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2 **Supplementary Information for**

3 **Decadal Trends in the Ocean Carbon Sink**

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8 **This PDF file includes:**

9 Supplementary text

10 Figs. S1 to S3

11 Table S1

12 References for SI reference citations

13 Supporting Information Text

14 **SI Methods.** This Appendix provides additional information on the models and methods used in this study.

15 **pCO₂-based flux mapping products.** We used a subset of the SOCOM models that capture climate-driven variability in the ocean
16 CO₂ sink over at least two decades (1, 2): UEA-SI (3), Jena-MLS (4), CU-SCSE (2), AOML-EMP (5), JMA-MLR (6),
17 ETH-SOMFFN (7), CARBONES-NN (2), NIES-NN (8), and PU-MCMC (9). The reader is referred to ref. (2) for further
18 details on the methods used by each of these models.

19 **Inverse models (OCIM).** The two different OCIM versions capture the effects of different processes on ocean CO₂ uptake. The
20 OCIM with steady circulation (OCIM-steady) (10) does not capture variability in circulation, biology, or solubility, and does
21 not simulate the cycling of "natural" (pre-anthropogenic) CO₂ in the ocean. Error estimates are derived from the 10 different
22 versions of the model that vary in terms of their sub-gridscale diffusivities and incorporation of observational errors as described
23 in ref. (10). The OCIM with decadal variations in ocean circulation (OCIM-variable) (11) captures variability in the natural
24 and anthropogenic CO₂ fluxes due to ocean circulation variability, but does not resolve variability due to solubility or biology.
25 The influence of solubility changes is small on decadal timescales as demonstrated by ref. (11), but the effect of changes in
26 biologically-driven CO₂ uptake is unknown. Error estimates are derived from 160 different versions of the model that vary in
27 terms of their physical and biogeochemical parameters as described in ref. (11).

28 **Global ocean biogeochemistry models (GOBMs).** As mentioned in the Materials and Methods, each modeling group performed three
29 simulations for this study. The first is the Global Carbon Budget 2017 (GCB17) simulation (12), which uses reanalysis climate
30 forcing and observed atmospheric CO₂ concentrations (simulation A: "CO₂+climate") from 1959-2017. "Climate forcing" in
31 this case refers to wind stress and surface heat and freshwater fluxes diagnosed from re-analysis products (see Table S1). The
32 second simulation uses constant climate forcing and atmospheric CO₂ (simulation B: "constant climate and CO₂"). The third
33 simulation uses constant climate forcing and observed atmospheric CO₂ concentrations 1959-2017 (simulation C: "constant
34 climate and increasing CO₂"). Using these runs we defined the oceanic CO₂ uptake due to both climate and CO₂ variability
35 (simulation A:"CO₂+climate"), the CO₂ uptake due to atmospheric CO₂ variability alone (simulation C – simulation B: "CO₂
36 only"), and the CO₂ uptake due to climate variability alone (simulation A – simulation C: "climate only"). We did not correct
37 for model drift, but we did verify that the model drift (from run B) has a negligible influence on the decadal trends reported
38 here.

39 The simulations run by each group differed slightly in terms of their model spin-up procedure, their choice of climatological
40 forcing for the "constant climate" run, and their choice of historical climate forcing for the variable-climate runs. These
41 differences are summarized in Table S1. All groups used the observed atmospheric CO₂ concentrations from the GCB17 (12)
42 for simulations A and C, and a constant atmospheric pCO₂ from 1959 for simulation B.

43 **Dynamic global vegetation models (DGVMs).** The DGVMs used here are the same as those appearing in the 2017 Global Carbon
44 Budget: CABLE (13), CLASS-CTEM (14), CLM4.5 (15), DLEM (16), ISAM (17), JSBACH (18), JULES (19), LPJ-GUESS
45 (20), LPJ (21), LPX-Bern (22), OCN (23), ORCHIDEE (24), ORCHIDEE-MICT (25), SDGVM (26), and VISIT (27).

