

The Southern Ocean carbon cycle 1985-2018: Mean, seasonal cycle, trends and storage

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Key Points:

- Ocean models and machine learning estimates agree on the mean Southern Ocean CO₂ sink, but the trend since 2000 differs by a factor of two.
- Compared with RECCAP1, the updated estimate for the Southern Ocean CO₂ uptake is 50% smaller.
- Large model spread in summer and winter indicates that sustained efforts are required to understand driving processes in all seasons.

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Abstract

We assess the Southern Ocean CO₂ uptake (1985-2018) using data sets gathered in the REgional Carbon Cycle Assessment and Processes Project phase 2 (RECCAP2). The Southern Ocean acted as a sink for CO₂ with close agreement between simulation results from global ocean biogeochemistry models (GOBMs, 0.75±0.28 PgC yr⁻¹) and pCO₂-observation-based products (0.73±0.07 PgC yr⁻¹). This sink is only half that reported by RECCAP1. The present-day net uptake is to first order a response to rising atmospheric CO₂, driving large amounts of anthropogenic CO₂ (C_{ant}) into the ocean, thereby overcompensating the loss of natural CO₂ to the atmosphere. An apparent knowledge gap is the increase of the sink since 2000, with pCO₂-products suggesting a growth that is more than twice as strong and uncertain as that of GOBMs (0.26±0.06 and 0.11±0.03 Pg C yr⁻¹ decade⁻¹ respectively). This is despite nearly identical pCO₂ trends in GOBMs and pCO₂-products when both products are compared only at the locations where pCO₂ was measured. Seasonal analyses revealed agreement in driving processes in winter with uncertainty in the magnitude of outgassing, whereas discrepancies are more fundamental in summer, when GOBMs exhibit difficulties in simulating the effects of the non-thermal processes of biology and mixing/circulation. Ocean interior accumulation of C_{ant} points to an underestimate of C_{ant} uptake and storage in GOBMs. Future work needs to link surface fluxes and interior ocean transport, build long overdue systematic observation networks and push towards better process understanding of drivers of the carbon cycle.

Plain Language Summary

The ocean takes up CO₂ from the atmosphere and thus slows climate change. The Southern Ocean has been long known to be an important region for ocean CO₂ uptake. Here, we bring together all available data sets that estimate the Southern Ocean CO₂ uptake, from models that simulate ocean circulation and physical and biological processes that affect the ocean carbon cycle, from surface ocean observation-based estimates, from atmospheric transport models that ingest atmospheric CO₂ observations, and from interior ocean biogeochemical observations. With these data sets, we find good agreement on the mean Southern Ocean CO₂ uptake 1985-2018, which is 50% smaller than previous estimates when recalculated for the time period and spatial extent used in the previous estimate. However, the estimates of the temporal change of the Southern Ocean CO₂ uptake differ by a factor of two and thus are not in agreement. We further highlight that knowledge gaps exist not only in winter when observations are typically rare, but equally in summer when biology plays a larger role, which is typically represented in a too simplistic fashion in the dynamic models.

1 Introduction

The Southern Ocean (Figure 1) is the primary conduit between the surface and the deep ocean (Talley, 2013; Morrison et al., 2022) making it a key region for the global carbon cycle and the climate system across time-scales from paleo to present day and into the future (Canadell et al., 2021). Firstly, water mass formation of Antarctic surface water occurs during large-scale upwelling of deep, old and carbon-rich water masses due to strong westerly winds (Russell et al., 2006; Marshall & Speer, 2012). Part of this water moves northwards by Ekman transport and contributes to the formation of Southern mode and intermediate waters (Ito et al., 2010; Sallée et al., 2012; Morrison et al., 2022) together with subtropical water masses (Iudicone et al., 2016). Another part moves southward and circulates in the large gyres of the Weddell and Ross Seas (Klatt et al., 2005). A fraction of these Antarctic surface waters densify on the Antarctic shelves through cooling and brine rejection during sea-ice formation on the Antarctic shelves to then flow

79 down the Antarctic slope and form Antarctic Bottom Water (Orsi et al., 1999; Jacobs,
80 2004).

81 Historically, in pre-industrial times, the Southern Ocean was a net source of CO₂
82 to the atmosphere due to upwelling of carbon-rich deep waters (Mikaloff Fletcher et al.,
83 2007). Importantly, the large-scale upwelling that drove the natural outgassing fluxes
84 in the polar and subpolar Southern Ocean still occurs today. However, since industri-
85 alisation, increasing atmospheric levels of CO₂ have shifted the thermodynamic equilib-
86 rium of CO₂ partial pressure between the ocean and the atmosphere in the favor of the
87 latter, thus overcompensating the natural outgassing (e.g., Hoppema, 2004). The con-
88 temporary net flux in the Southern Ocean can thus be understood as the sum of the out-
89 gassing of natural CO₂ and uptake of anthropogenic CO₂ (Gruber et al., 2009; Gruber,
90 Landschützer, & Lovenduski, 2019). Importantly, the Southern Ocean has acted as the
91 primary region of uptake for anthropogenic CO₂ in the industrialized era (Sarmiento et
92 al., 1992; Orr et al., 2001; Caldeira & Duffy, 2000; Khatiwala et al., 2009; Frölicher et
93 al., 2015; Mikaloff Fletcher et al., 2006), which is attributed to upwelling of old water
94 masses (with low anthropogenic carbon) in a region of high wind speeds, as well as sub-
95 sequent transport of excess carbon from the surface into the ocean interior through the
96 formation of Subantarctic Mode and Antarctic Intermediate Water (Waugh et al., 2006;
97 Mikaloff Fletcher et al., 2006; Bopp et al., 2015; Langlais et al., 2017; Sallée et al., 2012).
98 In the absence of evidence of substantial changes in the biological carbon pump over the
99 past decades, the role of biology for anthropogenic carbon uptake is thought to be small
100 (Murnane et al., 1999; Holzer & DeVries, 2022). However, the biological carbon pump
101 can have a strong imprint on the net fluxes during the summer when primary produc-
102 tion draws down natural CO₂ at the surface (e.g., E. Jones et al., 2012, 2015).

103 While the general importance of the Southern Ocean for the ocean carbon sink is
104 recognised, it is also the region with the largest uncertainty in the mean and trend of
105 the sink (Hauck et al., 2020; Friedlingstein et al., 2022). This is partly because the observation-
106 based estimates and model-based estimates measure different components of the ocean
107 carbon sink, and assumptions on fluxes associated with river discharge need to be made,
108 which carry high uncertainty themselves (Aumont et al., 2001; Lacroix et al., 2020). Fur-
109 ther, the decadal variability of the Southern Ocean and the underlying mechanisms thereof
110 are a key contributor to the uncertainty and are a topic of continued discussion (Le Quéré
111 et al., 2007; Landschützer et al., 2015; Gruber, Landschützer, & Lovenduski, 2019; Hauck
112 et al., 2020; McKinley et al., 2020; Canadell et al., 2021). A stagnation in the growth
113 of the Southern Ocean carbon sink in the 1990s is commonly attributed to a strength-
114 ening of the westerly winds and associated intensified upwelling of carbon- and nutrient-
115 rich deep water (Le Quéré et al., 2007; Lovenduski et al., 2007; Hauck et al., 2013). In-
116 deed, evidence for this stronger upwelling is indirectly observed by enhanced surface nu-
117 trient concentrations in all Southern Ocean basins (Hoppema et al., 2015; Panassa et al.,
118 2018; T. Iida et al., 2013; Ayers & Strutton, 2013; Pardo et al., 2017). The early 2000's
119 marked the start of the so-called reinvigoration of the Southern Ocean carbon sink (Landschützer
120 et al., 2015). The strength of the reinvigoration is uncertain due to the observation-based
121 products potentially overestimating the trends owing to data sparsity (Landschützer et
122 al., 2015; Gloege et al., 2021; Hauck et al., 2023), while further analysis on the trends
123 in the models is needed. Furthermore, the drivers of the reinvigoration are less well un-
124 derstood than for the stagnation, but it may be linked to changes in the atmospheric forc-
125 ing (Gruber, Landschützer, & Lovenduski, 2019) and/or changes in the overturning cir-
126 culation (DeVries et al., 2017). There is also evidence that both the stagnation and the
127 reinvigoration are part of a global response to variations in atmospheric CO₂ growth rate,
128 ocean temperature and circulation induced by the 1992 eruption of Mount Pinatubo (McKinley
129 et al., 2020; Eddebbar et al., 2019).

130 The Southern Ocean carbon sink is projected to continue to play an important role
131 in the future carbon cycle as shown by Earth System Model simulations (Hauck et al.,

132 2015; Kessler & Tjiputra, 2016; Canadell et al., 2021; Terhaar et al., 2021). However,
133 there are indications that system changes may occur, such as a shift to a larger propor-
134 tion of the CO₂ uptake occurring in the polar Southern Ocean (Hauck et al., 2015), and
135 a strong sensitivity of Southern Ocean carbon storage to physical ventilation and warm-
136 ing (Katavouta & Williams, 2021; Terhaar et al., 2021; Bourgeois et al., 2022).

137 In this study, we aim to synthesize and assess information on the Southern Ocean
138 carbon sink over the period 1985 to 2018 in the framework of the REgional Carbon Cy-
139 cle Assessment and Processes project, phase 2 (RECCAP2). This work builds on a pre-
140 vious assessment, RECCAP phase 1 (referred to as RECCAP1 for clarity), for the pe-
141 riod 1990 to 2009 (Lenton et al., 2013). In RECCAP1, the Southern Ocean was defined
142 as the ocean south of 44°S (building on earlier classification in the atmospheric inver-
143 sion community), which, however, cut through the major anthropogenic CO₂ uptake re-
144 gion at the northern edge of the Southern Ocean. The assessment was based on five global
145 ocean biogeochemical models, eleven atmospheric inversions, ten ocean inversions and
146 a single pCO₂ observation-based data set, the climatology of Takahashi et al. (2009). REC-
147 CAP1 resulted in a best estimate of the net Southern Ocean CO₂ uptake (1990-2009)
148 of 0.42 ± 0.07 PgC yr⁻¹ based on all models (including inversions), with a surface pCO₂-
149 based climatology (Takahashi et al., 2009) suggesting a lower number of 0.27 ± 0.13 PgC yr⁻¹
150 Lenton et al. (2013). The interannual variability was estimated to be $\pm 25\%$ around this
151 mean value. The largest proportion of the mean flux occurred in the region 44-58°S which
152 spans large parts of the Subantarctic Zone and of the Polar Frontal Zone with similar
153 contributions from the Atlantic, Pacific and Indian Ocean sectors. In the Antarctic Zone
154 (south of 58°S), individual estimates did not agree on the sign of the net CO₂ flux.

155 A major advance since RECCAP1 is the release and continued updating of the Sur-
156 face Ocean CO₂ Atlas (SOCAT Bakker et al., 2016), which currently provides 33.7 mil-
157 lion quality-controlled and curated surface ocean pCO₂ measurements with an accuracy
158 of < 5 μ atm in the 2022 release (Bakker et al., 2022). The release of SOCAT allowed for
159 the development of the surface ocean pCO₂ observation-based products (pCO₂-products)
160 that interpolate and extrapolate sparse ship-based observations from SOCAT to global
161 coverage. Based on these maps of surface pCO₂, the air-sea CO₂ flux is then calculated
162 using gas-exchange parameterizations and input data fields such as sea surface temper-
163 ature and wind fields (R. H. Wanninkhof, 2014). Since RECCAP1, a diverse set of sta-
164 tistical and machine-learning approaches have been developed (e.g., Landschützer et al.,
165 2014; Rödenbeck et al., 2014; Gregor et al., 2019; Chau et al., 2022). The pCO₂-products
166 allowed for observation-based investigation of interannual and decadal variability. They
167 confirmed the reported stagnation of the Southern Ocean carbon sink in the 1990s (Le Quéré
168 et al., 2007), and identified the aforementioned reinvigoration in the 2000s (Landschützer
169 et al., 2015; Ritter et al., 2017). However, these pCO₂-products have made the South-
170 ern Ocean’s long-standing issue of sparse observations even more evident. Observation
171 system simulation experiments (OSSEs) have shown that these methods are prone to re-
172 gional and temporal biases (Denvil-Sommer et al., 2021) and some pCO₂-products may
173 overestimate the decadal variability by 30% (Gloege et al., 2021). In fact, a recent study
174 showed that the SOM-FFN pCO₂-product used in the reinvigoration study of Landschützer
175 et al. (2015) overestimates the model-based decadal trend 2000-2018 by 130% in an ocean
176 model subsampling experiment (Hauck et al., 2023). However, these OSSEs have also
177 shown that augmenting ship-based observations with well-placed, high accuracy pCO₂
178 observations from autonomous platforms can reduce these biases (Denvil-Sommer et al.,
179 2021; Djetchouang et al., 2022; Hauck et al., 2023).

180 The gap in ship-based pCO₂ observations is slowly being addressed by a second
181 major advance, that is autonomous measurement devices. Among these are pH-equipped
182 biogeochemical Argo floats (BGC-floats) (Williams et al., 2016; Johnson et al., 2017).
183 With this approach, float pH measurements are combined with multi-linear regression-
184 derived alkalinity (Williams et al., 2016; Carter et al., 2016, 2018, 2021), to calculate es-

185 timates of pCO₂. Although uncertainties of the BGC-float based estimates of pCO₂ are,
186 to date, higher (theoretical uncertainty of 11 μatm, Williams et al., 2017) than for di-
187 rect pCO₂ measurements (2μatm, Bakker et al., 2016), some of these indirect pCO₂ es-
188 timates fill critical gaps in the sparsely sampled winter months. These novel data, either
189 on their own (Gray et al., 2018) or as additional input for pCO₂-products (Bushinsky
190 et al., 2019), reported a strong winter outgassing of CO₂ in the subpolar Southern Ocean
191 for the years 2015 through 2017 that also led to a substantially smaller estimate of the
192 annual Southern Ocean CO₂ uptake for these years. However, these larger-than-expected
193 winter outgassing estimates were challenged by airborne flux estimates and direct pCO₂
194 measurements from a circumpolar navigation by an uncrewed sailing drone (Long et al.,
195 2021; Sutton et al., 2021). The sailing drone observations were in agreement with ship-
196 based pCO₂-product estimates throughout all seasons (Sutton et al., 2021). The authors
197 attributed the discrepancy between BGC-floats and other estimates to either a bias of
198 the float measurement devices or interannual variability. In support of the latter argu-
199 ment, the BGC-Argo-based air-sea CO₂ flux in the years 2017-2019 also did not reveal
200 the strong winter outgassing signal of the years 2015 and 2016 (Sutton et al., 2021).

201 Another advance since RECCAP1 is that more global ocean biogeochemical mod-
202 els (GOBMs) have become available with improvements in resolution and physical and
203 biogeochemical process representation (R. H. Wanninkhof et al., 2013; Friedlingstein et
204 al., 2022). While the ability of the GOBMs to capture interannual variability of air-sea
205 CO₂ fluxes (FCO₂) was questioned by the larger variability of pCO₂-product estimates
206 (Le Quéré et al., 2018), the lower interannual variability of GOBMs now falls within the
207 range of the larger ensemble of pCO₂-products (McKinley et al., 2020; Hauck et al., 2020).
208 For the decadal variability of FCO₂, there is a moderate agreement between GOBMs and
209 pCO₂-products on a stagnation of the sink in the 1990s and an increase of the sink in
210 2002-2011 but with a larger amplitude of the multi-year/decadal variability in the pCO₂-
211 products (McKinley et al., 2020; Hauck et al., 2020; Gruber et al., 2023). Although the
212 GOBMs compare reasonably well to global and Southern Ocean observations of surface
213 ocean pCO₂ (Hauck et al., 2020), their estimates of the global ocean carbon sink remain
214 below those of interior ocean anthropogenic carbon accumulation estimates from 1994
215 to 2007 (Gruber, Clement, et al., 2019), atmospheric inversions, observed O₂/N₂ ratios
216 (Friedlingstein et al., 2022; Tohjima et al., 2019), and a similar underestimation was found
217 in Earth System Models (Terhaar et al., 2022).

218 The final major advance in the last decade are regional and global data-assimilating
219 global ocean biogeochemistry models (Verdy & Mazloff, 2017; Carroll et al., 2020). These
220 models bring together the process-based knowledge from GOBMs, but use data assim-
221 ilation schemes to minimize mismatches between simulated fields, and physical and bio-
222 geochemical observations.

223 Despite these recent advances in observations and models, the Southern Ocean is
224 still the region with the largest discrepancy in mean CO₂ flux (although within the un-
225 certainty of the fluxes associated with river discharge which are implicitly included in
226 the observation-based estimates, but not in the models, see sections 2.2.1 and 2.3.1) and
227 variability, as well as largest model spread (Friedlingstein et al., 2022; Canadell et al.,
228 2021). In this study, we aim to quantify the Southern Ocean (following the RECCAP2
229 biome shown in Figure 1) surface CO₂ fluxes and interior storage of anthropogenic car-
230 bon over the period 1985-2018 from different classes of models and observations, and to
231 identify knowledge gaps and ways forward.

232 This study is organized in the following way. In our methods, we describe the re-
233 gion (section 2.1), the datasets that we use throughout this synthesis (section 2.2), and
234 how the data were processed (section 2.3). Our results contain first the estimates of the
235 mean fluxes 1985-2018 and their decomposition into anthropogenic and natural fluxes,
236 and atmospheric CO₂ versus climate effects (section 3.1). This is followed by an anal-
237 ysis of summer and winter fluxes and the full seasonal cycle, where we also decompose

238 pCO₂ into seasonal thermal and non-thermal contributions (section 3.2). We then anal-
 239 yse the regionally averaged temporal trends of CO₂ flux and also of pCO₂ in compar-
 240 ison with in situ pCO₂ observations, as well as atmospheric CO₂ and climate effects as
 241 drivers of the trends (section 3.3). In the final part of the results, the study then eval-
 242 uates the GOBM simulation results with observation-based estimates of ocean interior
 243 storage of anthropogenic carbon in the Southern Ocean (section 3.4). The discussion first
 244 summarizes the results with a comparison of the RECCAP1 and RECCAP2 results (sec-
 245 tion 4.1). We also discuss the drivers of the seasonal cycle (section 4.2), the interannual
 246 and decadal variability (section 4.3), and the zonal asymmetry of the fluxes in the South-
 247 ern Ocean (section 4.4). Lastly, we discuss how our study links with and can inform ob-
 248 servational programs (section 4.5), before presenting a conceptual characterization of the
 249 Southern Ocean carbon cycle in the conclusions (section 5).

250 **2 Methods**

251 **2.1 Regions**

252 We use the RECCAP2 regions (DeVries, 2022) to define the Southern Ocean and
 253 its northern boundary (Figure 1). This definition of the Southern Ocean covers the sub-
 254 tropical seasonally stratified biome (STSS), the subpolar seasonally stratified biome (SPSS),
 255 and the ice biome (ICE) and is based on the global open ocean biome classification of
 256 Fay and McKinley (2014). This covers a larger area than the definition used in REC-
 257 CAP1 (44-58°S, 58-75°S Lenton et al., 2013) and has the advantage that it does not cut
 258 through the subtropical region with its large CO₂ flux into the ocean. The northernmost
 259 extent of the Southern Ocean in this definition is 35°S. For parts of our analysis, we fur-
 260 ther separate the Atlantic, Indian, and Pacific Ocean sectors along longitudes of 20°E,
 261 147°E, and 290°E (Figure 1).

262 **2.2 Data sets**

263 Here, we introduce data sets across four different data classes that are used for the
 264 assessment of the Southern Ocean CO₂ fluxes and storage, namely: ocean biogeochem-
 265 istry models (14), surface pCO₂-based data-products (11), data assimilated and ocean
 266 inverse models (3), and atmospheric inversion models (6).

267 **2.2.1 Ocean biogeochemistry models**

268 We used 13 global ocean biogeochemistry models (GOBMs) and 1 regional ocean
 269 biogeochemistry model (Table 1). These models simulate ocean circulation and biogeo-
 270 chemical fluxes caused by physics (advection, mixing, gas-exchange) and by biological
 271 processes. They are forced with atmospheric fields from reanalysis products, e.g., by ei-
 272 ther heat and freshwater fluxes directly or by air temperature, wind speed, precipitation
 273 and humidity, which are converted to heat and freshwater fluxes using bulk formulae (see
 274 references in Table 1; Large et al., 1994). From these 14 models, eleven models are global
 275 ocean models with roughly 1°×1° resolution, and two global models (FESOM_REcoM_HR
 276 and ORCA025-GEOMAR) and the regional model (ROMS-SouthernOcean-ETHZ) are
 277 available in ca. 0.25°×0.25° resolution. Details of global model set-ups are given in (DeVries
 278 et al., 2023). The ROMS-based regional Southern Ocean model has a northern bound-
 279 ary at 24°S.

280 For the ocean-models listed above, up to four different simulations were provided
 281 (see also Table S1 and DeVries et al., 2023). These differ in whether atmospheric CO₂
 282 and all other atmospheric forcing variables vary on interannual time scales, are repeated
 283 for a single year, or follow a multi-year climatology. In simulation A, the historical run,
 284 both atmospheric CO₂ and all other physical forcing variables vary on interannual time
 285 scales. In simulation B, the preindustrial control run, a repeated year or climatological

Table 1. Overview of data sets used in this paper. Sorted by data class, here: Global Ocean Biogeochemistry Models (GOBMs), Regional Ocean Biogeochemistry Model, and data assimilated models.

Data set	Time period	Specific information	Reference
Global Ocean Biogeochemistry Models		Simulations	
CCSM-WHOI	1985-2017	A, B, C, D	Doney et al. (2009)
CESM-ETHZ	1985-2018	A, B, C, D	Lindsay et al. (2014); S. Yang and Gruber (2016)
CNRM-ESM2-1	1985-2018	A, B, C, D	Séférian et al. (2019); Berthet et al. (2019); Séférian et al. (2020)
EC-Earth3	1985-2018	A, B, C, D	Döscher et al. (2022)
FESOM_REcoM_HR	1985-2018	A, B	Hauck et al. (2013); Schourup-Kristensen et al. (2014, 2018)
FESOM_REcoM_LR	1985-2018	A, B, C, D	Hauck et al. (2013); Schourup-Kristensen et al. (2014); Hauck et al. (2020)
MOM6-Princeton	1985-2018	A, B	Liao et al. (2020); Stock et al. (2020)
MPIOM-HAMOCC	1985-2018	A, B, C, D	Ilyina et al. (2013); Paulsen et al. (2017); Mauritsen et al. (2019)
MRI-ESM2-1	1985-2018	A, B, C, D	Urakawa et al. (2020)
NorESM-OC1.2	1985-2018	A, B, C, D	Schwinger et al. (2016)
ORCA025-GEOMAR	1985-2018	A, B, C, D	Madec and the NEMO team (2016); Kriest and Oschlies (2015); Chien et al. (2022)
ORCA1-LIM3-PISCES (IPSL-NEMO-PISCES)	1985-2018	A, B, C, D	Aumont et al. (2015)
PlankTOM12	1985-2018	A, B, C, D	Le Quéré et al. (2016); Buitenhuis et al. (2019); Wright et al. (2021)
Regional Ocean Biogeochemical Models		Simulations	
ROMS-SouthernOcean-ETHZ	1985-2018	A, B, D	A. Haumann (2016); Nissen et al. (2018)
Data-assimilated models			
B-SOSE	2013-2018		Verdy and Mazloff (2017)
ECCO-Darwin	1992-2017		Carroll et al. (2020, 2022)
OCIMv2021	1780-2018	A, B, C	DeVries (2022)

Table 2. Overview of data sets used in this paper (continued). Sorted by data class, here: pCO₂-products and atmospheric inversions. The atmospheric inversions were provided only since 1990.

Data set	Time pe- riod	Specific infor- mation	Reference
pCO₂-products			
AOML_EXTRAT	1998-2018		R. Wanninkhof (2023)
CMEMS-LSCE- FFNN	1985-2018		Chau et al. (2022)
CSIR-ML6	1985-2018		Gregor et al. (2019)
Jena-CarboScope (Mixed Layer Scheme)	1985-2018		Rödenbeck et al. (2013, 2022)
JMA-MLR	1985-2018		Y. Iida et al. (2021)
LDEO-HPD	1985-2018		Gloege et al. (2022)
NIES-ML3	1985-2018		Zeng et al. (2022)
OceanSODA-ETHZ	1985-2018		Gregor and Gruber (2021)
MPI-SOM-FFN	1985-2018		Landschützer et al. (2016, 2020)
Jena-CarboScope (SOCCOM)	2015-2018		Bushinsky et al. (2019) updated
MPI-SOM-FFN (SOCCOM)	2015-2018		Bushinsky et al. (2019) updated
Watson2020	1988-2018		Watson et al. (2020)
LDEO_climatology (Takahashi legacy)	climatology		Takahashi et al. (2009)
Atmospheric inversions		Ocean prior	
Jena CarboScope	1957-2020 (1990-2020)	CarboScope pCO ₂ -product	Rödenbeck et al. (2018)
CAMS	1979-2020 (1990-2020)	CMEMS- LSCE-FFNN pCO ₂ -product	Chevallier et al. (2005)
NISMON-CO2	1990-2020	JMA-MLR pCO ₂ -product	Niwa et al. (2017)
CarbonTrackerEurope (CTE)	2001-2020	CarboScope pCO ₂ -product	van der Laan-Luijkx et al. (2017)
UoE	2001-2020	Takahashi cli- matology	Feng et al. (2016)
CMS-Flux	2010-2020	MOM6 GOBM	Liu et al. (2021)

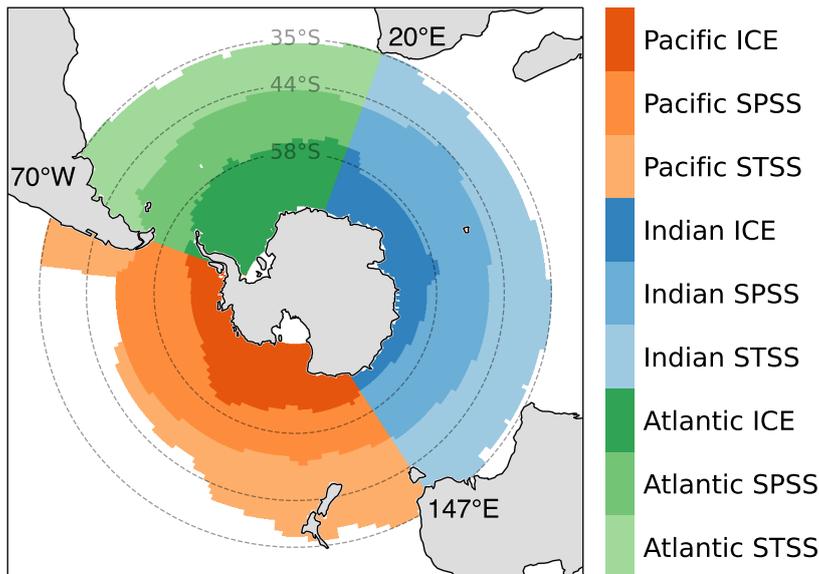


Figure 1. Study region. The Southern Ocean covers three biomes: The subtropical seasonally stratified (STSS), the subpolar seasonally stratified (SPSS), and the ice (ICE) biome. The biomes are defined following Fay and McKinley (2014). We further consider the Atlantic, Pacific, and Indian Ocean sectors separately in parts of the analysis. The dashed lines show the RECCAP2 Southern Ocean northernmost extent (35°S), the RECCAP1 Southern Ocean northernmost extent (44°S), and RECCAP1's boundary for the circumpolar region (58°S).

286 physical atmospheric forcing is used, and the atmospheric CO₂ levels are held constant
 287 at pre-industrial levels. In simulation C, the atmospheric CO₂ varies interannually and
 288 only the physical atmospheric forcing is climatological. In simulation D, the atmospheric
 289 CO₂ levels are held constant at pre-industrial levels, whereas the physical atmospheric
 290 forcing varies interannually. These simulations allow for the separation of the effects of
 291 the increase in atmospheric CO₂ and climate change and variability on air-sea CO₂ fluxes:
 292 the steady-state and non-steady state components of both natural and anthropogenic
 293 carbon. Here *anthropogenic* refers to the direct effect of increasing atmospheric CO₂ and
 294 *non-steady state* encompasses the effects of climate change and variability. For a detailed
 295 explanation, please see DeVries et al. (2023) and further explanation in Le Quéré et al.
 296 (2010); McNeil and Matear (2013); Hauck et al. (2020); Crisp et al. (2022); Gruber et
 297 al. (2023). Simulation A includes all components of the carbon fluxes. In the control sim-
 298 ulation B, only the steady-state component of natural carbon is considered. In simula-
 299 tion C, only the steady-state components of both natural and anthropogenic carbon are
 300 accounted for. Lastly, in simulation D, only the steady state and non-steady state com-
 301 ponents of natural carbon are represented.

