Multi-model ensemble prediction on seasonal timescales

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(Some material from Antje Weisheimer)

Structure of the lecture

1. The multi-model concept
2. Example: results from DEMETER
3. Under which conditions can a multi-model ensemble outperform the best single-model?
4. EUROSIP – operational multi-model forecasts

Model error

- By model error we mean problems, inadequacies and imperfections with the model formulation and its numerical implementation.
- This model error causes integrations of the model to produce results which are unrealistic in various ways; e.g. the model climate (mean, variability, features) may be unrealistic.
- The imperfections in the model also contribute to errors in any seasonal forecast produced by the model. This contribution we define as the model forecast error. We do not know its value in any particular case, but may try to estimate its statistical properties.

Examples of model error problems …

- Impact of coupled mean state bias on variability
  - E.g. if thermocline is depressed, SST variability will be damped

- Inadequate atmospheric wind variability
  - Can be true even when the SST is unbiased

- Incorrect distribution of mean precipitation
  - So shifts in precipitation inevitably give incorrect anomalies

- Countless others that we don’t know about ….
  - We believe that we have a broad spectrum of model errors
  - When we improve particular processes in a model, overall impact is almost as likely to be negative as positive

Multi-model ensemble

- Different coupled GCMs have different model errors

  - There may be lots of common errors, too.

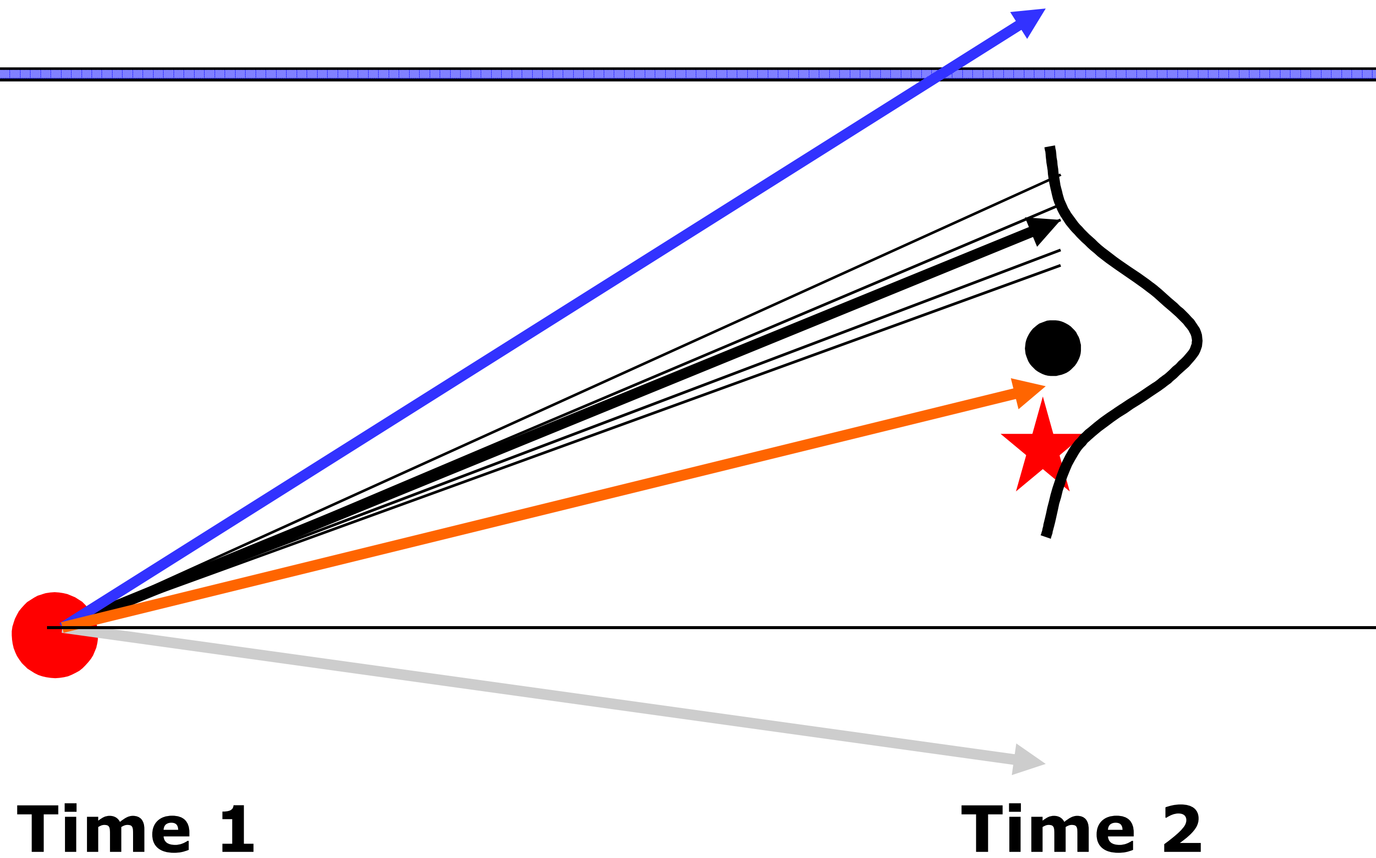
- So let's take an 'ensemble' of model forecasts:
  - The mean of the ensemble should be better, because at least some of the model forecast errors will be averaged out
  - The 'spread' of the ensemble should be better, since we are sampling some of the uncertainty

- An ensemble of *forecast values* or of *models?*

Multi-model ensemble of forecast values

- What would an 'ideal' multi-model system look like?
  - Assume fairly large number of models (10 or more)
  - Assume models have roughly equal levels of forecast error
  - Assume that model forecast errors are *uncorrelated*
  - Assume that each model has its own mean bias removed

  - A priori, for each forecast, we consider each of the models' forecasts equally likely [in a Bayesian sense – in reality, all the model pdfs will be wrong]
  - A posteriori, this is no longer the case: model forecasts with an ensemble mean near the centre of the multi-model distribution have higher likelihood
  - *Different* from a single model ensemble with perturbed ic's, which maps an initial pdf to a final pdf
  - Multi-model ensemble distribution is NOT a pdf



Error in ensemble mean = $\sigma_{mod\_err} / \sqrt{n}$

Non-ideal case

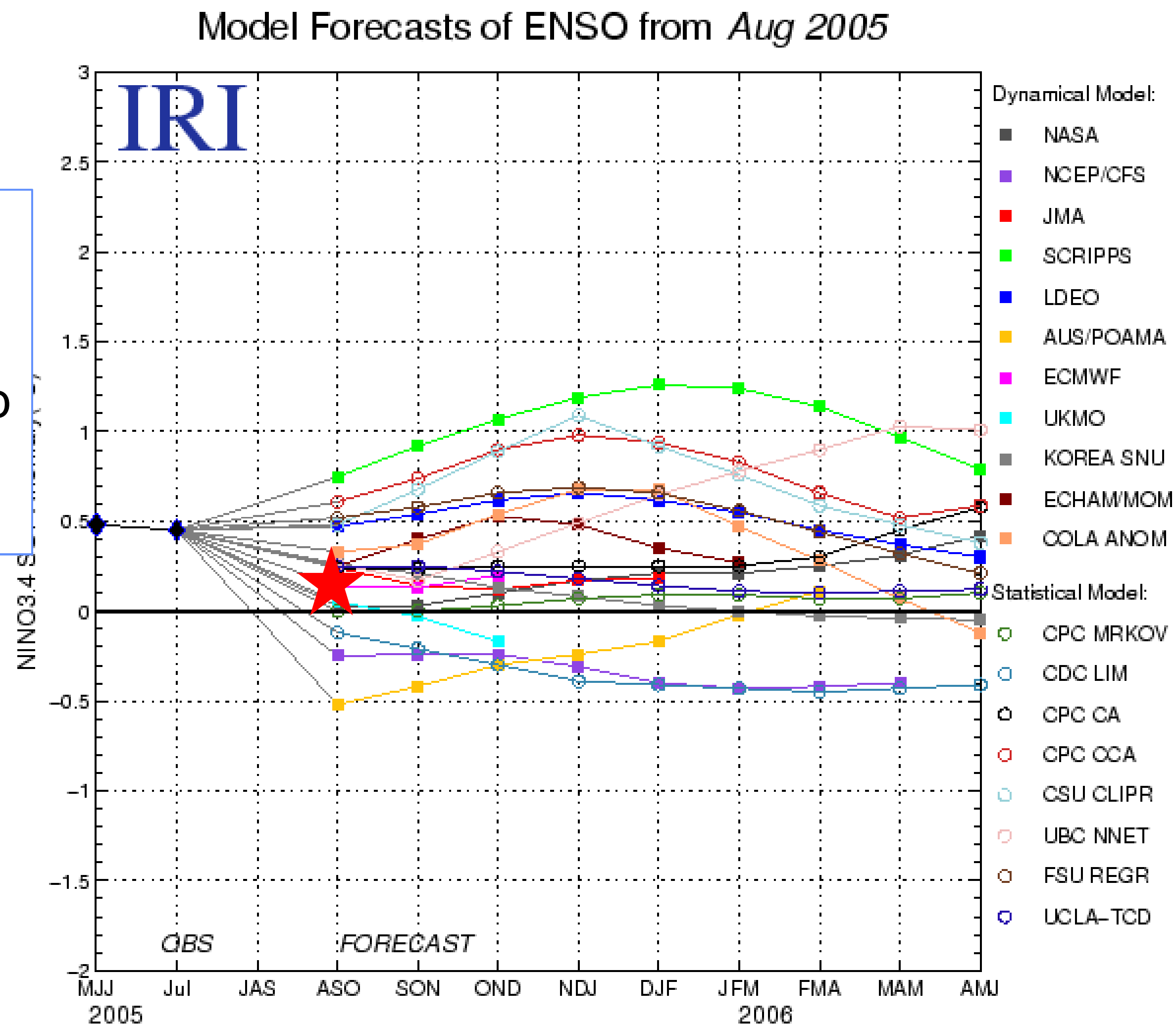
- Model forecast errors are *not* independent
  - Dependence will reduce degrees of freedom, hence the effective *n*; this will increase uncertainty
  - In some cases, reduction in *n* could be drastic

- Model forecast errors may have different amplitudes
  - And we may not know which models are better

- Initial condition error can be important
  - The foregoing analysis applies to the ‘model error’ contribution to error variance
  - Initial condition error could in principle be accounted for in the ensemble of initial conditions used by each model
  - In practice, initial condition uncertainty is poorly represented, and errors in initial conditions will have common component

Multi-model ensemble is not a pdf

Although we can choose to treat it as one if we want (and many people do).



Forecast process

Model output → Interpretation (forecast pdf) → Verification

Forecast pdf *should* be an appropriate interpretation of model ensemble, not an equivalence.