46 **Definitions of ocean regions.** For Figures 3, 4, S2, and S3 we calculated regional decadal trends by integrating fluxes over
47 distinct oceanographic regions. These regions are based on time-mean open-ocean biomes defined by sea-surface temperature,
48 chlorophyll concentrations, ice fraction, and mixed layer depth (28). The regions used here correspond to the biomes define
49 by ref. (28) as follows: "Southern Ocean" is the union of the Southern Ocean sub-tropical seasonally stratified biome, the
50 Southern Ocean sub-polar seasonally-stratified biome, and the Southern Ocean ice biome. "North Atlantic" is the union
51 of the North Atlantic sub-polar seasonally-stratified biome and the North Atlantic sub-tropical seasonally-stratified biome.
52 "North Pacific" is the union of the North Pacific sub-polar seasonally-stratified biome and the North Pacific sub-tropical
53 seasonally-stratified biome. "Low-latitude Atlantic" is the union of the North Atlantic sub-tropical permanently stratified
54 biome, the Atlantic equatorial biome and the South Atlantic sub-tropical permanently stratified biome. "Low-latitude Pacific
55 + Indian" is the union of the North Pacific sub-tropical permanently stratified biome, the Pacific equatorial western biome,
56 the Pacific equatorial eastern biome, the South Pacific sub-tropical permanently stratified biome, and the Indian sub-tropical
57 permanently stratified biome. We used the SOCOM air-sea CO₂ fluxes that are available pre-computed on these regions from
58 <http://www.bgc-jena.mpg.de/SOCOM/>.

59 **Structural uncertainties of the ocean CO₂ sink estimates.** All of the methods for estimating the oceanic CO₂ sink have structural
60 errors that affect their results. The primary sources of structural uncertainty in the SOCOM products are the choice of mapping
61 methodology, as well as a lack of data from winter seasons in the high latitudes with which to constrain the air-sea fluxes in
62 those regions. The main source of structural error in the OCIM is unresolved sub-decadal variability, which combined with the
63 sparse hydrographic data used to constrain the model could lead to substantial aliasing effects, with potentially large impacts
64 on the magnitude of decadal variability in ocean CO₂ uptake. The OCIM also neglects changes in biologically-driven CO₂
65 uptake, which could counteract the circulation-forced CO₂ variability. Structural sources of error associated with the GOBMs
66 include parameterizations of unresolved model physics such as subgridscale ocean eddies, parameterizations of carbon cycling
67 in marine ecosystems and biogeochemistry (which vary widely across different models (29)), and uncertainties in the climate
68 forcing datasets used as boundary conditions for the models.

69 Future work should focus on alleviating these structural uncertainties in the various methods. We suggest that for the
70 SOCOM pCO₂-based flux mapping products, the incorporation of data from ocean biogeochemical floats that can sample
71 year-round, along with improved statistical methods for correcting for the aliasing effects resulting from seasonally-biased
72 observations, could significantly improve their fidelity. For the OCIM method, there is a critical need to resolve sub-decadal
73 (i.e. seasonal to interannual) variability in ocean circulation in order to avoid aliasing effects introduced during the assimilation,
74 and to avoid unrealistic discontinuities in air-sea CO₂ fluxes introduced by the abrupt circulations changes at the decadal
75 transitions. For the GOBMs, work should focus on identifying the most accurate historical climate forcing data, quantifying the
76 physical and biological contributions to climate-driven changes in ocean CO₂ uptake, establishing the proper spin-up procedure
77 for model simulations, and quantifying the sensitivity of the modeled ocean CO₂ sink to climate drivers such as wind stress and
78 buoyancy fluxes. This work should help to identify the factors contributing to the muted variability of the GOBMs compared
79 to the observations.

