

Observed large-scale and deep-reaching compound ocean state changes over the past 60 years

In the format provided by the
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18 **Supplementary Discussions**

19 **Section A. Confidence level assessments of the key ocean climatic impact-drivers (CIDs) in IPCC-** 20 **AR6.**

21 **(1) Subsurface ocean temperature:** The ocean mean temperature is one of the most important ocean-
22 related CIDs. Moderate temperature determines the growth rates of marine species, but ocean warming
23 can cause stress to marine ecosystems, exacerbate marine heatwaves, and increase the mortality of marine
24 life¹. A large number of studies have shown that ocean warming would have adverse impacts ranging from
25 the individual level to the ecosystem level, including species redistribution², fishery production³, fish
26 range shifts⁴, extirpation/mortality of marine species⁵, seabird mortality⁶, sea urchin growth⁷, the tipping
27 points of phytoplankton production⁸, etc. The latest IPCC assessment shows high confidence levels of
28 mean temperature for the open ocean, coastal seas, and fisheries⁹.

29

30 **(2) Salinity:** Salinity change is another important CID in climate research, and the IPCC report has
31 assessed the impacts of this CID in the open ocean, coastal seas, and fisheries with medium confidence⁹.
32 Moderate salinity determines the physiological levels of marine species, but excessive/limited salinity
33 (freshening/salinization) can cause redistribution of marine life¹⁰. Salinity change will also affect the
34 nutrient fluxes, marine organisms, freshwater uptake, and ocean carbon uptake^{11,12}. All of these changes
35 could have a potential impact on disrupting marine ecosystems (e.g., disrupting the mangrove dispersal¹³,
36 altering the diversity and metabolic capacity of marine microorganisms¹²), the food chain of fish species¹¹
37 and increasing areas with harmful algal blooms¹².

38

39 **(3) Dissolved oxygen:** Deoxygenation is another important CID in climate research, with a medium
40 confidence level assessment from IPCC-AR6 affecting the open ocean, coastal seas, and fisheries⁹.
41 Increased deoxygenation, together with the increased ocean stratification caused by changes in

42 temperature and salinity, limits vertical oxygen exchange and leads to the formation of 'dead zones'
43 (hypoxic zone¹⁴). Moderate oxygen levels determine the respiration/growth of marine species, but limited
44 oxygen (deoxygenation) may cause mortality¹⁵, including loss of habitat for fish species¹⁶, and changes in
45 the structure and function of marine ecosystems¹⁷. The abundance of zooplankton, which are the vital prey
46 for many fish species, is expected to decrease in some regional shelf seas because of the increasing
47 occurrence of dead zones¹⁸.

48

49 **(4) Surface pH:** The anthropogenic-driven decrease in pH is often used to refer to ocean acidification¹⁹.
50 There is high confidence that this CID affects the open ocean, coastal seas, and fisheries⁹. Moderate pH
51 levels determine the production of calcium carbonate structures and support biodiversity growth and
52 reproduction, but a decrease in pH (acidification) causes shell dissolution and mortality for some
53 organisms²⁰. Acidification disrupts the dynamic balance of the carbonate system in the global ocean, and
54 has multiple effects on the marine species' survival, growth, diversity, photosynthesis, metabolism, and
55 calcification, of different groups of microorganisms^{21,22}.

56

57 **Section B. Data availability of ocean climatic impact-drivers (CIDs)**

58 In this study, our object is to provide a global 3D view from direct physical and biogeochemical
59 observations of the long-term change of compound CIDs, so we discuss the data availability in the scope
60 of the state of the global ocean observing system (GOOS).

61

62 The global ocean observing system has evolved significantly, particularly over the last 30 years. However,
63 gaps in global coverage remain, ranging from a lack of measurements in many parts of the deep ocean to
64 different areas of the globe²³. Moreover, measurements further back in time to allow for the analysis of
65 long-term changes in the ocean to capture climate-relevant evolutions remain a challenging task.

66 Considerable progress has been made in data processing and recovery efforts by the international
67 community, particularly for subsurface ocean temperature²⁴⁻²⁶ and ocean salinity²⁵⁻²⁷ back to the 1960s.
68 Global-scale products for ocean oxygen are beginning to emerge, but are still subject to non-negligible
69 uncertainties due to large data gaps^{28,29}. Similarly, progress has been made for ocean pH, albeit limited to
70 the surface layer, starting in the mid-1980s³⁰⁻³².

71

72 Progress also has been made for satellite-based observational products for ocean surface chlorophyll-a
73 and primary production since ~1998. However, this study will not investigate the long-term change of
74 these two CIDs due to the limited duration of available observational data (only has ~25 years of data,
75 which is too short to investigate their long-term change). Further examination of this topic is available in
76 the *SI Section C (5-6)* below.

77

78 **Section C. Result of time of emergence (ToE) of each CID (single emergence)**

79 Here, to further support the main findings in this manuscript, it is necessary to discuss the ToE results of
80 individual CIDs emergence.

81 **(1) Temperature**

82 Using the IAP temperature grid product, the ocean warming signal in the upper 1000 meters in 2023 is
83 about 0.23°C (relative to 1960-1979) at the global average, ~21 times of the global noise level. The
84 emergence year of global averaged warming signal is 1974 (Supplementary Fig. 14a). More specifically,
85 ocean temperature shows different ToE patterns at different depths (Extended Data Fig. 2). In the surface
86 layer (0m), a large part of the low-latitude (30S-30N) ocean regions show an emergence of ocean warming
87 after the 1990s, while the extratropical regions show a later ToE and even no emergence until 2023. These
88 results are in agreement with previous studies³³⁻³⁵. In the epipelagic zone (0-200m), most subtropical
89 regions (10N-30N and 30S-10S) show a significant emergence of ocean warming after 2000. In the

mesopelagic zone, the low-latitude Atlantic Ocean (50S-40N), the Southern Ocean (70S-40S), the tropical and northern Indian Ocean (10S-30N), and the Mediterranean Sea show a robust emergence after ~2000. Overall, 68.86% [67.03~71.34%], 56.87% [53.57~59.92%], and 51.72% [46.90~54.47%] of the global ocean areas show significant emergence of ocean warming in the 95% confidence interval before 2023 at the surface, epipelagic zone, and mesopelagic zone, respectively, with the Atlantic Ocean showing the largest percentage of emergence than the other basins (Extended Data Fig. 2d). Using the Ishii temperature product shows almost identical spatial and temporal emergence patterns compared to IAP data (v7.3.1; Ishii et al.²⁶). Specifically, ~72.0% (surface), 61.8% (epipelagic zone), and 62.1% (mesopelagic zone) of the global ocean areas show emergence of ocean warming before 2023, particularly in the tropical and subtropical North Atlantic Ocean, the Mediterranean Sea, the Southern Ocean, and the tropical and northern Indian Ocean (Extended Data Fig. 5), consistent with the IAP temperature product (Extended Data Fig. 2).

(2) Salinity

Globally, with the IAP salinity grid product estimation, the signal of salinity variation in the upper 1000 meters in 2023 is about 0.023 g/kg (relative to 1960-1979) indicated by the global salinity contrast index, ~10 times of the global noise level (Supplementary Fig. 14b). More specifically, we noted that the spatial patterns of salinity ToE differ considerably from those of temperature (Extended Data Fig. 3 versus Extended Data Fig. 2). Many regions in the Pacific Ocean show an emergence of freshening, and the areas in the Atlantic Ocean and North Indian Ocean experienced an emergence of salinization (Extended Data Fig. 3). These results are consistent with the previous finding of ‘salty gets saltier, fresh gets fresher’ patterns²⁷. On average, 11.33% [7.81%~16.37%] (surface), 29.71% [20.19~36.04%] (epipelagic zone), and 47.31% [32.12~67.67%] (mesopelagic zone) of the global ocean areas show a significant change in salinity by 2023 at the 95% data uncertainty confidence interval. Model simulations show a consistent

pattern of surface ToE for salinity³⁵. The uncertainty in the ToE for salinity is generally larger than that for temperature, mainly due to larger instrumental and sampling uncertainties for salinity.

By using the Ishii salinity product²⁶, the spatial pattern of salinization and freshening emergence is generally consistent to the IAP dataset (Extended Data Fig. 6 vs. Extended Data Fig. 3). More specifically, the emergence of salinity increase can be identified around the high exposure regions identified by the IAP products (i.e., the North Atlantic Ocean, Tropical Atlantic, Mediterranean Sea, the Arabian Sea; see Fig. 3 in the main text). A notable difference is the smaller fraction of emergence regions of the Ishii product as compared to the IAP results (Extended Data Fig. 6d v.s. Extended Data Fig. 3). Some regions show ‘no emergence’ in the Ishii data before 2022, for instance, the Subtropical Pacific Ocean. The percentages of the emergence area for the Ishii product are ~28.0% for the epipelagic zone and 33.8% for the mesopelagic zone, which are smaller than the IAP product (30% and 47% for the epipelagic and mesopelagic zone on average, respectively). This is likely because of the following reasons: 1) the salinity-contrast (SC) signal in the Ishii data is weaker than in IAP (Fig. 11 in the Cheng et al. 2020), mainly associated with the gap-infilling strategy difference in the two products. Ishii data interpolation is slightly biased to the climatology (i.e., ‘no data, no signal’) in data-sparse regions, leading to an underestimate of the long-term trends^{36,37}. 2) The data quality control (QC) process: The Ishii product is based on the Ishii et al.³⁸ QC procedures, while the IAP dataset is based on the CODC-QC schemes³⁹. Studies have shown that the difference in QC performance can lead to a different magnitude of data noise due to different impacts of data outliers^{40,41}. This can impact the noise estimate in the ToE calculation. 3) Other data processing differences, including the choice of climatology, differences in data sources, vertical interpolation.

(3) Dissolved oxygen

138 For the dissolved oxygen, the ocean deoxygenation signal in the upper1000 meters in 2022 is about
139 $3.323 \mu\text{mol}/\text{kg}$ (relative to 1960-1979) at the global average, ~ 9.6 times of the global noise level. The
140 emergence year of global averaged deoxygenation signal is 1992 (Supplementary Fig. 14c). Spatially,
141 approximately 44.49% [40.70~48.57%] and 53.45% [49.27~57.75%] of the epipelagic and mesopelagic
142 zones show significant deoxygenation emergence at the 95% confidence interval (Extended Data Fig. 4).
143 There are almost no regions with significant oxygen changes compared to the noise in the surface layer,
144 mainly because there is exceptionally large “noise” for surface oxygen due to the combination of low data
145 quality and complexity of physical and biogeochemical processes (Extended Data Fig. 4). Significant
146 regional patterns emerge, i.e., the deoxygenation in the Mediterranean Sea, tropical oxygen minimum
147 zones (OMZs), the North Pacific Subtropical Gyre, the North Atlantic Subtropical Gyre, and the northern
148 Indian Ocean. In particular, most of regions of tropical Atlantic OMZs within the epipelagic and
149 mesopelagic zone (mainly within 100-500m) have experienced significant emergence of deoxygenation
150 since ~ 2000 at 95% confidence level, consistent with previous results for the expansion of OMZs and
151 hypoxia areas^{15,42}. Specifically, the peak of deoxygenation emergence at $\sim 550\text{-}750\text{m}$ (Figure 1d) is mainly
152 attributed to the rising deoxygenation signals in an increasing area in the Indian Ocean, which is likely
153 because of the expansion and deepening of the Oxygen Minimum Zones (OMZs) in this region (e.g., the
154 Arabian Sea, the Bay of Bengal, the tropical Indian Ocean)⁴³. A large fraction of the global ocean with a
155 significant deoxygenation emergence implies an exacerbated effect on respiration and aerobic metabolism
156 ⁴⁴.

157

158 The uncertainty in the ToE estimates for dissolved oxygen is greater than for temperature (Extended Data
159 Fig. 4 versus Extended Data Fig. 2) because of the larger observational data gaps (sparse and irregular
160 distribution) for oxygen^{28,29}. Therefore, it would be helpful to further test the robustness of the ToE
161 estimate for dissolved oxygen with an independent observational gridded product: Global Upper Ocean

162 Dissolved Oxygen Anomaly Dataset (version 2) from 1965 to 2015 (referred to as the ‘Ito’ dataset²⁹). The
163 results are shown in Extended Data Fig. 7. With Ito data, the deoxygenation spatial pattern of ToE is
164 generally consistent with the IAP dataset, suggesting the robustness of the spatial distribution of oxygen
165 ToE. The global percentages of the emergence area in 2015 for Ito data are generally the same as for IAP
166 data, but the intensity and magnitude of emergence are quite different, and more refined spatial features
167 can be obtained in IAP data. The reasons are: 1) the signal estimate using the Ito dataset is much smaller
168 than the IAP dataset after the 2000s, with the maximum difference at the global average being about 3.5
169 $\mu\text{mol/kg}$ in 2015. This is mainly because the signals are relaxed to climatology (“no data, no signal”) in
170 data-sparse regions ²⁹. Detailed analyses suggest that this “no data, no signal” error can bias the global
171 oxygen trend by ~32% in⁴⁵ (investigated with climate models). 2) The IAP dataset is the monthly product
172 but combines three years of data for its monthly estimate. In contrast, the Ito dataset is an annual resolution
173 product that combines five years of data to estimate the annual mean oxygen change, resulting in a
174 difference in the noise calculation. Therefore, the noise level for Ito data is slightly smaller than that for
175 IAP data; 3) Additional differences can be attributed to differences in the data source (IAP used Bottle,
176 CTD, and Argo data; Ito used only Botte data) and data processing methods (i.e., mapping, climatology
177 choice, vertical interpolation, instrument bias correction, data quality control). Nevertheless, these
178 differences do not change our conclusions and our understanding of the dissolved oxygen ToE.

179

180 **(4) Surface pH**

181 The surface pH long-term change indicates that the noise level is much smaller than the signal level (the
182 $|\text{SNR}|$ is more than 35 at the global average; Supplementary Figure 14d), with nearly all global surface
183 oceans (~100%) have experienced a significant pH emergence before 2000 at a 95% confidence level
184 relative to a 1985-1989 baseline (we choose this short baseline than temperature, salinity because of the
185 seawater pH exhibits relatively smaller magnitude of natural variability). The time required for the pH

186 signal to emerge from the noise is typically within about 10($\pm$ 5) years (Extended Data Fig. 1). Furthermore,
187 the result from the Copernicus Global Ocean Surface Carbon data is consistent with that using the Ocean-
188 SODA ETHZ data, adding to the robustness of this assessment (Extended Data Fig. 1 and Supplementary
189 Figure 14d). Also, surface pH appears to be the most rapidly emerging CID compared to temperature,
190 salinity, and oxygen, consistent with previous findings^{46,47}.

191

192 **(5) Chlorophyll-a**

193 The ToE of chlorophyll-a is investigated monthly by the Ocean Color products developed by the ESA-
194 Climate Change Initiative⁴⁸ for 1998-2021 when satellite observations are available. The result shows that
195 in the past ~25 years, the global mean change of chlorophyll-a has not significantly emerged because of
196 substantial interannual and decadal variability. Spatially, our SNR approach shows that only 5% of the
197 global ocean has experienced an emergence of chlorophyll change before the end of 2022 (mainly
198 distributed in the tropical and subpolar Pacific Ocean) (Supplementary Fig. 15). In contrast to the other
199 variables examined in this study, chlorophyll-a requires a considerably longer period (more than 30-50
200 years) for its long-term trend to exceed the interannual and decadal scale variability^{35,49,50}.