DEMETER – a worked example of multi-model seasonal forecasts

The DEMETER project

multi-model of 7 coupled general circulation models

Partner	Atmosphere	Ocean
ECMWF	IFS	HOPE
LODYC	IFS	OPA 8.3
CNRM	ARPEGE	OPA 8.1
CERFACS	ARPEGE	OPA 8.3
INGV	ECHAM-4	OPA 8.2
MPI	ECHAM-5	MPI-OM1
UKMO	HadCM3	HadCM3

- hindcast production period: 1958-2001
- 9-member IC ensembles for each model
- ERA-40 initial conditions
- SST and wind perturbations
- 4 start dates per year: 1st of Feb, May, Aug, and Nov
- 6 month hindcasts

http://www.ecmwf.int/research/demeter/

multi-model of 7 coupled general circulation models

7 models x 9 ensemble members

→ 63-member multi-model ensemble

= 1 hindcast

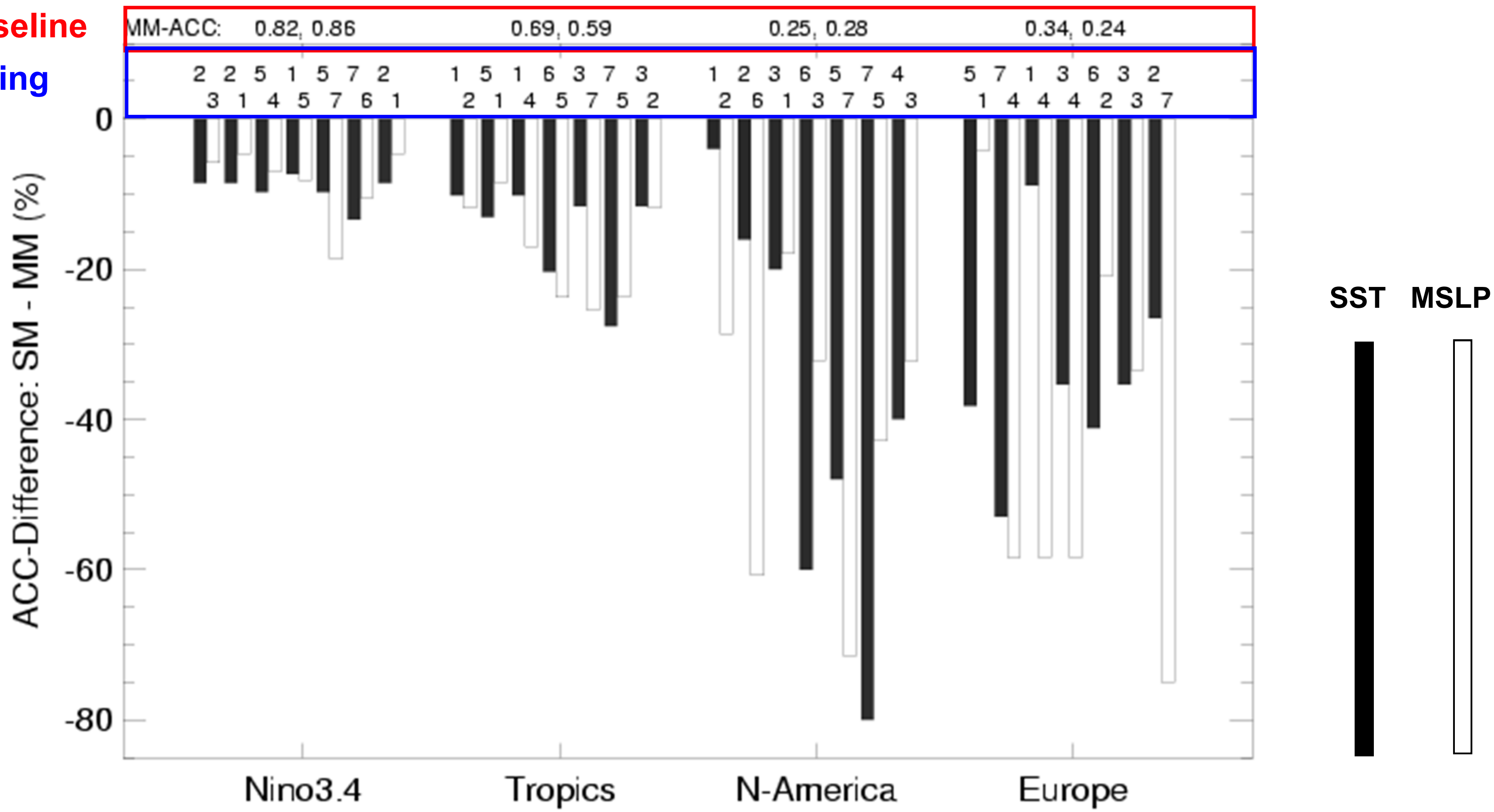
Production for 1958-2001 = 44x4 = 176 hindcasts

DEMETER: multi-model vs single-model

Relative ACC improvement of the multi-model compared to the single models for JJA from 1980-2001 (one month lead)

multi-model baseline

model ranking

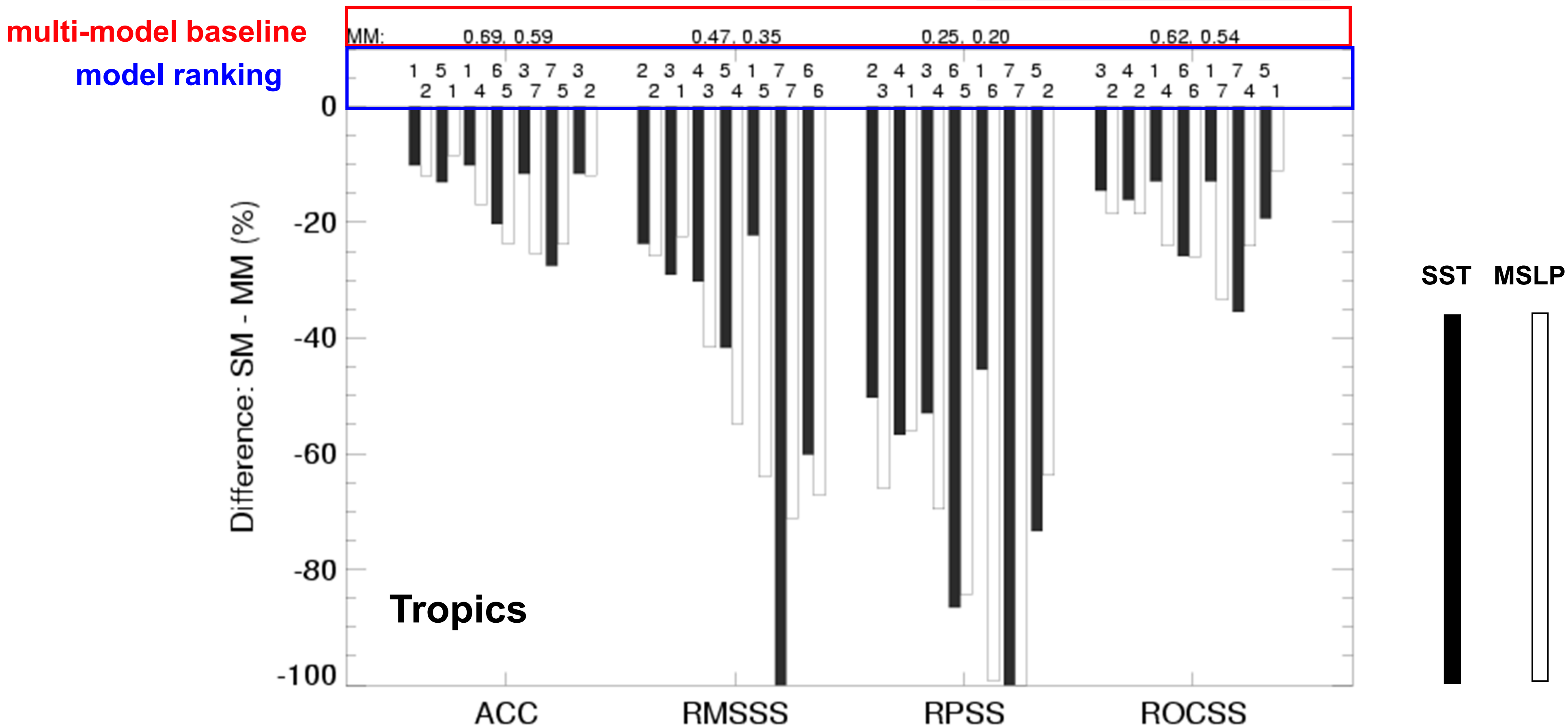


Hagedorn et al. (2005)

Anomaly Correlation Coefficients (ACC)

DEMETER: multi-model vs single-model

Relative improvement of the multi-model compared to the single models for JJA from 1980-2001 (one month lead) for different scores.

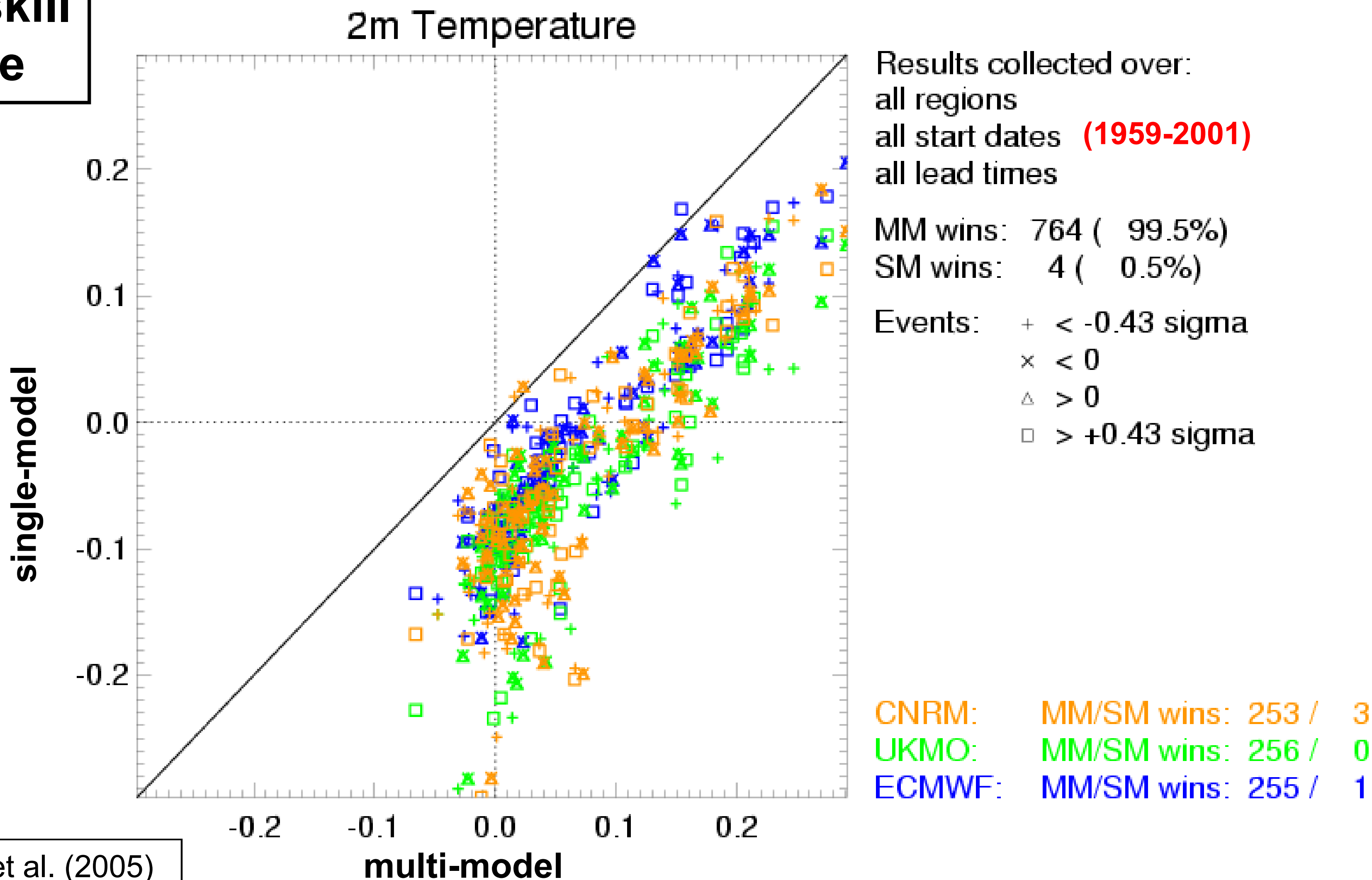


Anomaly Correlation Coefficients (ACC), root mean square skill score (RMSSS), Ranked Probability Skill Score (RPSS) and ROC Skill Score (ROCSS)

Hagedorn et al. (2005)

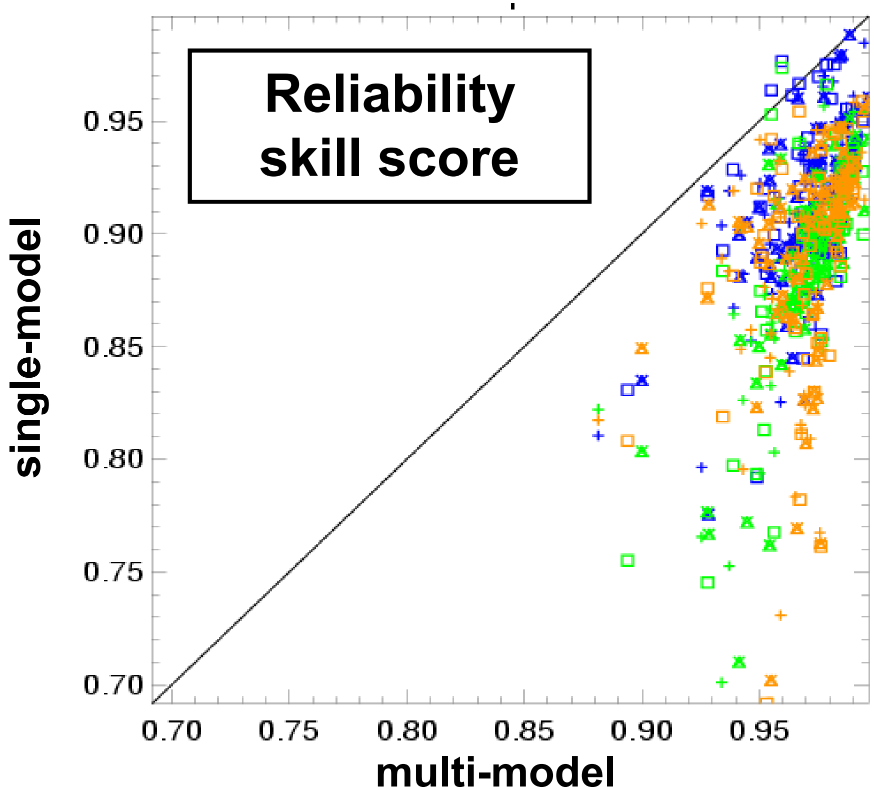
DEMETER: Brier score of multi-model vs single-model

