Supermodeling for improving the representation of climate variability

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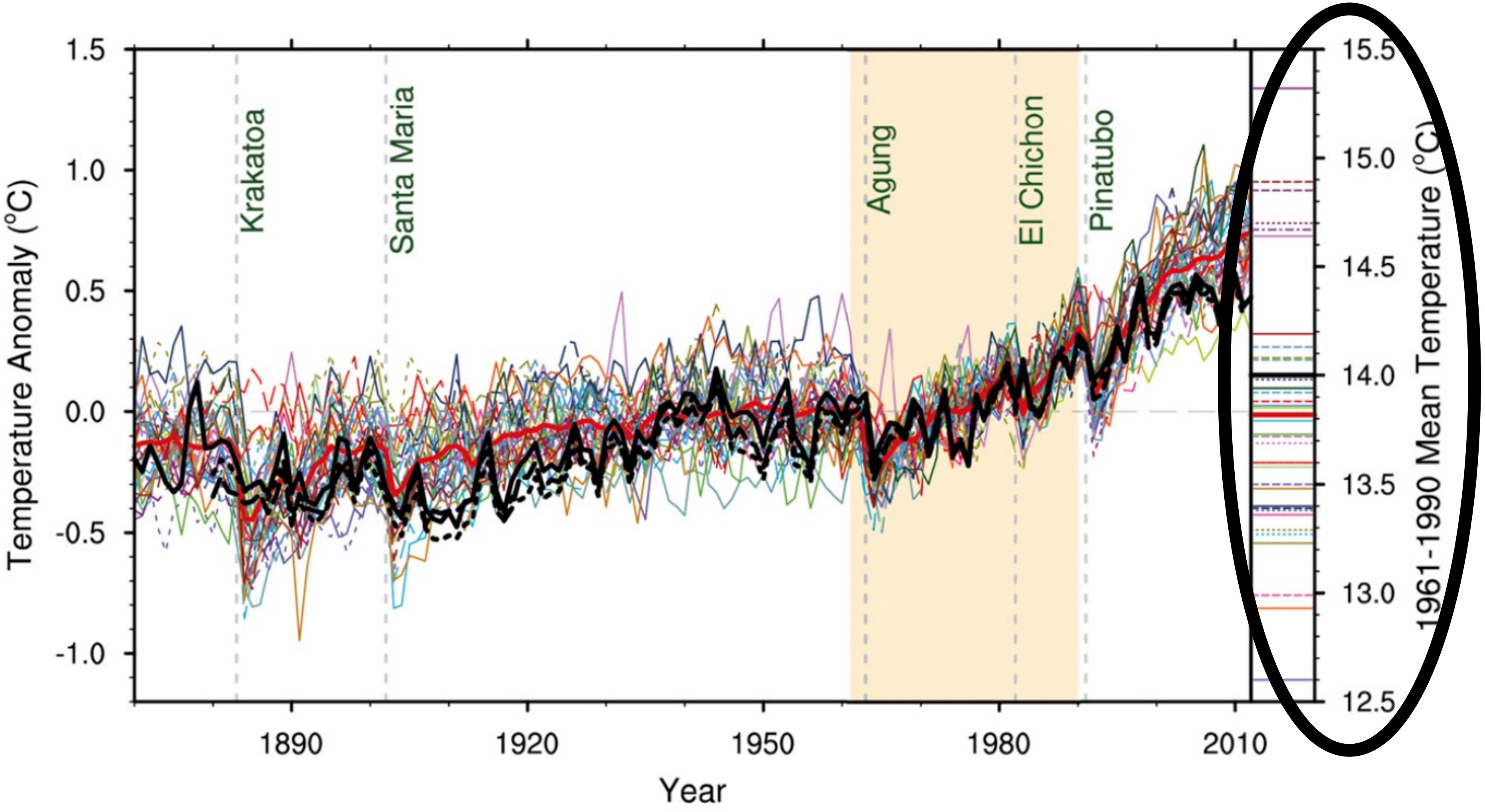
Bias is often larger than the signal we analyze or predict



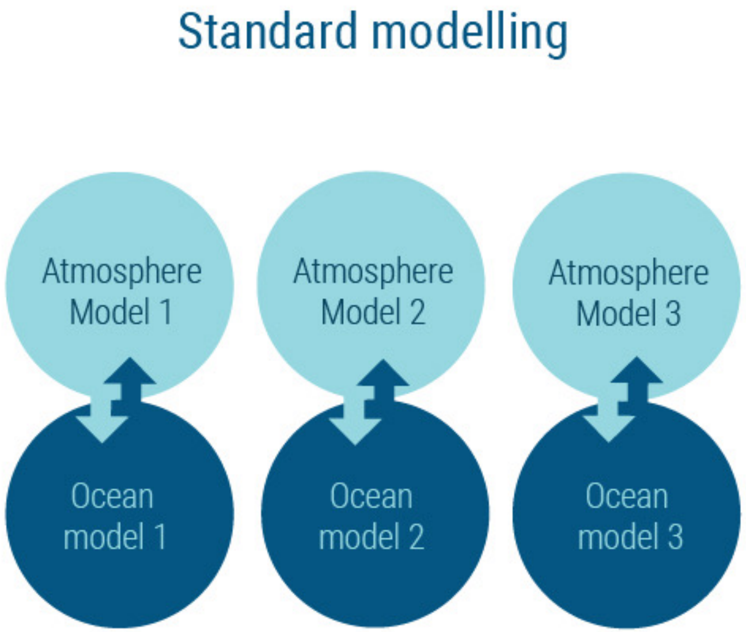
Palmer and Stevens, PNAS, 2019

Standard modelling

A standard approach to handle such bias is to take the multi-model mean, but
- It does not correct non-linear responses (e.g., climate sensitivity)
- Challenging to assess internal variability