201

202 It should be noted that Cael et al.⁵¹ indicate that 20 years of ocean color data are sufficient to confidently
203 detect the ocean color long-term climate change signal. However, this result is different from our study
204 because we used the chlorophyll-a data, which is univariate. In comparison, Cael et al.⁵¹ used the remote-
205 sensing reflectance data (which is not included as a CID in IPCC-AR6), which is multivariate that
206 chlorophyll-a is only part of the contribution to the reflectance. Also, the methodology for estimating the
207 ToE differs for the two studies. Therefore, to be consistent with other CIDs, the chlorophyll-a and remote
208 sensing reflectance of ocean color is not investigated in our study.

209

(6) Primary productivity

The ToE of ocean primary productivity is investigated using monthly satellite-based Global ocean color data from 1998 to 2022 implemented by the Copernicus Marine Service⁵². Over the past ~25 years, the global long-term trend has not significantly exceeded the noise at the 95% confidence level. Spatially, the |SNR| is less than 1 in almost all ocean regions, indicating a substantial local variability in primary productivity (Supplementary Fig. 16). Therefore, given the current data availability, this variable is not investigated in our study.

Section D. Discussions of three exposure metrics

To further explore how long, how strong, and how fast compound CIDs emerge, three metrics (duration of emergence, intensity of emergence, and magnitude of emergence) are defined based on their probability density (Box 1 Fig. 1b-c). Supplementary Fig. 4 shows the spatial maps of these three metrics. The most prolonged durations of double and triple emergence are mainly manifested in the North Atlantic subtropical gyre, and in the tropical Atlantic OMZ, with values exceeding ~25 years on average. The highest magnitude of double and triple emergence is observed mainly around the Gulf Stream in both the epipelagic zone and the mesopelagic zone. The spatial pattern of the intensity map is similar to that of the duration map (Supplementary Fig. 4e,f,h,i). In addition, most areas in the Mediterranean Sea, both in the epipelagic and mesopelagic zones, share a long duration, high intensity, and high magnitude. These three metrics are then used to estimate the exposure of individual and compound CIDs emergence (See Fig. 3 in the main text).

Section E. Sensitivity test of the impact of natural variability to the ToE estimation with CMIP6 piControl models

233 Since the long-term change signals associated with a warming climate may have resulted from the
234 responses of CIDs to naturally occurring different phases of ocean circulation variability, the 20-year
235 baseline and 25-year LOWESS smoothing windows of the “signal” in this study may not fully capture the
236 natural (multi-)decadal variability adequately, which could affect the results of the ToE. Although we had
237 been included this impact as one of the sources of uncertainty into the overall uncertainty in this study
238 (namely as ‘*Uncertainty due to decadal variability in the quantification of signal and the choice of*
239 *baseline*’; see Extended Data Figure 8). We use a different method here to determine whether significant
240 emergences can be obtained within the climate variability alone. A sensitivity test is performed using the
241 CMIP6 preindustrial (pi-Control) simulation (1850-1912; 62 years in total; the same time period as in the
242 main text) with a 20-year baseline of 1850-1869. Multi-model ensemble strategies (20 models for
243 temperature, 15 models for salinity, and 10 models for dissolved oxygen; see Supplementary Table 3) are
244 considered. The ‘model drift’ in each model is removed by using a ‘quadratic’ polynomial regression in
245 each grid box following the suggestions of Cheng et al.²⁷. The same ToE method described in the main
246 text was used here. Following Lyu et al.⁵³ and Silvy et al.⁵⁴, the ToE uncertainty range (95% confidence
247 interval) is represented by the model spread (i.e., model difference).

248

249 The results show that, for the ToE estimation of each individual model (Supplementary Figs. 17-19), we
250 found that only 3 out of 20 models of temperature in the mesopelagic zone show a large fraction (more
251 than 20% of global ocean areas) of emergence due to the climate variability. For salinity, this number is
252 3 out of 15 models. For dissolved oxygen, this number is 1 out of 10 models. These regions are mainly
253 distributed around the Atlantic Meridional Overturning Circulation and the North Pacific gyre
254 circulations, spanning multi-decadal time scales associated with the PDO and the AMO^{55,56}, and the
255 Southern Ocean circulation. It is possible that there may be unrealistic emergences due to the impact of
256 climate variability at different timescales by using the observational data. One of the possible reasons is

that the 20-year baseline may ‘capture’ some different phases of ocean (multi-)decadal variability in few models.

However, as indicated by Bopp et al.⁵⁷ and Kwiatkowski et al.⁵⁸, different models can simulate very different (multi-)decadal variability, and therefore, from a multi-model ensemble perspective, we found that for all the estimates of temperature, salinity, and dissolved oxygen, more than half of the models (over 50%) show ‘no emergence’ before 1912 in almost all global oceans (Supplementary Fig. 20a-c, Supplementary Fig. 21a-c, Supplementary Fig. 22a-b). This indicates that there are no ‘significant emergences’ associated only with internal variability during the 1850-1912 pi-Control period at 95% confidence level. Temporally, for temperature, there is no emergence before 1912 at the surface, and only ~1.5% (9.2%) of the global ocean has emerged in the epipelagic (mesopelagic) zones before 1912 (Supplementary Fig. 20d; median value). For salinity, these percentages are 1.6%, 3.4%, and 9.9%, respectively (Supplementary Fig. 21d). For dissolved oxygen, these percentages are 2.9% for epipelagic and 5.7% for mesopelagic zones (Supplementary Fig. 22c).

By comparing with the CMIP6 historical simulation results (Supplementary Fig. 20d vs. Supplementary Fig. 5d, Supplementary Fig. 21d vs. Supplementary Fig. 6d, Supplementary Fig. 22d vs. Supplementary Fig. 7c) in 1960-2022 (with 1960-1979 baseline), we also found that the spatial and temporal patterns in this test are significantly different from the result for 1960-2022 (with 1960-1979 baseline) at 95% confidence level (Student’s *t-test*, P-values <0.05).

Therefore, we conclude that the impact of (multi-)decadal variability to the ToE estimation is relatively small and no significant emergences that can be determined using the ensemble strategy.

Section F. Conservative estimation of ToE in a warming climate due to data availability

282 We have noted that previous estimates of ToE associated with global climate change typically start from
283 the beginning of the Industrial Revolution (1850s) with using more than 170 years (even more than 250
284 years) of model data with a 51-year baseline^{34,35,53}. However, since we only have ~62 years of
285 observational data in the subsurface ocean starting in 1960, and this relatively short record may not fully
286 capture the long-term change signal. Although we didn't make any formal attribution of our ToE estimate
287 anthropogenic global climate change in this study, we wonder if we want to put this study into the
288 perspective of climate change since the Industrial Revolution (1850s), how much is the difference between
289 ~60 years records (starting from 1960) and ~170 years records (starting from the 1850s) if they begin in
290 different years but end in the same year.

291

292 Therefore, we carried out the following comparison by using the CMIP6 multi-model historical
293 simulation. 1) Group A: Examine the ToE from 1850 to 2022 with a 51-year baseline from 1850 to 1900;
294 similar to Hawkins et al.³⁴; 2) Group B: Examine the ToE from 1960 to 2022 with a 20-year baseline from
295 1960 to 1979 (similar to the main text). Since the time span in these two groups all ends in 2022, and the
296 overlap period is 1960 to 2022, thus, we can compare the emergence difference between Group A and
297 Group B (Group A minus Group B) based on the same ToE method with the same CMIP6 historical model
298 choice (Supplementary Table 4). Model drift has also been removed. The same ToE estimation method
299 that consistent with the main text was used.

300

301 The results show that, the spatial and temporal patterns of the global emergence between these two groups
302 are very similar (Supplementary Figs. 23-25). However, we still find some differences between these two
303 groups. Specifically, for temperature, the global percentage of emergence in 2022 in group B is ~13.3%
304 (surface), 10.5% (epipelagic zone), and 10.2% (mesopelagic zone) smaller than that in group A
305 (Supplementary Fig. 23a; median value). These values are ~3.3% (surface), 3.1% (epipelagic zone), and

306 4.0% (mesopelagic zone) for salinity (Supplementary Fig. 24a) and 2.1% (epipelagic zone) and 0.3%
307 (mesopelagic zone) for dissolved oxygen (Supplementary Fig. 25a). This shows that the global percentage
308 of emergence in group B is always smaller than that in group A. In other words, more regions have actually
309 already emerged before 2022 than we initially thought (i.e., some emergences in a few regions cannot be
310 fully observed by using a short period of data such as that spanning from 1960 to 2022).

311

312 Spatially, the ‘more regions’ mentioned above are mainly distributed in the Southern Ocean (the
313 epipelagic zone; mainly attributed to warming emergence; see red dots in the Supplementary Fig. 23b-d).
314 This is mainly because the Southern Ocean is one of the most important ‘pumps’ for the heat uptakes and
315 redistribution^{1,59,60}. The evolution of the heat uptake started before the 1960s and accounts for about 75%
316 of the global heat uptake over the historical period⁶¹. In other words, using only ~60 years of data starting
317 in the 1960s may underestimate the magnitude, duration, and intensity of double or triple emergences in
318 the Southern Oceans.

319

320 Although there are discrepancies in the rates of emergence due to different baseline choices, the findings
321 affirm that the ultimate outcome remains consistent in most regions across both groups (i.e., most of these
322 regions emerged before 1980 in Group A are agreed to emerged before 2022 in Group B; see the
323 ‘overlapped’ regions in the Supplementary Fig. 23b-d, Supplementary Fig. 24b-c. Supplementary Fig.
324 25b-c), especially the consistency of the ‘high exposure’ regions we determined in the manuscript. This
325 alignment indicates that despite methodological differences (i.e., the differing durations of data used (172
326 years for Group A and 62 years for Group B) and baseline choice), the paths of emergence, while initially
327 divergent, effectively converge over time.

328

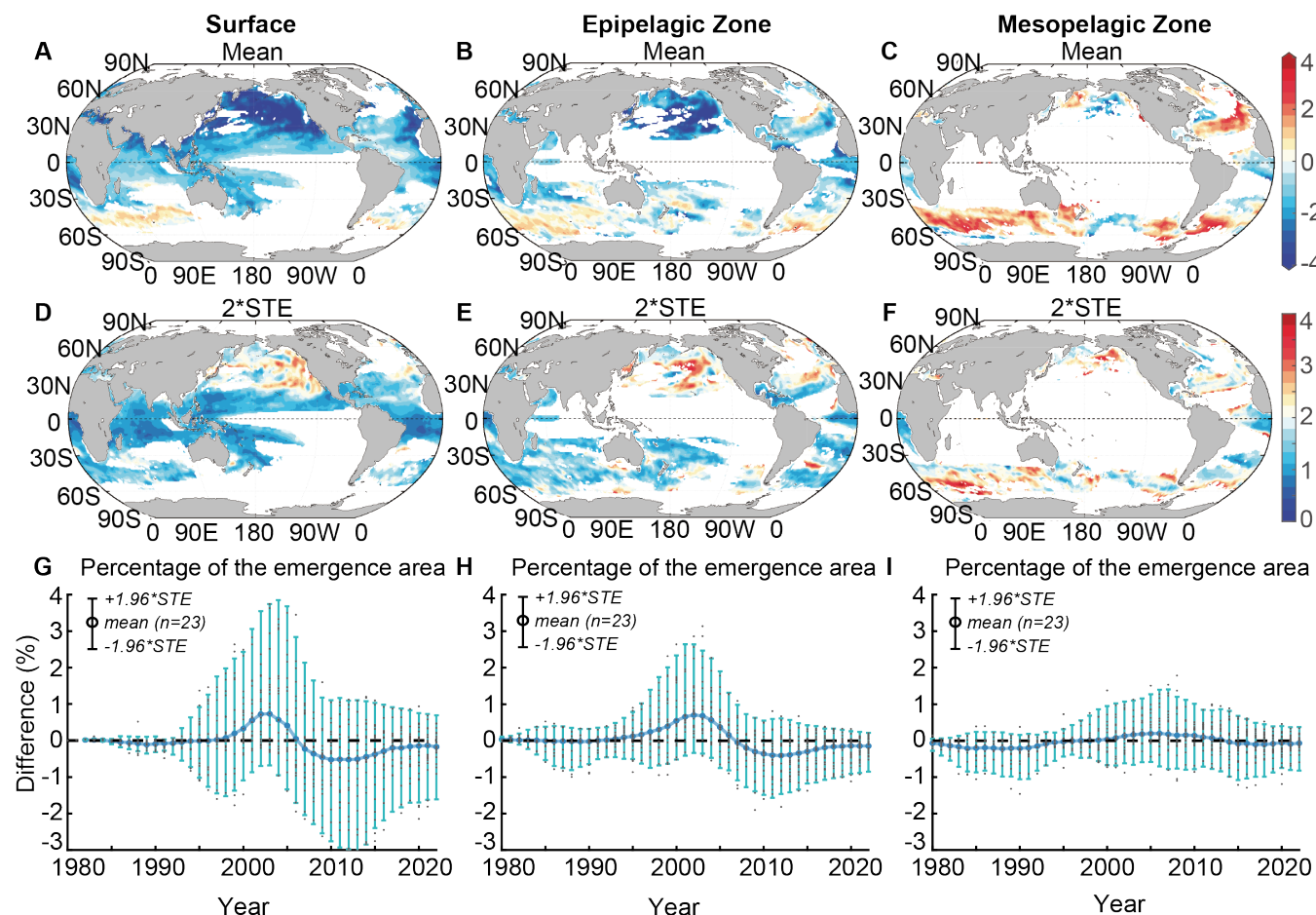
329 Therefore, we believe that the current ToE estimate in this manuscript, by using a period from 1960 to
330 2022 with observational data, is most likely a conservative estimate of the ToE from the perspective of
331 global climate change since the 1850s. It seems to be that more regions have already emerged before 2022
332 than we currently think (i.e., cannot be observed by using observational data given the relatively short
333 observational record).