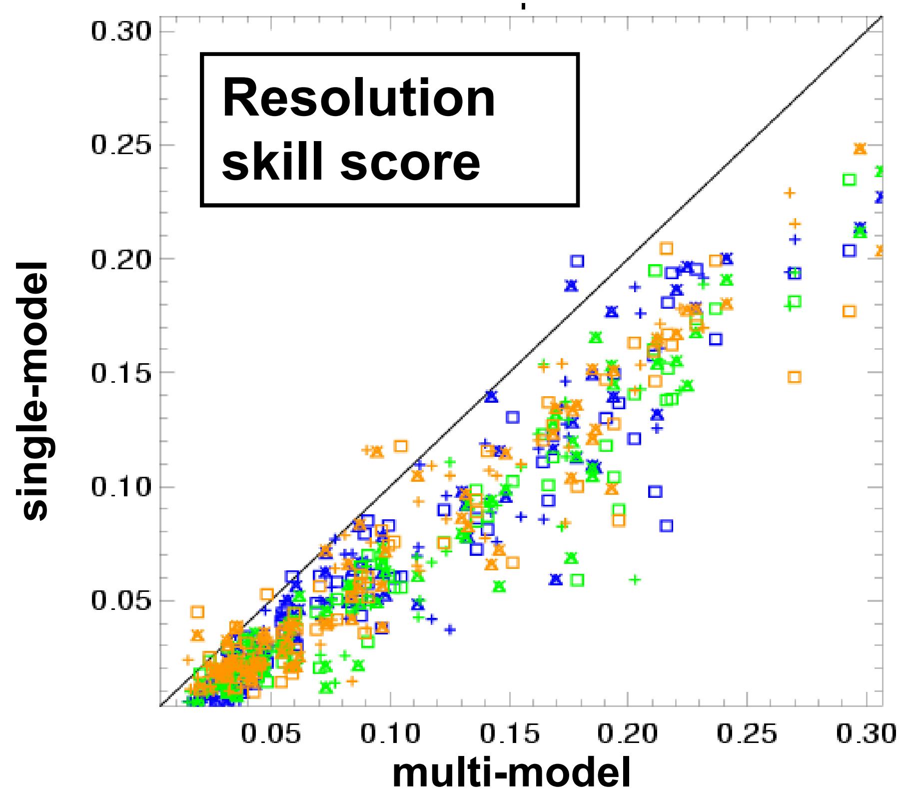
Brier skill score



Hagedorn et al. (2005)

DEMETER: Brier score of multi-model vs single-model





- improved **reliability** of the multi-model predictions
- improved **resolution** of the multi-model predictions

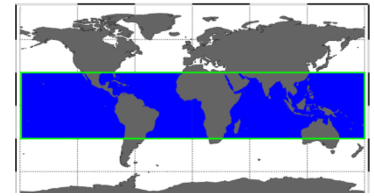
Hagedorn et al. (2005)

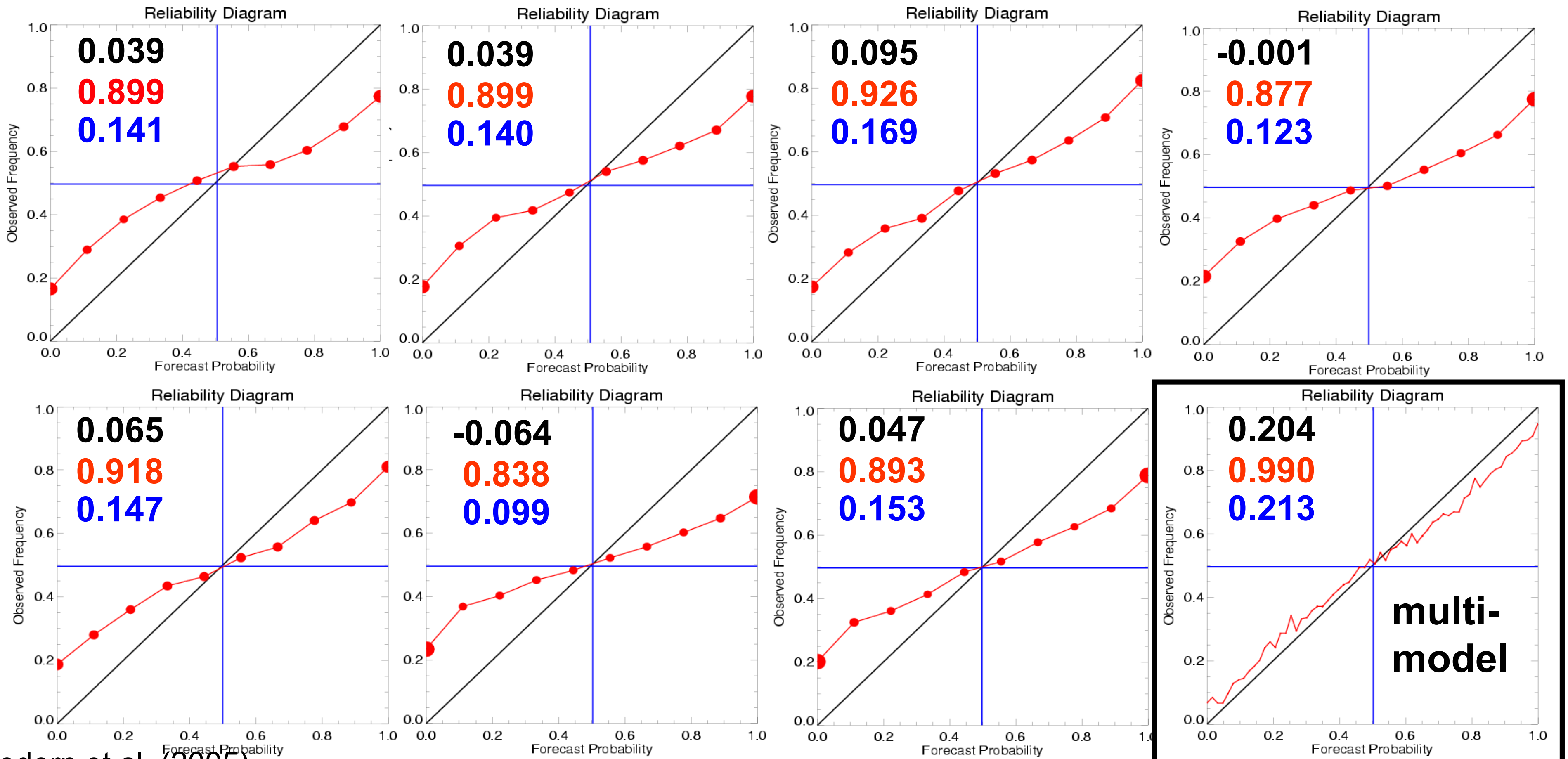
DEMETER: multi-model vs single-model

BSS
Rel-Sc
Res-Sc

Reliability diagrams (T2m > 0)

1-month lead, start date May, 1980 - 2001





Hagedorn et al. (2005)

DEMETER: impact of ensemble size

- **Is the multi-model skill improvement due to**
  - increase in ensemble size?
  - using different sources of information?

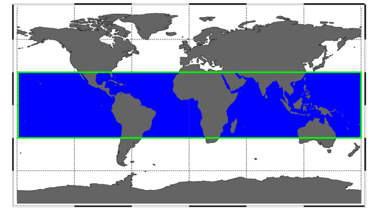
- **An experiment with the ECMWF coupled model and 54 ensemble members to assess**
  - impact of the ensemble size
  - impact of the number of models

DEMETER: impact of ensemble size

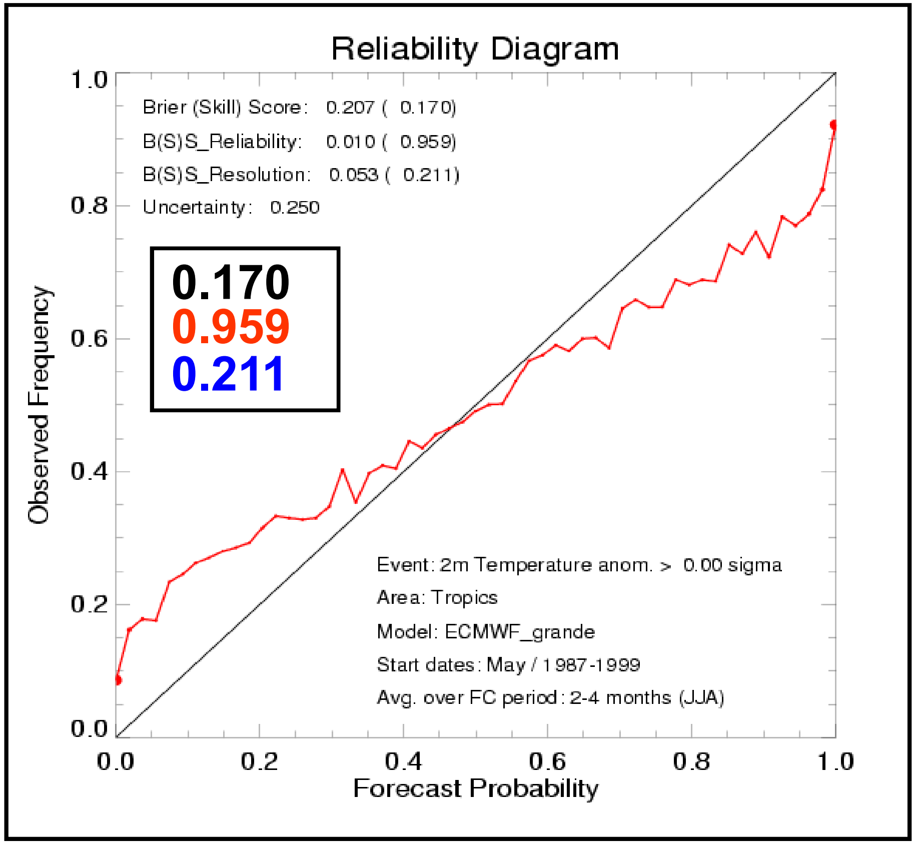
BSS
Rel-Sc
Res-Sc

Reliability diagrams (T2m > 0)

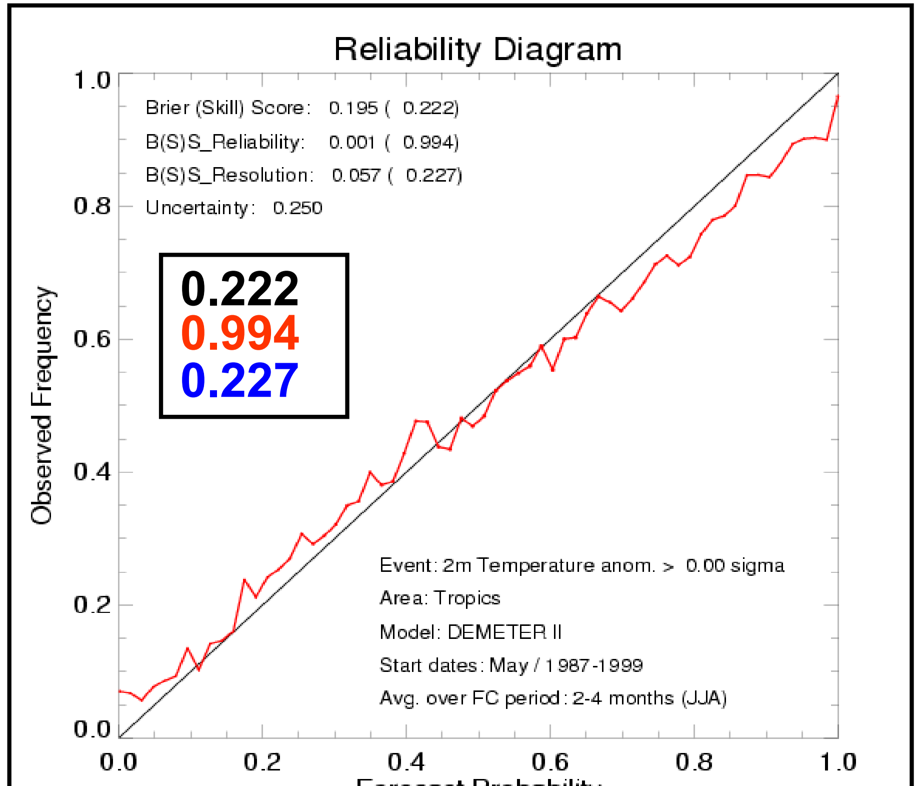
1-month lead, start date May, 1987 - 1999



single-model [54 members]

