Advances in data assimilation techniques
and their relevance to satellite data assimilation

ECMWF Seminar on Use of Satellite Observations in NWP

Andrew Lorenc, , 8-12 September 2014.

Content

1. Developments in DA methods
   - Hybrid-4DVar
   - 4D-Ensemble-Var
   - EnKF (e.g. LETKF)
2. Some potentially difficult problems relevant to satellite DA
   - How do the various methods fare?
3. Some personal opinions

Developments in DA methods

1. The ability to predict the evolution and growth of forecast errors was at the heart of the THORPEX.
2. Evolving capabilities & requirements of NWP:
   - Computing
   - Nonlinearity
   - Ensembles

Hybrid-4DVar – using EOTD information from ensemble

4DEnVar – using ensemble trajectories instead of model & adjoint

EnKF – general & **LETKF** – a popular flavour (related to 4DEnVar)

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4-Dimensional DA Methods

Each is a 4D best-fit to observations in a 6 hour window, assuming Gaussian background and observation errors. I use underline to denote 4D variables and operators:

$\underline{\mathbf{x}}^b$	background trajectory
$\underline{\mathbf{P}}$	4D error covariance of $\underline{\mathbf{x}}^b$
$\delta\underline{\mathbf{x}}$	4D analysis increment
$\underline{\mathbf{y}} = \underline{H}\left(\underline{\mathbf{x}}^b + \delta\underline{\mathbf{x}}\right)$	model estimate of obs
$J\left(\delta\underline{\mathbf{x}}\right) = \frac{1}{2}\delta\underline{\mathbf{x}}^T\underline{\mathbf{P}}^{-1}\delta\underline{\mathbf{x}} + \frac{1}{2}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)^T\underline{\mathbf{R}}^{-1}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)$	penalty function

$\underline{\mathbf{P}}$ is **big!** We cannot even estimate it fully, let alone compute $\frac{1}{2}\delta\underline{\mathbf{x}}^T\underline{\mathbf{P}}^{-1}\delta\underline{\mathbf{x}}$.

The solution is to model $\underline{\mathbf{P}}$ using a sequence of operations we can compute, then use these to transform $\delta\underline{\mathbf{x}}$ so that $\frac{1}{2}\delta\underline{\mathbf{x}}^T\underline{\mathbf{P}}^{-1}\delta\underline{\mathbf{x}}$ simplifies.

Met Office

4DVar: using climatological covariance $\mathbf{B}$

Model 3D covariance using transforms	$\mathbf{B} = \mathbf{U}\mathbf{U}^T$
3D analysis increment	$\delta\mathbf{x}_0 = \mathbf{U}\mathbf{v}^c$
made 4D using linear forecast model $\underline{\mathbf{M}}$	$\delta\underline{\mathbf{x}} = \underline{\mathbf{M}}\delta\mathbf{x}_0$
Implicit 4D prior covariance	$\underline{\mathbf{P}} = \underline{\mathbf{M}}\mathbf{B}\underline{\mathbf{M}}^T$
Transformed penalty function	$J(\mathbf{v}^c) = \frac{1}{2}\mathbf{v}^{cT}\mathbf{v}^c + \frac{1}{2}(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o)^T \underline{\mathbf{R}}^{-1}(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o)$

Weaknesses of 4DVar.

- $\mathbf{B}$ – no flow-dependent **E**rrors **O**f **T**he **D**ay
  1. Use recent ensembles to train a new $\mathbf{B}$
  2. Use current ensemble to supplement $\mathbf{B}$
- Parallelisation – sequential runs of $\underline{\mathbf{M}}$ & $\underline{\mathbf{M}}^T$
  1. Parallelise in time too
  2. Use an ensemble instead (4DEnVar)
- No direct analysis ensemble
  1. Use a perturbed observation ensemble of 4DVars
  2. Use a separate EnKF system

Ensemble covariance filtering

B is big! We need a large ensemble PLUS clever filtering to reduce sampling noise, based on 2 ideas:

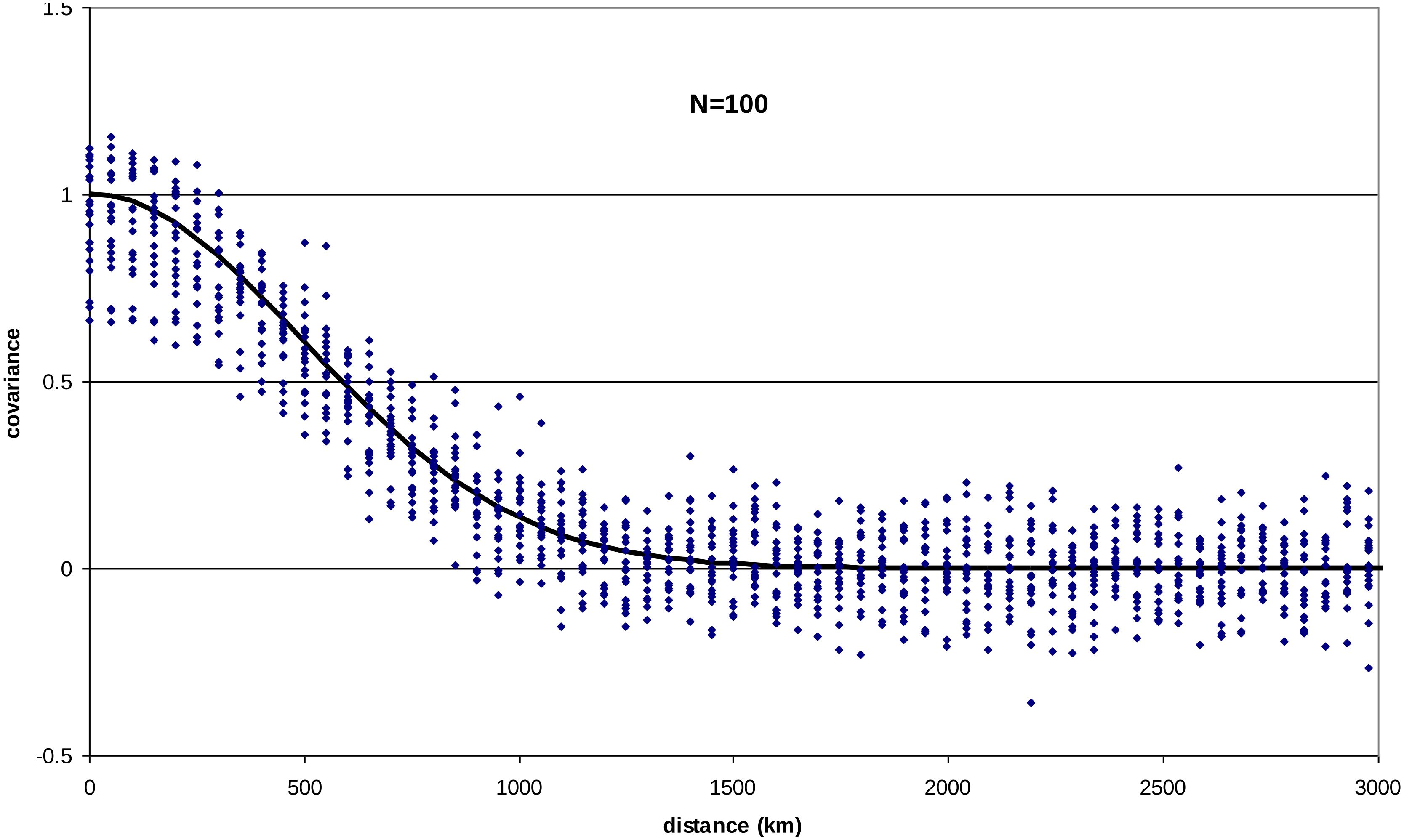
- Assume local homogeneity − apply smoothing:
  horizontal, rotational, and time
- Assume some correlations are near zero, & localise:
  horizontal, vertical, spectral, between transformed variables

Two approaches to hybrid covariances, using these ideas:

1. Train a covariance model using recent ensembles
2. Augment **B** by using localised ensemble perturbations

Horizontal localisation

Errors in sampled ensemble covariances

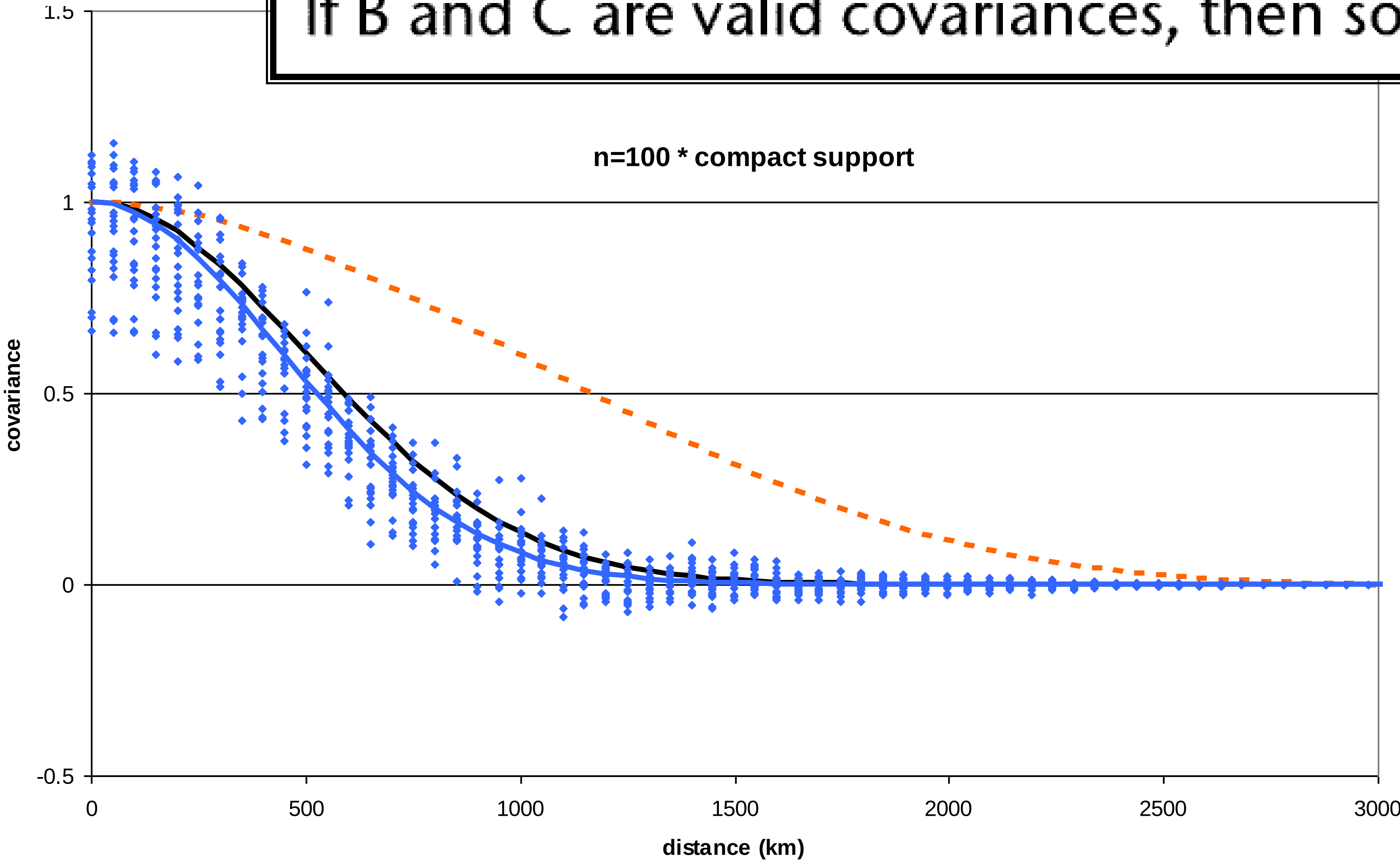


From Lorenc (2003)