334

335

336
337

Supplementary figures and tables



338

339 **Supplementary Fig. 1 | The difference of ToE ‘signal’ definitions (defined by 25-years versus 50-**

340 **years smoothing) and baseline choices (defined by 20-years baseline and 50-years baselines) based**

341 **on CMIP6 historical run models for temperature ToE in different layers** (left panel: surface layer;

342 **middle panel: epipelagic zone; right panel: mesopelagic zone). (a-c) the ToE mean difference (units:**

343 **years). (d-f) The two standard errors (2*STE) of the ToE difference (units: year). (g-i) The global**

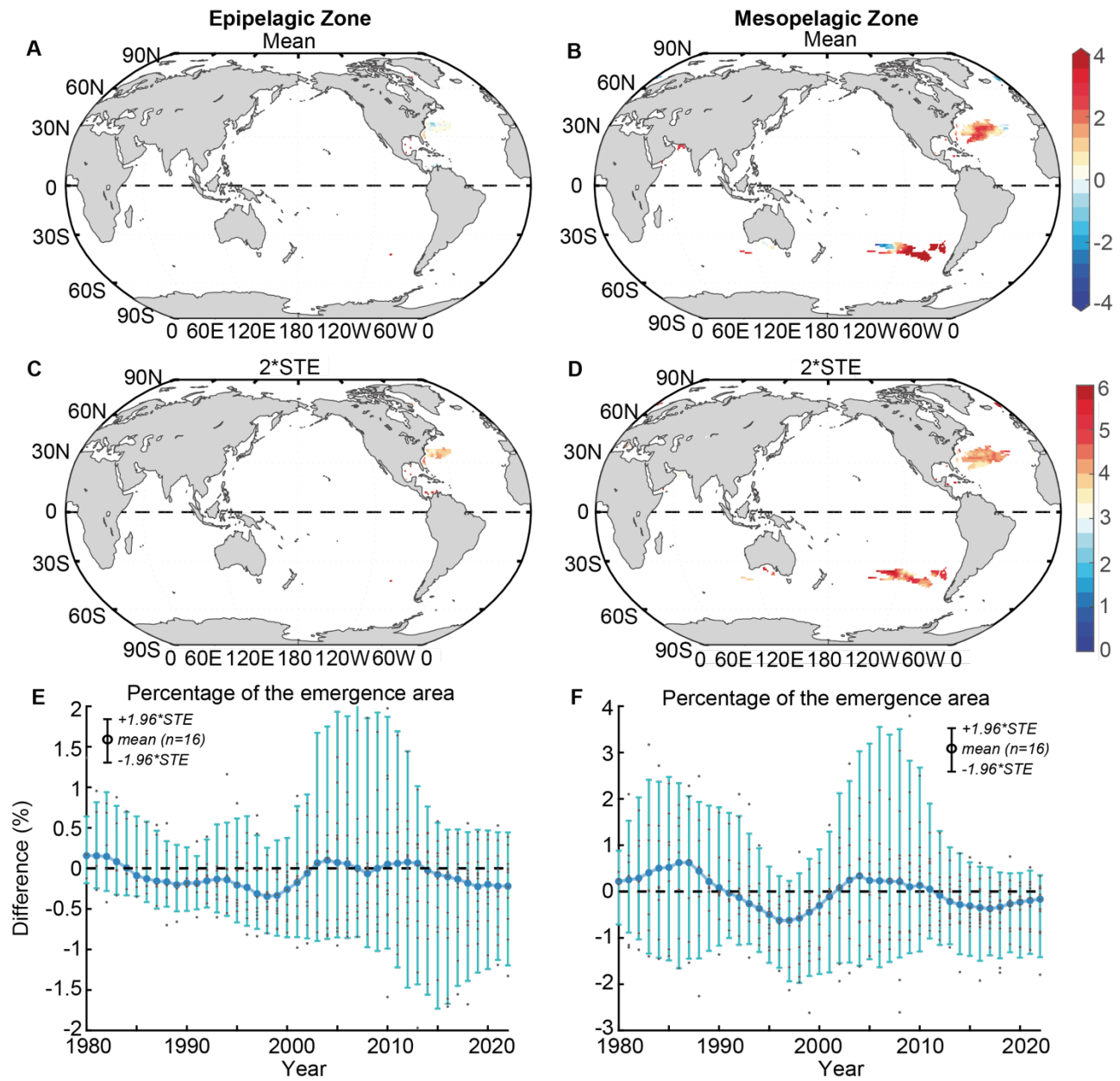
344 **percentage of the emergence area difference as a function of year. Only significant emergence regions**

345 **(see Extended Data Fig. 9 for the definition) are considered. The white color indicates no emergence**

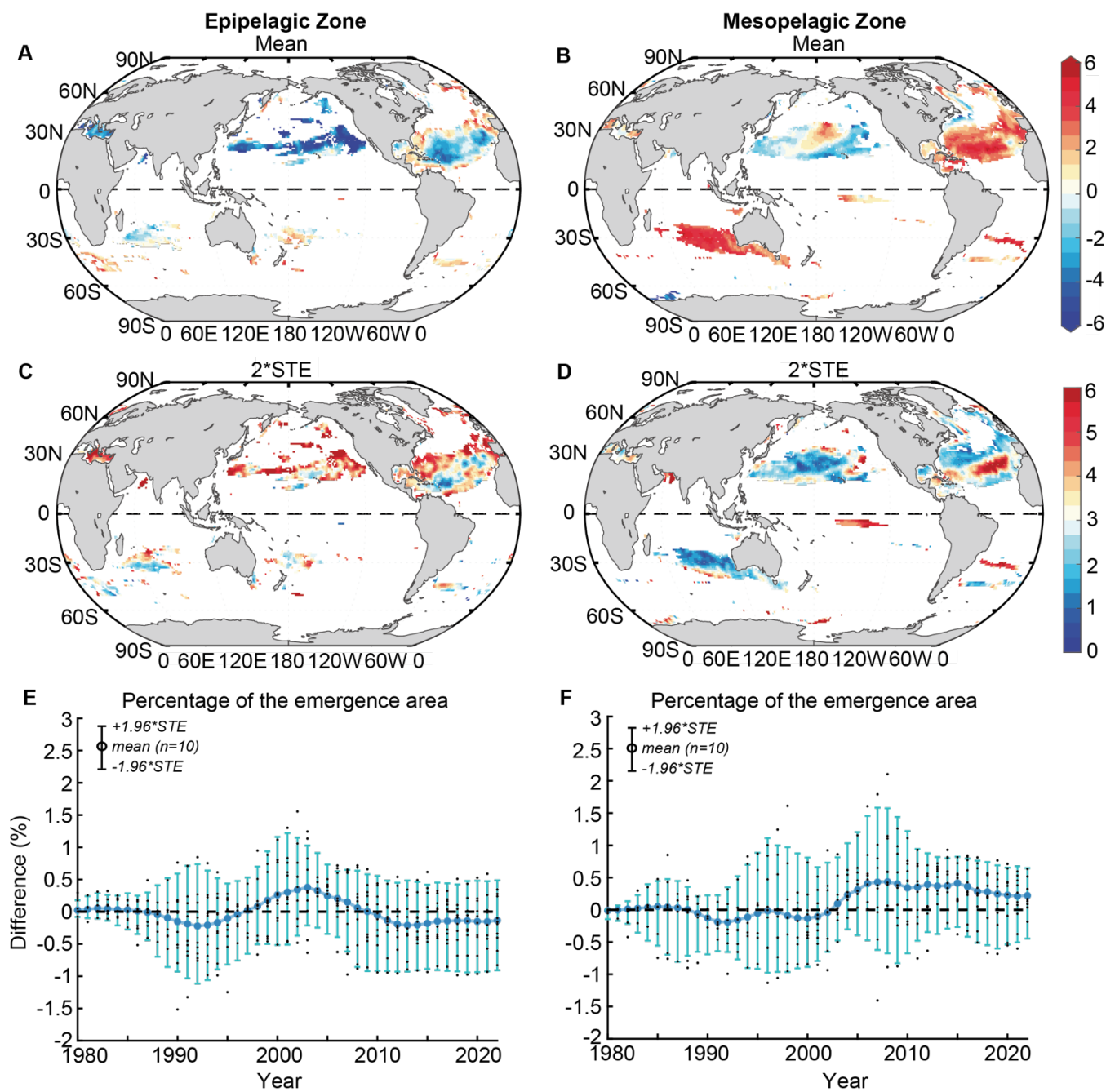
346 **regions. The error bar shows the 95% confidence level, the gray dots indicate the results of individual**

347 **models.**

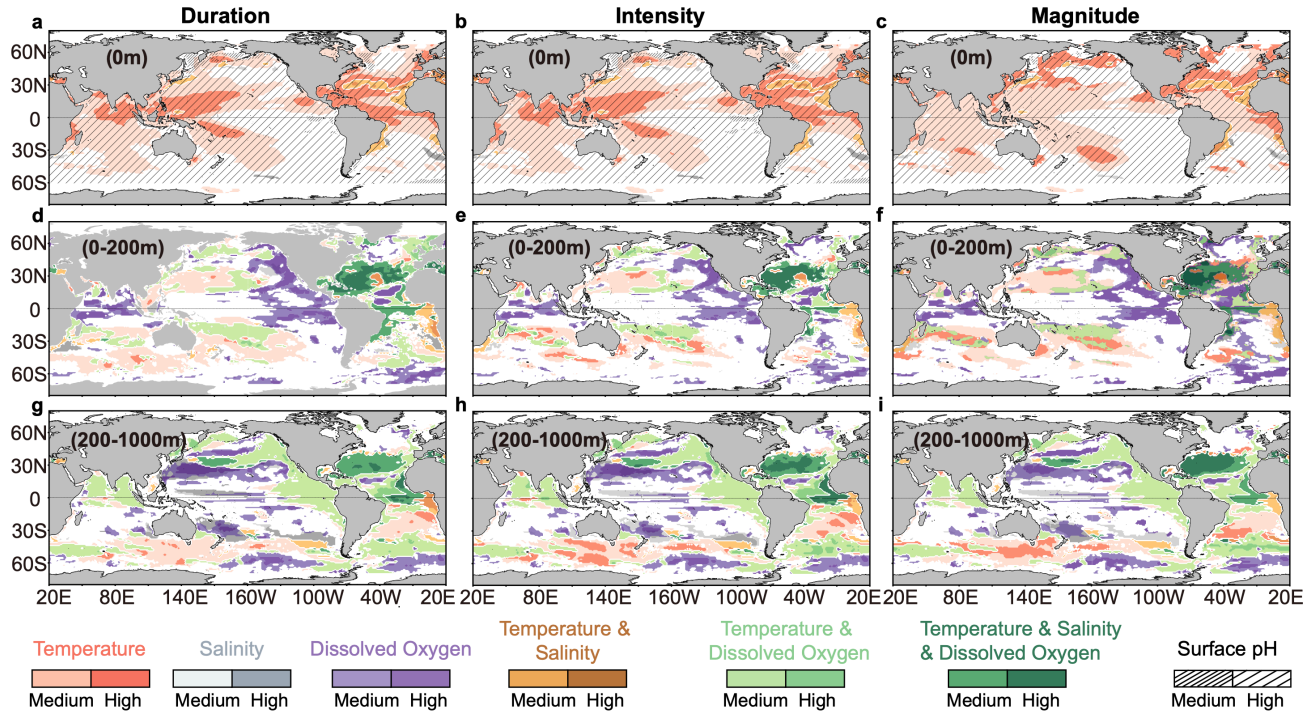
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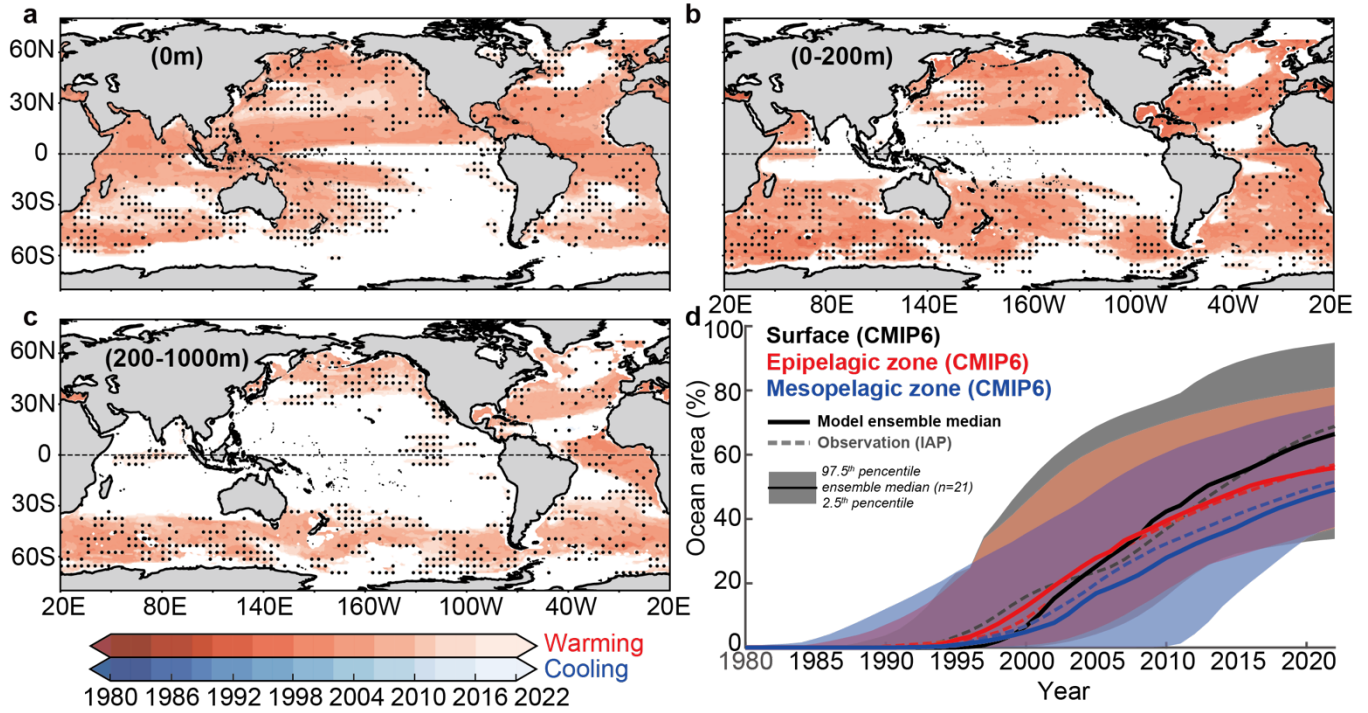
Supplementary Fig. 2 | Same as **Supplementary Fig. 1**, but for salinity in the epipelagic and mesopelagic zones, respectively.



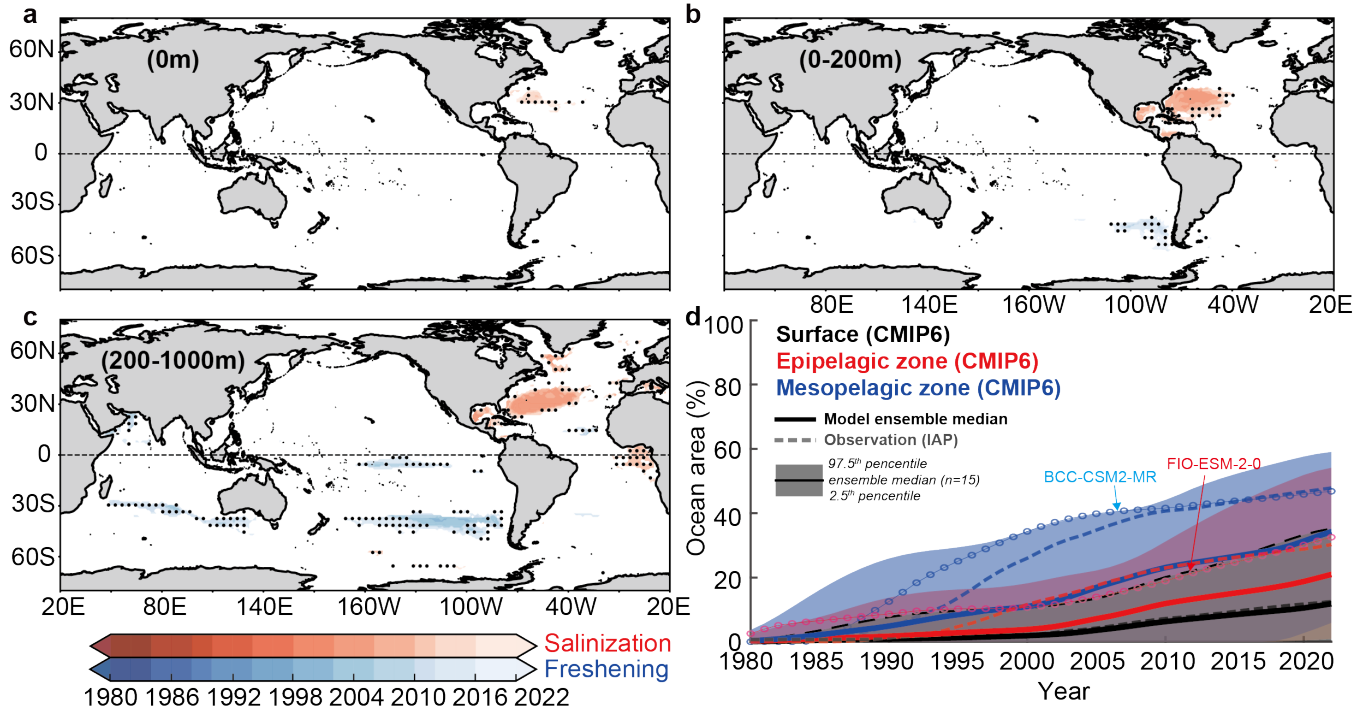
Supplementary Fig. 3 | Same as **Supplementary Fig. 1**, but for dissolved oxygen in the epipelagic and mesopelagic zones, respectively.



