Predictability and Extremes

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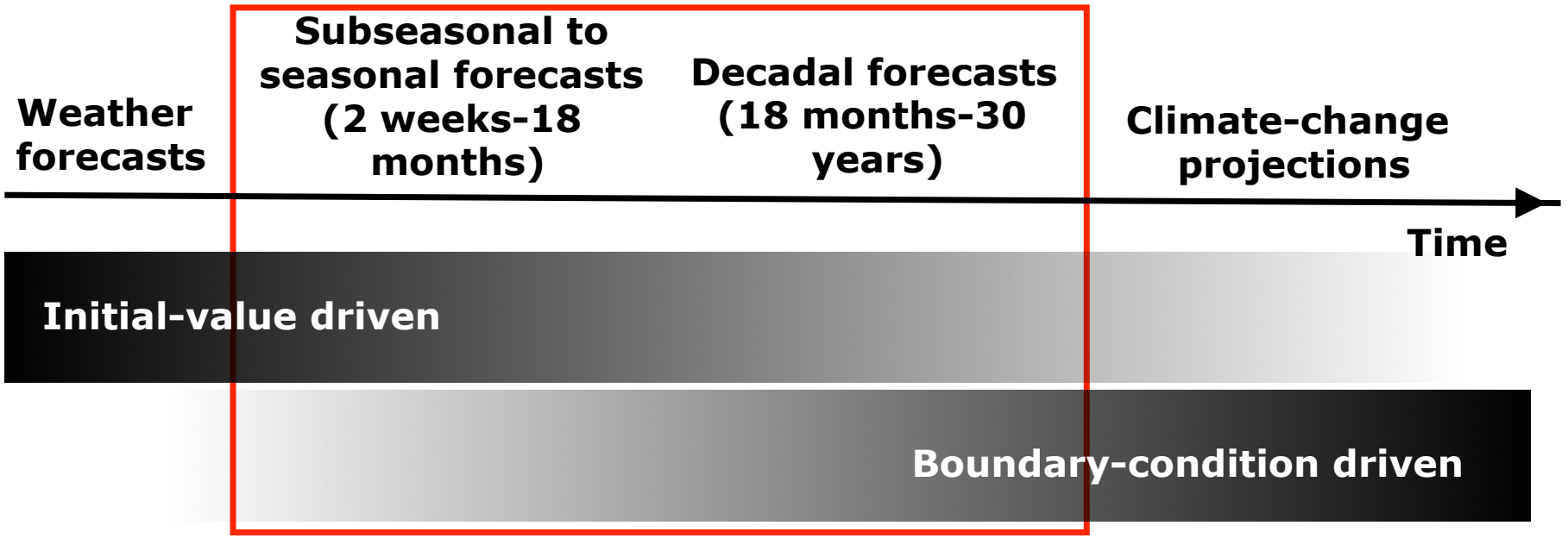
Barcelona, Spain

SEVENTH FRAMEWORK PROGRAMME

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

Prediction on climate time scales

Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and systematic comparison with a simultaneous reference.



Adapted from Meehl et al. (2009)

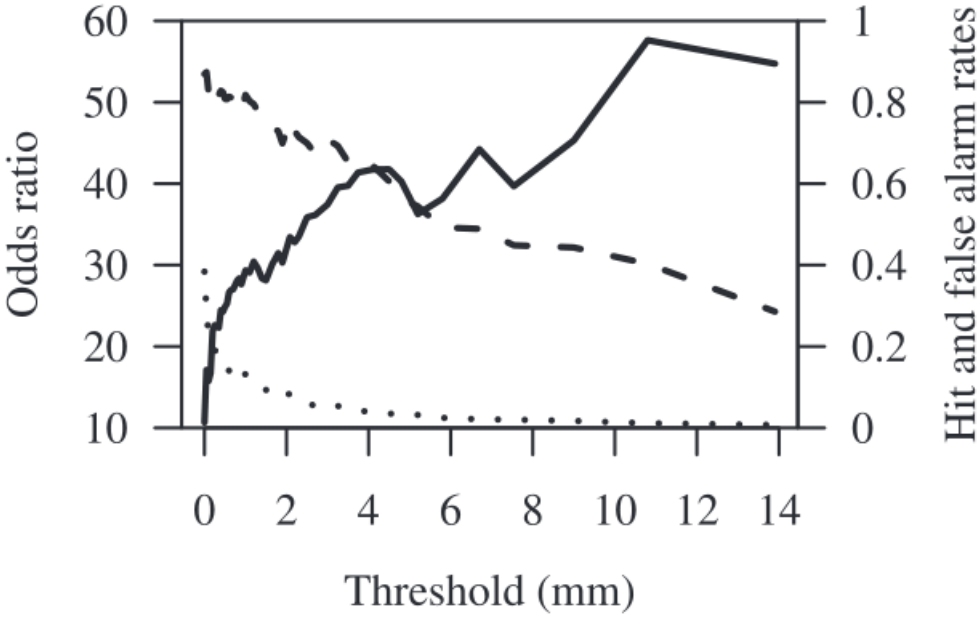
Extremes in climate predictions

- Aim to predict statistics of unusual (not necessarily rare) events at specific, relatively short periods (e.g. number of tropical cyclones over a season), not the specific timing of the individual events.
- Traditionally, events are defined for small p, but not for p«. Sample sizes are small (N≈30), as are ensemble sizes (M≈10-50), and p≈0.05-0.25. Hence, no use of EVT from this point on.
- Examples: number of tropical cyclones, number of days a variable is above a given percentile, a percentile of a variable over a given period (a month, a season, etc).
- However, adequate use of the EVT might lead to interesting results for predictions of extreme events (although with large confidence intervals).

Extremes in climate predictions

- A fundamental aspect is the need to verify the forecasts, (verify events that actually occurred).
- However, measures of forecast quality typically degenerate to trivial values as the rarity of the predicted event increases. Alternatives are the "extremal dependence index".

	Event observed	**Nonevent observed**	
Event forecast	a	b	a+b
Nonevent forecast	c	d	c+d
	a+c=pn	b+d=(1-p)n	n

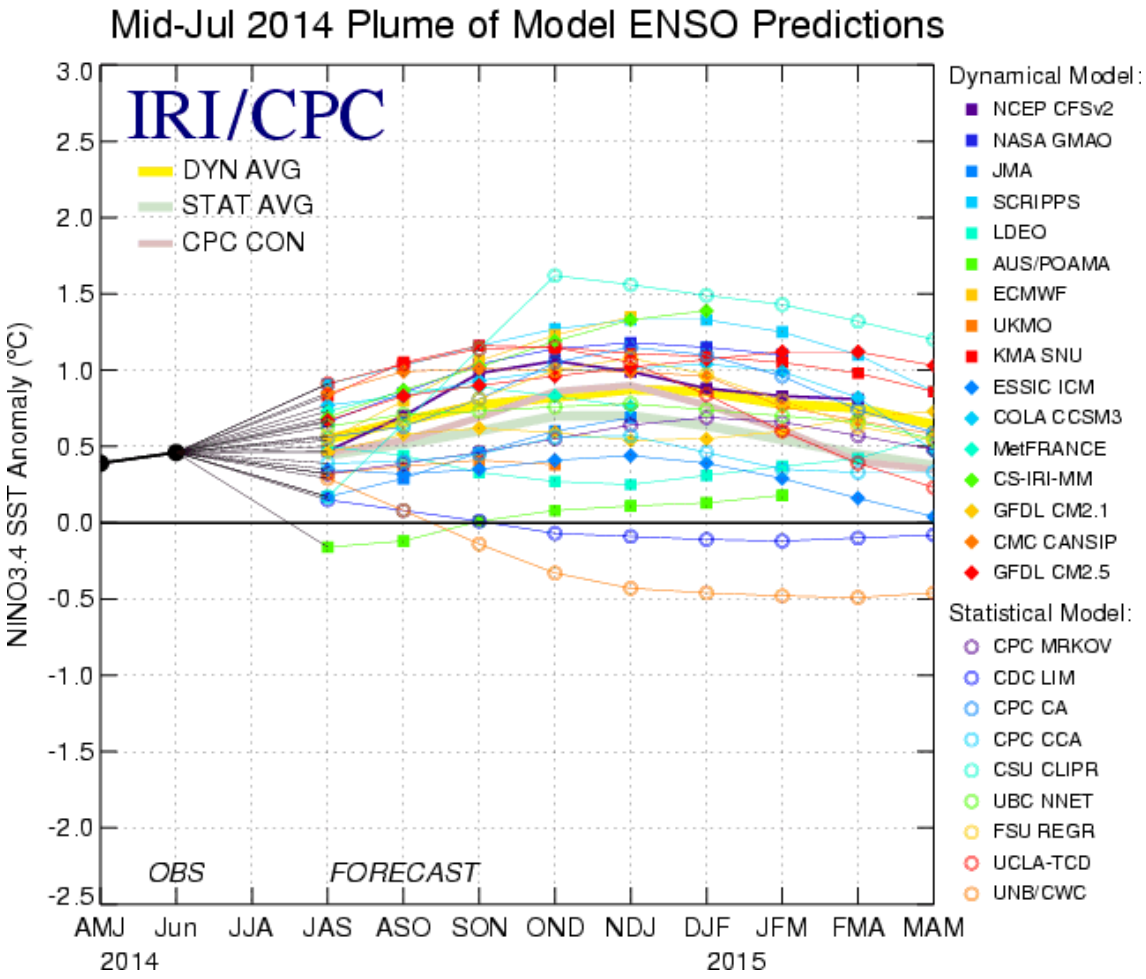


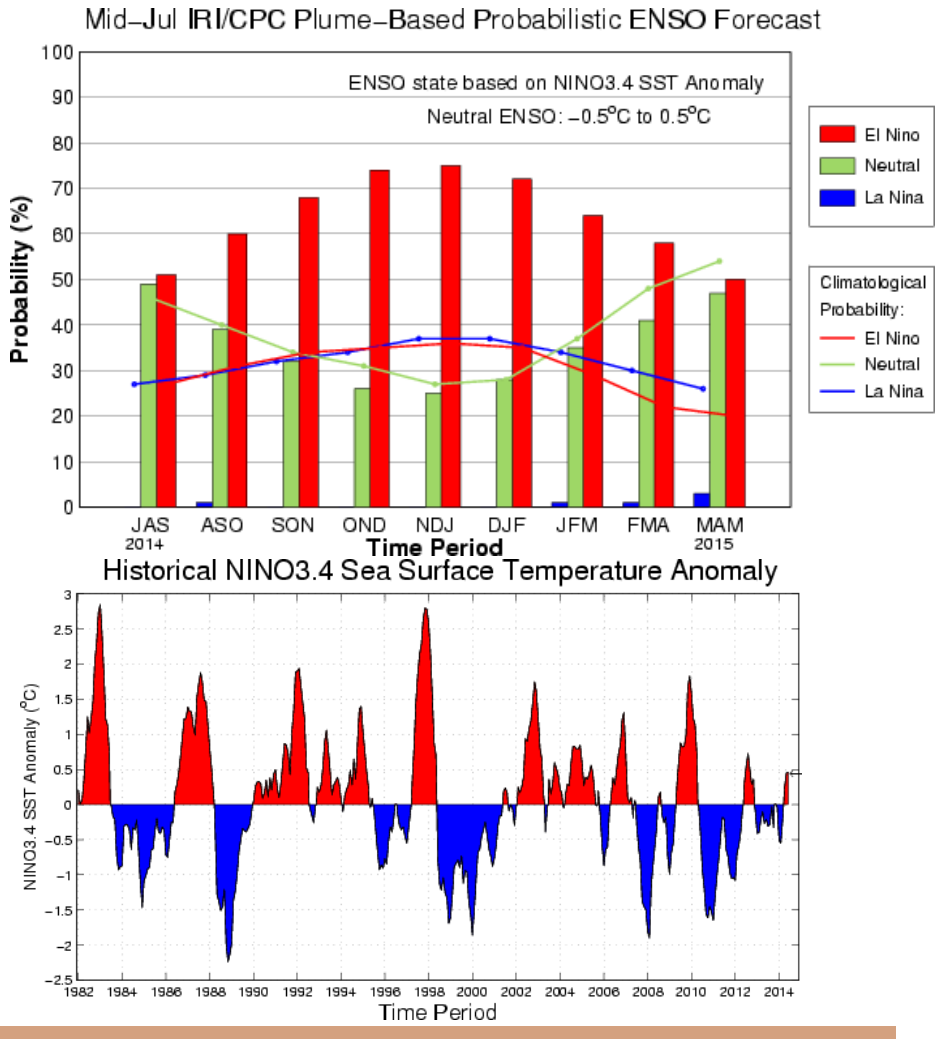
H=a/(a+c) dashed, F=b/(b+d) dotted, OR=ad/(bc) solid

Ferro and Stephenson (2011)

