

1 **Climatology and annual cycle of global ocean dissolved oxygen represented by multiple**
2 **observational gridded products**

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30 **Abstract:**

31 Ocean dissolved oxygen (O₂) is an essential climate variable crucial for sustaining the marine
32 life; thus, changes of O₂ at various spatiotemporal scales should be quantified and
33 understood. Here, we study the climatology and annual cycle of O₂ at regional to global
34 scales using eight available gridded observational products. These datasets are generated by
35 different groups using different primary data selection, quality control, bias correction, and
36 interpolation methods, including statistical and machine-learning-based mapping methods. A
37 common set of metrics was collaboratively developed by the community of the Gridded
38 Observational Dataset Intercomparison Project-Dissolved Oxygen (GODIP-DO) to facilitate
39 the inter-comparison. We find that global mean O₂ profiles are consistent among all products
40 ($\pm 3 \mu\text{mol kg}^{-1}$), with the well-established decrease from high surface values to a minimum
41 ~ 1000 meters, and subsequent increase to higher O₂ at depth, although local differences could
42 reach $\pm 25 \mu\text{mol kg}^{-1}$ (0-1000 m). The hemispheric O₂ annual cycle correlates strongly with

43 ocean temperature changes, suggesting the key driver of temperature for the O₂ annual cycle.
44 However, there is substantial variation in the global mean 0-100 m O₂ annual cycle, the
45 magnitude ranges from -1 to 0.8 μmol kg⁻¹, with a standard deviation of the datasets of ~0.3
46 μmol kg⁻¹. Average oxygen minimum zones (OMZ) volume among the products is 80.92 ×
47 10⁶ km³ (±1.95 %) for a 60 μmol kg⁻¹ threshold and 152.00 × 10⁶ km³ (±1.72 %) for a 90
48 μmol kg⁻¹ threshold. Our results help to depict and understand the spread among the available
49 O₂ gridded datasets.

50

51 **1 Introduction**

52 Anthropogenic climate change drives ocean warming, increases stratification, and alters
53 ocean circulation (Bindoff et al. 2019). These changes lead to the loss of ocean dissolved
54 oxygen (O₂), namely deoxygenation, because of the changes in the O₂ solubility, ventilation,
55 and deep ocean respiration (Keeling et al., 2010; Schmidtko et al., 2017; Breitburg et al.,
56 2018; Oschlies et al., 2018; Garcia-Soto et al., 2021). Deoxygenation occurred in most open
57 ocean regions during the mid-20th to early 21st centuries, such as the Mediterranean Sea,
58 tropical oxygen minimum zones (OMZ), and the North Atlantic Subtropical Gyre (Tan et al.,
59 2026), influencing marine ecosystems through resulting biogeochemical feedbacks such as
60 ocean productivity, nutrient cycling, carbon cycling, marine habitat, etc (Levin, 2018;
61 Bindoff et al., 2019). Given its importance, studying O₂ changes at various spatiotemporal
62 scales becomes critical.

63 Observations and model simulations document a robust decline of the global O₂
64 inventory, which is a grand challenge for the accurate assessment of deoxygenation (Ito et al.,
65 2017; Schmidtko et al., 2017; Breitburg et al., 2018). For trends, current assessments such as
66 the Intergovernmental Panel on Climate Change (IPCC) Special Report on the Ocean and
67 Cryosphere in a Changing Climate (SROCC) indicates that the open ocean is losing O₂
68 overall with a decadal variability of 0.3 %-2 % since the 1960s over all ocean depths and of
69 0.5 %-3.3 % between 1970 and 2010 from the ocean surface to 1000 m, with an expansion of
70 OMZ by 3-8 % (Bindoff et.al., 2019; Gulev et.al., 2021; Zhou et.al., 2022). In addition, a
71 recent observational-based assessment by Tan et al., 2026 shows that significant signal
72 emergence of long-term oxygen trend (both deoxygenation and oxygenation) can now be
73 detected across global ocean in a large-scale and deep-reaching pattern since the 1990s,
74 although the regional data uncertainty still needs to be taken into account. These studies
75 reveal substantial uncertainty in quantifying the open ocean O₂ trends, however, there is no

76 dedicated study assessing the available products on O₂ climatology and its annual cycle,
77 which is the key focus of the present study.

78 The differences among different O₂ products may arise from the instruments/platforms
79 used to obtain O₂ profiles and the data processing techniques including quality control
80 processes, bias correction approaches, vertical interpolation methods, mapping methods
81 (horizontal interpolation), land-ocean masks and so on. Since the late 19th century,
82 oceanographers have measured ocean O₂ using many instruments with varying sampling
83 resolutions. The very first instrument includes the chemical titration method developed by
84 Winkler (Ocean Station Data, OSD), which restricted the O₂ observations derived from water
85 samples to several depth levels. Electrochemical and optical sensors for measuring O₂
86 became prevalent in the 1960s-70s and are now widely used to make continuous
87 measurements on platforms such as the CTD (Conductivity-Temperature-Depth) profilers.
88 Biogeochemical Argo profiling floats (BGC-Argo) have provided increasing ocean O₂
89 observation profiles since the early 2000s, and underwater gliders (GLD) and moorings are
90 especially useful for regional oceanography (Gregoire et al., 2021; Gourteski et al., 2024).
91 The Winkler data are labour intensive with lower sampling resolution, whereas sensor-based
92 measurements have better spatiotemporal resolution, and the proliferation of the BGC-Argo
93 program has dramatically increased observations.

94 With the ocean O₂ observations collected using different observing systems, there have
95 been several quality controlled global ocean O₂ observation datasets from different research
96 organizations/groups such as the National Centers for Environmental Information (NCEI) of
97 the National Oceanic and Atmospheric Administration (NOAA) (Garcia et al., 2024; Garcia
98 et al., 2018; Boyer et al., 2018), Shanghai Jiao Tong University (SJTU, Zhou et al. 2022) and
99 the Institute of Atmospheric Physics (IAP) Chinese Academy of Sciences (Gourteski et al.,
100 2024). These quality controlled observations are then used to construct gridded O₂ data
101 products by filling data gaps with a mapping method where direct observations were not
102 available. The available mapping methods include objective analysis (Garcia et al., 2024),
103 ensemble optimal interpolation with dynamic ensemble (EnOI-DE, Cheng et al., 2024; Cheng
104 et al., 2017, Cheng and Zhu, 2016), Data Interpolating Variational Analysis (DIVA; Roach
105 and Bindoff, 2023), machine learning techniques (Sharp et al., 2023; Ito et al., 2024; Huang
106 et al., 2023; Liu et al., 2025), and geostatistical regression (Zhou et al., 2022).

107 All the previously mentioned instrumental data have measurement errors and biases,
108 and the data processing techniques are imperfect, leading to uncertainty in representing the
109 O₂ climatological mean state and its annual variation. A systematic multi-product

110 intercomparison at regional to global scales could serve as the primary tool to assess the
111 robustness of our observational understanding and to quantify the spread in current
112 climatological representations. The spread among different datasets includes all error factors
113 and is different from the recent single-factor assessment of Ito et al. (2025) who focused
114 solely on mapping methods. In particular, we employed eight ocean O₂ climatology products,
115 covering statistical and machine-learning based mapping methods whereas Ito et al. (2025)
116 included statistical mapping methods only. Our analysis includes the gridded O₂ dataset from
117 the Institute of Atmospheric Physics (hereafter, IAP; Gourteski et al., 2024), World Ocean Atlas
118 2023 (hereafter, WOA23; Garcia et al., 2024) and World Ocean Atlas 2018 (hereafter,
119 WOA18; Garcia et al. 2018, Boyer et al., 2018) by NCEI, a machine learning-based data
120 product by Sharp et al. (Gridded Ocean Biogeochemistry from Artificial Intelligence,
121 hereafter, GOBAI; Sharp et al. 2023), two data products based on DIVA by Roach and
122 Bindoff (hereafter, RB; Roach and Bindoff, 2023) and Global Ocean Data Analysis Project
123 (hereafter, GLODAP; Lauvset et al., 2016), a geostatistical gridded O₂ dataset from Shanghai
124 Jiao Tong University (hereafter, SJTU; Zhou et al., 2022), and a machine learning-based data
125 product (hereafter, Jingwei; Lu et al., 2024).

126 The rest of the paper is organized as follows. The gridded datasets and methods
127 employed in the study are presented in Section 2. In Section 3, the results of depicting the
128 characteristics and assessing the spread of O₂ climatology and annual cycle for different
129 products are introduced. The analysis related to OMZ distribution is also presented in Section
130 3. The results of the study are summarized and discussed in Section 4.

131

132 **2 Datasets description**

133 We used eight O₂ gridded products (IAP, WOA23, WOA18, GOBAI, RB, GLODAP,
134 SJTU, and Jingwei) which are different in many aspects including the instruments to get raw
135 O₂ profiles and also the data processing techniques, such as quality control and bias
136 correction approaches, vertical interpolation methods, mapping methods, land-ocean masks
137 and so on (**Table 1**).

