nature climate change

LETTERS

https://doi.org/10.1038/s41558-019-0503-z

Shifting habitats expose fishing communities to risk under climate change

Lauren A. Rogers[1,8]*, Robert Griffin[1,2], Talia Young[3,4,5], Emma Fuller[4], Kevin St. Martin[6] and Malin L. Pinsky[7]

Climate change is expected to have a profound impact on the distribution, abundance and diversity of marine species globally[1,2]. These ecological impacts of climate change will affect human communities dependent on fisheries for livelihoods and well-being[3]. While methods for assessing the vulnerability of species to climate change are rapidly developing[4] and socio-ecological vulnerability assessments for fisheries are becoming available[5], there has been less work devoted to understanding how impacts differ across fishing communities. We developed a linked socio-ecological approach to assess the exposure of fishing communities to risk from climate change, and present a case study of New England and Mid-Atlantic (USA) fishing communities. We found that the northern part of the study region was projected to gain suitable habitat and the southern part projected to lose suitable habitat for many species, but the exposure of fishing communities to risk was strongly dependent on both their spatial use of the ocean and their portfolio of species caught. A majority of fishing communities were projected to face declining future fishing opportunities unless they adapt, either through catching new species or fishing in new locations. By integrating climatic, ecological and socio-economic data at a scale relevant to fishing communities, this analysis identifies where strategies for adapting to the ecological impacts of climate change will be most needed.

Climate change is altering the distribution, abundance and diversity of marine species globally[1,2,6]. On a local scale, conditions will become more favourable for some species and less favourable for others, which will ultimately alter the mix of species available for harvesting in any given coastal ecosystem. Despite widespread acknowledgement that climate change is a key challenge for sustainable fisheries and communities[7,8], we have limited understanding of the relative exposure of fishing communities to climate change risk. Such information is critical for creating adaptation policies, prioritizing research and management efforts and for reducing community exposure to risk on the ground[7].

Ecological risk or vulnerability assessments identify which species or populations may be most at risk from climate change or other stressors. For fisheries, these assessments are usually aimed at the species or stock level (for example, ref. [4]). However, a fishing community's exposure to risk is dependent not only on which species or stocks it targets, but where in the ocean it targets them and how much flexibility it has to adapt to new conditions. Socio-ecological risk assessments can link ecological risk to community vulnerability[3,5], but methods to do so at the appropriate scale for adaptation planning are not well developed.

While fish species may shift in response to climate change[6], fishers are often limited in where they can fish based on local ecological knowledge, vessel size or gear type, geographic distance, spatial management or conservation measures and, in some cases, customary territories[9]. Peer groups of vessels from the same port and using the same gear type are often subject to a common set of spatial constraints (for example, shared local ecological knowledge, vessel mobility) and, as a result, typically exhibit distinct and relatively enduring spatial patterns of ocean use[10,11]. The 'communities-at-sea' concept[11] recognizes that shared patterns of ocean use indicate shared spatial constraints, as well as resident community processes and practices that shape both community identity and the capacity to adapt and respond to environmental change[12]. The community-at-sea concept was developed based on communities in the Northeast region of the USA (NEUS), but could be applied more generally to identify groups of fishers likely to face similar challenges and opportunities under climate change.

To develop and test socio-ecological methods used for assessing the exposure of fishing communities to risk under climate change, we integrated climatic, ecological and socio-economic data from the NEUS at the scale of communities-at-sea. First, we quantified the spatial patterns of projected changes in habitat suitability for individual species under climate change. We then linked these projected ecological changes to information on fishing community practices to assess the level of exposure to risk for fishing communities based on their harvest portfolios and spatial use of the ocean. We discuss these results in light of adaptation possibilities and barriers. Providing local-scale information on the projected changes to species habitat, and on the exposure of coastal communities to these changes, is an important step towards creating climate adaptation plans and prioritizing adaptation actions and investments.

Species distribution models fit to more than 40 years of scientific survey data indicated that temperature was a significant predictor of species occurrence in space and time based on out-of-sample predictive skill (Supplementary Table 1). For the majority of species (24 of 33), habitat was projected to improve in some regions of the NEUS shelf but to deteriorate in others by 2040–2050 (Fig. 1b). For instance, monkfish habitat was expected to expand in the Gulf

[1]The Natural Capital Project, Stanford University, Stanford, CA, USA. [2]Department of Fisheries Oceanography, School of Marine Science and Technology, University of Massachusetts, Dartmouth, New Bedford, MA, USA. [3]Department of Marine and Coastal Science, Rutgers University, New Brunswick, NJ, USA. [4]Department of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ, USA. [5]Graduate Program in Ecology and Evolution, Rutgers University, New Brunswick, NJ, USA. [6]Department of Geography, Rutgers University, New Brunswick, NJ, USA. [7]Department of Ecology, Evolution, and Natural Resources, Rutgers University, New Brunswick, NJ, USA. [8]Present address: Alaska Fisheries Science Center, National Marine Fisheries Service, National Oceanic and Atmospheric Administration, Seattle, WA, USA. *e-mail: lauren.rogers@noaa.gov

