Optimizing Ocean Biogeochemical Models Harnessing satellite ocean color data for spatially varying parameter estimation

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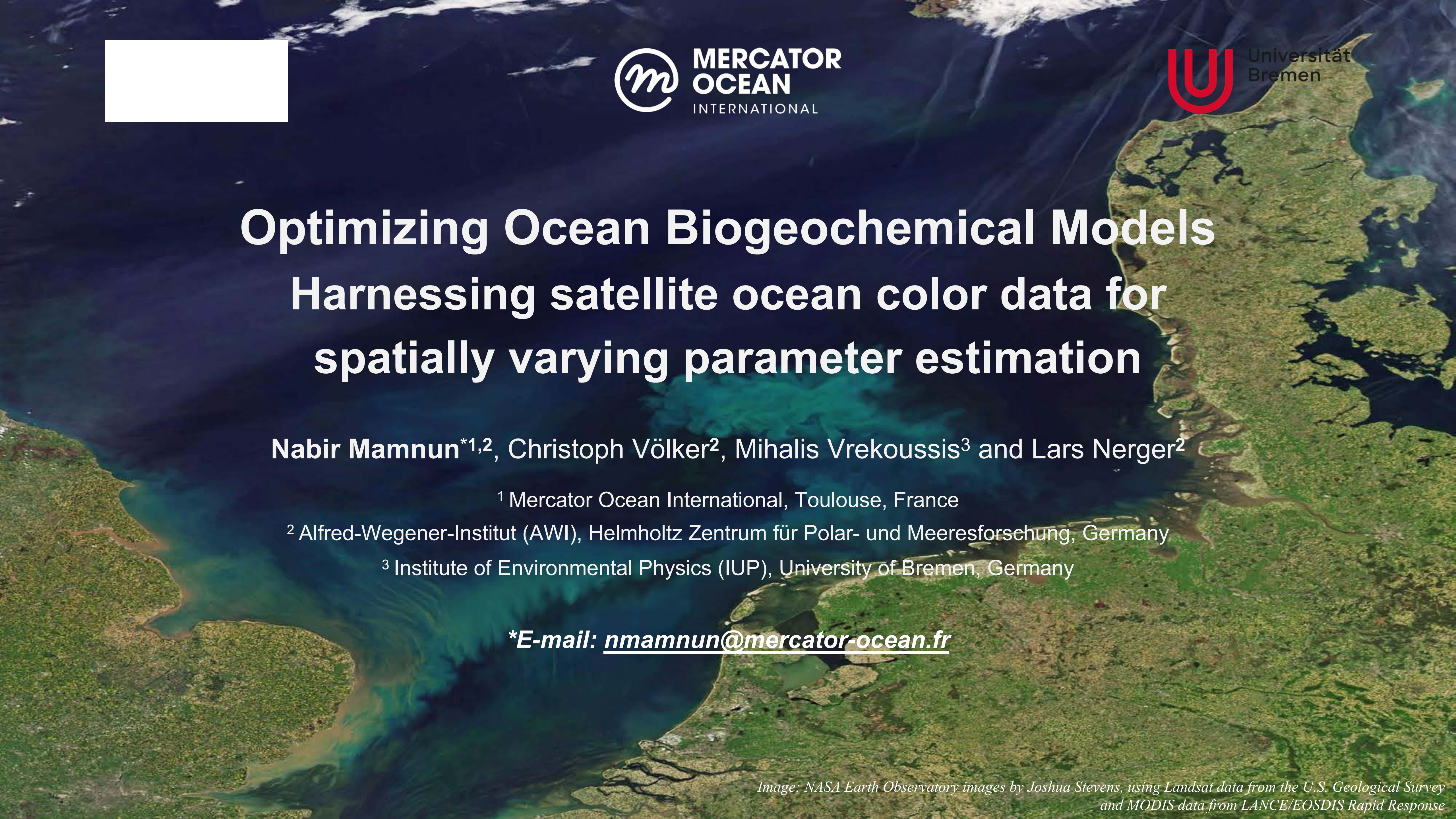


Image: NASA Earth Observatory images by Joshua Stevens, using Landsat data from the U.S. Geological Survey and MODIS data from LANCE/EOSDIS Rapid Response

