Frameworks for parameter estimation with NorCPM

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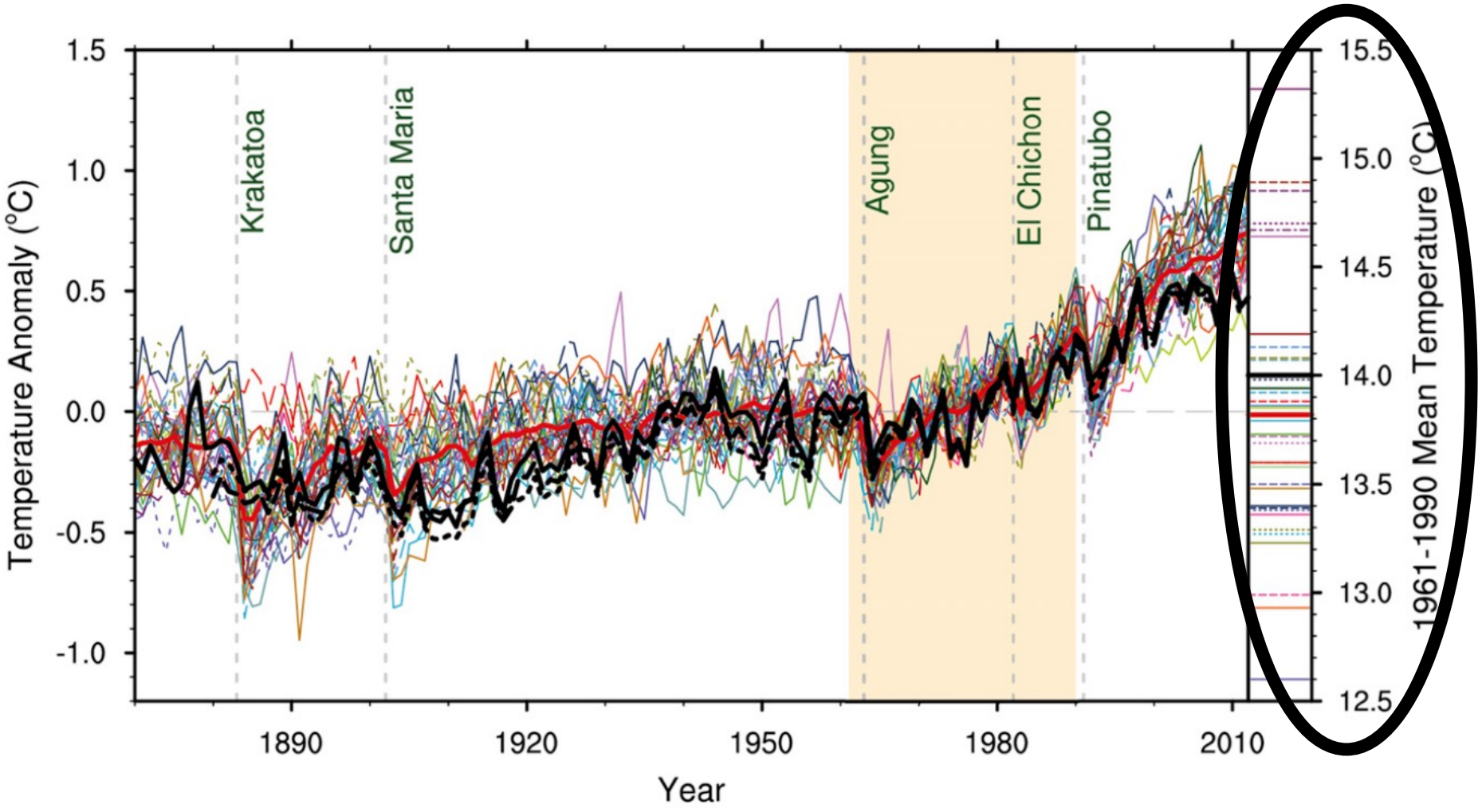
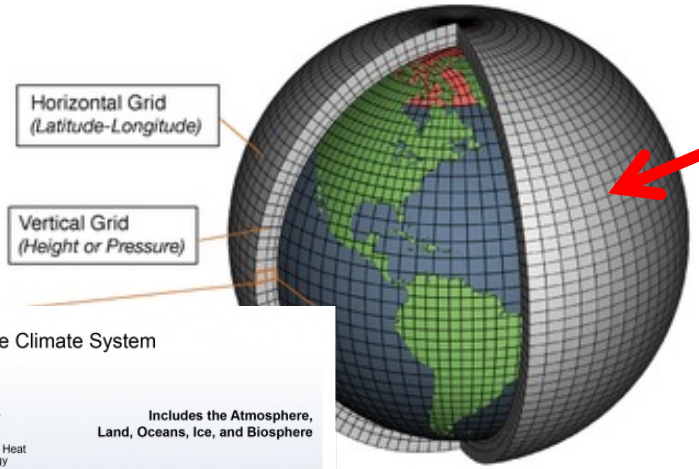
Bias is often larger than the signal we analyze or predict

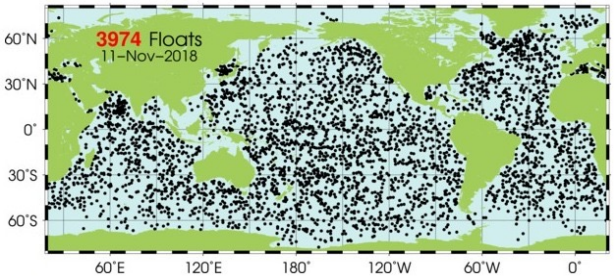


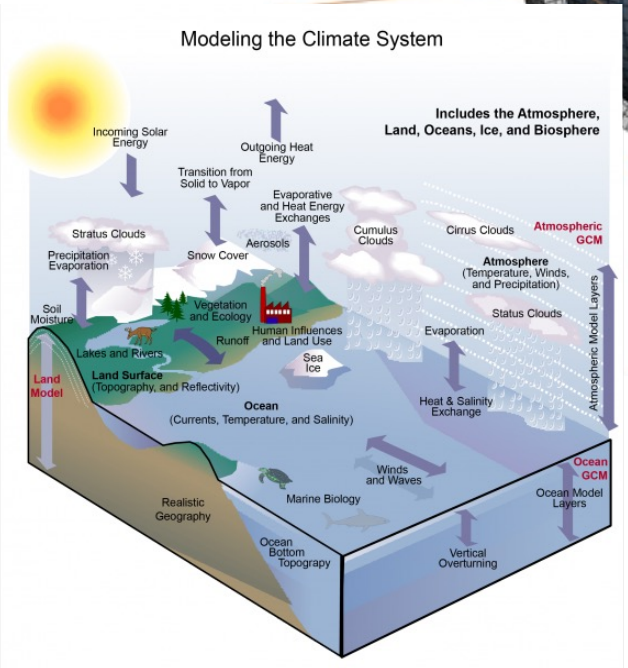
Palmer and Stevens, PNAS, 2019

Can we “tune” NorESM parameters to reduce model biases ?

