taxa either at local (Chin, Kyne, Walker, & McAuley, 2010) or global scales (Jones & Cheung, 2017), local coastal human communities (Adger, 1999), and national economies dependent on fisheries (Allison et al., 2009). Many studies have adopted the Intergovernmental Panel on Climate Change (IPCC) definition of vulnerability as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change," which is a function of exposure, sensitivity, and adaptive capacity (McCarthy, Canziani, Leary, Dokken, & White, 2001). Some studies have viewed vulnerability as a function of either sensitivity (i.e., defining how systems respond to climate change, analogous to developing dose–response relationships (Füssel & Klein, 2006; Turner et al., 2003) or exposure (i.e., the projected "climate-space" for a species; Foden et al., 2013; Guisan & Thuiller, 2005; Pearson & Dawson, 2003). Detailed analyses consist of correlative (i.e., empirical relationships between environmental variables and species distributions) or mechanistic (i.e., physiological responses to physical variables such as temperature, Pörtner & Knust, 2007, Pörtner & Peck, 2010; ocean acidification, Busch, Harvey, & McElhany, 2013; and salinity, Hettler, 1976) relationships to develop species distribution models (SDMs; Rowland, Davison, & Graumlich, 2011), which in some cases have advanced to include dispersion and simple population dynamics (Cheung et al., 2009, 2016). However, correlative and some mechanistic studies may not incorporate the full range of factors affecting vulnerability such as species interactions, behavior, and adaptive responses (Pacifici et al., 2015; Silber et al., 2017), prompting more attention to how life history traits influence climate vulnerability (Pacifici et al., 2017). Because it may be infeasible to develop detailed analyses for all relevant species within an ecosystem, relatively rapid trait-based vulnerability assessments have emerged as an assessment procedure in which investigators consider how the biological traits which underlie sensitivity and adaptive capacity influence the response to climate exposure (Comte & Olden, 2017; Foden et al., 2013; Garcia et al., 2014; Sunday, 2017).

A recent review of vulnerability assessments indicated that birds, mammals, and plants were more commonly studied than fishes (Pacifici et al., 2015), and vulnerability assessments, in general, are often focused on biodiversity and conservation biology (Foden et al., 2013; Garcia et al., 2014; Pacifici et al., 2015; Williams, Shoo, Isaac, Hoffmann, & Langham, 2008). However, climate vulnerability assessments have been increasingly applied to inform the management of harvested marine fish and invertebrate populations (Chin et al., 2010; Gaichas et al., 2014; Hare et al., 2016; Johnson & Welch, 2010; Pecl et al., 2014). These studies can provide necessary information for policymakers to increase the adaptive capacity of human communities affected by climate change (Colburn et al., 2016; Himes-Cornell & Kasperski, 2015), and assessment of the efficacy of adaption policies has been viewed as an ultimate stage in the evolution of climate vulnerability assessments (Füssel & Klein, 2006). Additionally, assessments of risk of marine fisheries to climate change are logical extensions of studies that assess the risk of marine fish stocks to overfishing (Hobday et al., 2011; Milton, 2001; Ormseth & Spencer, 2011; Patrick et al., 2010; Stobutzki, Miller, & Brewer, 2001). Similar to trait-based climate vulnerability assessments, these ecological risk assessments are semiquantitative, relatively rapid approaches to summarize the vulnerability of numerous component species in a system and identify priority species and interacting drivers (Holsman et al., 2017), as the timeframe for management decisions may not allow detailed studies for all species.

Because trait-based climate vulnerability assessments are intended as a rapid assessment approach based on expert evaluation, a challenge is incorporating available information for well-studied systems and accounting for the disparity of available information between stocks. For example, the eastern Bering Sea (EBS) is a high-latitude system expected to be impacted by climate change (Larsen et al., 2014). Alaska fisheries contributed 58% of US landings and 29% of US ex-vessel value in 2016 (National Marine Fisheries Service, 2017), with the majority of Alaska landings and value obtained from the EBS shelf (Fissel et al., 2017). The scientific and economic importance of the EBS has motivated substantial research on topics such as environmental variation, physical oceanography, projections of future climate conditions, primary and secondary production, biological oceanography, species interactions, the dynamics of fish, seabirds, and mammals, and socioeconomic analyses. Recent research is described in over 150 publications, many of which are contained in four special issues of the journal *Deep Sea Research Part II* (Ashjian et al., 2012, 2013, 2014, 2016). Much of the existing scientific information has direct relevance to climate vulnerability assessments, such as spatial projections of future environmental conditions (Hermann et al., 2013, 2016) and mechanistic and correlative studies relating environmental factors to population abundance and productivity that have often focused on highly valued stocks such as walleye pollock (*Gadus chalcogrammus*, hereafter pollock; Heintz, Siddon, Farley, & Napp, 2013; Hunt et al., 2011; Mueter, Bond, Ianelli, & Hollowed, 2011), flatfish (Spencer, 2008; Wilderbuer et al., 2002; Wilderbuer, Stockhausen, & Bond, 2013), and crabs (Punt, Foy, Dalton, Long, & Swiney, 2016; Punt, Poljak, Dalton, & Foy, 2014). In contrast, information for many EBS stocks is much less detailed, resulting in a wide dispersity of climate vulnerability information. Because trait-based climate vulnerability assessments often distill information on sensitivity and exposure into a discrete number of high-level attributes evaluated by expert judgment, it can be challenging to consider the disparity of information on the productivity and distribution of stocks and communicate uncertainty while still maintaining the essential features of a rapid assessment tool.

Communicating the uncertainty of climate vulnerability assessments is an important aspect of linking the results to future decisions

on policy options and research priorities (Wade, Hand, Kovach, Luikart, et al., 2017; Wade, Hand, Kovach, Muhlfeld, et al., 2017). In the United States, a consistent methodology for conducting climate vulnerability assessments was developed by Morrison et al. (2015) and first applied to the northeast United States by Hare et al. (2016). This method includes measures of uncertainty for specific biological traits and environmental variables, analytical bootstrap methods for characterizing uncertainty in vulnerability rankings, and data quality scores assessing the uncertainty in input information. The methodology also uses logic rules to assign ranks of sensitivity and exposure because measures of central tendencies such as means or medians may be insensitive to a small, but important, number of biological attributes or environmental variables with high sensitivity or exposure (Chin et al., 2010; Morrison et al., 2015). Additional sources of uncertainty are the choice of the thresholds that define the logic rule, variations in global climate models (or regionally downscaled models), and maps of species distributions.