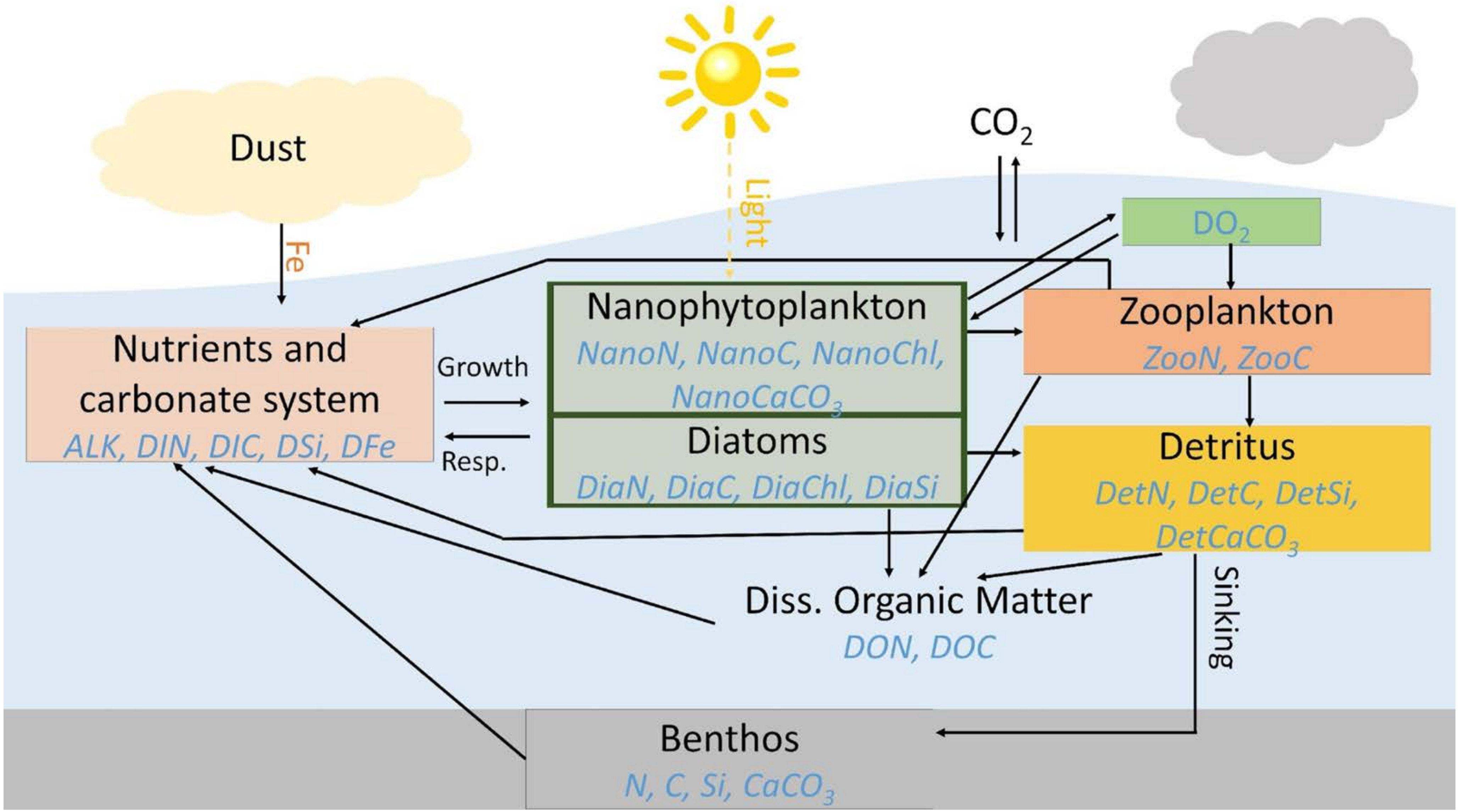
Parametrization is the major source of uncertainty

- Ocean biogeochemical models include numerous parameters, the values of which are **not precisely known**
- Uncertainty in parameter values leads to **significant uncertainty** in model outputs
- Parameter values depend on physical and ecological context, but models use **constant values in space and time**

→ estimate spatially and temporally varying parameters in a global ocean biogeochemical model

