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Approaches to ensemble prediction

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(Magritte)

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Part of the material of this lecture has been taken from a lecture given at the 2002 ECMWF Predictability Seminar (Roberto Buizza[(1)], Peter Houtekamer[(2)], Zoltan Toth[(3)], G Pellerin[(2)], Mozheng Wei[(4)] and Yuejian Zhu[(3)]).

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Outline

1. Global ensemble prediction at MSC, ECWMF and NCEP
2. Comparison of the performance of the three systems (MJJ02)
3. Trends in ensemble performance
4. Operational Global Ensemble Prediction Systems
5. On-going research at ECMWF, MSC and NCEP, and open issues

1. What are the objectives of ensemble prediction?

The objectives of ensemble prediction are to:

- estimate the probability density function of forecast states;
- simulate the effect of different sources of forecast error;
- identify areas of potentially low predictability;
- gauge flow dependent predictability;
- allow users to assess the probability of weather scenarios;
- ....

1. What should an ensemble prediction system simulate?

The sources of initial and model uncertainties are different:

- Model errors (e.g. due to a lack of resolution, simplified parameterization of physical processes, arbitrariness of closure assumptions, the effect of unresolved processes).
- Observation errors (observations have a finite precision, point observations may not be very representative of what happens inside a model grid box).
- Imperfect boundary conditions (e.g. roughness length, soil moisture, snow cover, vegetation properties, sea surface temperature).
- Data assimilation assumptions (e.g. relative weights given to observations, statistics).

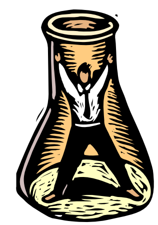
1. What should an ensemble prediction system simulate?

Two schools of thought:

- **Monte Carlo approach**: sample all sources of forecast error. Rationale: perturb any input variable (observations, boundary fields, …) and any parameter that is not perfectly known. Take into consideration as many sources as possible of forecast error.

- **Reduced sampling**: sample leading sources of forecast error (prioritize). Rationale: due to the complexity and high dimensionality of the system properly sampling the leading sources of errors is crucial. Rank sources, prioritize, optimize sampling: growing components will dominate forecast error growth.

There is a strong constraint: limited resources (man and computer power)!

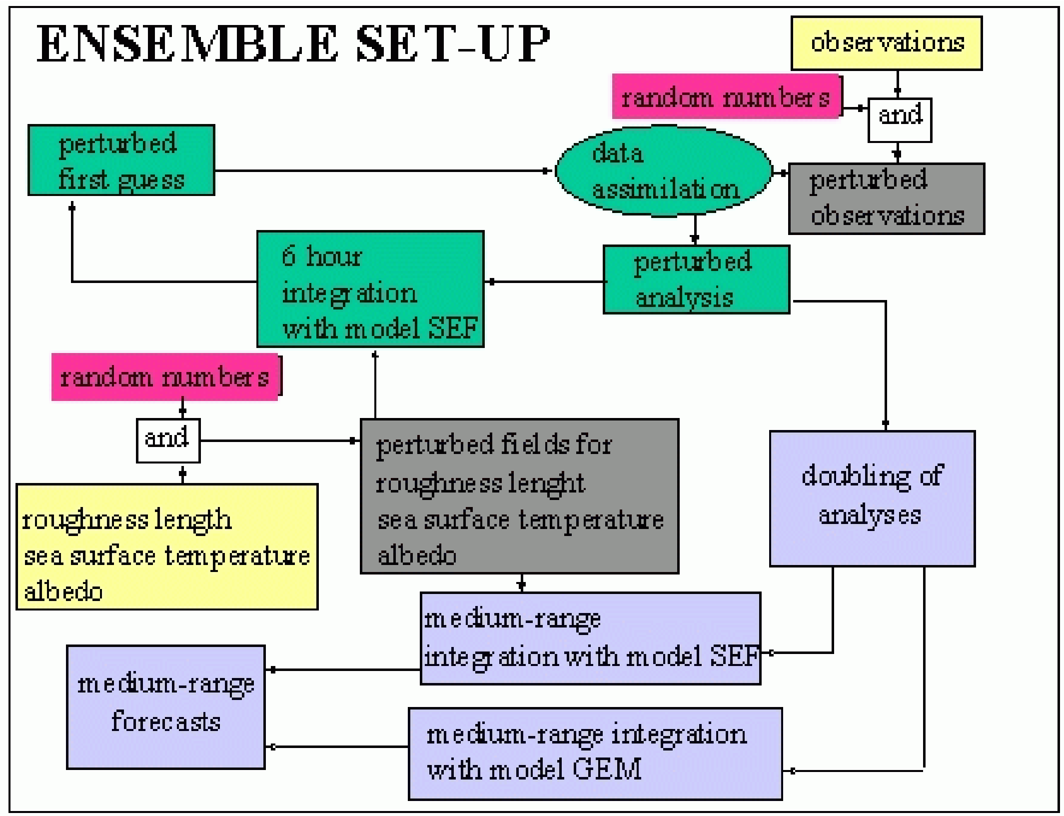


1. Monte Carlo approach (MSC): all-inclusive design

The MSC ensemble has been designed to simulate:

- observation errors (random perturbations);
- imperfect boundary conditions;
- model errors (2 models and different parameterisations).

The MSC ensemble



1. Simulation of initial uncertainties: selective sampling

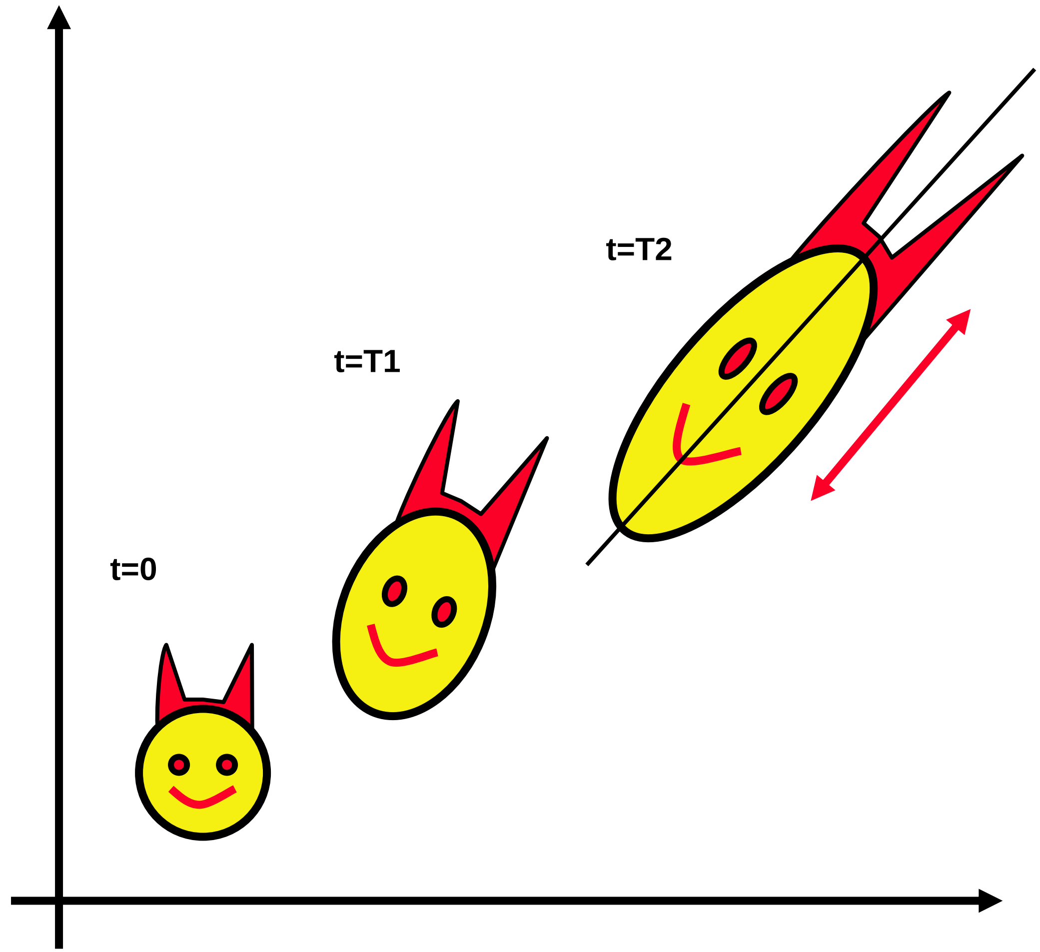
At MSC, the perturbed initial conditions are generated by running an ensemble of assimilation cycles that use perturbed observations and different models (Monte Carlo approach).

At ECMWF and NCEP the perturbed initial conditions are generated by adding perturbations to the unperturbed analysis generated by the assimilation cycle. The initial perturbations are designed to span only a subspace of the phase space of the system (selective sampling). These ensembles do not simulate the effect of imperfect boundary conditions.

1. Selective sampling: singular vectors (ECMWF)

Perturbations pointing along different axes in the phase-space of the system are characterized by different amplification rates. As a consequence, the initial PDF is stretched principally along directions of maximum growth.

The component of an initial perturbation pointing along a direction of maximum growth amplifies more than components pointing along other directions.



1. Selective sampling: singular vectors (ECMWF)

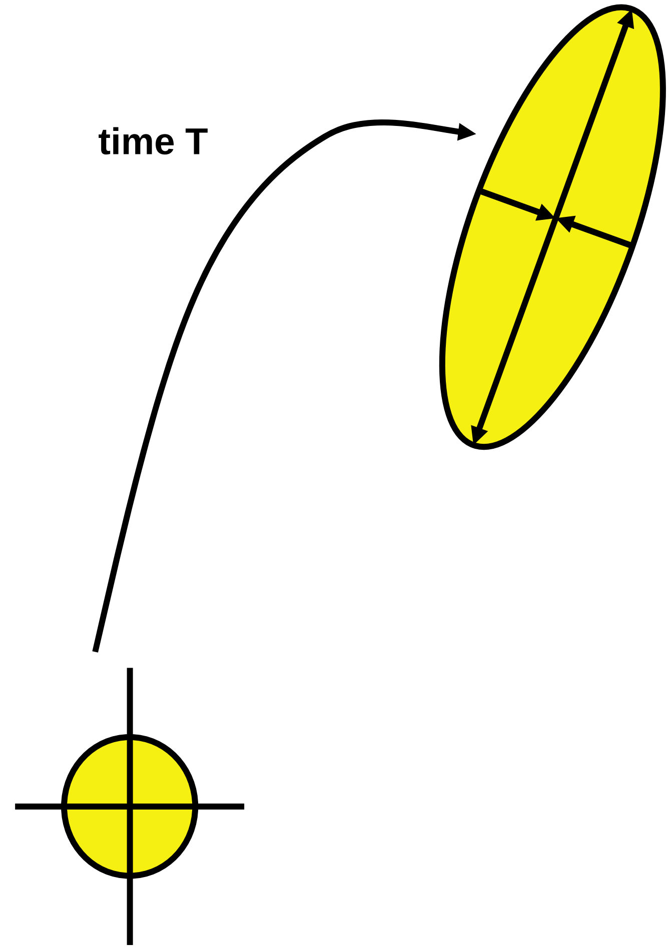
At ECMWF, maximum growth is measured in terms of total energy. A perturbation time evolution is linearly approximated:

$$z'(t) = L(t,0)z'_0$$

The adjoint of the tangent forward propagator with respect to the total-energy norm is defined, and the singular vectors, i.e. the fastest growing perturbations, are computed by solving an eigenvalue problem:

$$\left\| z'(t) \right\|^2 = < z'(t); Ez'(t) > = < L(t,0)z'_0; EL(t,0)z'_0 >$$

$$E^{-1/2} L^* E L E^{-1/2} \nu_j = \sigma_j^2 \nu_j$$

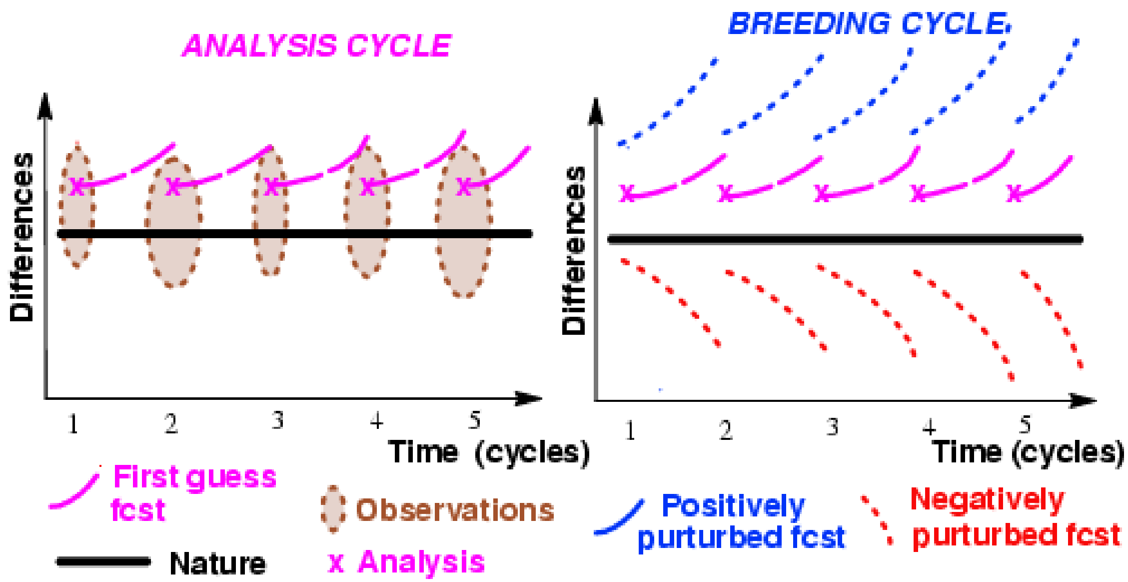


1. Selective sampling: breeding vectors (NCEP)

At NCEP a different strategy based on perturbations growing fastest in the analysis cycles (bred vectors, BVs) is followed. The breeding cycle is designed to mimic the analysis cycle.

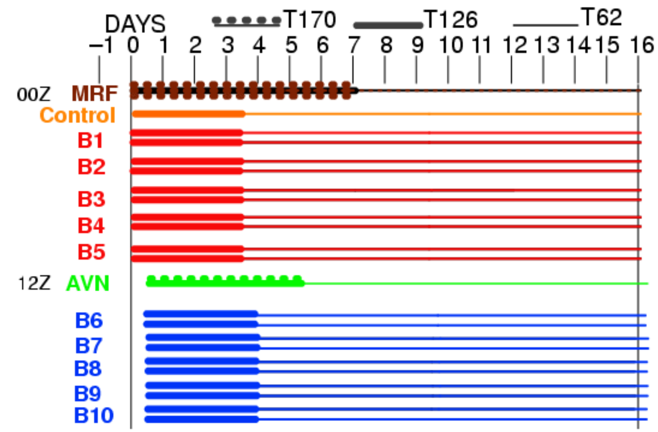
Each BV is computed by (a) adding a random perturbation to the starting analysis, (b) evolving it for 24-hours (soon to 6), (c) rescaling it, and then repeat steps (b-c).

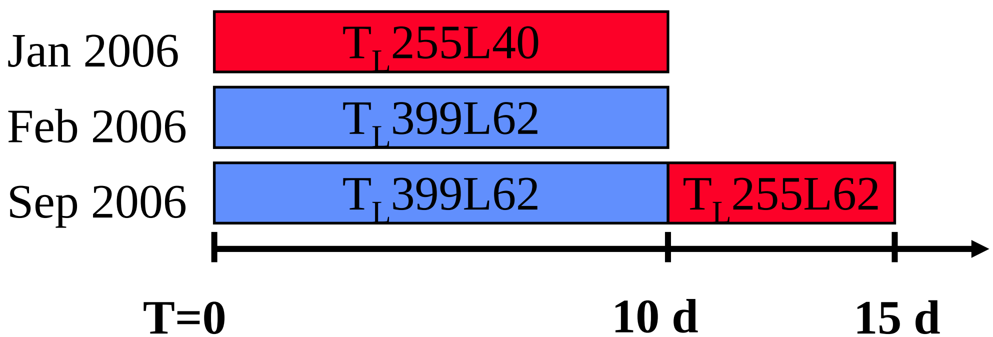
BVs are grown non-linearly at full model resolution.



1. Variable resolution (NCEP and ECMWF)

Between 2000 and 2006, NCEP used to run their 16-day individual integrations with variable resolution, with a T126 resolution up to forecast day 3.5 and T62 afterwards. In 2006, they have concluded that a T62 resolution was too low, and thus decided to increase the resolution between day 3.5 and 16 to T126, i.e. reversing to a constant resolution system.





In 2006, ECMWF decided to extend the forecast length of its ensemble system to 15 days, but using a variable resolution approach, with a T_L399 resolution between forecast day 0 and 10 and T_L255 from day 10 to 15.

FNMOC ensemble also uses a variable resolution: TL159 from day 0 to 3.5, and TL119 from day 3.5 to 10.

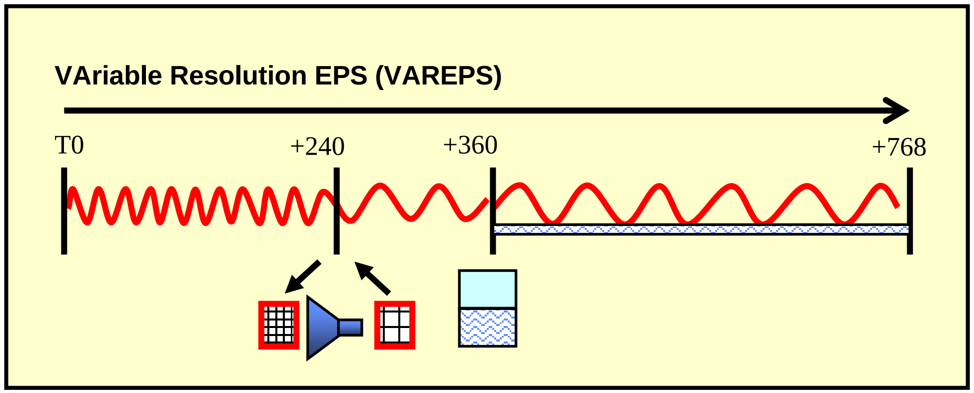
1. The ECMWF VAriable Resolution EPS (VAREPS)

The key idea behind VAREPS is to resolve small-scales in the forecast up to the forecast range when resolving them improves the forecast, but not to resolve them when unpredictable.

