Climate Prediction: Part 1, Seasonal timescales

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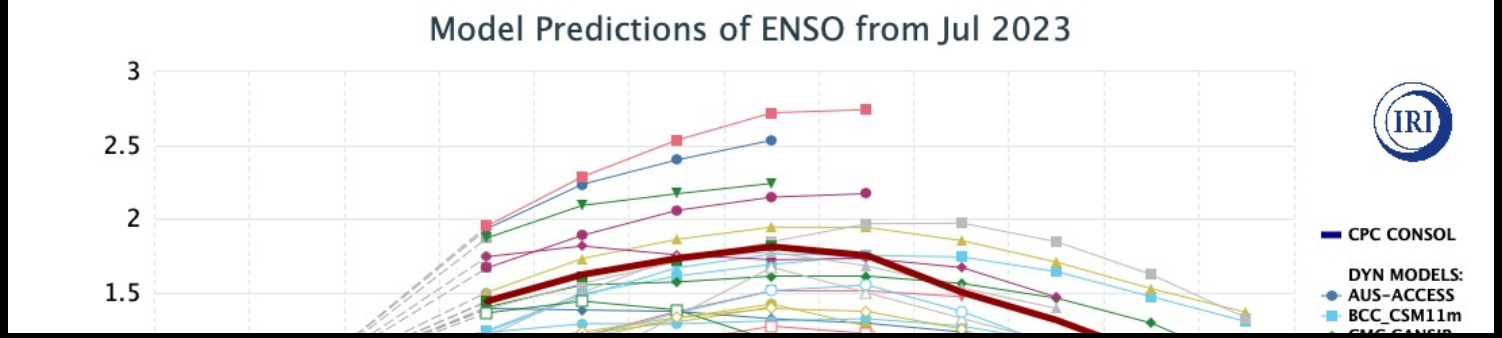
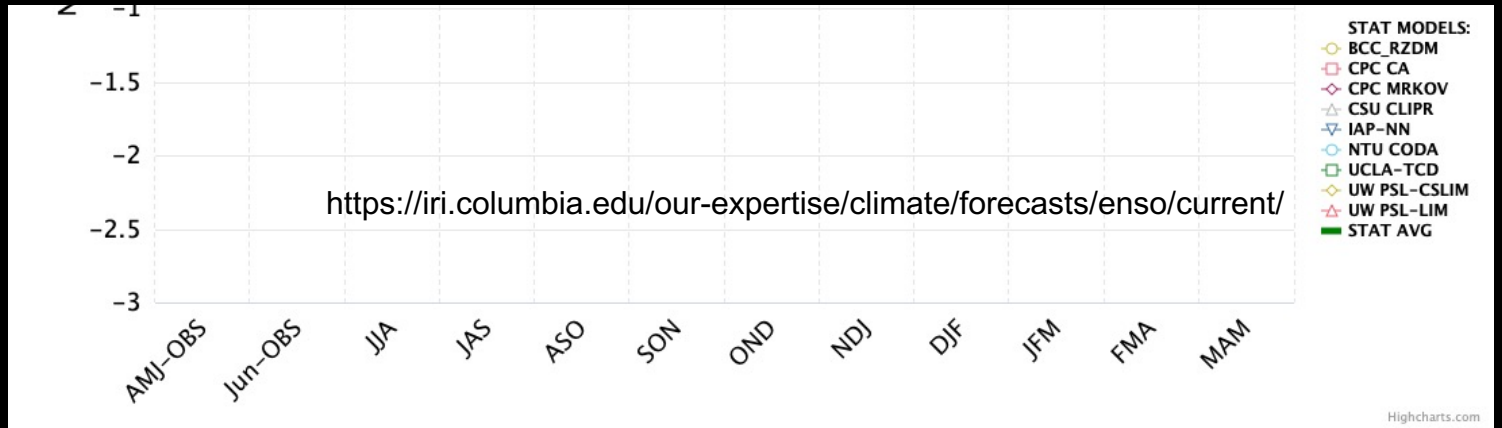


How long in advance do you think we can predict ENSO events?

How do tropical basin interactions influence seasonal prediction?



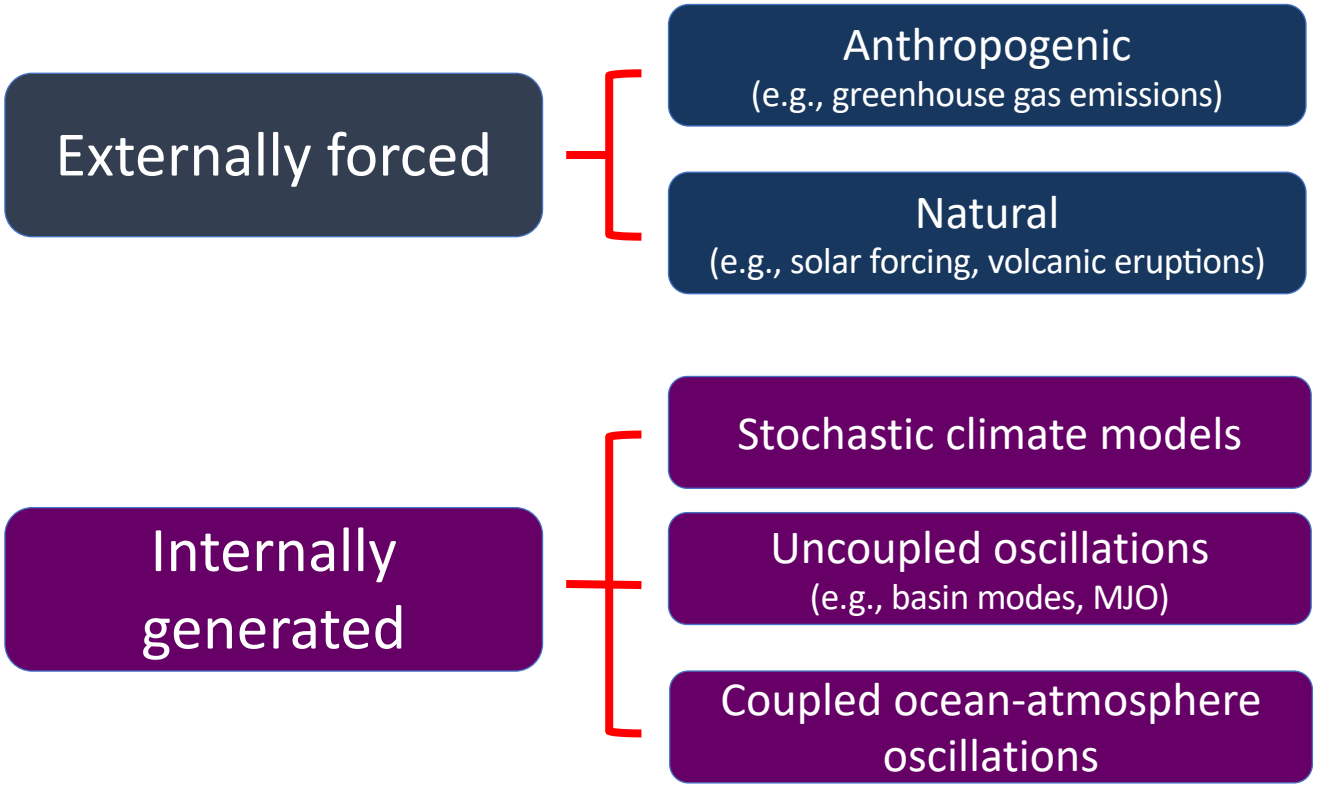
Topics to be covered in this lecture

1. Types of predictability
2. What is needed to make a climate prediction
3. Performing predictions with Earth System Models and estimating prediction skill
4. Seasonal prediction skill and tropical basin interactions
5. Some current challenges

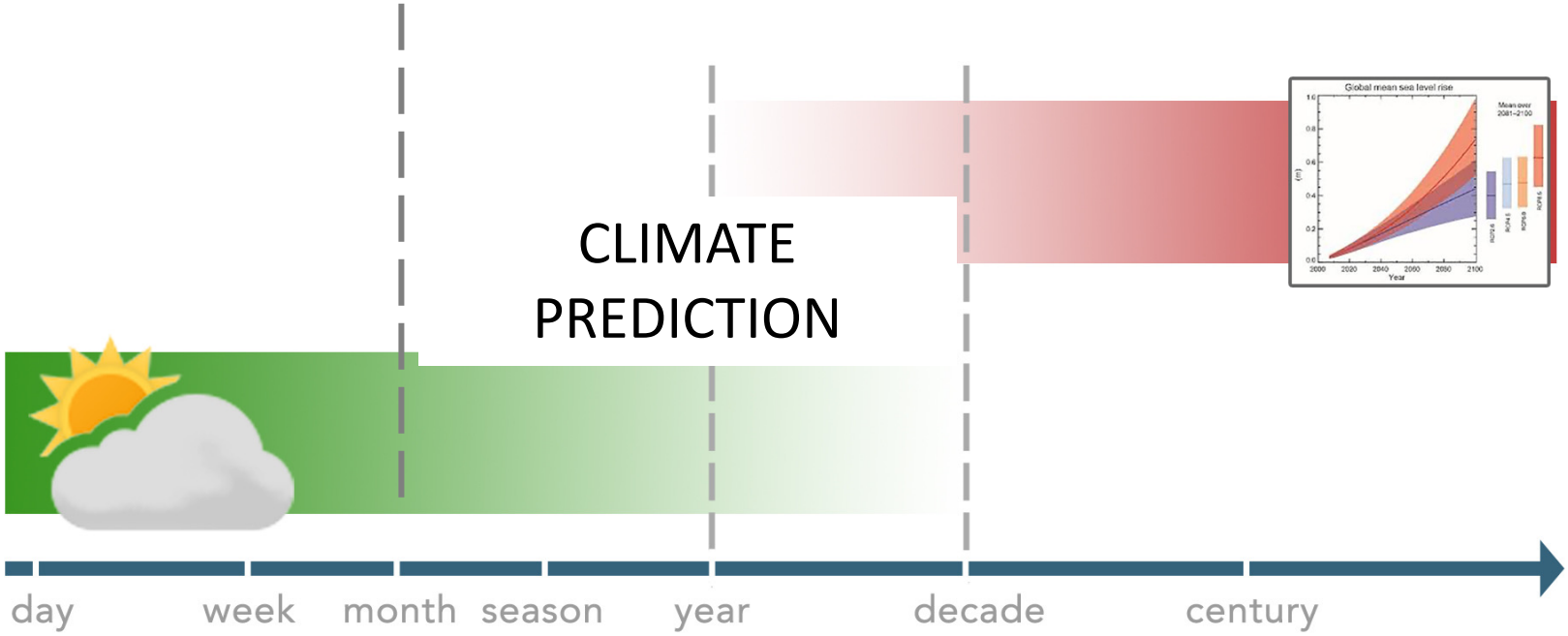
1. Types of predictability

- There are two types of predictability, one related to the initial state of the climate system, and one related to changes in external factors.
- There relevance depends on the timescales and mechanisms involved.

Mechanisms for climate variability

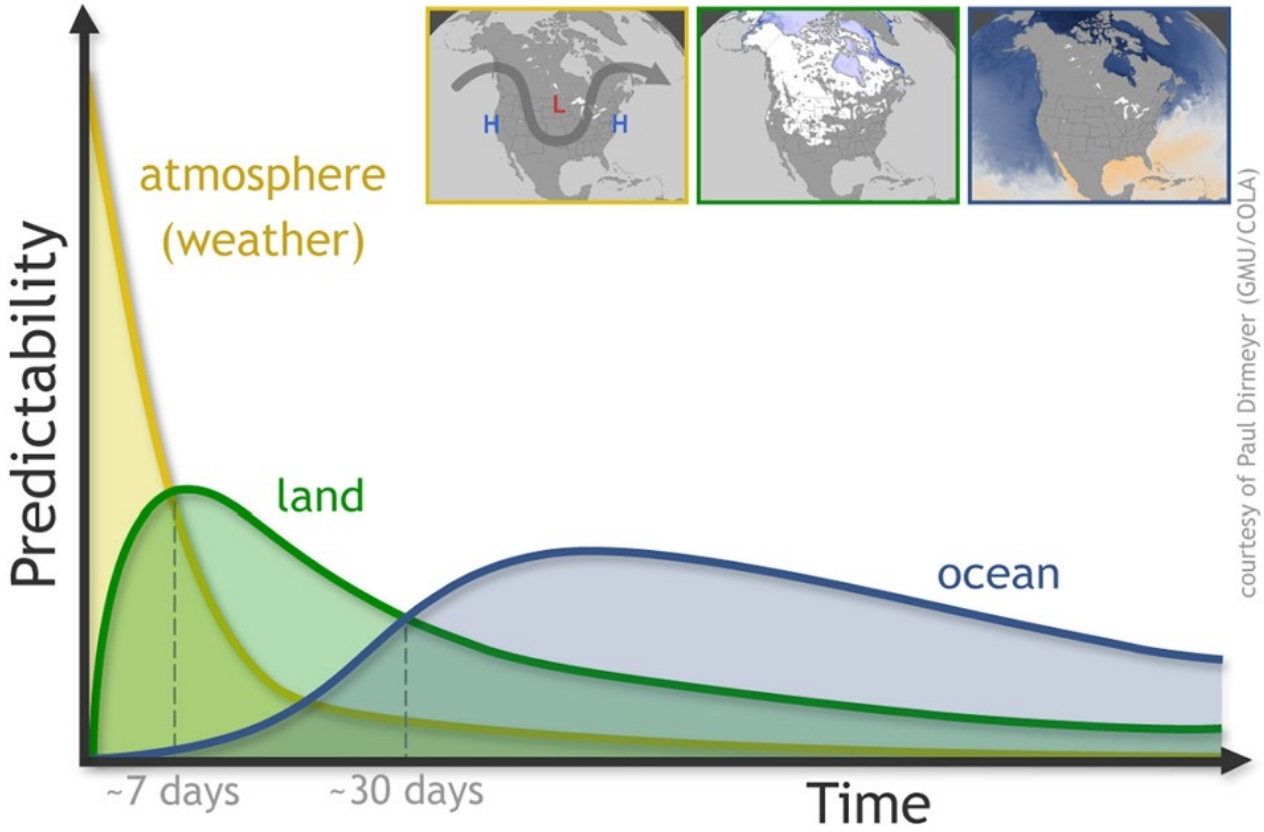


Climate prediction fills the gap between weather forecasts and climate change projections



