

1 **Projecting climate-driven shifts in demersal fish habitat in Iceland's waters**

2 **Authors:** Julia G. Mason<sup>1, 2</sup>, Pamela J. Woods<sup>3</sup>, Magnús Thorlacius<sup>3</sup>, Kristinn Guðnason<sup>3</sup>,  
3 Vincent S. Saba<sup>4</sup>, Patrick J. Sullivan<sup>2,5</sup>, Kristin M. Kleisner<sup>1</sup>

4 1. Environmental Defense Fund, Boston, MA, USA 02108  
5 2. Atkinson Center for Sustainability, Cornell University, Ithaca NY 14853  
6 3. Marine and Freshwater Research Institute, Hafnarfjörður, Iceland  
7 4. National Oceanic and Atmospheric Administration, National Marine Fisheries Service,  
8 Northeast Fisheries Science Center, Geophysical Fluid Dynamics Laboratory, Princeton  
9 University, Princeton, New Jersey, USA  
10 5. Department of Natural Resources and the Environment, Cornell University, Ithaca NY  
11 14853

12 **Correspondence:** [jmason@edf.org](mailto:jmason@edf.org)

13

14 **Keywords:** Climate change, Generalized additive model, Suitable thermal habitat, Species  
15 distribution modeling, Global climate model

16

17 **Abstract**

18 As climate change shifts marine species distribution and abundance worldwide, projecting local  
19 changes over decadal scales may be a valuable adaptive strategy for managers and industry. In  
20 Iceland, one of the top fish-producing nations in the world, long-term monitoring enables model  
21 simulations of groundfish species habitat distribution. We used generalized additive models to  
22 characterize suitable thermal habitat for 47 fish species in Iceland's waters. We then projected  
23 changes in thermal habitat by midcentury with an ensemble of five general circulation models  
24 from the Coupled Model Intercomparison Program 6 (CMIP6) and NOAA (CM2.6) and two  
25 scenarios (SSP 5-8.5 and SSP 2-4.5). We find a general northward shift in centroids of habitat  
26 distribution, with variable regional dynamics among species. Species thermal affinity was the  
27 most significant predictor of future habitat change, with warmer-water species more likely to see

28 projected increases in suitable habitat. We present spatially explicit habitat change projections  
29 for commercially and culturally important species. These projections might serve as guideposts  
30 to inform long-term management decisions about regional and species-specific suitability for  
31 Iceland's fisheries, infrastructure investment, and risk evaluation under climate change.

32

### 33 **Introduction**

34 Climate change is shifting marine species distribution and abundance worldwide  
35 (Parmesan, 2006; Poloczanska et al., 2013). These shifts are projected to continue as climate  
36 change intensifies (Molinos et al., 2016), with complex and unevenly distributed social-  
37 ecological consequences (Golden et al., 2016; Lam et al., 2016; Pinsky et al., 2018; Sumaila et  
38 al., 2011). Alongside the urgent need for bold action to reduce greenhouse gas emissions is the  
39 need for adaptive management approaches to maintain desired fishery outcomes under changing  
40 and novel conditions. Researchers project that implementing management that accounts for  
41 changes in fish species productivity and distribution can improve outcomes for fishery catches  
42 and profits under most climate scenarios (Free et al., 2020; Gaines et al., 2018). For fisheries  
43 with adequate scientific and technical capacity, conducting forecasts and incorporating future  
44 climate scenarios into management decisions is a key aspect of climate-adaptive management  
45 (Free et al., 2020; Holsman et al., 2019; Karp et al., 2019; Pinsky & Mantua, 2014). While  
46 seasonal and interannual forecasts may be of most immediate use for management and industry,  
47 climate-scale projections allow managers and practitioners to evaluate risk, plan for future losses  
48 or gains in suitability, and inform longer term decision-making processes such as national  
49 legislation or international negotiations (Hobday et al., 2018; Holsman et al., 2019).

50 In Iceland, the economic and cultural importance of fisheries and the sophistication of its  
51 management and scientific systems mean that projecting future change in fish stocks could be a  
52 key priority for achieving climate-adaptive fisheries (Kleisner et al. in press). Consistently  
53 ranking among the top twenty marine fish capture producing countries worldwide (FAO, 2020),  
54 Iceland is located in a highly productive transition zone between warm Atlantic and cold Polar  
55 currents. The interactions of these currents create high spatial and temporal oceanographic  
56 variability within Iceland's waters, and the ecosystem is highly sensitive to their dynamics  
57 (Astthorsson et al., 2007). Environmental conditions have fluctuated over the past century in  
58 relation to multidecadal oscillations and local atmospheric dynamics with profound ecological  
59 and economic consequences: Relatively warm periods were associated with fishery booms that  
60 drove the development of Iceland's commercial fisheries and economy, and cooler-water periods  
61 (in combination with overfishing) associated with devastating fishery crashes (Astthorsson et al.,  
62 2007; Ogilvie & Jónsdóttir, 2000; Valtýsson & Jónsson, 2018).

63 Recently, a warm anomaly from the mid-1990s to late 2010s drove substantial changes in  
64 fish abundance and distribution around Iceland, including documentation of new species and  
65 increases of warmer-water species (Astthorsson & Palsson, 2006; Valdimarsson et al., 2012;  
66 Valtýsson & Jónsson, 2018). Particularly notorious was the abrupt expansion of Atlantic  
67 mackerel (*Scomber scombrus*) into Iceland's waters (Olafur S. Astthorsson et al., 2012;  
68 Olafsdottir et al., 2019) that quickly became an economic boon for Iceland, but led to  
69 international political conflict over the fishing of the stock (Spijkers & Boonstra, 2017).  
70 Researchers also noted significant shifts in groundfish distribution and community assemblage,  
71 with heterogeneous regional trends associated with oceanographic conditions and the influence

72 of coastal fjord systems on predator-prey dynamics (Jónsdóttir et al., 2019; Stefánsdóttir, 2008;  
73 Stefánsdóttir, 2019).

74 Given these past temperature-related changes, a logical next step might be to project how  
75 future change might affect fish species abundance and distribution. Global studies have projected  
76 that Iceland, like other high-latitude countries, could be a climate “winner,” potentially  
77 experiencing increased biodiversity and fisheries catch potential as warmer waters move fish  
78 poleward (Cheung et al., 2009; Molinos et al., 2016). However, given the highly local and  
79 variable dynamics of Iceland climatic conditions and differing ecological, economic, and cultural  
80 importance of its fish species, higher-resolution projections indicating specific species and  
81 regional dynamics could be more applicable for fisheries managers and industry. Campana et al.  
82 (2020) used Iceland bottom trawl survey data to model fish habitat and projected that a uniform  
83 1°C increase in bottom temperature would drive a general northward shift in habitat distribution,  
84 with significant variation across species and quadrants of the exclusive economic zone (EEZ).  
85 The authors noted a high level of regional and temporal variation in past warming trends and  
86 warned that future warming is unlikely to be homogenous nor linear.

87 Iceland’s fishery managers have collected standardized fisheries independent and  
88 fisheries dependent data since the 1980s, allowing for detailed analyses of species abundance and  
89 distribution in relation to environmental conditions that can inform future projections. These  
90 long-term monitoring data are ideal for a common but data-intensive approach to anticipating  
91 regional or global species distribution shifts: pairing statistical models of species suitable habitat  
92 with global climate model outputs (Stock et al., 2011). Given the uncertainty inherent to  
93 projecting both the dynamics of the global climate and the human actions and policies that  
94 influence those dynamics, using an ensemble of climate models across different scenarios is

95 advised (Morley et al., 2018, 2020). Here we use long-term fisheries independent trawl data and  
96 an ensemble of the newest generation of global climate models from the Coupled Model  
97 Intercomparison Project (CMIP6) to project how future climate change will affect suitable  
98 thermal habitat of 47 species in Iceland's waters at a  $0.25^\circ \times 0.25^\circ$  resolution. These spatially  
99 explicit climate projections can more directly inform Iceland's fishing industry and fisheries  
100 management's needs for adapting to climate-driven changes in fish distribution, and illustrate to  
101 other nations and regions how these projections might be considered in long-term climate-  
102 adaptive management.

