

possible links between the ocean carbon sink and fire

- The ocean carbon sink: status and questions (based on GCP analyses)
- Possible links between fire aerosols and ocean carbon (with input from SCOR WGs 151 and 167)

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1) Net anthropogenic CO2 uptake



Integrated ocean carbon research: a summary of ocean carbon research, and vision of coordinated ocean carbon research and observations for the next decade, IOC, Technical Series 158, 2021; Numbers: 2009-2018, Friedlingstein et al., 2019; map: Crisp et al., 2022

The Global Carbon Budget ocean sink estimate



Global Carbon Budget 2022, Friedlingstein et al., 2022

Methods to estimate the ocean carbon sink

Global ocean biogeochemistry models

Global ocean circulation model with representation of biogeochemistry, forced with observed atm CO₂ and atm reanalysis fields

+ constrained by ocean circulation (transport of C into interior ocean = bottle-neck of ocean C uptake)





pCO₂-observation based data products

Statistical mapping of SOCAT CO₂ observations, 98% gap-filling

+ closely linked to observations, which carry imprints of variability

 sensitive to uncertainties in gasexchange parameterization

 no constraint by ocean interior / ocean dynamics

The GCB ocean carbon sink: key results





- In the last decade, 2012-2021, the ocean took up 2.9±0.4 PgC yr⁻¹ (26% of all CO₂ emissions).
- The increase in the ocean sink is driven by atm CO₂ increase
- The effect of climate change is much weaker; without climate change, the ocean sink would have been 5% higher.

Uncertainty and gaps in understanding?



- The difference between model mean and pCO₂-product mean (0.8 PgC yr⁻¹) as large as current EU fossil CO₂ emissions
- The range of all estimates in 2021 (1.7 PgC yr⁻¹) is twice EU fossil CO₂ emissions
- The growth rate of the ocean sink since 2002 differs by a factor of three
- The discrepancy between models and pCO₂-products increases over time

Discrepancy in trends comes from high-latitudes



Global Carbon Budget 2021, Friedlingstein et al., 2022

Model biases in mean CO₂ flux



Majority of models underestimate the ocean CO₂ sink, based on:

1) Atmospheric inversions 2) observation-based ocean interior anthropogenic carbon accumulation 3) O_2/N_2 -based estimate

Biases likely related to:

- ocean overturning circulation (N Atlantic, Southern Ocean)
 - surface ocean **buffering capacity**

Based on: Friedlingstein et al., 2022, Gruber et al., 2019, Tohjima et al., 2019; Terhaar et al., 2022; Terhaar, Goris et al RECCAP model evaluation chapter

Figure credit: Ingrid Luijkx, Friedlingstein et al., GCB 2022

Model biases in trends?



Models compare reasonably well to SOCAT surface ocean CO_2 data and its **temporal evolution** when subsampled for data locations. No indication (so far) for an underestimation of the trend.

Hauck et al., 2020

pCO₂-product biases in trends?



Effect of data sparsity on pCO₂-based estimates



SOCAT pCO₂ distribution **skewed towards low values** after year 2000 Ideal sampling scheme reproduces pCO₂ distribution

Skewed distribution has its origin in the Southern Ocean

Hauck et al., 2023 Phil. Trans. B

2) Fire induced variations in natural CO₂ fluxes

Wanted:

• Effects of climate change and variability on natural and anthropogenic CO₂ fluxes



Several cases now where an ocean reaction to a large fire event could be shown; either related to Fe (Tang et al, 2021, South Pacific) or to N (Ardyna et al, 2022, Arctic Ocean) deposition

Tang et al., 2021

the atmospheric role: more than transport!



Most deposited iron is not soluble (and thus available for growth)

Solubility depends or aerosol source (industrial > fire > lithogenic) but also on chemistry:

lower acidity (industrial pollution) and high organics (fire) lead to increasing solubility in transport

So feedbacks do not only depend on emissions!

Conditions on the receiving side



On the ocean side, different element are limiting to growth in different ocean regions

so the effect of deposited aerosols depends on where they arrive

Moore et al, Nat. Geoscience 2013

Recycled vs. scavenged elements



P: long residence time, accumulation with depth and along overturning Al: Particle reactive, decrease with depth, influenced by local dust Fe: Particle reactive, but biologically cycled; why no inter-basin gradient?

