

Bio-ORACLE v3.0. Pushing marine data layers to the CMIP6 Earth system models of climate change research

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validated, and distributed by ACRI-ST, France) and the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP. For CMIP, the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

Biosketch

Jorge Assis is an associate researcher at the Centre of Marine Sciences, University of Algarve (Portugal), where he leads the Biodiversity Data Sciences research group. He is also a professor at Nord University (Norway). His research is focused on developing data science tools to well-inform biodiversity conservation and management.

Data availability statement

The layers are openly available at the ERDDAP instance hosted at the Flanders Marine Institute Data Centre (<https://erddap.bio-oracle.org/erddap>), through the Bio-ORACLE website (temporary link for peer-review: <https://www.bio-oracle.org/downloads-to-email-v3.php>) and the R and Python packages available in the permanent GitHub repository (<https://github.com/bio-oracle>).

1 Abstract

2 **Motivation:** Impacts of climate change on marine biodiversity are often projected with species
3 distribution modelling, using standardized data layers representing physical, chemical and biological
4 conditions. Yet, the available data layers (1) have not been updated to incorporate data of the Sixth
5 Phase of the Coupled Model Intercomparison Project (CMIP6), which comprise the Shared
6 Socioeconomic Pathway (SSP) scenarios; (2) consider a limited number of Earth System Models
7 (ESMs); and (3) miss important variables expected to influence future biodiversity distributions.
8 These limitations might undermine biodiversity impact assessments, by failing to integrate them
9 within the context of the most up-to-date climate change projections, raising the uncertainty in
10 estimates and misinterpreting the exposure of biodiversity to extreme conditions. Here, we provide
11 a significant update of Bio-ORACLE, extending biologically relevant data layers from present-day
12 conditions to the end of the 21st century Shared Socioeconomic Pathway scenarios based on a multi-
13 model ensemble with data from CMIP6. Alongside, we provide R and Python packages for seamless
14 integration in modelling workflows. The data layers aim to enhance the understanding of the
15 potential impacts of climate change on biodiversity and to support well-informed research,
16 conservation and management.

17 **Main types of variable contained:** Surface and benthic layers for, chlorophyll-*a*, diffuse attenuation
18 coefficient, dissolved iron, dissolved oxygen, mixed layer depth, nitrate, ocean temperature, pH,
19 phosphate, photosynthetic active radiation, total phytoplankton, total cloud fraction, salinity,
20 silicate, sea-water direction, sea-water velocity, topographic slope, topographic aspect, terrain
21 ruggedness index, topographic position index and bathymetry, and surface layers for air
22 temperature, sea-ice cover and sea-ice thickness.

23

24 **Spatial location and grain:** Global at 0.05° resolution.

25

26 **Time period and grain:** Decadal from present-day to the end of the 21st century (2000-2100).

27

28 **Major taxa and level of measurement:** Marine biodiversity associated with surface and epibenthic
29 habitats.

30

31 **Software format:** A package of functions developed for Python and R software.

32

33 **Introduction**

34 Research quantifying the impacts of climate change on biodiversity relies heavily on species
35 distribution modelling (Peterson *et al.*, 2011) using high-resolution data layers representing
36 physical, chemical and biological conditions at the global scale (Tyberghein *et al.*, 2012; Assis *et al.*,
37 2017b; Fick & Hijmans, 2017). Initiatives providing essential climate layers uniform in extent and
38 resolution, like MERRAclim (Vega *et al.*, 2017) and WorldClim (Fick & Hijmans, 2017) for terrestrial
39 environments and the World Ocean Atlas (Levitus *et al.*, 2013), Hexacoral (Fautin & Buddemeier,
40 2008), Marspec (Sbrocco & Barber, 2013), Bio-ORACLE (Tyberghein *et al.*, 2012; Assis *et al.*, 2017b)
41 and OCLE (de la Hoz *et al.*, 2018) for marine environments, established solid standards to estimate
42 future climate-induced pressures on the world's ecosystems and associated ecosystem services
43 (Assis *et al.*, 2017a, 2022b; Gouvêa *et al.*, 2020, 2022; Martins *et al.*, 2021). But despite their
44 relevance, current marine datasets have three main limitations that can preclude the development
45 of well-informed conservation and management strategies (Arneith *et al.*, 2020; Arafeh-Dalmau *et*
46 *al.*, 2021).

