Sources of uncertainty
(EC/TC/PR/RB-L1)

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Abstract and key learning points

The aim of this session is to introduce the main sources of uncertainty that lead to forecast errors. The weather prediction problem will be discussed, and stated in terms of an appropriate probability density function (PDF). The concept of ensemble prediction based on a finite number of integration will be introduced, and the reason why it is the only feasible method to predict the PDF beyond the range of linear growth will be illustrated.

By the end of the session you should be able to:

- explain which are the main sources of forecast error
- illustrate why numerical prediction should be stated in probabilistic terms
- describe the rationale behind ensemble prediction

Outline

1. The Numerical Weather Prediction (NWP) problem
2. Sources of forecast uncertainties and chaotic behaviour
3. Ensemble prediction as a practical tool for probabilistic prediction
4. The ECMWF medium-range/monthly ensemble

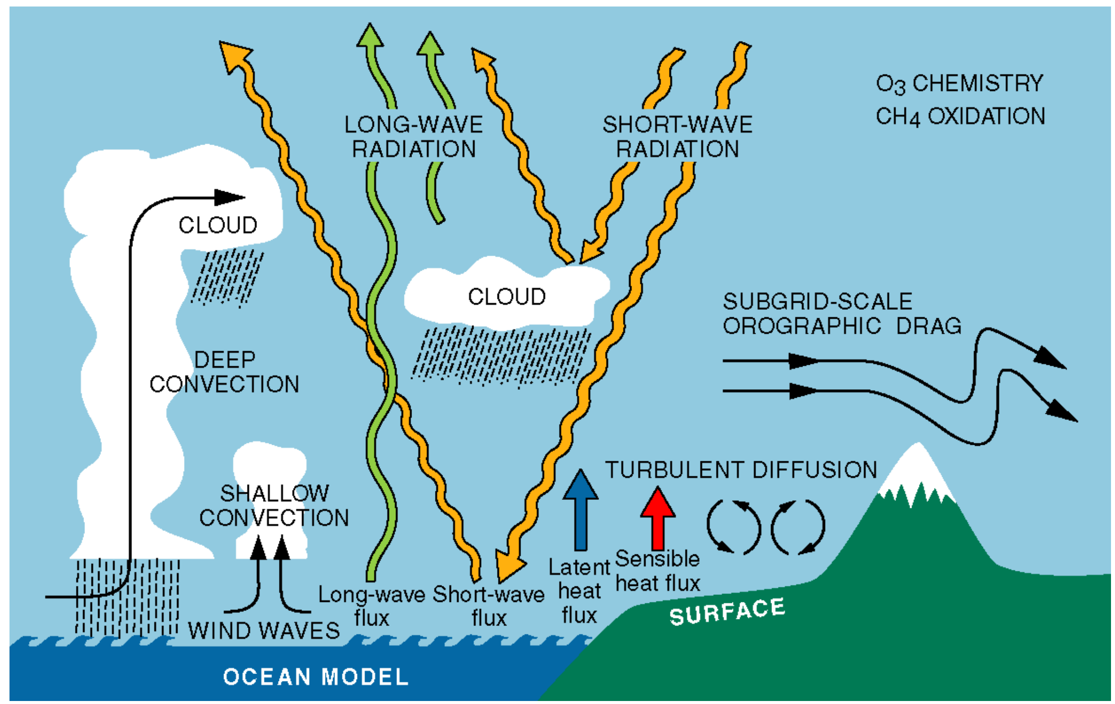
1. Numerical Weather Prediction (NWP) models

The behavior of the atmosphere is governed by a set of physical laws that express how the air moves, the process of heating and cooling, the role of moisture, and so on.

Interactions between the atmosphere and the underlying land and ocean are important in determining the weather.

ECMWF MODEL / ASSIMILATION SYSTEM

ATMOSPHERE	STRATOSPHERE	DYNAMICS–RADIATION–SIMPLIFIED CHEMISTRY		
	TROPOSPHERE	DYNAMICS–RADIATION–CLOUDS–ENERGY & WATER CYCLE		
OCEAN / LAND		OCEAN	LAND HYDROSPHERE	LAND BIOSPHERE
		OCEAN SURFACE WAVES OCEAN CIRCULATION SIMPLIFIED SEA ICE	SNOW ON LAND SOIL MOISTURE FREEZING	LAND SURFACE PROCESSES SOIL MOISTURE PROCESSES SIMPLIFIED VEGETATION



1. Numerical Weather Prediction (NWP) models

Momentum conservation

$$\frac{d\vec{v}}{dt} = -2\cdot\vec{\Omega}\times\vec{v} - \frac{1}{\rho}\vec{\nabla}p + \vec{g} + \vec{P}_v$$

Energy conservation

$$\frac{dT}{dt} = \frac{R\cdot T\cdot\omega}{c_p p_s \sigma} + P_T$$

Water vapour conservation

$$\frac{dq}{dt} = P_q$$

Mass conservation

$$\frac{dp_s}{dt} = p_s\cdot\left(\vec{\nabla}\cdot\vec{v} + \frac{d}{d\sigma}\frac{d\sigma}{dt}\right)$$

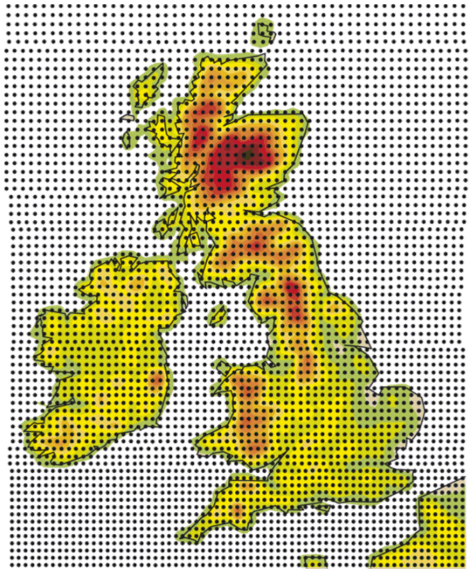
Hydrostatic balance

$$\frac{d\Phi}{d\sigma} = -\frac{R\cdot T}{\sigma}$$

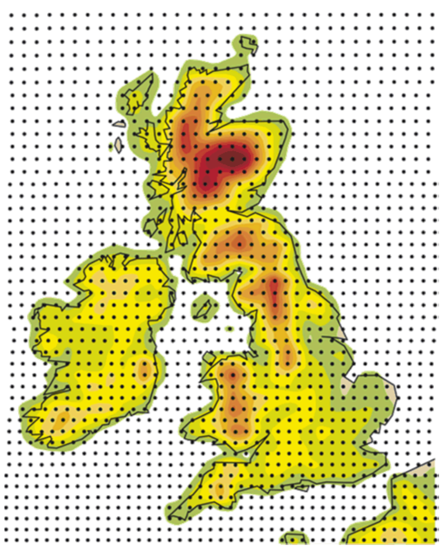
These terms represent the effect of clouds, mountains, radiation, vegetation, waves, …

1. Model grid & v-levs of the T1279/T639 models

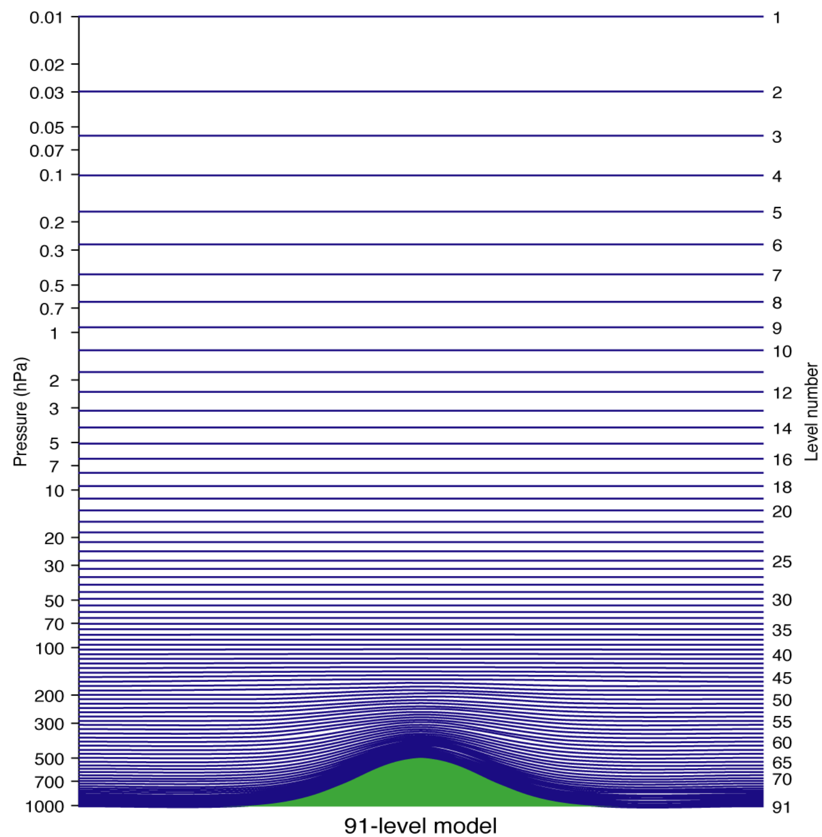
T_L1279
(HRES)



T_L639
(ENS)



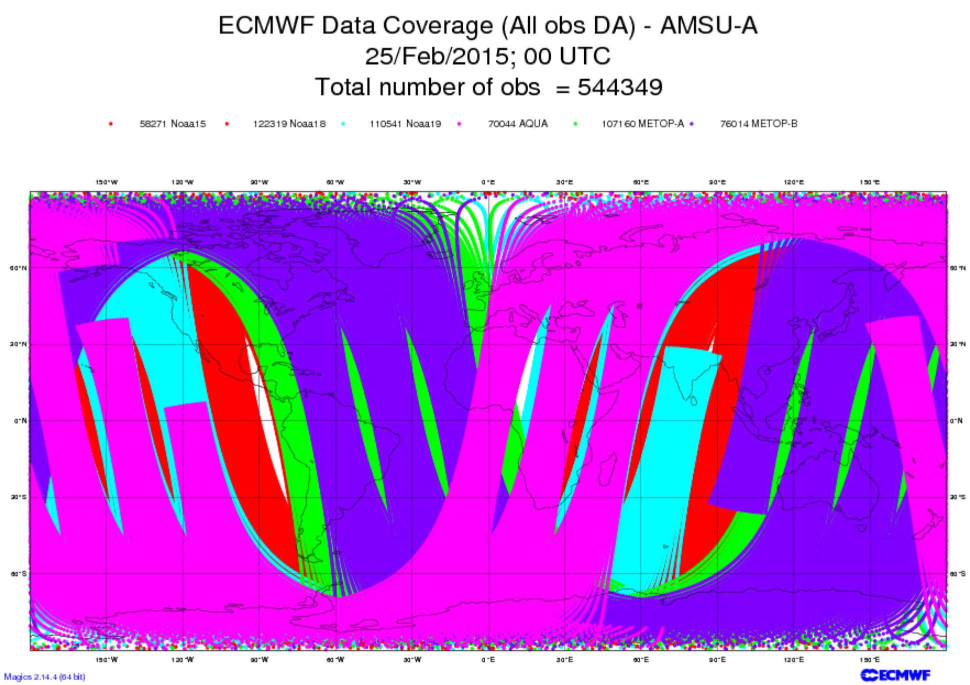
L91
(ENS)

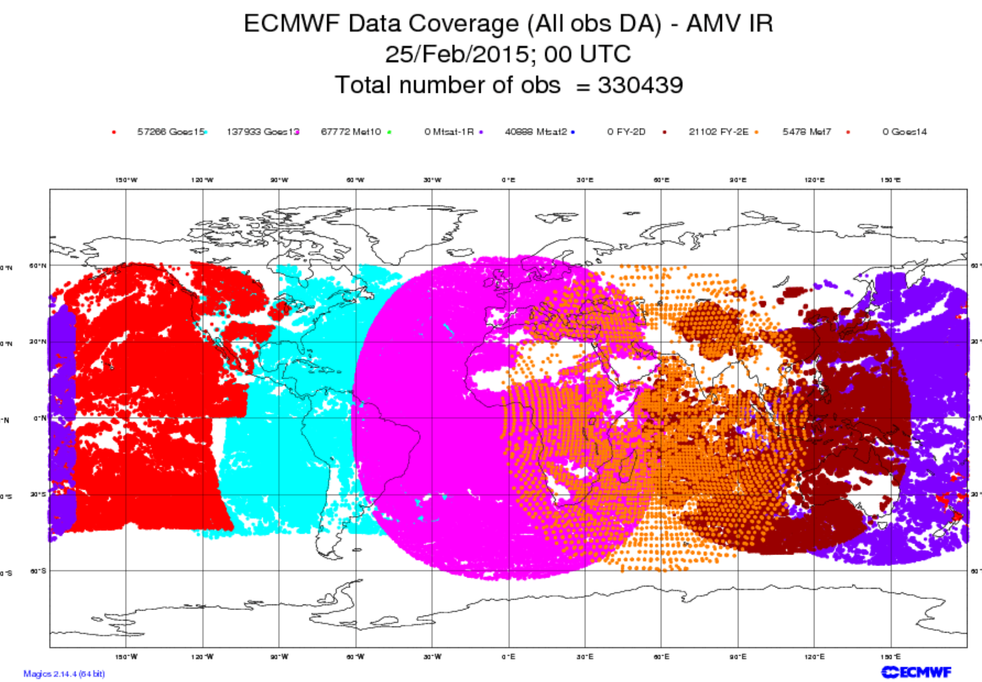


1. Observations coverage and accuracy

To make accurate forecasts it is important to know the current weather:

- ~ 155M obs (99% from satellites) are received daily;
- ~ 15M obs (96% from satellites) are used every 12 hours.





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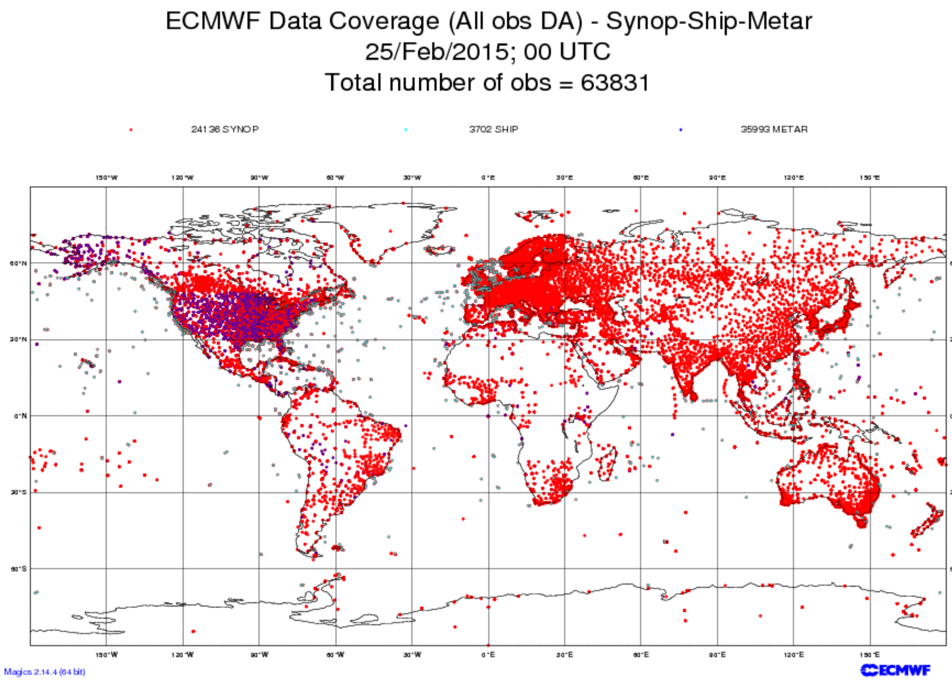
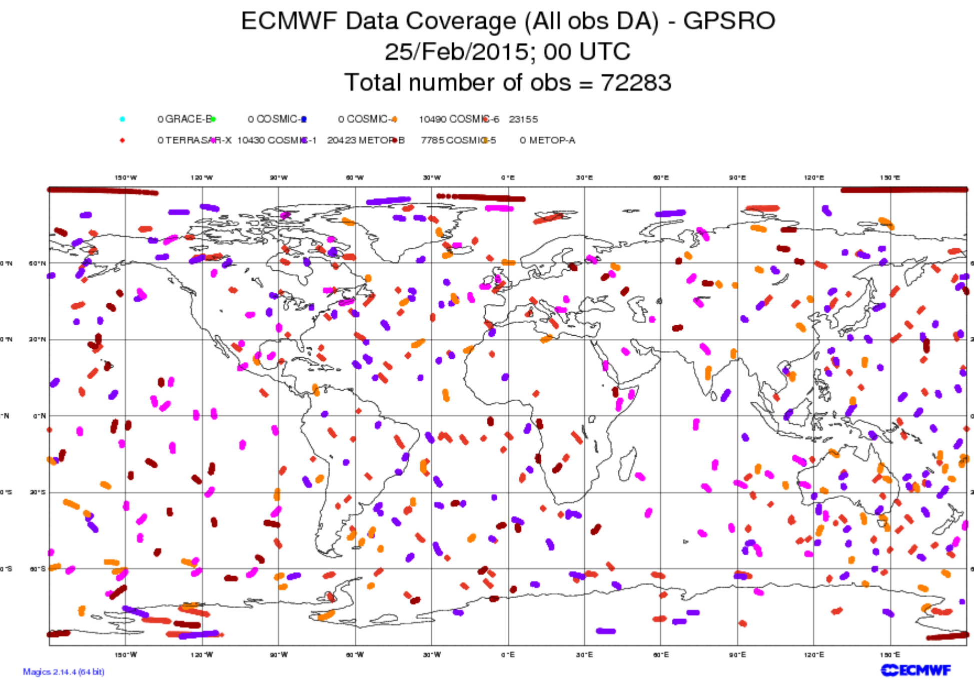
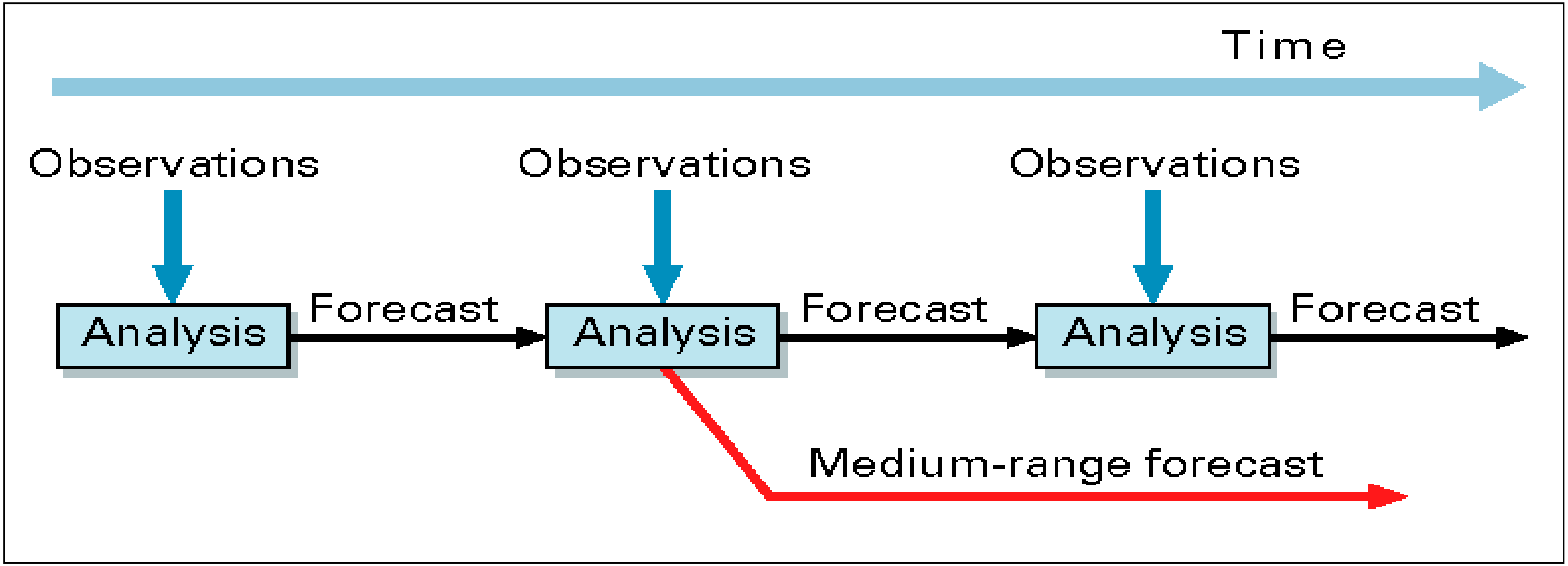


