Three techniques to represent model uncertainty in ensembles of dynamical seasonal and interannual forecasts

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First ENSEMBLES objective

- ENSEMBLES is a EU-funded project that run from 2004 to 2009, with ~70 partners and that worked on the development of an EPS across space and time scales.
- First objective: Develop an ensemble prediction system for climate changes based on the principal state-of-the-art, high resolution, global and regional Earth System models developed in Europe, validated against quality controlled, high resolution gridded datasets for Europe, to produce for the first time, an objective probabilistic estimate of uncertainty in future climate at the seasonal to decadal and longer timescales.

Framework: Seamless systems

- Main hypothesis: seasonal-to-interannual climate forecasts could be used to infer some aspects of the quality of climate-change predictions in a seamless framework.
- The goal is to complement other methods of assessing the quality of climate-change predictions (e.g., reliability ensemble averaging, climate prediction index) with estimations of the forecast quality (including reliability) of regional probabilistic predictions and assessments of typical model errors.

Centennial global simulations

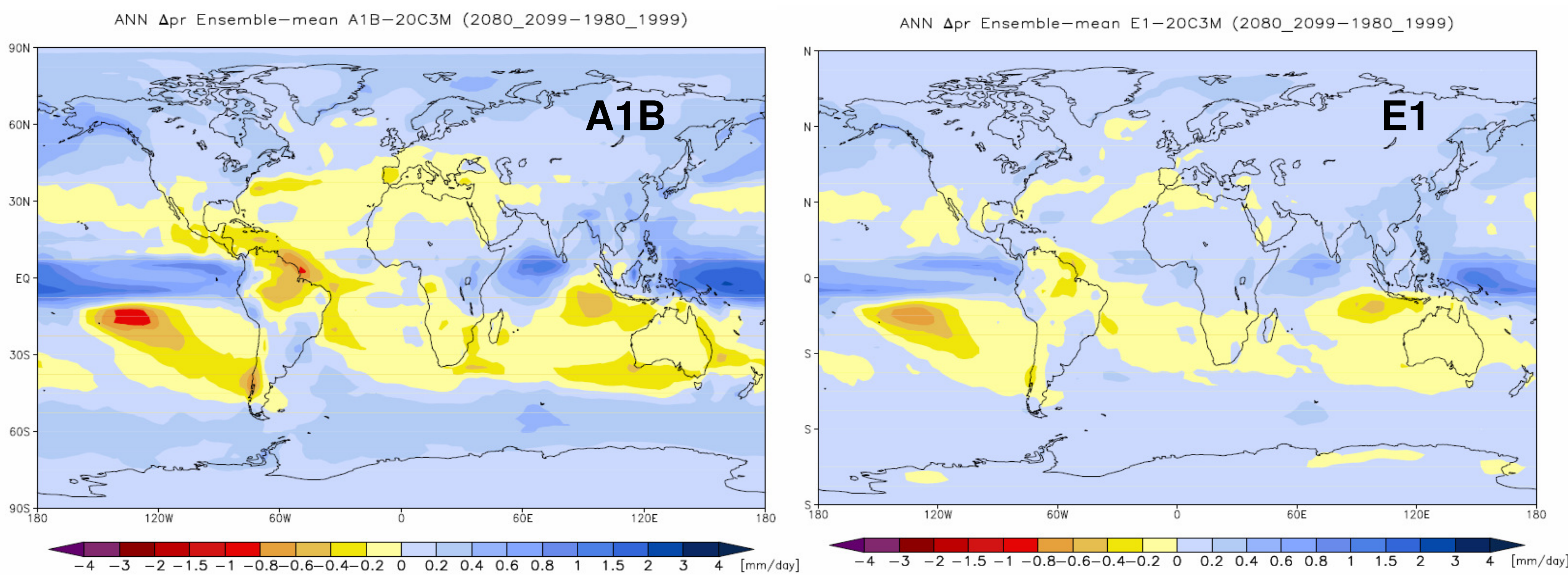
- Use of common forcings and experimental set-up
  - ➢ Control simulations (multicentennial) with 1860 preindustrial forcings and 1860-2000 with
    - o Anthropogenic only (based on IPCC)
    - o Anthropogenic+Natural forcings
  - ➢ 2000-2100 simulations
    - o Stream 1: IPCC SRES scenarios A1B, B1, A2
    - o Stream 2: improved models (land-use, carbon cycle, aerosol transport) and additional scenarios
    - o New stabilisation scenario (E1= 450-eq CO_2)
- Multi-model and perturbed parameters

Multi-model centennial global simulations

- Simulations available on the CERA (M&D) database

Multi-model composition		Model components			1860-2000 simulations (LU=land-use, GA=GHGs + Aerosol, V=solar+volcanic)				2000-2100 scenarios		
Partners	**Model**	**LU**	**C**	**AT**		**GA+LU**	**GA+LU+SV**	**Other**	**A1B-SRES**	**E1**	**A1B-IMAGE**
METO-HC	HadGEM2-AO HadCM3C	X -	 X	X X		1 1			2 1	2 1	1
IPSL	IPSL-CM4 IPSL-LOOP	X -	 X			3 1	3	GA.SV	3 1	3 1	1
MPIMET (+DMI)	ECHAM5-C	X	X			6			6	3	
FUB	EGMAM2	X		X		2	2	SV.LU	1	2	
INGV	C-ESM	-	X			1			1	1	
CNRM (+DMI)	CNRM-CM3.3	X				3	1		1	3	1
NERSC	BCM2 BCM-C	X X	 X			1 1		SV	1 1	1 1	

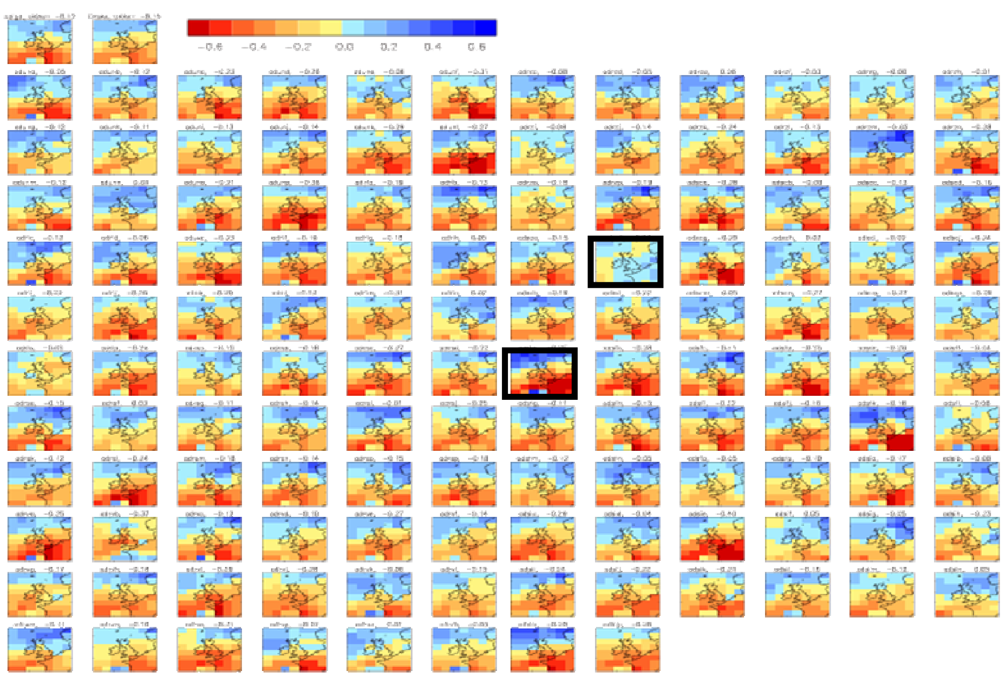
Multi-model centennial global simulations

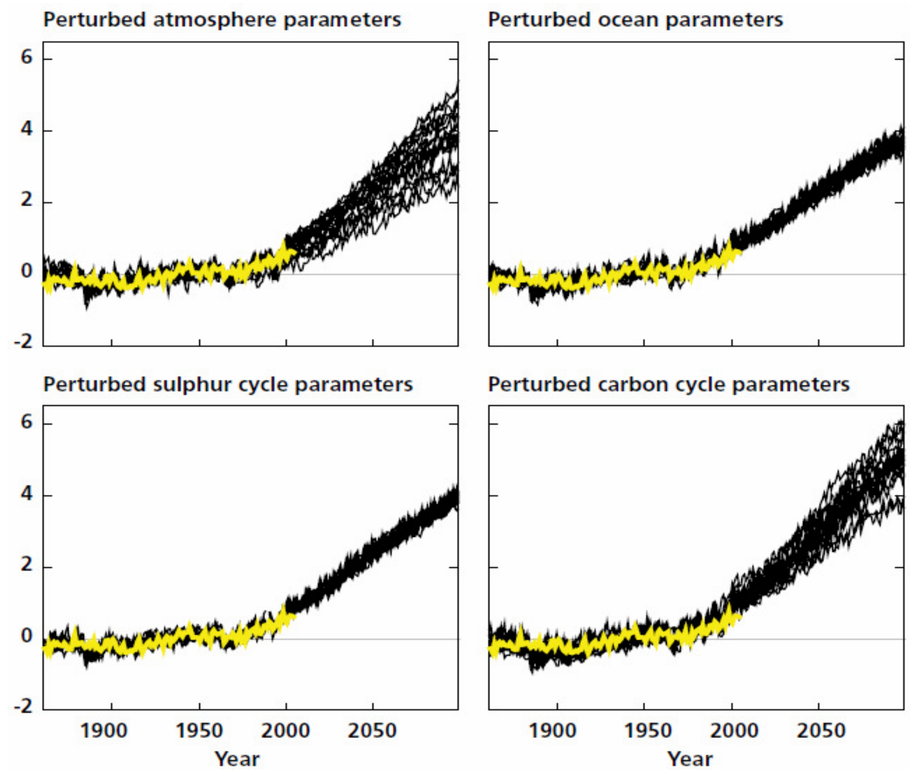


- Anomaly of multi-model mean annual-mean precipitation (2080-99 minus 1980-99) in scenarios A1B and E1

Perturbed-parameter global simulations

- Introducing parameter perturbations on a GCM (HadCM3) to sample key uncertainties.





Met Office
Hadley Centre

Ensemble of s2d global simulations

- Common experimental set-up with realistic initialization using multi-model, perturbed parameters and stochastic physics
  - Seasonal and annual (14 months) hindcasts + decadal (10 years) hindcasts
  - Two streams
    - Stream 1: 1991-2001, May and Nov start dates, nine members
    - Stream 2: 1960-2005, 4 start dates per year for seasonal/annual (9 members), one every 5 years for decadal (3 members)
    - Precursor of IPCC AR5 decadal and and contributor to CLIVAR's TFSP seasonal experiments

Ensemble of s2d global simulations

partner	Atmospheric model; resolution	Ocean model; resolution	initialization		external forcing	Additional components, comments	references
			atmosphere and land	ocean			
ECMWF	IFS CY31R1; T159/L62	HOPE; 0.3º-1.4º/L29	ERA-40/oper. analysis, atmospheric singular vectors	wind stress perturbations to generate ensemble of ocean reanalyses; SST perturbations at initial time	observed global well-mixed GHGs and sulphate aerosol and A1B from 2000, observed solar activity, no volcanic aerosol nor ozone	Operational Seasonal Forecasting system S3	*Stockdale et al.* (2010)*; Balmaseda et al.* (2008)
	IFS CY33R1; T159/L62	HOPE; 0.3º-1.4º/L29	ERA-40/oper. analysis, atmospheric singular vectors	wind stress perturbations to generate ensemble of ocean reanalyses; SST perturbations at initial time	“	used for the decadal hindcasts only	*Bechtold et al.* (*2008*)
	IFS CY35R2; T159/L62	HOPE; 0.3º-1.4º/L29	ERA-40/oper. analysis, atmospheric singular vectors	wind stress perturbations to generate ensemble of ocean reanalyses; SST perturbations at initial time	“	used with the stochastic physics approach	*Palmer et al.* (*2009*)
UKMO	HadGEM2-A; N96/L38	HadGEM2-O; 0.33º-1º/L20	ERA-40/oper. analysis, anomaly assimilation for soil moisture	wind stress perturbations to generate ensemble of ocean reanalyses; SST perturbations at initial time	observed global well-mixed GHGs, ozone and sulphate aerosol emissions and A1B from 2000, persisted solar activity and volcanic aerosol	fully interactive sea ice module	*Collins et al.* (2008)
	HadAM3; 3.75x2.5°	HadOM	anomaly assimilation of ERA-40/oper. analysis	anomaly assimilation of an ocean reanalysis	“	perturbed-parameter ensemble	*Smith et al.* (2007)
MF	ARPEGE4.6; T63	OPA8.2; 2°/L31	ERA-40/oper. analysis	wind stress, SST and water flux perturbations to generate ensemble of ocean reanalyses	observed global well-mixed GHGs and sulphate aerosol and A1B from 2000, no solar activity nor volcanic aerosol, dynamical ozone	GELATO sea ice model	*Daget et al.* (2009)*; Salas y Melia* (2002)
IFM-GEOMAR	ECHAM5; T63/L31	MPI-OM1; 1.5º/L40	initial condition permutations of three coupled climate simulations from 1950 to 2005 with SSTs restored to observations		observed global well-mixed GHGs, ozone and sulphate aerosol emissions and A1B from 2000, persisted solar activity and volcanic aerosol	-	*Keenlyside et al.* (2005)*; Jungclaus et al.* (2006)
CMCC-INGV	ECHAM5; T63/L19	OPA8.2; 2°/L31	AMIP-type simulations with forced SSTs	wind stress perturbations to generate ensemble of ocean reanalyses, SST perturbations at initial time	observed global well-mixed GHGs and sulphate aerosol and A1B from 2000, no volcanic aerosol nor ozone	dynamical snow-sea ice model and land-surface model	*Weisheimer et al.* (2009); *Alessandri et al.* (2010)

