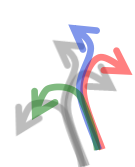


Sources of uncertainty (EC/TC/PR/RB-L1)



Antje Weisheimer
- presented for Roberto Buizza-

European Centre for Medium-Range Weather Forecasts
(<http://www.ecmwf.int/en/staff/Roberto-buizza>)



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 integrations 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:

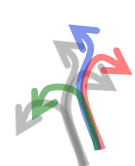
- explain which are the main sources of forecast error
- illustrate why numerical prediction should be stated in probabilistic terms
- describe the rationale behind ensemble prediction



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





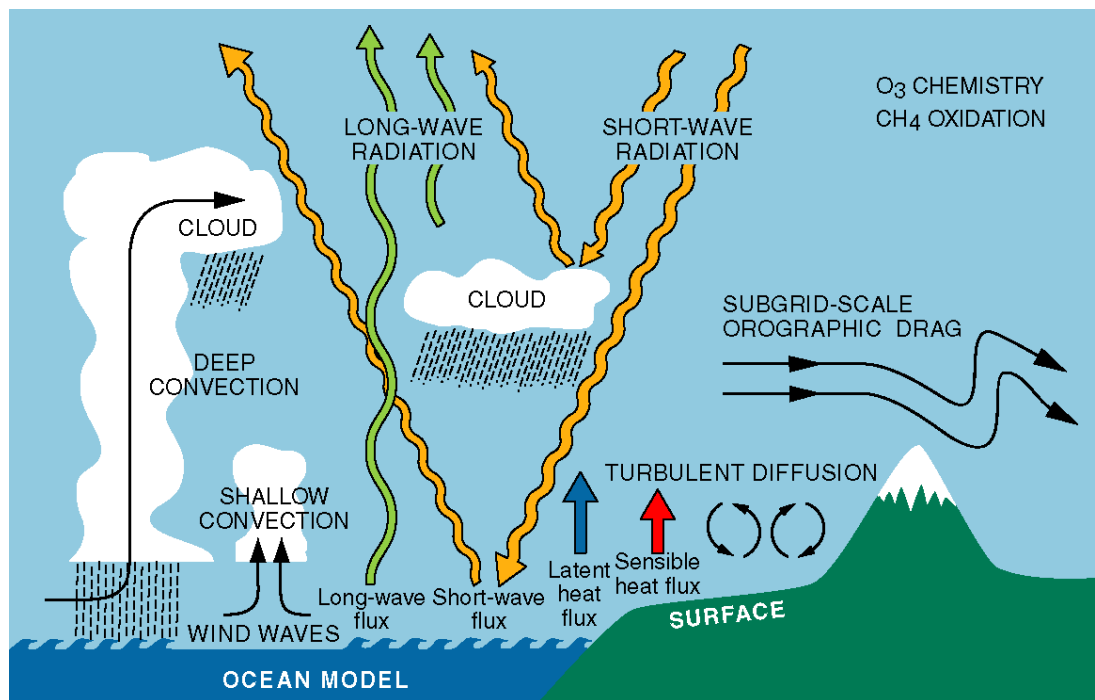
1. Numerical Weather Prediction (NWP) models

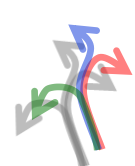
The behavior of the atmosphere is governed by a set of physical laws that express how the air moves, the process of heating and cooling, the role of moisture, and so on.

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

ECMWF MODEL / ASSIMILATION SYSTEM

A T M O S P H E R E	STRATOSPHERE	DYNAMICS–RADIATION–SIMPLIFIED CHEMISTRY		
	TROPOSPHERE	DYNAMICS–RADIATION–CLOUDS–ENERGY & WATER CYCLE		
O C E A N	OCEAN	OCEAN	LAND HYDROSPHERE	LAND BIOSPHERE
	LAND	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

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

Energy
conservation

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

Water vapour
conservation

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

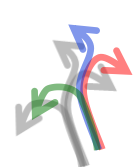
Mass
conservation

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

Hydrostatic
balance

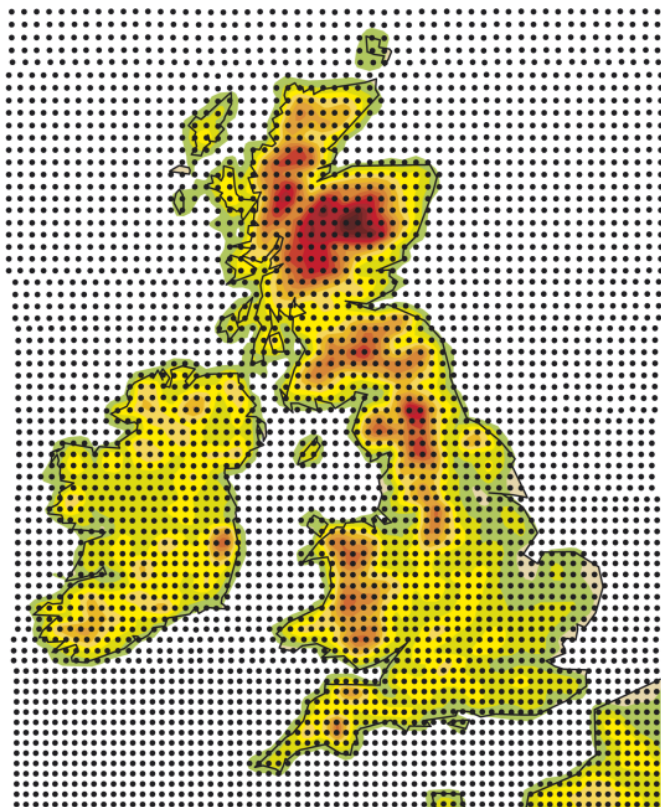
$$\frac{d\Phi}{d\sigma} = - \frac{R \cdot T}{\sigma}$$

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

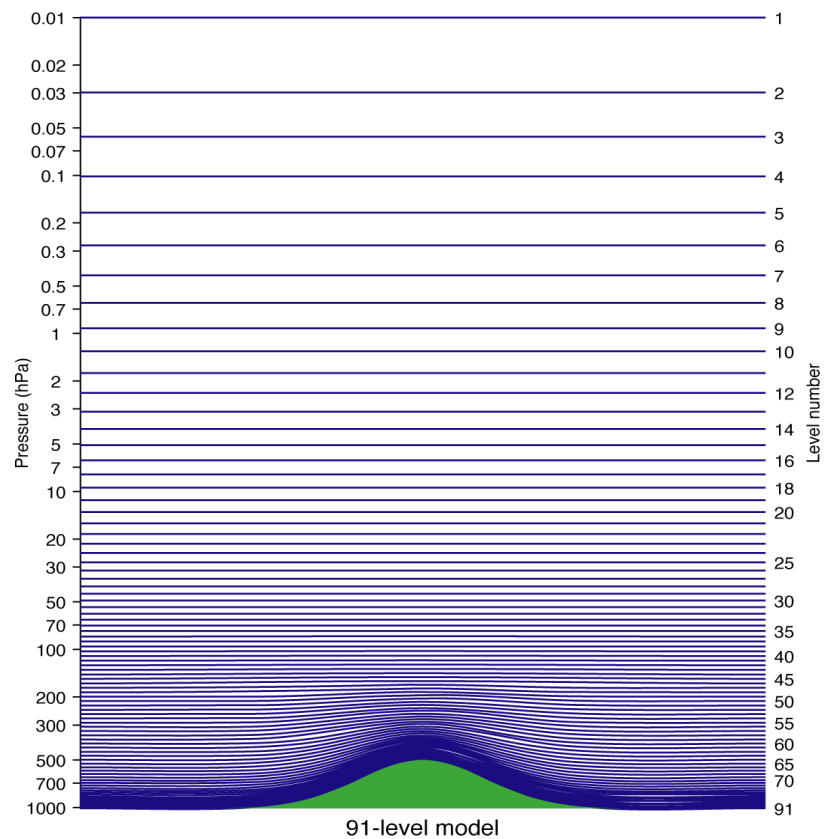


1. Model grid & v-levs of the Tco639L91 ENS

**T_{CO}639
(ENS)**



**L91
(ENS)**





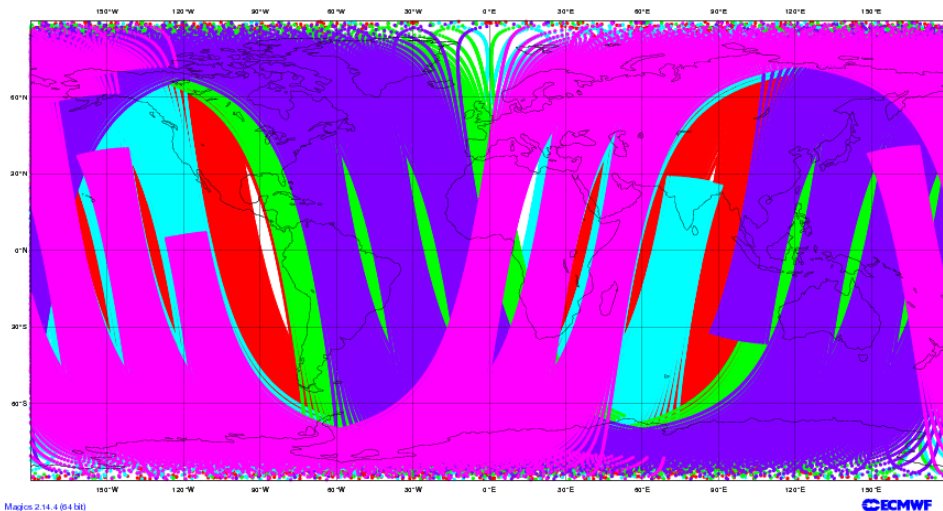
1. Observations coverage and accuracy

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.

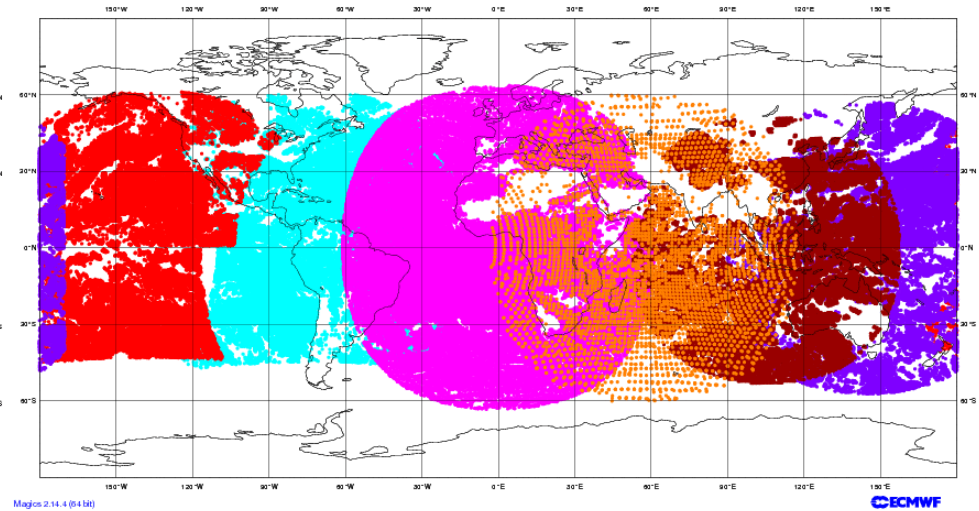
ECMWF Data Coverage (All obs DA) - AMSU-A
25/Feb/2015; 00 UTC
Total number of obs = 544349

• 58271 Noaa15 • 122319 Noaa18 • 110541 Noaa19 • 70044 AQUA • 107160 METOP-A • 76014 METOP-B



ECMWF Data Coverage (All obs DA) - AMV IR
25/Feb/2015; 00 UTC
Total number of obs = 330439

• 57266 Goss15 • 137933 Goss13 • 87772 Met10 • 0 MtSat1R • 40888 MtSat2 • 0 FY-2D • 21102 FY-2E • 5478 Met7 • 0 Goss14



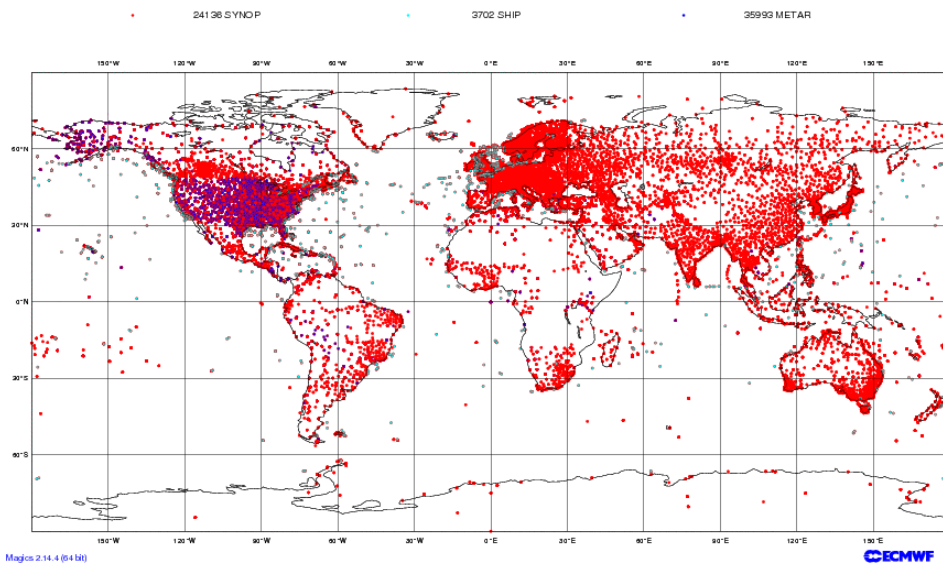


1. Observations coverage and accuracy

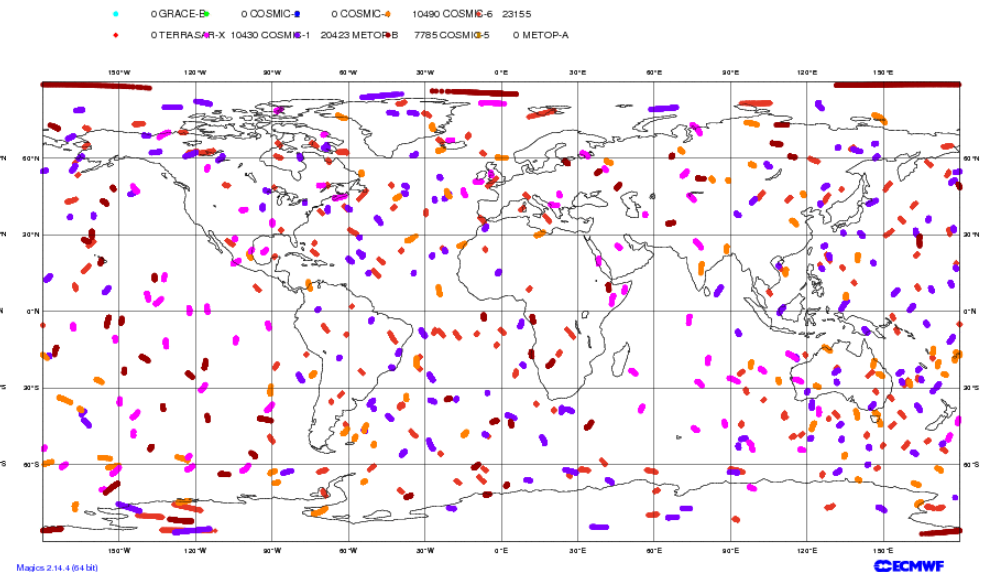
To make accurate forecasts it is important to know the current weather:

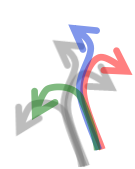
- ~ 155M obs (99% from satellites) are received daily;
- ~ 15M obs (96% from satellites) are used every 12 hours.

