

1 The Seasonal Cycle of pCO₂ and CO₂ fluxes in the Southern Ocean: Diagnosing 2 Anomalies in CMIP5 Earth Systems Models

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9 10 Abstract

11
12 The Southern Ocean forms an important component of the global carbon cycle as a sink of CO₂ and heat.
13 Recent studies based on the Coupled Model Intercomparison Project version 5 (CMIP5) Earth System
14 Models (ESMs) show that CMIP5 models disagree on the phasing of the seasonal cycle of the CO₂ flux
15 (FCO₂) and poorly compare with available observations estimates in the Southern Ocean. Because the
16 seasonal cycle is the dominant mode of CO₂ variability in the Southern Ocean, its proper simulation is
17 necessary to model long-term oceanic CO₂ changes and their related climate impacts. Here we examine the
18 competing roles of temperature and dissolved inorganic carbon (DIC) as drivers of the seasonal cycle of
19 pCO₂ in the Southern Ocean to explain the mechanistic basis for the seasonal biases in CMIP5 models,
20 comparing them with observational products. We find that despite significant differences in the spatial
21 characteristics of the mean annual fluxes, models show greater zonal homogeneity in the seasonal cycle of
22 FCO₂ than observational products. The CMIP5 models can be grouped into one or the other of two main
23 categories (group-SST and group-DIC) while observational products show a modest influence of both, with a
24 dominance of DIC changes as the main driver of seasonal FCO₂ variability. Group-SST models show an
25 exaggeration of the seasonal rates of change of sea surface temperature (SST) in autumn and spring during
26 the cooling and warming peaks. The higher-than-observed rates of SST change tip the control of the
27 seasonal cycle of pCO₂ and FCO₂ towards SST and result in a divergence between the observed and
28 modelled seasonal cycles, particularly in the Sub-Antarctic Zone. While almost all analysed models (9 out of
29 10) show these SST-driven biases, 3 out of 10 (namely NorESM1-ME, HadGEM-ES and MPI-ESM, collectively
30 the group-DIC models) compensate the solubility bias because of their overly-exaggerated primary
31 production, such that biologically-driven DIC changes mainly regulate the seasonal cycle of FCO₂. Group-
32 DIC models reproduce the observed phasing of FCO₂ as a result of an incorrect scaling of the
33 biogeochemical fluxes. In the Antarctic zone, CMIP5 models compare better with observations relative to

34 the Sub-Antarctic Zone. This is mostly because both the CMIP5 models and the observational product show
35 a spatial and temporal uniformity in the characteristics of FCO_2 in the Antarctic zone. It is unfortunately not
36 possible to assess if CMIP5 models effectively perform better in this region or if the observational products
37 are limited by the lack of *in situ* data. The suggested mechanisms should be investigated further with CMIP6
38 models and new available data from autonomous platforms, and our analysis framework is proposed as a
39 useful tool to diagnose the dominant drivers.

40

41 **1. Introduction**

42

43 The Southern Ocean (south of $30^\circ S$) takes up about a third of the total oceanic CO_2 uptake, slowing down
44 the accumulation of CO_2 in the atmosphere (Fung et al., 2005; Le Quere et al., 2016; Takahashi et al., 2012).
45 The combination of upwelling deep ocean circumpolar waters (which are rich in carbon and nutrients) and
46 the subduction of fresh-colder mid-latitude waters makes it a key region in the role of sea-air gas exchange
47 and heat (Barbero et al., 2011; Gruber et al., 2009; Sallée et al., 2013). The Southern Ocean supplies about
48 a third of the total nutrients responsible for biological production north of $30^\circ S$ (Sarmiento et al., 2004),
49 and accounts for about 75% of total ocean heat uptake (Frölicher et al., 2015). Recent studies suggests that
50 the Southern Ocean CO_2 sink is expected to change as result of anthropogenic warming, however, the sign
51 and magnitude of the change is still disputed (Leung et al., 2015; Roy et al., 2011; Sarmiento et al., 1998;
52 Segschneider and Bendtsen, 2013). While some studies suggest that the Southern Ocean CO_2 sink is
53 weakening and will continue to do so (e.g. Le Quéré et al., 2007; Son and Gerber, 2010; Thompson et al.,
54 2011), other recent studies infer an increasing CO_2 sink (Landschutzer et al., 2015; Takahashi et al., 2012;
55 Zickfeld et al., 2008).

56

57 Although the Southern Ocean plays a crucial role as a CO_2 reservoir and regulator of nutrients and heat, it
58 remains under-sampled, especially during the winter season (JJA, Australian annual cycle) (Bakker et al.,
59 2014; Monteiro et al., 2010). Consequently we largely rely on Earth System Models (ESM), inversions and
60 ocean models for both process understanding and future simulation of CO_2 processes in the Southern
61 Ocean. The Coupled Model Intercomparison Project (CMIP) provides an example of such a globally
62 organized platform (Taylor et al., 2012). Recent studies based on CMIP5 ESMs, forward and inversions
63 models show that CMIP5 models agree on the CO_2 annual mean sink, they disagree with available
64 observations on the phasing of the seasonal cycle of sea-air CO_2 flux (FCO_2) in the Southern Ocean (e.g.
65 Anav et al., 2013; Lenton et al., 2013).

66

67 The seasonal cycle is a major mode of variability for chlorophyll (Thomalla et al., 2011) and CO₂ in the
68 Southern Ocean (Monteiro et al., 2010; Lenton et al., 2013). The large-scale seasonal states of sea-air CO₂
69 fluxes (FCO₂) in the Southern Ocean comprise of extremes of strong summer ingassing with a weaker
70 ingassing or even outgassing in winter (Metzl et al., 2006). These extremes are linked by the autumn and
71 spring transitions. In autumn CO₂ ingassing weakens linked to the increasing entrainment of sub-surface
72 waters, which are rich in dissolved inorganic carbon (DIC), (Lenton et al., 2013; Metzl et al., 2006;
73 Sarmiento and Gruber, 2006). During spring, the increase of primary production consumes DIC at the
74 surface and increases the ocean capacity to take up atmospheric CO₂ (Gruber et al., 2009; Le Quéré and
75 Saltzman, 2013; Pasquer et al., 2015; Gregor et al., 2017). The increase of sea surface temperature (SST) in
76 summer reduces surface CO₂ solubility, which counteracts the biological uptake and reduces the CO₂ flux
77 from the atmosphere (Takahashi et al., 2002; Lenton et al., 2013).

78

79 FCO₂ is also spatially variable in the Southern Ocean at the seasonal scale. North of 50°S is generally the
80 main CO₂ uptake zone (Hauck et al., 2015; Sabine et al., 2004). This region forms a major part of the sub-
81 Antarctic zone and is characterized by the confluence of upwelled, colder and nutrient-rich deep
82 circumpolar water and mid-latitudes warm water (McNeil et al., 2007; Sallée et al., 2006) . It is
83 characterized by enhanced biological uptake during spring and solubility driven CO₂ uptake due to cool
84 surface waters (Marinov et al., 2006; Metzl, 2009; Takahashi et al., 2012). South of 60°S towards the
85 marginal ice zone, CO₂ fluxes are largely dominated by outgassing, driven by the upwelling of circumpolar
86 waters, which are rich in DIC (Matear and Lenton, 2008; McNeil et al., 2007).

87

88 The inability of CMIP5 ESM to simulate a comparable FCO₂ seasonal cycle with available observations
89 estimates in the Southern Ocean has been the subject of recent literature (e.g. Anav et al., 2013; Kessler
90 and Tjiputra, 2016) and the mechanisms associated with these biases are still not well understood. This
91 model-observations disagreement highlights that the current ESMs might not adequately capture the
92 dominant seasonal processes driving the FCO₂ in the Southern Ocean. It also questions the sensitivity of
93 models to adequately predict the Southern Ocean century scale CO₂ sink and its sensitivity to climate
94 change feedbacks (Lenton et al., 2013). Efforts to improve simulations of CO₂ properties with respect to
95 observations in the Southern Ocean are ongoing using forced ocean models (e.g. Pasquer et al., 2015;
96 Rodgers et al., 2014; Visinelli et al., 2016; Rosso et al., 2017). However it remains a challenge for fully
97 coupled simulations. In a previous study, we developed a diagnostic framework to evaluate the seasonal
98 characteristics of the drivers of FCO₂ in ocean biogeochemical models (Mongwe et al., 2016). We here
99 apply this approach to 10 CMIP5 models against observation product estimates in the Southern Ocean. The
100 subsequent analysis is divided as follows; the methods section (section 2) explains our methodological

101 approach, followed by results (section 3), which comprise four subsections. Section 3.1 explores the spatial
102 variability of the annual mean representation of FCO_2 in the 10 CMIP5 models against observation product
103 estimates; section 3.2 quantitatively the biases in the FCO_2 seasonal cycles in the 10 models. Section 3.3
104 investigates surface ocean drivers of FCO_2 changes (temperature driven solubility and primary production),
105 and finally section 3.4 examines the source terms in the DIC surface budget (primary production,
106 entrainment rates and vertical gradients) and their role in surface pCO_2 changes. The discussion (section 4)
107 is an examination of the mechanisms behind the pCO_2 and FCO_2 biases in the models. We conclude with a
108 synthesis of the main findings and implications.

109

110 **2. Methods**

111

112 The Southern Ocean is here defined as the ocean south of the Sub-Tropical Front (STF, defined according to
113 Orsi et al., (1995), 11.3°C isotherm at 100m). It is divided into two main domains, the Sub-Antarctic Zone;
114 between the STF and the Polar Front (PF: 2°C isotherm at 200m) and the Antarctic Zone, south of the PF.
115 Within the Sub-Antarctic Zone and Antarctic Zone, we further partition the domain into the three main
116 basins of the Southern Ocean i.e. Pacific, Atlantic and the Indian Ocean.

117

118 **2.1 Observations datasets**

119

120 We used the Landschützer et al (2014) data product (FCO_2 and partial pressure of CO_2 (pCO_2)) as the main
121 suite of observations-based estimates against to which compare the models throughout the analysis.
122 Landschützer et al (2014) dataset is synthesized from Surface Ocean CO_2 Atlas version 2 (SOCAT2)
123 observations and high resolution winds using a Self Organizing Map (SOM) through a Feed Forward Neural
124 Network (FNN) approach (Landschützer et al., 2013). While Landschützer et al (2014) dataset is based on
125 more *in situ* observations (SOCAT2, 15 million source measurements Bakker et al., 2014) in comparison to
126 Takahashi et al., 2009 (3 million surface measurements), used in Mongwe et al., (2016). We are nevertheless
127 mindful that due to paucity of observations in Southern Ocean, this data product is still subject to
128 significant uncertainties discussed in Ritter et al., (2018). To evaluate the uncertainty between data
129 products we compare the Landschützer et al (2014) data with Gregor et al (2017) data product, which is
130 based on two independent empirical models: Support Vector Regression (SVR) and Random Forest
131 Regression (RFR) as well as against Takahashi et al (2009) for pCO_2 in the Southern Ocean. We compare
132 pCO_2 instead of FCO_2 firstly, because Gregor et al., (2017) only provided fugacity and pCO_2 , and being
133 mindful that the choice of wind product and transfer velocity constant in computing FCO_2 would increase

134 the level of uncertainty (Swart et al., 2014). Secondly, while the focus of the paper is on the examination
135 biases in the air-sea flux of CO₂, the major part of our diagnostic analysis is based on pCO₂, which primarily
136 determines the direction and part of the magnitude of the fluxes. We find that the three data products
137 agree on the seasonal phasing of pCO₂ in the Sub-Antarctic zone, but they show differences in the
138 magnitudes (Fig. S1). In the Antarctic zone, all three datasets agree in both phasing and amplitude (Fig. S1).
139 At this stage it is not clear whether this agreement is due to all the methods converging even with the
140 sparse data or the reason for agreement is the lack of observations is reason for the agreement.
141 Nevertheless more independent in situ observations will be helpful to resolve this issue In this regard float
142 observations from the SOCCOM program (Johnson et al., 2017) and glider observations (Monteiro et al.,
143 2015) for example are likely to become helpful in resolving these data uncertainties in addition to ongoing
144 ship based measurements.