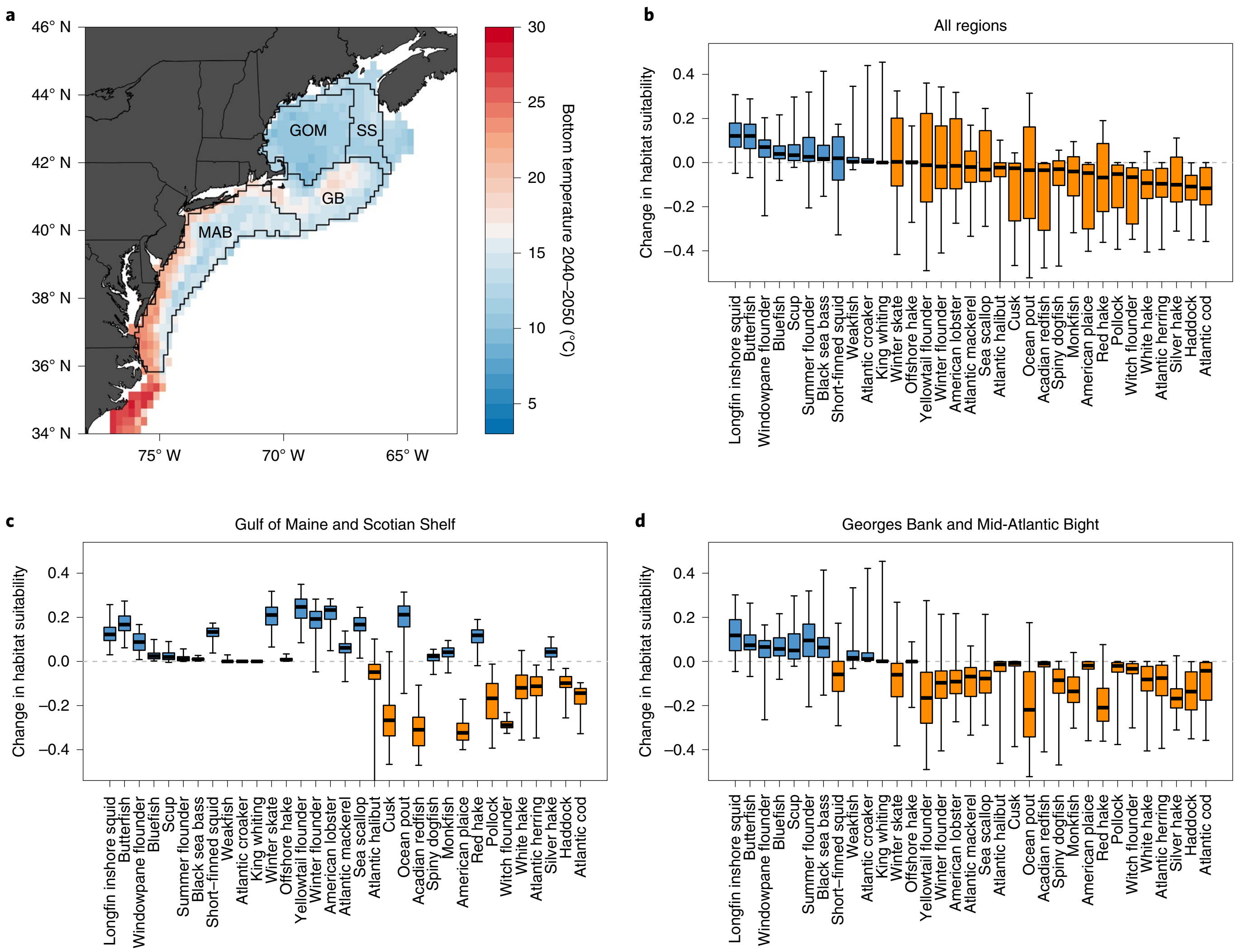

Fig. 1 | Projected changes in the thermal environment and species-specific habitat suitability on the NEUS shelf. a, Mean projected future (2040–2050) bottom temperatures for the months September–November, calculated to correspond to historical survey timing. The Gulf of Maine (GOM), Scotian Shelf (SS), Georges Bank (GB) and Mid-Atlantic Bight (MAB) are indicated. **b–d**, The distributions (summarizing across space) of projected changes in habitat suitability for 33 species are shown for the entire shelf (**b**), GOM and SS (**c**) and GB and MAB (**d**). Positive values indicate an increase in suitability in 2040–2050 over 1963–2005. Boxes show the median, 25th and 75th percentiles, and whiskers show the full range. Colours indicate whether the median is above (blue) or below (orange) zero.

of Maine (GOM) but become less suitable throughout the Mid-Atlantic Bight (Fig. 1c,d). Only two species were expected to have improved habitat throughout the region, while seven were expected to have generally decreased habitat suitability (Fig. 1b). Atlantic cod was one of the species expected to experience entirely negative impacts, and temperatures even in the coldest areas were expected to exceed the thermal optimum for cod by 2050. In fact, rapid warming in the past decade has already contributed to the collapse of GOM cod[13]. In general, the northern part of the study region was expected to have more 'winners' (species gaining habitat suitability) while the Mid-Atlantic Bight and Georges Bank had more 'losers' (species losing suitability). However, we included only species that were historically common in the trawl survey, thus missing species that may expand into the Mid-Atlantic in a warmer future.

Fishing communities varied drastically in the size and location of their servicesheds, or customary fishing grounds (see Methods, Supplementary Fig. 1 and Supplementary Table 2). Of the four vessel/gear types examined here, communities of large bottom trawlers (>20 m) had the largest servicesheds (mean, 40,000 km^2), extending often to the continental shelf break. Communities of small trawlers typically utilized much smaller areas (mean, 4,300 km^2) closer to port. Beyond gear type, even nearby communities showed little overlap in their spatial use of the marine environment in some cases (Supplementary Fig. 2). These geographic differences translated into different exposures of fishing communities to the ecological impacts of climate change, even when targeting the same species (for example, among gillnetters harvesting monkfish in Massachusetts; Fig. 2).