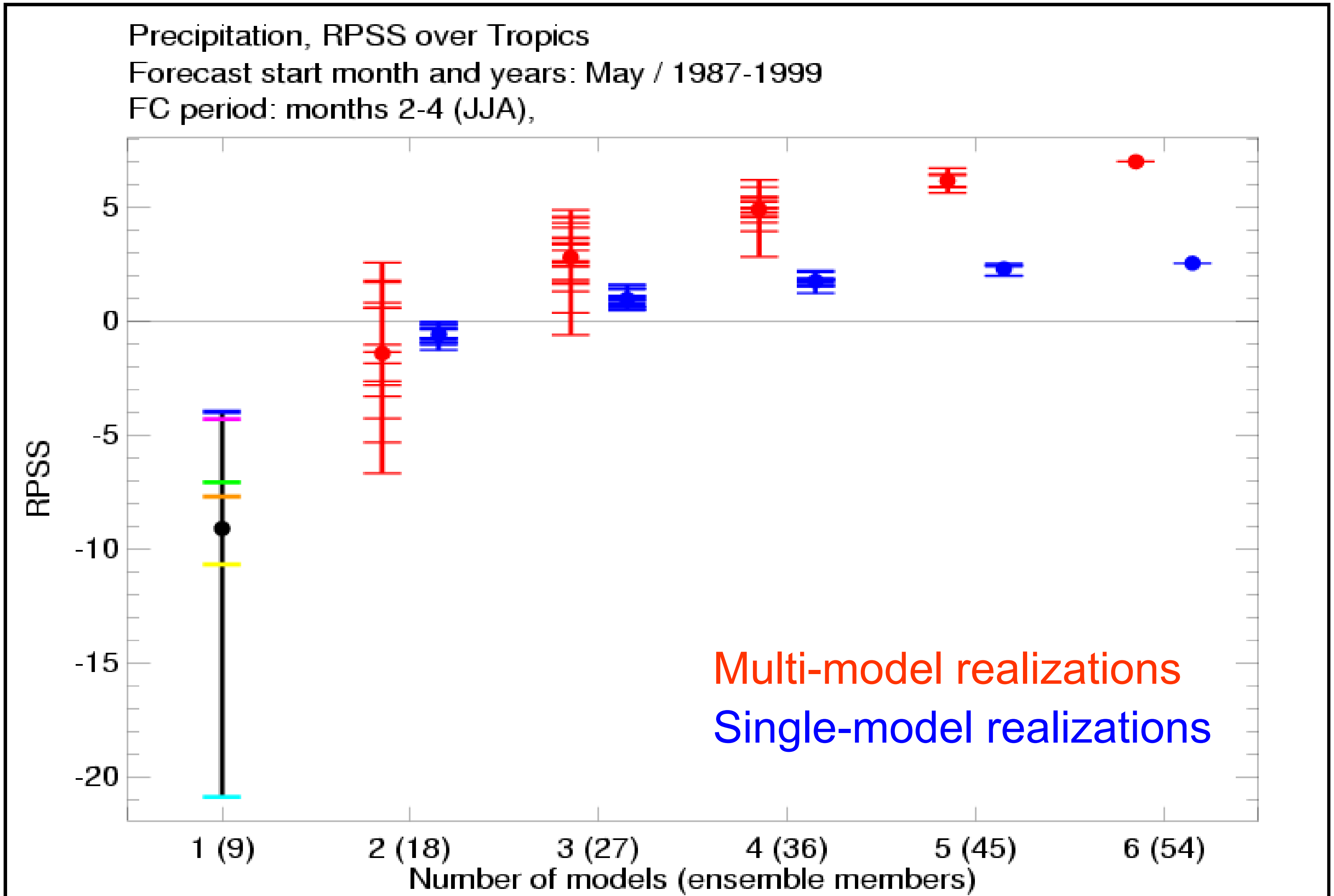


multi-model [54 members]



Hagedorn et al. (2005)

DEMETER: impact of number of models



Under which conditions can a multi-model ensemble outperform the best single-model?

Where does the success of the multi-model come from?

Weigel, Liniger and Appenzeller (2008):

- Toy model: Synthetic forecast generator for perfectly calibrated single model ensembles of any size and skill with prescribed ensemble underdispersion (or overconfidence)

$$\boxed{\begin{pmatrix} f_1 \\ f_2 \\ \ldots \\ f_M \end{pmatrix} = \alpha x + \varepsilon_\beta + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \ldots \\ \varepsilon_M \end{pmatrix}}$$

$$x \sim N(0,1)$$

$$\varepsilon_\beta \sim N(0,\beta)$$

$$\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_M \sim N(0, \sqrt{1-\alpha^2-\beta^2})$$

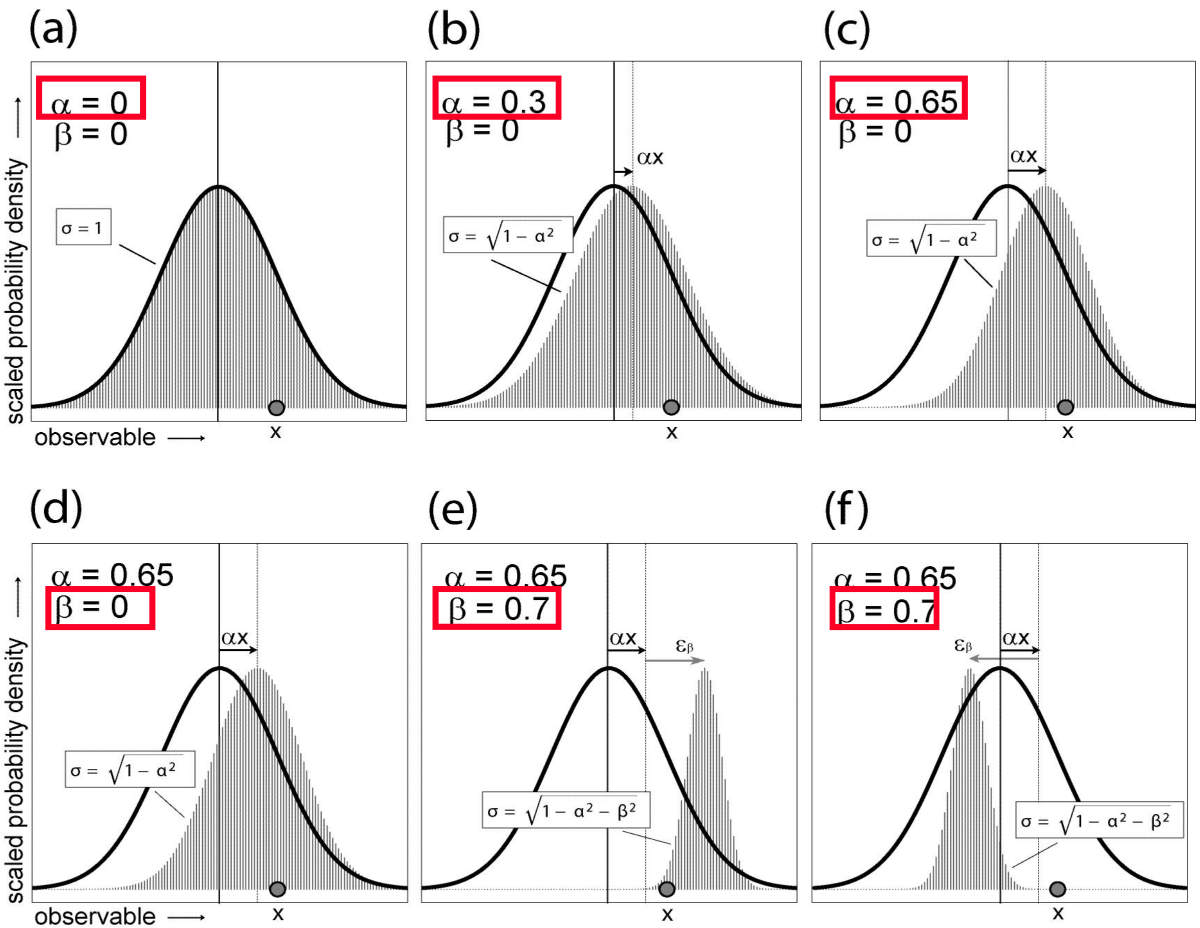
$$\alpha^2 \leq 1$$

$$0 \leq \beta \leq \sqrt{1-\alpha^2}$$

x: observation
f(x): ensemble forecast
α: average correlation coefficient between f_i and x
β: overconfidence parameter (β=0 well-dispersed ensemble)

Where does the success of the multi-model come from?

Illustration of the toy model



effect of correlation α for a well-dispersed ensemble (β=0)

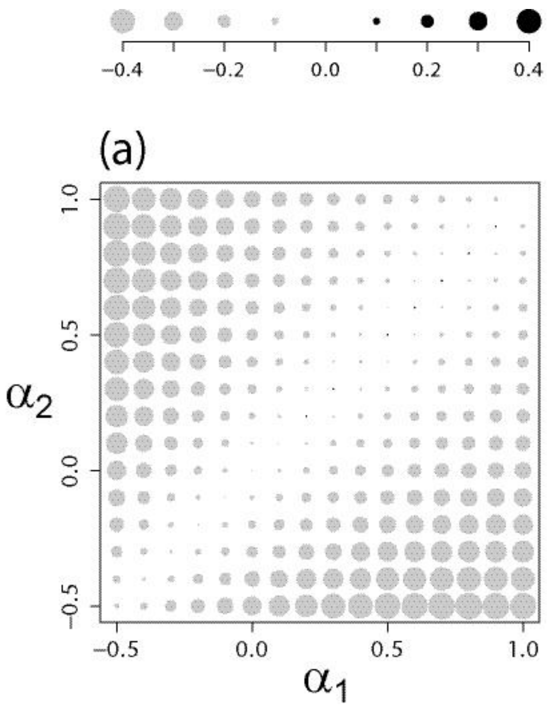
effect of overconfidence β for a constant correlation (α=0.65)

Two examples of ε_β

Weigel et al. (2008)

Multi-model ensemble can locally outperform the best member, but only if the single model ensembles are overconfident

Two well dispersed (β=0) single-model ensembles α_1, α_2



i.e. if model forecast error exists

RPSS skill matrix

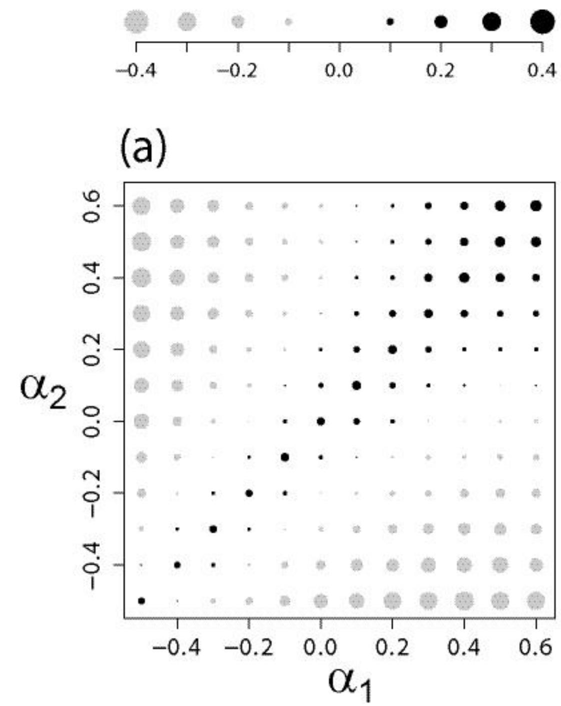
$RPSS_{multi\text{-}model}$

minus

$RPSS_{best\ single\ model}$

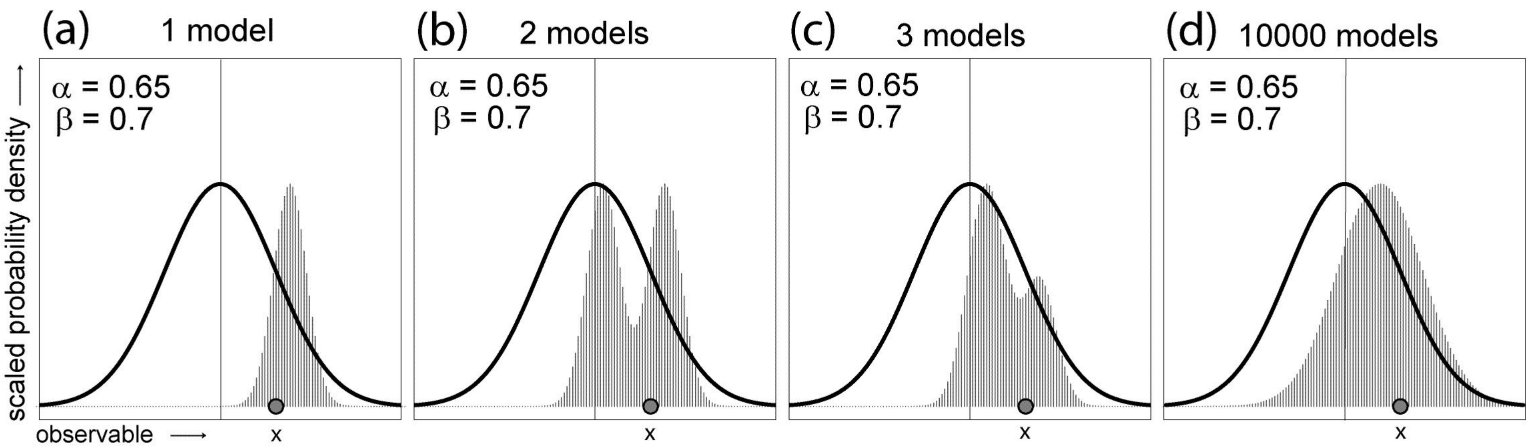
Weigel et al. (2008)

Two overconfident (β=0.7) single-model ensembles α_1, α_2



Where does the success of the multi-model come from?

