

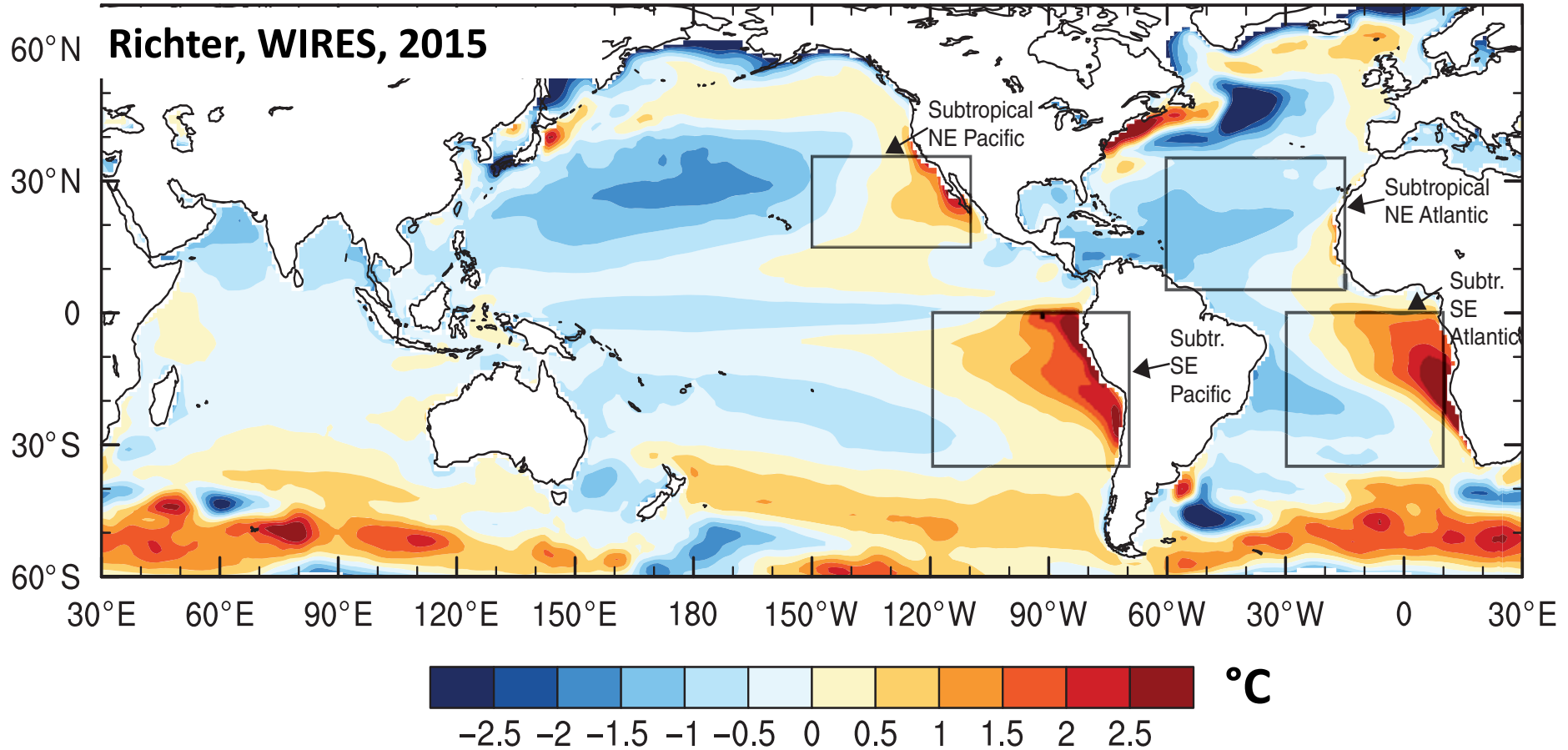


The role of model bias for prediction skill and methods to constrain it

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I. BETHKE, T. TONIAZZO*



Persistent model biases – dramatic improvement unlikely soon

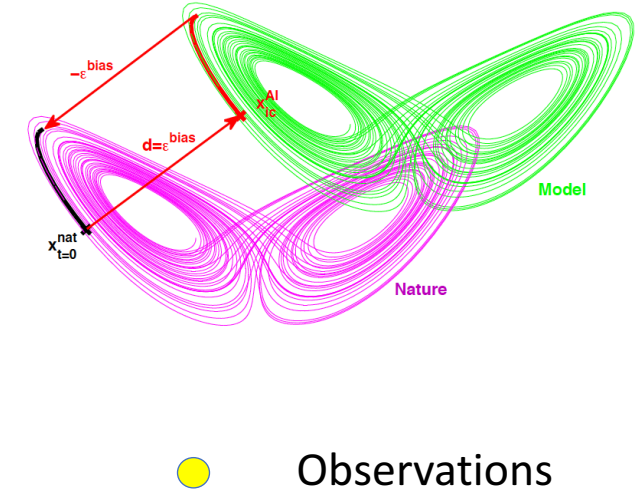
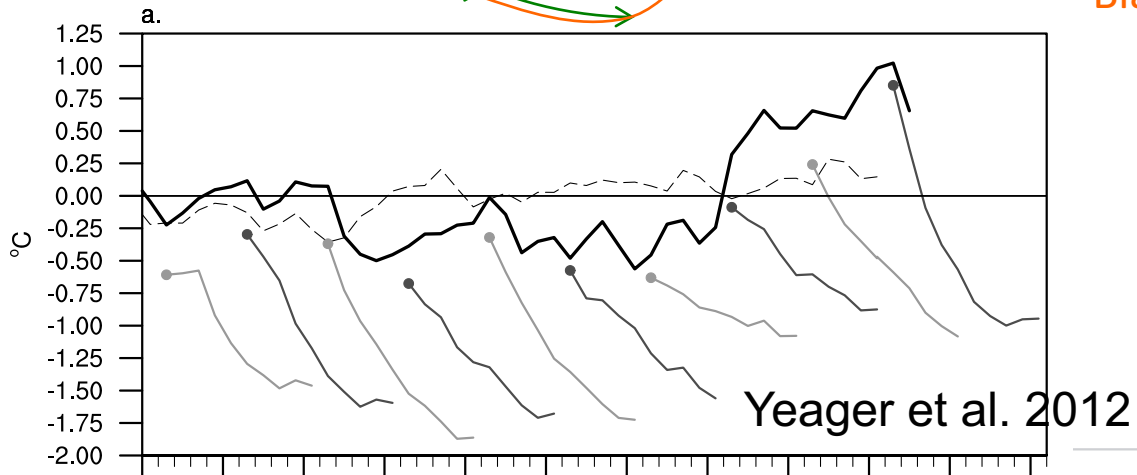
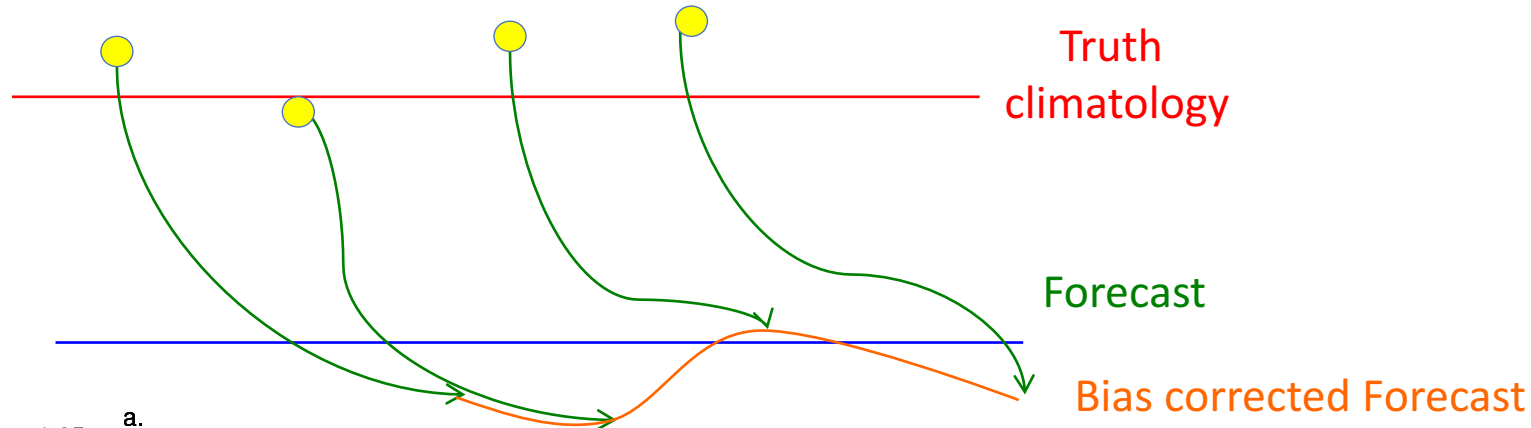


