Using Argo data to improve biogeochemical models, a case study for the Nordic Seas and the Arctic operational model

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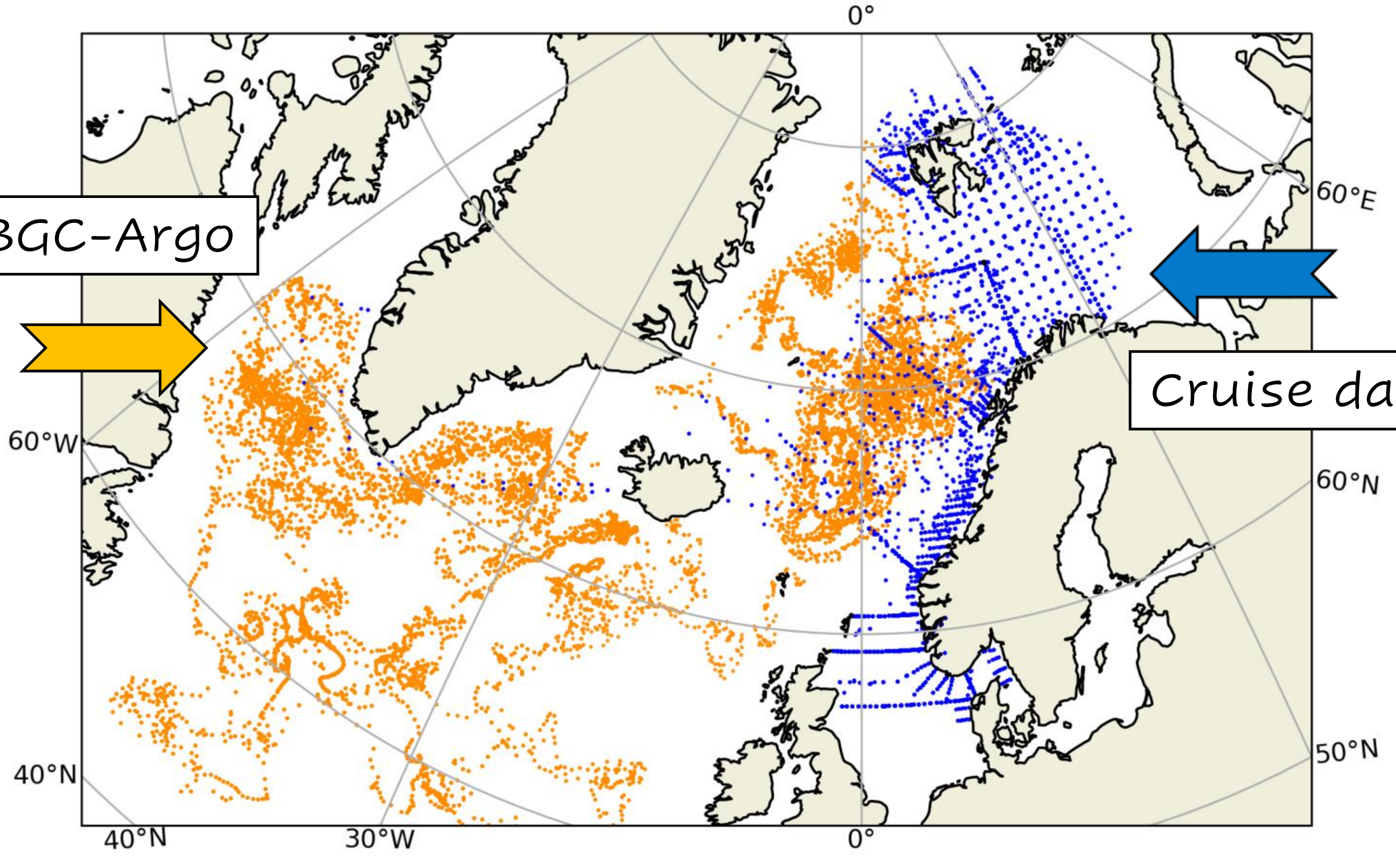
BGC-Argo in the Nordic Seas

BGC-Argo



Cruise data

Sample profile locations between 2010 – 2018, IMR, Norway

Biogeochemical-Argo (BGC-Argo) provides:

- regional coverage
- higher temporal resolution compared to satellite and in situ data along its trajectory
- data below surface
- a range of variables
  - **Chlorophyll**
  - **Oxygen**
  - **Suspended particles**
  - **Nitrate**
  - **pH**
  - **Downwelling irradiance**

Outline

Objective: Utilize BGC-Argo data for along-track 1D modelling experiments towards the development and validation of the 3D Arctic operational model

- Proof-of-concept study
- Ensemble simulations towards parameter tuning
- Application towards improving 3D regional model parameters

Models used in this study

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GOTM - 1D ocean turbulence model

Used for the Argo trajectory simulations

HYCOM - 3D hybrid z/isopycnal layer model

FABM coupler

ECOSMO – NPZD type biogeochemical model (4 nut, 3 phy, 2 zoo, det, doc, oxy)

A component of the Copernicus Arctic operational model

Further use cases:
hindcasts, climate projections

Argo trajectory simulations

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This framework configures 1D model experiments along BGC-Argo tracks

- Prepares along-track atmospheric forcing, climatologies and model configuration files

- Configures the model T and S to be nudged towards BGC-Argo T and S
  <u>With strong nudging</u>:
  the model physics imitate the Argo T and S, improving the timing and the strength of the MLD

- This allows a better focus on the performance of the ecosystem model

- Validate and improve the model formulation and parameterization

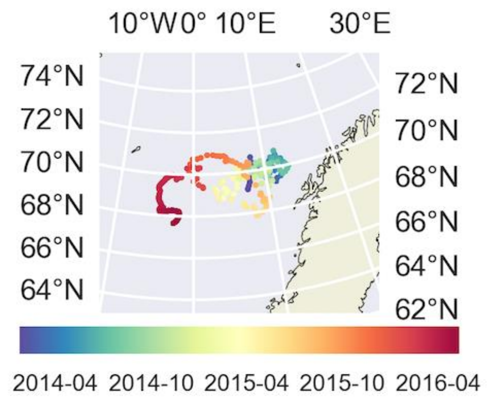
GOTM physics model ← Coupler → **FABM** ECOSMO