Ultimately, fishing community exposure to risk (defined as projected changes in resource availability due to changes in habitat) is dependent on both its spatial use of the ocean and the portfolio of species caught. Revenue-weighted risk scores showed that a majority (64 of 85) of communities were exposed to increased risk by mid-century (Fig. 3), suggesting declines in future fishing opportunities based on current practices. Exposure varied by state and vessel/gear type ($P < 0.01$; Supplementary Fig. 3). Communities of small trawlers in Maine were most exposed because of their historical dependence on species expected to lose habitat suitability in the future

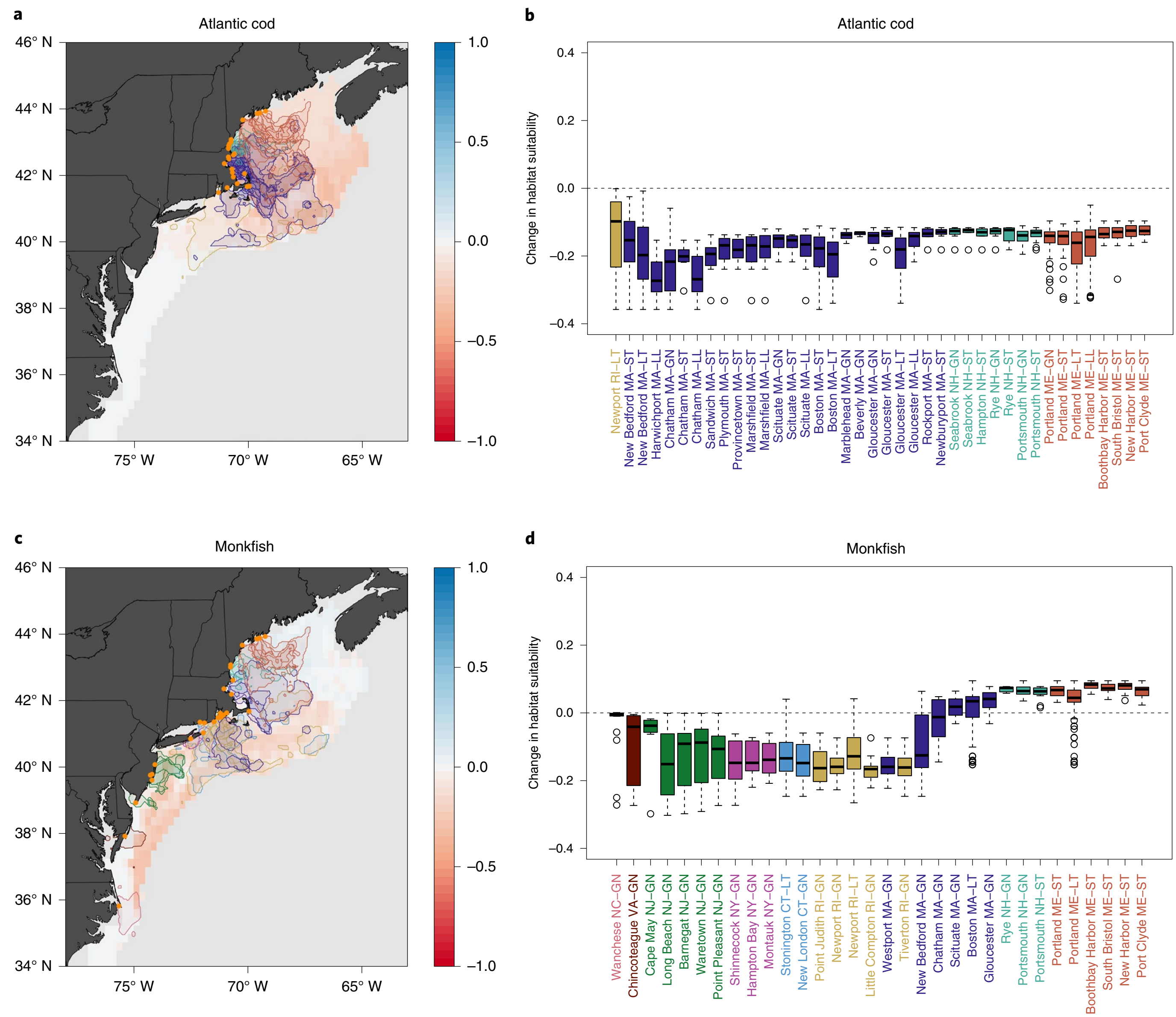

Fig. 2 | Projected changes in habitat suitability for Monkfish and Atlantic cod within community servicesheds. a,**c**, Maps showing projected changes in habitat suitability by mid-century (2040–2050) for Atlantic cod (**a**) and monkfish (**c**). Blue indicates improved habitat suitability while red indicates reduced habitat suitability. Overlaid are outlines of servicesheds for communities-at-sea for which the species makes up at least 5% of revenues, coloured by state to match **b** and **d**. Ports for individual communities are indicated by orange circles. **b**,**d**, Boxplots summarize predicted changes in habitat suitability for species within the serviceshed for each community. Boxplots show the median, 25th and 75th percentiles, and whiskers show 1.5-times the interquartile range. Boxplots are coloured by state and arranged from south to north on the *x* axis. Vessel/gear type is indicated in the label for each community by either ST (small trawl), LT (large trawl), GN (gillnet) or LL (longline).

(for example, Atlantic cod and witch flounder). However, we also found small-scale differences. For instance, communities-at-sea for small groundfishing vessels in Sandwich and Chatham, MA were only 45 km apart but had different risk profiles due to their differing catches and non-overlapping servicesheds (Supplementary Fig. 4). The Sandwich community was dependent on winter flounder (67% of revenue), cod (8%) and yellowtail flounder (5%), while Chatham's community had the greatest contributions to revenue from witch flounder (24%), cod (21%) and winter flounder (10%). Sandwich was expected to be less exposed to risk and to have increased opportunities under climate change, whereas nearby Chatham was projected to be exposed to increasing risk. Notably, all but three out of 85 communities in this study have historically targeted at least one species that was projected to gain habitat within their serviceshed under climate change (Fig. 3).

