

# A variant of the anomaly intialisation approach for global climate forecast models



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## A – Background

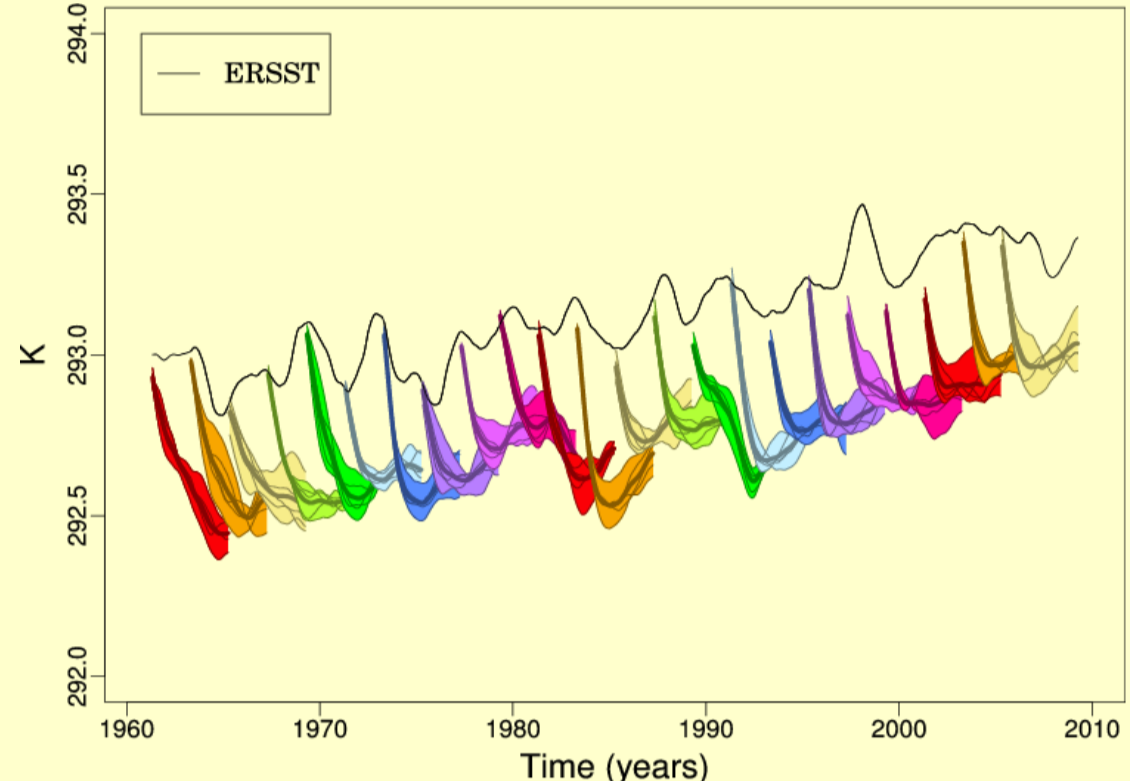
With the aim of comparing the prediction skill of the model initialised with different techniques we compare:

➤ **Full field initialisation (FFI)** experiment, where the model is initialised with an estimate of the contemporaneous observed state (the reanalysis):

$$x^a = x^b + H^T [y^o - Hx^b] \quad (A1)$$

- $x^a$  → initial condition
- $x^b$  → background field (from a long run of the model)
- $H$  → observation operator ( $H=I$  in these experiments)

Sea surface temperature in FFI experiment



**Drawback:** the model drifts towards its preferred climate state

➤ **Anomaly initialisation (AI)** experiment, where the phase of the simulated variability is constrained towards the contemporaneous observed one, at the initialisation time. The model initial state is given by the observed anomalies plus the model climate:

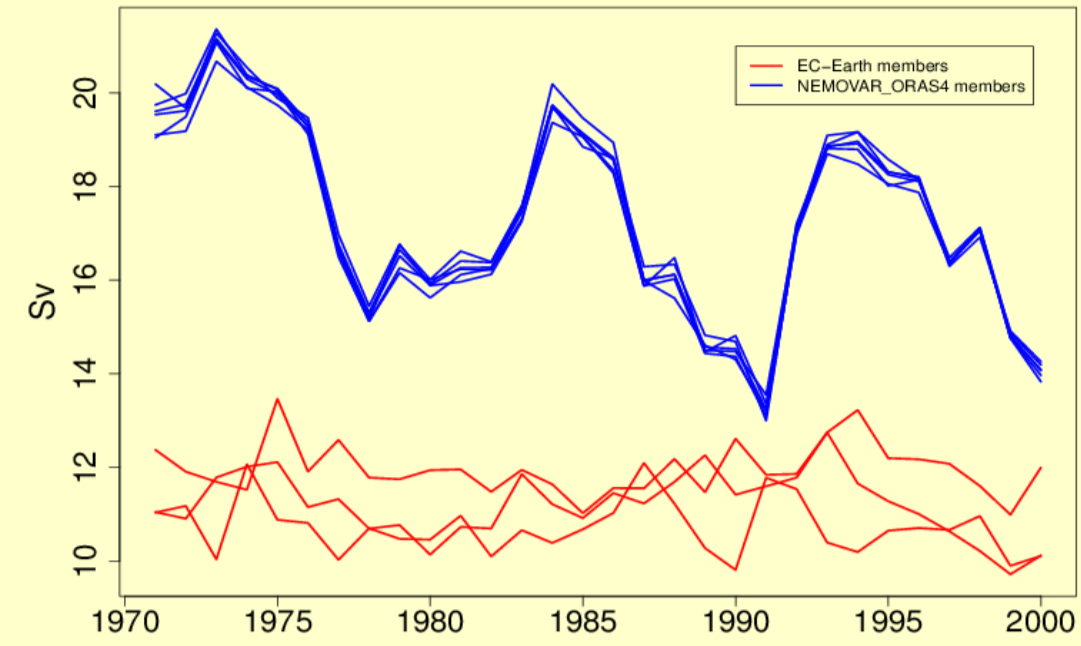
$$x^a = x^b + H^T [y^o - \langle y^o \rangle + Hx - Hx^b] \quad (A2)$$

- $\langle \rangle$  → averaging operator over an arbitrary period of time
- $y^o - \langle y^o \rangle$  → pseudo-observation vector (anomalies)

## B – Modified AI technique

➤ **Issue:** the model and observed internal variability have a difference in amplitudes, which the standard anomaly initialisation implementation does not account for.

AMOC EC-Earth vs NEMOVAR\_ORAS4 (30N40N 1-2km)



➤ **Modification:** to avoid the risk of introducing anomalies that are out of the model internal variability range, the observed anomalies used to initialize the model have been normalized:

$$x^a = x^b + H^T [\Gamma (y^o - \langle y^o \rangle) + H \langle x \rangle - Hx^b] \quad (B1)$$

- $\Gamma$  → diagonal matrix with entries the weights  $\Gamma_{i,i} = \frac{\sigma(x_i^b)}{\sigma(y_i^o)}$

➤ **Issue:** the density plays a key role in the thermohaline circulation but in the standard anomaly initialisation implementation it is not directly assimilated into the model but it is calculated from the assimilated temperature and salinity.

➤ Calling  $f(T,s)$  the equation of state of the density ( $\rho$ ), and  $AI(x)$  the anomaly initialisation equation:

Standard AI	Modified AI
$f \circ AI$	$AI \circ f$
$f \circ AI (T^o, s^o) \neq AI \circ f (T^o, s^o)$	
$f (T^a, s^a) \neq AI (\rho^o)$	
$\rho^{ini} \neq \rho^a$	

➤ Can we improve the skill of the prediction with the modified anomaly initialization implementation?

## C – Methodology

➤ The model used is **EC-Earth v.2.3**: IFS with 62 vertical level and a TL159 horizontal resolution for the atmosphere. NEMO2 with ORCA1 configuration for the ocean. Sea-ice model LIM2 directly embedded in NEMO. Coupler OASIS3.

➤ The reanalysis used for initialization are NEMOVAR-ORA\_S4 for the ocean, ERA40 and ERA-Interim for the atmosphere and the HistDfsNudg sea-ice reconstruction proposed by Guemas et al (2014) for the sea-ice.

➤ Start dates every 2 years from 1960 to 2004, 5 members, running for 5 years

➤ **FFI** experiment: all model components initialised as in (A1).

➤ **OSI-AI** experiment: ocean and sea-ice components initialised as in (A2).

➤ **p-OSI-wAI** experiment: ocean and sea-ice components initialised as in (B1), including  $\rho$  initialisation.

