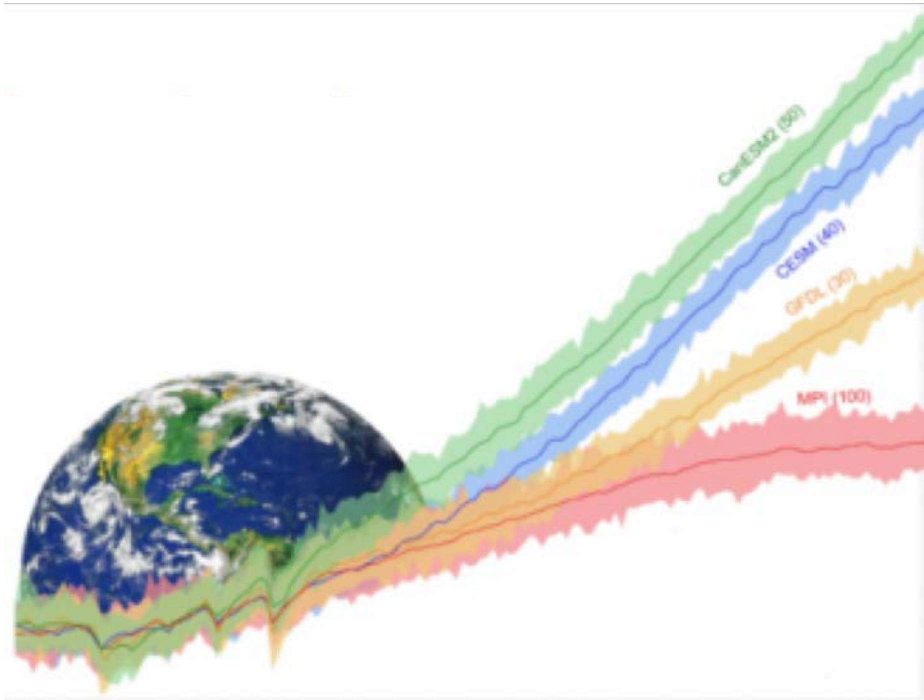
Lamont-Doherty Earth Observatory
COLUMBIA UNIVERSITY | EARTH INSTITUTE