Dealing with systematic errors

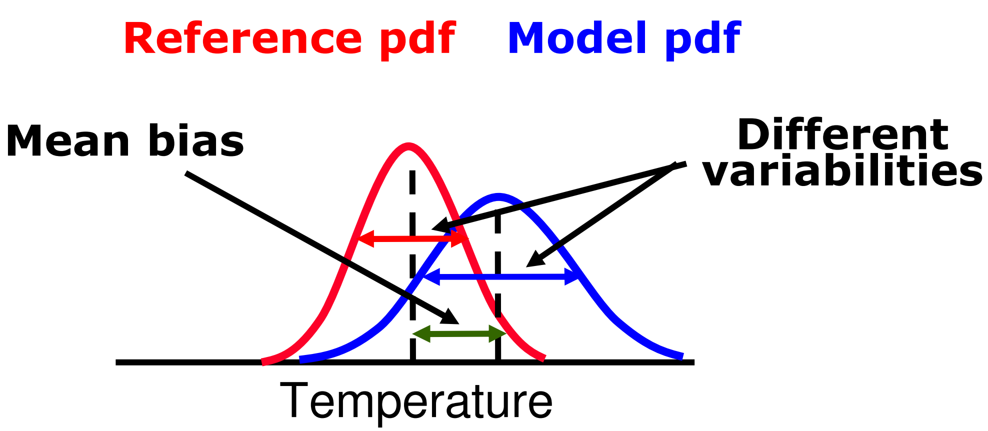
- Model drift is typically comparable to signal
  - Both in ocean and atmosphere fields.
- Predictions are made *relative* to past model integrations
  - Model climate estimated from all available years and all ensemble members, performed separately for each single-model or model version.
  - Model climate is a function of start date and lead time.
  - Anomalies computed in one-year out cross-validation.
- Implicit assumption of linearity
  - We implicitly assume that a shift in the model forecast relative to the model climate corresponds to the expected shift in a true forecast relative to the true climate, despite differences between model and true climate.
  - Most of the time, the assumption seems to work pretty well. But it's still a strong assumption.

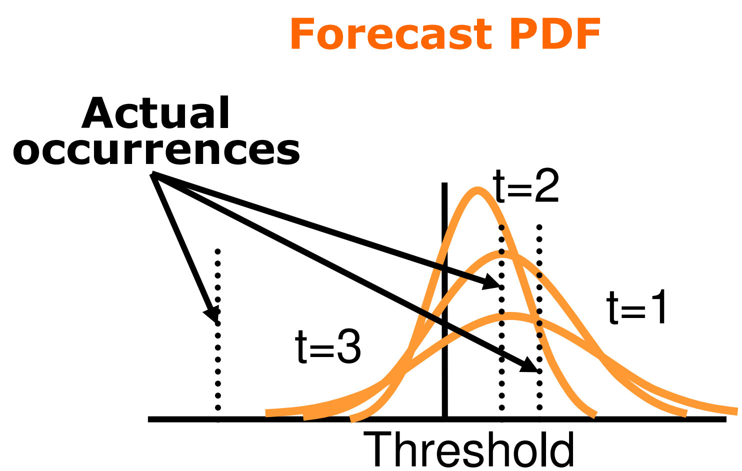
Systematic errors in ensemble forecasts

Main systematic errors in dynamical climate forecasts:

- Differences between the model climatological pdf (computed for a lead time from all start dates and ensemble members) and the reference climatological pdf (for the corresponding times of the reference dataset): systematic errors in mean and variability.
- Conditional biases in the forecast pdf: errors in conditional probabilities implying that probability forecasts are not trustworthy. This type of systematic error is best assessed using the reliability diagram.

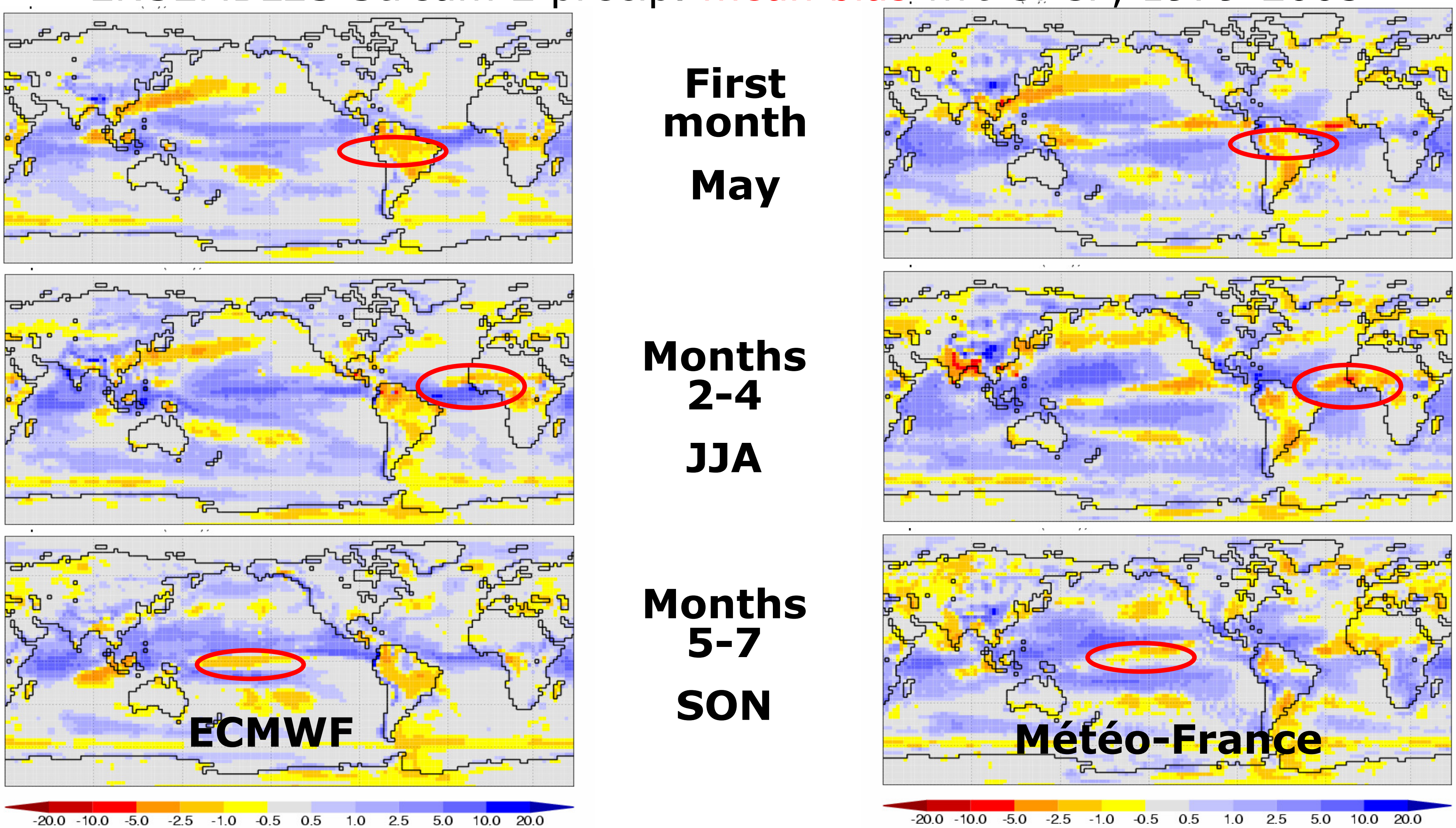
Differences in climatological pdfs





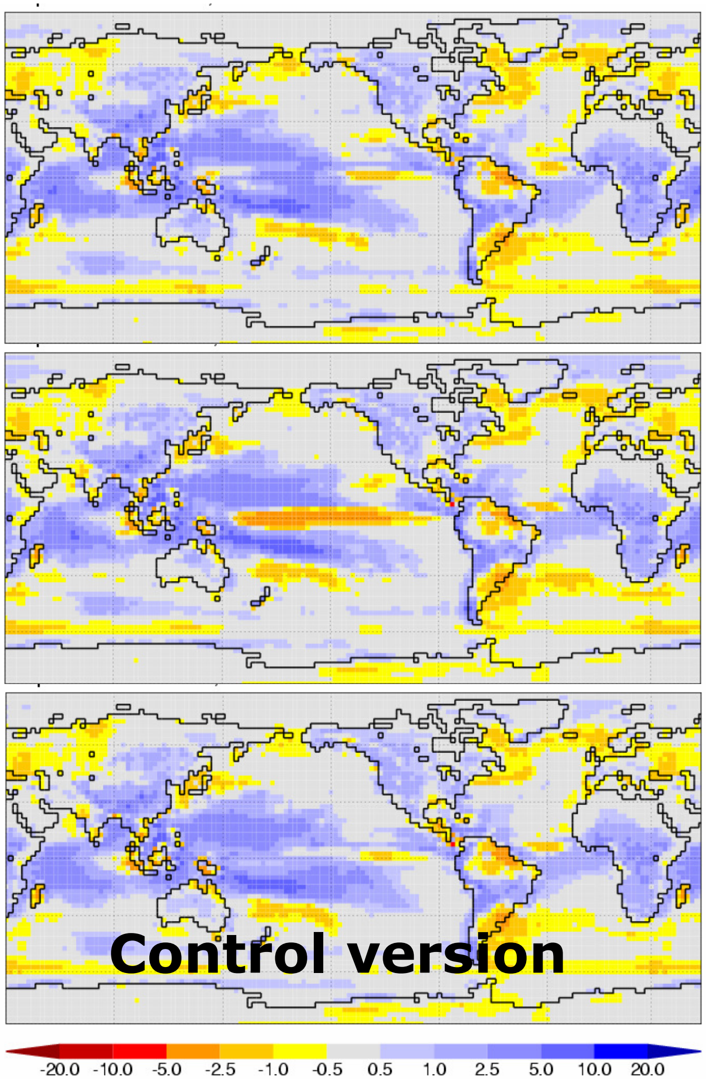
Systematic error in seasonal forecasts

ENSEMBLES Stream 2 precip. mean bias wrt GPCP, 1979-2005



Systematic error in interannual hindcasts

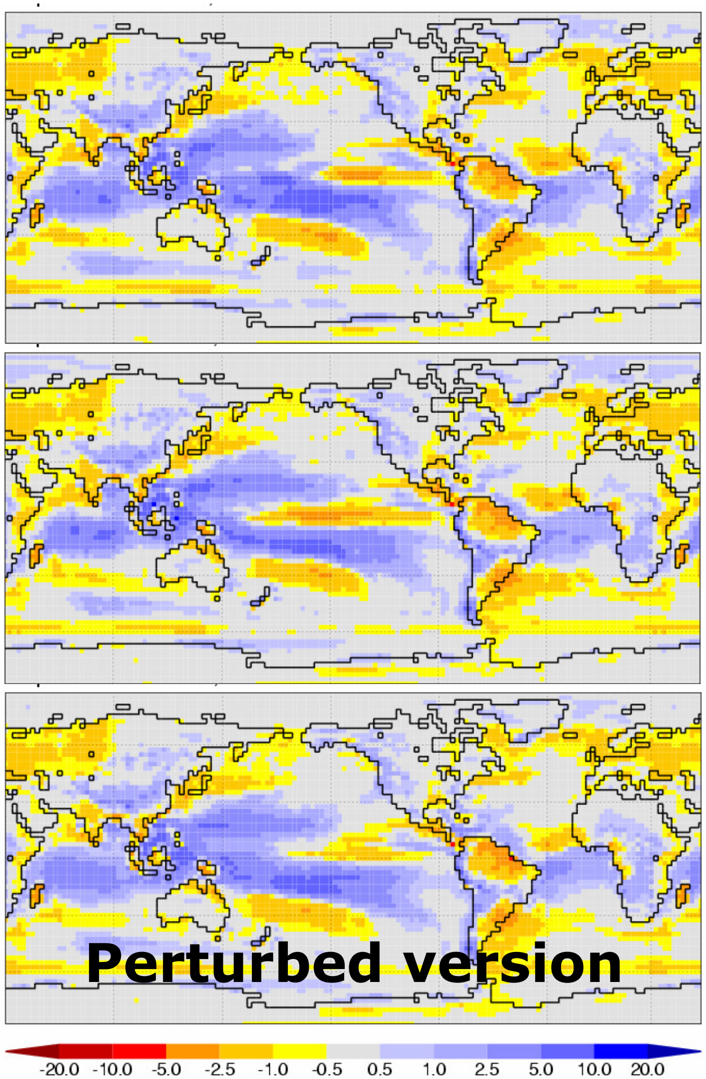
Perturbed-parameter precipitation mean bias wrt GPCP, May start date, 1991-2001



3-14 months

15-26 months

27-62 months



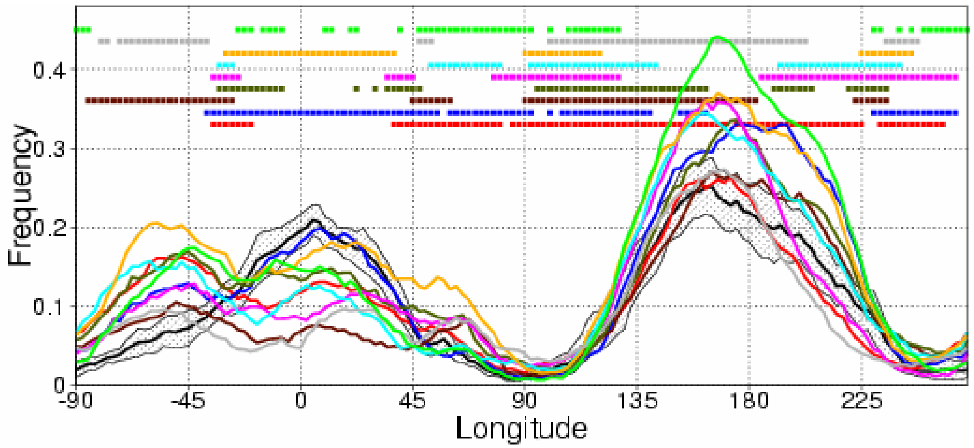
Systematic error: Blocking frequency

Northern Hemisphere DJF blocking frequency for 1-month lead seasonal hindcasts for the 9 versions of DePreSys_PP (left) and ENSEMBLES Stream 1 (right) over the period 1991-2001. Results are for the Tibaldi and Molteni index (reversal of the meridional gradient of Z500).