At ECMWF, VAREPS aims to increase the value of its ensemble system:

- in the short range, by providing more skilful predictions of the small scales
- in the medium-range, by extending the range of skilful products to 15 days

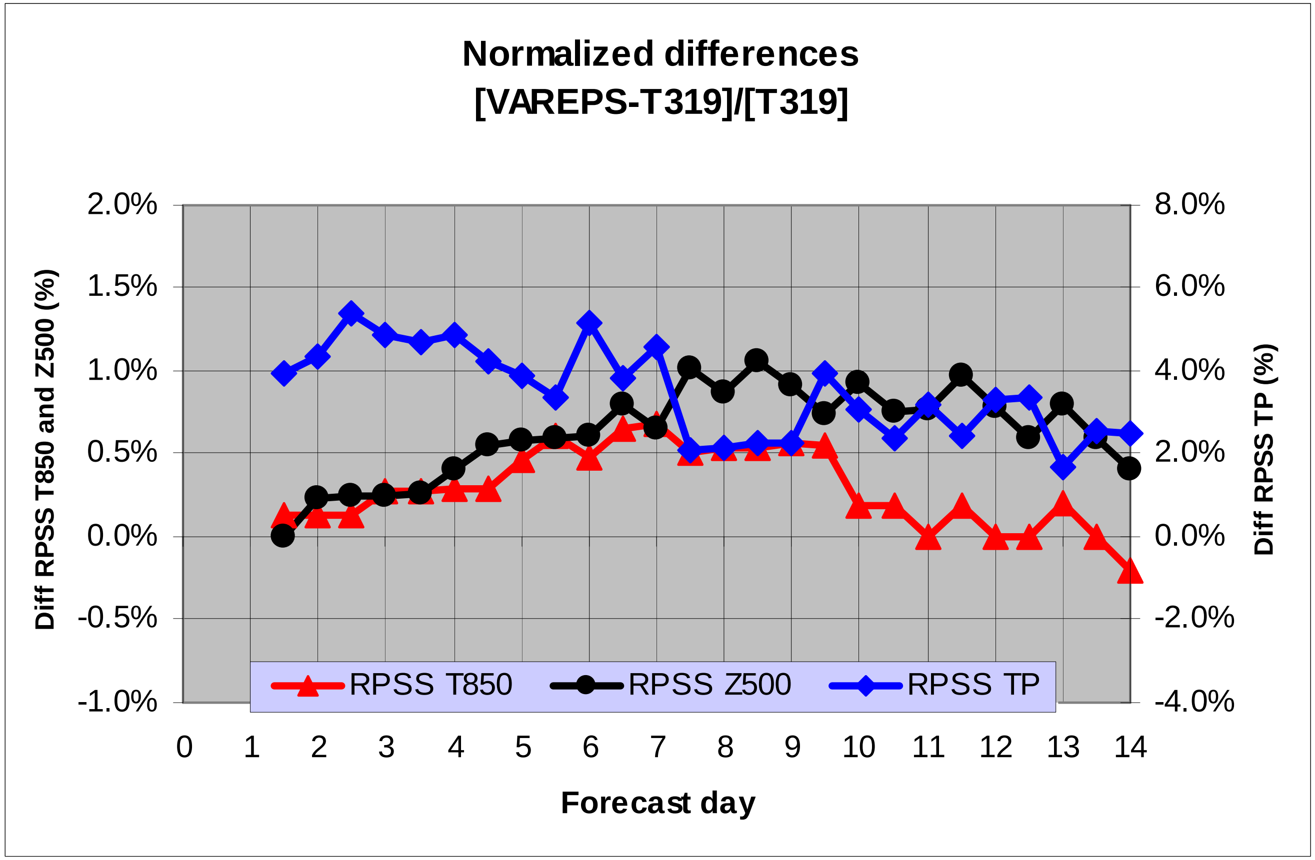
The 15-day VAREPS currently operational at ECMWF will provide the first 2-legs of the ECMWF planned seamless ensemble system, which will be extended initially (by end of 2007) to one month, and then possibly to a longer forecast time.



1. VAREPS outperforms a T319 constant-resolution EPS

One of the key questions linked to the implementation of VAREPS was whether it would outperform an equal-cost, T319 constant resolution EPS.

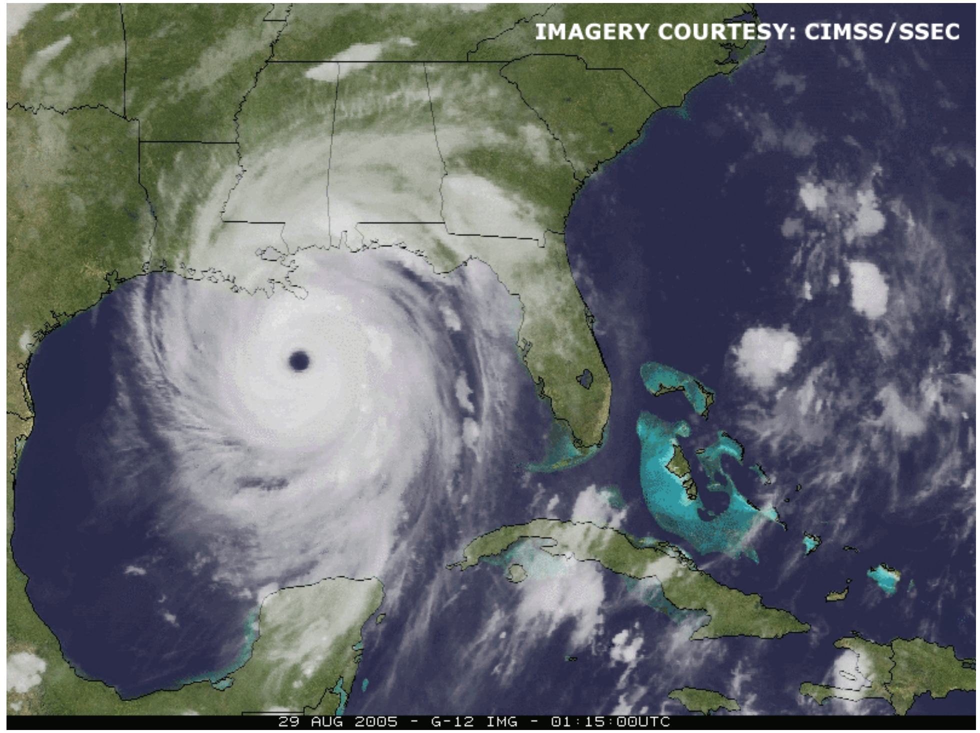
Results indicate that this is the case, especially for surface variables such as T850 and TP.



1. Hurricane Katrina: 26-29 August 2005

One of the main advantages of using a variable resolution is that more resources are available to increase the resolution in the early forecast range. The analysis of hurricane Katrina gives a very clear example of the advantages that increasing the resolution brings in the early forecast range.

Katrina was one of the strongest storms of the last 100y, with sustained winds at landfall of 140mph, and minimum central pressure recorded of 920hPa (3rd lowest recorded for a land-falling Atlantic storm in the US). Katrina developed initially as a tropical depression southeast of the Bahamas on 23 Aug, reached Cat-I when landed in Florida, Cat-V on 28 August and Cat IV at landing in New Orleans.



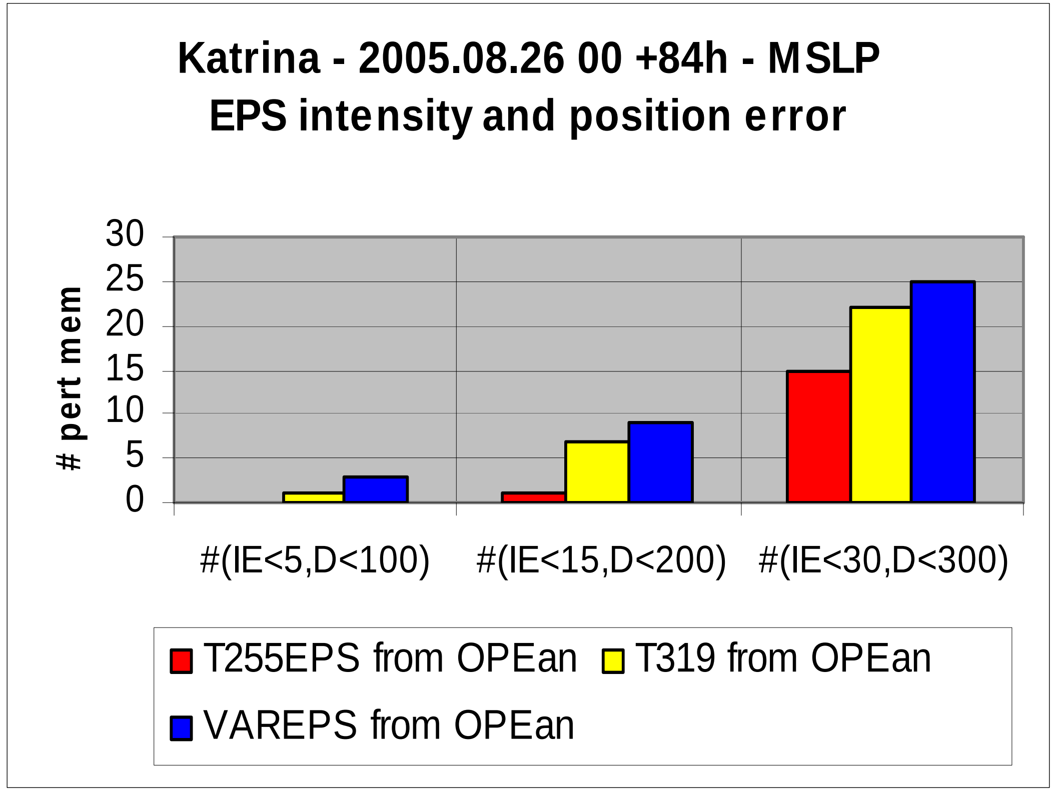
1. Kat: intensity and position error in +84h MSLP fcs

The three sets of bars show the number of perturbed members with intensity (IE) and position (D) errors inside three categories:

- IE<5hPa and D<100km
- IE<15hPa and D<200km
- IE<30hPa and D<300km

(with respect to OPE T_L511L60 analysis)

Three ensemble configurations (started from OPE analysis) are compared: T_L255L40, T_L319L40 and T_L399L40 (from a VAREPS exp).



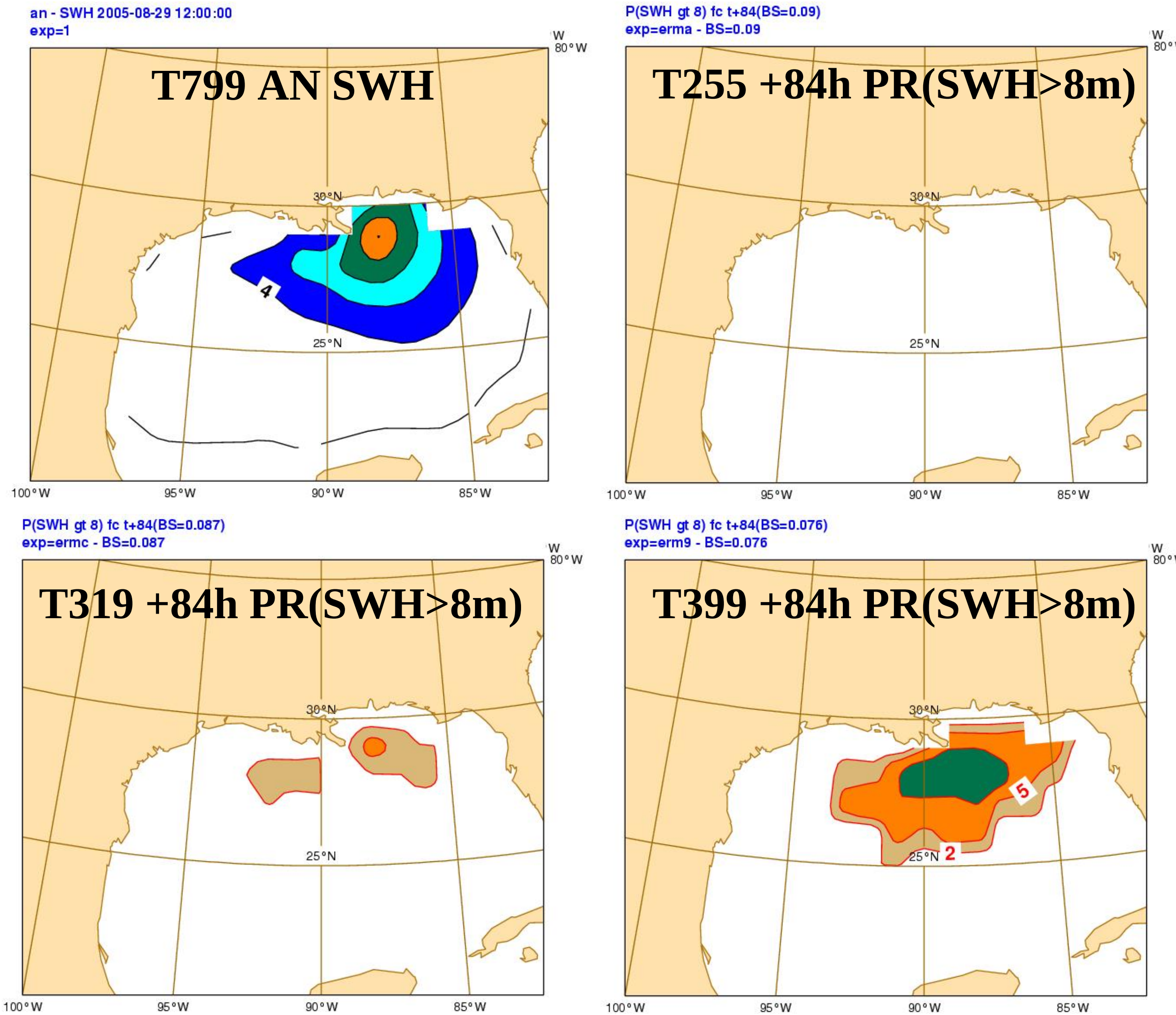
1. Kat: SWH prob in T255 from OPEan in +84h fcs

The top-left panel shows the significant wave height (SWH) in the T799 analysis (cont interval is 2m).

The other panels show the probabilities of SWH>8m in three ensemble forecasts:

- T255 (top-right)
- T319 (bottom-left)
- T399 (bottom-right)

Prob cont iso are 2/5/10/20%.



1. Some considerations on selective sampling

Reduced sampling is more efficient if one is interested in one/few questions only (e.g. sample initial uncertainties dominating forecast error growth defined in terms of total energy during the first 2 days).

Reduced sampling based on singular vectors (ECMWF) is valid only in the linear regime, requires a tangent forward and adjoint model. Perturbations are metric sensitive.

Reduced sampling based on breeding vectors (NCEP) is easier to implement, less expensive, but it does not emulate the scale-selective effect of observations during the analysis cycle.

The MSC Monte Carlo approach requires running an ensemble of assimilation cycles, the maintenance of different models.

1. Description of the ECMWF, MSC and NCEP systems

Each ensemble member evolution is given by integrating the following equation

$$e_j(T) = e_j(0) + \int_{t=0}^{T} [P_j(e_j,t) + dP_j(e_j,t) + A_j(e_j,t)]dt$$

where $e_j(0)$ is the initial condition, $P_j(e_j,t)$ represents the model tendency component due to parameterized physical processes, $dP_j(e_j,t)$ represents random model errors (e.g. due to parameterized physical processes or sub-grid scale processes) and $A_j(e_j,t)$ is the remaining tendency component.

	MSC	ECMWF	NCEP
Pj (model uncertainty)	Diff. Phys. Param.	Pj=P0 (single model)	Pj=P0 (single model)
dPj (random model error)	Diff. Phys. Param.	dPj=rj*Pj (stoch. physics)	dPj=0
Aj	2 models	Aj=A0 (single model)	Aj=A0 (single model)

1. Description of the ECMWF, MSC and NCEP systems

The perturbed initial conditions can be defined directly by a perturbed analysis

$$e_j(0) = \aleph[e_j(-\tau), o_j(-\tau \div \tau), A_j, P_j]$$

or by adding a perturbation to the unperturbed analysis $e_0(0)$

$$e_j(0) = e_0(0) + de_j(0)$$

$$e_0(0) = \aleph[e_0(-\tau), o_0(-\tau \div \tau), A_0, P_0]$$

where $e_j(-\tau)$ is the assimilation starting point and $o_j(-\tau \div \tau)$ represents observations.