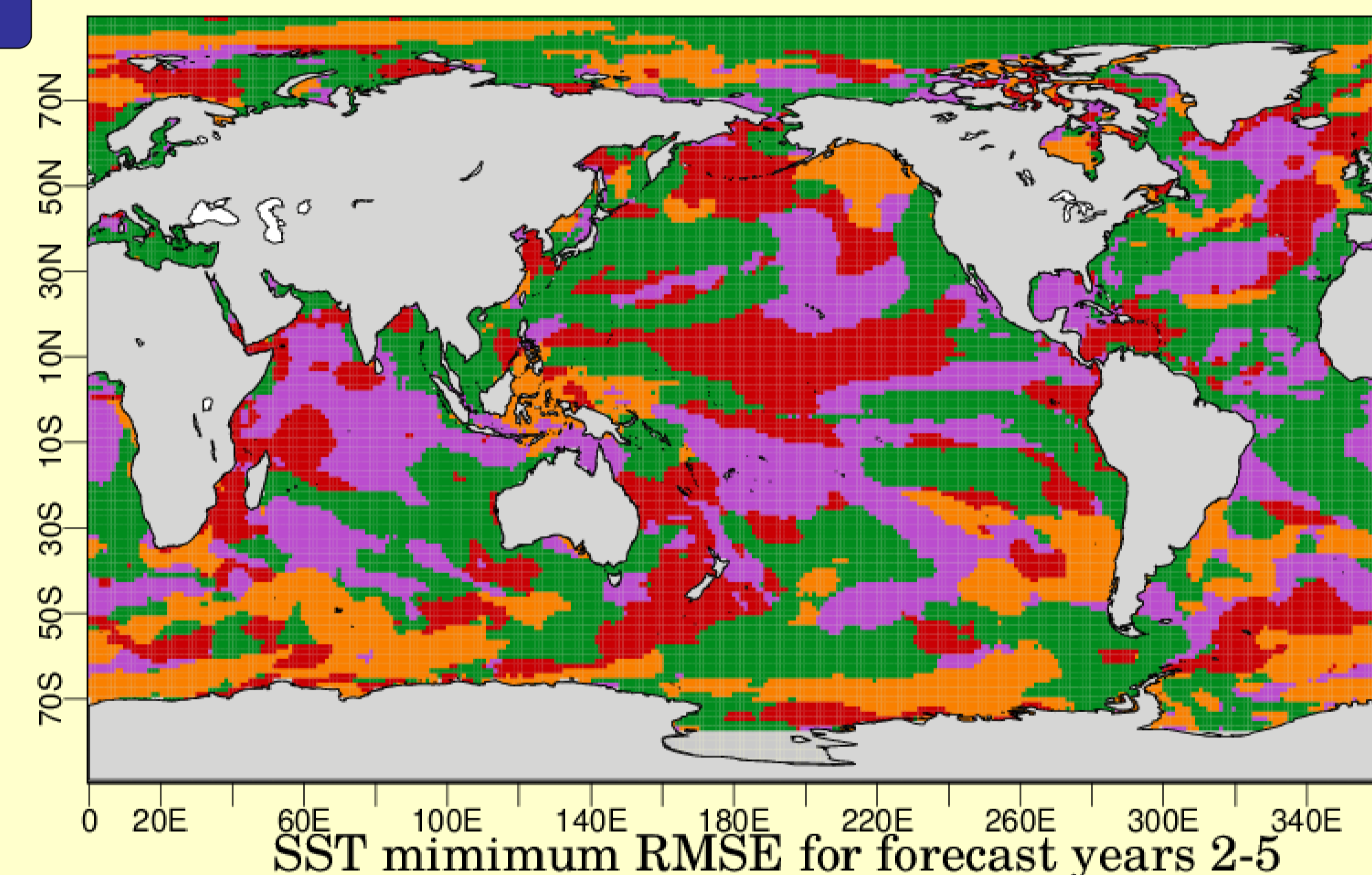
➤ Compared to sister ensemble built from a 3-member historical simulation until 2005 and the RCP4.5 projections afterwards = **NOINI**

➤ **Observational data** : For sea surface temperature (SST), ERSST v3b. For sea-ice, the HistDfsNudg sea-ice reconstruction .