By combining biophysical projection models with community-level data on fishing practices, we show that the exposure of fishing communities to climate risk is dependent not only on biophysical changes in the ocean, but also on how those changes intersect with community practices. Communities differ substantially in the species they target and where they target them, resulting in different risk profiles for communities even in close proximity. These findings echo community impacts that have been documented when areas of the ocean have been closed to fishing[14], but in this case the impacts were driven by a changing environment. Our species-level results are broadly consistent with previous projections of

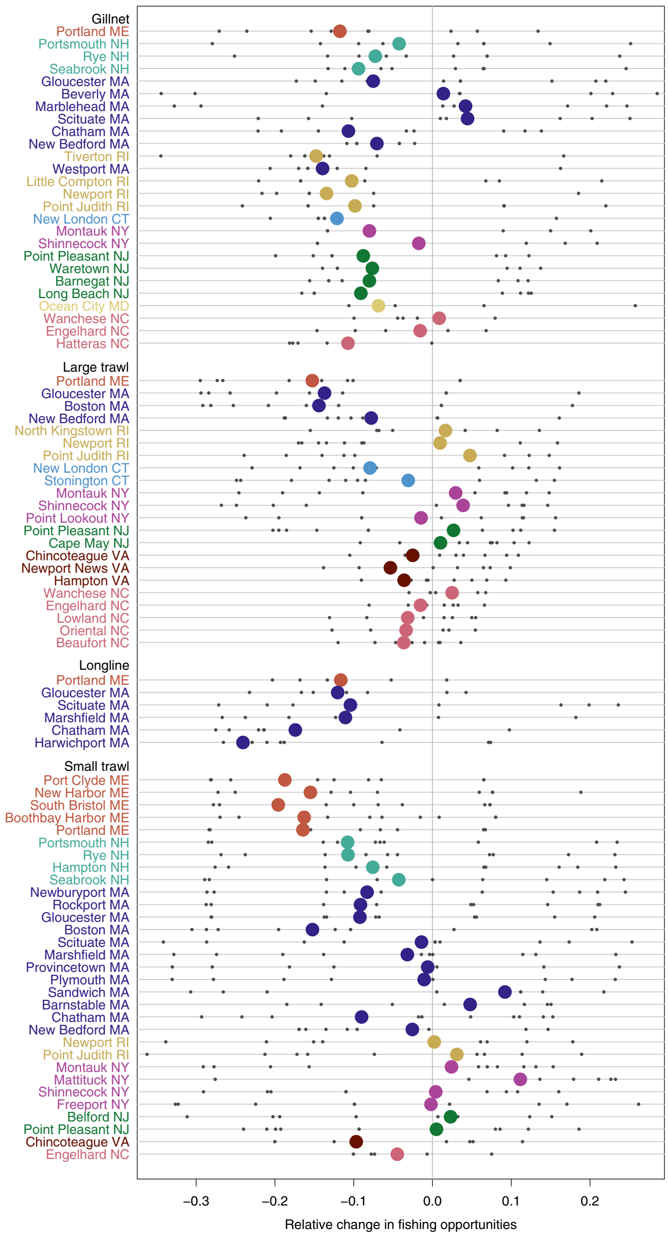

Fig. 3 | Exposure of communities-at-sea to risk from climate change impacts on harvested species. Coloured circles show revenue-weighted risk scores. Positive values indicate expanding opportunities for communities based on their historical fishing revenue portfolios and projected changes to species habitat at sea, while negative values indicate shrinking opportunities and increased exposure to risk. Within each gear type, ports are ordered by latitude and coloured by state. Smaller black dots indicate mean change in habitat suitability for individual species that contribute to the community risk score (that is, those that have historically comprised at least 5% of the revenues for a community).

climate change impacts in the region (refs. [4,15]; Supplementary Table 3, Supplementary Figs. 5 and 6 and Supplementary Discussion). However, by considering variation in habitat alongside differing community practices, we captured variation relevant at the scale of communities. This emphasizes the importance of considering heterogeneity in both community practices and ecological responses when evaluating exposure to risk.

Our analysis indicated which communities-at-sea were most exposed to risk and most likely to need to adapt to a changing environment. Adaptation at the community level will probably require either shifting where vessels fish to follow their target species[16] or rebalancing the species caught, towards winners rather than losers. In both cases, the speed at which a community might adapt will be determined by a range of factors. Evidence suggests that the overwhelming determinant of where fishers fish is their historical pattern of fishing[10]. This context suggests that fishers will be slow to adapt to distributional shifts, preferring instead traditional fishing grounds over new, less familiar, locations. Information sharing through social networks can lead to faster adaptation[14,17] but, while fishers in the NEUS have strong social capital in general, information sharing has been declining[18]. Practical and regulatory considerations also shape how easily communities can follow their target species through space. Small vessels are limited in how far they can travel from port[16], and all vessels face travel costs. Shoreside infrastructure requirements and regulations dictating where species may be landed further hinder the ability of communities to move fishing grounds[19]. Differences among communities in their responses to ongoing shifts in fish distributions have already been observed, including in the NEUS[16,20] and Alaska[21], and probably reflect community-specific constraints to adaptation.

We have assessed the exposure of communities to risk based on their recent catch and revenue portfolios. However, one of the most important ways that communities can adapt to a changing ocean environment is by shifting their species portfolio. There is evidence that this is already happening, including the blueline tilefish fishery that emerged north of Cape Hatteras, NC in the early 2000s[22]; new fisheries for squid, John dory, red mullet and sea bass that have emerged in the United Kingdom[23]; and squid fisheries in the Gulf of Maine that developed during the particularly hot summer of 2012 (ref. [24]). However, there are also constraints to switching to new species, including limited entry in many fisheries or the high cost of permits or quota shares[25]. Catch diversification can buffer fishers and communities against ocean change[16,25,26], but market forces can also incentivize specialization[27]. Additional research is needed to understand how regulatory, economic, social and other incentives shape adaptive capacity in fishing communities.

