Characterizing tropical Pacific SST predictability

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Newman, Matthew, and Prashant Sardeshmukh, 2017: Are we near the predictability limit of tropical sea surface temperatures? *Geophys. Res. Lett.,* doi: 10.1002/2017GL074088
Ding, Hui, Matthew Newman, Michael A. Alexander, and Andrew T. Wittenberg, 2018: Skillful climate forecasts of the tropical Indo-Pacific ocean using model-analogs. *J. Climate,* doi: 10.1175/JCLI-D-17-0661.1

A hierarchy of anomaly models

from nonlinear GCMs (top) to linear stochastically forced models (bottom)

$$\frac{dx}{dt} = \underbrace{A(x)}_{\text{resolved}} + \underbrace{P(x)}_{\text{parameterized}} + \underbrace{R}_{\text{unparameterized}}$$

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2. Approximate chaotically nonlinear portions of A(x) and P(x) as linear terms plus noise. Missing terms are deterministic nonlinearity

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$$\approx Lx + S\eta$$

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3. Combine terms.

4. Ignore state-dependent noise

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Q: How much of the predictability of x can we capture this way?
OR: How much skill is lost to the missing terms?

Linear Inverse Model (LIM)

Empirically model the *evolution* of climate anomalies with the linear stochastically forced dynamical system

$$d\mathbf{x}/dt = \mathbf{L}\mathbf{x} + S\eta$$

x(*t*): series of maps, **L**: stable operator, $S\eta$: white noise (also maps) where **S** could be linearly dependent on **x**

- **Linear model, not linearization of equations**: characterize predictable dynamics in nonlinear system
- **Multivariate, not univariate, nonnormal linear dynamics:** anomalies can growth and evolve
- (Ensemble mean) forecasts for lead τ : $\mathbf{x}(t+\tau) = exp(\mathbf{L}\tau)\mathbf{x}(t)$; ensemble spread due to noise
- “Forecast the forecast skill”: based on forecast signal-to-noise

<u>“C-LIM”: monthly mean tropical anomalies (1958-2010)</u>

Ocean: ***SST/SSH (sea surface height)***

Atmosphere: ***200&850 mb wind***

Low-order model (prefiltered in 28 EOF space: 85/63/25% variance retained)

Determine LIM from 0 and 1-lag covariance of **x** [$\mathbf{C}(1)\mathbf{C}(0)^{-1}$, as in AR1 model]

Hindcasts: determined from ten-fold cross-validation, verification data *not* EOF filtered

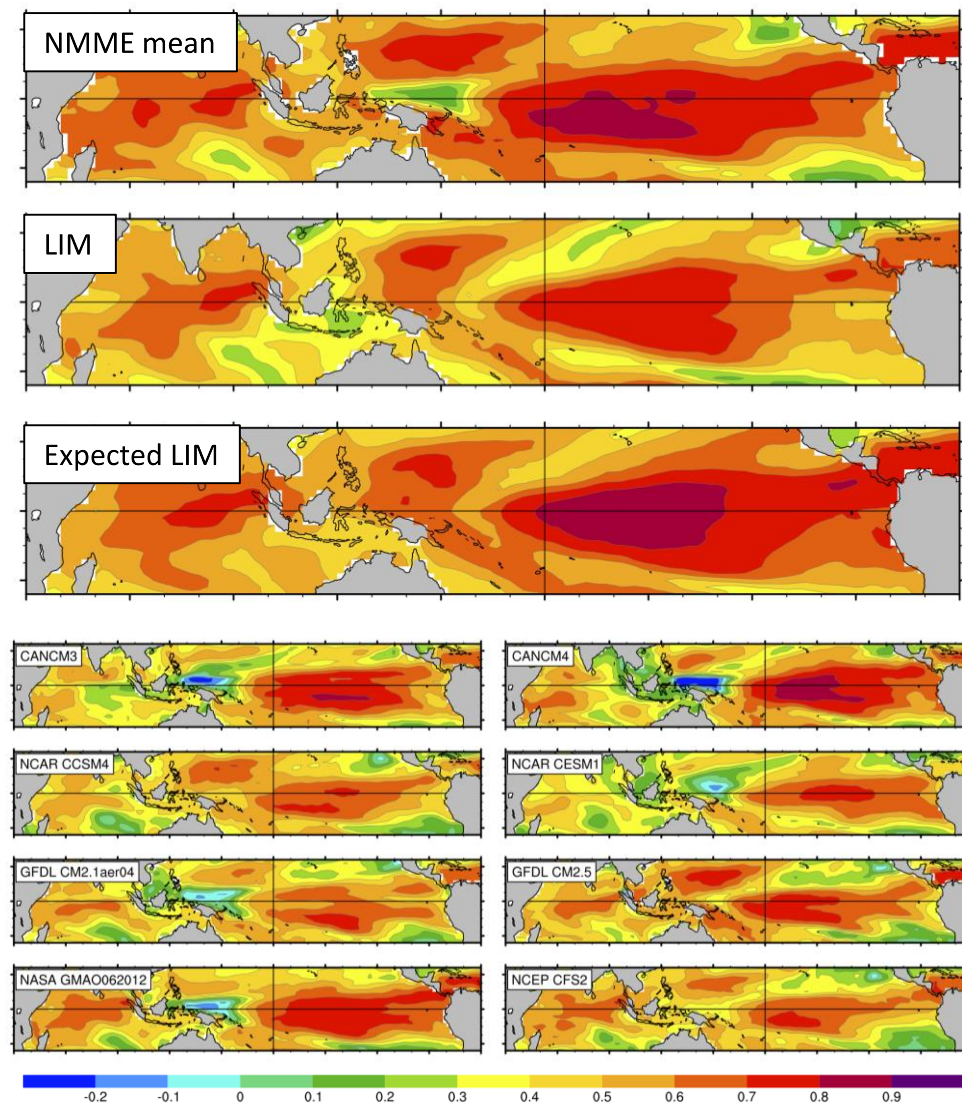
*Simplifications: assume noise is independent of **x**, fixed **L** over analysis dataset*

