Mining large climate model data sets to make multi-year initialized global SST forecasts

Hui Ding[1,2], Matt Newman[1,2], Mike Alexander[2], Andrew Wittenberg[3] , Yan Wang[1,2] and Sam Lillo[1,2]

1. CIRES, University of Colorado Boulder; 2. NOAA ESRL PSL; 3. NOAA GFDL

Newman, Matthew, Hui Ding, Samuel P. Lillo, Michael A. Alexander, and Andrew T. Wittenberg, 2020: Mining large climate model data sets to make multi-year initialized global SST forecasts. *Sci. Adv.*, in preparation.

Societally-Relevant Multi-Year Climate Predictions Workshop, March 28-30, 2022

Multi-model forecast skills at six-month lead, anomaly correlation

Motivation:

Model-analog forecasts display comparable forecast skill with traditional assimilation-initialized seasonal forecasts (see left).

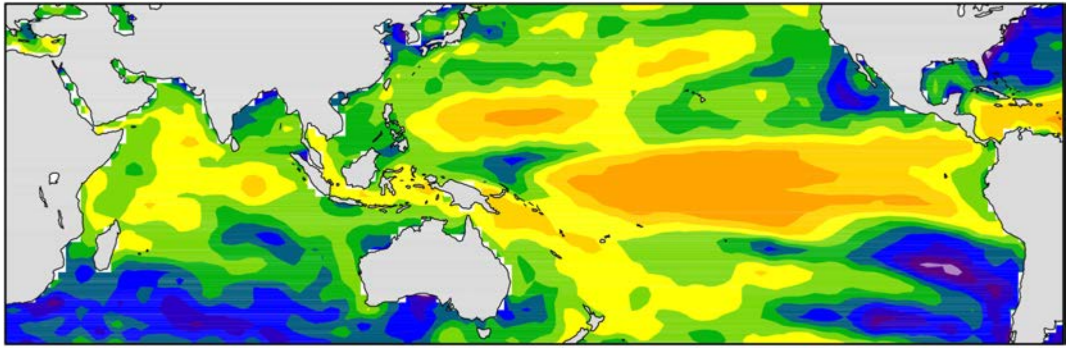
This motivates us to make multi-year SST forecasts using the model-analog method.

- Model-analog forecasts are initialized from pre-existing control simulations.
- Therefore, no computer time is required.

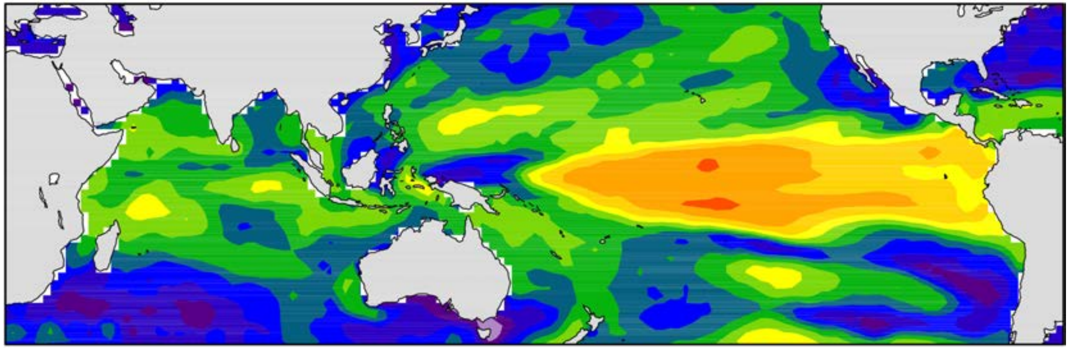
NMME (the **N**orth **A**merican **M**ulti-**M**odel **E**nsemble seasonal forecasting system)

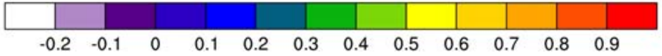
The 4 models are CM2.1, CM2.5 FLOR, CCSM4 and CESM1