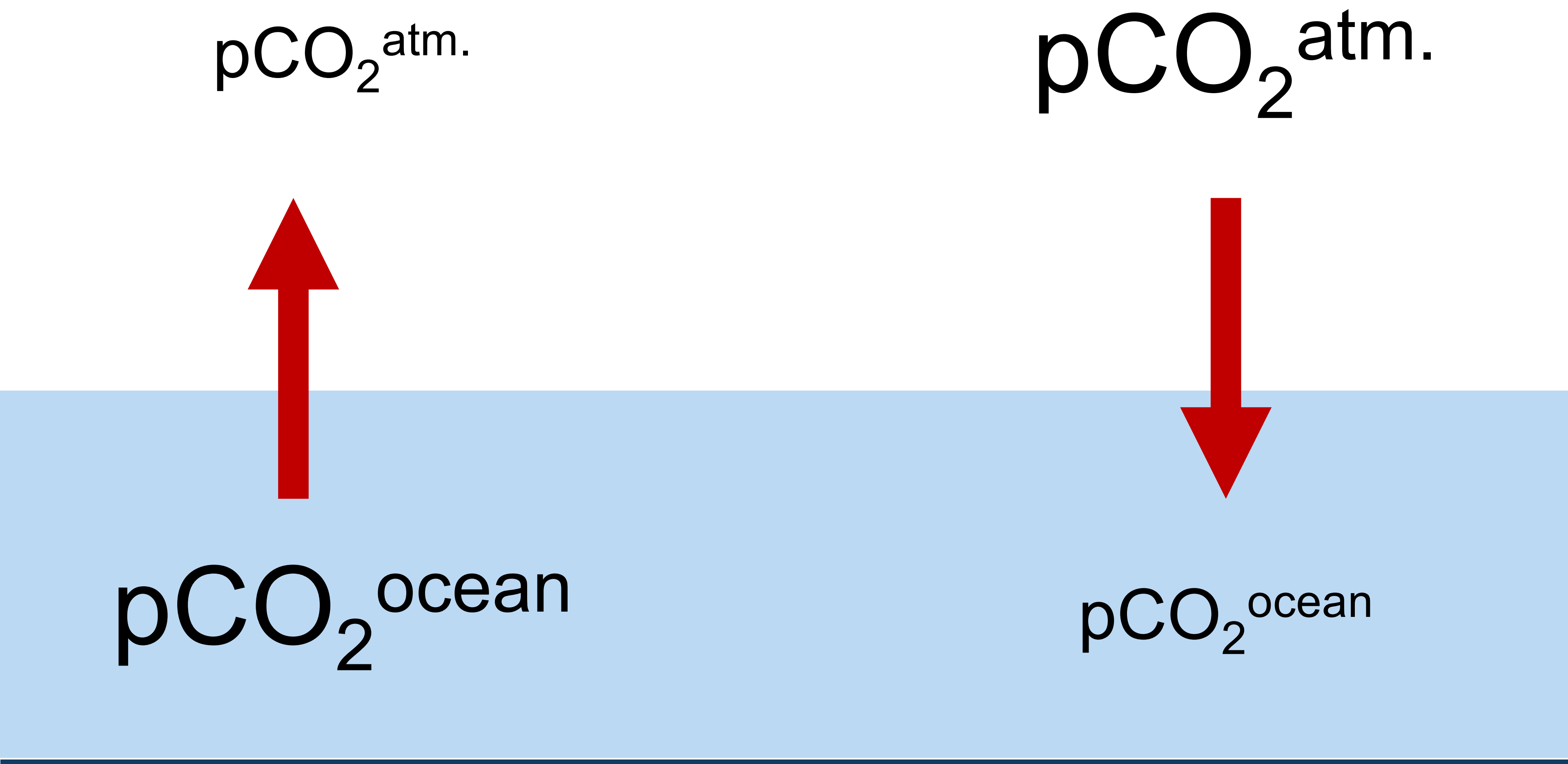
Large ensemble testbed

Evaluating pCO_2 interpolation methods

Luke Gloege

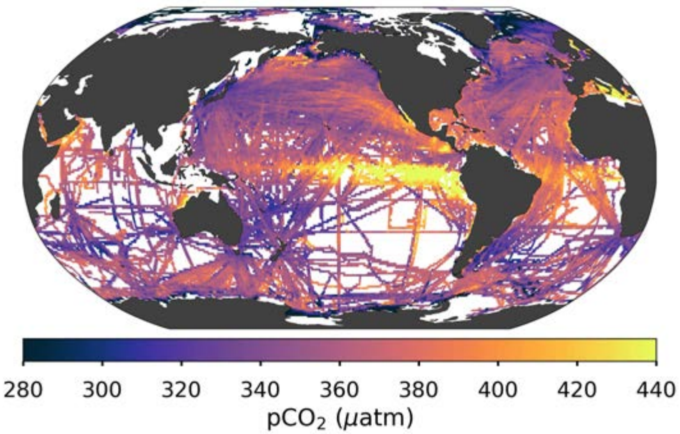


Air-Sea CO_2 exchange

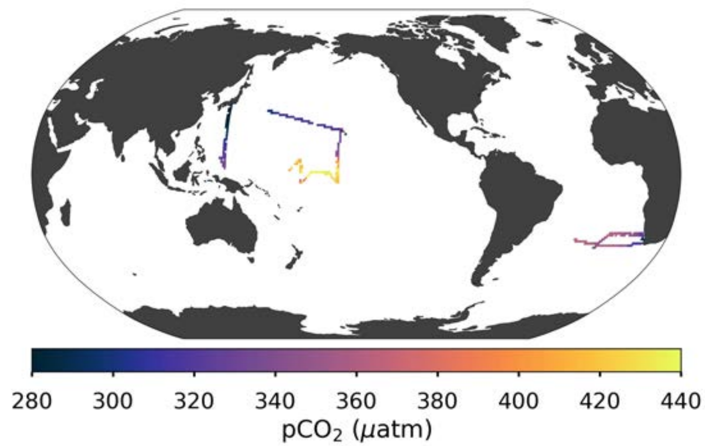


Surface Ocean CO_2 Atlas

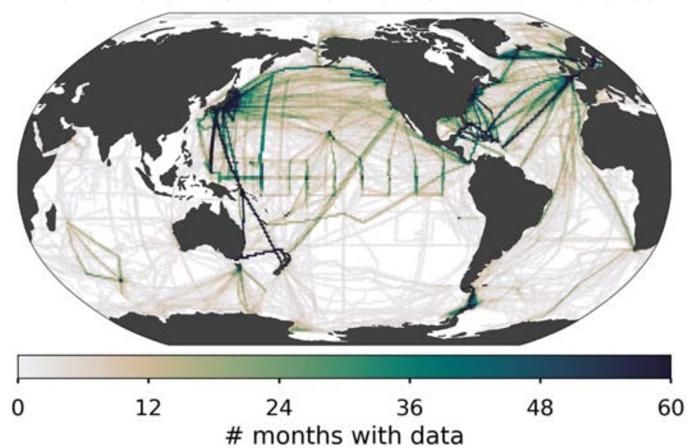
Global average (1982-2015)



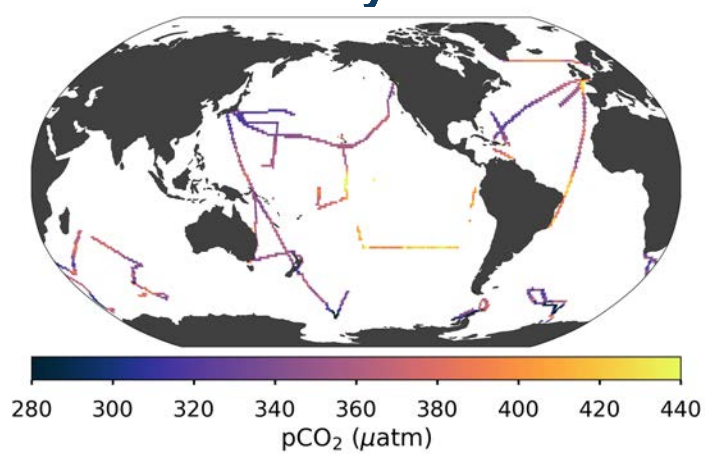
January 1989



Number of months with data



January 2010



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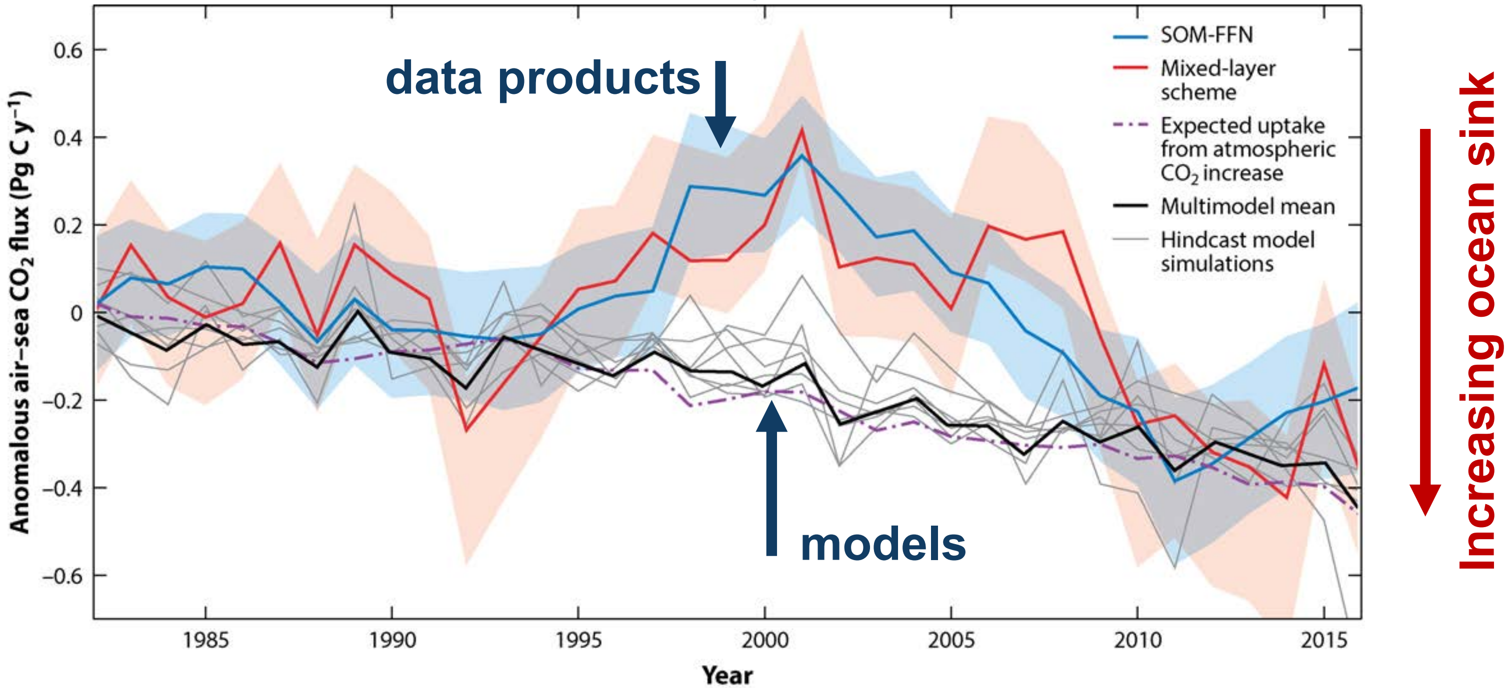
Models and data products mismatch

- Data products are more variable than models
- Different interpretation for evolution of ocean carbon sink
- Which is correct : models or data products?