LIM skill is comparable to NMME ensemble mean and is often better than NMME component models

LIM and NMME mean have similar patterns of SST skill, *which can be explained by <u>expected LIM skill</u>*

Individual NMME model ensemble means
(bias corrected by model)

Month 6 anomaly correlation (AC) skill



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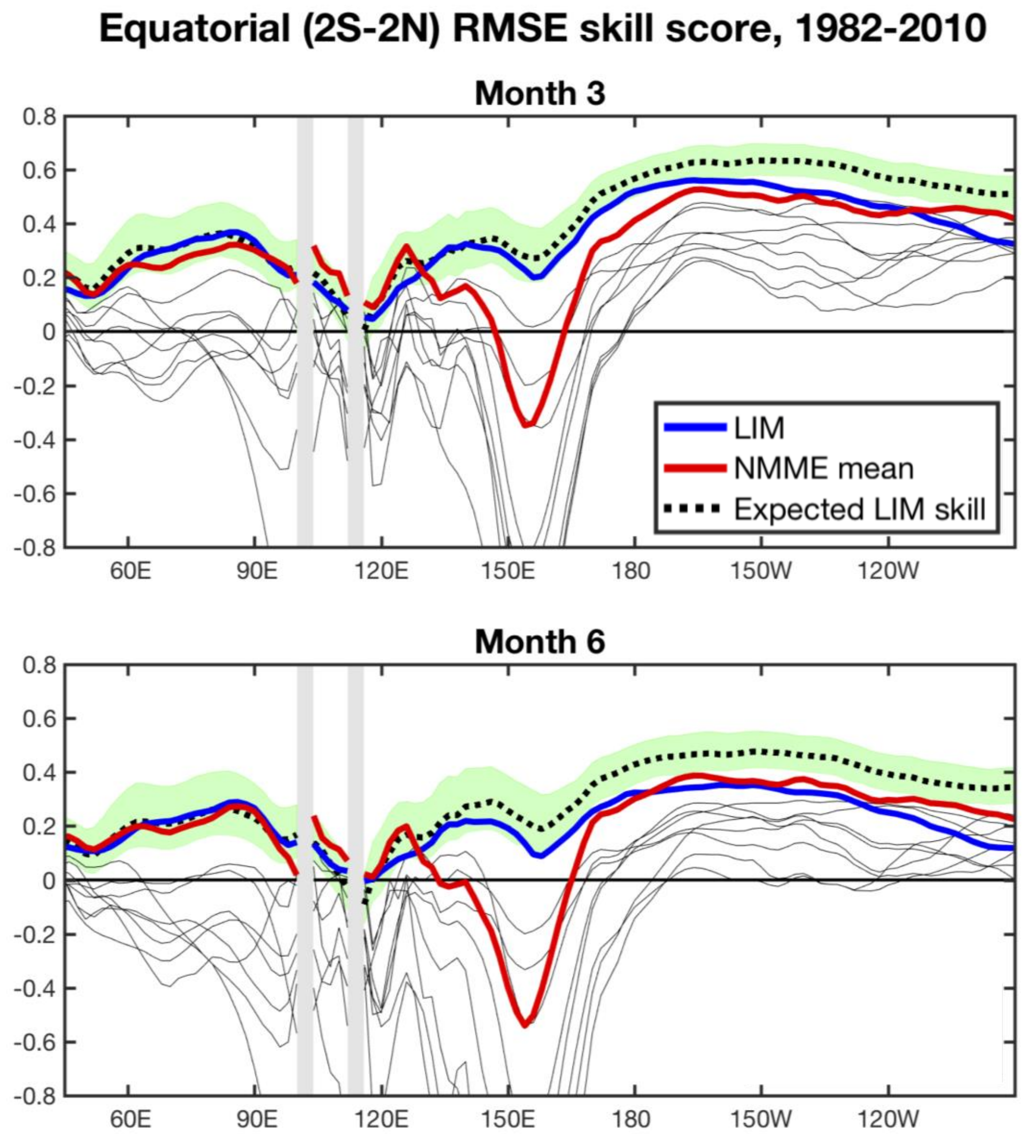
Most individual CGCMs have skill below both LIM and NMME multi-model mean skill, except in far eastern tropical Pacific

