Alternatives methods for mitigating bias in Earth System models

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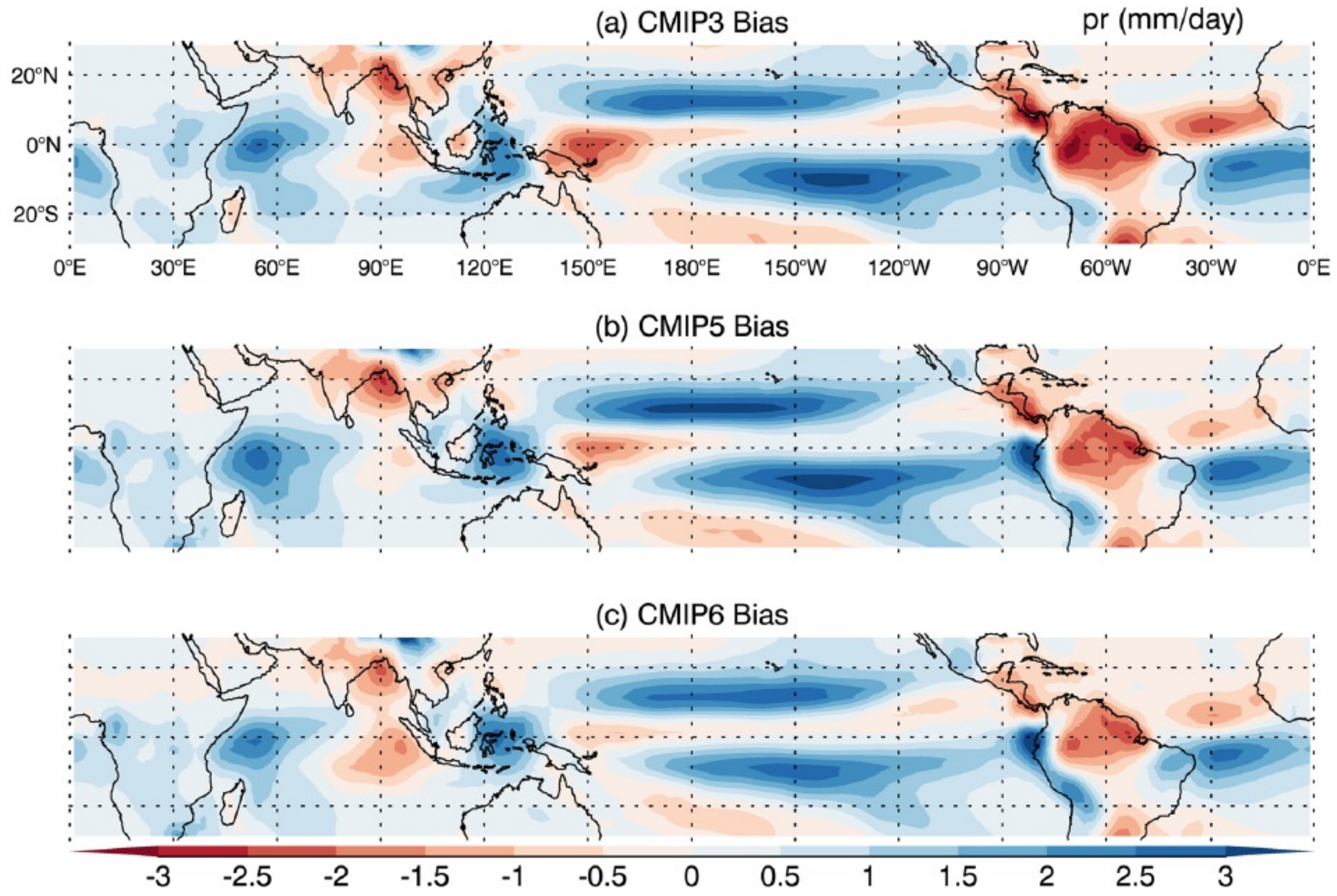
EnKF Workshop 16th of June

Persistent model biases along model development



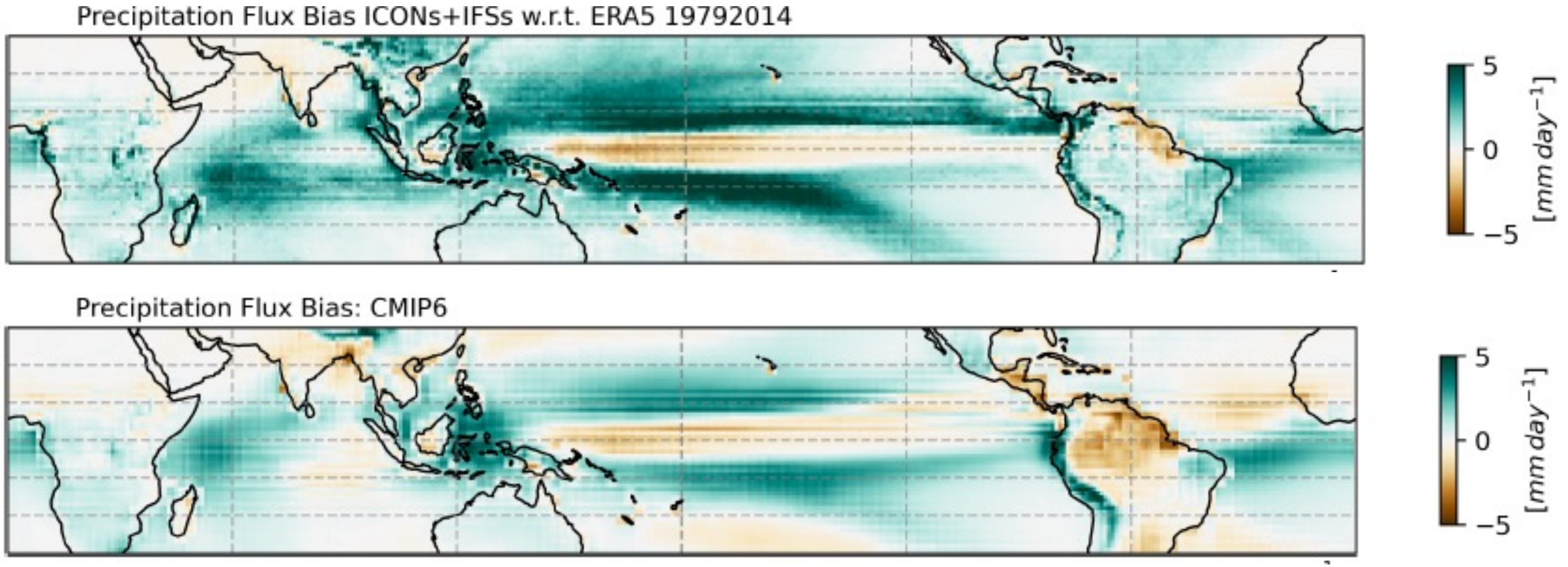
Tian and Dong 2020

….. storm-resolving models are no silver bullet

Precipitation bias

Ensemble average of km-scale models (ICON + IFS/FESOM)

