

1 **Shifting habitats expose fishing communities to risk under climate**
2 **change**

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22 **Introductory paragraph**

23 Climate change is expected to profoundly impact the distribution, abundance, and diversity of
24 marine species globally (1, 2). These ecological impacts of climate change will affect human
25 communities dependent on fisheries for livelihoods and wellbeing (3). While methods for assessing
26 the vulnerability of species to climate change are rapidly developing (4) and socio-ecological
27 vulnerability assessments for fisheries are becoming available (5), there has been less work to
28 understand how the ecological impacts of climate change will differentially affect fishing
29 communities. We developed a linked socio-ecological approach to assess the exposure of fishing
30 communities to risk from climate change that draws on nearly two decades of data on fishing
31 community practices and five decades of surveys on marine fish and the physical environment.
32 Using a case study of New England and Mid-Atlantic (USA) fishing communities, we found that
33 community-level differences in fishing practices, together with spatial differences in projected
34 habitat suitability for species, led to a wide range of exposures to risk among fishing communities
35 even within the same region. By integrating climate, ecological, and socio-economic data at a scale
36 relevant to fishing communities, this analysis identifies where strategies for adapting to the
37 ecological impacts of climate change will be most needed.

38 **Introduction**

39 Climate change is altering the distribution, abundance, and diversity of marine species globally (1,
40 2, 6). On a local scale, conditions will become more favorable for some species and less favorable for
41 others, which will ultimately alter the mix of species available for harvest in any given coastal
42 ecosystem. Despite widespread acknowledgement that climate change is a key challenge for
43 sustainable fisheries and communities (7, 8), we have limited understanding of the relative
44 exposure of fishing communities to climate change risk. Such information is critical for creating

45 adaptation policies, prioritizing research and management efforts, and for reducing community
46 exposure to risk on the ground (7).

47 Ecological risk or vulnerability assessments identify which species or populations may be most at
48 risk from climate change or other stressors. For fisheries, these assessments are usually aimed at
49 the species or stock level (e.g. 4). However, a fishing community's exposure to risk depends not only
50 on which species or stocks they target, but where in the ocean they target them and how much
51 flexibility they have to adapt to new conditions. Social-ecological risk assessments can link
52 ecological risk to community vulnerability (3, 5), but methods to do so at the appropriate scale for
53 adaptation planning have not been well-developed.

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

66 To develop and test socio-ecological methods for assessing the exposure of fishing communities to
67 risk under climate change, we integrated climate, ecological, and socio-economic data from the
68 NEUS at the scale of communities-at-sea. First, we quantified the spatial patterns of projected

69 changes in habitat suitability for individual species under climate change. We then linked these
70 projected ecological changes to information on fishing community practices to assess how exposed
71 fishing communities were to risk based on their harvest portfolios and spatial use of the ocean. We
72 discuss these results in light of adaptation possibilities and barriers. Providing local-scale
73 information on the projected changes to species habitat, and the exposure of coastal communities
74 to these changes, is an important step towards creating climate adaptation plans and prioritizing
75 adaptation actions and investments.

76 **Results**

77 Species distribution models fit to more than 40 years of scientific survey data indicated that
78 temperature was a significant predictor of species occurrence in space and time based on out-of-
79 sample predictive skill (Table S1). For the majority of species (24 of 33), habitat was projected to
80 improve in some regions of the NEUS shelf, but deteriorate in others by 2040-2050 (Figure 1B). For
81 instance, monkfish habitat was expected to expand in the Gulf of Maine (GOM) but become less
82 suitable throughout the Mid-Atlantic Bight (Figures 1C, 1D). Only two species were expected to
83 have improved habitat throughout the region, while seven were expected to have generally
84 decreased habitat suitability (Figure 1B). Atlantic cod was one of the species expected to experience
85 entirely negative impacts, and temperatures even in the coldest areas were expected to exceed the
86 thermal optimum for cod by 2050. In fact, rapid warming in the last decade has already contributed
87 to the collapse of GOM cod (13). In general, the northern part of the study region was expected to
88 have more “winners” (species gaining habitat suitability), while the Mid-Atlantic Bight and Georges
89 Bank had more “losers” (species losing suitability). However, we only included species that were
90 historically common in the trawl survey, thus missing species that may expand into the Mid-
91 Atlantic in a warmer future.

92 Fishing communities varied drastically in the size and location of their servicesheds, or customary
93 fishing grounds (see Methods; Figure S1, Table S2). Of the four vessel/gear types examined here,
94 communities of large bottom trawlers (>65ft) had the largest servicesheds (mean 40,000 km²),
95 extending often to the continental shelf break. Communities of small trawlers typically utilized
96 much smaller areas (mean 4300 km²) closer to port. Beyond gear type, even nearby communities
97 showed little overlap in their spatial use of the marine environment in some cases (Figure S2).
98 These geographic differences translated into different exposures of fishing communities to the
99 ecological impacts of climate change, even when targeting the same species (e.g. among gillnetters
100 harvesting monkfish in MA; Figure 2).