The purpose of this study is to conduct an assessment of the vulnerability of fish and invertebrate stocks in the EBS shelf to climate change. The study follows the methodology developed by Morrison et al. (2015) and is thus comparable to the Hare et al. (2016) study, which was also an application to a relatively data-rich region of high economic importance. We incorporate detailed environmental and biological information by using projections from three dynamically downscaled climate models, and use SDMs to describe stock distributions. Additionally, we develop graphic characterizations of the variation in climate projections between climate models and between seasons, and conduct a sensitivity analysis of the logic rules determining the vulnerability ranking.

2 | METHODS

The vulnerability assessment was applied to 36 stocks in the EBS, organized into 11 functional groups (Table 1). These stocks are managed under U.S. Fishery Management Plans, and represent the major EBS groundfish, salmon, and crab stocks. The spatial area for assessment is the US continental shelf waters of the EBS, extending north to 66°N (Figure 1); however, for salmon stocks, the study area extended inland from the coast to consider factors affecting salmon habitat during freshwater phases (i.e., spawning, egg incubation, hatching, and freshwater juvenile rearing). The assessment was applied to stocks (rather than species) or portions of a stock within the study area; for example, the two separate EBS stocks of red king crab (*Paralithodes camtschaticus*) were analyzed separately, and only the portion of the sablefish (*Anoplopoma fimbria*) stock (which extends to the Aleutian Islands and Gulf of Alaska) within the EBS was analyzed. For salmon and Pacific herring (*Clupea pallasii*), multiple stocks within a species were analyzed as a unit, as stocks within a species share similar migration patterns and/or seasonal spatial distributions, biological characteristics, and management.

A set of 12 sensitivity attributes were used to characterize the potential biological response of a stock to climate change (Table 2).

TABLE 1 Stocks included in the eastern Bering Sea climate vulnerability assessment, and their associated functional group

Stock	Scientific name	Functional group
Giant Pacific octopus	*Enteroctopus dofleini*	Cephalopod
Magistrate armhook squid	*Berryteuthis magister*	Cephalopod
Smoothskin octopus	*Benthoctopus leioderma*	Cephalopod
Plain sculpin	*Myoxocephalus jaok*	Sculpin
Bristol Bay red king crab	*Paralithodes camtschaticus*	Crab
Norton Sound red king crab	*Paralithodes camtschaticus*	Crab
Snow crab	*Chionoecetes opilio*	Crab
Tanner crab	*Chionoecetes bairdi*	Crab
Alaska skate	*Bathyraja parmifera*	Elasmobranch
Commander skate	*Bathyraja lindbergi*	Elasmobranch
Pacific sleeper shark	*Somniosus pacificus*	Elasmobranch
Salmon shark	*Lamna ditropis*	Elasmobranch
Alaska plaice	*Pleuronectes quadrituberculatus*	Flatfish
Arrowtooth flounder	*Atheresthes stomias*	Flatfish
Flathead sole	*Hippoglossoides elassodon*	Flatfish
Greenland turbot	*Reinhardtius hippoglossoides*	Flatfish
Kamchatka flounder	*Atheresthes evermanni*	Flatfish
Northern rock sole	*Lepidopsetta polyxystra*	Flatfish
Pacific halibut	*Hippoglossus stenolepis*	Flatfish
Starry flounder	*Platichthys stellatus*	Flatfish
Yellowfin sole	*Limanda aspera*	Flatfish
Capelin	*Mallotus villosus*	Forage
Pacific herring	*Clupea pallasii*	Forage
Eastern Bering Sea Pacific cod	*Gadus macrocephalus*	Gadid
Eastern Bering Sea pollock	*Theragra chalcogramma*	Gadid
Giant grenadier	*Albatrossia pectoralis*	Grenadier
Sablefish	*Anoplopoma fimbria*	Sablefish
Pacific ocean perch	*Sebastes alutus*	Rockfish
Rougheye rockfish	*Sebastes aleutianus*	Rockfish
Shortraker rockfish	*Sebastes borealis*	Rockfish
Shortspine thornyhead	*Sebastolobus alascanus*	Rockfish
Chinook salmon	*Oncorhynchus tshawytscha*	Salmon
Chum salmon	*Oncorhynchus keta*	Salmon
Coho salmon	*Oncorhynchus kisutch*	Salmon
Pink salmon	*Oncorhynchus gorbuscha*	Salmon
Sockeye salmon	*Oncorhynchus nerka*	Salmon

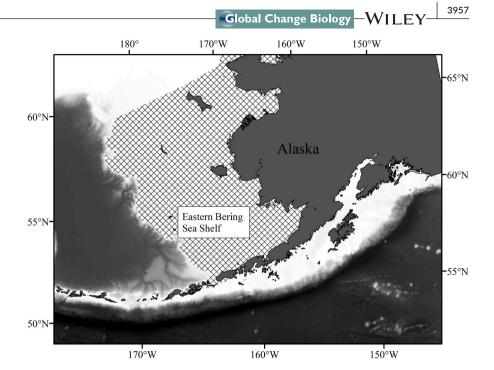**FIGURE 1** Map of eastern Bering Sea shelf, Alaska

TABLE 2 Description of sensitivity attributes used in the eastern Bering Sea climate vulnerability assessment

Sensitivity attribute	Description/rationale
Adult mobility	Evaluation of the capacity of adults to move to new habitats in order to maintain preferred environmental conditions
Complexity in reproductive strategy	Evaluation of the complexity of the reproductive strategy and its dependence on specific environmental conditions
Dispersal of early life stages	Evaluation of the capacity to colonize new habitats via dispersal of eggs and larvae
Early life history survival and settlement requirements	Evaluation of the specificity of conditions for early survival and settlement
Habitat specificity	Evaluation of whether a stock is a habitat generalist or specialist
Other stressors	Evaluation of sources of mortality other than fishing (e.g., habitat degradation, invasive species, pollution, disease, etc.)
Population growth rate	Evaluation of the relative stock productivity (i.e., the maximum intrinsic rate of population increase)
Prey specificity	Evaluation of whether a stock is a prey generalist or specialist
Sensitivity to ocean acidification	Evaluation of a stock's sensitivity to ocean acidification, either directly or via dependence on sensitive taxa
Sensitivity to temperature	Evaluation of sensitivity to temperature, using physiological studies or evaluation of temperatures occupied by the stock
Spawning cycle	Evaluation of the duration of spawning within a year
Stock size/status	Evaluation of the stress imposed on the stock from fishing and stock depletion

Sensitivity attributes are traits intrinsic to a species that affect its susceptibility to climate change (Chin et al., 2010; Morrison et al., 2015; Williams et al., 2008). These sensitivity attributes pertain to several aspects of a stock's productivity and ecological requirements including specificity of habitat and prey, reproductive biology and early life history, sensitivity to temperature and ocean acidification, population growth rate, and dispersal/mobility. Some studies also consider the adaptive capacity of stocks or the ability to respond to environmental conditions (Williams et al., 2008). Because adaptive capacity and sensitivity are closely related (Wade, Hand, Kovach, Muhlfeld, et al., 2017), they are sometimes considered within a single group (Chin et al., 2010; Williams et al., 2008), and some of our sensitivity attributes (i.e., dispersal, specificity of habitat and prey) can be considered as indicative of adaptive capacity. The effects of fishing and other stressors on stock productivity and/or abundance (relative to unfished conditions) were included to incorporate anthropogenic impacts on the potential stock response. The list of sensitivity attributes was consistent with those developed by Morrison

et al. (2015). A "species profile" (Hare et al., 2016; Pecl et al., 2014) was prepared for each stock that summarized the relevant life history characteristics and was used as a reference when scoring the sensitivity attributes.