Parameter estimation can effectively reduce bias, but:
- Parameters are not necessarily continuous
- Hard to disentangle bias origin in a coupled system
- We can train climate sensitivity but

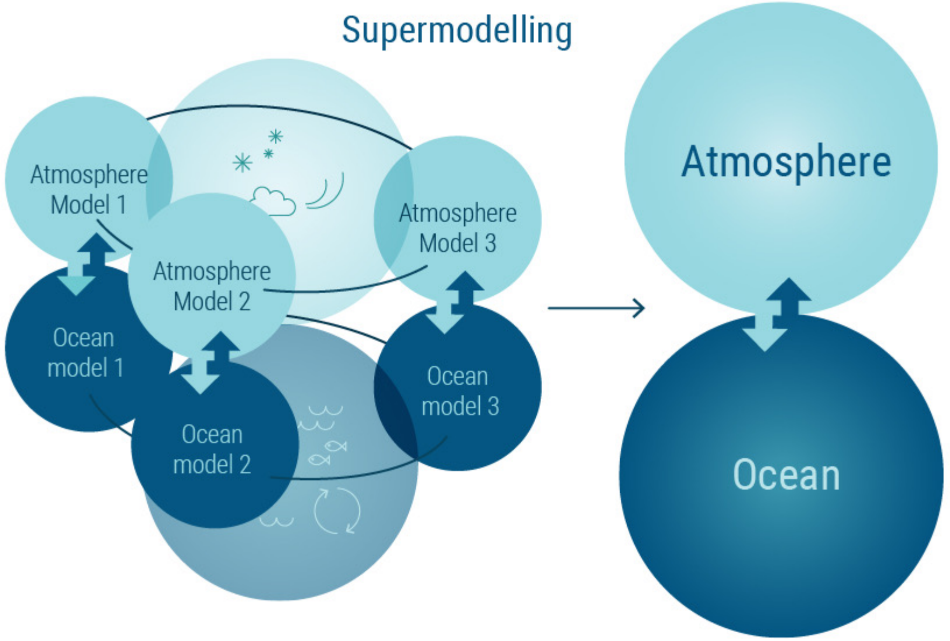
what is the independent validation period

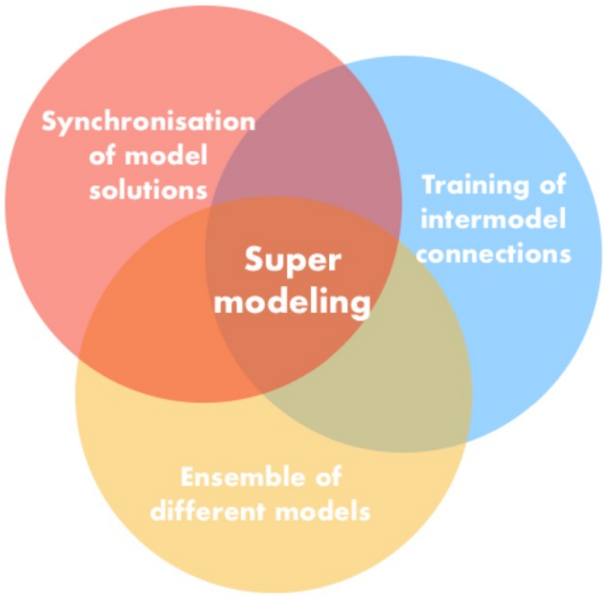


Supermodelling

The different models are connected as they run :

- As models synchronise, internal variability of the multi-model mean is preserved
- Model diversity is used to train a better climate model

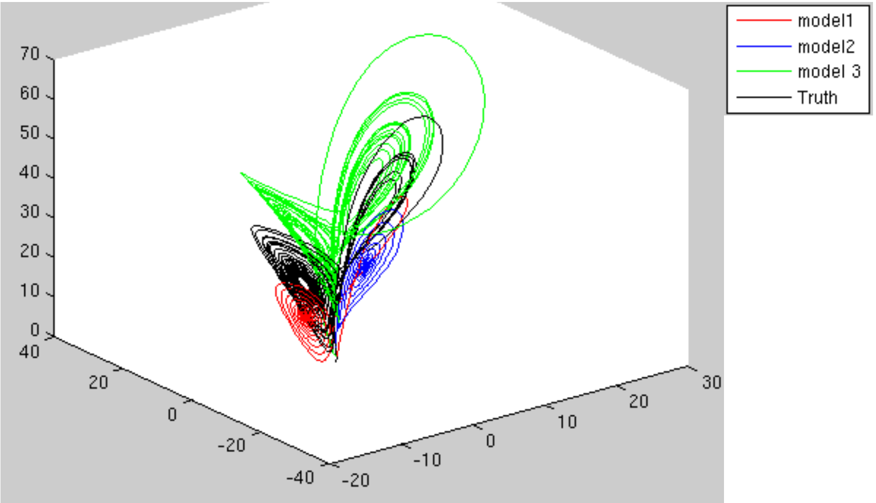




An example with L63

	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

$$\dot{x} = \sigma(y - x)$$
$$\dot{y} = x(\rho\text{-z})\text{-y}$$
$$\dot{z} = xy\text{-}\beta z$$



A super model add connections to the other imperfect models

Example:

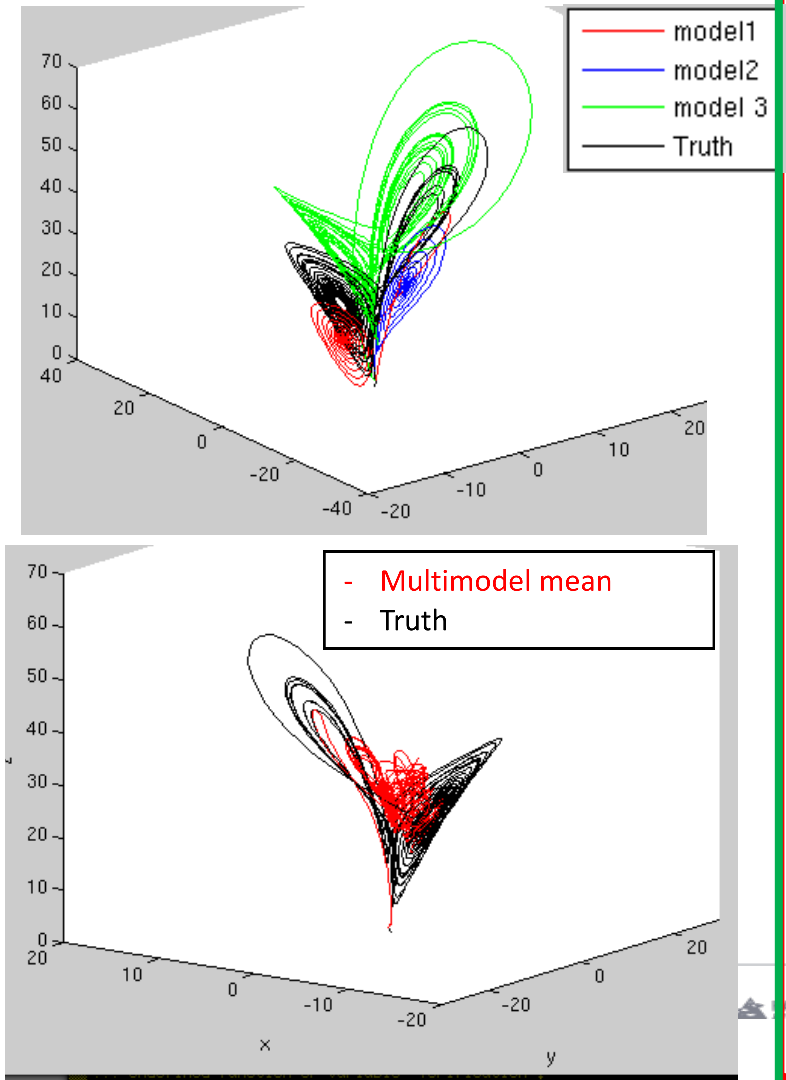
$$\dot{x}_1 = \sigma_1(y_1 - x_1) + \underbrace{C^x_{12}(x_2 - x_1) + C^x_{13}(x_3 - x_1)}_{\text{Nudging to other models}}$$

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

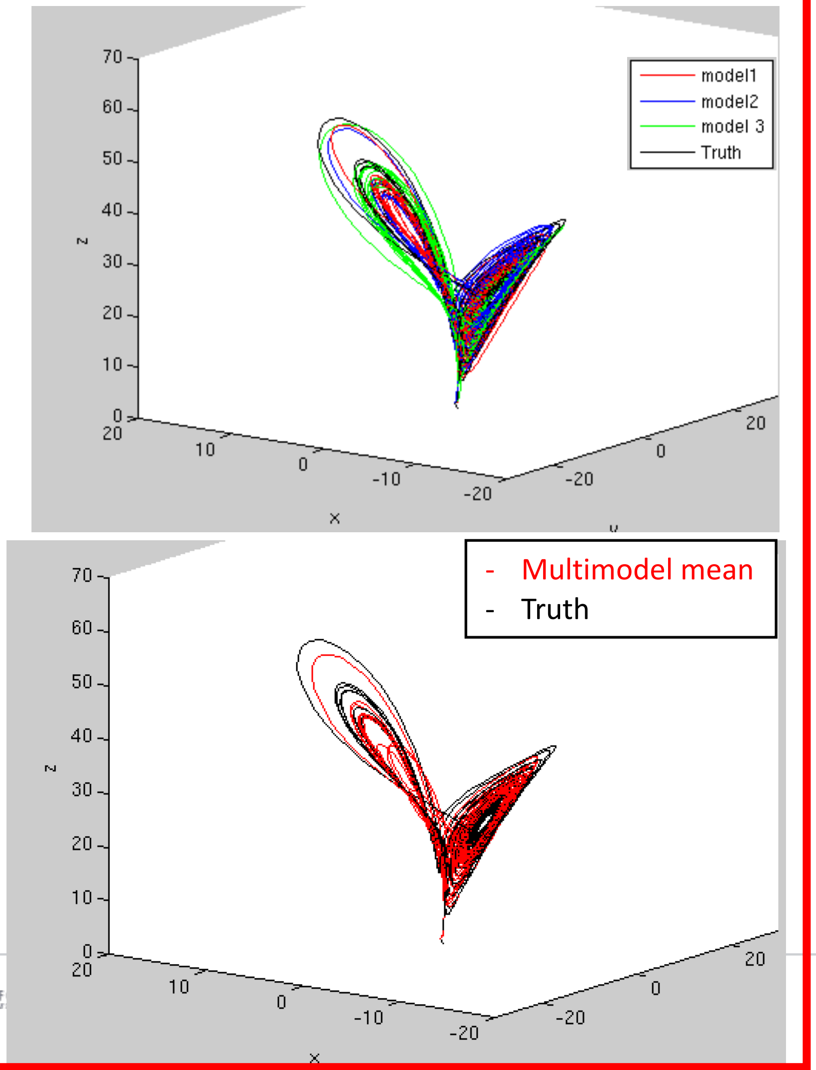
In **verification phase:** coefficients are frozen and the system can be used as a new dynamical system

