



# Online atmosphere/ocean bias correction in CanESM5 and its impact on seasonal hindcast skill

*Bill Merryfield, Slava Kharin, Woo-Sung Lee, John Scinocca and Reinel Sospedra-Alfonso*

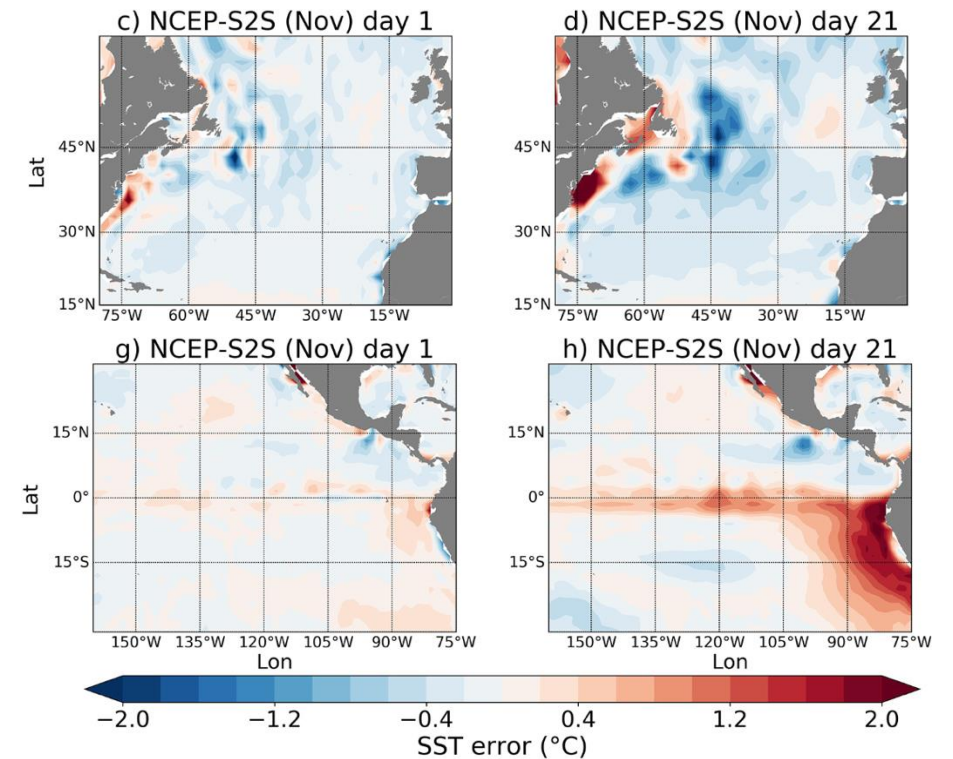
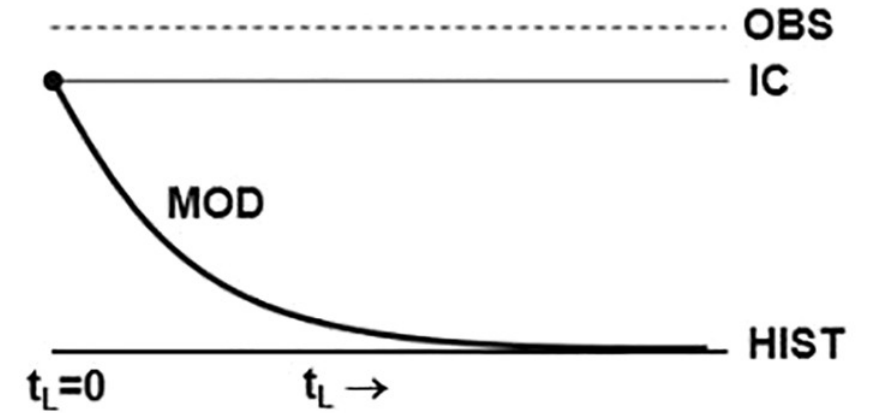
Canadian Centre for Climate Modelling and Analysis (CCCma)



Canada 

# Motivation

- As long as model physics and numerics remain imperfect, prediction models initialized close to observations will *drift* toward **biased states** →
- A **pragmatic alternative**: compensate “missing” physical tendencies based on assimilation increments



# The basic idea

- Consider atmospheric (or other) model component constrained by

- nudging to gridded reanalysis time series, or

$$\frac{\partial X}{\partial t} = F(X) - \frac{1}{\tau}(X - X_R)$$

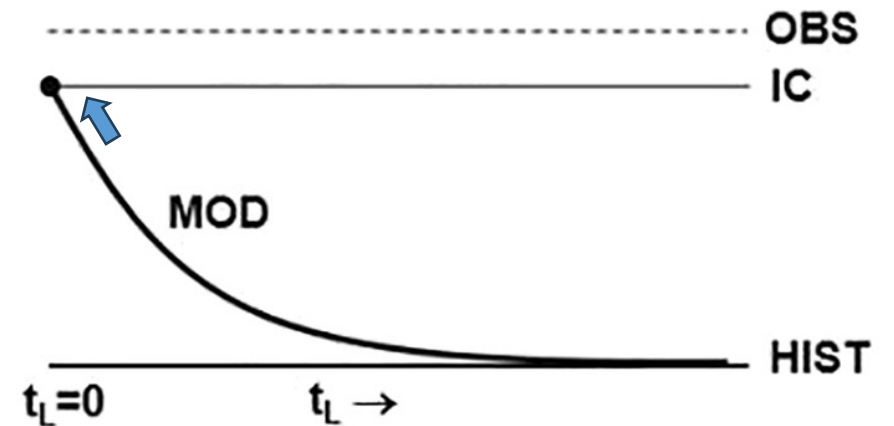
- data assimilation

- Save time series of the nudging terms (or assimilation increments), compute mean annual cycle:

$$-\frac{1}{\tau} \overline{(X - X_R)}^{AC}$$

- Insert as a **tendency correction** in forecast runs:

$$\frac{\partial X}{\partial t} = F(X) - \frac{1}{\tau} \overline{(X - X_R)}^{AC}$$



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→ Reduced biases, modestly improved skill

