Budgets of heat, salt, biological, and geochemical tracers in an eddy in the Southern Ocean Polar Frontal Zone estimated from a regional high resolution data set and an inverse coupled general circulation ecosystem model

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1 Overview

Combining models and data with data assimilation or state estimation techniques is promising when both data and models separately exhibit some skill. However, in oceanography more often than not, data and in particular sub-surface data are sparse and the prediction skill of ocean models tends to be poor on long time scales. We present a state estimation experiment, in which we exploit the availability of a high-resolution regional data set: Hydrographic, tracer and velocity data from the European Iron Fertilization EXperiment (EIFEX) are used to constrain a high-resolution coupled ecosystem-ocean circulation model of the experimental site in Atlantic sector of the Antarctic Polar Frontal Zone.

2 EIFEX: European Iron Fertilization EXperiment

EIFEX was aimed at testing the hypothesis that iron limits phytoplankton blooms in the Southern Ocean. For the open ocean experiment, a patch with a diameter of 16 km inside of a cyclonic, mesoscale eddy in the polar frontal zone was fertilized on February 12–13 and February 26–27, 2004 with dissolved iron. Subsequently the oceanic response was monitored. The eddy was identified with the help of in-situ measurements (CTD sensor and ship mounted ADCP) and satellite altimetry. It extended over 60 km by 100 km. with the center near 49°24'S 02°15'E in the South Atlantic
During the course of the experiment both hydrographic and dynamic parameters and bio-geochemical quantities were measured at CTD stations inside and outside the fertilized patch and along the ship track. Many measurements covered the water column down to 500 m depth.

3 MITgcm and state estimation

The M.I.T. general circulation model (MITgcm Marshall et al., 1997) has been adapted for use with the Tangent linear and Adjoint Model Compiler (TAMC), and its successor TAF (Transformation of Algorithms in Fortran, Giering and Kaminski, 1998). Efficient (w.r.t. CPU/memory), exact (w.r.t. the model's transient state) derivative code can be generated for up-to-date versions of the MITgcm and its newly developed packages in a wide range of configurations (Heimbach et al., 2002, 2004). Here, the MITgcm is configured to cover the experimental region of the EIFEX cruise of appoximately 150 km by 194 km with a mean horizontal grid spacing of approximately 3.6 km; vertical grid spacing increases from 10 m near the surface to 25 m at 500 m depth. The integration time spans the length of the experiment (39 days).

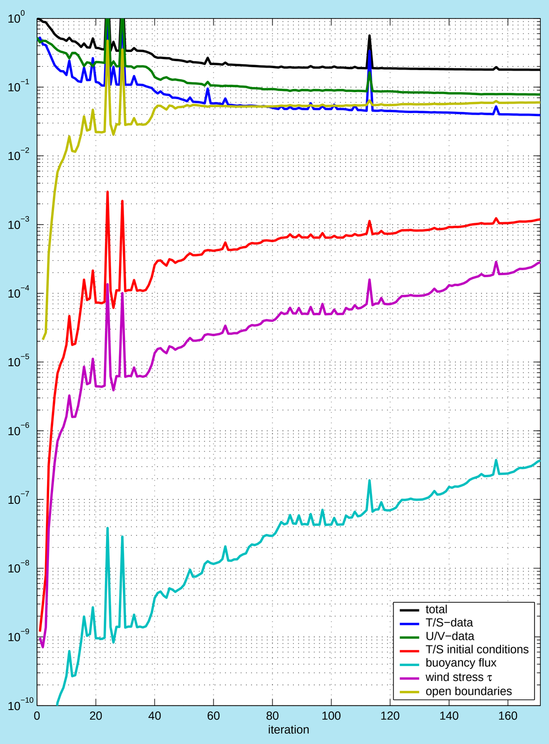

Figure 1: Evolution of different contributions to the objective function J with iteration number of the BFGS-descend algorithm. Hydrographic data from CTD-stations and ship-mounted ADCP-current measurements are used to assimilate the model using the variational data assimilation technique (state estimation, "4D-VAR"). During the minimization of the objective function J that describes the quadratic deviation of the model from data and also penalizes deviations from the first guess, initial conditions for temperature and salinity, open boundary conditions for temperature, salinity, and velocity, and surface fluxes of heat, fresh water, and momentum are adjusted to give the best fit to observations.