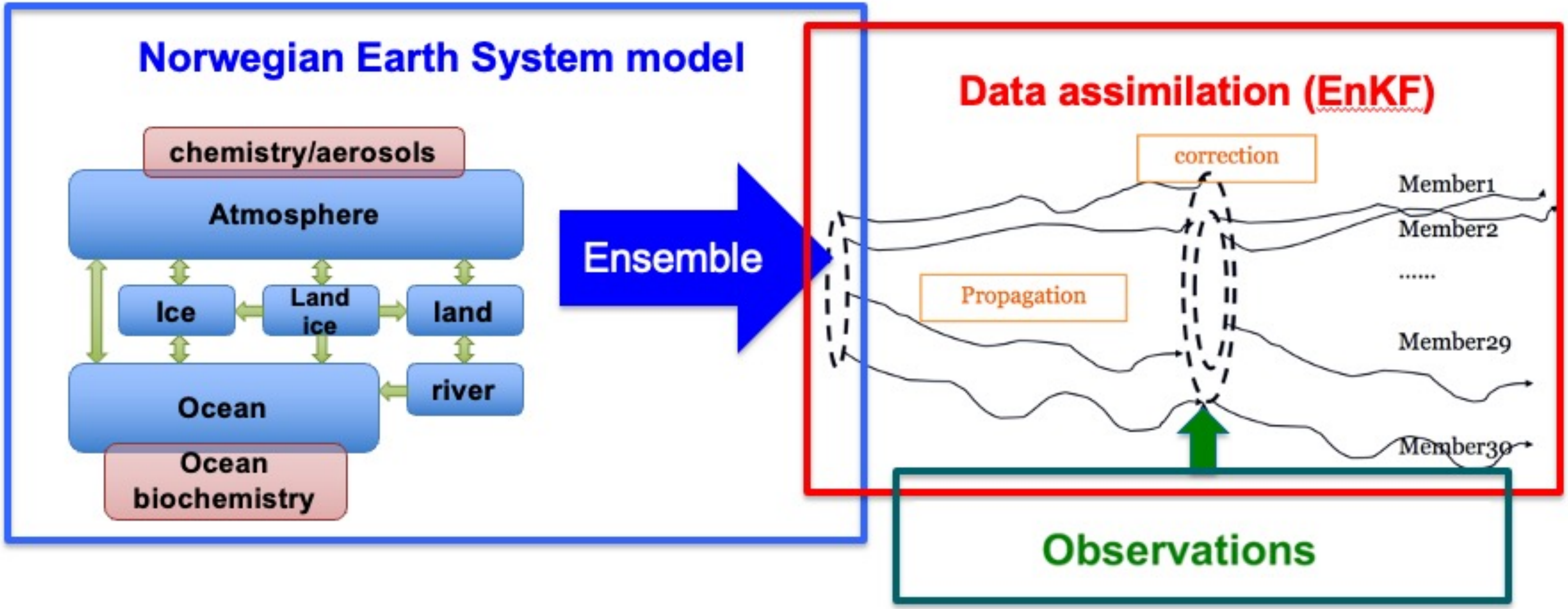
CMIP6 (coupled)



Tian et al. 2024, NextGEMS deliverable 6.1

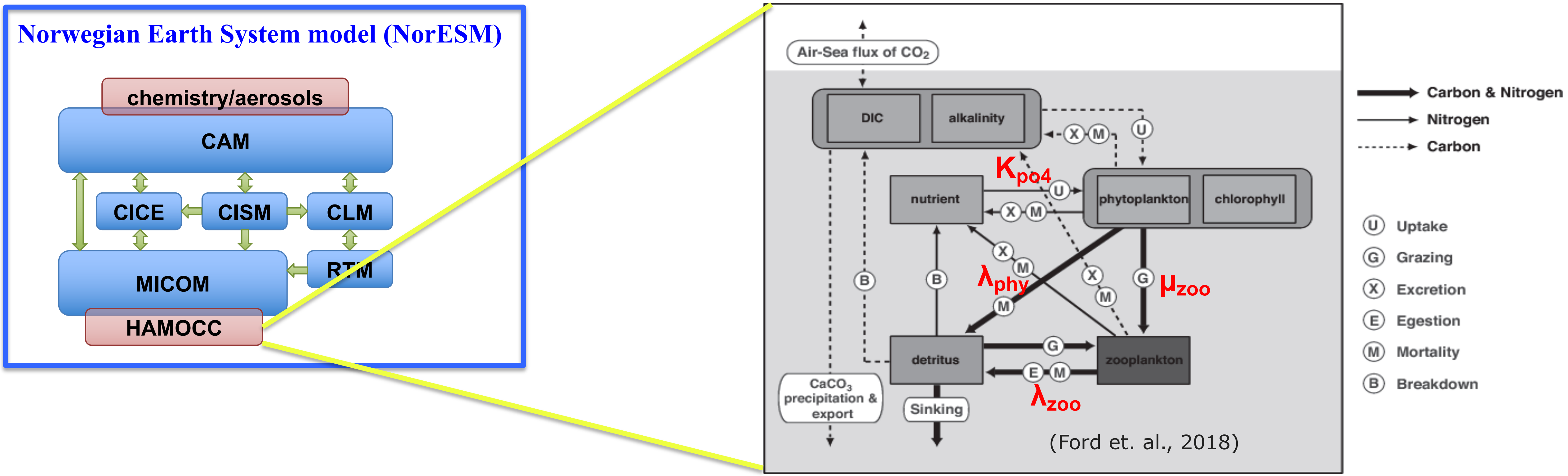
NextGEMS

Norwegian Climate Prediction Model (NorCPM)



[e.g. Counillon et al. 2016]

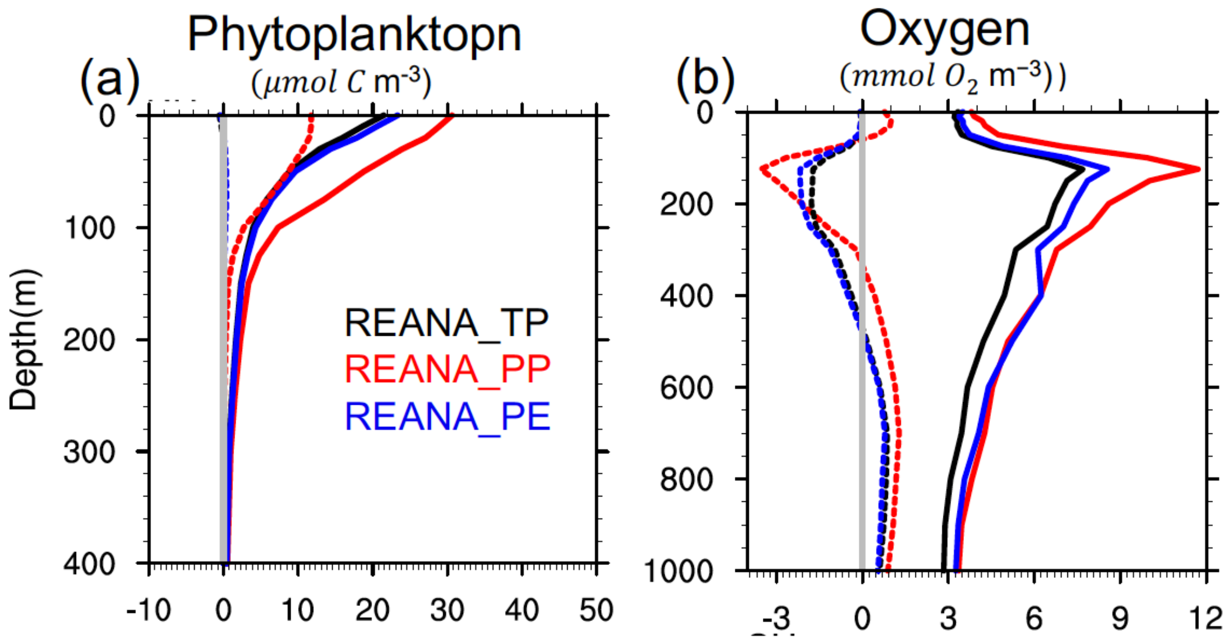
Ocean Biogeochemical (BGC) Processes in an Earth System Model



(1) Half-saturation constant for nutrient uptake during phytoplankton growth (**BKPHY**)
(2) Maximum zooplankton grazing rate (**GRAZRA**)
(3) Sinking speed for particulate organic carbon (**WPOC**)
(4) Deep ocean remineralisation constant of particulate organic carbon (**DREMPOC**)
(5) Half-saturation constant for silicate uptake during biogenic opal production (**BKOPAL**)

Proof of concept in idealised twin experiment

Use the Dual One Step Ahead Smoother (DOSA, Gharamti et al. 2017)
➔ method converges quickly (less than a year) and largely reduces the errors in the BGC parameters and retrieves the spatial pattern even with very sparse observation network.



