



# Ideas for adding flow-dependence to the Met Office VAR system.

ECMWF Seminar, June 2007

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☁️ Ideas tried during development of VAR system (1993 start, 1999 3D-Var, 2004 4D-Var):

⌚ Geostrophic Coordinate transform.

⌚ Error Modes Of The Day.

⌚ 4D-Var.

⌚ Assimilation of layer clouds.

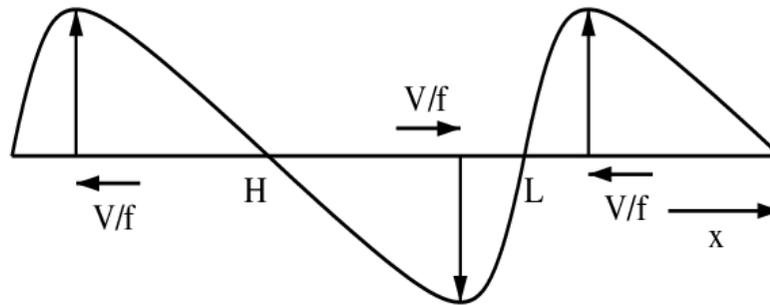
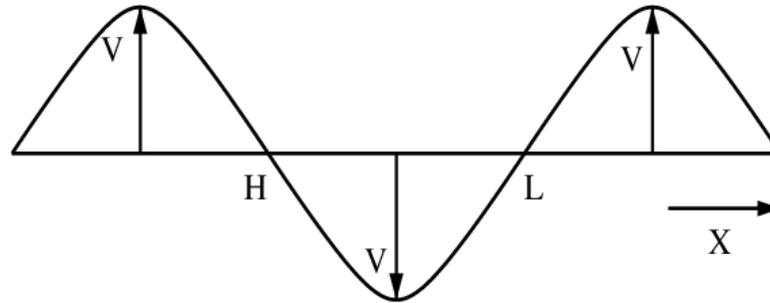
☁️ Comments.

☁️ Plans.

# Geostrophic Coordinate transform



$$x_G = x_R + \frac{1}{f} v_g$$
$$y_G = y_R - \frac{1}{f} u_g$$



Mark Dubal

Desroziers, Gerard 1997: "A coordinate change for data assimilation in spherical geometry of frontal structures" *Mon. Wea. Rev.*, **125**, 3030-3039.

☁️  $\mathbf{U}$  ( $=\mathbf{U}_p \mathbf{U}_g \mathbf{U}_v \mathbf{U}_h$ ) converts  $\mathbf{v}$  to  $\mathbf{w}'$ .

☁️  $\mathbf{U}_g$  operates on  $\chi'$ ,  $\psi'$ ,  $Ap'$ , and  $\mu'$  along global model layers (no LAM version).

☁️ Uses smoothed LS rotational wind instead of geostrophic.

☁️ Displacement is like semi-lagrangian advection, with departure point calculation and interpolation.

*Mark Dubal*

☁️ After trials, development was suspended in favour of EOTD modes (next).

☁ Idea is to use EOTD modes to fit observations, as well as standard control variables:

$$J(\mathbf{w}', \boldsymbol{\alpha}) = \frac{1}{2} \mathbf{w}'^T \mathbf{B}^{-1} \mathbf{w}' + \frac{1}{2} \boldsymbol{\alpha}^T \mathbf{C}^{-1} \boldsymbol{\alpha} + \frac{1}{2} (\mathbf{y} - \mathbf{y}^o)^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}^o)$$
$$\mathbf{y} = H(\mathbf{x}^g + \mu_1 \mathbf{w}' + \mu_2 \mathbf{X}^f \circ \boldsymbol{\alpha})$$

☁ If  $\mathbf{X}^f$  are ensemble perturbations, then variational determination of  $\boldsymbol{\alpha}$  is equivalent to mean analysis in localised ensemble Kalman filter (Lorenc 2003, Wang et al. 2007).

## Basic EnKF

$$\mathbf{P}_e^f = \mathbf{X}^f \mathbf{X}^{fT} .$$

Define transform from  $\boldsymbol{\alpha}$  :  $\mathbf{x} = \overline{\mathbf{x}^f} + \mathbf{X}^f \boldsymbol{\alpha}$  .

Let covariance  $\mathbf{B}_{(\boldsymbol{\alpha})} = \langle \boldsymbol{\alpha} \boldsymbol{\alpha}^T \rangle = \mathbf{I}$  .

Then  $\langle (\mathbf{x} - \overline{\mathbf{x}^f})(\mathbf{x} - \overline{\mathbf{x}^f})^T \rangle = \mathbf{P}_e^f$  .

So the variational analysis for the transformed variable  $\boldsymbol{\alpha}$  is obtained by minimising

$$J(\boldsymbol{\alpha}) = \frac{1}{2} \boldsymbol{\alpha}^T \boldsymbol{\alpha} + \frac{1}{2} (\mathbf{y} - \mathbf{y}^o)^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}^o)$$

$$\mathbf{y} = H \left( \overline{\mathbf{x}^f} + \mathbf{X}^f \boldsymbol{\alpha} \right)$$

(2)

Similarly, VAR can use ensemble covariances modified by a Schur product:

### *EnKF with Schur product*

Use as control variable a vector  $\alpha$  of  $N$  2D fields  $\alpha_i$ , each with covariance  $C$ .

The variational problem is then to minimise

$$J(\alpha) = \frac{1}{2} \alpha^T \begin{pmatrix} \mathbf{C} & & 0 \\ & \ddots & \\ 0 & & \mathbf{C} \end{pmatrix}^{-1} \alpha + \frac{1}{2} (\mathbf{y} - \mathbf{y}^o)^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}^o)$$

$$\mathbf{y} = H \left( \overline{\mathbf{x}^f} + (\mathbf{X}^f \circ \alpha) \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \right)$$

As in standard 3D-Var methods, the inversion of the block diagonal matrix is avoided by a further horizontal transform of each field  $\alpha_i$  into spectral space.

(3)

VAR can use the ensemble to augment the “traditional” covariance model with some  
*Errors Of The Day.*

### Hybrid Var-EnKF with Schur product

Use the traditional variation control variable  $\mathbf{v}$  supplemented by  $\boldsymbol{\alpha}$ , so that we minimise

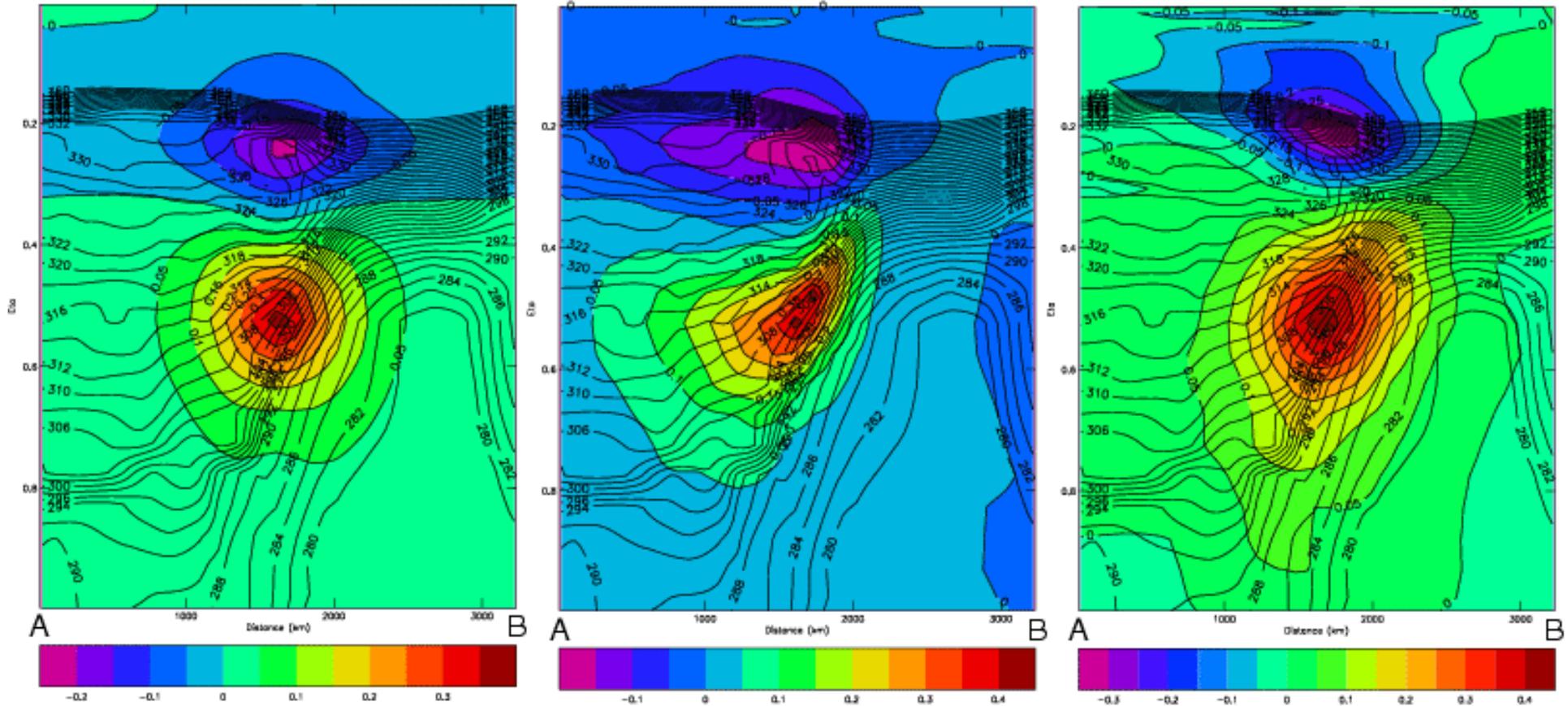
$$J(\mathbf{v}, \boldsymbol{\alpha}) = \frac{1}{2} \mathbf{v}^T \mathbf{v} + \frac{1}{2} \boldsymbol{\alpha}^T \begin{pmatrix} \mathbf{C} & & 0 \\ & \ddots & \\ 0 & & \mathbf{C} \end{pmatrix}^{-1} \boldsymbol{\alpha} \\ + \frac{1}{2} (\mathbf{y} - \mathbf{y}^o)^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}^o) \\ \mathbf{y} = H \left( \mathbf{x}^g + \mathbf{U}\mathbf{v} + (\mathbf{X}^f \circ \boldsymbol{\alpha}) \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \right)$$

Should reduce “traditional” error covariances to compensate for those represented by the ensemble.

- ☁️ Uses 2D  $\alpha$  (no vertical localisation) on  $\chi'$ ,  $\psi'$ ,  $Ap'$ , and  $\mu'$
- ☁️ Tested with single mode from an error breeding system, in global system. (Code should work with more modes, and in LAM).
- ☁️ Results encouraging in case studies, but no significant overall impact.
- ☁️ Preconditioning and tuning needed.
- ☁️ Because of small impact using 1 mode, and effort needed to develop and run EBS, testing was suspended in 2004 until MOGREPS is available in 2007.
- ☁️ *Done by Dale Barker, who has continued at NCAR.*

# Response to a single T ob

Contours - UM analysis, theta



Basic 3D-Var

VAR+GCT

3D-Var + 1 bred mode

Dale Barker EOTD expts.

Mark Dubal GCT expts.

Adrian Semple, 2001: A Meteorological Assessment of the Geostrophic Co-ordinate Transform and Error Breeding System When used in 3D Variational Data Assimilation. NWP Tech Rep 357.

# Why should 4D-Var beat 3D-Var?



*Met Office pre-operational trials showed a significant improvement for 4D-Var over similar 3D-Var.*

*This might be because 4D-Var uses:*

- ☁ more accurate times of observations;
- ☁ evolved covariances, giving dynamically consistent structure functions;
- ✗ time-tendency information from more frequent observations;
- ✗ observations of precipitation etc.

*Not in the experiments reported here.*

# Incremental VAR schemes used



☁️ Basic 3D-Var

☁️ 3D-Var with FGAT

Uses First-Guess at Appropriate Time.

Operational at Met Office before Oct 2004.

☁️ “Synoptic” 4D-Var

Treats obs times like 3D-Var with FGAT.

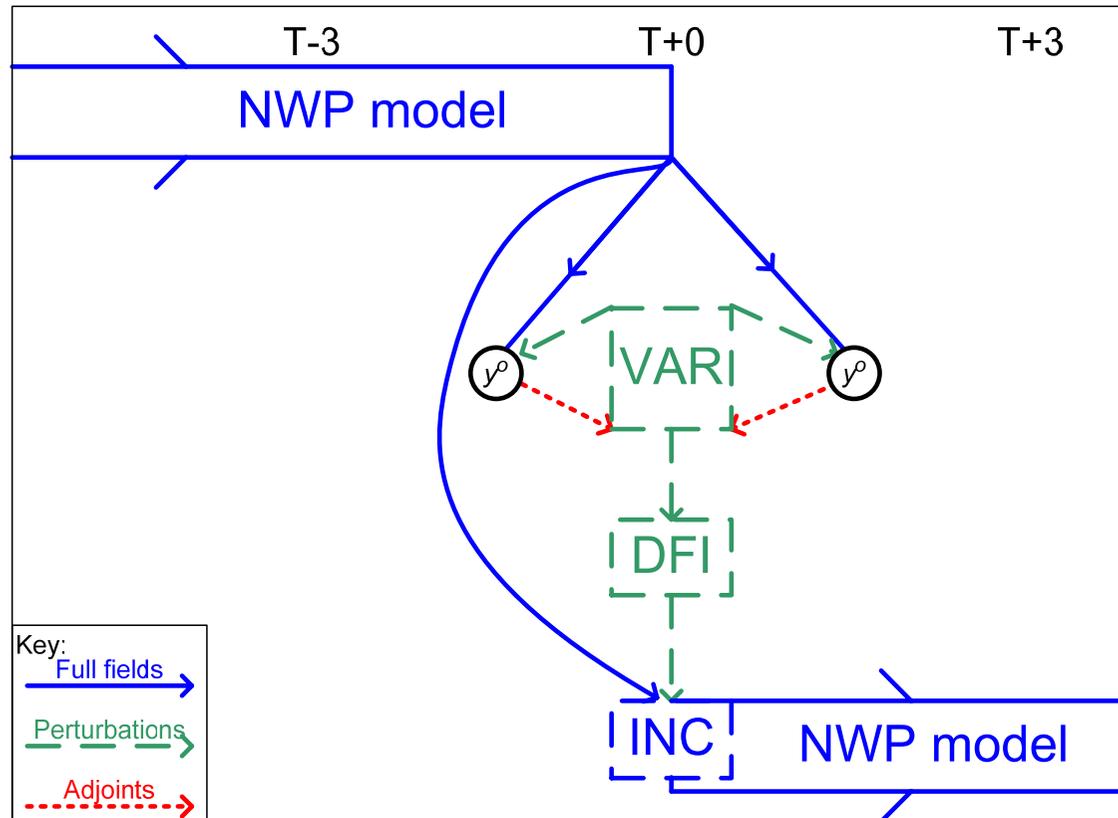
Has evolved covariances like basic 4D-Var.

☁️ Basic 4D-Var

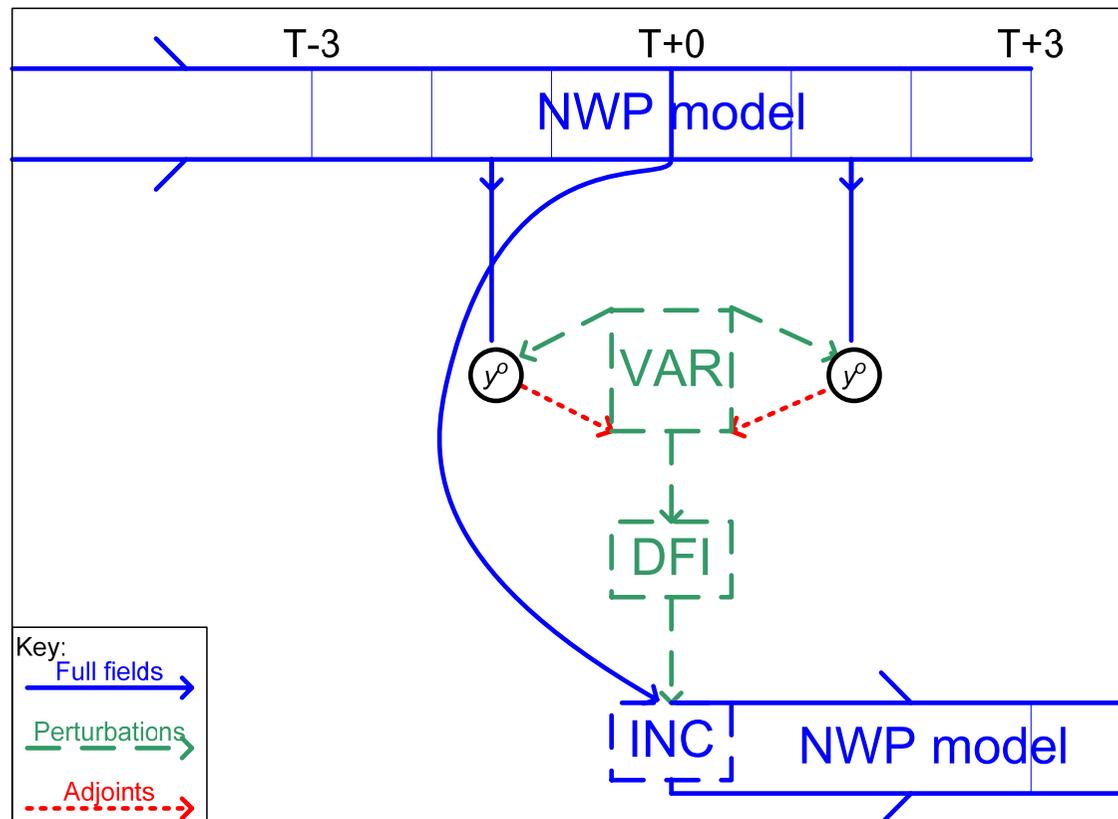
No outer-loop iteration. Very simple physics.