The dots on top of each panel show the longitudes where the mean frequency of an experiment is significantly equal with 95% confidence to the mean frequency in ERA40

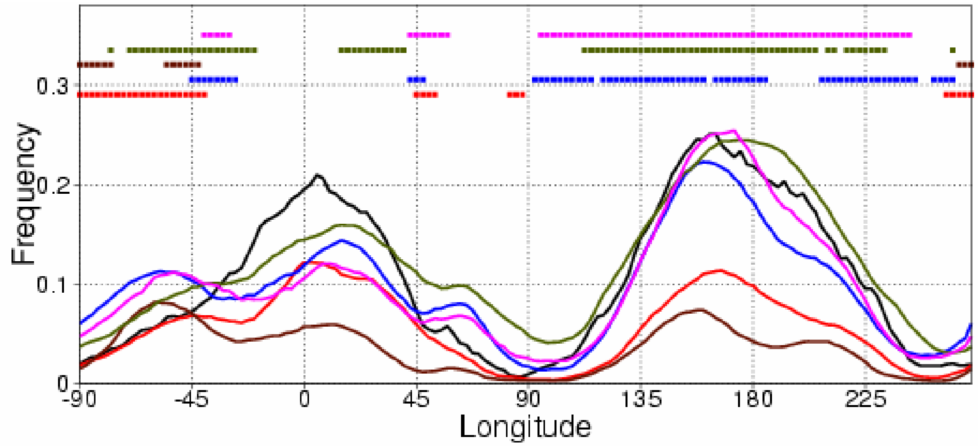
ENSEMBLES PP Stream 1

ERA40, DePreSys and eight perturbed versions



ENSEMBLES MM Stream 1

ERA40 ECMWF Glosea CNRM IfM DePreSys



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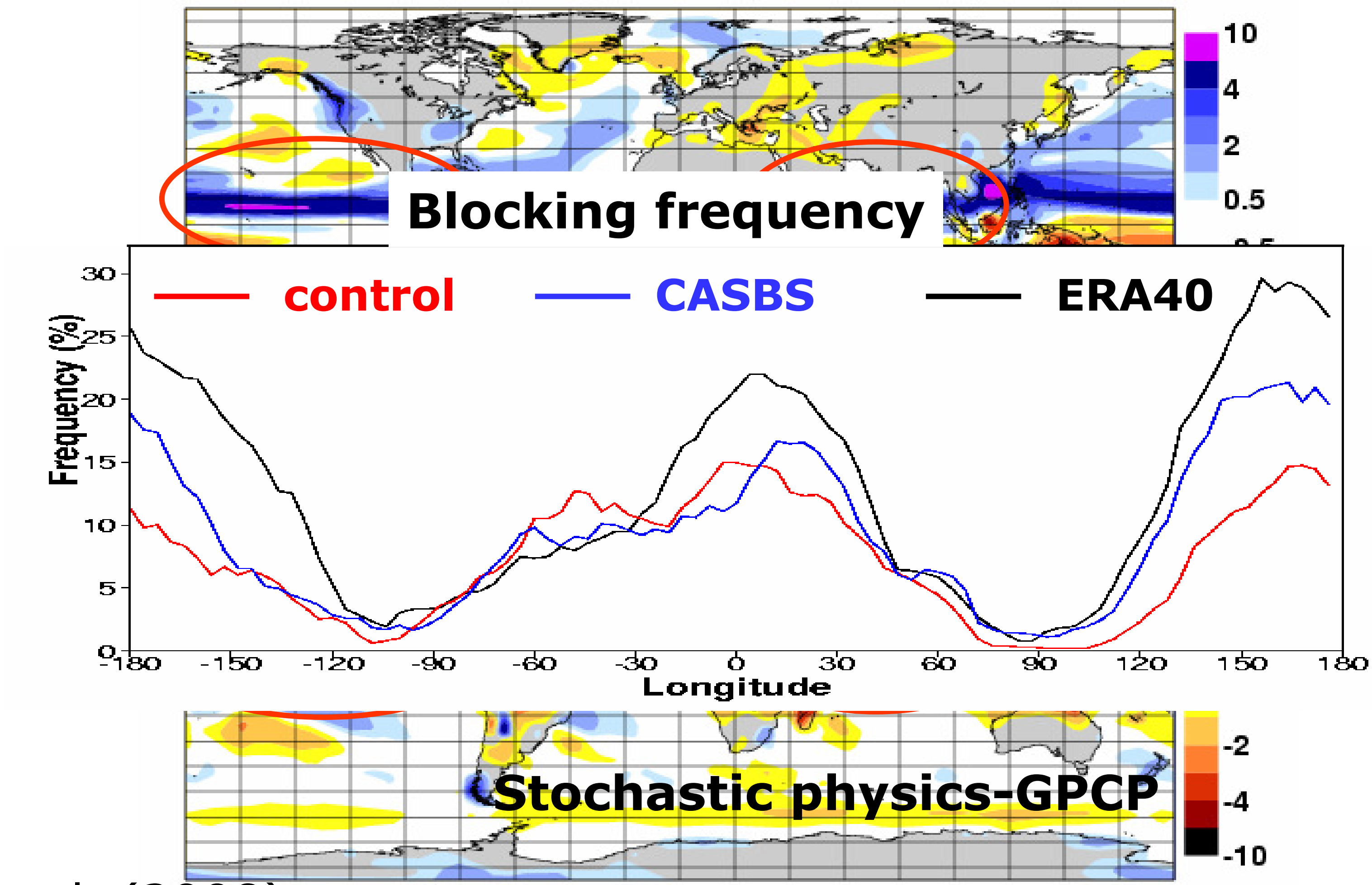
Error reduction: stochastic physics

Precipitation bias (DJF, 1-month lead, 1991-2001, CY29R2)

CASBS reduces the tropical and blocking frequency biases

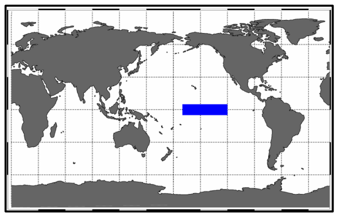


Berner et al. (2008)

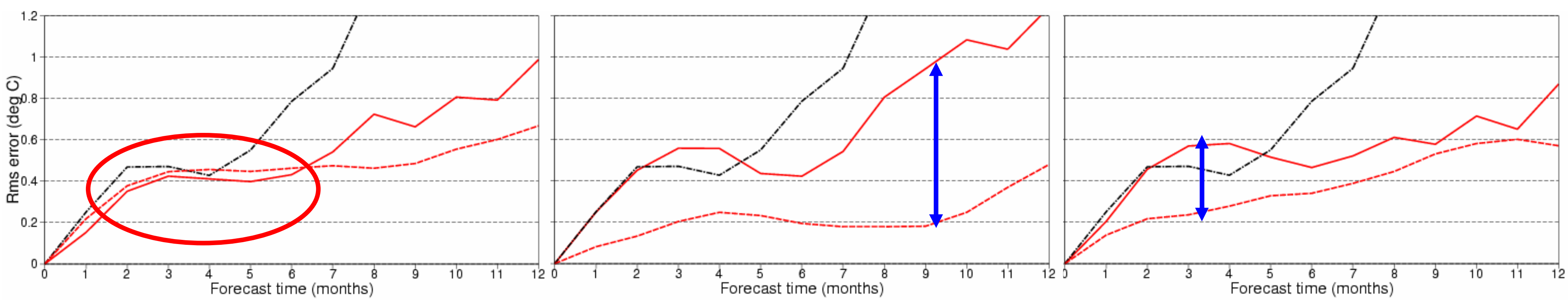
Reliability: Systematic error in spread

Sea surface temperature RMSE (solid) and spread (dashed) averaged over the Niño3.4 region for the ENSEMBLES Stream 1hindcasts of the 1st November start dates over the period 1991-2001. Persistence RMSE in dashed black.

All forecast systems beat simple persistence. The multi-model is the most skilful system, with highest deterministic reliability (RMSE~spread), in the first 6 months, while perturbed parameters is as good for longer lead times.

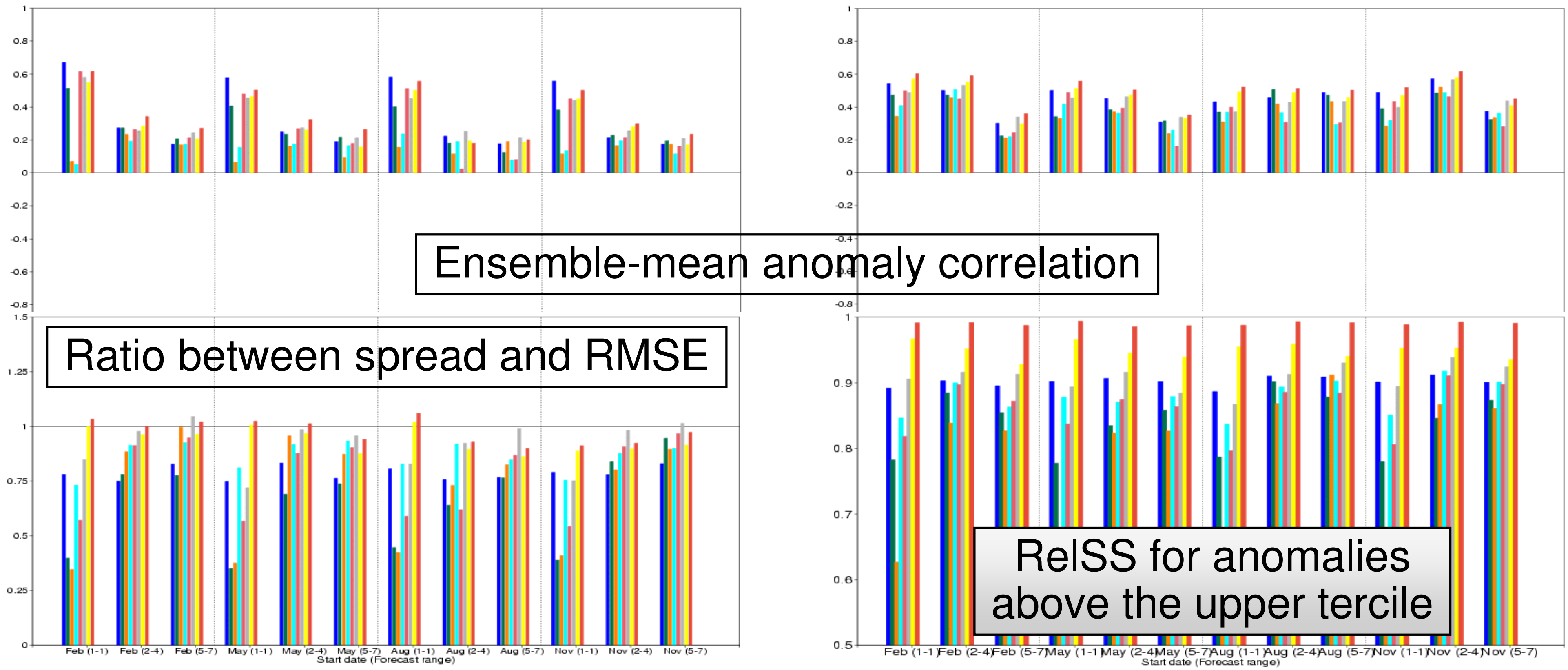


Multi-model (5 models, 45 members) **ECMWF Stochastic Physics (9 members)** **Perturbed Parameters (9 members)**