… any biogeochemical model can easily be applied through FABM

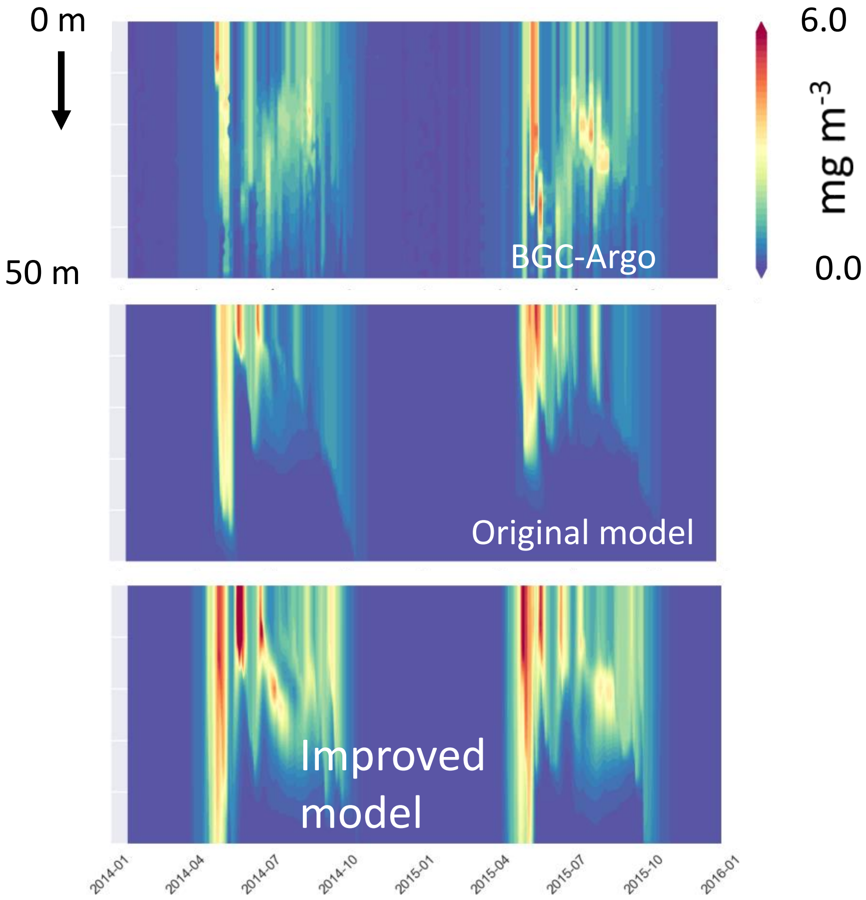
(Yumruktepe et al., 2023, *GMD*)

Objective: Utilize BGC-Argo data for along-track 1D modelling experiments towards the development and validation of the 3D Arctic operational model

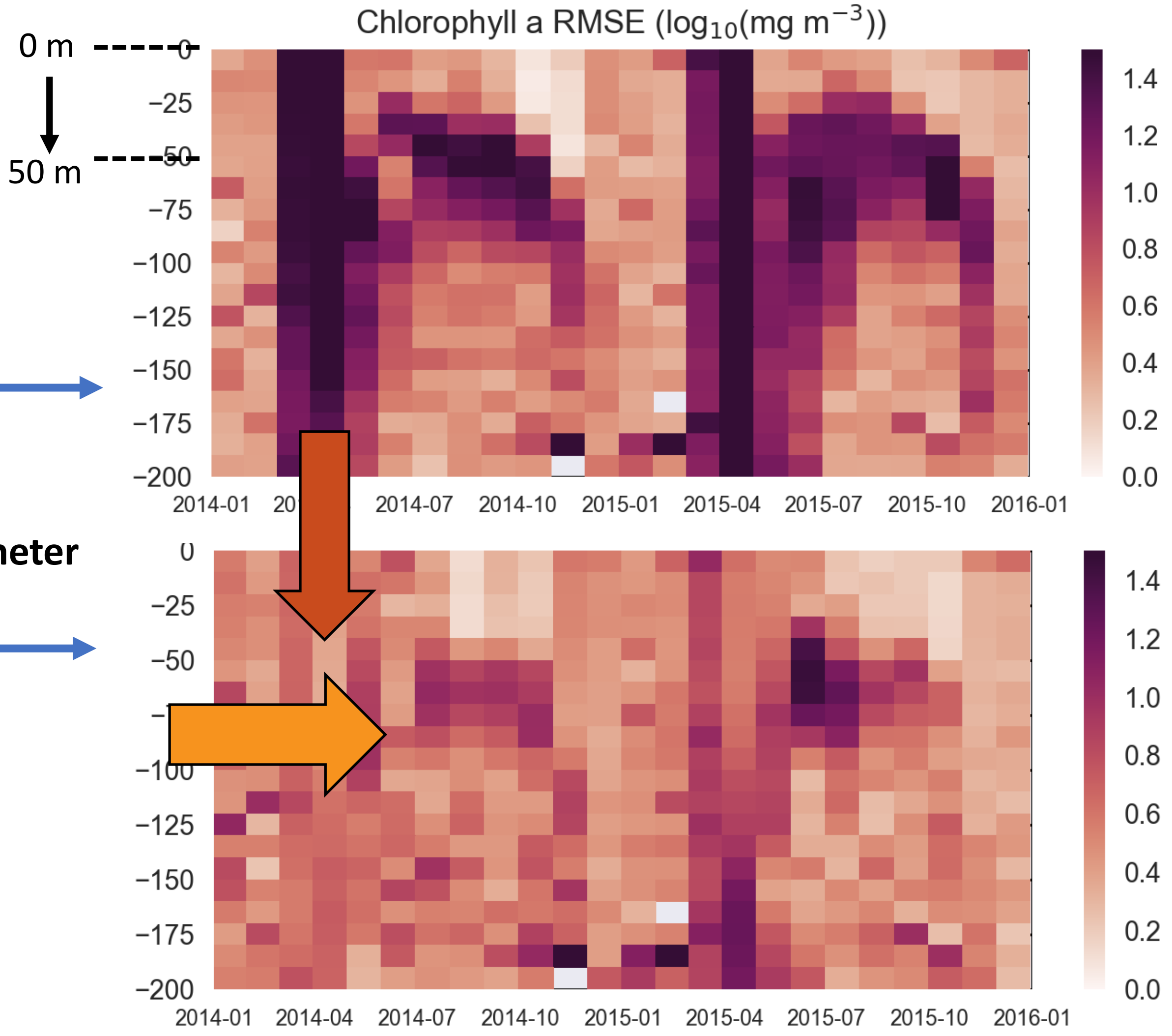
- Proof-of-concept study (Case 1a)