138 The observations used by IAP, WOA23, WOA18, RB, SJTU and Jingwei are mainly
139 from WOD (World Ocean Database, Boyer et al., 2018; Mishonov et al., 2024) and BGC-
140 Argo. Observations from GLODAP are also used in GOBAI product. The IAP, WOA23,
141 WOA18 and GOBAI datasets include monthly climatology, and the remaining four data
142 products only provide the annual mean climatology. So, analyses related to the annual
143 variation of the global ocean O₂ and the annual cycle are restricted to the four datasets with

144 monthly climatology. The gridded data products of IAP, WOA23, WOA18, RB, GLODAP,
 145 and Jingwei reach the ocean bottom of about 5500 m/6000 m. GOBAI, and SJTU only cover
 146 the top 2000m. The horizontal resolution of the data product of RB and SJTU is $0.5^\circ \times 0.5^\circ$
 147 and $2^\circ \times 2^\circ$, respectively, and all the other six products are at a resolution of $1^\circ \times 1^\circ$. The
 148 horizontal space coverages of all the datasets are also slightly different. The space coverage
 149 of the GOBAI data is limited by the distribution of the temperature and salinity data product
 150 on which it is based, so GOBAI only covers 64.5° S- 79.5° N of the open ocean (O_2 in the
 151 coastal regions and oceans with complex topography are not reconstructed). The mapping
 152 method for WOA18 and WOA23 is based on objective analysis (OA) and that for IAP is the
 153 ensemble optimal interpolation with dynamic-ensemble (EnOI-DE). GLODAP and RB both
 154 adopt the Data-Interpolating Variational Analysis (DIVA) method to generate gap-filled
 155 fields. SJTU develops the geostatistical regression (GR) interpolation method. The feed-
 156 forward neural network and the spatio-temporal graph hypernetwork are used for the machine
 157 learning (ML) process of the GOBAI and Jingwei data products, respectively (**Table 1**). To
 158 illustrate the spatiotemporal characteristics of the observation profiles, the spatial distribution
 159 and annual number of the three main observation platforms (OSD, CTD, BGC-Argo) for
 160 1960-2024 are shown in Fig. 1.

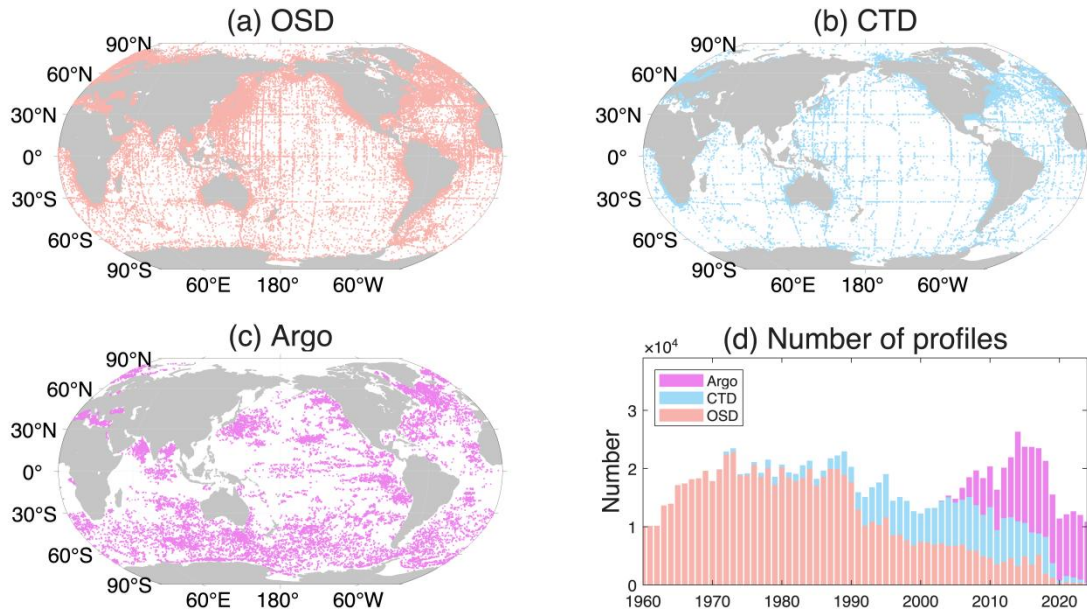
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162 **Table 1** Global ocean O_2 gridded datasets employed in the comprehensive inter-comparison
 163 of the climatology.

O_2 datasets	mapping	quality control	time period	resolution	depth/ layers	observations
IAP Gourteski et al., 2024	EnOI-DE	IAP	1960-2022	$1^\circ \times 1^\circ$	6000 m/119	OSD, CTD, A rgo
WOA23 Garcia et al., 2024	OA	NCEI	1965-2022	$1^\circ \times 1^\circ$	5500 m/102	OSD, CTD, A rgo
WOA18 Boyer et al., 2018	OA	NCEI	1960-2017	$1^\circ \times 1^\circ$	5500 m/102	OSD
GOBAI Sharp et al., 2023	ML	GLODAP , Argo	2004-2024	$1^\circ \times 1^\circ$	1975 m/58	OSD, Argo

RB Roach and Bindoff, 2023	DIVA	NCEI	1960-2017	$0.5^\circ \times 0.5^\circ$	6100 m/108	OSD, CTD
GLODAPv2 Lauvset et al., 2016	DIVA	GLODAP	1972-2013	$1^\circ \times 1^\circ$	5500 m/33	OSD, WOCE, CLIVAR/GO-SHIP
SJTU Zhou et al., 2022	GR	NCEI, SJTU	1960-2019	$2^\circ \times 2^\circ$	2000 m/61	OSD, CTD, GLD, Argo
Jingwei Lu et al., 2024	ML	NCEI	1960-2023	$1^\circ \times 1^\circ$	5500 m/33	OSD, CTD, Argo

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Figure 1 Spatial distribution (a: OSD, b: CTD, c: Argo) and annual number (d) of observation profiles.

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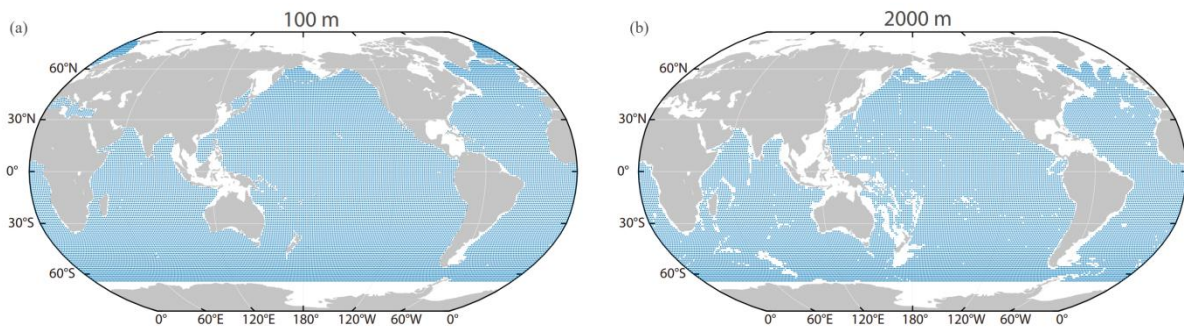
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This study used a common ocean mask, which is defined as ocean grid points with all data products available. The common land-ocean masks for the layers of 100 m and 2000 m are presented in **Fig. 2** and the common masks for the other layers (1000 m, 3000 m, 4000 m and 5000 m) are available in **Fig. S1**. This will be a uniform comparison and remove the impacts of different data coverage on the results. The datasets of RB and SJTU were interpolated to a common $1^\circ \times 1^\circ$ resolution as all the other datasets to facilitate the

175 comparison, but the interpolation has a negligible impact on the results presented in this
176 work.

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185 **Figure 2** Grid point distribution of the common land-ocean mask for the layers of 100 m (a)
186 and 2000 m (b).

187

188 **3 Results**

189 **3.1 Global mean O₂**

190 The global area-weighted mean O₂ profile is first presented in **Fig. 3a**, showing a well-
191 established vertical structure and a good consistency among all products. O₂ is higher near
192 the surface than in the deeper ocean because of the gas exchange with the atmosphere and
193 photosynthesis. The O₂ reaches the lowest value at ~1000 m because of the respiration and
194 limited O₂ supply from the surface. The O₂ increases from ~1000 m to the deep ocean (~5000
195 m) because of the weaker respiration and the intermediate, deep and bottom water formation
196 that supplies higher O₂ water into the deep layers, where cold, dense surface water sinks, and
197 is then distributed globally by deep ocean currents, slowly losing O₂ along its centuries-long
198 journey (Musun et al., 2023).

199 To better quantify the differences among the datasets, we take the difference between all
200 seven other data products (WOA23, WOA18, GOBAI, RB, GLODAP, SJTU, and Jingwei),
201 and IAP data (**Fig. 3b**). The differences are mostly within $\pm 3 \mu\text{mol kg}^{-1}$ among all the
202 datasets with a common land-ocean mask from ocean surface to 5500 m, except that the
203 differences for SJTU and Jingwei range between -6 and $5 \mu\text{mol kg}^{-1}$ for the upper 200 meters.

