Preliminary Results of recent Decadal Predictions with EC-Earth

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Recent really means recent

1. Decadal Climate Prediction Project – DCPP

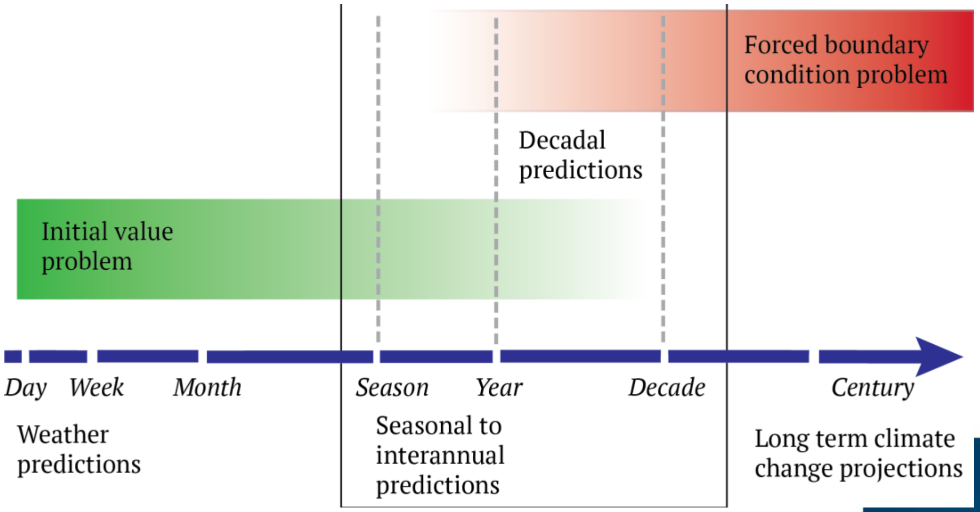
2. Model Setup + Initialisation

3. First Quality Assessement of Decadal Hindcast Set

4. Climate Sensitivity in Historical Experiments

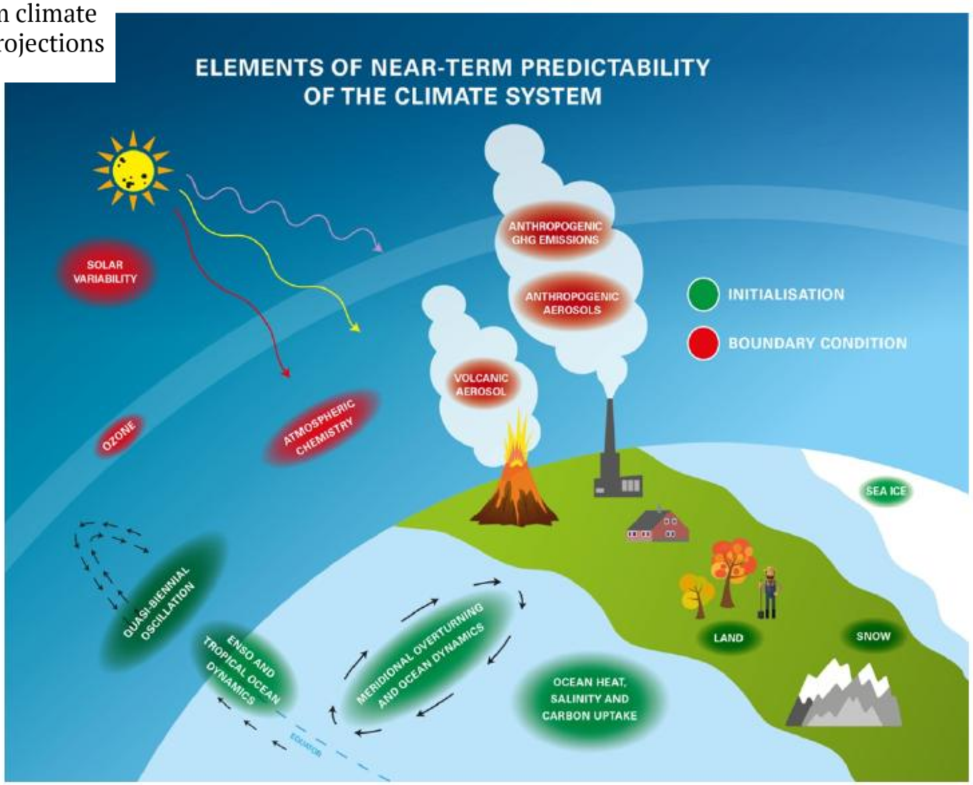
5. What am I actually doing here?

Near Term Climate Prediction



Meehl et al. 2009

Kushnir et al. 2018



Near Term Climate Prediction - DCPP

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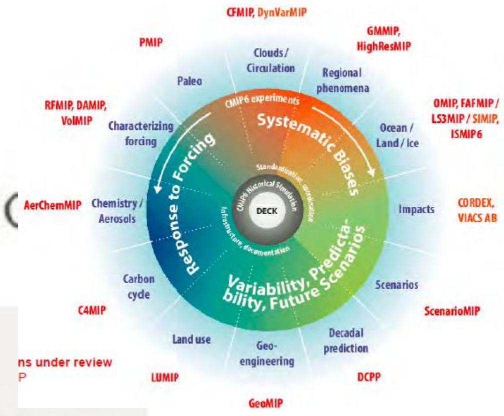
World Climate Research Programme

WMO



The Decadal Climate Prediction Project (DCPP)

The term ""decadal prediction"" encompasses predictions on annual, multi-annual to decadal timescales. The possibility of making skilful forecasts on these timescales and the ability to do so is investigated by means of predictability studies and retrospective predictions (hindcasts) made using the current generation of climate models and by empirical methods. Skilful decadal prediction of relevant climate parameters is a Key Deliverable of the WCRP's Grand Challenge of Near-term Climate Prediction

The DCPP envisions three components:

- A ○ ***Hindcasts***: the design and organization of a coordinated decadal prediction (hindcast) component of CMIP6 in conjunction with the seasonal prediction and climate modelling communities
- B ○ ***Forecasts***: the ongoing production of experimental quasi-operational decadal climate predictions in support of multi-model annual to decadal forecasting and the application of the forecasts
- C ○ ***Predictability, mechanisms and case studies:*** the organization and coordination of decadal climate predictability studies and of case studies of particular climate shifts and variations including the study of the mechanisms that determine these behaviours

DCPP A Protocol

- yearly initialised Experiments 1960-2017
- 10 members
- 10 years

Near Term Climate Prediction - DCPP

Group/Model	Institution	Country	Component A	B	C
EC-Earth	BSC/SMHI	Spain/Sweden	Y/M	Y/M	M/M
GFDL	NOAA	USA	Y	Y	M
FIO-ESM	FIO	China	Y	Y	M
NUIST-CSM	IPRC	USA/China	Y	Y	N
BCC	BCC	China	Y	N	N
CAS-ESM	CAS	China	M	M	M
MIROC	JAMEST/JMA	Japan	Y	y	Y
Can-ESM5	CCCma	Canada	Y	Y	M
CNRM-CERFACS	CNRS	France	M	M	Y
MetOffice	MetOffice	UK	Y	Y	Y
Ureading/Stat	UReading	UK	Y	Y	Y
IPSL	LOCEAN	France	Y	N	Y
NERCS/NorCPS	GRI	Norway	Y	Y	Y
CMCC	CMCC	Italy	M	M	Y
MPG	MPI	Germany	Y	Y	Y
NCAR/CESM	NCAR	USA	Y	Y	Y
BESM	INPE	Brazil	Y	M	M
FGOALS	IAP	China	Y	M	Y
INM	RAS	Russia	Y	N	Y

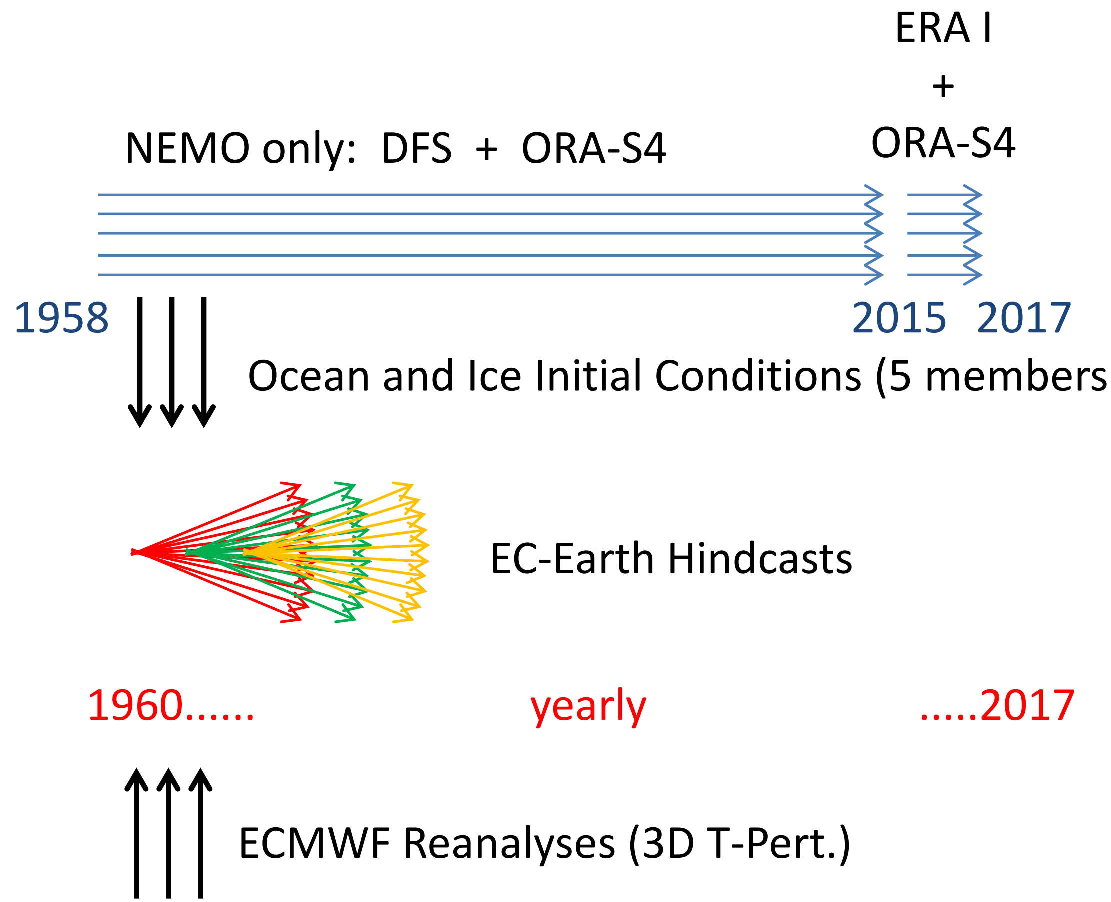
20 Groups

- 13 Countries
- Component A (hindcasts)
  - 16 Yes, 4 Maybe
- Component B (forecasts)
  - 11 Yes, 6 Maybe, 3 No
- Component C (mechanisms)
  - 11 Yes, 7 Maybe, 2 No

Model Setup

EC-Earth 3.3
yearly start dates
1960-2017, starting 1st Nov
10 members

Model:
Atmosphere: IFS, T255L91
Ocean: NEMO, ORCA1L75
Sea ice: LIM 3
+ OASIS coupler