4 NMME model forecast grandmean

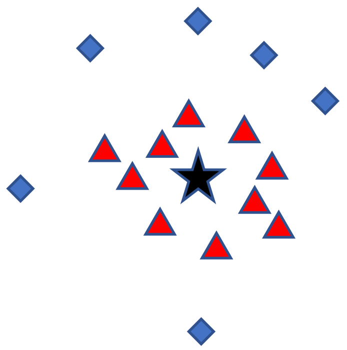


Model-analog applied to the same 4 models, grandmean





Model-analog method



A long control simulation as data library

: an initial observed state

: analogs defined as the nearest K models states in data library to the initial observed state

: other states in the data library

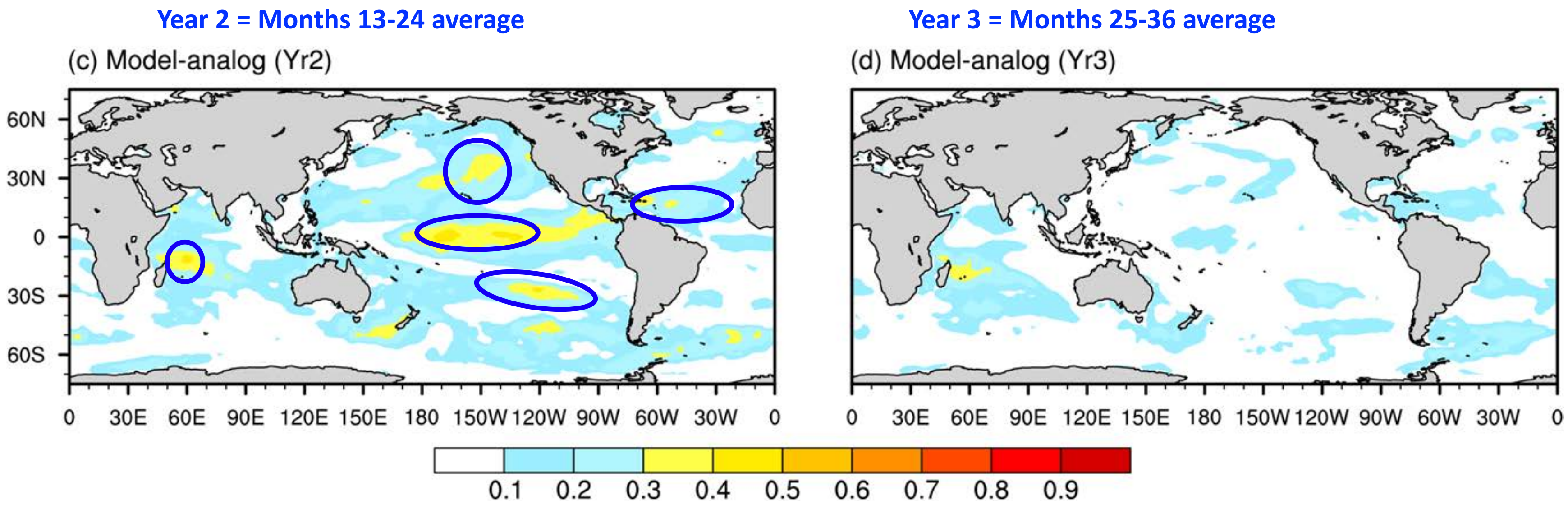
- Observed state is defined by observed SSH and SST anomalies globally (60°S-60°N).
- It is often the best to take an ensemble of 10-20 nearest states (i.e., analogs)
- Root-mean-square (RMS) distance is used to measure similarity between states (Ding et al, 2018)
- Forecast is the following time evolution of analogs
- Analogs are constrained to be from the same calendar month
- Refer to Ding et al, (2018, 2019) for details

Control runs

Model	Year of radiative forcing	Length of run (in years)
CM2.1	1860	4000
CM2.5 FLOR	1990	700
CCSM4	1850	1100
CESM1	2000	700