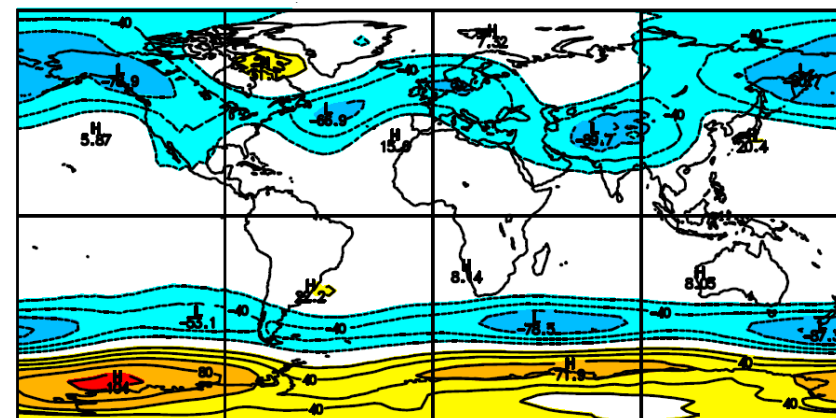
## Geophysical Research Letters\*

### The impact of model fidelity on seasonal predictive skill

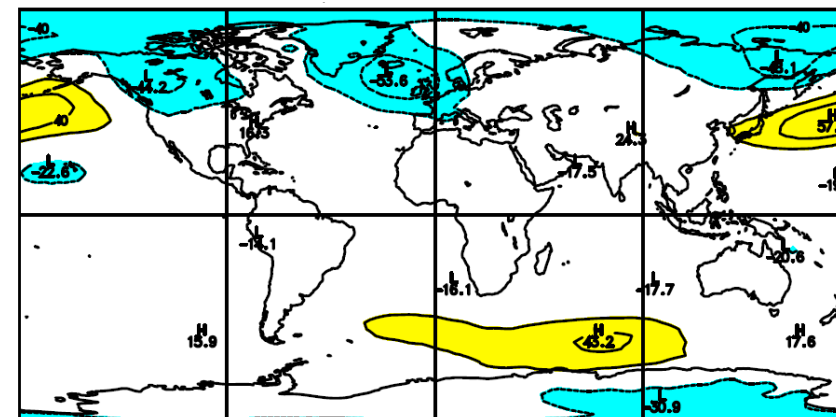
V. V. Kharin ✉ J. F. Scinocca

First published: 22 September 2012 | <https://doi.org/10.1029/2012GL052815> | Citations: 44

Z500 RMSE no bias correction



Z500 RMSE with bias correction



# Related methods

## NASA GEOS

- Estimate tendency corrections from **atmospheric** assimilation increments
- Apply long-term averaged increments (retaining diurnal and annual cycles) as forcing terms to atmospheric  $u$ ,  $v$ ,  $T$ , and  $p_s$
- Atmospheric/surface biases reduced
- “Modest at best” improvements in S2S skill

## GFDL SPEAR

- Estimate tendency adjustments from **ocean** T/S assimilation increments during 2007-2018
- Apply OTA from annual cycle of increments
- SST and subsurface biases greatly reduced
- Improved ENSO skill after first months

Journal of Climate

Tendency Bias Correction in Coupled and Uncoupled Global Climate Models with a Focus on Impacts over North America

Y. Chang, S. D. Schubert, R. D. Koster, A. M. Molod, and H. Wang

Print Publication: 15 Jan 2019

DOI: <https://doi.org/10.1175/JCLI-D-18-0598.1>

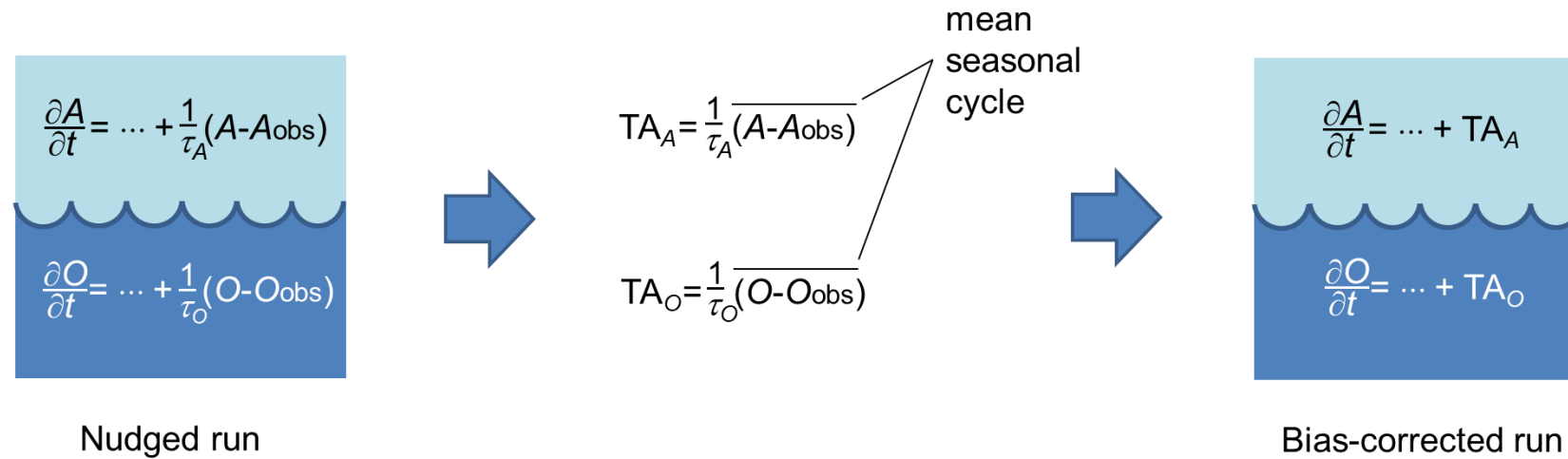
**JAMES** | Journal of Advances in  
Modeling Earth Systems\*

**GFDL's SPEAR Seasonal Prediction System: Initialization and Ocean Tendency Adjustment (OTA) for Coupled Model Predictions**

Feiyu Lu ✉, Matthew J. Harrison, Anthony Rosati, Thomas L. Delworth, Xiaosong Yang, William F. Cooke, Liwei Jia, Colleen McHugh, Nathaniel C. Johnson, Mitchell Bushuk, Yongfei Zhang, Alistair Adcroft

First published: 03 November 2020 | <https://doi.org/10.1029/2020MS002149> | Citations: 31

# Tendency adjustment methodology for CanESM5



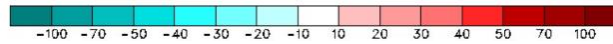
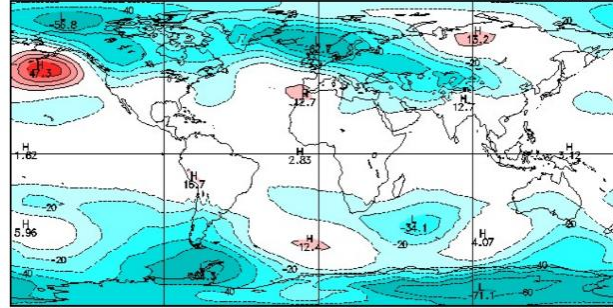
- Atmosphere
  - **default** settings:  $\tau_A=24\text{h}$ , apply on scales  $\geq 1000\text{km}$
  - **optimized** settings:  $\tau_A(z)$ , spectral truncation per variable
- Ocean
  - $\tau_O=30$  days for T/S in upper 800m, 360 days below
  - no nudging within  $\pm 2^\circ$  of Equator
- Evaluate CanESM5 free runs and hindcasts using
  - no bias correction
  - default bias correction settings
  - **optimized atm bias correction settings**

CanESM5 AMIP  
runs 2004-2008

no BC

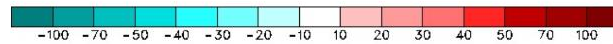
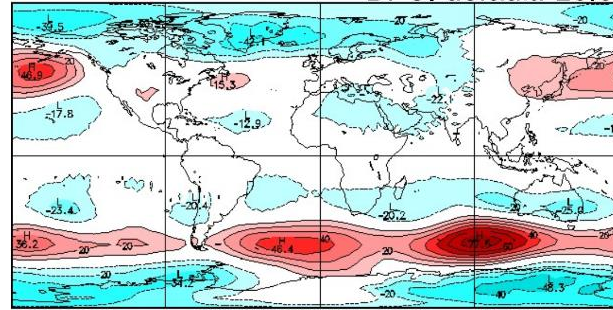
Z500 bias