Exposure to climate change was evaluated with 12 physical and biological variables (Table 3). The exposure factors of surface and bottom temperature, and mixed layer depth, were included due to their specific relevance to the EBS shelf. The EBS shelf has a well-mixed inner domain (0–50 m bathymetry) affected by tidal currents, a summer-stratified middle domain (50–100 m bathymetry) affected by sea-ice extent, and a gradually stratified outer domain (100–200 m bathymetry; Coachman, 1986; Kachel et al., 2002). For each stock, we identified and excluded exposure factors which did not directly affect the stock's environment; for example, air temperature was excluded from the assessment for stocks with largely benthic life history stages.
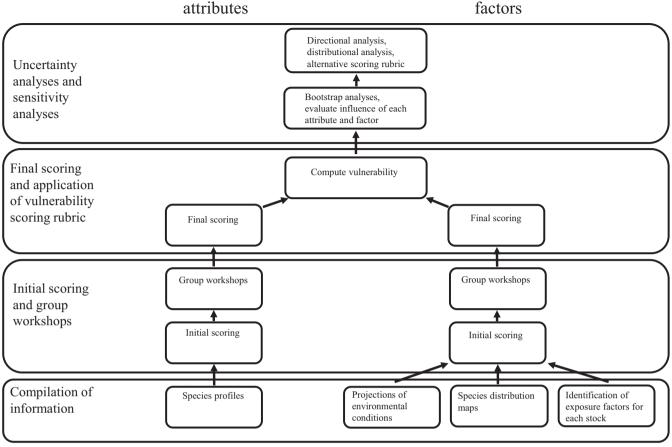
Projected future values of most of the exposure factors were obtained from dynamic downscaling using the output of general circulation models (GCMs) as surface forcing, boundary, and initial conditions for regional physical/biological models (Hermann et al., 2013, 2016). The regional model used was a Regional Ocean Modeling System (ROMS; Hermann et al., 2016) coupled with a nutrient–phytoplankton–zooplankton (NPZ) model (Gibson & Spitz, 2011). The ROMS model is a descendent from Danielson, Curchitser, Hedstrom, Weingartner, and Stabeno (2011), and has a 10 km horizontal spatial resolution with 10 vertical layers. The ROMS–NPZ model was used for hindcasting (1970–2012) and forecasting (2003–2039). Three global models from the IPCC Assessment Report 4, with emissions scenario A1B, were used for forecasting. The ECHO-G model (Hamburg Atmospheric-Ocean Coupled Circulation Model,

from the Max Planck Institute) had the least amount of warming. The CGCM3-t47 model (Coupled Global Climate Model-t47 grid, from the Canadian Centre for Climate Modeling and Analysis) had the most warming, with the MIROC3.2-Medres (Model for Interdisciplinary Research on Climate, medium resolution, from a consortium of Japanese scientific agencies) showing an intermediate level of warming. The variables not obtained from the ROMS-NPZ downscaling include surface pH, which was instead obtained from the Geophysical Fluid Dynamics Laboratory global model GFDL-ESM2M with biogeochemistry ([TOPEZ]; Dunne et al., 2012; Stock, Dunne, & John, 2014) and precipitation, which was obtained directly from the three aforementioned global climate models.

The process for scoring either sensitivity or exposure consists of compilation of information (i.e., species profiles, projections from climate models, species distribution maps), initial scoring and group workshops, and final scoring. Vulnerability was computed from applying a scoring rubric to the final sensitivity and exposure scores, after which a series of uncertainty analyses and sensitivity analyses were applied. A flowchart of these steps is shown in Figure 2.

A total of 34 analysts were involved in scoring the sensitivity attributes, representing seven separate academic and government institutions. The group was divided by taxonomic expertise into subgroups of three to five for scoring the sensitivity of specific groups of stocks (i.e., elasmobranchs, salmon, etc.). The analysts classified each sensitivity attribute using four categories (i.e., low, moderate, high, and very high), with numerical values for these categories ranging from 1 (low sensitivity) to 4 (very high sensitivity). The scoring categories were based on the criteria described in Morrison et al. (2015) and were consistent across all species. For each sensitivity

TABLE 3 Description of exposure factors used in the eastern Bering Sea climate vulnerability assessment, and the stocks for which each exposure factor was considered

Exposure factor	Units	Applicable stocks
Sea surface temperature	°C	All stocks except giant grenadier, smoothskin octopus, Alaska skate, and commander skate
Air temperature	°C	Only starry flounder, Giant Pacific octopus, salmon, and forage stocks (herring and capelin)
Salinity	PSU (practical salinity unit; g/kg)	All stocks except giant grenadier, smoothskin octopus, Alaska skate, and commander skate
Ocean acidification	pH of surface water	All stocks
Precipitation	10^{-4} kg/(s × m^2)	Only salmon
Currents	Meters/second, surface water, in either the northeast or northwest direction	All stocks except the elasmobranchs, salmon, smoothskin octopus, and giant grenadier
Sea surface height	Meters	Only salmon shark, starry flounder, Giant Pacific Octopus, salmon, and the forage stocks (Pacific herring and capelin)
Large zooplankton biomass	mg C/m^3	All stocks
Phytoplankton biomass	mg C/m^3	All stocks
Bottom temperature	°C	All stocks
Phytoplankton bloom timing	Day of year	All stocks
Mixed layer depth	Meters; defined as depth at which the density is 0.1 sigma units greater than the value at 5 m depth	All stocks

FIGURE 2 Flowchart of the process for obtaining scores for sensitivity, exposure, and vulnerability, and conducting uncertainty and sensitivity analyses
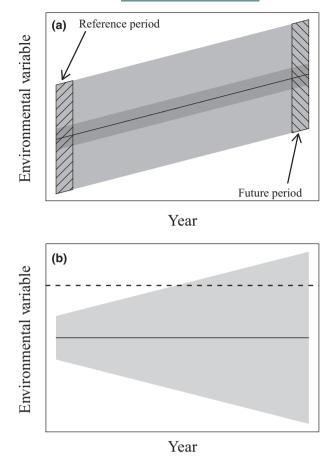
attribute, the analysts had five tallies to distribute among the four categories (this forced one category to have more tallies than the others). The distribution of tallies across the scoring categories can be interpreted as uncertainty by the analyst in the degree of sensitivity or, alternatively, as life history variation not completely described by a single category.

