Using ECCO to advance climate prediction and understand climate projection

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A proof-of-concept study to improve seasonal prediction of regional sea level anomaly (SLA)

Method:

- Predict regional SLA by convolving SL sensitivities to forcings with the anomalies of atmospheric forcings.
- Sensitivities: pre-computed using ECCO adjoint.
- Forcings: ECCO forcings (for $t<t_0$) concatenated with coupled-model predicted forcings (for $t>t_0$), seasonally de-biased by ECCO forcing seasonal climatology.

Key Results:

- Seasonal hindcasts of Charleston SLA using this method have much better skill than that of coupled model SLA hindcasts, and beats “damped persistence” up to 7-month lead time.
- SLA hindcasts using only ECCO forcings have even better skill for lead times > 1 month, indicating the **importance of slow ocean dynamic memory (“Dynamic persistence”) in** SLA **predictability**.

JGR Oceans

A Hybrid Dynamical Approach for Seasonal Prediction of Sea-Level Anomalies: A Pilot Study for Charleston, South Carolina

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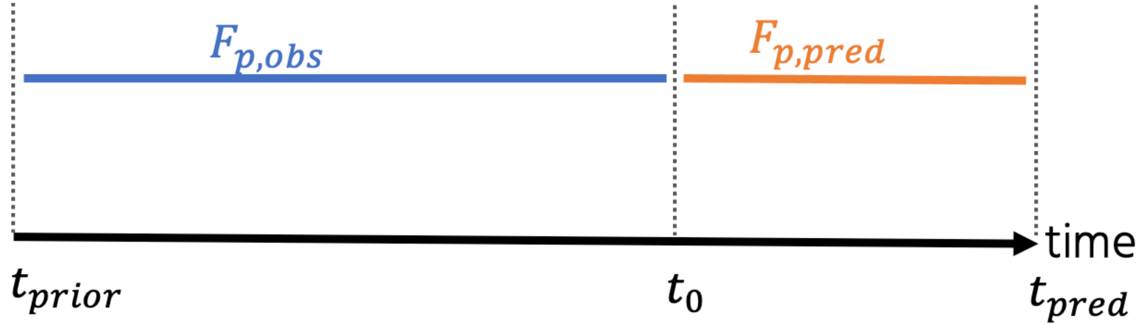
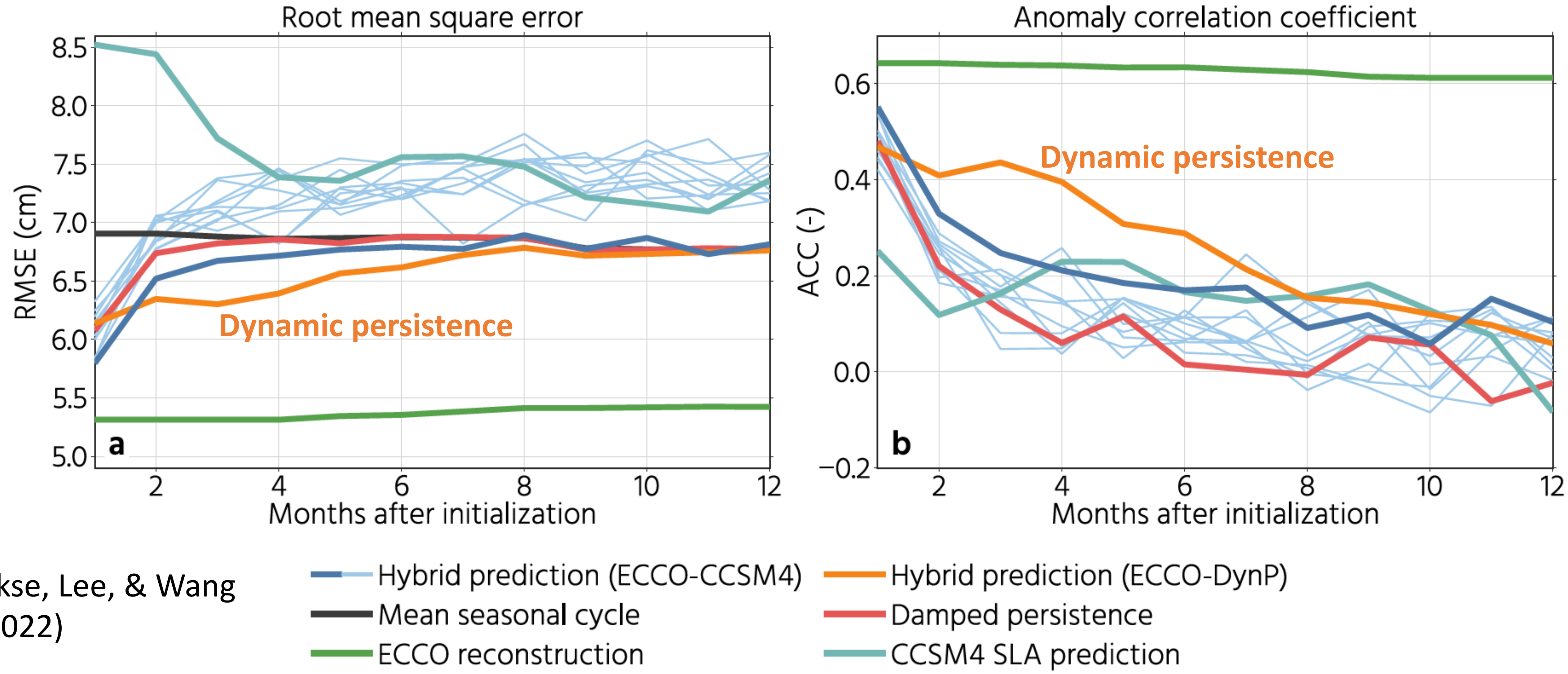