	MSC	ECMWF	NCEP
oj (obs error)	Random perturbations	-	-
ej (initial uncertainty)	ej directly from Anal. Cycles	ej=e0+dej(SV)	ej=e0+dej(BV)

1. Description of the ECMWF, MSC and NCEP systems

The three ensembles differ also in size, resolution, daily frequency and forecast length. In April 2007, the three systems had the following characteristics:

	MSC	ECMWF	NCEP
Pj (model uncertainty)	2 models + Diff. Ph. Par.	Pj=P0 (single model)	Pj=P0 (single model)
dPj (random mod err)	2 models + Diff. Ph. Par.	dPj=rj*Pj (stoch. physics)	dPj=0
Aj	2 models	Aj=A0 (single model)	Aj=A0 (single model)
oj (obs error)	Random perturbations	-	-
ej (initial uncertainty)	ej from Anal. Cycles	ej=e0+dej(SV)	ej=e0+dej(BV)
hor-res HRES control	-	-	T170(d0-16)
hor-res control	TL149	TL399(d0-10)+TL255 (d10-15)	T126(d0-16)
hor-res pert members	TL149	TL399(d0-10)+TL255 (d10-15)	T126(d0-16)
vertical levels (c&pf)	27	62	28
top of the model	10hPa	5hPa	3hPa
perturbed members	16	50	20
forecast length	16 days	15 days	16 days
daily frequency	00 and 12 UTC	00 and 12 UTC	00, 06, 12 and 18 UTC
operational impl.	February 1998	December 1992	December 1992

1. Some considerations on model error simulation

The MSC multi-model approach is very difficult to maintain: in fact MSC is planning to change its configuration to one based on one model only with different parameterisation schemes plus stochastic schemes to simulate the effect of model error.

On the contrary, the ECMWF stochastic approach is easy to implement and maintain (NCEP is developing a similar scheme), but its disadvantage is that it only samples uncertainty on short-scales and it is not designed to simulate model biases.

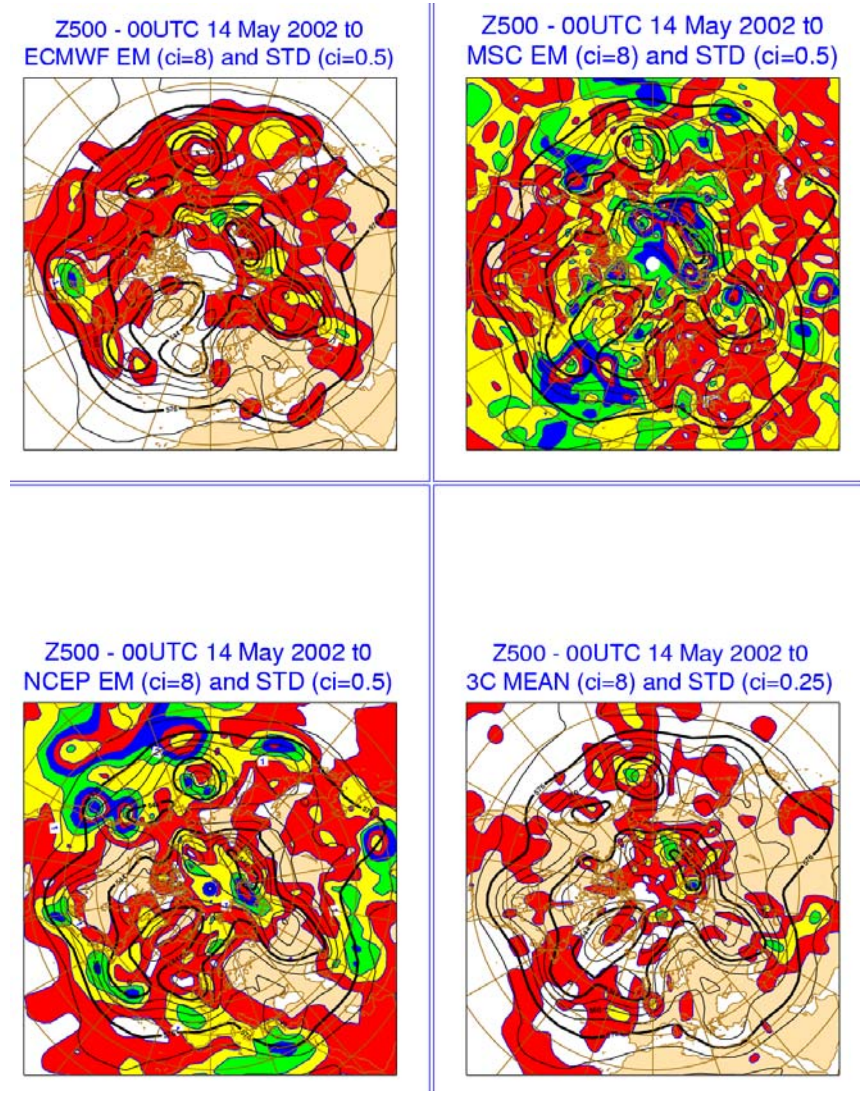
A possible way forward is to use one model, one set of parameterisation schemes but different sets of tuning parameters in each perturbed member, plus stochastic schemes to simulate model uncertainty.

1. Similarities in EM & STD: 14 May '02, t=0

Due to the different methodologies, the ensemble initial states are different.

This figure shows the ensemble mean and standard deviation at initial time for 00UTC of 14 May 2002. The bottom-right panel shows the mean and the std of the 3 centers' analyses.

- Area: the three ensembles' put emphasis on different areas; EC has the smallest amplitude over the tropics.
- Amplitude: the ensembles' stds are larger than the std of the 3-centers' analyses (2 times smaller contour interval); EC has ~2 times lower values over NH.



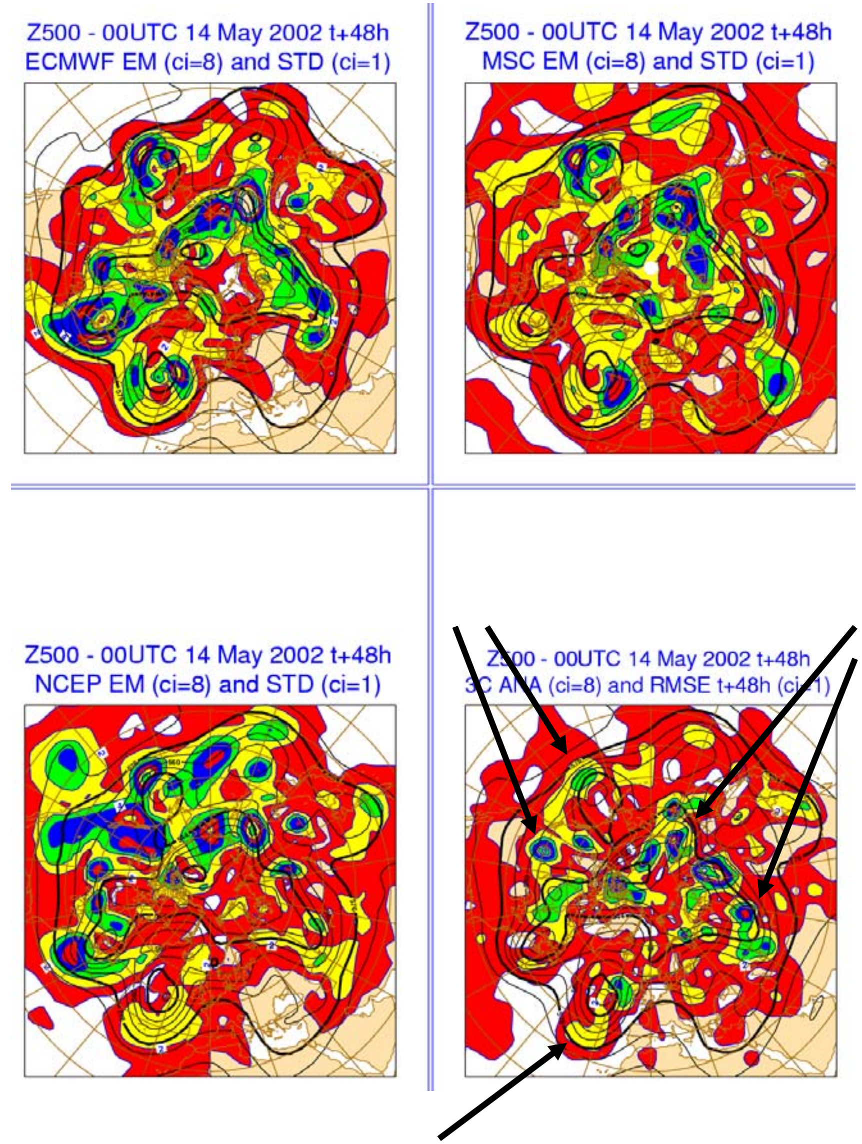
1. Similarities in EM & STD: 14 May ‘02, t+48h

This figure shows the t+48h ensemble mean and standard deviation started at 00UTC of 14 May 2002. The bottom-right panel shows the 3-centers’ average analysis and root-mean-square error.

• Area: there is some degree of similarity among the areas covered by the evolved perturbations.

• Amplitude: similar over NH; EC smaller over tropics.

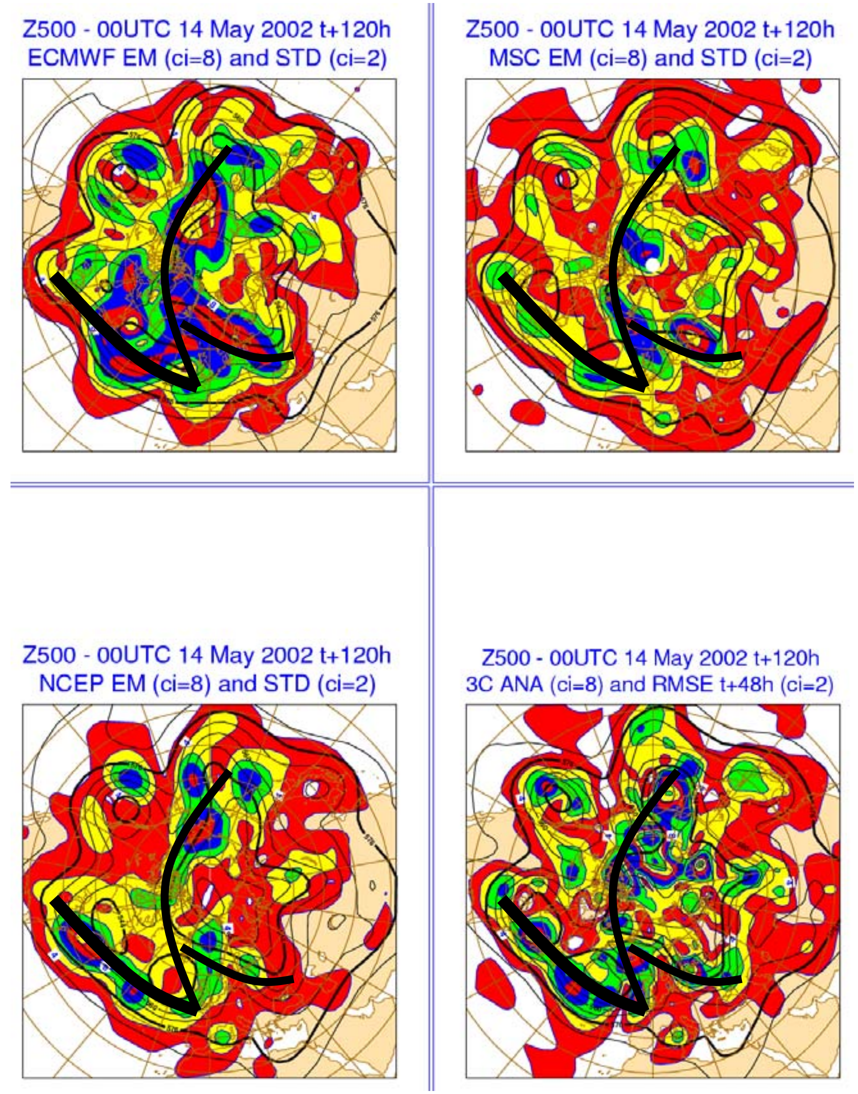
• Std-vs-rmse: certain areas of large spread coincide with areas of large error.



1. Similarities in EM & STD: 14 May ‘02, t+120h

This figure shows the t+120h ensemble mean and standard deviation started at 00UTC of 14 May 2002. The bottom-right panel shows the 3-centres’ average analysis and average forecast root-mean-square error.

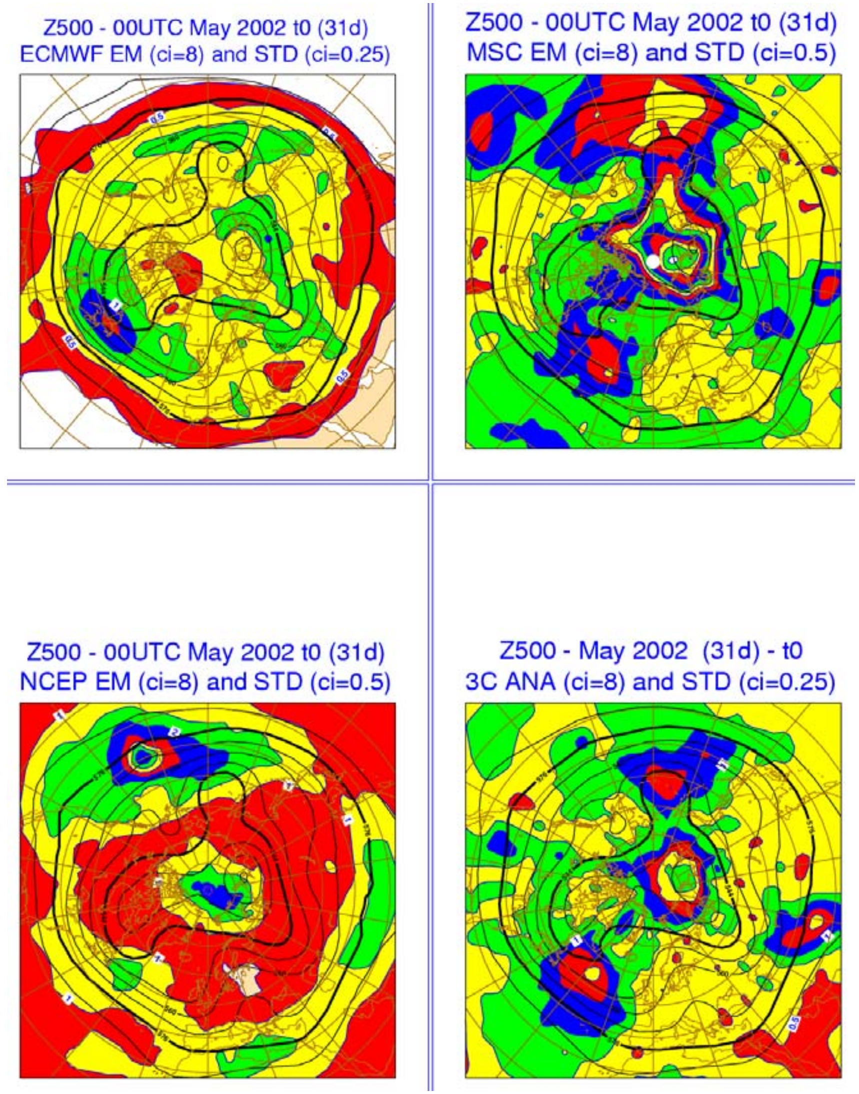
- <u>Area</u>: perturbations show maximum amplitude in similar regions.
- <u>Amplitude</u>: EC perturbations have larger amplitude.
- <u>Std-vs-rmse</u>: there is a certain degree of agreement between areas of larger error and large spread.



1. Similarities in EM & STD: May ‘02, t=0

This figure shows the May02-average ensemble mean and standard deviation at initial time (10 members, 00UTC). The bottom-right panel shows the average and the std of the 3-centres’ analyses.

- <u>Area</u>: NCEP and MSC peak over the Pacific ocean and the Polar cap while EC peaks over the Atlantic ocean; MSC shows clear minima over Europe and North America.
- <u>Amplitude</u>: MSC and NCEP are ~2 times larger than the std of the 3 centres’ analyses (2-times larger contour interval); EC has amplitude similar to 3C-std over NH but has too small amplitude over the tropics.



1. Similarities in EM & STD: May ‘02, t=0

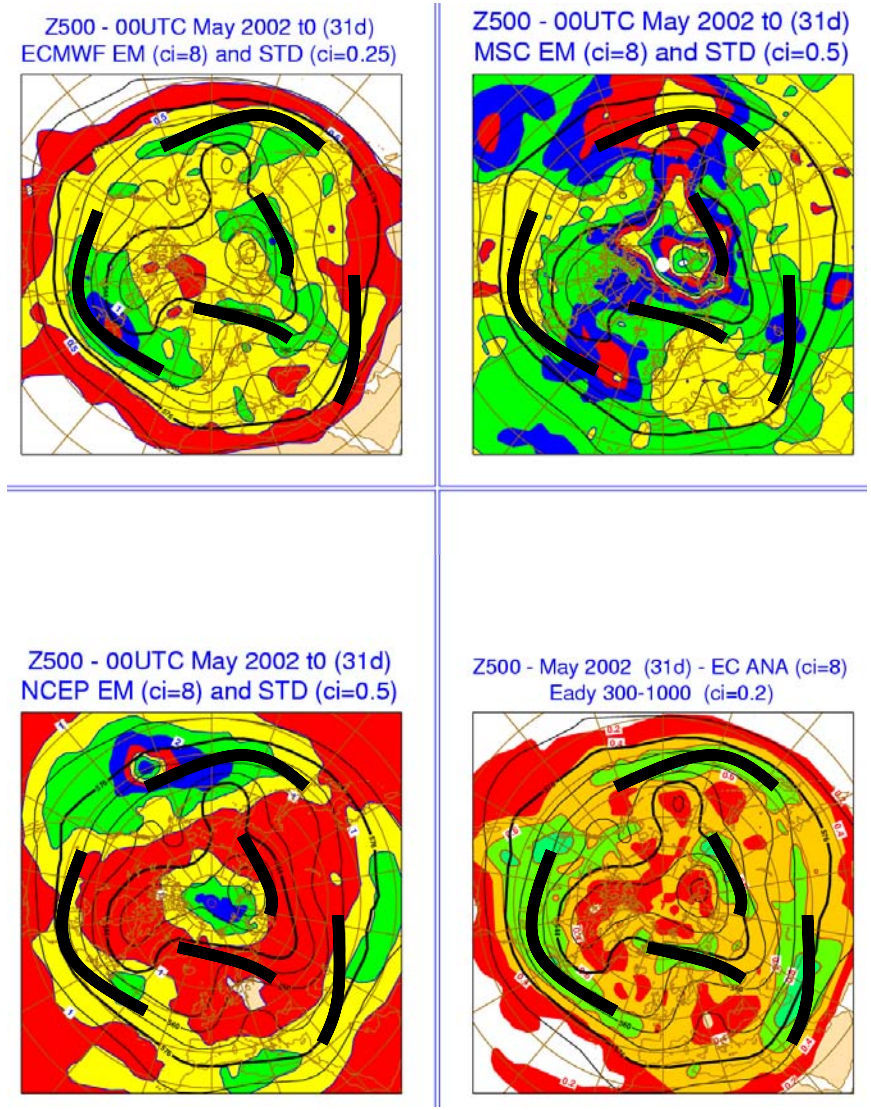
This figure shows the May02-average ensemble mean and standard deviation at initial time (10 members, 00UTC).