The type of community risk profiles we developed may be useful for climate adaptation in practice. Long-term projections for a community can help guide strategic decisions by individual fishers, processors or other business owners about investment and divestment in permits, quotas, boats, gear or in the time spent gaining or maintaining the local ecological knowledge to fish for particular species[8]. Risk profiles could help guide strategic decisions by a port or municipality about infrastructure investment, community cooperatives or the role of fishing in the local economy, especially when considered alongside indicators of social vulnerability[5]. For a fisheries manager, understanding how fishing opportunities will change for communities can be important for charting out adaptation pathways and removing barriers along those pathways[28].

Notwithstanding the potential utility of our projections, several caveats should be noted. Temperature structures the physiology of marine species[29], but the species distribution models that we used detected correlations (not causation) and did not consider parameters such as pH or oxygen. The models implicitly assumed that species distributions were in equilibrium with their environment, that species interactions, phenology, disease and acclimation will stay the same in the future and that evolution will not be important. We explored parametric uncertainty (Supplementary Fig. 7), but future work should also explore structural uncertainty and sensitivity to the climate model. Coarse-scale global climate models, for example, may underestimate future warming on the NEUS shelf[30].

Our work highlights the importance of matching ecological and social scales in climate vulnerability assessments. We suggest that, to assess vulnerability at scales relevant to fishing communities, finer-scale information on both ecological processes and community practices is needed. Habitat heterogeneity and its interaction with species preferences results in spatial variation in impacts to species. Overlaid on these are enduring and unique patterns of ocean use by fishing communities that result in differential exposure of communities to climate change risk. Integrated, data-driven socio-ecological approaches can advance adaptation planning in communities dependent upon climate-sensitive resources.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of code and data availability and associated accession codes are available at https://doi.org/10.1038/s41558-019-0503-z.

Received: 9 November 2018; Accepted: 13 May 2019;
Published online: 17 June 2019

References

1. Sydeman, W. J., Poloczanska, E., Reed, T. E. & Thompson, S. A. Climate change and marine vertebrates. *Science* **350**, 772–777 (2015).
2. Cheung, W. W. L. et al. Projecting global marine biodiversity impacts under climate change scenarios. *Fish. Fish.* **10**, 235–251 (2009).
3. Allison, E. H. et al. Vulnerability of national economies to the impacts of climate change on fisheries. *Fish. Fish.* **10**, 173–196 (2009).
4. Hare, J. A. et al. A vulnerability assessment of fish and invertebrates to climate change on the Northeast U.S. continental shelf. *PLoS ONE* **11**, 1–30 (2016).
5. Colburn, L. L. et al. Indicators of climate change and social vulnerability in fishing dependent communities along the Eastern and Gulf Coasts of the United States. *Mar. Policy* **74**, 323–333 (2016).
6. Pinsky, M. L., Worm, B., Fogarty, M. J., Sarmiento, J. L. & Levin, S. A. Marine taxa track local climate velocities. *Science* **341**, 1239–1242 (2013).
7. Miller, D. D., Ota, Y., Sumaila, U. R., Cisneros-Montemayor, A. M. & Cheung, W. W. L. Adaptation strategies to climate change in marine systems. *Glob. Change Biol.* **24**, e1–e14 (2018).
8. Sumaila, U. R., Cheung, W. W. L., Lam, V. W. Y., Pauly, D. & Herrick, S. Climate change impacts on the biophysics and economics of world fisheries. *Nat. Clim. Change* **1**, 449–456 (2011).
9. St Martin, K. Making space for community resource management in fisheries. *Ann. Assoc. Am. Geogr.* **91**, 122–142 (2001).
10. Holland, D. S. & Sutinen, J. G. Location choice in New England trawl fisheries: old habits die hard. *Land Econ.* **76**, 133 (2000).
11. St. Martin, K. & Hall-Arber, M. The missing layer: geo-technologies, communities, and implications for marine spatial planning. *Mar. Policy* **32**, 779–786 (2008).
12. St. Martin, K. & Olson, J. in *Conservation for the Anthropocene Ocean* 123–141 (Academic Press, 2017); https://doi.org/10.1016/B978-0-12-805375-1.00007-6
13. Pershing, A. J. et al. Slow adaptation in the face of rapid warming leads to collapse of the Gulf of Maine cod fishery. *Science* **350**, 809–812 (2015).
14. Murray, G. et al. Creeping enclosure, cumulative effects and the marine commons of New Jersey. *Int. J. Commons* **4**, 367–389 (2010).
15. Kleisner, K. M. et al. Marine species distribution shifts on the U.S. Northeast Continental Shelf under continued ocean warming. *Prog. Oceanogr.* **153**, 24–36 (2017).
16. Young, T. et al. Adaptation strategies of coastal fishing communities as species shift poleward. *ICES J. Mar. Sci.* **76**, 93–103 (2019).
17. Barnes, M. L., Lynham, J., Kalberg, K. & Leung, P. Social networks and environmental outcomes. *Proc. Natl Acad. Sci. USA* **113**, 6466–6471 (2016).
18. Holland, D. S., Pinto da Silva, P. & W. Kitts, A. Evolution of social capital and economic performance in New England harvest cooperatives. *Mar. Resour. Econ.* **30**, 371–392 (2015).
19. Dubik, B. A. et al. Governing fisheries in the face of change: social responses to long-term geographic shifts in a U.S. fishery. *Mar. Policy* **99**, 243–251 (2019).
20. Pinsky, M. L. & Fogarty, M. Lagged social-ecological responses to climate and range shifts in fisheries. *Clim. Change* **115**, 883–891 (2012).
21. Watson, J. T. & Haynie, A. C. Paths to resilience: the walleye pollock fleet uses multiple fishing strategies to buffer against environmental change in the Bering Sea. *Can. J. Fish. Aquat. Sci.* **75**, 1977–1989 (2018).
22. Pinsky, M. L. et al. Preparing ocean governance for species on the move. *Science* **360**, 1189–1191 (2018).
23. Cheung, W. W. L., Pinnegar, J., Merino, G., Jones, M. C. & Barange, M. Review of climate change impacts on marine fisheries in the UK and Ireland. *Aquat. Conserv. Mar. Freshw. Ecosyst.* **22**, 368–388 (2012).
24. Mills, K. et al. Fisheries management in a changing climate: lessons from the 2012 ocean heat wave in the Northwest Atlantic. *Oceanography* **26**, 191–195 (2013).
25. Anderson, S. C. et al. Benefits and risks of diversification for individual fishers. *Proc. Natl Acad. Sci. USA* **114**, 10797–10802 (2017).
26. Cline, T. J., Schindler, D. E. & Hilborn, R. Fisheries portfolio diversification and turnover buffer Alaskan fishing communities from abrupt resource and market changes. *Nat. Commun.* **8**, 1–7 (2017).
27. Kasperski, S. & Holland, D. S. Income diversification and risk for fishermen. *Proc. Natl Acad. Sci. USA* **110**, 2076–2081 (2013).
28. Pinsky, M. L. & Mantua, N. J. Emerging adaption approaches for climate ready fisheries management. *Oceanography* **27**, 146–159 (2014).
29. Sunday, J. M., Bates, A. E. & Dulvy, N. K. Thermal tolerance and the global redistribution of animals. *Nat. Clim. Change* **2**, 686–690 (2012).
30. Saba, V. S. et al. Enhanced warming of the Northwest Atlantic Ocean under climate change. *J. Geophys. Res. Ocean.* **121**, 118–132 (2016).