$$\eta'\left(t_{pred}\right) = \sum_{p=1}^{4}\left(\iiint_{t_{pred}-t_{prior}}^{t_{pred}-t_{init}} S_p\left(x,y,m_{pred},\tau\right)\cdot F'_{p,ECCO}\left(x,y,t_{pred}-\tau\right)dxdyd\tau + \iiint_{t_{pred}-t_{init}}^{0} S_p\left(x,y,m_{pred},\tau\right)\cdot F'_{p,pred}\left(x,y,t_{pred}-\tau\right)dxdyd\tau\right)$$



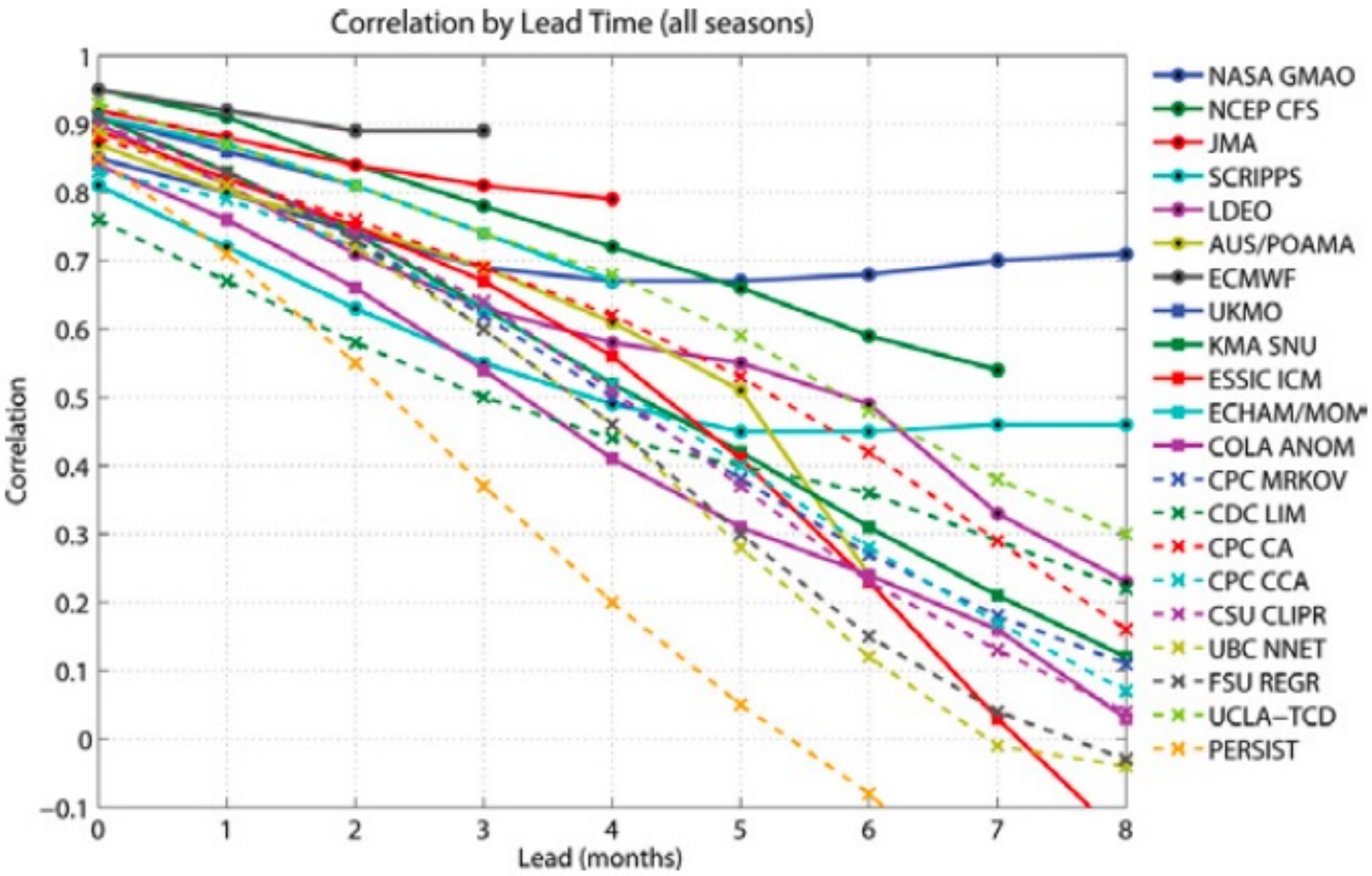
Frederikse, Lee, & Wang et al. (2022)