The bottom-right panel shows the EC analysis and the Eady index (*Hoskins and Valdes* 1990), which is a measure of baroclinic instability:

$$\sigma_E = 0.31 \frac{f}{N} \frac{du}{dz}$$

(the static stability N and the wind shear have been computed using the 300- and 1000-hPa potential temperature and wind).

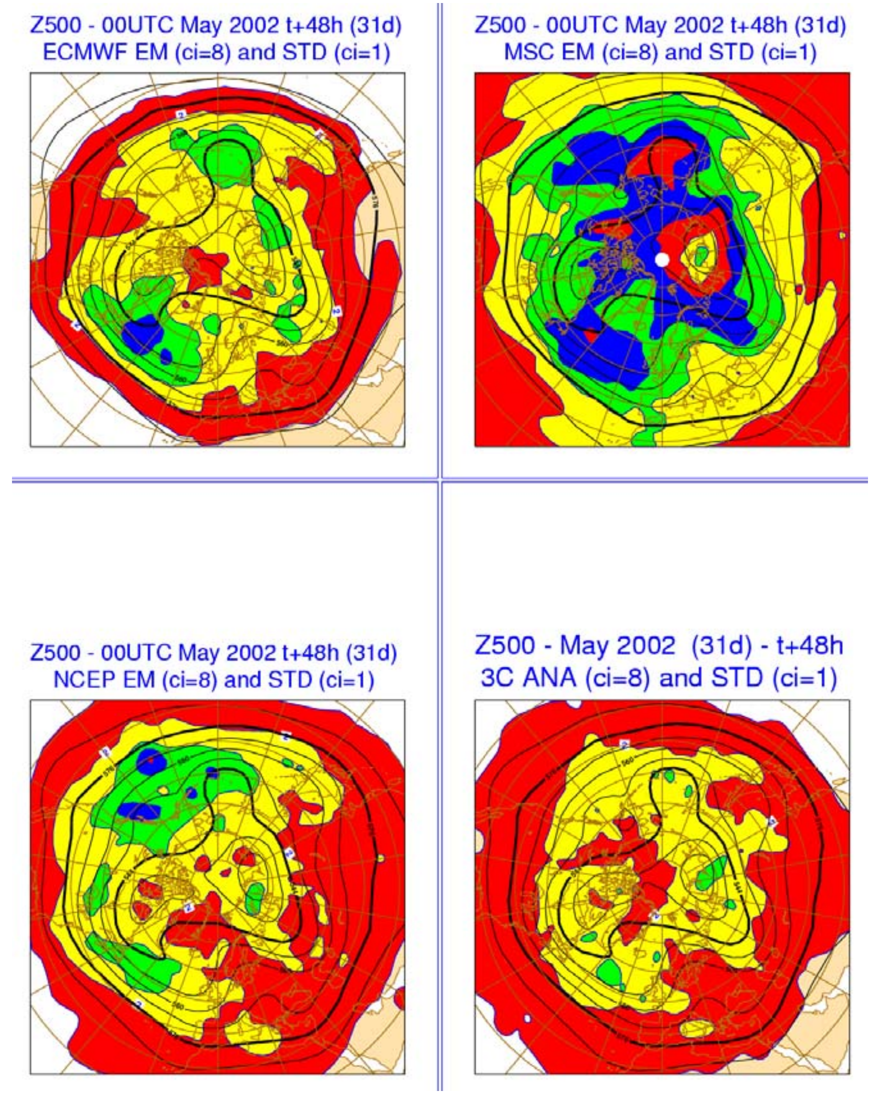
EC std shows a closer agreement with areas of baroclinic instability.



1. Similarities in EM & STD: May ‘02, t+48h

This figure shows the May02-average ensemble mean and standard deviation at t+48h (10 members, 00UTC) The bottom-right panel shows the average and the std of the 3-centres’ analyses.

- Area: NCEPS and MSC give more weight to the Pacific while EC gives more weight to the Atlantic; NCEP initial relative maximum over the North Pole cap has disappeared; MSC shows still a large amplitude north of Siberia.
- Amplitude: MSC has the largest amplitude over NH; EC has the smallest amplitude over the tropics.



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2. The test period and the verification measures

- The test period is May-June-July 2002 (MJJ02).

- Scores for Z500 forecasts over NH (20:80°N) are shown.
- All forecasts data are defined on a regular 2.5-degree latitude-longitude grid.
- Each ensemble is verified against its own analysis.

- For a fair comparison, only 10 perturbed members are used for each ensemble system (from 00UTC for MSC and NCEP and from 12UTC for ECMWF).

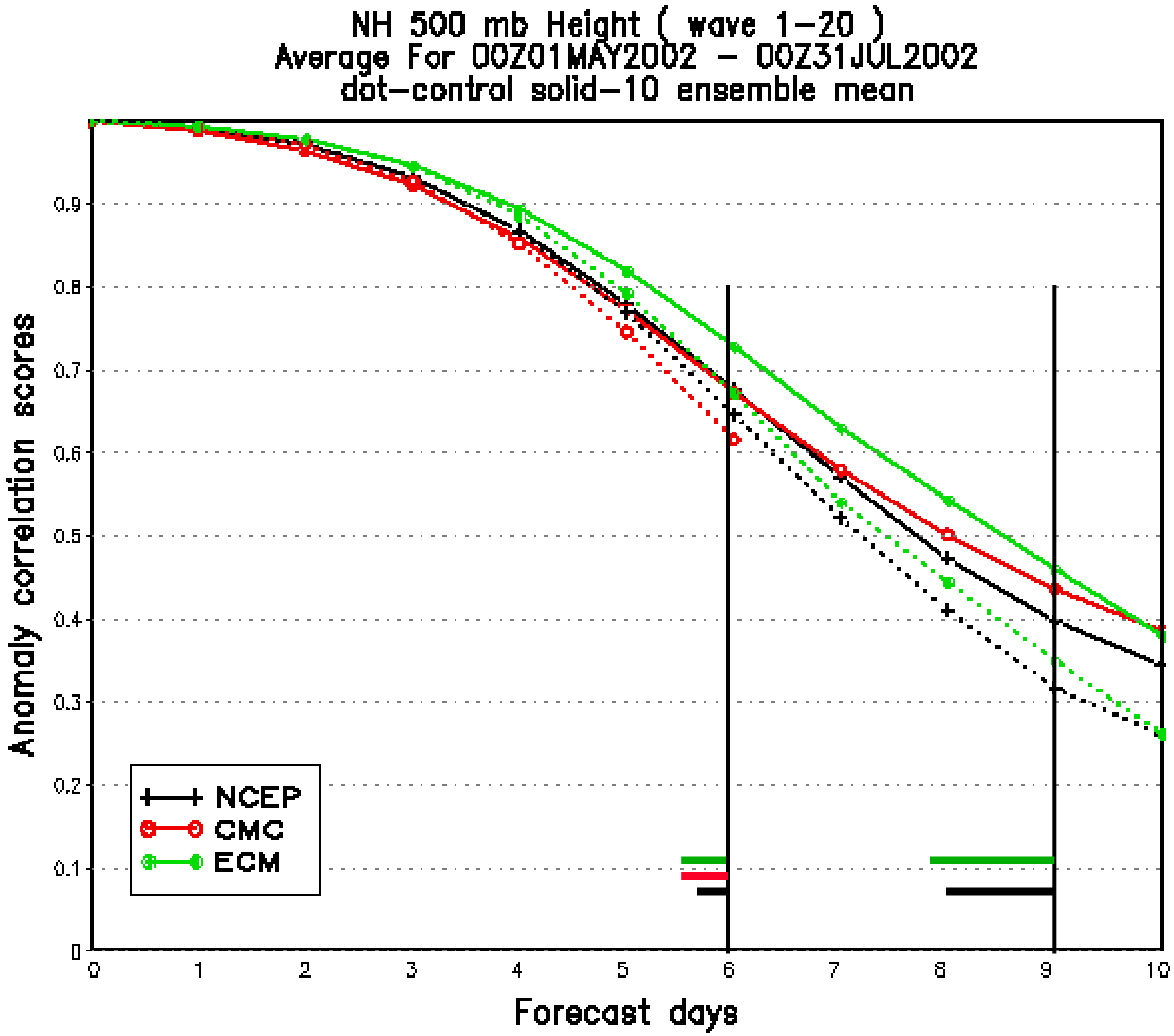
- Probability forecasts' accuracy has been measured using the Brier skill score (BSS), the area under the relative operating characteristic curve (ROC) and the ranked probability skill score (RPSS). Probabilistic forecasts are average scores computed considering 10 climatologically equally likely events.

2. Control and ensemble-mean performance - NH

This figure shows the MJJ02 average ACC for the control (dotted lines) and ensemble-mean (solid lines) forecasts over NH.

At forecast day 6 (9), ensemble-mean forecasts are ~12h (~24h) more skilful than control forecasts.

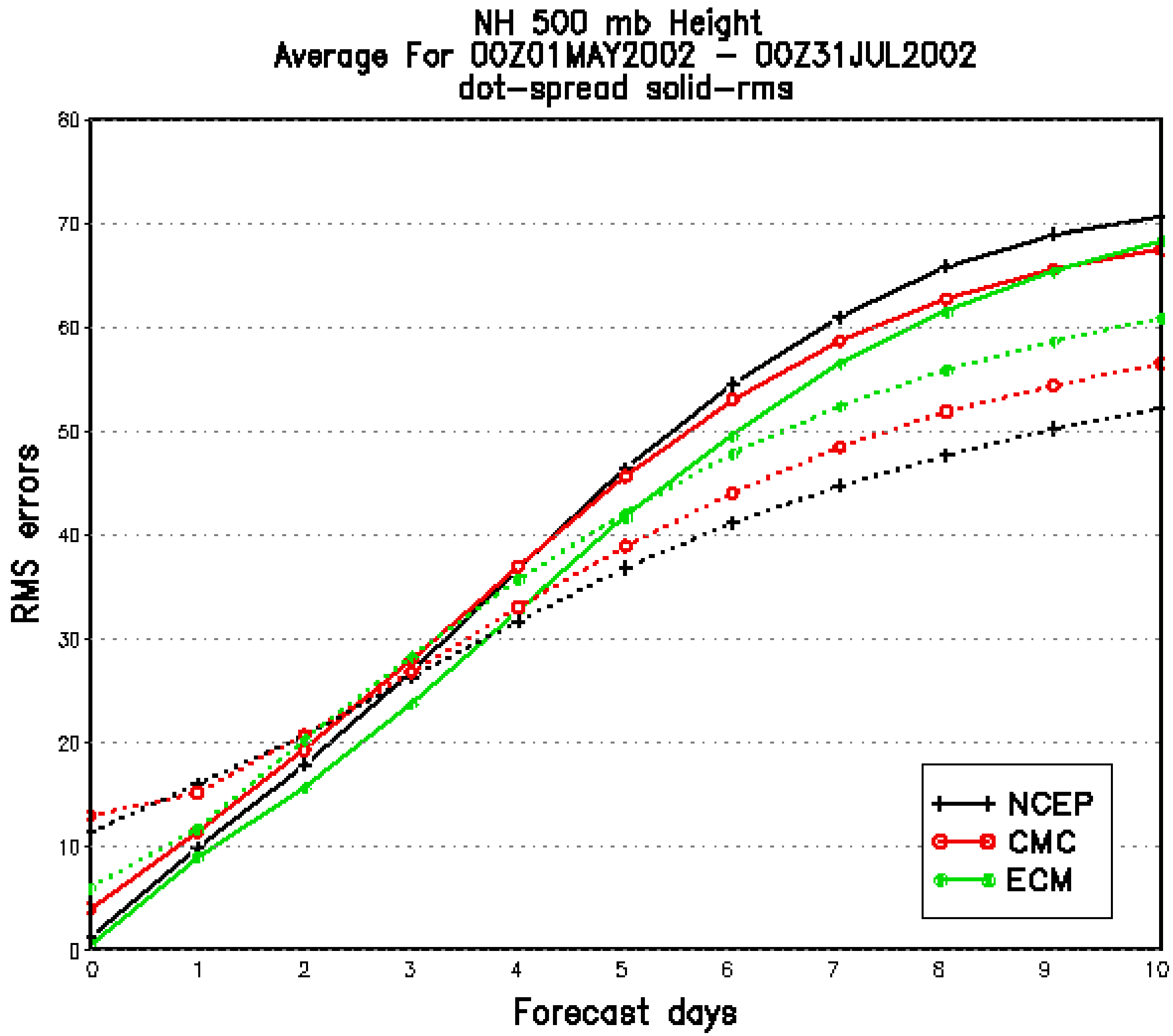
Again, note the strong similarity between the skill of the control and the skill of the ensemble-mean forecasts.



2. Average EM error and ensemble STD – NH

This figure shows the MJJ02 average ensemble-mean RMS error (solid) and the ensemble standard deviation (dotted lines) over NH.

The three ensembles have similar spread between day 2 and 4, while the EC-EPS has the smallest values up to day 2 and largest value after day 4.



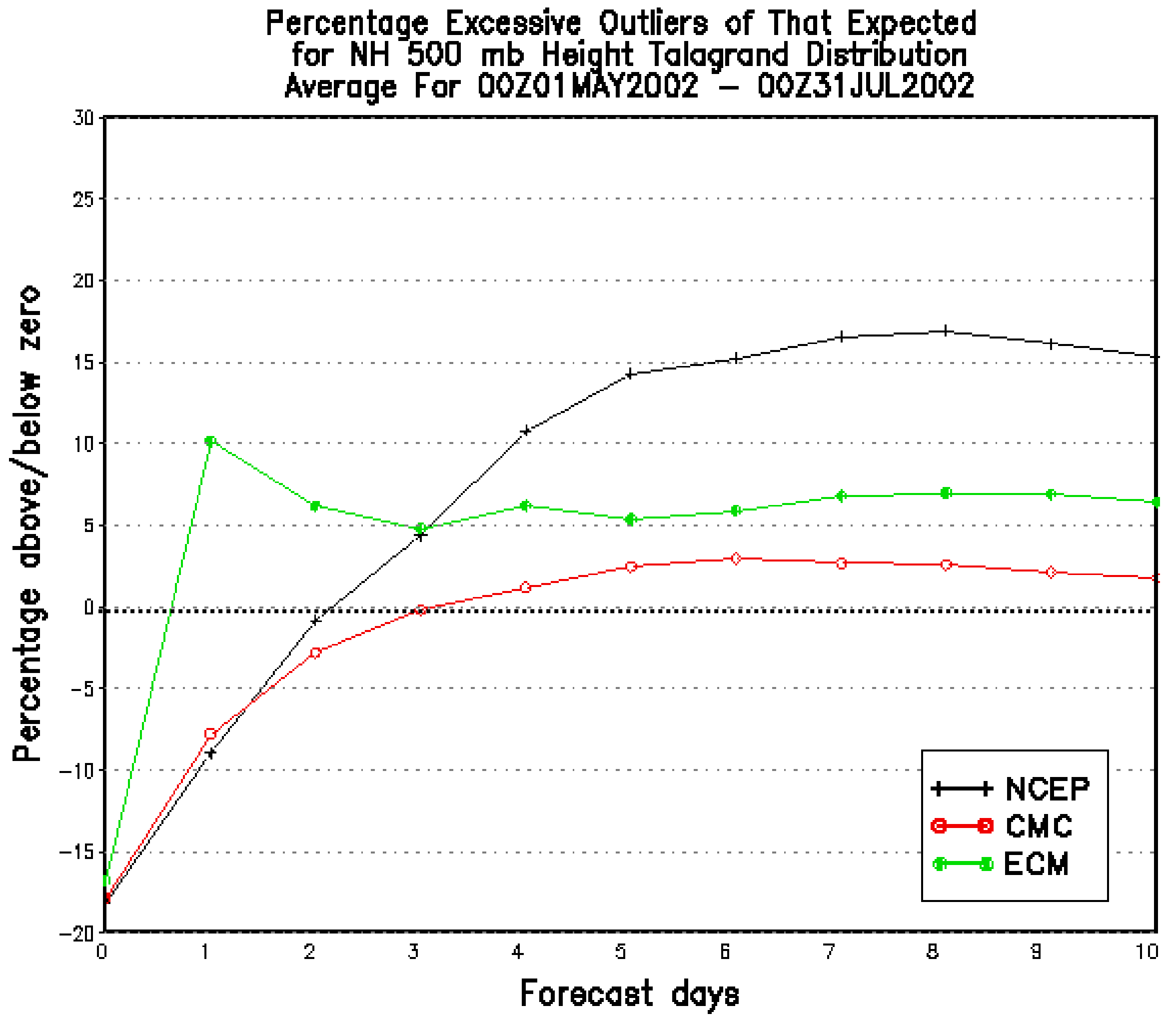
2. Percentage of excessive outliers - NH

The percentage of outliers p_{out} is the percentage of analysis values lying outside the ensemble forecast range.