Seasonal forecasting

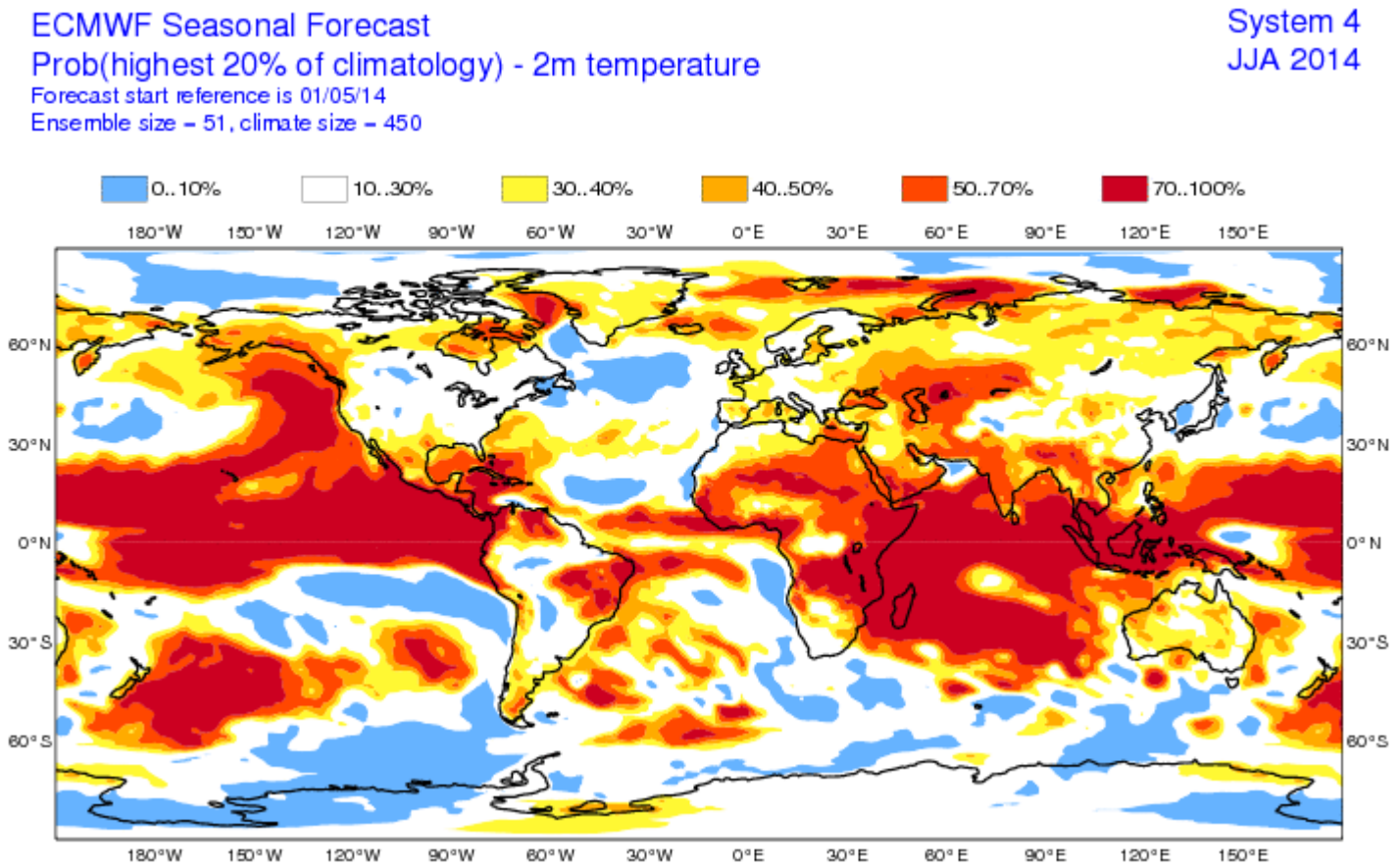
2014 ENSO predictions: July start date





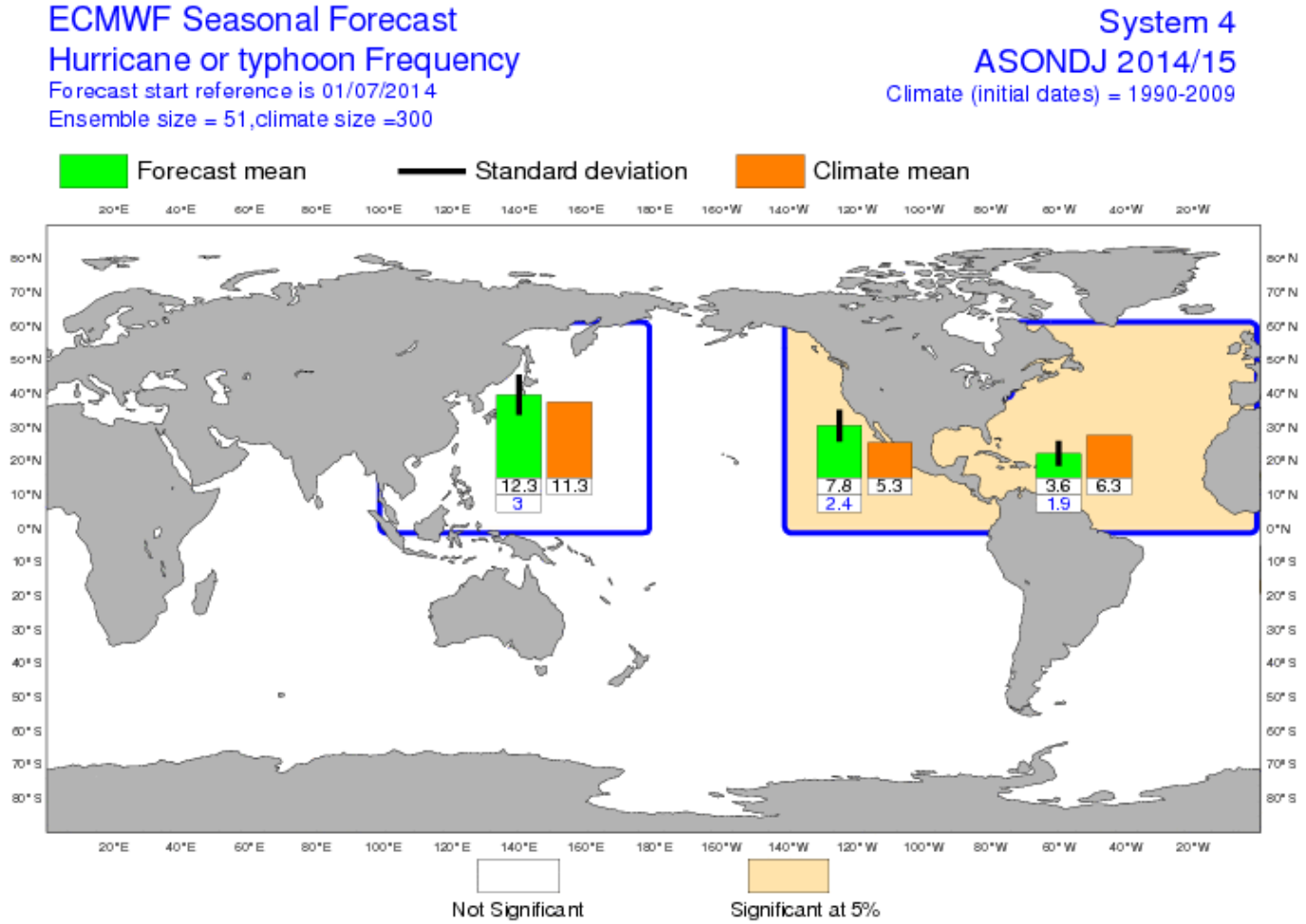
Seasonal forecasting

2014 ECMWF System 4 temperature JJA seasonal forecast with May start date: upper quintile category.



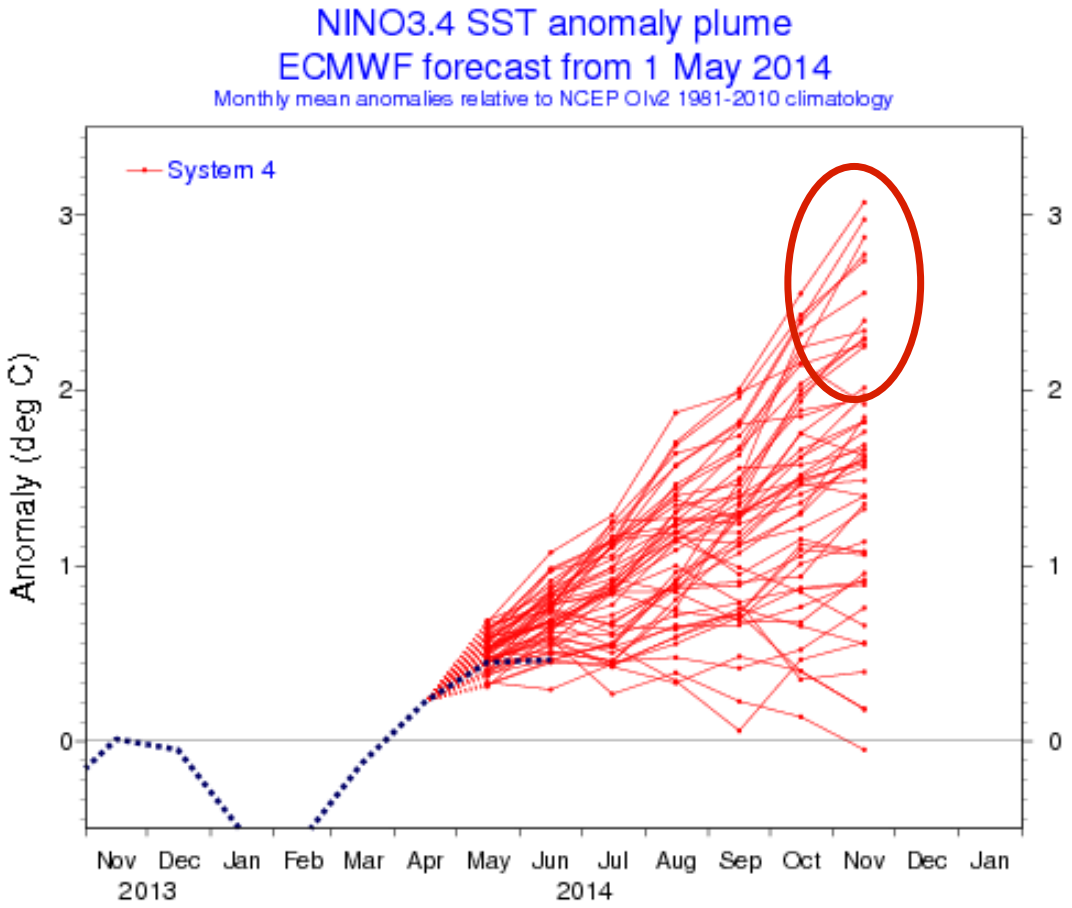
Seasonal forecasting

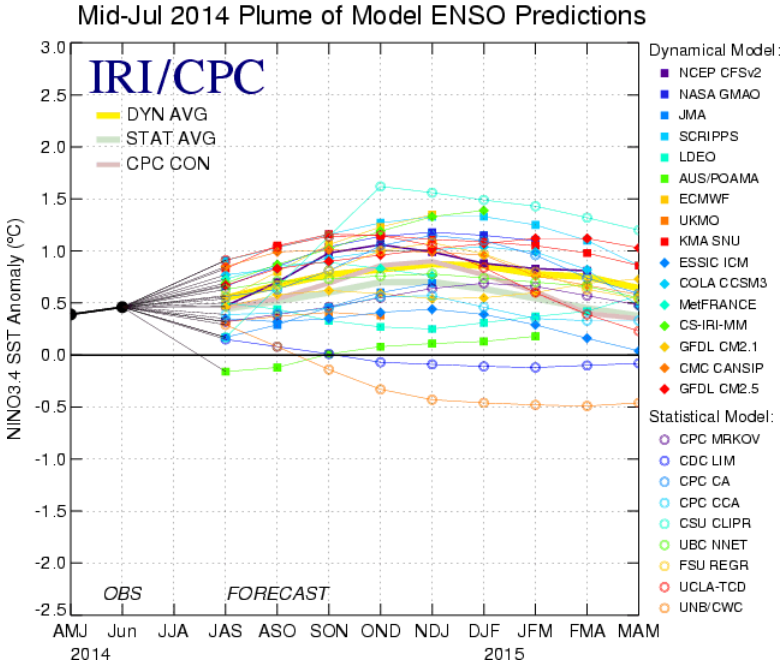
2014 ECMWF System 4 hurricane or typhoon frequency seasonal forecast with July start date.



Seasonal forecasting

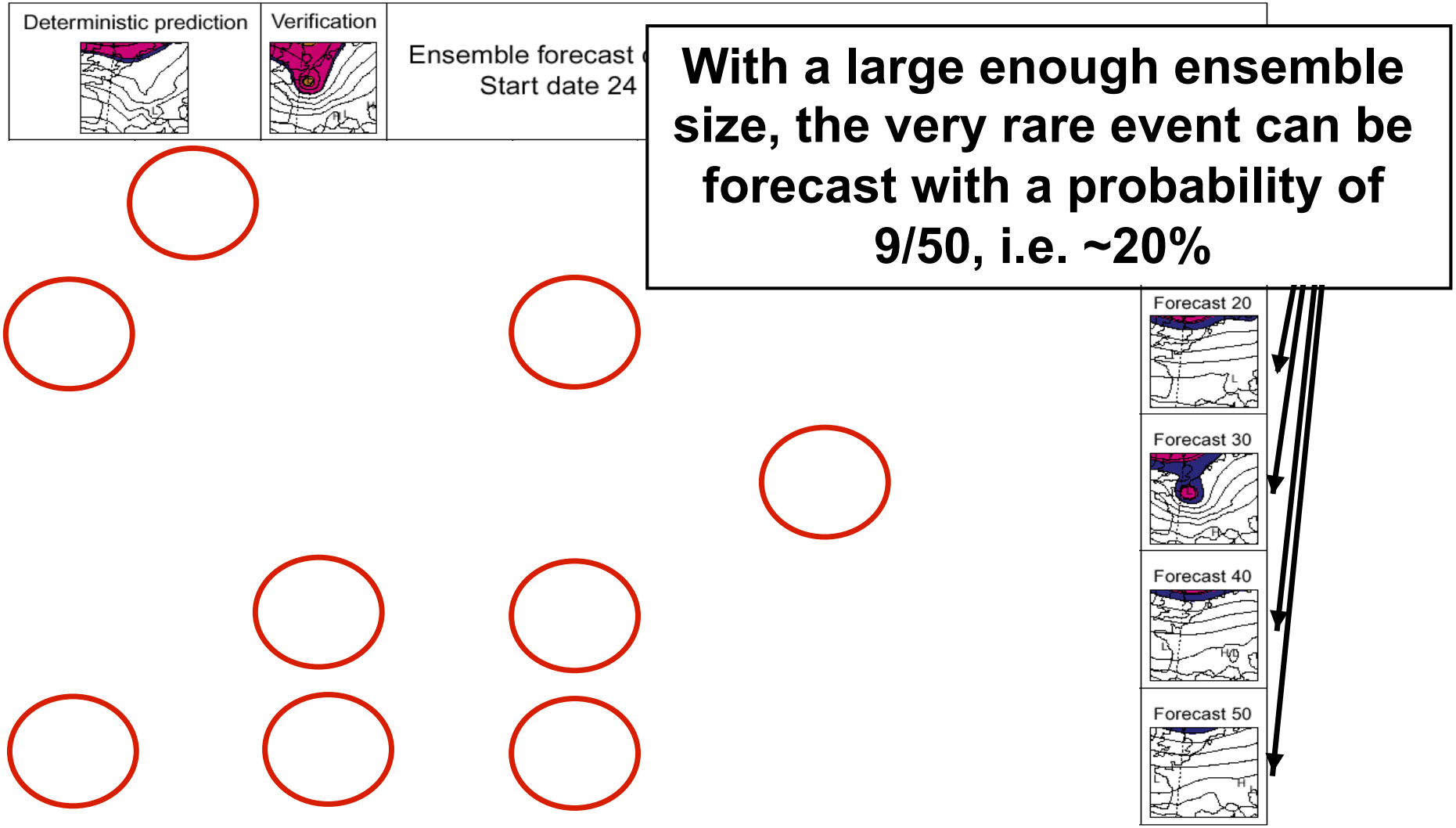
2014 ECMWF System 4 Niño3.4 seasonal forecast with May start date.





