

1 **Biologically meaningful distribution models highlight the benefits of the Paris**
2 **Agreement for demersal fishing targets in the North Atlantic Ocean**

3

4 **Running Head:** Future of demersal fish in differing scenarios

5 **Abstract**

6

7 **Aim:** With climate change challenging marine biodiversity and resource management, it is crucial
8 to anticipate future latitudinal and depth shifts under contrasting global change scenarios to support
9 policy-relevant biodiversity impact assessments (e.g., Intergovernmental Panel on Climate Change;
10 IPCC). We aim to demonstrate the benefits of complying to the Paris Agreement (UN Framework
11 Convention on Climate Change) and limiting environmental changes, by assessing future
12 distributional shifts of 10 commercially important demersal fish species.

13

14 **Location:** Northern Atlantic Ocean

15

16 **Time period:** Distributional shift analyses compared near present-day conditions (2000-2017) with
17 two Representative Concentration Pathway (RCP) scenarios of future climate changes (2090-2100).
18 One following the Paris Agreement climate forcing (RCP2.6) and another without stringent
19 mitigation measures (RCP8.5).

20

21 **Major taxa studied:** Demersal fish

22

23 **Methods:** We use machine learning distribution models coupled with biologically meaningful
24 predictors to project future latitudinal and depth shifts. Structuring projections with information
25 beyond temperature-based predictors allowed us to better encompass species physiological
26 limitations.

27

28 **Results:** Our models highlighted the additional role of temperature, primary productivity, and
29 dissolved oxygen to shape fish distributions (average relative contribution to the models of
30 $32.12 \pm 10.24\%$, $15.6 \pm 7.5\%$ and $12.1 \pm 6.1\%$, respectively). We anticipated a generalized trend of
31 poleward shifts in both future scenarios, with aggravated changes in suitable area with RCP8.5
32 (average area loss with RCP2.6= $13.3 \pm 4.1\%$; RCP8.5= $40.9 \pm 13.3\%$). Shifts to deeper waters were also
33 predicted to be of greater magnitude with RCP8.5 (average depth gain= $25.4 \pm 21.5\text{m}$) than with
34 RCP2.6 (average depth gain= $10.4 \pm 7.9\text{m}$). Habitat losses were mostly projected in the
35 Mediterranean, Celtic and Irish Seas, the southern areas of the North Sea and along the NE coast of
36 North America.

37

38 **Main conclusions:** Including biologically meaningful predictors beyond temperature in species
39 distribution modelling can improve predictive performances. Limiting future climate changes by
40 complying with the Paris Agreement can translate into reduced distributional shifts, supporting
41 biodiversity conservation and resource management.

42

43 **Keywords:** Biologically meaningful predictors, Climate change, Demersal fish, North Atlantic
44 fisheries, Paris Agreement, Species Distribution Modelling

45 **Introduction**

46 Empirical evidence shows climate-driven changes producing poleward and depth shifts
47 across marine taxa (Pinsky et al., 2020). Future changes in physical (e.g. temperature), chemical
48 (e.g. oxygen content) and biological (e.g. primary productivity) ocean components, linked to
49 greenhouse gas emissions, are expected to further shift the distribution of species and ecosystems
50 (Champion et al., 2018; Cheung et al., 2010), with severe implications for marine biodiversity and
51 fisheries (Poloczanska, 2013; Sumaila et al., 2011; Weatherdon et al., 2016). On one side, local
52 population extinctions at low latitude distributional margins might produce negative cascading
53 effects and reduce global genetic pools (Cheung et al., 2013). On the other side, expansions to higher
54 latitudes might change biological interactions (e.g., competition) and restructure the composition
55 of biological communities (Pecl et al., 2017).

56 To timely address potential changes, the Paris Agreement was developed to provide a
57 roadmap limiting global warming below 2°C above pre-industrial levels while striving to contain
58 the increase to 1.5°C (United Nations Framework Convention on Climate Change, 2015). This
59 initiative considered climate change impact assessments on biodiversity (e.g., Intergovernmental
60 Panel on Climate Change; IPCC) based on policy-relevant research (Geden, 2016). Such assessments
61 are mostly performed with Species Distribution Modelling (SDM) contrasting near present-day
62 distributions with projections derived from atmosphere-ocean general circulation models
63 (AOGCMs), which estimate climate conditions under different concentrations of greenhouse gases
64 and mitigation strategies (Handorf & Dethloff, 2012; Melo-Merino et al., 2020). SDM has the
65 advantage of allowing ecological applications across taxa and systems, however, models not
66 incorporating the broad complexity of environmental conditions driving geographic distributions
67 could yield misleading impact assessments (McHenry et al., 2019; Spence & Tingley, 2020). For
68 instance, marine SDM generally miss important drivers beyond thermal conditions, even though

69 the distribution of organisms is influenced by additional drivers like dissolved oxygen, salinity,
70 primary productivity, nutrients, among others (Duncan et al., 2020; Pörtner & Farrell, 2008;
71 Pörtner & Knust, 2007; Sunday et al., 2012).

72 Here we produce a policy-relevant biodiversity impact assessment anticipating future
73 distributional shifts of 10 demersal fish species with high commercial value in the intensively
74 exploited northern Atlantic Ocean (EU, 2018; FAO Fisheries Department, 2011). In this broad area,
75 climate conditions are changing significantly (Cheung et al., 2010; Free et al., 2019) and producing
76 distributional shifts for demersal fish, both latitudinally and in depth (Mills et al., 2013; Perry et al.,
77 2005). For instance, exposure to oxygen minimum zones (OMZ) is escalating in the northern
78 Atlantic, with most of the worlds' anoxic regions (Breitburg et al., 2018) expanding to coastal areas
79 where fishing targets reside (Diaz & Rosenberg, 2008). In the same way, the expected changes in
80 primary productivity and nutrient availability might further produce a challenging environment
81 for fish to thrive (Cheung et al., 2010). Accordingly, fisheries management might be less effective
82 in the face of environmental changes (Baudron et al., 2020), with conflicts over catch allocation as
83 fishing targets shift across management boundaries which can lead to the discard of high fished
84 volumes due to poor allocation of fish stocks based on outdated species distribution information
85 (Bell et al., 2015; Miller & Munro, 2004).

86 Previous studies striving to anticipate future distributions of fish species in the northern
87 Atlantic Ocean have mostly been focused on single species and largely neglected additional
88 predictors such as oxygen availability or productivity changes (Kleisner et al., 2017; Rutterford et
89 al., 2015). We use machine learning SDM fitting a comprehensive dataset of species' occurrence
90 records with biologically meaningful predictors (i.e. predictors that are known to directly impact
91 species physiology, and therefore potentially structure distributional limits; Rödder & Lötters, 2010)
92 tailored for demersal conditions. Near present-day distributional patterns are compared with two

93 scenarios of future climate change: the Representative Concentration Pathway 2.6 (van Vuuren et
94 al., 2011), following the Paris Agreement expectations of global warming levels below 2 °C (Wang
95 et al., 2018), and the Representative Concentration Pathway 8.5 (Riahi et al., 2011), with minimal
96 mitigation measures and greater climatic changes. By comparing contrasting future scenarios we
97 aim to provide key information for IPCC impact assessments, for the fulfilment of the Sustainable
98 Development Goals of the 2030 Agenda (United Nations General Assembly, 2015) and for better-
99 informed conservation and management. We hypothesize that (i) additional drivers beyond
100 thermal conditions are key to model the distribution of demersal fish and that (ii) latitudinal and
101 depth shifts are positively correlated with anthropogenic greenhouse gas emissions, so that there is
102 a substantial benefit to comply with the Paris Agreement (as inferred for terrestrial climate; Warren
103 et al., 2018), limiting global changes and consequently biodiversity losses.

104

105 **Methods**

106 **Focal species and study area**

107 We modelled near present-day and future distributions of 10 demersal fish species (Table
108 1) throughout the northern Atlantic Ocean and adjacent Seas (i.e., the Mediterranean Sea, the Black
109 Sea and the Barents Sea; study area extending from 120°E to 120°W and from 30°N to 90°N). In this
110 region, fishing gears targeting demersal species (demersal purse seiners and trawlers) are more
111 prominently present in the North-East (Fig. 1b). For this reason, we focused our study on species
112 that are geographically concentrated on the eastern side of the ocean while still having high
113 commercial value on the whole Atlantic (EU, 2018; FAO Fisheries Department, 2011). Focal species
114 have different depth ranges, which were considered while modelling distributions (Table 1), and
115 are exclusively demersal, with the exceptions of *Clupea harengus* and *Micromesistius poutassou*.
116 The former is a demersal spawner (Stratoudakis et al., 1998) and the latter performs diel vertical

117 migrations and spends a large portion of the daytime near the bottom (Johnsen & Godø, 2007). Both
118 species are frequently caught by fishing gears targeting demersal fish assemblages (Afzali et al.,
119 2021; Sousa et al., 2005).

120

121 **Data sources**

122 Occurrence records for each species were obtained from GBIF (<https://www.gbif.org/>) and
123 OBIS (<https://www.obis.org/>; Refer to Appendix S1 for all downloaded dataset citations). These
124 were pruned to ensure that those included in the modelling framework matched each species
125 known distribution and also the time span of predictors (2000 and 2017; please refer to Appendix
126 S2). Predictors were obtained from Bio-ORACLE, a dataset providing layers at 5 arcmin resolution
127 (data processing detailed by Assis et al., 2018; Tyberghein et al., 2012). These included long-term
128 maximum and minimum temperatures (MaxTemp and MinTemp; °C), long-term minimum salinity
129 (Salinity; PSS), mean dissolved oxygen concentration (Oxygen; mol.m⁻³) and mean primary
130 productivity (Productivity; g.m⁻³.day⁻¹). Predictors focused on the benthic realm (i.e., along the
131 bottom) for near present-day conditions (long-term climatologies between 2000 and 2017) and the
132 two contrasting scenarios of global change RCP2.6 and RCP8.5. From the 3 benthic layers available
133 per predictor in Bio-ORACLE, we choose to model species' distributions with the average depth
134 layer. The RCP layers are provided as the ensemble of distinct models from the Coupled Model
135 Intercomparison Project, namely, CCSM4, GFDL-ESM2G, HadGEM2-ES, IPSL-CM5A-LR and
136 MIROC-ESM for temperatures and salinity, GFDL-ESM2G, HadGEM2-ES, IPSL-CM5A-LR for
137 dissolved oxygen concentration and GFDL-ESM2G, IPSL-CM5A-LR, MIROC-ESM for primary
138 productivity. Prior to modelling, Pearson's correlation coefficient was determined for all pairs of
139 predictors, as well as the Variance Inflation Factor (VIF).

140 Gridded data of fishing effort from 2012-2016 (average hours per cell) was obtained from
141 the Global Fishing Watch (Kroodsma et al., 2018) and filtered to only include fishing gear relevant
142 to our focal species (demersal purse seiners and trawlers). These data were resampled using nearest
143 neighbour method (Hofstra et al., 2008) to match the resolution and spatial extent of predictors.

144

145 **Species Distribution Modelling**

146 The distribution of species was modelled by ensembling (Araújo & New, 2007) the response
147 of Boosted Regression Trees (BRT) and Adaptive Boosting (AdaBoost), two machine learning
148 algorithms with high predictive performances in SDM (Assis, Araújo, et al., 2018; Krause-Jensen et
149 al., 2020) that automatically fit complex interactions between predictor variables and non-linear
150 relationships, while reducing overfitting by optimal parametrization and monotonicity responses
151 (Elith et al., 2008; Hofner et al., 2011). The algorithms fitted occurrence records per species
152 (presences and pseudo-absences) against the predictor variables. Pseudo-absences were randomly
153 generated in a 1:1 ratio with each species presence records, in locations where no presences were
154 recorded (Barbet-Massin et al., 2012) and geographically limited to the biogeographic provinces
155 (Spalding et al., 2007) where the species occur and their neighbouring provinces. This kept pseudo-
156 absences in areas where dispersal might potentially occur, a crucial step to accurately produce SDM
157 (Barve et al., 2011). To eliminate excessive information, the correlation between predictors within
158 the range of occurrence records was assessed as a function of geographic distance (Boavida et al.,
159 2016). This was accomplished by building a correlogram to identify the shortest distance between
160 occurrence records, at which predictors were not spatially correlated. Records were then thinned
161 by randomly selecting one record from the groups falling within correlated distances.

162 A cross-validation (CV) framework with 10-fold latitudinal bands was implemented to find
163 the optimal hyperparameter combination reducing overfitting and improving the potential for

164 model's transferability (Assis, Araújo, et al., 2018; Krause-Jensen et al., 2020; Vignali et al., 2020).
165 The "grid search" method was used to test all possible hyperparameter combinations of number of
166 trees (50 to 1000, step 50), tree complexity (1 to 6) and learning rate (0.01, 0.005 and 0.001) for BRT,
167 and number of interactions (50–250, step 50), shrinkage (0.25–1, step 0.25) and degrees of freedom
168 (1–12) for AdaBoost (Fragkopoulou et al., 2021; Krause-Jensen et al., 2020). Models trained
169 interactively the different hyperparameters by fitting occurrence records with one withheld
170 latitudinal band at a time, where performance was tested with the area under the curve (AUC) of
171 the receiver operating characteristic curve (Fragkopoulou et al., 2021; Vignali et al., 2020). The
172 optimal hyperparameter combination was found as the one producing models with higher AUC in
173 CV (Fragkopoulou et al., 2021; Krause-Jensen et al., 2020; Vignali et al., 2020). Overfitting was
174 further controlled by forcing predictors to fit monotonic responses based on the biological effect
175 (positive or negative) expected on species' probability of occurrence (Hofner et al., 2011). MaxTemp
176 fitted negative monotonic responses, while MinTemp, Salinity, Oxygen and Productivity fitted
177 positive monotonic responses. Species' depth range, predictor choice and monotonic responses were
178 set based on literature (Appendix S1). The cross-validation framework further allowed estimating
179 the performance and potential transferability of the models in independent data, by reporting the
180 average AUC obtained in CV when modelling with the optimal hyperparameters (e.g., Assis,
181 Araújo, et al., 2018; Boavida et al., 2016; Fragkopoulou et al., 2021; Krause-Jensen et al., 2020).