Ideally, for an ensemble with N members which randomly samples the forecast probability distribution, the percentage of outliers should be $p_{ref}=2/(N+1)$.

The percentage of excessive outliers is $p_{eo} = p_{out} - p_{ref}$

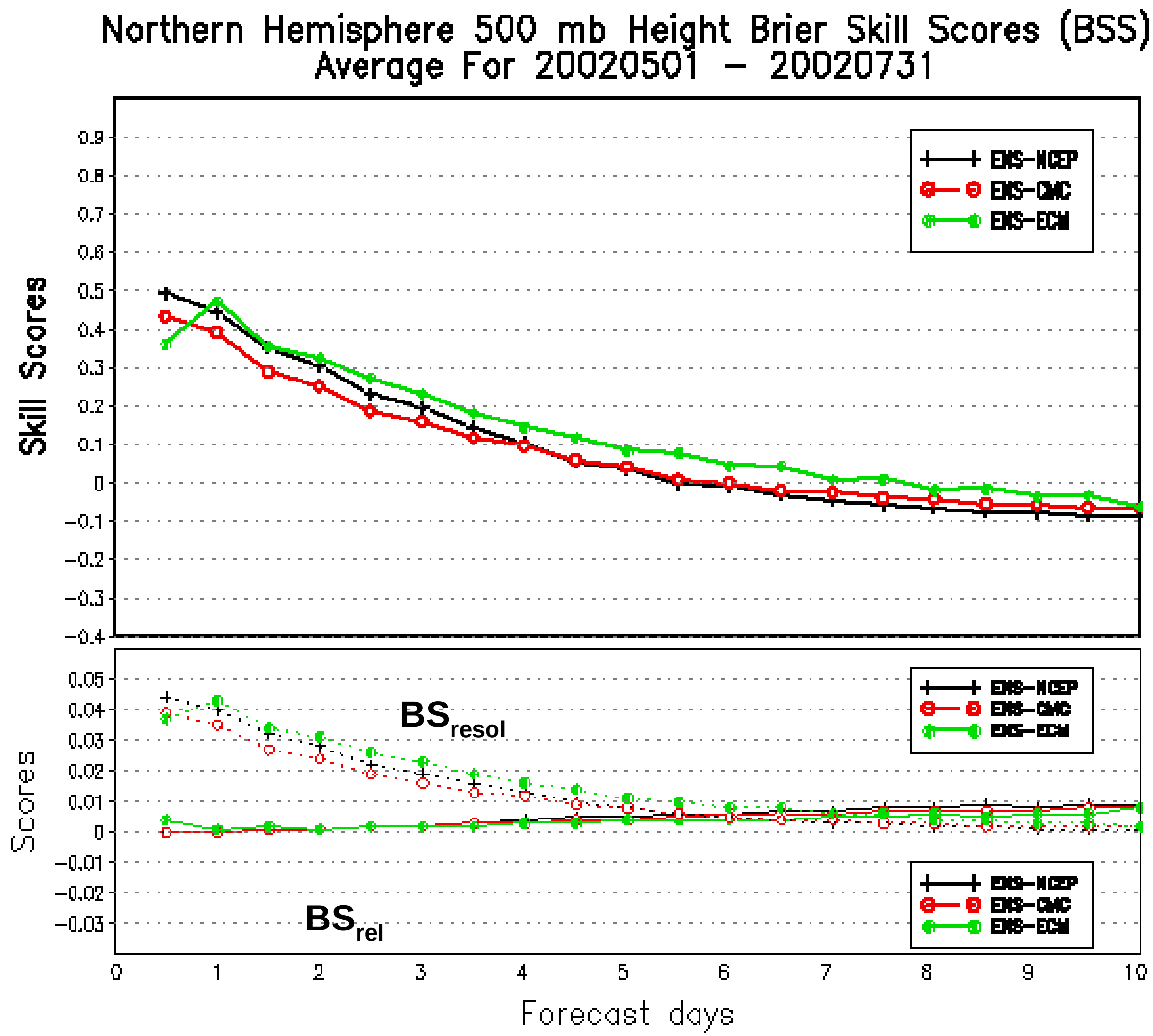
($p_{eo} \rightarrow 0$ for a reliable system).



2. Brier score and Brier skill score - NH

The Brier score (BS) is the most commonly used score for the verification of probability forecasts of dichotomous events. The BS is the mean-squared error of probability forecasts. The Brier skill score (BSS) is the % of BS improvement over climatology.

The top panel shows the BSS (BSS→1 for a perfect system). The bottom panel shows the resolution and reliability terms of the BS.



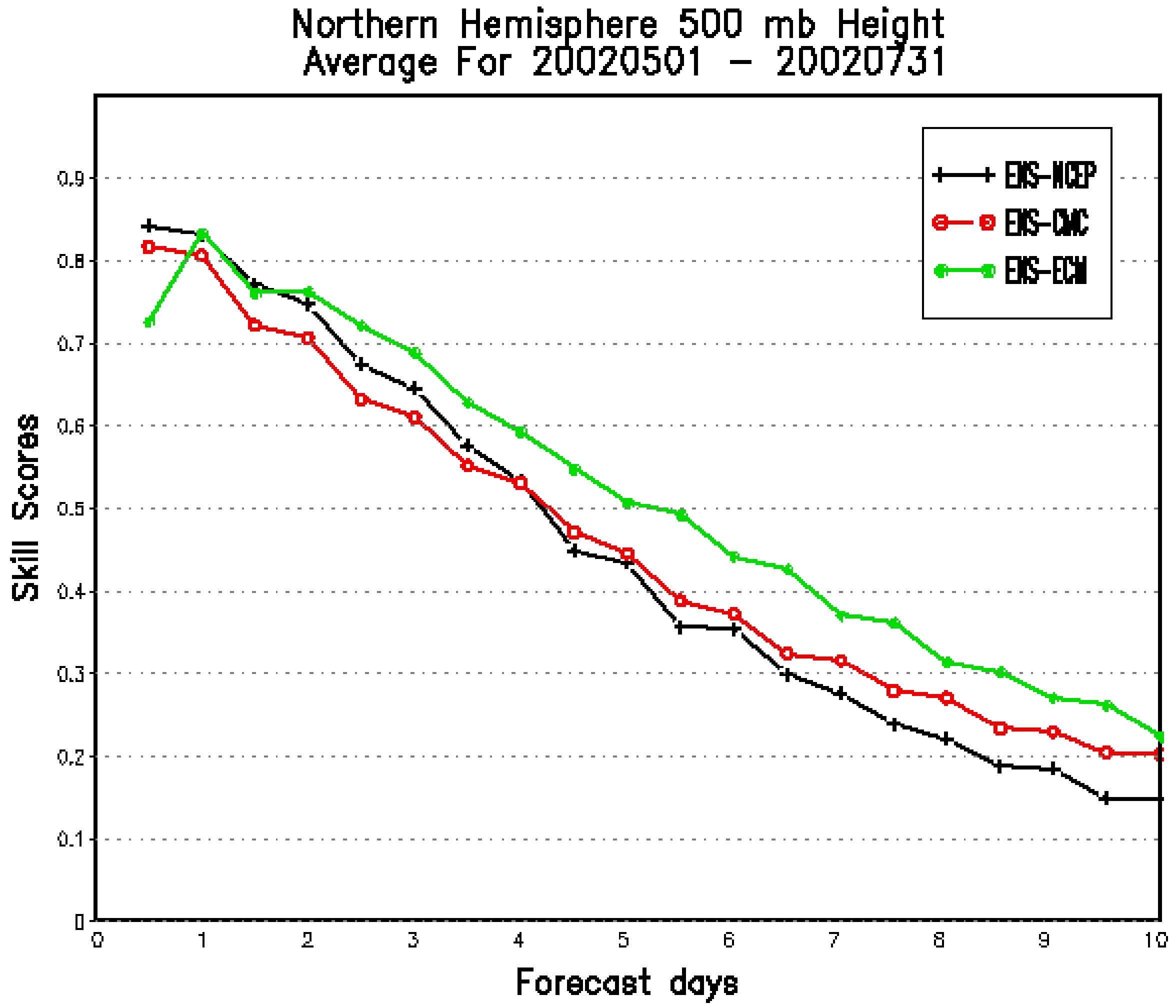
2. Area under relative operating characteristic curve - NH

The area under the relative operating characteristic curve (ROCA) measures the capacity of a system to discriminate between hits and false alarms.

The ROCA-skill score is defined as:

*ROCA-skill=2*ROCA-1*

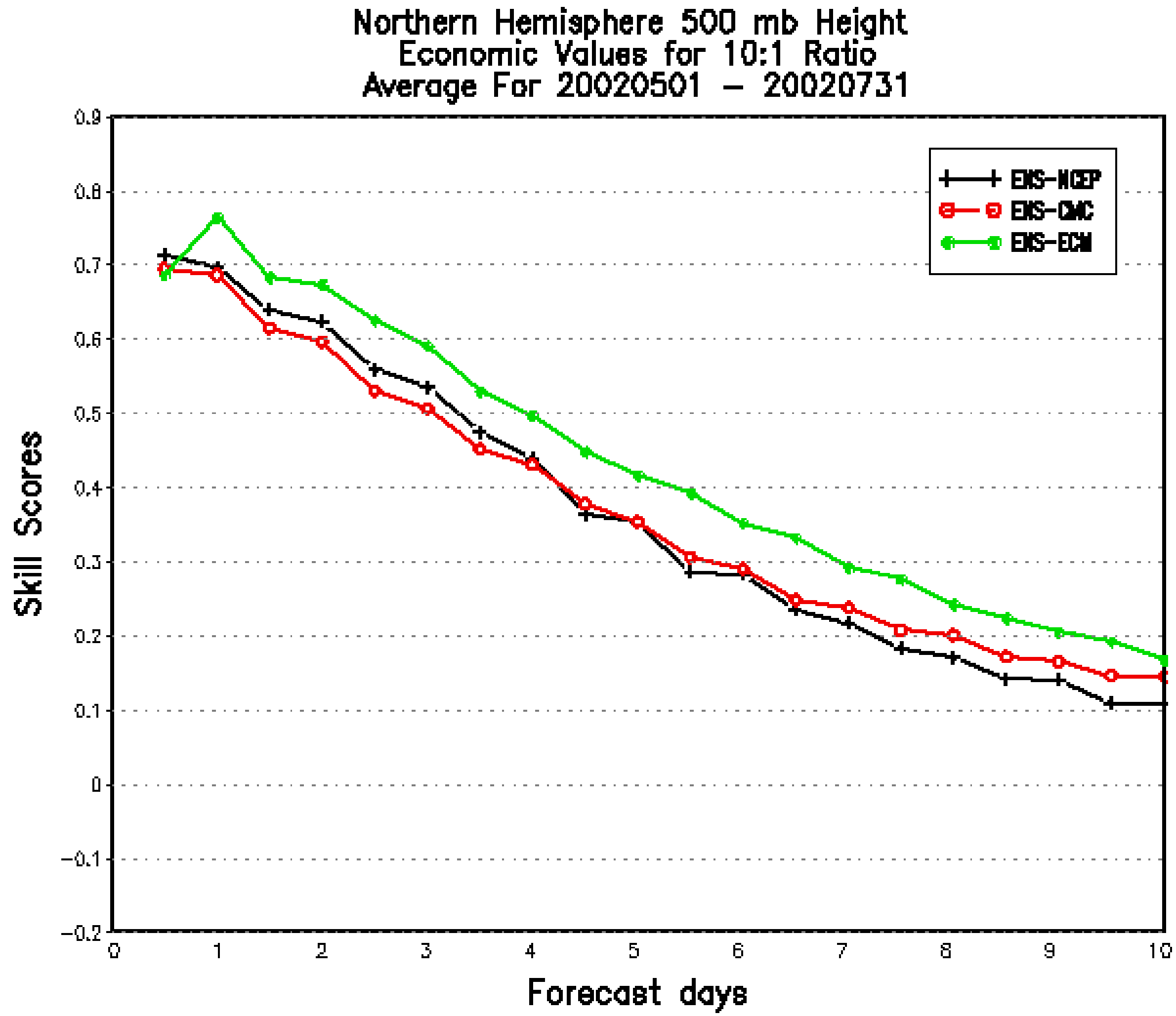
(ROCA-skill→1 for a skilful system).



2. Potential economic value - NH

The potential economic value (EV) is defined by coupling contingency tables and cost-loss decision models. The EV measures the potential reduction of the mean expenses that can be achieved by using the ensemble forecasts.

The EV skill score (EV-skill) is defined as the reduction of the mean expenses with respect to the reduction that can be achieved by using a perfect forecast (EV-skill→1 for a valuable system).



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3. Long-term trends in ECMWF ensemble performance

- EC-EPS monthly-average scores for Z500 (2.5 degrees regular grid) have been computed from the 1st of May, 1994. Probabilistic forecasts (highest possible resolution) have been computed for +/- anomalies (with respect to long-term climate) of 0.5/1/1.5 analysis std.

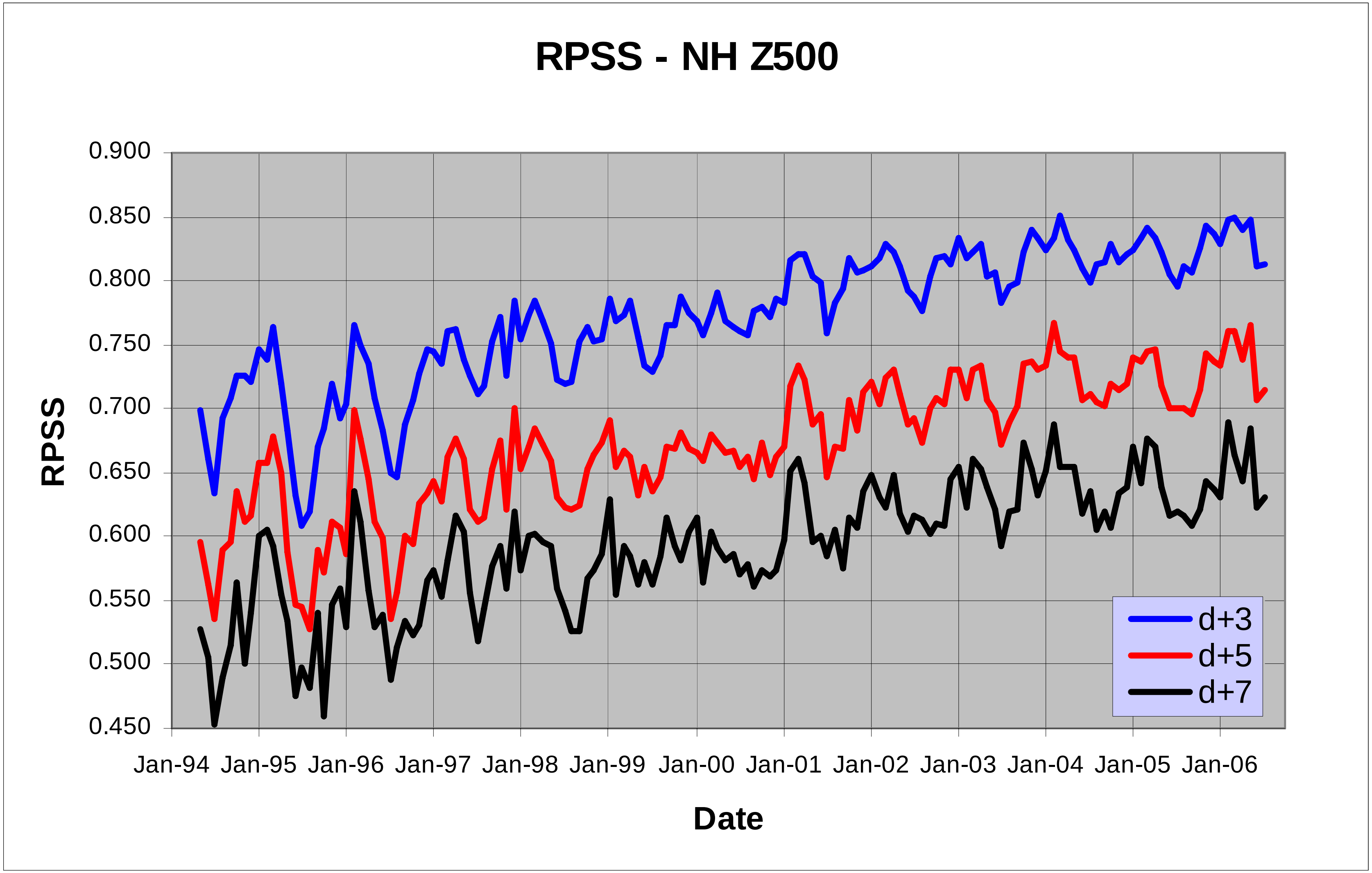
- Attention is focused on probabilistic forecasts.

- Accuracy has been measured using the ranked probability skill score (RPSS), the area under the relative operating characteristic curve (ROC) and the Brier skill score (BSS).