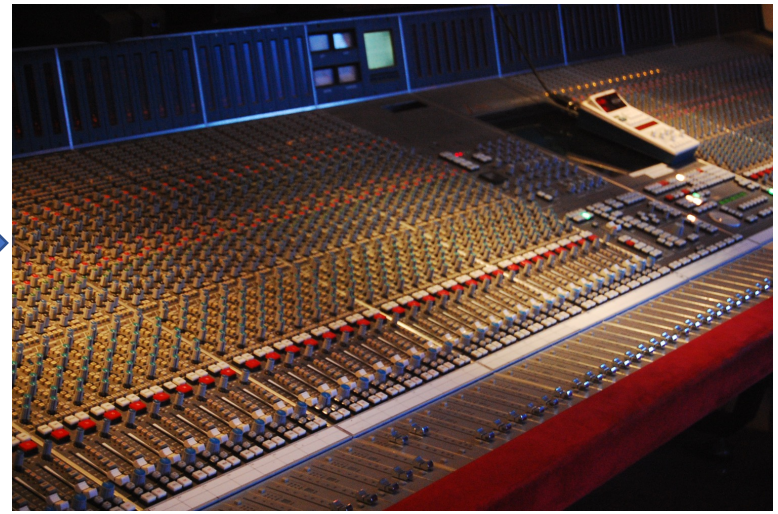


From ship, float and satellites

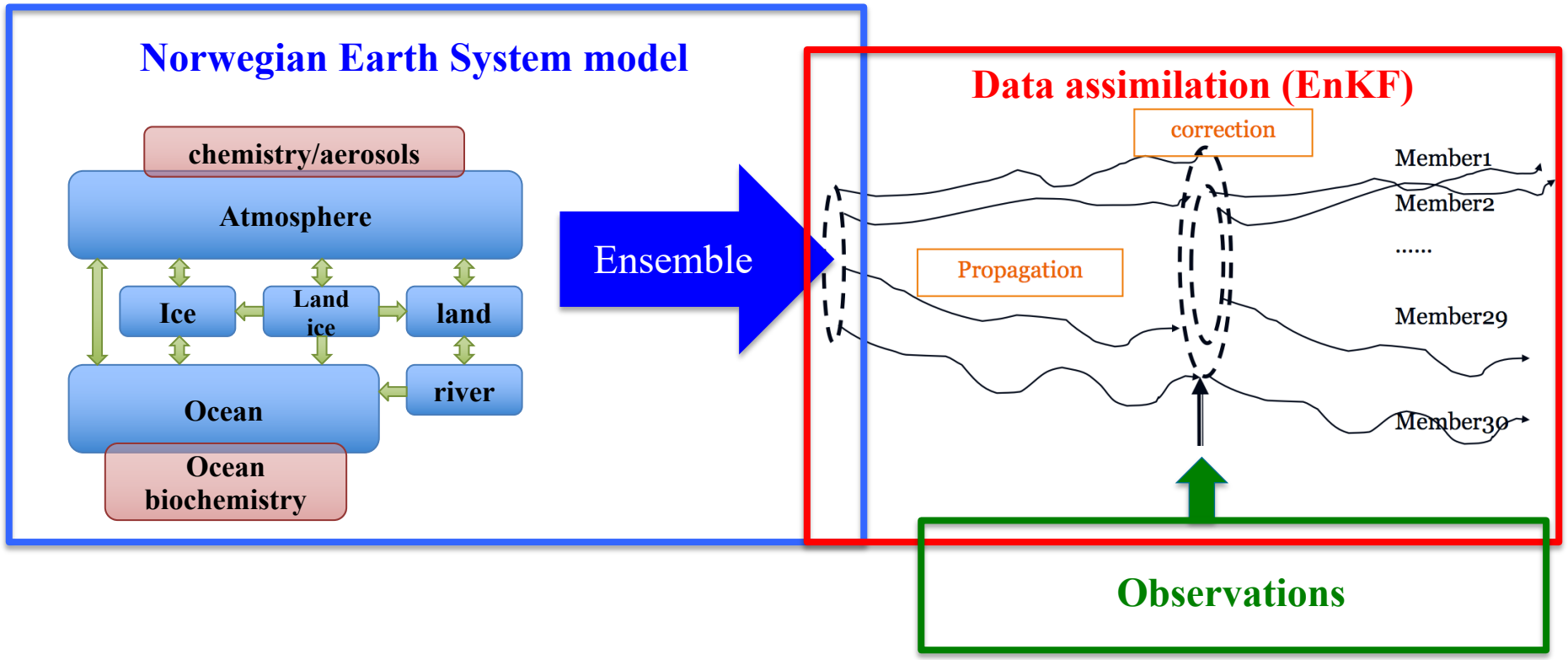




Many of these processes are not resolved and need to be parametrised



Norwegian Climate Prediction Model (NorCPM)

