

Socioeconomic risk of coastal Alaskan fishing communities to climate-driven changes in Pacific cod distributions

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Abstract

Rising ocean temperatures and other climate impact drivers are altering the abundance and distribution of economically and culturally important marine species. In the Eastern Bering Sea, climate change threatens communities through reduced economic opportunities and food security in fishing-reliant areas. We apply a risk assessment framework integrated with statistical modelling and regionally downscaled ocean models to hindcast and project the distribution of adult and juvenile Pacific cod abundance in the Eastern Bering Sea under two shared socioeconomic pathways (SSP1-2.6 and SSP5-8.5), leveraging commercial fisheries catch data and publicly available socioeconomic information to assess the exposure and sensitivity of Alaska fishing communities' to the geographical redistribution of Pacific cod. To compare risk among seven federally recognized Alaska census areas, we adapt a recognized framework that integrates hazards, sensitivity, and exposure as equally weighted components of risk. To assess how distributions and relative risk may shift from both historic and more recent abnormal environmental conditions, we compare future projections against two contrasting climate baselines: a 'normal' period (1980–2000) and a recent abnormally warm period (warm years post-2000). Projections of Pacific cod distributions across multiple climate scenarios indicate a progressive shift in abundance from the southern to the northern Eastern Bering Sea. The extent of this geographical change, coupled with lower adaptive capacity and higher dependence on this fish as a resource, results in heightened risk for southern Eastern Bering Sea communities. Our findings highlight the need for adaptive, place-based fisheries management strategies that are tailored to regional sensitivities to projected shifts in marine resources under a changing climate.

Keywords: Pacific cod; climate change; species distribution; fisheries; community risk

Introduction

Anthropogenic climate change poses significant threats to high-latitude ecosystems, such as the Eastern Bering Sea (EBS). Known as one of the most productive marine ecosystems in the world, the EBS supports rich marine biodiversity and accounts for >40% of the USA's annual commercial fish catch (Voorhees and Lowther 2010). As climate change intensifies, the EBS ecosystem is expected to face increasing disruptions (Stabeno and Bell 2019) and amplified risk of adverse impacts to ecological and socioeconomic benefits (Constable et al. 2022, Holsman et al. 2020, Reum et al. 2020, Thorson et al. 2021, Whitehouse et al. 2021, Hollowed et al. 2022, Szuwalski et al. 2023b).

The ecological and physical dynamics of the EBS shelf are linked to variable annual sea-ice formation/retreat and the subsequent extent of the cold pool (Stabeno et al. 2001, 2012b, Hirawake and Hunt 2020, Stabeno et al. 2023). The cold pool, or an area of relatively cold bottom water, serves as refuge for many forage fish species and acts as an important thermal barrier (Ciannelli and Bailey 2005, Hollowed et al. 2012, Stabeno et al. 2012b, Kotwicki and Lauth 2013, Stevenson and Lauth 2019). Changes in the degree of sea-ice cover and melt timing have influenced cold pool size and extent, which have altered species assemblages and geographic distributions of many fish species in the EBS in recent years (Stabeno et al. 2012a, Stevenson and Lauth 2019).

The EBS has historically exhibited significant oceanographic variability due to interannual fluctuations in temperature and oceanographic mixing (Stabeno et al. 2017), particularly in relation to sea-ice extent and timing, which drives many of its physical and biological processes (Stabeno et al. 2001, 2012b, Hirawake and Hunt 2020). Prior to 2000, this variability followed a relatively predictable pattern, with annual or biannual transitions between cold and warm years as part of the normal climate regime (Stabeno et al. 2012b). However, the year 2000 marked a transition to multi-year periods of warm or cold conditions (Stabeno et al. 2023), with notable intermittent marine heatwaves during 2014–2016 (Bond et al. 2015, Siddon and Zador 2017) and 2017–2019 (Siddon 2023, Szuwalski et al. 2023b). This departure from the historic interannual variability reflects a broader trend towards climate instability in the region, with bottom temperatures in the EBS projected to increase as much as 5°C by the end of the century (Hermann et al. 2019, 2021, Kearney et al. 2020, Cheng et al. 2021).

Variations in temperature are one important factor driving the geographical distribution of marine species, particularly for poikilothermic species such as fish and crabs, whose physiological processes are intricately linked to ambient temperature (Pörtner and Farrell 2008). Climate change-driven temperature changes are thus causing shifts in seasonal habitat use, poleward movements in distribution, and general species

migration to deeper, cooler waters (Dulvy *et al.* 2008, Fosheim *et al.* 2015). Geographically restricted species that are unable to adjust their distribution to stay within their thermal tolerance range are particularly vulnerable to ecological consequences of a warming climate (Dulvy *et al.* 2008, Rijnsdorp *et al.* 2009), such as phenotypic changes (Blaisdell *et al.* 2021; Poloczanska *et al.* 2013), increased metabolic stress (Madeira *et al.* 2016), and food web disruptions (Ainsworth *et al.* 2011, Beaugrand *et al.* 2015).

The fishing industry in Alaska is a pivotal component of the local and state economies, a source of cultural unity, and is directly linked to food security. The economic (e.g. profit, employment) and social (e.g. community and cultural sustainability, social cohesion, and cross-generational knowledge transfer) benefits derived from Alaskan fisheries are closely intertwined with the resilience of these communities. Alaska fisheries make up 40% of the national seafood harvest, fuelling the global seafood market, and providing jobs for 1 in 7 Alaskan residents (ASMI 2024, Voorhees and Lowther 2010). In 2021, Alaskan fisheries generated >60 000 jobs in the state and >\$15 billion in economic output (Alaska Department of Labor & Workforce Development 2024). In addition to being an important source of employment and nutrition, fishing is also central to many cultural customs (Fall 2011, Holen 2014, Reedy 2019). Each year, the Bering Sea supplies >25 million pounds of subsistence food to Alaskan residents, predominantly Alaska Natives residing in small coastal communities (Brown *et al.* 2023). Specifically, coastal communities along Alaska's northwest coast heavily rely on the commercial and subsistence fishing and fish processing sectors, with a substantial portion of their economic input being derived from the regional fisheries (Seung and Miller 2018). Reduced fisheries productivity in these areas could lead to unemployment, decreased food security, and other social and economic impacts.

Fishers, particularly those operating on a small scale, are limited in where they can fish by technical (size of vessels and gear types), social (local ecological knowledge and cultural support), and regulatory constraints (area and seasonal closures and cost of permits) (St. Martin 2001, Holsman *et al.* 2019, Abbott *et al.* 2023). As species undergo climate-driven geographical redistributions, communities will likely experience shifts in the accessibility of such commercial and subsistence resources, necessitating adaptations in fishing practices (Adger *et al.* 2005, Young *et al.* 2019, Abbott *et al.* 2023).

Pacific cod (*Gadus macrocephalus*) is the second largest commercial groundfish fishery in the USA, generating \$225.4 million in 2022 (Alaska Fisheries Science Center). Over the last several decades, Pacific cod in the EBS have demonstrated large-scale shifts in their distribution patterns into the northern EBS, thought to be the result of a retreating cold pool (Spies *et al.* 2019, Stevenson and Lauth 2019). These spatial reconfigurations, characterized by poleward movements or shifts to deeper waters, present significant challenges for small-boat fishers seeking to sustain their livelihoods (Link *et al.* 2011, Ojea *et al.* 2020, Liu *et al.* 2023).

Risk assessment frameworks provide a structure for understanding the progressively severe, interrelated, and frequently irreversible ramifications of climate-driven events on communities (Ara Begum *et al.* 2022, IPCC 2022). Specifically, risk assessments offer a systematic approach to determining hazards and risks that could impact a system, community, or resource (IPCC 2022). Studies employing interdisciplinary methods ad-

dressing the complex interaction between climate change, fisheries, and communities remain scarce [except see (Ekstrom *et al.* 2015, Mathis *et al.* 2015, Rogers *et al.* 2019, Magel *et al.* 2020, Samhouri *et al.* 2023)]. These multifaceted frameworks can help in developing strategies to mitigate the adverse impacts of climate change on fisheries, thereby enhancing the resilience of fishing communities.

Here, we employ biological and socioeconomic data to explore patterns of community dependence on Pacific cod within Alaska. We adapt a risk assessment framework developed by the Intergovernmental Panel on Climate Change (IPCC) to quantify fishing community risk to changes in Pacific cod distributions under different climate scenarios. Our findings highlight how climate-driven shifts in species distributions can lead to uneven and altered patterns of risk across fishing-reliant communities in western Alaska. By integrating ecological projections with community-level socioeconomic indicators, this work offers insights into the complex interactions between climate, species distributions, and fishing community resilience.

Methods

Risk index framework

The application of risk and risk management frameworks to mitigate or alleviate the negative consequences of climate change has gained prominence in the previous two decades (Ara Begum *et al.* 2022). Risk, defined as the potential for adverse outcomes due to climate hazard intersecting with social sensitivity to changes in resources (Ara Begum *et al.* 2022, IPCC 2022), acknowledges that the degree of adverse outcome or risk, varies across societal and individual values and goals within social-ecological systems. Risk assessment frameworks provide a structure for understanding the progressively severe, interrelated, and frequently irreversible ramifications of climatic-driven events on communities.

