

Biogeochemical Parameter and State Estimation MITgcm - BLING

Angela M. Kuhn, Matthew R. Mazloff, Ariane Verdy, Sarah T. Gille & ECCO@Scripps

UC San Diego



SCRIPPS INSTITUTION OF OCEANOGRAPHY



SOCCOM



Schmidt Sciences



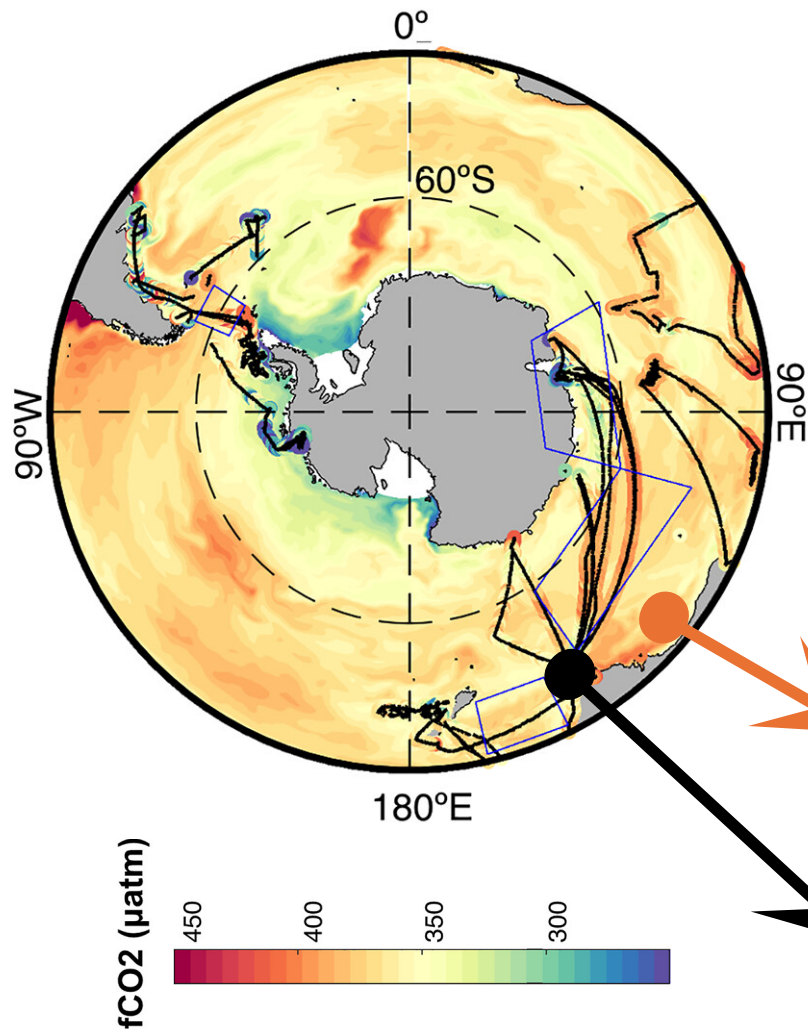
Biogeochemical Parameter and State Estimation

MITgcm - BLING

1. Parameter estimation to improve $p\text{CO}_2$ model biases
2. Regional state estimation
3. Proposed work

BGC parameter estimation: $p\text{CO}_2$ model biases

a. Surface $f\text{CO}_2$ Sep - Feb



JGR Biogeosciences

Research Article | [Full Access](#)

Understanding Regional $p\text{CO}_2$ Model Biases and Uncertainties in the Biogeochemical Southern Ocean State Estimate (B-SOSE)

[Angela M. Kuhn](#) ✉, [Matthew R. Mazloff](#), [Sarah T. Gille](#), [Ariane Verdy](#)

First published: 21 May 2026 | <https://doi.org/10.1029/2025JG009491> |

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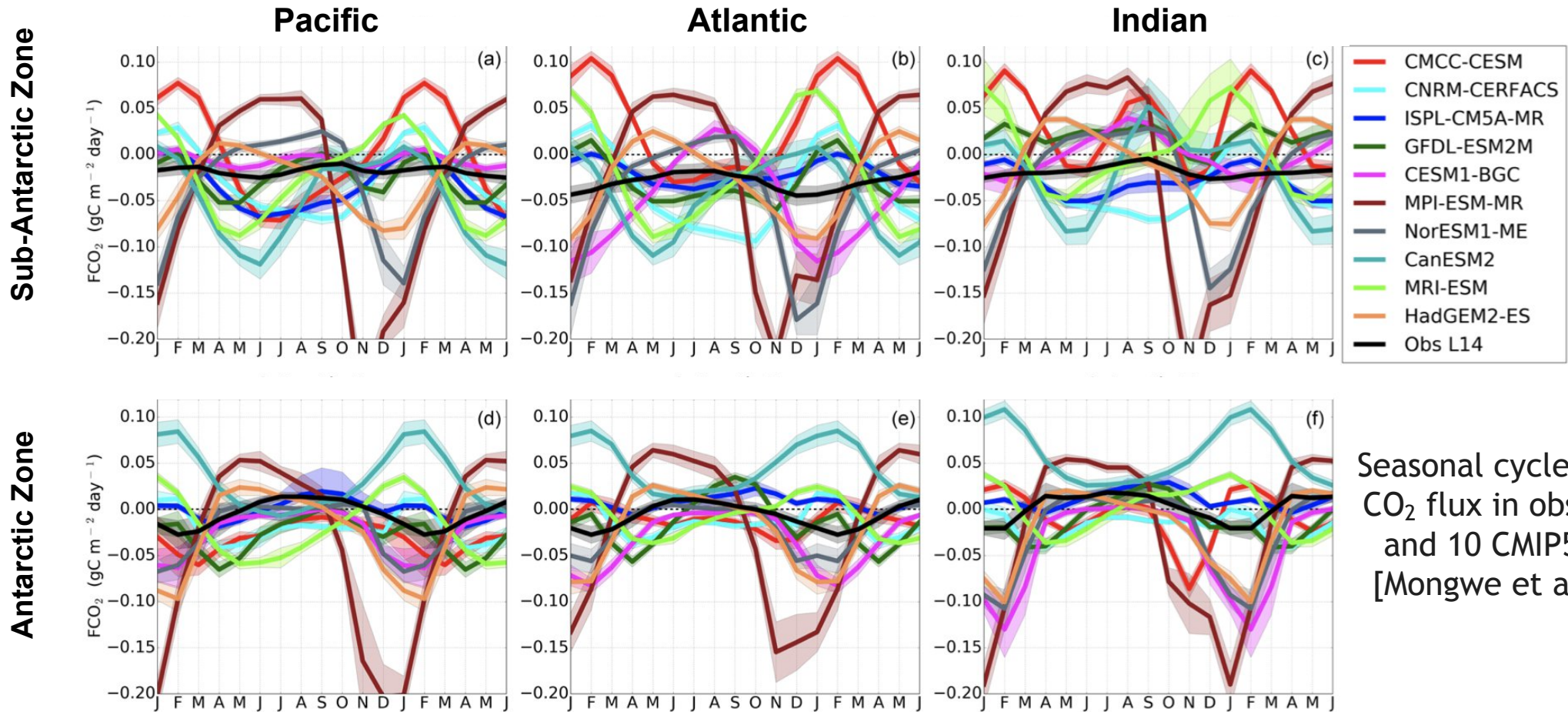
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B-SOSE
(control run 2019 - 2020)

SOCAT $f\text{CO}_2$

BGC parameter estimation: pCO₂ model biases

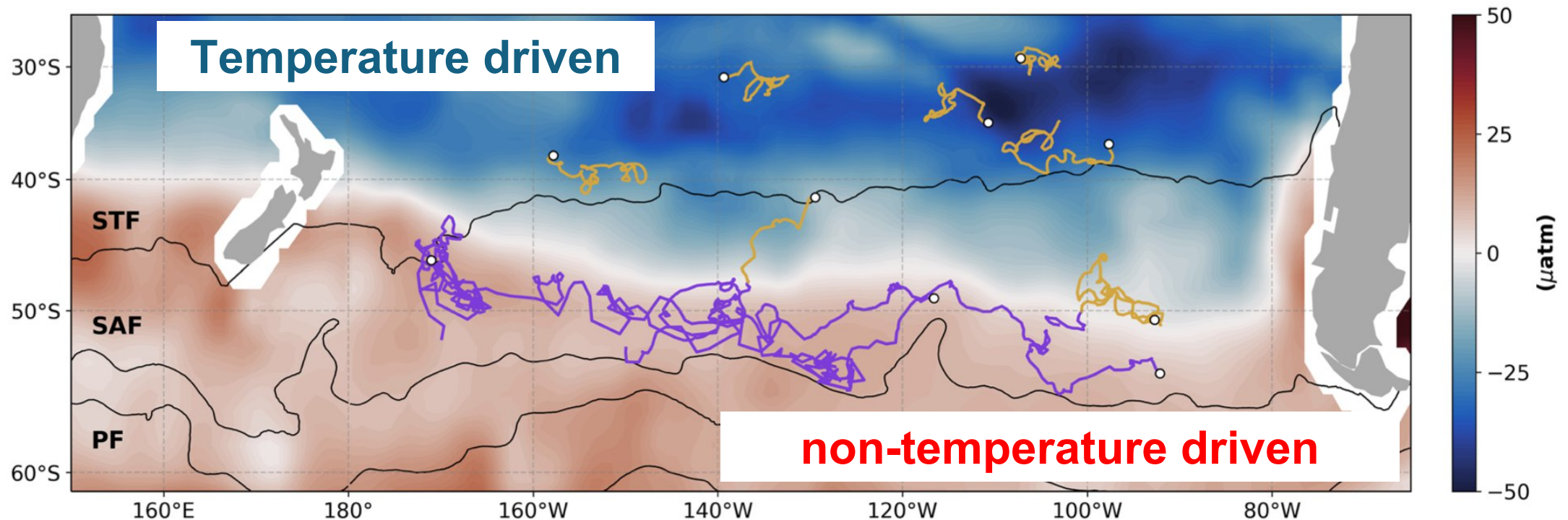
Climate models often poorly represent the phasing air-sea CO₂ flux in the Southern Ocean