Free: 19.3



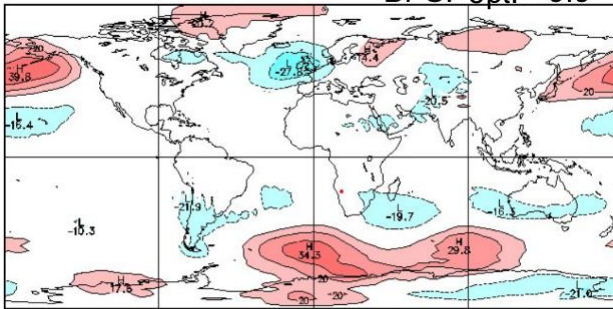
default BC

B.-C. default: 16.0



optimized BC

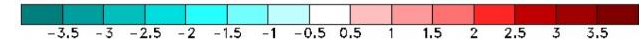
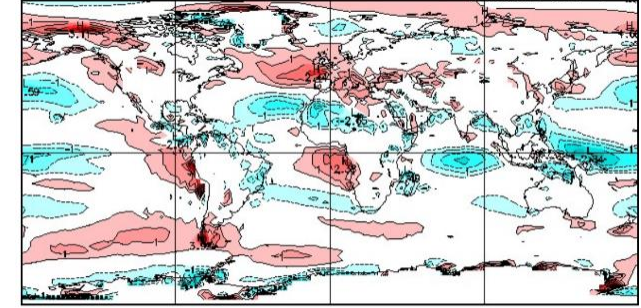
B.-C. opt: 9.9



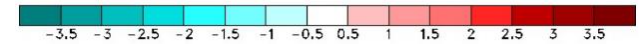
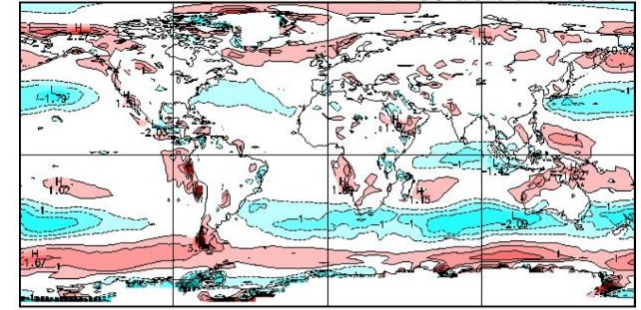
m

U10 bias

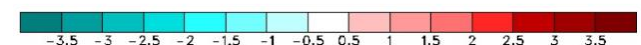
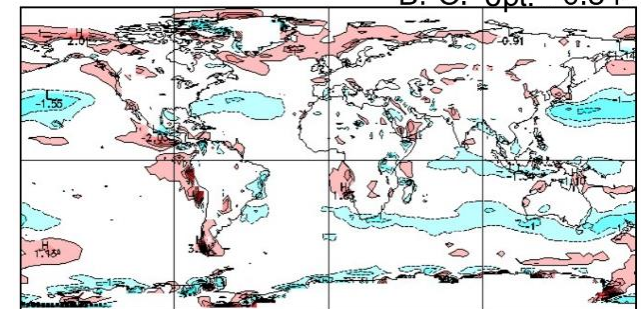
Free: 0.74



B.-C. default: 0.70



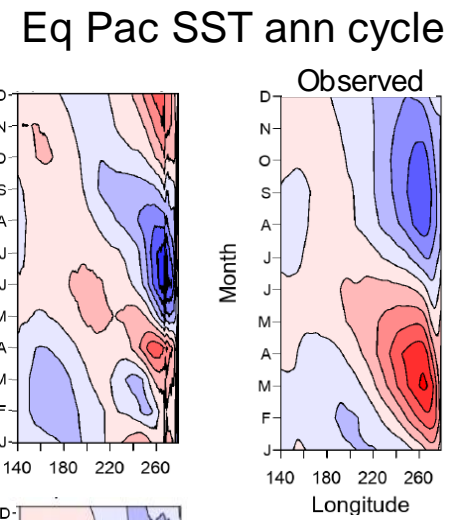
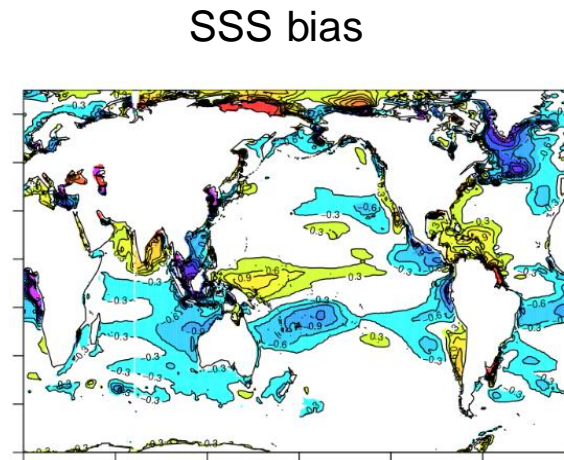
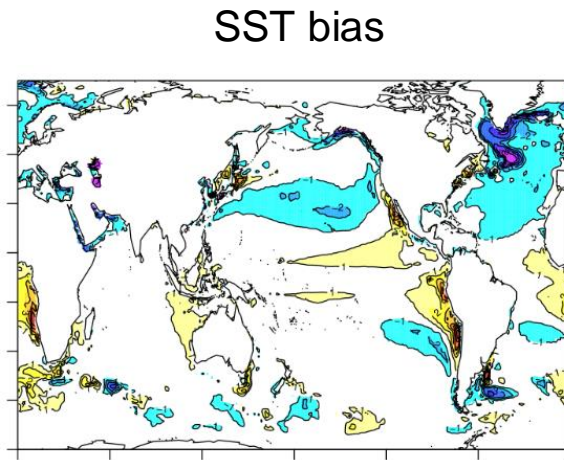
B.-C. opt: 0.54



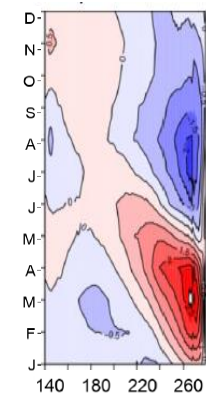
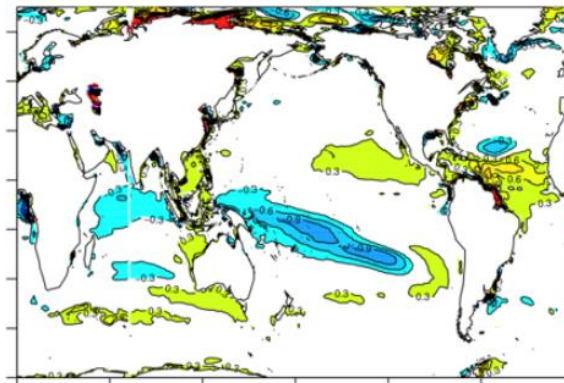
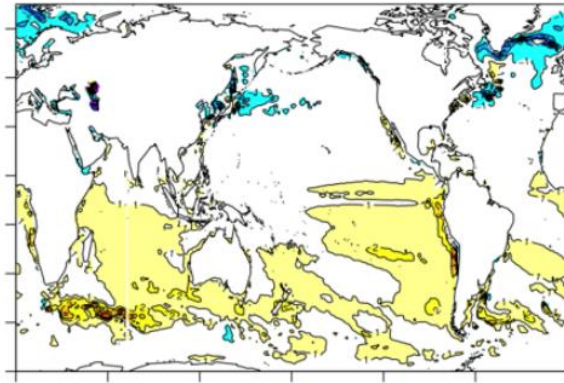
m/s