47 First, current standardized climate layers have not been updated to incorporate data of the Sixth
48 Phase of the Coupled Model Intercomparison Project (CMIP6), which serves as the core contribution
49 to the latest Intergovernmental Panel on Climate Change Assessment Report (IPCC). The CMIP6
50 dataset includes an updated set of variables (Séférian *et al.*, 2020), which better capture the spatial
51 and temporal variability of physical and biogeochemical properties of the global ocean (Séférian *et*
52 *al.*, 2020), and the Shared Socioeconomic Pathway (SSP) scenarios, a set of narratives on possible
53 global change trajectories throughout the 21st century, with and without climate policy responses
54 (Riahi *et al.*, 2017; van Vuuren *et al.*, 2017). Compared to the previous Representative
55 Concentration Pathway scenarios (van Vuuren *et al.*, 2011), despite producing similar forcing
56 pathways, the SSPs use more up-to-date socioeconomic assumptions (Burgess *et al.*, 2023) and
57 encompass the Paris Agreement expectations, which allows estimating the biodiversity benefits of
58 compliance to international climate policies (Sanderson *et al.*, 2016; Martins *et al.*, 2021).

59 Second, current standardized climate layers projecting future conditions consider a limited number
60 of Earth System Models (ESMs) (Schoeman *et al.*, 2023). These are intensive computer simulations
61 tuned by specific parameters and conditions (e.g., greenhouse gas concentrations, solar forcing,
62 land-use, as well as atmospheric and ocean dynamics (Mechoso & Arakawa, 2015)) that can resolve
63 global atmospheric and oceanic conditions across different time scales. There are, however, inherent
64 uncertainties of ESMs projections due to the complexity of the Earth's climate system, as well as the
65 limited understanding and the challenges in incorporating particular processes in the models.

66 Accordingly, the multi-model ensemble offers a straightforward approach in species distribution
67 modelling (Araújo & New, 2007; Assis *et al.*, 2017b; Gouvêa *et al.*, 2022), yet at the cost of
68 incorporating ESM that do not perform well in reproducing historical climates over time (please refer
69 to the ‘hot model’ problem; Hausfather *et al.*, 2022). The previous version of Bio-ORACLE (Assis
70 *et al.*, 2017b) was based on a multi-model ensemble, yet limited to two ESMs from the dozens
71 available, limiting the breadth of projections of climate change impact.

72 Third, current standardized climate layers miss projections of biologically meaningful variables
73 beyond temperature, salinity and sea ice conditions (Tyberghein *et al.*, 2012; Assis *et al.*, 2017b).
74 For instance, dissolved oxygen, primary productivity and pH (among other variables) are expected to
75 change in the coming decades and are emerging as limiting factors for marine biodiversity
76 (Krumhardt *et al.*, 2017; Fragkopoulou *et al.*, 2021; Martins *et al.*, 2021; Shi *et al.*, 2021). Failing
77 to consider them in climate change projections might misinterpret biodiversity exposure to novel
78 detrimental conditions.

79 To address these gaps in the marine climate data space, we provide a substantial extension of Bio-
80 ORACLE, including a set of essential variables for bioclimatic modelling from present-day conditions
81 to the end of the 21st century SSP scenarios, for both surface and benthic (i.e., along the seafloor)
82 conditions. These were built by ensembling numerous ESMs provided by the CMIP6, from the higher
83 (SSP1, in line with the Paris Agreement) to the lower mitigation (SSP5) trajectories of global change.
84 These new layers are provided under the FAIR principle (Findability, Accessibility, Interoperability,
85 and Reusability (Wilkinson *et al.*, 2016)) with a finer spatial and temporal resolution (0.05° spatial
86 resolution; decadal climatologies). Alongside the data layers, R and Python packages were developed
87 for programmatic data access and easy integration in available bioclimatic modelling workflows
88 (Thuiller *et al.*, 2009; Naimi & Araújo, 2016). The extension of Bio-ORACLE aims to improve
89 understanding of the potential impacts of climate change on marine organisms and support well-
90 informed research and management.