Estimated parameter performs nearly as good as with perfect parameters both for the free and reanalysis run

[Singh et al. 2022]

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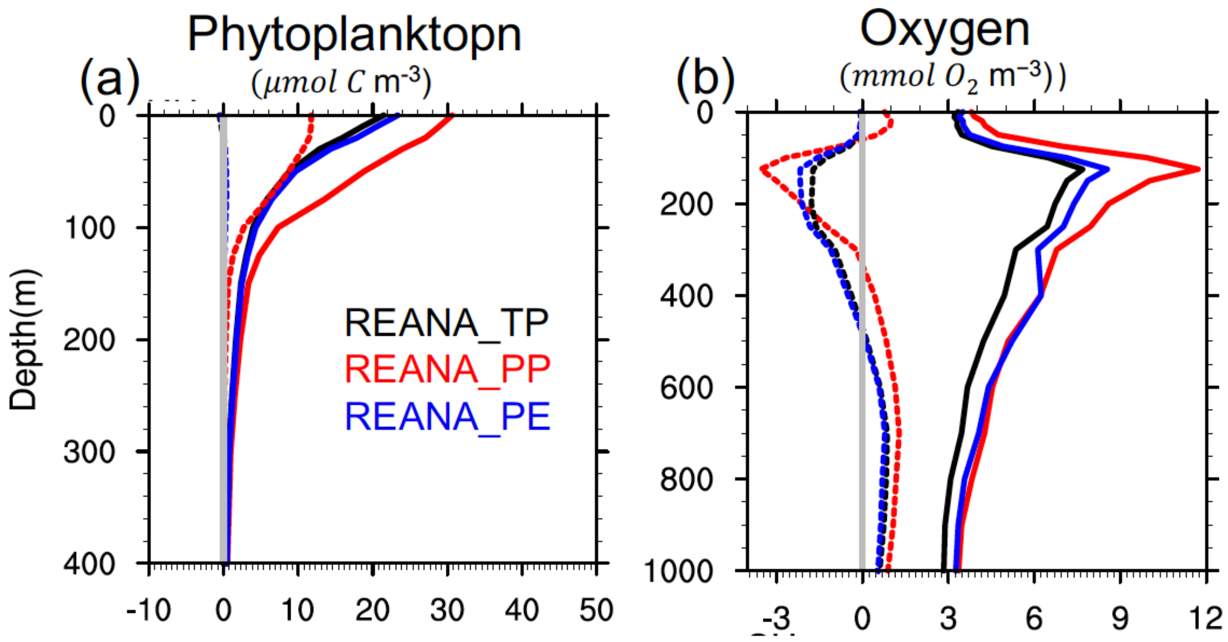


Estimated parameter performs nearly as good as with perfect parameters both for the free and reanalysis run

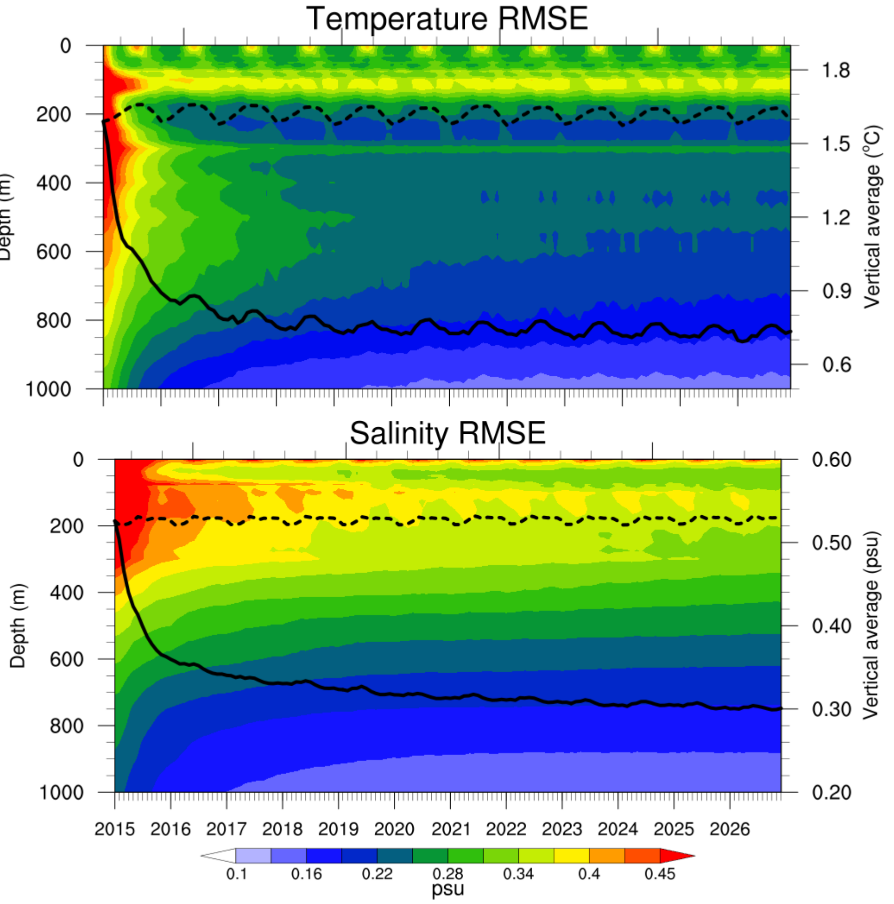
[Singh et al. 2022]

However, it does not work in real framework :
parameter gets unrealistic and perform degraded in a validation run

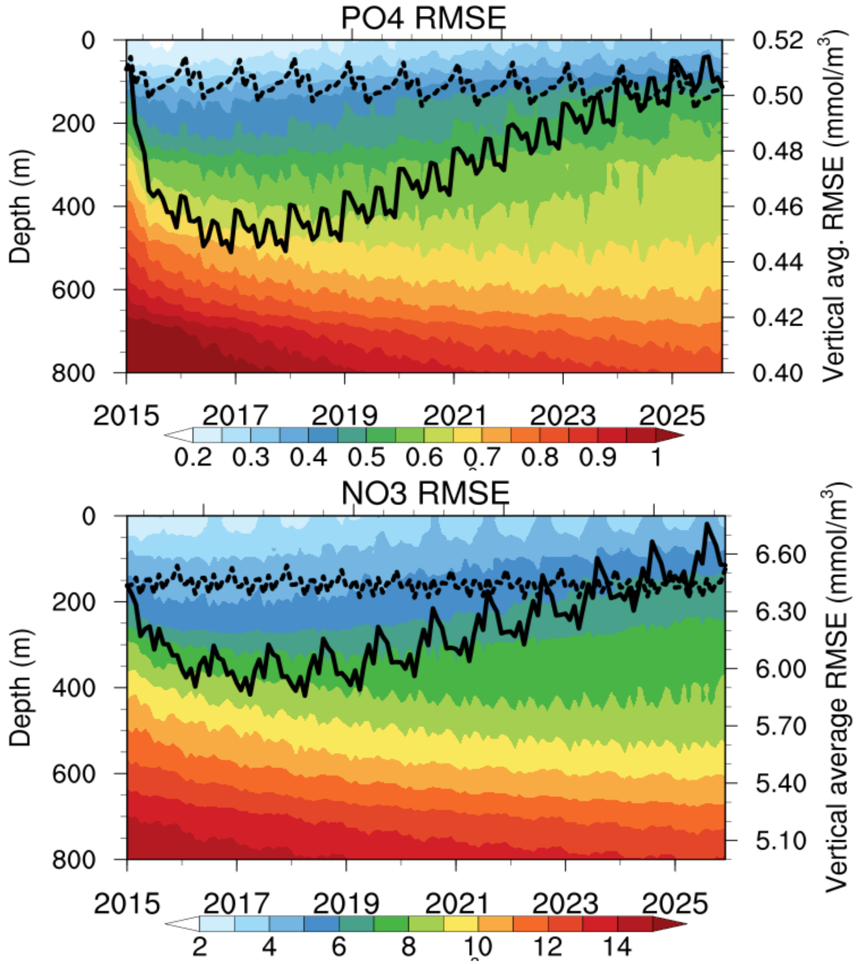
What happens to the BGC when the ocean physical bias is reduced?