Multi-model combination reduces overconfidence.
That is, ensemble spread is widened
while the average ensemble mean error is reduced



- net gain in prediction skill over best model because probabilistic skill scores penalize overconfidence
- even the addition of an objectively poor model can improve multi-model skill

Weigel et al. (2008)

Where does the success of the multi-model come from?

- Is multi-model better than "inflating" a single model ensemble to get a pdf? If so, why?

- Generally yes.
- "Inflation" applies to all forecasts. A multi-model system contains information on which cases are more trustworthy (high consensus) and which are less so. It really adds information.
- As long as the additional models are not too poor compared to the best single model (or best subset).

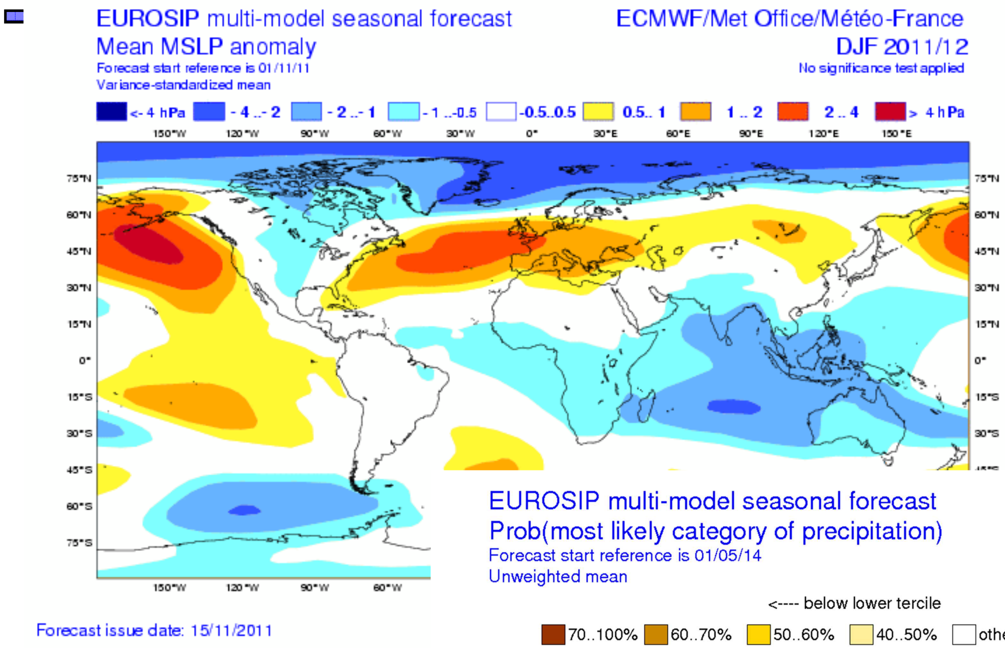
EUROSIP multi-model ensemble

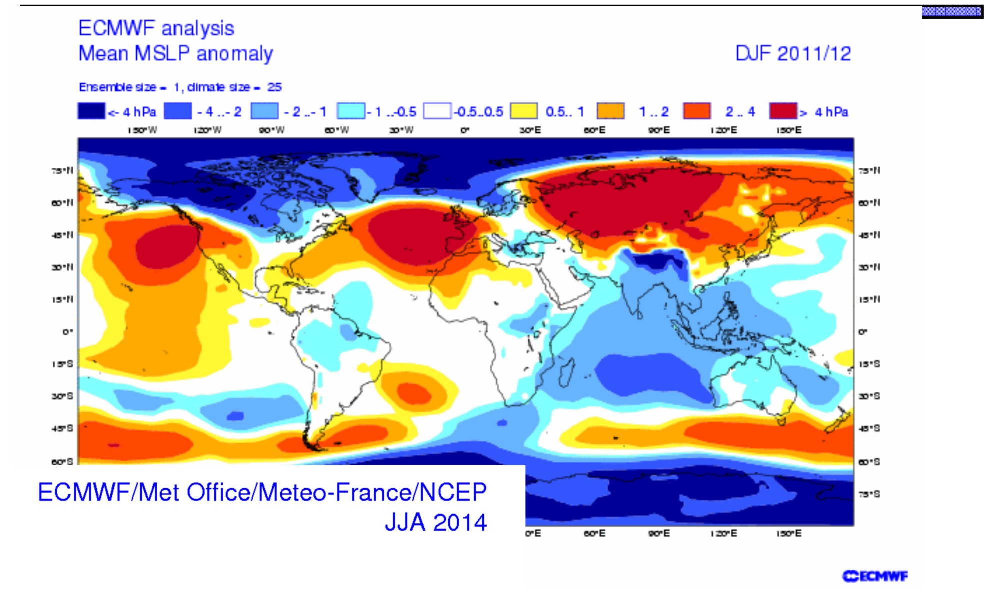
- Four models at ECMWF:
  - ECMWF – as described
  - Met Office – HADGEM model, Met Office ocean analyses
  - Météo-France – Météo-France model, Mercator ocean analyses
  - NCEP – CFSv2

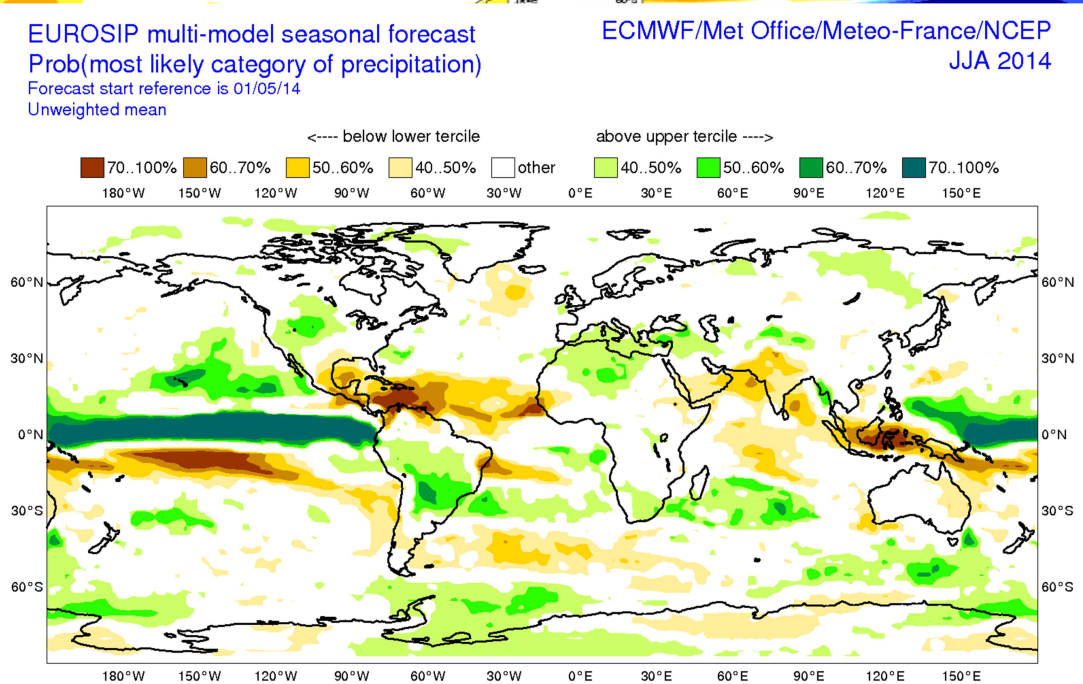
- Unified system
  - Real-time since mid-2005
  - All data in ECMWF operational archive
  - Common operational schedule (products released at 12Z on 15th)
  - Recent changes at Met Office have limited the system somewhat

  - See "EUROSIP User Guide" on web for details, and also the ECMWF Newsletter article (Issue No. 118, Winter 2008/09)

EUROSIP web products







EUROSIP data

- Individual model data archived in MARS
  - Monthly means, daily data from some models
  - Data policy allows additional restrictions, but in most cases:
    - Available to Member States for official duty use
  - Available for research and education (not real-time)

- Multi-model data products
  - Created and archived in MARS
  - Available for dissemination, also for commercial customers

- International support
  - WMO access to multi-model web products
  - Multi-model data supplied to EUROBRISA project in Brazil

Variance scaling

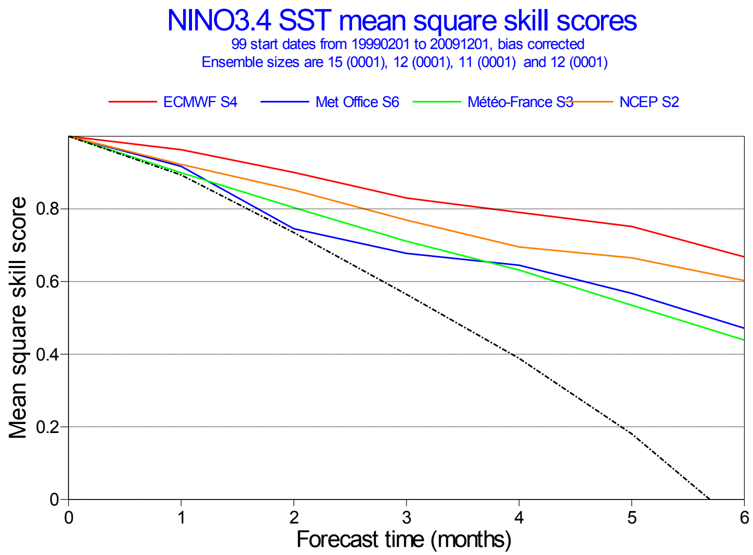
- Robust implementation
  - Limit to maximum scaling (1.4)
  - Weakened upscaling for very large anomalies