91

92 **Marine data layers**

93 The current data descriptor provides information on the approach used to generate a set of essential
94 variables for bioclimatic modelling. This comprises the acquisition of physical, chemical, biological
95 and topographic data and the techniques used to generate variables for present-day conditions and
96 the SSP scenarios of future climate change.

97 Data for present-day conditions (period 2000 to 2020) were acquired at a monthly basis from the
98 Global Ocean Physics Reanalysis and Forecast and the Global Ocean Biogeochemistry Analysis and
99 Forecast, two pre-processed re-analyses of Copernicus Marine Environment Monitoring Service
100 (<https://data.marine.copernicus.eu/products>), provided at a 0.08° and 0.25° degree resolution with
101 50 and 75 vertical levels, respectively. These integrate and assimilate a comprehensive range of
102 satellite and in-situ data (Jean-Michel *et al.*, 2021). Specifically for Photosynthetic Active Radiation
103 and Diffuse Attenuation Coefficient, data were acquired as monthly averages from GlobColour
104 (<https://www.globcolour.info>), a dataset at a ~0.04° resolution that merges MERIS, MODIS and
105 SeaWiFS sensors (Maritorena *et al.*, 2010). Data for the SSP1-1.9, SSP1-2.6, SSP2-4.6, SSP3-7.0
106 and SSP5.8.5 scenarios (period 2000 to 2100) were acquired at the monthly basis from numerous
107 ESMs provided by the CMIP phase 6 (Earth System Grid Federation), namely, ACCESS-ESM1-5
108 (Australian Community Climate and Earth System Simulator; 1.875×1.25° resolution and 38 vertical
109 levels), CanESM5 (Canadian Earth System; 1° resolution and 45 vertical levels), CESM2-WACCM
110 (Community Earth System Model 2 – Whole Atmosphere Community Climate Model; ~0.88×0.56°
111 resolution and 60 vertical levels), CNRM-ESM2-1 (Centre National de Recherches Météorologiques;
112 0.25° resolution and 75 vertical levels), GFDL-ESM4 (Geophysical Fluid Dynamics Laboratory; 0.25°
113 resolution and 75 vertical levels), GISS-E2-1-G (Goddard Institute for Space Studies; 1×1.25°
114 resolution and 40 vertical levels), IPSL-CM6A-LR (Institut Pierre Simon Laplace; 1° resolution and 75
115 vertical levels), MIROC-ES2L (Model for Interdisciplinary Research on Climate; 1° resolution and 63
116 vertical levels), MPI-ESM1-2-LR (Max Plank Institute; 1.5° resolution and 40 vertical levels), MRI-
117 ESM2-0 (Meteorological Research Institute; 1° resolution and 63 vertical levels) and UKESM1-0-LL
118 (United Kingdom Earth System Model; 1° resolution and 75 vertical levels).

119 The monthly data of present-day and future conditions were used to generate six statistics per
120 decade and variable: the average, maximum and minimum records of a given decade, long-term
121 average of the yearly maxima and minima of a given decade (e.g., the average temperature of the
122 warmest month in the period 2000-2010), and range, which represents the average absolute
123 difference between the maximum and minimum records per year. These statistics were produced for
124 air temperature, chlorophyll-a, diffuse attenuation coefficient, dissolved iron, dissolved oxygen,
125 mixed layer depth, nitrate, ocean temperature, pH, phosphate, photosynthetically active radiation,
126 primary productivity (total phytoplankton), total cloud fraction, salinity, silicate, sea-ice cover, sea-
127 ice thickness and sea-water direction and velocity (Table 1).