Seasonal cycle of sea-air CO₂ flux in observations and 10 CMIP5 models [Mongwe et al., 2018]

BGC parameter estimation: $p\text{CO}_2$ drivers

Model limitations may arise from misrepresentation of the spatial distribution of $p\text{CO}_2$ drivers



Winter minus summer mean surface ocean $p\text{CO}_2$ from Landschützer climatology. Blue = thermally driven. Red = non-thermally driven [Prendt et al. 2022]

BGC parameter estimation: B-SOSE (BLING)

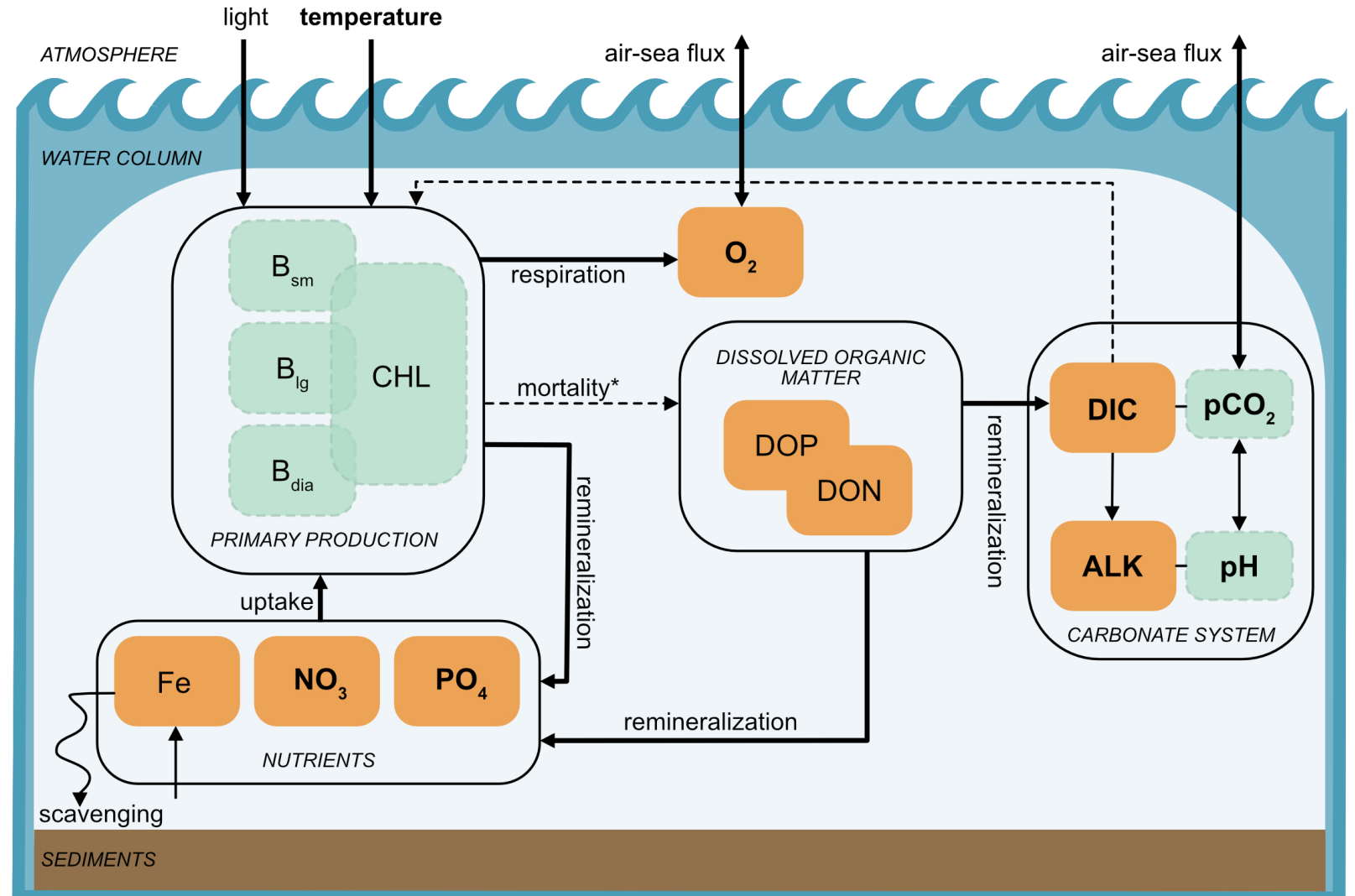
B-SOSE

Physics:

- MITgcm + ECCO configuration
- Resolution of $1/3^\circ$ and 52 vertical levels

Biogeochemistry: N-BLING

- Intermediate-complexity model
- 9 prognostic tracers
- Total phytoplankton biomass divided into 3 groups



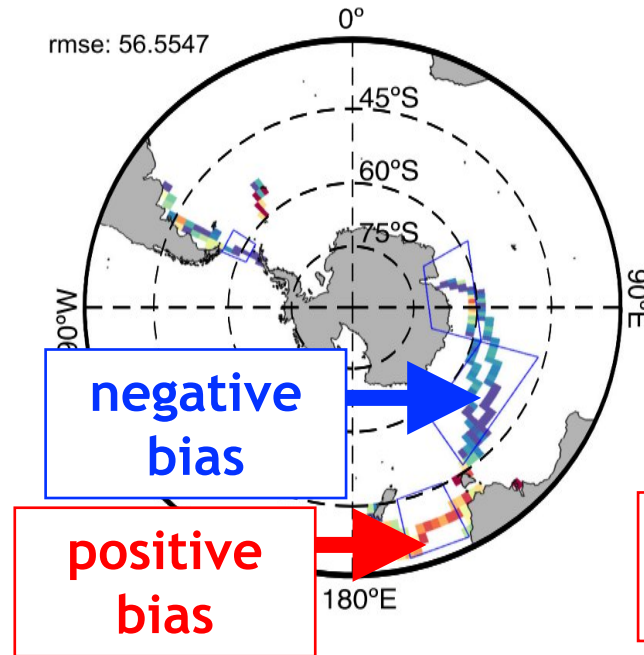
BGC parameter estimation: pCO₂ model biases

- **Distinct temporal and spatial structure** related to latitudinal gradients and coastal features.

Sep. 2019 - Aug. 2020 simulations

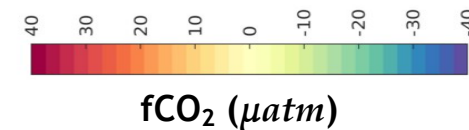
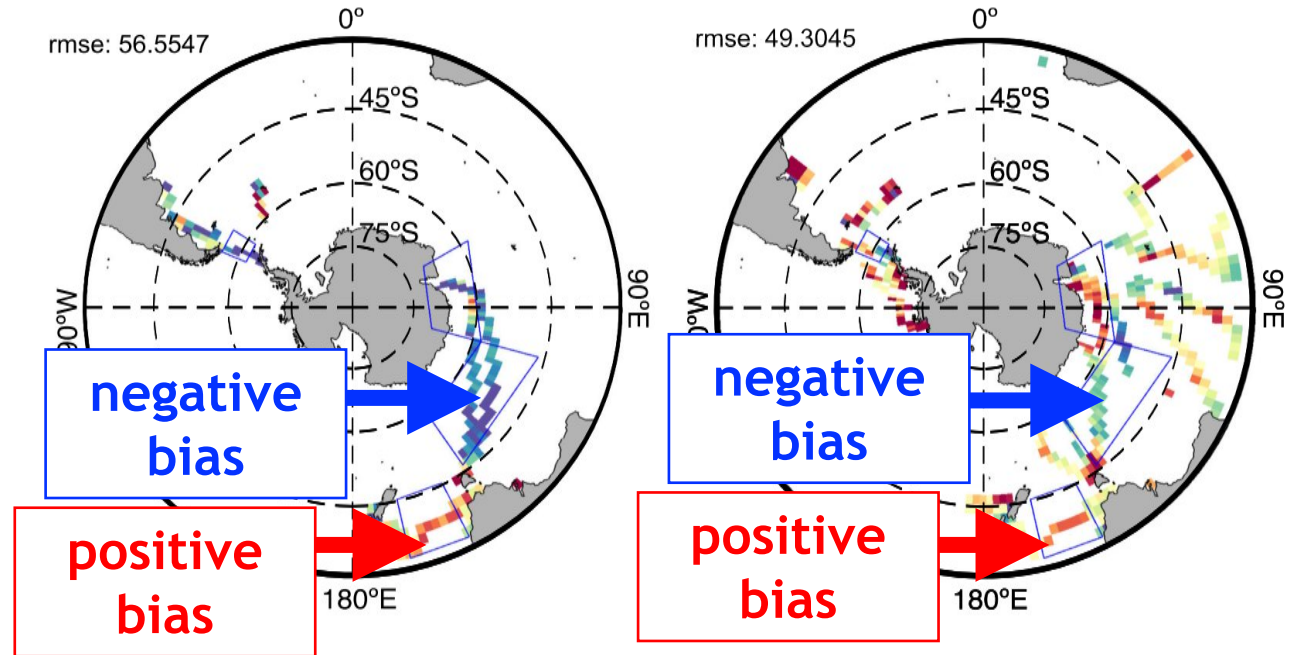
a. B-SOSE - SOCAT bias Sep - Nov

rmse: 56.5547



b. B-SOSE - SOCAT bias Dec - Feb

rmse: 49.3045



[Kuhn et al., 2026]