The Schur Product

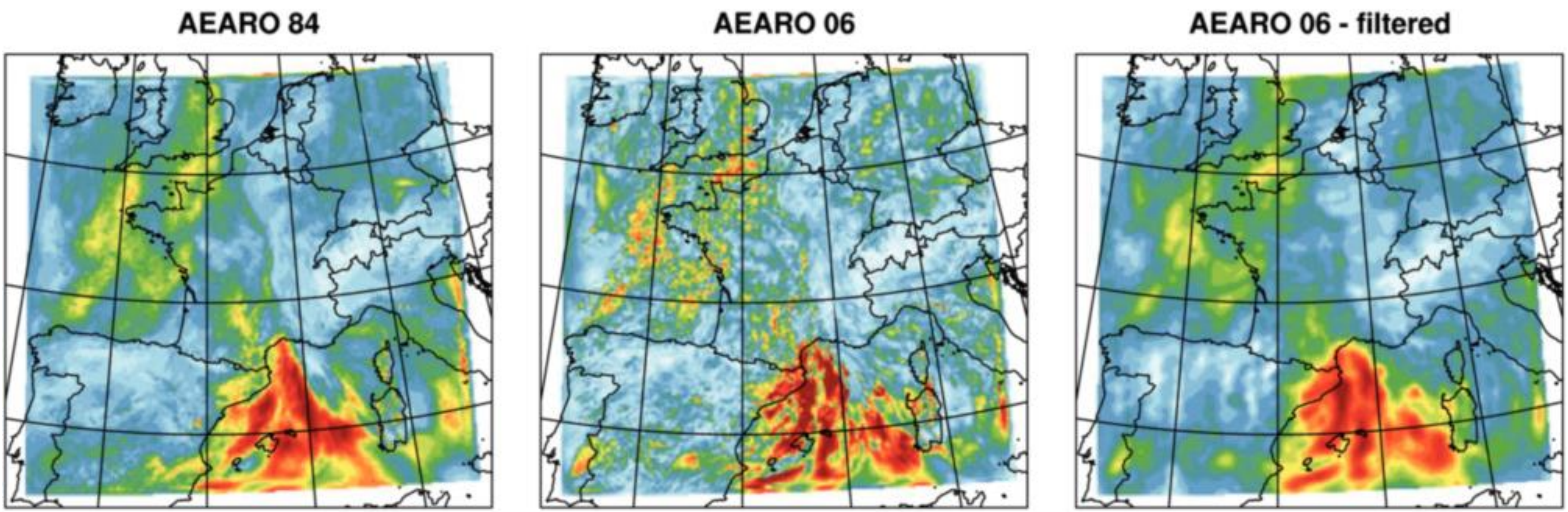
$\mathbf{A} = \mathbf{B} \circ \mathbf{C}$ such that $A_{i,j} = B_{i,j} C_{i,j}$.

If B and C are valid covariances, then so is A.



From Lorenc (2003)

Convective-scale ensemble s.d. of humidity at 945hPa



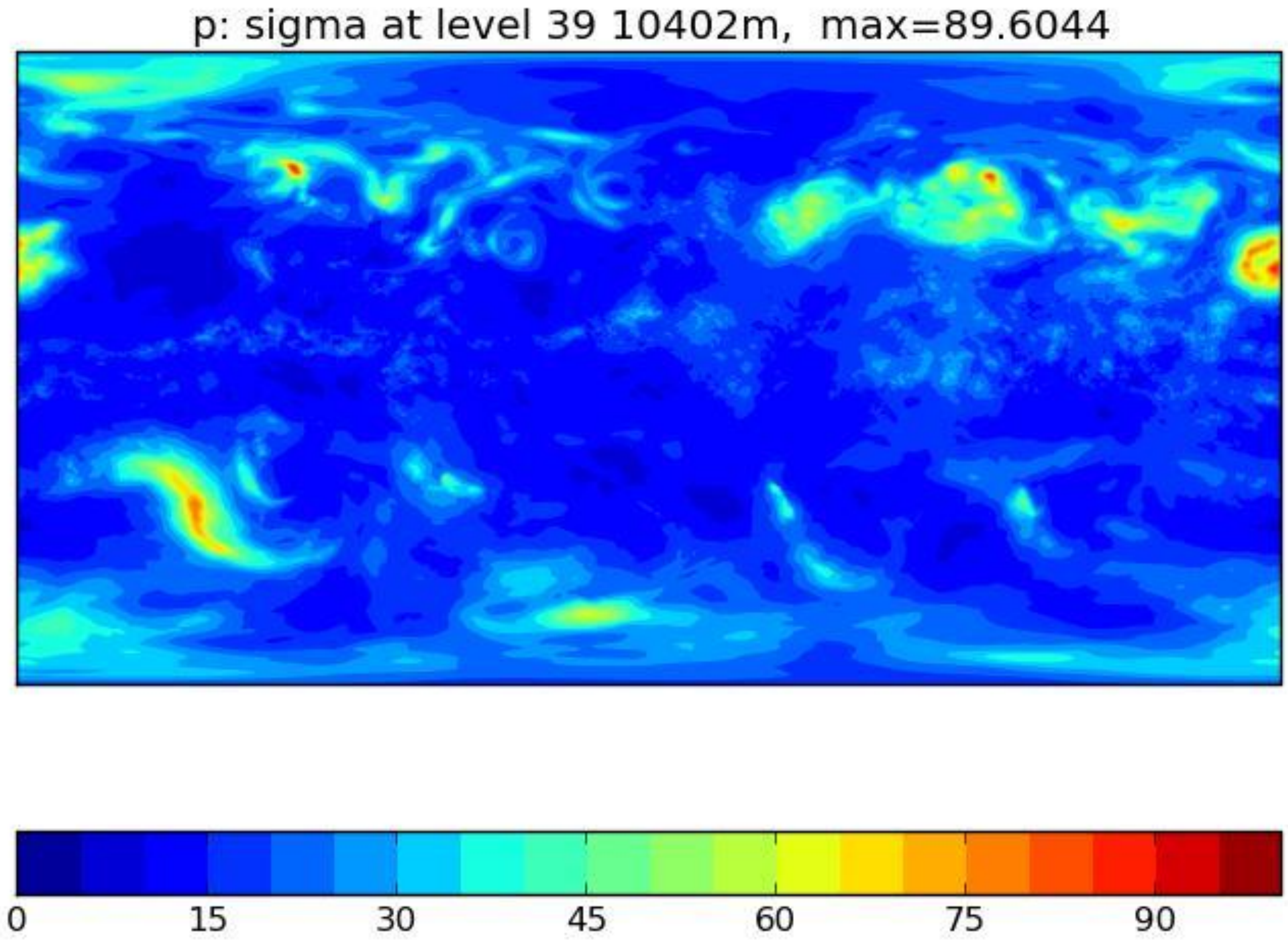
Large ensemble (84 members)

Small ensemble (6 members)