Operational at Met Office after Oct 2004.

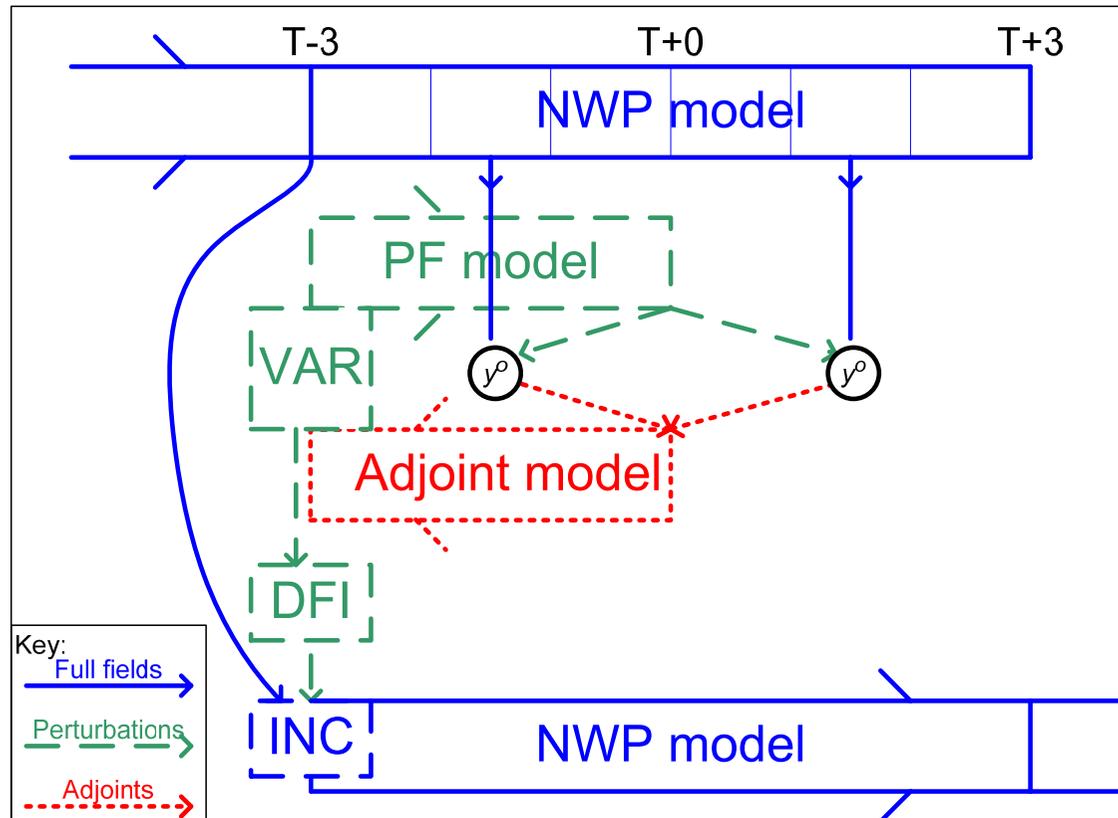
# Basic 3D-Var



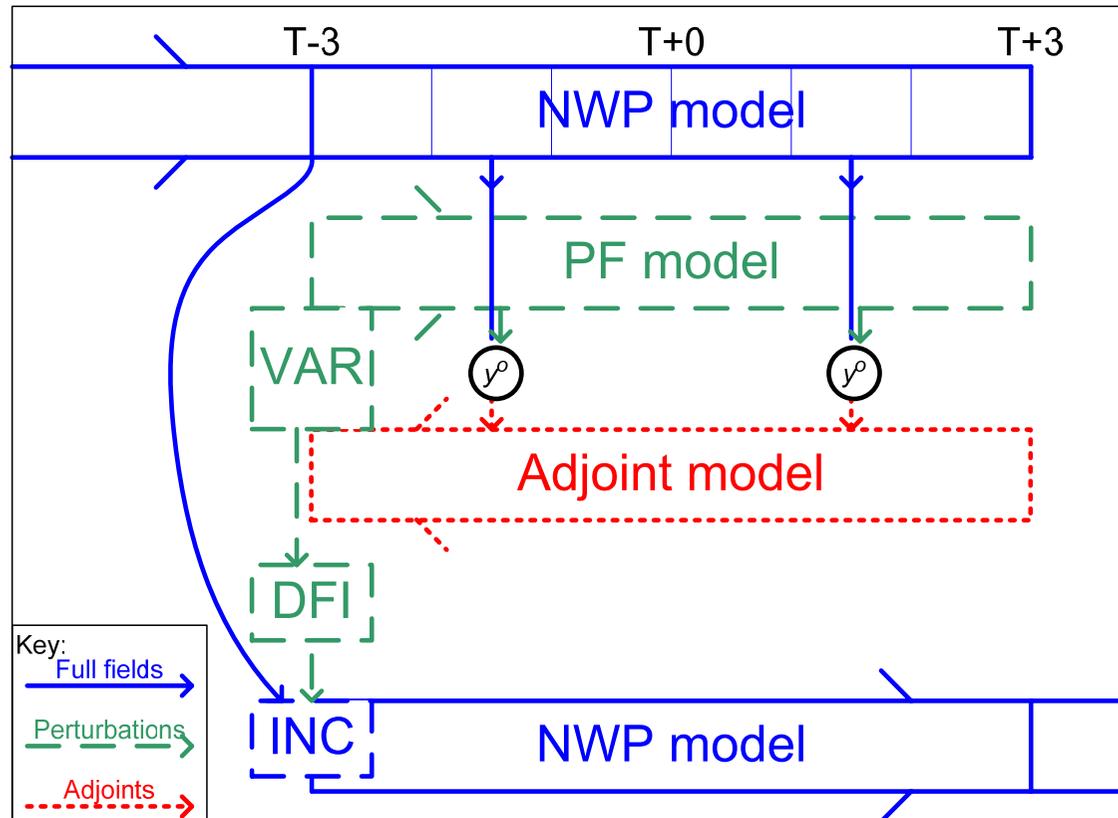
# 3D-Var with FGAT



# Synoptic 4D-Var



# Basic 4D-Var



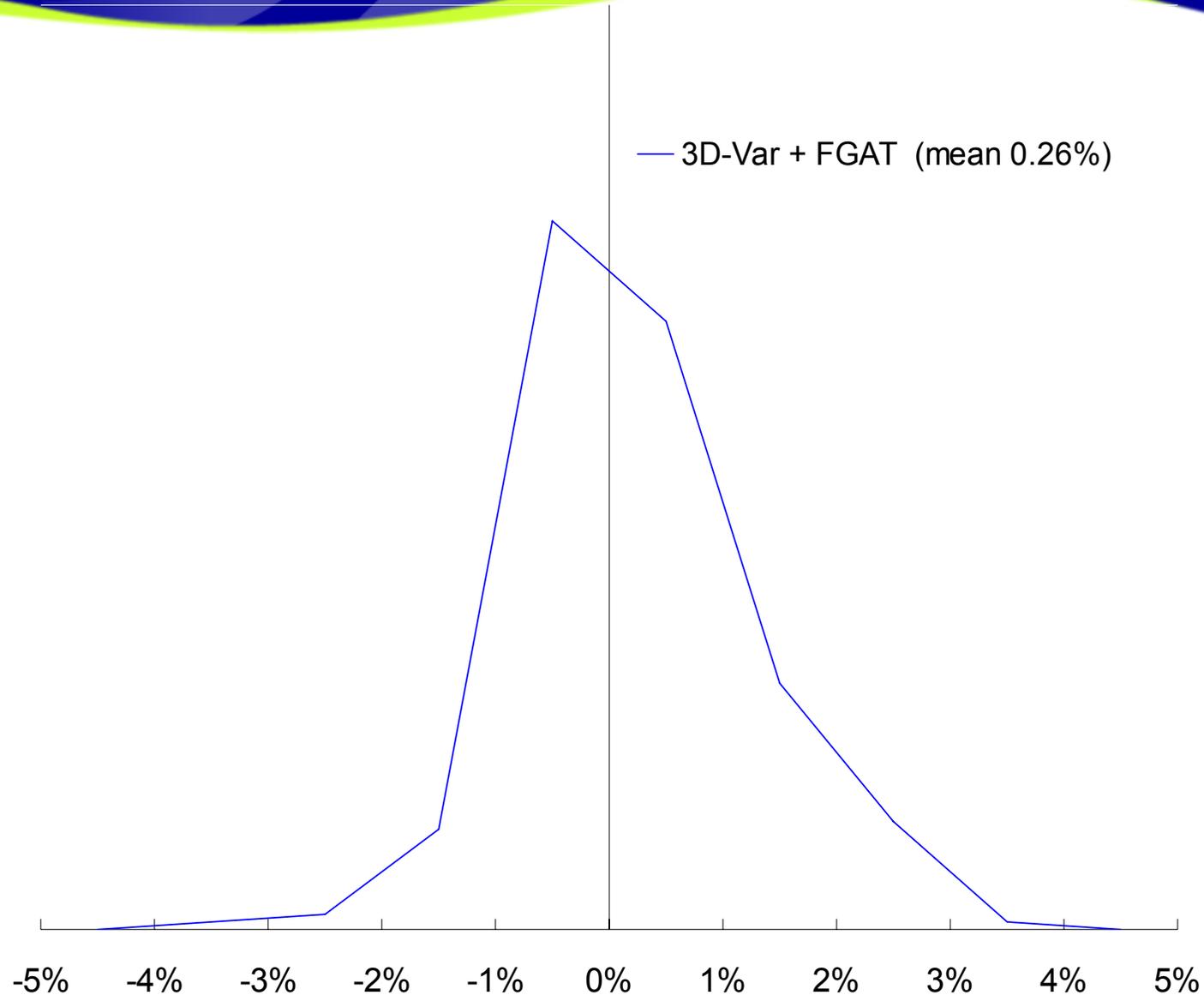
# Experimental design



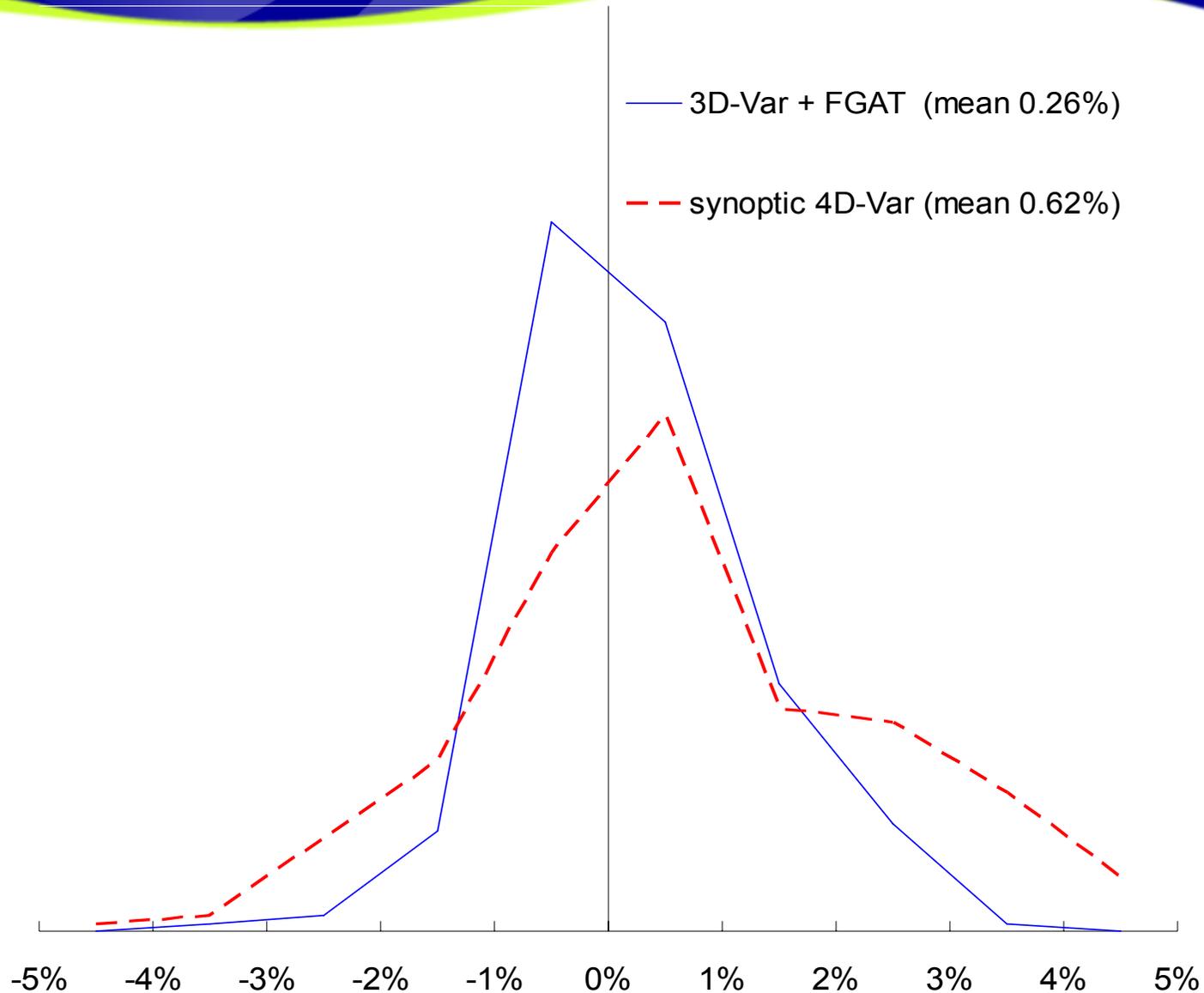
- ☁️ Parallel trials for July 2003.
- ☁️ 6hr cycle with a 6day forecast each 12Z.
- ☁️ Much lower resolution (N48) than operational.
- ☁️ Observation selection tuned for 3D-Var.
- ☁️ 234 forecast fields verified:

3 areas:	Tropics and northern and southern extratropics.	
6 times:	Forecast days 1 to 6.	
13 fields:	3 variables:	geopotential height, temperature and vector wind.
	at 4 levels:	850, 700, 500 and 250 hPa.
	Pressure at mean sea-level.	