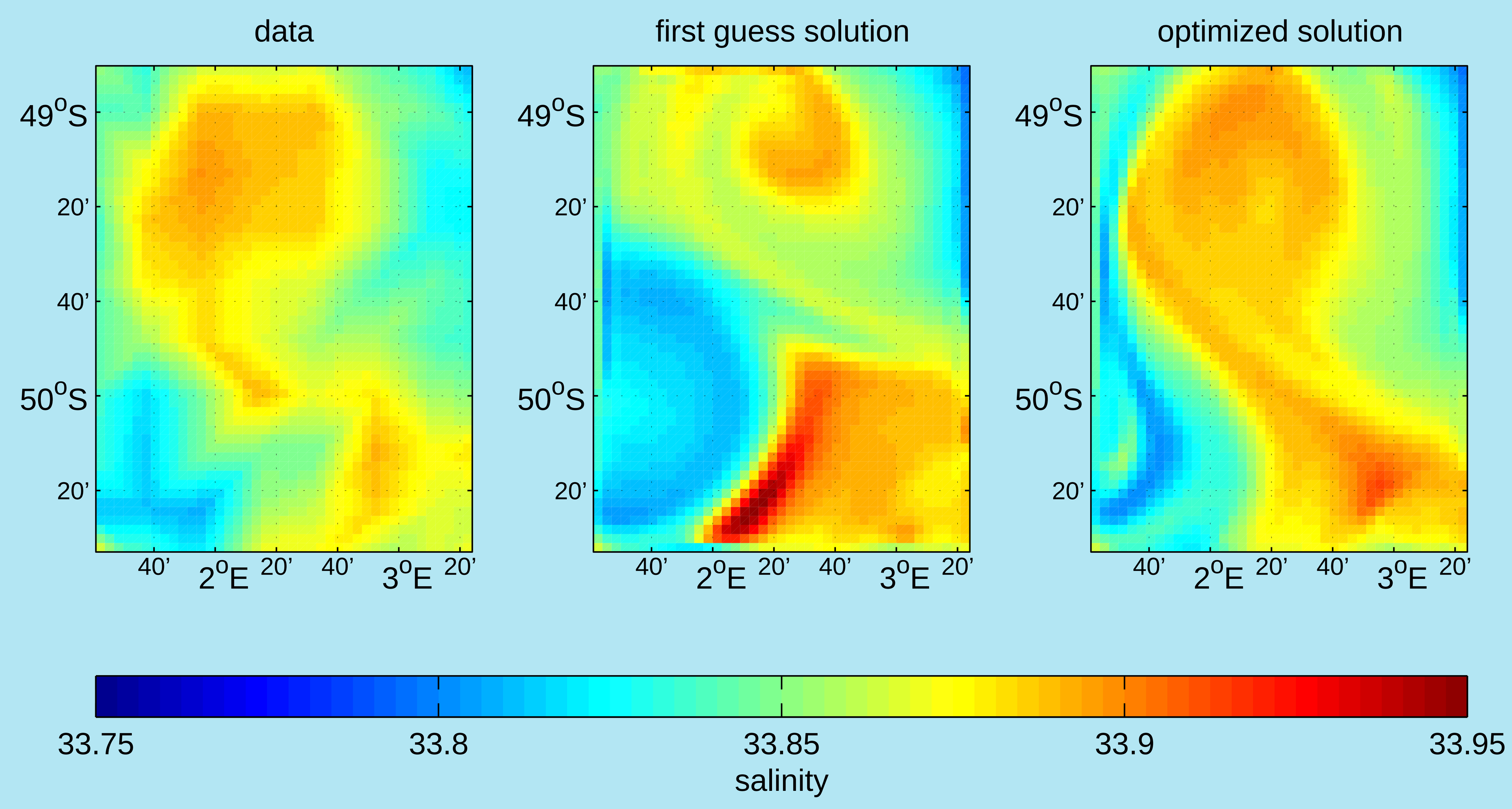

Figure 2: Comparison with in-situ data shows that data assimilation improves the position of the eddy by adjusting open boundary conditions, initial hydrography, and (to a lesser extend) surface flux boundary conditions. Left: surface salinity from hydrographic measurements, average over first 10 days of the experiment. Center: surface salinity of modeled eddy on day 5 without data assimilation; initial conditions and boundary conditions for this first guess are obtained by interpolating and extrapolating all available data; the amount of data is not sufficient to allow for time dependent boundary conditions, which appears to be the major