One group of seven analysts familiar with EBS environmental variability scored the exposure factors. Scores for the exposure factors were also based on analysts distributing five tallies across four categories based on the projected spatial overlap of stock distributions and the exposure factors in the future (years 2030–2039). Exposure factors quantified changes in both the mean and variance between two 10-year periods representing a recent reference period (2003–2012) and a future period (2030–2039), giving a total of 24 exposure factors for the 12 environmental variables. Temporal change in the mean was quantified with Z-scores:

$$Z = \frac{\bar{x}_f - \bar{x}_r}{\sigma_r}, \tag{1}$$

where $\bar{x}_r$ and σ_r are the mean and standard deviation of the reference period, and $\bar{x}_f$ is the mean of the future period (Figure 3a). Values of $\bar{x}_r$ and σ_r were calculated separately at each location and

for each downscaling run, using the yearly values of reference and future conditions. These estimates were averaged across the three downscaled models to obtain the final values used in calculating Z. Seasonal averages for each year were calculated using 3-month bins for Mar–Apr–May (spring), Jun–Jul–Aug (summer), Sep–Oct–Nov (fall) and Dec–Jan–Feb (winter). Values of Z were computed over the EBS study area, and the absolute value of Z was used to bin and map the change in the means between the current and future periods into four categories representing "low" ($|Z| \leq 0.5$, probability = 38.3%), moderate ($0.5 < |Z| \leq 1.5$, probability = 48.3%), "high" ($1.5 < |Z| \leq 2.0$, probability = 8.9%), and "very high" ($|Z| > 2.0$, probability = 4.5%). Note that the exposure bins measure either an increased or decreased mean relative to the 2003–2012 reference period.

Changes in the variability in environmental conditions, apart from an overall trend in mean conditions, have long been recognized as of equal (or perhaps more) importance than the overall trend in average conditions (Jentsch, Kreyling, & Beierkuhnlein, 2007; Katz & Brown, 1992). While some long-lived organisms that navigate a gauntlet of variable environmental events during early life often exhibit sporadically strong year classes (King & McFarlane, 2003; Spencer & Collie, 1997), unusually warm and prolonged extreme

FIGURE 3 Schematic indicating how a mean (a) and variance (b) may change over time. The change in the mean is identical for cases with high variance (light gray) and low variance (dark gray), and the latter would be viewed as a more significant change between the reference and projection periods (hatched areas). In the bottom panel, the variance (gray) increases over time; if a stock had a critical threshold (dashed line), it would be exceeded with greater frequency in the future despite the mean value remaining constant

events at regional scales such as heat waves (Hobday et al., 2016) are typically associated with negative outcomes, as in the recent marine heat wave in the northeast Pacific from 2014 to 2016 (Bond, Cronin, Freeland, & Mantua, 2015). Temporal change in the variability was quantified with *F*-ratios:

$$F = \frac{V_f}{V_r}, \tag{2}$$

where V_f and V_r are the variance of the future and reference periods, respectively (Figure 3b). As with the Z-scores, the *F*-ratios were binned into four categories representing "low" to "very high" change over time, with the thresholds chosen to achieve consistent probability density between the Z and F distributions.

Maps of stock distributions were obtained from the results of SDMs conducted for analyzing essential fish habitat (Laman et al., 2017). The specific modeling method depended on data availability and quality, and included general additive models (GAMs), hurdle GAMs, maximum entropy models (based on presence data), and

maps of catch per unit effort or observed presence. Density was well determined for most stocks in the assessment, but only presence data were used for salmon (freshwater phase), cephalopods, and some elasmobranchs. The analysts' distribution of their exposure tallies largely reflected the estimated proportion of the stock within spatial areas corresponding to the four exposure categories.

For both the sensitivity attributes and exposure factors, initial scores were developed independently by the analysts and finalized after discussing the rationale within each small group. Two coauthors (PS, MN) participated in all small group discussions to discuss scoring consistency. The analysts also estimated the quality of data used for the sensitivity attributes and exposure factors (Table S1); for the exposure factors, the data quality score reflects both the data and methodologies applied for the environmental variables and the estimated stock distribution maps.

Analysts used plots of the exposure factors describing seasonal, spatial, and temporal variation. An example is shown in Figure 4 for sea surface temperature, where the seasonal patterns are shown in the first four rows and the annual pattern (integrated across the seasons) is shown in the bottom row. The first two columns show the temperature and standard deviation, respectively, averaged across the three climate models for the reference period (2003–2012). The third column shows the deviation in average temperature between the projection period (2030–2039) and the reference period. Presenting these outputs is useful to examine the exposure factors in their original units, whereas the dimensionless Z-score is shown in the fourth column and was obtained by dividing column 3 by column 2. Finally, time series of the modeled exposure factors from 2003 to 2039 (averaged across the EBS area) for each downscaled projection model is shown in fifth column, and frequency distributions of the exposure factors for the reference (solid lines) and projection (dashed line) periods are shown in the sixth column. The latter two columns are useful for assessing whether unusual event-scale values of the exposure factor have been hindcast for previous years or forecasted for the future.

An average score for each sensitivity attribute or exposure factor was computed from the distribution of tallies from all the scorers for each stock. Overall exposure and sensitivity component scores were computed with the logic rule used in Hare et al. (2016; Table S2) based on the number of sensitivity attributes or exposure factors with mean scores exceeding specified thresholds. The categories for exposure and sensitivity component scores were identical to those for individual sensitivity attributes and exposure factors (i.e., low, moderate, high, and very high) and assigned numerical values of 1–4, respectively. The overall vulnerability score is a function of the product of the exposure and sensitivity component scores, with values of 1–3 classified as low, 4–6 moderate, 8–9 high, and 12–16 very high.