CanESM5 free  
coupled runs  
1981-2020

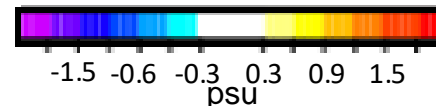
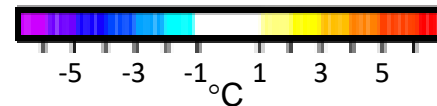
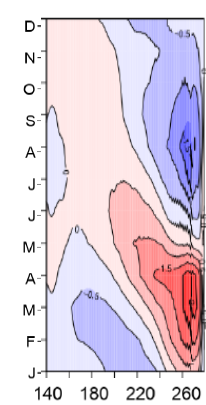
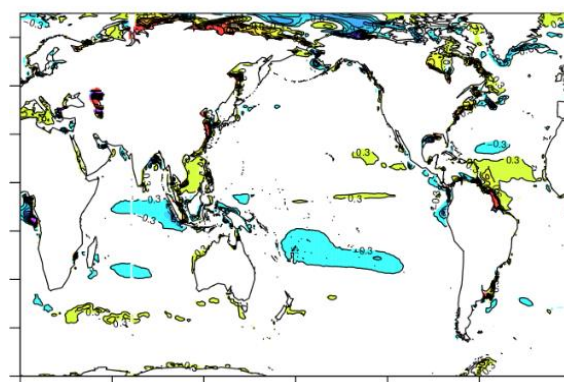
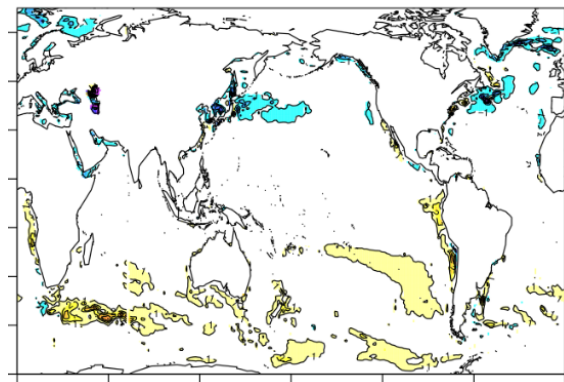
no BC



default BC



✓ optimized BC

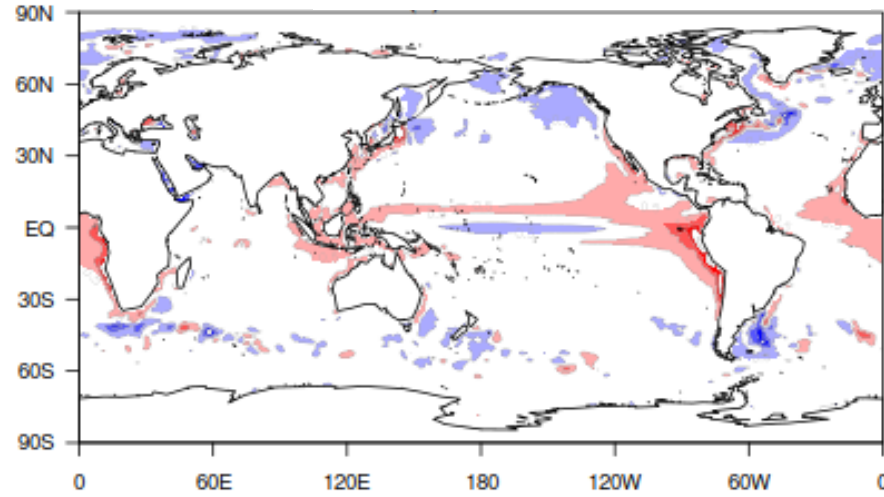




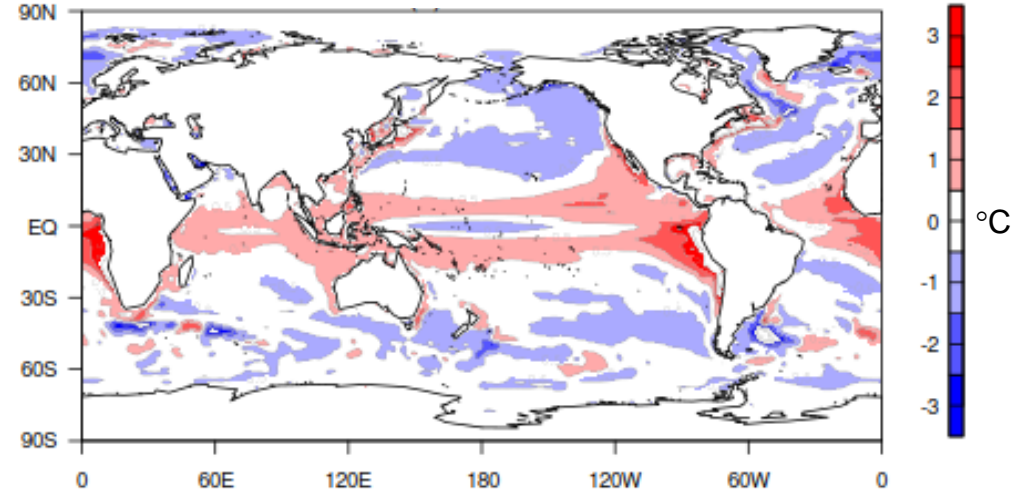
CanESM5  
hindcasts  
1991-2020

no BC

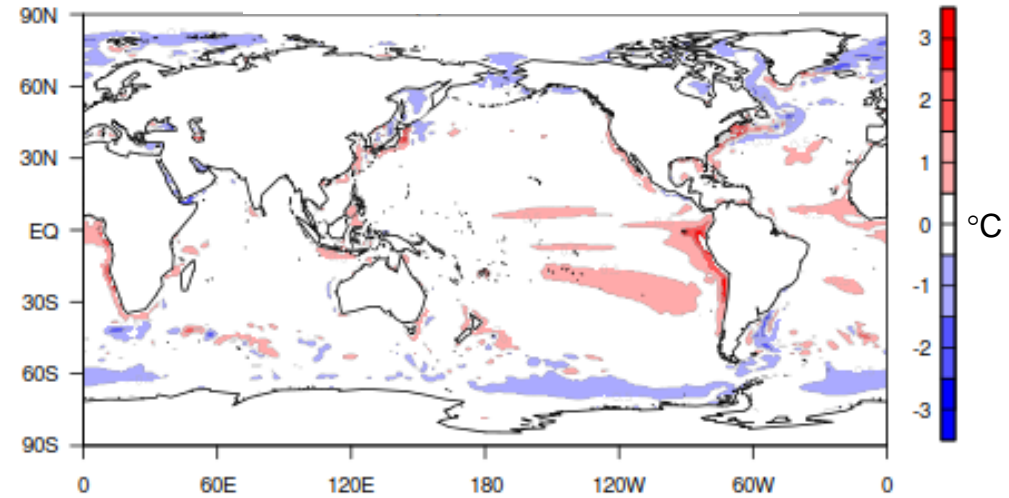
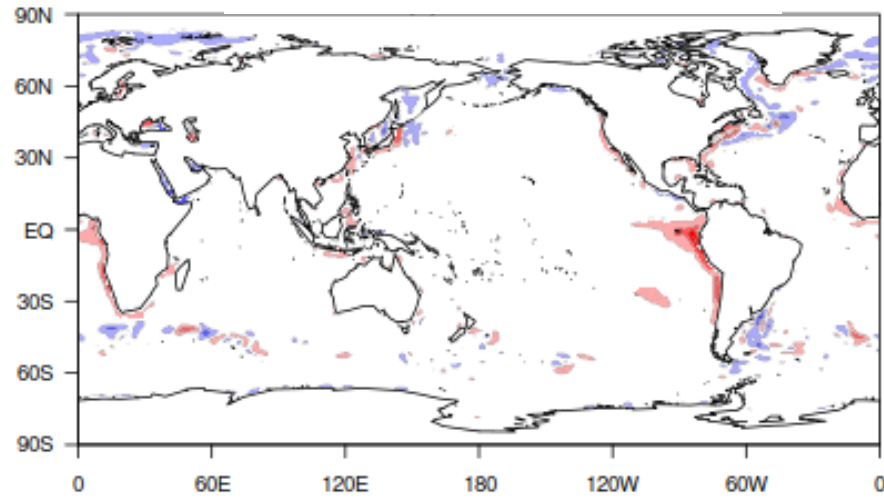
SST bias  
lead 1 month