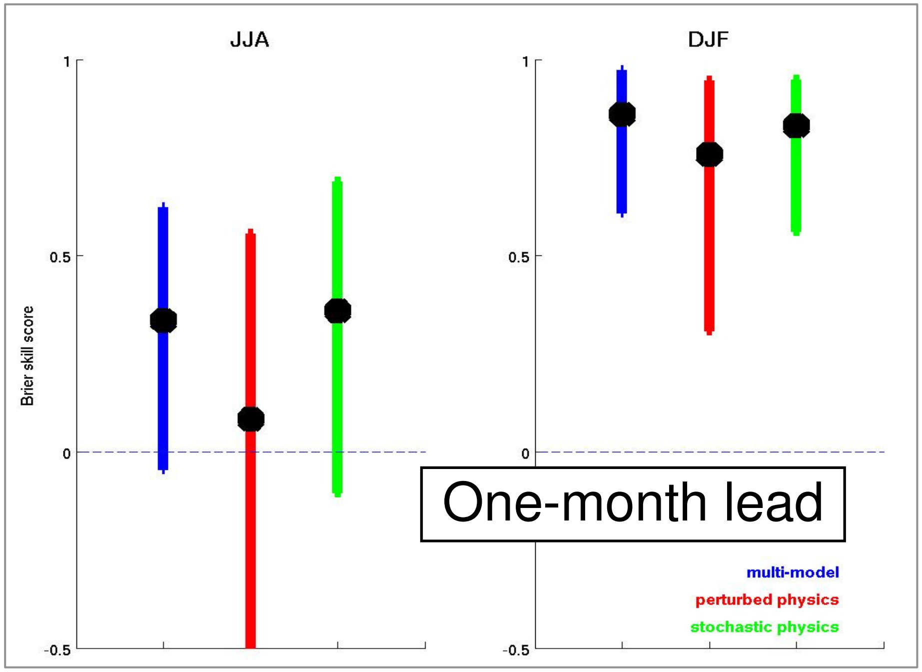
Forecast quality comparison

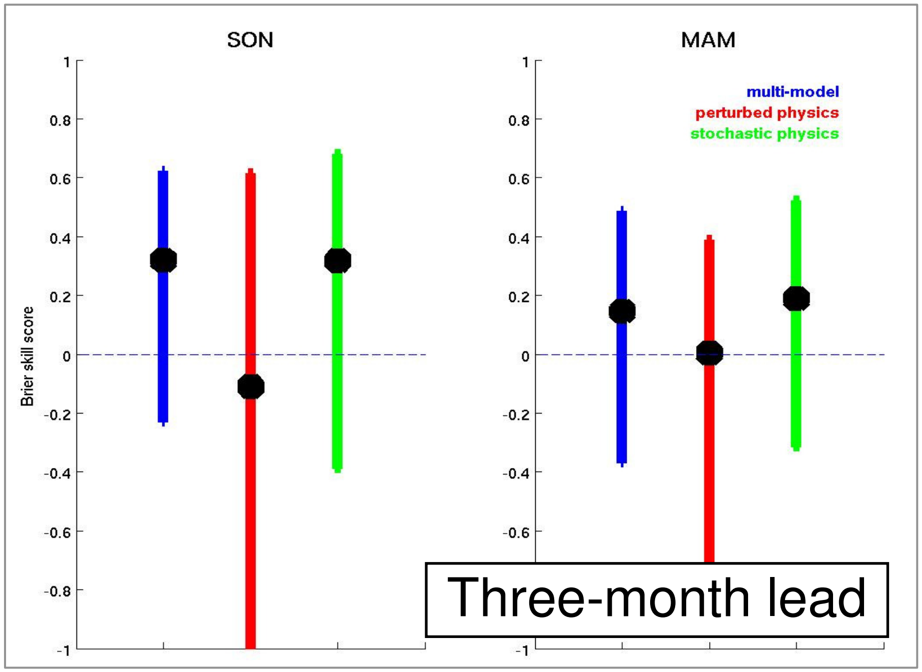
Scores for Northern extratropics T2m (left) and tropical band precipitation (right) from ECMWF, Météo-France, INGV, IfM, Met Office, Perturbed Parameters, reduced multi-model (nine-member ensembles) and multi-model (5 models, 45 members). Temperature verified with ERA40/ERA-Int over 1960-2005 and precipitation verified against GPCP over 1980-2005.



Forecast quality comparison

Debiased (i.e., taking into account the different ensemble size) Brier skill score of one-month lead (left) and three-month lead (right) predictions of Niño 3.4 SST anomalies above the upper tercile for Multi-model (45 members), Perturbed parameters (9 members) and Stochastic physics (9 members) over 1991-2005. The first (second) set of bars in each panel are for the May (November) start dates. Bars represent the 95% confidence interval of the skill score.





Forecast quality comparison

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Debiased Brier skill score of one-month lead predictions of land temperature over the Giorgi regions for Multi-model (45 members, left columns), Perturbed parameters (9 members, central columns) and Stochastic physics (9 members, right members) over 1991-2005. Significantly positive or negative scores are in bold.

	NEAR-SURFACE TEMPERATURE											
	JJA		DJF		JJA		DJF		JJA		DJF	
	cold	warm	cold	warm	cold	warm	cold	warm	cold	warm	cold	warm
Australia	**11.5**	**13.9**	3.2	6.7	-0.3	**11.0**	0.5	5.2	7.0	**17.3**	**11.8**	8.0
Amazon Basin	0.2	17.1	4.5	**23.4**	-13.7	2.8	-6.3	11.2	3.9	14.7	2.6	16.9
Southern South America	**9.2**	**9.0**	1.8	**9.9**	-2.8	7.2	2.9	**14.7**	**16.9**	8.8	4.5	**9.3**
Central America	5.9	**11.6**	-2.6	4.5	2.4	5.5	-3.9	3.3	1.2	-0.3	0.2	-3.7
Western North America	10.2	**12.2**	6.3	**12.5**	6.7	-1.2	3.3	8.9	2.8	8.0	6.4	4.7
Central North America	-0.2	**-7.3**	-3.3	10.4	-8.5	**-12.7**	7.2	13.8	**-21.4**	**-20.3**	-2.6	8.8
Eastern North America	4.1	-7.0	-4.5	10.1	-9.9	-14.7	**32.2**	8.2	-13.4	**-10.9**	-11.3	4.0
Alaska	-0.8	-0.9	-0.6	0.6	-0.4	-2.9	6.5	4.8	0.5	**12.2**	**-20.3**	-1.0
Greenland	**15.1**	**8.7**	**13.2**	**12.3**	12.7	-1.5	**17.3**	**15.1**	3.2	3.1	**12.3**	**16.3**
Mediterranean	**18.0**	**12.8**	5.8	4.3	**18.3**	**15.5**	**-17.5**	**-14.5**	**22.7**	**12.2**	6.2	2.6
Northern Europe	-3.3	0.2	4.9	0.5	1.1	4.6	-0.6	-4.0	4.6	6.3	1.5	5.2
Western Africa	7.9	7.0	7.3	**20.5**	-14.8	3.6	3.6	10.6	7.8	-2.0	10.9	**15.8**
Eastern Africa	**9.4**	**7.3**	-7.7	0.9	**-19.5**	-7.1	-3.9	-5.4	**-9.7**	-3.1	-3.7	8.2
Southern Africa	**14.0**	4.7	1.7	**10.6**	-3.2	10.2	-1.7	2.7	0.0	7.7	6.0	**13.6**
Sahel	**12.9**	7.2	**11.5**	**15.4**	**9.9**	**13.1**	6.6	**15.7**	**16.3**	**10.1**	**13.9**	**14.7**
South East Asia	**8.6**	**12.4**	**11.6**	13.4	-9.3	4.2	13.9	6.1	-0.6	9.6	3.8	1.6
East Asia	10.6	**10.2**	0.3	5.8	8.3	**10.5**	-4.2	10.1	6.4	**14.1**	3.1	-0.4
South Asia	**8.7**	**13.3**	**14.4**	**10.6**	4.3	9.2	0.1	9.3	12.9	**15.7**	**13.8**	**18.1**
Central Asia	**14.3**	**8.2**	-2.4	7.1	**14.1**	**11.8**	-2.0	**19.1**	**21.1**	**10.1**	-8.5	6.5
Tibet	**16.9**	**16.1**	-0.1	4.1	7.8	7.2	**-10.4**	3.8	8.3	**15.7**	5.6	7.6
North Asia	**7.3**	3.9	4.2	**8.5**	6.2	**8.4**	-1.5	**12.6**	4.2	1.6	-1.9	1.2
	multi-model				perturbed parameters				stochastic physics			

Forecast quality comparison

Debiased Brier skill score of one-month lead predictions of land temperature over the Giorgi regions for Multi-model (45 members, left columns), Perturbed parameters (9 members, central columns) and Stochastic physics (9 members, right members) over 1991-2005. Significantly positive or negative scores are in bold.

	PRECIPITATION											
	JJA		DJF		JJA		DJF		JJA		DJF	
	dry	wet	dry	wet	dry	wet	dry	wet	dry	wet	dry	wet
Australia	7.6	7.0	0.9	3.0	5.1	8.0	**12.4**	5.2	2.5	5.0	**10.5**	6.6
Amazon Basin	**10.3**	**10.3**	**16.0**	14.3	**8.8**	5.4	3.4	0.5	**12.2**	**11.4**	**16.1**	16.8
Southern South America	6.2	7.1	4.6	6.0	1.3	1.6	-4.5	-1.7	3.3	**9.0**	-4.7	0.2
Central America	**9.2**	**7.8**	**23.4**	**18.9**	**12.9**	5.2	**23.3**	**25.9**	**10.6**	7.7	**24.9**	**23.7**
Western North America	2.4	**8.1**	**7.2**	**7.8**	4.5	**7.5**	4.5	4.9	**9.1**	**8.4**	5.7	5.3
Central North America	0.6	2.2	7.7	**10.4**	-3.5	-5.7	**10.0**	**10.4**	1.7	3.0	2.1	5.5
Eastern North America	-1.9	-1.1	**8.3**	**10.6**	**-9.6**	**-11.1**	9.7	**13.2**	**-15.0**	-6.8	7.5	2.1
Alaska	-1.3	0.0	4.0	-2.2	-2.3	-1.0	**11.3**	3.7	-4.3	-0.7	0.2	-2.5
Greenland	2.6	**2.8**	**-3.7**	**-3.0**	1.4	0.2	**7.5**	-1.7	**-6.8**	-2.6	-2.2	-2.1
Mediterranean	-1.2	1.2	-1.0	-1.3	-6.1	-4.4	-3.0	0.1	-0.9	0.1	**11.5**	10.7
Northern Europe	2.3	2.1	-3.1	**-4.7**	**7.7**	**11.5**	-1.8	-1.6	**8.2**	6.0	6.6	1.6
Western Africa	-1.5	-0.1	-0.5	1.3	**-10.9**	-3.8	4.8	-1.6	-4.8	2.4	**-13.7**	-0.1
Eastern Africa	-2.8	1.8	3.9	2.5	-7.0	**-7.6**	**14.4**	**13.2**	-1.5	3.4	0.9	5.7
Southern Africa	3.5	1.0	5.7	**9.5**	**7.2**	4.7	**6.0**	**11.3**	7.8	9.2	7.7	8.9
Sahel	**-4.6**	**-3.6**	**-3.2**	-1.5	**-9.2**	**-6.7**	-2.7	-2.4	**-10.0**	-1.0	**-8.2**	-3.6
South East Asia	**14.3**	9.7	**8.8**	**8.3**	5.5	4.8	5.6	8.3	10.3	1.1	9.6	**12.5**
East Asia	0.5	-0.5	4.7	**4.6**	**5.6**	1.4	8.9	3.6	2.8	0.6	8.9	**15.7**
South Asia	0.2	0.9	**6.5**	**7.4**	0.6	-2.7	7.0	9.4	2.7	1.9	5.5	**10.2**
Central Asia	-0.8	0.2	7.4	5.7	0.8	-3.1	**10.3**	**8.4**	-1.5	0.2	2.9	1.6
Tibet	5.5	3.5	**6.5**	5.4	-1.4	-0.9	1.2	7.8	4.2	**6.4**	**10.7**	**10.0**
North Asia	**2.4**	**2.6**	3.1	0.6	3.3	2.9	2.1	-1.0	1.0	0.6	2.5	-1.9
	multi-model				perturbed parameters				stochastic physics			

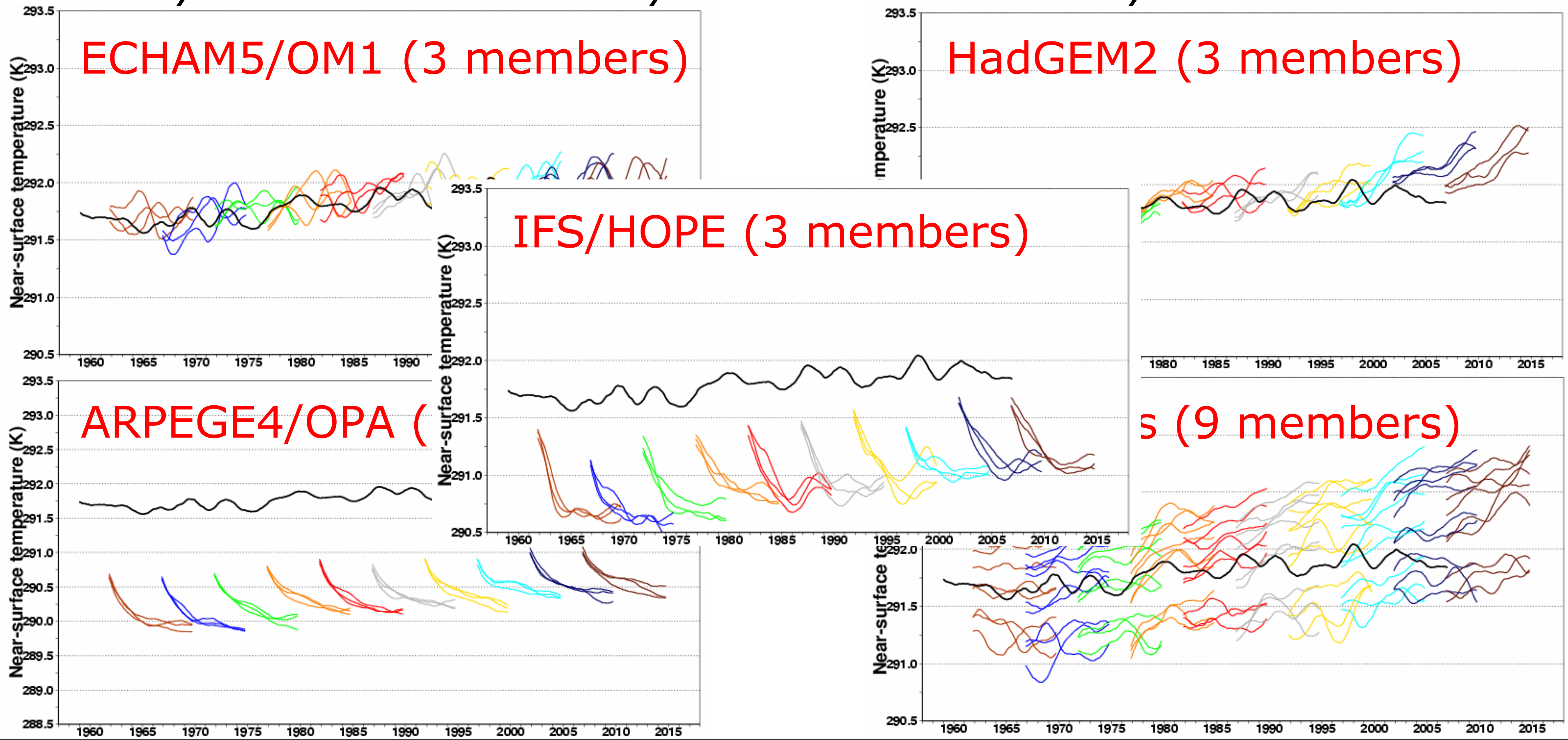
Summary: seasonal and annual

- Substantial systematic error, including lack of reliability, is still a fundamental problem in dynamical forecasting and forces *a posteriori* corrections to obtain useful predictions.
- Comprehensive assessments of the forecast quality measures (including estimates of their standard error) are indispensable in forecast system comparisons.
- Stochastic physics schemes can reduce systematic error without affecting forecast quality (unlike post-processing).
- Perturbed-parameter ensembles are competitive with multi-model ensembles, with gains both in accuracy and reliability with respect to their reference system.
- A comparison of the three methods does not allow for a definite answer.