Improve formulation and validate



RMSE
(monthly & 10 meter intervals)



Summary:

General reduction in model error

Improved timing of spring bloom

Formation of DCM

Ensemble simulations towards parameter tuning (Case-1b)

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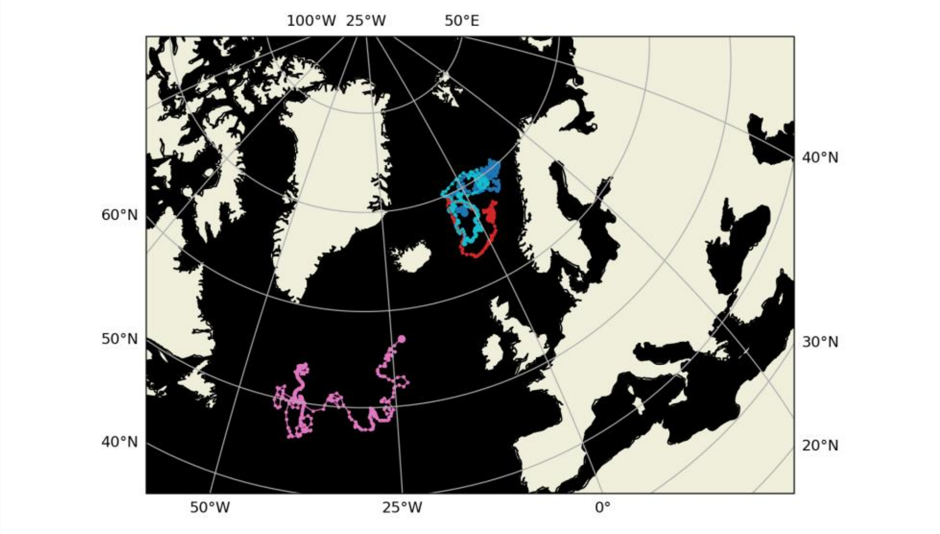
Problem: Models are highly sensitive to biogechemistry parameters and we often rely on predefined set of parameter values

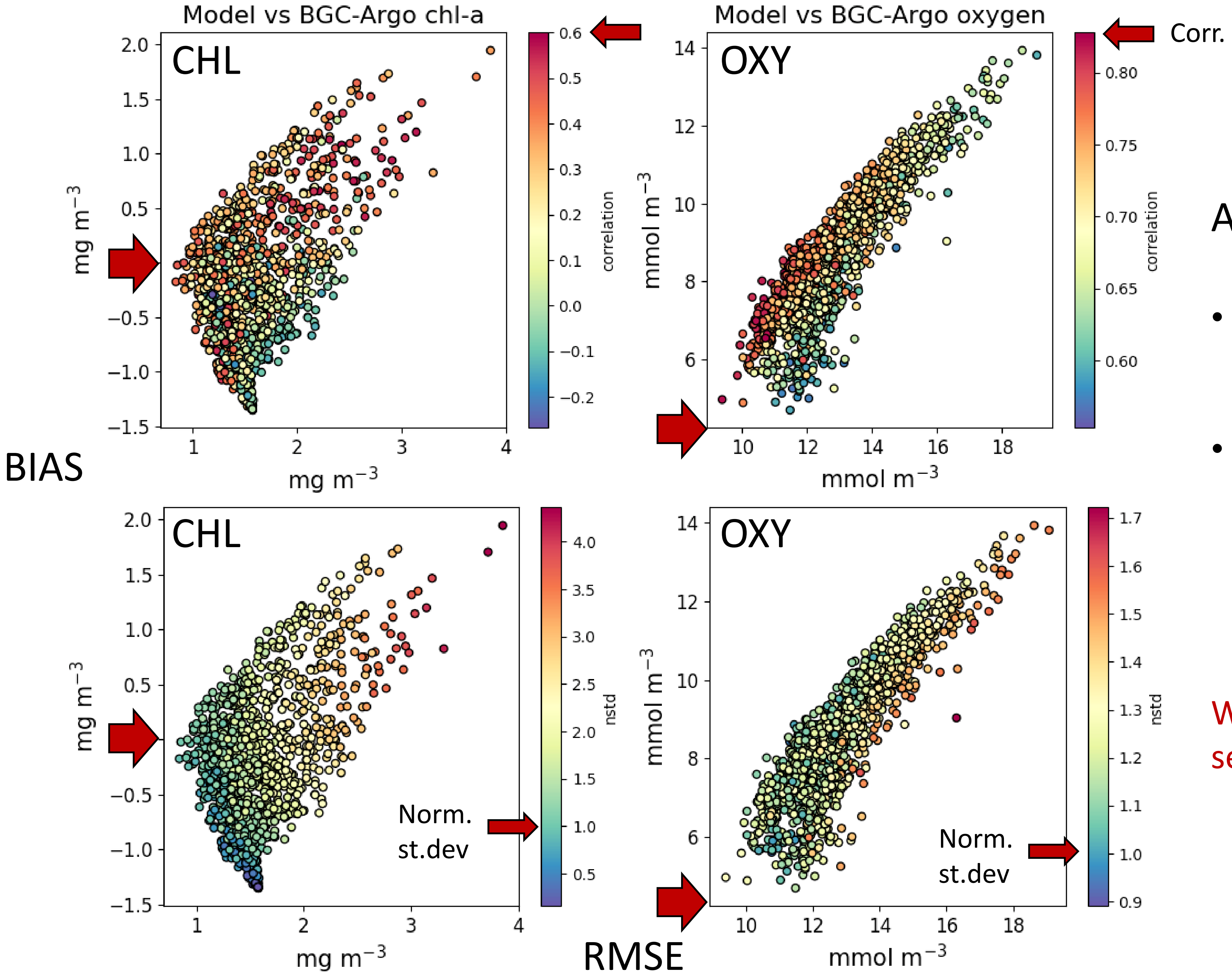
Objective: Tune model parameterization using an ensemble approach