RMSE skill score = 1 – standardized error

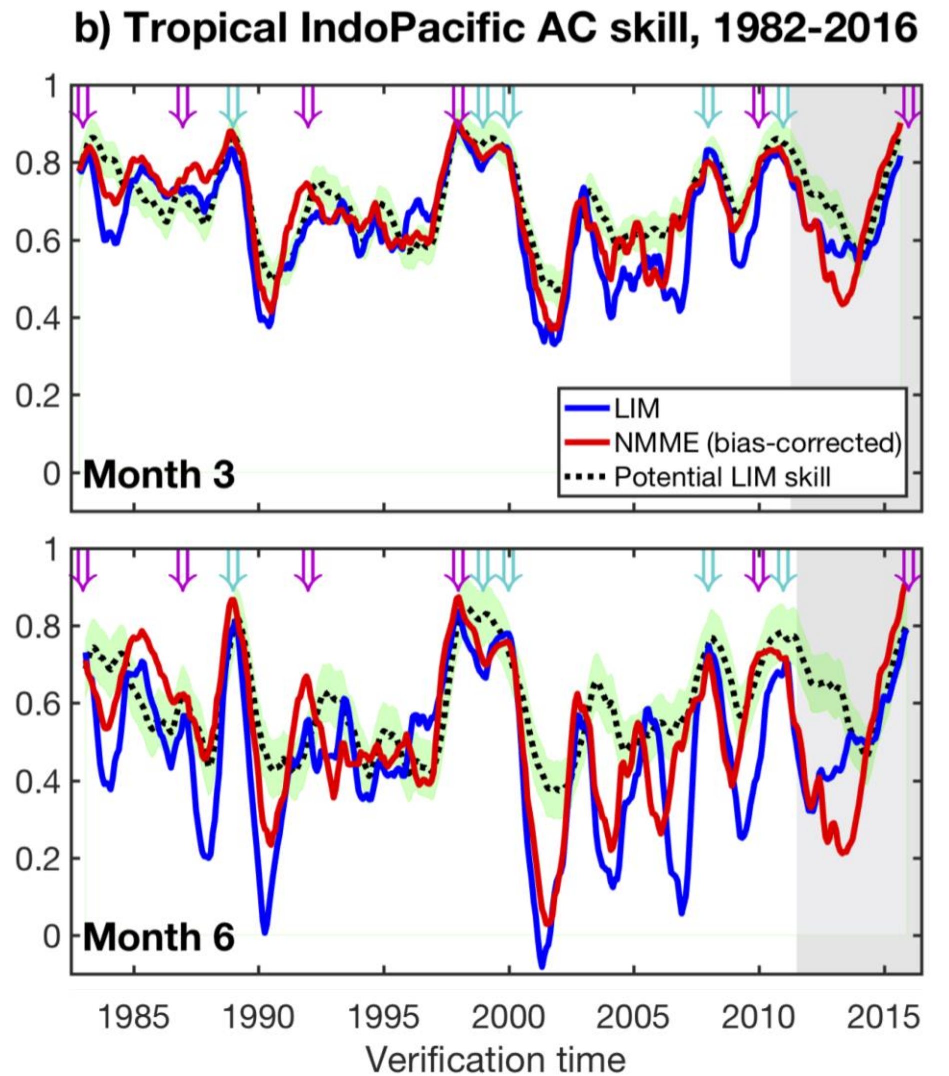
Green shading: sampling uncertainty of expected LIM skill



LIM predicts both LIM and NMME variations in SST skill: some years are more predictable than others

Monthly tropical IndoPacific pattern correlation skill, smoothed with 13-month running mean

r(NMME,LIM)=0.9/0.8
$r(\rho_\infty$,LIM)=0.9/0.7

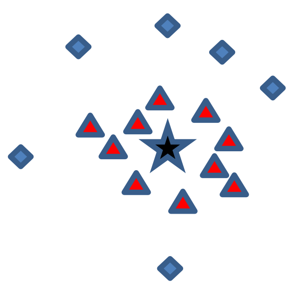


LIM dynamics fixed → variations in skill due to random variations in initial conditions

And now for something completely different…

“Model-analog” technique

- **Match observations to states from a long CGCM control simulation**
- Since these states are fully in balance in the model, we already know how they will evolve
- So: *construct an analog model of the model itself to make forecasts, with no additional model integration necessary (reproduce model attractor)*