Supermodel verification

Unconnected mean



Supermodel



- All models have corrected the bias
- Internal variability is in line with the truth

Van den Berge et al. 2011

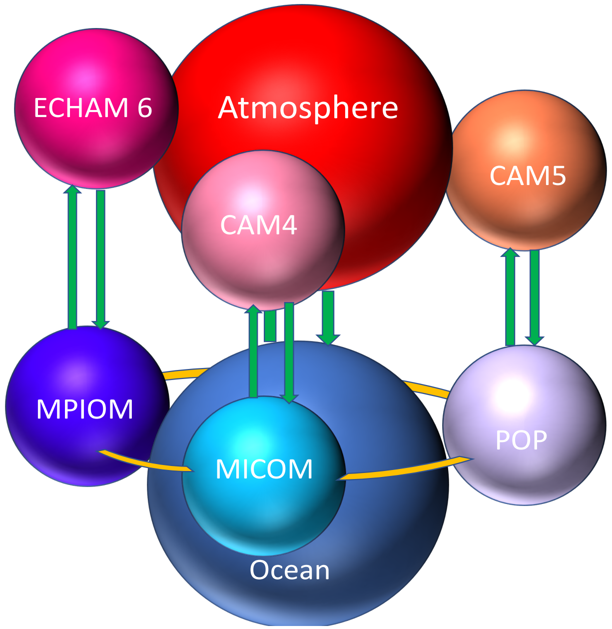
Supermodelling

Supermodels are demonstrated with idealised models, but their application to climate models is challenging because they **do not share the same state space, grid and resolution**

Can data assimilation provide a framework to handle this challenge ?

An ocean connected super-ESM with DA

Model version	Ocean	atmosphere
NorESM1-ME	MICOM(σ; 1°)	CAM4 (finite-volume, 2°)
CESM1.1.2	POP2 (z, 1°)	CAM5 (finite-volume, 1°)
MPI-ESM1-LR	MPIOM (z,1.5°)	ECHAM6 (spectral, 2°)



Recursive approach:

1. models are propagated for 1 month
2. Generate pseudo-observations (from SST; *i.e.*, weighted mean)
3. Assimilate the pseudo-observations back into each model (correct the full ocean state) with the Ensemble Optimal Interpolation

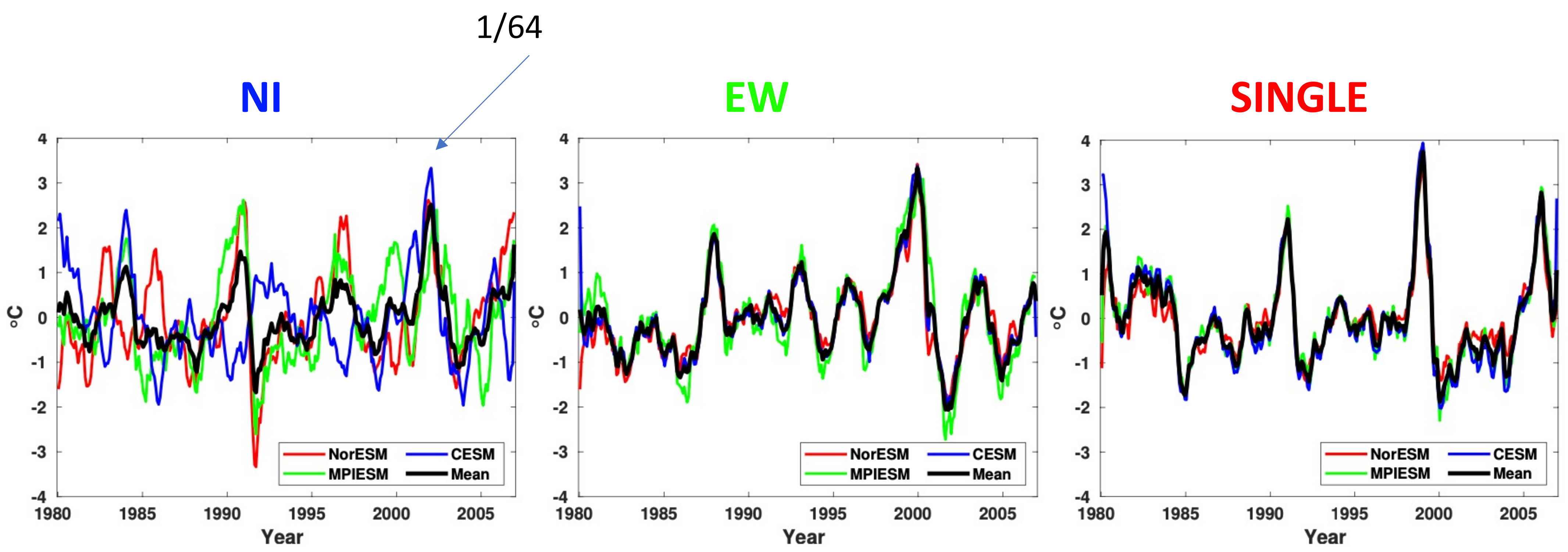
11 nodes 1408 CPU, ~10 model-year per day (on BullSequana XH2000)

Can synchronisation be achieved ?

We compare the performance of different approaches for 1980-2006:

1. A posteriori averaging of non-interactive models (**NI**)
2. Supermodel with equal weight (**EW**)
3. Supermodel where all models are attracted to a single model (**SINGLE**)

ENSO variability (NINO 3.4)



- Internal variability in the Nino 3.4 seems well synchronised.
- Is internal variability damped?