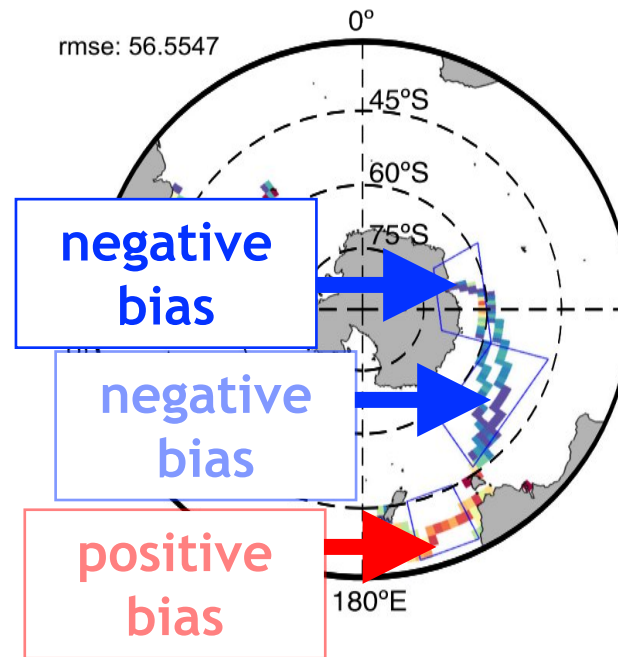
BGC parameter estimation: pCO₂ model biases

- Distinct temporal and spatial structure related to latitudinal gradients and coastal features.
- Biases flip from negative to positive between seasons in some areas.

Sep. 2019 - Aug. 2020 simulations

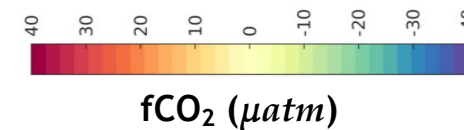
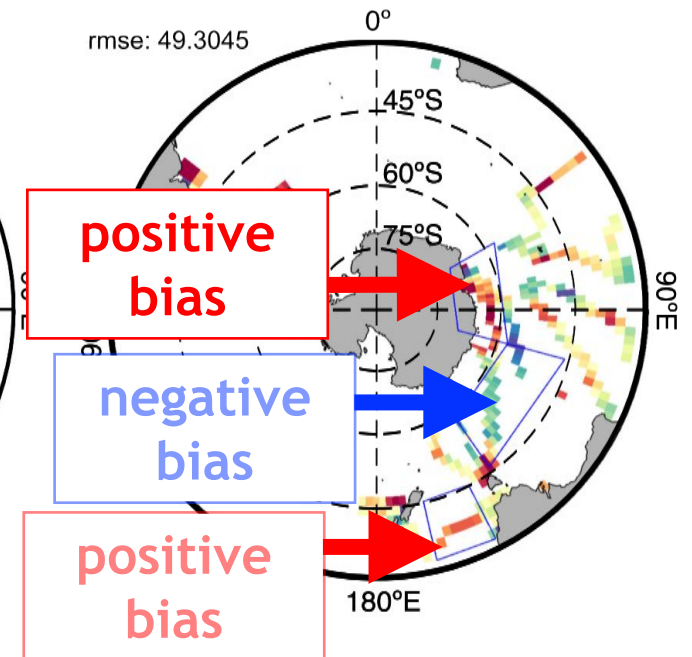
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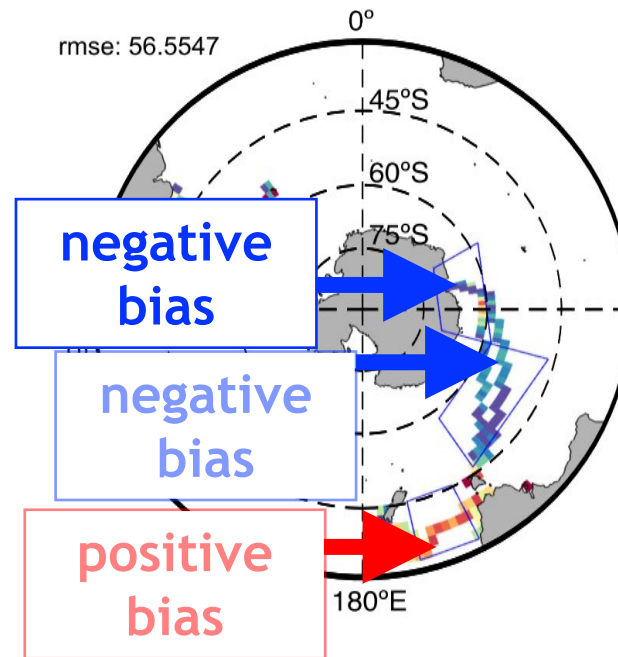
BGC parameter estimation: pCO₂ model biases

- Distinct temporal and spatial structure related to latitudinal gradients and coastal features.
- Biases flip from negative to positive between seasons in some areas.
- Temporal and spatial offsets.

Sep. 2019 - Aug. 2020 simulations

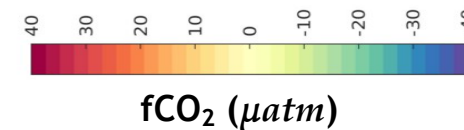
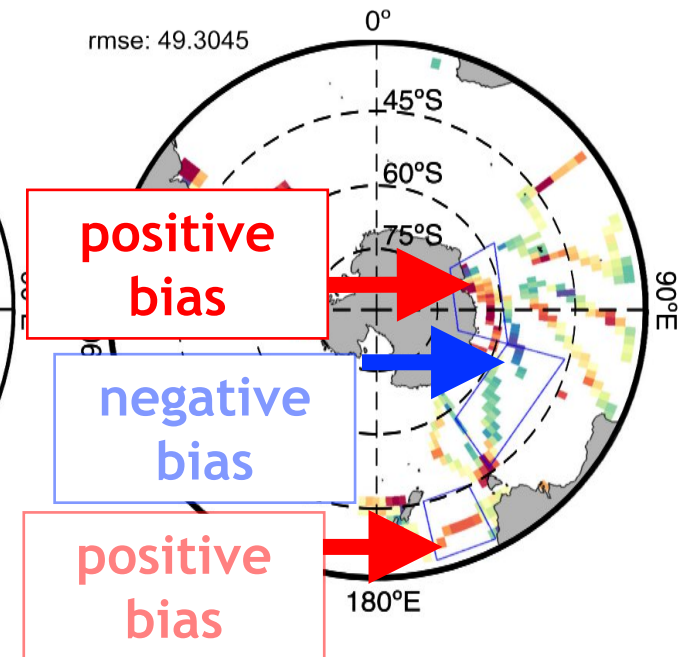
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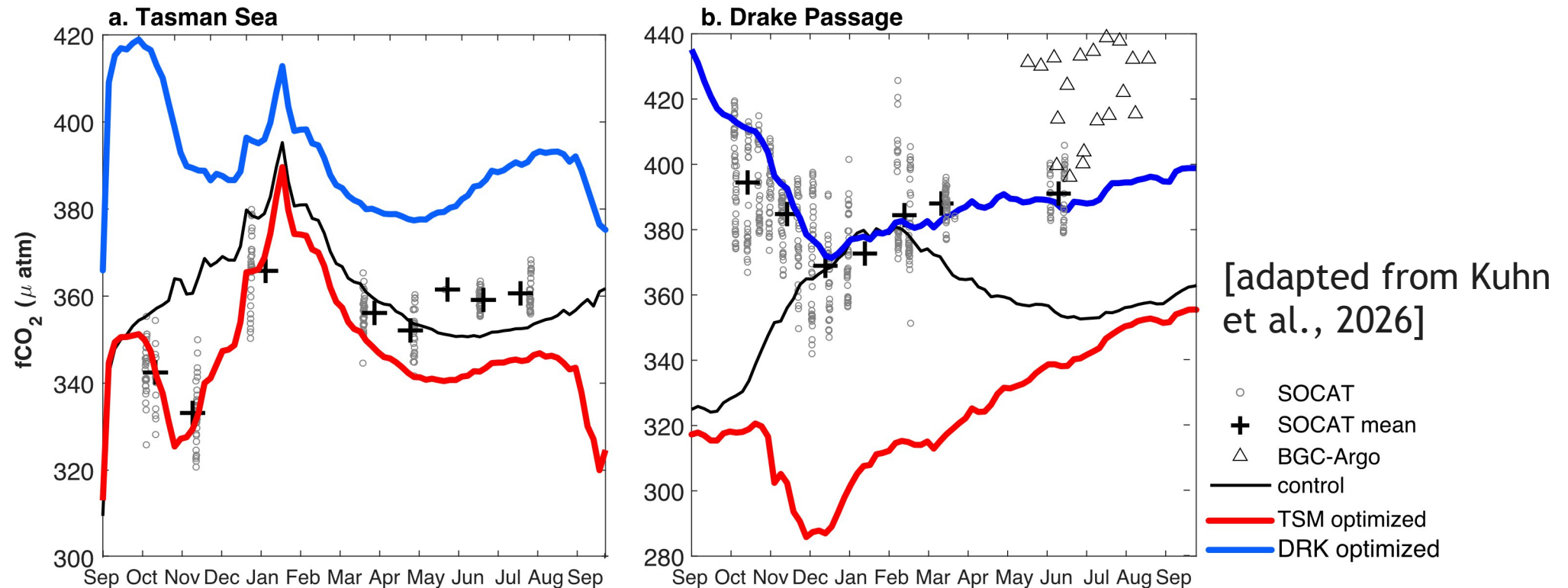
rmse: 49.3045



[Kuhn et al., 2026]

BGC parameter estimation: pCO₂ optimized results

- Optimization for individual sub-regions obtained 1. similar changes in bgc parameters and 2. different changes to alkalinity initial conditions.
- BGC parameters and initial conditions control different aspects of the fCO₂ model response.

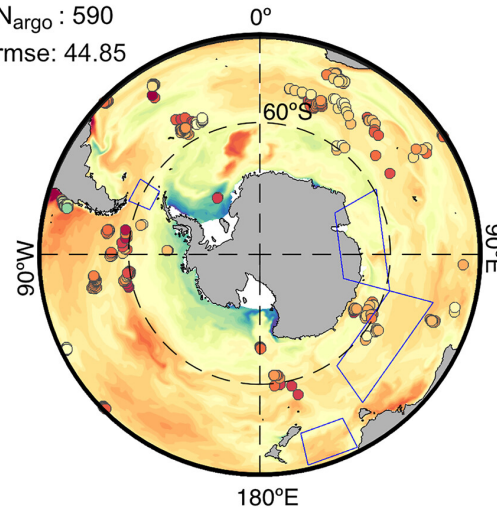


BGC parameter estimation: pCO₂ optimized results

- Increased fCO₂ throughout the entire domain.
- Increased the **similarity to BGC-Argo** observations with high fCO₂

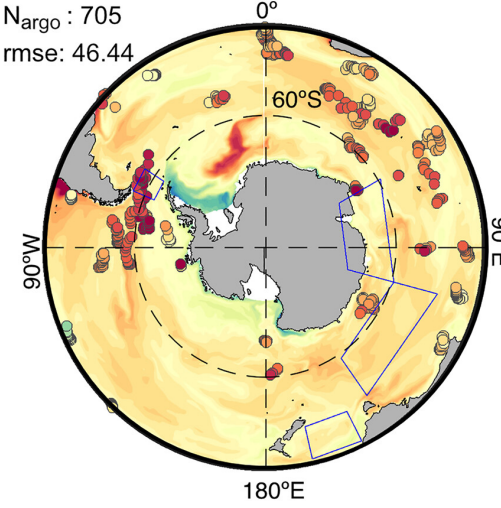
a. Control Sep - Feb

N_{argo} : 590
rmse: 44.85



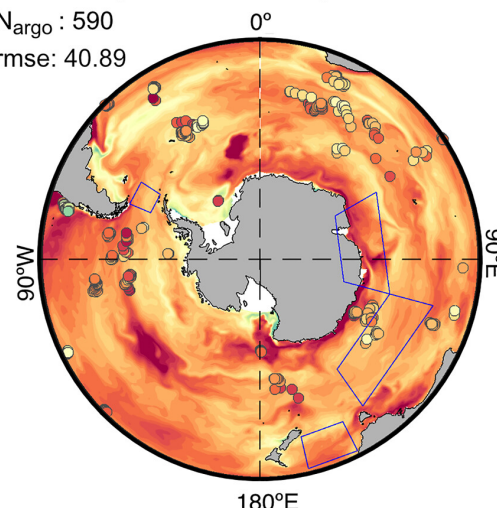
b. Control Mar - Aug

N_{argo} : 705
rmse: 46.44



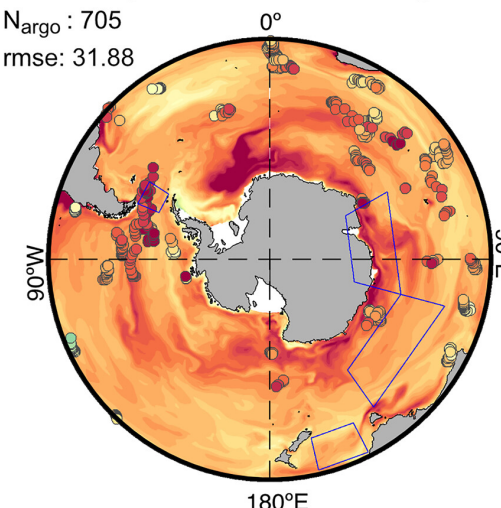
c. DRK optimization Sep - Feb

N_{argo} : 590
rmse: 40.89

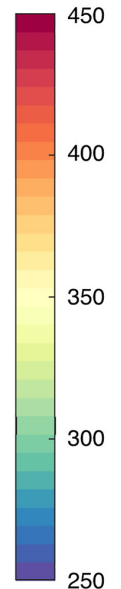


d. DRK optimization Mar - Aug

N_{argo} : 705
rmse: 31.88



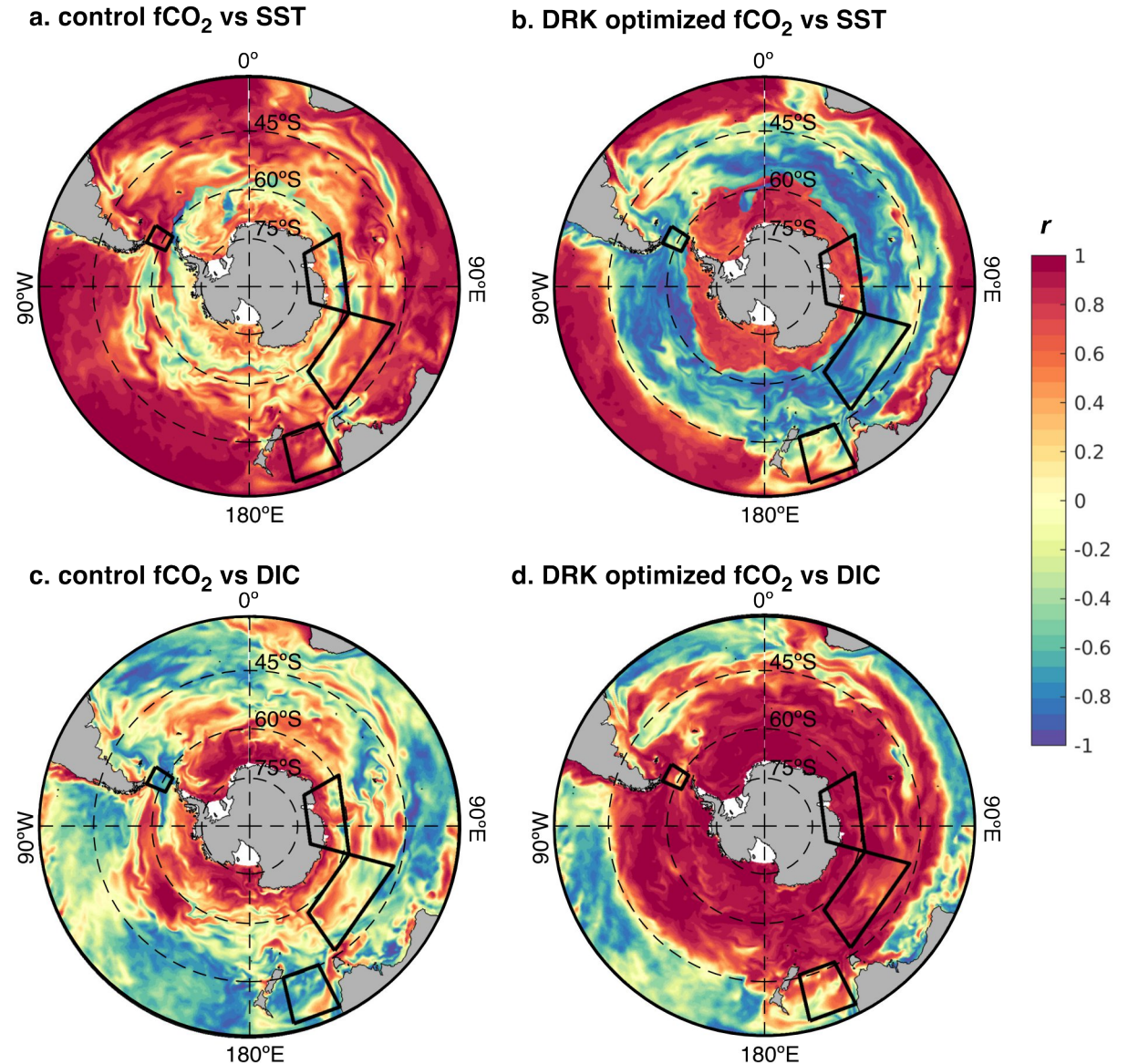
fCO₂ (μatm)



BGC parameter estimation: $p\text{CO}_2$ optimized drivers

Emergent spatial patterns of $p\text{CO}_2$ drivers agree with observational studies:

- $p\text{CO}_2$ strongly correlated with SST in subtropical areas.
- $p\text{CO}_2$ strongly correlated with DIC in subpolar areas.



BGC Parameter estimation: summary

- **Improved B-SOSE fCO₂ results**; 18%–79% rmse reduction & 67%-92% correlation improvement.
- **Improved spatial patterns of fCO₂ drivers** of seasonal variability.
- **BGC parameters and initial conditions control different aspects** of the fCO₂ model response in the Southern Ocean:
- **BGC parameters affect the phasing** of the fCO₂ seasonal cycle; BGC optimization improves correlation to observations.
- **Alkalinity initial conditions affect sub-regional mean fCO₂ differences**; uncertainties still affect model solution.

Regional State Estimation

Matthew R. Mazloff & ECCO@Scripps group

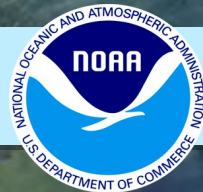
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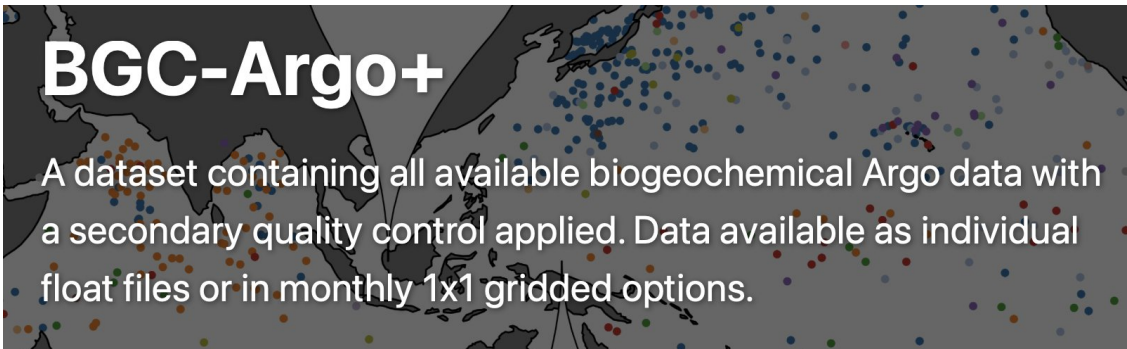


in situ BGC constraints processing

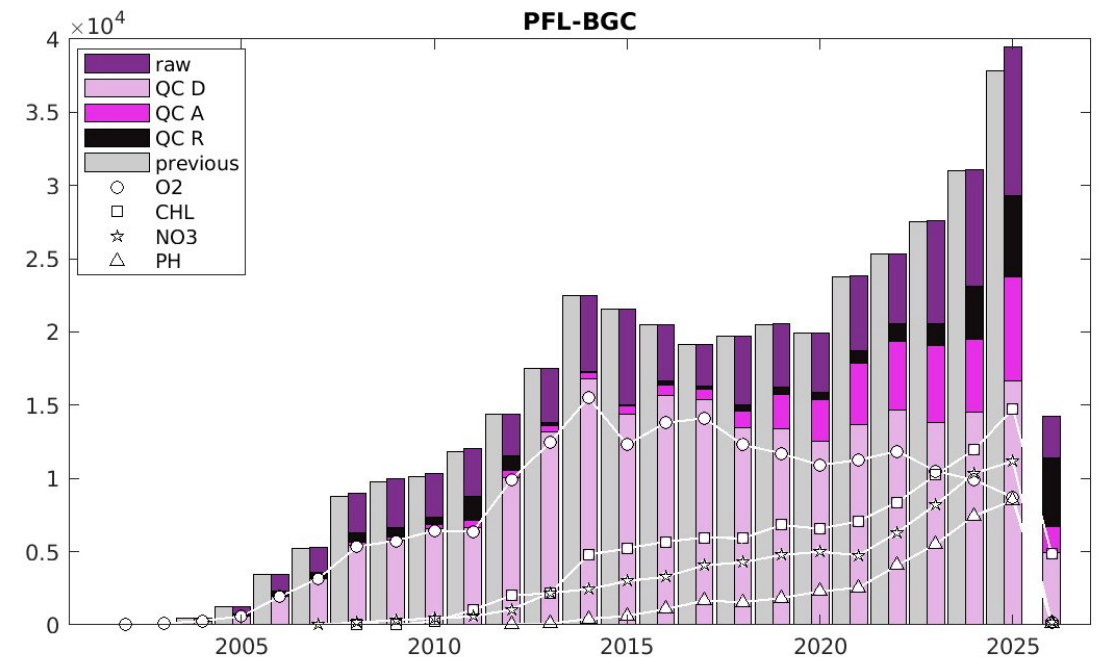
- bgc-Argo 2005-2026
- WOD 1992-2026
- SOCATv2025 2012-2024
- GLODAPv2 1992-2021

In progress:

Improved QC, BGC-Argo+ (Bushinski, Nashod)



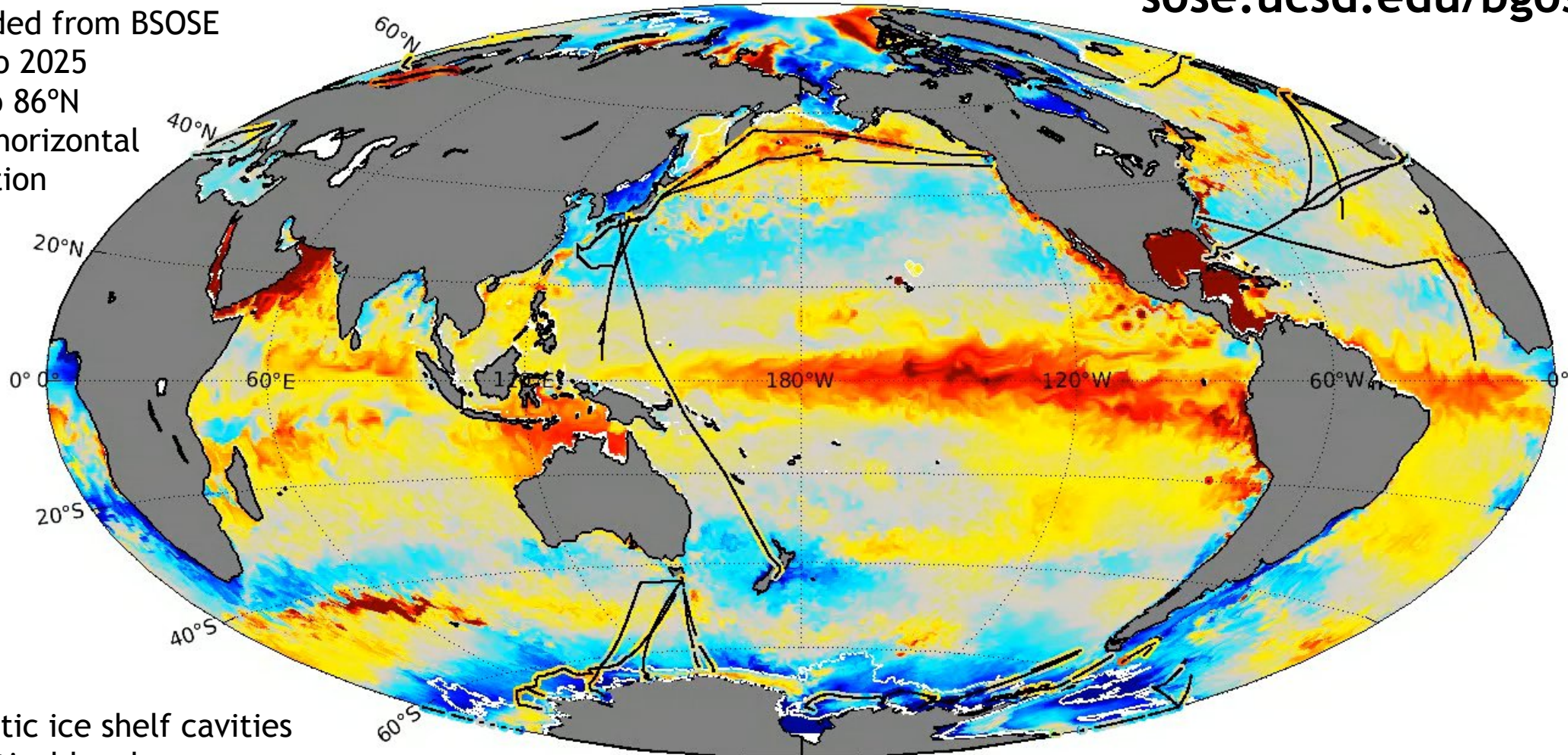
ecco.ucsd.edu/assim.html



Biogeochemical Global Ocean State Estimate (BGOSE)

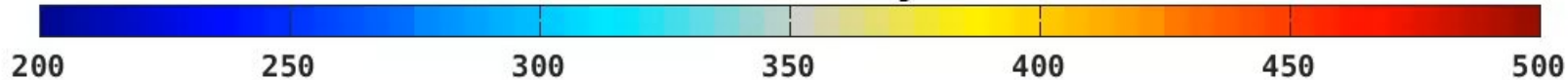
sose.ucsd.edu/bgose.html

- Expanded from BSOSE
- 2013 to 2025
- 83°S to 86°N
- 1/6th horizontal resolution

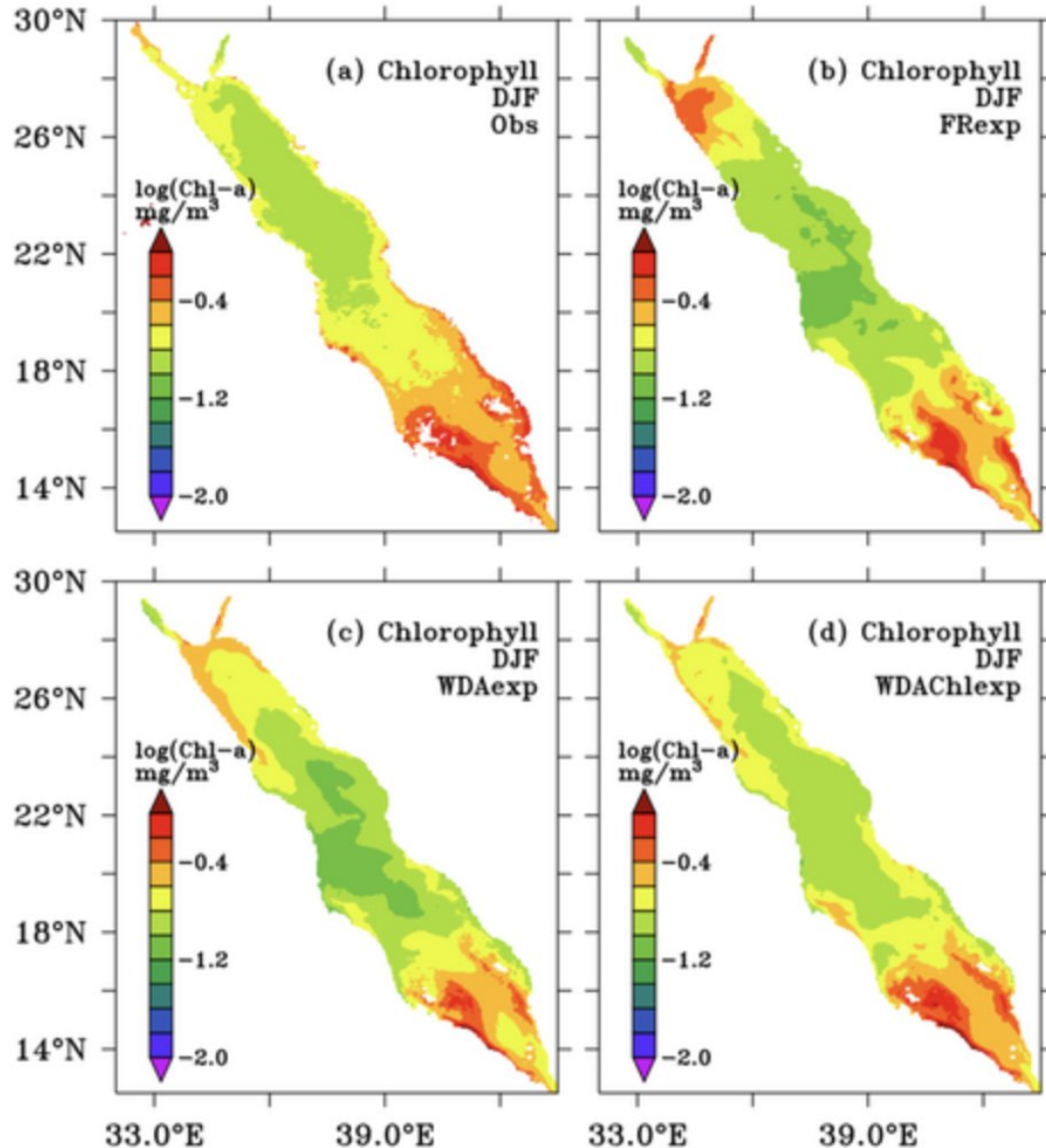


- Antarctic ice shelf cavities
- 52 vertical levels

pCO₂ (μatm)
BGOSE6 Iter041 01-Jan-2013



BGC in the Red Sea



JAMES | Journal of Advances in
Modeling Earth Systems*

Research Article | [Open Access](#) |

Evaluating a Hybrid Ensemble Data Assimilative Coupled Physical-Biogeochemical Ecosystem Model of the Red Sea

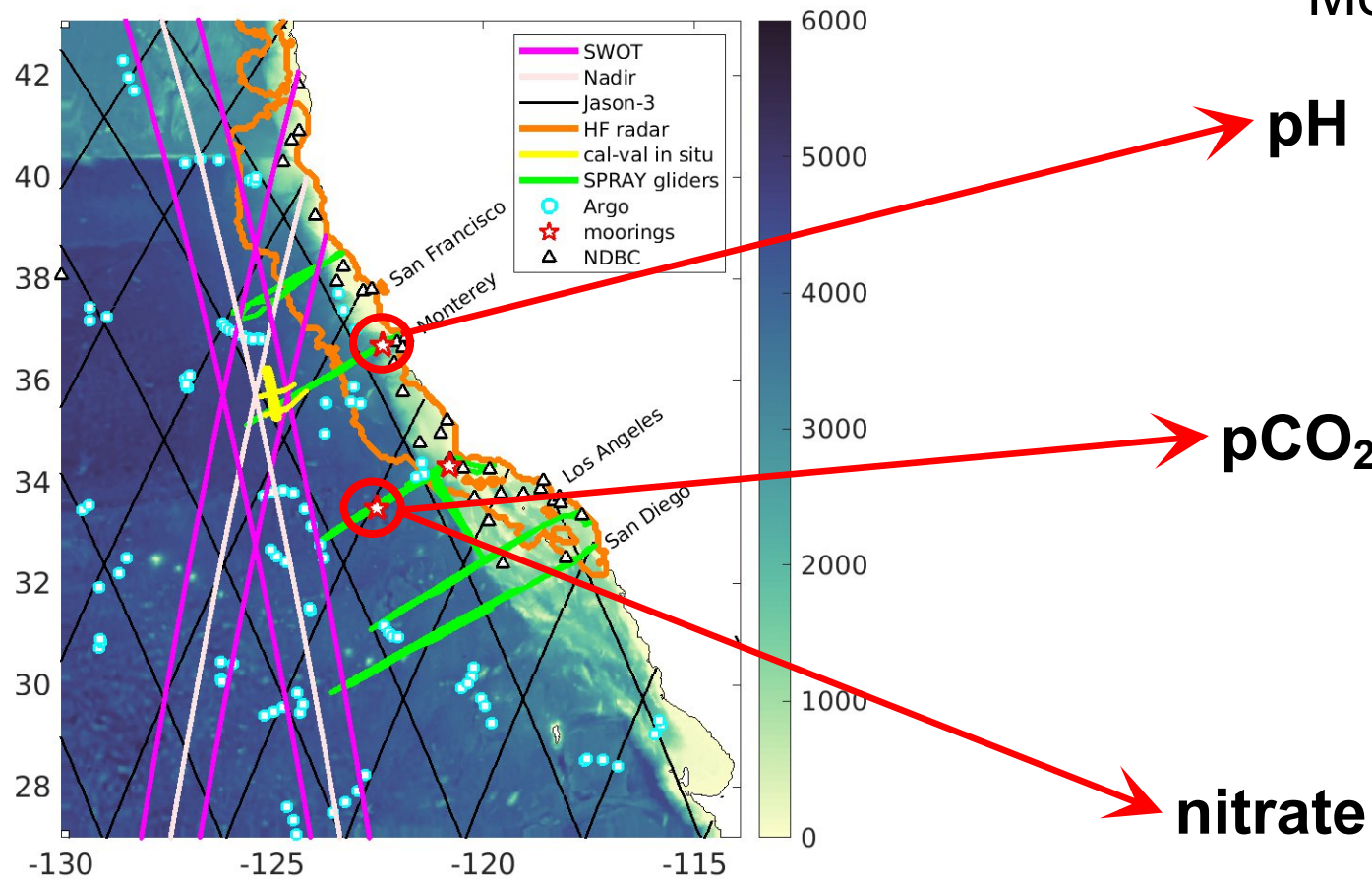
[Sivareddy Sanikommu](#), [Yixin Wang](#), [Mohamad El Gharamti](#), [Matthew R. Mazloff](#), [Ariane Verdy](#), [Naila Raboudi](#), [Rui Sun](#), [Benjamin K. Johnson](#), [Aneesh C. Subramanian](#), [Bruce D. Cornuelle](#), [Sabique Langodan](#), [Ibrahim Hoteit](#) ✉ ... See fewer authors ^

First published: 10 December 2025 | <https://doi.org/10.1029/2025MS005086> |

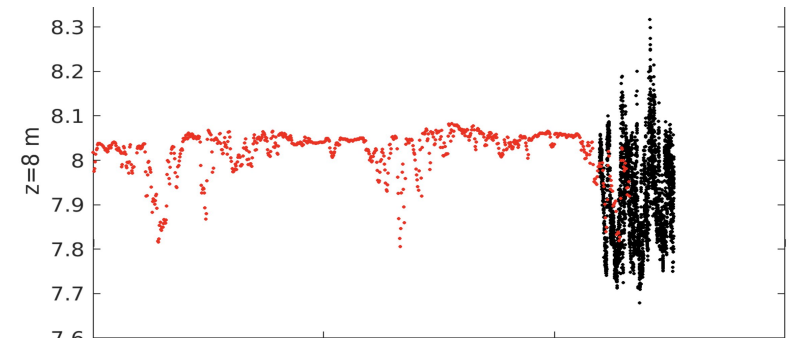
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Get it at

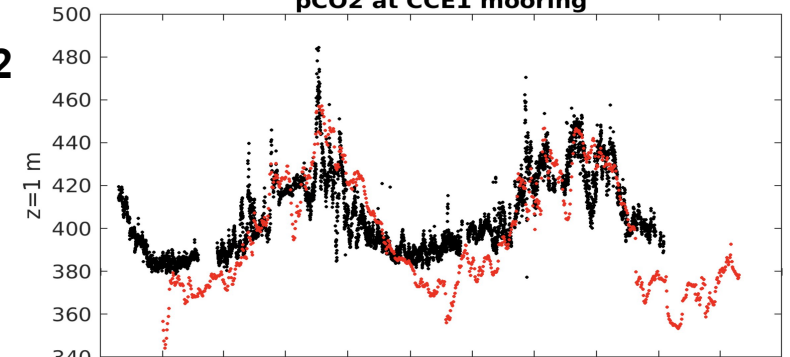
BGC in the California Current System (CCS)