- Bias is often larger than the signal we analyze or predict
- Observation network is too small to constrain it



How is bias handled currently

Full field assimilation

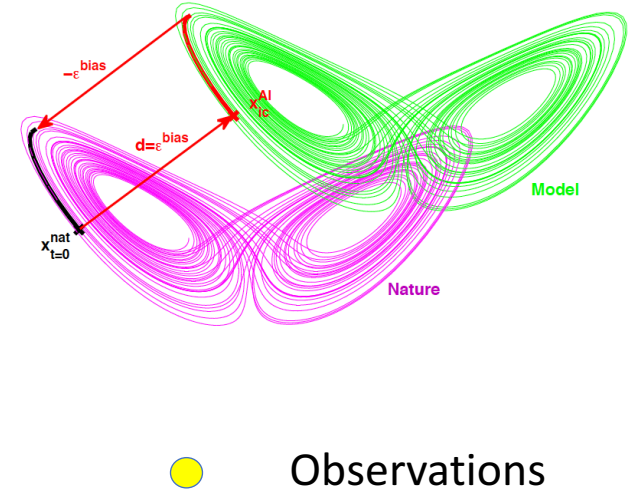
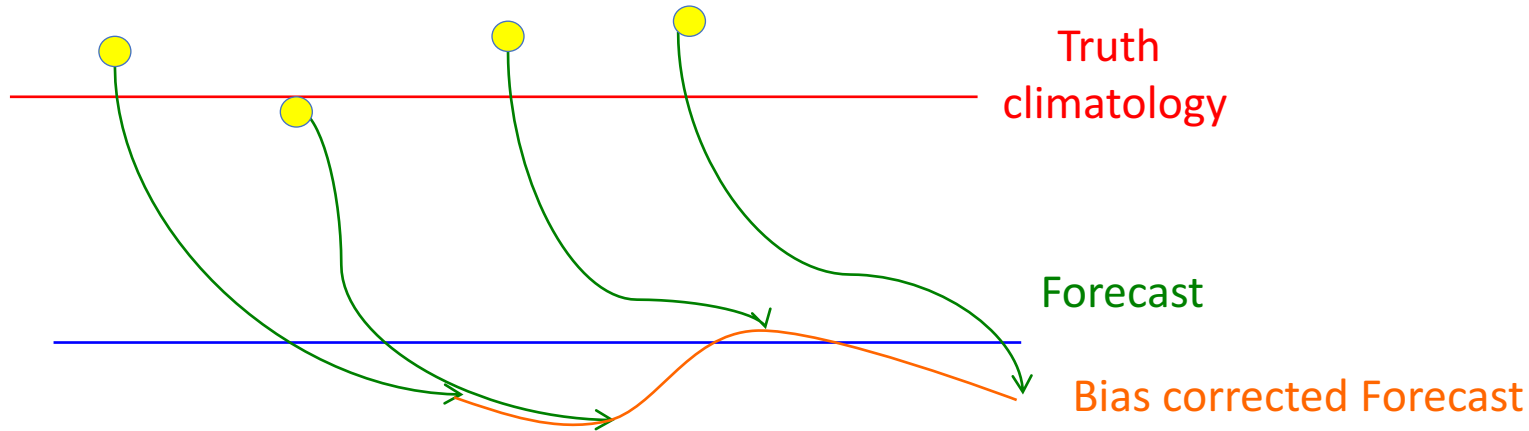


- Good:**
- Mean state is close to the truth
- Bad:**
- Large shock
 - Propagate the bias from observed variables to non observed variables (sparse inhomogeneous obs)



How is bias handled currently

Full field assimilation

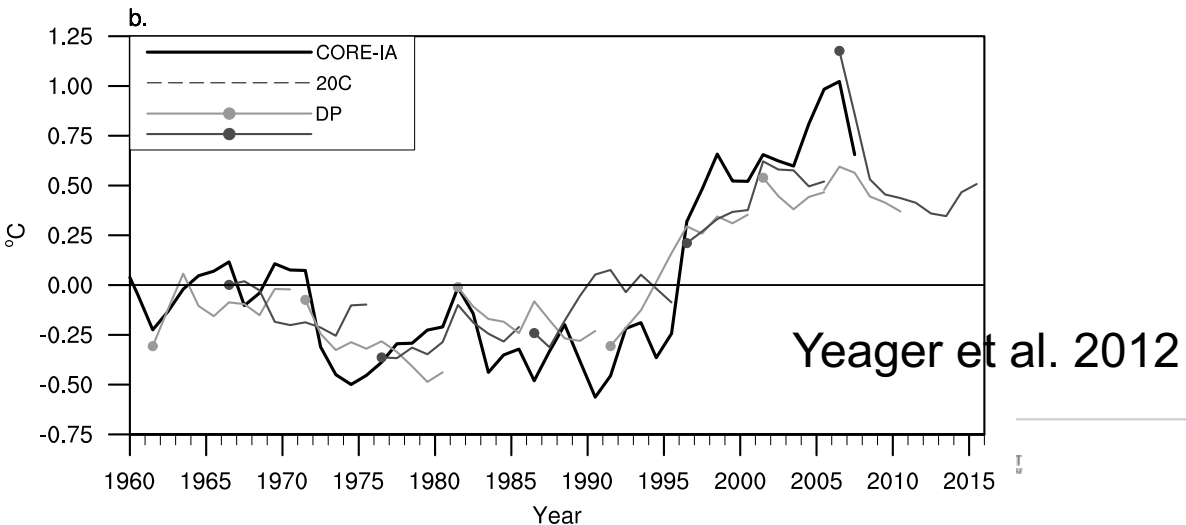


Good:

- Mean state is close to the truth

Bad:

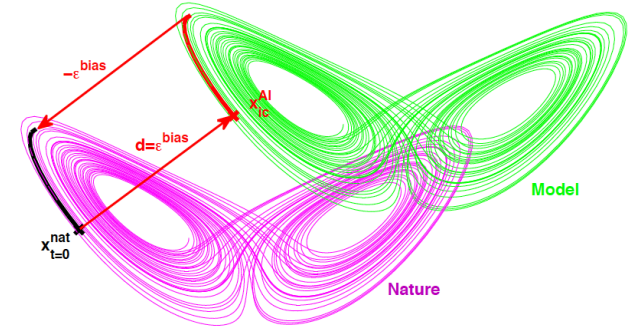
- Large shock
- Propagate the bias from observed variables to non observed variables (sparse inhomogeneous obs)



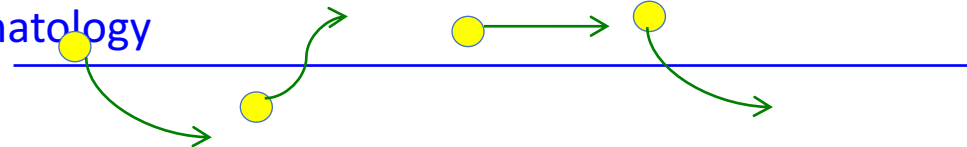


How is bias handled currently

Anomaly assimilation



Model
climatology



Forecast

● Obs - clim

Good:

- Less assimilation shock (no need for post processing)

Bad:

- Covariance are still biased
- Mean state influence the solution

Outlines

Data assimilation assumes the model to be unbiased

- analysis retains some of the bias
- updates are suboptimal

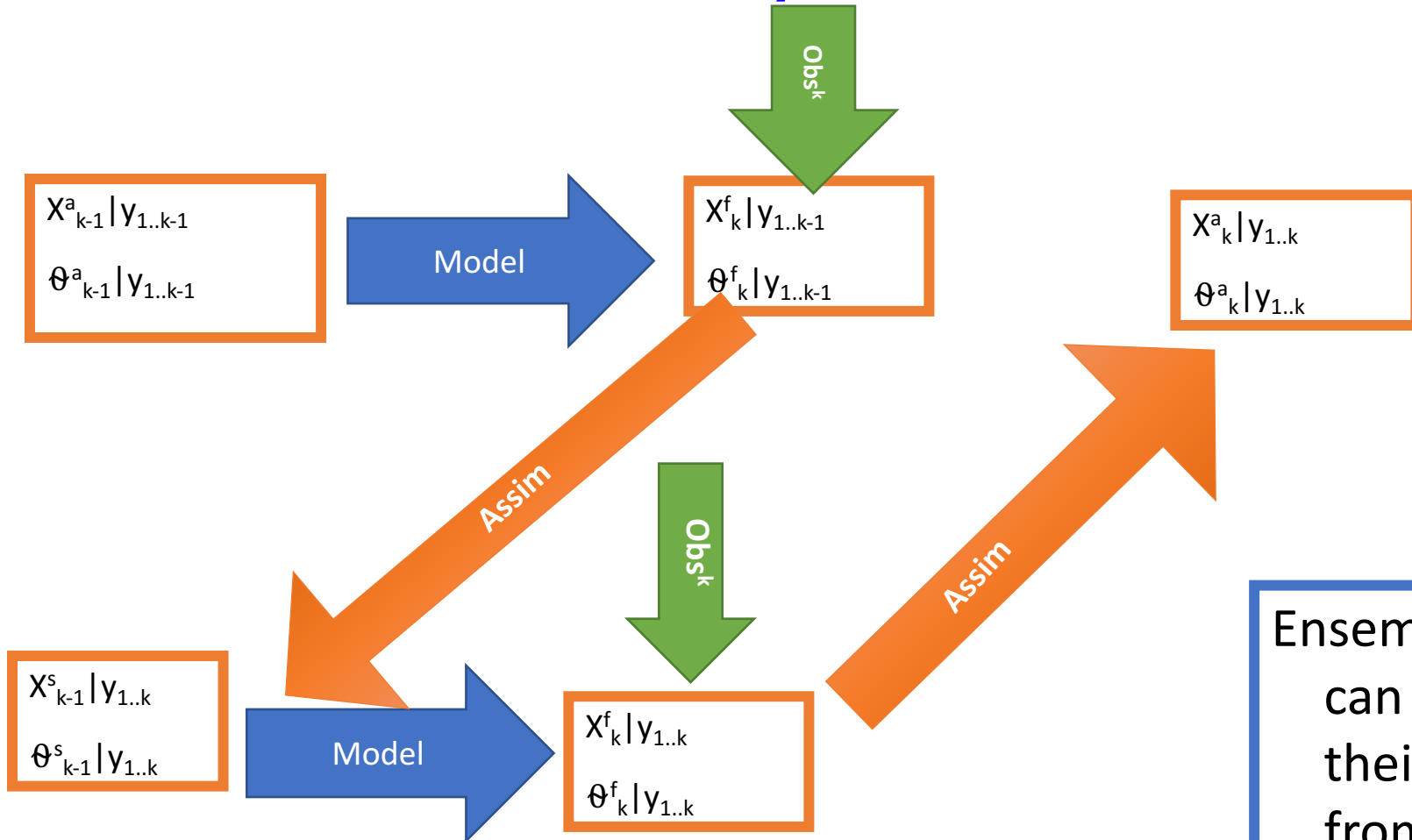
We are considering 3 approaches to reduce model bias:

- Parameter estimation
- Supermodelling
- Flux correction method



Parameter estimation with data assimilation

Dual one step ahead smoother scheme (Gharamti et al. 2017)



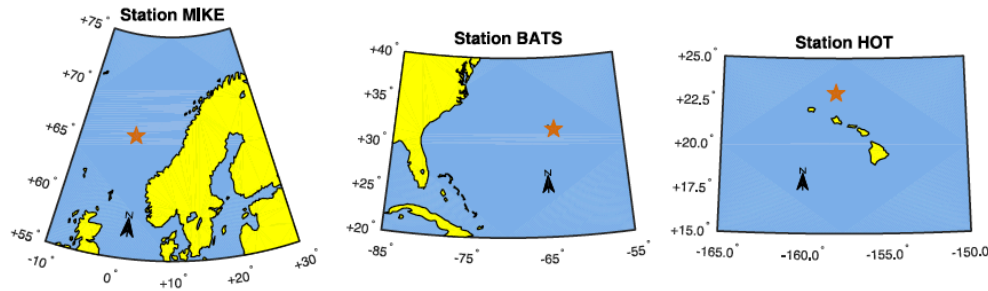
Ensemble data assimilation methods can estimate parameter based on their correlation with the misfits from observation



Parameter estimation

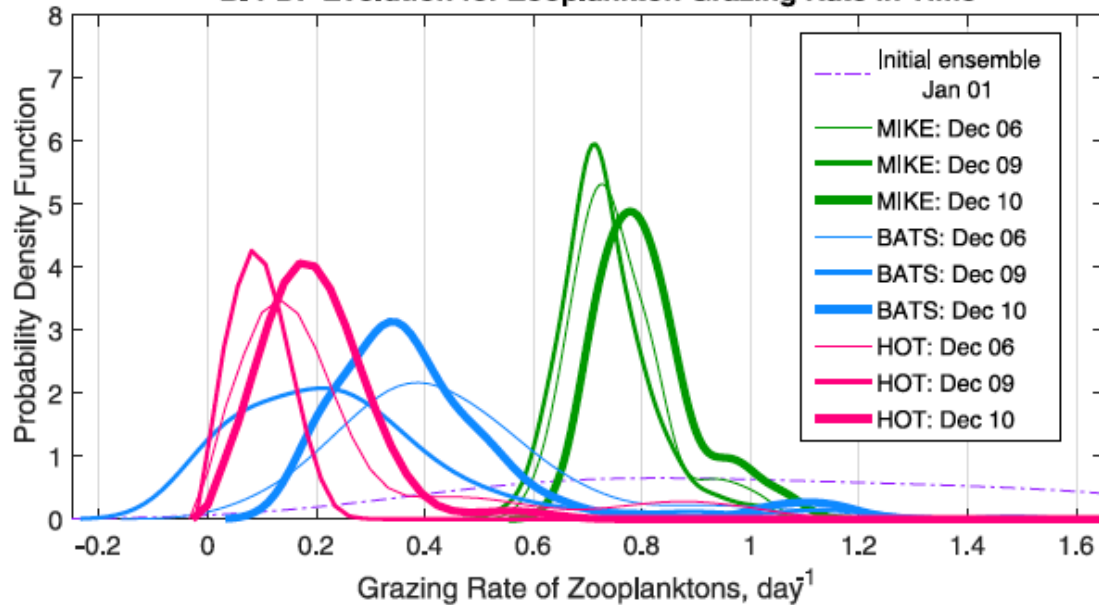
Dual one step ahead smoother scheme (Gharamti et al. 2017)

Gharamti et al. (2017)



The method was successfully tested for tuning BGC parameter and improved net primary production and air-gas exchange

B. PDF Evolution for Zooplankton Grazing Rate in Time



We will use NorCPM to tune ocean and BGC parameter in NorESM and reduce model bias



Super modelling

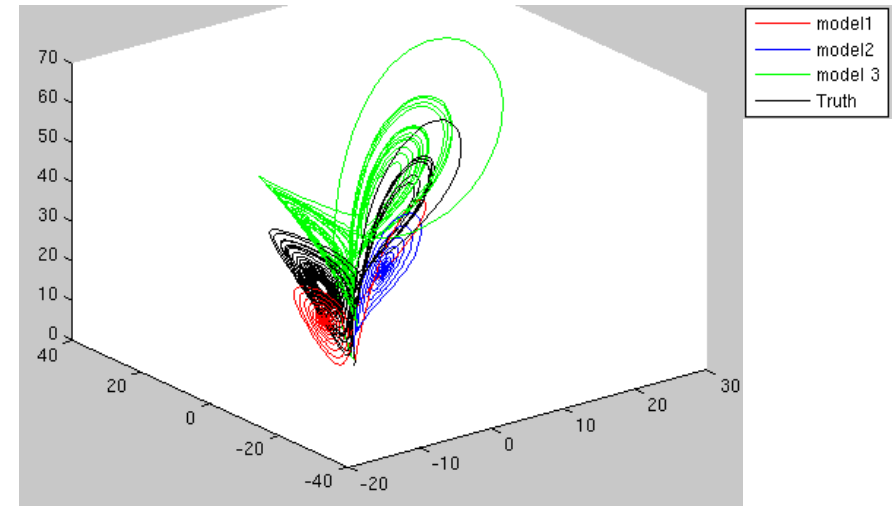
An example with L63

	σ	ρ	β
Truth	10	28	8/3
Model 1	13.25	19	3.5
Model 2	7	18	3.7
Model 3	6.5	38	1.7

$$\dot{x} = \sigma(y - x)$$

$$\dot{y} = x(\rho - z) - y$$

$$\dot{z} = xy - \beta z$$



A super model add connections to the other imperfect models

Example:

$$\dot{x}_1 = \sigma_1(y_1 - x_1) + \underbrace{C_{12}^x(x_2 - x_1) + C_{13}^x(x_3 - x_1)}_{\text{Nudging to other supermodel}}$$