How many members: ensemble size

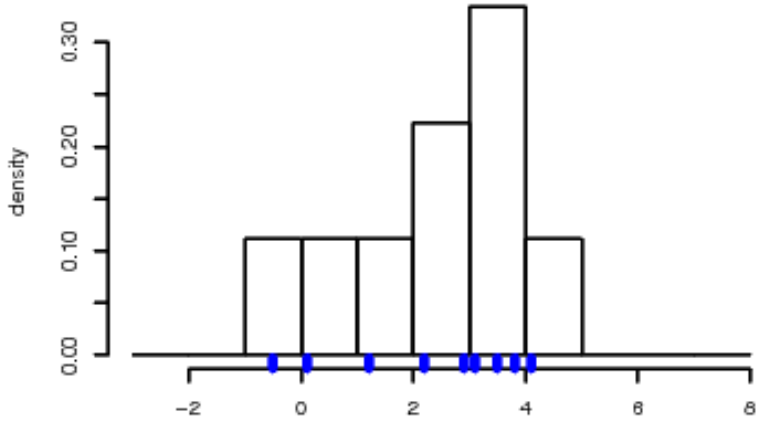
ECMWF forecasts (D+42) for the storm Lothar

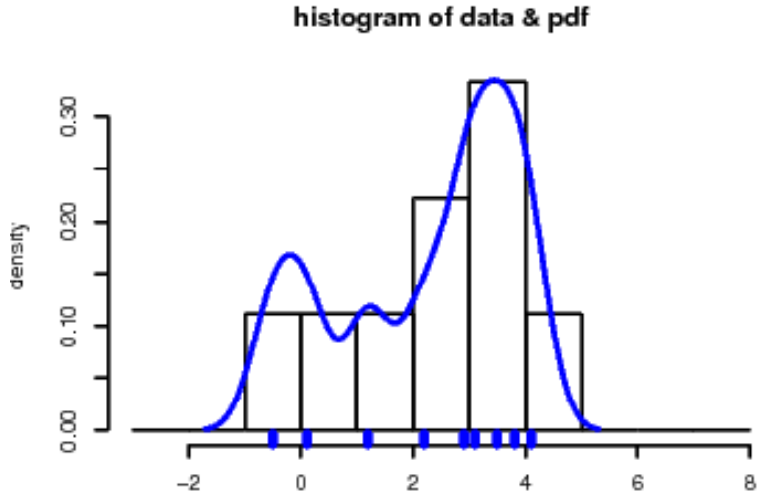


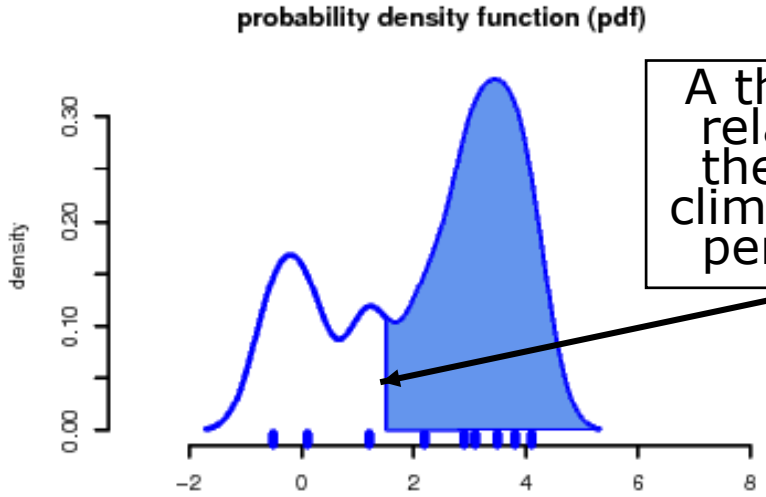
With a large enough ensemble size, the very rare event can be forecast with a probability of 9/50, i.e. ~20%

From ensembles to probability forecasts

Constructing a probability forecast from a nine-member ensemble



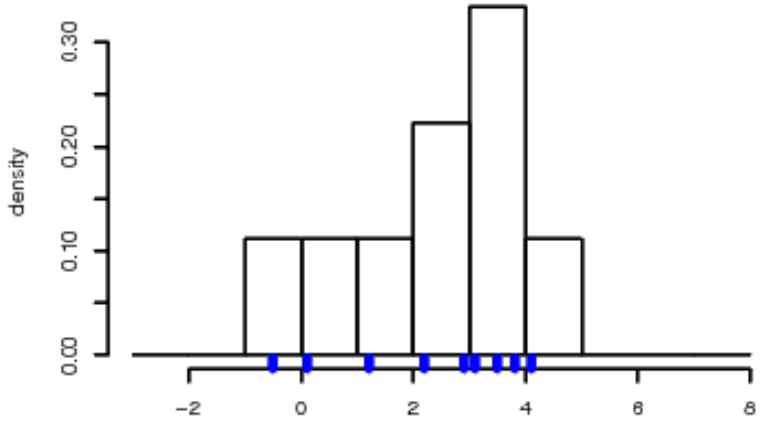


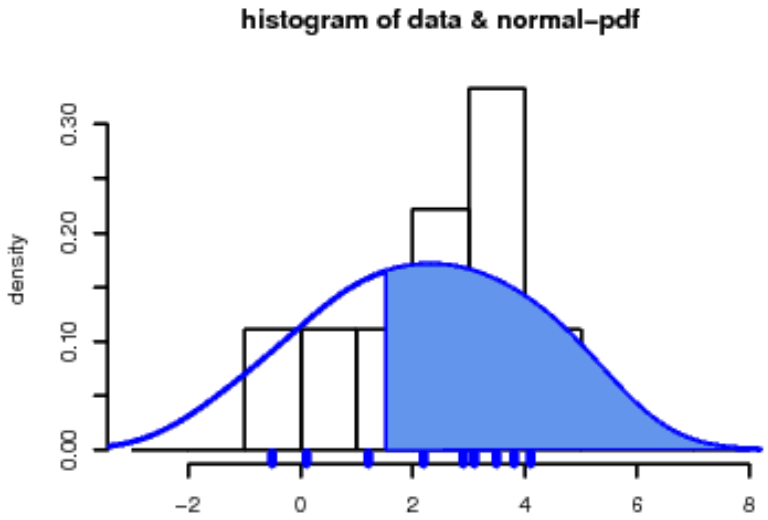


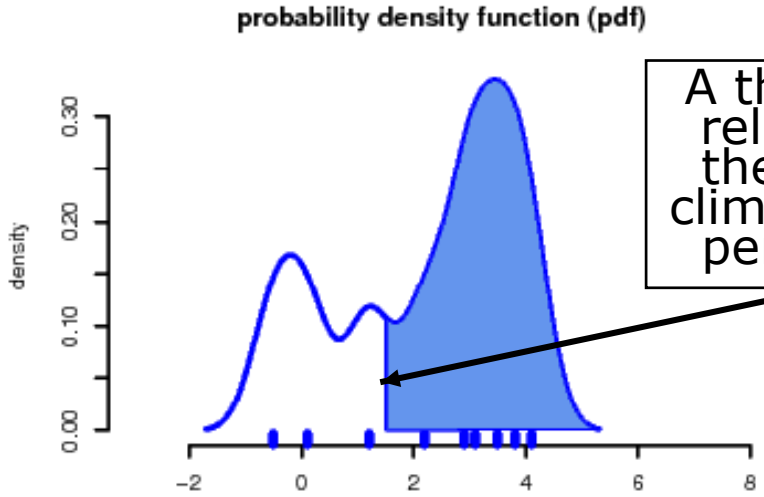
A threshold relative to the model climate (e.g. percentile)

From ensembles to probability forecasts

Constructing a probability forecast from a nine-member ensemble







A threshold relative to the model climate (e.g. percentile)

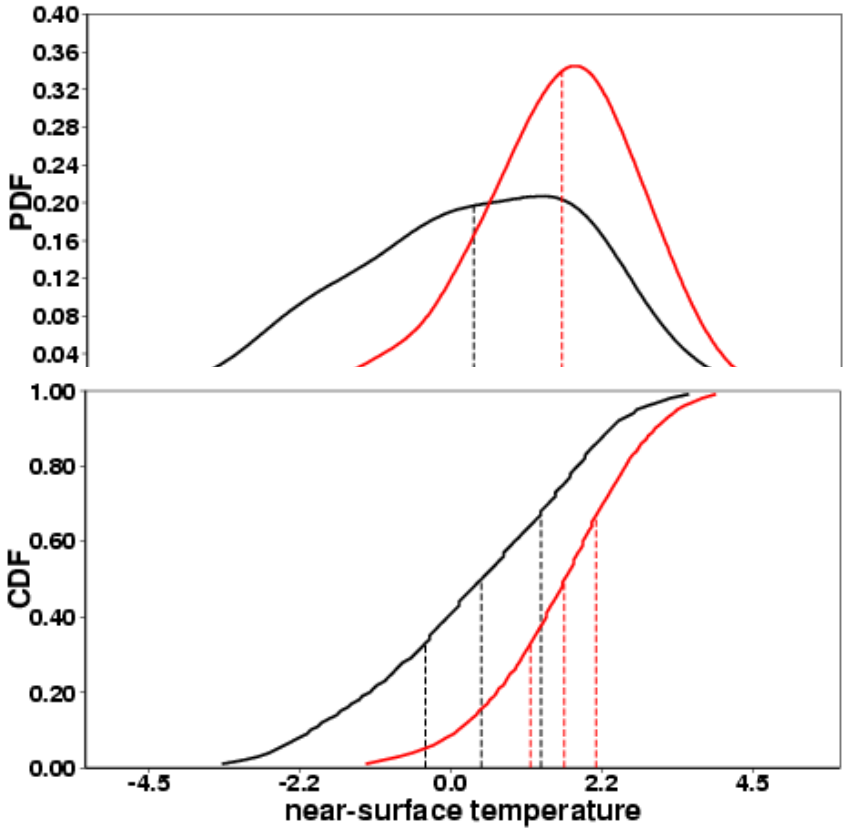
Systematic error: climatological pdf

Climatological PDF of DJF T2m (°C) for ERA-40/OPS and ECMWF System 3 computed over the period 1960-2005

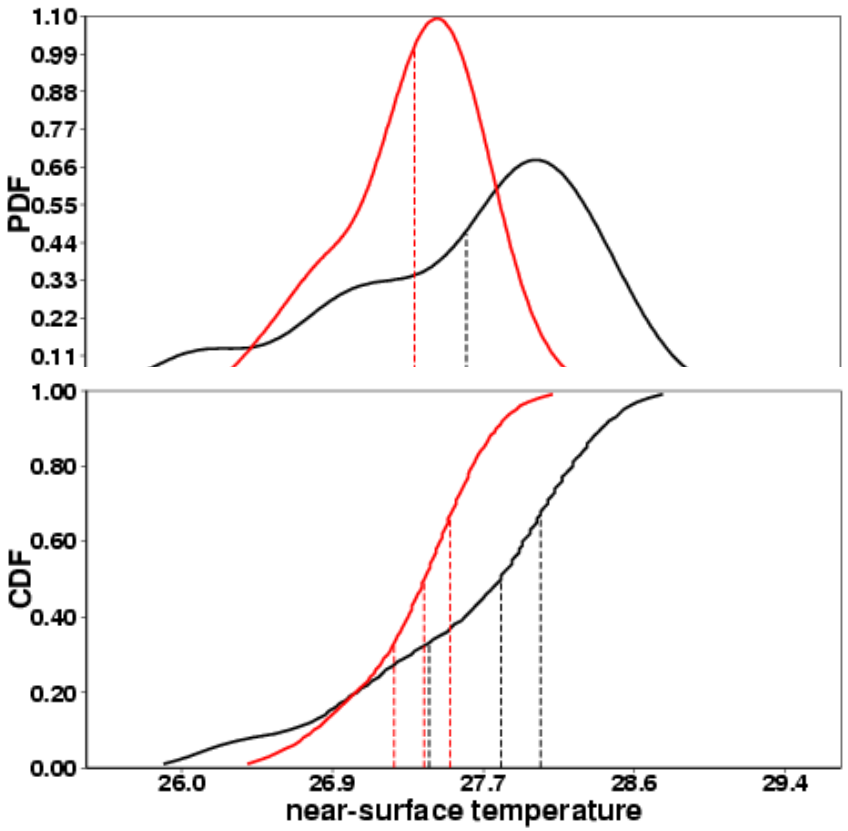
For deterministic forecasts, compute tercile limits, respect to the corresponding mean

For probabilistic forecasts, compute probabilities with respect to the corresponding mean and reference thresholds (terciles)

Central Europe (50°N, 10°E)

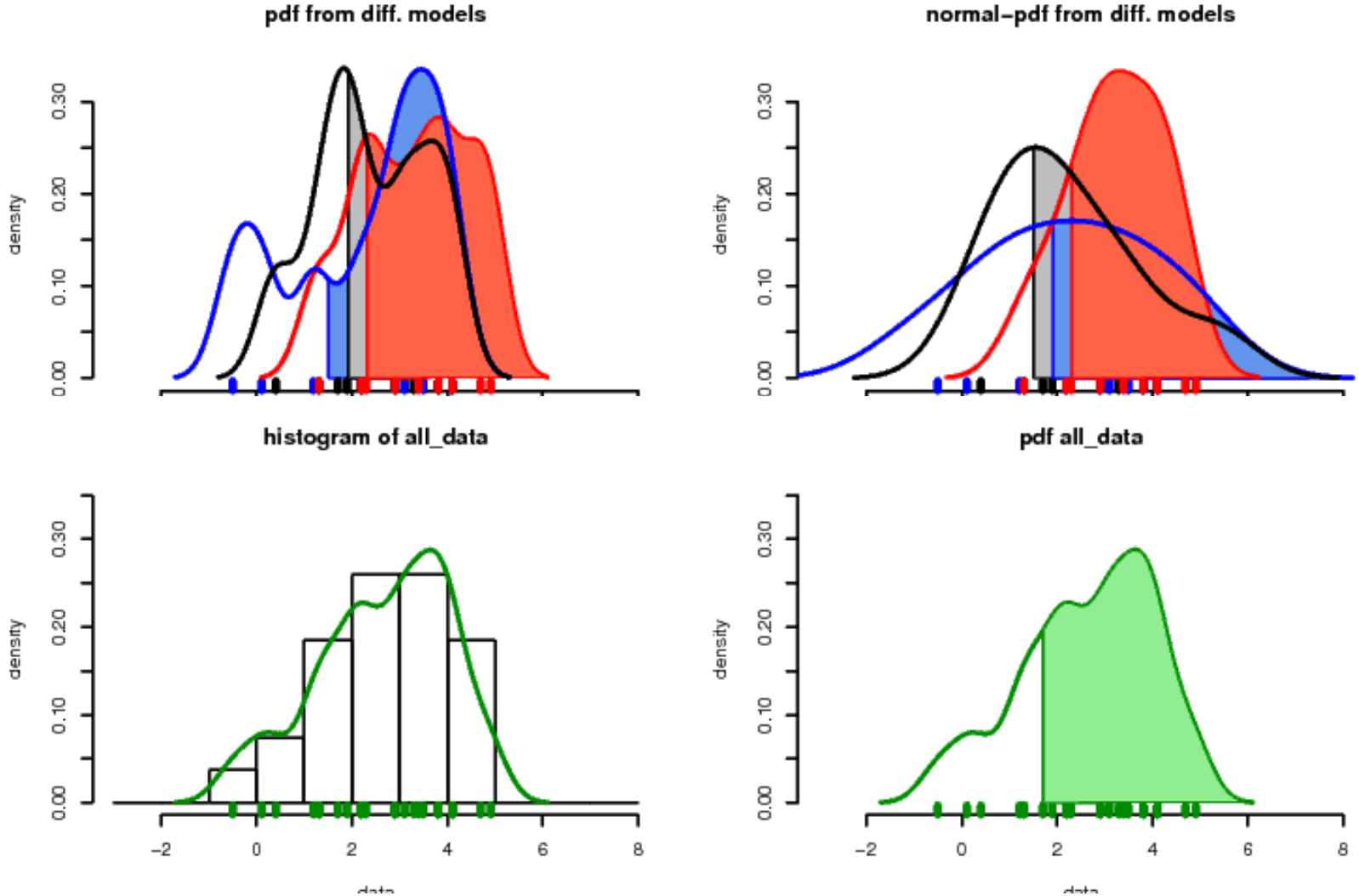


Equatorial Pacific (0, 180°)