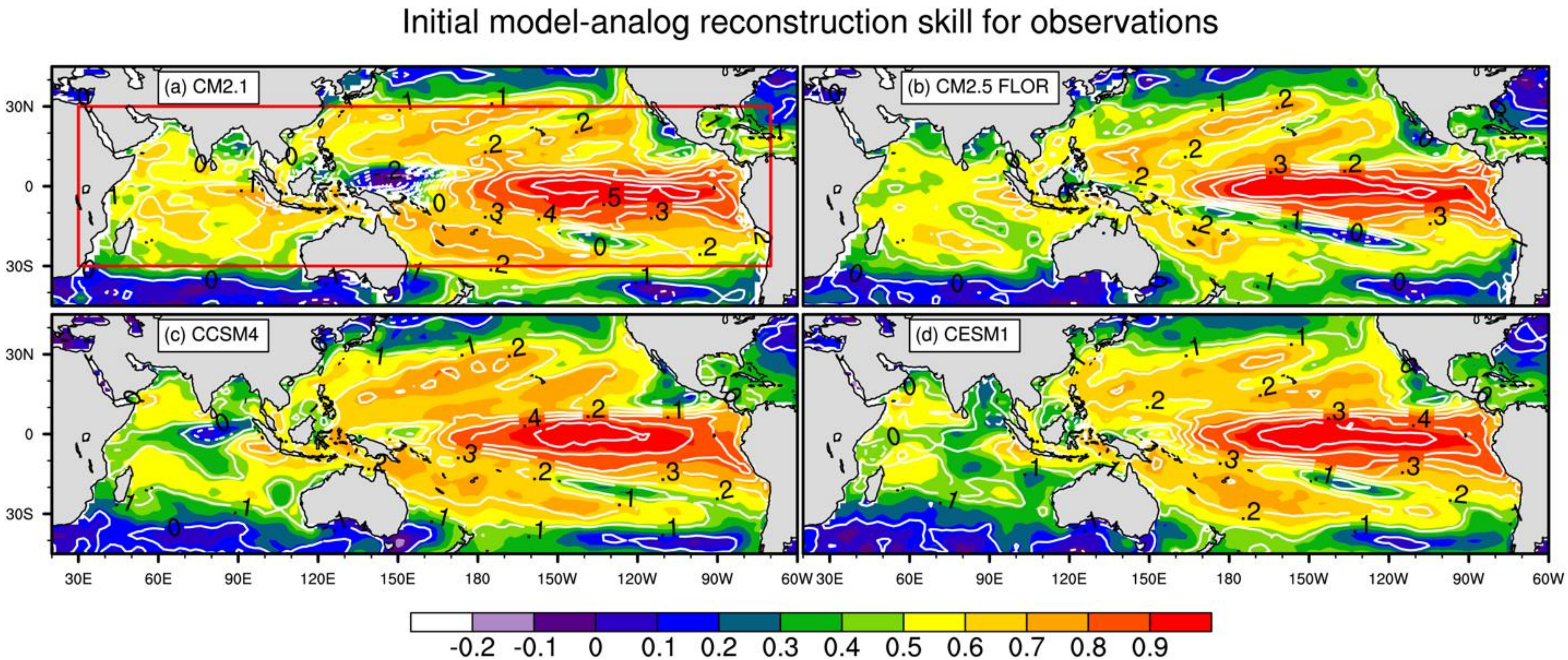
: a target state

: analogs defined as the nearest *k* states to the target state

: other states in the training period

- For target state: analog ensemble is the *k* nearest states, defined by root-mean-square (RMS) distance (grid space; low-order PC space is similar)
- No weighting of members: ensemble-mean forecast is mean of evolution of analog ensemble (~20 members from ~500-yr run is sufficient)
- Analogs defined from SST/SSH anomalies from the tropical Indo-Pacific (30E-80W, 30S-30N); equally weighted (i.e., **same state vector as LIM**)

Initial model-analog representation of observations is only fair…



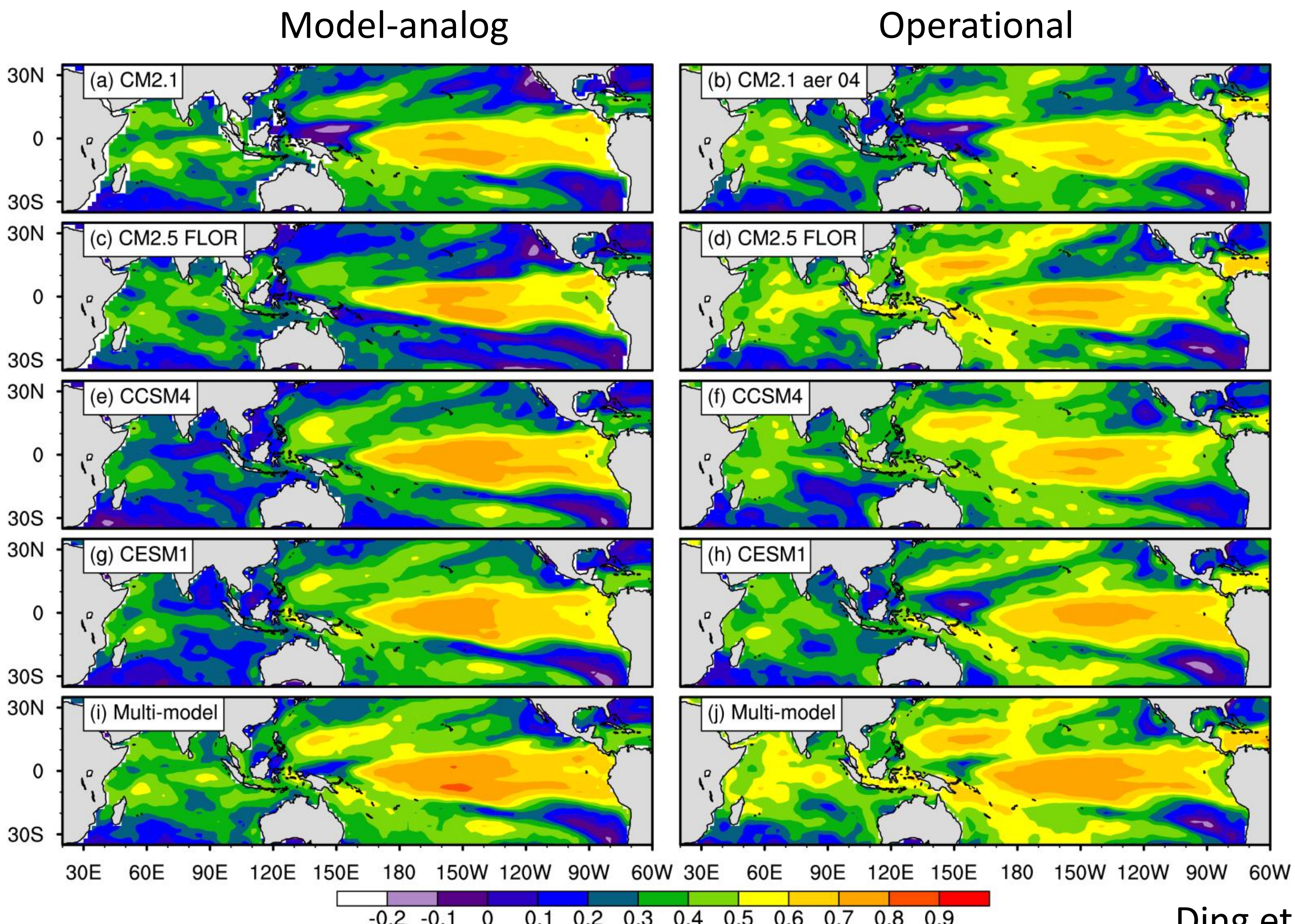
Correlation (shaded) and rms skill score (1-standardized error; contours) of ensemble mean analogs with target anomaly