problem for this solution. Right: surface salinity of modeled eddy on day 5 after full time-dependent state estimation; the eddy has moved southward and away from the boundary and its position is now in much better agreement with observations (Left).

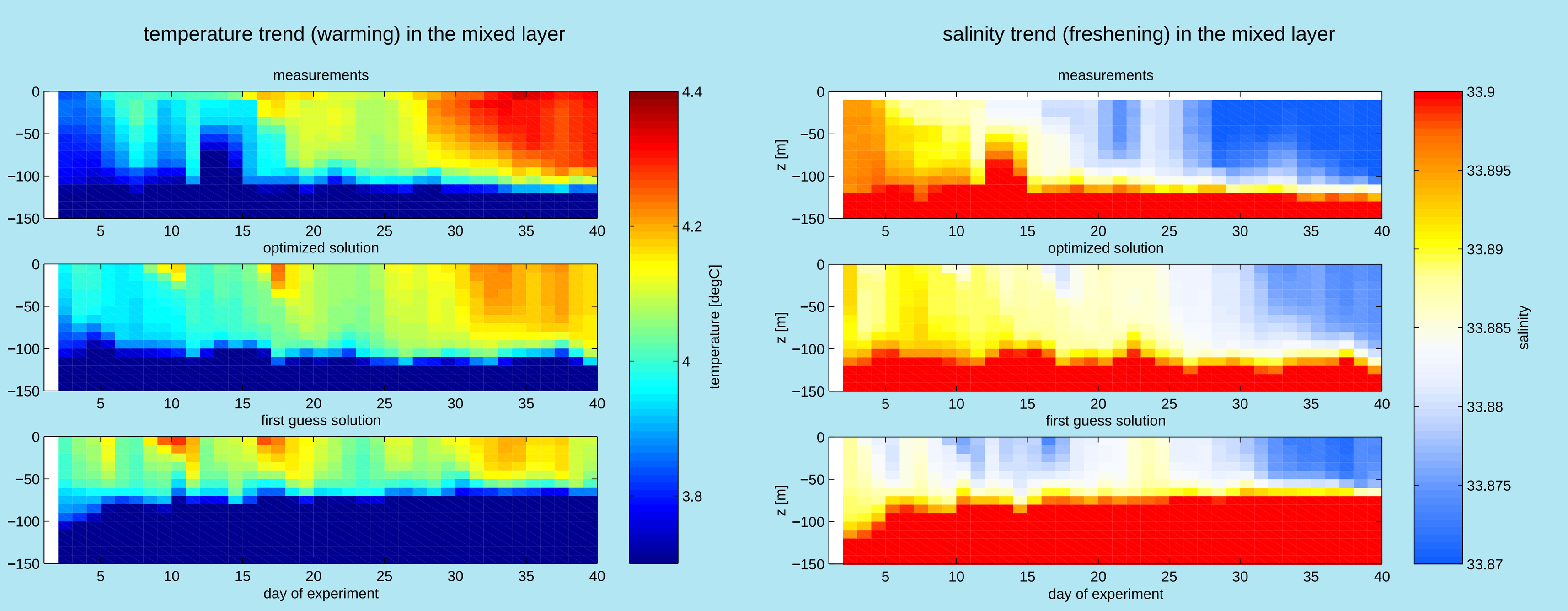

Figure 4: Horizontally averaged temperature (left) and salinity (right) in the fertilized patch; data (top panels), optimized model (middle panels), first guess model (bottom panels). The optimization improves the description of the mixed layer depth dramatically, so that the optimized solution describes the warming and freshening of the mixed layer more accurately than the first guess solution.