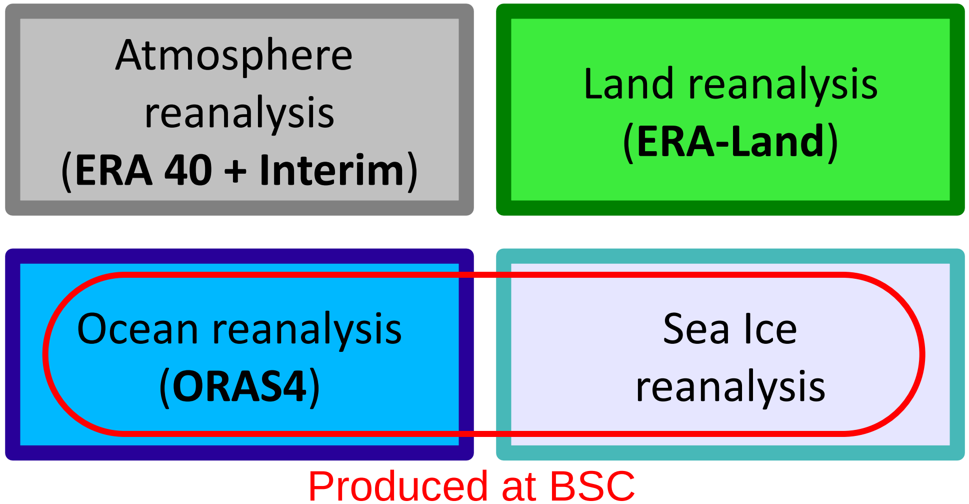


Initial conditions, full-field
<u>Atmosphere:</u>
ECMWF reanalyses (ERAInt + ERA40)
with GPCP-corrected land surface
<u>Ocean and sea-ice reconstruction:</u>
ICs are produced using a NEMO only simulation
forced by DFS (ERA-I) fluxes and nudged towards ORA S4

Following Guemas et al. (Clim. Dyn., 2014)

Initial Conditions

ATM:
Interpolated to model grid with OpenIFS (now performed locally at BSC)



LAND:
Offline land-surface simulation with near-surface meteorology and corrected fluxes from ERA-Interim

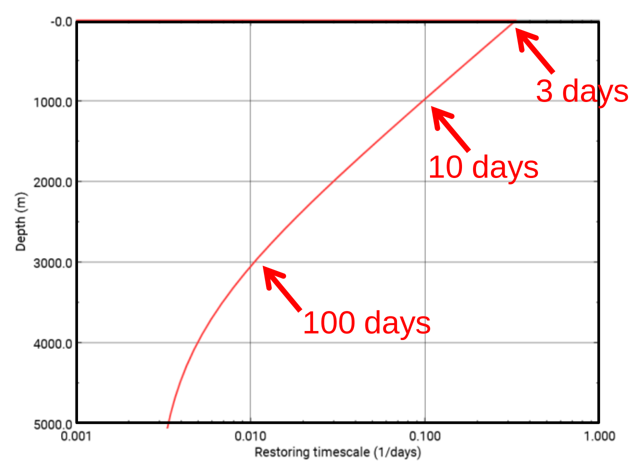
OCE+ SI:
Historical reconstruction with NEMO-LIM stand alone, forced with ERA-40/Interim fluxes, and nudged globally towards 3D T and S from ORAS4

Default surface restoring coefficients

γ_T = -40W/m²/K

γ_S = -150 kg/m2/s/psu

Default 3D restoring timescales

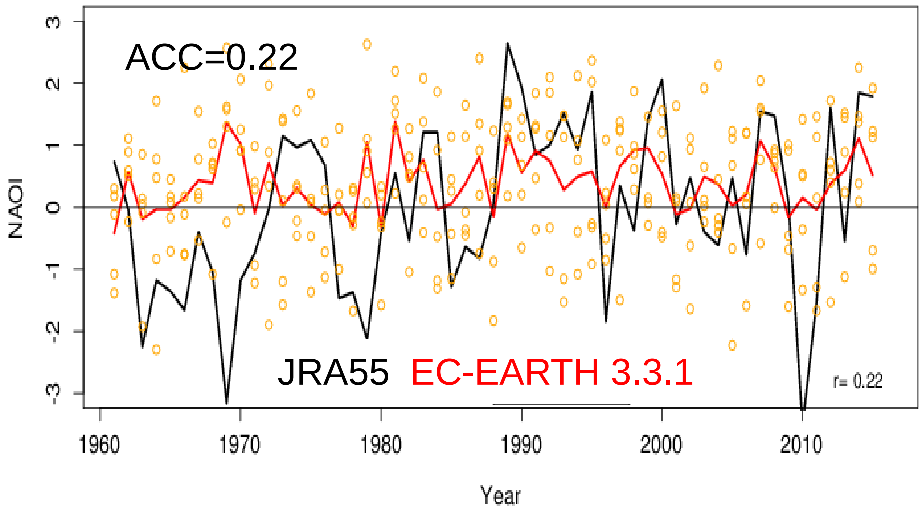


Predictability of atmospheric variables

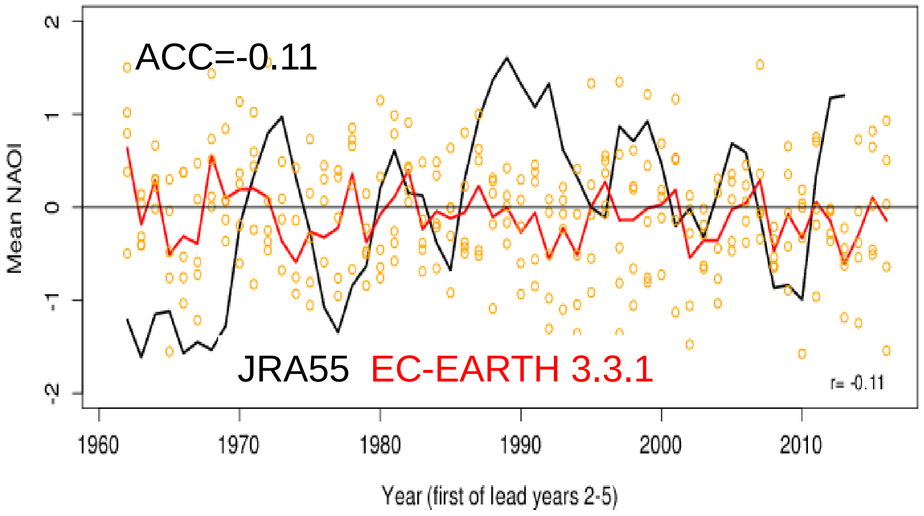
NAO-Index as defined in Jianping & Wang (2003):

35N-65N difference of standardised zonally averaged winter MSLP anomalies in the longitudinal band **80W-40E**

NAO DJF **Year 1** (forecast months 2-4)



NAO DJF **Years 2-5**



Unlike in other prediction systems, no significant skill in the NAO is obtained

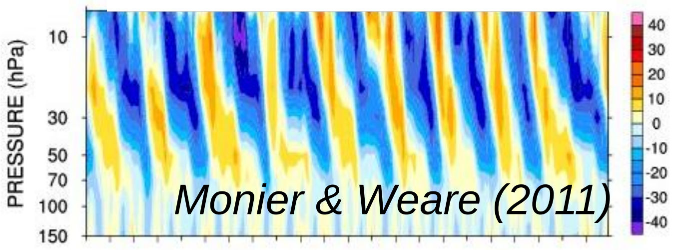
Larger ensemble sizes might be needed to detect the predictable NAO component

Predictability of atmospheric variables

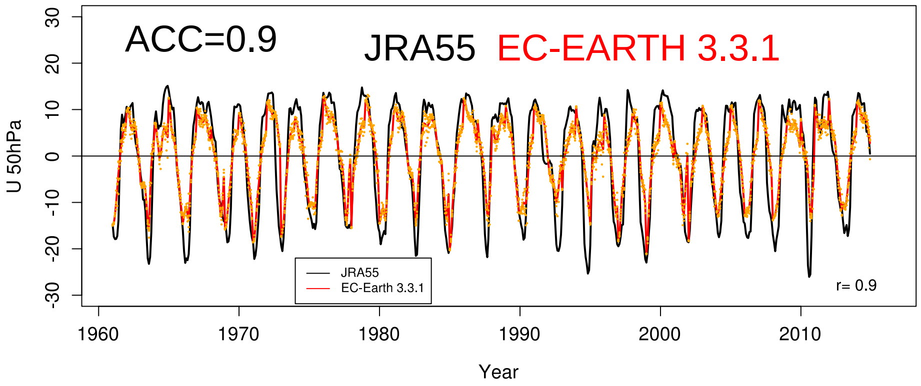
QBO-Index defined as the zonally averaged zonal wind at the **Equator and 50hPa**

Anomalies are computed with respect to the seasonal mean (as a function of lead time)

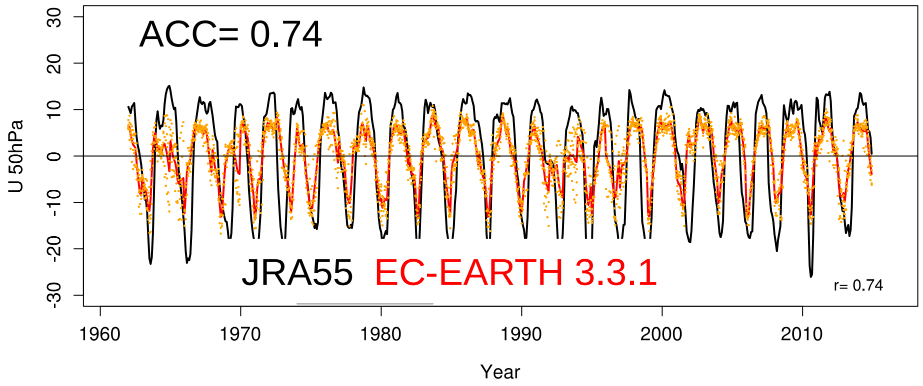
Equatorial Zonal Wind (m/s)



QBO in forecast year 1 (months 1-12)



QBO in forecast year 2



The QBO seems to be highly predictable in the first and second forecast years

This skill is unrelated to the effect of the seasonal cycle

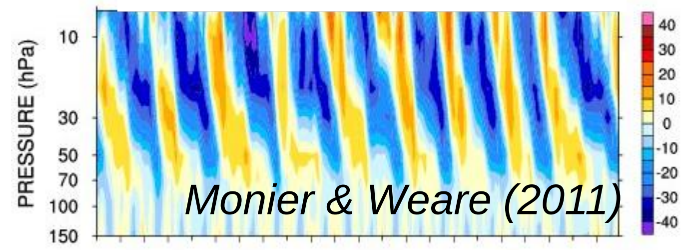
Preliminary results from DCPP Component A

Predictability of atmospheric variables

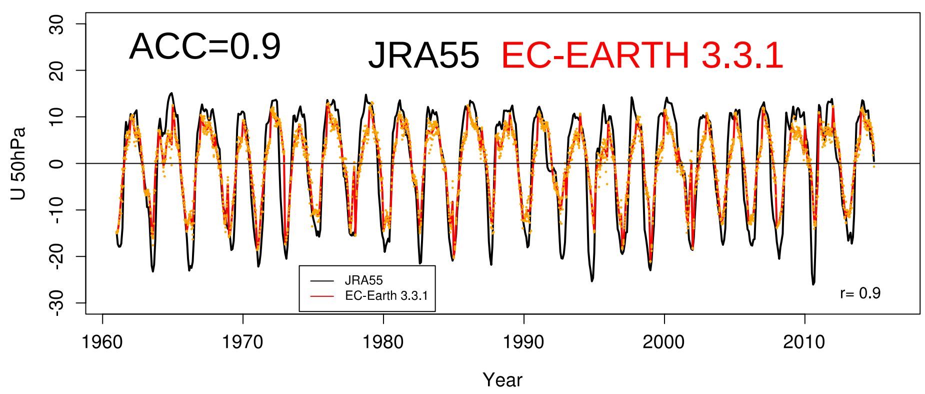
QBO-Index defined as the zonally averaged zonal wind at the **Equator and 50hPa**

Anomalies are computed with respect to the seasonal mean (as a function of lead time)