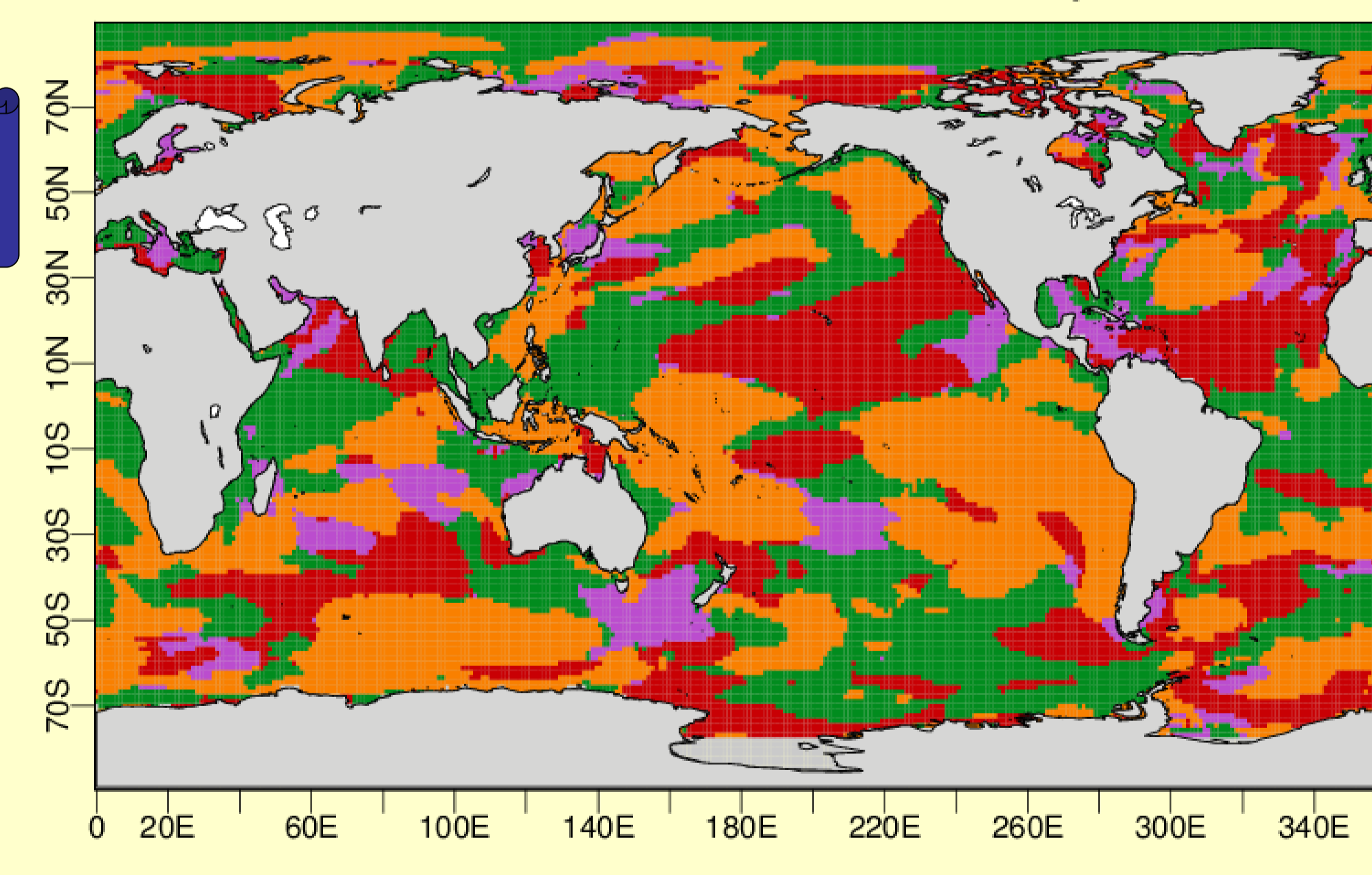
## F – Temperature

Minimum SST root mean square error (RMSE). Each grid point takes the color of the experiment which has the minimum SST RMSE averaged respectively along the first year and along the year two to five

SST minimum RMSE for forecast year 1



SST minimum RMSE for forecast years 2-5



Legend: FFI (red), p-OSI-wAI (green), OSI-AI (purple), NOINI (orange)