Adapted from Meehl et al. 2009

Different sources of predictability from weather to seasonal timescales



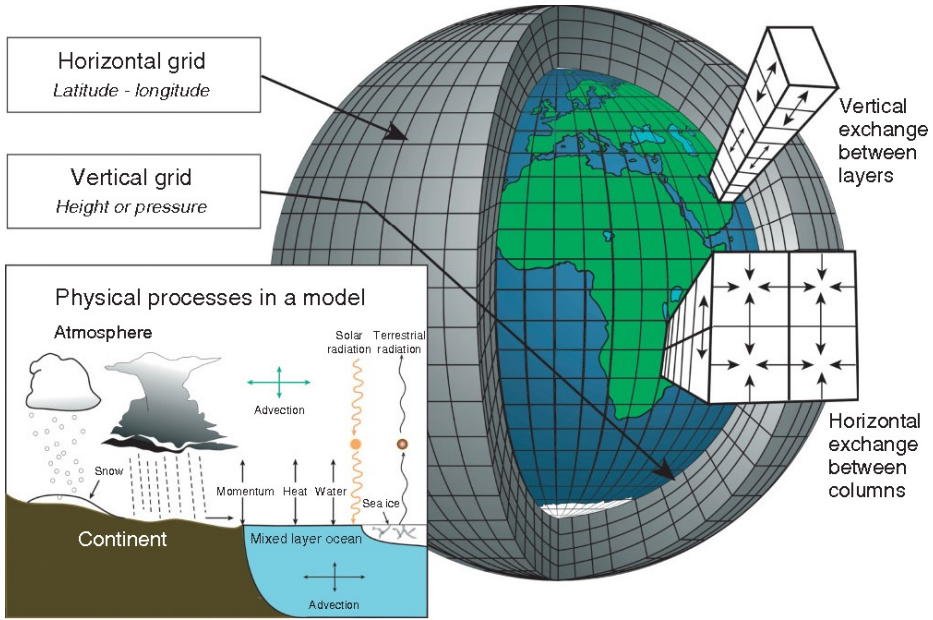
2. What is needed to make a climate prediction

- Models and sufficient computing resources
- Observations
- Data assimilation

The Model

- Dynamical models
  - Represent key dynamics
  - Complex (Climate models, Earth System Models)
  - Simplified (ENSO models)
- Statistical models
  - Analogs
  - Regressions
- Statistical-dynamical

Schematic of climate model

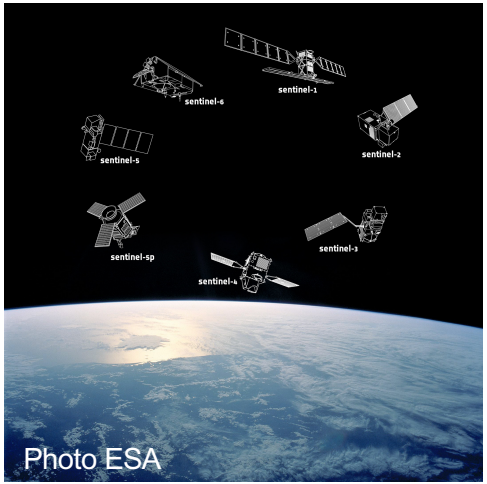


Edwards, "History of climate modeling." *Wiley Interdisciplinary Reviews: Climate Change* 2021

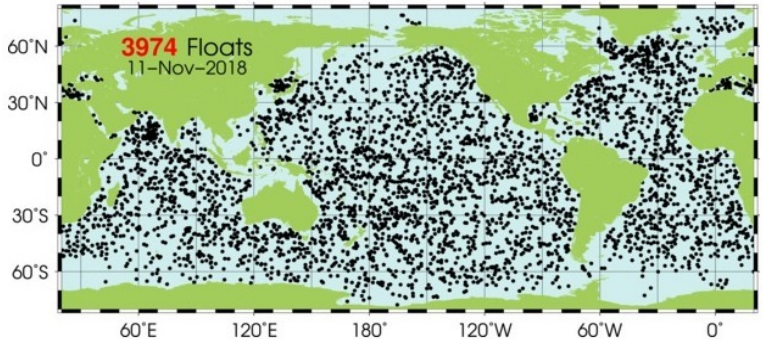
Global observing system

New technologies are providing an unprecedent amount of observations

Sentinels Satellites, European Space Agency

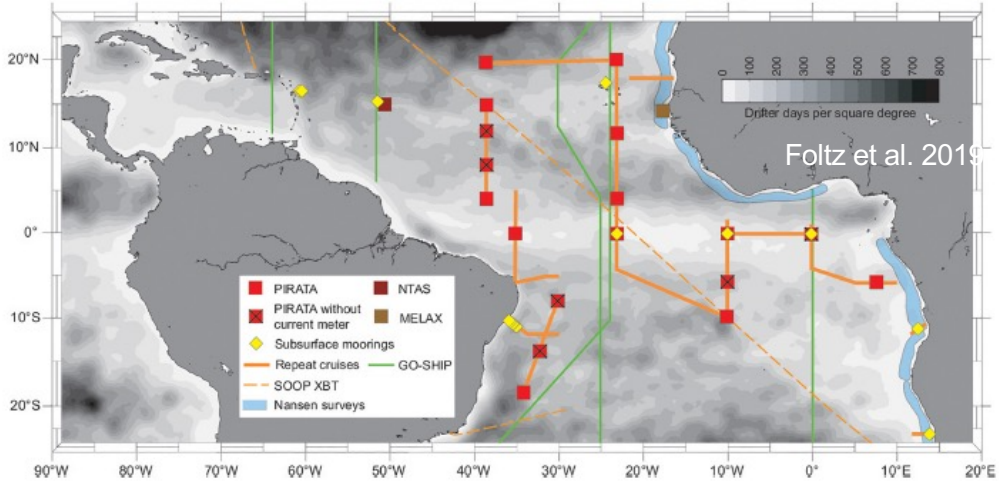


ARGO profiling floats monitoring the ocean



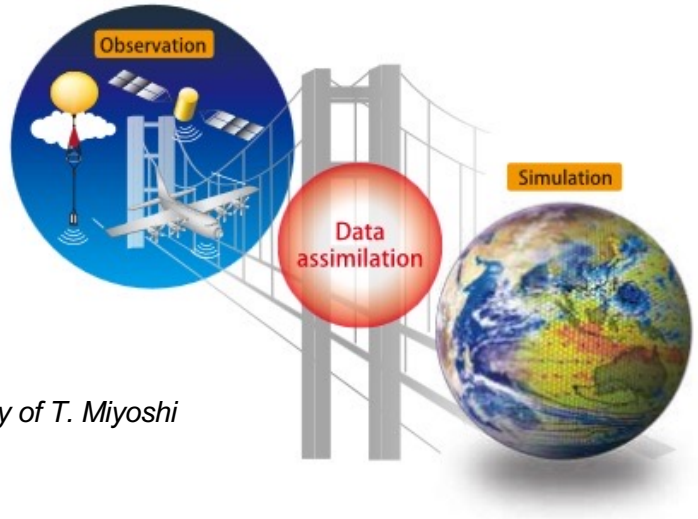
http://www.argo.ucsd.edu

Moored arrays, drifters, ship tracks



https://www.pmel.noaa.gov/gtmba/pmel-theme/atlantic-ocean-pirata

Data assimilation – combine model and observations

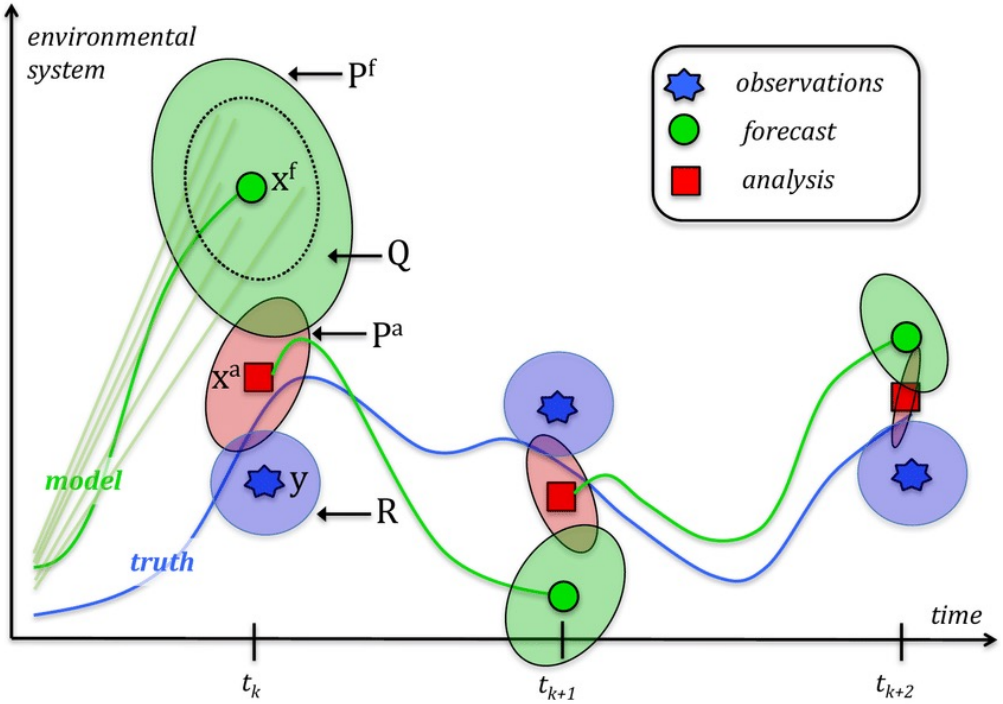


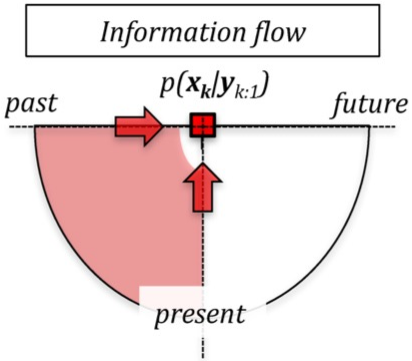
Courtesy of T. Miyoshi

- Observations are often sparse in time and space, and have errors
- Models are complete but are inaccurate
- Neither observations or models are truth, both are uncertain
- Data assimilation is the statistical technique used to optimally combine observations and models to estimate the ”true” state, for our purposes (the initial condition)

Data assimilation is a recursive process

Schematic view showing how model is adjusted so as to have the truth between it and the observations





Carrassi et al. WIRES, 2018

Some key points and questions

- Earth System Models driven with external forcing are used to make long-term climate change projections (i.e., predictability of the 2nd kind)
- Q: Name two external factors that are important to consider for decadal prediction
- A: Greenhouse gas concentrations (CO2) and aerosol loadings
- Adding data assimilation allows the prediction of shorter term variability (i.e., predictability of the 1st kind)
- Q: Which components of the climate system are important for predictability of the 1st kind? What data should be assimilated?
- A: Ocean (temperature and salinity, sea surface height) – seasonal to decadal
- A: Sea ice and land-surface (soil moisture) conditions – subseasonal - seasonal

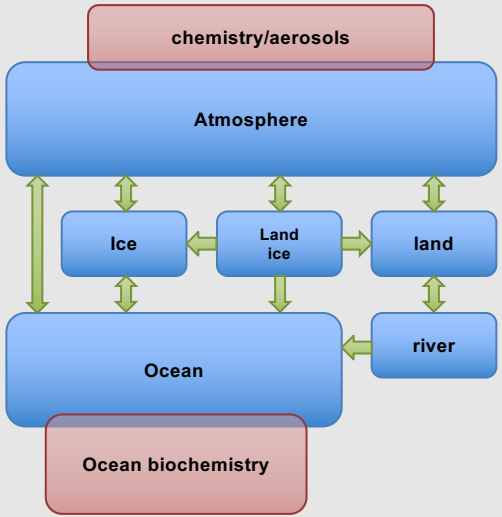
3. Performing predictions with Earth System Models and estimating prediction skill

- State-of-the-art climate prediction system (e.g., Norwegian Climate Prediction Model)
- Constraining the ocean state with limited observations and data assimilation
- Performing retrospective predictions (hindcasts) to estimate prediction skill
- Multi-model ensemble as a method to reduce errors and produce more reliable predictions

A state-of-the-art prediction system

The Norwegian Climate Prediction Model (NorCPM)

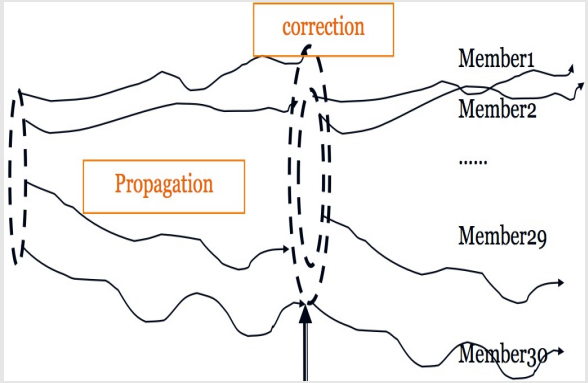
Norwegian Earth System model



External forcing
(greenhouse gases, aerosols, etc.)