Decadal predictions: ocean temperature

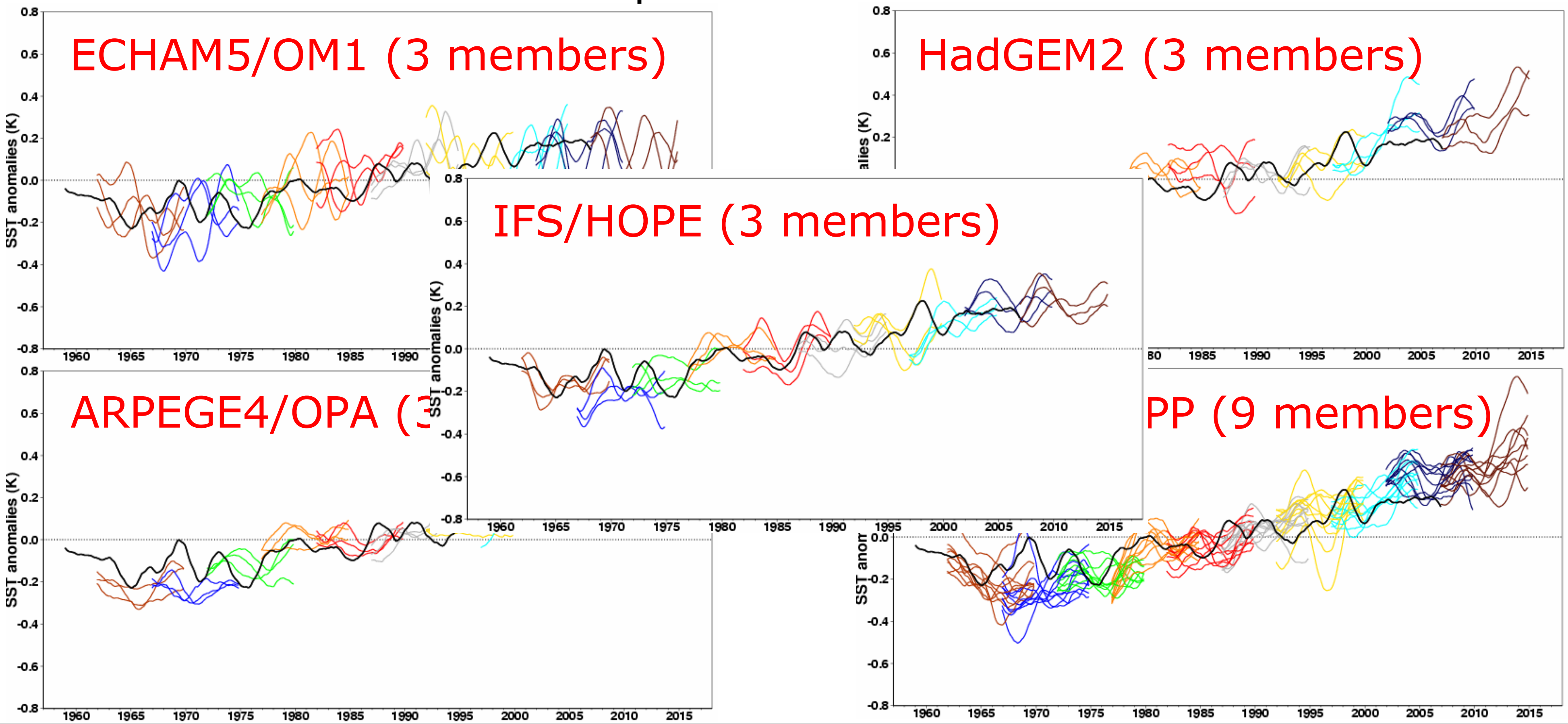
Ocean-point (70°N-60°S) mean near-surface air temperature (2-year running mean applied) from the ENSEMBLES re-forecasts. Each hindcast is shown with a different colour. ERA40/OPS is used as reference.

The systematic error is very different from one system to another.



Decadal predictions: anomalies

Ocean-point (70°N-60°S) mean sea surface temperature anomaly (2-year running mean applied) from the ENSEMBLES re-forecasts. ERA40/OPS is used as a reference. The mean systematic error has been removed over the period 1960-2005.



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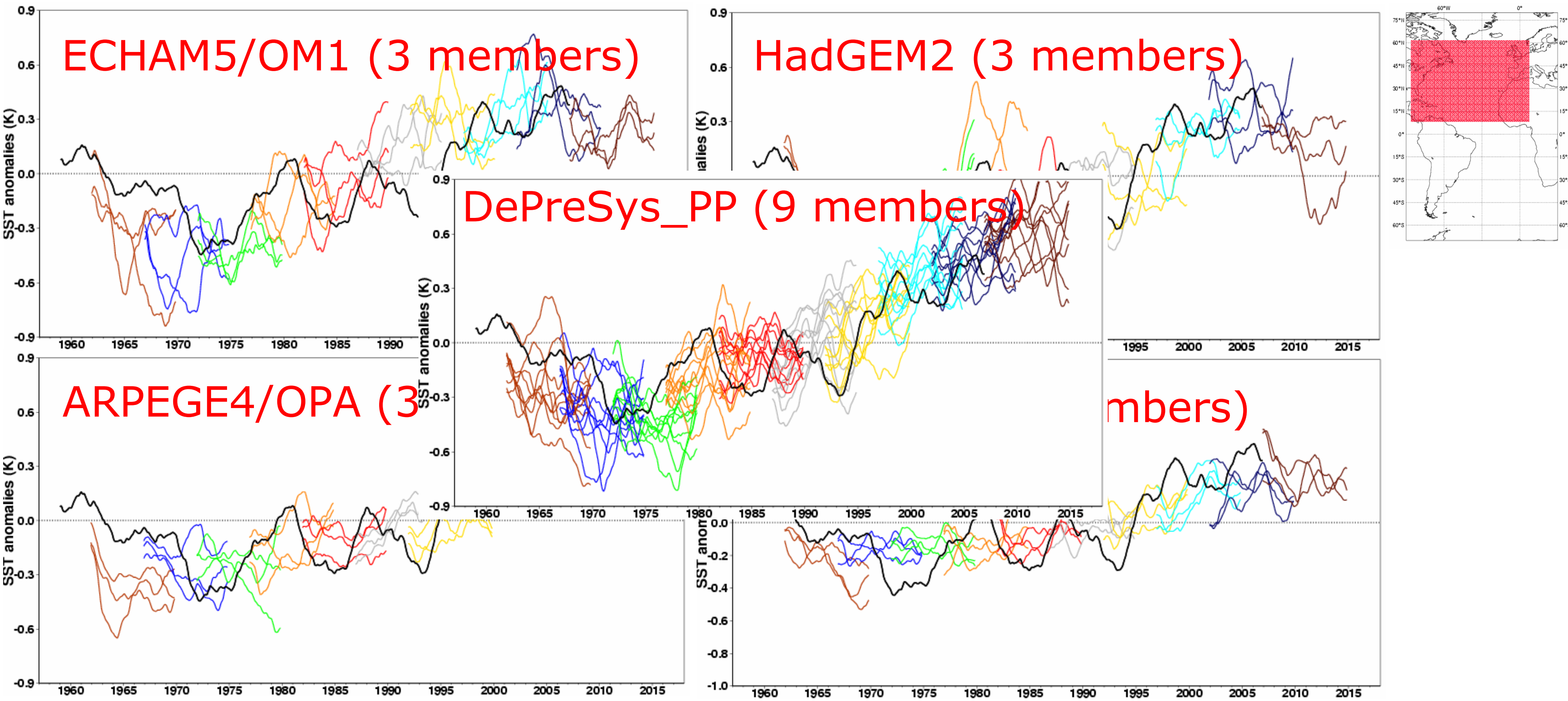
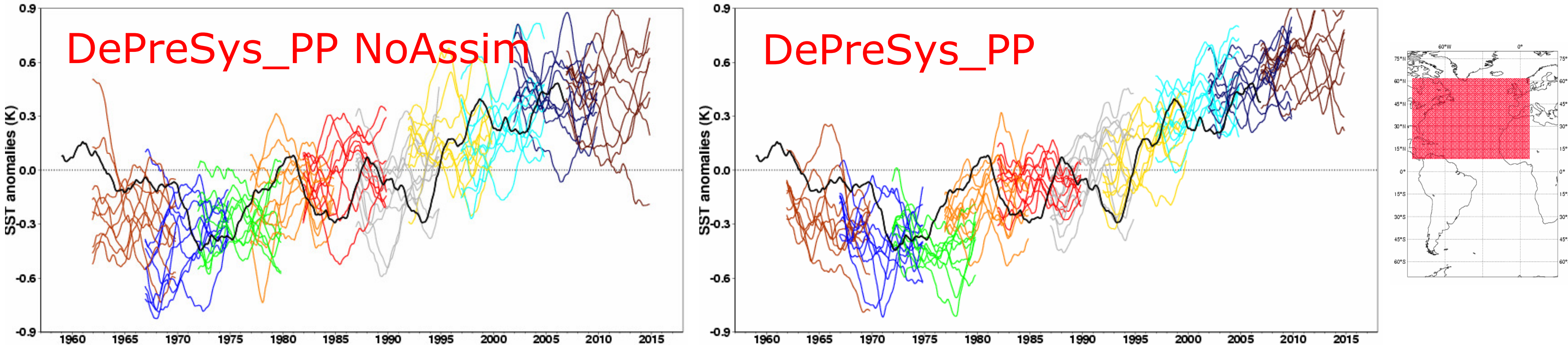
Decadal predictions: anomalies

North Atlantic average SST anomalies (2-year running mean applied).
Mean systematic error removed over the period 1960-2005.



DePreSys: initialization

North Atlantic average SST anomaly



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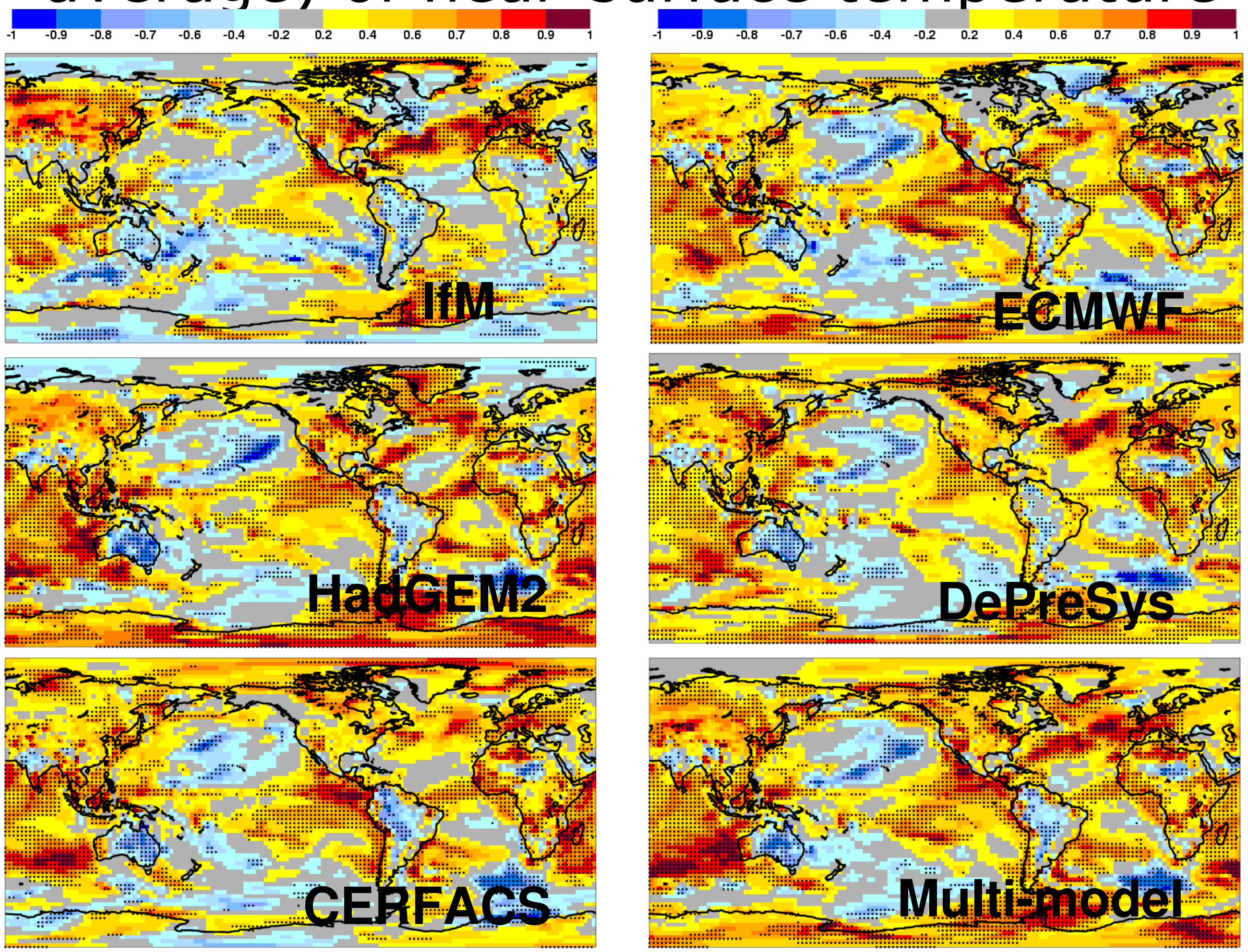
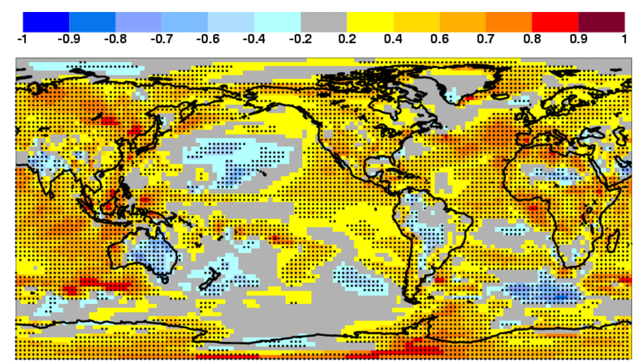
Decadal prediction forecast quality

