



# Hybrid Variational/Ensemble Data Assimilation

Dale Barker, Andrew Lorenc, Adam Clayton + many others...  
ECMWF Data Assimilation Seminar, 6 September 2011



# Outline of Talk

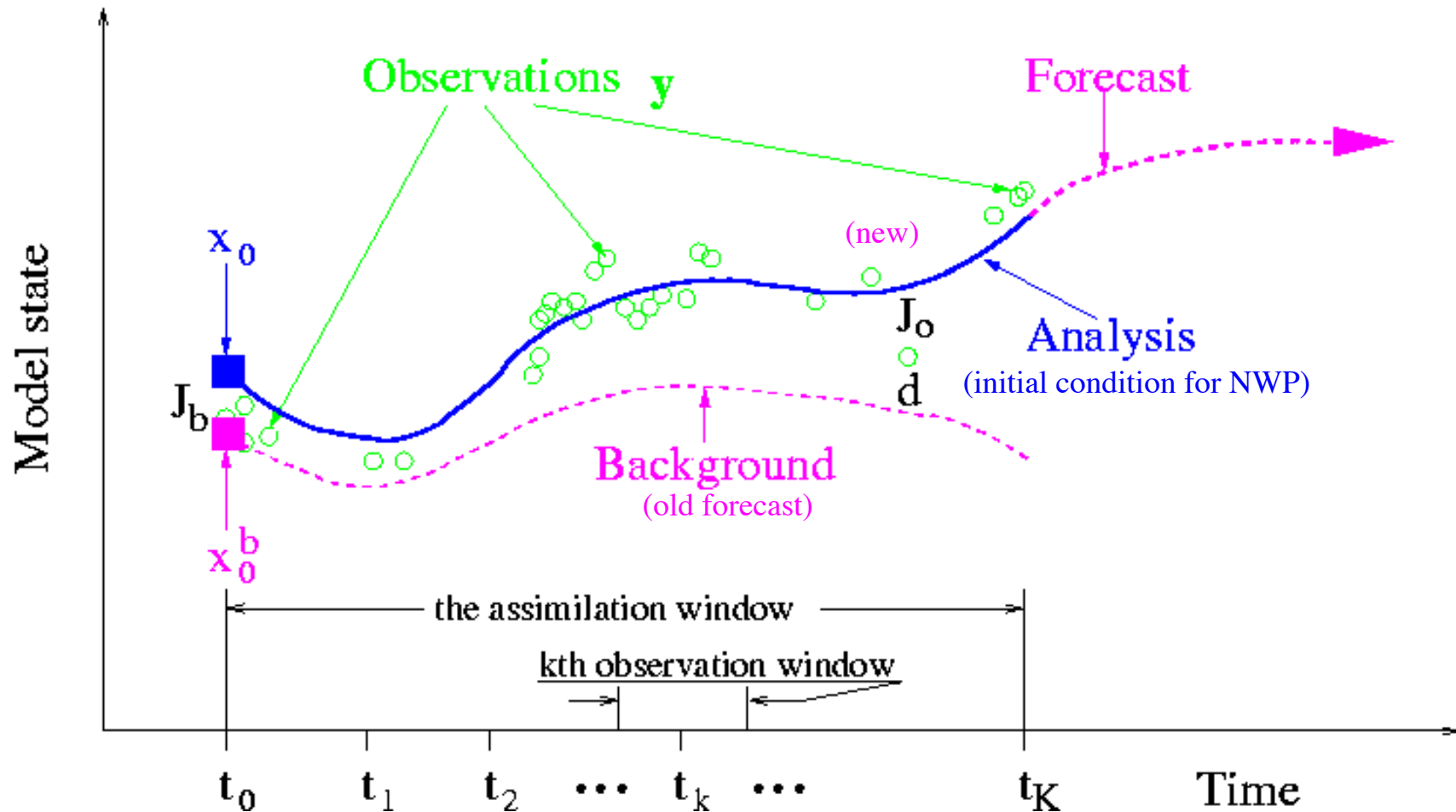
1. 4D-Var and the Ensemble Filter
2. Hybrid Variational/Ensemble Data Assimilation
3. The Met Office Hybrid 4D-Var/ETKF Algorithm
4. Met Office Future Plans



# 1. 4D-Var and the Ensemble Filter



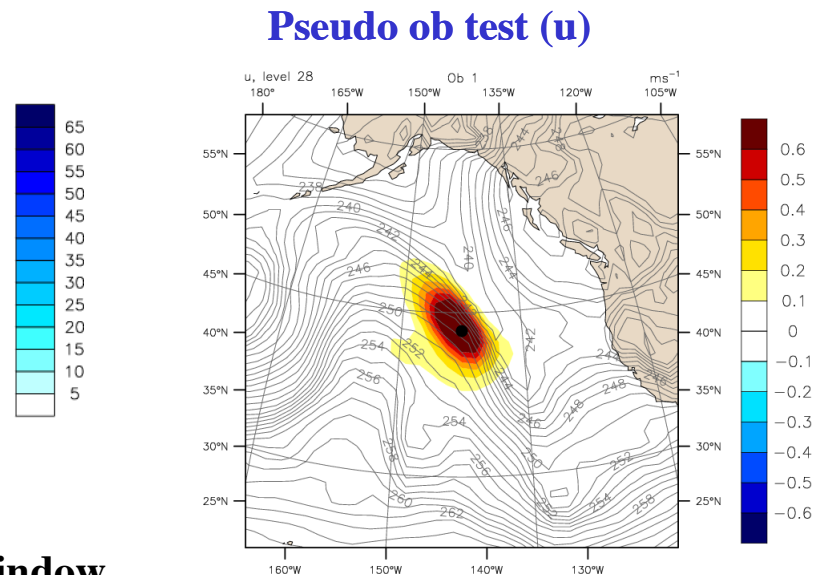
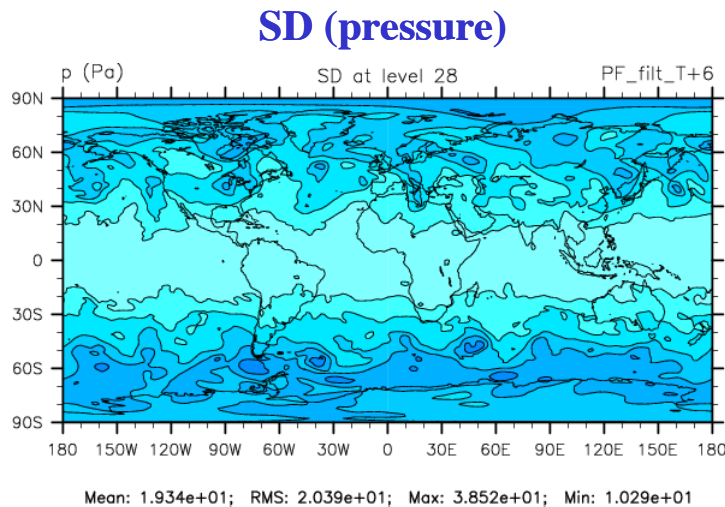
# 4D Variational Data Assimilation (4D-Var)



# Climatological covariances ( $B_c$ )

- Standard 4D-Var is based wholly on climatological covariances (COV):
  - Choose control variable fields that are approximately uncorrelated:
 

$\psi$ : streamfunction       $\chi$ : velocity potential  
 $Ap$ : Unbalanced pressure     $\mu$ : humidity
  - COV covariance model typically imposes constraints e.g. homogeneity, isotropy.
  - Illustrate 4D-Var flow-dependence using 500 samples from climatological B:

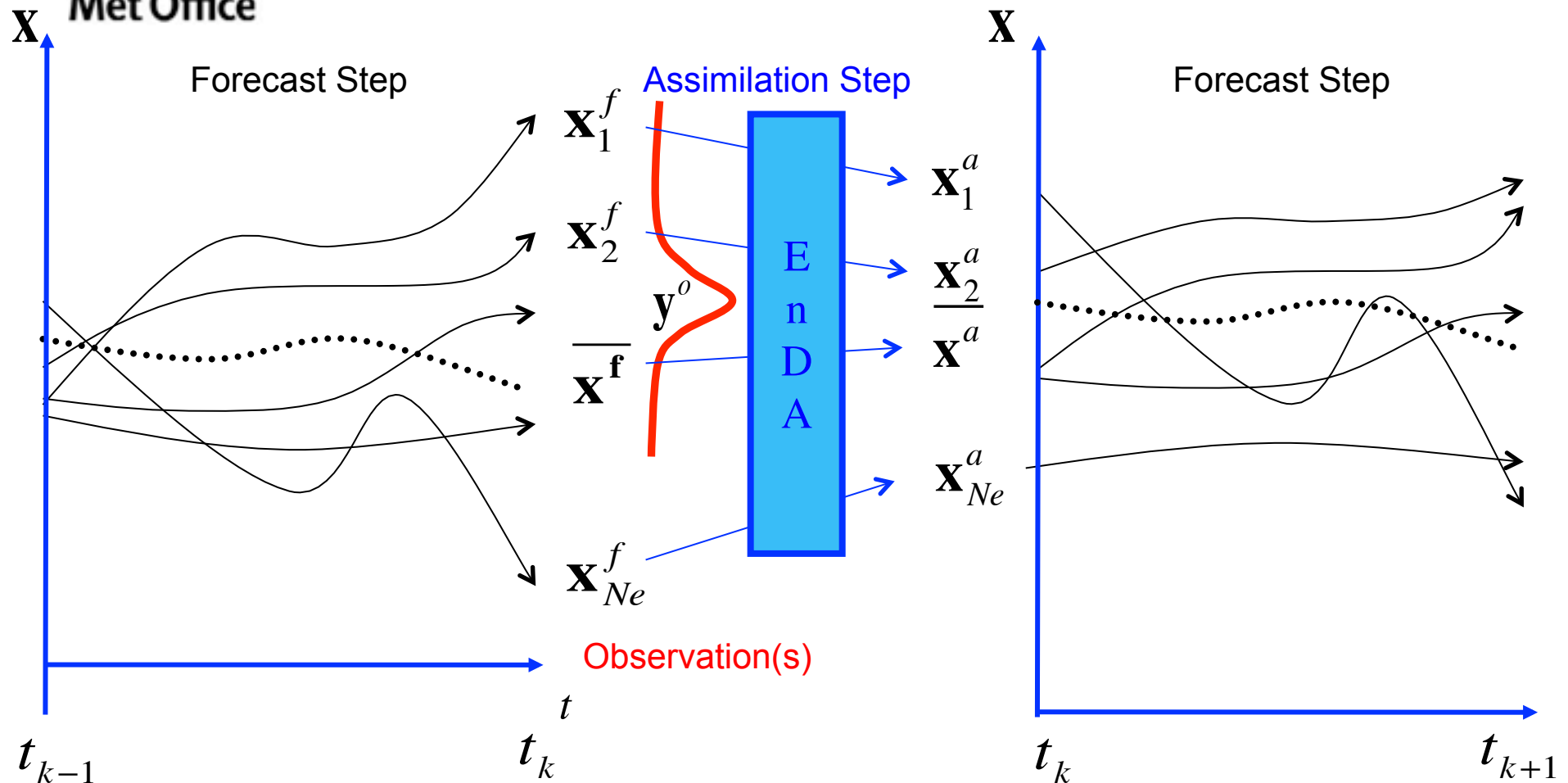


**End of window**



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# Ensemble Data Assimilation (EnDA)

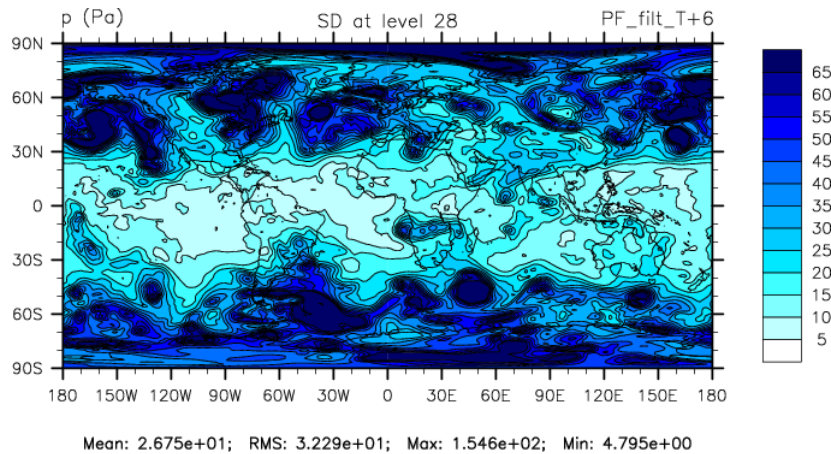


- $N_e$  = Ensemble Size (typically 20-200 for real-world NWP).
- Many different flavours of the EnDA algorithm.

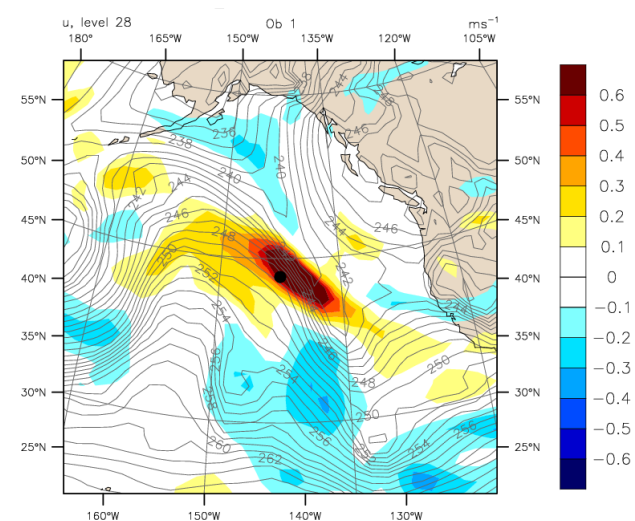
# Ensemble covariances ( $P_e$ )

- MOGREPS-G:
  - 23 perturbed members (N216L70), aimed at the short-range
  - Ensemble covariance is a simple outer product of the forecast perturbations:
 
$$P_e = XX^T; \quad X = \frac{1}{\sqrt{K-1}}(x_1 - \bar{x}, x_2 - \bar{x}, \dots, x_K - \bar{x})$$
  - Provides covariances that should reflect the observation distribution, and the effects of recent instabilities; i.e., the “Errors of the Day”