Decadal variability south of 35°S

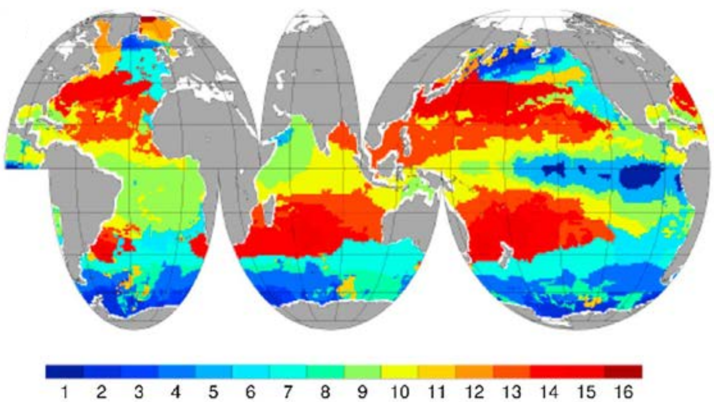


Gruber N, et al. 2019.
Annu. Rev. Mar. Sci. 11:159–86

Gruber, Landschützer, and Lovenduski (2019).

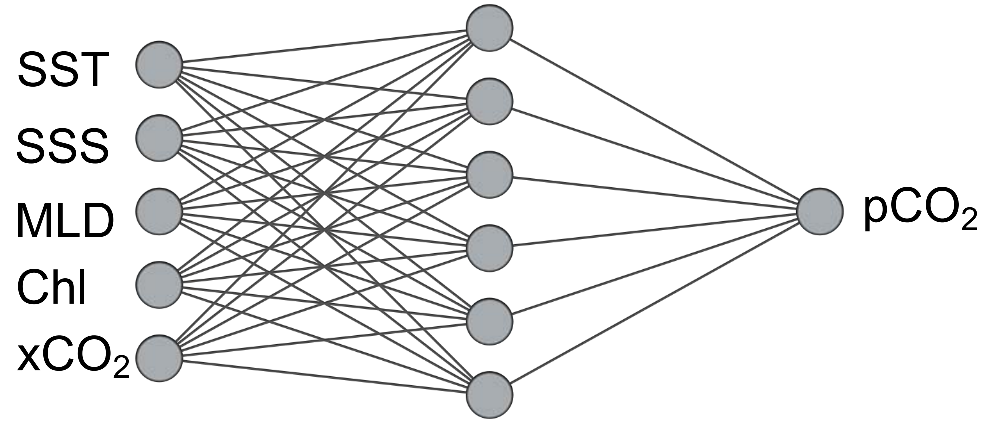
Two-step neural network (SOM-FFN)

SOM : Self organizing map



1. Climatological pCO_2, SSS, SST, and MLD
2. Data grouped using self organizing map

FFN : feed-forward neural network

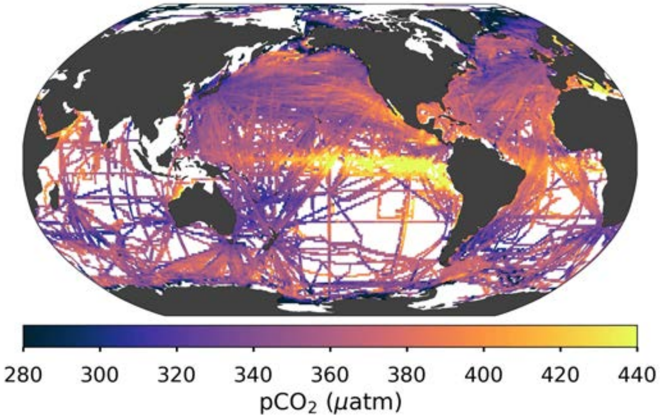


- Learns a non-linear relationship between global features and pCO_2
- Inputs are proxies for processes affecting ocean pCO_2

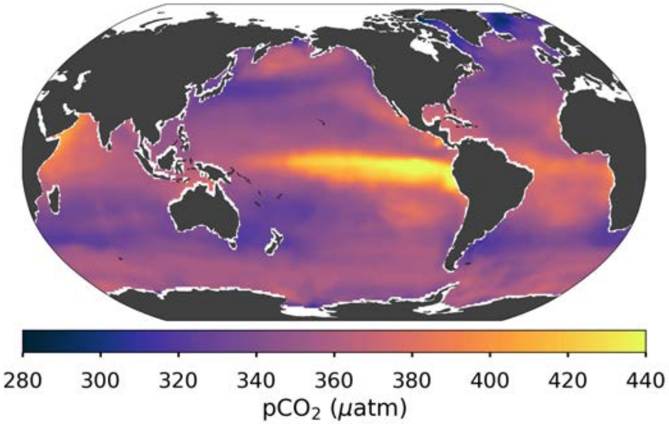
Landschützer et al. 2013, 2014, 2016

Comparing SOM-FFN and SOCAT

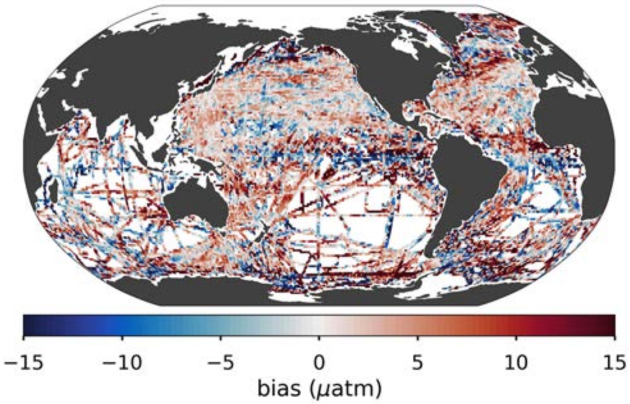
SOCATv2019 data



SOM-FFN product



Bias (global avg. 2.15 µatm)