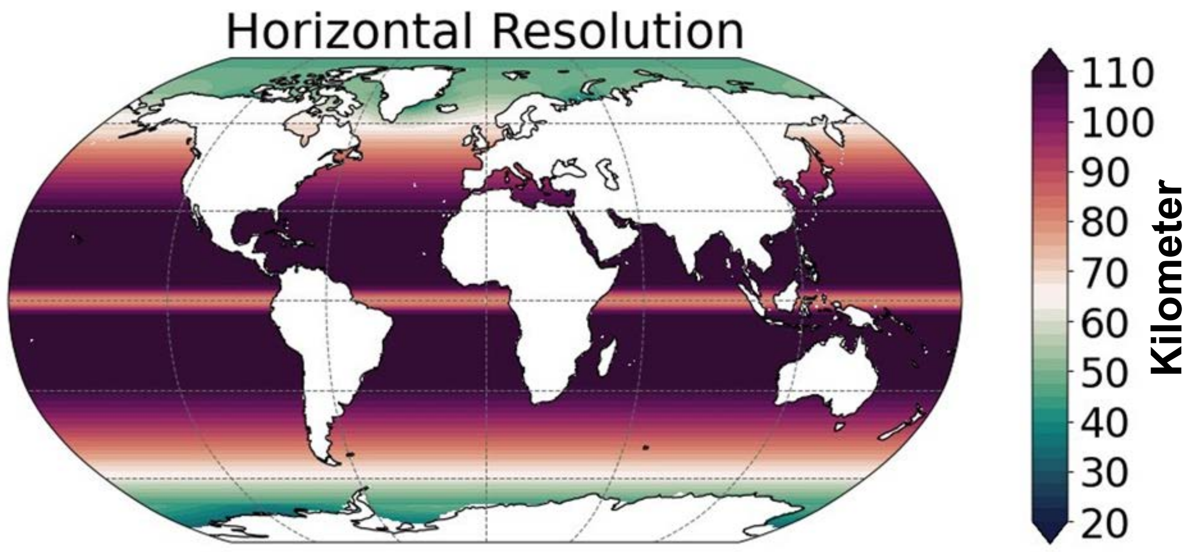
The Regulated Ecosystem Model Version 2 (REcoM2)

REcoM2 (*Hauck et al., 2013*); **Figure:** *Mamnun et al. (2023)*



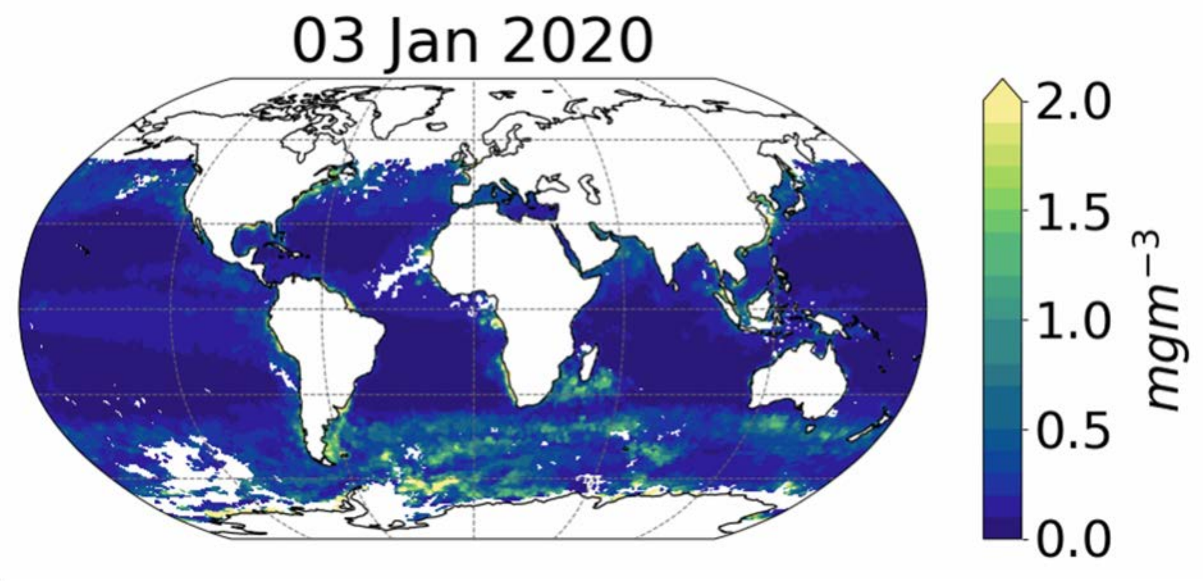
MITgcm-REcoM2

- REcoM2 is coupled with a global configuration of **MITgcm**
- Horizontal resolution varies spatially, ranging from **20 to 110 kilometer**
- **50** vertical levels



Observations

- **Satellite chlorophyll-a concentration** from Ocean Colour - ESA Climate Change Initiative (**OC-CCI**)
- **5-day composite** data product
- Dataset include per-pixel uncertainty information