145

146 We also used the Takahashi et al. (2009) in situ FCO₂ dataset as a complementary source for comparison of
147 spatial FCO₂ properties in the Southern Ocean. Takahashi et al., (2009) data estimates are comprised of a
148 compilation of about 3 million surface measurements globally, obtained from 1970 – 2000 and corrected
149 for reference year 2000. This dataset is used, as provided, on a 4° (latitude) x 5° (longitude) resolution.
150 Using monthly mean sea surface temperature (SST) and salinity from the World Ocean Atlas 2013 (WOA13)
151 dataset (Locarnini et al., 2013), we reconstructed total alkalinity (TALK) using the Lee et al. (2006)
152 formulation. We also use this dataset as the main observations platform in section 2.3. To calculate the
153 uncertainty of the computed TALK, we compared the calculated total alkalinity (TALK_{obs}) based on ship
154 measurements of SST and surface salinity dataset with actual observed TALK_{obs} of the same measurements
155 for a set of winter (August) data collected in the Southern Ocean. We found that TALK_{calc} compares well with
156 TALK_{obs} (R² = 0.79) (Fig. S2, Supplementary). We then used this computed monthly TALK and pCO₂ from
157 Landschützer et al (2014) to compute DIC using CO2SYS (Pierrot et al., 2006,
158 http://cdiac.ornl.gov/ftp/co2sys/CO2SYS_calc_XLS_v2.1), using K1, K2 from Mehrbach et al., 1973 refitted
159 by Dickson and Millero, 1987. For interior ocean DIC, we used the Global Ocean Data Analysis Project
160 version 2 (GLODAP2) annual means dataset (Lauvset et al., 2016). The Mixed Layer Depth (MLD) data was
161 taken from de Boyer Montégut et al. (2004), on a 1° x 1° grid, the data is provided as monthly means
162 climatology and was used as provided. We also use satellite chlorophyll dataset from Johnson et al., (2013).

163

164 **2.2 CMIP5 Model data**

165

166 We used 10 models from the Coupled Model Intercomparison Project version 5 (CMIP5) Earth System
 167 Models (ESM) shown in Table 1. The selection criterion for the models was based on the availability of
 168 essential variables for the analysis in the CMIP5 data portal (<http://pcmdi9.llnl.gov>) at the time of writing:
 169 i.e. monthly FCO₂, pCO₂, chlorophyll, net primary production (NPP), surface oxygen, surface Dissolved
 170 Inorganic Carbon (DIC), MLD, Sea Surface Temperature (SST), vertical temperature fields and annual DIC for
 171 the historical scenario. The analysis is primarily based on the climatology over 1995 – 2005, which was
 172 selected to match a period closest to the available observational data product (Landschützer et al (2014),
 173 1998 – 2011). However we do examine the consistency of the seasonality of FCO₂ over periods longer than
 174 10 years by comparing the seasonal cycle of FCO₂ and temporal standard deviation of 30 years (1975 –
 175 2005) vs 10 years (1995 – 2005) for HadGEM2-ES and CanESM2. We find that the seasonal cycle of FCO₂
 176 remains consistent (R = 0.99) in both HadGEM2-ES and CanESM2 over 30 year (Fig. S3). All CMIP5 model
 177 outputs were regridded into a common 1°x1° regular grid throughout the analysis, except for annual CO₂
 178 mean fluxes, which were computed on the original grid for each model.

179

180 **Table 1:** A description of the 10 CMIP5 ESMs that were used in this analysis. It shows the ocean resolution,
 181 atmospheric resolution, and available nutrients for the biogeochemical component, sea-ice model, vertical
 182 levels and the marine biogeochemical component for each ESM.

183

Full name and Source	Model Name	Ocean Resolution	Atmospheric Resolution	Nutrients	Sea ice model	Vertical Coordinate & Levels	Ocean Biology	Reference
Canadian Centre for Climate Modelling and Analysis, Canada	CanESM2	CanOM4 0.9° x 1.4°	2.8125° x 2.8125°	N (accounts for Fe limitation)	CanSIM1	z 40 levels	NPZD	Zahariev et al., 2008
Centro Euro-Mediterraneo Sui Cambiamenti Climatici, Italy	CMCC-CESM	OPA8.2 0.5-2° x 2°	3.8° x 3.7°	P, N, Fe, Si	CICE4	z 21 levels	PELAGOS	Vichi et al., 2007
Centre National de Recherches Météorologiques-Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique, France	CNRM-CM5	NEMOv3.3 1°	1.4°	P, N, Fe, Si	GELATO5	z 42 levels	PISCES	Séférian et al., 2013

Institut Pierre-Simon Laplace, France	IPSL-CM5A-MR	NEMO2.3 0.5-2° x 2°	2.58° x 1.25°	P, N, Fe, Si	LIM2	z 31 levels	PISCES	Séférian et al., 2013
Max Plank Institute for Meteorology, Germany	MPI-ESM-MR	MPIOM 1.41°x0.89°	1.875° x 1.875°	P, N, Fe, Si	MPIOM	z 40 levels	HAMOCC 5.2	Ilyina et al., 2013
Community Earth System Model, USA	CESM1-BGC	0.3° x1°	0.9° x 1.25°	(P), N, Fe, Si		z 60 levels	BEC	Moore et al., 2004
Norwegian Earth System Model, Norway	NorESM1-ME	MICOM 0.5° x 0.9°	2.5° x 1.9°	P, N, Fe, Si	CICE4.1	ρ 53 levels	HAMOCC	Tjiputra et al., 2013

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185

186 2.3 Sea-Air CO₂ Flux Drivers: The Seasonal Cycle Diagnostic Framework

187

188

189 The seasonal cycle diagnostic framework was developed as a way of scaling the rates of change of SST and
190 the total DIC driven changes to the seasonal cycle of pCO₂ on a common DIC scale (Mongwe et al., 2016).

191 We use the framework to explore how understanding differences emerging from the temperature and DIC
192 driven CO₂ variability could be helpful as a diagnostic of the apparent observations –model seasonal cycle
193 biases in the Southern Ocean.

194

195 The total rate of change of DIC in the surface layer consists of the contribution of air-sea exchanges,
196 biological, vertical and horizontal transport-driven changes (Eq. 1).

197

$$198 \left(\frac{\partial DIC}{\partial t}\right)_{Tot} = \left(\frac{\partial DIC}{\partial t}\right)_{air-sea} + \left(\frac{\partial DIC}{\partial t}\right)_{Bio} + \left(\frac{\partial DIC}{\partial t}\right)_{Vert} + \left(\frac{\partial DIC}{\partial t}\right)_{Hor} \quad (1)$$

199 Because we used zonal means from medium resolution models, we assume that the horizontal terms are
200 negligible, which leaves air-sea exchange, vertical fluxes (advection and diffusion) and biological processes
201 as the dominant drivers of DIC. In order to constrain the contribution of temperature on the seasonal
202 variability of pCO₂ and FCO₂ we derived a new “DIC equivalent term” (DIC_T) defined as the magnitude of DIC
203 change that would correspond to a change in pCO₂ driven by a particular temperature change. In this way
204 the ΔpCO₂, driven solely by modelled or observed temperature change, is converted into equivalent DIC
205 units, which allows its contribution to be scaled against the observed or modelled total surface DIC change
206 (Eq.1).

207 This calculation of DIC_T is done in two steps: firstly, the temperature impact on pCO_2 is calculated using the
 208 Takahashi et al., (1993) empirical expression that linearizes the temperature dependence of the equilibrium
 209 constants.

$$210 \left(\frac{\partial pCO_2}{\partial t} \right)_{SST} = 0.0423 \times pCO_2 \times \left(\frac{\partial pCO_2}{\partial SST} \right) \quad (2)$$

211 Though this relationship between $dSST$ and $dpCO_2$ is based on a linear assumption (Takahashi et al., 1993),
 212 this formulation has been shown to hold and has been widely used in literature (e.g. Bakker et al., 2014;
 213 Feely et al., 2004; Marinov and Gnanadesikan, 2011; Takahashi et al., 2002; Wanninkhof et al., 2010;
 214 Landschützer et al., 2018). We show in the supplementary material that the extension of this expression
 215 into polar temperature ranges ($SST < 2^\circ C$) only introduces a minor additional uncertainty of 4 -5% (SM Fig.
 216 S4)

217 Secondly, the temperature driven change in pCO_2 is converted to an equivalent DIC_T using the Revelle
 218 factor.

$$219 \left(\frac{\partial DIC_T}{\partial t} \right)_{SST} = \frac{DIC}{\gamma_{DIC} \times pCO_2} \left(\frac{\partial pCO_2}{\partial t} \right)_{SST} \quad (3)$$

220 Here we also used a fixed value for the Revelle Factor ($\gamma_{DIC}=14$), typical of polar waters the Southern Ocean
 221 but in order to assess the error linked to this assumption. We recomputed the Revelle factor in the Sub-
 222 Antarctic and Antarctic zones using annual mean climatologies of TAlk, salinity, sea surface surface
 223 temperature and nutrients. Firstly we examined DIC changes for the nominal range of pCO_2 change (340 –
 224 399 $\mu atm:1 \mu atm$ intervals) and then used this dataset to derive the Revelle factor. The range of calculated
 225 Revelle factors in the Southern Ocean was between $\gamma_{DIC} \sim 12 - 15.5$ with an average of $\gamma_{DIC} = 13.9 \pm 1.3$. This
 226 justifies our use of $\gamma_{DIC} = 14$ for the conversion of the solubility driven pCO_2 change to an equivalent DIC
 227 (DICT) throughout the analysis. We have provided the uncertainty that this conversion makes into the
 228 temperature constraint DIC_T , by using the upper and lower limits of the Revelle factor ($\gamma_{DIC} = 12 - 15.5$) in
 229 the model framework. In the Supplementary Material (Fig. S5) we show an examples for observations in
 230 the Sub-Antarctic and Antarctic zones, which show that the extremes of the Revelle factor values ($\gamma_{DIC} = 12$
 231 – 15.5) do not alter the phasing or magnitude of the relative controls of temperature or DIC on the seasonal
 232 cycle of pCO_2 .

233 The rate of change of DIC was discretized on a monthly mean as follows:

234

235
$$\left(\frac{\partial DIC_T}{\partial t}\right)_{SST} \approx \left(\frac{\Delta DIC}{\Delta t}\right)_{n,l} = \frac{DIC_{n+1,l} - DIC_{n,l}}{1 \text{ month}} \quad (4)$$

236

237 Where n is time in month, l is vertical level (in this case the surface, $l=1$). We here take the forward
 238 derivative such that November rate is the difference between December the 15th and November the 15th,
 239 thus being centered at the interval between the months.

240 Finally, to characterize periods of temperature or DIC dominance as main drivers of the instantaneous
 241 (monthly) pCO_2 change we subtract Eq. 4 from Eq. 1, which yields a residual indicator M_{T-DIC} Eq. 5. M_{T-DIC} is
 242 then used as indicator of the dominant driver of instantaneous pCO_2 changes, in this scale monthly time
 243 scale.

244

245
$$M_{T-DIC} = \left| \left(\frac{\partial DIC_T}{\partial t}\right)_{SST} \right| - \left| \left(\frac{\partial DIC}{\partial t}\right)_{Tot} \right| \quad (5)$$

246

247 $M_{T-DIC} > 0$ indicates that the pCO_2 variability is dominated by the temperature driven solubility and when
 248 $M_{T-DIC} < 0$, it indicates that pCO_2 changes are mainly modulated by DIC processes (i.e. Biological CO_2 changes
 249 and vertical scale physical DIC mechanisms). We also the following DIC processes; i.) Biological DIC changes
 250 using chlorophyll, NPP, export carbon, surface oxygen, and ii.) . Physical DIC mechanisms using estimated
 251 entrainment rates at the base of the mixed layer: details of this calculation are in section 2.4.

