

OCEAN BIOGEOCHEMICAL MODEL UNCERTAINTIES

Application of ensemble data assimilation to a one-dimensional model

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Introduction

Ocean biogeochemical models are increasingly used in the Earth system modelling efforts for climate simulations, and also for the development of marine environmental applications and services. However, they are associated with large undefined uncertainties. Data assimilation (DA) has been well received in the geoscience community as an effective method in characterizing the model uncertainties while estimating parameters, prognostic, and diagnostic variables. In this study, we apply an ensemble data assimilation method for characterization and quantification of the uncertainty arising within biogeochemical models.

Model Set-up

The biogeochemical model Regulated Ecosystem Model 2 (REcoM2) is coupled with MIT General Circulation Model (MITgcm) in a 1-D vertical configuration at the Bermuda Atlantic Time-series Study (BATS) station. The station BATS was selected because of availability of long-term time-series data.

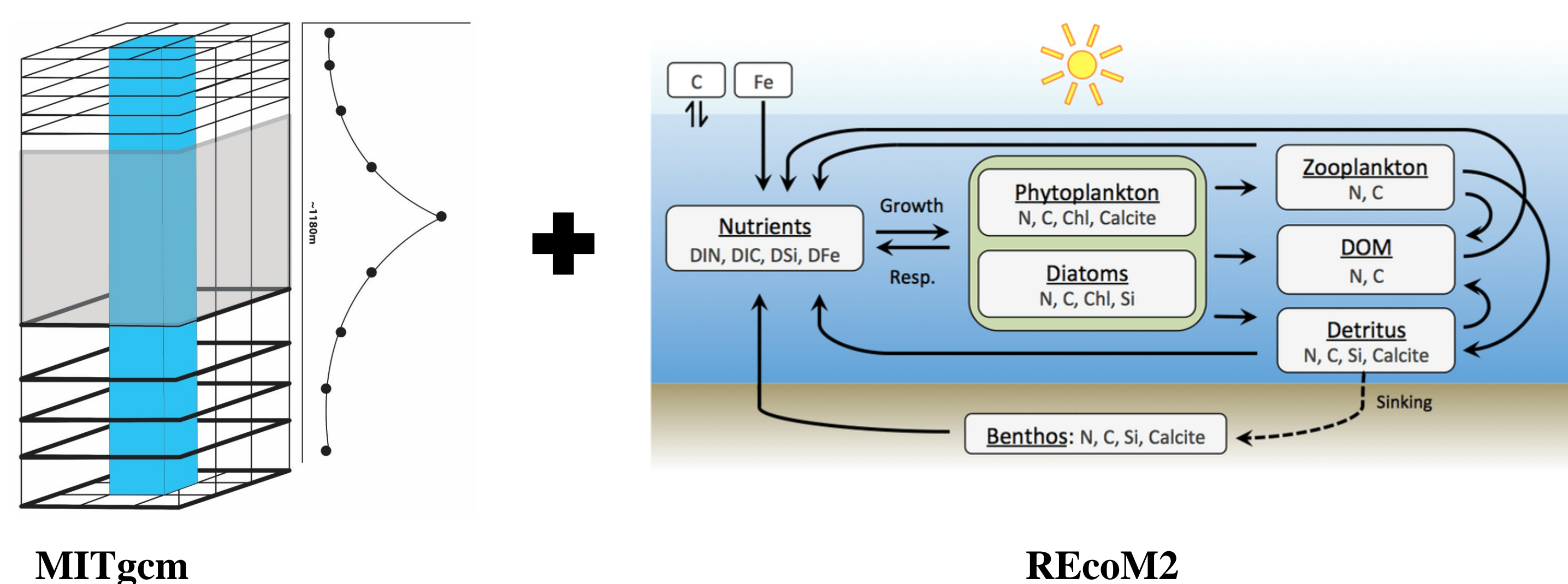
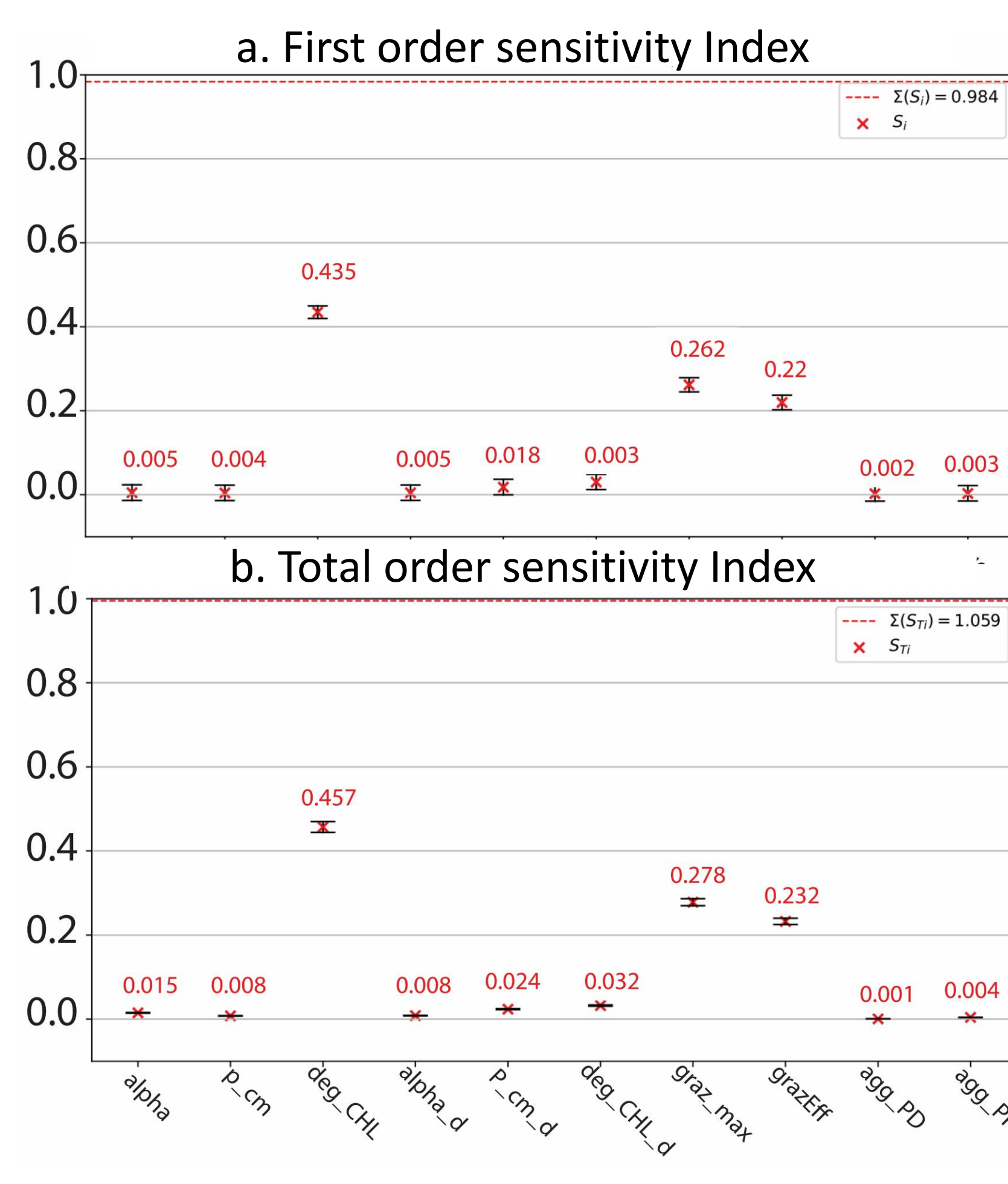


Fig. 2 The coupled MITgcm-REcoM2 model. REcoM2 has two phytoplankton classes, one zooplankton and four nutrients. Dead organic matter is transferred to detritus by aggregation. The sinking and advection of detritus is represented explicitly.