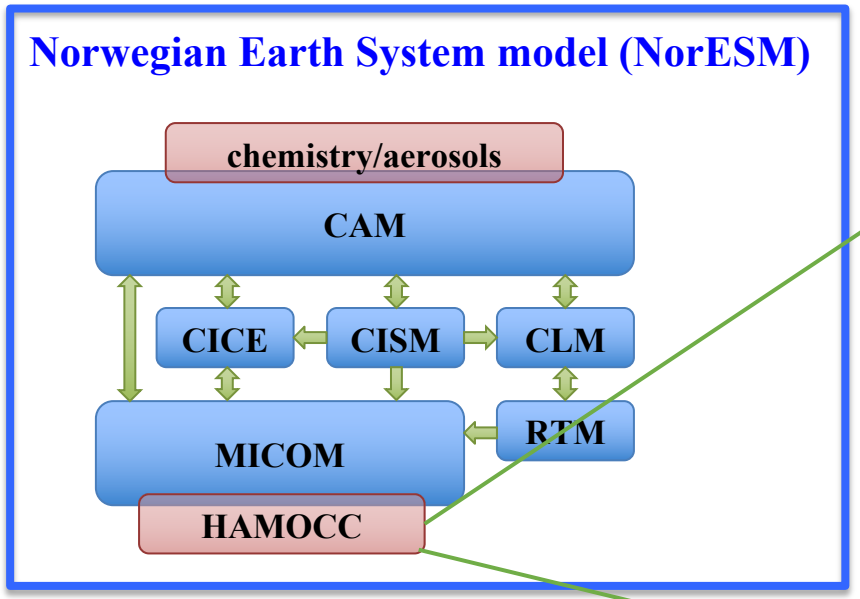


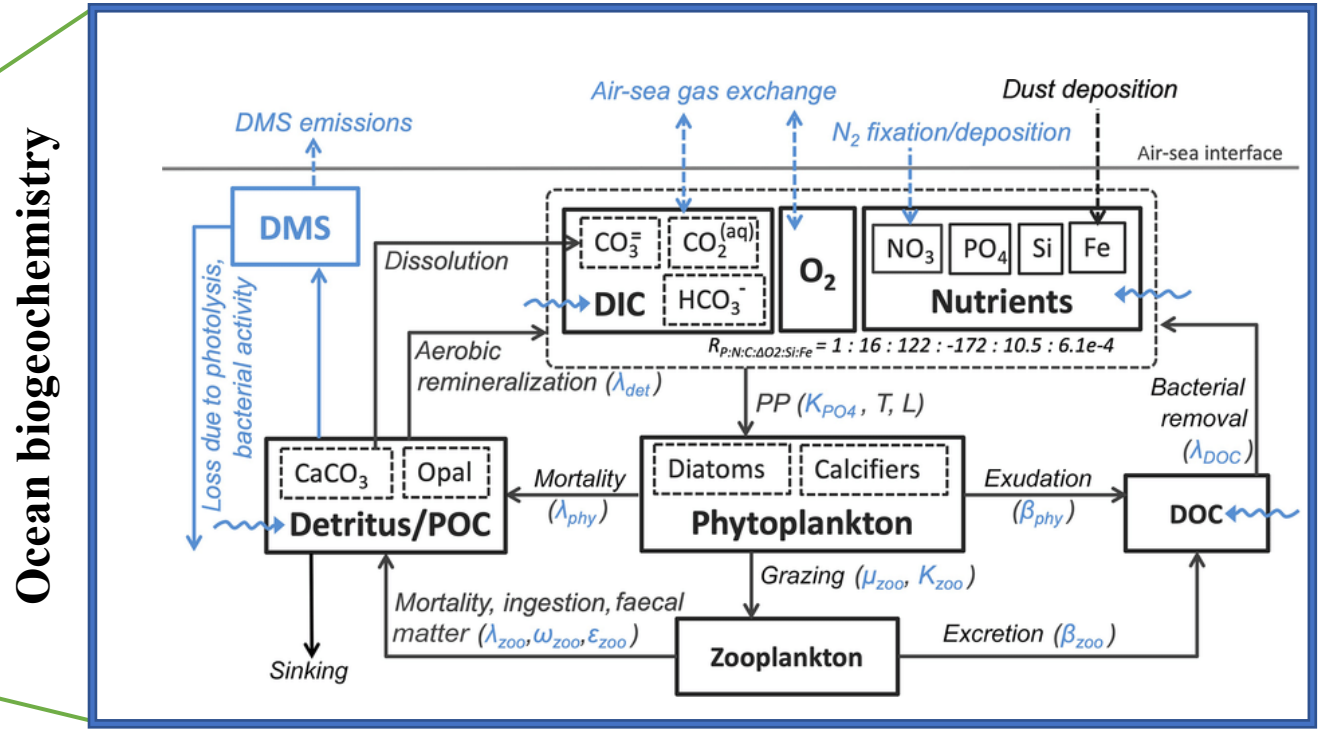
(Bethke et al. 2021)

Objectives:

- **Long climate reanalysis (historical until now)**
- **Climate prediction (Seasonal-to-decadal)**
- **Tunning parameters to reduce the model bias ?**

An attempt with the ocean Biogeochemical (BGC) component in NorESM





- Ocean BGC models utilise numerous poorly constrained parameters to simplify the marine ecosystem complexity.
- Optimal value of the biogeochemical parameter can vary spatially.

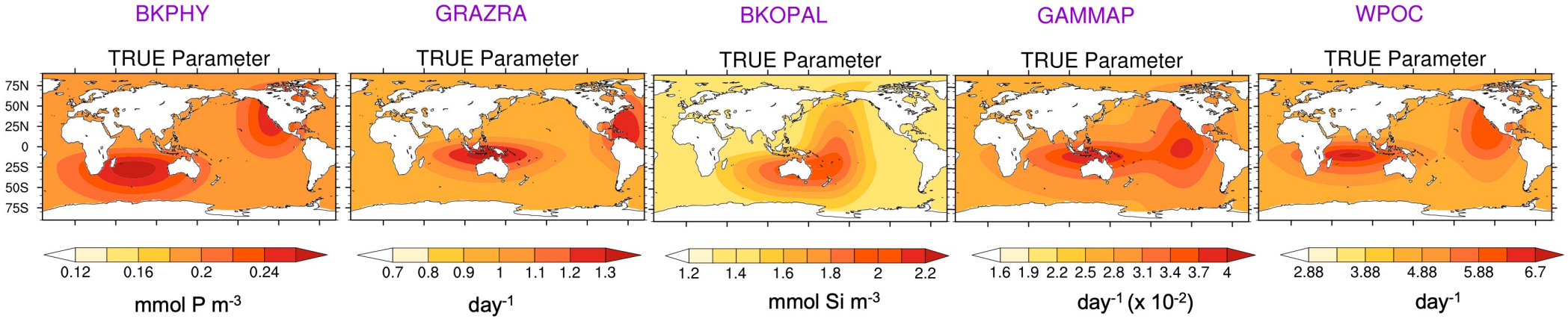
BGC parameter estimation test in NorCPM

- ✓ Test in an idealised framework
- ✓ Test in a real framework

Formulate an idealised framwork

Identical Twin Experiment setup

- We select **five** HAMOCC parameters : **BKPHY, GRAZRA, BKOPAL, GAMMAP, WPOC**
- Construct spatially varying true values (purely artificial) for all parameters.