# Reductions in RMS verification v obs compared to Basic 3D-Var



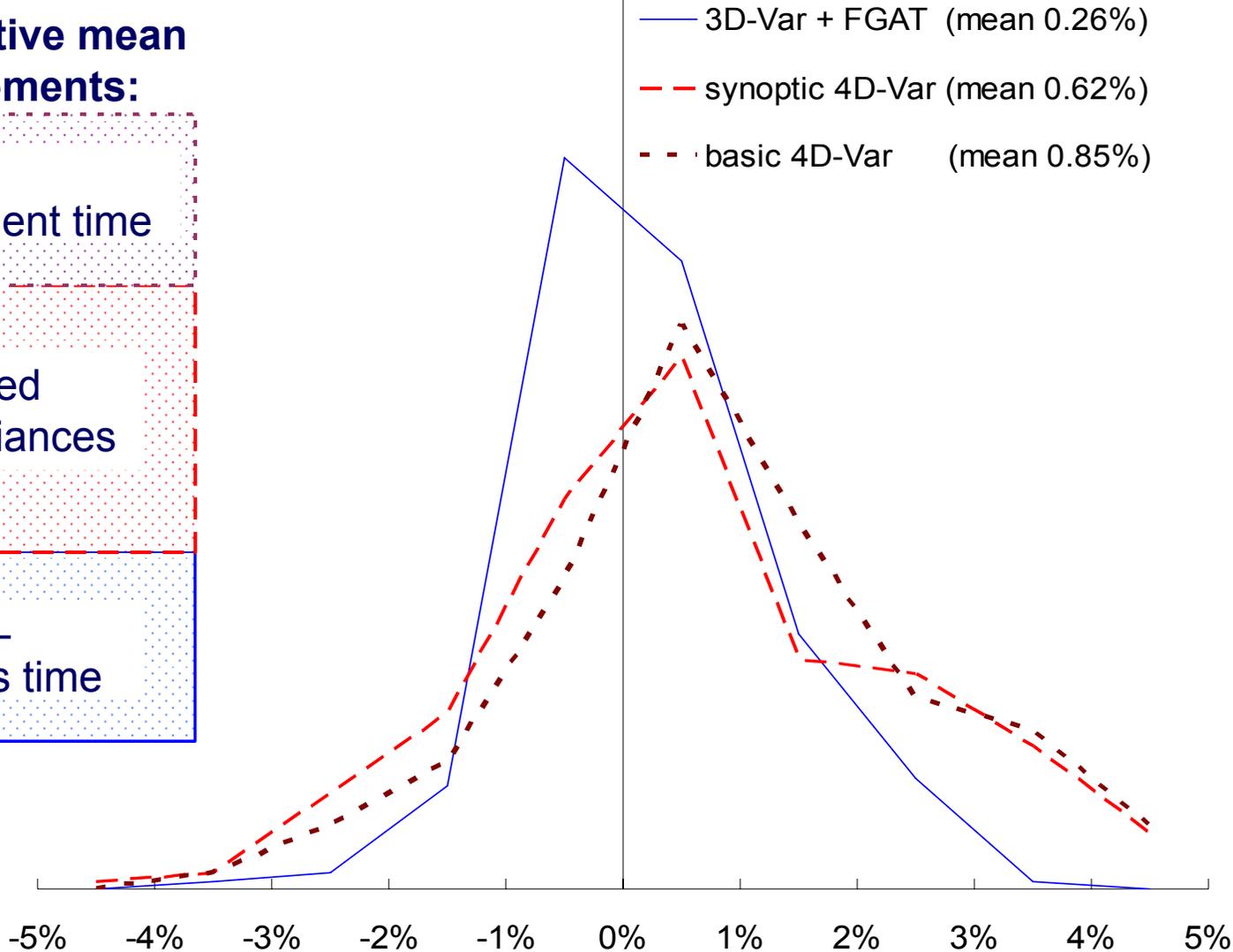
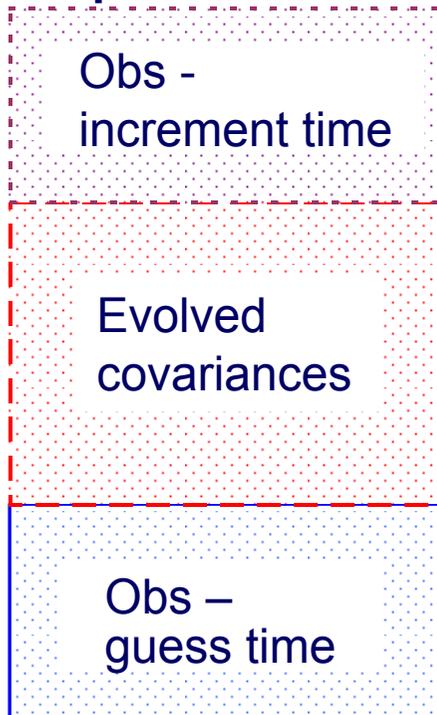
# Reductions in RMS verification v obs compared to Basic 3D-Var



# Reductions in RMS verification v obs compared to Basic 3D-Var



## Cumulative mean improvements:



# Cloud-topped Inversions



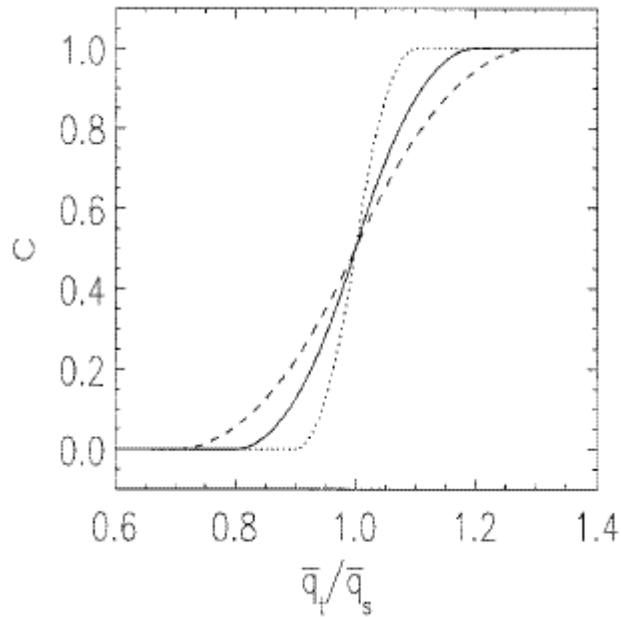
- ☁️ Probably the commonest cause of forecast error in the UK is the misrepresentation of inversions and strato-cumulus layers.
- ☁️ For many years we have had some success using MOPS (Macpherson et al. 1996):
  - ⚙️ Pre-process to give 3D cloud analysis for UK;
  - ⚙️ Nudge model RH towards fitting the cloud.
- ☁️ It is awkward to combine MOPS nudging with 4D-Var, but direct assimilation of MOPS cloud in VAR has not done as well.
- ☁️ This is because VAR's vertical correlations of RH across the inversion are too large.

# High impact weather!



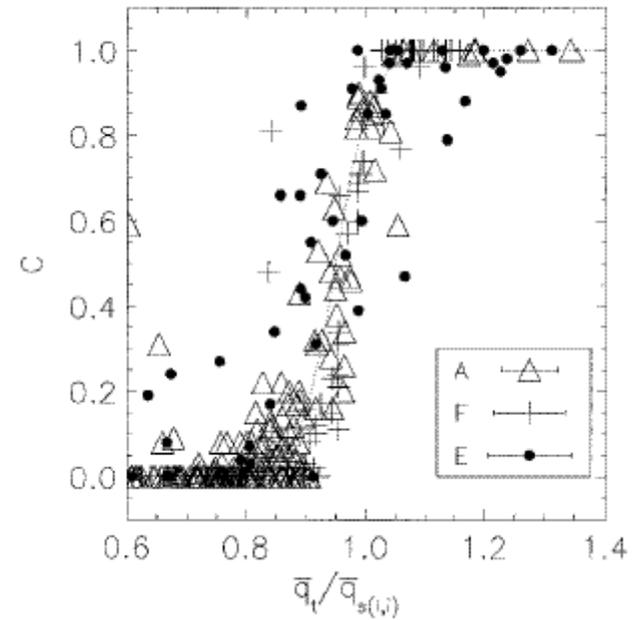
1000 flights were cancelled just before Christmas 2006

# Cloud-RH diagnostic



Smith scheme

QJRMS 1990



aircraft data

Rob Wood, JAS 2000

observation penalty function

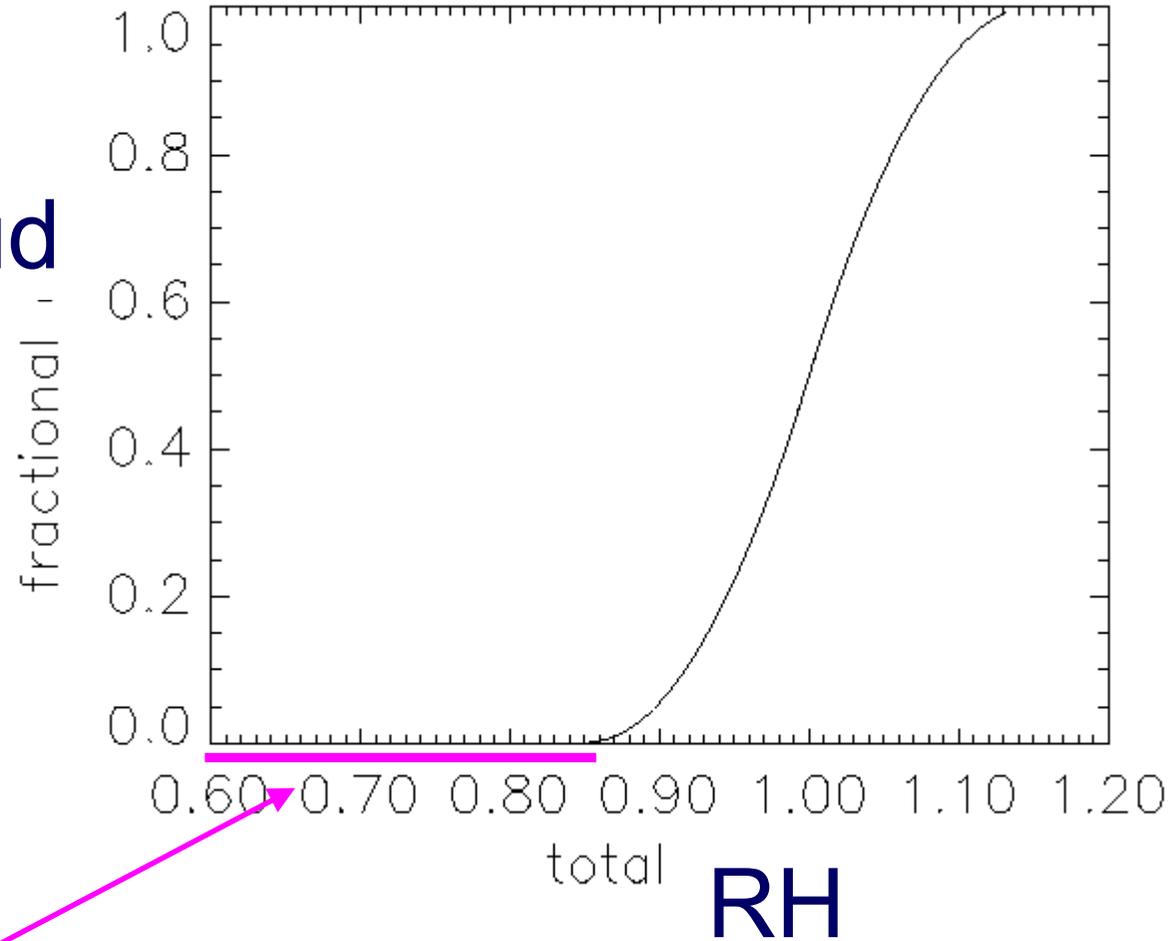
$$J_o = \frac{1}{2}(y(x) - y_{ob})^2 / \sigma^2$$

$$\frac{\partial J_o}{\partial x} = \frac{\partial y}{\partial x} (y(x) - y_{ob}) / \sigma^2$$



Smith: Cloud fraction  $\leftrightarrow$  RHtotal

cloud



$$d[\text{cloud}] / d[\text{RH}] = 0$$

# observation cost function

$$J_o = 1/2(x - f^{-1}(y_{ob}))^2 / \sigma^2$$

$$\frac{\partial J_o}{\partial x} = (x - f^{-1}(y_{ob})) / \sigma^2$$

$x$  = analysis RH

$f^{-1}(y_{ob})$  = “observed RH”