128 To produce gridded layers with uniform spatial extent and resolution, the statistics generated for
129 present-day conditions were interpolated to 0.05 degrees (approx. 5.5 km at the equator) with inverse

130 distance weighting (IDW). This is a well-established algorithm in climate change research (Ozelkan
131 *et al.*, 2016; Assis *et al.*, 2017b) and was chosen based on a performance and tuning test against
132 the kriging algorithm (Supplement 1). The inverse distance weighting algorithm fitted the 8 nearest
133 values of each focal cell with an inverse distance power of 2. For surface layers, the algorithm
134 performed bilinear interpolation, considering the position of each cell (i.e., longitude and latitude)
135 and the information comprised in the top vertical levels (i.e., defining the surface of the ocean) of
136 each dataset (e.g., Copernicus) and variable. For benthic layers, the algorithm performed trilinear
137 interpolation, by further considering the depth of each cell and the multiple vertical levels of each
138 dataset and variable (Boavida *et al.*, 2016; Assis *et al.*, 2017b). To this end, the depth of each cell
139 was extracted from the general bathymetric chart of the oceans (GEBCO_2023 Grid), a global terrain
140 model providing elevation data at a 0.004 degrees resolution (GEBCO Bathymetric Compilation
141 Group 2023, 2023). Because focal cells at 0.05° comprise a wide range of depth values, the benthic
142 layers were developed for the minimum, average and maximum depth within focal cells, as in Bio-
143 ORACLE version 2.0 (Assis *et al.*, 2017b). The process of interpolation does not add local detail in
144 climate data, but rather smooths it across the generated layers.

145 The layers projecting future conditions were produced with the change-factor method (also known
146 as the delta change method). This involved adding the changes projected in climate by the ESMs (as
147 interpolated anomalies, i.e., differences) to high-resolution climatologies representing present-day
148 conditions (Assis *et al.*, 2017b; Maraun *et al.*, 2017; Schoeman *et al.*, 2023). In detail, the method
149 was based on (1) computing the climate change anomaly (i.e., difference) between the future and the
150 historical conditions with data of each ESM, at their native spatial resolution, and for the period of
151 2000-2014 (ESM projections start in the year 2015); (2) interpolating the climate change anomalies
152 to the common 0.05° resolution with inverse distance weighting to be uniform in extent and
153 resolution, as described for the present-day statistics; (3) averaging the interpolated climate change
154 anomalies of the multiple ESM; and (4) applying the averaged downscaled anomalies to the
155 downscaled layers defining the conditions of the present-day period. This approach, considering the
156 magnitude of climate change (i.e., the change-factor), allowed removing mean state biases of the
157 ESM (Schoeman *et al.*, 2023), while providing a high confidence level in climate change projections
158 (Hall & Hall, 2014), linking greenhouse gas emissions with global climate change with and without
159 climate policy responses (Riahi *et al.*, 2017). The change-factor approach was not used in diffuse
160 attenuation and photosynthetically active radiation, as these variables are not provided by the CMIP.
161 The standard deviation of the ESM projected data was also computed (Supplement 2).

162 Additional topographic layers, namely, slope (expressing depth changes over distance), aspect
163 (expressing the direction that slope faces), terrain ruggedness index (expressing depth changes
164 between adjacent focal cells), topographic position index (comparing the depth of focal cells to the
165 mean elevation of adjacent focal cells), as well as the minimum, average and maximum depth of each
166 focal cell, were generated at 0.05 degrees resolution based on the general bathymetric chart of the
167 oceans (GEBCO Bathymetric Compilation Group 2023, 2023).

168 All layers were archived as NetCDF (network Common Data Form) and deposited into an ERDDAP
169 (Environmental Research Division's Data Access Program) server to facilitate filtering and
170 downloading of the layers in common data formats (Wilson *et al.*, 2020). Additionally, Python
171 ([pyo_oracle](#)) and R ([biooracler](#)) packages were developed for facilitated data retrieval and improved
172 integration in available frameworks of bioclimatic modelling (Thuiller *et al.*, 2009; Naimi & Araújo,
173 2016). Such packages act as clients for ERDDAP's REST API, an interoperable web protocol for data
174 transfer, and thus can be used for integration into most generic web-based applications.