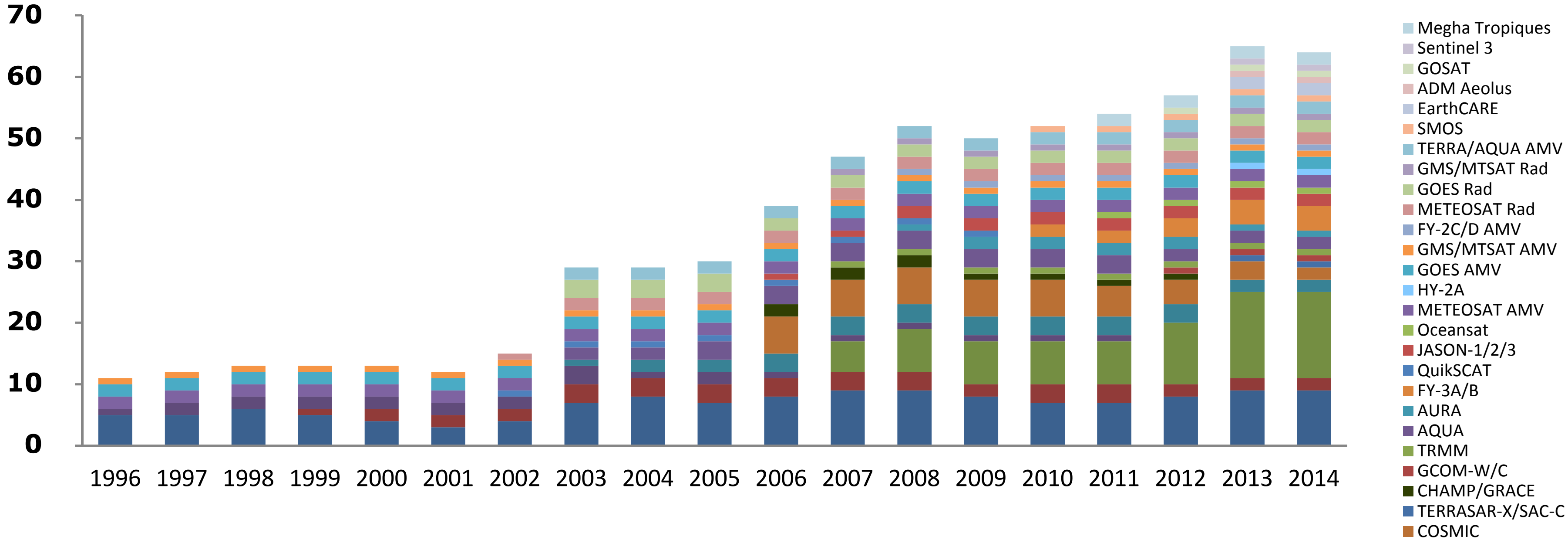


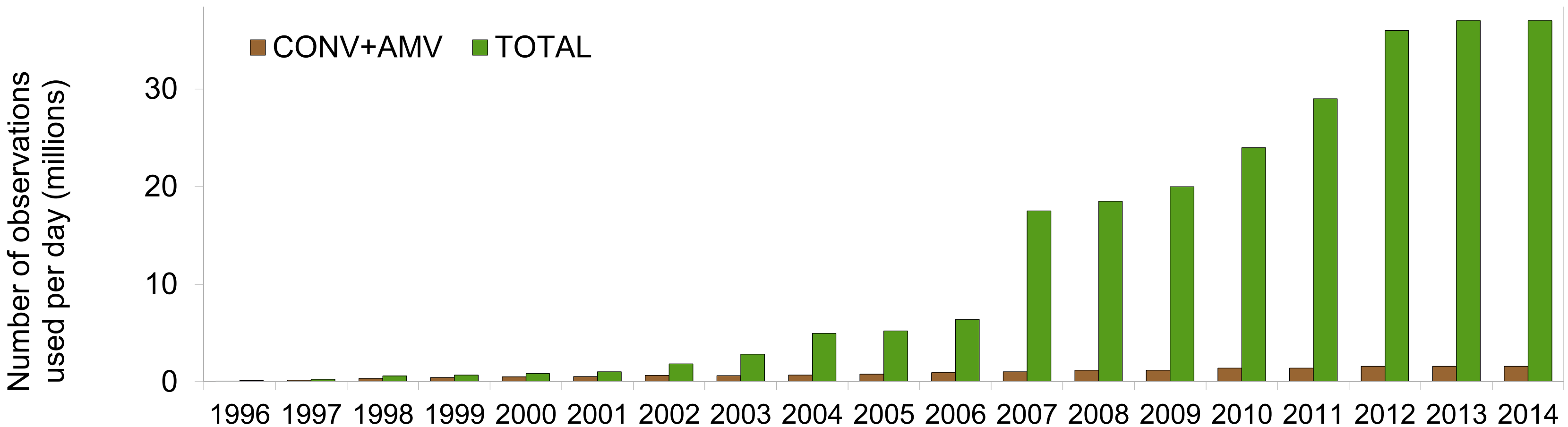
1. Obs are assimilated to estimate the initial state



- Observations are used to correct errors in the short forecast from the previous analysis time
- Every 12 hours ~ 15M observations are assimilated to correct the 100M variables that define the model's virtual atmosphere
- The assimilation relies on the quality of the model

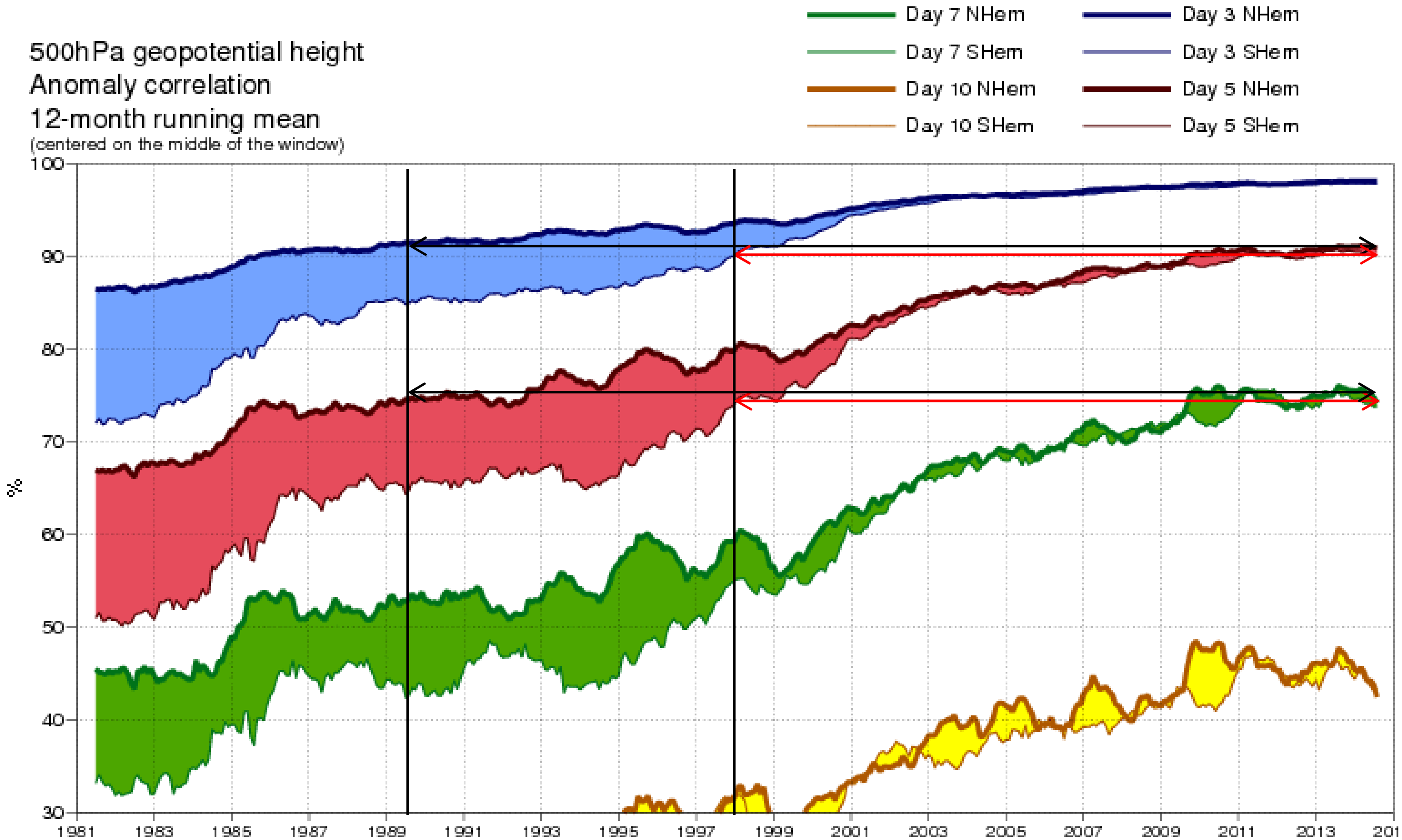
1. Satellite data used at ECMWF





1. Forecast improvements over NH and SH for Z500

Improved models and data-assimilation systems, larger number of satellite observations and increased computer power contributed to forecast improvements, and a reduction of the gap between NH and SH scores.



NH: 2d/25y (2014-1989)

SH: 2d/16y (2014-1998)

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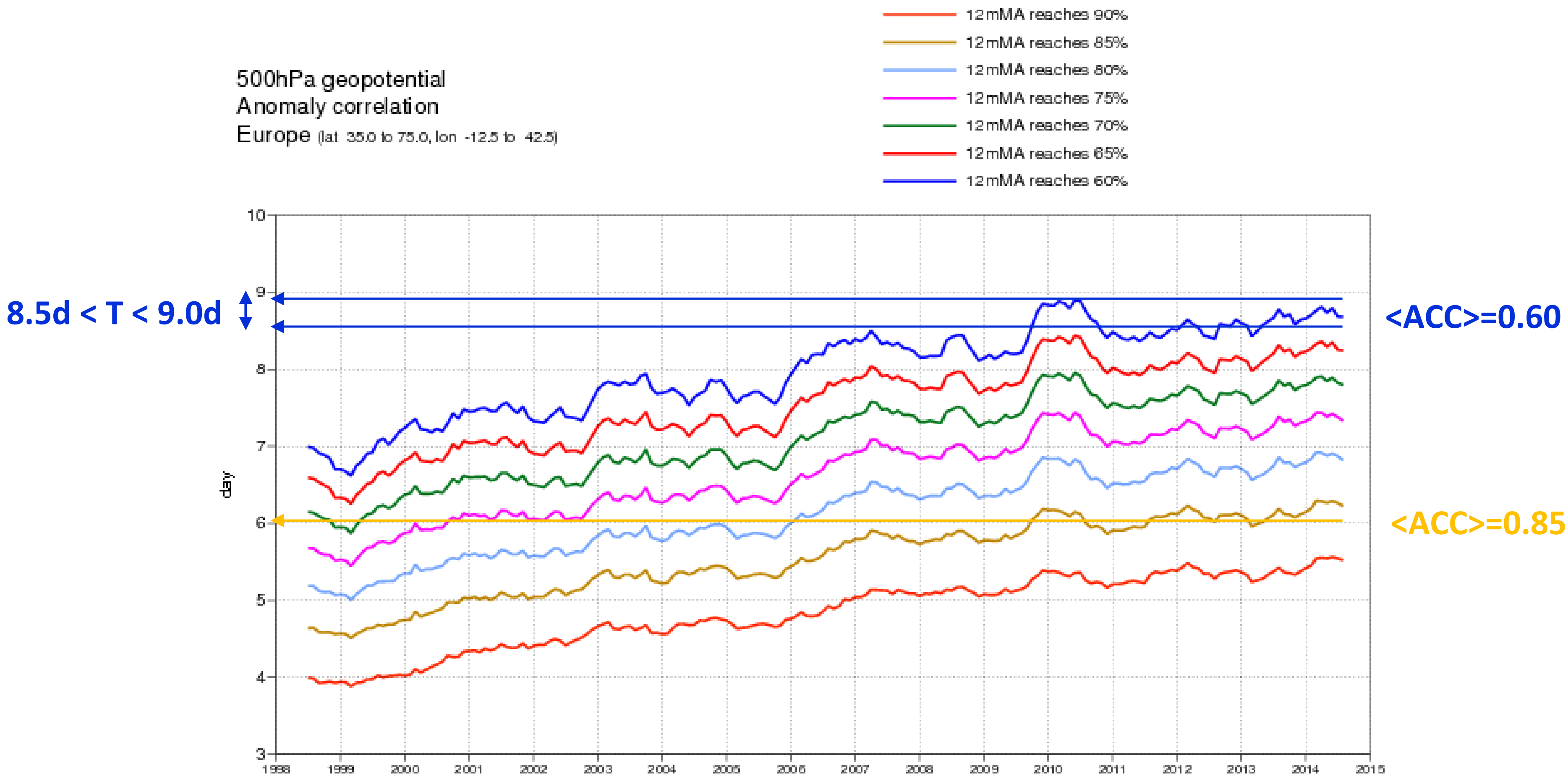
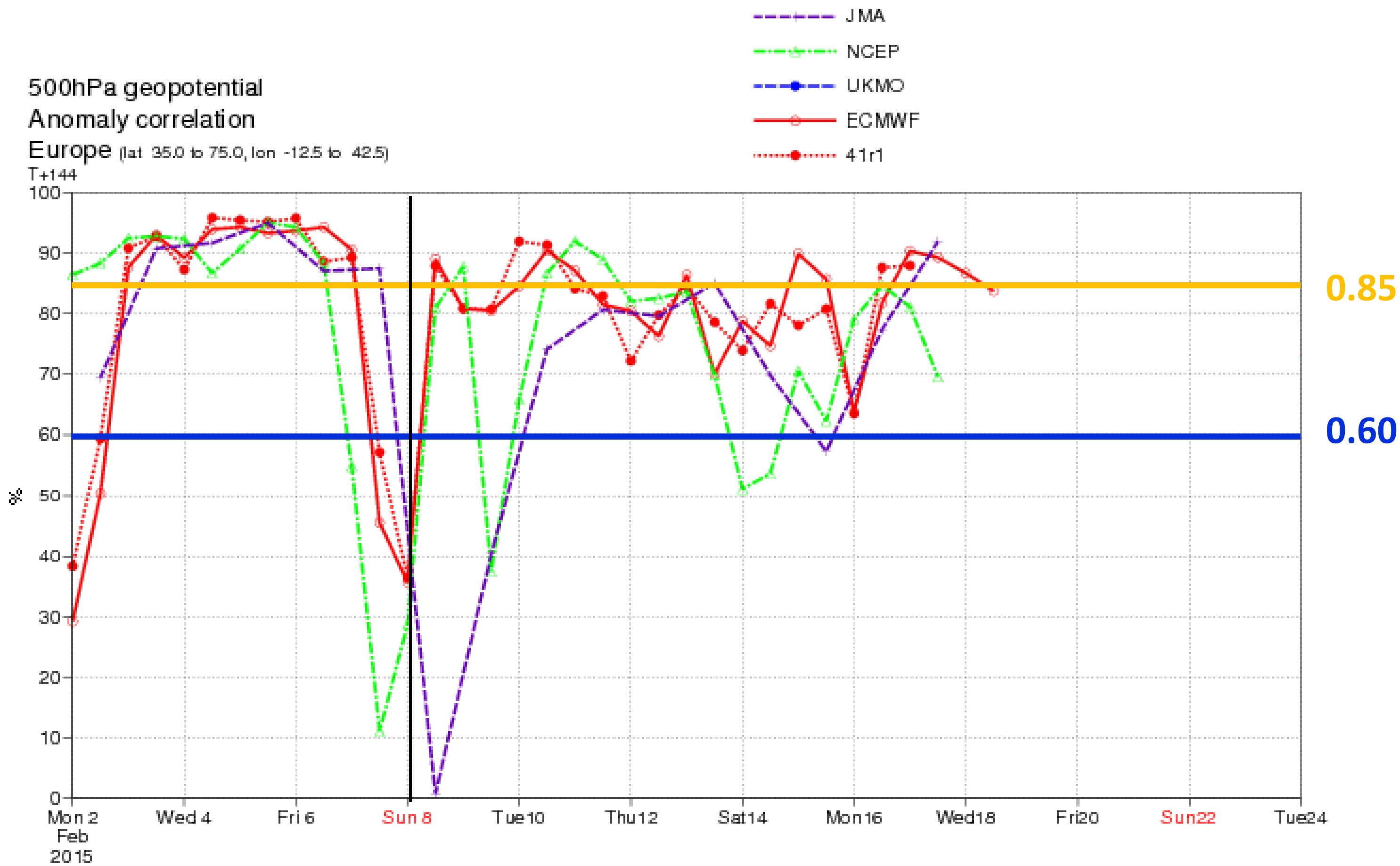
2. Forecast improvements over Europe for Z500

Over Europe, on average 6-day forecasts for Z500 have ACC of about 0.85, and forecasts have ACC of about 0.6 up to about 8.5-9 days.