80 **Evaluation of global ocean biogeochemistry models.** Although a thorough evaluation of the GOBMs used here is beyond the scope
81 of the present study, we provide some additional analysis of the GOBM results in order to demonstrate the differences among
82 the various models, and to provide a comparison to high-fidelity pCO₂-based reconstructions. **Fig. S1** compares the global
83 and regional interannual variability of the GOBMs to results from two of the SOCOM pCO₂-based flux mapping products:
84 the Jena-MLS (4) and the ETH-SOMFFN (7). These products were identified by the SOCOM analysis as the ones that best
85 match the interannual variability of the pCO₂ observations (2). At a global scale, we see that the models CSIRO, NorESM,
86 MITgcm-REcoM-JRA, and NEMO-PlankTOM5 have the best agreement ($r > 0.6$) with the interannual variability in air-sea
87 CO₂ fluxes diagnosed by the ETH-SOMFFN product. The three regions with the greatest decadal variability in the ocean CO₂
88 sink are the Southern Ocean, North Pacific, and low-latitude Pacific+Indian, and so model performance is most critical in
89 these regions. In the Southern Ocean, the NEMO-PISCES (CNRM) model performs best ($r = 0.56$), and also demonstrates
90 the largest decadal variability of any of the GOBMs (see **Fig. 3b**). In the North Pacific, the NorESM model performs the best
91 ($r = 0.62$) and also has the largest decadal variability of any of the GOBMs (see **Fig. 3d**). In the low-latitude Indian+Pacific
92 ocean, the MITgcm-REcoM-JRA and CSIRO models perform noticeably better than the other models, and also display the
93 largest decadal variability of the GOBMs (see **Fig. 3f**). Clearly, the models at capturing the regional interannual variability
94 best also demonstrate the largest regional decadal variability.

95 We also examined Hovmöller diagrams for the zonally-integrated CO₂ fluxes anomalies due to climate variability in each of
96 the GOBMs (**Fig. S1**). These were calculated by first isolating the CO₂ fluxes due to climate variability by subtracting the
97 air-sea CO₂ fluxes of run C (“constant climate and increasing CO₂”) from the air-sea CO₂ fluxes of run A (“CO₂+climate”).
98 The resulting air-sea fluxes at each model grid point were corrected by subtracting the 30-year mean air-sea CO₂ flux over
99 the period 1985-2015, like in ref. (30). Here we focus on the Pacific Ocean and Southern Ocean regions as these are the
100 most important for decadal variability. These results can be compared to similar diagrams that demonstrated large decadal
101 variations in air-sea CO₂ fluxes in the ETH-SOMFFN pCO₂-based flux mapping product (30), although we should also note
102 that the ETH-SOMFFN results include the influence of atmospheric pCO₂ variability, whereas here we have just focussed on
103 the climate-driven variability. The first thing to note is that none of the models show the same degree of decadal variability as
104 that demonstrated by the ETH-SOMFFN product (30). However, in the Southern Ocean the NEMO-PISCES (CNRM) model
105 is the one that best captures the decadal variability demonstrated by the ETH-SOMFFN. In the Equatorial Pacific, the CSIRO
106 and CCSM-BEC models best capture the patterns of interannual variability demonstrated by the ETH-SOMFFN. Differences
107 between the climate forcing products also become clear in the equatorial Pacific, where the MITgcm-REcoM with JRA forcing
108 captures the interannual variability in air-sea CO₂ fluxes much better than the MITgcm-REcoM with NCEP forcing. In the
109 North Pacific the NorESM comes closest to matching the patterns of decadal variability demonstrated by the ETH-SOMFFN.
110 Further analysis is needed to explain the driving forces behind these patterns and the reasons for the muted variability in the
111 models compared to the observation-based flux products.