252 In the Southern Ocean, salinity and TAlk are considered lower order drivers of the seasonal cycle of pCO_2
 253 (Takahashi et al., 1993). In the supplementary material (Fig. S6), we show that salinity and TAlk do not play
 254 a major role as drivers of the local seasonal cycle of pCO_2 . We do so by computing the equivalent rate of
 255 change of DIC resulting from seasonal variability of salinity and TAlk as done for temperature (Eq. 2), i.e.
 256 still assuming empirical linear relationships from Takahashi et al (1993): $\left(\frac{\ln(pCO_2)}{\ln(TAlk)} \approx -9.4\right)$ and $\left(\frac{\ln(pCO_2)}{\ln(Sal)} =\right.$
 257 $0.94)$. By applying these relationships to the model data, we confirmed that indeed salinity and TAlk are
 258 secondary drivers of pCO_2 changes i.e. $\left[\left(\frac{\partial DIC}{\partial t}\right)_{Tot}\right]_{average} \approx 5 \mu\text{mol kg}^{-1} \text{ month}^{-1}$, while $\left[\left(\frac{\partial DIC}{\partial t}\right)_{Tot}\right]_{average}$
 259 $\approx 0.6 \mu\text{mol kg}^{-1} \text{ month}^{-1}$ and $\left[\left(\frac{\partial DIC}{\partial t}\right)_{TAlk}\right]_{maximum} \approx 0.4 \mu\text{mol kg}^{-1} \text{ month}^{-1}$.

260 The seasonal cycle of the ocean-atmosphere pCO_2 gradient (ΔpCO_2) is the main driver of the variability of
 261 FCO_2 over comparable periods (Sarmiento and Gruber, 2006; Wanninkhof et al., 2009; Mongwe et al.,
 262 2016). Wind speed plays a dual role as a driver of FCO_2 : it drives the seasonal evolution of buoyancy-
 263 mixing dynamics, which influences the biogeochemistry and upper water column physics but these

264 processes are incorporated into the variability of the DIC. Wind speed also drives the rate of gas exchange
 265 across the air - seas interface (Wanninkhof et al., 2013) however, because winds in the Southern Ocean do
 266 not have large seasonal variation (Young, 1999), for this analysis we neglect the role of wind as secondary
 267 driver of the seasonal cycle of FCO₂. Consequently, the seasonal cycle of FCO₂ is directly linked to surface
 268 pCO₂ are driven by changes in temperature, salinity, TALK and DIC (Sarmiento and Gruber, 2006;
 269 Wanninkhof et al., 2009). In this analysis we use this assumption as a basis to explore how the seasonal
 270 variability of temperature and DIC regulate the seasonal cycle of pCO₂ in CMIP5 models relative to
 271 observational product estimates.

272
 273

274 **2.4 Entrainment mixing**

275

276 CO₂ uptake by the Southern Ocean has been shown to weaken during winter in the Southern Ocean linked
 277 to the entrainment of sub-surface DIC as the MLD deepens (e.g. Lenton et al., 2013; Metzl et al., 2006;
 278 Takahashi et al., 2009). Here we estimate this rate of entrainment (RE) using Eq. 6, which estimate the
 279 advection of preformed DIC at the base of the mixed layer:

280

$$281 \quad RE = U_e \left(\frac{\partial DIC}{\partial z} \right)_{MLD} \quad (6)$$

$$282 \quad RE_n = \left(\frac{\Delta MLD_n}{\Delta t} \right) \left(\frac{\Delta DIC}{\Delta z} \right)_{n,MLD} \quad (7)$$

$$283 \quad \left(\frac{\Delta DIC}{\Delta z} \right)_{n,MLD} = \frac{DIC_{n,MLD_{n+1}} - DIC_{n,MLD_n}}{\Delta z} \quad (8)$$

284

285 In which U_e is an equivalent entrainment velocity based on the rate of change of the MLD. This
 286 approximation of vertical entrainment is necessary as it is not possible to compute this term from the
 287 CMIP5 data because the vertical DIC distribution is only available as annual means. We use the entrainment
 288 rates to estimates the influence of subsurface/bottom DIC changes on surface DIC changes driven and
 289 subsequently pCO₂ and FCO₂. Because we are mainly interested in the period autumn – winter, where the
 290 MLD ≥ 60 m in the Sub-Antarctic zone and ≥ 40 m in the Antarctic zone, at this depth seasonal variations in
 291 DIC are anticipated to be minimal thus these estimates can be used. The monthly and annual mean DIC
 292 from a NEMO PISCES 0.5 x 0.5o model output was used to estimate the uncertainty by comparing RE
 293 computed from both (Dufour et al., 2013). We found that the annual and monthly estimates to be indeed
 294 comparable with minimal differences (not shown). It is noted as a caveat that this rate of entrainment is
 295 only a coarse estimate because we were using annual means, and is intended only for the autumn-winter
 296 period when MLDs are deepen.

297

298 **3. Results**

299

300 **3.1 Annual climatological sea-air CO₂ fluxes**

301

302 The annual mean climatological distribution of FCO₂ in the Southern Ocean obtained from observational
303 products is spatially variable but mainly characterized by two key features: (i) CO₂ in-gassing north of 50°-
304 55°S (Polar Frontal zone, PFZ) within and north of the Sub-Antarctic Zone, and (ii), CO₂ out-gassing between
305 the PF (~ 58°S) and the Marginal Ice Zone (MIZ, ~ 60° - 68°S) (Fig. 1a-b). Most CMIP5 models broadly
306 capture these features, however, they also show significant differences in space and magnitude between
307 the basins of the Southern Ocean (Fig. 1). With the exception of CMCC-CESM, which shows a northerly-
308 extended CO₂ outgassing band between about 40°S and 50°S, CMIP5 models generally show the CO₂
309 outgassing zone between 50°S – 70°S in agreement with observational estimates (Fig. 1).

310

311 The analyzed 10 CMIP5 models show a large spatial dispersion in the spatial representation of the
312 magnitudes of FCO₂ with respect to observations (Fig. 1, Table 2). They generally overestimate the
313 upwelling-driven CO₂ outgassing (55°S -70°S) in some basins relative to observations. IPSL-CM5A, CanESM2,
314 MPI-ESM, GFDL-ESM2M and MRI-ESM, for example, show CO₂ outgassing fluxes reaching up to 25 g m⁻² yr⁻¹,
315 while observations only show a maximum of 8 g m⁻² yr⁻¹ (Fig. 1). Between 40°S - 56°S (Sub-Antarctic zone),
316 observations and CMIP5 models largely agree, showing a CO₂ in-gassing feature, which is mainly
317 attributable to biological processes (McNeil et al., 2007; Takahashi et al., 2012). South of 65°S, in the MIZ,
318 models generally show an excessive CO₂ ingassing with respect to observations (with the exception of
319 CanESM2, IPSL-CM5A-MR and CNRM-CM5). Note that as much as this bias south of the MIZ might be a true
320 divergence of CMIP5 models from the observed ocean, it is also possibly due to the lack of observations in
321 this region, especially during the winter season (Bakker et al., 2014; Monteiro, 2010).

322

323 Table 2 shows the Pattern Correlation Coefficient (PCC) and the Root Mean Square Error (RMSE), which are
324 here used to quantify the model spatial and magnitude performances against Landschützer et al (2014)
325 data product. Out of the 10 models, 6 show a moderate spatial correlation with Landschützer et al (2014)
326 (PCC = 0.40 – 0.60), i.e. CNRM-CM5, GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-MR, CESM1-BGC, NorESME-
327 ME and CanESM2. While MPI-ESM-MR (PCC = 0.37), MRI-ESM (PCC = 0.36) and CMCC-CESM (PCC = -0.09)
328 show a weak to null spatial correlation with observations, the latter mainly due to the overestimated
329 outgassing region. Spatially, GFDL-ESM2M and NorESM1-ME are the most comparable to Landschützer et al

330 (2014), (RMSE < 9), while CCMC-CESM, CanESM2, MRI-ESM and CNRM-CM5 shows the most differences
331 (RMSE > 15). The rest of the models show a modest comparison (RMSE 9 – 11).

332

333 NorESM1-ME and CESM1-BGC are the only 2 of the 10 models showing a consistent spatial (RMSE < 10)
334 and magnitude (PCC = 0.50) performance. From Table 2, it is evident that an appropriate representation of
335 the spatial properties of FCO₂ with respect to observations does not always correspond to comparable
336 magnitudes. CanESM2 for example shows a good spatial comparison (PCC = 0.54), yet a poor estimation of
337 the magnitudes (RMSE = 19.5). In this case caused by an overestimation of CO₂ uptake north of 55°S (≈ - 28
338 g m⁻² yr⁻¹) and CO₂ outgassing (> 25 g m⁻² yr⁻¹) in the Antarctic zone, resulting in a net total Southern Ocean
339 annual weak sink (-0.05 Pg C m⁻² yr⁻¹). These inconsistencies in the spatial and magnitude performances
340 highlights some of the limitations of using annual mean indicators to evaluate model performance and thus
341 a process-based diagnostic approach could be useful in understanding the departure of models from
342 observed estimates.

343

344 **3.2 Sea-Air CO₂ Flux Seasonal Cycle Variability and Biases**

345

346 The seasonal cycle of FCO₂ is shown in Fig. 2. The seasonality of FCO₂ in the 10 CMIP5 models shows a large
347 dispersion in both phasing and amplitude, but mostly disagree with observations in the phase of the
348 seasonal cycle as well as with each other. More quantitatively, CMIP5 models show weak to negative
349 correlations with the Landschützer et al (2014) data product in the Sub-Antarctic Zone and have slightly
350 higher correlations in the Antarctic Zone (see supplementary Fig. S7). This discrepancy is consistent with
351 Anav et al., (2013) findings, who however used fixed latitude criteria. Based on the phasing, the seasonality
352 of FCO₂ in CMIP5 models can be a priori divided in two main groups: group-DIC models, comprising of MPI-
353 ESM, HadGEM-ES and NorESM1-ME, and group-SST models, the remainder i.e. GFDL-ESM2M, CMCC-CESM,
354 CNRM-CERFACS, IPSL-CM5A-MR, CESM1-BGC, MRI-ESM and CanESM2. The naming convention is
355 suggestive of the mechanism driving the seasonal cycle, as it will be clarified further on. A similar grouping
356 was also identified by Kessler and Tjiputra (2016) using a different criterion. Fig. 3 shows the seasonal cycle
357 of FCO₂ of an equally-weighted ensemble of the two groups compared to observations, the shaded area
358 shows the decadal standard deviation for the models and the Landschützer et al (2014) data product for
359 1998 -2014 standard deviation for in the various regions.

360

361 In the Sub-Antarctic zone, the observational products show a weakening of CO₂ uptake during winter (less
362 negative values in June-August) with values close to the zero at the onset of spring (September) in all three
363 basins. Similarly, during the spring season, all three basins are seen to maintain a steady increase of CO₂

364 uptake until mid-summer (December), while they differ during autumn (March-May). The Pacific Ocean
365 shows an increase in CO₂ uptake during autumn that is not observed in the other basins (only marginally in
366 the Indian Ocean). In the Antarctic zone, the observed FCO₂ seasonal cycle is mostly similar in all three
367 basins (Fig. 3d-f). While this seasonal cycle consistency may suggest a spatial uniformity of the mechanisms
368 of FCO₂ at the Antarctic, we are also mindful that this may be due to a result of the paucity of observations
369 in this area. In the Antarctic zone, all three basins show a weakening of CO₂ uptake from the onset of
370 autumn (March) until mid-winter (June–July) when it outgasses. The winter CO₂ outgassing is followed by a
371 strengthening of the CO₂ uptake throughout spring to summer, when it reaches a CO₂ ingassing peak.

372
373 The differences in the seasonal cycle of FCO₂ across the three basins of the Sub-Antarctic zone found in the
374 observational product (Fig. 2), likely resemble the differences in the spatial behavior seen in Fig. 1. To verify
375 this, we correlate the seasonal cycles from the Landschützer et al (2014) observational product in the three
376 basins (Fig. 4). The FCO₂ seasonal cycle in the Sub-Antarctic Atlantic and Indian basins is the only one that is
377 similar ($R = 0.8$), while the other basins are quite different to each other ($R = -0.1$ for Pacific – Atlantic and
378 $R \sim 0.4$ for Pacific – Indian). Contrary to the observational product, CMIP5 models show the same seasonal
379 cycle phasing across all three basins in the Sub-Antarctic zone (basin – basin correlation coefficients are
380 always larger than 0.50 in Fig. 4), with the exception of three models (i.e. CMCC-CESM, CESM-BGC1 and
381 GFDL-ESM2M). In the Antarctic zone, CMIP5 models agree with observations in the spatial uniformity of the
382 seasonal cycle of FCO₂ among the three basins.

