# Operational Data Assimilation at ECMWF and medium term plans

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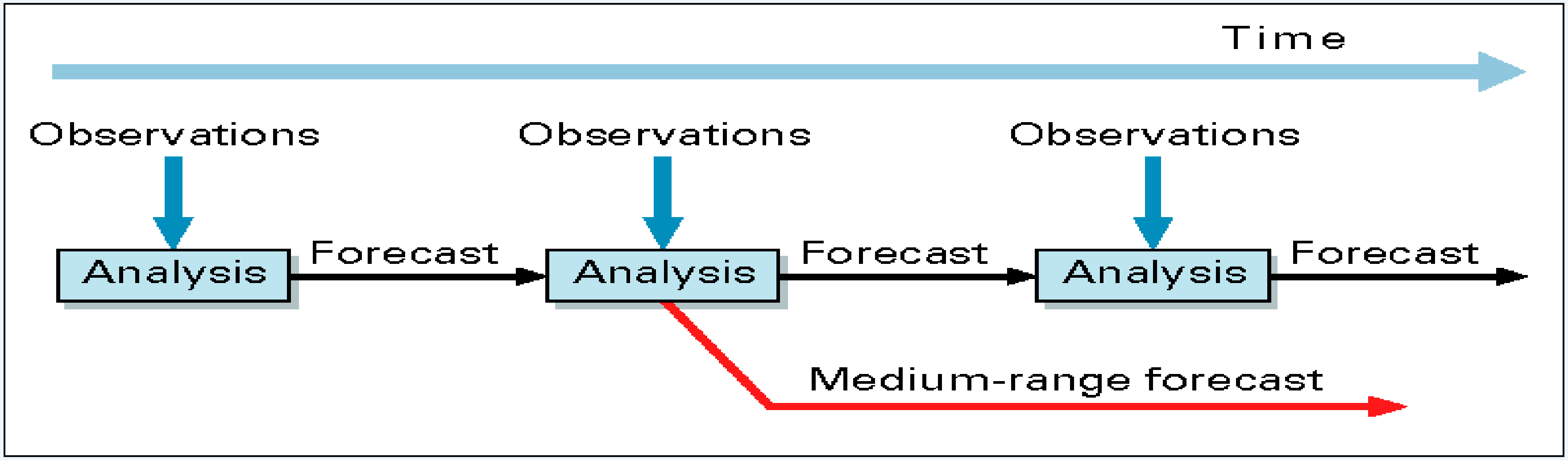
Kristian Mogensen, Dick Dee and Anne Fouilloux

# Outline

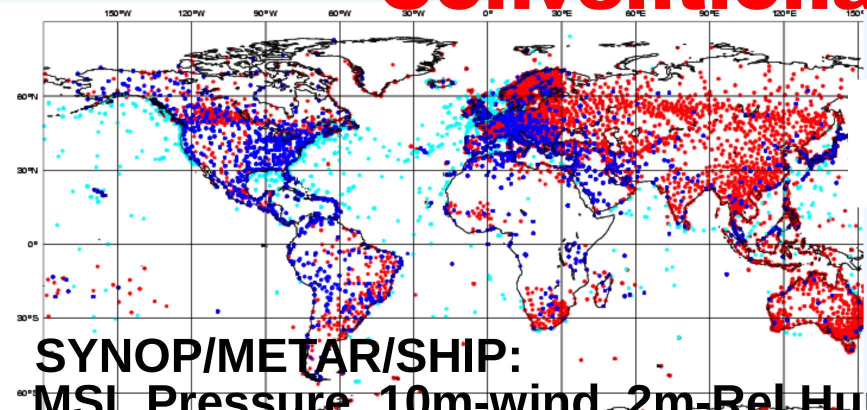
- Operational Data Assimilation at ECMWF
- Resolution and performance
- Hybrids methods: the best of both worlds?
- Ensemble of Data Assimilations (EDA)
- Future DA software: modularity and flexibility
- Scalability issues

# Data assimilation system (4D-Var)

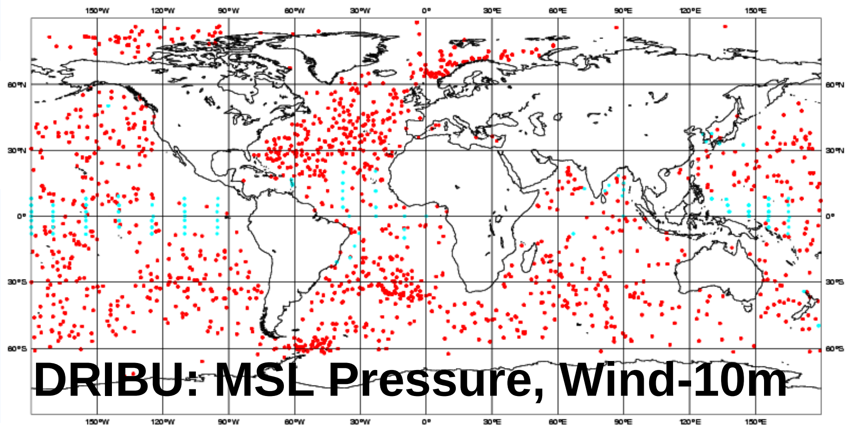



- The observations are used to correct errors in the short forecast from the previous analysis time.
- Every 12 hours we assimilate 7 – 9,000,000 observations to correct the 80,000,000 variables that define the model's virtual atmosphere.
- This is done by a careful 4-dimensional interpolation in space and time of the available observations; this operation takes as much computer power as the 10-day forecast.

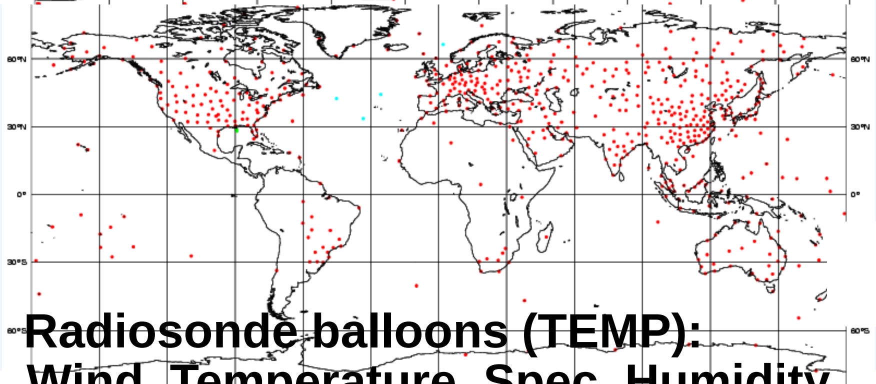
# Conventional observations used



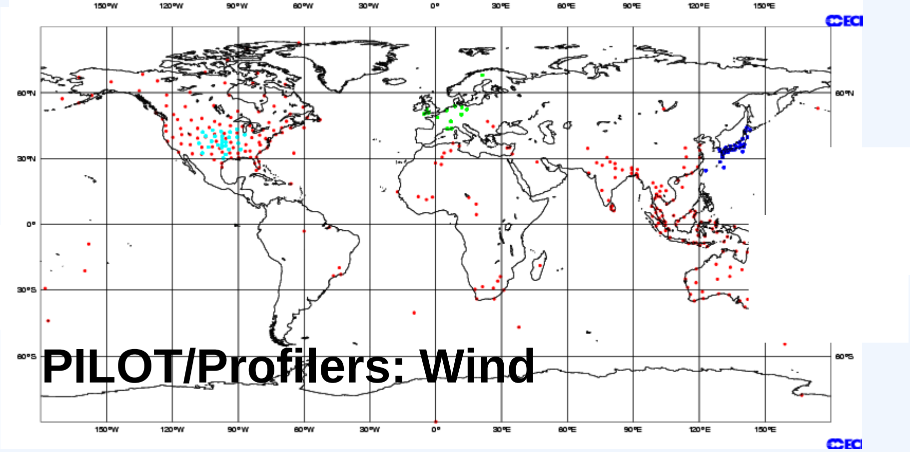
SYNOP/METAR/SHIP:
MSL Pressure, 10m-wind, 2m-Rel.Hum.