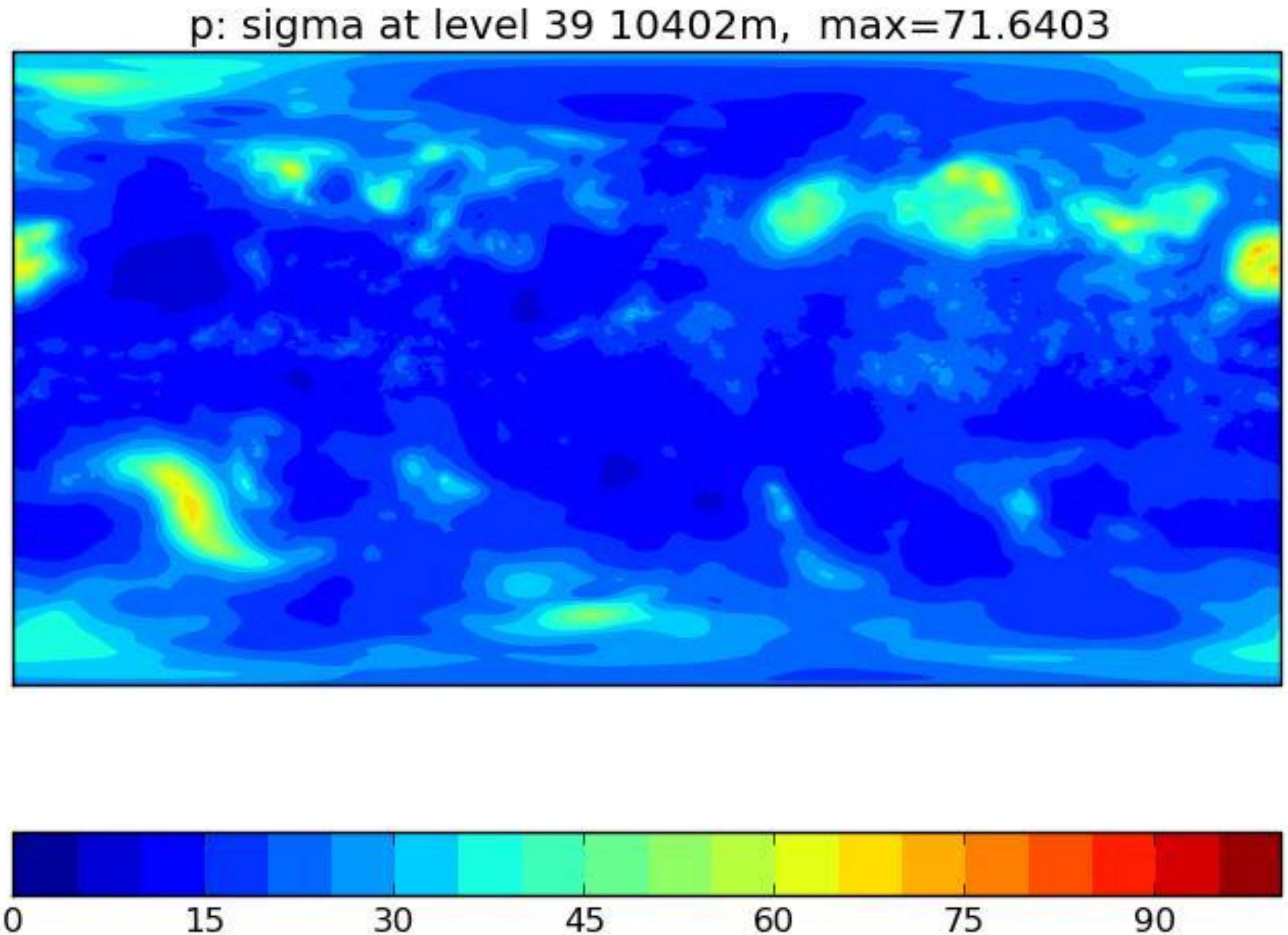
Horizontally filtered small ensemble

Using the AROME ensemble (Ménétrier et al. 2014).

Sampled raw ensemble s.d.



s.d. after spectral localization

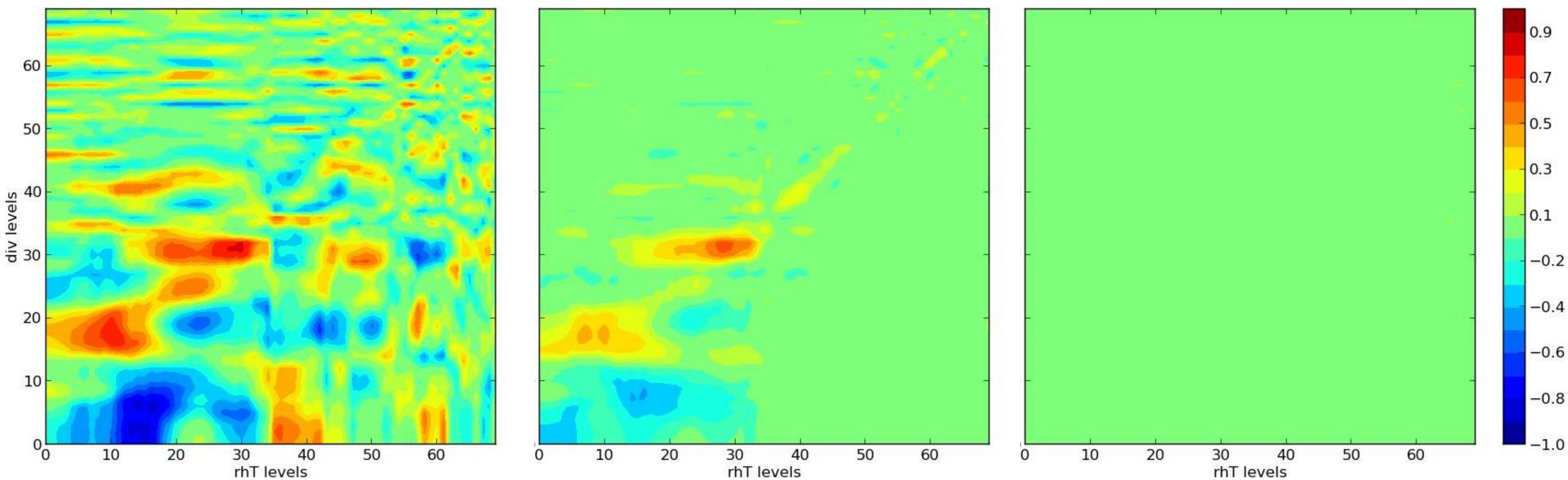


Column cross-correlations between: divergence (up) & relative humidity (across).

Raw ensemble

Horizontally, vertically & spectrally localized ensemble

Inter-variable localized ensemble



Ensemble covariance filtering: ***Conclusions***

The two approaches to hybrid covariances:

1. *Train a covariance model using recent ensembles*
2. *Augment $\mathbf{B}$ by using localised ensemble perturbations*

start from different ends; *1* starts from a climatological covariance model, then adds ensemble derived coefficients, *2* starts from a raw ensemble then filters the covariances. Eventually they might meet in the middle.

As we shall see later, there is less scope for these methods in the EnKF, other than simple spatial localisation.

En-4DVar: using an ensemble of 3D states which samples background errors

Ensemble perturbation matrix $\mathbf{X} = \left[\mathbf{x}'_1 \ \cdots \ \mathbf{x}'_N \right]$ where $\mathbf{x}'_k = \frac{1}{\sqrt{N-1}} \left(\mathbf{x}_k - \bar{\mathbf{x}} \right)$

Model 3D $\mathbf{P}$ as localised ensemble covariance,

$$\mathbf{P} = \mathbf{C} \circ \mathbf{X}\mathbf{X}^T$$

then model $\mathbf{C}$ using transforms

$$\mathbf{C} = \mathbf{U}^\alpha \mathbf{U}^{\alpha T}$$

3D localised linear combination of ensemble perturbations

$$\boldsymbol{\alpha}_k = \mathbf{U}^\alpha \mathbf{v}_k^\alpha$$

$$\delta\mathbf{x}_0 = \Sigma_{k=1}^{N} \boldsymbol{\alpha}_k \circ \mathbf{x}'_k$$

then linear forecast model $\underline{\mathbf{M}}$

$$\delta\underline{\mathbf{x}} = \underline{\mathbf{M}} \delta\mathbf{x}_0$$

Localized 4D covariance

$$\underline{\mathbf{P}} = \underline{\mathbf{M}} \left(\mathbf{C} \circ \mathbf{X}\mathbf{X}^T \right) \underline{\mathbf{M}}^T$$

concatenated control vectors

$$\mathbf{v}^T = \left[\mathbf{v}_1^{\alpha T} \cdots \mathbf{v}_N^{\alpha T} \right]$$

Transformed penalty function

$$J\left(\mathbf{v}\right) = \frac{1}{2}\mathbf{v}^T\mathbf{v} + \frac{1}{2}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)^T \underline{\mathbf{R}}^{-1} \left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)$$

hybrid-4DVar

4D analysis increment $\delta\underline{\mathbf{x}} = \underline{\mathbf{M}}\left(\beta_c \mathbf{U}\mathbf{v}^c + \beta_e \Sigma_{k=1}^{N} \mathbf{U}^\alpha \mathbf{v}_k^\alpha \circ \mathbf{x}'_k\right)$

Localized 4D covariance $\underline{\mathbf{P}} = \underline{\mathbf{M}}\left(\beta_c^2 \mathbf{B} + \beta_e^2 \mathbf{C} \circ \mathbf{X}\mathbf{X}^T\right)\underline{\mathbf{M}}^T$

concatenated control vectors $\mathbf{v}^T = \left[\mathbf{v}^{cT}, \mathbf{v}_1^{\alpha T} \cdots \mathbf{v}_N^{\alpha T}\right]$

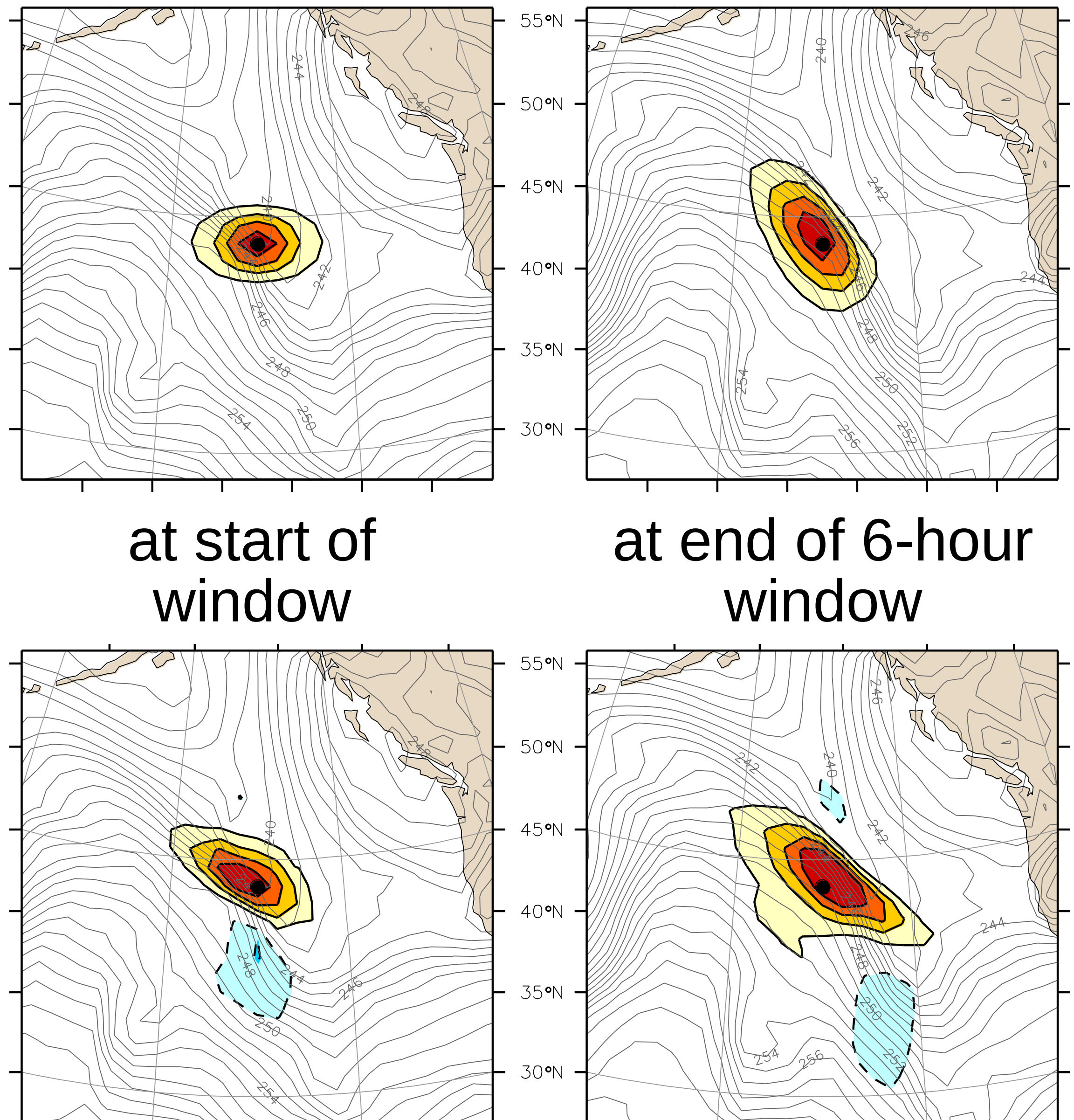
1% improvement in rms errors when implemented at Met Office (Clayton *et al*. 2013)

Met Office

u increments fitting a single u ob at 500hPa, at different times.