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- Apply an **Ensemble Kalman Filter**
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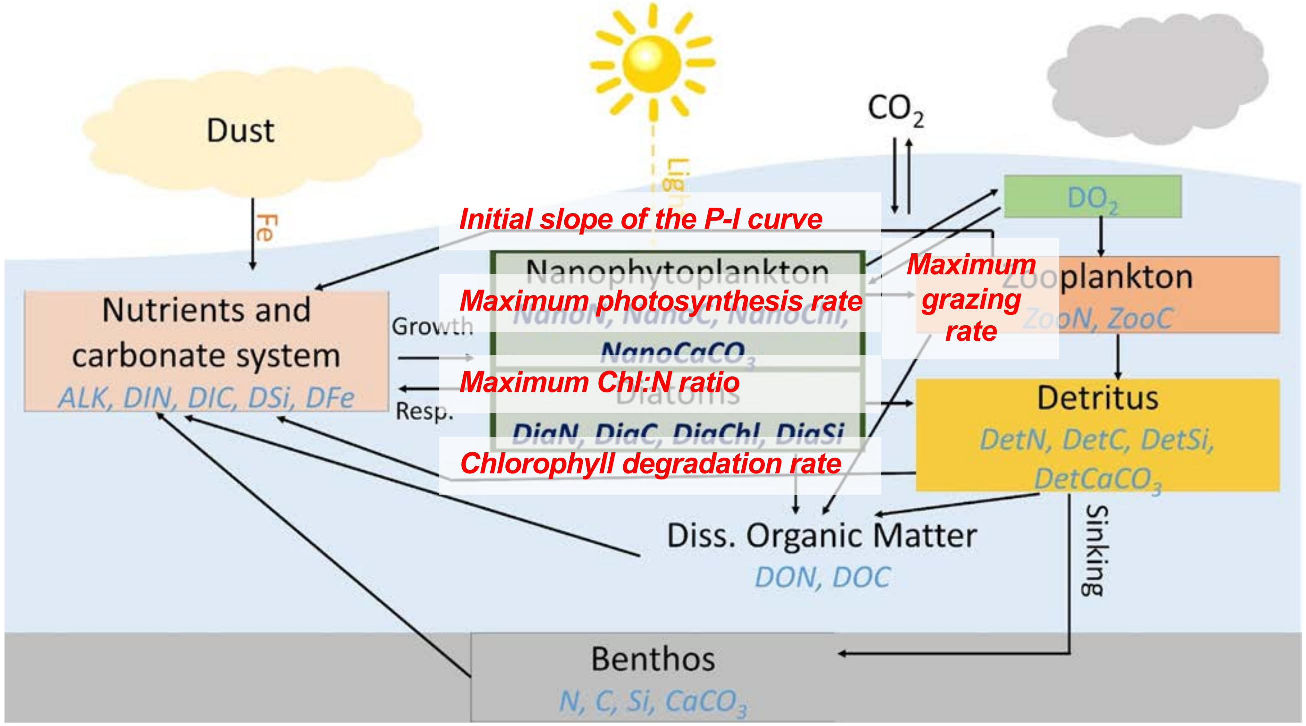

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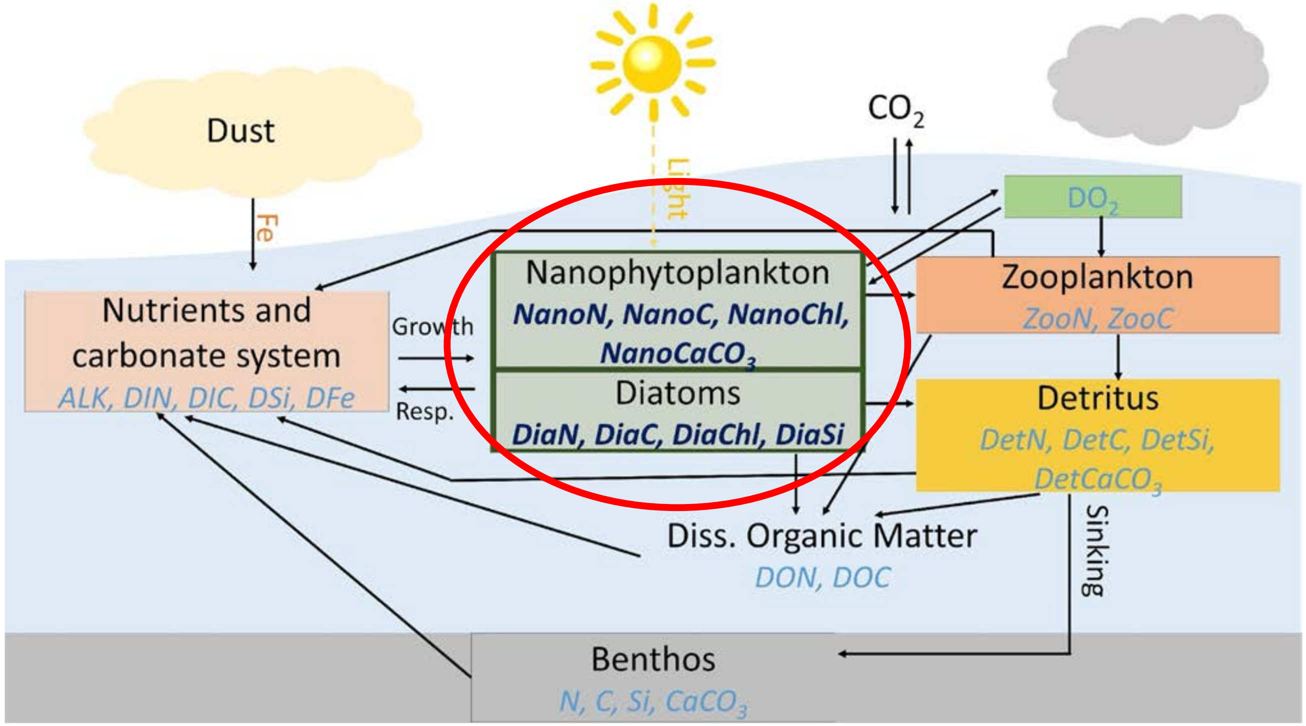
- Apply an **Ensemble Kalman Filter**
- **40 ensemble members** generated by perturbing parameters in a **lognormal distribution**
- Perturb **9 parameters** selected by a ***global sensitivity analysis***
- **Update 8 state variables** along with the 9 perturbed parameters