383
384 Group-DIC models are characterized by an exaggerated CO₂ uptake during spring-summer (Fig. 3) with
385 respect to observations estimates and CO₂ outgassing during winter. These models generally agree with
386 observations in the phasing of CO₂ uptake during spring, but overestimate the magnitudes. It is worth
387 noting that the seasonal characteristics of group-DIC models are mostly in agreement with the observations
388 in the Atlantic and Indian basin in Sub-Antarctic zone ($R > 0.5$ in Fig. 4). The large standard deviation (~ 0.01
389 $\text{g C m}^{-2} \text{ day}^{-1}$) during the winter and spring-summer seasons in the Atlantic Ocean shows that though group-
390 DIC models agree in the phase, magnitudes vary considerably (Fig. 3b). For example MPI-ESM reach up to
391 $0.06 \text{ g C m}^{-2} \text{ day}^{-1}$ outgassing during winter, while HadESM2-ES and NorESM2 peak only at $\sim 0.03 \text{ g C m}^{-2}$
392 day^{-1} . Group-SST models on the other hand are characterized by a CO₂ outgassing peak in summer (Dec-
393 Feb) and a CO₂ in-gassing peak at the end of autumn (May) and their phase is opposite to the observational
394 estimates in the Atlantic and Indian basins (Fig. 3b,c). Group-SST models only show a strengthening of CO₂
395 uptake during spring in the Indian Ocean. Interestingly, group-SST models compare relatively well with the
396 observed FCO₂ seasonal cycle in the Pacific Ocean, whereas group-DIC models disagree the most with the
397 observed estimates (Fig. 3a). This phasing differences within models and against observed estimates

398 probably suggests that the disagreement of CMIP5 models FCO_2 with observations is not a matter of a
399 relative error/constant magnitude offset, but likely point to differences in the seasonal drivers of FCO_2 .

400

401 In the Antarctic zone (Fig. 3d-f), both group-DIC and group-SST models perform better than the Sub-
402 Antarctic, also in more quantitative terms as shown by the correlation analysis in Fig. S7. However, the
403 similarity in the seasonality of the different basins found in the observational product is now properly
404 simulated by the models (Fig. 4, with the exception of MRI-ESM and CanESM2 where $R < 0$ for all three
405 basins). Here FCO_2 magnitudes oscillate around zero with the largest disagreements occurring during mid-
406 summer, where observations estimates shows a weak CO_2 sink ($\approx -0.03 \text{ gC m}^{-2} \text{ day}^{-1}$), group-SST showing a
407 zero net CO_2 flux and a strong uptake in group-DIC shows (e.g. $\approx -0.12 \text{ gC m}^{-2} \text{ day}^{-1}$ in the Pacific Ocean). The
408 large standard deviation ($\approx 0.01 \text{ gC m}^{-2} \text{ day}^{-1}$) here indicates considerable differences among models (Fig.
409 3d-f).

410

411 3.3 Seasonal Scale Drivers of Sea-Air CO_2 Flux

412

413 We now examine how changes in temperature and DIC regulate FCO_2 variability at the seasonal scale
414 following the method described in Sec. 2.3. Fig. 5 shows the monthly rates of change of SST ($dSST/dt$) for
415 the 10 models compared with WOA13 SST. CMIP5 generally shows agreement in the timing of the switch
416 from surface cooling ($dSST/dt < 0$) to warming ($dSST/dt > 0$) and vice versa; i.e. March (summer to
417 autumn), and September (winter to spring) respectively. In both the Sub-Antarctic and Antarctic zone
418 CMIP5 models agree with observations in this timing (Fig. 5). However, while they agree in phasing, the
419 amplitude of these warming and cooling rates are overestimated with respect to the WOA13 dataset with
420 exception of NorESM1-ME. Subsequently these differences in the magnitude of $dSST/dt$ have important
421 implications for the solubility of CO_2 in seawater; larger magnitudes of $|dSST/dt|$ are likely to enhance the
422 response of the pCO_2 to temperature through CO_2 solubility changes. For example, because the
423 observations in the Indian Ocean shows a warming rate of about $0.5^\circ\text{C month}^{-1}$ lower compared to the
424 other two basins, we expect a relatively weaker role of surface temperature in this basin.

425

426 As described in sec. 2.3, the computed $dSst/dt$ magnitudes were used to estimate the equivalent rate of
427 change of DIC driven by CO_2 solubility using Eq. 2. The seasonal cycle of $|(dDIC_T/dt)_{SST}|$ vs $|(dDIC/dt)_{Tot}|$,
428 for the 10 models and observations is presented in the supplementary material (Fig. S8), here we show the
429 seasonal mean of M_{T-DIC} Eq. 3. As articulated in sec. 2.3, M_{T-DIC} (Fig. 6) is the difference between the total
430 surface DIC rate of change of DIC (Eq. 1) and the estimated equivalent temperature driven solubility DIC
431 changes Eq. 3, such that when $|(dDIC_T/dt)_{SST}| > |(dDIC/dt)_{Tot}|$, temperature is the dominant driver of the

432 instantaneous $p\text{CO}_2$ changes, and conversely when $|(\text{dDIC}_T/\text{dt})_{\text{SST}}| < |(\text{dDIC}/\text{dt})_{\text{Tot}}|$, DIC processes is the
433 dominant mode in the instantaneous $p\text{CO}_2$ variability. The models showing the former feature are SST-
434 driven and belong to group-SST, while the models showing the latter are DIC-driven and belong to group-
435 SST.

436

437 According to the $M_{\text{T-DIC}}$ magnitudes in Fig. 6, the seasonal cycle of $p\text{CO}_2$ in the observational estimates is
438 predominantly DIC-driven most of the year in both the Sub-Antarctic and Antarctic zone. Note that,
439 however, during periods of high $|\text{dSST}/\text{dt}|$, i.e. autumn and spring, observations show a moderate to weak
440 DIC control ($M_{\text{T-DIC}} \approx 0$). The Antarctic zone is mostly characterized by a stronger DIC control (mean Annual
441 $M_{\text{T-DIC}} > 3$) except for the spring season (Fig. 6). Consistent with the similarity analysis presented in Fig. 4,
442 the Antarctic zone shows coherence in the sign of the temperature –DIC indicator ($M_{\text{T-DIC}} > 0$) within the
443 three basins.

444

445

446 **3.4 Source terms in the DIC surface budget**

447

448 To further constrain the surface DIC budget in Eq. 1, we examine the role of the biological source term
449 using chlorophyll and Net Primary Production (NPP) as proxies. Fig. 8 shows the seasonal cycle of
450 chlorophyll, NPP and the rate of surface DIC changes (dDIC/dt). The observed seasonal cycle of chlorophyll
451 (Johnson et al., 2013) shows a similar seasonal cycle within the three basins during the spring – summer
452 seasons (autumn-winter data are removed due to the satellite limitation) in both Sub-Antarctic and
453 Antarctic zone. Magnitudes are however different in the Sub-Antarctic zone; the Atlantic basin shows larger
454 chlorophyll magnitudes (Chlorophyll reach up to 1.0 mg m^{-3}) compared to the Pacific and Indian basins (Chl
455 $< 1 \text{ mg m}^{-3}$).

456

457 CMIP5 models here show a clear partition between group-DIC and group-SST models. While they mostly
458 maintain the same phase, group-DIC shows larger amplitudes of chlorophyll relative to group-SST and
459 observed estimates in the Sub-Antarctic zone. This difference is even clearer in NPP magnitudes, where
460 group-DIC models show a maximum of $\text{NPP} > 1 \text{ mmol m}^{-2} \text{ s}^{-1}$ in summer, while group-SST magnitudes shows
461 about half of it. Except for CESM1-BGC and CMCC-CESM (and NorESM1-ME for NPP), each CMIP5 model
462 generally maintains a similar chlorophyll seasonal cycle (phase and magnitude) in all three basins of the
463 Southern Ocean. This is contrary to the observations, which show differences in the magnitude.

464 Consistently with the observational product, CESM1-BGC simulates larger amplitude in the Atlantic basin.

465 While CMCC-CESM also has this feature, it also shows an overestimated chlorophyll peak in the Indian

466 Ocean. In the Antarctic zone both observations and CMIP5 models generally agree in both phase and
467 magnitude (except for CanESM2) of the seasonal cycle of chlorophyll in all three basins.

468

469 We now examine the influence of the vertical DIC rate in Eq. 1, using estimated entrainment rates (RE, Eq.
470 5) based on MLD and vertical DIC gradients (see sec. 2.3). Fig. 7 shows the seasonal changes of MLD
471 compared with the rate from the observational product. CMIP5 models largely agree on the timing of the
472 onset of MLD deepening (February in the Pacific Ocean, and March for the Atlantic and Indian Ocean) and
473 shoaling (September) in the Sub-Antarctic zone (with the exception of NorESM1-ME and IPSL-CM5A in the
474 Pacific Ocean). The Indian Ocean generally shows deeper winter MLD in both observations and CMIP5
475 models in the Sub-Antarctic zone. Note that while CMIP5 models generally show the observed deeper
476 MLDs in the Indian Ocean, they show a large variation; for example, the winter maximum depth range from
477 100 m (CMCC-CESM, Pacific Ocean) to 350 m (CanESM2, Indian Ocean) in the Sub-Antarctic zone. In the
478 Antarctic zone CMIP5 models are largely in agreement on the timing of the onset of MLD deepening
479 (February), but also variable in their winter maximum depth. It is worth noting that the observed MLD
480 seasonal cycle might be biased due to limited in situ observations particularly in the Antarctic zone (de
481 Boyer Montégut et al., 2004).

482

483 The estimated RE values in Fig. 10 show that almost all CMIP5 (with the exception of NorESM1-ME) entrain
484 subsurface DIC into the mixed layer during autumn–winter in agreement with the observational estimates.
485 In the Sub-Antarctic zone, the estimates using the observational products show the strongest entrainment
486 in the Atlantic Ocean in May (RE reaches up to $10 \mu\text{mol kg}^{-1} \text{month}^{-1}$), while it is lower in the other basins. In
487 the Antarctic zone, observed RE conversely shows stronger entrainment rates in the Pacific and Indian
488 Ocean ($\text{RE} > 15 \mu\text{mol kg}^{-1} \text{month}^{-1}$) in comparison to the Atlantic basin ($\text{RE} = 11 \mu\text{mol kg}^{-1} \text{month}^{-1}$). CMIP5
489 models entrainment rates are variable but not showing any particular deficiency when compared with the
490 observational estimates. Also, the group-DIC and group-SST models show no clear distinction, the major
491 striking features being the relatively stronger entrainment in MPI-ESM and CanESM2 across the three
492 basins in the Sub-Antarctic zone in mid to late winter ($\text{RE} = 15 \mu\text{mol kg}^{-1} \text{month}^{-1}$) and the large winter
493 entrainment in IPSL-CM5A-MR in the Antarctic Pacific Ocean. The supply of DIC to the surface due to vertical
494 entrainment is therefore generally comparable between model simulations and the available estimate.

495

496 However, our RE estimates are estimated at the base of the mixed layer, which is not necessarily a
497 complete measure of the vertical flux of DIC at the surface. We therefore investigate the annual mean
498 vertical DIC gradients in Fig. 10 as an indicator of where the surface uptake processes occur. The simulated
499 CMIP5 profiles are similar to GLODAP2, but some differences arise. In the Sub-Antarctic zone, GLODAP2

500 shows a shallower surface maximum in the Atlantic basin consistent with higher biomass in this basin (Fig.
501 8) $((dDIC/dz)_{smax} = 0.55 \mu\text{mol kg}^{-1} \text{m}^{-1}$, at 50 m) compared to the Pacific $((dDIC/dz)_{smax} = 0.60 \mu\text{mol kg}^{-1} \text{m}^{-1}$, at
502 80 m) and Indian basin $((dDIC/dz)_{smax} = 0.40 \mu\text{mol kg}^{-1} \text{m}^{-1}$, at 80 m). CMIP5 models generally do not show
503 this feature in the Sub-Antarctic zone, except for CESM1-BGC1 $((dDIC/dz)_{smax} = 0.50 \mu\text{mol kg}^{-1} \text{m}^{-1}$, at 50 m).
504 Instead, they show the surface maxima at the same depth in all three basins. In the Antarctic zone both
505 CMIP5 models and observations shows larger $(dDIC/dz)_{smax}$ magnitudes and nearer surface maxima (with
506 the exception of CanESM2 and CESM1-BGC). This difference in the position and magnitude of the DIC
507 maxima between the Sub-Antarctic and Antarctic zone has important implications for surface DIC changes
508 and subsequently $p\text{CO}_2$ seasonal variability. Because of the nearer surface DIC maxima in the Antarctic
509 zone, surface DIC changes are mostly influenced by these strong near surface vertical gradients than MLD
510 changes. This implies that even if the entrainment rates at the base of the MLD are comparable between
511 the Sub-Antarctic and the Antarctic, the surface supply of DIC may be larger in the Antarctic zone.