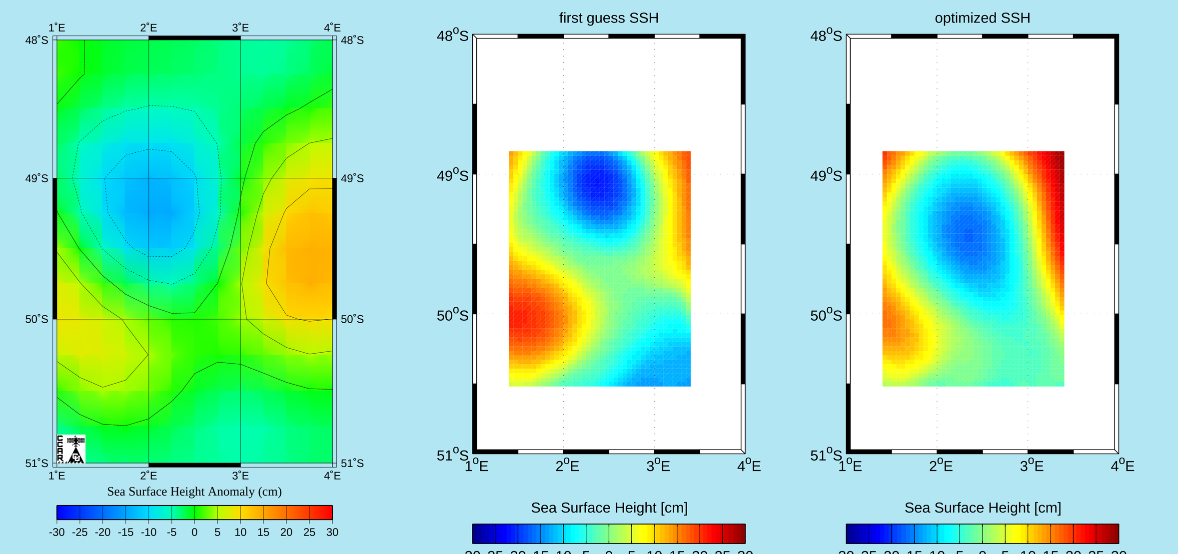

Figure 3: Left: sea surface height (SSH) anomaly from satellite altimetry on day 37 of the experiment (not used in the assimilation; source: `http://www-ccar.colorado.edu/~realtime/gsfc_global-real-time_ssh`). Center: SSH of modeled eddy on day 37 without data assimilation. Right: SSH of modeled eddy on day 37 after full time-dependent state estimation; the eddy extends further south than before, but the comparison of *absolute* SSH with height *anomalies* is ambiguous.

4 Ecosystem Model REcoM and SIR

In a one-dimensional configuration, a mixed layer model (KPP, Large et al., 1994) is driven by meterological parameters (POLDAT, G. König-Langlo) that were collected during the EIFEX cruise to obtain vertical mixing coefficients. The mixed-layer dynamics drives a regulated ecosystem model (REcoM, M. Schartau and M. Losch, personal communications) that includes phytoplankton, heterotrophic zooplankton and detritus, dissolved inorganic matter and extra cellular organic matter for three nutrient groups (nitrate, carbon, and silicium) and the limiting effect of iron. With the physical parameters held fixed, REcoM is assimilated to chlorophyll bottle data collected during the EIFEX cruise (C. Klaas, personal communications) in order to obtain an optimal parameter set for the time of the cruise. Ecosystem model dynamics are notoriously nonlinear. Therefore we use a Sequential Importance Resampling (SIR) filter for the assimilation.