- Ensemble-mean correlation for decadal forecasts (2-5 year average) of near-surface temperature (nine start dates)

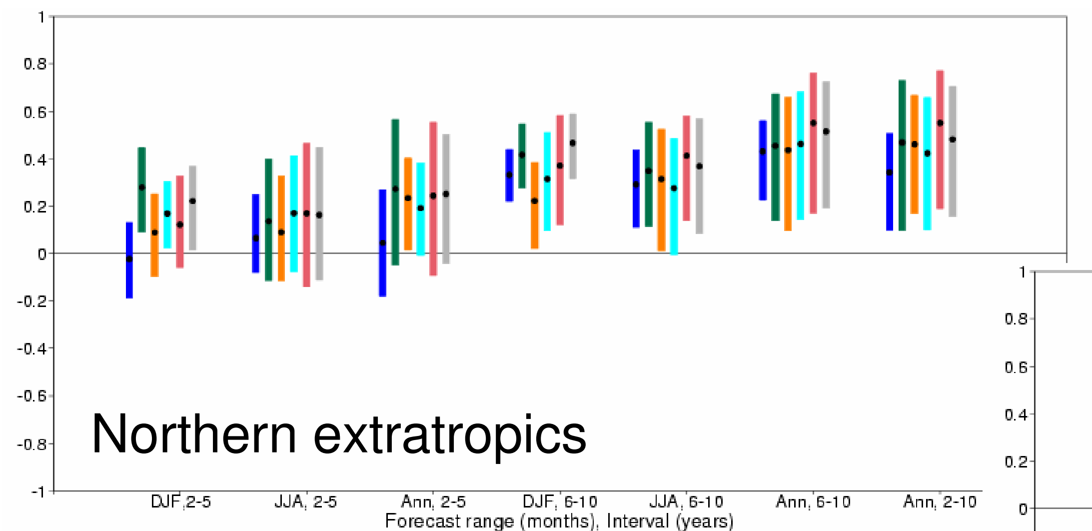


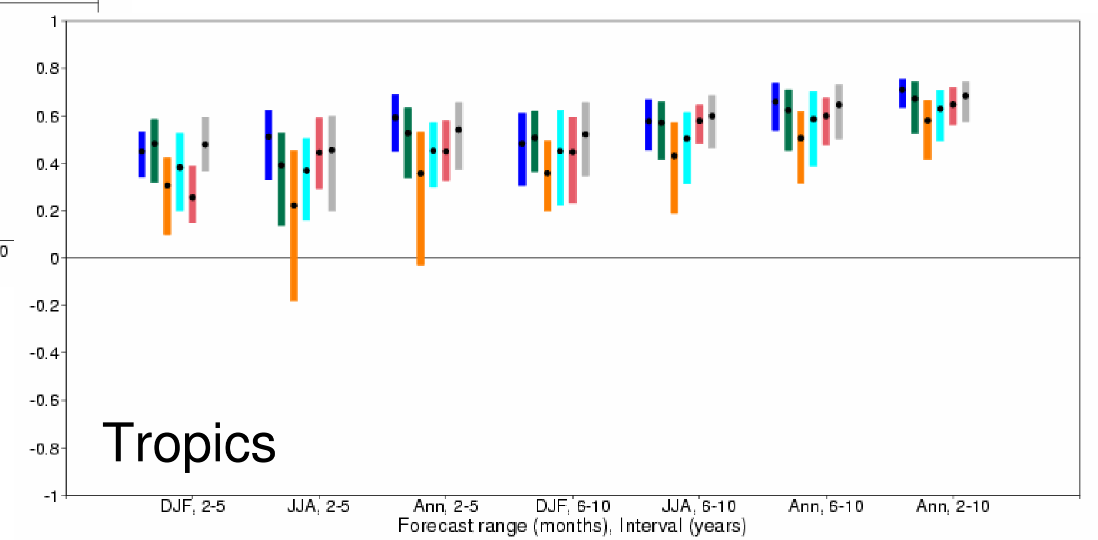


DePreSys (one start date per year)

Decadal prediction forecast quality

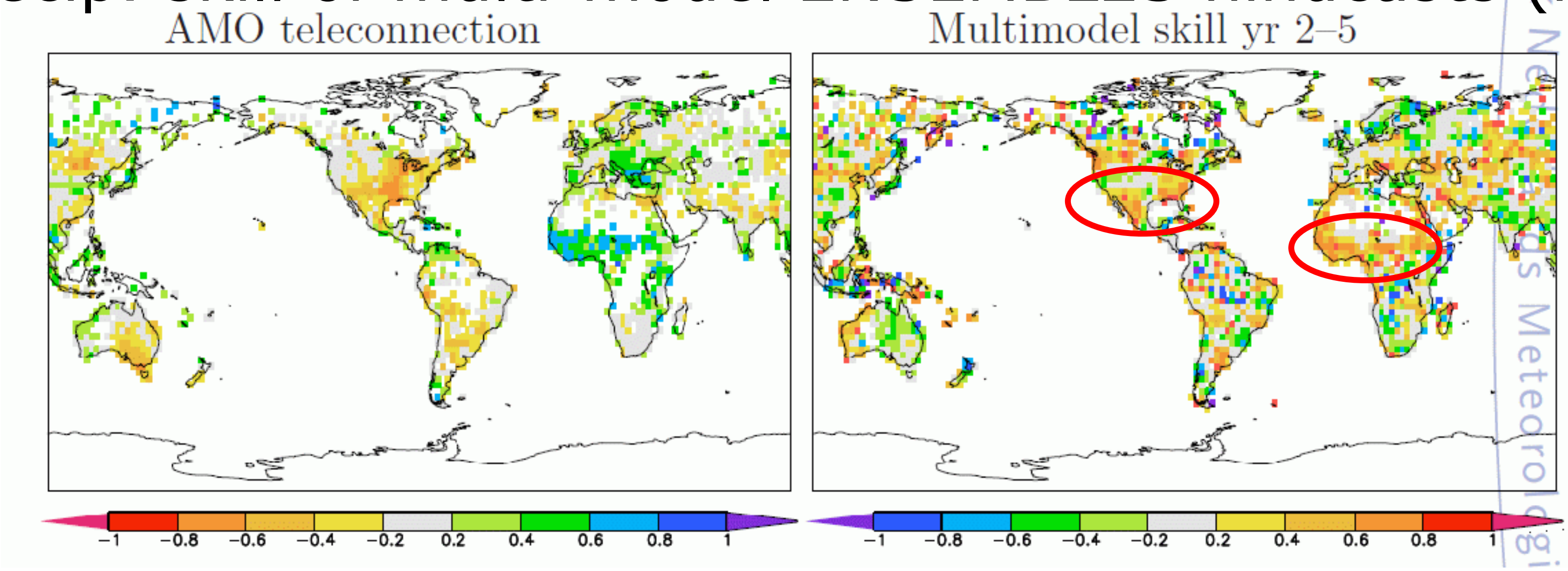
Ensemble-mean correlation for northern extratropics and tropics and T850 from ECMWF, CERFACS, IfM, HadGEM2, DePreSys_PP and multi-model (4 models, 12 members). Temperature verified with ERA40/ERA-Int over 1960-2005. The black dots depict the sample values and the bars the 95% confidence intervals.



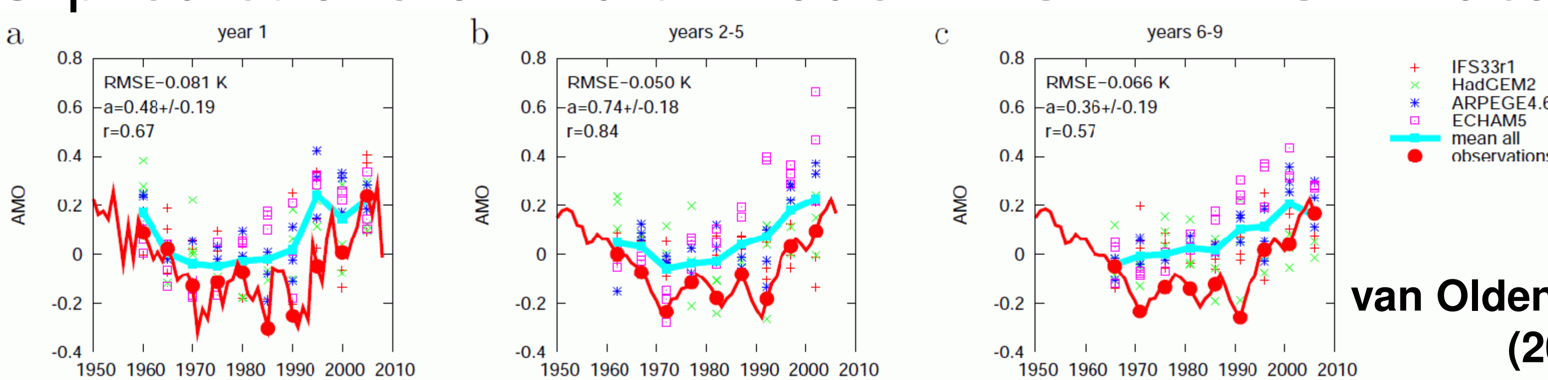


Using surrogate information: AMO

Observed AMO teleconnections (left) and 2-5 year average precip. skill of multi-model ENSEMBLES hindcasts (right).



AMO predictions of multi-model ENSEMBLES hindcasts.



van Oldenborgh et al. (2010)

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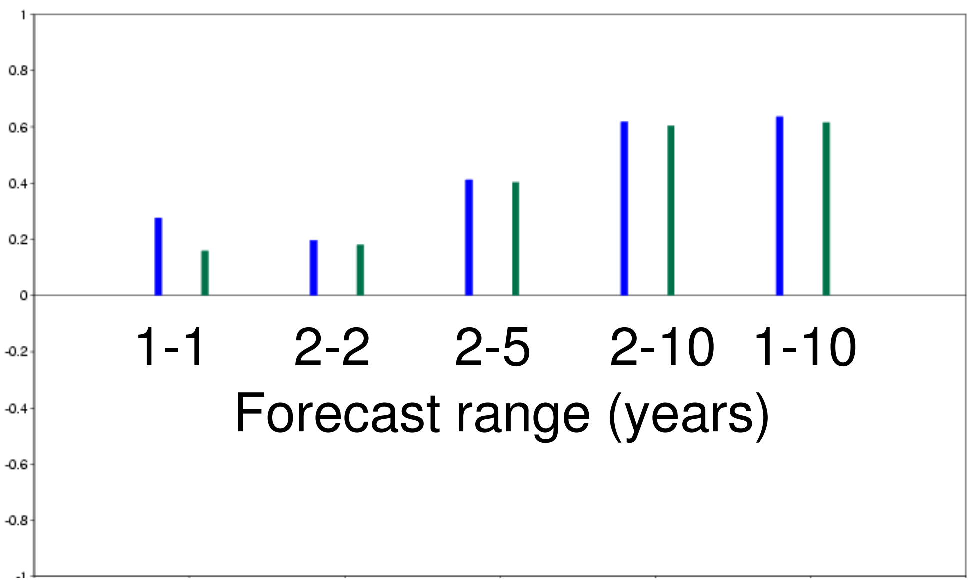
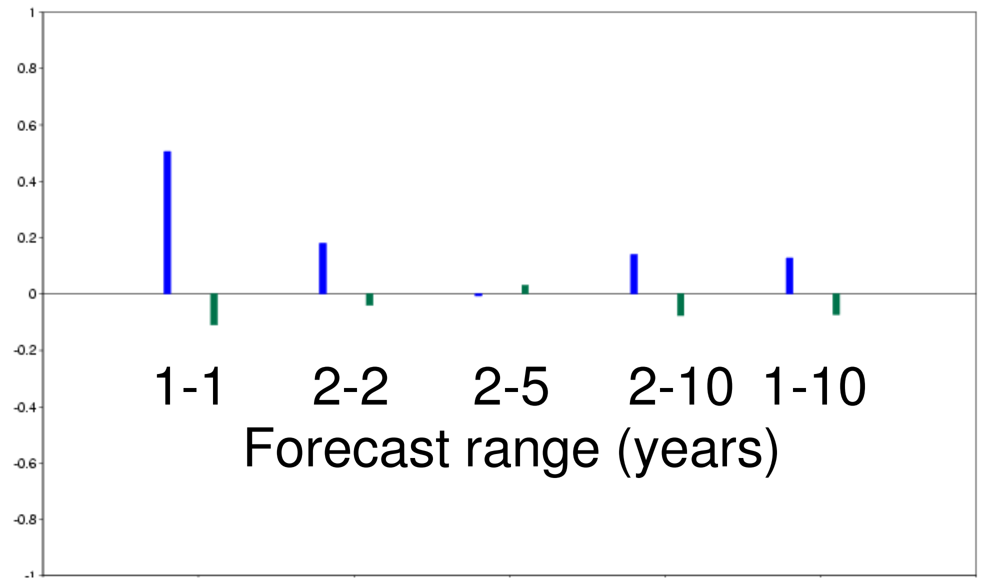
DePreSys: impact of initialization