175

176 **Data Records**

177 The dataset (Assis, 2023) comprises: (1) decadal time series of six statistics for each of 19 essential
178 physical, chemical and biological variables at the global scale, for surface and benthic conditions, at
179 a spatial resolution of 0.05 degrees, and a temporal resolution of 10 decadal steps, from 2000 to 2100,
180 under the scenarios SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5; (2) seven
181 topographic layers at a spatial resolution of 0.05 degrees (Table 1).

182

183 **Technical Validation**

184 The reliability of data layers was estimated by means of cross-validation against quality-controlled
185 data provided by the Global Ocean Data Analysis Project (GLODAP (Olsen *et al.*, 2016; Lauvset *et al.*,
186 2021)), for the variables available in this dataset (dissolved oxygen, nitrate, phosphate, salinity,
187 silicate and temperature). Following additional applications (Davies & Guinotte, 2011; Assis *et al.*,
188 2015, 2017b, 2022a; Boavida *et al.*, 2016), GLODAP records, which are in situ observations, were
189 compared at every given location with the data used to develop the layers. To this end, the data was
190 interpolated with inverse distance weighting, as previously described, to the locations reported on
191 GLODAP (i.e., longitude, latitude and depth). Then, the paired records were statistically analyzed

192 with Pearson's correlation coefficient, root mean square error, and mean absolute error. The
193 difference between paired records was also mapped globally onto a 2.5 degrees grid (average of
194 differences within grid cells (Davies & Guinotte, 2011; Assis *et al.*, 2017b).

195

196 Overall, the layers mirrored the climatic patterns of quality-controlled data, as verified elsewhere
197 (Assis *et al.*, 2017b, 2022a). All variables retrieved high correlation coefficients, ranging from 0.93
198 to 0.99, and low error rates (Supplement 3). Nitrate, phosphate, salinity and temperature displayed
199 discrete anomalies restricted to specific regions (e.g., the transition between the warm and cold
200 temperate Northwest Atlantic and Pacific oceans), with no relationship with depth. The errors for
201 dissolved molecular oxygen and silicate were mostly distributed in the Southern Ocean, also with no
202 relationship with depth (Supplement 3).

203

204 The marine data layers produced with information from the Global Ocean Physics Reanalysis and
205 Forecast and the Global Ocean Biogeochemistry Analysis and Forecast from the Copernicus Marine
206 Environment Monitoring Service, and the numerous ESMs from CMIP phase 6, have climate data in
207 all gridded cells. However, 7.81 % of the cells of Photosynthetic Active Radiation and 4.22 % of the
208 cells of Diffuse Attenuation Coefficient have missing information at latitudes above 70° N / S. This is
209 due to missing satellite information from MERIS, MODIS and SeaWiFS sensors (Maritorena *et al.*,
210 2010) at such higher latitudes, as reported elsewhere (Tyberghein *et al.*, 2012).

211

212

213 **Usage notes**

214 This major update of Bio-ORACLE presents twenty-six physical, chemical, biological and topographic
215 marine data layers, with global coverage and uniform grid system. These layers, provided with
216 improved 0.05° spatial resolution (to better capture geomorphological features; Supplement 4) and
217 per decade, have numerous potential applications in biogeography, ecology, evolutionary biology
218 and climate change research, which can enhance our understanding of anthropogenic impacts on
219 biodiversity and support well-informed conservation and management strategies. In particular, the
220 layers can be used in Species Distribution Modeling (SDM) (Peterson *et al.*, 2011) to predict the
221 distribution of species at the global scale (Chefaoui *et al.*, 2015; Fragkopoulou *et al.*, 2022),
222 including non-native species (Assis *et al.*, 2015), address niche-based questions (Lee-Yaw *et al.*,
223 2016; Hu *et al.*, 2021; Song *et al.*, 2021) and phylogeographic hypotheses (Neiva *et al.*, 2014),
224 identify biodiversity hotspots (Fragkopoulou *et al.*, 2022) and support the conservation and
225 management of marine biodiversity (Hobday *et al.*, 2010; Boavida *et al.*, 2016). In the scope of

226 SDM, by letting users filter historical data into two time periods (decades 2000-2010 and 2010-2020),
227 the current version allows generating independent data for temporal cross-validation, which can
228 assist in evaluating model performance and prediction error (Ko *et al.*, 2013). Moreover, the
229 development of biologically meaningful variables for future climate change scenarios (e.g., dissolved
230 oxygen, primary productivity and pH) allows more realistic estimates of the anthropogenic pressures
231 that may lead to extinction and turnover of populations (Martins *et al.*, 2021; Assis *et al.*, 2022b;
232 Gouvêa *et al.*, 2022).