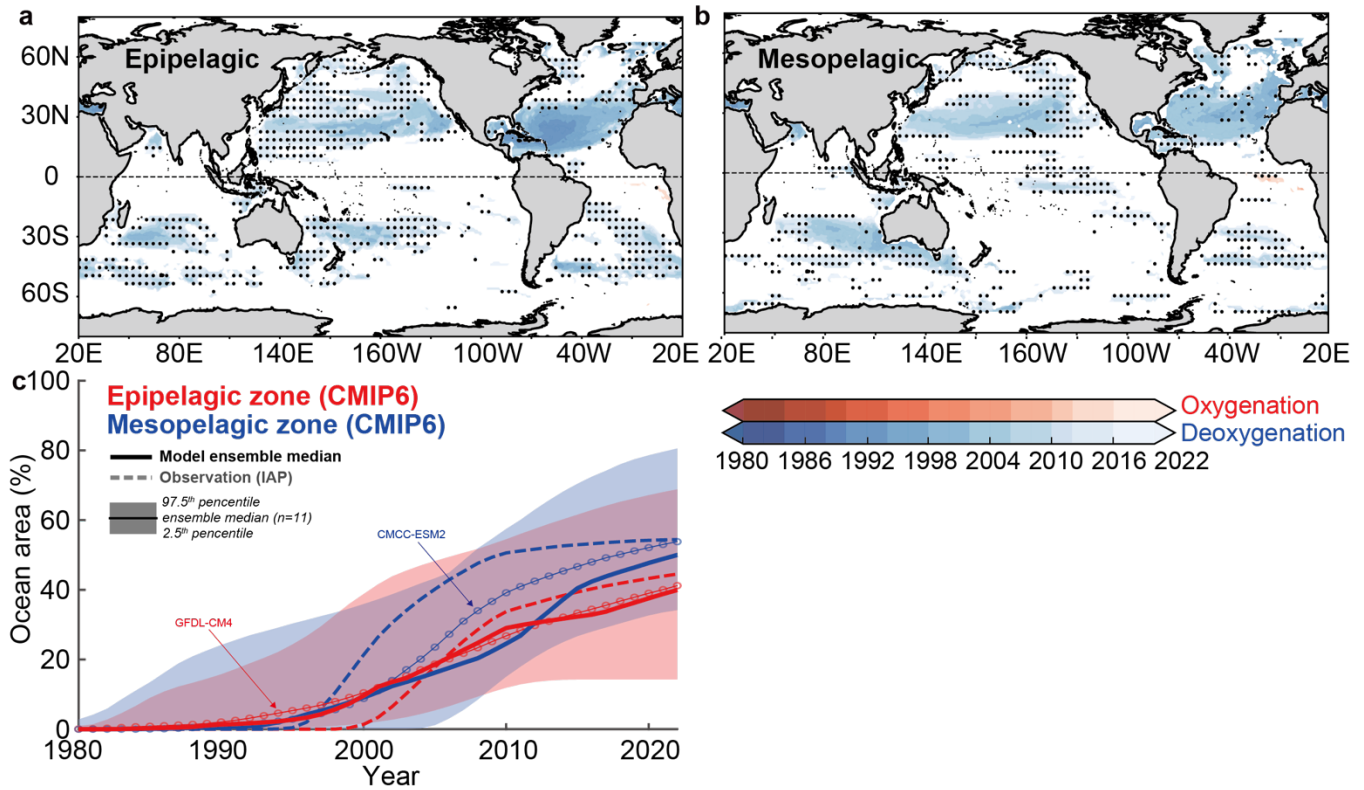
Supplementary Fig. 4 | Spatial distribution of three emergence metrics: duration (left panel), intensity (middle panel), and magnitude (right panel) for statistically significant emergence regions (the significance level is defined in the Extended Data Fig.9 and Supplementary Fig. 13) of individual and compound CIDs: (a-c) are for the surface layer, (d-f) are for the epipelagic zone (0-200m), and (g-i) are for the mesopelagic zone (200-1000m). Areas in white indicate regions with short duration, or low intensity, or low magnitude. Surface pH is analyzed separately from other CIDs (black slash). This result is used as the metrics for produce the Fig. 4 in the main text.



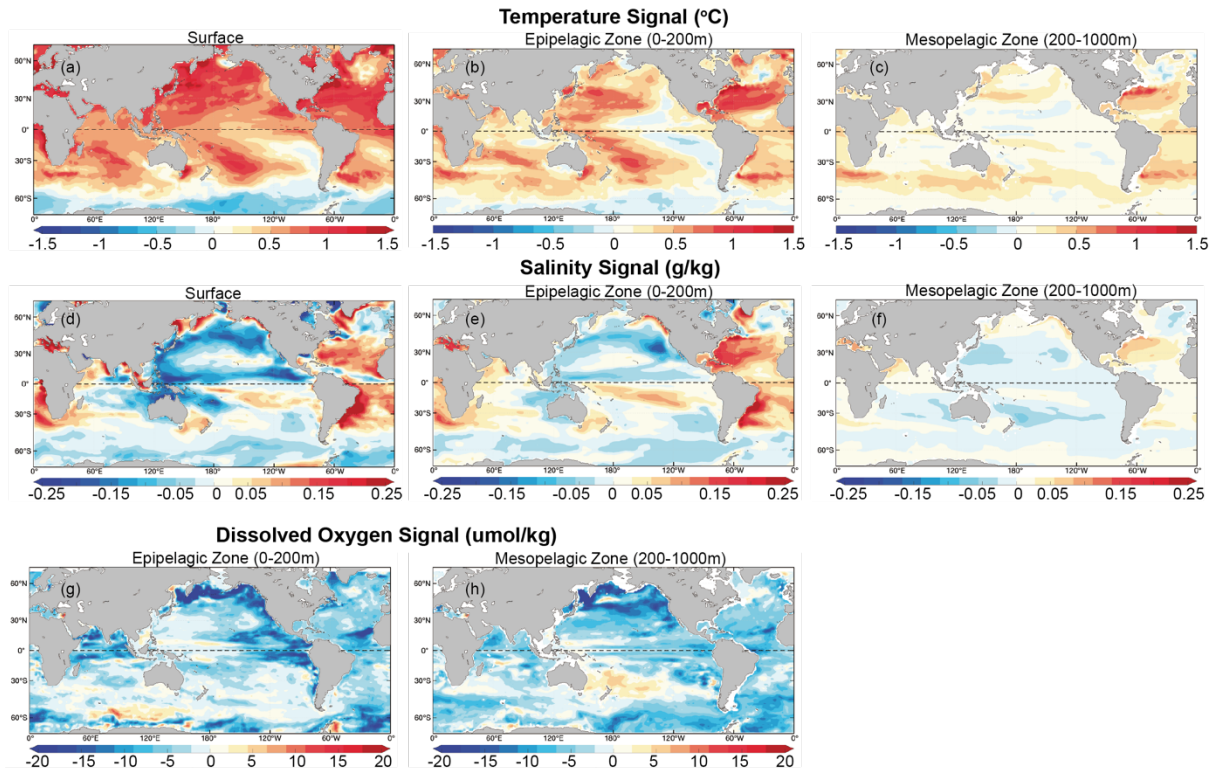
Supplementary Fig. 5 | The temperature ToE (unit: year) in different layers using the CMIP6 historical simulation (1960-2014) and SSP2.45 (2015-2022) ensemble median (21 members) temperature gridded product: (a) surface, (b) epipelagic zone (0-200m), and (c) mesopelagic zone (200-1000m). Two emergence directions are indicated (red: warming emergence; blue: cooling emergence). The white color indicates no emergence before 2022. Areas with insignificant emergence before 2022 (as defined in Extended Data Fig. 9) are marked as black dots to account for the uncertainty due to model differences. (d) is the same as (a-c), but shows the global percentage area of emergence as a function of the year, the shaded area represents the data uncertainty arising from ensemble members of the data products (see Methods). The reference period (baseline) is 1960-1979. The observational-based analyses by using IAP temperature gridded product are indicated as dashed lines. The polar regions (beyond 70N and 70S) are not examined due to lack of data. Details of the models used are shown in the **Supplementary Table 4**.

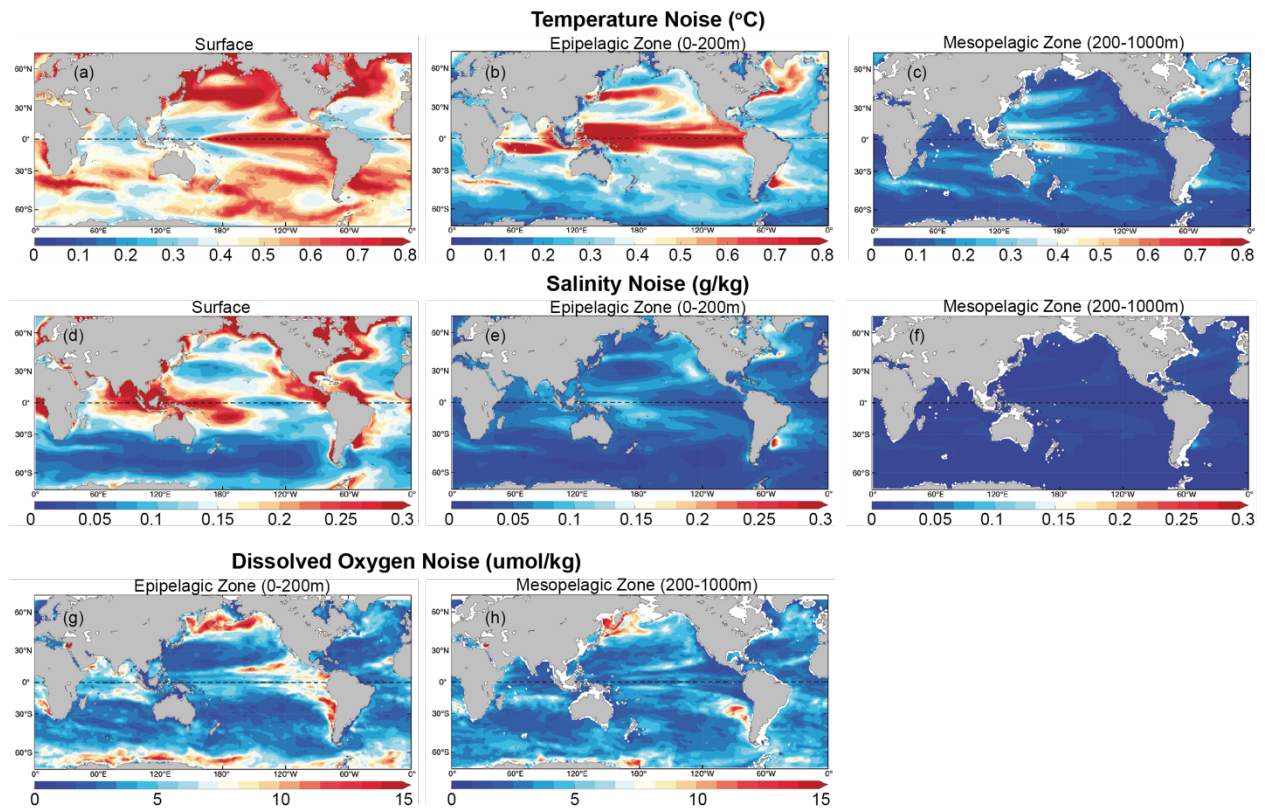


Supplementary Fig. 6 | Same as **Supplementary Fig. 5**, but for the salinity ToE (unit: year) in different layers using the CMIP6 historical simulation (1960-2014) and SSP2.45 (2015-2022) ensemble median (18 members) salinity gridded product. Two emergence directions are shown (red: salinization emergence; blue: freshening emergence). The observational-based analyses by using IAP temperature gridded product are indicated as dashed lines. Specifically, individual CMIP6 models that have the most similar evolution compared with observational-based analysis are indicated as solid lines with circles. Details of the models used are shown in the **Supplementary Table 4**.

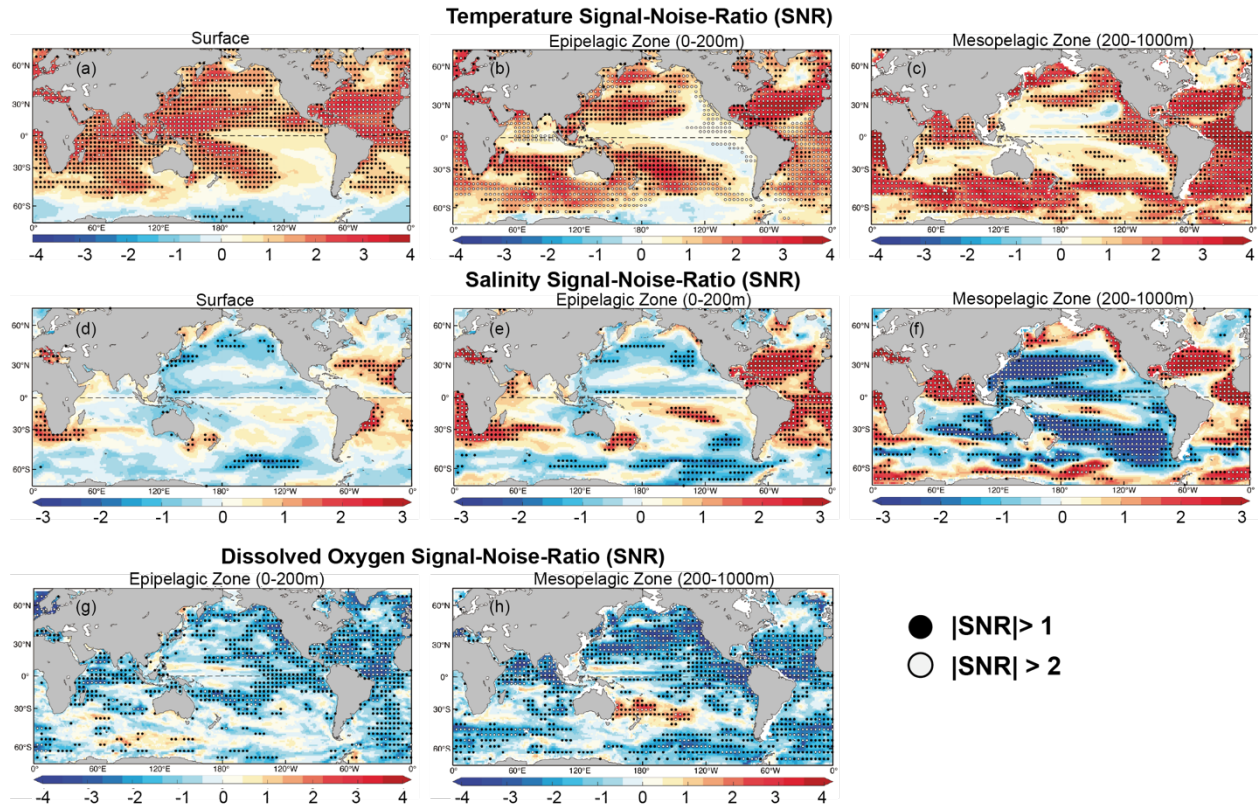


Supplementary Fig. 7 | Same as **Supplementary Fig. 5**, but for the dissolved oxygen ToE (unit: year) in different layers (epipelagic zone and mesopelagic zone) using the CMIP6 historical simulation (1960-2014) and SSP2.45 (2015-2022) ensemble median (11 members) gridded product. Two emergence directions are shown (red: oxygenation emergence; blue: deoxygenation emergence). The observational-based analyses by using IAP temperature gridded product are indicated as dashed lines. Specifically, individual CMIP6 models that have the most similar evolution compared with observational-based analysis are indicated as solid lines with circles. Details of the models used are shown in **the Supplementary Table 4**.