103

## 104 **Methods**

### 105 *Projecting future temperature changes in Iceland's waters*

106 We used a suite of global climate models to project future ocean surface and bottom  
107 temperatures in Iceland's waters, including a high-resolution global climate model (CM2.6 from  
108 the National Oceanic and Atmospheric Administration Geophysical Fluid Dynamics Laboratory,  
109 NOAA GFDL) and four coarser global climate models from the Coupled Model Intercomparison  
110 Project 6 (CMIP6). Researchers have found that CM2.6 (10-km ocean resolution) resolves the  
111 ocean circulation in the Northwest Atlantic more realistically than coarser models (Saba et al.,  
112 2016). However, this model has a cold bias in sea surface and bottom temperature in Iceland's  
113 waters in the historical period from 1982-2012, so we selected the highest resolution CMIP6  
114 models that have a range of cold and warm biases to complement the higher resolution CM2.6.  
115 These were GFDL CM4 (25-km ocean resolution) from the National Oceanic and Atmospheric  
116 Administration Geophysical Fluid Dynamics Laboratory, U.S.A; CNRM-CM6 (25-km ocean

117 resolution) from the Centre National de Recherches Meteorologiques and Centre European de  
118 Recherche et de Formation Avancee en Calcul Scientifique, France; HadGEM3-GC31 (100-km  
119 ocean resolution) from the Met Office Hadley Centre, U.K.; and IPSL-CM6A-LR (100-km  
120 ocean resolution) from L’Institut Pierre Simon Laplace, France. We downloaded CMIP6 data  
121 using the xarray package (version 0.15.1) in Python (version 3.7.6) (Hoyer & Hamman, 2017).

122 The CMIP6 models use future scenario simulations that combine the Representative  
123 Concentration Pathways (RCPs) of radiative forcings used in the Intergovernmental Panel on  
124 Climate Change’s Fifth Assessment Report (IPCC AR5) with Shared Socioeconomic Pathways  
125 (SSPs) of societal development (Eyring et al., 2016; O’Neill et al., 2017). We examined two  
126 future scenarios for the years 2015-2100: SSP 2-4.5, a “middle of the road” scenario where  
127 countries continue along historical social, economic, and technological development trajectories  
128 as they strive toward sustainable development goals; and SSP 5-8.5, a “fossil-fueled  
129 development” scenario where accelerated economic growth emphasizes fossil fuels (O’Neill et  
130 al., 2017). The CM2.6 projects an idealized transient climate response (1% per year increase in  
131 atmospheric CO<sub>2</sub>) simulation over 80 years, where the last 20 years are comparable to years  
132 2061-2080 of SSP 5-8.5. We thus focused on this 2061-2080 period for our future projections.

133 We standardized the models using the “delta method,” where we calculated the difference  
134 between each model’s monthly projections and modeled historical control (mean of 1985-2015),  
135 and then added these deltas to a standard climatology (Anandhi et al., 2011; Kleisner et al., 2017;  
136 Morley et al., 2018). We used a sea surface temperature (SST) climatology from daily NOAA  
137 Optimum Interpolated Sea Surface Temperature (OISST) data from 1982-2012 and a bottom  
138 temperature climatology from the NOAA Greenland-Iceland-Norwegian Seas Regional  
139 Climatology version 2 (GINS RC v2) from 1985-2012 (Seidov et al. 2013). All projections were

140 interpolated to a standard  $0.25^{\circ} \times 0.25^{\circ}$  grid to match the OISST resolution. We ran a monthly  
141 SST and bottom temperature hindcast for the years 2000-2018 using the Mercator Ocean Global  
142 Reanalysis (GLORYS) dataset from the Copernicus Marine Environment Monitoring Service  
143 and a projection for the years 2061-2080 for each of the five models and two scenarios on a  
144 projection grid of the 2,312  $0.25^{\circ}$  cells in Iceland's EEZ.

145

146 *Modeling species thermal habitat*

147 The Icelandic Marine and Freshwater Research Institute (MFRI) conducts annual  
148 standardized bottom trawl surveys in the spring and autumn to inform groundfish stock  
149 assessments. The spring survey has been conducted since 1985 at about 590 fixed stations  
150 covering Iceland's continental shelf to 500m depth (Solmundsson et al., 2020). The autumn  
151 survey, initiated in 1996 and expanded in 2000, covers about 400 fixed stations that additionally  
152 include deeper waters along the continental slope (400-1500m; Campana et al. 2020). Fish  
153 lengths and standard weight conversions are used to calculate biomass (kg) per nautical mile.  
154 Surface temperature and bottom temperature are also measured in situ. We used surveys through  
155 March 2020, excluding the autumn survey before it was expanded in 2000 and 2011 when a  
156 labor strike interrupted the survey, for  $n = 27,524$  total survey tows (Figure 1). We combined the  
157 spring and autumn surveys to better account for the full thermal envelope each species  
158 experiences throughout the year (Kleisner et al., 2017).

159 We modeled individual species distributions with two-stage generalized additive models  
160 (GAMs), using the mgcv package (version 1.8.33) in R (version 4.0.2) (Wood, 2011). The first  
161 stage was a presence-absence model with a binomial error distribution, and the second stage was

162 a biomass given presence model using a log-link transform on non-zero observations with a  
163 gaussian error distribution. For both stages, we included a penalized likelihood to reduce model  
164 complexity (Morley et al., 2018; Wood, 2006). We calculated suitable thermal habitat as the  
165 product of the presence-absence model predictions, the back-transformed log-biomass model  
166 predictions, and a smearing estimate (the mean of the log-biomass model residuals) to correct for  
167 retransformation bias (Duan 1983; Kleisner et al., 2017; Morley et al., 2018). This suitable  
168 thermal habitat value does not directly represent species abundance, but rather the potential  
169 suitable habitat and species density solely based on model predictor variables (Kleisner et al.,  
170 2017; Morley et al., 2018).

171 The predictor variables for the models included tow and environmental information from  
172 the trawl surveys and more complex temperature variables from GLORYS. From the surveys, we  
173 used in situ surface and bottom temperature and the starting depth of the tow. We used GLORYS  
174 temperature data to characterize broader spatial and temporal aspects of thermal habitat that  
175 could influence species distribution, including the annual minimum and maximum surface and  
176 bottom temperature (that is, the minimum or maximum temperature over the preceding twelve  
177 months in the  $0.25^\circ \times 0.25^\circ$  cell where the tow was conducted) and spatial standard deviation of  
178 surface and bottom temperature (using a  $3 \times 3$  window around each  $0.25^\circ \times 0.25^\circ$  cell) to  
179 approximate frontal activity (Abrahms et al., 2019; Morley et al., 2018), which is known to  
180 influence species distribution in Iceland's waters (Asthþorsson et al., 2007) . We removed the  
181 annual minimum bottom temperature as a predictor variable because it was highly correlated  
182 with the survey in situ bottom temperature (Spearman's rho = 0.77).

183 To account for habitat suitability factors not captured by depth and temperature, we  
184 added Bormicon regions (Figure 1), which are habitat zones used in MFRI's multispecies

185 modelling efforts (Stefansson, 2004), as a parametric term. These regions were delineated based  
186 on topography (the depth contour of the continental shelf and submarine ridges), hydrography  
187 (salinity distribution and mixing patterns), and general patterns of spawning, migration, and  
188 fishing effort for key demersal species (Stefansson & Palsson, 1997). We selected these regions  
189 based on their management relevance and in the absence of more detailed habitat quality data but  
190 recognize risks of tautology in using these regions to simulate species distribution. We  
191 performed additional tests of the suitability of this predictor during initial model selection and  
192 determined that it improved model performance in terms of prediction error, deviance explained,  
193 and Akaike's Information Criterion (AIC) for the majority of species. The fact that there are  
194 relatively few survey tows in the offshore regions also limits predictive performance, so we  
195 focus our subsequent results and discussion on habitat dynamics along the continental shelf and  
196 provide the caveat that this variable should be interpreted with caution, particularly for any  
197 species for which models project offshore habitat changes.

198 Thus, the final model formulas were as follows, where  $s()$  represents a thin plate spline  
199 smooth term:

200 Presence ~ intercept + Bormicon region +  $s(\text{tow depth})$  +  $s(\text{SST})$  +  $s(\text{bottom}$   
201  $\text{temperature})$  +  $s(\text{min SST})$  +  $s(\text{max SST})$  +  $s(\text{sd SST})$  +  $s(\text{max BT})$  +  $s(\text{sd BT})$   
202 Log-biomass (kg) ~ intercept + Bormicon region +  $s(\text{tow depth})$  +  $s(\text{SST})$  +  
203  $s(\text{bottom temperature})$  +  $s(\text{min SST})$  +  $s(\text{max SST})$  +  $s(\text{sd SST})$  +  $s(\text{max BT})$  +  
204  $s(\text{sd BT})$

205 The GLORYS data were available from 1993-2018, so the final models were fitted with n  
206 = 19759 tows with all predictor data available. For species with no presences observed in a

207 particular Bormicon region, we randomly replaced 10% of the tows in those regions with near-  
208 zero ( $1^{-10}$ ) biomass values to allow log-biomass projections in those areas, following Morely et  
209 al. (2018). Because these surveys were designed to sample demersal fish, we removed  
210 invertebrate and pelagic species for analysis. We ran models for 56 fish species with sufficient  
211 observations for the model parameters.