Grid-point ensemble-mean anomaly correlation for DePreSys_PP and DePreSys_PP_NoAssim over 1960-2005

ACC NH
near-surface temperature

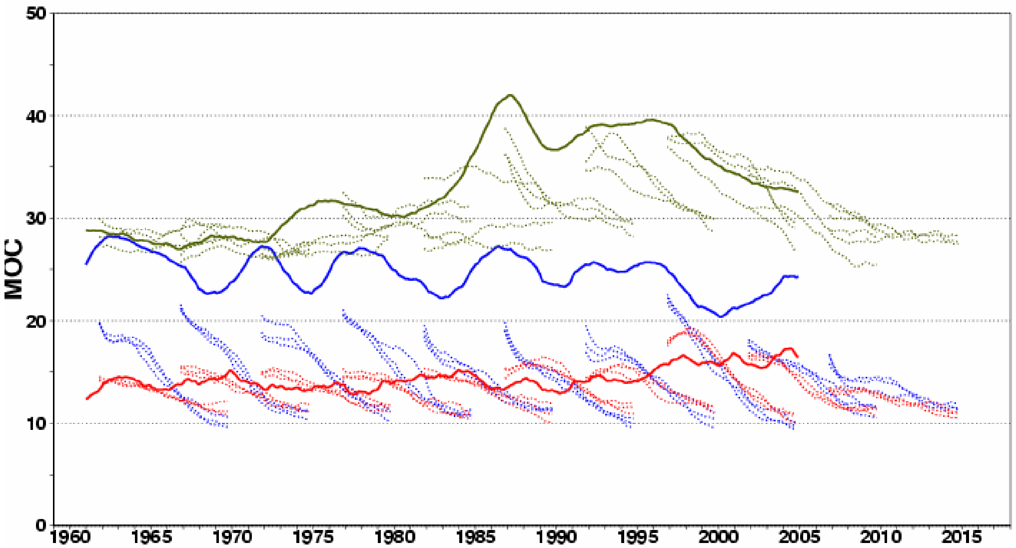


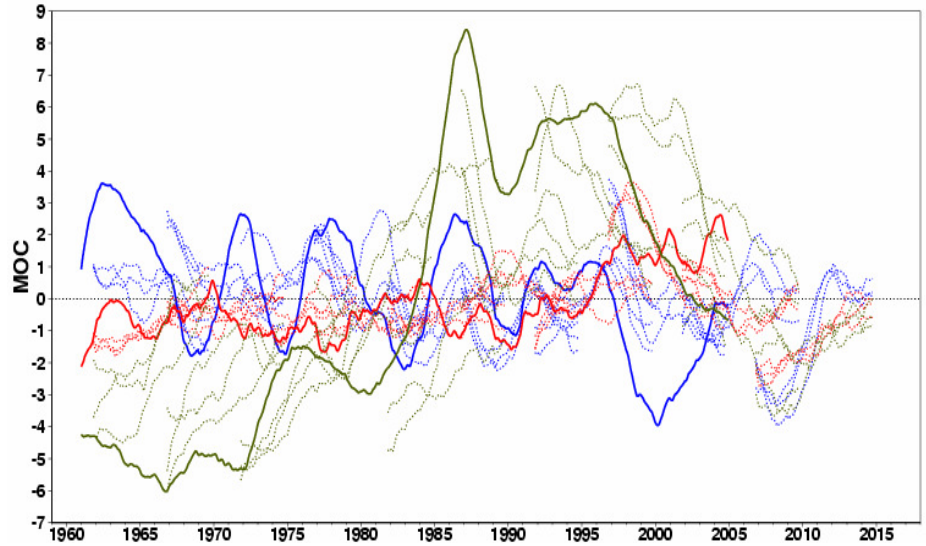
Tropics ACC
precipitation



Decadal prediction: AMOC

Atlantic meridional ocean circulation intensity estimates (left, Sv) and anomalies (right) for the ocean analyses (thick solid) and the hindcasts (thin solid) for ECMWF, IfM and CERFACS. A two-year running mean has been applied to the time series.





Summary: decadal

- Multi-model and perturbed parameter decadal ensemble forecasts have being carried out as part of ENSEMBLES.
- Substantial systematic error (mean and variability) can be found even for systems with anomaly initialization.
- Global and regional mean near-surface air temperature is well predicted, though the improvement with respect to uninitialized forecasts is low. Ocean decadal variability shows some skill. Other variables have very low skill beyond the first year.
- Uncertainty in ocean circulation and thermal structure in available re-analyses is large; this affects the construction of a useful reference dataset for model validation and forecast verification.

Seasonal predictions

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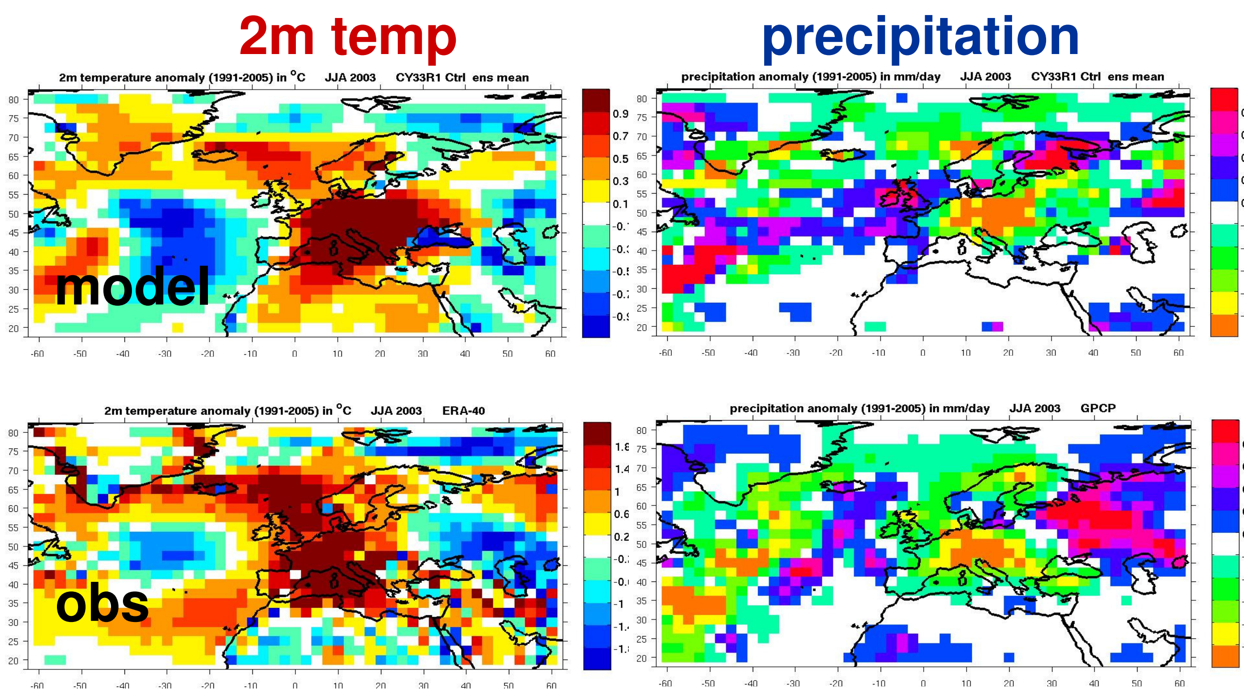
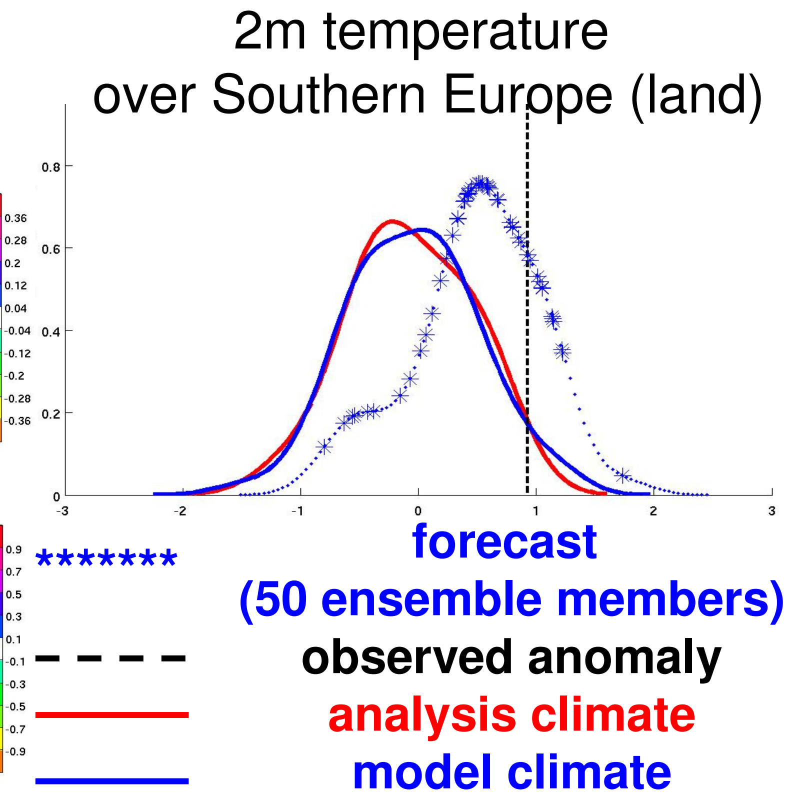
IC3

- Seasonal predictions for summer 2003 with start date on the 1st of May. Anomalies computed with the hindcast period 1991-2005





ECMWF

Antje Weisheimer

First ENSEMBLES objective

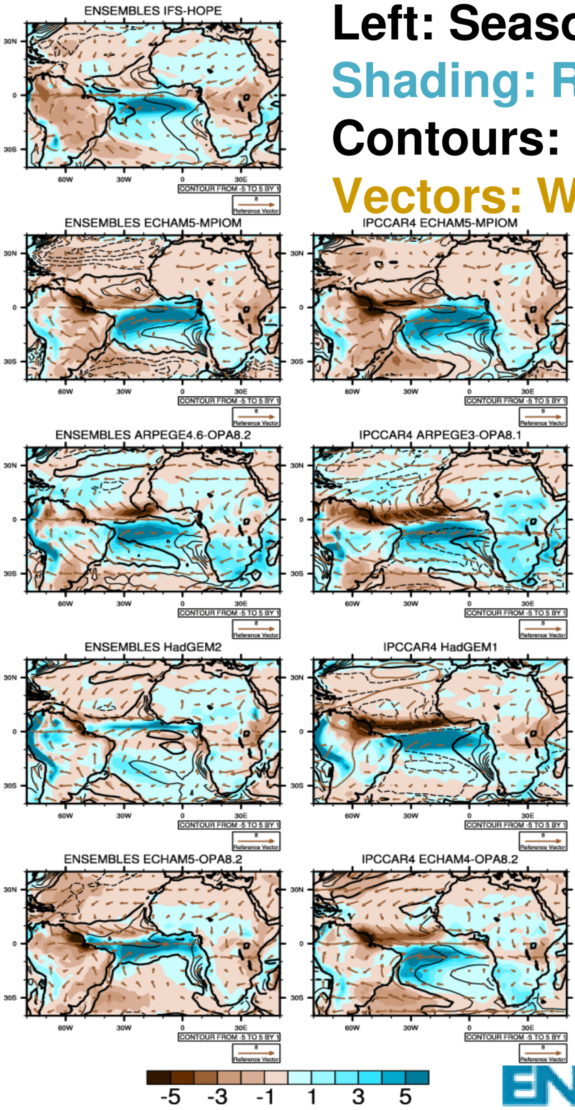
- The objective is not just to perform all those simulations and validate them individually against high-quality reference datasets.