2. February 2015: drop in forecast skill

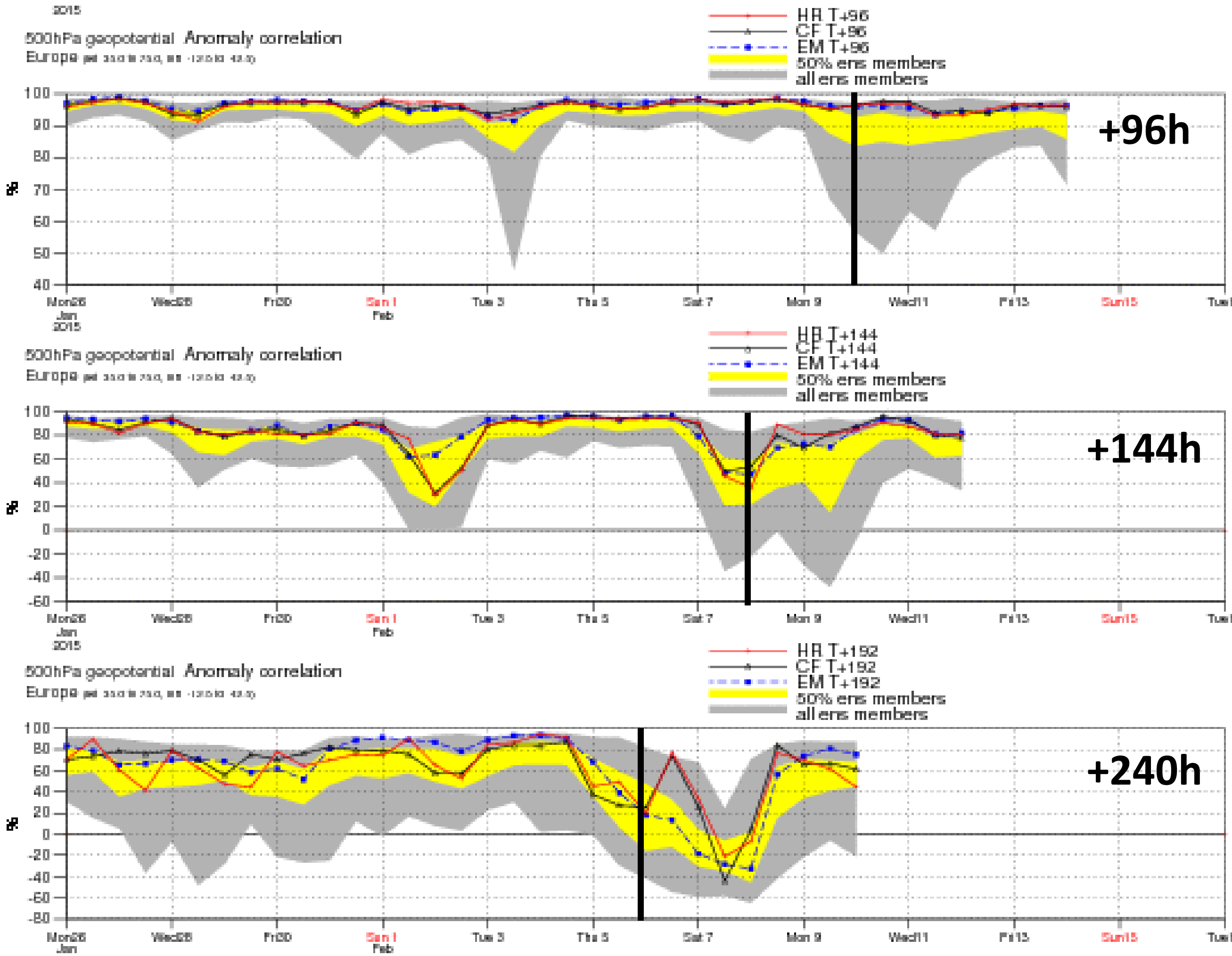
But on single cases we still see severe forecast busts. In February 2015, 6-day forecasts issued on the 2nd and the 8th had ACC of about 40%, much less than their average ACC value of 0.85.



2. February 2015: drop in forecast skill

Consider the t+144h forecasts issued on 8@00 and valid for 14@00 (middle): not only the HRES and the ENS-control, but also the whole ENS members showed a drop in skill. This can be detected also 2 days earlier (bottom) and later (top).

This unpredictable situation was flagged by the ENS, which showed a very large spread.



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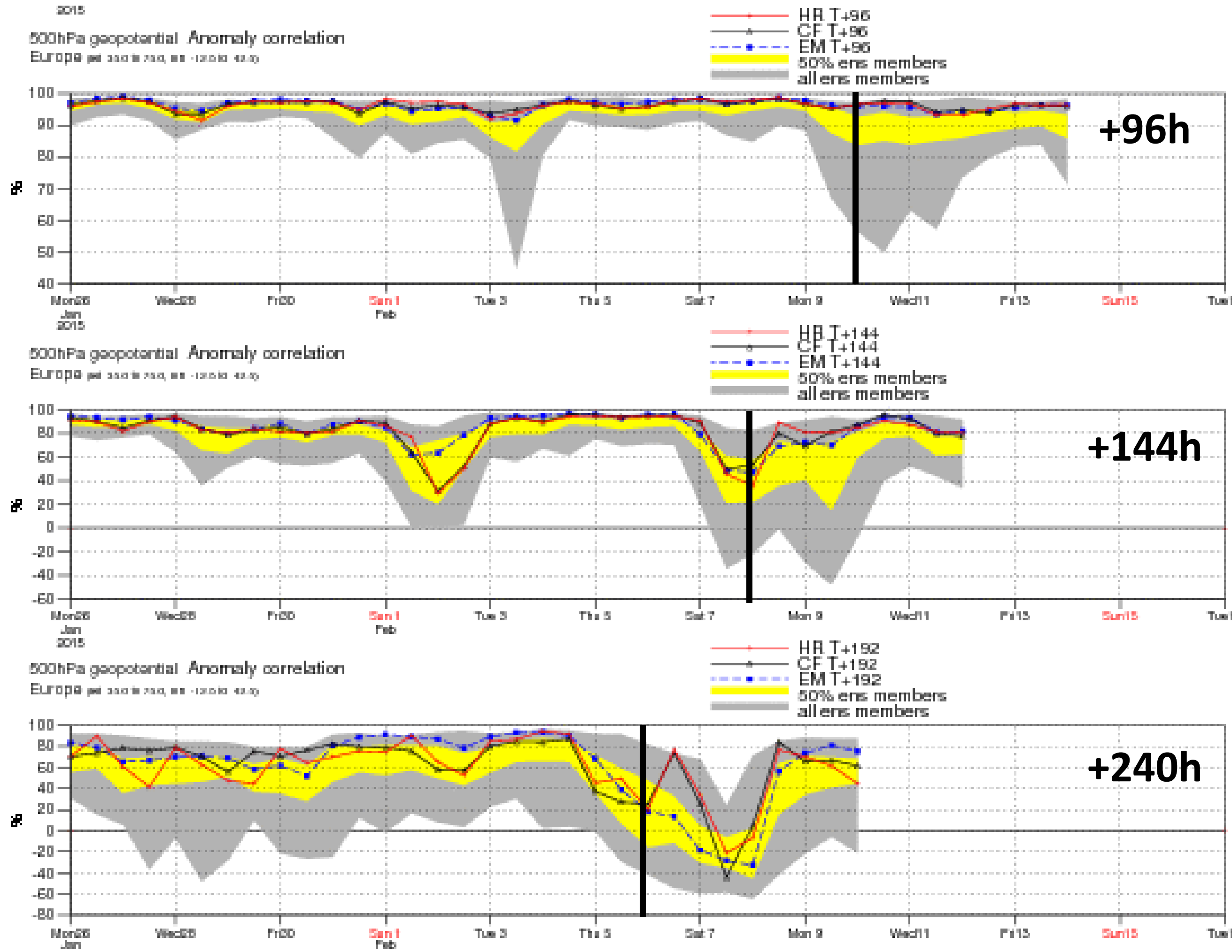


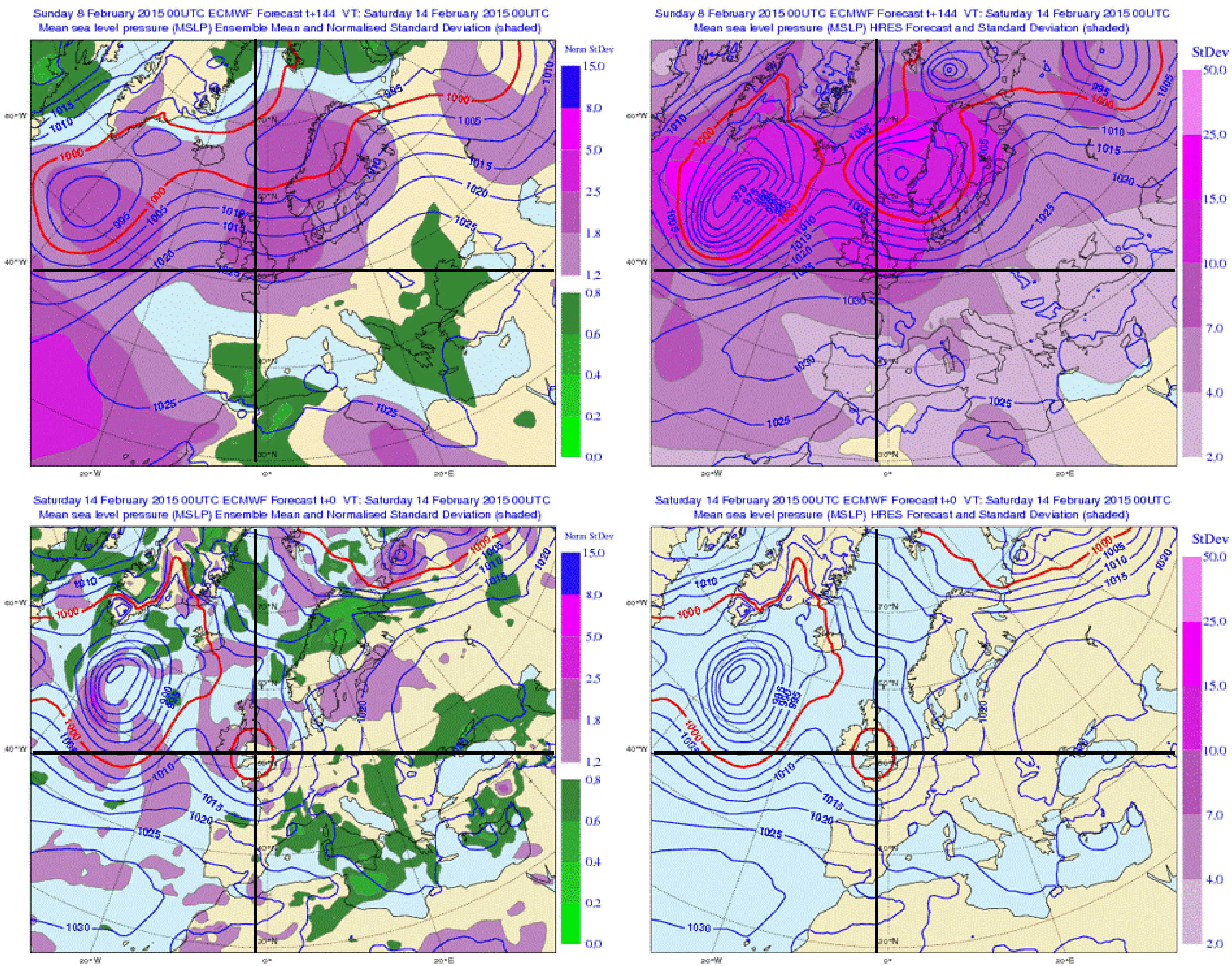
2. February 2015: drop in forecast skill

08@00+6d
<ENS>+NSTD

08@00+6d
HRES+STD

14@00
<ENS>+NSTD

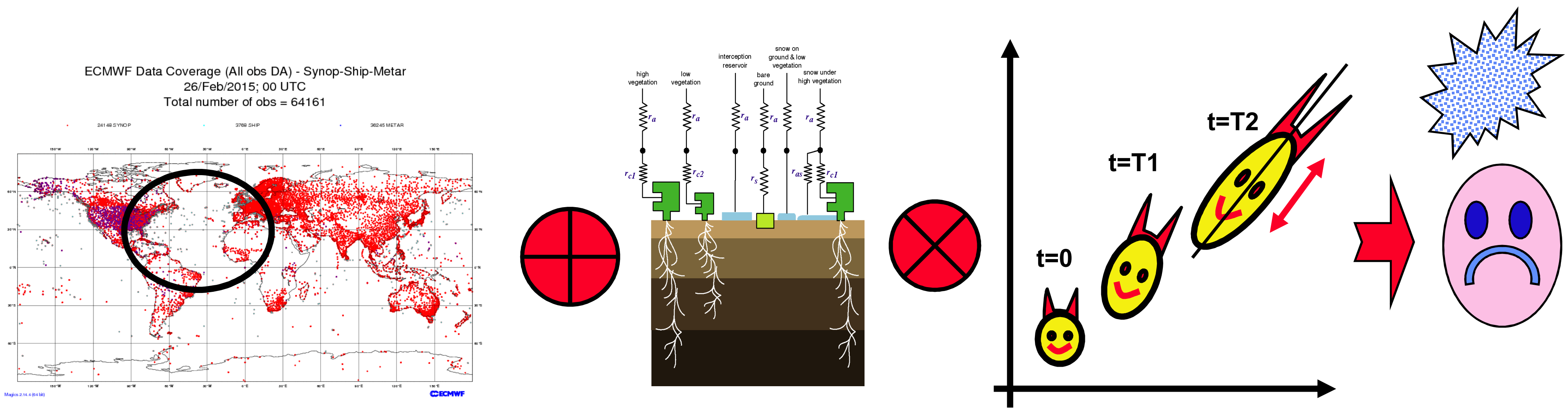
14@00
HRES+STD



2. Why do forecasts fail?

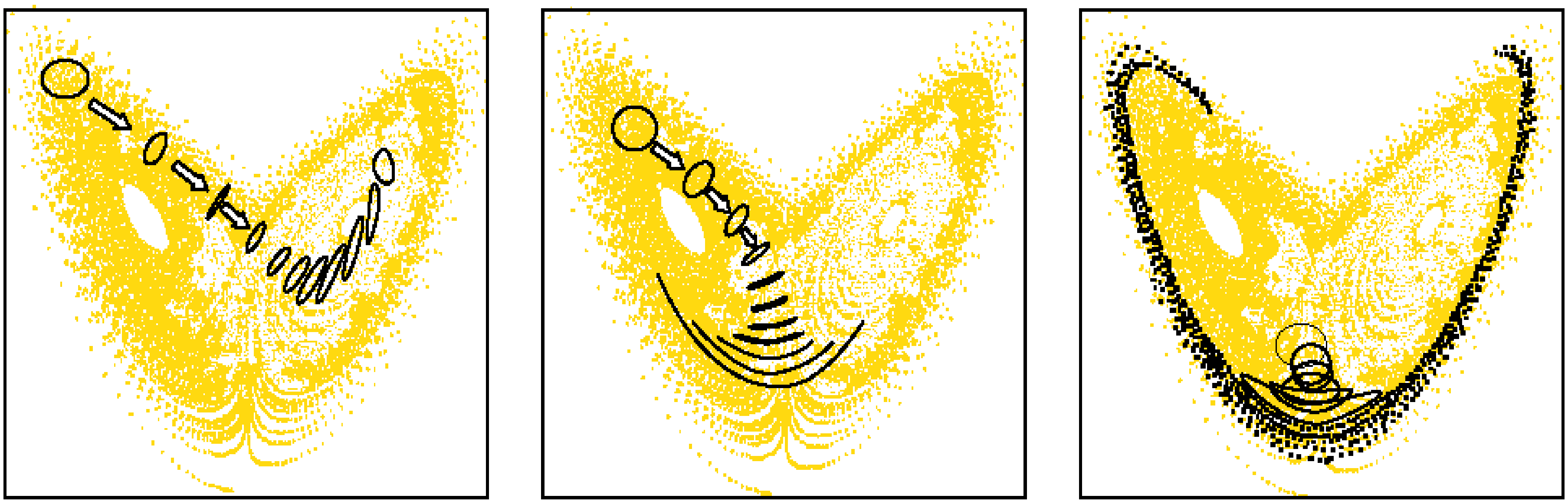
Forecasts can fail because:

- The initial conditions are not accurate enough, e.g. due to poor coverage and/or observation errors, or errors in the assimilation (initial uncertainties).
- The model used to assimilate the data and to make the forecast describes only in an approximate way the true atmospheric phenomena (model uncertainties).



2. The atmosphere chaotic behavior

Furthermore, the **atmosphere is a chaotic system**, with flow-dependent errors growth. This was illustrated for the first time by Edward Lorenz, with his 3-dimensional model.