212 We assessed model performance by training the presence-absence models with tows  
213 through 2013 (approximately 80% of the tows), and testing predictions on the remaining 20% of  
214 the tows. We assessed presence-absence models using true skill statistic (TSS), a measure suited  
215 to spatial presence-absence prediction performance, where a score of 1 represents perfect  
216 agreement and a score  $< 0$  is no better than random (Allouche et al., 2006). All species had a TSS  
217 score  $> 0.25$ , so we did not remove any species from analysis based on this metric. To evaluate  
218 the importance of each predictor variable in contributing to model explanatory power, we  
219 compared the percent deviance explained from the full model and a model with that covariate  
220 dropped for each species.

221 We considered the suitability of a temperature-based model by comparing the prediction  
222 error in the combined presence-absence and log-biomass thermal suitable habitat predictions  
223 with that of a “naïve” model with temperature variables removed (i.e., just depth and Bormicon  
224 region as predictors). Models were considered suitable if the ratio of the full model to naïve  
225 model error was  $< 1$  and the Diebold-Mariano test p-value was  $< 0.05$  (see Kleisner et al., 2017).  
226 We removed nine species from analysis based on this assessment and present results for the 47  
227 remaining species. We performed these tests using the dismo package (version 1.3.2) in R  
228 (Hijmans et al., 2020). Other model results reported (deviance explained, suitable thermal habitat

229 values) are based on the models fitted on all data, not split into training and testing. See  
230 supplemental information for model performance results for all species.

231 *Projecting future thermal habitat*

232 We calculated the amount of available suitable habitat as the sum of all modeled thermal  
233 habitat values in the full EEZ projection grid (Morley et al., 2018). We compared the mean  
234 available habitat in the historical period (2000-2018) with the future period (2061-2080) for each  
235 species. Because some changes were quite large (orders of magnitude), we present  $\log_{10}$  x-fold  
236 change ( $\log(\text{mean future thermal habitat} / \text{mean historical thermal habitat})$ ) so that relative  
237 increases and decreases can be compared. We calculated the centroid of distribution for each  
238 species as mean latitude and longitude weighted by the modeled thermal habitat value, and  
239 calculated the distance (km) and direction (degrees) shifted between the historical and future  
240 period with the geosphere package (version 1.5.10) in R (Hijmans, 2019). Additionally, we  
241 calculated the shifts in warm and cold edges of species distributions as the difference in the 95<sup>th</sup>  
242 and 5<sup>th</sup> respective percentile latitude of thermal habitat values  $> 0.05$  (Fredston-Hermann et al.,  
243 2020).

244 We grouped species by thermal affinity indices outlined in Campana et al. (2020), based  
245 on bottom temperatures and depths from the trawl surveys. We calculated thermal bias as the  
246 difference in median biomass-weighted bottom temperature for each species and the median  
247 bottom temperature of all survey tows, stenothermal index as the range of 5<sup>th</sup> and 95<sup>th</sup> percentiles  
248 of those biomass-weighted bottom temperatures for each species, and depth as the biomass-  
249 weighted median tow depth for each species. Because the spring and autumn surveys sample  
250 different areas and depths, we calculated separate index values for each season and took a  
251 weighted mean based on the number of observations in each season. Following Campana et al.

252 (2020), we categorized species into warm water (positive thermal bias), cool water (-3°C to 0°C  
253 thermal bias), and cold water (< -3°C thermal bias) niches. We tested associations between  
254 thermal affinity indices and projected shifts in thermal habitat availability and distribution with  
255 ordinary least squares regression.

256 **Results**

257 *Projected climate change*

258 The projected climate model deltas resulted in a mean increase in surface temperatures in  
259 Iceland's EEZ of 1.96°C for SSP 2-4.5 (ranging from 0.76°C, CNRM to 2.40°C, MOHC) and  
260 2.40°C for SSP 5-8.5 (ranging from 1.00°C, CM2.6 to 3.40°C, IPSL) by 2061-2080. For bottom  
261 temperatures, the mean projected increase for 2061-2080 was 0.06°C for SSP 2-4.5 (ranging  
262 from -1.5°C, GFDL to 1.21°C, IPSL) and 0.20°C for SSP 5-8.5 (ranging from -1.35°C, GFDL to  
263 1.47°C, IPSL) in 2061-2080 (see supplemental information for time series of individual climate  
264 model projections). Spatially, surface warming was projected throughout Iceland's EEZ and  
265 most pronounced in offshore northeast waters for both scenarios (Figure 2a). The variation  
266 among climate model surface temperature projections was also highest in Iceland's northern  
267 waters, which likely reflects uncertainty in the mixing dynamics between Atlantic and polar  
268 waters (Figure 2b). Bottom temperature deltas showed cooling in Iceland's southern waters  
269 beyond the continental shelf, and concentrated warming along the northern shelf and east along  
270 the Iceland-Faroes ridge in the southeast (Figure 2c). Variation among models was highest in the  
271 east where warming is most pronounced, as well as offshore southern waters (Figure 2d).

272 *Projected changes in suitable thermal habitat*

273 The presence-absence GAMs explained mean 44% of deviance (sd 16; range 10-81)  
274 across the 47 species and had a mean TSS of 0.68 (sd 0.15, range 0.36-0.95). The log-biomass  
275 models explained mean 31% of deviance (sd 15, range 10-72). Tow depth and Bormicon region  
276 contributed the most to variance explained in both the presence-absence and log-biomass  
277 models. Models fitted without depth lost mean 12.9% variance explained for presence-absence  
278 (sd 9.11, range -2.05-32.1) and 5.5% for log-biomass (sd 4.64, range -0.05-16.3). Models fitted  
279 without Bormicon region lost mean 10.5% (sd 9.51, range -4.04-32.0) and 2.8% (sd 1.74, range -  
280 0.14 -7.02) variance explained in presence-absence and log-biomass models, respectively. For  
281 the presence-absence models, the remaining temperature variables contributed between 8.9-9.6%  
282 variance explained on average, whereas for log-biomass models, lost variance explained was  
283 minimal, ranging from 0.2% for SST standard deviation and maximum to 0.86% for bottom  
284 temperature.

285 Warmer water species were generally projected to see an increase in suitable thermal  
286 habitat in 2061-2080 relative to 2000-2018, while cold and cool water species were generally  
287 projected to see a decrease in habitat (Figure 3). The magnitude of decreases was higher than the  
288 magnitude of increases, and patterns were similar across the two scenarios. Thirteen species had  
289 a projected increase in habitat for all models for SSP 2-4.5 and fifteen for SSP 5-8.5, whereas  
290 fifteen species had a projected decrease in habitat for all models in SSP 2-4.5 and sixteen for SSP  
291 5-8.5. Thermal bias was significantly positively correlated with median change in projected  
292 suitable habitat for SSP 5-8.5 (adjusted  $r^2 = 0.12$ ,  $p < 0.01$ ; for SSP 2-4.5, adjusted  $r^2 = 0.03$  and  
293  $p = 0.13$ ), whereas stenothermic index and median depth did not show a significant relationship  
294 with projected suitable thermal habitat change in either scenario (stenothermic index:  $p = 0.13$ ,  
295 0.10; median depth:  $p = 0.12$ , 0.37).