182 Final predictive BRT and AdaBoost models were trained with the full occurrence dataset,
183 the predictor variables and the optimal hyperparameters found in cross-validation (Assis, Araújo,
184 et al., 2018; Vignali et al., 2020). Predictive performance was also assessed with AUC and sensitivity
185 (both metrics vary between 0 and 1) with models with $AUC > 0.8$ considered excellent performing
186 models and sensitivity describing the proportion of accurately predicted occurrences (Allouche et
187 al., 2006; Hosmer & Lemeshow, 2000). The relative contribution of predictors to the models was

188 assessed by computing the increase in AUC when each predictor was added to its alternative full
189 model (i.e., model including all predictors except that being tested). Wilcoxon Rank tests inferred
190 the significant increase of each predictor contribution when compared to its alternative full model.

191 Distribution maps representing habitat suitability per species were produced for near
192 present-day conditions and the two global change scenarios with BRT and AdaBoost. These maps
193 were further reclassified to binomial presence-absence surfaces using a threshold maximizing both
194 sensitivity and specificity (i.e. true negative rate; Assis, Araújo, et al., 2018; Jiménez-Valverde &
195 Lobo, 2007). Climatic physiological limitations to species' distributions, i.e., tipping points from
196 which the models predict absence, were inferred by producing individual response functions for
197 each predictor, while accounting for the average effect produced by all alternative predictors (Assis
198 et al., 2017; Elith et al., 2008). Along each individual response function, tipping points were
199 captured by extracting the extreme climatic values (maximum or minimum depending on the
200 predictor) setting the transition between suitable and unsuitable habitat conditions, while
201 considering the reclassified binomial predictive surface (Boavida et al., 2016).

202

203

204 **Latitudinal and depth distributional shifts**

205 Latitudinal and depth distributional shifts were inferred by ensembling (mean function;
206 Araújo & New, 2007) the maps produced with BRT and AdaBoost for near present-day conditions
207 and each of the RCP scenarios. The ensembles followed the previously detailed reclassification
208 approach to binomial presence-absence surfaces using the maximization of sensitivity and
209 specificity. Distributional shifts were characterized by mirror density plots reflecting species'

210 potential latitudinal changes and by producing aggregated maps reflecting gained and lost habitats
211 from near present-day conditions to future times.

212 The average and maximum predicted depth was determined per species by crossing a
213 bathymetry layer obtained from Bio-ORACLE with the reclassified binomial maps. Depth shifts
214 were assessed by comparing the median depth of species distributions in the present and future
215 scenarios. Finally, the 50% and 75% kernel density of the distribution of fishing effort was
216 estimated to assess if areas of current high fishing effort might suffer future changes of suitable
217 habitats for demersal fish. The assessment was made by comparing the proportion of species'
218 distributions in areas of high fishing activity in near-present day conditions and in future
219 conditions.

220

221 **Results**

222 **Species Distribution Models**

223 The distribution models using the optimal combination of hyperparameters (Appendix S3)
224 produced predictions with high performance rates, both when tested in cross-validation (average
225 AUC in CV of BRT: 0.86 ± 0.03 ; average AUC in CV of AdaBoost: 0.82 ± 0.04 ; Table 1; Appendix
226 S3) and when ensembled in unique models (average AUC: 0.92 ± 0.02 ; Table 1). The ensembles
227 reflected each species known distributional and depth ranges (see Appendix S2 for maps contrasting
228 occurrence records and predicted distributions). Focal fish species distributions were mostly
229 predicted in the Celtic, Irish and North Seas, and along the coasts of Norway and Iceland (Fig. 1a).

230 **Table 1** Modelled species, their known depth range (in meters) and performance of Boosted Regression Trees
231 (BRT) and Adaptive Boosting (AdaBoost) distribution models in cross-validation and when ensemble in a
232 final predictive model. For more comprehensive information of model performance refer to Appendix S3.

233 ¹(Wright et al., 2000) ; ²(Coad & Reist, 2004); ³(Frimodt, 1995); ⁴(Cohen et al., 1990); ⁵(Muus & Nielsen, 1999);
234 ⁶(Lloris et al., 2005); ⁷(Relini et al., 1999).

235

236 **Figure 1** Proportion of near present-day suitable habitats, fishing effort and distributional range shifts (loss
237 and gain of suitable habitats from near present-day conditions, 2000-2017, to future RCP climate change
238 scenarios, 2090-2100; please refer to Appendix S2 for individual projections per species). Colour gradients
239 reflect the proportion of species (panel a) predicted with suitable habitats and (panels c-f) who lost or gained
240 suitable habitats (yellow to dark red depicting >0 to 1 proportion scale). In panel b, the 50% (blue) and 75%
241 (red) kernel utilization distribution of the fishing activity in the study area are represented.

242

243 The predictors considered in the models significantly increased predictive performances (>
244 0.8 proportion of improved models; Fig. 2). Temperatures (i.e., maximum, and minimum) alongside
245 productivity were the main drivers explaining distributions, with a combined average contribution
246 of 79.9% (TempMax: 27.9%; TempMin: 36.4%; Productivity: 15.6%; Fig. 2a). Oxygen and salinity
247 had lower contributions (oxygen: 12.1%; salinity: 7.9%; Fig. 2a) nevertheless, for some species,
248 these predictors reached up to 23.0% and 17.2% contribution, respectively (e.g., *Dicentrarchus*
249 *labrax*). Additional contribution extremes/outliers were verified for *M. poutassou* (minimum
250 temperature: 58.6%; salinity: -0.8%; productivity 1.4%) and *Ammodytes marinus* (productivity:
251 30.5%; for species specific variable contributions see Appendix S3). These findings are supported
252 by the overall low correlation found between predictors; only minimum and maximum
253 temperatures showed stronger correlation (Pearson's Correlation 0.82; VIF > 5; Appendix S4 -
254 Figure S4a; Table S4), yet their opposite monotonic fit in both BRT an AdaBoost (positive for
255 minimum temperature and negative for maximum temperature) allowed removing potential
256 confounding inferences about the contribution of both predictors.

257 Focal species were predicted to find suitable habitat conditions in areas with near present-
258 day average minimum temperatures between 0.1°C - 5.4°C, maximum temperatures ranging from
259 13.6°C - 20.2°C, dissolved oxygen concentrations inside the range 160.4 mol.m⁻³ - 248.3 mol.m⁻³,
260 and salinity between 7.8 PSS - 33.9 PSS. Productivity tipping points were found above oligotrophic
261 conditions of 0 - 0.1 g.m⁻³.day⁻¹ (Fig. 2b; for species specific variable tipping points see Appendix
262 S3).

263

264 **Figure 2** Average relative contribution (a) and physiological tipping point (b) of each predictor inferred with
265 Boosted Regression Trees and Adaptive Boosting across all species. Horizontal lines represent the mean
266 contribution and tipping points (i.e., physiological tolerances) of each predictor. Values above boxes indicate
267 the proportion of models developed for each species where predictors retrieved significantly higher
268 contributions to their performance. Variable units: Oxygen (mol.m⁻³); MinTemp, MaxTemp (°C); Salinity
269 (PSS); Productivity (g.m⁻³.day⁻¹).

270

271 **Latitudinal and depth distributional shifts**

272 All species were projected to shift distributions poleward in both future scenarios, yet with
273 greater changes in suitable areas (Fig. 1c-f; Table 2) and latitudinal limits (Fig. 3) when considering
274 RCP8.5 (average range gain: 54.5±35.7%; average range loss: 40.9±13.4%) than with RCP2.6
275 (average range gain: 17.9±11.8%; average range loss: 13.4±4.1%). Latitudinal shifts were often
276 coupled with depth shifts to deeper waters, which were also greater with RCP8.5 (average depth
277 gain= 25.4±21.5m; 7 out of 10 species shift to deeper waters) than with RCP2.6 (average depth gain=
278 10.4±7.9m; 8 out of 10 of species shift to deeper waters; Fig. 3).

279 In terms of suitable habitats, *C. harengus*, *Gadus morhua*, *Melanogrammus aeglefinus* and
280 *M. poutassou* had the greatest range gain, while being among those with lower range loss (Table 2).
281 These species have the potential to colonize coastal and open waters in the Barents, Kara,
282 Norwegian, Greenland, and Iceland Seas, the Hudson Bay and Western Arctic ocean (see Appendix
283 S2 for species specific distribution projections under all scenarios analysed). Contrarily, *A. marinus*,
284 *D. labrax*, *Merluccius merluccius*, *Pleuronectes platessa*, *Raja clavata* and *Solea solea* had smaller
285 range gain and greater loss (with loss being concentrated in the southern section of their ranges).
286 These species mostly colonize coastal waters in Norwegian, Iceland, and Greenland Seas (Appendix
287 S2). Changes in latitudinal range were a result of the colonization of the northernmost regions of
288 the study area (especially for species with greater range gain) and the loss of southern suitable range
289 (particularly evident for species with greater range loss; Fig. 3).

290

291 **Figure 3** Latitudinal and depth shifts projected for demersal fish in the northern Atlantic with the scenarios
292 RCP2.6 and RCP8.5 (future scenarios cover the time period 2090-2100). Yellow represents near present-day
293 distributions; purple and blue represent distributions under RCP2.6 and RCP8.5, respectively. Dashed lines
294 represent the median latitude and median depth of occurrence.

295

296 **Table 2** Near present-day (from year 2000 to year 2017): total area (km²) and percentage of species'
297 distributions inside areas of high fishing effort (FE50 and FE75). RCP2.6 and RCP8.5 (from 2090-2100):
298 Percentage of lost and gained habitats in each future global change scenario, and percentage of future
299 distribution inside areas of high fishing effort. FE50 and FE75 represent 50% and 75% kernel utilization
300 distribution of fishing effort, respectively. Bold values depict area changes above 50% and values between
301 parentheses show difference in percentage of species distributions inside areas of high fishing effort between
302 near present-day and each future scenario.

303

304 Loss of suitable range is mostly concentrated in the Mediterranean Sea, Celtic and Irish Seas,
305 southern areas of the North Sea (especially along the English Channel), and in the NE North
306 American coast (Fig. 1c, Fig. 1d). Poleward shifts are mostly projected towards the Barents,
307 Greenland, Kara, Norwegian, Iceland Seas, Hudson Bay and Western Arctic Ocean (Fig. 1e, Fig. 1f).
308 The geographic pattern of where species might lose or gain suitable areas are similar in both
309 scenarios, yet more pronounced in RCP8.5 (Fig. 1c-f; Table 2).

310 Areas of high fishing effort are predominantly distributed in the northeast Atlantic,
311 particularly in the Celtic, North, Iceland, Norwegian and Barents Seas (Fig. 1b). This matched
312 regions where species are predicted to be distributed in near present-day conditions (suitable
313 habitats overlapping areas of high fishing effort: $FE_{50}=61.75\pm 16.54\%$, Table 2) and projected in the
314 future, (suitable habitats overlap ranging from $52.16\pm 27.16\%$ to 79.36 ± 16.19 , depending on the
315 climate scenario and fishing effort, Table 2). The projected distributional changes in areas of high
316 fishing effort are more pronounced in RCP85 than RCP26 (Table 2), while the gain in suitable
317 habitats in these areas (i.e., in Iceland, Norwegian and Barents Seas) surpass the projected losses,
318 regardless of the climate scenario (i.e., in Celtic and North Seas; Fig. 1c-f; Table 2).

319

320 **Discussion**

321 In the present study we anticipate future distributional shifts for demersal fish of high
322 commercial value in the northern Atlantic Ocean. On rare occasions, past studies have modelled
323 species distributions based on predictors beyond temperature (e.g. Jones & Cheung, 2015), yet, to
324 our knowledge, this is the first attempt to integrate biologically meaningful predictors like oxygen,
325 primary productivity, and salinity alongside temperature conditions, to assess the potential

326 consequences of future climate changes to marine fish biodiversity at such large scales. Along the
327 lines of previous research looking at species' response to past and future climate change (Morato et
328 al., 2020; Pinsky et al., 2020), our models predicted generalized poleward shifts across all modelled
329 species. As hypothesized, greater changes to species' distributions (i.e., suitable areas, latitudinal
330 and depth distributions) were predicted under the higher greenhouse gas emission scenario
331 (RCP8.5), suggesting that broad compliance with the Paris Agreement might potentially mitigate
332 the negative impacts of global climate change to fish biodiversity, benefiting commercial fisheries
333 and resource management (Baudron et al., 2020; Bell et al., 2015; Miller & Munro, 2004).

334 Overall, the most important predictors shaping demersal fish distributions (i.e., extreme
335 temperatures and productivity) are in line with previous studies (Valavanis et al., 2004).
336 Temperature directly impacts species' physiology, and the modelled species, with contrasting
337 distributional patterns, exhibited specific thermal limits and predictor affinities. Minimum
338 temperature, for instance, contributed more than average to *M. poutassou*, a species with its
339 northern range bordering the Arctic waters, where extreme cold conditions potentially impose an
340 important physiological barrier. Contrarily, the lower contribution of maximum temperature to *D.*
341 *labrax* can result from its warmer affinity (Beare et al., 2004), allowing the species to extend ranges
342 to the low latitude limits of our study area. Besides temperature dependent niche affinities, fish
343 species favour high productivity waters (Cheung et al., 2008), and this was evident for most
344 modelled species (productivity tolerance limits above oligotrophic conditions). In particular, *A.*
345 *marinus* strongly relied on this variable since its distribution exclusively comprises the productive
346 waters of the North and Irish Seas and the inner seas of the West coast of Scotland (Capuzzo et al.,
347 2018). Beyond these areas, productivity sharply decreases and so does the species known and
348 predicted distribution. Contrastingly, productivity had a lower contribution for *M. poutassou*. In
349 pair with its wide-ranging distribution in the northern Atlantic Ocean, this species is also found in

350 the Mediterranean Sea, a region known for poor nutrient / productivity conditions (Huertas et al.,
351 2012). Salinity and dissolved oxygen were further identified as important drivers to model demersal
352 fish species. The first controls osmoregulation mechanisms, with areas falling outside tolerance
353 limits presenting sharp distributional barriers (Evans & Claiborne, 2009). Such premise was verified
354 for the species with salinity tolerance limits above 28 PSS and absent from the Baltic Sea, the wider
355 hyposaline region of the study area (Bagdonas et al., 2011). The more tolerant species *P. platessa*
356 and *C. harengus* (tolerance limits of 7.66 PSS and 9.66 PSS, respectively) can expand ranges into
357 such conditions. Low oxygen barriers prevail where species oxygen demand, as well as their
358 capacity for extraction and metabolic suppression exceeds local availability (Pörtner & Knust, 2007).
359 Overall, the inferred tolerance limits largely match known thresholds of hypoxia for marine fish
360 (average of approx. 200 mol.m⁻³; Vaquer-Sunyer & Duarte, 2008), highlighting the key role of this
361 variable for marine fish and strengthening the ecological significance of our models.