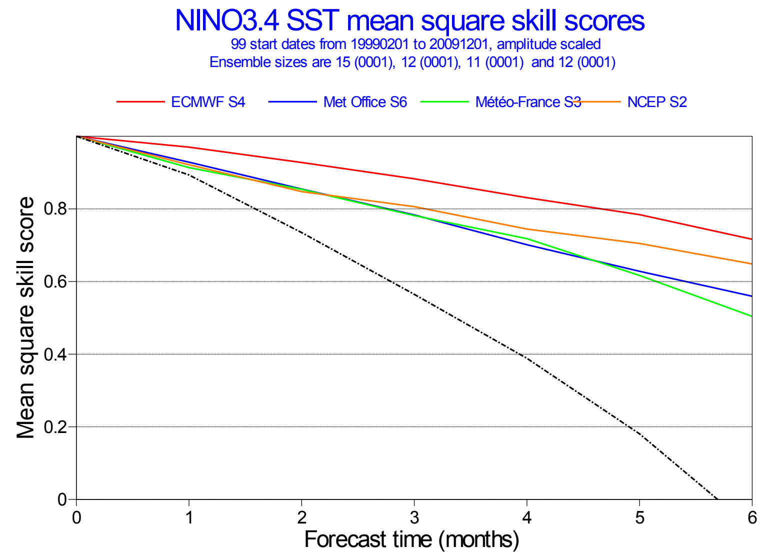
- Improves *every* individual model

- Improves consistency between models

- Improves accuracy of multi-model ensemble mean

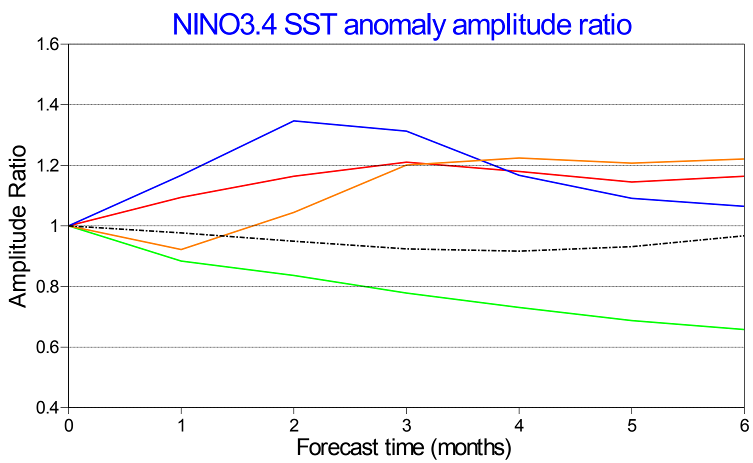
Variance scaling

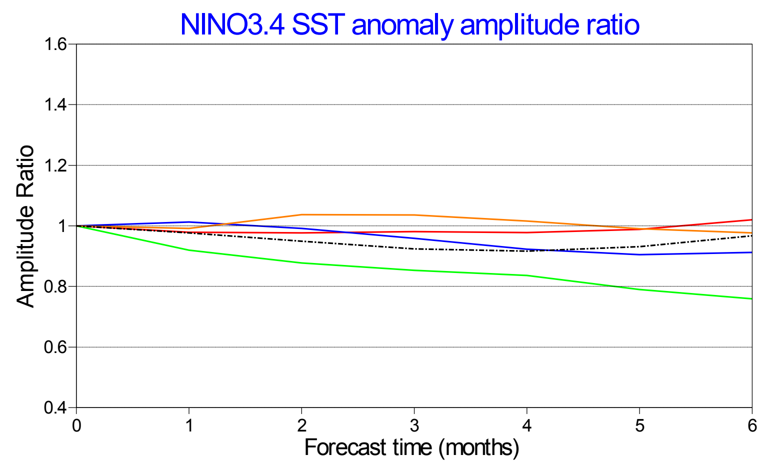




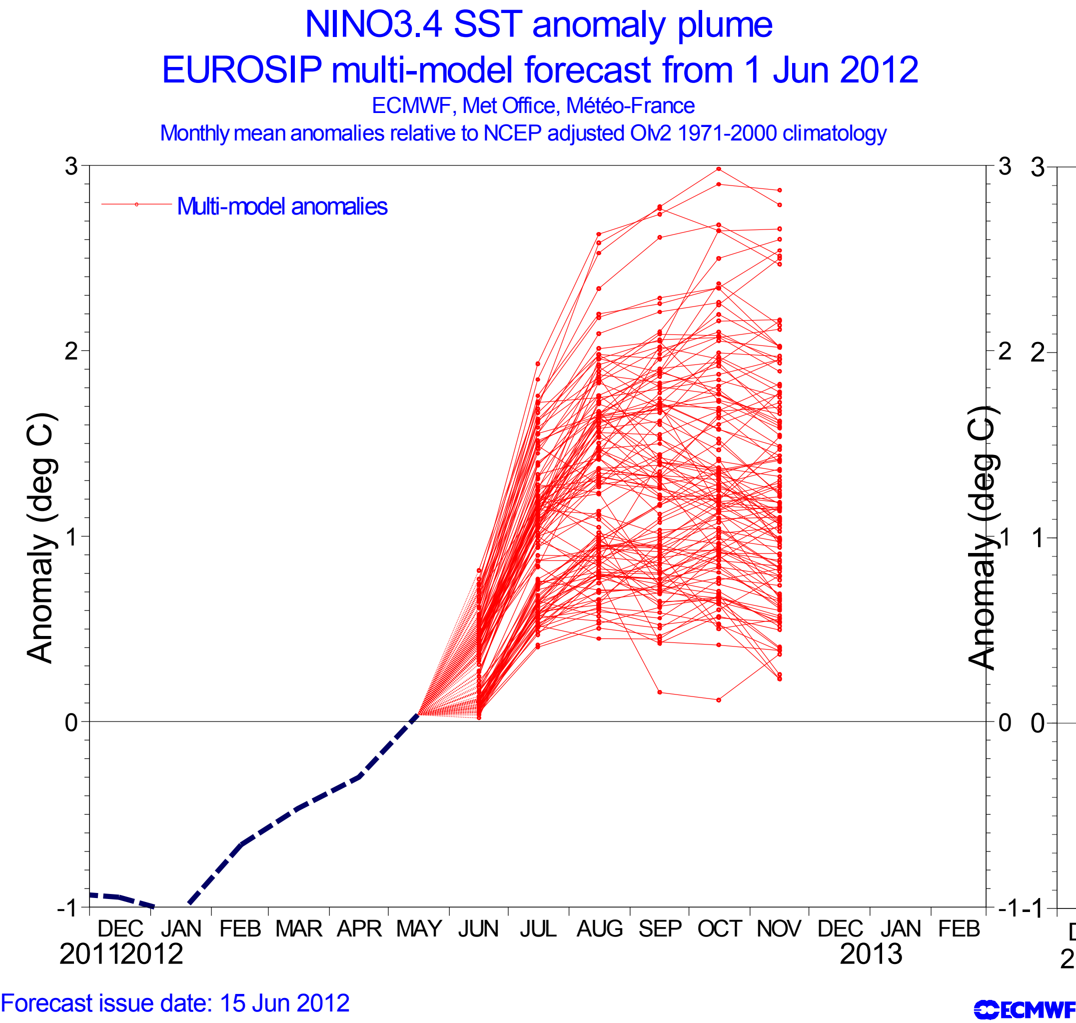
Bias corrected only

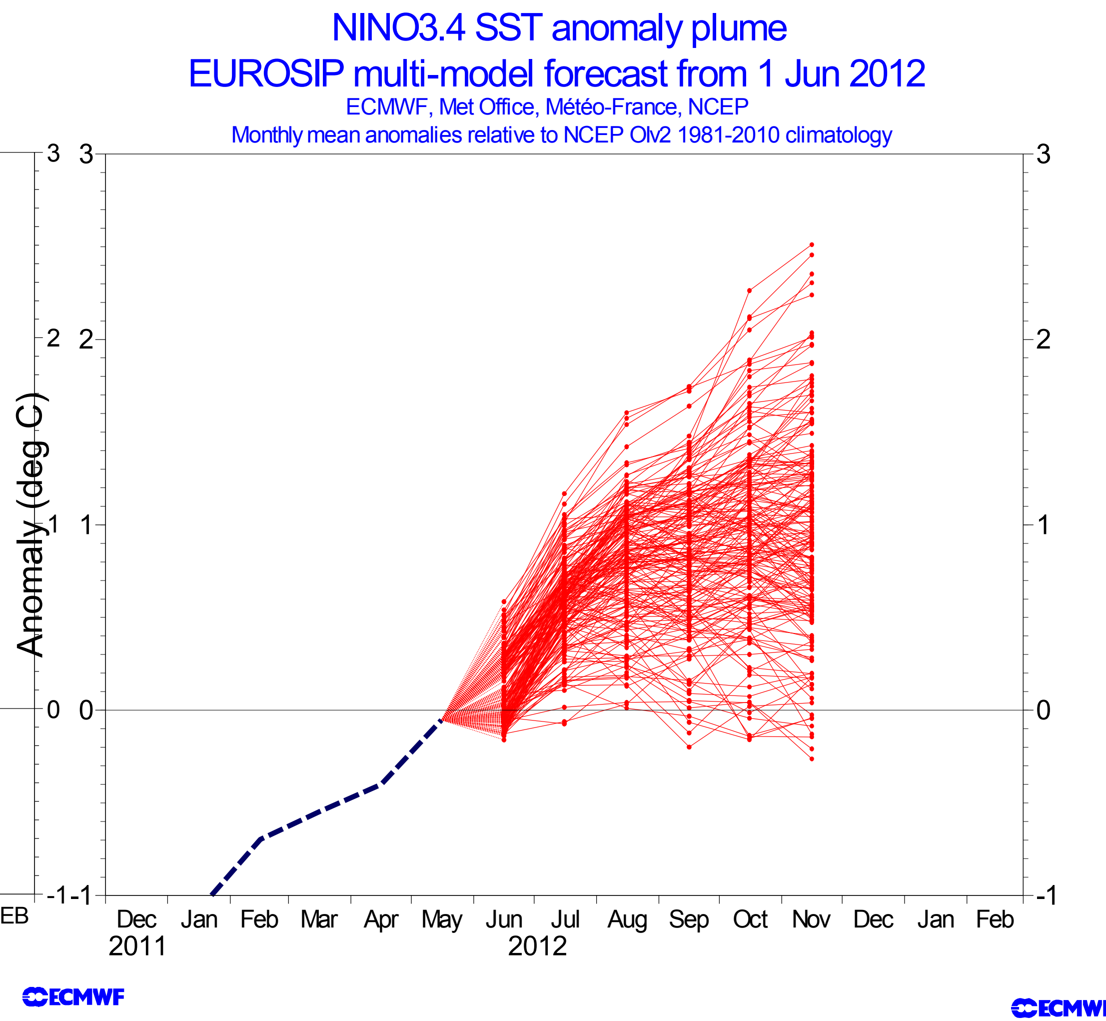
With variance scaling



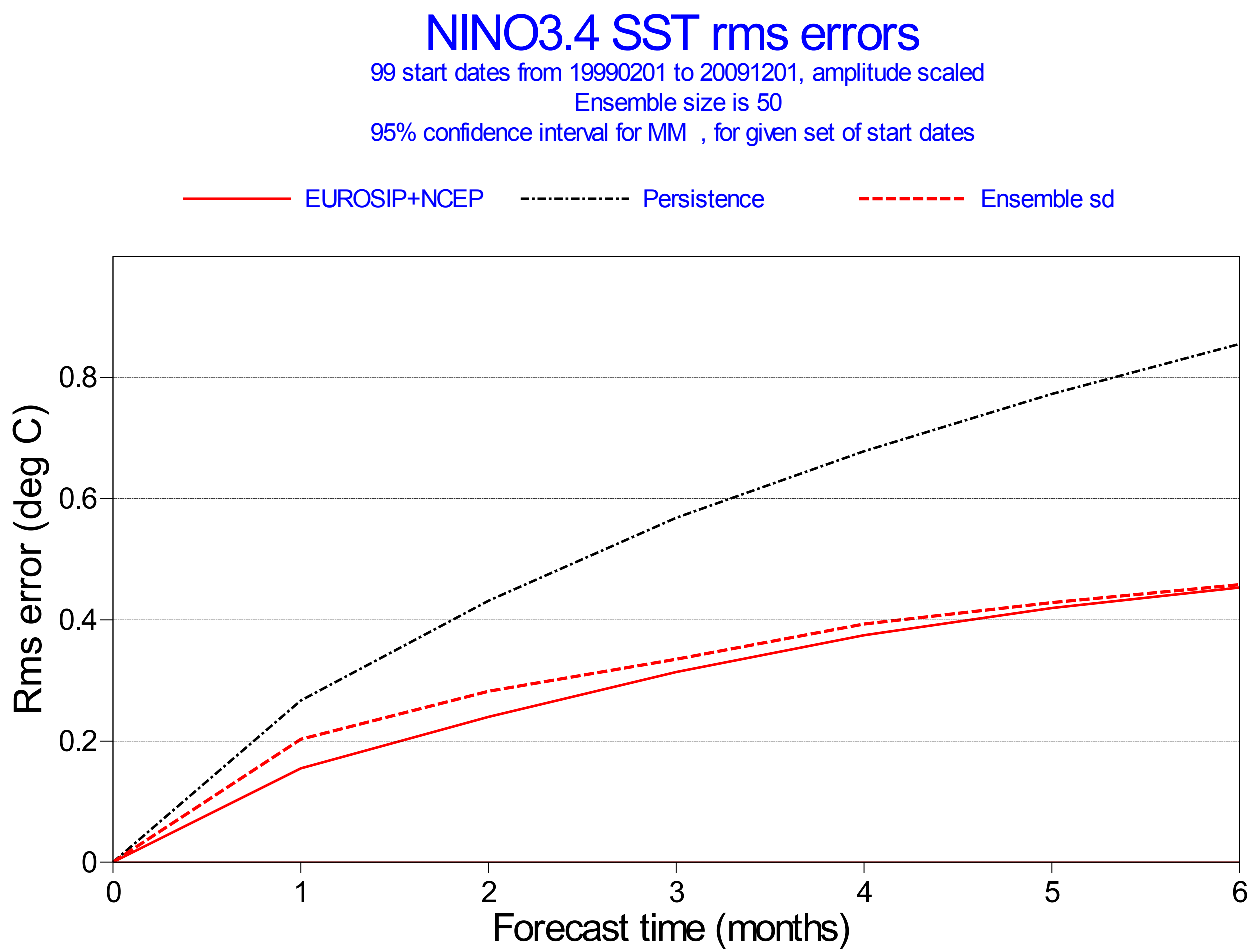


Revised Nino plumes

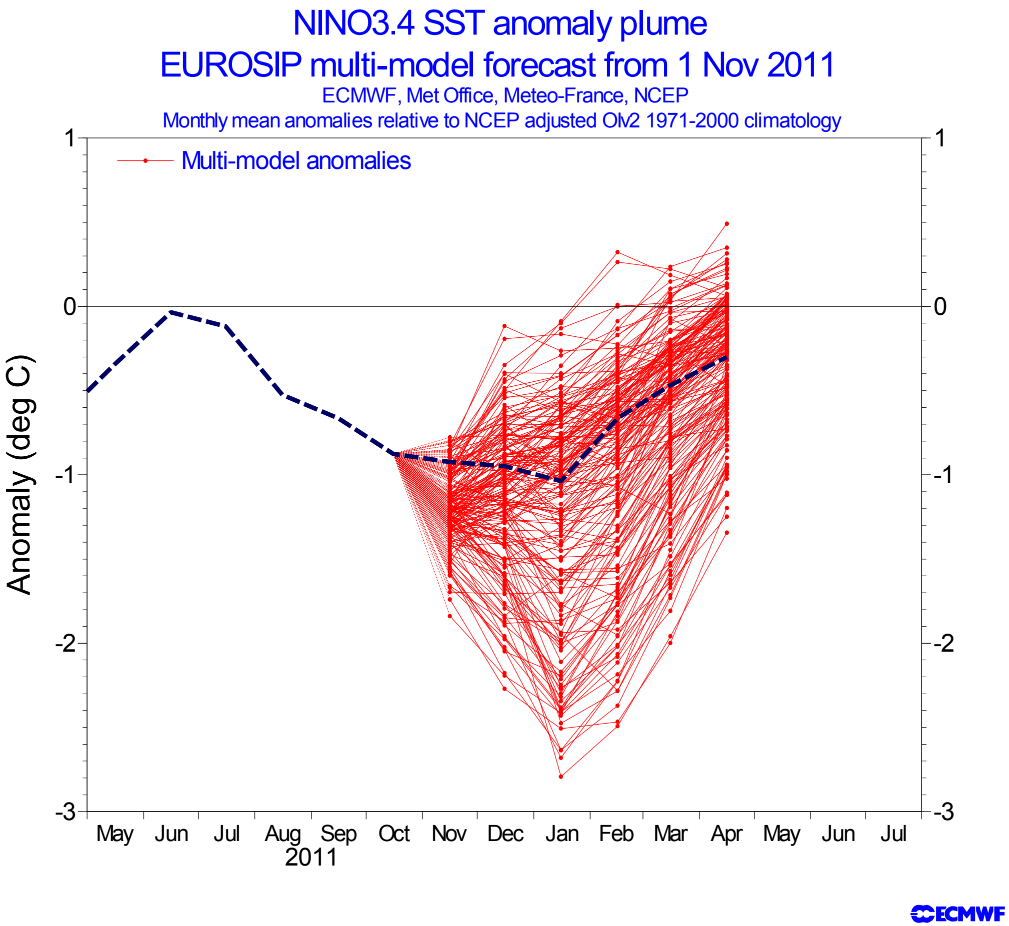


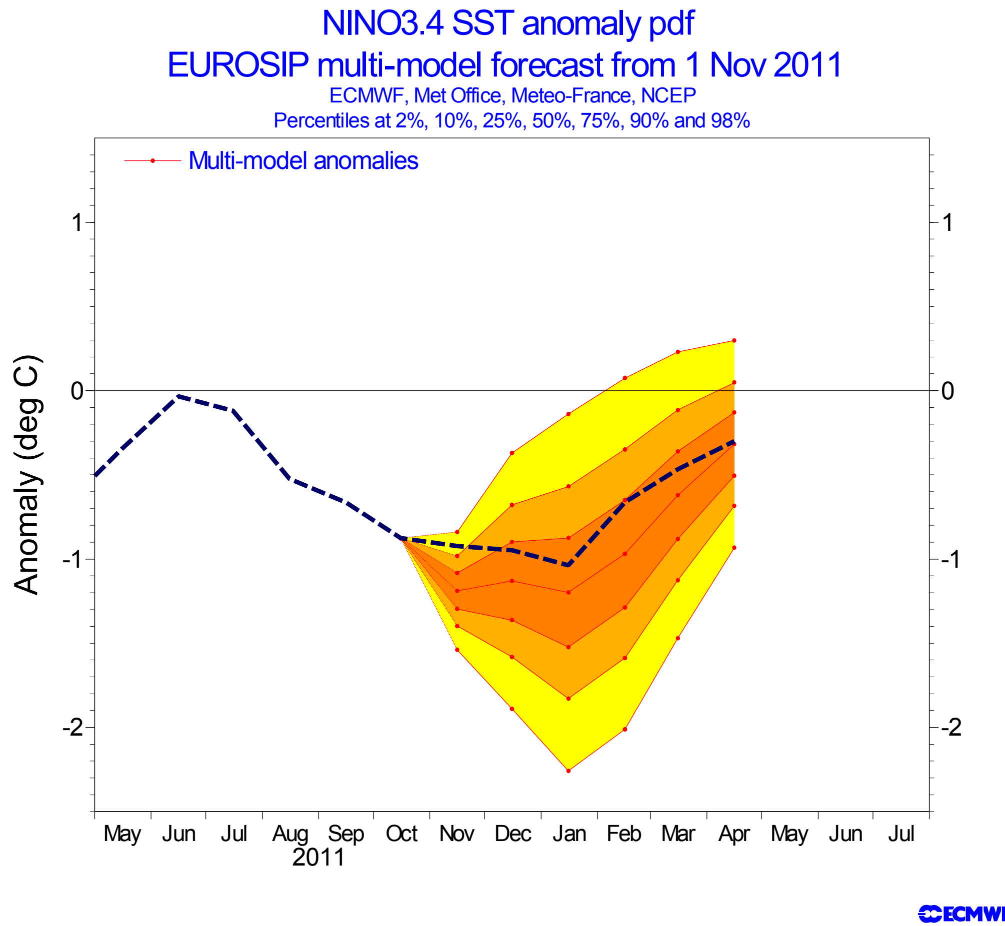


Error vs spread (uncalibrated)



Nino 3.4 plume and pdf





Method for p.d.f. estimation (1)

- Assume underlying normality

- Calculate robust skill-weighted ensemble mean
  - Do not try a multivariate fit (very small number of data points)
  - Weights estimated ~1/(error variance). Would be optimal for independent errors – i.e., is conservative.
  - Then use 50% uniform weighting, 50% skill dependent

- Comments:
  - Rank weighting also tried, but didn't help.
  - QC term tried, using likelihood to downplay impact of outliers, but again didn't help. Outliers are usually wrong, but not always.
  - Models usually agree reasonably well, and tweaks to weights have very little impact anyway.

Method for p.d.f. estimation (2)

- Re-centre lower-weighted models
  - To give correct multi-model ensemble mean