SST bias  
lead 6 months

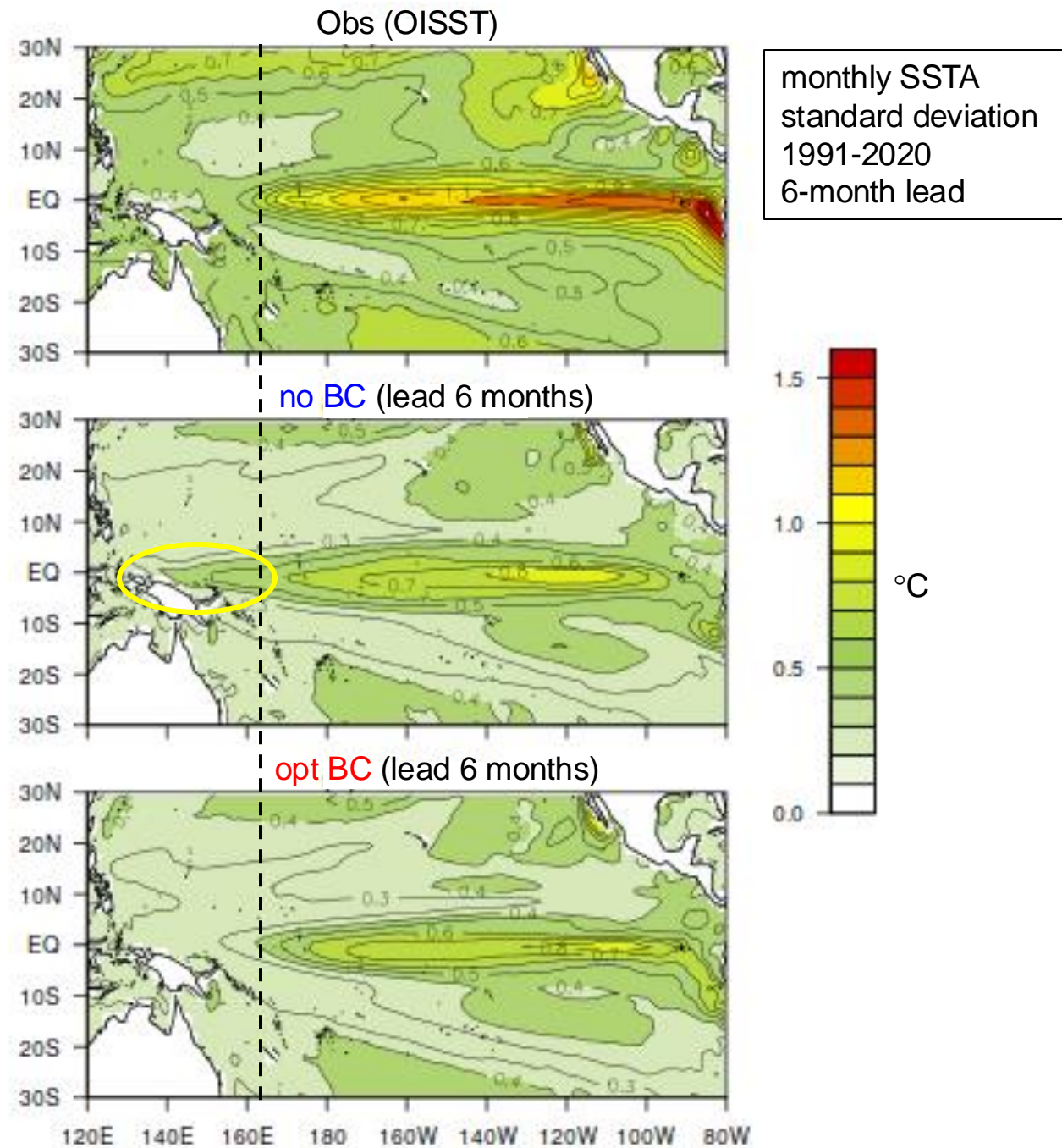


optimized BC



## ENSO variability in hindcasts

- ENSO in hindcasts is weaker than observed
- Bias correction doesn't help
- However, bias correction **reduces the unrealistic westward extension** of El Niño/La Niña SST anomalies (a common error in climate models)
- This impacts skill in the affected region, and possibly teleconnected regions as well