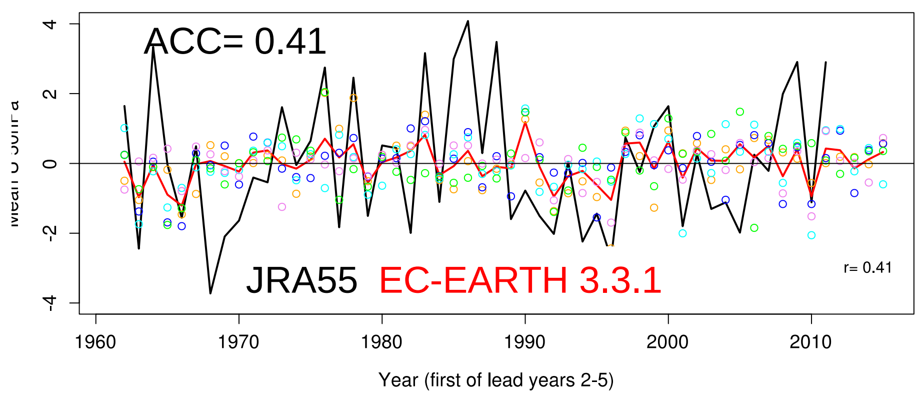
Equatorial Zonal Wind (m/s)



QBO in forecast year 1 (months 1-12)



QBO in forecast years 2-5



The QBO seems to be partly predictable from the second to fifth forecast years

Skill is unrelated to the seasonal cycle, and is a consequence of its strong periodicity

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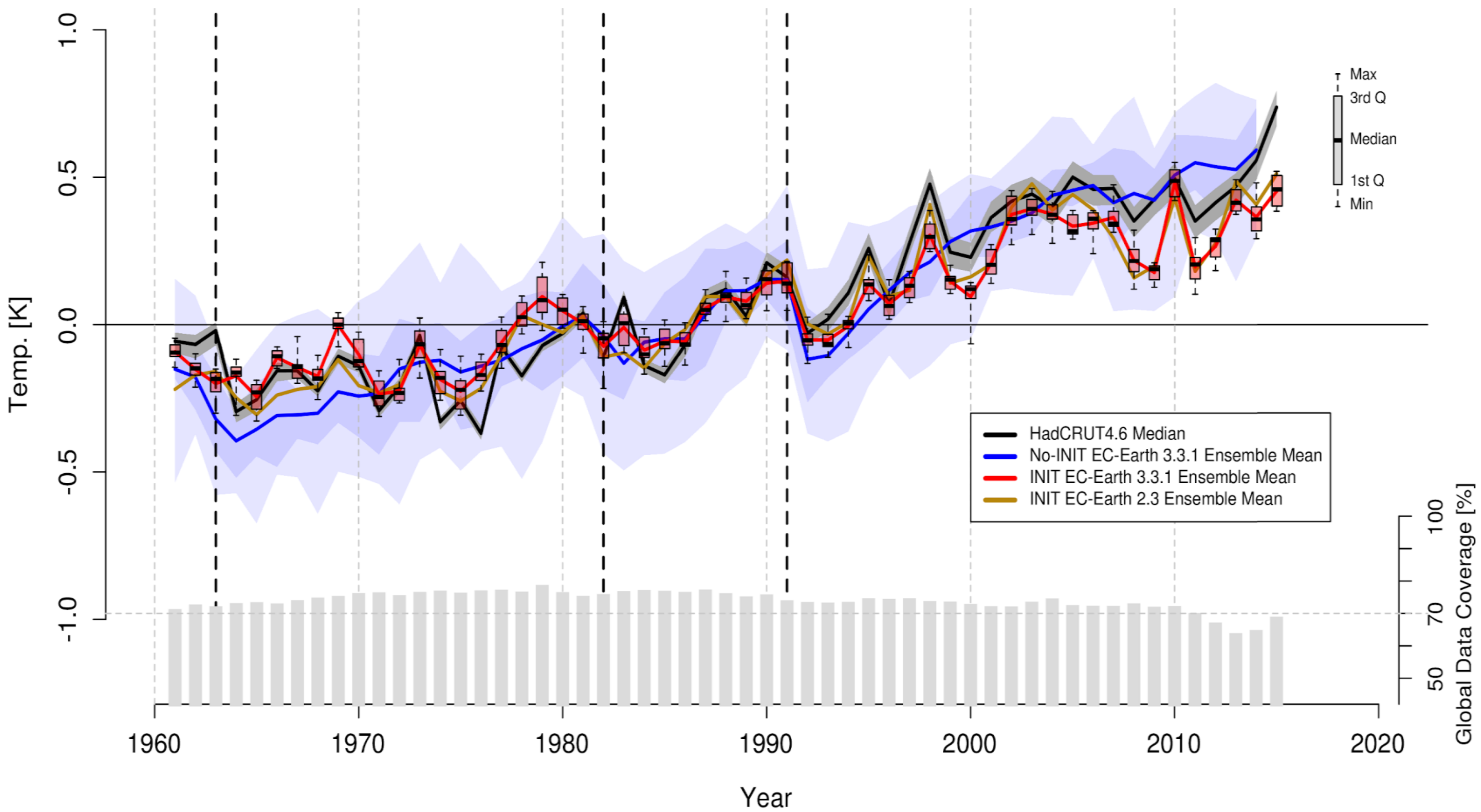
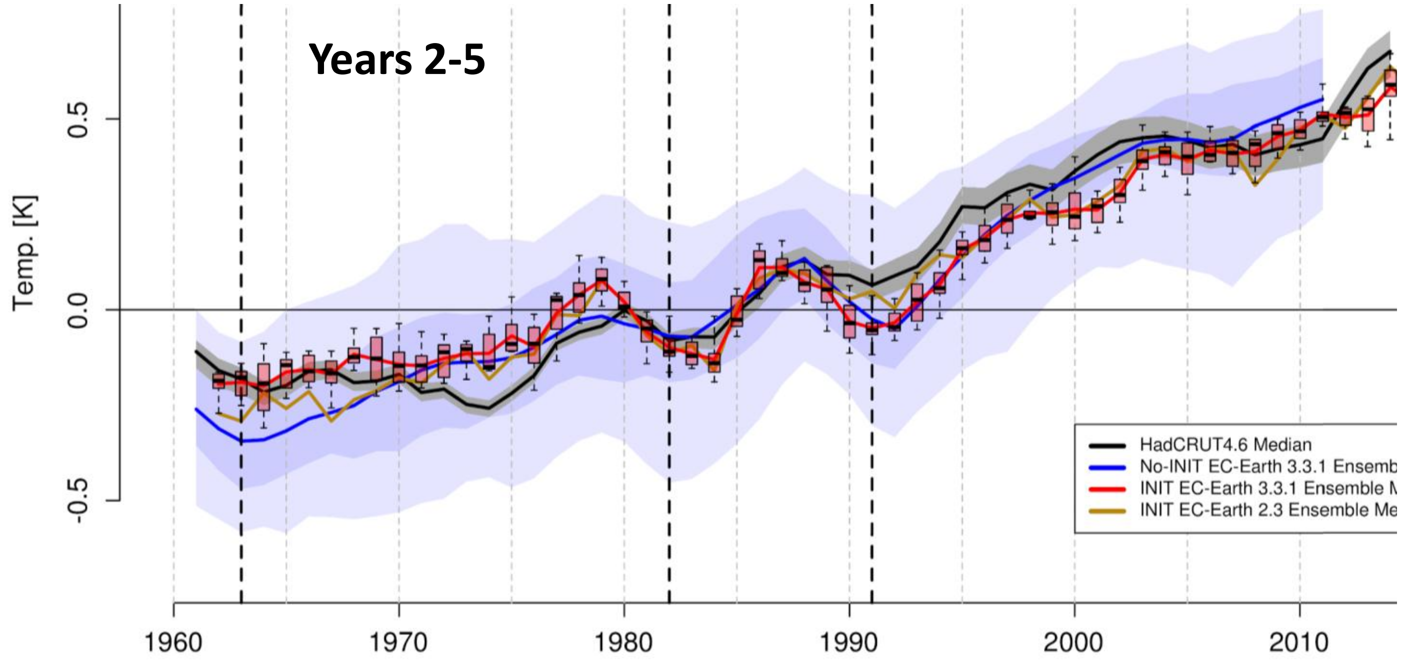
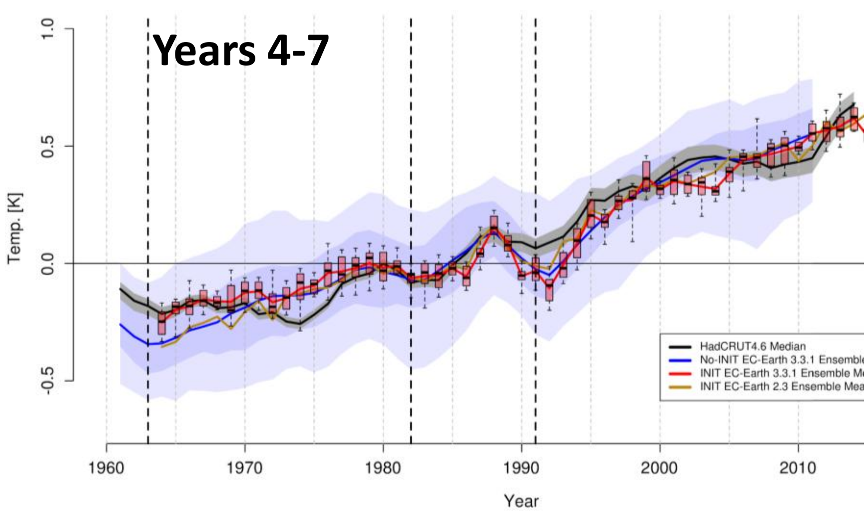
Forecast Year 1 (M3-14)

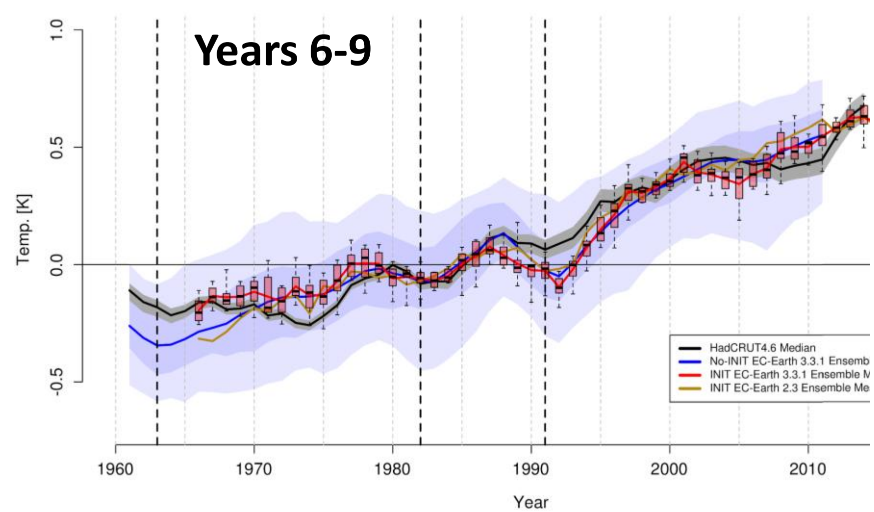
Combination of 2m temperature over land and SST over ocean



