Improving ocean ecosystem predictions

Application of ensemble data assimilation for improved prediction of ocean ecosystem indicators

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In Short

- Coupled ocean-biogeochemical modeling is used to predict ocean ecosystem indicators
- Data assimilation is applied to combine the model information with observational data
- Different data assimilation scenarios are studied to assess their effect in improving the model predictions

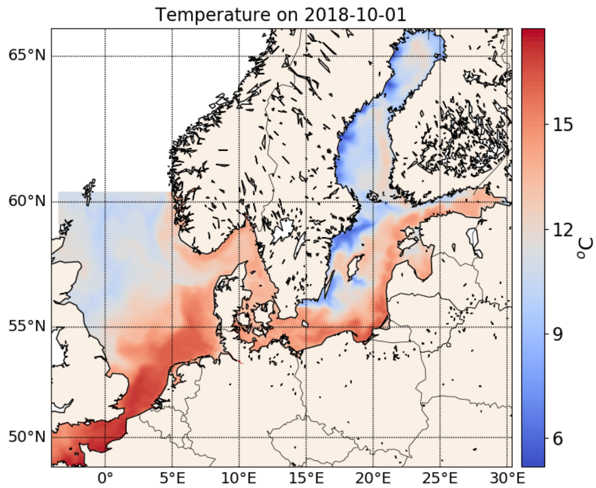

***Figure 1:** Model domain of NEMO-NORDIC used by the CMEMS Monitoring Forecasting Center for the Baltic Sea showing the sea surface temperature on 1st October 2018. The full North Sea and Baltic Sea are simulated at a resolution of 1 nautical mile.*

In this project we study the effect of assimilating observations of ocean physics and biology onto the prediction of ecosystem indicators like particular organic carbon, trophic efficiency, or dissolved oxygen. Data assimilation is the methodology to quantitatively combine models with observations. Here, we apply ensemble data assimilation, which uses an ensemble of model simulations to estimate the uncertainty of the model state as well as the error-covariances between different model variables. The ensemble data assimilation methods are provided by the parallel data assimilation framework PDAF [1,2], which we have developed at the Alfred Wegener Institute.

We use the ocean circulation model NEMO [4], which is a widely used model for research and operational use at the marine service CMEMS [3] of the EU Copernicus program. The particular variant of NEMO we use here is NEMO-NORDIC [5] that is used operationally by the CMEMS Monitoring and Forecasting Center for the Baltic Sea (BAL-MFC). The model domain covers the full North Sea and Baltic Sea as shown in Fig. 1. Compared to [5] we use an upgraded version of NEMO-NORDIC, which is based on NEMO 4.0 and uses a resolution of 1 nautical mile and 56 model layers. The model grid has 1238 grid points in the longitudinal direction and 1046 in the latitudinal direction and hence a large potential for scaling by using domain-decomposition. In addition, the model setup uses the IO-Server XIOS to allow for efficient parallel IO. NEMO has the feature to mask out MPI subdomains that do not contain ocean points, so that the compute resources can be optimally used.

The second model component is the marine biogeochemical model ERGOM see [6,7]. It's structure is shown in Fig. 2. ERGOM simulates biogeochemical progresses and includes bacteria, two phytoplankton groups as well nutrients, zooplankton and detritus. In addition a carbonate cycle allows to simulate the partial pressure of CO2, pH, and particular carbon. The model was recently coupled to NEMO within the BAL-MFC with the aim of operational biogeochemical forecasting.

The first objective of this project is to apply the ensemble data assimilation to assimilate both sea surface temperature and chlorophyll observations into the coupled ocean-biogeochemical model NEMO-ERGOM. The resulting model forecasts will be analyzed with regard to the influence of the assimilation on ecosystem indicators, in particular particular organic carbon, trophic efficiency, dissolved oxygen, primary production, and pH.

The second objective of this project is to examine how far strongly-coupled data assimilation can be applied. In strongly-coupled data assimilation cross-covariances between the ocean physics and biogeochemistry are used to jointly update the coupled model state. Thus, in practice this enable us to e.g. assimilate sea surface temperature into the biogeochemical model. This approach is expected to provide joint model states of better consistency compared to the case that the model physics and biogeochemistry are corrected separately (so-called weakly coupled data assimilation). Some positive effects of strongly-coupled data assimilation were reported by [8].

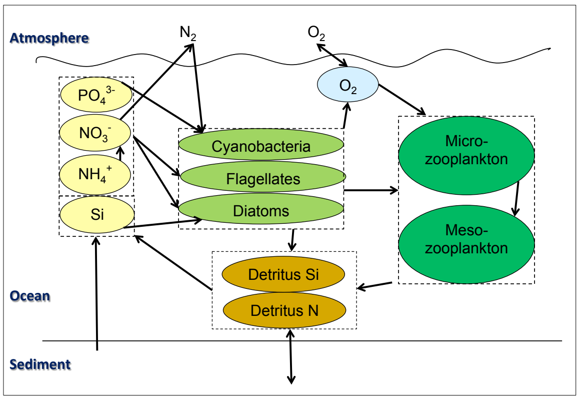

Figure 2: *Schematic overview of the ERGOM biogeochemical model (modified by I. Lorkowski (BSH) after [7]).*

Finally, the effect of nonlinear data assimilation methodology will be assessed in this project. It is known that the dynamics of the ocean physics at the high resolution of the model are nonlinear. Likewise the ocean-biogeochemical processes are nonlinear and the ocean variables are not normally distributed. As such the usually used ensemble Kalman filters, like the error-subspace transform filter [9] are expected to operate sub-optimally. In contrast nonlinear data assimilation methods, e.g. particle filters, can handle nonlinear models and the resulting non-Gaussian error distribution. To assess the effect of nonlinear data assimilation, we will apply the hybrid nonlinear-Kalman ensemble transform filter [10] and compare the results obtained using the linear ensemble Kalman filter method with those of the hybrid filter.

Due to the integration of an ensemble of model state realizations, ensemble data assimilation is computationally very costly. However, the methodology has a high parallel scalability and is hence optimally suited for a supercomputer like HLRN.

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https://www.awi.de

More Information

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DFG Subject Area

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