# Modification when Ob = 0 and Model Cloud = 0

$$J_o = \frac{1}{2} (x - RH_{\text{crit}})^2 / \sigma^2$$

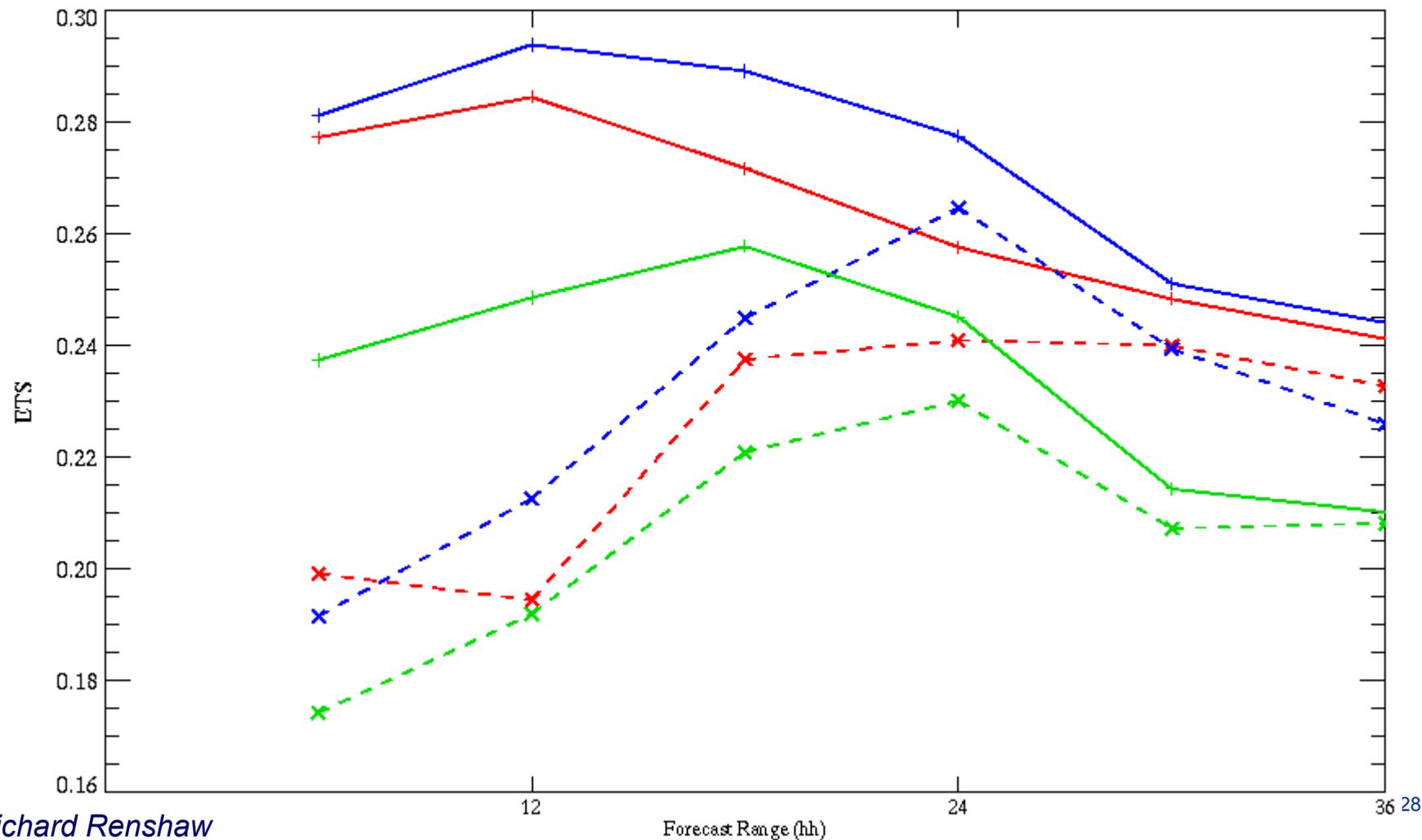
Instead set  $J_o = 0$

# Var Cloud performance, Feb 2006 trial



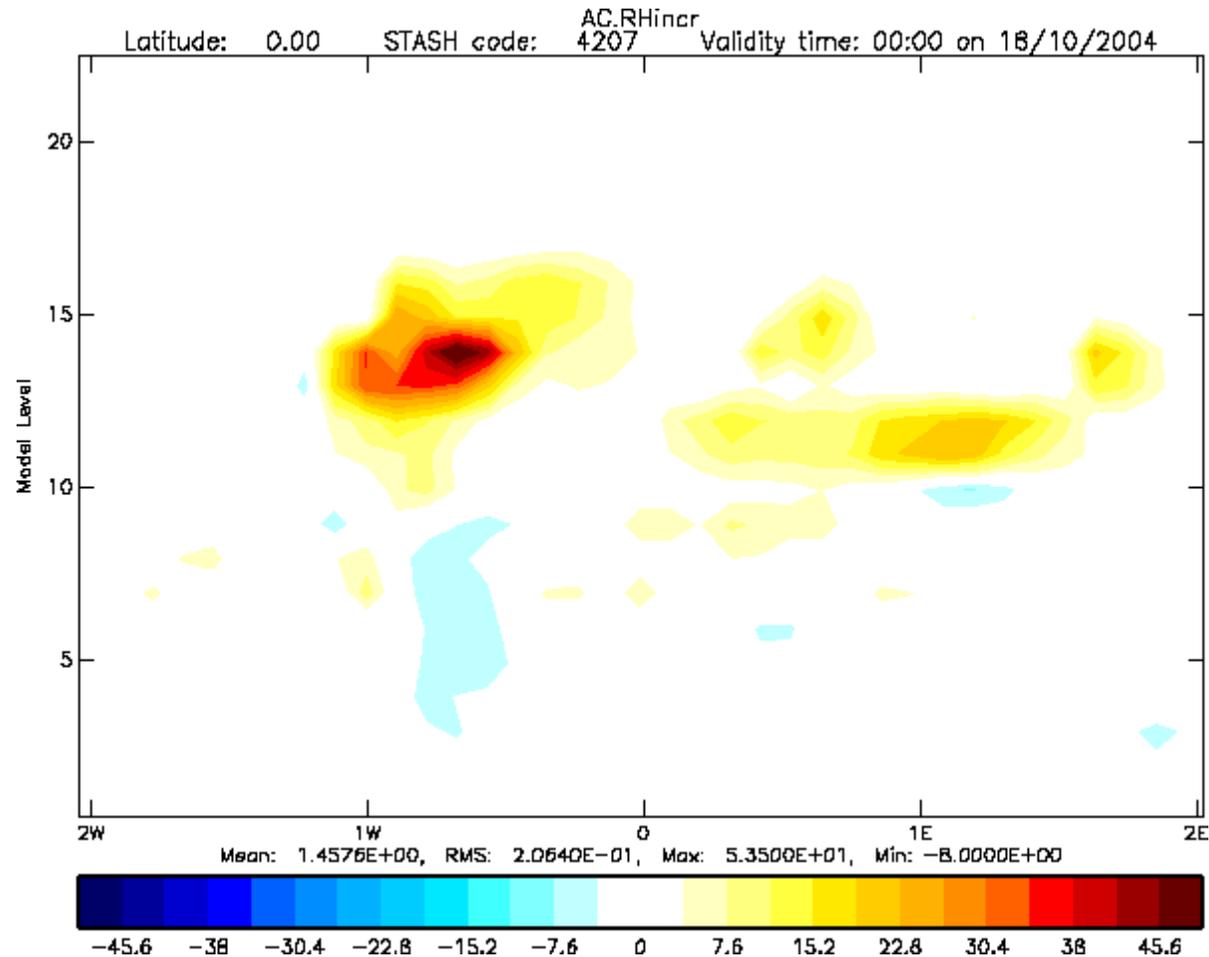
Fractional Cloud Cover: Surface Obs  
Reduced Mesoscale Model area  
Meaned from 30/1/2006 00Z to 8/2/2006 18Z

Cases: +——+ AC with fix    × — — × Var MOPS 2  
Obs Categories: — 0.3    — 0.6    — 0.8





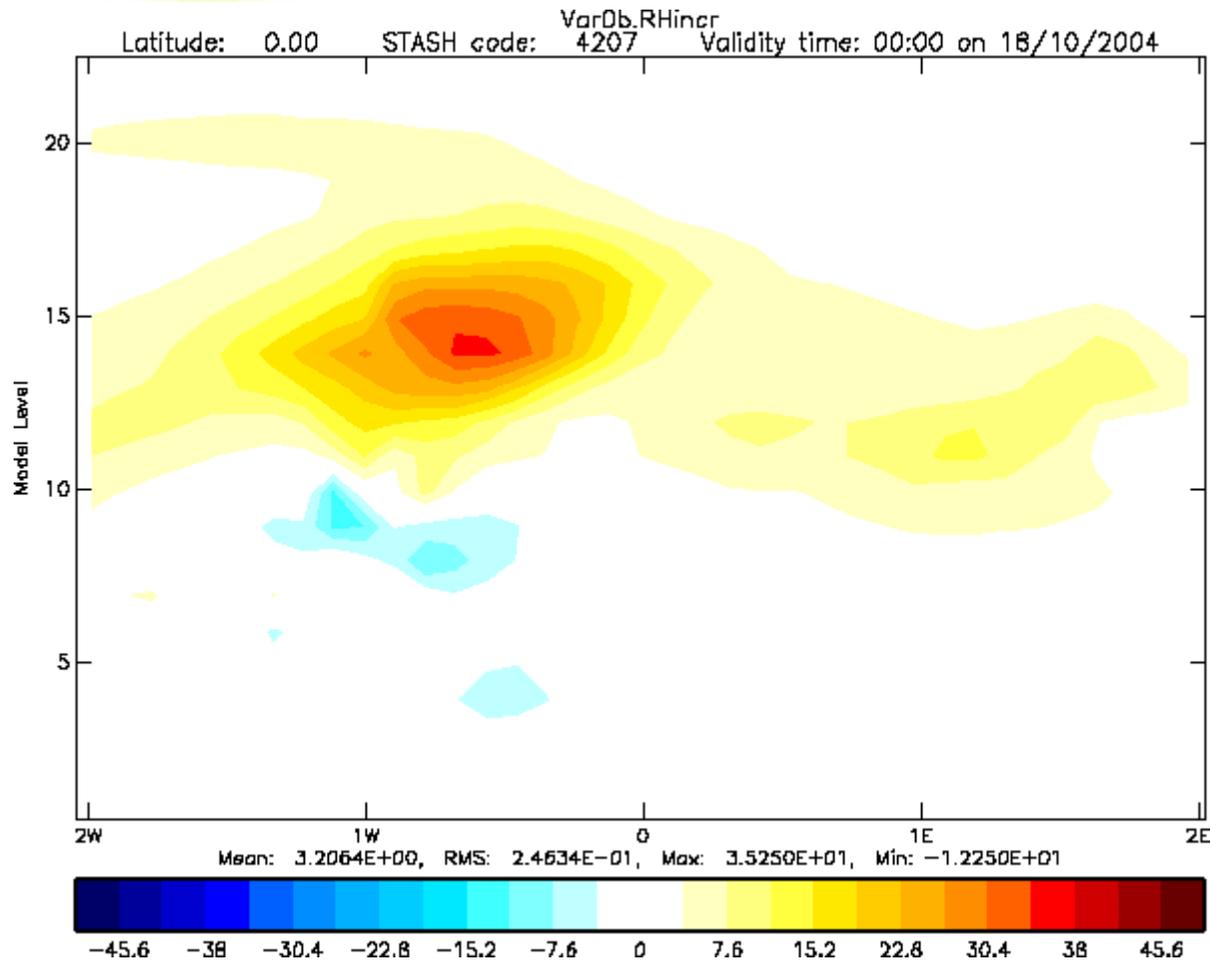
# RH increments from AC



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# RH increments from Var



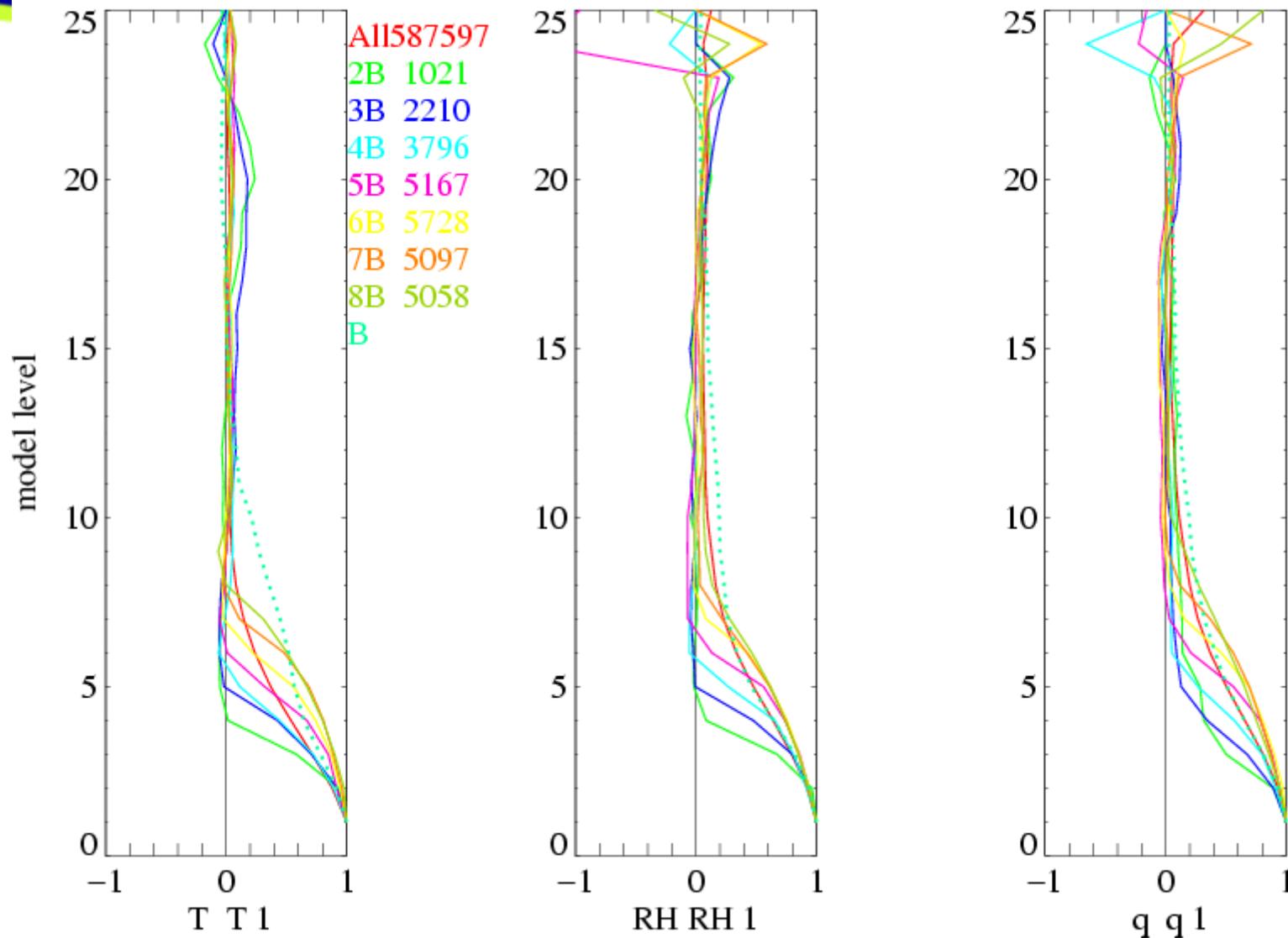
*Richard Renshaw*

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# Background-sonde correlations with model level 1



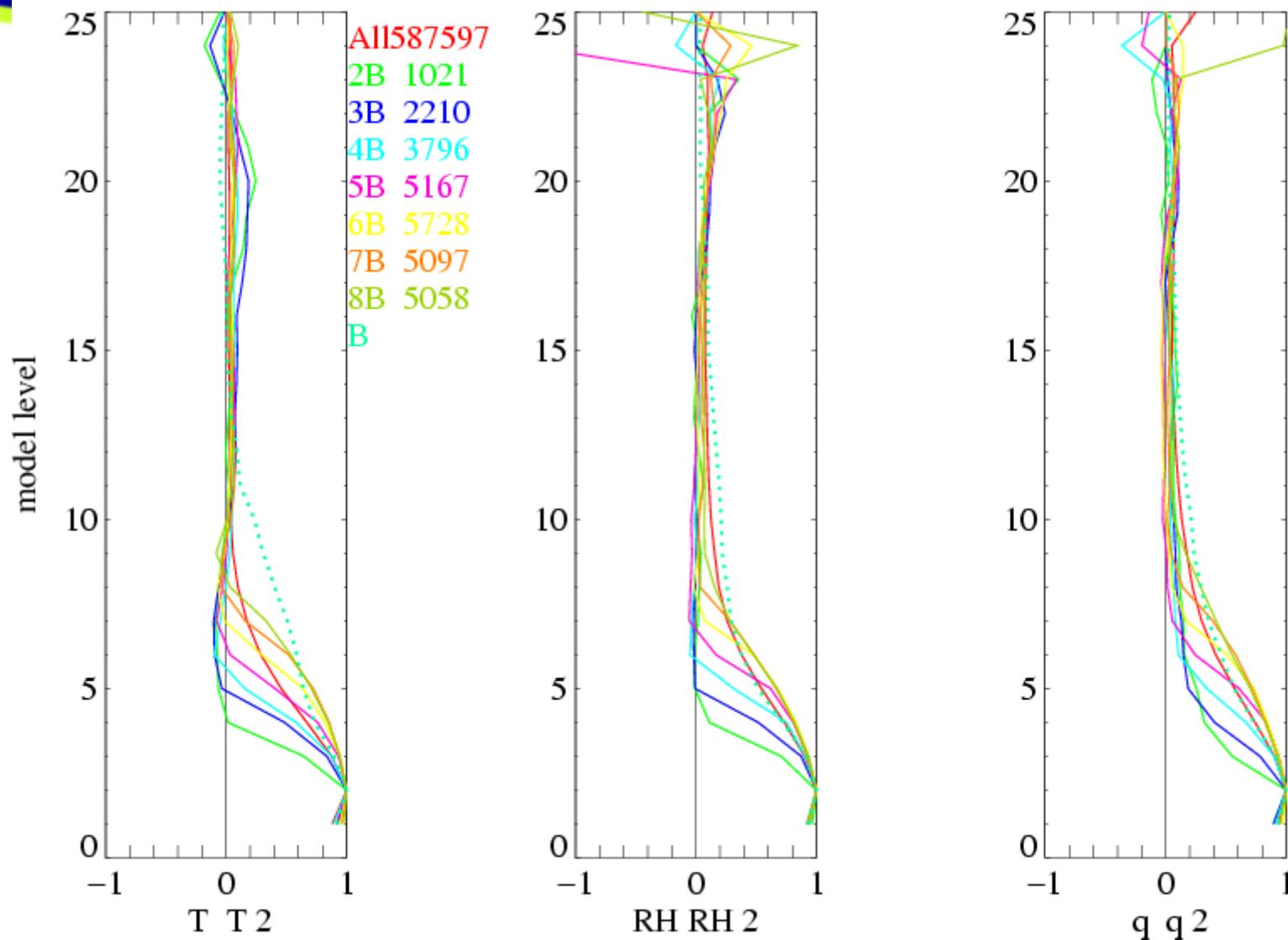
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 2



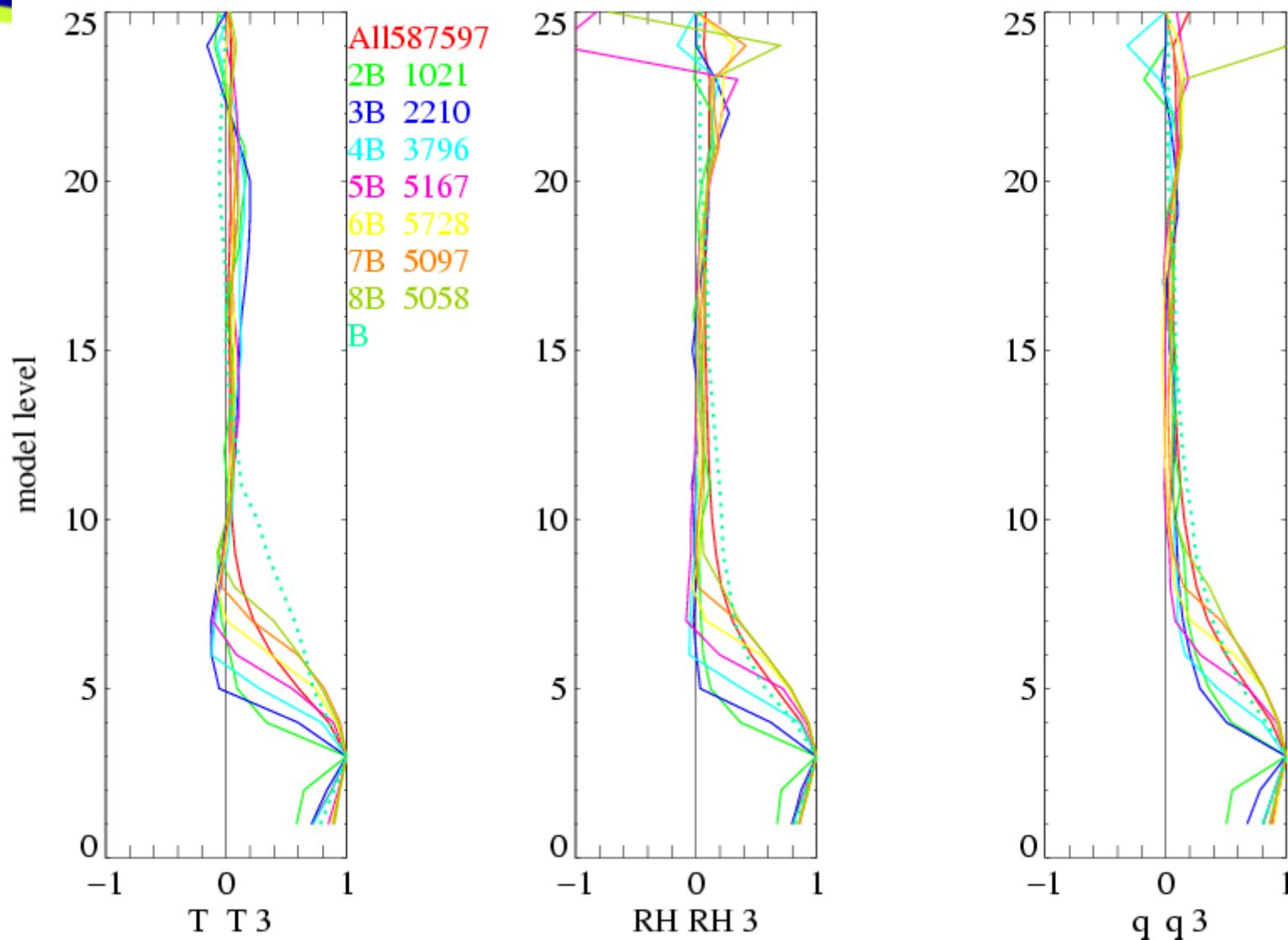
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 3



