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## **Air-Sea fluxes of CO<sub>2</sub> in the Indian Ocean between 1985 and 2018: A synthesis based on Observation-based surface CO<sub>2</sub> , hindcast and atmospheric inversion models**

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1 **Air-Sea fluxes of CO<sub>2</sub> in the Indian Ocean between 1985 and 2018: A synthesis based on**  
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3

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23

24

25 **Abstract**

26

27 The Indian Ocean significantly influences the global carbon cycle but it is one of the  
28 undersampled regions in the global ocean with reference to surface ocean pCO<sub>2</sub>. As a part of  
29 the Regional Carbon Cycle Assessment and Processes-2 (RECCAP2) project, several  
30 approaches, such as interpolated observational climatology, hindcast model, observation-  
31 based surface CO<sub>2</sub> (empirical models), and atmospheric inversion models have been  
32 employed for estimating net sea-to-air CO<sub>2</sub> fluxes between 1985 and 2018. The seasonal,  
33 spatial and long-term variability in sea-to-air fluxes of CO<sub>2</sub> were compared with  
34 observational climatology. The mean value of CO<sub>2</sub> in the Indian Ocean (north of 37.5°S)  
35 using all models is estimated to be -0.19±0.1 PgC yr<sup>-1</sup> and it is consistent with the  
36 observational climatology (-0.07±0.14 PgC yr<sup>-1</sup>). The Indian Ocean north of 18°S is found to

37 be the mean annual source ( $0.04 \pm 0.05 \text{ PgC yr}^{-1}$ ) whereas a net sink ( $-0.23 \pm 0.11 \text{ PgC yr}^{-1}$ ) in  
38 the south of  $18^\circ\text{S}$ . All models captured observed spatial patterns but underestimated the net  
39 source of  $\text{CO}_2$  in the Oman/Somalia upwelling, the Equatorial Indian Ocean (EIO) and the  
40 Bay of Bengal (BoB) whereas  $\text{CO}_2$  sink is overestimated in the South Indian Ocean (SIO).  
41 Overall, all models captured the seasonality in  $\text{pCO}_2$  levels and  $\text{CO}_2$  fluxes but overestimated  
42 the amplitude of their variability. All models suggested the strengthening of the sink over the  
43 period between 1985 and 2018 by  $0.02 \text{ PgC yr}^{-1} \text{ decade}^{-1}$ . A significant increase in the  
44 collection of surface ocean  $\text{pCO}_2$  and atmospheric  $\text{CO}_2$  measurements improves the model  
45 simulations in the Indian Ocean.

46

47 Keywords: Surface  $\text{pCO}_2$ ;  $\text{CO}_2$  fluxes; Hindcast models; atmospheric inversions; Indian  
48 Ocean

49 **1. Introduction**

50

51 The atmospheric carbon dioxide (CO<sub>2</sub>) levels are ever increasing since the Industrial  
52 Revolution due to several anthropogenic activities such as fossil fuel burning and land-use  
53 changes. The enhanced anthropogenic activities led to the acceleration of the rate of CO<sub>2</sub>  
54 accumulation in the atmosphere from  $\sim 1.7 \pm 0.1$  PgC yr<sup>-1</sup> in the 1960s to  $5.3 \pm 0.1$  PgC yr<sup>-1</sup> in  
55 2021 (Friedlingstein et al., 2022). About half of the total anthropogenic emission remains in  
56 the atmosphere, and the remaining half is stored in the ocean and land (Canadell et al. 2021).  
57 According to the Global Carbon Project assessment of 2022, the ocean has taken up about  
58 28% ( $2.9 \pm 0.4$  PgC yr<sup>-1</sup>) of the total anthropogenic CO<sub>2</sub> emissions during 2021  
59 (Friedlingstein et al., 2022). It is also well established that the ocean carbon sink increased  
60 since the 60s with inter-annual variability (IAV) not fully captured by ocean models.

61

62 The Indian Ocean is a small basin compared to the other two major basins of the Pacific and  
63 Atlantic and has a unique geography as it is closed in the north at a low latitude. More than  
64 30% of the global population is dwelling along the Indian Ocean coast where rapid  
65 industrialization is taking place. As a result, the highest levels of aerosol optical depth (AOD)  
66 are observed over the northern Indian Ocean with the highest rate of increase over the globe  
67 (Zhang and Reid, 2010; Yadav et al., 2021). The northeastern Indian Ocean (Bay of Bengal;  
68 BoB) receives a significant amount of freshwater from major rivers, such as the Ganges,  
69 Brahmaputra, and Irrawaddy-Salween systems. The northern Indian Ocean experiences  
70 strong seasonality due to a change in direction of monsoonal wind resulting in a reversal in  
71 direction of surface currents (Schott and McCreary, 2001), which strongly modulates the  
72 biogeochemical cycling of carbon and nitrogen. The northern Indian Ocean is one of the most

73 productive regions in the globe and contributes up to 20% of global ocean primary  
74 productivity (Behrenfield and Falkowski, 1997).  
75  
76 Despite the importance of the Indian Ocean in the global carbon cycle, this region is poorly  
77 studied with reference to the biogeochemical cycling of carbon compared to the other two  
78 major basins. The seasonal cycle of pCO<sub>2</sub> and carbon fluxes was studied only in the Arabian  
79 Sea (George et al., 1994; Goyet et al., 1998; Sarma et al., 1998; 2003; 2013, De Verneil et al.,  
80 2022; Chakraborty et al., 2021), the BoB (Sarma et al., 2012; 2015; 2020; 2021; Chakraborty  
81 et al., 2021) and the south-western Indian ocean (Metzl et al., 1998) whereas the long-term  
82 variability was only recently studied in the southwestern Indian Ocean region (Metzl et al.,  
83 2022) as the other regions in the Indian Ocean was either sampled once or twice during last  
84 few decades (Takahashi et al., 2009; Sarma et al., 2013). The studies carried out in the aegis  
85 of the Joint Global Flux Study (JGOFS) and the Bay of Bengal Process Studies (BoBPS)  
86 suggested that the seasonal amplitude of pCO<sub>2</sub> goes beyond 200 µatm in the Arabian Sea  
87 (George et al., 1994; Goyet et al., 1998; Sarma et al., 1998; 2003) and BoB (Kumar et al.,  
88 1996; Sarma et al., 2012; 2015; 2019). The large amplitude of variability in pCO<sub>2</sub> is driven  
89 by variabilities in physical transport, such as upwelling, and convective mixing, in the  
90 Arabian Sea, whereas freshwater input by rivers and atmospheric pollutants deposition in the  
91 BoB (Sarma et al., 2000; 2012). River discharge displays significant inter-annual variability  
92 (Papa et al., 2012). Sarma et al. (2012) found that peninsular rivers bring acidic and high  
93 pCO<sub>2</sub> waters to the coast whereas glacial rivers, such as Ganges and Brahmaputra, bring  
94 relatively basic and low pCO<sub>2</sub> waters to the BoB. Therefore, the source of river water  
95 determines the direction of the flux of CO<sub>2</sub> at the air-sea interface. Kumar et al. (1996)  
96 suggested that the BoB is a sink for atmospheric CO<sub>2</sub> in the 1990s whereas Sarma et al.  
97 (2015; 2021) found that it is a mild source of the atmosphere due to the deposition of

98 atmospheric pollutants. More recently Sridevi and Sarma (2021) indicated that salinity in the  
99 surface waters of the BoB is decreasing over the past two decades due to an increase in the  
100 warming of Himalayan glaciers (Goes et al., 2020). Since the pH of the Ganges and  
101 Brahmaputra River waters are relatively basic (Sarma et al., 2012), an increase in pH and a  
102 decrease in pCO<sub>2</sub> was noticed in the past two decades in the central and eastern BoB (Sridevi  
103 and Sarma, 2021).

104

105 Unlike the other two major basins, upwelling is weak in the equatorial Indian Ocean due to  
106 the prevalence of westerly winds along the equatorial Indian Ocean (Schott et al., 2009). A  
107 flat thermocline is observed in the equatorial Indian Ocean in the east-west direction  
108 (Murtugudde and Bualacchi, 1999; Xie et al., 2002). The southern tropical and subtropical  
109 region is influenced by the inflow of Pacific waters from the Indonesian Through Flow (ITF)  
110 (Schott and McCreary, 2001). A major subduction zone occurs in the South Indian Ocean  
111 between 15 and 50°S due to positive wind stress curl (Schott et al., 2009). The subducted  
112 water masses are advected to the northern Indian Ocean (Miyama et al., 2003; Schott et al.,  
113 2002), carrying nutrients and anthropogenic CO<sub>2</sub> (Sabine et al., 1999). A perennial sink of  
114 atmospheric CO<sub>2</sub> was reported in the south Indian Ocean (SIO; Metzl et al., 1991; Poisson et  
115 al., 1993; Metzl et al., 1995; 1998; 2022; Metzl, 2009).

116

117 The Indian Ocean experiences strong zonal variability driven by the Indian Ocean  
118 Dipole/Zonal Mode (IOD/IODZM) in addition to El Nino-Southern Oscillation (ENSO) and  
119 the Southern Annular Mode (SAM) (Saji et al., 1999; Murthugude et al., 2000; Thompson  
120 and Solomon, 2002). These climate modes of variability modulate several physical and  
121 biogeochemical processes resulting in significant modifications in the CO<sub>2</sub> flux (Sarma 2006;  
122 Valsala et al., 2020). The influence of SAM was suggested in the SIO for the period 1991-

123 2007 with large spatial variability in CO<sub>2</sub> growth rate with lower rates in the north of 40°S  
124 than south of 40°S during austral winter but higher and uniform rates during austral summer  
125 (Metzl, 2009).

126

127 Gruber et al. (2009) identified a significant mismatch between top-down and bottom-up  
128 inversion in the tropical Indian Ocean and attributed it to a lack of atmospheric CO<sub>2</sub> data.  
129 Sarma et al. (2013) compared CO<sub>2</sub> fluxes from the Indian Ocean between 1990 and 2009  
130 using a suite of models (both ocean biogeochemistry and atmospheric inversions) under the  
131 aegis of the RECCAP1 project. For the band 30°N-44°S, the median annual sea-air CO<sub>2</sub> flux  
132 from models was  $-0.37 \pm 0.06$  PgC yr<sup>-1</sup> and it was consistent with  $-0.24 \pm 0.12$  PgC yr<sup>-1</sup> using  
133 observations. They further noticed that although all models captured the spatial patterns, CO<sub>2</sub>  
134 outgassing was underestimated in the upwelling region and overestimated sink in the BoB,  
135 whereas CO<sub>2</sub> uptake was underestimated in the subtropical convergence zone.

136

137 Recent use of regional models to study the dynamics of regional ecosystems and  
138 biogeochemical cycles in the Indian Ocean revealed an improved representation of key  
139 processes relative to global coarse resolution models. For instance, the representation of  
140 oxygen minimum zones (OMZ) in the northern Indian Ocean indicates large discrepancies  
141 with observations in both CMIP5 and CMIP6 global models, but shows a much-improved  
142 agreement with data in regional model simulations, both in terms of their structure, size and  
143 intensity (Bopp et al., 2013, Cocco et al., 2013, Kwiatkowski et al., 2020, Al Azhar et al.,  
144 2017, Lachkar et al., 2016, 2018, 2021). This was linked to the importance of eddy fluxes -  
145 typically inaccurately parameterized in global coarse-resolution models but resolved in finer-  
146 resolution regional models – in shaping OMZs (e.g., Lachkar et al., 2016, Bettencourt et al.,  
147 2015, Brandt et al., 2015, Chakraborty et al., 2019). Furthermore, accurately representing the

148 structure and intensity of these low-O<sub>2</sub> bodies in regional models is critical to represent their  
149 recent and future changes under ongoing climate change (Lachkar et al., 2021). Mesoscale  
150 eddies were also shown to have a significant impact on the carbon cycle in the northern  
151 Indian Ocean (Sarma et al., 2016; 2019; 2021). Additionally, significant improvements in  
152 parameterizations of river discharge, monsoon mixing and associated biological response in  
153 the high-resolution regional models lead to a better representation of the upper ocean cycle in  
154 the regional models (Chakraborty et al., 2018; 2021; Ghosh et al., 2022; Valsala et al., 2021).  
155 Therefore, eddy-resolving regional models may lead to an improved representation of the  
156 carbon cycle in the region. This work aims to evaluate the net air-sea CO<sub>2</sub> fluxes by different  
157 global and regional models and quantify how these simulated net CO<sub>2</sub> fluxes in the Indian  
158 Ocean are comparable with observational climatology and identify potential reasons for  
159 deviations, if any, in the Indian Ocean.

160

## 161 **2. Methods**

162

### 163 2.1. Study region

164

165 Based on the RECCAP2 regional definitions, the entire Indian Ocean, north of 37.5°S, was  
166 considered as one region. Due to the complexity of the regional physical processes in the  
167 Indian Ocean, we define here the following five regions for analysis: i) the entire Indian  
168 Ocean (30°N-37.5°S), ii) the Arabian Sea (0-30°N; 38-78°E), iii) the Bay of Bengal (BoB; 0-  
169 30°N; 78-110°E), iv) Equatorial Indian Ocean (EIO; 0-18°S) and v) South Indian Ocean (SIO;  
170 18°S-37.5°S) (Figure 1a).

171

### 172 2.2 Data sets



173

174 To describe the regional CO<sub>2</sub> fluxes for the Indian Ocean, RECCAP2 global CO<sub>2</sub> flux  
175 products were used that include observations (climatology referenced to the year 2000;  
176 Takahashi et al., 2009), Global hindcast (GHM), regional hindcast (RHM) models,  
177 observation-based (empirical) surface pCO<sub>2</sub> models and atmospheric inversion models.

178

#### 179 2.2.1. Observational climatology

180

181 The Indian Ocean is one of the least sampled basins in the world ocean for surface pCO<sub>2</sub>  
182 measurements with reference to space and time (Figure 1b; Bakker et al., 2016). The major  
183 addition of data was done during 1990-1999 whereas in the next decade (2000-2009) some  
184 data were added in the SIO and one transect in the BoB and good coverage of the Bay was  
185 done in 2010-2019 (Bakker et al., 2020; Supplementary Figure S1). Within the Indian Ocean,  
186 the seasonal and inter-annual pCO<sub>2</sub> data are available in the western basin (the Arabian Sea  
187 and the southwestern Indian Ocean). In contrast, only 2 to 3 times were sampled in the  
188 eastern basin (Supplementary Figure S1). In addition to this, time-series pCO<sub>2</sub> (water and air)  
189 data are available in the central BoB, as a part of the RAMA (Moored array for African-  
190 Asian-Australian Monsoon Analysis and Prediction) buoy program (BOBOA, Sutton et al,  
191 2019), from 2013 onwards (Figure 1). Nevertheless, understanding seasonality in pCO<sub>2</sub> is a  
192 challenge in the Indian Ocean due to the weak spatial and seasonal data coverage. Takahashi  
193 et al. (2009) (Figure 1c) compiled the available pCO<sub>2</sub> data in the Indian Ocean and gridded it  
194 to 4° x 5° using two-dimensional advection-diffusion equations to interpolate with reference  
195 to space and time. The major challenge here is that the observations (henceforth called  
196 climatology) are not absolutely observations alone but were interpolated in the regions where  
197 data were unavailable. There is uncertainty associated with the techniques used for

198 developing climatology. Due to the lack of seasonal data in some regions, the seasonality  
199 shown in the data is significantly driven by the model used to interpolate. However, the  
200 performance of the seasonality driven by the model used to derive climatology is tested using  
201 pCO<sub>2</sub> data generated by the BOBOA buoy in the central BoB. Nevertheless, the observed  
202 CO<sub>2</sub> fluxes carry several errors due to sparse coverage of data, wind speed measurements and  
203 transfer velocity parameterizations and the uncertainty of the CO<sub>2</sub> fluxes is about 50%  
204 (Gruber et al., 2009).