4D-Var

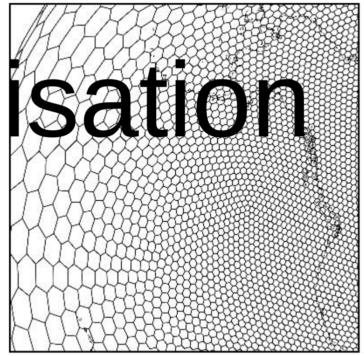
Hybrid 4D-Var

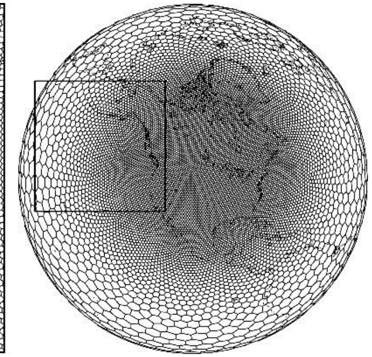


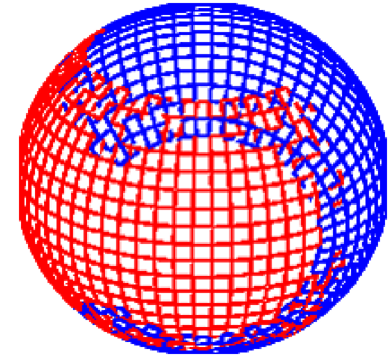
Unfilled contours show T field.

Clayton *et al.* 2013

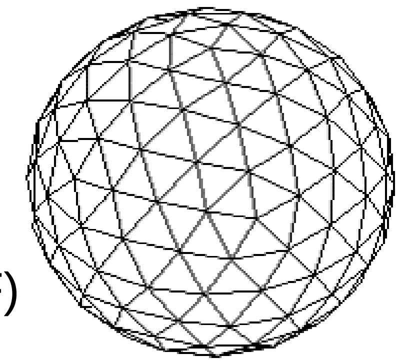
Parallelisation

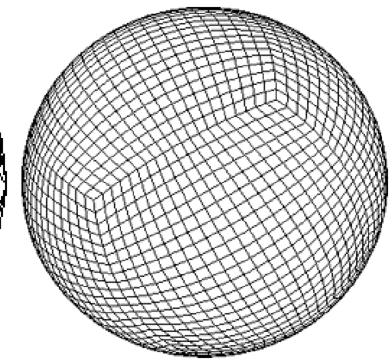






4DVar has several potential problems looming in the next decade - their timing for each centres will depend on their computers and models:





1. Need new design to use millions of parallel threads, especially in sequential runs of linear (PF) and Adjoint models.

2. Forecast models are being redesigned to address this − a maintenance issue for the PF and Adjoint models.

A simple solution is to use the ensemble trajectories, pre-calculated in parallel, instead of the models inside 4DVar.

If Fourier filters and Poisson solvers are not available then the LETKF is an easier approach.

4DEnVar: using an ensemble of 4D trajectories which samples background errors

Ensemble trajectory matrix $\underline{\mathbf{X}} = \left[\underline{\mathbf{x}}'_1 \ \cdots \ \underline{\mathbf{x}}'_N\right]$ where $\underline{\mathbf{x}}'_k = \frac{1}{\sqrt{N-1}}\left(\underline{\mathbf{x}}_k - \bar{\underline{\mathbf{x}}}\right)$

Model 4D $\underline{\mathbf{P}}$ directly, as localised ensemble covariance,

$$\underline{\mathbf{P}} = \underline{\mathbf{C}} \circ \underline{\mathbf{X}}\underline{\mathbf{X}}^T$$

then model $\underline{\mathbf{C}}$ using transforms

$$\underline{\mathbf{C}} = \underline{\mathbf{U}}^\alpha \underline{\mathbf{U}}^{\alpha T}$$

4D localised linear combination of ensemble trajectories

$$\underline{\boldsymbol{\alpha}}_k = \underline{\mathbf{U}}^\alpha \mathbf{v}_k^\alpha$$

$$\delta\underline{\mathbf{x}} = \Sigma_{k=1}^N \underline{\boldsymbol{\alpha}}_k \circ \underline{\mathbf{x}}'_k$$

concatenated control vectors

$$\mathbf{v}^T = \left[\mathbf{v}_1^{\alpha T} \cdots \mathbf{v}_N^{\alpha T}\right]$$

Transformed penalty function

$$J(\mathbf{v}) = \tfrac{1}{2}\mathbf{v}^T\mathbf{v} + \tfrac{1}{2}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)^T \underline{\mathbf{R}}^{-1}\left(\underline{\mathbf{y}} - \underline{\mathbf{y}}^o\right)$$

4DEnVar: using an ensemble of 4D trajectories which samples background errors

Extra Details

model $\underline{\mathbf{C}}$ using transforms

$$\underline{\mathbf{C}} = \underline{\mathbf{U}}^{\alpha}\underline{\mathbf{U}}^{\alpha T}$$

It is common to use a 3D $\mathbf{C}$

$$\mathbf{C} = \mathbf{U}^{\alpha}\mathbf{U}^{\alpha T}$$

and persistence in time: $\underline{\mathbf{I}}$

$$\underline{\mathbf{C}} = \underline{\mathbf{I}}\mathbf{C}\underline{\mathbf{I}}^{T}$$

4D localised linear combination of ensemble trajectories

$$\delta\underline{\mathbf{x}} = \Sigma_{k=1}^{N}\, \underline{\boldsymbol{\alpha}}_k \circ \underline{\mathbf{x}}'_k$$

can be built from 3D localised perturbations and constant $\boldsymbol{\alpha}_k$.

$$\boldsymbol{\alpha}_k = \mathbf{U}^{\alpha}\mathbf{v}_k^{\alpha}$$

$$\delta\mathbf{x}(t) = \Sigma_{k=1}^{N}\boldsymbol{\alpha}_k \circ \mathbf{x}'_k(t)$$

Matrix notation:

$$\mathbf{A} = \left[\, \boldsymbol{\alpha}'_1 \;\cdots\; \boldsymbol{\alpha}'_N \,\right]$$

$\mathbf{1}_N$ is a column vector of N 1s

$$\delta\mathbf{x}(t) = (\mathbf{A} \circ \mathbf{X}(t))\, \mathbf{1}_N$$

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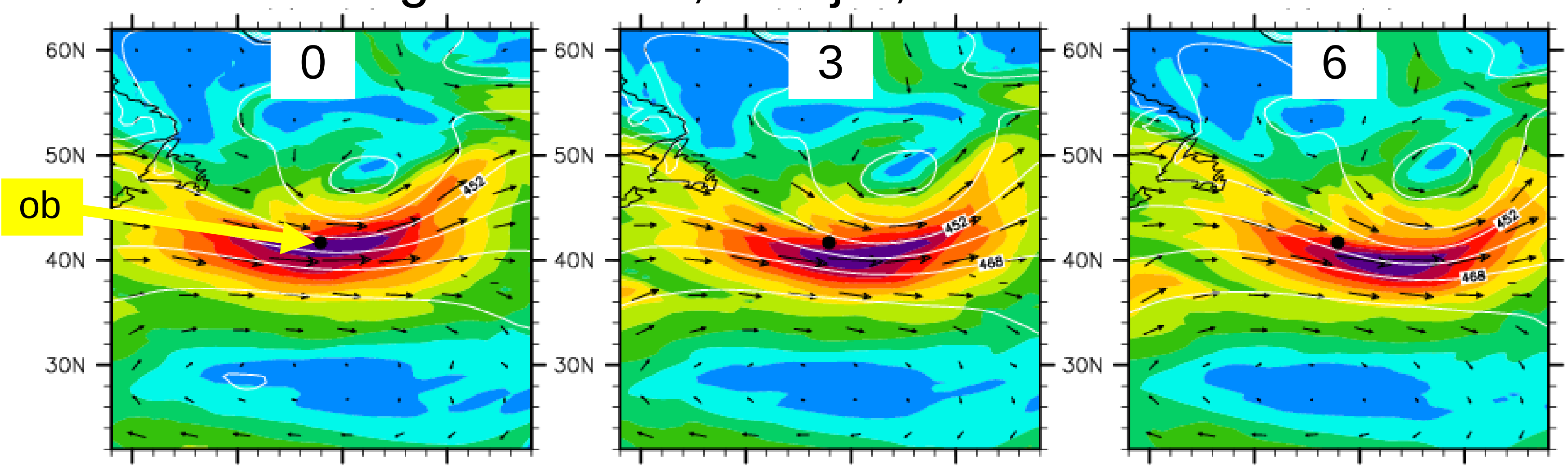
An new form of linear model