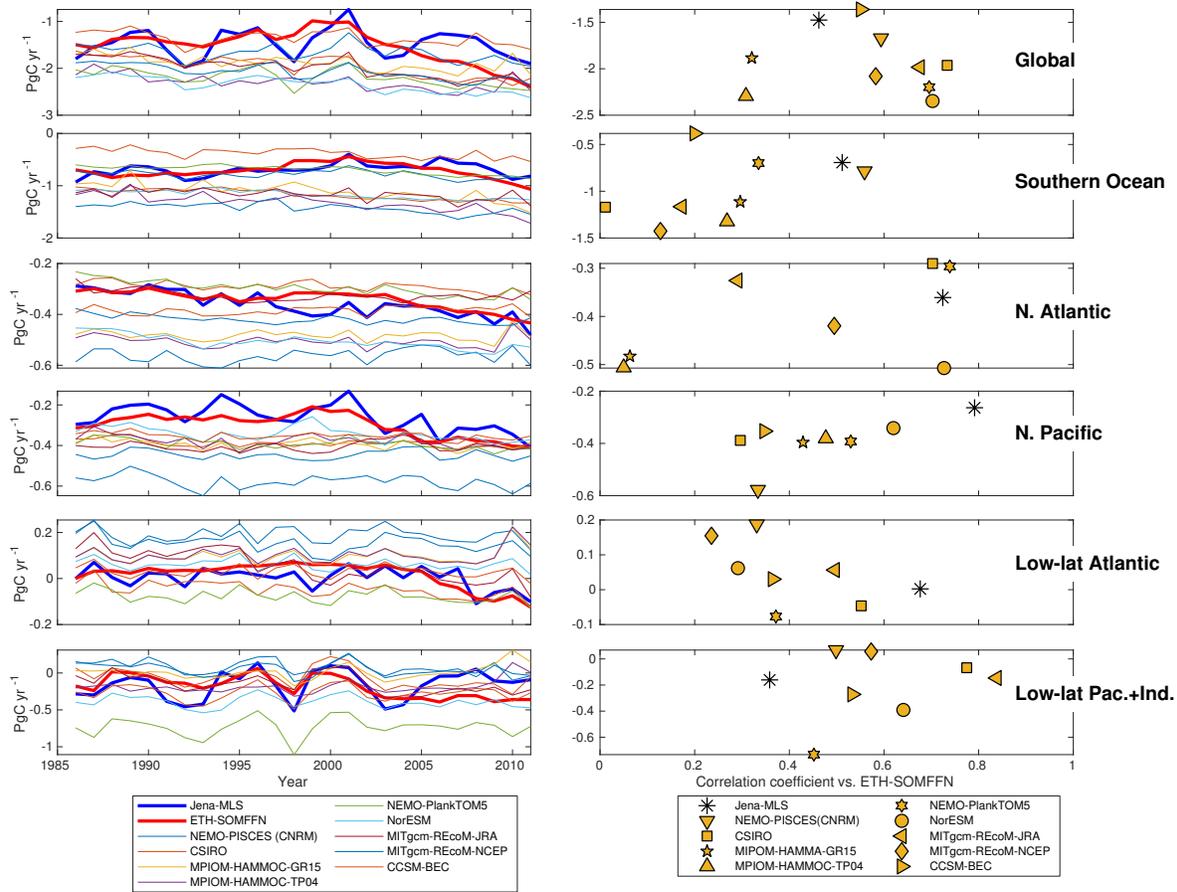


Fig. S1. (Left column) Interannual variability of the regionally-integrated air-sea CO₂ fluxes from the GOBMs used here, and two of the pCO₂-based flux products (ETH-SOMFFN (7) and Jena-MLS (4)) that best match the interannual variability of the pCO₂ observations (2). (Right column) Correlation of the regionally-integrated annual air-sea CO₂ fluxes predicted by the GOBMs used here, with the annual air-sea fluxes predicted by the ETH-SOMFFN (7) for the ocean regions used in Figures 3 and 4. Also shown is the correlation of the Jena-MLS air-sea CO₂ fluxes with the ETH-SOMFFN air-sea CO₂ fluxes for the same regions. The *y*-axis value for these plots is the mean air-sea CO₂ flux for each model for the period 1985-2015. Some models have negative correlation coefficients in some regions and are not shown here.