- 4 Argo tracks: increase sample set and regional coverage
- selected 44 parameters (producivity & organic matter focus)
- each parameter is ranged with 30 values within -30% --> 30% of ref. value (parsac code; *Bolding & Bruggemann*)
- Ensemble has 5k+ experiments

- Identify the sub-experiment that best represents BGC-Argo CHL and OXY



6902547 6901180 6903549 6903554



Argo 6902547 experiments

- Argo profiles are interpolated to model depths
- Bias, RMSE, correlation and norm. standard deviation is calculated
  (CHL: 0-50 m)
  (OXY: 0-100 m)

Which experiment (parameter set) is objectively the best ?

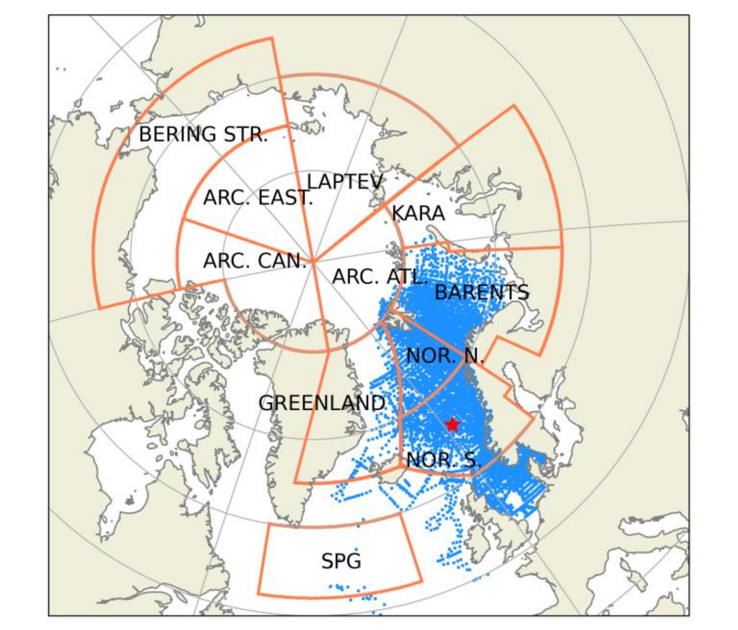
Application of the framework to improve 3D regional model parameters

Are statistically the better parameter sets in 1D domain applicable to 3D ?

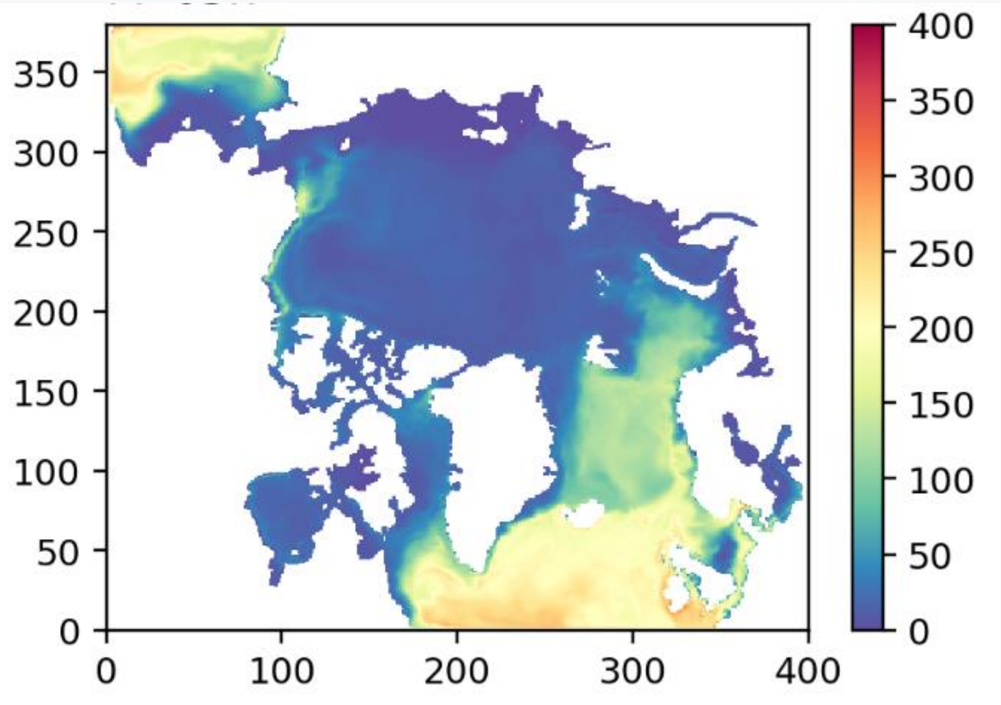
HYCOM-ECOSMO model

17 km average grid size, 50 hybrid vertical layers
(same region as Copernicus ARC MFC model but coarser)