Nudging to other supermodel

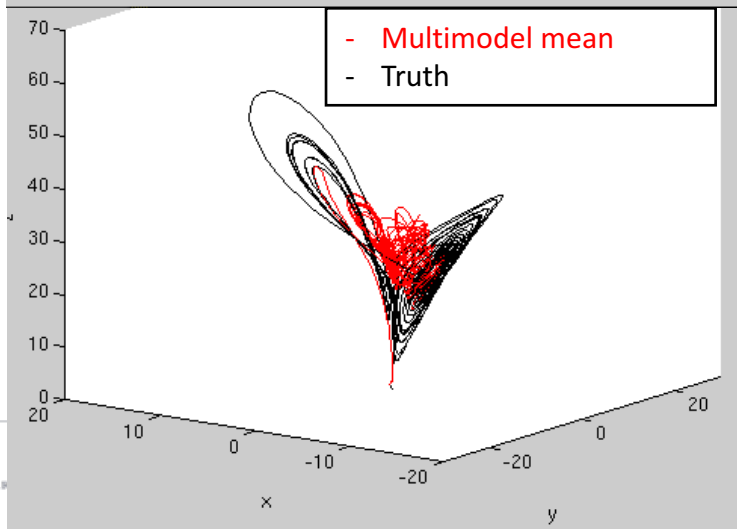
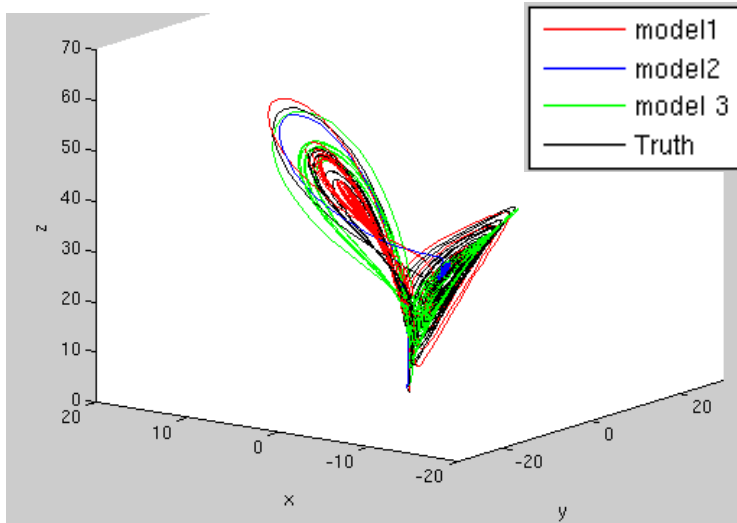
In **training phase** you use observations to estimate the nudging coefficients (and constrain the state during)

In **verification phase** the coefficient are frozen and the system can be use as a new dynamical system



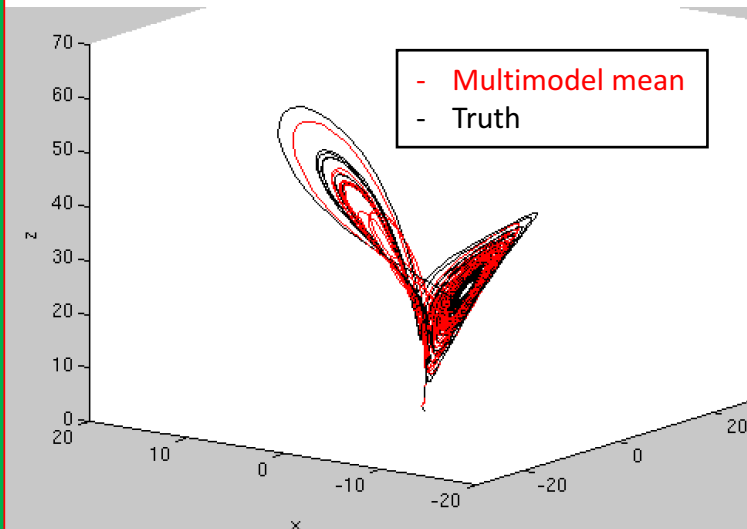
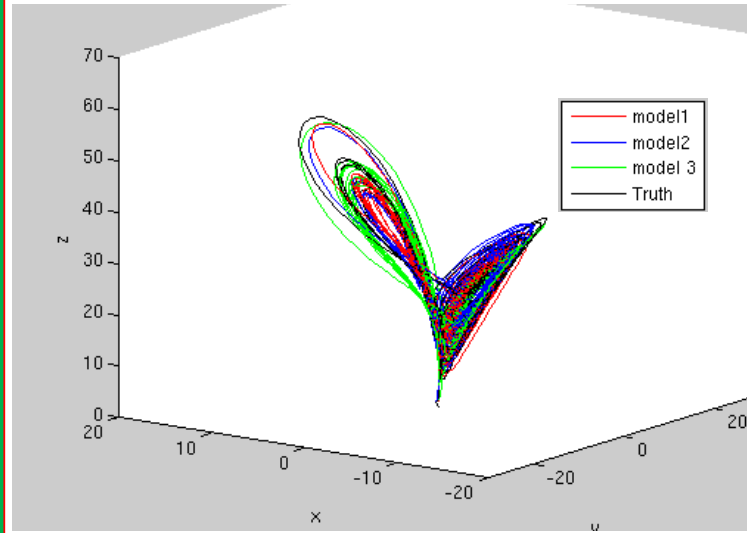
Super ensemble

Mean of unconnected models



Supermodel

Verification





Super modelling

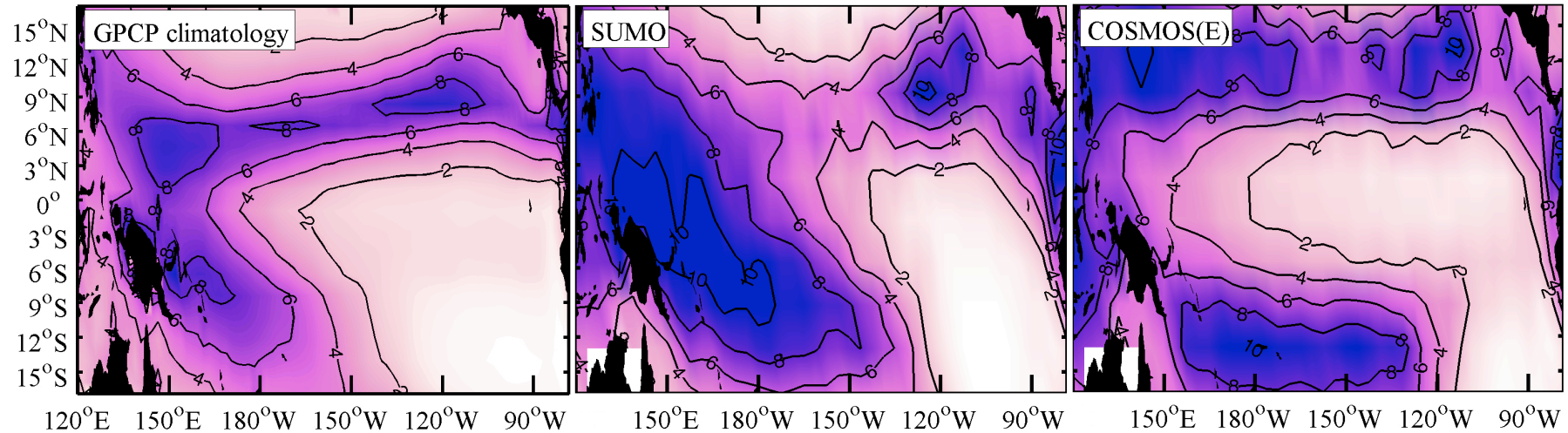
A first attempt with GCM

Climatological Precipitation in Tropical Pacific

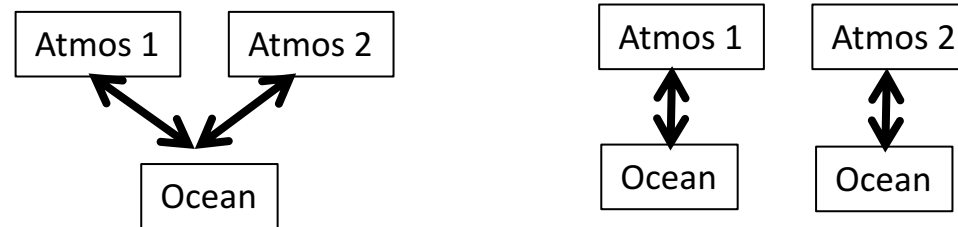
Observed

Super model

Standard ensemble mean

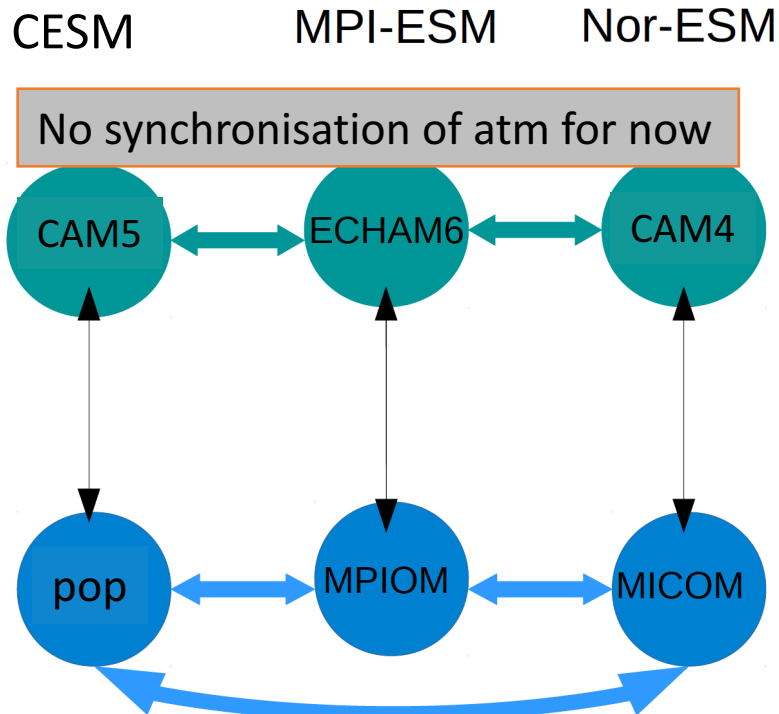


(Shen et al. 2016, 2017)