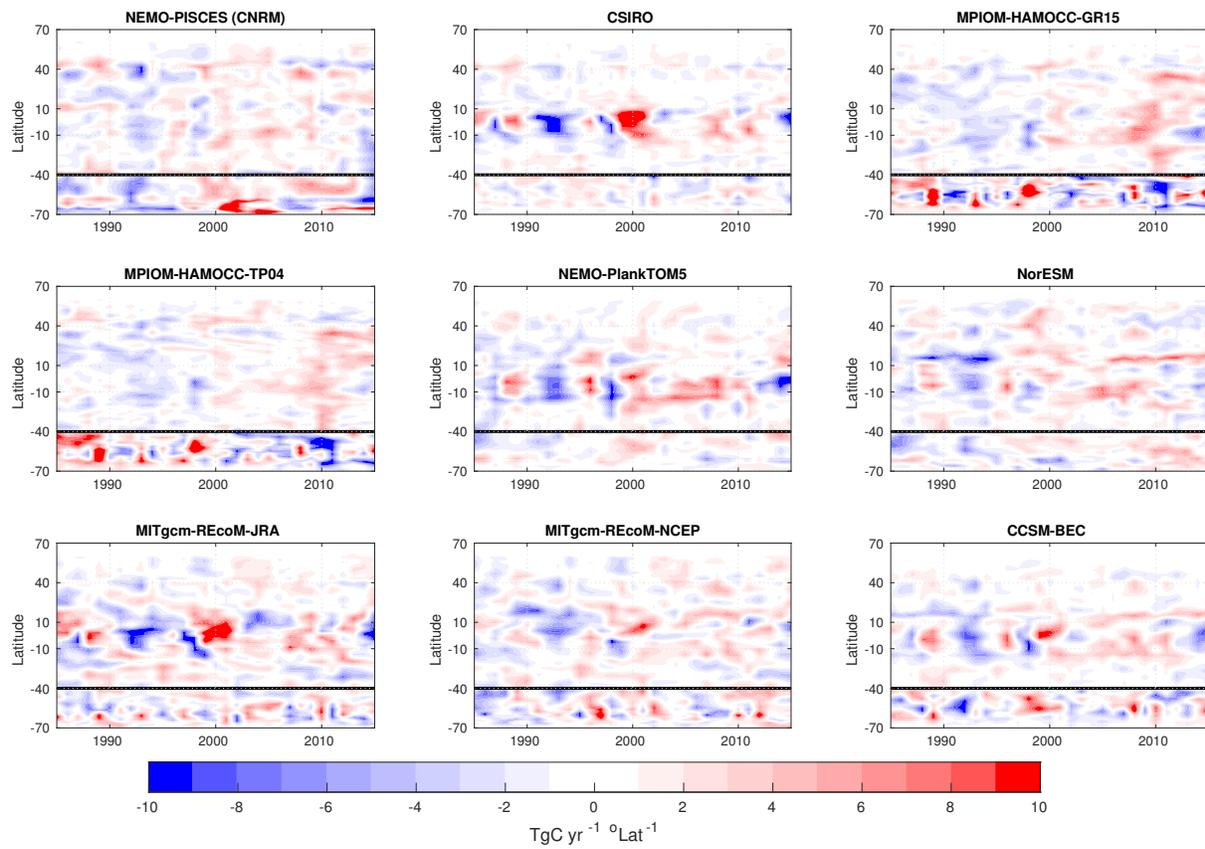


Fig. S2. Hovmöller diagrams of climate-forced variability in air-sea CO₂ fluxes for the nine GOBMs used here. The results for north of 40°S are for the Pacific Ocean, while the results south of 40°S are for the Southern Ocean (all basins). These can be compared to results for the ETH-SOMFFN discussed in ref (30) (their Figure 3).