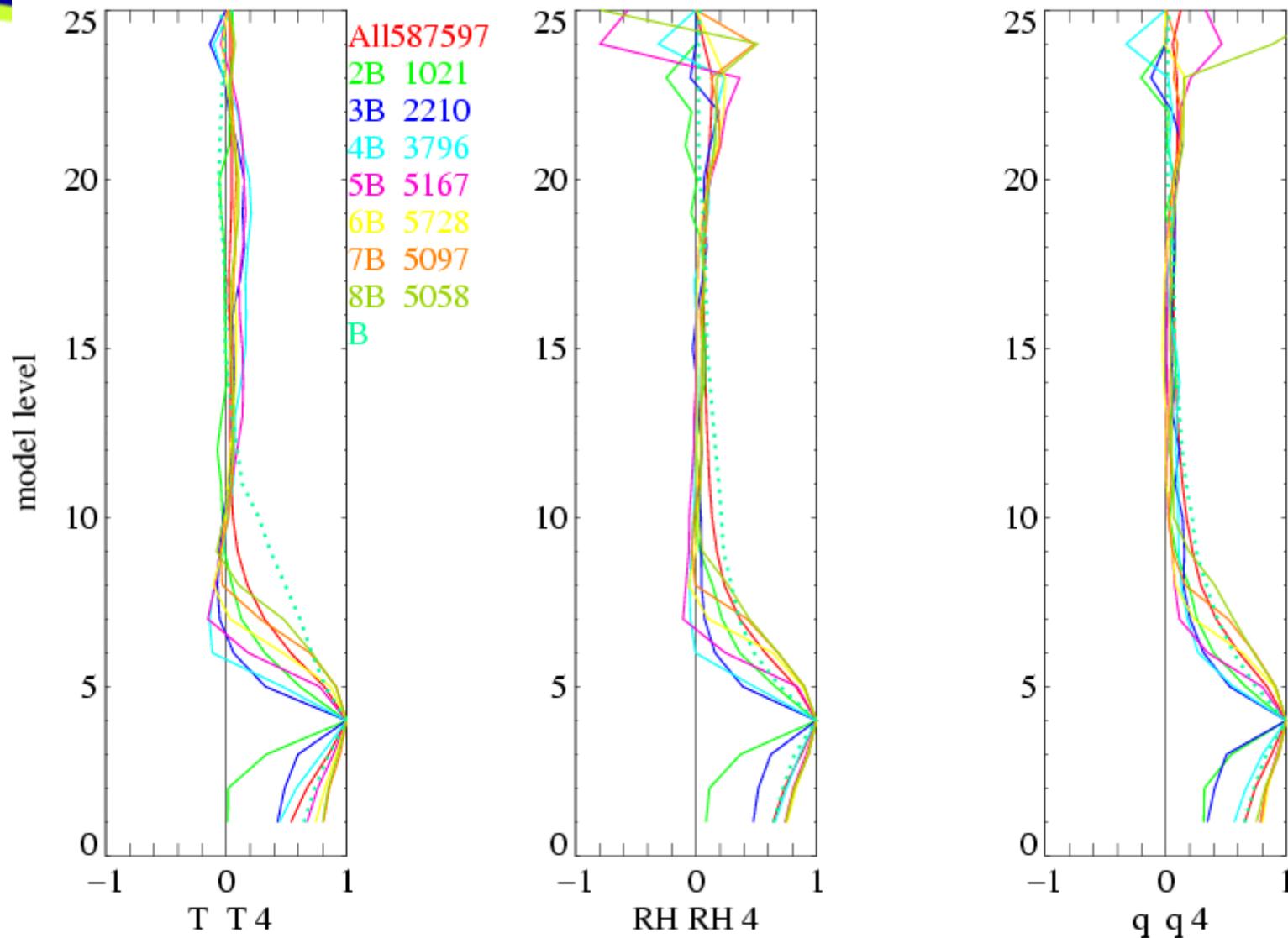
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 4



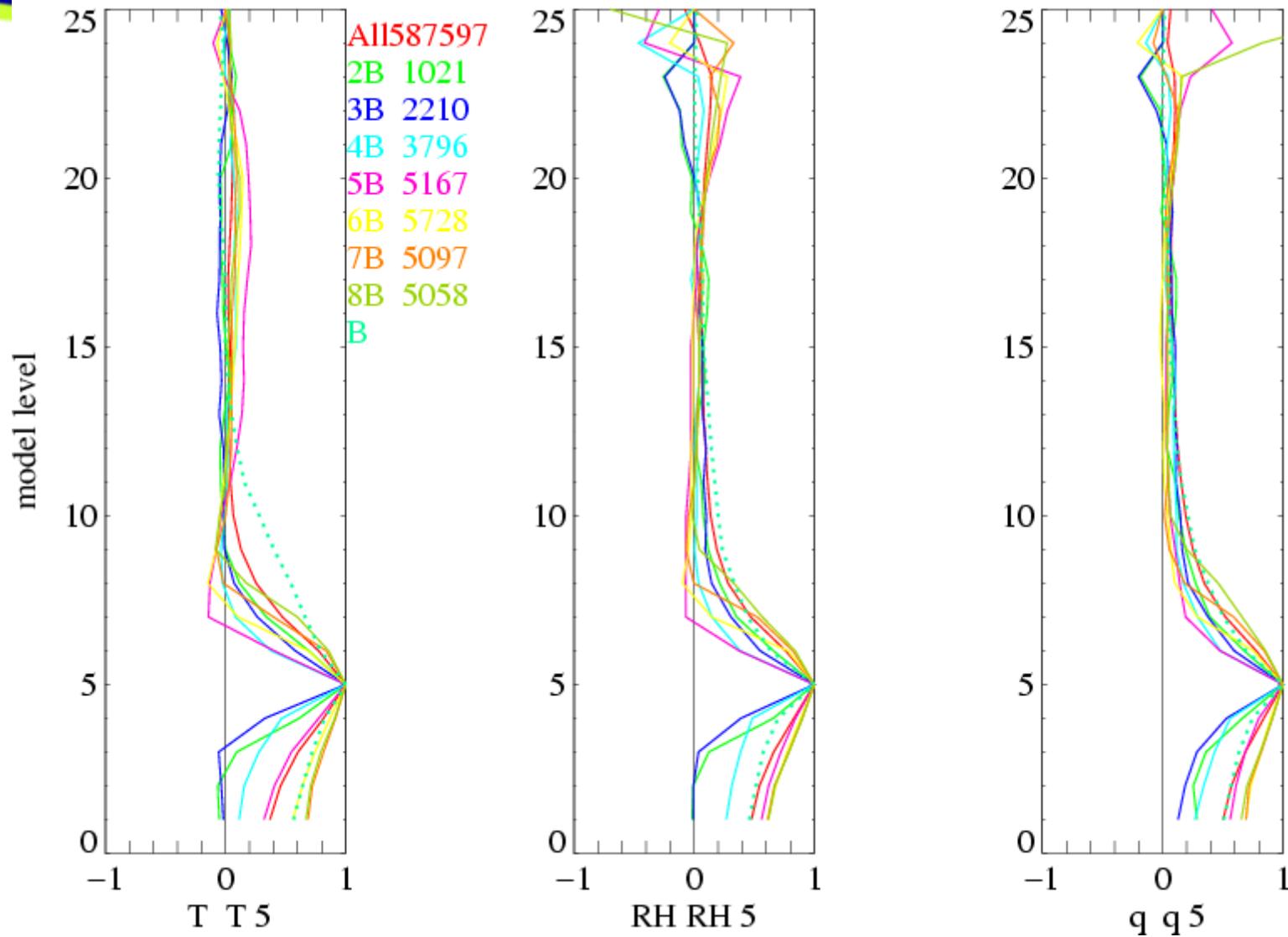
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 5



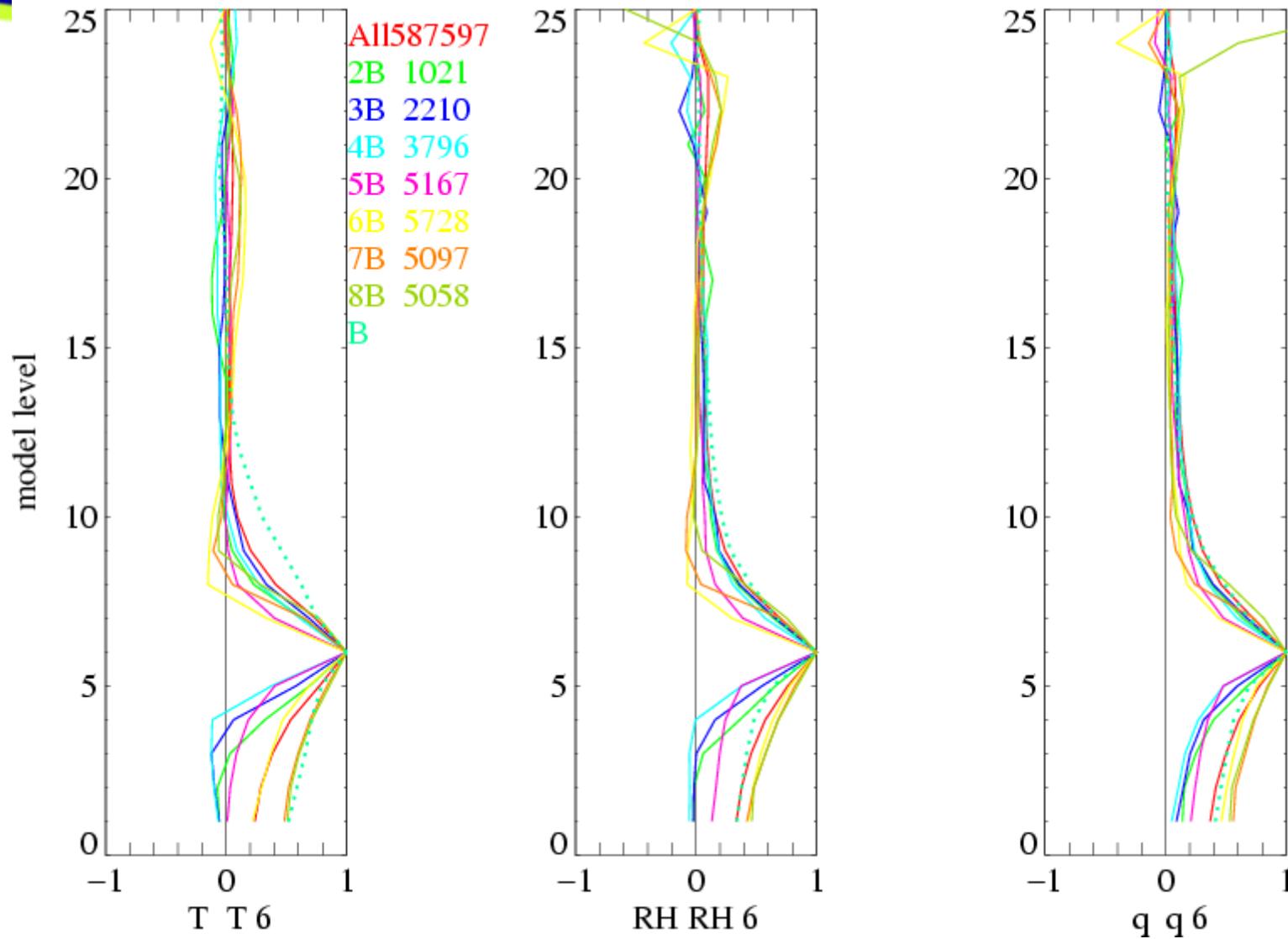
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 6



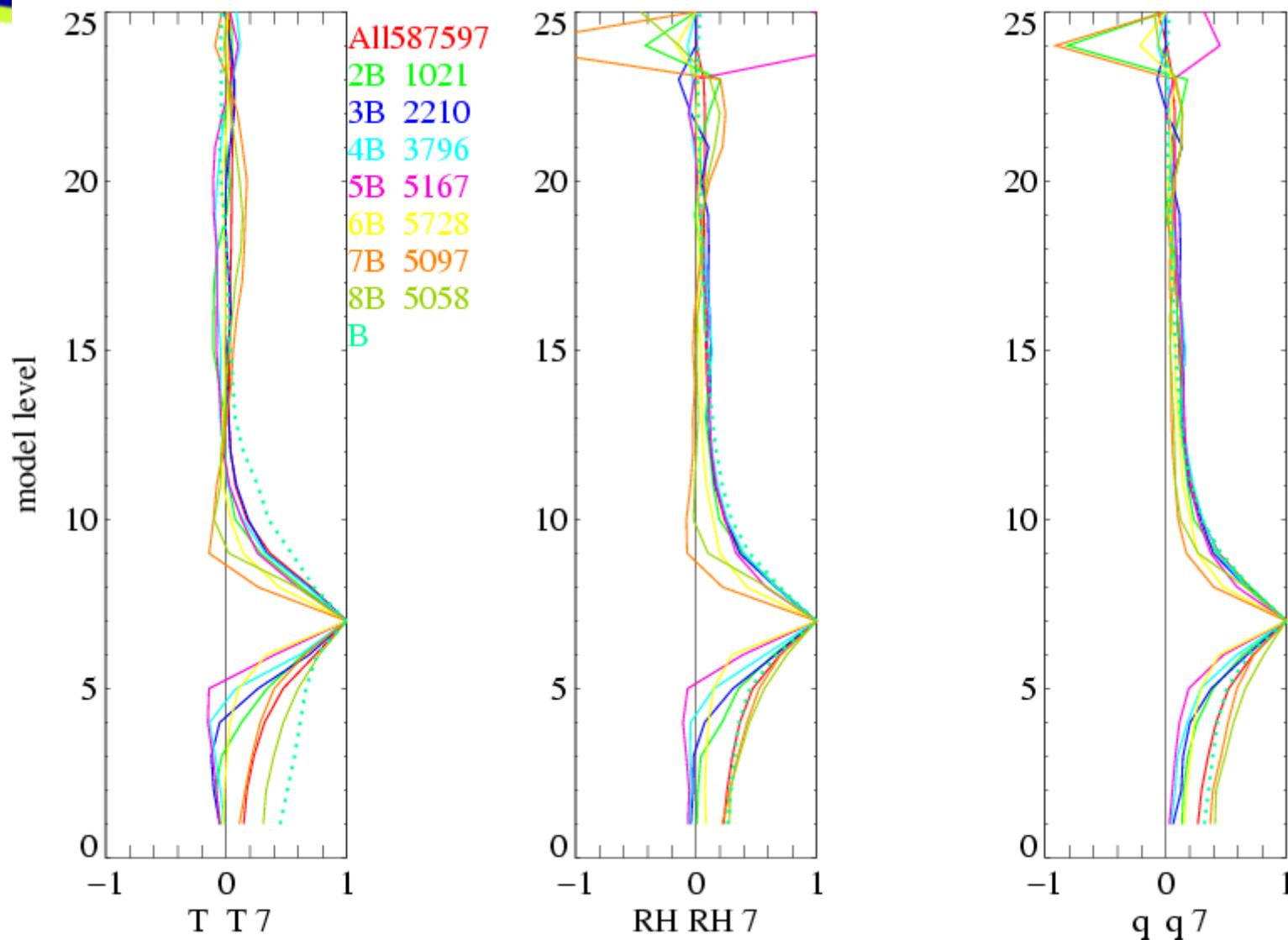
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 7