Ensemble

Data assimilation (EnKF)



Observations

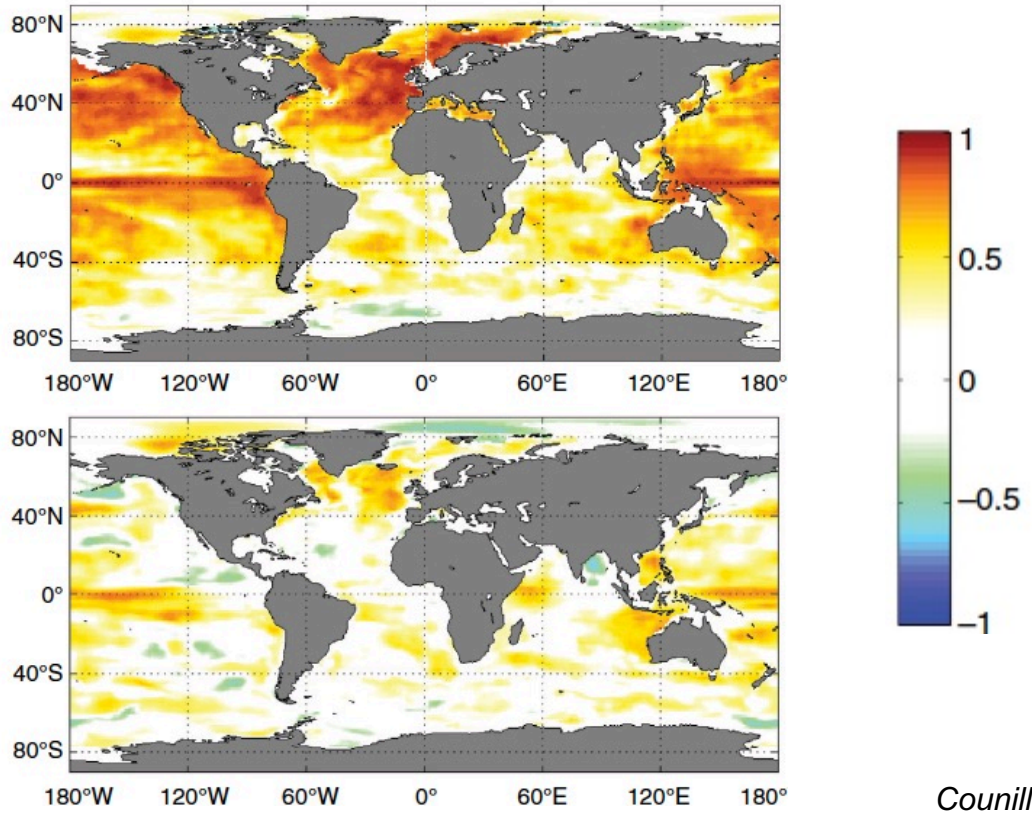
(Counillon et al. 2016)

Some data assimilation results, only using observed sea surface temperature

Correlation with observations for the period 1950-2010

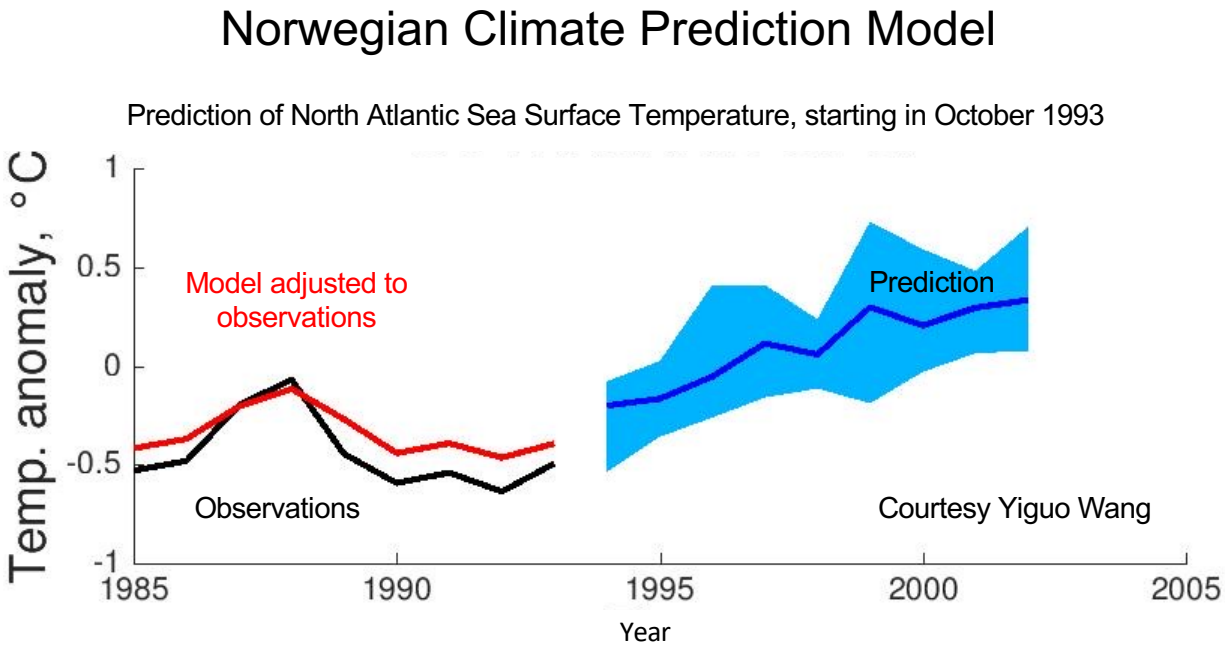
Temperature in the upper 200m

Salinity in the upper 200m



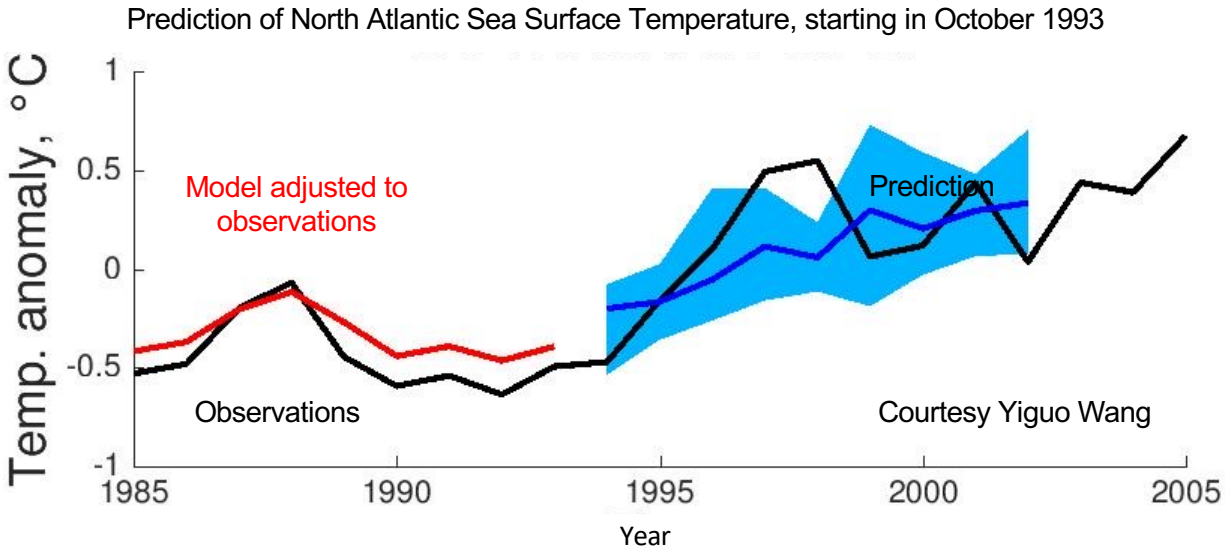
Counillon et al, 2016

Retrospective predictions for assessing skill

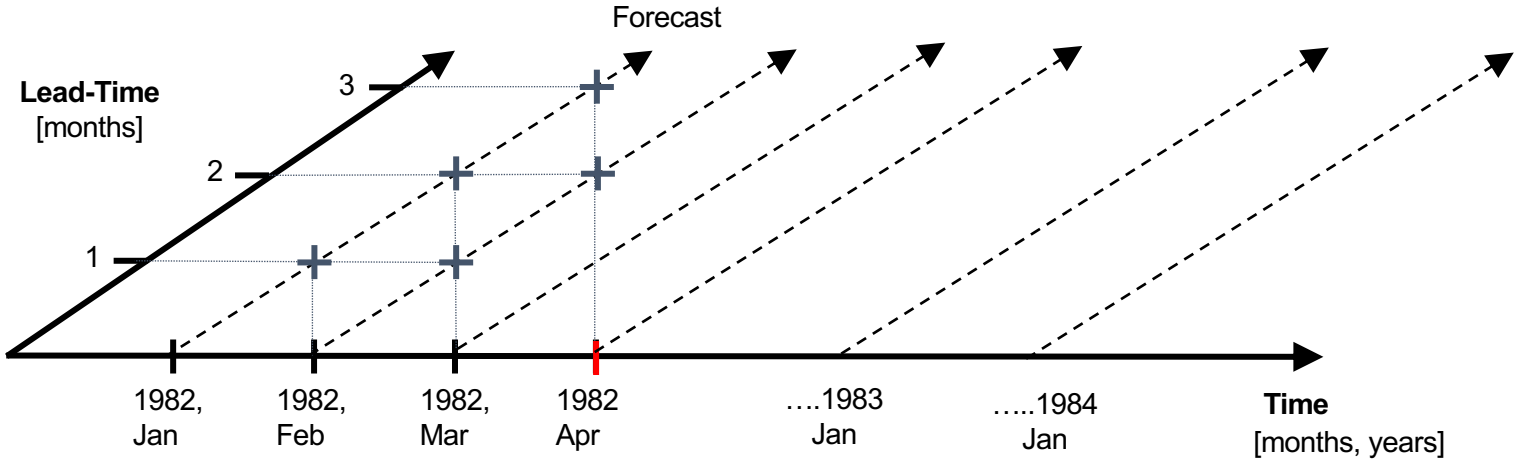


Retrospective predictions for assessing skill

Norwegian Climate Prediction Model



Measuring skill using retrospective forecasting (hindcasting)

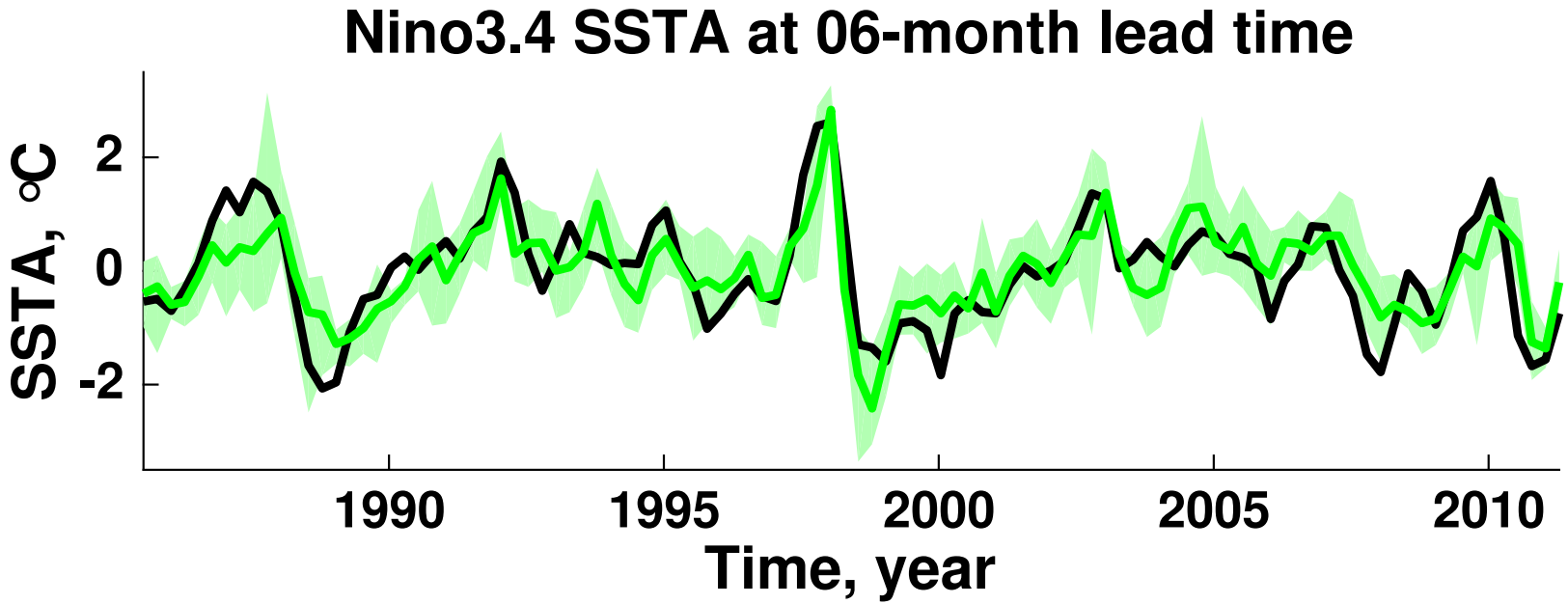


Skill can be estimated for example by the correlation or root mean square error between forecast and observed time series for different lead times