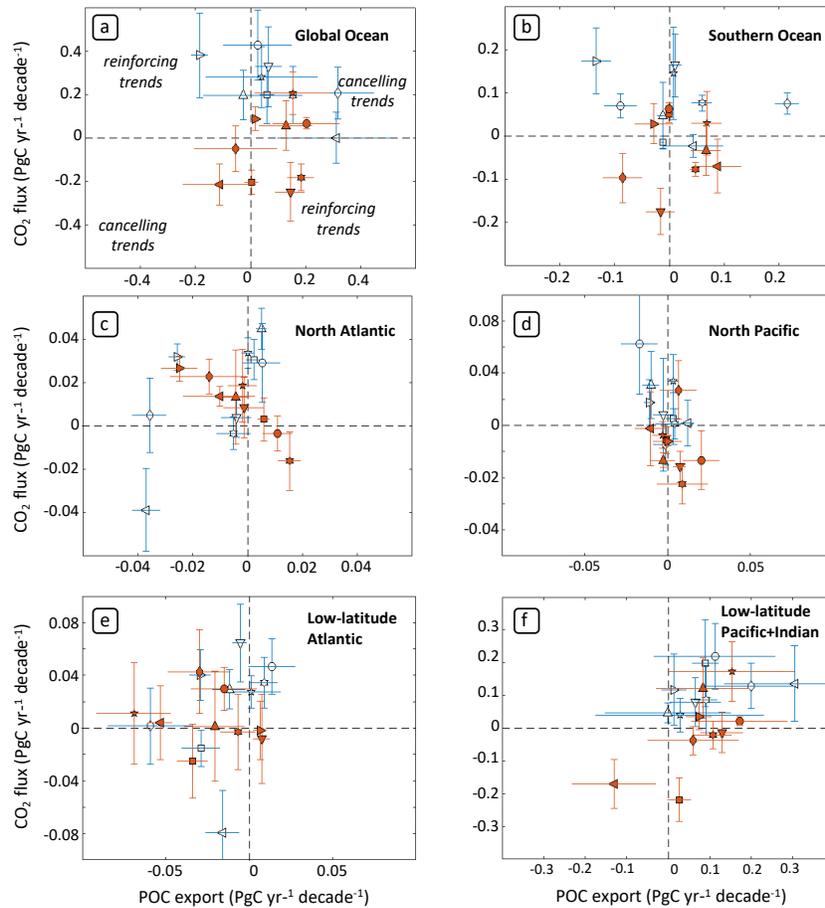


Fig. S3. Decadal trends in oceanic CO₂ uptake vs. decadal trends in POC export in the GOBMs during the 1990s (open symbols) and 2000s (filled symbols) for the ocean regions used in Figures 3 and 4. Each symbol represents a single model as defined in Figure 3. Error bars (one standard deviation) are based on varying the end points of the trend calculation by ± 1 year. All results are from the “climate only” simulation in order to focus on climate-driven trends.

Table S1. Spin-up procedure and climate forcing for global ocean biogeochemical models. Refer to Table A2 in the 2017 Global Carbon Budget (12) for additional model details.

Model	Spin-up procedure	Constant climate forcing	Variable climate forcing
CCSM-BEC (31)	Pre-spin-up of 740 years with CORE (32) normal-year forcing Additional spin-up using NCEP forcing 1958-2017	NCEP (33) forcing for year 1958	NCEP forcing 1958-2017
NorESM (34)	CORE normal year forcing for 1000 years	CORE normal year forcing	NCEP re-analysis with CORE-II corrections 1948-2016 NCEP forcing 1958-2017
NEMO-PlankTOM5 (35)	Initialization from GLODAP (36) plus 30-year spin-up under NCEP forcing from 1980	NCEP forcing 1980 repeated	NCEP forcing 1958-2017
CSIRO (37)	600-year spin-up using JRA-55 (38) pre-industrial forcing plus 2 cycles of JRA-55 from pre-industrial to 1957	JRA-55 forcing 1959 repeated	JRA forcing 1958-2016
MITgcm-REcoM-JRA (39)	2 cycles of JRA forcing (1958-2015)	JRA climatology (1958-2015)	JRA forcing 1958-2016
MITgcm-REcoM-NCEP (39)	48 years with CORE climatology	CORE climatology	NCEP forcing 1948-2016
NEMO-PISCES (CNRM) (40)	3000 years offline + 300 years online under NCEP forcing	NCEP forcing 1980 repeated	NCEP forcing 1948-2016
MPIOM-HAMOCC-GR15 (41) ¹	Pre spin-up of > 1000 years + additional spin-up with ERA-20C (42) forcing 1905-1930	ERA-20C forcing 1959 repeated	ERA-20C forcing 1930-2017
MPIOM-HAMOCC-TP04 (41) ²	Pre spin-up of > 1000 years + additional spin-up with ERA-20C (42) forcing 1905-1930	ERA-20C forcing 1959 repeated	ERA-20C forcing 1930-2017

¹ Coarse-resolution version of the model, used in the 2017 Global Carbon Budget

² Finer-resolution eddy-permitting tripolar grid version of the model (41)