302 The majority of models do not account for the river-induced outgassing of carbon
 303 (DeVries et al., 2023; Terhaar et al., 2023), hence the air-sea CO₂ flux in simulation A
 304 corresponds to the *S_{OCEAN}* definition used in the Global Carbon Budget (Friedlingstein
 305 et al., 2022), which differs from pCO₂-product estimates by the river-induced term. Note
 306 that the river-induced term will be discussed in greater detail in section 4.1. In addition,
 307 simulation A may include a model bias (mean offset) and drift (temporally changing off-
 308 set). We assess the model drift of the air-sea CO₂ flux by calculating the linear trend
 309 of the integrated CO₂ flux time series for the period 1985-2018 in simulation B for each
 310 model and each biome. The time series plots and the linear trends reported in Figure

8 are drift corrected by subtracting the trend from simulation B. We note that this drift-correction only marginally impacts the reported trends in the result section, as the trends in simulation B are small compared to the mean fluxes for all models (see supplementary material: Text S1 and Figure S1). In contrast to a global bias (any deviation of the global mean CO₂ flux from 0 in simulation B, see Hauck et al., 2020), the regional bias in the simulated flux cannot be assessed by the set of simulations as it cannot be separated from the natural steady-state air-sea CO₂ flux (Terhaar et al., 2023), which is non zero on a regional level.

We use the full suite of models in all analyses, with two exceptions. Firstly, we excluded the MPIOM-HAMOCC model in all seasonal analyses (Fig. 4-7) because its amplitude of the seasonal cycle is a factor 3-6 larger than in the other models in the three main Southern Ocean biomes (Figure S2), and including this outlier would skew the ensemble mean disproportionately. The exaggerated seasonal cycle in the MPIOM-HAMOCC model was found in earlier studies and is attributed to excessive net primary production in the Southern Ocean (Mongwe et al., 2018). Secondly, the decomposition into natural and anthropogenic CO₂ fluxes was not possible with GOBMs that only provided simulations A and B (MOM6-Princeton and FESOM-REcoM-HR). See section 2.3.4 for further restrictions on GOBM use and interpretation for the interior ocean anthropogenic carbon accumulation.

2.2.2 *Surface pCO₂-based data-products*

As a second data class, we use surface ocean pCO₂ observation-based data products (pCO₂-products) (Table 2, for more details see DeVries et al., 2023). These pCO₂-products extrapolate or interpolate sparse ship-based measurements of pCO₂ using statistical modeling approaches. All pCO₂-based data-products use SOCAT as the target dataset. The majority of pCO₂-products use similar gridded prediction datasets to fill the gaps, including sea surface temperature, sea surface salinity, mixed-layer depth, and chlorophyll-a estimates for the open ocean. We use 8 such pCO₂-products that all cover the full time-series 1985-2018 for the ensemble mean of pCO₂-products. AOML_EXTRAT covers a shorter period, and is thus not included in the ensemble mean 1985-2018, but is included in the ensemble mean 2015-2018. The largest methodological difference between the pCO₂-products stems from the algorithm choice. The majority of the methods use regression approaches (a.k.a. machine learning) such as artificial neural networks (e.g. MPI-SOM-FFN) and gradient boosted decision trees (e.g., CSIR-ML6) to capture the relationship between the ship-based measurements and the predictor variables. The Jena-CarboScope product includes a mechanistic understanding of mixing, entrainment, and fluxes of CO₂ into and out of the mixed layer (Rödenbeck et al., 2014). The HPD-LDEO method adjusts global ocean biogeochemistry model estimates of pCO₂ to be closer to observed ship-based measurements and is thus an observation-based posterior correction to the GOBM estimates (Gloege et al., 2022).

Further, two additional variants of MPI-SOM-FFN and Jena-CarboScope by Bushinsky et al. (2019, ship+float estimates are used here) include additional BGC-float-derived pCO₂ for the Southern Ocean (referred to as BGC-float pCO₂-products, 2015-2018). We also use the Watson2020 product, which is a neural network approach (based on MPI-SOM-FFN) but applies an adjustment to SOCAT pCO₂ that accounts for the difference between ship intake temperature and satellite sea surface temperature (Watson et al., 2020). The BGC-float pCO₂-products (2015-2018) and Watson2020 (1988-2018) are not included in the pCO₂-product ensemble averages, as they are based on fundamentally different pCO₂ values. We also use a monthly climatology product (LDEO-clim) that is centered on the year 2010 (Takahashi et al., 2009). The LDEO-clim product fills the gaps using a combination of inverse distance weighted interpolation and a diffusive-advective interpolation scheme (Takahashi et al., 2009). Note that this product is only used in representations of the seasonal cycle, and not for trend analyses. All these pCO₂-products

363 estimate the bulk air-sea CO₂ flux with:

$$FCO_2 = K_0 \cdot k_w \cdot (pCO_2^{\text{sea}} - pCO_2^{\text{atm}}) \cdot (1 - \text{ice}) \quad (1)$$

364 where K_0 is the solubility of CO₂ in seawater, k_w is the gas transfer velocity, pCO_2^{sea} is
 365 the oceanic estimate of pCO_2 from the pCO_2 -product, pCO_2^{atm} is the atmospheric pCO_2 ,
 366 and ice is the sea-ice fraction, with the majority of the open ocean having a fraction of
 367 0. Other than pCO_2^{sea} , k_w is the largest source of uncertainty in the calculation of bulk
 368 air-sea CO₂ fluxes R. H. Wanninkhof (2014); Fay et al. (2021). However, most of the pCO_2 -
 369 products use a quadratic formulation of k_w as described by R. Wanninkhof et al. (1993)
 370 meaning that the product spread is reduced due to similar choices – details are shown
 371 in Global chapter’s Table S2 (DeVries et al., 2023). An exception is the Watson2020 prod-
 372 uct (Watson et al., 2020) that calculates air sea CO₂ fluxes using the formulation described
 373 in Woolf et al. (2016) where a cool and salty skin adjustment is applied.

374 **2.2.3 Data-assimilated models**

375 We use three data-assimilating models (Table 1). The Biogeochemical Southern
 376 Ocean State Estimate (B-SOSE Verdy & Mazloff, 2017) is an eddy-permitting 1/6-degree
 377 resolution data-assimilating model, which assimilates the data from Southern Ocean Car-
 378 bon and Climate Observations and Modelling (SOCCOM) BGC-Argo floats as well as
 379 shipborne and other autonomous observations (i.e., GLODAP and SOCAT) over the pe-
 380 riod 2013-2018. In situ and satellite observations of the physical state are also assimi-
 381 lated. B-SOSE is based on the MIT general circulation model (MITgcm Campin et al.,
 382 2011) and uses software developed by the consortium for Estimating the Circulation and
 383 Climate of the Ocean (ECCO Stammer et al., 2002; Wunsch & Heimbach, 2013) to build
 384 on the SOSE physical model framework by adding the Nitrogen version of the Biogeo-
 385 chemistry with Light, Iron, Nutrients, and Gases (N-BLING; evolved from Galbraith et
 386 al., 2010) biogeochemical model. Consistency with the data is achieved by systemati-
 387 cally adjusting the model initial conditions and the atmospheric state through the 4D-
 388 Var assimilation methodology. This B-SOSE assimilation methodology does not break
 389 the model biogeochemical or physical budgets. The budgets are closed, which allows one
 390 to understand signal attribution, though limits the control we have over the solution. For
 391 this reason B-SOSE is only consistent with the data on the timescales longer than ap-
 392 proximately 90 days; the mesoscale eddies are reproduced statistically and not determin-
 393 istically. Even with this assimilation methodology some seasonal biases still exist, and
 394 B-SOSE is still a work in progress.

395 The ECCO-Darwin data-assimilation model (Carroll et al., 2020) is based on a global
 396 ocean and sea ice configuration (about 1/3 degree) of the MIT general circulation model
 397 and is available from January 1992 to December 2017. Besides being global and cover-
 398 ing a longer duration than B-SOSE, this product also uses a different biogeochemical model
 399 and assimilation technique. The ECCO circulation estimates used in this version are cou-
 400 pled online with the Darwin ecosystem model (Dutkiewicz et al., 2009), which represents
 401 the planktonic ecosystem dynamics coupled with biogeochemical cycles in the ocean. The
 402 R. Wanninkhof (1992) parameterization of gas transfer velocity is used and pCO_2^{atm} is
 403 the National Oceanic and Atmospheric Administration Marine Boundary Layer Refer-
 404 ence product (Dlugokencky et al., 2021). The biogeochemical observations used to eval-
 405 uate and adjust ECCO-Darwin include (1) surface ocean fugacity (fCO_2) from the monthly
 406 gridded Surface Ocean CO₂ Atlas (SOCATv5 Bakker et al., 2016), (2) GLODAPv2 ship-
 407 based profiles of NO₃, PO₄, SiO₂, O₂, dissolved inorganic carbon (DIC), and alkalinity
 408 (Olsen et al., 2016), and (3) BGC-Argo float profiles of NO₃ and O₂ (Drucker & Riser,
 409 2016; Riser et al., 2018). To adjust the model’s fit to the global biogeochemical obser-
 410 vations, the Green’s function approach is used to adjust biogeochemical initial conditions
 411 and model parameters.

OCIMv2021 is an inverse model that assimilates observations of temperature, salinity, CFCs and radiocarbon to achieve an estimate of the climatological mean ocean circulation (DeVries, 2022). This steady-state circulation model is used together with an abiotic carbon cycle model and atmospheric CO₂ forcing to simulate anthropogenic carbon uptake and its redistribution within the ocean. It uses a monthly time-step and simulates the period 1780 to 2018. No assimilation takes place during this period.

2.2.4 Atmospheric inversions

Six atmospheric inversions are available for our analysis (Table 2). Atmospheric inversions make use of the worldwide network of atmospheric CO₂ observations. They ingest a dataset of fossil fuel emissions, which are assumed to be well known, into an atmospheric transport model and then solve for the spatio-temporal distribution of land and ocean CO₂ fluxes while minimizing the mismatch with atmospheric CO₂ observations (Friedlingstein et al., 2022). Thus, the resulting land and ocean carbon fluxes are bound to the atmospheric CO₂ growth rate, but the estimated regional fluxes depend on the number of stations in the observational network. The inversions also start from prior estimates of land and ocean fluxes. For four inversion data sets that we use here, the ocean prior is taken from pCO₂ -products that are used in this analysis as well (Table 2). One inversion (UoE) uses the Takahashi climatology as a prior and one (CMS-Flux) an ocean biogeochemical model. The atmospheric inversions are thus not independent from the other data classes (Friedlingstein et al., 2022, their Table A4). The atmospheric inversion data were submitted for RECCAP in the same version as in the Global Carbon Budget 2021 (Friedlingstein et al., 2022), but only since 1990. The three inversions starting later (2001 or 2010) are only included in averages reported for 2015-2018 (Figures 4 and 5), and as individual lines in the time-series figure (Figure 8).

2.3 Processing

Throughout this study, we report the air-sea CO₂ exchange as the net flux (FCO₂), which is the sum of natural, anthropogenic and river-induced air-sea CO₂ flux (see e.g., DeVries et al., 2023; Hauck et al., 2020; Crisp et al., 2022). As the GOBMs vary widely in their choices on river carbon and nutrient input into the ocean and burial at the seafloor (see DeVries et al., 2023; Terhaar et al., 2023), an adjustment is applied to make all data classes comparable.

2.3.1 River flux adjustment

Globally, the majority of GOBMs produce a small imbalance of riverine carbon inflow and burial globally (<0.14 PgC yr⁻¹), which is smaller than the current best estimate of river-induced CO₂ ocean outgassing of 0.65 PgC yr⁻¹ (Regnier et al., 2022). The imbalances are due to manifold choices and illustrate the lack of a closed land-ocean carbon loop in the GOBMs. As the GOBMs do not adequately account for the river discharge and its fate within the ocean, and thus for river-derived ocean CO₂ outgassing (Terhaar et al., 2023), we account for this outgassing by using the spatial patterns of river-induced air-sea CO₂ fluxes from Lacroix et al. (2020) that are scaled to the global value of 0.65 PgC yr⁻¹ (Regnier et al., 2022). Southern Ocean outgassing from rivers amounts to 0.04 PgC yr⁻¹, i.e., around 6% of the global river flux. It is distributed over the Southern Ocean biomes as follows (positive outgassing): 0.00036 PgC yr⁻¹ in the ICE biome, 0.053 PgC yr⁻¹ (SPSS biome), -0.014 (STSS biome). The estimated riverine CO₂ fluxes were added to biome-integrated fluxes in simulation A for all GOBMs, so that these are comparable to the pCO₂-products. They are not added to spatial maps of CO₂ fluxes due to large uncertainties in the regional attribution by Lacroix et al. (2020). The riverine fluxes are one (ICE) to multiple (SPSS, STSS) orders of magnitude smaller than the

460 mean fluxes quantified in this study. The uncertainty associated with the river flux ad-
 461 justment is discussed in section 4.1.

462 **2.3.2 Treatment of different area coverage**

463 Air-sea CO₂ fluxes in all data classes were integrated over the area available for each
 464 GOBM, pCO₂-product etc., i.e., fluxes were not scaled to the same ocean area here. Rel-
 465 ative to the ocean area in the RECCAP mask, the covered ocean areas in the GOBMs
 466 and data-assimilating models corresponds to 96.2-100% (minimum for CCSM-WHOI)
 467 and to 95.6-100% in the pCO₂-products (minimum for JMA-MLR). These differences
 468 mainly stem from the ICE biome. We assume that the discrepancy arising from differ-
 469 ences in covered area are smaller than the uncertainty arising from any extrapolation to
 470 the same area.

471 **2.3.3 pCO₂ decomposition**

472 To separate temperature driven changes in pCO₂ from biological processes and mixing-
 473 driven entrainment, pCO₂ is decomposed into thermal and non-thermal components (Takahashi
 474 et al., 1993). The thermal component (pCO_2^T) is calculated as

$$pCO_2^T = \overline{pCO_2} \cdot e^{(0.0423 \cdot \Delta T)} \quad (2)$$

475 where $\overline{pCO_2}$ is the annual mean of pCO₂ and ΔT difference of the monthly mean tem-
 476 perature from the annual mean temperature. The non-thermal contribution (pCO_2^{nonT})
 477 is estimated as the difference of the thermal contribution (pCO_2^T) from the monthly-averaged
 478 pCO₂. The first derivatives of these two components are subtracted from each other to
 479 create the pCO₂ seasonal driver metric, denoted as λpCO_2 :

$$\lambda pCO_2 = \left| \frac{pCO_2^T}{\delta t} \right| - \left| \frac{pCO_2^{nonT}}{\delta t} \right| \quad (3)$$

480 Here, positive values indicate periods when the thermal component is a larger contrib-
 481 utor to pCO₂, and negative values show where the DIC processes (non-thermal) play a
 482 dominant role in surface pCO₂ changes. We also denote the first derivatives as $pCO_2^{T'}$
 483 and $pCO_2^{nonT'}$ for brevity.

484 **2.3.4 Anthropogenic carbon inventories**

485 Anthropogenic CO₂ (C_{ant}) is defined as the change in ocean dissolved inorganic
 486 carbon (DIC) since preindustrial times due to the direct effect of increasing CO₂ con-
 487 centration in the atmosphere. It is computed as the DIC difference between experiments
 488 A and D. The accumulation of C_{ant} can be separated into a steady-state component (C_{ant}^{ss} ,
 489 DIC difference between experiments C and B), that is influenced only by the increased
 490 atmospheric CO₂, and a non-steady-state component (C_{ant}^{ns}), which considers the effect
 491 of climate variability and change on C_{ant} (and which is maximally 10-20% of C_{ant} , Text
 492 S2 and Figures S3-S4). Here we focus mainly on the change in C_{ant} that has occurred
 493 over the period 1994-2007 (hereafter ΔC_{ant}), to correspond to the years covered by the
 494 eMLR(C*) observation-based estimate (Gruber, Clement, et al., 2019). The eMLR(C*)
 495 method (Clement & Gruber, 2018) uses ocean measurements of DIC from GLODAP2
 496 (Olsen et al., 2016) over more than 30 years as the foundation to determine ΔC_{ant} be-
 497 tween nominal years 1994 and 2007. The method has been shown to be accurate at global
 498 and basin scales, but is more uncertain at sub-basin scales and should not be used be-
 499 low 3000 m depth. The (2 sigma) uncertainty of the eMLR(C*) product is estimated to
 500 be around 19% for the Southern Hemisphere (Gruber, Clement, et al., 2019). The eMLR(C*)
 501 method differs fundamentally from past indirect or model-based methods used to esti-
 502 mate C_{ant} accumulated since pre-industrial times (Gruber et al., 1996; Sabine et al., 2004;
 503 Waugh et al., 2006; DeVries, 2014). Of these, we used the 1800-1994 cumulative C_{ant}

504 estimate based on (Sabine et al., 2004), which is characterized by an uncertainty of about
 505 20% globally (Sabine et al., 2004; Matsumoto & Gruber, 2005). In terms of GOBMs, we
 506 used all those listed in Table 1, with the exception of FESOM-REcoM-HR and MOM6-
 507 Princeton who provided only experiments A and B. For most GOBMs, we analyze C_{ant}^{tot} ,
 508 to allow for a more accurate comparison with the observation-based data set (eMLR(C^*)).
 509 However, for MPIOM-HAMOCC and CNRM-ESM2-1 it was only possible to compute
 510 C_{ant}^{ss} , because of physical forcing inconsistencies between experiments A and D. We be-
 511 lieve that the advantage of including all GOBMs in the analysis outweighs the disadvan-
 512 tages of having an incoherent definition of C_{ant} among GOBMs. It should be noted that
 513 the spin-up procedure of ROMS-SouthernOcean-ETHZ, which uses atmospheric CO_2 from
 514 1969 to 1978 (for a ten year spin-up of the biogeochemical component), makes it suit-
 515 able only for the analysis of ΔC_{ant} between 1994 and 2007, and not of cumulative C_{ant}
 516 until 1994 nor of air-sea C_{ant} fluxes in specific years. As explained in the RECCAP2 model
 517 evaluation chapter (Terhaar et al., 2023), all GOBMs are forced with a very similar at-
 518 mospheric CO_2 mixing ratio (xCO_2) over the historical period. However, the atmospheric
 519 xCO_2 in the pre-industrial control simulations across the GOBM ensemble varies between
 520 278 ppm and 287.4 ppm, leading to an underestimate of the C_{ant} storage for those mod-
 521 els with a late starting date (Terhaar et al., 2023).

522 3 Results

523 3.1 Mean air-sea CO_2 fluxes 1985-2018

524 We start with a comparison of the average air-sea CO_2 flux in the two data classes
 525 (GOBMs, p CO_2 -products) that cover the full period 1985-2018. We exclude data classes
 526 with fewer products for the sake of robustness, and show the comparison between all data
 527 classes in sections 3.2 and 3.3. The mean net Southern Ocean air-sea CO_2 flux 1985-2018
 528 by the GOBM ensemble is -0.75 ± 0.28 PgC yr⁻¹ and -0.73 ± 0.07 PgC yr⁻¹ (flux into
 529 the ocean) for the p CO_2 -product ensemble mean (Figure 2a). While both ensemble means
 530 result in an almost identical ocean uptake of CO_2 , the GOBM ensemble spread is four
 531 times larger.

532 All Southern Ocean regions are sinks of CO_2 based on the ensemble averages of the
 533 GOBMs and p CO_2 -products (Figure 2). The subtropical seasonally stratified biome (STSS),
 534 which is a subduction area with deep winter mixed layer depth and intermediate chloro-
 535 phyll concentration (Fay & McKinley, 2014), is the largest sink according to all data sets
 536 (GOBMs: -0.53 ± 0.17 PgC yr⁻¹, p CO_2 -based products: -0.62 ± 0.06 PgC yr⁻¹, Figure
 537 2a). Second is the subpolar seasonally stratified biome (SPSS) (GOBMs: -0.13 ± 0.14 PgC yr⁻¹,
 538 p CO_2 -products: -0.07 ± 0.02 PgC yr⁻¹), which is characterized by upwelling of old wa-
 539 ter, rich in natural carbon but with low anthropogenic carbon content. The upwelled wa-
 540 ter is also rich in nutrients, and thus a region with important biological activity. Note
 541 that three GOBMs simulate the SPSS to be a source of CO_2 to the atmosphere. The marginal
 542 sea ice (ICE) biome is the weakest CO_2 sink (GOBMs: -0.09 ± 0.13 PgC yr⁻¹; p CO_2 -products:
 543 -0.05 ± 0.02 PgC yr⁻¹) due to sea ice acting as a lid that prevents carbon outgassing in
 544 winter, and is the smallest of all three biomes covering an area of about 60% the size of
 545 STSS or SPSS (Fay & McKinley, 2014). Four individual models suggest that the ICE
 546 biome is a weak outgassing region, but no other data set supports this.

547 In a zonal mean view (Figure 2b), the smallest uptake occurs between 62 and 55°S
 548 and the largest uptake around 40°S. However, the amplitude differs between data classes,
 549 with the p CO_2 -products having a larger difference between minima and maxima (1.96 mol C m⁻² yr⁻¹),
 550 than the GOBM ensemble mean (1.19 mol C m⁻² yr⁻¹). Some of the individual GOBMs
 551 deviate from this pattern (see supplementary figure S5a for zonal means of individual
 552 models).

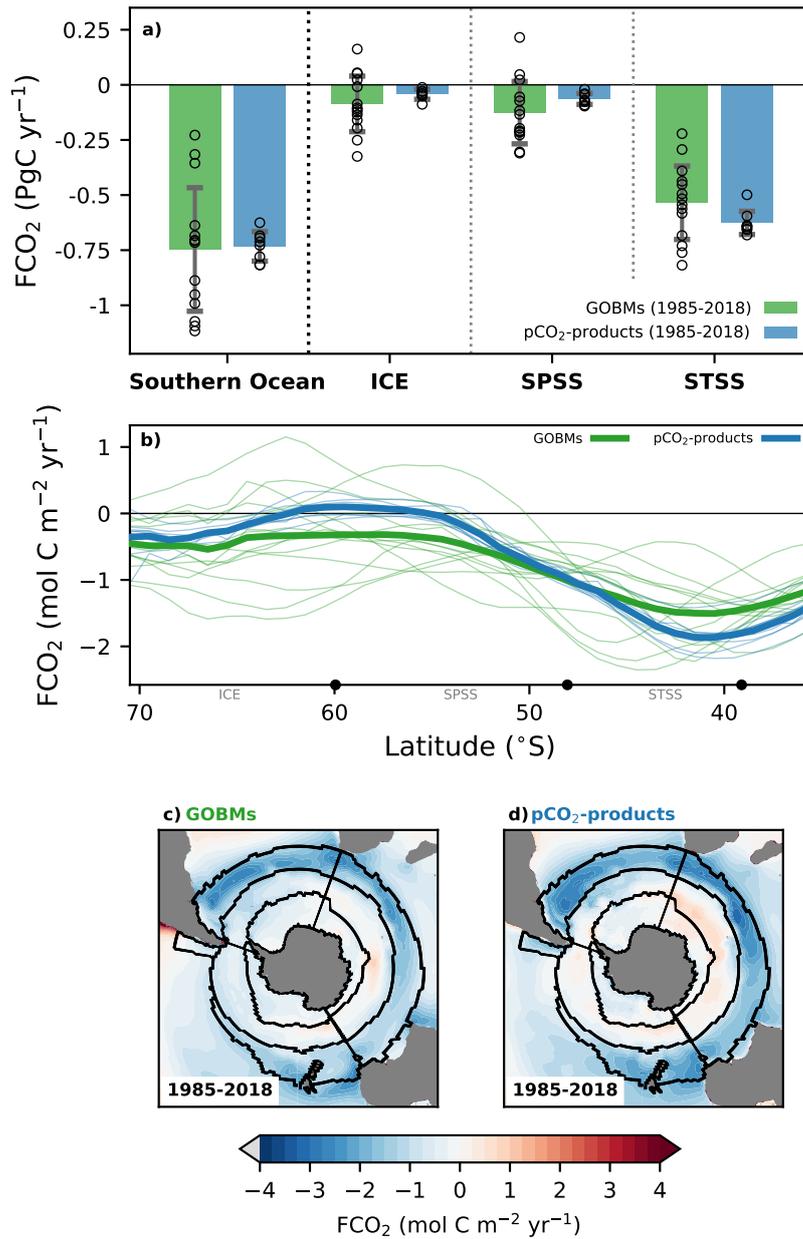


Figure 2. Temporal average of the Southern Ocean CO₂ net flux (FCO₂). A positive flux denotes outgassing from ocean to atmosphere. The temporal average is calculated over the period 1985 to 2018 for the global ocean biogeochemistry models (GOBMs) and pCO₂-products (Table 1). (a) The green and blue bar plots show the ensemble mean of the GOBMs and pCO₂-based data-products, and open circles indicate the individual GOBMs and pCO₂-products. The ensemble standard deviation (1σ) is shown by the error bars. The river flux adjustment added to the GOBMs is small (0.04 PgC yr⁻¹), its distribution over the biomes is described in section 2.3.1. (b) zonal mean flux density of the different data sets. Thick green and blue lines show the ensemble means, and thin green and blue lines show the individual GOBMs and pCO₂-products. Approximate boundaries for biomes are marked with black points on the x-axis. (c-d) maps of spatial distribution of net CO₂ flux for ensemble means of GOBMs, and pCO₂-products.

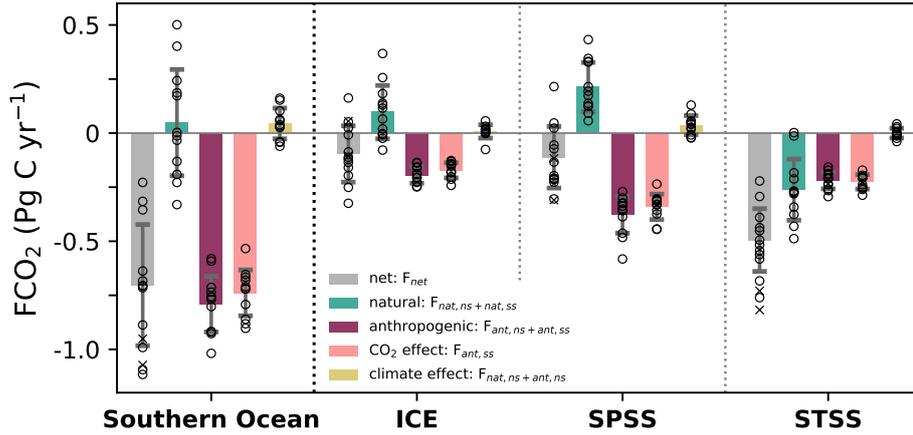


Figure 3. Decomposition of the modeled net air-sea CO_2 flux 1985-2018 into natural and anthropogenic CO_2 fluxes; as well as into CO_2 and climate effects. See method section 2.2.1 for explanation on this decomposition. The separation into natural and anthropogenic CO_2 fluxes is not possible for FESOM-REcoM-HR and MOM6-Princeton models as only simulations A and B are available. These models are only shown as crosses for net FCO_2 but not used for averaging. Hence, separation within this figure is coherent, but the net FCO_2 is slightly different from the net FCO_2 in Figure 2.

Regionally, significant differences emerge between the Atlantic, Indian and Pacific sectors of the Southern Ocean (Figure 2c-d). Within the STSS, large CO_2 fluxes into the ocean occur in the Atlantic and Indian sector across all data classes (Figure 2b-c, mean flux density: $-1.93 \text{ mol C m}^{-2} \text{ yr}^{-1}$ and $-2.05 \text{ mol C m}^{-2} \text{ yr}^{-1}$ for GOBMs and pCO_2 -products, respectively, in the Atlantic sector, $-1.44 \text{ mol C m}^{-2} \text{ yr}^{-1}$ and $-1.89 \text{ mol C m}^{-2} \text{ yr}^{-1}$ in the Indian sector, and $-1.22 \text{ mol C m}^{-2} \text{ yr}^{-1}$ and $-1.54 \text{ mol C m}^{-2} \text{ yr}^{-1}$ in the Pacific sector). CO_2 outgassing locations differ across the data classes. In the GOBM ensemble mean, the outgassing is mainly confined to the Indian sector of the SPSS, whereas it is more widely spread in the pCO_2 -product ensemble mean covering the Pacific and Indian Ocean sectors of the SPSS and the Indian sector in the ICE biome. The smooth appearance of the outgassing signal in the GOBM and pCO_2 -product ensemble means may be partly attributable to averaging over multiple data sets and months and years.