101 Ultimately, fishing community exposure to risk (defined as projected changes in resource
102 availability due to changes in habitat) depended on both their spatial use of the ocean and the
103 portfolio of species caught. Revenue-weighted risk scores showed that a majority (64 of 85) of
104 communities were exposed to increased risk by midcentury (Figure 3), suggesting declines in
105 future fishing opportunities based on current practices. Exposure varied by state and vessel/gear
106 type ($p < 0.01$; Figure S3). Communities of small trawlers in Maine were most exposed because of
107 their historical dependence on species expected to lose habitat suitability in the future (e.g., Atlantic
108 cod and witch flounder).

109 However, we also found small-scale differences. For instance, communities-at-sea for small
110 groundfishing vessels in Sandwich and Chatham, MA, were only 45 km apart but had different risk
111 profiles due to their differing catches and servicesheds (Figure S4). The Sandwich community
112 depended on winter flounder (67% of revenue), cod (8%) and yellowtail flounder (5%). Chatham's
113 community had a more diverse revenue portfolio, with the greatest contributions from witch
114 flounder (24%), cod (21%), and winter flounder (10%). Sandwich was expected to be less exposed
115 to risk and have increased opportunities under climate change, whereas nearby Chatham was

116 projected to be exposed to increasing risk. Notably, all but three out of 85 communities in this study
117 have historically targeted at least one species that was projected to gain habitat within their
118 serviced under climate change (Figure 3).

119 **Discussion**

120 By combining biophysical projection models with community-level data on fishing practices, we
121 show that the exposure of fishing communities to climate risk depends not only on biophysical
122 changes in the ocean, but also on how those changes intersect with community practices.

123 Communities differ substantially in the species they target and where they target them, resulting in
124 different risk profiles for communities even in close proximity. These findings echo community
125 impacts that have been documented when areas of the ocean have been closed to fishing (14), but
126 in this case, the impacts were driven by a changing environment. Our species-level results were
127 broadly consistent with previous projections of climate change impacts in the region (4, 15; Table
128 S3, Figure S5, S6, Supplementary Discussion). However, by considering variation in habitat
129 alongside differing community practices, we captured variation relevant at the scale of
130 communities. This emphasizes the importance of considering heterogeneity in both community
131 practices and ecological responses when evaluating exposure to risk.

132 Our analysis indicated which communities-at-sea were most exposed to risk and most likely to need
133 to adapt to a changing environment. Adaptation at the community level will likely require either
134 shifting where vessels fish to follow their target species (16) or rebalancing the species caught
135 towards winners rather than losers. In both cases, the speed at which a community may adapt will
136 be determined by a range of factors. Evidence suggests that the overwhelming determinant of
137 where fishers fish is their historical pattern of fishing (10). This context suggests that fishers will be
138 slow to adapt to distributional shifts, preferring traditional fishing grounds over new, less familiar

139 locations. Information sharing through social networks can lead to faster adaptation (14, 17), but
140 while fishers in the NEUS have strong social capital in general, information sharing has been
141 declining (18). Practical and regulatory considerations also shape how easily communities can
142 follow their target species through space. Small vessels are limited in how far they can travel from
143 port (16), and all vessels face travel costs. Shoreside infrastructure requirements and regulations
144 dictating where species may be landed further hinder the ability of communities to move fishing
145 grounds (19). Differences among communities in their responses to ongoing shifts in fish
146 distributions have already been observed, including in the NEUS (16, 20) and Alaska (21) and likely
147 reflect community-specific constraints to adaptation.

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

160 The type of community risk profiles we developed may be useful for climate adaptation in practice.
161 Long-term projections for a community can help guide strategic decisions by individual fishers,
162 processors, or other business-owners about investment and divestment in permits, quota, boats,

163 gear, or in the time gaining or maintaining the local ecological knowledge to fish for particular
164 species (8). Risk profiles could help guide strategic decisions by a port or municipality about
165 infrastructure investment, community cooperatives, or the role of fishing in the local economy,
166 especially when considered alongside indicators of social vulnerability (5). For a fisheries manager,
167 understanding how fishing opportunities will change for communities can be important for
168 charting out adaptation pathways and removing barriers along those pathways (28).

169 Notwithstanding the potential utility of our projections, several caveats should be noted.
170 Temperature structures the physiology of marine species (29), but the species distribution models
171 that we used detected correlations (not causation) and did not consider parameters such as pH or
172 oxygen. The models implicitly assumed that species distributions were in equilibrium with their
173 environment; that species interactions, phenology, disease, and acclimation will stay the same in
174 the future; and that evolution will not be important. We explored parametric uncertainty (Figure
175 S7), but future work should also explore structural uncertainty and sensitivity to the climate model.
176 Coarse-scale GCMs, for example, may underestimate future warming on the NEUS shelf (30).

177 **Conclusions**

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

186

187 **Methods**

188 **Characterizing thermal habitat suitability for species**

189 Bottom trawl data from the NOAA Northeast Fisheries Science Center (NEFSC) fall (1963-2014)
190 surveys were used to characterize the realized thermal niches of species. At each survey station,
191 fish of each species were counted and weighed, and surface and bottom temperature
192 measurements were taken (details in (31)). Correction factors were applied to standardize catch
193 rates for changes in vessel and gear type. A total of 33 species were selected based on their near
194 continuous presence in the survey as well as relative importance to commercial fisheries. For 4
195 species, data from 1972 onwards were used because observations were irregular prior to that year.