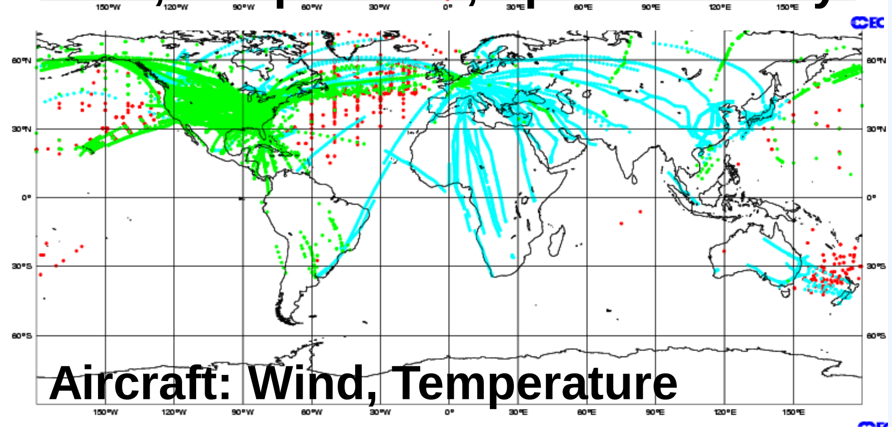
DRIBU: MSL Pressure, Wind-10m



Radiosonde balloons (TEMP):
Wind, Temperature, Spec. Humidity



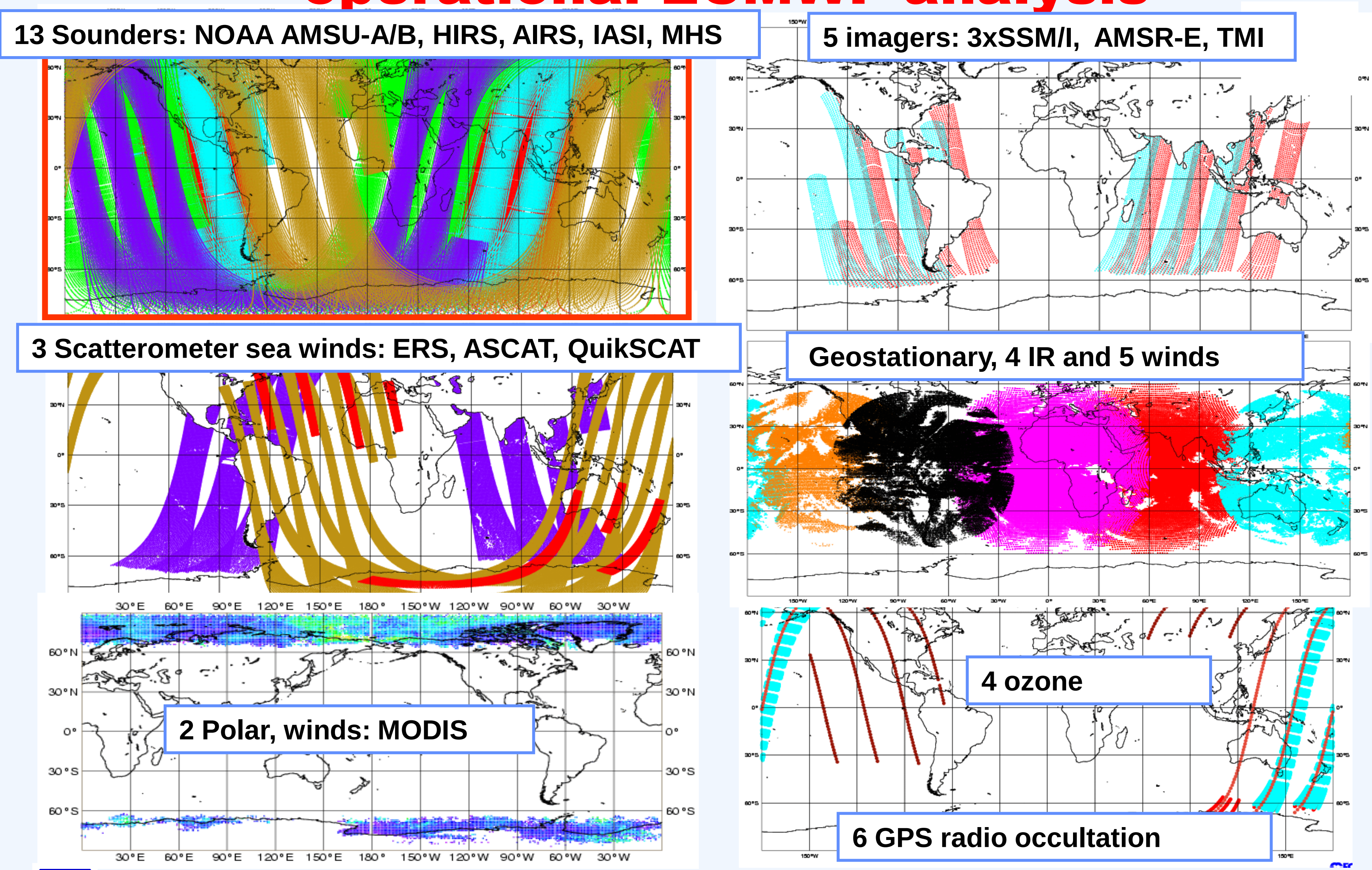
PILOT/Profilers: Wind

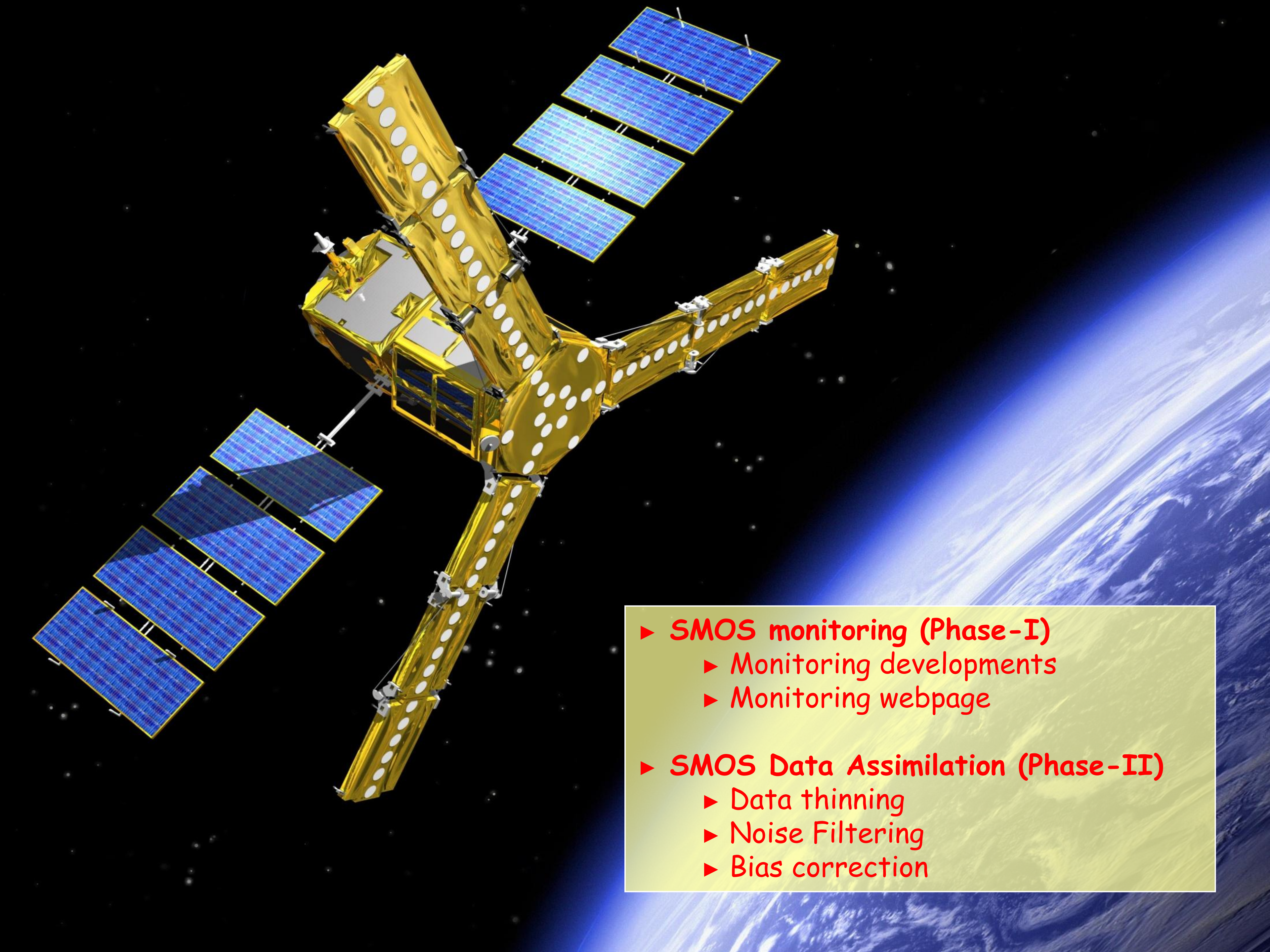


Aircraft: Wind, Temperature

**Note: We only use a limited number of the observed variables; especially over land.**

# Satellite data sources used in the operational ECMWF analysis



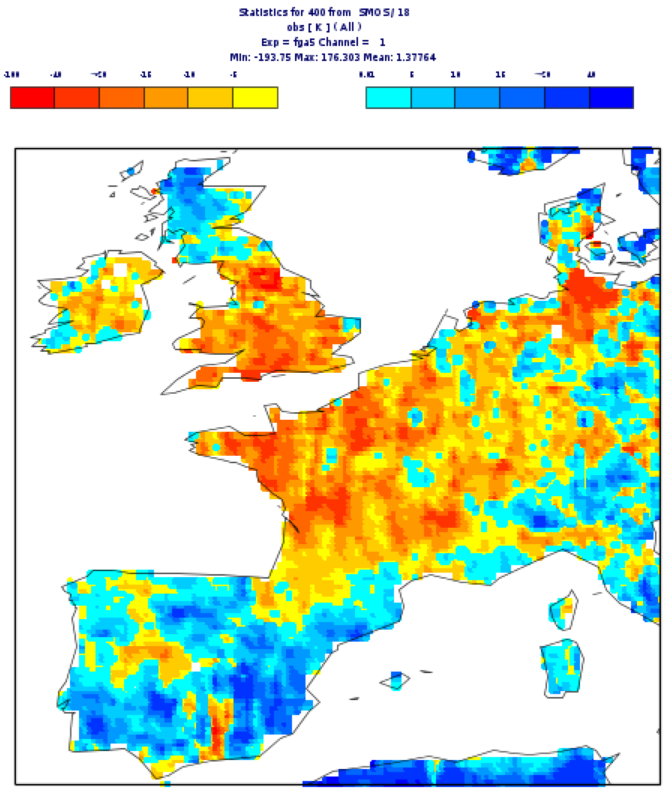


- **SMOS monitoring (Phase-I)**
  - Monitoring developments
  - Monitoring webpage
- **SMOS Data Assimilation (Phase-II)**
  - Data thinning
  - Noise Filtering
  - Bias correction

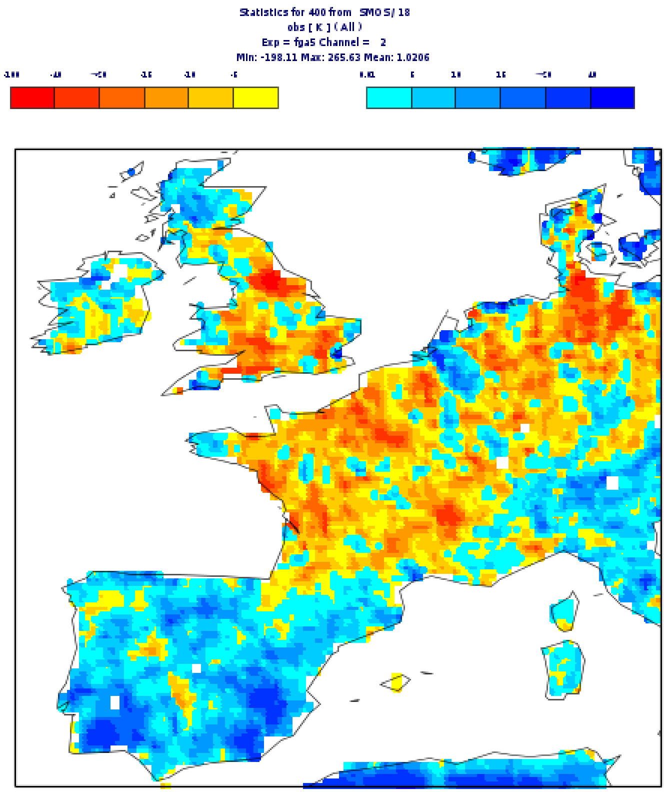
# UK–France droughts vs. Iberian floods

$T_B$ [first – last] week of April 2011

H-pol




V-pol

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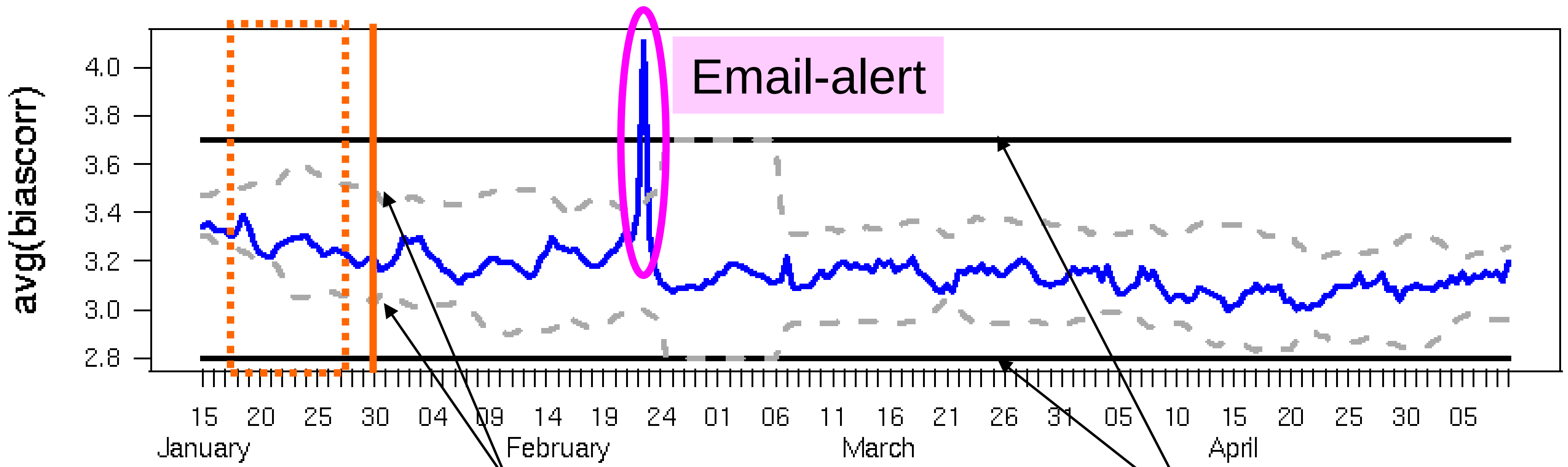
Selected statistics are checked against an expected range.

E.g., global mean bias correction for GOES-12 (in blue):



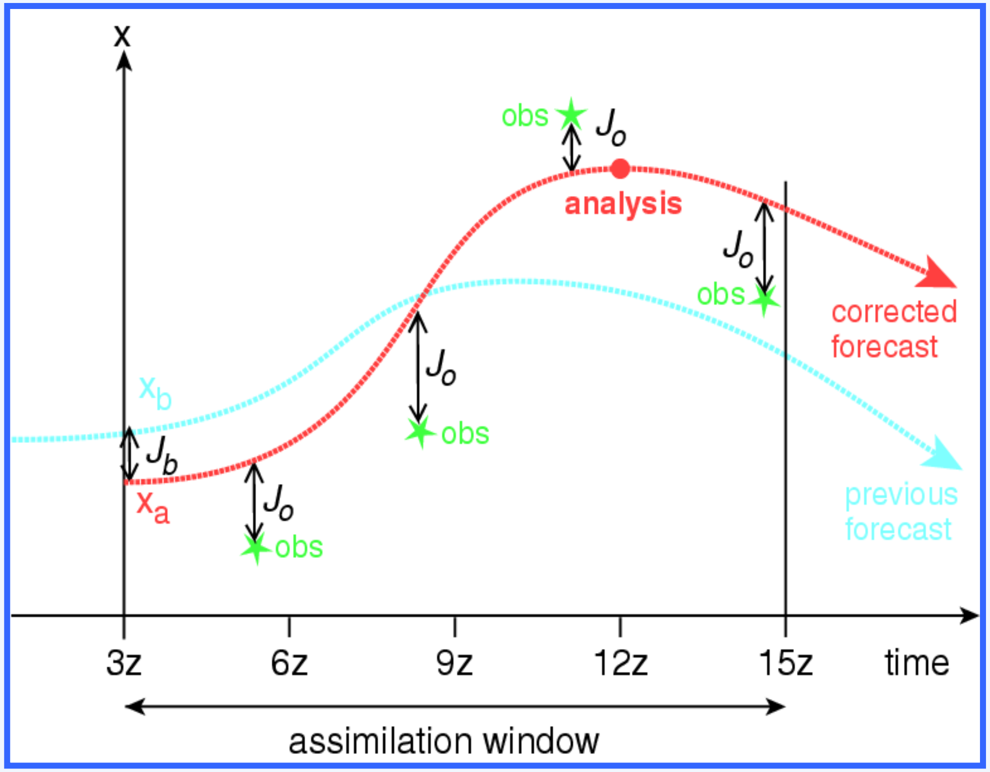

Soft limits (mean ± 5 stdev of statistic to be checked, calculated from past statistics over a period of 20 days, ending 2 days earlier)

Hard limits (fixed)

# ECMWF uses a 4D-Var assimilation system

**All observations within a 12-hour period (~8,000,000) are used simultaneously in one global (iterative) estimation problem**

- **Observation minus model differences are computed <u>at the observation time</u> using the full forecast model at T1279 (16 km) resolution**
- **4D-Var finds the 12-hour forecast evolution that optimally fits the available observations. A linearized forecast model is used in the minimization process based on the adjoint method**
- **It does so by adjusting surface pressure, the upper-air fields of temperature, wind, specific humidity and ozone**
- **The analysis vector consists of 80,000,000 elements at T255 resolution (80 km)**

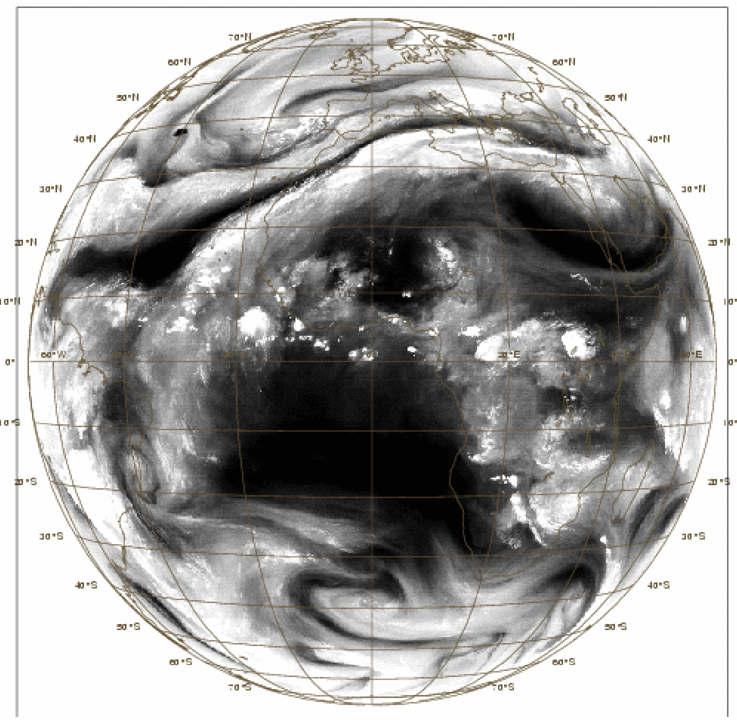


# Variational assimilation of satellite radiances

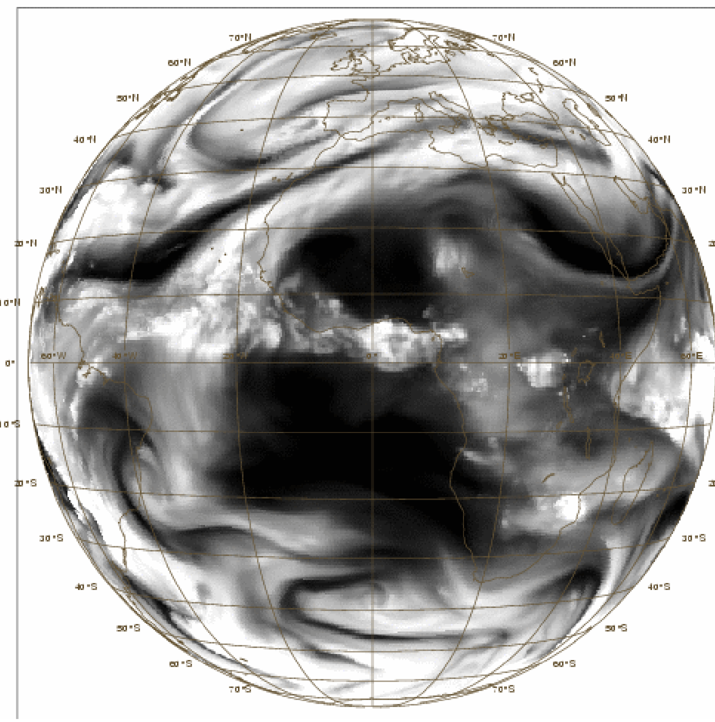
Adjust the model state to improve the match with observations:

$$\mathbf{J(x) = (x_b - x)^T B^{-1} (x_b - x) + [y - h(x)]^T R^{-1} [y - h(x)]}$$