205

206 Since RECCAP1 (Sarma et al., 2013) important progress has been made on both pCO<sub>2</sub> data  
207 delivery each year in the public domain for updating SOCAT data-product ([www.socat.info](http://www.socat.info),  
208 Pfeil et al., 2013; Bakker et al., 2014, 2016) and the development of empirical methods that  
209 reconstruct pCO<sub>2</sub> fields, including in synthesis studies (SOCOM project, Rödenbeck et al.,  
210 2015). Here we used 9 empirical methods based on the SOCAT data (version v2020) and to  
211 compare our new results with RECCAP1, we also used the original climatology of Takahashi  
212 et al (2009) (Figure 1c). Recall that climatology was constructed for the reference year 2000  
213 which would have to be taken into account when comparing pCO<sub>2</sub> fields for the recent year.  
214 However, this would not dramatically impact the mean CO<sub>2</sub> fluxes assuming that over 1985-  
215 2018 ocean pCO<sub>2</sub> increase is close to the atmospheric growth rate as observed in some parts  
216 of the Indian Ocean (e.g. Metzl, 2009; Lauvset et al., 2015; Metzl et al., 2022; Lo Monaco et  
217 al., 2021).

218

### 219 2.2.2. Ocean Hindcast models

220

221 CO<sub>2</sub> fluxes and surface water pCO<sub>2</sub> data were obtained from 12 GHM and 2 RHM (Table 1).

222 These models represent physical, chemical and biological processes controlling the marine

223 carbon cycling and exchange of CO<sub>2</sub> at the sea-to-atmosphere interface. The GHM have a  
224 coarse or an eddy-permitting horizontal resolution whereas RHM is eddy-resolving (Table 1).  
225 The simulations are forced with meteorological reanalysis products, given in Table 1. The  
226 models were run for different periods mostly between 1980 and 2019 with the period of each  
227 model given in Table 1. In order to make it uniform for all models, we have considered the  
228 runs between 1985 and 2018 in this study that gives the reference year of 2002. GHM and  
229 RHM have been integrated from the pre-industrial period to the present day with the same  
230 atmospheric CO<sub>2</sub> history. Although the model simulations were carried out following the  
231 RECCAP2 ocean modelling protocol, each model is different from others with respect to  
232 forcing, experimental configuration, representation of biogeochemical processes and sub-grid  
233 parameterizations (Table 1).

234

#### 235 2.2.4. Atmospheric inversions

236

237 Atmospheric inversions (top-down) estimate the surface CO<sub>2</sub> fluxes based on the variability  
238 in the measured atmospheric CO<sub>2</sub> using an atmospheric transport model. In the atmospheric  
239 inversion models, a priori information about the surface CO<sub>2</sub> fluxes is used from bottom-up  
240 estimates (e.g., Takahashi et al., 2009) or an ocean GHM or an empirical upscaling model. In  
241 the Indian Ocean region and surrounding, atmospheric CO<sub>2</sub> measurements are available from  
242 only 8 sites that are used in the atmospheric inversion models. Among them, only two  
243 stations have long-record and others have short records. However, most inversions did not  
244 correct the oceanic prior fluxes significantly when the empirical upscaling model fluxes were  
245 used. Here we have chosen to show sea-air CO<sub>2</sub> fluxes from inversion models, one using  
246 prior flux from Takahashi et al. (2009) in the MIROC4-ACTM system (Chandra et al., 2022)  
247 and the other model (CAMsv20r1) using prior fluxes from an empirical model (Chevallier et

248 al., 2005). The atmospheric inversion model runs are available between 2001 and 2018 which  
249 gives the reference year of 2009.

250

251 2.2.5. Observation-based Surface pCO<sub>2</sub> (Empirical models)

252

253 Global sea-air CO<sub>2</sub> fluxes can also be estimated from pCO<sub>2</sub> measurements along the ship  
254 tracks over the past several decades. The first and simple upscaling method was implemented  
255 by Takahashi et al. (2009) where all the past measurements of CO<sub>2</sub> are separated in monthly-  
256 mean flux maps based on SST and salinity. This method relied on the extrapolation of  
257 Delta\_pCO<sub>2</sub> data from limited measurements along the cruise tracks to the global ocean. With  
258 the development of neural networks and other artificial intelligence tools and organised  
259 archival of the SOCAT CO<sub>2</sub> database, several methods are now implemented to calculate  
260 gridded CO<sub>2</sub> flux including the interannual variation, taking into account the physical state of  
261 sea-surface conditions (Table 2; Rödenbeck et al., 2015; Landschützer et al., 2016; Fay et al.,  
262 2021). The estimated CO<sub>2</sub> fluxes between 1985 and 2018 were considered in this study with  
263 the reference year of 2002.

264

### 265 **3. Results and Discussion**

266

267 The simulations of CO<sub>2</sub> uptake by the Indian Ocean by GHM, RHM, empirical and  
268 atmospheric inversion models are compared with climatology with reference to (i) annual, (ii)  
269 seasonal and (iii) interannual timescales.

270

271 3.1. Annual mean CO<sub>2</sub> fluxes in the Indian Ocean between 1985 and 2018

272

273 3.1.1. Tropical Indian Ocean (north of the 37.5°S)

274

275 The annual mean sea-air CO<sub>2</sub> fluxes for 1985 to 2018 are presented in Table 3 and Figure 1d  
276 for the entire Indian Ocean (37.5°S –30°N; 25-125°E), Arabian Sea (30-78°E and 0-30°N),  
277 BoB (78-110°E and 0-30°N), EIO (30-125°E, 0-17°S) and SIO (37.5-17°S and 25-130°E).

278 The spatial variability in mean annual uptake for the entire Indian Ocean by GHM and RHM  
279 (Figure 2), empirical (Figure 3) and atmospheric models (Figure 4) are given to evaluate the  
280 spatial variability in CO<sub>2</sub> fluxes.

281

282 The simulated mean annual CO<sub>2</sub> sea–air fluxes by different models varied between -0.27 and  
283 -0.13 PgC yr<sup>-1</sup> for the Indian Ocean (Table 3), with a relatively lower sink estimated by  
284 empirical models (-0.13±0.04 PgC yr<sup>-1</sup>) than hindcast (-0.21±0.10 PgC yr<sup>-1</sup>) and  
285 atmospheric inversion models (-0.27±0.16 PgC yr<sup>-1</sup>). Both hindcast and atmospheric  
286 inversion models overestimated the sink of CO<sub>2</sub> by 3 times that of climatology (-0.07±0.14  
287 PgC yr<sup>-1</sup>) whereas empirical models are close to the observations. The observational pattern  
288 of CO<sub>2</sub> flux shows that the SIO is a dominant sink whereas the Arabian Sea is a strong source  
289 while EIO and the BoB are weak sources of atmospheric CO<sub>2</sub>. All models simulated similar  
290 patterns of spatial variations of the CO<sub>2</sub> fluxes (Figures 2 to 4) that are in agreement with  
291 observations, but the magnitudes of fluxes are different. For instance, the modelled CO<sub>2</sub>  
292 fluxes were spread around the climatological values with relative overestimation of the sink  
293 in the south of 22°S, in contrast, underestimation of the source was noticed by all models in  
294 the north of 22°S in the Indian Ocean. In contrast, the RHM (both INCOIS-BIO-ROMS and  
295 ROMS\_NYUAD) reproduced CO<sub>2</sub> fluxes well in comparison with the climatology. Since the  
296 ROMS\_NYUAD model simulation was submitted up to 31.5°S only, we did not include it in  
297 the SIO region as it was considered up to 37.5°S for other models. Similarly, the simulated

298 CO<sub>2</sub> fluxes by empirical models are in good agreement with the climatology (Figure 3). In the  
299 case of the atmospheric inversions, a higher CO<sub>2</sub> sink in the south of 15°S whereas sources of  
300 CO<sub>2</sub> in the north of 15°S than the observational climatology was observed (Figure 4). The  
301 CO<sub>2</sub> fluxes by all models are in near perfect agreement with each other for the entire Indian  
302 Ocean within the standard deviation of the estimates, however, they are different on the  
303 regional subdivisions such as the Arabian Sea, BoB, EIO and SIO.

304

305 The standard deviation for the atmospheric inversion was large in the annual uptake (-  
306  $0.27 \pm 0.16$  PgC yr<sup>-1</sup>) while the smallest for the empirical models ( $-0.13 \pm 0.04$  PgC yr<sup>-1</sup>; Table  
307 3). The highest standard deviation in the atmospheric inversion comes from the sparse  
308 atmospheric CO<sub>2</sub> measurements, transport model uncertainties and differences in the prior  
309 flux assumptions for the Indian Ocean. The atmospheric CO<sub>2</sub> time series data are available  
310 only at 8 locations within the Indian Ocean resulting in high variability in the estimates. The  
311 climatology also has a very high standard deviation ( $-0.07 \pm 0.14$  PgC yr<sup>-1</sup>) due to a lack of  
312 enough data in the Indian Ocean as most of the Indian Ocean region is either sampled once or  
313 twice and inter and extrapolation of the data (Takahashi et al., 2009).

314

315 The zonal integrated CO<sub>2</sub> fluxes by different models are given in Figure 5 and it shows that  
316 most of the GHM underestimated CO<sub>2</sub> sink in the south of 25°S whereas over estimated north  
317 of 25°S. The RHM (INCOIS-BIO-ROMS and ROMS\_NYUAD) simulated exceptionally  
318 well the zonal mean CO<sub>2</sub> fluxes in the Indian Ocean between 37.5°S and 27.5°N. However, a  
319 slight underestimation was noticed for both the RHM and GHM in the north of 5°N (Figure  
320 5a). In the case of empirical models (Figure 5b), Jena-MLS, JMAMLR and UOEX\_WAT20  
321 were over-estimated in the south of 15°S and well performed in the north of 15°S with  
322 reference to climatology. In the case of atmospheric inversions, a stronger sink is noticed in

323 the south of 15°S and a stronger source in the north of 10°S, compared to the empirical and  
324 hindcast models (Figure 5c).

325

326 Both spatial variations and zonal integration in the CO<sub>2</sub> fluxes (Figures 2-5) suggest that the  
327 model simulations significantly deviated from the climatology at several zones, namely the  
328 Oman/Somali upwelling region in the Arabian Sea, freshwater discharge region in the BoB,  
329 equatorial upwelling region and south equatorial current (SEC) and subtropical convergence  
330 zone regions in the southern tropical Indian Ocean. The potential reasons responsible for the  
331 regional variations in the CO<sub>2</sub> fluxes were discussed in detail below.

332

### 333 **3.1.2. Northwestern Indian Ocean (Arabian Sea)**

334

335 The Arabian Sea is simulated as a net source of CO<sub>2</sub> to the atmosphere by the hindcast  
336 models (0.006 to 0.058 PgC yr<sup>-1</sup> with a mean of 0.03±0.01 PgC yr<sup>-1</sup>), empirical models  
337 (0.052 to 0.098 with a mean of 0.08±0.01 PgC yr<sup>-1</sup>) and atmospheric inversions (0.16±0.12  
338 PgC yr<sup>-1</sup>; Table 3) and it is consistent with the observations (Sarma, 2003; Goyet et al., 1998;  
339 Millero et al., 1998) and climatological fluxes (0.08±0.06 PgC yr<sup>-1</sup>) (Table 3). Considering  
340 the standard deviation of climatology, and models, the mean of all modelled fluxes in the  
341 Arabian Sea (0.06±0.05 PgC yr<sup>-1</sup>) is close to that of climatology (0.08±0.06 PgC yr<sup>-1</sup>; Table  
342 3). The large source of CO<sub>2</sub> to the atmosphere from the Indian Ocean is driven by the  
343 upwelling off Oman/Somali coasts, where pCO<sub>2</sub> levels as high as >600 µatm were reported  
344 during the peak southwest monsoon period (Körtzinger et al., 1997; Goyet et al., 1998; Sarma,  
345 2003; Sabine et al., 2000). Most of the models poorly simulated CO<sub>2</sub> fluxes in the  
346 Oman/Somali upwelling region (Figures 2-4). Within the hindcast models, both MRI-ESM2-  
347 1 and ROMS\_NYUAD models simulated CO<sub>2</sub> fluxes close to the observations (Figure 2).

348

349 The simulation of upwelling in the Arabian Sea may be a challenge due to the complex  
350 interplay of winds, bottom topography, monsoonal circulation and mixing, to capture the  
351 observed response by the models. The monsoon mixing is intense during summer (June to  
352 September) resulting in high pCO<sub>2</sub> levels in the entire Arabian Sea with maximum off Oman  
353 and Somalia coasts (Sarma et al., 1996; 1998; Goyet et al., 1998; Körtzinger et al., 1997). It  
354 was estimated that the mixing effect is a dominant controlling factor of surface ocean pCO<sub>2</sub>  
355 in the Arabian Sea during the monsoon period while biological effect, mainly bacterial  
356 degradation, dominates during the non-monsoon period (Louanchi et al., 1996; Sarma et al.,  
357 2000). All hindcast models failed to simulate the monsoon mixing well resulting in weaker  
358 fluxes of CO<sub>2</sub> (Figure 2) to the atmosphere. Since empirical models are mainly driven by  
359 observations, they could simulate the impact of upwelling on pCO<sub>2</sub> reasonably well (Fig. 3).  
360 In the case of atmospheric models, MACTM over-estimated coastal upwelling whereas  
361 CAMSv20r1 remained close to that of the prior flux field from CEMES\_LSCE\_FFNN  
362 (Figure 4). Sarma et al. (2013) noticed weak mixing in the GHM, and ocean inversion models  
363 in the Arabian Sea between 1990 and 2009 and no improvements were noticed with reference  
364 to mixing in the Arabian Sea in the past decade.