4. Seasonal prediction skill and tropical basin interactions

ENSO events can be well predicted

Norwegian Climate Prediction Model



Wang et al. 2019

ENSO events can be predicted up to 12 months ahead

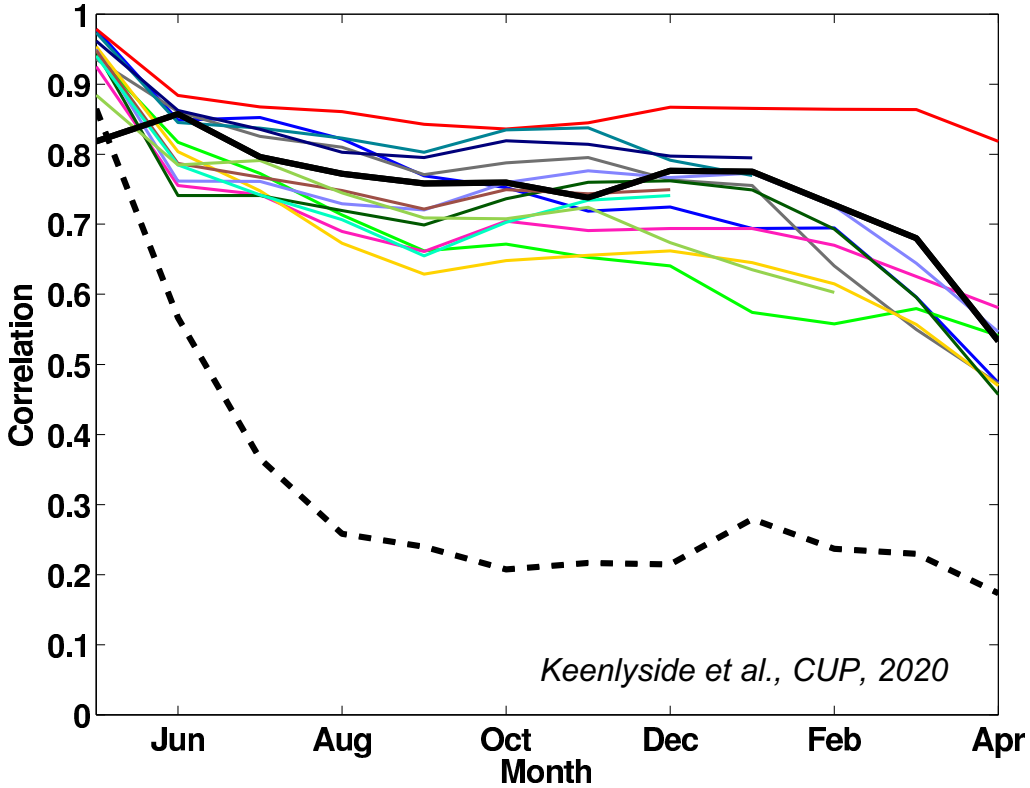
Anomaly Correlation skill in predicting Nino 3.4 sea surface temperature
N. American Multi-Model Ensemble, period 1985-2010

Forecasts started 1st May

Different models (coloured),

NorCPM forecast (Black solid)

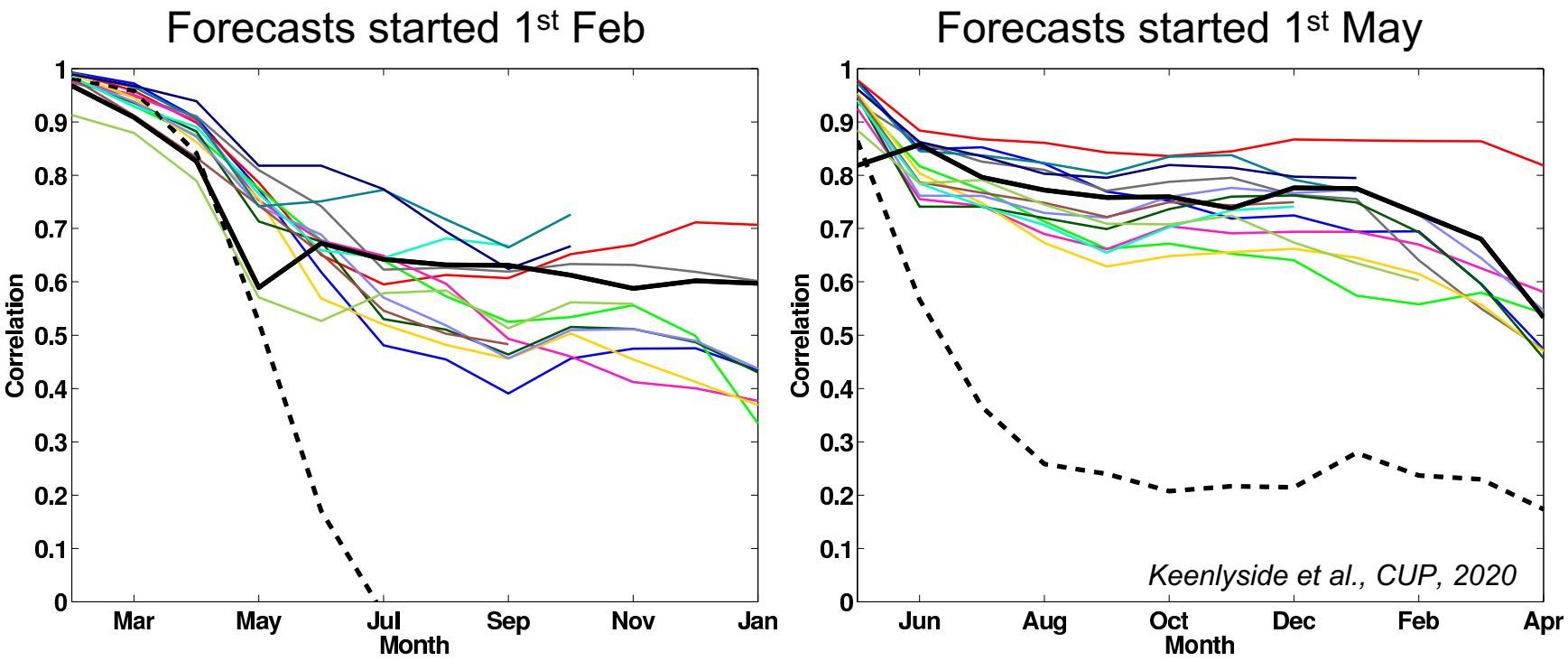
Persistence forecast(dashed)



Lead time (months)

Skill depends in predicting ENSO depends on initial month

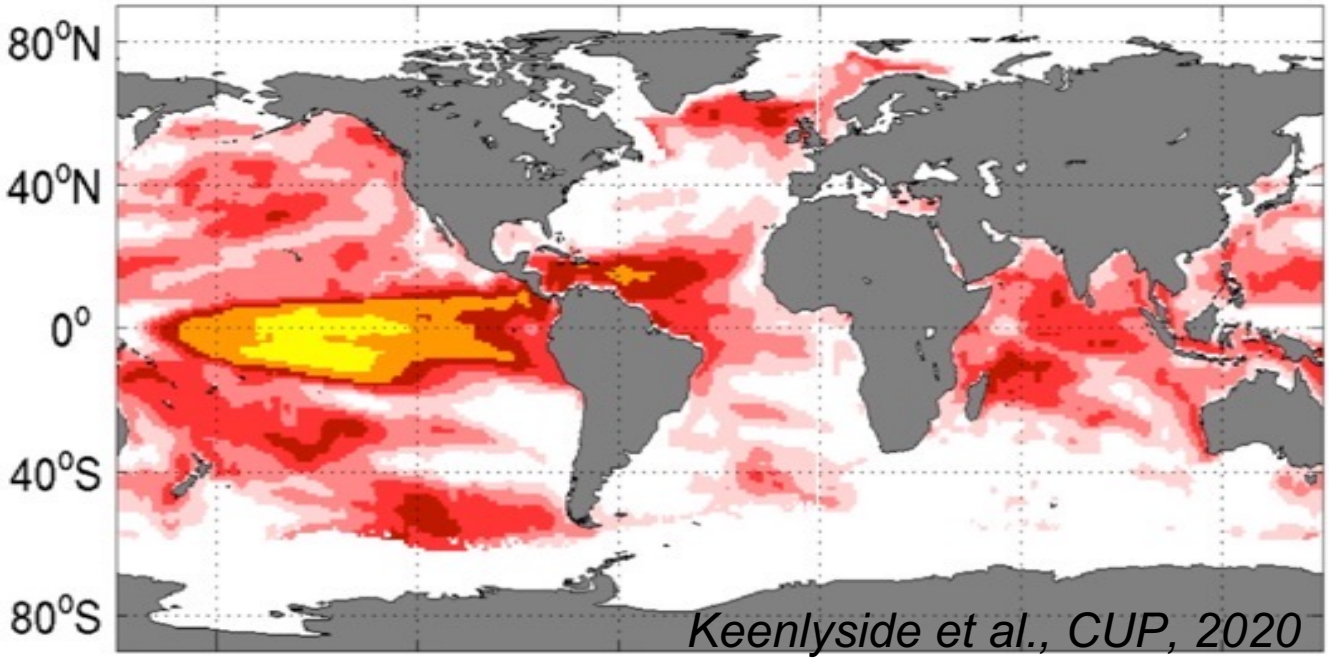
Anomaly Correlation skill in predicting sea surface temperature
N. American Multi-Model Ensemble, period 1985-2010



Different models (coloured), NorCPM forecast (Black solid), Persistence forecast(dashed)

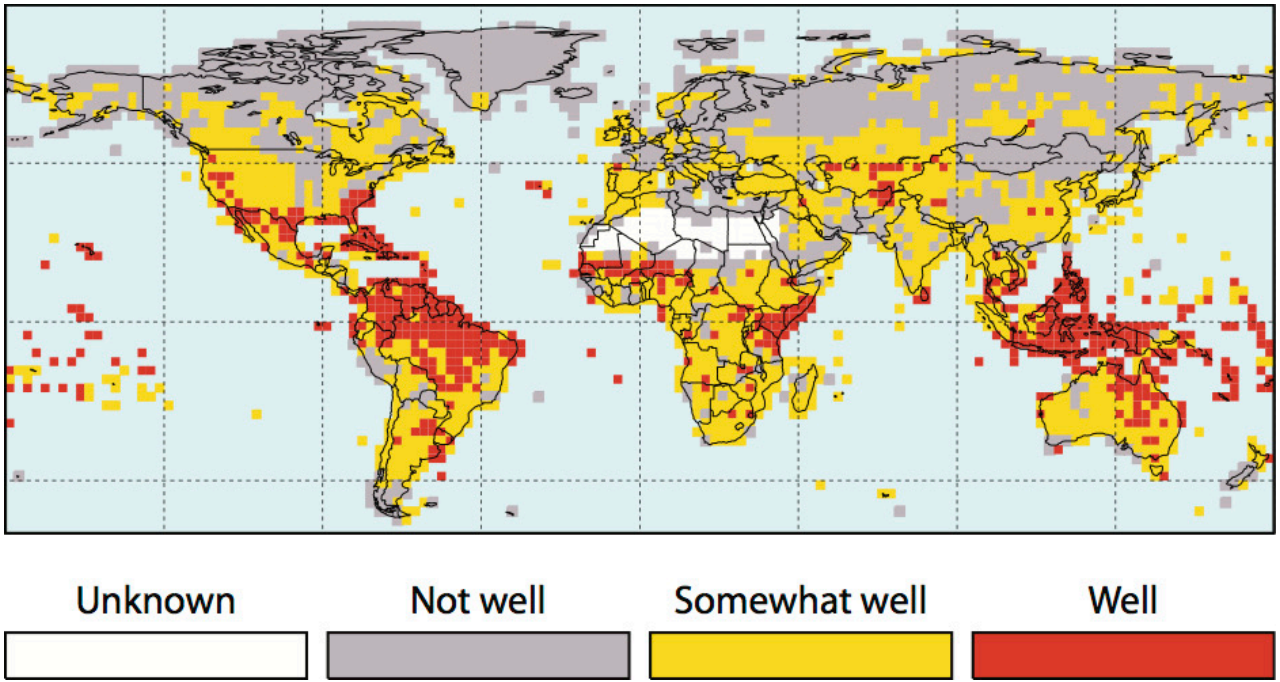
Skill of seasonal predictions for sea surface temperature

Anomaly Correlation skill in predicting sea surface temperature at six months lead
N. American Multi-Model Ensemble (ave.), period 1985-2010