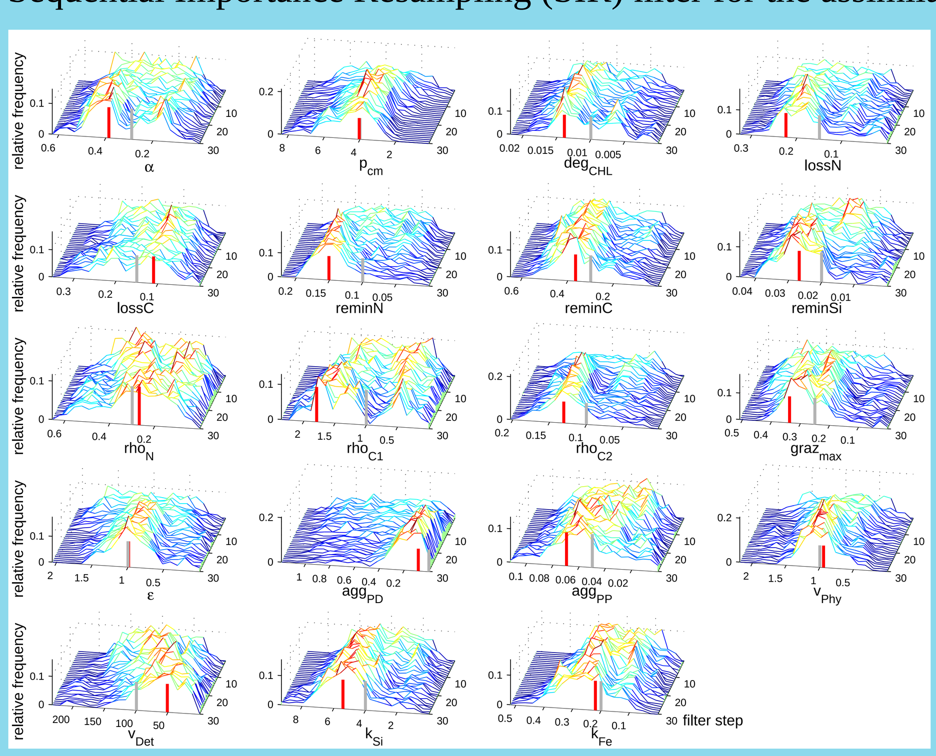

Figure 5: Evolution of 19 adjusted model parameters with filter step in the one-dimensional experiment. After 30 integrations (filter steps) of 500 Ensemble members, some parameters emerge with clear optimal values, for example, the maximum of the C-specific rate of photosynthesis P_{cm} and the sinking velocities v_{Det} and v_{Phy}; other parameters have a bimodal PDF, for example, the Chl-specific initial slope of the P-I curve α and the degradations constations of extracellular organic carbon ρ_{C1}. The grey bars represent the first guess values, the red bars represent the maximum of the PDF.