3.1.1 Decomposition into anthropogenic and natural carbon fluxes and climate versus atmospheric CO_2 effects on the mean CO_2 flux

With the aid of the additional model simulations, we can decompose the net Southern Ocean air-sea CO_2 flux into natural and anthropogenic components, and separate the indirect effects of physical climate change and the direct geochemical effect of increasing atmospheric CO_2 mixing ratios. The GOBM ensemble mean indicates that the *natural* Southern Ocean carbon cycle without anthropogenic perturbation would be a small CO_2 source to the atmosphere of 0.05 PgC yr^{-1} , although with a large model spread as indicated by the standard deviation of 0.25 PgC yr^{-1} (Figure 3). In fact, six GOBMs simulate negative natural CO_2 fluxes, i.e., into the ocean, and six GOBMs simulate positive natural fluxes, i.e., out of the ocean. This also illustrates that the GOBM spread of net fluxes (standard deviation: 0.28 PgC yr^{-1}) is, to the first order, dominated by the model differences of natural fluxes (standard deviation: 0.25 PgC yr^{-1}), which may contain artifacts from model biases and drift (Terhaar et al., 2023). The spread of anthro-

579 pogenic fluxes is smaller (0.13 PgC yr^{-1}). The small *natural* outgassing signal in the en-
 580 semble mean is a balance of natural CO_2 uptake in the STSS ($-0.26 \pm 0.14 \text{ PgC yr}^{-1}$) and
 581 outgassing in the SPSS ($0.21 \pm 0.11 \text{ PgC yr}^{-1}$) and ICE ($0.10 \pm 0.12 \text{ PgC yr}^{-1}$) biomes.
 582 This is in qualitative agreement with the patterns of natural CO_2 fluxes by Mikaloff Fletcher
 583 et al. (2007).

584 The *anthropogenic* perturbation ($-0.79 \pm 0.13 \text{ PgC yr}^{-1}$) has turned the SPSS and
 585 ICE biomes, and possibly the entire Southern Ocean, from source to sink. The large an-
 586 thropogenic flux contribution in the SPSS ($-0.38 \pm 0.08 \text{ PgC yr}^{-1}$) suppresses the nat-
 587 ural CO_2 outgassing flux. The STSS is a sink for both natural and anthropogenic flux
 588 components. The *direct effect of increasing atmospheric CO_2* enhances the Southern Ocean
 589 sink by $-0.74 \pm 0.11 \text{ PgC yr}^{-1}$ and is the largest signal in the anthropogenic perturbation.
 590 A smaller component stems from the climate change effect on this steady state CO_2 -induced
 591 flux (Figure S6). The direct CO_2 effect is largest in the SPSS ($-0.34 \pm 0.06 \text{ PgC yr}^{-1}$) where
 592 old water masses reach the surface that are undersaturated in anthropogenic carbon, fol-
 593 lowed by the STSS and ICE biomes ($-0.23 \pm 0.03 \text{ PgC yr}^{-1}$ and $-0.17 \pm 0.03 \text{ PgC yr}^{-1}$).
 594 In the upwelling regions, the primary effect of rising atmospheric CO_2 is thus to suppress
 595 the outgassing of natural carbon.

596 The *effect of physical climate change and variability*, i.e., warming and changes in
 597 wind speed patterns and strength that provoke changes in circulation (Le Quéré et al.,
 598 2007; Lovenduski et al., 2007; Hauck et al., 2013), reduces the CO_2 flux into the ocean
 599 ($+0.04 \pm 0.07 \text{ PgC yr}^{-1}$), but is overall small in comparison to the direct CO_2 effect. This
 600 climate change induced outgassing stems nearly entirely from the SPSS ($+0.04 \pm 0.04 \text{ PgC yr}^{-1}$),
 601 with the largest contribution from the Indian sector followed by the Pacific (Figure S7).
 602 Thus, the climate change effect amplifies the natural CO_2 outgassing, which is also the
 603 largest in the Indian and Pacific sectors of the SPSS. The climate effect is a combina-
 604 tion of climate effects on natural and anthropogenic CO_2 fluxes, which partly oppose each
 605 other (Figure S6).

606 3.2 The seasonal cycle of air-sea CO_2 fluxes in the Southern Ocean

607 We now shift our focus to seasonal fluxes by separating fluxes into separate win-
 608 ter (Figure 4) and summer (Figure 5) mean CO_2 fluxes. For this, we examine the pe-
 609 riod 2015-2018, for which all data sets are available (see Figure S8 for an annual mean
 610 figure for 2015-2018).

611 3.2.1 Winter

612 In winter, all but two data sets (one GOBM and BGC-float pCO_2 -products) agree
 613 that the Southern Ocean is a sink of CO_2 (GOBMs: $-0.83 \pm 0.40 \text{ PgC yr}^{-1}$, pCO_2 prod-
 614 ucts: $-0.48 \pm 0.08 \text{ PgC yr}^{-1}$; Figure 4a). The general pattern of strong uptake towards
 615 the north and a reduction towards the south is common to all data classes, though ex-
 616 ceptions for individual GOBMs do exist (Figure 4a,b). Expounding on this, the strong
 617 uptake in the STSS is shown by all data sets, but further south the coherence disinte-
 618 grates. Within the SPSS, there is considerable variation in position and magnitude of
 619 maximum outgassing with some GOBMs being a sink along the entire zonal mean (Fig-
 620 ure 4a,b). Towards the southern reaches of the ICE biome, fluxes are more coherent as
 621 they are constrained by sea-ice cover in winter (Figure 4b). For the zonal means of in-
 622 dividual GOBMs, see Figure S5.

623 The divergence between data class average flux estimates for the Southern Ocean
 624 are explained nearly entirely by differences in the SPSS (GOBMs: $-0.15 \pm 0.32 \text{ PgC yr}^{-1}$
 625 and pCO_2 products: $0.15 \pm 0.09 \text{ PgC yr}^{-1}$, in Figure 4a). Note also that the spread of
 626 the individual GOBMs is the largest in the SPSS (0.32 PgC yr^{-1}), although it is also
 627 substantial in the other biomes (STSS: 0.29 PgC yr^{-1} , ICE: 0.13 PgC yr^{-1}) (Figure 5a).

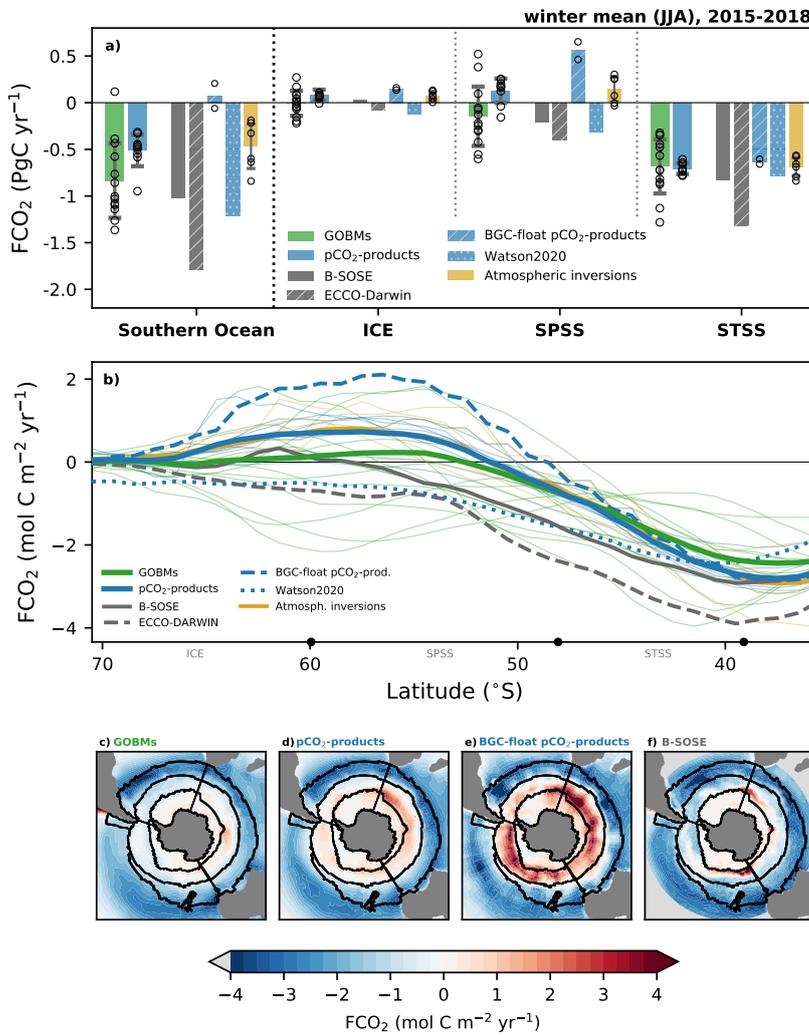


Figure 4. Average winter (June-August) air-sea CO_2 fluxes (FCO_2) in the period 2015-2018, (a) averaged over biomes, (b) zonal mean flux density, (c-f) maps of flux density. Same as Figure 2, but including also data sets with shorter coverage, and a map of the CO_2 flux from the BGC-float pCO_2 -products (panel e), and B-SOSE (f), and hence focussing on the period 2015-2018 for all data sets for comparability. Note that the MPI model is excluded here. The zonal mean of individual models are presented in Figure S5c.

628 The SPSS is also where we see the largest impact of the inclusion of floats in the BGC-
 629 float pCO₂-products (Figure 4d,e), with the mean outgassing flux more than doubling
 630 that of the regular pCO₂-product ensemble.

631 The zonal differences and features of fluxes between data classes are also most dis-
 632 tinct in the SPSS (Figures 4c-f). In short, the Atlantic sector of the SPSS has the low-
 633 est flux (weak source or even sink), while the Indian and Pacific sectors dominate the
 634 outgassing. The data-assimilated model B-SOSE has stronger localized outgassing com-
 635 pared with the other data classes but bear in mind that B-SOSE is only one data sets
 636 (Figure 4f), while the other data classes (Figures 4c-e) represent up to 13, thus poten-
 637 tially averaging out local signals. The outgassing hotspot at the boundary between the
 638 Atlantic and Indian sectors of the SPSS can also be recognized in the pCO₂-products
 639 (Figure 4d). The second hotspot in the western Pacific SPSS is not distinguishable in
 640 the other data sets.

641 3.2.2 Summer

642 In summer, GOBMs, pCO₂-products and inversions largely show CO₂ uptake within
 643 the three Southern Ocean biomes, and outgassing north of the STSS (Figure 5a-b). In
 644 contrast to winter, the GOBM ensemble mean for summer 2015-2018 (-1.04 ± 0.77 PgC yr⁻¹)
 645 underestimates the CO₂ uptake relative to the pCO₂-product ensemble mean (-1.46 ± 0.18 PgC yr⁻¹,
 646 Figure 5a). This also holds true for the data-assimilated models, where B-SOSE even
 647 simulates outgassing in the SPSS (Figure 5a,b,f). Otherwise, the data-assimilated mod-
 648 els, B-SOSE and ECCO-Darwin, deviate substantially from the other data classes. The
 649 differences between pCO₂-products with and without BGC-float data are hardly appar-
 650 ent in summer (Figure 5a, compared to 4a). This could be due to a smaller discrepancy
 651 between float and ship-data in summer, and/or a dominance of SOCAT data in sum-
 652 mer for the ship+float estimate. For context, for the period 2015 through 2018, BGC-
 653 float data account for up to 70% of winter pCO₂ monthly by 1°×1° measurements in
 654 the Southern Ocean (SOCAT + floats), while in summer the floats represent only 20%
 655 (Bakker et al., 2016; Bushinsky et al., 2019).

656 While the STSS was a region of coherence between data classes in winter (Figure
 657 4), it is the main source of the discrepancy between the GOBM and pCO₂-product en-
 658 semble means in summer (GOBMs: -0.40 ± 0.28 PgC yr⁻¹, pCO₂-products: -0.73 ± 0.08 PgC yr⁻¹).
 659 The discrepancy is comparatively smaller in the SPSS (GOBMs: -0.33 ± 0.34 PgC yr⁻¹,
 660 pCO₂-products: -0.42 ± 0.06 PgC yr⁻¹). We note that CO₂ fluxes for both GOBMs and
 661 pCO₂-products show less variation from ICE to STSS in summer compared to winter
 662 (Figure 4b vs 5b, respectively). There is, nevertheless, an offset with lower GOBM CO₂
 663 uptake than in pCO₂-products north of 55°S, and vice versa to the south. Also, the GOBM
 664 spread in the represented magnitude of the fluxes is large. In absolute terms, the GOBM
 665 ensemble spread of fluxes in summer (from -2.03 to +0.28 PgC yr⁻¹) is larger than in
 666 winter (from -1.36 to 0.12 PgC yr⁻¹) or than the spread in the annual mean (from -1.30
 667 to -0.38 PgC yr⁻¹; see Figure S5b for zonal means of individual GOBMs). This mirrors
 668 the difficulty in representing the balance between physical and biological processes in sum-
 669 mer, which is further assessed in the next two sections 3.2.3 and 3.2.4.

670 3.2.3 The full seasonal cycle

671 We diagnose distinctly different seasonal cycles in the three biomes. The ICE biome
 672 has a rather clear maximum uptake in summer in the GOBM and pCO₂-product ensem-
 673 ble means, as well as most individual data sets (Figure 6a). In the STSS, the pCO₂-products
 674 suggest a weak seasonal cycle with a maximum uptake in autumn (Figure 6c), while the
 675 majority of GOBMs simulate a maximum CO₂ uptake in winter and a substantially smaller
 676 flux in summer. The largest disagreement occurs in the SPSS, where the seasonal cy-
 677 cle transitions from winter outgassing in the ICE biome to summer outgassing in the STSS

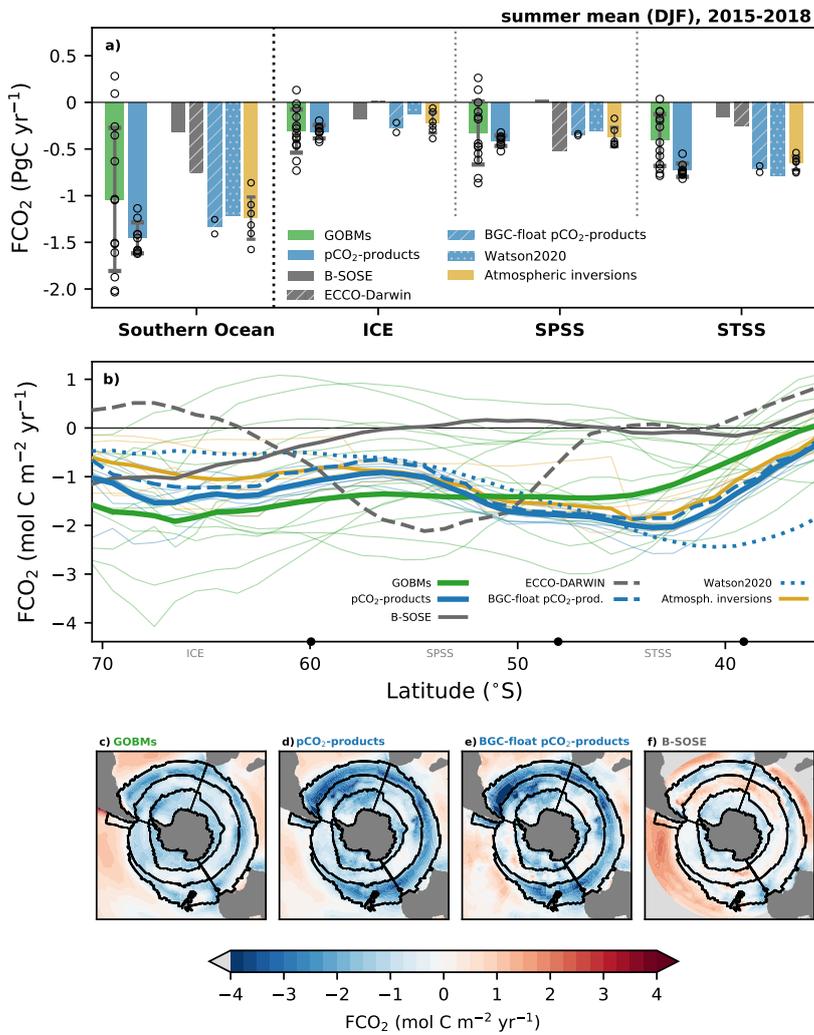


Figure 5. Average summer (December-February) air-sea CO_2 fluxes (FCO_2) in the period 2015-2018. Same as Figure 4, but for summer. The zonal mean of individual models are presented in Figure S5b.

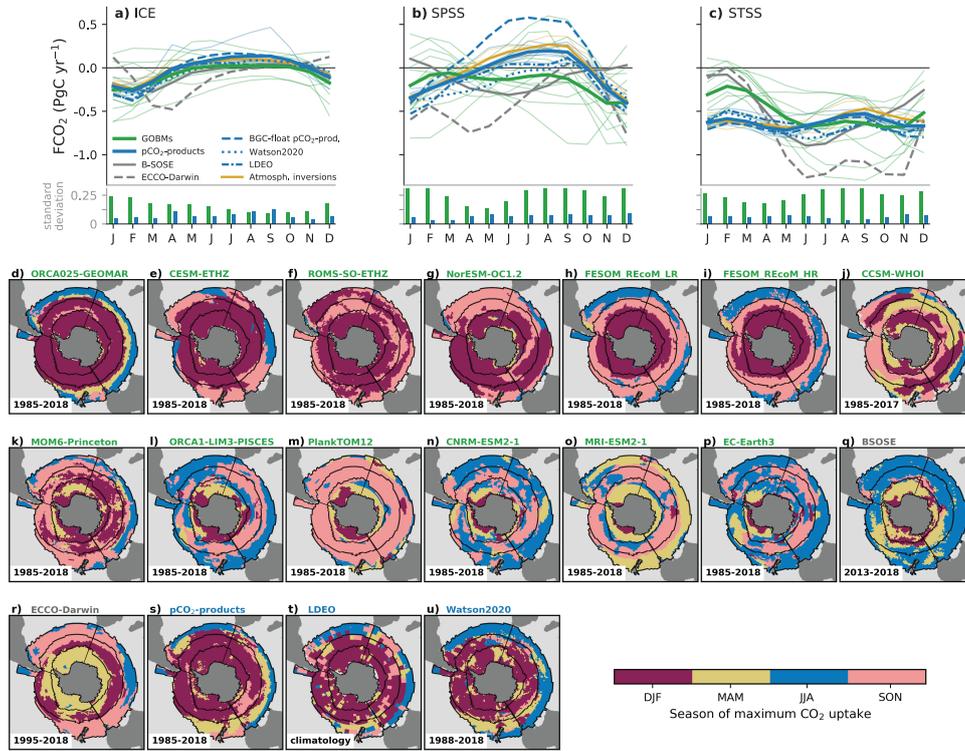


Figure 6. The seasonal cycle of air-sea CO₂ flux in the Southern Ocean separated by biomes for all data sets as indicated in the legend, a) subtropical seasonally stratified (STSS) biome, b) subpolar seasonally stratified (SPSS) biome, c) ice (ICE) biome. Thin green and blue lines depict individual GOBMs and pCO₂-products, and thick lines indicate their ensemble means. Note that the MPI model is excluded here. The ensemble standard deviation (1σ) is shown by the bars for each month. Panels (d-u) present the season of maximum CO₂ uptake per grid cell in the individual GOBMs, data-assimilated models and the ensemble mean of the pCO₂-products over the period indicated in the panels (varies by data set). See Figure S9 for the individual pCO₂-products (panel d-u equivalents) and Figure S10 for the seasonal cycle in all nine subregions (equivalent to panels a-c but further split into Atlantic, Pacific and Indian Ocean sectors).

678 biomes. Here, atmospheric inversions and pCO₂-products (including the BGC-float pCO₂
 679 products), suggest the maximum CO₂ uptake to be in summer. In winter, the BGC-float
 680 pCO₂-products more than double the estimates of outgassing relative to the other pCO₂
 681 products (Figure 6b). The GOBM ensemble average roughly agrees with this seasonal
 682 pattern, but simulates a reduced seasonal cycle amplitude (Figure 6b). The GOBM spread
 683 is large, not only in terms of magnitude but also phasing of the seasonal cycle in the SPSS
 684 (8 out of 13 GOBMs simulate the maximum uptake between November and January;
 685 Figure 6d-r). This illustrates how the transition between the different seasonal cycle regimes
 686 affects particularly the representation of the seasonality in the SPSS. In summary, most
 687 GOBMs and pCO₂-products agree on a summer peak in the ICE biome (but exceptions
 688 exist, Figure 6d-r), and a winter peak to the north of the Southern Ocean biomes. The
 689 largest discrepancy between data sets is where and how swift this transition occurs. While
 690 the use of static biomes adds to the discrepancies seen in the averaged seasonal cycles
 691 (Figure 6a-c), the disagreement between the phasing of individual GOBMs is likely a much
 692 larger contributor to these discrepancies (Figure 6d-p). We now turn to an investigation
 693 of the thermal and non-thermal effects on the seasonal cycle, which may help explain these
 694 discrepancies.

695 *3.2.4 Thermal versus non-thermal effects on the seasonal cycle*

696 The seasonal cycle of CO₂ fluxes in the Southern Ocean is a balancing act between
 697 competing thermal and non-thermal drivers (Mongwe et al., 2016, 2018; Prend et al., 2022).
 698 DIC drawdown by biological production leads to a summer maximum in CO₂ uptake,
 699 whereas upwelling and entrainment of DIC-rich water into the mixed layer in autumn
 700 and winter leads to a minimum in CO₂ uptake or even outgassing (Metzl et al., 2006;
 701 Mongwe et al., 2018). Seasonal variations in mixed layer temperature further affect the
 702 solubility of CO₂, with lower (higher) temperatures increasing (decreasing) solubility and
 703 thus promoting CO₂ uptake (outgassing) (Takahashi et al., 2002).

704 The thermal and non-thermal components of pCO₂ can be decomposed to deter-
 705 mine the dominant driver on monthly timescales (Figure 7; Mongwe et al., 2018). Here,
 706 we do this by estimating the absolute difference of the rate of change of the thermal and
 707 non-thermal components (Figure 7; Eq. 3). The contribution of salinity and total alka-
 708 linity to seasonal pCO₂ changes are small in the Southern Ocean and compensate for each
 709 other on a seasonal scale (e.g., Sarmiento & Gruber, 2006; Lauderdale et al., 2016), thus
 710 we here consider the non-thermal component to be predominantly DIC-driven.

711 In general, the seasonal cycle phasing of the thermal component of the GOBMs agrees
 712 well with those of the pCO₂-products (Figure 7a-c). This should not come as a surprise,
 713 as GOBMs are forced by atmospheric reanalyses which assimilate observed SST (Doney
 714 et al., 2007). As a result, the thermal component of the pCO₂ seasonal cycle in the GOBMs
 715 (forced by reanalyses) compare much better to the thermal component derived from the
 716 pCO₂-products than fully coupled Earth System Models (Mongwe et al., 2016, 2018).
 717 The non-thermal contribution is thus the primary reason for the spread between GOBMs,
 718 and for the differences between GOBMs and pCO₂-products (Fig. 7a-c). Thus, we group
 719 GOBMs based on whether they are predominantly DIC or thermally driven across all
 720 three biomes (Fig. 7d-f, Table S2), which we term DIC-dominant or DIC-weak respec-
 721 tively.

722 In DIC-weak GOBMs, the strong underestimation of the non-thermal component
 723 causes these models to be too strongly temperature driven across the year (Figure 7).
 724 This then tends to shift the timing of uptake towards the colder months (when CO₂ sol-
 725 ubility is largest), while the role of biologically driven uptake in spring and summer is
 726 suppressed in favor of warming driven outgassing. This effect is largely confined to the
 727 SPSS and to a lesser extent also the STSS, and can account for the mismatch in the sea-
 728 sonal cycle seen in some GOBMs. For example, in the SPSS, nearly all GOBMs and specif-

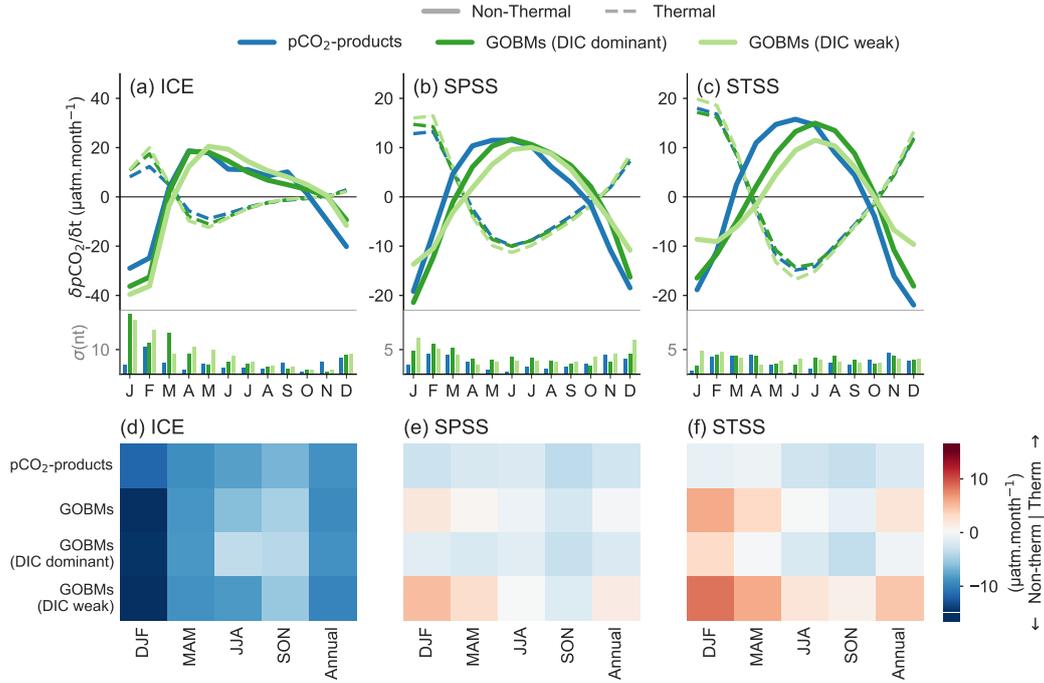


Figure 7. (a-c): Seasonal cycle of the rate of change of the thermal ($pCO_2^{T'}$, dashed lines) and non-thermal ($pCO_2^{nonT'}$, solid lines) components of ocean surface pCO_2 on monthly time scales given in $\mu atm \cdot month^{-1}$ (Eq. 2). The bars on the bottom show standard deviations of the non-thermal component. Models have been grouped into DIC dominant/weak, where the DIC weak models have a thermal contribution >0 for the mean of the STSS and SPSS (shown in d-f; see Figure S11 for individual global and regional ocean biogeochemistry models, and Table S2 for the DIC dominant/weak model groups). (d-f): λpCO_2 , the difference of the thermal and non-thermal (DIC) components of ocean surface pCO_2 as in Mongwe et al. (2018). When $\lambda pCO_2 > 0$ (red) indicates temperature dominance, and $\lambda pCO_2 < 0$ (blue) indicates that the non-thermal component (i.e., DIC) is dominant. The MPI model is excluded in this analysis.

729 ically all DIC-weak GOBMs have a shifted season of maximum uptake from summer to
 730 spring/winter, i.e., towards the colder months. (Fig. 6 and Table S2). In terms of the
 731 underlying mechanisms driving the too weak non-thermal component, we hypothesize
 732 that a lack of deep vertical mixing in winter leads to too little entrainment of DIC-rich
 733 deep waters, while simultaneously allowing for too early primary production (which may
 734 then shift the growing season earlier and reduce biologically driven summer uptake). No-
 735 tably, the bias in $p\text{CO}_2$ is largest in summer (DJF), followed by autumn (MAM), and
 736 is about twice as large in the DIC-weak GOBMs than in the DIC-dominant GOBMs (Fig-
 737 ure S13). This further supports the lesser importance of thermal processes in the STSS
 738 and SPSS regions evident in the $p\text{CO}_2$ -products.

739 In the ICE biome GOBMs and $p\text{CO}_2$ -products tend to agree much more closely
 740 in terms of their representation of the seasonal cycle (Fig. 6a). This is likely related to
 741 the strong role the seasonal advance and retreat of sea ice plays in air-sea CO_2 fluxes,
 742 both through its effect as a physical barrier, as well as through its effect on vertical mix-
 743 ing and light availability (thus impacting both physical and biological pathways of DIC
 744 into and out of the mixed layer, (Bakker et al., 2008; Shadwick et al., 2021; M. Yang et
 745 al., 2021)).