**y** : observed radiances



**h(x)** : model-simulated radiances

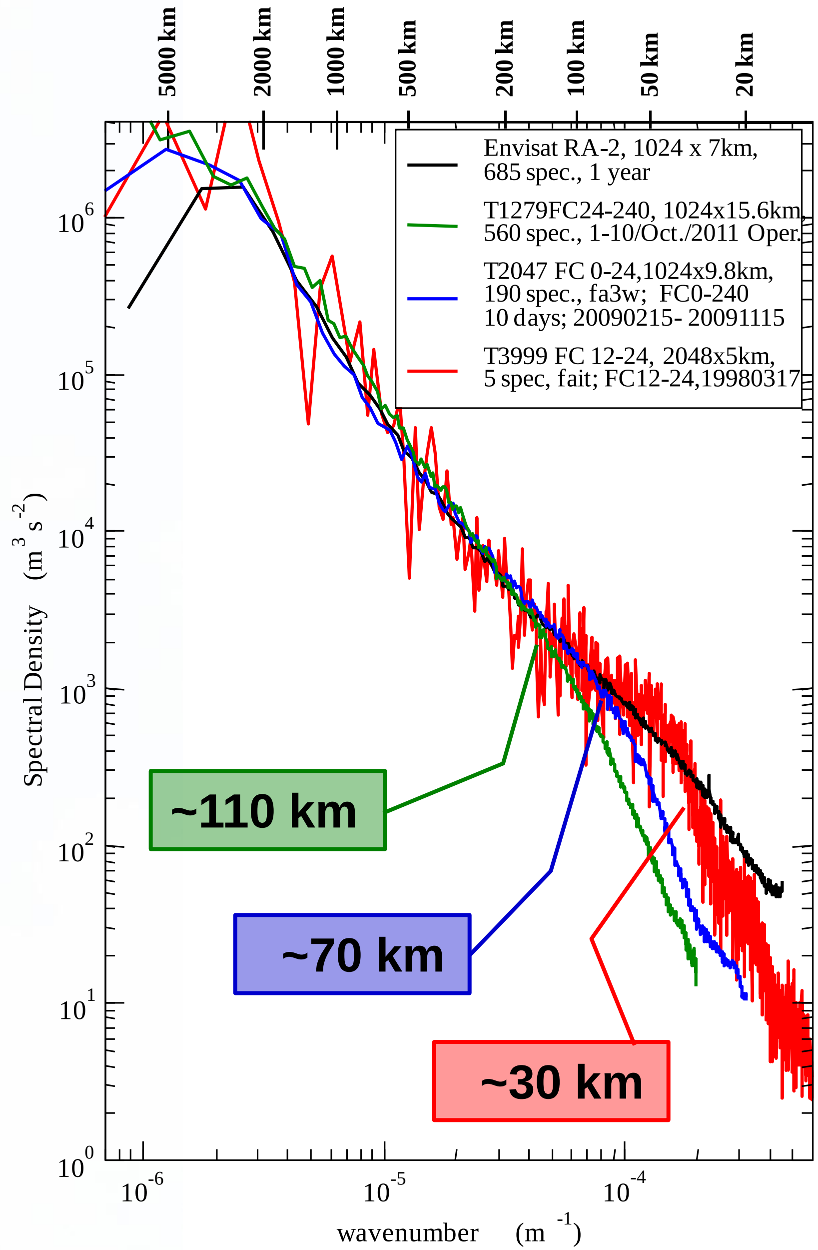


- ECMWF HPC systems
  - At the moment IBM Power6 (2x9200 cores)
  - Is now being upgraded to IBM Power7 (2x24500 cores)

- Operational Forecast and 4D-Var assimilation configuration
  - We are using the IFS - Integrated Forecast System
  - 10-day T1279L91 Forecast (16 km horizontal grid)
  - 12 hour 4D-Var T1279 outer loop T255/T159 inner loop
  - Operational Ensemble of Data Assimilations (EDA)
    - 10 member 4D-Var T399 outer and T95/T159 inner loop

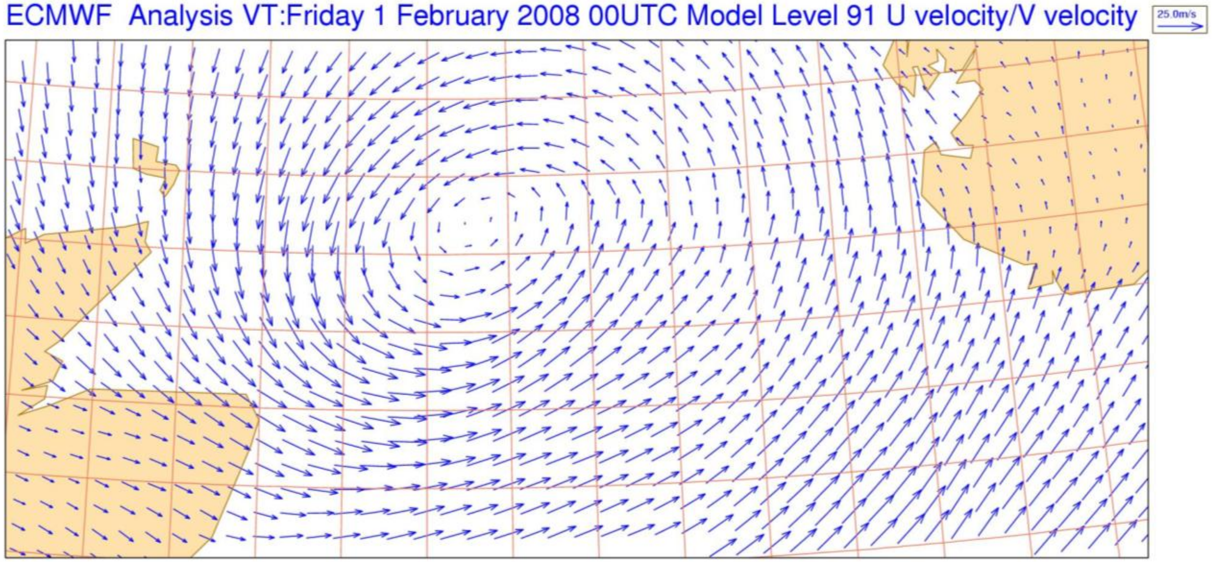
# Impact of Model Resolution

- **Black line: Observations: Envisat Altimeter RA-2 data.**
- **Green line: Resolution ~16 km**
  T1279, Current ECMWF operational model resolution.
- **Blue line: Resolution ~10 km**
  T2047, Next ECMWF model resolution ~2014.
- **Red line: Resolution ~5 km**
  T3999, ECMWF model resolution ~2020.

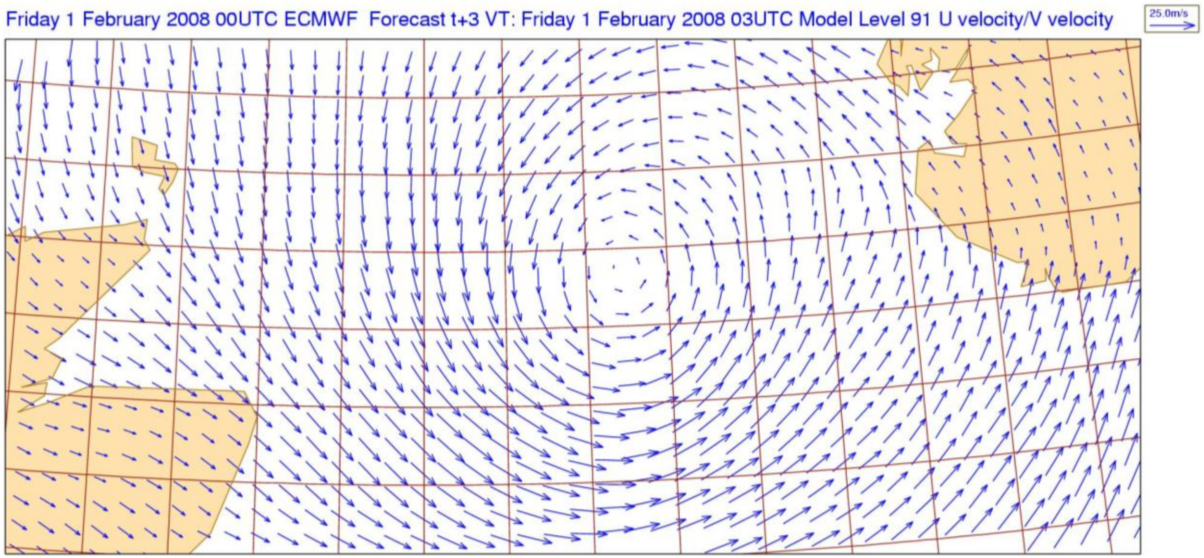


# 10m wind field from ECMWF analysis and 3h forecast T1279 resolution (16km grid) to be used from 2009

ECMWF Analysis VT:Friday 1 February 2008 00UTC Model Level 91 U velocity/V velocity



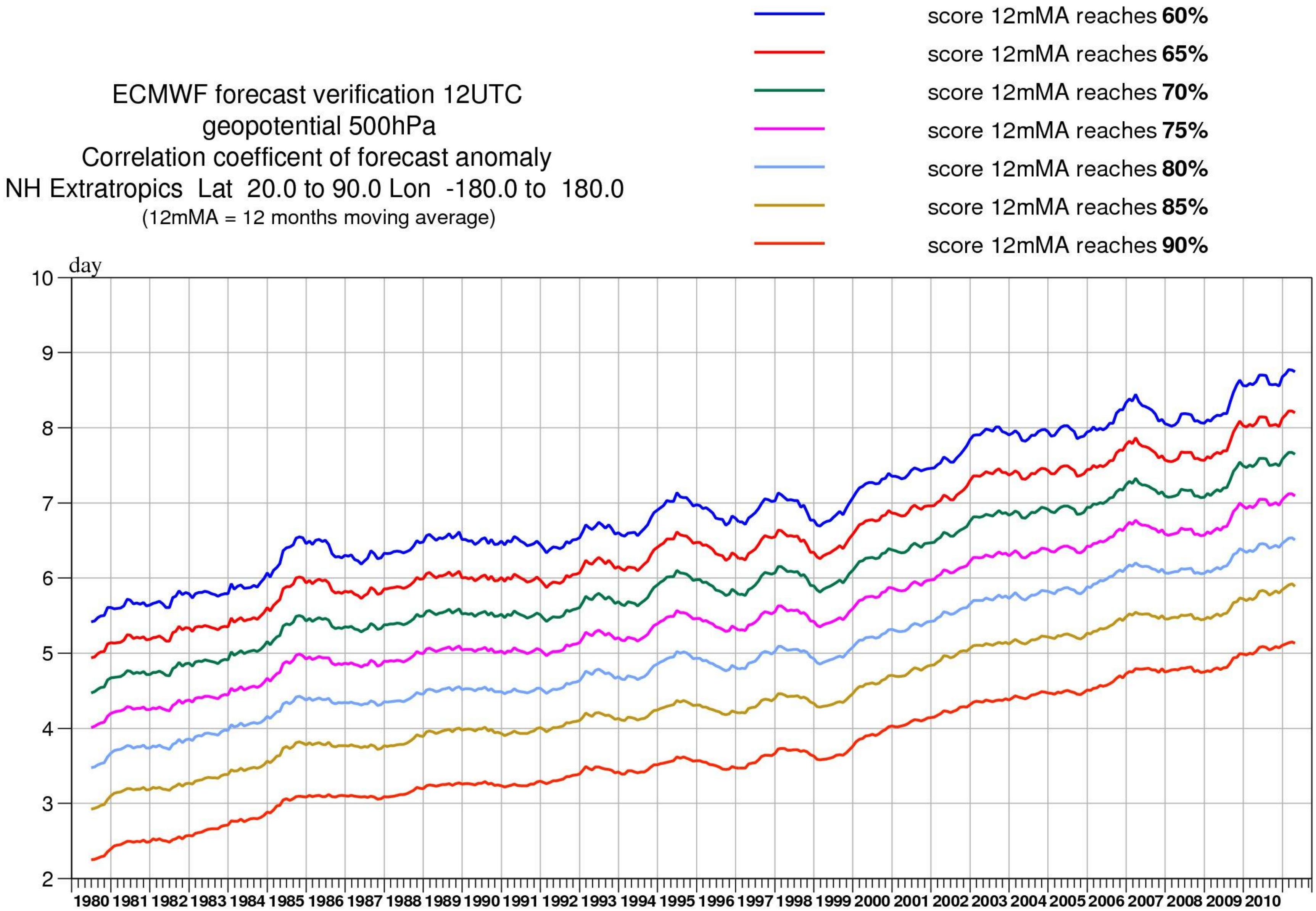
Friday 1 February 2008 00UTC ECMWF Forecast t+3 VT: Friday 1 February 2008 03UTC Model Level 91 U velocity/V velocity