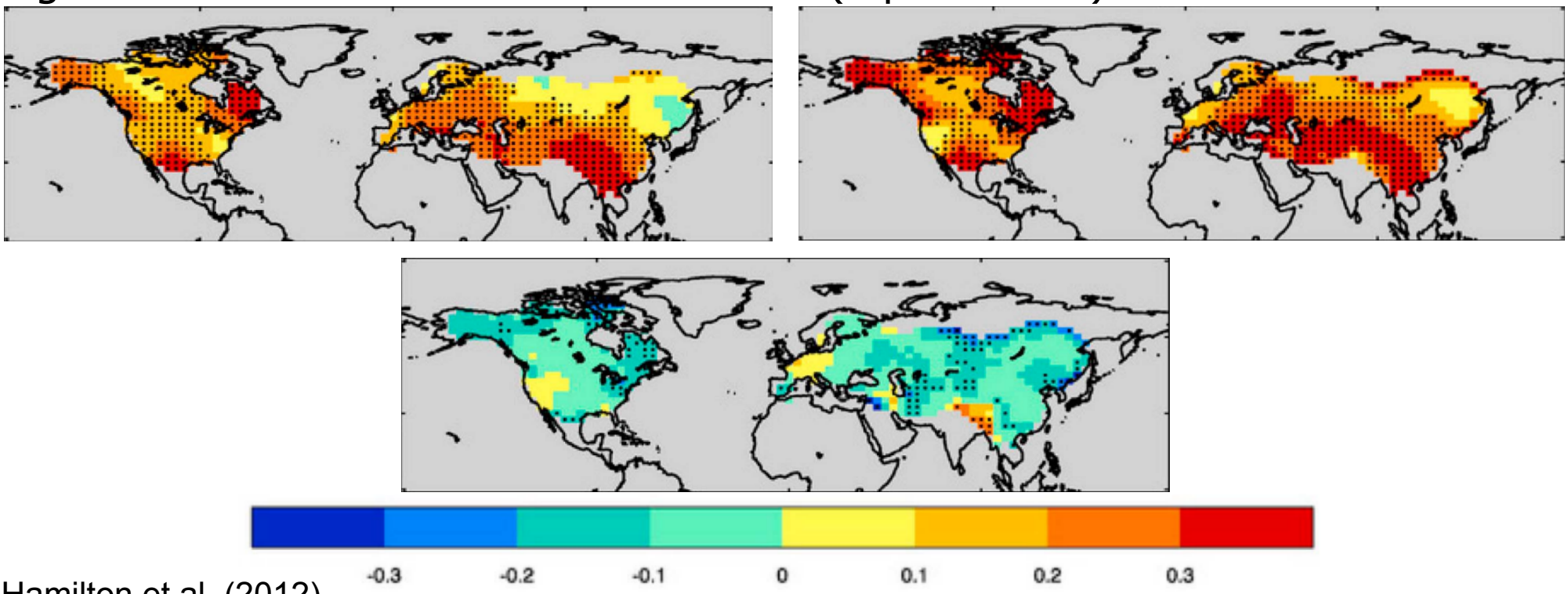
From ensembles to probability forecasts

Constructing a probability forecast from a multi-model ensemble



Forecast quality for unusual events

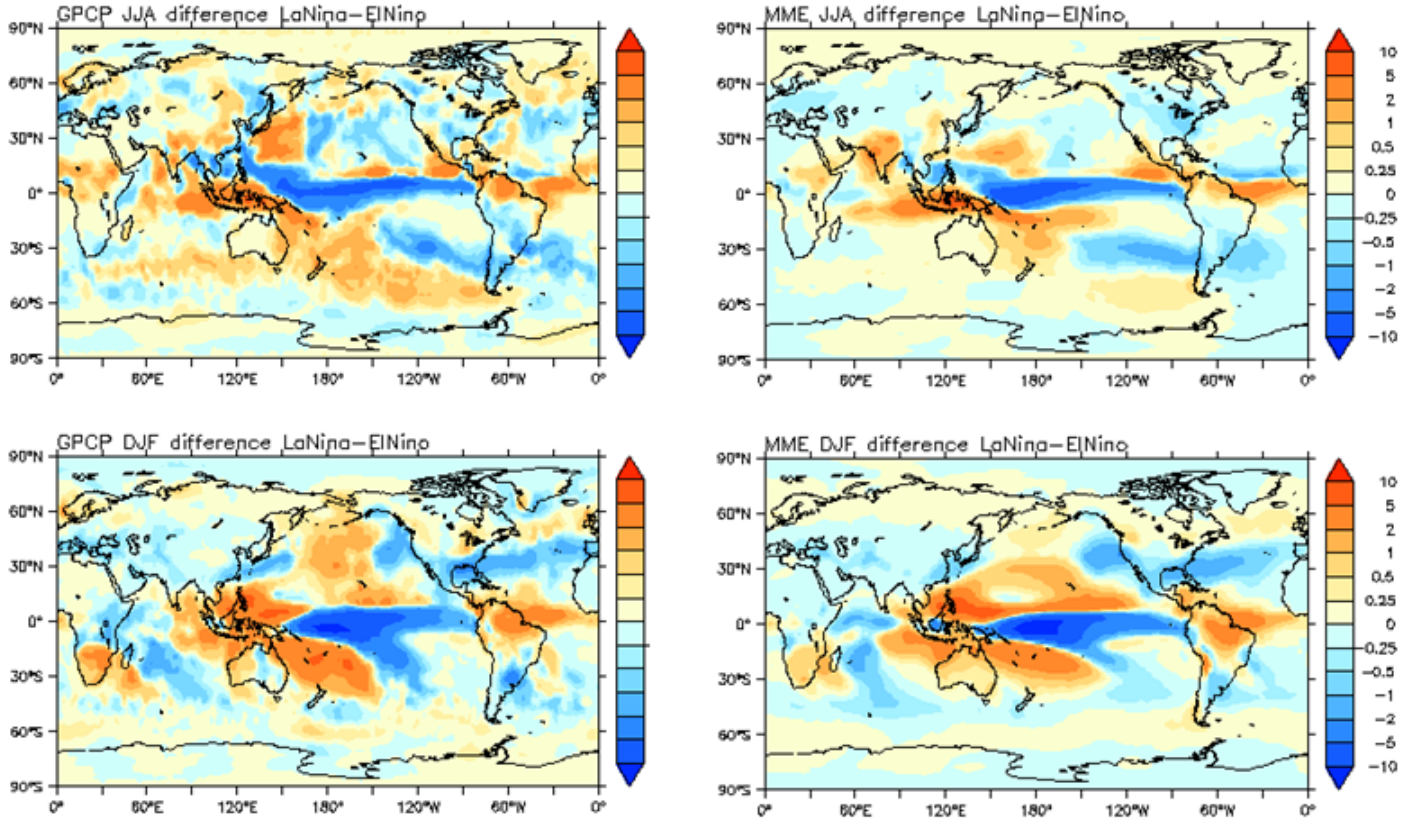
Rank correlation of number of days maximum/minimum temperature is above/below the 90%/10% climatological percentile for the GloSea4 seasonal hindcasts over 1989-2009 (reference HadGHCND) using percentiles estimates from (left) daily data, (right) seasonal averages and (bottom) their difference. All seasons confounded. Dots for statistically significant correlations and differences (alpha=0.05).



Hamilton et al. (2012)

Tropical/extra-tropical links

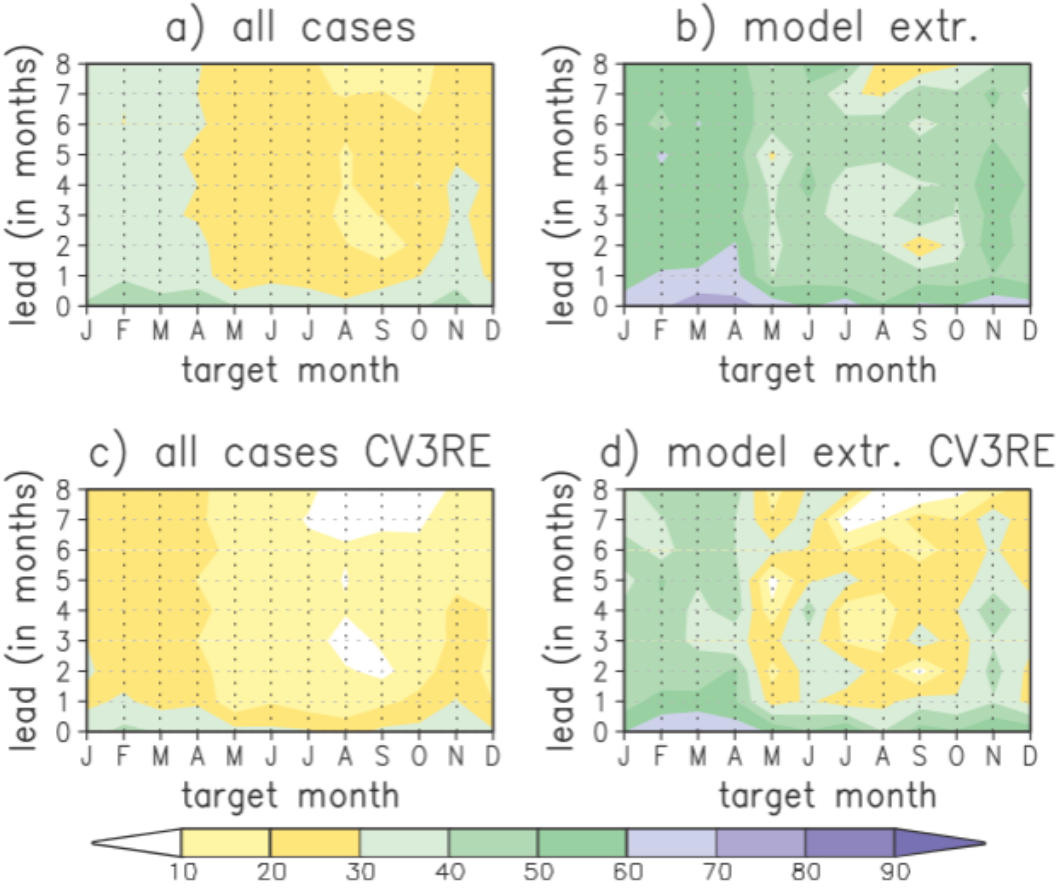
Composite precipitation differences (La Niña minus El Niño) based on years which observed seasonal mean Nino3.4 exceeds ±1 standard deviation over 1982-2009, from GPCP observations (left) and the CHFP ensemble at 1-month lead time (right), for JJA (top) and DJF (bottom).



Kirtman et al. (in prep.)

Forecast quality for unusual events

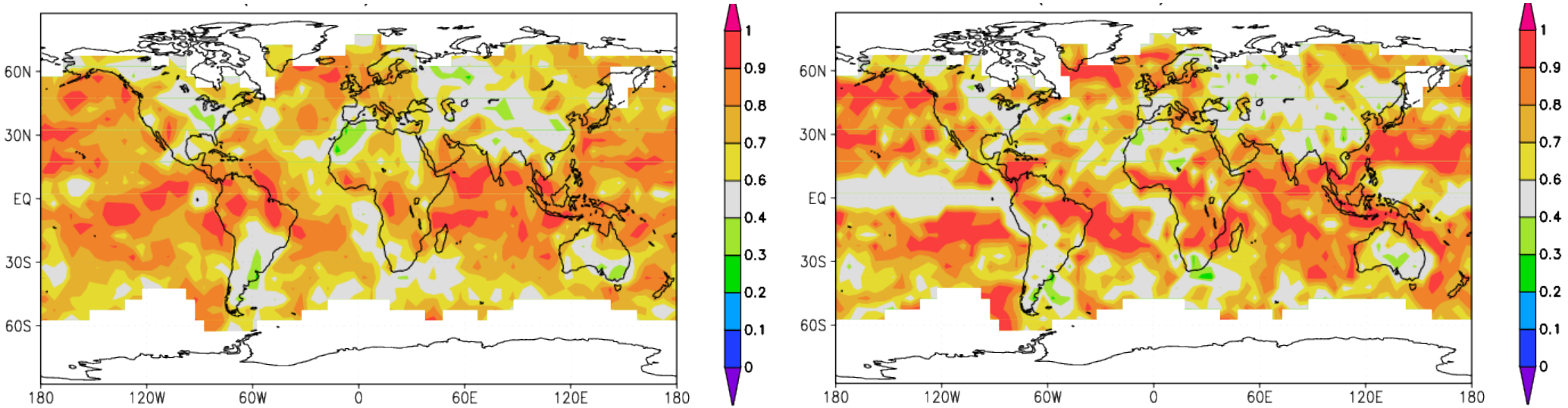
Anomaly correlation for 2-metre temperature CFSv2 forecasts as a function of lead time and target month for all (left) and extreme (right, 95th percentile) monthly mean anomalies with (bottom) and without (top) cross-validation in the calculation of the climatology.



Becker et al. (2013)

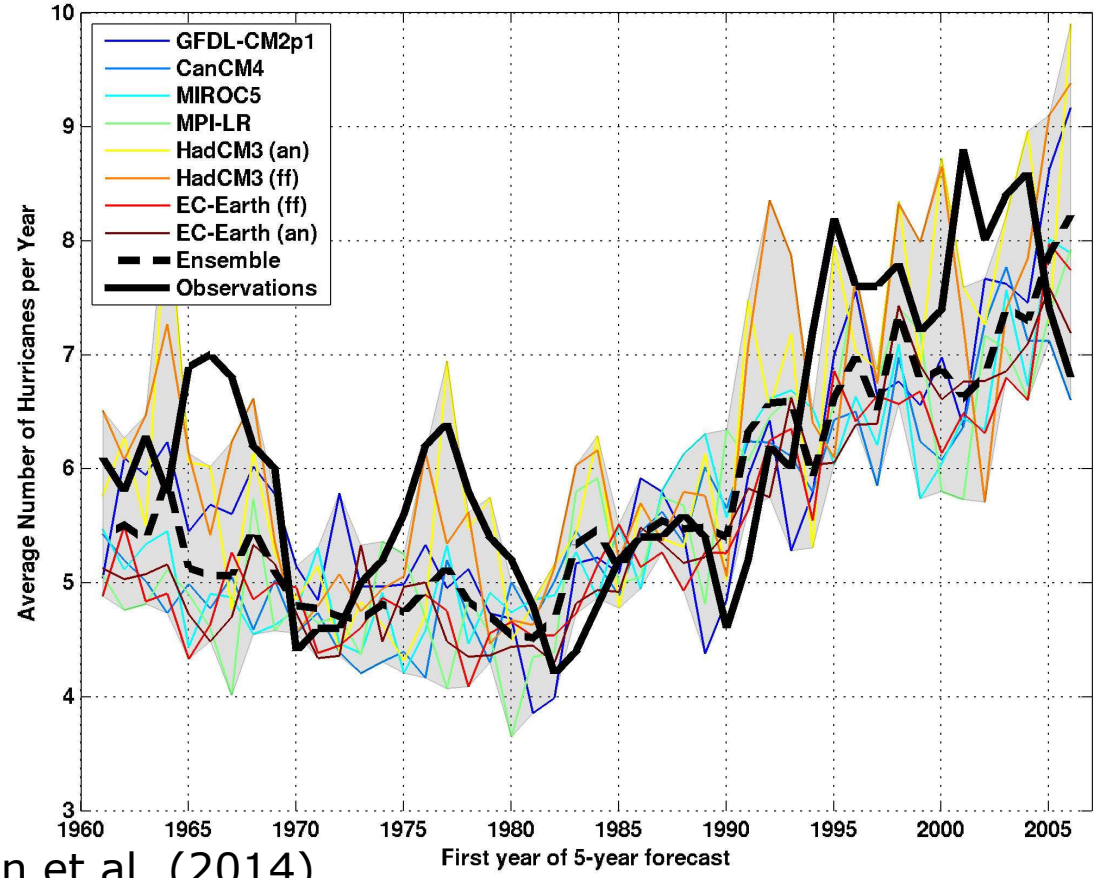
Forecast quality for unusual events

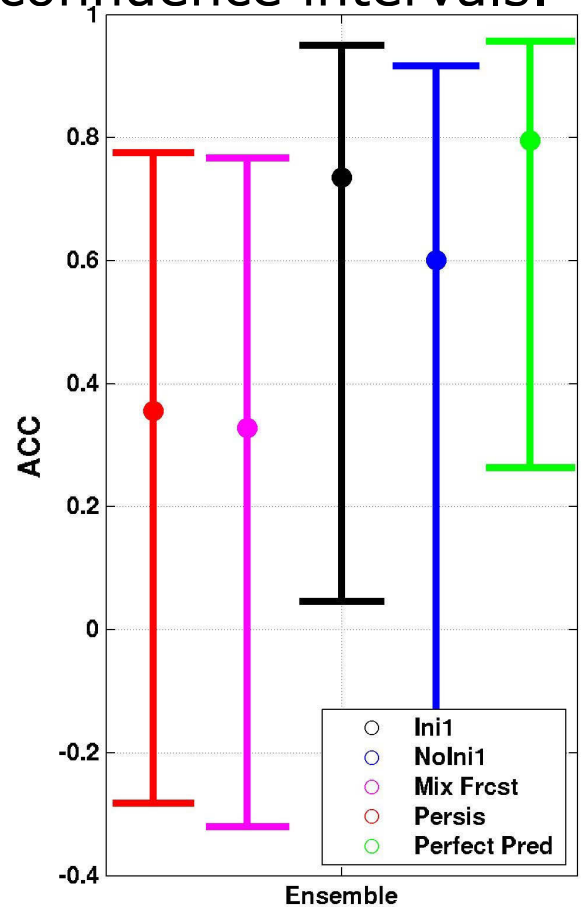
ROC area for near-surface temperature MAM (1-month lead time) predictions with ECMWF ENSEMBLES wrt NCDCv3 over 1979-2005: 75th (left) and 90th (right) percentile thresholds.