746 3.3 Temporal variability and trends in Southern Ocean air-sea CO_2 flux

747 We next inspect the temporal evolution of the air-sea CO_2 fluxes from 1985-2018
 748 (Figure 8). In this annually-resolved perspective, we also discuss the mean fluxes for data
 749 sets that are not available for the full time-period. While the STSS was a net-sink re-
 750 gion throughout the period, the SPSS and ICE have turned from neutral (around 0 PgC yr^{-1})
 751 to net sink regions since 1985, based on GOBM and $p\text{CO}_2$ -product ensemble mean es-
 752 timates. This also holds for most individual GOBMs as only two of them simulate ei-
 753 ther the ICE or the SPSS biome to still be regions of outgassing at the end of the time
 754 series (CCSM-WHOI and EC-Earth3).

755 Acknowledging some agreement between GOBMs and $p\text{CO}_2$ -based product ensem-
 756 ble means despite large spread across GOBMs (Figure 8 bars), substantial deviations among
 757 individual data sets appear. B-SOSE (2015-2018) suggests a 0.25 PgC yr^{-1} smaller up-
 758 take than the GOBM and $p\text{CO}_2$ -product ensemble means for the entire Southern Ocean
 759 (Figure 8a). ECCO-Darwin has the largest flux estimate into the ocean in the SPSS and
 760 the entire Southern Ocean (1.30 PgC yr^{-1} , 1985-2018). Notably, the two data-assimilated
 761 models B-SOSE and ECCO-Darwin differ by a factor of 2 for the Southern Ocean wide
 762 estimate. In agreement with previous reports (Bushinsky et al., 2019), BGC-float $p\text{CO}_2$ -
 763 products suggest Southern Ocean uptake to be 40% (0.4 PgC yr^{-1}) smaller than the $p\text{CO}_2$ -
 764 products without BGC-float data (2015-2018). This discrepancy originates largely in the
 765 SPSS, where the BGC-float $p\text{CO}_2$ -products estimate outgassing of 0.14 PgC yr^{-1} , and
 766 the ensemble mean of the SOCAT-only-based $p\text{CO}_2$ -products estimate a CO_2 uptake of
 767 $-0.13 \text{ PgC yr}^{-1}$. Smaller contributions to the deviation stem from the STSS and ICE biomes
 768 where BGC-float $p\text{CO}_2$ -products report a smaller uptake by 0.14 PgC yr^{-1} when com-
 769 pared with the regular $p\text{CO}_2$ -products. The Watson2020-product is generally close to
 770 the other $p\text{CO}_2$ -products, with the exception of the SPSS where it suggests a flux of -
 771 0.18 PgC yr^{-1} (1985-2018), which is larger than any other $p\text{CO}_2$ -product. The origin
 772 of the large SPSS difference in Watson2020 could, in part, be attributed to subtle dif-
 773 ferences in method choices in addition to different flux parameterisations (Watson et al.,
 774 2020). The atmospheric inversions produce a somewhat lower sink ($-0.64 \text{ PgC yr}^{-1}$, av-
 775 erage over three inversions 1985-2018), but are generally close to the $p\text{CO}_2$ -products, as
 776 they mostly use surface $p\text{CO}_2$ -products as a prior (Table 2 and Friedlingstein et al., 2022).
 777 There is also slightly higher interannual variability in the atmospheric inversion ensem-
 778 ble mean, but this is likely due to the small ensemble size.

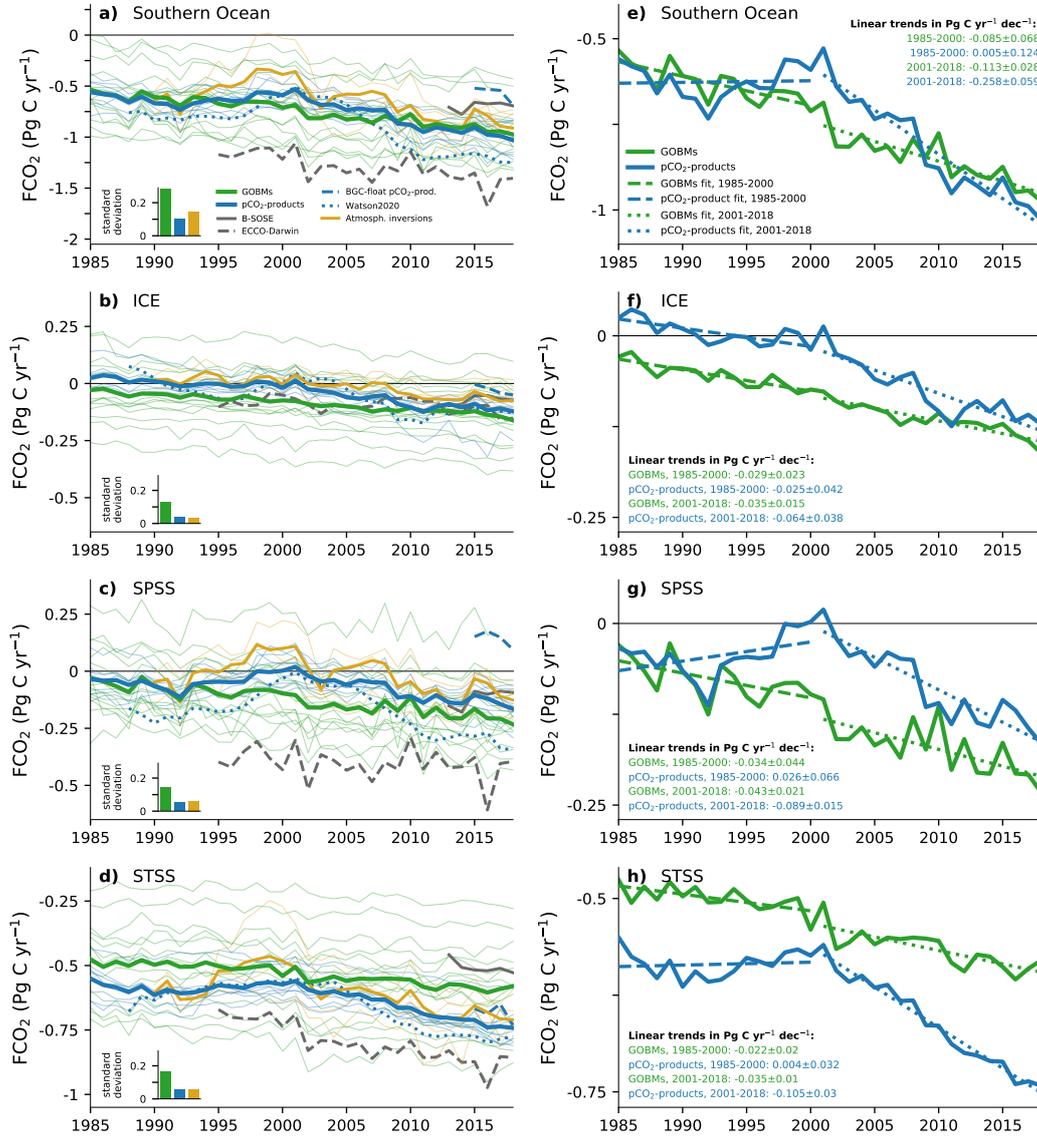


Figure 8. Temporal evolution of the Southern Ocean air-sea CO₂ flux for a) the entire Southern Ocean, and the b) subtropical seasonally stratified, c) subpolar seasonally stratified, and d) ice biomes. The ensemble standard deviation (1σ) averaged over the whole time series, is shown by the bars. Panels (e-h) are the same as panels (a-d) for the GOBM ensemble average and pCO₂-product ensemble average only, with linear trends between 1985-2000 and 2001-2018 as the dashed and dotted lines, respectively. The uncertainty range of the trend is calculated as one standard deviation of the trends across all GOBMs and pCO₂-products, respectively. Note the different y-axis scales. The separation into Atlantic, Pacific and Indian Ocean sectors is shown in Figure S12.

779 The temporal variability is quantified as the amplitude of ‘interannual variability’
 780 (IAV). This is calculated as the standard deviation of the detrended time-series, as de-
 781 fined in Rödenbeck et al. (2015); Friedlingstein et al. (2022) which, in reality, captures
 782 both interannual and decadal variability components. Following this definition, the pCO₂-
 783 products have a larger interannual variability for the Southern Ocean wide integrated
 784 flux (0.09 PgC yr⁻¹, range 0.04 to 0.16 PgC yr⁻¹) compared to the GOBMs (0.06 PgC yr⁻¹,
 785 range 0.03 to 0.10 PgC yr⁻¹). Notably, the MPI-SOM-FFN pCO₂-product, which formed
 786 the basis of previous reports on Southern Ocean decadal variability (Landschützer et al.,
 787 2015), has the largest IAV of 0.16 PgC yr⁻¹, about 60% larger than the next largest pCO₂-
 788 product IAV. This is in line with previous studies that found that the MPI-SOM-FFN
 789 approach may overestimate Southern Ocean variability by 30% (Gloege et al., 2021) and
 790 the decadal trend 2000-2018 by 130% (Hauck et al., 2023). Within the Southern Ocean,
 791 the strongest IAV is found in the SPSS region (0.04 PgC yr⁻¹ GOBMs, 0.05 PgC yr⁻¹ pCO₂-
 792 products), followed by the STSS (0.02 PgC yr⁻¹ GOBMs, 0.03 PgC yr⁻¹ pCO₂-products)
 793 and ICE biome (0.02 PgC yr⁻¹ for both data classes). Within the subpolar biome, the
 794 Indo-Pacific sector has a higher IAV (0.02 PgC yr⁻¹) than the Atlantic sector (0.01 PgC yr⁻¹).
 795 The large contribution to interannual variability in the SPSS may well be linked to the
 796 largest amplitude of the seasonal cycle of CO₂ flux (see section 3.2.3).

797 To assess the decadal-scale trends, we fit linear trends to the periods 1985-2000 and
 798 2001-2018 (Figure 8e-h) with the year 2000 marking roughly the mid of the considered
 799 time period and the inflection point in global ocean CO₂ uptake (Gruber et al., 2023;
 800 Landschützer et al., 2016). The pCO₂-products suggest a stagnation of the flux in the
 801 STSS, and even a flux decrease in the SPSS prior to 2000. In contrast, GOBMs suggest
 802 a continued increase in the sink in the STSS and SPSS in the same period. In the ICE
 803 biome, GOBMs and pCO₂-products result in an increasing trend (Figure 8h). After 2000,
 804 pCO₂-products and GOBMs agree on a trend towards more CO₂ uptake, which is sig-
 805 nificantly different from zero in all biomes except for pCO₂-products in the ICE biome
 806 (see numbers in Figure 8e-h). However, they differ substantially in magnitude between
 807 GOBM and pCO₂-product ensemble means, particularly in the STSS (Figure 8f). The
 808 discrepancies in the magnitude of the trend act to decrease the gap between GOBM and
 809 pCO₂-product ensemble means in the SPSS and ICE biomes, but lead to the divergence
 810 in the flux estimate in the STSS.

811 On a sub-biome level (i.e., Atlantic, Indian, and Pacific sectors), all three sectors
 812 in the STSS were CO₂ sinks throughout the period and had weaker trends (less nega-
 813 tive) before 2000 compared to the period after 2000 (Figure S12). In the SPSS, the In-
 814 dian and Pacific sectors are characterized by intermittent outgassing and uptake patterns,
 815 in line with observations from BGC-floats (Prend et al., 2022). In the SPSS, only the
 816 Atlantic sector has a net uptake throughout the period, and the Indian Ocean sector shows
 817 the largest model spread of all three sectors (as in the STSS). In the ICE biome, a con-
 818 sistent quasi-linear evolution is apparent in all sectors. We further analyze divergence
 819 and drivers of trends in section 3.3.2.

820 **3.3.1 Comparison with in-situ pCO₂**

821 Here, we evaluate the accuracy of pCO₂ across data classes since pCO₂ is the dom-
 822 inant driver of air-sea CO₂ flux variability at a monthly scale (Landschützer et al., 2016).
 823 All data sets are compared with observations (monthly gridded SOCAT v2022 data set
 824 Sabine et al., 2013; Bakker et al., 2016, 2022). The RECCAP2 data sets are subsampled
 825 to match the SOCAT observations in time and space, meaning that we do not assess sam-
 826 pling biases, but rather the mismatch between the observed and estimated pCO₂.

827 The comparison of the RECCAP2 GOBMs and pCO₂-products with gridded in-
 828 situ pCO₂ from SOCAT v2022 shows relatively good agreement (Figure 9a). The SO-
 829 CAT pCO₂ data shows large interannual variability due to spatially and temporally vary-

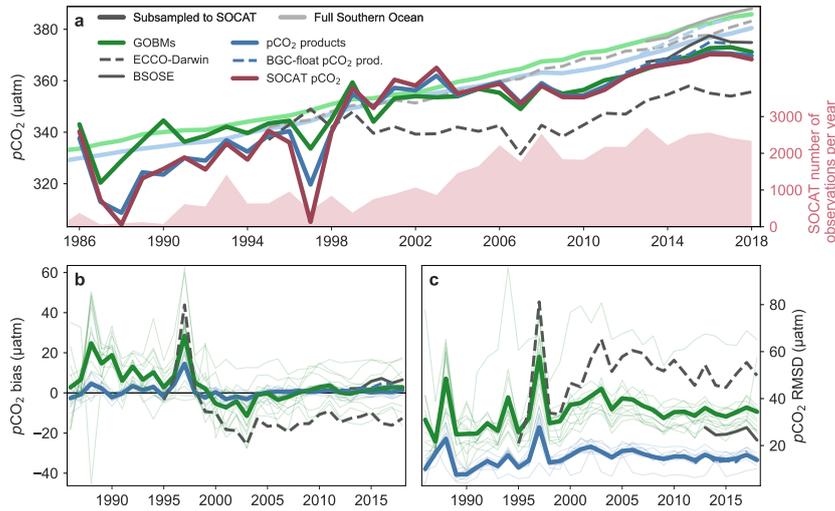


Figure 9. Comparison of surface mean pCO₂ for the whole Southern Ocean between global ocean biogeochemistry models (GOBMs) and pCO₂-products with in situ observations (gridded SOCAT v2022 data set Sabine et al., 2013). (a) Time-series of annually-averaged pCO₂ from GOBMs (green), data-assimilated models (grays), and pCO₂-products (blue). The darker shaded lines show the annual mean as calculated from the data sets subsampled to match the historic SOCAT sampling. The lighter shades show the annual mean calculated for the full coverage. The dark red line depicts the annual mean pCO₂ from SOCAT observations without interpolation. The assimilation products (ECCO-Darwin and B-SOSE) are kept separate as they have different time series lengths (shown by dashed and solid gray lines respectively). The light red area plot (right y-axis) shows the number of monthly by 1°×1° gridded SOCAT observations per year. (b) The bias of pCO₂ for all data classes (subsampled to match SOCAT observations, dark lines in a) relative to SOCAT pCO₂ observations (solid dark red line in a). (c) The root mean squared difference (RMSD) between SOCAT observations and estimates for all data classes. Bias and RMSD were calculated on a monthly by 1°×1° resolution, and the bias and RMSD were averaged to annual means afterwards. A plot of RMSE and bias for SPSS and STSS biomes and different seasons is presented in supplementary Figure S13.

ing sampling efforts from year to year, particularly prior to 2000 when samples are fewer and thus carry more weight (Figure 9a). For example, in 1997, SOCAT pCO₂ is anomalously low due to high sampling density in the Ross Sea during summer when primary production drives intense CO₂ drawdown (Arrigo & van Dijken, 2007). The pCO₂ products have a lower bias and a narrower spread than the GOBMs prior to 2000 ($1.7 \pm 4.3 \mu\text{atm}$ and $10.7 \pm 8.0 \mu\text{atm}$ respectively), with the bias and the spread decreasing after 2000 for both classes ($-0.3 \pm 2.6 \mu\text{atm}$ and $-0.9 \pm 3.9 \mu\text{atm}$, Figure 9b). This comparison of simulated to observed pCO₂ at observation sites demonstrates that GOBMs are capable of reproducing SOCAT pCO₂ and its temporal evolution on large spatial and annual time-scales. Thus, for the period after 2000, the differences in CO₂ flux trend for the entire Southern Ocean between GOBMs and pCO₂-products (Figure 8) cannot be attributed to differences in pCO₂ in the regions where observations were taken. Instead, the differences arise primarily from areas where no pCO₂ observations exist, as also concluded in Hauck et al. (2020). The pCO₂ time-series calculated from the full coverage results in a lower pCO₂ value in the pCO₂-products than in the GOBMs (Figure 9a), which could explain the stronger CO₂ flux trend in the pCO₂-products (Figure 8). This discrepancy between pCO₂-products and GOBMs is larger in the last ten years (2009-2019: $5.8 \mu\text{atm}$) than the previous decade (1999-2008: $2.8 \mu\text{atm}$, Figure 9a). Nevertheless, the RMSD calculated from monthly mean data is higher in GOBMs than in pCO₂-products (Figure 9c). This is expected as the pCO₂-products are trained to fit the observations and further illustrates the GOBMs' deficiencies in simulating seasonal and spatial variability of the CO₂ uptake.

The assimilation model, ECCO-Darwin, has a negative bias after 2000 ($-13.5 \pm 3.0 \mu\text{atm}$; Figure 4b), but this negative bias is not strongly reflected in the mean of the non-sampled data, with the mean pCO₂ still being larger than that of the pCO₂-products, which do not underestimate the pCO₂ relative to SOCAT. This further emphasizes that sampling distribution may play an important role in the magnitude of the biases calculated in any model. The pCO₂ summer sampling bias in the Southern Ocean has long been recognised as a potential source of biases in pCO₂ estimates, particularly for the pCO₂-products that rely heavily on the in-situ data (Metzl et al., 2006; Gregor et al., 2017; Ritter et al., 2017; Djeutchouang et al., 2022). The SOCCOM project increased the number of winter samples with pH-enabled profiling floats (from 2014), suggesting stronger outgassing during winter than previously shown (Gray et al., 2018). In RECCAP2, the B-SOSE assimilation model and the BGC-float pCO₂-products both make use of this data (Verdy & Mazloff, 2017; Bushinsky et al., 2019). Both of these estimates overestimate pCO₂ relative to SOCAT pCO₂ highlighting the challenge in consolidating ship-based SOCAT and BGC-float data.

3.3.2 *Climate versus CO₂ effects on trends in CO₂ flux*

Our analysis so far has indicated that the GOBMs reproduce seasonal temperature effects on CO₂ flux reasonably well (Figure 7), and a larger uncertainty is associated with imprints of circulation and biological activity. Next, we inspect the zonal mean and spatial patterns of the CO₂ flux trend 1985-2018 (Figure 10). The pCO₂-products place the largest trend towards more CO₂ uptake in the entire ICE biome; however, data in this region is sparse and there is larger variability between pCO₂ products here (see also Figure 8). The pCO₂-products show a secondary peak in the STSS between about 40 to 45°S. The GOBMs in contrast have a large meridional gradient in the ICE biome with a peak in the trend between 60 and 65°S that is reduced in magnitude towards Antarctica. The secondary peak in the STSS is hardly apparent and also displaced southwards compared to the pCO₂-products. In addition, the pCO₂-products exhibit trends towards less CO₂ uptake in the Pacific and eastern Indian sector of the SPSS (Figure 10a-b). Although the difference in flux density between GOBMs and pCO₂-products is larger in the ICE biome, the discrepancy in the STSS contributes more to the total flux trend discrepancy due to the larger area of the STSS biome (Figure 8). The trend over 1985-2018

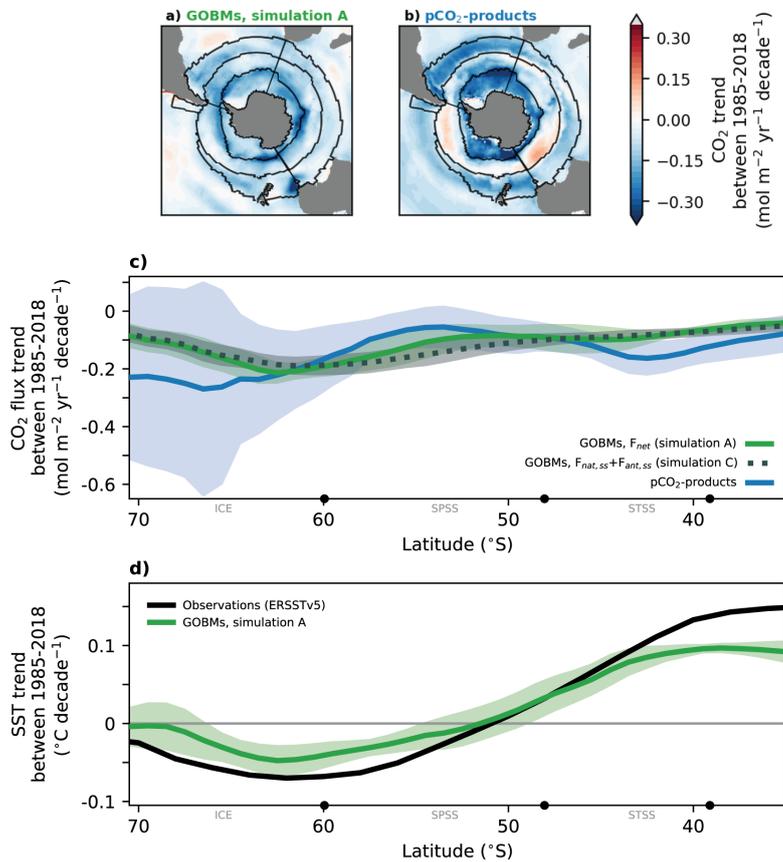


Figure 10. CO₂ flux trend between 1985 and 2018. (a-b) Spatial maps of the net CO₂ flux trend, for (a) the global ocean biogeochemistry models and (b) the pCO₂-products. (c) Zonal mean CO₂ flux trend 1985-2018 for the net CO₂ flux (blue: pCO₂-products, green: GOBMs) and the GOBM flux of $F_{nat,ss}$ and $F_{ant,ss}$, i.e., the flux as expected from increasing atmospheric CO₂ alone (green, dashed). (d) The sea surface temperature (SST) trend 1985-2018 in the GOBMs (green) and in the observational data set (black, NOAA Extended Reconstructed Sea Surface Temperature, ERSST, Version 5 (Huang et al., 2017)). Supplementary figures split this analysis in the periods 1985-2000 (Figure S14) and 2001-2018 (Figure S15). Individual GOBM trends for F_{net} , as well as $F_{nat,ss}$ plus $F_{ant,ss}$ and SST are shown in Figure S16.

883 includes some compensation between the trends over 1985-2000 and 2001-2018 (see Fig-
 884 ures S14-S15). While the GOBMs show similar weak trends towards more uptake be-
 885 fore and after 2000, the pCO₂-products show a trend towards less uptake in the earlier
 886 period 1985-2000 throughout the Southern Ocean except in the Weddell and Ross Seas.
 887 In the later period 2001-2018, the pCO₂ products estimate a much stronger trend to-
 888 wards more CO₂ uptake everywhere, as also shown in Figure 8. The CO₂ flux trends in
 889 the GOBMs are largely driven by increasing atmospheric CO₂ levels (simulation C in
 890 Figure 10c). However, the trend is reduced by climate change and variability through-
 891 out the SPSS and strengthened in the northern part of the ICE biome (compare sim-
 892 ulations A that represents net FCO₂ and C that represents only steady state natural and
 893 anthropogenic fluxes, in Figure 10c). The effect of climate change and variability is sub-
 894 stantially smaller than the uncertainty in the pCO₂-products. In line with GOBMs cap-
 895 turing the thermally-driven component of the pCO₂ seasonal cycle (Figure 8), we can
 896 also demonstrate that the GOBMs simulate sea surface temperature trends 1985-2018
 897 rather well (Figure 10d). This is related to the choice of forcing the GOBMs with reanal-
 898 ysis data that itself depends on sea surface temperature observations (Doney et al., 2007).
 899 In contrast to fully coupled Earth System models in CMIP6 (Beadling et al., 2020), the
 900 suite of models used here capture the decadal trend pattern of warming along the north-
 901 ern flank of the Antarctic Circumpolar Current (ACC), and cooling in the south (Figure
 902 10, Armour et al., 2016; F. Haumann et al., 2020). The lack of warming south of 50°S
 903 was previously related to the wind-driven upwelling of deep water that had not yet been
 904 exposed to anthropogenic warming and by northward heat transport (Armour et al., 2016).
 905 More recently, the cooling was suggested to be caused by increased freshwater export from
 906 the ice region, which increases stratification and thus reduces the upward heat flux from
 907 below by warm water masses (F. Haumann et al., 2020). While the GOBM ensemble mean
 908 captures the latitudinal structure of the SST trend well, it underestimates the magni-
 909 tude of peak cooling at around 60°S as well as peak warming north of 40°S. Overall, how-
 910 ever, the GOBM ensemble mean captures the latitudinal structure of the SST trend well.
 911 We can therefore not relate the discrepancies in the trend of the CO₂ flux to temper-
 912 ature biases. This leaves data sparsity as a reason for potential biases in the trend in the
 913 pCO₂-products, and biases in ocean circulation, sea ice and biology as possible reasons
 914 for biases in GOBMs.

915 3.4 Interior ocean storage of anthropogenic carbon

916 The focus of this section is the anthropogenic perturbation of dissolved inorganic
 917 carbon (DIC) in a subset of the GOBMs (see section 2.2.1), and in particular its accu-
 918 mulation rate over the period 1994 to 2007 (ΔC_{ant}), in comparison with the eMLR(C*)
 919 observational estimate (Gruber, Clement, et al., 2019) and the ocean inverse model OCIMv2021
 920 (DeVries, 2022). The eMLR(C*) product uses a multiple linear regression approach to
 921 estimate ΔC_{ant} and captures both the influence of CO₂-driven and climate-driven change
 922 in sea-air CO₂ fluxes and transports, whereas OCIMv2021 captures only the CO₂-driven
 923 changes.

924 All data classes agree in having the largest ΔC_{ant} inventories within and to the north
 925 of the STSS biome (Figure 11), whose southern boundary approximately corresponds
 926 to the northern edge of the ACC. This pattern is related to the mechanisms by which
 927 C_{ant} is taken up at the surface and exported to depth (Mikaloff Fletcher et al., 2006; Mor-
 928 rison et al., 2022; Bopp et al., 2015). Subpolar upwelling exposes old C_{ant} -poor waters
 929 to elevated atmospheric CO₂ concentrations and this, combined with strong winds, drives
 930 a large influx of C_{ant} in the SPSS biome (Figure 12a-c). A small fraction of the C_{ant} moves
 931 southward and is exported within Antarctic Bottom Waters, while the largest fraction
 932 is transported northward within the upper cell of the meridional overturning circulation.
 933 C_{ant} air-sea fluxes remain elevated throughout the northward path, and are reinforced
 934 by the deep mixed layers in the regions where mode and intermediate waters are formed,

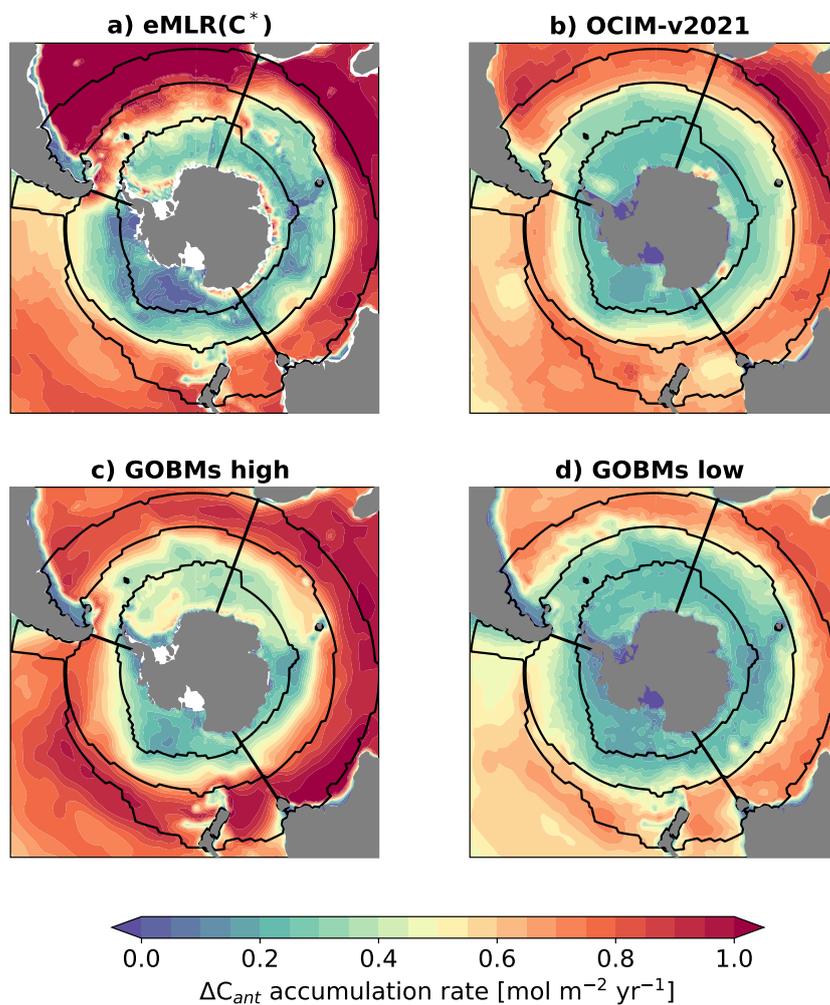


Figure 11. ΔC_{ant} yearly accumulation rate over the period 1994-2007 integrated until 3000 m depth in the observationally-constrained estimates a) eMLR(C*) (Gruber et al., 2019) and b) OCIM-v2021, in c) “GOBMs high” and in d) “GOBMs low” (individual GOBMs shown in Fig. S4). The robustness of the patterns has been tested as explained in Text S4 of the Supplement. Contours show the boundaries of the ICE, SPSS and STSS biomes. Values below 3000 m are not shown because of the low signal-to-uncertainty ratio in eMLR(C*).