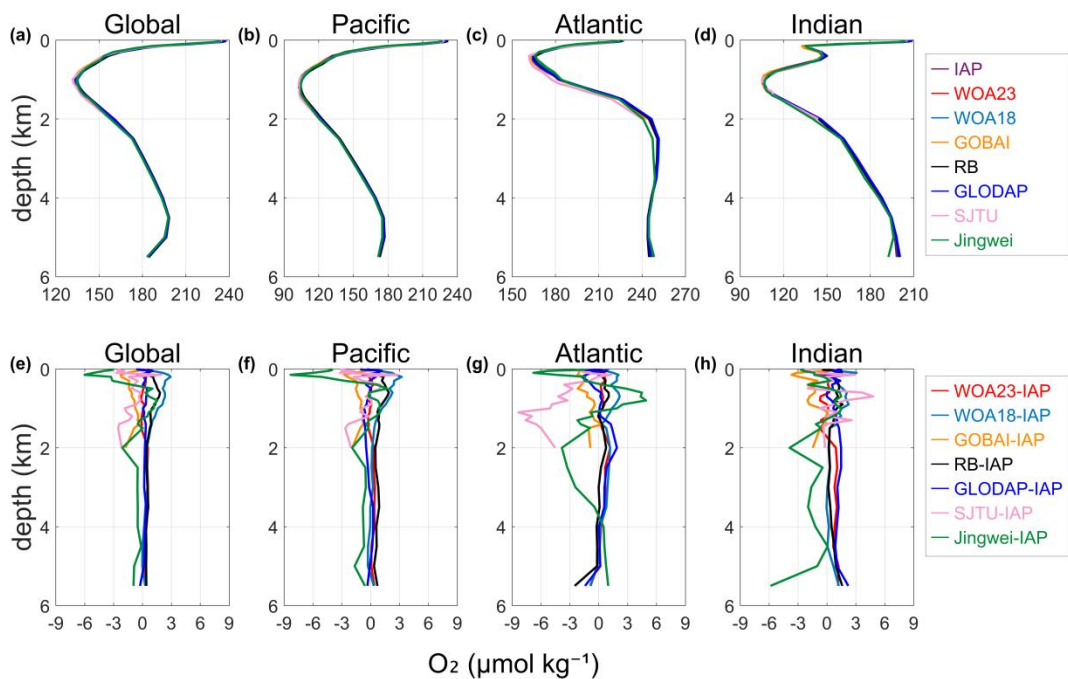
204 The differences are comparable to the magnitude of O₂ anomaly, whose semi-decadal median
205 is within $\pm 10 \mu\text{mol kg}^{-1}$ within major ocean basins (Schmidtko et al., 2017).

206 There is a negative offset between GOBAI and IAP ($\sim -2 \mu\text{mol kg}^{-1}$). The differences
207 between WOA18, RB and IAP are positive. One possible reason for these differences is that
208 different data products construct climatology using data from different time periods with
209 different resolutions. The SJTU climatology uses CTD, OSD, Argo, and additional GLD
210 data, then interpolate them at coarser 2° resolution. The GOBAI climatology is reflective of a
211 more recent period compared to the other datasets (2004-2024), which might at least partly
212 explain the negative difference between GOBAI and IAP (where data from 1960-2022 are
213 used). Because of the general deoxygenation trend, a “newer” climatology is expected to
214 show less global mean O₂ than an “older” climatology. IAP is close to WOA23 at the upper
215 2000 m within $1 \mu\text{mol kg}^{-1}$, which is reasonable because both IAP and WOA23 used bottle
216 (OSD), CTD and delayed-mode Argo data using the same 1° data resolution, and they have
217 similar time coverage of data used to generate climatology (IAP, 1960-2022 and WOA23,
218 1965-2022).

219 Below 2000 m, there is an offset between IAP and WOA23: WOA23 O₂ is 0.2-0.6 μmol
220 kg^{-1} higher than IAP. Possible explanations may be the differences in quality control and
221 mapping methods. Another possibility is the ‘jump’ around 2000 m of IAP minus WOA23. It
222 is common to have a discontinuity around 2000 m because of the big differences in data
223 amount and data distributions at upper and deeper layers (Observations are concentrated in
224 the upper ocean and most of the Argo data are in the upper 2000 m). Differences in infilling
225 the empty grid nodes during the mapping procedure may also play a significant role in deep
226 ocean layers where the number of observation data is severely limited. Results of applying
227 different mapping methods to the same in situ datasets suggest that mapping methods may
228 contribute to a difference of less than $\pm 1 \mu\text{mol kg}^{-1}$ for the 0-5500 m area-weighted averaged
229 O₂ (Ito et al., 2025). And using two different quality control processes and the same mapping
230 procedure yields a difference of only $\pm 0.5 \mu\text{mol kg}^{-1}$ (Ito et al., 2025).

231 The mean O₂ profiles and the differences between datasets for major ocean basins
232 (Pacific, Atlantic, Indian) are calculated separately and presented in **Fig. 3b-d** and **Fig. f-h**.
233 The differences are mostly within $\pm 4 \mu\text{mol kg}^{-1}$ among all the datasets for the Pacific and
234 Indian Ocean, except that the difference for Jingwei ranges between -8 and $2 \mu\text{mol kg}^{-1}$ for
235 the upper 200 meters in the Pacific Ocean (**Fig. 3f**). The mean O₂ profiles for the Atlantic
236 Ocean show more notable differences compared to other ocean basins (**Fig. 3c**), including

237 that the mean O₂ profile of SJTU data shows a difference of -10 to -5 μmol kg⁻¹ for the depth
 238 of 1000-2000 m, while the differences of all the other datasets are constrained to -5 to 5 μmol
 239 kg⁻¹ from ocean surface to the depth of 5500 m (**Fig. 3g**). For the Atlantic Ocean, the mean
 240 O₂ reached the minimum at the depth of ~500 m (**Fig. 3c**) which is much shallower than the
 241 O₂ minimum layers for the Pacific Ocean and Indian Ocean (~1000 m, **Fig. 3b, 2d**), possibly
 242 due to a combined effect of the formation, transport and mixing process of the North Atlantic
 243 Deep Water (NADW), the ventilation processes such as Atlantic Meridional Ocean
 244 Circulation (AMOC) and so on (Levin, 2018; Koelling et al., 2022; Musan et al., 2023; Ruhl
 245 et al., 2025).
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 248 **Figure 3** Area-weighted mean O₂ climatology (a-d) and difference (e-h) relative to the IAP
 249 for the Global, Pacific, Atlantic and Indian Ocean from ocean surface to 5500 m with a
 250 common ocean mask for different ocean basins in units of μmol kg⁻¹. The subplots for O₂
 251 climatology (a-d) use different scales.

252 253 3.2 Zonal mean structure

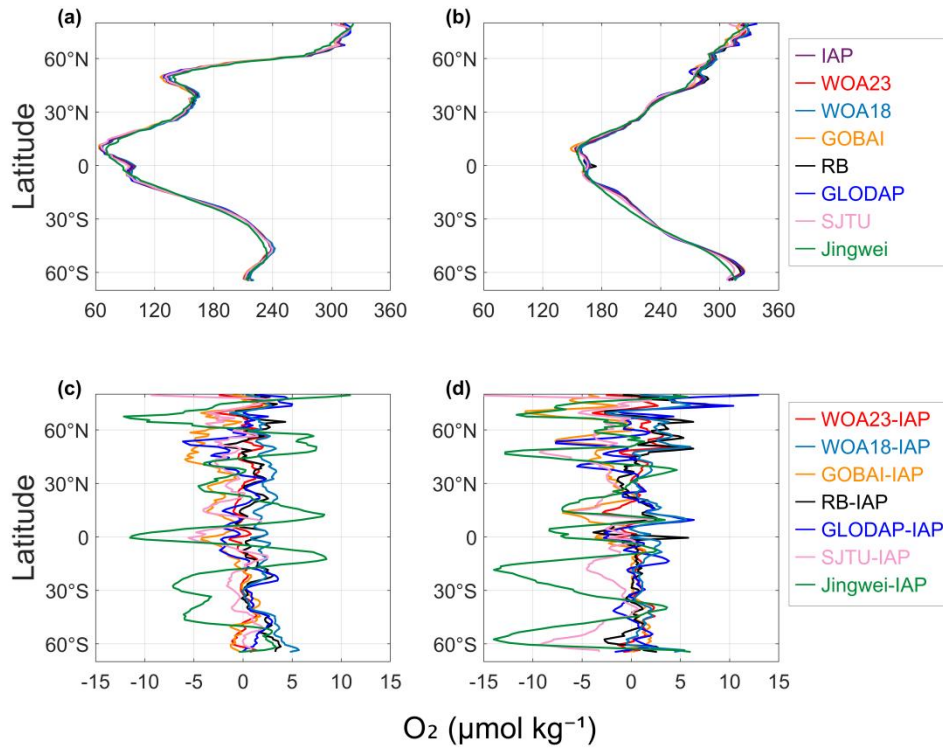
254 The global zonal mean O₂ concentration of the eight datasets for the upper 1000 m
 255 shows consistency for the zonal structure (**Fig. 4a**). There is a minimum of mean O₂ levels
 256 around the tropical regions for all the datasets, associated with a shoaling of the tropical and
 257 subtropical thermocline depth (Deutsch et al., 2011) and the presence of the tropical upper
 258 ocean OMZ. The differences in the global zonal mean O₂ for the upper 1000m between the

259 seven data products (WOA23, WOA18, GOBAI, RB, GLODAP, SJTU and Jingwei) and IAP
260 are shown in **Fig. 4b**). The differences in zonal mean 0-1000 m averaged O₂ are mostly
261 within ~5 μmol kg⁻¹. The zonal mean O₂ difference between IAP and WOA23 is the smallest,
262 which is generally within ~1.5 μmol kg⁻¹. The zonal mean of GOBAI is generally lower than
263 that of IAP, especially in the Northern Hemisphere, which may imply stronger deoxygenation
264 trends in the Northern Hemisphere, as the GOBAI climatology baseline is newer than that of
265 IAP. The zonal mean of the RB dataset is higher than that of IAP by ~0.78 μmol kg⁻¹ on
266 average, consistent with the positive offset shown in **Fig. 3**. Jingwei dataset has the strongest
267 differences from IAP and other products, showing a notable zonal fluctuation.