**A low in the North Sea shows the T1279 forecast model's ability to represent scales below 50km resolution**

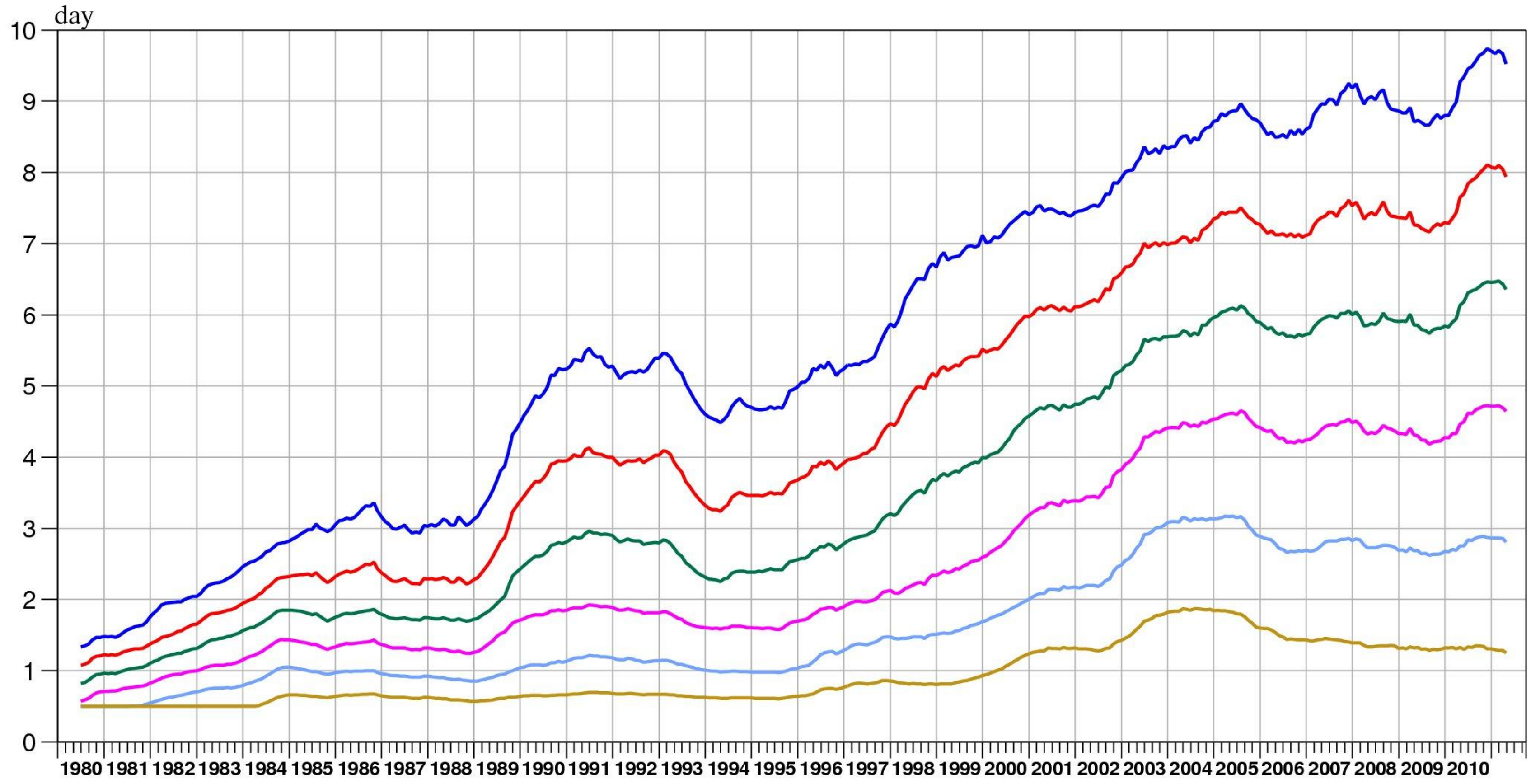
**Each box on the plot is approx. 50kmx50km**

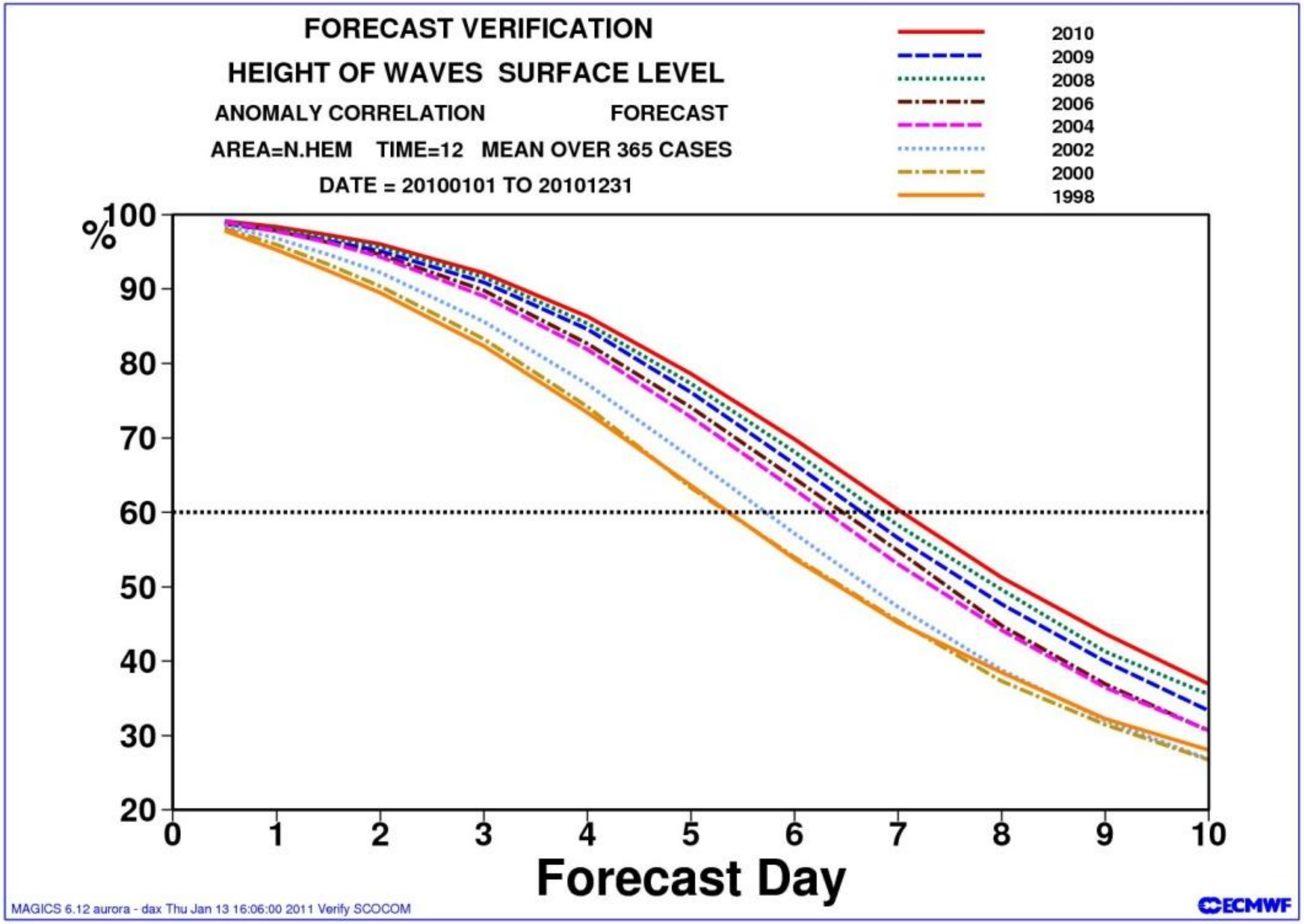
**Note the distinct land/sea contrast in wind speed that is well presented by the model at sub 50km resolution**


ECMWF forecast verification 12UTC
geopotential 500hPa
Correlation coefficent of forecast anomaly
NH Extratropics Lat 20.0 to 90.0 Lon -180.0 to 180.0
(12mMA = 12 months moving average)
score 12mMA reaches 60%
score 12mMA reaches 65%
score 12mMA reaches 70%
score 12mMA reaches 75%
score 12mMA reaches 80%
score 12mMA reaches 85%
score 12mMA reaches 90%
day
10
9
8
7
6
5
4
3
2
1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010

ECMWF forecast verification 12UTC
vector wind 850hPa
Correlation coefficent of forecast
Tropics Lat -20.0 to 20.0 Lon -180.0 to 180.0
(12mMA = 12 months moving average)

score 12mMA reaches **65%**
score 12mMA reaches **70%**
score 12mMA reaches **75%**
score 12mMA reaches **80%**
score 12mMA reaches **85%**
score 12mMA reaches **90%**




FORECAST VERIFICATION
HEIGHT OF WAVES SURFACE LEVEL
ANOMALY CORRELATION FORECAST
AREA=N.HEM TIME=12 MEAN OVER 365 CASES
DATE = 20100101 TO 20101231
2010
2009
2008
2006
2004
2002
2000
1998
%
100
90
80
70
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50
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30
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0
1
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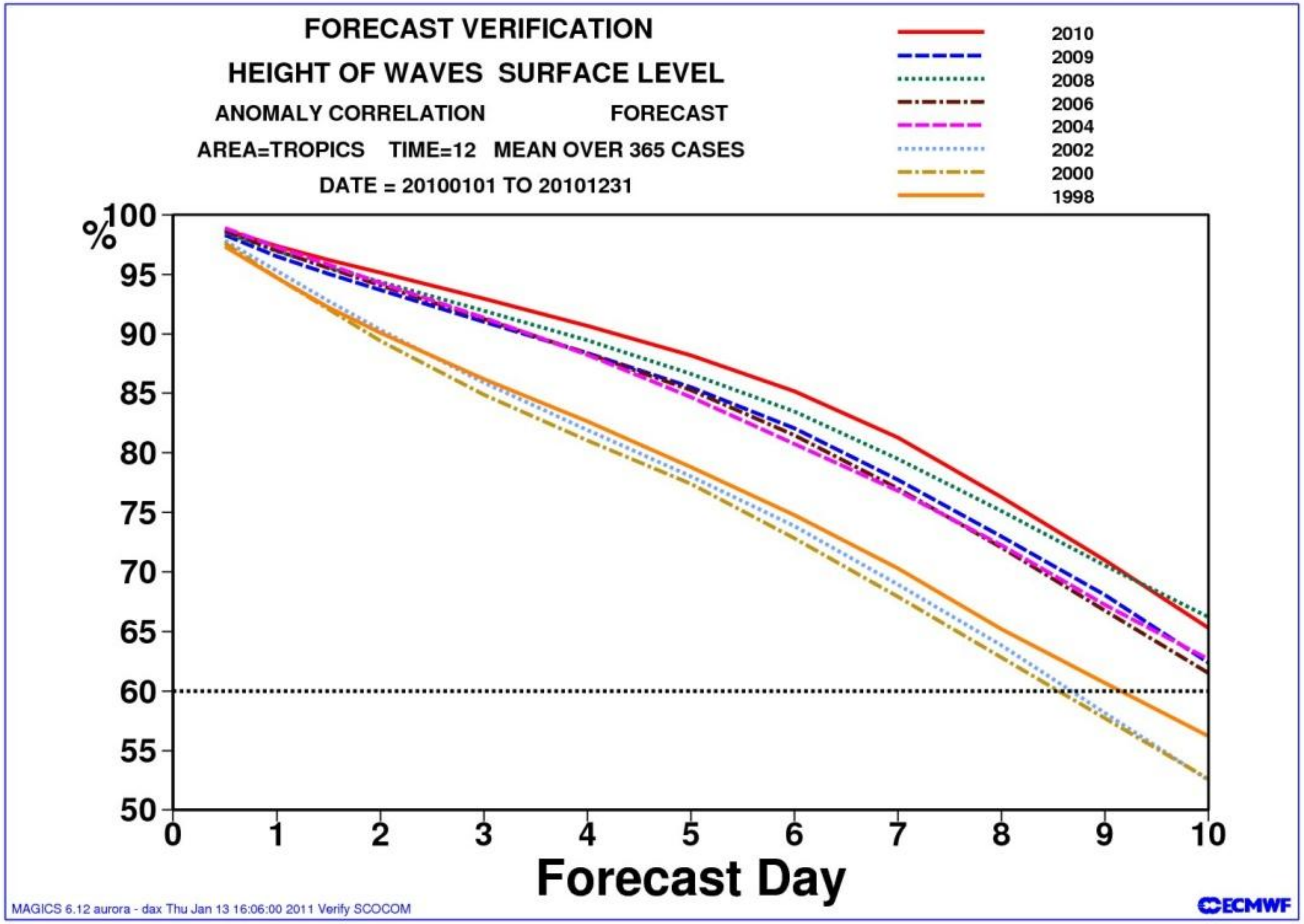
10
Forecast Day
MAGICS 6.12 aurora - dax Thu Jan 13 16:06:00 2011 Verify SCOCOM
ECMWF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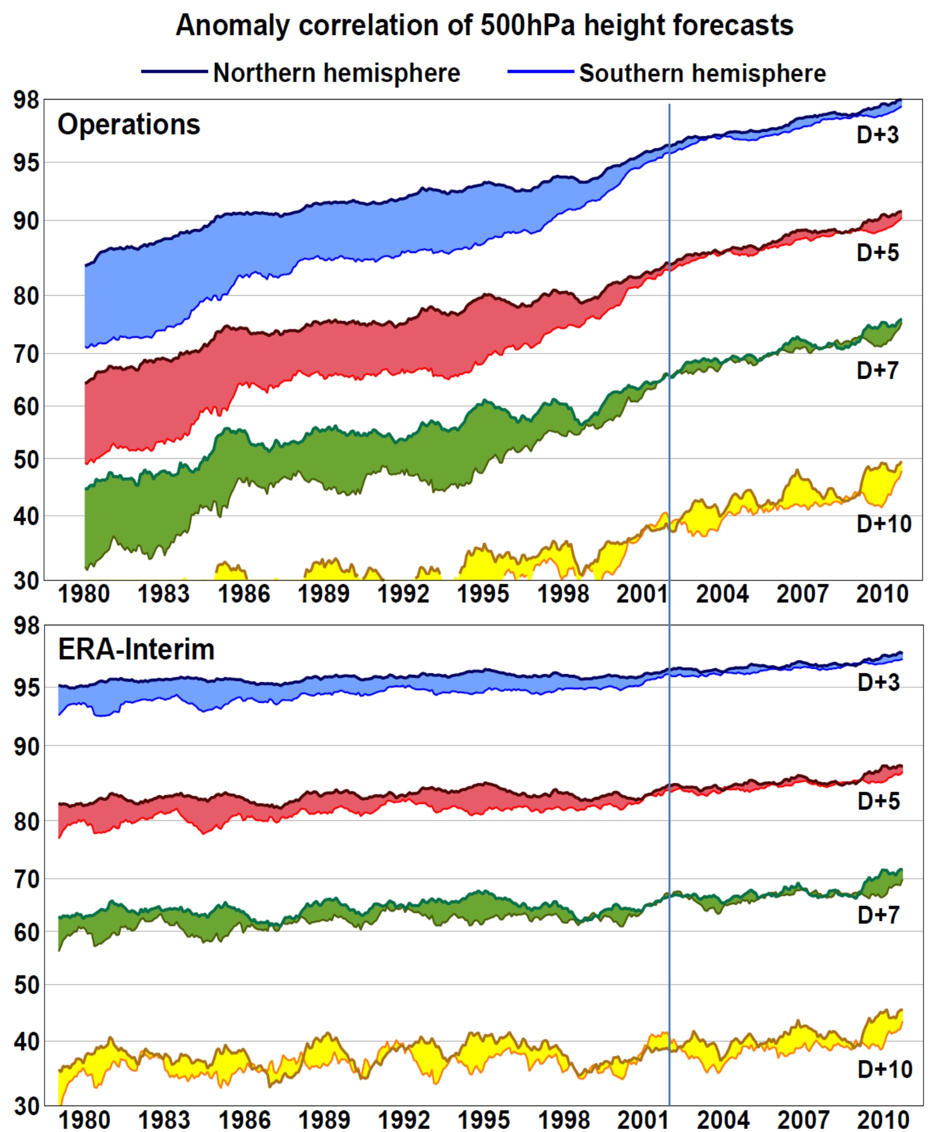
0 1 2 3 4 5 6 7 8 9 10
Forecast Day
MAGICS 6.12 aurora - dax Thu Jan 13 16:06:00 2011 Verify SCOCOM
ECMWF

# ERA-interim: Performance compared to operations



# Why use an Ensemble of Data Assimilations (EDA)?

a) Kalman Filter is computationally unfeasible for realistic NWP;

b) Non-sequential approx. (4D-Var) do not cycle state error estimates: work well for short assimilation windows (6-12h), but longer windows have proved more difficult;

c) Sequential approx. (EnKF) cycle low-rank estimates of state error covariances, but analysis increments are confined to perturbations subspace;

….