Data assimilation implementation

- Data assimilation experiment for **one-year 2020**
- Implemented using **Parallel Data Assimilation Framework (PDAF)**

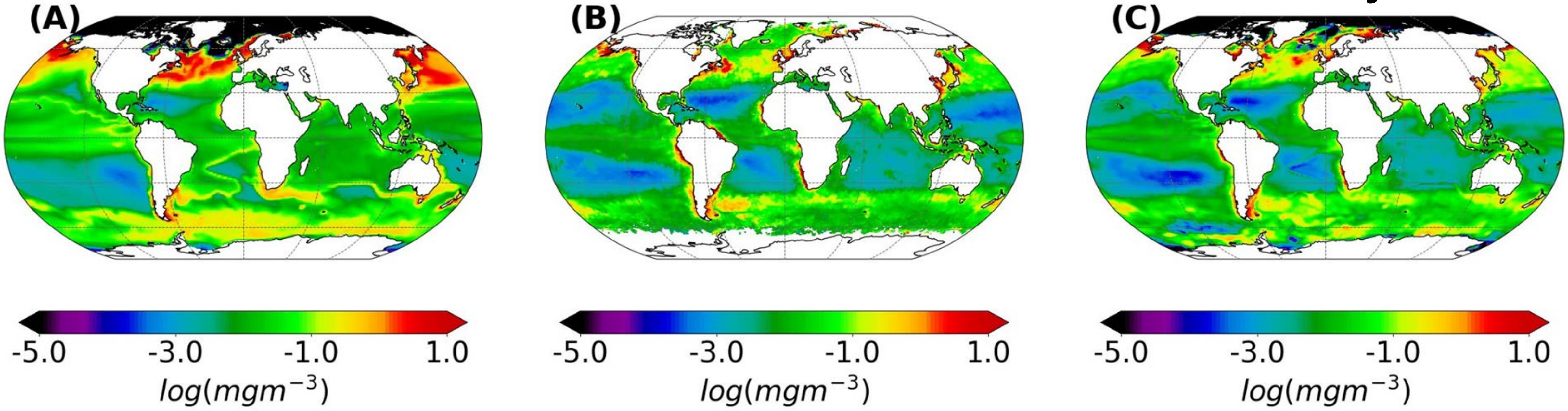
PDAF Parallel
Data Assimilation
Framework