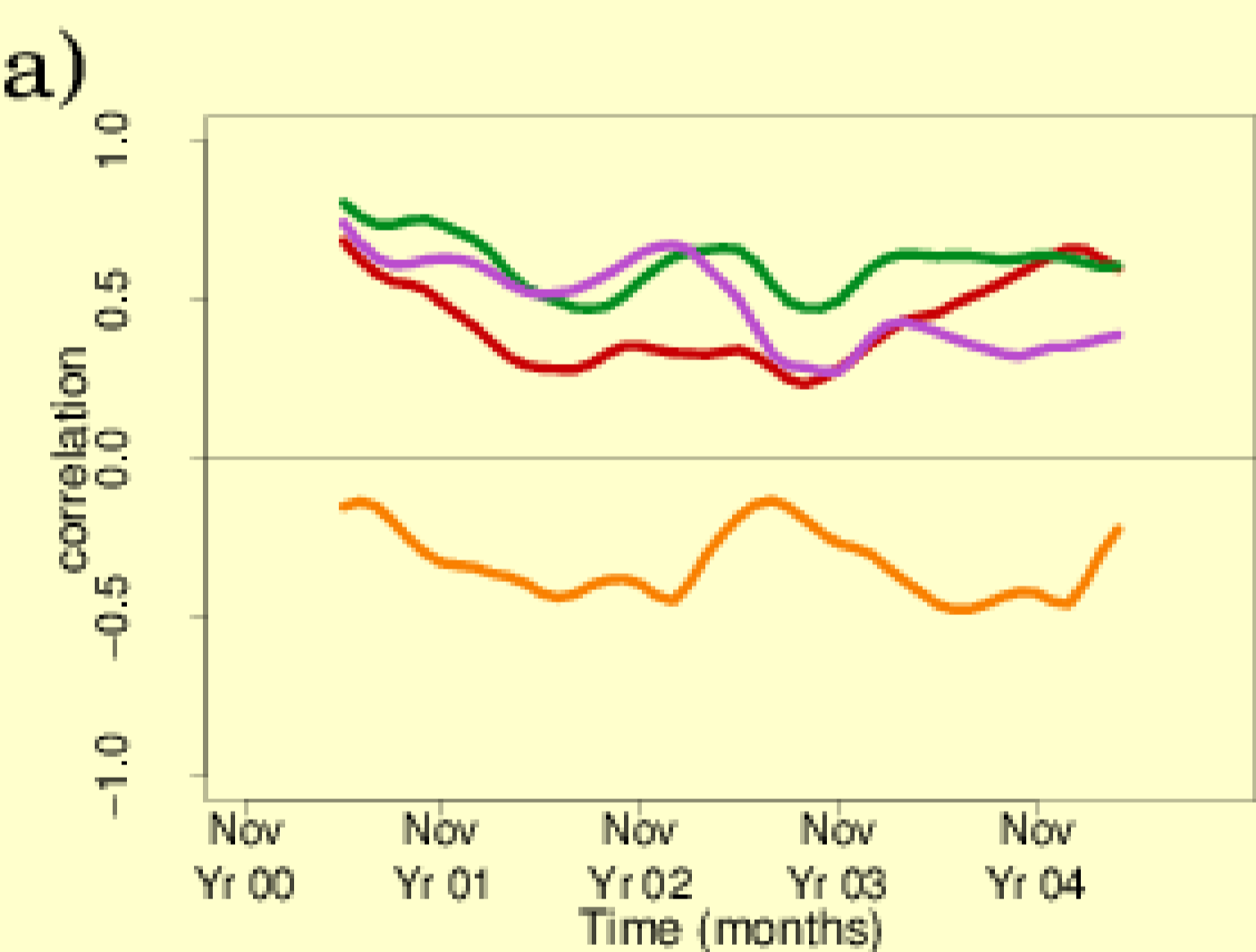
- **Forecast year 1:** **p-OSI-wAI** performs the best in most regions and **FFI** performs best in the Tropical Pacific.
- **Forecast years 2-5:** **p-OSI-wAI** performs the best in the Arctic but **NOINI** performs the best over about half of the regions