Global SST forecasts through Year 3

Year 2 and Year 3 hindcast skill, 1961-2015, anomaly correlation

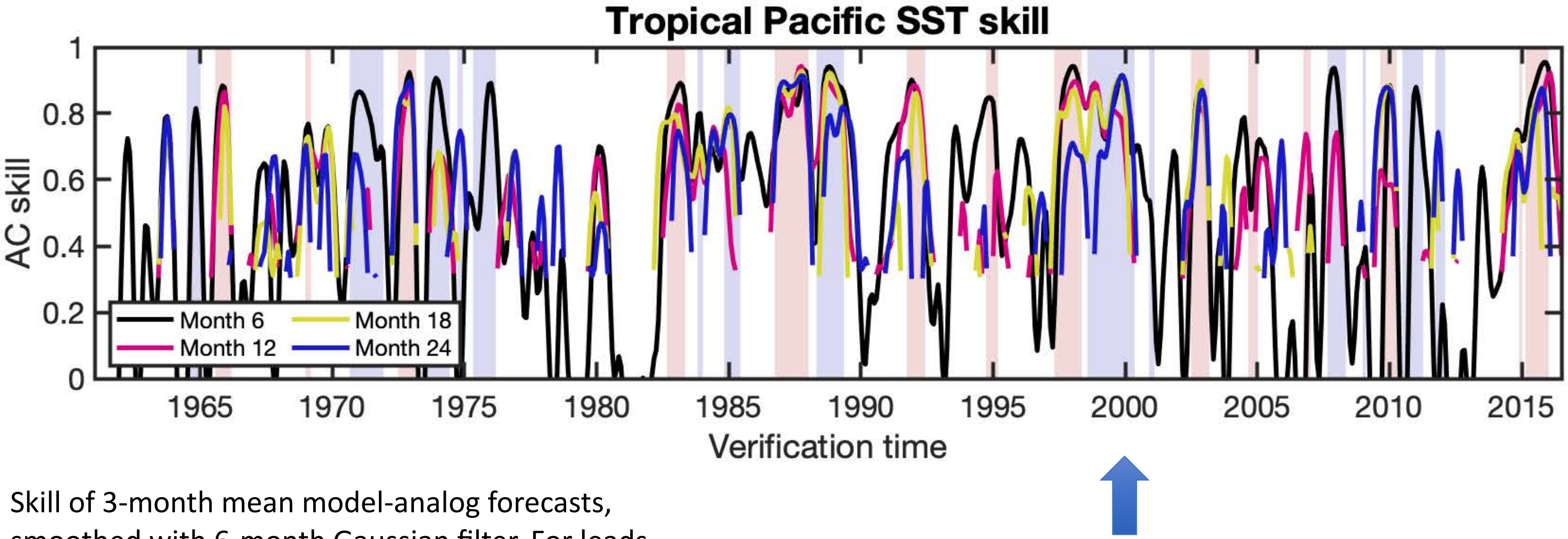


We make forecasts at leads of 1-36 months

Model-analogs determined globally between 60°S-60°N

Model-analogs determined from detrended observations

Some ENSO events are predictable at least 2 years ahead



Skill of 3-month mean model-analog forecasts, smoothed with 6-month Gaussian filter. For leads >=12 months, only values above 0.4 are shown.