Hurricane frequency prediction

Average number of hurricanes per year estimated from observations and from the CMIP5 multi-model decadal prediction ensemble (forecast years 1-5). The correlation of the ensemble mean for the initialized, uninitialized and statistical predictions are shown with the 95% confidence intervals.



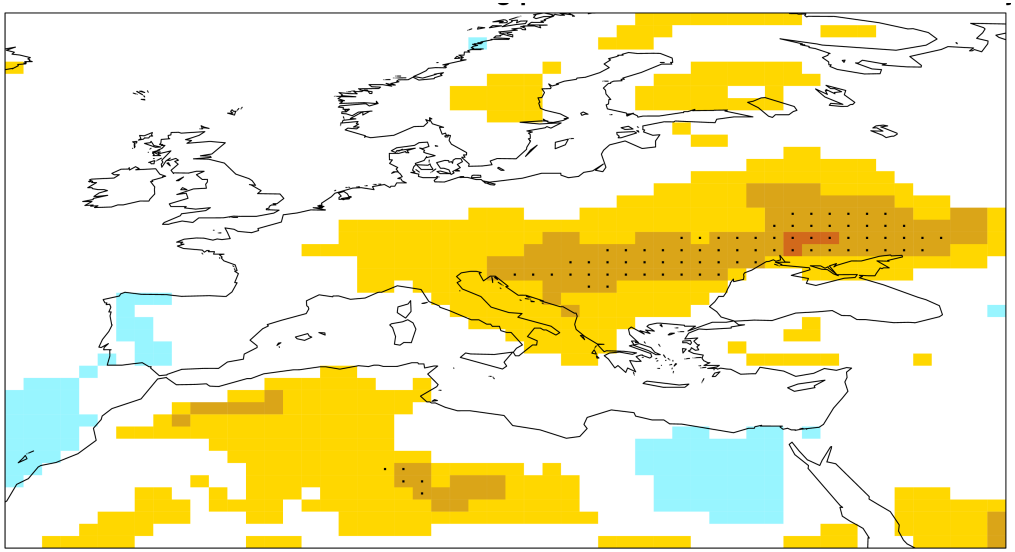


Caron et al. (2014)

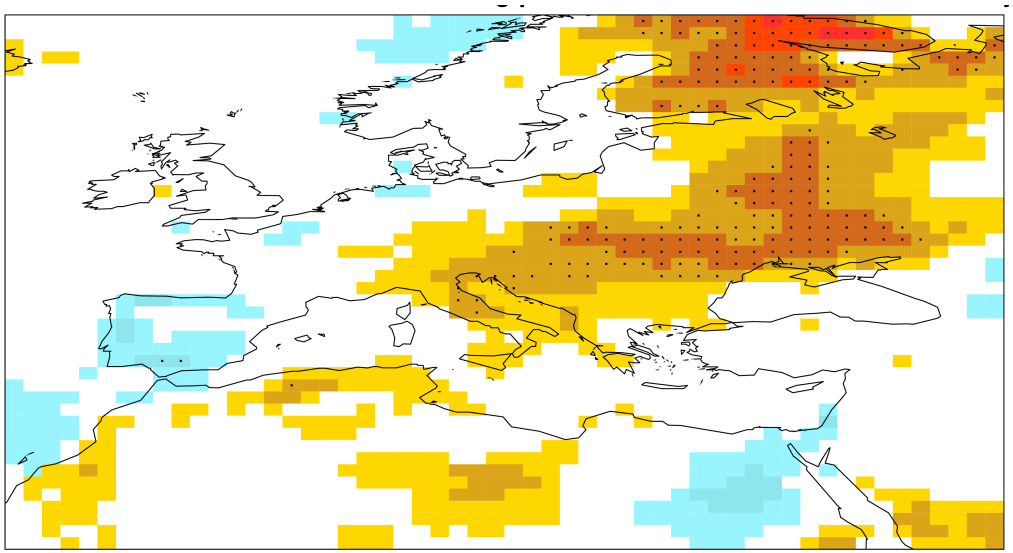
An application: soil moisture impact

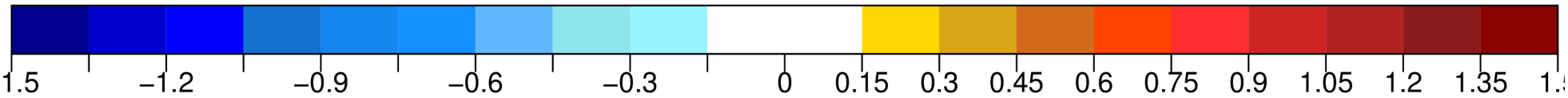
Difference in the correlation of the ensemble-mean near-surface temperature from two experiments, one using a realistic and another a climatological land-surface initialisation. Results for EC-Earth2.3 started every May over 1979-2010 with ERAInt and ORAS4 initial conditions and a sea-ice reconstruction.

Skill difference for mean T



Skill difference for T max

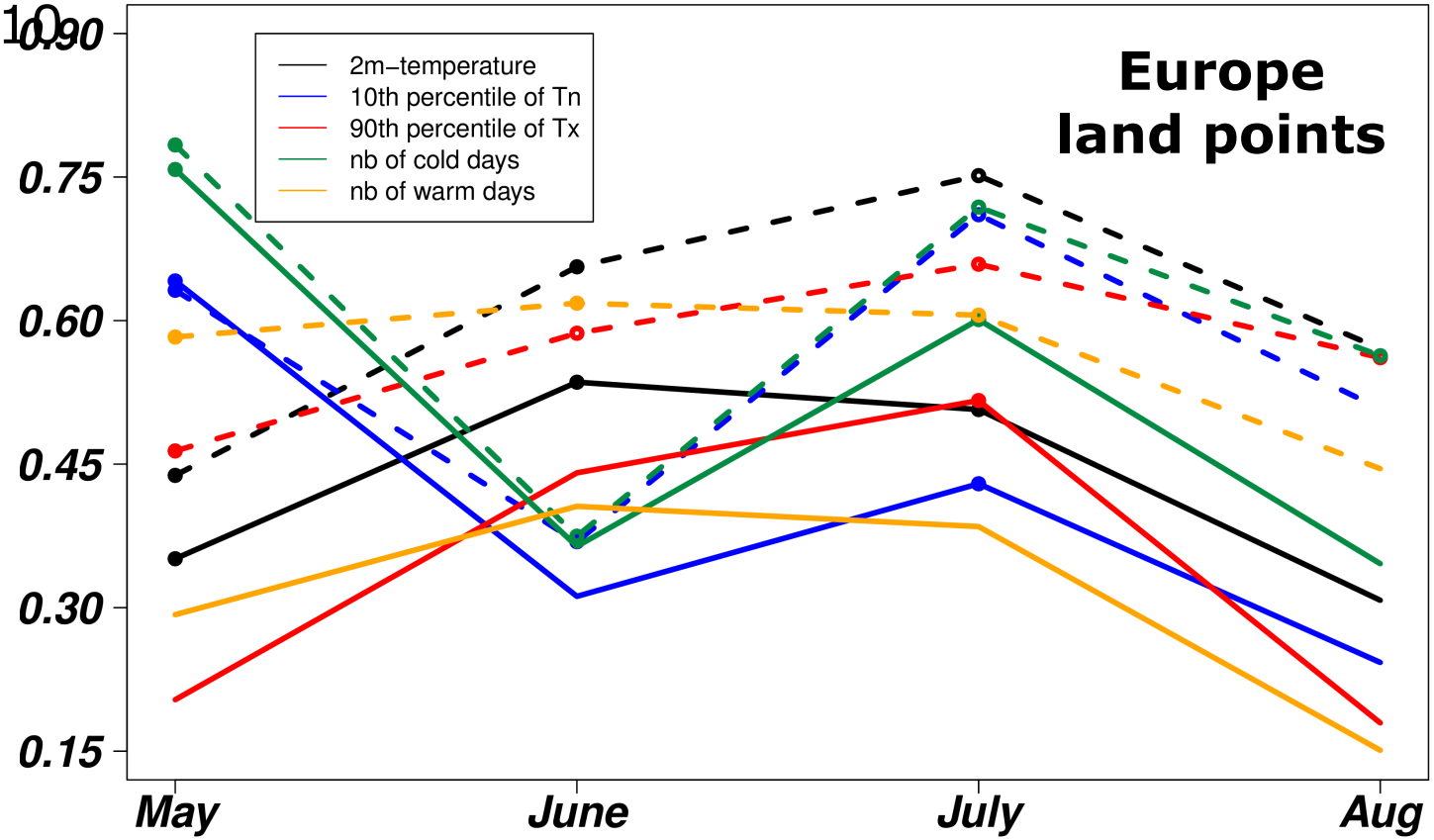




C. Prodhomme (IC3)

An application: soil moisture impact

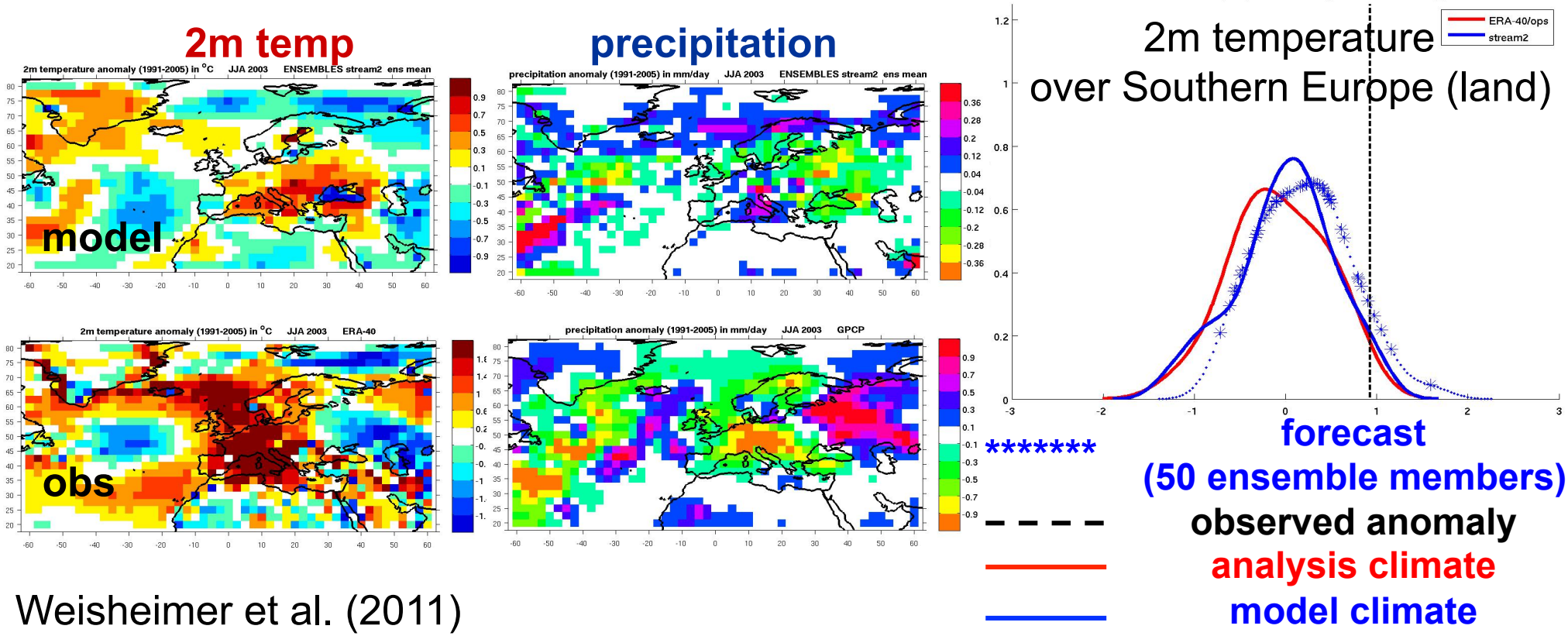
GLACE2 Series 1 and Series 2 skill. Correlation of the ensemble-mean for temperature from experiments with realistic (dashed) and climatological (solid) land-surface initialisation. EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.



C. Prodhomme (IC3)

Model improvement and extreme prediction

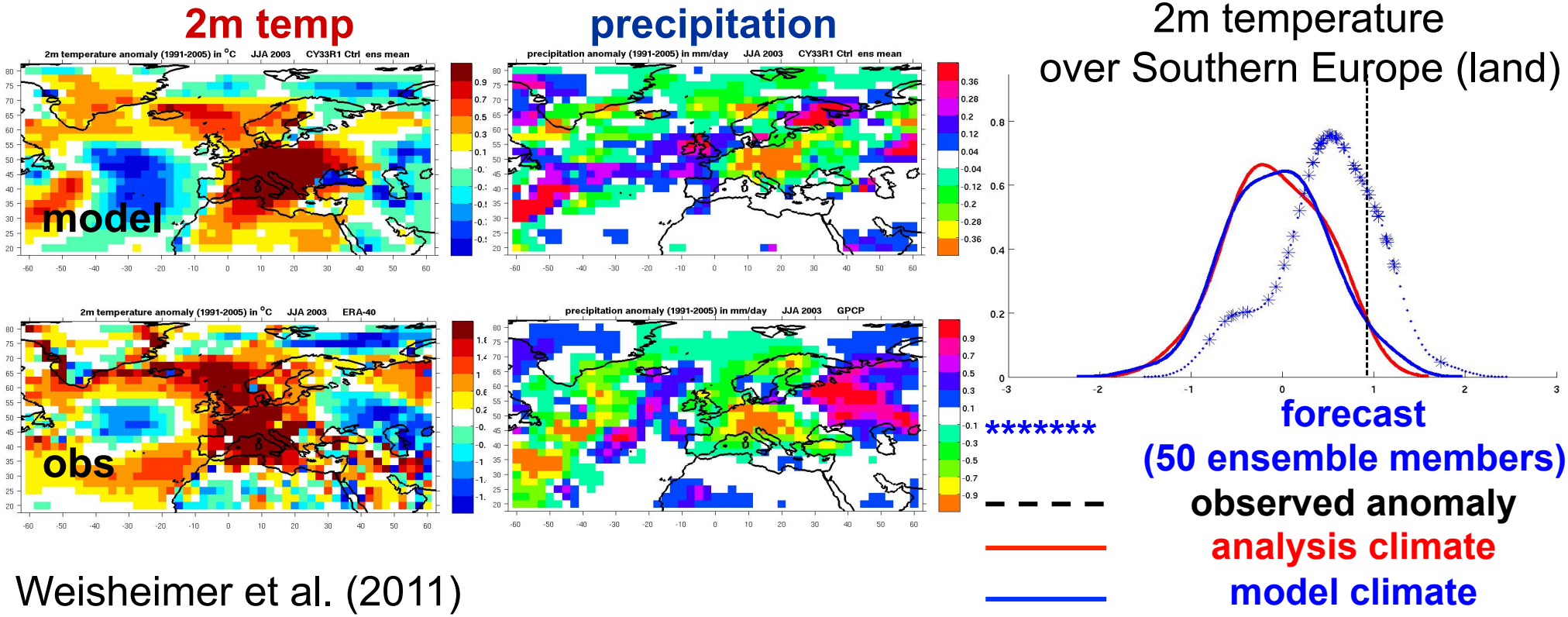
ECMWF ENSEMBLES operational seasonal prediction for summer 2003 with May start date. Anomalies wrt period 1991-2005.