Figure 6. Statistics of the hybrid prediction. Panel a shows the root-mean-squared error of each reconstruction and prediction with respect to tide-gauge observations. Panel b shows the correlation coefficient of the monthly anomalies after removing the mean seasonal cycle. Correlations above 0.16 are significant on the 95% confidence level, based on a *t*-test statistic that takes into account the reduced number of degrees of freedom due to serial correlation in observed sea level. The statistics with respect to altimetry observations are shown in Figure S4 in Supporting Information S1.

The hybrid dynamical approach is applicable not only to seasonal prediction of SLA, but also to predictions for other phenomena/variables/time scales (e.g., ENSO SSTA)

Niño3.4 SSTA prediction skill w.r.t. observed values as a function of lead time

Fig.6 from
Barnston, Tippett, & L'Heurex et al. (2012, BAMS):
"Skill of Real-Time Seasonal ENSO Model Predictions during 2002–11: Is Our Capability Increasing?"



Anomalous (temporal) correlation coefficient between model forecasts and observed Nino3.4 SSTA as a function of lead time, for 12 dynamical models (solid), 8 statistical models (dashed), and statistical persistence (yellow dashed) https://doi.org/10.1175/BAMS-D-11-00111.1

ECCO results underscore the importance of dynamic persistence in ENSO predictability

Skills of ECCO dynamical persistence added to the previous slide (analysis performed by Ou Wang):
Blue curve: adjoint-based
Orange curve: forward-based (12-month "hindcasts" initialized from ECCO I.C. at every month of different years, using climatological seasonal forcings)