ECMWF Data Coverage (All obs DA) - Synop-Ship-Metar
25/Feb/2015; 00 UTC
Total number of obs = 63831

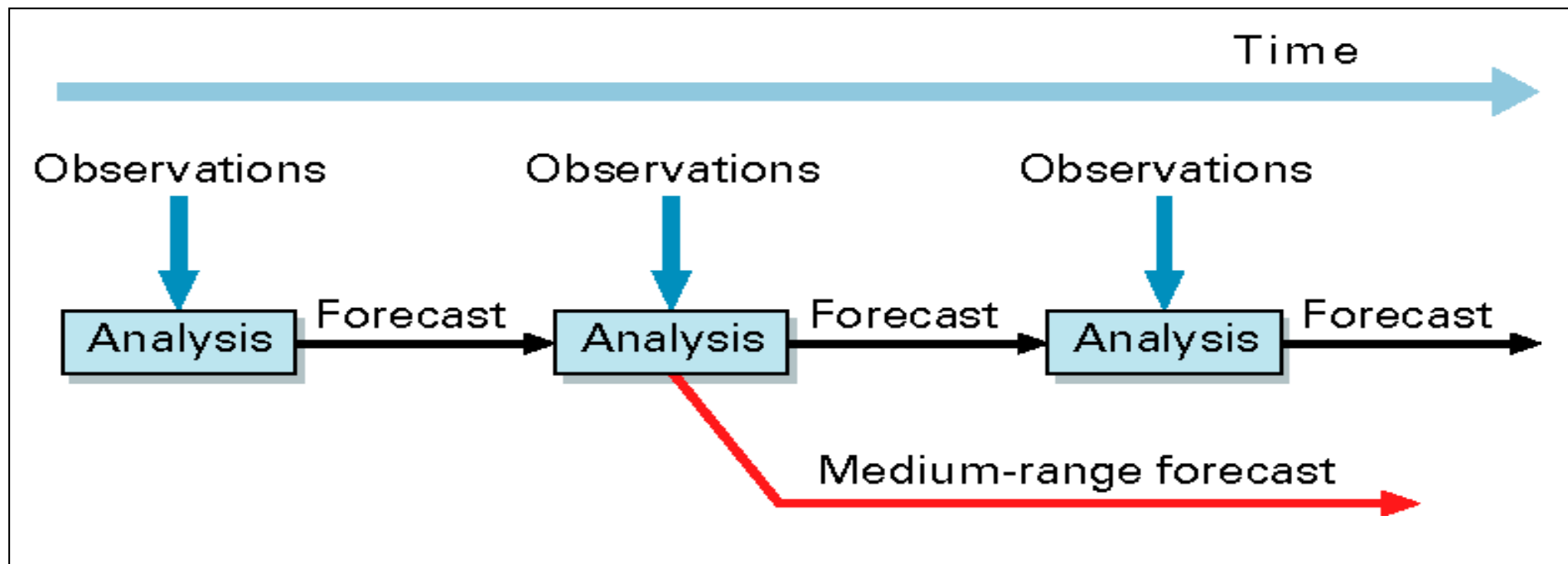


ECMWF Data Coverage (All obs DA) - GPSRO
25/Feb/2015; 00 UTC
Total number of obs = 72283

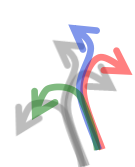




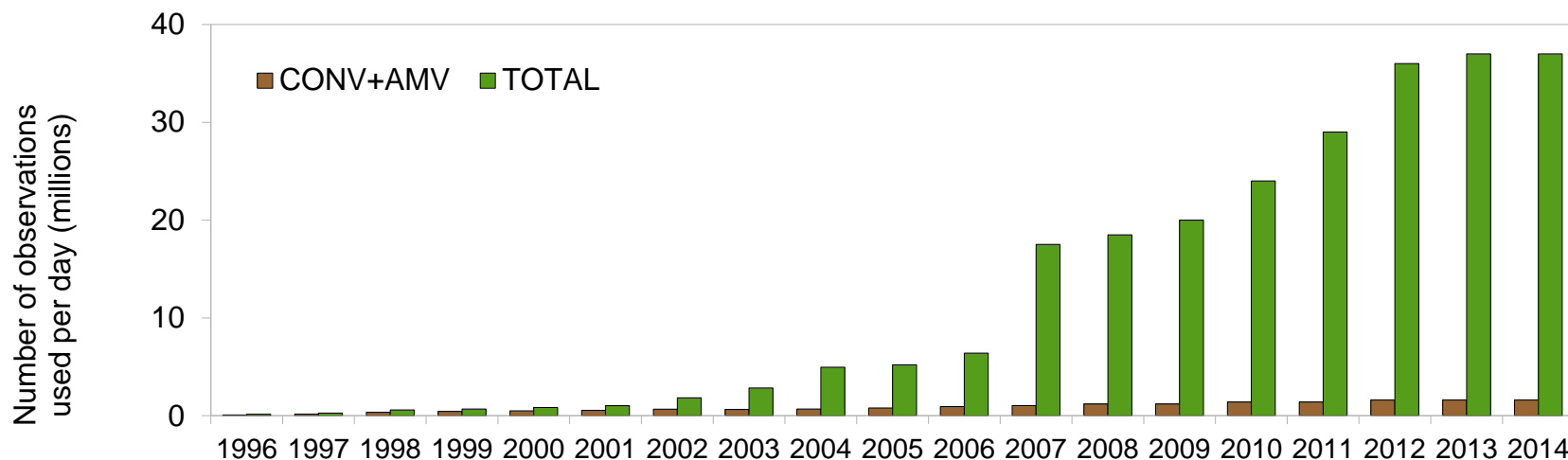
1. Obs are assimilated to estimate the initial state



- 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

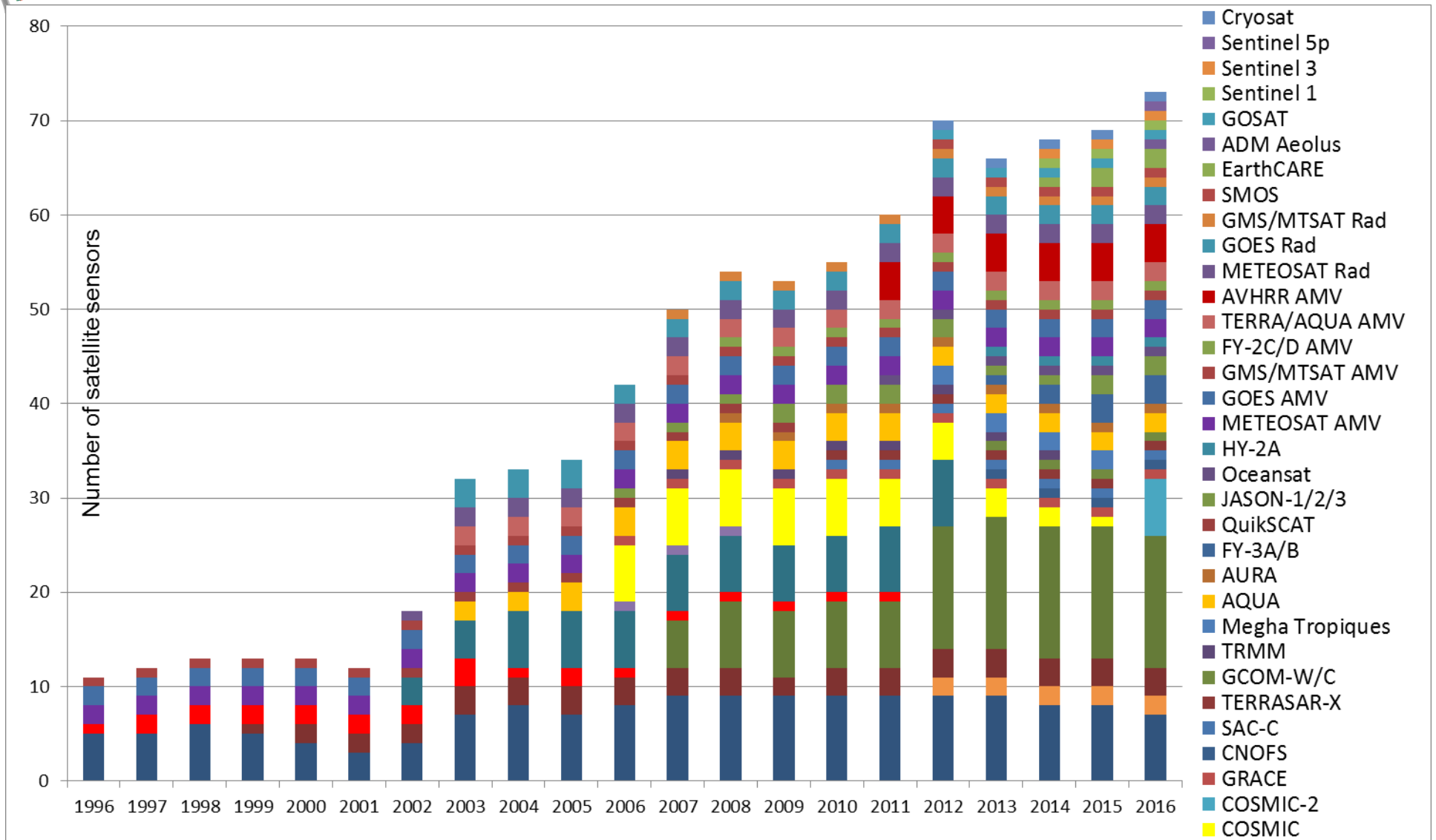


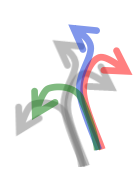
1. Observations used at ECMWF





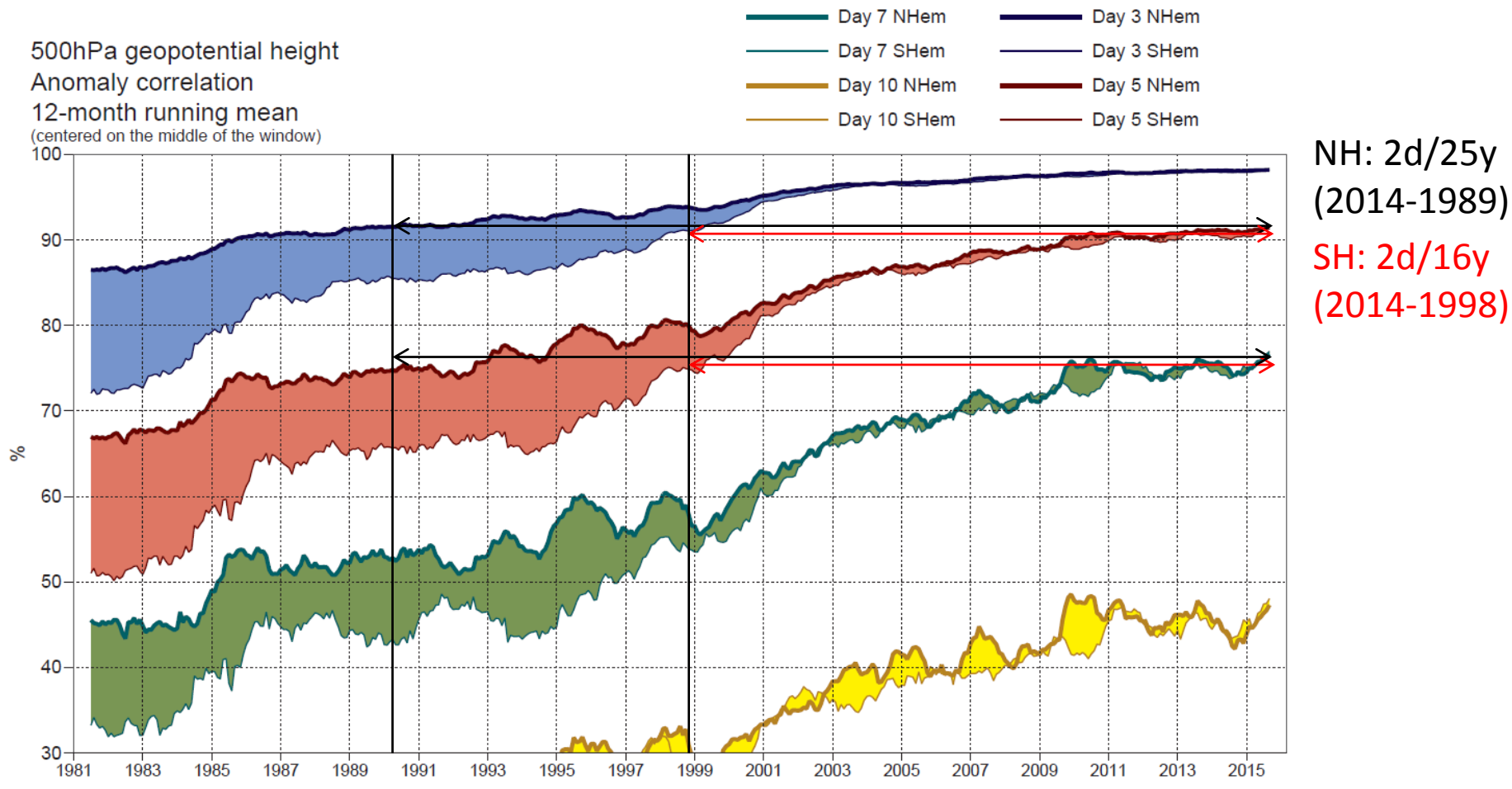
1. Satellite data used at ECMWF





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.

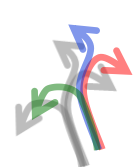




Outline

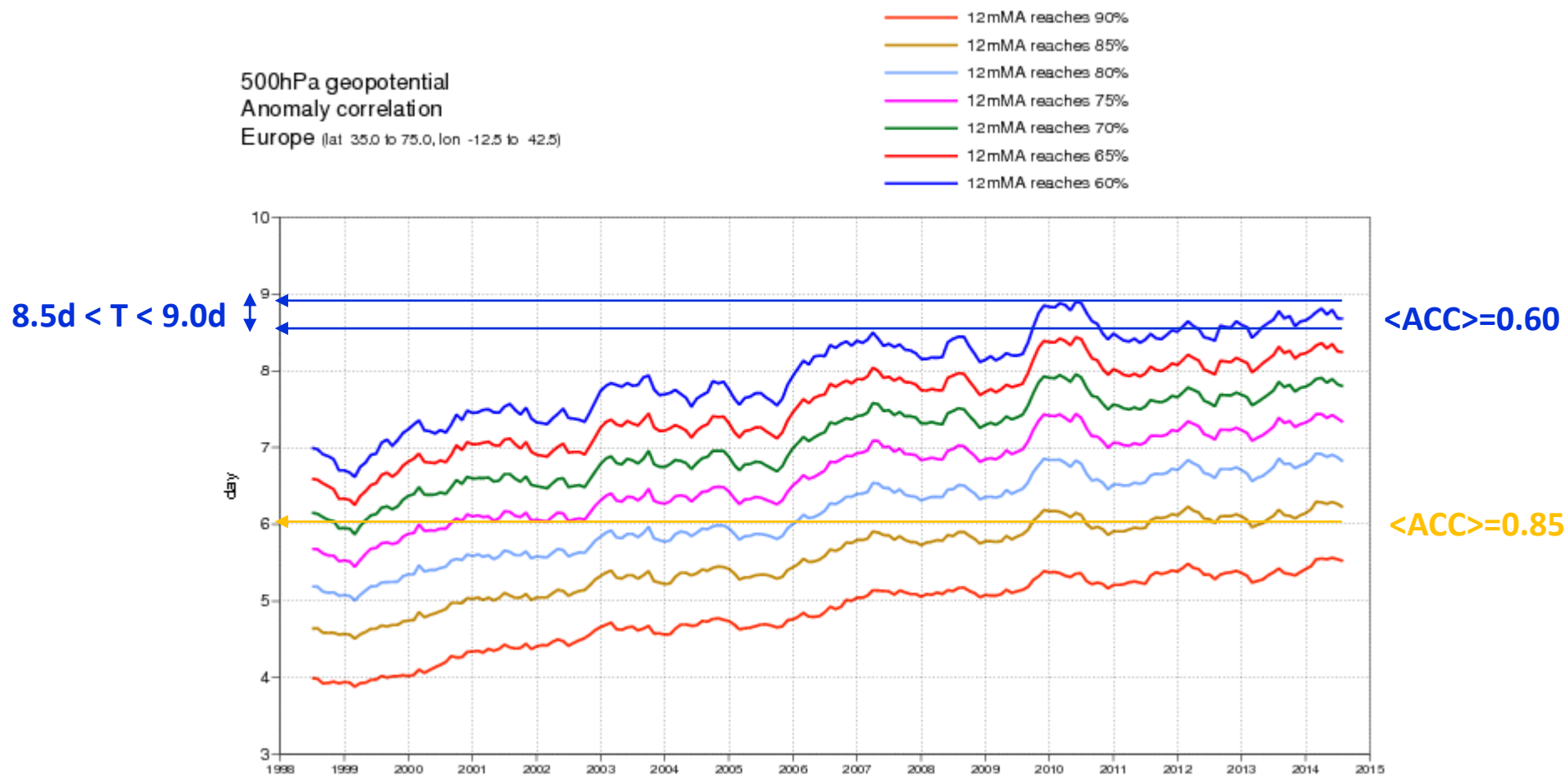
1. The Numerical Weather Prediction (NWP) problem
2. Sources of forecast uncertainties and chaotic behaviour
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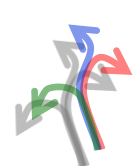




2. Forecast improvements over Europe for Z500

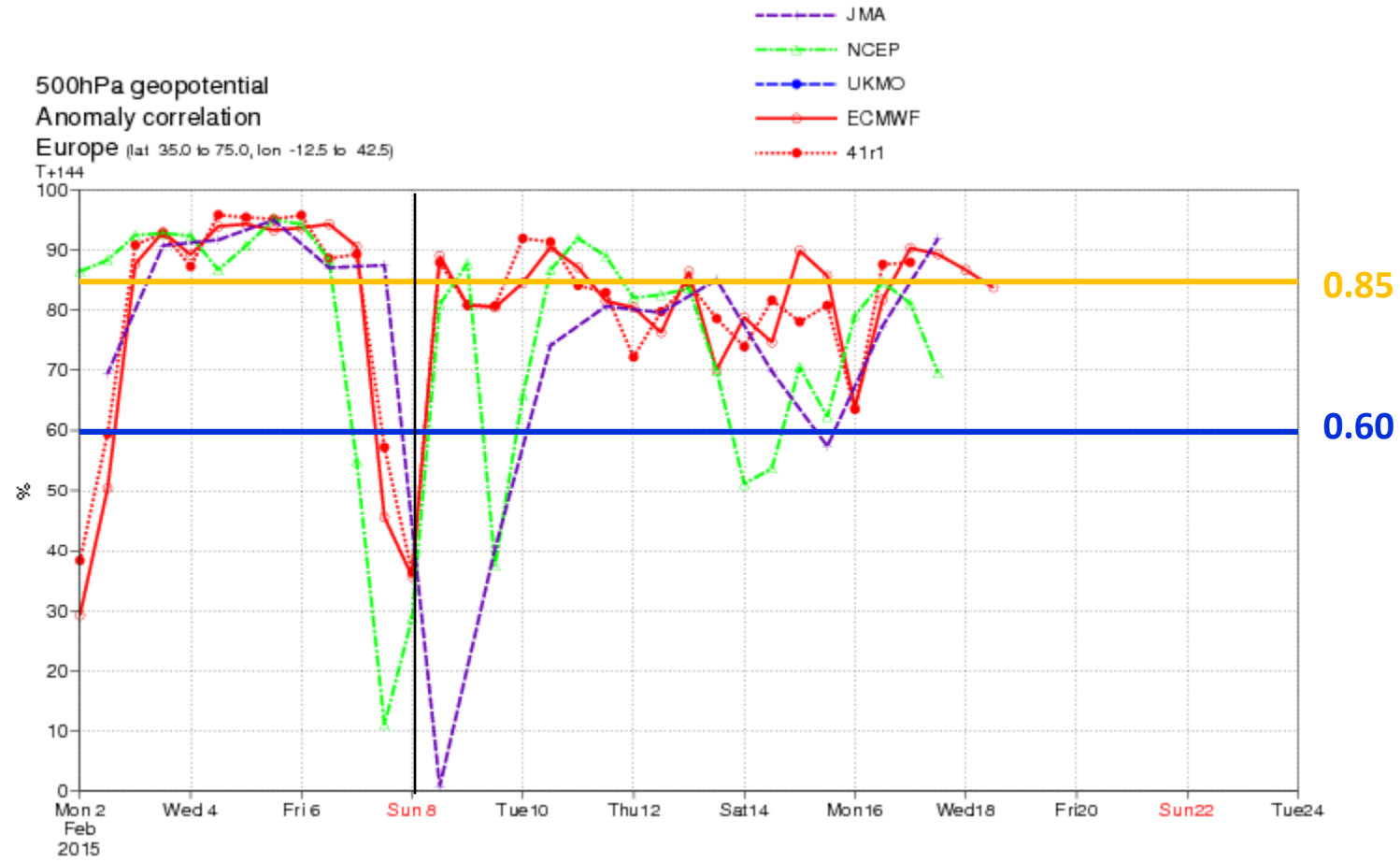
Over Europe, on average 6-day forecasts for Z500 have ACC of about 0.85, and forecasts have ACC of about 0.6 up to about 8.5-9 days.