268 The results for the depth layers 0-600 m and 0-2000 m (**Fig. S2**) show similar variation
269 pattern to the depth layer 0-1000 m. The differences in the global zonal mean O₂ between
270 data products are mostly within ~5 μmol kg⁻¹ for 0-600 m and within ~3 μmol kg⁻¹ for 0-2000
271 m (**Fig. S2b, S2d**). For 0-600 m, the zonal mean O₂ difference between IAP and WOA23 is
272 the smallest and Jingwei shows the strongest differences from IAP and other products. For 0-
273 2000 m, the depth average makes the difference between datasets much smaller. Jingwei still
274 shows relatively large discrepancy from the other datasets in the regions around 60° N and
275 the equator. Within the latitude range 20° S-50° S where all other data products show the best
276 agreement, Jingwei exhibits a significant deviation of ~5 μmol kg⁻¹ from the rest.

277 However, the zonal mean O₂ concentration for 0-100 m (**Fig. 4b**) shows a relatively
278 distinct pattern. The zonal mean O₂ decreases linearly with the decrease of latitude for all the
279 datasets, except that for the high latitude range 60° S-80° S, the zonal mean O₂ profiles
280 maintain a relatively stable value and the estimations between different data products vary to
281 an extent of ~20 μmol kg⁻¹ (**Fig. 4d**), which illustrates the relatively higher uncertainty in the
282 data reconstruction in this high latitude range.

283



284

285 **Figure 4** Global zonal mean O₂ concentration and differences for 0-1000 m (a, c) and 0-100
 286 m (b, d) (unit: μmol kg⁻¹)

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288 3.3 Spatial pattern

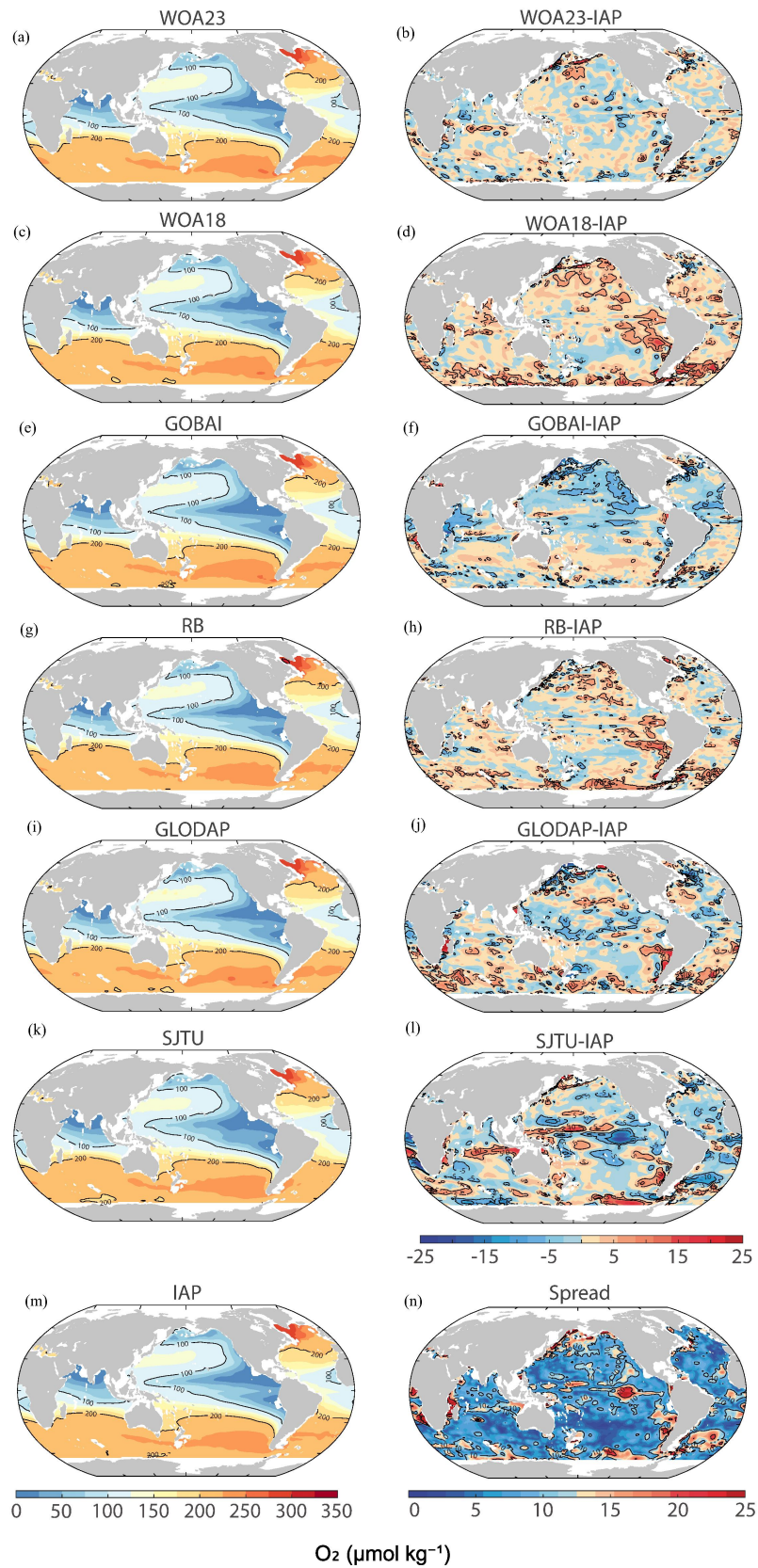
289 The spatial distribution of the upper 1000 m mean O₂ and the difference between IAP
 290 and six other datasets is shown in **Fig. 5a-m**. The dataset of Jingwei is not included because
 291 the spatial maps are not currently available. The difference of the 0-1000 m mean O₂ is
 292 mainly within the magnitude of ~15 μmol kg⁻¹, which shows substantial local differences
 293 even though their differences are relatively small when averaged globally (~3 μmol kg⁻¹, **Fig.**
 294 **3**). The mean O₂ of the GOBAI dataset is generally lower than IAP for 0-1000m (**Fig. 5f**),
 295 consistent with the conclusions from the previous comparisons. There are bigger differences
 296 located in the regions such as the subpolar North Pacific, the Southern Ocean fronts and the
 297 eastern Pacific regions close to OMZ boundaries, where the strong spatial O₂ gradient, makes
 298 the reconstruction sensitive to the mapping process and data distribution (Ito et al. 2025).
 299 GOBAI, SJTU and GLODAP show a negative difference (~-15 μmol kg⁻¹) compared to IAP
 300 for the upper 1000 m mean O₂ in most of the north and equatorial Pacific Ocean, and
 301 equatorial Atlantic Ocean. WOA23 and GOBAI show a similar pattern of difference in the
 302 Indian and Pacific Oceans: more positive offsets in the eastern Pacific/Indian Oceans and
 303 negative offsets in the western Pacific/Indian Oceans. For the two generations of WOA

304 products, the difference between WOA23 and IAP is more negative globally than the
305 difference between WOA18 and IAP, likely due to the use of more recent data in WOA23.
306 SJTU exhibits a distinct pattern of differences, with substantial negative differences
307 occurring in the tropics.

308 The spatial map of the spread of the upper 1000 m mean climatological O₂ among all the
309 datasets except Jingwei is presented in **Fig. 5n**. The spread here is defined as the maximum
310 absolute value of the differences between all the other products and IAP. The spread is within
311 12 $\mu\text{mol kg}^{-1}$ in most of the ocean areas, with the largest spread reaching 25 $\mu\text{mol kg}^{-1}$ where
312 strong spatial O₂ gradients exist. The spread is generally lower in the Southern Hemisphere
313 than in the Northern Hemisphere, in contrast to the fact that there are more observations in
314 the North. This might be related to three issues: 1) A common error in the mapping method,
315 where the spatial interpolation generates over-smoothed or similar-biased fields in the
316 Southern Hemisphere; 2) the variability is lower in the Southern Hemisphere than in the
317 Northern Hemisphere, which reduces the reconstruction errors in the Southern Hemisphere; 3)
318 the deoxygenation trends are higher in the Northern Hemisphere than in the Southern thus the
319 spread reveals the O₂ level at different periods.

320 The exact reason can be explored with single-factor reconstruction experiments such as
321 Ito et al. (2025), which use the same input data but different mapping methods to isolate the
322 impact of mapping on climatology reconstruction. Further analyses are required, but it is
323 useful to know the differences between the products. When comparing the depth-mean O₂
324 between the eight datasets we adopted here which didn't distinguish different impact factors
325 in the process of generating gridded data products and aimed to illustrate a comprehensive
326 discrepancy, the difference for all the datasets for 0-300 m is within $\pm 25 \mu\text{mol kg}^{-1}$ and the
327 spread is up to 35 $\mu\text{mol kg}^{-1}$ (**Fig. S3**). The regions of high variability mainly locate in the
328 tropical and East Pacific, subpolar North Pacific and Southern Ocean fronts where there are
329 strong spatial O₂ gradients. However, when using the same quality-controlled observational
330 data as input and constraining the impact on data reconstruction to only the mapping method,
331 the difference of the mapped O₂ concentration between different mapping methods is within
332 $\pm 10 \mu\text{mol kg}^{-1}$ for 0-300 m (Ito et al., 2025). The overall difference between the data products
333 is more than two times of the difference constrained to a single factor of the mapping method,
334 indicating that the other factors, such as the quality controlled technique, bias correction,
335 vertical interpolation and so on, also contribute to the error source to a large extent. Further
336 analyses are required to assess and quantify the impact of every individual procedure on the

337 whole process of O₂ data reconstruction, but it is useful to know the differences between the
 338 data products as a start.
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340

341 **Figure 5** The spatial patterns of the upper 1000 m climatological mean O₂ concentration
342 (unit: $\mu\text{mol kg}^{-1}$). (a) WOA23, (b) WOA23-IAP, (c) WOA18, (d) WOA18-IAP, (e) GOBAl,
343 (f) GOBAl-IAP, (g) RB, (h) RB-IAP, (i) GLODAP, (j) GLODAP-IAP, (k) SJTU, (l) SJTU-
344 IAP, (m) IAP, (n) Spread is calculated as the difference of the upper 1000 m climatological
345 mean O₂ among the datasets.