## D – Skill in predicting climate indices

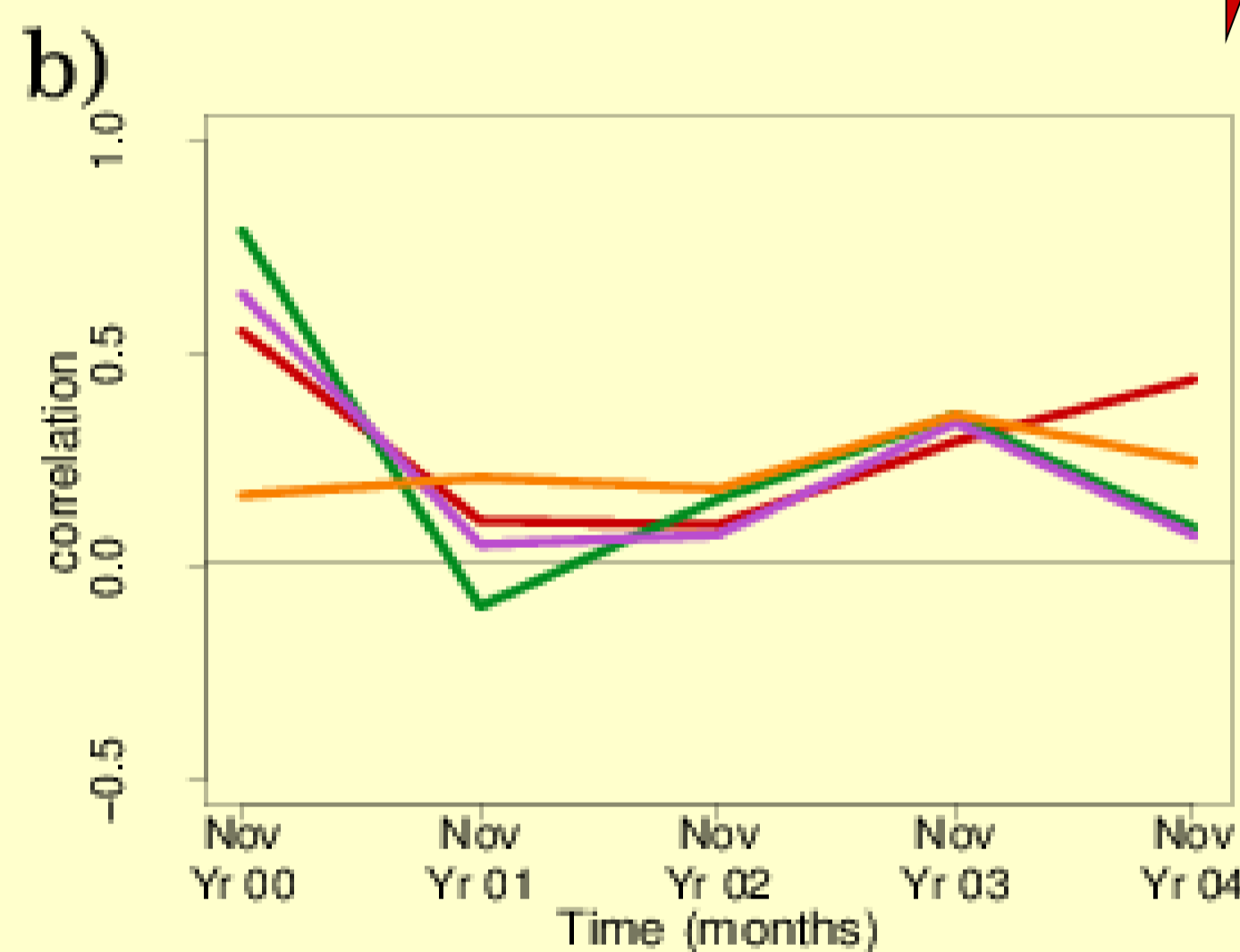
### Correlation



#### AMO



#### PDO



The AMO skill is **significantly** improved over **NOINI**:

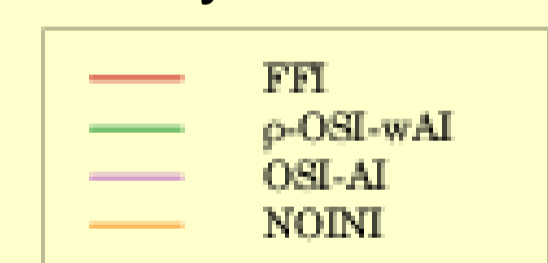
- By **FFI** for the first few forecast months.
- By **OSI-AI** for the first 2 forecast years.
- By **p-OSI-wAI** for the whole forecast period.

The PDO skill is improved for the first forecast year but the improvements are not statistically significant.