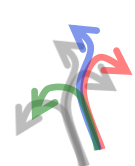




2. February 2015: drop in forecast skill

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.

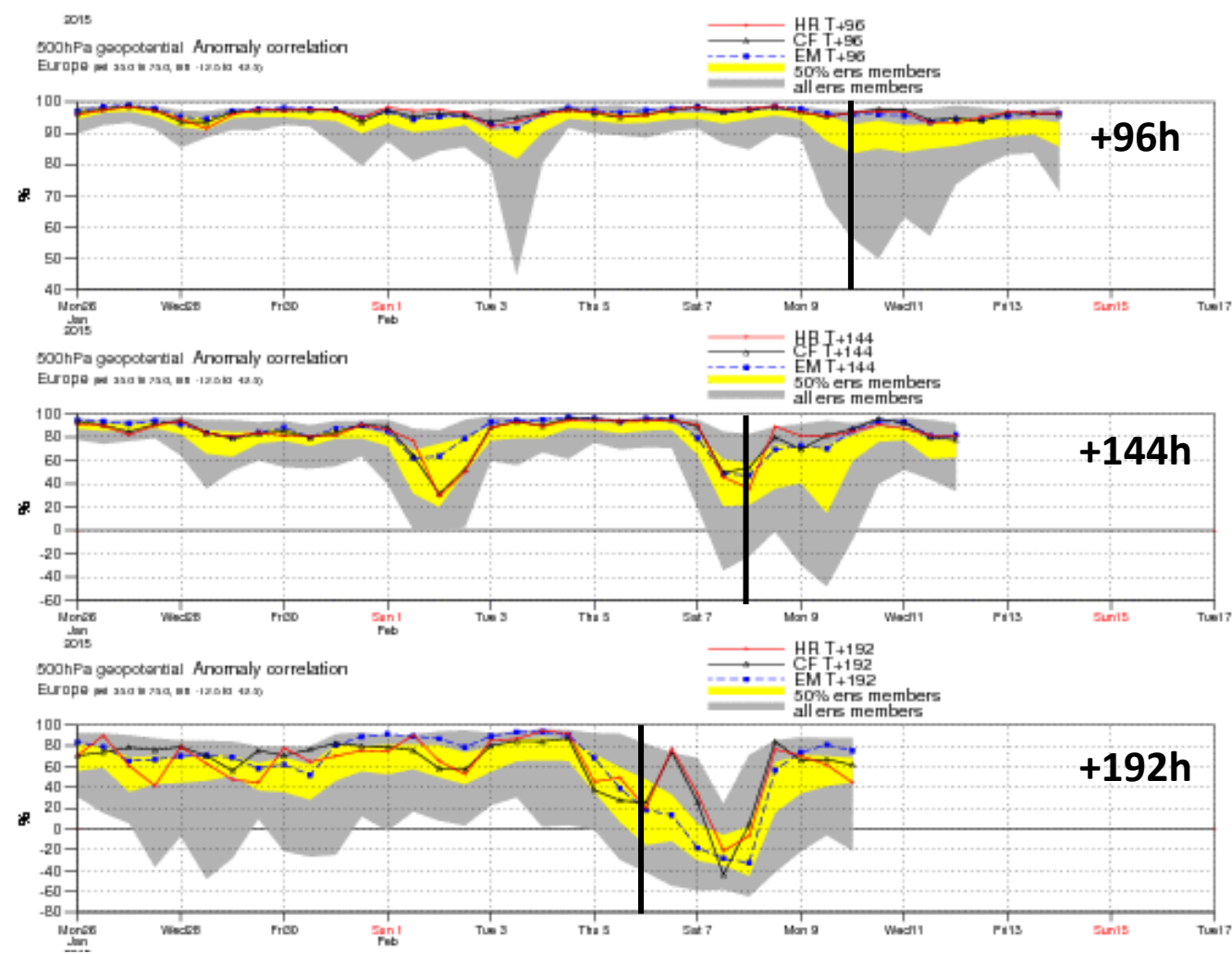


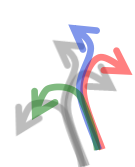


2. February 2015: drop in forecast skill

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).

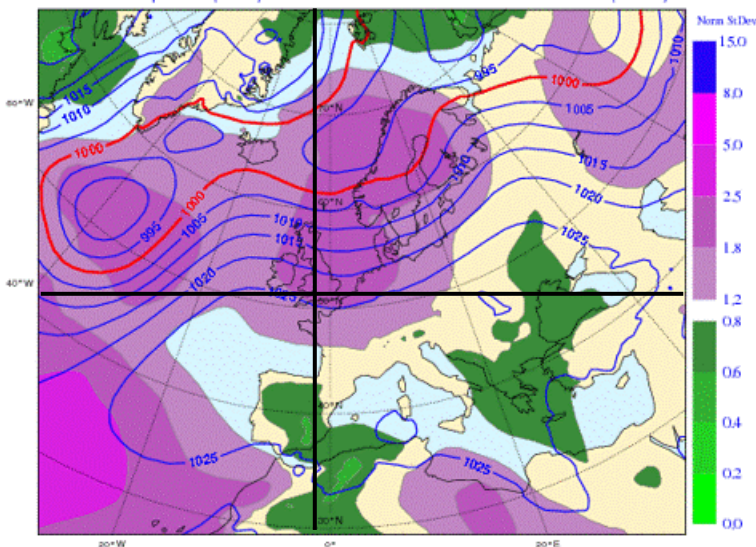
This unpredictable situation was flagged by the ENS, which showed a very large spread.



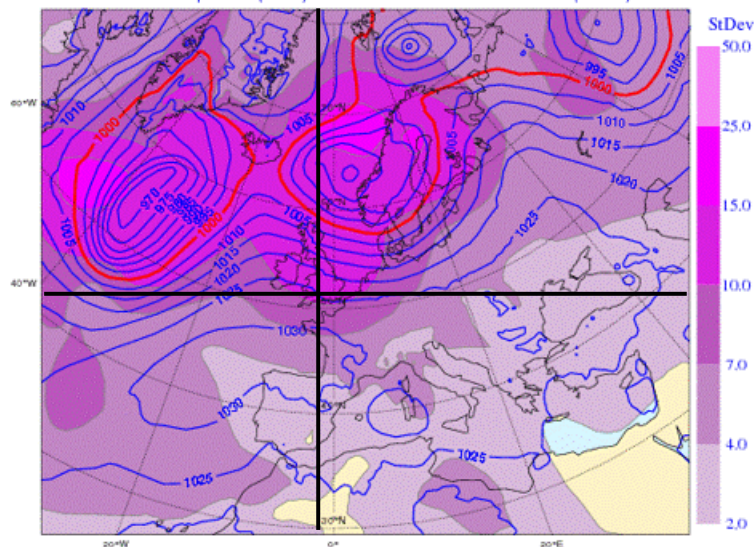


2. February 2015: drop in forecast skill

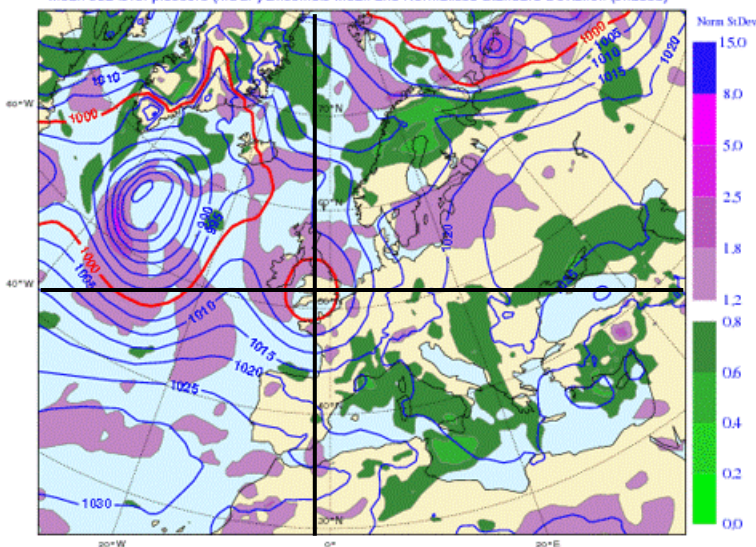
Sunday 8 February 2015 00UTC ECMWF Forecast t+144 VT: Saturday 14 February 2015 00UTC
Mean sea level pressure (MSLP) Ensemble Mean and Normalised Standard Deviation (shaded)



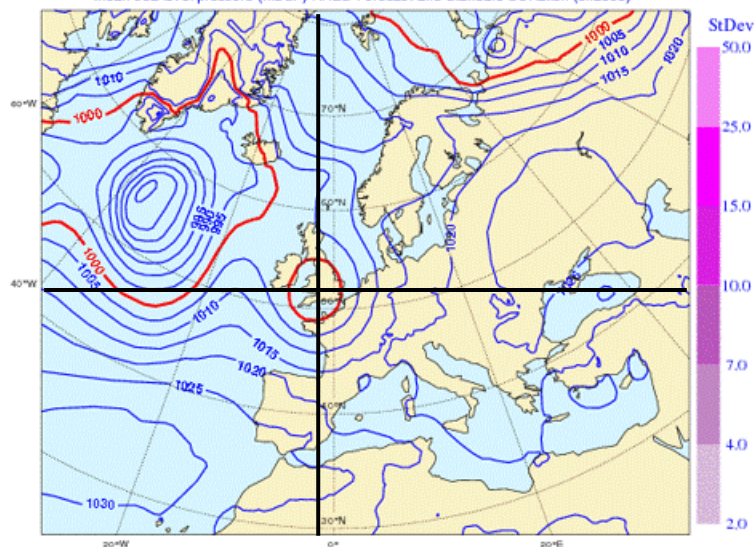
Sunday 8 February 2015 00UTC ECMWF Forecast t+144 VT: Saturday 14 February 2015 00UTC
Mean sea level pressure (MSLP) HRES Forecast and Standard Deviation (shaded)



Saturday 14 February 2015 00UTC ECMWF Forecast t+0 VT: Saturday 14 February 2015 00UTC
Mean sea level pressure (MSLP) Ensemble Mean and Normalised Standard Deviation (shaded)



Saturday 14 February 2015 00UTC ECMWF Forecast t+0 VT: Saturday 14 February 2015 00UTC
Mean sea level pressure (MSLP) HRES Forecast and Standard Deviation (shaded)

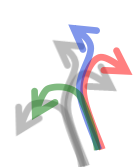


08@00+6d
<ENS>+NSTD

08@00+6d
HRES+STD

14@00
<ENS>+NSTD

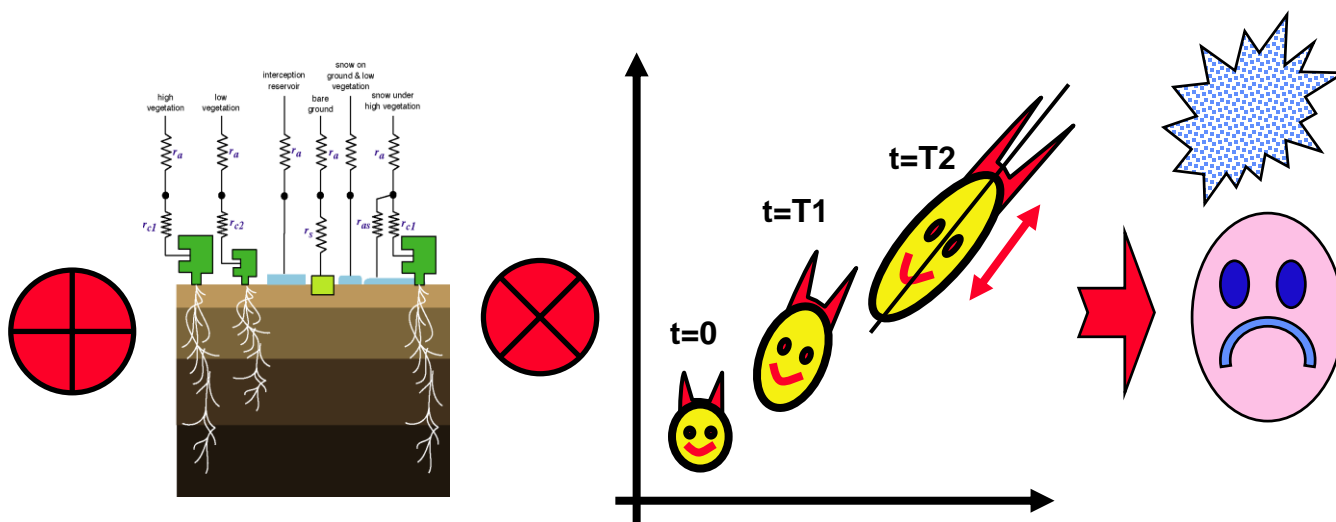
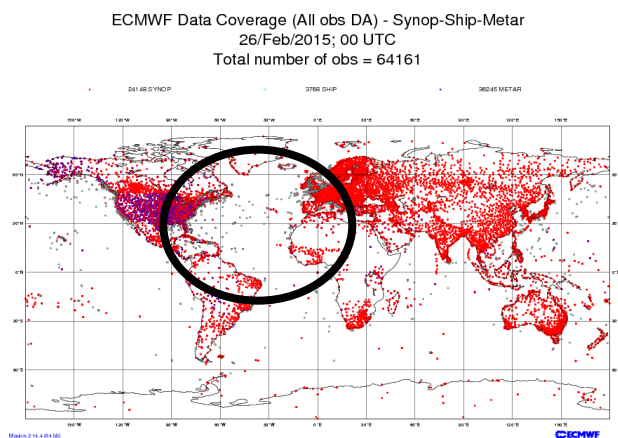
14@00
HRES+STD

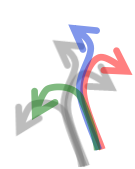


2. Why do forecasts fail?

Forecasts can fail because:

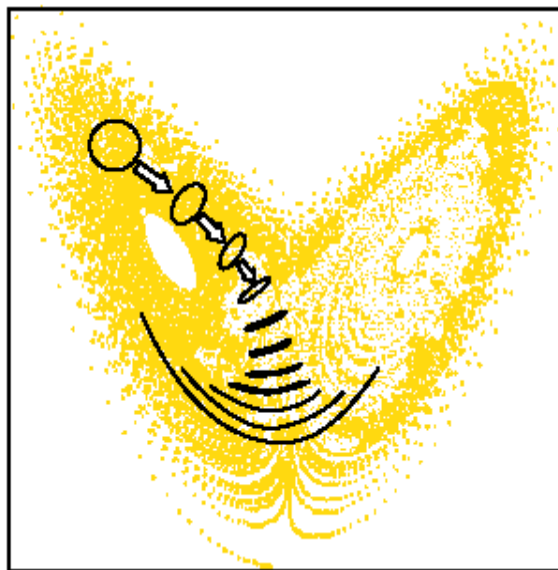
- The initial conditions are not accurate enough, e.g. due to poor coverage and/or observation errors, or errors in the assimilation (**initial uncertainties**).
- The model used to assimilate the data and to make the forecast describes only in an approximate way the true atmospheric phenomena (**model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

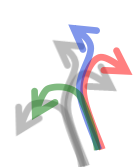




Outline

1. The Numerical Weather Prediction (NWP) problem
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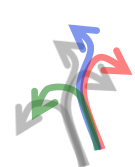