Vertically RMSE of ocean physics and BGC in a coupled reanalysis that assimilates temperature and salinity climatology observations

Ocean physics



Ocean BGC



FREE_DP
REANA_DP

Reducing ocean bias yields a reduction in BGC bias initially , but BGC error grows slowly

Singh et al., 2025

Challenges of parameter estimation with ESM

- Biases are transferred from other components (e.g., ocean, atmosphere)

  Solution: Sustain errors at a low level with state data assimilation in other components
- Error growth from ocean BGC is much slower than that of ocean physics (and the smoother window)

  Solution: Let the error grow in the BGC component over a long period (long window)
- Error in BGC dominated by intermittent events (bloom) that occur at different times depending on the regions

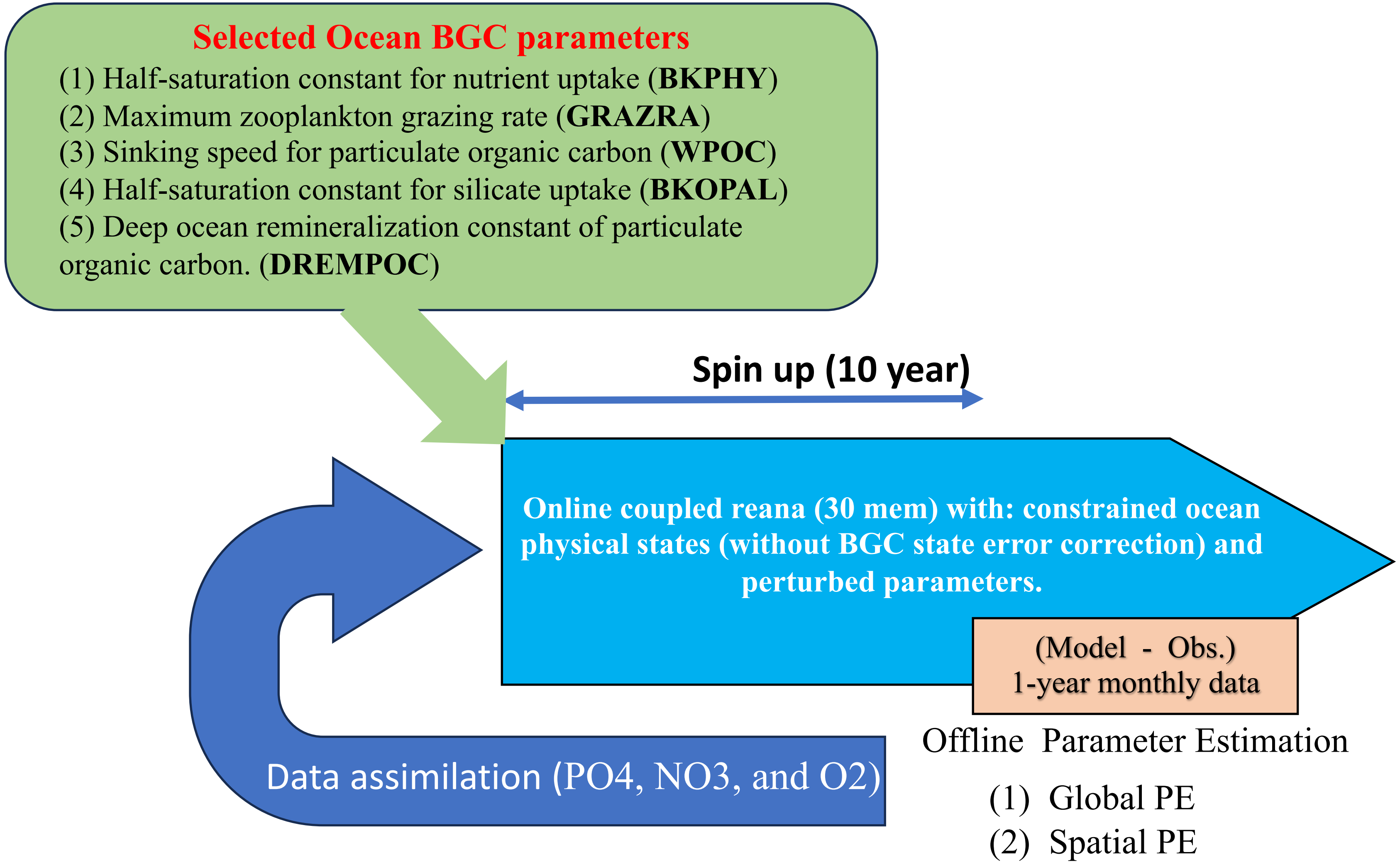
  ➔ For global parameters, the estimation is highly sensitive to when we start the estimation

  Solution: Estimate the optimal parameter subspace over a full-year cycle
- The estimation in nonlinear

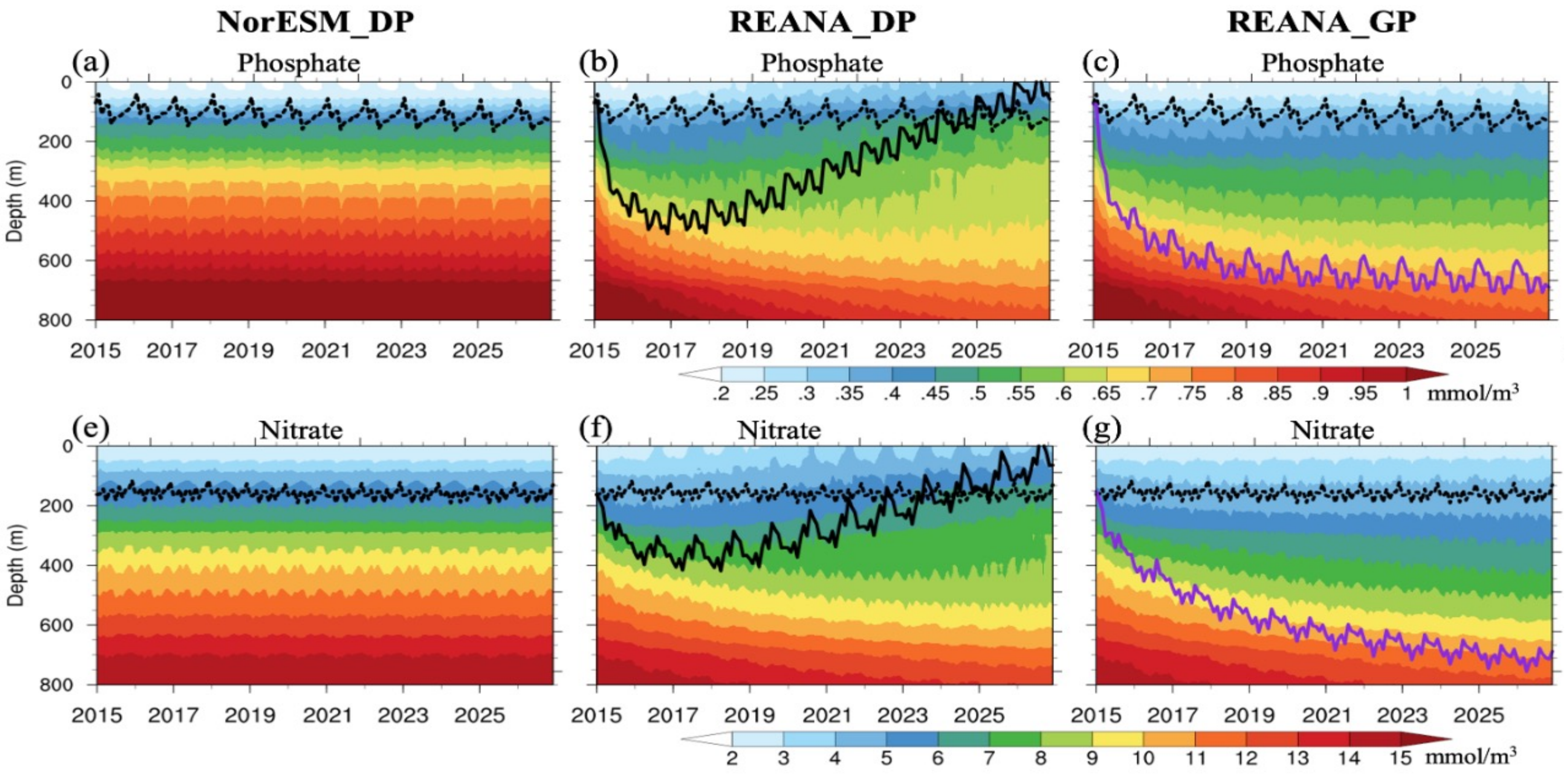
  Solution: Use an iterative approach

Iterative ensemble smoother for parameter estimation

We let the parametric error builds and estimate parameter over a full yearly cycle