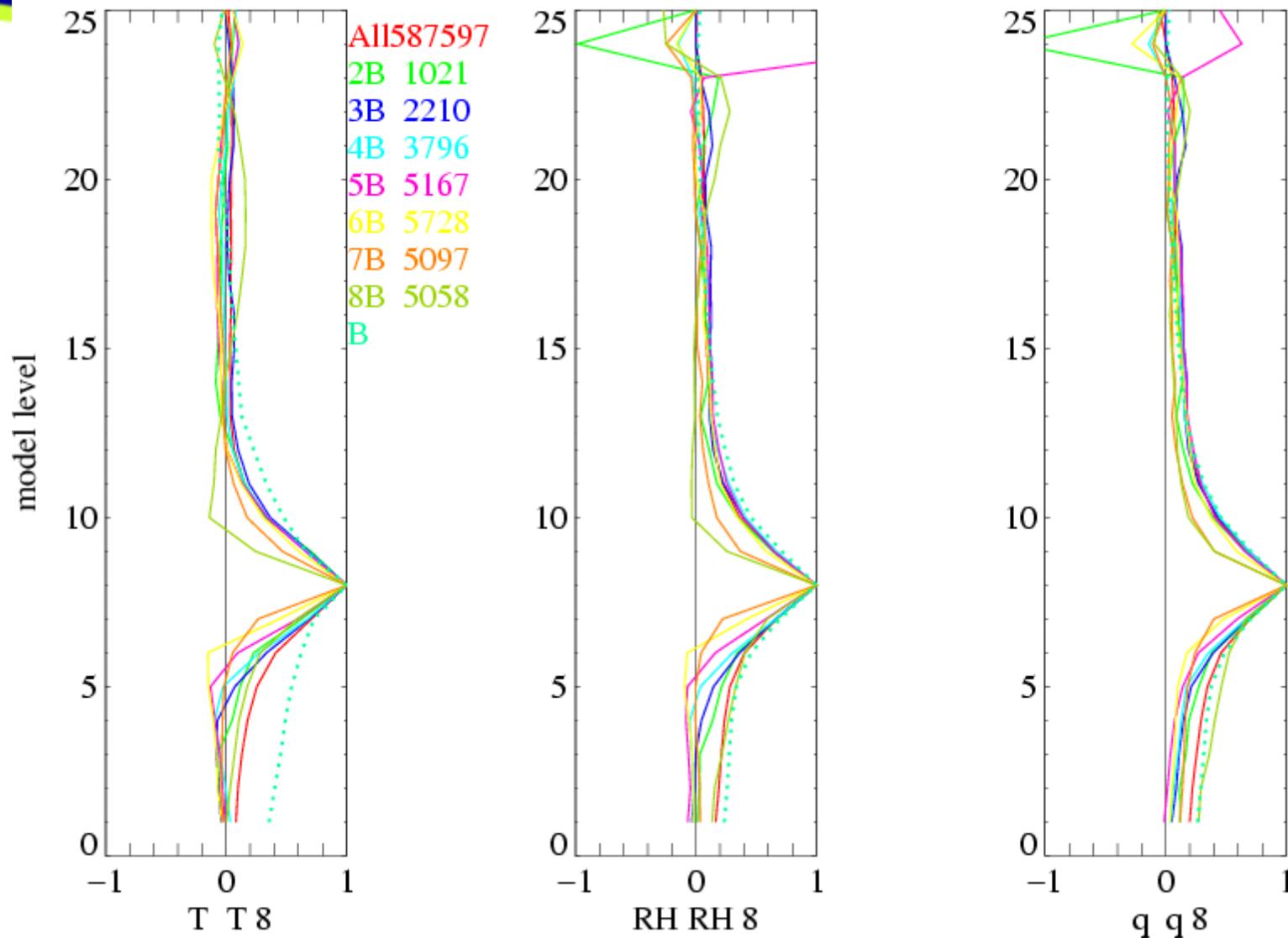
b-o correlation in GL0512to0703 classified by BL cloud top in background



# Background-sonde correlations with model level 8



b-o correlation in GL0512to0703 classified by BL cloud top in background



# Simple Var RH operator



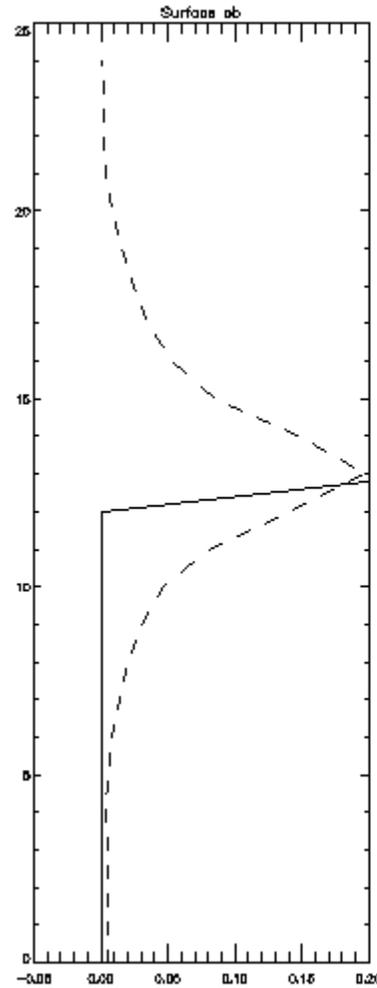
MOPS cloud



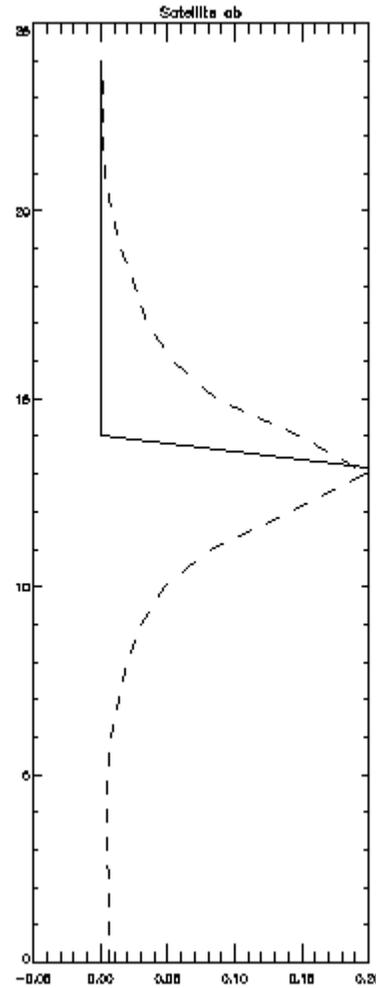
RH increment



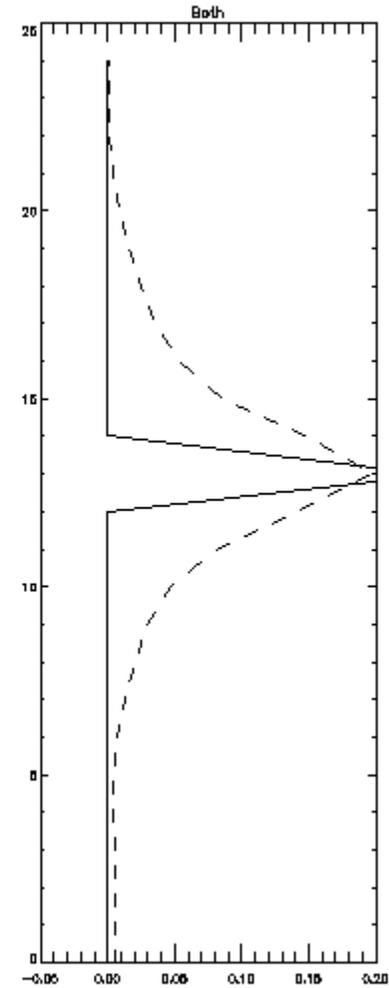
### Surface ob



### Satellite data



### Both



# Redesigned operator



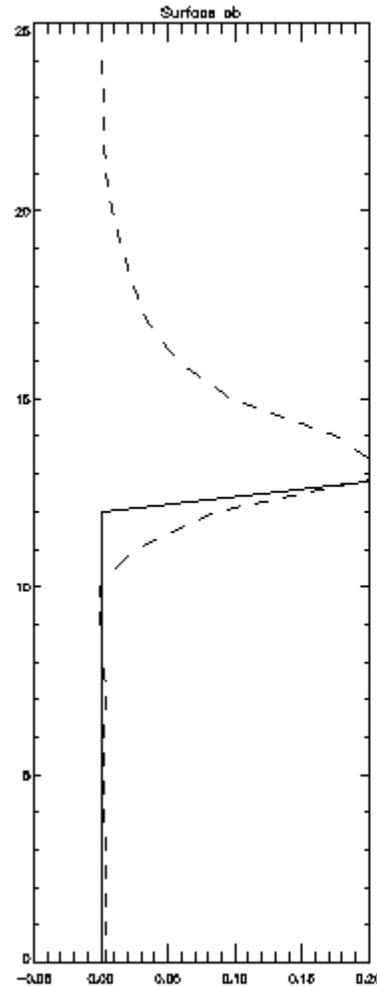
MOPS cloud



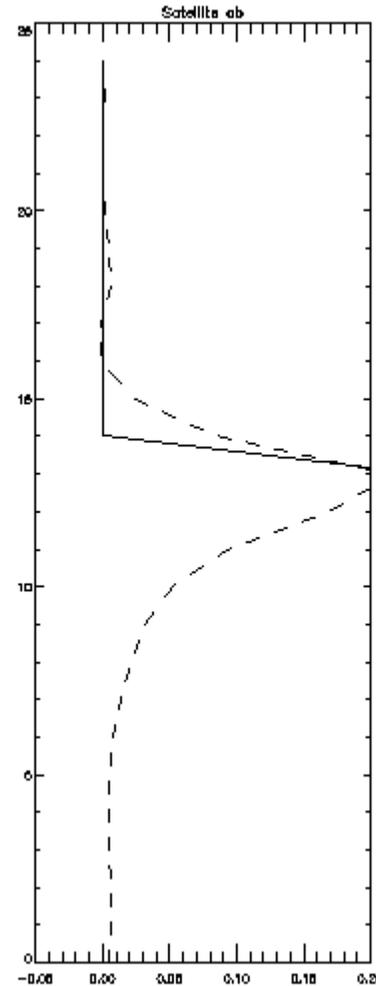
RH increment



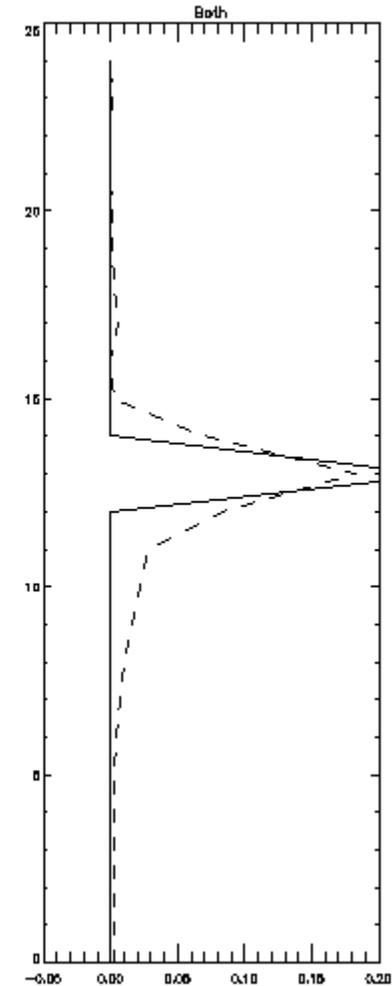
Surface ob



Satellite data



Both



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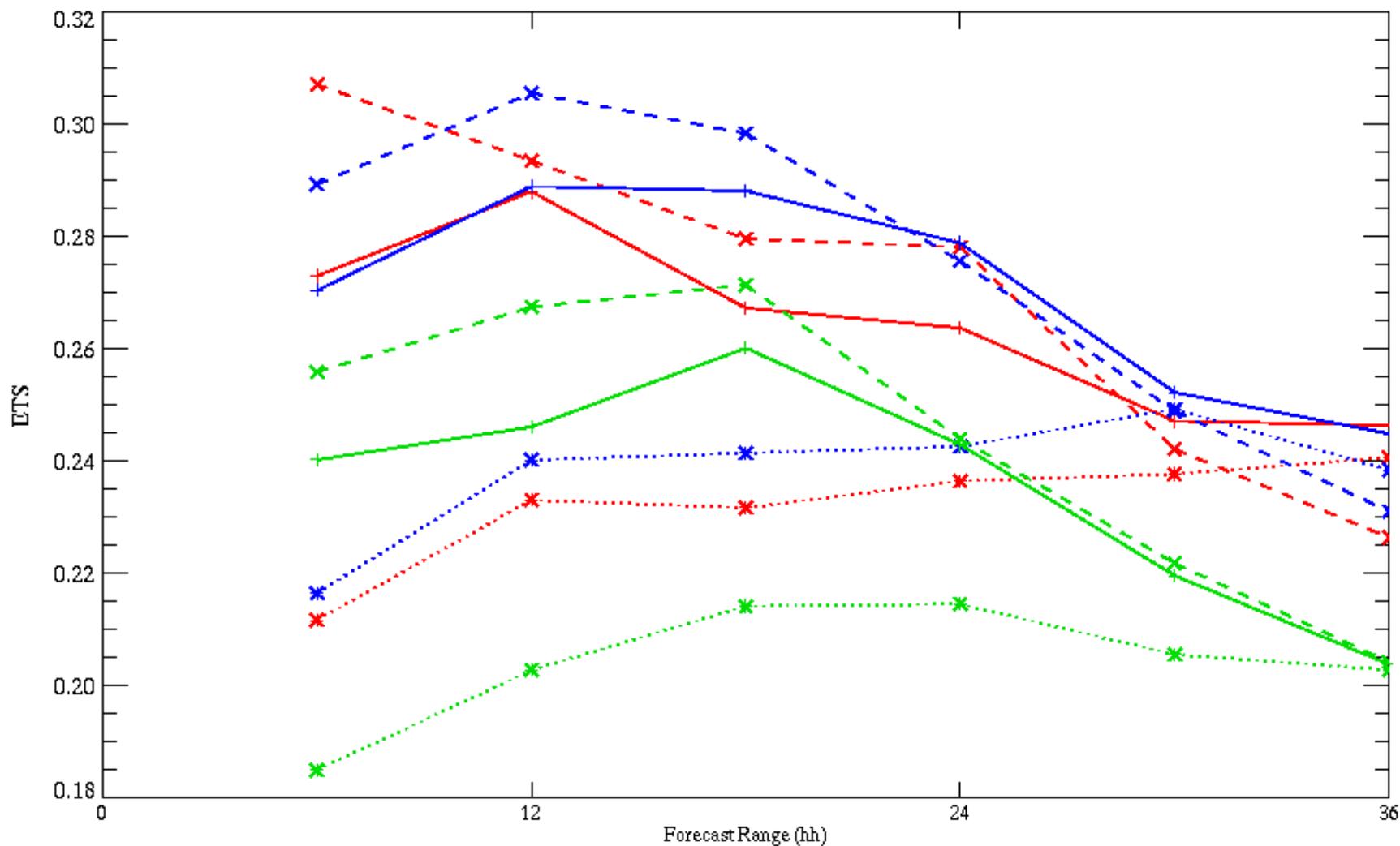
# Var cloud performance, 3D-Var mes trial



Fractional Cloud Cover: Surface Obs  
 Reduced Mesoscale Model area  
 Meaned from 30/1/2006 00Z to 8/2/2006 18Z

Cases: +——+ AC cloud    ×——× Var cloud    \*.....\* No Cloud

Obs Categories:    — 0.3    — 0.6    — 0.8



And

19/10/2006 - 10/11/2006

- 1<sup>st</sup> half mobile flow  
depressions, wind, rain
- 2<sup>nd</sup> half anti-cyclonic  
frost + fog