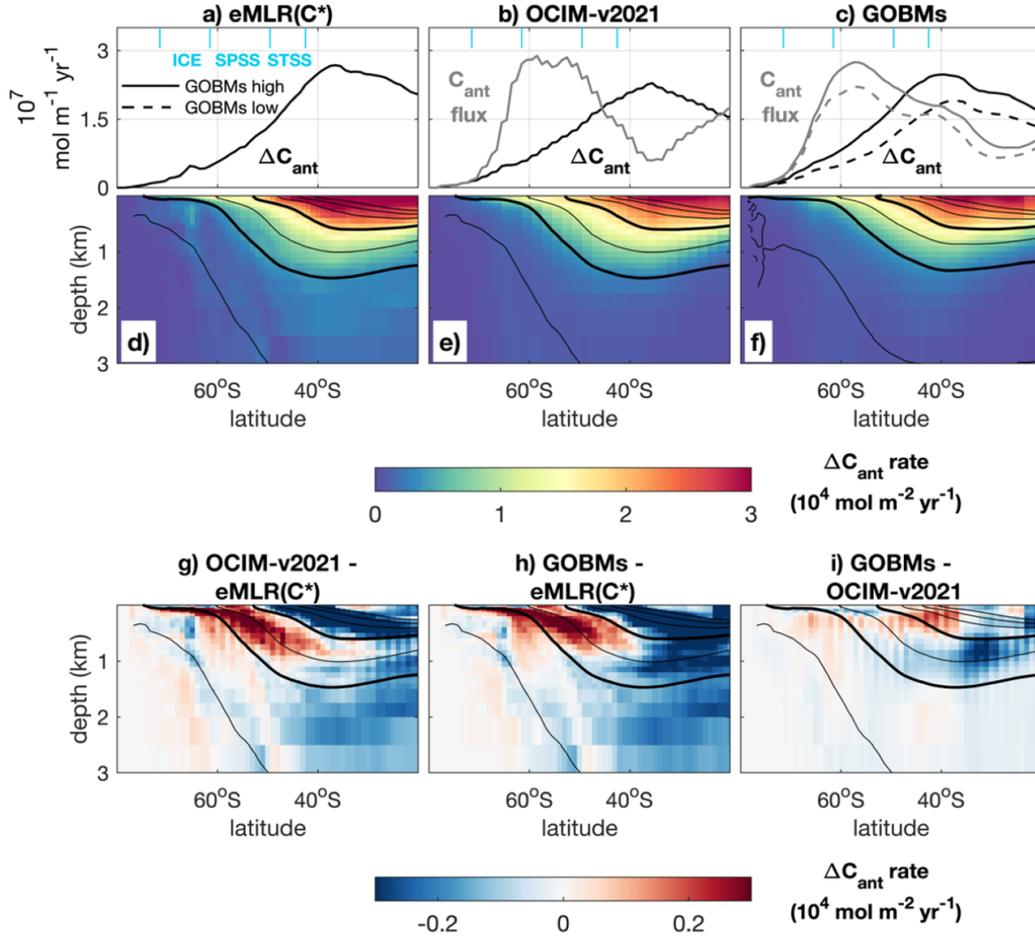


Figure 12. Zonal integrals of ΔC_{ant} yearly accumulation rate from 1994 to 2007 and of air-sea C_{ant} fluxes (positive downwards) averaged between 1994 and 2007 for a,d) eMLR(C*), b,e) OCIM-v2021 and c,f) GOBMs. a-c) (black line) ΔC_{ant} column inventory (0-3000 m) and (grey line) air-sea C_{ant} fluxes; for the GOBMs, the distinction is made between “GOBMs high” (full lines) and “GOBMs low” (dashed lines). g-i) Anomalies of ΔC_{ant} accumulation rates in g) OCIM-v2021 with respect to eMLR(C*), h) GOBMs with respect to eMLR(C*) and i) GOBMs with respect to OCIM-v2021. In all sections, contours show mean potential density (with a 0.03 kg m^{-3} spacing) referenced to the surface in World Ocean Atlas 2018 (Boyer et al., 2018), where thick lines indicate the 1026.9 kg m^{-3} and 1027.5 kg m^{-3} isopycnals. Anomalies of individual GOBMs shown in Fig. S18 (with respect to eMLR(C*)) and Fig. S19 (with respect to OCIMv2021).

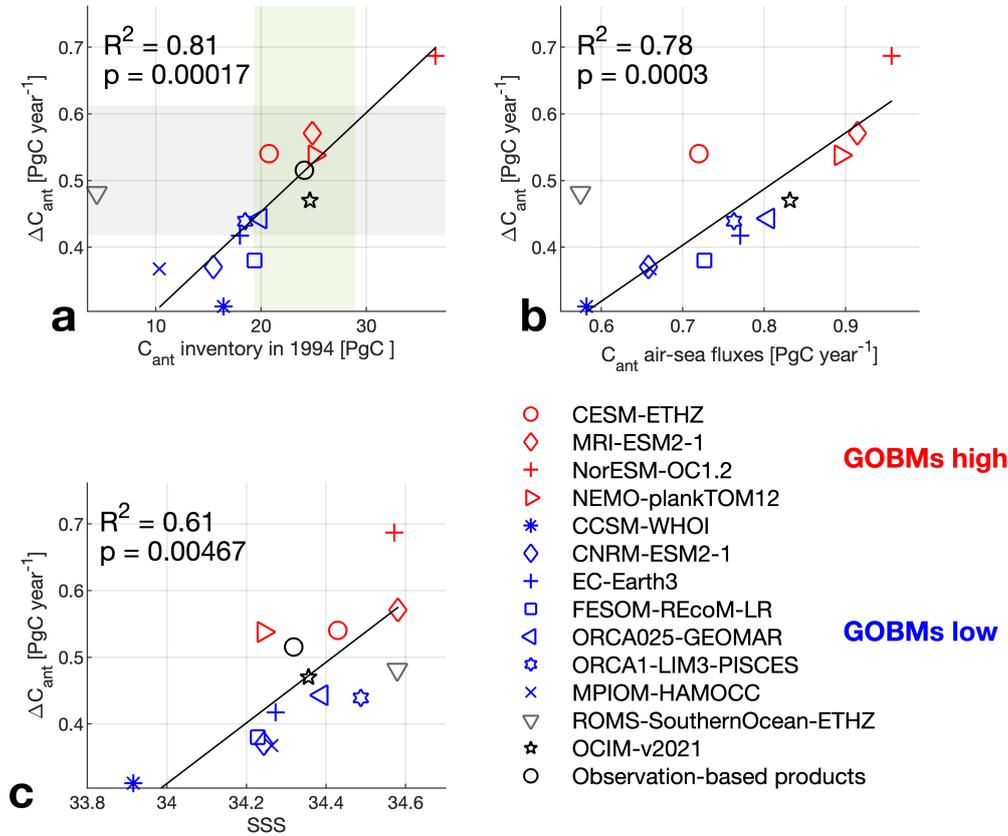


Figure 13. Scatter plots showing relationships between ΔC_{ant} accumulation rates between 1994 and 2007 (integrated to 3000 m) and different quantities namely a) the cumulative C_{ant} in 1994 integrated over the Southern Ocean, b) air-sea C_{ant} fluxes averaged between 1994 and 2007 and integrated over the Southern Ocean, c) sea surface salinity (SSS) horizontally averaged over the SPSS and STSS biomes (which show consistent SSS anomaly patterns, Fig. S17). Shown are a subset of the GOBMs (see 2.3), the OCIM-v2021 data-assimilated model, the observation-based cumulative C_{ant} until 1994 (C^* method, Sabine et al., 2004) and the 1994-2007 ΔC_{ant} from (eMLR(C^*) method, Gruber, Clement, et al., 2019), and SSS from EN4.2.1 (Good et al., 2013). Thin black lines show the linear fit of the data for the GOBMs only, with the explained variance (R^2) and the p -value indicated for each regression. The grey shading in a) indicates the 19% uncertainty levels around the mean of eMLR(C^*) (Southern Hemisphere uncertainty estimate, based on Table 1, Gruber, Clement, et al., 2019) and the green shading the 20% uncertainty levels around the C^* -based estimate of cumulative C_{ant} until 1994 (global uncertainty estimate Sabine et al., 2004; Matsumoto & Gruber, 2005). Models that have a ΔC_{ant} storage higher than the average of the two observationally-constrained data sets (“GOBMs high”) are shown in red, whereas the models in which it is lower (“GOBMs low”) are shown in blue. Because of its different spin-up procedure, ROMS-SouthernOcean-ETHZ is shown in the plots but has been excluded from the regression analysis. For OCIM-v2021, CNRM-ESM2-1 and MPIOH-HAMOCC the ΔC_{ant}^{SS} is shown, whereas in others the sum of steady state and non steady state is shown. As discussed in Text S2, ΔC_{ant}^{SS} accumulation rates are about 10-20% of the total ΔC_{ant} .

935 which results in a secondary peak at around 40°S in some GOBMs, diluted by the en-
936 semble mean (Fig. 12c).

937 The effective transport of C_{ant} into the ocean interior relies on a number of phys-
938 ical processes, the dominant of which is the northward transport by the overturning cir-
939 culation of the C_{ant} ventilated in the ocean interior by deep winter mixing (Frölicher et
940 al., 2015; Morrison et al., 2022). The absorbed C_{ant} spreads northward along density sur-
941 faces within mode and intermediate waters (Figure 12d-f) and is circulated within and
942 out of the Southern Ocean by the subtropical gyres (Frölicher et al., 2015; D. C. Jones
943 et al., 2016; Waugh et al., 2019). As a result, the largest C_{ant} inventories are displaced
944 to the north with respect to the maximum air-sea C_{ant} influx (Figure 12b,c). Another
945 pathway by which the C_{ant} inventory can build up without a corresponding surface in-
946 flux is by southward advection and subsequent subduction of high- C_{ant} Subtropical Wa-
947 ters (Iudicone et al., 2016; Morrison et al., 2022).

948 The observation-based product eMLR(C^*) and the ocean inverse model OCIM-v2021
949 have similar ΔC_{ant} accumulation rates when integrated over the Southern Ocean for the
950 period 1994 through 2007 (0.52 PgC yr^{-1} and 0.47 PgC yr^{-1} , respectively, Figure 13),
951 but differ in their horizontal (Figure 11) and vertical (Figure 12) patterns. The eMLR(C^*)
952 exhibits particularly low ΔC_{ant} values at subpolar and high latitudes (Figure 12g), es-
953 pecially in the Pacific sector (Figure 11). The GOBMs multi-model-mean of ΔC_{ant} ac-
954 cumulation rates over the same 1994 through 2007 period and integrated within the South-
955 ern Ocean (Figure 13) is $0.46 \pm 0.11 \text{ PgC yr}^{-1}$, i.e., 7% lower than the mean of the two
956 observational estimates considered here. 6 out of the 12 GOBMs fall within the 19% range
957 of the observational eMLR(C^*) uncertainty. Two thirds of all GOBMs (hereafter “GOBMs
958 low”) have lower than observed ΔC_{ant} accumulation rates ($0.39 \pm 0.11 \text{ PgC yr}^{-1}$, about
959 20% lower than the observational estimates). The remaining GOBMs (hereafter “GOBMs
960 high”) have higher than observed ΔC_{ant} accumulation rates ($0.58 \pm 0.07 \text{ PgC yr}^{-1}$, about
961 17% higher than the observational estimates). “GOBMs high” have a higher ΔC_{ant} stor-
962 age than “GOBMs low” throughout the Southern Ocean (Figures 11c,d and 12c), higher
963 C_{ant} air-sea fluxes (Figure 12c), higher sea surface salinity (SSS) in the SPSS and STSS
964 biomes and mixed layer depths especially in the SPSS biome (Text S3, S4 and Figure
965 S17). Along the zonal mean section, all GOBMs show a southward shift in ΔC_{ant} with
966 respect to eMLR(C^*) shown by a north-south dipole in the upper 1 km (Figure 12h),
967 as similarly found in the comparison between OCIM-v2021 and eMLR(C^*) (Figure 12g).
968 With respect to OCIM-v2021, GOBMs show higher ΔC_{ant} above 1000 m depth and lower
969 ΔC_{ant} beneath (Figure 12i). This could point to insufficient ventilation of C_{ant} in “GOBMs
970 low” models (Figure S19), which represent the majority of the GOBMs. The amount of
971 spread and the overall underestimate of ΔC_{ant} in the GOBMs is consistent with Earth
972 System Models analyzed by Frölicher et al. (2015) and Terhaar et al. (2021), support-
973 ing the argument that biased ocean model dynamics and water mass properties rather
974 than biases in the atmospheric forcing cause the C_{ant} underestimate (Terhaar et al., 2021;
975 Bourgeois et al., 2022).

976 Integrated over the Southern Ocean, we find that the model spread in ΔC_{ant} ac-
977 cumulation rates from 1994 to 2007 can be largely explained (81% variance explained)
978 by the spread in accumulated C_{ant} until 1994 (Figure 13), suggesting a coherent scal-
979 ing between long-term and recent C_{ant} accumulation rates. The model spread in ΔC_{ant}
980 accumulation rates is also related with the spread in C_{ant} air-sea fluxes averaged over
981 1994-2007 (78% variance explained). These results show that past long-term ΔC_{ant} ac-
982 cumulation rates are a better predictor for present ΔC_{ant} accumulation rate than present
983 C_{ant} air-sea fluxes. The reason for this is that C_{ant} air-sea fluxes are linked to changes
984 in C_{ant} storage through ocean transport, which may differ substantially between mod-
985 els (Frölicher et al., 2015; Terhaar et al., 2021; Bourgeois et al., 2022). This becomes ob-
986 vious when considering the myriad of processes involved, including the strength of the
987 overturning circulation, the strength of the subtropical gyres, the isopycnal stirring by

Table 3. Comparison of the Southern Ocean carbon sink estimate with the estimate presented in RECCAP1 (Lenton et al., 2013), which used a different definition of the Southern Ocean region (44-75°S) and covered a different period (1990-2009). GOBMs: Global Ocean Biogeochemistry Models. Reported numbers are means \pm one standard deviation. Note for RECCAP1 the median of all models is reported.

Estimate	GOBMs	Observation-based
RECCAP2 1985-2018	-0.75 ± 0.28 PgC yr ⁻¹	-0.73 ± 0.07 PgC yr ⁻¹
RECCAP2 1985-2018 (44°-75°S)	-0.39 ± 0.24 PgC yr ⁻¹	-0.30 ± 0.04 PgC yr ⁻¹
RECCAP2 1990-2009 (44°-75°S)	-0.22 ± 0.25 PgC yr ⁻¹	-0.14 ± 0.09 PgC yr ⁻¹
RECCAP1 1990-2009 (44°-75°S)	-0.43 ± 0.38 PgC yr ⁻¹	-0.27 ± 0.13 PgC yr ⁻¹

mesoscale eddies, and localized subduction dynamics (Sallée et al., 2012; Morrison et al., 2022). The different way in which the GOBMs simulate these transport processes is possibly linked to the large model spread in ΔC_{ant} accumulation rates among GOBMs. Past studies have found that SSS affects the surface ocean density in the formation regions of mode and intermediate waters and could be used as a constraint of the C_{ant} air-sea fluxes, and thus of the C_{ant} storage within the recently-ventilated water masses (Terhaar et al., 2021). In this study and in Terhaar et al. (2023), we find that SSS explains a lower variance in the ΔC_{ant} accumulation rates ($R^2=61\%$; Figure 13) and in the C_{ant} air-sea fluxes ($R^2=57\%$ Terhaar et al., 2023) with respect to the ESMs ($R^2=0.74$) analyzed by Terhaar et al. (2021). The relationship may be weaker due to the different suite of models used in the ESM and GOBM ensembles and remaining biases associated with incomplete spin-up (Terhaar et al., 2023).

1000 4 Discussion

1001 4.1 Summary and progress since RECCAP1

1002 We provide an updated estimate of the Southern Ocean carbon sink (see Figure
1003 1 for regional extent). The numbers we present (Table 3) are not directly comparable
1004 with the RECCAP1 estimate (Lenton et al., 2013) due to different region definitions (Fig-
1005 ure 1) and periods (1990-2009 vs. 1985-2018). The RECCAP1 regional definition of the
1006 Southern Ocean (44-75°S) cut across and missed a large part of the strong CO₂ uptake
1007 north of the Subantarctic Front. Recalculating the RECCAP2 numbers for the REC-
1008 CAP1 region would reduce the Southern Ocean CO₂ sink to 52% (GOBMs) or 41% (pCO₂-
1009 products) of its original value (Table 3). Adjusting RECCAP2 numbers for the 1990-
1010 2009 period would further reduce fluxes by about another 50%. Compared on equal foot-
1011 ing (44°-75°S and 1990-2009), we find the Southern Ocean to be a weaker carbon sink
1012 in RECCAP2 compared to RECCAP1.

1013 The observational and modeling communities have made substantial progress on
1014 quantifying and characterizing the Southern Ocean carbon sink since RECCAP1 (Lenton
1015 et al., 2013). The creation of the Surface Ocean CO₂ Atlas and its annual updates have
1016 marked a step-change by facilitating the development of statistical models (a.k.a. pCO₂-
1017 products). The large and diverse ensemble of pCO₂-products help to identify the robust
1018 features of the Southern Ocean carbon sink. The pCO₂-products have a relatively small
1019 spread compared to the global ocean biogeochemistry models in terms of mean and sea-
1020 sonal cycle, indicating that the uncertainty from differences in mapping methods is small.
1021 However, the spread in the trend estimates is in fact larger in the products than in the
1022 GOBMs (Figure 10). Further, the narrow spread in mean and seasonal cycle does not

1023 include the uncertainties due to sparse pCO₂ observations in the Southern Ocean, particu-
 1024 larly in winter and before the 2000's (Ritter et al., 2017). In addition, pCO₂-products
 1025 share the uncertainties associated with the bulk formulation of air-sea CO₂ exchange (R. H. Wan-
 1026 ninkhof et al., 2009; Fay et al., 2021). While they do have their shortcomings, the pCO₂
 1027 products are an advance for constraining the Southern Ocean carbon sink compared to
 1028 the atmospheric inversions that were used in RECCAP1 (Lenton et al., 2013). This is
 1029 because the surface ocean pCO₂ observations provide a more direct constraint on the
 1030 air-sea CO₂ flux than the relatively small atmospheric CO₂ signals over the ocean that
 1031 form the basis of the atmospheric inversions.

1032 The larger GOBM ensemble provides a more representative process-based estimate
 1033 and the spread in GOBMs has been reduced since RECCAP1 (see Table 3 Lenton et al.,
 1034 2013). The remaining spread is nevertheless large and points towards critical need for
 1035 model development, where the largest sources of uncertainty stem from biological pro-
 1036 cess description and circulation, which vary in importance depending on flux component
 1037 (natural, anthropogenic, etc.), and spatio-temporal scale of interest. In terms of the an-
 1038 thropogenic component, the 12 GOBMs analyzed here have a 24% spread (standard de-
 1039 viation around the mean) in the C_{ant} accumulation rates, which is marginally larger than
 1040 the $\sim 20\%$ uncertainty associated with the observational estimates of ΔC_{ant} and C_{ant}
 1041 (even though caution is warranted when directly comparing the uncertainty estimates,
 1042 which are computed formally different across data classes; Gruber, Clement, et al., 2019;
 1043 Sabine et al., 2004). Overall, the GOBM ensemble mean underestimates the observa-
 1044 tion-based estimates of the C_{ant} accumulation up to 1994 by 19% and the change between
 1045 1994-2007 by 7%. Admittedly, the GOBM ensemble analyzed here is relatively small,
 1046 and the underestimation of C_{ant} and ΔC_{ant} is in the range of the uncertainty ranges of
 1047 the observational estimates. We can nonetheless speculate that the detected underes-
 1048 timation is likely related to a combination of physical, chemical and methodological fac-
 1049 tors. First, our results point to too little or too shallow ventilation of mode and inter-
 1050 mediate waters (Figure 12i), the causes of which can be related to insufficient vertical
 1051 mixing or too sluggish northward export of the subducted waters (Morrison et al., 2022).
 1052 However, while sea-surface salinity (SSS) was singled out as a strong predictor of C_{ant}
 1053 air-sea fluxes in an ESM ensemble analyzed by (Terhaar et al., 2021), in our study and
 1054 in (Terhaar et al., 2023), SSS was not found to be a clear constraint of the anthropogenic
 1055 CO₂ uptake and its interior storage in the GOBMs. Rather, Terhaar et al. (2023) find
 1056 that biases in the normalized surface Revelle factor could explain the underestimation
 1057 of C_{ant} uptake. Finally, the relatively high pre-industrial CO₂ mixing ratios related to
 1058 late starting dates in several GOBMs are likely causing an underestimation of the cu-
 1059 mulative C_{ant} storage, which is especially large in the Southern Ocean (Terhaar et al.,
 1060 2023). For the natural carbon fluxes, the difficulty in capturing the delicate balance be-
 1061 tween physical and biological processes is clearly manifested by the large model spread
 1062 (Figure 3). In addition, the different spin-up procedures could play a role. Terhaar et
 1063 al. (2023) indicate that the natural CO₂ flux component may be biased towards uptake
 1064 that is too strong, possibly related to GOBMs not being in steady-state (Terhaar et al.,
 1065 2023), which is particularly relevant in the Southern Ocean where old water masses resur-
 1066 face. While long preindustrial spin-ups would bring the GOBMs closer to steady-state
 1067 and thus reduce drift, they may come at the cost of less realistic surface conditions and
 1068 their response to climate change and variability (Séférián et al., 2016). Interestingly, the
 1069 two data-assimilated GOBMs differ to a large extent, illustrating that dynamical pro-
 1070 cesses in these models may still override information gained from assimilated observa-
 1071 tions.

1072 The averages of the GOBM and pCO₂-product ensembles agree for many key es-
 1073 timates, showing progress over the past 10 years: the mean and spatial distribution of
 1074 the sink is in good agreement (Figure 2), although discrepancies of the magnitude and,
 1075 particularly, the trends still persist (Figures 8 and 10; see also Canadell et al., 2021). The
 1076 fact that these ensemble means agree so well in many respects provides some confidence

1077 in the Southern Ocean CO₂ flux estimates because they are nearly independent. How-
 1078 ever, the agreement of GOBMs and pCO₂-products on the mean CO₂ flux is partly a
 1079 result of compensation of regional and seasonal discrepancies (Figures 4, 5, 8). The agree-
 1080 ment is also highly susceptible to the choice of river flux adjustment that either locates
 1081 most outgassing of river-derived carbon in the Southern Ocean (Aumont et al., 2001)
 1082 or in the tropical Atlantic (Lacroix et al., 2020). Reasons for the discrepancy between
 1083 Aumont et al. (2001) and Lacroix et al. (2020) may be because of specific choices in nu-
 1084 trient and carbon input, lability of organic matter, resulting ocean model transport (see
 1085 also the discussion in Terhaar et al., 2023). We here chose to use the river flux adjust-
 1086 ment of Lacroix et al. (2020), scaled up to a global value of 0.65 PgC yr⁻¹, resulting in
 1087 a small adjustment for the Southern Ocean of 0.04 PgC yr⁻¹. In contrast, the South-
 1088 ern Ocean (south of 20°S) adjustment based on Aumont et al. (2001) that is so far used
 1089 in the Global Carbon Budget is higher by one order of magnitude (0.32 PgC yr⁻¹) and
 1090 can explain the large mismatch in the mean flux (but not its trend) between GOBMs
 1091 and pCO₂ products in the Southern Ocean in the Global Carbon Budget (Friedlingstein
 1092 et al., 2022). The discrepancies in the trend cannot be explained by GOBM biases in warm-
 1093 ing trends as these are well reproduced (Figure 10). Similarly, the GOBM ensemble is
 1094 not systematically biased towards formation of mode and intermediate waters that is too
 1095 weak, in contrast to the ESMs, and an effect on the trend of the ocean carbon sink could
 1096 not be evidenced (Terhaar et al., 2023). Further potential candidates for GOBM biases,
 1097 which were not explored here, are stratification (Bourgeois et al., 2022), mixing, and mixed
 1098 layer dynamics, which could also lead to excess carbon accumulation in the surface layer
 1099 and thus may be the driver for the overestimation of the surface Revelle factor. In the
 1100 pCO₂-products, the trend might be biased by data sparsity (Gloege et al., 2021; Hauck
 1101 et al., 2023).

1102 4.2 Seasonal cycle and thermal versus non-thermal drivers

1103 As a community, we have a good understanding of the mechanisms that drive pCO₂
 1104 seasonality in the Southern Ocean (Lenton et al., 2013), but we do not fully understand
 1105 their magnitudes, opposing or synergistic, in different seasons and regions (Mongwe et
 1106 al., 2018). Part of this lack of understanding is due to a lack of observations through-
 1107 out all seasons, though particularly acute during winter (Gray et al., 2018; Bushinsky
 1108 et al., 2019; Sutton et al., 2021). Further, complex biological processes affecting pCO₂
 1109 in summer are more difficult to accurately describe in GOBMs (Mongwe et al., 2018).

1110 While pCO₂ products require little to no understanding to reconstruct the seasonal
 1111 cycle, they may still suffer from a lack of data (Ritter et al., 2017). This may be shown
 1112 by the narrow ensemble spread of the pCO₂-products during winter (Figure 7d-f), which
 1113 may result from poor sampling distribution. That being said, an observation system sim-
 1114 ulation experiment (OSSE) showed that the seasonal cycle in most of the Southern Ocean
 1115 is in fact well captured by one pCO₂ product (Gloege et al., 2021). The narrower GOBM
 1116 spread of the non-thermal pCO₂ component during winter may also suggest that winter-
 1117 time processes (circulation) are less complex than summer (circulation and biology, Fig-
 1118 ure 7d-f).

1119 The introduction of biogeochemical Argo floats since the mid 2010's has increased
 1120 the number of winter observations (relative to the available ship-based observations), al-
 1121 beit inferred from pH and estimated total alkalinity and thus associated with a higher
 1122 uncertainty (Williams et al., 2017). The machine learning approaches that include float-
 1123 based observations result in stronger winter outgassing (Figure 4, Bushinsky et al., 2019).
 1124 Direct pCO₂ measurements showed that the years used to train the machine learning
 1125 model (2015-2018) may have had anomalously high pCO₂ (Sutton et al., 2021). How-
 1126 ever, if this is in fact the case, and not related to sampling locations, this may indicate
 1127 much larger interannual variability in the Southern Ocean than the majority of the pCO₂-
 1128 products currently estimate (Figure 8). Incorporating these data is thus potentially an

1129 important goal for pCO₂-products, but it has proven difficult to incorporate the float-
 1130 based pCO₂ estimates further back in time than 2015, the start of the BGC-float record
 1131 and account for their higher uncertainty (Bushinsky et al., 2019; Williams et al., 2017).

1132 GOBMs also have a lower pCO₂ ensemble spread during winter compared with sum-
 1133 mer and agree on the spatial location of the winter flux minimum (Figure 4). Neverthe-
 1134 less, the range in magnitude is still more than twice as large as those of the pCO₂-products
 1135 (Figure 7d-f). Since the thermal component is well captured in GOBMs (Figure 7d-e),
 1136 the non-thermal physical drivers (i.e., circulation) determines the uncertainty observed
 1137 in winter. In summer, GOBMs have difficulty capturing the delicate balance between
 1138 biological and physical processes that leads to a large spread in model pCO₂ and fluxes
 1139 (Mongwe et al., 2018). GOBMs may thus benefit from more process-based studies that
 1140 further our understanding of pCO₂ drivers during summer, i.e., biological productivity,
 1141 respiration, remineralization and sinking of organic carbon as part of the biological car-
 1142 bon pump.