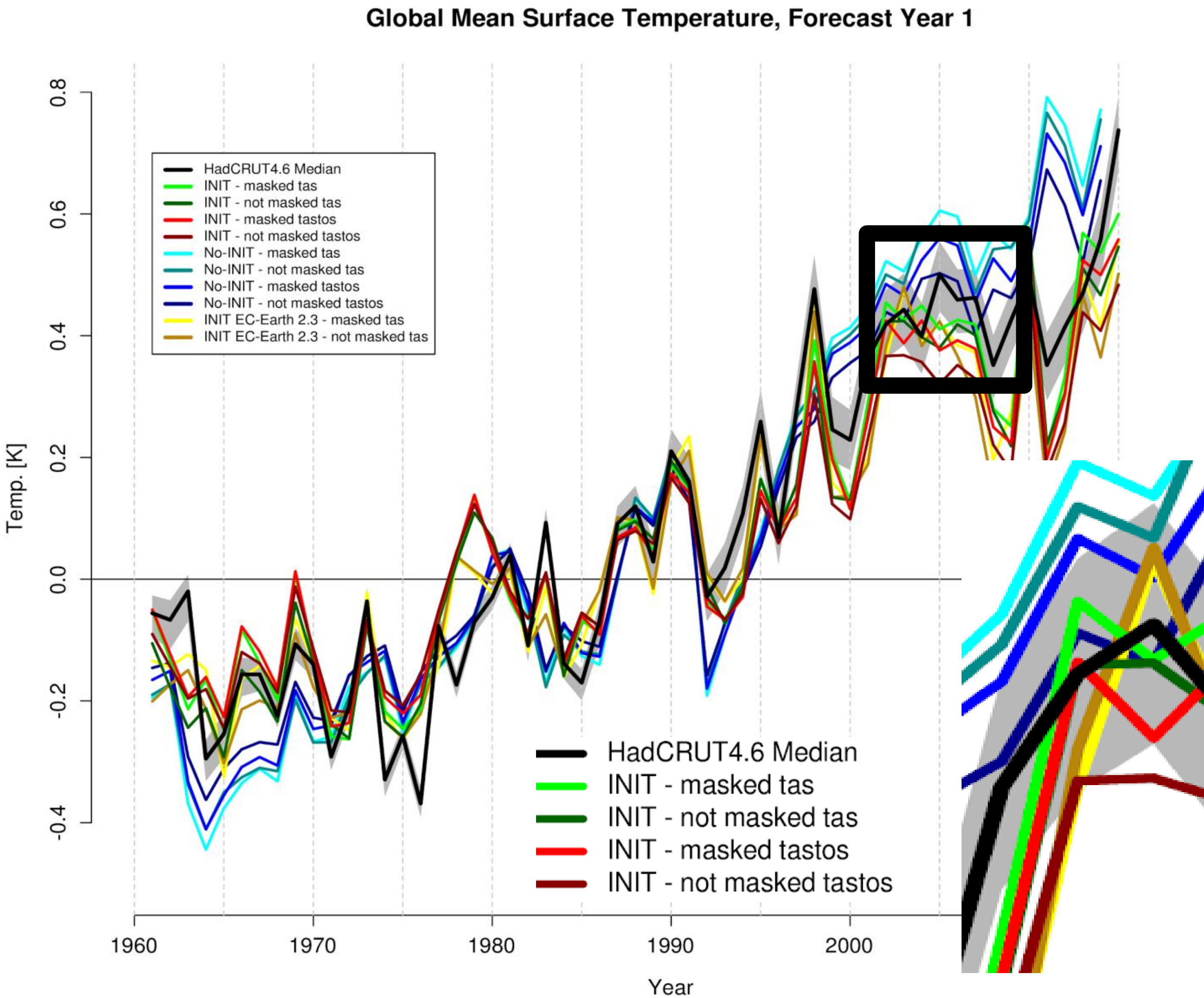
Global Mean Surface Temperature

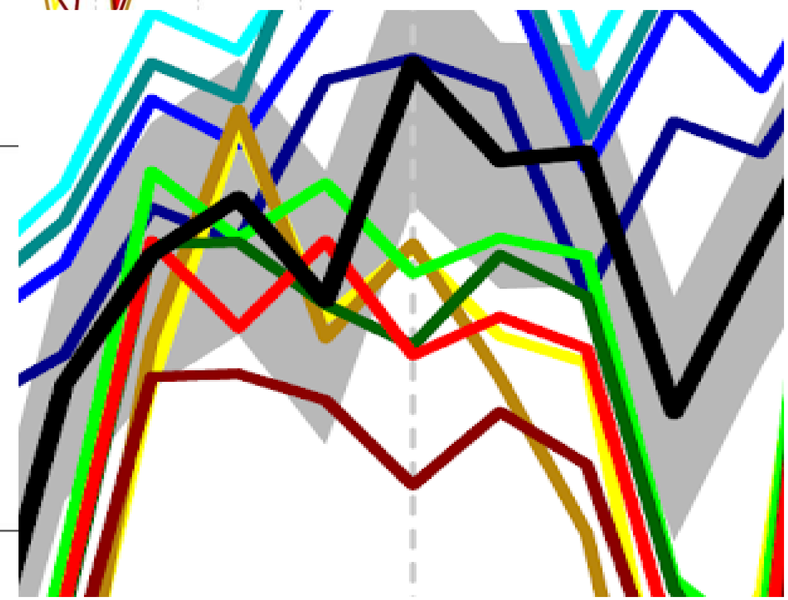






Effect of combining 2m Temp and SST





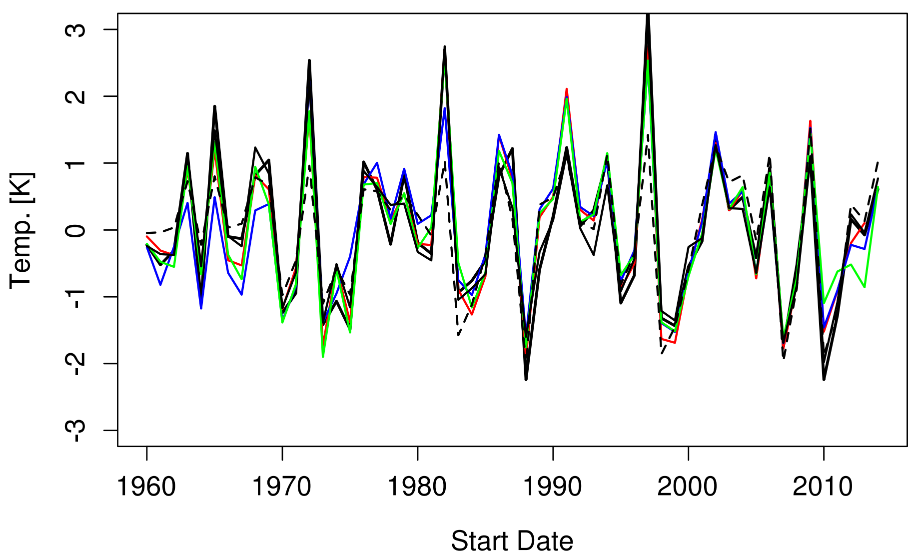
Effect of masking missing values has similar magnitude to effect of combining Temp2m and SST

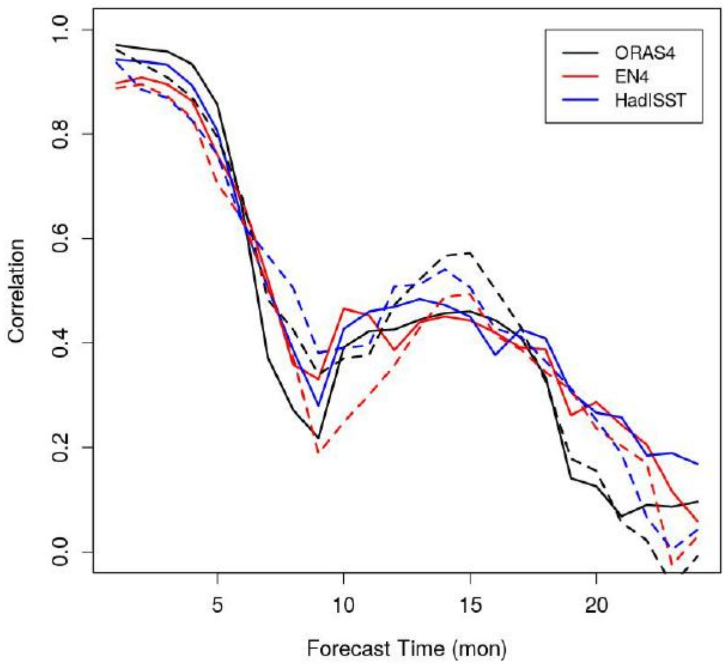
Predictability of ocean variables

ENSO-Index: Niño3.4

Regional average of SST anomalies in the box **[5N-5S, 170W-120W]**

Observed and Forecasted Niño3.4





The hindcast maintains high ENSO skill during the first 5 forecast months (DEC through APR), and experiences some skill reemergence in the second winter

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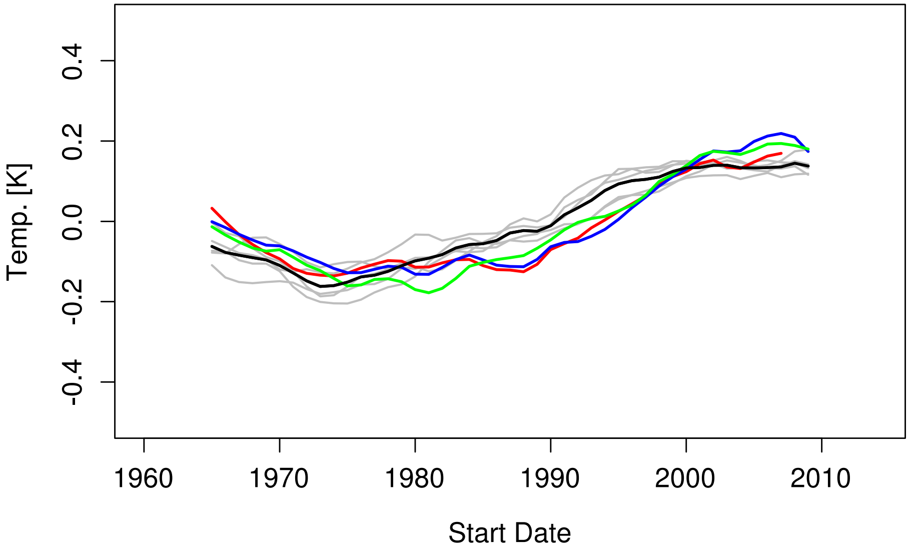
Predictability of ocean variables

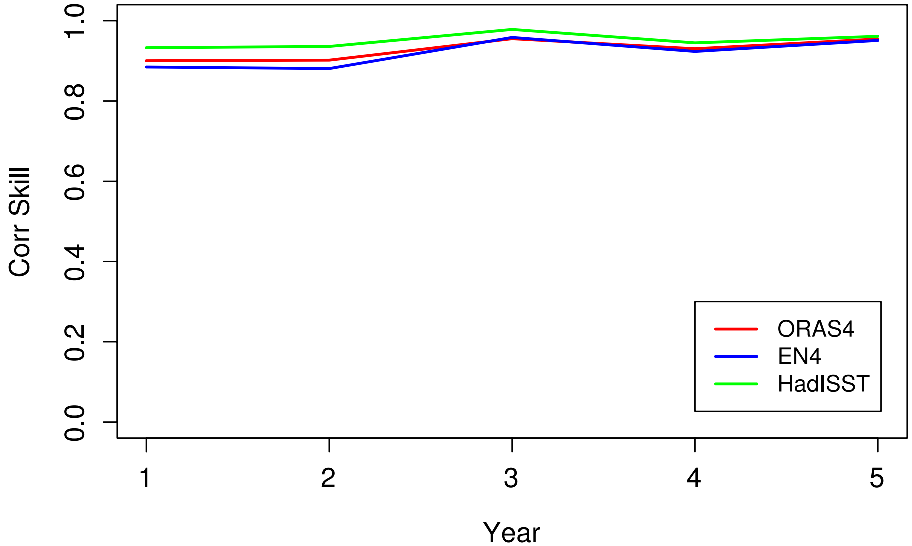
AMV-Index as defined in Trenberth & Shea (2006):