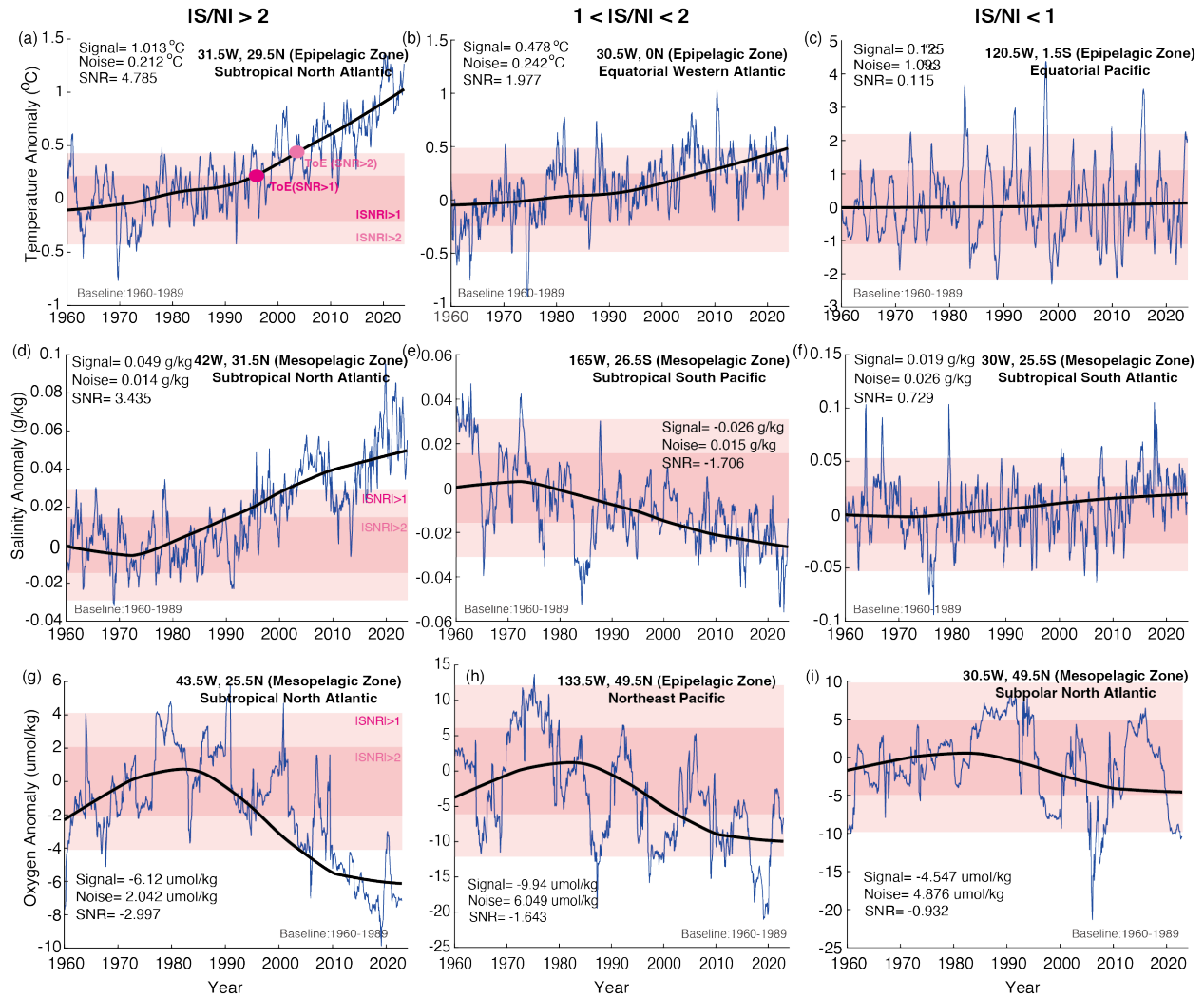




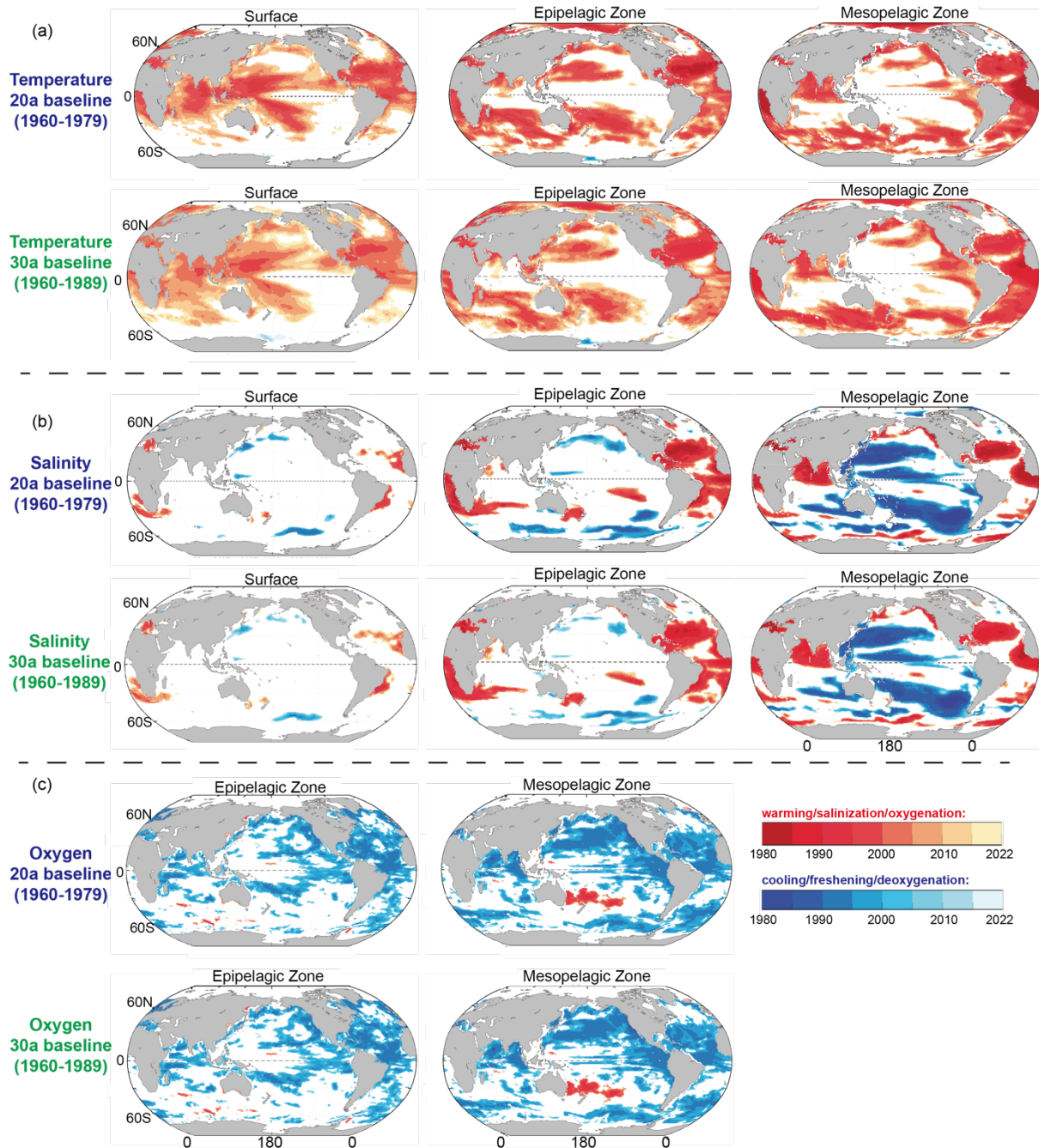
Supplementary Fig. 9 | The same as the **Supplementary Fig. 8**, but for the noise spatial maps.

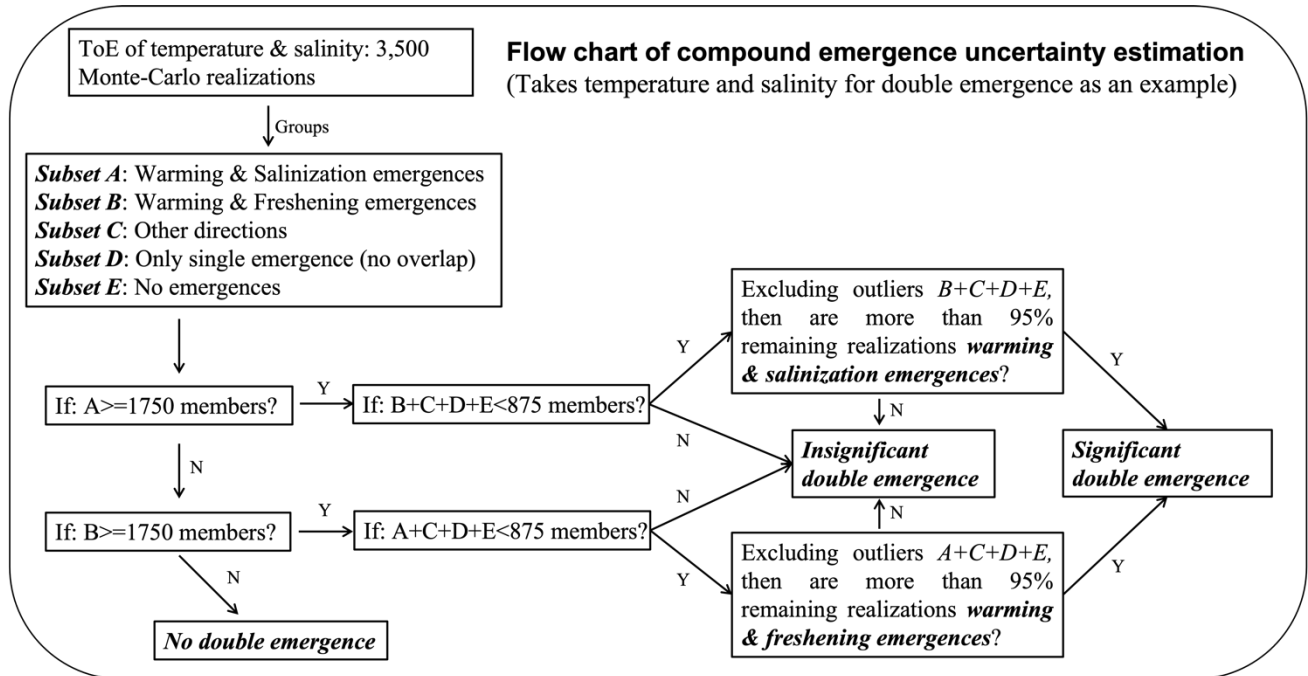


Supplementary Fig. 10 | The same as the **Supplementary Fig. 8**, but for the signal-to-noise-ratio (SNR) spatial maps. Here, the SNR and its confidence level of the estimated natural variability defined by noise are indicated with dots.



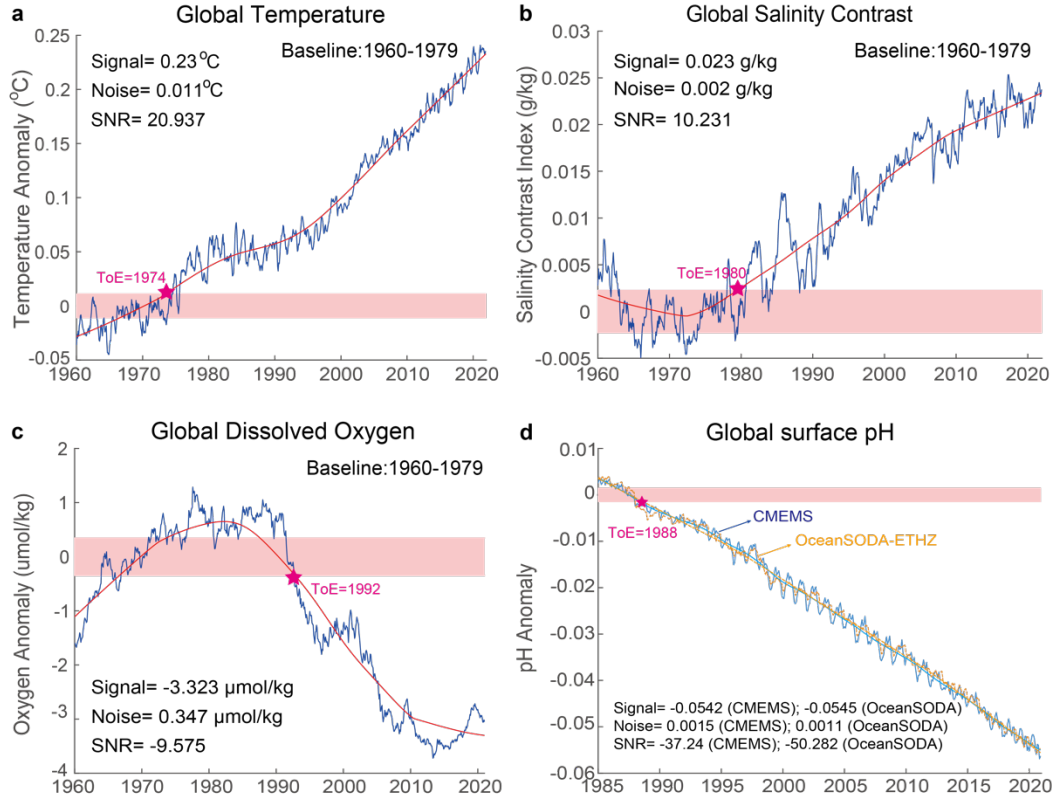
Supplementary Fig. 11 | Emergence of the local individual CID emergence at some selected representative locations and layers. Here, the signal-to-noise ratio (SNR) in thresholds 1 and 2 is shown. The year of local time of emergence (ToE) is marked by a purple circle in (a). Left, middle, and right columns correspond to cases where emergence occurs with $|\text{SNR}| > 2$, between $|\text{SNR}| > 1$ and $|\text{SNR}| > 2$, and where no emergence occurs ($|\text{SNR}| < 1$), respectively.