Pattern correlation in the ENSO region (**170E-70W, 20S-20N)**

DJF 1999/2000 could have been predicted in June 1997

Niño3.4 time series

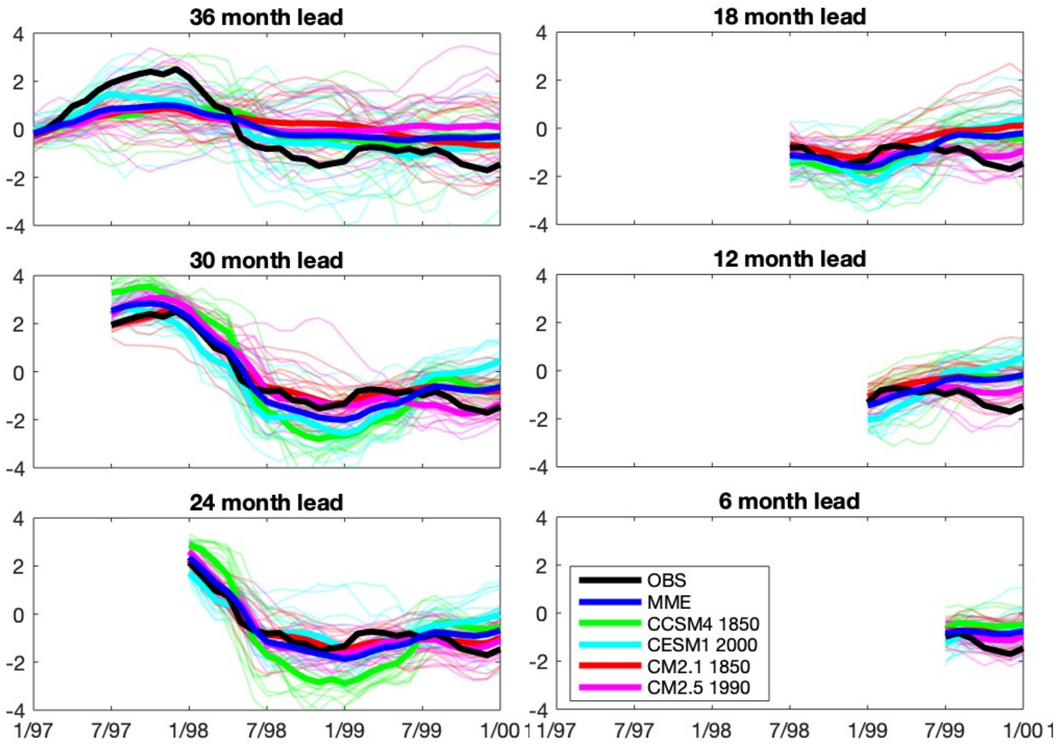
Black : Obs

Blue : Multi-model ensemble mean

Color lines: ensemble members

Niño3.4 hindcast evolution
(same verification time, different leads)

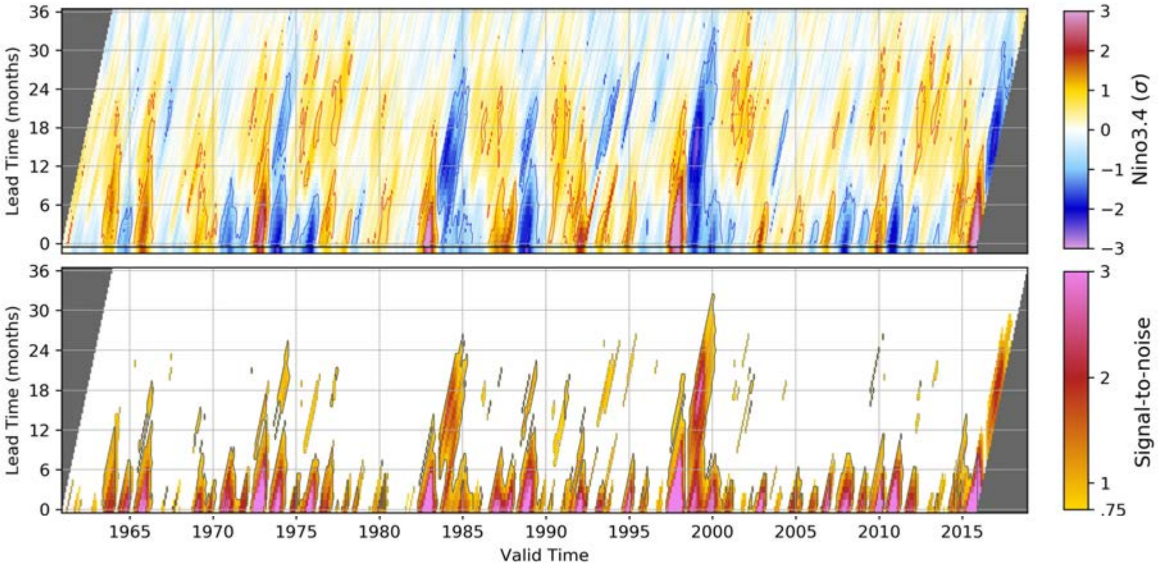
DJF 1999/2000



Can we identify which long-lead forecasts are skillful when we make the forecast?