Hybrid approach: Use flow-dependent state error estimates (from an EnKF/EDA system) in a 3/4D-Var analysis algorithm

# Hybrid methods: How EDA works

1. We can use an ensemble of perturbed 4D-Var to simulate the ***errors*** of our reference high resolution 4D-Var

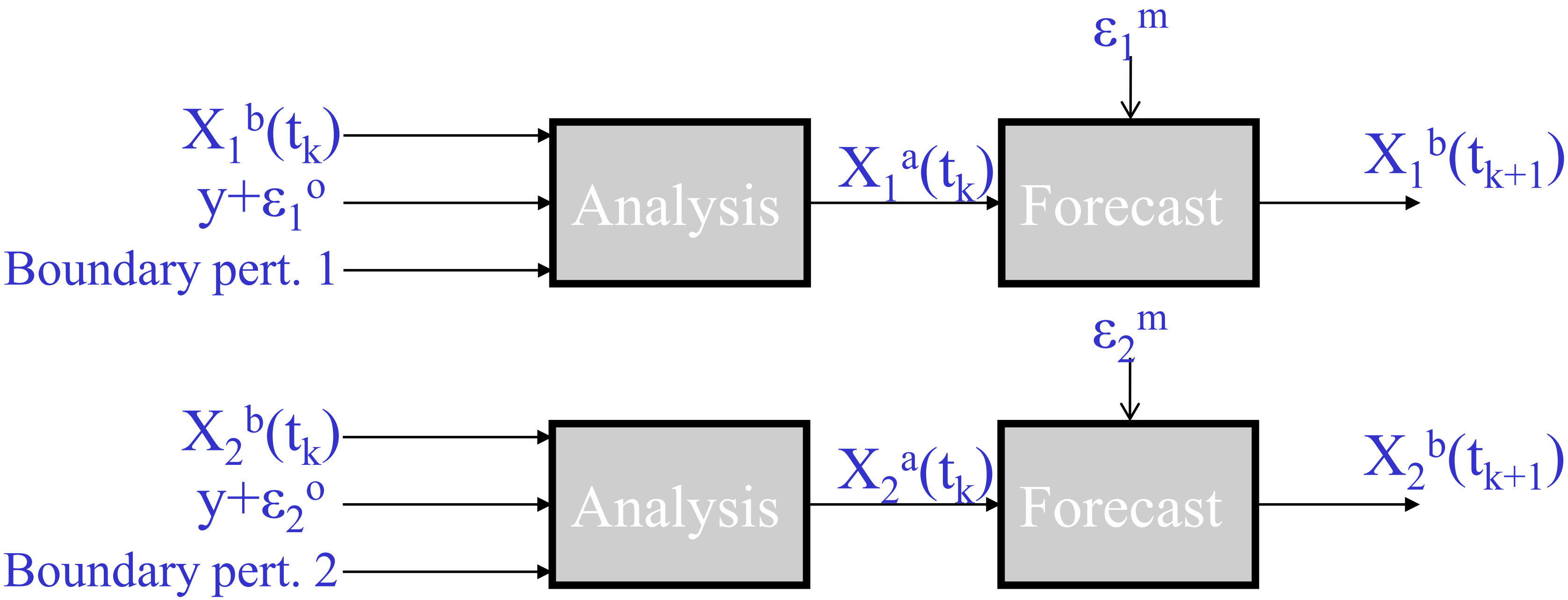
2. The ensemble of perturbed DAs should be as similar as possible to the reference DA (i.e., same or similar **K** matrix)

3. The applied observation error and model error perturbations must have represent the  error covariances ($\mathbf{R}$, $\mathbf{Q}$); however we do not need an explicit covariance model of $\mathbf{Q}$

4. Important applications: To provide a flow-dependent sample of background errors at the initial time of the 4D-Var assimilation window. But also to provide analysis error estimates.

# Hybrid methods: How EDA works

The Ensemble of Data Assimilations (EDA, Isaksen *et al.* 2010) can be considered a flow-dependent extension of the way the *climatological background error matrix* is estimated (Fisher, 2003).



# Using EDA in 4D-Var to provide uncertainty estimation

**Hybrid approx**.: Use flow-dependent state error estimates (from an EnKF/EDA system) in a 3/4D-Var analysis algorithm

This solution would:

1) Integrate flow-dependent state error covariance information into the variational analysis
2) Keep the full rank representation of $\mathbf{B}$ and its implicit evolution inside the assimilation window
3) More robust than pure EnKF for limited ensemble sizes and large model errors
4) Allow (eventual) localization of ensemble perturbations to be performed in state space;
5) Allow for flow-dependent QC of observations

# The operational EDA at ECMWF

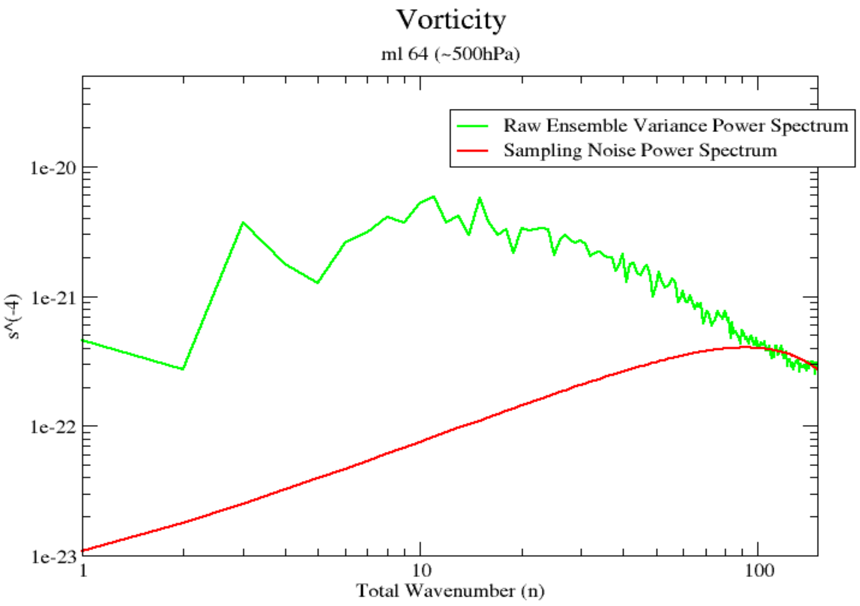
- **10** ensemble members using 4D-Var assimilations
- **T399** outer loop, T95/T159 inner loops. (Reference DA: T1279 outer loop, T159/T255/T255 inner loops)
- Observations randomly perturbed according to their specified $\mathbf{R}$
- SST perturbed with realistically scaled structures
- Model error represented by stochastic methods (**SPPT,** Leutbecher, 2009)

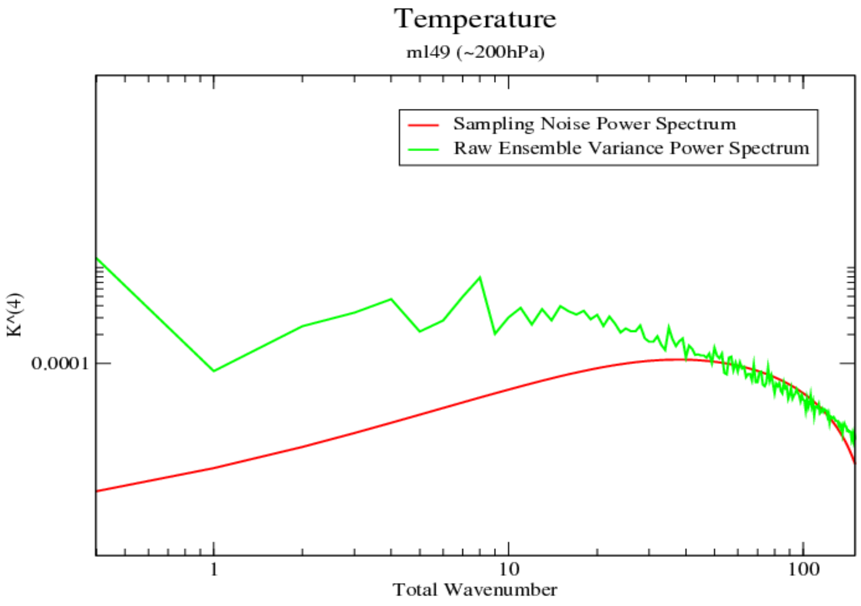
# EDA variances – sampling noise issues

a) Sampling Noise due to the small EDA dimensionality ($N_{eda}$=10)

The key insight is to recognise that *sampling noise is small scale with respect to the error variance field* (Raynaud *et al.*, 2008)

We may use a **spectral filter** to disentangle noise error from the signal



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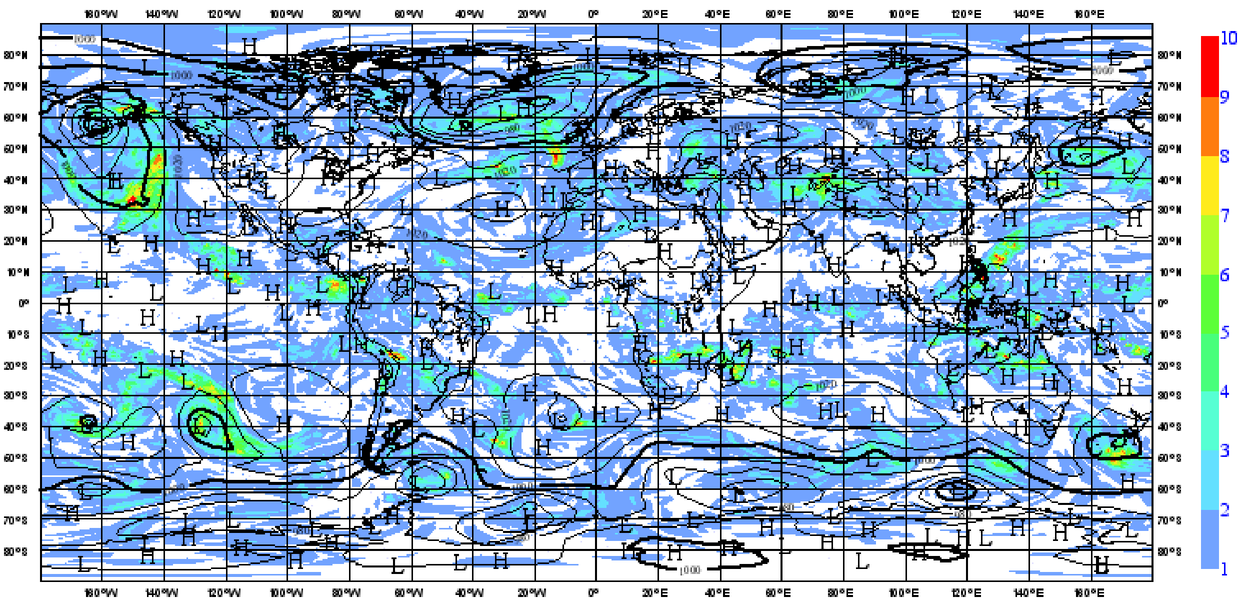
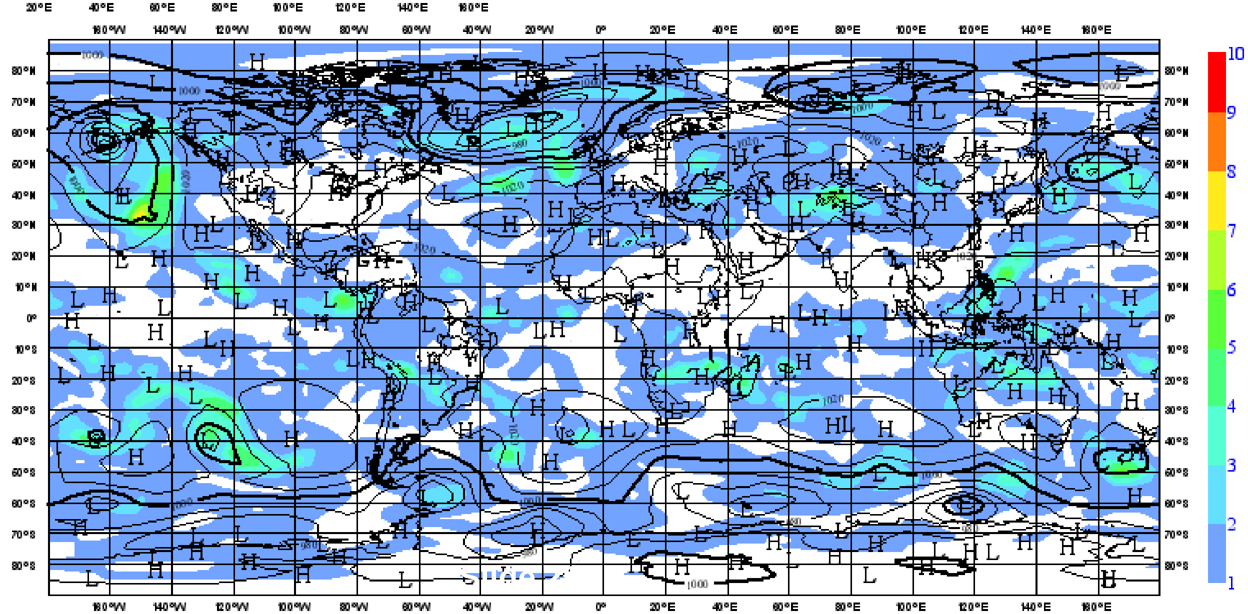
# EDA variances – sampling noise issues