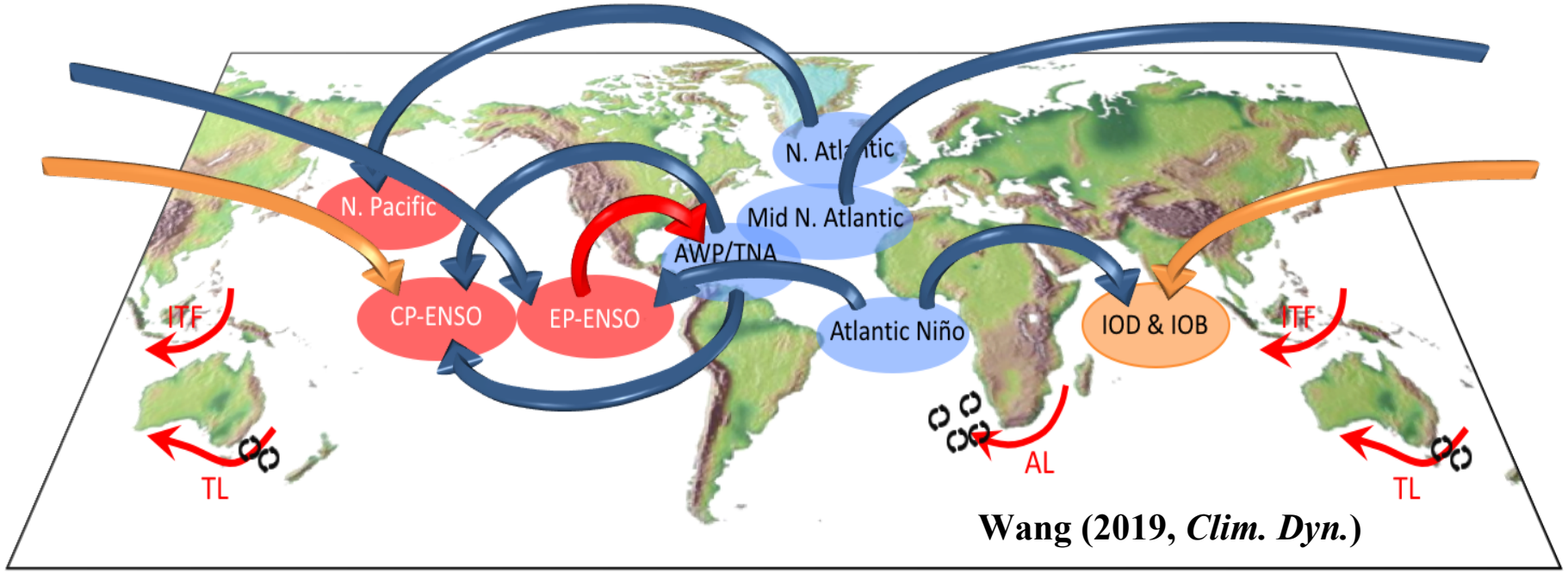
Seasonal climate prediction is skillful in the tropics

Indicates skill of 3-month forecasts of rainfall for at least one season of the year



Source: IRI-International Federation of Red Cross/Red Crescent seasonal forecasts in context

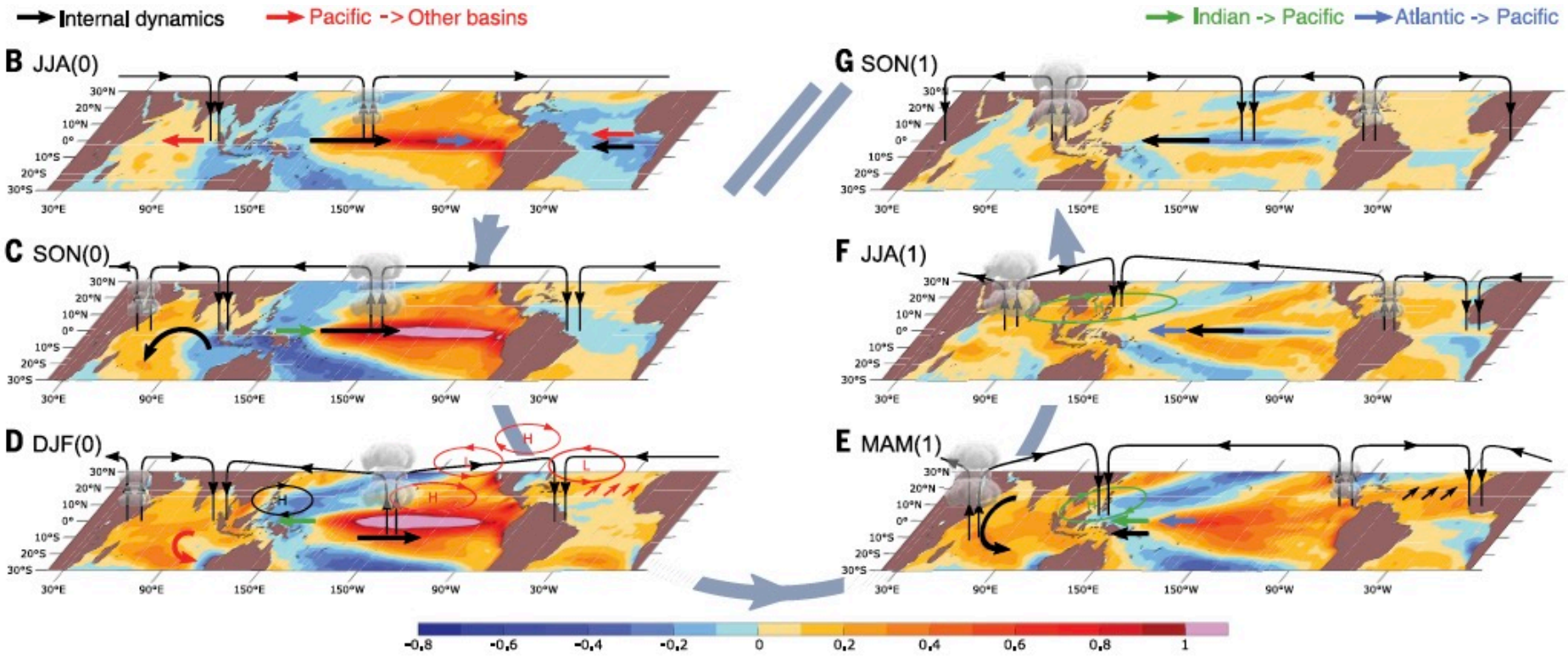
Importance of tropical basin interactions for seasonal prediction



Wang (2019, *Clim. Dyn.*)

Tropical basin interactions across seasons

Shading: observed lagged correlation of DJF Niño index on to SST

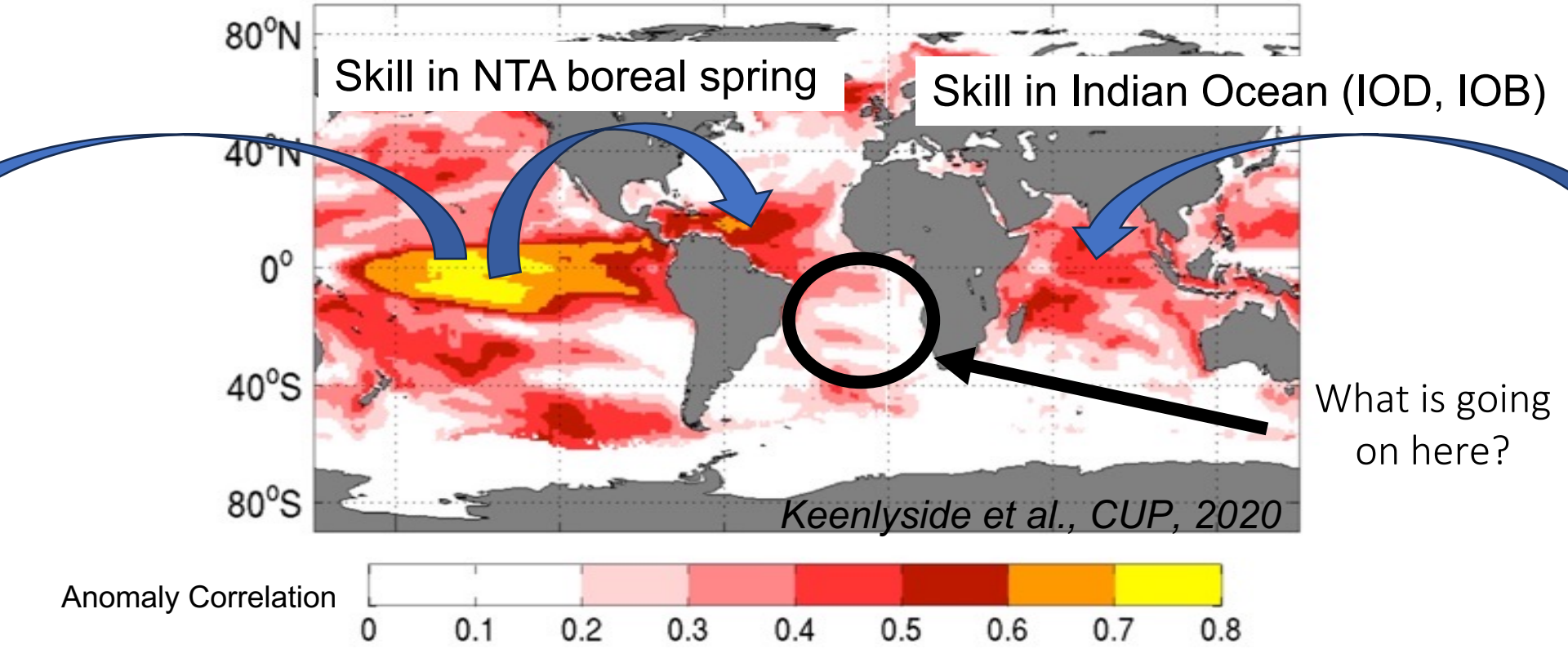


Cai et al. 2019

First, lets consider the ENSO impacts on other tropical basins

Skill of seasonal predictions for sea surface temperature

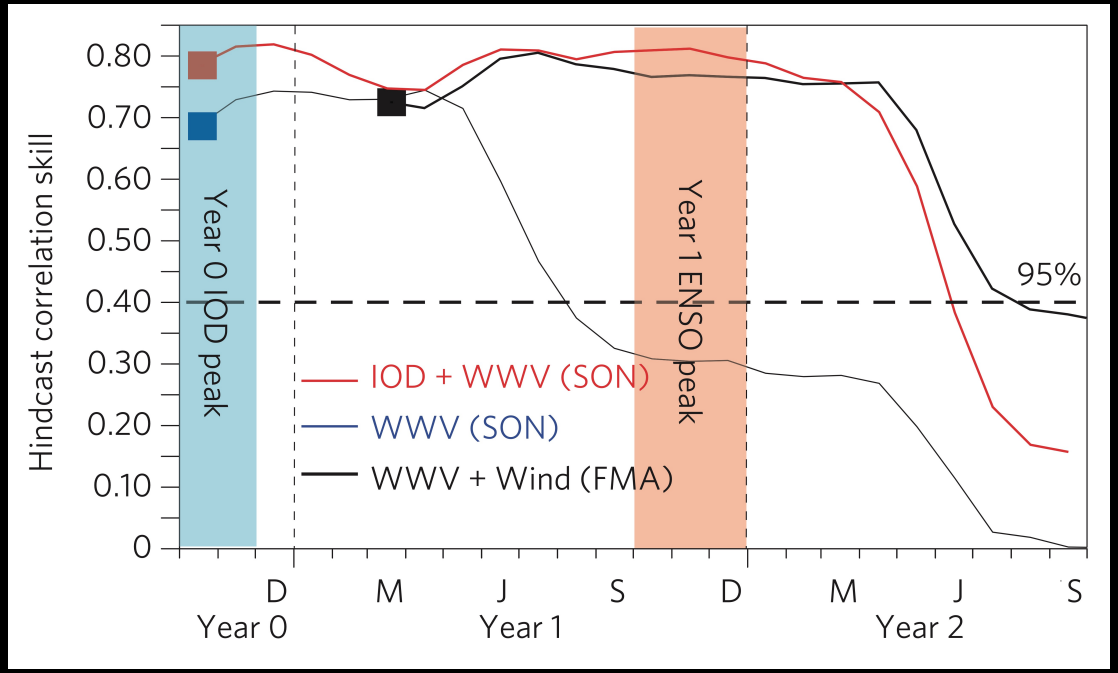
Anomaly Correlation skill in predicting sea surface temperature at six months lead
N. American Multi-Model Ensemble (ave.), period 1985-2010



Second, lets consider the impacts of tropical Atlantic and Indian Ocean on ENSO

Accounting for Indian Ocean variability can enhance ENSO prediction

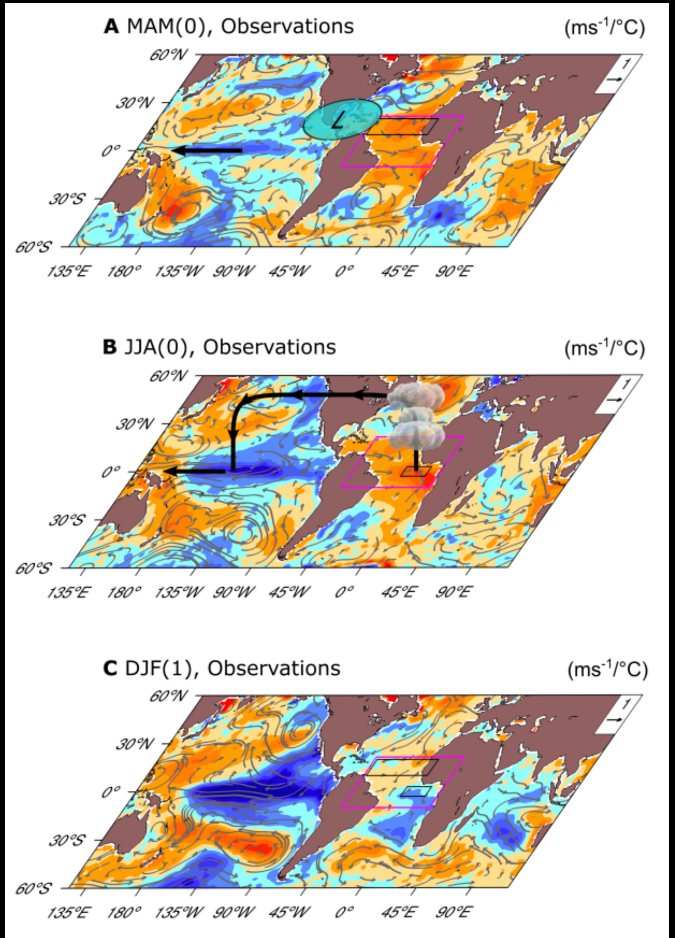
Skill of a statistical prediction using IOD and WWV 14 months prior (red) achieves skill similar to forecasts initialised with Pacific only data 8 months prior (BLACK)