Outline

1. The Numerical Weather Prediction (NWP) problem
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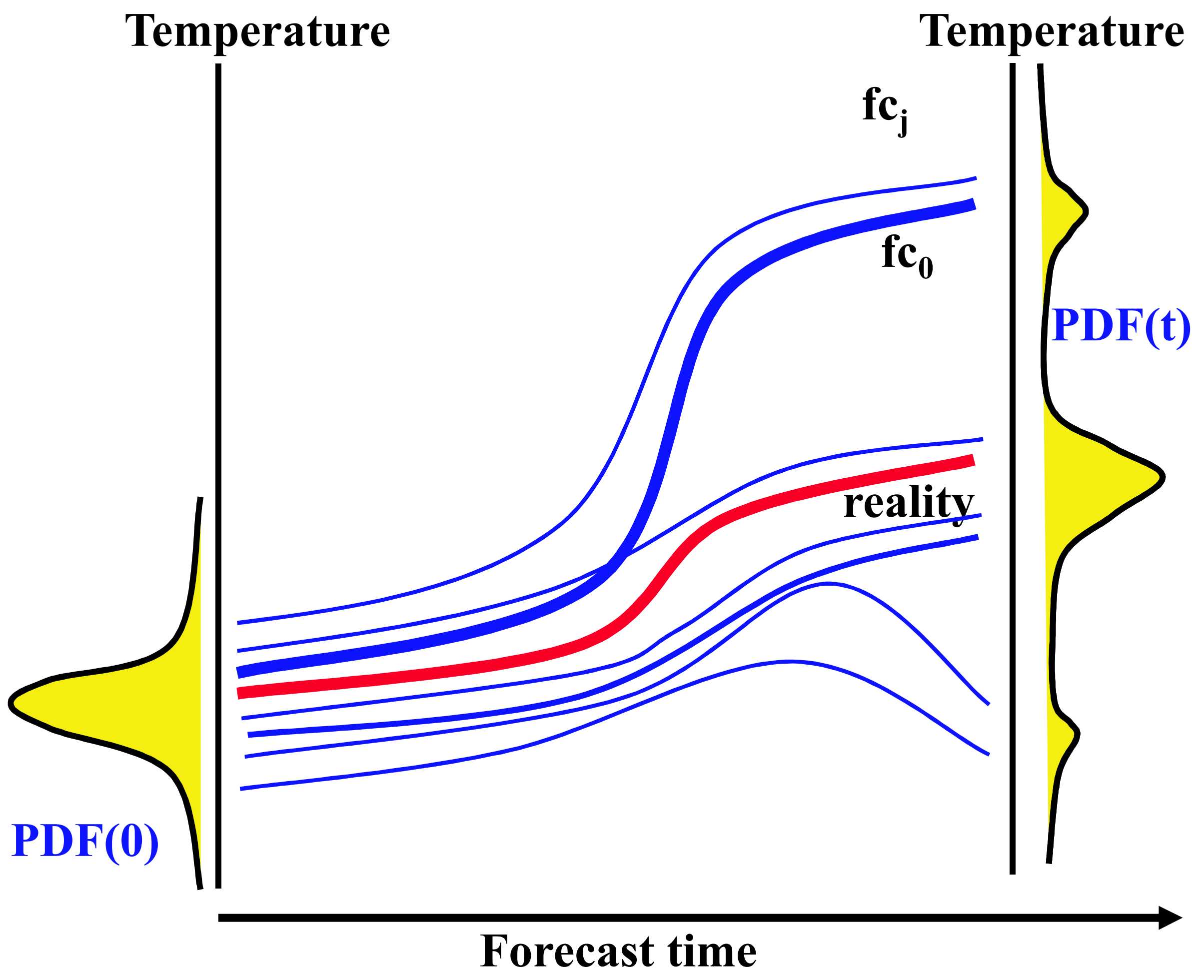
3. What is the aim of weather forecasting?

We have seen that single forecasts can fail due to a combination of **initial** and **model uncertainties**, and that the NWP problem is made extremely complex by the **chaotic nature of the atmosphere**.

- Does it make sense to issue single forecasts?
- Can something better be done?
- More generally, what is the aim of weather forecasting?
- Should it be to predict only the most likely scenario, or should it aim to predict also its uncertainty, for example expressed in terms of weather scenarii or probabilities that different weather conditions can occur?

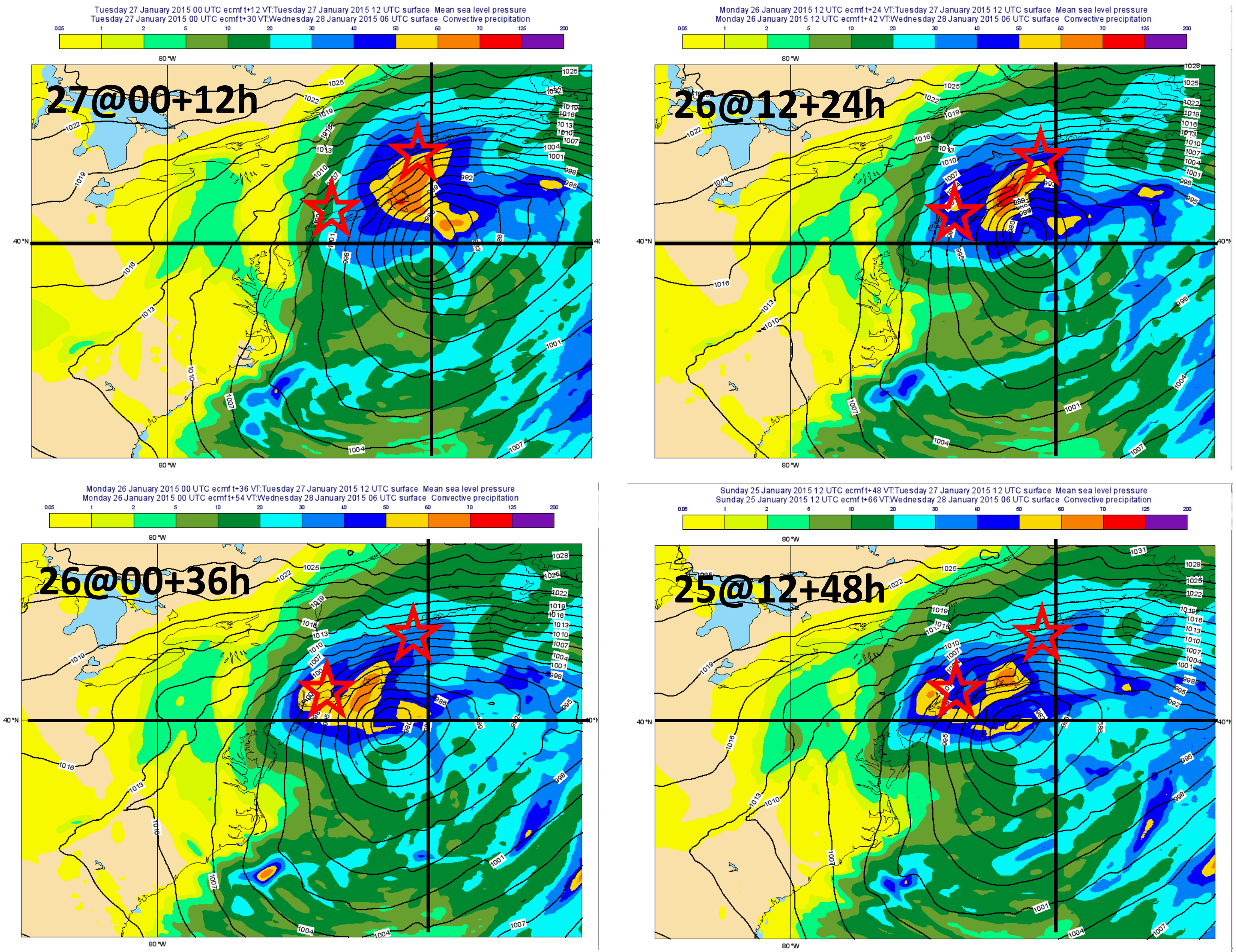
3. Ensemble prediction



3. US Storm, 27-28/01/2015: single HRES fc

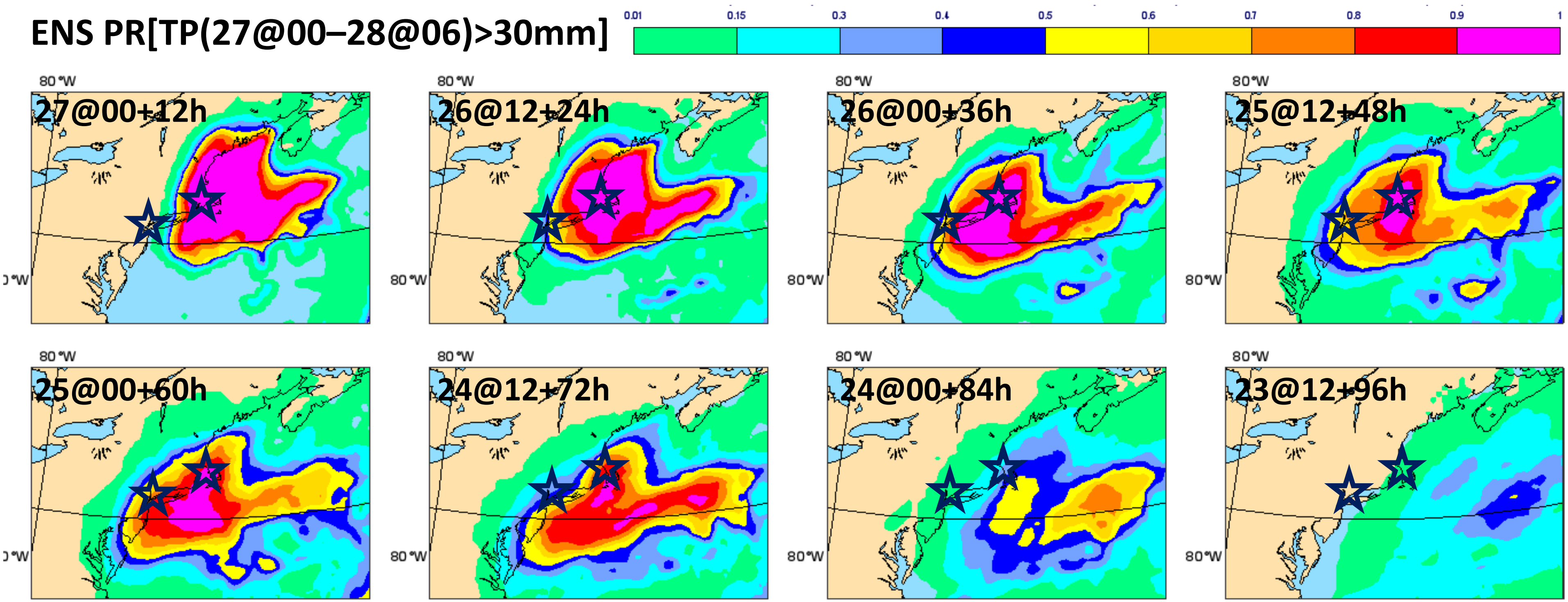
Single HRES fcs failed to positioned correctly the storm, and this lead to snowfall overestimation for NY of in the 24-36-48h forecasts.

MLSP+TP maps show a 150-200 km eastward shift in the storm centre.



3. US Storm, 27-28/01/2015: ENS PR fcs

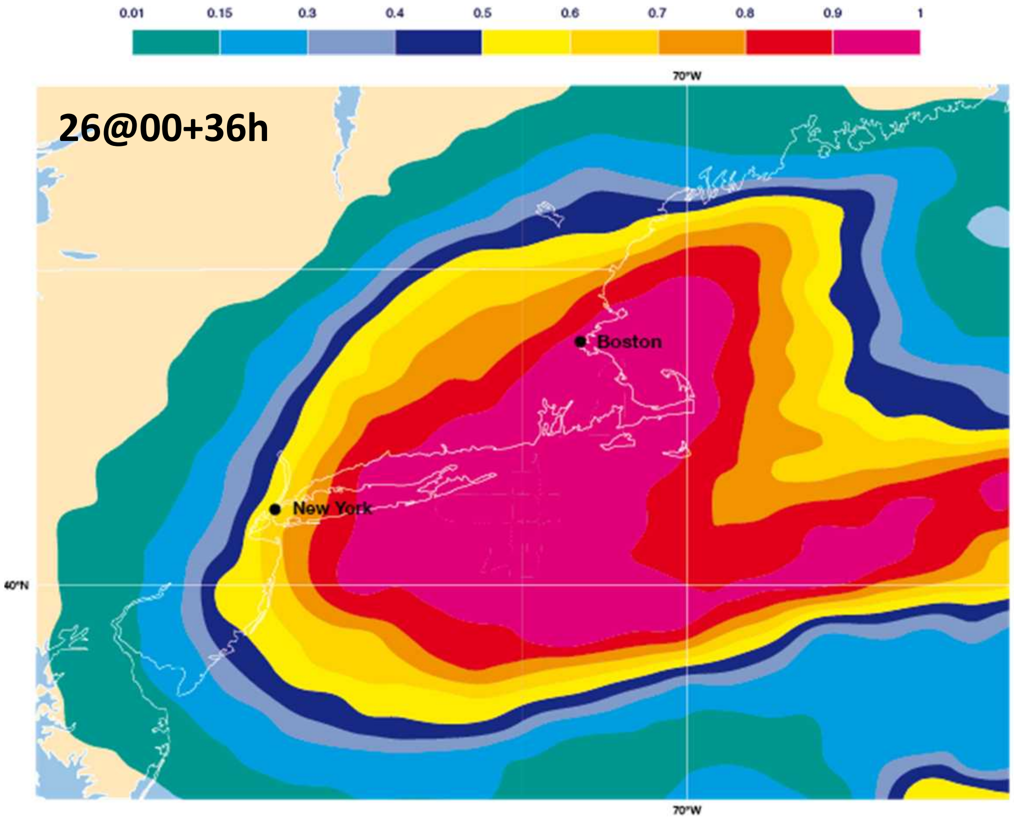
ENS-based probabilistic forecasts can be used to estimate the level of confidence (predictability) of single forecasts. They show that NY was closer to the edge of the area with high probability of more than 30mm of precipitation (between 27@00 and 28@06) than Boston, indicating higher uncertainty.

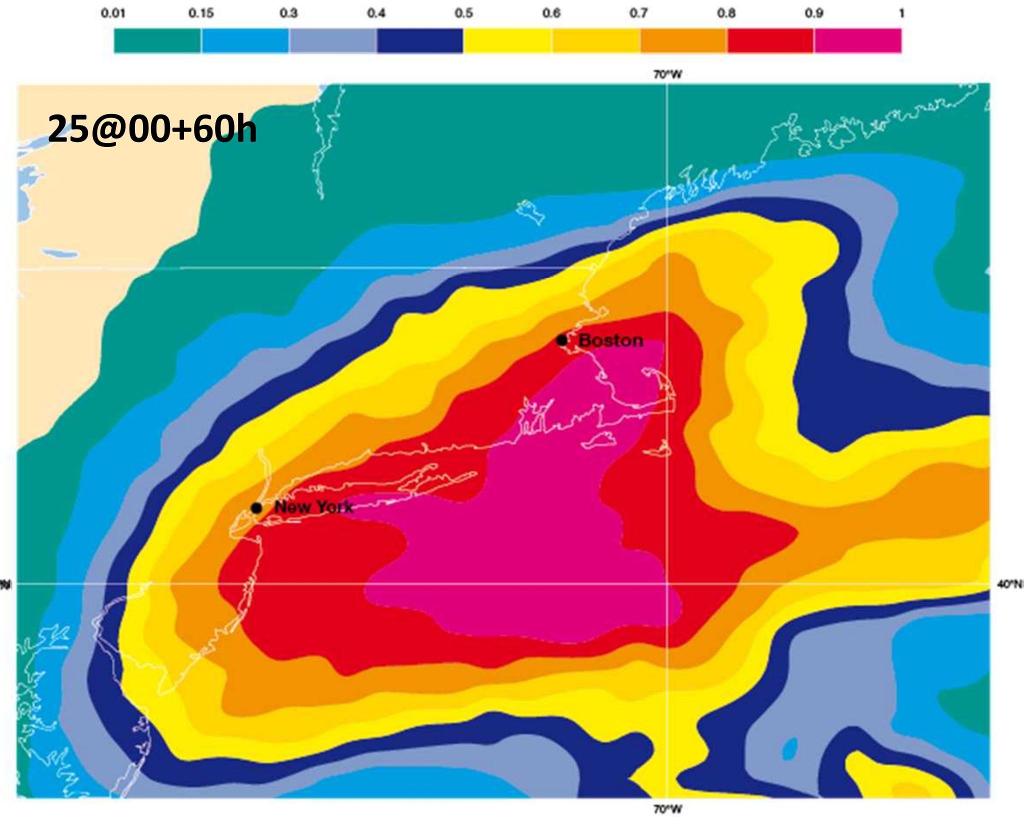


3. US Storm, 27-28/01/2015: ENS PR fcs

These figures show a larger version of the probability maps issued on 26@00 (left; t+36h) and 25@00 (right; t+60h).