Training run is entire control run for each model (varies in length)

Verification: 1982-2009 (observations)

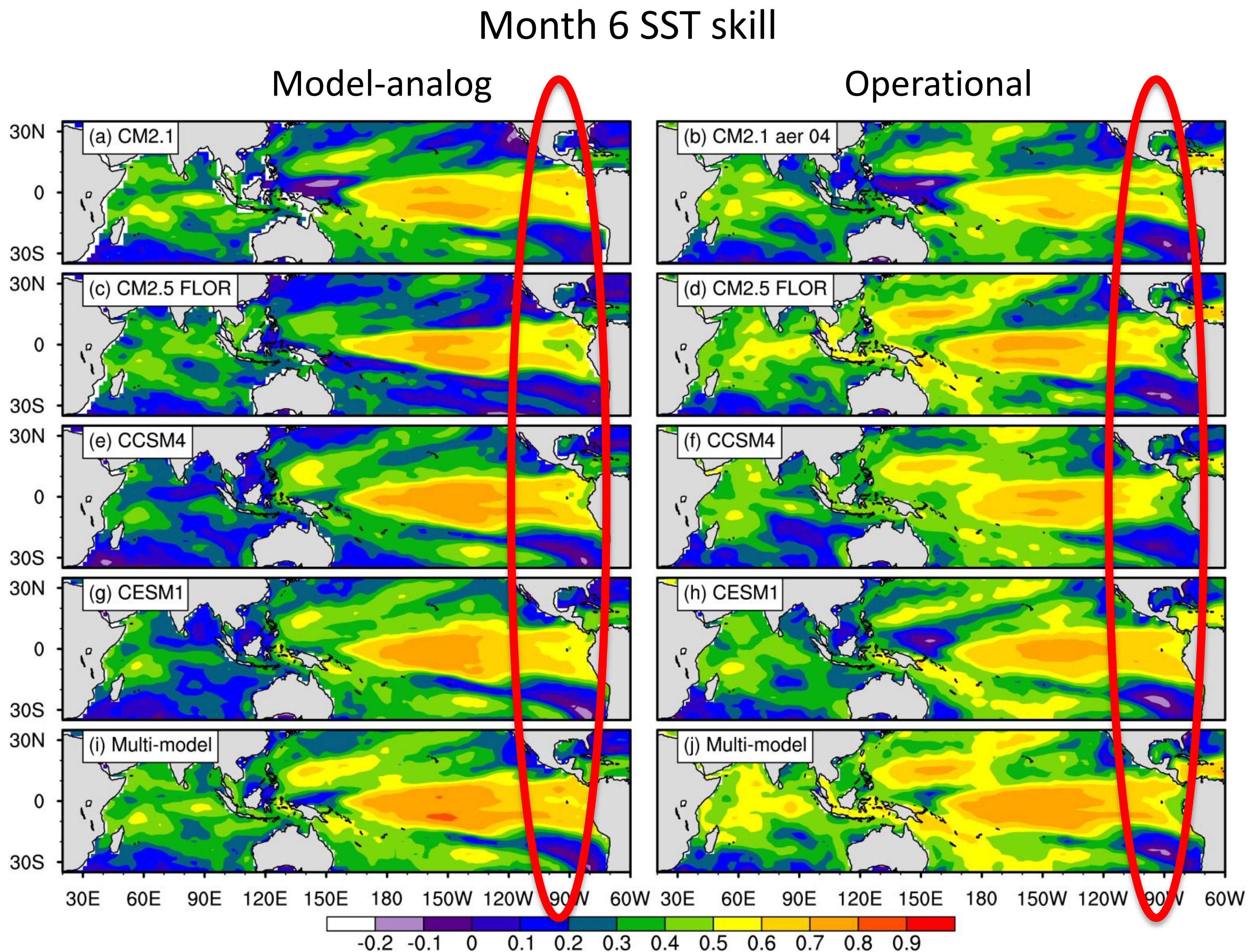
...yet model-analog skill matches corresponding model hindcast skill (1982-2009)