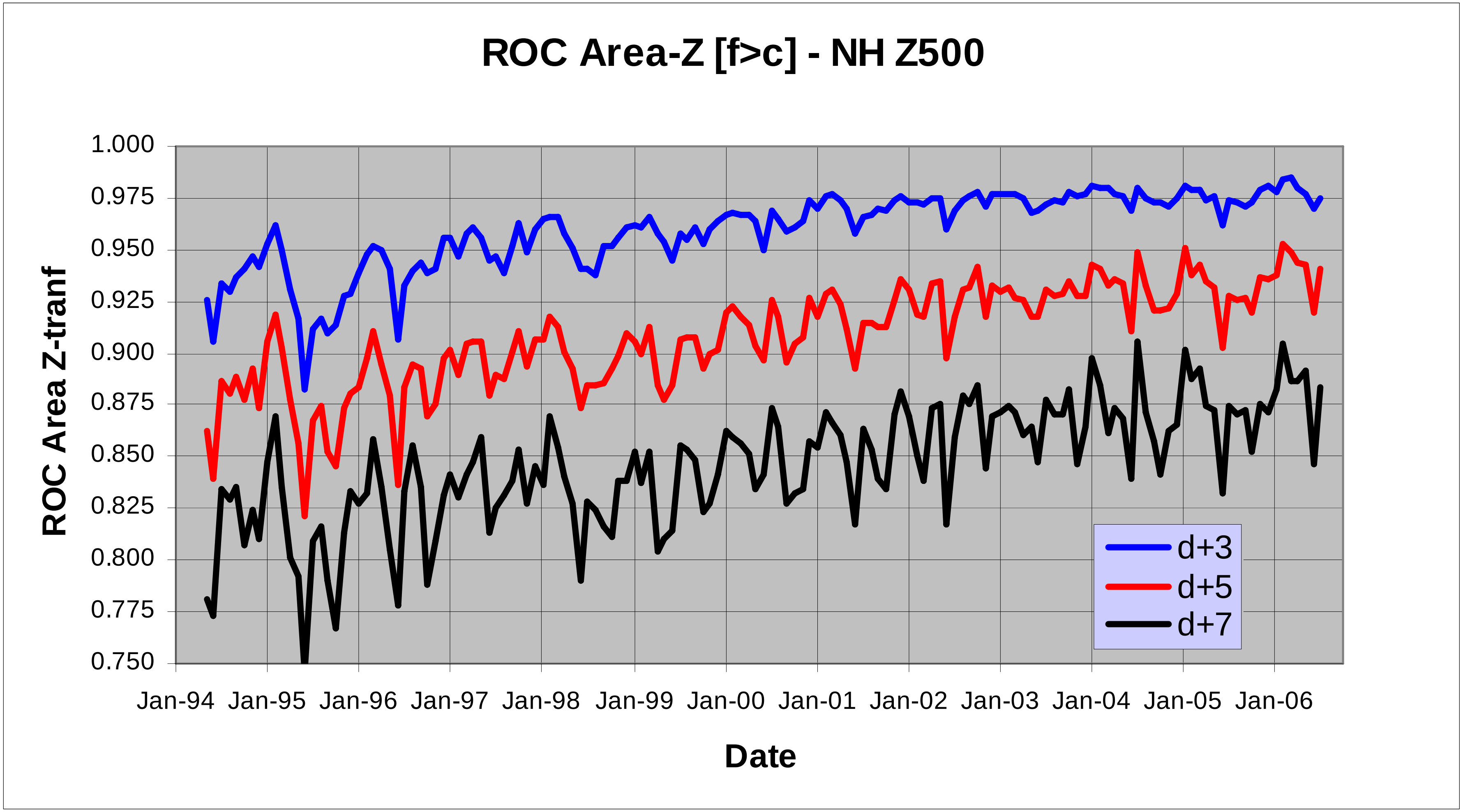
- Annual trends in scores have been estimated.

(Unfortunately historical data for the MSC and the NCEP ensembles were not available)

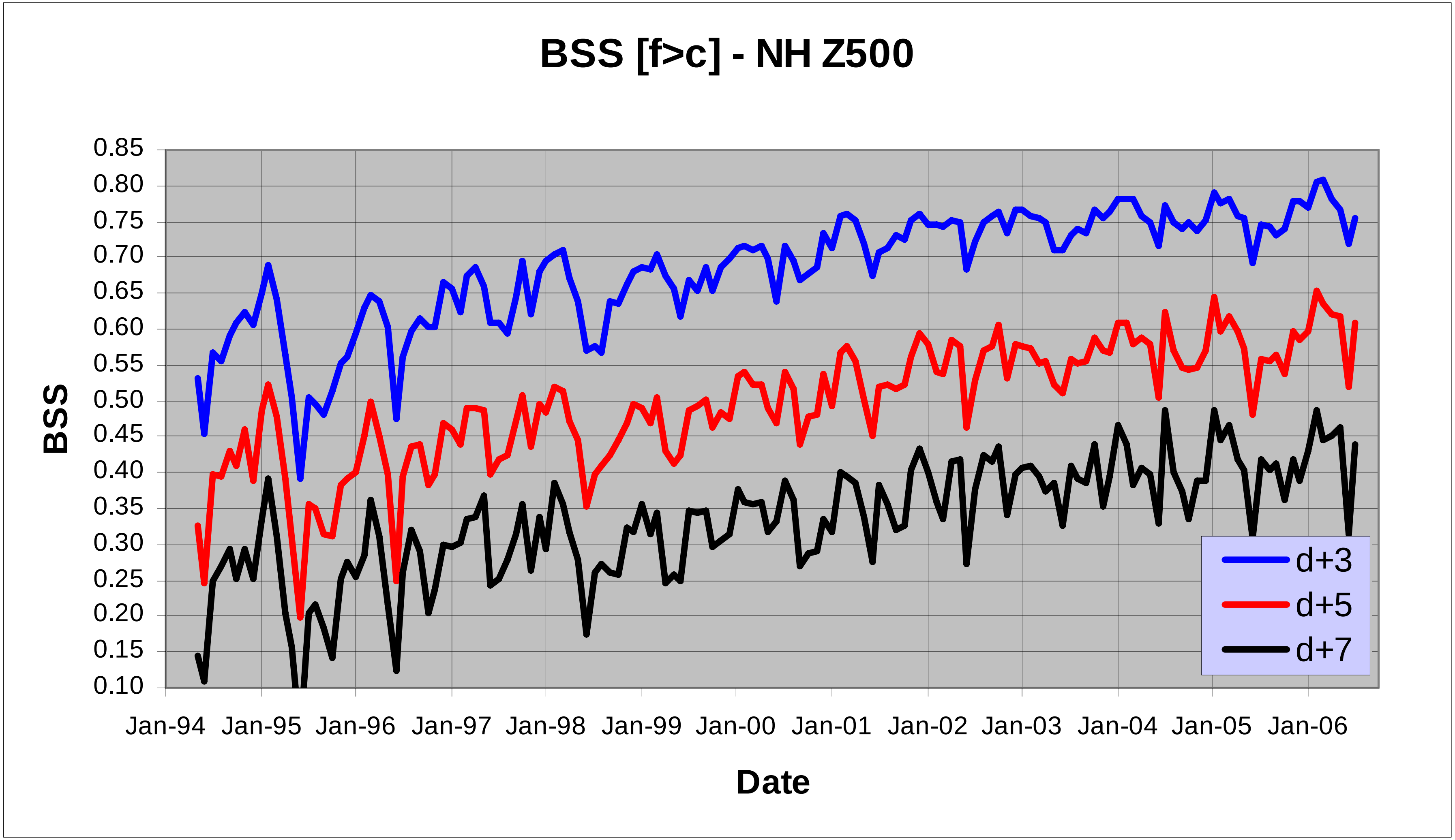
3. NH: EPS RPSS - d+3, d+5 and d+7



3. NH: EPS ROCA-Z for (f>c) - d+3, d+5 and d+7



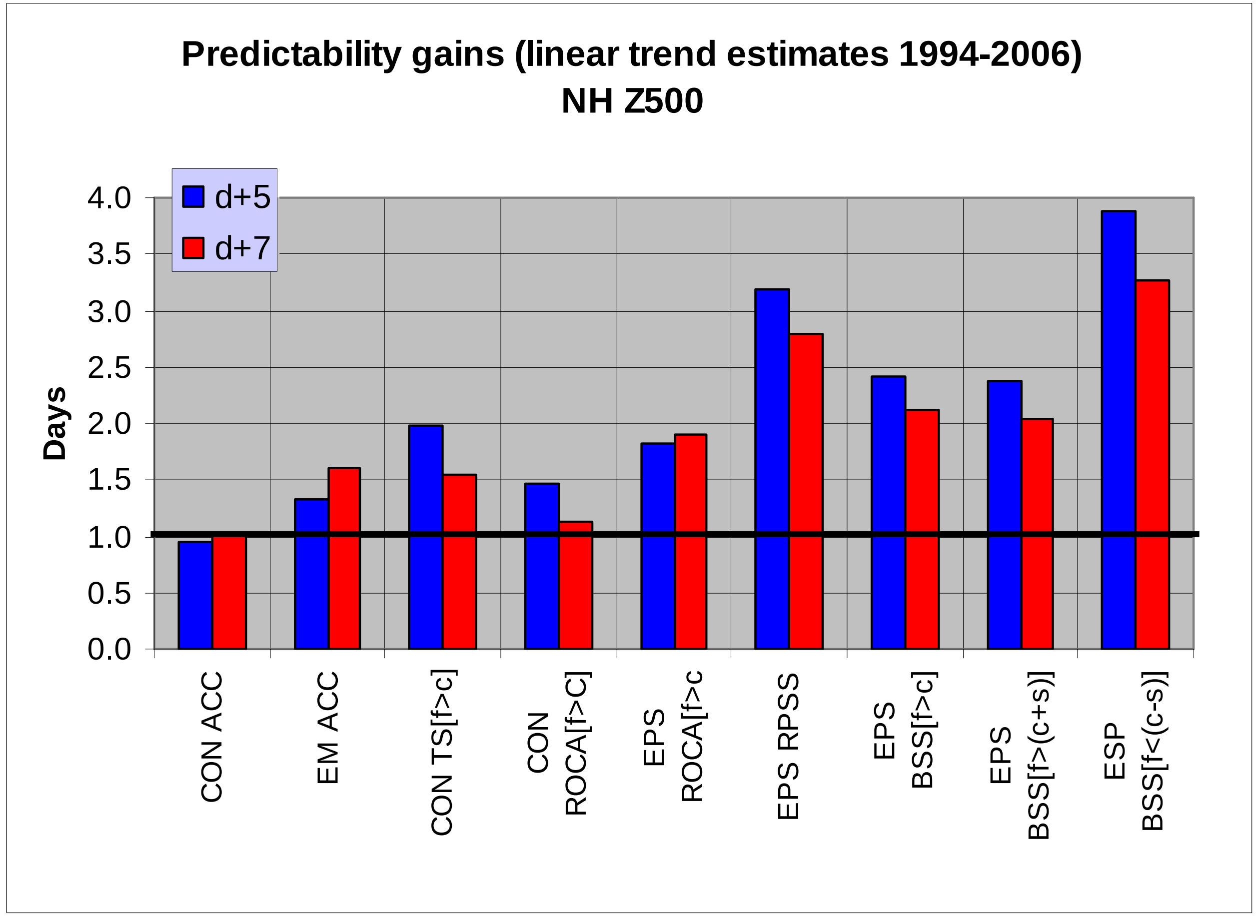
3. NH: EPS BSS for (f>c) - d+3, d+5 and d+7



3. Trends in EPS performance – NH Z500

Results indicate that over NH, for Z500 forecasts at d+5 and d+7:

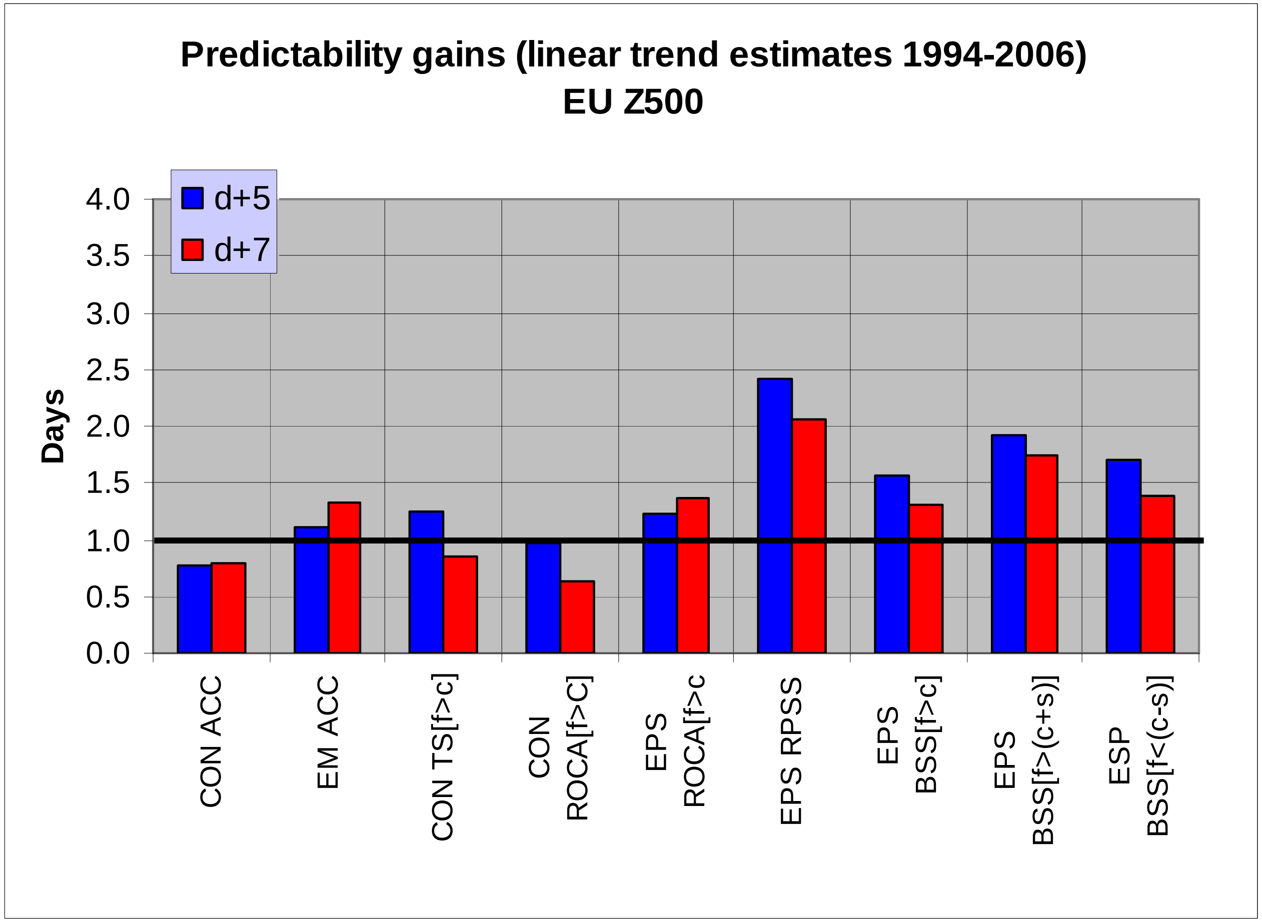
- the EPS control has improved by ~ 1 day/decade
- the EPS ens-mean has improved by ~ 1.5 day/decade
- the EPS probabilistic products have improved by ~2-3 day/decade



3. Trends in ensemble performance – Eur Z500

Results indicate that over Europe, for Z500 forecasts at d+5 and d+7:

- the EPS control has improved by ~ 0.7 day/decade
- the EPS ens-mean has improved by ~ 1 day/decade
- the EPS probabilistic products have improved by ~1.5-2 day/decade



Outline

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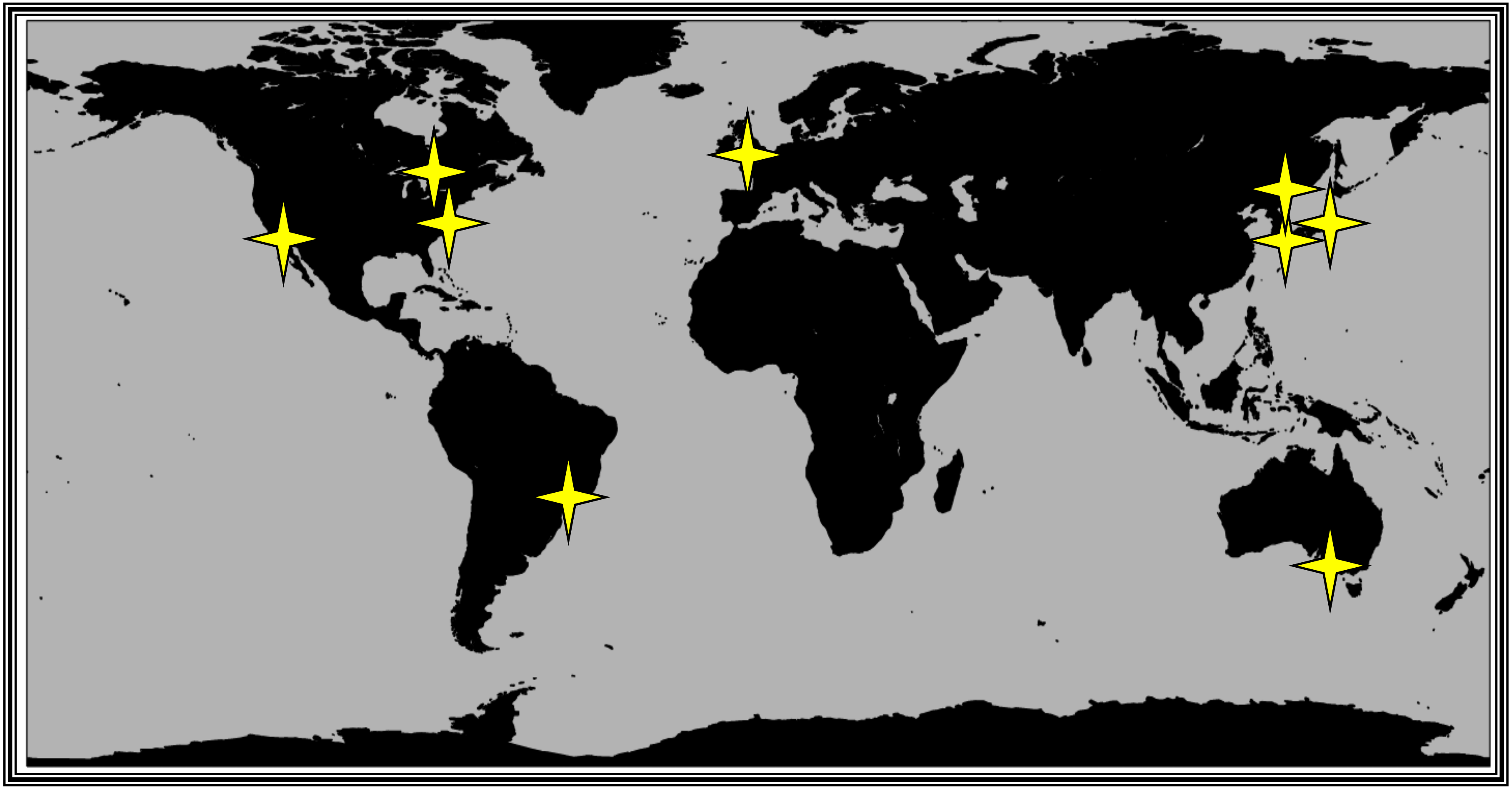
4. Operational Global Ensemble Prediction