196 GAMs were used to estimate the realized thermal niches of species. We restricted k (number of
197 knots) to 4 or 6 for each of our covariates to ensure biologically meaningful responses. Our
198 response variable was probability of occurrence in a trawl haul, and we used a binomial response
199 with logit transform:

$$200 \quad p(\text{occur}_{y,j}) \sim \text{logit}^{-1} (s(ST_{y,j})+s(BT_{y,j})+s(\text{meanbiomass}_y)+s(\text{rugosity}_j))$$

201 where $ST_{y,j}$ and $BT_{y,j}$ are sea surface temperature and bottom temperature measured at each haul
202 location j in year y , and meanbiomass_y is the average annual catch across all hauls to account for
203 interannual changes in abundance due to, e.g., fishing. Rugosity_j is a measure of benthic habitat
204 roughness, measured as the Terrain Ruggedness Index (32), using the GEBCO 2014 30-arcsecond
205 bathymetry data (downloaded 4 Feb 2015 from <http://www.gebco.net/>). The resulting estimated
206 smooth functions describing the relationship between probability of occurrence and temperature
207 can be interpreted as realized thermal niches. Temperature may also be a proxy for other ecological

208 conditions, such as prey availability. We did not include other habitat variables such as oxygen
209 concentration or pH because of a lack of long-term spatial data for those variables.

210 For each species, the change in predicted probability of occurrence under future (2040-2050)
211 projected climate conditions was compared to historical (1963-2005) conditions for each cell
212 within a 0.25°x0.25° spatial grid. Because the modeled probability of occurrence included a
213 component of catchability, values for each species were scaled by dividing by the maximum
214 observed or predicted probability of occurrence across the study area. Positive values for a grid
215 square indicated a projected increase in probability of occurrence, whereas negative values
216 indicated a projected decrease in probability of occurrence. Throughout the study we refer to
217 habitat suitability rather than probability of occurrence to specifically focus on climate-driven
218 changes in habitat, as actual species occurrence depends on additional factors such as harvest
219 policies.

220 **Model performance and uncertainty**

221 To test whether including temperature provided predictive information about species presence-
222 absence, predictive error was quantified for the full models and models without temperature
223 covariates. Models were fit to a training dataset consisting of the first 80% of samples (1963 -
224 2004), and model predictions for the test dataset (2005 - 2014) were compared with observations.
225 The mean absolute error (MAE) was calculated as:

$$226 \quad MAE = \frac{1}{n} \sum_i^n |f_i - y_i|$$

227 where f_i are predictions from the model and y_i are observed data. Note that the split of data into
228 testing and training datasets was only used to assess model performance, and models fit to all

229 available data were used for the rest of the study in order to best describe the realized thermal
230 niches.

231 To assess the impact of uncertainty in model parameters on our results, we drew 1000 samples
232 from the posterior distributions for the estimated GAM coefficients and then calculated predictions
233 of historical and future probabilities of occurrence. For each cell on the projection grid, the 5th and
234 95th percentiles of calculated risk (change in scaled probability of occurrence) across the 1000
235 simulations were taken as prediction intervals.

236 **Climate projections**

237 Future temperatures were calculated by adding projected changes in surface and bottom
238 temperatures to surface and bottom temperature climatologies (delta method; 33, 34).

239 Climatologies were calculated from the surface and bottom temperature records in the NEFSC fall
240 bottom trawl surveys 1963-2005. Records were averaged within 0.25x0.25° grids within each
241 decade, then averaged across decades to reduce the impact of changes in the number of data points
242 available in each decade (see (34)).

243 Projected changes in surface and bottom temperatures were calculated from a set of 13 global
244 climate models from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (see Table S4)
245 under Representative Concentration Pathway (RCP) 8.5, which represents a “business-as-usual”
246 scenario. These models were used in the Fifth Assessment Report of the Intergovernmental Panel
247 on Climate Change. Changes were calculated as the difference between the base historical period
248 (1963-2005) and each future year (2006-2100), averaged across the months of the climatology
249 (September-December). Changes in temperature in each future year were additionally corrected for
250 climate model drift, as assessed in the climate model’s control simulation (no increase in
251 greenhouse gases) by regressing temperature against year. The climate models were evaluated on a
252 1x1° grid, as is standard for these models. Models not on a 1x1° grid were interpolated to that scale

253 before analysis. Changes in temperature from each model were then matched to the appropriate
254 grid and depth of the surface and bottom temperatures in the climatology. Any grid cells in the
255 climatology that were not directly overlapped by a grid in a climate model were interpolated with
256 inverse distance weighting. For this study, we focused on projected conditions during the period
257 2040-2050 to reflect conditions approximately one human generation into the future.