Sensitivity Analysis

To determine which model parameters are the most influential on output values of Chlorophyll-a concentration and net primary production, we conducted a global sensitivity analysis based on Sobol indices. It quantifies the respective influence of uncertain parameters either through their direct effect (first order sensitivity index) or through their mutual interaction (total order sensitivity index). We apply a full Monte Carlo method for sampling from parameter space of 10 parameters. Fig. 3 shows the sensitivity indices for the average of highest chlorophyll-a concentration over five years. Parameter *deg_CHL*, Chlorophyll degradation for small phytoplankton, is clearly the most sensitive parameter. The grazing parameters *grazmax* and *grazEff* also contribute a considerable part to the overall sensitivity. The values of the total order indices are slightly higher than their corresponding first-order index, which indicates that some parameters have mutual dependencies which is expressed in higher order sensitivity indices.



Data Assimilation

We assimilate surface satellite chlorophyll-a concentration obtained from the OC-CCI for three years using the ensemble data assimilation (EnDA) technique. We use the Parallel Data Assimilation Framework – PDAF software package for implementation of the EnDA. To generate ensemble members, we perturbed the ten biogeochemical parameters (those we use for sensitivity analysis) related to chlorophyll-a. The data assimilation experiment was conducted with 5-days analysis cycles.

Fig. 4 shows that the chlorophyll-a concentration from the assimilation experiment is lower than the free run in the bloom period. Fig. 5 confirms that the model surface chlorophyll-a concentration is much higher compared to the satellite data during the spring bloom period - assimilation reduces the concentrations, bringing the model closer to the satellite data. Data assimilation results in 23% and 27% reduction of root-mean-square error and bias, respectively, in the simulated surface chlorophyll – a concentration. Fig. 6 shows assimilation effects on the biomass concentration of carbon (C), nitrogen (N) and silicate (Si). Overall the concentration of C, N and Si reduces during the bloom period which is as expected.