Synchronisation and damping metrics

If we decompose the model as the sum of the muli-model mean and anomaly

$$\mathbf{x}_i^j = \mathbf{x}_i^s + \mathbf{a}_i^j,$$

its time variability is :

$$\sigma_j^2 = \sigma_s^2 + \sigma_{aj}^2,$$

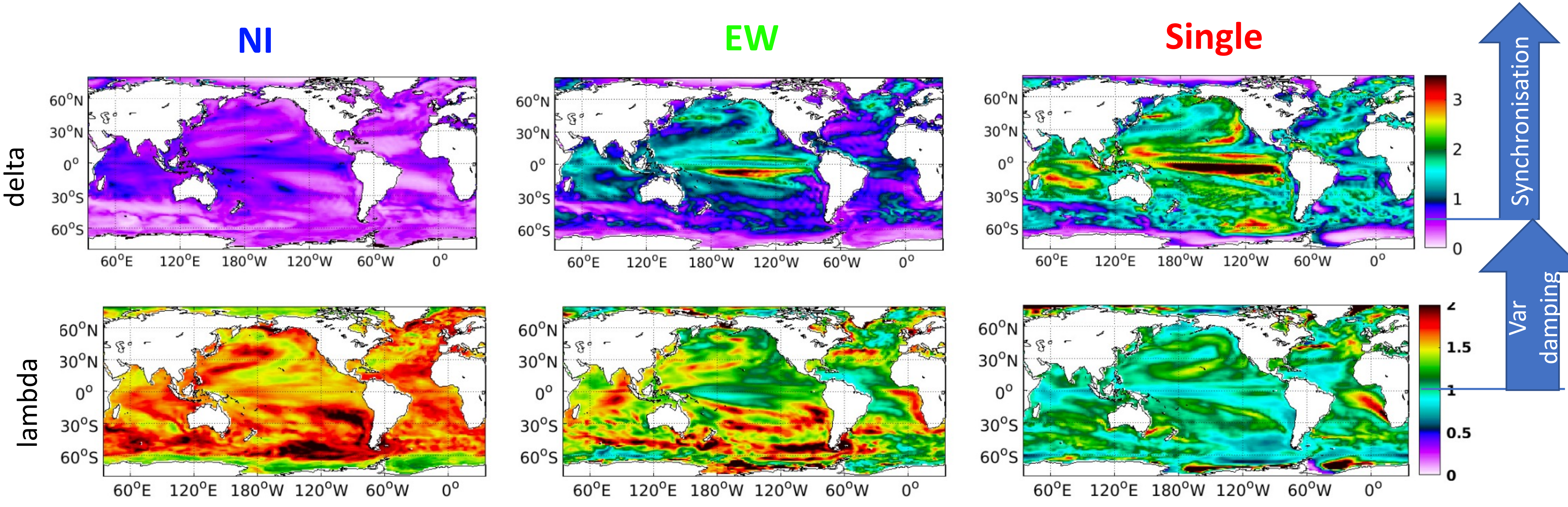
$$\delta^2 = \frac{\sigma_s^2}{\frac{1}{N_s}\sum_{j=1}^{N_s}\sigma_{aj}^2}$$

Quantifies how well the multi-model are synchronized
=1/(N-1) for a random process

$$\lambda^2 = \frac{\frac{1}{N_s}\sum_{i=1}^{N_s}\sigma_j^2}{\sigma_s^2}$$

Quantifies whether the time standard deviation is
damped (=1 mean no damping)

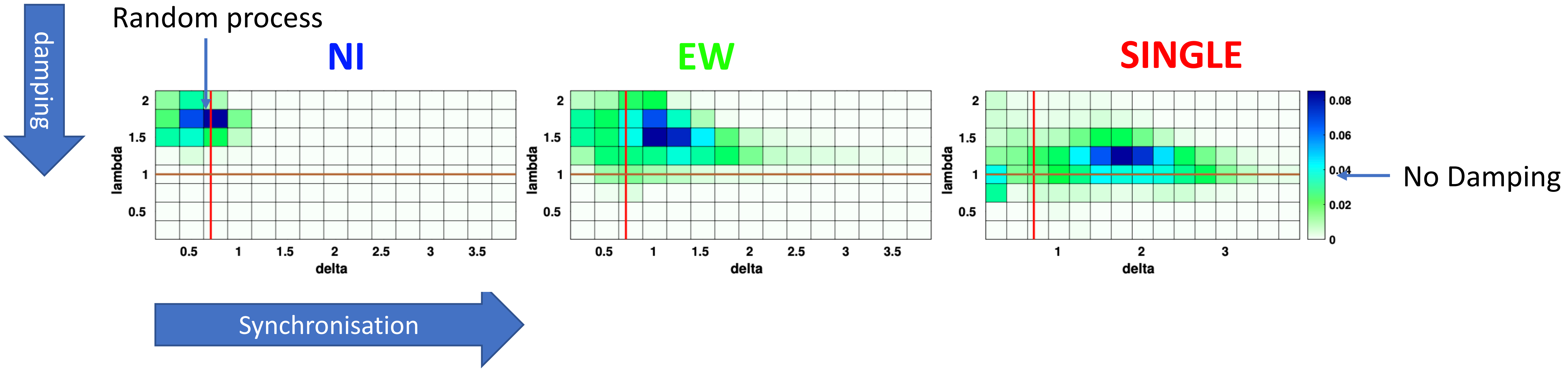
SST synchronization and damping



- **Tropical Pacific is well-connected (also Nordic Seas)**
- **Damping in the variability of the ensemble mean is reduced**