**SD (pressure)**



**Pseudo ob test (u)**

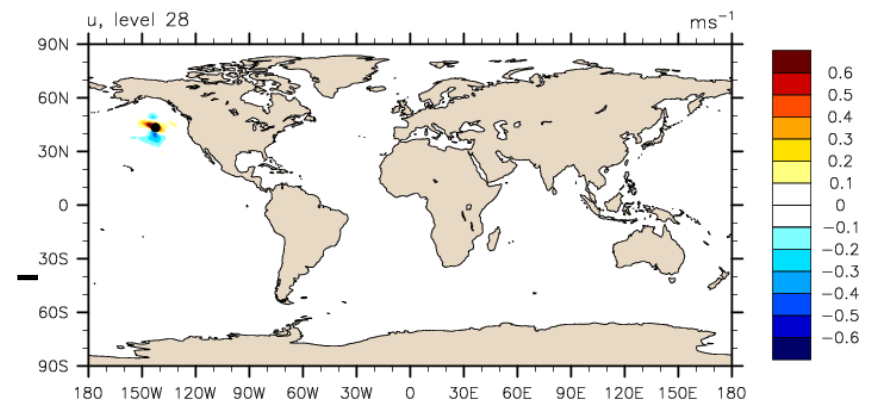
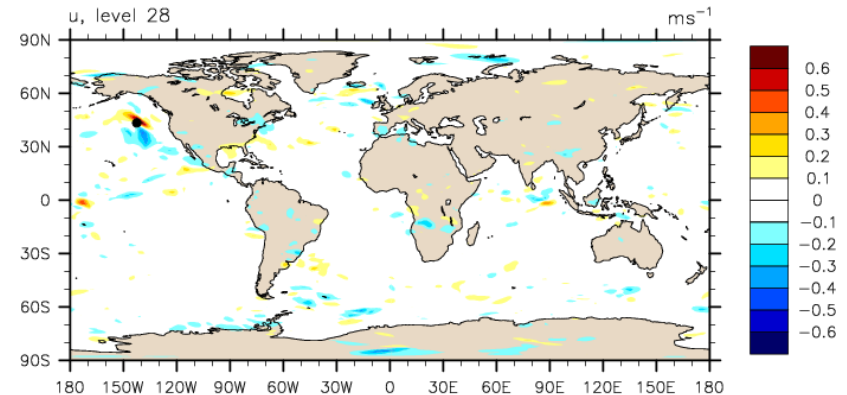
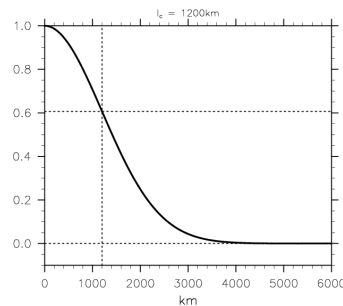


**End of window**

# The need to localise $\mathbf{P}_e$

- Due to the finite ensemble size, ensemble covariances are noisy, for example spurious long-range correlations:
- Solution is to localise the covariances by multiplying pointwise with a localising covariance

$$\mathbf{P}_e \circ$$



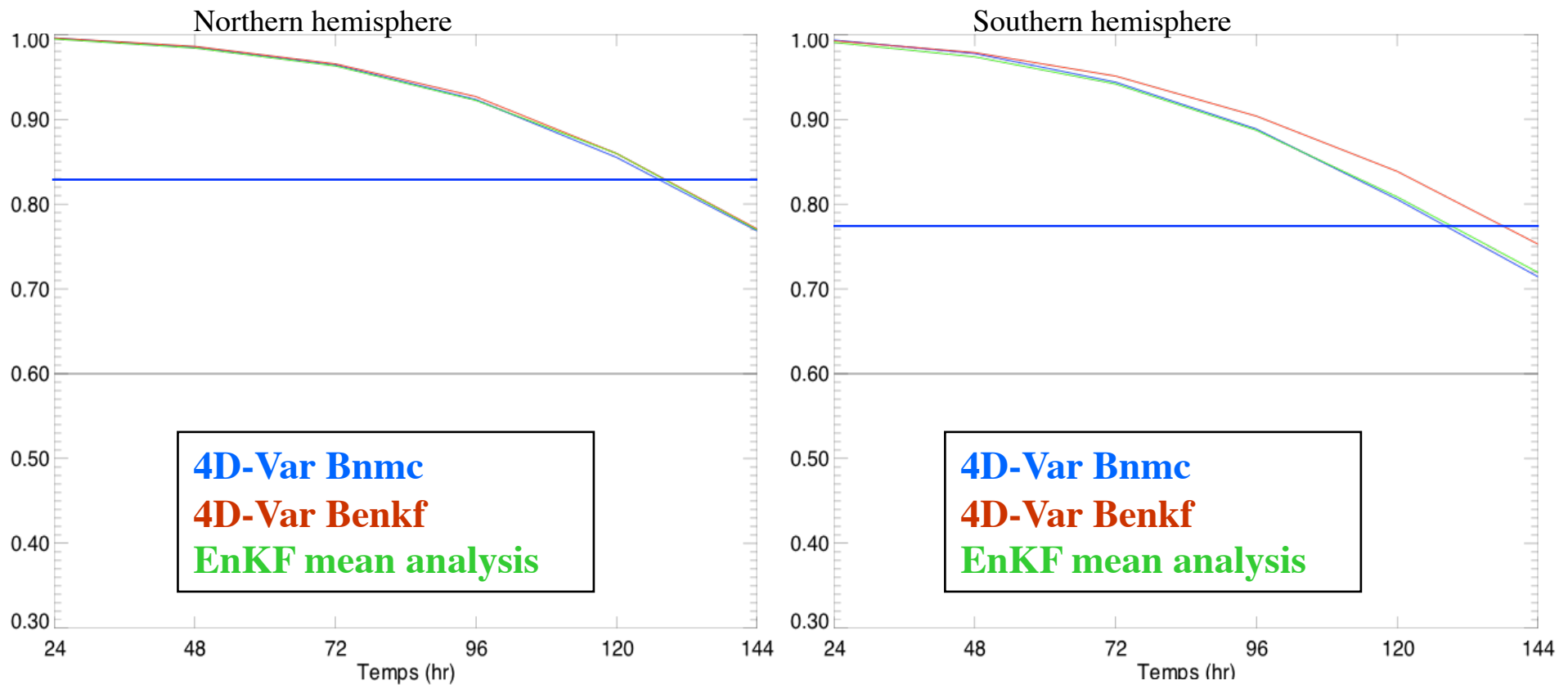
- Crucially, localisation also increases the ‘rank’ of the ensemble covariance; the number of independent structures available to fit the observations.





# Comparison of 4D-Var/EnKF (Buehner et al 2010)

\*\*\*Verifying analyses from 4D-Var with Bnmc\*\*\*



**Conclusion: Combined 4D-Var + EnKF covariances->~10hrs SH skill**



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## 2. Hybrid Variational/Ensemble Data Assimilation



# Hybrid Var/EnDA: Motivation

- 1) Forecast errors often highly flow-dependent.
- 2) 4D-Var can introduce flow-dependence, but limited by linearity assumption and static  $J_b$ .
- 3) Ensemble filters provide flow-dependent covariances, but suffer from effects of sampling error.
- 4) Evidence of optimal mix (hybrid) of static/ensemble background error covariances in OI/3D-Var-based studies, e.g. Hamill and Snyder (2000):

$$\mathbf{B} = b\mathbf{B}_{c\text{ lim}} + (1 - b)\mathbf{B}_{\text{flow-dep}}$$

- 5) Simple model experiments have shown promise, but need to extend to full operational testing.



# Example Hybrid Result (Etherton and Bishop 2004)

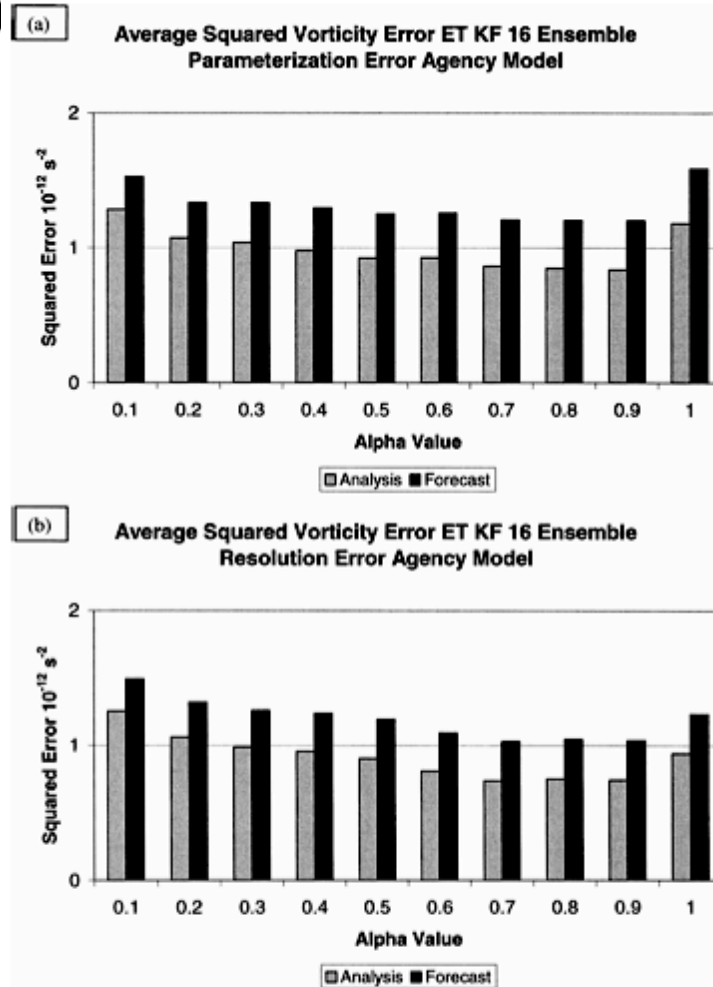


FIG. 5. The daily average squared vorticity error as a function of the parameter alpha ( $\alpha = 0$  being pure ETKF,  $\alpha = 1$  being pure 3DVAR) for when the agency's forecast model had (a) parameterization error or (b) resolution error. A 16-member ETKF-generated ensemble was used for the construction of the flow-dependent error statistics.

- Barotropic vorticity model.
- ETKF not localized.
- 3D-Var framework.
- Optimal mix of Var/Ens covariance  $\sim 70/30\%$ .



## Hybrid Var/EnDA Via The 'Alpha Control Variable' (Barker 1999, Lorenc 2003)

- Vector of Ensemble Perturbations  $\delta\mathbf{X}_f = (\delta\mathbf{x}_{f1}, \delta\mathbf{x}_{f2}, \dots, \delta\mathbf{x}_{fN})$
- Hybrid analysis increment defined as

$$\delta\mathbf{x}_0 = \delta\mathbf{x}_{clim} + \delta\mathbf{x}_{flow-dep} = \mathbf{B}^{1/2}\mathbf{v} + \delta\mathbf{X}_f \circ \mathbf{a}$$

- Ensemble weights  $\mathbf{a}$  constrained by an additional cost-function,

$$J = \frac{W_b}{2} \delta\mathbf{x}_0^T \mathbf{B}^{-1} \delta\mathbf{x}_0 + \frac{W_\alpha}{2} \mathbf{a}^T \mathbf{A}^{-1} \mathbf{a} + \frac{1}{2} \sum_{i=0}^n \left[ \mathbf{H}_i \delta\mathbf{x}(t_i) - \mathbf{d}_i \right]^T \mathbf{R}_i^{-1} \left[ \mathbf{H}_i \delta\mathbf{x}(t_i) - \mathbf{d}_i \right]$$

- Variance conservation implies  $\frac{1}{W_b} + \frac{1}{W_\alpha} = 1$
- $W_b=1$  is standard 3/4D-Var.  $W_b=0$  fully ensemble covariance (e.g. Liu et al 2008, Buehner et al 2010). **Hybrid is the space in-between!**



# Comments on The ACV Method

- ‘Incremental, balance-aware’ covariance localization is trivial, e.g.

$$\delta\psi_0 = \delta\psi_{c\text{lim}} + \delta\psi_f \circ \mathbf{a} \quad \delta\chi_{u0} = \delta\chi_{uc\text{lim}} + \delta\chi_{uf} \circ \mathbf{a}$$

- Covariance  $\mathbf{A}$  equivalent to model-space covariance localization (Lorenz 2003).
- So, like  $\mathbf{B}$  we can define a covariance (localization) model for  $\mathbf{A}$ , e.g.

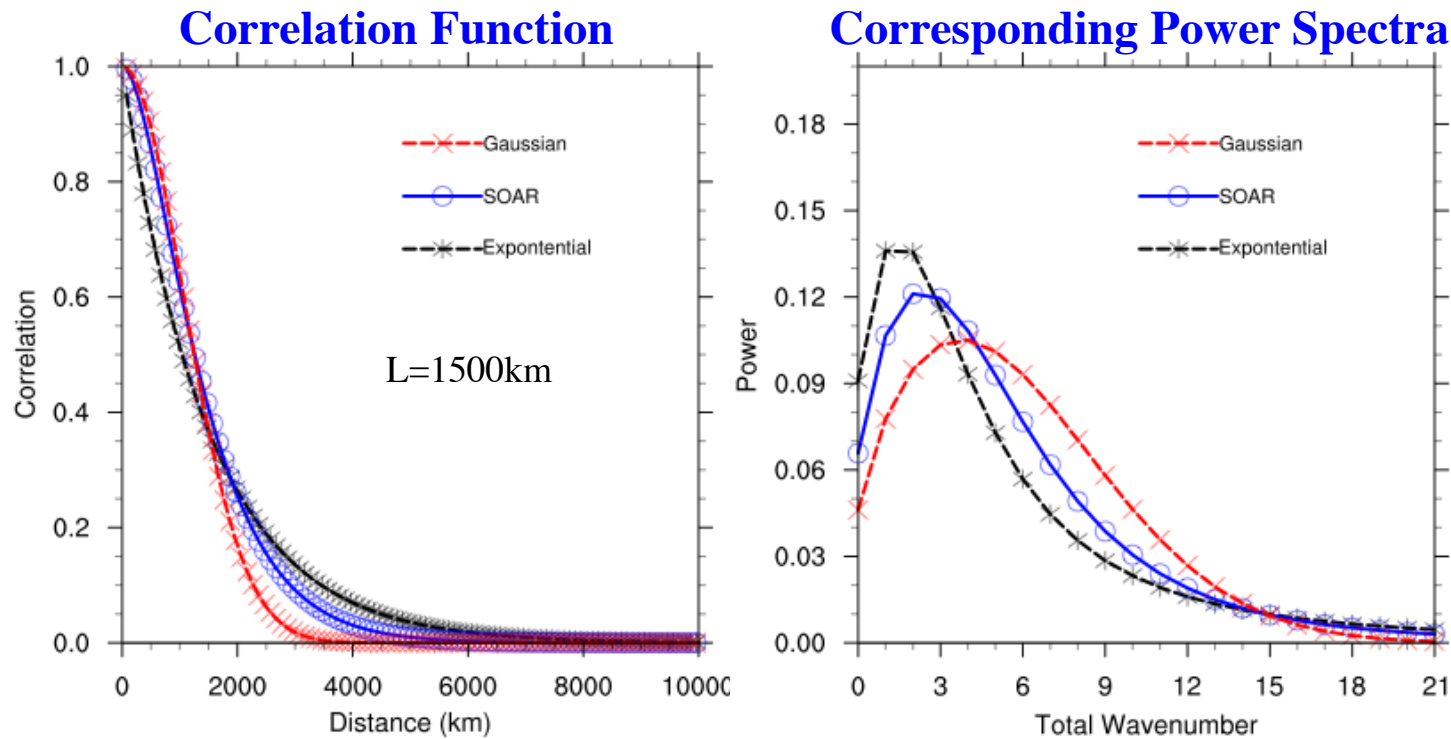
$$\mathbf{a} = \mathbf{A}^{1/2} \boldsymbol{\alpha} \equiv \sigma_{\alpha}^2 \mathbf{A}_v \mathbf{A}_h \boldsymbol{\alpha}$$

- $\mathbf{A}=\mathbf{I}$  implies no localization. Only need one scalar per ensemble member.
- Convenient to use standard control variable transforms for localization operators  $\mathbf{A}_v, \mathbf{A}_h$ , but not essential.