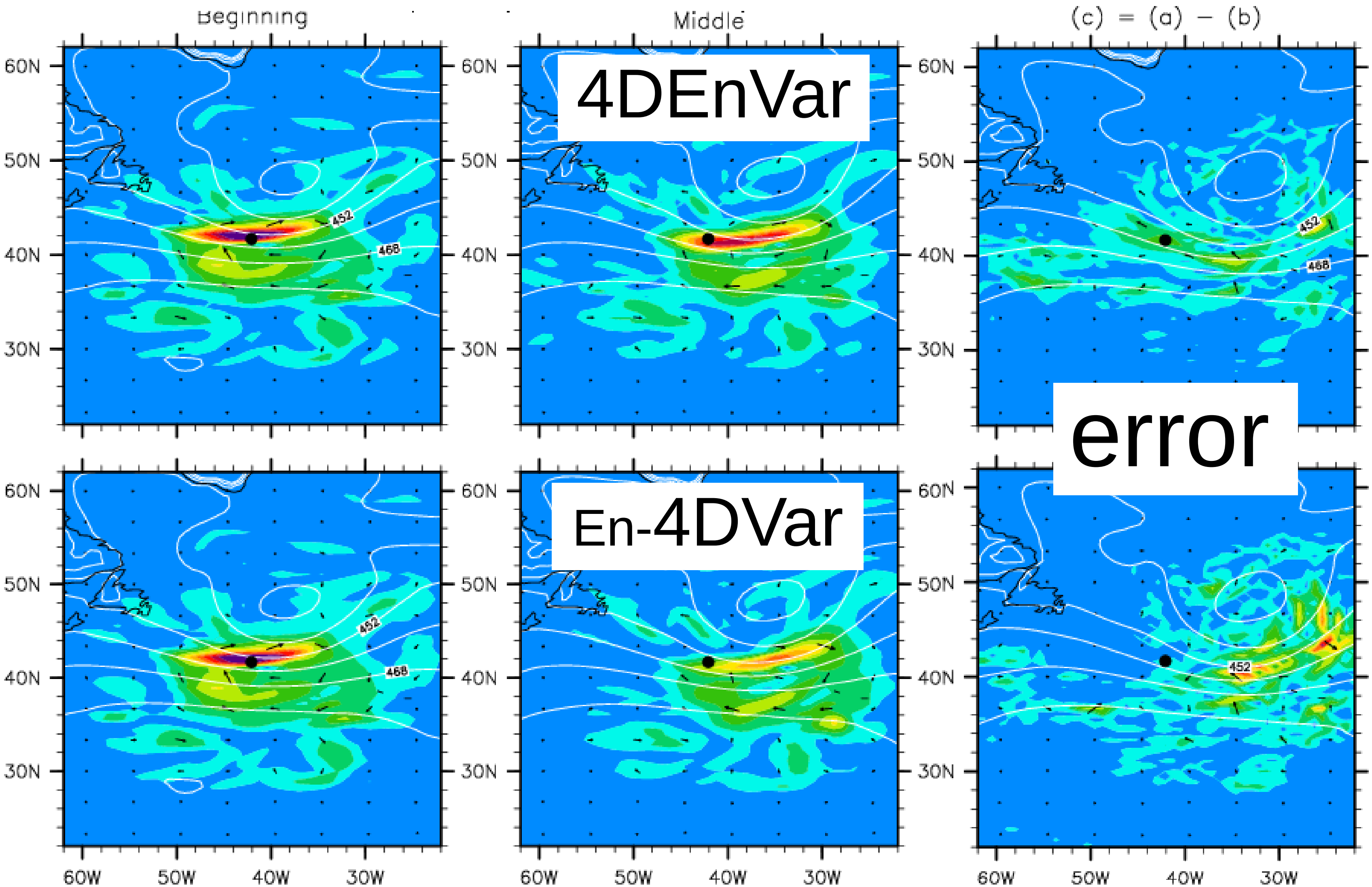
En-4DVar analysis increment $\delta\underline{\mathbf{x}} = \underline{\mathbf{M}}\, \Sigma_{k=1}^{N} \boldsymbol{\alpha}_k \circ \mathbf{x}'_k$

4DEnVar analysis increment $\delta\underline{\mathbf{x}} = \Sigma_{k=1}^{N} \underline{\boldsymbol{\alpha}}_k \circ \underline{\mathbf{x}}'_k$

Test with a single wind ob, in a jet, at the start of the window



100% ensemble
1200km localization scale



Met Office trial of 4DEnVar
Lorenc et al. (2014)

Our first trial copied settings from the hybrid-4DVar:

- C with localisation scale 1200km,
- hybrid weights $\beta_c^2=0.8$, $\beta_e^2=0.5$

Results were disappointing:

hybrid-4DVar
3.6% better

hybrid-4DEnVar
0.5% better

hybrid-3DVar = hybrid-3DEnVar

The reason was the large weight given to the climatological covariance, which is treated like 3DVar in 4DEnVar

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hybrid-4DEnVar

4D analysis increment $\delta\underline{\mathbf{x}} = \beta_c \underline{\mathbf{I}} \delta\mathbf{x}_0 + \beta_e \Sigma_{k=1}^{N} \underline{\boldsymbol{\alpha}}_k \circ \underline{\mathbf{x}}'_k$

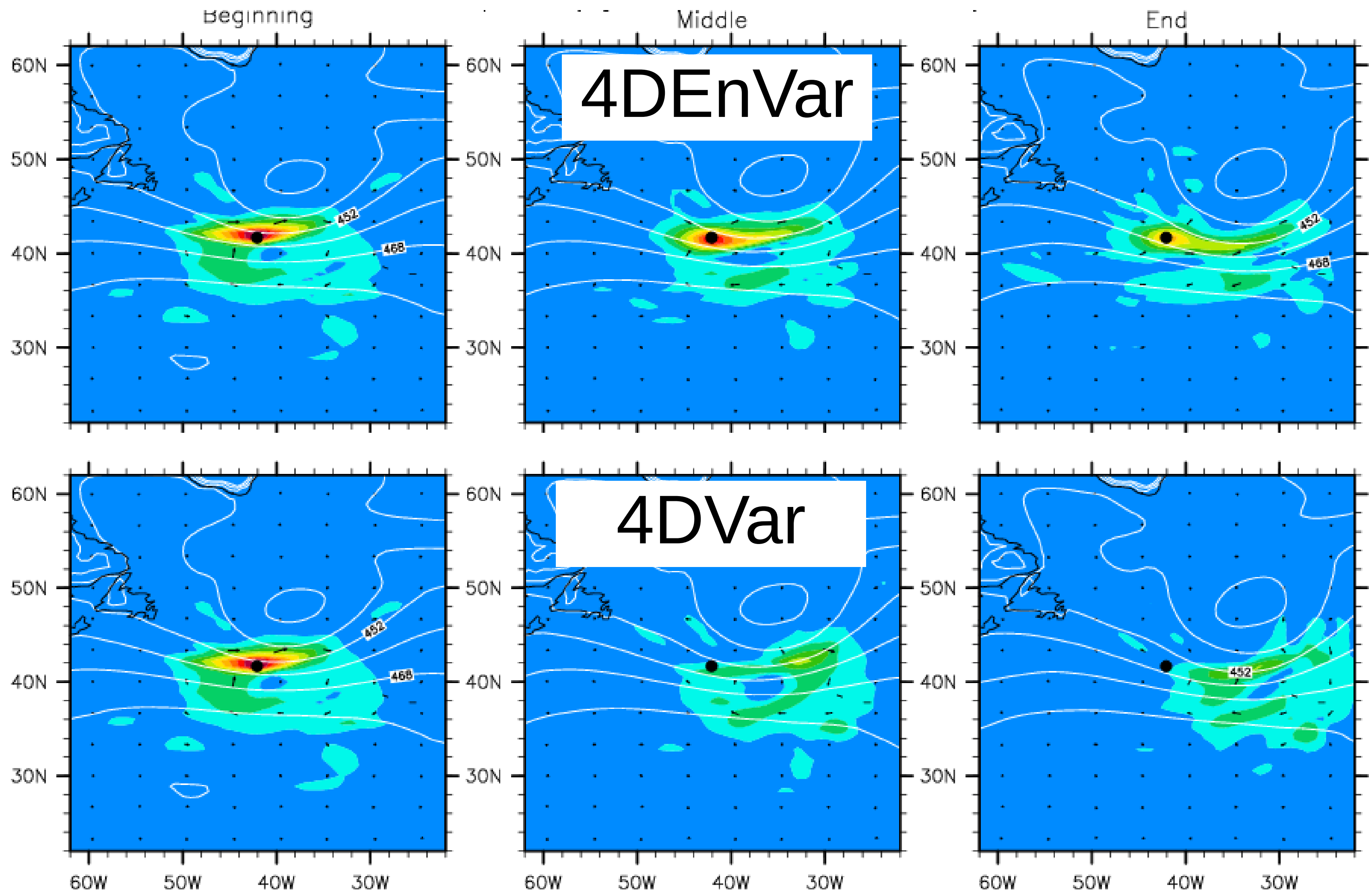
Localized 4D covariance $\underline{\mathbf{P}} = \beta_c^2 \underline{\mathbf{I}}\mathbf{B}\underline{\mathbf{I}}^T + \beta_e^2 \underline{\mathbf{C}} \circ \underline{\mathbf{X}}\underline{\mathbf{X}}^T$

hybrid-4DVar

4D analysis increment $\delta\underline{\mathbf{x}} = \underline{\mathbf{M}} \left(\beta_c \delta\mathbf{x}_0 + \beta_e \Sigma_{k=1}^{N} \boldsymbol{\alpha}_k \circ \mathbf{x}'_k \right)$

Localized 4D covariance $\underline{\mathbf{P}} = \underline{\mathbf{M}} \left(\beta_c^2 \mathbf{B} + \beta_e^2 \mathbf{C} \circ \mathbf{X}\mathbf{X}^T \right) \underline{\mathbf{M}}^T$

50-50% hybrid
1200km localization scale



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EnKF – common properties

Produce an analysis ensemble – need to distinguish $\underline{\mathbf{X}}^b$ (previously $\underline{\mathbf{X}}$) and $\underline{\mathbf{X}}^a$

Use the matrix of ensemble model-ob perturbations. For linear H $\underline{\mathbf{Y}}^b = \mathbf{H}\underline{\mathbf{X}}^b$

but it is calculated using nonlinear H:

$$\underline{\mathbf{y}}'_k = \frac{1}{\sqrt{N-1}}\left(\underline{H}\left(\underline{\mathbf{x}}_k^b\right) - \overline{\underline{H}\left(\underline{\mathbf{x}}^b\right)}\right)$$

$$\underline{\mathbf{Y}}^b = \left[\underline{\mathbf{y}}'_1 \cdots \underline{\mathbf{y}}'_N\right]$$

Most use the localised ob-gridpoint covariance $\underline{\mathbf{C}} \circ \underline{\mathbf{Y}}^b \underline{\mathbf{X}}^{bT}$

Stochastic filters (Houtekamer *et al.*, 2014) use the same analysis equation for each member and perturb observations (as in ensembles of 4DVar).