Fe is complex(ed)



The unusual behaviour of Fe is to a large degree by binding to organic ligands; these ligands include smaller molecules, but also to some extent the large pool of not-so-well characterized dissolved organic matter' Binding is influenced e.g. by pH (feedbacks!)

Witter et al, Mar Chem 2000

Fe is complicated



Many (not all) of these aspects are now present in ocean biogeochemical models

Iron is scavenged, but stabilized by ligands. It has many sources: Aerosols, sediments, hydrothermal, rivers. There is active photochemistry occurring. It influences the composition between N-fixers and other phytoplankton, ...

Tagliabue et al., 2017

NPP and carbon export in CMIP5/6

| | 1 | | | | | | | | ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~ | | | | |
|----------------|----------------------|-----------|------------------------|-------|------|-----------------------|-----------|------|--|------|------------|-------------------------|-------|
| | at surface | | | | | at 100 m | | | | | | | |
| | Net Carbo | on Uptake | Net Primary Prod. | | | Carbon export | | | Calcite Export | | | Silicate export | |
| | [Pg C | C y-1] | [Pg C y–1] | | | [Pg C y–1] | | | [Pg C y–1] | | | [Tmol Si y–1] | |
| Observations | 2.1–2.3 ^a | | 38.8–52.1 ^b | | | 5.8–12.9 ^c | | | 0.38–1.64 ^d | | | 94.5–115.5 ^e | |
| BCC-CSM2-MR | | 1.83 | | | • | | | - | / | | - | / | — |
| BCC-CSM1.1-M | 2.49 | | - | | | - | | | — | | | — | |
| CanESM5 | | 2.06 | | 24 | .7 | 07779 | | 7.31 | | | 0.49 | | - |
| CanESM2 | 1.94 | | 33.0 |)7 | | 11.8 | 36 | | 0.66 | | | — | |
| CanESM5-CanOE | / | 2.38 | | 26 | .6 | | The | 5.7 | | | 0.51 | | - |
| CanESM2 | 1.94 | | 33.0 |)7 | | 11.8 | 86 | TIM | 0.66 | | | — | |
| CESM2 | | 2.11 | | 48. | 98 | | | 7.06 | 7777777 | | 0.78 | | 80.35 |
| CESM1-BGC | 2.08 | | 56.2 | 25 | | 7.9 | 5 | | 0.74 | | | 101 | |
| CNRM-ESM2-1 | | 2.11 | | 57 | .3 | | | 9.43 | | | 1.23 | | 100.5 |
| CNRM-ESM1 | 1.6 | | 26.1 | 6 | - | 2.4 | 2 | | 0.12 | | | 48.44 | |
| GFDL-CM4 | | 2.4 | | 49 | .3 | Imm | | 10.4 | 7777777777 | | 5/AX/// | | - |
| GFDL-ESM2M | 2.33 | | 81.9 | 3 | | 7.7 | 3///// | mm | 0.39 | | | 158.2 | |
| GFDL-ESM4 | | 2.33 | | 51. | 18 | 11/1/1 | | 6.27 | Man | | 0.34 | | 86.96 |
| GFDL-ESM2M | 2.33 | | 81.9 | 3 | | 7.7 | 3//// | | 039 | M | TITT | 158.2 | |
| GISS-E2-1-G-CC | | 2.22 | | 24. | 48 | | - | 4.78 | | | 0.56 | | - |
| GISS-E2-R-CC | 1.44 | | 15. | 1 | | 6. | | TIM | - | | | _ | |
| UKESM1-0-LL | | 2.05 | | 46. | 74 | | (| 9.51 | | | \$%.A\$/// | Manna. | 84.72 |
| HadGEM2-ES | 2.16 | | 35.5 | 54 | | 5.4 | 3 | | 0.26 | | | 95.16 | Imm |
| IPSL-CM6A-LR | | 2.43 | | 42 | .7 | 0///// | | 7.33 | | | 0.82 | | 74.94 |
| IPSL-CM5A-LR | 2.51 | | 33.7 | 76 | | 7.0 | 5 | | 0.35 | | | 122.4 | |
| MIROC-ES2L | | 2.38 | | 29. | 87 | | | 7.93 | | | 0.6 | | _ |
| MIROC-ESM | 2.16 | | 28.3 | 38 | | 6.9 | 6 | | 0.35 | | | _ | |
| MPI-ESM1-2-LR | | 2.18 | - | 48. | 05 | | | 6.63 | | | 0/53// | | 107.5 |
| MPI-ESM-LR | 2.31 | | 58.6 | 6 | | 8.3 | 8 | | 0.82 | | | 117.02 | |
| MRI-ESM2-0 | | 2.56 | | 21. | 58 | Imm | | 9.9 | | //// | 0.47 | | - |
| MRI-ESM1 | 2.14 | | 28.1 | | 7.75 | | | 0.64 | | | _ | | |
| NorESM2-LM | | 2.26 | | 33.64 | | 4.94 | | | 0.66 | | | | 76.5 |
| NorESM1-ME | 2.61 | | 41 | | 8.02 | | 0.49///// | | 107.5 | | | | |
| -100 % - | -80 % | -60 % -4 | 10 % | -20 % | -5 | % | 5% | 20 9 | % 40 | % | 60 % | 80 % | |
| | - | - | - | | - | - | - | - | - | | - | | - |
| -80 % | -60 % - | -40 % -2 | 20 % | -5 % | 5 | % | 20 % | 40 9 | 60 | % | 80 % | 100 % | S |