365

366 To examine the variability in the simulation of mixing in the Oman/Somalia upwelling  
367 regions by different GHM and RHM, the sea surface temperature (SST) simulated by the  
368 hindcast models was compared (Supplementary Figure S2). All models simulated upwelling  
369 features off Oman/Somalia region, however, the intensity of mixing was different among  
370 models, as reflected in the SST. It was noticed that mixing was weaker in CCSM-WHOI, EC-  
371 Earth3, MOM6-Princeton, NorESM-OC1.2, ORCA025-GEOMAR and Planktom12 models  
372 than in other GHM as former models showed relatively warmer SSTs than later models



373 compared to the climatology. Since a significant amount of data was contributed to the  
374 climatology from the Oman/Somali upwelling region, we can confidently attribute that the  
375 mixing and pCO<sub>2</sub> input from the subsurface layers in the Oman/Somalia upwelling region  
376 needs to be improved in the GHM for accurate simulations.

377

### 378 3.1.3. Northeastern Indian Ocean (Bay of Bengal)

379

380 All models simulated that the BoB is a mild source of CO<sub>2</sub> (0.00 to 0.01 PgC yr<sup>-1</sup> with a  
381 mean of 0.00±0.01 PgC yr<sup>-1</sup>) and it is consistent with the climatology (0.01±0.01 PgC yr<sup>-1</sup>;  
382 Takahashi et al., 2009; Table 3). Sarma et al. (2012) reported that the peninsular river  
383 discharge increased the pCO<sub>2</sub> levels whereas glacial rivers (Ganges and Brahmaputra)  
384 discharge decrease the pCO<sub>2</sub> levels (Kumar et al., 1996; Mukhopadhyay et al., 2002). More  
385 recently Sarma et al. (2019) reported that cyclonic eddies enhance pCO<sub>2</sub> levels due to  
386 upwelling in the core of the eddy while anticyclonic eddies sink for atmospheric CO<sub>2</sub>. Several  
387 recent investigations suggested that rapid acidification is being occurred in the BoB due to  
388 the deposition of atmospheric pollutants (Sarma et al., 2015; 2021; Kumari et al., 2022a,b)  
389 leading to an increase in pCO<sub>2</sub> levels. Unfortunately, neither GHM nor RHM has the  
390 atmospheric component to consider its impact.

391

392 Since river discharge enhances the CO<sub>2</sub> sink to the BoB, the differences in the sink of CO<sub>2</sub> in  
393 the BoB may be caused by variable use of river discharge data as this would influence the  
394 salinity of the upper ocean in the BoB. The existence of a strong linear relationship between  
395 salinity and pCO<sub>2</sub> levels was reported in the BoB (Kumar et al., 1996; Sarma et al., 2012;  
396 2021). Recently, Sridevi and Sarma (2021) observed decreasing trends in surface pCO<sub>2</sub> levels  
397 due to a decrease in salinity over the past two decades due to the warming of Himalayan

398 glaciers (Goes et al., 2020). Therefore, salinity is a crucial parameter in controlling the pCO<sub>2</sub>  
399 levels in the BoB.

400

401 To examine this, the salinity simulations by different models were examined (Supplementary  
402 Figure S3). All GHM simulated low salinity in the northern Bay but the magnitude of salinity  
403 is different in the north of 15°N. The lower salinity in the northern Bay was simulated in  
404 CCSM-WHOI, MOM6-Princeton and ORCA1-LIM3-PISCES, whereas relatively high  
405 salinity was simulated in CNRM-ESM2-1 and Planktom12. However, the sink in CO<sub>2</sub> was  
406 observed in both high and low-salinity simulated models suggesting that variability in the  
407 sink of CO<sub>2</sub> is not caused by river discharge/salinity in the GHM. An insignificant  
408 relationship was observed between salinity and pCO<sub>2</sub> levels among different GHM and RHM  
409 in the northern BoB (Figure is not shown) suggesting salinity or river discharge may not be a  
410 controlling factor on variable CO<sub>2</sub> fluxes in the BoB. The absence of a relationship between  
411 salinity and pCO<sub>2</sub> levels in the models suggests that the role of freshening surface waters by  
412 rivers was not well constrained in the hindcast models.

413

#### 414 3.1.4. Equatorial Indian Ocean (EIO)

415

416 The empirical models ( $0.02 \pm 0.02$  PgC yr<sup>-1</sup>) and atmospheric inversions models ( $0.02 \pm 0.03$   
417 PgC yr<sup>-1</sup>) simulated a mild source of the atmospheric CO<sub>2</sub> and it is consistent with the  
418 climatology ( $0.04 \pm 0.03$  PgC yr<sup>-1</sup>), in contrast, hindcast models estimated sink ( $-0.05 \pm 0.04$   
419 PgC yr<sup>-1</sup>) in the EIO. All models simulated that the western equatorial Indian Ocean is a  
420 source whereas the eastern region is either a sink or close to balance. The higher sink  
421 simulated by GHM is caused by weaker Somalia upwelling as discussed in section 3.1.2.  
422 RHM simulated that the equatorial Indian Ocean is a mild source of atmospheric CO<sub>2</sub>

423 (0.01±0.06 and 0.03±0.08 PgC yr<sup>-1</sup> by ROMS-NYUAD and INCOIS-BIO-ROMS  
424 respectively). This can be noticed from the spatial distribution of SST, which is relatively  
425 warmer in the GHM in the western equatorial region compared to the RHM (Supplementary  
426 Figure S4) suggesting better simulation of upwelling in the RHMs. The spatial variations in  
427 CO<sub>2</sub> fluxes by RHM and atmospheric inversions (Figures 2 and 4) are consistent with the  
428 observations in the EIO region (Figure 1c).

429

### 430 3.1.5. The South Indian Ocean (SIO)

431

432 The SIO comprises two key oceanographic regimes of oligotrophic waters in the north and  
433 Southern Ocean waters in the south. These two regions are separated by the subtropical front  
434 (STF). We have considered the STF region as part of the SIO in this study. The estimated  
435 mean fluxes in this region by all models are -0.23±0.11 PgC yr<sup>-1</sup> suggesting a strong sink of  
436 atmospheric CO<sub>2</sub> that agrees well with climatology (-0.20±0.16 PgC yr<sup>-1</sup>; Table 3). The  
437 atmospheric inversions estimated a larger sink (-0.46±0.3 PgC yr<sup>-1</sup>), which is mainly caused  
438 by MATCM whereas the CAMSv20r1 model performed well by staying close to the prior  
439 model. Despite atmospheric observations available in the SIO at Amsterdam Island at 38°S,  
440 the overestimation of the sink by the atmospheric model must be examined. Both empirical  
441 models (-0.22±0.04 PgC yr<sup>-1</sup>) and hindcast models, including RHM, (-0.20±0.07 PgC yr<sup>-1</sup>)  
442 estimated CO<sub>2</sub> fluxes close to that of climatology (-0.22±0.04 PgC yr<sup>-1</sup>). The CO<sub>2</sub> fluxes in  
443 the SIO are closer in magnitude to the annual uptake for the entire Indian Ocean (-0.19±0.1  
444 PgC yr<sup>-1</sup>) indicating that the majority of the net uptake of CO<sub>2</sub> occurs in the SIO, as suggested  
445 by other studies (Sabine et al., 2000; Bates et al., 2006; Metzl, 2009; Takahashi et al., 2009;  
446 Sarma et al., 2013).

447

448 The spatial variability in the magnitude of CO<sub>2</sub> flux within the SIO was variable among  
449 hindcast models (Figure 2) in comparison to climatology (Figure 1c). For instance, the  
450 climatology suggests a strong sink between 15°S and 35°S whereas the sink was simulated by  
451 most of the hindcast models between 10°S and 25°S. Sabine et al. (1999) observed the highest  
452 concentration and deepest penetration of anthropogenic carbon in the subtropical  
453 convergence zone (30-40°S). In contrast, a mild source is simulated by most of the models in  
454 the south of 30°S suggesting that the sink was underestimated in this zone. The outcropping  
455 of these density surfaces and the subsequent sinking of surface waters provide a pathway for  
456 excess CO<sub>2</sub> to enter the interior of the ocean. Overestimation of the CO<sub>2</sub> uptake by the  
457 models in these zones suggests that vertical mixing was not constrained properly in the  
458 models, leading to excess deep mixing, which increased surface water pCO<sub>2</sub> and a decrease in  
459 the flux of the ocean (Figure 2).

460

### 461 3.2. Seasonal variations in pCO<sub>2</sub> levels and air-sea CO<sub>2</sub> fluxes in the Indian Ocean

462

463 To examine the seasonal variability of CO<sub>2</sub> fluxes by various modelling approaches, the  
464 simulated surface pCO<sub>2</sub> levels and CO<sub>2</sub> fluxes were analysed (Figure 6). This provides  
465 insights into the ability of the models to represent the complex interplay of physical and  
466 biological processes on pCO<sub>2</sub> levels and sea-air CO<sub>2</sub> exchange. The ability of a model to  
467 reproduce the seasonal cycle also provides some reassurance that the models are correctly  
468 projecting climate sensitivity of the processes that could influence long-term projections of  
469 the ocean CO<sub>2</sub> uptake (Fig. 6).

470

#### 471 3.2.1. The Entire Indian Ocean

472

473 The increase in pCO<sub>2</sub> levels is expected in the tropical Indian Ocean between June and  
474 September due to an increase in mixing driven by the southwest monsoon in the north  
475 whereas deeper mixing in the SIO (Louanchi et al., 1996; Sarma et al., 2000; Sabine et al.,  
476 2000; Bates et al., 2006). All hindcast models overestimated the sink between June and  
477 September but were close to observation during other months (Fig. 6) due to weak mixing of  
478 pCO<sub>2</sub>-rich subsurface waters with surface. Among the other models, ROMS-NYUAD and  
479 MPIOM-HAMOCC displayed relatively better seasonality in CO<sub>2</sub> fluxes compared to  
480 climatology (Figure S5). The mean empirical models followed seasonality close to that of  
481 observations. The atmospheric inversions overestimated the sink from March to October  
482 mainly in the SIO compared to other models and climatology. Since the seasonality in CO<sub>2</sub>  
483 fluxes is variable with space, the same in different regions of the Indian Ocean are examined.

484

### 485 3.2.2. Northwestern Indian Ocean (Arabian Sea)

486

487 The Arabian Sea shows strong seasonality with higher CO<sub>2</sub> fluxes from June to September  
488 associated with monsoon mixing and high winds compared to other seasons (George et al.,  
489 1994; Sarma et al., 1996; 1998; Sarma, 2003). The climatological amplitude of seasonality  
490 was close to 0.2 PgC yr<sup>-1</sup> with a maximum in June-August and a minimum in October-  
491 December (Figure 6). The seasonality was perfectly captured by the empirical models  
492 whereas atmospheric inversion and hindcast models failed to simulate as they over and  
493 underestimated respectively. Though atmospheric inversion models mostly captured the high  
494 CO<sub>2</sub> fluxes to the atmosphere from June to August but with a large spread compared to other  
495 simulations by hindcast and empirical models. In contrast, hindcast models showed a  
496 response but it was strongly out of phase with the observations by giving maximum fluxes in  
497 May to June and minimum fluxes in July to September with approximately 3-4 months ahead

498 of the climatological peak in CO<sub>2</sub> fluxes. The two GHM (MRI-ESM2-1 and NorESM-OC1.2)  
499 and RHM (ROMS-NYUAD) simulated peak fluxes between June and August in the Arabian  
500 Sea (Figure S5).

501

502 All GHM failed to simulate seasonality in pCO<sub>2</sub> (Figure 6) levels as the higher pCO<sub>2</sub> levels  
503 were observed during July to September in the observations whereas April to May in the  
504 models. High pCO<sub>2</sub> levels were reported from June to August due to enhanced vertical  
505 mixing caused by monsoon winds in the Arabian Sea (Sarma et al., 1996; 1998; Körtzinger et  
506 al., 1997; Millero et al., 1998; Sarma, 2003). Sarma et al. (2000) observed that mixing is the  
507 dominant controlling factor of pCO<sub>2</sub> levels from June to August in the Arabian Sea followed  
508 by biological effects (Louanchi et al., 1996; Goyet et al., 1998). The difference in pCO<sub>2</sub>  
509 levels between mean hindcast models and observations varied between 15 and 50 µatm  
510 whereas it was <20 µatm in the case of empirical models (Figure 6). The reference year for  
511 climatology is 2000 (Takahashi et al., 2009) whereas the reference year for hindcast and  
512 empirical models are 2002 (1985-2018). The difference in pCO<sub>2</sub> levels caused by variable  
513 reference year may differ up to 4 µatm considering the 2 µatm/y as a growth rate of surface  
514 ocean pCO<sub>2</sub> (Metzl, 2009) suggesting that weaker mixing in the models underestimated the  
515 seasonality in pCO<sub>2</sub> and CO<sub>2</sub> fluxes in the Indian Ocean.

516

517 3.2.3. Northeastern Indian Ocean (Bay of Bengal; BoB)

518

519 The BoB also displayed large seasonality with higher CO<sub>2</sub> fluxes from May to August  
520 associated with monsoon mixing and decreased between October and December due to river  
521 discharge and stratification (Figure 6; Sarma et al., 2016; 2018; 2019). All models simulated  
522 high CO<sub>2</sub> fluxes during May but decreased to low by July-August (Figure 6). The observed

523 amplitude of seasonality was close to  $0.02 \text{ PgC yr}^{-1}$  with the maximum in May-June ( $0.02$   
524  $\text{PgC yr}^{-1}$ ) and minimum in February ( $0 \text{ PgC yr}^{-1}$ ). The mean hindcast models simulated  
525 similar amplitude ( $0.02 \text{ PgC yr}^{-1}$ ) but they showed sink ( $0$  and  $-0.02 \text{ PgC yr}^{-1}$ ) instead of  
526 source in the climatology. The atmospheric inversion models displayed too low (high sink  
527 during February) and high source from August to October.

528

529 All GHM simulate seasonality in  $\text{pCO}_2$  levels in the BoB with a maximum in April and May  
530 and a minimum in February (Figure 6). The magnitude of seasonal variability in  $\text{pCO}_2$  is  $\sim 15$   
531  $\mu\text{atm}$  in the climatology whereas hindcast models simulated  $15\text{-}40 \mu\text{atm}$  with lower  
532 variability ( $<20 \mu\text{atm}$ ) during April and May and higher ( $>35 \mu\text{atm}$ ) during other months. The  
533 underestimation of  $\text{pCO}_2$  in the BoB may be caused by strong stratification in the model  
534 leading to lower input from  $\text{pCO}_2$ -rich subsurface waters. In addition to this, the difference  
535 between simulations and observation may also be caused by the lack of enough data in the  
536 observations as the BoB is severely under-sampled with reference to seasons. To resolve this  
537 issue, the  $\text{pCO}_2$  data collected by the BOBOA mooring buoy in the central BoB (Figure 1a) is  
538 used for comparison. This buoy collected data between 2013 and 2018 (Sutton et al 2019)  
539 and the monthly climatology of this data was compared with Takahashi climatology. The  
540 BOBOA climatology showed an increase in  $\text{pCO}_2$  starting in April with a peak in May  
541 whereas Takahashi climatology displayed during April suggesting that Takahashi  
542 climatology well reproduced the observed seasonality although the climatology was not  
543 constrained with BOBOA data. Most of the hindcast models displayed peaks in April-May in  
544 the BoB and were also consistent with the climatology (Figure S5).