It can effectively reduce bias in the BGC variables



[Singh et al., 2025]

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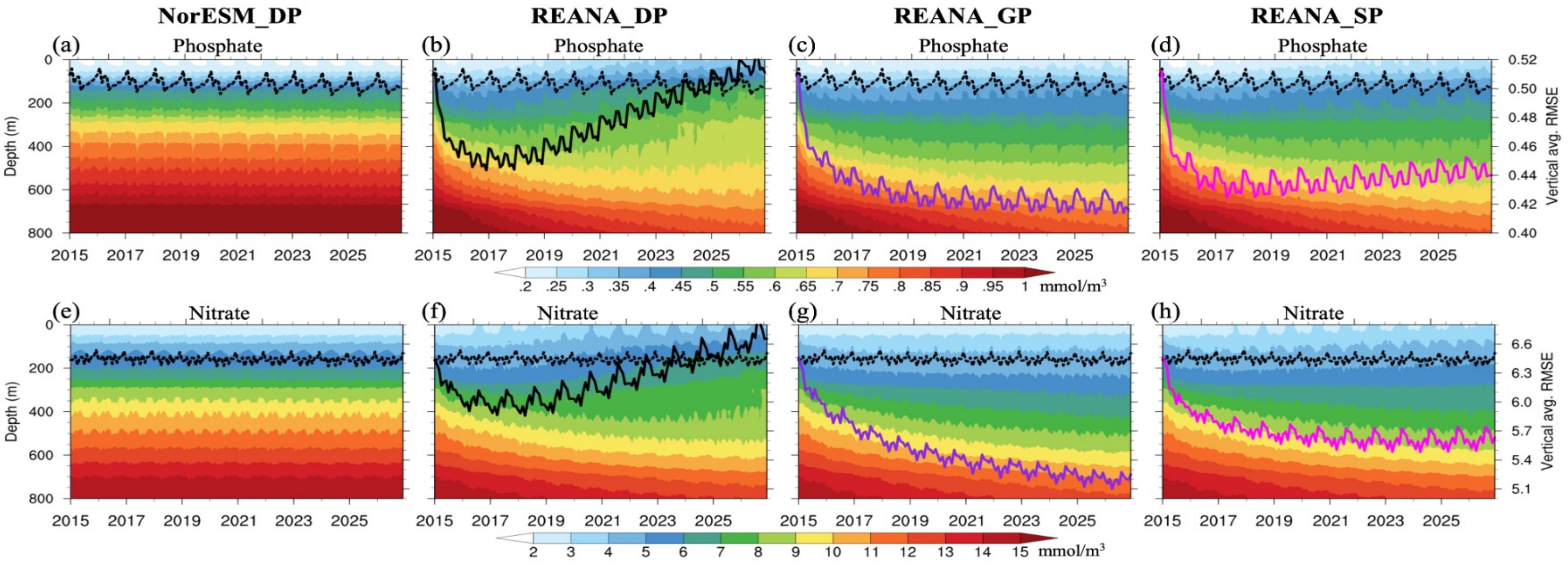
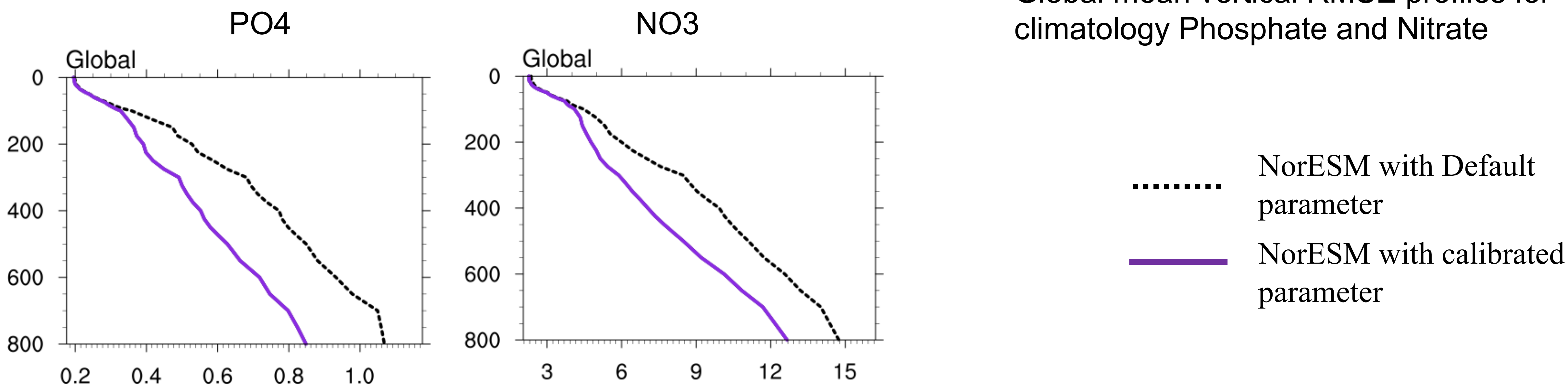


Spatial parameter estimation degrades overall due to spurious value where there are few observations

Verification of the new parameter after 2 iterations

NorCPM reanalysis for the period 1993-2022 with time-varying ocean physics observations (OISST2 SST and T-S profiles)

Global mean vertical RMSE profiles for climatology Phosphate and Nitrate



[Singh et al., 2025]

Perspective of parameter estimations with Earth System Model

Ensemble data assimilation provides an efficient, automated and non-subjective framework to calibrate parameters with ESMs

Evidence that parameters in NorESM are calibrated to compensate for bias in another component
➔ brings no guarantee that the system will show the best performance in the future (e.g. Löptien and Dietze 2019)

Instead, one could optimise each ESM component parameter in coupled mode by sustaining the bias in other components at a low level (DA)

- ➔ *More reliable estimation of model uncertainty*
- ➔ *More proactive attitude to upgrade components in the community ESM code*

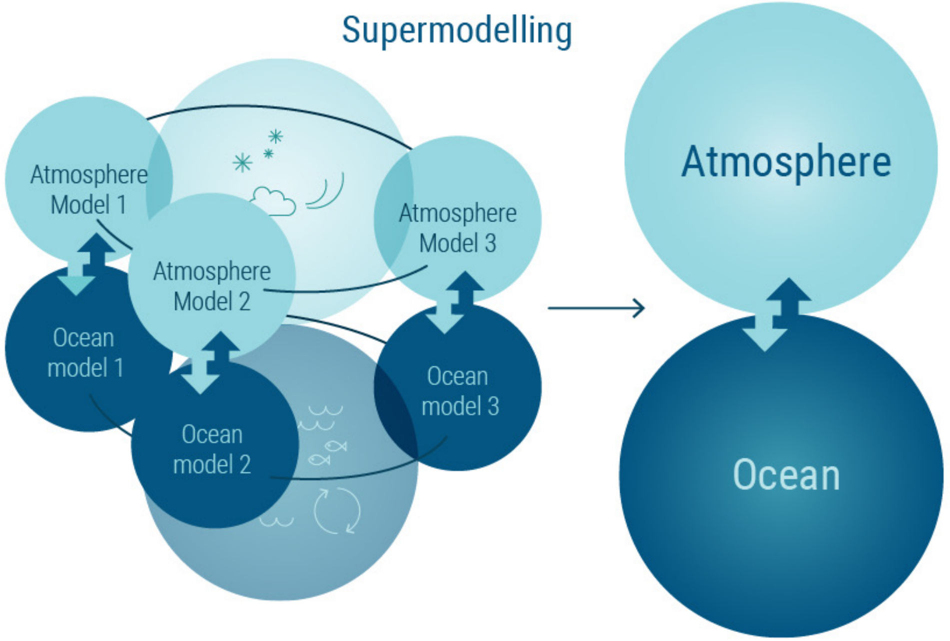
Currently tested for ocean BGC, CLUBB scheme (cloud), ocean mixing and sea ice dynamics