Bakker et al. 2016 EESD; Sabine et al. 2013

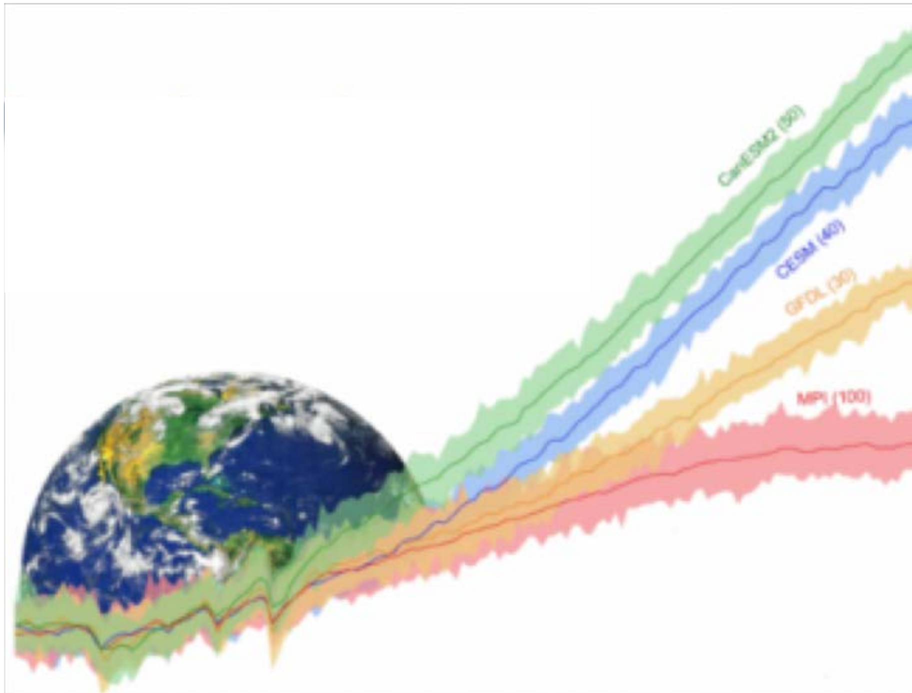
Landschützer et al. 2013, 2014, 2016

How large ensembles can help

- **Evaluate performance across different climate states**

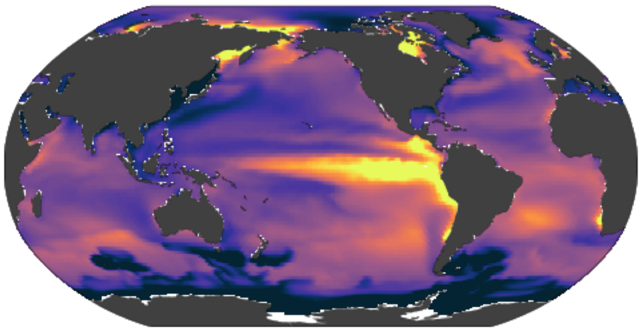
- **100 randomly selected ensemble members**
  - CanESM2 (25)
  - CESM (25)
  - GFDL (25)
  - MPI (25)

- **Each climate state is equally likely**
- **Only considering 1982-2015**



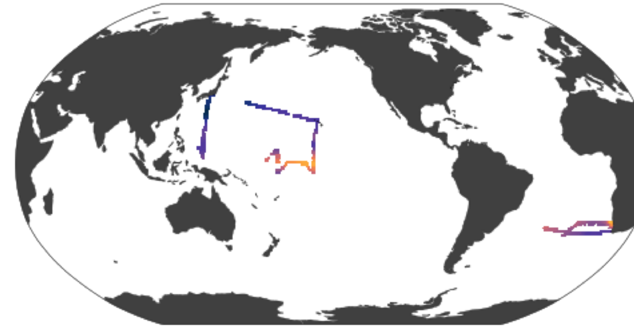
Large ensemble pCO_2 testbed

CESM 002

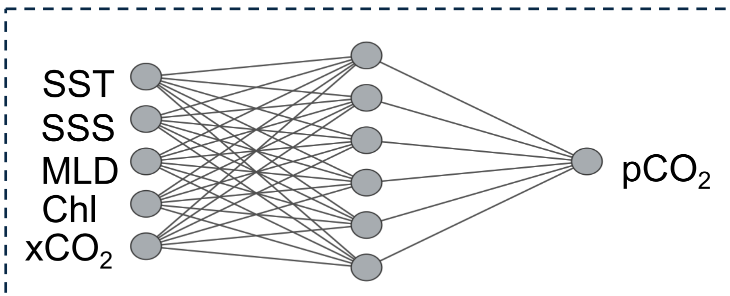


x100 members

1. Sample model member as SOCAT monthly pCO_2 product



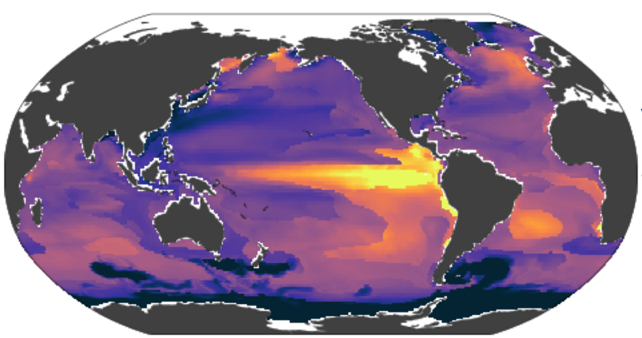
2. Train, evaluate, test reconstruction method at sampled locations