545

546 3.2.4. Equatorial Indian Ocean (EIO)

547

548 The CO<sub>2</sub> fluxes in the EIO displayed seasonality with high fluxes from January to May and  
549 low from June to October with a minimum in August (Figure 6). The mean observed CO<sub>2</sub>  
550 fluxes are the source of the atmosphere during all seasons whereas all hindcast models  
551 simulated sink, especially between May and November. All models displayed similar  
552 seasonal variability in CO<sub>2</sub> fluxes but underestimated from May to November. The RHM  
553 simulated better seasonality in the CO<sub>2</sub> fluxes compared to GHM (Figure S5).

554

555 The EIO displays relatively weak pCO<sub>2</sub> seasonality with a high from February to April and a  
556 low from June to October. The amplitude of seasonality in pCO<sub>2</sub> was <10 µatm in the  
557 climatology. All models simulated the seasonality but they were under-estimated pCO<sub>2</sub> by  
558 ~20 µatm from that of climatology (Figure 6).

559

### 560 3.2.5. The South Indian Ocean (SIO)

561

562 The SIO displayed large seasonality in fluxes with CO<sub>2</sub> source during January to March and  
563 CO<sub>2</sub> sinks during other months (Figure 6). All models reproduced seasonality very well in  
564 the SIO (Figure S5).

565

566 All GHM simulate seasonality in pCO<sub>2</sub> levels in the SIO with a maximum in January and  
567 March and a minimum in July-August. The magnitude of seasonal variability in pCO<sub>2</sub> is ~15  
568 µatm in the climatology whereas hindcast models simulated <20 µatm. The difference in  
569 pCO<sub>2</sub> between simulation and observations was up to 40 µatm (Figure S5). The large  
570 difference in pCO<sub>2</sub> seasonality in the SIO may be caused by weaker mixing simulations in the  
571 models in austral winter and the opposite in summer.

572



### 573 3.3. Interannual variability (IAV)

574

575 The interannual variability and trends in pCO<sub>2</sub> levels and their fluxes at the air-water  
576 interface was also investigated in 1985-2018 using different models (Figure 7). The rate of  
577 increase in surface ocean pCO<sub>2</sub> levels varied from 1.54 to 1.73 μatm yr<sup>-1</sup> between 1985 and  
578 2018 with a lower rate of increase in the BoB and higher in the EIO and SIO. The growth rate  
579 of pCO<sub>2</sub> in the surface waters by both hindcast and empirical models is close to that of  
580 atmospheric growth and observed surface pCO<sub>2</sub> growth in the Southwestern Indian Ocean  
581 (Metzl, 2009; Lo Monaco et al., 2021; Leseurre et al., 2022). Due to the lack of basin-scale  
582 observational time-series data in the Indian Ocean, the performance of the IAV by the models  
583 cannot be assessed. Given the variability of IOD and ENSO index (Figure 7), we divided the  
584 IAV trends into three timelines, i.e., a) 1985-2000, b) 2001-2018 and c) 1985 to 2018 (Figure  
585 7; Tables 4 and 5) to examine the possible changes in growth rate in the recent decades from  
586 that of earlier. To avoid biasing the magnitude of the seasonality, we first de-trend the  
587 simulated time series of IAV.

588

#### 589 3.3.1. The entire Indian Ocean

590

591 Both hindcast and empirical models simulated IAV in the surface pCO<sub>2</sub> levels in the entire  
592 Indian Ocean as 1.67 to 1.70 μatm yr<sup>-1</sup> between 1985 and 2018. The rate of increase in pCO<sub>2</sub>  
593 levels was lower from 1985 to 2000 (1.41-1.49 μatm yr<sup>-1</sup>) and increased in the recent decades  
594 (2001-2018) to 1.84-1.96 μatm yr<sup>-1</sup> (Table 4). Within the variability in the estimations, both  
595 empirical and hindcast models simulated similar growth rates in pCO<sub>2</sub> levels (Figure 7).

596

597 The range of sea-to-air CO<sub>2</sub> fluxes for the period of 1985 to 2018 was significantly different  
598 for GHM (-0.48 to -0.06 PgC yr<sup>-1</sup>), empirical (-0.31 to 0.03 PgC yr<sup>-1</sup>) and atmospheric  
599 inversion models (-0.63 to 0.09 PgC yr<sup>-1</sup>) (Figure 7). The IAV trend between 1985 and 2018  
600 was close for hindcast (-0.023±0.003 PgC yr<sup>-1</sup> decade<sup>-1</sup>) and empirical models (-0.021±0.003  
601 PgC yr<sup>-1</sup> decade<sup>-1</sup>; Table 5). The trends in IAV by hindcast models between 2001 and 2018 (-  
602 0.023±0.007 PgC yr<sup>-1</sup> decade<sup>-1</sup>) were slightly lower compared to 1985-2000 (-0.028±0.012  
603 PgC yr<sup>-1</sup> decade<sup>-1</sup>) for the entire Indian Ocean suggesting the rate of sinking of CO<sub>2</sub> in the  
604 Indian Ocean is decreasing in the recent decades. In contrast, empirical models displayed  
605 larger IAV between 2001-2018 (-0.046±0.005 PgC yr<sup>-1</sup> decade<sup>-1</sup>) and 1985-2000  
606 (+0.007±0.007 PgC yr<sup>-1</sup> decade<sup>-1</sup>). Such differences in the empirical models may come from  
607 the lack of satellite Chl-a data before 1998. Therefore, the simulations of empirical models  
608 may be less accurate before 1998 than after. Interestingly IAV by empirical models during  
609 2001-2018 were more than double (-0.046±0.005 PgC yr<sup>-1</sup> decade<sup>-1</sup>) than that of hindcast  
610 models (-0.023±0.007 PgC yr<sup>-1</sup> decade<sup>-1</sup>) which may be driven by variability in wind  
611 products and transfer velocity coefficients used. To examine the spatial variability in IAV,  
612 the same is studied in different regions of the Indian Ocean.

613

### 614 3.3.2. Northwestern Indian Ocean (Arabian Sea)

615

616 The pCO<sub>2</sub> growth of 1.64 to 1.68 μatm yr<sup>-1</sup> was simulated between 1985 and 2018 and it was  
617 lower during 1985-2000 (1.32-1.41 μatm yr<sup>-1</sup>) than 2001-2018 (1.76-1.88 μatm yr<sup>-1</sup>) (Table 4)  
618 in the Arabian Sea. The growth rates in pCO<sub>2</sub> levels in the Arabian Sea are close to that of the  
619 atmospheric growth rate of CO<sub>2</sub> (WMO Bulletin; <https://gml.noaa.gov/ccgg/trends/>).

620

621 The IAV in the CO<sub>2</sub> fluxes by the hindcast models in the Arabian Sea was small (0.00 to 0.06  
622 PgC yr<sup>-1</sup>), it was larger than the mean flux to the atmosphere from 1985 to 2018 (0.03±0.01  
623 PgC yr<sup>-1</sup>). This suggests that the mean CO<sub>2</sub> flux to the atmosphere may vary significantly  
624 from year to year (Figure 7).. In contrast, the atmospheric inversions (for the period 2001-  
625 2018) gave a much larger standard deviation than hindcast models suggesting that about 50%  
626 of the total Indian Ocean variability occurs in the NIO. The high variability in the  
627 atmospheric inversions may come from the period and region of atmospheric CO<sub>2</sub> data used  
628 in the models. The empirical models estimated lower IAV (0.03 to 0.12 PgC yr<sup>-1</sup>) compared  
629 to hindcast and atmospheric inversion models.

630

631 To examine the IAV trends in the recent decades, the trends between 1985-2000 and 2001-  
632 2018 were compared. The IAV between 2001-2018 is lower (-0.005±0.002 PgC yr<sup>-1</sup> decade<sup>-1</sup>)  
633 <sup>1</sup>) than 1985-2000 (-0.001±0.002 PgC yr<sup>-1</sup> decade<sup>-1</sup>) by hindcast models suggesting that the  
634 source of the CO<sub>2</sub> to the atmosphere from the Arabian Sea is decreasing in the recent  
635 decades. This is possible that rapid warming of the western Arabian Sea was reported in  
636 recent decades (Roxy et al.,2015; Sridevi et al., 2023) resulting in weak vertical transport of  
637 CO<sub>2</sub>, and nutrients resulting in a decrease in primary production (Dunstan et al., 2018; Roxy  
638 et al., 2016; Sridevi et al., 2023). A decline in Somali upwelling intensity and decreased  
639 evaporation due to the weakening of winds led to the warming of the Indian Ocean was  
640 reported in recent decades (D'Mello and Prasanna Kumar (2018). Sarma et al. (2000)  
641 estimated that vertical mixing is the major contributor to high pCO<sub>2</sub> levels and fluxes to the  
642 atmosphere in the Arabian Sea. The decrease in mixing may also weaken primary production  
643 resulting in an increase in CO<sub>2</sub> flux. Recently Sridevi et al. (2023) found that net primary  
644 production was decreasing only in the southern Arabian Sea (south of 12°N) whereas the  
645 decrease in nutrient inputs through mixing is compensated by increased atmospheric

646 deposition of nutrients. Therefore, the weakening of upwelling intensity decreased the CO<sub>2</sub>  
647 source to the atmosphere in the past 4 decades in the Arabian Sea. The empirical models also  
648 simulated a decrease in the CO<sub>2</sub> fluxes from  $-0.002 \pm 0.002 \text{ PgC yr}^{-1} \text{ decade}^{-1}$  in 1985-2000 to  
649  $-0.011 \pm 0.001 \text{ PgC yr}^{-1} \text{ decade}^{-1}$  in 2001-2018 and the magnitude of the decrease is higher  
650 than hindcast models. Nevertheless, this analysis suggests that the source of CO<sub>2</sub> to the  
651 atmosphere from the Arabian Sea is decreasing due to the warming of the basin leading to  
652 stratification and a decrease in upwelling intensity in the western basin.

653

### 654 3.3.3. Northeastern Indian Ocean (Bay of Bengal; BoB)

655

656 The IAV trends of pCO<sub>2</sub> simulated by hindcast and empirical models were close ( $1.54 \pm 0.04$   
657 and  $1.64 \pm 0.02 \text{ } \mu\text{atm yr}^{-1}$  respectively) between 1985 and 2018 in the BoB and these rates are  
658 almost close to that of in the Arabian Sea (Table 4). The pCO<sub>2</sub> growth rate increased between  
659 1985 and 2000 ( $1.34\text{-}1.46 \text{ } \mu\text{atm yr}^{-1}$ ) to 2001-2018 ( $1.71\text{-}1.76 \text{ } \mu\text{atm yr}^{-1}$ ; Table 4) and it is  
660 consistent with the atmospheric growth rate (<https://gml.noaa.gov/ccgg/trends/>).

661

662 The IAV in the BoB simulated by the hindcast models is small ( $-0.02$  to  $+0.02 \text{ PgC yr}^{-1}$ ), and  
663 it is larger than the mean flux to the atmosphere from 1985 to 2018 ( $0.00 \pm 0.02 \text{ PgC yr}^{-1}$ ).

664 This suggests that the mean CO<sub>2</sub> flux to the atmosphere may vary from a net weak sink to a  
665 weak source to the atmosphere. The standard deviation is large suggesting that large IAV  
666 occurs in the BoB. In contrast, the atmospheric inversions showed a large standard deviation  
667 in comparison to hindcast models suggesting high IAV could occur in the BoB ( $-0.03$  to  
668  $+0.04 \text{ PgC yr}^{-1}$ ). On the opposite the empirical models showed low IAV in CO<sub>2</sub> fluxes ( $0.00$   
669 to  $0.02 \text{ PgC yr}^{-1}$ ) and it is close to that of the annual mean flux to the atmosphere

670 (0.01±0.005 PgC yr<sup>-1</sup>; Table 3 ). The empirical models estimated very low IAV compared to  
671 hindcast and atmospheric inversion models in the BoB (Figure 7).

672

673 The IAV in the CO<sub>2</sub> fluxes in the BoB from the hindcast models decreased from 1985-2000 (-  
674 0.002±0.002 PgC yr<sup>-1</sup> decade<sup>-1</sup>) to 2001-2018 (-0.005±0.001 PgC yr<sup>-1</sup> decade<sup>-1</sup>) but not  
675 statistically different. (Table 5). Similarly, empirical models simulated a decrease in the  
676 fluxes of CO<sub>2</sub> in the BoB in recent decades (Table 5). The decrease of the CO<sub>2</sub> sink may be  
677 potentially caused by the deposition of atmospheric pollutants. Recently Sridevi and Sarma  
678 (2021) analyzed long-term trends (1998-2015) in pCO<sub>2</sub> levels in the BoB using an empirical  
679 model and noticed that pCO<sub>2</sub> decreased at the rate of -0.1 to -2.9 μatm yr<sup>-1</sup> in the central and  
680 eastern Bay associating with the decrease in salinity. The decrease in salinity is manifested by  
681 the melting of Himalayan glaciers due to climate change (Goes et al., 2020). In contrast, an  
682 increase in pCO<sub>2</sub> levels was noticed in the head bay and western BoB (0.1 to 2.4 μatm yr<sup>-1</sup>)  
683 due to the deposition of atmospheric pollutants (Sarma et al., 2015; 2022). Therefore the  
684 decrease in the rate of CO<sub>2</sub> flux from the atmosphere in the recent decade may be caused by a  
685 decrease in salinity and deposition of atmospheric pollutants in the BoB.