112 **References**

- 113 1. Ritter R, et al. (2017) Observation-Based Trends of the Southern Ocean Carbon Sink. *Geophysical Research Letters*
114 44(24):12–339.
- 115 2. Rödenbeck C, et al. (2015) Data-based estimates of the ocean carbon sink variability—first results of the Surface Ocean
116 pCO₂ Mapping intercomparison (SOCOM). *Biogeosciences* 12:7251–7278.
- 117 3. Jones SD, Le Quéré C, Rödenbeck C, Manning AC, Olsen A (2015) A statistical gap-filling method to interpolate global
118 monthly surface ocean carbon dioxide data. *Journal of Advances in Modeling Earth Systems* 7(4):1554–1575.
- 119 4. Rödenbeck C, et al. (2014) Interannual sea–air CO₂ flux variability from an observation-driven ocean mixed-layer scheme.
120 *Biogeosciences* 11:4599–4613.
- 121 5. Park GH, et al. (2010) Variability of global net sea–air CO₂ fluxes over the last three decades using empirical relationships.
122 *Tellus B: Chemical and Physical Meteorology* 62(5):352–368.
- 123 6. Iida Y, et al. (2015) Trends in pCO₂ and sea–air CO₂ flux over the global open oceans for the last two decades. *Journal*
124 *of oceanography* 71(6):637–661.
- 125 7. Landschützer P, Gruber N, Bakker D, Schuster U (2014) Recent variability of the global ocean carbon sink. *Global*
126 *Biogeochemical Cycles* 28(9):927–949.
- 127 8. Nakaoka S, et al. (2013) Estimating temporal and spatial variation of ocean surface pCO₂ in the North Pacific using a
128 self-organizing map neural network technique. *Biogeosciences* 10(9):6093–6106.
- 129 9. Majkut JD, Sarmiento J, Rodgers K (2014) A growing oceanic carbon uptake: Results from an inversion study of surface
130 pCO₂ data. *Global Biogeochemical Cycles* 28(4):335–351.
- 131 10. DeVries T (2014) The oceanic anthropogenic CO₂ sink: Storage, air-sea fluxes, and transports over the industrial era.
132 *Global Biogeochemical Cycles* 28(7):631–647.
- 133 11. DeVries T, Holzer M, Primeau F (2017) Recent increase in oceanic carbon uptake driven by weaker upper-ocean overturning.
134 *Nature* 542(7640):215.
- 135 12. Le Quéré C, et al. (2018) Global Carbon Budget 2017. *Earth System Science Data* 10(1):405–448.
- 136 13. Haverd V, et al. (2018) A new version of the CABLE land surface model (Subversion revision r4601) incorporating land
137 use and land cover change, woody vegetation demography, and a novel optimisation-based approach to plant coordination
138 of photosynthesis. *Geoscientific Model Development* 11(7).
- 139 14. Melton J, Arora V (2016) Competition between plant functional types in the Canadian Terrestrial Ecosystem Model
140 (CTEM) v. 2.0. *Geoscientific Model Development* 9(1):323–361.
- 141 15. Oleson K, et al. (2013) Technical Description of version 4.5 of the Community Land Model (CLM).
- 142 16. Tian H, et al. (2015) North American terrestrial CO₂ uptake largely offset by CH₄ and N₂O emissions: toward a full
143 accounting of the greenhouse gas budget. *Climatic Change* 129(3–4):413–426.
- 144 17. Jain AK, Meiyappan P, Song Y, House JI (2013) CO₂ emissions from land-use change affected more by nitrogen cycle,
145 than by the choice of land-cover data. *Global change biology* 19(9):2893–2906.
- 146 18. Reick C, Raddatz T, Brovkin V, Gayler V (2013) Representation of natural and anthropogenic land cover change in
147 MPI-ESM. *Journal of Advances in Modeling Earth Systems* 5(3):459–482.
- 148 19. Clark D, et al. (2011) The Joint UK Land Environment Simulator (JULES), model description—Part 2: carbon fluxes and
149 vegetation dynamics. *Geoscientific Model Development* 4(3):701–722.
- 150 20. Smith B, et al. (2014) Implications of incorporating N cycling and N limitations on primary production in an individual-
151 based dynamic vegetation model. *Biogeosciences* 11:2027–2054.
- 152 21. Sitch S, et al. (2003) Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic
153 global vegetation model. *Global Change Biology* 9(2):161–185.
- 154 22. Keller KM, et al. (2017) 20th century changes in carbon isotopes and water-use efficiency: tree-ring-based evaluation of
155 the CLM4. 5 and LPX-Bern models. *Biogeosciences (Online)* 14(10).
- 156 23. Zaehle S, Friend A (2010) Carbon and nitrogen cycle dynamics in the O-CN land surface model: 1. Model description,
157 site-scale evaluation, and sensitivity to parameter estimates. *Global Biogeochemical Cycles* 24(1).
- 158 24. Krinner G, et al. (2005) A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system.
159 *Global Biogeochemical Cycles* 19(1).
- 160 25. Guimberteau M, et al. (2018) ORCHIDEE-MICT (v8. 4.1), a land surface model for the high latitudes: model description
161 and validation. *Geoscientific Model Development* 11(1):121.
- 162 26. Woodward FI, Smith TM, Emanuel WR (1995) A global land primary productivity and phytogeography model. *Global*
163 *biogeochemical cycles* 9(4):471–490.
- 164 27. Kato E, Kinoshita T, Ito A, Kawamiya M, Yamagata Y (2013) Evaluation of spatially explicit emission scenario of land-use
165 change and biomass burning using a process-based biogeochemical model. *Journal of Land Use Science* 8(1):104–122.
- 166 28. Fay A, McKinley G (2014) Global open-ocean biomes: mean and temporal variability. *Earth System Science Data*
167 6(2):273–284.
- 168 29. Laufkotter C, et al. (2015) Drivers and uncertainties of future global marine primary production in marine ecosystem
169 models. *Biogeosciences* 12(23):6955–6984.
- 170 30. Landschuetzer P, Gruber N, Bakker DC (2016) Decadal variations and trends of the global ocean carbon sink. *Global*
171 *Biogeochemical Cycles* 30(10):1396–1417.
- 172 31. Doney SC, et al. (2009) Mechanisms governing interannual variability in upper-ocean inorganic carbon system and