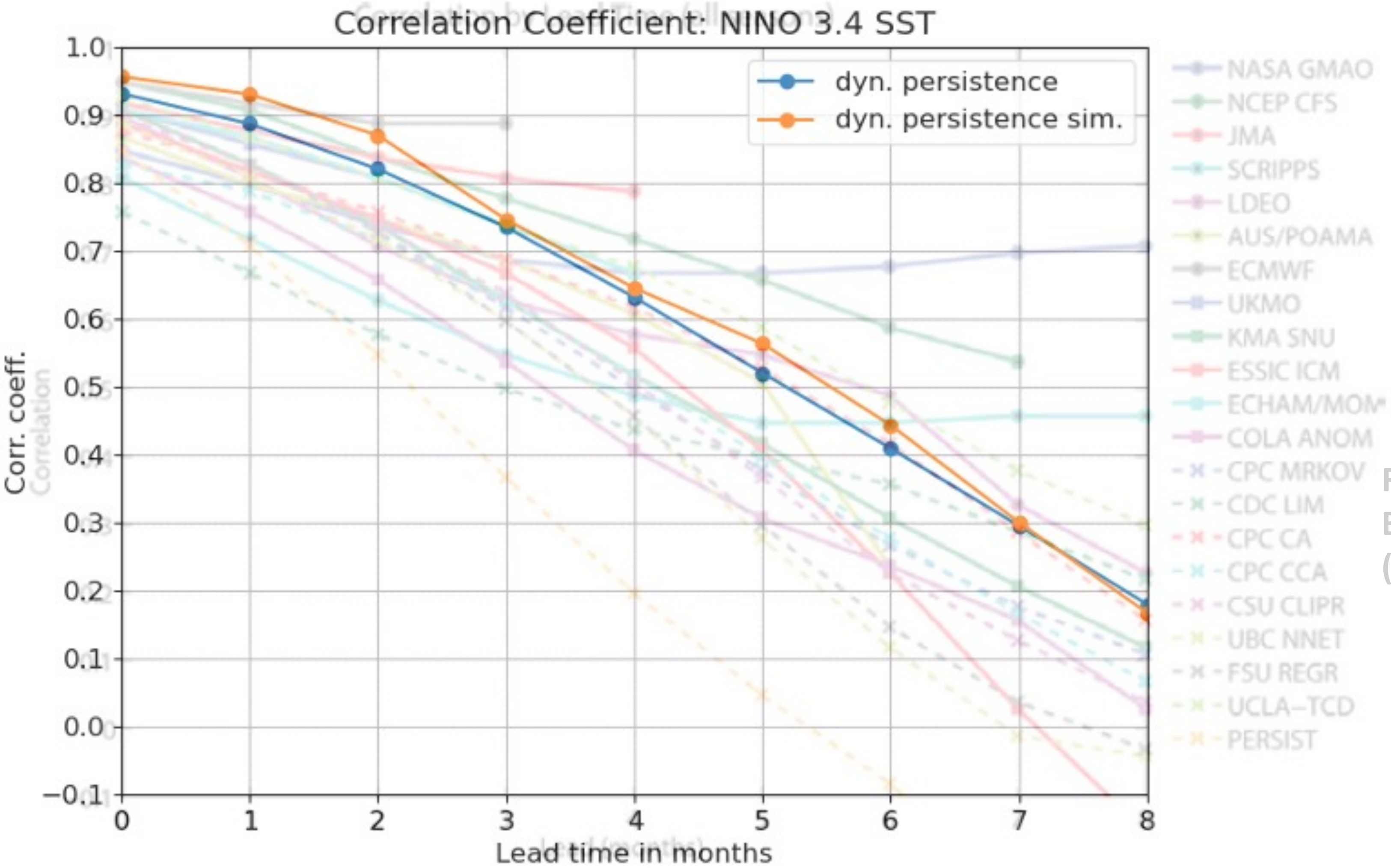


Fig.6 from Barnston et al. (2012), BAMS.

- ECCO dynamic persistence raises the bar for ENSO prediction skill assessment metrics (>>statistical persistence).
- Being developed: **a hybrid dynamical RT forecast system** for ENSO, IOD, etc. using the method of Frederikse et al. (2022): convolve ECCO adjoint sensitivities with ensemble reanalysis forcings (for $t<t_0$) & coupled-model predicted forcings (for $t>t_0$):
  - Skill-weight coupled model forcings (for particular models & particular forcings) based on hindcast performance.

Using ECCO adjoint sensitivities and CMIP6 projected change of atmospheric forcings **to understand the nature of projected SL change** at Nantucket

(analysis performed by Thomas Frederikse)

- Nantucket SL sensitivities to atmos. forcings are computed by ECCO adjoint (Wang, Lee, & Piecuch et al. 2022, JGR).
- The sensitivities are convolved with projected atmos. forcings (SSP5-8.5) from the German MPI ESM to reconstruct the expected Nantucket SL change (relative to GMSL).
- The reconstructed SL reproduces the MPI-model projected change of Nantucket SL (a).
- Decomposition of the reconstructed SL to contributions by various forcings (b).