296 These projected habitat suitability shifts were spatially heterogeneous within Iceland's  
297 waters, with most species showing relatively localized increases and/or decreases (Figure 4). Cod  
298 (*Gadus morhua*), saithe (*Pollachius virens*), and redfish (*Sebastes marinus*), key commercial  
299 species, showed increases along Iceland's northern continental shelf. For cod, a cool water  
300 species, habitat suitability increases were more pronounced in the north and east, with potential  
301 suitability decreases in the southwest and southeast (Figure 4a). Redfish showed a pronounced  
302 decrease in southwest offshore waters. Long rough dab (*Hippoglossoides platessoides*), a cool  
303 water species, showed nearly the opposite pattern to cod, with decreases along the northern  
304 continental shelf and increases in the south/southeast (for SSP 2-4.5) (Figure 4b). Whiting  
305 (*Merlangius merlangus*), along with several other warm-water species including monkfish  
306 (*Lophius piscatorius*), witch (*Glyptocephalus cynoglossus*), megrim (*Lepidorhombus*  
307 *whiffiagonis*), and Norway haddock (*Sebastes viviparus*), showed habitat suitability increases  
308 along Iceland's southern and western continental shelf (Figure 4c). Lumpfish (*Cyclopterus*  
309 *lumpus*, cool water), Atlantic wolffish (*Anarhichus lupus*, cool water), plaice (*Pleuronectes*  
310 *platessa*, warm water) and dab (*Limanda limanda*, warm water) all show inshore decreases,  
311 concentrated in the northwest fjords for lumpfish, wolffish, and dab and along the west coast  
312 bays for plaice (Figure 4d). Lemon sole (*Microstomus kitt*, warm water), on the other hand,  
313 shows nearshore increases around the island. Maps indicating projected habitat changes for all  
314 analyzed species and all projection periods are available in the supplemental information.

315 Taken together, these projected shifts in species distribution show general northward  
316 movement, trending north and northwest in SSP 2-4.5 and north and slightly northeast among  
317 warmer water species in SSP 5-8.5 (Figure 5). There was no significant relationship between  
318 thermal bias, stenothermic index, and depth with the distance or bearing of centroid change.

319 Species with a higher thermal bias (i.e. warmer water species) were significantly more likely to  
320 see northward movement of the cold edge of their range ( $\text{adj } r^2 = 0.10$ ,  $p = 0.02$  for SSP 2-4.5,  
321  $\text{adj } r^2 = 0.14$ ,  $p = 0.005$  for SSP 5-8.5), but there were no significant relationships observed for  
322 movement of the southern warm range edge or with other thermal affinity indices.

323

324 **Discussion**

325 These results corroborate previous projections that future climate change could result in  
326 significant shifts in fish species abundance and distribution in Iceland's waters, and further  
327 illustrate potential variability in responses among species and regions. Consistent with global  
328 hypotheses and Campana et al. (2020)'s analyses, our results indicate an overall northward shift  
329 in center of biomass distribution for Iceland's demersal fish species, with warmer water species  
330 more likely to expand the cold edge of their range. Species thermal bias was a more significant  
331 predictor of future habitat suitability change than stenothermic index or depth preference, results  
332 also similar to Campana et al. (2020)'s findings. In general, our analyses suggest similar trends  
333 to those observed during the mid-1990s warming period (Valtýsson & Jónsson, 2018) could be  
334 expected by midcentury, with many warmer water species likely to experience overall increases  
335 in suitable thermal habitat in Iceland's EEZ. However, these patterns are localized and may be  
336 accompanied by regional decreases.

337 It is encouraging that many commercially important species are projected to see increases  
338 in suitable habitat in Iceland's waters. However, regional heterogeneity in habitat suitability  
339 changes may be of interest to managers and the fishing industry. For example, the overall  
340 increase in habitat suitability for cod, a flagship commercial species for Iceland, is largely along

341 the northern coast, where fishing capacity and infrastructure has declined following industry  
342 consolidation (Kokorsch & Benediktsson, 2018). Meanwhile, the capital region and western  
343 coast where cod catches have historically been highest may see decreases under the high-CO<sub>2</sub>  
344 emission scenario. Fishers in these waters may see cod supplemented by warmer-water species  
345 such as monkfish and megrim. The impact of these shifts may be felt unevenly within the fishing  
346 industry as larger companies with more technological capacity are less dependent on proximity  
347 to fishing grounds than smaller companies (Edvardsson et al. 2018). Local small boat operations  
348 could be further disadvantaged by the projected decreased habitat suitability for several species  
349 in inshore areas, particularly in the fisheries-dependent northwest region. Declining inshore  
350 habitat suitability for lumpfish may be particularly challenging for communities where the  
351 fishery is a cultural mainstay (Chambers, 2016). The potential movement of lumpfish offshore  
352 may present an additional management concern if it increases lumpfish bycatch rates in other  
353 fisheries, but could be beneficial if it alleviates interactions with pinnipeds and seabirds. Thus,  
354 these multidecadal scale projections might be a consideration in long-term planning not only for  
355 fishery development but also broader infrastructure policy, as investment in energy transmission  
356 and roads is critical for the competitiveness of smaller and more remote processing facilities  
357 (Reynisson et al. 2012).

358 Further examination of the life history and ecology of these species may aid in  
359 interpreting the trends we present here and highlight any results that may warrant further, finer-  
360 scale investigation. For example, a potentially puzzling result is that the species with the largest  
361 projected suitable habitat decreases, dab and plaice, are both warm-water species. These species  
362 are found in shallow waters, and therefore may be particularly sensitive to temperature or limited  
363 in their habitat. Survey coverage and timing may also factor into the uncertainty of these results.

364 For example, dab have an especially patchy distribution with few high-volume tows (MFRI,  
365 2020), which likely reduces model predictive power. Plaice spawn during the early spring,  
366 concurrent with the spring surveys (Solvundsson et al., 2005), which may result in aggregations  
367 that could bias the survey. These spawning dynamics may in part explain why plaice show a  
368 different pattern from lemon sole, another warm and shallow water species that spawns later in  
369 the year. While our analyses were intended as an exploration of overall trends rather than fitting  
370 individual models for each species, a more tailored approach that incorporates these specific  
371 spawning dynamics would be advisable for any planning regarding these species. Similarly, a  
372 species-specific approach could reveal climate sensitivity in species we dropped from analysis  
373 based on MASE performance. For example, Greenland halibut appear to be sensitive to the  
374 interaction between bottom temperature and depth based on model performance in initial trials.

375 In addition to refining habitat models, more complex approaches are likely needed to  
376 accurately project future fish productivity and distribution in Iceland's waters. Our estimates of  
377 suitable thermal habitat represent maximum potential abundances with all other factors held  
378 equal, and do not capture changes in physiology, species interactions, or fishing pressure, all of  
379 which could change in coming decades. Predator-prey interactions could be a dominant  
380 ecological driver in Iceland's waters: During the mid-1990s warming period, increasing cod and  
381 other gadoid stocks along Iceland's northern coast is believed to have triggered the decline of a  
382 commercially important shrimp fishery, as these fish preyed heavily on northern shrimp and  
383 other species in closed fjord systems (Jónsdóttir et al., 2019). More recently, mackerel predation  
384 has been associated with declines in other warm-water species despite continued warming  
385 (Valtýsson & Jónsson, 2018). Such predator-prey interactions, while not accounted for in our  
386 models, would be key management considerations under warming conditions.

387            Additionally, we did not differentiate size or age classes among species, nor other  
388    intraspecific population structures that may have distinct suitable thermal habitats and thus future  
389    climate-driven dynamics. Cod, for example, exhibit ontogenetic regional shifts that follow the  
390    clockwise flow of currents around Iceland (Astthorsson et al., 2007), as well as behavioral  
391    ecotypes with separate temperature and depth niches (Grabowski et al., 2011). Combining  
392    autumn and spring survey data in our models was a step toward reducing bias based on seasonal  
393    dynamics, but more specific models for species known to have age-differentiated temperature  
394    responses could provide more nuanced projections of how climate change could affect ecological  
395    interactions and fisheries productivity.

396            Another limitation of our study is that as the survey data are limited to Iceland's EEZ,  
397    they may not capture the full thermal or depth range for these species. Thus, our  
398    characterizations of suitable habitat may be too restrictive, and our projections cannot account  
399    for potential migration of more southern stocks into Iceland's waters. However, since many of  
400    Iceland's demersal stocks are relatively constrained to Iceland's continental shelf (Valtýsson &  
401    Jónsson, 2018), limiting this analysis to Iceland's EEZ may be appropriate for the species  
402    discussed here. Expanding these models to include data from more southern surveys, such as the  
403    Western and Southern areas of the International Council for Exploration of the Sea International  
404    Bottom Trawl Survey, could more comprehensively capture species temperature niches and  
405    potential future climate responses. Such an analysis would be valuable for identifying dynamics  
406    of straddling stocks and informing priorities for international negotiations.