Following an IPCC approach to assess climate risk (IPCC 2022), we quantified risk (R) for seven Alaskan census areas as the function of a hazard (H), as well as communities' exposure (E), and sensitivity (S) (Fig. 1):

$$R = H + E + S$$

While our risk framework conceptually aligns with the IPCC model (where risk is a function of hazard, exposure, and vulnerability), we adapt its terminology to reflect more precise and socially responsive language. Specifically, we avoid the term vulnerability to describe people or communities, as it can carry negative connotations or imply inherent weakness. Instead, based on feedback from community partners and informed by literature such as Munari *et al.* (2021), we refer to the vulnerability dimension as 'sensitivity'. Further, the IPCC incorporates sensitivity and adaptive capacity as dimensions of vulnerability; here, we use 'dependency' in place of what the IPCC refers to as sensitivity. The overall framing of risk used here follows similar studies that have evaluated the risk of fisheries losses from climate change (Ekstrom *et al.* 2015, Mathis *et al.* 2015, Magel *et al.* 2020, Koehn *et al.* 2022). However, here we consider the geographical redistribution of a species as a hazard and are projecting distribution changes under different climate scenarios to predict risk.

It is important to note the IPCC distinguishes between risk (pre-adaptation) and residual risk (post-adaptation), as

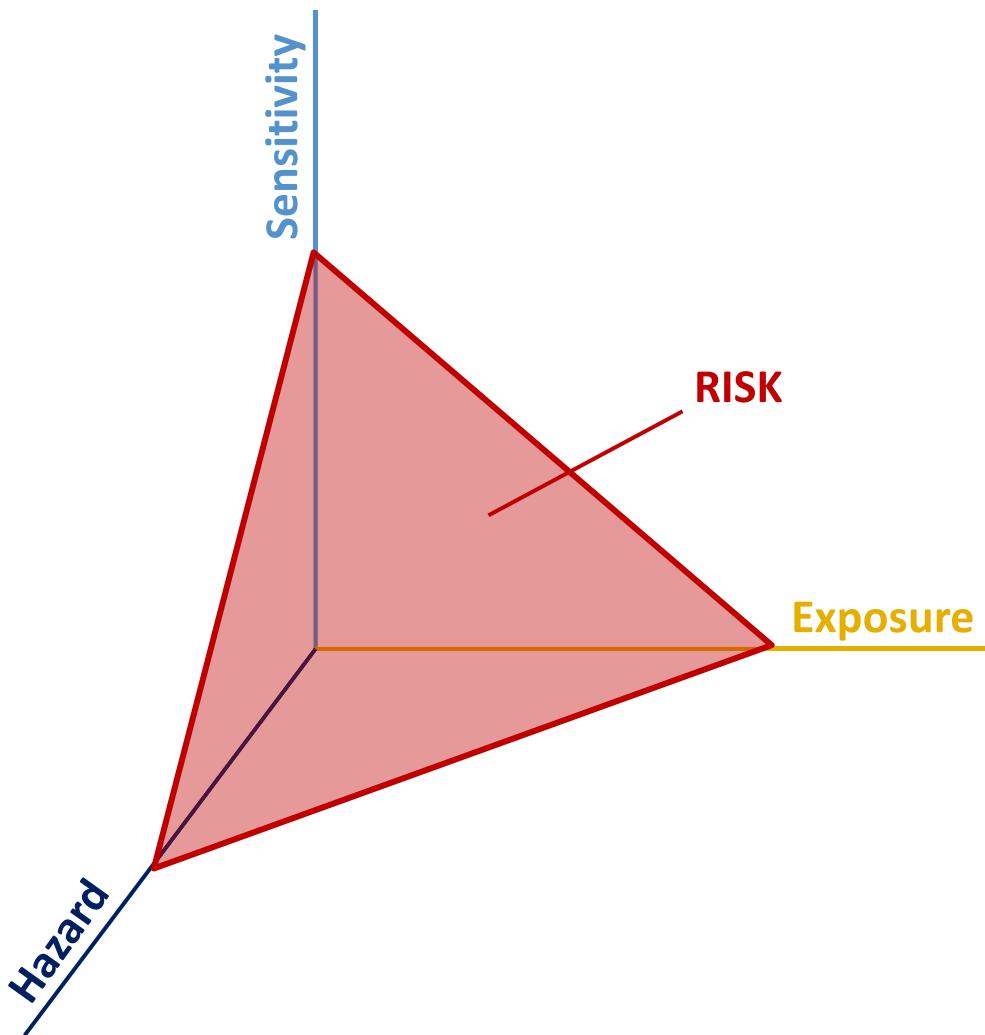


Figure 1. Conceptual risk framework applied in this study. Adapted from the IPCC AR6 CCP6 (Constable et al. 2022).

incorporation of adaptive strategies can alter sensitivity and exposure (IPCC 2022). In this study, we primarily focus on residual risk (henceforth referred to as 'risk' unless otherwise specified); however, to illustrate the potential influence of adaptation, we also quantify risk without the adaptive capacity component (henceforth referred to as 'initial risk'). While we adopt the IPCC's conceptual framing, we acknowledge that this approach does not capture actual changes resulting from implementing adaptation strategies. Instead, our comparison between initial and residual risk serves as a simplified sensitivity analysis, intended to demonstrate the theoretical importance of adaptive capacity rather than the realized outcomes of adaptation.

Hazard (H) has traditionally been defined as a climatic driver of risk (Ara Begum et al. 2022, IPCC 2022; Table 1). Previous adaptations of fisheries-related hazard within community-focused risk assessments have encompassed analyses of risks associated with natural disasters (Hoang et al. 2020), variability in ocean-atmosphere circulation (Magel et al. 2020), and ocean acidification (Ekstrom et al. 2015, Mathis et al. 2015). In the context of this analysis, we considered hazard to be the geographic redistributions of species in response to changes in environmental conditions and the driver of community risk. This perspective of hazard is a relatively nascent

approach and has only recently begun to see implementation (Reisinger et al. 2020).

Exposure (E) is defined as the presence of people, livelihoods, services, environmental resources, or economic, social, or cultural assets in locations which could be adversely affected by climate change (Ara Begum et al. 2022, IPCC 2022; Table 1). As we aim to evaluate the susceptibility of fishing communities to distribution shifts in Pacific cod, our focus lies on assessing the repercussions on livelihoods. Consequently, we consider exposure to be an indicator of the extent of engagement in species fisheries. The IPCC framework also considers that adaptation can reduce exposure (e.g. people move away from coastal areas reducing exposure to SLR), however in the context of this paper we assumed that adaptation was not being used to reduce exposure, i.e. we evaluated baseline, pre-adaptation, exposure hazard.

Following the definition established by Wisner et al. (2004) and applied within the IPCC framework, community specific sensitivity to climate effects (S) was the characteristics of a community which impact ability to anticipate, cope with, resist, and recover from the impact of a hazard. In this sense, sensitivity to climate effects is not only an imperative component of risk, but also an independent dimension, as it enables deeper understanding of the unequal impacts of climate

Table 1. Summary of the components, definitions, variables, and data sources used to calculate risk.

Component	Definition	Variables	Data sources
Hazard H	Ecological response to a climatic-driven event (based on definition from IPCC 2022).	Percent change in predicted Pacific cod distribution for each climate model	AFSC, 2023
Exposure E	The presence of people, livelihoods, services, environmental resources, or economic, social, or cultural assets in locations which could be adversely affected by climate change (IPCC 2022). Represented here as the level of engagement with the fishery.	Vessel permits, vessel ownership, fixed gear commercial landings, presence of processing facilities	AFSC, 2023
Sensitivity S	The characteristics of a community which determines the strength of the impact and community level capacity to anticipate, cope with, resist, and recover from the impact of a hazard (Wisner et al. 2004).	Adaptive capacity, dependency	
Adaptive Capacity A	Capacity to adjust or respond to climate change to reduce the impact of a given hazard, including the capacity to adapt, absorb impacts, and recover (IPCC 2022). Calculated as the sum of indicators for local economic stability and community accessibility, similarly to Mathis et al. (2015).	Unemployment, employment by industry, educational attainment, per capita income, fuel cost, road accessibility	U.S. Census ACS, 2022; ADCCED, 2023; ADOT&PF, 2023
Dependency δ	The extent of dependence (economic or nutritional) on the availability of a resource (IPCC 2022).	Commercial price per pound, percent of households using as subsistence resource	ADF&G CSIS, 2023; AFSC, 2023

Alaska Fisheries Science Center—AFSC. Alaska Department of Commerce, Community, and Economic Development—ADCCED. American Community Survey—ACS. Alaska Department of Transportation & Public Facilities—ADOT&PF. Alaska Department of Fish & Game Community Subsistence Information System—ADF&G CSIS.

change across individuals (Ara Begum et al. 2022; Table 1). Here, sensitivity to climate effects includes communities' dependency on a resource and their adaptive capacity. Sensitivity refers to the degree of reliance, whether economic or nutritional, on the availability of a particular resource. Adaptive capacity assesses a community's capability to mitigate the effects of climate change (IPCC 2022). A high adaptive capacity suggests a community has the necessary resources and capabilities required to adapt and offset the cost of the changes they are faced with, typically by diversifying or altering their use of (dependency on) a resource (Ojea et al. 2020).