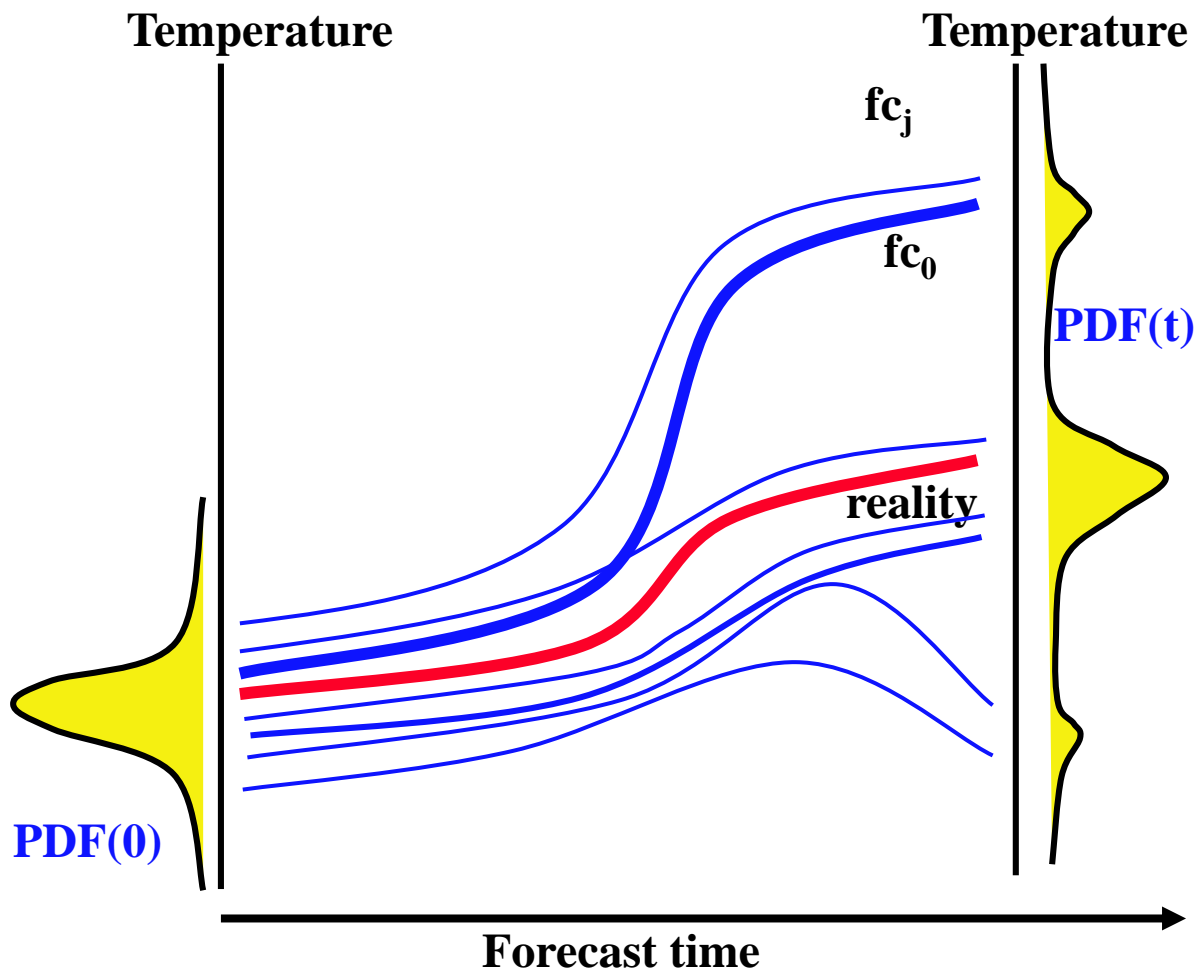
3. What is the aim of weather forecasting?

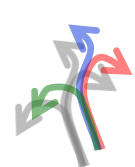
We have seen that single forecasts can fail due to a combination of **initial** and **model uncertainties**, and that the NWP problem is made extremely complex by the **chaotic nature of the atmosphere**.

- 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 (give a 'confidence band'), for example expressed in terms of weather scenarios or probabilities that different weather conditions can occur?



3. Ensemble prediction

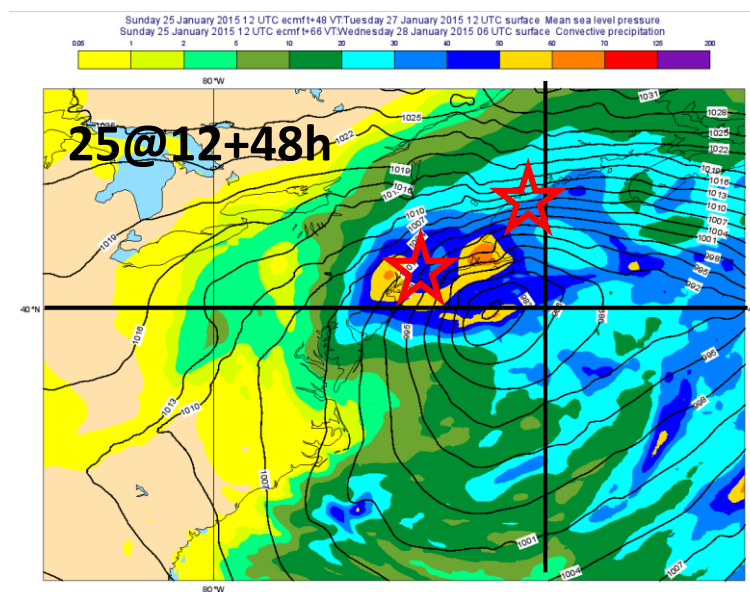
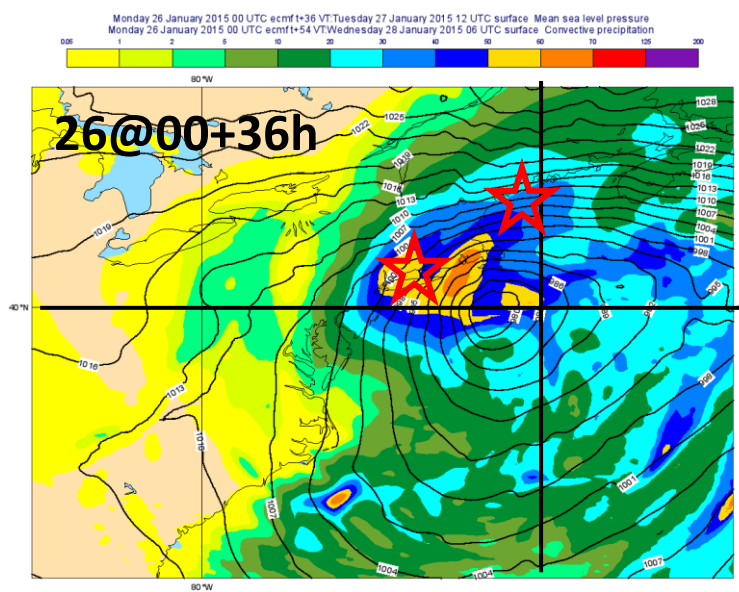
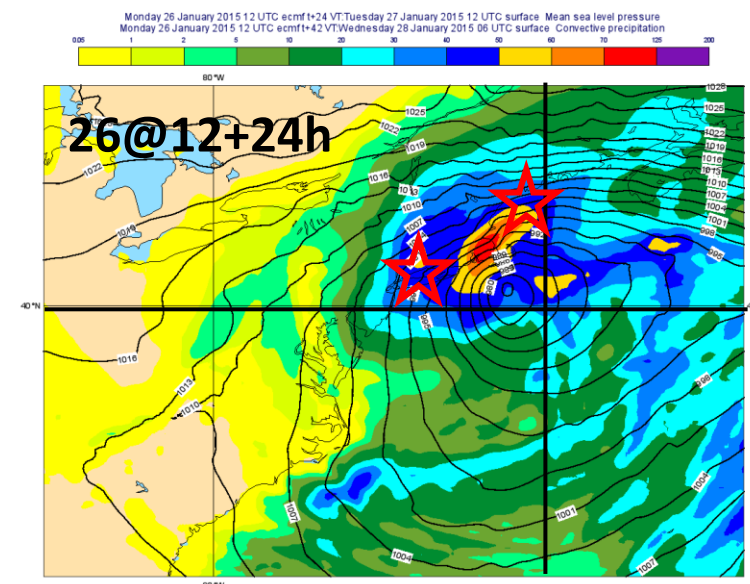
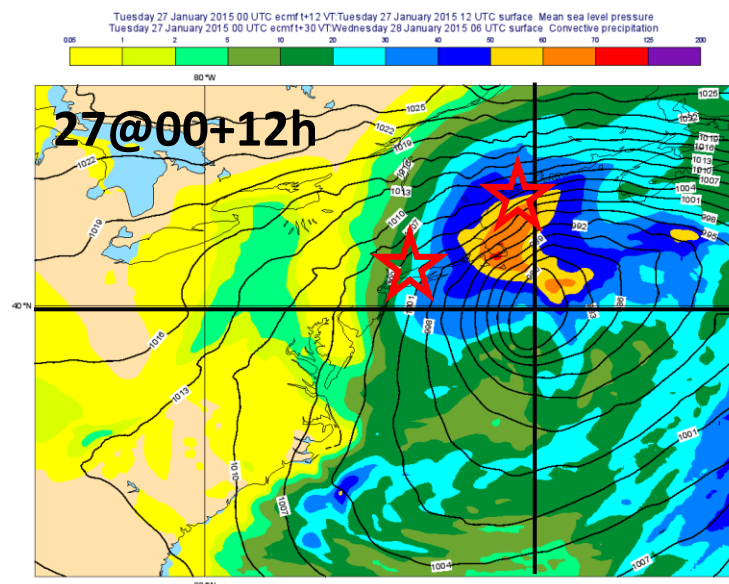


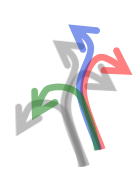


3. US Storm, 27-28/01/2015: single HRES fc

Single HRES fcs failed to position correctly the storm, and this led 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.

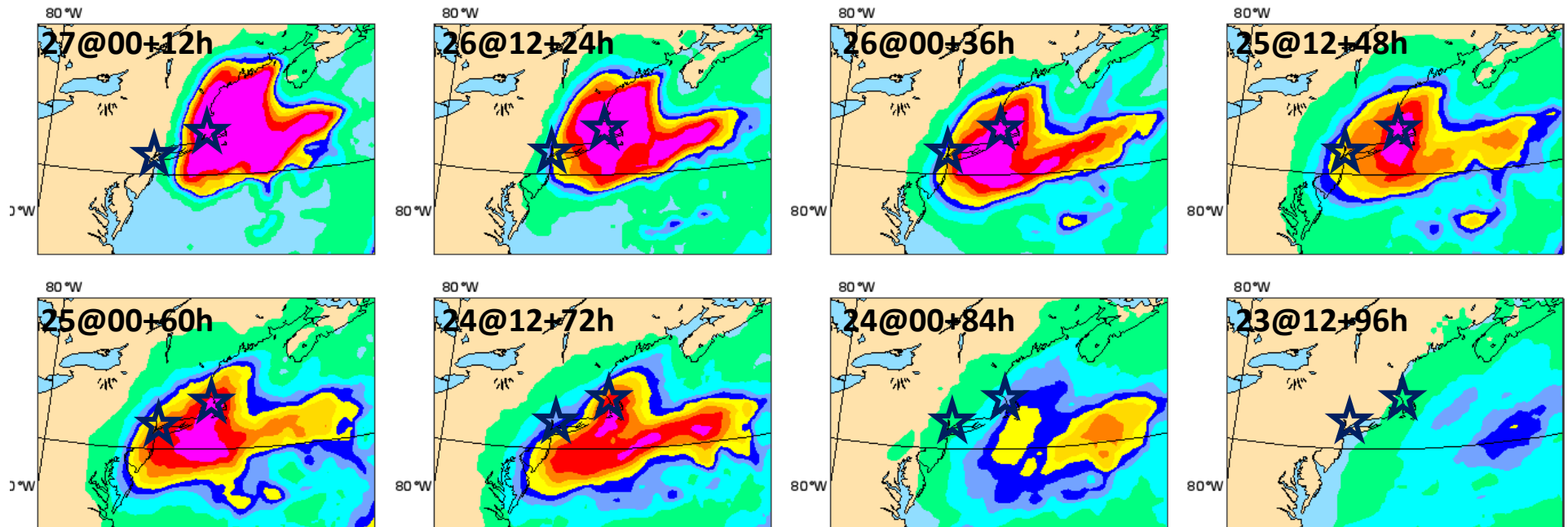


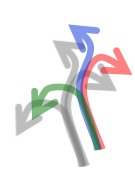


3. US Storm, 27-28/01/2015: ENS PR fcs

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.

ENS PR[TP(27@00–28@06)>30mm]

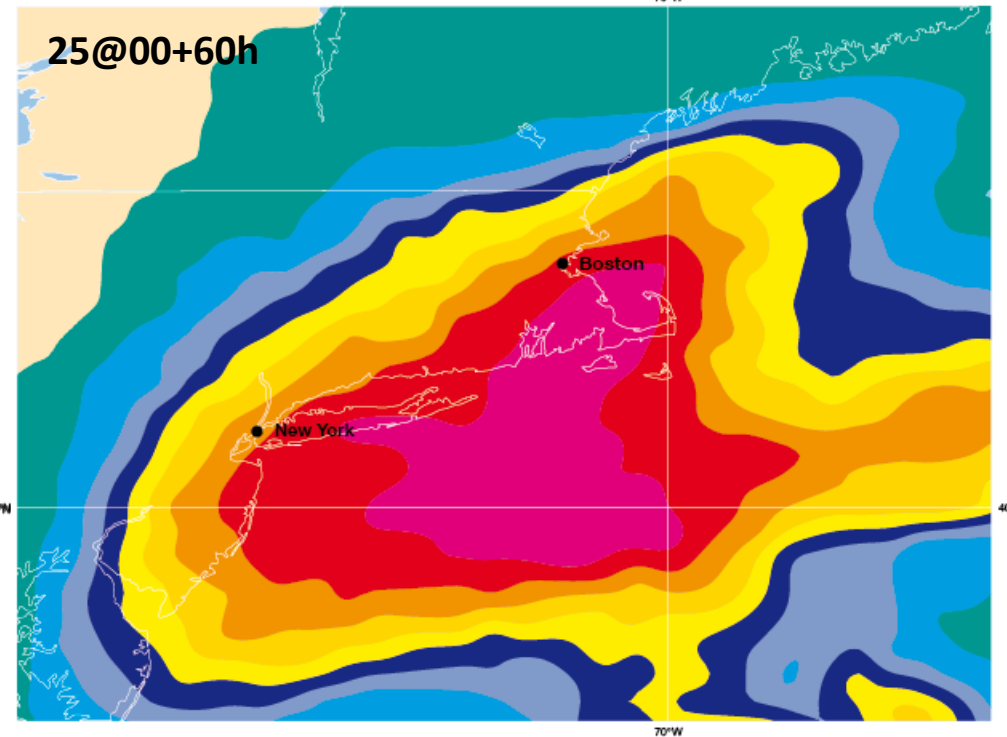
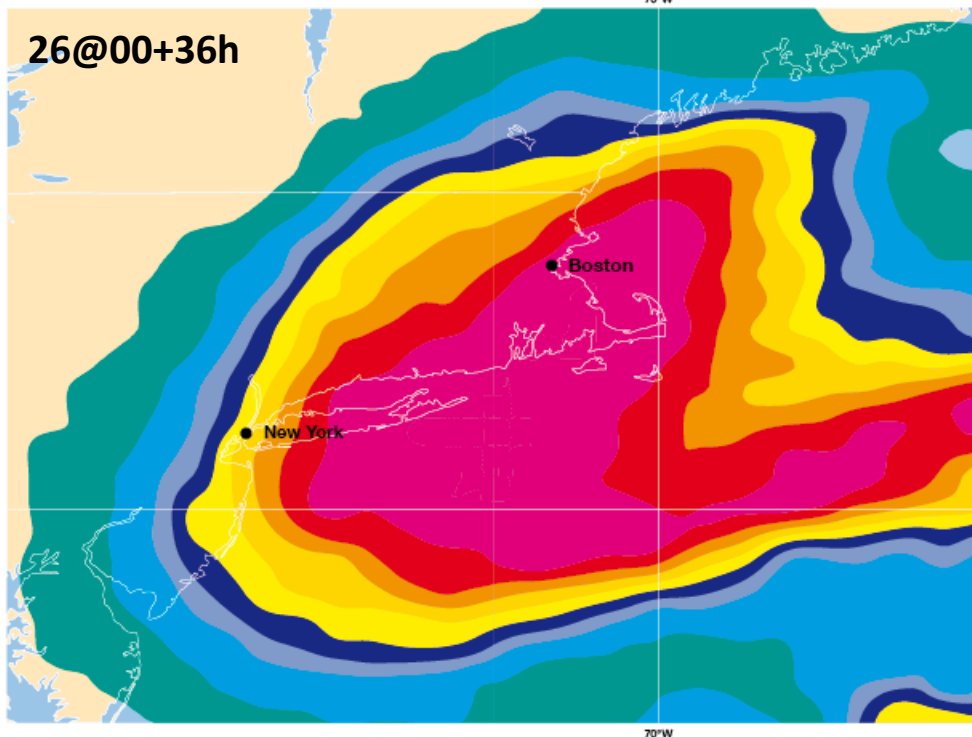
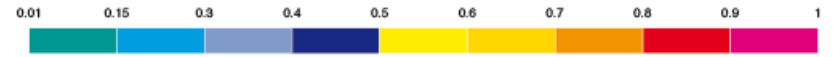





3. US Storm, 27-28/01/2015: ENS PR fcs

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]