346

347 **3.4 Annual cycle**

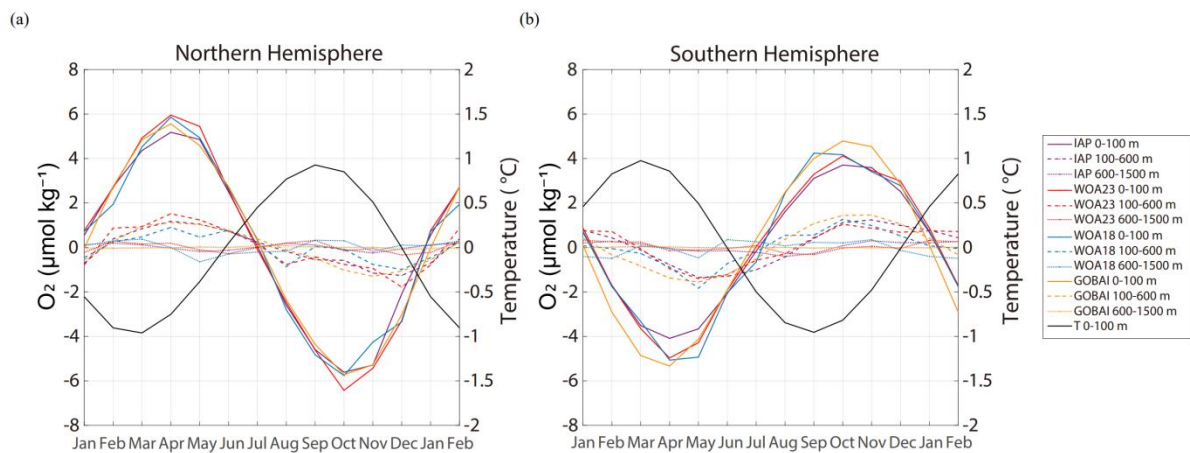
348 The annual cycle of the four products that provide a monthly climatology (IAP,
349 WOA23, WOA18 and GOBAl) is presented in **Fig. 6** for the 0-100 m, 100-600 m, and 600-
350 1500 m, and for northern and southern hemispheres, respectively calculated by the monthly
351 anomalies derived by subtracting the annual mean climatology of every data product
352 respectively. The annual cycle of the 0-100 m temperature for northern and southern
353 hemispheres is also calculated using the gridded temperature climatology product of IAP
354 (Cheng, et al., 2024). The magnitude of the O₂ seasonal cycle, defined as the maximum
355 amplitude of the annual variation, is greatest near the surface and decreases with depth.
356 Specifically, it is approximately $6 \mu\text{mol kg}^{-1}$ for the 0-100 m layer and $2 \mu\text{mol kg}^{-1}$ for the
357 deeper layer (100-600 m). The reduced annual cycle with depth is associated with stronger
358 annual variations of ocean temperature, wind-driven ventilation and biological processes in
359 the upper ocean compared to the deep ocean.

360 The appearance time of maximum (Apr.) and minimum (Oct.) O₂ levels in the northern
361 hemisphere are consistent among the four datasets for 0-100 m global mean O₂. Moreover,
362 the O₂ maximum in the depth layer in the northern and southern hemispheres for 0-100 m
363 lags about one month behind the temperature change, reflecting that besides the dominant
364 thermal induced increase in O₂ solubility, some physical/biological processes also impact the
365 concentration of ocean O₂ (Garcia et al., 2005; Wang et al., 2022). For the northern
366 hemisphere, the annual variation of the subsurface 100-600m layer also shows a pattern of
367 annual cycle with the maximum (Apr.) and minimum (Dec.) similar to the surface 0-100 m
368 layer, indicating that the O₂ annual cycle could penetrate to the deeper layer of ~ 600 m. It's
369 primarily due to the mechanisms including climatological winter mixed layer deepening,
370 which ventilates the subsurface, and seasonal thermocline dynamics coupled with organic
371 matter remineralization (Stamma et al., 2010). For the southern hemisphere, similar patterns
372 also exist.

373 Although the two hemispheric O₂ annual cycles can be well-defined, the global mean is
374 more subtle, as different products show large differences in patterns of the global mean

375 annual cycle (**Fig. 7**). It appears that global 100-600 m O₂ annual cycles are more consistent
 376 across data products than 0-100 m, probably associated with noisier data and more natural
 377 variability near the sea surface. For global 100-600 m O₂, all datasets suggest an O₂ reduction
 378 from March to September and an increase from October to February, consistent with the
 379 Southern Hemisphere changes (**Fig. 7b** versus **Fig. 6b**). The magnitude of the global 0-100 m
 380 and 100-600 m annual cycle ranges from -1~0.8 μmol kg⁻¹ for the four datasets, but the
 381 standard deviation among the four datasets is ~0.3 μmol kg⁻¹ (~0.2 μmol kg⁻¹), indicating a
 382 similar level of signal and noise (**Fig. 7**).

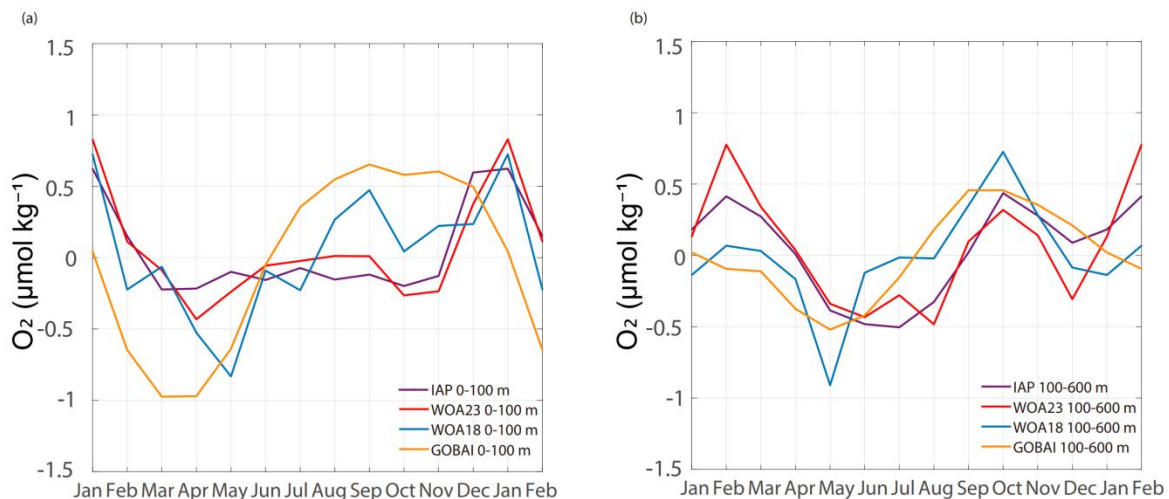
383



384

385 **Figure 6** Annual variation of the (a) Northern Hemisphere and (b) Southern Hemisphere
 386 global mean O₂ for IAP, WOA23, WOA18 and GOBAI datasets.

387

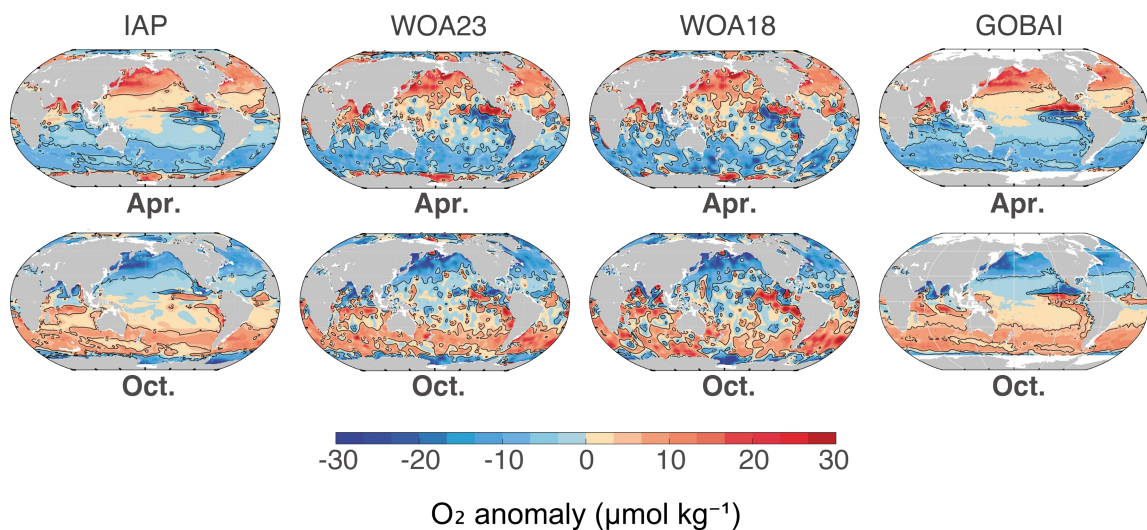


388

389 **Figure 7** Global annual variation of the (a) 0-100 m and (b) 100-600 m global mean O₂ for
 390 IAP, WOA23, WOA18 and GOBAI datasets