Acknowledgements

We thank A. Guerry and M. Ruckelshaus whose insights shaped the early development of this project. We thank NOAA-NEFSC for making data available from bottom trawl surveys and vessel trip reports, particularly M. Fogarty, J. Olson and S. Lucey. We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups for producing and making available their model output. T. Frölicher helped with processing of the CMIP5 data. Funding for this project was provided by the Gordon and Betty Moore Foundation and by the National Science Foundation (No. OCE-1426891). E. F. and T. Y. were supported by NSF (Nos. GRFP & GEO-1211972 and GRFP DGE: 0937373, respectively).

Author contributions

L.A.R., R.G. and M.L.P. designed research. K.St.M. provided data and the framework for characterizing communities-at-sea and their servicesheds. L.A.R., T.Y., E.F. and M.L.P. conducted analyses. All authors contributed to conceptual development. L.A.R. and M.L.P. wrote the manuscript with input from all authors.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41558-019-0503-z.

Reprints and permissions information is available at www.nature.com/reprints.

Correspondence and requests for materials should be addressed to L.A.R.

Peer review information: *Nature Climate Change* thanks Natalie Ban and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Publisher's note: Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Methods

Bottom trawl data from the National Oceanic and Atmospheric Administration (NOAA) Northeast Fisheries Science Center (NEFSC) fall (1963–2014) surveys were used to characterize the realized thermal niches of species. At each survey station, fish of each species were counted and weighed and surface and bottom temperature measurements were taken (details in ref. [31]). Correction factors were applied to standardize catch rates for changes in vessel and gear type. A total of 33 species were selected based on their near continuous presence in the survey, as well as on their relative importance to commercial fisheries. For four species, data from 1972 onwards were used because observations were irregular before that year.

Generalized additive models were used to estimate the realized thermal niches of species. We restricted k (number of knots) to 4 or 6 for each of our covariates to ensure biologically meaningful responses. For each species, our response variable was the probability of occurrence in a trawl haul (P), and we used a binomial error structure with logit transform:

$$P_{y,j} = \text{logit}^{-1}(s(\text{ST}_{y,j}) + s(\text{BT}_{y,j}) + s(\text{meanbiomass}_y) + s(\text{rugosity}_j)) \quad (1)$$

where ST_{yj} and BT_{yj} are sea surface temperature and bottom temperature, respectively, measured at each haul location j in year y, and meanbiomass_y is the average annual catch of the species across all hauls to account for inter-annual changes in abundance due to, for example, fishing. Rugosity_j is a measure of benthic habitat roughness, measured as the terrain ruggedness index[32] using the GEBCO 2014 30-arcsecond bathymetry data (downloaded 4 February 2015 from http://www.gebco.net/). The resulting estimated smooth functions describing the relationship between probability of occurrence and temperature can be interpreted as realized thermal niches. Temperature may also be a proxy for other ecological conditions, such as prey availability. We did not include other habitat variables such as oxygen concentration or pH, because of a lack of long-term spatial data for those variables.

For each species, the change in predicted probability of occurrence under future (2040–2050) projected climate conditions was compared to historical (1963–2005) conditions for each cell within a 0.25° × 0.25° spatial grid. Because the modelled probability of occurrence included a component of catchability, values for each species were scaled by dividing by the maximum observed or predicted probability of occurrence across the study area. Positive values for a grid square indicated a projected increase in probability of occurrence, whereas negative values indicated a projected decrease in probability of occurrence. Throughout the study we refer to habitat suitability rather than probability of occurrence to specifically focus on climate-driven changes in habitat, as actual species occurrence depends on additional factors such as harvest policies.