Develop an ensemble prediction system for climate changes based on the principal state-of-the-art, high

ensemble = together

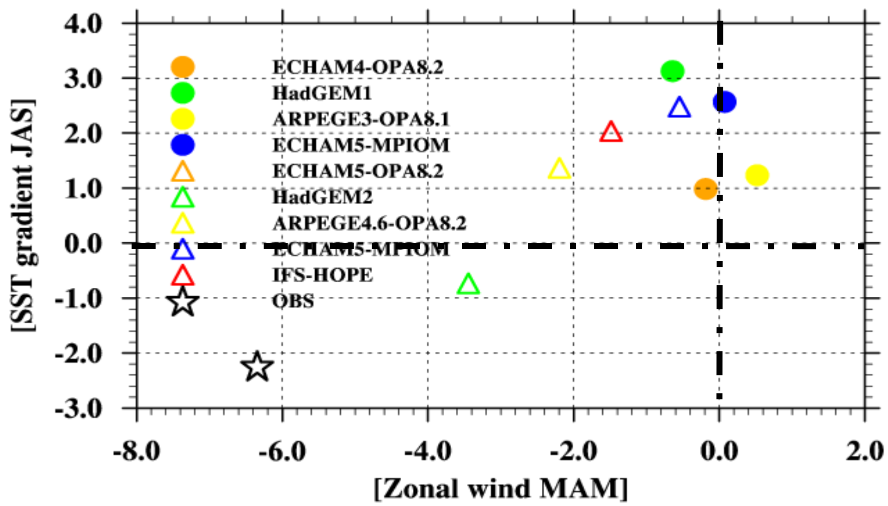
to produce for the first time, an objective probabilistic estimate of uncertainty in future climate at the seasonal to decadal and longer timescales.

Understanding WAM systematic errors



Left: Seasonal integrations; Right: AR4 integrations
Shading: Rainfall biases (mm/day)
Contours: SST biases (K)
Vectors: Wind biases 850 hPa (m/s)

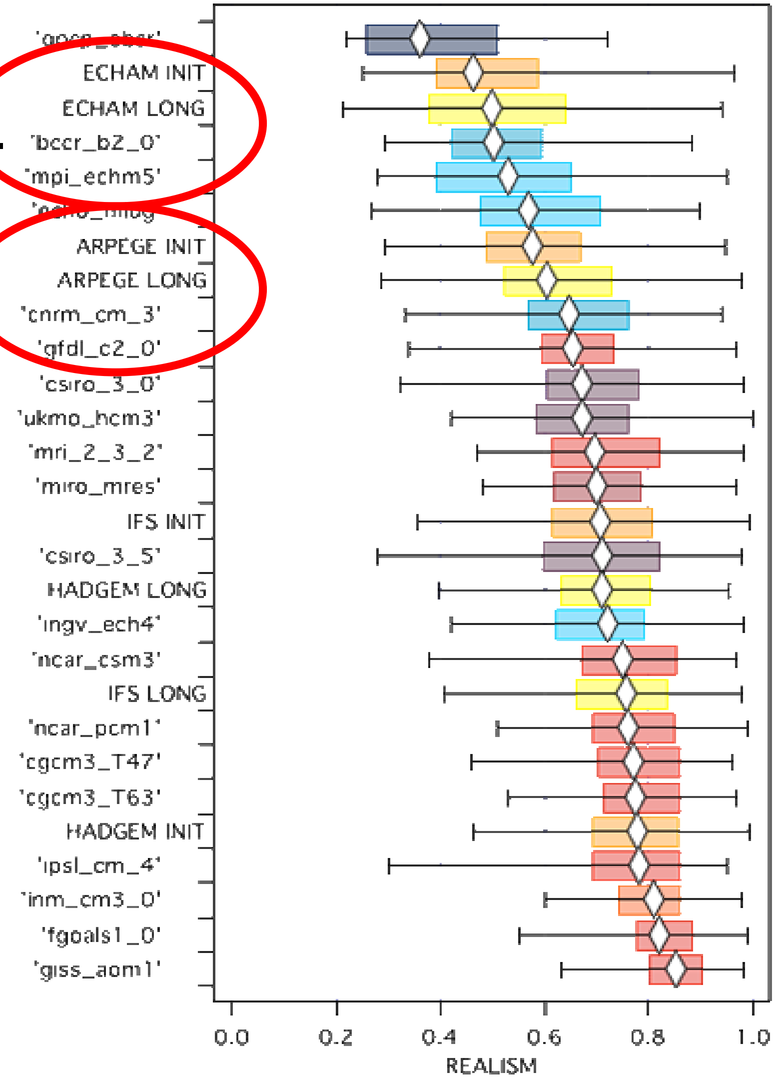
CMIP3 (circles), ENSEMBLES (triangle) and obs (star) of MAM U850 hPa (m/s, 2° N-2° S/40° W-10° W) and JAS SST (40° W wrt 8° E, K averaged 2° N-2° S)



Cyril Caminade, Paolo Ruti

Understanding ISV systematic errors

- A metric (realism) for the tropical ISV is defined based on the spatio-temporal characteristics of precipitation intraseasonal propagating perturbations. It measures the distance wrt the mean observed pattern.
- Results are valid for JJAS, but with different lead times:
  - ➢ Init: two-month lead time (Seasonal runs)
  - ➢ Long: eight-month lead time (Annual runs)



Sciences de l'environnement Institut Pierre Simon Laplace

Met Office Hadley Centre

J.-Ph. Duvel, B. Ouslati, P. Xavier

Understanding ISV systematic errors

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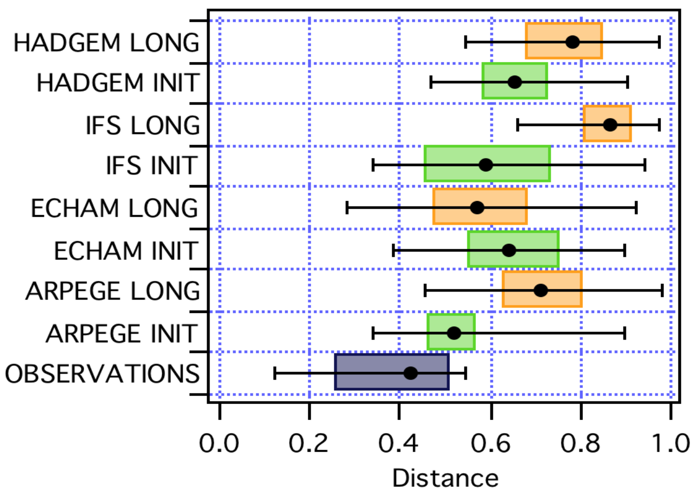
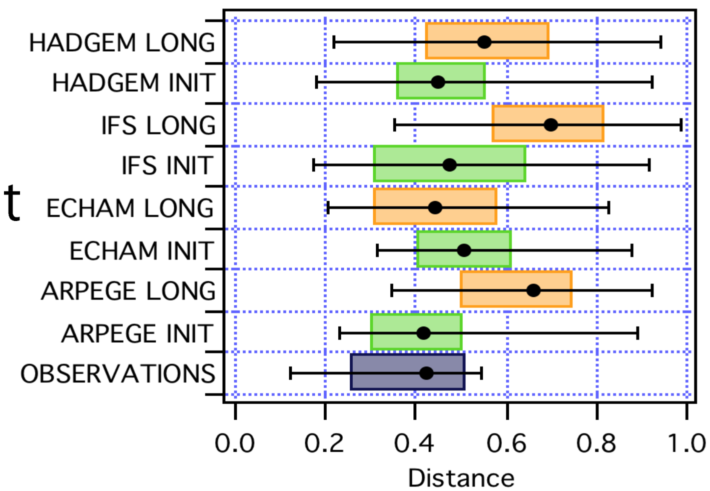
- Two metrics for the summer tropical ISV are defined based on the spatio-temporal characteristics of precip. intraseasonal propagating perturbations. Realism measures the distance to the mean observed pattern and reproducibility the distance to the mean model pattern.
- Results are valid for May, but with different lead times:
  - Init - first month of the integration (Seasonal runs)
  - Long - seventh month of the integration (Annual runs)

Realism



Reproducibility



Met Office Hadley Centre
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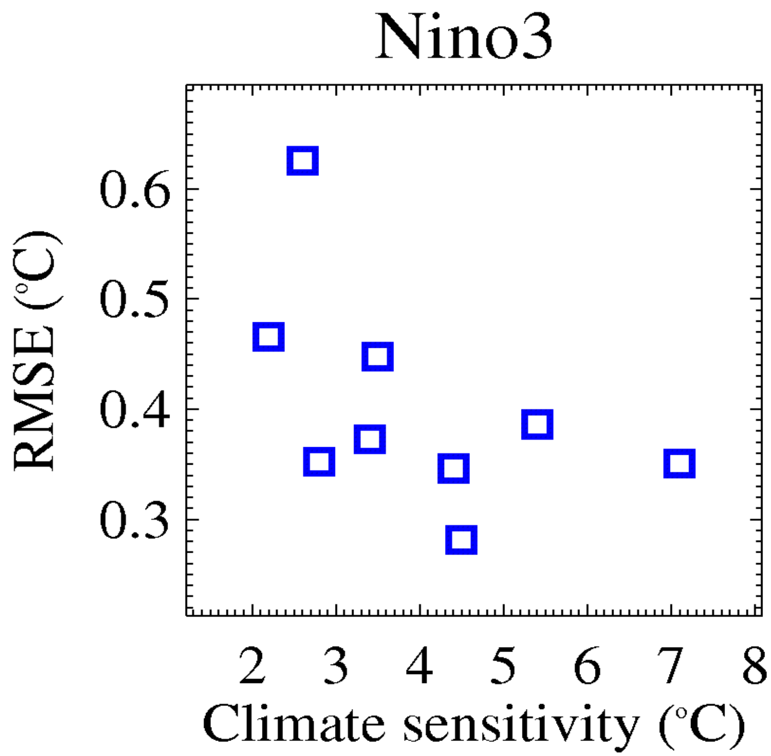
J.-Ph. Duvel, B. Ouslati, P. Xavier

Forecast skill versus climate sensitivity

- RMSE of the 2-4 month (November start date, DJF) Niño3 forecasts over the 1991-2001 period and climate sensitivity obtained from the corresponding slab ocean integrations from DePreSys



Doug Smith

Weighting using a toy model

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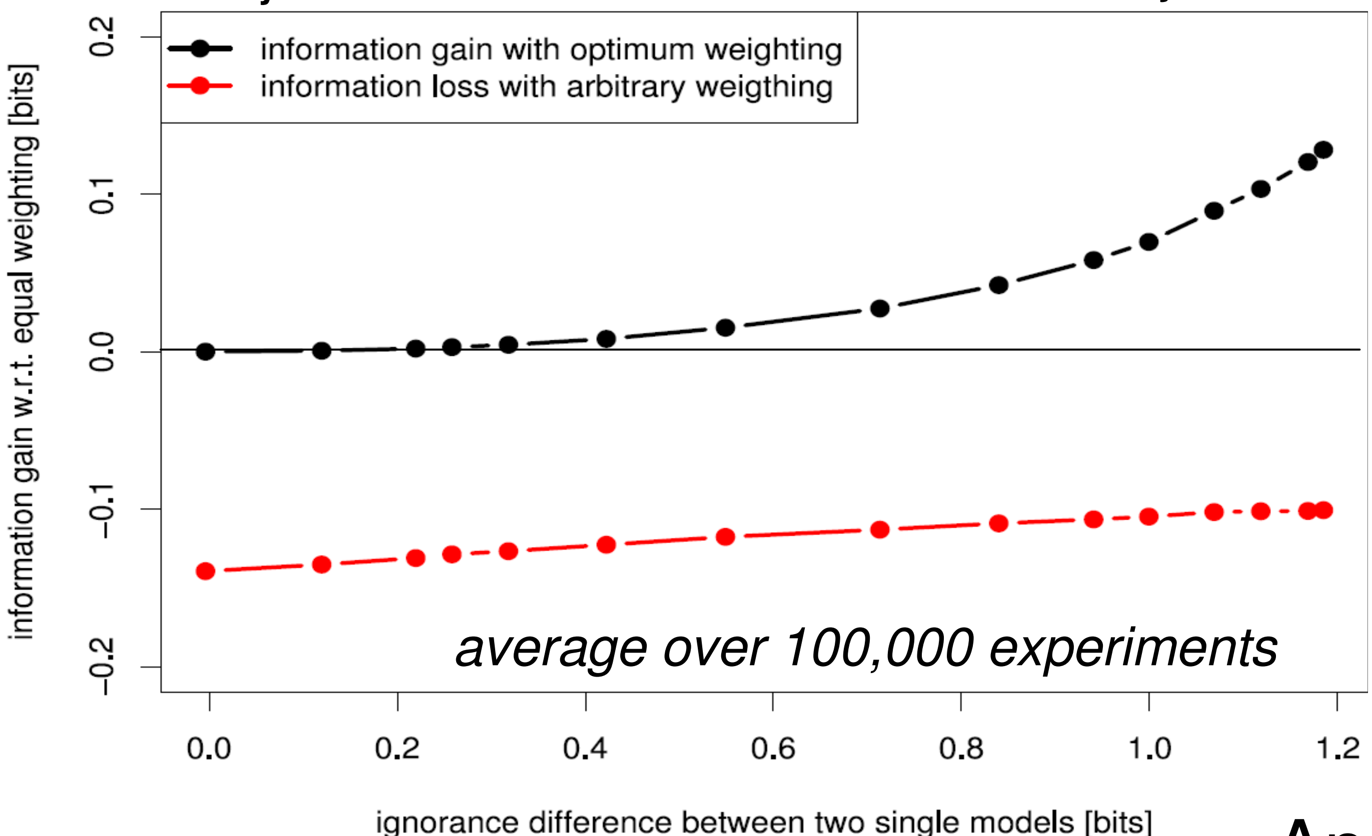
Information gain (in terms of ignorance score) with respect to an equal weighting scheme in a combination of two models

single models very similar → **single models very different**



better than equal weighting

worse than equal weighting

Andreas Weigel

Summary

- Extensive seasonal, annual, decadal and centennial ensemble coordinated experiments have been carried out with both global and regional models.
- The set of ensemble experiments include an unprecedented set of strategies to deal with the main uncertainties. The results suggest that is extremely complicated to improve over a multi-model ensemble.
- A new type of collaborative efforts that employs the full range of climate information sources acknowledging the seamlessness of climate variability and change has been explored in ENSEMBLES.