233 The marine layers can be used in additional analyses beyond SDM, such as those based on univariate
234 algorithms of climate velocity (Burrows *et al.*, 2014) or multivariate algorithms of climate analogs
235 (Mahony *et al.*, 2017), to estimate biodiversity exposure to climate change (Mackintosh *et al.*,
236 2023), or identify climate connectivity corridors promoting future distribution range shifts (García
237 Molinos *et al.*, 2016). In this scope, the availability of the Shared Socioeconomic Pathway scenarios,
238 comprising the mitigation strategies of the Paris Agreement, coupled with the ensemble of multiple
239 ESMs, allows supporting international climate policies and agendas (Martins *et al.*, 2021). The
240 increased interoperability via the ERDDAP data server (Wilson *et al.*, 2020) opens the door for Bio-
241 Oracle to be used in digital twinning, such as the European Digital Twin of the Ocean, or private
242 initiatives like the Microsoft Planetary Computer. This aligns with the United Nations Decade of
243 Ocean Science for Sustainable Development, which aims to boost the development of Digital Twins
244 of the Ocean for supporting blue growth and global governance.

245

246 **Data availability statement**

247 The layers are openly available at the ERDDAP instance hosted at the Flanders Marine Institute Data
248 Centre (<https://erddap.bio-oracle.org/erddap>), through the Bio-ORACLE website (temporary link for
249 peer-review: <https://www.bio-oracle.org/downloads-to-email-v3.php>) and the R and Python
250 packages available in the permanent GitHub repository (<https://github.com/bio-oracle>).

251

252 **Code availability**

253 The R language code used to generate the layers is available in the permanent GitHub repository at
254 <https://github.com/bio-oracle/data-layers>.

255

256 **Author contributions**

257 J.A., L.T., H.V. and O.D.C. conceived the study. J.A. designed the data pipelines. J.A. wrote the
258 manuscript. V.S., F. L. and B. V. set up the ERDDAP server and F.L. and B.V. will maintain it. S.F. and
259 V. S. wrote the documentation, published the dataset on ERDDAP and developed the R and Python
260 clients. All authors reviewed the manuscript.

261

262 **Competing interests**

263 The authors declared no conflict of interest.

264

265 **Tables**

266 Table 1. Marine data layers and units, realm (surface layers, benthic layers, or both, where
267 appropriate), accuracy assessed with in situ quality-control data (for the variables comprised in
268 GLODAP (Olsen *et al.*, 2016; Lauvset *et al.*, 2021); MAE: mean absolute error; RMSE: root mean
269 square error; Cor: Pearson's correlation; additional estimates per depth in Supplement 3), number of
270 quality-control records (n), range of values for present conditions, and change (anomaly) between
271 the present (decade 2010-2020) and the future (decade 2090-2100) under contrasting scenarios
272 SSP1-1.9 and SSP5-8.5.