Neural network reconstruction method

3. Estimate monthly varying pCO_2 on global scale using trained model

x100 members

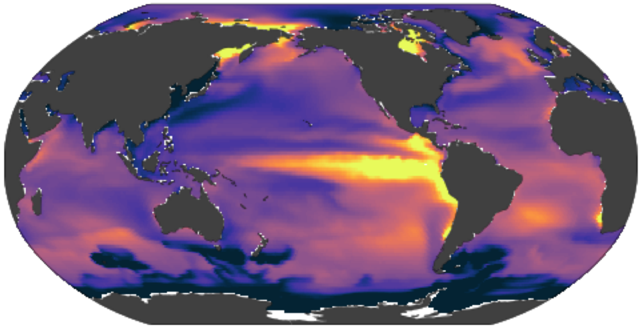


reconstruction

4. Statistically compare reconstructed pCO_2 to model truth. Each spatial point is temporally decomposed

Large ensemble pCO_2 testbed

CESM 002



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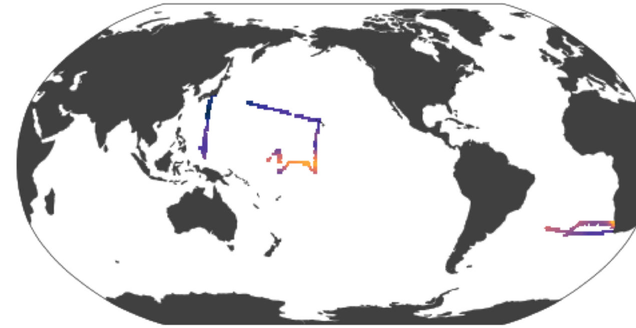

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Large ensemble pCO_2 testbed

CESM 002

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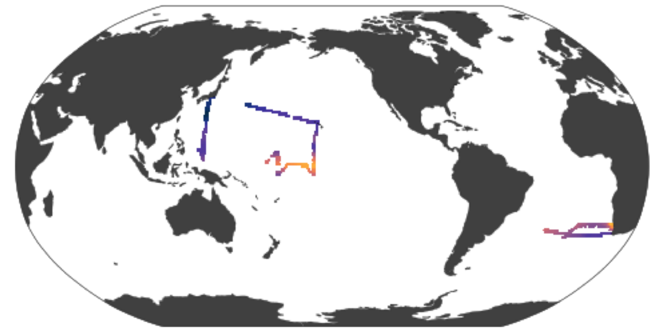

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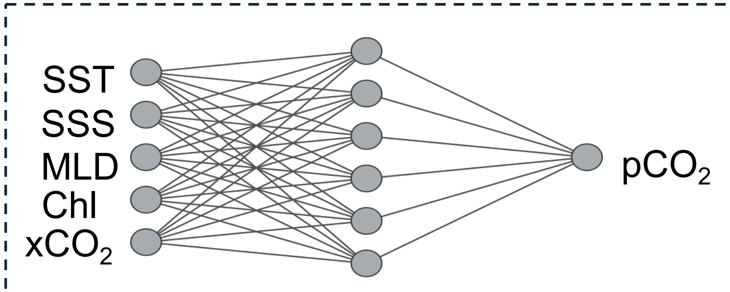

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Large ensemble pCO_2 testbed

CESM 002

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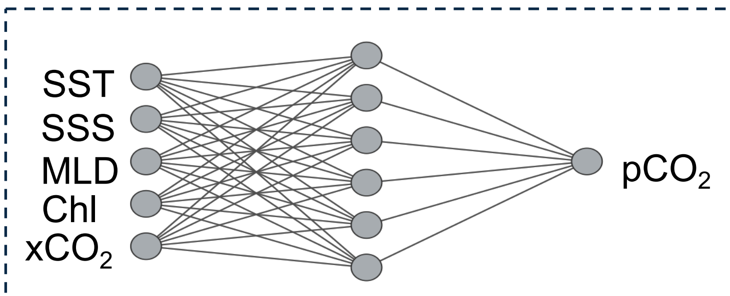

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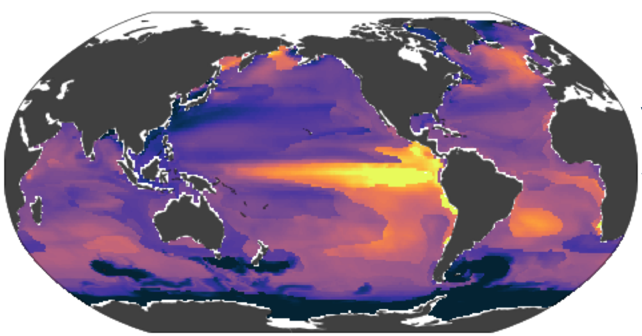

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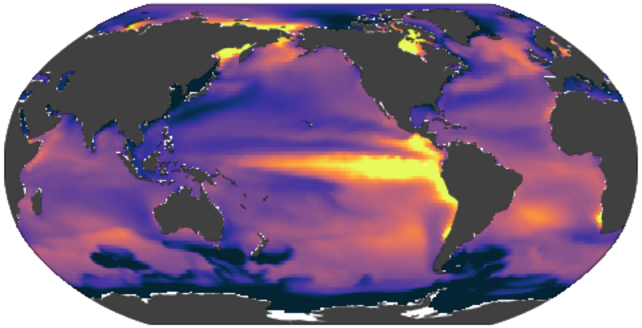
Large ensemble pCO_2 testbed

CESM 002



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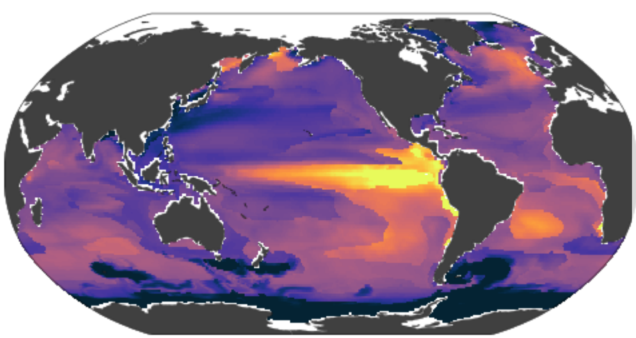


reconstruction

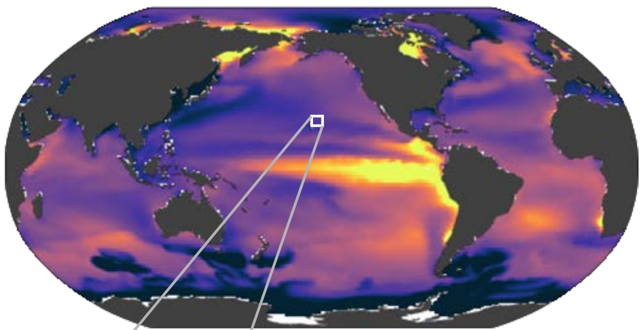
3. Estimate monthly varying pCO_2 on global scale using trained model