362 Distribution models reflecting meaningful biological traits showed the species favouring
363 cold and eutrophic conditions that might change in the years to come. In particular, the critically
364 identified regions with potential habitat losses (i.e., the Mediterranean Sea, the Celtic and Irish
365 Seas, the southern proportion of the North Sea and the NE coast of North America) have been
366 previously signed for faster warming rates and prone to future losses across biodiversity (Dulvy et
367 al., 2008; Lejeune et al., 2010; Saba et al., 2016; Weinert et al., 2016). Projected latitudinal shifts
368 were further coupled with depth shifts, as hypothesized. Much like altitudinal shifts in terrestrial
369 climates, stable deeper regions, less prone to abrupt warming when compared to superficial waters,
370 seem crucial refugia for species to successfully cope with future climate conditions (Jorda et al.,
371 2020). However, for some of the modelled species, distributional shifts produced shallower ranges,
372 stemming from the loss of suitable deeper areas in near present-day conditions. This is likely to

373 occur in deep areas of low latitude ranges where near present-day environmental conditions already
374 border physiological tolerances (Osovitz & Hofmann, 2007).

375 Ensemble model projections showed how higher emission scenarios might translate into
376 synergistic climate interactions linked to global warming, and greater distributional changes for
377 demersal fish species. For instance, reduced dissolved oxygen is associated with warming conditions
378 (Pörtner & Knust, 2007). This is particularly evident in projections along the coastlines of the
379 northern Atlantic Ocean (Appendix S4 – Fig. S4d), acting synergistically with temperature in
380 creating unsuitable habitats. Salinity is also projected to change in the years to come, yet with some
381 regions impacted by an overall increase (Saba et al., 2016), while others by salinity reductions due
382 to freshwater runoff from melting ice (Belkin et al., 1998). The spatial variation of this driver in the
383 future ocean is likely to pose great challenges to species distributional ranges. In terms of primary
384 productivity, projections show an actual increase in coastal waters (Appendix S4 – Fig. S4f),
385 benefiting fish populations inhabiting regions where future temperatures do not surpass species'
386 specific tolerance limits.

387 The produced biodiversity impact assessment has an inherent degree of uncertainty and
388 oversimplification that should be acknowledged and discussed. Firstly, it did not account for biotic
389 interactions that might impact the capacity of species to shift distributions and successfully colonize
390 new suitable areas (Selden et al., 2018). Neglecting this component might have led to overestimating
391 species' potential to colonize new habitats in previously unsuitable areas. Secondly, it did not
392 consider species' ability to adapt to new conditions imposed by climate change. While adaptation
393 to new conditions has much relevance in the scope of anticipating climate-induced distributional
394 shifts, it is highly unlikely to take place within the time frame considered (the next 80 years; Henson
395 et al., 2017; Pinsky et al., 2020). Thirdly, other potential meaningful predictors such as sea bottom
396 substrate (e.g. Koubbi et al., 2006; Maravelias et al., 2000; Maxwell et al., 2009) were not included

397 in the SDM framework due to their unavailability at this study's spatial scale. This may have led to
398 overestimated predicted distributions, hence, our results should be interpreted as estimates of
399 abiotic niche conditions rather than fully realized niches. Finally, given the large spatial scale of
400 this study, it is also possible that local conditions were not completely captured by AOGCM, like
401 upwelling areas structuring future climate refugia (Lourenço et al., 2016). Nevertheless, models
402 mimicked species' distributions and physiological tolerances, while integrating the best bioclimatic
403 data available beyond thermal conditions alone.

404 Minimal climate change mitigation translated into greater environmental changes (RCP8.5)
405 might produce larger negative consequences for demersal fish and the fisheries industry as a whole.
406 Such is the case because more severe poleward shifts associated with greater environmental changes
407 will be reflected in (i) increased need for investment in new fishing gear to adapt to new fishing
408 conditions (Poloczanska, 2013; Sumaila et al., 2011) and (ii) will raise fishing trip costs to reach
409 fishing grounds further north when compared to the potential cost associated with contained
410 poleward shifts (Weatherdon et al., 2016). Coincidentally, areas that currently have higher fishing
411 effort were among those predicted to suffer greater species turnover in the future (area losses: Celtic
412 and North Seas; area gain: Iceland, Norwegian and Barents Seas). By limiting distributional shifts,
413 the need for fishing adaptation and changes in effort distribution is minimized. Furthermore, it
414 allows species to more efficiently allocate resources to tackle additional threats alongside current
415 climate change (e.g. overfishing and invasive processes). For instance, the combined effects of
416 climate change, high fishing pressure and invasive processes have already caused great biodiversity
417 loss in the Mediterranean Sea (Marbà et al., 2015; Occhipinti-Ambrogi, 2007). Together, our results
418 emphasize the potential benefits of complying to the Paris Agreement, limiting global warming
419 levels (Wang et al., 2018) and therefore changes to range shifts in commercially valuable demersal
420 fish. Nonetheless, in either climate change scenario, adaptive measures such as fishing effort

421 redistribution and fishing stock allocation are needed to reach sustainable exploitation of fish stocks
422 and achieve SDG 14 targets. When rearranging the distribution of fishing effort, managers should
423 strive to guide fishers to areas where targeted species are found, allowing for greater yield per
424 fishing trip. Additionally, the allocation of fishing stocks per country should reflect species'
425 distributions at time of allocation and their vulnerability to environmental conditions. Lack of
426 consideration of climate change induced range shifts has already caused overfishing, massive
427 discarding of fished volume and conflicts between neighbouring regions due to poor allocation of
428 fishing effort and fish stocks (Baudron et al., 2020; Baudron & Fernandes, 2015). Conservation
429 planning strategies should consider climate change impacts to achieve their maximum
430 effectiveness. Marine spatial planning and MPAs in particular are promising conservation tools yet,
431 the inclusion of climate change threats is still rare which reduces their potential effectiveness (Rilov
432 et al., 2019). Accurate predictions that truly grasp species' physiological limitations as the ones here
433 presented are key to provide a reliable policy-relevant biodiversity impact assessment (e.g., IPCC)
434 and contribute with baseline projections for fishing stocks distribution and allocation of fishing
435 effort.

436

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441

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703

704 **Data Accessibility Statement**

705 The data that support the findings of this study are available from the corresponding author, upon
706 reasonable request.

707

708 **Conflict of Interest Statement**

709 Authors declare no conflict of interest.

710 **Table 1** Modelled species, their known depth range (in meters) and performance of Boosted Regression Trees
711 (BRT) and Adaptive Boosting (AdaBoost) distribution models in cross-validation and when ensemble in a
712 final predictive model. For more comprehensive information of model performance refer to Appendix S3.
713 ¹(Wright et al., 2000) ; ²(Coad & Reist, 2004); ³(Frimodt, 1995); ⁴(Cohen et al., 1990); ⁵(Muus & Nielsen, 1999);
714 ⁶(Lloris et al., 2005); ⁷(Relini et al., 1999).

Scientific name	Common name	Depth range (m)	Cross-validation	Final ensemble	
			AUC (BRT / AdaBoost)	AUC	Sensitivity
<i>Ammodytes marinus</i>	Lesser sand eel	10-150 ¹	0.92 / 0.89	0.97	0.95
<i>Clupea harengus</i>	Atlantic herring	0-364 ²	0.82 / 0.73	0.87	0.79
<i>Dicentrarchus labrax</i>	European seabass	0-100 ³	0.83 / 0.80	0.92	0.95
<i>Gadus morhua</i>	Atlantic cod	0-600 ⁴	0.82 / 0.73	0.89	0.89
<i>Melanogrammus aeglefinus</i>	Haddock	0-450 ⁵	0.86 / 0.81	0.93	0.92
<i>Merluccius merluccius</i>	European hake	30-1075 ⁶	0.87 / 0.85	0.93	0.92
<i>Micromesistius poutassou</i>	Blue whiting	150-3000 ⁴	0.84 / 0.82	0.92	0.79
<i>Pleuronectes platessa</i>	European plaice	0-200 ⁵	0.89 / 0.86	0.95	0.97
<i>Solea solea</i>	Common sole	0-150 ⁵	0.86 / 0.82	0.93	0.88
<i>Raja clavata</i>	Thornback ray	0-700 ⁷	0.84 / 0.81	0.93	0.91

715

716

717 **Table 2** Near present-day (from year 2000 to year 2017): total area (km²) and percentage of species'
718 distributions inside areas of high fishing effort (FE50 and FE75). RCP2.6 and RCP8.5 (from 2090-2100):
719 Percentage of lost and gained habitats in each future global change scenario, and percentage of future
720 distribution inside areas of high fishing effort. FE50 and FE75 represent 50% and 75% kernel utilization
721 distribution of fishing effort, respectively. Bold values depict area changes above 50% and values between
722 parentheses show difference in percentage of species distributions inside areas of high fishing effort between
723 near present-day and each future scenario.

Species	Near present-day			RCP2.6				
	Area (x10 ³ km ²)	% FE50	% FE75	Area loss (%)	Area gain (%)	% FE50	% FE75	Area loss
<i>Ammodytes marinus</i>	1,014.39	90.75	99.06	13.44	6.86	88.67 (-2.08)	99.35 (+0.29)	74.7
<i>Clupea harengus</i>	4,393.32	48.14	74.21	13.01	31.78	39.43 (-8.71)	64.98 (-9.23)	36.6
<i>Dicentrarchus labrax</i>	1,170.77	67.92	85.92	9.67	8.1	75.91 (+7.99)	90.55 (+4.63)	30.8
<i>Gadus morhua</i>	4,993.17	36.97	61.28	6.64	32.51	27.79 (-9.18)	49.82 (-11.45)	29.7
<i>Melanogrammus aeglefinus</i>	3,394.86	49.91	72.65	9.39	25.2	41.25 (-8.66)	65.82 (-6.83)	30.5
<i>Merluccius merluccius</i>	2,051.04	57.72	78.12	20.14	10.88	68.49 (+10.77)	86.02 (+7.9)	37.7
<i>Micromesistius poutassou</i>	4,392.44	44.82	66.54	18.92	37.7	40.55 (-4.27)	62.09 (-4.44)	33.2

<i>Pleuronectes platessa</i>	1,624.06	80.31	94.76	13.45	9.76	78.52 (-1.79)	90.18 (-4.57)	55.3
<i>Raja clavata</i>	2,066.72	62.78	79.44	16.89	10.91	73.8 (11.02)	88.35 (+8.92)	42.0
<i>Solea solea</i>	1,323.13	78.11	93.43	12.25	5.13	83.67 (5.56)	96.48 (+3.05)	37.7
	Average	61.75	80.54	13.38	17.88	61.81	79.36	40.8
	SD	16.54	11.9	4.06	11.82	20.97	16.19	13.3

724

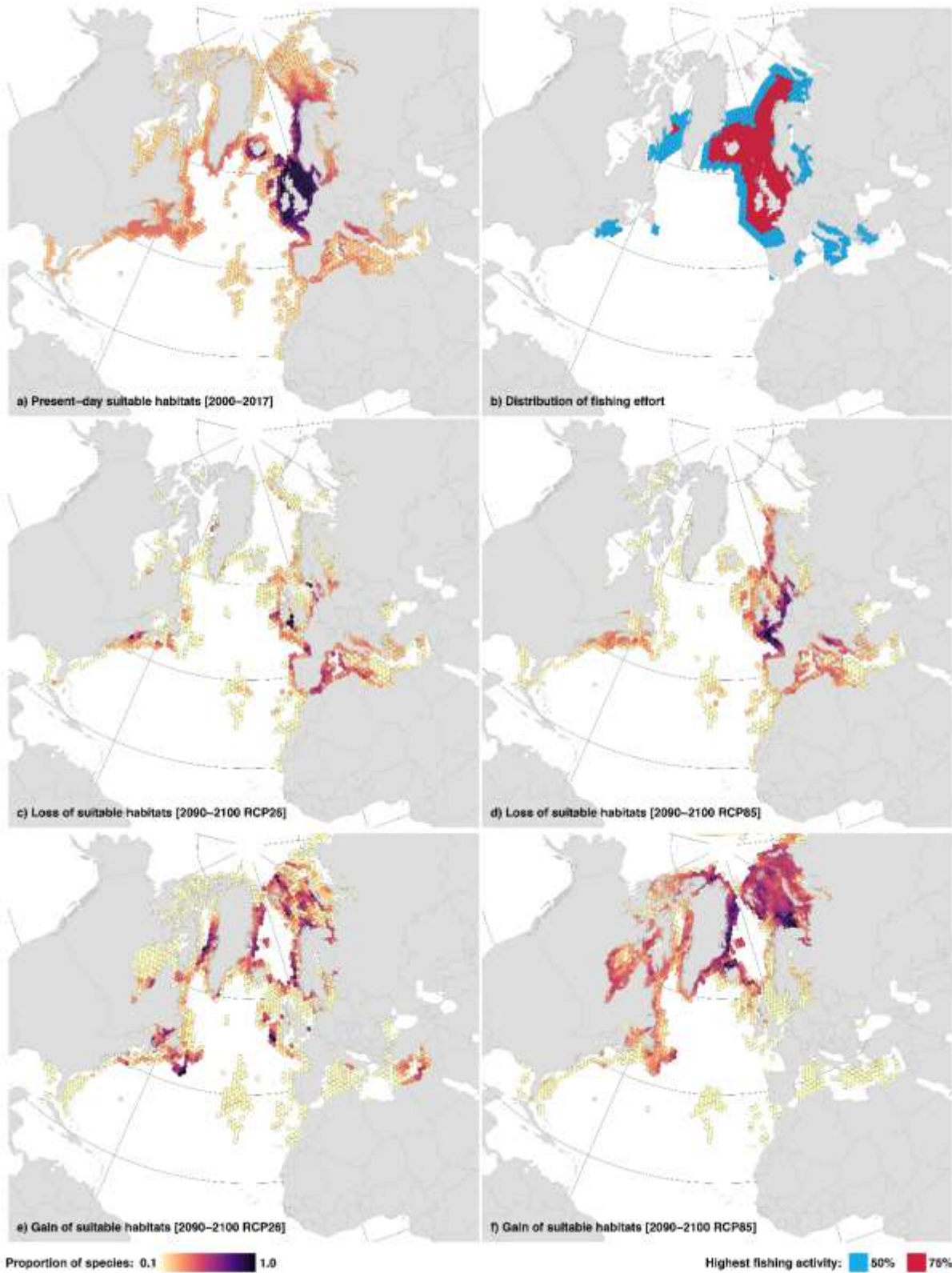
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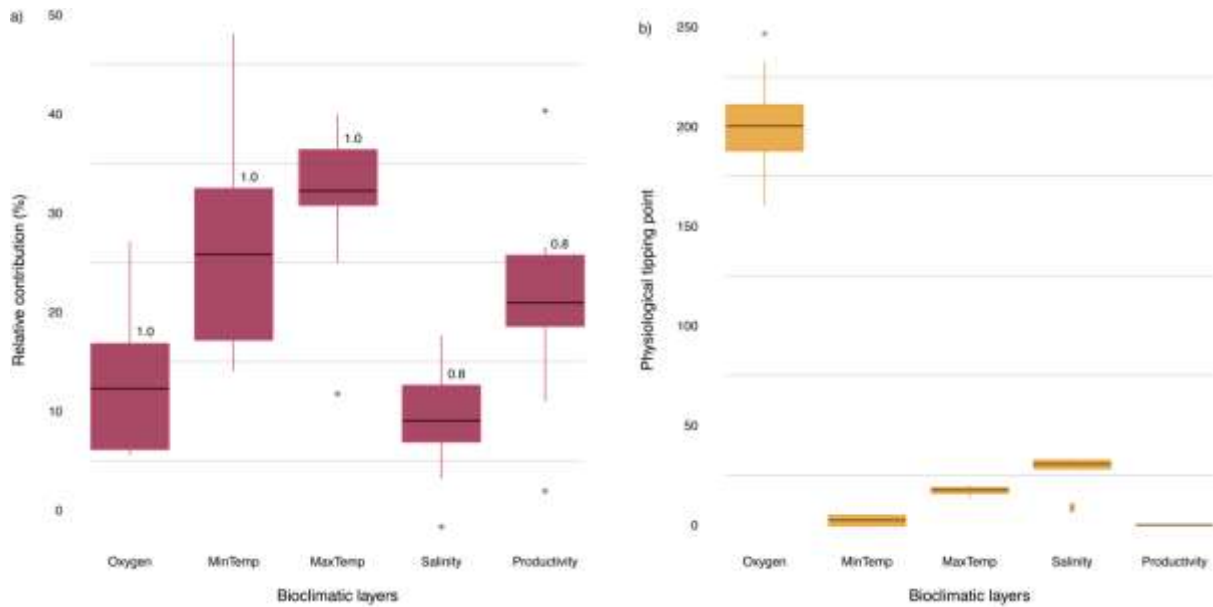
731 **Figure 1** Proportion of near present-day suitable habitats, fishing effort and distributional range shifts (loss