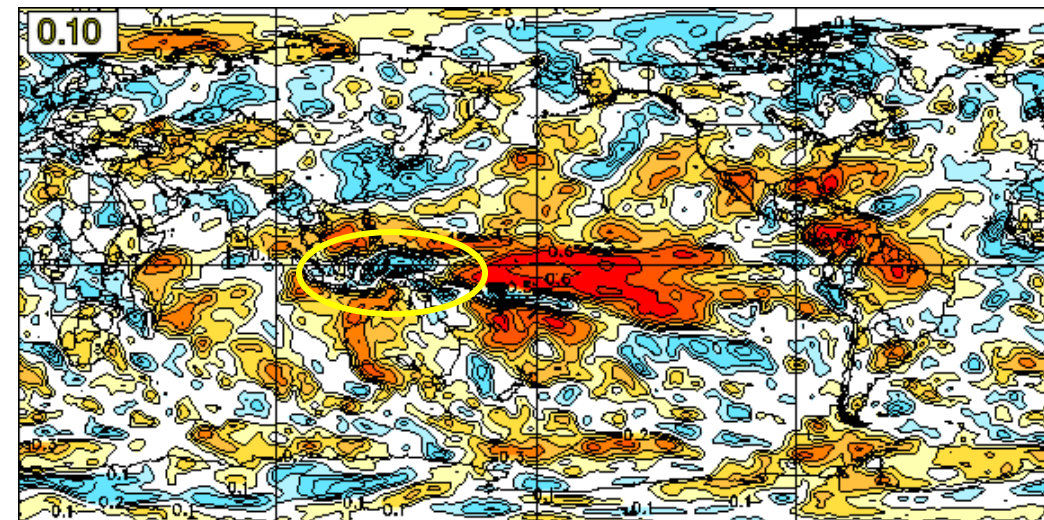
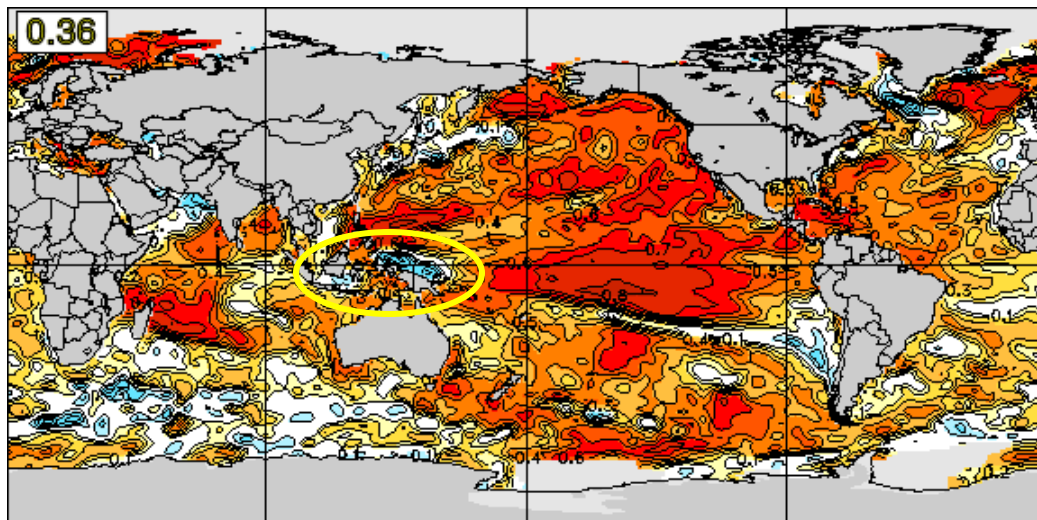


# DJF anomaly correlation from June (lead 6 months)

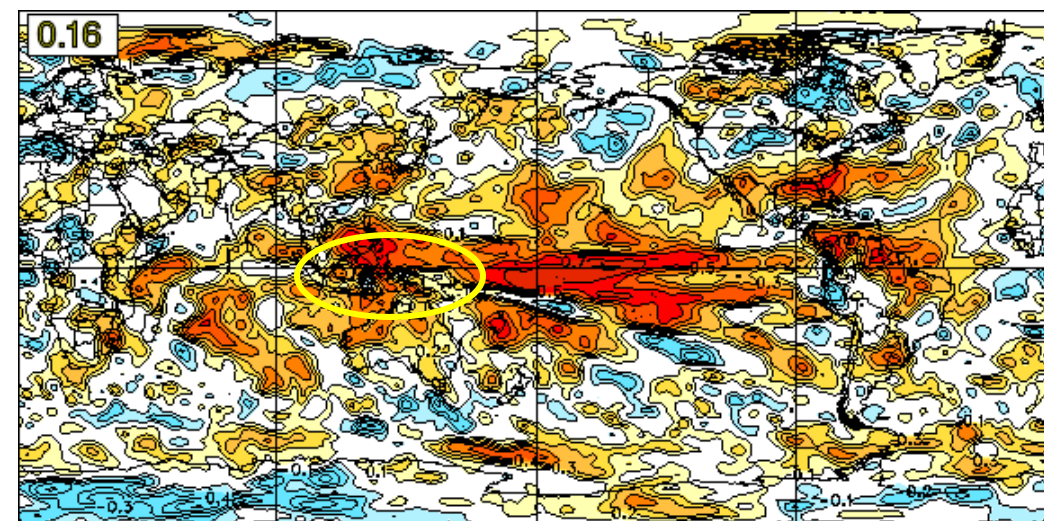
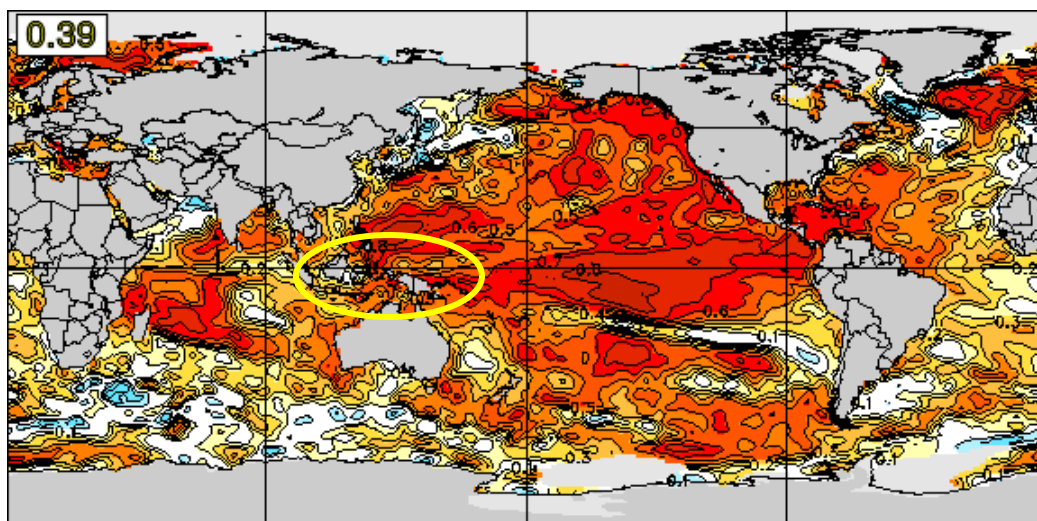
SST