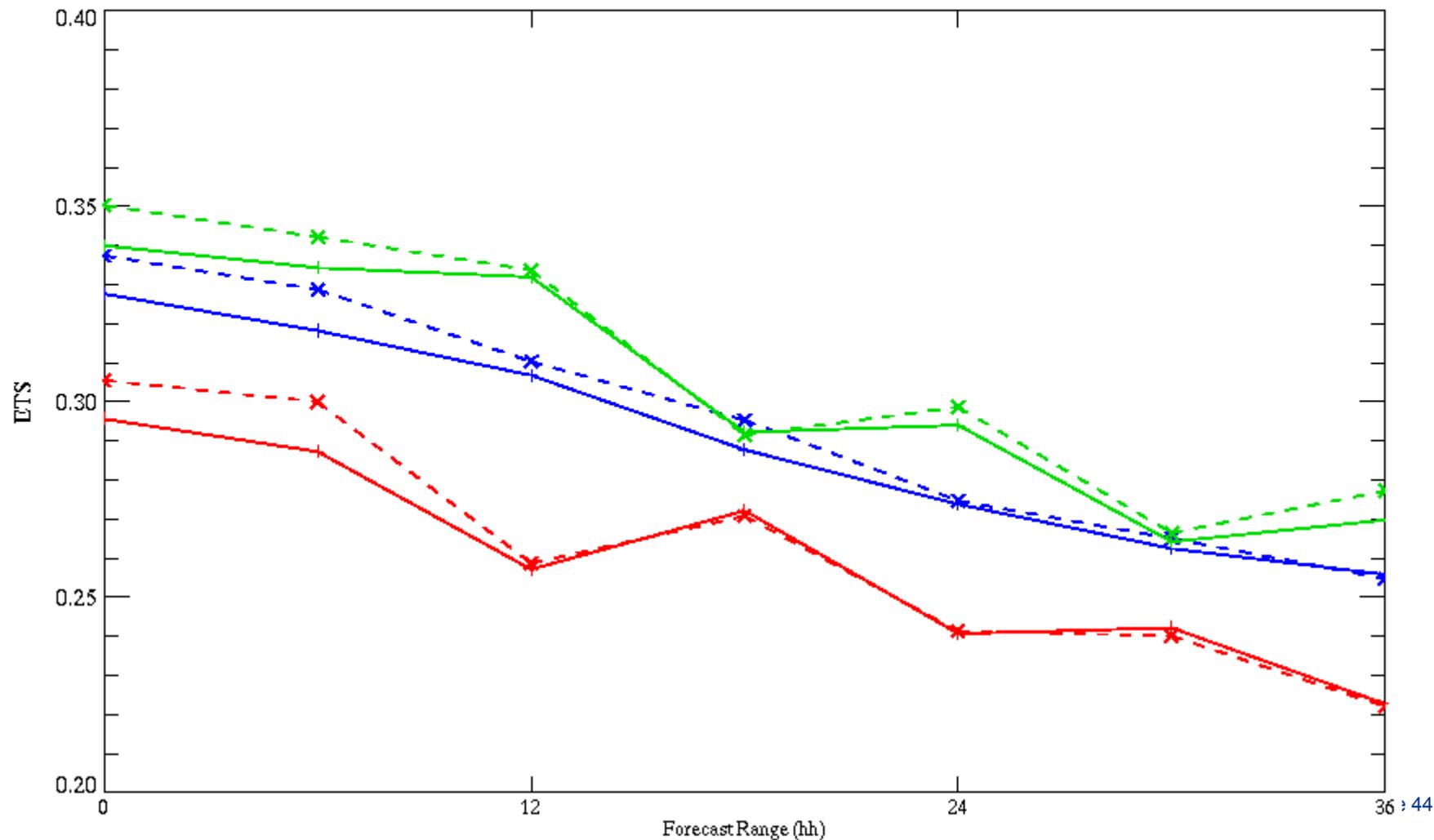
# Var vs No Cloud , 4D-Var NAE Period 1



Fractional Cloud Cover: Surface Obs  
Reduced NAE Model area  
Meaned from 19/10/2006 00Z to 1/11/2006 18Z

Cases: +——+ PS14 no cloud    \* - - \* PS14 Var cloud

Obs Categories:    — 0.3    — 0.6    — 0.8



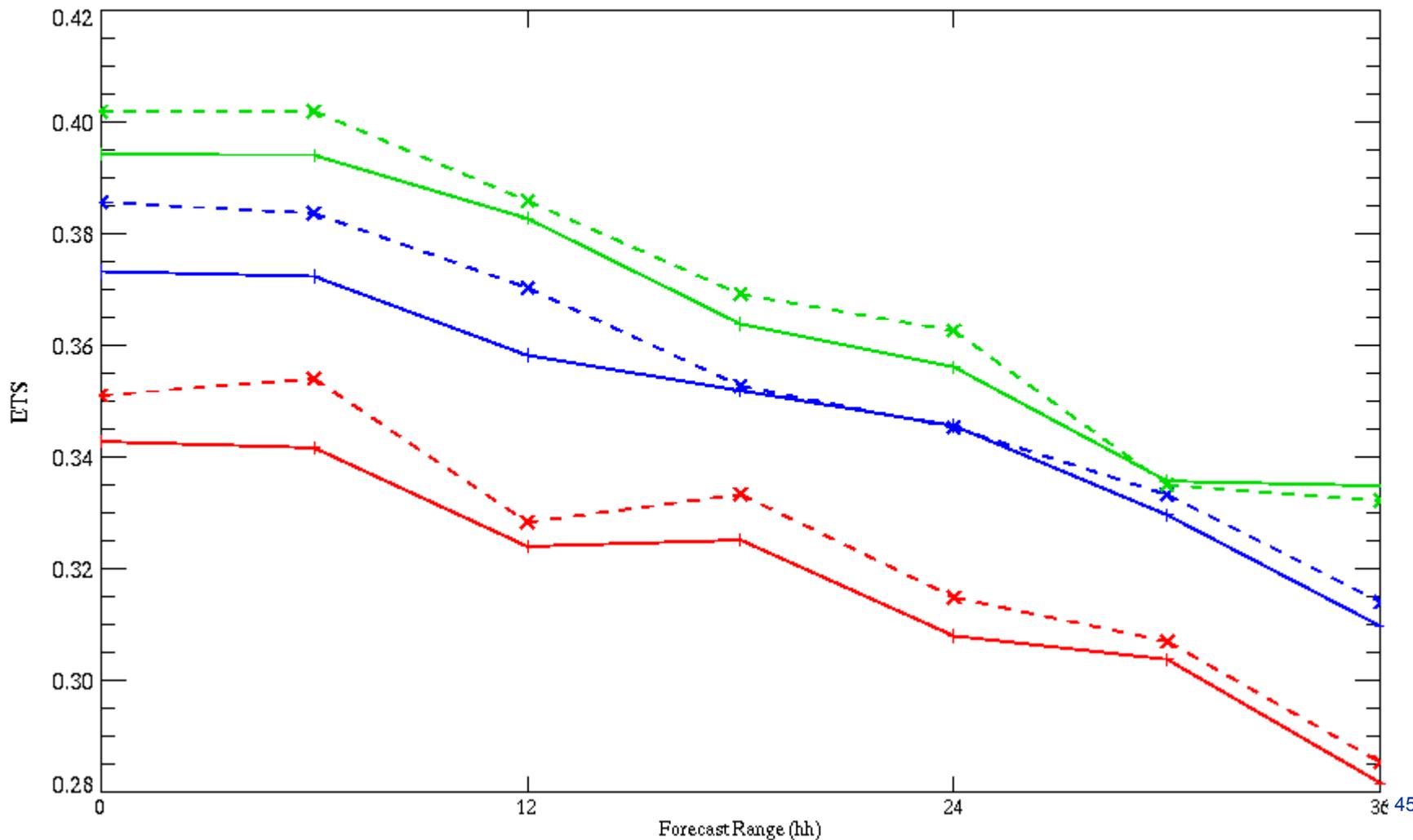
# Var vs No Cloud , 4D-Var NAE Period 2



Fractional Cloud Cover: Surface Obs  
 Reduced NAE Model area  
 Meaned from 1/11/2006 00Z to 12/11/2006 18Z

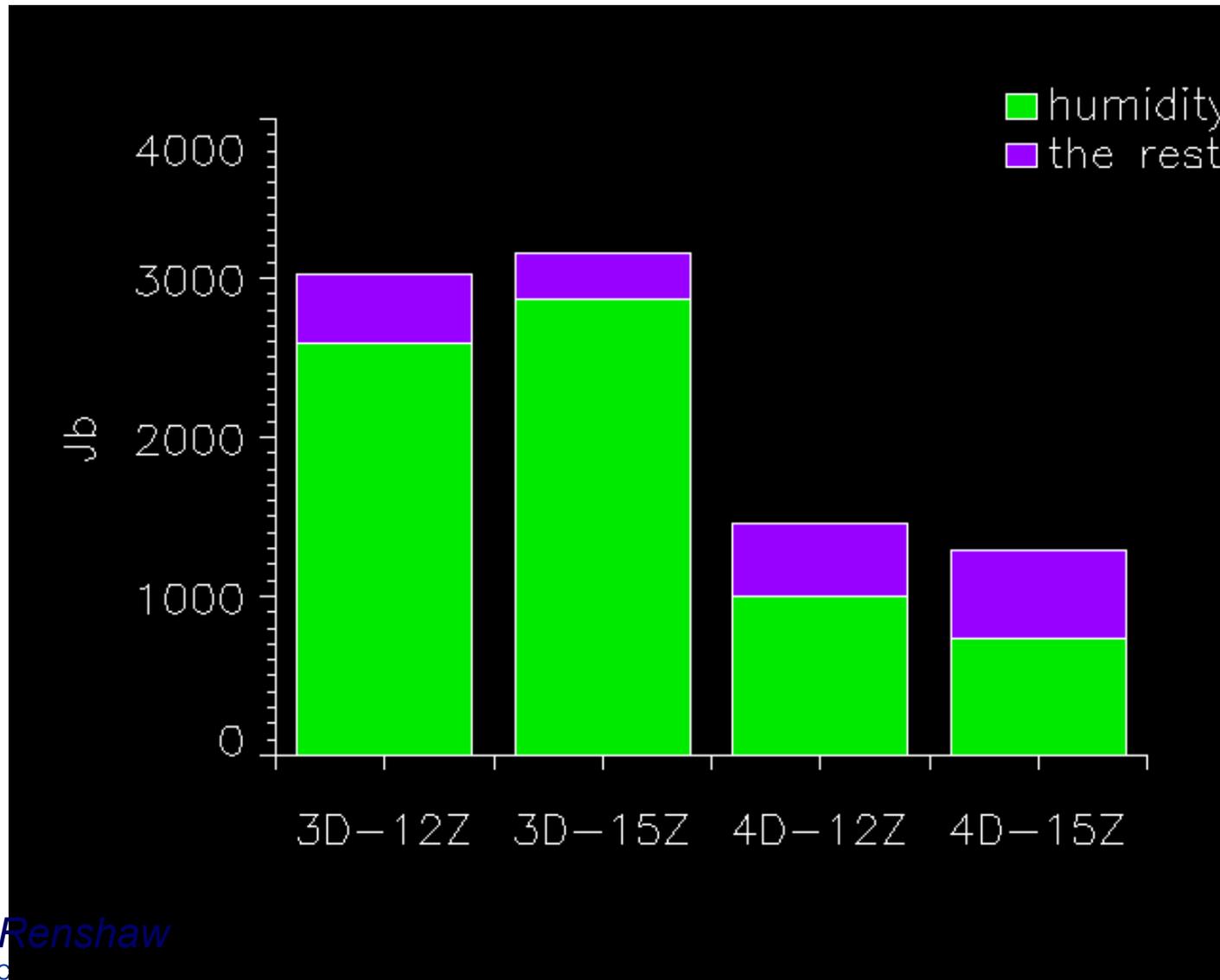
Cases: +——+ PS14 no cloud    × - - × PS14 Var cloud

Obs Categories:    — 0.3    — 0.6    — 0.8

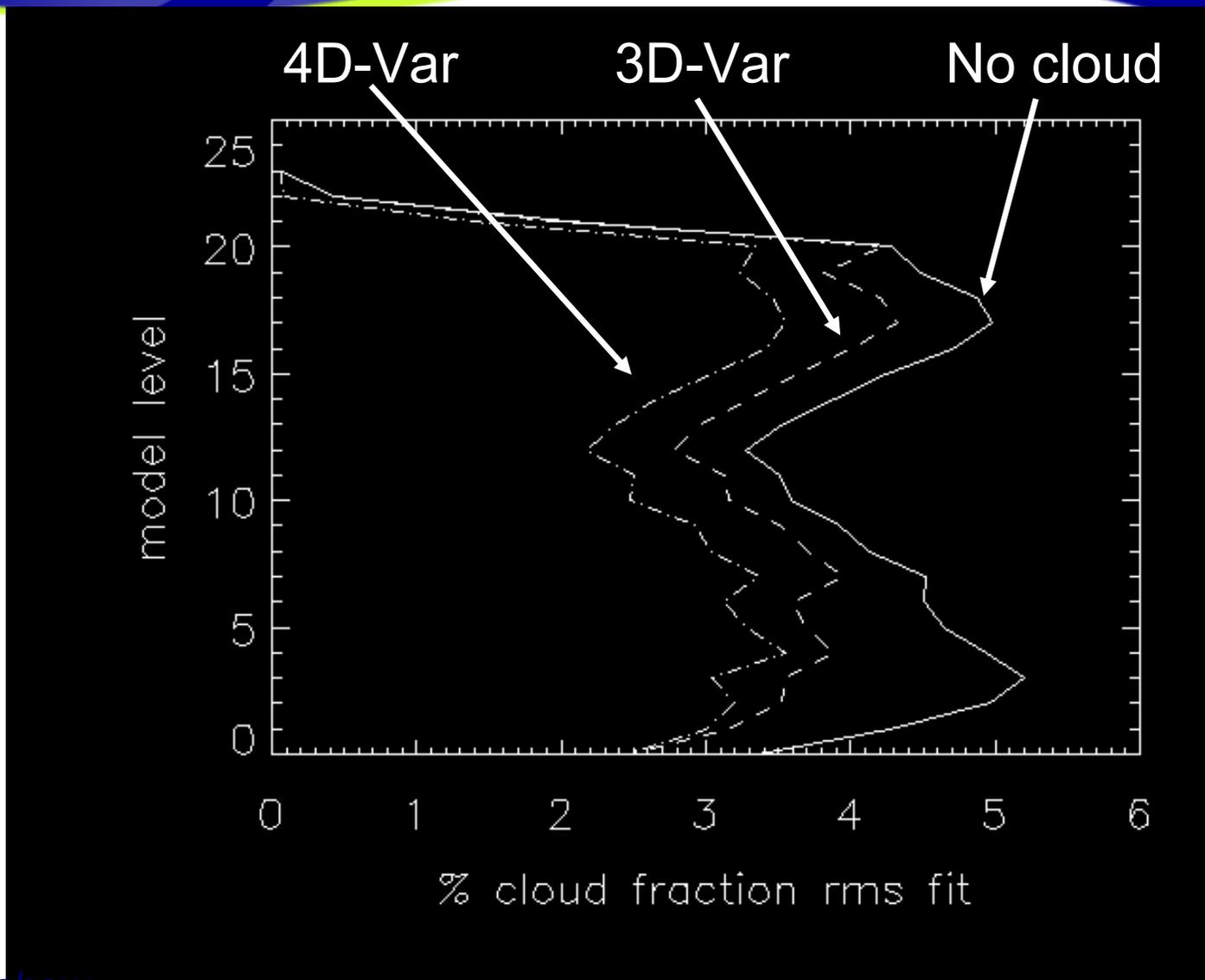


And

# Breakdown of the increments - Jb



# T+3 fit to NIMROD cloud



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- ☁️ GC transform works, but impact small and difficult to do LAM – dropped.
- ☁️ EOTD modes, using  $\alpha$ , equivalent to localised Ensemble KF. Impacts small from 1 mode – suspended pending MOGREPS.
- ☁️ Evolved covariances in 4D-Var as important as treating obs at correct time.
- ☁️ Assimilation of layer cloud not useful with average vertical covariances. Can be made useful by reducing vertical spreading.

- ☁️ **Get the basics right first.** VAR results are still sensitive to changes in the covariance model smaller than believed inaccuracies.
- ☁️ **Model variability determines analysis resolution.** VAR schemes which generate their covariances from the NMC method, or ensemble perturbations, can only fit structures which are common in the learning set, i.e. which the model can spontaneously generate.
- ☁️ **Non-Gaussian PDF means even perfect covariances are not sufficient.** Coherent structures (inversions, fronts, cyclones, convective cells) which have position errors lead to non-Gaussian PDFs. VAR theory (least squares best fit, using covariances to characterise errors) breaks down!