A sensitivity analysis for the logic rule used to categorize sensitivity or exposure was conducted (Table S2). For individual sensitivity attributes or exposure factors, a score of 2 is assigned to the "moderate" category, but the scoring rubric assigns a component score of moderate only if two or more individual attributes or factors have
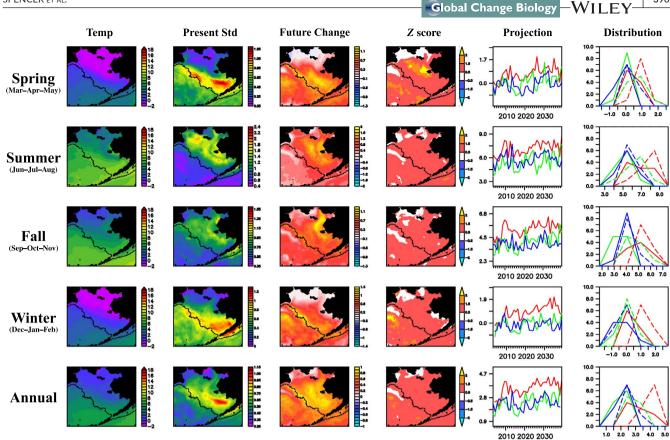
FIGURE 4 Sea surface temperature and variability from downscaled global climate models; see text for explanation

mean values ≥2.5. Thus, cases where all of the individual attributes or factors were scored as moderate would result in the overall score for sensitivity or exposure not being scored as moderate. The alternative logic rule centers the thresholds on the values used for the individual attributes or factors; for example, attributes or factors with mean scores between 2.5 and 3.5 would be considered as "high," and mean scores between 1.5 and 2.5 would be considered as "moderate."

Additional analyses described in the Supporting Information include: (a) bootstrapping to estimate a certainty score (i.e., the percentage of bootstrapped vulnerability rankings which were identical to the original ranking); (b) evaluation of the influence of each sensitivity attribute and exposure factor on the vulnerability score; (c) evaluation of the ability of stocks to change their species distribution in response to climate change; and (d) a directional analysis that evaluates whether climate change would affect stocks in a positive, neutral, or negative manner.

3 | RESULTS

The sensitivity for EBS stocks ranged from low to high, with at least eight stocks in each of these categories (Figure 5; Table 4). Rockfish, crab, and five of the nine flatfish stocks were ranked as high sensitivity due to low population growth rates, limited spawning cycles, and (for crab) sensitivity to ocean acidification. Additionally, salmon were ranked as high sensitivity due to limited spawning cycle and

complexity in reproductive strategy, and limited dispersal of early life stages. In contrast, both gadid stocks (Pacific cod [*Gadus macrocephalus*] and pollock) and two of the three cephalopods (magistrate armhook squid [*Berryteuthis magister*] and giant Pacific octopus [*Enteroctopus dofleini*]) were ranked as low sensitivity due to relatively high adult mobility, dispersal of early life stages, and population growth rates.

Exposure to climate change was distributed across the low (26 stocks) and moderate (10 stocks) categories, and thus, the overall vulnerabilities were also scored as low and moderate (Figure 5; Table 4). Stocks with moderate exposure (the rockfish stocks, flathead sole [*Hippoglossoides elassodon*], Tanner crab [*Chionoecetes bairdi*], Kamchatka flounder [*Atheresthes evermanni*], sablefish, giant grenadier [*Albatrossia pectoralis*], and salmon shark [*Lamna ditropis*]) occurred on the EBS outer shelf and slope, where the projected variance in salinity and temperature was larger than on the shallower middle and inner EBS shelf. The most vulnerable EBS stocks were the four rockfish stocks, flathead sole, and Tanner crab, as their ranking of high sensitivity and moderate exposure resulted in an overall vulnerability ranking of moderate. The distributions of sensitivity attributes and exposure factors across the ranking categories, and the percentages of these attributes and factors with data quality scores ≥2, are shown in Table S3.

Twenty stocks had certainty scores ≥85%, whereas 12 stocks had certainty scores <75%. The highest certainty scores were observed in the forage fish, gadid, and sculpin functional groups. In contrast,

FIGURE 5 Sensitivity and exposure for eastern Bering Sea stocks, with certainty scores from bootstrapping shown in parentheses. Vulnerability categories are colored from green ("low") to red ("very high")

crabs, grenadier, sablefish, and rockfish had no stocks with certainty scores ≥95%, and five of the nine flatfish had certainty scores <75%. Sockeye salmon (*Oncorhynchus nerka*) had a certainty score below 50%, with the vulnerability ranked as low, but the majority of vulnerability ranks from the bootstrap analysis being scored as moderate. This resulted from the means of the reproductive strategy attribute and the salinity variance exposure factor being close to the threshold values of 3.5 and 2.5, respectively.

Sensitivity to climate change varied among the attributes and stock functional groups, as indicated by the median of scores across stocks within the functional groups (Figure 6a). Prey specificity showed low values for median sensitivity and a small range from 1.125 (gadids) to 2.08 (giant grenadier). Low sensitivity was also observed for stock status, other stressors, and dispersal of early life stages (except for salmon). In contrast, early life history and survival had median scores above 2.04 for all functional groups except elasmobranchs. A wide range of median scores was observed for spawning cycle, from a low of 1.7 for elasmobranchs to a high of 4 for salmon. Similarly, median scores for population growth rate ranged widely from a low of 1.47 for cephalopods to a high of 3.78 for rockfish. Elasmobranchs had the lowest (or nearly the lowest) sensitivity across functional groups for several attributes, including habitat specificity, prey specificity, adult mobility, early life history

survival and settlement requirements, and ocean acidification. In contrast, salmon and forage fish showed the highest sensitivity for habitat specificity, early life history survival, complexity in reproductive strategy, and other stressors. Salmon also showed the highest sensitivity for dispersal of early life stages, and forage fish and rockfish showed the highest sensitivities to temperature.

The vulnerability scores were not highly influenced by any single sensitivity attribute (Figure 6b). The number of stocks for which the vulnerability score changed when omitting a sensitivity attribute was ≤2 for each attribute, and was zero for 9 of the 12 attributes. The vulnerability score could potentially be influenced by omitting a single sensitivity attribute only when the sensitivity attribute was ranked as "moderate" or higher and was ranked equal to or lower than the exposure ranking, which only occurred for two stocks (sablefish and Kamchatka flounder).