For this study, we used independent sources of information available across communities as indices of sensitivity, dependence, and adaptive capacity. To facilitate comparison across census areas and ensure equal weighting, we normalized continuous indicator variables and binned them into quartiles prior to calculating component scores. While this method enables comparison of scores across regions, it should be considered a relative metric to frame future discussions and place the redistribution of fish species in the context of social dimensions. That said, it is not intended to be a holistic characterization of the hazard, dependence, sensitivity, or adaptive capacity of each community and we acknowledge that resilience and adaptive capacity are complex and dynamic processes that warrant future in-depth evaluations. The initial approach defined in this study will help provide the foundational framework for future evaluations of community level risk to climate-driven impacts on fishery resources.

Hazard

To project future Pacific cod distribution in the EBS, we developed a Generalized Additive Model (GAM) informed by historical fishery-independent abundance data and environ-

mental covariates derived from regional ocean model outputs. Specifically, environmental input variables were sourced from a high-resolution implementation of the Bering Sea Regional Ocean Modeling System (ROMS), referred to as Bering10K.

Abundance and environmental covariate data

Pacific cod abundance data were obtained from the Alaska Fisheries Science Center (AFSC) EBS groundfish bottom trawl surveys. Since 1982, the AFSC has conducted an annual EBS shelf survey, providing comprehensive geographic coverage of the shelf and detailed data on the abundance and distribution of adult and subadult groundfish and invertebrates during the summer (see supplementary materials for more details).

To characterize ocean conditions, we use a Bering Sea implementation of the ROMS, referred to as the Bering10K. Encompassing the Bering Sea and the northern Gulf of Alaska, the Bering10K ROMS domain has a horizontal resolution of 10 km and 30 vertical layers. The Bering10K has demonstrated its ability to accurately represent physical characteristics crucial for biological processes, such as circulation patterns, temperature, salinity, and the seasonal sea ice patterns (Hermann et al. 2013, Kearney et al. 2020). This study utilizes multiple simulations from the Bering10K model. We use a reanalysis-forced hindcast simulation, which spanned 1970–2023 and accurately demonstrated observed variability during that period (see Kearney et al. (2020) for a full description of the Bering10K model, including the reanalysis forcing and model configuration). Bottom temperature data from this simulation were co-located to survey locations using nearest neighbour analysis.

For forecasting, we use dynamically downscaled projections from Phase 6 of the Coupled Model Intercomparison Project (CMIP6; O'Neill et al. 2016), including downscaled simulations forced by three Earth System Models (ESMs):

MIROC Earth System version 2 for long-term simulations (Hajima et al. 2020), CESM version 2 (Danabasoglu et al. 2020), and GFDL Earth System Model version 4.1 (Dunne et al. 2020). For each ESM, we used two different emission scenarios to capture an envelope of future climates: SSP1-2.6 (high emission mitigation) and SSP5-8.5 (low emission mitigation) (O'Neill et al. 2016, Cheng et al. 2021, Hermann et al. 2021). For forecast simulations, we extracted annual average summer (June 1st –August 31st) bottom temperature values for each grid cell. Bottom temperature values were bias corrected following the methodology described in Holsman et al. (2020; see supplementary material for detailed bias correction methodology) and co-located to survey locations using nearest neighbour analysis. All statistical analyses were done using R Statistical Software (v4.3.2; R Core Team 2023).

Species distribution modelling

We modelled Pacific cod abundance and distribution in the EBS using a spatially variable coefficient GAM (e.g. Bartolino et al. 2011, Baker 2021) with a Tweedie response distribution. Model selection was based on AIC (see Table S1), and this formulation was identified as the best fitting model. Spatially variable coefficient GAMs are well-suited for testing spatially or temporally variable relationships between ocean conditions and fish abundance (e.g. Ciannelli et al. 2012). The covariates used in the final model included latitude (ϕ), longitude (λ), bottom depth (d), sediment size (φ), co-located bottom temperature ($temp$), and year as a random effect (yr) to enable forecasting. Additionally, the average annual middle shelf bottom temperature (mid) was modelled as a spatially varying coefficient term. Both temperature variables ($temp$ and mid) serve as proxies for the cold pool, a key oceanographic feature influencing Pacific cod habitat in the EBS (Ciannelli and Bailey 2005, Stabeno et al. 2012b, Stevenson and Lauth 2019). A link function was used to estimate the linear predictor, μ , which represented Pacific cod catch per unit effort (CPUE) plus 1 to facilitate model convergence. All dimensions and variables in the model were included additively and the GAM was fitted using the R package 'mgcv' (v 1.9–1; Wood 2023). Model assumptions were assessed by examining residual diagnostics, including testing for temporal autocorrelation using an autocorrelation function (ACF) plot of yearly mean residuals and testing for spatial autocorrelation using Moran's I with a 40-km spatial neighbourhood. The equation for the final model is as follows:

$$\begin{aligned} \mu_{\phi, \lambda} = & s_1(d) + s_2(\phi, \lambda) + s_3(\phi, \lambda) * mid + s_4(\varphi) \\ & + s_5(temp) + re(yr) \end{aligned}$$

Hazard calculation

To link shifts in Pacific cod distributions to census areas, we spatially matched Alaska Department of Fish and Game (ADF&G)'s commercial groundfish statistical areas (BS 508, 509, 512, 514, 516, 517, 519) with distinct census areas (Fig. 2). We selected ADF&G statistical areas for their spatial resolution rather than for alignment with National Marine Fisheries Service (NMFS) data. As Alaskan residents engage in Pacific cod commercial and subsistence fishing close to shore, only statistical areas adjacent to the coastline were considered. Statistical areas BS 509, 512, 514, 516, 517, and 519 were grouped into one region to spatially align with census areas, while BS 518 was subdivided at Kusilvak Census Area's southernmost

latitude to improve resolution (Fig. 2). Given this method of linking oceanic and terrestrial areas, it is assumed in our analysis that the regions that encompass multiple census areas experience the same hazard. We geographically segmented the annual average predicted Pacific cod CPUE during the summer season in each of the four pre-established marine geographical regions by assigning each grid cell to the predefined marine region using the *in.chull* function from the 'sgeostat' package (v1.0-27; Majure 2016).

To explore a variety of hazard scenarios and assess the predicted impact of changing environmental conditions on Pacific cod distributions, we developed three distinct hazard models: a reference hazard scenario covering 2001–2022 and two projected hazard scenarios, each spanning from 2015–2099. We divided each projections into early (2015–2039), middle (2040–2069), and late century (2070–2099) intervals. We then averaged CPUE predictions across the ESMs for each grid cell to produce spatially explicit, SSP-specific abundance estimates over the three time periods. We use hazard under current environmental and socioeconomic conditions as a reference scenario to contextualize future projections under SSP1-2.6 and SSP5-8.5. While risk is inherently forward-looking, this baseline provides a useful point of comparison to understand the magnitude of change in projected hazard and is not intended to represent observed impacts.

We assessed projected changes in hazard using two different baseline periods. The first, henceforth referred to as the Standard Baseline, uses 1980–2000 as the baseline, representing historically 'normal' Bering Sea conditions. The second, referred to as the Extreme Baseline, uses anomalously warm years post 2000 to capture average Pacific cod distributions. Given the environmental conditions in the EBS have deviated from historical norms over the past two decades (Stabeno et al. 2012b, 2019, Stabeno and Bell 2019), comparing future projections to both baselines allows us to evaluate whether projected conditions represent a departure from historical norms or a continuation of recent extremes. Abnormally warm baseline years were defined by calculating the average middle shelf bottom temperature, used here as a thermal index, for each year since 2000 and identifying years exceeding the 75th percentile (2.35°C) as warm, below the 25th percentile (1.28°C) as cold, and intermediate years as moderate (Table S3). We then used the average CPUE from the warm years as the baseline for comparing CPUE projections under different climate scenarios.

We calculated hazard as the average % change in predicted accessible (available for harvest by small-scale fishers) Pacific cod abundance for each marine area as:

$$\text{Percent change} = \frac{\text{Contrast} - \text{Baseline}}{\text{Baseline}} \times 100,$$

where *Baseline* is the average CPUE from the reference period, and *Contrast* is the average predicted CPUE from the comparison period for each climate scenario. The marine area with the highest positive average % change received the lowest hazard score (1), as higher accessible abundance of Pacific cod would indicate lower risk for communities. Conversely, the lowest % change (most negative or smallest % change) received the highest score (4), indicating less or similar accessible abundance compared to the reference period, which would be associated with higher community risk levels. Uncertainty was