Top: Model-analog Niño3.4 observations (bottom row, same as black line), "Month 0" model-analog reconstruction (next row, same as white line), and hindcasts for leads of 1-36 months, all verifying at the same time. ***Contours show where 62.5% of hindcast ensemble members are predicted in the upper/lower tercile.***

Bottom: Forecast signal-to-noise ratio (SNR); SNR < 0.75 are *not* shaded. ***Contours show where ensemble mean verified as either hit (solid) or false alarm (dashed); contours also not shown for SNR < 0.75.***



For Gaussian ensemble, SNR = 0.75 → 62.5% ensemble members shifted to predicted tercile. Above this threshold, most model-analog ensemble-mean forecasts appear to be hits.

Variations in ensemble spread from year-to-year are ~10-20%, and variations in SNR arises from those in the ensemble mean.

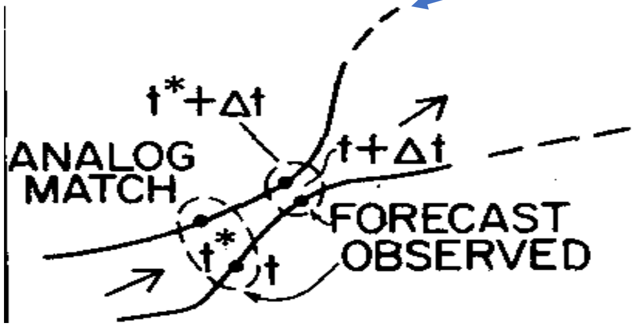
Conclusion

- Model-analog method provides a cheap and easy way of making multi-year ocean forecasts (which can be initialized every month)
- Some ENSO events are predictable two or more years ahead
- These may be identified beforehand by ensemble-mean signal-to-noise ratio

What is analog forecast?

- If two states in the atmosphere or climate system are very close to each other, they can be called each other's analog.
  - Analog forecasting is a very old idea in meteorology (e.g., Namias, 1951, Lorenz, 1969).
- The assumption of an analog forecast is that if two states are very close initially, they will remain close for a period of time and thus can be used to predict future conditions (e.g., Namias, 1951, Lorenz, 1969, Barnett and Preisendorfer, 1978).

A trajectory in the data library



A trajectory to be forecasted from time **t**

In this work, data library is a long control simulation.

Schematic of an analog forecast (Barnett and Preisendorfer, 1978)

Motivation

- Some known climate model forecast issues
  - Model drift: model mean state ≠ observed mean state
  - Coupling shock: imbalance between initial conditions and model physics