Weisheimer et al. (2011)

Model improvement and extreme prediction

Seasonal prediction with improved ECMWF system (changes in radiation, soil scheme and convection) for summer 2003 with May start date. Anomalies wrt period 1991-2005.

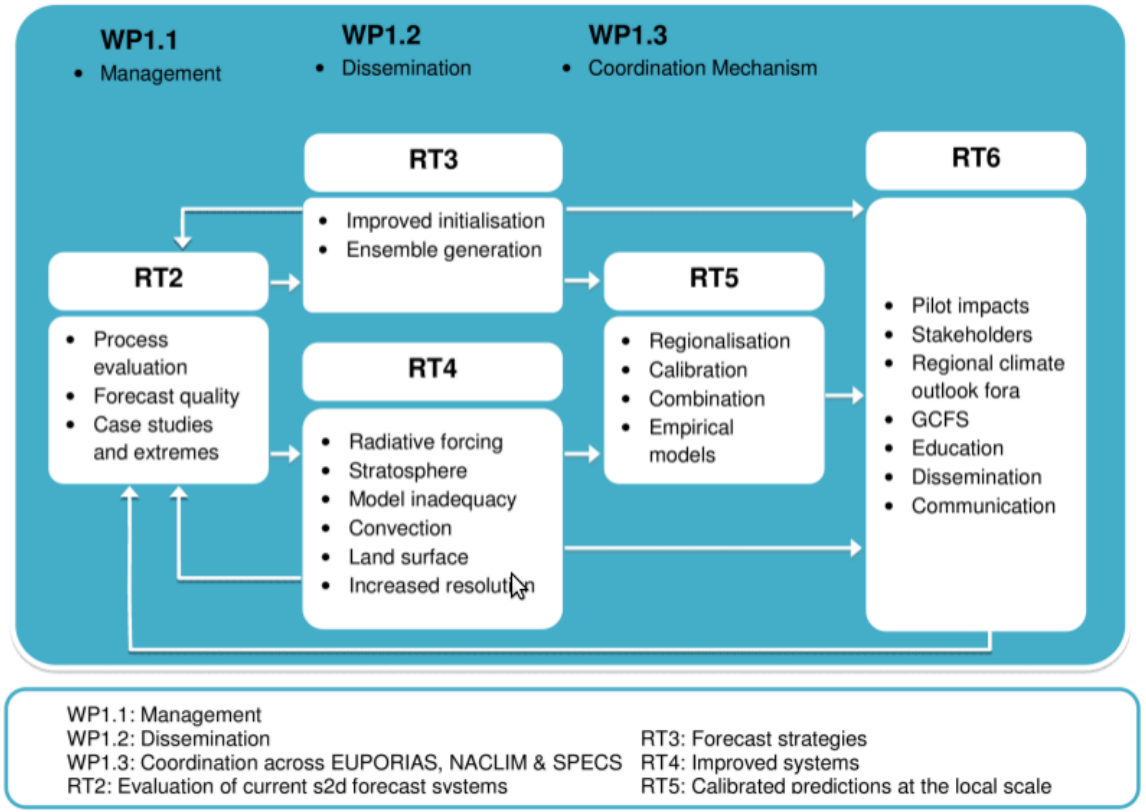


Weisheimer et al. (2011)

SPECS FP7

SPECS will deliver *a new generation of European climate forecast systems, including initialised Earth System Models (ESMs) and efficient regionalisation tools to produce quasi-operational and actionable local climate information over land at seasonal-to-decadal time scales with improved forecast quality and a focus on extreme climate events, and provide an enhanced communication protocol and services to satisfy the climate information needs of a wide range of public and private stakeholders*.

Forecast System	Project Partners
CNRM-CM5	CNRM, CERFACS
EC-Earth	KNMI, SMHI, IC3, ENEA
IFS/NEMO	ECMWF, UOXF
IPSL-CM5	CNRS
MPI-ESM	MPG, UniHH
UM	UKMET

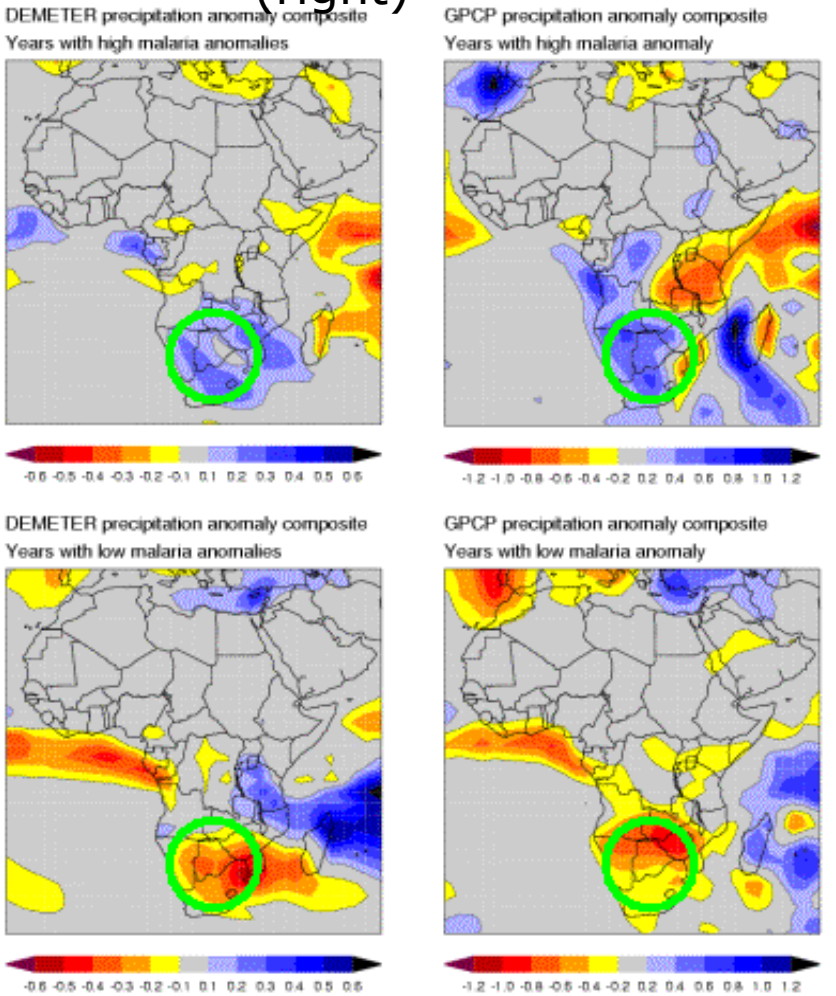


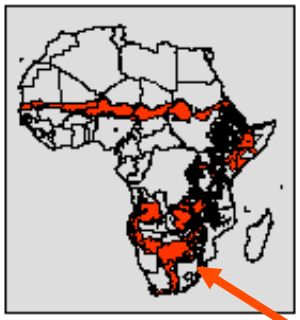
SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

Seasonal forecasts for malaria warning

Precipitation composites for the five years with the highest (top row) and lowest (bottom row) standardised malaria incidence for DJF DEMETER (left) and CMAP (right)

Quartiles define extreme events (outbreaks) for malaria prediction





Areas with epidemic malaria

Thomson et al. (2006)

Malaria warning with climate information

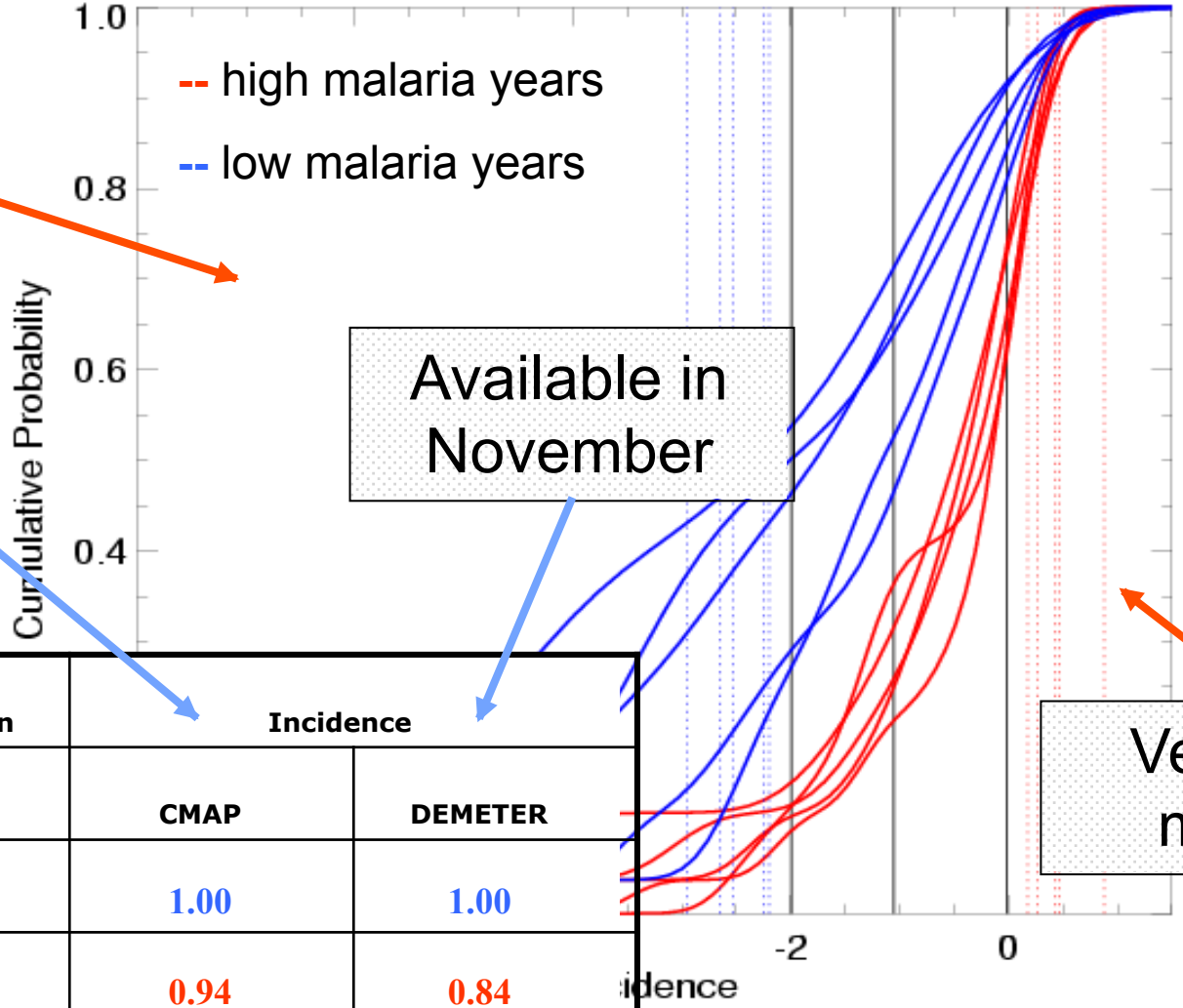
Probabilistic predictions of standardised malaria incidence quartile categories in Botswana with five months lead time

Very low malaria

Available in March

Available in November

Very high malaria



ROC Score	Precipitation	Incidence	
Event	DEMETER	CMAP	DEMETER
Very low	0.95	1.00	1.00
Very high	0.52	0.94	0.84

Communicating extreme predictions

Alarm in Europe: 2013's summer predicted as the closest to 1816, the year without summer. Canal Météo used external sources.

Actualité > **Société**

Météo : l'été sera-t-il vraiment «pourri» ?

Publié le 28.05.2013

Recommander 3 395 personnes le recommandent. Tweeter 155 +1 Share

77 réactions

Hiver froid, printemps frais, été gâché ? A en croire certains prévisionnistes, le temps maussade qui s'est abattu sur la France depuis plusieurs mois... ne devrait pas être chassé par les doux rayons du soleil estival. Pis, Météo Consult table carrément sur «un été pourri» en France.

AUDIO. Du soleil en été ? «Il y a de l'espoir» pour Frédéric Decker, de Météo News.

Le Parisien, 28 May 2013

Météo 2013 : une année sans été ?