Layer	Surface	Benthic	MAE	RMSE	Cor	n	Range	Future change (SSP1-1.9; SSP5-8.5)
Air temperature (°C)	X		-	-	-	-	-57.96; 40.97	0.72±1.08; 4.67±3.53
Chlorophyll-a concentration (mmol · m ⁻³)	X	X	-	-	-	-	0; 21.95	0±0.03; 0.01±0.03
Diffuse attenuation coefficient (m ⁻¹)	X		-	-	-	-	0; 1.19	-
Dissolved iron concentration (mmol · m ⁻³)	X	X	-	-	-	-	0; 0.101	-0.01±0.01; -0.01±0.01
Dissolved oxygen concentration (mmol · m ⁻³)	X	X	5.222	25.648	0.930	558,720	41.70; 456.98	-1.26±4.93; -14.33±11.33
Mixed layer depth (m)	X		-	-	-	-	0; 3728.89	0.27±11.36; -7.19±19.35
Nitrate concentration (mmol · m ⁻³)	X	X	0.467	3.082	0.946	642,133	0; 303.75	-0.38±0.91; -1.11±1.29
Ocean temperature (°C)	X	X	0.141	0.823	0.991	823,531	-1.94; 36.49	0.38±0.40; 2.97±0.98
pH	X	X	-	-	-	-	7; 8.53	-0.03±0.02; -0.39±0.04
Phosphate concentration (mmol · m ⁻³)	X	X	0.028	0.218	0.948	612,203	0; 4.38	-0.03±0.09; -0.10±0.11
Photo. active radiation (E · m ⁻² · yr ⁻³)	X		-	-	-	-	0; 69.13	-
Total phytoplankton concentration (mmol · m ⁻³)	X	X	-	-	-	-	0.02; 57.20	-0.01±0.16; -0.10±0.29
Total cloud fraction (fraction)	X		-	-	-	-	0; 1	0.01±0.04; -0.01±0.05
Salinity	X	X	0.012	0.217	0.974	824,173	0; 47.54	-0.01±0.32; -0.22±0.51
Silicate concentration (mmol · m ⁻³)	X	X	1.762	9.484	0.929	645,495	0.23; 680.78	-0.83±3.33; -1.60±3.53
Sea-Ice Cover (fraction)	X		-	-	-	-	0; 1	-0.02±0.05; -0.09±0.20
Sea-Ice Thickness (m)	X		-	-	-	-	0; 7.87	-0.13±0.37; -0.28±0.68
Sea-water direction (°)	X	X	-	-	-	-	0; 360	0.45±40.66; 2.59±45.39
Sea-water velocity (m / s)	X	X	-	-	-	-	0; 3.05	0.02±0.05; 0.02±0.05
Topographic slope		X	-	-	-	-	0; 30.71	-
Topographic aspect		X	-	-	-	-	0; 360	-
Terrain ruggedness index		X	-	-	-	-	0; 2512.92	-

Topographic position index		X	-	-	-	-	-1963; 2512	-
Minimum depth (m)		X	-	-	-	-	-10363; 0	-
Average depth (m)		X	-	-	-	-	-10699; 0	-
Maximum depth (m)		X	-	-	-	-	-10977; 0	-

273

274 Table 2. List of R and Python functions to facilitate listing and extraction of data layers (refer to the
275 permanent GitHub repository for additional information; <https://github.com/bio-oracle>).

Function	Language	Description
list_layers()	R and Python	Lists the data layers available in the Bio-ORACLE ERDDAP server, either as a list or a dataframe containing metadata. Users may subset layers based on attributes, such as variable or SSP scenario.
download_layers()	R and Python	Downloads one or more data layers from the Bio-ORACLE ERDDAP server. Users may filter data using attributes, such as sets of coordinates or time periods, and select the data format to be downloaded*.
list_local_data()	R and Python	Lists local data that has been downloaded by the Bio-ORACLE client.
config	R and Python	Shows configuration values, <i>i.e.</i> the path to the local data directory and the address of the Bio-ORACLE server.

276 * Refer to the ERDDAP server for the complete list of data formats ([https://erddap.bio-](https://erddap.bio-oracle.org/erddap/griddap/documentation.html#fileType)
277 [oracle.org/erddap/griddap/documentation.html#fileType](https://erddap.bio-oracle.org/erddap/griddap/documentation.html#fileType)).

278

279 Additional information

280 Supplementary information 1: Performance and tuning test between inverse distance weighting and
281 kriging algorithms.

282 Supplementary information 2: Standard deviation of the ensemble of Earth System Models.

283 Supplementary information 3: Reliability of climate layers estimated with cross-validation.

284 Supplementary information 4: Comparison between the current and the previous spatial resolution
285 of Bio-ORACLE datasets (version 2.0 vs version 3.0).

286 Supplementary information 5: Availability of Earth System Models per variable and shared
287 socioeconomic pathway scenario.

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