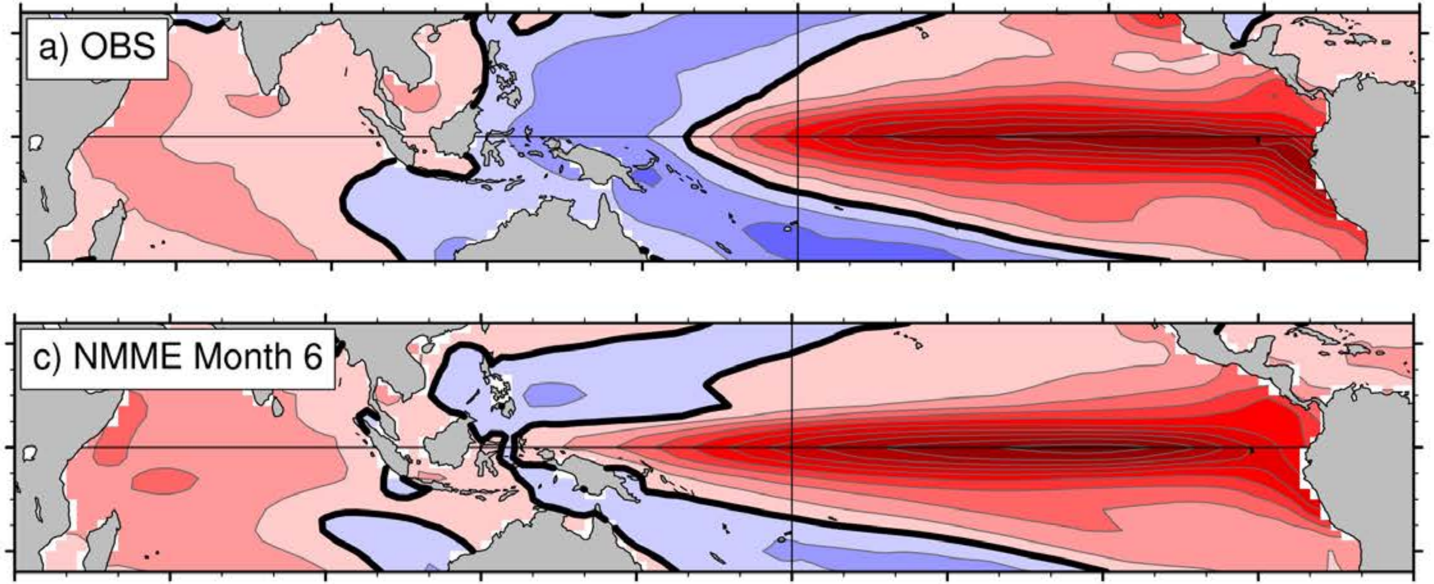
- The two issues motivate us to make model-analog (i.e., model-based analog) forecasts using a long control simulation, in which
  - Take a long control run as data library
  - Then we initialize forecast with an ensemble of model states (model analogs) from the control run that are closest to the observed state
  - We can immediately make forecast using the following time evolution after the model analogs since we already have it from the control run

- The analogs and their subsequent time evolution are fully in balance in the control simulation so that the model-analog forecasts avoid model drift and coupling shock automatically