258 **Characterizing communities-at-sea and their servicesheds**

259 Communities-at-sea are peer-groups of vessels which share a gear type and are associated with a
260 particular port (e.g., vessels from New Bedford, MA that use gillnets). For vessels using trawl gear,
261 small and large trawlers are considered separate communities according to vessel length (\leq 65
262 feet). We used Vessel Trip Report (VTR) data for commercial fishing trips from 1996 to 2014, as
263 reported by vessel captains, to determine the at-sea "servicesheds" or customary fishing grounds
264 of communities. We use "serviceshed" to describe the area from which a community has historically
265 received ecosystem services (35), specifically fish in this case. A trip was classified as belonging to a
266 community if it shared the community's gear type and landing port, and either the vessel either
267 declared that port as its principal port or landed in that port at least 50% of its trips that year (see
268 (12, 16)).

269 Once aggregated into communities, trips were then weighted by a variable ("fisherdays") indicating
270 labor time expended on each trip: trip length (in days) multiplied by the number of crew on board
271 (see (12)). Fisherdays indicate how important an area at sea is to a community in terms of how
272 much time they invest in that location.

273 Given reported trip locations and fisherdays, we then created raster maps using a kernel density
274 method. The resultant maps distribute fisherdays using different size kernels depending upon the
275 fishery/gear-type/length. Nearshore fishing was processed using a smaller kernel (7.5 - 10 km)
276 than offshore fishing (10 - 15 km). We used the area defined by a 90% volume contour (i.e., an area

277 which encompasses 90% of fisherdays) to define the customary fishing grounds or servicesheds for
278 a community. While fishing locations are reported with some error on VTRs (36), interviews with
279 fishers indicated that aggregate maps of servicesheds were reasonably accurate (11;
280 Supplementary Methods). For this analysis we focused on communities using gear that targets
281 species also captured well in the NEFSC trawl survey (large trawlers, small trawlers, gillnet, and
282 longline). Furthermore, we only analyzed communities present in the dataset for at least 8 years.
283 These filters resulted in a subset of 98 communities for which we assessed exposure to climate
284 change risk.

285 While the VTR program is designed to document all fishing trips by federally permitted vessels
286 since 1994, the dataset is not complete: earlier years suffer from clear under-reporting, some Mid-
287 Atlantic states did not collect VTR in early years, vessels without federal permits (e.g., those fishing
288 exclusively in state waters) do not file VTRs, and some vessels with federal permits are occasionally
289 exempt when fishing in state waters. Communities with fewer than 3 vessels were omitted to
290 maintain confidentiality.

291 **Landings and prices**

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

299 **Fishing community exposure to risk**

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

$$305 \quad Risk_c = \sum_{s=1}^{33} S_{s,c} * pRev_{s,c},$$

306 where $S_{s,c}$ is the mean projected change in habitat suitability for species s across the serviceshed of
307 community c , and $pRev_{s,c}$ is the proportion of historical revenues from fishing that the community
308 has derived from species s . Because some communities harvested species not included in our study
309 (e.g. whelk), but which may represent significant sources of income, we only computed risk for a
310 community if at least 70% of their historical revenues were accounted for by species in this study,
311 resulting in scores for 85 communities. Note that by focusing on species well-sampled by the trawl
312 survey, risk exposure scores did not include potential emergent fisheries for species expanding into
313 the study area from the south. Positive risk exposure scores indicated expanding opportunities for
314 communities based on their historical fishing revenue portfolios and projected changes to species
315 habitat at sea, while negative values indicated shrinking opportunities and increased exposure to
316 negative impacts of climate change. This approach considers the exposure of a community to risk
317 based on their historical practices, thus highlighting when and where adaptation may be necessary,
318 It does not attempt to predict how a community might alter their fishing grounds or catch portfolios
319 in the future. Risk based on catch proportions was highly correlated ($r = 0.94$) with risk based on
320 revenues (Figure S8).]

321

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331 **Author contributions**

332 LAR, RG, and MLP designed research; KStM provided data and the framework for characterizing
333 communities-at-sea and their servicesheds; LAR, TY, EF, and MLP conducted analyses; all authors
334 contributed to conceptual development; LAR and MLP wrote the manuscript with input from all
335 authors.