Decadally smoothed difference between the SST average in the **North Atlantic [0-60N, 80W-0]** and the **global mean SST**

Observed and Forecasted AMV



AMV Anomaly Correlation Coefficient



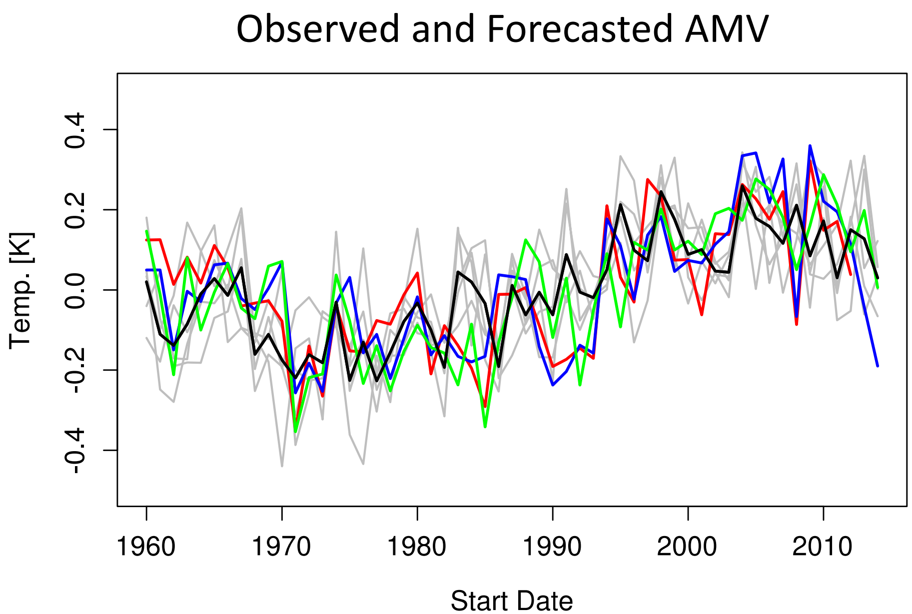
The models has really high AMV skill, at least for the first 5 forecast years

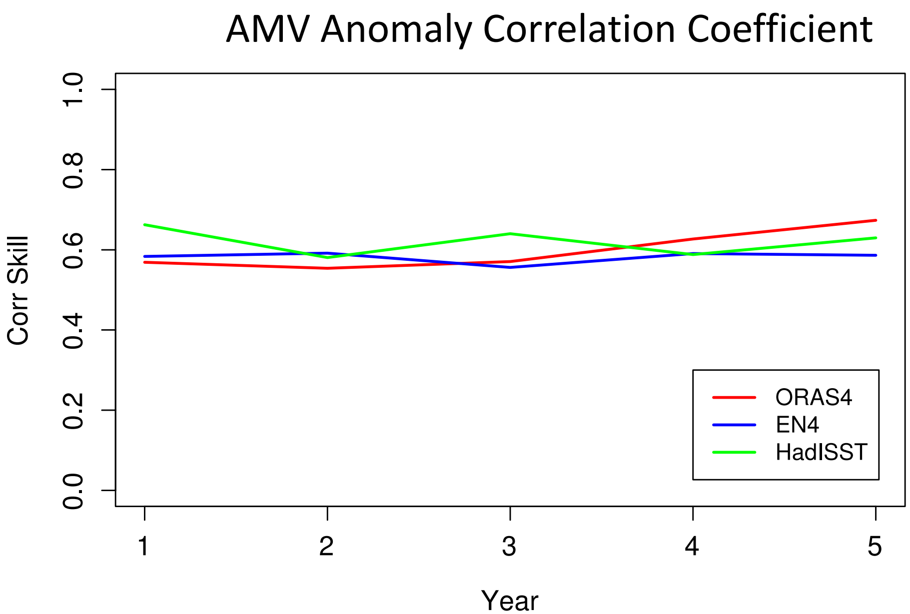
It might be due to the reduced degrees of freedom as a result of the smoothing

Predictability of ocean variables

AMV-Index as defined in Trenberth & Shea (2006):

Raw difference between the SST average in the **North Atlantic [0-60N, 80W-0]** and the **global mean SST**





The skill drops but remains high also for the unfiltered timeseries

Preliminary results from DCPP Component A

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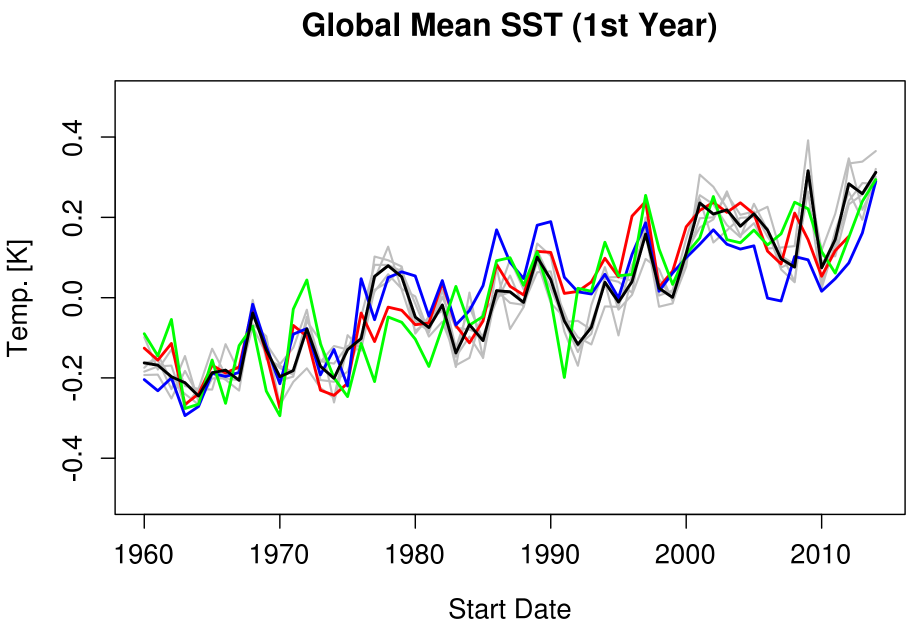
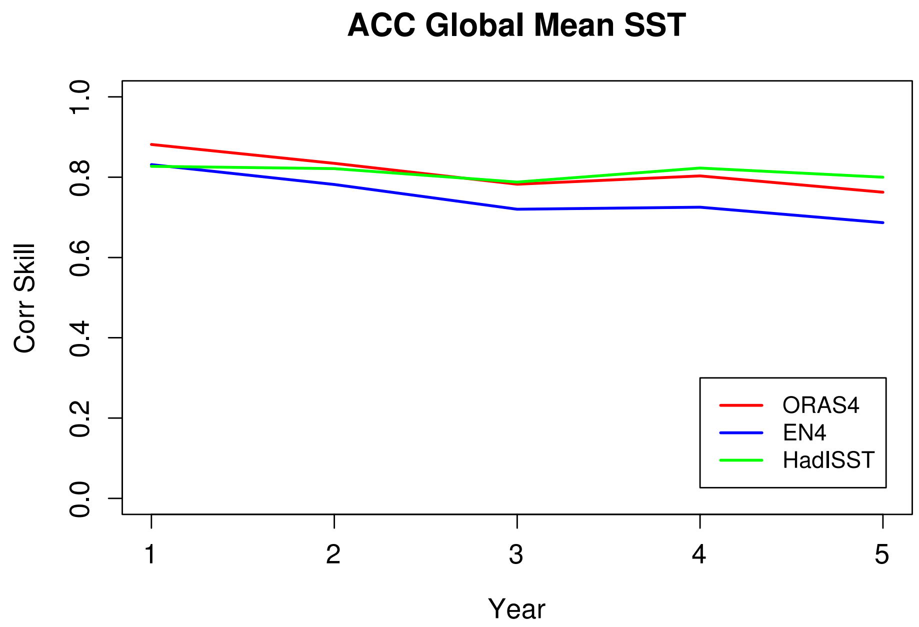
Predictability of ocean variables

Global Mean SST





Global mean temperature is also largely predictable, although a non-negligible contribution comes from the long-term trend.

Preliminary results from DCPP Component A

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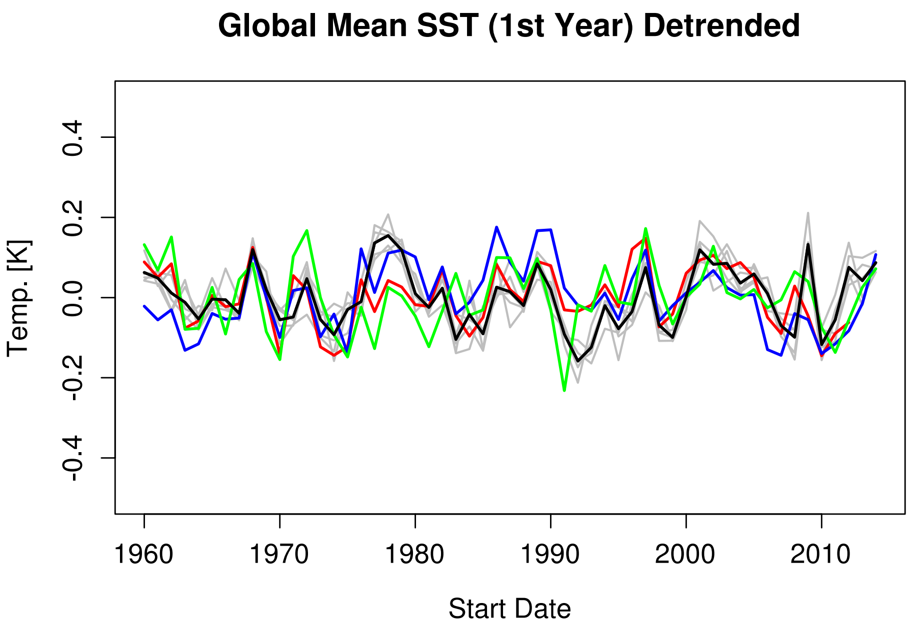
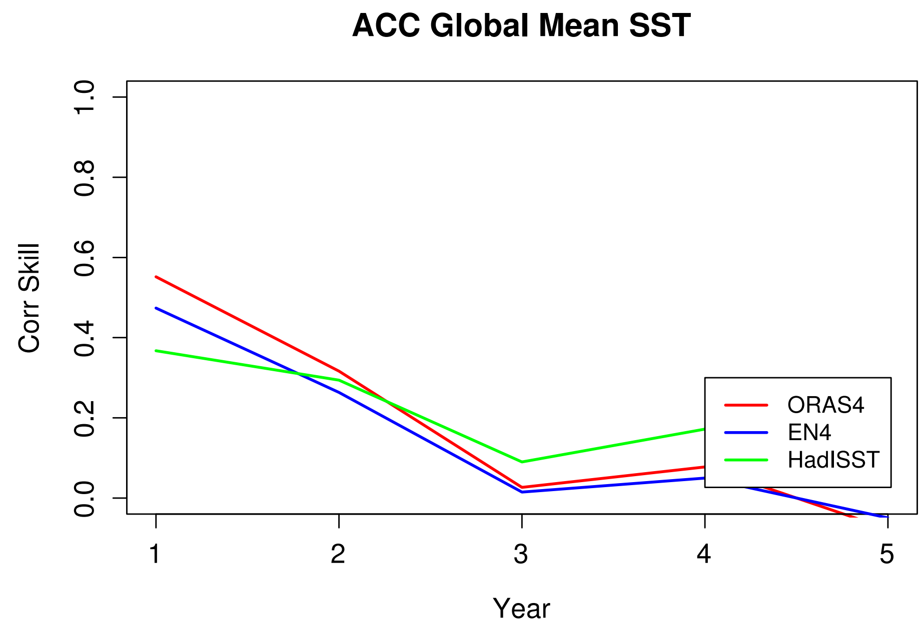
Predictability of ocean variables