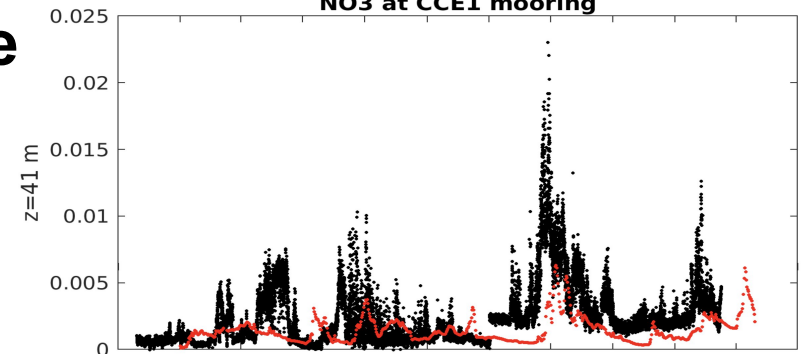
Mooring data vs **BLING** forward run



pCO₂ at CCE1 mooring

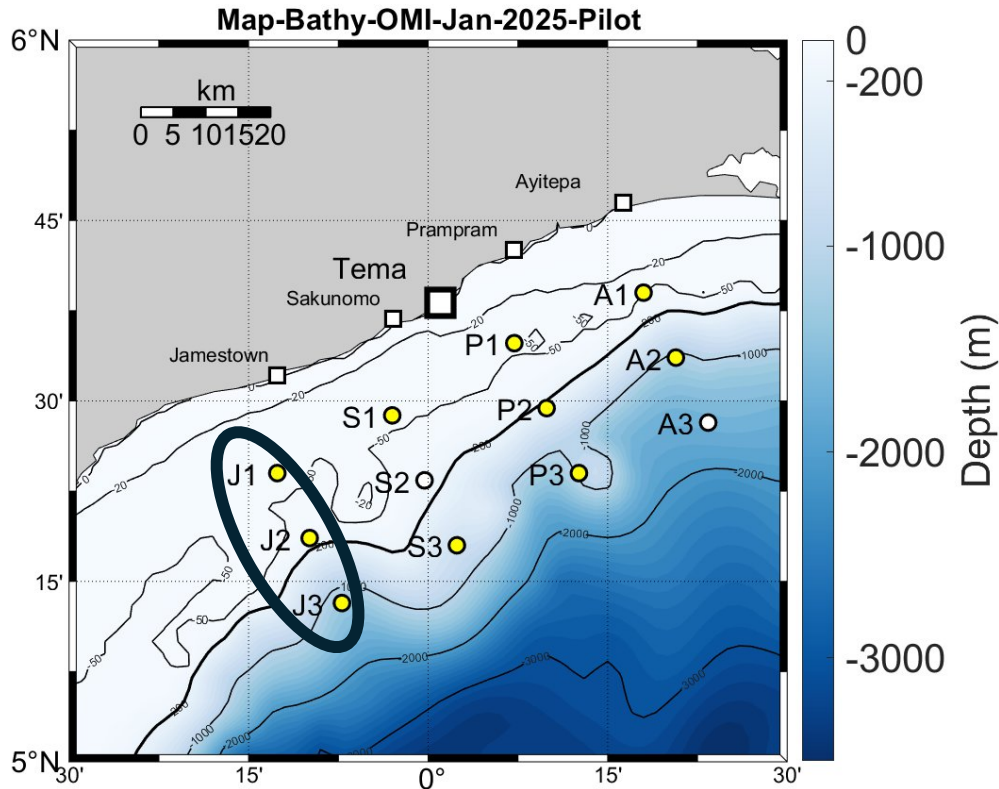


NO₃ at CCE1 mooring

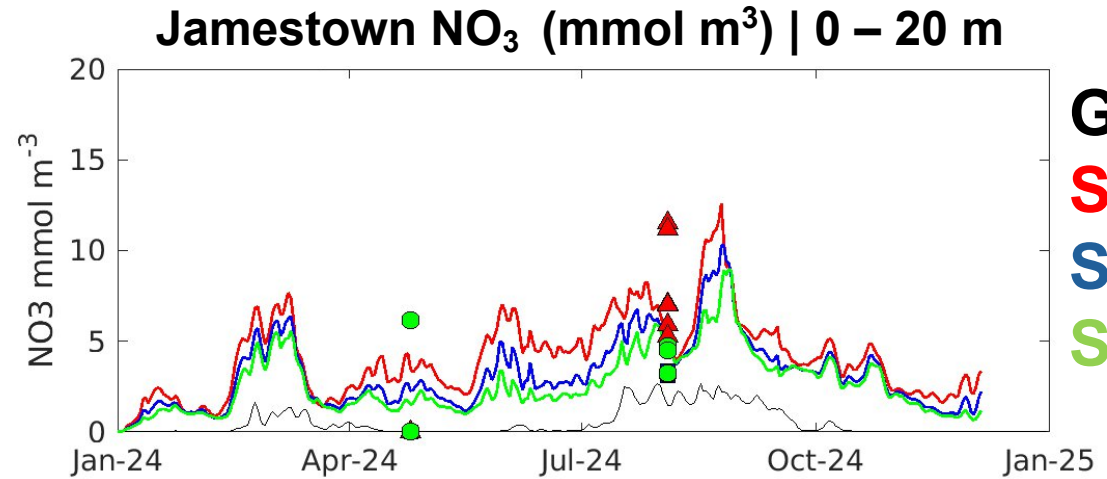


In progress:
How does data assimilation impact vertical motion simulation, and what are the implications for BGC?

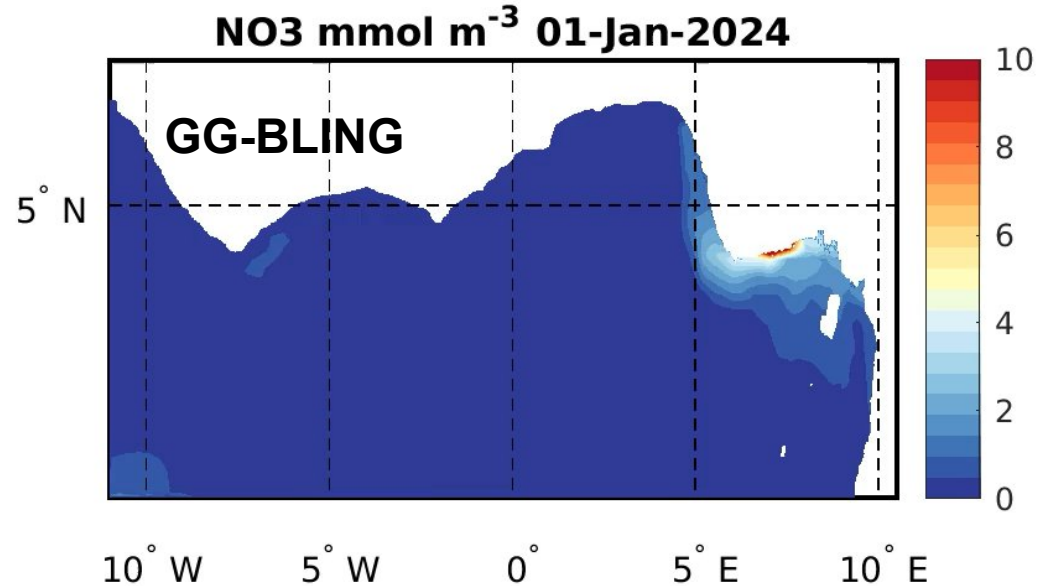
BGC in the Gulf of Guinea (GG)



In progress:
Cross-shelf heat, carbon and nutrient fluxes



GLORYS
Station J1
Station J2
Station J3



A satellite image of Earth showing ocean currents. The colors represent different temperatures and depths, with warm waters in shades of red and orange, and cold waters in shades of blue and purple. The currents are swirling and flowing across the ocean surface. The text "Proposed Work" is overlaid in the center in a large, white, sans-serif font.

Proposed Work

Proposed: “mechanistic- AI” forecasting

HABWISE

Harmful Algal Bloom Warning through Integrated State Estimation and Machine Learning

HABWISE combines artificial intelligence, advanced ocean modeling, satellite and in situ observations to deliver accurate, low-latency regional HAB forecasts