Super modelling for an earth system model



We use DA to synchronise the system and ensure dynamical consistency and multivariate updates

- We generate synthetic observations (Here mean of models SST, every month) that are assimilated into each individual models (with the EnOI)
- The three models are then propagated
- Possible to assimilate real data in addition

We now start by setting the weight to (1/3,1/3,1/3)

Can the centralized scheme works ?_

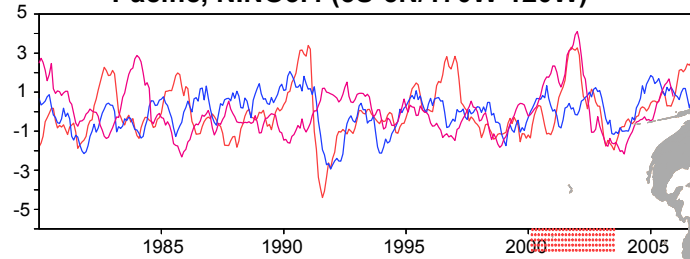
- Does the models synchronized ?
- Is internal variability damped ?



Is variability synchronised ?

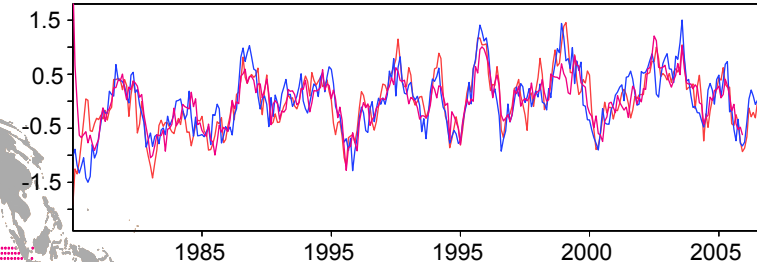
Unconnected

Pacific, NINO3.4 (5S-5N/170W-120W)

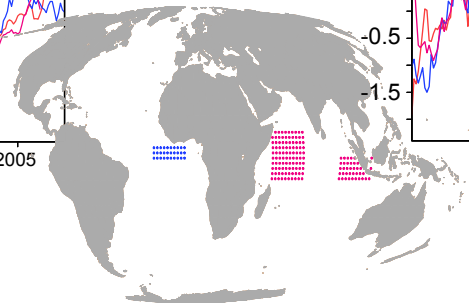


Supermodel

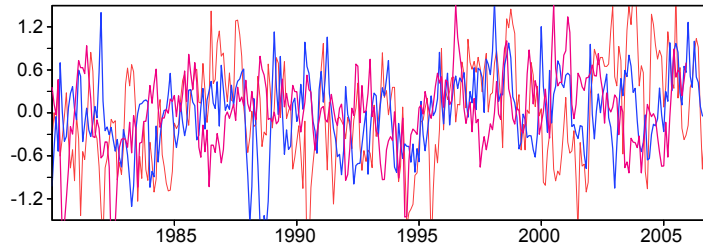
Pacific, NINO3.4 (5S-5N/170W-120W)



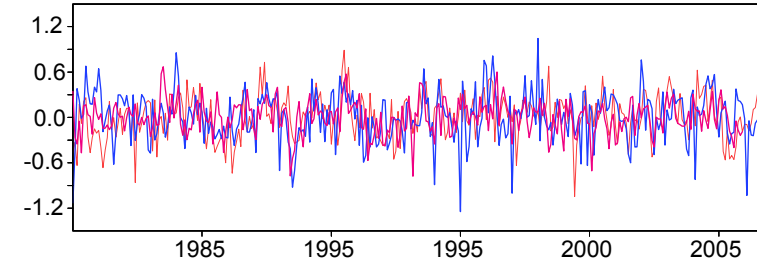
NorESM
MPIESM
CESM



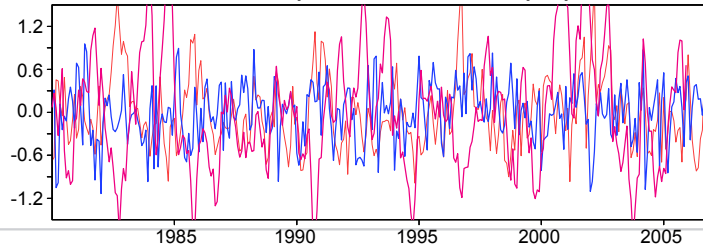
Atlantic, ATL3 (3S-3N/20W-0)



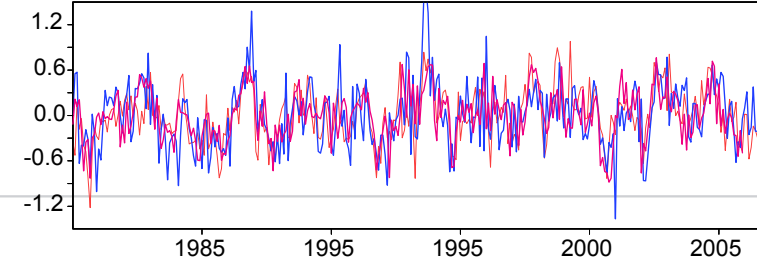
Atlantic, ATL3 (3S-3N/20W-0)



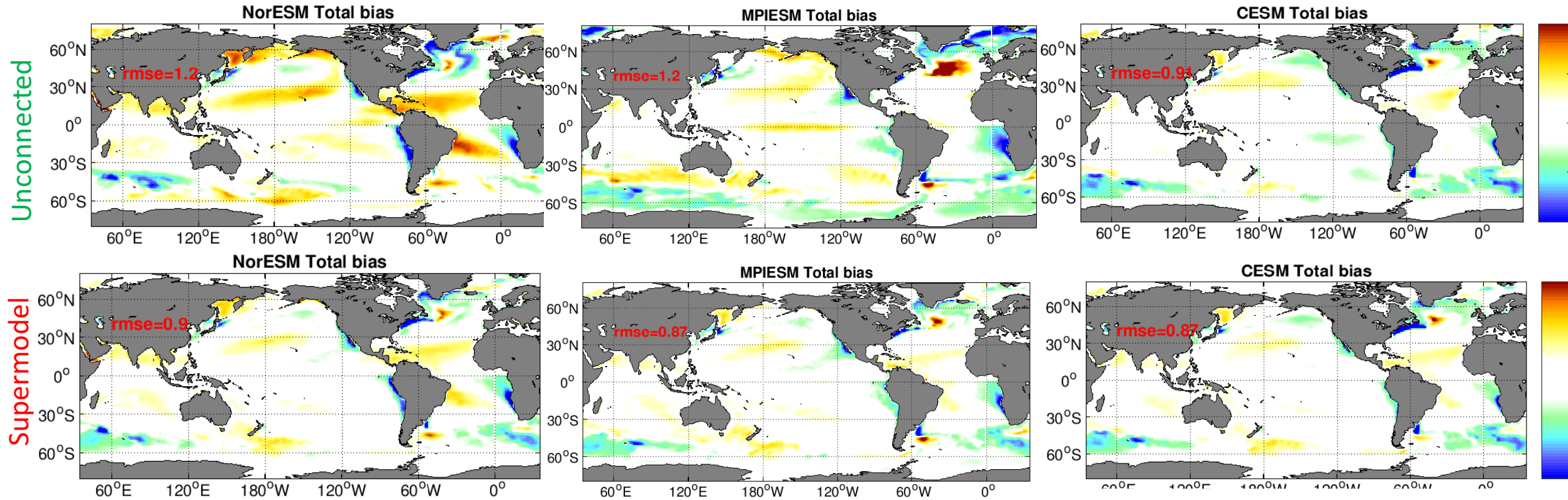
Indian Ocean, IOD (10S-10N/50E-70E) - (10S-0/90E-110E)



Indian Ocean, IOD (10S-10N/50E-70E) - (10S-0/90E-110E)



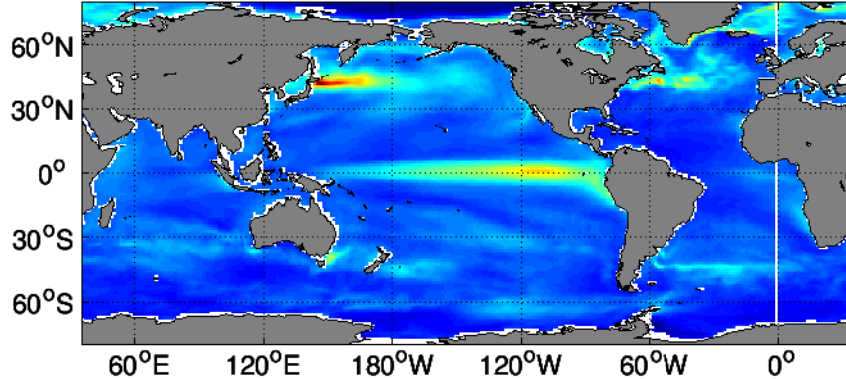
Is bias improved ?