391

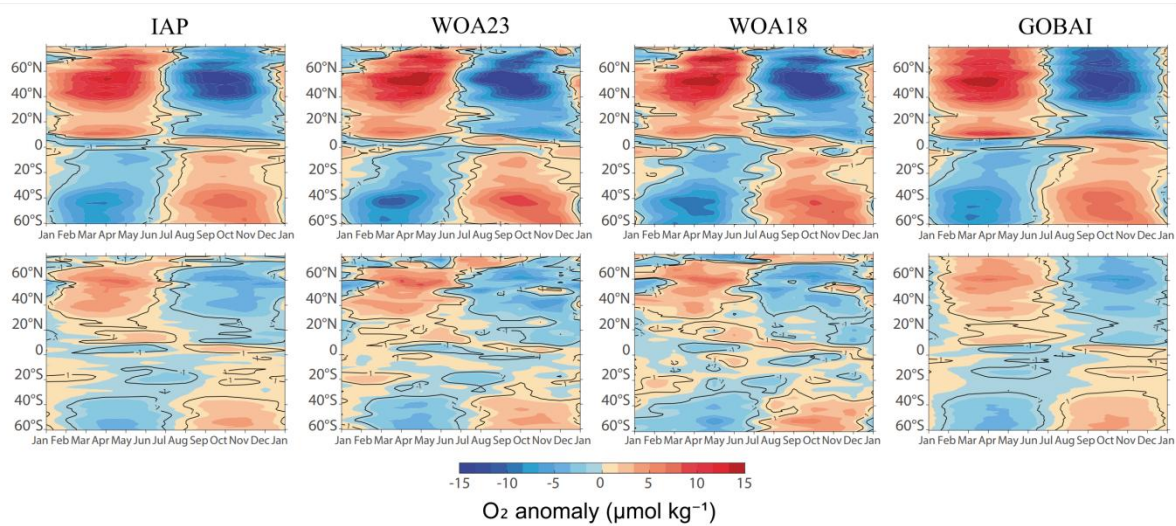
392 The annual cycle of O₂ anomalies shows a distinct spatial pattern (0-100 m mean O₂,
 393 April versus October, **Fig. 8**). The anomalies are calculated by subtracting the annual mean
 394 from the monthly climatologies for the four datasets (IAP, WOA23, WOA18, and GOBAI)
 395 respectively. In April, the O₂ anomalies of 0-100 m in most of the northern hemisphere are
 396 positive, and they turn negative in October. The tropical ocean annual cycle is not easily
 397 defined, as many regions have semi-annual variability. Different products exhibit a consistent
 398 pattern of change, whereas the detailed structures are quite distinct. In general, WOA23 and
 399 WOA18 have more patchy characteristics than IAP and GOBAI, likely related to the
 400 mapping methods employed by each: WOA uses an anti-distance weighted function to
 401 interpolate the field; on the other hand, IAP uses model simulations to provide covariance
 402 and GOBAI takes advantage of correlations between O₂ and temperature and salinity, both
 403 building physical ocean properties into the reconstruction.
 404



405
 406 **Figure 8** Spatial distribution of the O₂ anomaly (0-100 m) for the IAP, WOA23, WOA18
 407 and GOBAI climatology.
 408

409 The zonal mean structure of the annual cycle is shown in **Fig. 9**, and all the datasets
 410 show similar annual cycle patterns with some difference in smoothness and magnitude for
 411 both 0-100 m and 100-600 m mean O₂. For 0-100 m, the largest seasonal changes occur in
 412 the extra-tropics in the 30° to 60° belts of the northern hemisphere. In the southern
 413 hemisphere, the largest seasonal changes occur in the latitudinal band centered near 40° S.
 414 For both 0-100 m and 100-600 m, the phase transitions occur around Jul. and Jan. for all
 415 datasets, which are consistent with the annual variation analysis in Fig. 6. The phase change

416 of O₂ lags about one month behind the temperature change (Jun. and Dec. as shown in Fig.
 417 S12), reflecting that some physical/biological processes also impact the concentration of O₂
 418 besides the dominant thermally induced increase in O₂ solubility. Semi-annual cycles near the
 419 equator are visible in the upper ocean for almost all products. There is a distinction of the
 420 annual cycle at about 10° N, corresponding to the location of the intertropical convergence
 421 zone (ITCZ) (Garcia et al., 2005).

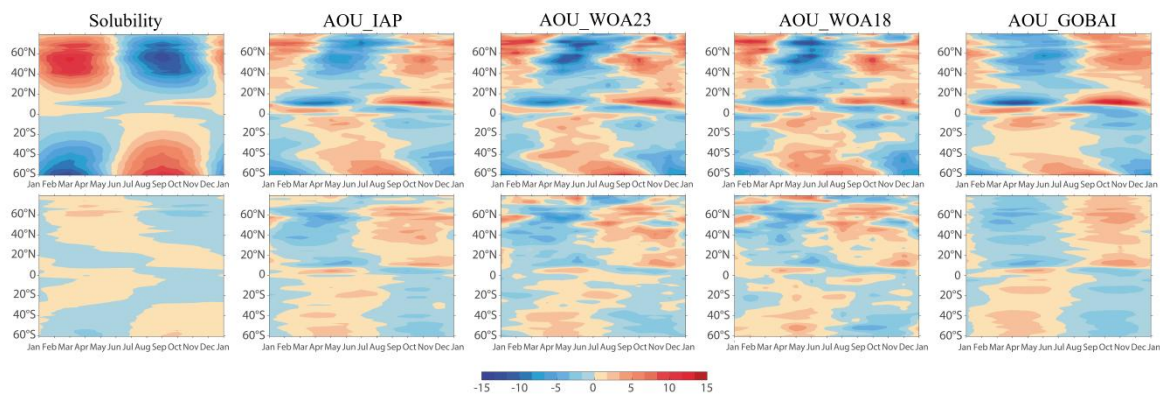


422
 423 **Figure 9** Zonal mean annual cycles for 0-100 m (upper) and 100-600 m (lower) for different
 424 data products.

425
 426 The zonal mean annual cycles of solubility and Apparent Oxygen Utilization (AOU) of
 427 different data products for 0-100 m and 100-600 m are shown in Fig. 10. The solubility is
 428 calculated using the gridded temperature and salinity products of IAP (Cheng et al., 2024)
 429 following the Garcia and Gordon (1992) method. Generally, the zonal 0-100 m O₂ seasonal
 430 cycle is mainly dominated by the solubility, whereas the AOU dominates the 100-600 m O₂
 431 pattern.

432 For 0-100 m, the AOU seasonal cycle in the mid-latitude is about two to three months
 433 lagging that of the temperature/solubility seasonal variation (Figs. 6, 10, S12). Within 20° N-
 434 60° N, the zonal mean AOU anomaly of 0-100 m is mostly negative from March to August.
 435 The phase transition of AOU occurs in March, which corresponds to the temperature
 436 minimum/solubility maximum. And AOU reaches a minimum in about May/June,
 437 corresponding to the phase transition of the zonal mean temperature/solubility anomaly (Fig.
 438 S12, 10). A possible explanation is from the combined impacts of biological and physical
 439 processes. The spring phytoplankton bloom lags the onset of temperature increase (starting in
 440 Mar.) because phytoplankton proliferation requires sufficient light from increasing spring

441 insolation and nutrient entrainment due to a shallower mixed layer (Martin, 2012). And the
 442 net community production (NCP, the difference between gross community photosynthesis
 443 and community respiration) reaches a maximum in about May (Wang et al., 2022). The
 444 solubility reaches a minimum in September, which corresponds with the phase change of
 445 AOU. And the maximum of AOU lags about two months behind the temperature
 446 maximum/solubility minimum, which is also a combined effect of the prolonged response
 447 time of biological processes and the physical processes possibly induced by the deepening
 448 autumn mixed layer. The situation in 20° S-60° S is similar to 20° N-60° N for 0-100 m,
 449 mainly with the signs reversed. For 100-600 m, the annual variation in temperature/solubility
 450 is relatively small, and the pattern of AOU variation dominates, with the underlying
 451 processes requiring further investigation.
 452



453
 454 **Figure 10** Zonal mean annual cycles of the solubility and AOU anomaly of different data
 455 products for 0-100 m (upper) and 100-600 m (lower) (unit: $\mu\text{mol kg}^{-1}$).

456
 457 To assess the patterns of annual cycle regionally, the zonal mean structures of the annual
 458 cycle for different ocean basins are shown in **Fig. S4-S6**. Distinct seasonal changes exist in
 459 the Pacific, Atlantic and Indian Ocean. The annual cycle patterns for the Pacific and Atlantic
 460 Ocean coincide with the global O_2 annual cycle both for the 0-100 m and 100-600 m layers
 461 closely. For the Indian Ocean, there are larger seasonal changes in the latitude range of $\sim 10^\circ$ -
 462 20° N for 0-100 m than the Pacific and Atlantic Ocean. The annual variations of the mean O_2
 463 for three major ocean basins (Pacific, Atlantic, Indian) for 0-100 m and 100-600 m are shown
 464 in **Fig. S7-S9**, and also for the North and South Pacific/Atlantic respectively in **Fig. S10-S11**.
 465 The magnitude of the O_2 seasonal cycle is greatest in the Atlantic Ocean ($\sim 3 \mu\text{mol kg}^{-1}$) for
 466 the 0-100 m layer, which corresponds to a magnitude of $\sim 6 \mu\text{mol kg}^{-1}$ in the North Atlantic
 467 and $\sim 4 \mu\text{mol kg}^{-1}$ in the South Atlantic. The minimum and maximum O_2 levels ($-4/6 \mu\text{mol kg}^{-1}$

468 ¹⁾ and also occurrence time (Jul./Oct.) of WOA18 for 0-100 m differ the most from those of
469 the other three datasets in the South Atlantic (**Fig. S11b**).