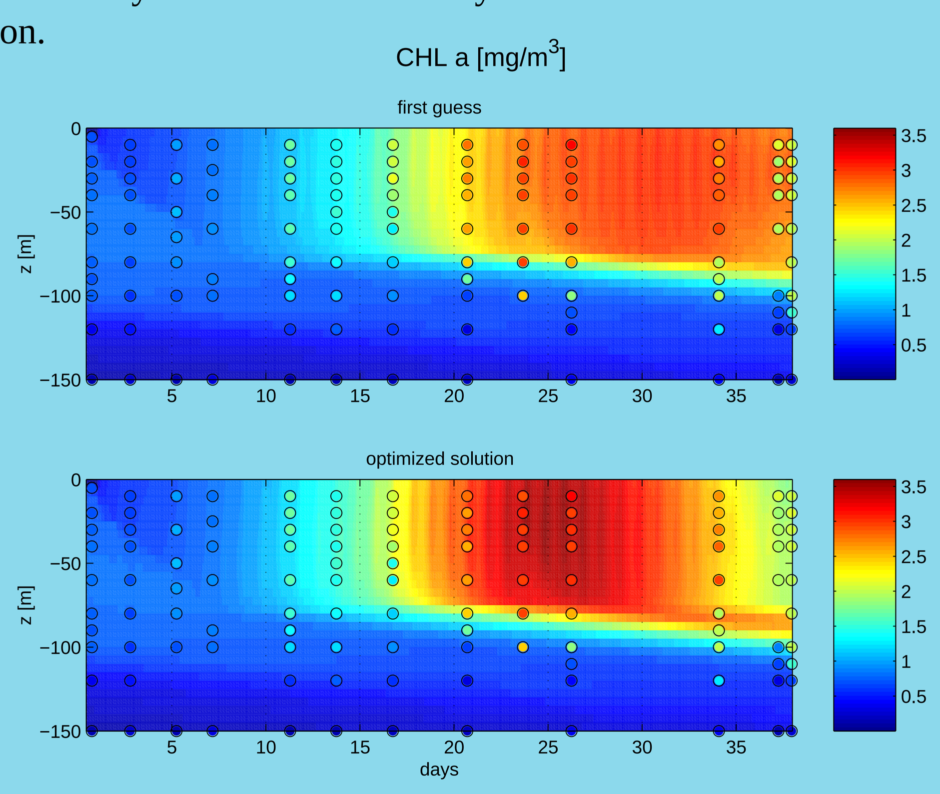

Figure 6: Temporal evolution of cholorphyll a (Chl a) without data assimilation (top) and with data assimilation (bottom) in the one-dimensional experiment. Filled circles represent data values used in assimilation. The assimilated model captures the beginning and the end of the phytoplankton bloom where the unassimilated model fails. Mixed layer physics is not adjusted not affected by data assimilation, therefore the mixed layer is too shallow in both models; consequently they fail to explain high chlorophyll values at the bottom of the observed mixed layer which extends below 100 m depth.