732 and gain of suitable habitats from near present-day conditions, 2000-2017, to future RCP climate change

733 scenarios, 2090-2100; please refer to Appendix S2 for individual projections per species). Colour gradients

734 reflect the proportion of species (panel a) predicted with suitable habitats and (panels c-f) who lost or gained
 735 suitable habitats (yellow to dark red depicting >0 to 1 proportion scale). In panel b, the 50% (blue) and 75%
 736 (red) kernel utilization distribution of the fishing activity in the study area are represented.

737



738

739 **Figure 2** Average relative contribution (a) and physiological tipping point (b) of each predictor inferred with
 740 Boosted Regression Trees and Adaptive Boosting across all species. Horizontal lines represent the mean
 741 contribution and tipping points (i.e., physiological tolerances) of each predictor. Values above boxes indicate
 742 the proportion of models developed for each species where predictors retrieved significantly higher
 743 contributions to their performance. Variable units: Oxygen (mol.m^{-3}); MinTemp, MaxTemp ($^{\circ}\text{C}$); Salinity
 744 (PSS); Productivity ($\text{g.m}^{-3}.\text{day}^{-1}$).

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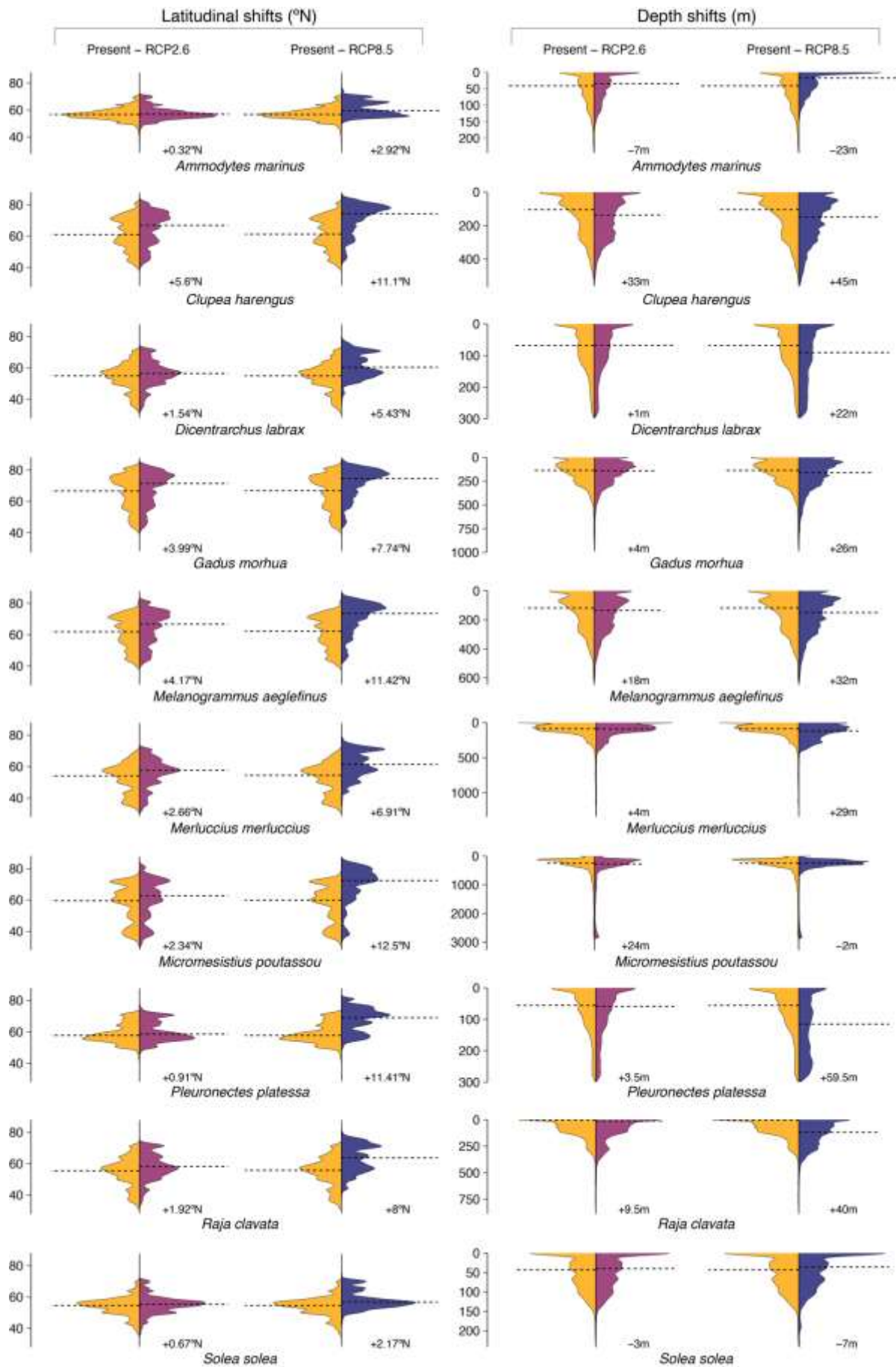
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754 **Figure 3** Latitudinal and depth shifts projected for demersal fish in the northern Atlantic with the scenarios
755 RCP2.6 and RCP8.5 (future scenarios cover the time period 2090-2100). Yellow represents near present-day
756 distributions; purple and blue represent distributions under RCP2.6 and RCP8.5, respectively. Dashed lines
757 represent the median latitude and median depth of occurrence.

758

759

760 **Appendix S1**

761

762 **Citations on previous work on focus species SDM and habitat preferences**

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Appendix S2 – Species specific occurrence points and distribution projections in present and future (RCP2.6 and RCP8.5) scenarios

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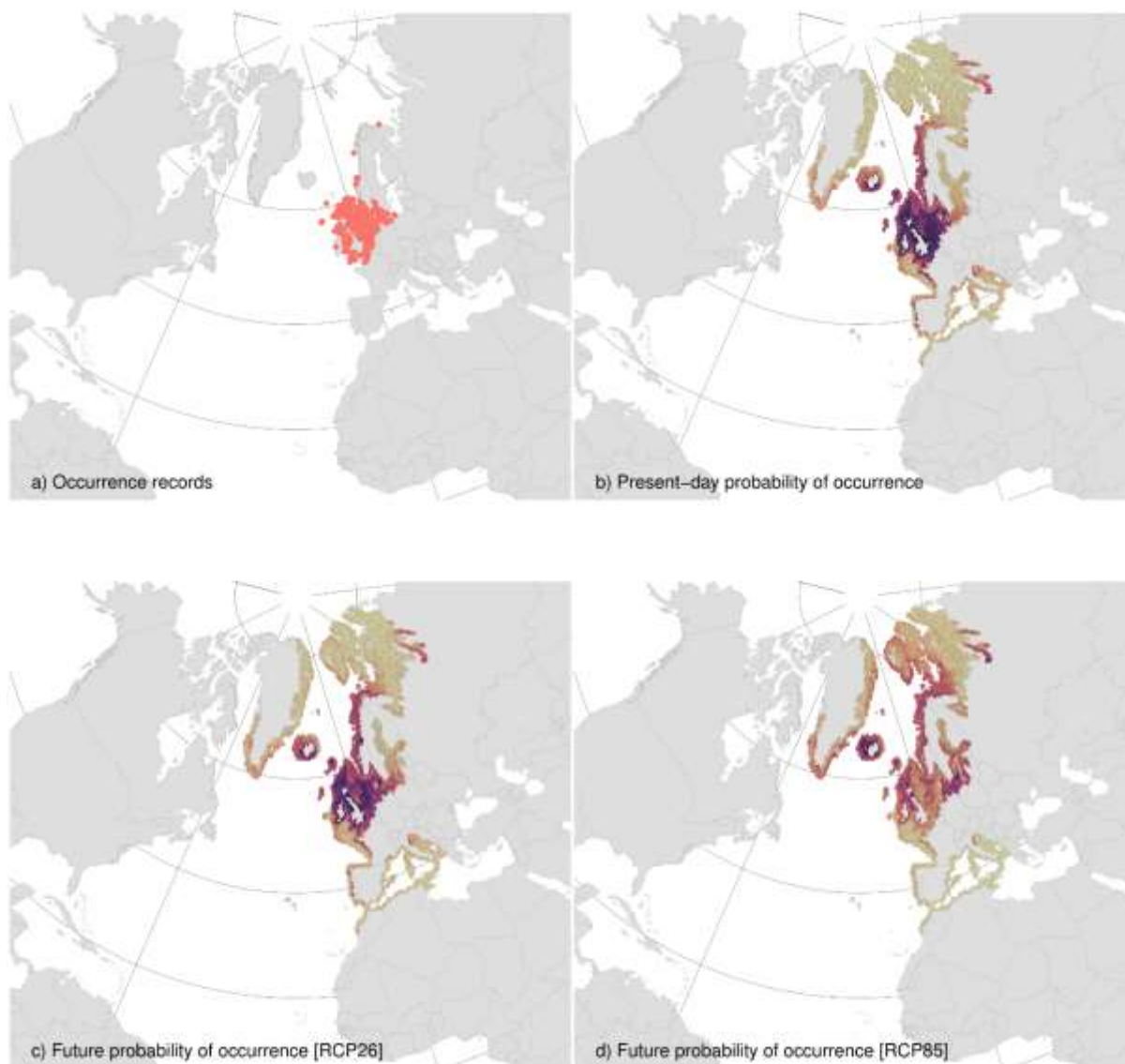
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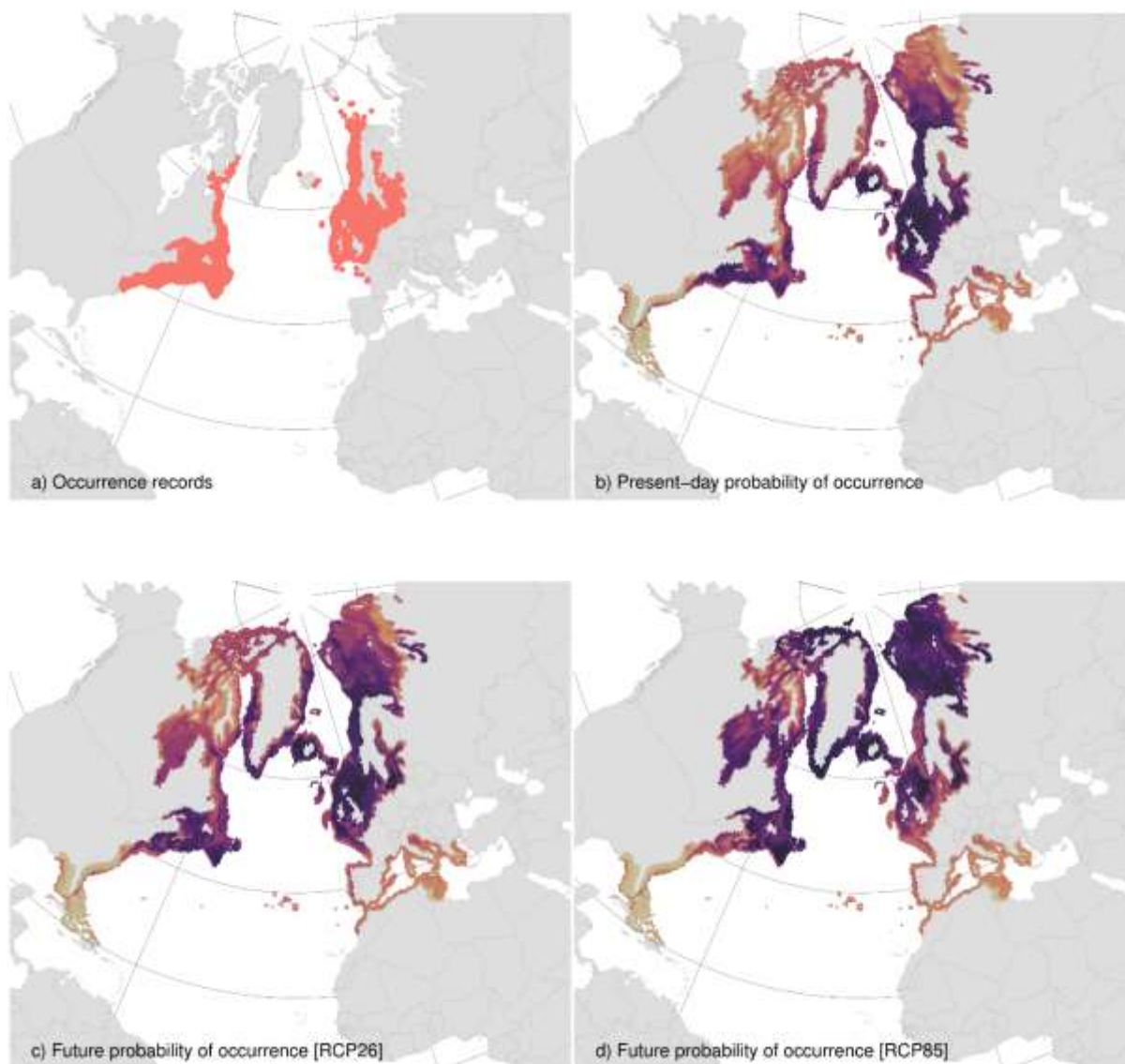
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1394 **Fig S2a** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1395 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Ammodytes*
1396 *marinus*. In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1
1397 is maximum suitability.