# $A_h$ : Horizontal Covariance Localization

- Example: Truncated power spectrum from empirical correlation with scale  $L$ :



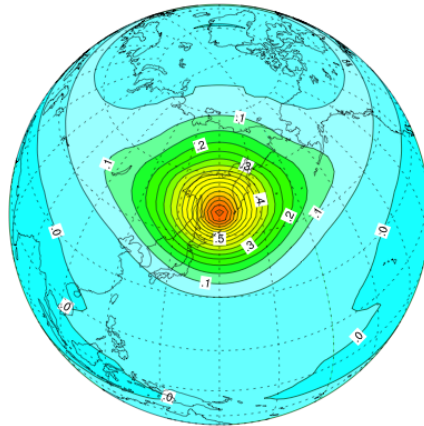
- Spectral localization permits significant reduction in size of alpha control variable.



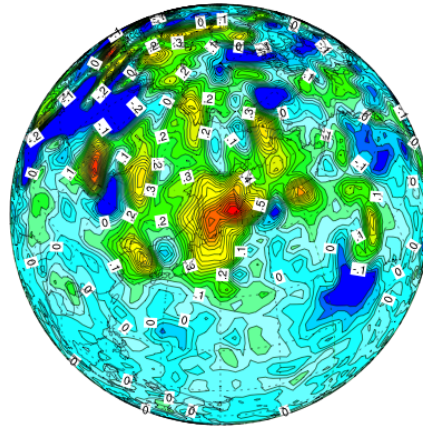
# Alpha Covariance Localization (Extreme example: 1 ob + 2 members!)

- Single T observation (O-B,  $s_o=1K$ ) at 50N, 150E, 500hPa.

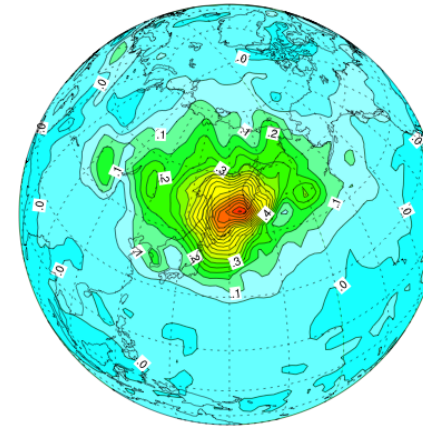
T' increment



3D-Var

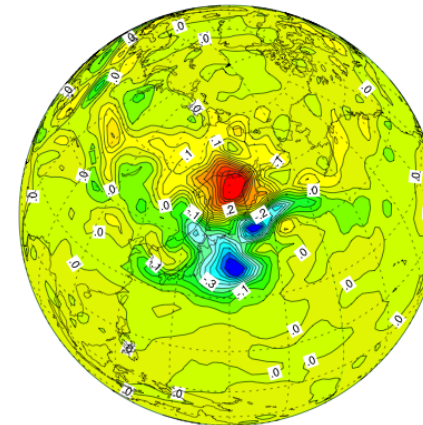
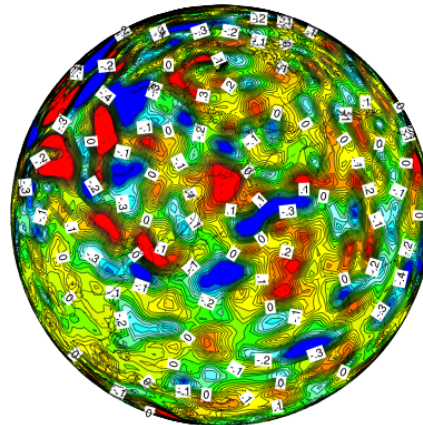
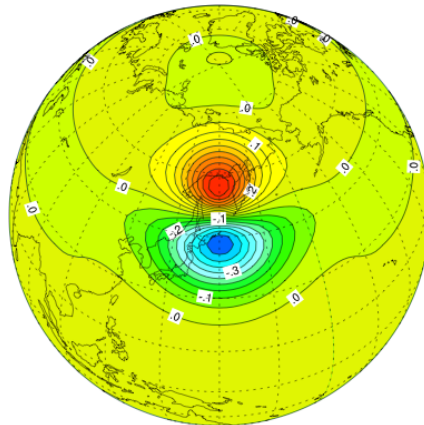


EnDA: No Localization



EnDA: With localization

u' increment







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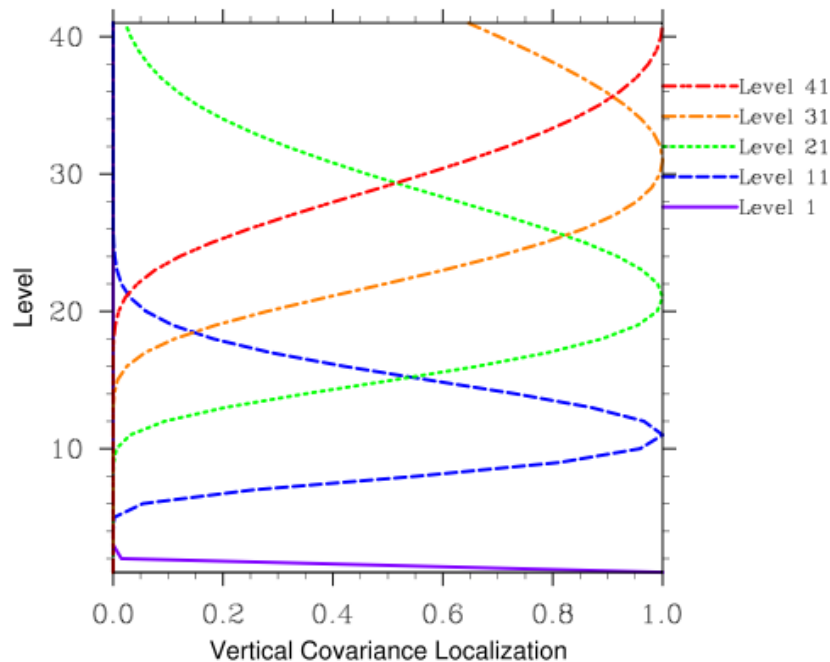
# $A_v$ : Vertical Covariance Localization

WRF Example: Gaussian with level-dependent localization scale:

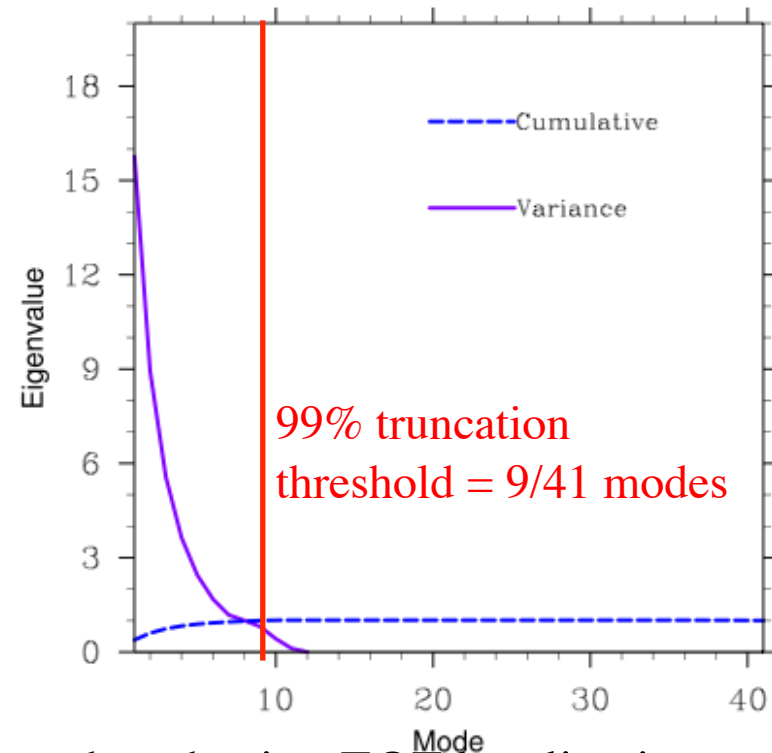
$$\rho(k - k_c) = \exp\left[-(k - k_c)^2 / L_c^2\right]$$

$$L_c = 20k_c / 41$$

### Correlation Function



### Eigenvalues

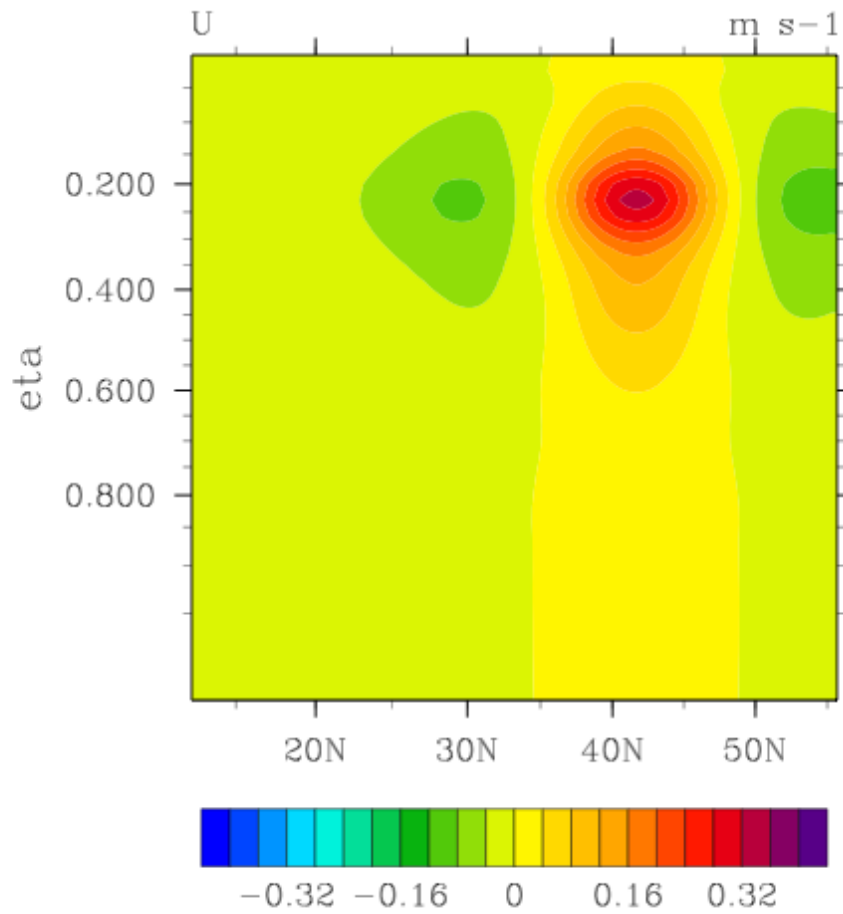


Again, number of additional control variables reduced using EOF localization.

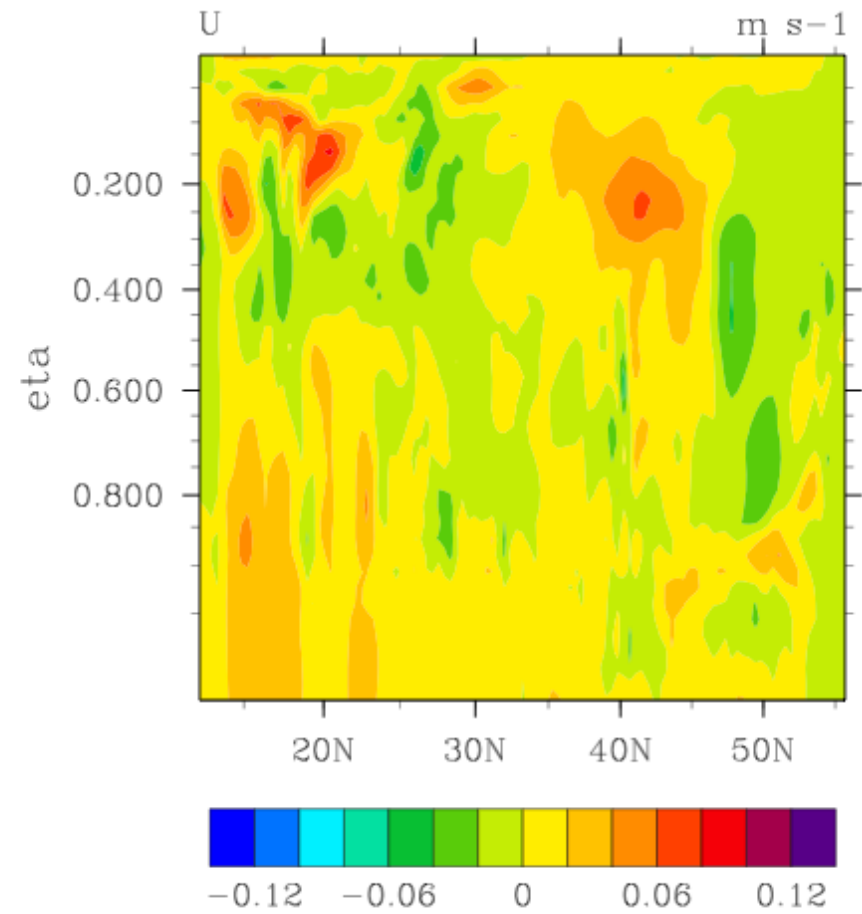


# Single ob test

(250hPa u, O-B=1m/s, sigma\_o=3.3m/s)