1143 4.3 Temporal variability of CO₂ fluxes

1144 Our analysis reduces the previously reported discrepancy in variability of South-
 1145 ern Ocean air-sea CO₂ fluxes between data classes (GOBMs and pCO₂-product ense-
 1146 mble means, Gruber, Landschützer, & Lovenduski, 2019). We relate the growing agree-
 1147 ment to the larger ensemble of pCO₂-products in our study, with the newer additions
 1148 having a substantially lower variability than the two pCO₂-products (Jena-CarboScope
 1149 and SOM-FFN) used by Gruber, Landschützer, and Lovenduski (2019). A recent study
 1150 using the same RECCAP data base also concluded that there is agreement on the mag-
 1151 nitude of interannual variability between GOBMs and pCO₂-products (Mayot et al., 2023).

1152 The interannual to decadal variability of Southern Ocean air-sea CO₂ fluxes was
 1153 discussed extensively in the literature, and was often related to variations in the South-
 1154 ern Annual Mode (SAM) (Le Quéré et al., 2007; Lovenduski et al., 2007; Lenton & Mearns,
 1155 2007; Hauck et al., 2013; Nicholson et al., 2022; Mayot et al., 2023). Also, regional wind
 1156 variability linked to the zonal wavenumber 3 was suggested as a driver of interannual CO₂
 1157 flux variability driving both the weakening in the 1990's and the strengthening in the
 1158 2000's (Landschützer et al., 2015; Keppler & Landschützer, 2019). The arguments of SAM
 1159 or wave number 3 as dominant drivers of CO₂ flux interannual variability might not be
 1160 fully independent from each other, as previously a wave number 3 like pattern was re-
 1161 ported to describe MLD anomalies during positive SAM events (Sallée et al., 2010).

1162 The fact that the maximum IAV of GOBMs is found in the SPSS Indo-Pacific sec-
 1163 tor (section 3.3, Figure S12) supports the argument of the above mentioned references
 1164 that upwelling of carbon-rich deep water and related outgassing of natural carbon in re-
 1165 sponse to a positive SAM and strengthening of westerly winds may be the dominant driver
 1166 of interannual variability (DeVries et al., 2017). This is further supported by studies of
 1167 atmospheric potential oxygen (APO), which can be used as a tracer of ocean-only pro-
 1168 cesses from measurements of CO₂ and O₂ at atmospheric stations (Stephens et al., 1998).
 1169 Nevison et al. (2020) showed that the interannual variations of APO seasonal minimum
 1170 from stations in the Southern Hemisphere were strongly correlated with the SAM dur-
 1171 ing years of positive phase. Further, they showed that GOBMs (as analyzed in this study)
 1172 can capture the variability of CO₂ and APO fluxes driven by the SAM variations dur-
 1173 ing the austral winter months. However, the study of Nevison et al. (2020) also illustrated
 1174 that the SAM index variability cannot fully explain the changes in APO seasonal win-
 1175 ter minima suggesting that other factors or modes of variability such as ENSO could im-
 1176 pact the CO₂ and O₂ air-sea fluxes of the Southern Ocean as also previously suggested
 1177 in an ocean modeling study (Verdy et al., 2007).

1178 On top of the interannual variability, on which pCO₂ products and GOBMs seem
 1179 to reach reasonable agreement, discrepancies in the CO₂ flux trend since 2000 have emerged

1180 (Figure 8, Friedlingstein et al., 2022). These discrepancies highlight a major knowledge
 1181 gap and urgently need to be resolved by critical analysis of potential biases in pCO₂-products
 1182 as well as GOBMs (see section 4.1). While there is no evidence so far that adjustments
 1183 of CO₂ fluxes based on model evaluation of interfrontal salinity and Revelle factor af-
 1184 fect the trend (Terhaar et al., 2023), data sparsity tends to lead to an overestimation of
 1185 decadal variability and trend in at least two of the pCO₂-products (Gloege et al., 2021;
 1186 Hauck et al., 2023). Hence, both data classes need to be inspected for deficiencies.

1187 4.4 Zonal asymmetry of the fluxes

1188 While the primary spatial mode of variability in the Southern Ocean is from north
 1189 to south, zonal variability in the dynamics, biogeochemistry, and carbon fluxes have been
 1190 reported in the literature (Landschützer et al., 2015; Tamsitt et al., 2016; Rintoul, 2018;
 1191 Prend et al., 2022). Similarly, we find substantial zonal asymmetry in both the mean states,
 1192 and seasonal and interannual variability of the Southern Ocean CO₂ fluxes (Figures S10,
 1193 S12); yet many of our results have been presented in a zonally-averaged perspective for
 1194 the sake of brevity.

1195 In this work, we find that the largest zonal asymmetries in the Southern Ocean mean
 1196 air-sea CO₂ flux occur in the SPSS biome (Figure 4b-e, S12). Here, the Pacific and In-
 1197 dian sectors are larger sources (or weaker sinks) of CO₂ to the atmosphere than the At-
 1198 lantic sector. This is consistent with the pCO₂-based products (Figure S12d-f). The float-
 1199 based pCO₂-products amplify this winter outgassing dramatically. However, the GOBMs
 1200 and the assimilative model ensemble averages do not show a coherent and convincing in-
 1201 crease in outgassing in the Indian and Pacific relative to the Atlantic. The zonal asym-
 1202 metry reported in the observation-based products is consistent with a recent BGC-float-
 1203 based study that reported stronger outgassing in the Indian and Pacific sectors of the
 1204 Southern Ocean (Prend et al., 2022). The authors attributed this dominance to stronger
 1205 winter-time entrainment of deep waters to the surface in these regions. The zonal asym-
 1206 metry is also apparent in the air-sea CO₂ fluxes decomposed into natural and anthro-
 1207 pogenic contributions (Figure S7). Here, too, the SPSS is the region with the greatest
 1208 asymmetry. In the Indian sector, the large natural outgassing fluxes of the ensemble mean
 1209 are nearly perfectly opposed by the anthropogenic uptake.

1210 4.5 Link large-scale synthesis to observational programs

1211 The analysis presented here provides a synthesis of large-scale datasets with a fo-
 1212 cus on budgets, spatial and temporal patterns of fluxes and carbon accumulation, and
 1213 a first-order assessment of large-scale processes (e.g., thermal versus non-thermal, an-
 1214 thropogenic vs natural carbon fluxes). In particular, it highlights spatio-temporal win-
 1215 dows for which discrepancies between data classes are largest (e.g., magnitude of win-
 1216 ter outgassing, delicate balance of physical versus biological processes in summer, mag-
 1217 nitude of decadal trend of the Southern Ocean carbon sink). Importantly, this synthe-
 1218 sis builds on contributions from many individual groups contributing repeat observations
 1219 of surface and interior ocean biogeochemical properties from research vessels and ships
 1220 of opportunity (e.g., Talley et al., 2016; Hoppema et al., 1998; van Heuven et al., 2014;
 1221 Metzl et al., 1999; Pardo et al., 2017). The ship-based observations form the cornerstone
 1222 for many of the data classes in this study: observation-based ocean interior estimates of
 1223 CO₂ storage assess changes in deep ocean measurements of CO₂, the surface pCO₂ es-
 1224 timates use observations from ships of opportunity, and the GOBMs are evaluated against
 1225 ocean interior observations. And while sampling biases and gaps in the ship-based mea-
 1226 surements may be filled by autonomous platforms with lower accuracy (e.g., BGC-floats),
 1227 they will always require crossover validation measurements from the high-accuracy ship-
 1228 board measurements. This emphasizes that the ship-based observations need to continue
 1229 into the future to characterize the evolution of the Southern Ocean carbon cycle. This
 1230 will only become more important, once stabilization of atmospheric CO₂ will lead to a

1231 larger weight on ocean processes for control of air-sea fluxes relative to the current quasi-
 1232 exponential growth rate of atmospheric CO₂.

1233 Further, detailed regional process studies employing a wide range of methodolo-
 1234 gies across disciplines are also important to further our holistic understanding of the South-
 1235 ern Ocean carbon cycle and to improve the description of biogeochemistry and ecosys-
 1236 tem dynamics in GOBMs, particularly in summer. One example for such an interdisci-
 1237 plinary field program is along the continental shelf west of the Antarctic Peninsula where
 1238 shipboard observations indicate a strong, near-shore summer undersaturation of surface
 1239 pCO₂ (Eveleth et al., 2017) and seasonal reduction in surface dissolved inorganic car-
 1240 bon (Hauri et al., 2015). The seasonal trends in the ocean CO₂ system on the shelf re-
 1241 flect a combination of biological net community production (Ducklow et al., 2018) and
 1242 meltwater input diluting surface dissolved inorganic carbon and alkalinity (Hauri et al.,
 1243 2015). Regional ocean biogeochemical models simulate similar onshore-offshore gradi-
 1244 ents in surface chlorophyll, biological productivity, dissolved inorganic carbon, and pCO₂
 1245 as well as the observed large interannual biophysical variability associated with year-to-
 1246 year variations in seasonal sea-ice advance and retreat phenology (Schultz et al., 2021).
 1247 Observed decadal trends for the region from the early 1990s to late 2010s indicate that
 1248 reduced sea-ice extent associated with climate change drives an increase in upper ocean
 1249 stability, phytoplankton biomass and biological dissolved inorganic carbon drawdown,
 1250 resulting in a growing net downward air-sea CO₂ flux during summer (Brown et al., 2019).
 1251 Recent year-round, autonomous mooring observations of pCO₂ and pH suggest a grad-
 1252 ual increase in surface ocean pCO₂ and dissolved inorganic carbon over the fall and win-
 1253 ter, with CO₂ outgassing during winter when pCO₂ is supersaturated largely blocked
 1254 by sea-ice cover (Shadwick et al., 2021; M. Yang et al., 2021). Similar large-scale pro-
 1255 grams are needed in other parts of the Southern Ocean given its size and importance in
 1256 the global carbon cycle. On-going research activities, also as part of the Southern Ocean
 1257 Observing System (SOOS), e.g., in the Ross (Smith et al., 2021) and Weddell Seas (Arndt
 1258 et al., 2022) have the potential of being extended.

1259 5 Conclusions

1260 Here, we present a schematic overview that summarizes the main characteristics
 1261 of the Southern Ocean carbon cycle 1985-2018, as derived in this analysis and its sup-
 1262plementary material (Figure 14). In general, the sink strength for atmospheric CO₂ (net
 1263 CO₂ flux, FCO₂) increases from South to North, but with important zonal asymmetry.
 1264 The Atlantic and Indian Ocean sectors of the Subtropical Seasonally Stratified biome
 1265 (STSS) are the regions that act as strongest sinks. In the Subpolar Seasonally Stratified
 1266 biome (SPSS), the Atlantic sector stands out as the only sector acting as an annual mean
 1267 CO₂ sink. Also the seasonal cycle shows a distinct north-south gradient. In the ice-covered
 1268 biome (ICE) the peak uptake occurs in summer and is driven by the seasonal cycle of
 1269 dissolved inorganic carbon (DIC), i.e. by physical DIC transport and biological processes.
 1270 In contrast, the dominant driver of the seasonal cycle of CO₂ uptake in the STSS is tem-
 1271 perature, and thus the season of peak uptake occurs in winter. Trends in net CO₂ up-
 1272 take derived from Global Ocean Biogeochemistry Models (GOBMs) and surface ocean
 1273 pCO₂ observation based products (pCO₂-products) disagree in all biomes, but the dis-
 1274 crepancy is strongest in the Pacific sector of the STSS. In terms of anthropogenic CO₂
 1275 (C_{ant}), the strongest uptake occurs in the SPSS. This is not visible in the map of net
 1276 CO₂ flux, because the anthropogenic uptake manifests itself as a suppression of natu-
 1277 ral CO₂ outgassing. The largest anthropogenic carbon storage occurs in the STSS and
 1278 northward.

1279 Our analysis confirms the important role of the Southern Ocean in the global car-
 1280 bon cycle. We have highlighted key knowledge gaps that need to be closed through ex-
 1281 tended observation systems and augmented process descriptions in the dynamic mod-
 1282 els in order to further reduce uncertainties.

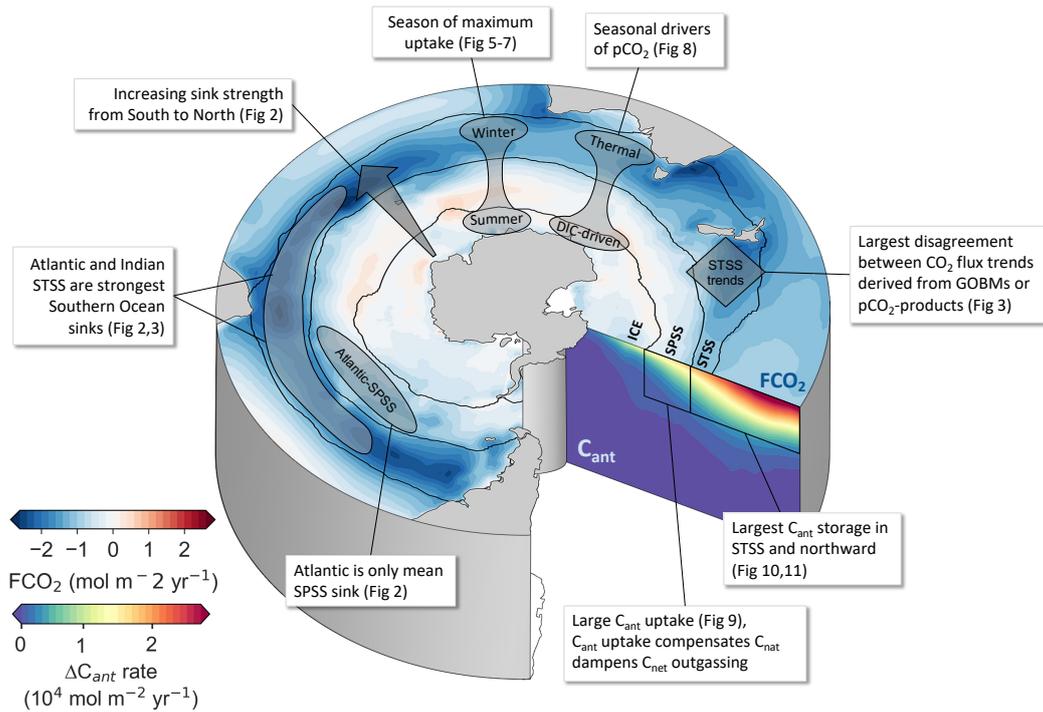


Figure 14. Main characteristics of the Southern Ocean carbon cycle 1985-2018. The surface ocean color shading depicts the net air-sea CO₂ flux (FCO₂) as the average of the ensemble means from pCO₂-products and Global Ocean Biogeochemistry Models (GOBMs). Blue color denotes a CO₂ flux into the ocean, and red color a flux out of the ocean. The zonal mean section shows the anthropogenic carbon (C_{ant}) accumulation in the ocean interior from GOBMs. ICE: ice-covered biome, SPSS: Subpolar Seasonally Stratified Biome, STSS: Subtropical Seasonally Stratified Biome.

1283 **Open Research Section**

1284 All RECCAP2 data is hosted on <https://zenodo.org/>. Link will be updated dur-
 1285 ing the review process.

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1288 **References**

- 1289 Armour, K. C., Marshall, J., Scott, J. R., Donohoe, A., & Newsom, E. R. (2016).
 1290 Southern Ocean warming delayed by circumpolar upwelling and equatorward
 1291 transport. *Nature Geoscience*, *9*(7), 549–554. doi: 10.1038/ngeo2731
- 1292 Arndt, S., Janout, M., Biddle, L., Campbell, E., & Thomalla, S. (2022). *The*
 1293 *Weddell Sea and Dronning Maud Land (WSDML) Regional Working Group*
 1294 *Virtual Science Workshop, 14–16 June 2022* (Tech. Rep.). Zenodo. Re-
 1295 trieved 2023-02-22, from <https://zenodo.org/record/6931424> doi:
 1296 10.5281/ZENODO.6931424
- 1297 Arrigo, K. R., & van Dijken, G. L. (2007). Interannual variation in air-sea CO₂
 1298 flux in the Ross Sea, Antarctica: A model analysis. *Journal of Geophysical Re-*
 1299 *search*, *112*(C3), C03020. doi: 10.1029/2006JC003492
- 1300 Aumont, O., Ethé, C., Tagliabue, A., Bopp, L., & Gehlen, M. (2015). PISCES-v2:
 1301 An ocean biogeochemical model for carbon and ecosystem studies. *Geoscientific*
 1302 *Model Development*, *8*(8), 2465–2513. doi: 10.5194/gmd-8-2465-2015
- 1303 Aumont, O., Orr, J. C., Monfray, P., Ludwig, W., Amiotte-Suchet, P., & Probst,
 1304 J. L. (2001). Riverine-driven interhemispheric transport of carbon. *Global*
 1305 *Biogeochemical Cycles*, *15*(2), 393–405. doi: 10.1029/1999GB001238
- 1306 Ayers, J. M., & Strutton, P. G. (2013). Nutrient variability in Subantarctic Mode
 1307 Waters forced by the Southern Annular Mode and ENSO. *Geophysical Re-*
 1308 *search Letters*, *40*(13), 3419–3423. doi: 10.1002/grl.50638
- 1309 Bakker, D., Alin, S. R., Becker, M., Bittig, H. C., Castaño-Primo, R., Feely, R. A.,
 1310 ... Wilson, D. (2022). *Surface ocean CO₂ atlas database version 2022 (SO-*
 1311 *CATv2022)*, *NCEI accession 0253659*. NOAA National Centers for Environ-
 1312 mental Information. Retrieved from <https://doi.org/10.25921/1h9f-nb73>
- 1313 Bakker, D., Hoppema, M., Schröder, M., Geibert, W., & Baar, H. J. W. D. (2008).
 1314 A rapid transition from ice covered CO₂-rich waters to a biologically mediated
 1315 CO₂ sink in the eastern Weddell Gyre. *Biogeosciences*, *5*, 1373–1386. doi:
 1316 10.5194/bg-5-1373-2008
- 1317 Bakker, D., Pfeil, B., Landa, C. S., Metzl, N., O’Brien, K. M., Olsen, A., ... Xu,
 1318 S. (2016). A multi-decade record of high-quality CO₂ data in version 3 of
 1319 the Surface Ocean CO₂ Atlas (SOCAT). *Earth System Science Data*, *8*(2),
 1320 383–413. doi: 10.5194/essd-8-383-2016
- 1321 Beadling, R. L., Russell, J. L., Stouffer, R. J., Mazloff, M., Talley, L. D., Good-
 1322 man, P. J., ... Pandde, A. (2020). Representation of Southern Ocean
 1323 Properties across Coupled Model Intercomparison Project Generations:
 1324 CMIP3 to CMIP6. *Journal of Climate*, *33*(15), 6555–6581. doi: 10.1175/
 1325 JCLI-D-19-0970.1
- 1326 Berthet, S., Séférian, R., Bricaud, C., Chevallier, M., Voltaire, A., & Ethé, C.
 1327 (2019). Evaluation of an Online Grid-Coarsening Algorithm in a Global Eddy-
 1328 Admitting Ocean Biogeochemical Model. *Journal of Advances in Modeling*
 1329 *Earth Systems*, *11*(6), 1759–1783. doi: 10.1029/2019MS001644
- 1330 Bopp, L., Lévy, M., Resplandy, L., & Sallée, J. B. (2015). Pathways of anthro-
 1331 pogenic carbon subduction in the global ocean. *Geophysical Research Let-*
 1332 *ters*, *42*(15), 6416–6423. Retrieved from [http://doi.wiley.com/10.1002/](http://doi.wiley.com/10.1002/2015GL065073)
 1333 [2015GL065073](http://doi.wiley.com/10.1002/2015GL065073) doi: 10.1002/2015GL065073

- 1334 Bourgeois, T., Goris, N., Schwinger, J., & Tjiputra, J. F. (2022). Stratifica-
 1335 tion constrains future heat and carbon uptake in the Southern Ocean be-
 1336 tween 30°S and 55°S. *Nature Communications*, *13*(1), 340. doi: 10.1038/
 1337 s41467-022-27979-5
- 1338 Boyer, T. P., Garcia, H. E., Locarnini, R. A., Zweng, M. M., Mishonov, A. V.,
 1339 Reagan, J. R., ... Smolyar, I. V. (2018). *World Ocean Atlas 2018*.
 1340 NOAA National Centers for Environmental Information. Retrieved from
 1341 <https://www.ncei.noaa.gov/archive/accession/NCEI-WO18>
- 1342 Brown, M. S., Munro, D. R., Feehan, C. J., Sweeney, C., Ducklow, H. W., &
 1343 Schofield, O. M. (2019). Enhanced oceanic CO₂ uptake along the rapidly
 1344 changing West Antarctic Peninsula. *Nature Climate Change*, *9*(9), 678–683.
 1345 Retrieved from <http://dx.doi.org/10.1038/s41558-019-0552-3> doi:
 1346 10.1038/s41558-019-0552-3
- 1347 Buitenhuis, E. T., Le Quéré, C., Bednaršek, N., & Schiebel, R. (2019). Large Contri-
 1348 bution of Pteropods to Shallow CaCO₃ Export. *Global Biogeochemical Cycles*,
 1349 *33*(3), 458–468. doi: 10.1029/2018GB006110
- 1350 Bushinsky, S. M., Takeshita, Y., & Williams, N. L. (2019). Observing Changes
 1351 in Ocean Carbonate Chemistry: Our Autonomous Future. *Current Climate*
 1352 *Change Reports*. doi: 10.1007/s40641-019-00129-8
- 1353 Caldeira, K., & Duffy, P. B. (2000). The Role of the Southern Ocean in Uptake and
 1354 Storage of Anthropogenic Carbon Dioxide. *Science*, *287*(5453), 620–622. doi:
 1355 10.1126/science.287.5453.620
- 1356 Campin, J.-m., Hill, C., Jones, H., & Marshall, J. (2011). Super-parameterization
 1357 in ocean modeling : Application to deep convection. *Ocean Modelling*, *36*(1-2),
 1358 90–101. doi: 10.1016/j.ocemod.2010.10.003
- 1359 Canadell, J., Monteiro, P., Costa, M., Cotrim da Cunha, L., Cox, P., Eliseev, A.,
 1360 ... Zickfeld, K. (2021). Global Carbon and other Biogeochemical Cycles
 1361 and Feedbacks. In V. Masson-Delmotte et al. (Eds.), *Climate Change 2021:*
 1362 *The Physical Science Basis. Contribution of Working Group I to the Sixth*
 1363 *Assessment Report of the Intergovernmental Panel on Climate Change* (pp.
 1364 673–816). Cambridge, United Kingdom: Cambridge University Press. doi:
 1365 10.1017/9781009157896.007
- 1366 Carroll, D., Menemenlis, D., Adkins, J. F., Bowman, K. W., Brix, H., Dutkiewicz,
 1367 S., ... Zhang, H. (2020). The ECCO-Darwin Data-Assimilative Global Ocean
 1368 Biogeochemistry Model: Estimates of Seasonal to Multidecadal Surface Ocean
 1369 pCO₂ and Air-Sea CO₂ Flux. *Journal of Advances in Modeling Earth Systems*,
 1370 *12*(10), 1–28. doi: 10.1029/2019MS001888
- 1371 Carroll, D., Menemenlis, D., Dutkiewicz, S., Lauderdale, J. M., Adkins, J. F., Bow-
 1372 man, K. W., ... Zhang, H. (2022). Attribution of Space-Time Variability
 1373 in Global-Ocean Dissolved Inorganic Carbon. *Global Biogeochemical Cycles*,
 1374 *36*(3), 1–24. doi: 10.1029/2021GB007162
- 1375 Carter, B. R., Bittig, H. C., Fassbender, A. J., Sharp, J. D., Takeshita, Y., Xu,
 1376 Y.-Y., ... Barbero, L. (2021). New and updated global empirical seawater
 1377 property estimation routines. *Limnol. Oceanogr.: Methods*, *19*, 785–809. doi:
 1378 10.1002/lom3.10461
- 1379 Carter, B. R., Feely, R. A., Williams, N. L., Dickson, A. G., Fong, M. B., &
 1380 Takeshita, Y. (2018). Updated methods for global locally interpolated es-
 1381 timation of alkalinity, pH, and nitrate. *Limnology and Oceanography: Methods*,
 1382 *16*(2), 119–131. Retrieved from <http://doi.wiley.com/10.1002/lom3.10232>
 1383 doi: 10.1002/lom3.10232
- 1384 Carter, B. R., Williams, N. L., Gray, A. R., & Feely, R. A. (2016). Locally inter-
 1385 polated alkalinity regression for global alkalinity estimation. *Limnology and*
 1386 *Oceanography: Methods*, *14*(4), 268–277. doi: 10.1002/lom3.10087
- 1387 Chau, T. T. T., Gehlen, M., & Chevallier, F. (2022). A seamless ensemble-
 1388 based reconstruction of surface ocean pCO₂ and air-sea CO₂ fluxes over

- 1389 the global coastal and open oceans. *Biogeosciences*, *19*(4), 1087–1109. doi:
1390 10.5194/bg-19-1087-2022
- 1391 Chevallier, F., Fisher, M., Peylin, P., Serrar, S., Bousquet, P., Bréon, F. M., ...
1392 Ciais, P. (2005). Inferring CO₂ sources and sinks from satellite observations:
1393 Method and application to TOVS data. *Journal of Geophysical Research*
1394 *Atmospheres*, *110*(24), 1–13. doi: 10.1029/2005JD006390
- 1395 Chien, C. T., Durgadoo, J. V., Ehlert, D., Frenger, I., Keller, D. P., Koeve, W., ...
1396 Oschlies, A. (2022). FOCI-MOPS v1 - integration of marine biogeochem-
1397 istry within the Flexible Ocean and Climate Infrastructure version 1 (FOCI
1398 1) Earth system model. *Geoscientific Model Development*, *15*(15), 5987–6024.
1399 doi: 10.5194/gmd-15-5987-2022
- 1400 Clement, D., & Gruber, N. (2018). The eMLR(C*) Method to Determine Decadal
1401 Changes in the Global Ocean Storage of Anthropogenic CO₂. *Global Biogeo-*
1402 *chemical Cycles*. doi: 10.1002/2017GB005819
- 1403 Crisp, D., Dolman, H., Tanhua, T., McKinley, G. A., Hauck, J., Bastos, A.,
1404 ... Aich, V. (2022). How Well Do We Understand the Land-Ocean-
1405 Atmosphere Carbon Cycle? *Reviews of Geophysics*, *60*(2), 1–64. doi:
1406 10.1029/2021RG000736
- 1407 Denvil-Sommer, A., Gehlen, M., & Vrac, M. (2021). Observation system simulation
1408 experiments in the Atlantic Ocean for enhanced surface ocean pCO₂ recon-
1409 structions. *Ocean Science*, *17*(4), 1011–1030. doi: 10.5194/os-17-1011-2021
- 1410 DeVries, T. (2014). The oceanic anthropogenic CO₂ sink: Storage, air-sea fluxes,
1411 and transports over the industrial era. *Global Biogeochemical Cycles*, *28*(7),
1412 631–647. doi: 10.1002/2013GB004739
- 1413 DeVries, T. (2022). The Ocean Carbon Cycle. *Annual Review of Environment and*
1414 *Resources*, *47*(1). doi: 10.1146/annurev-environ-120920-111307
- 1415 DeVries, T., Holzer, M., & Primeau, F. (2017). Recent increase in oceanic car-
1416 bon uptake driven by weaker upper-ocean overturning. *Nature*, *542*(7640),
1417 215–218. doi: 10.1038/nature21068
- 1418 DeVries, T., Yamamoto, K., Wanninkhof, R., Gruber, N., Hauck, J., Müller, J. D.,
1419 ... others (2023). Magnitude, trends, and variability of the global ocean
1420 carbon sink from 1985–2018. *in review at Global Biogeochemical Cycles*.
- 1421 Djeutchouang, L. M., Chang, N., Gregor, L., Vichi, M., & Monteiro, P. M. (2022).
1422 The sensitivity of pCO₂ reconstructions to sampling scales across a South-
1423 ern Ocean sub-domain: a semi-idealized ocean sampling simulation approach.
1424 *Biogeosciences*, *19*(17), 4171–4195. doi: 10.5194/bg-19-4171-2022
- 1425 Dlugokencky, E., Thoning, K., Lan, X., Tans, P., & Laboratory, N. G. M. (2021).
1426 NOAA Greenhouse Gas Marine Boundary Layer Reference - CO₂. NOAA
1427 GML. Retrieved from <https://gml.noaa.gov/ccgg/mb1/index.html> doi:
1428 <https://doi.org/10.15138/DVNP-F961>
- 1429 Doney, S., Lima, I., Moore, J. K., Lindsay, K., Behrenfeld, M. J., Westberry, T. K.,
1430 ... Takahashi, T. (2009). Skill metrics for confronting global upper ocean
1431 ecosystem-biogeochemistry models against field and remote sensing data. *Jour-*
1432 *nal of Marine Systems*, *76*(1-2), 95–112. doi: 10.1016/j.jmarsys.2008.05.015
- 1433 Doney, S., Yeager, S., Danabasoglu, G., Large, W. G., & McWilliams, J. C. (2007).
1434 Mechanisms governing interannual variability of upper-ocean temperature in
1435 a global ocean hindcast simulation. *Journal of Physical Oceanography*, *37*(7),
1436 1918–1938. doi: 10.1175/JPO3089.1
- 1437 Döscher, R., Acosta, M., Alessandri, A., Anthoni, P., Arsouze, T., Bergman, T.,
1438 ... Zhang, Q. (2022). The EC-Earth3 Earth system model for the Coupled
1439 Model Intercomparison Project 6. *Geoscientific Model Development*, *15*(7),
1440 2973–3020. doi: 10.5194/gmd-15-2973-2022
- 1441 Drucker, R., & Riser, S. C. (2016). In situ phase-domain calibration of oxygen op-
1442 todes on profiling floats. *Methods in Oceanography*, *17*, 296–318. doi: 10.1016/
1443 j.mio.2016.09.007