Synchronisation with partial synchronisation

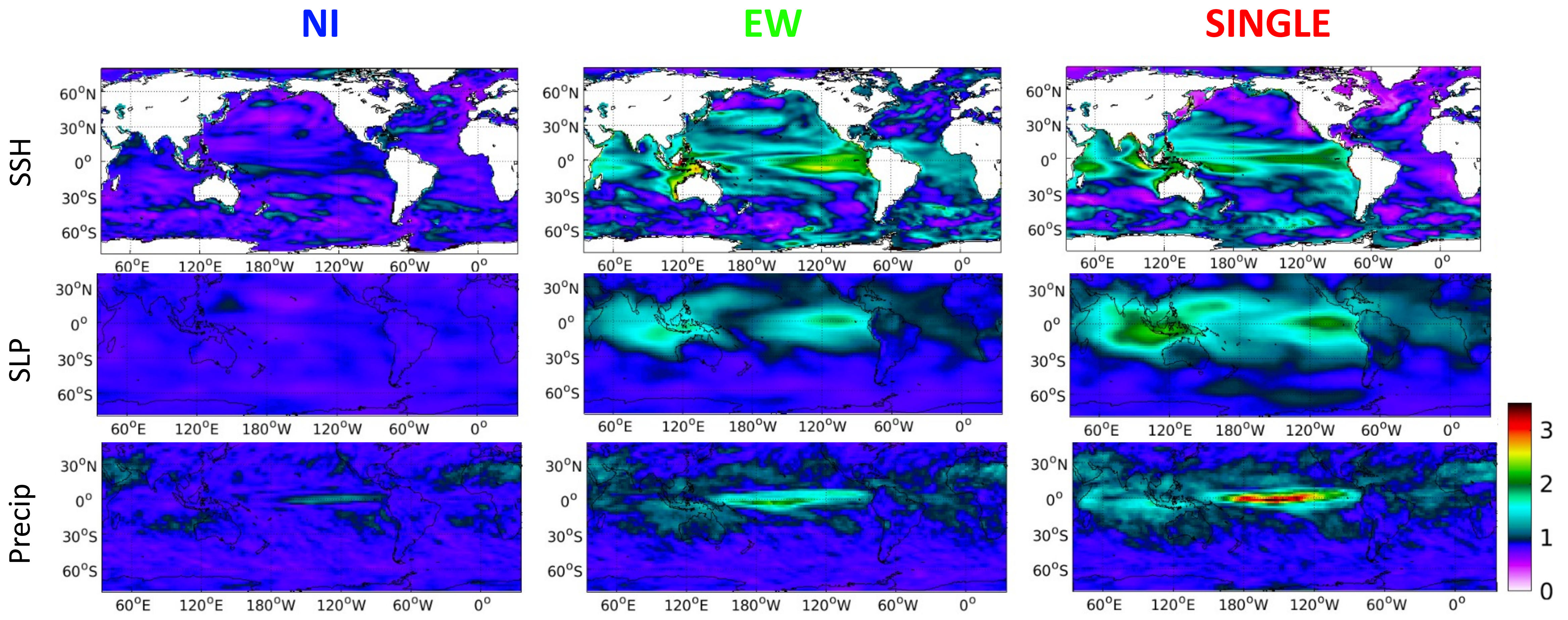
2D pdf of synchronisation and damping



Damping is reduced where synchronization is achieved

The damping also affects variability of the individual models in EW !

Synchronization in ocean interior and atmosphere



Synchronization is multivariate

Supermodel with simple training

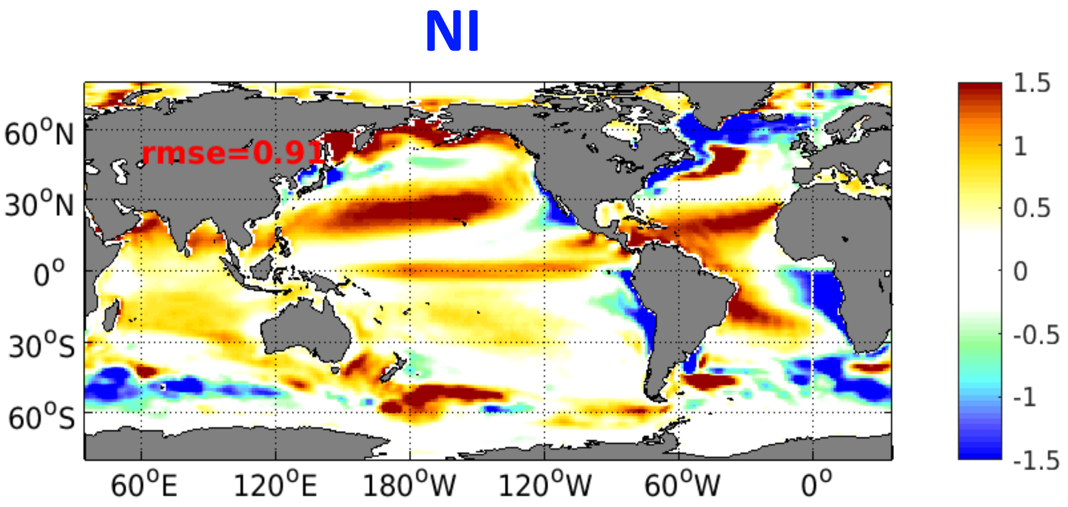
Supermodel with spatially and monthly varying trained weight (**TW**).