x100 members

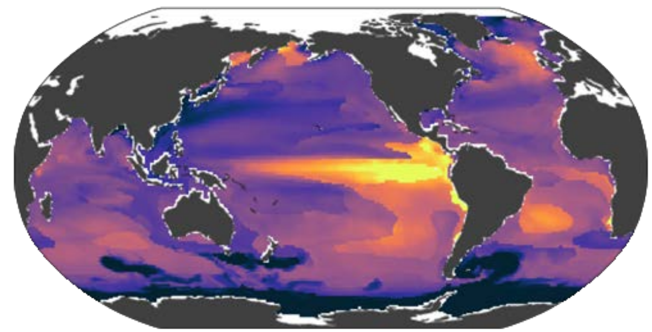
Neural network reconstruction method

Temporal decomposition

Ensemble member

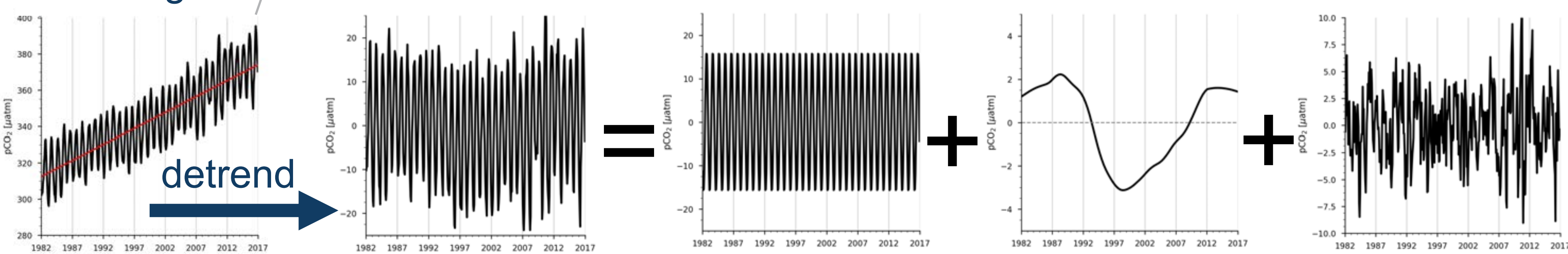


Reconstruction



Each location in each member and reconstruction decomposed into seasonal, decadal, and sub-decadal variability

Full Signal | Detrended | Seasonal | Dec. var. | Sub-dec. var.



Cleveland et al. (1990) *Journal of official statistics*.

Statistical metrics

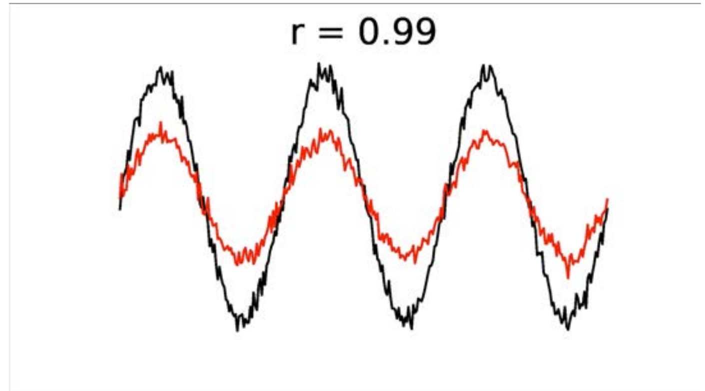
Model **Reconstruction**

Phasing

Is reconstruction in phase with model?

Correlation

$$\mathbf{r} = \frac{cov(m,r)}{\sigma_r \sigma_m}$$

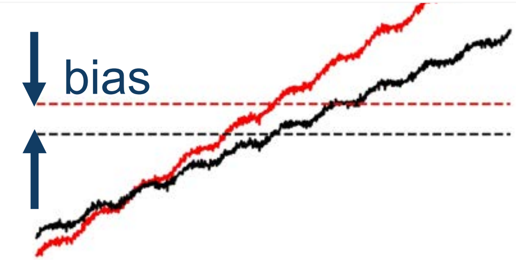


Long-term mean

is there a systemic offset?

Bias

$$Bias = \bar{m} - \bar{r}$$

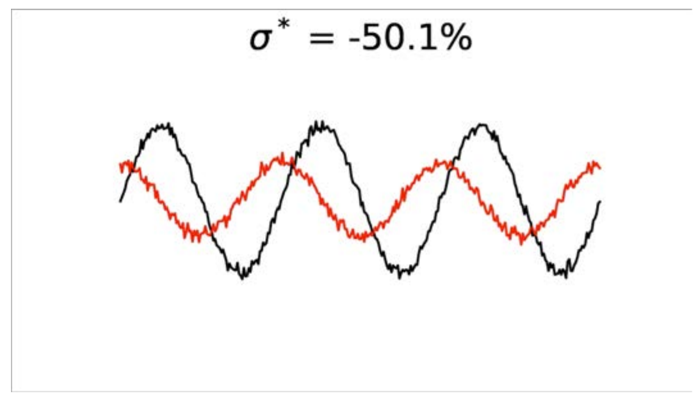


Variability

does reconstruction capture observed variability?

Normalized STD

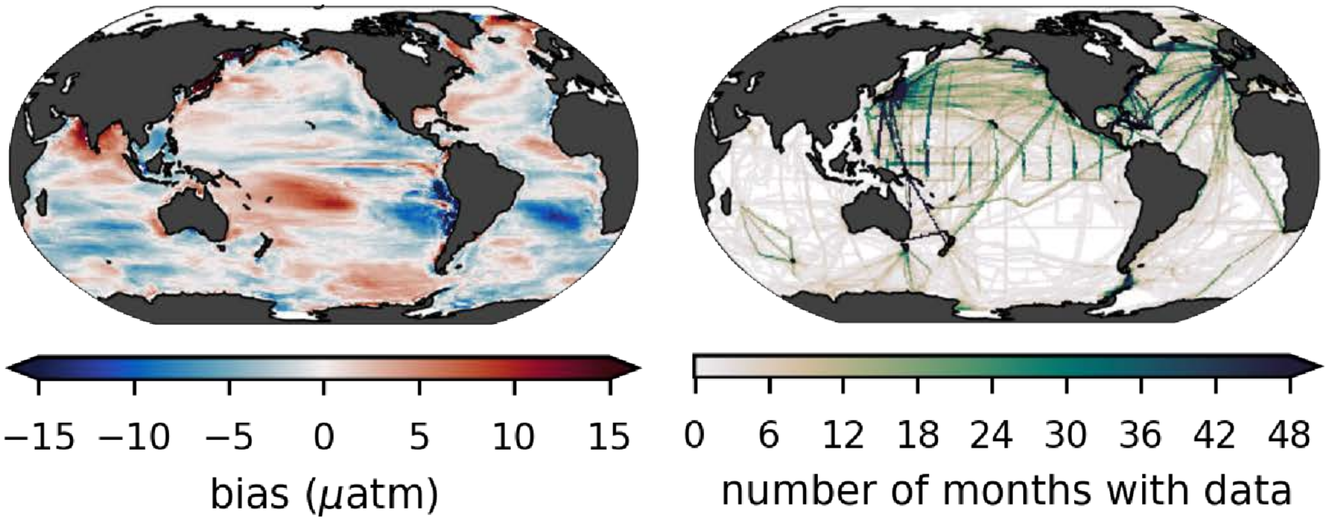
$$\sigma^* = \left[\left(\frac{\sigma_r}{\sigma_m}\right) - 1\right] * 100\%$$