686

#### 687 3.3.4. Equatorial Indian Ocean (EIO)

688

689 The pCO<sub>2</sub> simulations displayed significant IAV by hindcast and empirical models in the  
690 equatorial Indian Ocean (1.65-1.72 μatm yr<sup>-1</sup>) between 1985 and 2018. The enhanced pCO<sub>2</sub>  
691 growth rate was observed during the recent decade (2001-2018; 1.52-2.01 μatm yr<sup>-1</sup>; Table 4)  
692 than between 1985 and 2000 (1.43-1.52 μatm yr<sup>-1</sup>). The IAV in the CO<sub>2</sub> fluxes in the EIO  
693 simulated by the hindcast models is small (-0.11 to 0.06 PgC yr<sup>-1</sup>), and it is larger than the  
694 mean flux to the atmosphere from 1985 to 2018 (-0.03±0.05 PgC yr<sup>-1</sup>). The large standard

695 deviation in the IAV by hindcast models suggested large variations in the CO<sub>2</sub> fluxes in the  
696 EIO and the mean CO<sub>2</sub> flux to the atmosphere may vary between weak sink to the source to  
697 the atmosphere. In contrast, both empirical and atmospheric inversion models displayed a  
698 decrease in the source for the past three decades. The hindcast models displayed a rate of  
699 decrease in CO<sub>2</sub> fluxes from the EIO between 1985-2000 ( $-0.004 \pm 0.005 \text{ PgC yr}^{-1} \text{ decade}^{-1}$ )  
700 to 2001-2018 ( $-0.006 \pm 0.003 \text{ PgC yr}^{-1} \text{ decade}^{-1}$ ) whereas a decrease was also noticed by  
701 empirical models but the magnitude was higher ( $+0.01 \pm 0.003$  and  $-0.018 \pm 0.002 \text{ PgC yr}^{-1}$   
702  $\text{decade}^{-1}$  during 1985-2000 and 2001-2018 respectively). This analysis suggests that the CO<sub>2</sub>  
703 sink in the EIO is increasing in recent decades possibly due to the weakening of upwelling in  
704 the western basin due to rapid warming (D'Mello and Prasanna Kumar, 2018; Roxy et al.,  
705 2015) leading to less DIC import in surface.

706

### 707 3.3.5. The South Indian Ocean (SIO)

708

709 The IAV of pCO<sub>2</sub> simulated by hindcast and empirical models in the SIO were close  
710 ( $1.73 \pm 0.03$  and  $1.70 \pm 0.02 \text{ } \mu\text{atm yr}^{-1}$  respectively) between 1985 and 2018. The lower pCO<sub>2</sub>  
711 growth rate was observed between 1985 and 2000 ( $1.43\text{-}1.50 \text{ } \mu\text{atm yr}^{-1}$ ) while increased in  
712 the recent decades of 2001-2018 ( $1.91\text{-}1.98 \text{ } \mu\text{atm yr}^{-1}$  (Table 4). A slight increase in the  
713 surface ocean pCO<sub>2</sub> growth rate from north (Arabian Sea;  $1.88 \pm 0.06 \text{ } \mu\text{atm yr}^{-1}$  between 2001-  
714 2018) to SIO ( $1.98 \pm 0.05 \text{ } \mu\text{atm yr}^{-1}$ ) was observed in the hindcast models whereas such trends  
715 were not noticed in the empirical models (Table 4). In the period 1991–2007, Metzl (2009)  
716 calculated an oceanic pCO<sub>2</sub> growth rate of  $2.11 \pm 0.11 \text{ } \mu\text{atm yr}^{-1}$ , which is  $0.4 \text{ } \mu\text{atm yr}^{-1}$  faster  
717 than in the atmosphere, suggesting that this region acts as a reducing sink of atmospheric  
718 CO<sub>2</sub>. Recently Lo Monaco et al. (2021) reported increasing trends of pCO<sub>2</sub> in the southern  
719 Mozambique Channel ranging from  $1.14 \text{ } \mu\text{atm yr}^{-1}$  from 1963 to 1995,  $1.70 \text{ } \mu\text{atm yr}^{-1}$  from

720 1995 to 2004 and  $2.41 \mu\text{atm yr}^{-1}$  from 2004 to 2019, and these rates are close to that of  
721 atmospheric  $\text{CO}_2$  trend. The growth rate of  $\text{pCO}_2$  estimated by both hindcast and empirical  
722 models appears close to that of measured values in the SIO (Metzl, 2009; Lo Monaco et al.,  
723 2021; Leseurre et al., 2022).

724

725 The IAV in the SIO by the hindcast models is small ( $-0.41$  to  $-0.03 \text{ PgC yr}^{-1}$ ), and it is larger  
726 than the mean flux to the atmosphere from 1985 to 2018 ( $-0.03 \pm 0.05 \text{ PgC yr}^{-1}$ ). The large  
727 standard deviation in the IAV by hindcast models suggested large variations in the  $\text{CO}_2$   
728 fluxes in the SIO and the mean  $\text{CO}_2$  flux to the atmosphere may vary between weak sink to  
729 the source to the atmosphere. In contrast, the empirical model did not show large variability  
730 but atmospheric inversion models displayed large standard deviations (Figure 7) with a  
731 higher increase in the sink from  $-0.4$  to  $-0.45 \text{ PgC yr}^{-1}$  between 2001 and 2018. The hindcast  
732 models displayed a decrease in  $\text{CO}_2$  fluxes from the SIO between 1985-2000 ( $-0.02 \pm 0.006$   
733  $\text{PgC yr}^{-1} \text{ decade}^{-1}$ ) to 2001-2018 ( $-0.006 \pm 0.005 \text{ PgC yr}^{-1} \text{ decade}^{-1}$ ) whereas a decrease was  
734 also noticed by empirical models but the magnitude was higher ( $-0.003 \pm 0.005$  to -  
735  $0.012 \pm 0.004 \text{ PgC yr}^{-1} \text{ decade}^{-1}$  during 1985-2000 and 2001-2018 respectively).

736

#### 737 3.4. Role of climate variability on $\text{CO}_2$ flux

738

739 The IAV in sea-air  $\text{CO}_2$  fluxes in the Indian Ocean has been linked to the IOD and ENSO.  
740 Valsala and Maksyutov (2013) reported a strong correlation between the IODZM and sea-air  
741  $\text{CO}_2$  flux IAV in the Arabian Sea and that the roles of these two (ENSO and IODZM) modes  
742 are complementary in the period 1985-2018. The strong IOD event occurred in 1994, 1997  
743 and 2006 within the period considered in this study with a Dipole Mode Index (DMI) value  
744  $>0.6$ . The simulated IAV by hindcast models shows an annual mean higher  $\text{CO}_2$  flux during

745 1994, 1997 and 2006 by 9-14% in the Arabian Sea whereas a decrease by 5-30% was noticed  
746 in other regions (BoB; EIO and SIO) than in adjacent years. This is consistent with earlier  
747 observations (Sarma, 2006; Valsala and Maksyutov, 2013). Interestingly, empirical models  
748 displayed an increase in CO<sub>2</sub> fluxes by 8% in 1994 but a decrease in flux by 10% was noticed  
749 between 1997 and 2006 compared to the normal period in the Arabian Sea. In contrast, a  
750 significant increase in CO<sub>2</sub> fluxes in the EIO by 3 to 45% was simulated by empirical models  
751 whereas a decrease of 6-30% was simulated by hindcast models. Jabaud-Jan et al. (2004)  
752 noticed sea-to-air fluxes in the subtropical zone (20°S-37°S) associated with warming in  
753 January 1998, when strong IOD occurred, compared to sink observed in the same region  
754 during 2000 suggesting warming induced by IOD enhanced CO<sub>2</sub> fluxes to the atmosphere.  
755 However, neither hindcast nor empirical models captured these features. The monthly mean  
756 CO<sub>2</sub> fluxes simulated by hindcast and empirical models in the Indian Ocean, including in the  
757 Arabian Sea, did not show significant relation with Dipole Mode Index (DMI) between 1985  
758 and 2018 suggesting that weak IOD may not have a significant impact on CO<sub>2</sub> fluxes in the  
759 Indian Ocean.

760

761 The strong ENSO event (index value >1.0) occurred in 1987, 1992, 1997, 2010 and 2016  
762 within the period considered in this study. During these events increase in annual mean CO<sub>2</sub>  
763 fluxes by 6-26% was observed in the Arabian Sea and BoB whereas a decrease in CO<sub>2</sub> fluxes  
764 was noticed in the EIO and SIO by hindcast models. In contrast, empirical models showed a  
765 decrease in CO<sub>2</sub> fluxes in the ENSO years in the Arabian Sea, BoB and SIO but an increase  
766 in the EIO. The monthly ENSO index displayed a significant linear correlation with CO<sub>2</sub>  
767 fluxes by hindcast models in the Arabian Sea and BoB ( $p < 0.001$ ) but an insignificant  
768 relationship in the EIO and SIO ( $p > 0.01$  and  $p > 0.1$  respectively) whereas insignificant  
769 relation was observed with CO<sub>2</sub> fluxes by empirical models in all regions. Valsala and



770 Maksyutov (2013) found a positive relationship between the ENSO index and CO<sub>2</sub> fluxes in  
771 the Arabian Sea and Southern Peninsular India. Nevertheless, this study suggests that  
772 empirical models did not capture either ENSO or IOD impacts on the CO<sub>2</sub> fluxes in the  
773 Indian Ocean.  
774  
775 Significant negative anomalies in the CO<sub>2</sub> fluxes were reported in the tropical Indian and  
776 Pacific Oceans and the absence of such anomaly was reported in the Southern Ocean  
777 (McKinley et al., 2020; Bennington et al., 2022). Bennington et al. (2022) reported an  
778 increase in >30% of the sink after the Pinatubo eruption. Interestingly significant decrease in  
779 CO<sub>2</sub> flux was observed between 1991 and the mean of 1992-93 in the Arabian Sea (0.038 and  
780 0.032 PgC/y respectively), BoB (0.0033 and 0.002 PgC/y), EIO (-0.026 and -0.041) with  
781 decrease by 16 to 57% whereas it was smaller in the case of SIO (-0.18 and -0.19 PgC/y)  
782 associated with Pinatubo volcanic eruption (Fig. 7). These observations are consistent with  
783 the earlier studies (McKinley et al., 2020; Bennington et al., 2022). Recently Fay et al. (2023)  
784 reported high oxygen and carbon anomalies associated with Pinatubo volcanic eruptions for  
785 several years in the northern and tropical Pacific and tropical Indian Ocean but an  
786 insignificant impact is noticed in the Southern Ocean. The models used in this study also  
787 suggest an impact of the Pinatubo volcanic eruption on Indian Ocean CO<sub>2</sub> fluxes around  
788 1991-1992 most pronounced in the EIO region (Fig. 7).

789

#### 790 **4. Conclusions**

791

792 The Indian Ocean is severely under-sampled with reference to surface pCO<sub>2</sub> levels. In order  
793 to estimate the uptake of CO<sub>2</sub> by the Indian Ocean, CO<sub>2</sub> fluxes were simulated using several  
794 approaches, such as a) hindcast, b) atmospheric inversions, and c) empirical models, were

795 analyzed at different time scales and compared with spatially interpolated observations  
796 (called climatology). Our study suggests that the annual mean CO<sub>2</sub> uptake by the entire  
797 Indian Ocean (north of 37.5°S) from all approaches varied between -0.27 and -0.13 PgC yr<sup>-1</sup>  
798 with a mean value of all models of -0.19±0.01 PgC yr<sup>-1</sup>. The SIO (south of 18°S) region is a  
799 dominant annual sink for the atmospheric CO<sub>2</sub> with a mean of all models of -0.23±0.11 PgC  
800 yr<sup>-1</sup>. In contrast, a mild source of CO<sub>2</sub> in the atmosphere was simulated by all models  
801 (0.02±0.05 PgC yr<sup>-1</sup>) in the north of 18°S. The estimation of CO<sub>2</sub> uptake by the Indian Ocean  
802 was shown little variations among models.

803

804 All models simulated spatial variability in CO<sub>2</sub> fluxes in the Indian Ocean except for the  
805 underestimation of upwelling fluxes off Oman/Somalia coasts, and the EIO and  
806 overestimation of sink in the BoB due to poor monsoon mixing and freshwater discharge  
807 simulations in the hindcast models. The RHM have improved the simulation of CO<sub>2</sub> fluxes,  
808 compared to GHM, in these regions but has not reached close to the climatology. Variations  
809 in CO<sub>2</sub> fluxes by different models were also driven by variations in wind products, transfer  
810 velocity parameterization and atmospheric CO<sub>2</sub> data used in the flux estimations.

811

812 The atmospheric growth rate of pCO<sub>2</sub> was well simulated by all models and they captured the  
813 seasonal cycle in the sea-air CO<sub>2</sub> fluxes, however, the stronger amplitudes were simulated by  
814 all models than climatology. The empirical models simulated the seasonal cycle of sea-air  
815 CO<sub>2</sub> fluxes reasonably well with the observations. The difference between the hindcast and  
816 atmospheric inversion models and also in comparison with climatology may reflect errors in  
817 the model formulations and also poor observational data both in the atmosphere and ocean  
818 surface.

819

820 The inter-annual variability in CO<sub>2</sub> fluxes by the hindcast models is relatively weaker  
821 compared to the atmospheric inversions. The hindcast models suggest a slight weakening of  
822 the sink over the period of 1985-2018 in the SIO. In contrast, a decrease in the source of CO<sub>2</sub>  
823 in the atmosphere was simulated in the Arabian Sea, BoB and EIO by the hindcast and  
824 empirical models. It is difficult to conclude how models are performing about IAV due to the  
825 lack of time-series atmospheric and surface ocean pCO<sub>2</sub> observations. All models projected  
826 the influence of atmospheric extreme events, such as IODZM and ENSO on CO<sub>2</sub> fluxes in the  
827 Indian Ocean.

828

829 Unless the monsoon mixing is represented well in the models, it will remain difficult to  
830 confidently project the future changes in CO<sub>2</sub> fluxes in the Indian Ocean. The lack of  
831 seasonal data in most parts of the Indian Ocean is another serious problem to validate the  
832 models. Significant improvement in model performance was not noticed since the RECCAP1  
833 comparison between models and observations due to the lack of addition of new data in this  
834 region (Sarma et al., 2013). Therefore, intensive ocean observations of pCO<sub>2</sub> and atmospheric  
835 tower observations are required for further improvements of the models.

836

837 The Indian Ocean experiences extreme events such as eddies (Chen et al., 2012) and tropical  
838 cyclones and both cause enormous effluxes of CO<sub>2</sub> to the atmosphere that would influence  
839 local CO<sub>2</sub> fluxes (Byju and Prasanna Kumar, 2011; Ye et al., 2019). Swapna et al. (2022)  
840 projected an increase in cyclonic activity in the future in the Indian Ocean that may result in  
841 enhanced CO<sub>2</sub> fluxes at the air-sea interface. High resolution, with reference to space and  
842 time, is required to capture such features. The regional models are highly useful to capture  
843 such signatures than global models. It would be interesting to segregate the contribution of  
844 CO<sub>2</sub> fluxes due to an increase in cyclonic activity due to climate change.