  - Done so as to minimize disturbance to multi-model spread

- Compare past ensemble and error variances
  - Use above method (cross-validated) to generate past ensembles
  - Unbiased estimates of multi-model ensemble variance and observed error variance
  - Scale forecast ensemble variance
  - 50% of variance is from the scaled climatological value, 50% from the scaled forecast value

- Comments:
  - For multi-model, use of predicted spread gives better results
  - For single model, seems not to be so.

Method for p.d.f. estimation (3)

- Estimate t distribution
  - Variance estimates are based on small samples, ~15 points
  - Need to use 't' distribution to estimate resulting p.d.f.
  - Finite d.o.f. due to both number of years and ensemble size

- Plot p.d.f.
  - Specified percentiles, or plume with 2%ile intervals
  - Or plot forecast values with calibrated mean and variance

- Comments:
  - Can apply to single model or multi-model
  - Small ensemble size -> large width of p.d.f.

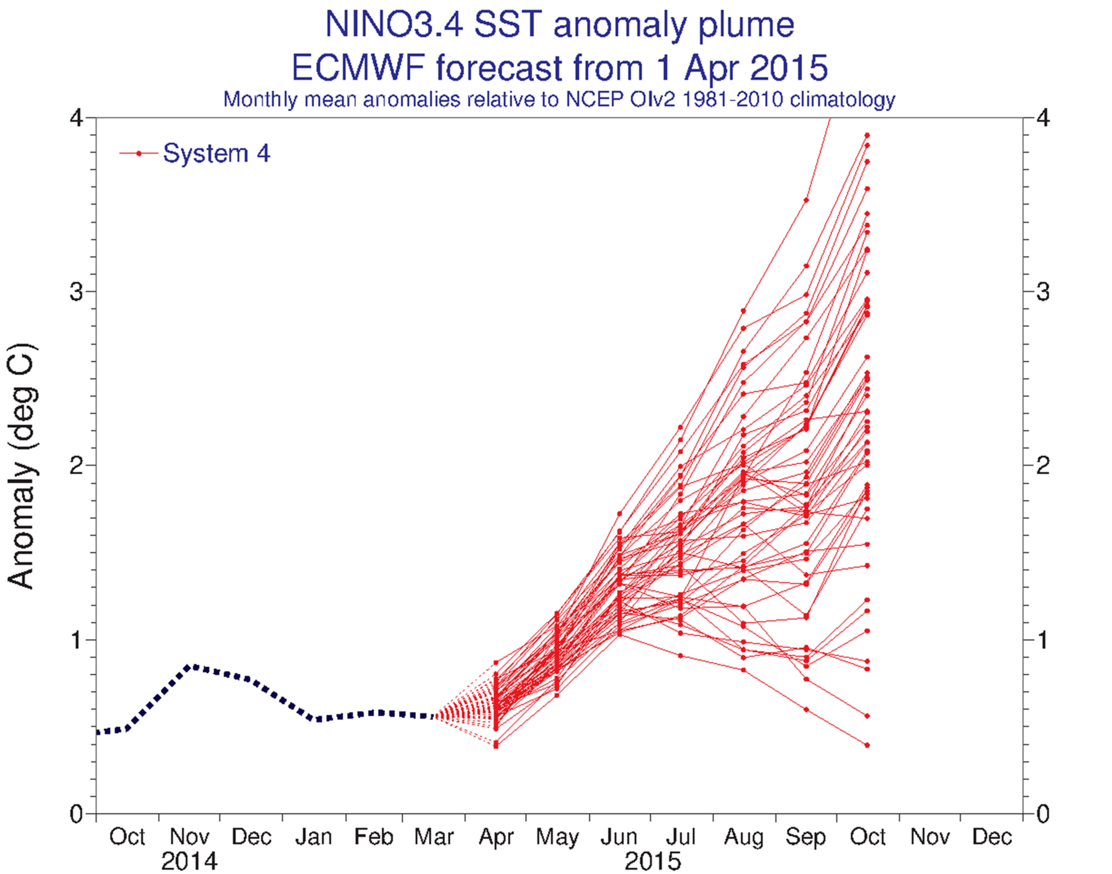
p.d.f. interpretation

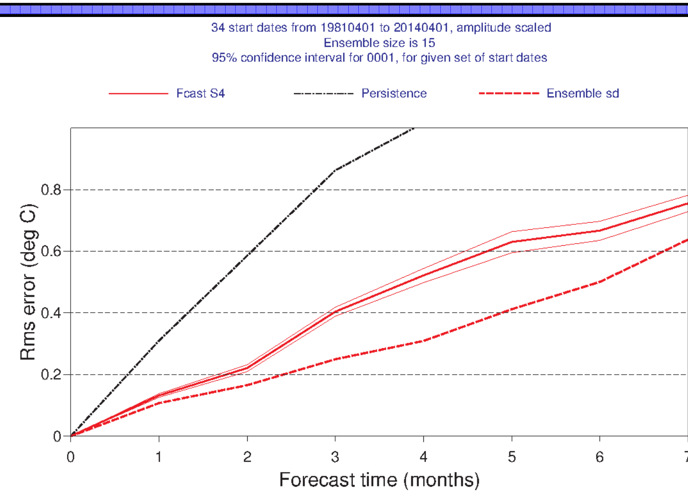
- p.d.f. based on past errors
  - The risk of a real-time forecast having a new category of error is not accounted for. E.g. Tambora volcanic eruption.
  - We plot 2% and 98%ile. Would not go beyond this in tails.
  - Risk of change in bias in real-time forecast relative to re-forecast.

