Towards better models for ocean biogeochemistry

Calibration of ocean biogeochemistry for different circulations and model spin-up times

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In Short

- Global biogeochemical ocean models vary in present day and future projections of many tracers and processes.
- Variation can be attributed to representation of biogeochemistry, circulation and model spin-up time.
- We calibrate and assess global biogeochemical model setups with regard to different time scales and metrics, with the ultimate aim to provide reliable model parameters to an Earth system model.

Biogeochemical ocean models coupled to Earth system models (ESMs) are applied not only to investigate the ocean's interaction with the global carbon cycle, but their projected primary production now also serves as a basis to estimate future changes in marine fisheries [1,2]. Further, the fraction of primary production exported to the deep ocean supplies food to mesopelagic fish, which could be considered as potentially relevant for mankind, but which are poorly understood [3,4]. However, uncertainties and computational restrictions of these models can lead to a large range of simulated primary production [5,6] and OMZ volume [5], which might affect estimates of higher trophic levels. The uncertainties can be ascribed to biogeochemical parameterisations [7,8], circulation [8,9], and model spinup time [10].



Figure 1: Schematic of the global biogeochemical optimisation platform. The biogeochemical ocean model is simulated in parallel with λ different paramater sets. After evaluation of the misfit to observations, the optimiser CMAES evaluates the different misfit values, and proposes new sets of parameters. The cycle is repeated until misfit converges to a sufficiently small value.

In addition, biogeochemical model calibration and validation are often only carried out for a subset of model tracers (usually nutrients, oxygen and inorganic carbon) which may give rise to a calibration bias [12]. However, observations of inorganic tracers may not be sufficient to constrain parameters of higher trophic levels [13]. We therefore consider it necessary to better assess and evaluate global biogeochemical ocean models with respect to organic components, and – if possible – also to better constrain their uncertain model parameters. At the same time we want to investigate how circulation and model spin-up time reflect upon changes in biogeochemical turnover and functioning under future climate change scenarios.



Figure 2: Graphic summarising the different sources of variability among model setups from six different optimisations for various diagnostics (rectangles). *x*-axis: the range due to different model parameters. *y*-axis: range due to spin-up time. OMZ volume defined by a criterion of 50 mmol $O_2 m^{-3}$. Fish biomass diagnosed from export production and zooplankton grazing [3] and scaled by OMZ thickness.

As a direct calibration of a computationally expensive ESM does not seem feasible at this time, we use a biogeochemical model calibration framework (Fig. 1), that combines a marine biogeochemical model of intermediate complexity [14] with offline circulations using the Transport Matrix Method [15,16] and an efficient optimisation algorithm [17,18]. This tool has already been shown to perform well in global biogeochemical model optimisation, while maintaining computational efficiency [13,20].

To avoid the calibration bias we optimise the biogeochemical model against observations of nutrients, oxygen, plankton, dissolved and particulate organic matter. First results of short-term optimisations show that the choice of data sets can have a considerable effect on some optimal parameters, and thus on global biogeochemical fluxes (Fig. 2), which can, in end-to-end models, impinge on biomass estimates of higher trophic levels.



Figure 3: OMZ volume bias over the trajectory of six model setups (coloured lines). Circles indicate values listed in Table 2 of [5]. Vertical bars at the abscissa denote the model spin-up times listed in [21].

An open question remains if and how higher organisms or their predators are affected by OMZs, which are very sensitive to parameters arising from the calibration strategy (Fig. 2), and can exhibit an intrinsic non-linear trajectory over time (Fig. 3). We will investigate the cascading effects of biogeochemical model uncertainty on model turnover, OMZ volume and higher trophic levels. The effects of model uncertainty will be compared to effects caused by transient simulations with an ESM that includes the same biogeochemical model applied in the optimisations.

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More Information

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