845

846 Rapid warming of the Indian Ocean (Roxy et al., 2015) is experiencing and began to play an  
847 important role in global ocean heat uptake (Li et al, 2018). The decrease in the rate of  
848 warming due to aerosols was reported in the northern Indian Ocean (Sridevi et al., 2023). The  
849 decrease in the primary production in the western Indian Ocean (Roxy et al., 2016;  
850 Dalpadado et al., 2021; Sridevi et al., 2023), was reported due to the decline in wind speed  
851 and upwelling intensity. The lack of primary productivity trends due to an increase in the  
852 deposition of nutrients from the atmosphere was reported (Sarma et al., 2022; Sridevi et al.,  
853 2023). Rapid rate of ocean acidification was reported due to the atmospheric deposition of  
854 pollutants (Sarma et al., 2015; 2021; Kumar et al., 2022). Therefore the inclusion of  
855 atmospheric pollutants in the model improves the simulations of future changes in CO<sub>2</sub> fluxes  
856 significantly. Evaluating the changes in possible drivers due to climate change would be an  
857 interesting issue to look into in the future.

858

859 One serious drawback in the present study to use of observational climatology of CO<sub>2</sub> fluxes  
860 to compare with the model simulations. Due to a lack of observational data in the Indian  
861 Ocean, inter and extrapolations were done based on the advection-diffusion model  
862 (Takahashi et al., 2009). Recently Davis and Goyet (2021) suggested a new method to fill the  
863 gaps to balance the error in the undersampled regions. Utilizing such tools, as shown by  
864 Guglielmi et al. (2022 a, b), may further decrease errors associated with climatology and the  
865 evaluation of model simulations will be enhanced.

866

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1222 Table 1: Details of the hindcast models (including regional models) with reference to a period of the run, products used, parameterization of  
 1223 transfer velocity and resolution of the model.  
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Global hindcast model	Period for Analysis	Spun-up	Initial conditions/physical forcing	wind	Riverine input used	Transfer velocity	resolution
CCSM-WHOI	1958-2017						$1^0 \times 1^0$
CESM-ETHZ	1980-2018	Spun-up to preindustrial steady state with 287.4 ppm	POP2 model was initialized with Levitus data and state of rest Does not include the phosphoric and silicic acid systems	JRA	No	Wanninkhof 1992	$\sim 1^0 \times 1.125^0$
CNRM-ESM2-1	1980-2018	Preindustrial; 1850 global average CO2 set to 286.46 ppm	Physical: NCEP-2; air-sea flux data: CORE II; atm.CO2: <b>GCP</b> Global averaged annual CO2 Includes the phosphoric and silicic acid systems		Yes	Wanninkhof 2014	$1^0 \times 1^0$
EC-Earth3	1980-2018	Preindustrial steady state 284.32 ppm for 1850	O2, Nutrients: WOA13 DIC, Alkalinity: GLODAPv2; Freshwater input: OMIP2 from JRA1.4-55	JRA55	Yes	Wanninkhof 1992	$1 \times 1^0$
FESOM_REcoM_LR (FESOM-1.4-REcoM2-LR)	1981-2019	Physical spun-up on HR mesh 1 with constant atm. CO2 BGC fields on LR mesh of 1980 year 278 ppm	atm.CO2: <b>GCP</b> Global averaged annual CO2 O2, Nutrients: WOA13 DIC, Alkalinity: GLODAPv2	JRA55	No	Wanninkhof 2014	$1^0 \times 1^0$
MOM6-Princeton	1980-2018	Atm. CO2 for preindustrial steady state: 278 ppm, Spun-up starting from 1959,	SST, SSS, nutrients: WOA13; DIC & Alkalinity: GLODAPv2; does not include Phosphoric and silicic acid systems. Alkalinity is influenced by inputs from river, calcium carbonate burial to the sediment and nitrogen redox change	JRA	Yes	Wanninkhof 1992	$0.5^0 \times 0.5^0$
MPIOM-HAMOCC	1980-2019	Preindustrial steady state 296.2 ppm atm.CO2	Atmospheric CO2 concentrations are according to the link provided in the RECCAP2 protocol Included phosphoric and silicic acid systems	NCEP	No	Wanninkhof 1992 & 2014	Bipolar grid with $1.5^0$ near equator
MRI-ESM2-1	1980-2018	Preindustrial steady state 284.32 ppm	Initialized with those derived from GLODAPv2 and WOA13v2. SST, SSS, nutrients: WOA13v2	JRA 55	No	Wanninkhof 1992 & 2014	Nominally 100 km
NorESM-OC1.2	1980-2018	Preindustrial steady state	Nutrients: WOA13;		No	Wanninkhof 1992	Nominal $1^0$

		for 1000 years CO2 set to 278 ppm	DIC and Alkalinity: GLODAPv2 Included phosphoric and silicic acid systems				
ORCA1_LIM3-PISCES (IPSL-NEMO-PISCES)	1980-2018	Initialized with observations in year 1836 and CO2 set to 286.46 ppm at 1870 level	DIC & Alkalinity GLODAPv2 Included phosphoric and silicic acid systems	JRA55	Yes	Wanninkhof 1992	1 <sup>0</sup> x 1 <sup>0</sup>
ORCA025-GEOMAR	1980-2018	Preindustrial steady state for 137 years and CO2 set to 284.32 ppm	Levitus 1998; (SST & SSS) Nutrients: WOA v2 DIC & Alk: GLODAP Pre-spin-up for sea ice from different experiments	JRA55	No	Wanninkhof 1992	1/4 <sup>0</sup>
Planktom12	1980-2018	Spun-up to 1750-1947 with looped 1990 NCEP forcing; Preindustrial steady state 278 ppm	NCEP forcing Sea-ice: NEMO-LIM2 model Included phosphoric and silicic acid systems			Wanninkhof 1992	1 <sup>0</sup> x 1 <sup>0</sup>
<b>Regional hindcast models</b>							
INCOIS-BIO-ROMS	1980-2018	Initialized with observations for a particular year (1970) RECCAP2 Strategy 1	Atm.CO2: Keeling et.al., 1995 at monthly resolution. The physical state variables have been initialized using ECDA system simulated reanalysis data produced by GFDL. The biological state variables (NO3, Chlorophyll-a, O2, etc.) have been initialized using the climatological state of January generated from the climatological run of the model. The model state of the carbon state variables has been initialized using the Global Ocean Data Product (GLODAP; Key et al., 2004).	JRA55-do	Yes	Wanninkhof 2014	1/12 <sup>0</sup>
ROMS-NYUAD	1980-2018	1950-1979 (repeated normal year for physical forcing, increasing pCO2 from Joos and Spahni (2008) and Keeling et al. (2005).	temp, salinity, u, v, SSH: ORAS5; O2 & nitrate: WOA18 Chl-a: CMEMS (SeaWiFS& MODIS) DIC & Alk, GLODAPv2	ERA-Interim	Yes	Wanninkhof 1992	0.1 x 0.1

1226  
 1227 Table 2: The methods used in the different observation-based surface CO<sub>2</sub> models used in this study.  
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<b>Observation-based surface CO<sub>2</sub> models</b>	<b>Method</b>	<b>Reference</b>
CMEMS-LSCE-FFNN	Feed Forward Neural Network (FFNN)	Chau et al., 2022
CSIRML6	Machine Learning/CSIR-ML6	Gregor et al., 2019
Jena-MLS (CarboScope)	/ocean mixed layer model	Rodenbeck et al., 2013
JMAMLR	Multiple Linear Regression model	Iida et al., 2021
SpcO <sub>2</sub> LDEO HPD	Global Ocean Biogeochem Model/Extreme Gradient Boosting (XGB)	Gloege et al., 2022
SOMFNN	Neural Network	Landschutzer et al., 2016
NIES-MLR3	Feed Forward Neural Network (FFNN)	Zeng et al., 2014
OceanSODAETHZ	Geospatial Random Cluster Ensemble Regression (GRaCER)	Gregor and Gruber 2021
UOEX WAT20	Multiple Linear Regression/ Feed Forward Neural Network (FFNN)	Watson et al., 2020

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1232 Table 3: The annual mean uptake ( $\pm$ standard deviation) of CO<sub>2</sub> from the climatology (Takahashi et al, 2009), hindcast, empirical and atmospheric  
 1233 inversion models. All units in PgC yr<sup>-1</sup>. The negative values represent CO<sub>2</sub> flux into the ocean and the positive ones into the atmosphere.  
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Region	Climatology	Hindcast Models (Includes 2 Regional models) (n=14)	Observation- based models (n=9)	Atmospheric Inversion models (n=2)	All models (n=25)	Surface area (km <sup>2</sup> )
Arabian Sea	0.08 $\pm$ 0.06	0.03 $\pm$ 0.01	0.08 $\pm$ 0.01	0.16 $\pm$ 0.12	0.06 $\pm$ 0.05	0.70 x 10 <sup>7</sup>
Bay of Bengal	0.01 $\pm$ 0.01	-0.00 $\pm$ 0.01	0.01 $\pm$ 0.00	0.01 $\pm$ 0.01	0.00 $\pm$ 0.01	0.44 x 10 <sup>7</sup>
Equatorial Indian Ocean	0.04 $\pm$ 0.03	-0.05 $\pm$ 0.04	0.02 $\pm$ 0.02	0.02 $\pm$ 0.03	-0.02 $\pm$ 0.05	1.55 x 10 <sup>7</sup>
South Indian Ocean	-0.20 $\pm$ 0.16	-0.19 $\pm$ 0.06	-0.23 $\pm$ 0.02	-0.46 $\pm$ 0.30	-0.23 $\pm$ 0.11	1.24 x 10 <sup>7</sup>
Indian Ocean	-0.07 $\pm$ 0.14	-0.21 $\pm$ 0.10	-0.13 $\pm$ 0.04	-0.27 $\pm$ 0.16	-0.19 $\pm$ 0.10	3.92 x 10 <sup>7</sup>

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1252 Table 4: The growth rate ( $\pm$ standard deviation) of pCO<sub>2</sub> ( $\mu$ atm yr<sup>-1</sup>) in the different regions of the Indian Ocean and different periods. The p-  
 1253 value of the regression of time-series pCO<sub>2</sub> variability is given in bracket.  
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Period ( $\mu$ atm/yr)	Arabian Sea		Bay of Bengal		Equatorial Indian Ocean		South Indian Ocean		Indian Ocean	
	hindcast	Empirical	hindcast	Empirical	hindcast	Empirical	hindcast	Empirical	hindcast	Empirical
1985-2018	1.68 $\pm$ 0.03 (7.7E-32)	1.64 $\pm$ 0.02 (1.8E-39)	1.54 $\pm$ 0.04 (5.4E-28)	1.64 $\pm$ 0.02 (7.2E-38)	1.72 $\pm$ 0.03 (1.1E-31)	1.65 $\pm$ 0.02 (1.3E-38)	1.73 $\pm$ 0.03 (1.8E-32)	1.70 $\pm$ 0.02 (2.6E-37)	1.70 $\pm$ 0.03 (4.6E-33)	1.67 $\pm$ 0.02 (4.7E-39)
1985-2000	1.32 $\pm$ 0.07 (3.7E-11)	1.41 $\pm$ 0.04 (3.3E-15)	1.34 $\pm$ 0.15 (5.2E-07)	1.46 $\pm$ 0.05 (1.4E-13)	1.43 $\pm$ 0.09 (1.6E-10)	1.52 $\pm$ 0.04 (5.00E-15)	1.43 $\pm$ 0.08 (6.9E-11)	1.50 $\pm$ 0.05 (4.6E-14)	1.41 $\pm$ 0.08 (2.9E-11)	1.49 $\pm$ 0.04 (1.6E-15)
2001-2018	1.88 $\pm$ 0.06 (2.1E-15)	1.76 $\pm$ 0.03 (9.6E-21)	1.71 $\pm$ 0.06 (1.6E-14)	1.76 $\pm$ 0.05 (4.7E-17)	2.01 $\pm$ 0.05 (5.2E-17)	1.82 $\pm$ 0.04 (1.30E-17)	1.98 $\pm$ 0.05 (9.4E-17)	1.91 $\pm$ 0.03 (8.1E-21)	1.96 $\pm$ 0.04 (3.9E-18)	1.84 $\pm$ 0.03 (9.3E-20)

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1265 Table 5: Rate of changes in CO<sub>2</sub> fluxes ( $\pm$ standard deviation) (PgC yr<sup>-1</sup> decade<sup>-1</sup>) in the Indian Ocean during different time periods. The p-value  
 1266 of the regression of time-series CO<sub>2</sub> variability is given in bracket. The negative values represent the decrease in source and vice versa for the  
 1267 positive.  
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Period	Arabian Sea		Bay of Bengal		Equatorial Indian Ocean		South Indian Ocean		Indian Ocean	
	hindcast	Empirical	hindcast	Empirical	hindcast	Empirical	hindcast	Empirical	hindcast	Empirical
1985-2018	-0.003 $\pm$ 0.001 (3.5E-05)	-0.006 $\pm$ 0.001 (2.7E-09)	-0.004 $\pm$ 0.000 (2.4E-09)	-0.002 $\pm$ 0.0001 (3.14E-05)	-0.007 $\pm$ 0.001 (7.3E-06)	-0.006 $\pm$ 0.002 (6.0E-04)	-0.010 $\pm$ 0.002 (1.9E-05)	-0.008 $\pm$ 0.002 (1.8E-05)	-0.023 $\pm$ 0.003 (1.4E-08)	-0.021 $\pm$ 0.003 (1.2E-07)
1985-2000	-0.001 $\pm$ 0.002 (5.4E-01)	-0.002 $\pm$ 0.002 (4.7E-01)	-0.002 $\pm$ 0.002 (2.4E-01)	0.001 $\pm$ 0.001 (2.3E-01)	-0.004 $\pm$ 0.005 (3.7E-01)	0.010 $\pm$ 0.003 (4.2E-03)	-0.020 $\pm$ 0.006 (4.2E-03)	-0.003 $\pm$ 0.005 (5.0E-01)	-0.028 $\pm$ 0.012 (3.2E-02)	0.007 $\pm$ 0.007 (3.7E-01)
2001-2018	-0.005 $\pm$ 0.002 (7.8E-03)	-0.011 $\pm$ 0.001 (1.8E-07)	-0.005 $\pm$ 0.001 (3.0E-06)	-0.005 $\pm$ 0.0001 (8.5E-09)	-0.006 $\pm$ 0.003 (8.1E-02)	-0.018 $\pm$ 0.002 (1.1E-07)	-0.006 $\pm$ 0.005 (2.0E-01)	-0.012 $\pm$ 0.004 (9.1E-03)	-0.023 $\pm$ 0.007 (4.0E-03)	-0.046 $\pm$ 0.005 (6.2E-08)

1270 Figure 1: a) Figure showing the sub-regions of the Indian Ocean used in this study: South  
1271 Indian Ocean (SIO; Brown), equatorial Indian Ocean (EIO; red), Arabian Sea (AS; Blue) and  
1272 Bay of Bengal (BoB; green). b) shows the location of observations of oceanic pCO<sub>2</sub> collected  
1273 since 1958 (Bakker et al., 2020), c) CO<sub>2</sub> flux climatology based on the observations and  
1274 interpolated to a 4 x 5° grid (Takahashi et al., 2009) and d) Annual mean uptake from  
1275 climatology, hindcast, empirical and atmospheric inversions models (PgC yr<sup>-1</sup>) for the  
1276 reference year of 2002. The error bars represent the standard deviation. The negative values  
1277 represent fluxes into the ocean and positive to the atmosphere.