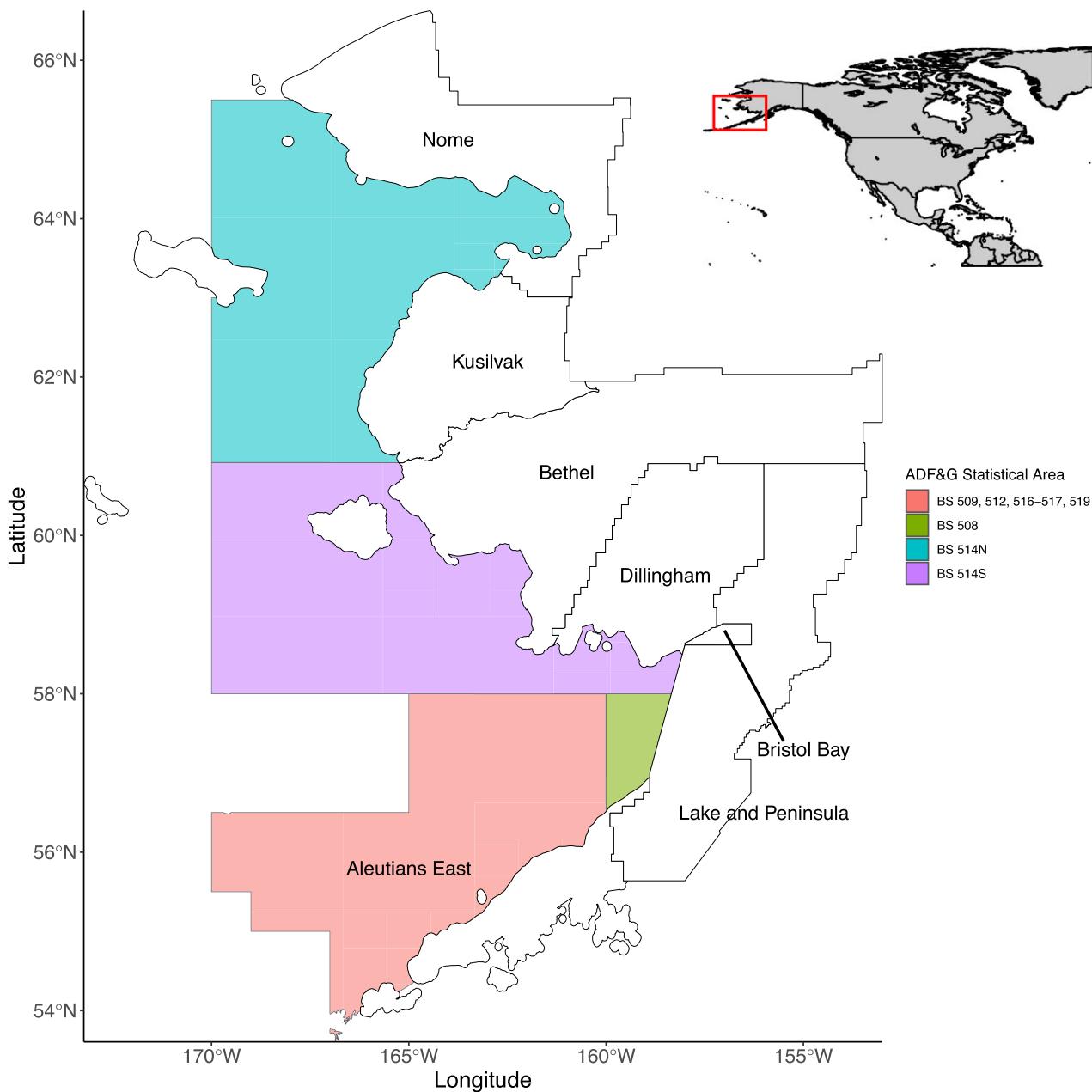


Figure 2. Map of the study census areas and spatially aligned commercial groundfish statistical areas.

tested using 95% confidence intervals for each marine area across the baseline and contrast years.

Exposure

Following Mathis et al. (2015) and Wise et al. (2021), exposure was considered to be a measure of communities' engagement with the potentially affected fishery and assessed using vessel and catch metrics. For each census area, we quantified exposure as the sum of vessel permits, vessel ownership, the proportion of fixed gear landings by census area, and presence of processing facilities (Table 1). Given that most commercial Pacific cod landings are conducted by large trawling vessels owned by and employing residents of Washington or Oregon (AFSC 2023), we used only fixed gear landings to better understand small-boat participation in fisheries. The value for each variable was standard-

ized to be between 0 and 1.0 and then divided into quartiles, where higher scores indicated greater exposure. Each component was equally weighted in the calculation of total exposure:

$$E = 0.25E_P + 0.25E_O + 0.25E_L + 0.25E_F,$$

where E_P is the quartile-classified vessel permits and E_O is the quartile-classified vessel owners. E_L is the quartile-classified proportion of fixed gear landings and E_F is quartile-classified processing facilities. To classify resulting exposure scores as low, moderate, or high, the range of values was divided into three equal groups.

Sensitivity

Dependency and adaptive capacity values for each census area were standardized on a scale of 0 to 1.0, then segmented

into quartiles and assigned scores ranging from 1 (lowest) to 4 (highest). For dependency, higher standardized values received higher quartile-derived scores, which would reflect increased sensitivity, and ultimately increased risk. In contrast, the ranking of adaptive capacity was scored inversely, with the highest standardized values receiving lower quartile-derived scores. This is based on the logic that higher values for these socioeconomic indicators implies greater capacity to adapt, and thus lower overall sensitivity and risk. The scored values for dependency and adaptive capacity were evenly weighted and summed for each census area to determine overall sensitivity (S):

$$S = 0.5\delta + 0.5A,$$

where δ is quartile-classified dependency, and A is quartile-classified adaptive capacity. The final sensitivity score was divided into three equal groups to classify each census area as having low, moderate, or high sensitivity.

Dependency

Dependency (δ) was derived from metrics for both commercial and subsistence harvest (Table 1). For our purposes, economic reliance was based on each census area's commercial price per pound (P) values for each species. To incorporate nutritional reliance into sensitivity, subsistence data on the percentage of households participating in the subsistence harvest (Sub) of Pacific cod for the most recent year available was used. The sum of these two equally weighted indicators equalled total sensitivity:

$$\delta = 0.5Sub + 0.5P.$$

Adaptive capacity

Similarly to Mathis et al. (2015), adaptive capacity is considered to consist of two dimensions: local economic stability and accessibility (Table 1). These dimensions were selected to reflect the ability of a community to respond to or recover from change. Local economic stability reflects the financial and institutional flexibility available to individuals and communities in the face of disruptions. We evaluated this through indicators such as job diversity (specifically, employment by industry), unemployment rates, and per capita income. Additionally, educational attainment, representing individuals' ability to access and apply new information, was measured by the percentage of the population 25 years and older that received a high school diploma.

The second component of adaptive capacity, accessibility, captures the degree to which communities can physically and economically access broader infrastructure needed to adapt. Here, we used indicators such as average annual fuel costs as a financial burden of transportation and road accessibility to represent physical connectivity. The sum of these variables equalled total adaptive capacity (A):

$$A = 0.16Emp + 0.16Unemp + 0.16PCI + 0.16Edu + 0.16FC + 0.16RA,$$

where employment by industry is represented by Emp , unemployment is $Unemp$, and per capita income is PCI . Educational attainment is represented in the equation by Edu , and fuel cost and road accessibility are represented by FC and RA , respectively.

Results

Cod distribution

All variables in the most supported model explaining the distribution of Pacific cod were statistically significant (Table S2). The model explained 32.4% of the null deviance in the data. The two temperature metrics in the model were moderately positively correlated ($r = 0.39$), and both were important in explaining the distribution of Pacific cod. CPUE varied spatially according to average temperature on the middle shelf, such that increasing temperatures positively (negatively) affected abundance in the northern (southern) EBS (Fig. 3a). An increase in bottom temperature led to decreases in abundance throughout the sample period (Fig. 3d). ACF analysis of the mean residuals by year indicated no strong temporal autocorrelation. Moran's I test on residuals revealed a small but statistically significant positive spatial autocorrelation ($I = 0.055$, $P < 0.001$), reduced from that observed in the raw CPUE ($I = 0.117$, $P < 0.001$), which is expected given spatial clustering of fish in ecological data.

Model predicted distribution generally aligned with observed survey data during the corresponding time period (Fig. 4). Historical distribution trends also reflected those seen in survey observations, particularly during years with contrasting environmental conditions. Under both SSP scenarios, the model predicted a northward shift in Pacific cod distributions (Fig. S1). By late century (2070–2099), the northern EBS is projected to contain 42% of Pacific cod abundance under SSP1-2.6 and 54% under SSP5-8.5, compared to 33% from the hindcast predictions (2001–2022). Statistically significant changes in abundance are evident, with no overlap in 95% confidence intervals between baseline (1980–2000) and late-century projections (2070–2099), indicating major shifts in Pacific cod distributions.

Hazard

Using 2001–2022 as the period for the reference hazard, the northernmost marine region, covering Nome and Kusilvak census areas, had the highest hazard score (indicating the smallest % change in accessible Pacific cod abundance) (Table S5). In contrast, Lake and Peninsula received the lowest hazard score, reflecting the greatest positive % change in accessible Pacific cod abundance across the past two decades.

Across the Standard Baseline timeframe (2015–2099) and under both climate scenarios, the marine region encompassing Nome and Kusilvak census areas are expected to experience the highest positive % change in accessible abundance, thus receiving the lowest predicted hazard score. Under these conditions, the census areas along the Alaska Peninsula (Aleutians East and Lake and Peninsula) had the highest projected hazard scores (Table S5).

Hazard projections using abundance from historically warm years as a baseline (Extreme Baseline) reveal differences across SSP1-2.6 and SSP5-8.5. Under SSP1-2.6, the northernmost marine region encompassing Nome and Kusilvak showed the lowest abundance change (highest projected hazard score), while Bethel, Bristol Bay, and Dillingham had the highest abundance change (lowest projected hazard score) (Table S5). Conversely, projected hazard scores under SSP5-8.5 were highest for the regions along the Alaska Peninsula (Aleutians East and Lake and Peninsula boroughs), and lowest for the northernmost census areas (Table S5).