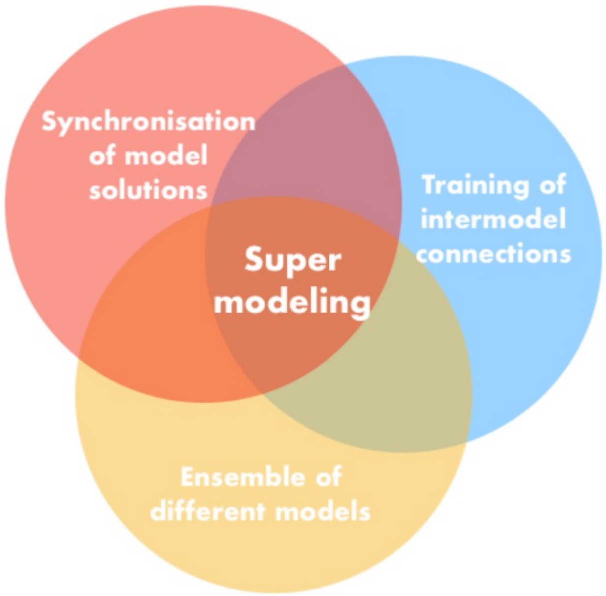
Supermodelling

Not all bias can be handled by parameter estimation !

A supermodel connects different models as they run :

- As models synchronise, internal variability of the multi-model mean is preserved
- Model diversity is used to train a better climate model





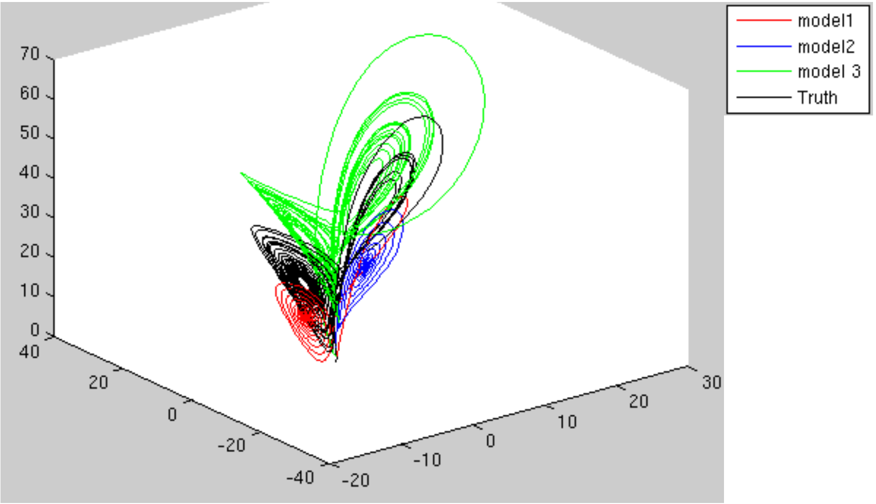
An example with L63

	σ	ρ	β
Truth	10	28	8/3
Model 1	13.25	19	3.5
Model 2	7	18	3.7
Model 3	6.5	38	1.7

$$\dot{x} = \sigma(y - x)$$

$$\dot{y} = x(\rho\text{-z})\text{-y}$$

$$\dot{z} = xy\text{-}\beta z$$



A super model add connections to the other imperfect model

Example:

$$\dot{x}_1 = \sigma_1(y_1 - x_1) + C^x_{12}(x_2 - x_1) + C^x_{13}(x_3 - x_1)$$

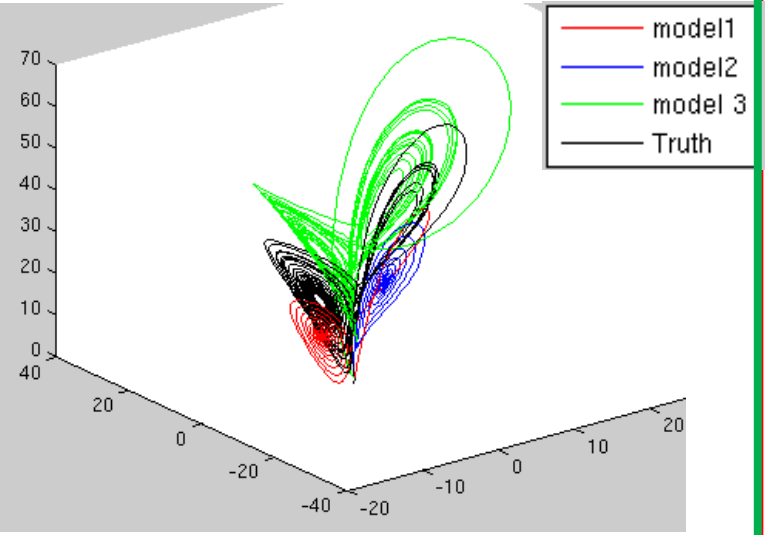
Nudging to other supermodel

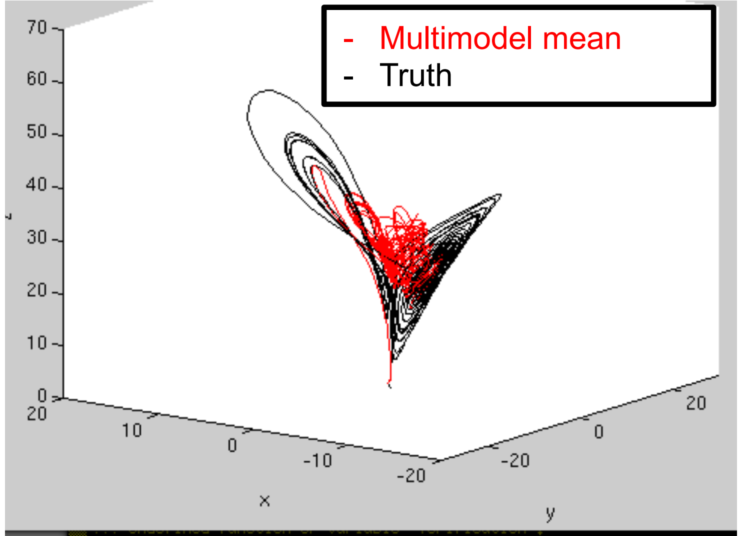
In **training phase**: use observations to estimate the nudging coefficients (and constrain the state during)

In **verification phase:** coefficients are frozen and the system can be used as a new dynamical system