5 Coupling of Optimized Ecosytem Model to the Optimized Circulation Model

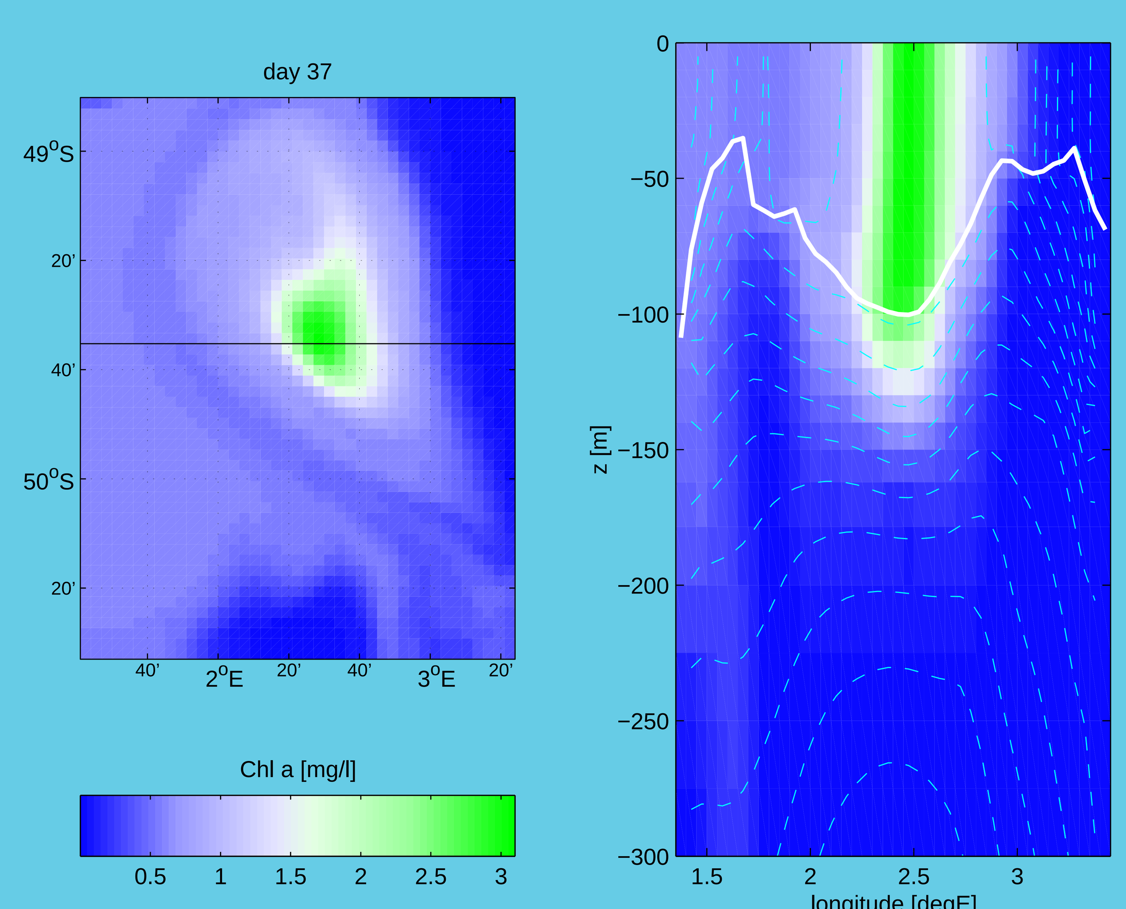

Figure 7: 24 h-mean of modeled chlorophyll concentration on day 37 of the experiment with the optimized coupled ecosystem circulation model; left: top view; right: section through the fertilized patch along black line of top-view graph. Dashed black lines are contours of potential density that show the stratification. Mixed layer depth is indicated by the thick white line.

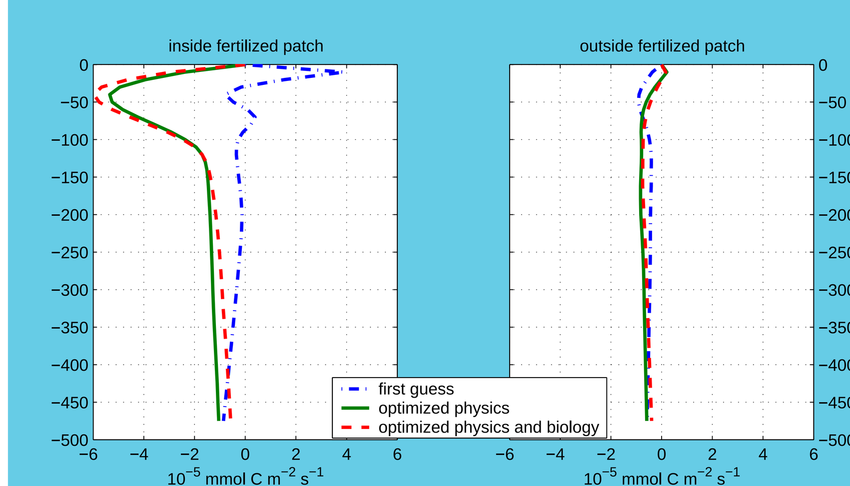

Figure 8: Vertical flux of particulate organic carbon (POC, in mmol C m^{-2} s^{-1}) averaged over the fertilized patch and the entire experiment period for three different experiments: (1) first guess physics and ecosystem parameters (blue), (2) assimilated physical trajectory and first guess ecosystem parameters (green), (3) assimilated physical trajectory and optimized ecosystem parameters (red). Clearly, improving the physical trajectory has a larger impact than optimizing the ecosystem model's parameters. Outside the fertilized patch the effects of improved physics and biology are small.

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