1278  
1279 Figure 2: Annual mean uptake (in mol m<sup>-2</sup> yr<sup>-1</sup>) from the 14 hindcasts (2 regional) models for  
1280 the reference year of 2002. The negative values reflect fluxes into the ocean and are positive  
1281 for the atmosphere.

1282  
1283 Figure 3: Annual mean uptake (in mol m<sup>-2</sup> yr<sup>-1</sup>) from the 9 observation-based models for the  
1284 reference year of 2002. The negative values reflect fluxes into the ocean and are positive for  
1285 the atmosphere.

1286  
1287 Figure 4: Annual mean uptake (in mol m<sup>-2</sup> yr<sup>-1</sup>) from the 2 atmospheric inversion models. The  
1288 CAMSv20r1 used inter-annually varying prior fluxes from an empirical model CEMES,  
1289 while MACTM used annually repeating prior flux seasonality from Takahashi et al. (2009).  
1290 The negative values reflect fluxes into the ocean and are positive for the atmosphere.

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1292 Figure 5: The zonally integrated, annual mean CO<sub>2</sub> uptake (30°N-37.5°S) from a) hindcast, b)  
1293 empirical and c) atmospheric inversion models.

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1295 Figure 6: Seasonal cycle of the CO<sub>2</sub> fluxes (PgC yr<sup>-1</sup>; left panel) and δpCO<sub>2</sub> (µatm; right  
1296 panel) in the Indian Ocean from observations, mean hindcast, empirical and atmospheric  
1297 inversion models in the Indian Ocean, Arabian Sea, BoB, EIO and SIO.

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1299 Figure 7: The inter-annual variability from hindcast, empirical and atmospheric inversion  
1300 models. The upper panel shows the ENSO (<https://ggweather.com/enso/oni.htm>) and IOD  
1301 index (<http://www.bom.gov.au/climate/iod/>) and the other panels for the entire Indian Ocean,  
1302 Arabian Sea, Bay of Bengal, equatorial Indian Ocean, and South Indian Ocean. The trends of  
1303 mean hindcast, empirical and atmospheric inversion are given in PgC yr<sup>-1</sup> decade<sup>-1</sup>.

Figure 1.

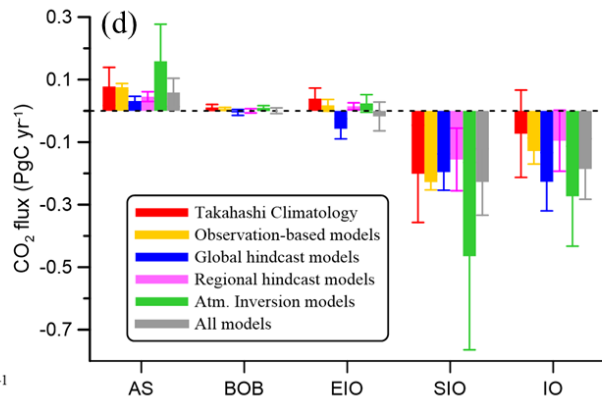
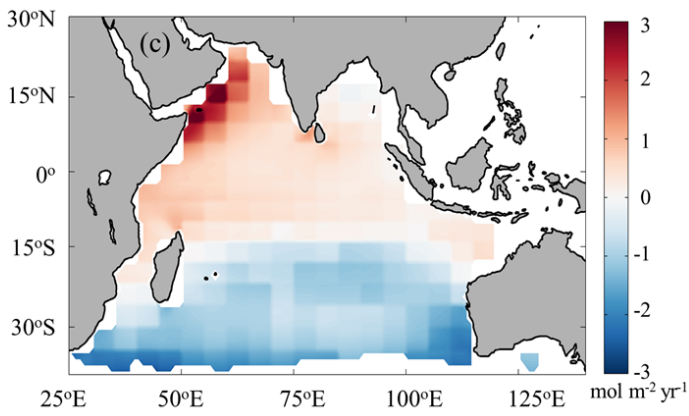
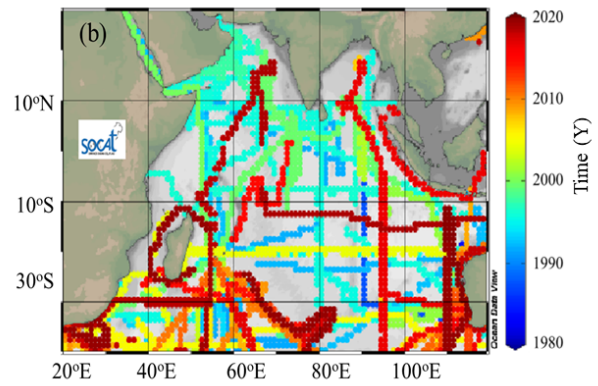
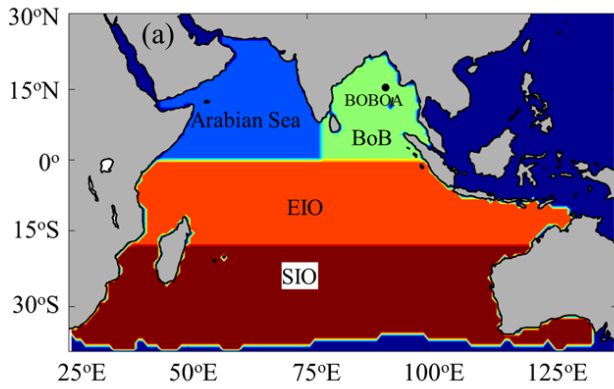


Figure 2.

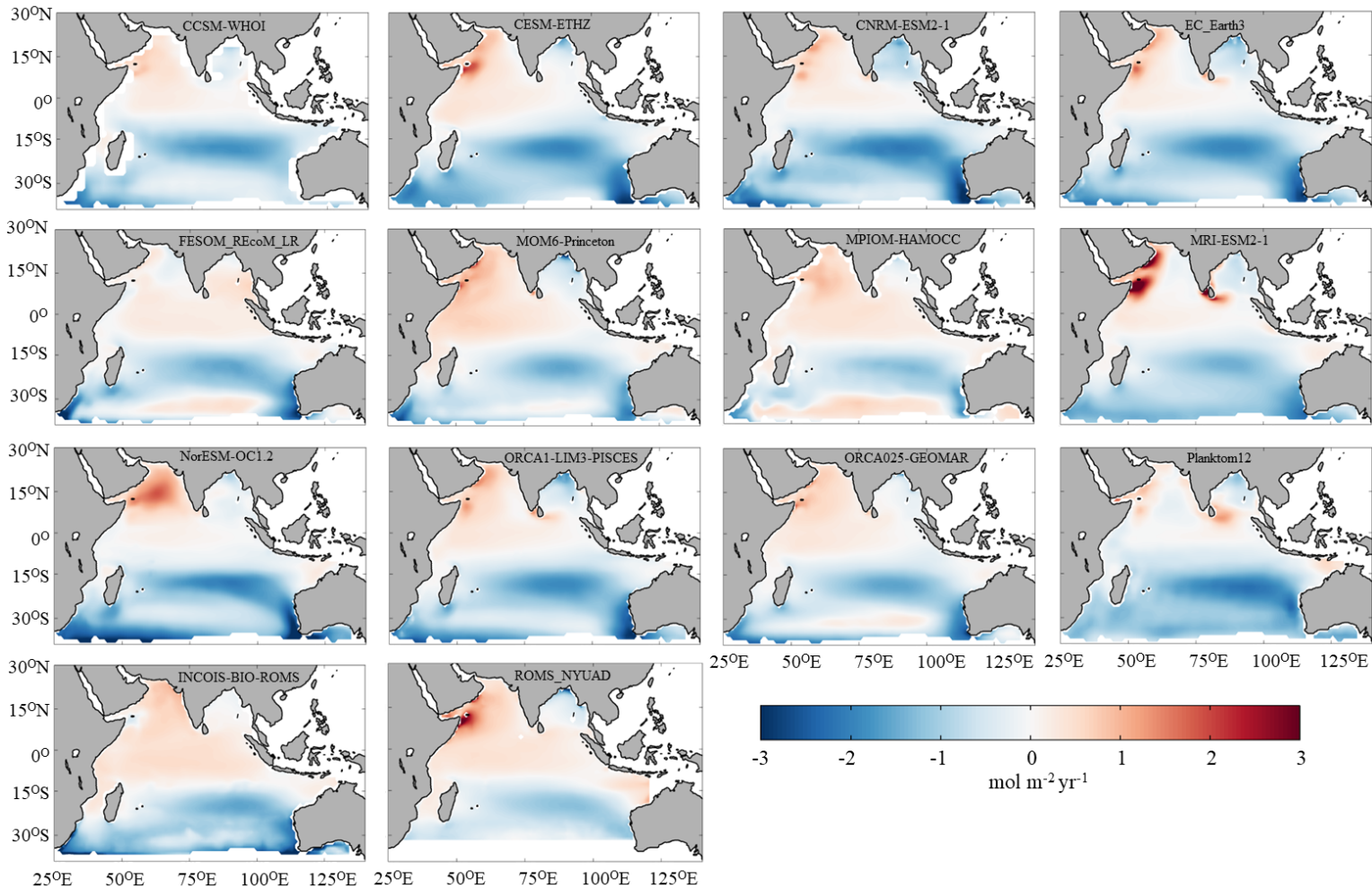




Figure 3.

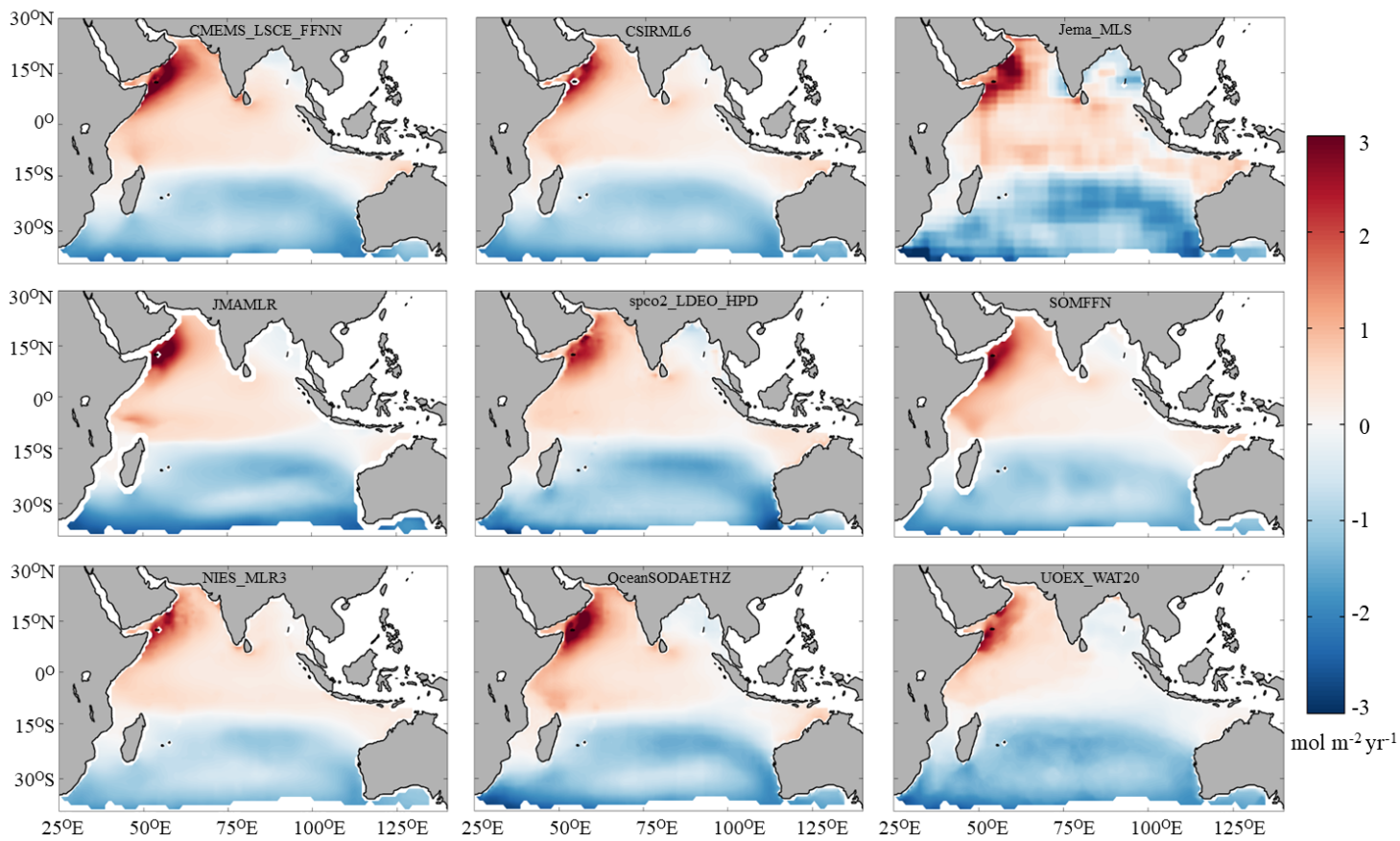


Figure 4.

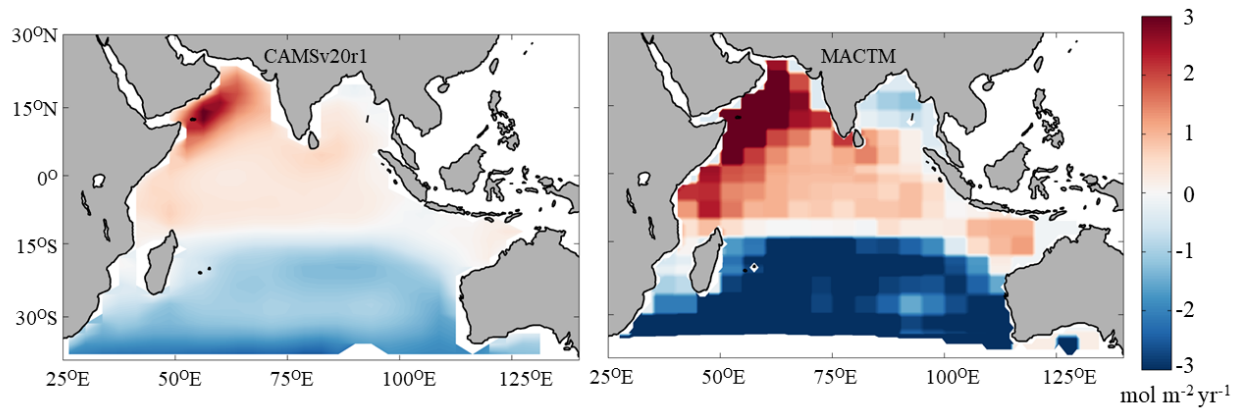


Figure 5.