ENSO pattern predicted by NMME extends too far west

Leading SST EOF of observations and Month 6 forecasts from NMME

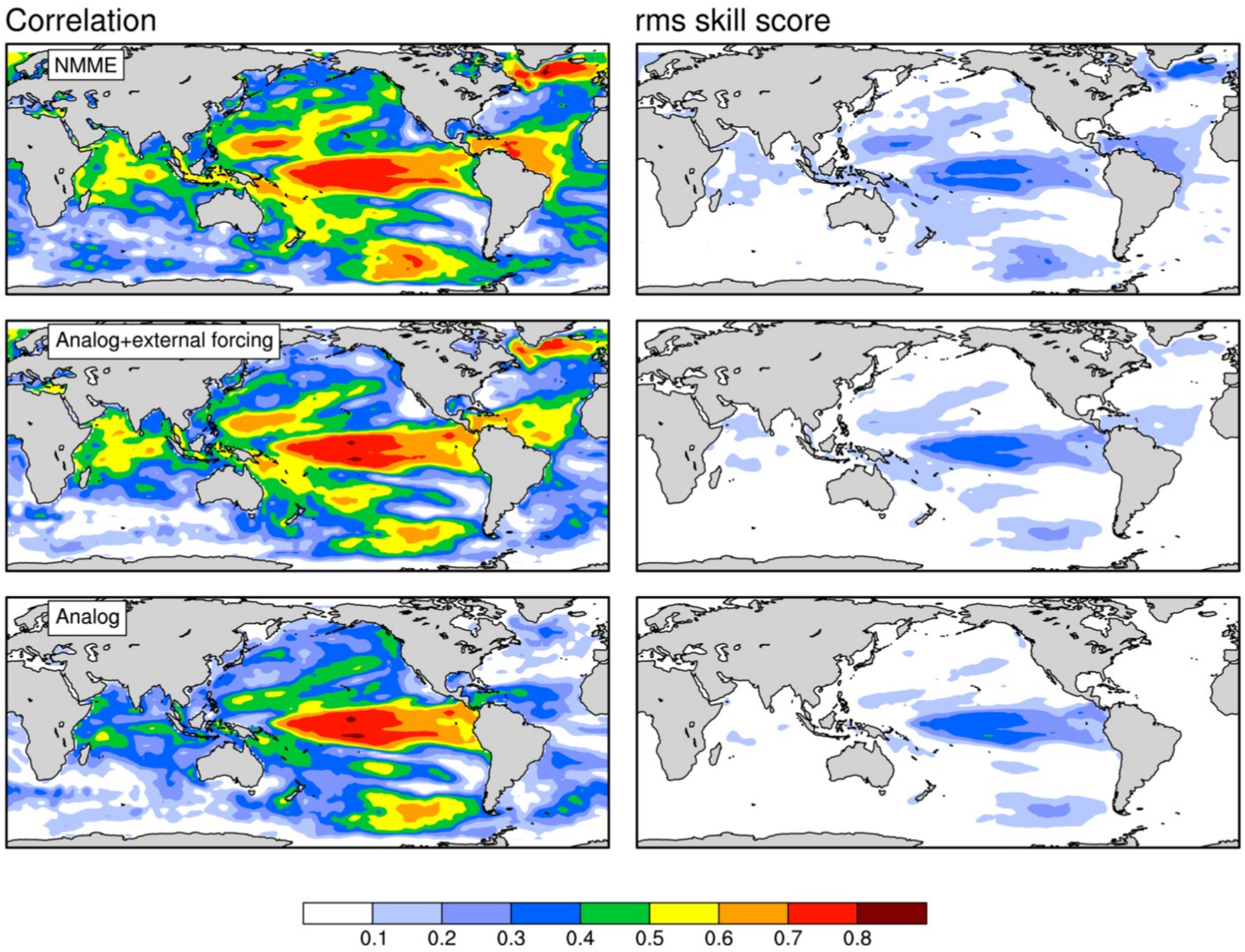
NMME forecast ENSO looks like typical CGCM ENSO: *phase error in western tropical Pacific*



NMME (the **N**orth American **M**ulti-**M**odel **E**nsemble seasonal forecasting system)

Newman and Sardeshmukh 2017, GRL

Month 6 hindcast skill of observed SST anomalies

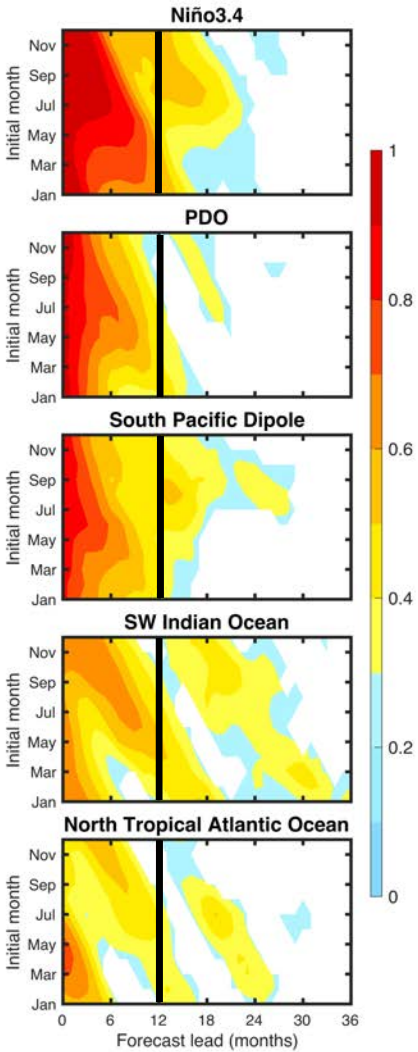


ENSO, PDO and the other three indices are predictable 2 years ahead

Multi-model ensemble-mean skill has strong seasonal dependence

AC skill (1961-2015) as a function of *initialization* month for 3-month running mean anomalies (lead is based on center month of 3-month mean; Month 0 shows reconstruction skill). All shaded values 95% significant (as estimated from bootstrapping)