512

513

514 **4. Discussion**

515

516 Recent studies have highlighted that important differences exist between the seasonal cycle of $p\text{CO}_2$ in
517 models and observations in the Southern Ocean (Lenton et al., 2013; Anav et al., 2015; Mongwe, 2016).
518 Paradoxically, although the models may be in relative agreement for the mean annual flux, they diverge in
519 the phasing and magnitude of the seasonal cycle (Lenton et al., 2013; Anav et al., 2015; Mongwe, 2016).
520 These differences in the seasonal cycle raise questions about the climate sensitivity of the carbon cycle in
521 these models because they may reflect differences in the process sensitivities to drivers that are
522 themselves climate sensitive.

523

524 In this study we expand on the framework proposed by Mongwe et al. (2016), which examined the
525 competing roles of temperature and DIC as drivers of $p\text{CO}_2$ variability and the seasonal cycle of $p\text{CO}_2$ in the
526 Southern Ocean, to explain the mechanistic basis for seasonal biases of $p\text{CO}_2$ and FCO_2 between
527 observational products and CMIP5 models. This analysis of 10 CMIP5 models and one observational
528 product (Landschutzer et al., 2014) highlighted that although the models showed different seasonal modes
529 (Fig. 2), they could be grouped into two categories (SST- and DIC-driven) according to their mean seasonal
530 bias of temperature or DIC control (Fig. 3 & 6).

531

532 A few general insights emerge from this analysis. Firstly, despite significant differences in the spatial
533 characteristics of the mean annual fluxes (Fig. 1), models show unexpectedly greater inter-basin coherence

534 in the phasing seasonal cycle of FCO_2 and SST-DIC control than observational products (Fig. 3 & 6). Clear
535 inter-basin differences have been highlighted in studies on the climatology and interannual variability that
536 examined pCO_2 and CO_2 fluxes based on data products (Landschutzer et al., 2015; Gregor et al., 2017) as
537 well as phytoplankton chlorophyll based on remote sensing (Thomalla et al., 2011; Carranza et al., 2016).
538 Briefly, the Atlantic Ocean shows the highest mean primary production in contrast to the Pacific Ocean,
539 which has the lowest (Thomalla et al., 2011). Similarly, strong inter-basin differences for pCO_2 and FCO_2
540 have been highlighted and ascribed to SST control (Landschützer et al., 2016) and wind stress - mixed layer
541 depth (Gregor et al., 2017). The combined effect of these regional differences in forcing of pCO_2 and FCO_2
542 would be expected to be reflected in the CMIP5 models as well. A quantitative analysis of the correlation
543 of the phasing of the seasonal cycle of FCO_2 between basins for different models shows that all the models
544 except 3 (CMCC-CESM, GFDL-ESM2M CESM1-CESM) are characterized by strong inter-basin correlation in
545 both the SAZ and the AZ (Fig. 4). This suggests that the carbon cycle in these CMIP5 models is not sensitive
546 to inter-basin differences in the drivers as is the case for observations.

547

548 Secondly, an important part of this analysis is based on the assumption that the observational products
549 that are used to constrain the spatial and temporal variability of pCO_2 and FCO_2 reflect the correct seasonal
550 modes of the Southern Ocean. This assumption requires significant caution not only due to the limitations
551 in the sparseness of the *in situ* observations but also due to limitations of the empirical techniques in
552 overcoming these data gaps (Landschutzer et al., 2014; Rödenbeck et al., 2015; Gregor et al., 2017a,b;
553 Ritter et al., 2018). The uncertainty analysis from these studies suggests that, while the seasonal bias in
554 observations may be less in the SAZ and PFZ, it is the highest in the AZ where access is limited mostly to
555 summer, and winter ice cover result in uncertainties that may limit the significance of the data - model
556 comparisons. It is important to note that though the observation product we use here (Landschützer et al.,
557 (2014) is based on more surface measurement (10 millions, SOCAT v3) compared to previous datasets (e.g.
558 Takahashi et al., 2009, 3 millions), the data are still sparse in time and space in the Southern Ocean. Thus
559 using this data product as our main observational estimates for this analysis we are mindful of the
560 limitations in its discussion below.

561

562 Thirdly, the seasonal cycle of ΔpCO_2 is the dominant mode of variability in FCO_2 (Mongwe et al., 2016;
563 Wanninkhof et al., 2009). Though winds provide the kinematic forcing for air-sea fluxes of CO_2 and
564 indirectly affect FCO_2 through mixed layer dynamics and associated biogeochemical responses (Mahadevan
565 et al., 2012; du Plessis et al., 2017), ΔpCO_2 sets the direction of the flux. Surface pCO_2 changes are mainly
566 driven by DIC and SST (Hauck et al., 2015; Takahashi et al., 1993). Subsequently the sensitivity of CMIP5
567 models to how changes in DIC and SST regulates seasonal cycle of FCO_2 is fundamental to the model's

568 ability to resolve observed FCO_2 seasonal cycle. Thus here we examined the influence of DIC and SST on
569 FCO_2 at seasonal scale for 10 CMIP5 models with respect to observed estimates. But because temperature
570 does not directly affects DIC changes, we first scaled up the impact of SST changes on pCO_2 through surface
571 CO_2 solubility to equivalent DIC units using the Revelle factor (section 2.3). In this way we can distinguish
572 the influence of surface solubility and DIC changes (i.e. biological and physical) on pCO_2 and hence then
573 FCO_2 .

574

575 Fourthly, using this analysis framework (sec 2.3, summarized in Fig. 6) we found that CMIP5 models FCO_2
576 biases cluster in two groups, namely group-DIC ($M_{\text{T-DIC}} < 0$) and group-SST ($M_{\text{T-DIC}} > 0$). Group-DIC models are
577 characterized by an overestimation of the influence of DIC on pCO_2 with respect to observations estimates,
578 which instead indicate that physical and biogeochemical changes in the DIC concentration mostly regulate
579 the seasonal cycle of FCO_2 (in short, DIC control). Group-SST models show an excessive temperature
580 influence on pCO_2 ; here surface CO_2 solubility biases are mainly responsible for the departure of modeled
581 FCO_2 from the observational products. While CMIP5 models mostly show a singular dominant influence of
582 these extremes, observations show a modest influence of both, with a dominance of DIC changes as the
583 main driver of seasonal FCO_2 variability. Below we discuss the seasonal cycle characteristics and possible
584 mechanisms for these two groups of CMIP5 models in the Sub-Antarctic and Antarctic Zones of the
585 Southern Ocean.

586

587 **4.1 Sub-Antarctic Zone (SAZ)**

588

589 Our diagnostic analysis indicates that the seasonal cycle of pCO_2 in the observational product (Landschützer
590 et al., 2014) is mostly DIC controlled across all three basins of the SAZ ($M_{\text{T-DIC}} < 0$ in Fig. 6). The Atlantic
591 Ocean shows a stronger DIC control (Annual mean $M_{\text{T-DIC}} \geq 2$) compared to the Pacific and Indian Ocean
592 (Annual mean $M_{\text{T-DIC}} \approx 1$). This stronger influence of DIC on pCO_2 in the Atlantic Ocean is consistent with
593 higher primary production in this basin (Graham et al., 2015; Thomalla et al., 2011), here shown by the
594 larger mean seasonal chlorophyll from remote sensing in the Atlantic basin with respect to the Pacific and
595 Indian basin (Fig. 8). This significant basin difference is most likely linked to a number of factors: the
596 Atlantic basin has longer periods of shallow MLD compared to the Pacific and Indian basins (Fig. 7a-c, Nov –
597 Mar & Nov - Feb respectively) and has been shown to have higher supplies of continental shelves and land
598 based iron (Boyd and Ellwood, 2010; Tagliabue et al., 2012; 2014). These conditions are more likely to
599 enhance primary production that translates into a higher rate of change of surface DIC (Fig. 8), which
600 becomes the major driver of FCO_2 variability. In contrast, shorter periods of shallow MLD and lower iron
601 inputs in the Pacific Ocean (Tagliabue et al., 2012), likely account for lower chlorophyll biomass and hence

602 the weaker DIC control evidenced in our analysis ($M_{T-DIC} \approx 0$ in Fig. 6). In the Indian Ocean, the winter mixed
603 layer is deeper than in the Atlantic and deepens earlier in the season (Fig. 7c). These conditions limit
604 chlorophyll concentration (Fig. 8) and possibly contribute to the lower rates of surface temperature change
605 because of the enhanced mixing (cf Fig. 5a-c). As a consequence the resulting net driver in the Indian and
606 Pacific basins is a weaker DIC control, because both biological DIC and solubility changes are relatively
607 weaker and they oppose each other. Because of this, when the magnitudes of the rate of change of SST are
608 larger during cooling and warming seasonal peaks (autumn and spring respectively), DIC control is weaker
609 ($M_{T-DIC} \approx 0$) during these seasons.

610
611 CMIP5 models do not capture these basin-specific features as demonstrated with the correlation analysis in
612 Fig. 4, with the exception of three group-SST models (i.e. CESM1-BGC, GFDL-ESM2M and CMCC-CESM).
613 These, in contrast, mostly show comparable FCO_2 phasing in the three basins. This spatial uniformity of
614 CMIP5 models is both zonal and meridional for most models in the Southern Ocean (Fig. 3, 4), which is in
615 contrast to observation products (Fig. 3). This suggests that CMIP5 models show equal sensitivity to basin
616 scale FCO_2 drivers, suggesting that pCO_2 and FCO_2 driving mechanisms are less local than for observations.

617
618 The major feature of group-SST models in the SAZ is the outgassing during summer and ingassing in winter
619 (Fig. 3a-c, Dec-Feb), which our diagnostics in Fig. 6 attribute to temperature (solubility) control. The
620 summer period coincides with the highest warming rates ($dSST/dt$, Fig 5a-c), and associated reduction in
621 solubility of CO_2 . Similarly, exaggerated cooling rates at the onset of autumn (Fig. 5a-c) enhance CO_2
622 solubility causing a change in the direction of FCO_2 into strengthening CO_2 ingassing (Fig 3a-c). Thus, while
623 group-SST models have seasonal amplitude of FCO_2 comparable to observations, they are out of phase (Fig.
624 3) as was the case in a previous analysis of a forced ocean model (Mongwe et al., 2016).

625
626 In addition to increasing CO_2 solubility, the rapid cooling at the onset of autumn also deepens the MLD
627 (March-June, Fig. 7), which induces entrainment of DIC, increasing surface CO_2 concentration and
628 weakening the ocean-atmosphere gradient and, in some instances, reversing the air-sea flux to outgassing
629 (Lenton et al., 2013a; Mahadevan et al., 2011; Metzl et al., 2006). While these processes (cooling and DIC
630 entrainment) are likely to co-occur in the Southern Ocean, in CMIP5 models they are characterized by their
631 extremes: temperature impact of solubility exceeds the rate of entrainment (Fig. 6 & 10). Because of the
632 dominance of the solubility effect in group-SST models, the impact of DIC entrainment on surface pCO_2
633 changes, the weakening of CO_2 ingassing / outgassing only happens in mid-late winter (June-July -August)
634 when entrainment fluxes peak (Fig. 10) and the SST rate approaches zero (Fig. 5).