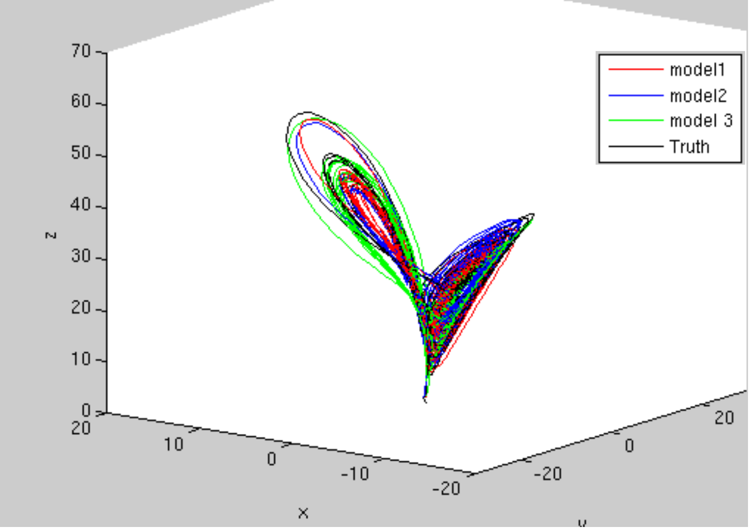
Supermodel verification

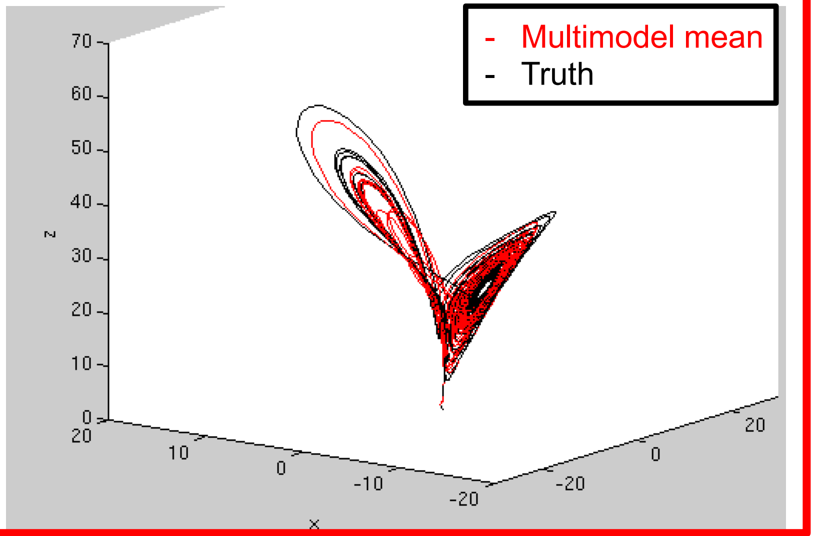
Unconnected mean





Supermodel





Van den Berge et al. 2011

Supermodelling

Supermodels have been demonstrated with idealised models, but their application to climate models is challenging because they **do not share the same state space, grid and resolution**

Can data assimilation provide a framework to handle this challenge ?

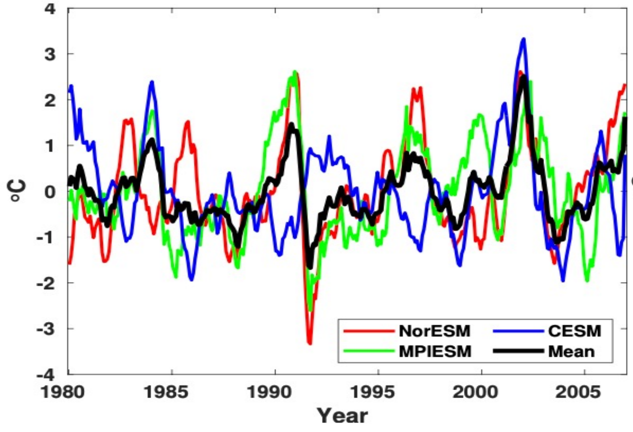
1. Generate pseudo-obs from other models
2. Pseudo-obs are a weighted mean of individual system
3. Assimilate them to synchronise the systems

An ocean connected super-ESM with DA

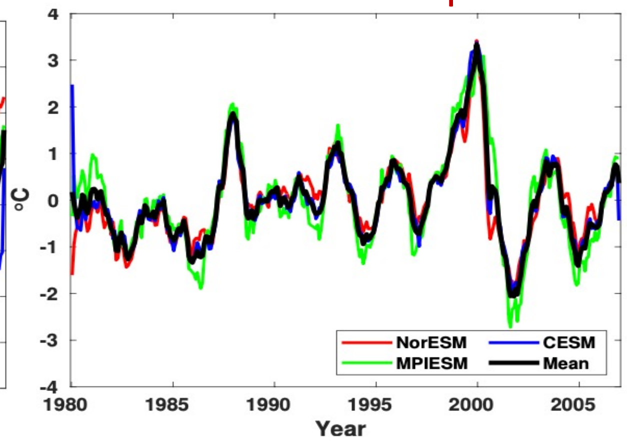
Model version	Ocean	atmosphere
NorESM1-ME	MICOM(σ; 1°)	CAM4 (finite-volume, 2°)
CESM1.1.2	POP2 (z, 1°)	CAM5 (finite-volume, 1°)
MPI-ESM1-LR	MPIOM (z,1.5°)	ECHAM6 (spectral, 2°)

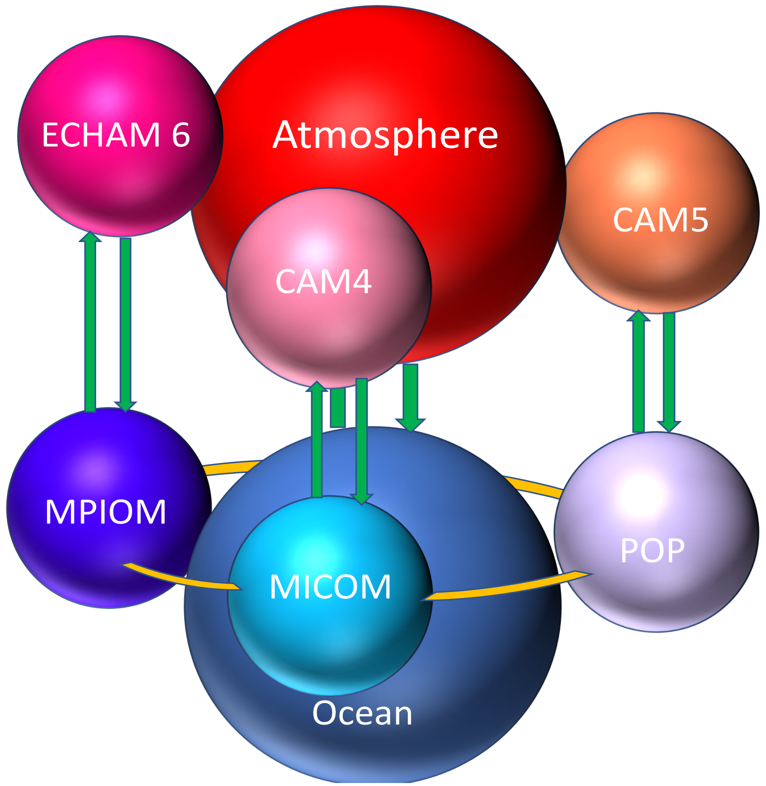
ENSO variability (NINO 3.4)