Izumo et al. 2010

Two pathways for tropical Atlantic to impact ENSO

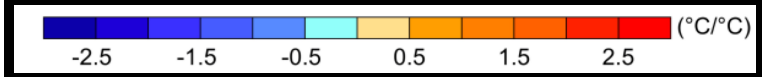
Regression of tropical Atlantic SST (MAMJJA) onto global SST



Boreal Spring
North tropical Atlantic pathway
(Ham et al 2013a,b)

Boreal Summer
Equatorial Atlantic pathway
(Rodriguez-Fonseca et al. 2009)

Boreal winter
La Niña like conditions



Cai et al. 2019

Models reproduce tropical Atlantic impacts on ENSO

Regression of tropical Atlantic SST (MAMJJA) onto global SST

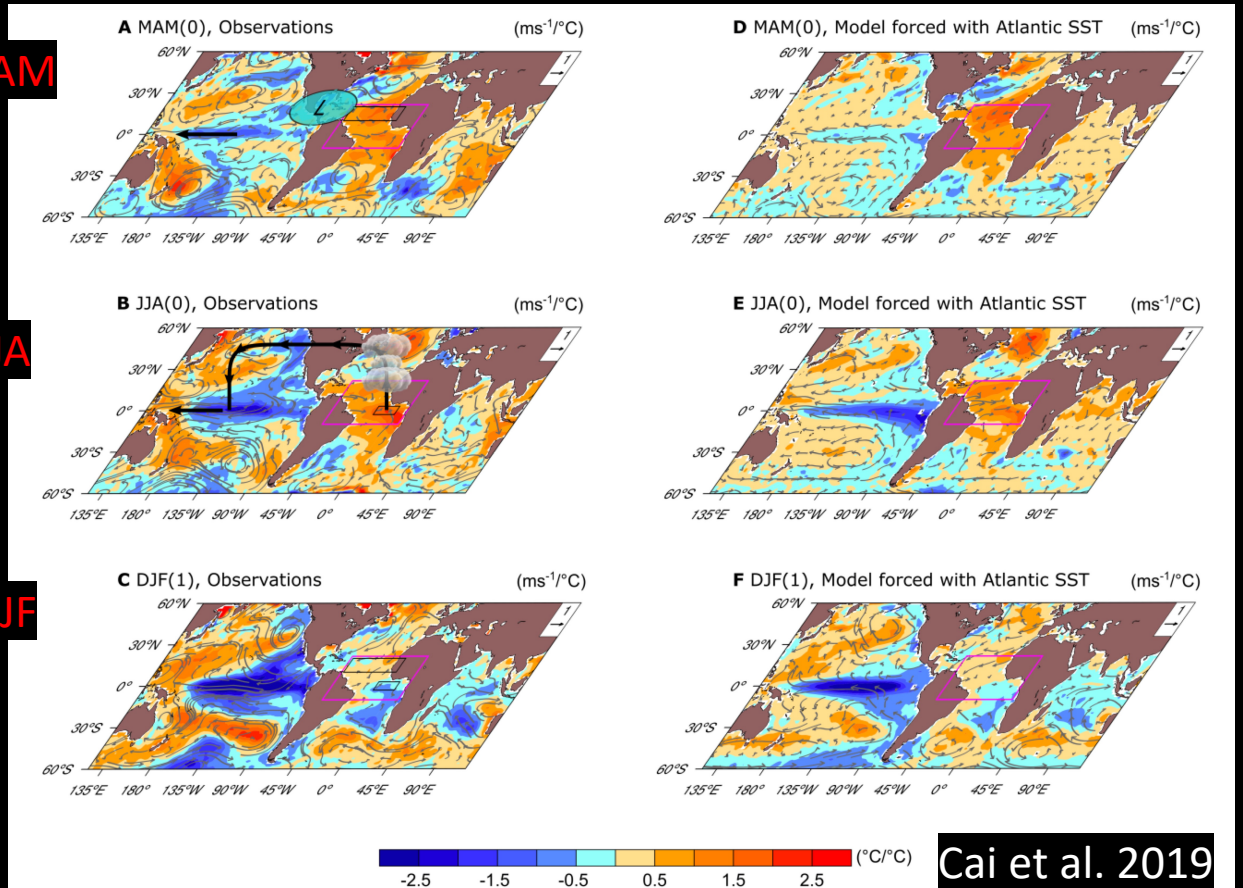
Observations

Pace maker experiment (Ding et al. 2011)

MAM

JJA

DJF

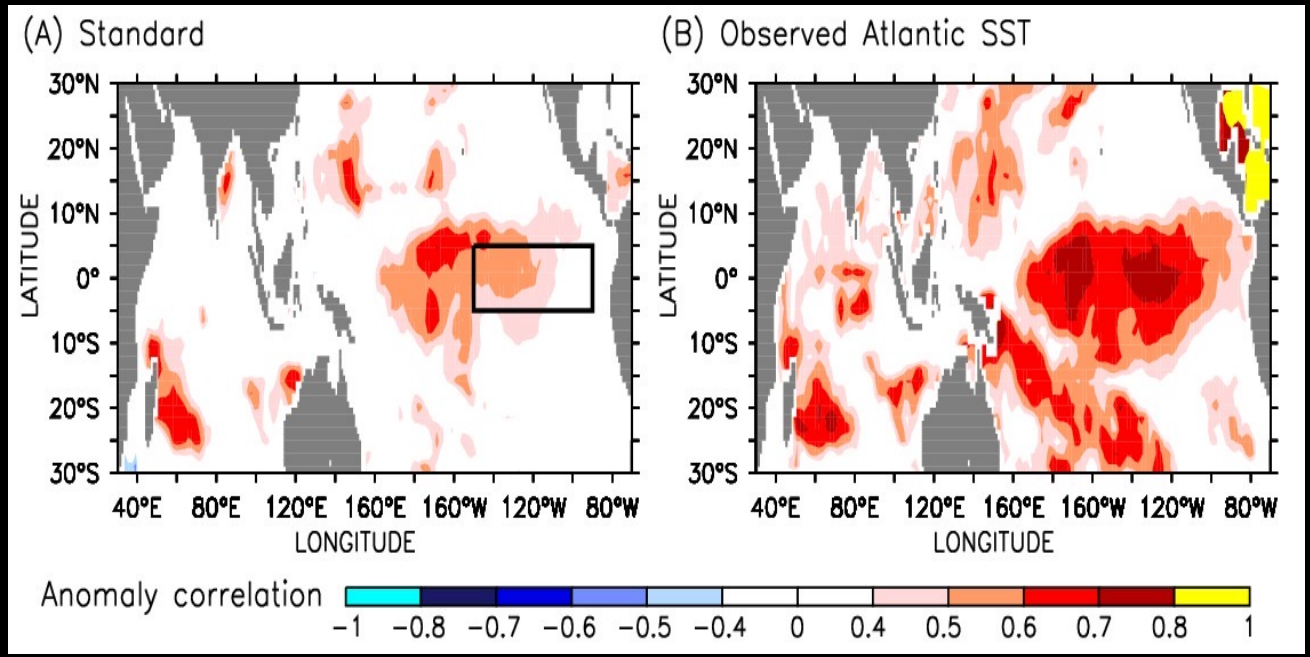


Cai et al. 2019

Observed Atlantic SST enhances ENSO prediction

Prediction experiments 1980-2005, nine member, MPI model

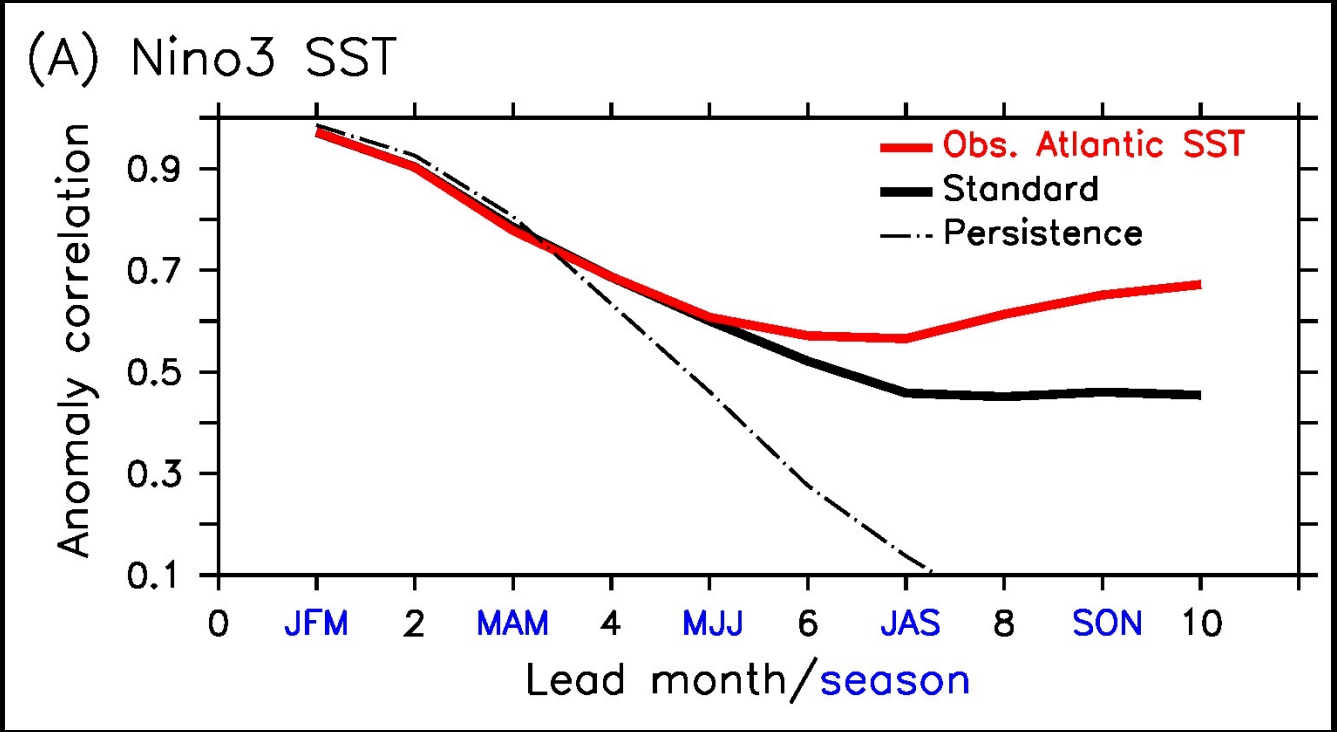
Anomaly correlation, Feb Start, Oct-Dec SST



Keenlyside et al. 2013 (See also, Jansen et al. 2009; Martin-Rey et al., 2015, Exarchou et al. 2021)

Prediction skill increases across boreal summer

ECHAM5/MPIOM, 1980-2005, **Feb start**



Keenlyside et al. 2013

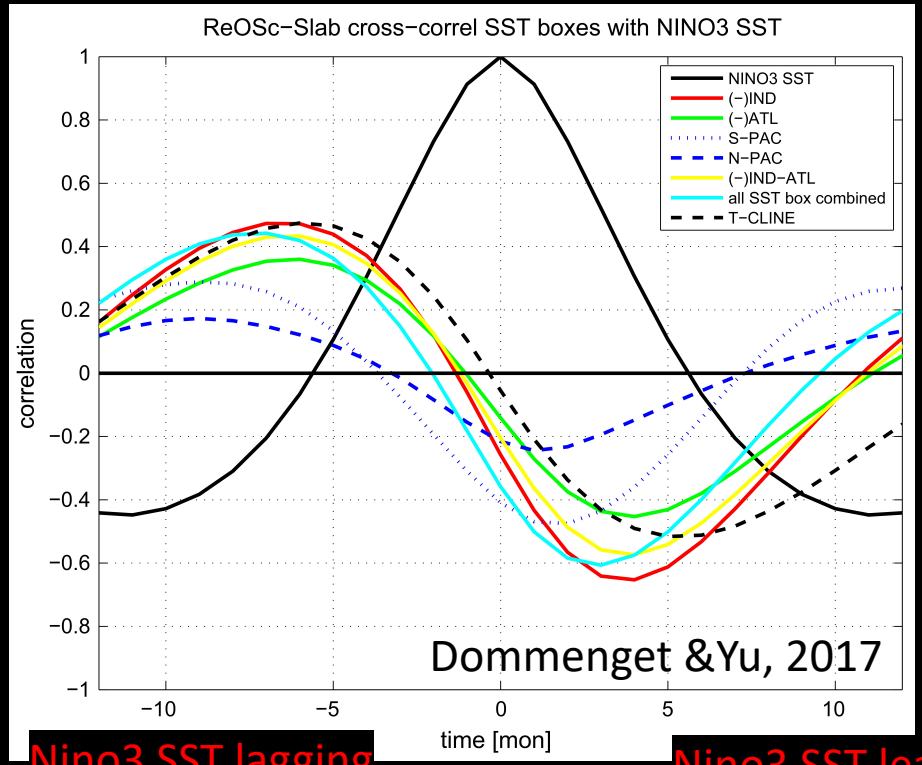
Last, lets consider three basin interactions

Interactions with Atlantic and Indian Ocean enhance the ENSO delayed negative feedback

Cross-correlation Nino3 SST with thermocline depth and remote SST indices
Experiments with AGCM – slab/recharge oscillator model

Pacific Thermocline (dashed)

Negative Atlantic and Indian Ocean SST (coloured)