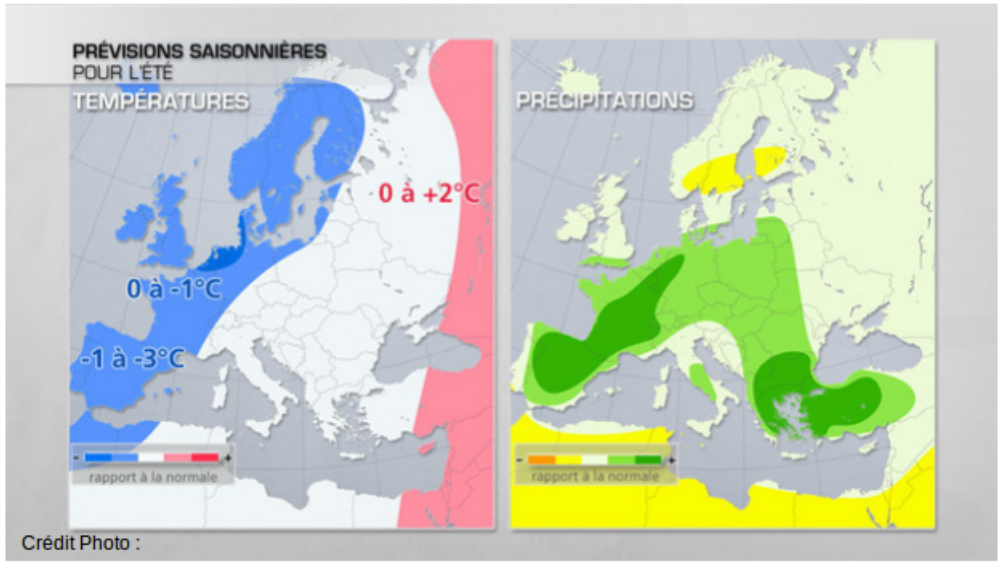
France

Dernière modification le samedi 25 mai 2013 à 16h29

Commenter cet article

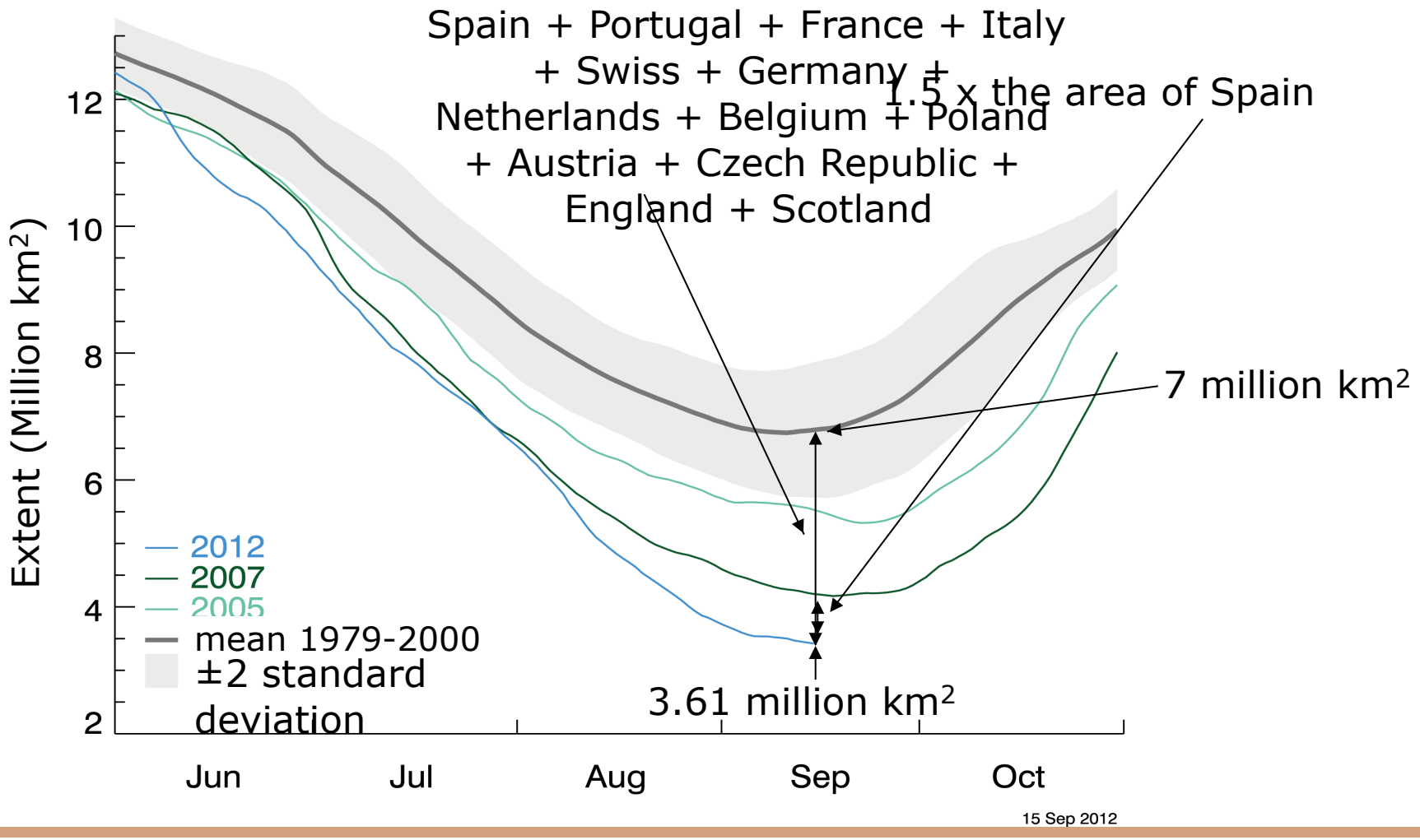
+1 24 Tweeter 99 Like 151 Evaluer l'article 19

Climat



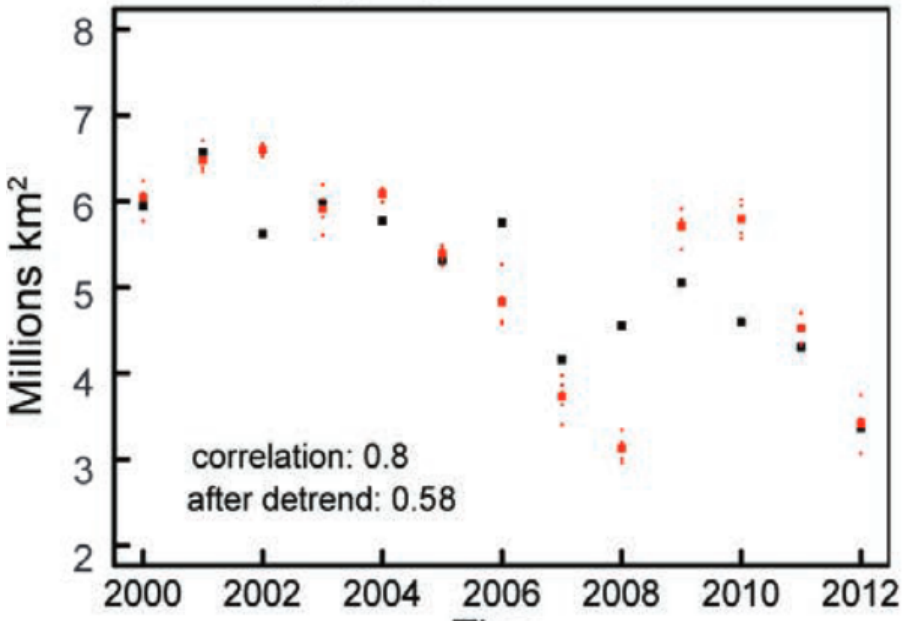
Canal Météo, 25 May 2013

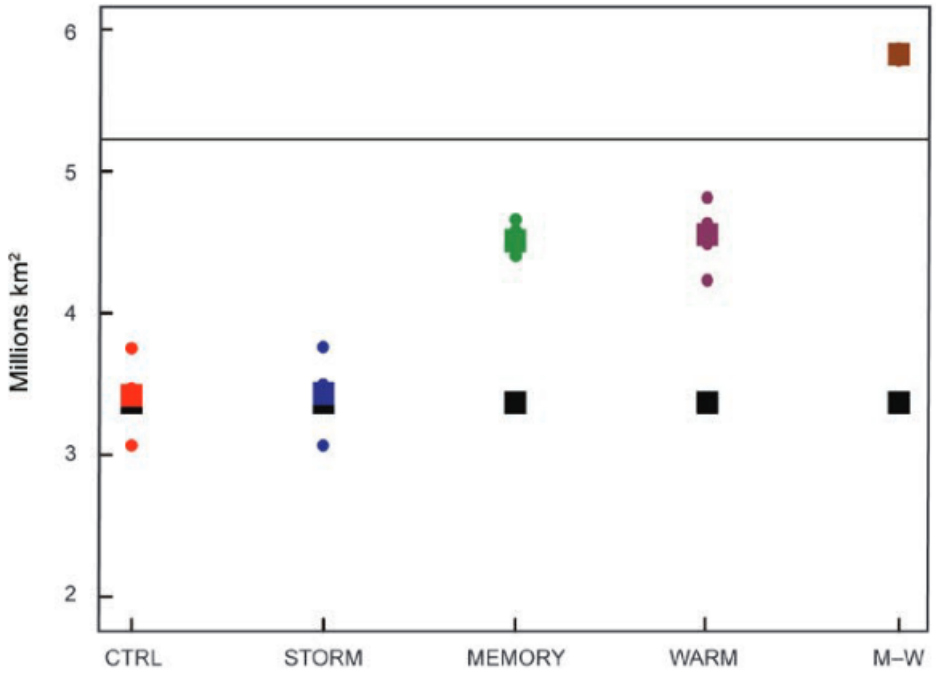
Attribution: The 2012 sea-ice minimum



The 2012 sea-ice minimum

Arctic sea-ice area from calibrated NEMO-LIM simulations forced by ERAInt (left); NSIDC data in black and 5-member ensemble experiments in red. (Right) Attribution of the 2012 sea-ice minimum to several factors: the storm of 5-8 August (STORM), initial conditions (MEMORY), air temperature and humidity (WARM) and initial conditions and air temperature (M-W).

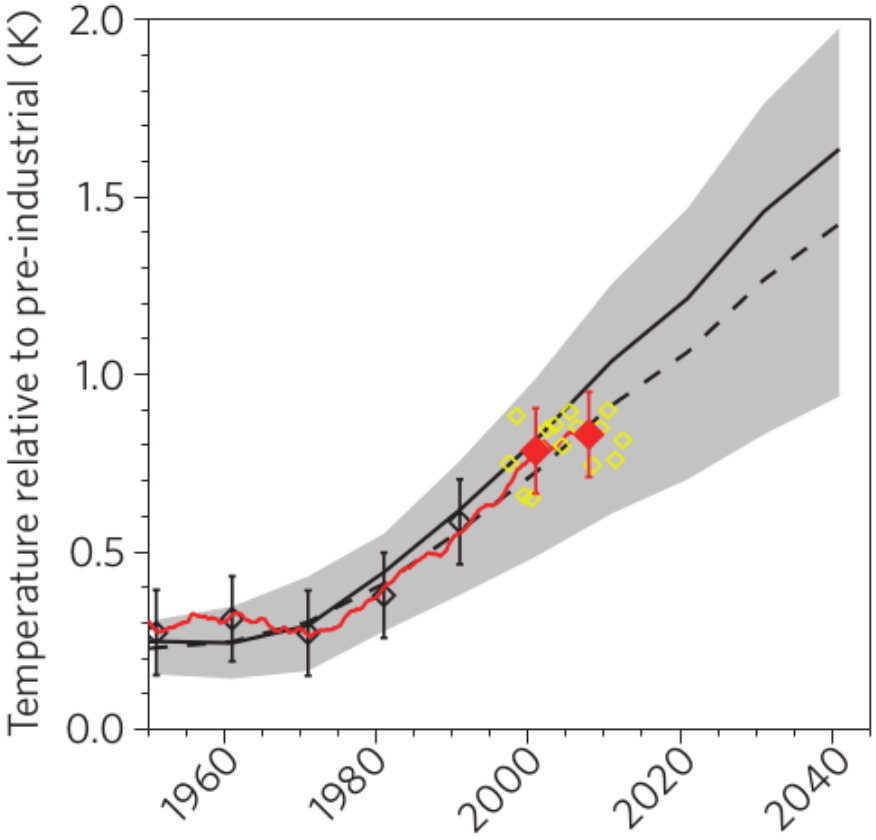




Guemas et al. (2013)

CMIP5 near-term projections: verification

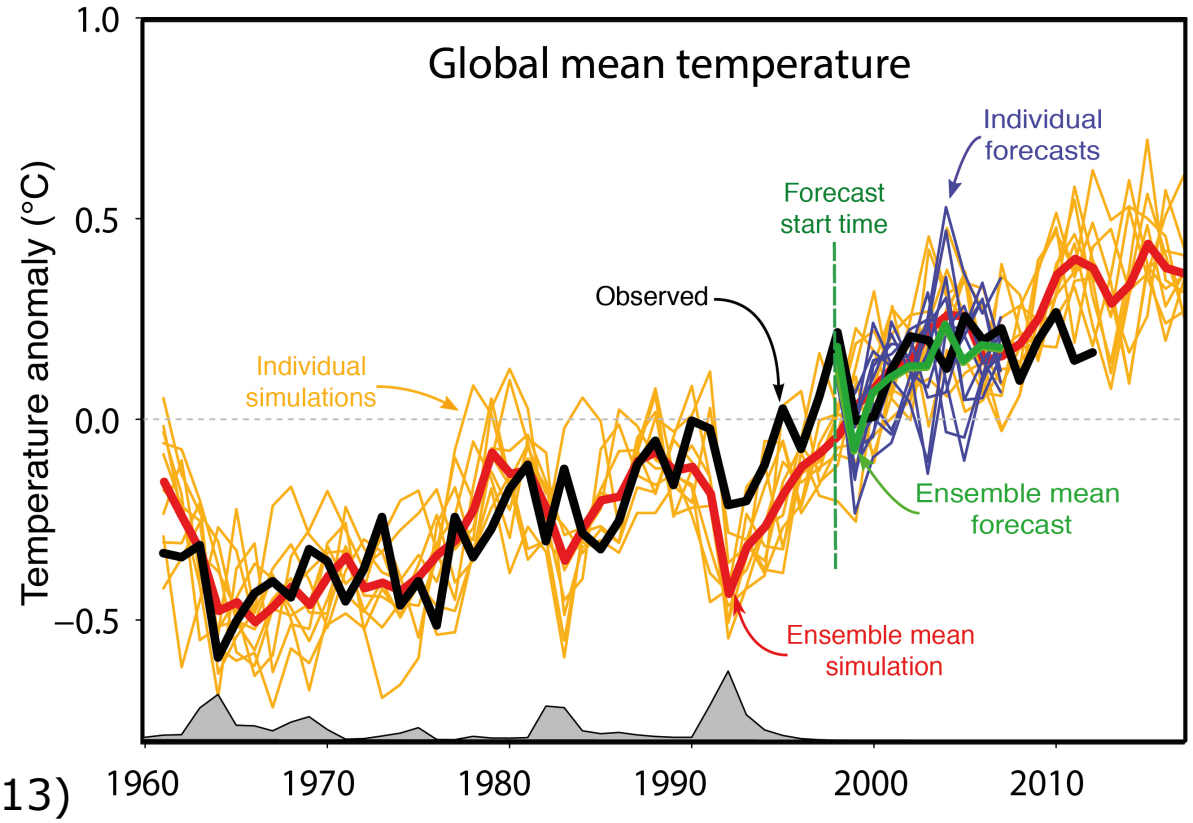
Time series of global-mean decadal mean surface temperature anomalies (relative to preindustrial conditions) from CMIP3 experiments (black solid), after pattern scaling (black dashed) and observations (diamonds). Yellow diamonds for annual observations.



Allen et al. (2013)

CMIP5 simulations

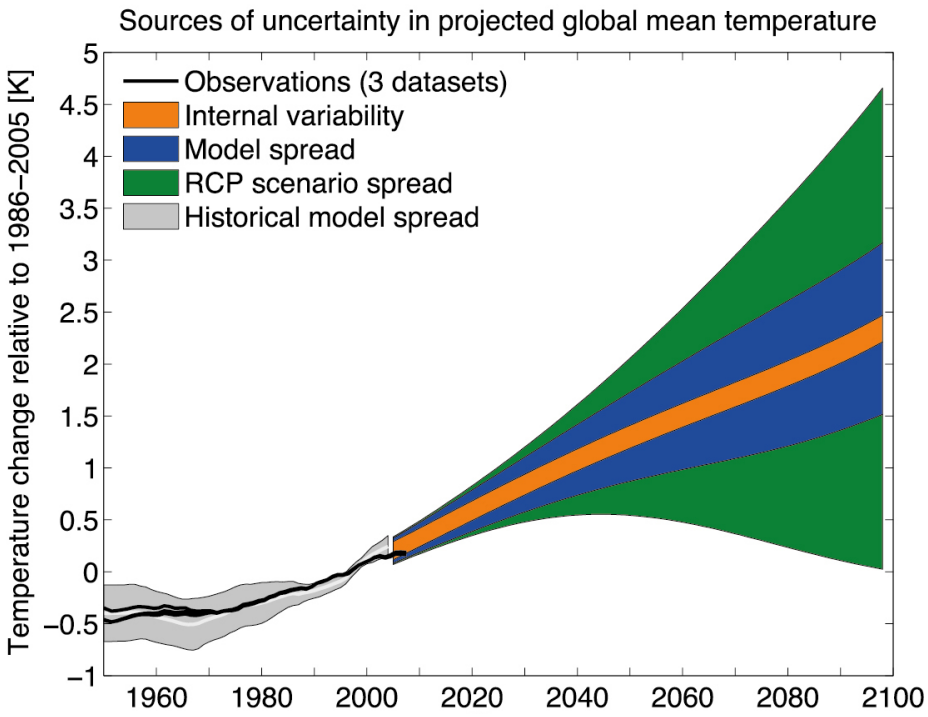
Time series of global-mean annual mean surface air temperature anomalies (relative to 1986–2005) from CMIP5 simulations (yellow lines). An ensemble of forecasts of global annual mean temperature initialized in 1998 is plotted as thin purple lines (average, green line). The grey areas along the axis indicate the presence of external forcing associated with volcanoes.