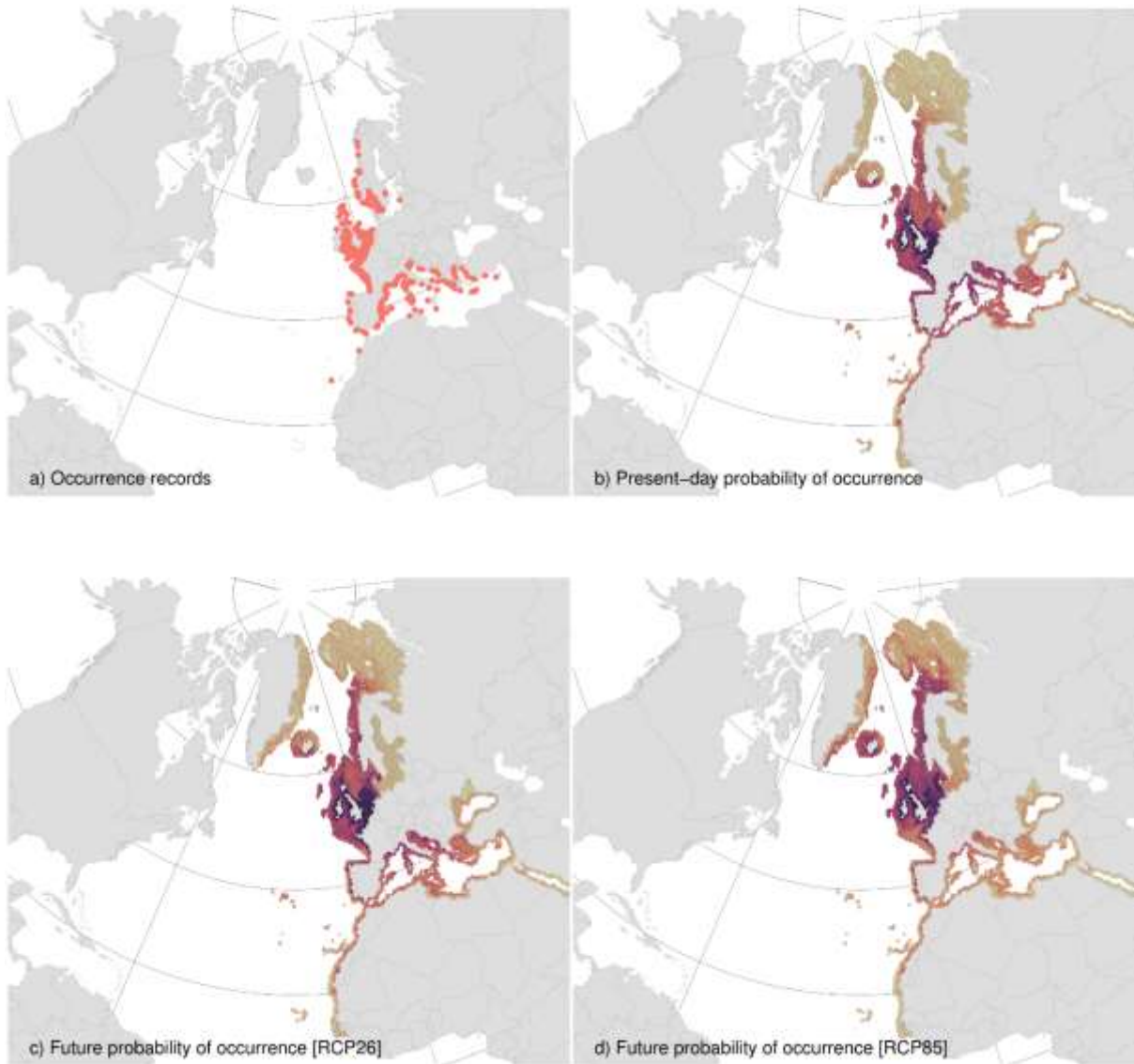
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1401 **Fig S2b** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1402 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Clupea*
1403 *harengus*. In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1
1404 is maximum suitability.

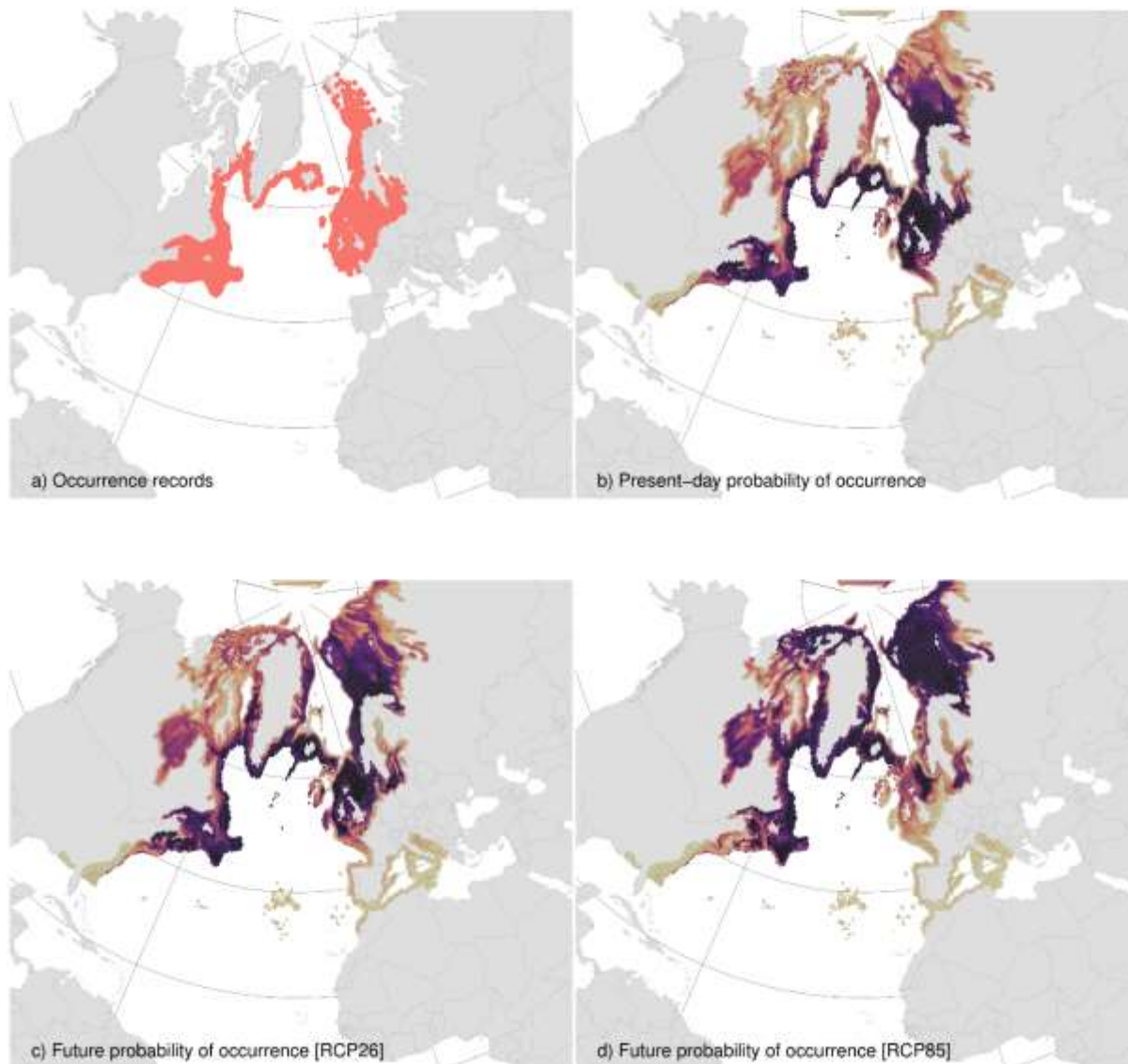
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1408 **Fig S2c** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1409 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Dicentrarchus*
1410 *labrax*. In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1 is
1411 maximum suitability.

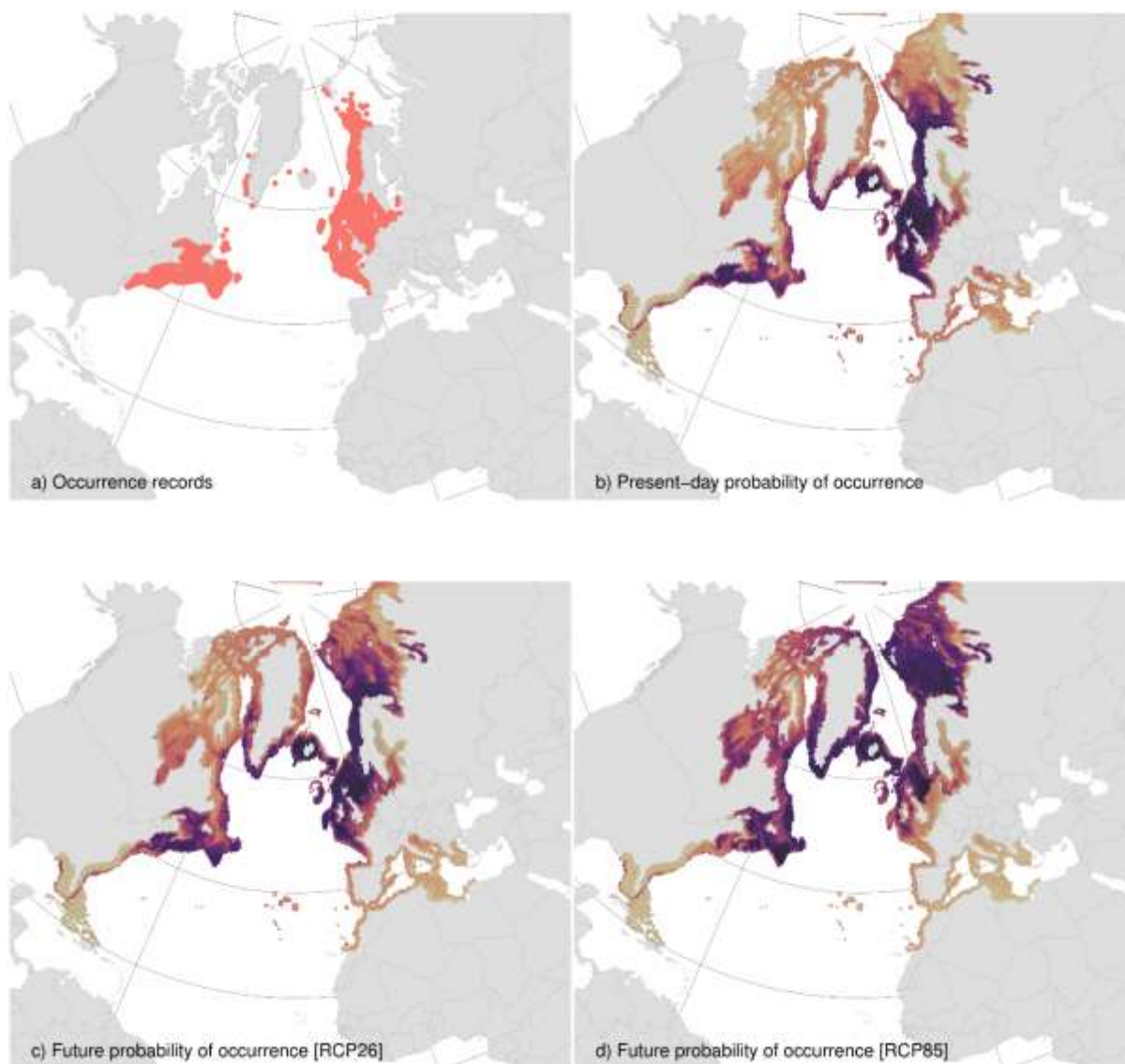
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1415 **Fig S2d** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1416 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Gadus morhua*.
1417 In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1 is
1418 maximum suitability.