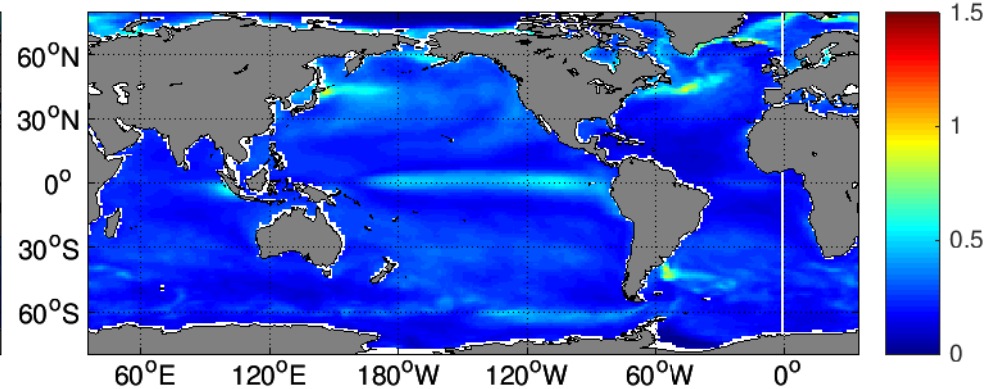
The bias of each model is reduced

Is variability damped ?

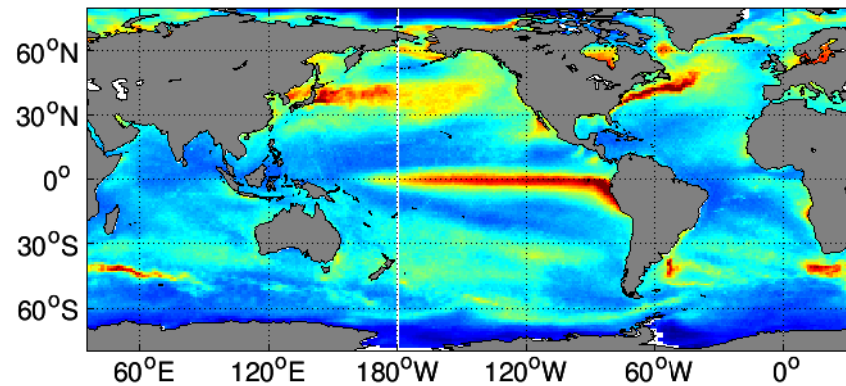
Spread Free SST



Spread SuperM SST



Spread obs SST

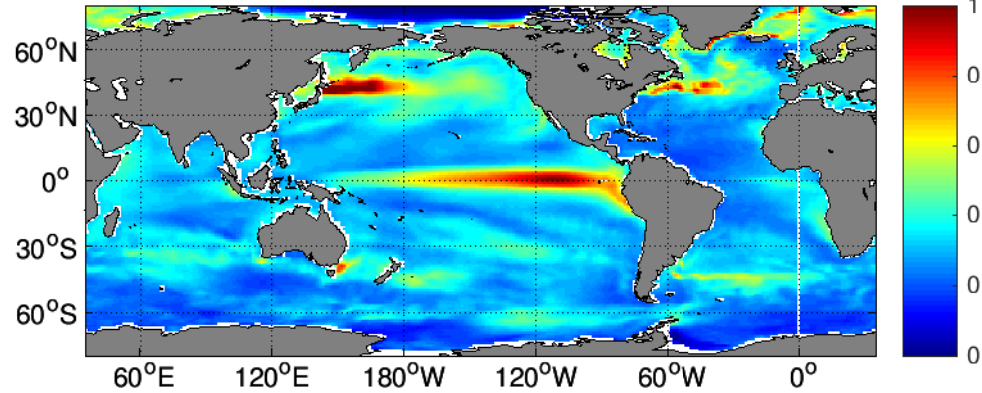


- Variability is even more reduced than taking the mean of unsynchronized model
- Is assimilation of a weighted mean causing an artificial damping of variability ?

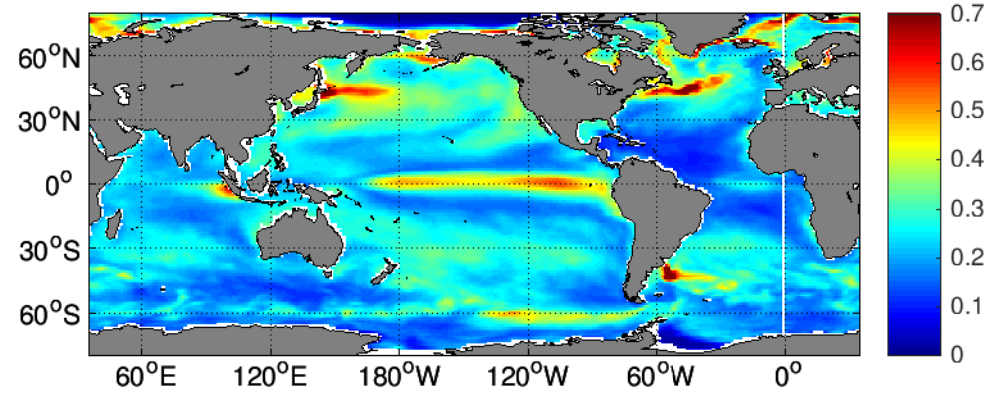


Is variability damped ?

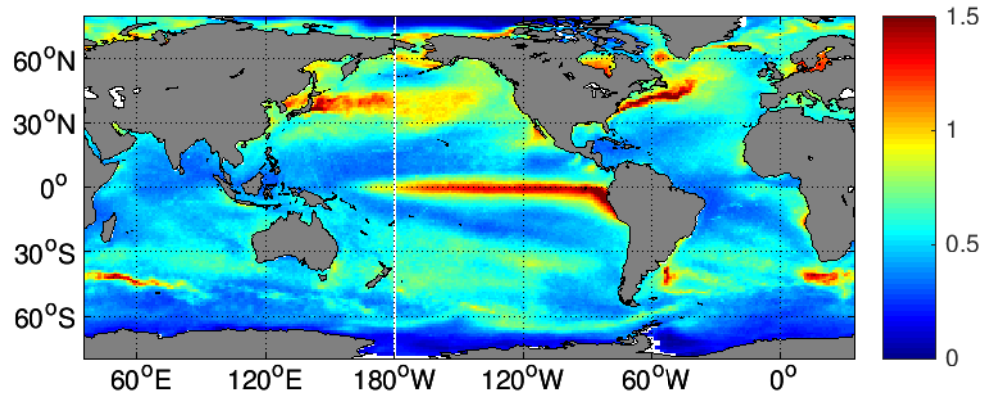
Spread Free SST



Spread SuperM SST



Spread obs SST



If we scale the amplitude, there seems to be a better spatial coherency with the obs