3D-Var



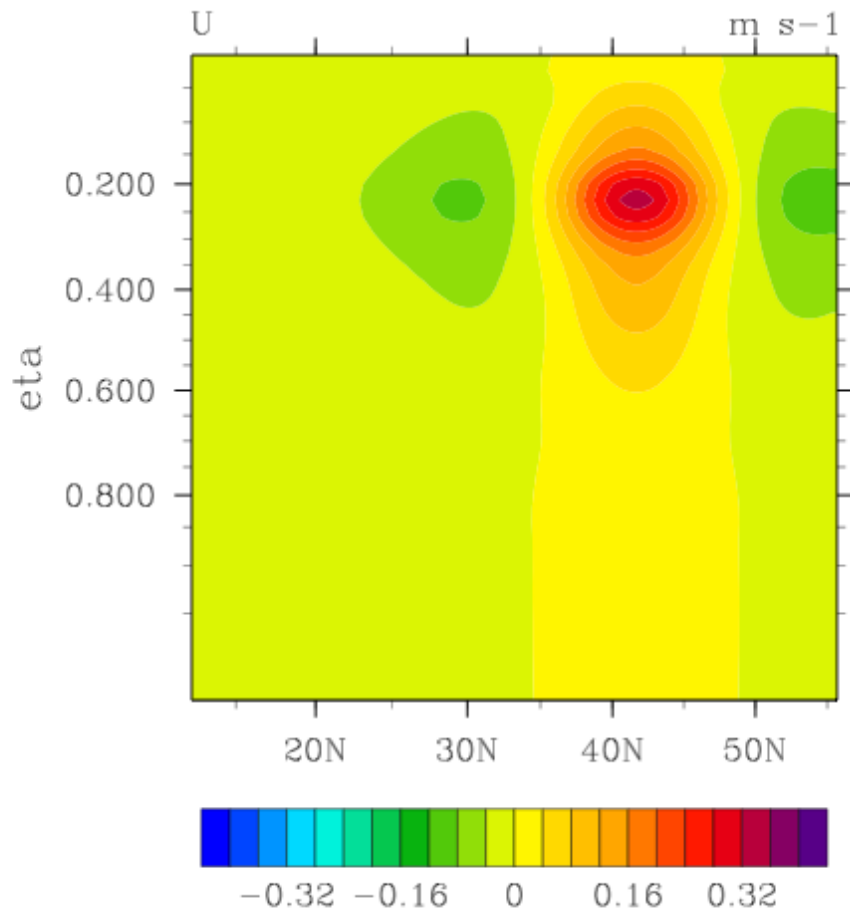
W<sub>b</sub>=0, A=I



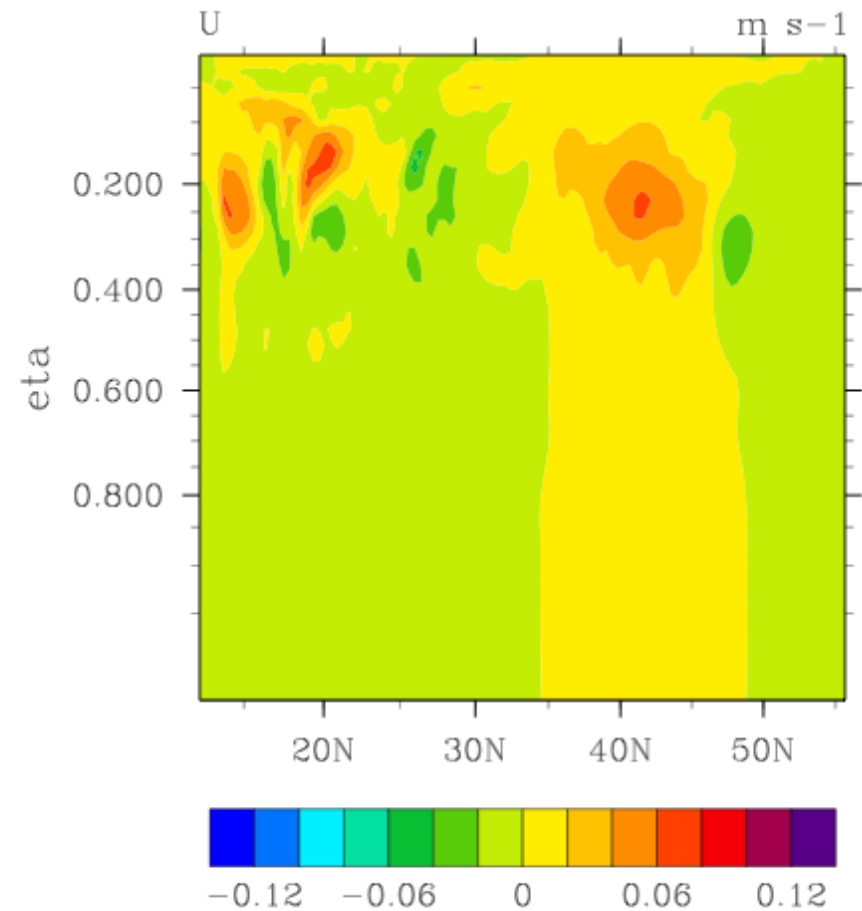
# Single ob test

(250hPa u, O-B=1m/s, sigma\_o=3.3m/s)

## Impact of Vertical Localization



3D-Var

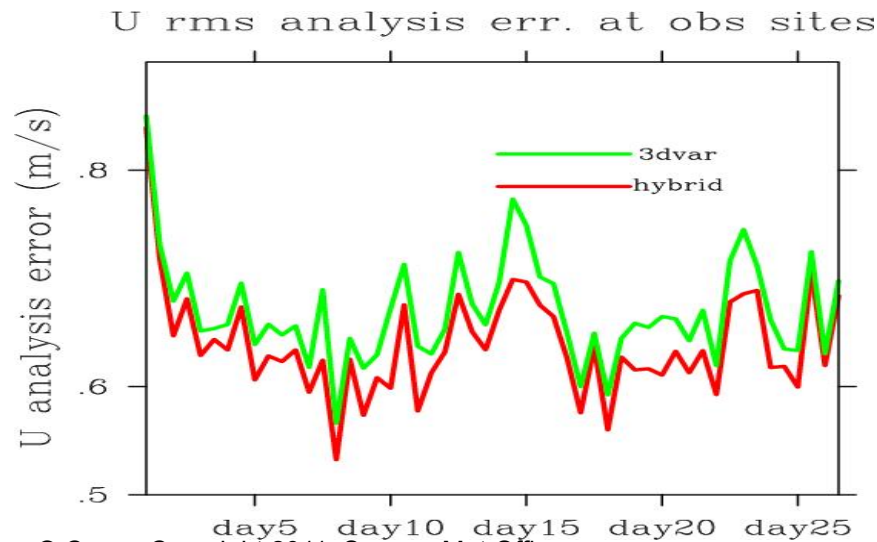


$W_b=0, \mathbf{A}=\mathbf{A}_v$

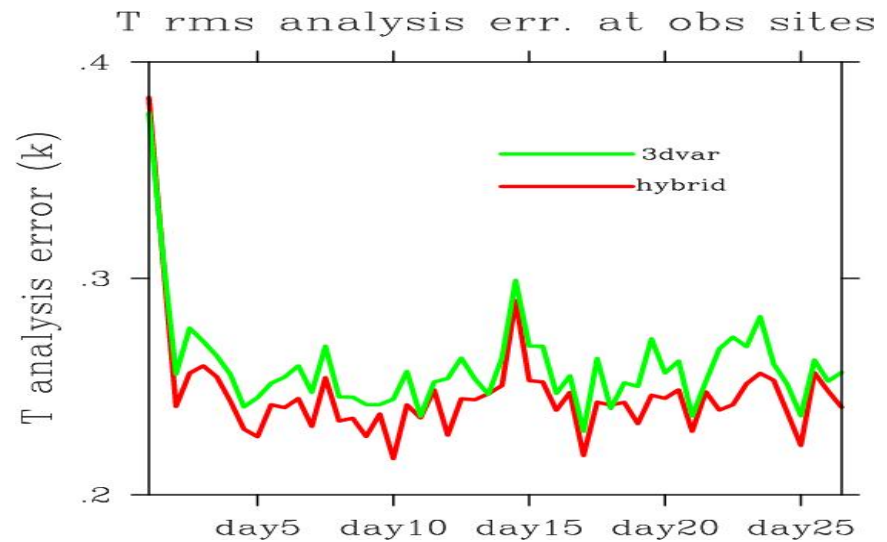


# Hybrid 1-Month OSSE Trial: Analysis Error (Wang, Barker, Hamill and Snyder 2008a)

- WRF 3D-Var-based study in US domain.
- Low (200km) resolution.
- Sondes only. No cycling.
- Equal weight (0.5) on static/ETKF error covariances
- Hybrid significantly better than the pure 3D-Var:



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## 3. The Met Office Hybrid 4D-Var/ETKF



# Operational NWP Models: 19<sup>th</sup> July 2011

## Global

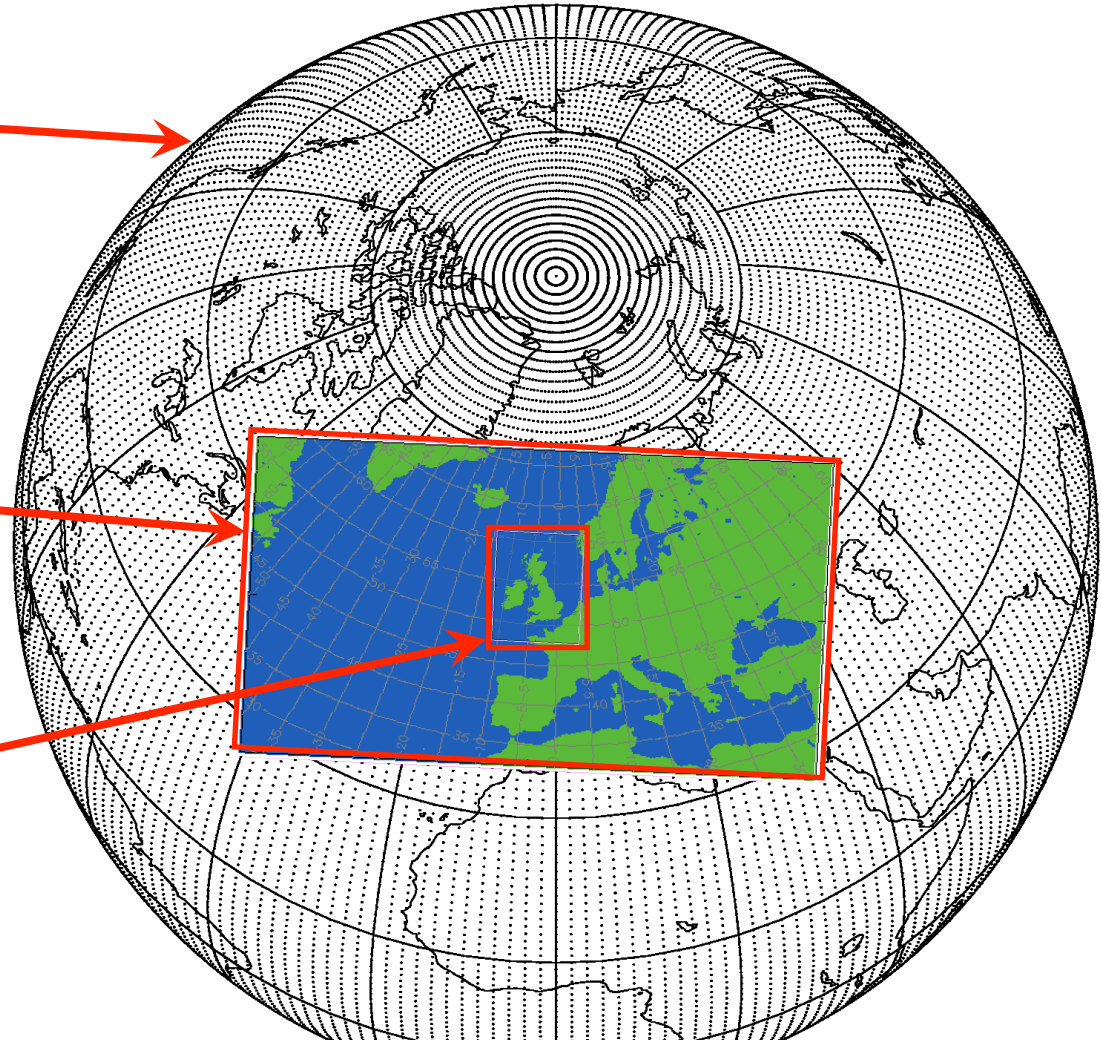
- 25km 70L
- 4DVAR – 60km inner loop
- 60h forecast twice/day
- 144h forecast twice/day
- +24member EPS at 60km 2x/day

## NAE

- 12km 70L
- 4DVAR – 24km
- 60h forecast
- 4 times per day
- +24member EPS at 18km 2x/day

## UK-V (& UK-4)

- 1.5km 70L
- 3DVAR (3 hourly)
- 36h forecast
- 4 times per day



Met Office Global Regional Ensemble Prediction System = MOGREPS



# Operational NWP Models: 20<sup>th</sup> July 2011

## Global

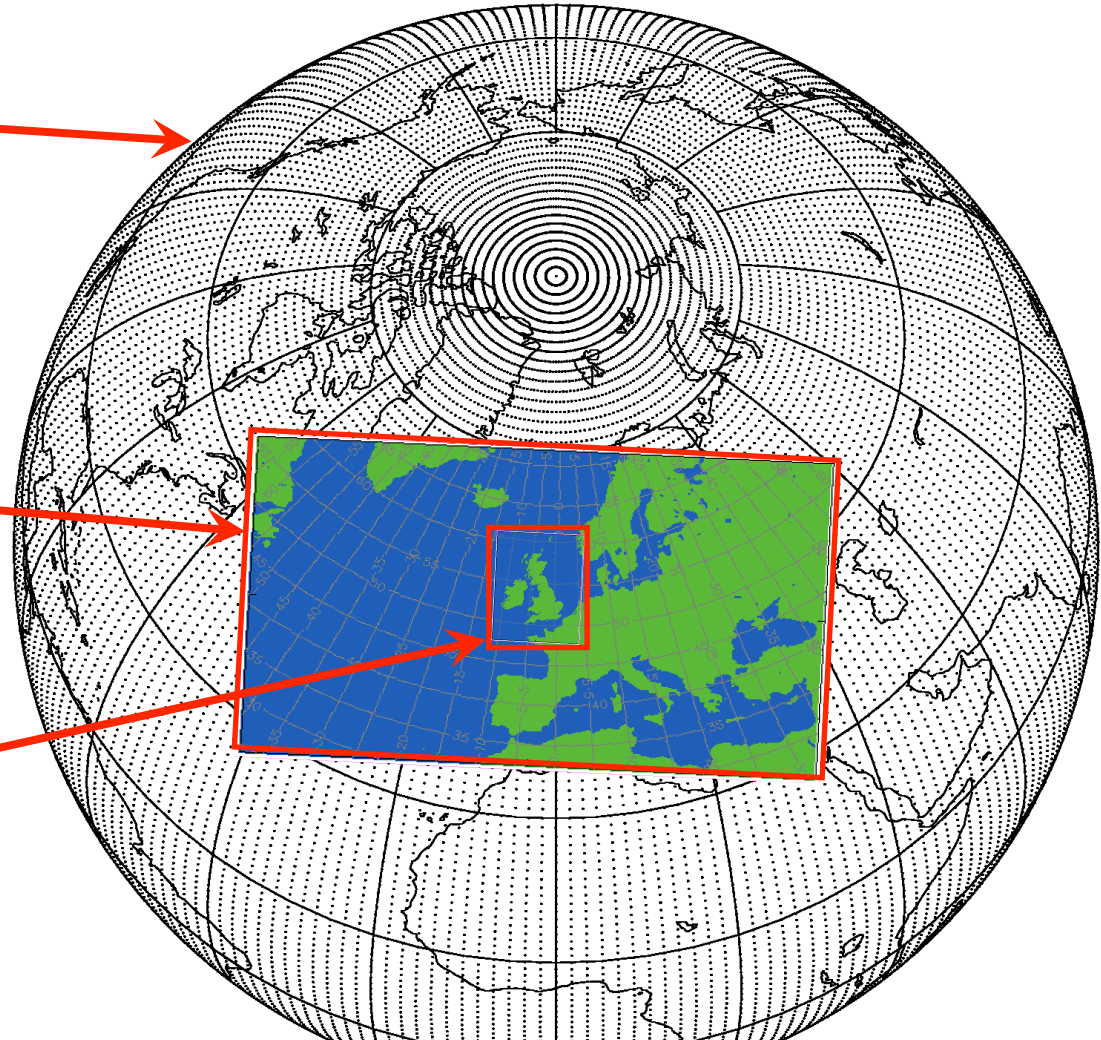
- 25km 70L
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- 144h forecast twice/day
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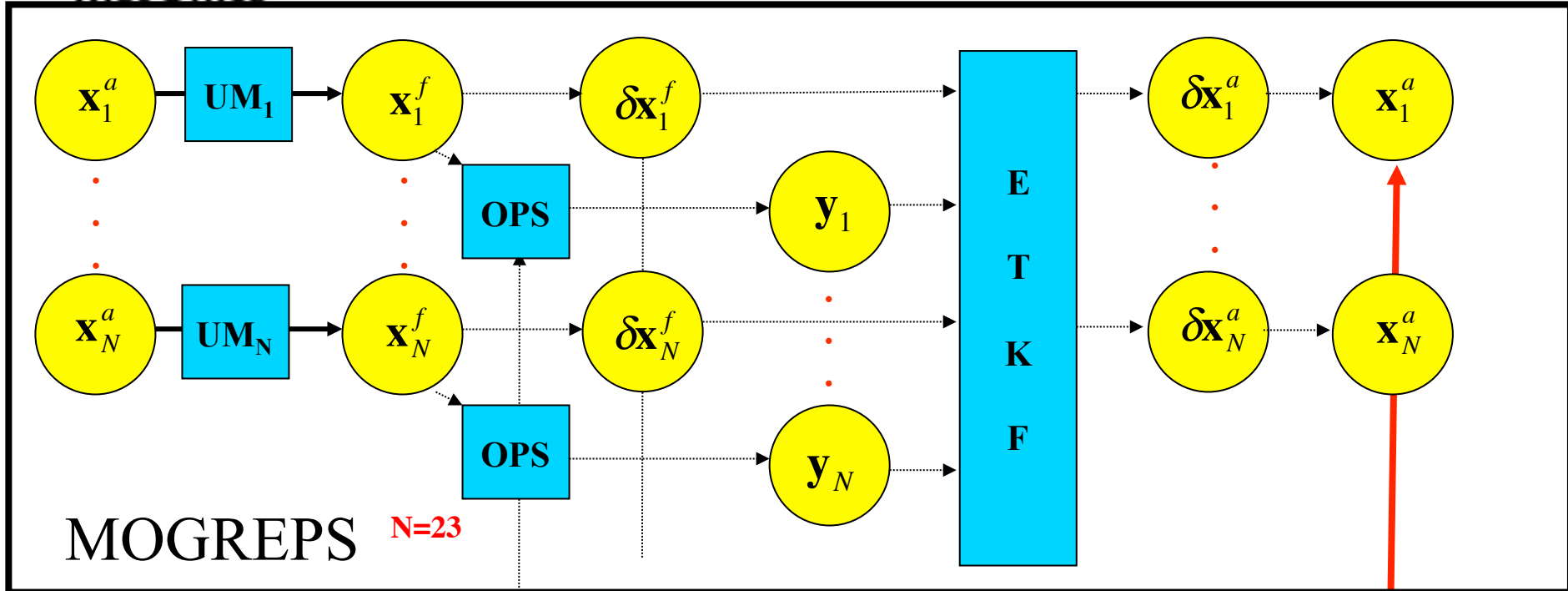
Met Office Global Regional Ensemble Prediction System = MOGREPS