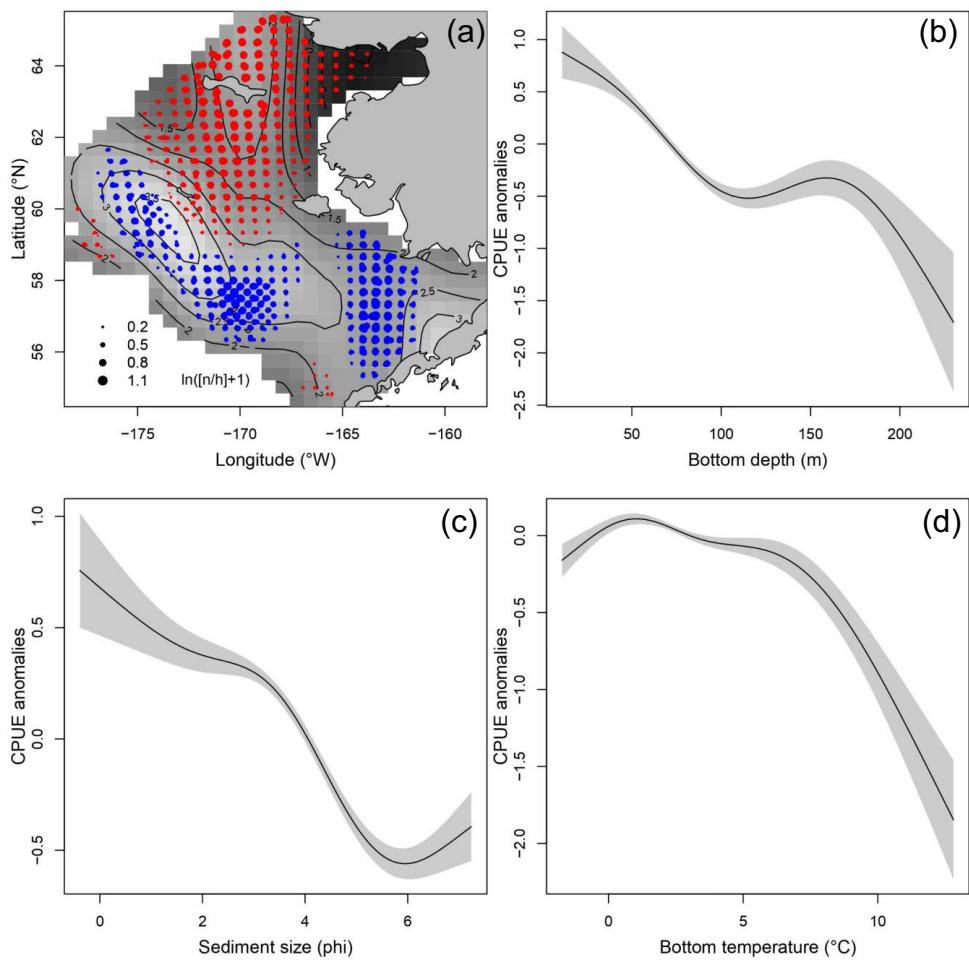


Figure 3. a) CPUE anomalies per unit change in annual average middle shelf bottom temperature. Negative (positive) effects are indicated by blue (red) bubbles. Panels b-d depict the additive effects of bottom depth, sediment size, and bottom temperature, respectively.

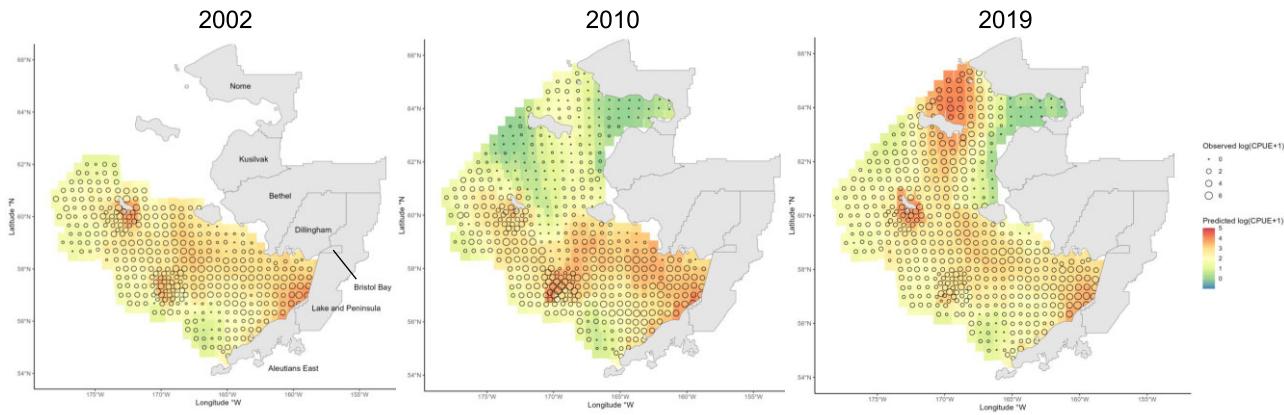


Figure 4. Predicted (scaled) and observed (bubbles) Pacific cod abundance for moderate (2002), cold (2010), and warm (2019) years. The northern EBS was not sampled in 2002.

Comparing observed Pacific cod abundance under warm historic years to the Extreme Baseline SSP-based predictions revealed that early-to-middle century (SSP1-2.6) and early century (SSP5-8.5) scenarios exhibited similar hazard scoring, with the northernmost census areas facing the highest projected hazard and the Bristol Bay region and Alaska Penin-

sula regions having the lowest projected hazard. With both SSP scenarios, these early periods align with less pronounced warming (Table S4), indicating maintained Pacific cod distributions similar to their traditional ranges in the southern EBS.

By the late century under SSP1-2.6 and middle-to-late century under SSP5-8.5, more extreme distribution shifts become

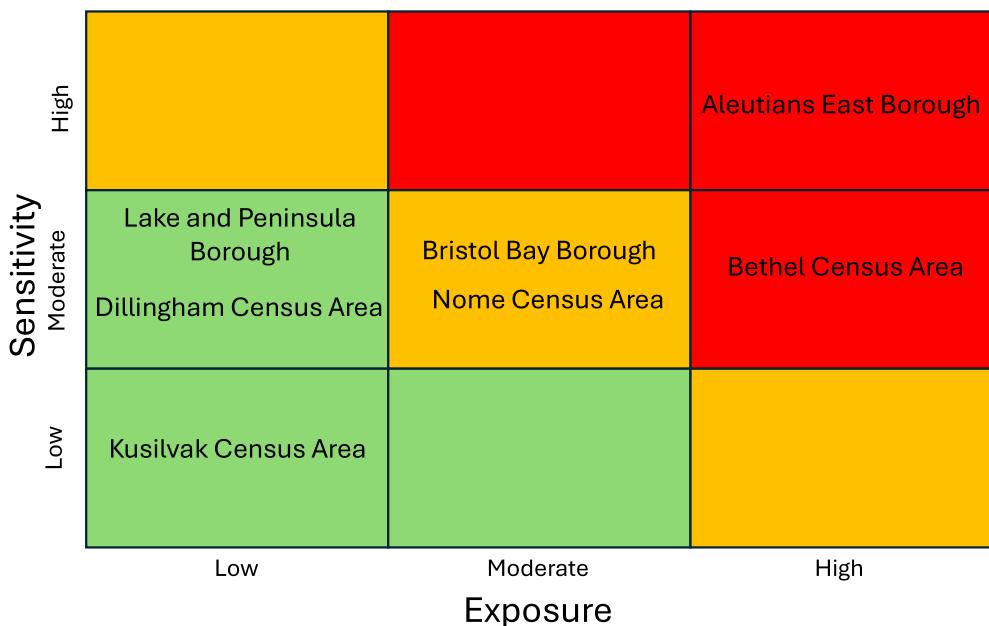


Figure 5. Exposure and sensitivity scores classified as low, moderate, and high for each census area.

apparent. In these periods, regions along the Alaska Peninsula and Bristol Bay are projected to have less accessible abundance, while northern census areas will see high positive % changes. This suggests that substantial and sustained distribution shifts from recent warm-year patterns are not anticipated until the middle or late century.

Exposure

In this study, exposure was used as a measure of social engagement with the fishery. Census areas in the southern portion of the EBS, such as Aleutians East and Bethel, exhibited high exposure (Fig. 4). Bristol Bay and Nome census areas were found to have moderate exposure, whereas Lake and Peninsula, Dillingham, and Kusilvak census areas had low exposure, indicating these areas are not highly engaged in the Pacific cod fishery (Fig. 5).

Sensitivity

Sensitivity in this study consisted of two components: dependency and adaptive capacity. Dependency reflects the degree of community-specific economic and nutritional reliance on Pacific cod. Nutritional dependence was measured by the average percentage of households harvesting Pacific cod per census area, while economic dependence was assessed based on the commercial price per pound. Overall, Aleutians East demonstrated the highest sensitivity, being the only census area to receive the highest score of 4.0. Dillingham and Kusilvak census areas had the lowest sensitivity scores.

Adaptive capacity refers to the ability of communities to mitigate negative impacts or adapt their resource use. We assume that lower values in these indices reflect alternative employment and nutritional options if Pacific cod availability diminishes. Adaptive capacity was evaluated using data on local economic stability and food accessibility, and analysis of this component of climate Sensitivity exhibits distinct regional trends. Census areas along the southern portion of the

EBS, including Bristol Bay and Lake and Peninsula, had the lowest index scores, whereas northern areas such as Kusilvak and Nome had the highest.