407            Finally, management decisions are likely to be more significant determinants of fish  
408    abundance and distribution than long-term climate trends, particularly for the next few decades  
409    (Mullon et al., 2016). Our habitat suitability projections can provide an idea of regions or species

410 that could be important to develop or to protect, but the future outcomes will depend largely on  
411 human actions. This study demonstrates the value of using global climate models to make  
412 spatially explicit projections of fish suitable habitat, which may serve as guideposts for long-term  
413 scenario planning, investment in fisheries and infrastructure, and risk evaluation. For Iceland and  
414 other regions with available data to support habitat modeling, such forward-looking studies could  
415 be a valuable strategy for achieving climate-adaptive fisheries.

416

#### 417 **Data statement**

418 NOAA High Resolution SST data were provided by the NOAA/OAR/ESRL PSL, Boulder,  
419 Colorado, USA, from their website at <https://www.ncdc.noaa.gov/oisst>. GLORYS data were  
420 provided by the Copernicus Marine Environmental Monitoring Service at  
421 [https://resources.marine.copernicus.eu/?option=com\\_csw&view=details&product\\_id=GLOBAL](https://resources.marine.copernicus.eu/?option=com_csw&view=details&product_id=GLOBAL)  
422 \_REANALYSIS\_PHY\_001\_031.

423 Code for downloading climate data and performing these analyses is available at  
424 [https://github.com/juliagmason/iceland\\_climate\\_resilient\\_fisheries](https://github.com/juliagmason/iceland_climate_resilient_fisheries).

425

#### 426 **References**

427 Abrahms, B., Welch, H., Brodie, S., Jacox, M. G., Becker, E. A., Bograd, S. J., Irvine, L. M.,  
428 Palacios, D. M., Mate, B. R., & Hazen, E. L. (2019). Dynamic ensemble models to  
429 predict distributions and anthropogenic risk exposure for highly mobile species. *Diversity  
430 and Distributions*, 25(8), 1182–1193.

431 Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution  
432 models: Prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*,  
433 43(6), 1223–1232.

434 Anandhi, A., Frei, A., Pierson, D. C., Schneiderman, E. M., Zion, M. S., Lounsbury, D., &  
435 Matonse, A. H. (2011). Examination of change factor methodologies for climate change  
436 impact assessment. *Water Resources Research*, 47(3).  
437 <https://doi.org/10.1029/2010WR009104>

438 Astthorsson, O., Gislason, A., & Jonsson, S. (2007). Climate variability and the Icelandic marine  
439 ecosystem. *Deep Sea Research Part II: Topical Studies in Oceanography*, 54(23–26),  
440 2456–2477.

441 Astthorsson, O. S., & Palsson, J. (2006). New fish records and records of rare southern species in  
442 Icelandic waters in the warm period 1996–2005. *ICES CM*, 100, 20.

443 Astthorsson, Olafur S., Valdimarsson, H., Gudmundsdottir, A., & Óskarsson, G. J. (2012).  
444 Climate-related variations in the occurrence and distribution of mackerel (Scomber  
445 scombrus) in Icelandic waters. *ICES Journal of Marine Science*, 69(7), 1289–1297.  
446 <https://doi.org/10.1093/icesjms/fss084>

447 Chambers, C. P. (2016). *FISHERIES MANAGEMENT AND FISHERIES LIVELIHOODS IN  
448 ICELAND*. University of Alaska Fairbanks.

449 Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R., & Pauly, D.  
450 (2009). Projecting global marine biodiversity impacts under climate change scenarios.  
451 *Fish and Fisheries*, 10(3), 235–251. <https://doi.org/10.1111/j.1467-2979.2008.00315.x>

452 Duan, Naihua (1983). “Smearing Estimate: A Nonparametric Retransformation Method.”  
453 *Journal of the American Statistical Association* 78, no. 383: 605–10.  
454 <https://doi.org/10.1080/01621459.1983.10478017>.

455 Edvardsson, Kristinn Nikulás, Cezara Pástrav, and Karl Benediktsson. “Mapping the  
456 Geographical Consolidation of Fishing Activities in Iceland during the Maturation of the  
457 ITQ Fisheries Management System.” *Applied Geography* 97 (August 2018): 85–97.  
458 <https://doi.org/10.1016/j.apgeog.2018.05.013>.

459 Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E.  
460 (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6)  
461 experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–  
462 1958. <https://doi.org/10.5194/gmd-9-1937-2016>

463 FAO. (2020). *The State of World Fisheries and Aquaculture 2020* (Sustainability in Action).  
464 FAO. <https://doi.org/10.4060/ca9229en>

465 Fredston-Hermann, A., Selden, R., Pinsky, M., Gaines, S. D., & Halpern, B. S. (2020). Cold  
466 range edges of marine fishes track climate change better than warm edges. *Global  
467 Change Biology*, 26(5), 2908–2922. <https://doi.org/10.1111/gcb.15035>

468 Free, C. M., Mangin, T., Molinos, J. G., Ojea, E., Burden, M., Costello, C., & Gaines, S. D.  
469 (2020). Realistic fisheries management reforms could mitigate the impacts of climate  
470 change in most countries. *PLOS ONE*, 15(3), e0224347.  
471 <https://doi.org/10.1371/journal.pone.0224347>

472 Gaines, S. D., Costello, C., Owashi, B., Mangin, T., Bone, J., Molinos, J. G., Burden, M.,  
473 Dennis, H., Halpern, B. S., Kappel, C. V., Kleisner, K. M., & Ovando, B. (2018).  
474 Improved fisheries management could offset many negative effects of climate change.  
475 *Science Advances*, 4(8), eaao1378.

476 Golden, C. D., Allison, E. H., Cheung, W. W. L., Dey, M. M., Halpern, B. S., McCauley, D. J.,  
477 Smith, M., Vaitla, B., Zeller, D., & Myers, S. S. (2016). Nutrition: Fall in fish catch  
478 threatens human health. *Nature*, 534(7607), 317–320. <https://doi.org/10.1038/534317a>

479 Grabowski, T. B., Thorsteinsson, V., McAdam, B. J., & Marteinsdóttir, G. (2011). Evidence of  
480 Segregated Spawning in a Single Marine Fish Stock: Sympatric Divergence of Ecotypes  
481 in Icelandic Cod? *PLOS ONE*, 6(3), e17528.  
482 <https://doi.org/10.1371/journal.pone.0017528>

483 Hijmans, R. J. (2019). *geosphere: Spherical Trigonometry*. <https://CRAN.R-project.org/package=geosphere>

484 Hijmans, R. J., Phillips, S., Leathwick, J., & Elith, J. (2020). *dismo: Species Distribution  
485 Modeling*. <https://CRAN.R-project.org/package=dismo>

486 Hobday, A. J., Spillman, C. M., Eveson, J. P., Hartog, J. R., Zhang, X., & Brodie, S. (2018). A  
487 Framework for Combining Seasonal Forecasts and Climate Projections to Aid Risk  
488 Management for Fisheries and Aquaculture. *Frontiers in Marine Science*, 5.  
489 <https://doi.org/10.3389/fmars.2018.00137>

490 Holsman, K. K., Hazen, E. L., Haynie, A., Gourguet, S., Hollowed, A., Bograd, S. J., Samhouri,  
491 J. F., & Aydin, K. (2019). Towards climate resiliency in fisheries management. *ICES  
492 Journal of Marine Science*.

493 Hoyer, S., & Hamman, J. (2017). xarray: N-D labeled arrays and datasets in Python. *Journal of  
494 Open Research Software*, 5(1). <https://doi.org/10.5334/jors.148>

495 Jónsdóttir, I. G., Bakka, H., & Elvarsson, B. T. (2019). Groundfish and invertebrate community  
496 shift in coastal areas off Iceland. *Estuarine, Coastal and Shelf Science*, 219, 45–55.

497 Karp, M. A., Peterson, J. O., Lynch, P. D., Griffis, R. B., Adams, C. F., Arnold, W. S., Barnett,  
498 L. A. K., deReynier, Y., DiCosimo, J., Fenske, K. H., Gaichas, S. K., Hollowed, A.,  
499 Holsman, K., Karnauskas, M., Kobayashi, D., Leising, A., Manderson, J. P., McClure,  
500 M., Morrison, W. E., ... Link, J. S. (2019). Accounting for shifting distributions and  
501 changing productivity in the development of scientific advice for fishery management.  
502 *ICES Journal of Marine Science*, 76(5), 1305–1315.  
503 <https://doi.org/10.1093/icesjms/fsz048>

504 Kleisner, K. M., Fogarty, M. J., McGee, S., Hare, J. A., Moret, S., Perretti, C. T., & Saba, V. S.  
505 (2017). Marine species distribution shifts on the US Northeast Continental Shelf under  
506 continued ocean warming. *Progress in Oceanography*, 153, 24–36.