# 1-Way Coupled 4D-Var/ETKF

$$\mathbf{y}_n = H(\mathbf{x}_n^f), \sigma_o, \dots$$

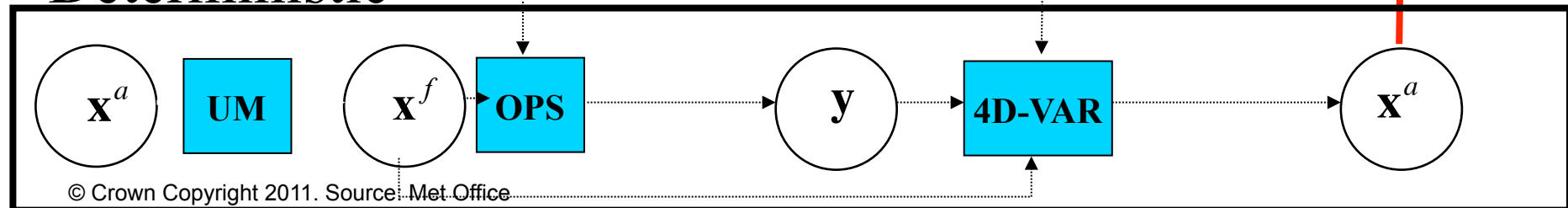
$$\mathbf{x}_n^a = \mathbf{x}^a + \delta\mathbf{x}_n^a$$



(UM = Unified Model)

(OPS = Observation Preprocessing System)

## Deterministic



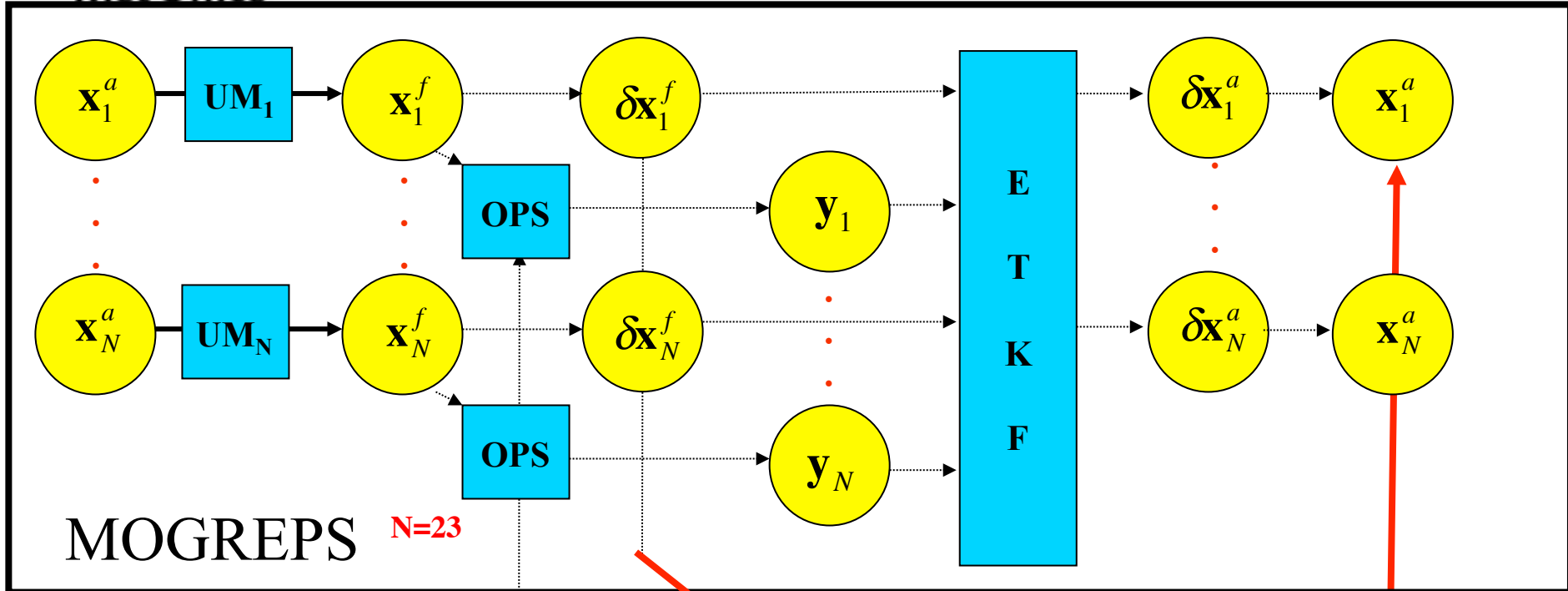




# 2-Way Coupled 4D-Var/ETKF

$$\mathbf{y}_n = H(\mathbf{x}_n^f), \sigma_o, \dots$$

$$\mathbf{x}_n^a = \mathbf{x}^a + \delta\mathbf{x}_n^a$$

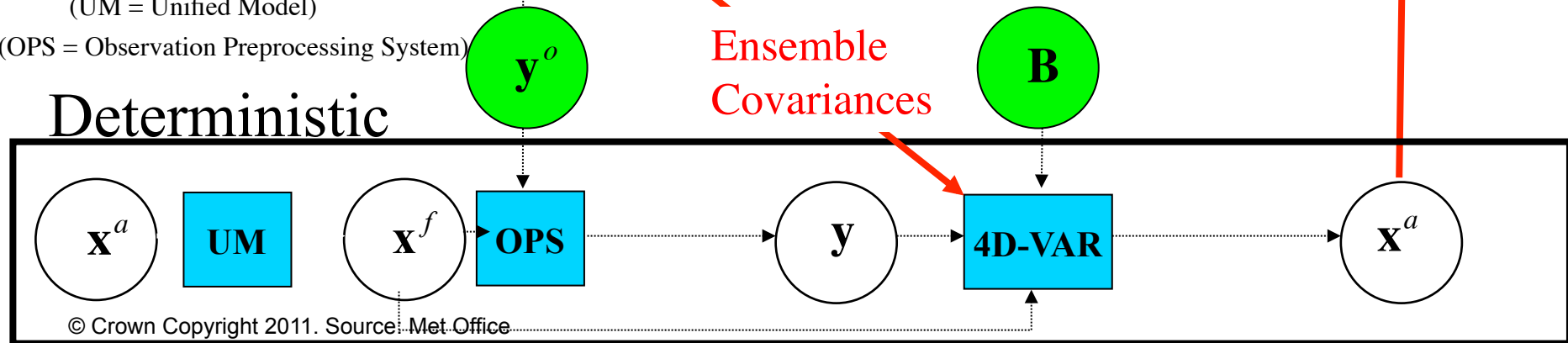


MOGREPS N=23

(UM = Unified Model)

(OPS = Observation Preprocessing System)

Deterministic





# Hybrid V0.0: Trial Configurations

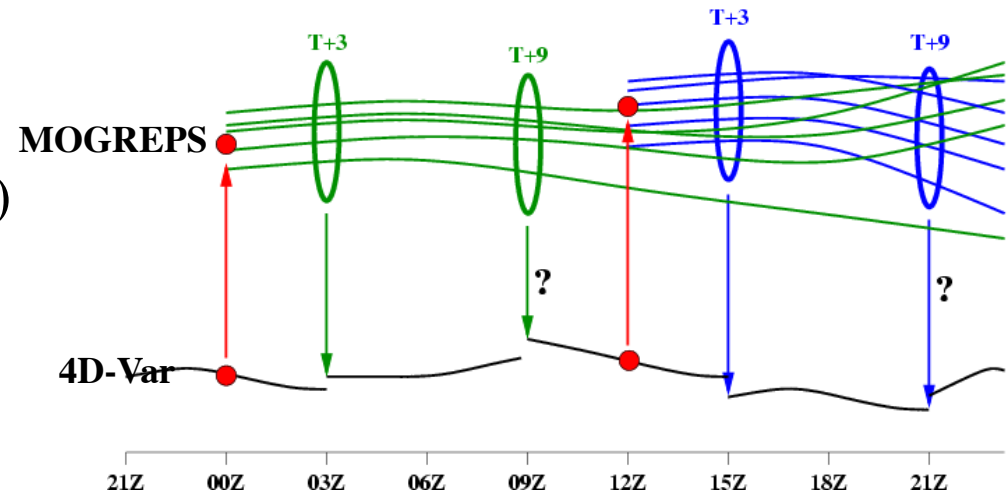
- **Global ~90km L38** model
  - Incremental 3/4D-Var (~120km)
  - 24m ETKF ensemble (~90km)

- **Trial period:** 5 – 31<sup>st</sup> May 2008

- **Observations:** Surface, Scatwind, Satwind, Aircraft, Sonde, ATOVS, SSMI, AIRS, GPSRO, SSMIS, IASI

- **Hybrid configuration:**

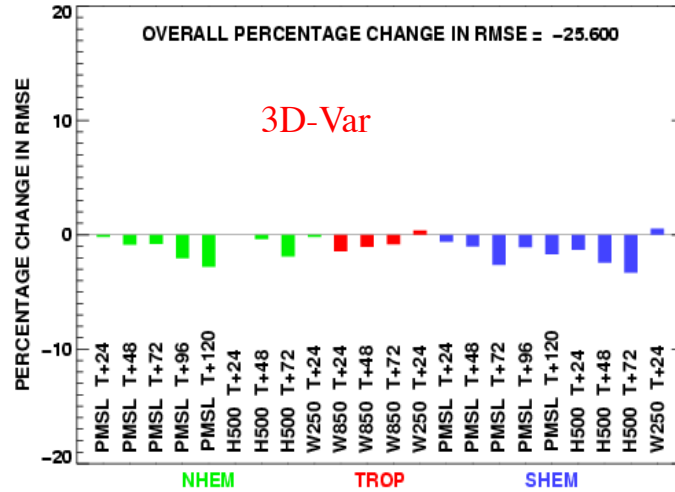
- Localization: 1500km (T10) Gaussian. Horizontal only. ‘Balance-aware’.
- Climatological/Ensemble Covariances Given Equal Weight ( $W_b=2$ ).
- No tuning.



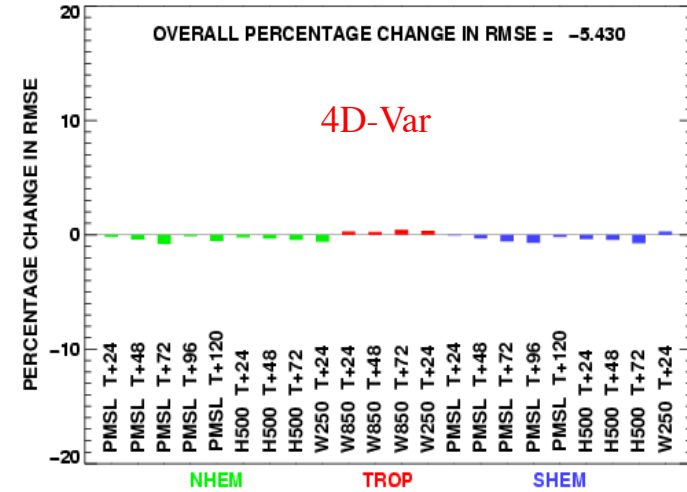


# V0.0 3/4D-Var Hybrid Trial Results

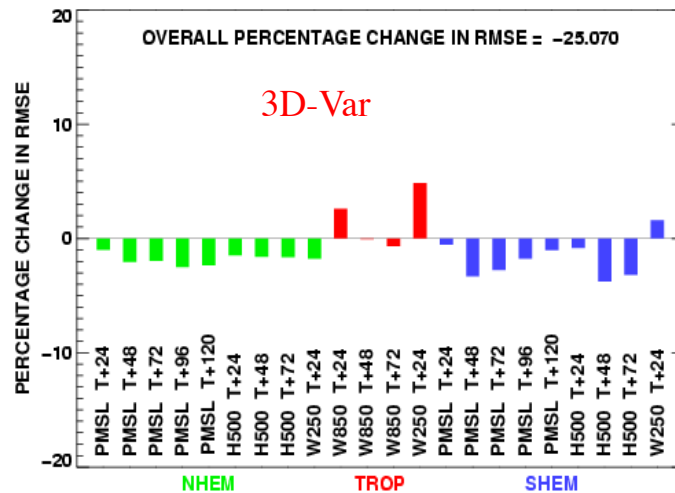
VERIFICATION VS OBSERVATIONS  
OVERALL CHANGE IN NWP INDEX = 0.889