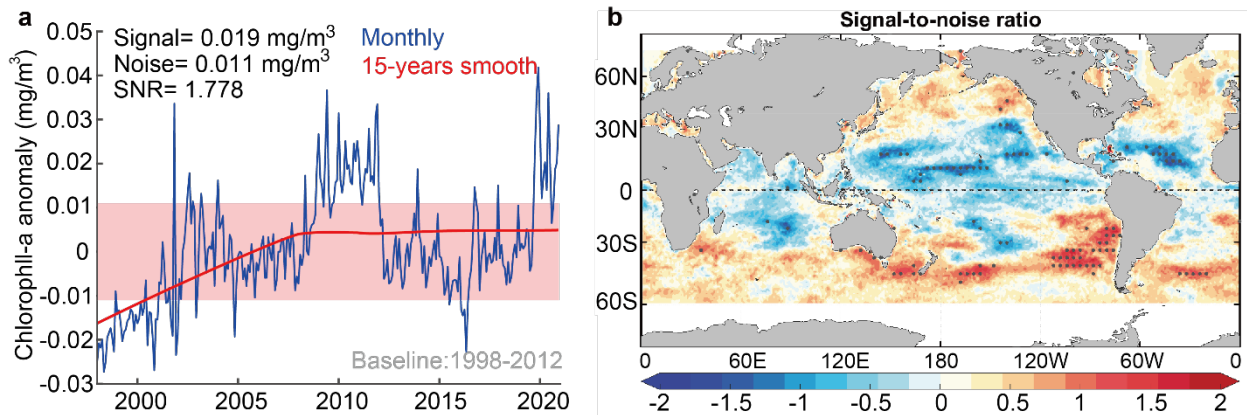


Supplementary Fig. 13 | Schematic illustrating the method used to estimate the uncertainty of double and triple emergence (compound CIDs), shown with temperature and salinity as an example.

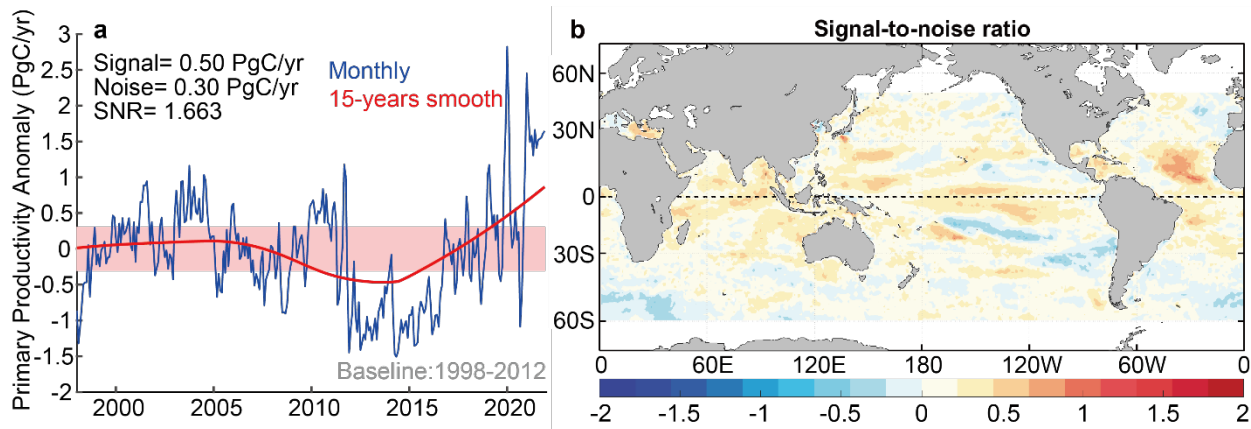
The same approach is applied to T & DO and T & S & DO.



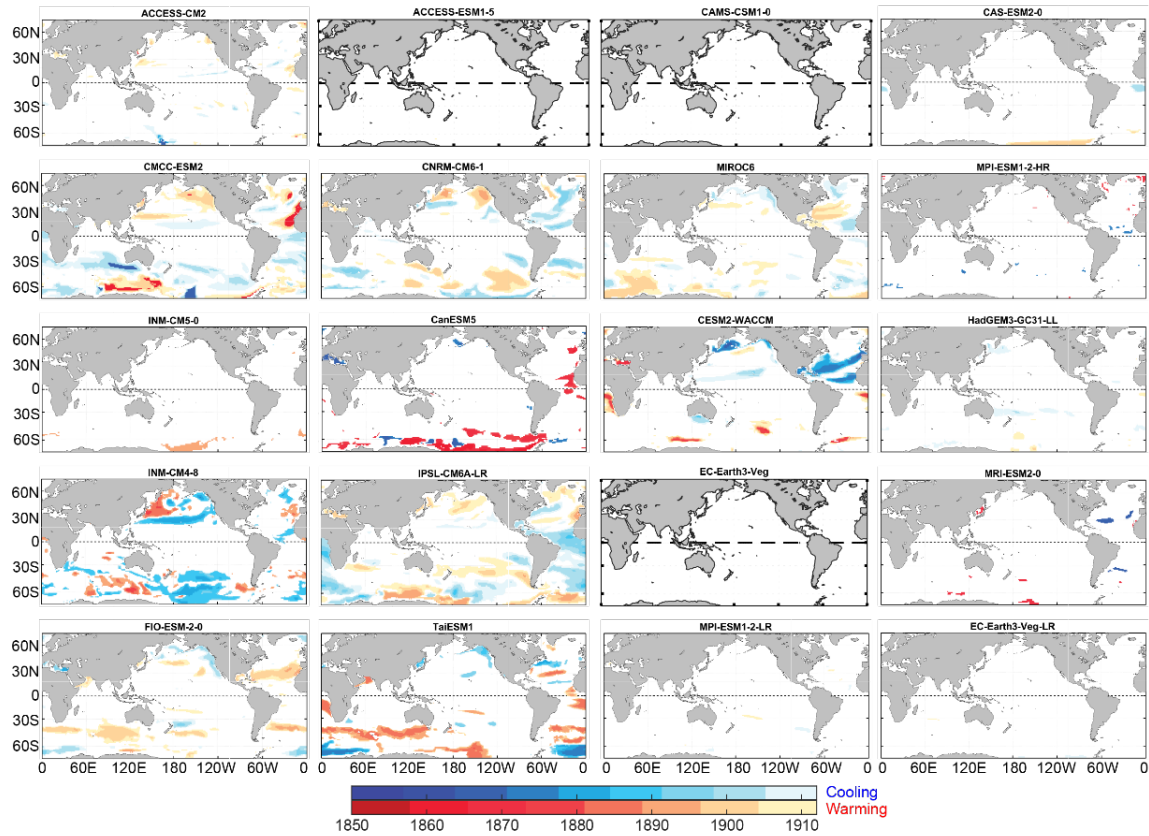
Supplementary Fig. 14 | The same as the **Supplementary Fig. 11**, but for the emergence of global average (a) temperature, (b) salinity contrast (SC), and (c) dissolved oxygen change in the upper 1000m from 1960 to 2022 using the objective analysis field, as well as (d) surface pH changes from 1985 to 2021, smoothed with a 25-year LOWESS filter (red lines; signal). The shaded bands indicate the noise level. The signal-to-noise ratio (SNR) is attached. The time-of-emergence year on global average is marked as purple stars.



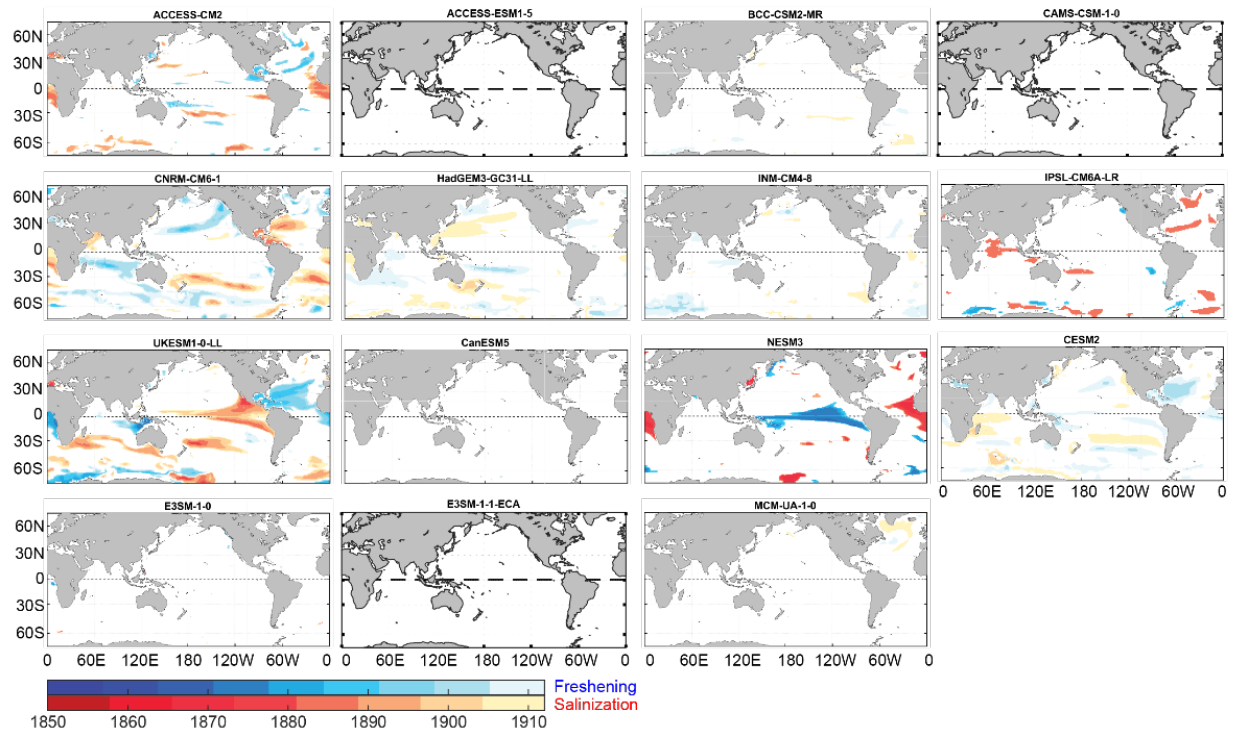
439 **Supplementary Fig. 15 | (a)** Global average surface chlorophyll-a anomalies relative to a 1998-2012
 440 baseline using the Ocean Color products developed by the ESA-Climate Change Initiative⁴⁸. Here, the
 441 blue line is the monthly time series, and the red line is the corresponding time series after 15 years of
 442 LOWESS smoothing. The shaded purple area represents the noise. **(b)** The spatial pattern of the signal-
 443 to-noise ratio (SNR) of surface chlorophyll-a. Here, the black dots indicate the region where $|\text{SNR}|$ is
 444 greater than 1. The polar regions (beyond 70N and 60S) are not examined due to lack of data.



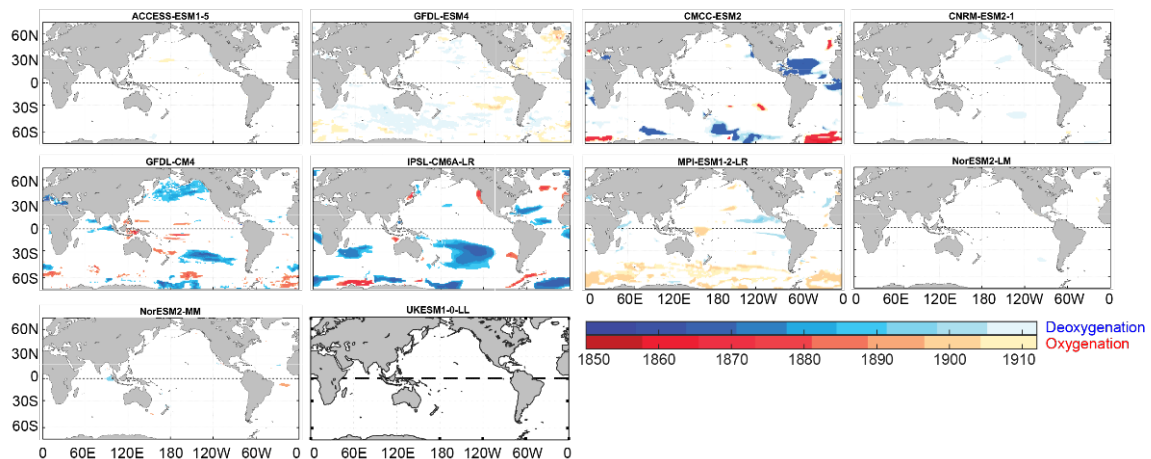
446 **Supplementary Fig. 16 | (a)** Global surface primary productivity (expressed as carbon) anomalies relative
 447 to 1998-2012 using the Global Ocean Colour (Copernicus-GlobColour), Bio-Geo-Chemical, L4 (monthly
 448 and interpolated) from satellite observations⁵². Here, the blue line is the monthly time series, and the red
 449 line is the time series after 15 years LOWESS smoothing. The shaded purple area indicates the noise. **(b)**
 450 The spatial pattern of the signal-to-noise ratio (SNR) of surface primary productivity. Here, the black dots
 451 denote the region where $|\text{SNR}|$ is greater than 1. The polar regions (beyond 60N and 60S) are not examined
 452 due to lack of data.



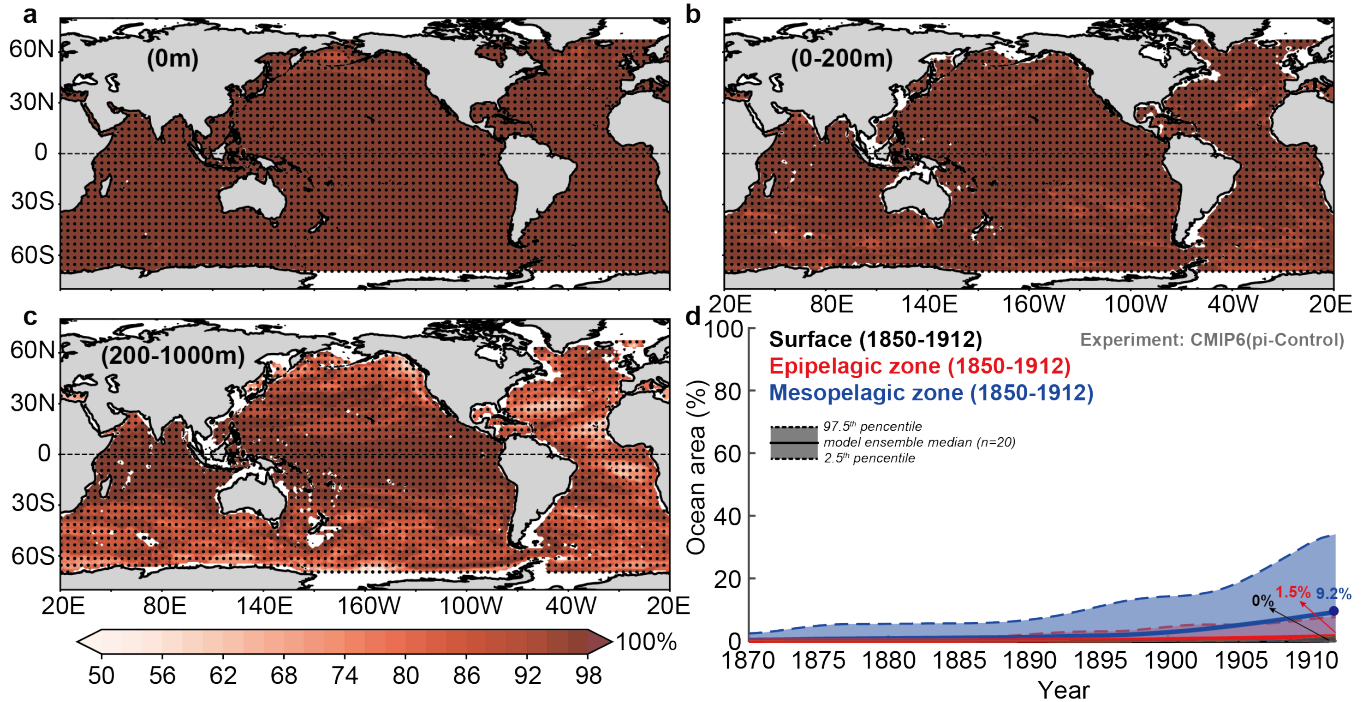
Supplementary Fig. 17 | Spatial distribution of the time of emergence (ToE) of temperature in mesopelagic zones (200-1000m) for individual CMIP6 pi-Control model (20 models in total). The ToE is calculated from 1850-1912 with a baseline of 1850-1869. White color indicates no emergence before 1912. The red color denotes the warming emergence, while the blue colors indicate the cooling emergence. The details of the models used are shown in the **Supplementary Table 3**.