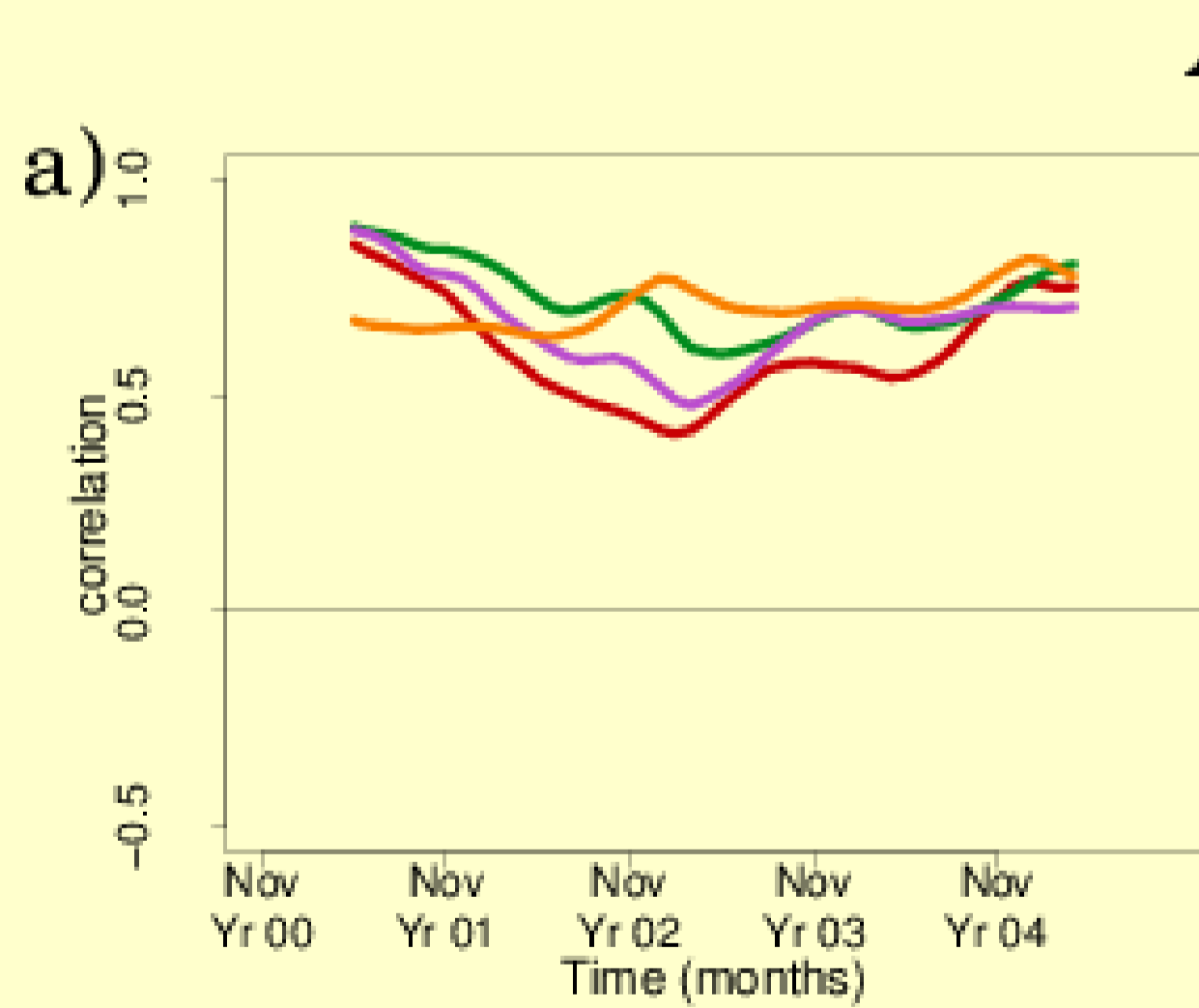
## E – Arctic sea-ice variables

In order to verify the performance of the sea-ice anomaly initialisation we focus on the Arctic sea-ice variables:

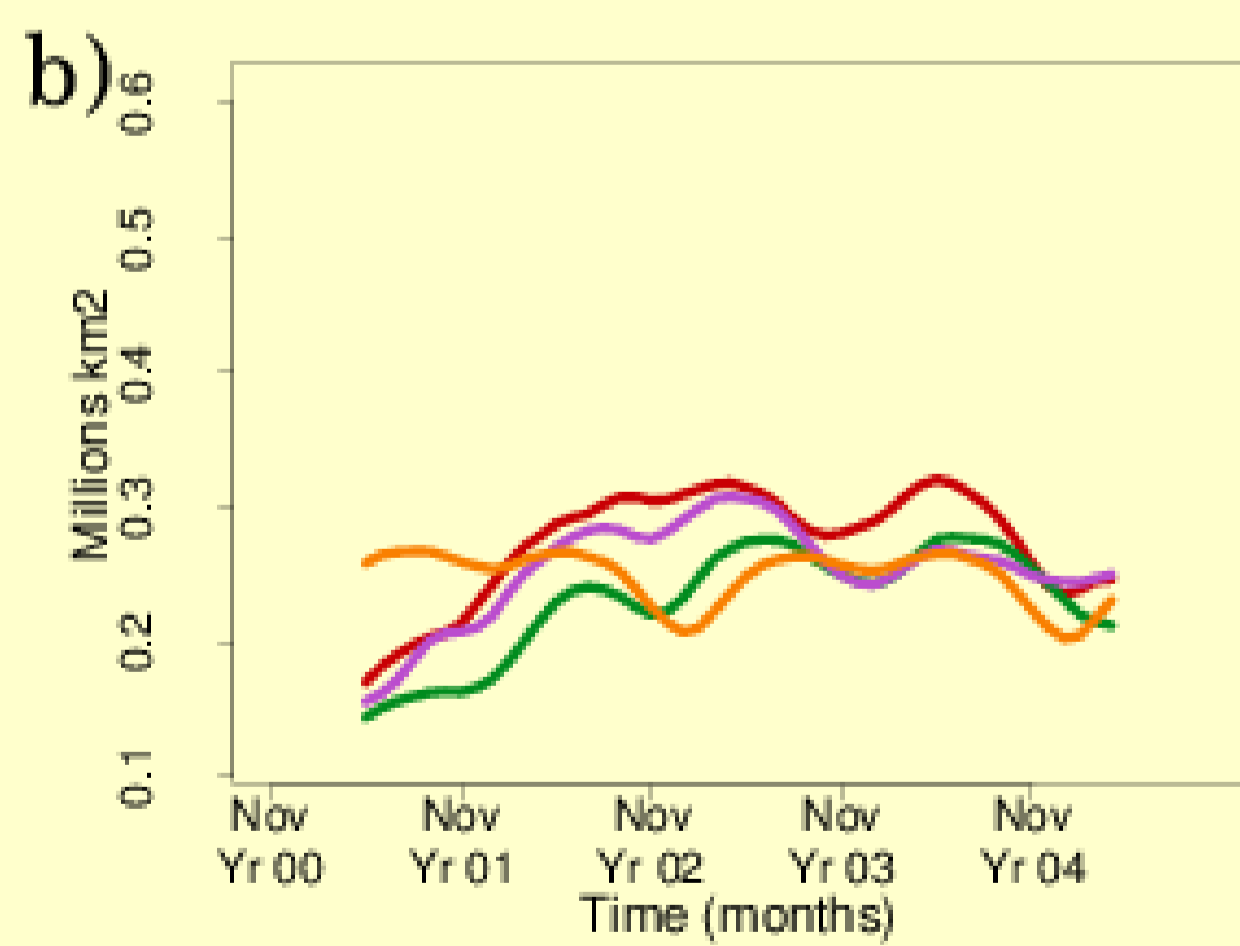
### Arctic sea ice



#### Correlation



#### Area



- The **p-OSI-wAI** experiment performs the best for the Arctic sea-ice area for the first 2 forecast years, but the improvements are not significant.
- The two **AI** experiments perform the best in predicting the Arctic sea-ice volume for the first 3 forecast years.

### Conclusions

- We aimed at improving the AI initialisation technique by 1) weighting the observed anomaly and 2) anomaly initialising the density. We have compared the performance of this new technique (**p-OSI-wAI**) with the standard anomaly initialisation method (**OSI-AI**), the full field initialisation (**FFI**) and an historical simulation (**NOINI**).
- The AMO skill is significantly improved by **OSI-AI** for the first two forecast years and by **p-OSI-wAI** experiment along the whole forecast period. The PDO is improved for the first forecast year.
- The **p-OSI-wAI** has higher skill than the other simulations in Arctic sea-ice area (first two forecast years) and volume (three forecast years).
- During the forecast year 1, for SST, **p-OSI-wAI** performs the best in most regions and **FFI** performs the best in the Tropical Pacific.
- Work in progress : anomaly nudging experiment where the anomalies are weighted for  $\rho$  and temperature ( $T$ ) and then the salinity ( $s$ ) is recovered. Finally  $T$  &  $s$  are nudged.

### References :

Guemas V., Doblas-Reyes F.J., Mogensen K., Tang Y. and Keely S. 2014, Ensemble of sea ice initial conditions for interannual climate predictions, Clim.Dyn., doi:10.1007/s00382-014-2095-7

Carrassi A., Weber R., Guemas V., Doblas-Reyes F.J., Asif M. and Volpi D. 2014, Full-field and anomaly initialisation using a low-order climate model: a comparison and proposals for advances formulations, Nonlin. Processes Geophys., 21, 1–17, doi:10.5194/npg-21-1-2014