CMIP5/CMIP6 models also still have quite a span in how complicated the represent the iron cycle;

not only due to this, they have quite a range in mean NPP and export production

Séférian et al., 2020

Open end 1: what is solubility / bioavailability?



Atmospheric chemistry models can describe the evolution of trace metal solubility over transport

But: how relevant is that, after aerosol particles get deposited on the ocean surface?

Conditions (e.g. pH, ligands) change drastically. Photochemistry happens. Role of this and the sea surface microlayer?

See Meskhidze et al. 2019, Mar Chem.

Open end 2: colimitation, norm rather than exception



Co-limitation by more than one trace metal (here Mn and Fe) has been found in eastern boundary upwelling regions, Southern Ocean, ...

Challenge for models to describe several TMs (Fe, Mn, Zn, Co?), hopefully not all as complicated as Fe

Browning et al, 2021

Open end 3: integration within ESMs

Capturing the effects of fire on the marine C cycle in earth system models requires

- a) a fire-enabled terrestrial ecosystem model
- b) an aerosol transport (and ideally chemistry) model
- c) a marine biogeochemical model that represent some of the complexities mentioned

Even if the components exist, they each require expertise to judge the model outcomes and interaction on their meaning

So in many cases, a simpler approach is taken: Take output from one model, transplant it into another model. How bad is that?

Two issues with that: consistency, absence of feedbacks

adaptive models allowing for co-limitation



Pahlow et al, 2013

Describing cellular regulations in phytoplankton allows to tackle co-limitation

Examples: optimality-based model (Pahlow 2013), Geider et al. (1998) used in REcoM; extensions for Fe exist

Allow for flexible stoichiometry, bur more importantly regulation, some photophysiology, ... But: role of metals beyond Fe?

Effect of data sparsity on pCO₂-based estimates



With the ideal sampling, the **bias in the mean CO₂ flux** of 9–12% is reduced to 2–9% globally and from 14–26% to 5–17% in the Southern Ocean

With the ideal sampling, the bias in the CO₂ flux trend of +20 to +35% is reduced to -10 to -2% globally and from 50-130% to 0-15% in the Southern Ocean

Hauck et al., 2023, Phil. Trans. B

Total number of observations



Globally, SOCAT has more observations than the ideal (bgcArgo case)

Not in the Southern Ocean.

Hauck et al., 2023, Phil. Trans. B

pCO₂ biases



The bgcArgo floats are equipped with pH sensors, and hence pCO_2 needs to be derived from pH and a multi-linear regression-derived alkalinity estimate. Currently, this procedure is associated with uncertainties that are substantially larger than for the pCO_2 measurements on ships. Our analysis reveals that systematic biases of around 5µatm can lead to large errors in reconstructed pCO_2 and CO_2 flux.

As the array of biogeochemical Argo floats expands, it will be essential to conduct on-going intercomparisons between float and ship-based measurements with the goal of developing an unbiased multi-platform sampling array that captures the relevant spatial and temporal variability. This may involve more extensive sampling of surface pH and alkalinity on research vessels and ships of opportunity to allow better assessment of float pH and salinity-derived alkalinity and targeting float locations for purposeful crossover comparisons.