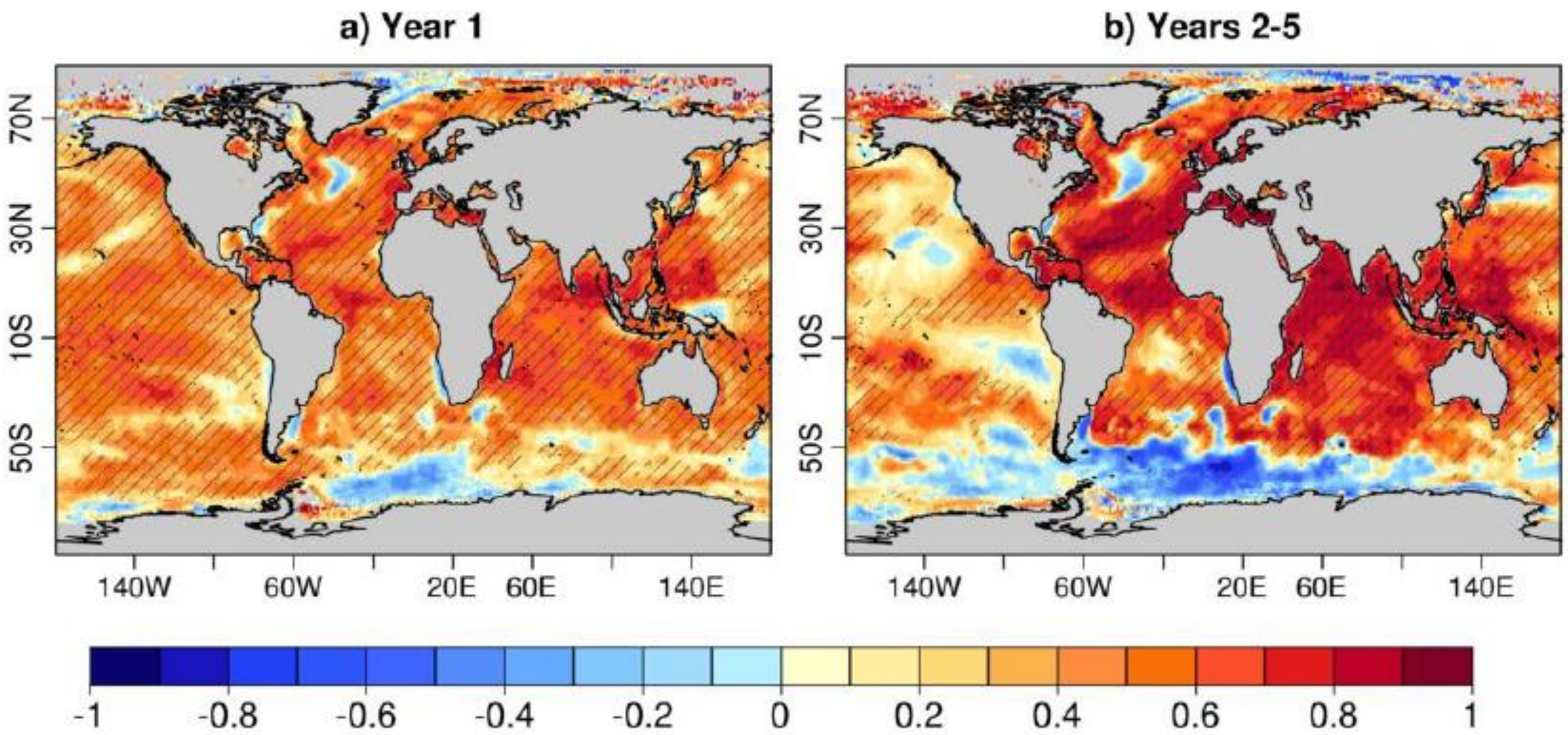
Global Mean SST



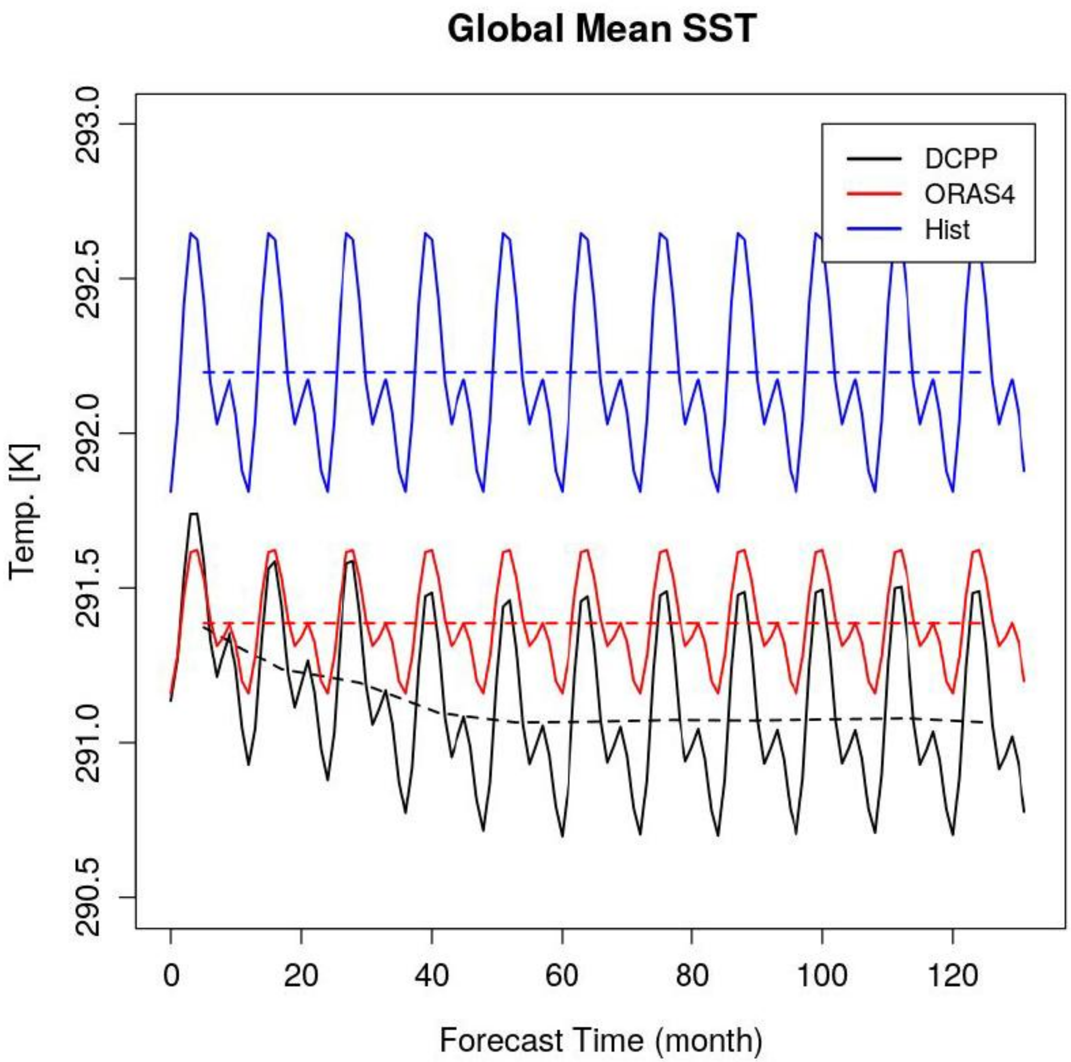


After a linear detrending (which is a rather artificial approach) the skill of global mean temperature goes down substantially, especially after the 2^{nd} forecast year