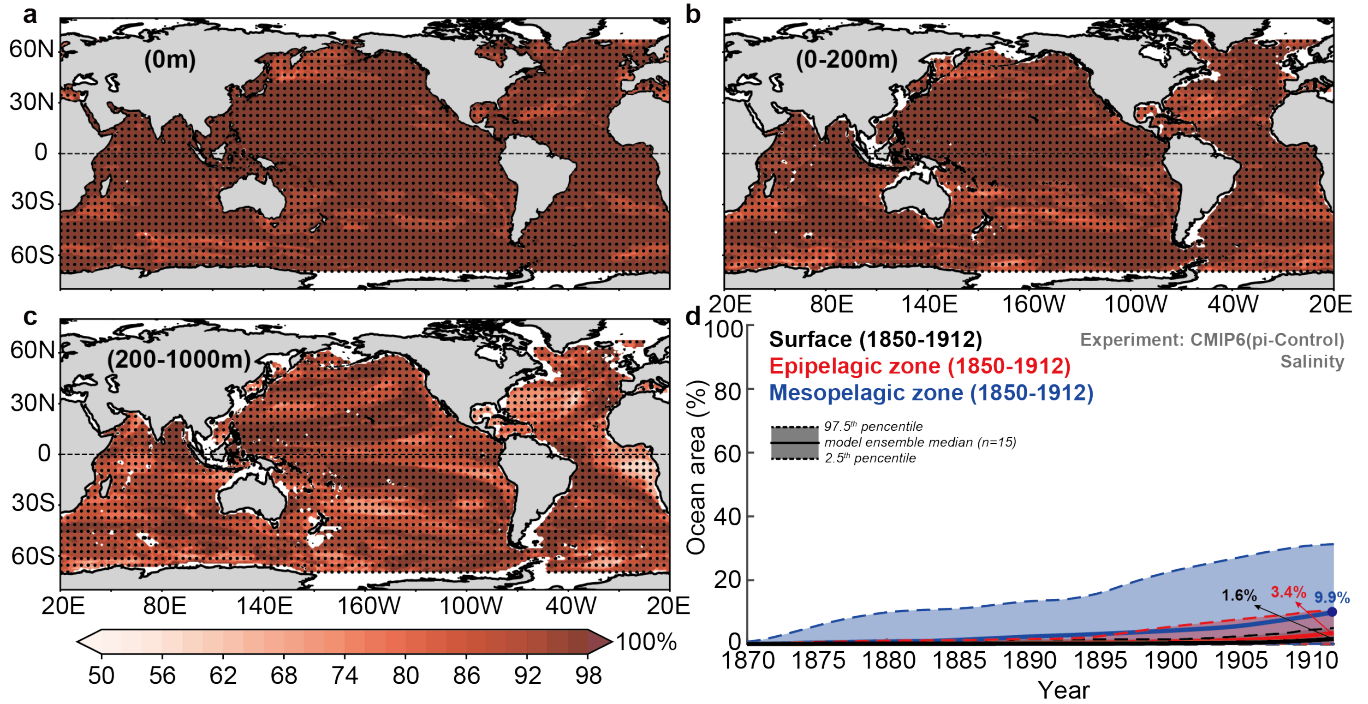
Supplementary Fig. 18 | Same as the **Supplementary Fig. 17**, but for the salinity ToE in mesopelagic zones (200-1000m). The red color denotes the salinization emergence, while the blue colors denotes the freshening emergence.



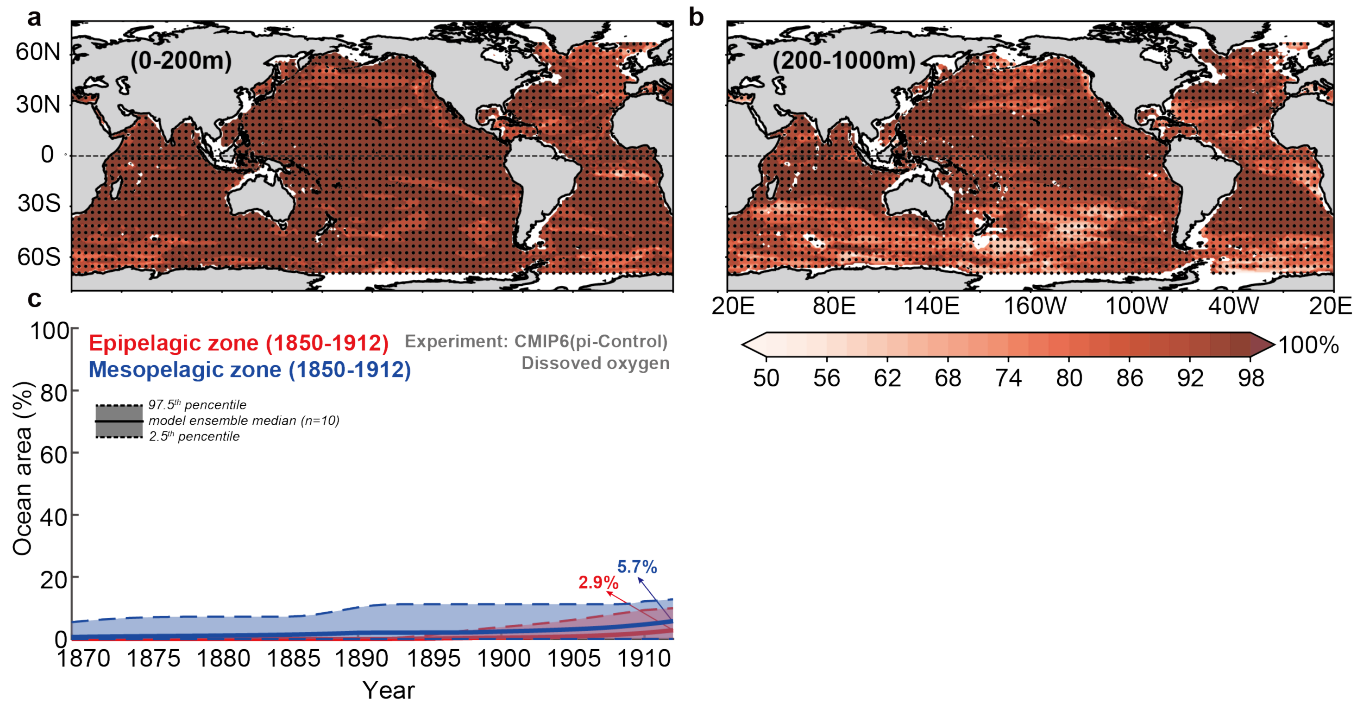
Supplementary Fig. 19 | Same as the **Supplementary Fig. 17**, but for the dissolved oxygen ToE in mesopelagic zones (200-1000m). The red color denotes the oxygenation emergence, while the blue color denotes the deoxygenation emergence.



Supplementary Fig. 20 | The percentage of models showing no temperature emergence (the ratio of models with no emergence to the total number of models) across different layers using the CMIP6 pre-industrial control (pi-Control) simulation (1850-1912) ensemble (20 members) temperature gridded product: (a) surface, (b) epipelagic zone (0-200m), and (c) mesopelagic zone (200-1000m). Areas greater than 50% (i.e., more than half of members show ‘no emergence’) are marked as black dots, indicating no significant emergence. (d) is the global percentage area of emergence as a function of the year, with the shading indicating the 95% confidence level by accounting for the model difference. The reference period (baseline) is 1850-1869. Details of the models used are shown in **the Supplementary Table 3**.

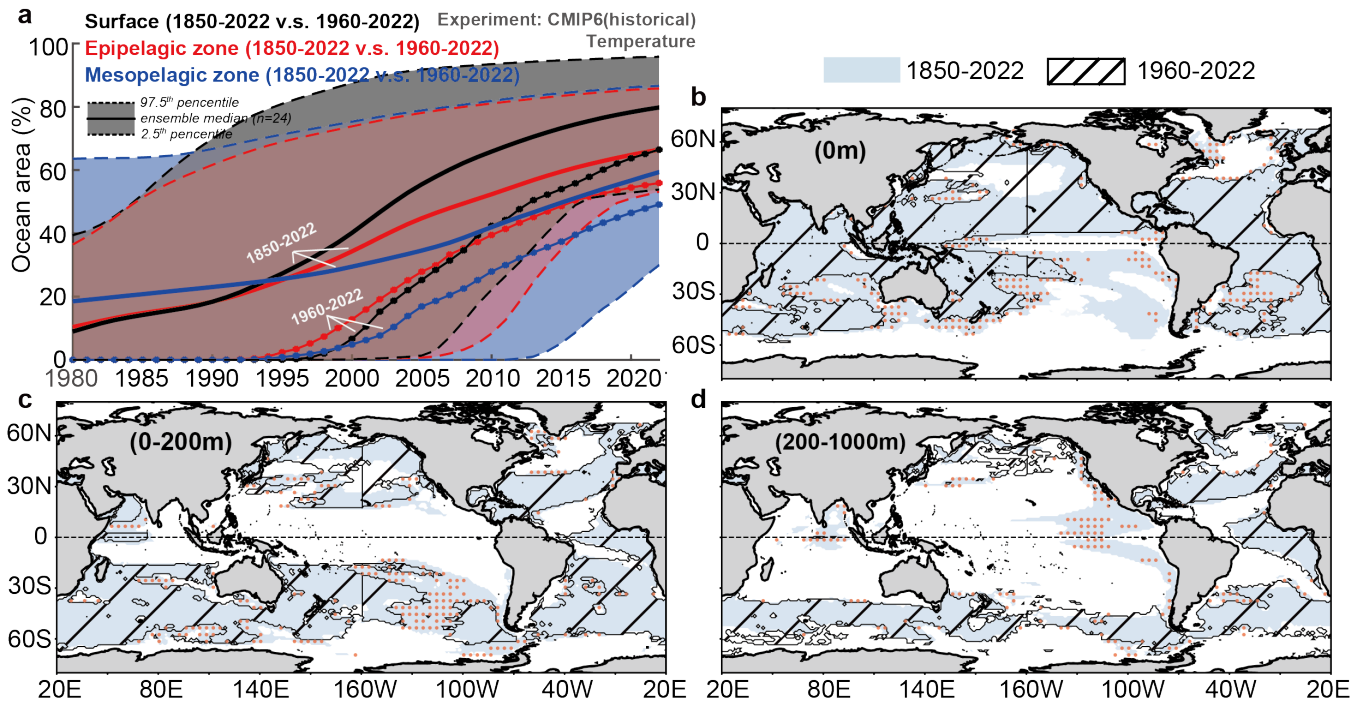


Supplementary Fig. 21 | Same as **Supplementary Fig. 20**, but for the salinity ToE performance using the CMIP6 pre-industrial control (pi-Control) simulation (1850-1912) ensemble (15 members) salinity gridded product. Details of the models used are shown in the **Supplementary Table 3**.



485 **Supplementary Fig. 22** | Same as **Supplementary Fig. 20**, but for the dissolved oxygen ToE performance
 486 using the CMIP6 pre-industrial control (pi-Control) simulation (1850-1912) ensemble (10 members)
 487 gridded product. Details of the models used are shown in the **Supplementary Table 3**.

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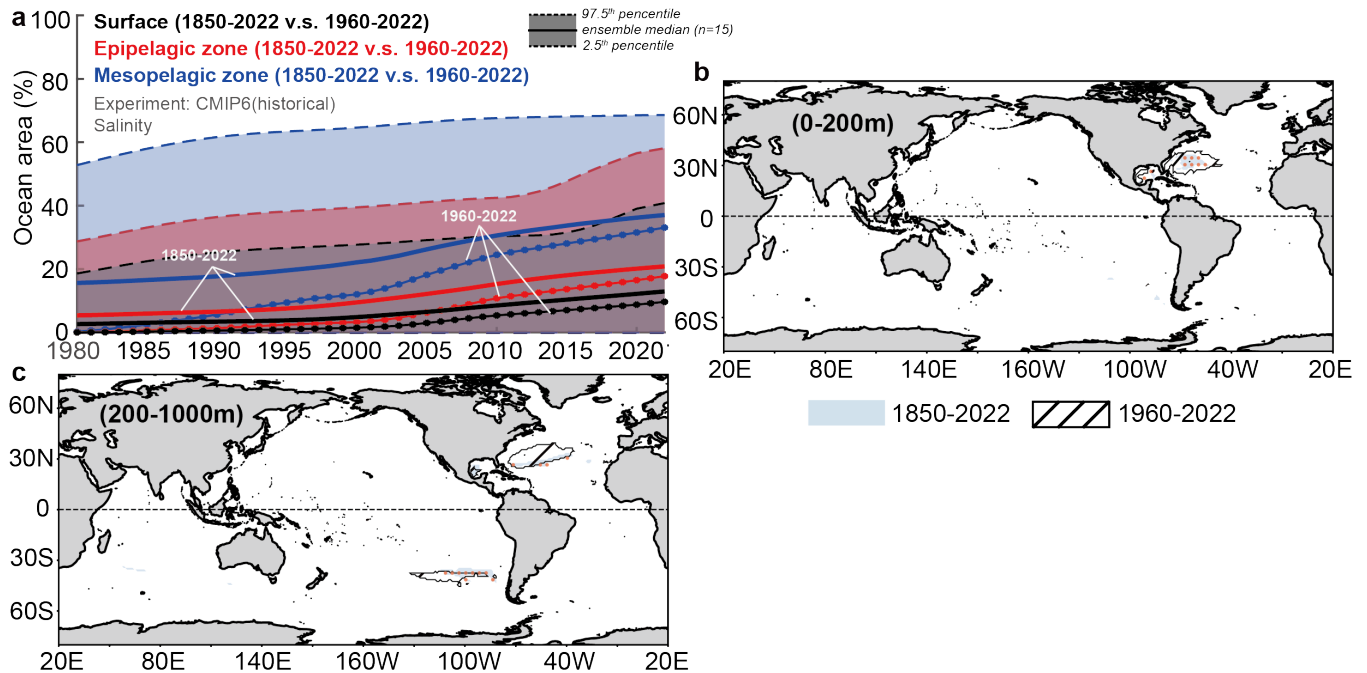