635

636

637 In the spring-summer transition, primary production is anticipated to enhance the net CO₂ uptake
638 (Thomalla et al., 2011; Le Quéré and Saltzman, 2013). However, the elevated surface warming rates during
639 spring reduces CO₂ solubility in group-SST models and overwhelms the role of primary production in the
640 seasonal cycle of pCO₂ and FCO₂ (atmospheric CO₂ uptake). As a consequence, these group-SST models
641 mostly show a constant or weakening net CO₂ uptake flux during spring in the Pacific and Atlantic Ocean
642 even though primary production is occurring and is relatively elevated (Fig. 3 & 8). Though some models
643 show chlorophyll concentrations comparable to observations (e.g. GFDL-ESM2M, CNRM-CM5, CanESM2),
644 and sometimes greater (e.g. MRI-ESM), the impact of temperature driven solubility dominates due the
645 phasing of the rates of the two drivers (Fig. 2a-c). The Indian Ocean however shows the only exception to
646 this phenomenon. Here, the amplitude of the seasonal surface warming is relatively smaller ($\sim 0.5 \text{ }^{\circ}\text{C}^{-1}$
647 month⁻¹ lower than the Pacific and Atlantic basins), and the biologically driven CO₂ uptake becomes notable
648 and show a net strengthening of the sink of CO₂ during spring (Fig. 3c).

649

650 Though almost all analysed CMIP5 models (with the exception of NorESM1-ME) exaggerate the warming
651 and cooling rates in autumn and spring, group-DIC models do not manifest the expected temperature-
652 driven solubility impact on pCO₂ and FCO₂ (Fig. 2) Instead, the seasonal cycle of pCO₂ and FCO₂ are
653 controlled by DIC changes. However, this is driven by an overestimated seasonal primary production and
654 the associated carbon export fluxes (Fig. 8). It is striking how in these models the seasonal cycle of
655 chlorophyll and FCO₂ are in phase (Fig 3a-c, 8a-c, with linear correlation coefficients always larger than 0.9,
656 not shown) but, as we discuss below, this is not because the temperature rates of change are correctly
657 scaled but because the biogeochemical process rates are exaggerated (Fig. 8).

658

659 Because of the particularly enhanced production in group-DIC models, the CO₂ sink is stronger (Fig. 8) with
660 respect to observation estimates during spring. This is visible in the reduction of surface DIC (negative
661 dDIC/dt in Fig. 8a, g-i), which can only be explained by drawdown due to the formation and export of
662 organic matter (Le Quéré and Saltzman, 2013). However, note that in the same way, after the December
663 production peak, both CMIP5 models and observations show an increase of surface DIC concentrations
664 (positive dDIC/dt) until March (Fig. 8, g-i). These DIC growth rates are particularly enhanced in group-DIC
665 models compared to some group-SST and observations (Fig. S9). The onset of these DIC increases also
666 coincides with the depletion of surface oxygen (Fig. S9), which we makes us speculate that this is due to the
667 remineralisation of organic matter to DIC through respiration. Unfortunately, only a few models have
668 stored the respiration rates, therefore the ultimate reason for this DIC rebound remains to be examined at
669 a later stage. We would however tend to exclude other processes, because the onset of CO₂ outgassing

670 seen in March in group-DIC models occurs prior to significant MLD deepening (Fig. 7) and entrainment
671 fluxes, therefore remineralization is likely be a key process here (Fig. 8).

672

673 **4.2 Antarctic Zone (AZ)**

674

675 The seasonal cycle framework summarized in Fig. 6 shows that the variability of FCO_2 and pCO_2 in the
676 Landschützer et al. (2014) product is characterized by a stronger DIC control (annual mean $M_{\text{T-DIC}} < -2$)
677 relative to the Sub-Antarctic ($M_{\text{T-DIC}} \approx -1$), except in the spring season ($M_{\text{T-DIC}} > -1$). This DIC control is
678 spatially uniform in the Antarctic zone across all three basins (Fig. 4). The available datasets indicate that
679 the combination of weaker SST rates due to lower solar heating fluxes (Fig. 5), and stronger shallower
680 vertical DIC maxima (Fig. 10) favour a stronger DIC control through larger surface DIC rates. The spatial
681 uniformity in the seasonality of FCO_2 is also evident in the satellite chlorophyll and calculated dDIC/dt from
682 GLODAP2 in Fig. 9. Contrary to the Sub-Antarctic this might be suggesting that FCO_2 mechanisms are here
683 less local. It could be hypothesized that the seasonal extent of sea-ice, deeper mixing and heat balance
684 differences affect this region more uniformly compared to the Sub-Antarctic zone, and hence the
685 mechanisms of FCO_2 are spatially homogeneous. However, we cannot forget that sparseness of
686 observations in this region is a known key limitation to data products (Bakker et al., 2014; Gregor et al.,
687 2017; Monteiro et al., 2010; Rödenbeck et al., 2013) that might hamper the emergence of basin specific
688 features. Consequently, this highlights the importance and need to prioritize independent observations in
689 the Southern Ocean south of the polar front and in the Marginal Ice Zone. Increased observational efforts
690 should also include a variety of platforms such as autonomous vehicles like gliders (Monteiro et al., 2015)
691 and biogeochemical floats (Johnson et al., 2017) in addition to ongoing ship-based measurements.

692

693 In general terms, CMIP5 models are mostly in agreement (with an exception of MRI-ESM) with the
694 observational product on the dominant role of DIC to regulating the seasonal cycle of FCO_2 (Fig. 6d-f),
695 though not all models agree in the phase of the seasonal cycle of FCO_2 (e.g. CanESM2, Fig. 2). Though
696 CMIP5 models still mostly show the SST rates biases in autumn and spring with respect to observed
697 estimates, the stronger and near surface vertical DIC maxima (Fig. 10), likely favor DIC as a dominant driver
698 of FCO_2 changes. , Differences between group-SST and group-DIC models are only evident in mid-summer
699 when SST rates heighten and primary production peaks (Fig. 3 & 9). Probably because of sea ice presence,
700 the onset of SST warming is a month later (November) here in comparison to the Sub-Antarctic (October).
701 This subsequently allows the onset of primary production before the surface warming, which then permits
702 the biological CO_2 uptake to be notable in group-SST models. We notice here that the reason why CMIP5
703 models develop a winter bloom in the AZ requires further investigation (Hague and Vichi, submitted). Thus

704 the two model groups here agree in the FCO₂ ingassing during spring with group-SST models being the
705 closest to the observational product. The MRI-ESM is the only model showing anomalous solubility
706 dominance during autumn and spring as in the Sub-Antarctic zone.

707

708 This coherence of CMIP5 models and observations in the Antarctic zone, may suggest that CMIP5 models
709 compare better to observations in this region (Fig. 4). However, because CMIP5 models also show this
710 spatial homogeneity in the Sub-Antarctic Zone (contrary to observational estimates), it not clear whether
711 this indicates an improved skill in CMIP5 model to the mechanisms of FCO₂ in this region, or both CMIP5
712 models and observational product lacks spatial sensitivity to the drivers of FCO₂. The sparseness of
713 observations in the AZ points to the latter.

714

715 **5. Synthesis**

716

717 We used a seasonal cycle framework to highlight and examine two major biases in respect of pCO₂ and
718 FCO₂ in 10 CMIP5 models in the Southern Ocean.

719

720 Firstly, the general exaggeration of the seasonal rates of change of SST in autumn and spring seasons during
721 peak cooling and warming respectively with respect to available observations. These elevated rates of SST
722 change tip the control of the seasonal cycle of pCO₂ and FCO₂ towards SST from DIC and result in a
723 divergence between the observed and modelled seasonal cycles, particularly in the Sub-Antarctic Zone.

724 While almost all analysed models (9 of 10) show these SST-driven biases, 3 of the 10 (namely NorESM1-ME,
725 HadGEM-ES and MPI-ESM) don't show these solubility biases because of their overly exaggerated primary
726 production (and remineralization) rates such that biologically driven DIC changes mainly regulate the
727 seasonal cycle of FCO₂. These models reproduce the observed phasing of FCO₂ as a result of an incorrect
728 scaling of the biogeochemical fluxes. In the Antarctic zone, CMIP5 models compare better with
729 observations relative to the Sub-Antarctic Zone. This is mostly because both CMIP5 models and
730 observational product estimates show a spatial and temporal uniformity in the characteristics of FCO₂ in
731 the Antarctic zone. However, it is not certain if this is because model process dynamics perform better in
732 this high latitude zone or that the observational products variability is itself limited by the lack of *in situ*
733 *data*. This remains an open question that needs to be explored further and highlights the need for
734 increased scale sensitive and independent observations south of the Polar Front and into the sea ice zone.

735

736 The second major bias is that contrary to observational products estimates, CMIP5 models generally show
737 an equal sensitivity to basin scale FCO₂ drivers (except for CMCC-ESM, GFDL-ESM2M and CESM1-BGC) and

738 hence the seasonal cycle of FCO₂ has similar phasing in all three basins of the Sub-Antarctic zone. This is in
739 contrast to observational and remote sensing products that highlight strong seasonal and interannually
740 varying basin contrasts in both pCO₂ and phytoplankton biomass. It is not clear if this is due to inadequate
741 carbon process parameterization or gaps in the dynamics of the physics. This should be investigated
742 further with CMIP6 models and our analysis framework is proposed as a useful tool to diagnose the
743 dominant drivers. Contrary to observed estimates, CMIP5 models simulate FCO₂ seasonal dynamics that
744 are zonally homogeneous and for this reason it is suggested that any investigation of local (basin scale)
745 mechanisms, dynamics and long term trends of FCO₂ using CMIP5 models should be cautious. This
746 highlights a key area of development for CMIP6.

747

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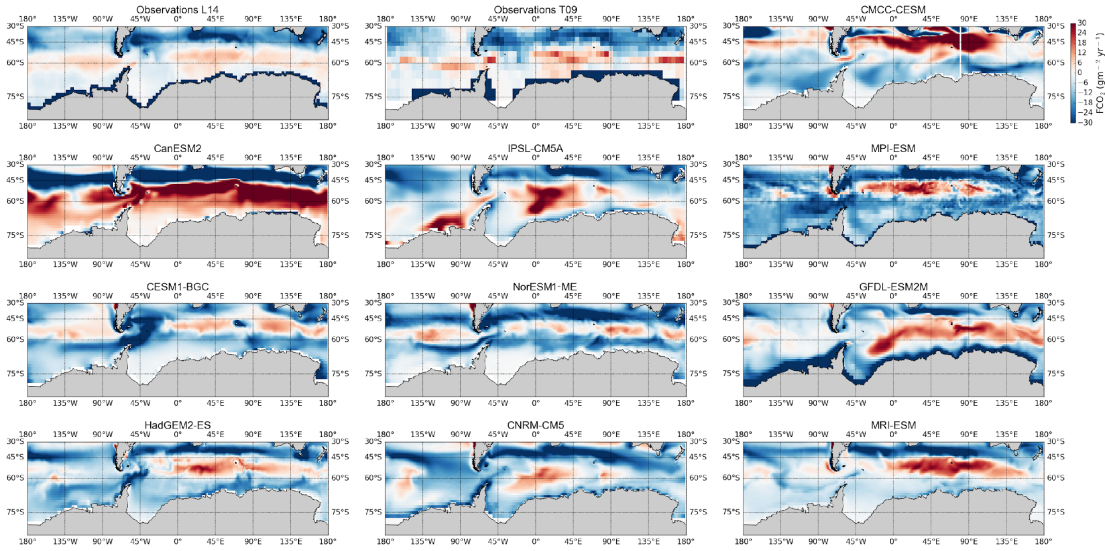
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1105 **Figures**

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1108 **Fig. 1:** Annual climatological Sea-Air CO₂ Flux (FCO₂, in gC m⁻² yr⁻¹) for observations (L14:Landschützer et al.,
1109 2014 and T09: Takahashi et al., 2009) and 10 CMIP5 models over 1995 – 2005.