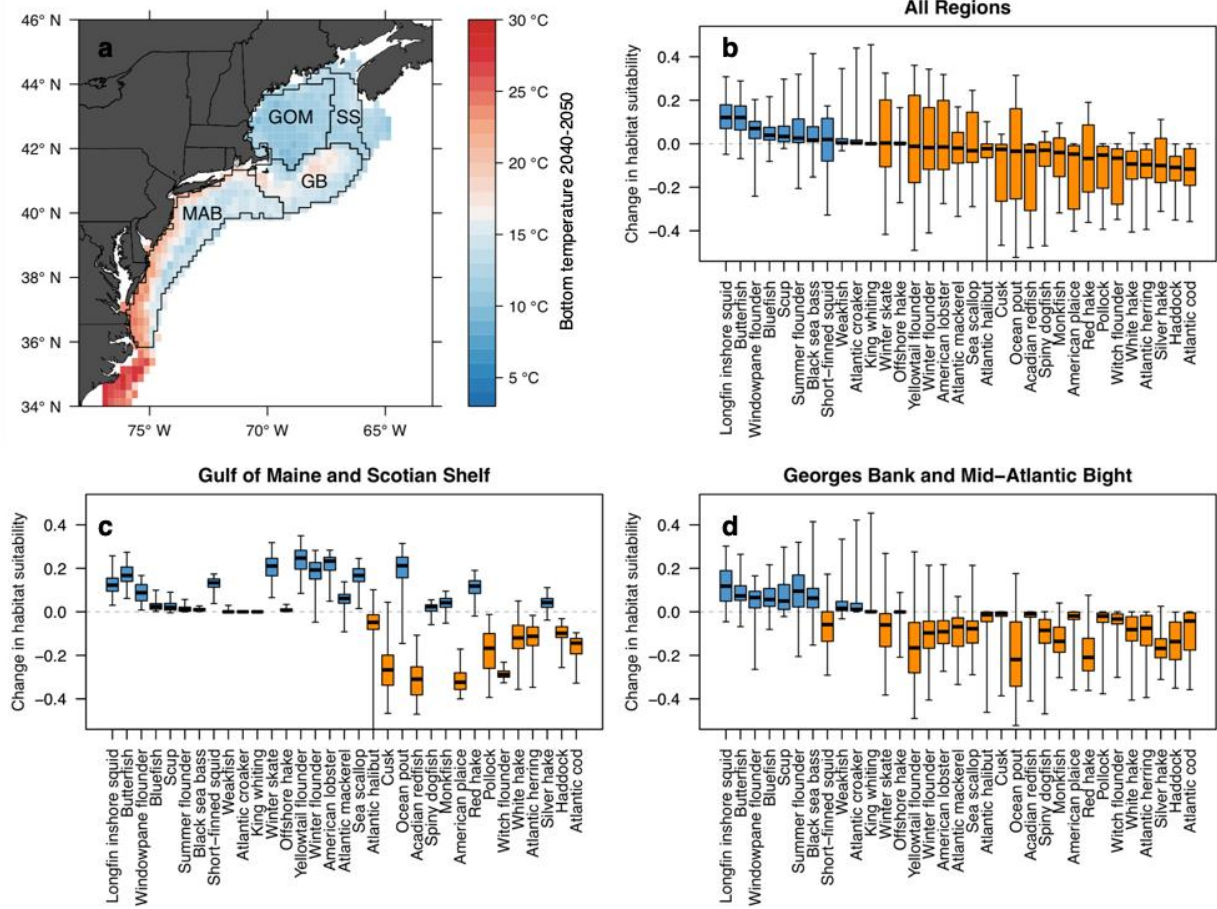
336 **References**

- 337 1. Sydeman, W. J., Poloczanska, E., Reed, T. E. & Thompson, S. A. Climate change and marine
338 vertebrates. *Science (80-.)*. **350**, 772–777 (2015).
- 339 2. Cheung, W. W. L. *et al.* Projecting global marine biodiversity impacts under climate change
340 scenarios. *Fish Fish.* **10**, 235–251 (2009).
- 341 3. Allison, E. H. *et al.* Vulnerability of national economies to the impacts of climate change on
342 fisheries. *Fish Fish.* **10**, 173–196 (2009).
- 343 4. Hare, J. A. *et al.* A vulnerability assessment of fish and invertebrates to climate change on the
344 Northeast U.S. continental shelf. *PLoS One* **11**, 1–30 (2016).