10-year simulation



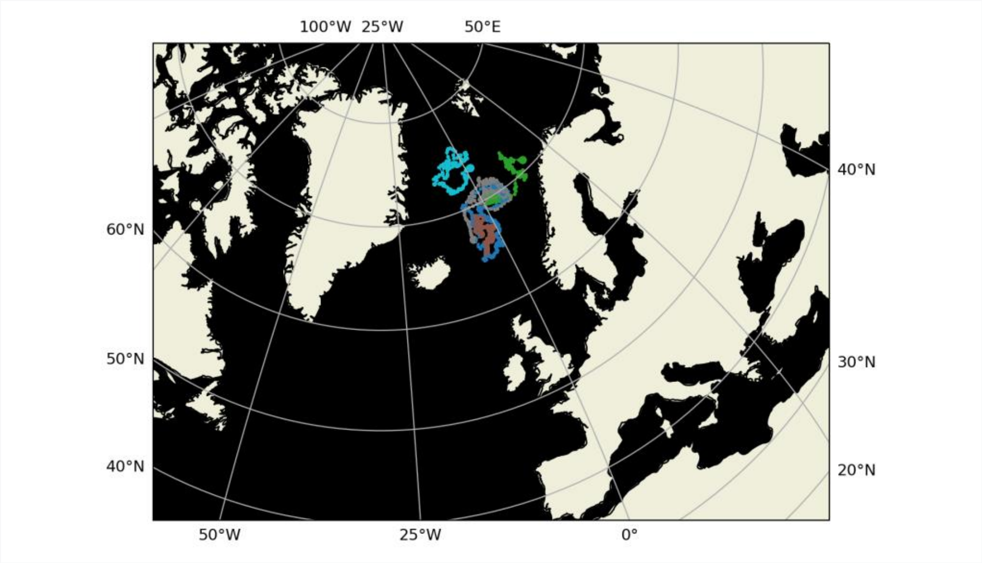
Model domain
example annually averaged int. GPP (mg C m^{-2} d^{-1})



Application of the framework to improve 3D regional model parameters

Are statistically the better parameter sets in 1D domain applicable to 3D ?

Problem with Case-1a and Case-1b
→ Too productive



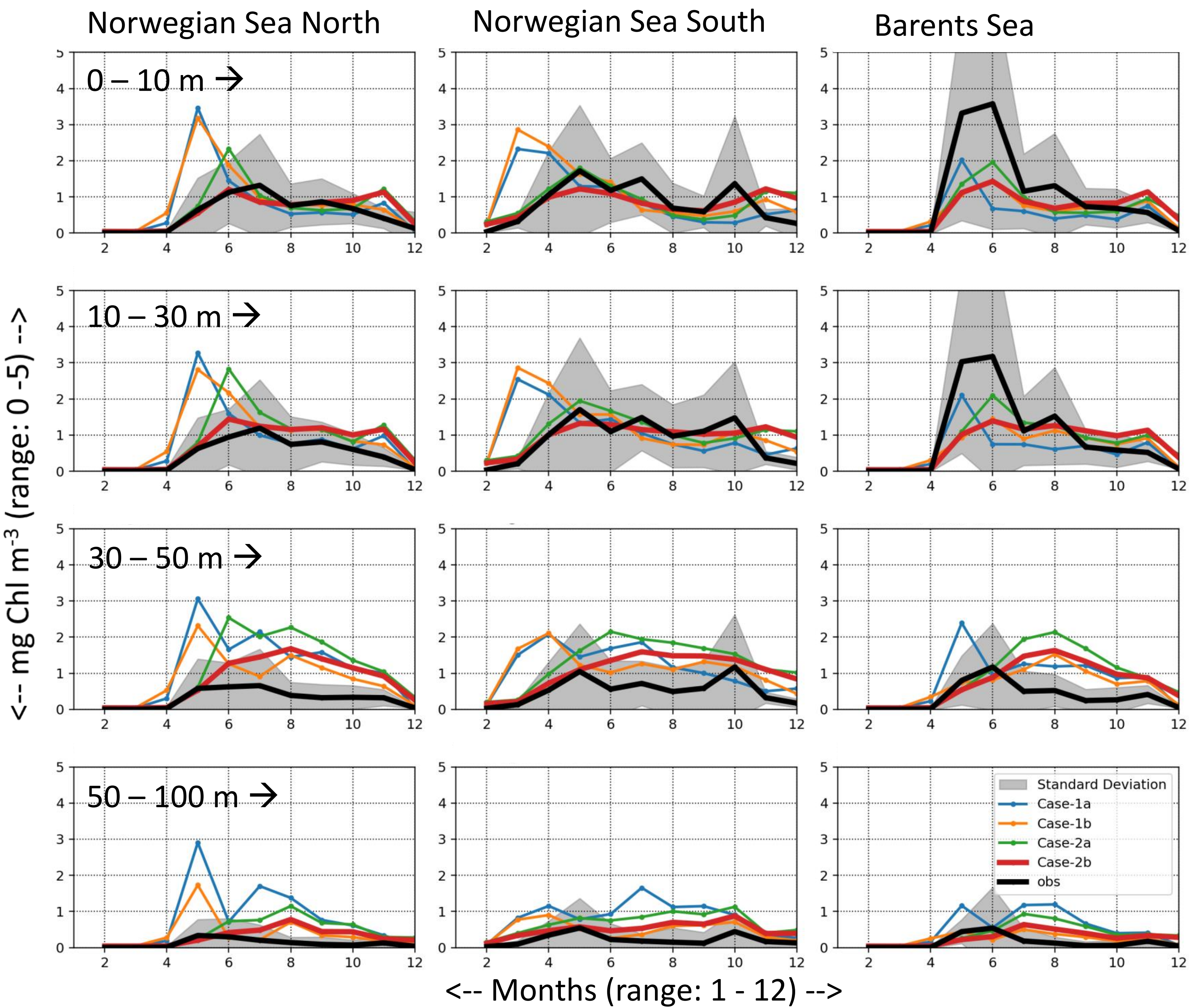
Model formulation change
→ Added density dependent mortality
→ Case-2a (Parameters similar to Case-1a)