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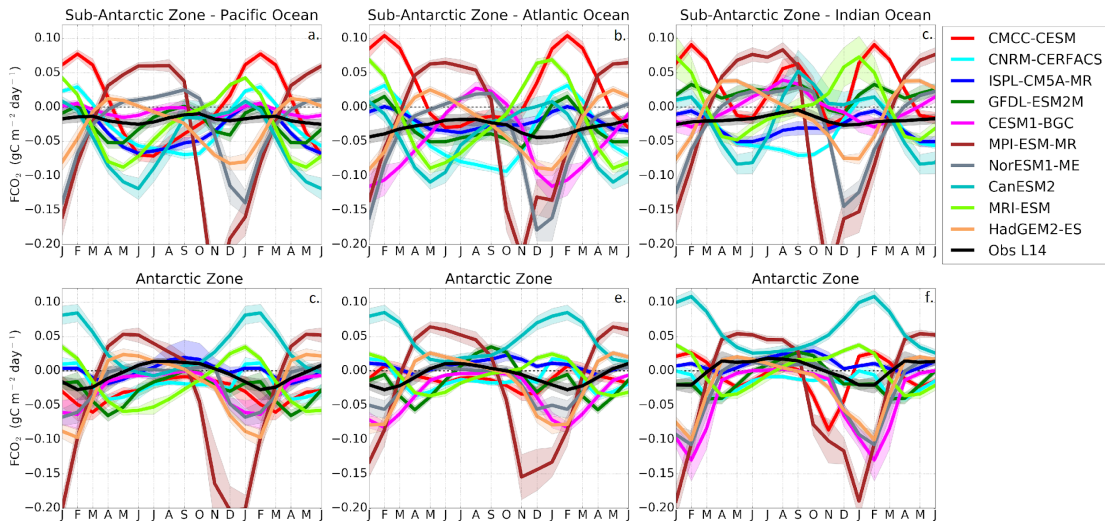
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Fig. 2: Seasonal cycle of Sea-Air CO₂ Flux (FCO₂, in gC m⁻² yr⁻¹) in observations and 10 CMIP5 models in the Sub-Antarctic and Antarctic zones of the Pacific Ocean (first column), Atlantic Ocean (second column) and Indian Ocean (third column). The shaded area shows the temporal standard deviation over the considered period (1995 – 2005).

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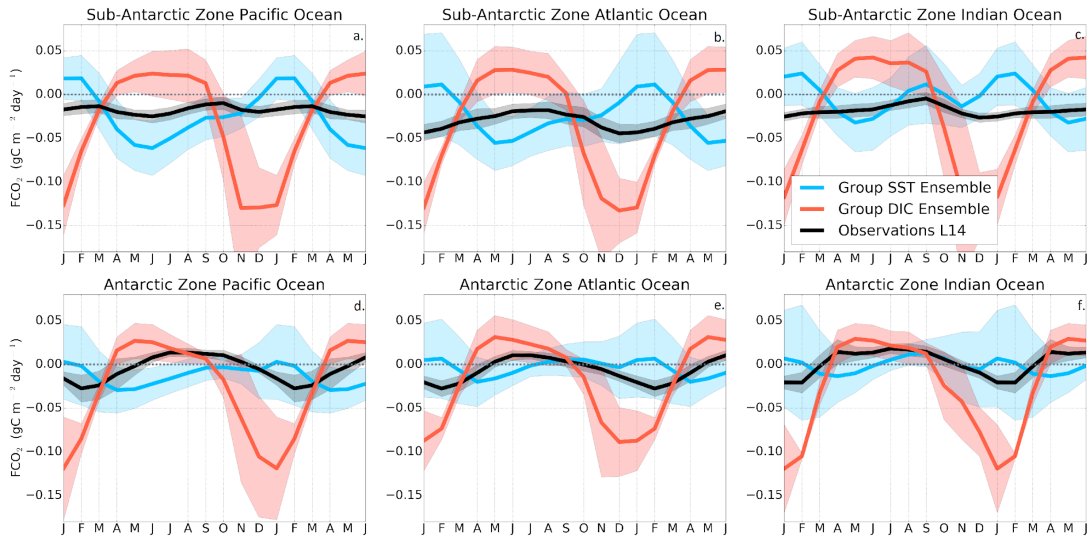
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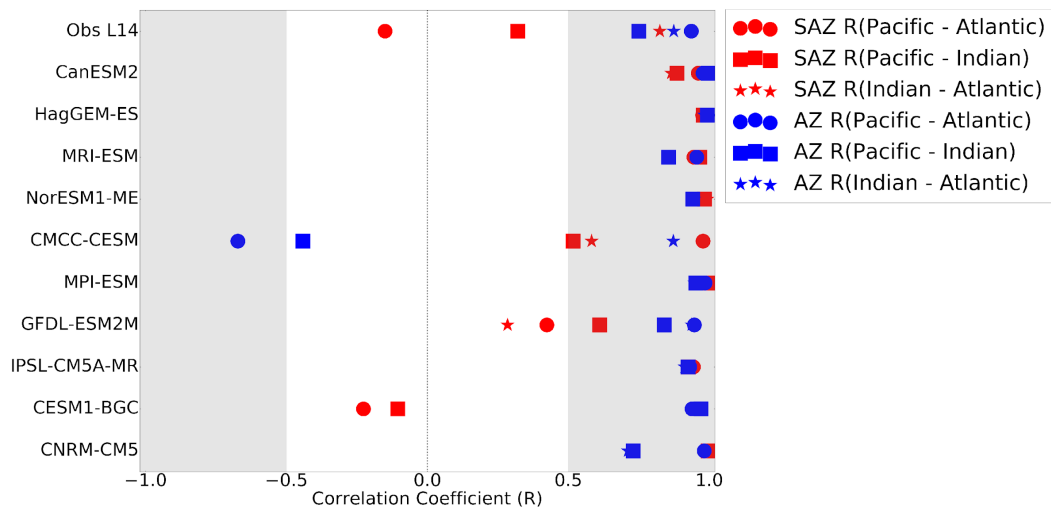
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Fig. 3. Seasonal cycle of the equally weighted ensemble means of FCO₂ (gC m⁻² yr⁻¹) from Fig. 2 for group DIC models (MPI-ESM, HadGEM-ES and NorESM), and group SST models (GFDL-ESM2M, CMCC-CESM, CNRM-CERFACS, IPSL-CM5A-MR, CESM1-BGC, NorESM2, MRI-ESM and CanESM2). The shaded areas show the ensemble standard deviation. The black line is the Landschützer et al., (2014) observations.



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1155 **Fig. 4:** The correlation coefficients (R) of basin – basin seasonal cycles of FCO₂ for observations
 1156 (Landschützer et al., 2014) and 10 CMIP5 models in the three basins of the Southern Ocean i.e. Pacific,
 1157 Atlantic and Indian basin.

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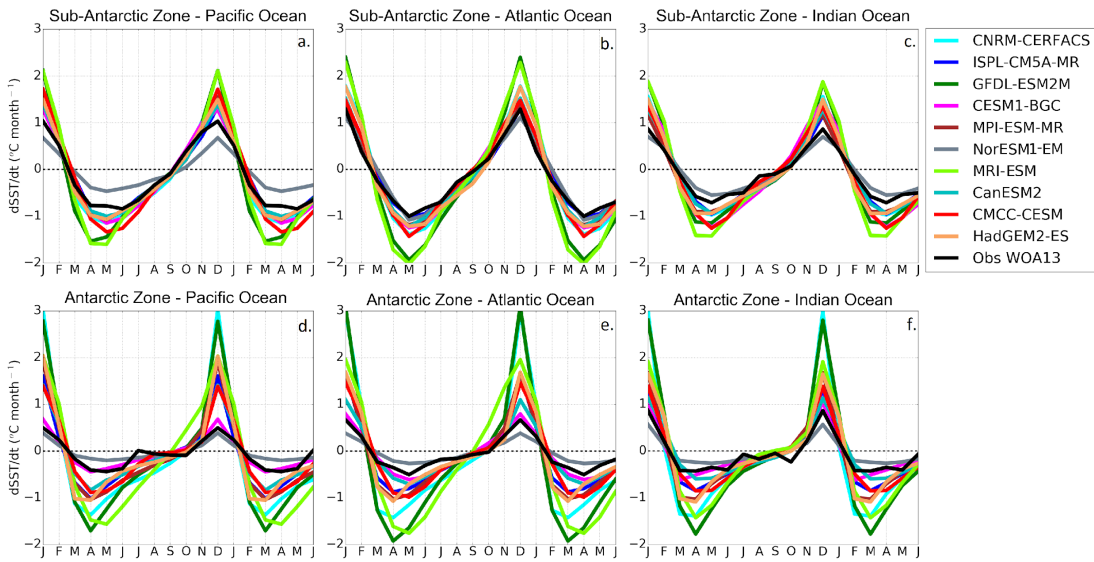
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Fig. 5: Mean seasonal cycle of the estimated rate of change of sea surface temperature ($dSST/dt$, $^{\circ}C\ month^{-1}$) for the Sub-Antarctic and Antarctic zones of the Pacific Ocean (first column), Atlantic Ocean (second column) and Indian Ocean (third column).

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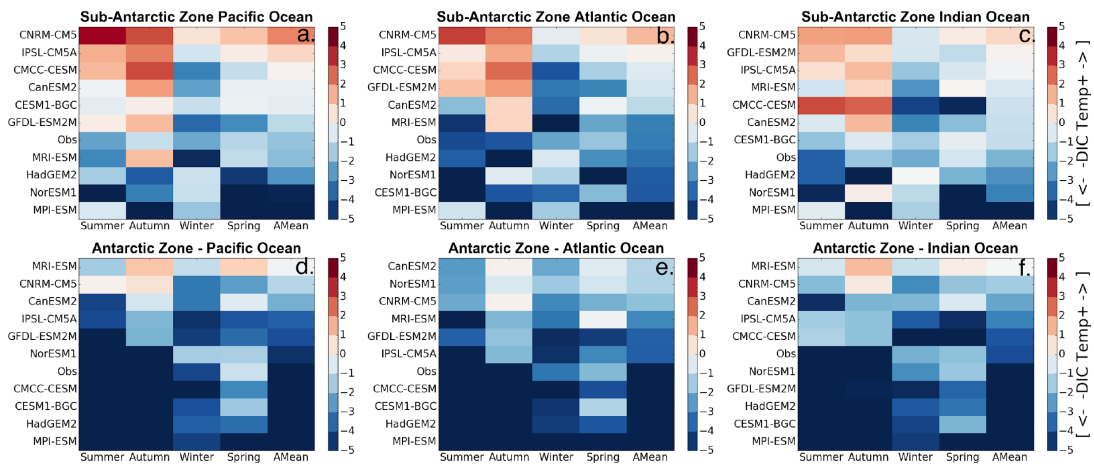
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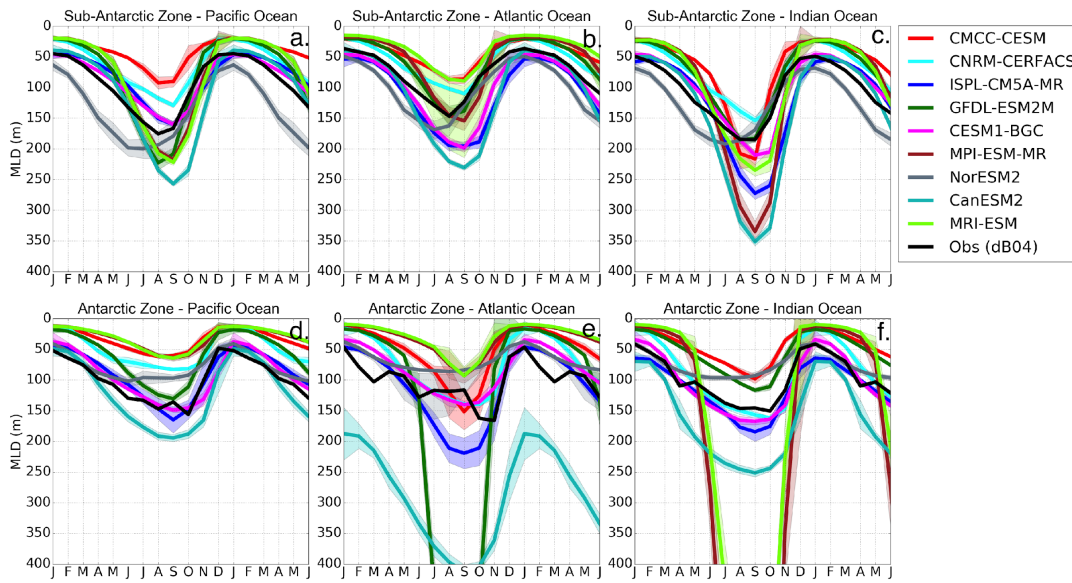
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Fig. 6: Mean seasonal and annual values of the DIC–temperature control index (M_{T-DIC}). The increase in the red color intensity indicates increase in the strength of the temperature driver and the blue intensity shows the strength of the DIC driver. The models are sorted according to the annual mean value of the indicator presented in the last column (Amean)



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1215 **Fig. 7:** Seasonal cycle of the Mixed Layer Depth (MLD) in the Sub-Antarctic and Antarctic zones of the Pacific
 1216 Ocean (first column), Atlantic Ocean (second column) and Indian Ocean (third column).