To test whether the inclusion of temperature would provide predictive information about species presence/absence, predictive error was quantified for the full models and models without temperature covariates. Models were fit to a training dataset consisting of the first 80% of samples (1963–2004), and model predictions for the test dataset (2005–2014) were compared to observations. The mean absolute error (MAE) was calculated as

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |(f_i - y_i)| \quad (2)$$

where f_i are predictions from the model and y_i are observed data. Note that the splitting of data into testing and training datasets was performed only to assess model performance, and models fit to all available data were used for the rest of the study to best describe the realized thermal niches.

To assess the impact of uncertainty in model parameters on our results, we drew 1,000 samples from the posterior distributions for the estimated generalized additive model coefficients and then calculated predictions of historical and future probabilities of occurrence. For each cell on the projection grid, the 5th and 95th percentiles of calculated risk (change in scaled probability of occurrence) across the 1,000 simulations were taken as prediction intervals.

Future temperatures were calculated by adding projected changes in surface and bottom temperatures to surface and bottom temperature climatologies (delta method[33,34]). Climatologies were calculated from the surface and bottom temperature records in the NEFSC fall bottom trawl surveys 1963–2005. Records were averaged within 0.25°×0.25° grids within each decade, then averaged across decades to reduce the impact of changes in the number of data points available in each decade (see ref. [34]).

Projected changes in surface and bottom temperatures were calculated from a set of 13 global climate models from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (see Supplementary Table 4) under representative concentration pathway 8.5, which represents a 'business-as-usual' scenario. These models were used in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Changes were calculated as the difference between the base historical period (1963–2005) and each future year (2006–2100), averaged across the months of the climatology (September–December). Changes in temperature in each future year were additionally corrected for climate model drift, as assessed in the climate model's control simulation (no increase in greenhouse gases) by regressing temperature against year. The climate models were evaluated on a 1°× 1° grid, as is standard for these models. Models not on a 1°× 1° grid were interpolated to that scale before analysis. Changes in temperature from each model were then matched to the appropriate grid and depth of the surface and bottom temperatures in the climatology. Any grid cells in the climatology that were not directly overlapped by a grid in a climate model were interpolated with inverse distance weighting. For this study, we focused on projected conditions during the period 2040–2050 to reflect conditions approximately one human generation into the future.

Communities-at-sea are peer groups of vessels which share a gear type and are associated with a particular port (for example, vessels from New Bedford, MA that use gillnets). For vessels using trawl gear, small and large trawlers are considered separate communities according to vessel length (less than or greater than 20 m). We used vessel trip report (VTR) data for commercial fishing trips from 1996 to 2014, as reported by vessel captains, to determine the at-sea servicesheds or customary fishing grounds of communities. We use the term serviceshed to describe the area from which a community has historically received ecosystem services[35], specifically fish in this case. A trip was classified as belonging to a community if it shared the community's gear type and landing port, and the vessel either declared that port as its principal port or landed in that port at least 50% of its trips that year (see refs. [12,16]).

Once aggregated into communities, trips were then weighted by a variable ('fisherdays') indicating labour time expended on each trip: trip length (in days) multiplied by the number of crew on board (see ref. [12]). Fisherdays indicate the importance of an area at sea to a community in terms of how much time it invests in that location.

Given reported trip locations and fisherdays, we then created raster maps using a kernel density method. The resultant maps distribute fisherdays using different-sized kernels depending upon the fishery/gear type/length. Nearshore fishing was processed using a smaller kernel (7.5–10 km) than offshore fishing (10–15 km). We used the area defined by a 90% volume contour (that is, an area encompassing 90% of fisherdays) to define the customary fishing grounds or serviceshed for a community. While fishing locations are reported with some error on VTRs[36], interviews with fishers indicated that aggregate maps of servicesheds were reasonably accurate (ref. [11]; Supplementary Methods). For this analysis we focused on communities using gear that targets species also captured well in the NEFSC trawl survey (large trawlers, small trawlers, gillnet and longline). Furthermore, we analysed only those communities present in the dataset for at least 8 years. These filters resulted in a subset of 98 communities for which we assessed exposure to climate change risk.

While the VTR programme is designed to document all fishing trips by federally permitted vessels since 1994, the dataset is not complete: earlier years suffer from clear under-reporting, some Mid-Atlantic states did not collect VTR in early years, vessels without federal permits (for example, those fishing exclusively in state waters) do not file VTRs and some vessels with federal permits are occasionally exempt when fishing in state waters. Communities with fewer than three vessels were omitted, to maintain confidentiality.

To compare the relative historical importance of particular species to a community-at-sea, landings data were compiled from VTRs and summed over the available years of data for each community. Price information was extracted from NOAA Fisheries, Fisheries Statistics Division (https://www.st.nmfs.noaa.gov/st1/commercial/landings/annual_landings.html). We used the average price (per pound weight) by species, adjusted for inflation (real 2014 prices in US$), over the period for which we had community-level data. State-level prices were used when available, and otherwise regional prices were used.

