Towards better models for ocean O_2 and N_2O

Optimisation of biogeochemical model parameters relevant for regions of low oxygen, and their impact on the release of N_2O

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In Short

- Global biogeochemical ocean models show large uncertainties in their representation of regions with low oxygen and N_2O emissions.
- Optimisation against observations can help to reduce some of these uncertainties, and results in improved global biogeochemical fluxes.
- We apply an optimisation framework to constrain parameters relevant for oceanic oxygen minimum zones (OMZs) and N_2O production.
- The outcome is also expected to provide a better understanding of OMZs, and the release of climate-relevant N_2O to the atmosphere.

Global ocean models that simulate biogeochemical interactions are subject to many uncertainties, among them those related to circulation and the parameterisation of biological processes. These uncertainties can have large effects on simulated oxygen concentrations [1,2], its oceanic inventory [3] and volume of regions with low oxygen, so-called oxygen minimum zones (OMZs) [3,4]. Possible reasons for errors in the representation of OMZs are circulation [5] or biogeochemical interactions [4]. Not only local, but also remote biogeochemical interactions may play a role [6], illustrating the need for long enough model simulations.

OMZs are important as a habitat for marine organisms, among them commercially relevant fish species [7]. They are also hot-spots for the release of climate relevant nitrous oxide [8,9]. In this project, we aim to better understand and improve the representation of these regions in global biogeochemical ocean models, and to disentangle the mutual effects of circulation and biogeochemistry. Our main focus lies on the parameterisation of dissolved and particulate organic matter supply to OMZs (as one factor causing the formation and extent of OMZs), and on the production and consumption of nitrous oxide (N_2O) via nitrification and denitrification.

To investigate these questions we apply a framework for global biogeochemical ocean model calibration, that couples different biogeochemical models to an offline circulation and a quasi-evolutionary optimisation algorithm [10].

Methods We apply a global model of oceanic biogeochemical processes (MOPS) [11], that has been extended to simulate nitrous oxide and particle size spectra, the latter following [12]. For coupling between the biogeochemical model and different and circulations, we use the Transport Matrix Method [13] which applies transport matrices (TMs) derived from the advective and diffusive components of ocean circulation models. We use three sets of TMs, derived from different ocean circulation models of different resolution and type: One is derived from a 2.8° global configuration of the MIT ocean model with 15 vertical levels [14]. We also apply TMs derived from a circulation of the Estimating the Circulation and Climate of the Ocean (ECCO) project, which provides circulation fields that yield a best fit to hydrographic and remote sensing observations on a spatial resolution of $1^\circ \times 1^\circ$ horizontal resolution with 23 vertical levels [15]. The third is derived from the University of Victoria (UVic) Earth system model [16], and is again of rather coarse spatial resolution ($1.8^\circ \times 3.6^\circ$).

All optimisations consider the misfit to global distributions of annual mean nutrients and oxygen. The representation of OMZs is carried out using the metric proposed by [4]. These two metrics are tested and applied together with the normalised root-mean-squared-error of N_2O, and complemented by comparison against data sets for dissolved organic phosphorus (DOP) and organic particle abundance and size spectra, and mesozooplankton biomass.

For biogeochemical model optimisiation we use the Covariance Matrix Adaption Evolution Strategy [17,18], a meta-heuristic method for parameter optimisation, which has shown good performance with respect to quality and efficiency [10,19]. However, good parameters ($=$ biogeochemical model constants) with respect to one type of observations can be bad for another type. Single-objective optimisation can join different terms into one single metric by assigning weights, but this approach can be difficult and subjective. To circumvent this, we also use multi-objective optimisation to calibrate the model against different objectives at the same time. The outcome of such an optimisation is a limited number of good incomparable solutions.

First results Encouragingly, optimisation reduces the spread of global mean oxygen profiles and OMZ volumes caused by different circulations and/or biogeochemistry found in earlier studies [1,3,4,20], even if optimal parameters are transferred among different circulation. Overall, after optimisation the remaining spread can be attributed almost equally to changes in biogeochemistry and circulation (Fig. 1).

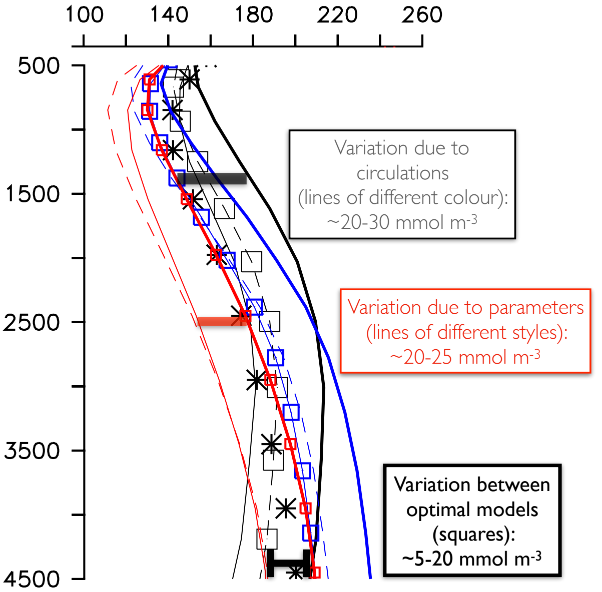

Figure 1: *Global mean oxygen concentrations below 500 m of model optimised in three different circulations (MIT2.8, ECCO1.0, UVic) and furher results from portability experiments. Colours indicate different circulations. Line styles indicate different biogeochemical parameter sets. Open squares: with optimal model parameters for the respective circulation. Stars: Observations.*

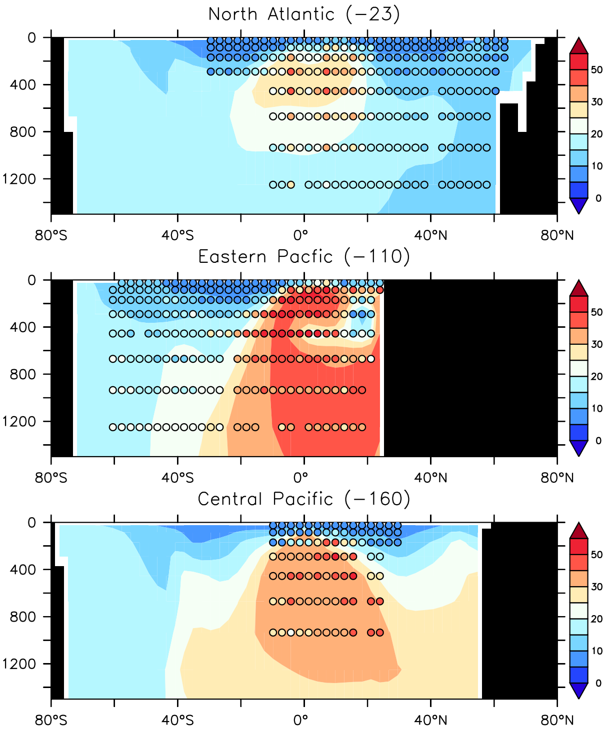

Figure 2: *Simulated N_2O (nmol L^{-1}), averaged over $\pm 5°$ along 23° W, 110° W and 160° W , for a model setup from the Pareto-front optimal with respect to N_2O concentrations. Filled circles denote observations, plotted on the same colour scale. Observations compiled and provided by Annette Kock, GEOMAR.*

Optimisation of models results in a good spatial representation of N_2O, even if optimisation was carried out in the coarse resolution of MIT2.8 (Fig. 2). Because multi-objective optimisation accounts for several objectives at the same time, this good fit to N_2O does not sacrifice too much of the fit to nutrients and oxygen, as indicated from the simultaneously good match to these tracers. All three optimal models support the "hidden" N_2O turnover during denitrification suggested by [21], i.e., a high loss and gain during denitrification, but only small net fluxes.

Observations [22] and first experiments, in which the model is calibrated against observed particle concentrations of large and small particles after only a spin-up of 10 years further indicate that zooplankton, as a component that controls formation, consumption and vertical transport of particles, could be essential for a correct representation of the particle size distribution, and therefore can exert an influence on OMZs.

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More Information

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