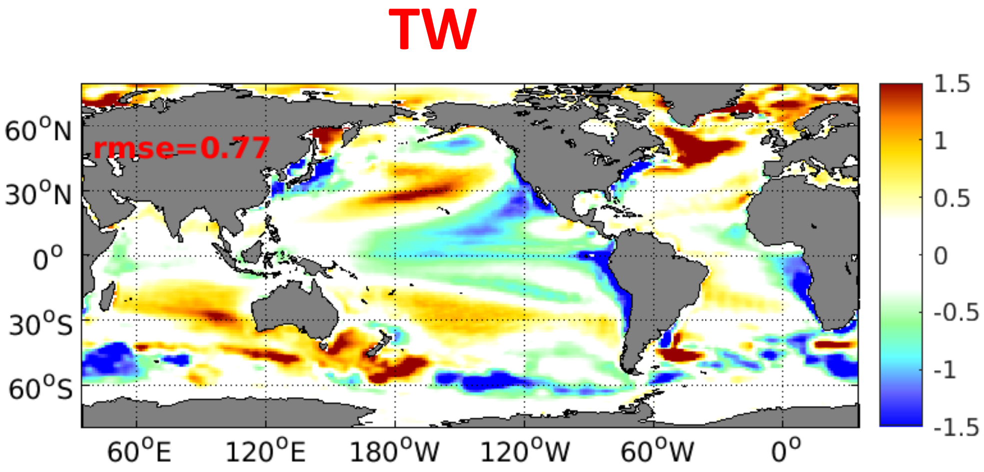
Weights (positive and normalized) are estimated offline from individual model SST biases (1980-2005)

$$w_i \propto \exp\left(-\frac{1}{2}(\mathbf{Hx}_i - \mathbf{d})^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{Hx}_i - \mathbf{d})\right),$$

We verify the performance of the bias for the period 2006 -2021 compared to NI

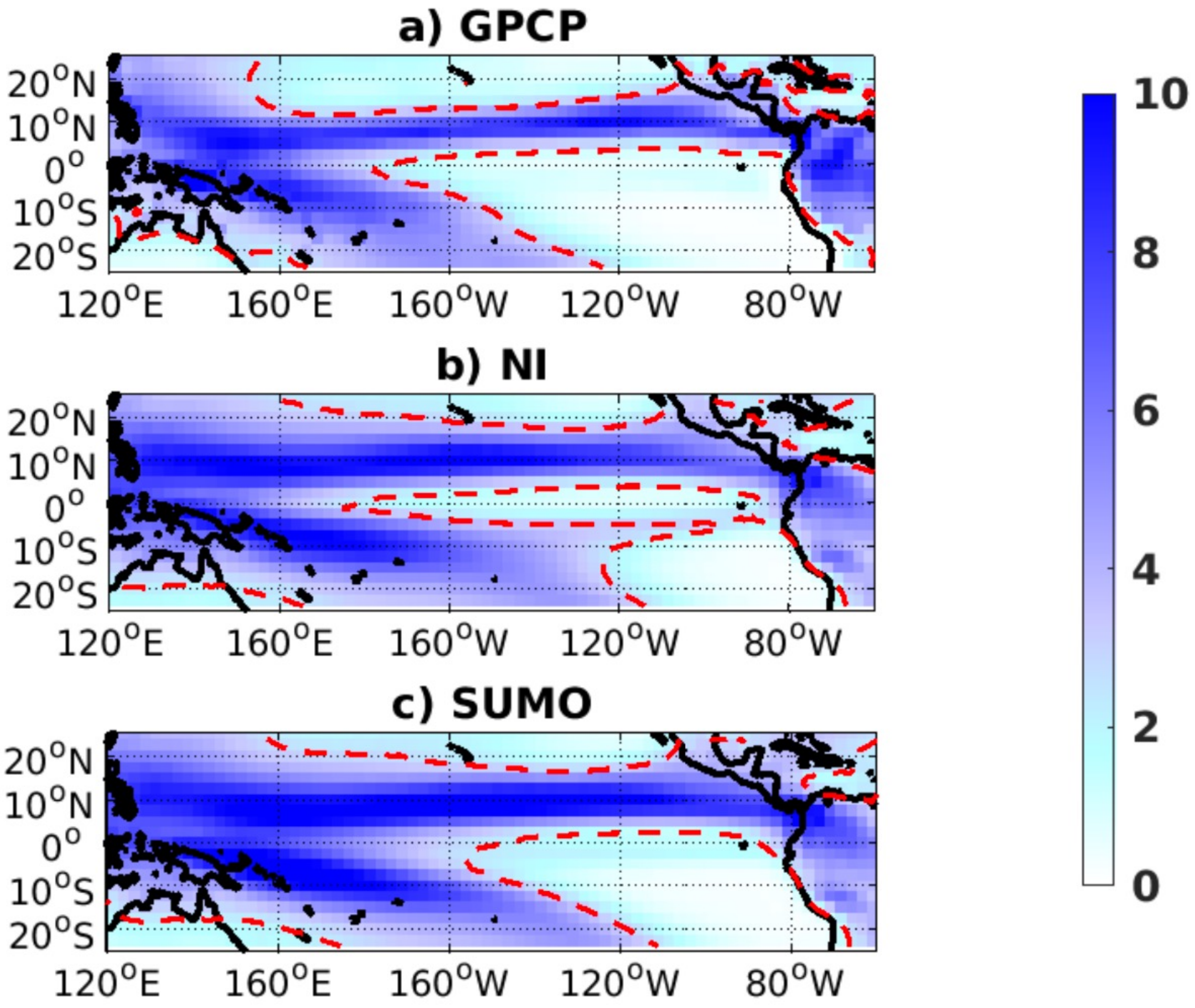
Multi-model mean SST bias (2006-2021)