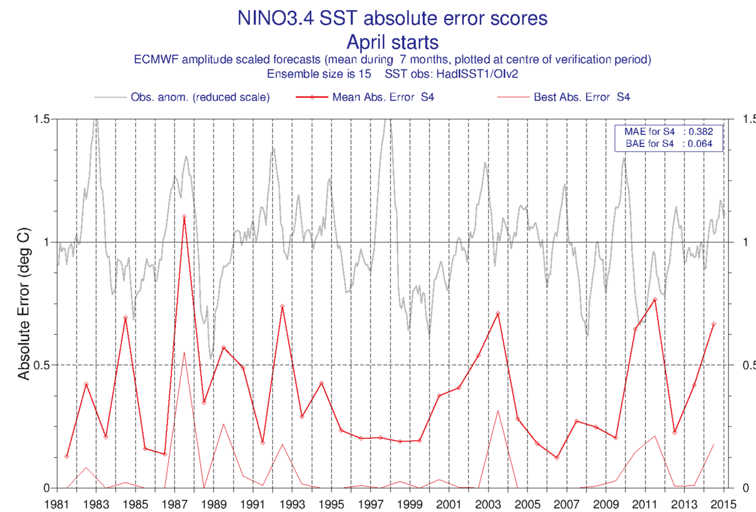
- Bayesian p.d.f.
  - Explicitly models uncertainty coming from errors in forecasting system
  - Two different systems will calculate different pdf's – both are correct

- Validation
  - Rank histograms show pdf's are remarkably accurate (cross-validated)
  - Verifying different periods shows relative bias of different periods can distort pdf – sampling issue in our validation data.

ECMWF forecast: ENSO

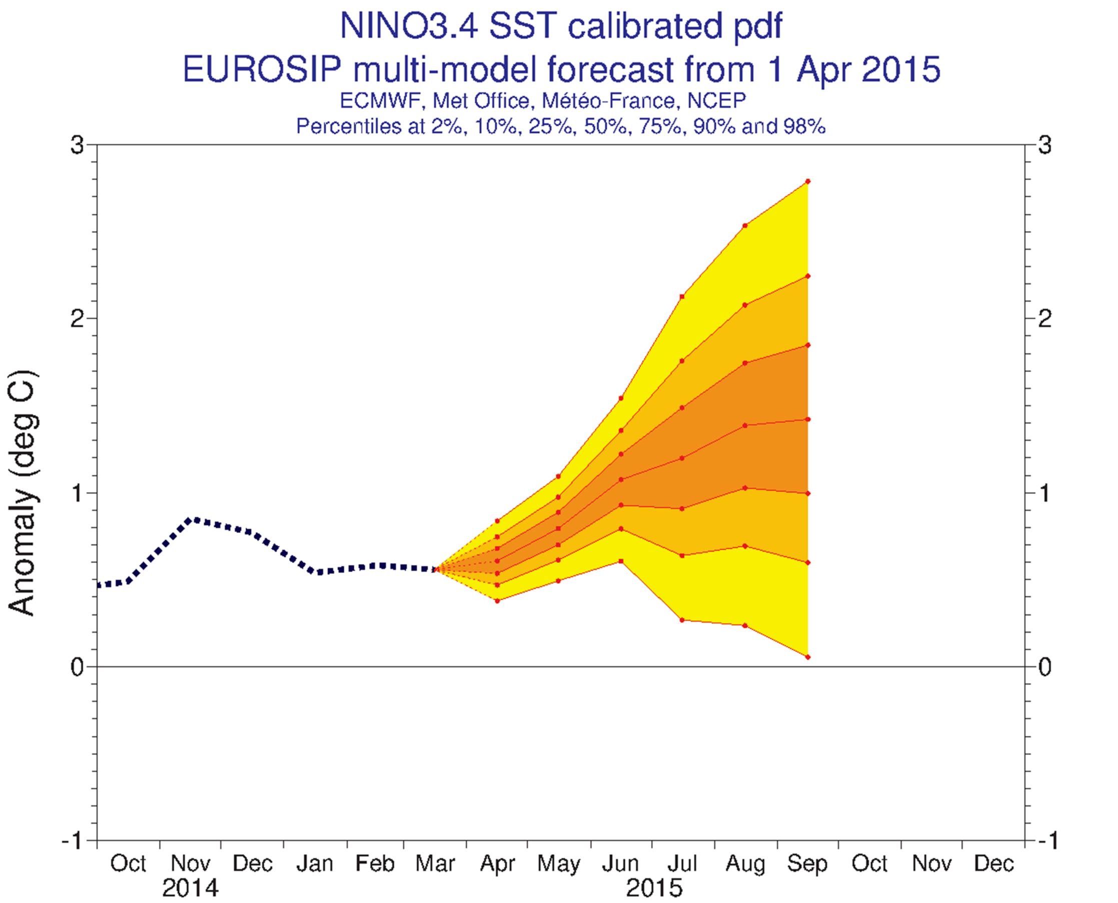


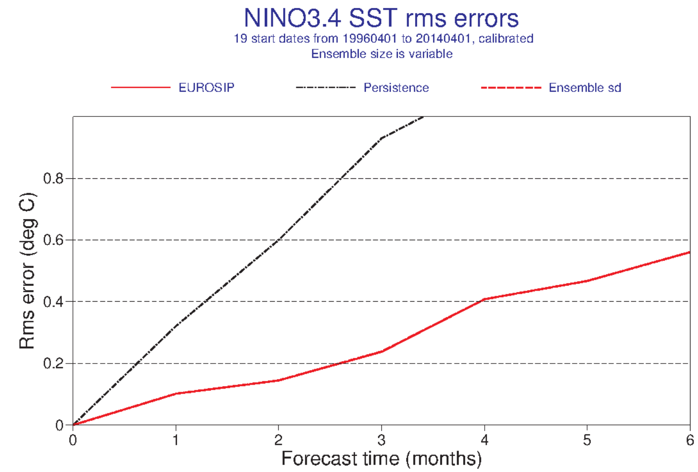


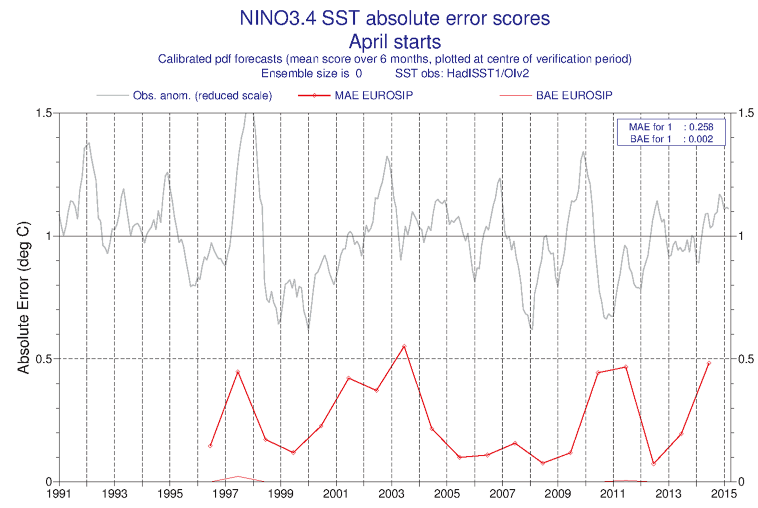


Past performance

EUROSIP forecast: ENSO



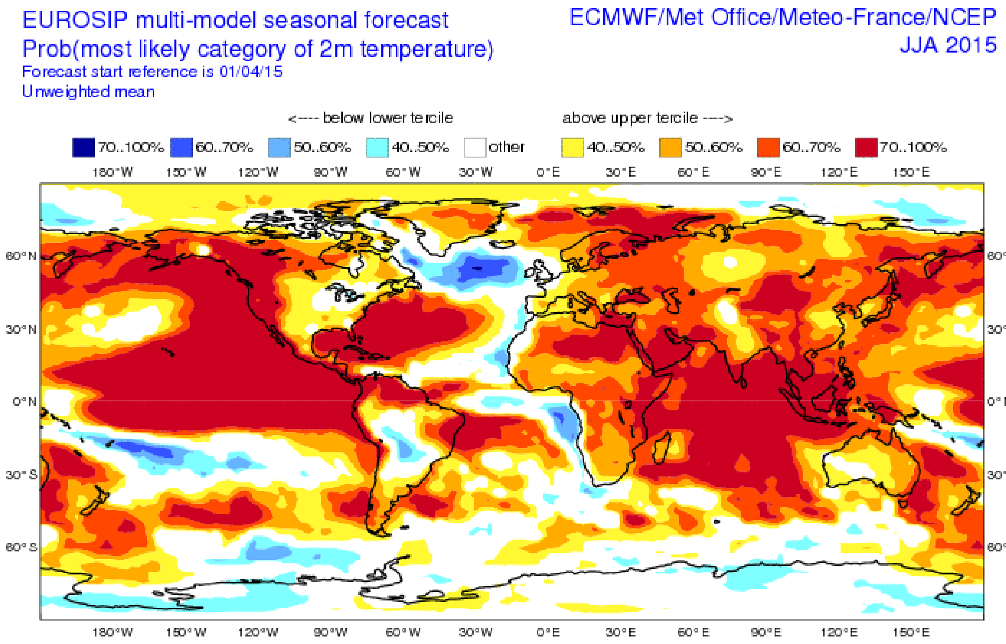


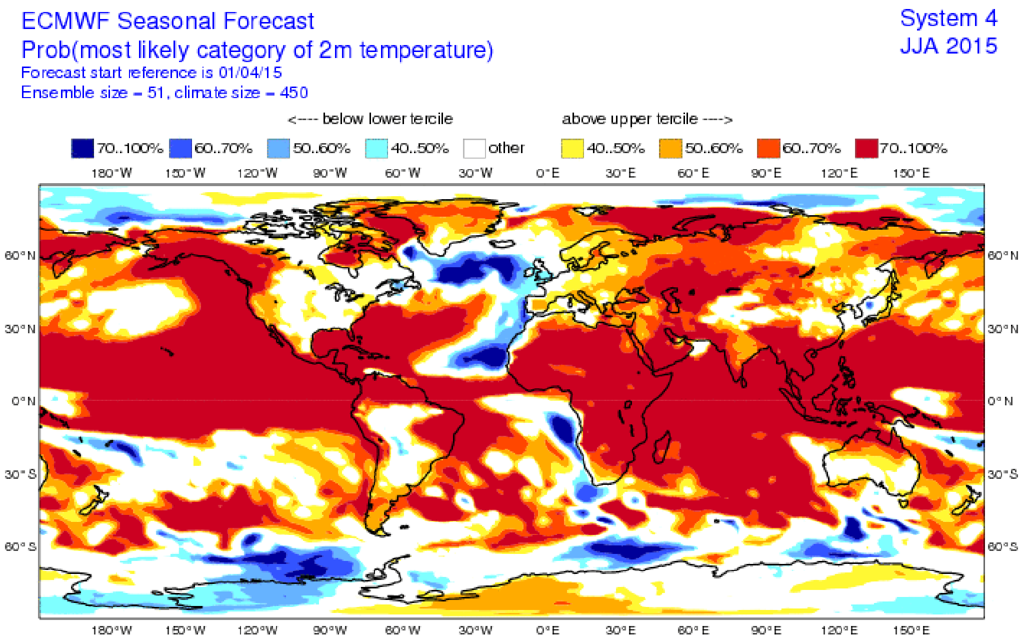


Past performance

Multi-model

Single model





Summary

- Multi-model ensemble forecasting is a pragmatic and efficient method to filter out some of the model errors present in the individual ensemble forecasts and enhance ensemble spread

- Multi-model predictions yield, on average, more accurate predictions than any of the individual single-model ensembles (e.g., DEMETER)

- The improvement is mainly due to more consistency and increased reliability and due to the reduced overconfidence from single-model ensembles

- Still need better models!

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