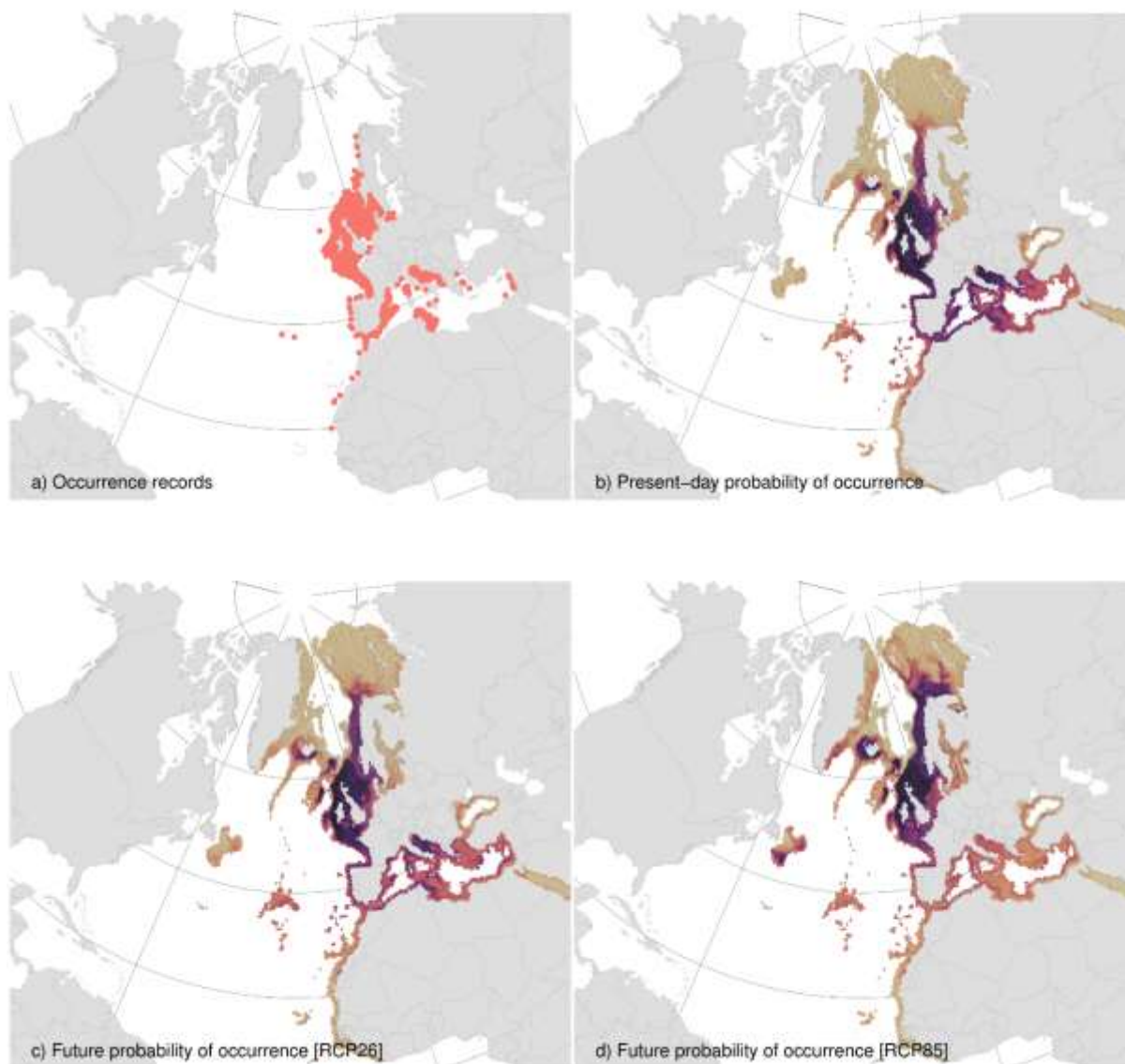
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1422 **Fig S2e** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1423 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for
1424 *Melanogrammus aeglefinus*. In panels b-d colour scale of yellow to dark red depicting habitat suitability
1425 from >0 to 1 where 1 is maximum suitability.

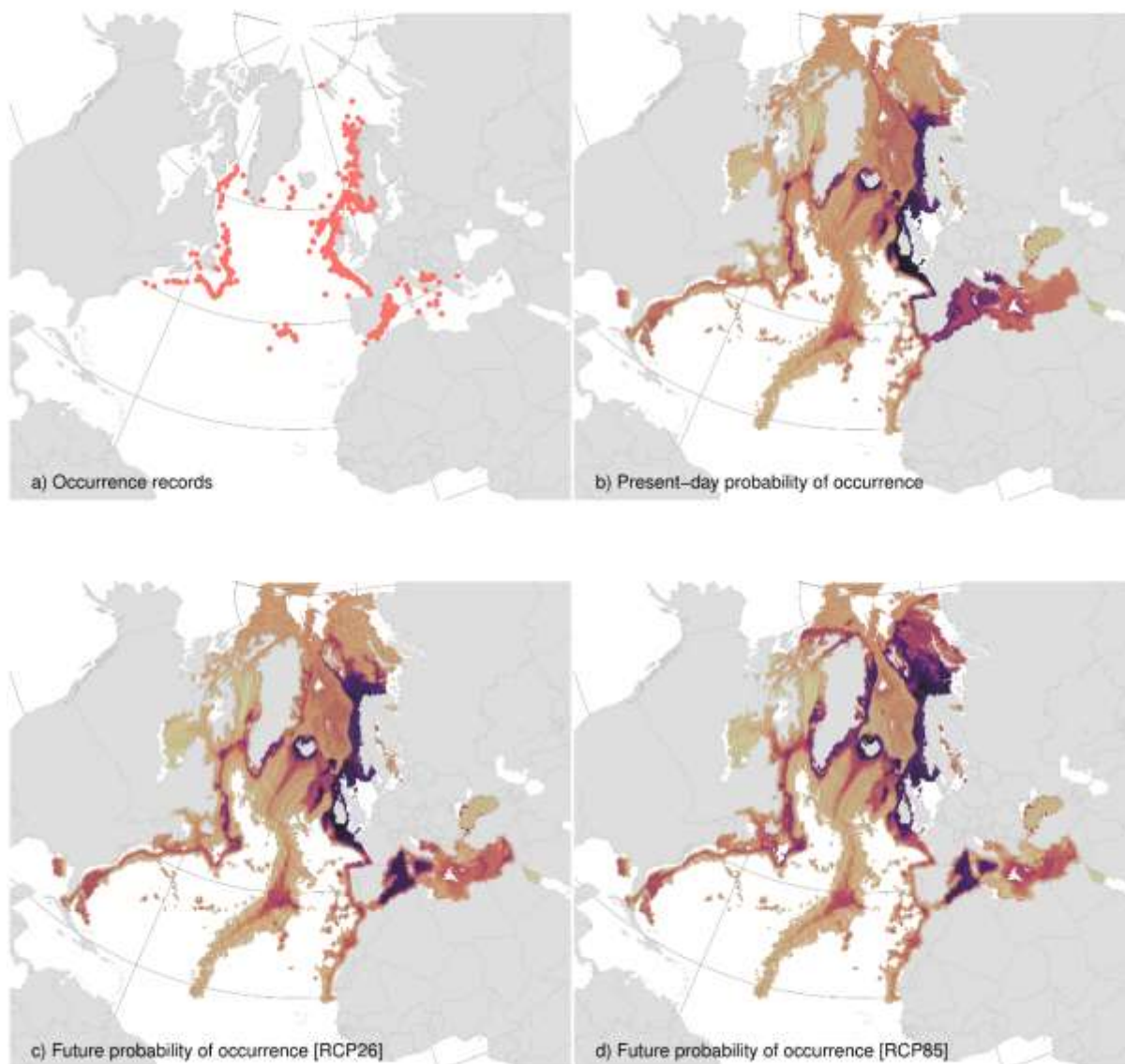
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1429 **Fig S2f** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1430 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Merluccius*
1431 *merluccius*. In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where
1432 1 is maximum suitability.

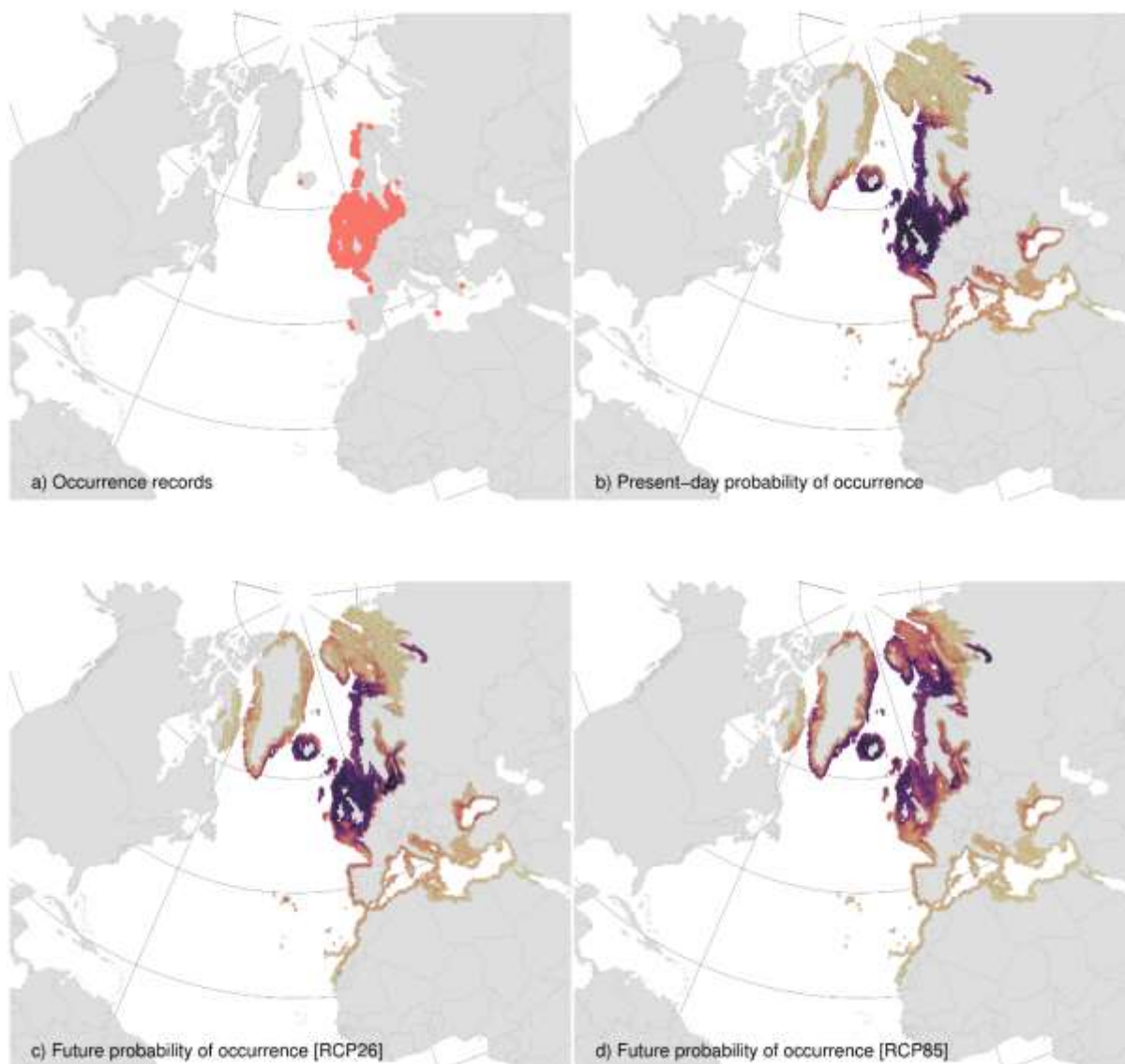
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1436 **Fig S2g** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1437 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Micromesistius*
1438 *poutassou*. In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1
1439 is maximum suitability.

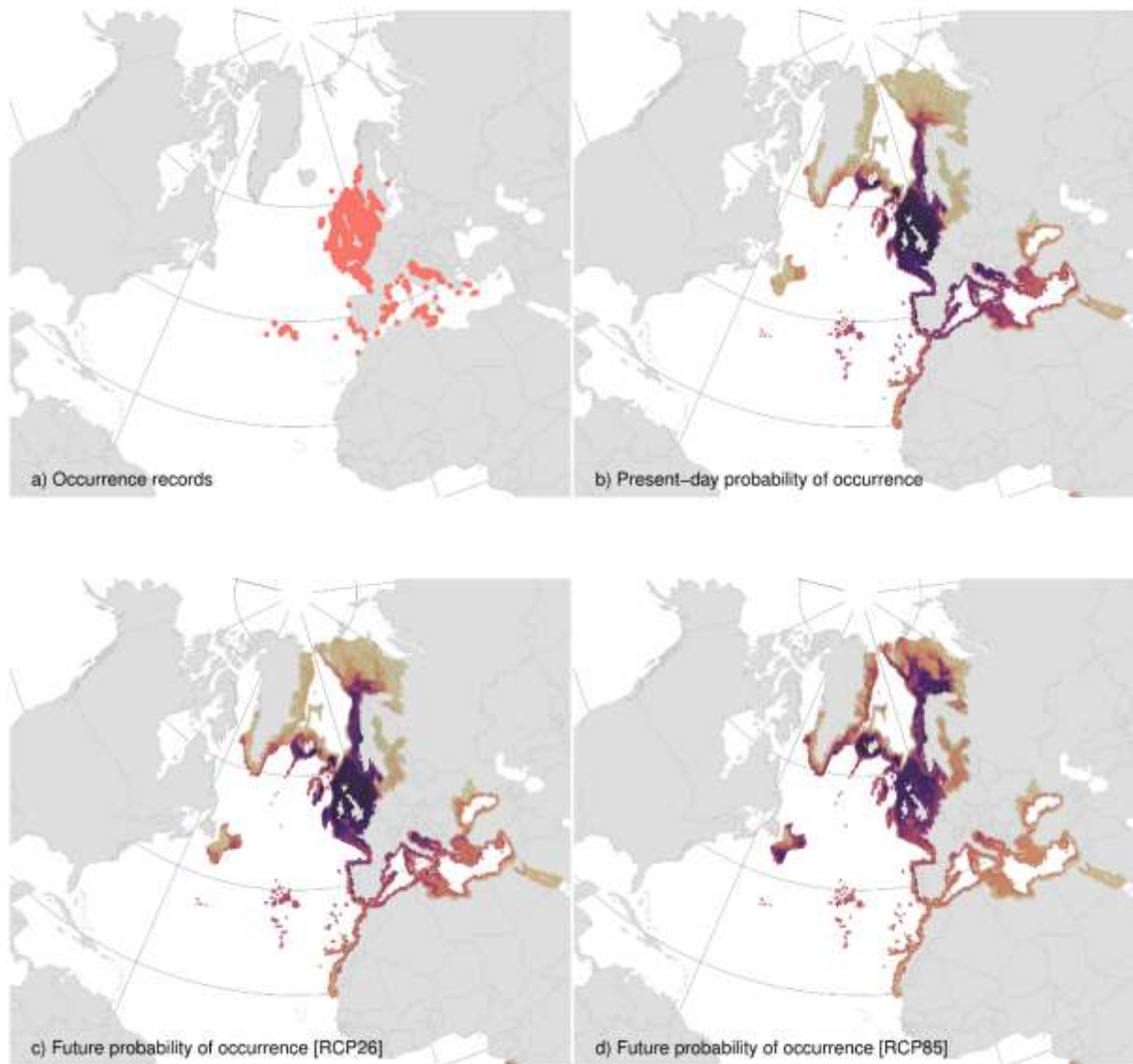
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1443 **Fig S2h** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1444 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Pleuronectes*
1445 *platessa*. In panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1 is
1446 maximum suitability.