https://pdaf.awi.de

Joint State-Parameter Estimation

Log transform surface chlorophyll-a concentrations in April 2020

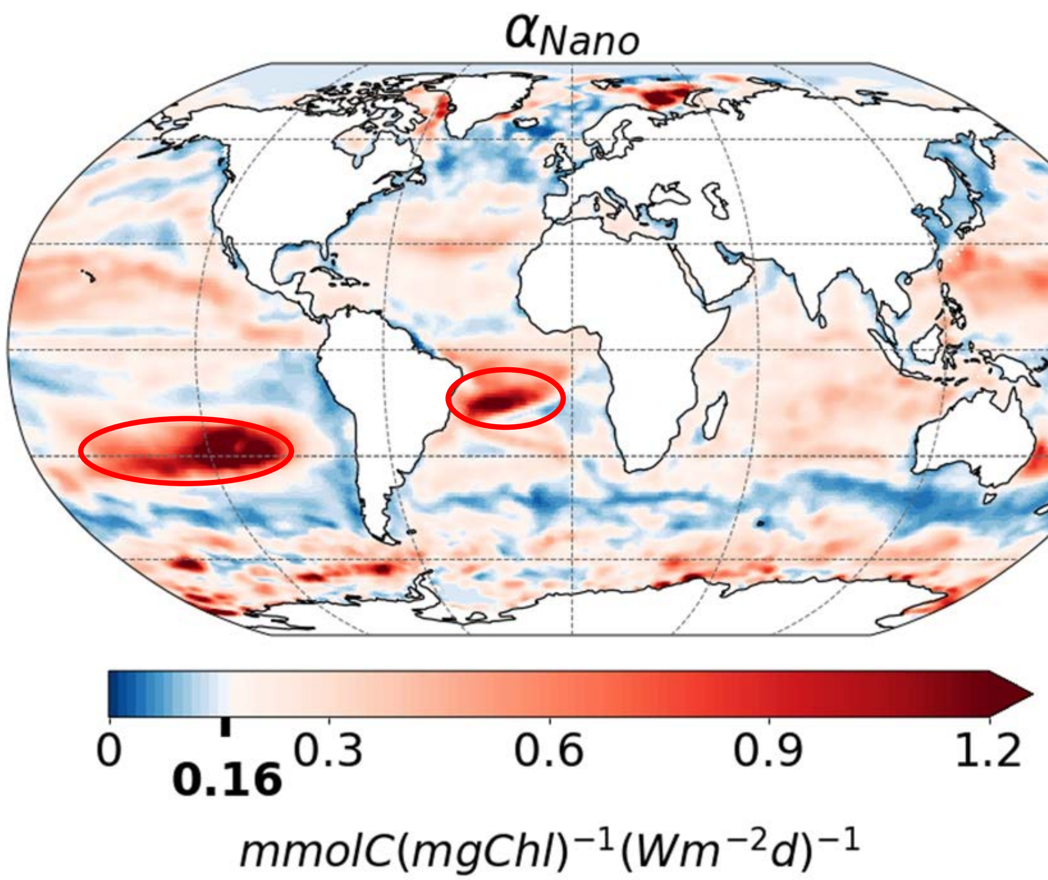
Free run **OC-CCI** **DA Analysis**



Free run performs poorly but **Joint state-parameter estimation substantially improves** the simulation of surface chlorophyll-a concentrations.