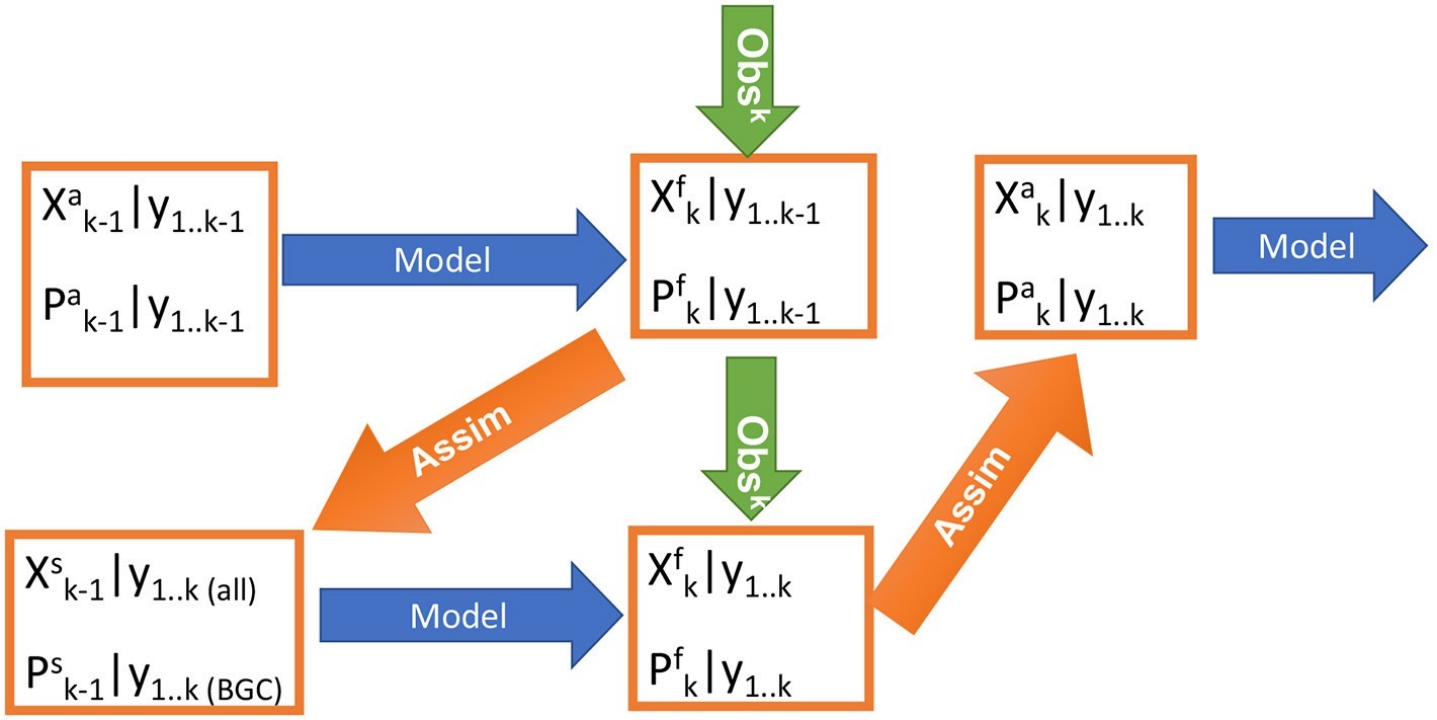
- **First guess/perturbed parameters**: Spatially uniform, ensemble mean = 25% lower than the global mean of true value
- **Synthetic observations** (TEM, SAL, PHYTO, SI, O2, PO4, NO3) **:** Model free run performed with True parameters values + additive perturbation

NorCPM run with perturbed parameter values and estimate them from the **synthetic state observations**

- Can we retrieve the parameter ?
- If so at which accuracy and how quickly ?

DA method for online parameter estimation

Dual one step ahead smoother (DOSA) scheme (Gharamti et al. 2017)

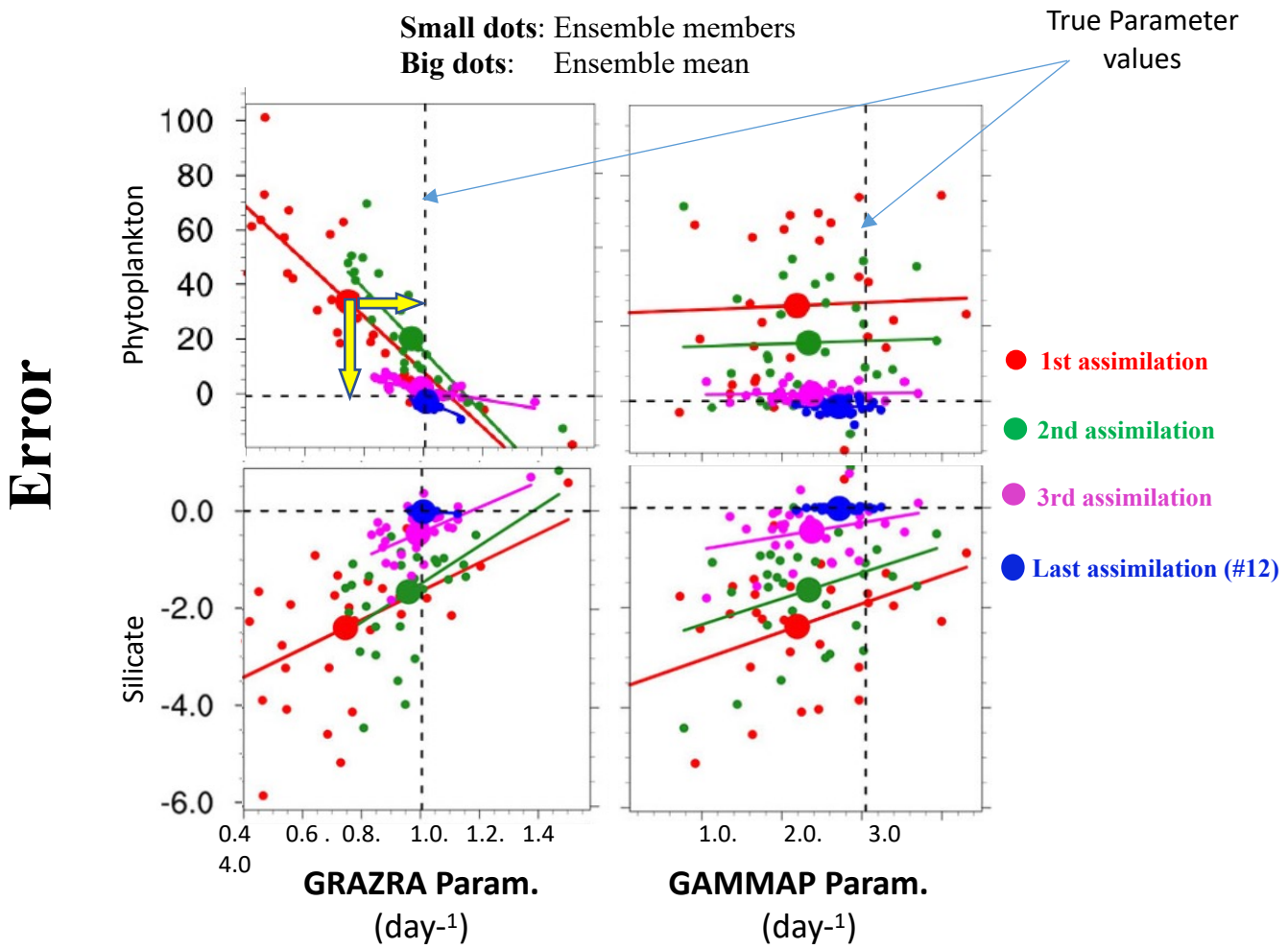


- The DOSA scheme keeps error of the initial state small ➔ error dominated by the parameter
- Converge very efficiently by correlating parameters with the misfits to the observations