507 Kleisner, K. M., Ojea, E., Amoros, S., Battista, W., Burden, M., Cunningham, E., Fujita, R.,  
508 Karr, K., Mason, J., Rader, D., Rovegno, N., Thomas-Smyth, A. (in press). Identifying  
509 policy approaches to build social-ecological resilience in marine fisheries with differing  
510 capacities and contexts. *ICES Journal of Marine Science*.

511 Kokorsch, M., & Benediktsson, K. (2018). Prosper or perish? The development of Icelandic  
512 fishing villages after the privatisation of fishing rights. *Maritime Studies*, 17(1), 69–83.

513 Lam, V. W. Y., Cheung, W. W. L., Reygondeau, G., & Sumaila, U. R. (2016). Projected change  
514 in global fisheries revenues under climate change. *Scientific Reports*, 6(1), 32607.  
515 <https://doi.org/10.1038/srep32607>

516 Marine and Freshwater Research Institute (2020). *Technical report: Dab—Sandkoli* (18 pp).  
517 [https://www.hafogvatn.is/static/extras/images/27-dab\\_tr1206897.pdf](https://www.hafogvatn.is/static/extras/images/27-dab_tr1206897.pdf)

518 Molinos, J. G., Halpern, B. S., Schoeman, D. S., Brown, C. J., Kiessling, W., Moore, P. J.,  
519 Pandolfi, J. M., Poloczanska, E. S., Richardson, A. J., & Burrows, M. T. (2016). Climate  
520 velocity and the future global redistribution of marine biodiversity. *Nature Climate  
521 Change*, 6(1), 83.

522 Morley, J. W., Frölicher, T. L., & Pinsky, M. L. (2020). Characterizing uncertainty in climate  
523 impact projections: A case study with seven marine species on the North American

524

525 continental shelf. *ICES Journal of Marine Science*, fsaa103.  
526 <https://doi.org/10.1093/icesjms/fsaa103>

527 Morley, J. W., Selden, R. L., Latour, R. J., Frölicher, T. L., Seagraves, R. J., & Pinsky, M. L.  
528 (2018). Projecting shifts in thermal habitat for 686 species on the North American  
529 continental shelf. *PLoS ONE*, 13(5). <https://doi.org/10.1371/journal.pone.0196127>

530 Mullon, C., Steinmetz, F., Merino, G., Fernandes, J. A., Cheung, W. W. L., Butenschön, M., &  
531 Barange, M. (2016). Quantitative pathways for Northeast Atlantic fisheries based on  
532 climate, ecological–economic and governance modelling scenarios. *Ecological  
533 Modelling*, 320, 273–291. <https://doi.org/10.1016/j.ecolmodel.2015.09.027>

534 Ogilvie, A. E., & Jónsdóttir, I. (2000). Sea ice, climate, and Icelandic fisheries in the eighteenth  
535 and nineteenth centuries. *Arctic*, 53(4), 383–394.

536 Olafsdottir, A. H., Utne, K. R., Jacobsen, J. A., Jansen, T., Óskarsson, G. J., Nøttestad, L.,  
537 Elvarsson, B. P., Broms, C., & Slotte, A. (2019). Geographical expansion of Northeast  
538 Atlantic mackerel (*Scomber scombrus*) in the Nordic Seas from 2007 to 2016 was  
539 primarily driven by stock size and constrained by low temperatures. *Deep Sea Research  
540 Part II: Topical Studies in Oceanography*, 159, 152–168.  
541 <https://doi.org/10.1016/j.dsr2.2018.05.023>

542 O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van  
543 Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., Levy, M., & Solecki, W.  
544 (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world  
545 futures in the 21st century. *Global Environmental Change*, 42, 169–180.  
546 <https://doi.org/10.1016/j.gloenvcha.2015.01.004>

547 Parmesan, C. (2006). Ecological and Evolutionary Responses to Recent Climate Change. *Annual  
548 Review of Ecology, Evolution, and Systematics*, 37(1), 637–669.  
549 <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>

550 Pinsky, M. L., Reygondeau, G., Caddell, R., Palacios-Abrantes, J., Spijkers, J., & Cheung, W.  
551 W. (2018). Preparing ocean governance for species on the move. *Science*, 360(6394),  
552 1189–1191.

553 Pinsky, M., & Mantua, N. (2014). Emerging Adaptation Approaches for Climate-Ready  
554 Fisheries Management. *Oceanography*, 27(4), 146–159.  
555 <https://doi.org/10.5670/oceanog.2014.93>

556 Poloczanska, E. S., Brown, C. J., Sydeman, W. J., Kiessling, W., Schoeman, D. S., Moore, P. J.,  
557 Brander, K., Bruno, J. F., Buckley, L. B., Burrows, M. T., Duarte, C. M., Halpern, B. S.,  
558 Holding, J., Kappel, C. V., O'Connor, M. I., Pandolfi, J. M., Parmesan, C., Schwing, F.,  
559 Thompson, S. A., & Richardson, A. J. (2013). Global imprint of climate change on  
560 marine life. *Nature Climate Change*, 3(10), 919–925.  
561 <https://doi.org/10.1038/nclimate1958>

562 Reynisson, Reinhard, Jóna Matthiassdóttir, Tryggvi Finnsson, and Ari Pall Palsson. “Northeast  
563 Iceland Infrastructure Analysis.” Husavík, Iceland: Northeast Iceland Development  
564 Agency, 2012.

565 Saba, V. S., Griffies, S. M., Anderson, W. G., Winton, M., Alexander, M. A., Delworth, T. L.,  
566 Hare, J. A., Harrison, M. J., Rosati, A., & Vecchi, G. A. (2016). Enhanced warming of  
567 the Northwest Atlantic Ocean under climate change. *Journal of Geophysical Research: Oceans*, 121(1), 118–132.

568 Seidov, Dan; Baranova, Olga K.; Biddle, Mathew; Boyer, Tim P.; Johnson, Daphne R.;  
569 Mishonov, Alexey V.; Paver, Christopher R.; Zweng, Melissa M. (2013). Greenland-  
570

571 Iceland-Norwegian Seas Regional Climatology (NCEI Accession 0112824). NOAA  
572 National Centers for Environmental Information. Dataset. [https://doi-](https://doi.org/10.7289/v5gt5k30)  
573 [proxy.library.cornell.edu/10.7289/v5gt5k30](https://doi.org/10.7289/v5gt5k30). Accessed 14-07-2020.

574 Solmundsson, J., Karlsson, H., Bjornsson, H., Jonsdottir, I. G., Jakobsdóttir, K., & Bogason, V.  
575 (2020). *A manual for the Icelandic groundfish survey in spring 2020*. Marine and  
576 Freshwater Research Institute.

577 Solmundsson, J., Palsson, J., & Karlsson, H. (2005). Fidelity of mature Icelandic plaice  
578 (*Pleuronectes platessa*) to spawning and feeding grounds. *ICES Journal of Marine*  
579 *Science*, 62(2), 189–200. <https://doi.org/10.1016/j.icesjms.2004.11.012>

580 Spijkers, J., & Boonstra, W. J. (2017). Environmental change and social conflict: The northeast  
581 Atlantic mackerel dispute. *Regional Environmental Change*, 17(6), 1835–1851.  
582 <https://doi.org/10.1007/s10113-017-1150-4>

583 Stefánsdóttir, L. (2008). *Groundfish species diversity and assemblage structure in Icelandic*  
584 *waters during a period of rapid warming (1996-2007)*.

585 Stefánsdóttir, R. B. (2019). *Climate change and northward distribution shifts in Icelandic*  
586 *groundfish species*. University of Iceland.

587 Stefansson, G. (2004). *Development of structurally detailed statistically testable models of*  
588 *marine populations* (No. QLK5-CT1999-01609; p. 200).