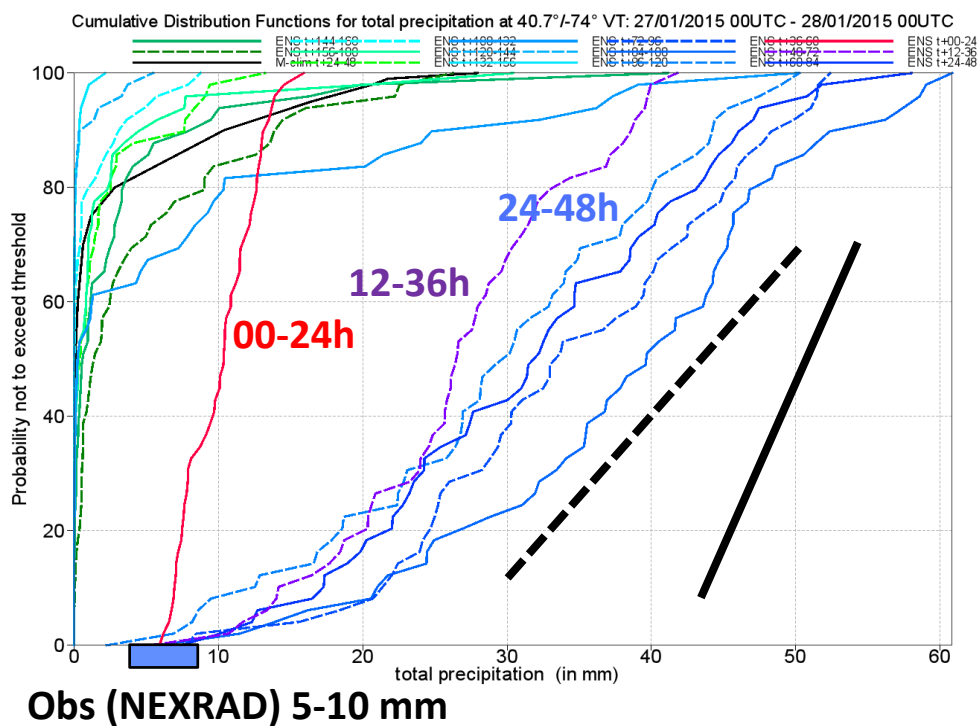




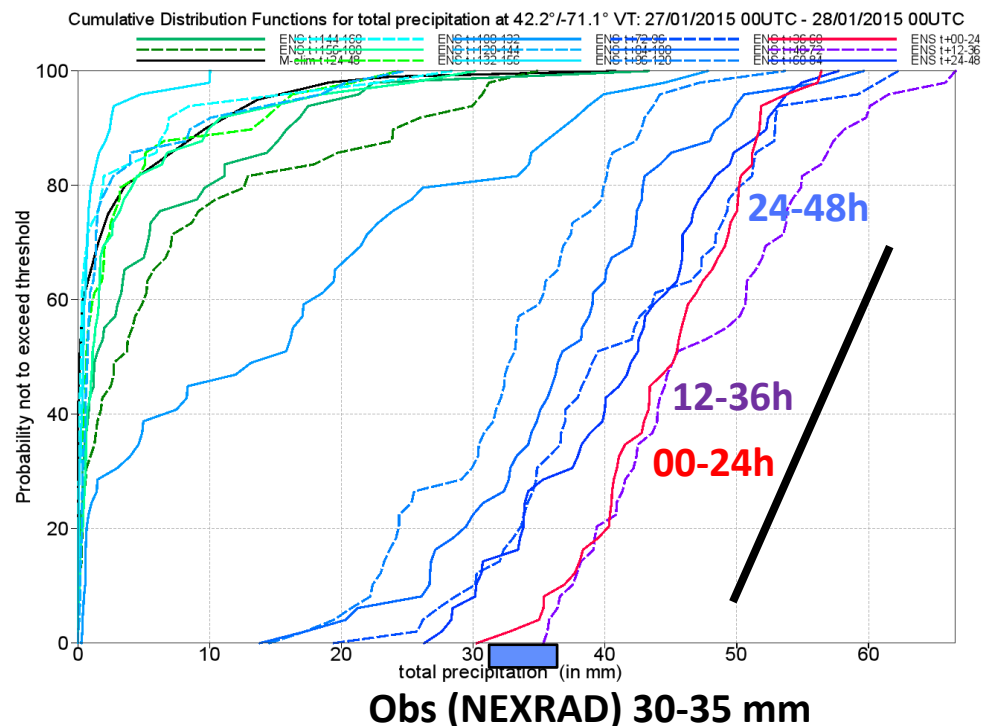
3. US Storm, 27-28/01/2015: ENS PR fcs

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.

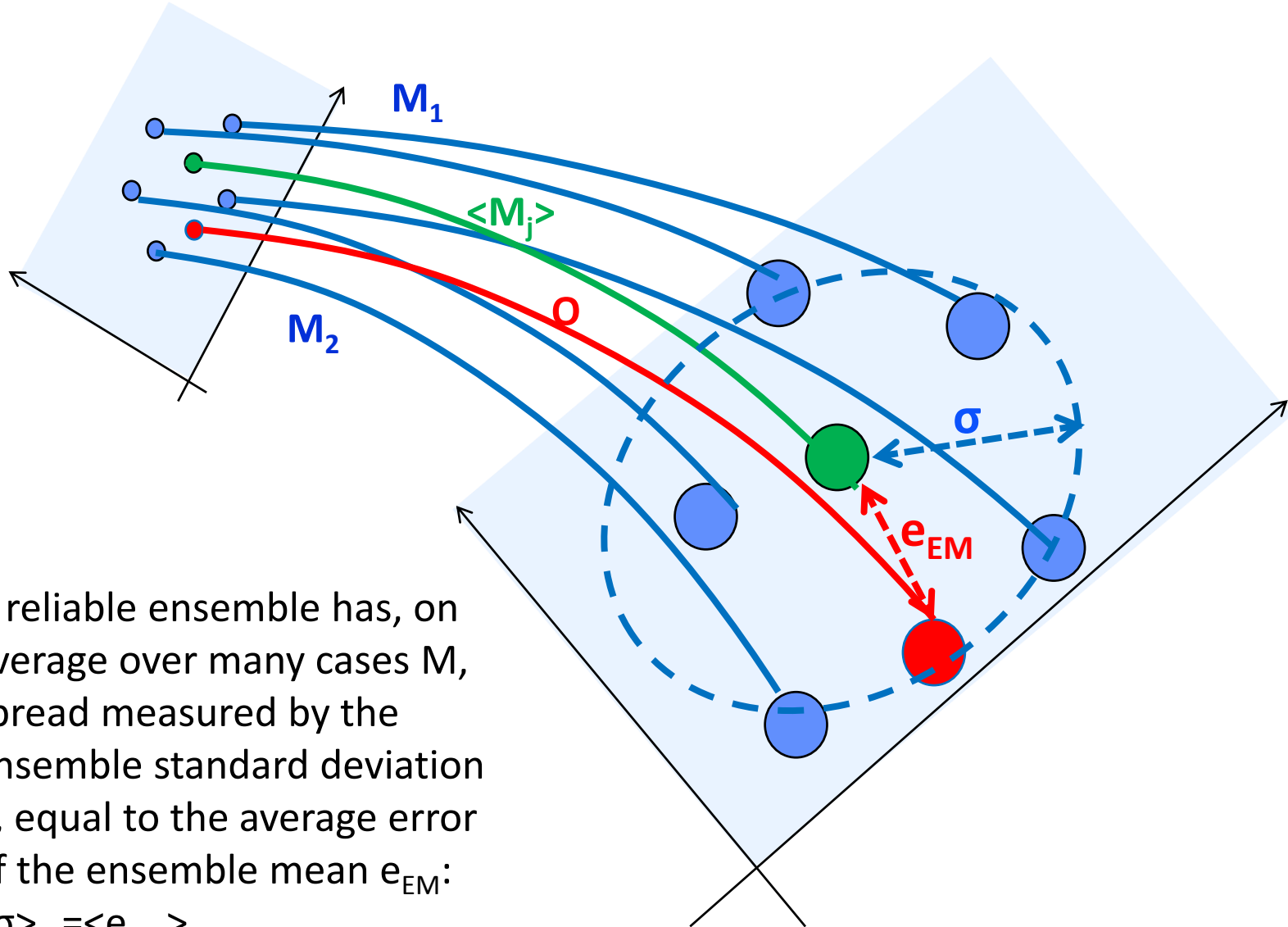
New York



Boston



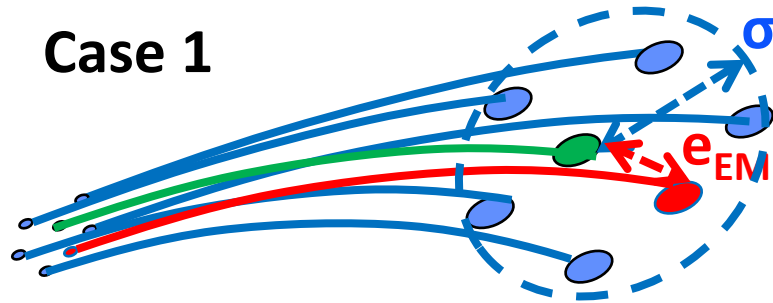
3. A necessary ensemble property: reliability



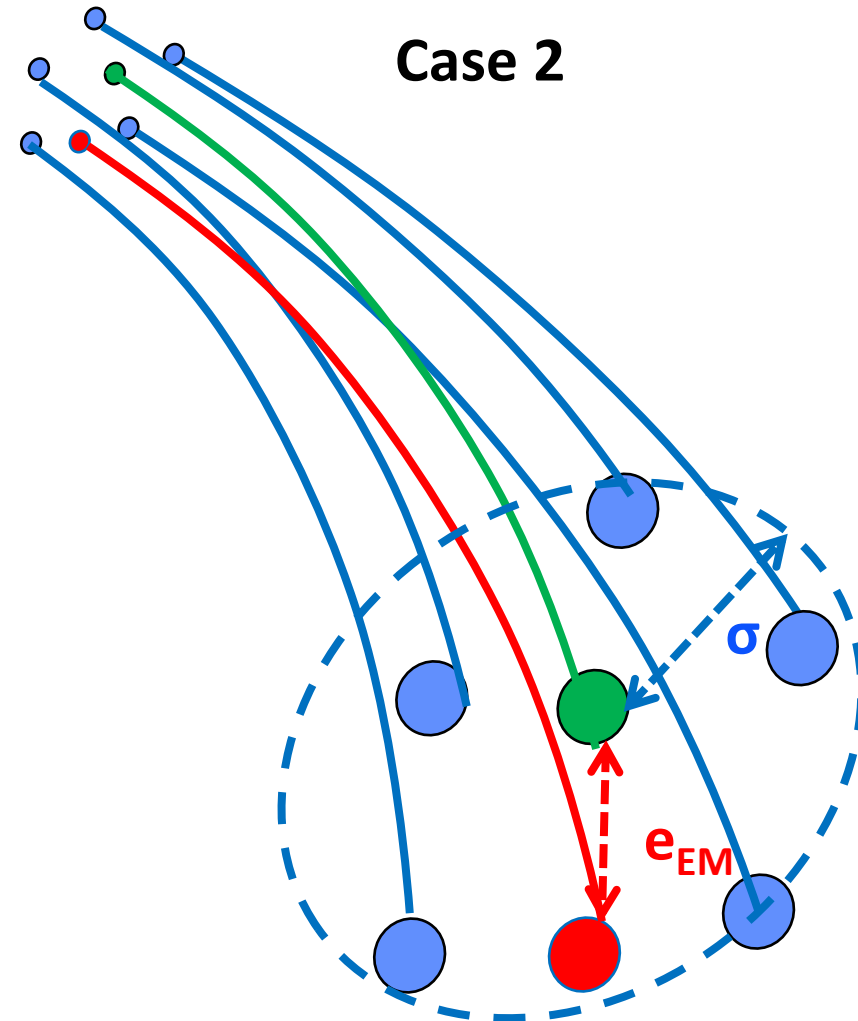
A reliable ensemble has, on average over many cases M , spread measured by the ensemble standard deviation σ , equal to the average error of the ensemble mean e_{EM} :

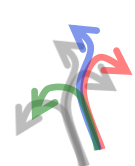
$$\langle \sigma \rangle_M = \langle e_{EM} \rangle_M$$

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} .



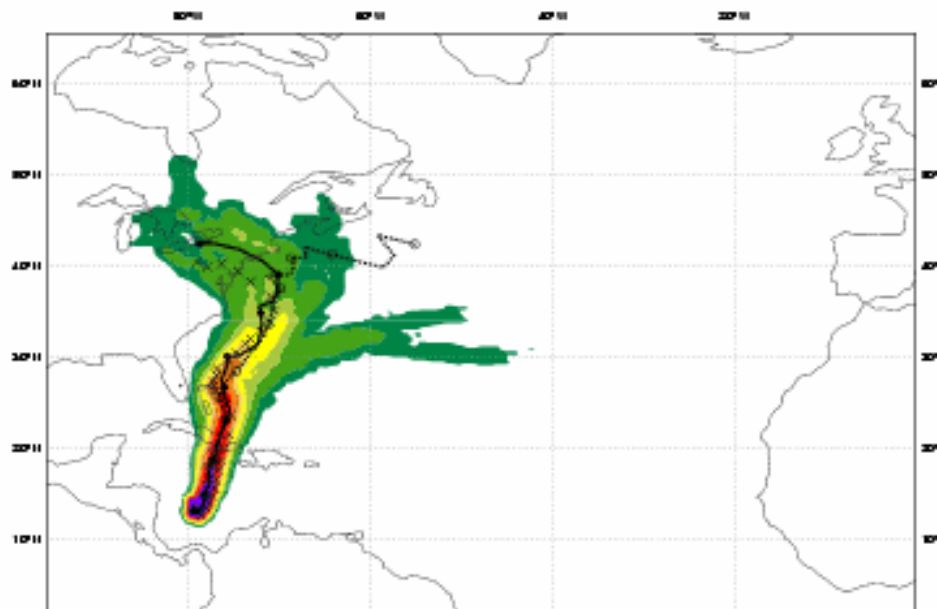


3. Track dispersion & predictability: Sandy (Oct 2012)

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.

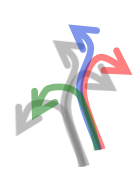


Date 20121023 00 UTC @ ECMWF
 Probability that SANDY will pass within 120 km radius during the next 240 hours
 tracks: solid-OPER; dot-Ens Mean [reported minimum central pressure (hPa) 998]



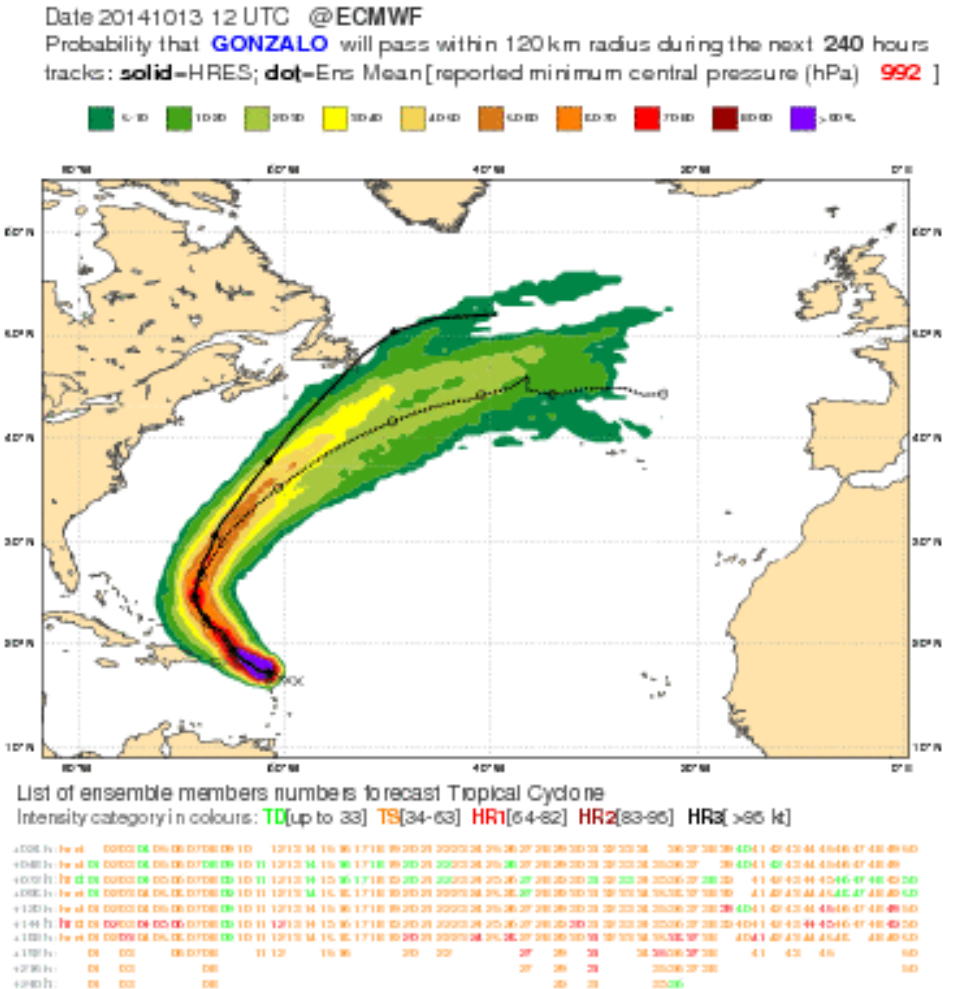
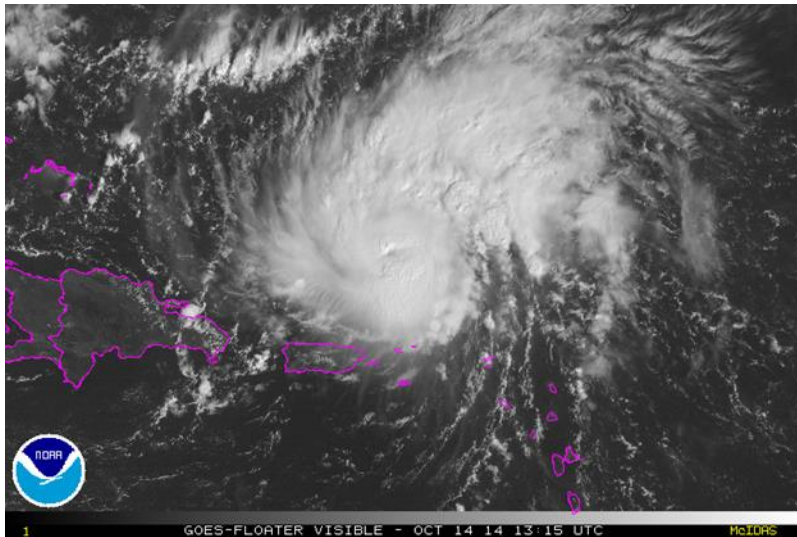
List of ensemble members numbers forecast Tropical Cyclone
 Intensity category in colours: TD [up to 33] TS [34-63] HR1 [64-82] HR2 [83-95] HR3 [>95 kt]