We assessed a community's exposure to risk based on its historical dependence on species and spatial fishing patterns. A community was more exposed to risk if the species from which it historically earned the most revenue were projected to lose habitat in the locations where the community has traditionally fished. Specifically, risk exposure scores for communities were calculated as

$$\text{Risk}_c = \sum_{s=1}^{33} S_{s,c} \times \text{pRev}_{s,c} \quad (3)$$

where $S_{s,c}$ is the mean projected change in habitat suitability for species s across the serviceshed of community c, and $\text{pRev}_{s,c}$ is the proportion of historical revenues from fishing that the community has derived from species s. Because some communities harvested species not included in our study (for example, whelk) but which may represent significant sources of income, we computed risk for a community only if at least 70% of its historical revenues were accounted for by species included in this study, resulting in scores for 85 communities. Note that by focusing on species well sampled by the trawl survey, risk exposure scores did not include potential emergent fisheries for species expanding into the study area from the south. Positive risk exposure scores indicated expanding opportunities for communities based on their historical fishing revenue portfolios and projected changes to species habitat at sea, while negative values indicated shrinking opportunities and increased exposure to negative impacts of climate change. This approach considers the exposure of a community to risk based on its historical practices, thus highlighting when and where adaptation may be necessary. It does not attempt to predict how a community might alter its fishing grounds or catch portfolios in the future. Risk based on catch proportions was highly correlated ($r = 0.94$) with risk based on revenues (Supplementary Fig. 8).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

Many of the data analysed in this study are publicly available. NEFSC bottom trawl data may be downloaded from OceanAdapt (https://oceanadapt.rutgers.edu). Landings and price information are available from the NOAA Fisheries, Fisheries Statistics Division (https://www.st.nmfs.noaa.gov/st1/commercial/landings/annual_landings.html). The remaining data and derived quantities that support the findings of this study, including polygons of servicesheds for communities-at-sea, community-level landings data, projected changes in habitat suitability for each species and community risk exposure scores, are archived on the National Science Foundation BCO-DMO repository[37–39].

Code availability

All analyses were conducted in R v.3.4.4 (ref. [40]). Code is available from the corresponding author upon request.

References

31. Azarovitz, T. R. in *Bottom Trawl Surveys* (eds Doubleday, W. G. & Rivard, D.) 62–67 (Government of Canada Fisheries and Oceans, 1981).
32. Wilson, M. F. J., O'Connell, B., Brown, C., Guinan, J. C. & Grehan, A. J. Multiscale terrain analysis of multibeam bathymetry data for habitat mapping on the continental slope. *Mar. Geod.* **30**, 3–35 (2007).
33. Anandhi, A. et al. Examination of change factor methodologies for climate change impact assessment. *Water Resour. Res.* **47**, 1–10 (2011).
34. Hare, J. A. et al. Cusk (*Brosme brosme*) and climate change: assessing the threat to a candidate marine fish species under the US Endangered Species Act. *ICES J. Mar. Sci.* **69**, 1753–1768 (2012).
35. Tallis, H., Kennedy, C. M., Ruckelshaus, M., Goldstein, J. & Kiesecker, J. M. Mitigation for one & all: an integrated framework for mitigation of development impacts on biodiversity and ecosystem services. *Environ. Impact Assess. Rev.* **55**, 21–34 (2015).
36. DePiper, G. S. *Statistically Assessing the Precision of Self-reported VTR Fishing Locations* NOAA Technical Memo NMFS NE 229 (NOAA, 2014); https://doi.org/10.7289/V53F4MJN
37. Rogers, L. et al. *Projected changes in habitat suitability for 33 marine species on the Northeast US shelf based on species distribution models fit to bottom trawl survey data from the NOAA Northeast Fisheries Science Center* (BCO-DMO, 2019).
38. Rogers, L. et al. *Total catches and estimated revenue by species for communities-at-sea based on landings reported on Vessel Trip Reports* (BCO-DMO, 2019).
39. Rogers, L. et al. *Attributes of communities-at-sea, including the size of servicesheds and climate change risk exposure scores, determined from Vessel Trip Report (VTR) data for commercial fishing trips from 1996 to 2014* (BCO-DMO, 2019).
40. R Core Team. *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical Computing, 2018); https://www.R-project.org/

nature research

Corresponding author(s): Lauren Rogers

Last updated by author(s): Apr 17, 2019

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see Authors & Referees and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☒	☐	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☒	☐	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection.
Data analysis	All analyses were conducted in R 3.4.4 (R Core Team 2018). Code is available from the corresponding author upon request.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

Many of the data analyzed in this study are publicly available. NEFSC bottom trawl data may be downloaded from OceanAdapt (http://oceanadapt.rutgers.edu/download/). Landings and price information are available from the NOAA Fisheries, Fisheries Statistics Division (https://www.st.nmfs.noaa.gov/st1/commercial/landings/annual_landings.html). The remaining data and derived quantities that support the findings of this study, including polygons of servicesheds for communities-at-sea, community-level landings data, projected changes in habitat suitability for each species, and community risk exposure scores are archived on the National Science Foundation BCO-DMO repository (doi: tbd).

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study used existing databases to assess the risk to fishes and fishing communities from changes in thermal habitat.
Research sample	Fish species were chosen based on their representation in the bottom trawl database. Fishing communities were chosen based on their size (>=3 vessels), temporal persistence (>= 7 years) and dependence on species in this study (>70% of historical revenues).
Sampling strategy	We used existing data.
Data collection	We used existing data, much of which was collected by the NOAA Northeast Fisheries Science Center.
Timing and spatial scale	Bottom trawl data were analyzed from 1963 - 2014. Community-at-sea data from 1996 - 2014 were used in this study. The spatial scale is the Northeast US continental shelf from North Carolina to the Canadian border.
Data exclusions	Fish species were excluded if they were not consistently represented in the bottom trawl survey data. If a species was not present in the catch for at least 10 years and a minimum of 300 hauls, it was excluded. Communities-at-sea were excluded if they were too small (<3 vessels), not persistent (< 7 years), or if they did not depend primarily on species included in this study (as indicated by species catches accounting for <70% of their revenues).
Reproducibility	This was not an experimental study.
Randomization	This was not an experimental study.
Blinding	Blinding was not relevant to this study as the data were collected for purposes unrelated to this study.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology
☒	☐	Animals and other organisms
☒	☐	Human research participants
☒	☐	Clinical data

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging