Machine-learned sea ice bias correction in a global fully-coupled climate model

Polar Climate Working Group Meeting, March 4th

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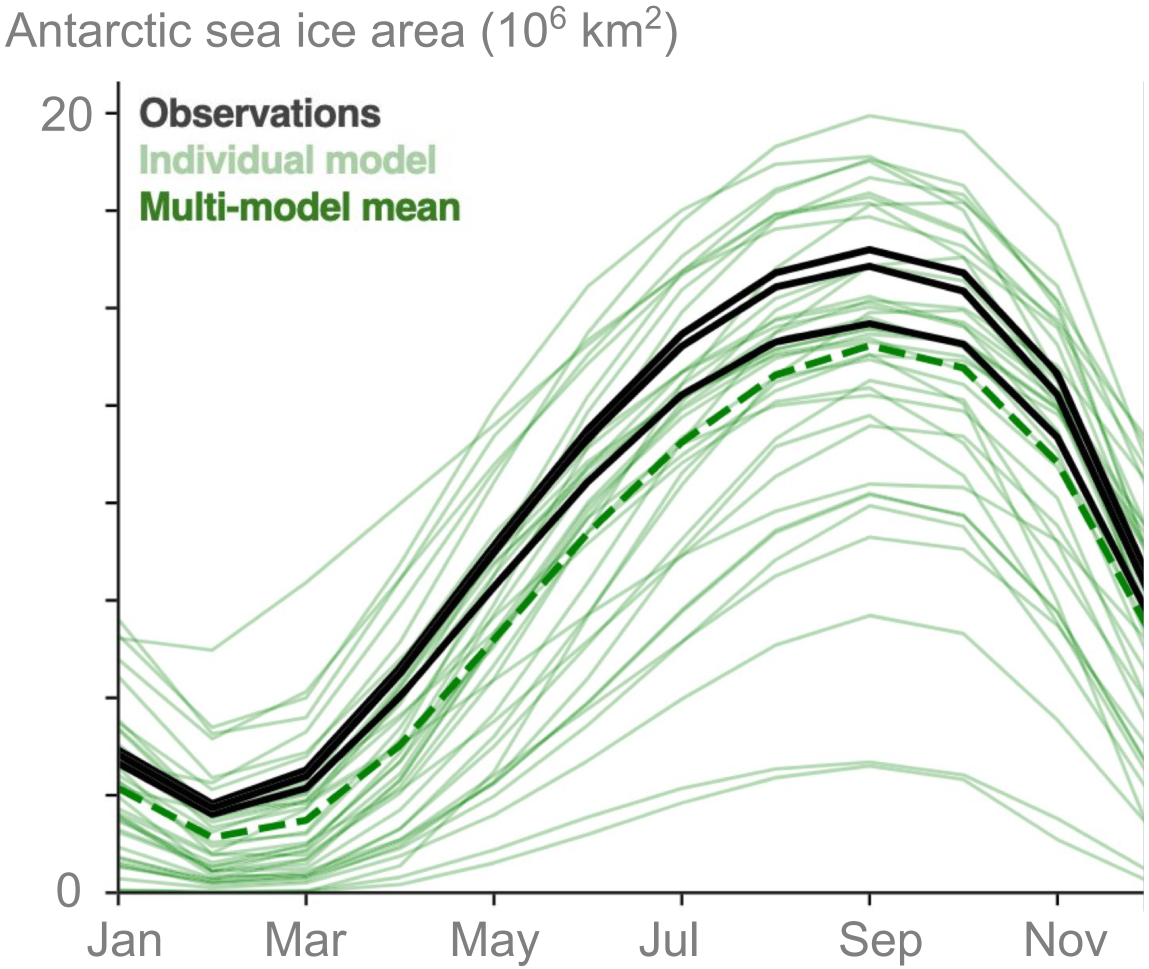
Additional thanks to the M^{2}LInES team

Climate models (CMIP6) show significant spread in the sea ice mean state

Climatology of Antarctic sea ice area over 1979 – 2014 – **individual models are biased**

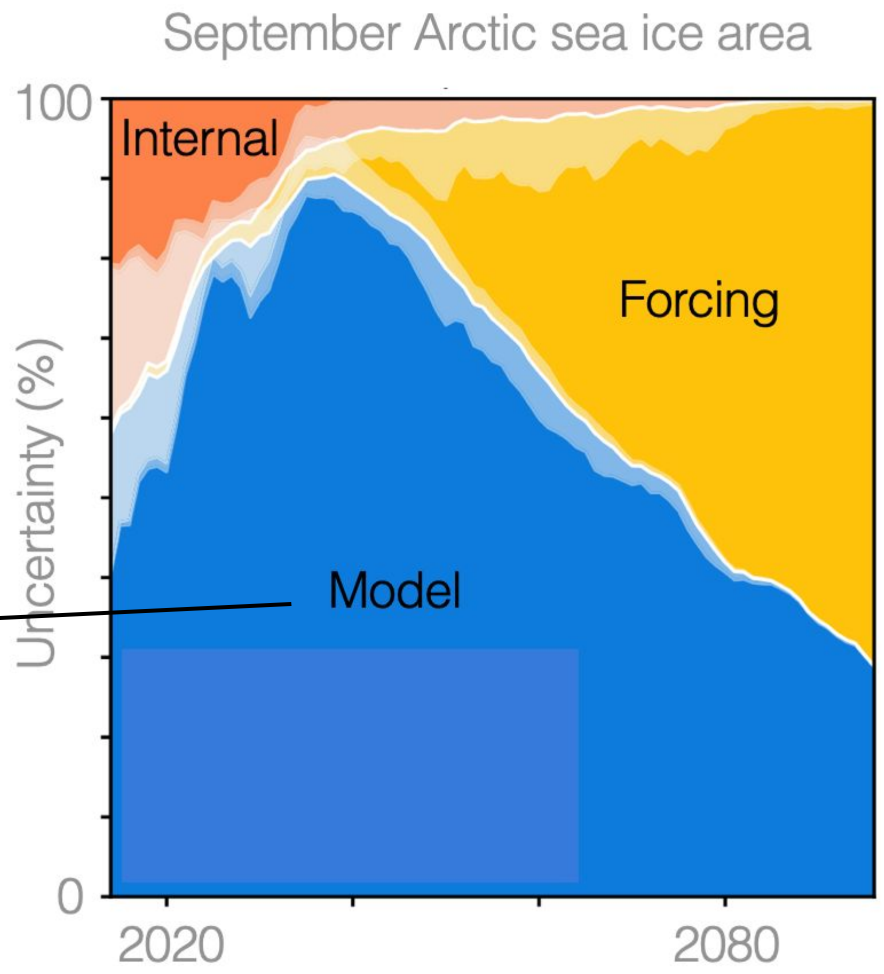


Roach et al. Antarctic sea ice area in CMIP6. *GRL*. 2020.

Sea ice biases have implications for the future projections

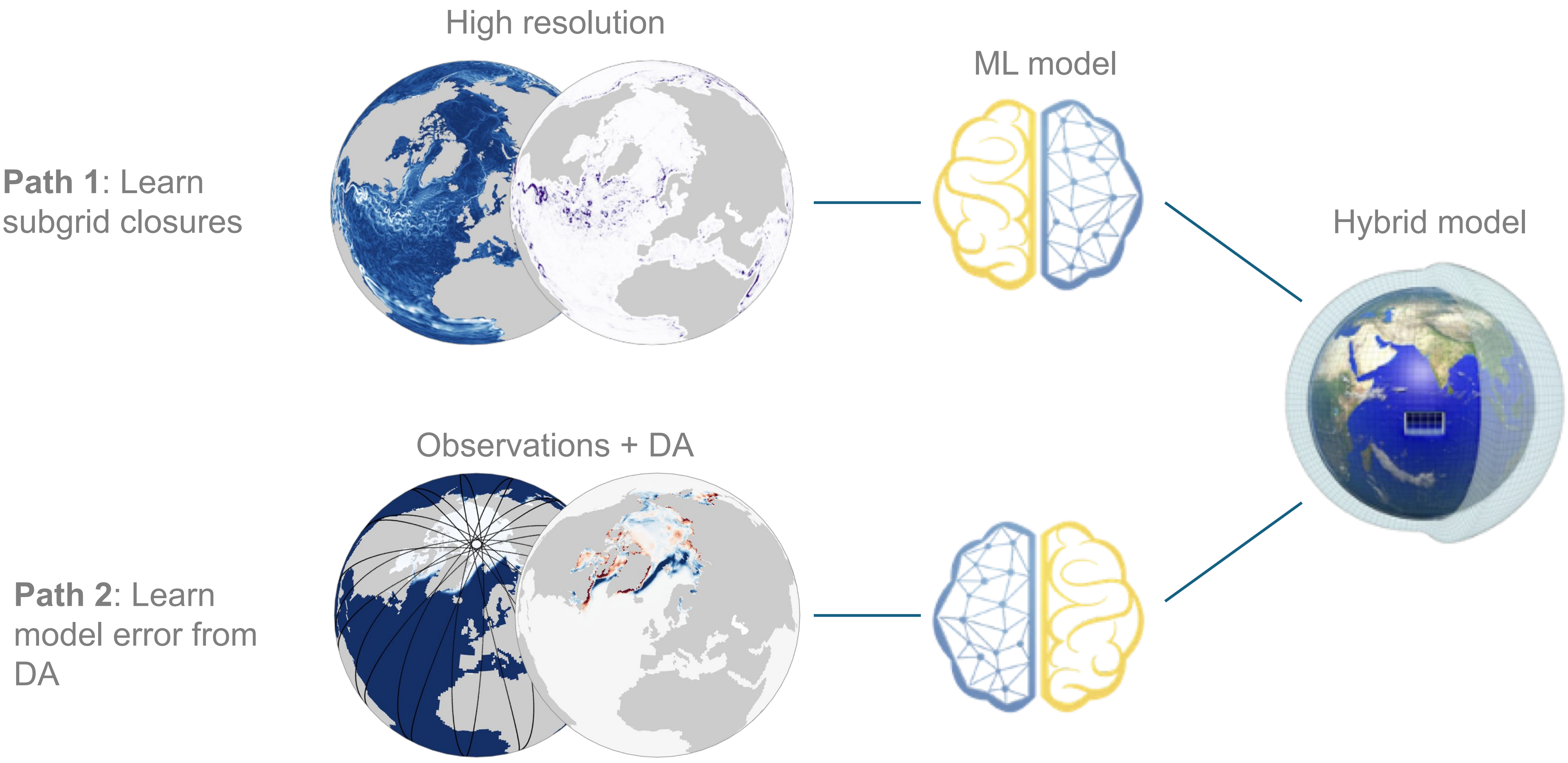
Errors in model physics contribute up to 70% of the uncertainty in mid-century sea ice projections

M²LInES aims to improve climate model biases at the air-sea interface through data-driven model physics

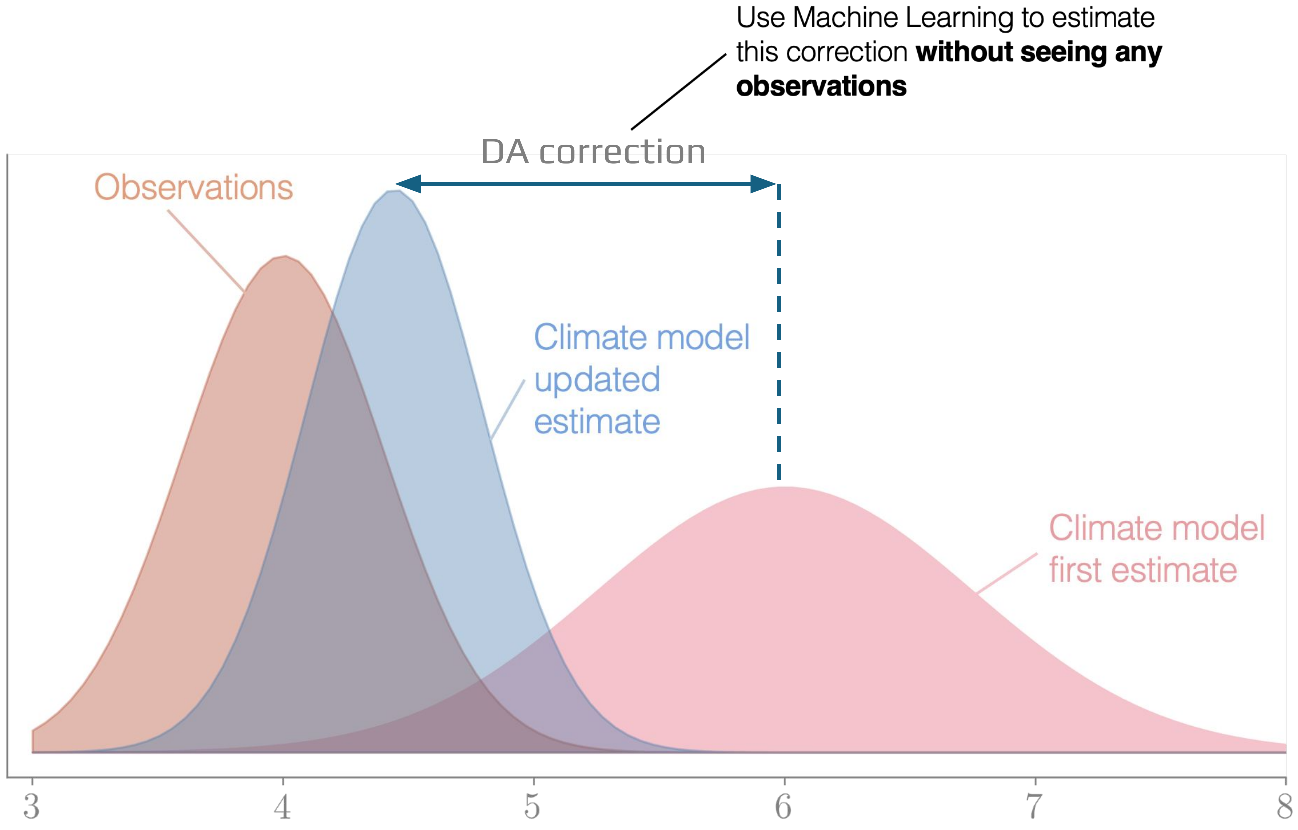


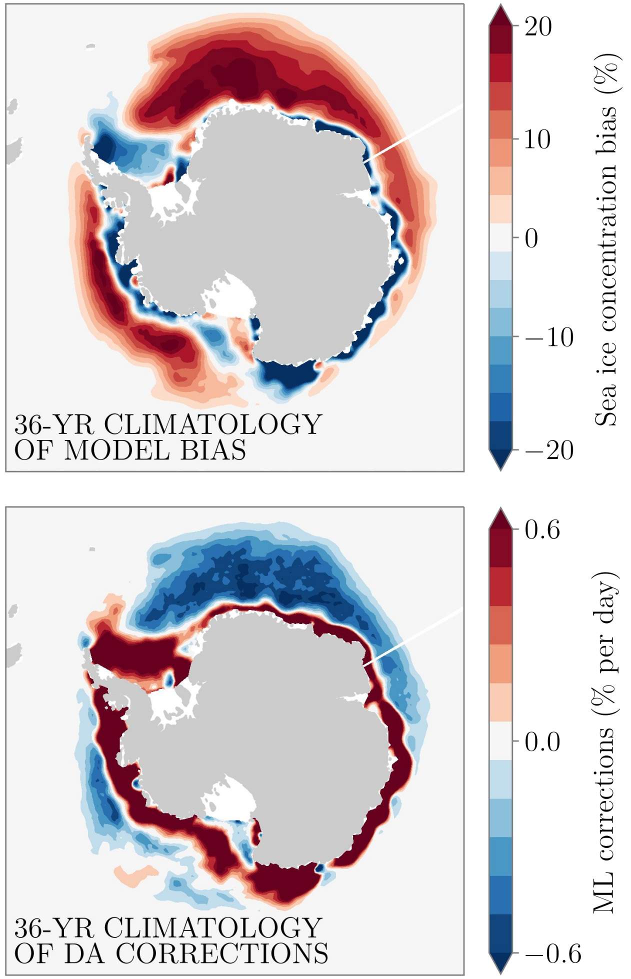
Bonan et al. Partitioning uncertainty in projections of Arctic sea ice. *Environmental Research Letters.* 2021.

M²LInES aims to improve climate models through data-driven parameterizations



Fast-physics errors can mirror the systematic model bias

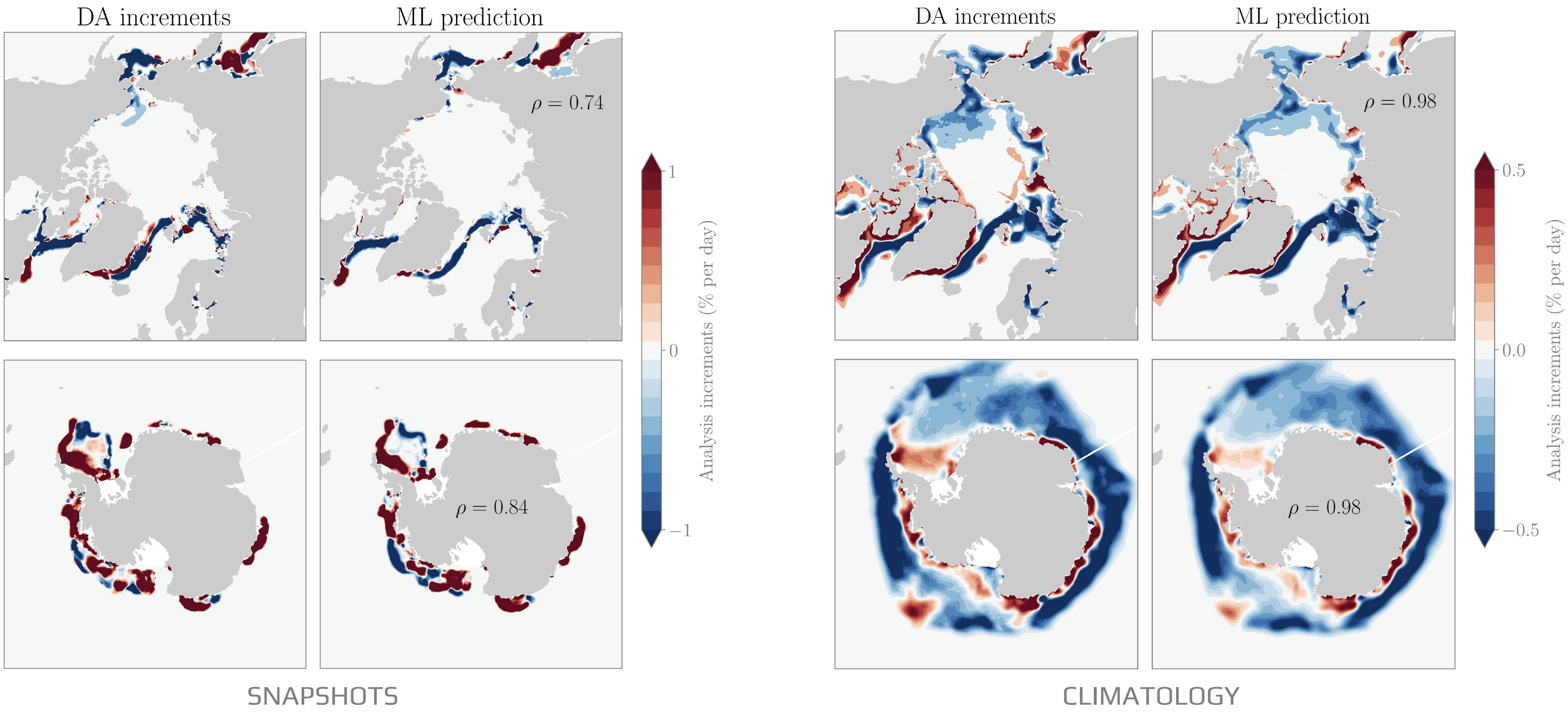




Gregory et al. Deep learning of systematic sea ice model errors from data assimilation increments. *JAMES*. 2023

JRA-forced global ice-ocean simulations

High (OFFLINE) skill shows sea ice model errors are largely state-dependent



$\rho =$ Spatial pattern correlation

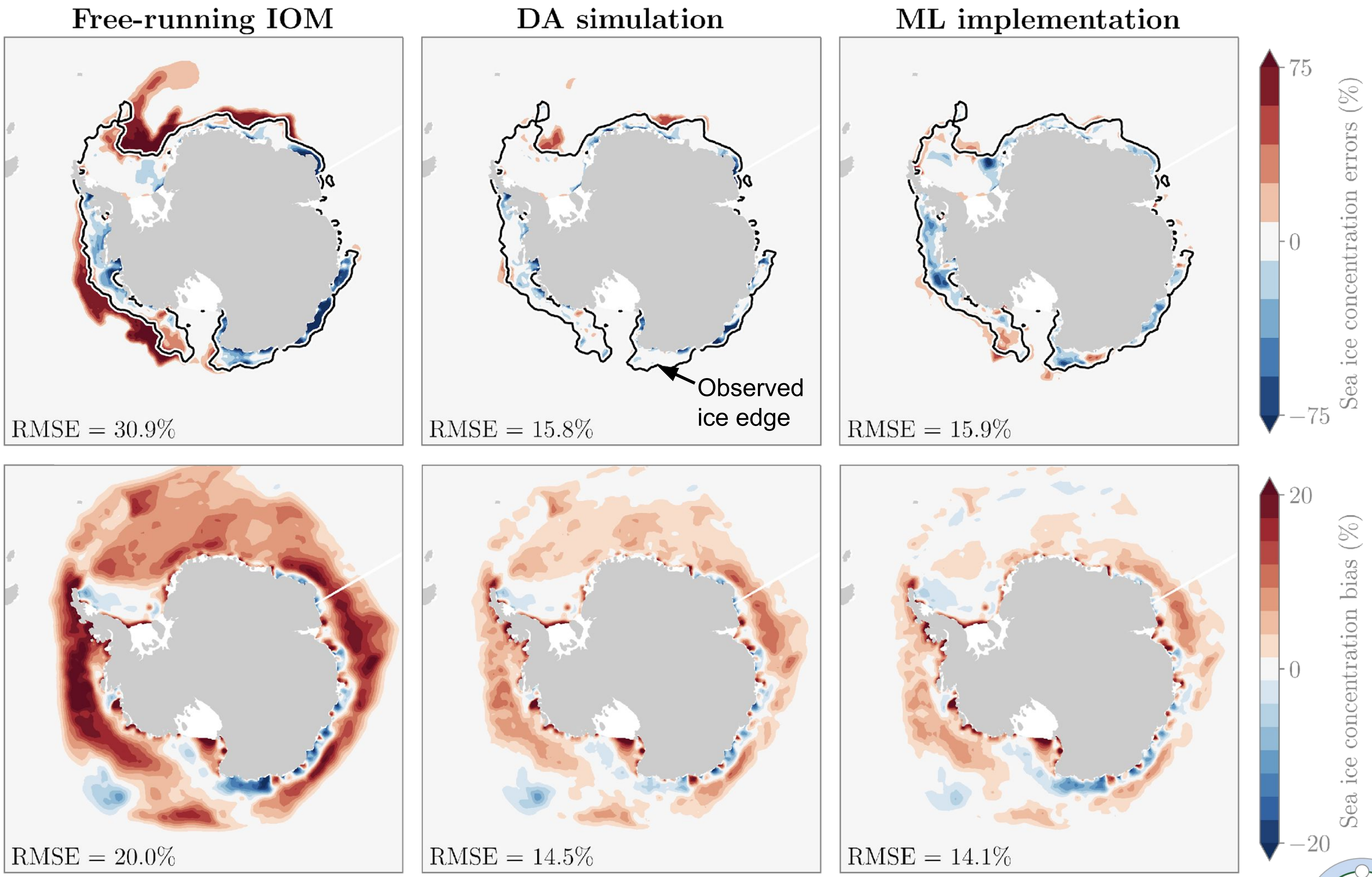
Gregory et al. Deep learning of systematic sea ice model errors from data assimilation increments. *JAMES*. 2023

Correcting ice-ocean simulations with ML model can significantly reduce model error

SNAPSHOTS

ML model emulates the DA process (without the need for observations)

CLIMATOLOGY



Gregory et al. Machine learning for online sea ice bias correction within global ice-ocean simulations. *GRL*. 2024

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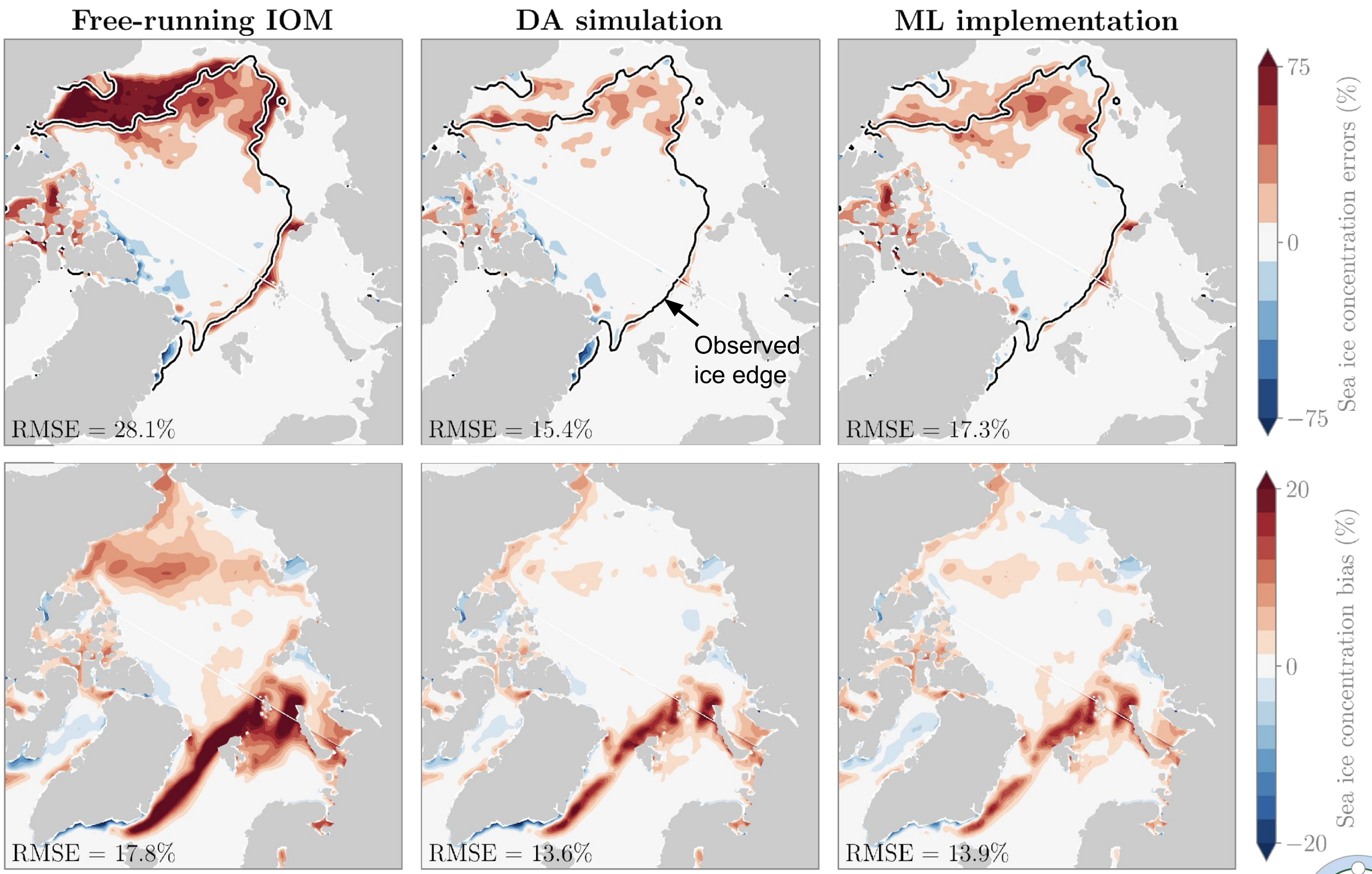


Gregory et al. Machine learning for online sea ice bias correction within global ice-ocean simulations. *GRL*. 2024

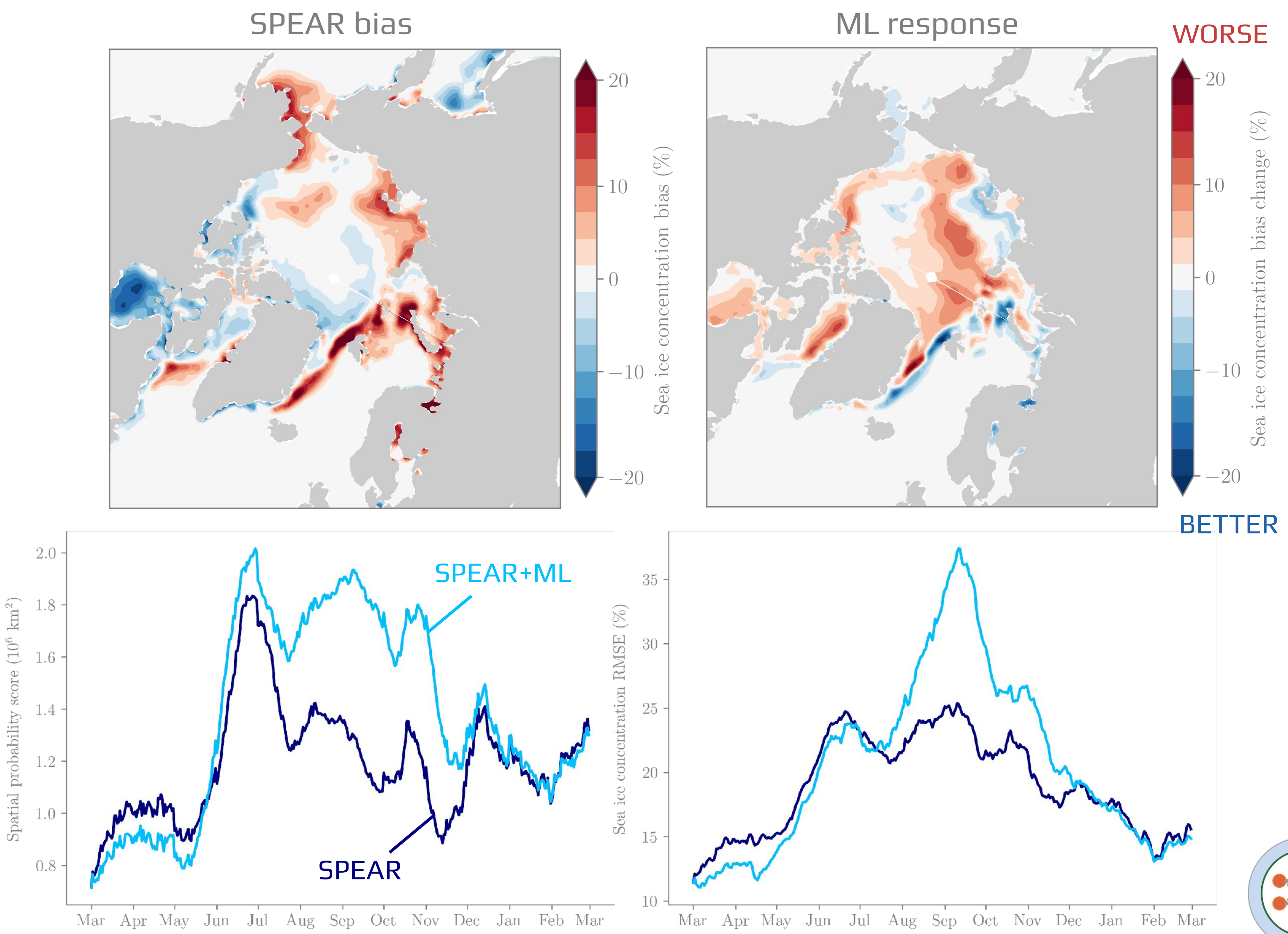
Fully-coupled global reforecasts, with SPEAR

(work in progress)

March initialized reforecasts are degraded ☹

15-member ensemble 1-year reforecasts

Free-running atmosphere and ocean



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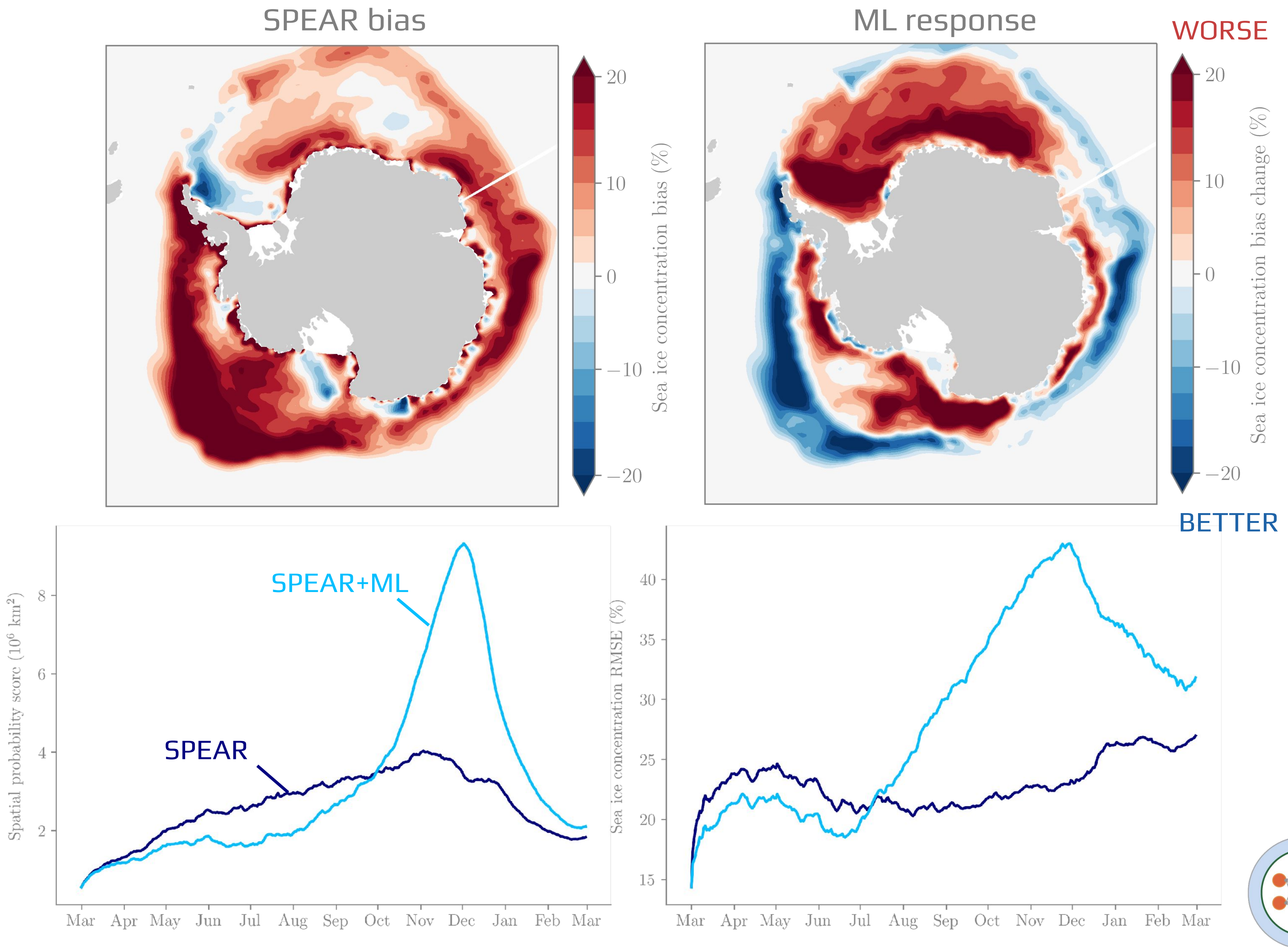
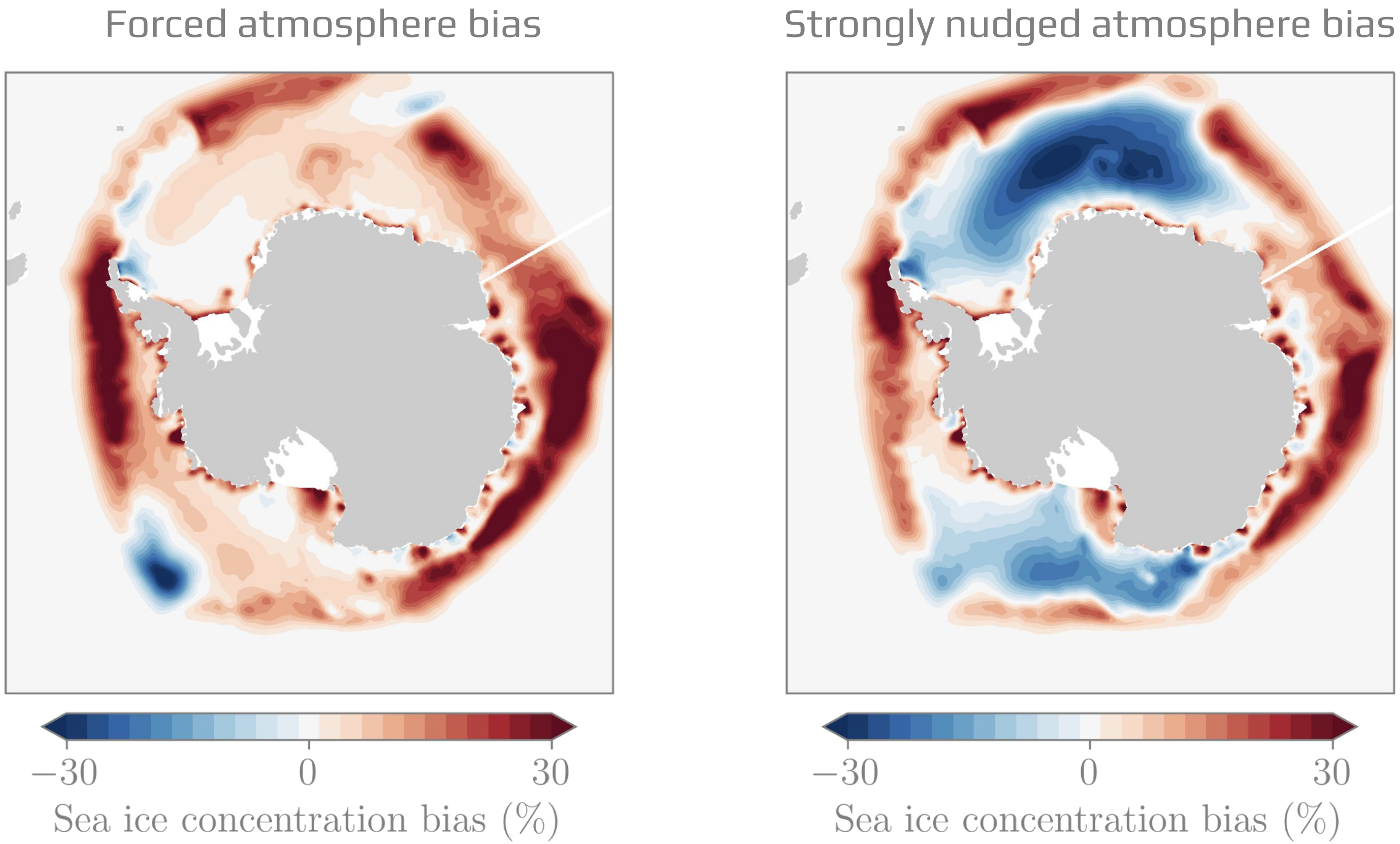


Hypothesis: we need to include the coupled atmospheric feedbacks in the training



Simulations with the same ice and ocean configuration

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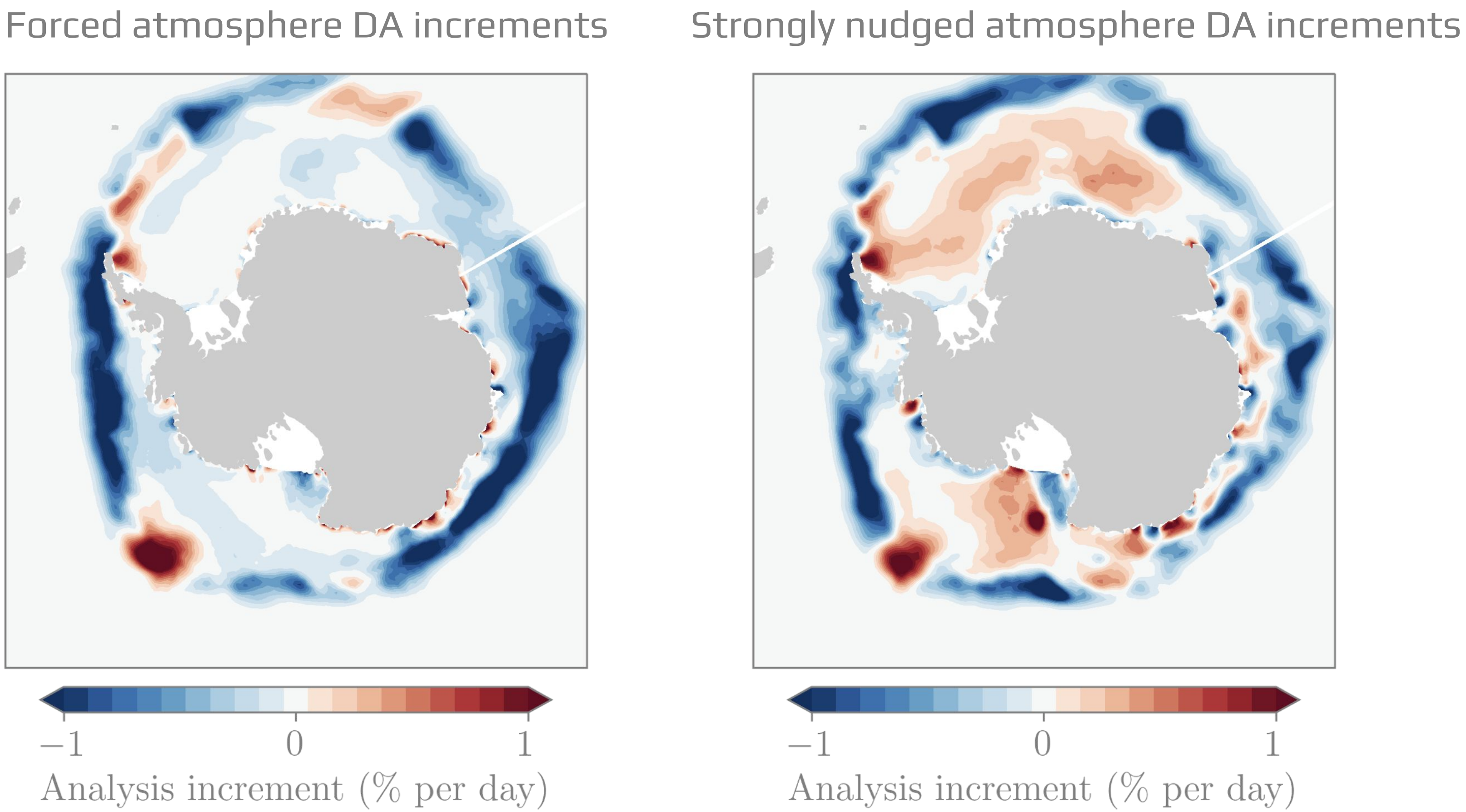

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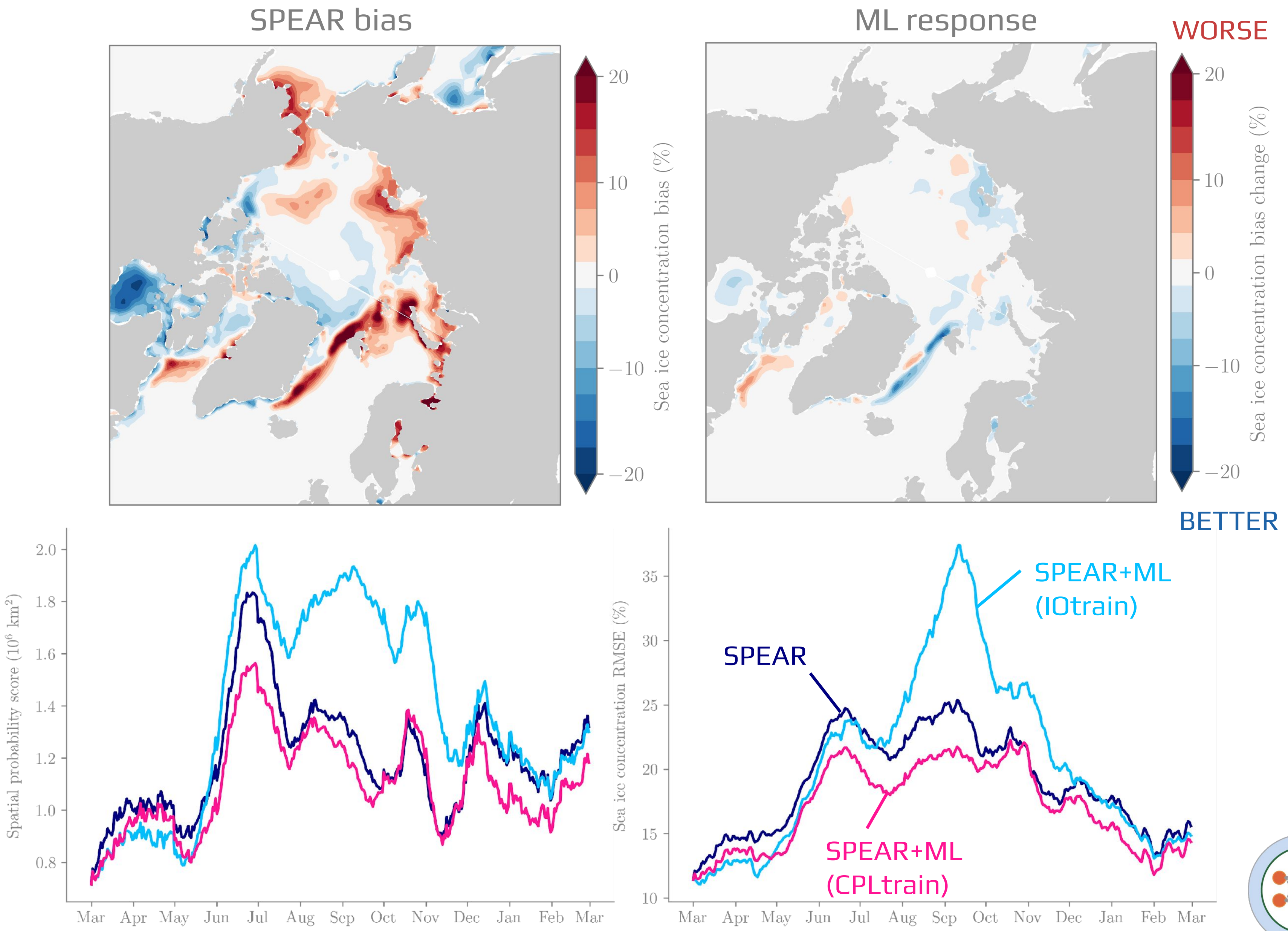

March initialized reforecasts are improved (mostly!) ☺️

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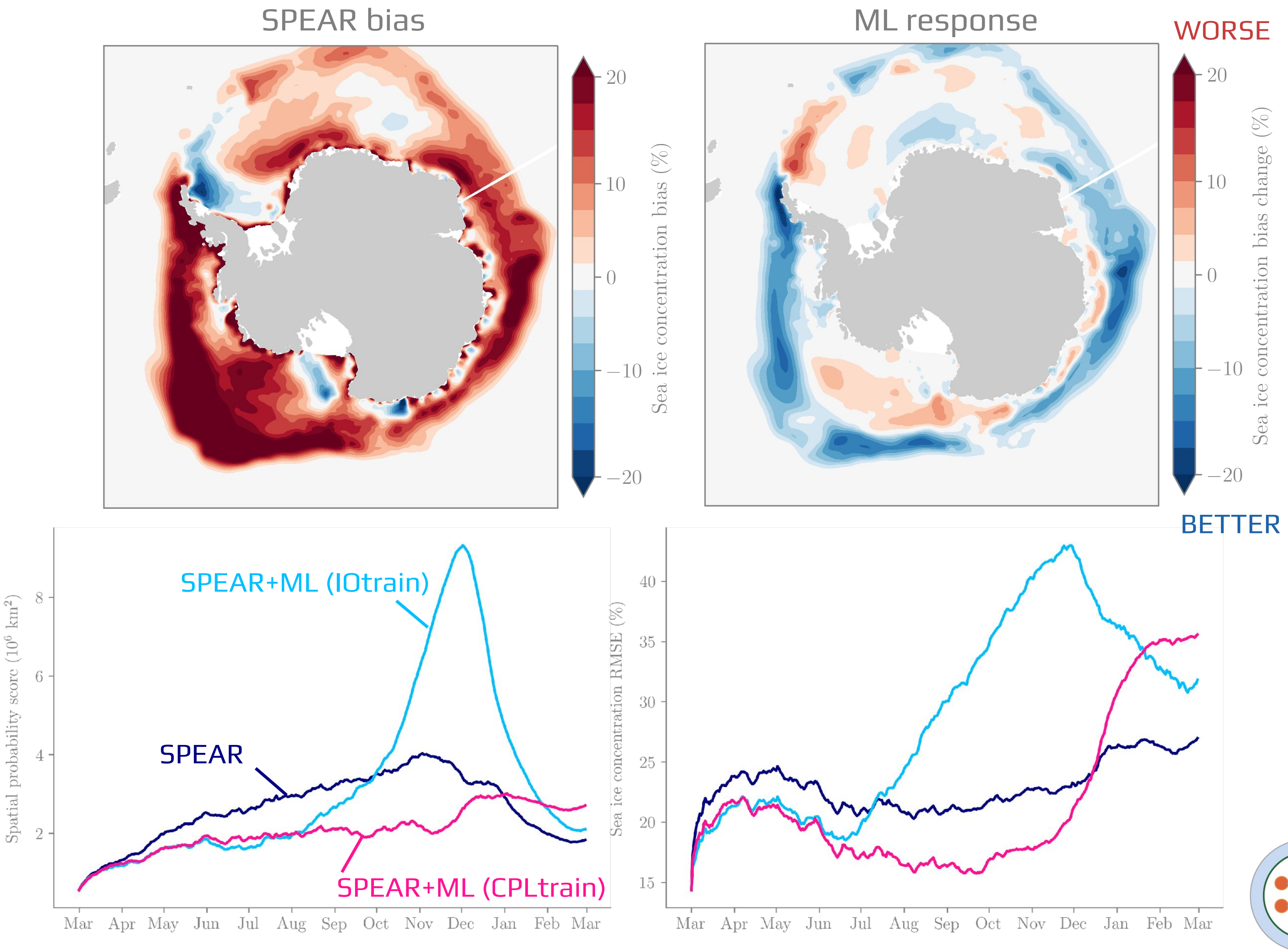
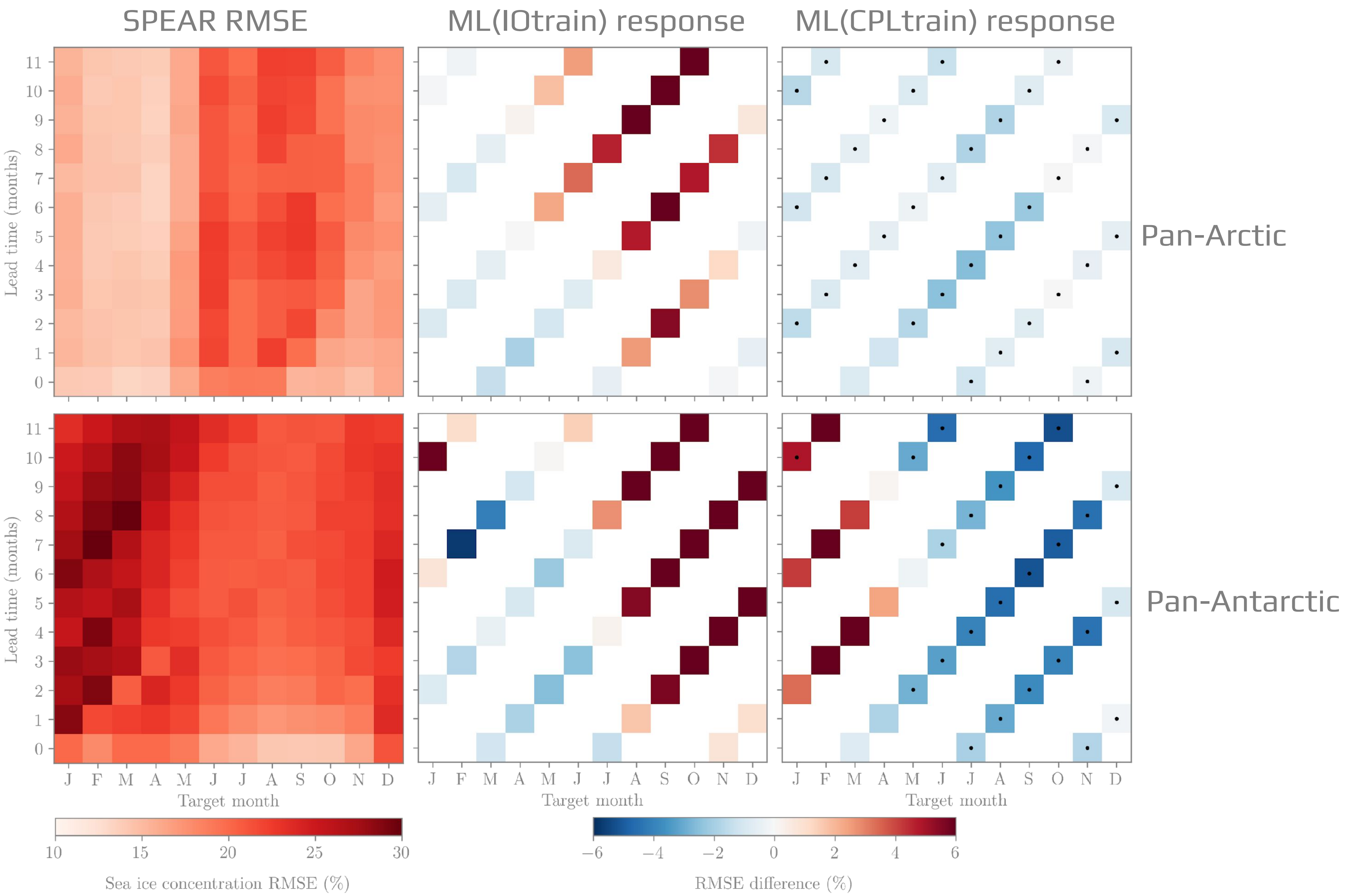


Coupled training improves forecast skill on average



From SPEAR to CESM

Getting this workflow up and running in CESM should be straightforward!

Step 1: Do Data Assimilation

https://github.com/William-gregory/DA-ML/blob/main/Kalman_Filter/EAKF_sequential_mpi.py

Step 2: Train ML model

https://github.com/William-gregory/DA-ML/blob/main/offline_learning/final_network.py

https://github.com/William-gregory/DA-ML/blob/main/NNetwork.py

Step 2: Implement network into CICE

https://github.com/William-gregory/SIS2/blob/ML_pure_fortran/src/SIS_ML.F90

Also chat to Will Chapman! He has implemented this workflow for atmospheric bias correction in CESM