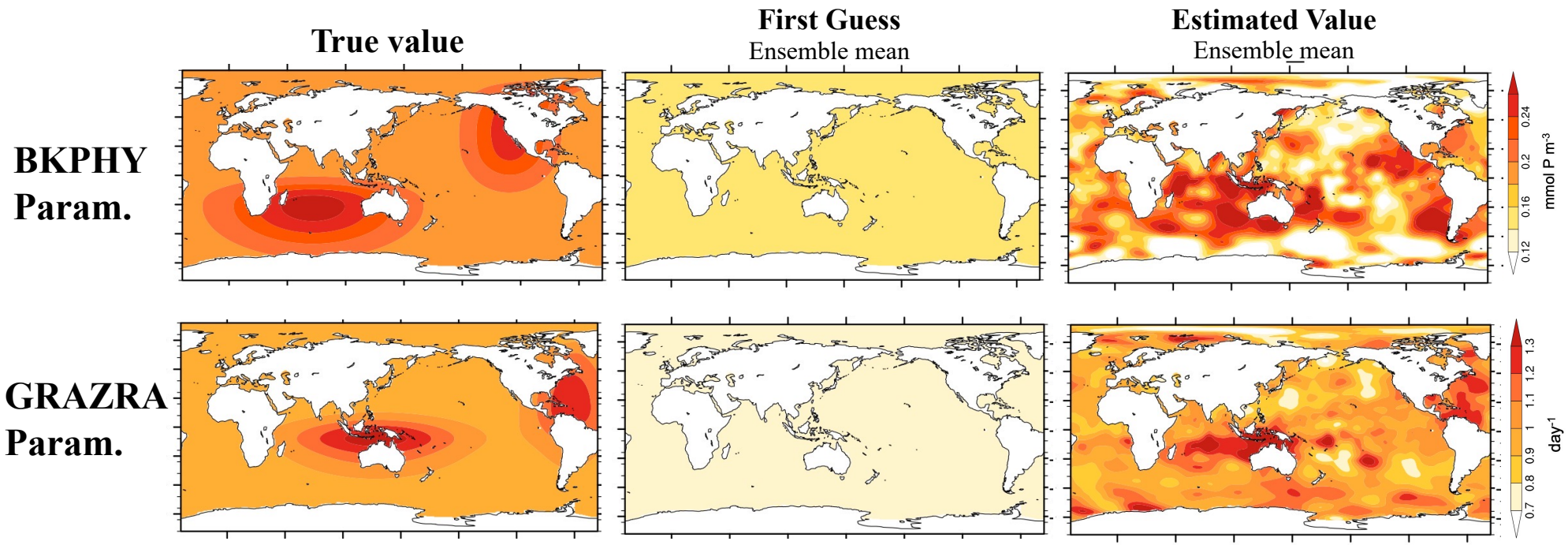
Does estimated parameters converge and reduce error in BGC states ?

Monthly assimilation for 1 year

Global mean error Vs Parameter



Spatial map of parameters



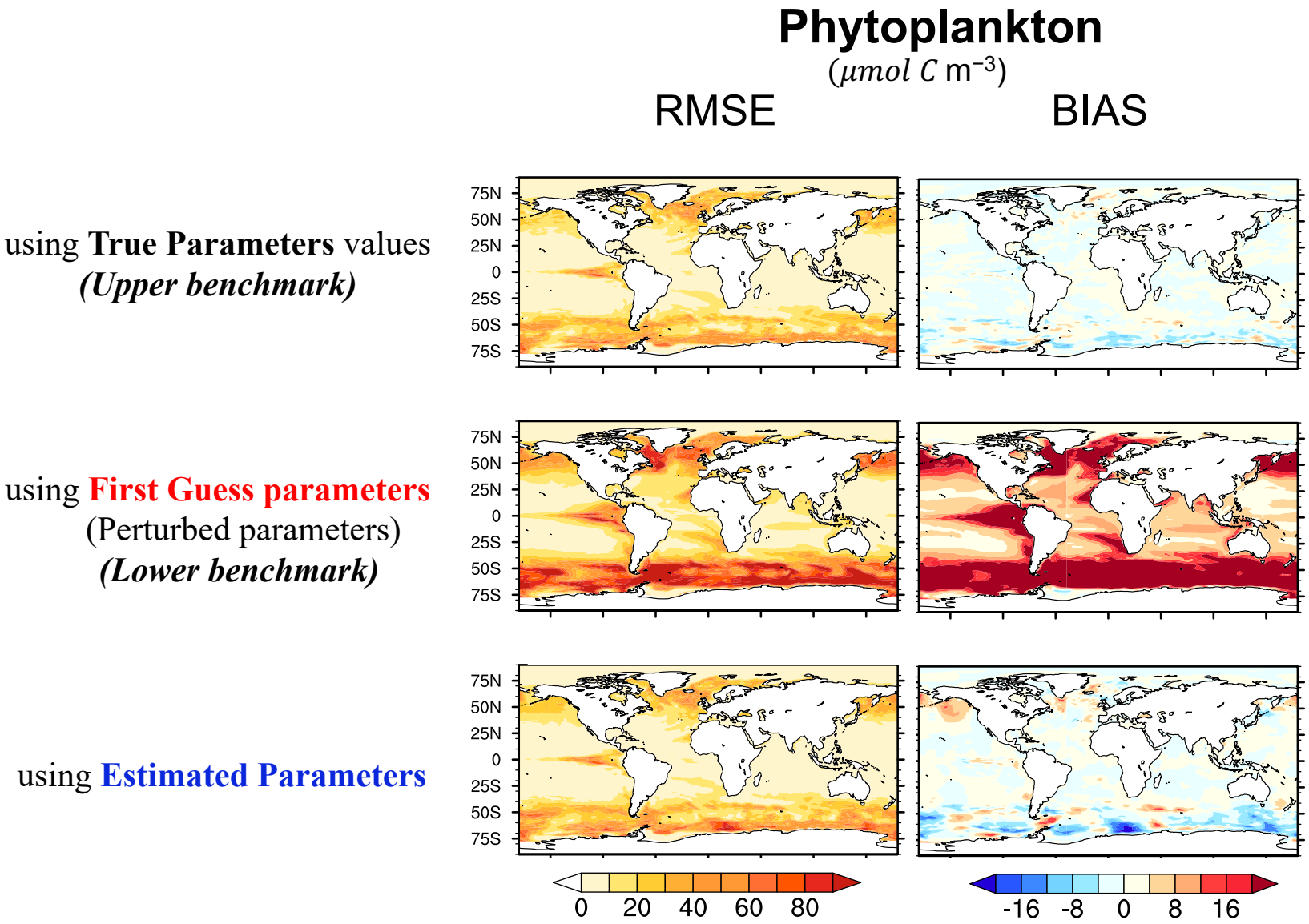
- **What is the impact on the state variables** ?