Raw Ensemble StDev
VO ml64



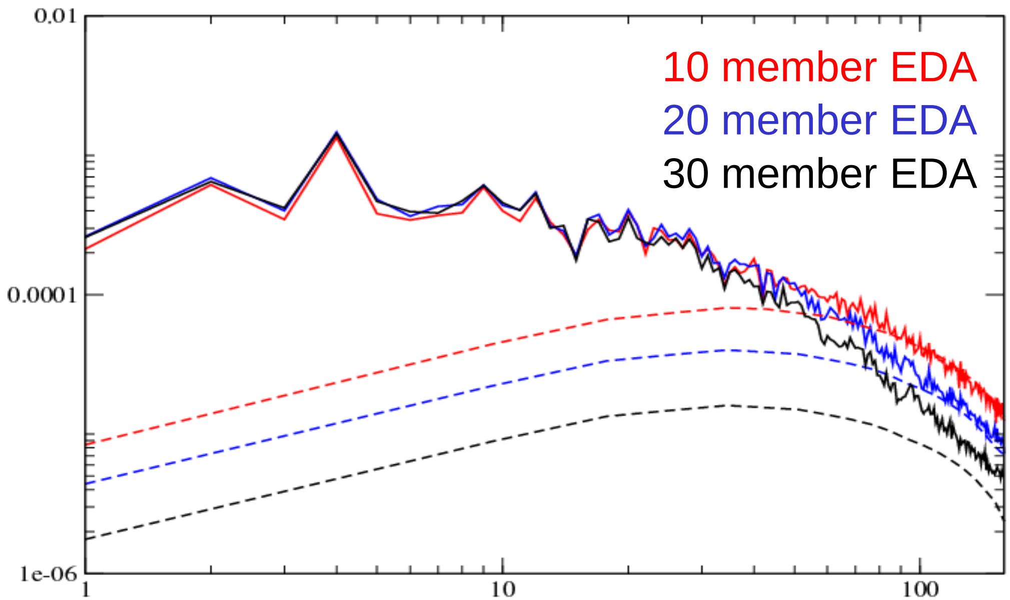
Filtered Ensemble StDev
VO ml64

# EDA variances: Ensemble Size

The sampling noise effectively limits the scales that we can robustly estimate from the EDA.

The effective spatial resolution of the diagnosed errors is much coarser than the nominal EDA resolution (T399) and is primarily determined by the ensemble size (Bonavita et al., 2010)

Temperature ml 49 (~200 hPa)



# EDA variances – systematic errors

b) Systematic errors due to incorrect specification of error sources in the EDA (i.e., mis-specification of **R**, **Q**, uncertainties in the boundary conditions)

A statistically consistent ensemble should satisfy:

$$\left(1-\frac{1}{N_{ens}}\right)^{-1}\left\langle \frac{1}{N_{ens}}\sum_{i=1}^{N_{ens}}\left(x_i-\bar{x}\right)^2\right\rangle = \left(1+\frac{1}{N_{ens}}\right)^{-1}\left\langle\left(\bar{x}-x^*\right)^2\right\rangle$$

<ensemble variance> ≈ <squared ensemble mean error>



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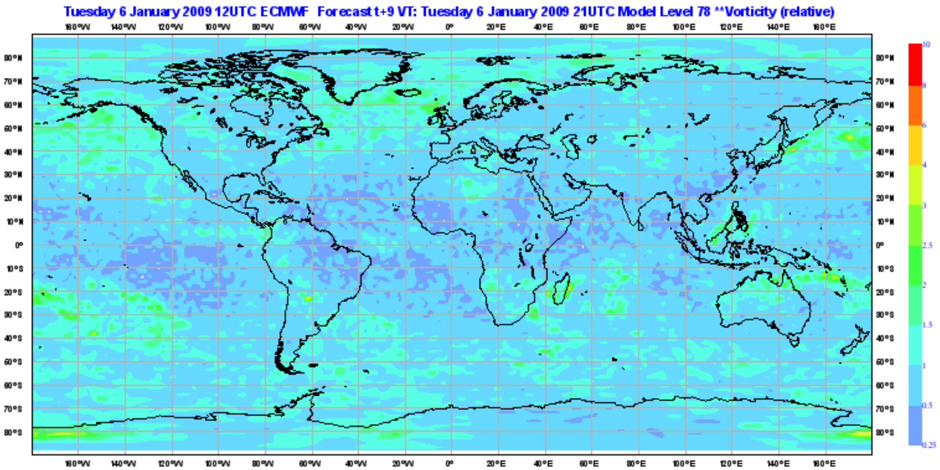
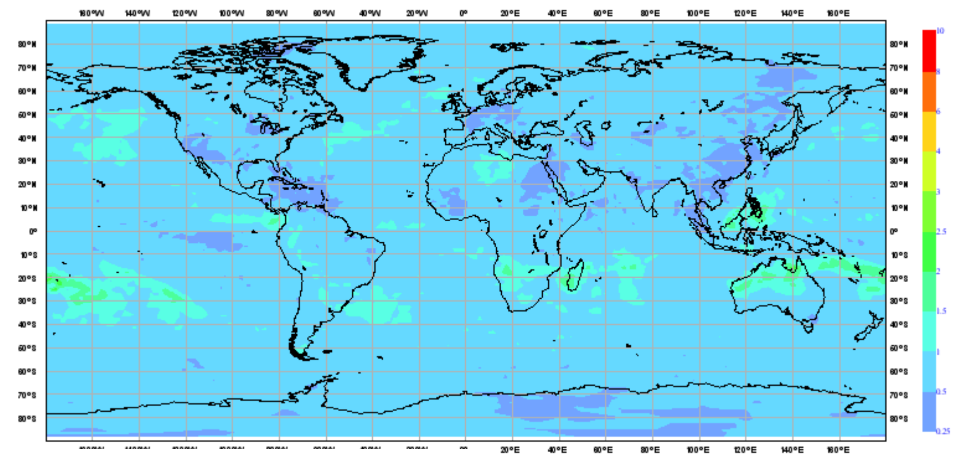
# What type of errors affect EDA sample stats.?

## Vorticity model level 78 (~850hPa)

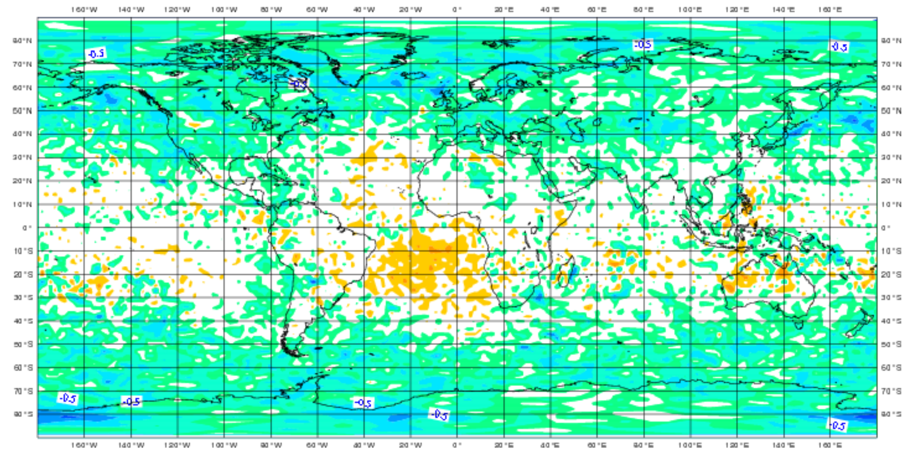
Ensemble mean error



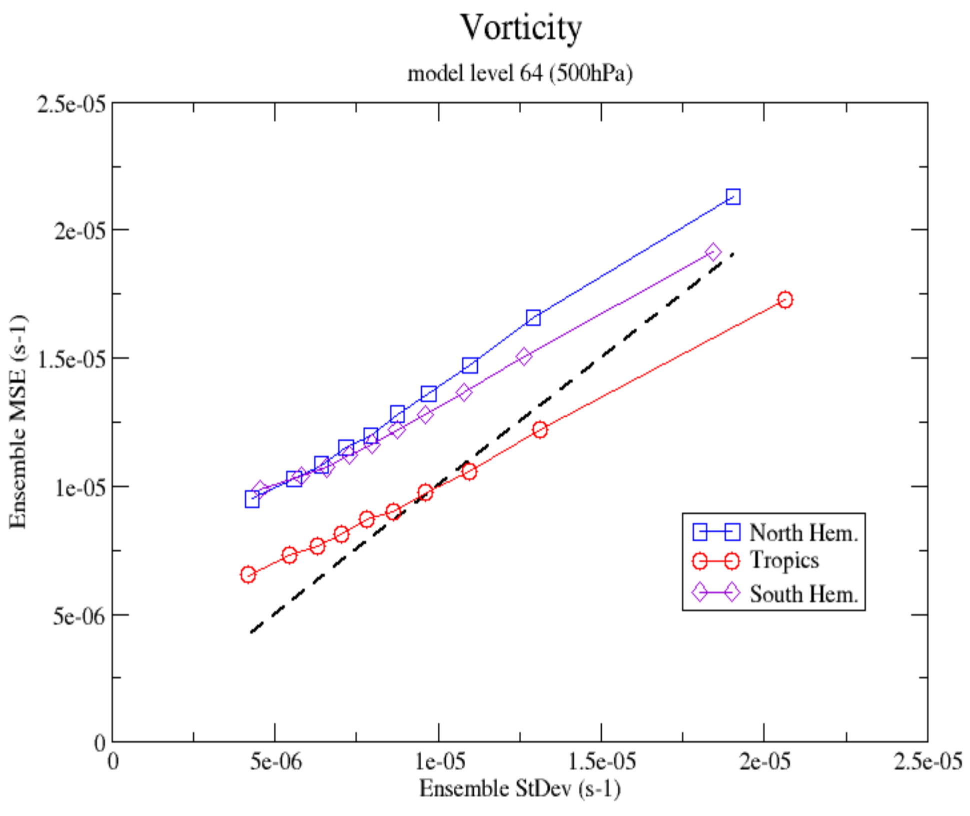

Ensemble Spread



Spread - Error



# EDA variances

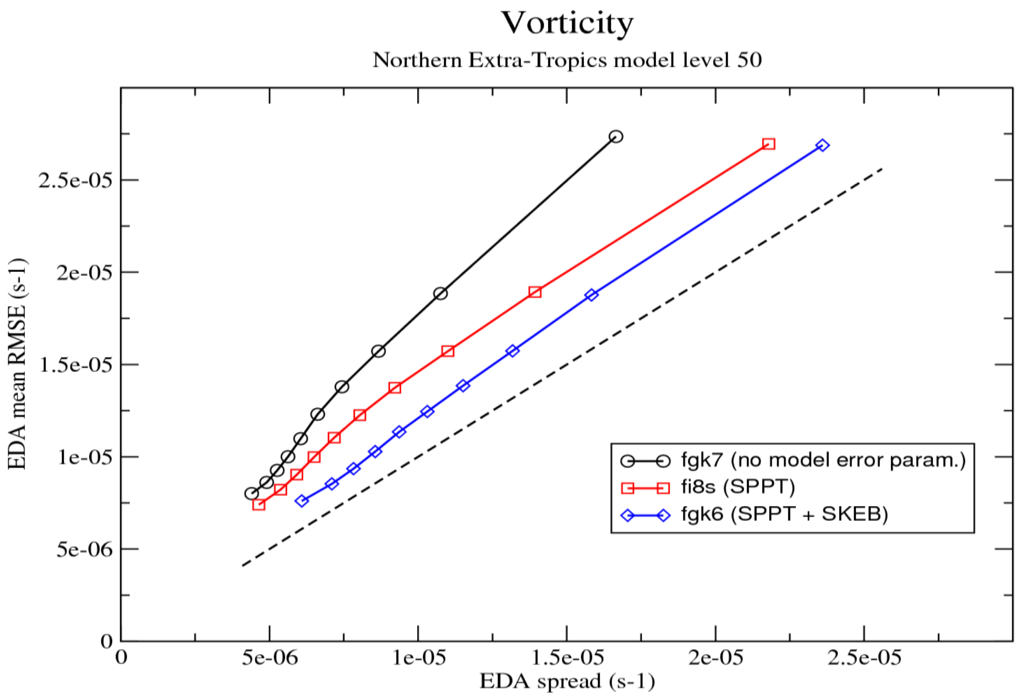



Conditional distribution of the EDA mean background RMS error for given EDA background standard deviation