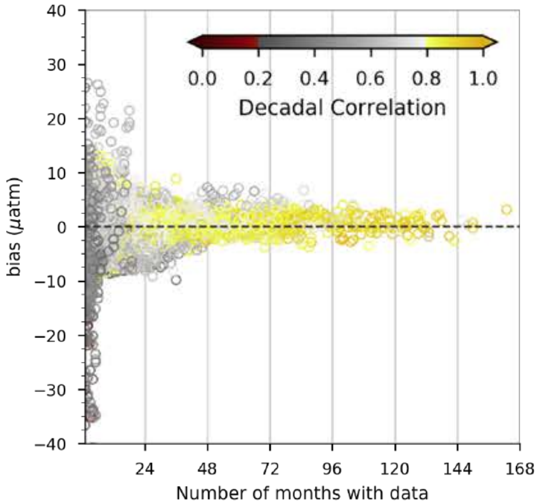


Bias and number of observations

Is the reconstruction offset from the model?

Global avg = -0.44 µatm





- Bias spatially varying but global average is low
- Less spread in bias in regions with more data
- Higher decadal correlation in regions with more data

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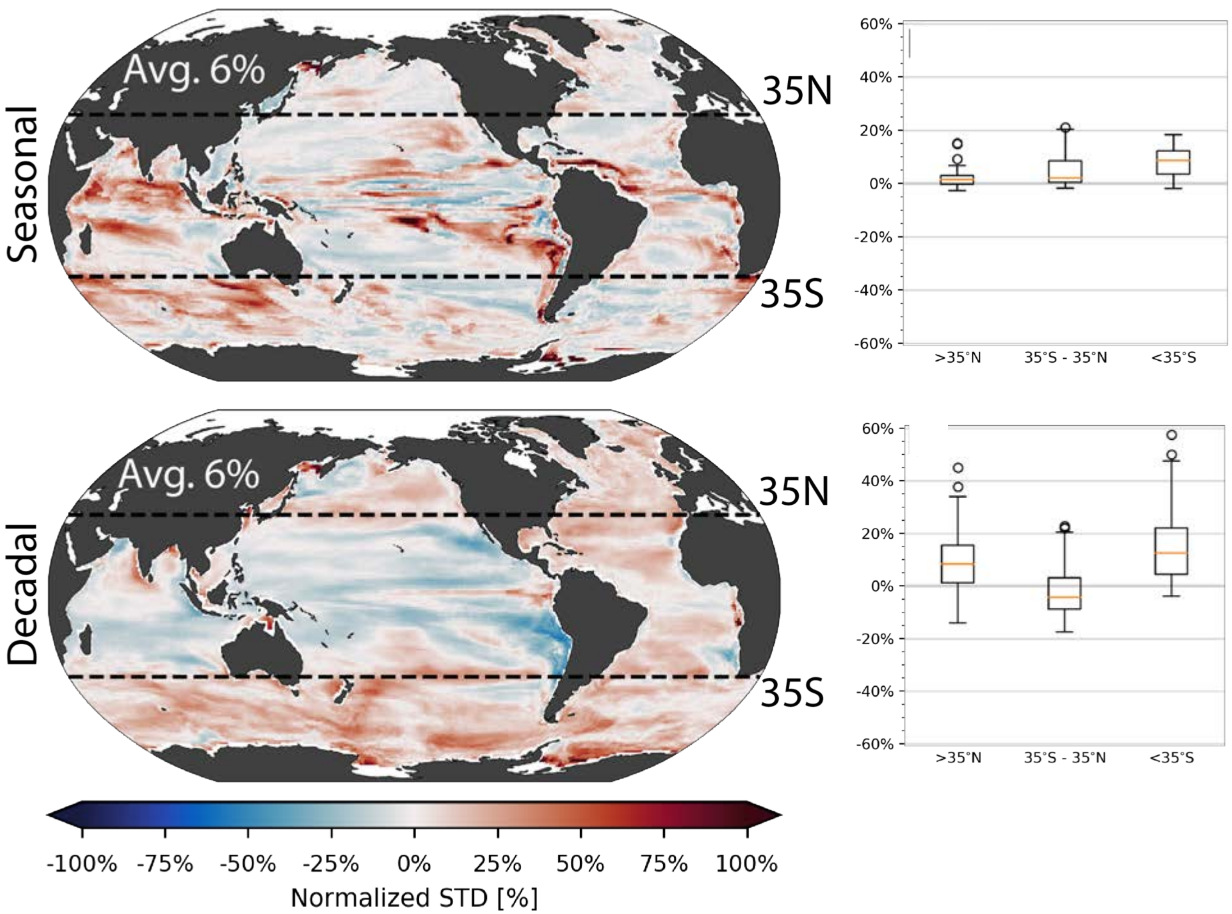
Normalized standard deviation

Does the reconstruction capture the model's variability?



- Overestimates decadal variability in Southern Ocean by about 12%
- Reconciles gap between models and SOM-FFN