Precipitation

no BC



opt BC

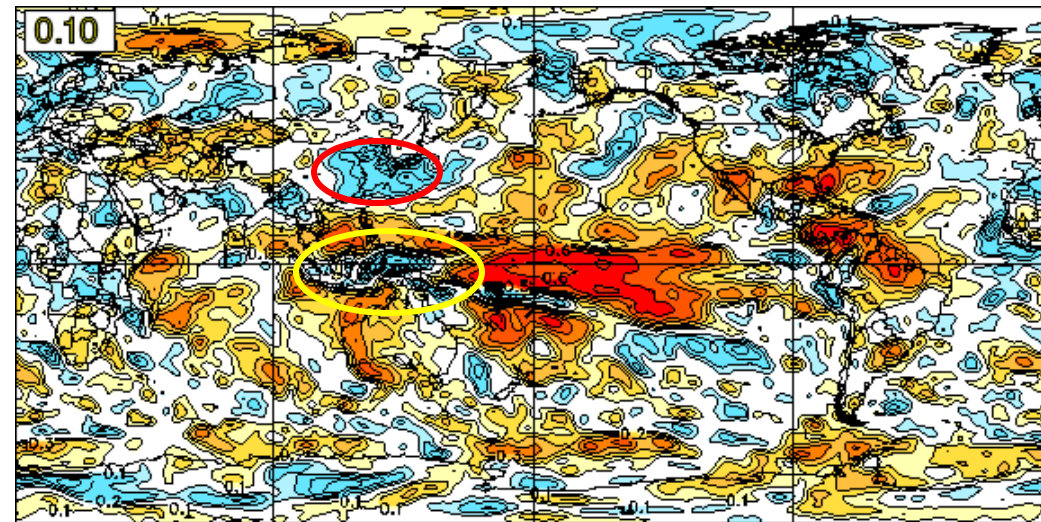
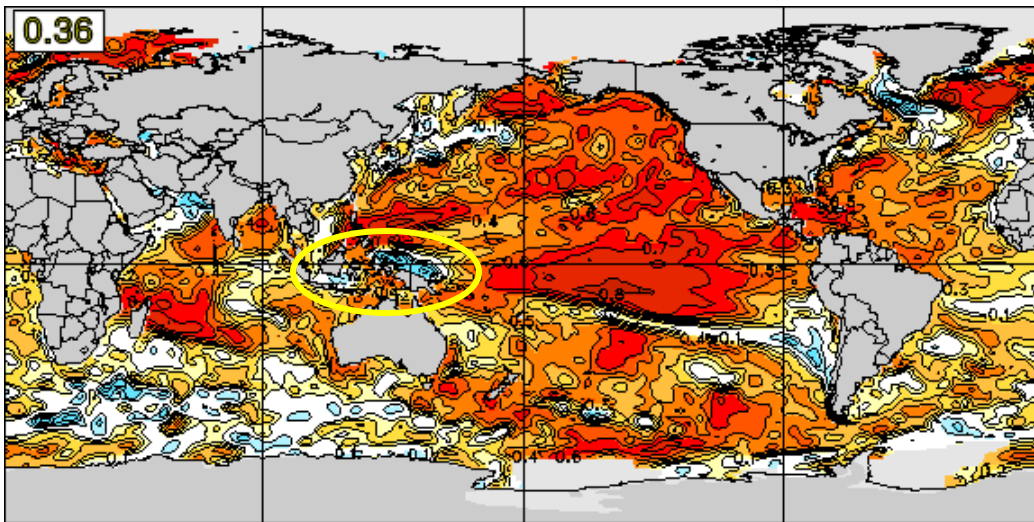


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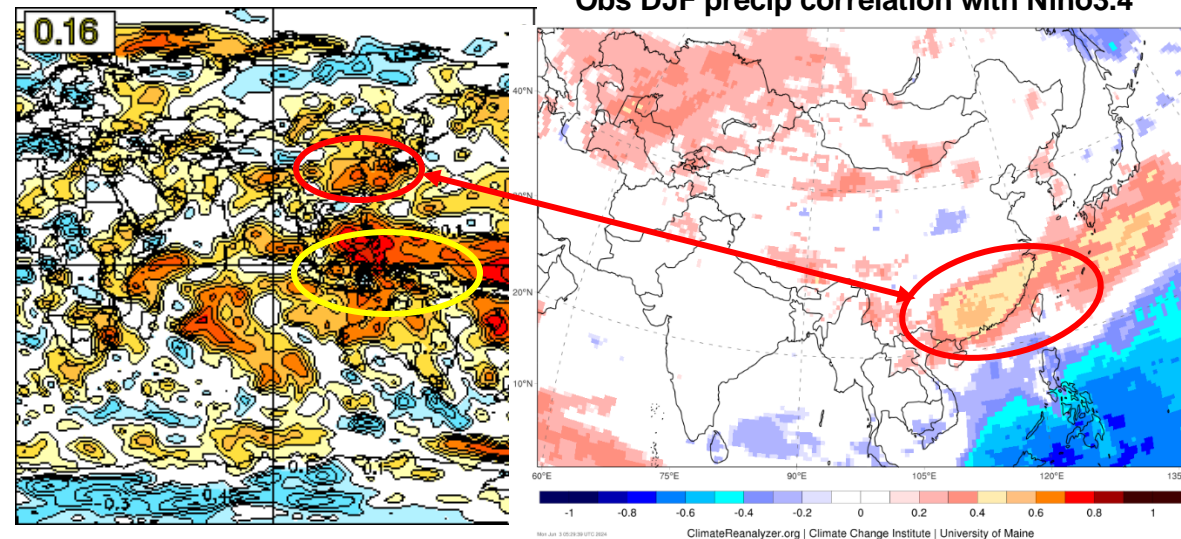
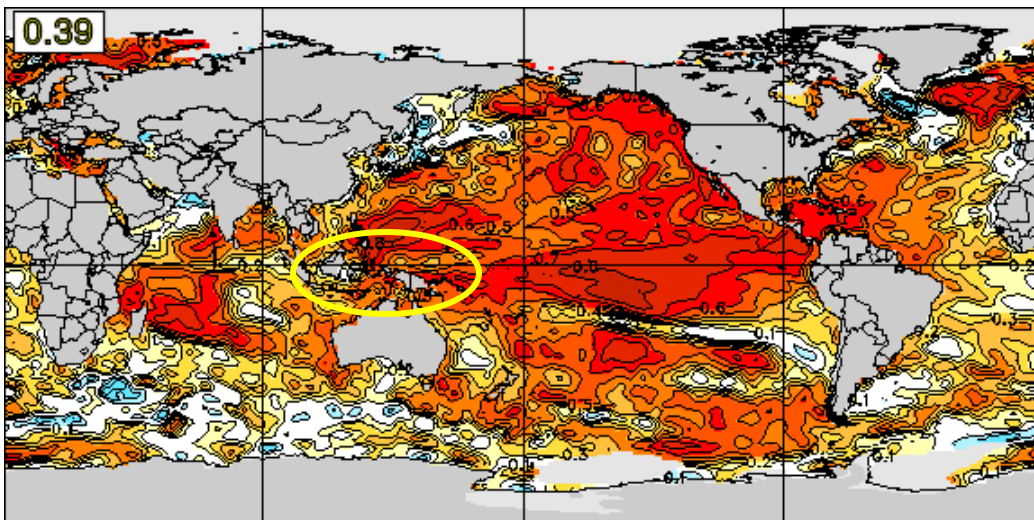
SST