589 Stefansson, G., & Palsson, O. K. (1997). *BORMICON: A Boreal Migration and Consumption*  
590 *Model* (No. 58; p. 233). Marine Research Institute.  
591 <https://www.hafogvatn.is/static/research/files/fjolrit-058.pdf>

592 Stock, C. A., Alexander, M. A., Bond, N. A., Brander, K. M., Cheung, W. W. L., Curchitser, E.  
593 N., Delworth, T. L., Dunne, J. P., Griffies, S. M., Haltuch, M. A., Hare, J. A., Hollowed,  
594 A. B., Lehodey, P., Levin, S. A., Link, J. S., Rose, K. A., Rykaczewski, R. R., Sarmiento,  
595 J. L., Stouffer, R. J., ... Werner, F. E. (2011). On the use of IPCC-class models to assess  
596 the impact of climate on Living Marine Resources. *Progress in Oceanography*, 88(1), 1–  
597 27. <https://doi.org/10.1016/j.pocean.2010.09.001>

598 Sumaila, U. R., Cheung, W. W. L., Lam, V. W. Y., Pauly, D., & Herrick, S. (2011). Climate  
599 change impacts on the biophysics and economics of world fisheries. *Nature Climate*  
600 *Change*, 1(9), 449–456. <https://doi.org/10.1038/nclimate1301>

601 Valdimarsson, H., Astthorsson, O. S., & Palsson, J. (2012). Hydrographic variability in Icelandic  
602 waters during recent decades and related changes in distribution of some fish species.  
603 *ICES Journal of Marine Science*, 69(5), 816–825.

604 Valtýsson, H. Þ., & Jónsson, S. (2018). Impacts of a Changing Climate on Icelandic Marine  
605 Stocks. In F. J. Mueter, M. R. Baker, S. C. Dressel, & A. B. Hollowed (Eds.), *Impacts of*  
606 *a Changing Environment on the Dynamics of High-latitude Fish and Fisheries*. Alaska  
607 Sea Grant, University of Alaska, Fairbanks.

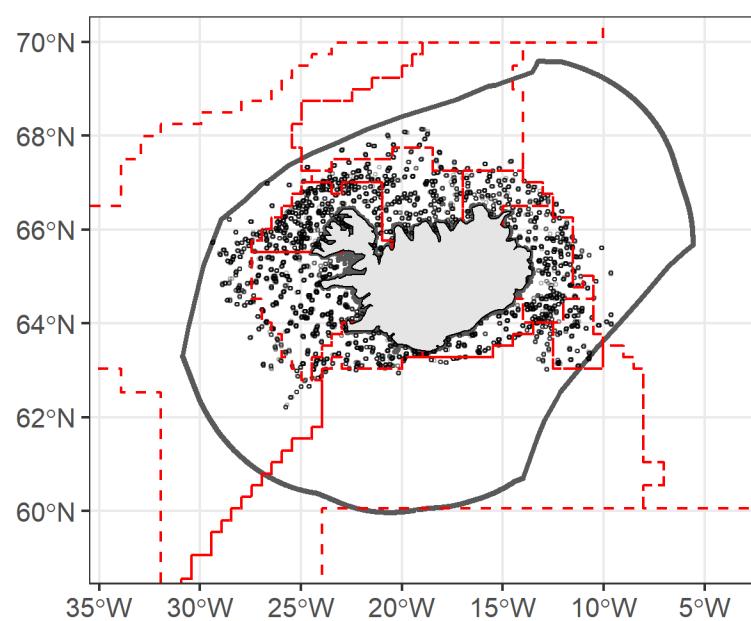
608 Wood, S. N. (2006). *Generalized additive models: An introduction with R*. (Chapman and  
609 Hall/CRC: Florida).

610 Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood  
611 estimation of semiparametric generalized linear models. *Journal of the Royal Statistical*  
612 *Society (B)*, 73(1), 3–36.

613

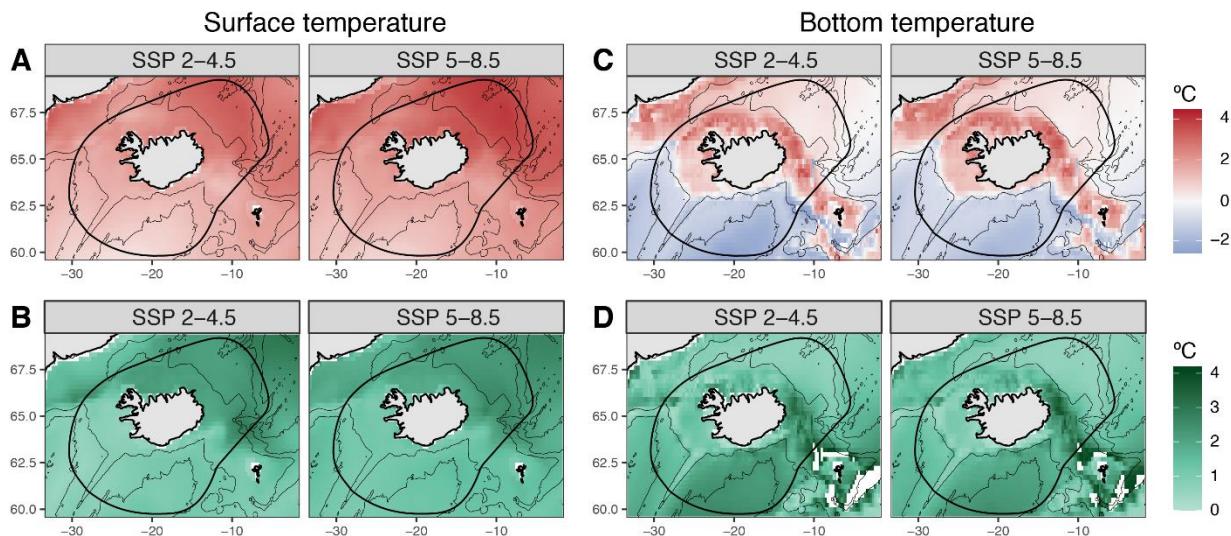
614 **Figures**

615



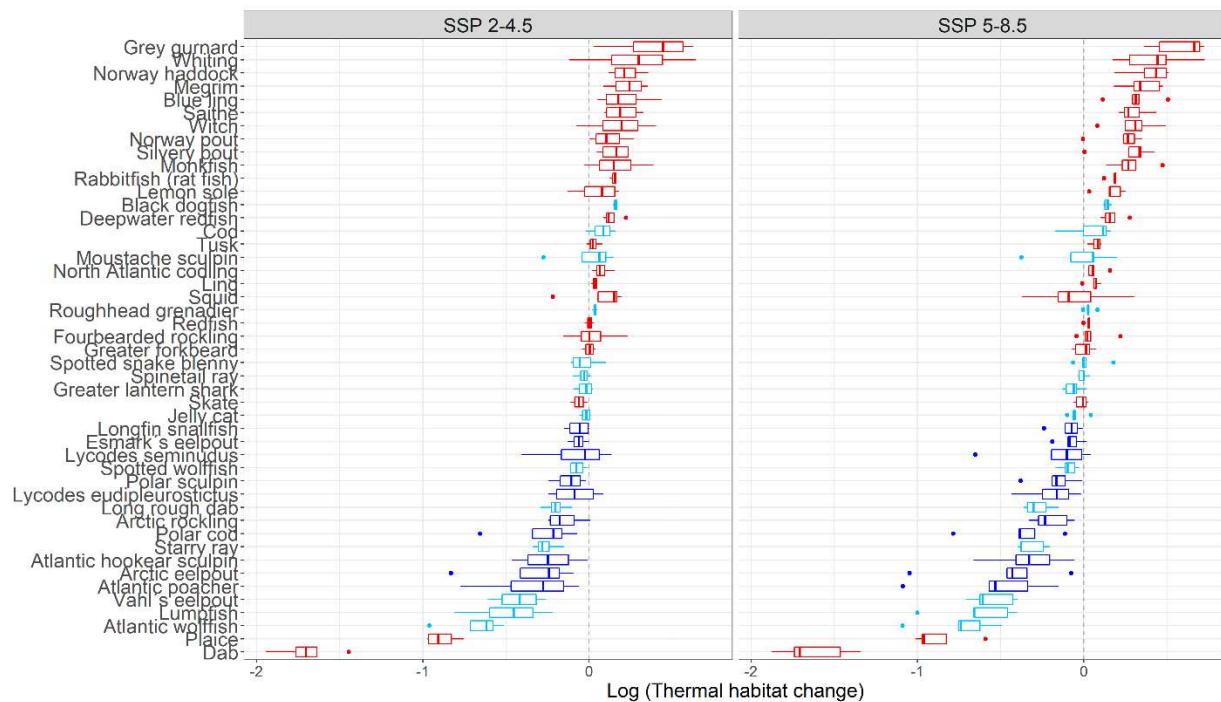
616

617 Figure 1: Study region indicating Iceland's Exclusive Economic Zone (EEZ, solid line),  
618 Bormicon regions (red dashed lines), and bottom trawl survey points.