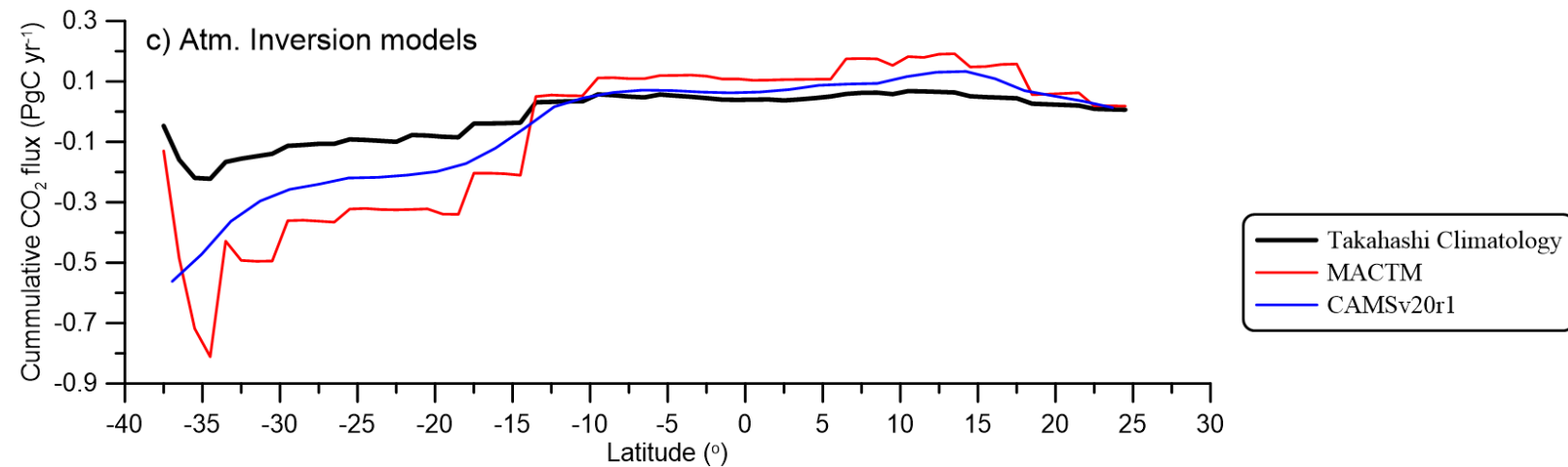
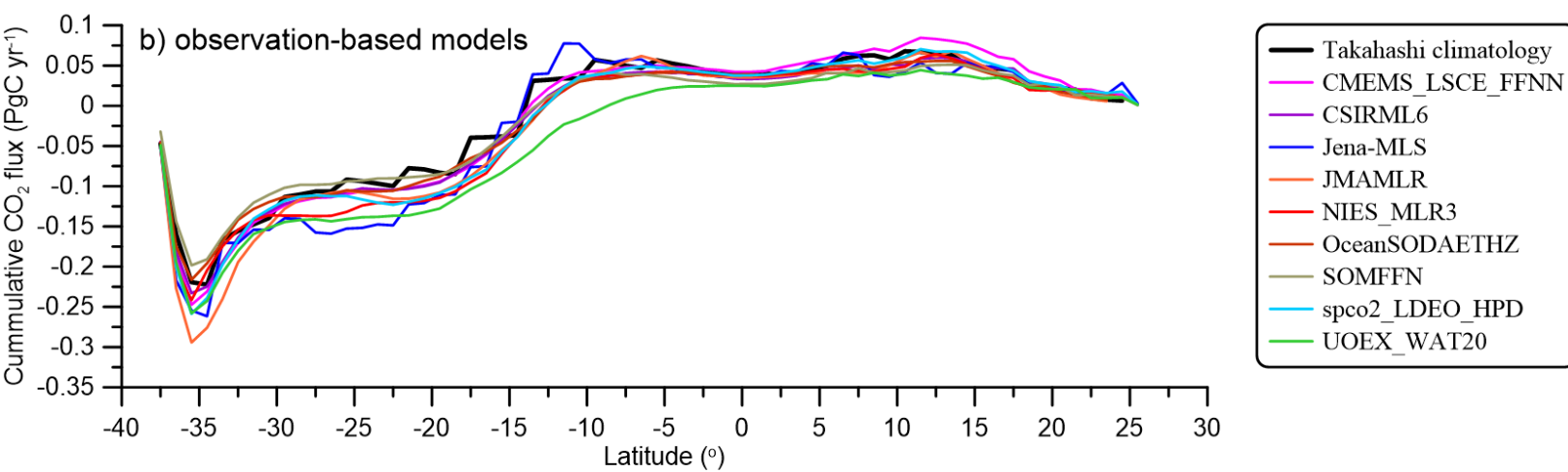
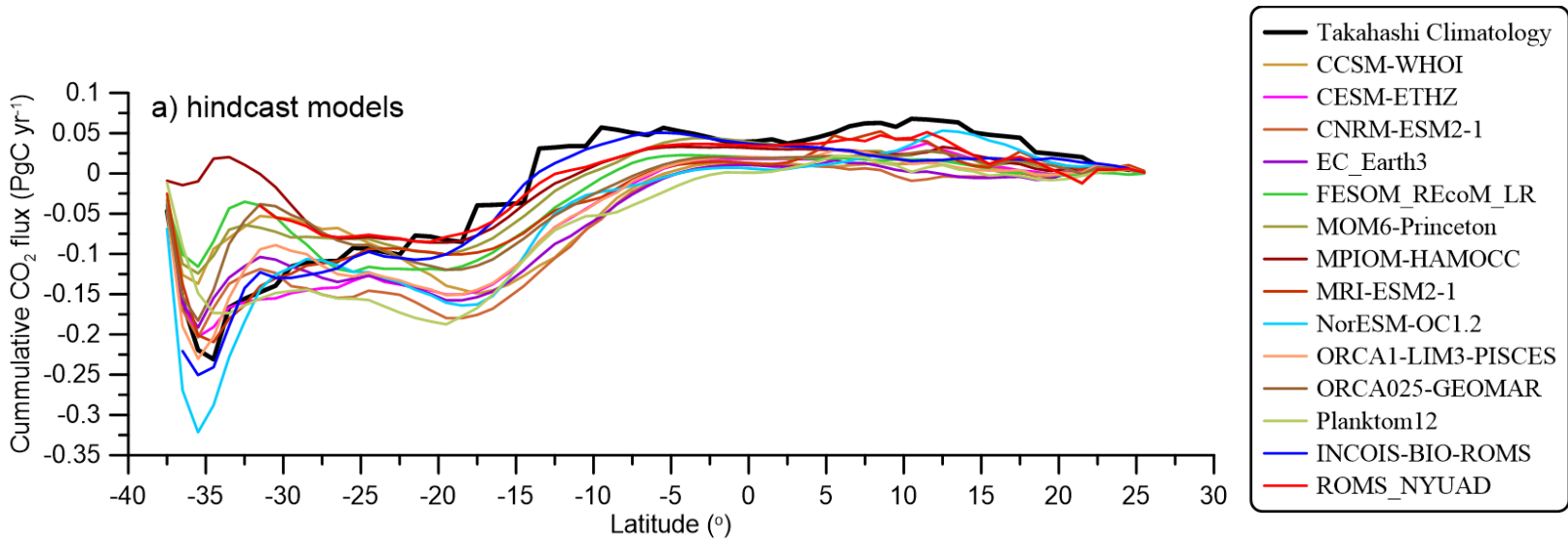


Figure 6.

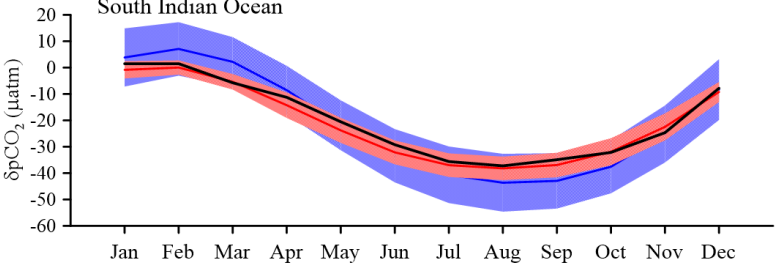
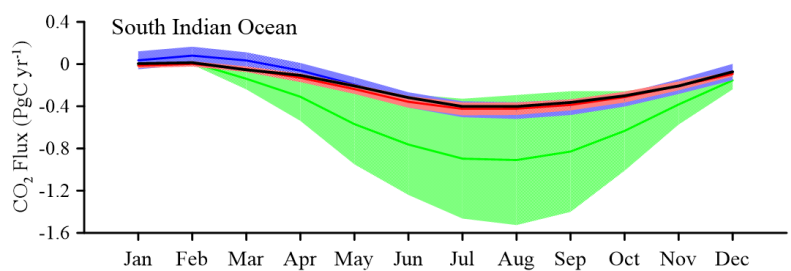
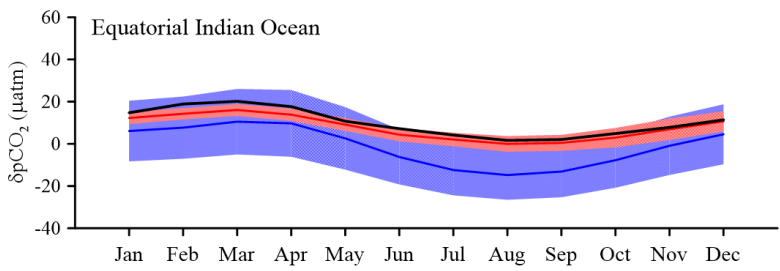
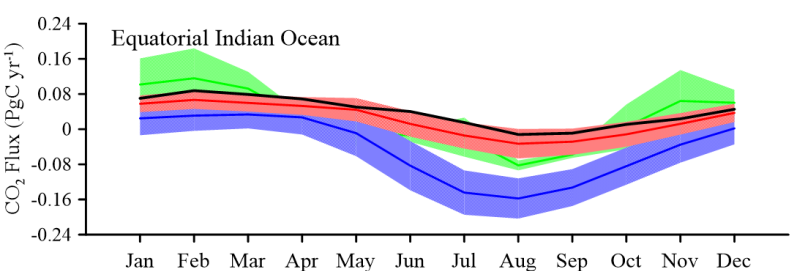
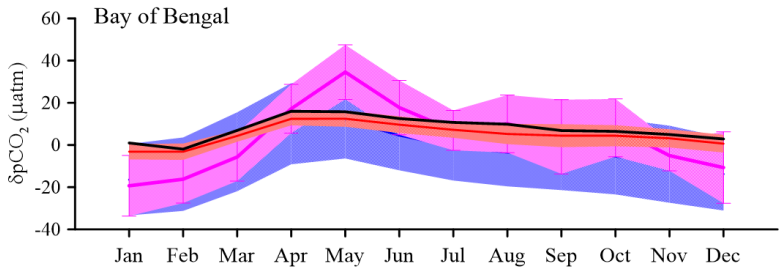
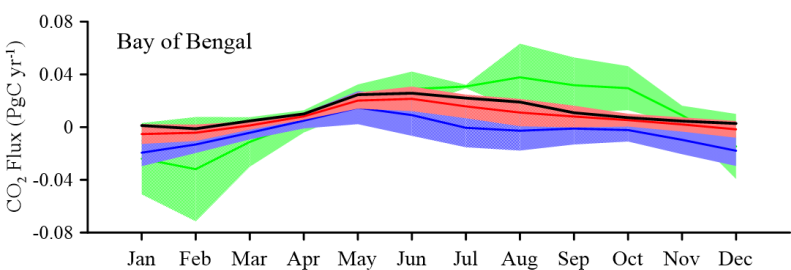
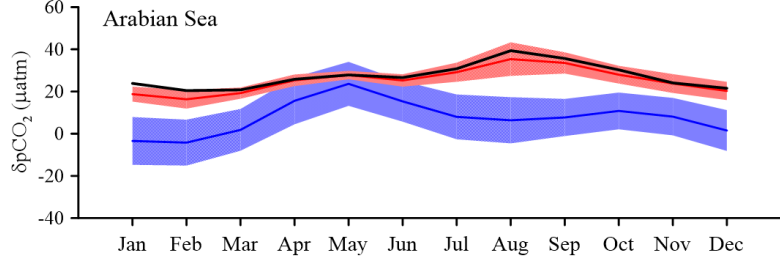
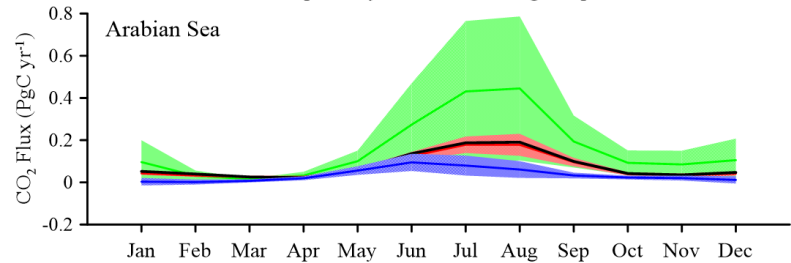
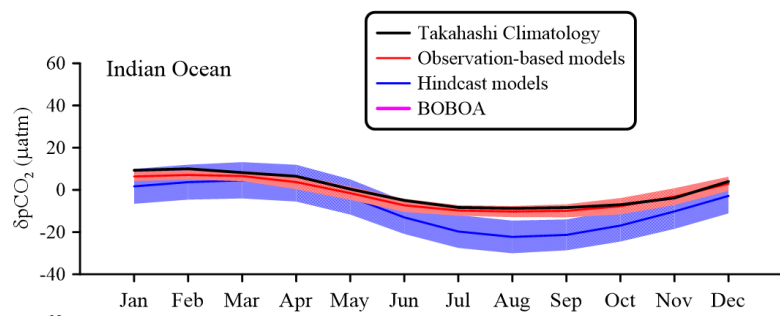
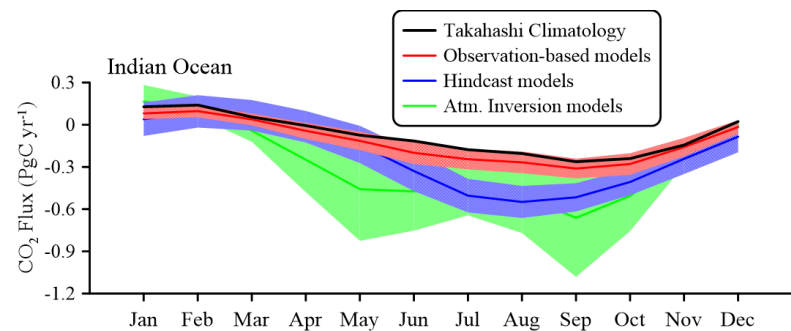




Figure 7.