Nino3 SST lagging

Nino3 SST leading

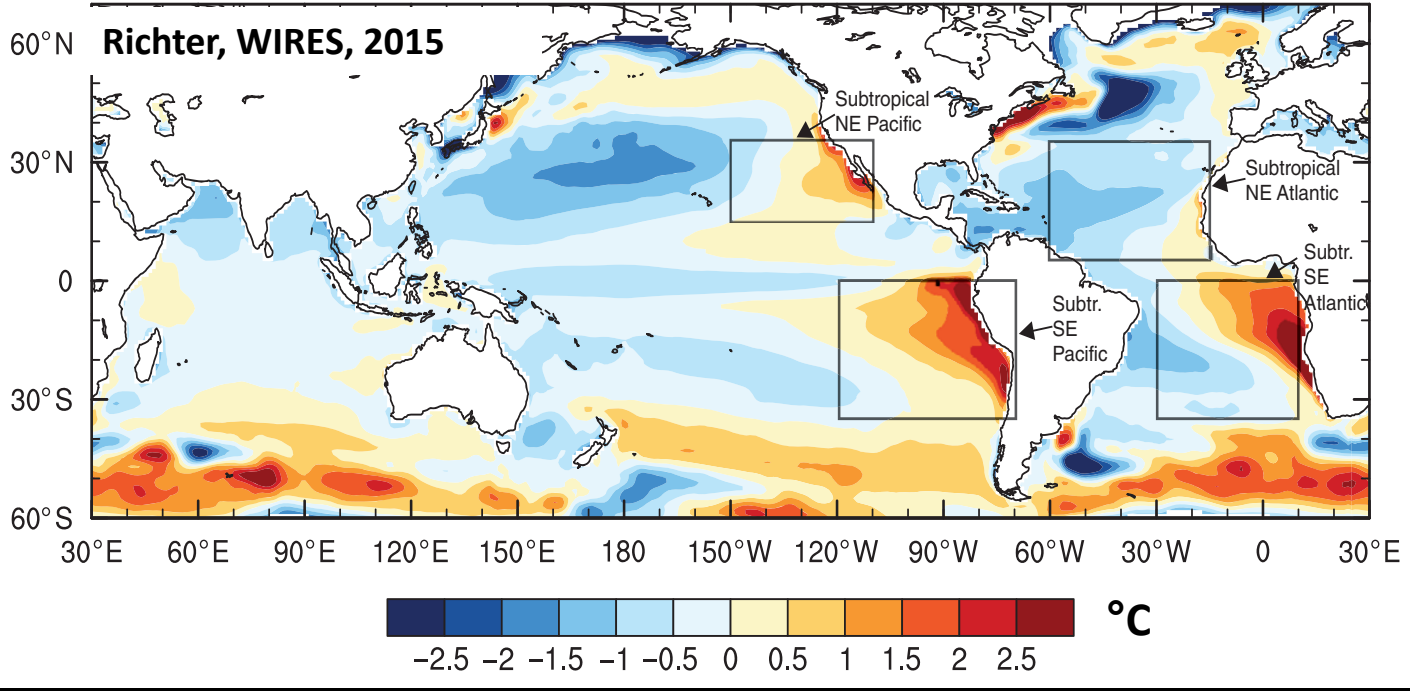
Last, lets consider three basin interactions

- Interactions modify the dynamics
- Could they contribute to super ENSO (Chunzai's workshop talk)?
- Could they contribute to allow ENSO prediction to two years?

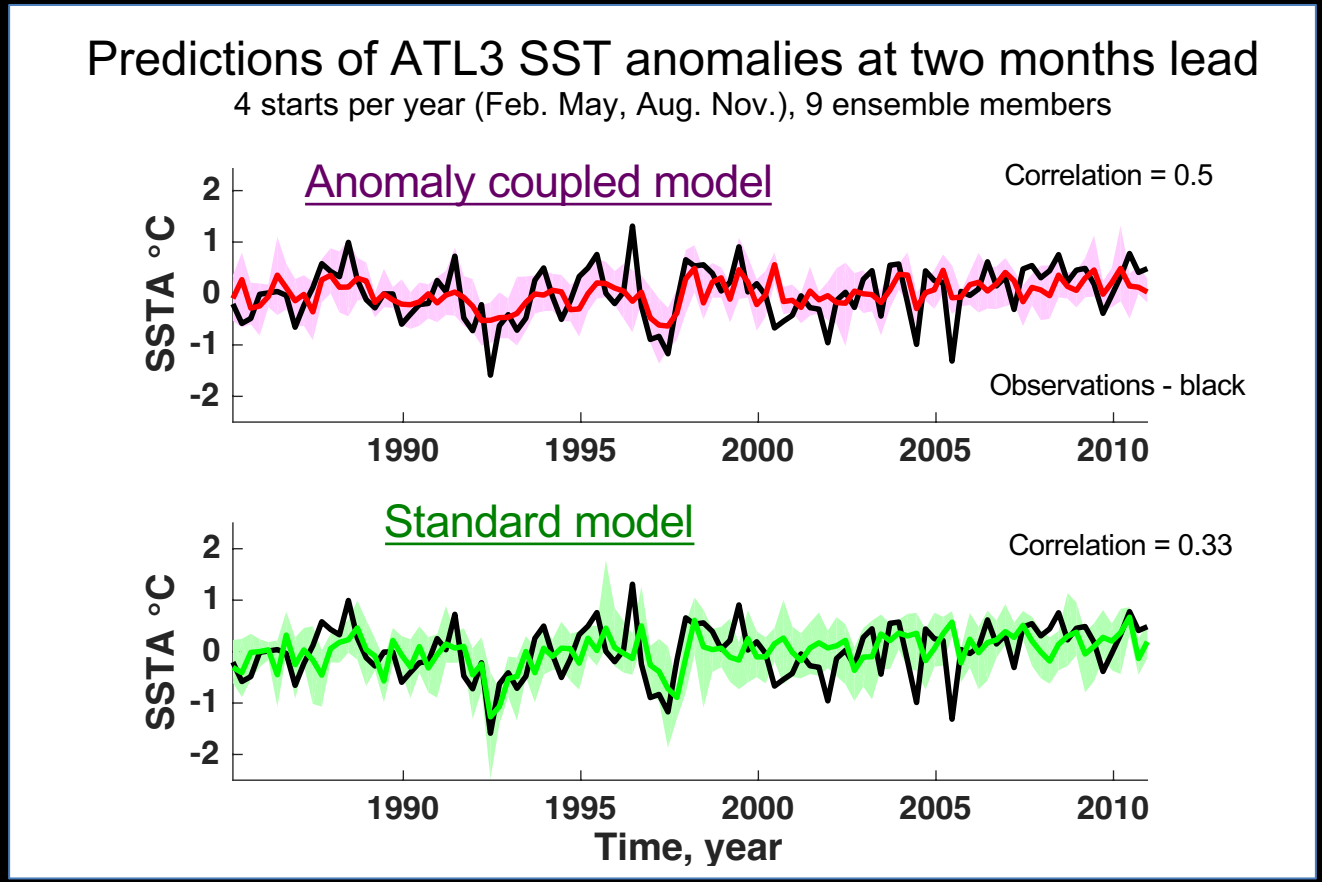
5. Some current challenges

Model biases in the South Eastern Tropical Atlantic among the most severe

CMIP5 multi-model mean sea surface temperature error



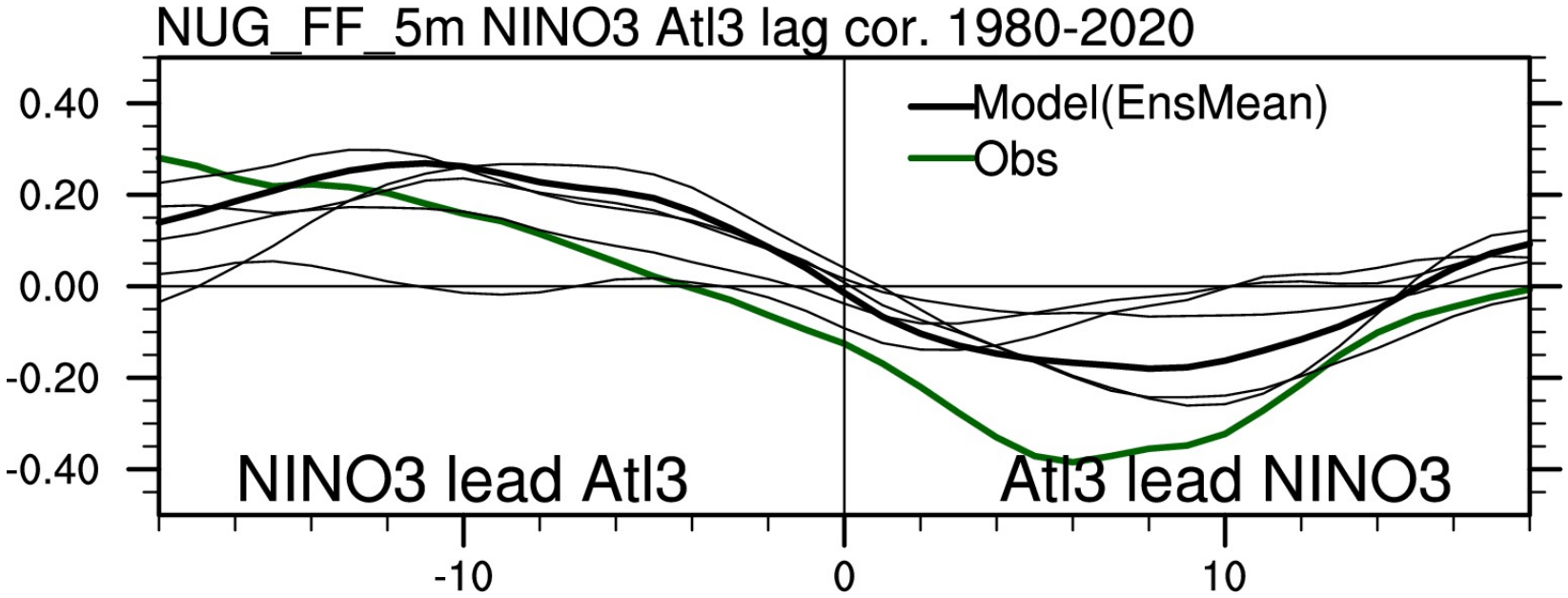
Reducing biases enhances Atlantic Niño prediction



Counillon et al. 2021

Model challenged in reproducing the equatorial Atlantic-Pacific connection

NorESM1 – cross-correlation – full field restoring in the Atlantic 10S-10N



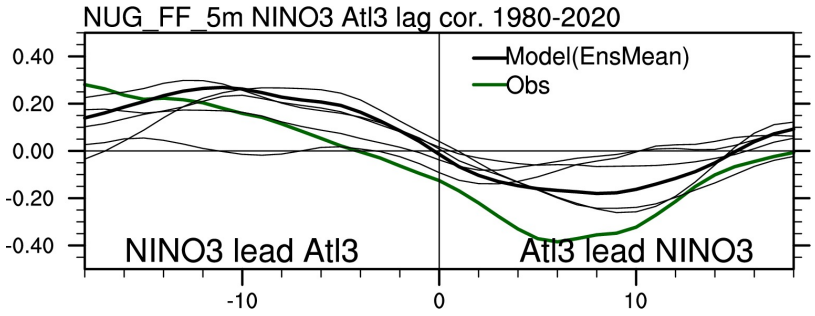
Ping-Gin Chiu

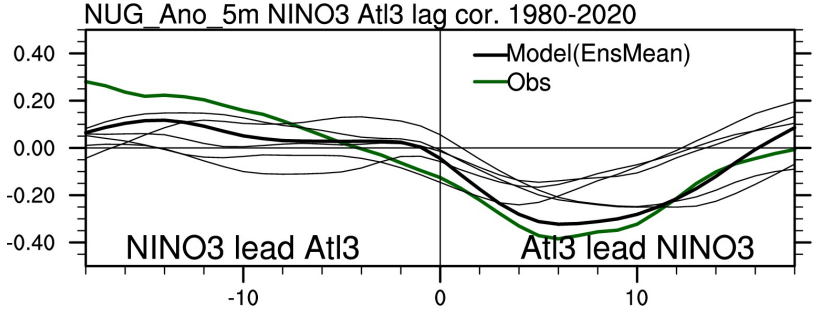
Model challenged in reproducing the equatorial Atlantic-Pacific connection