Supermodelling reduces SST model biases

Annual-mean precipitation climatology in the tropical Pacific



Schevenhoven et al. sub

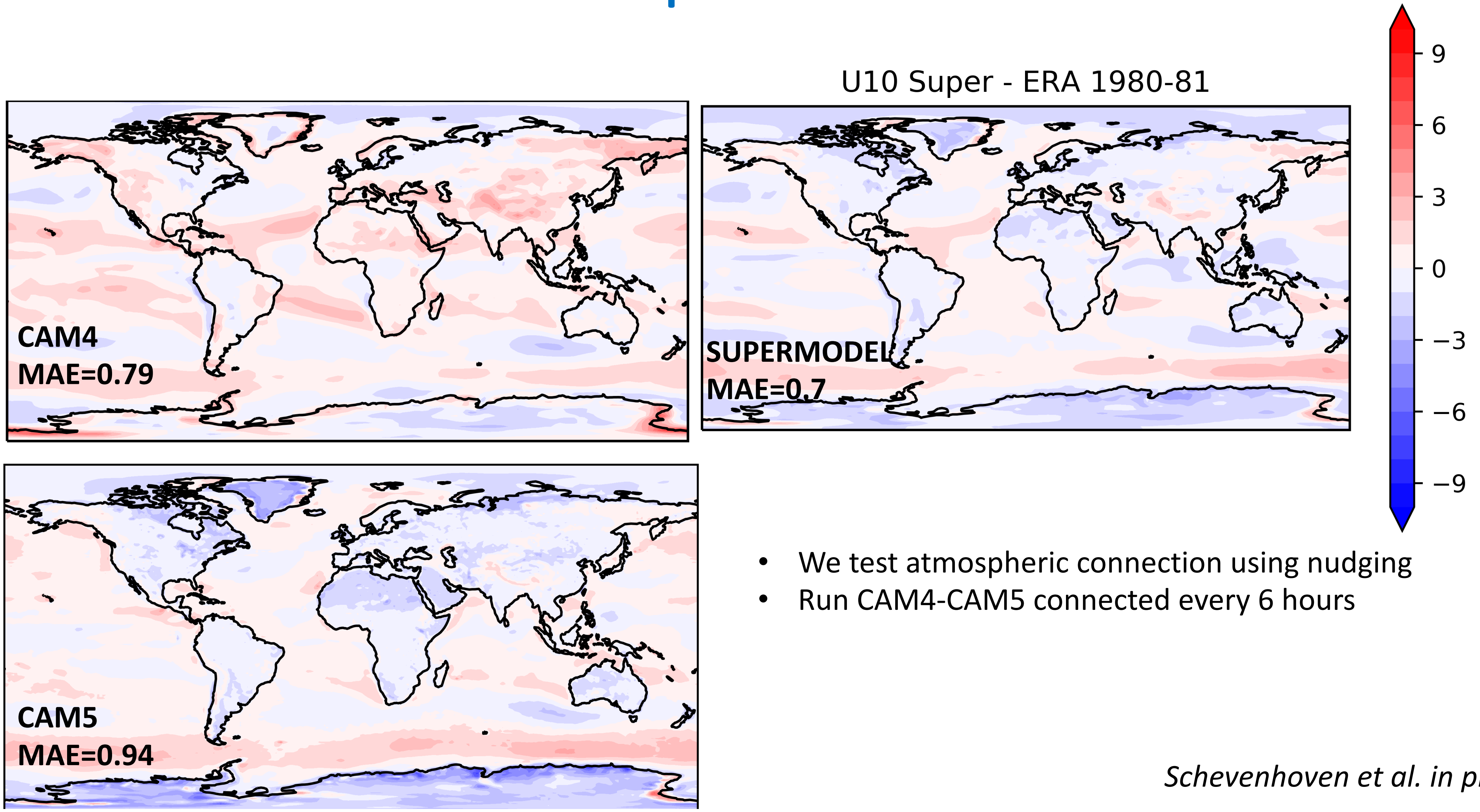
It mitigates the double ITCZ problem !

Summary

- A supermodel based on 3 ESMs is connected by ocean assimilation
- Monthly synchronisation (via SST) can achieve partial synchronisation
- Weighted mean supermodel causes damping of variability under partial synchronisation
- Supermodel reduces SST and precipitation biases where synchronization is achieved
- Improvements greater than the standard ensemble mean, because of non-linear properties of the climate system
- Atmospheric synchronisation is ongoing

- Counillon, F et al. . Framework for an ocean-connected supermodel of the Earth System, JAMES 2023
- Schevenhoven, F., et al. . Supermodeling: improving predictions with an ensemble of interacting models, submitted to BAMS

Atmosphere connection



- We test atmospheric connection using nudging
- Run CAM4-CAM5 connected every 6 hours

Schevenhoven et al. in prep

Future steps

- Test the added value for prediction
- Improve synchronization by increasing the frequency of synchronization steps and synchronising other components (atmosphere, ice , land, …)
- Handle the damping issue by adding a surrogate model in the pseudo-observation of the unsynchronised processes
- Use supermodel for downscaling (synchronisation between outer and inner model)
- Can we connect the models via the cloud ?

- Van den Berge, L.A., Selten, F.M., Wiegerinck, W.A.J.J. and Duane, G.S., 2011. A multi-model ensemble method that combines imperfect models through learning. Earth System Dynamics, 2(1), pp.161-177.

- Counillon, F., et al. "Framework for an Ocean-Connected Supermodel of the Earth System." *Journal of Advances in Modeling Earth Systems* 15.3 (2023): e2022MS003310.

- Schevenhoven, F., Keenlyside, N., Carrassi, A., Counillon, F., Devilliers, M., Koseki, S., Duane, G. (submitted). Supermodeling: improving predictions with an ensemble of interacting models. BAMS.