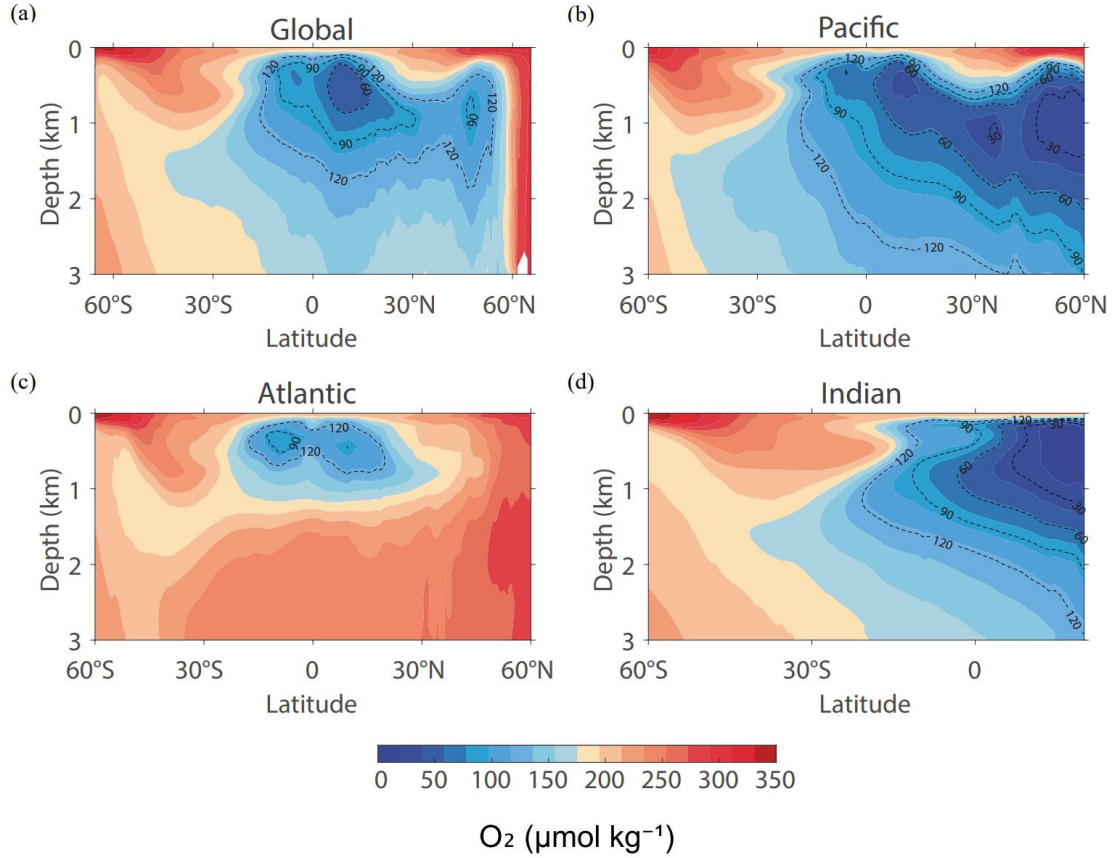
470

471 **3.5 Oxygen minimum zones**

472 Oxygen minimum zones (OMZ) are important regions that impact marine organism
473 distributions and biogeochemical cycling. OMZ occur in various regions such as the tropical
474 Pacific and Atlantic Oceans, the North Pacific, and the North Indian Ocean, posing
475 challenges for marine organisms adapted to higher O₂ concentrations (Strammer et al., 2021).
476 In various studies, OMZ are bounded by different thresholds of O₂ levels. Here, we select
477 thresholds of 60 μmol kg⁻¹ and 90 μmol kg⁻¹ to define OMZ, referred to as OMZ60 and
478 OMZ90, respectively.

479 The zonal mean O₂ of the IAP climatology dataset for global and three major basins are
480 shown in **Fig. 11**. Globally, the zonal mean OMZ90 regions are mainly located within 200-
481 1200 m and 5° S-30° N, associated with upwelling and high O₂ consumption. The Pacific
482 Ocean contains the largest volume of OMZ60 and OMZ90 among the three ocean basins,
483 with the OMZ90 extending from ~15° S to ~60° N and from a depth of ~200 m to ~3000 m.
484 There is a gradual increase in the max depth of OMZ90 and OMZ60 in the Pacific Ocean
485 from ~15° S to ~60° N; thus, the OMZ in the North Pacific Ocean has greater vertical extent.
486 The OMZ in the North Pacific is also more severe because there is a notable region with
487 zonal O₂ levels less than 30 μmol kg⁻¹ in the ~700 to ~1500 m layer. The OMZ90 in the
488 Indian Ocean extends from ~10°S to the northernmost end and is located from ~20 down to a
489 maximum depth of 1800 m. In the Atlantic Ocean, the OMZ90 is located within a 300-500 m
490 layer, with an area much smaller than that of the Pacific and Indian Oceans (**Table 2**).

491



492

493 **Figure 11** Comparison of zonal mean O₂ climatology (IAP climatology, unit: $\mu\text{mol kg}^{-1}$) in
 494 the (a) Global Ocean, (b) Pacific, (c) Atlantic, and (d) Indian oceans.

495

496 We also calculated the volume of OMZ60 and OMZ90 globally and for each basin in
 497 **Table 2** using six datasets, (excluding GOBAI and SJTU because their maximum depth only
 498 reaches about 2000 m below the ocean surface). The global volume of OMZ60 and OMZ90
 499 is generally consistent among the datasets, with a standard deviation of 1.95 % and 1.72 %
 500 across the products for OMZ60 and OMZ90, respectively. The Pacific Ocean contains most
 501 of the OMZ (83.05 % of the global OMZ60 and 81.29 % of the global OMZ90), with a
 502 standard deviation of 3.93 % and 2.37 % across the products. The Atlantic Ocean contains
 503 about 1.04 % and 2.38 % of the global OMZ60 and OMZ90, respectively, which is the lowest
 504 among the three ocean basins. The standard deviation is 20.24 % and 10.77 % for the Atlantic
 505 Ocean OMZ60 and OMZ90, respectively. The estimated OMZ for the Atlantic Ocean may be
 506 more sensitive to the horizontal resolution, mapping method and so on.

507

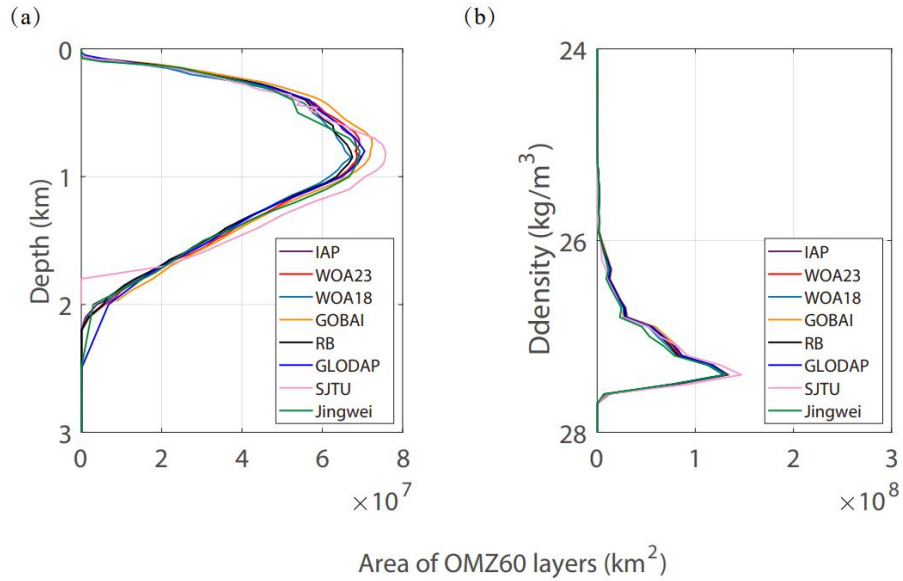
508 **Table 2** The volume of OMZ60 and OMZ90 calculated from the annual mean climatology
 509 for each basin and for different products. The values are in the units of 10^6 km^3 .

	OMZ60				OMZ90			
Datasets	Global	Pacific	Atlantic	Indian	Global	Pacific	Atlantic	Indian
IAP	81.76	68.98	0.85	11.91	152.78	125.56	3.83	23.36
WOA23	83.79	69.90	0.88	12.49	155.46	126.86	3.72	24.33
WOA18	79.42	66.71	0.74	11.46	152.23	124.93	3.50	23.28
RB	80.93	67.73	0.94	11.74	152.69	124.95	3.93	23.26
GLODAP	80.68	68.18	1.07	11.42	146.69	119.85	3.93	22.90
Jingwei	78.99	61.74	0.52	12.63	152.14	119.19	2.81	23.70
Mean	80.92	67.21	0.84	11.94	152.00	123.56	3.62	23.47
Standard Deviation	1.58	2.64	0.17	0.47	2.62	2.93	0.39	0.45

510
511

512 The OMZ areas as a function of depth and density are shown in **Fig. 12**. The density
513 layers are calculated with the Gibbs-SeaWater (GSW) Oceanographic Toolbox (IOC et al.,
514 2010; McDougall & Barker, 2011; Kwiecinski and Babbin, 2021), using the gridded
515 temperature and salinity climatology products of IAP (Cheng, et al., 2024). The maximum
516 OMZ60 area occurs at a depth of ~800 m and a density of 27.75 kg m⁻³ for all the datasets.
517 Most OMZ60s exist in the upper 2000 m. So that all the climatologies including GOBAI and
518 SJTU with the maximum depth of 2000 m could be involved in the analysis of OMZ areas at
519 depth levels. GOBAI and SJTU exhibit a larger OMZ60 volume within the upper 2000 m
520 compared to other products, and the maximum depth of SJTU OMZ60 is ~1700 m, which is
521 shallower than that of the other products. At density levels, the products are very consistent,
522 and SJTU shows a larger area of OMZ60 near the 27.4 kg m⁻³ level and Jingwei shows a
523 smaller area of OMZ60 near the 27 kg m⁻³ level.