Non-interactive models



Ocean connected supermodel



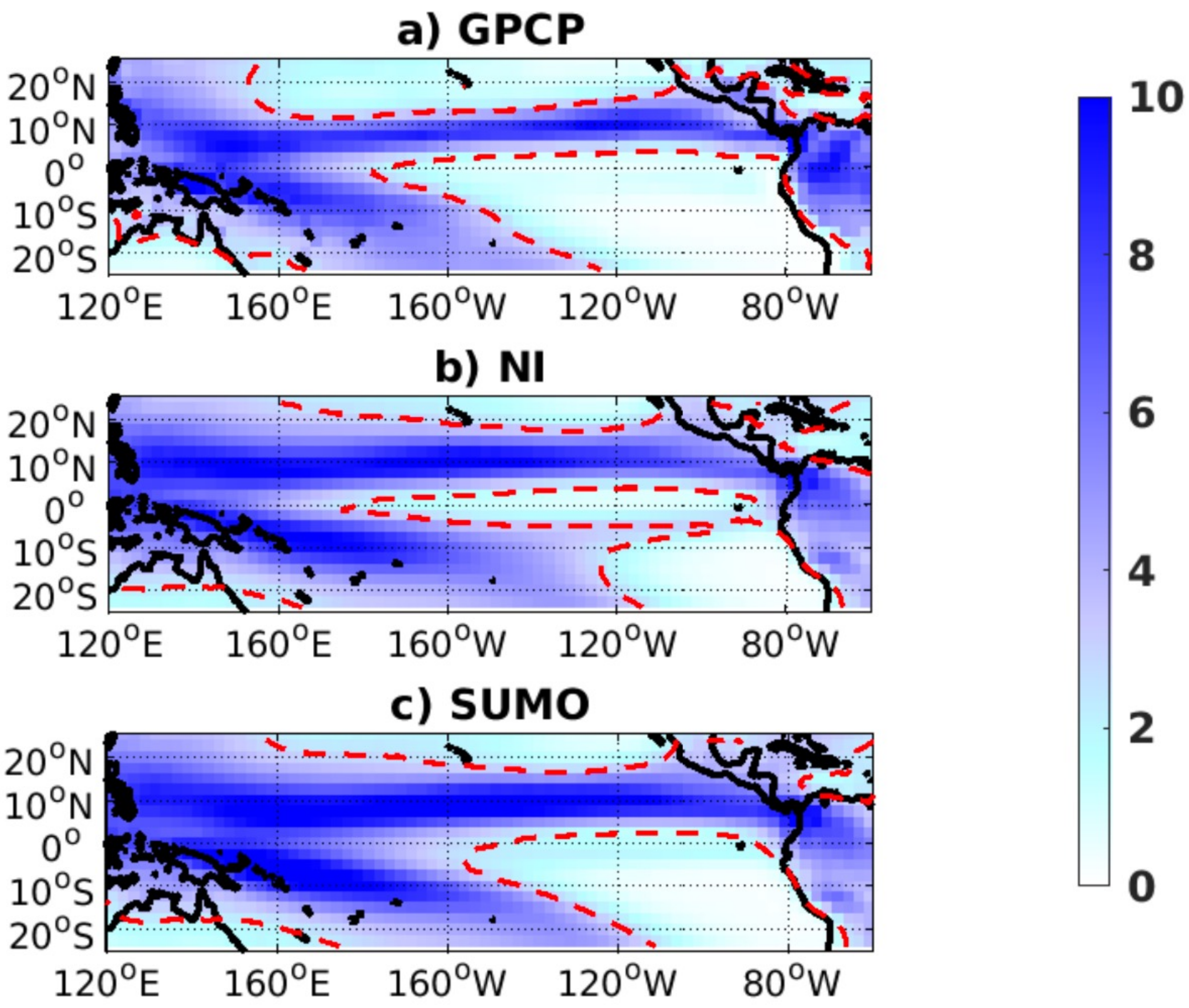


Internal variability in the Nino 3.4 is well synchronised in the supermodel.

Counillon et al. 2023

Annual-mean precipitation climatology in the tropical Pacific

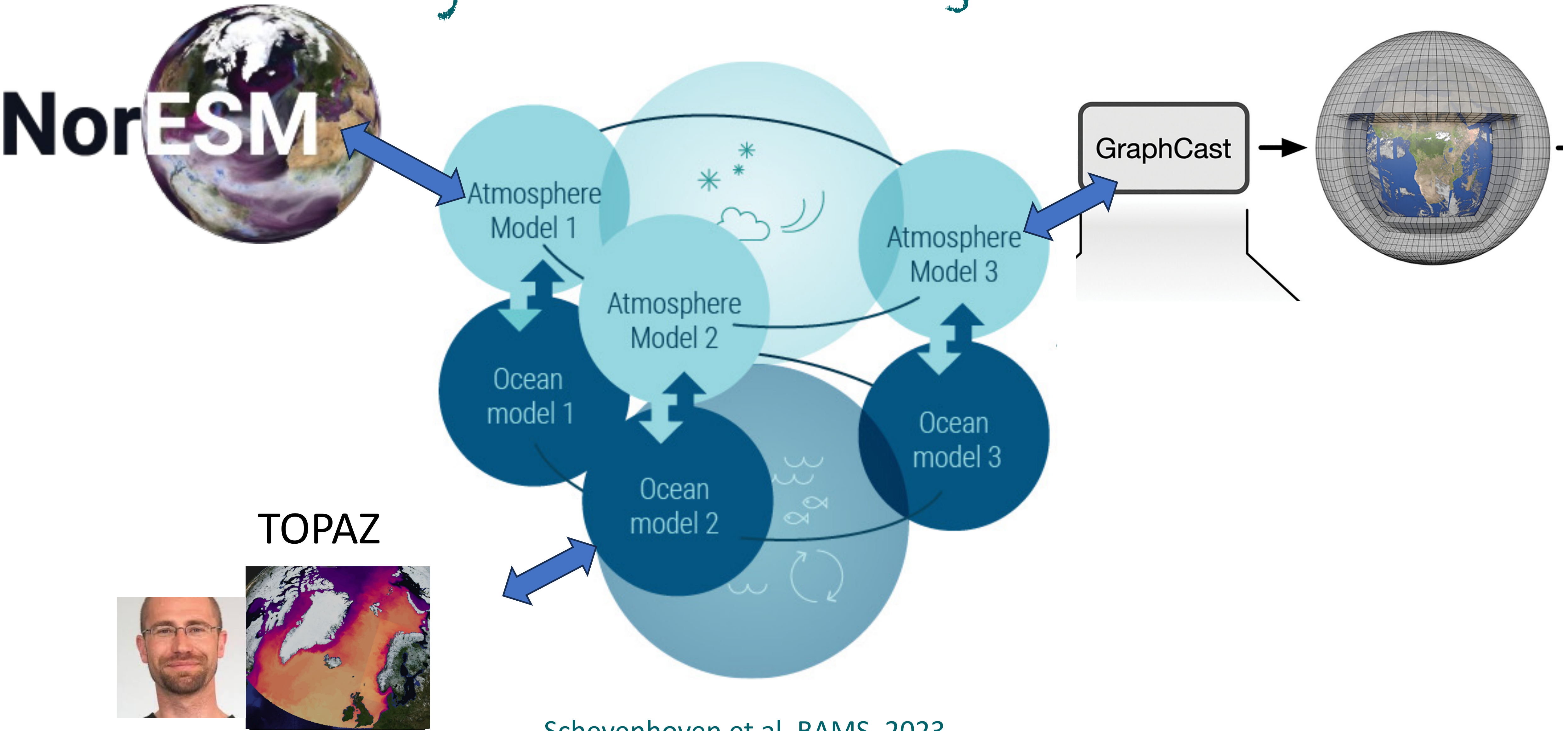
Weights (positive and normalized) are estimated offline from individual model SST biases (1980-2005)



It mitigates the double ITCZ problem !

Schevenhoven et al. 2024

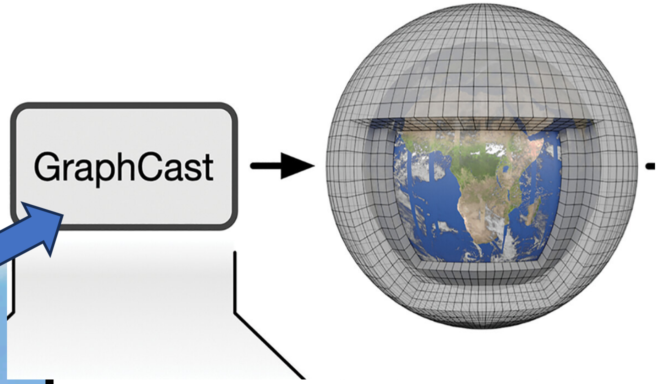
Supermodelling - Combining AI and dynamical downscaling



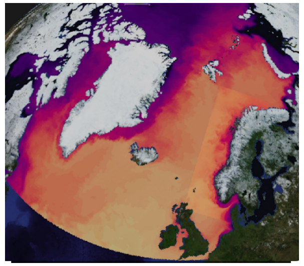
Schevenhoven et al. BAMS, 2023

Supermodelling - Combining AI and dynamical downscaling

Hva er en Super klimamodell?



TOPAZ



Francine Schevenhoven