ENS PR[TP(27@00–28@06)>30mm]

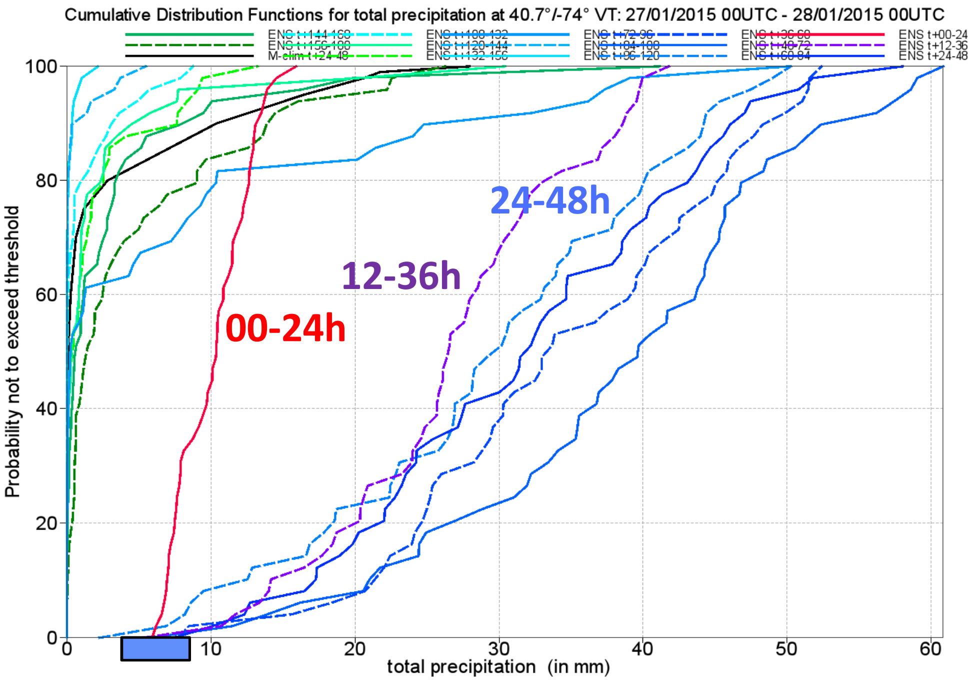




3. US Storm, 27-28/01/2015: ENS PR fcs

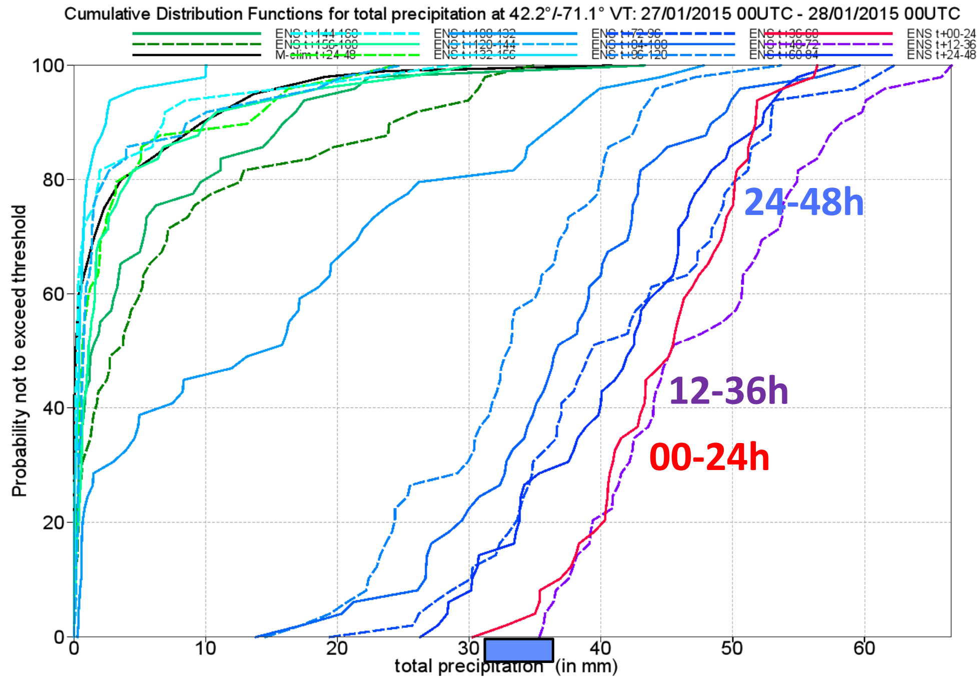
ENS-based probabilistic forecasts expressed in terms of CDF shows that the fcs for NY were more uncertain (the slope of the CDF curves is steeper) than the fcs for Boston.

New York



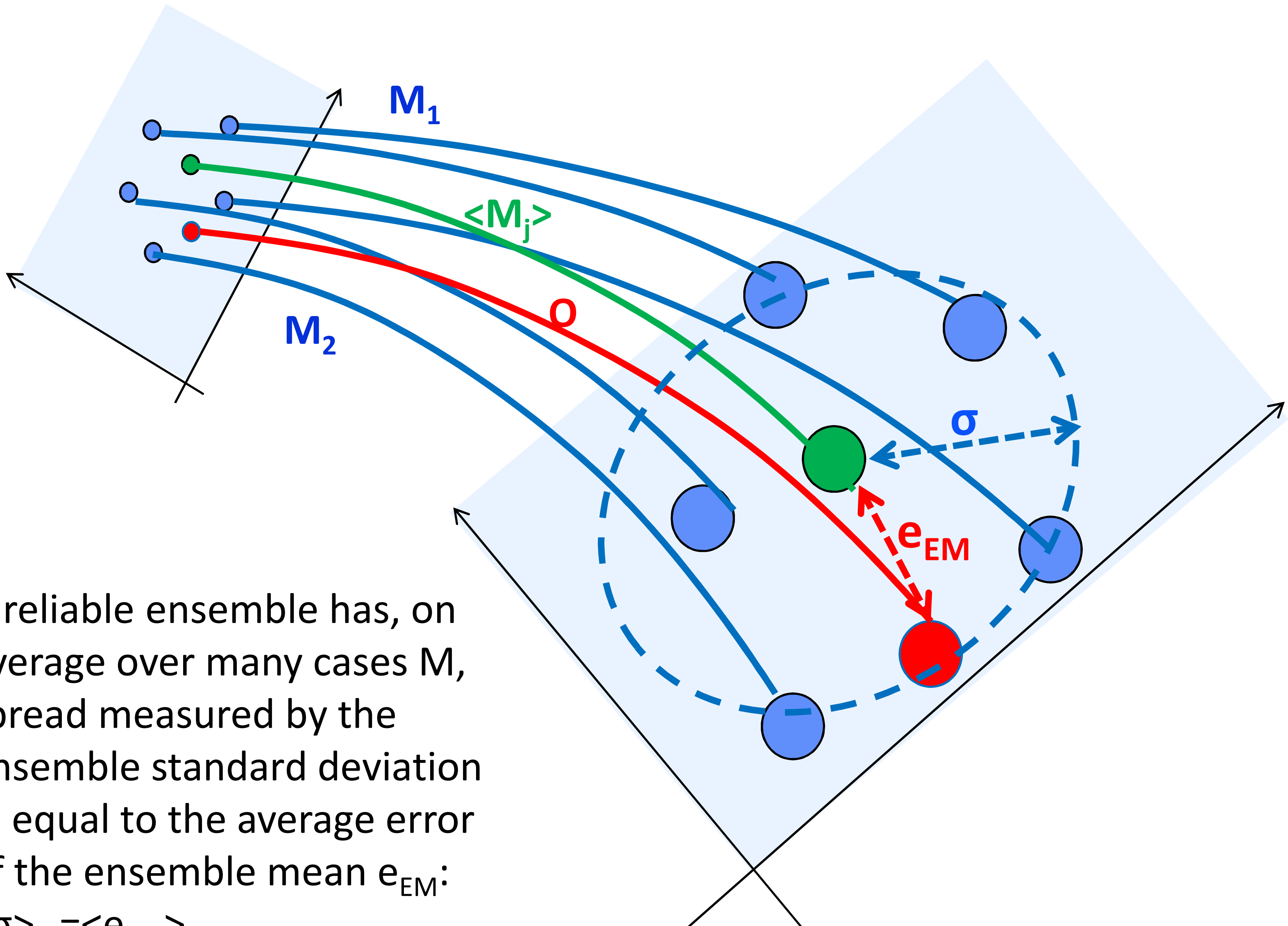
Obs (NEXRAD) 5-10 mm

Boston



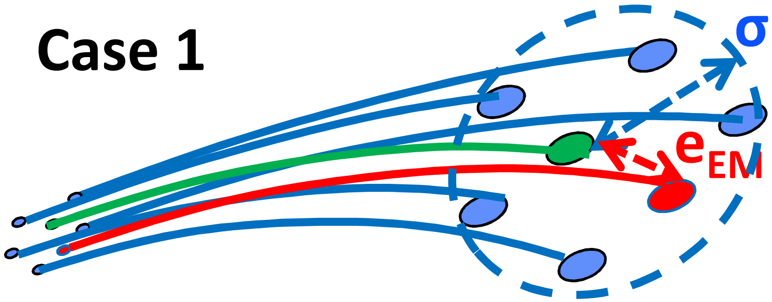
Obs (NEXRAD) 30-35 mm

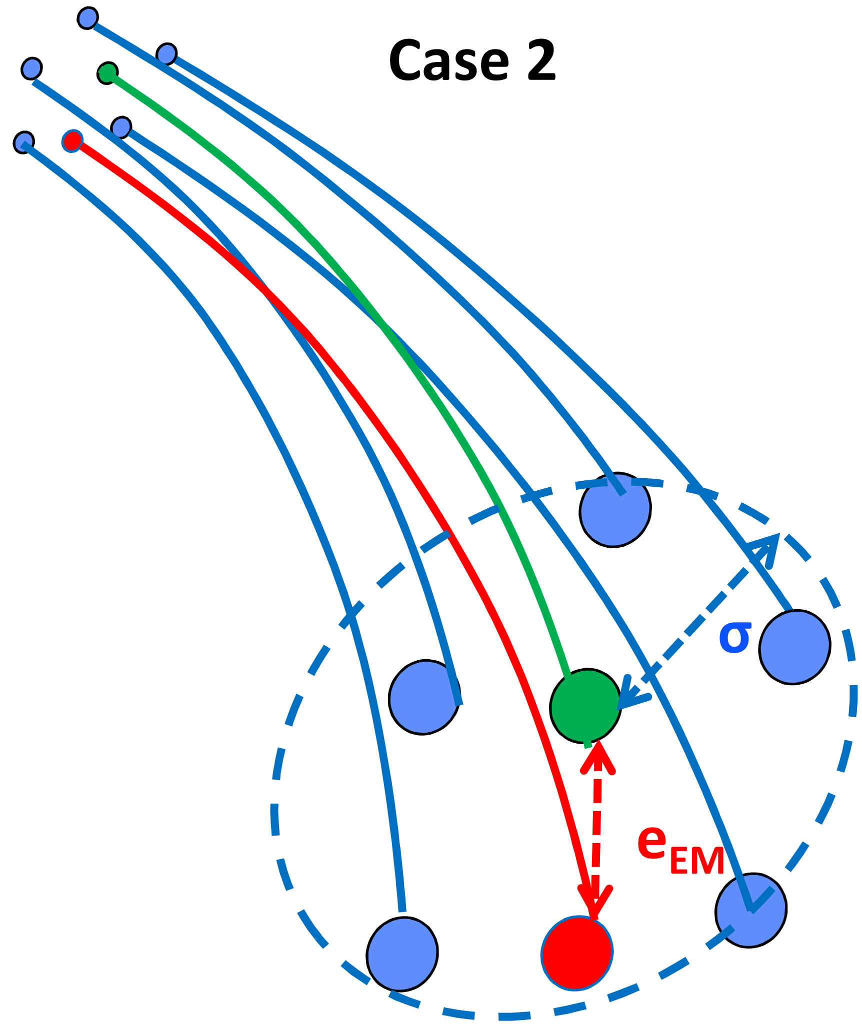
3. A necessary ensemble property: reliability



A reliable ensemble has, on average over many cases M, spread measured by the ensemble standard deviation σ, equal to the average error of the ensemble mean e_{EM}: $\langle\sigma\rangle_M = \langle e_{EM}\rangle_M$

3. In a reliable ensemble, small spread>small error

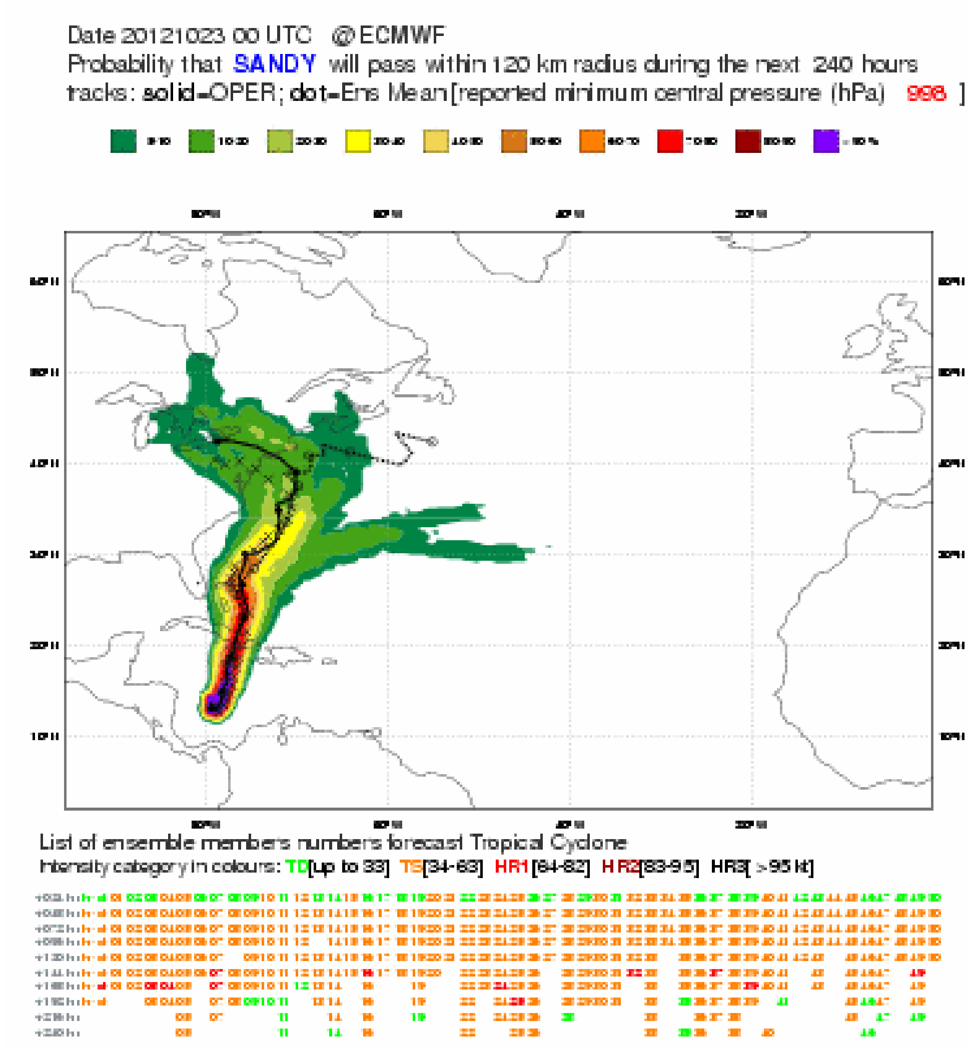




In a reliable ensemble, small ensemble standard deviation indicates a more predictable case, i.e. a small error of the ensemble mean e_{EM}.

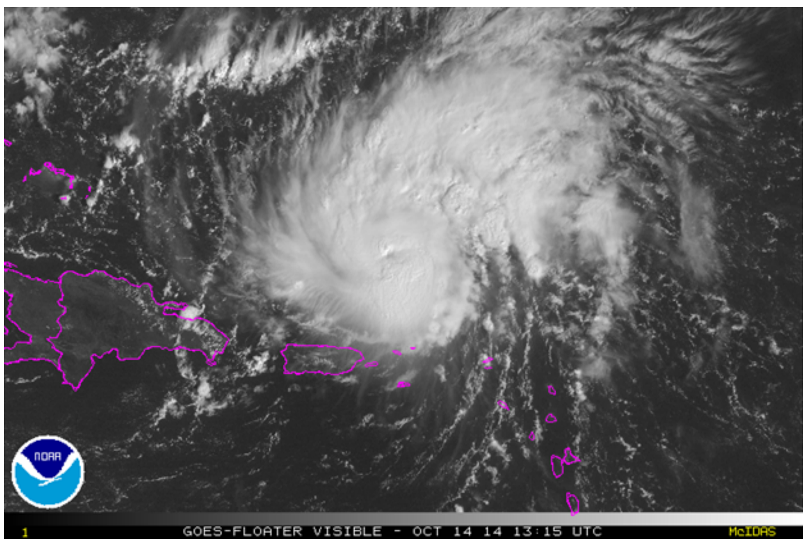
3. Track dispersion & predictability: Sandy (Oct 2012)

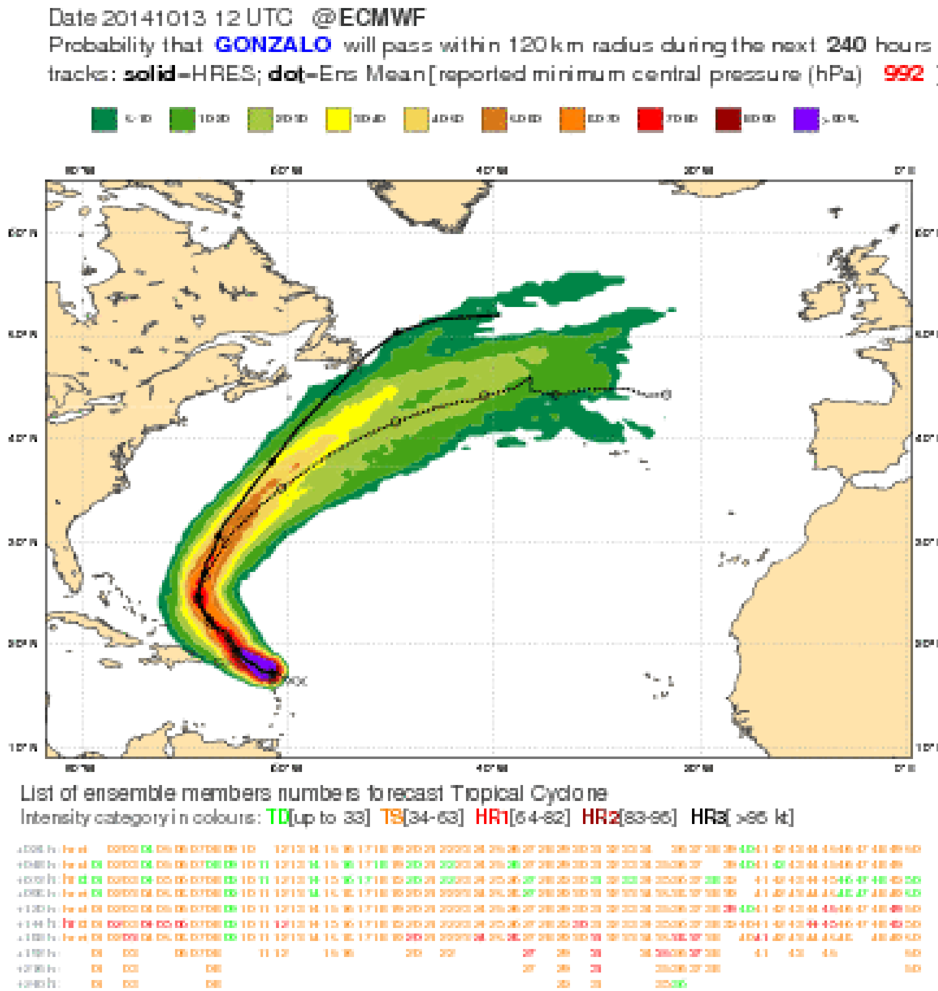
Sandy (Oct 2012) - Dispersion of ENS tracks in the 10d forecast issued on 2012.10.23@00 was relatively large after forecast day 5, indicating high uncertainty on direction and landfall location.