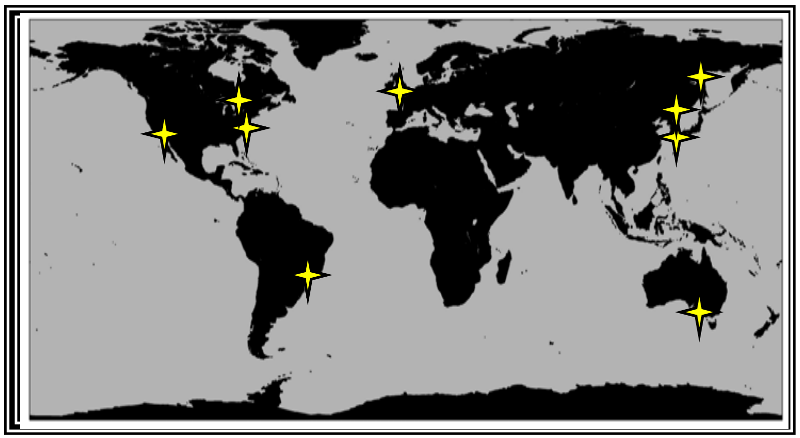
4. Key characteristics of the 9 Operational Global EPSs

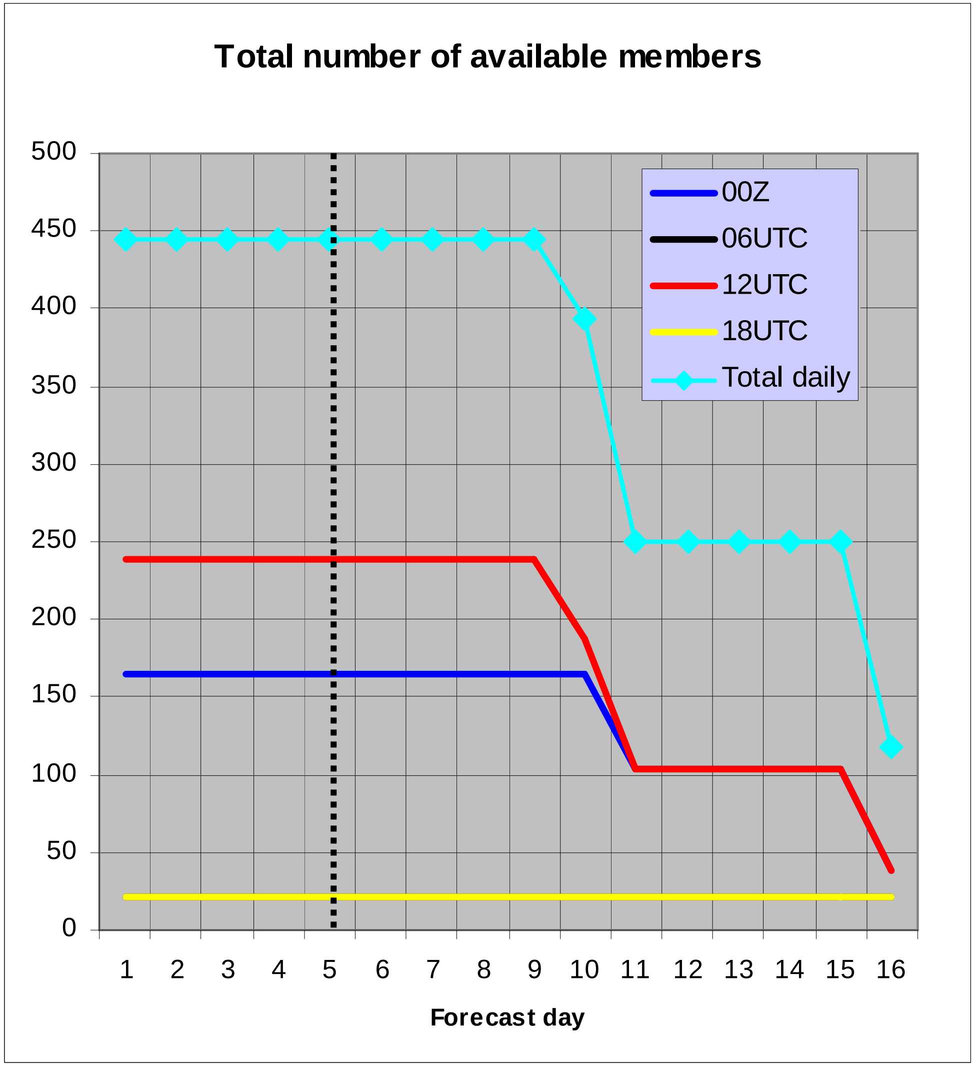
Updated 2 April 2007	BMRC	CMA	CPTEC	ECMWF	FNMOC	JMA	KMA	MSC	NCEP
	Australia	China	Brazil	Europe	US	Japan	Korea	Canada	US
simul model syst uncert	NO	NO	NO	NO	NO	NO	NO	YES (16 models)	NO
simul model random uncert	NO	NO	NO	YES (stoch ph)	NO	NO	NO	YES (16 models)	NO
simul observation error	NO	NO	NO	NO	NO	NO	NO	YES (rand pert)	NO
initial pert strategy	SVs	SVs & BVs	EOF-based	SVs	BVs	BVs	BVs	analyses cycl	BVs
hor-resol init pert	TL42	?	T126	TL42	T119	T106	T106	TL149	T126
Initial perturbed area	ExTR (<20S, >20N)	?	TR (45S:30N)	ExTR (<30S, >30N) + upto 6 TR-area	Globe	?	NH+TR (>20S)	Globe	Globe
hor-resol forecasts	TL119	T106	T126	TL399(0-10) TL255(10-15)	T119	T106	T106	TL149	T126
top of the model (hPa)	10	?	3	5	1	0.4	10	10	3
forecast length (days)	10	10	15	15	10	9	8	16	16
# runs per day (UTC)	2 (00,12)	1 (12)	2 (00,12)	2 (00,12)	1 (00)	1 (12)	1 (12)	2 (00, 12)	4 (00,06,12,18)
# pert mem per run	32	32	14	50	16	24	16	16	20
# ens mem per day	66	33	30	102	17	25	17	34	84

4. Total number of daily available ensemble members

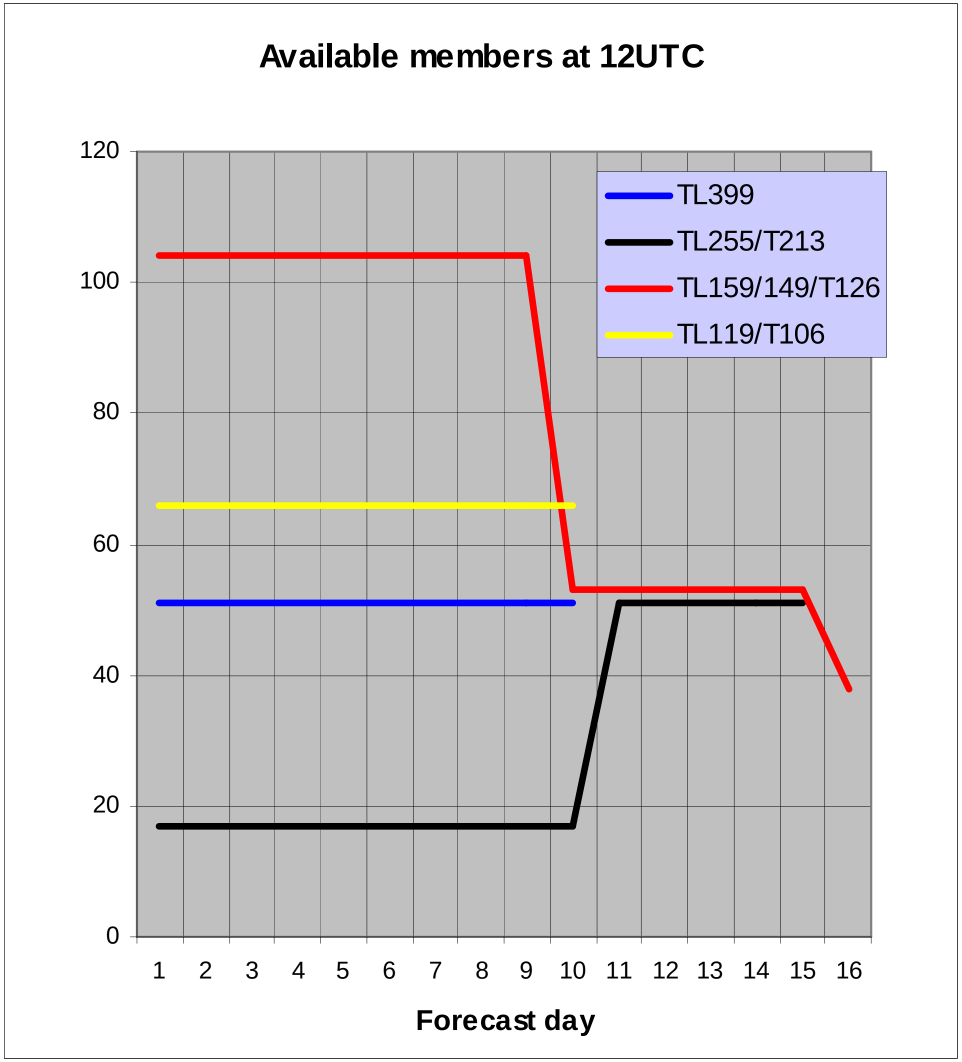
Due to differences in the ensemble configurations, the number of available ensemble members varies with the initial time. At forecast day 5, e.g., the number of available ensemble members is in total 408, with:

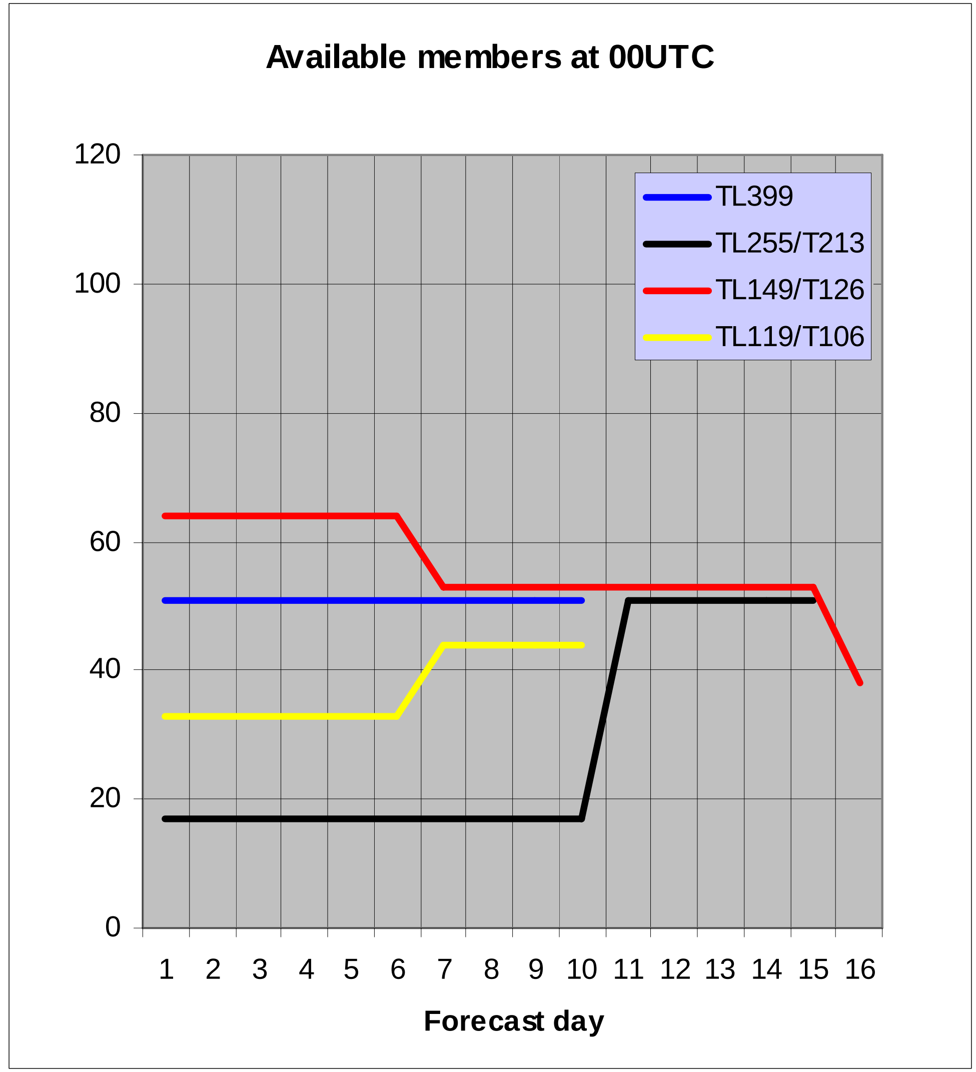
- 165 members at with init time 00 UTC
- 21 members at with init time 06 UTC
- 238 members at with init time 12 UTC
- 21 members at with init time 18 UTC





4. The resolution of the available global ensembles varies





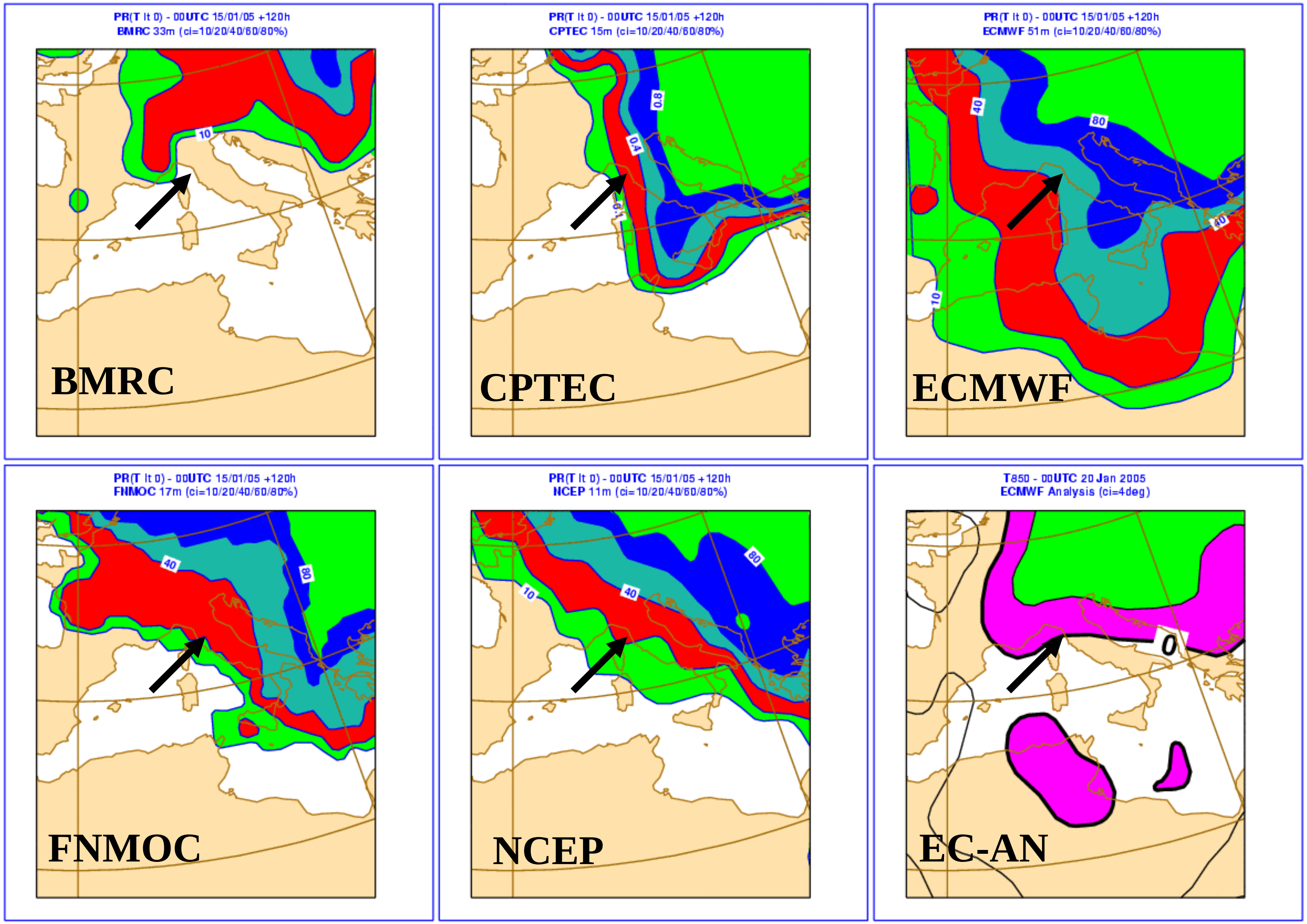
4. π_{T850}(00,120h) form 5 systems

Europe: 120h forecast probability of T850<0 degrees.