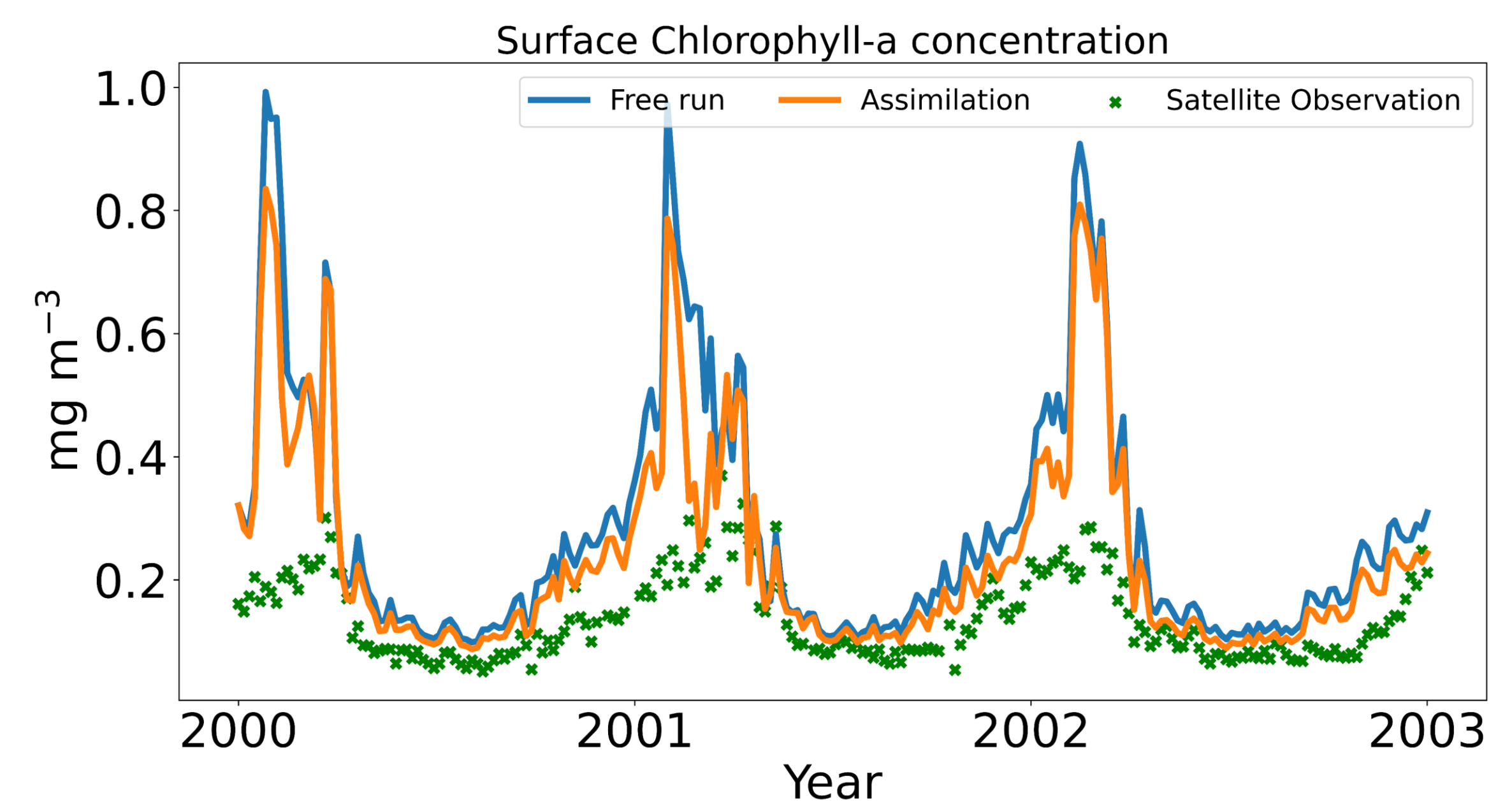
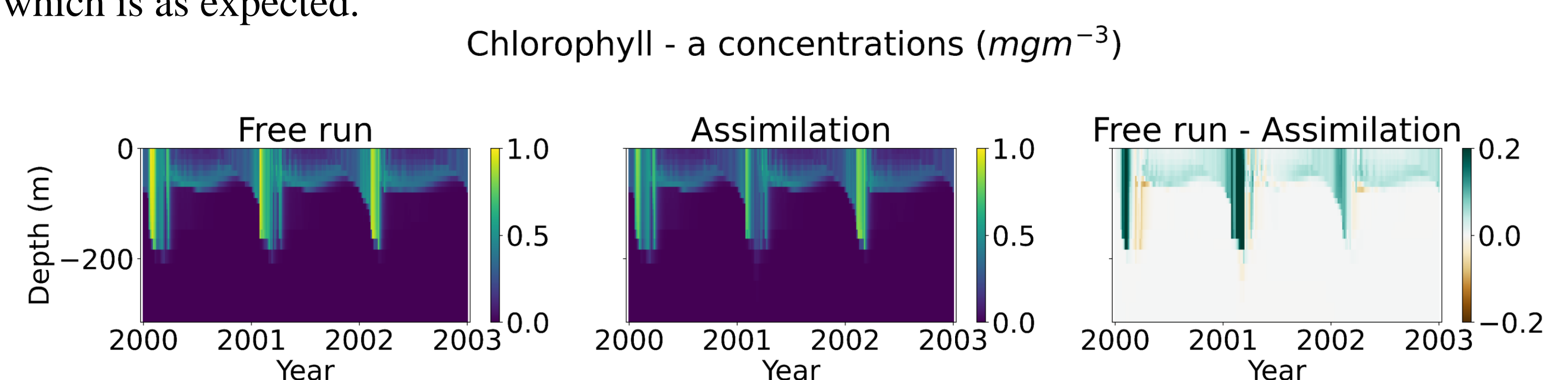


Fig. 5 Comparison of simulated surface chlorophyll-a concentration against satellite data