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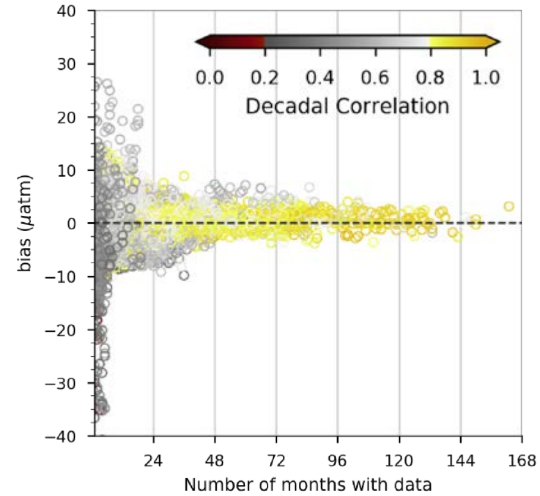
Conclusions

performance dependent on data density



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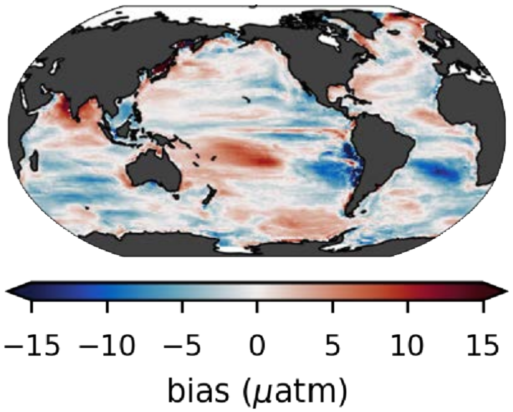
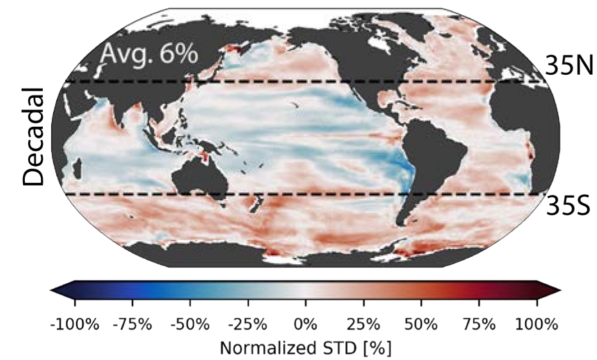


Bias is spatially heterogenous, but negligible on a global scale

Overestimation of decadal variability reconciles the discrepancy with models



This testbed serves a platform to develop and test new methodologies

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Acknowledgements

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University of Colorado

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Max Planck Institute for biogeochemistry

Keith Rodgers

IBS center for climate physics

Thomas Frölicher

Physics Institute, University of Bern

Tatiana Ilyina

Max Planck Institute for Meteorology

Yohei Takano

Max Planck Institute for Meteorology

John Fyfe

Environment and climate change Canada

Sarah Schlunegger

Princeton University

Lamont-Doherty Earth Observatory
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Take a picture to access the testbed

Testbed URL

figshare.com/s/4337ae68dccbcf34e14c

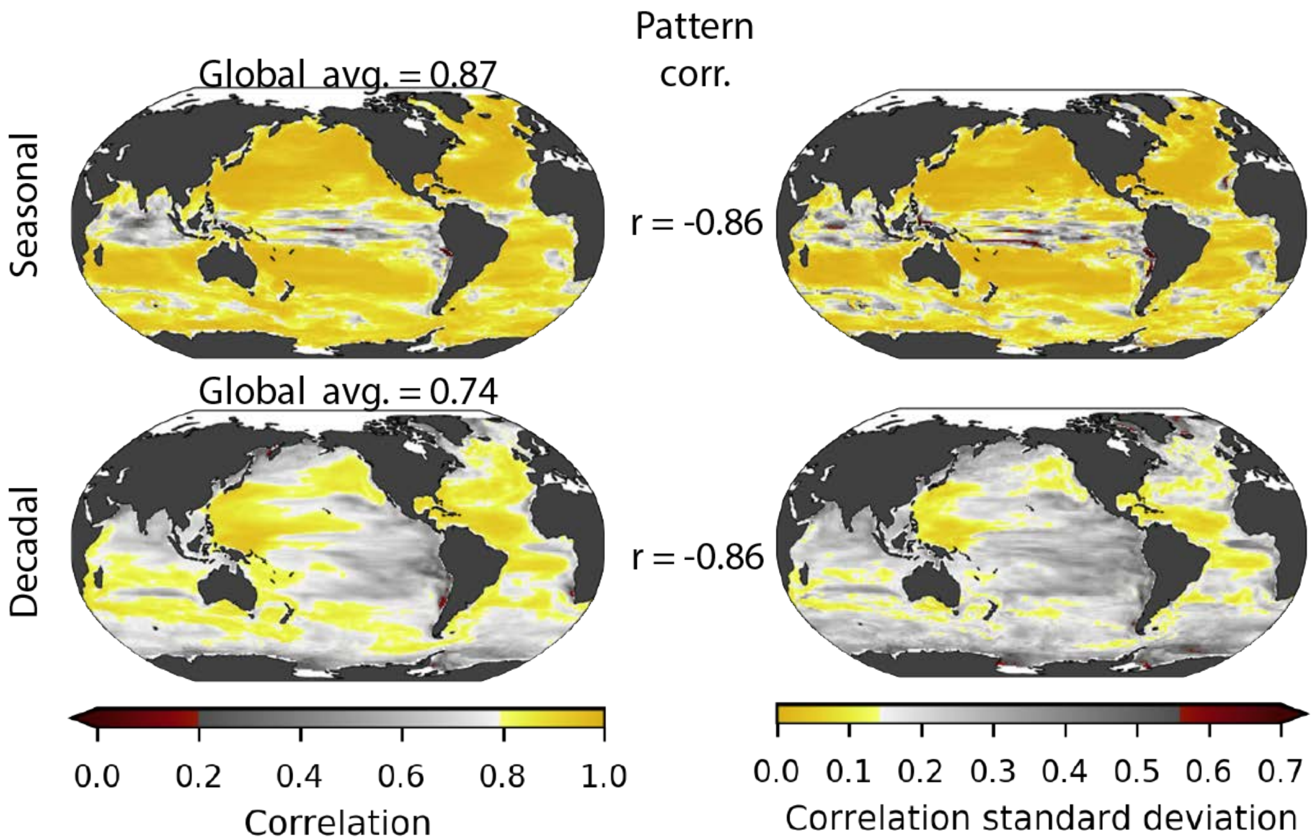
Email

gloege@ldeo.columbia.edu

Extra slides

Correlation

Is the reconstruction in phase with the model?



- Higher correlations in sub-tropics
- Correlations are consistent across ensemble members

Calculate air-sea CO_2 exchange

Air-sea CO_2 flux
(relative to atmosphere)

Ice fraction

$$F_{CO_2} = k_w S_{CO_2}(1 - f_{ice})(pCO_2^{ocn} - pCO_2^{atm})$$

Gas-transfer velocity and solubility

Ocean and atmosphere pCO_2

- ERA-interim 6-hourly global atmospheric reanalysis used to estimate monthly varying wind-speed covariance
- Calculated air-sea CO_2 exchange following Landschützer et al. 2014

Weiss 1974, Wanninkhof 1992, Sweeney et al. 2007