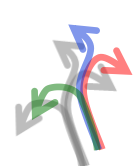
Time	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18														
+02h	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
+06h	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
+12h	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
+18h	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
+24h	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
+30h	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50



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

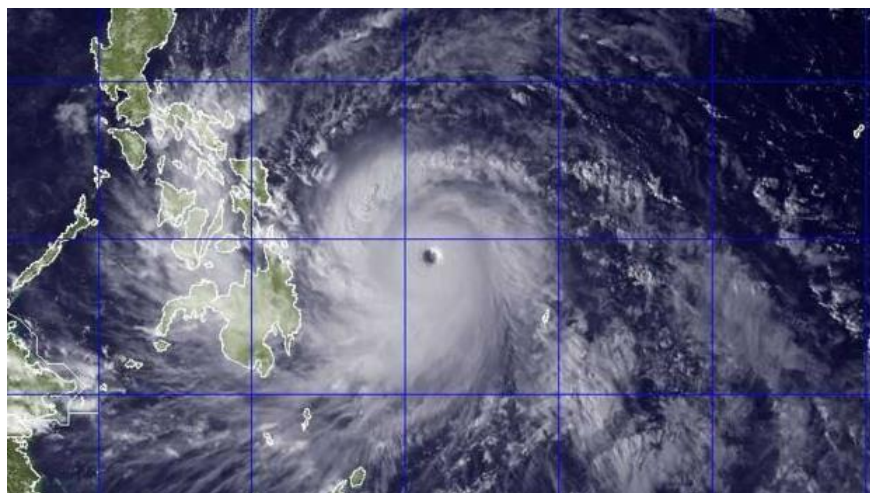
Gonzalo (Oct 2014) - Dispersion of ENS tracks in the 10d forecast issued on 2014.10.13@12 was relatively small for the whole 10 day range, indicating more confidence on direction of travel.





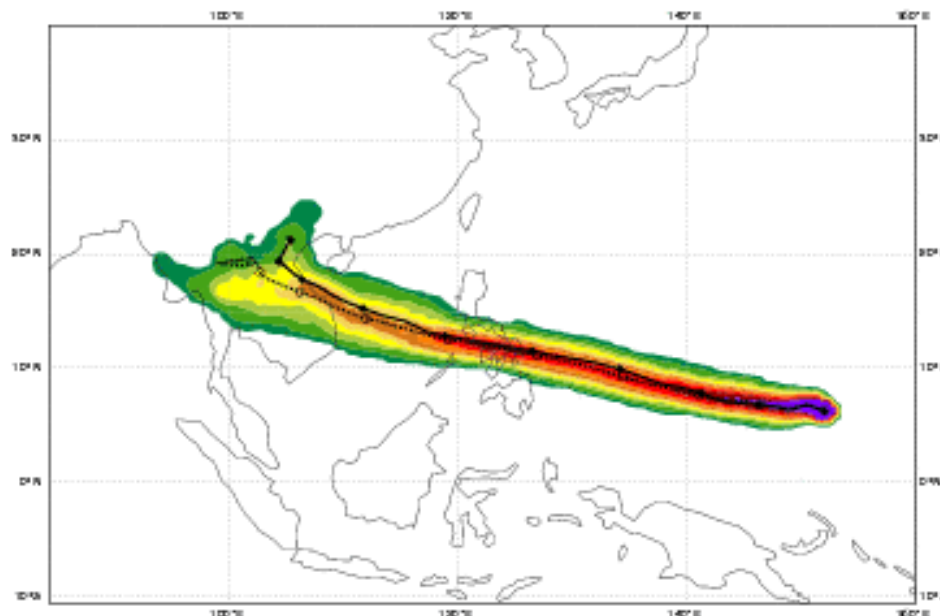
3. Track dispersion & predictability: Haiyan (Nov 2013)

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.



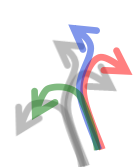
Date 20131104 00 UTC @ECMWF
Probability that HAIYAN will pass within 120 km radius during the next 240 hours
tracks: solid=OPER; dot=Ens Mean [reported minimum central pressure (hPa) 1002]

Legend for intensity categories: 5-10, 10-20, 20-30, 30-40, 40-50, 50-60, 60-70, 70-80, 80-90, >90 %



List of ensemble members numbers to forecast Tropical Cyclone
Intensity category in colours: TD[up to 33] TS[34-63] HR1[64-82] HR2[83-95] HR3[>95 kt]

+006 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+048 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+120 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+144 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+168 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+216 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+288 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50
+360 h	Ensemble members: 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50

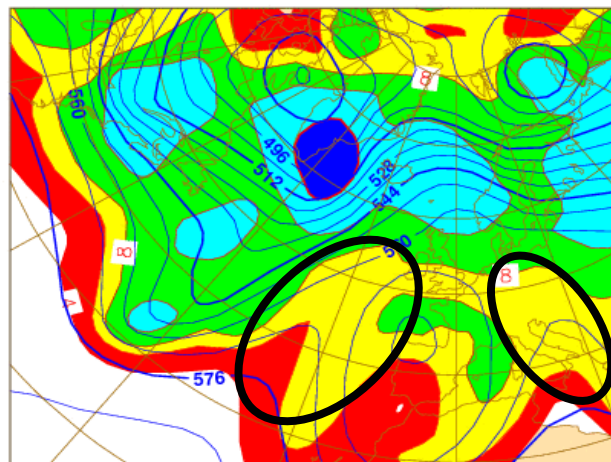


3. ENS spread as an index of predictability

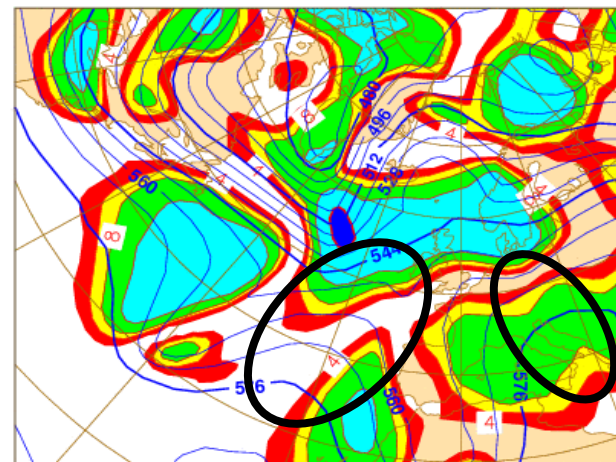
Small ensemble spread should identify predictable conditions:

- 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

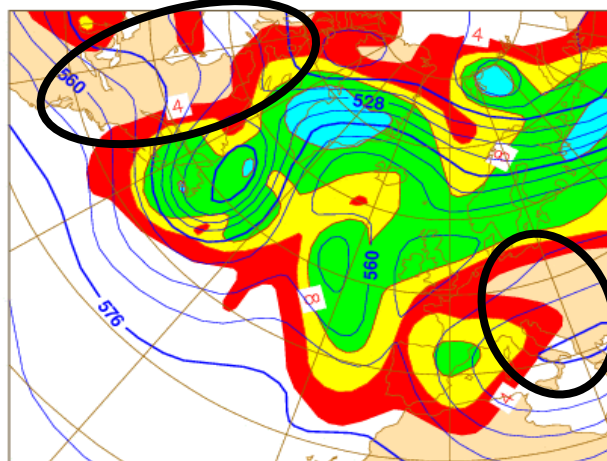
CON+SP - Z500 1997-01-18 12h fc t+120



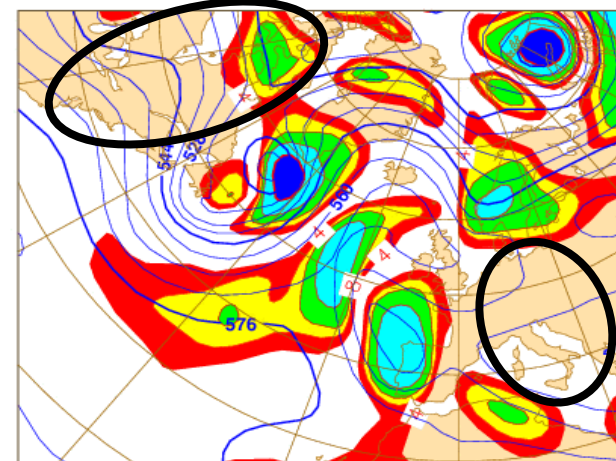
ANA+ERRCON - Z500 1997-01-23 12h fc

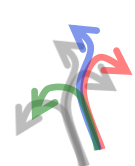


CON+SP - Z500 1998-01-18 12h fc t+120



ANA+ERRCON - Z500 1998-01-23 12h fc





3. In a reliable ensemble, $\langle \text{spread} \rangle \sim \langle \text{er}(\text{EM}) \rangle$

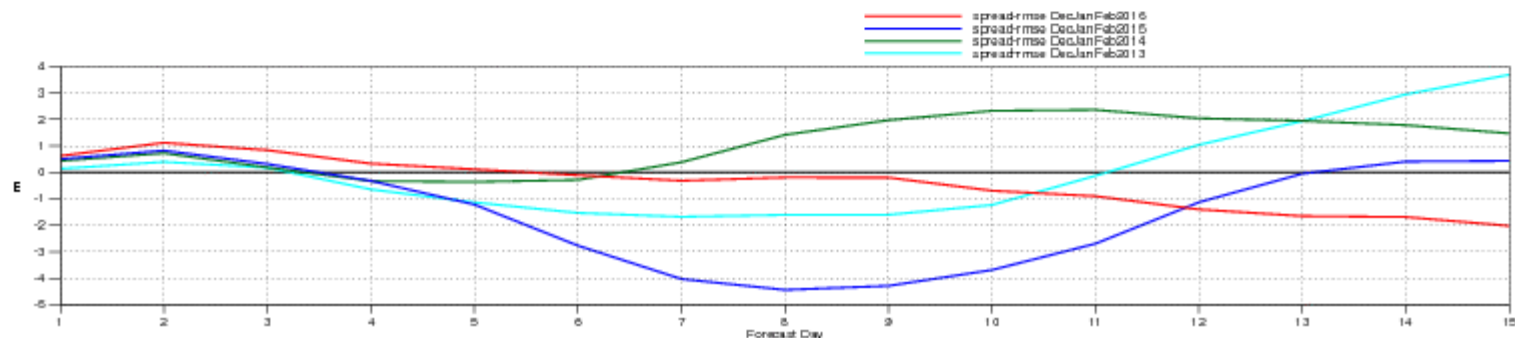
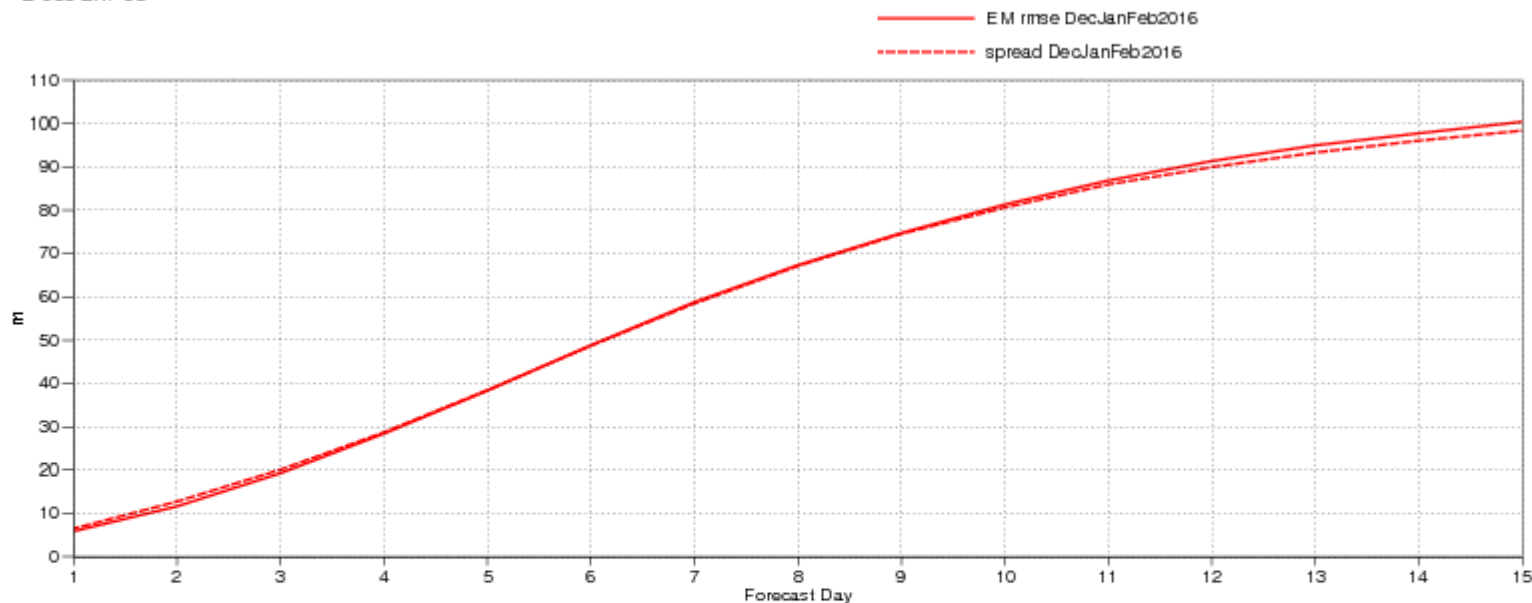
One way to check the ensemble reliability is to assess whether the time evolution of the seasonal average ensemble standard deviation and error of the ensemble mean are similar.

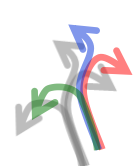
This plot shows these two curves for Z500 over NH in DN14J15.

ENS Mean RMSE and ENS Spread

500hPa geopotential
NHem Extratropics (lat 20.0 to 90.0, lon -180.0 to 180.0)
DecJanFeb

Z500 - NH

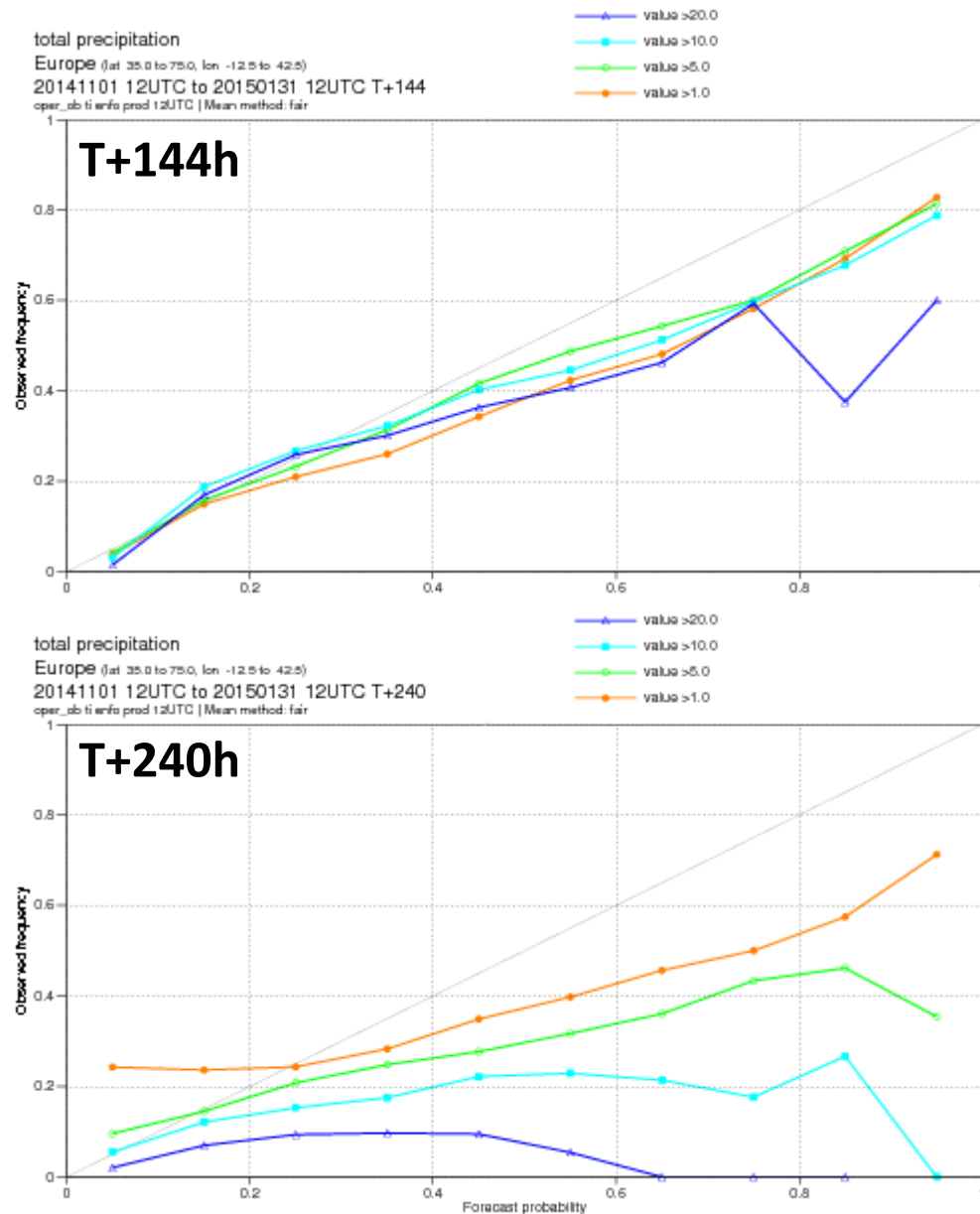


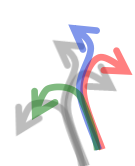


3. In a reliable ensemble, $\langle \text{fc-prob} \rangle \sim \langle \text{obs-prob} \rangle$

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).