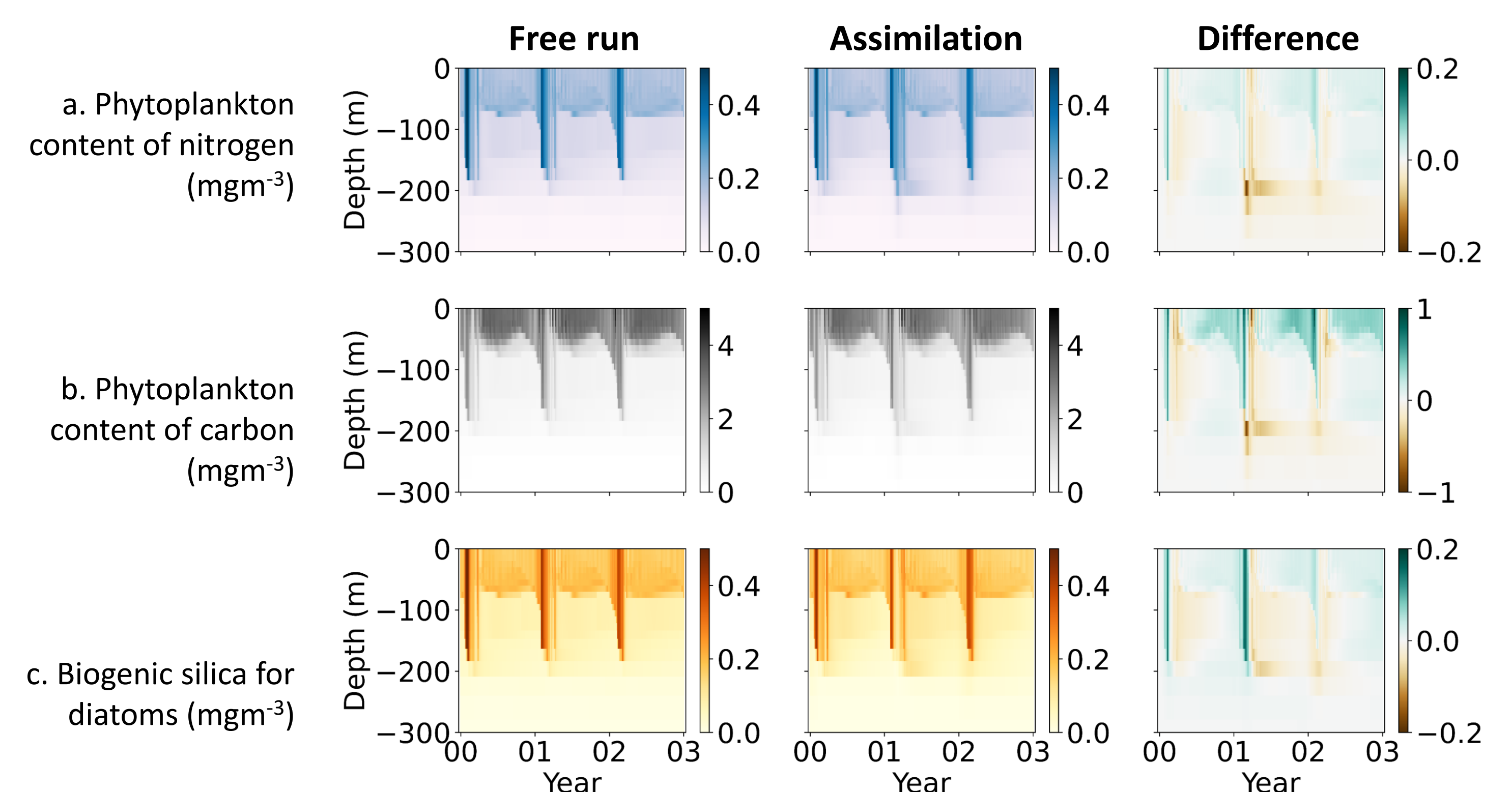


Fig. 6 Biomass concentration in C, N and Si units in the water column obtained using the REcoM2 ensemble mean between 2000 and 2002.

Future plan

- From the Fig. 5 we can see large bias in model simulation both with and without data assimilation. The next step would be the calibration of model results by adjusting parameter values in light of the data and to learn from the temporally varying estimated parameters.
- The experiment in the station BATS provides good insight on the uncertainty of model fields and parameters, however, may not be valid for other region. We would therefore test the modeling system one or more sites. Next plan is to implement the sensitivity analysis and data assimilation system for the DYFAMED station at the Mediterranean sea.
- We will implement the assimilation system in a global model in 3D model setup for parameter estimation and to study the effect of estimated spatially and temporally varying parameters on the biogeochemical fields and dynamics for insights into BGC processes and modeling.