  Test performance of a system with (final) **Estimated parameter** *vs* one with **True parameter** & another with **First Guess parameter**

  (1) for an ensemble of free run (no assimilation)

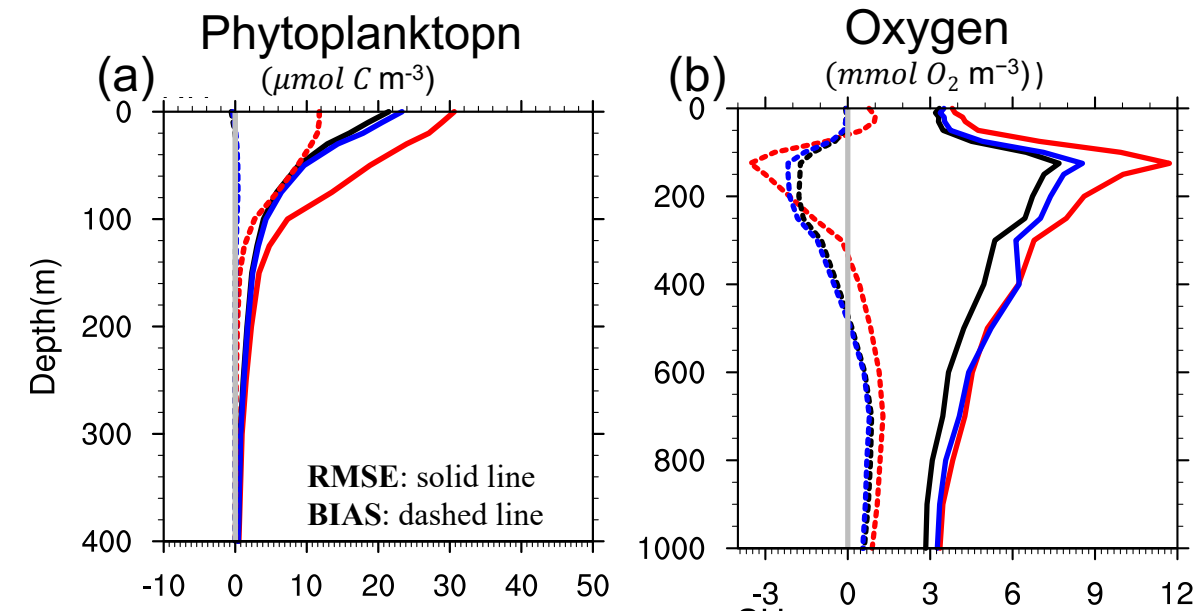
  (2) For a reanalysis (run with assimilation)

Model ensemble free run with different parameters



Reanalysis run with different parameters

Reanalysis with **True Parameters**
Reanalysis with **First Guess parameters**
Reanalysis with **Estimated Parameters**



Summary

- ✓ Estimated parameter performs nearly as good as with True/perfect parameters both for the free and reanalysis run
- ✓ Similar result are achieved when estimated from a **BGC climatology observations** data set (not shown)

From an Idealised to a Real Framework

- Ideal framwork work very well but parameter estimation in a real framwork is more complex

➔ Challenging because BGC parameters is not necessarly the dominant source of error in the BGC state

❖ Error in BGC state is dominated by error in ocean physics (even with joint assimilation OCN+BGC within a monthly assimilation cycle)

✓ *We only update the ocean physics and let the error grow in the BGC state*

➔ Time varying real BGC observations are very sparse

✓ *We use monthly climatology of BGC observations to train parameter*

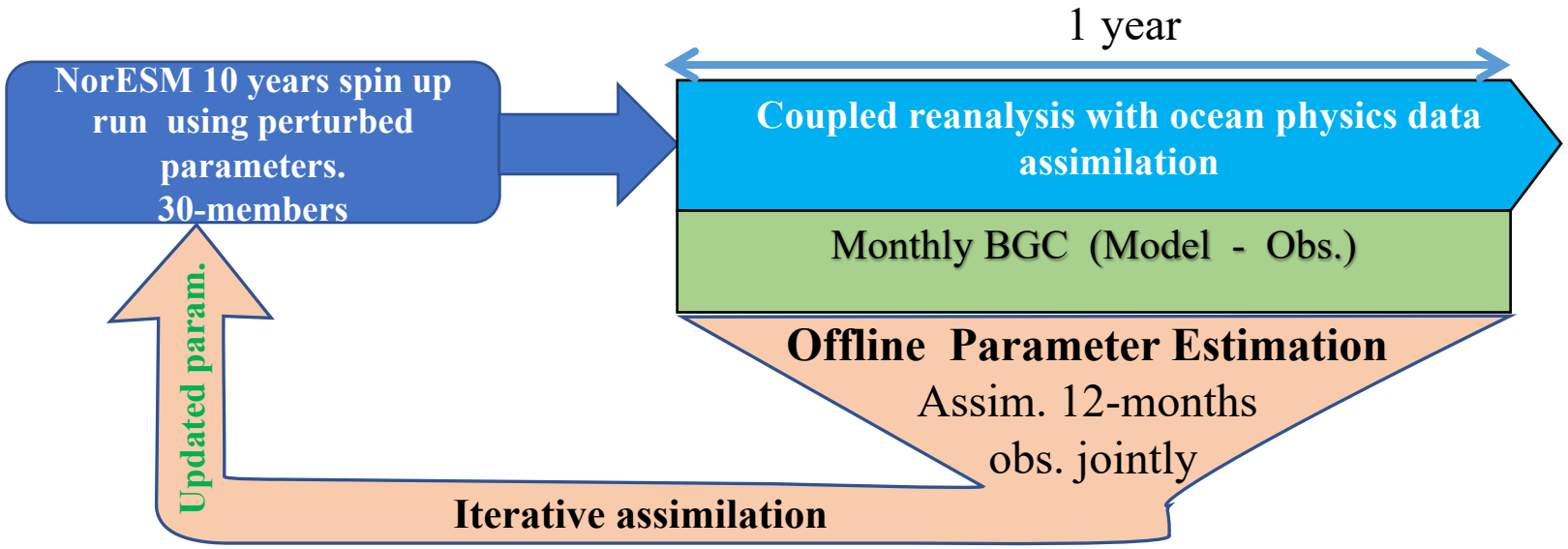
Parameter estimation with real observations
Online vs Offline Estimation

- Online parameter estimation (monthly cycle)
  - Parameter Converges within few assimilation cycle (Spread collapse)
  - Parameter spread inflation (Relaxation to Prior Spread, *Whitaker and Hamill 2012*) do not help (Degraded performance!)