Month 6 SST skill



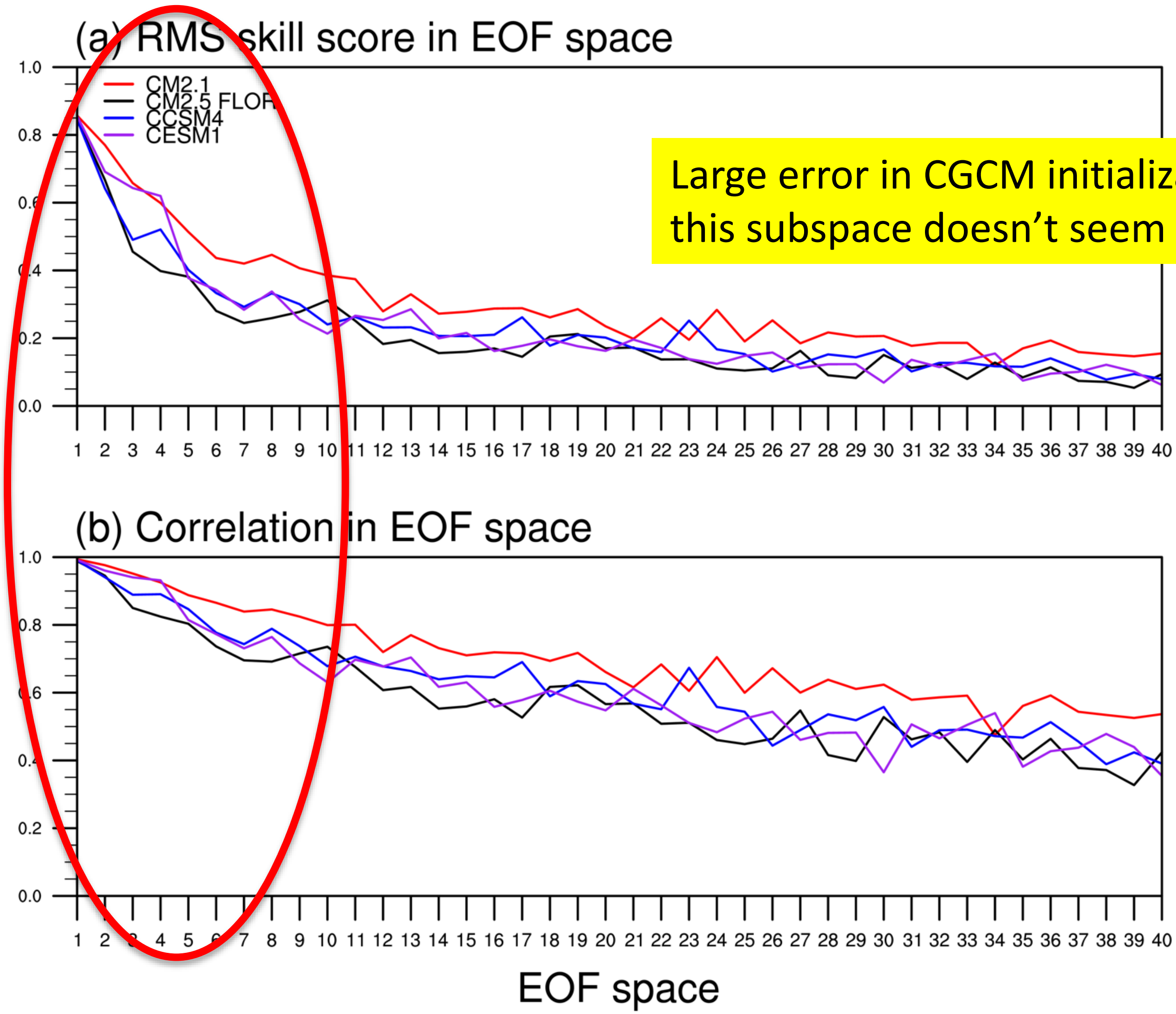
Ding et al 2018a

Model-analog skill *exceeds* corresponding model hindcast skill in eastern tropical Pacific