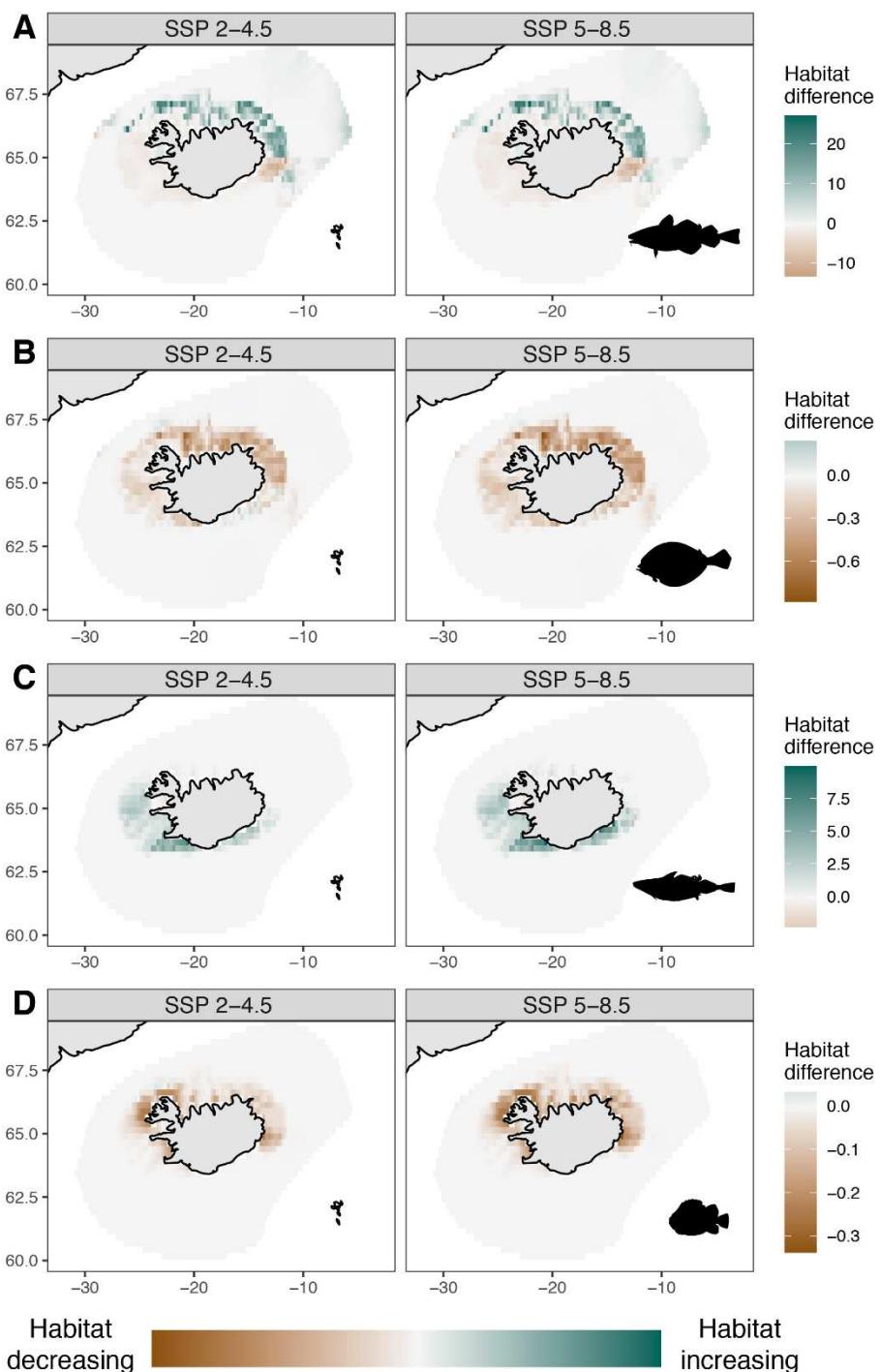
619

620 Figure 2: Projected ensemble means (A, C) and standard deviation (B, D) for sea surface and  
621 bottom temperature deltas for the years 2061-2080 for the middle of the road (SSP 2-4.5) and  
622 fossil-fueled development (SSP 5-8.5) scenarios. Thin lines indicate 1000m isobaths and thick  
623 lines indicate Iceland's EEZ.



624

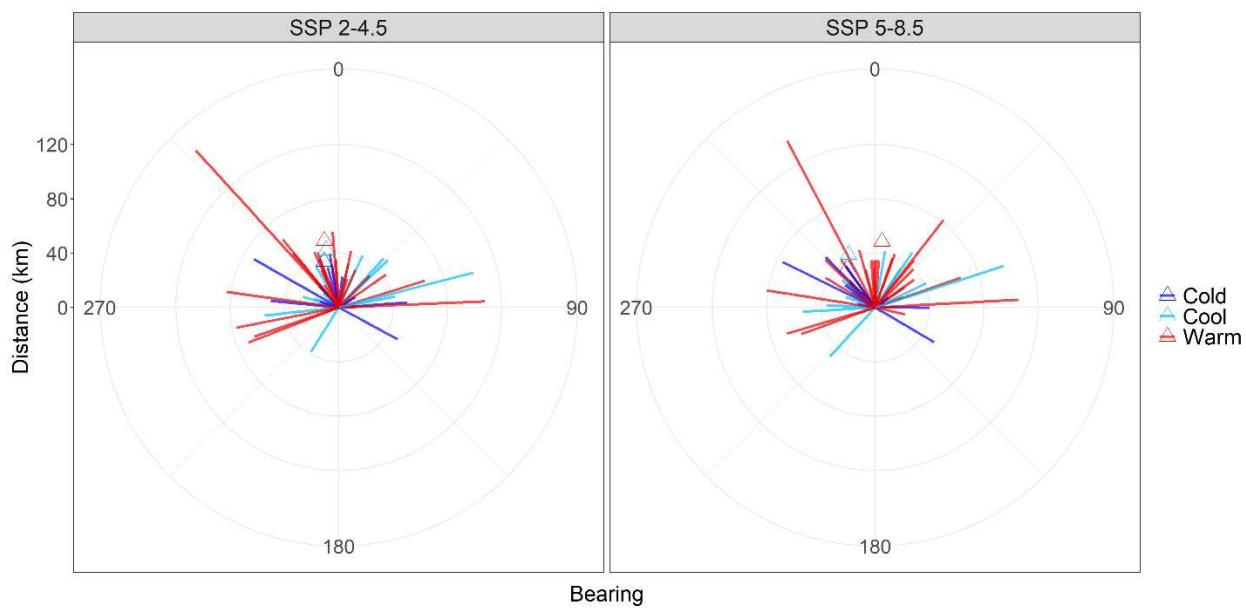
625 Figure 3: Projected changes in suitable thermal habitat for modeled species for 2061-2080  
626 relative to 2000-2018 for middle of the road (SSP 2-4.5, left) and fossil-fueled development (SSP  
627 5-8.5, right) scenarios. Boxplots represent the distribution of suitable habitat projections from  
628 each of the climate models. Colors represent species thermal niche: red species are warm water,  
629 light blue are cool water, and dark blue are cold water (see methods and Campana et al., 2020 for  
630 classifications). Note that x-axis is on a log10 scale, so a species with a value of -1 would have  
631 10% of the total projected suitable thermal habitat in 2061-2080 relative to 2000-2018.



632

633 Figure 4: Projected changes in future habitat suitability for cod (A), long rough dab (B), whiting  
634 (C), and lumpfish (D) in 2061-2080 relative to 2000-2018 under the middle of the road (SSP 2-  
635 4.5, left) and fossil fueled development (SSP 5-8.5, right) scenarios. Green regions indicate  
636 increases in suitable habitat whereas brown regions indicate decreases in suitable habitat.

637



638

639 Figure 5: Projected distance (km) and direction (bearing, 0-360 degrees) of shifts in the centroid  
640 of suitable thermal habitat distribution between 2061-2080 and 2000-2018 under the middle of  
641 the road (SSP 2-4.5, left) and fossil fueled development (SSP 5-8.5, right) scenarios. Colors  
642 represent species thermal niche (see Figure 3). Triangles indicate the circular average value for  
643 the bearing change, grouped by thermal niche. Version with species labels available in the  
644 supplemental information.