Case-2b
→ Ensemble tuning with 7 recent BGC-Argo
→ (vs 4 in Case-1b)
→ Reference parameter set: Case-2a
→ BGC-Argo variables: CHL, OXY, NIT, POC
→ (vs CHL, OXY in Case-1b)

vs regionally and monthly averaged in situ **chl-a**

Obs vs Case 2b vs Case 1a

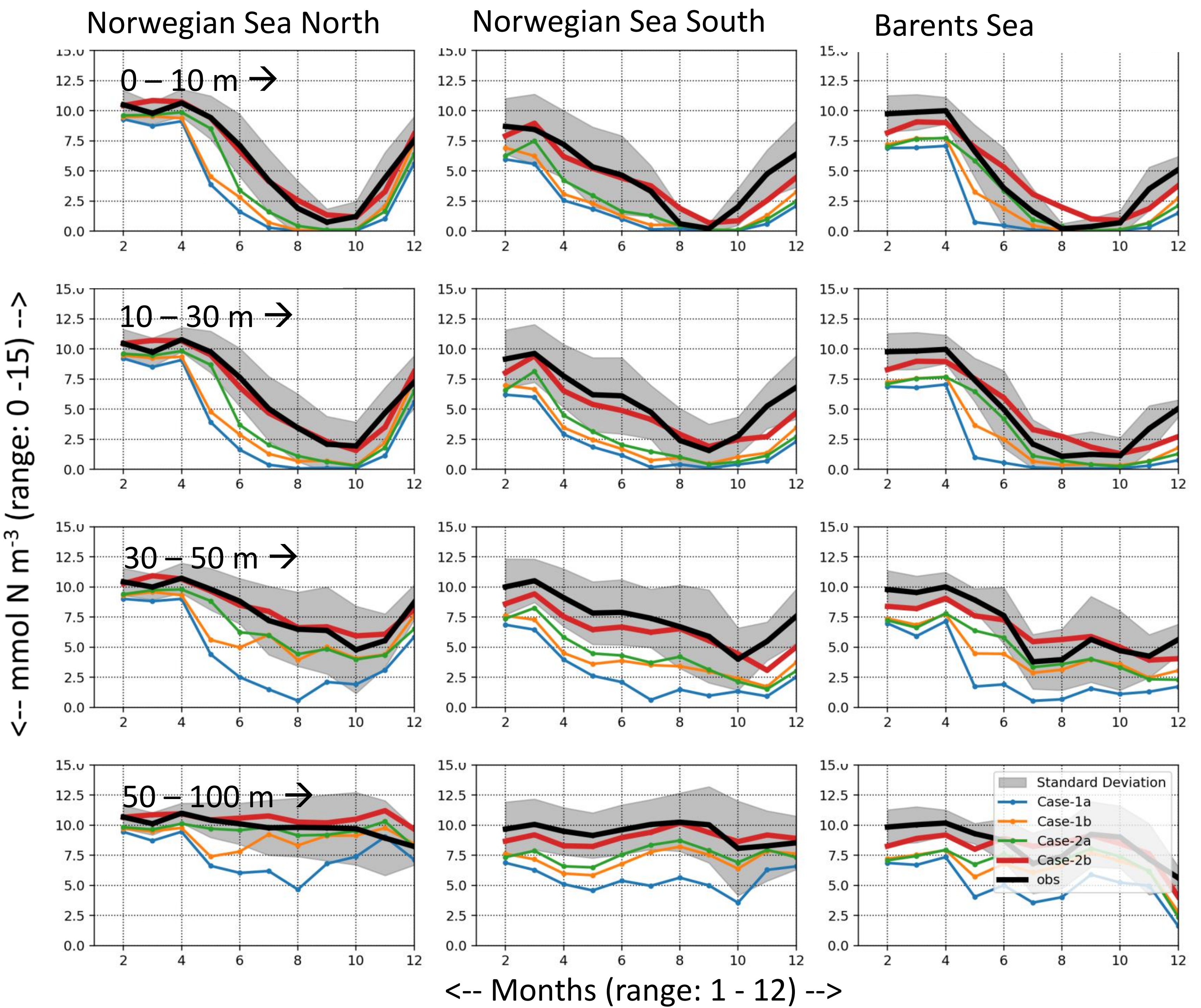
- **Reduction** of excess chl-a concentration compared to the reference experiments in the Norwegian Sea
- Improved spring bloom across different depth intervals
- More experimentation is required for the Barents Sea



vs regionally and monthly averaged in situ **nitrate**

Obs vs Case 2b vs Case 1a

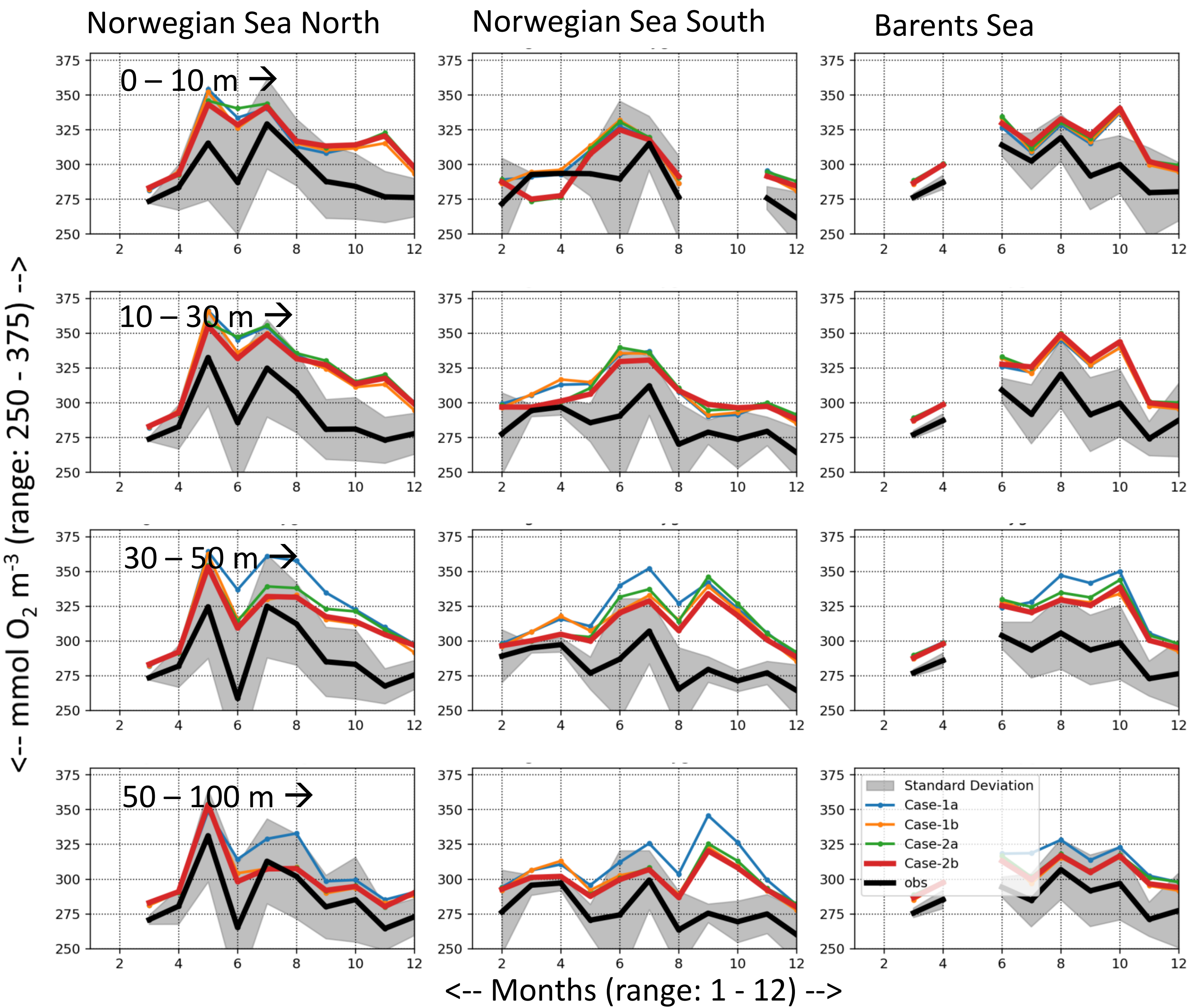
- **Reduction** of excess nitrate consumption compared to the reference experiments
- Improvements in every subregion and season