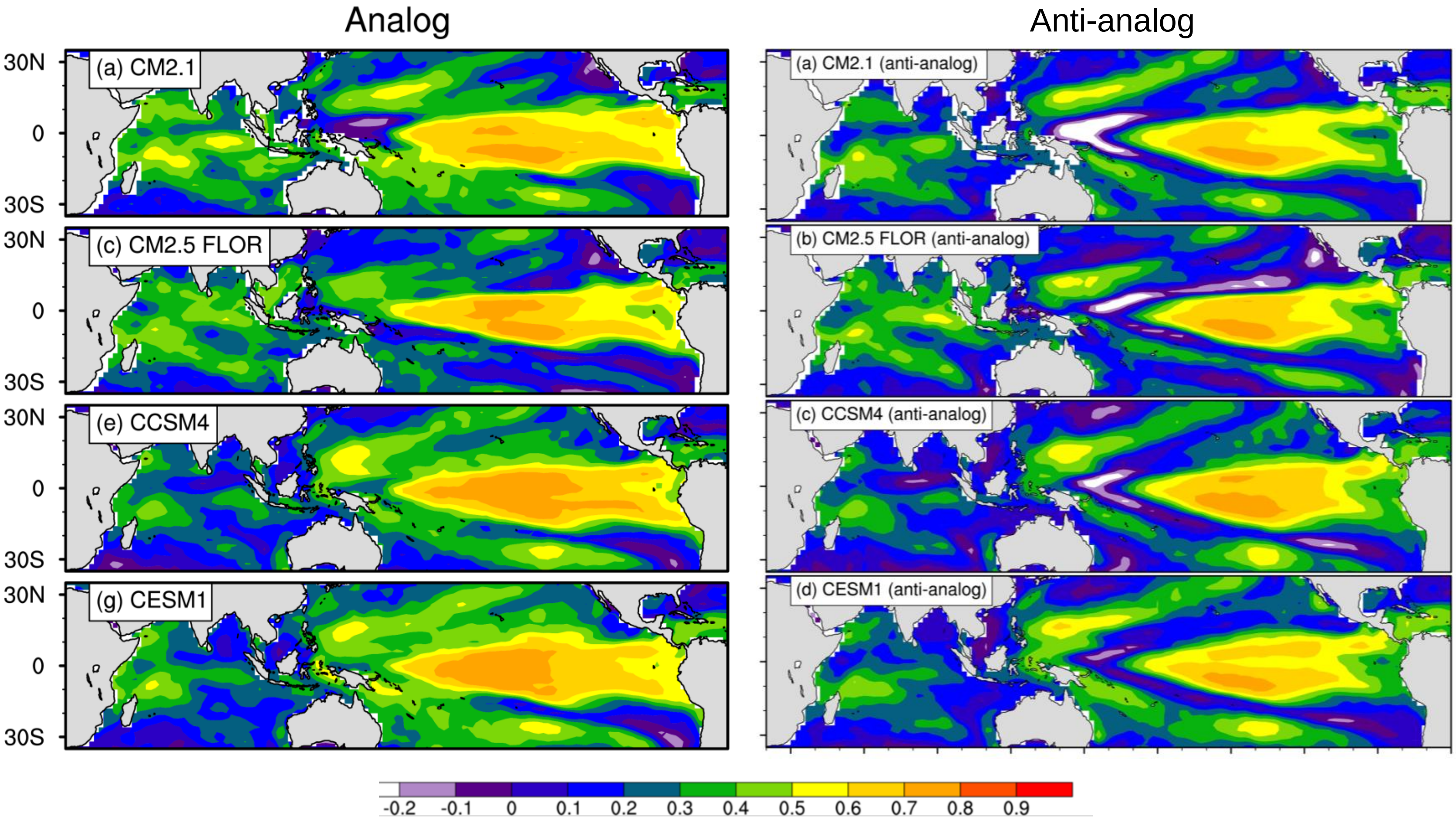
Ensemble mean analog representation of target anomalies better in low order EOFs

CGCM initialization in this subspace seems to be enough



Large error in CGCM initialization in this subspace doesn't seem to matter

How much of the model-analog skill is linear?