SQRT filters (Tippett *et al.*, 2003) analyses the ensemble mean, then calculate perturbations such that $\underline{\mathbf{X}}^a \underline{\mathbf{X}}^{aT} = \underline{\mathbf{P}}^a$.

LETKF

The equations of Hunt *et al.* (2007); Harlim and Hunt (2007) apply the factor $1/\sqrt{N-1}$ to $\mathbf{w}$ & $\boldsymbol{\alpha}$ rather than $\mathbf{X}^b$.

ETKF for mean analysis

$$\delta\underline{\mathbf{x}} = \underline{\mathbf{X}}^b\mathbf{w}$$

$$\mathbf{w} = \tilde{\mathbf{P}}^a\left(\underline{\mathbf{Y}}^b\right)^T\mathbf{R}^{-1}\left(\underline{\mathbf{y}}^o - \underline{H}\left(\underline{\mathbf{x}}^b\right)\right)$$

The ensemble-space matrix inversion is solved directly

$$\tilde{\mathbf{P}}^a = \left[\mathbf{I} + \left(\underline{\mathbf{Y}}^b\right)^T\mathbf{R}^{-1}\underline{\mathbf{Y}}^b\right]^{-1}$$

SQRT-filter for the analysis pertubations

$$\underline{\mathbf{X}}^a = \left(\tilde{\mathbf{P}}^a\right)^{1/2}\underline{\mathbf{X}}^b$$

LETKF solves these equations separately for each grid-point, with local observations.

Each point's $\mathbf{w}$ is a row of matrix

$$\mathbf{A} = \left[\,\boldsymbol{\alpha}'_1 \ \cdots \ \boldsymbol{\alpha}'_N\,\right]$$

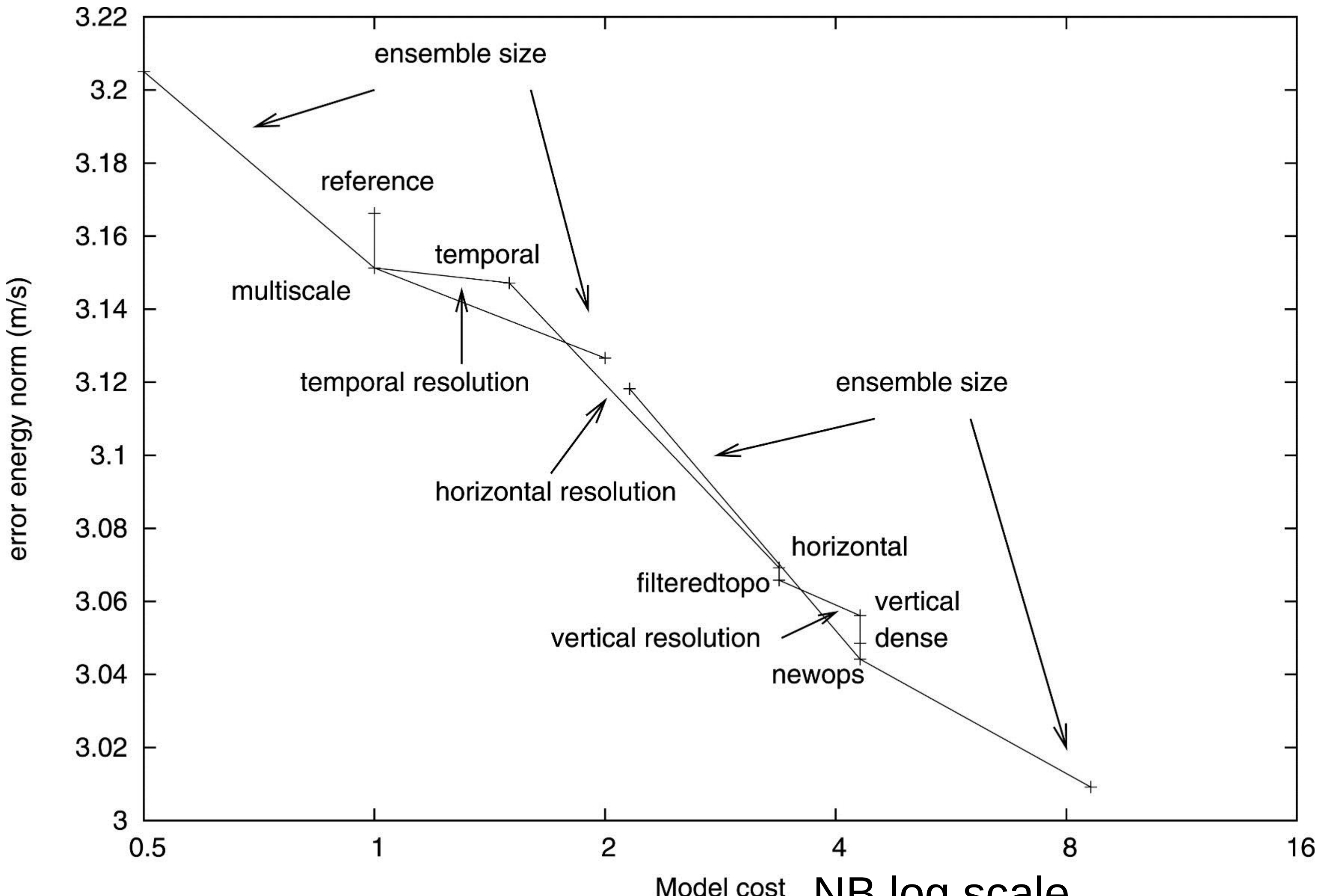
Equivalent to 4DEnVar

$$\delta\mathbf{x}(t) = (\mathbf{A} \circ \mathbf{X}(t))\,\mathbf{1}_N$$

EnKF summary

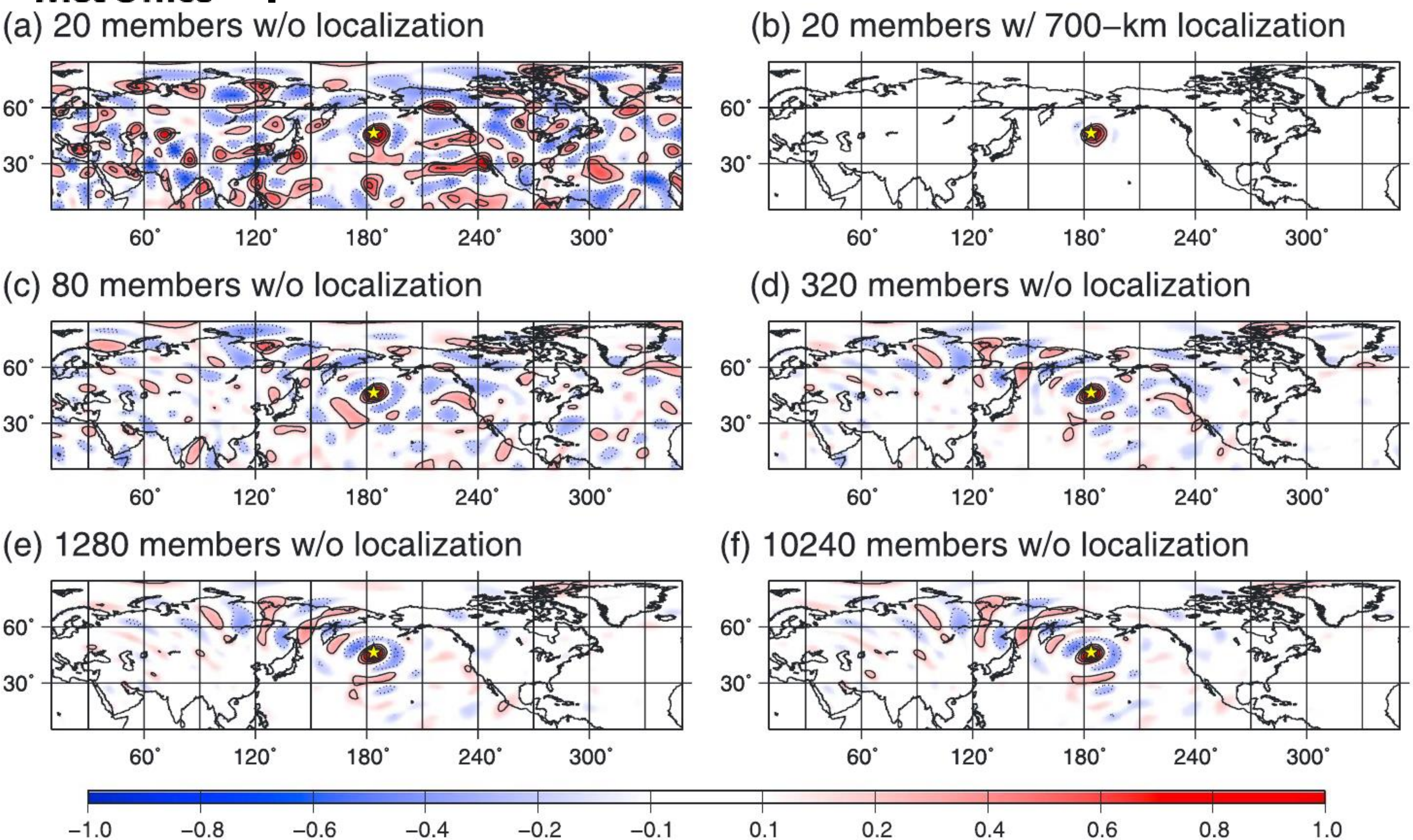
- EnKF are usually implemented in more straightforwardly way than variational schemes: model-ob values are calculated from each member, and used to calculate covariances with all model variables.
- A design goal in to keep the analysis cost small compared to that of the ensemble forecasts.
- Spatial localisation is used, in observation space.
  The localisation should select <*N* useful observations.
- Ensemble sizes can be quite large, e.g. Houtekamer et al. (2014) showed benefit from increasing the ensemble size above 196.
  In an experiment with the SPEEDY model, Miyoshi *et al*. 2014 tested ensemble up to 10240!