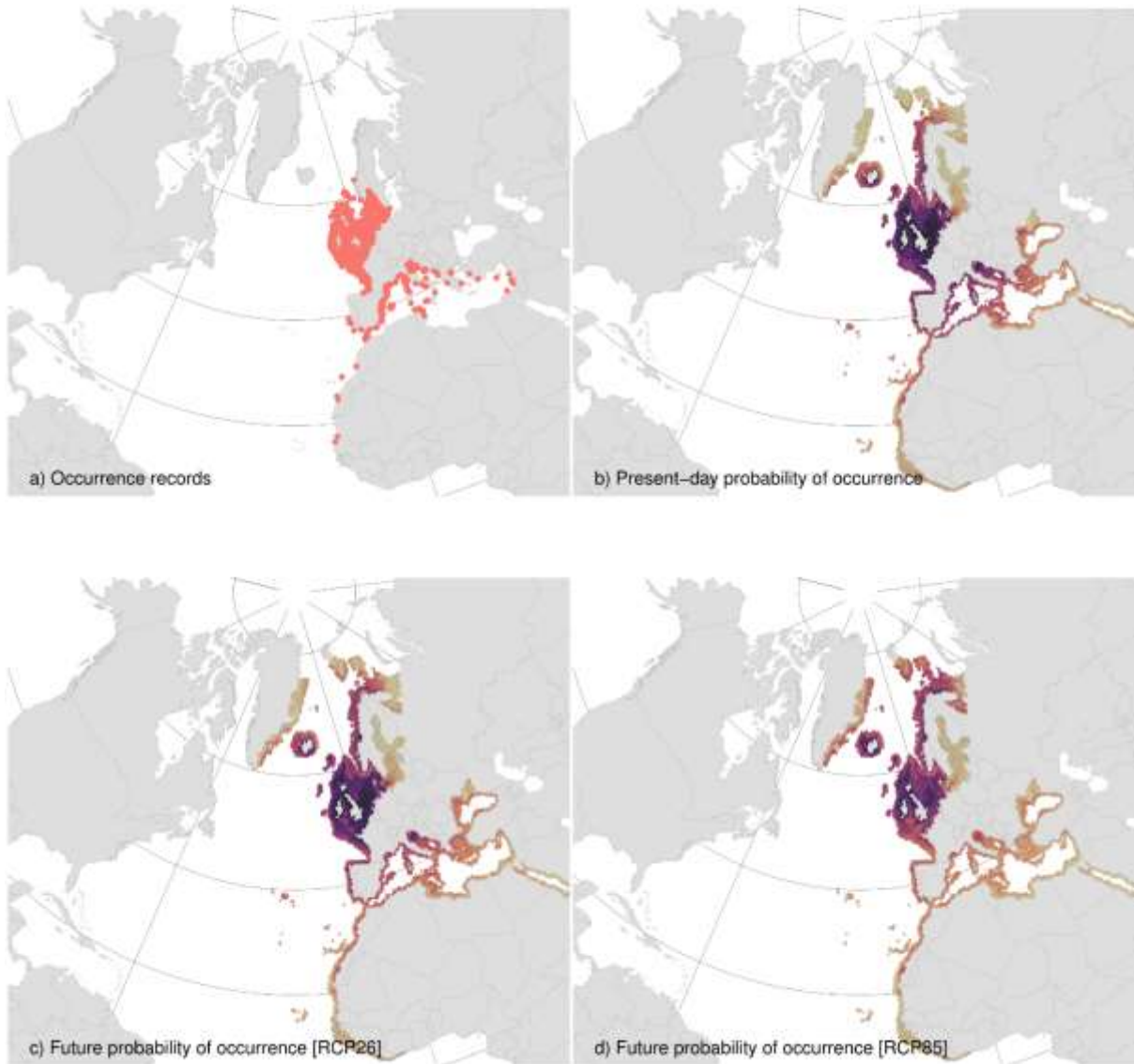
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1450 **Fig S2i** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1451 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Raja clavata*. In
1452 panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1 is maximum
1453 suitability.

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1457 **Fig S2j** Occurrence points included in model (panel a) and habitat suitability in all scenarios modelled
1458 (panel b: near present-day scenario; panel c: scenario RCP2.6; panel d: scenario RCP8.5) for *Solea solea*. In
1459 panels b-d colour scale of yellow to dark red depicting habitat suitability from >0 to 1 where 1 is maximum
1460 suitability.

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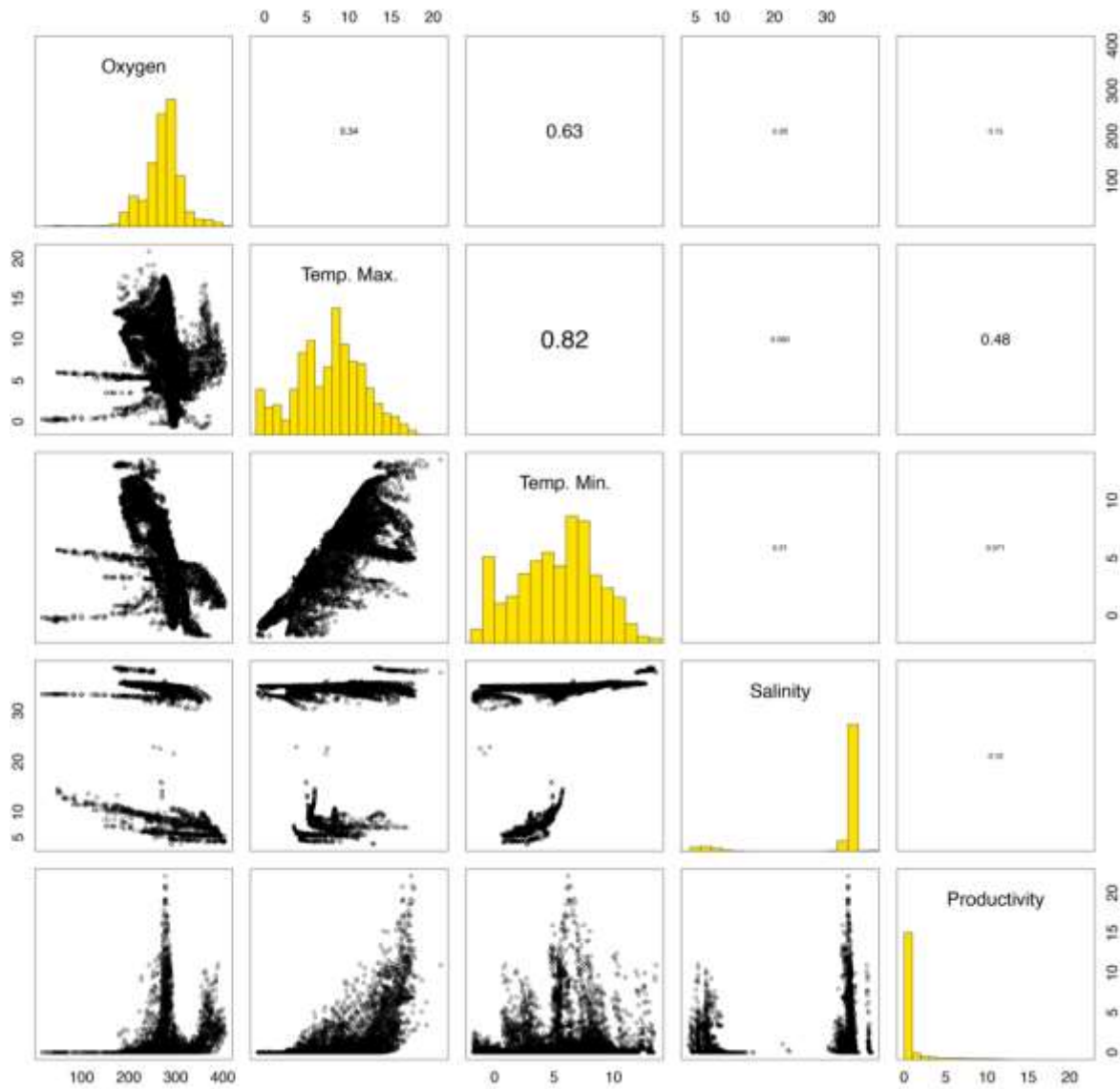
1468 Appendix S3 – Excel file named Appendix S3

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1471 Appendix S4 – Environmental predictor statistic

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1474 Figure S4a Correlogram showing Pearson's Correlation between predictors included in species
1475 distribution modelling (SDM).

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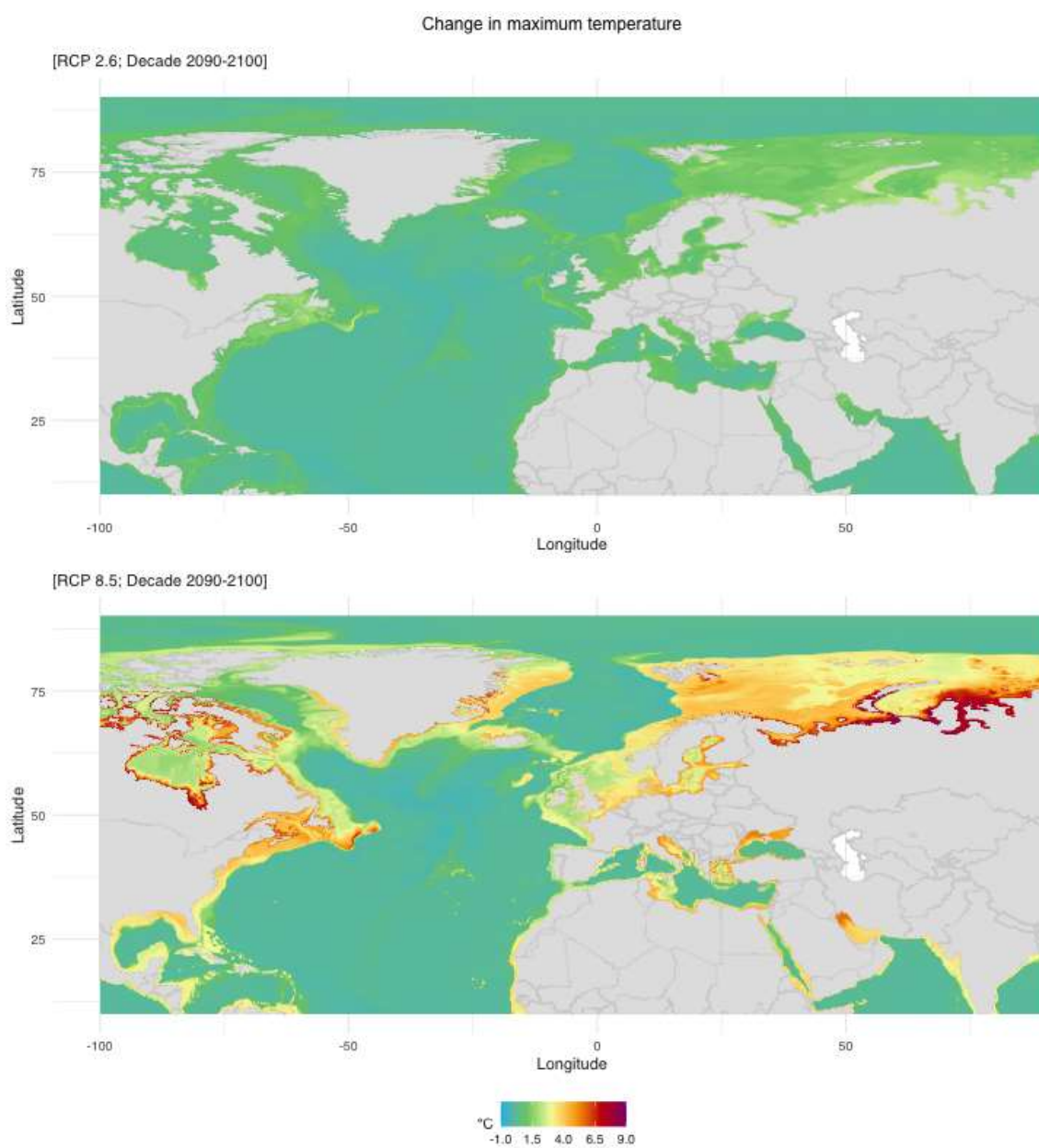
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1481 Table S4. Variance inflation factors (VIF) for each predictor used in SDM. Variance inflation
1482 factors range from 1 upwards, with values above 5 showing strong collinearity (Everitt &
1483 Skrondal, 2010).