Overall Sensitivity was calculated as the equally weighted sum of dependency and adaptive capacity. Aleutians East was the only census area considered to have high sensitivity to climate driven change in cod distributions (Fig. 5). The majority of the census areas in this study demonstrated moderate sensitivity to changes, and only Kusilvak and Dillingham were classified as low sensitivity (Fig. 5).

Total risk

Under the reference hazard scenario based on conditions from the last two decades, Lake and Peninsula was the only census area classified as low risk of negative impacts from climate-driven change to Pacific cod distribution (Fig. 6a). In contrast, Nome, Aleutians East, Bethel, and Bristol Bay were categorized as high risk (Fig. 6a), with Nome and Aleutians East facing the highest potential for negative impacts under present day conditions (Fig. 7). In this reference scenario, elevated risk of impacts in Aleutians East and Bethel stemmed from moderate hazard, high sensitivity, and substantial fishery engagement. For Nome, high hazard scores combined with moderate sensitivity and fishery engagement were key drivers of relative risk associated with Pacific cod redistributions.

Using the Standard Baseline, which used normal conditions as a baseline, relative risk rankings among census areas under SSP1-2.6 and SSP5-8.5 scenarios remained consistent across early, middle, and late-century periods. Aleutians East and Bethel consistently had the highest risk scores, while Kusilvak and Lake and Peninsula had the lowest (Fig. 6; Table 2). Only Aleutians East, Bethel, and Bristol Bay were classified as high risk under these scenarios (Fig. 6b).

Using anomalously warm historic years as a baseline (Extreme Baseline scenario), spatial patterns in relative risk outcomes diverged between SSP1-2.6 and SSP5-8.5. Northern

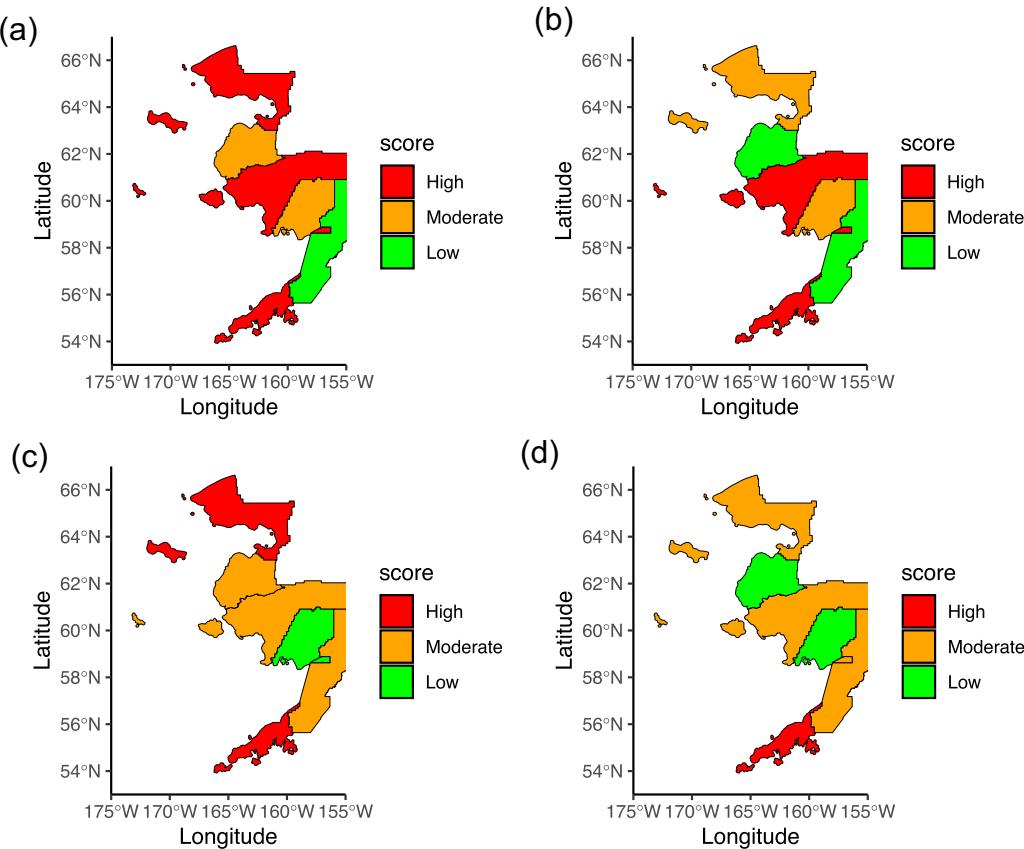


Figure 6. Total risk classifications for a) reference scenario, b) Standard Baseline SSP1-2.6 and SSP5-8.5 (results for these were the same and are thus represented on one map for clarity), c) Extreme Baseline SSP1-2.6, and d) Extreme Baseline SSP5-8.5.

census areas such as Nome and Kusilvak ranked higher in relative risk under SSP1-2.6 compared to the Standard Baseline scenario, while Aleutians East remained high risk (Fig. 7). In contrast, SSP5-8.5 produced lower risk scores for northern census areas, with Nome and Kusilvak ranking 5th and 7th, respectively (Table 2).

SSP1-2.6 predictions for this projection indicated increased risk classifications for Nome, Kusilvak, and Lake and Peninsula, while Bethel and Dillingham saw decreased relative risk levels, and Bristol Bay dropped from high to low risk. Aleutians East remained high risk (Fig. 6c). For SSP5-8.5, Nome, Kusilvak, and Aleutians East maintained their risk levels, while Bethel, Dillingham, and Bristol Bay decreased a level, and Lake and Peninsula increased (Fig. 6d).

Using the Extreme Baseline, early and middle-century predictions under SSP1-2.6 and early-century predictions under SSP5-8.5 suggested higher risk for northern census areas, reflecting lower Pacific cod abundance in the northern EBS compared to previous warm years. However, late-century SSP1-2.6 and mid-to-late century SSP5-8.5 predictions aligned with earlier findings, showing reduced risk for northern census areas. Southern census areas, particularly those along the Alaska Peninsula and south of Kusilvak, are projected to face increased risks as warming intensifies.

To quantify risk reduction through adaptation, initial risk was quantified for each census area. For three of the seven census areas, inclusion of adaptive capacity in the risk model decreased risk (Fig. S2). However four census areas (Bristol Bay, Dillingham, Kusilvak, and Lake and Peninsula) demonstrated a slight increase in risk (Fig. S2).

Discussion

Our work demonstrates that climate change presents differential risk to socioeconomic well-being across coastal Alaskan communities. Differential risk scores arise due to community level variability in hazard strength, exposure to change, and dependency on redistributed groundfish resources under changing conditions. Further, adaptation ability indices at the community level modulated risk for three census areas, demonstrating the capacity for local adaptation responses to increase long-term climate resilience.

Our findings support existing literature showing anthropogenic climate change is driving geographical shifts in the distribution of Pacific cod located in the EBS (Spies et al. 2019, Stevenson and Lauth 2019). Although the redistribution of marine species at regional scales due to changing oceanic temperature has been well documented (e.g. Dulvy et al. 2008, Poloczanska et al. 2013, Fossheim et al. 2015, Christiansen et al. 2016), the impact of these changes on the socioeconomic cohesion of coastal communities reliant on stable and abundant fishing grounds has not yet been quantified in a risk framework. In the EBS, the availability of detailed economic and environmental data allowed us to explore modelled risk levels of climate-induced species redistribution on Alaskan communities reliant on Pacific cod.

Impacts of environmental conditions on Pacific cod distributions

The shifting distributions of groundfish species in the EBS, and the influence of bottom temperature, the cold pool, and

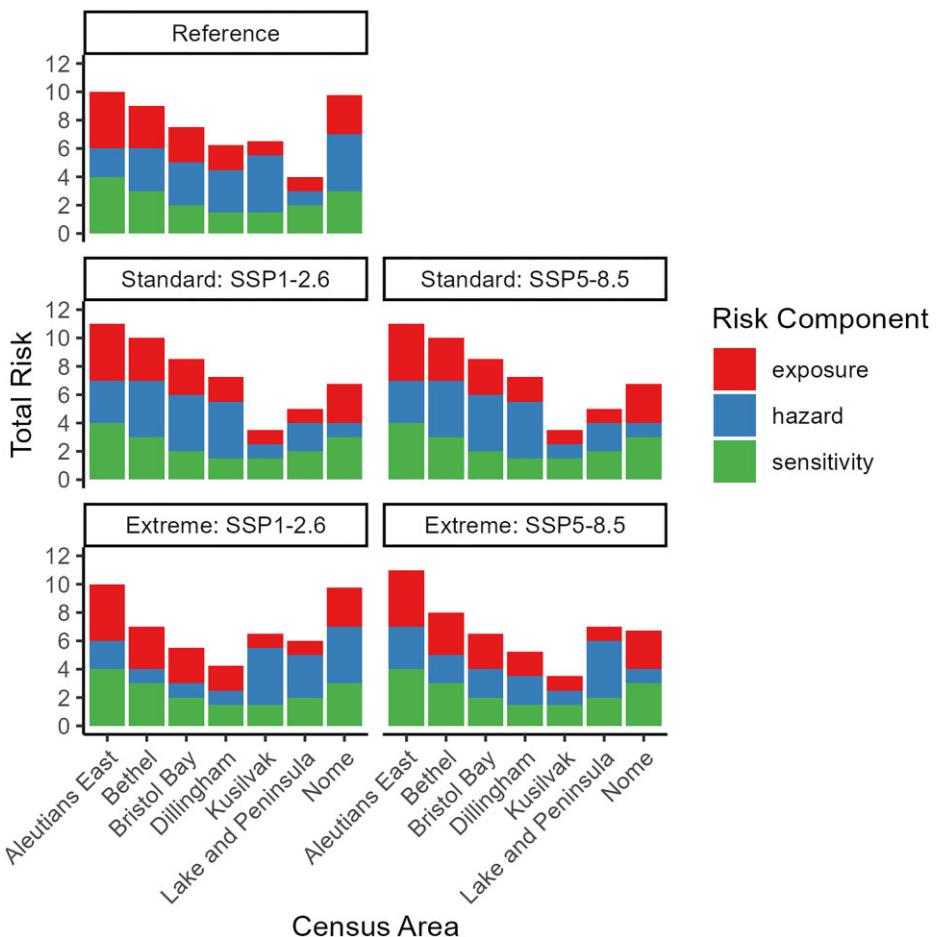


Figure 7. Total risk scores for each census area. Standard Baseline scenarios used 1980–2000 as the baseline for predictions, and the Extreme Baseline scenarios used abnormally warm years after 2000 as the baseline for predictions.