  ➔Estimated parameters vary with different assimilation starts month

- Offline parameter estimation
  - Can utilize observations from a long period (e.g., 1 year) jointly to train the parameters.
  - No issues of spread collapse or dependencies to start months

Iterative Ensemble Smoother for BGC Parameter Estimation



Singh et al. in prep

Global BGC parameters

(1) Half-saturation constant for nutrient uptake
(2) Maximum zooplankton grazing rate
(3) Sinking speed for particulate organic carbon
(4) Half-saturation constant for silicate uptake
(5) Calcium carbonate to organic phosphorous production ratio
(6) Deep ocean remineralization constant of particulate organic carbon.

Workflow

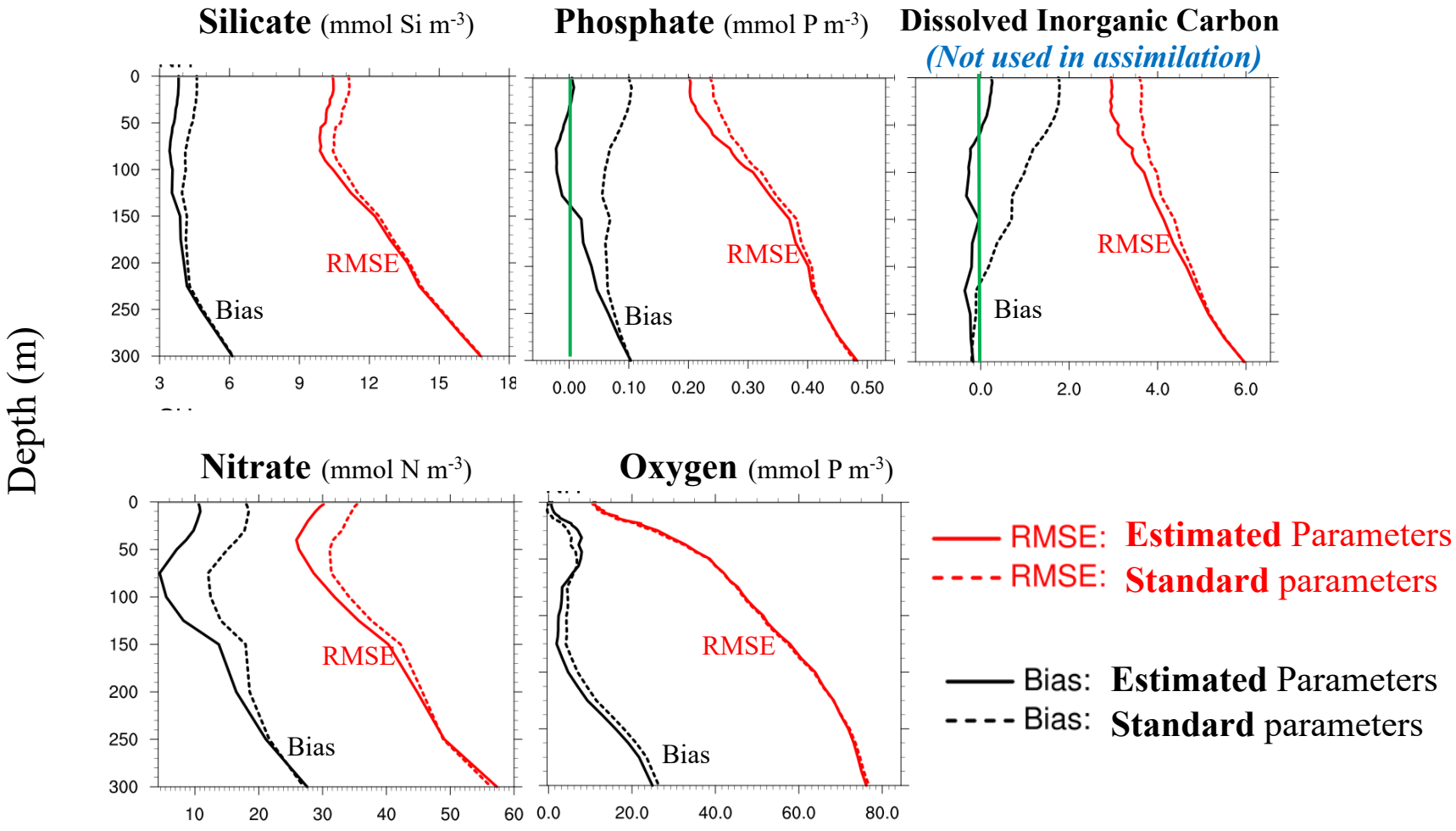
(1) Ensemble with perturbed parameter spin up for 10 years
➔ *Sensitivity to error in parameter grows*

(2) Run a 1-year coupled reanalysis with ocean physics data that assimilates climatological TEM, SAL monthly observation
➔*BGC error grows with near-perfect ocean*

(3) Estimate BGC parameters from monthly climatological Obs. SI, PO4, NO3, O2

Impact of the estimated parameter on state variables (verification)

RMSE & Bias: Global profile (independent period): Iteration-1



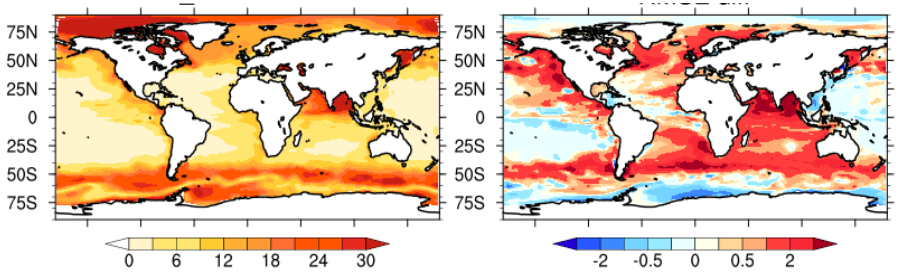
Variable Names	% Error reduction by Estimated parameters
Silicate	7%. 😊
Phosphate	14% 😊
Nitrate	**18**%. 😊
Oxygen	-1.1% 😐
Dissolved Inorganic Carbon (DIC)	15% 😊

Spatial distribution of the error reduction

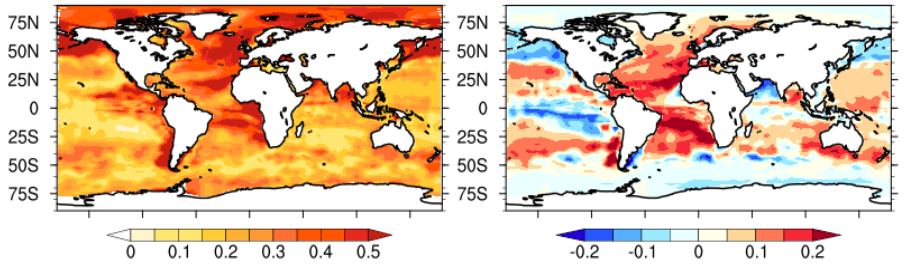
RMSE
Standard Param.