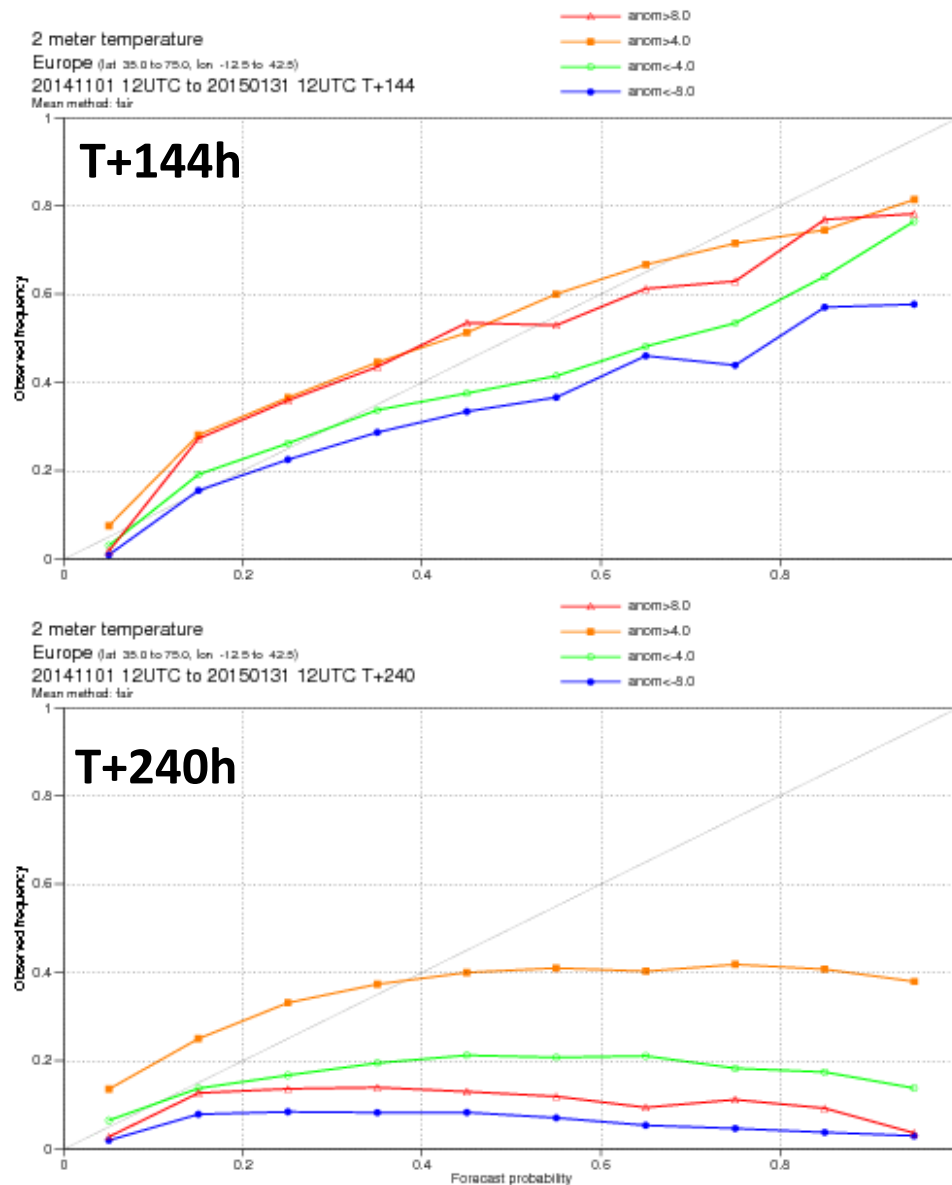


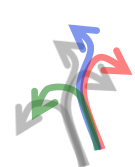


3. In a reliable ensemble, $\langle \text{fc-prob} \rangle \sim \langle \text{obs-prob} \rangle$

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

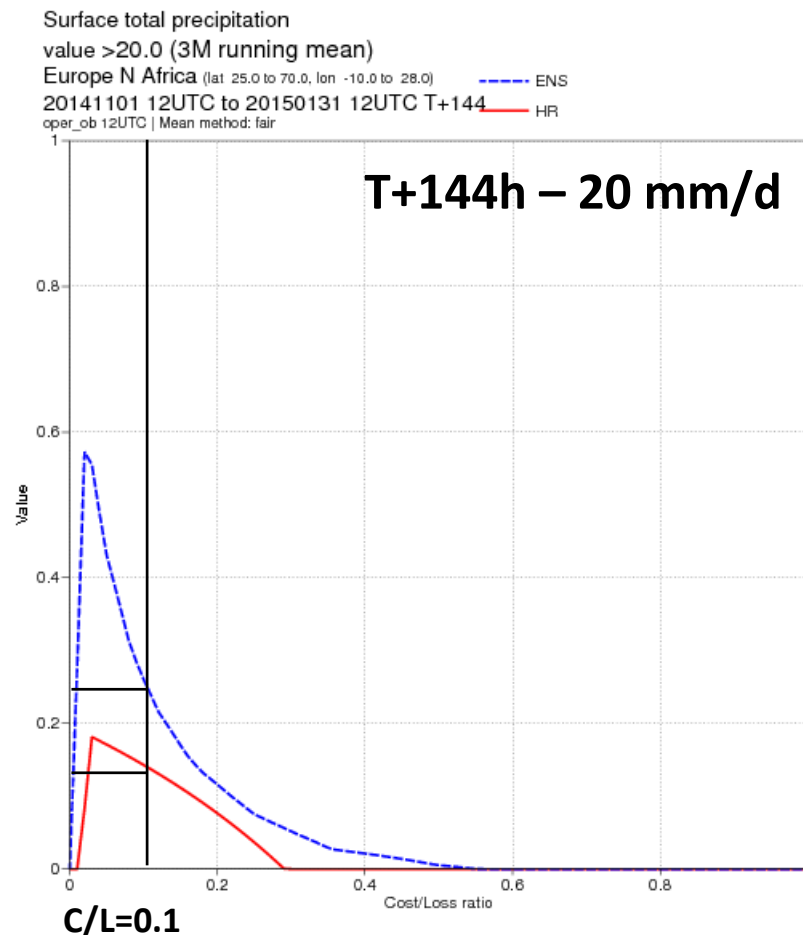
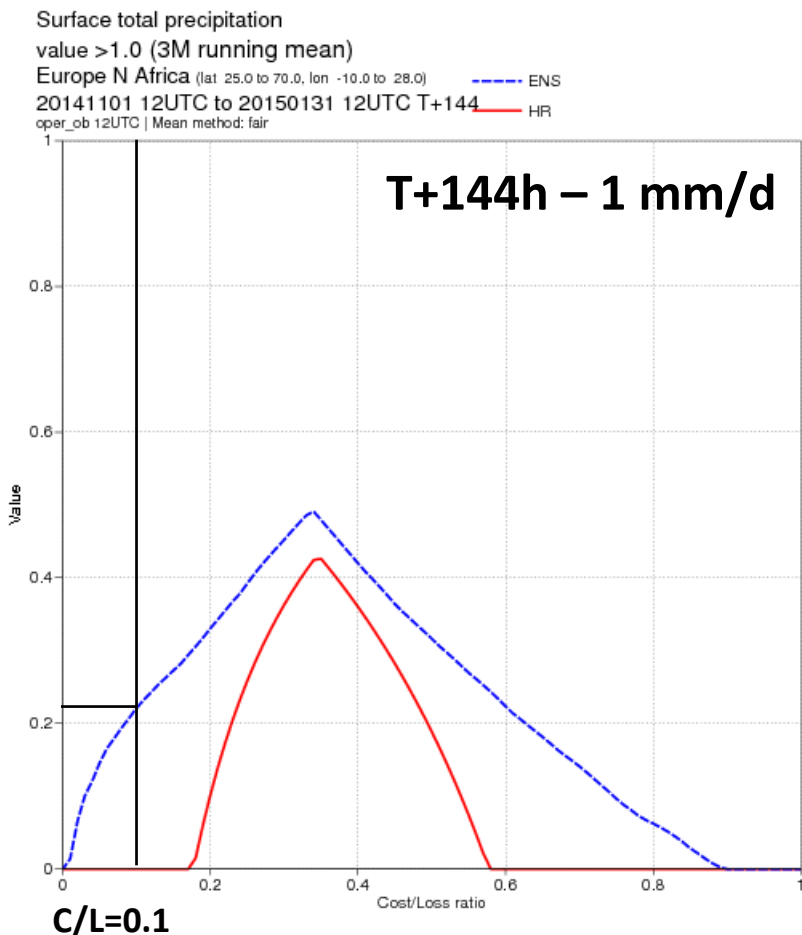
These plots compare the two probabilities at t+144h and t+240h for the event '2-meter temperature anomaly lower than -8/-4 and higher than +4/+8 degrees' over Europe for ND14J15 (verified against observations).

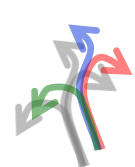




3. Are ensembles more valuable than single fcs?

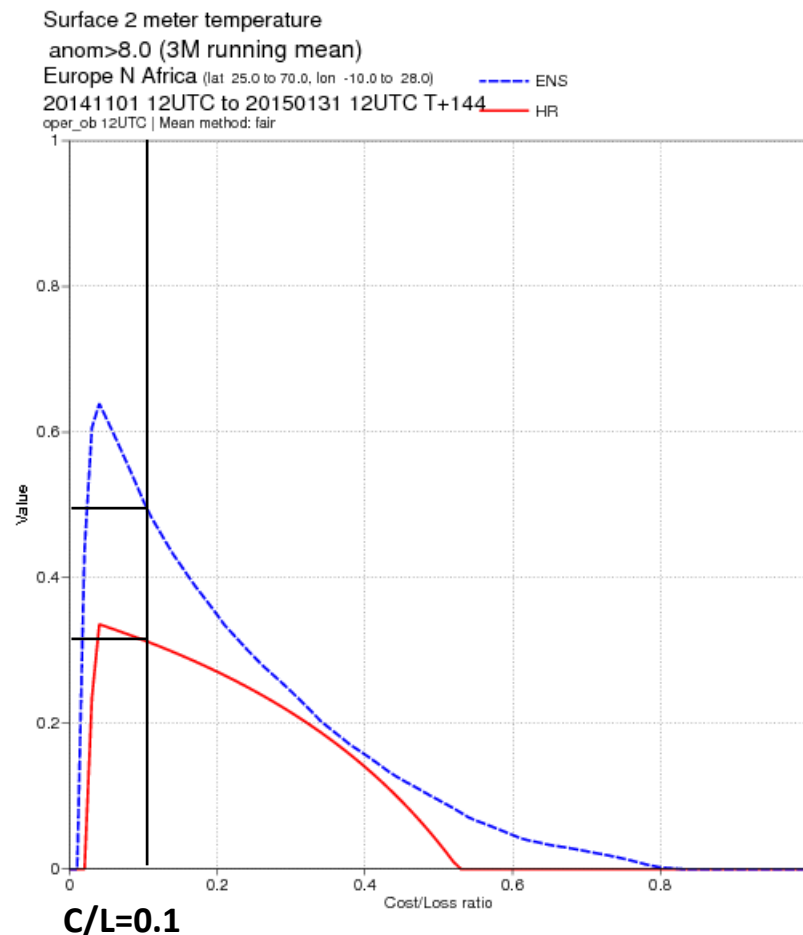
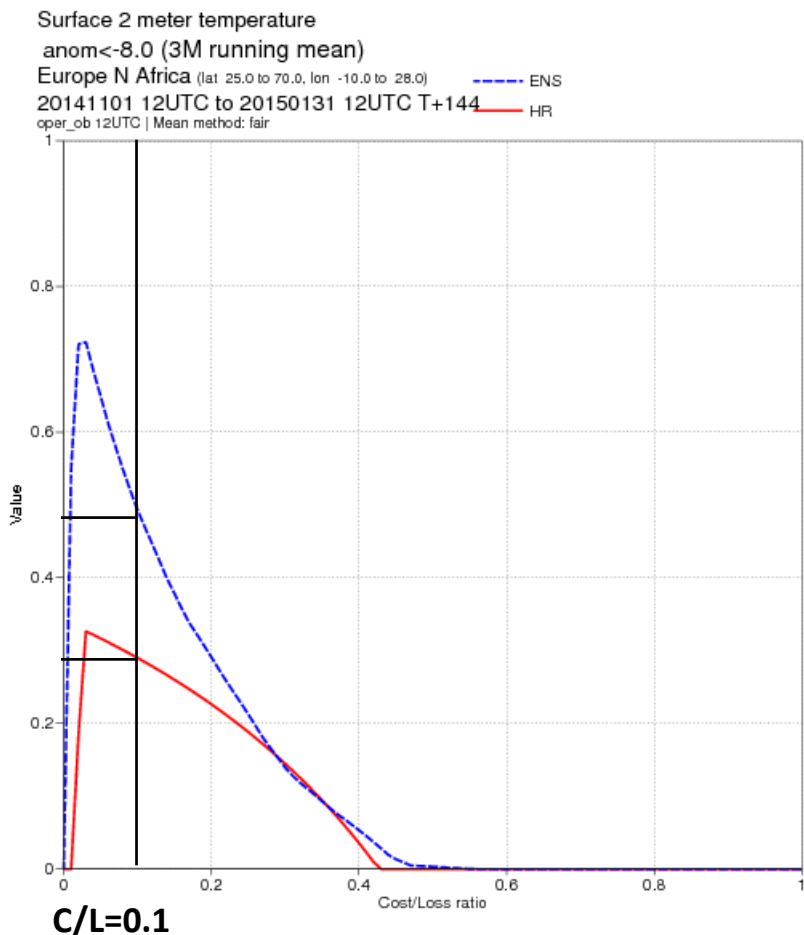
ENS probabilistic forecasts have higher Potential Economic Value (PEV) than the single high-resolution forecast. These plots refer to t+144h precipitation forecasts (ND14J15).

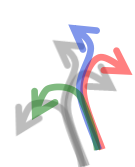




3. Are ensembles more valuable than single fcs?

ENS probabilistic forecasts have higher Potential Economic Value (PEV) than the single high-resolution forecast. These plots refer to t+144h 2m temp. forecasts (ND14J15).

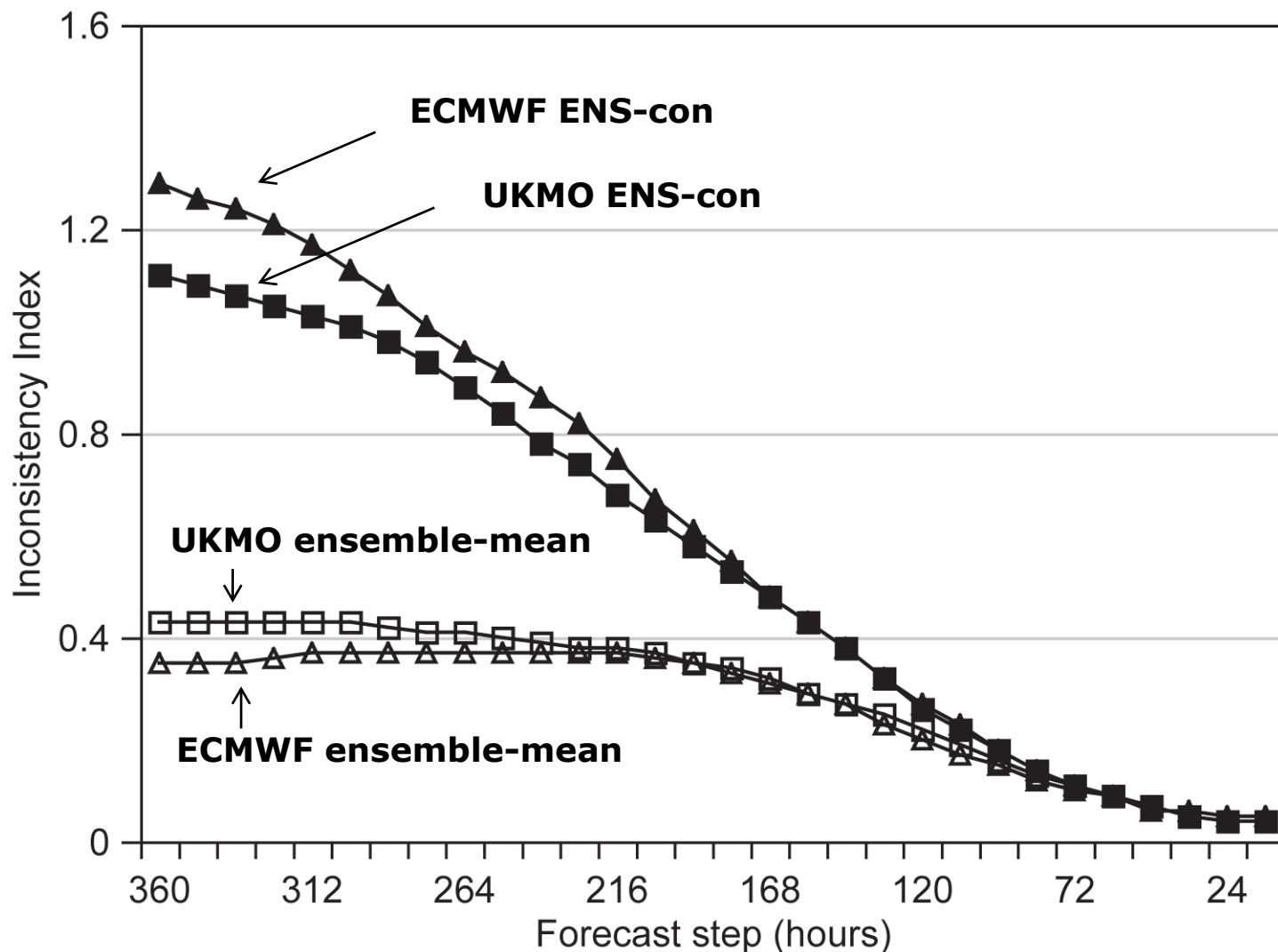




3. Ensembles are more consistent

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).