X-axis is forecast lead month while y-axis is forecast initial month



Global SST forecasts through Year 3

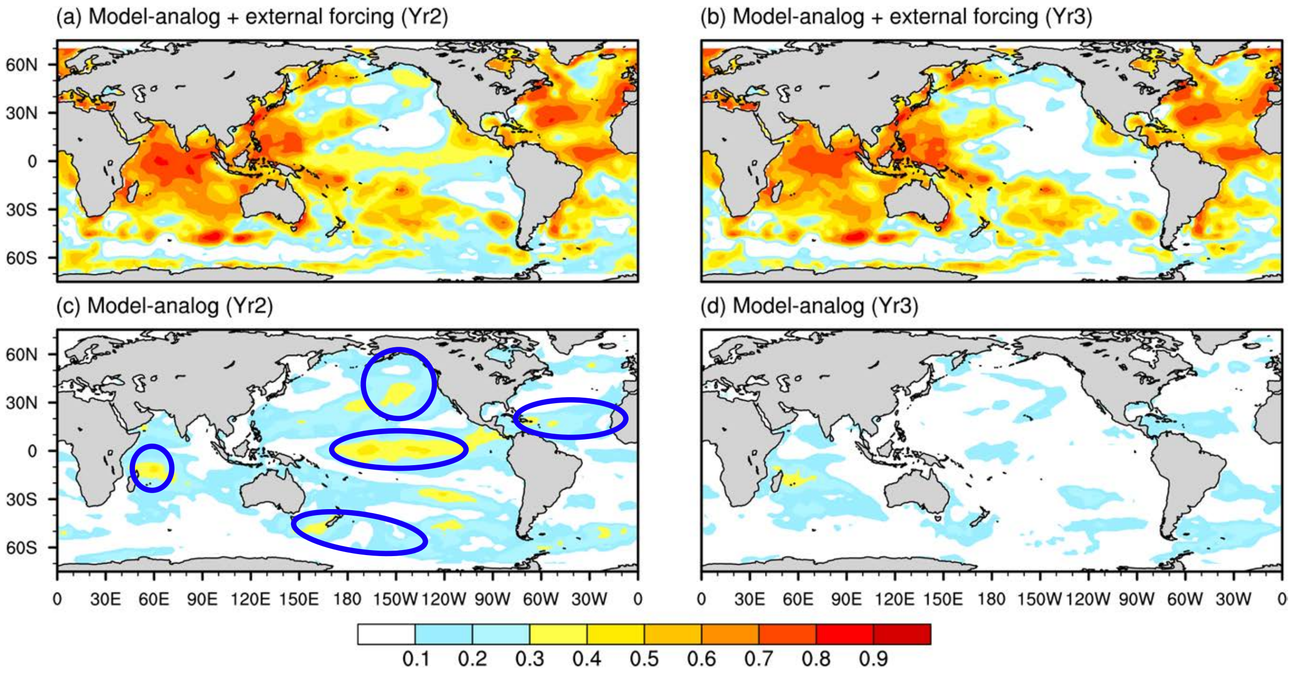
Now: Model-analogs determined globally between 60ºS-60ºN

Top : **including** predicted trend from external forcing (determined from CMIP5 historical ensemble mean; Ding et al. 2019)

Model-analogs determined from detrended observations

Bottom: same but **without** trend

Year 2 and Year 3 hindcast skill, 1961-2015



Year 2 = Months 13-24 average; Year 3 = Months 25-36 average

From now on, we will look at the “initialized” skill, *without the trend*, for selected indices

Can we identify which long-lead forecasts are skillful when we make the forecast?

Bottom: Niño3.4 time series (black) compared with model-analog reconstruction (white); green indicates model-analog initial spread