- 173 air-sea CO₂ fluxes: Physical climate and atmospheric dust. *Deep Sea Research Part II: Topical Studies in Oceanography*
174 56(8-10):640–655.
- 175 32. Large WG, Yeager S (2009) The global climatology of an interannually varying air-sea flux data set. *Climate dynamics*
176 33(2-3):341–364.
- 177 33. Saha S, et al. (2014) The NCEP climate forecast system version 2. *Journal of Climate* 27(6):2185–2208.
- 178 34. Schwinger J, et al. (2016) Evaluation of NorESM-OC (versions 1 and 1.2), the ocean carbon-cycle stand-alone configuration
179 of the Norwegian Earth System Model (NorESM1). *Geoscientific Model Development* 9:2589–2622.
- 180 35. Buitenhuis ET, Rivkin RB, Sailley S, Le Quéré C (2010) Biogeochemical fluxes through microzooplankton. *Global*
181 *biogeochemical cycles* 24(4).
- 182 36. Key RM, et al. (2004) A global ocean carbon climatology: Results from Global Data Analysis Project (GLODAP). *Global*
183 *biogeochemical cycles* 18(4).
- 184 37. Law RM, et al. (2017) The carbon cycle in the Australian Community Climate and Earth System Simulator (ACCESS-
185 ESM1)–Part 1: Model description and pre-industrial simulation. *Geoscientific Model Development* 10(7):2567–2590.
- 186 38. Kobayashi S, et al. (2015) The JRA-55 reanalysis: General specifications and basic characteristics. *Journal of the*
187 *Meteorological Society of Japan. Ser. II* 93(1):5–48.
- 188 39. Hauck J, Köhler P, Wolf-Gladrow D, Völker C (2016) Iron fertilisation and century-scale effects of open ocean dissolution
189 of olivine in a simulated CO₂ removal experiment. *Environmental Research Letters* 11(2):024007.
- 190 40. Séférian R, et al. (2013) Skill assessment of three earth system models with common marine biogeochemistry. *Climate*
191 *Dynamics* 40(9-10):2549–2573.
- 192 41. Ilyina T, et al. (2013) Global ocean biogeochemistry model HAMOCC: Model architecture and performance as component
193 of the MPI-Earth system model in different CMIP5 experimental realizations. *Journal of Advances in Modeling Earth*
194 *Systems* 5(2):287–315.
- 195 42. Poli P, et al. (2016) ERA-20C: An atmospheric reanalysis of the twentieth century. *Journal of Climate* 29(11):4083–4097.