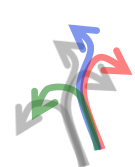




Outline

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



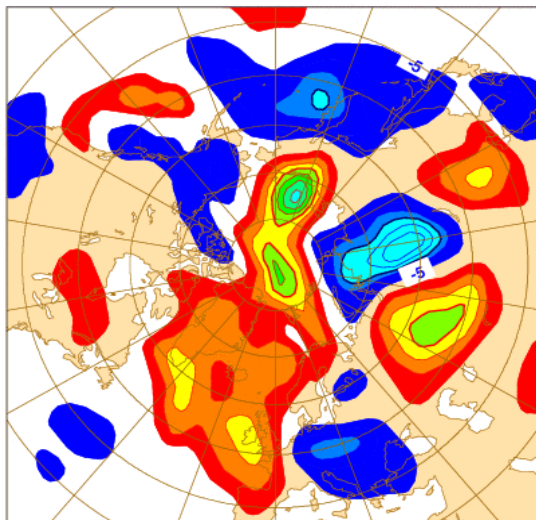


4. Sensitivity to initial and model uncertainty

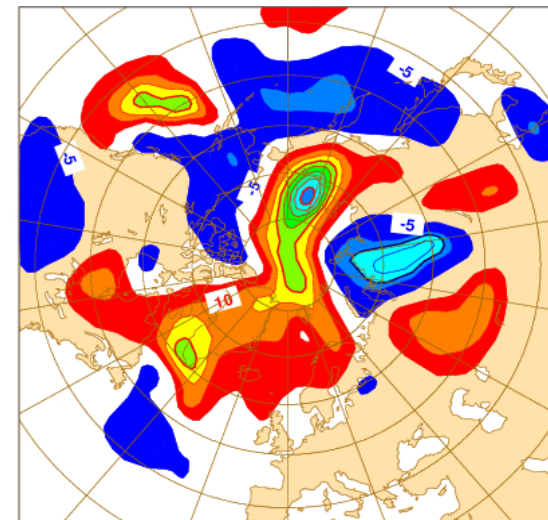
What is the relative contribution of initial and model uncertainties to forecast error?

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.

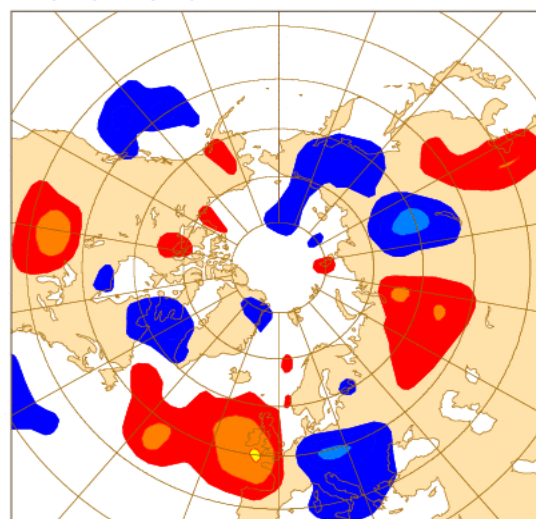
UK(UK)-EC(EC) Z500 1996-12-17 12h t+120



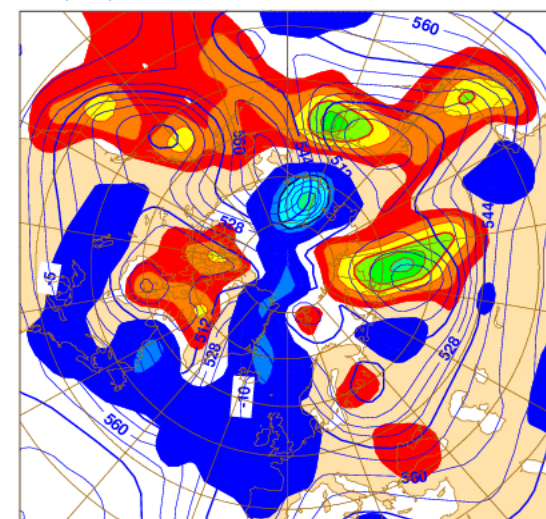
EC(UK)-EC(EC) Z500 1996-12-17 12h t+120

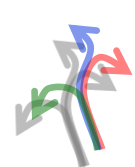


UK(UK)-EC(UK) Z500 1996-12-17 12h t+120



EC(EC)-ANA Z500 1996-12-17 12h t+120

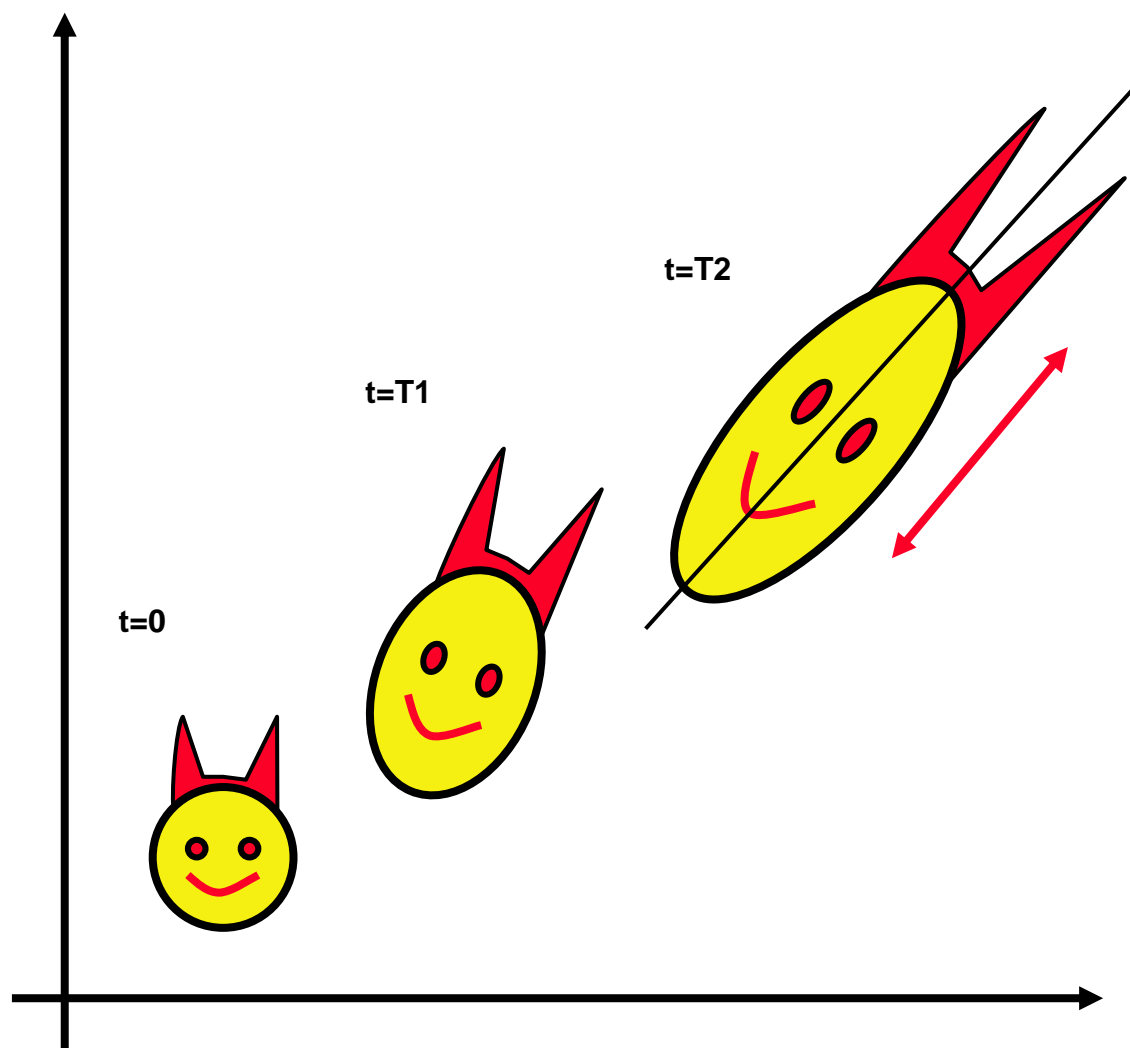




4. How should initial uncertainties be defined?

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.

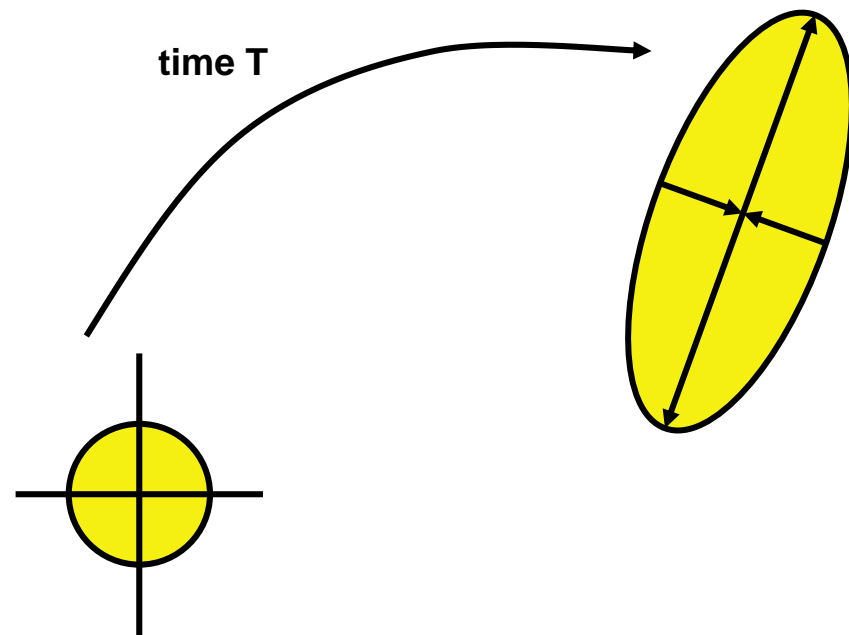




4. Definition of the initial perturbations

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.



$$\begin{aligned}
 \langle x; E_{TE} y \rangle = & \frac{1}{2} \iint (\nabla \Delta^{-1} \zeta_x \cdot \nabla \Delta^{-1} \zeta_y + \nabla \Delta^{-1} D_x \cdot \nabla \Delta^{-1} D_y + \frac{C_p}{T_r} T_x T_y) d\Sigma \frac{\partial p}{\partial \eta} d\eta \\
 & + \int (R_d \frac{T_r}{P_r} \ln \pi_x \ln \pi_y) d\Sigma
 \end{aligned}$$

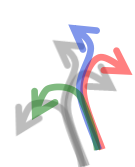


4. Asymptotic and finite-time instabilities

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.



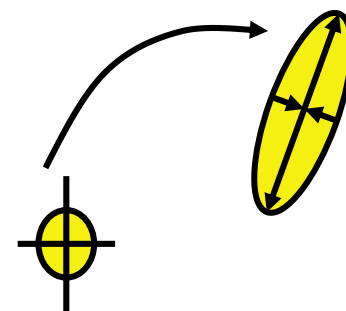
4. Singular vectors

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

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

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





1. The operational ensemble in 2016

ENS includes 51 forecasts with resolution:

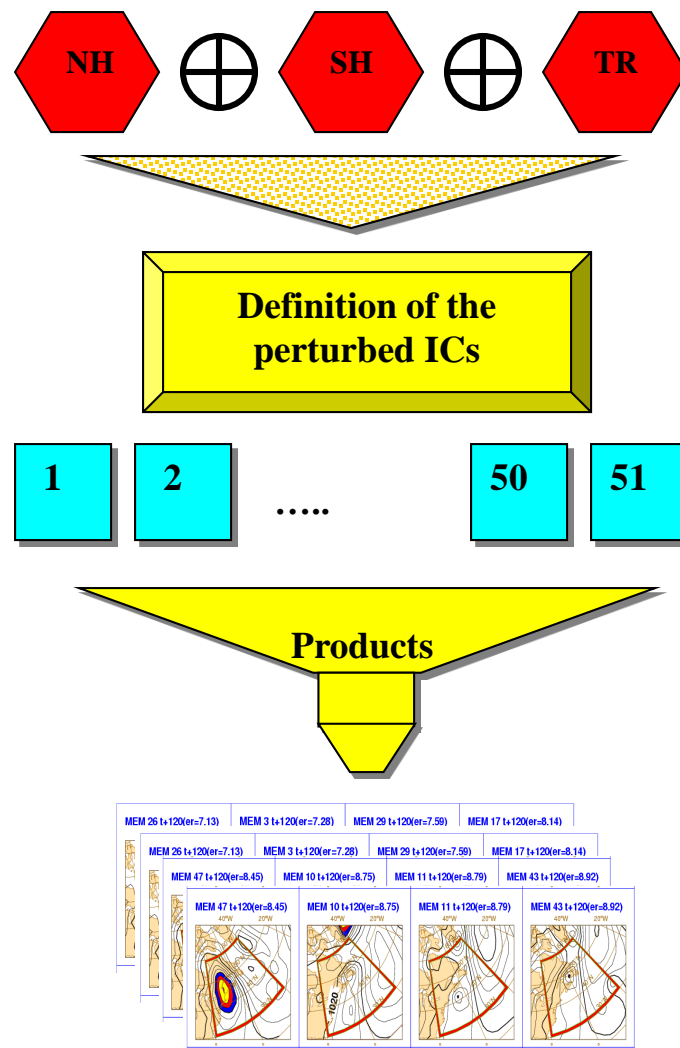
- $T_{co}639L91$ (~16km, 91 levels) from day 0 to 15
- $T_{co}319L91$ (~32km, 91 levels) from day 15 to 32 (only at 00UTC on Mon and Thu).

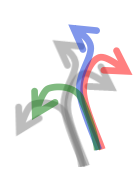
Initial uncertainties are simulated by adding to the unperturbed analyses a combination of T42L91 singular vectors, computed to optimize total energy growth over a 48h time interval (OTI), and perturbations generated by the ECMWF Ensembles of Data Assimilation (EDA) system.

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 $T_{co}1279L137$ 4DVAR. The EDA resolution is $T_{co}639L137$.

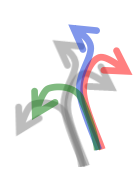
ENS runs daily at 00 and 12 UTC, with a TOA at 0.01 hPa.





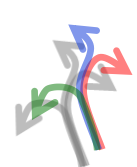
4. Major changes of ENS configuration (updated May 2016)

	Description	Singular Vectors's characteristics							Forecast characteristics						
		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	siml	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	1*5*18y
Sep 2009	Rev SPPT	"	"	"	"	"	"	"	"	"	"	"	"	"	"
Jan 2010	hor resol	"	"	"	"	"	"	"	TL639(0-10) / TL319(10-15)	"	"	"	revSTP	"	"
Jun 2010	EDA EPS	"	"	"	"	10*EDA	"	"	"	"	"	"	"	"	"
Nov 2010	Rev Stoch scheme	"	"	"	"	"	"	"	"	"	15d/32d	"	revSTP+BS	"	"
Nov 2011	New ocean model	"	"	"	"	"	"	"	"	"	"	"	"	NEMO from d10	"
Jun 2012	Rev EDA-pert & refc suite	"	"	"	"	"	"	"	"	"	"	"	"	"	1*5*20y
Nov 2013	vert resol & coupling from d0	"	L91	"	"	25*EDA	"	"	TL639(0-10) / TL319(10-15)	L91	15d/32d	"	"	NEMO from d0	"
May 2015	Extension to 46d and REFC suite to 22m	"	"	"	"	25*EDA	"	"	TL639(0-10) / TL319(10-15)	"	15d/46d	"	"	"	2*11*20y
Mar 2016	hor resol	T42	L91	48h	(NH+SH)x+TC	25*EDA	SVINI	Gauss	Tco639(0-15) / Tco319(15-45)	L91	15d/46d	51	revSTP+BS	NEMO from d0	2*11*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.



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. The work of all contributors is acknowledged.

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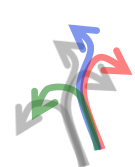
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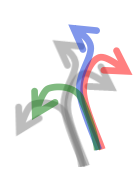
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