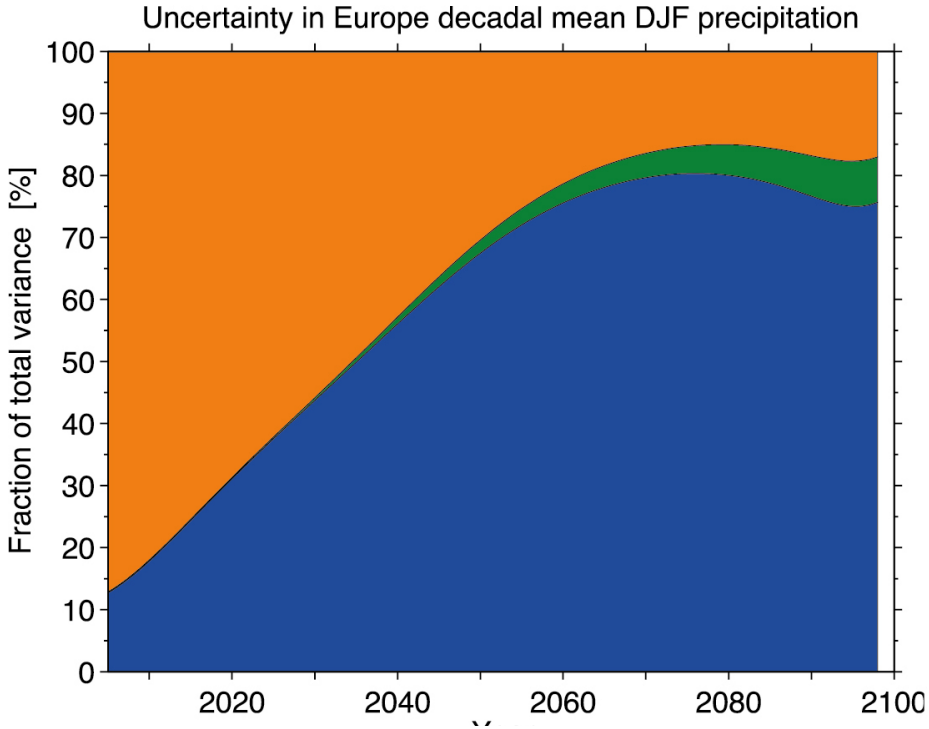


IPCC AR5 WGI (2013)

The hope to predict

The sources of uncertainty include the internal variability, model differences and scenario spread. The internal variability is an uncertainty source particularly important for the near term that could be reduced, especially at regional scales.

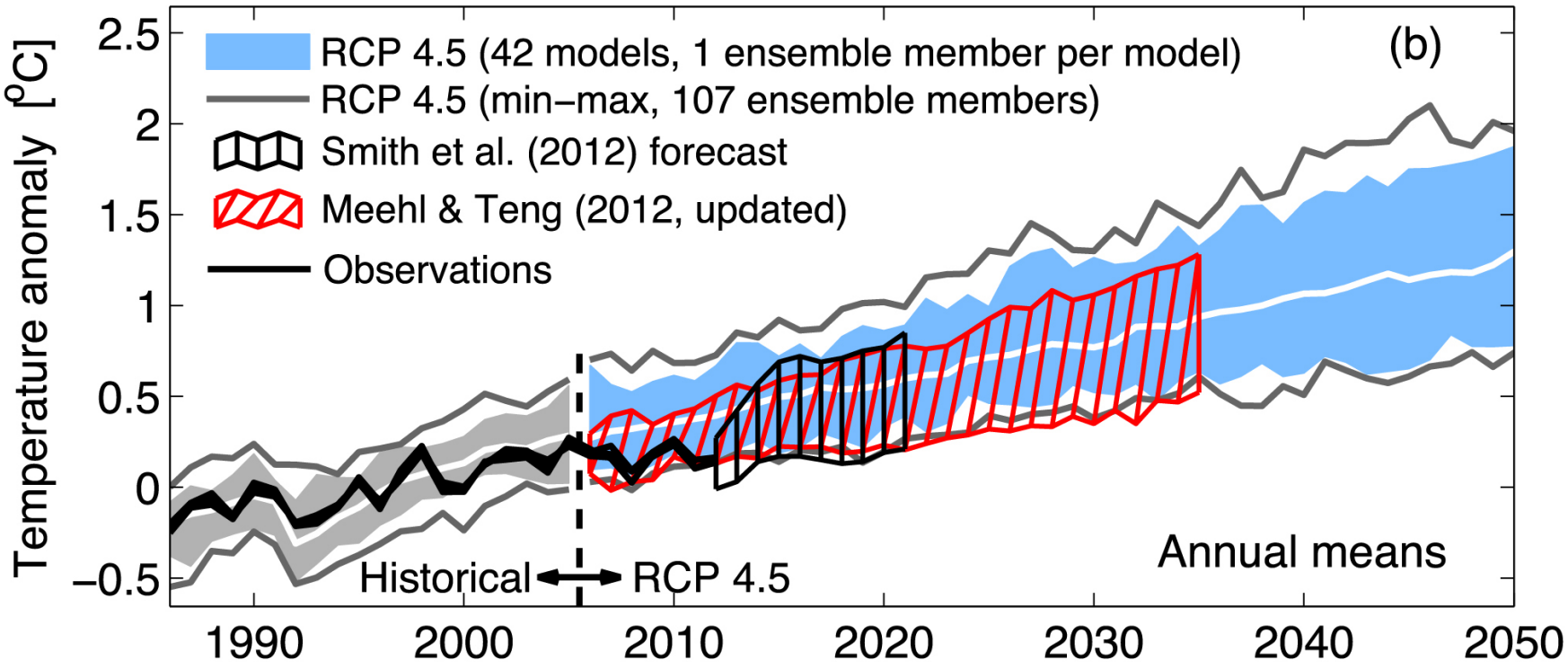




IPCC AR5 WGI (2013)

Predictions and projections

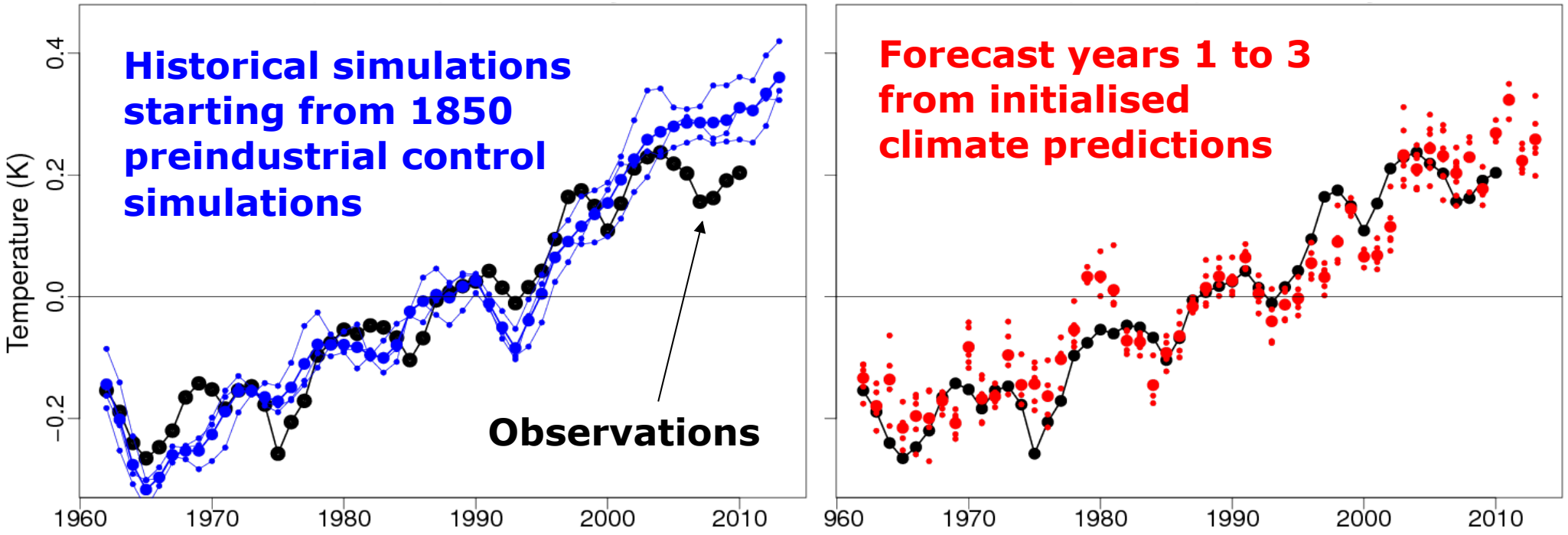
Annual-mean global-mean temperature predictions and projections from CMIP5.



IPCC AR5 WGI (2013)

Attribution of the XXIst century hiatus

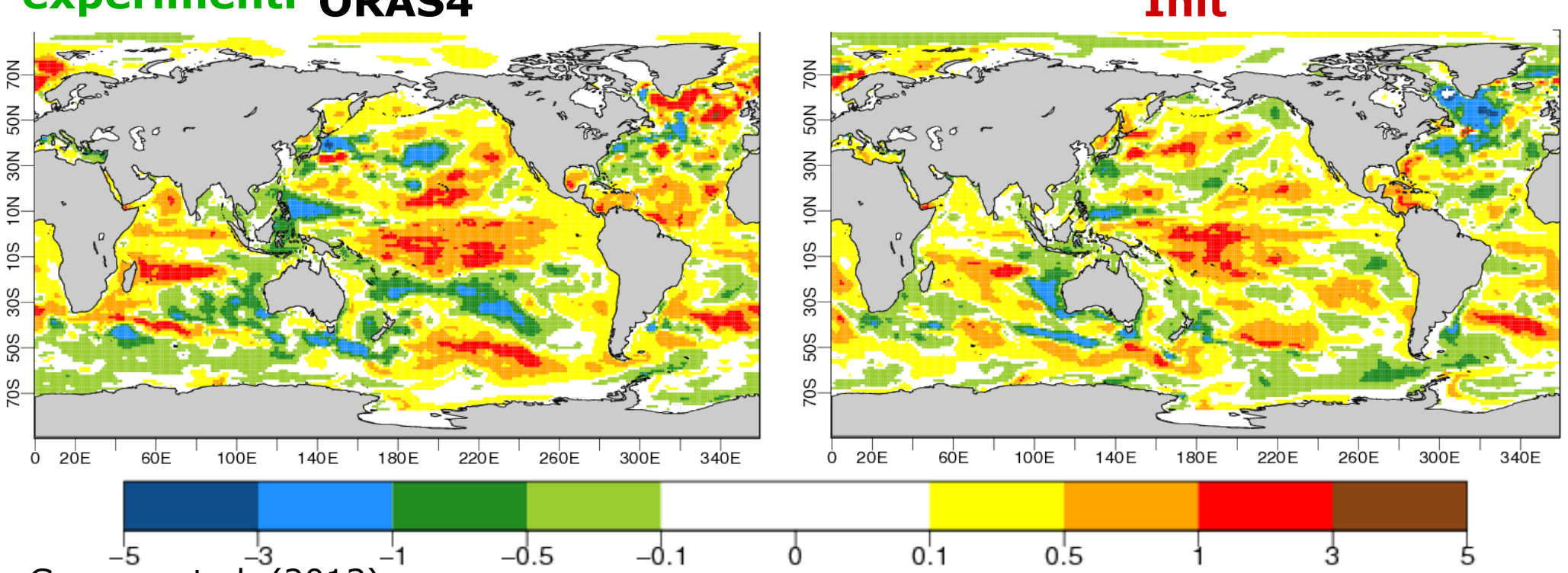
Predictions of the recent global-temperature slow down with EC-Earth 2.3. Global-mean SST from observations (ERSST) and simulations, three-year averages. **The experiments suggest an important role of the internal variability, especially increased capture of heat in the ocean, in the hiatus.**



Guemas et al. (2013)

Attribution of the XXIst century hiatus

Predictions of the recent global-temperature slow down with EC-Earth 2.3. OHC for the top 800 m (10^9 J, excluding the mixed layer) for the ORAS4 reanalysis and the initialised hindcasts, three-year average at the onset of the hiatus. **The hiatus is associated with an increased ocean heat absorption, especially in the Pacific. This is captured by the Init experiment.**



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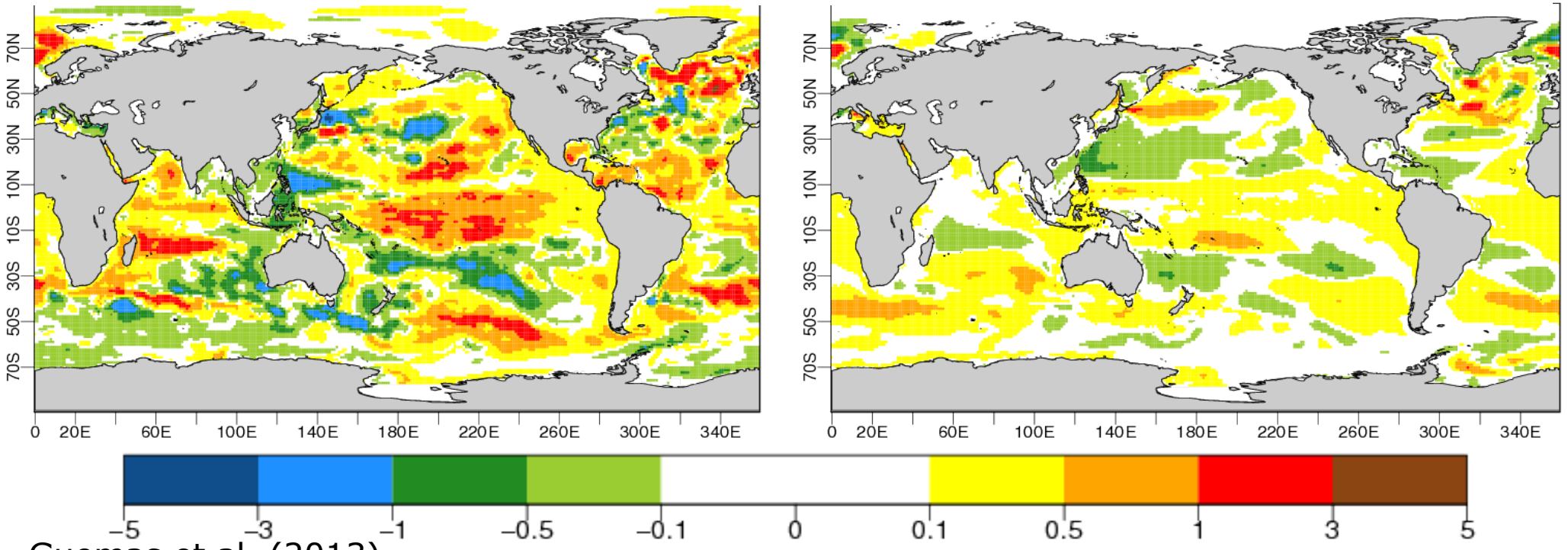

Guemas et al. (2013)