524



525

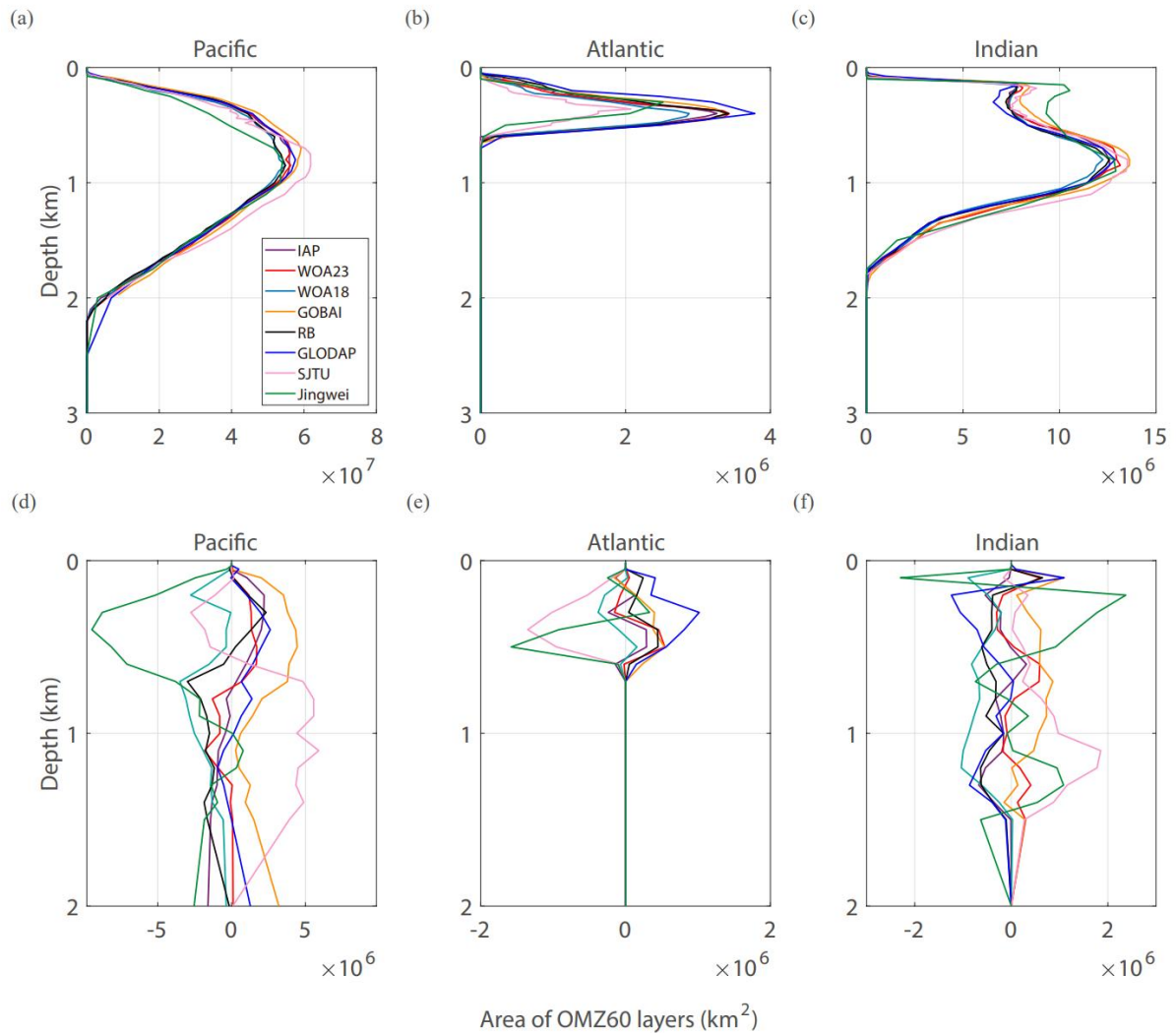
526 **Figure 12** The global horizontal area of OMZ60 in each interpolated layer with respect to

527

(a) depth and (b) density.

528

529 **Figure 11a-c** shows the horizontal OMZ60 area at depth levels for the Pacific, Atlantic,
 530 and Indian Ocean basins, respectively. Consistent with the volume assessment in Table 2, the
 531 Pacific Ocean contains the largest OMZ60 area, followed by the Indian and Atlantic Oceans.
 532 The maximum OMZ60 area occurs at a depth of about 800m in the Pacific and Indian
 533 Oceans, but at a much shallower depth of ~400 m in the Atlantic Ocean. Jingwei shows the
 534 largest difference from the other products in the Pacific and Indian Oceans at the upper 500
 535 m depth. SJTU shows a larger area of OMZ60 in the Pacific and Indian Oceans but a smaller
 536 area in the Atlantic Ocean than the other products (**Fig. 13**). Collectively, different products
 537 show a spread of $\pm 4 \times 10^6 \text{ km}^2$ for the Pacific OMZ60, $\pm 1 \times 10^6 \text{ km}^2$ for the Indian and
 538 Atlantic OMZ60 (**Fig. 13d-f**), except that Jingwei shows a very large difference of up to -9
 539 $\times 10^6 \text{ km}^2$ at the depth around 500m for the Pacific OMZ60 area compared to the ensemble
 540 mean (**Fig. 13d**).



541

542 **Figure 13** OMZ60 area for the Pacific, Atlantic, and Indian Ocean basins in units of 10^6 km^2 .

543 The upper row is the vertical distribution of the OMZ areas: (a) Pacific, (b) Atlantic, (c)
 544 Indian. The lower row is the differences in the OMZ areas relative to the ensemble mean: (d)
 545 Pacific, (e) Atlantic, (f) Indian.

546

547 **4 Conclusion**

548 Observationally-based gridded data products provide a basis for detecting and
 549 understanding ocean O_2 changes at various spatial and temporal scales. These observational
 550 datasets are also used to validate the computational ocean biogeochemistry and earth system
 551 models. This study provides a quantitative description of the O_2 climatology, annual cycle
 552 and OMZ distribution with eight O_2 data products. There have been several new O_2 data
 553 products developed in recent years, which makes this comparative analysis timely.

554 The global mean O_2 shows a well-established high-low-high vertical structure and a
 555 good consistency among all products. The global mean O_2 concentrations of the products

556 over depth generally agree within $\pm 3 \mu\text{mol kg}^{-1}$. Regionally, the gridded mean difference of
557 the 0-1000 m mean O_2 is mainly within $\sim 12 \mu\text{mol kg}^{-1}$. For the global 0-100 m O_2 annual
558 cycle, O_2 anomalies (differences from the annual mean) ranges from -1 to $0.8 \mu\text{mol kg}^{-1}$, but
559 the inter-products difference (defined by the standard deviation of four datasets that provide a
560 monthly climatology) can be as large as $\sim 0.3 \mu\text{mol kg}^{-1}$, indicating a similar signal-to-noise
561 ratio among the four datasets of monthly climatology. We also analyze the OMZ distribution
562 for different climatology datasets. Different products show a spread of $\pm 4 \times 10^6 \text{ km}^2$ for the
563 Pacific OMZ60 and $\pm 1 \times 10^6 \text{ km}^2$ for the Indian and Atlantic OMZ60.

564 The assessments presented in this study demonstrate the consistency and differences
565 among available products, supporting their future use. Substantial local differences ($\pm 25 \mu$
566 mol kg^{-1} for the upper 1000 m climatological mean) can be seen, which could influence the
567 baseline from which anomalies and trends are calculated and could give an insight into
568 regions that are relatively more sensitive in the process of gridded data reconstruction, such
569 as the subpolar North Pacific, the Southern Ocean fronts and the eastern Pacific regions close
570 to OMZ boundaries where the spatial O_2 gradient is large.

571 The overall spread across products results from all uncertainty sources (e.g.,
572 measurement errors, mapping errors, different time periods, etc.). Controlled
573 intercomparisons that isolate each error source are needed in the future to understand the
574 contribution of a single factor, especially in regions showing a large spread. It will eventually
575 help the community to improve the methodologies and reduce the spread in the future.
576 Another caveat is that only a limited number of products are included in this inter-
577 comparison. We hope to maintain and extend this activity in the future and serve as a regular
578 intercomparison exercise to provide critical information to the data users.

579

580 **Data availability**

581 All the gridded data products used in this study are available at:

582 GODIP-DO Group: Global Dissolved Oxygen Gridded Climatological Datasets, Zenodo[data
583 set], <https://doi.org/10.5281/zenodo.16664650>. 2025.

584

585 **Author contributions**

586 JD and LC-conceptualization, supervision, methodology; JD-formal analysis, visualization,
587 writing; JD, LC, HEG, ZW, JDS, CJR, YZ and BL-data curation; TI, HEG, ZW, JDS, GGN,
588 SMB and SM-writing.

589

590 **Competing interests**

591 The contact author has declared that none of the authors has any competing interests.

592

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