# Tephigram showing 4D-Var fit to sonde

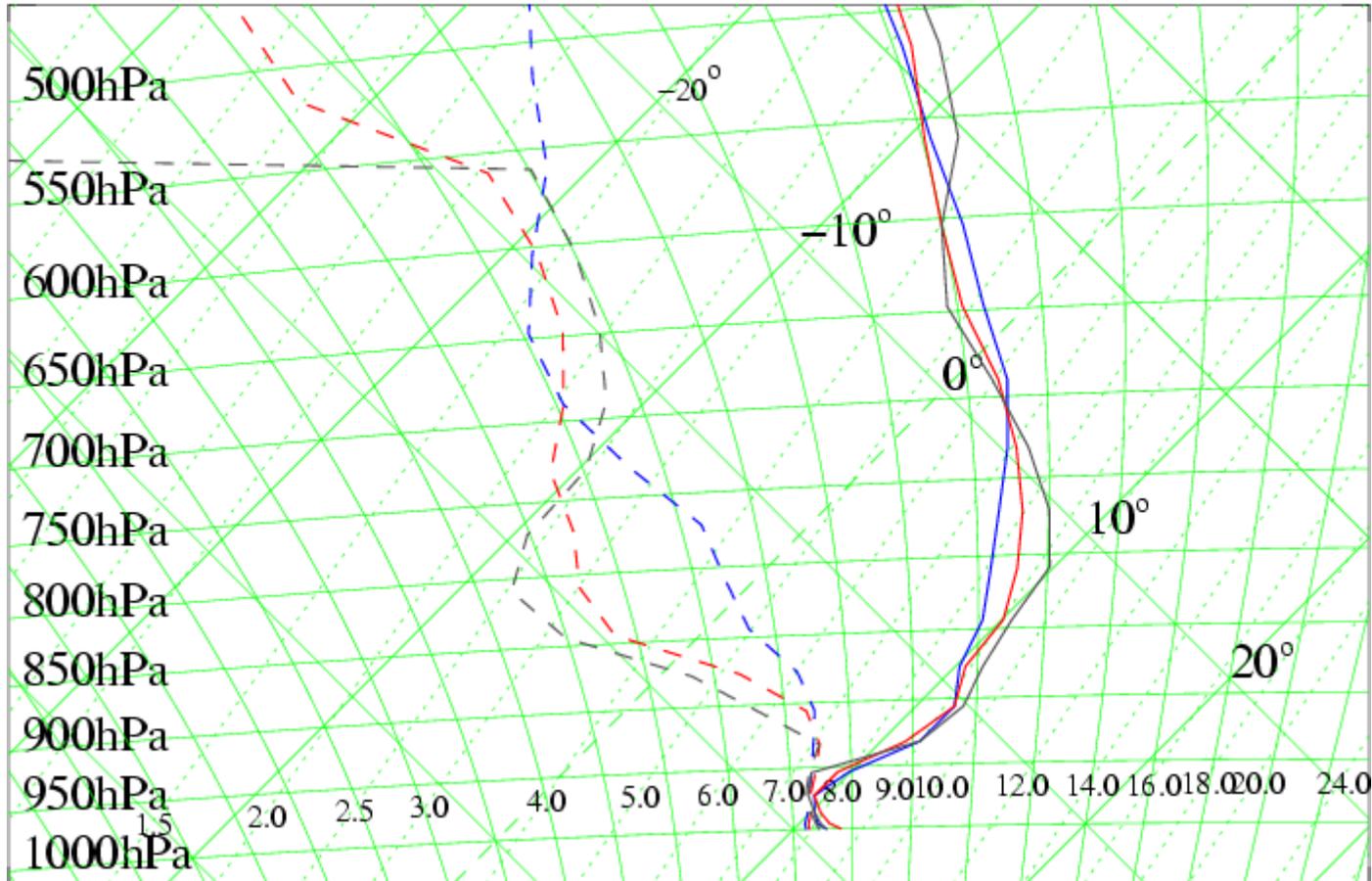


background

analysis

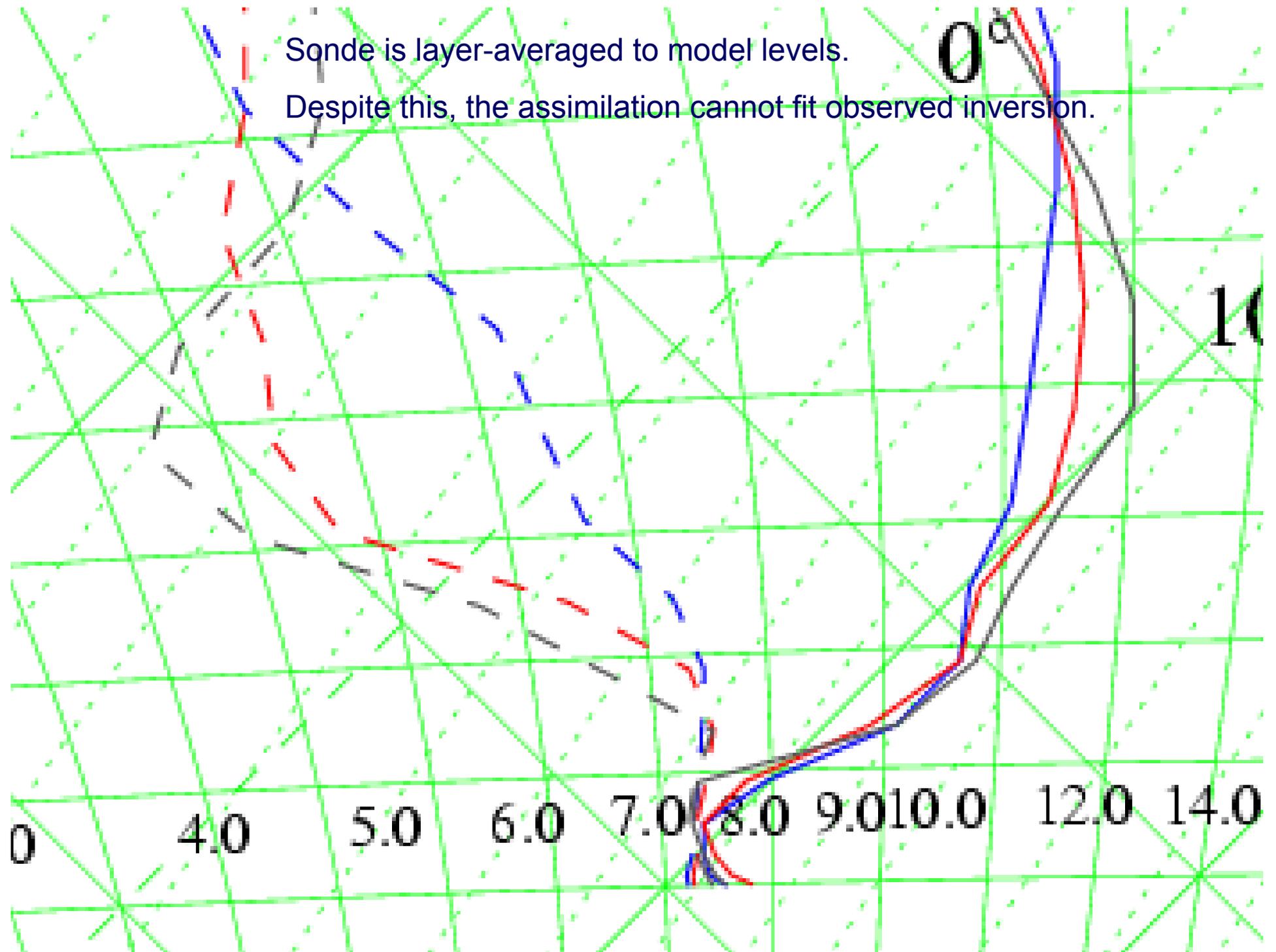
layer-mean ob

85799 -41.43N -73.10E 2005/12/14 11:02



Sonde is layer-averaged to model levels.

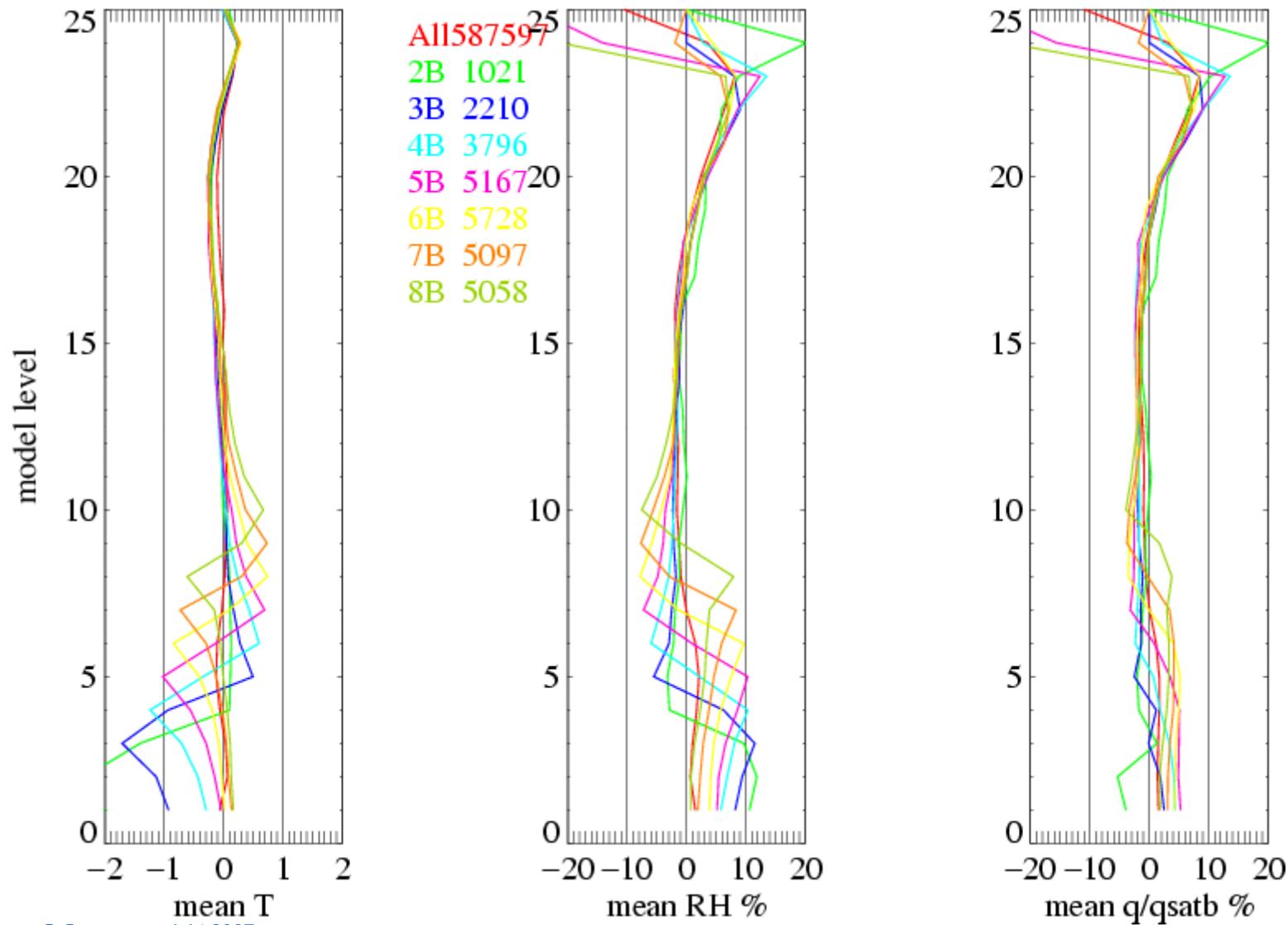
Despite this, the assimilation cannot fit observed inversion.



# Non-Gaussian PDF: skewed distribution has biased mean which is smoother than background



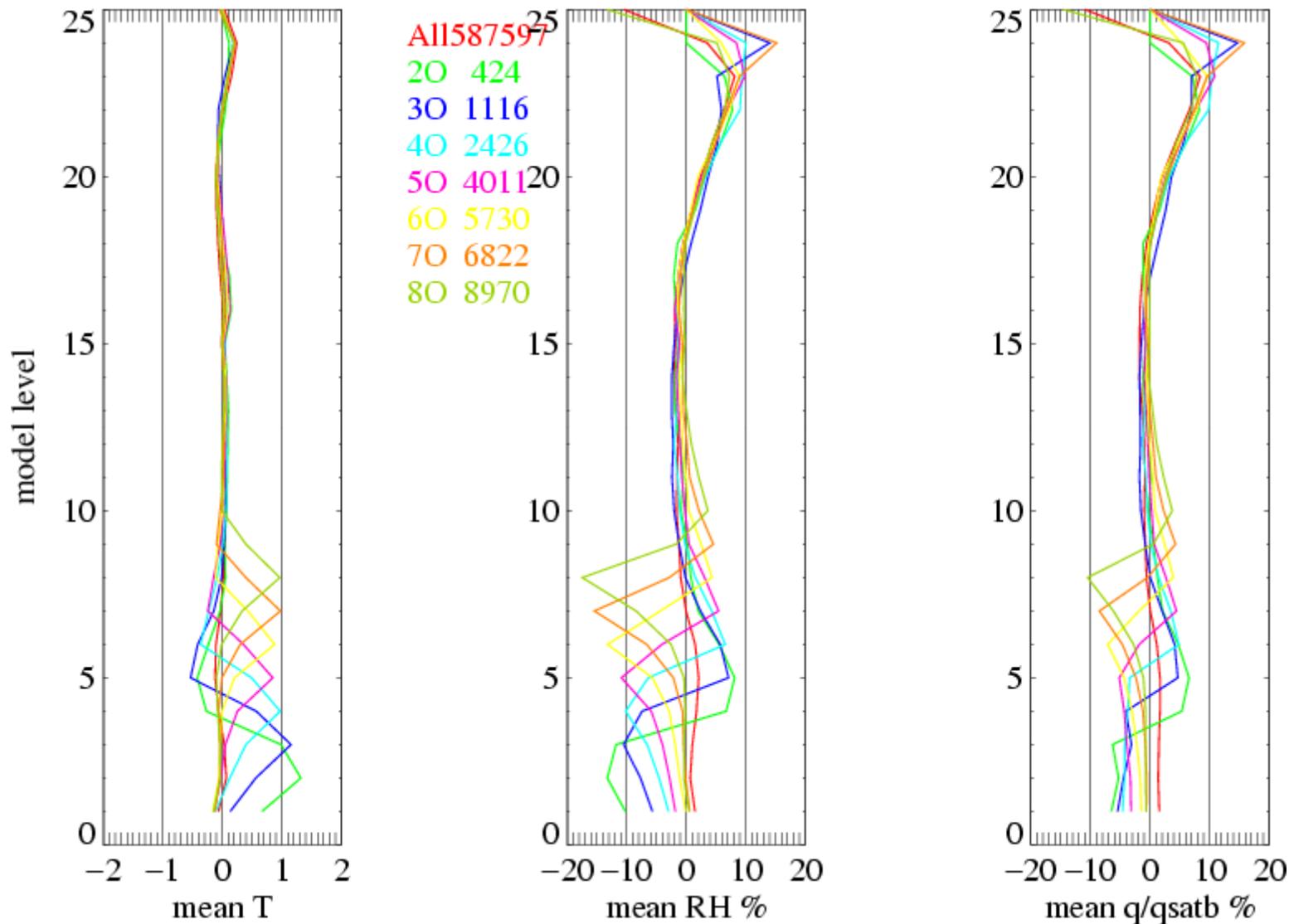
Mean background-sonde in GL0512to0703 classified by BL cloud top in background



# Compositing by observed cloud top reverses the bias



Mean background-sonde in GL0512to0703 classified by BL cloud top in sonde



*Most effort into getting basics right first – improved covariance and PF models.*

- ❖ Evaluate MOGREPS T+6 perturbations as a sample of errors.
- ❖ If necessary improve the localised ETKF and stochastic perturbations to model.
- ❖ Generate improved covariances.
- ❖ Then go on to restart EOTD modes work.
  
- ☁ Implement “MOPS in VAR” in operation regional 4D-Var and UK 3D-Var.
- ☁ Extend to 1D-Var cloud retrievals from IR sounders, over a wider area.

- o Revise covariance model to allow more flexible horizontal variation (wavelet-based).
- o Use the spread of the MOGREPS ensemble to modulate local variances.
  
- Institute a vertical transform as well as, or instead of, the GC transform. The grid to be chosen to keep same domain but seek to equalise spacing in isentropic coordinates.