3. Track dispersion & predictability: Gonzalo (Oct 2014)

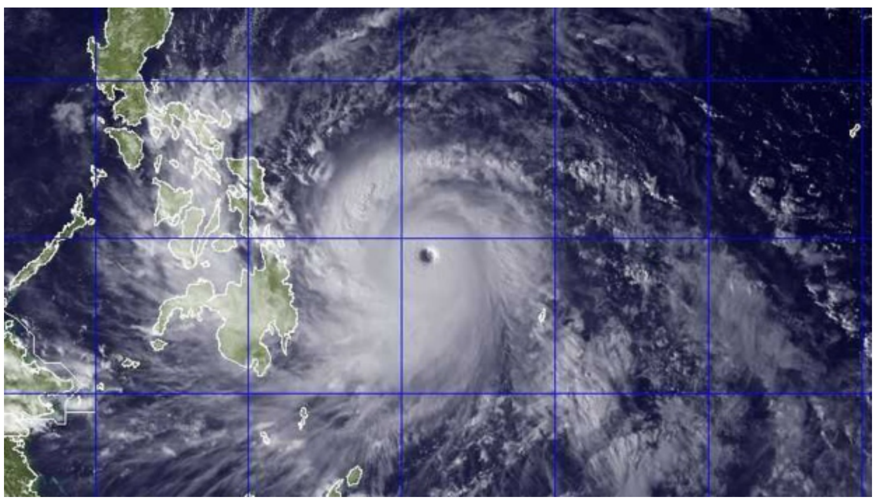
Gonzalo (Oct 2014) - Dispersion of ENS tracks in the 10d forecast issued on 2014.10.13@12 was relatively small for the whole 10 day range, indicating more confidence on direction of travel.

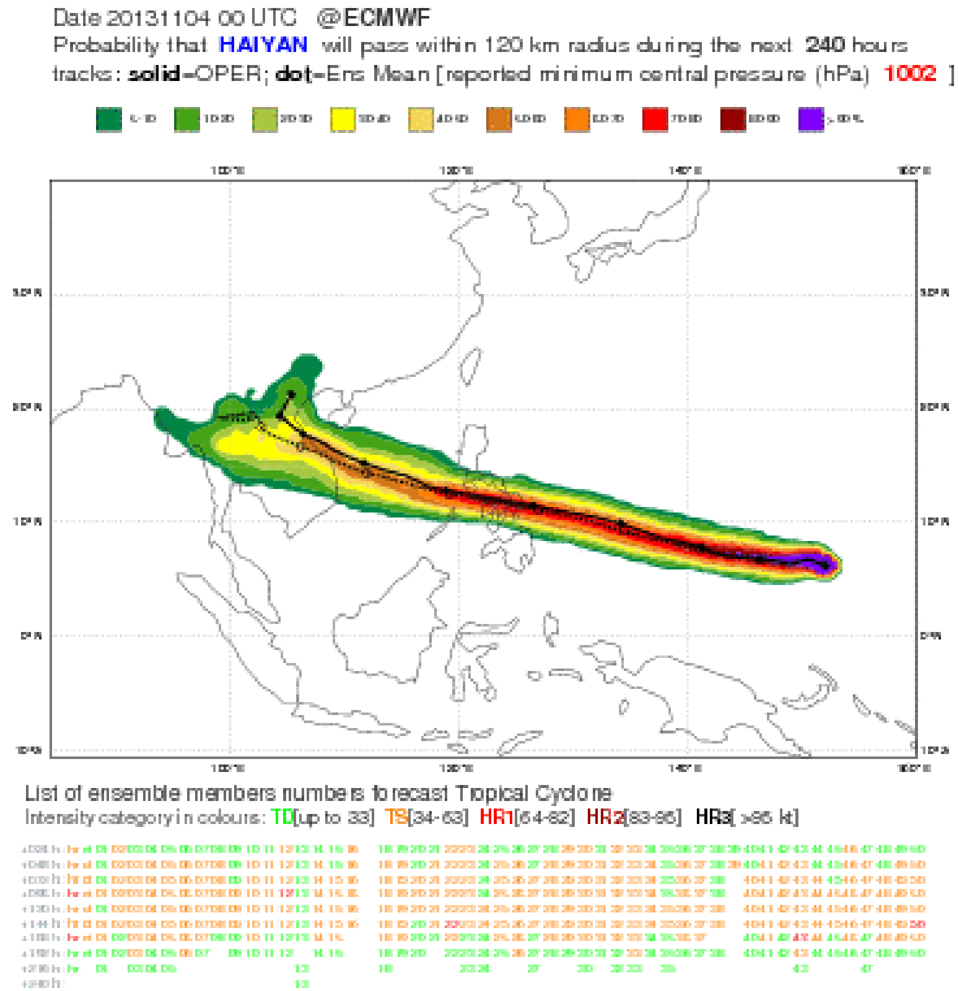




3. Track dispersion & predictability: Haiyan (Nov 2013)

Haiyan (Nov 2013) - Dispersion of ENS tracks in the 10d forecast issued on 2014.10.13@12 was very small for the whole 10 day range, indicating high confidence on direction of travel.

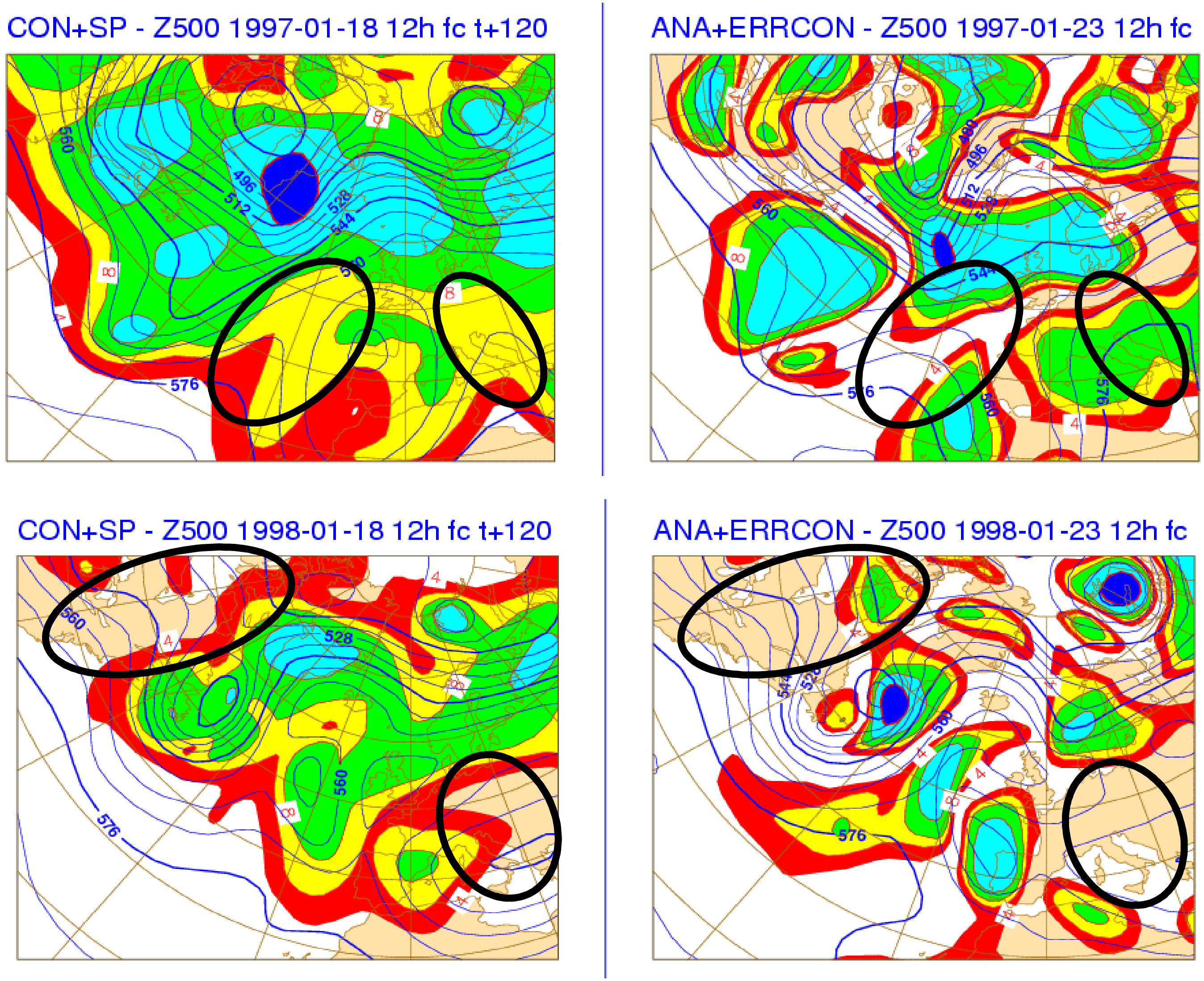




3. ENS spread as an index of predictability

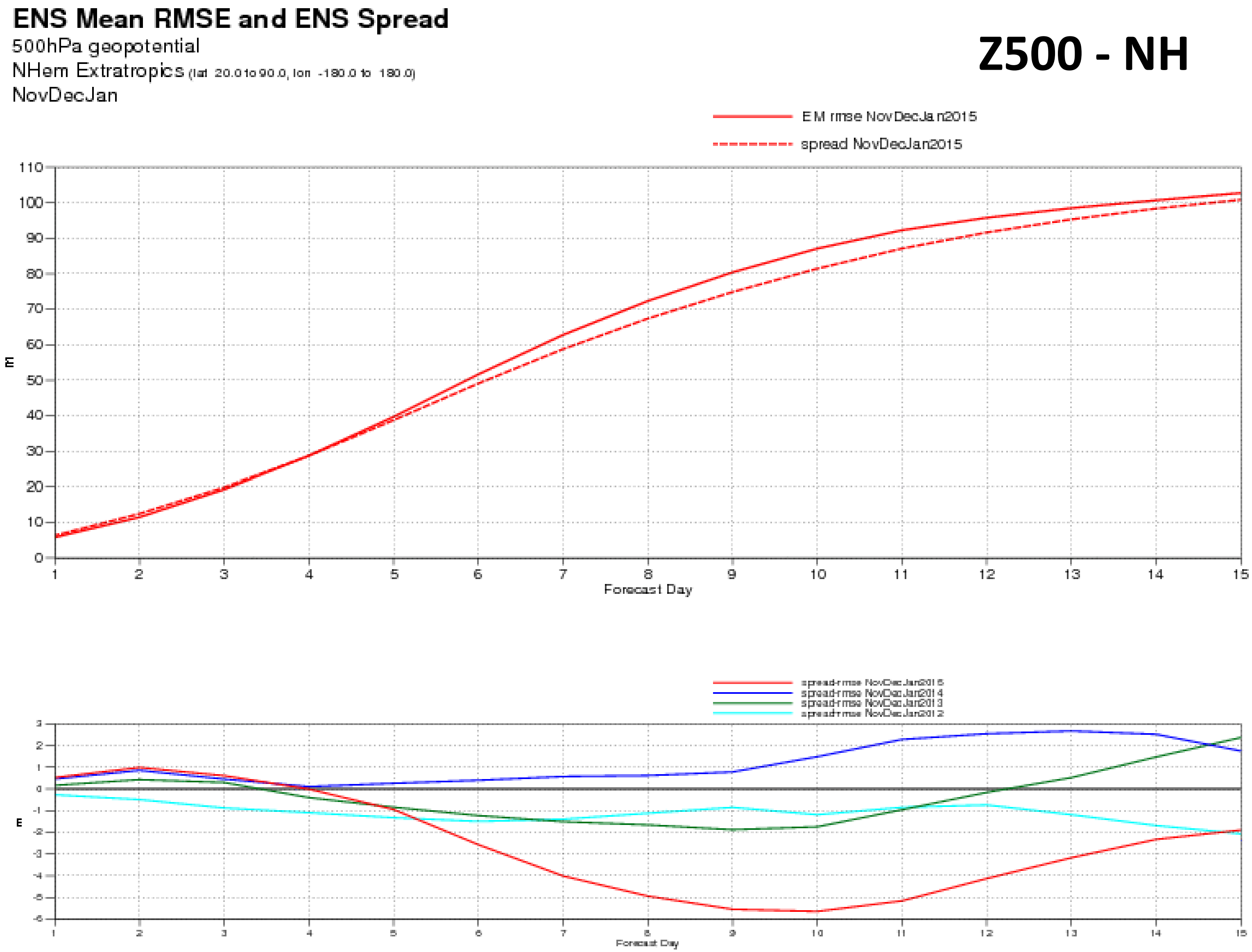
Small ensemble spread should identify predictable conditions:

- On average, the spread in 1998 (top left) is smaller than in 1997 (bottom left), and the control error is also smaller (right)
- For both cases, areas of smaller spread indicates areas of small error



3. In a reliable ensemble, <spread>~<er(EM)>

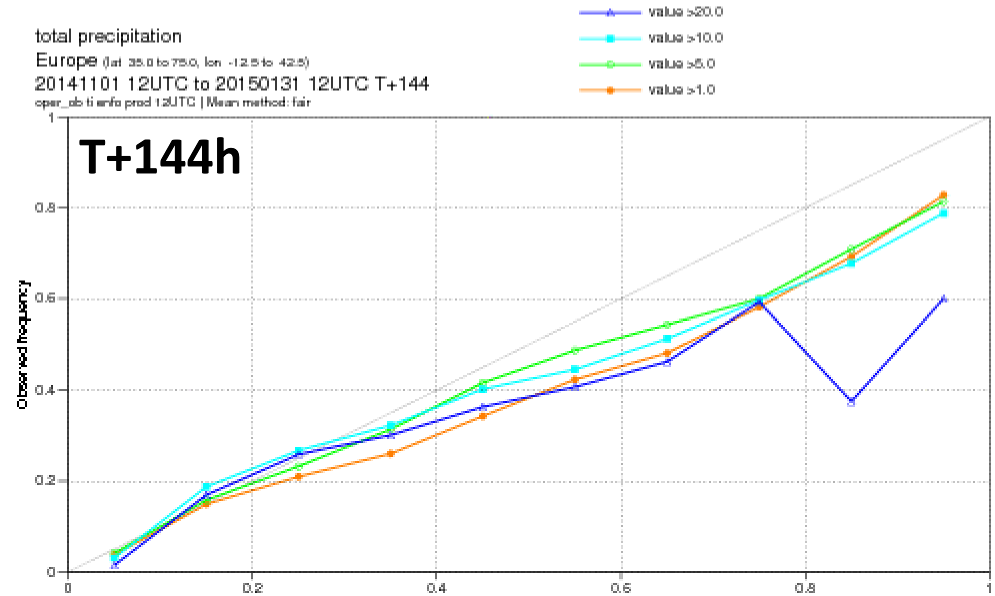
One way to check the ensemble reliability is to assess whether the time evolution of the seasonal average ensemble standard deviation and error of the ensemble mean are similar.
This plot shows these two curves for Z500 over NH in DN14J15.

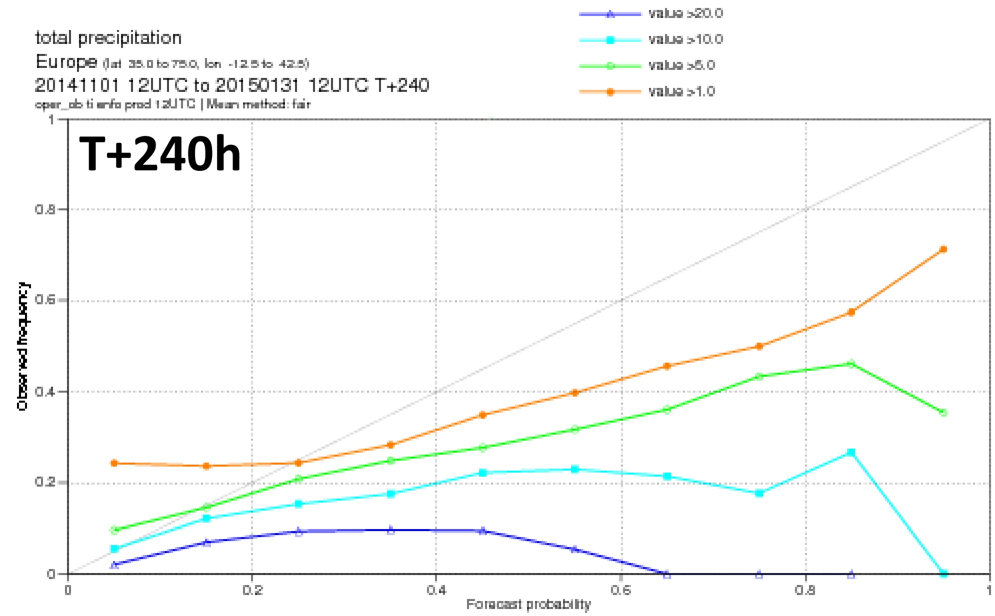


3. In a reliable ensemble, <fc-prob>~<obs-prob>

One way to check the ensemble reliability is to assess whether the average forecast and observed probabilities of a certain event are similar.

These plots compare the two probabilities at t+144h and t+240h for the event ‘24h precipitation in excess of 1/5/10/20 mm’ over Europe for ND14J15 (verified against observations).