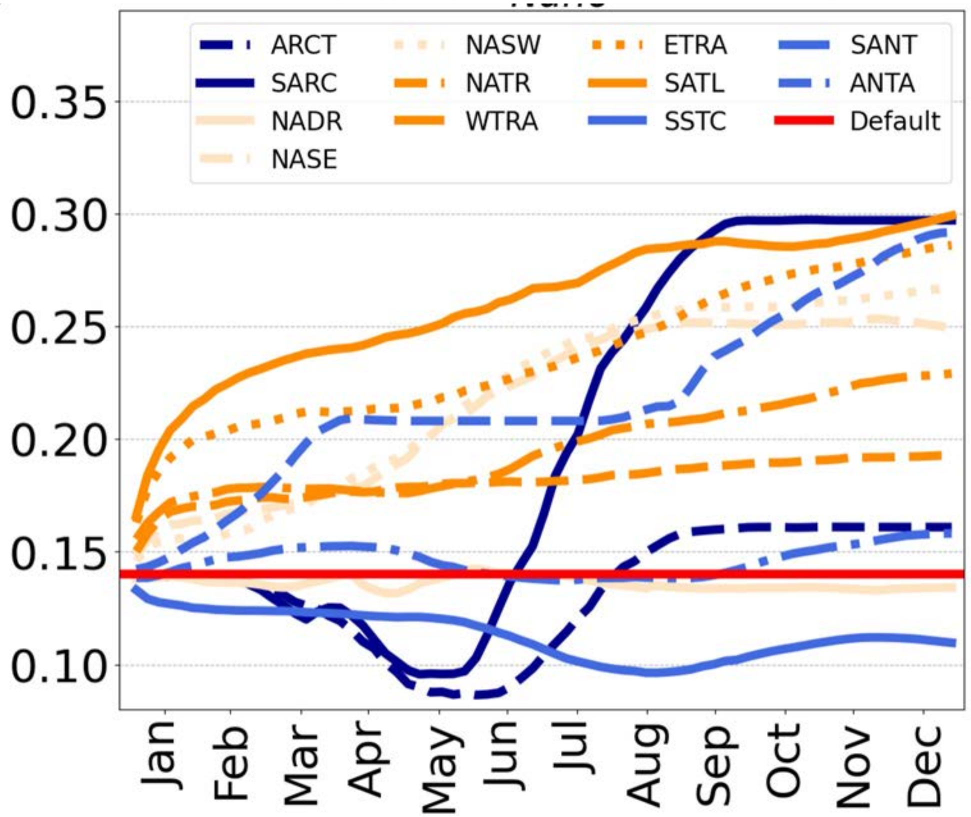
Spatially varying parameter estimates

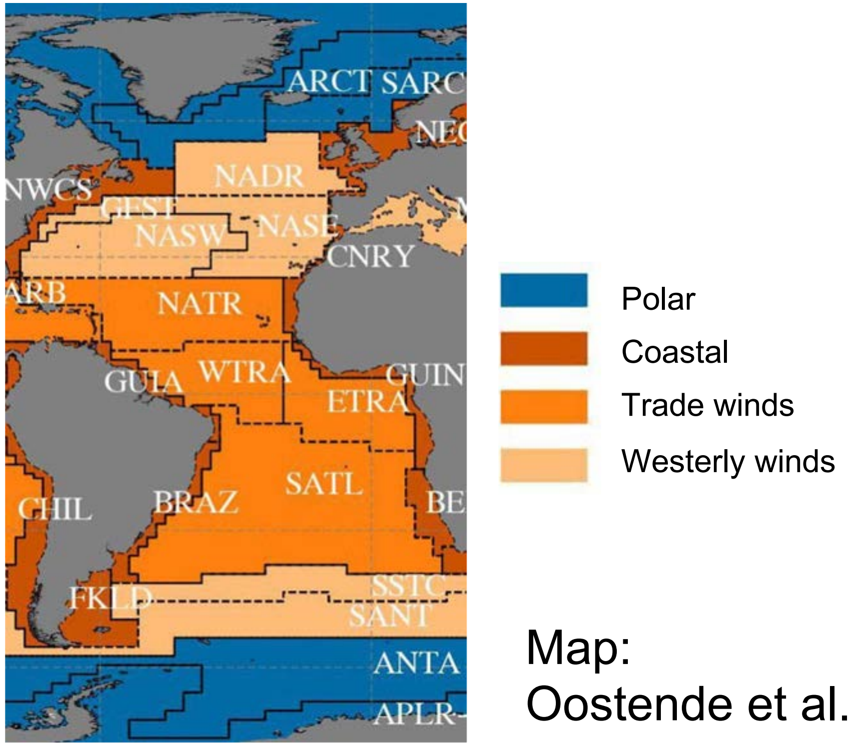
- Spatial varying estimated values of the nanophytoplankton initial slope of the photosynthesis-irradiance curve ($\boldsymbol{\alpha_{Nano}}$).
- A higher value means that less chlorophyll-a is needed to achieve the same primary production under light limiting conditions.
- The spatial range and dynamics are **consistent with observations** (*Bouman et al., 2018*).



Temporal evaluation of parameter estimates

Nanophytoplankton Initial slope of the P-I curve (α_{Nano})





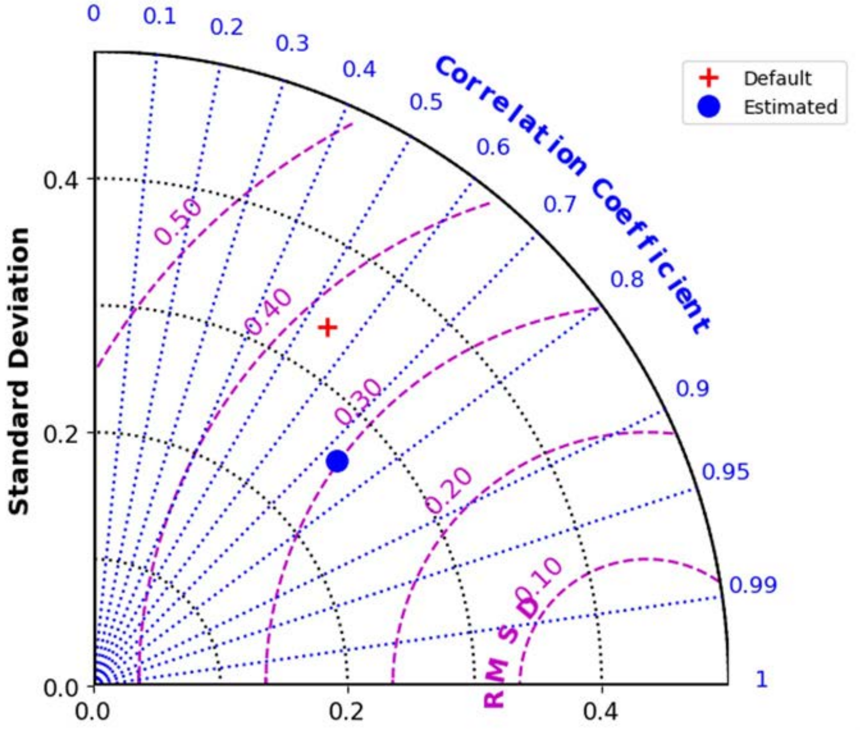
Map:
Oostende et al. (2023)

- Mid and low latitudes: Most variations in α_{Nano} during the initial cycles of DA experiments
- **Polar provinces: Large temporal variability** in α_{Nano}