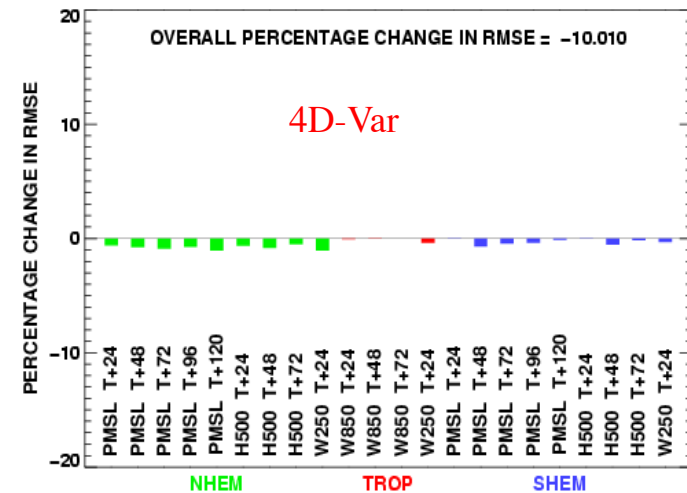
VERIFICATION VS OBSERVATIONS  
OVERALL CHANGE IN NWP INDEX = -0.022



VERIFICATION VS ANALYSIS  
OVERALL CHANGE IN NWP INDEX = 1.114



VERIFICATION VS ANALYSIS  
OVERALL CHANGE IN NWP INDEX = 0.696





# Hybrid V0.0: Trial Results (2010)

- First tests of impact of hybrid in a full observation 4D-Var.
- Initial month-long trials performed (May 2008 period). Verification:

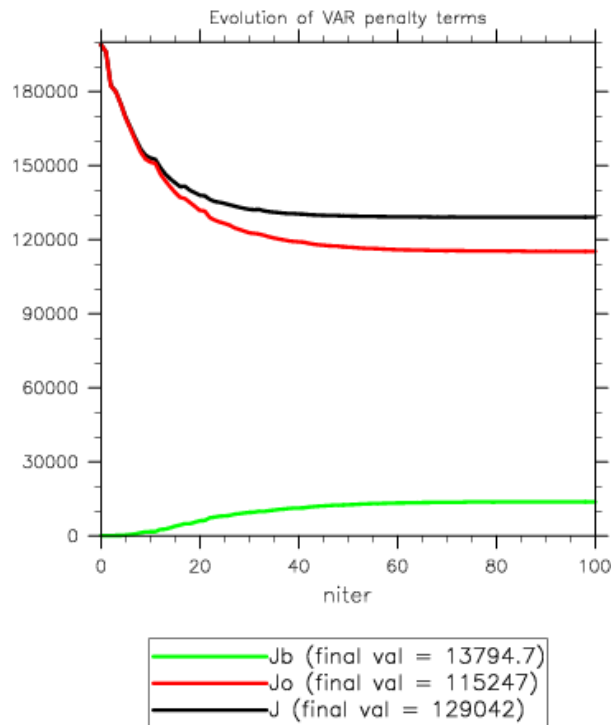
<b>Impact on NWP Index</b>	<b>3D-Var Hybrid vs. 3D-Var</b>	<b>4D-Var Hybrid vs. 4D-Var</b>	<b>4D-Var vs. 3D-Var</b>
Verification vs. Obs	+0.78%	-0.39%	+2.7%
Verification vs. Analysis	+0.94%	+1.33%	+1.3%

- Positive benefit vs. 3D-Var mode, neutral in 4D-Var.
- Reasonably pleasing result given system has not yet been tuned at all.
- Still work to do to justify operational implementation.....

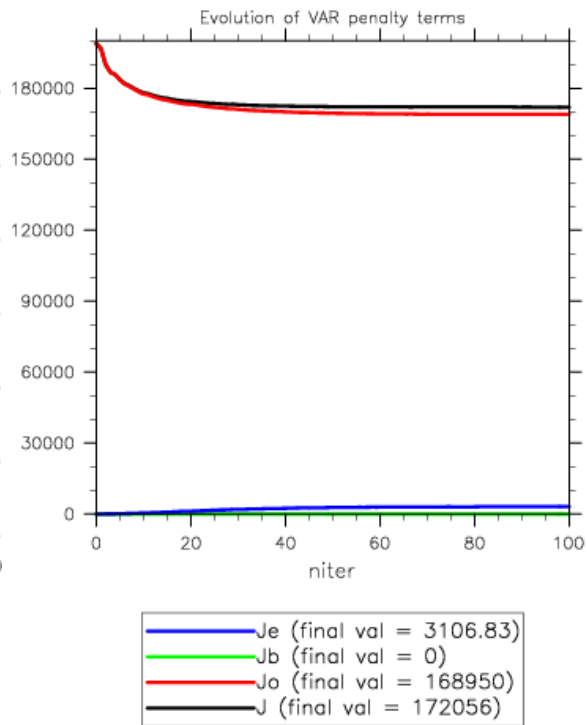


# 3D-Var Hybrid Cost Function Evolution

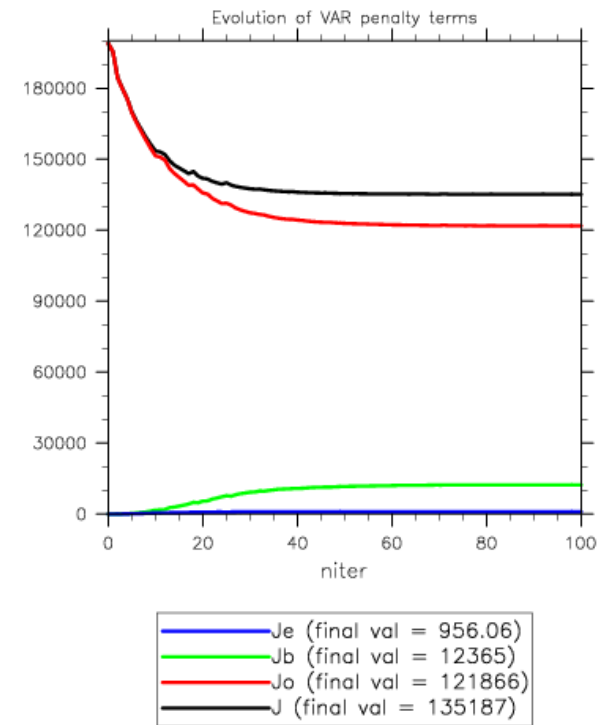
Pure 3D-Var



Pure Ensemble Covariance,  
Horizontal Localization



Hybrid Covariance,  
Horizontal Localization



- Ensemble covariances from 24 member ETKF are significantly rank-deficient.
- Observations massively underused.
- Hybrid helps, but still underfitting observations relative to pure 3D-Var.

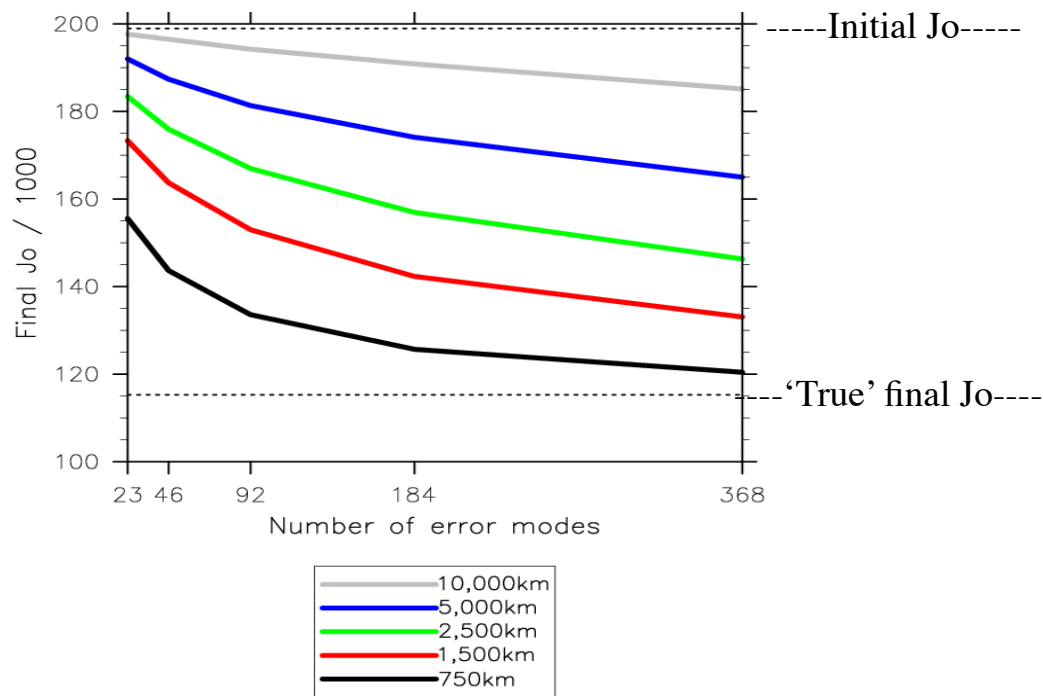


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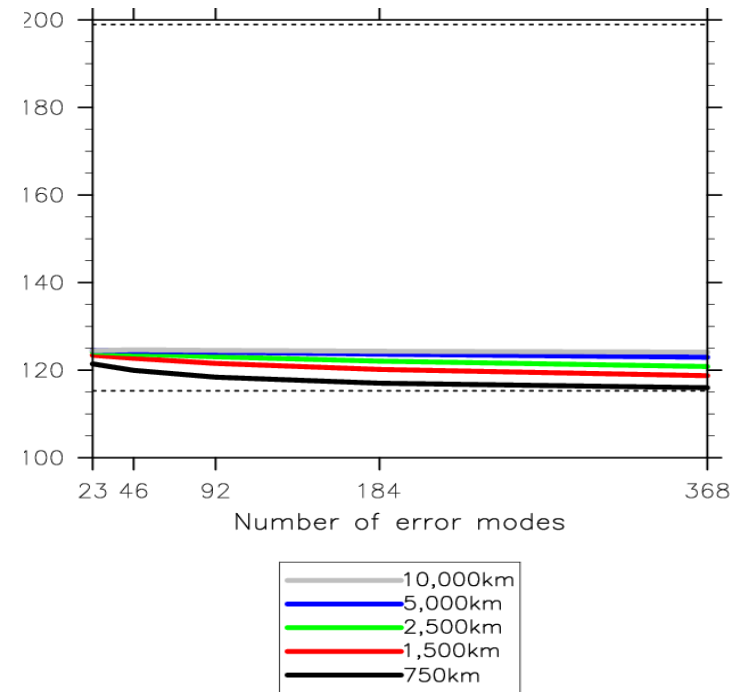
# Estimation of Ensemble Sampling Error

**Method:** Simulate ensemble by sampling climatological **B**. Study effect of ensemble size, localization, hybrid on minimization.

Pure Ensemble Covariance



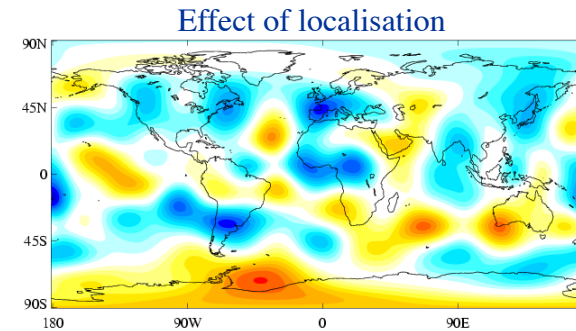
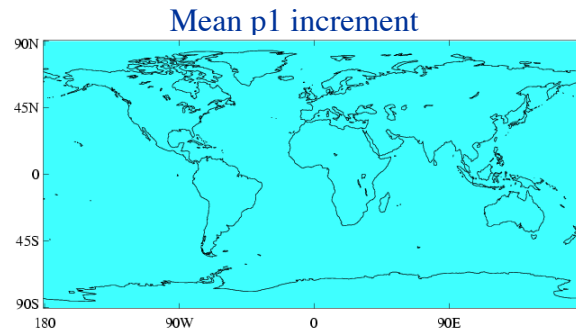
Hybrid Covariance



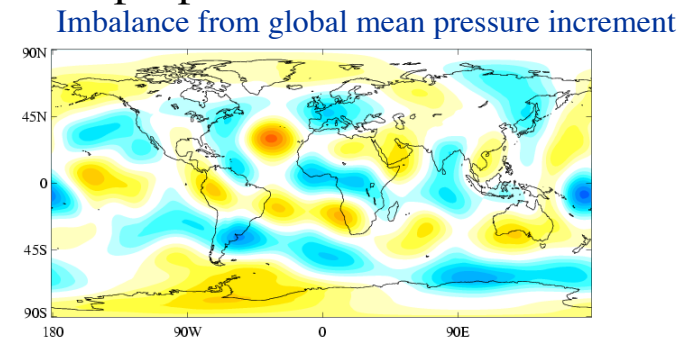
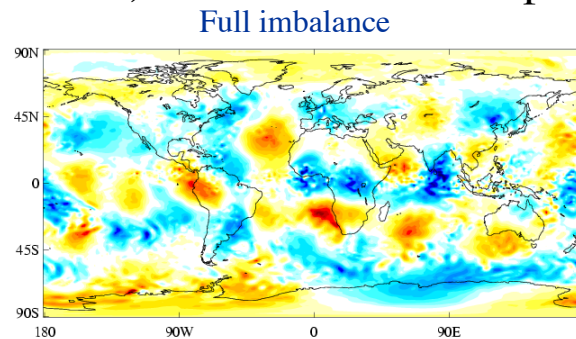
- Pure ensemble covariance still significantly underfitting observations, even with  $O(400)$  ensemble members, and reduced localization scales.
- **Solution: Additional covariance inflation to maintain Var fit to observations.**

# Impact Of Imbalance

- Despite ‘balance-aware’ localization, hybrid introduces significant imbalance to analysis.
- Cause is large-ensemble pressure perturbations, which get projected onto the localisation scale:



- Mean p (level 1) increment alone explains significant proportion of imbalance:

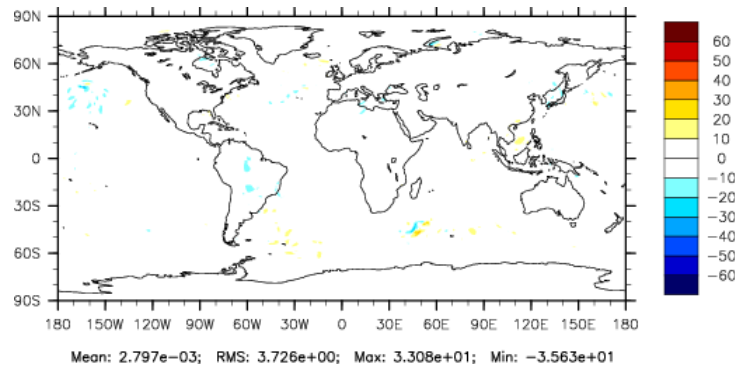




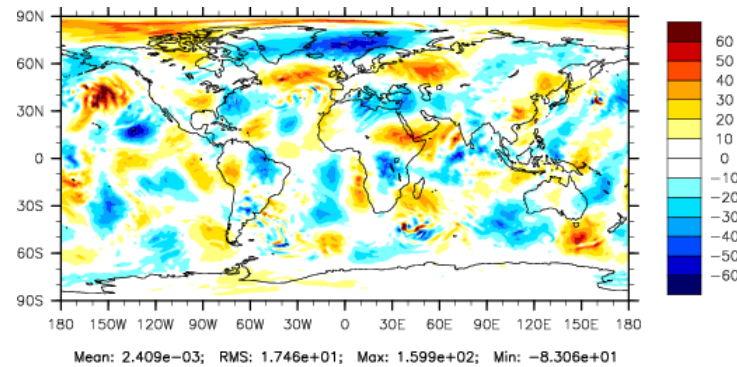
# High-pass “anti-aliasing” filter

- **Solution: Scales  $\gg$  localisation scale filtered from input ensemble perturbations**