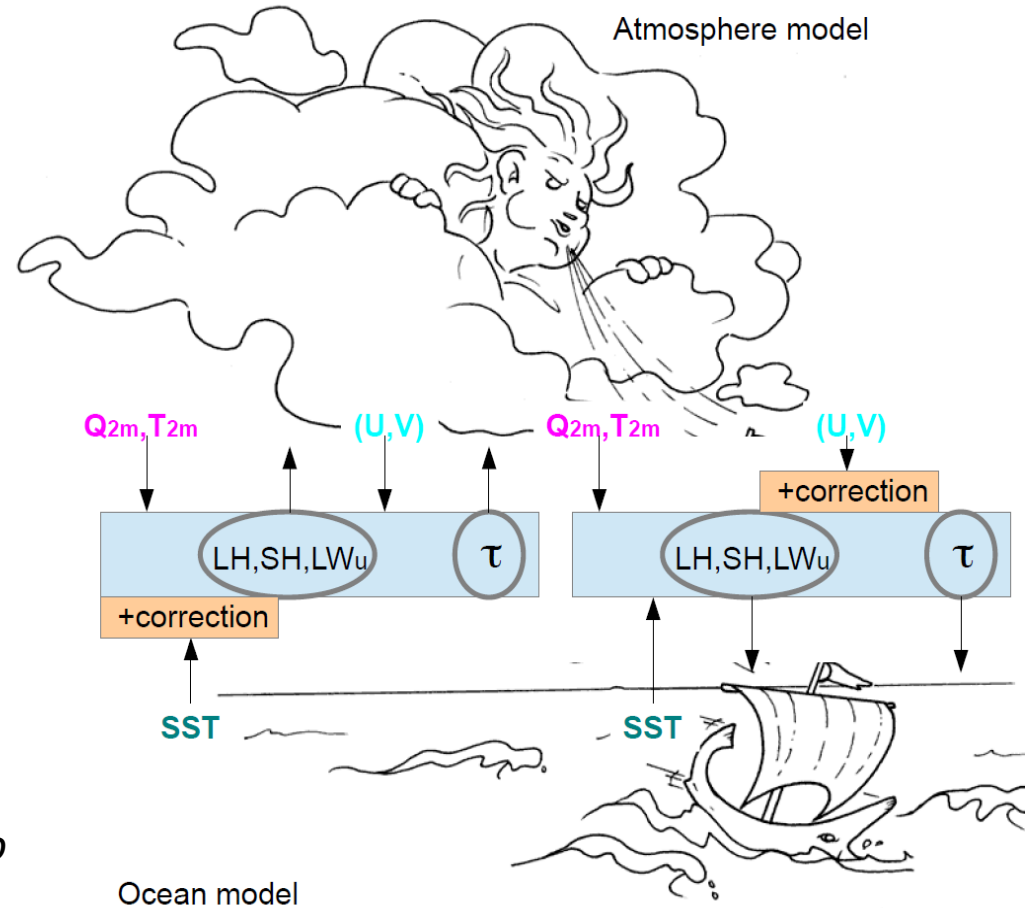


A methodology to correct mean state biases: Anomaly coupled model

Standard flux correction techniques were abandoned because they alter (damp) variability

Here :

- correction estimated with the coupled system
- Estimation is iterative



Correction added to quantities exchanged between atmosphere and ocean

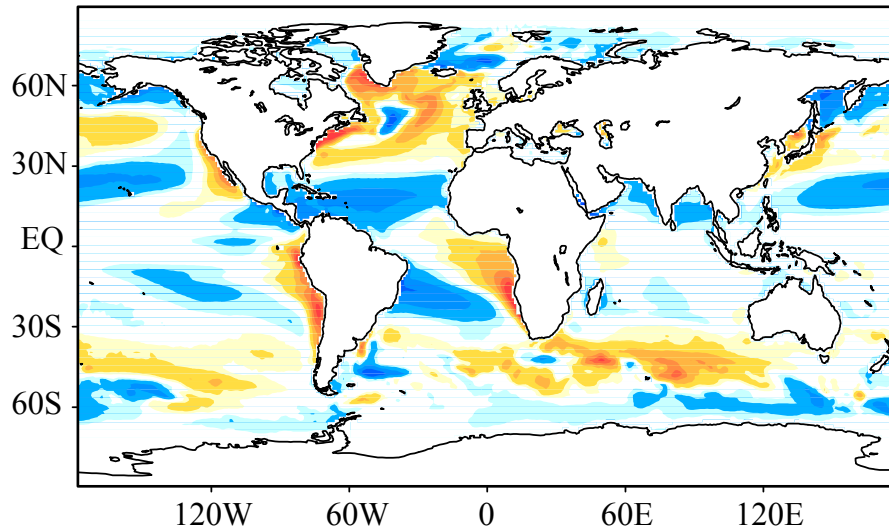
Courtesy: Thomas Toniazzo



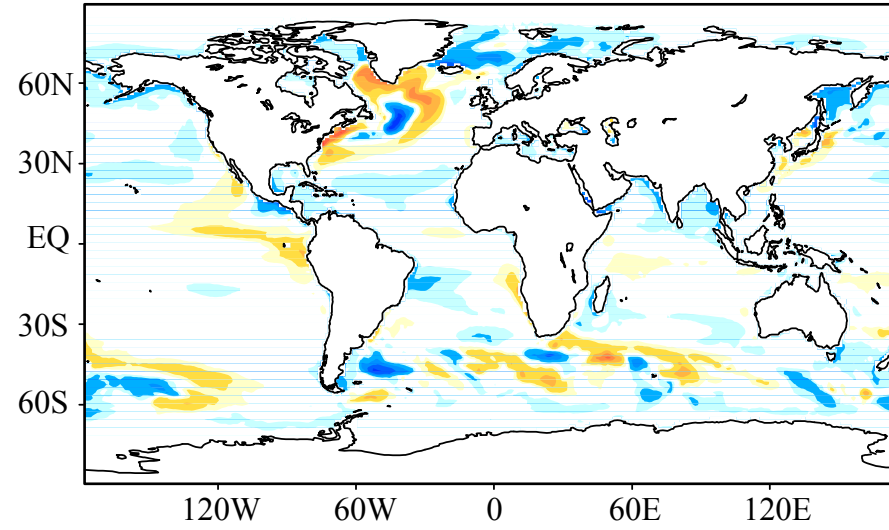
A methodology to correct mean state biases: Anomaly coupled model

An alternative method referred to as anomaly coupling has been implemented and tested with NorESM (Toniazzi and Koseki, 2018)

(a) NorESM_CTL - OISST



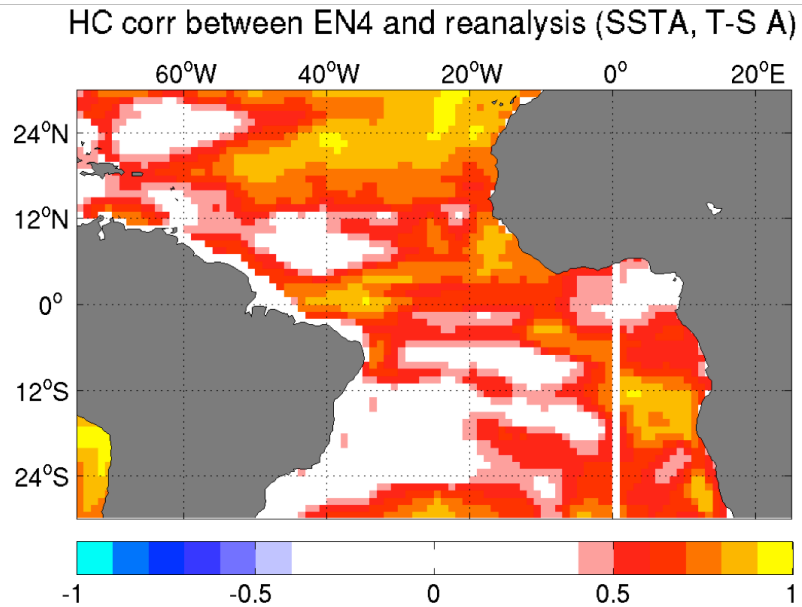
(c) NorESM_AC - OISST



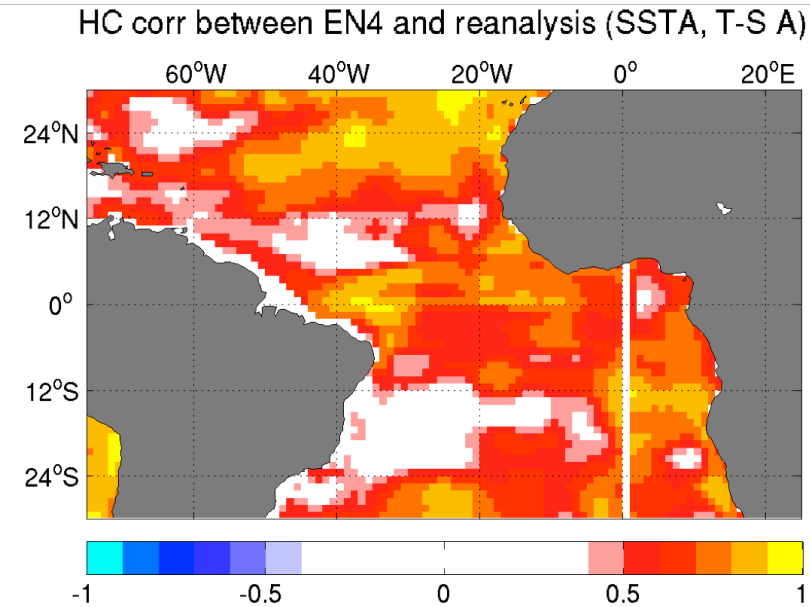
The anomaly coupling approach reduces strongly the bias in the tropics