With the exception of ocean acidification, stocks in the EBS were not projected to experience large relative changes in mean values for the exposure factors (Figure 7a). The median value for the ocean acidification scores was 4 for each functional group. The exposure factors with the next highest levels were bottom temperature and sea surface temperature, with the average of the median scores (across the functional groups) of 2.11 and 2.03, respectively. The range of median exposure scores across the

TABLE 4 Sensitivity, exposure, and vulnerability rankings for the original and alternative scoring rubrics

Stock	Sensitivity		Exposure		Vulnerability	
	Original rubric	Alternative rubric	Original rubric	Alternative rubric	Original rubric	Alternative rubric
Giant Pacific octopus	Low	Moderate	Low	Moderate	Low	Moderate
Magistrate armhook squid	Low	Moderate	Low	Moderate	Low	Moderate
Smoothskin octopus	Moderate	High	Low	Moderate	Low	Moderate
Plain sculpin	Low	Moderate	Low	Moderate	Low	Moderate
Bristol Bay red king crab	High	High	Low	Moderate	Low	Moderate
Norton Sound red king crab	High	High	Low	Moderate	Low	Moderate
Snow crab	High	High	Low	Moderate	Low	Moderate
Tanner crab	High	High	Moderate	High	Moderate	High
Alaska skate	Moderate	High	Low	Moderate	Low	Moderate
Commander skate	Moderate	High	Low	Moderate	Low	Moderate
Pacific sleeper shark	Moderate	High	Low	Moderate	Low	Moderate
Salmon shark	Low	Moderate	Moderate	High	Low	Moderate
Alaska plaice	High	High	Low	Moderate	Low	Moderate
Arrowtooth flounder	Low	Moderate	Low	Moderate	Low	Moderate
Flathead sole	High	High	Moderate	High	Moderate	High
Greenland turbot	Moderate	High	Low	Moderate	Low	Moderate
Kamchatka flounder	Moderate	High	Moderate	High	Moderate	High
Northern rock sole	High	High	Low	Moderate	Low	Moderate
Pacific halibut	Moderate	High	Low	Moderate	Low	Moderate
Starry flounder	High	High	Low	Moderate	Low	Moderate
Yellowfin sole	High	High	Low	Moderate	Low	Moderate
Capelin	Moderate	High	Low	Moderate	Low	Moderate
Pacific herring	High	High	Low	Moderate	Low	Moderate
Eastern Bering Sea Pacific cod	Low	Moderate	Low	Moderate	Low	Moderate
Eastern Bering Sea pollock	Low	Moderate	Low	Moderate	Low	Moderate
Giant grenadier	Low	Moderate	Moderate	High	Low	Moderate
Sablefish	Moderate	High	Moderate	High	Moderate	High
Pacific ocean perch	High	High	Moderate	High	Moderate	High
Rougheye rockfish	High	High	Moderate	High	Moderate	High
Shortraker rockfish	High	High	Moderate	High	Moderate	High
Shortspine thornyhead	High	High	Moderate	High	Moderate	High
Chinook salmon	High	High	Low	Moderate	Low	Moderate
Chum salmon	High	High	Low	Moderate	Low	Moderate
Coho salmon	High	High	Low	Moderate	Low	Moderate
Pink salmon	High	High	Low	Moderate	Low	Moderate
Sockeye salmon	High	High	Low	Moderate	Low	Moderate

functional groups was generally small for most exposure factors (≤0.54), indicating broadscale spatial similarity in the projected relative change in mean value. In contrast, the range in the median exposure scores was larger for phytoplankton (0.97), sea surface height (0.83), and large zooplankton biomass (0.74).

EBS stocks were also generally not projected to experience large changes in the variance of exposure factors (Figure 7b). The median values for change in the variance in exposure factors were generally at or below 2, corresponding to "moderate" and "low" exposure. An exception was salinity, where the median score for each functional group was above 2, with the highest values of 2.66 and 2.54 for rockfish and sablefish, respectively. A wider range of median values was observed for phytoplankton, bottom temperature, and mixed layer depth. The median values for bottom temperature for rockfish,
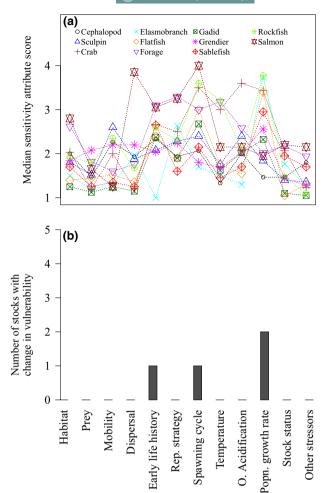
FIGURE 6 Median sensitivity attribute scores by stock functional group (a), and the number of stocks for which the vulnerability score changed as a result of omitting sensitivity attributes (b)

FIGURE 7 Median scores for a change in the mean (a) and variance (b) of exposure factors, by stock functional group, and the number of stocks for which the vulnerability score changed as a result of omitting exposure factors (c)

sablefish, and giant grenadier were approximately 2.8, whereas the median values for these functional groups (and cephalopods) for mixed layer depth were approximately 2.25.

Similar to the sensitivity attributes, the vulnerability scores were not highly influenced by any single exposure factor (Figure 7c). The number of stocks for which the vulnerability score changed when omitting an exposure factor was less than four for each attribute, and was zero for 11 of the 12 exposure factors for a change in the mean, and 10 of the 12 exposure factors for a change in the variance. The exposure factor with the most influence on the vulnerability ranking (affecting three stocks) was the change in the mean ocean acidification, as this was ranked as very high for all stocks.

The data quality for the sensitivity attributes and exposure factors varied among the species functional groups, particularly for the sensitivity attributes (Figure 8a). The sculpin and grenadier groups each comprised a single species and showed the lowest data quality, with the lowest two median values for 5 of the 12 attributes. In contrast, crab and flatfish had the highest two median values for data quality for three attributes, and crab had the highest median data quality for an additional four attributes. Exposure
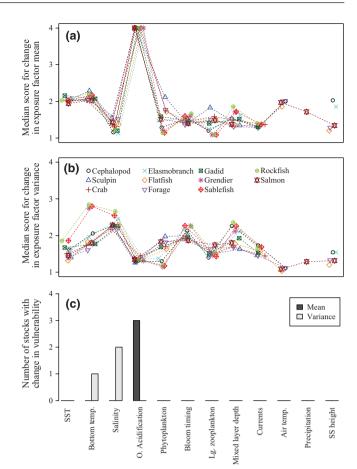
factor data quality was lowest for phytoplankton biomass, large zooplankton biomass, phytoplankton bloom timing, and mixed layer depth (Figure 8b). Differences in exposure factor data quality among stock functional groups reflect differences in the quality of data and models used to estimate stock distributions. For example, the data quality for the ocean acidification exposure factor was 3 for sculpin, crab, flatfish, forage fish, gadids, and grenadier; for these groups, stock distributions were obtained from GAM models applied to summer survey trawl data, or (for Pacific herring) were obtained from standardized fishery-dependent catch data. In contrast, the data quality for ocean acidification was 2 for cephalopods, elasmobranchs, sablefish, and rockfish; in these cases, limited observations were obtained from the survey data and a maximum entropy model was used to model presence.