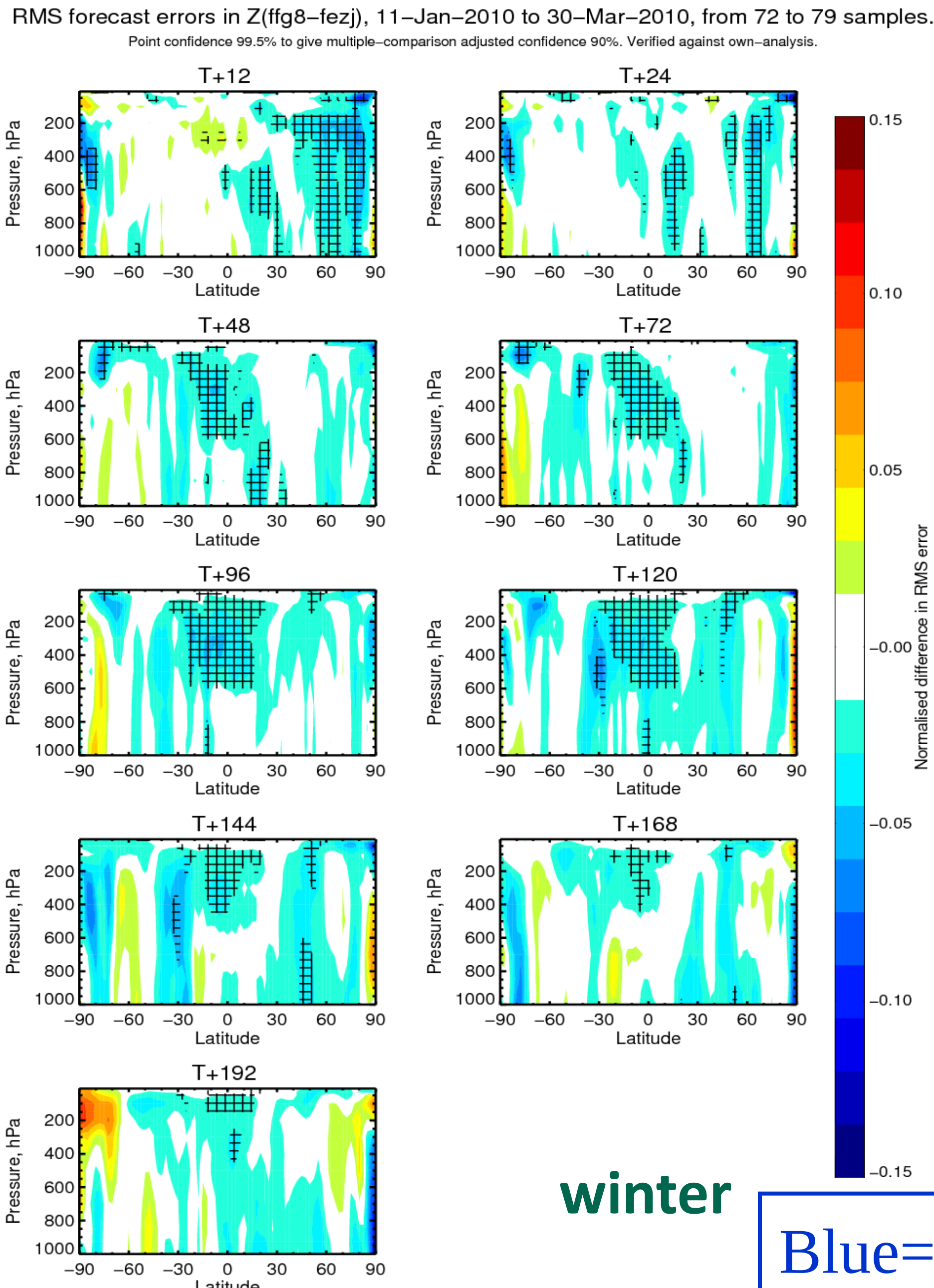
# EDA variances

"Spread-Skill" regressions of the type shown serve two purposes:

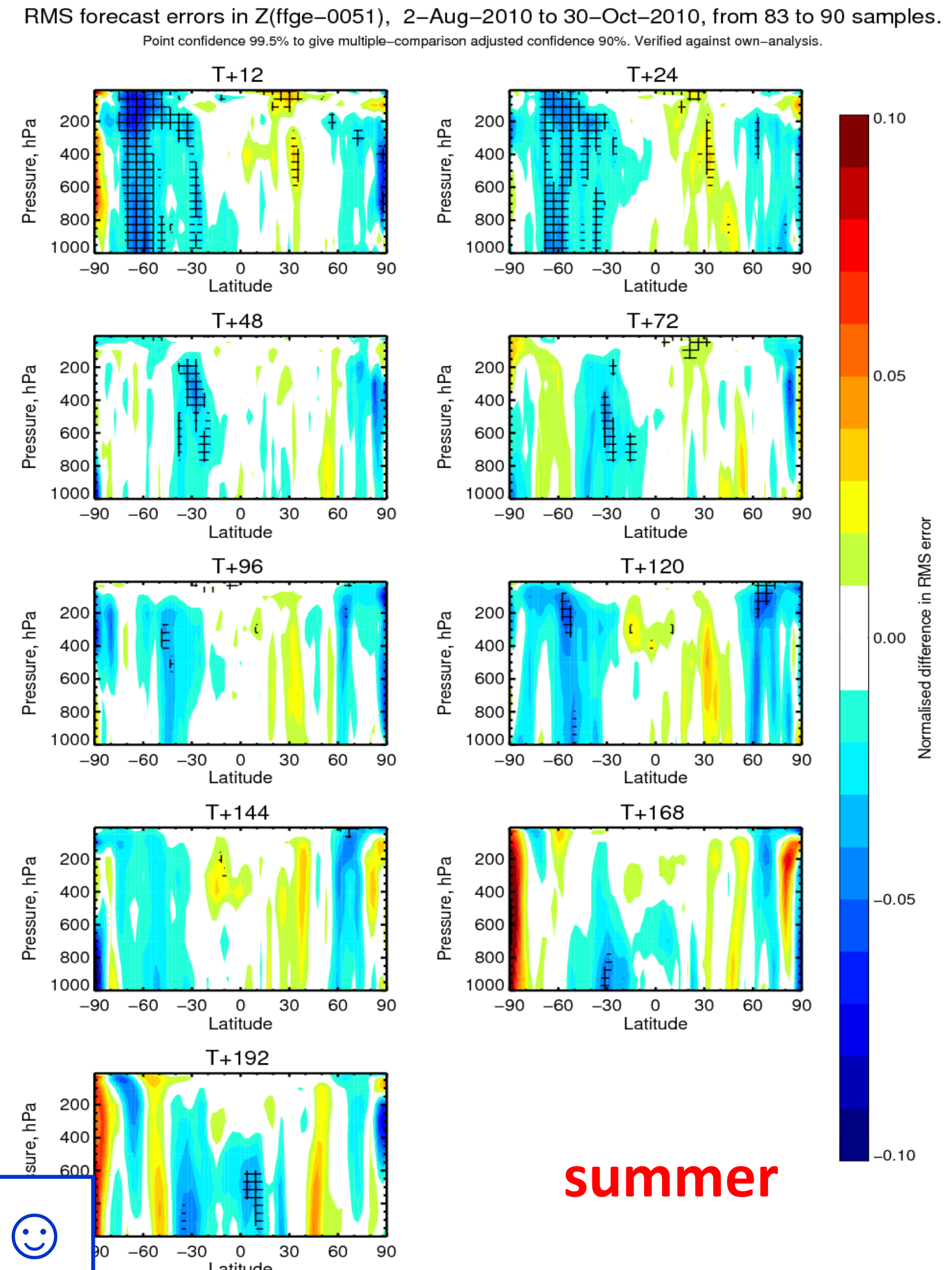
1. Diagnose the progress (or lack thereof!) in the modelling of system uncertainties in the EDA
2. Calibrate on-line the EDA sample variances to obtain realistic estimates of background errors (Ensemble Variance Calibration, *Kolczynsky et al.*, 2009, 2011; *Bonavita et al*., 2011)



# It works well: Geopotential RMSE reduction




winter



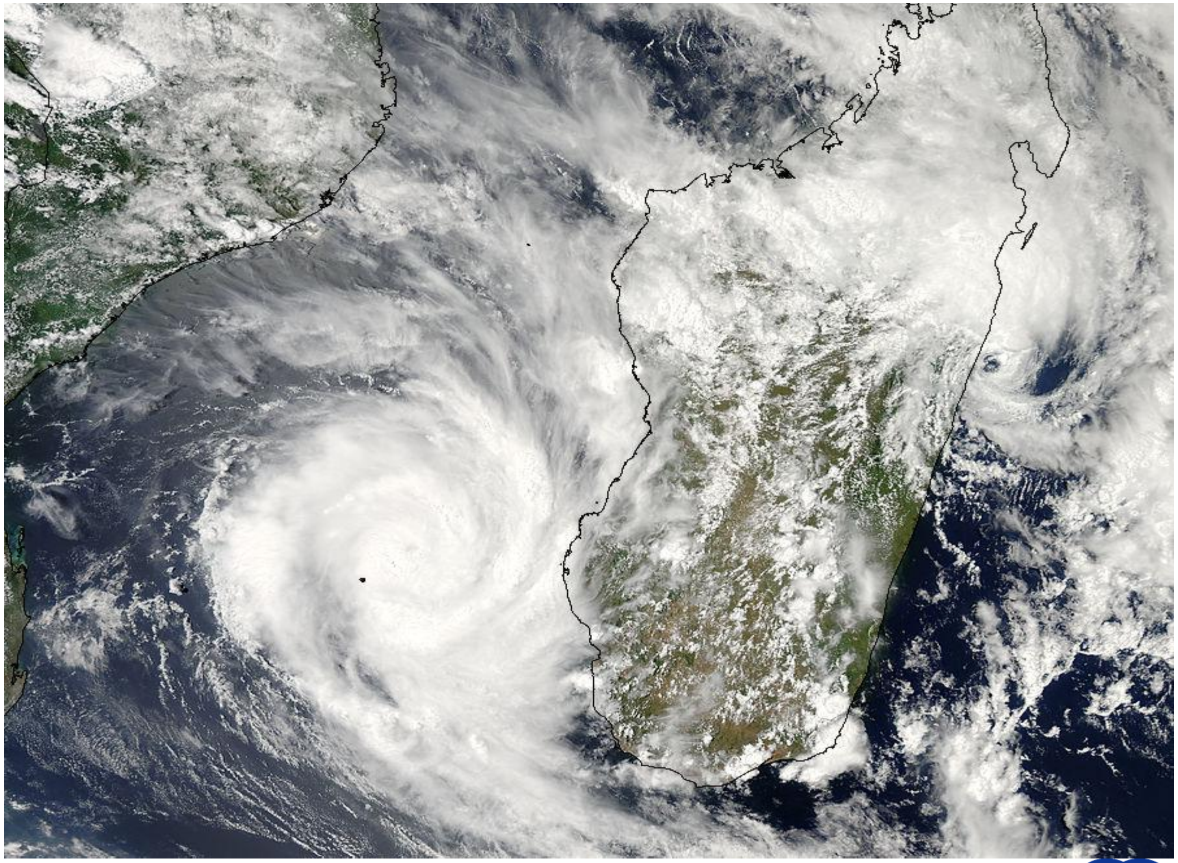

summer

Blue= ☺

# Hybrids next step: EDA Covariance estimation

**Diagnosing the Background Error Correlation Length-Scales**

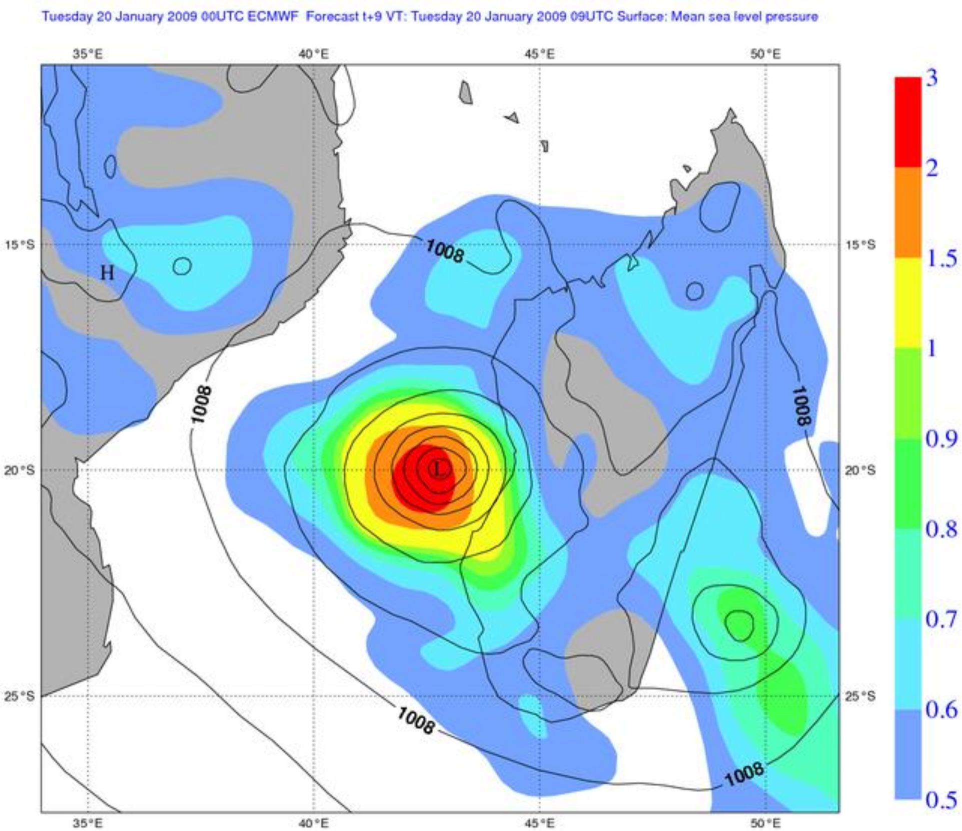
Hurricane Fanele, 20 January 2009



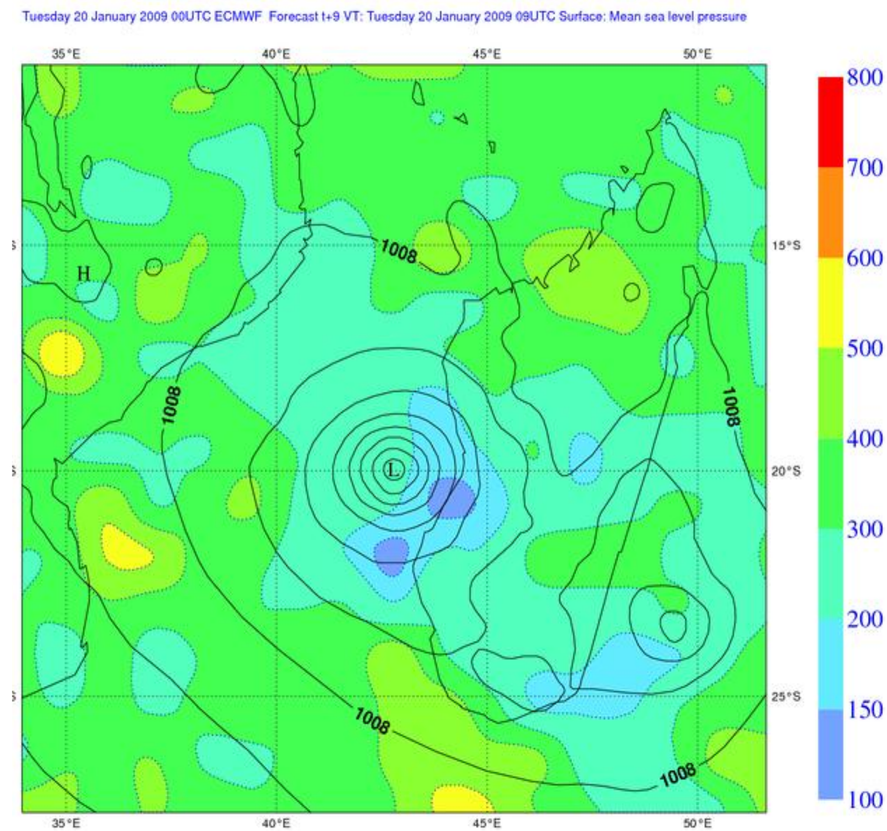
# Hybrids next step: EDA Covariance estimation