- 345 5. Colburn, L. L. *et al.* Indicators of climate change and social vulnerability in fishing dependent
346 communities along the Eastern and Gulf Coasts of the United States. *Mar. Policy* **74**, 323–333
347 (2016).
- 348 6. Pinsky, M. L., Worm, B., Fogarty, M. J., Sarmiento, J. L. & Levin, S. A. Marine taxa track local
349 climate velocities. *Science (80-.)*. **341**, 1239–1242 (2013).
- 350 7. Miller, D. D., Ota, Y., Sumaila, U. R., Cisneros-Montemayor, A. M. & Cheung, W. W. L.
351 Adaptation strategies to climate change in marine systems. *Glob. Chang. Biol.* **24**, e1–e14
352 (2018).
- 353 8. Sumaila, U. R., Cheung, W. W. L., Lam, V. W. Y., Pauly, D. & Herrick, S. Climate change impacts
354 on the biophysics and economics of world fisheries. *Nat. Clim. Chang.* **1**, 449–456 (2011).
- 355 9. St Martin, K. Making space for community resource management in fisheries. *Ann. Assoc. Am.*
356 *Geogr.* **91**, 122–142 (2001).
- 357 10. Holland, D. S. & Sutinen, J. G. Location choice in New England trawl fisheries: old habits die
358 hard. *Land Econ.* **76**, 133 (2000).
- 359 11. St. Martin, K. & Hall-Arber, M. The missing layer: Geo-technologies, communities, and
360 implications for marine spatial planning. *Mar. Policy* **32**, 779–786 (2008).
- 361 12. St. Martin, K. & Olson, J. Creating space for community in marine conservation and
362 management. in *Conservation for the Anthropocene Ocean* 123–141 (2017).
363 doi:10.1016/B978-0-12-805375-1.00007-6
- 364 13. Pershing, A. J. *et al.* Slow adaptation in the face of rapid warming leads to collapse of the Gulf
365 of Maine cod fishery. *Science (80-.)*. **350**, 809–812 (2015).
- 366 14. Murray, G. *et al.* Creeping enclosure, cumulative effects and the marine commons of New
367 Jersey. *Int. J. Commons* **4**, 367–389 (2010).
- 368 15. Kleisner, K. M. *et al.* Marine species distribution shifts on the U.S. Northeast Continental Shelf
369 under continued ocean warming. *Prog. Oceanogr.* **153**, 24–36 (2017).
- 370 16. Young, T. *et al.* Adaptation strategies of coastal fishing communities as species shift
371 poleward. *ICES J. Mar. Sci.* **76**, 93–103 (2019).
- 372 17. Barnes, M. L., Lynham, J., Kalberg, K. & Leung, P. Social networks and environmental
373 outcomes. *Proc. Natl. Acad. Sci.* **113**, 6466–6471 (2016).
- 374 18. Holland, D. S., Pinto da Silva, P. & W. Kitts, A. Evolution of social capital and economic
375 performance in New England harvest cooperatives. *Mar. Resour. Econ.* **30**, 371–392 (2015).
- 376 19. Dubik, B. A. *et al.* Governing fisheries in the face of change: Social responses to long-term
377 geographic shifts in a U.S. fishery. *Mar. Policy* **99**, 243–251 (2019).

- 378 20. Pinsky, M. L. & Fogarty, M. Lagged social-ecological responses to climate and range shifts in
379 fisheries. *Clim. Change* **115**, 883–891 (2012).
- 380 21. Watson, J. T. & Haynie, A. C. Paths to resilience: the walleye pollock fleet uses multiple fishing
381 strategies to buffer against environmental change in the Bering Sea. *Can. J. Fish. Aquat. Sci.*
382 **75**, 1977–1989 (2018).
- 383 22. Pinsky, M. L. *et al.* Preparing ocean governance for species on the move. *Science (80-.)*. **360**,
384 1189 LP-1191 (2018).
- 385 23. Cheung, W. W. L., Pinnegar, J., Merino, G., Jones, M. C. & Barange, M. Review of climate change
386 impacts on marine fisheries in the UK and Ireland. *Aquat. Conserv. Mar. Freshw. Ecosyst.* **22**,
387 368–388 (2012).
- 388 24. Mills, K. *et al.* Fisheries management in a changing climate: lessons from the 2012 ocean heat
389 wave in the Northwest Atlantic. *Oceanography* **26**, 191–195 (2013).
- 390 25. Anderson, S. C. *et al.* Benefits and risks of diversification for individual fishers. *Proc. Natl.*
391 *Acad. Sci.* **114**, 10797–10802 (2017).
- 392 26. Cline, T. J., Schindler, D. E. & Hilborn, R. Fisheries portfolio diversification and turnover
393 buffer Alaskan fishing communities from abrupt resource and market changes. *Nat. Commun.*
394 **8**, 1–7 (2017).
- 395 27. Kasperski, S. & Holland, D. S. Income diversification and risk for fishermen. *Proc. Natl. Acad.*
396 *Sci.* **110**, 2076–2081 (2013).
- 397 28. Pinsky, M. L. & Mantua, N. J. Emerging adaption approaches for climate ready fisheries
398 management. *Oceanography* **27**, 146–159 (2014).
- 399 29. Sunday, J. M., Bates, A. E. & Dulvy, N. K. Thermal tolerance and the global redistribution of
400 animals. *Nat. Clim. Chang.* **2**, 686–690 (2012).
- 401 30. Saba, V. S. *et al.* Enhanced warming of the Northwest Atlantic Ocean under climate change. *J.*
402 *Geophys. Res. Ocean.* **121**, 118–132 (2016).
- 403 31. Azarovitz, T. R. A brief historical review of the Woods Hole laboratory trawl survey time
404 series. in *Bottom Trawl Surveys. Canadian Special Publication of Fisheries and Aquatic*
405 *Sciences 58* (eds. Doubleday, W. G. & Rivard, D.) 62–67 (1981).
- 406 32. Wilson, M. F. J., O’Connell, B., Brown, C., Guinan, J. C. & Grehan, A. J. Multiscale terrain analysis
407 of multibeam bathymetry data for habitat mapping on the continental slope. *Mar. Geod.* **30**,
408 3–35 (2007).
- 409 33. Anandhi, A. *et al.* Examination of change factor methodologies for climate change impact
410 assessment. *Water Resour. Res.* **47**, 1–10 (2011).