Reduced biases enhances Comparison of reanalysis with objective analysis

NorCPM reanalysis



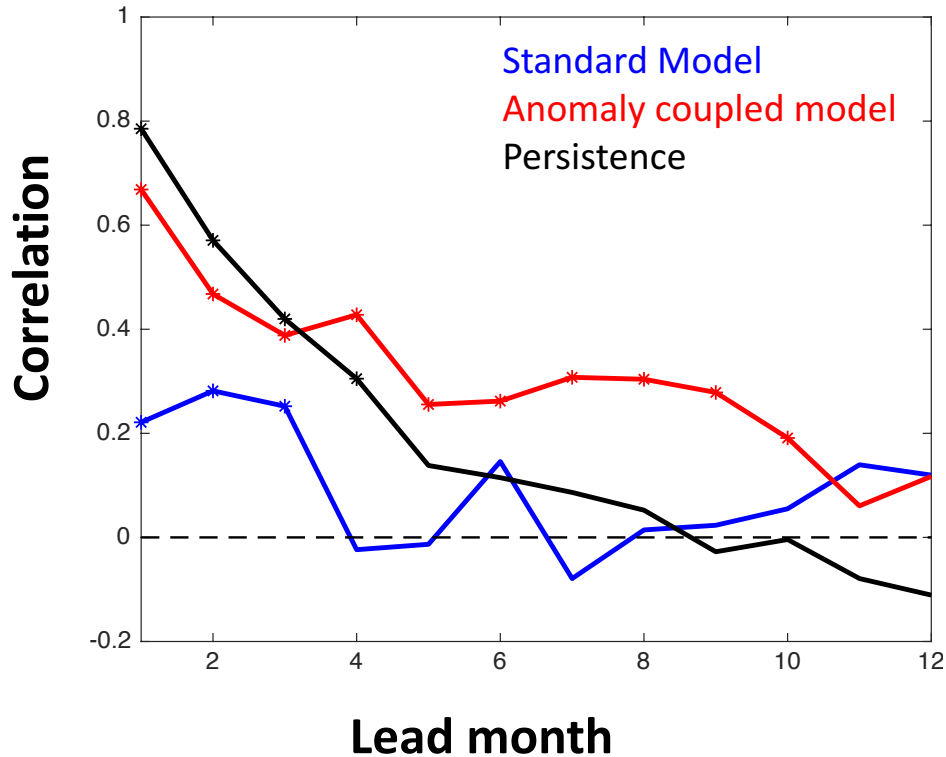
NorCPM anomaly coupled reanalysis



Higher match with assimilated observation in the Tropical Atlantic

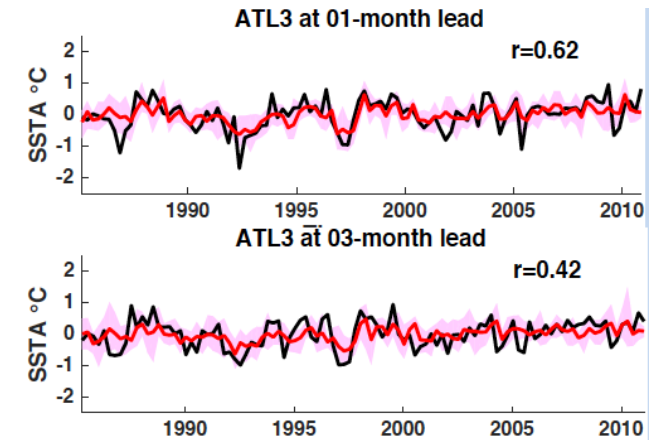
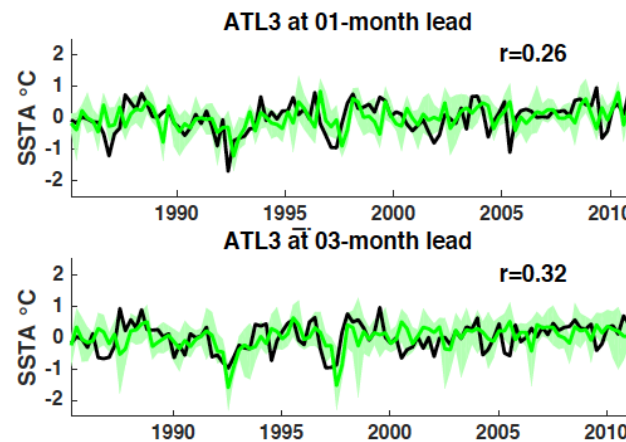


Reduced biases enhances seasonal prediction skill for the Atlantic Niño



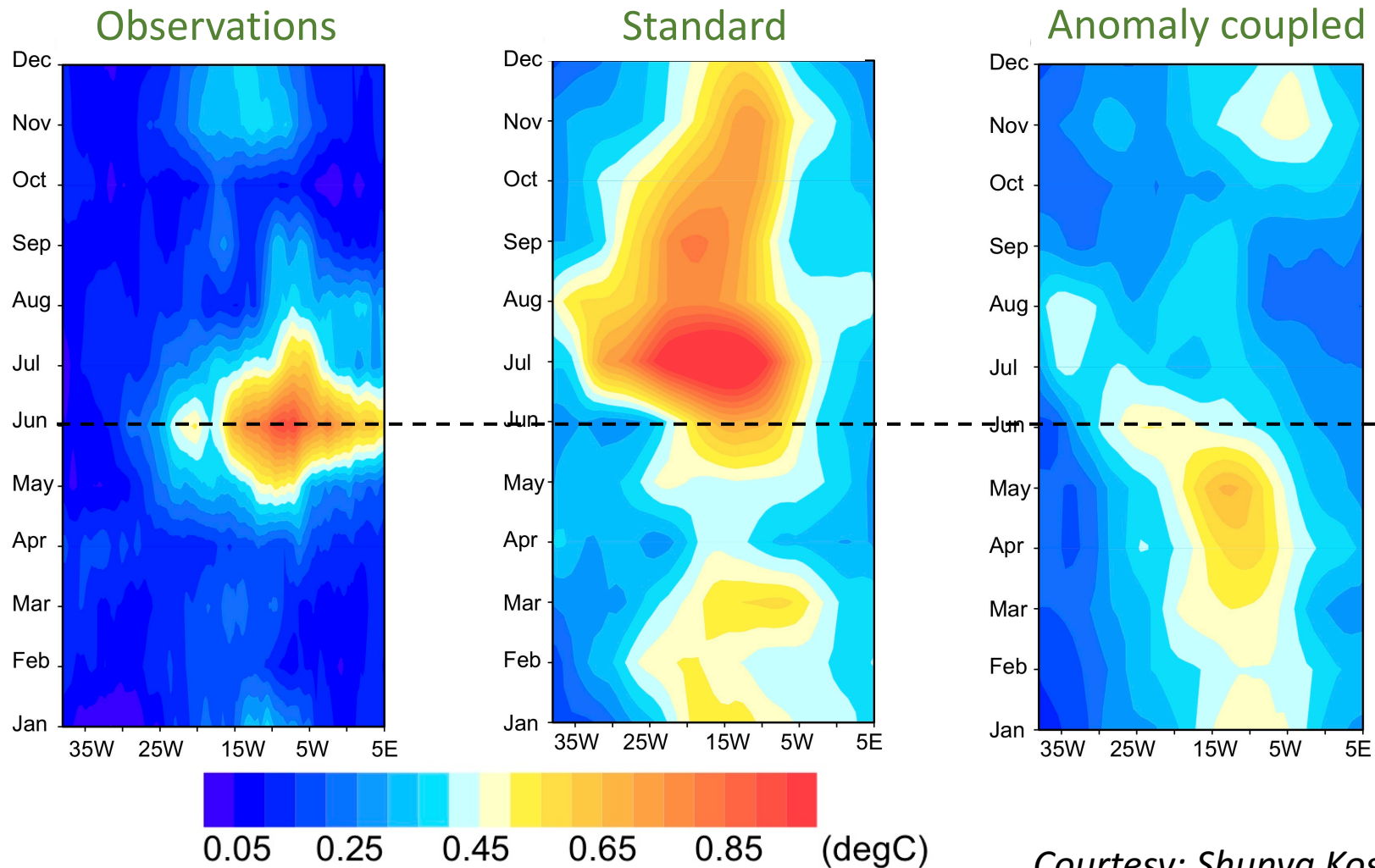
Skill is improved:

- but mechanism of predictability were still misrepresented in some season
- Tendency to dampen the variability of the signal



Reduced bias -> better equatorial variability

Standard deviation of SST along the equator, January - December



Courtesy: Shunya Koseki

Conclusions

Different techniques are tested to reduce model bias and enhance prediction skill

1. Parameter estimation using advance data assimilation have been developed in NorCPM
2. Anomaly coupling reduces bias and improved skill but fails to improve mechanism of predictability in all seasons and tends to damp variability
3. Supermodel allow a reduction of bias using models as black box
 - It worked well with idealized model
 - Show promising result for a GCM with two atmospheres
 - Use DA to synchronised 3 ESMs:
 - ESMs are synchronised and bias reduced but variability totally damped
 - ➔ Need to identify why the implementation induce and artificial damping