- 1444 Ducklow, H. W., Stukel, M. R., Eveleth, R., Doney, S. C., Jickells, T., Schofield,
1445 O., . . . Cassar, N. (2018). Spring-summer net community production, new
1446 production, particle export and related water column biogeochemical processes
1447 in the marginal sea ice zone of the Western Antarctic Peninsula 2012-2014.
1448 *Philosophical Transactions of the Royal Society A: Mathematical, Physical and*
1449 *Engineering Sciences*, *376*(2122). doi: 10.1098/rsta.2017.0177
- 1450 Dutkiewicz, S., Follows, M. J., & Bragg, J. G. (2009). Modeling the coupling of
1451 ocean ecology and biogeochemistry. *Global Biogeochemical Cycles*, *23*(4), 1–15.
1452 doi: 10.1029/2008GB003405
- 1453 Eddebbar, Y. A., Rodgers, K. B., Long, M. C., Subramanian, A. C., Xie, S.-P., &
1454 Keeling, R. F. (2019). El Niño–Like Physical and Biogeochemical Ocean
1455 Response to Tropical Eruptions. *Journal of Climate*, *32*(9), 2627–2649. doi:
1456 10.1175/JCLI-D-18-0458.1
- 1457 Eveleth, R., Cassar, N., Doney, S. C., Munro, D. R., & Sweeney, C. (2017). Biolog-
1458 ical and physical controls on O₂/Ar, Ar and pCO₂ variability at the Western
1459 Antarctic Peninsula and in the Drake Passage. *Deep-Sea Research Part II:*
1460 *Topical Studies in Oceanography*, *139*, 77–88. doi: 10.1016/j.dsr2.2016.05.002
- 1461 Fay, A. R., Gregor, L., Landschützer, P., McKinley, G. A., Gruber, N., Gehlen, M.,
1462 . . . Zeng, J. (2021). SeaFlux: harmonization of air-sea CO₂ fluxes from surface
1463 pCO₂ data products using a standardized approach. *Earth System Science*
1464 *Data*, *13*(10), 4693–4710. doi: 10.5194/essd-13-4693-2021
- 1465 Fay, A. R., & McKinley, G. A. (2014). Global open-ocean biomes: Mean and tempo-
1466 ral variability. *Earth System Science Data*, *6*(2), 273–284. doi: 10.5194/essd-6
1467 -273-2014
- 1468 Feng, L., Palmer, P. I., Parker, R. J., Deutscher, N. M., Feist, D. G., Kivi, R., . . .
1469 Sussmann, R. (2016). Estimates of European uptake of CO₂ inferred from
1470 GOSAT XCO₂ retrievals: Sensitivity to measurement bias inside and out-
1471 side Europe. *Atmospheric Chemistry and Physics*, *16*(3), 1289–1302. doi:
1472 10.5194/acp-16-1289-2016
- 1473 Friedlingstein, P., O’Sullivan, M., Jones, M. W., Andrew, R. M., Gregor, L., Hauck,
1474 J., . . . Zheng, B. (2022). Global Carbon Budget 2022. *Earth System Science*
1475 *Data*, *14*(11), 4811–4900. doi: 10.5194/essd-14-4811-2022
- 1476 Frölicher, T. L., Sarmiento, J. L., Paynter, D. J., Dunne, J. P., Krasting, J. P., &
1477 Winton, M. (2015). Dominance of the Southern Ocean in anthropogenic car-
1478 bon and heat uptake in CMIP5 models. *Journal of Climate*, *28*(2), 862–886.
1479 doi: 10.1175/JCLI-D-14-00117.1
- 1480 Galbraith, E. D., Gnanadesikan, A., Dunne, J. P., & Hiscock, M. R. (2010). Re-
1481 gional impacts of iron-light colimitation in a global biogeochemical model. *Bio-*
1482 *geosciences*, *7*(3), 1043–1064. doi: 10.5194/bg-7-1043-2010
- 1483 Gloege, L., McKinley, G. A., Landschützer, P., Fay, A. R., Frölicher, T. L., Fyfe,
1484 J. C., . . . Takano, Y. (2021). Quantifying Errors in Observationally Based
1485 Estimates of Ocean Carbon Sink Variability. *Global Biogeochemical Cycles*,
1486 *35*(4), 1–14. doi: 10.1029/2020GB006788
- 1487 Gloege, L., Yan, M., Zheng, T., & McKinley, G. A. (2022). Improved Quantification
1488 of Ocean Carbon Uptake by Using Machine Learning to Merge Global Models
1489 and pCO₂ Data. *Journal of Advances in Modeling Earth Systems*, *14*(2), 1–19.
1490 doi: 10.1029/2021MS002620
- 1491 Good, S. A., Martin, M. J., & Rayner, N. A. (2013). EN4: Quality controlled
1492 ocean temperature and salinity profiles and monthly objective analyses with
1493 uncertainty estimates. *Journal of Geophysical Research: Oceans*, *118*(12),
1494 6704–6716. doi: 10.1002/2013JC009067
- 1495 Gray, A. R., Johnson, K. S., Bushinsky, S. M., Riser, S. C., Russell, J. L., Tal-
1496 ley, L. D., . . . Sarmiento, J. L. (2018). Autonomous Biogeochemical
1497 Floats Detect Significant Carbon Dioxide Outgassing in the High-Latitude
1498 Southern Ocean. *Geophysical Research Letters*, *45*(17), 9049–9057. doi:

- 1499 10.1029/2018GL078013
- 1500 Gregor, L., & Gruber, N. (2021). OceanSODA-ETHZ: a global gridded data
1501 set of the surface ocean carbonate system for seasonal to decadal studies
1502 of ocean acidification. *Earth System Science Data*, *13*(2), 777–808. doi:
1503 10.5194/essd-13-777-2021
- 1504 Gregor, L., Kok, S., & Monteiro, P. M. S. (2017). Empirical methods for the esti-
1505 mation of Southern Ocean CO₂: support vector and random forest regression.
1506 *Biogeosciences*, *14*(23), 5551–5569. doi: 10.5194/bg-14-5551-2017
- 1507 Gregor, L., Lebehot, A. D., Kok, S., & Scheel Monteiro, P. M. (2019). A com-
1508 parative assessment of the uncertainties of global surface ocean CO₂ esti-
1509 mates using a machine-learning ensemble (CSIR-ML6 version 2019a) - have
1510 we hit the wall? *Geoscientific Model Development*, *12*(12), 5113–5136. doi:
1511 10.5194/gmd-12-5113-2019
- 1512 Gruber, N., Bakker, D. C. E., DeVries, T., Gregor, L., Hauck, J., Landschützer,
1513 P., ... Müller, J. D. (2023). Trends and variability in the ocean car-
1514 bon sink. *Nature Reviews Earth & Environment*, *4*(2), 119–134. Re-
1515 trieved from <https://doi.org/10.1038/s43017-022-00381-x> doi:
1516 10.1038/s43017-022-00381-x
- 1517 Gruber, N., Clement, D., Carter, B. R., Feely, R. A., van Heuven, S., Hoppema,
1518 M., ... Wanninkhof, R. (2019). The oceanic sink for anthropogenic
1519 co2 from 1994 to 2007. *Science*, *363*(6432), 1193–1199. Retrieved from
1520 <https://www.science.org/doi/abs/10.1126/science.aau5153> doi:
1521 10.1126/science.aau5153
- 1522 Gruber, N., Gloor, M., Mikaloff Fletcher, S. E., Doney, S. C., Dutkiewicz, S., Fol-
1523 lows, M. J., ... Takahashi, T. (2009). Oceanic sources, sinks, and transport
1524 of atmospheric CO₂. *Global Biogeochemical Cycles*, *23*(1), n/a–n/a. doi:
1525 10.1029/2008GB003349
- 1526 Gruber, N., Landschützer, P., & Lovenduski, N. S. (2019). The Variable Southern
1527 Ocean Carbon Sink. *Annual Review of Marine Science*, *11*(1), 159–186. doi:
1528 10.1146/annurev-marine-121916-063407
- 1529 Gruber, N., Sarmiento, J. L., & Stocker, T. F. (1996). An improved method for de-
1530 tecting anthropogenic CO₂ in the oceans. *Global Biogeochemical Cycles*, *10*(4),
1531 809–837. Retrieved from <http://doi.wiley.com/10.1029/96GB01608> doi: 10
1532 .1029/96GB01608
- 1533 Hauck, J., Nissen, C., Landschützer, P., Rödenbeck, C., Bushinsky, S., & Olsen,
1534 A. (2023). Sparse observations induce large biases in estimates of the global
1535 ocean CO₂ sink: an ocean model subsampling experiment. *Philosophical*
1536 *Transactions of the Royal Society A: Mathematical, Physical and Engineering*
1537 *Sciences*, *381*(2249). Retrieved from [https://royalsocietypublishing.org/](https://royalsocietypublishing.org/doi/10.1098/rsta.2022.0063)
1538 [doi/10.1098/rsta.2022.0063](https://doi.org/10.1098/rsta.2022.0063) doi: 10.1098/rsta.2022.0063
- 1539 Hauck, J., Völker, C., Wang, T., Hoppema, M., Losch, M., & Wolf-Gladrow, D. A.
1540 (2013). Seasonally different carbon flux changes in the Southern Ocean in
1541 response to the southern annular mode. *Global Biogeochemical Cycles*, *27*(4),
1542 1236–1245. doi: 10.1002/2013GB004600
- 1543 Hauck, J., Völker, C., Wolf-Gladrow, D. A., Laufkötter, C., Vogt, M., Aumont, O.,
1544 ... Totterdell, I. (2015). On the Southern Ocean CO₂ uptake and the role of
1545 the biological carbon pump in the 21st century. *Global Biogeochemical Cycles*,
1546 *29*(9), 1451–1470. doi: 10.1002/2015GB005140
- 1547 Hauck, J., Zeising, M., Le Quéré, C., Gruber, N., Bakker, D. C. E., Bopp, L., ...
1548 Séférian, R. (2020). Consistency and Challenges in the Ocean Carbon Sink Es-
1549 timate for the Global Carbon Budget. *Frontiers in Marine Science*, *7*, 571720.
1550 doi: 10.3389/fmars.2020.571720
- 1551 Haumann, A. (2016). *Southern ocean response to recent changes in surface freshwa-*
1552 *ter fluxes* (Doctoral dissertation). doi: 10.3929/ETHZ-B-000166276
- 1553 Haumann, F., Gruber, N., & Münnich, M. (2020). Sea-Ice Induced Southern Ocean

- 1554 Subsurface Warming and Surface Cooling in a Warming Climate. *AGU Ad-*
 1555 *vances*, 1(2). doi: 10.1029/2019av000132
- 1556 Hauri, C., Doney, S. C., Takahashi, T., Erickson, M., Jiang, G., & Ducklow, H.
 1557 (2015). Two decades of inorganic carbon dynamics along the West Antarctic
 1558 Peninsula. *Biogeosciences*, 12(22), 6761–6779. doi: 10.5194/bg-12-6761-2015
- 1559 Holzer, M., & DeVries, T. (2022). Source-Labeled Anthropogenic Carbon Reveals
 1560 a Large Shift of Preindustrial Carbon From the Ocean to the Atmosphere.
 1561 *Global Biogeochemical Cycles*, 36(10). doi: 10.1029/2022GB007405
- 1562 Hoppema, M. (2004). Weddell Sea turned from source to sink for atmospheric CO₂
 1563 between pre-industrial time and present. *Global and Planetary Change*, 40(3-
 1564 4), 219–231. doi: 10.1016/j.gloplacha.2003.08.001
- 1565 Hoppema, M., Bakker, K., van Heuven, S. M., van Ooijen, J. C., & de Baar, H. J.
 1566 (2015). Distributions, trends and inter-annual variability of nutrients along a
 1567 repeat section through the Weddell Sea (1996-2011). *Marine Chemistry*, 177,
 1568 545–553. doi: 10.1016/j.marchem.2015.08.007
- 1569 Hoppema, M., Fahrback, E., Stoll, M. H., & de Baar, H. J. (1998). Increase of
 1570 carbon dioxide in the bottom water of the Weddell Sea, Antarctica. *Marine*
 1571 *Chemistry*, 59(3-4), 201–210. doi: 10.1016/S0304-4203(97)00094-7
- 1572 Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T. P., Chepurin, G., Lawrimore,
 1573 J. H., . . . Zhang, H.-M. (2017). *NOAA Extended Reconstructed Sea Surface*
 1574 *Temperature (ERSST), Version 5*. NOAA National Centers for Environmental
 1575 Information. doi: 10.7289/V5T72FNM
- 1576 Iida, T., Odate, T., & Fukuchi, M. (2013). Long-Term Trends of Nutrients and
 1577 Apparent Oxygen Utilization South of the Polar Front in Southern Ocean
 1578 Intermediate Water from 1965 to 2008. *PLoS ONE*, 8(8), e71766. doi:
 1579 10.1371/journal.pone.0071766
- 1580 Iida, Y., Takatani, Y., Kojima, A., & Ishii, M. (2021). Global trends of ocean CO₂
 1581 sink and ocean acidification: an observation-based reconstruction of surface
 1582 ocean inorganic carbon variables. *Journal of Oceanography*, 77(2), 323–358.
 1583 doi: 10.1007/s10872-020-00571-5
- 1584 Ilyina, T., Six, K. D., Segschneider, J., Maier-Reimer, E., Li, H., & Núñez-Riboni, I.
 1585 (2013). Global ocean biogeochemistry model HAMOCC: Model architecture
 1586 and performance as component of the MPI-Earth system model in different
 1587 CMIP5 experimental realizations. *Journal of Advances in Modeling Earth*
 1588 *Systems*, 5(2), 287–315. doi: 10.1029/2012MS000178
- 1589 Ito, T., Woloszyn, M., & Mazloff, M. (2010). Anthropogenic carbon dioxide trans-
 1590 port in the Southern Ocean driven by Ekman flow. *Nature*, 463(7277), 80–83.
 1591 doi: 10.1038/nature08687
- 1592 Iudicone, D., Rodgers, K. B., Plancherel, Y., Aumont, O., Ito, T., Key, R. M., . . .
 1593 Ishii, M. (2016). The formation of the ocean’s anthropogenic carbon reservoir.
 1594 *Scientific Reports*, 6(1), 35473. doi: 10.1038/srep35473
- 1595 Jacobs, S. S. (2004). Bottom water production and its links with the ther-
 1596 mohaline circulation. *Antarctic Science*, 16(4), 427–437. doi: 10.1017/
 1597 S095410200400224X
- 1598 Johnson, K. S., Plant, J. N., Coletti, L. J., Jannasch, H. W., Sakamoto, C. M.,
 1599 Riser, S. C., . . . Sarmiento, J. L. (2017). Biogeochemical sensor performance in
 1600 the SOCCOM profiling float array. *Journal of Geophysical Research: Oceans*,
 1601 122(8), 6416–6436. doi: 10.1002/2017JC012838
- 1602 Jones, D. C., Meijers, A. J. S., Shuckburgh, E., Sallée, J.-B., Haynes, P., McAufield,
 1603 E. K., & Mazloff, M. R. (2016). How does Subantarctic Mode Water venti-
 1604 late the Southern Hemisphere subtropics? *Journal of Geophysical Research:*
 1605 *Oceans*, 121(9), 6558–6582. doi: 10.1002/2016JC011680
- 1606 Jones, E., Bakker, D. C., Venables, H. J., & Hardman-Mountford, N. J. (2015).
 1607 Seasonal cycle of CO₂ from the sea ice edge to island blooms in the Sco-
 1608 tia Sea, Southern Ocean. *Marine Chemistry*, 177, 490–500. doi: 10.1016/

- 1609 j.marchem.2015.06.031
- 1610 Jones, E., Bakker, D. C., Venables, H. J., & Watson, A. J. (2012). Dynamic seasonal
1611 cycling of inorganic carbon downstream of South Georgia, Southern Ocean.
1612 *Deep Sea Research Part II: Topical Studies in Oceanography*, 59–60, 25–35.
1613 doi: 10.1016/j.dsr2.2011.08.001
- 1614 Katavouta, A., & Williams, R. G. (2021). Ocean carbon cycle feedbacks in CMIP6
1615 models: contributions from different basins. *Biogeosciences*, 18(10), 3189–3218.
1616 doi: 10.5194/bg-18-3189-2021
- 1617 Keppeler, L., & Landschützer, P. (2019). Regional Wind Variability Modulates the
1618 Southern Ocean Carbon Sink. *Scientific Reports*, 9(1), 7384. doi: 10.1038/
1619 s41598-019-43826-y
- 1620 Kessler, A., & Tjiputra, J. (2016). The Southern Ocean as a constraint to reduce
1621 uncertainty in future ocean carbon sinks. *Earth System Dynamics*, 7(2), 295–
1622 312. doi: 10.5194/esd-7-295-2016
- 1623 Khatiwala, S., Primeau, F., & Hall, T. (2009). Reconstruction of the history of
1624 anthropogenic CO₂ concentrations in the ocean. *Nature*, 462(7271), 346–349.
1625 doi: 10.1038/nature08526
- 1626 Klatt, O., Fahrback, E., Hoppema, M., & Rohardt, G. (2005). The transport
1627 of the weddell gyre across the prime meridian. *Deep Sea Research Part II:
1628 Topical Studies in Oceanography*, 52(3), 513–528. Retrieved from [https://
1629 www.sciencedirect.com/science/article/pii/S0967064504003066](https://www.sciencedirect.com/science/article/pii/S0967064504003066)
1630 (Direct observations of oceanic flow: A tribute to Walter Zenk) doi:
1631 <https://doi.org/10.1016/j.dsr2.2004.12.015>
- 1632 Kriest, I., & Oschlies, A. (2015). MOPS-1.0: Towards a model for the reg-
1633 ulation of the global oceanic nitrogen budget by marine biogeochemi-
1634 cal processes. *Geoscientific Model Development*, 8(9), 2929–2957. doi:
1635 10.5194/gmd-8-2929-2015
- 1636 Lacroix, F., Ilyina, T., & Hartmann, J. (2020). Oceanic CO₂ outgassing and bio-
1637 logical production hotspots induced by pre-industrial river loads of nutrients
1638 and carbon in a global modeling approach. *Biogeosciences*, 17(1), 55–88. doi:
1639 10.5194/bg-17-55-2020
- 1640 Landschützer, P., Gruber, N., & Bakker, D. C. (2016). Decadal variations and
1641 trends of the global ocean carbon sink. *Global Biogeochemical Cycles*, 30(10),
1642 1396–1417. doi: 10.1002/2015GB005359
- 1643 Landschützer, P., Gruber, N., & Bakker, D. C. E. (2020). *An observation-based
1644 global monthly gridded sea surface pCO₂ product from 1982 onward and its
1645 monthly climatology (NCEI Accession 0160558)* (Tech. Rep.). Retrieved from
1646 [https://www.ncei.noaa.gov/access/ocean-carbon-acidification-data
1647 -system/oceans/SPC02{_}1982{_}present{_}ETH{_}SOM{_}FFN.html](https://www.ncei.noaa.gov/access/ocean-carbon-acidification-data-system/oceans/SPC02{_}1982{_}present{_}ETH{_}SOM{_}FFN.html)
- 1648 Landschützer, P., Gruber, N., Bakker, D. C. E., & Schuster, U. (2014). Recent vari-
1649 ability of the global ocean carbon sink. *Global Biogeochemical Cycles*, 28(9),
1650 927–949. doi: 10.1002/2014GB004853
- 1651 Landschützer, P., Gruber, N., Haumann, F. A., Rödenbeck, C., Bakker, D. C. E.,
1652 van Heuven, S., ... Wanninkhof, R. (2015). The reinvigoration of
1653 the Southern Ocean carbon sink. *Science*, 349(6253), 1221–1224. doi:
1654 10.1126/science.aab2620
- 1655 Langlais, C. E., Lenton, A., Matear, R., Monselesan, D., Legresy, B., Cougnon, E.,
1656 & Rintoul, S. (2017). Stationary Rossby waves dominate subduction of anthro-
1657 pogenic carbon in the Southern Ocean. *Scientific Reports*, 7(1), 17076. doi:
1658 10.1038/s41598-017-17292-3
- 1659 Large, W. G., McWilliams, J. C., & Doney, S. C. (1994). Oceanic Vertical Mixing -
1660 a Review and a Model with a Nonlocal Boundary-Layer Parameterization. *Re-
1661 views of Geophysics*, 32(94), 363–403. doi: 10.1029/94rg01872
- 1662 Lauderdale, J. M., Dutkiewicz, S., Williams, R. G., & Follows, M. J. (2016). Quan-
1663 tifying the drivers of ocean-atmosphere CO₂ fluxes. *Global Biogeochemical Cy-*

- 1664 *cles*, 30(7), 983–999. doi: 10.1002/2016GB005400
- 1665 Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Hauck, J., Pongratz, J.,
1666 ... Zheng, B. (2018). Global Carbon Budget 2018. *Earth System Science*
1667 *Data*, 10(4), 2141–2194. doi: 10.5194/essd-10-2141-2018
- 1668 Le Quéré, C., Buitenhuis, E. T., Moriarty, R., Alvain, S., Aumont, O., Bopp, L., ...
1669 Vallina, S. M. (2016). Role of zooplankton dynamics for Southern Ocean phy-
1670 toplankton biomass and global biogeochemical cycles. *Biogeosciences*, 13(14),
1671 4111–4133. doi: 10.5194/bg-13-4111-2016
- 1672 Le Quéré, C., Takahashi, T. T., Buitenhuis, E. T., Rödenbeck, C., & Suther-
1673 land, S. C. (2010). Impact of climate change and variability on the global
1674 oceanic sink of CO₂. *Global Biogeochemical Cycles*, 24(4), 1–10. doi:
1675 10.1029/2009GB003599
- 1676 Lenton, A., & Matear, R. J. (2007). Role of the Southern Annular Mode (SAM) in
1677 Southern Ocean CO₂ uptake. *Global Biogeochemical Cycles*, 21(2), 1–17. doi:
1678 10.1029/2006GB002714
- 1679 Lenton, A., Tilbrook, B., Law, R. M., Bakker, D., Doney, S. C., Gruber, N., ...
1680 Takahashi, T. (2013). Sea-air CO₂ fluxes in the Southern Ocean for the period
1681 1990–2009. *Biogeosciences*, 10(6), 4037–4054. doi: 10.5194/bg-10-4037-2013
- 1682 Le Quéré, C., Rödenbeck, C., Buitenhuis, E. T., Conway, T. J., Langenfelds, R.,
1683 Gomez, A., ... Heimann, M. (2007). Saturation of the Southern Ocean
1684 CO₂ Sink Due to Recent Climate Change. *Science*, 316, 1735–1738. doi:
1685 10.1126/science.1136188
- 1686 Liao, E., Resplandy, L., Liu, J., & Bowman, K. W. (2020). Amplification of the
1687 Ocean Carbon Sink During El Niños: Role of Poleward Ekman Transport and
1688 Influence on Atmospheric CO₂. *Global Biogeochemical Cycles*, 34(9), 1–23.
1689 doi: 10.1029/2020GB006574
- 1690 Lindsay, K., Bonan, G. B., Doney, S. C., Hoffman, F. M., Lawrence, D. M., Long,
1691 M. C., ... Thornton, P. E. (2014). Preindustrial-control and twentieth-century
1692 carbon cycle experiments with the Earth system model CESM1(BGC). *Jour-
1693 nal of Climate*, 27(24), 8981–9005. doi: 10.1175/JCLI-D-12-00565.1
- 1694 Liu, J., Baskaran, L., Bowman, K., Schimel, D., Anthony Bloom, A., Parazoo, C. N.,
1695 ... Wofsy, S. (2021). Carbon Monitoring System Flux Net Biosphere Exchange
1696 2020 (CMS-Flux NBE 2020). *Earth System Science Data*, 13(2), 299–330. doi:
1697 10.5194/essd-13-299-2021
- 1698 Long, M. C., Stephens, B. B., McKain, K., Sweeney, C., Keeling, R. F., Kort,
1699 E. A., ... Wofsy, S. C. (2021). Strong Southern Ocean carbon uptake
1700 evident in airborne observations. *Science*, 374(6572), 1275–1280. doi:
1701 10.1126/science.abi4355
- 1702 Lovenduski, N. S., Gruber, N., Doney, S. C., & Lima, I. D. (2007). Enhanced
1703 CO₂ outgassing in the Southern Ocean from a positive phase of the South-
1704 ern Annular Mode. *Global Biogeochemical Cycles*, 21(2), n/a–n/a. doi:
1705 10.1029/2006GB002900
- 1706 Madec, G., & the NEMO team. (2016). *NEMO reference manual 3.6-STABLE:
1707 "NEMO ocean engine" Note du Pôle de modélisation*. Paris, France: Institut
1708 Pierre-Simon Laplace (IPSL).
- 1709 Marshall, J., & Speer, K. (2012). Closure of the meridional overturning circulation
1710 through Southern Ocean upwelling. *Nature Geoscience*, 5(3), 171–180. doi: 10
1711 .1038/ngeo1391
- 1712 Matsumoto, K., & Gruber, N. (2005). How accurate is the estimation of anthro-
1713 pogenic carbon in the ocean? An evaluation of the ΔC^* method. *Global Bio-
1714 geochemical Cycles*, 19(3). Retrieved from [http://doi.wiley.com/10.1029/
1715 2004GB002397](http://doi.wiley.com/10.1029/2004GB002397) doi: 10.1029/2004GB002397
- 1716 Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., ...
1717 Roeckner, E. (2019). Developments in the MPI-M Earth System Model version
1718 1.2 (MPI-ESM1.2) and Its Response to Increasing CO₂. *Journal of Advances*