Preliminary results from DCPP Component A

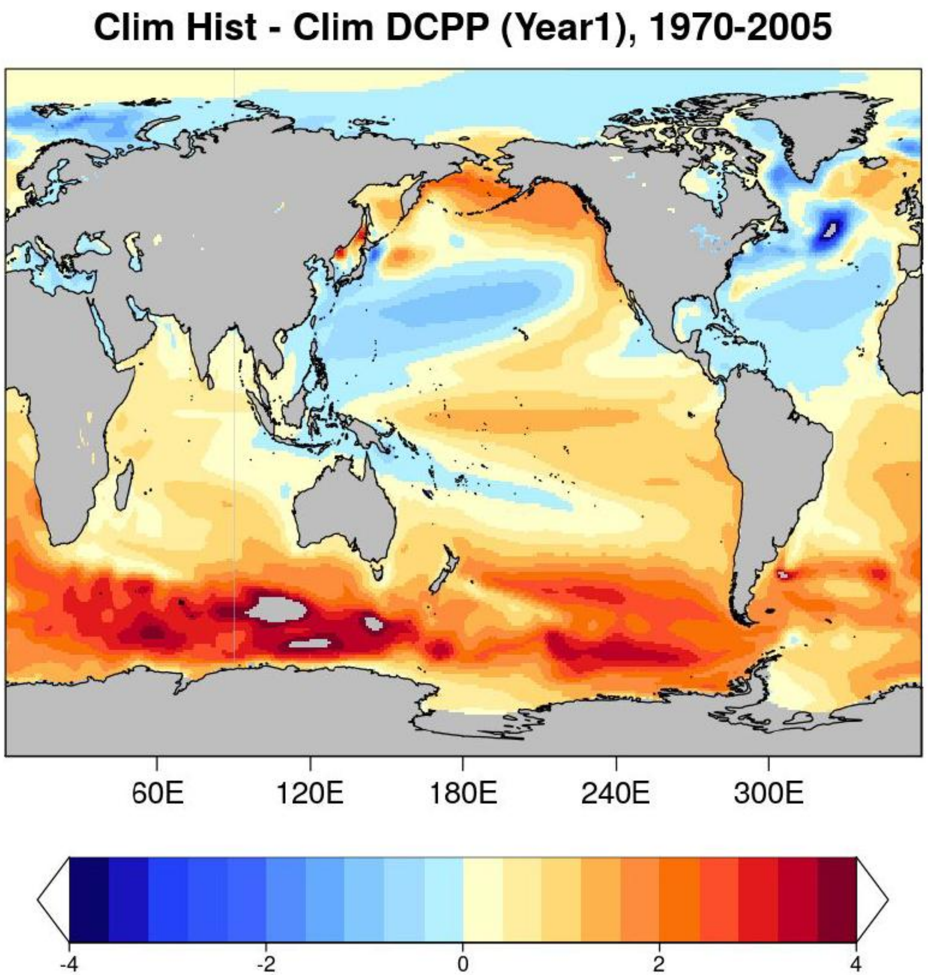


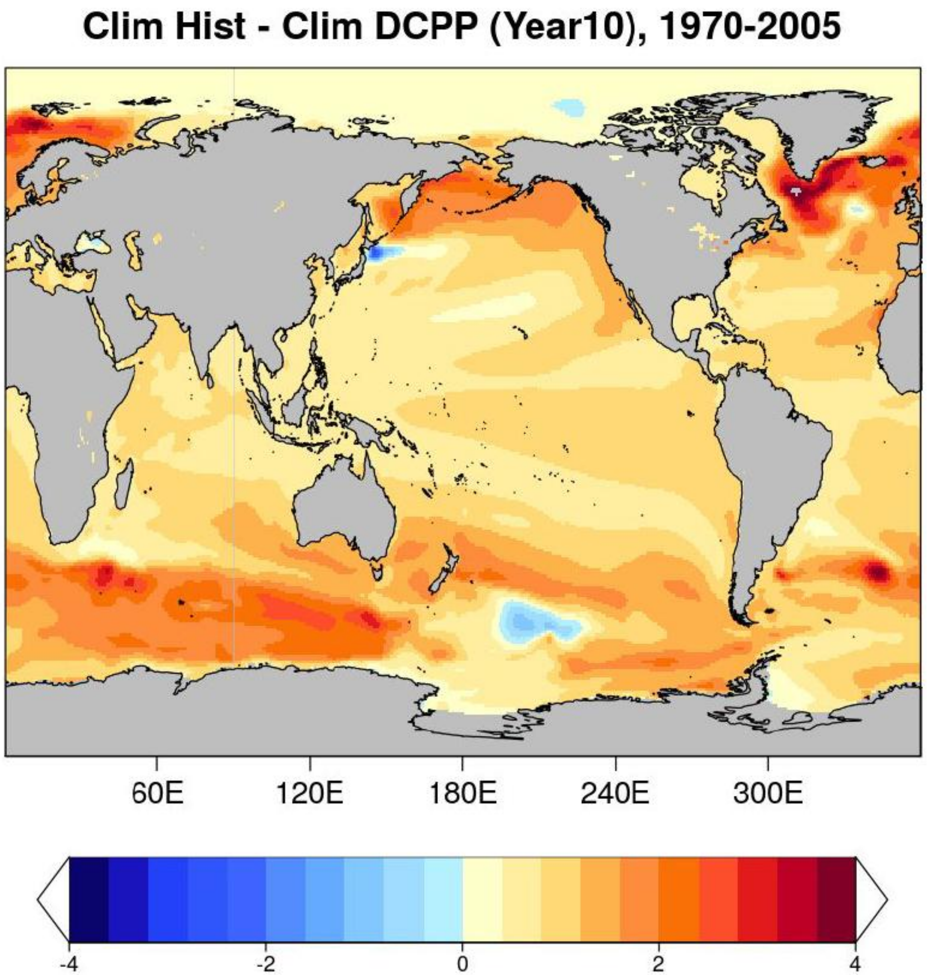
Drift in Decadal Predictions



- Stronger seasonal cycle in model
- Predictions drift away from historicals
- Different attractor in historical and decadal experiments

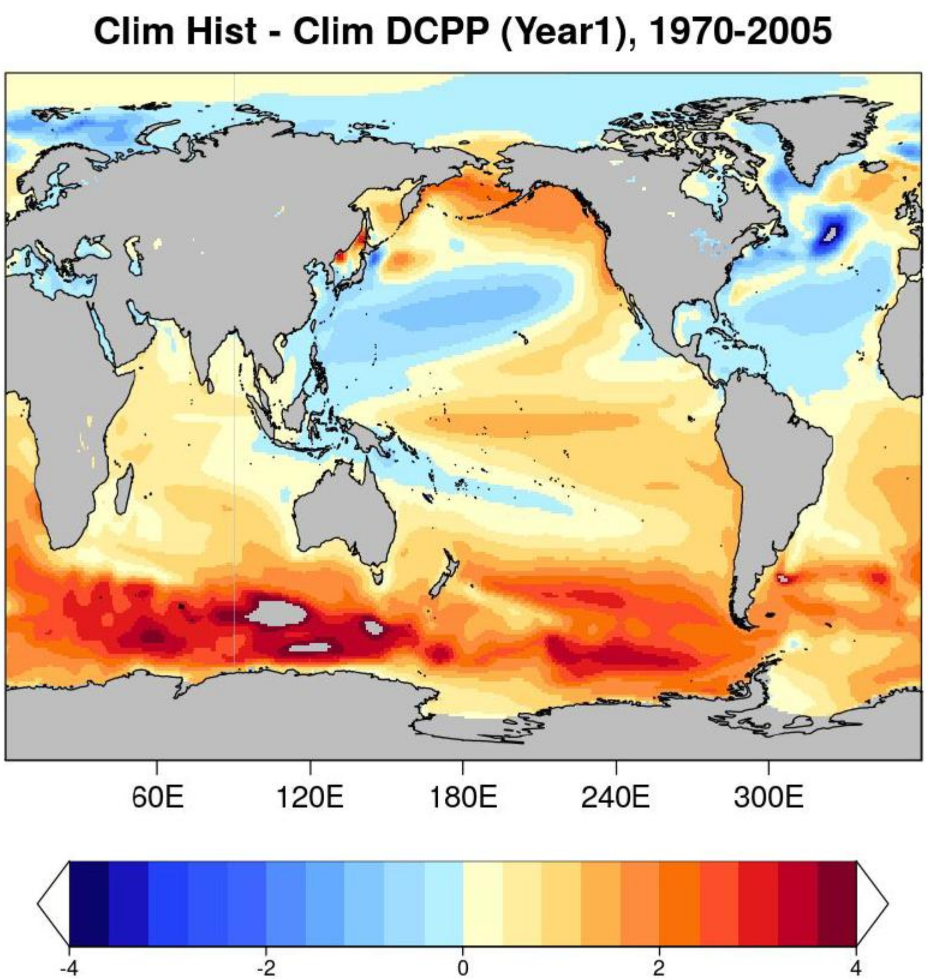
Drift in Decadal Predictions

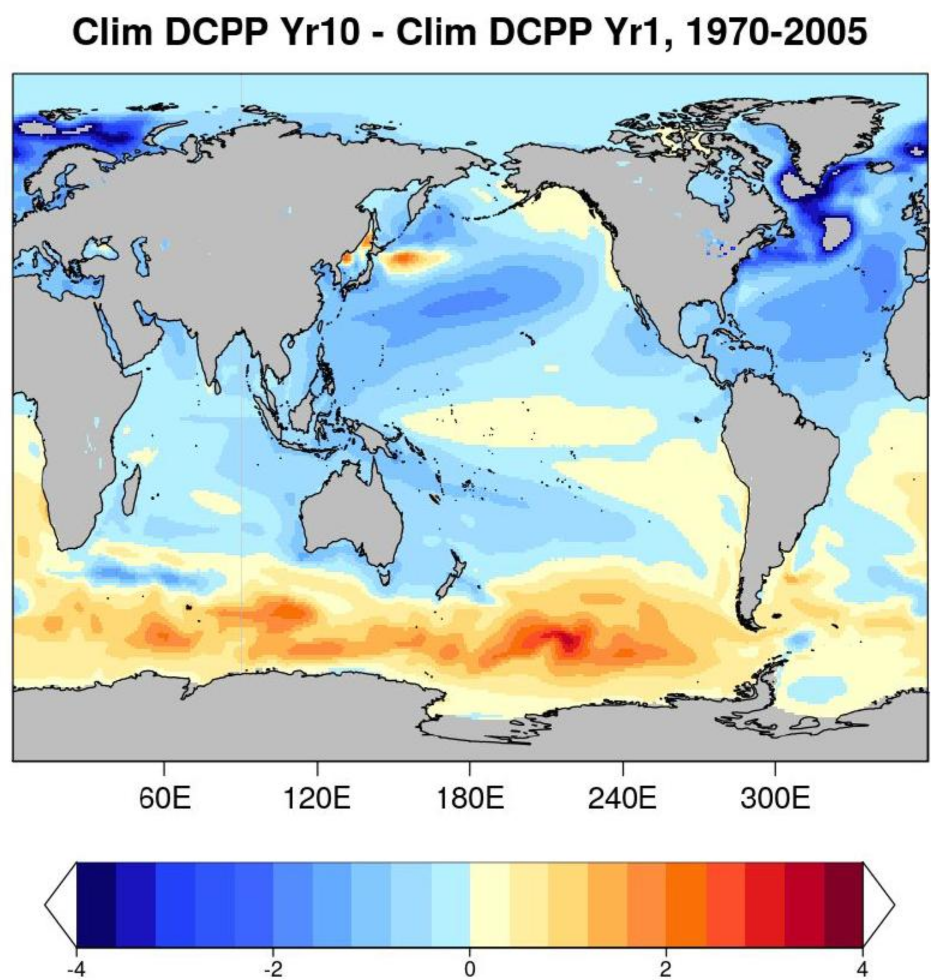




Strong warm bias in Southern Ocean, cold bias in North Atlantic

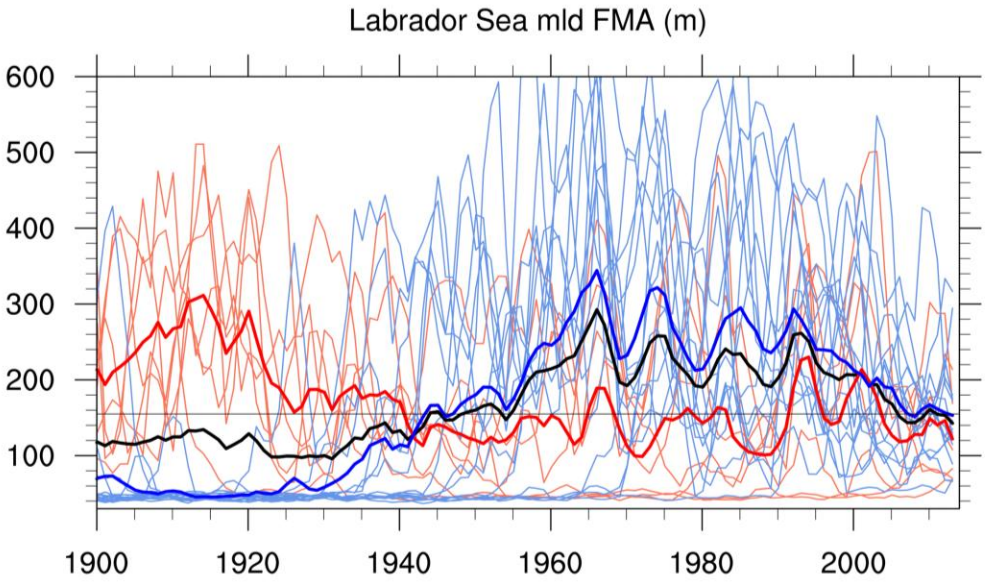
Drift in Decadal Predictions

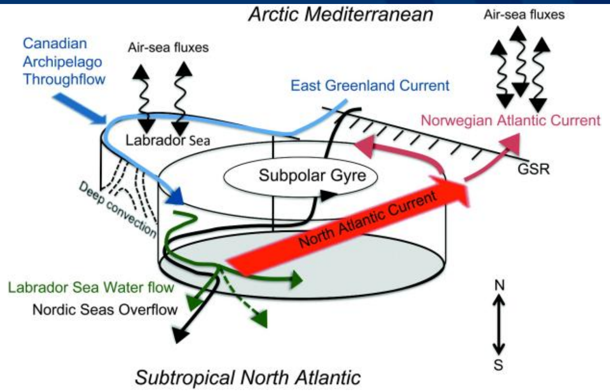




Weak AMOC in predictions?