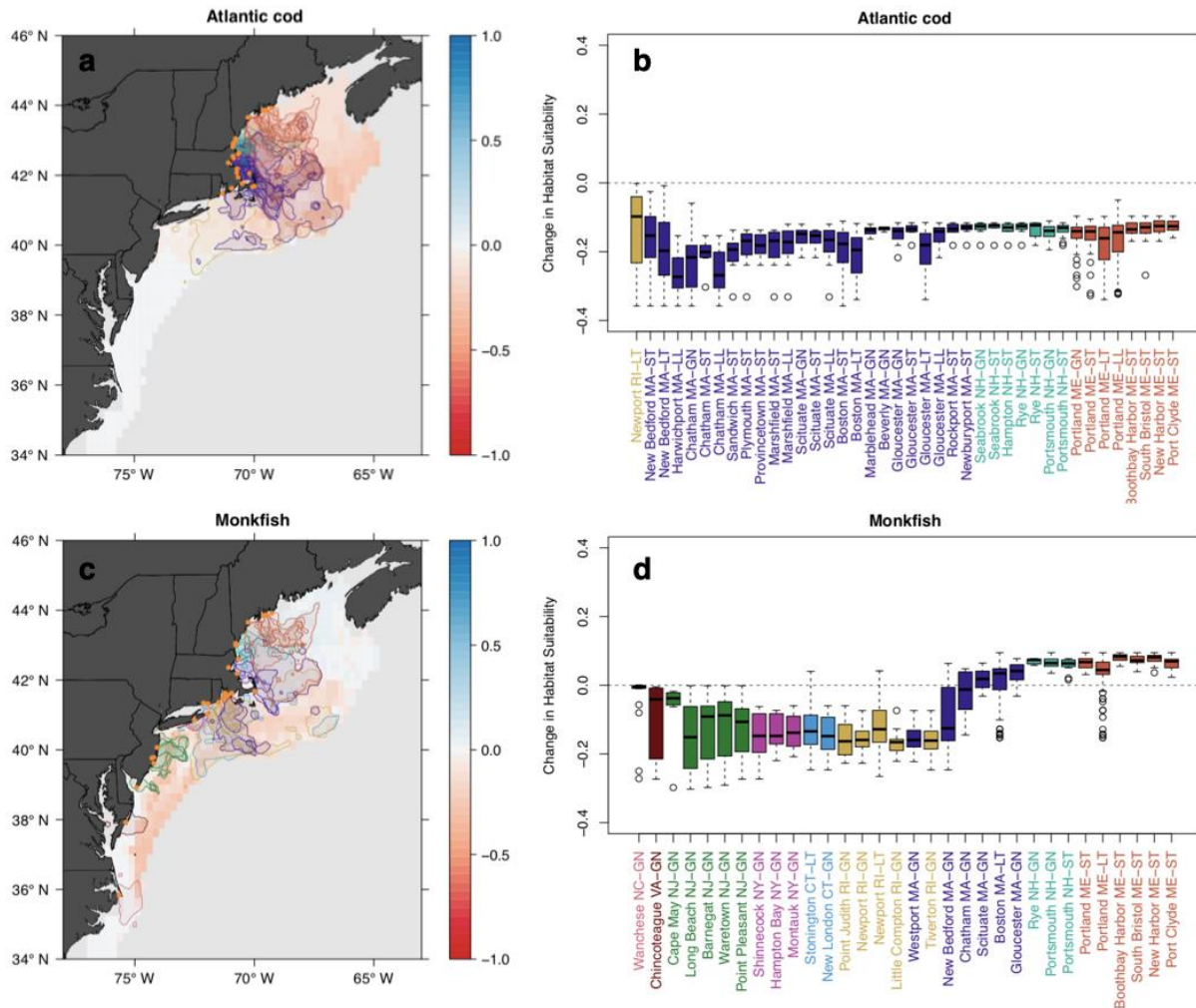
- 411 34. Hare, J. A. *et al.* Cusk (*Brosme brosme*) and climate change: assessing the threat to a candidate
412 marine fish species under the US Endangered Species Act. *ICES J. Mar. Sci.* **69**, 1753–1768
413 (2012).
- 414 35. Tallis, H., Kennedy, C. M., Ruckelshaus, M., Goldstein, J. & Kiesecker, J. M. Mitigation for one &
415 all: An integrated framework for mitigation of development impacts on biodiversity and
416 ecosystem services. *Environ. Impact Assess. Rev.* **55**, 21–34 (2015).
- 417 36. DePiper, G. S. Statistically assessing the precision of self-reported VTR fishing locations.
418 NOAA Tech Memo NMFS NE 229; 16 p. doi: 10.7289/V53F4MJN (2014).
- 419



421

422 **Figure 1:** Projected changes in the thermal environment and species-specific habitat suitability on
 423 the NEUS shelf. a) Mean projected future (2040-2050) bottom temperatures, calculated for the
 424 months of Sep. – Nov. to correspond to historical survey timing. The Gulf of Maine (GOM), Scotian
 425 Shelf (SS), Georges Bank (GB) and Mid-Atlantic Bight (MAB) are indicated. The distributions
 426 (summarizing across space) of projected changes in habitat suitability for 33 species are shown for
 427 (b) the entire shelf, (c) GOM and SS, and (d) GB and MAB. Positive values indicate an increase in
 428 suitability in 2040-2050 over 1963-2005. Colors indicate whether the median is above (blue) or
 429 below (orange) zero.