Table 2. Total risk ranking (where 1 is the highest total risk and 7 is the lowest total risk) of each census area under the different hazard scenarios.

Census Area	Reference Hindcast	Standard baseline SSP1-2.6/SSP5-8.5	Extreme baseline SSP1-2.6	Extreme baseline SSP5-8.5
Aleutians East	2	1	2	1
Lake and Peninsula	7	6	5	3
Bristol Bay	4	3	6	4
Bethel	3	2	4	2
Dillingham	6	4	7	6
Kusilvak	5	7	3	7
Nome	1	5	1	5

The Standard Baseline used 1980–2000 as the baseline for predictions, and the Extreme Baseline used abnormally warm years post-2000 as the baseline for predictions.

sea-ice extent as significant drivers of these range expansions, has been well documented (Mueter and Litzow 2008, Boldt et al. 2012, Stabeno et al. 2012b, Nichol et al. 2019, Spies et al. 2019, Stevenson and Lauth 2019, Baker 2021, Rooper et al. 2021). This study demonstrated similar findings, with bottom temperature and a thermal index acting as a proxy for the cold pool, being statistically significant in explaining Pacific cod distributions in the EBS. Further, this study aligns with previous work predicting northward movement of the stock (Rooper et al. 2021), with biomass in the northern EBS estimated to increase as much as 63% by late-century under climate scenarios of extreme warming.

Comparable studies examining the impact of a warming climate on Pacific cod distributions have highlighted both a northward shift in adult spawning habitat and differences in the distance moved between life stages. Using the Bering10K, Bigman et al. (2023) predicted changes in Pacific cod spawning habitat, which demonstrated a general increase and shift northward. Rooper et al. (2021) provided evidence of predicted northward shifts in the centre of gravity for both adult and juvenile Pacific cod, with adult fish exhibiting relatively minor shifts (<75 km) and juvenile distributions moving >200 km. Spies et al. (2019) also observed northward movement of both adult and juvenile Pacific cod, attributing the presence of juveniles in the northern EBS to shifts in adult

spawning habitats and learned migratory behaviour. Although this study did not analyse the difference in distributional shifts between adults and juveniles, the contrast in migratory abilities between these life stages, as well as adult spawning behaviour, likely influenced the results of this analysis; further studies should account for differential impacts of a warming climate across life stages. These life stage-specific shifts could have distinct implications for fishery-reliant communities, as shifts in juvenile distributions may affect future recruitment dynamics and the predictability of adult populations.

This study revealed that the lowest average % changes (i.e. highest hazard scores) in accessible abundance under the reference hazard scenario occurred in the northernmost census areas compared to other regions in Alaska. This marine region bordering Nome and Kusilvak census areas experienced both the largest and smallest % change across the reference period in this hazard scenario. The observed negative average % change in Pacific cod abundance in this northern marine geographical area was likely due to a period of cold years from 2007 to 2013, during which Pacific cod were predominantly distributed within the southern EBS. This southward contraction during the prolonged cold period likely skewed the reference hazard calculations, underscoring the importance of considering the multi-year climate regimes that the EBS has undergone over the last two decades when assessing fishing community risk.

Climate driven changes to distribution were postulated under both climate projections, but with early-to-middle century estimates indicating higher abundance within the traditional summer range of Pacific cod in the southern EBS. In contrast, middle-to-late century projections for both scenarios showed increased Pacific cod abundance in the northern EBS. This suggests that in the near term, while Pacific cod may temporarily move northward during anomalously warm years, they are likely to return to their southern range during cooler periods. However, by mid-century (SSP5-8.5) or late century (SSP1-2.6), the model predicted the average summer distribution of Pacific cod will shift more definitively towards the northern EBS. This is likely due to continued contraction of the cold pool during warm conditions, and as the EBS is currently the northern limit of the species' thermal tolerance, they will be able to occupy areas that were formerly covered by the cold pool (Ciannelli and Bailey 2005, Mueter and Litzow 2008). This northward movement aligns with other studies predicting similar latitudinal shifts in marine species as they track suitable environmental conditions under climate change (Dulvy *et al.* 2008, Mueter and Litzow 2008, Vestfals *et al.* 2016, Rooper *et al.* 2021).

Impacts of shifting fish distributions on Alaskan communities

This study found that areas along the southern EBS face the highest risk to community level socioeconomic outcomes resulting from climate-driven redistributions of Pacific cod. This arises in part from high levels of reliance and the extent of Pacific cod's shifting range. Among the seven census areas included in this study, Aleutians East was the only region to be categorized as high risk across all scenarios. Rural regions with low educational attainment, employment opportunities, and high unemployment are among the most sensitive to climate driven change. This trend aligns with previous indicator-based sensitivity assessments, which have identified rural and

economically constrained communities are particularly sensitive to ocean acidification (Mathis *et al.* 2015), climate change (Allison *et al.* 2009), and changes in general ocean health (Halpern *et al.* 2012).

The time communities have to adapt their fishing behaviours to mitigate losses varies under different warming scenarios, based on when sustained spatial shifts in Pacific cod distributions are projected to occur. As this study demonstrates, if future conditions align with SSP1-2.6 projections, fishers may have more time to develop long-term adaptation strategies, as sustained distribution shifts beyond those observed during anomalously warm years are unlikely to occur until the late century. Conversely, under SSP5-8.5 projections, fishers will need to adapt by mid-century to mitigate losses due to changes in the fishery. This perspective, however, does not account for the current multi-year variability in environmental conditions and the impact of this that is already being observed in the fishery. Small-scale fishers in Alaska are already being required to adapt, or they risk significant losses, depending on the environmental conditions each year. This is likely a substantial force driving fishing communities' sensitivity to climate effects, as they are being required to alter fishing behaviour interannually.

Fisheries participants have historically employed a variety of adaptive strategies in response to shifting conditions, including expanding the number of species they target to create more diverse fishing portfolios (Cline *et al.* 2017, Young *et al.* 2019, Robinson *et al.* 2020), shifting to new fishing locations (Papaioannou *et al.* 2021, Young *et al.* 2019), modifying gear or harvesting practices (Papaioannou *et al.* 2020, Young *et al.* 2019, Szymkowiak and Rhodes-Reese 2020), and in some cases, leaving the fishery entirely to seek other livelihoods (Young *et al.* 2019, Szymkowiak and Rhodes-Reese 2020). Small-scale and subsistence fishers in Alaska have responded to climate-driven changes with a range of strategies, including investing in climate-resilient infrastructure, seeking diversification through emerging boutique fisheries, and adjusting subsistence practices and sharing networks to reflect shifting species availability (Hollowed *et al.* 2022).

The ability of fishing communities to adapt to climate-driven changes in the distribution of marine species is constrained by social, technical, and economic factors (Holsman *et al.* 2019, Ojea *et al.* 2020, Abbott *et al.* 2023). Adaptive strategies, such as portfolio diversification or shifting fishing grounds, present significant challenges, including the necessity of changing gear types, the high cost of entry for permits, and the need for new knowledge and skills to effectively exploit different fish stocks (Seara *et al.* 2020, Papaioannou *et al.* 2021, Powell *et al.* 2022). Additionally, the financial burden associated with these changes can be prohibitive for many fishers, particularly those in small-scale or subsistence fisheries (Papaioannou *et al.* 2021, Powell *et al.* 2022). In addition to these barriers, small-scale fishers in Alaska have reported safety concerns that limit their ability to shift fishing grounds, as well as hesitation to investment in technical modernization and innovation due to uncertainty about future fishing conditions (Hollowed *et al.* 2022).