489 **Supplementary Fig. 23** | Comparisons between the temperature ToE from 1850 to 2022 with a 51 year
 490 baseline (1850-1900; group A) and the ToE from 1960 to 2022 with a 20 year baseline (1960-1979; group

491 B) by using the CMIP6 historical simulation ensemble median (24 members) temperature gridded product
 492 in the surface (0m), epipelagic (0-200m) and mesopelagic (200-1000m) zones: (a) is the global percent
 493 area of emergence as a function of the year with the shading indicating the 95% confidence level that
 494 accounts for the model differences. The solid line represents the mean result for the period 1850-2022
 495 with shaded areas, while the dotted line represents the mean result for the period 1960-2022. (b-d) are the
 496 spatial distribution of the ToE (units: years) of these two groups in different layers (surface, epipelagic
 497 zone, and mesopelagic zone). The blue patch indicates significant emergence (as defined in the Extended
 498 Data Fig. 9) in the ToE in group A, and the black slash patch denotes the significant emergence in the ToE
 499

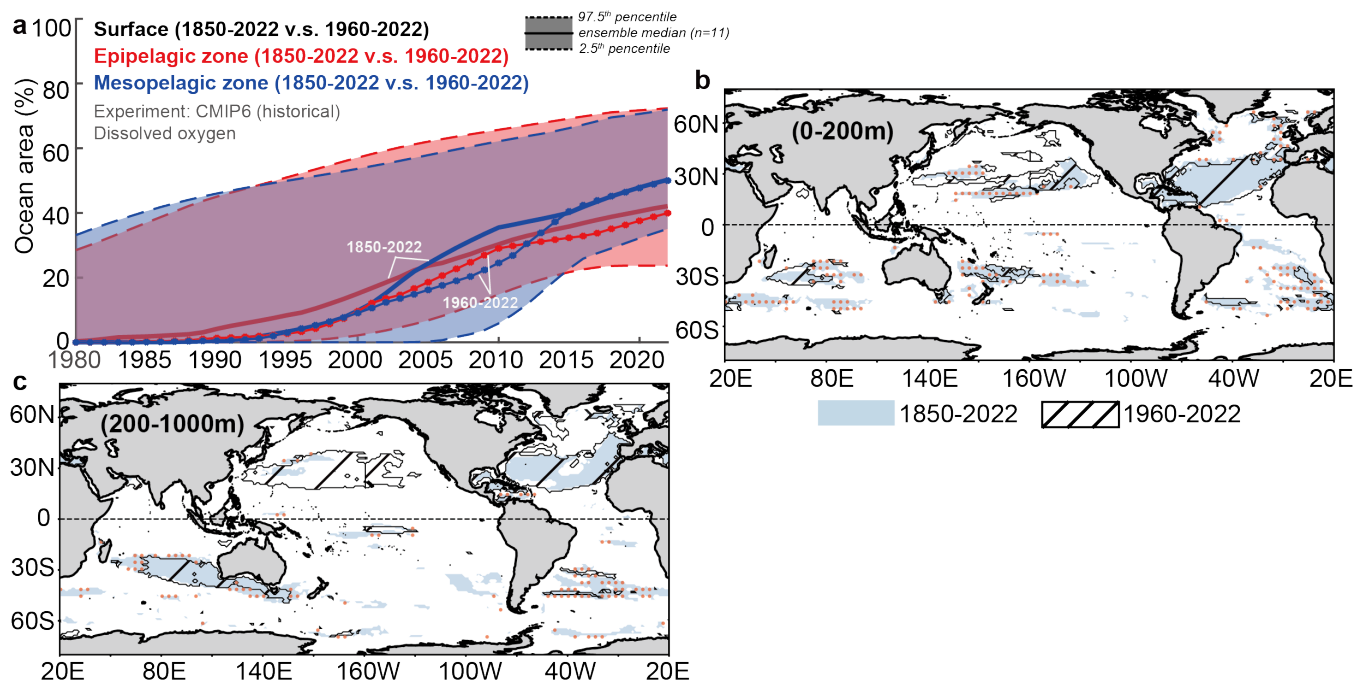
500 in group B. The regions marked as red dots indicate no significant emergence before 2022 in group B but
 501 has significant emergence in group A (i.e., no agreement between group A and group B). The white color
 502 indicates no significant emergence (at 95% confidence) regions in both groups. The model used for this
 503 comparison is shown in the **Supplementary Table 4**.

504



505 **Supplementary Fig. 24** | Same as **Supplementary Fig. 23**, but for the comparison of salinity ToE in the
 506 epipelagic (0-200m) and mesopelagic (200-1000m) zones. Note that there are no significant emergence
 507 (as defined in the Extended Data Fig. 9) regions in both groups at the surface. Details of the model used
 508 for this comparison are described in the **Supplementary Table 4**.

510



Supplementary Fig. 25 | Same as the **Supplementary Fig. 23**, but for the comparison of dissolved oxygen ToE in the epipelagic (0-200m) and mesopelagic (200-1000m) zones. Details of the model used for this comparison are described in the **Supplementary Table 4**.

Supplementary Table 1 | Ensemble CMIP6 members used for the sensitivity test of uncertainty due to decadal variability in the quantification of the ‘signal’ and baseline choice for the ToE estimate. (Experiment: CMIP6 historical simulation from 1935 to 2022; monthly product; horizontally interpolated to 1-degree box).

	Model name	Institute	T (thetao)	S (salinity)	DO
1	IPSL-CM6A-LR	Institute Pierre Simon Laplace (IPSL), Paris, France	✓	✓	✓
2	CNRM-ESM2-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse		✓	
3	MPI-ESM1-2-HR	Max Planck Institute for Meteorology (MPI)	✓		
4	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI)	✓		✓
5	CanESM5	Canadian Center for Climate modeling and analysis (CCCma)	✓	✓	✓
6	CNRM-ESM2-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse, France			✓

7	GFDL-CM4	Geophysical Fluid Dynamics Laboratory (GFDL), United State			✓
8	UKESM1-0-LL	Met Office Hadley Centre (MOHC)		✓	✓
9	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory (GFDL), United State	✓	✓	✓
10	ACCESS-CM2	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	✓	✓	
11	ACCESS-ESM1-5	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	✓	✓	
12	BCC-CSM2-MR	Beijing Climate Center (BCC)		✓	
13	CAMS-CSM1-0	Chinese Academy of Meteorological Sciences (CAMS)	✓	✓	
14	CNRM-CM6-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse	✓	✓	
15	HadGEM3-GC31-LL	Met Office Hadley Centre (MOHC)	✓	✓	
16	INM-CM4-8	Institute of Numerical Mathematics (INM)	✓	✓	
17	INM-CM5-0	Institute of Numerical Mathematics (INM)	✓		
18	MIROC6	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan	✓		
19	CESM2-WACCM	National Center for Atmospheric Research (NCAR)	✓	✓	
20	NESM3	Nanjing University of Information Science and Technology (NUIST), China		✓	
21	CAS-ESM2-0	Chinese Academy of Sciences (CAS)	✓		
22	CMCC-ESM2	Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Bologna, Italy	✓		✓
23	CESM2	National Center for Atmospheric Research (NCAR), US		✓	
24	E3SM-1-0	Department of Energy (DOE), US		✓	
25	EC-Earth3-Veg	EC-Earth3 Earth system model	✓		
26	EC-Earth3-Veg-LR	EC-Earth3 Earth system model	✓		
27	EC-Earth3	EC-Earth3 Earth system model	✓		
28	NorESM2-LM	Norwegian Climate Center (NCC)			✓
29	NorESM2-MM	Norwegian Climate Center (NCC)			✓
30	CMCC-CM2-SR5	Cambiamenti Climatici (CMCC), Bologna, Italy	✓		
31	MRI-ESM2-0	Meteorological Research Institute (MRI), Japan	✓		
32	FIO-ESM-2-0	First Institute of Oceanography (FIO) of the Ministry of Natural Resources, China	✓		
33	TaiESM1	Research Center for Environmental Changes, Academia Sinica, Taiwan, China	✓		

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522 **Supplementary Table 2 | A quantitative definition of intensity, magnitude, and duration for**
523 **individual CID and compound CIDs.** Here, T, S, and DO are the abbreviations for temperature, salinity,
524 and dissolved oxygen, respectively. MAD is the abbreviation for Median Absolute Deviation.

	High (Long)	Medium	Low (Short)
T	(median + 1*MAD, 1]	(0, median + 1*MAD)	No emergence regions and insignificant emergence regions
S	(median + 1*MAD, 1]	(0, median + 1*MAD)	No emergence regions and insignificant emergence regions
DO	(median + 1*MAD, 1]	(0, median + 1*MAD)	No emergence regions and insignificant emergence regions
surface pH	(5 th percentile, 1)	(0, 5 th percentile]	No emergence regions and insignificant emergence regions
T & S	High T & High S	High T & Medium S Medium T & High S Medium T & Medium S	No emergence regions and insignificant emergence regions
T & DO	High T & High DO	High T & Medium DO Medium DO & High T Medium T & Medium DO	No emergence regions and insignificant emergence regions
T & S & DO	High T & High S & High DO High T & High S & Medium DO High T & Medium S & High DO Medium T & High S & High DO	High T & Medium S & Medium DO Medium T & High S & Medium DO Medium T & Medium S & High DO Medium T & Medium S & Medium DO	No emergence regions and insignificant emergence regions

525
526
527 **Supplementary Table 3 | Ensemble CMIP6 members used for the sensitivity test of uncertainty due to**
528 the sensitivity of baseline choice for the ToE estimate (Experiment: CMIP6 pre-industrial control
529 simulation from 1850 to 1912; monthly product; horizontally interpolated to 1-degree box). The results
530 and discussions of this experiment are shown in the Section D of the Supplementary Information.

	Model name	Institute	T	S	DO
1	IPSL-CM6A-LR	Institute Pierre Simon Laplace (IPSL), Paris, France	✓	✓	✓
2	MPI-ESM1-2-HR	Max Planck Institute for Meteorology (MPI)	✓		
3	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI)	✓		✓
4	CanESM5	Canadian Center for Climate modeling and analysis (CCCma)	✓	✓	✓

5	CNRM-ESM2-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse, France			✓
6	GFDL-CM4	Geophysical Fluid Dynamics Laboratory (GFDL), United State			✓
7	UKESM1-0-LL	Met Office Hadley Centre (MOHC)		✓	✓
8	ACCESS-CM2	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	✓	✓	
9	ACCESS-ESM1-5	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	✓	✓	✓
10	BCC-CSM2-MR	Beijing Climate Center (BCC), China		✓	
11	CAMS-CSM1-0	Chinese Academy of Meteorological Sciences (CAMS)	✓	✓	
12	CNRM-CM6-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse, France		✓	
13	HadGEM3-GC31-LL	Met Office Hadley Centre (MOHC), UK	✓	✓	
14	INM-CM4-8	Institute of Numerical Mathematics (INM)	✓	✓	
15	INM-CM5-0	Institute of Numerical Mathematics (INM)	✓		
16	MIROC6	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan	✓		
17	CESM2-WACCM	National Center for Atmospheric Research (NCAR), US	✓		
18	CAS-ESM2-0	Chinese Academy of Sciences (CAS)	✓		
19	CMCC-ESM2	Centro Euro-Mediterraneo per i Cambiamenti Climatici (CMCC), Bologna, Italy	✓		✓
20	NESM3	Nanjing University of Information Science and Technology (NUIST), China		✓	
21	CESM2	National Center for Atmospheric Research (NCAR), US		✓	
22	E3SM-1-0	Department of Energy (DOE), US		✓	
23	E3SM-1-1-ECA	Department of Energy (DOE), US		✓	
24	MCM-UA-1-0	Main Geophysical Observatory (MGO), Russia		✓	
25	NorESM2-LM	Norwegian Climate Center (NCC)			✓
26	NorESM2-MM	Norwegian Climate Center (NCC)			✓
27	CNRM-CM6-1	Centre National de Recherches Météorologiques (CNRM), France	✓		
28	EC-Earth3-Veg	EC-Earth3 Earth system model	✓		
29	EC-Earth3-Veg-LR	EC-Earth3 Earth system model	✓		
30	MRI-ESM2-0	Meteorological Research Institute (MRI), Japan	✓		
31	FIO-ESM-2-0	First Institute of Oceanography (FIO) of the Ministry of Natural Resources, China	✓		
32	TaiESM1	Research Center for Environmental Changes, Academia Sinica, Taiwan, China	✓		

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533 **Supplementary Table 4** | Ensemble CMIP6 members used for the comparisons between the ToE from
534 1850 to 2022 with a 51 year baseline and the ToE from 1960 to 2022 with a 20 years baseline (Experiment
535 of **Section E**: Conservative estimation of ToE in a warming climate due to data availability; CMIP6

536 historical-run models; monthly product; horizontally interpolated to 1-degree box). The results and
537 discussions of this experiment are shown in the Section E of the Supplementary Information.

	Model name	Institute	T	S	DO
1	IPSL-CM6A-LR	Institute Pierre Simon Laplace (IPSL), Paris, France	✓	✓	✓
2	MPI-ESM1-2-HR	Max Planck Institute for Meteorology (MPI)	✓		
3	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI)	✓	✓	✓
4	CanESM5	Canadian Center for Climate modeling and analysis (CCCma)	✓	✓	✓
5	CNRM-ESM2-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse, France		✓	✓
6	GFDL-CM4	Geophysical Fluid Dynamics Laboratory (GFDL), US		✓	✓
7	UKESM1-0-LL	Met Office Hadley Centre (MOHC)		✓	✓
8	ACCESS-CM2	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	✓	✓	
9	ACCESS-ESM1-5	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	✓	✓	✓
10	BCC-CSM2-MR	Beijing Climate Center (BCC), China		✓	
11	CAMS-CSM1-0	Chinese Academy of Meteorological Sciences (CAMS)	✓		
12	CNRM-CM6-1	Centre National de Recherches Meteorologiques (CNRM), Toulouse, France	✓	✓	
13	HadGEM3-GC31-LL	Met Office Hadley Centre (MOHC), UK	✓		
14	INM-CM4-8	Institute of Numerical Mathematics (INM)	✓	✓	
15	INM-CM5-0	Institute of Numerical Mathematics (INM)	✓		
16	MIROC6	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan	✓	✓	
17	CESM2-WACCM	National Center for Atmospheric Research (NCAR), US	✓		
18	CAS-ESM2-0	Chinese Academy of Sciences (CAS)	✓		
19	CMCC-ESM2	Centro Euro-Mediterraneo per i Cambiamenti Climatici (CMCC), Bologna, Italy	✓		✓
20	NESM3	Nanjing University of Information Science and Technology (NUIST), China		✓	
21	CIESM	Institute of Atmospheric Physics, Chinese Academy of Sciences		✓	
22	NorESM2-LM	Norwegian Climate Center (NCC)			✓
23	NorESM2-MM	Norwegian Climate Center (NCC)			✓
24	EC-Earth3-Veg	EC-Earth3 Earth system model	✓		
25	EC-Earth3-Veg-LR	EC-Earth3 Earth system model	✓		
26	MRI-ESM2-0	Meteorological Research Institute (MRI), Japan	✓		
27	FIO-ESM-2-0	First Institute of Oceanography (FIO) of the Ministry of Natural Resources, China	✓		
28	TaiESM1	Research Center for Environmental Changes, Academia Sinica, Taiwan, China	✓		

29	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory (GFDL), US	✓	✓	✓
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