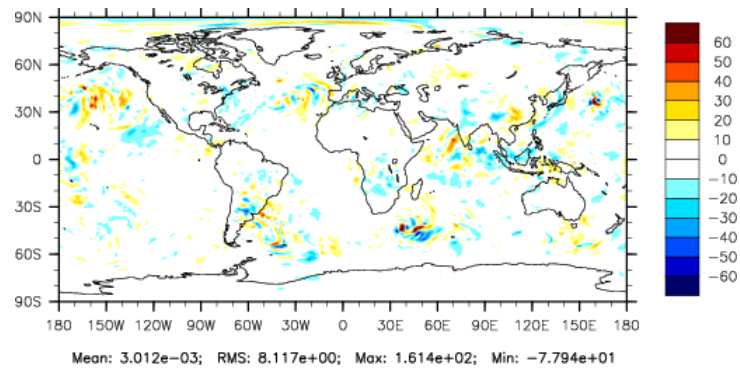
**p1 time-filter increment (Pa): without localisation**



**with localisation**



**with localisation and high-pass filtering**







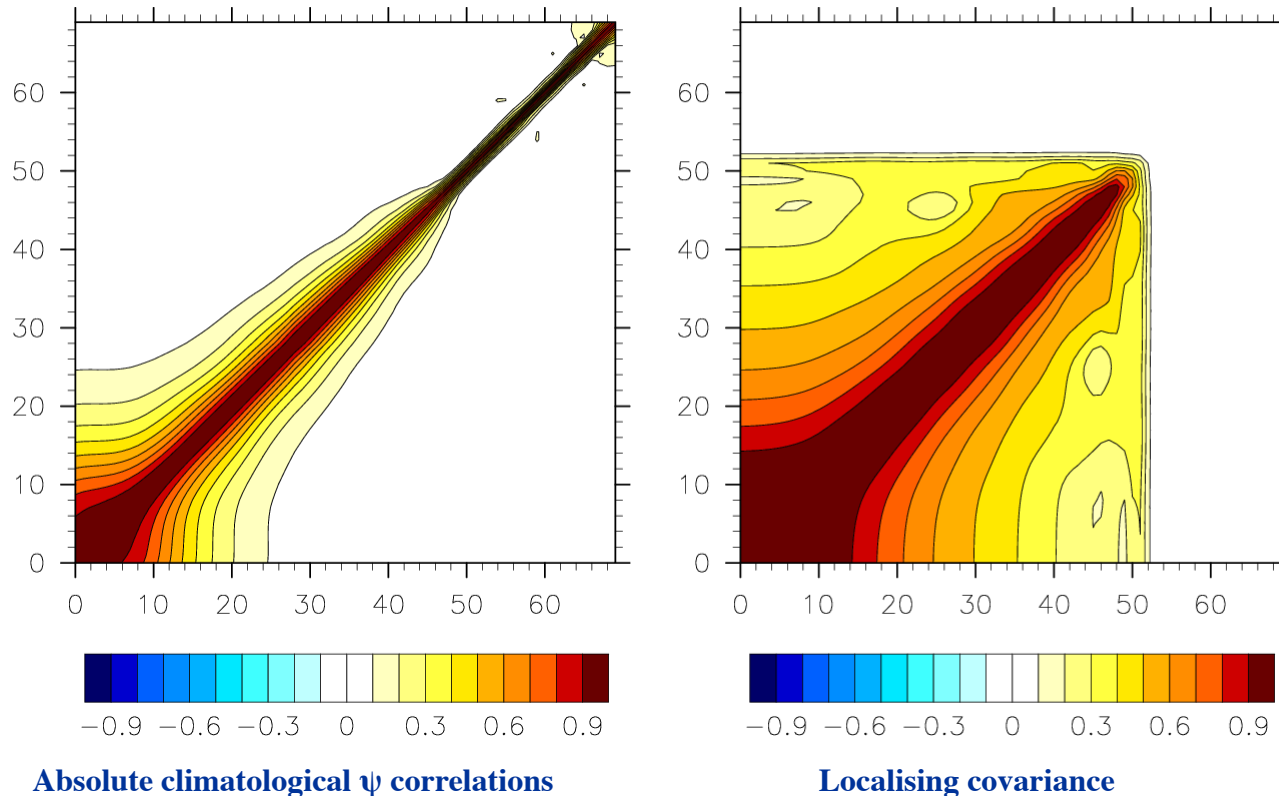
# V1.0 4D-Var Hybrid Trials (2011)

- Two periods: Dec09/Jan10 (29 days, uncoupled); Jun10 (28 days, coupled + uncoupled).
- **Model configuration:**
  - **Global forecast model:** N320L70: ~40km, 70 levels (80km model top).
  - **MOGREPS-G:** N216L70: ~60km. 23 perturbed members.
  - **4D-VAR:** N108L70/N216L70: ~120km→~60km.
- Horizontal localisation scale reduced to  $L_c = 1200\text{km}$ .
- Vertical localization: EOFS defined by climatological streamfunction covariances
- Relaxation to standard climatological covariances between 16 and 21km.



# Met Office Vertical Localisation

- Vertical localisation obtained by modifying the streamfunction correlations from  $\mathbf{B}_c$ :



- Problem: Significant spurious correlations within stratosphere/mesosphere.
- Solution: Ensemble covariance removed above 21 km (~ level 54), for safety!**



# V1.0 4D-Var Hybrid Trial Results

## Verification vs. observations

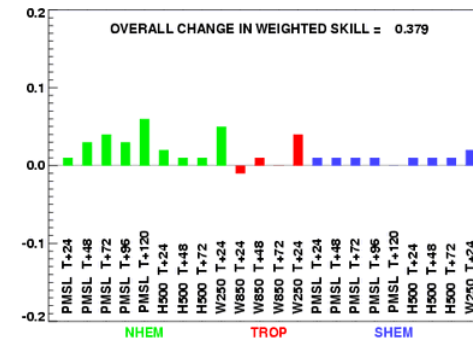
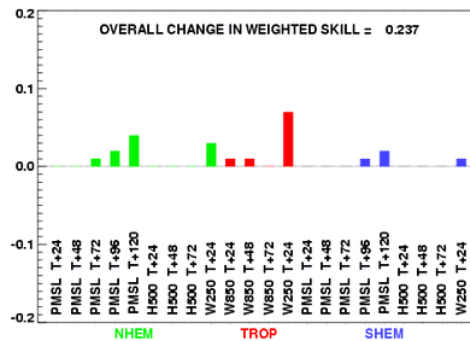
Better/neutral/worse

	NH	TR	SH
Dec uncoupled (29 days)	29/94/0	6/117/0	12/109/2
Jun coupled (28 days)	34/89/0	9/114/0	46/74/3

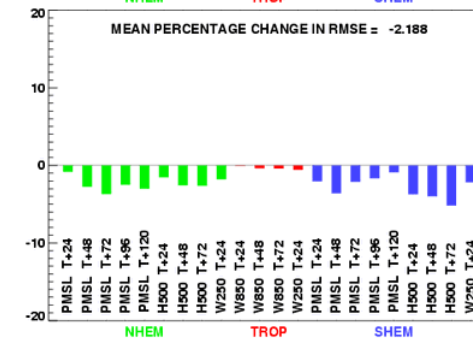
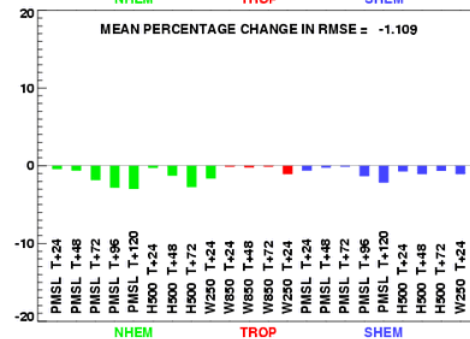
Dec uncoupled: +1.2

Jun coupled: +1.6

Skill:



RMSE:





# V1.0 4D-Var Hybrid Trial Results

## Verification vs. Met Office analyses

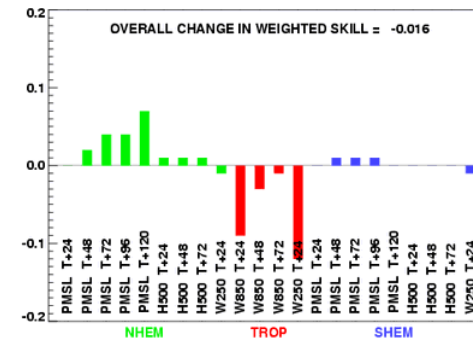
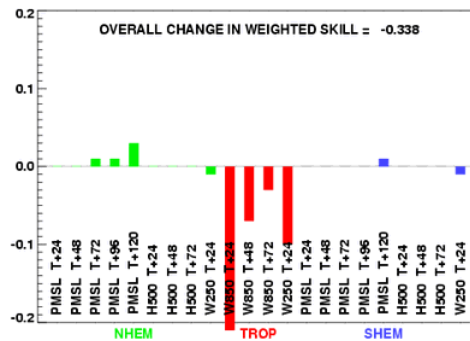
Better/neutral/worse

	NH	TR	SH
Dec uncoupled (29 days)	16/91/16	7/69/47	3/106/14
Jun coupled (28 days)	49/63/11	9/86/28	18/82/23

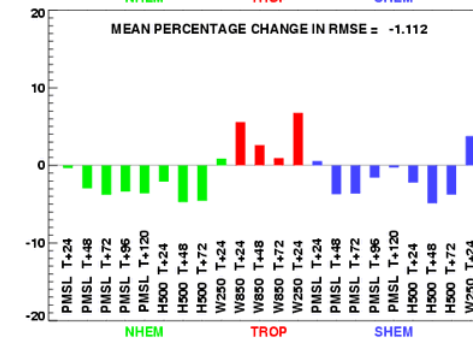
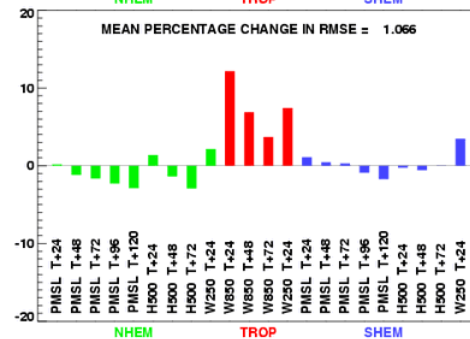
Dec uncoupled: -4.0

Jun coupled: -0.2

Skill:



RMSE:





# V1.0 4D-Var Hybrid Trial Results

## Verification vs. ECMWF analyses

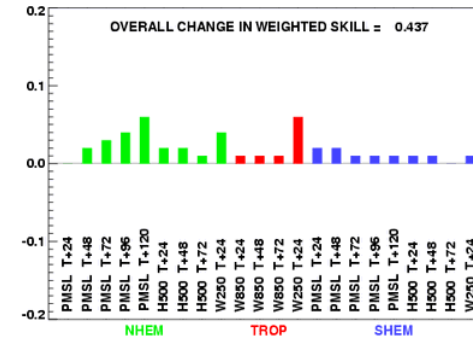
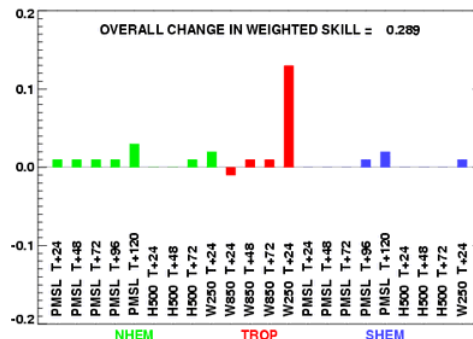
Better/neutral/worse

	NH	TR	SH
Dec uncoupled (29 days)	35/79/0	39/75/0	14/100/0
Jun coupled (23/28 days)	51/63/0	27/87/0	46/66/2

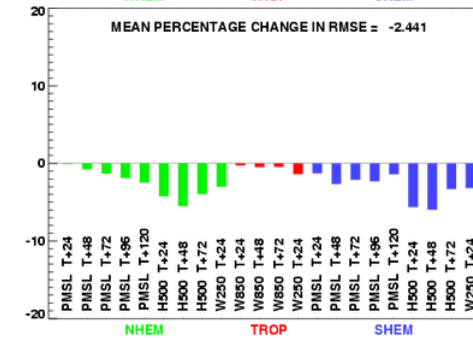
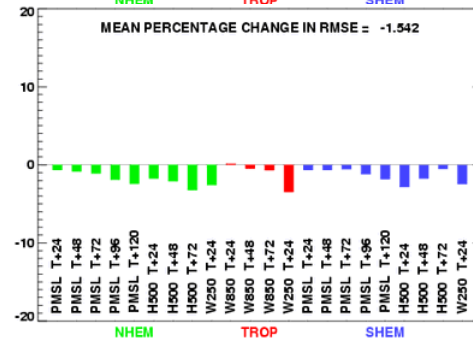
Dec uncoupled: 1.721 (1.338%)

Jun coupled: 1.337 (1.298%)

Skill:



RMSE:





# July 2011 Global Data Assimilation Upgrade **Package**

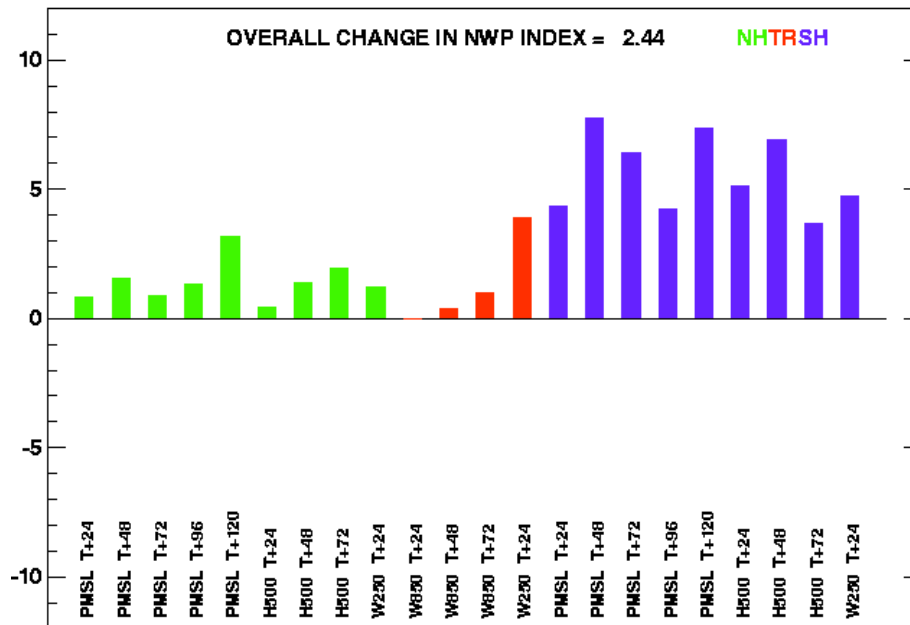
- Assimilation method
  - Hybrid 4D-Var algorithm.
  - Moisture control variable: Replacing RH with scaled humidity variable
- Observation changes
  - Introduce METARS
  - GOES/Msat-7 clear-sky radiances, extra IASI (land)
  - Revisions to MSG clear-sky processing and GPSRO
  - Reduced spatial thinning (ATOVS/SSMIS/IASI/AIRS/ aircraft)