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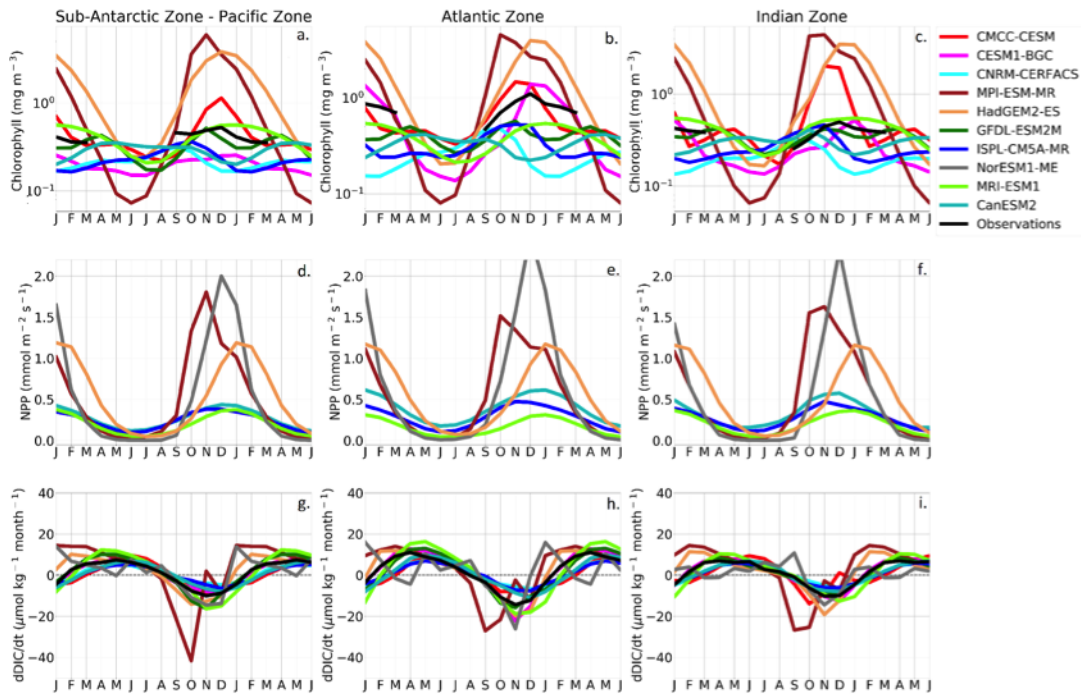
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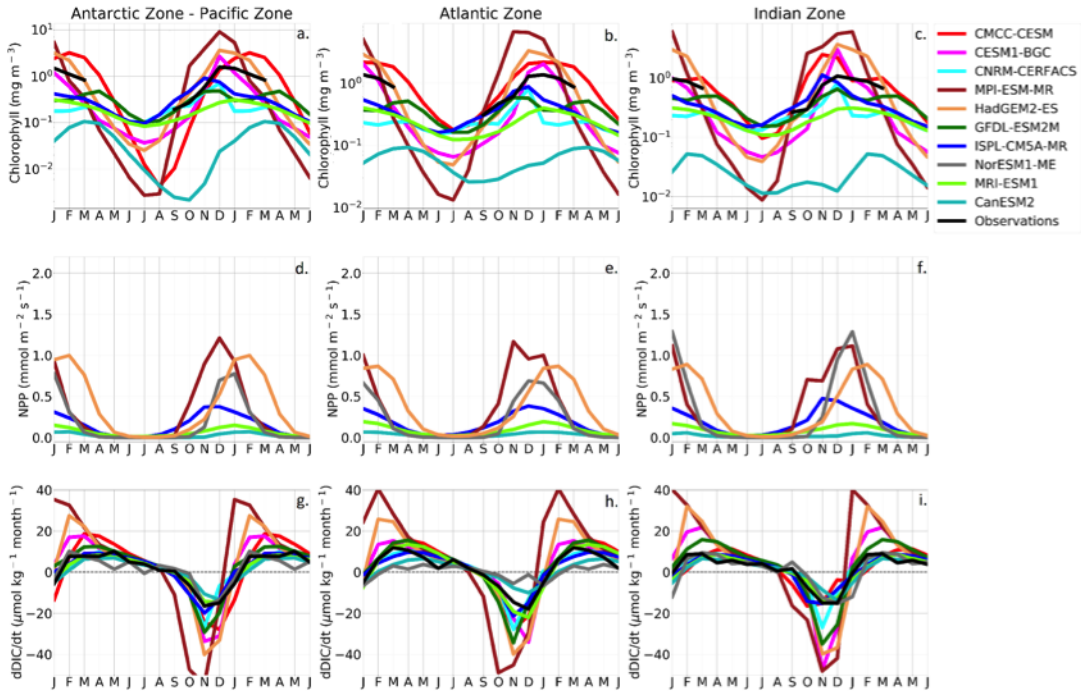
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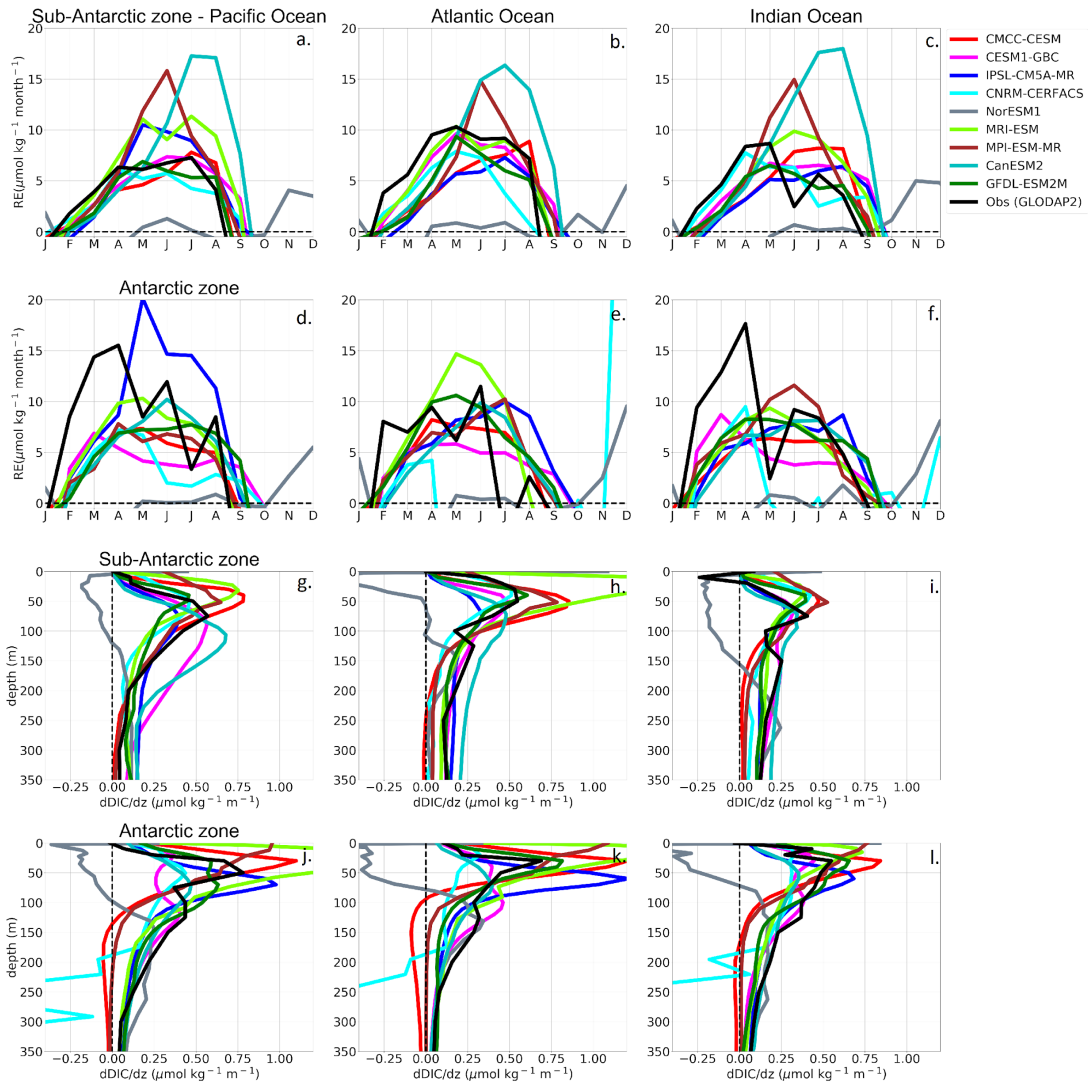
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Fig. 8: The seasonal cycle of chlorophyll (mg m^{-3}), Net Primary Production ($\text{mmol m}^{-2} \text{s}^{-1}$) and the surface rate of change of DIC ($\mu\text{mol kg}^{-1} \text{month}^{-1}$) in the Sub-Antarctic zone of the Pacific Ocean (first column), Atlantic Ocean (second column) and Indian Ocean (third column).



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Fig. 9 Same as Fig. 8 for the Antarctic zone.



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Fig. 10: (a-f) Estimated DIC entrainment fluxes (mol kg month^{-1}) at the base of the mixed layer and (g-i)

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vertical DIC gradients ($\mu\text{mol kg}^{-1} \text{m}^{-1}$) in the Sub-Antarctic and Antarctic zone of the Pacific Ocean (first

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column), Atlantic Ocean (second column) and Indian Ocean (third column).

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1255 **Table 2:** Sea-Air CO₂ fluxes (Pg C yr⁻¹) annual mean uptake in the Southern Ocean (first column), here
1256 defined as south of the Sub-tropical front, Sub-Antarctic zone (second column) and Antarctic zone (third
1257 column). The third and forth column shows the Pattern Correlation Coefficient (PCC) and Root Mean
1258 Square Error (RMSE) for the whole Southern Ocean for each model.

Table 2: Sea-Air CO₂ Fluxes Mean Annual Uptake, PCC and RMSE

Model	Southern Ocean	Sub-Antarctic zone	Antarctic zone	PCC	RMSE
CNRM-CM5	-0.823 ± 0.003	-0.682 ± 0.002	-0.122 ± 0.001	0.44	17.9
GFDL-ESM2M	-0.161 ± 0.005	-0.074 ± 0.004	-0.077 ± 0.002	0.43	8.47
HadGEM2-ES	-0.489 ± 0.005	-0.284 ± 0.003	-0.197 ± 0.001	0.55	10.9
IPSL-CM5A-MR	-0.496 ± 0.003	-0.582 ± 0.006	0.101 ± 0.003	0.53	10.5
MPI-ESM-MR	-0.870 ± 0.006	-0.530 ± 0.002	-0.326 ± 0.002	0.37	9.87
MRI-ESM	-0.048 ± 0.002	0.022 ± 0.003	-0.070 ± 0.001	0.36	15.6
NorESM1	-0.699 ± 0.004	-0.412 ± 0.003	-0.270 ± 0.002	0.60	8.96
CESM1-BGC	-0.532 ± 0.006	-0.132 ± 0.003	-0.385 ± 0.004	0.47	9.15
CMCC-CESM	0.121 ± 0.006	0.367 ± 0.004	-0.225 ± 0.003	-0.09	17.9
CanESM2	-0.058 ± 0.008	-0.720 ± 0.006	0.661 ± 0.004	0.54	19.5
Observations	-0.253 ± 0.3	-0.296 ± 0.3	0.053 ± 0.3		