vs regionally and monthly averaged in situ **oxygen**

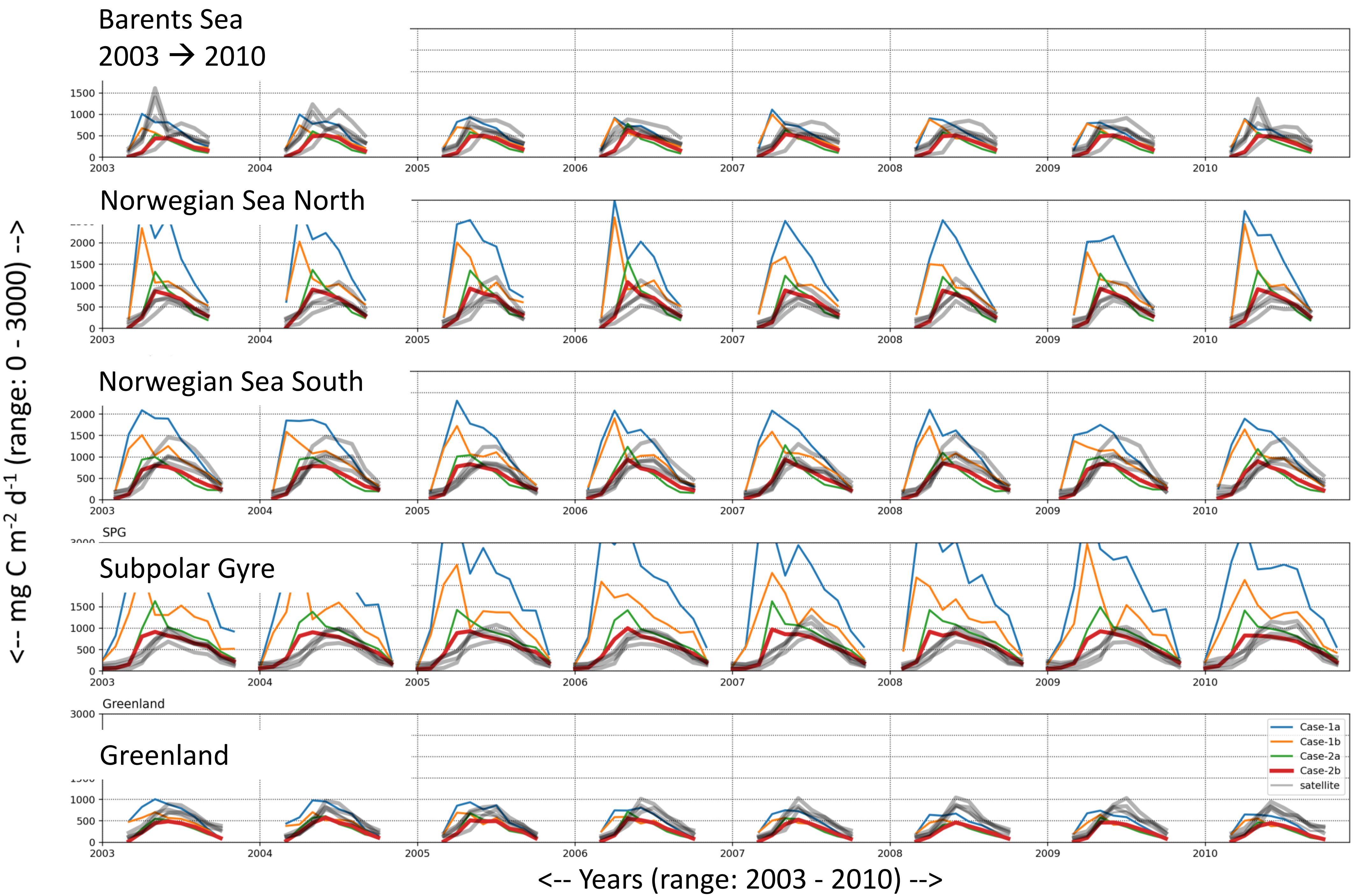
Obs vs Case 2b vs Case 1a

- Reduction of excess oxygen concentration compared to the reference experiments ***below the surface***