Cost & benefit of improvements to the EC EnKF system (Houtekamer *et al*. 2014)



NB log scale

Corellations with the central point ⭐ (Miyoshi *et al*. 2014)



Difficult Issues relevant to satellite DA

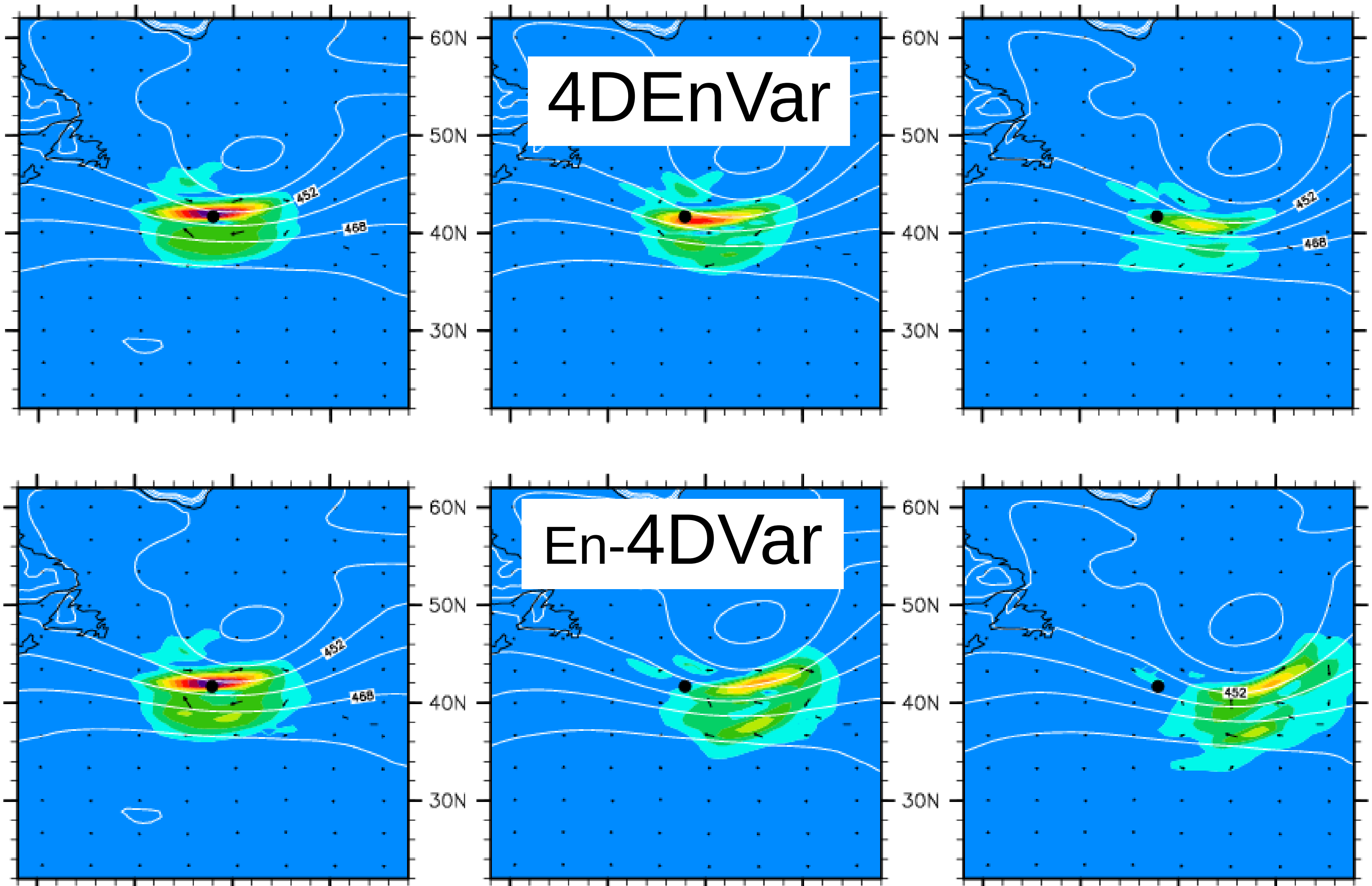
A small selection of potential difficulties -- their relevance depends on the application and NWP system.

- Dense but incomplete observations, tracers
- Synergistic observations
- Cloudy inversions
- Non-Gaussian observed variables
- Initialisation – Spin-up – Staying near the attractor

Dense but incomplete observations, tracers

- Remote sensing normally gives dense but incomplete obs
- Prognostic eqns link space & time gradients of variables
- Tracers give simplest example (but others as important)
- 4DVar can get winds from tracers (Mary Forsythe's talk)
- So can Extended KF, if obs network is good (Daley 1996)
- For the EnKF, strong spatial localisation hinders deriving longer-scales in wind field.
- For 4DEnVar, scale-dependent localisation may help (work in progress)

100% ensemble
500km localization scale



Synergistic observations

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- If observations' "footprints" (i.e. the model variables which predict them) overlap, then it helps to use them together
- Observation-space localisation $\underline{\mathbf{C}} \circ \underline{\mathbf{Y}}^b \underline{\mathbf{X}}^{bT} = \underline{\mathbf{C}} \circ \mathbf{H}\underline{\mathbf{X}}^b \underline{\mathbf{X}}^{bT}$ damages this. Model-space localisation $\underline{\mathbf{C}} \circ \underline{\mathbf{X}}^b \underline{\mathbf{X}}^{bT}$ (as in 4DEnVar) does not.
- Campbell et al. (2010) showed that observation space localisation degraded a 1D ensemble DA of radiances.
- My example is >30 years old!

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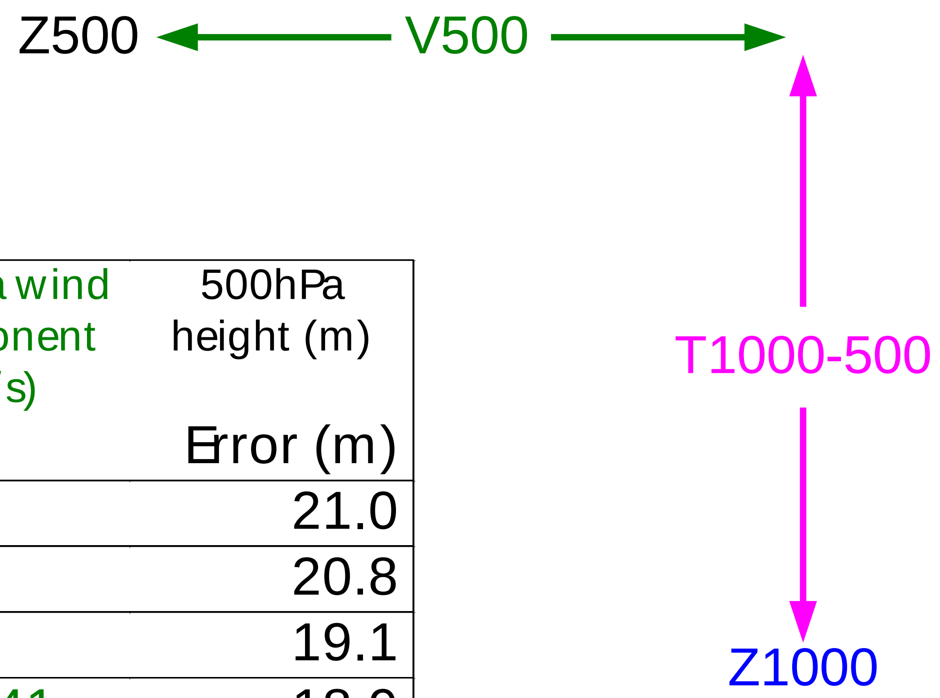
Analysis error for 500hPa height for different combinations of error-free observations.



1000hPa height (m) (surface P)	1000-500hPa thickness (m) (layer-mean T)	500hPa wind component (m/s)	500hPa height (m)
	weights		Error (m)
			21.0
0.143			20.8
	0.419		19.1
		0.441	18.9
	0.611	0.628	14.4
0.192		0.461	18.4
0.520	0.699		16.7
0.853	1.147	0.880	1.9

Lorenc, A.C. 1981: "A global three-dimensional multivariate statistical analysis scheme." *Mon. Wea. Rev.*, **109**, 701-721.

N.B. using perfect obs

Low cloud

- Top priority problem for Met Office users
- Lorenc (2007) study of cloudy inversions in sondes & model

  ⇒The prior PDF is highly non-Gaussian

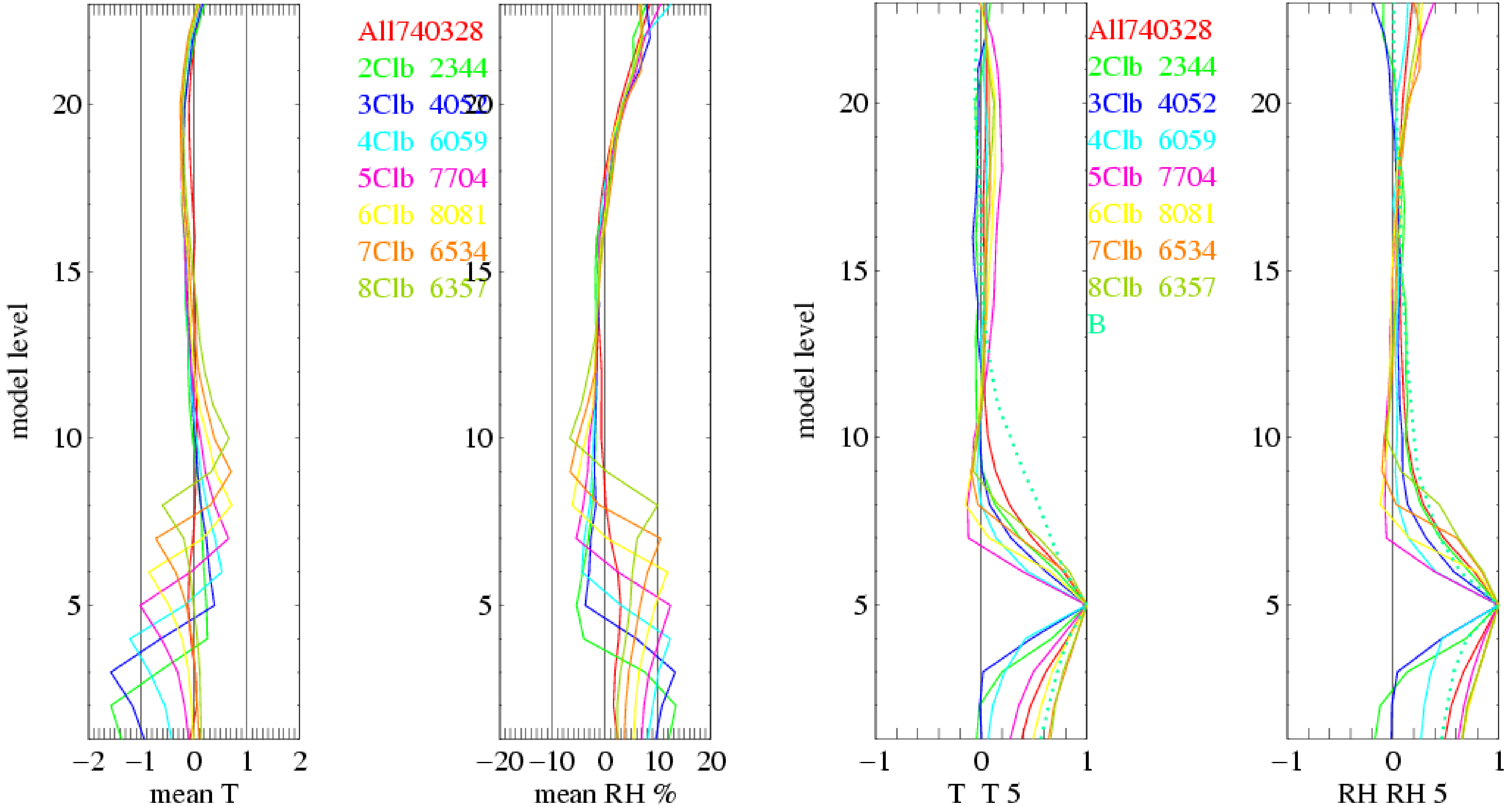
  ⇒High variances, & small correlation across inversion