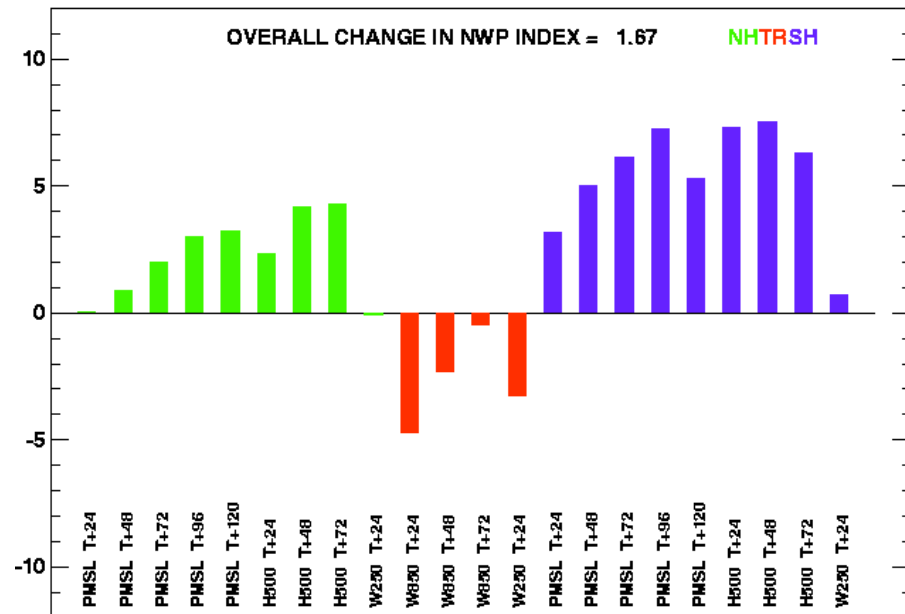
# DA/SA Upgrade Pre-Operational Testing: June 20 – July 27 2011

%Reduction in RMSE For Critical Met Office Forecast Parameters:

**Vs. Observations**



**Vs. Met Office analyses**



- Biggest reduction in overall global forecast error for many years.
- First time in memory that all parameters have reduced error vs obs. (usually a mix).



## 4. Future Work





# Operational NWP Configs: Spring 2013 (Tentative)

## Global

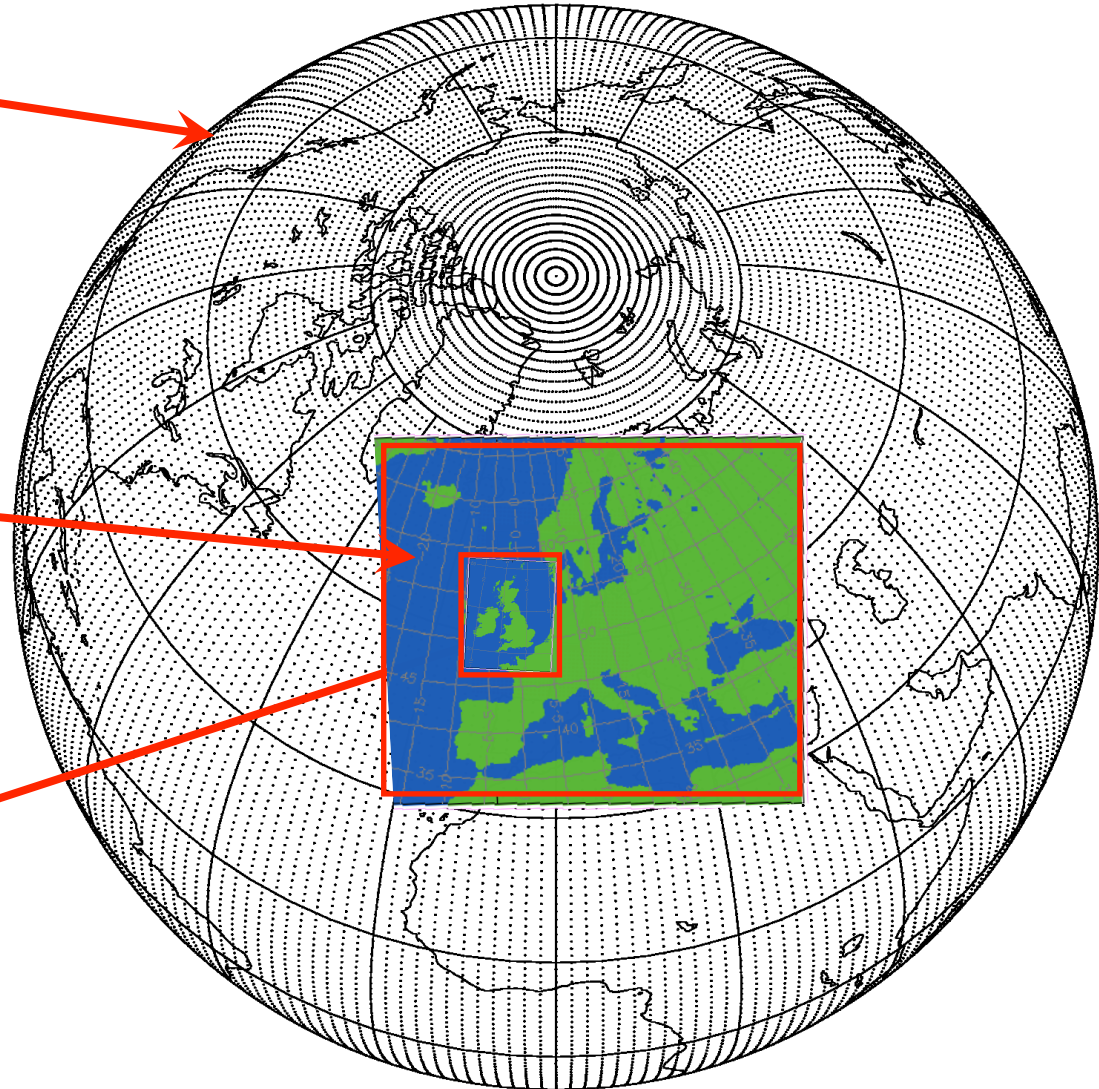
- 16-20km 85L (85km top)
- Hybrid 4DVAR (50km inner-loop)
- 60 hour forecast twice/day
- 144 hour forecast twice/day
- 48/12member 40km MOGREPS-G 4\*

## MOGREPS-EU

- Common NWP/reanalysis domain.
- 12Km 70L (40km top)
- 3D-Var (or NoDA)
- 48 hour forecast
- 12 members ; 4 times per day

## UKV

- 1.5km 70L (40km top)
- 3DVAR (hourly)
- 36 hour forecast, 4 times per day
- 12 member 2.2km MOGREPS-UK





# Operational NWP Configs: Dec 2015(Very Tentative!)

## Global

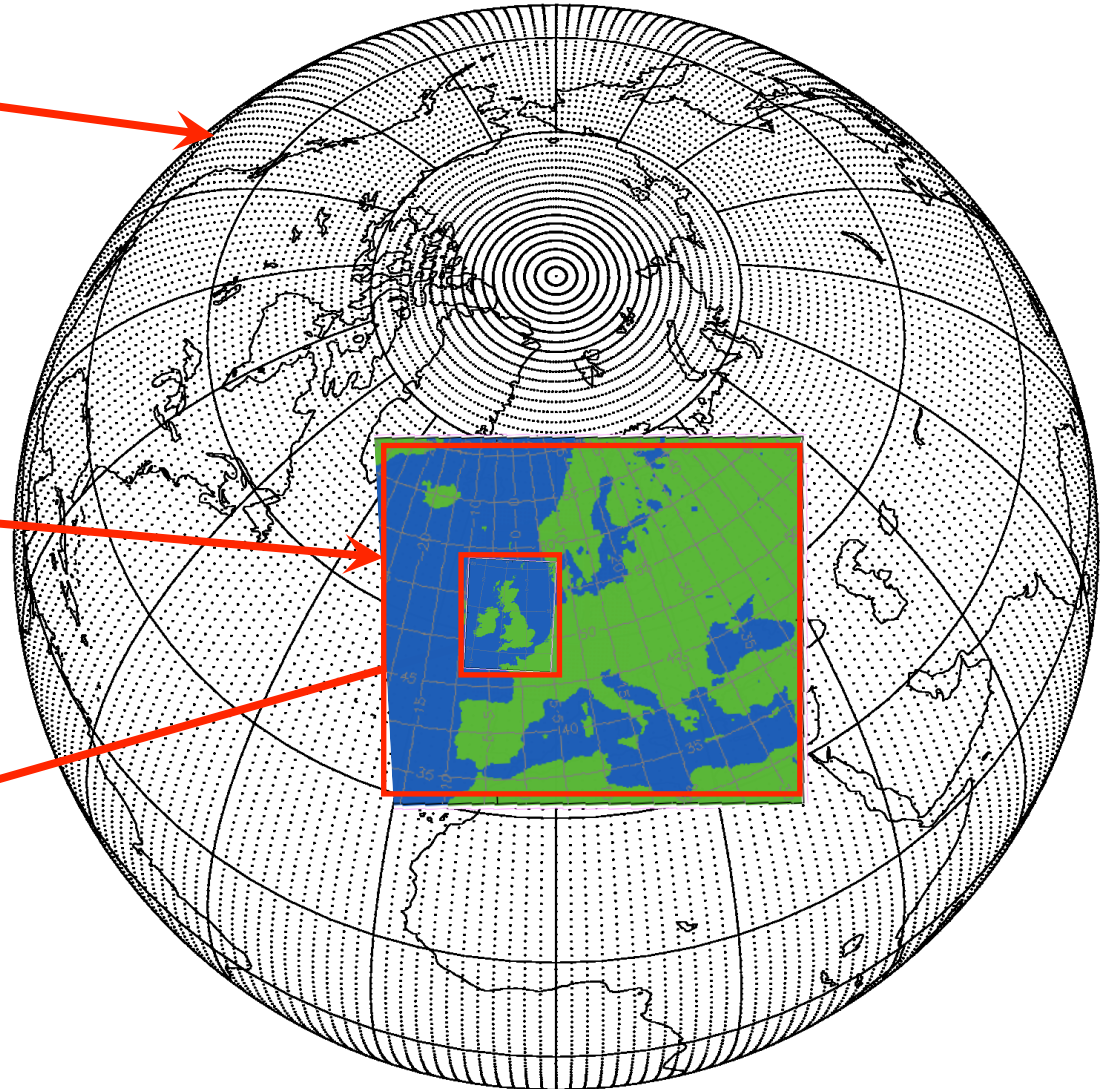
- 12-14km 110L (85km top)
- EnDA (in variational framework)
- 60 hour forecast twice/day
- 144 hour forecast twice/day
- 192/24member 30km MOGREPS-G

## MOGREPS-EU

- Common NWP/reanalysis domain.
- 12Km 70 L (40km top)
- NoDA (or possibly still 3D-Var?)
- 48 hour forecast
- 4 times per day

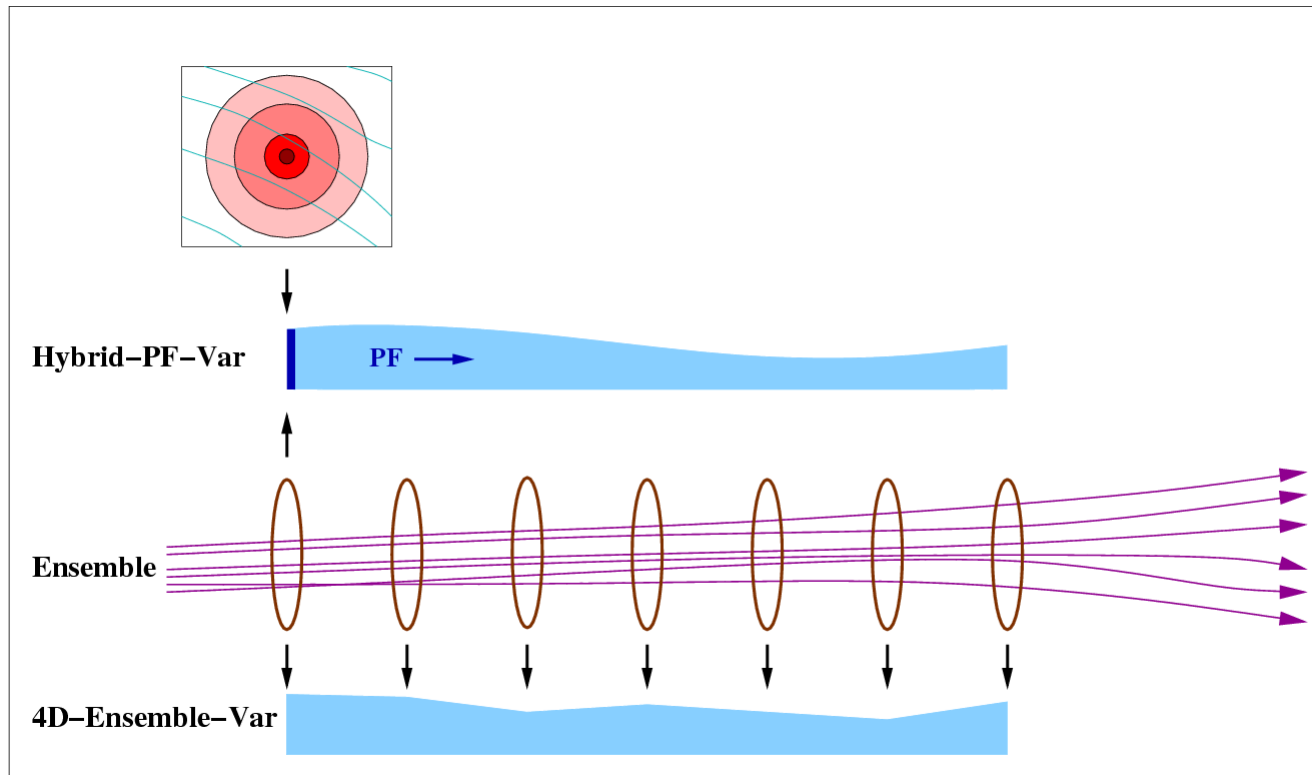
## UKV

- 1.5km 70L (40km top)
- Hybrid 4DVAR (or EnDA?)
- 36 hour forecast
- 4 times per day
- 40 member 2.2km MOGREPS-UK



# Beyond hybrid: 4D-Ensemble-Var

- Current hybrid just the first step in tighter coupling of DA and ensemble forecasting...





# Strategy Going Forward

- Continue to optimize 4D-Var: SE + algorithmic changes.
- Continue to develop hybrid for short/medium-term (1997-2015):
  - Increase ensemble size, more sophisticated localization, etc.
  - Consider replacing ETKF as ensemble perturbation generator.
  - Develop convective-scale hybrid 3/4D-Var (2012-2015).
- Develop 4D-Ensemble-Var:
  - Code and test within current VAR framework (2011-2013).
  - Extend to an 'Ensemble of 4D-Ensemble-Vars' (2013-2015).
  - Retire PF model if/when 4D-Ensemble-Var beats 4D-PF-Var.



**Met Office**

**Thank you!**