Precip

no BC

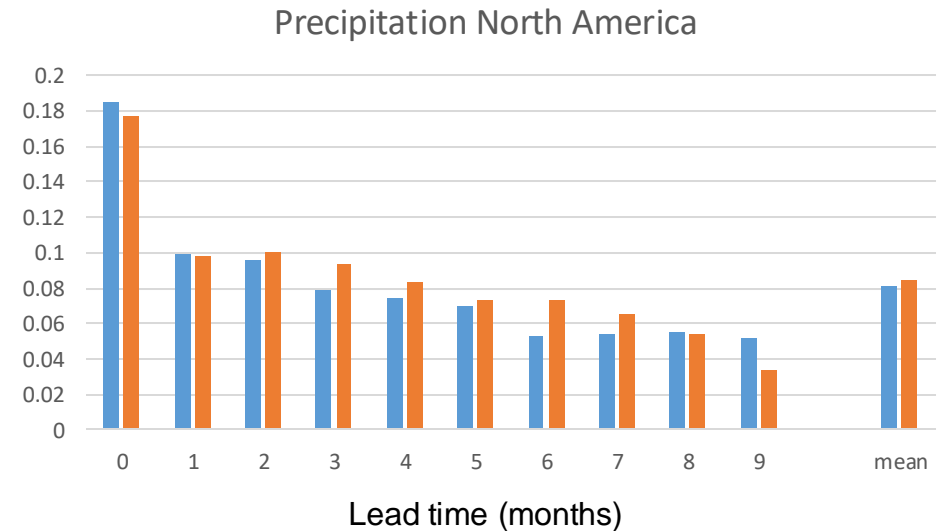
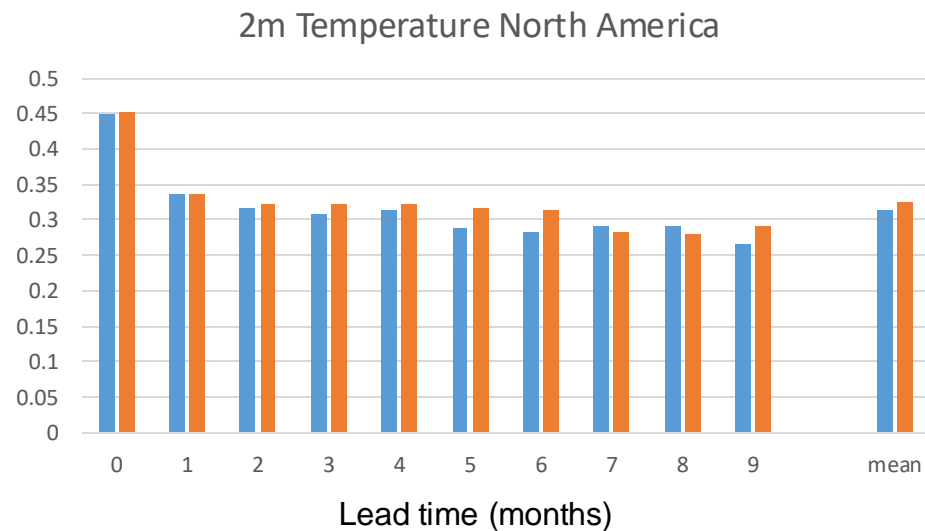
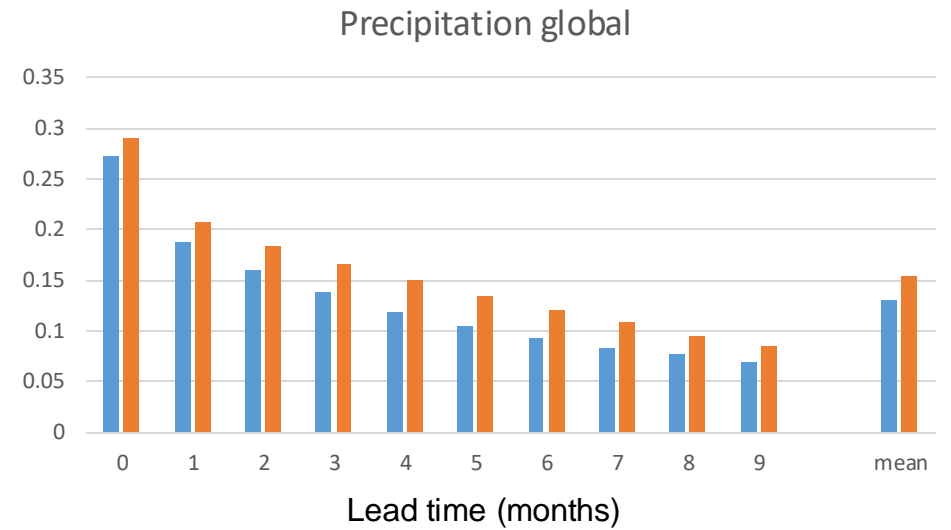
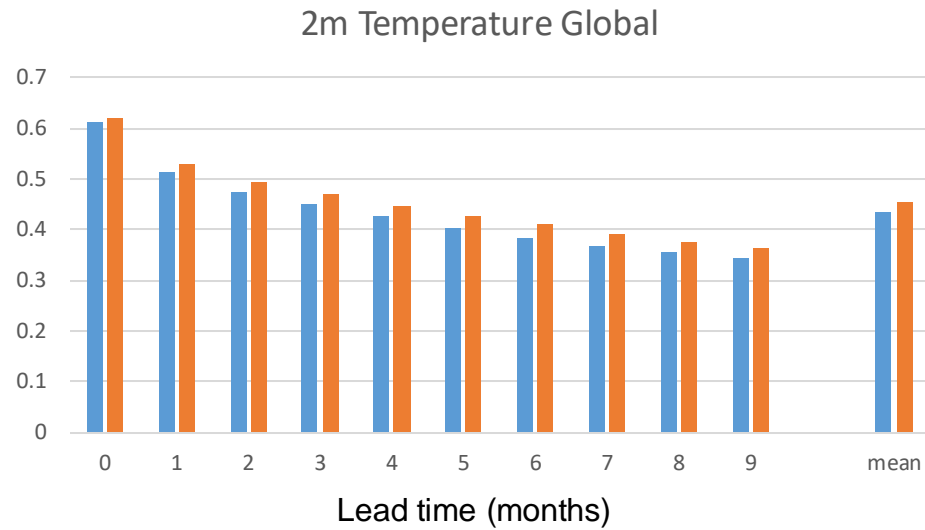


opt BC



# Anomaly correlation vs lead time (10 ensemble members, all initial months)

no BC opt BC



# Outlook

- Tendency adjustments thus far in ECCO/GFDL/NASA models have been **state-independent**
- Current research on multiple fronts is exploring **state-dependent** tendency adjustment facilitated by **machine learning**

Quarterly Journal of the  
Royal Meteorological Society



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## Using machine learning to correct model error in data assimilation and forecast applications

Alban Farchi [✉](#), Patrick Laloyaux, Massimo Bonavita, Marc Bocquet

First published: 02 July 2021 | <https://doi.org/10.1002/qj.4116> | Citations: 39

## Geophysical Research Letters\*

Research Letter | [Open Access](#) | [CC](#) [i](#) [S](#)

## Correcting Weather and Climate Models by Machine Learning Nudged Historical Simulations

Oliver Watt-Meyer [✉](#), Noah D. Brenowitz, Spencer K. Clark, Brian Henn, Anna Kwa, Jeremy McGibbon, W. Andre Perkins, Christopher S. Bretherton

First published: 15 July 2021 | <https://doi.org/10.1029/2021GL092555> | Citations: 38

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## Correcting Systematic and State-Dependent Errors in the NOAA FV3-GFS Using Neural Networks

Tse-Chun Chen [✉](#), Stephen G. Penny, Jeffrey S. Whitaker, Sergey Frolov, Robert Pincus, Stefan Tulich

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## Correcting Coarse-Grid Weather and Climate Models by Machine Learning From Global Storm-Resolving Simulations

Christopher S. Bretherton [✉](#), Brian Henn, Anna Kwa, Noah D. Brenowitz, Oliver Watt-Meyer, Jeremy McGibbon, W. Andre Perkins, Spencer K. Clark, Lucas Harris

First published: 21 January 2022 | <https://doi.org/10.1029/2021MS002794> | Citations: 24

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## Deep Learning to Estimate Model Biases in an Operational NWP Assimilation System

Patrick Laloyaux [✉](#), Thorsten Kurth, Peter Dominik Dueben, David Hall

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## Deep Learning of Systematic Sea Ice Model Errors From Data Assimilation Increments

William Gregory [✉](#), Mitchell Bushuk, Alistair Adcroft, Yongfei Zhang, Laure Zanna

First published: 27 September 2023 | <https://doi.org/10.1029/2023MS003757> | Citations: 4