Several functional groups had generally high or very high scores for distribution potential (Figure 9). Both gadid stocks had very high distribution potential, and the scores for flatfish stocks were divided between very high (three stocks) and high (six stocks). The crab, forage fish, rockfish, sablefish, and sculpin functional groups all had high distribution potential, whereas salmon generally had low distribution potential except for pink salmon (*Oncorhynchus gorbuscha*), which had moderate distribution potential. Distribution potential
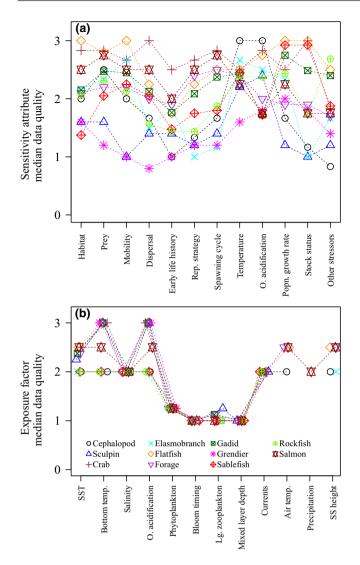
FIGURE 8 Data quality scores for sensitivity attributes (a) and exposure factors (b)

FIGURE 9 Number of stocks across the distribution potential (left) and directional analysis (right) categories, by functional group

for elasmobranchs ranged between medium and very high, whereas cephalopods had distribution potential between low (smoothskin octopus [*Benthoctopus leioderma*]) and very high (magistrate armhook squid).

Directional analysis scores ranged between negative and neutral, with no stocks having a positive score (Figure 9). Elasmobranchs, salmon, cephalopods, flatfish, and giant grenadier had neutral scores (with the exception of Greenland turbot [*Reinhardtius hippoglossoides*], which was negative), whereas forage fish, sculpins, and sablefish had negative scores. The remaining functional groups (crabs, gadids, and rockfish) had scores roughly evenly distributed between the negative and neutral categories.

Application of the alternative scoring rubric resulted in stocks being distributed across the moderate (eight stocks) and high (28 stocks) sensitivity categories, and across the moderate (26 stocks) and high (10 stocks) exposure categories (Table 4). Relative to the original scoring rubric, the sensitivity ranking increased from low to moderate for eight stocks, from moderate to high for nine stocks, and was unchanged for 19 stocks. The exposure and vulnerability

rankings increased by one category for each stock, with eight stocks increasing from moderate to high vulnerability, and the remaining 28 stocks increasing from low to moderate vulnerability.

4 | DISCUSSION

The quality of trait-based vulnerability assessments in data-rich systems can be improved by incorporating information such as downscaled climate models, SDMs, and (for data-rich stocks) detailed studies on how productivity is affected by environmental conditions. The EBS is influenced by strong tidal mixing that establishes biophysical domains and seasonal ice cover and the formation of a benthic "cold pool" in the summer. The increased spatial resolution of the downscaled physical models (Hermann et al., 2013, 2016) was able to resolve the cold pool, whereas this feature was not resolved in the three IPCC global models that were downscaled. The downscaled models were also able to model processes such as tidal mixing, which resulted in a change

in the scale of modeled temperature relative to the IPCC models (Hermann et al., 2016). An additional benefit of downscaling was that it facilitated connection to a biological NPZ model (Gibson & Spitz, 2011) which allowed projections of important biological features such as phytoplankton and zooplankton distribution and abundance. Finally, the use of quantitative SDMs improved the estimates of stock distributions relative to simple measures of stock range. Without these refinements, the estimated exposure to climate change could be mischaracterized. Future improvements could be obtained by using SDMs to project future stock distributions and exposure; for example, Thomas et al. (2011) developed a framework that considers both existing and projected ranges and recognizes that exposure is affected by movement to different locations.

Correlative and mechanistic research in data-rich systems can improve trait-based vulnerability assessments by refining the sensitivity attributes, in addition to the more commonly viewed pathway of vulnerability studies being used to prioritize more detailed future research (Holsman et al., 2017). Because trait-based climate vulnerability assessments are often intended to be rapid assessment tools and/or applied on large spatial scales (Foden et al., 2013; Pecl et al., 2014), sensitivity attributes have sometimes focused on course descriptions of physiological tolerances and habitat use. The increased precision of stock distribution maps generated by SDMs can also offer empirical information that may refine several sensitivity attributes such as habitat specificity and sensitivity to temperature; additionally, more detailed process and biological studies allow consideration of other sensitivity attributes included in this study such as early life history survival and complexity in reproductive processes.

The sensitivity of fish and invertebrate stocks in the EBS ranged from low to high, whereas exposure and vulnerability to climate change were ranked from low to moderate. A similar study for the northeast US continental shelf also found that sensitivity was mostly ranked between low and high, but climate exposure and vulnerability were ranked from high to very high (Hare et al., 2016). The differences in the results between these studies likely results, in part, from the interval between the midpoints of the reference period and projection period spanning 50 years in Hare et al. (2016) but 27 years in this study, differences in the end year of the projections (2055 in Hare et al., 2016 but 2039 in this study), and differences in the climate emission scenarios. Relative to studies intended for long-term planning that extend to the end of the 21st century (Cheung et al., 2010; Chin et al., 2010; Foden et al., 2013; IPCC, 2014), both this study and the northeast U.S. study adopted shorter forecast horizons that correspond more closely to the timeframe of fishery management decisions. However, projected climate impacts begin to deviate from current conditions beginning in the mid-21st century (IPCC, 2014), thus introducing some variation between projected conditions in 2039 and 2055. Additionally, Hare et al. (2016) use the "business as usual" carbon emission scenario of Representative Concentration Pathway 8.5, whereas this study used a more moderate carbon emission scenario A1B (i.e., energy production is balanced between fossil and nonfossil sources; McCarthy et al., 2001) which does not show marked change until approximately 2050.

Data-rich systems such as the EBS may offer the opportunity to compare results from vulnerability assessments to more detailed studies, which have been recommended as a validation exercise (Wade, Hand, Kovach, Muhlfeld, et al., 2017). For example, walleye pollock were ranked as having low sensitivity, reflecting their mobility, broad spatial distributions, and lack of habitat specificity. In contrast, projections of increased water temperature have led to forecasts of reduced pollock recruitment (Mueter et al., 2011; Spencer et al., 2016), with the mechanism thought to be the effect of high SST on reducing zooplankton prey abundance in the late summer and increasing overwinter mortality of age-0 pollock (Heintz et al., 2013; Hunt et al., 2011). This was considered in the attribute assessing early life history survival; however, the attribute score narrowly missed being ranked in the "moderate" category (despite receiving the second highest score among pollock sensitivity attributes). More generally, the projected temperatures in the study from 2030 to 2039 are comparable to those of the recent northeast Pacific marine heat wave (Stabeno et al., 2017), which has been associated with numerous biological impacts (Walsh et al., 2018). These types of comparisons can be made in "species narratives" (i.e., text descriptions of the vulnerability results that provide an opportunity to describe uncertainties not reflected in the numerical analyses), which were conducted for the northeast U.S. vulnerability study and will be produced for this vulnerability study in a subsequent report.