vs regionally and monthly averaged **MODIS NPP algorithms**

Case 2b is better aligned with satellite estimations across the model domain



Conclusions

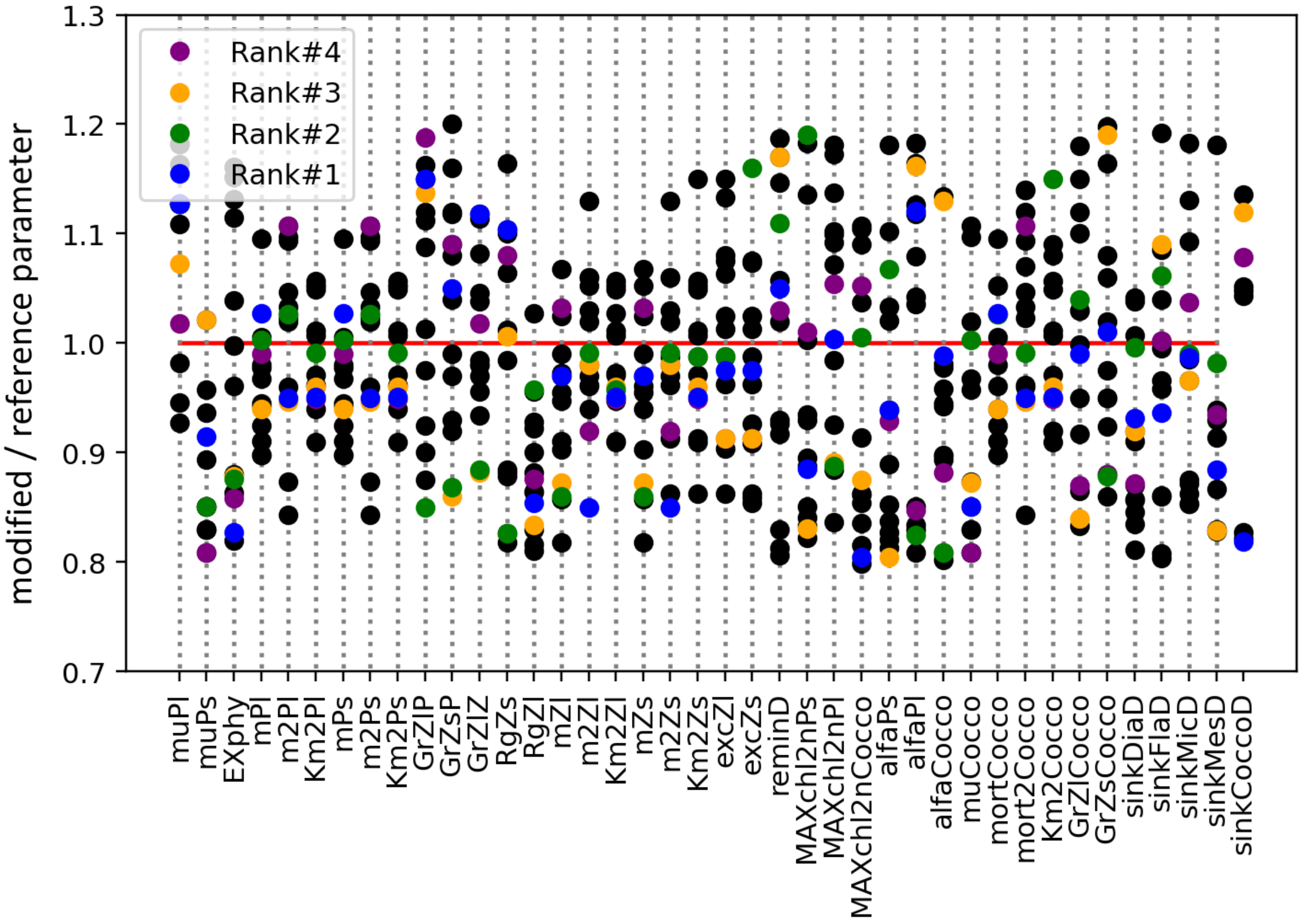
Model parameters are objectively analysed using an ensemble aproach along BGC-Argo tracks in the Nordic Seas to identify an optimal parameter set to achieve:

→ general reduction in model error in chl-a, nitrate and oxygen, primary production
→ improved seasonal trends
→ improved variations in concentrations across different depth intervals

Next steps:

- Increase the number of Argo trajectories
- Use this framework for analyzing new model formulations / adjust its parameterization

The ensemble framework can be used to evaluate parameter trends



Key points for use cases

Target BGC-Argos that stay in similar regions for the duration of experiments

- If necessary, divide the trajectories into multiple experiments

I benefited in limiting the along-track experiments to 1-year

- Remember that model variable relaxation is turned off, avoid drift in concentrations

Use multiple BGC-Argo variables for the statistical analyses

- Avoid overfitting to a single model variable

1D model setup has its limitations

- Limited to non-existing lateral interactions
- Avoid trajectories with complex water mass interactions
- Limited control on deeper layers

Extra material

BIAS	Nor.N.	Nor.S.	Barents
CHL bias Case-1a	0.493	0.293	**0.058**
CHL bias Case-1b	0.349	0.216	0.081
CHL bias Case-2a	0.451	0.38	0.206
CHL bias Case-2b	**0.233**	**0.119**	0.206
NIT bias Case-1a	-2.757	-3.403	-2.378
NIT bias Case-1b	-1.697	-2.553	-1.586
NIT bias Case-2a	-1.106	-2.21	-1.266
NIT bias Case-2b	**0.128**	**-0.57**	**-0.127**
OXY bias Case-1a	16.995	22.798	20.838
OXY bias Case-1b	**10.884**	19.973	**18.177**
OXY bias Case-2a	12.397	20.034	20.226
OXY bias Case-2b	10.998	**18.1**	19.787

RMSE	Nor.N.	Nor.S.	Barents
CHL rmse Case-1a	1.816	1.923	1.062
CHL rmse Case-1b	1.642	1.812	0.999
CHL rmse Case-2a	1.252	1.337	0.982
CHL rmse Case-2b	**0.824**	**1.102**	**0.907**
NIT rmse Case-1a	3.882	4.744	3.363
NIT rmse Case-1b	2.934	3.931	2.659
NIT rmse Case-2a	2.499	3.695	2.48
NIT rmse Case-2b	**1.953**	**2.624**	**2.16**
OXY rmse Case-1a	35.104	36.316	34.254
OXY rmse Case-1b	**29.817**	32.676	**31.579**
OXY rmse Case-2a	31.968	32.827	33.75
OXY rmse Case-2b	30.259	**30.385**	33.048

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