What is the PR(T850<0) in Firenze?

BMRC gives 0%, the others more than 20% probability.*

** This is just one case: probability forecasts should be verified on a large dataset.*



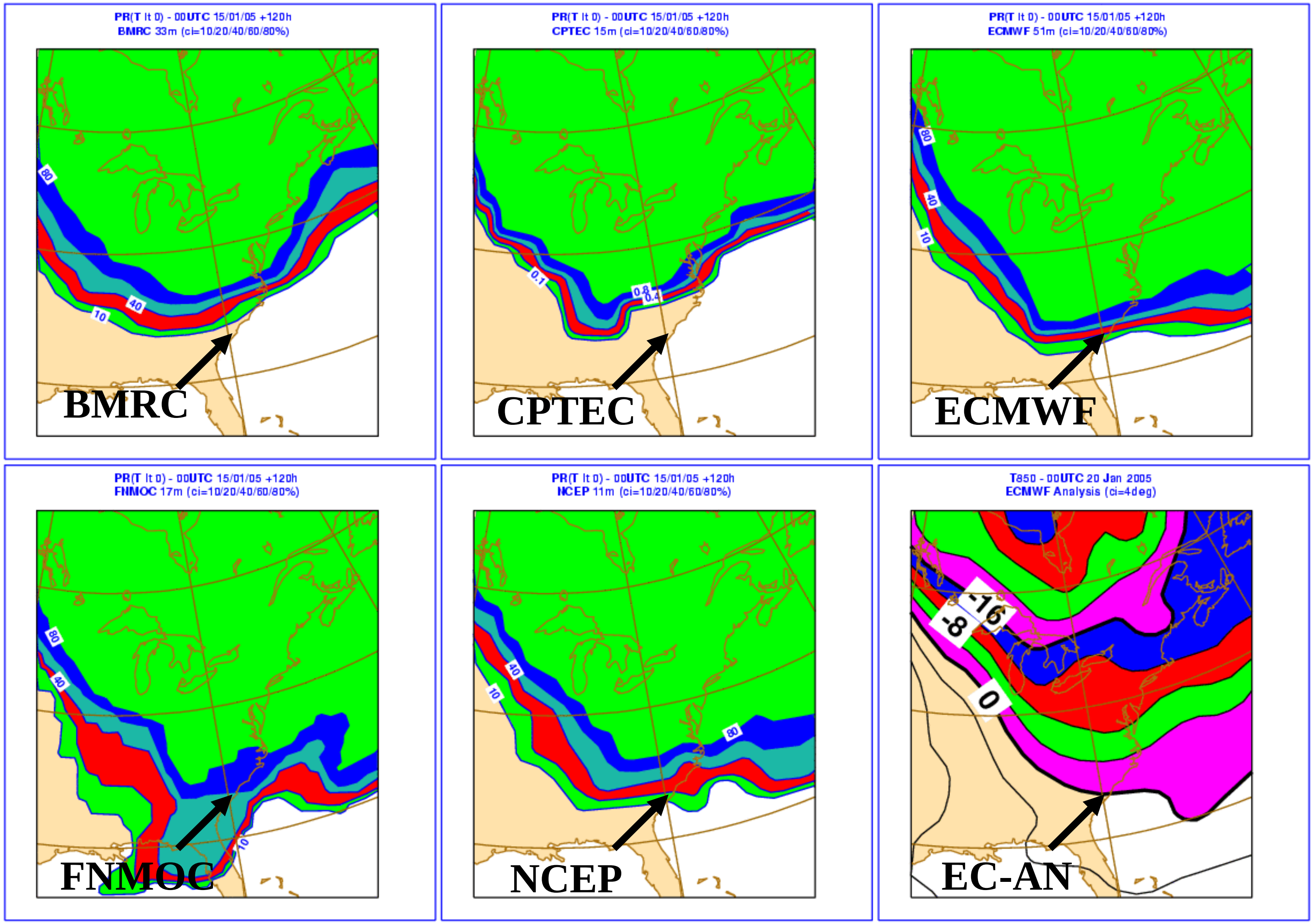
4. π_{T850}(00,120h) from 5 systems

US: 120h forecast probability of T850<0 degrees.

What is the PR(T850<0) at ~33°N?

*BMRC/CPTEC gives 0%, ECMWF/NCEP 10% and FNMOC 50%.**

** This is just one case: probability forecasts should be verified on a large dataset.*



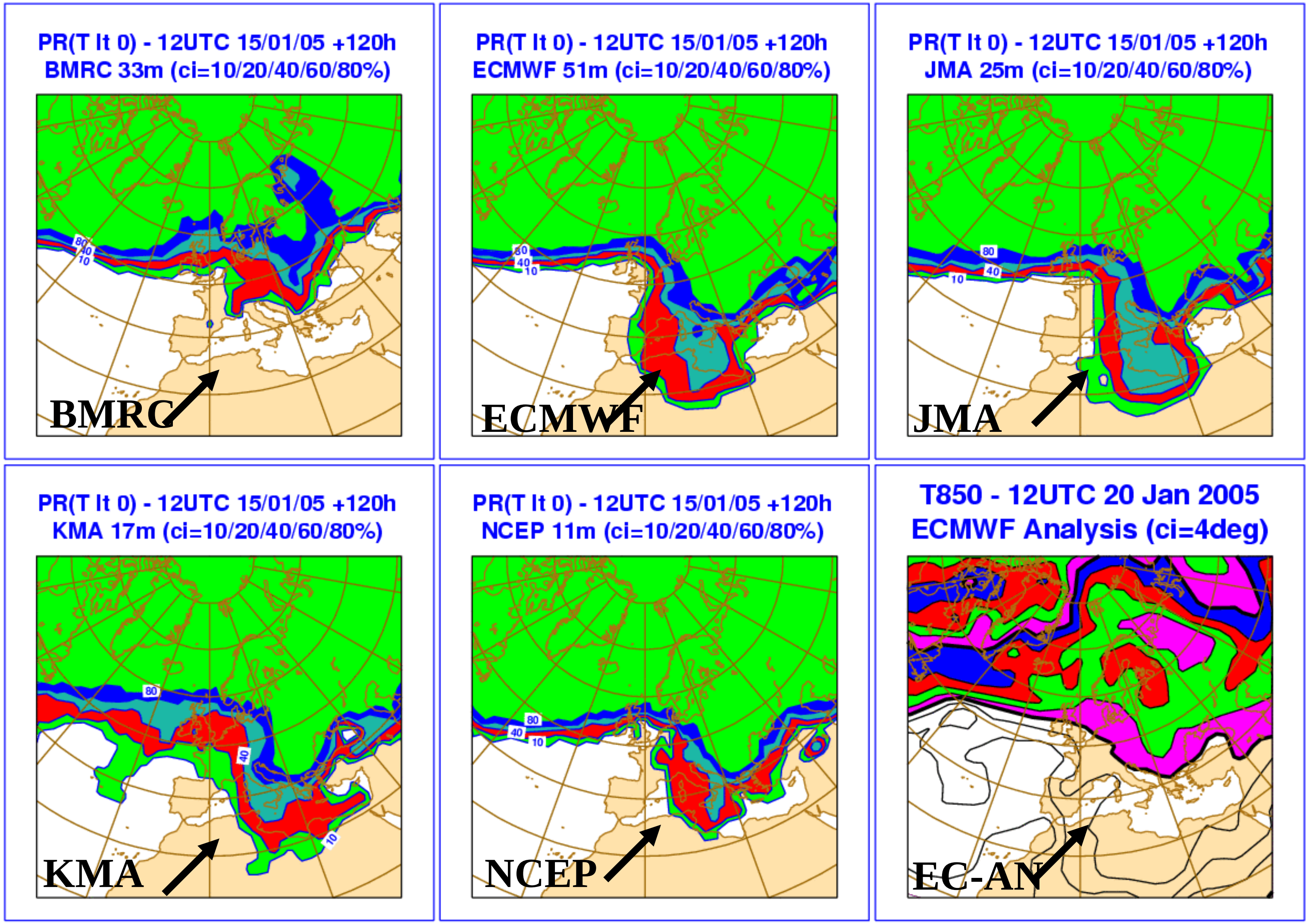
4. π_{T850}(12,120h) from 5 systems

Europe: 120h forecast probability of T850<0 degrees.

What is the PR(T850<0) in Tunisia?

*BMRC gives a zero probability.**

** This is just one case: probability forecasts should be verified on a large dataset.*



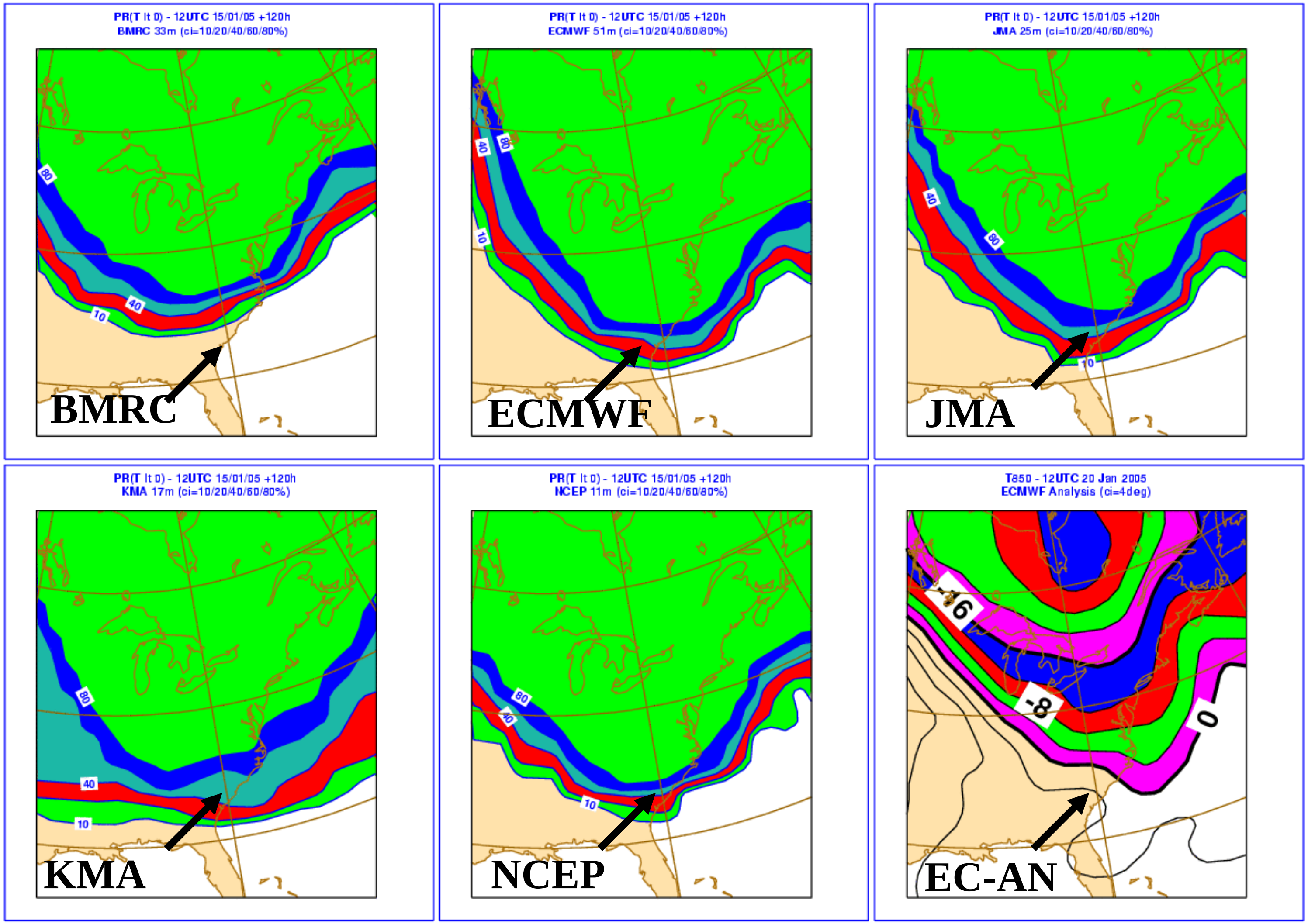
4. π_{T850}(12,120h) from 5 systems

US: 120h forecast probability of T850<0 degrees.

What is the probability of below freezing temperatures at ~33°N?

*BMRC gives zero probability, the others ~50%.**

** This is just one case: probability forecasts should be verified on a large dataset.*



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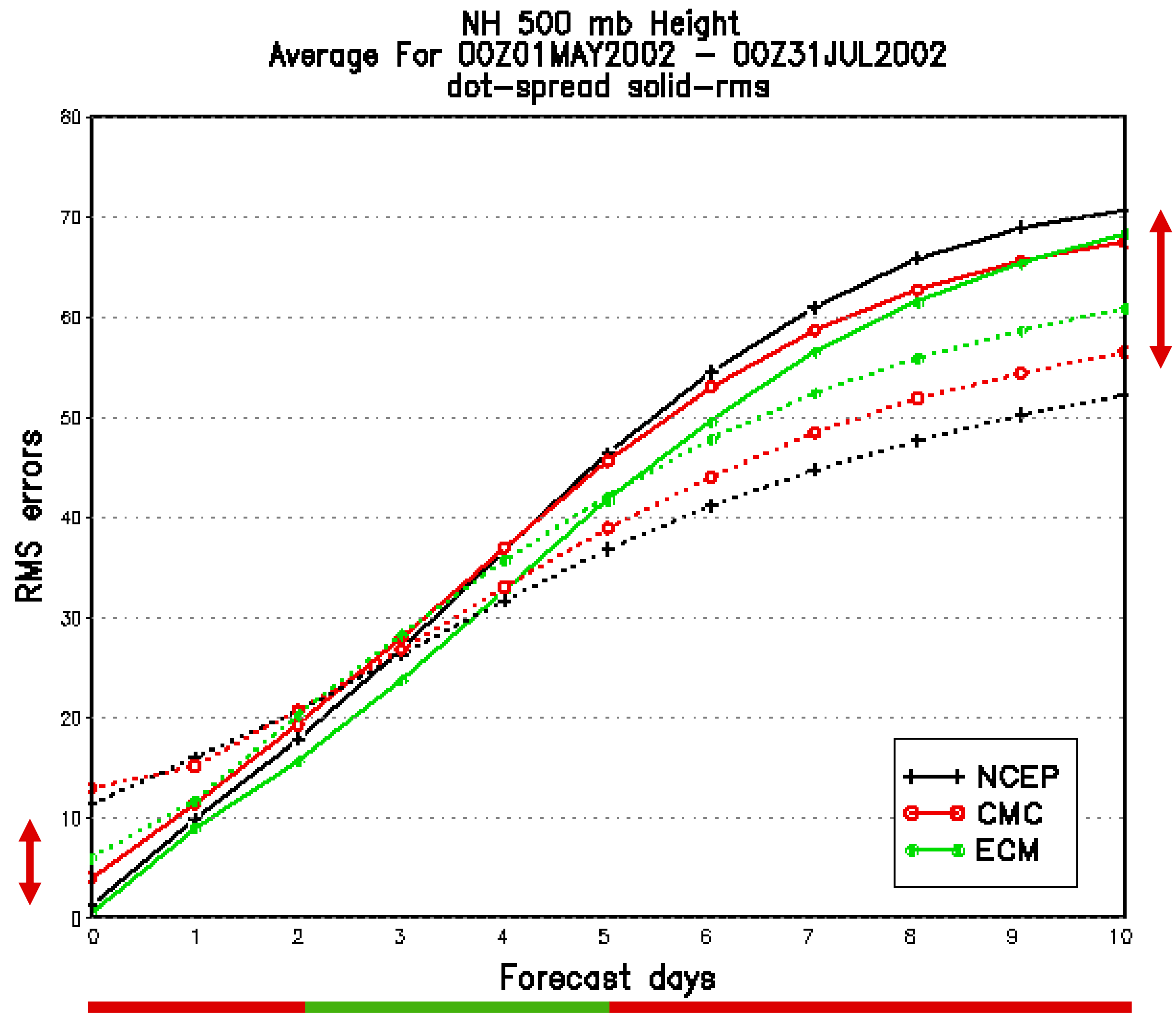
5. Open issues: the ensemble spread is still too little …

This figure shows the MJJ02 average ensemble-mean RMS error (solid) and the ensemble standard deviation (dotted lines) over NH.

The three ensembles have a well-tuned ensemble spread between day 2 and 4, but they have too much spread initially and too little spread in the medium-range.

This suggests that some sources of errors are not well simulated.



5. How are the 3 centers going to improve their systems?

These are the methods/approaches that could be used to improve our systems:

- Model errors – By combining different models (eg NAEFS, TIGGE); by developing new stochastic schemes (eg MSC, NCEP, ECMWF); by using BCs from different models in regional ensemble systems (eg DWD Germany, IMS Spain)

- Observation errors – By estimating more accurately observation correlation errors (MSC); by testing ensemble data assimilation methods (eg ECMWF)

- Imperfect boundary conditions – By perturbing soil moisture (eg NCEP SREF)

- Data assimilation assumptions – By improving the simulation of observation biases (eg MSC) ?

5. Some more open issues in ensemble prediction

- Is random or selective sampling more beneficial?

  Possible convergence into coupling of data-assimilation and ensemble.

- How can ensemble data-assimilation and ensemble prediction be coupled?

  Area of intense research.

- Is optimisation necessary?

  Area of discussion.

- How should model error be simulated?

  Need for simulating both random and systematic errors.

- Is having a larger ensemble size or a higher resolution model more important?

  Practical considerations, user needs, post-processing will determine the answer.

Acknowledgements

The success of the ECMWF EPS is the result of the continuous work of ECMWF staff, consultants and visitors who had continuously improved the ECMWF model, analysis, diagnostic and technical systems, and of very successful collaborations with its member states and other international institutions.

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