Beyond individual responses, global experiences highlight the importance of systemic and community-level strategies to support long-term adaptation in fisheries. Across several countries, effective responses to climate-driven shifts in marine ecosystems have emphasized co-management structures, the incorporation of Indigenous and place-based knowledge,

government assisted investments in adaptive infrastructure, and increased coordination across governance scales (Bennett et al. 2016, Carter 2019, Hoerterer et al. 2020, Galappaththi et al. 2022). These efforts move beyond short-term coping mechanisms to foster adaptation pathways that align with local priorities and cultural values. However, changes in fishing behaviour due to environmental change can disrupt long-standing traditions, threaten cultural heritage, and undermine the social cohesion and identity of fishing communities (Meier et al. 2014, Bennett 2018, Salomon et al. 2019, Ojea et al. 2020, Pisor et al. 2023). Without intentional support, such disruptions can contribute to social exclusion or reinforce poverty traps, further exacerbating the community specific sensitivity to climate effects (Cinner and Barnes 2019). Preserving cultural continuity is as essential to fishery resilience as ensuring economic viability (Pinkerton 2017), and adaptation strategies that integrate cultural identity are increasingly recognized as key components of resilient fisheries systems (Johnson et al. 2014, Pisor et al. 2023).

The findings of this study highlight the need for adaptive management strategies that can respond to both short-term fluctuations and long-term trends in Pacific cod distributions. In the early-to-middle century, management efforts will need to focus on regulating harvest levels across both the northern and southern EBS as distributions fluctuate. However, as the century progresses, management attention should shift towards addressing the challenges posed by a more fixed summer population of Pacific cod in the northern EBS. The impact of climate change on the EBS Pacific cod fishery necessitates a regionally tailored management approach to ensure the sustainability of the fishery. Managers and community members can play a crucial role in encouraging rapid adaptation, which will be essential to mitigating socioeconomic risk in fishing reliant communities, through promoting information sharing across social networks (Barnes et al. 2016), investment in infrastructure (Olson and Clay 2007), and implementation of strategies to improve community and fishery resilience (Cinner et al. 2018, Cinner and Barnes 2019, Holsman et al. 2019, Ojea et al. 2020). Drawing on lessons from other regions, such approaches may include emphasis on community-led planning, intergenerational knowledge transfer, multi-level governance coordination, or workforce retraining (Bennett et al. 2016, Carter 2019, Hoerterer et al. 2020, Galappaththi et al. 2022, Mason et al. 2023). Initiatives supporting intergenerational knowledge transfer, tribal governance, and culturally grounded adaptation planning may be especially relevant in the Alaskan context.

Overall total risk

The overall picture of risk presented by this study aligns with global trends in the regional disparities in sensitivity to climate-driven changes in fisheries (Allison et al. 2009, Blasiak et al. 2017, Ding et al. 2017, Tigchelaar et al. 2021). Census areas in the southern region of the EBS, such as Aleutians East and Bethel, consistently exhibited higher total scores across multiple scenarios and components of risk. The convergence of high exposure, sensitivity, and relatively low adaptive capacity in these southern EBS areas underscores their heightened sensitivity to the adverse effects of shifting Pacific cod distributions.

When quantifying risk reduction through incorporating adaptive capacity into the risk model, four census areas

demonstrated increased risk to changes in Pacific cod distributions. These areas had the lowest adaptive capacity scores, indicating the ability of a community to respond to and mitigate the impact of shifting Pacific cod distributions plays a substantial role in determining overall risk levels. This finding aligns with previous research on the role of adaptive capacity in shaping community sensitivity to fisheries changes in Alaska (Himes-Cornell and Kasperski 2016). These results emphasize the importance of increasing adaptive capacity at the community level through targeted interventions that support alternative livelihoods or remove barriers to portfolio diversification and underscores the need for localized management strategies.

Limitations

The assumption that community engagement with the Pacific cod fishery remains constant over time does not account for the dynamic relationship between fishery engagement and Pacific cod distributions. As Pacific cod populations shift geographically due to changing oceanic conditions, small-boat fishers may struggle to adapt without implementing adaptations that are financially or culturally disruptive, thereby limiting their ability to adjust and exacerbating their sensitivity to climate effects (Rogers et al. 2019, Ojea et al. 2020). Similarly, the socioeconomic variables employed in this risk assessment were assumed to remain static over time, overlooking potential changes in economic, social, and infrastructural factors that could influence community resilience and adaptability. These socioeconomic variables, such as income levels, employment rates, and educational attainment are often interdependent and shaped by external influences, making it difficult to isolate individual impacts (Beckley 1995, Fedderke and Klitgaard 1998, Himes-Cornell and Kasperski 2016).

Data handling posed challenges due to the disparities in variables, which were sometimes measured in different units (total, %, per capita) and varying temporal scales (bimonthly, annual, decadal). When data gaps were encountered, we averaged values across years or subregions when possible. Additionally, some datasets, particularly those related to subsistence use, were infrequently and inconsistently surveyed across communities. We also faced challenges when attempting to spatially relate marine geographical areas to coastal census areas, which necessitated having the same hazard for multiple census areas.

The primary limitation of this study stems from the scaling methodology used. Due to the confidential nature of much of the fishery-specific socioeconomic data and the necessary scaling for inclusion in the analysis, the census areas examined can only be compared to one another. Consequently, the results do not necessarily reflect actualized risk but rather represent relative risk compared to the other census areas within the study. This approach means that, while we can identify which areas are at higher or lower risk relative to each other, we cannot generalize these findings to absolute risk levels or compare them to other regions outside the study area.

Future directions

This study provides a valuable framework for assessing the impacts of anthropogenic climate change on a single fishery and evaluates the level of risk posed to coastal communities reliant on Pacific cod. While conducting large-scale fishery assessments in response to climate change is essential, under-

standing and addressing fine scale impacts on individual fisheries and reliant human communities is equally valuable to ensure sustainable harvests and continued economic success for these communities. However, we acknowledge that this study alone is insufficient for capturing total fishing community risk to climate-driven distribution changes in Alaska fisheries.

This paper focuses on the initial phase of the project to use an indicator-based risk framework, with the aim of identifying broad-scale patterns across the region. We recognize that this approach, while methodologically consistent, is limited in depth and nuance that will be enhanced through direct engagement with Bering Sea communities in subsequent phases. Future work will incorporate participatory mixed-methods approaches to better understand the social and institutional dimensions of adaptive capacity from the communities' perspectives. By incorporating community perspectives, future risk assessment research will be better grounded in local realities and priorities, which would ensure that the findings are on a relevant and actionable scale for communities. Further, similar future research should account for the multi-year variability in environmental conditions in the EBS as a driver of community sensitivity to climate effects. Incorporating dynamic socioeconomic models that consider potential adaptive strategies and changing social landscapes will provide a more comprehensive understanding of community sensitivity and resilience in the face of climate-driven changes in the distributions of many marine resources.

While our framework focuses on risk of adverse impacts, it is equally important to recognize that regions projected to experience increases in Pacific cod abundance may benefit from new opportunities available to them. In these cases, shifts in species distributions could generate new economic possibilities and enhance community resilience, especially where increases in abundance coincides with high adaptive capacity. Future work could build on this risk framework by incorporating an opportunity dimension, which would allow for a more balanced assessment of how climate-driven changes in species distributions may alter access to Alaska fisheries.

Although this study focuses on Pacific cod, other commercially and culturally important species in the Bering Sea, such as snow crab and walleye pollock, are also undergoing climate-driven shifts in their distributions (Stevenson and Lauth 2019, Szwalski *et al.* 2023a) which could compound or mitigate the risk associated with cod declines. Future analyses that include multiple species would offer a more comprehensive picture of the changing resources available to communities. Additionally, including a wider range of socioeconomic variables that contribute to adaptive capacity and reliance, such as average food cost, raw fish tax, and vessel size could enhance the robustness of the findings and provide a more comprehensive picture of the economic landscape. Similar analyses should include more census areas to make broader statements about overall risk within Alaska.

By demonstrating the application of single-fishery assessments and the incorporation of dynamic models, this research provides a framework for understanding the sensitivity of fishing reliant communities in Alaska to climate-driven impacts and resultant community-level risk of adverse impacts from climate change. The findings of this study can guide the development of community-specific management plans that incorporate local knowledge and address unique socioeconomic challenges. By identifying community specific risk to climate-driven changes in Alaska fisheries, management efforts can be

more locally tailored to help enhance the resilience of these communities.

Acknowledgements

The authors would like to acknowledge and thank all colleagues who provided valuable feedback, especially the members of the Alaska Climate Integrated Modeling project. We would also like to thank NOAA-AFSC for making data available from bottom trawl surveys and vessel trip reports.

Author contributions

Sarah E. Stone (Conceptualization [equal], Data curation [lead], Formal analysis [lead], Investigation [lead], Methodology [equal], Project administration [lead], Software [lead], Visualization [lead], Writing – original draft [lead], Writing – review & editing [lead]), Sarah Wise (Conceptualization [equal], Data curation [supporting], Formal analysis [supporting], Methodology [supporting], Writing – review & editing [supporting]), Michael Harte (Conceptualization [equal], Methodology [supporting], Writing – review & editing [supporting]), Kirstin Holsman (Conceptualization [equal], Methodology [supporting], Writing – review & editing [supporting]), and Lorenzo Ciannelli (Conceptualization [equal], Data curation [supporting], Formal analysis [supporting], Investigation [supporting], Methodology [supporting], Software [supporting], Visualization [supporting], Writing – review & editing [supporting]).

Supplementary data

Supplementary data is available at *ICES Journal of Marine Science* online.

Conflict of interest: The authors declare no competing interests.

Funding

This research was partially supported by the Cooperative Institute for Climate, Ocean, and Ecosystem Studies (Award Number: UWSC15757).

Data availability

Data on socioeconomic fisheries variables are confidential. All other data and the associated code are available from the corresponding author upon request.

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Handling Editor: Mark Gibbs