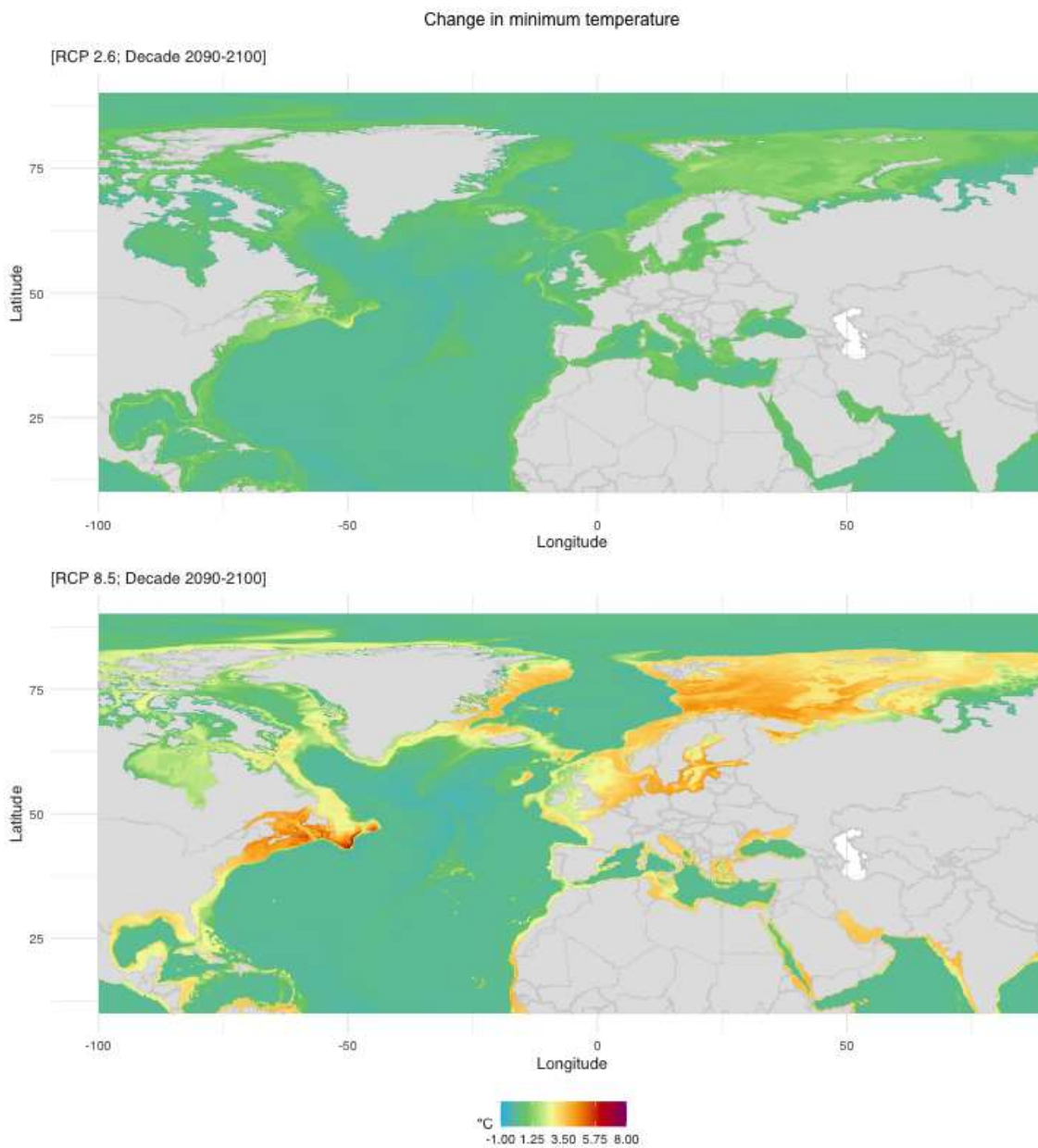
Predictor variable	VIF
Dissolved oxygen	2.105
Maximum temperature	8.070
Minimum temperature	8.394
Salinity	1.103
Productivity	2.309

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1486 Figure S4b Difference between present and future (RCP2.6 and RCP8.5) maximum temperature
1487 (°C) in the benthos of the North Atlantic.
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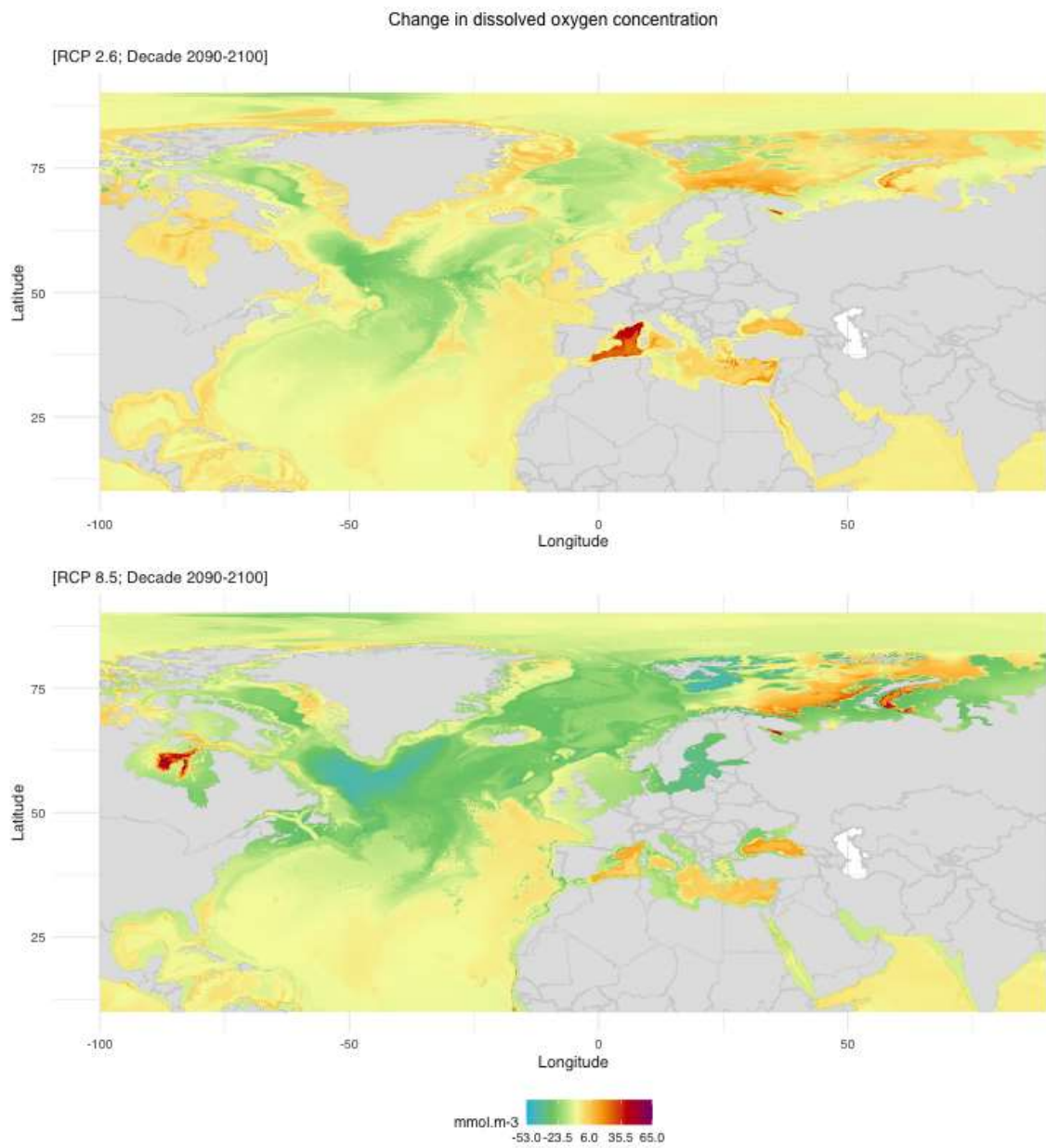
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1491 Figure S4c Difference between present and future (RCP2.6 and RCP8.5) minimum temperature
1492 (°C) in the benthos of the North Atlantic.
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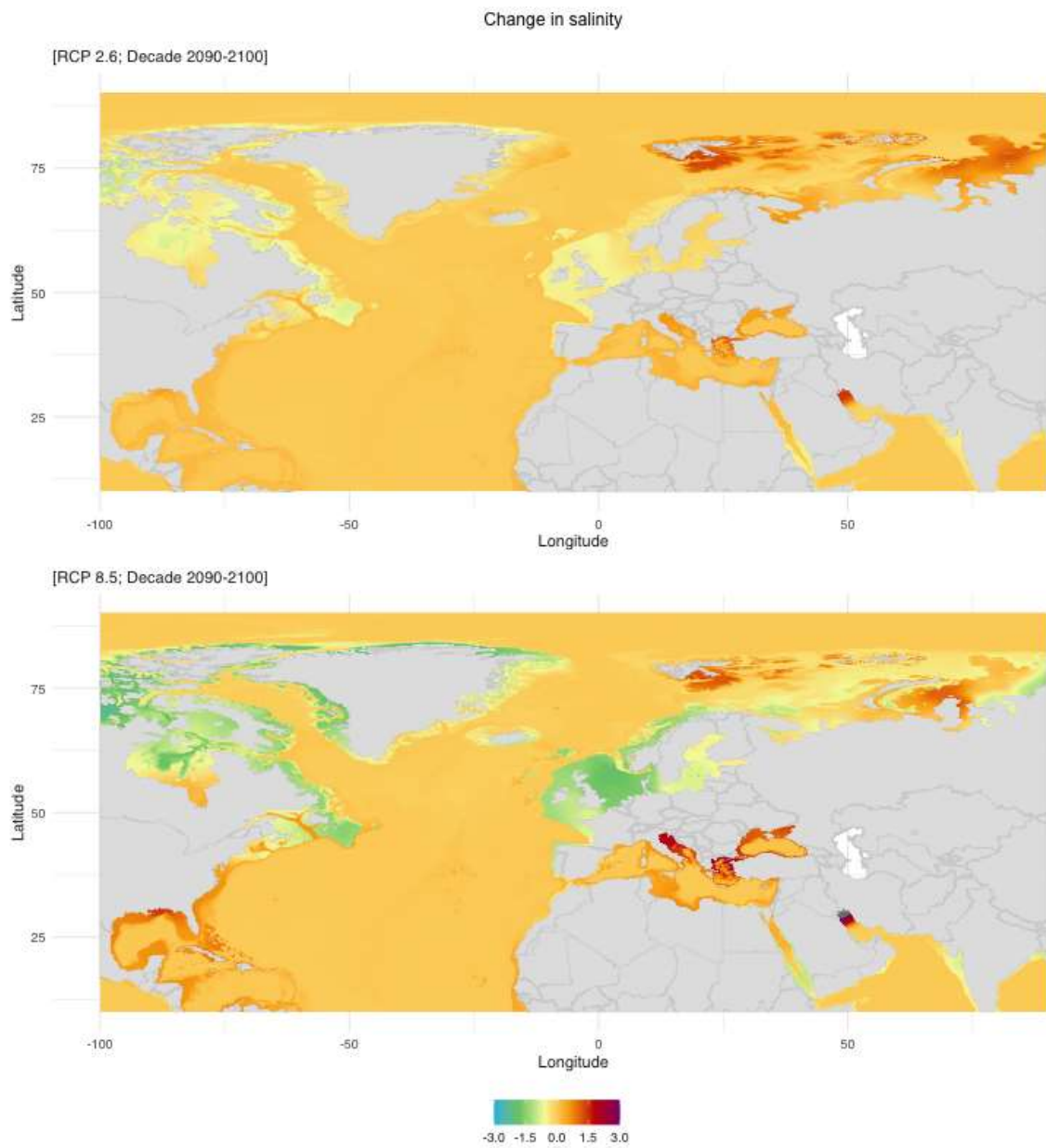
1502 Figure S4d Difference between present and future (RCP2.6 and RCP8.5) dissolved molecular
1503 oxygen (mol.m⁻³) in the benthos of the North Atlantic.

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1509 Figure S4e Difference between present and future (RCP2.6 and RCP8.5) salinity (PSS) in the
1510 benthos of the North Atlantic.

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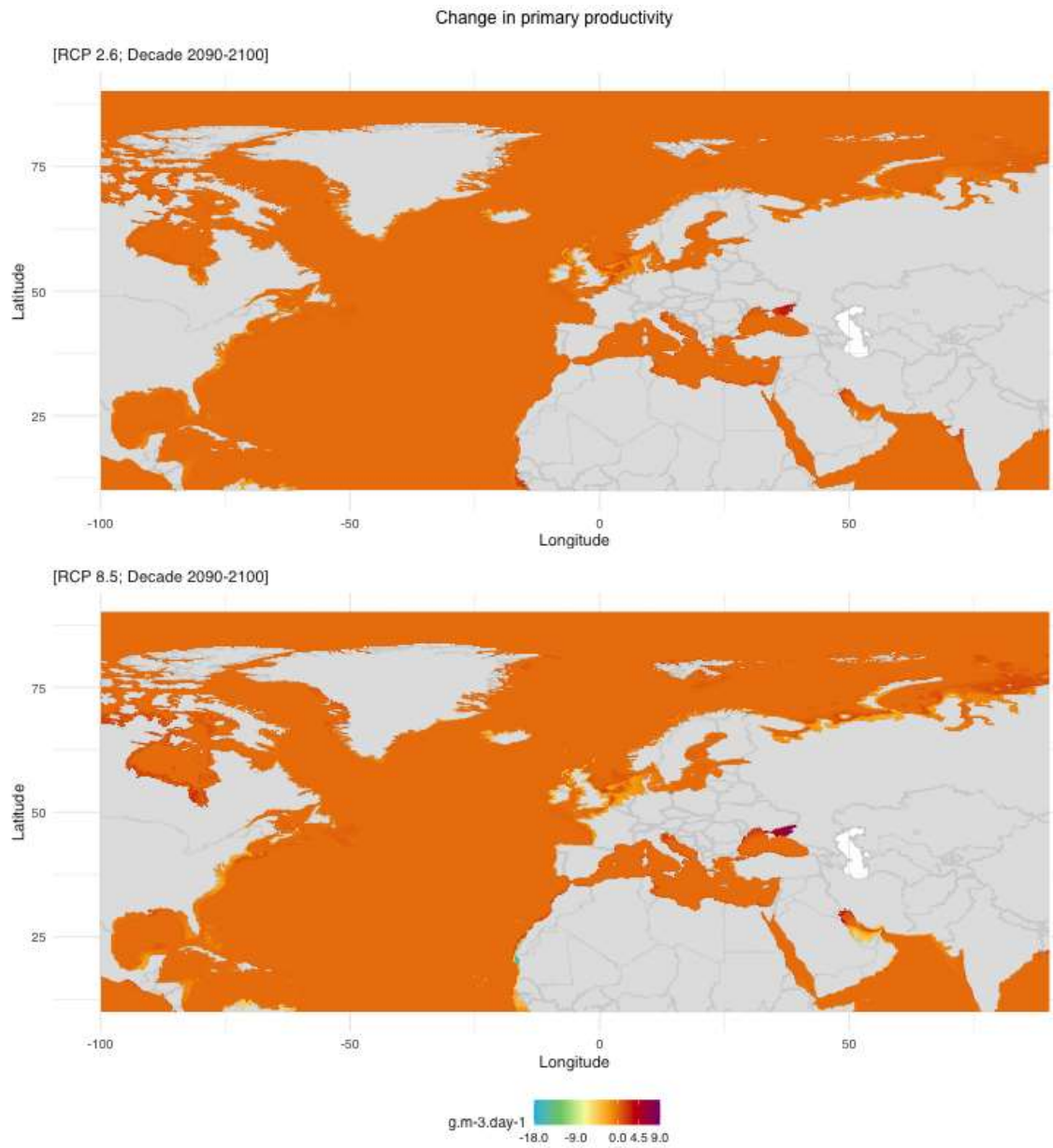
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1520 Figure S4f Difference between present and future (RCP2.6 and RCP8.5) primary productivity
1521 ($\text{g.m}^{-3}.\text{day}^{-1}$) in the benthos of the North Atlantic.

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1524 **References**

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