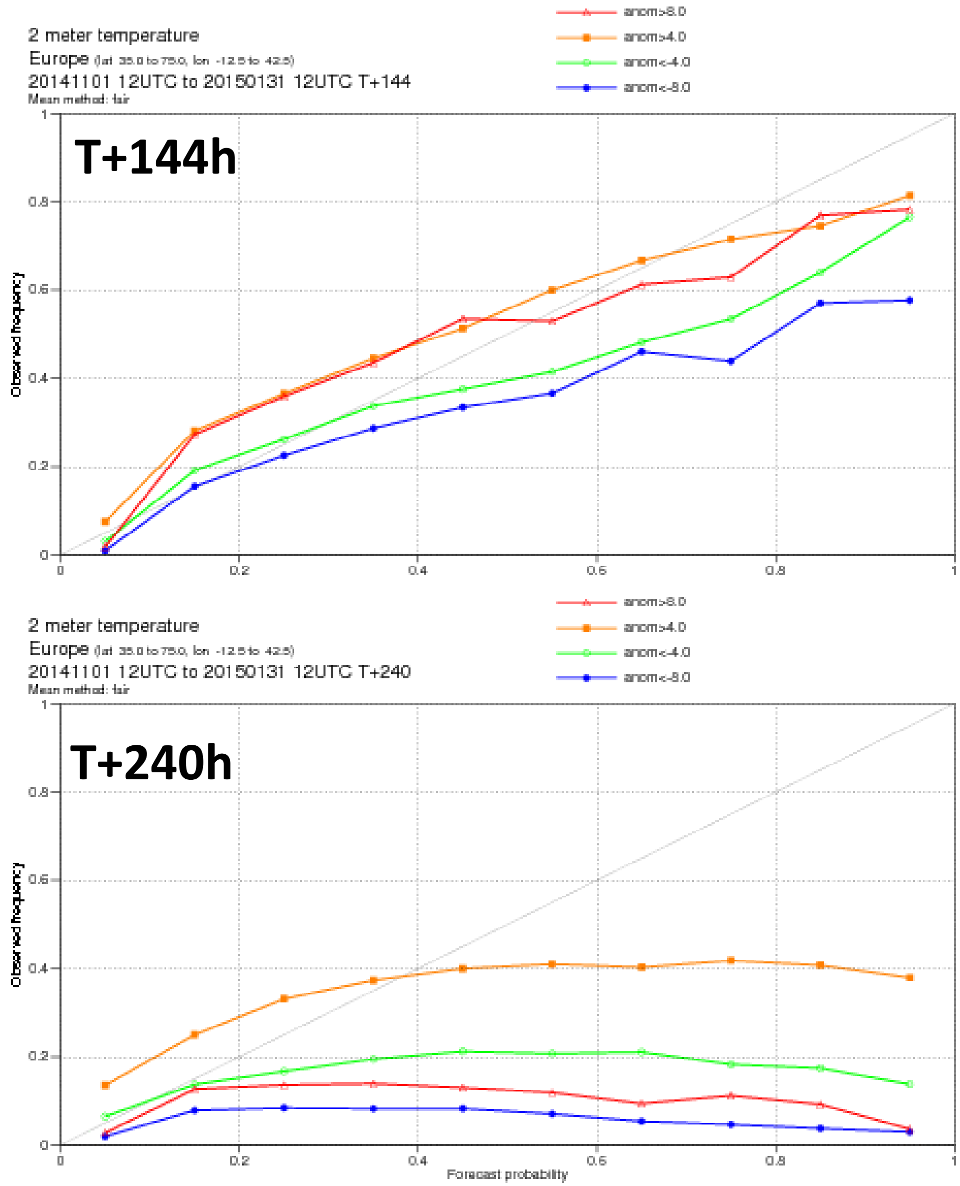




3. In a reliable ensemble, <fc-prob>~<obs-prob>

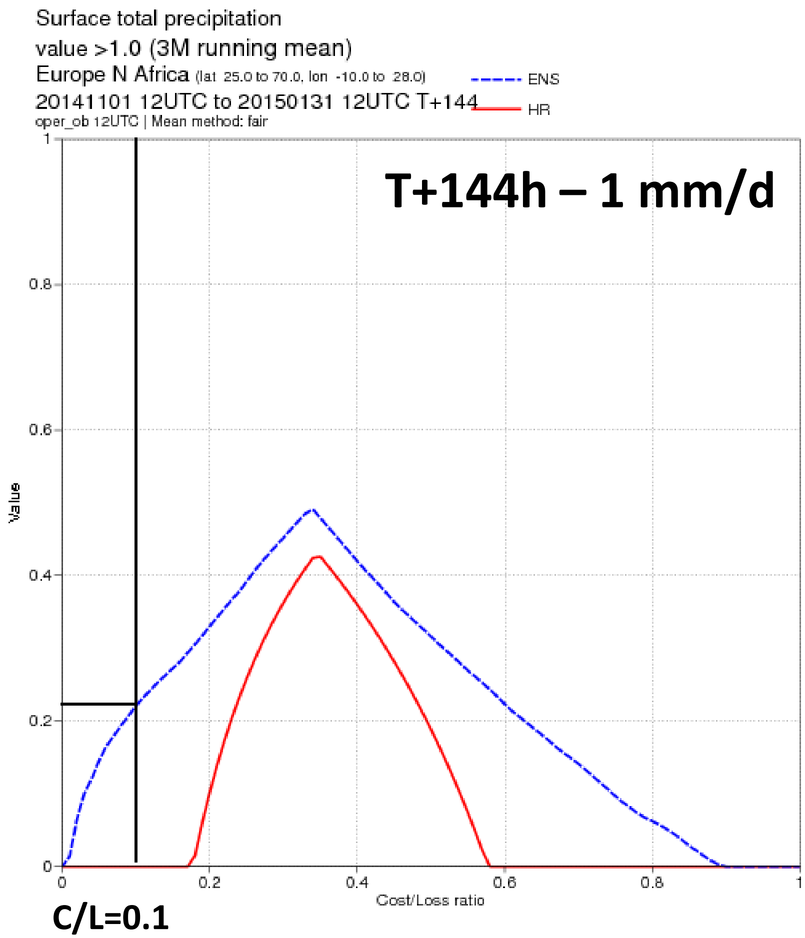
One way to check the ensemble reliability is to assess whether the average forecast and observed probabilities of a certain event are similar.

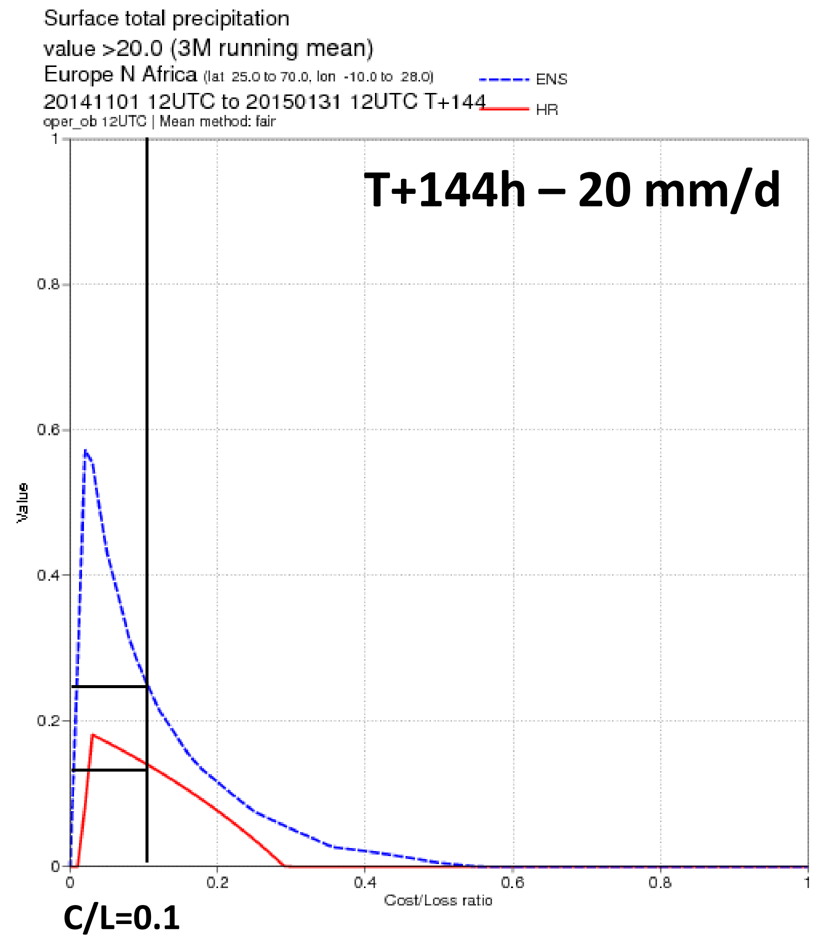
These plots compare the two probabilities at t+144h and t+240h for the event '2-meter temperature anomaly lower than -8/-4 and higher than +4/+8 degrees' over Europe for ND14J15 (verified against observations).



3. Are ensembles more valuable than single fcs?

ENS probabilistic forecasts have higher Potential Economic Value (PEV) than the single high-resolution forecast. These plots refer to t+144h precipitation forecasts (ND14J15).





3. Are ensembles more valuable than single fcs?

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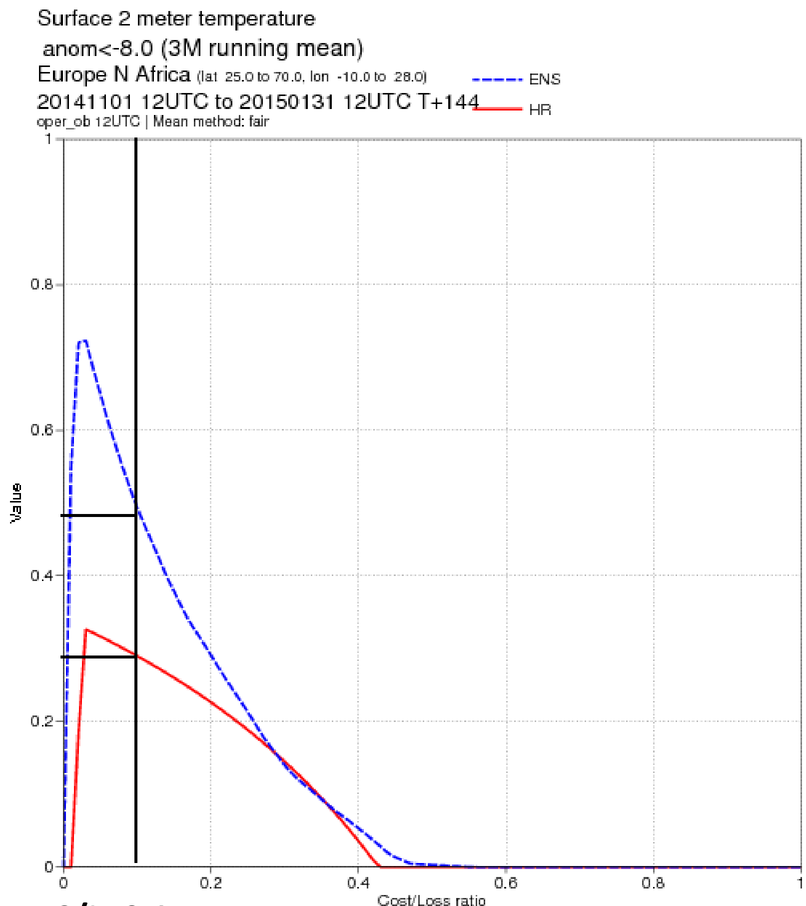
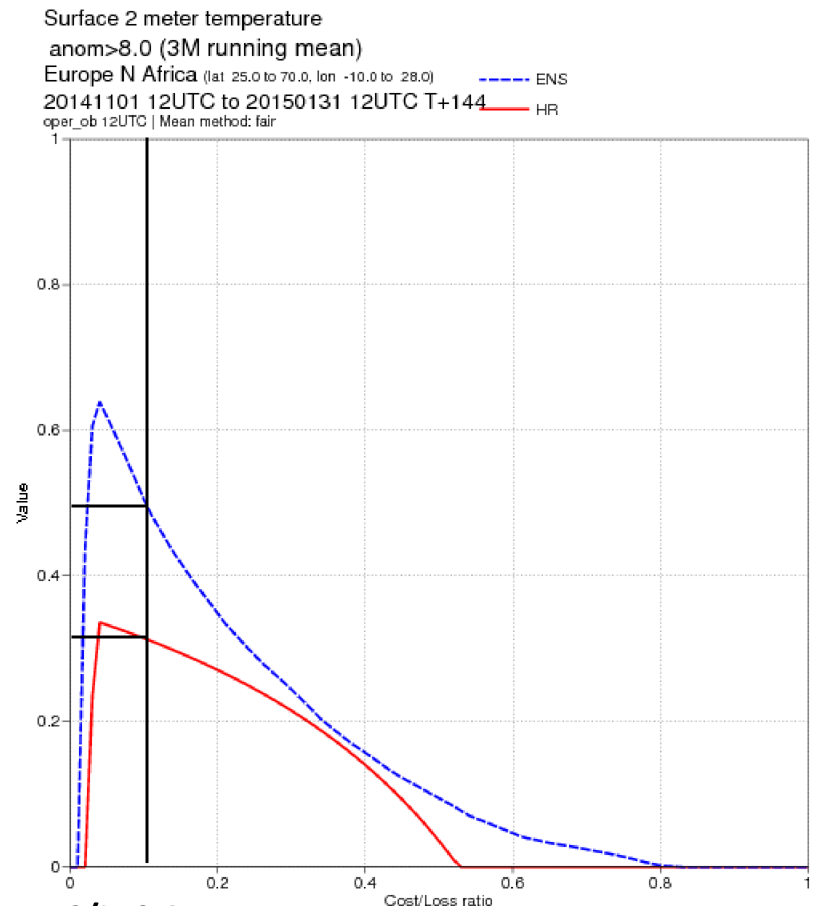


C/L=0.1

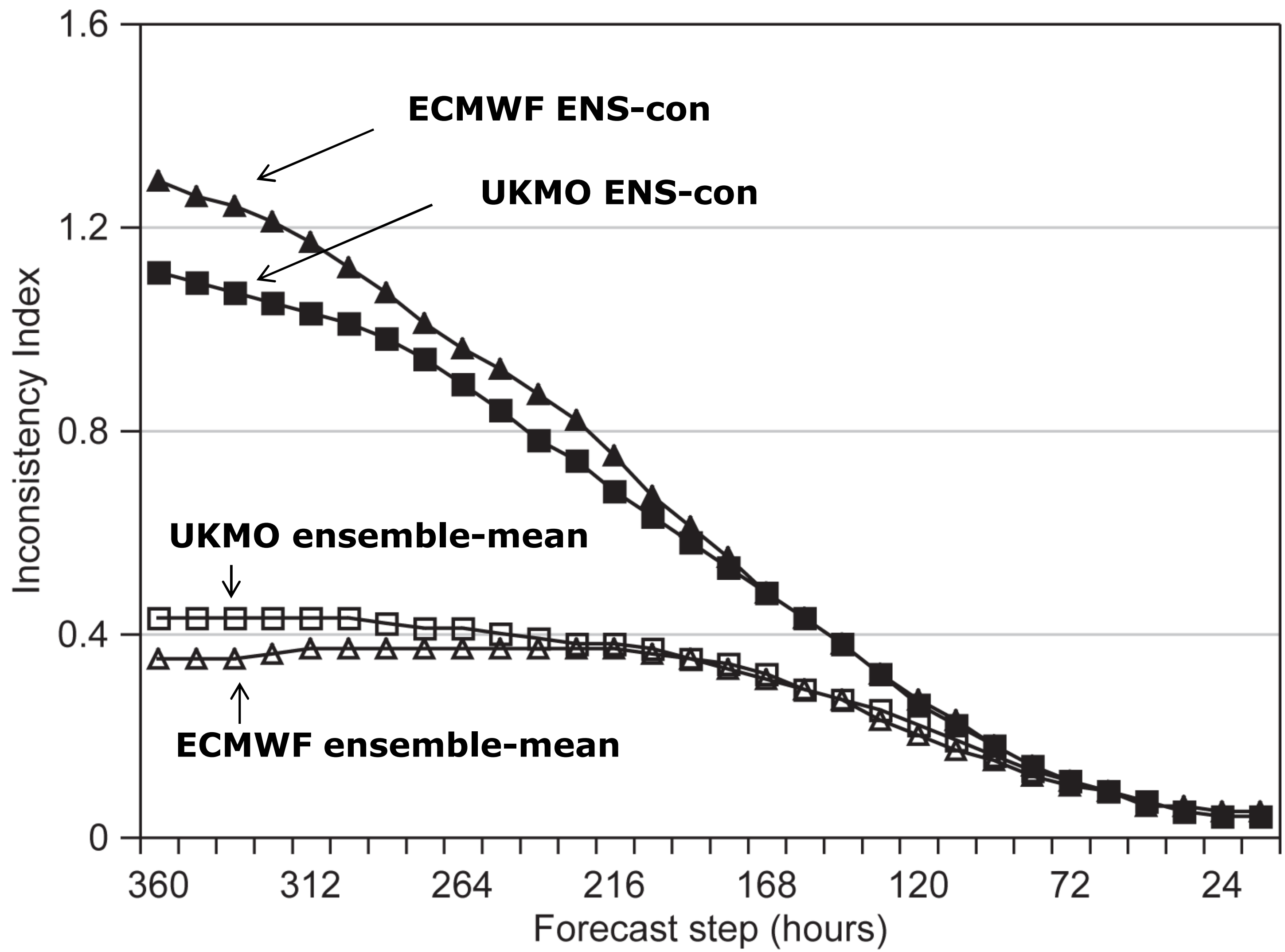


C/L=0.1

3. Ensembles are more consistent

Ensemble-mean forecasts issued 24-hour apart and valid for the same time are more consistent than corresponding single forecasts.

Ensemble-averaging filters dynamically the unpredictable scales *(Zsoter et al* 2009).