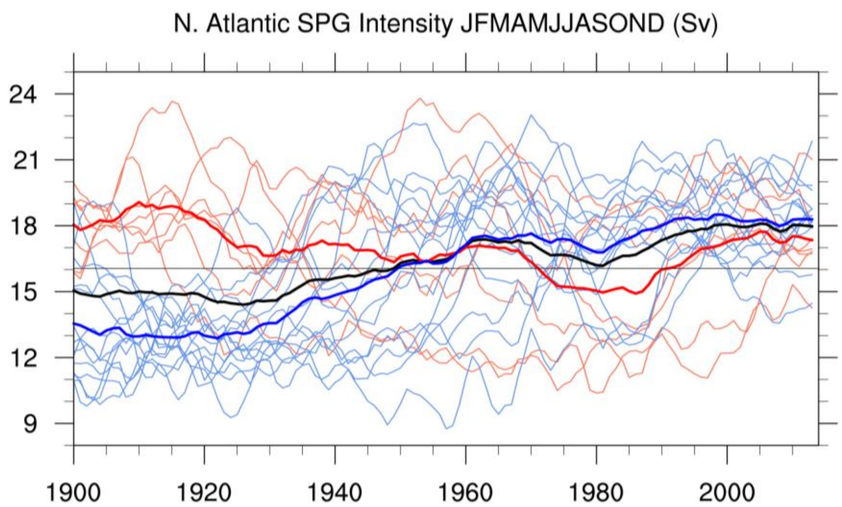
Results from Historical Ensemble

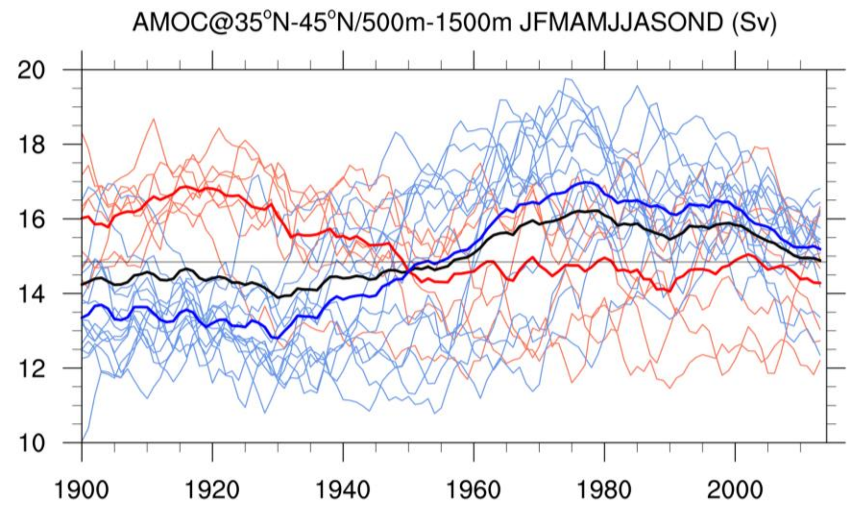




Blue members show

- no convection in Labrador Sea until 1930
- weaker Sub Polar Gyre intensity
- weaker AMOC than red members





Results from Historical Ensemble

Implications for estimation of added value of initialisation?

Summary

- Decadal Predictions with EC – Earth for CMIP6 DCPP Component A have completed and will be on ESGF soon (DECK experiments already are)

- First (quick) results show no surprises in quality of hindcast set
 → probabilistic verification still missing

- Ongoing investigations:

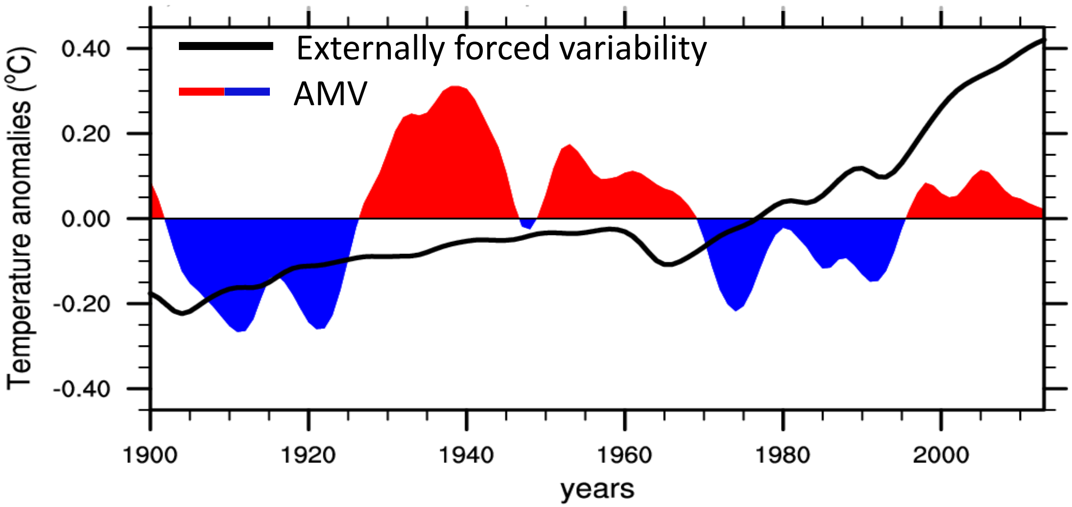
I. What is the best way to 'mimick' near surface temperature observations?
II. Why do not initialised and initialised experiments have different model attractor?
III. What can we learn from behaviour of historical simulations and what implications might that have for estimation of added value of initialisation?

What am I actually doing here?

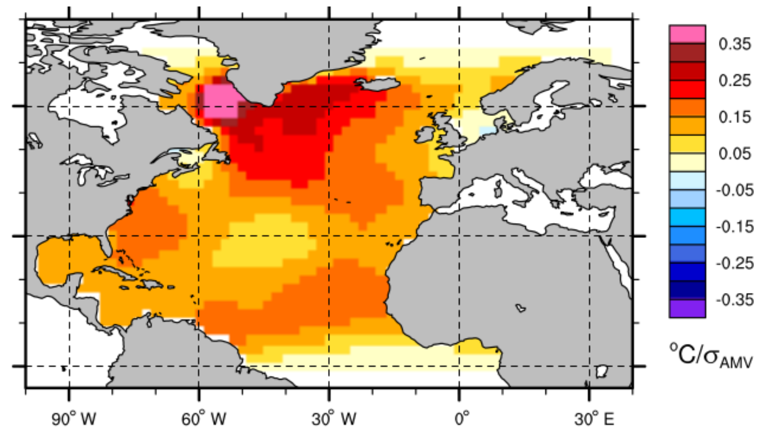
AMV impacts over Europe

- Model differences and similarities of AMV impacts on European climate
- How do pace maker experiments compare to free-running ones?

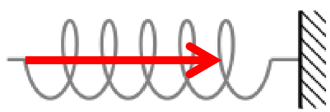
North Atlantic SST time series (Ting et al. 2009)



AMV pattern



(dataset: Ersst_v4)

Coupled model daily North Atlantic SST  Climatology **+/- AMV pattern**

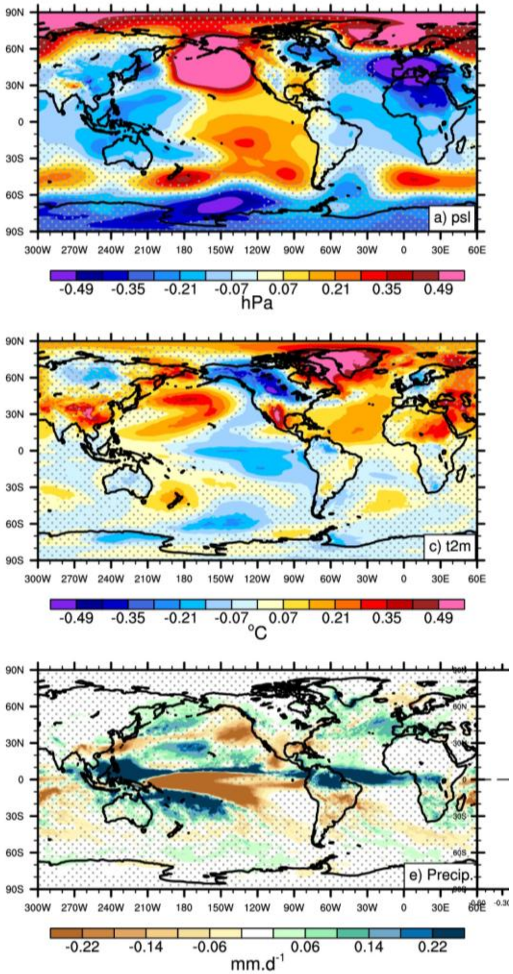
Restoring (like a spring) of SST through non-solar surface fluxes :

$$Q_k = Q_k^o + \gamma(SST_k^o - SST_{AMV})$$

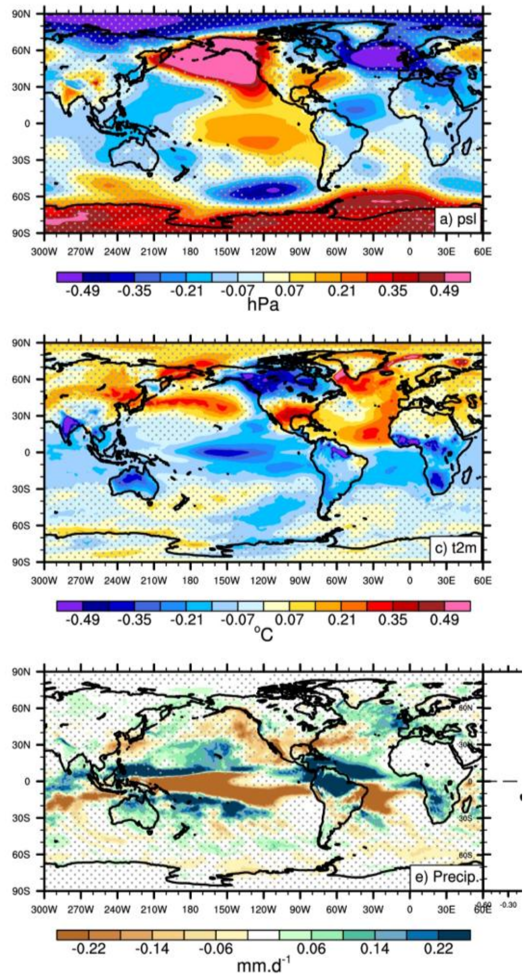
- Restoring coefficient of **γ = -40W/m²/K** over North Atlantic (Eq-70°N)
- Free ocean-ice-land-atmosphere interactions outside of North Atlantic

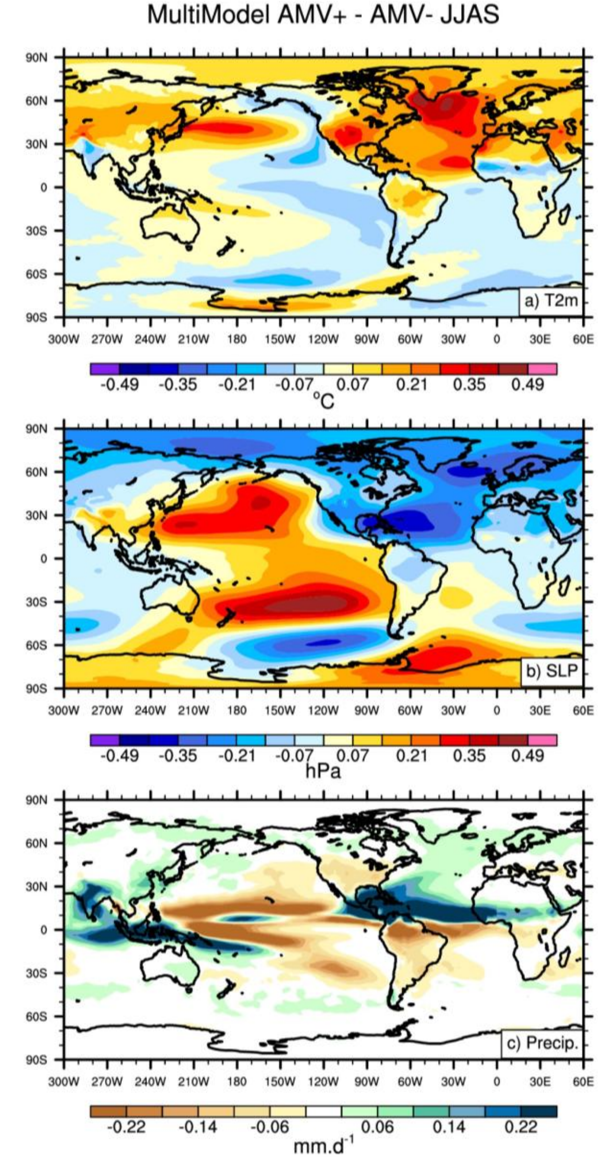
Pre DCPP C Experiments

ECMWF IFS HR
AMV+ minus AMV-
DJFM



MPI ESM 1-2 HR
AMV+ minus AMV-
DJFM





Thank You!

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