Error reduction
by Estimated Param.

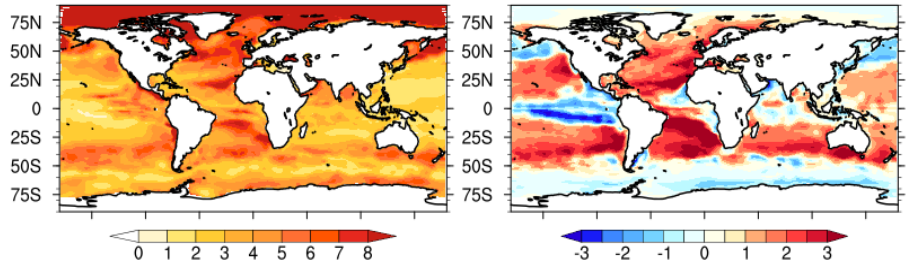
Silicate
(mmol Si m^{-3})
(0-100m)



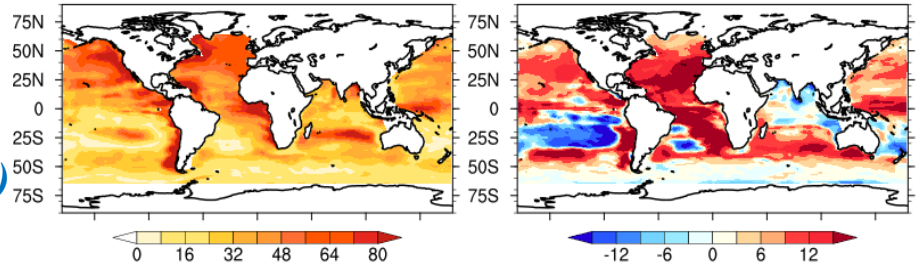
Phosphate
(mmol P m^{-3})
(0-100m)



Nitrate
(mmol N m^{-3})
(0-100m)

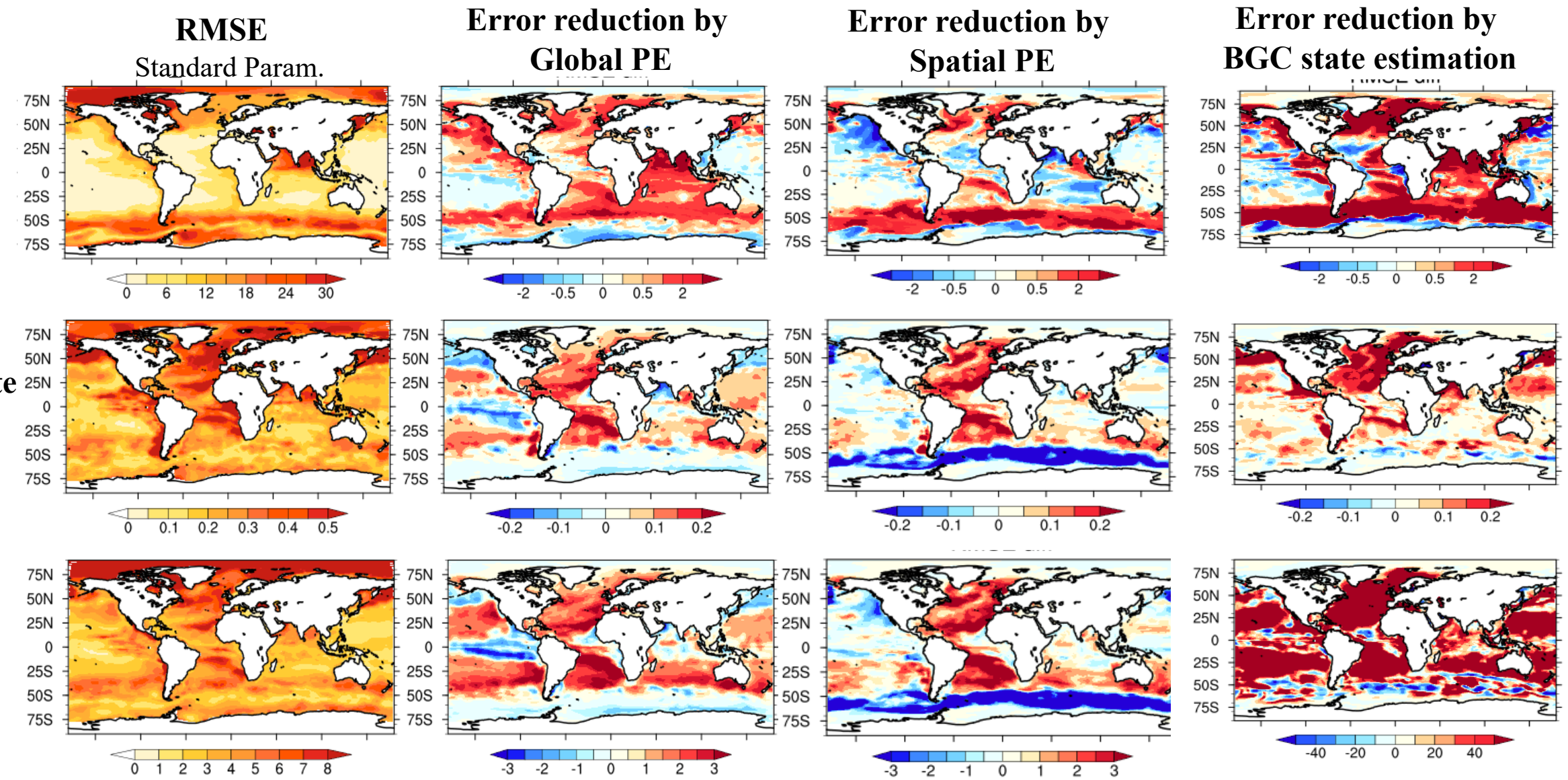


Dissolved Inorganic Carbon
(mmol C m^{-3})
(0-100m)
(Not used in assimilation)



Red=Improvement
Blue= Degradation
By Estimated parameters

Global vs Spatial parameter estimation



Red=Improvement, **Blue**= Degradation

❖ **Spatially varying parameters allows for some further regional improvements but perform overall poorer ?**

Summary and Future works

- In idealised framework, A DOSA scheme can estimate spatial parameter and perform nearly to perfect parameter.
- In real framework, only an Iterative ensemble smoother technique can yields improvement for estimating global parameter.
- Spatial varying parameter perform poorer than global one. We suspect that inherent predictability of the model and maybe the non-gaussian property of BGC are possible reason.
- We will try more iteration and CDF matching/anamorphosis

Thank You

For Your Attention!

Any Questions