Model Run with Estimated Parameters

- Simulation with spatially varying estimated parameters reduces root mean squared errors by 24%
- Correlation coefficient increases from 0.52 to 0.74

Taylor diagram of annual mean surface chlorophyll-a concentrationsfrom 2017 to 2021



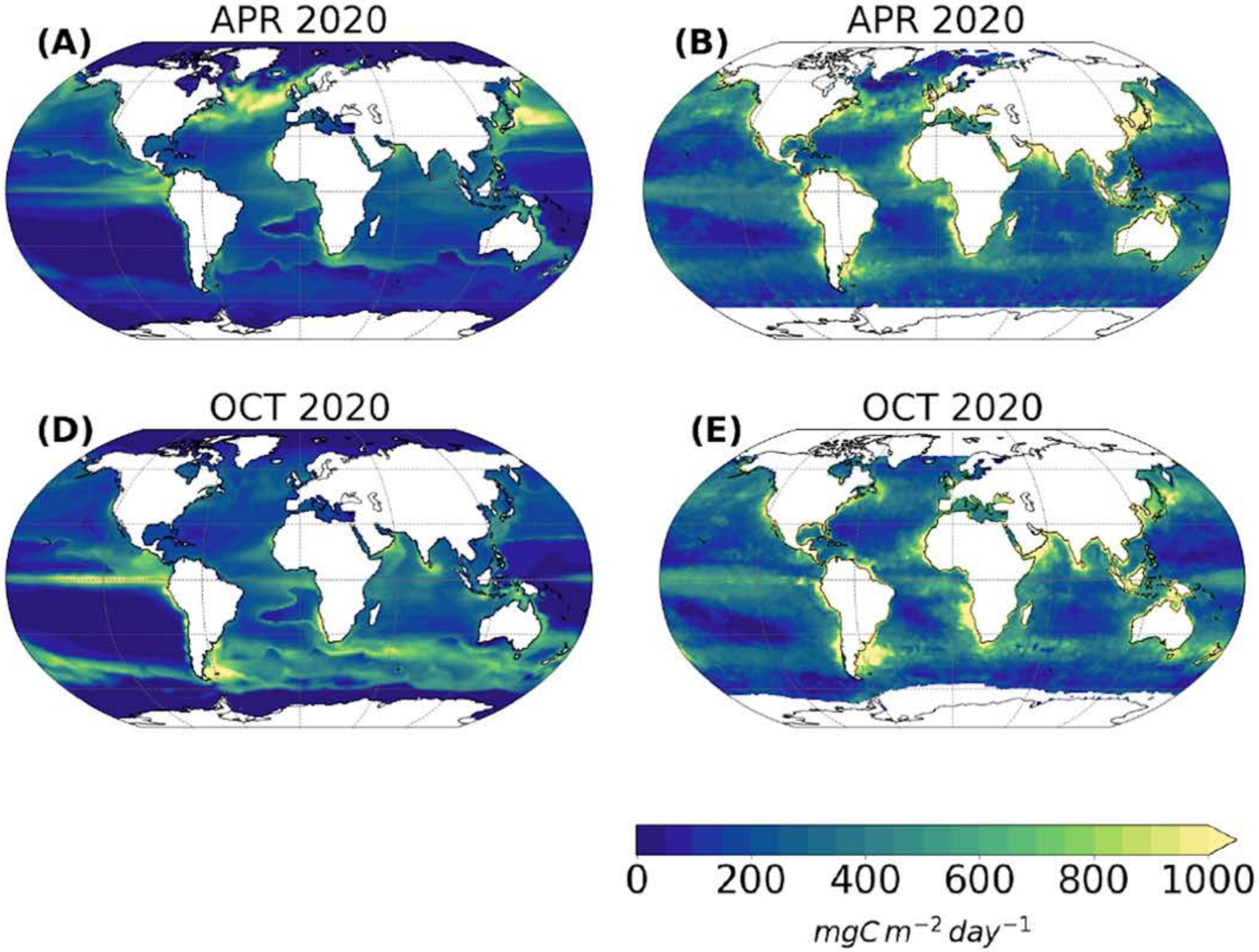
Model output using the estimated spatially varying parameter values is closer to the observations compared to the reference simulation based on uniform parameter values.

Net Primary Production

Simulation with uniform default parameters

Estimates based on satellite data

Simulation with spatially varying estimated parameters



Summary

- Estimate 9 spatially and temporally varying biogeochemical model parameters by assimilating satellite ocean color data in a global ocean model
- The dynamical ranges of spatially varying parameter values are consistent with observations
- Spatially and temporally varying parameter estimates increase usefulness for global and regional modeling

THANK YOU