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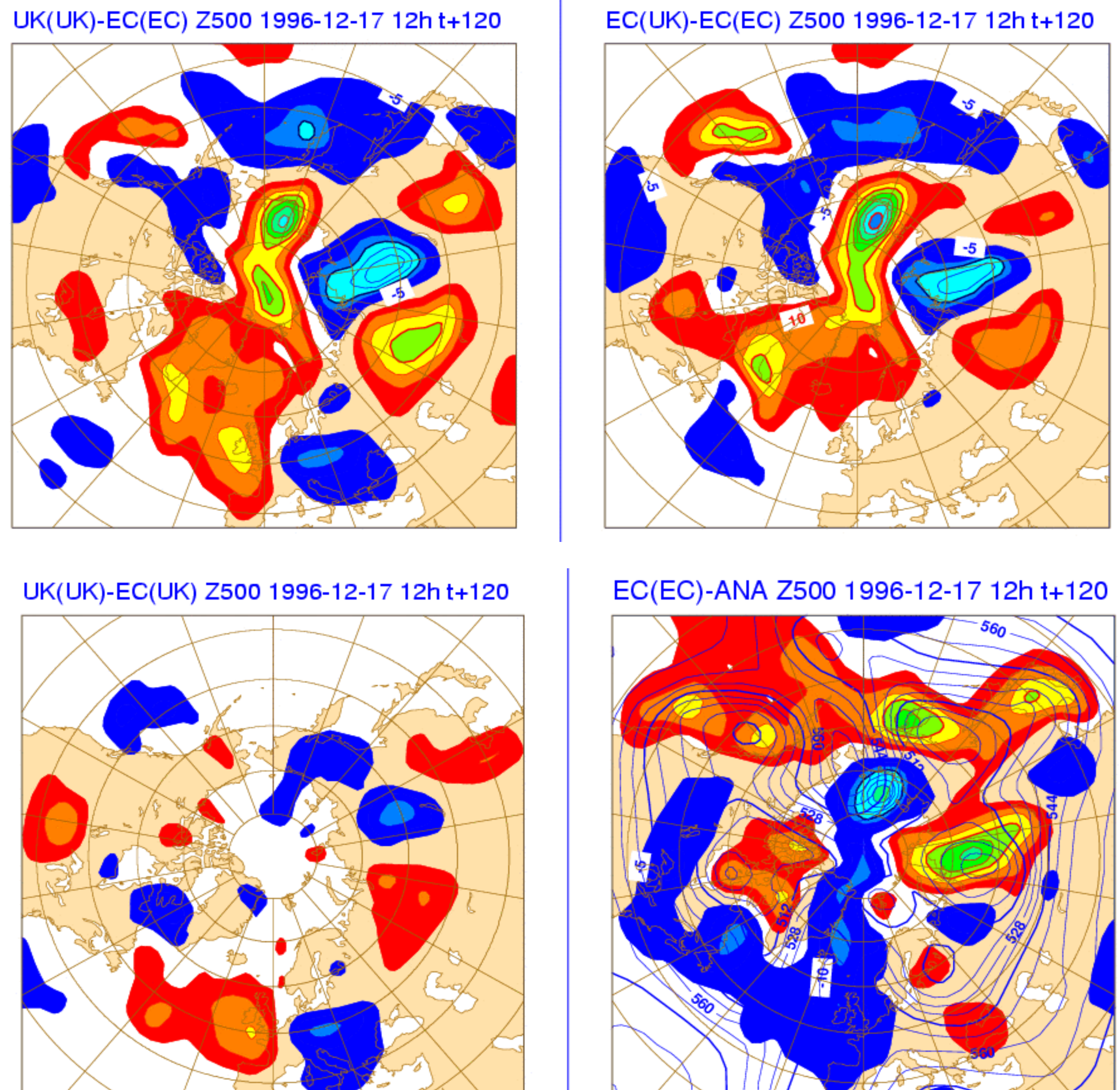
4. Sensitivity to initial and model uncertainty

What is the relative contribution of initial and model uncertainties to forecast error?

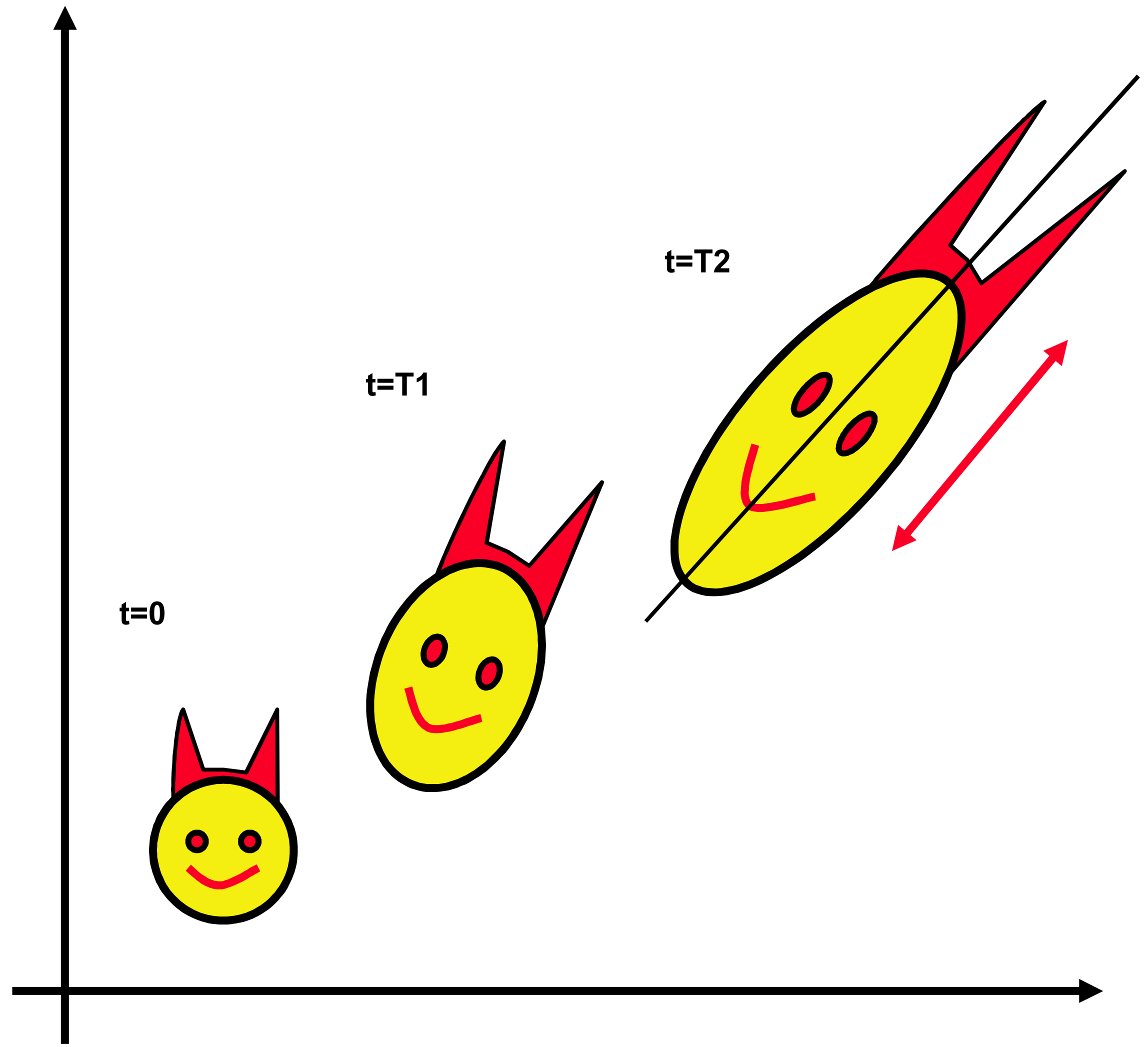
Harrison et al (1999) have shown that initial differences explains most of the differences between ECMWF-from-ECMWF-ICs and UKMO-from-UKMO-ICs forecasts.



4. How should initial uncertainties be defined?

The initial perturbations' components pointing along the directions of maximum growth amplify most.

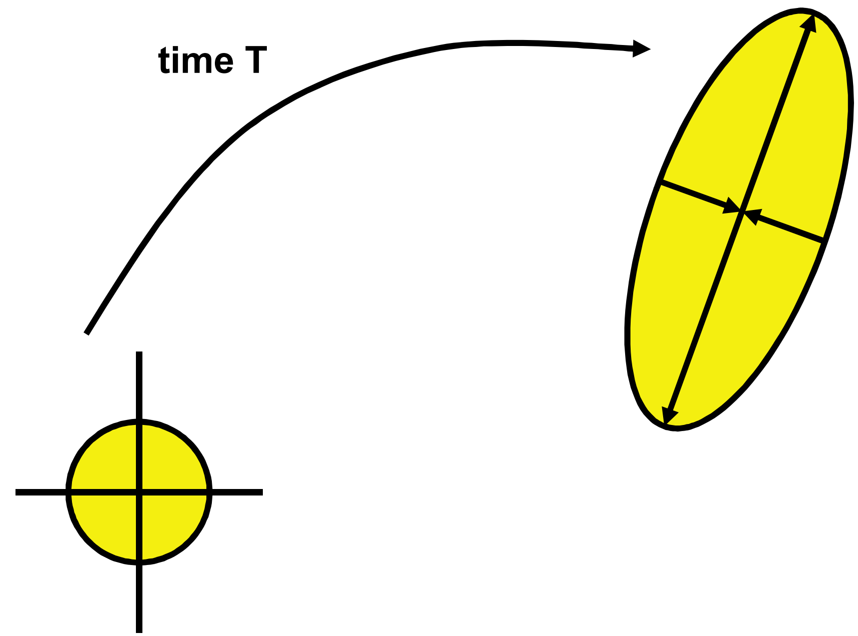
If we knew the directions of maximum growth we could estimate the potential maximum forecast error.



4. Definition of the initial perturbations

To formalize the computation of the directions of maximum growth a metric (inner product) should be defined to 'measure' growth.

The metric used at ECMWF in the ensemble system is total energy.



$$< x; E_{TE} y >= \frac{1}{2} \iint (\nabla\Delta^{-1}\zeta_x \cdot \nabla\Delta^{-1}\zeta_y + \nabla\Delta^{-1}D_x \cdot \nabla\Delta^{-1}D_y + \frac{C_p}{T_r} T_x T_y) d\Sigma \frac{\partial p}{\partial \eta} d\eta$$

$$+ \int (R_d \frac{T_r}{p_r} \ln\pi_x \ln\pi_y) d\Sigma$$

4. Asymptotic and finite-time instabilities

Farrell (1982) studying perturbations' growth in baroclinic flows noticed that the long-time asymptotic behavior is dominated by normal modes, but that **there are other perturbations that amplify more than the most unstable normal mode over a finite time interval**.

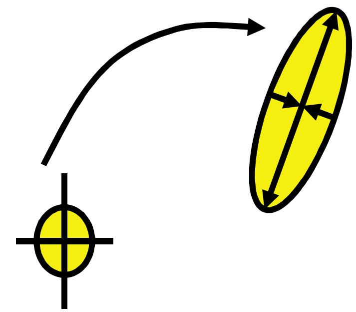
Farrell (1989) showed that perturbations with the fastest growth over a finite time interval could be identified solving an eigenvalue problem defined by the product of the tangent forward and adjoint model propagators. This result supported earlier conclusions by *Lorenz* (1965).

Calculations of perturbations growing over finite-time interval intervals have been performed, for example, by *Borges & Hartmann* (1992) using a barotropic model, *Molteni & Palmer* (1993) with a quasi-geostrophic 3-level model, and by *Buizza et al* (1993) with a primitive equation model.

4. Singular vectors

The problem of the computation of the directions of maximum growth of a time evolving trajectory is solved by an eigenvalue problem:

$$E_0^{-1/2} L^* E L E_0^{-1/2} \nu = \sigma^2 \upsilon$$



where:

- E_0 and E are the initial and final time metrics
- $L(t,0)$ is the linear propagator, and L* its adjoint
- The trajectory is time-evolving trajectory
- t is the optimization time interval

4. The operational ensemble in 2015

ENS includes 51 forecasts with resolution:

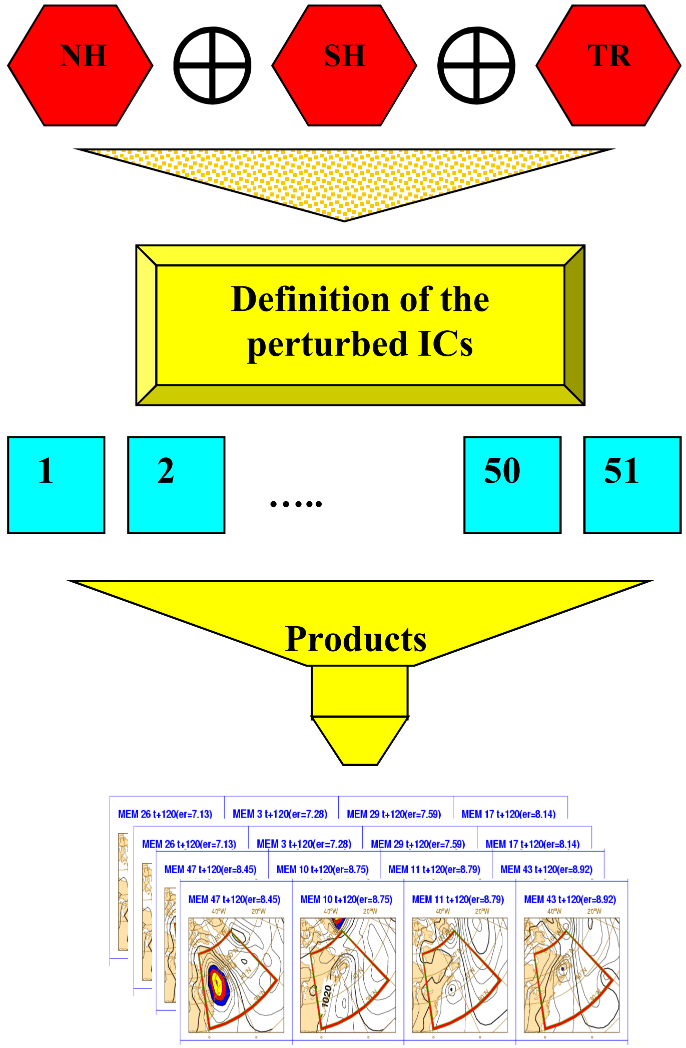
- T_L639L91 (~32km, 91 levels) from day 0 to 10
- T_L319L91 (~64km, 91 levels) from day 10 to 15 (32 at 00UTC on Mon and Thu).

Initial uncertainties are simulated by adding to the unperturbed analyses a combination of T42L91 singular vectors, computed to optimize total energy growth over a 48h time interval (OTI), and perturbations generated by the ECMWF Ensembles of Data Assimilation (EDA) system.

Model uncertainties are simulated by adding stochastic perturbations to the tendencies due to parameterized physical processes (SPPT and SKEB schemes).

The unperturbed analysis is given by the T_L1279L137 4DVAR.

ENS runs daily at 00 and 12 UTC, with a TOA at 0.01 hPa.



4. Major changes of the ensemble configuration

Since 1992 the ENS configuration has been modified significantly several times.

		Singular Vectors's characteristics							Forecast characteristics						
	Description	HRES	VRES	OTI	Area	past	future	sampl	HRES	VRES	Tend	#	Mod Unc	Coupling	refc suite
Dec 1992	Oper Impl	T21	L19	36h	globe	NO	SVINI	simm	T63	L19	10d	33	NO	NO	NO
Feb 1993	SV LPO	"	"	"	NHx	"	"	"	"	"	"	"	"	"	"
Aug 1994	SV OTI	"	"	48h	"	"	"	"	"	"	"	"	"	"	"
Mar 1995	SV hor resol	T42	"	"	"	"	"	"	"	"	"	"	"	"	"
Mar 1996	NH+SH SV	"	"	"	(NH+SH)x	"	"	"	"	"	"	"	"	"	"
Dec 1996	resol/mem	"	L31	"	"	"	"	"	TL159	L31	"	51	"	"	"
Mar 1998	EVO SV	"	"	"	"	SVEVO	"	"	"	"	"	"	"	"	"
Oct 1998	Stoch sch SPPT	"	"	"	"	"	"	"	"	"	"	"	STP	"	"
Oct 1999	vert resol	"	L40	"	"	"	"	"	"	L40	"	"	"	"	"
Nov 2000	FC hor resol	"	"	"	"	"	"	"	TL255	"	"	"	"	"	"
Jan 2002	TC SVs	"	"	"	(NH+SH)x+TC	"	"	"	"	"	"	"	"	"	"
Sep 2004	sampling	"	"	"	"	"	"	Gauss	"	"	"	"	"	"	"
Jun 2005	rev sampl	"	"	"	"	"	"	"	"	"	"	"	"	"	"
Feb 2006	resolution	"	L62	"	"	"	"	"	TL399	L62	"	"	"	"	"
Sep 2006	VAREPS	"	"	"	"	"	"	"	TL399(0-10) / TL255(10-15)	"	15d	"	"	"	"
Mar 2008	VAREPS-mon	"	"	"	"	"	"	"	"	"	15d/32d	"	"	HOPE from d10	5*18y
Sep 2009	Rev SPPT	"	"	"	"	"	"	"	"	"	"	"	"	"	"
Jan 2010	hor resol	"	"	"	"	"	"	"	TL639(0-10) / TL319(10-15)	"	"	"	revSTP	"	"
Jun 2010	EDA EPS	"	"	"	"	EDA	"	"	"	"	"	"	"	"	"
Nov 2010	Rev Stoch scheme	"	"	"	"	"	"	"	TL639(0-10) / TL319(10-15)	"	15d/32d	"	revSTP+BS	"	"
Nov 2011	New ocean model	"	"	"	"	"	"	"	"	"	"	"	"	NEMO from d10	"
Jun 2012	Rev EDA-pert & refc suite	"	"	"	"	"	"	"	"	"	"	"	"	"	5*20y
Nov 2013	vert resol & coupling from d0	T42	L91	48h	(NH+SH)x+TC	EDA	SVINI	Gauss	TL639(0-10) / TL319(10-15)	L91	15d/32d	51	revSTP+BS	NEMO from d0	5*20y

Conclusion

- A complete solution of the weather prediction problem can be stated in terms of an appropriate probability density function (PDF). Ensemble prediction is the only feasible method to predict the PDF using dynamical forecasts beyond the range of linear growth.

- Initial and model uncertainties are the main sources of error growth. Initial uncertainties dominate in the short range. Predictability is flow dependent.

- The initial error components along the directions of maximum growth contribute most to forecast error growth. These directions can be identified by the leading singular vectors, computed solving an eigenvalue problem.

- ENS has changed many times since 1992. Now it includes 51 15-day forecasts twice a day (00-12UTC), which are extended to 32 days twice a week (00UTC Mon/Thu). Each ENS ensemble member uses a coupled ocean-atmosphere forecasts with a T_L639v319 variable resolution in the atmosphere and 91 vertical levels, and a 1-degree resolution and 42 vertical levels in the ocean.

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