430



431

432 **Figure 2:** Predicted changes in habitat suitability by mid-century (2040-2050) for Monkfish (a) and
 433 Atlantic cod (c). Blue colors indicate improved habitat suitability, while red indicates reduced
 434 habitat suitability. Overlaid are outlines of servicesheds for communities-at-sea for which the
 435 species makes up at least 5% of revenues, colored by state to match panels c and d. Ports for
 436 individual communities are indicated by orange circles. Boxplots (b, d) summarize predicted
 437 changes in habitat suitability for the species within the serviceshed for each community. Boxplots
 438 are colored by state and arranged from south to north on the x-axis. Vessel/gear type is indicated in
 439 the label for each community by ST (small trawl), LT (large trawl), GN (gillnet), LL (longline).

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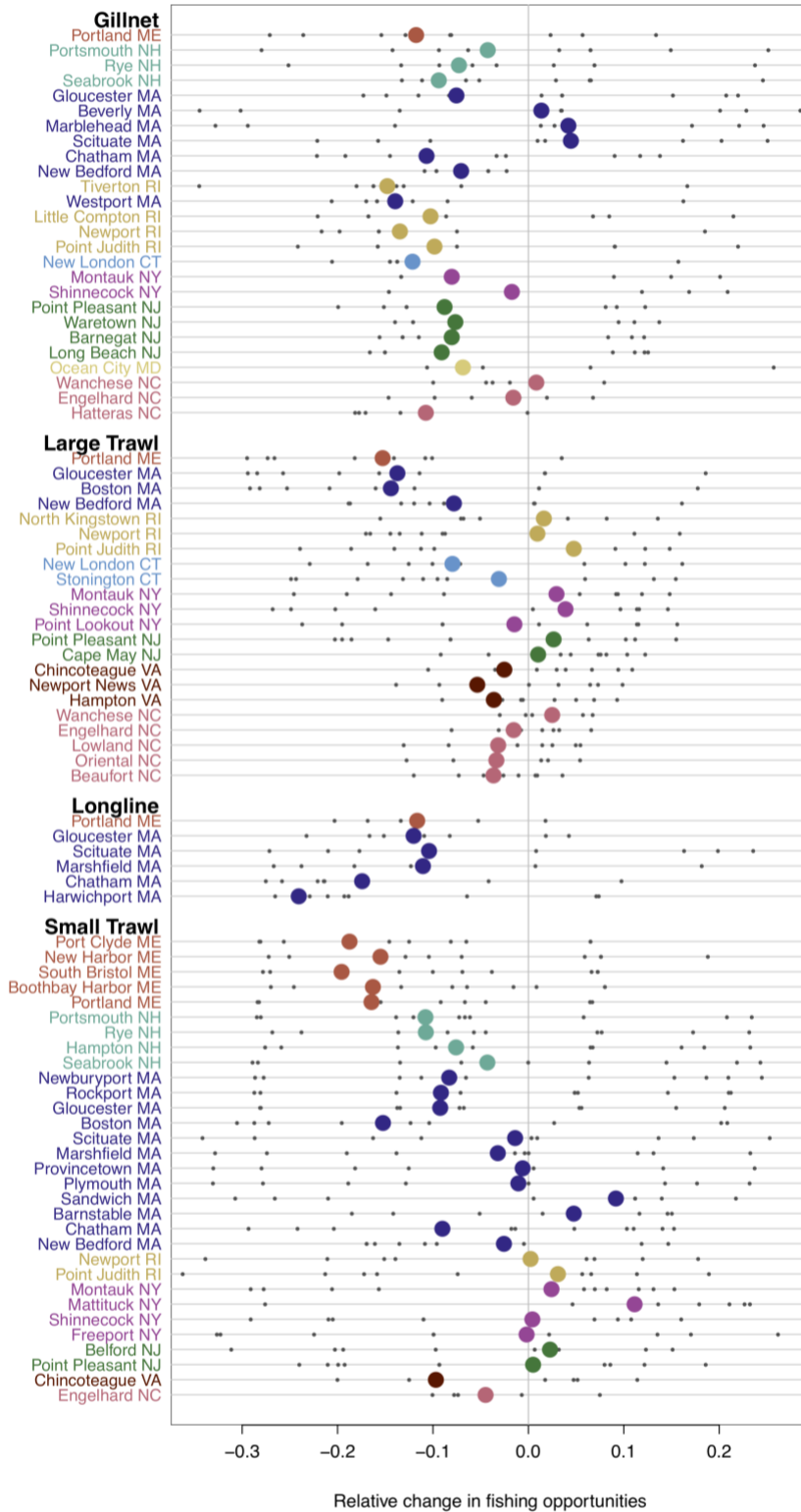


Figure 3: Exposure of communities-at-sea to risk from climate change impacts on harvested species (colored circles). Positive values indicate expanding opportunities for communities based on their historical fishing revenue portfolios and projected changes to species habitat at sea, while negative values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