- 1719 *in Modeling Earth Systems*, 11(4), 998–1038. doi: 10.1029/2018MS001400
- 1720 Mayot, N., Le Quéré, C., Rödenbeck, C., Bernardello, R., Bopp, L., Djeutchouang,
1721 L. M., ... Zeng, J. (2023). Climate-driven variability of the Southern
1722 Ocean CO₂ sink. *Philosophical Transactions of the Royal Society A: Math-*
1723 *ematical, Physical and Engineering Sciences*, 381(2249). Retrieved from
1724 <https://royalsocietypublishing.org/doi/10.1098/rsta.2022.0055> doi:
1725 10.1098/rsta.2022.0055
- 1726 McKinley, G. A., Fay, A. R., Eddedbar, Y. A., Gloege, L., & Lovenduski, N. S.
1727 (2020). External Forcing Explains Recent Decadal Variability of the Ocean
1728 Carbon Sink. *AGU Advances*, 1(2). doi: 10.1029/2019AV000149
- 1729 McNeil, B. I., & Matear, R. J. (2013). The non-steady state oceanic CO₂ signal:
1730 Its importance, magnitude and a novel way to detect it. *Biogeosciences*, 10(4),
1731 2219–2228. doi: 10.5194/bg-10-2219-2013
- 1732 Metzl, N., Brunet, C., Jabaud-Jan, A., Poisson, A., & Schauer, B. (2006). Summer
1733 and winter air-sea CO₂ fluxes in the Southern Ocean. *Deep-Sea Research Part*
1734 *I: Oceanographic Research Papers*, 53(9), 1548–1563. doi: 10.1016/j.dsr.2006
1735 .07.006
- 1736 Metzl, N., Tilbrook, B., & Poisson, A. (1999). The annual fCO₂ cycle and the air-
1737 sea CO₂ flux in the sub-Antarctic Ocean. *Tellus B: Chemical and Physical Me-*
1738 *teorology*, 51(4), 849. doi: 10.3402/tellusb.v51i4.16495
- 1739 Mikaloff Fletcher, S. E., Gruber, N., Jacobson, A. R., Doney, S. C., Dutkiewicz, S.,
1740 Gerber, M., ... Sarmiento, J. L. (2006). Inverse estimates of anthropogenic
1741 CO₂ uptake, transport, and storage by the ocean. *Global Biogeochemical*
1742 *Cycles*, 20(2). doi: 10.1029/2005GB002530
- 1743 Mikaloff Fletcher, S. E., Gruber, N., Jacobson, A. R., Gloor, M., Doney, S. C.,
1744 Dutkiewicz, S., ... Sarmiento, J. L. (2007). Inverse estimates of the oceanic
1745 sources and sinks of natural CO₂ and the implied oceanic carbon transport.
1746 *Global Biogeochemical Cycles*, 21(1). doi: 10.1029/2006GB002751
- 1747 Mongwe, N. P., Chang, N., & Monteiro, P. M. S. (2016). The seasonal cycle as a
1748 mode to diagnose biases in modelled CO₂ fluxes in the Southern Ocean. *Ocean*
1749 *Modelling*, 106, 90–103. doi: 10.1016/j.ocemod.2016.09.006
- 1750 Mongwe, N. P., Vichi, M., & Monteiro, P. M. S. (2018). The seasonal cycle
1751 of pCO₂ and CO₂ fluxes in the Southern Ocean: diagnosing anomalies in
1752 CMIP5 Earth system models. *Biogeosciences*, 15(9), 2851–2872. doi:
1753 10.5194/bg-15-2851-2018
- 1754 Morrison, A. K., Waugh, D. W., Hogg, A. M., Jones, D. C., & Abernathy, R. P.
1755 (2022). Ventilation of the Southern Ocean Pycnocline. *Annual Review of*
1756 *Marine Science*, 14(1), 405–430. doi: 10.1146/annurev-marine-010419-011012
- 1757 Murnane, R. J., Sarmiento, J. L., & Le Quéré, C. (1999). Spatial distribution of
1758 air-sea CO₂ fluxes and the interhemispheric transport of carbon by the oceans.
1759 *Global Biogeochemical Cycles*, 13(2), 287–305. doi: 10.1029/1998GB900009
- 1760 Nevison, C. D., Munro, D. R., Lovenduski, N. S., Keeling, R. F., Manizza, M.,
1761 Morgan, E. J., & Rödenbeck, C. (2020). Southern Annular Mode Influence
1762 on Wintertime Ventilation of the Southern Ocean Detected in Atmospheric
1763 O₂ and CO₂ Measurements. *Geophysical Research Letters*, 47(4), 1–9. doi:
1764 10.1029/2019GL085667
- 1765 Nicholson, S. A., Whitt, D. B., Fer, I., du Plessis, M. D., Lebéhot, A. D., Swart,
1766 S., ... Monteiro, P. M. (2022). Storms drive outgassing of CO₂ in the
1767 subpolar Southern Ocean. *Nature Communications*, 13(1), 1–12. doi:
1768 10.1038/s41467-021-27780-w
- 1769 Nissen, C., Vogt, M., Münnich, M., Gruber, N., & Alexander Haumann, F. (2018).
1770 Factors controlling coccolithophore biogeography in the Southern Ocean. *Bio-*
1771 *geosciences*, 15(22), 6997–7024. doi: 10.5194/bg-15-6997-2018
- 1772 Niwa, Y., Fujii, Y., Sawa, Y., Iida, Y., Ito, A., Satoh, M., ... Saigusa, N. (2017).
1773 A 4D-Var inversion system based on the icosahedral grid model (NICAM-TM

- 1774 4D-Var v1.0) - Part 2: Optimization scheme and identical twin experiment of
 1775 atmospheric CO₂ inversion. *Geoscientific Model Development*, 10(6), 2201–
 1776 2219. doi: 10.5194/gmd-10-2201-2017
- 1777 Olsen, A., Key, R. M., van Heuven, S., Lauvset, S. K., Velo, A., Lin, X., . . . Suzuki,
 1778 T. (2016). The Global Ocean Data Analysis Project version 2 (GLODAPv2)
 1779 - an internally consistent data product for the world ocean. *Earth System*
 1780 *Science Data*, 8(2), 297–323. doi: 10.5194/essd-8-297-2016
- 1781 Orr, J. C., Maier-Reimer, E., Mikolajewicz, U., Monfray, P., Sarmiento, J. L., Tog-
 1782 gweiler, J. R., . . . Boutin, J. (2001). Estimates of anthropogenic carbon
 1783 uptake from four three-dimensional global ocean models. *Global Biogeochem-*
 1784 *ical Cycles*, 15(1), 43–60. Retrieved from [http://doi.wiley.com/10.1029/](http://doi.wiley.com/10.1029/2000GB001273)
 1785 [2000GB001273](http://doi.wiley.com/10.1029/2000GB001273) doi: 10.1029/2000GB001273
- 1786 Orsi, A., Johnson, G., & Bullister, J. (1999). Circulation, mixing, and production
 1787 of Antarctic Bottom Water. *Progress in Oceanography*, 43(1), 55–109. doi: 10
 1788 .1016/S0079-6611(99)00004-X
- 1789 Panassa, E., Santana-Casiano, J. M., González-Dávila, M., Hoppema, M., van
 1790 Heuven, S. M., Völker, C., . . . Hauck, J. (2018). Variability of nutrients
 1791 and carbon dioxide in the Antarctic Intermediate Water between 1990 and
 1792 2014. *Ocean Dynamics*, 68(3), 295–308. doi: 10.1007/s10236-018-1131-2
- 1793 Pardo, P. C., Tilbrook, B., Langlais, C., Trull, T. W., & Rintoul, S. R. (2017).
 1794 Carbon uptake and biogeochemical change in the Southern Ocean, south of
 1795 Tasmania. *Biogeosciences*, 14(22), 5217–5237. doi: 10.5194/bg-14-5217-2017
- 1796 Paulsen, H., Ilyina, T., Six, K. D., & Stemmler, I. (2017). Incorporating a prognostic
 1797 representation of marine nitrogen fixers into the global ocean biogeochemical
 1798 model HAMOCC. *Journal of Advances in Modeling Earth Systems*, 9, 438–
 1799 464. doi: 10.1002/2016MS000737. Received
- 1800 Prend, C. J., Keerthi, M. G., Lévy, M., Aumont, O., Gille, S. T., & Talley, L. D.
 1801 (2022). Sub-Seasonal Forcing Drives Year-To-Year Variations of Southern
 1802 Ocean Primary Productivity. *Global Biogeochemical Cycles*, 36(7), 1–15. doi:
 1803 10.1029/2022GB007329
- 1804 Regnier, P. A., Resplandy, L., Najjar, R. G., & Ciais, P. (2022). The land-to-ocean
 1805 loops of the global carbon cycle. *Nature* 2022 603:7901, 603(7901), 401–410.
 1806 doi: 10.1038/s41586-021-04339-9
- 1807 Rintoul, S. R. (2018). The global influence of localized dynamics in the Southern
 1808 Ocean. *Nature*, 558(7709), 209–218. doi: 10.1038/s41586-018-0182-3
- 1809 Riser, S. C., Swift, D., & Drucker, R. (2018). Profiling Floats in SOCCOM: Techni-
 1810 cal Capabilities for Studying the Southern Ocean. *Journal of Geophysical Re-*
 1811 *search: Oceans*, 123(6), 4055–4073. doi: 10.1002/2017JC013419
- 1812 Ritter, R., Landschützer, P., Gruber, N., Fay, A. R., Iida, Y., Jones, S. D., . . . Zeng,
 1813 J. (2017). Observation-Based Trends of the Southern Ocean Carbon Sink. *Geo-*
 1814 *physical Research Letters*, 44(24), 12,339–12,348. doi: 10.1002/2017GL074837
- 1815 Rödenbeck, C., Bakker, D. C., Gruber, N., Iida, Y., Jacobson, A. R., Jones, S. D.,
 1816 . . . Zeng, J. (2015). Data-based estimates of the ocean carbon sink variability -
 1817 First results of the Surface Ocean pCO₂ Mapping intercomparison (SOCOM).
 1818 *Biogeosciences*, 12(23), 7251–7278. doi: 10.5194/bg-12-7251-2015
- 1819 Rödenbeck, C., Bakker, D. C., Metzl, N., Olsen, A., Sabine, C. L., Cassar, N.,
 1820 . . . Heimann, M. (2014). Interannual sea-air CO₂ flux variability from an
 1821 observation-driven ocean mixed-layer scheme. *Biogeosciences*, 11(17), 4599–
 1822 4613. doi: 10.5194/bg-11-4599-2014
- 1823 Rödenbeck, C., Devries, T., Hauck, J., Le Quéré, C., & Keeling, R. F. (2022). Data-
 1824 based estimates of interannual sea-air CO₂ flux variations 1957–2020 and their
 1825 relation to environmental drivers. *Biogeosciences*, 19(10), 2627–2652. doi:
 1826 10.5194/bg-19-2627-2022
- 1827 Rödenbeck, C., Keeling, R. F., Bakker, D. C., Metzl, N., Olsen, A., Sabine, C. L., &
 1828 Heimann, M. (2013). Global surface-ocean pCO₂ and sea-Air CO₂ flux vari-

- 1829 ability from an observation-driven ocean mixed-layer scheme. *Ocean Science*,
1830 *9*(2), 193–216. doi: 10.5194/os-9-193-2013
- 1831 Rödénbeck, C., Zaehle, S., Keeling, R., & Heimann, M. (2018). How does the terres-
1832 trial carbon exchange respond to inter-Annual climatic variations? A quantifi-
1833 cation based on atmospheric CO₂ data. *Biogeosciences*, *15*(8), 2481–2498. doi:
1834 10.5194/bg-15-2481-2018
- 1835 Russell, J. L., Dixon, K. W., Gnanadesikan, A., Stouffer, R. J., & Toggweiler, J. R.
1836 (2006). The Southern Hemisphere Westerlies in a Warming World: Propping
1837 Open the Door to the Deep Ocean. *Journal of Climate*, *19*(24), 6382–6390.
1838 doi: 10.1175/JCLI3984.1
- 1839 Sabine, C. L., Feely, R. A., Gruber, N., Key, R. M., Lee, K., Bullister, J. L., ...
1840 Rios, A. F. (2004). The Oceanic Sink for Anthropogenic CO₂. *Science*,
1841 *305*(5682), 367–371. doi: 10.1126/science.1097403
- 1842 Sabine, C. L., Hankin, S., Koyuk, H., Bakker, D. C., Pfeil, B., Olsen, A., ...
1843 Yoshikawa-Inoue, H. (2013). Surface Ocean CO₂ Atlas (SOCAT) grid-
1844 ded data products. *Earth System Science Data*, *5*(1), 145–153. doi:
1845 10.5194/essd-5-145-2013
- 1846 Sallée, J.-B., Speer, K., & Rintoul, S. R. (2010). Zonally asymmetric response of
1847 the Southern Ocean mixed-layer depth to the Southern Annular Mode. *Nature*
1848 *Geoscience*, *3*(4), 273–279. doi: 10.1038/ngeo812
- 1849 Sallée, J.-B., Matear, R. J., Rintoul, S. R., & Lenton, A. (2012). Localized subduc-
1850 tion of anthropogenic carbon dioxide in the Southern Hemisphere oceans. *Na-*
1851 *ture Geoscience*, *5*(8), 579–584. doi: 10.1038/ngeo1523
- 1852 Sarmiento, J. L., & Gruber, N. (2006). *Ocean Biogeochemical Dynamics*. Princeton,
1853 NJ: Princeton University Press.
- 1854 Sarmiento, J. L., Orr, J. C., & Siegenthaler, U. (1992). A perturbation simulation
1855 of CO₂ uptake in an ocean general circulation model. *Journal of Geophysical*
1856 *Research*, *97*(C3), 3621. Retrieved from [http://doi.wiley.com/10.1029/](http://doi.wiley.com/10.1029/91JC02849)
1857 [91JC02849](http://doi.wiley.com/10.1029/91JC02849) doi: 10.1029/91JC02849
- 1858 Schourup-Kristensen, V., Sidorenko, D., Wolf-Gladrow, D. A., & Völker, C. (2014).
1859 A skill assessment of the biogeochemical model REcoM2 coupled to the finite
1860 element sea ice-ocean model (FESOM 1.3). *Geoscientific Model Development*,
1861 *7*(6), 2769–2802. doi: 10.5194/gmd-7-2769-2014
- 1862 Schourup-Kristensen, V., Wekerle, C., Wolf-Gladrow, D. A., & Völker, C. (2018).
1863 Arctic Ocean biogeochemistry in the high resolution FESOM1.4-REcoM2
1864 model. *Progress in Oceanography*, *168*(August), 65–81. doi: 10.1016/
1865 [j.pocean.2018.09.006](https://doi.org/10.1016/j.pocean.2018.09.006)
- 1866 Schultz, C., Doney, S. C., Hauck, J., Kavanaugh, M. T., & Schofield, O. (2021).
1867 Modeling Phytoplankton Blooms and Inorganic Carbon Responses to Sea-Ice
1868 Variability in the West Antarctic Peninsula. *Journal of Geophysical Research:*
1869 *Biogeosciences*, *126*(4), 1–21. doi: 10.1029/2020JG006227
- 1870 Schwinger, J., Goris, N., Tjiputra, J. F., Kriest, I., Bentsen, M., Bethke, I., ...
1871 Heinze, C. (2016). Evaluation of NorESM-OC (versions 1 and 1.2), the
1872 ocean carbon-cycle stand-alone configuration of the Norwegian Earth System
1873 Model (NorESM1). *Geoscientific Model Development*, *9*(8), 2589–2622. doi:
1874 10.5194/gmd-9-2589-2016
- 1875 Séférian, R., Berthet, S., Yool, A., Palmiéri, J., Bopp, L., Tagliabue, A., ... Ya-
1876 mamoto, A. (2020). Tracking Improvement in Simulated Marine Biogeochem-
1877 istry Between CMIP5 and CMIP6. *Current Climate Change Reports*, *6*(3),
1878 95–119. doi: 10.1007/s40641-020-00160-0
- 1879 Séférian, R., Gehlen, M., Bopp, L., Resplandy, L., Orr, J. C., Marti, O., ... Ro-
1880 manou, A. (2016). Inconsistent strategies to spin up models in CMIP5: Impli-
1881 cations for ocean biogeochemical model performance assessment. *Geoscientific*
1882 *Model Development*, *9*(5), 1827–1851. doi: 10.5194/gmd-9-1827-2016
- 1883 Séférian, R., Nabat, P., Michou, M., Saint-Martin, D., Voldoire, A., Colin, J., ...

- 1884 Madec, G. (2019). Evaluation of CNRM Earth System Model, CNRM-
 1885 ESM2-1: Role of Earth System Processes in Present-Day and Future Climate.
 1886 *Journal of Advances in Modeling Earth Systems*, 11(12), 4182–4227. doi:
 1887 10.1029/2019MS001791
- 1888 Shadwick, E. H., De Meo, O. A., Schroeter, S., Arroyo, M. C., Martinson,
 1889 D. G., & Ducklow, H. (2021). Sea Ice Suppression of CO₂ Outgassing
 1890 in the West Antarctic Peninsula: Implications For The Evolving South-
 1891 ern Ocean Carbon Sink. *Geophysical Research Letters*, 48(11), 1–10. doi:
 1892 10.1029/2020GL091835
- 1893 Smith, W., Rivaro, P., Wang, Z., Larue, M., Heywood, K., Park, J., . . . Kim, M.
 1894 (2021). *Observational Activities in the Ross Sea: Current and Future National*
 1895 *Contributions to SOOS - An Update* (Tech. Rep.). Retrieved 2023-02-22, from
 1896 <https://zenodo.org/record/5762638> doi: 10.5281/ZENODO.5762638
- 1897 Stammer, D., Wunsch, C., Giering, R., Eckert, C., Heimbach, P., Marotzke, J., . . .
 1898 Marshall, J. (2002). Global ocean circulation during 1992-1997, estimated from
 1899 ocean observations and a general circulation model. *Journal of Geophysical*
 1900 *Research: Oceans*, 107(9). doi: 10.1029/2001jc000888
- 1901 Stephens, B. B., Keeling, R. F., Heimann, M., Six, K. D., Murnane, R., & Caldeira,
 1902 K. (1998). Testing global ocean carbon cycle models using measurements of
 1903 atmospheric O₂ and CO₂ concentration. *Global Biogeochemical Cycles*, 12(2),
 1904 213–230. doi: 10.1029/97GB03500
- 1905 Stock, C. A., Dunne, J. P., Fan, S., Ginoux, P., John, J., Krasting, J. P., . . . Zadeh,
 1906 N. (2020). Ocean Biogeochemistry in GFDL’s Earth System Model 4.1 and Its
 1907 Response to Increasing Atmospheric CO₂. *Journal of Advances in Modeling*
 1908 *Earth Systems*, 12(10). doi: 10.1029/2019MS002043
- 1909 Sutton, A. J., Williams, N. L., & Tilbrook, B. (2021). Constraining Southern Ocean
 1910 CO₂ Flux Uncertainty Using Uncrewed Surface Vehicle Observations. *Geophys-*
 1911 *ical Research Letters*, 48(3), 1–9. doi: 10.1029/2020GL091748
- 1912 Takahashi, T., Olafsson, J., Goddard, J. G., Chipman, D. W., & Sutherland, S. C.
 1913 (1993). Seasonal variation of CO₂ and nutrients in the high-latitude surface
 1914 oceans: A comparative study. *Global Biogeochemical Cycles*, 7(4), 843–878.
 1915 doi: 10.1029/93GB02263
- 1916 Takahashi, T., Sutherland, S. C., Sweeney, C., Poisson, A., Metzl, N., Tilbrook, B.,
 1917 . . . Nojiri, Y. (2002). Global sea-air CO₂ flux based on climatological sur-
 1918 face ocean pCO₂, and seasonal biological and temperature effects. *Deep-Sea*
 1919 *Research Part II: Topical Studies in Oceanography*, 49(9-10), 1601–1622. doi:
 1920 10.1016/S0967-0645(02)00003-6
- 1921 Takahashi, T., Sutherland, S. C., Wanninkhof, R., Sweeney, C., Feely, R. A., Chip-
 1922 man, D. W., . . . de Baar, H. J. (2009). Climatological mean and decadal
 1923 change in surface ocean pCO₂, and net sea-air CO₂ flux over the global oceans.
 1924 *Deep Sea Research Part II: Topical Studies in Oceanography*, 56(8-10), 554–
 1925 577. doi: 10.1016/j.dsr2.2008.12.009
- 1926 Talley, L. (2013). Closure of the Global Overturning Circulation Through the In-
 1927 dian, Pacific, and Southern Oceans: Schematics and Transports. *Oceanogra-*
 1928 *phy*, 26(1), 80–97. doi: 10.5670/oceanog.2013.07
- 1929 Talley, L., Feely, R., Sloyan, B., Wanninkhof, R., Baringer, M., Bullister, J.,
 1930 . . . Zhang, J.-Z. (2016). Changes in Ocean Heat, Carbon Content, and
 1931 Ventilation: A Review of the First Decade of GO-SHIP Global Repeat
 1932 Hydrography. *Annual Review of Marine Science*, 8(1), 185–215. doi:
 1933 10.1146/annurev-marine-052915-100829
- 1934 Tamsitt, V., Talley, L. D., Mazloff, M. R., Cerovecki, I., Cerovečki, I., Tamsitt, V.,
 1935 . . . Cerovečki, I. (2016). Zonal variations in the Southern Ocean heat budget.
 1936 *Journal of Climate*, 29(18), 6563–6579. doi: 10.1175/JCLI-D-15-0630.1
- 1937 Terhaar, J., Frölicher, T. L., & Joos, F. (2021). Southern Ocean anthropogenic
 1938 carbon sink constrained by sea surface salinity. *Science Advances*, 7(18),

- 1939 eabd5964. doi: 10.1126/sciadv.abd5964
- 1940 Terhaar, J., Frölicher, T. L., & Joos, F. (2022). Observation-constrained estimates
1941 of the global ocean carbon sink from Earth system models. *Biogeosciences*,
1942 *19*(18), 4431–4457. doi: 10.5194/bg-19-4431-2022
- 1943 Terhaar, J., Goris, N., Müller, J. D., DeVries, T., Gruber, N., Hauck, J., . . . Sefe-
1944 rian, R. (2023). Assessment of global ocean biogeochemical models for ocean
1945 carbon sink estimates in RECCAP2 and recommendations for future studies.
1946 *submitted to Global Biogeochemical Cycles*.
- 1947 Tohjima, Y., Mukai, H., MacHida, T., Hoshina, Y., & Nakaoka, S. I. (2019). Global
1948 carbon budgets estimated from atmospheric O₂:N₂ and CO₂ observations in
1949 the western Pacific region over a 15-year period. *Atmospheric Chemistry and
1950 Physics*, *19*(14), 9269–9285. doi: 10.5194/acp-19-9269-2019
- 1951 Urakawa, L. S., Tsujino, H., Nakano, H., Sakamoto, K., Yamanaka, G., & Toyoda,
1952 T. (2020). The sensitivity of a depth-coordinate model to diapycnal mixing
1953 induced by practical implementations of the isopycnal tracer diffusion scheme.
1954 *Ocean Modelling*, *154* (August), 101693. doi: 10.1016/j.ocemod.2020.101693
- 1955 van der Laan-Luijkx, I. T., van der Velde, I. R., van der Veen, E., Tsuruta, A.,
1956 Stanislawska, K., Babenhauserheide, A., . . . Peters, W. (2017). The Carbon-
1957 Tracker Data Assimilation Shell (CTDAS) v1.0: Implementation and global
1958 carbon balance 2001-2015. *Geoscientific Model Development*, *10*(7), 2785–
1959 2800. doi: 10.5194/gmd-10-2785-2017
- 1960 van Heuven, S., Hoppema, M., Jones, E. M., & de Baar, H. J. (2014). Rapid in-
1961 vasion of anthropogenic CO₂ into the deep circulation of the Weddell Gyre.
1962 *Philosophical Transactions of the Royal Society A: Mathematical, Physical and
1963 Engineering Sciences*, *372*(2019). doi: 10.1098/rsta.2013.0056
- 1964 Verdy, A., Dutkiewicz, S., Follows, M. J., Marshall, J., & Czaja, A. (2007). Car-
1965 bon dioxide and oxygen fluxes in the Southern Ocean: Mechanisms of in-
1966 terannual variability. *Global Biogeochemical Cycles*, *21*(2), 1–10. doi:
1967 10.1029/2006GB002916
- 1968 Verdy, A., & Mazloff, M. R. (2017). A data assimilating model for estimating South-
1969 ern Ocean biogeochemistry. *Journal of Geophysical Research: Oceans*, *122*(9),
1970 6968–6988. doi: 10.1002/2016JC012650
- 1971 Wanninkhof, R. (1992). Relationship Between Wind Speed and Gas Exchange. *Jour-
1972 nal of Geophysical Research, Oceans*, *97*(92), 7373–7382.
- 1973 Wanninkhof, R. (2023). Impact predictor variables on magnitude, variability and
1974 trend of global air-sea CO₂ fluxes using an Extra Trees machine learning ap-
1975 proach. *Global Biogeochemical Cycles*.
- 1976 Wanninkhof, R., Asher, W. E., Weppernig, R., Chen, H., Schlosser, P., Langdon, C.,
1977 & Sambrotto, R. (1993). Gas transfer experiment on Georges Bank using two
1978 volatile deliberate tracers. *Journal of Geophysical Research*, *98*(C11). doi:
1979 10.1029/93jc01844
- 1980 Wanninkhof, R. H. (2014). Relationship between wind speed and gas exchange
1981 over the ocean revisited. *Limnology and Oceanography: Methods*, *12*(JUN),
1982 351–362. doi: 10.4319/lom.2014.12.351
- 1983 Wanninkhof, R. H., Asher, W. E., Ho, D. T., Sweeney, C., & McGillis, W. R.
1984 (2009). Advances in Quantifying Air-Sea Gas Exchange and Environ-
1985 mental Forcing. *Annual Review of Marine Science*, *1*(1), 213–244. doi:
1986 10.1146/annurev.marine.010908.163742
- 1987 Wanninkhof, R. H., Park, G.-H. H., Takahashi, T. T., Sweeney, C., Feely, R. A.,
1988 Nojiri, Y., . . . Khatiwala, S. (2013). Global ocean carbon uptake: mag-
1989 nitude, variability and trends. *Biogeosciences*, *10*(3), 1983–2000. doi:
1990 10.5194/bg-10-1983-2013
- 1991 Watson, A. J., Schuster, U., Shutler, J. D., Holding, T., Ashton, I. G., Landschützer,
1992 P., . . . Goddijn-Murphy, L. (2020). Revised estimates of ocean-atmosphere
1993 CO₂ flux are consistent with ocean carbon inventory. *Nature Communications*,

- 1994 11(1), 1–6. doi: 10.1038/s41467-020-18203-3
- 1995 Waugh, D. W., Hall, T. M., McNeil, B. I., Key, R., & Matear, R. J. (2006). Anthro-
- 1996 pogenic CO₂ in the oceans estimated using transit time distributions. *Tellus,*
- 1997 *Series B: Chemical and Physical Meteorology*, 58(5), 376–389. doi: 10.1111/j
- 1998 .1600-0889.2006.00222.x
- 1999 Waugh, D. W., Hogg, A. M., Spence, P., England, M. H., & Haine, T. W.
- 2000 (2019). Response of Southern Ocean ventilation to changes in midlat-
- 2001 itude westerly winds. *Journal of Climate*, 32(17), 5345–5361. doi:
- 2002 10.1175/JCLI-D-19-0039.1
- 2003 Williams, N. L., Juranek, L. W., Feely, R. A., Johnson, K. S., Sarmiento, J. L., Tal-
- 2004 ley, L. D., . . . Takeshita, Y. (2017). Calculating surface ocean pCO₂ from
- 2005 biogeochemical Argo floats equipped with pH: An uncertainty analysis. *Global*
- 2006 *Biogeochemical Cycles*, 31(3), 591–604. doi: 10.1002/2016GB005541
- 2007 Williams, N. L., Juranek, L. W., Johnson, K. S., Feely, R. A., Riser, S. C., Talley,
- 2008 L. D., . . . Wanninkhof, R. (2016). Empirical algorithms to estimate water col-
- 2009 umn pH in the Southern Ocean. *Geophysical Research Letters*, 43, 3415–3422.
- 2010 doi: 10.1002/2016GL068539
- 2011 Woolf, D. K., Land, P. E., Shutler, J. D., Goddijn-Murphy, L., & Donlon, C. J.
- 2012 (2016). On the calculation of air-sea fluxes of CO₂ in the presence of tempera-
- 2013 ture and salinity gradients. *Journal of Geophysical Research: Oceans*, 121(2),
- 2014 1229–1248. doi: 10.1002/2015JC011427
- 2015 Wright, R. M., Le Quéré, C., Buitenhuis, E., Pitois, S., & Gibbons, M. J. (2021).
- 2016 Role of jellyfish in the plankton ecosystem revealed using a global ocean
- 2017 biogeochemical model. *Biogeosciences*, 18(4), 1291–1320. doi: 10.5194/
- 2018 bg-18-1291-2021
- 2019 Wunsch, C., & Heimbach, P. (2013). *Dynamically and kinematically consistent global*
- 2020 *ocean circulation and ice state estimates* (2nd ed., Vol. 103). Elsevier Ltd. doi:
- 2021 10.1016/B978-0-12-391851-2.00021-0
- 2022 Yang, M., Smyth, T. J., Kitidis, V., Brown, I. J., Wohl, C., Yelland, M. J., & Bell,
- 2023 T. G. (2021). Natural variability in air-sea gas transfer efficiency of CO₂.
- 2024 *Scientific Reports*, 11(1), 1–9. doi: 10.1038/s41598-021-92947-w
- 2025 Yang, S., & Gruber, N. (2016). The anthropogenic perturbation of the marine ni-
- 2026 trogen cycle by atmospheric deposition: Nitrogen cycle feedbacks and the 15N
- 2027 Haber-Bosch effect. *Global Biogeochemical Cycles*, 30(10), 1418–1440. doi:
- 2028 10.1002/2016GB005421
- 2029 Zeng, J., Iida, Y., Matsunaga, T., & Shirai, T. (2022). Surface ocean CO₂ con-
- 2030 centration and air-sea flux estimate by machine learning with modelled
- 2031 variable trends. *Frontiers in Marine Science*, 9(September), 1–14. doi:
- 2032 10.3389/fmars.2022.989233