SCALABLE

A roadmap to ocean biogeochemical AI-powered forecasting, scalable worldwide



ACCURATE

Physics-informed AI for reliable HAB predictions



LOW-LATENCY

Real-time forecasts for timely decisions



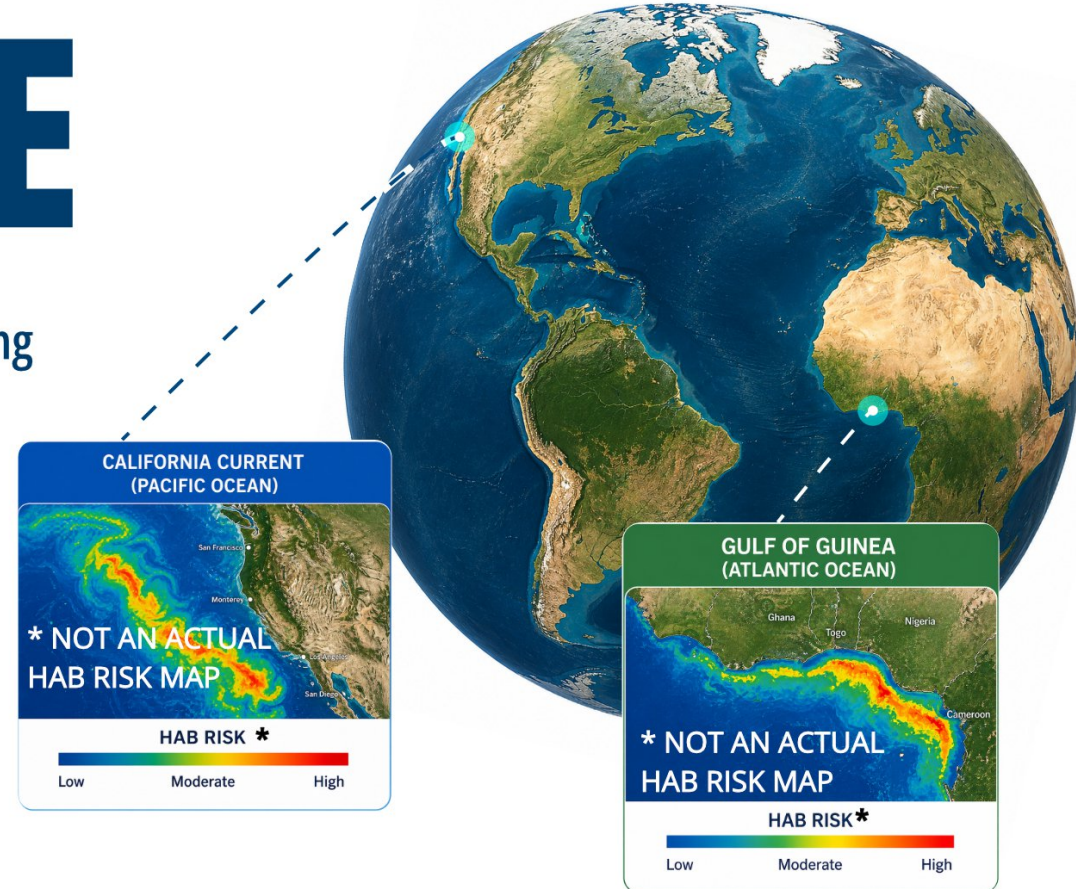
GLOBAL SCOPE

Built equitably for future scalability to data-rich and data-sparse regions



IMPACTFUL

Protecting health, economies and ecosystems



Proposed: "mechanistic- AI" forecasting

OUR APPROACH: FROM DATA TO DECISIONS

1. OBSERVING THE OCEAN

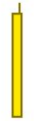
MULTI-SOURCE DATA



NASA PACE
multispectral
Ocean Color



SWOT
Sea Surface
Height



Argo, Gliders,
Moorings
in situ Profiles

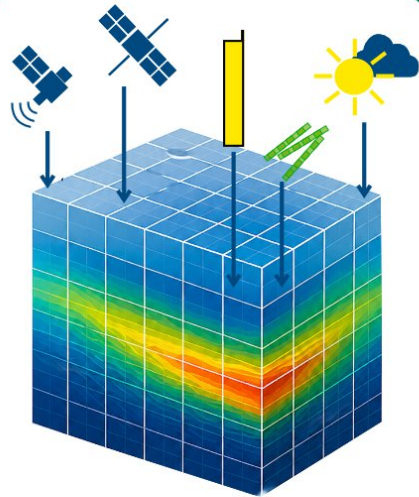


ERA5
Atmospheric
Reanalysis



in Situ HAB
Monitoring

2. DATA ASSIMILATION & OCEAN "DIGITAL TWIN"



MITgcm-BLING 4D-Var Reanalysis

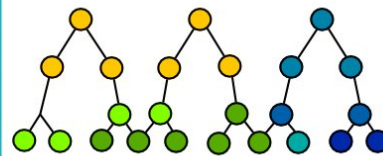
Physics-based ocean model
assimilates observations to
reconstruct complete,
high-resolution ocean state

3. AI MODELING & LEARNING

ML models learn complex,
non-linear drivers of HABs,
creating a hybrid
"mechanistic-AI" model

Solutions to test:

Tree-based models for
interpretability



Neural Networks for skill



4. HAB FORECASTS & PRODUCTS



Bloom Probability



Spatial Extent



Intensity



Duration

5. ACTIONABLE INSIGHTS



Public Health



Fisheries & Aquaculture



Waste Management



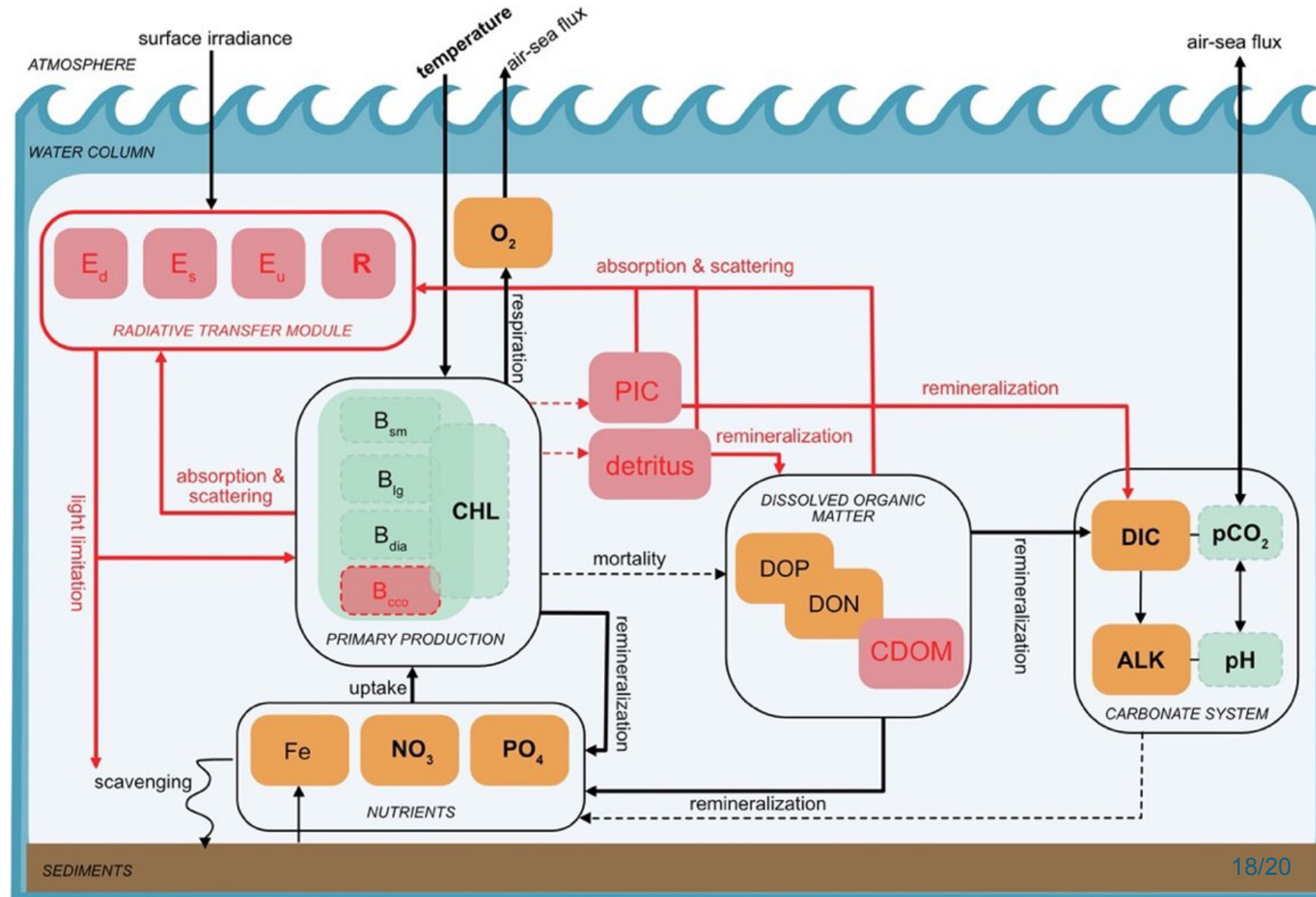
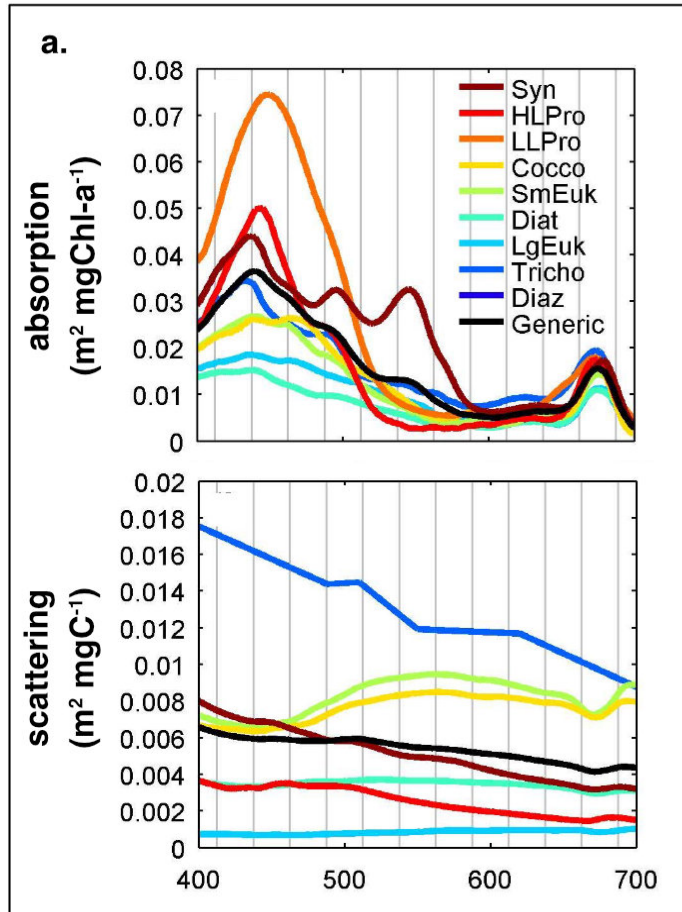
Coastal Communities



Researchers

Proposed: PACE data assimilation

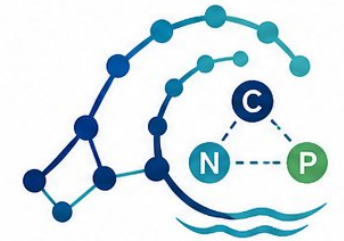
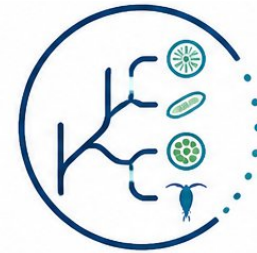
BLING + radiative transfer model



Proposed: pkg/D-Lite

- A simplified version of the Darwin model (“Darwin light”)
- Start with BLING structure (adjoint compatible)
- Add tracers: PIC, POC, 5 phytoplankton types, and 2 zooplankton types (following ECCO-Darwin)
- Couple to pkg/RadTrans for comparisons with PACE
- Run Darwin forward and D-Lite adjoint?
 (“Multi-ecosystem?”)

some AI designs...



D-Lite

OCEAN BIOGEOCHEMICAL MODEL

BGC MITgcm - BLING: Summary

- Tested cost-efficient and transferable calibration methodologies.
- Global and regional BGC state estimates products available: BGOSE, BSOSE, Red Sea, California, Gulf of Guinea
- Looking forward to new projects and collaborations (funding permitting).