This study was focused on stocks within a particular region, which was motivated by the spatial scale of resource management. In general, trait-based vulnerability assessments vary with respect to their spatial scale (i.e., global or regional) and the level of biological organization (functional species groups or guilds, Gaichas et al., 2014; species, Pacifici et al., 2015; or stocks). These issues are particularly important when the study area covers a portion of the range of species, and when biological traits differ between stocks within a species. Within fisheries stock assessment, it is well known that biological traits such as growth and maturity can vary spatially among stocks within a species (i.e., the growth of northern rockfish in the Aleutian Islands of Alaska; Logerwell et al., 2005). Some stocks in our study have species ranges that extended far beyond the EBS shelf; for example, Pacific ocean perch (*Sebastes alutus*) ranges from Mexico northward to the Bering Sea and west to Japan (Love, Yoklavich, & Thorsteinson, 2002), but Pacific ocean perch and several other *Sebastes* species show evidence of small-scale stock structure (Buonaccorsi, Kimbrell, Lynn, & Vetter, 2005; Buonaccorsi et al., 2004; Gharrett, Riley, & Spencer, 2012; Palof, Heifetz, & Gharrett, 2011). Marine fish and invertebrate stocks are expected to be adapted to their local environments (Conover, Clarke, Munch, & Wagner, 2006; Sanford & Kelly, 2011), and thus, critical thresholds for temperature can vary between stocks within a species (Bennett, Wernberg, Arackal Joy, de Bettignies, & Campbell, 2015). Although vulnerability assessments are often interpreted with respect to species, a recent

review found that 60% of studies were applied at a local or regional scale with only 4% at a global scale (Pacifici et al., 2015), thus potentially introducing some uncertainty when species-level vulnerability estimates are derived from a portion of their range without consideration of local adaptation. An additional consideration is that fishing mortality can affect sensitivity to climate change (Brander, 2007; Ottersen, Hjermann, & Stenseth, 2006; Rijnsdorp, Peck, Engelhard, Möllmann, & Pinnegar, 2009), and this can vary between stocks depending on the stock-specific management history. Exceptions for our assessment at the stock level were the several herring and Pacific salmon stocks; in these cases, it was found that the biology and management were similar enough to combine multiple stocks within each species. In general, consistency between the spatial scale of interest and the traits relevant for the stocks or species within that spatial scale can help reduce uncertainty.

Characterizing the uncertainty in vulnerability assessments becomes more complicated in regions such as the EBS in which detailed information such as downscaled climate projections and SDMs exist. The types of uncertainty for correlative models of climate vulnerability include climatic (i.e., uncertainty in the climatic projections from model formulations, alternative greenhouse gas emission scenarios, etc.), algorithmic (i.e., uncertainties in the predictions from statistical SDMs), and biotic (uncertainties in assumptions of the biology of stocks; Pacifici et al., 2015), and these also generally apply to trait-based vulnerability assessments. Recommendations for addressing uncertainty include evaluating a range of climate projections (Deser, Knutti, Solomon, & Phillips, 2012), allowing analysts to convey confidence in their rankings, conducting bootstrap analyses on the rankings (Rowland et al., 2011), conducting sensitivity analyses on specific attributes (Wade, Hand, Kovach, Muhlfeld, et al., 2017), and choosing SDMs appropriate for the information available (Pearson et al., 2006). These techniques were applied in this study, which also evaluated the uncertainty associated with logic rule used to determine sensitivity and exposure rankings. Fuzzy logic analyses are an alternative approach to addressing uncertainty in vulnerability (Jones & Cheung, 2017), and are designed for cases with disparities in uncertainty of input information and in the relationships between attributes and vulnerability. Irrespective of the methodology applied, communication of uncertainty is important to the goals of adaptation planning and prioritizing research (Wade, Hand, Kovach, Muhlfeld, et al., 2017), but has not been commonly conducted (Tonmoy, El-Zein, & Hinkel, 2014).

The use of quantitative information obtained from dynamically downscaled GCMs and SDMs in trait-based vulnerability assessments requires additional time and expertise, thus moving data-rich vulnerability assessments further from a "rapid" methodology unless this information is readily available. However, trait-based climate vulnerability assessments applied to terrestrial forest animals (Davison et al., 2011), birds (Gardali, Seavy, DiGaudio, & Comrack, 2012; Gregory et al., 2009), and a global analysis of birds, amphibians, and corals (Foden et al., 2013) share some aspects of data richness with this study. For example, projections of future suitable habitat were mapped into fine-scale spatial areas by Davison et al. (2011) and Foden et al. (2013), who also downscaled output from GCMs and considered several GCMs and emission scenarios. In less data-rich systems, it may not be practical to wait until downscaled GCMs, SDMs, and detailed mechanistic studies are developed prior to initiating a vulnerability assessment. In these cases, it becomes more critical to communicate the uncertainty and, if possible, compare results to similar species in other regions.

The climate vulnerability assessment of managed fish and invertebrate stocks in the EBS is anticipated to be part of the Bering Sea Fishery Ecosystem Plan (NPFMC, 2019), which will consider how climate change affects human communities and what types of adaptation strategies are suitable. Many existing studies on vulnerability have emphasized either socioeconomic vulnerability (Himes-Cornell & Kasperski, 2015; also see the bibliography on climate vulnerability in fisheries and aquaculture sectors in Barsley, De Young, & Brugère, 2013) or vulnerability of species. However, integration of socioeconomic and biological vulnerability is possible within a single model, as in the assessment of socio-economic impacts of coral bleaching in Kenyan coastal communities with separate biological and socio-economic submodels (Cinner et al., 2013), and in an analysis of US shellfisheries vulnerable to ocean acidification (Ekstrom et al., 2015). Alternatively, these submodels may be examined in sufficient detail to warrant separate, but linked, studies. For example, the result of the climate vulnerability assessment of fish species in the northeast US (Hare et al., 2016) was used, along with expected sea level rise, to evaluate vulnerability of fishing communities to climate change (Colburn et al., 2016). A similar approach was used to assess the socio-economic vulnerability in three Australian coastal communities (Metcalf et al., 2015) based on the results from trait-based vulnerability assessments of fish stocks in Australia (Pecl et al., 2014), and Mathis et al. (2015) analyzed the vulnerability of Alaska fishery sectors to ocean acidification based on dependence on sensitive target stocks. These methods can be applied in order to update existing studies of the social and economic vulnerability of Alaskan communities (Himes-Cornell & Kasperski, 2015) by considering climate projections and the projected impacts on natural populations.

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