**20 member EDA**

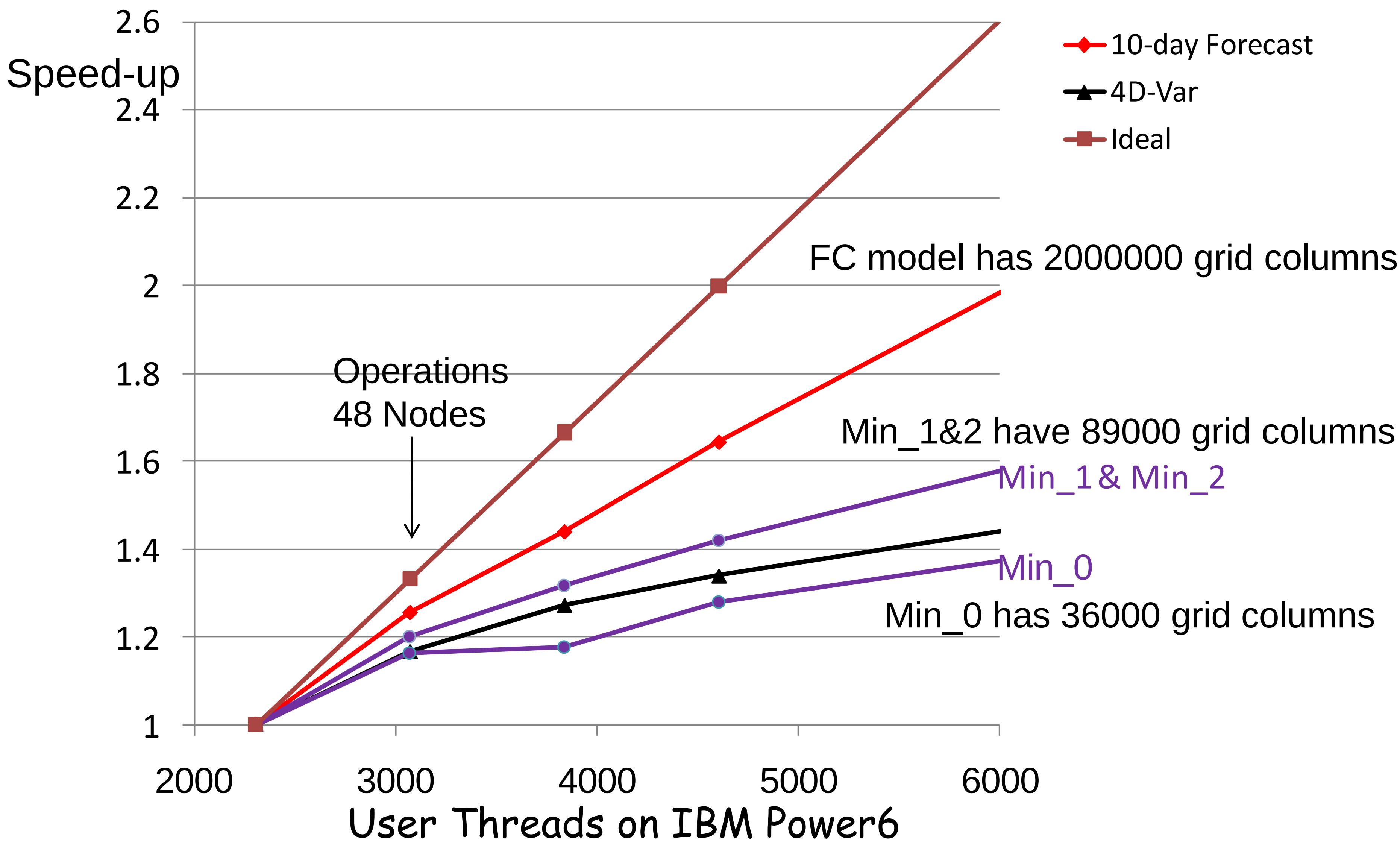
Surf. Press. Background Err. St.Dev.



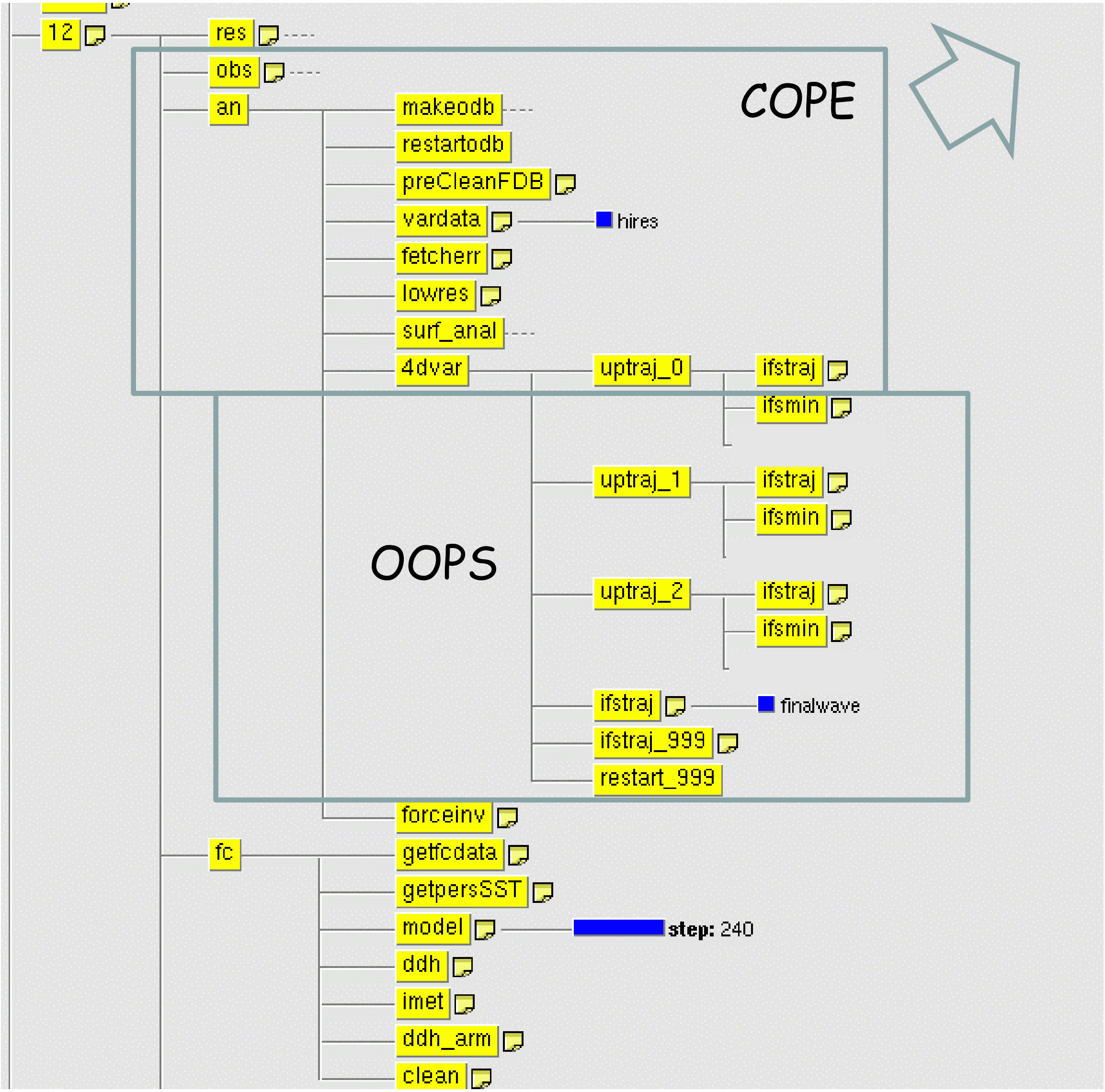

Surf. Press. BG Err. Correlation L. Scale



# Scalability of T1279 Forecast and 4D-Var



# Improving scalability of time critical DA suite




4D-var time window is 12 hours

Forecast &
Outer loop trajectories:

(Traj_0,1,2) are using T1279 resolution
Grid columns = $2 \times 10^6$

Three minimizations:

Min_0 : T159
Grid columns = 36000

Min _1 & 2 : T255
Grid columns = 89000

Vertical = 91 levels

# The 5 Dimensions of 4D-Var

- The bulk of the 4D-Var algorithm comprises 5 nested loop directions:

  1. Minimisation algorithm iterations (inner and outer),
  2. Time stepping of the model (and TL/AD),
  3. Latitude, `NPROMA`
  4. Longitude, `NPROMA`
  5. Vertical.

- Only two are parallel!

- We need to look at the other directions for more parallelism, for example:
  - Minimisation algorithm:
    - Parallel search directions,
    - Parallel preconditioner and less iterations,
    - Observation space algorithms, saddle point algorithms.
  - Time stepping:
    - Weak constraint 4D-Var.

- Scalability cannot be improved solely by technical or local optimizations!

# Object-Oriented Prediction System – The OOPS project

- Data Assimilation algorithms manipulate a limited number of entities (objects):
  - x (State), y (Observation),
  - H (Observation operator), M (Model), H*& M*(Adjoints),
  - B & R (Covariance matrices), etc.

  - To enable development of new data assimilation algorithms in IFS, these objects should be easily available & re-usable

- More Scalable Data Assimilation

- Cleaner, more Modular IFS

# OOPS → More Scalable Data Assimilation

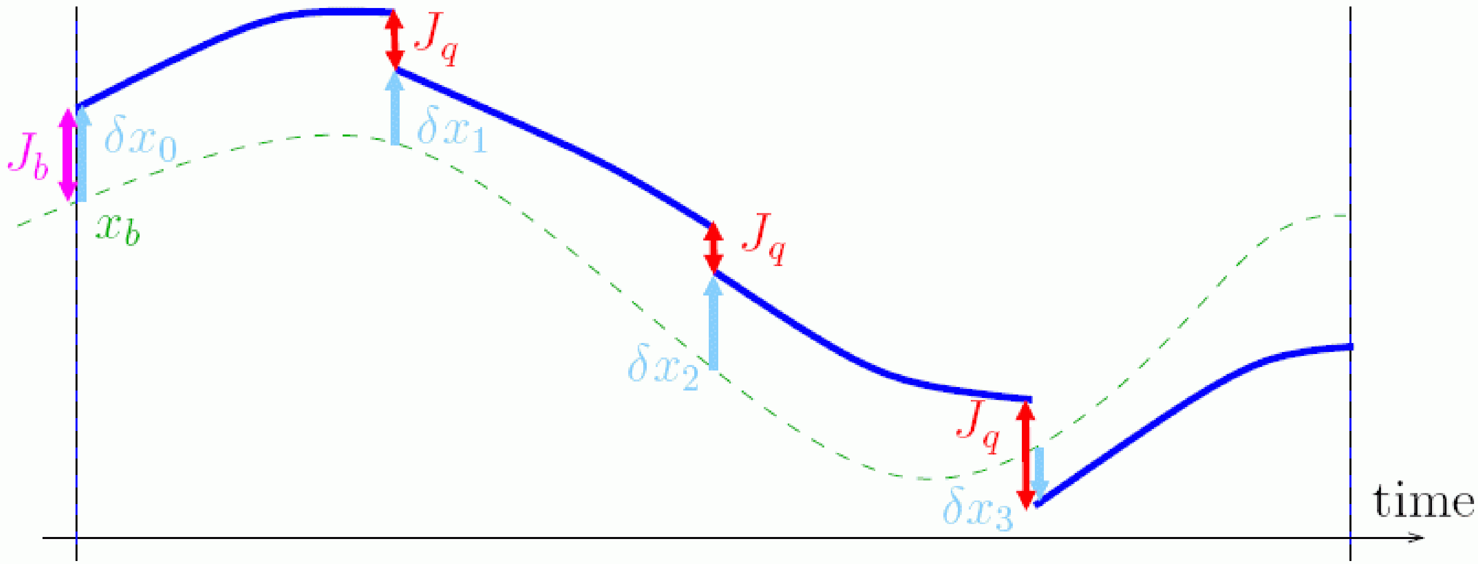
- One execution instead of many will reduce start-up - also I/O between steps will not be necessary

- New more parallel minimisation schemes
  - Saddle-point formulation

  (Only OOPS has made it possible for Mike Fisher to implement the saddle-point formulation so quickly!!)

- For long-window, weak-constraint 4D-Var: Minimization steps for different sub-windows can run in parallel as part of same analysis

# Weak Constraint 4D-Var




- Model integrations within each time-step (or sub-window) are independent:
  - Information is not propagated across sub-windows by TL/AD models,
  - $\mathcal{M}$ and $\mathcal{H}$ can be run in parallel over the sub-windows.
- Several shorter 4D-Var cycles are coupled and optimised together.
- 4D-Var becomes an elliptic problem and preconditioning becomes more complex.

# Conclusions and Perspectives

- Use of hybrids consistently improves deterministic analysis and forecast skill w.r.to pure sequential (EnKF) and non-sequential (4D-Var) solutions;
- EDA/EnKF, possibly re-centred around deterministic analysis, provide improved sampling of initial errors for Ensemble Prediction
- We can expect growing ensemble use in 4D-Var:
  1. A larger ensemble (both in the EDA and EnKF) improves error characterization and ultimately skill scores;
  2. 4D background error covariances sampled from an EDA/EnKF could be used over the all 4D-Var assimilation window (not only at the start!): En-4D-Var (Liu et al., 2008; Buehner et al., 2010). This would remove the need of developing and maintaining a TL and Adjoint version of the forecast model



ECMWF

# Conclusions and Perspectives

- We can expect growing ensemble use in 4D-Var:

3. Weak-constraint Long-window 4D-Var revolves around the estimation of $\mathbf{Q}$: It is conceivable that an EDA will provide a way of effectively sampling $\mathbf{Q}$

4. The EnKF is more computationally efficient than an ensemble of 4D-Var analysis (EDA): **if** it can be shown to be as accurate as standard 4D-Var with the full observing system, then it will provide a relatively cheap and efficient way of cycling error estimates in a hybrid system

# Summary of ECMWF's Data Assimilation strategy

- Hybrid DA system: Use EDA information in 4D-Var

    Flow dependent background error variances and covariances, and model error in 4D-Var

    Provides improved uncertainty estimation

- Long-window weak-constraint 4D-Var
- Unified Ensemble of Data Assimilations (EDA) and Ensemble Prediction System

    For estimation of analysis and short range forecast uncertainty that will benefit the deterministic 4D-Var

    For estimation of long range forecast uncertainty (the present role of the EPS)

Note: The EDA is a 'stochastic EnKF' with an expensive 4D-Var component. It may be replaced or supplemented by an LETKF system, if beneficial.