full field

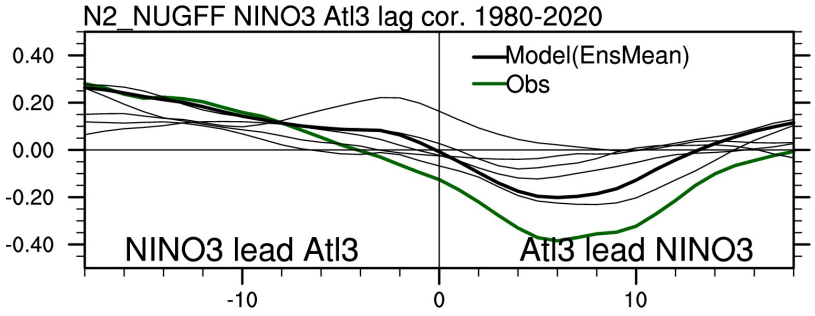
anomaly

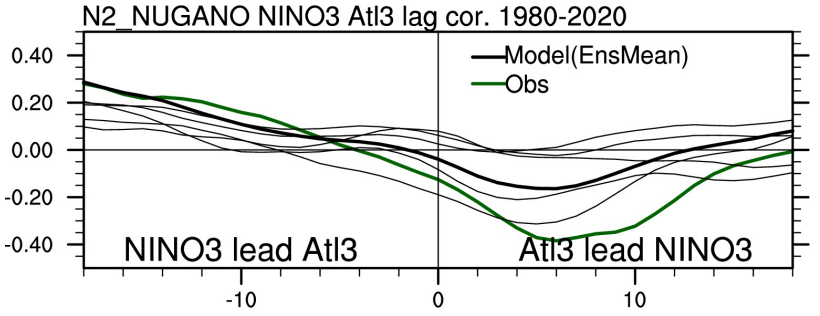
NorESM1





NorESM2





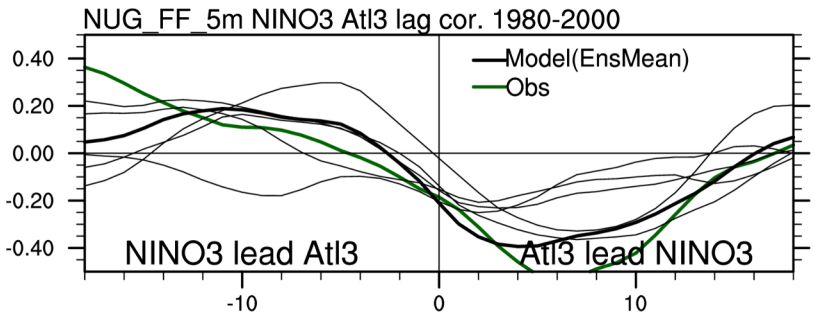
Ping-Gin Chiu

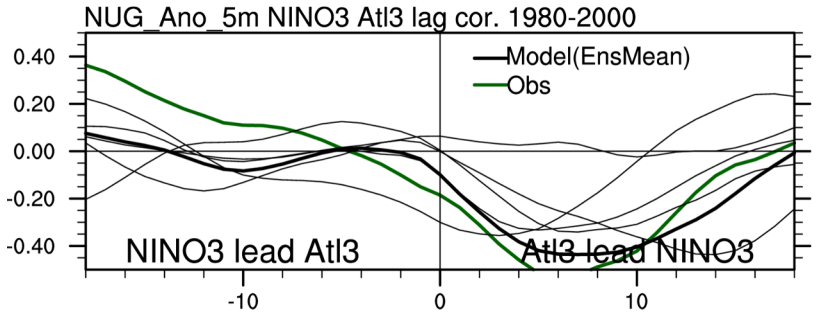
…but models appear to be capture relation during the “stronger” TBI period

full field

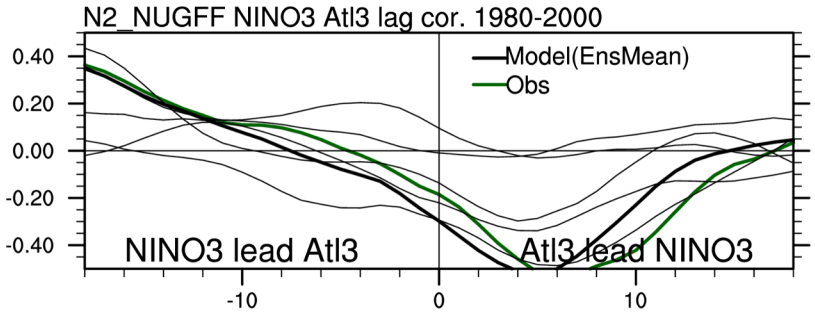
anomaly

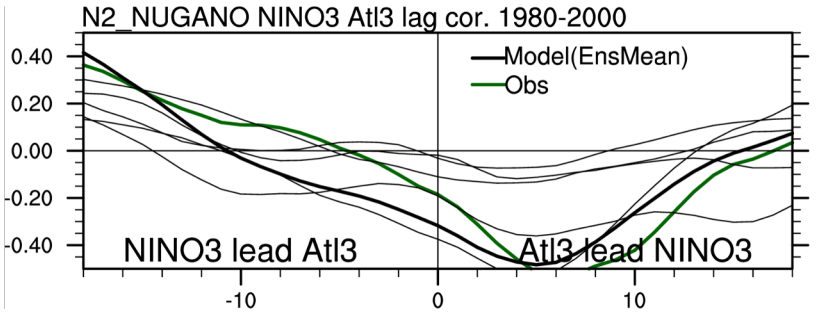
NorESM1





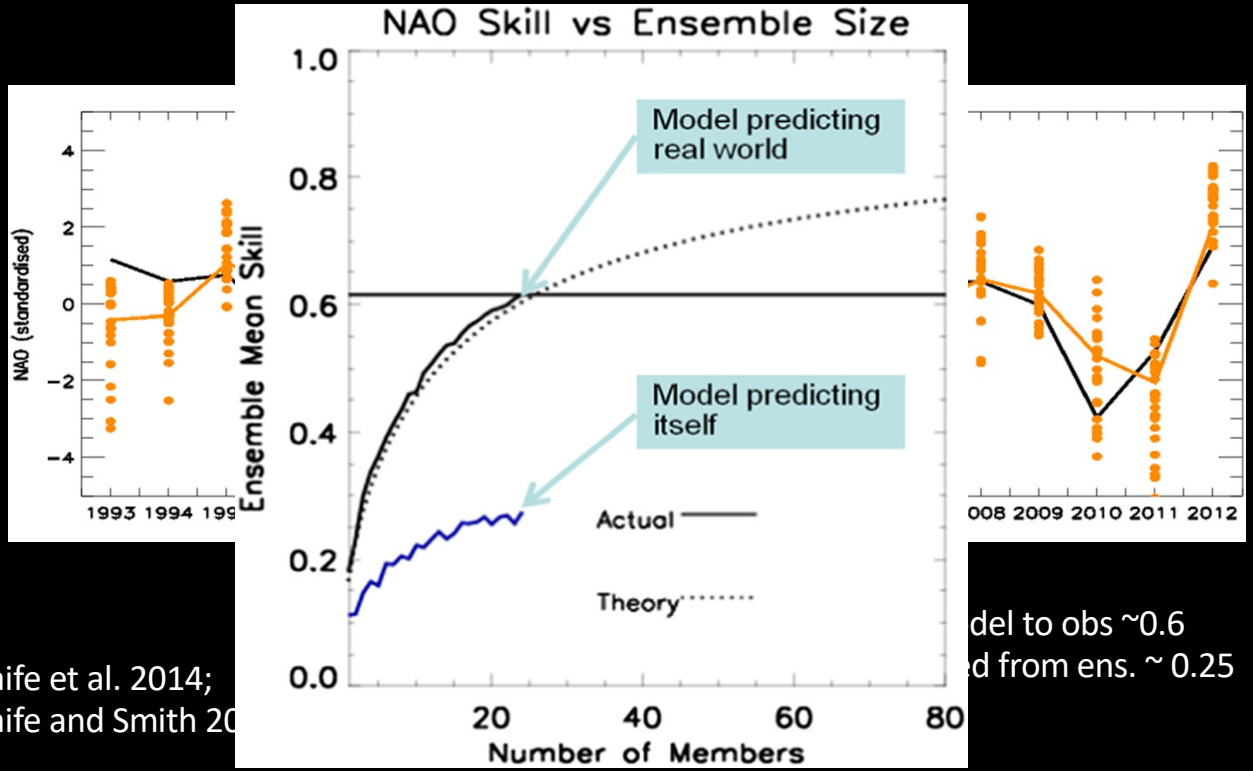
NorESM2





Ping-Gin Chiu

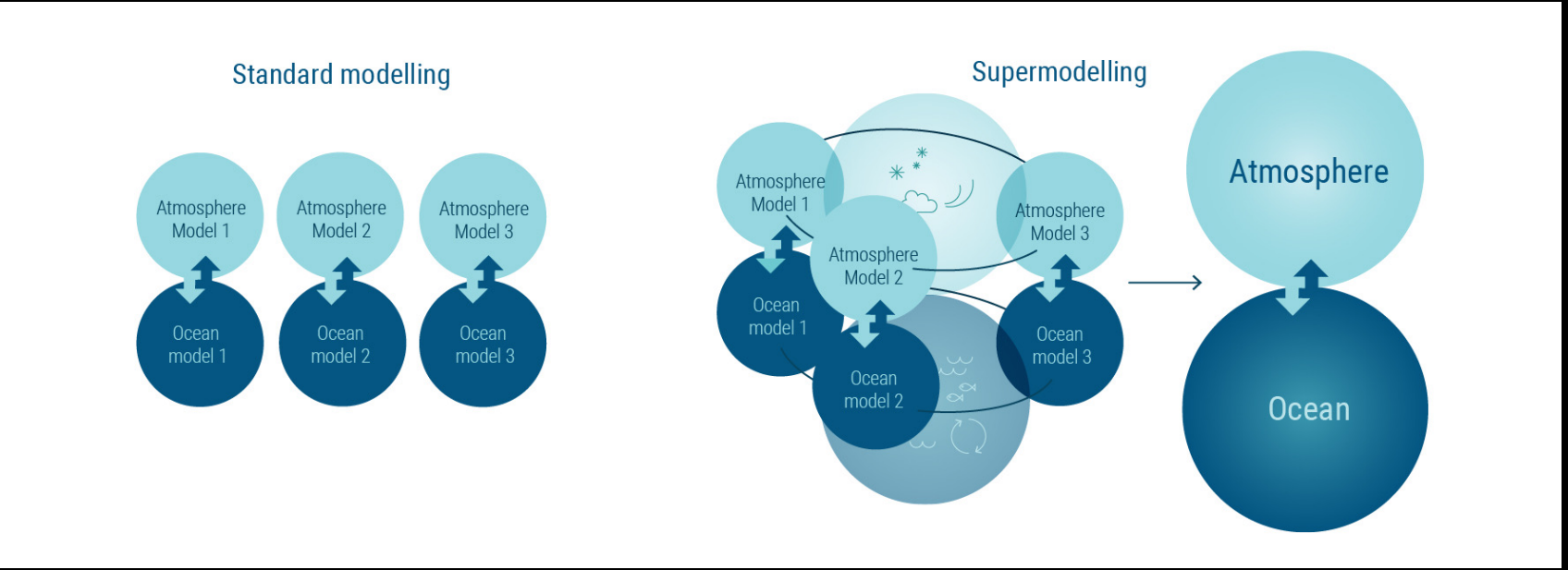
Predictions may suggested much larger impact of the ocean on the atmosphere



del to obs ~0.6
d from ens. ~ 0.25

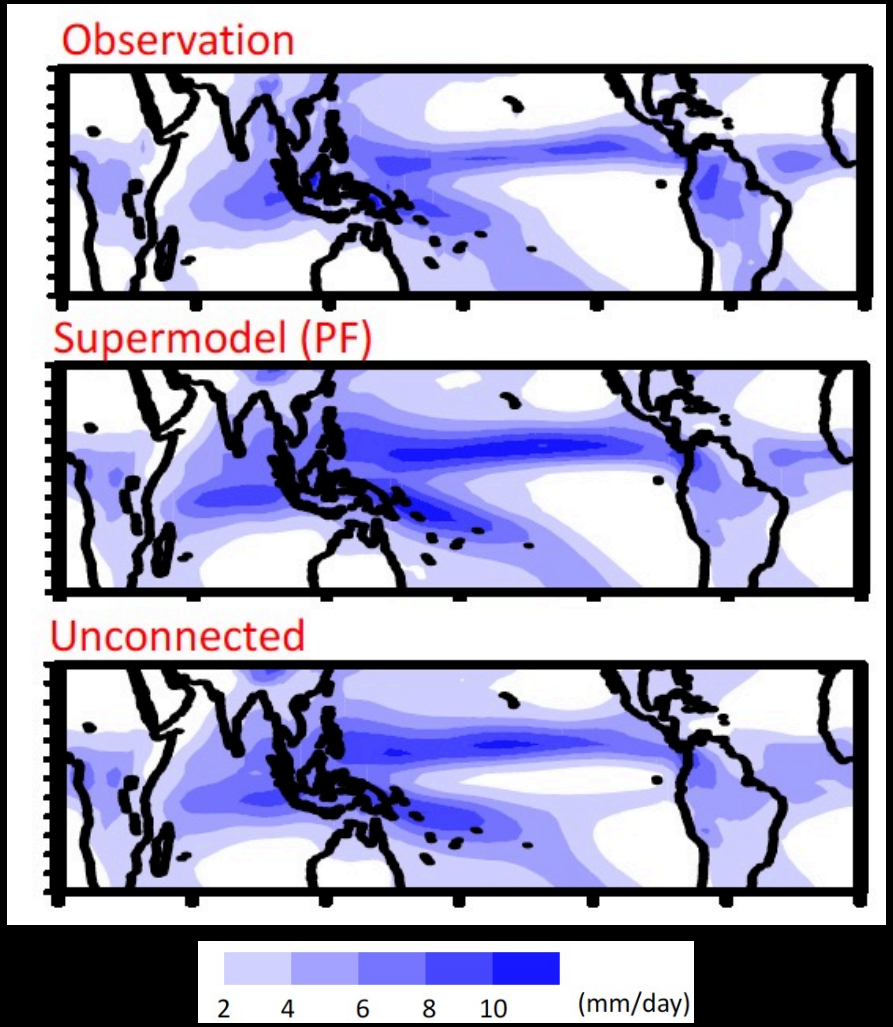
Scaife et al. 2014;
Scaife and Smith 20

A smarter ensemble approach – the supermodel



A supermodel is an optimal dynamical combination of models that is superior to its individual constituent models

Schevenhoven et al. 2023



Overall, rainfall patterns in the tropics are improved

Climatology mean for the period 1980-2005

Schevenhoven et al. 2023

The role of tropical basin-interactions in climate predictability

1. *Mechanisms are becoming understood*

2. *Potential to enhance prediction skill on seasonal-to-decadal timescales starting to be realised*

3. *Transforming our view of tropical climate variability, but key challenges exist – model biases*

Keenlyside et al. Basin Interactions and Predictability, CUPS, 2020