Anti-analog: same as model-analog but *change sign of target first*

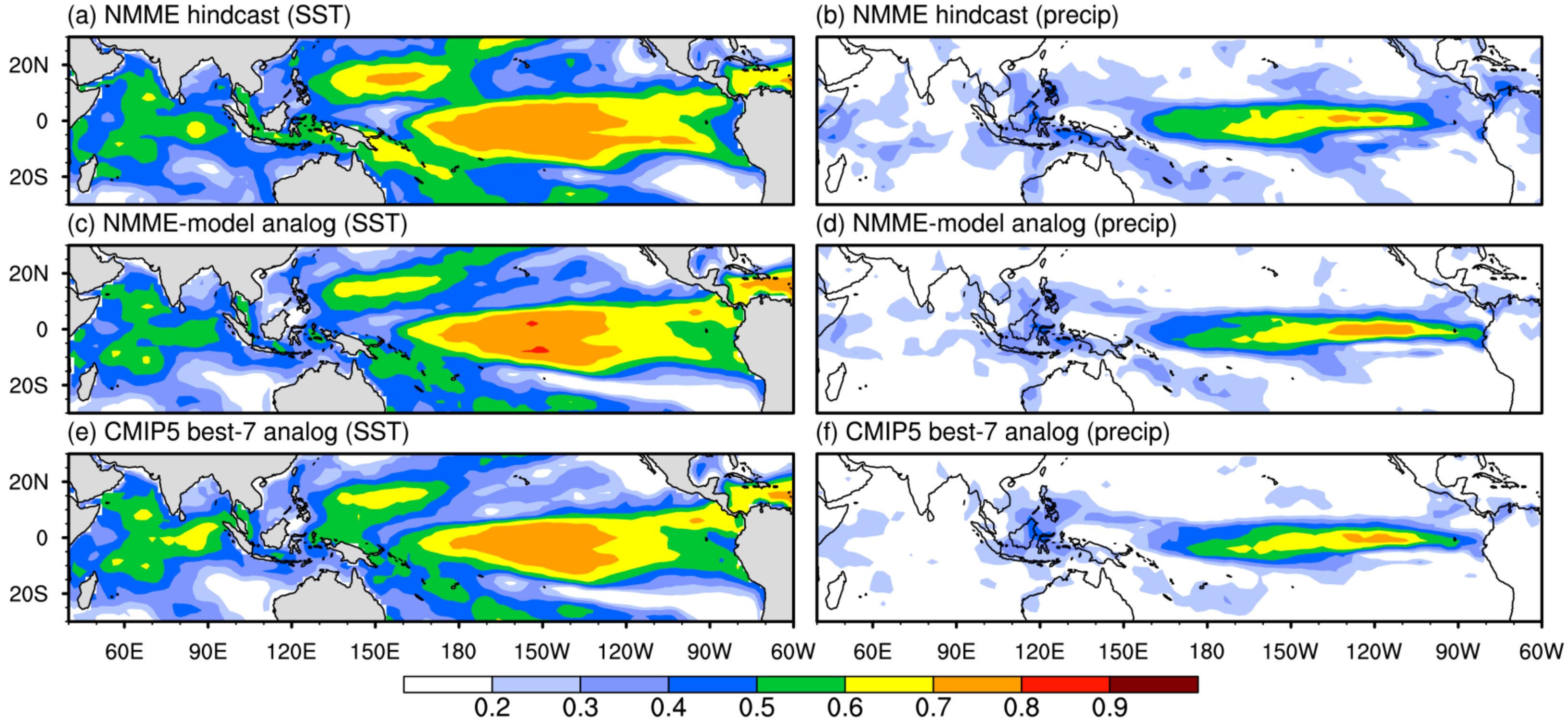
Where skill is similar, initial sign didn't matter → linear skill

Conclusion

- *Predictable* variations of tropical SST/SSH anomalies are driven by largely linear dynamics
  - Low-order linear model (LIM) reproduces multi-model CGCM ensemble skill <u>and largely predicts its variations</u>
  - Model-analogs reproduce multi-model CGCM ensemble skill, and most of this skill is low-order and linear
- Predictable nonlinear dynamics are of secondary importance except in eastern tropical Pacific (Niño1.2)
  - Skill of model-analogs still constrains dynamics there
- ENSO characteristics that are "nonlinear"

Climate forecasting for the masses

Month 6 hindcast skill, 1982-2009

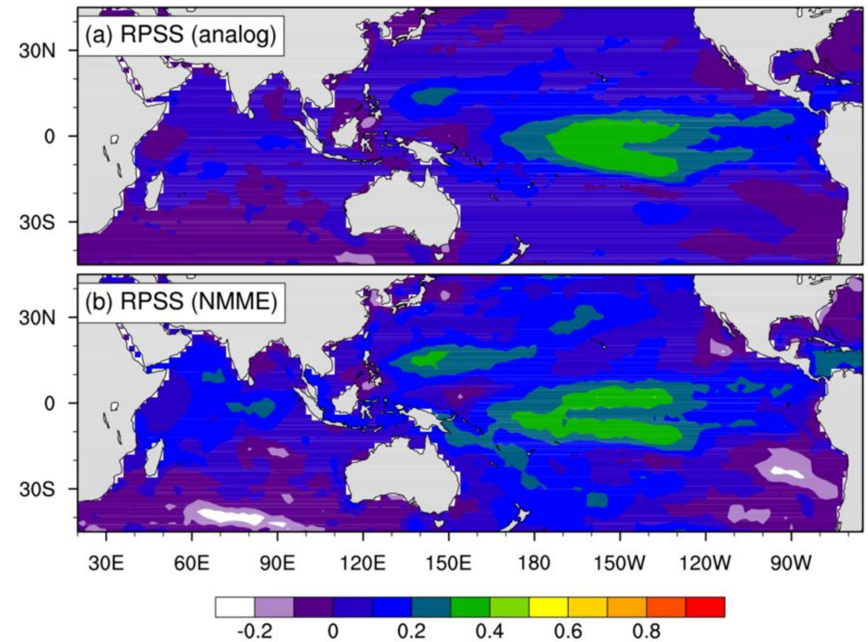


Operational model skill (top) compared with NMME model-analog skill (middle) and CMIP5 ”best-7” model-analog skill (bottom)

Download CMIP5 output and roll your own!

Ding et al, GRL, submitted

Month 6 probabilistic skill: model-analog ensemble is also comparable to hindcast ensemble, *despite large initial ensemble spread*



Top panels: RPSS (Rank Probability Skill Score) is higher for model-analog in tropical Pacific

Bottom panels: Reliability and frequency of occurrence (i.e., ”sharpness”): model-analogs are slightly more reliable and less sharp