- Ensemble covariances can help the second problem,
  but NOT the first.

Error PDFs composited by cloudy inversion level:

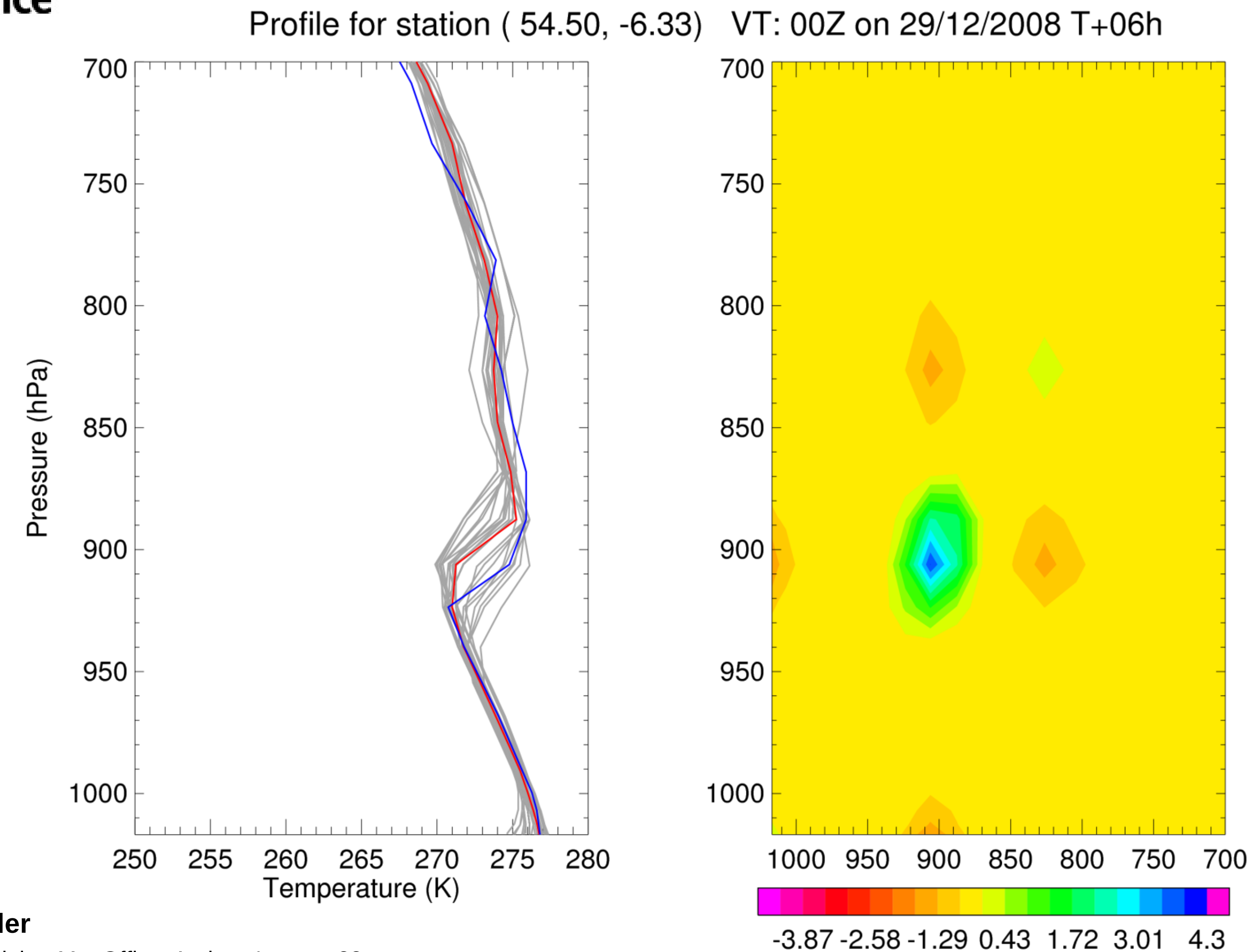
Left: mean of T & RH, ⇨ large bias

Right: correlations with level 5, ⇨ ~0 across inversion



Lorenc (2007)

Left: MOGREPS-R T profiles for a cloudy inversion: control sonde. Right: T covariances.



Neill Bowler

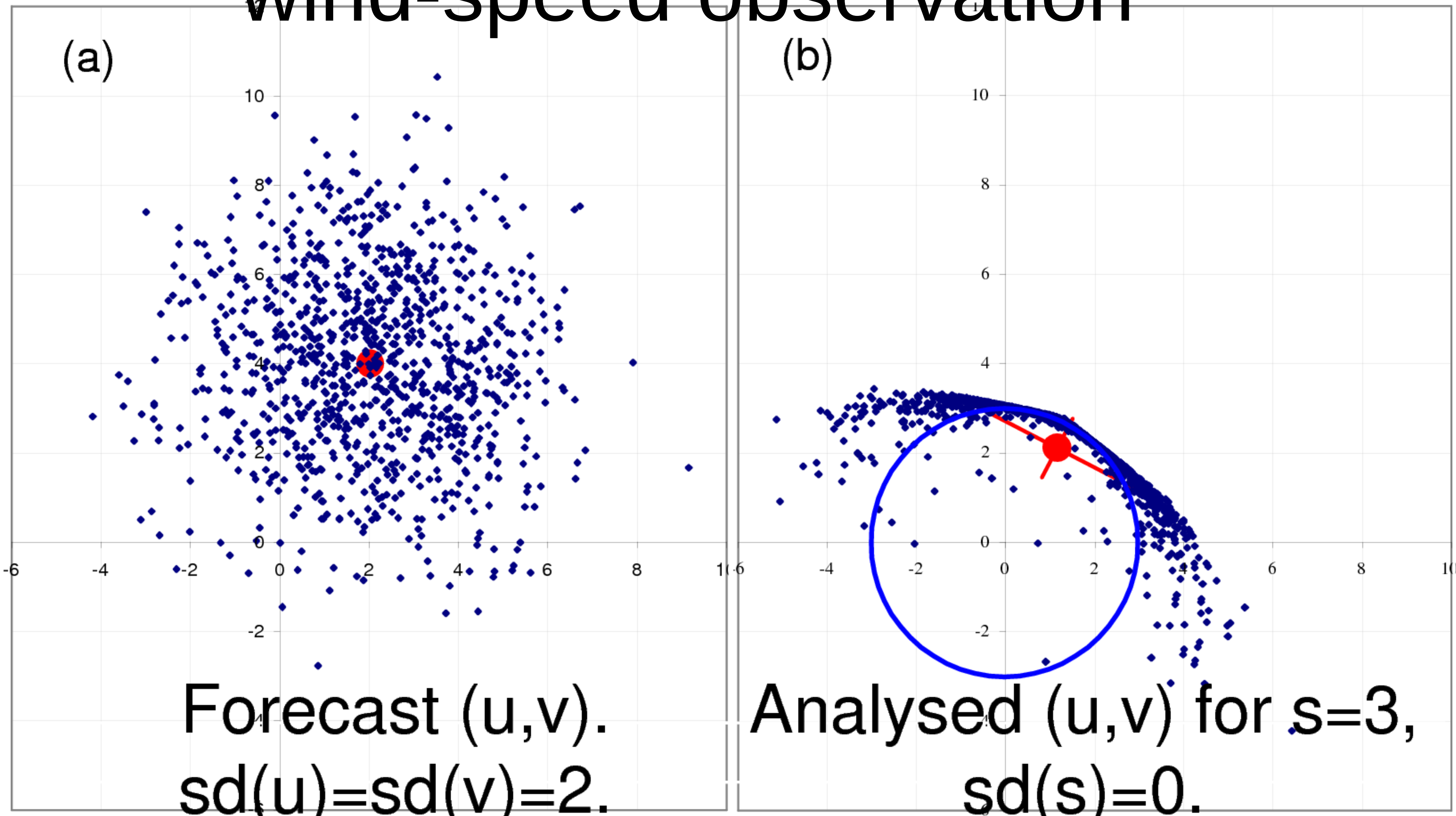
Nonlinear H non-Gaussian obs-errors

- Can be handled by 4DVar and 4DEnVar
  with outer-loop or nonlinear H in inner-loop.

- EnKF effectively linearises H using the background sample – this is not as accurate (but it is more robust)

- Observations of model-derived variables such as
  ppn, cloud, radar-reflectivity
  have been tried in 4DVar and EnKF.
  The EnKF is simpler to do.

Idealised EnKF of a perfect wind-speed observation



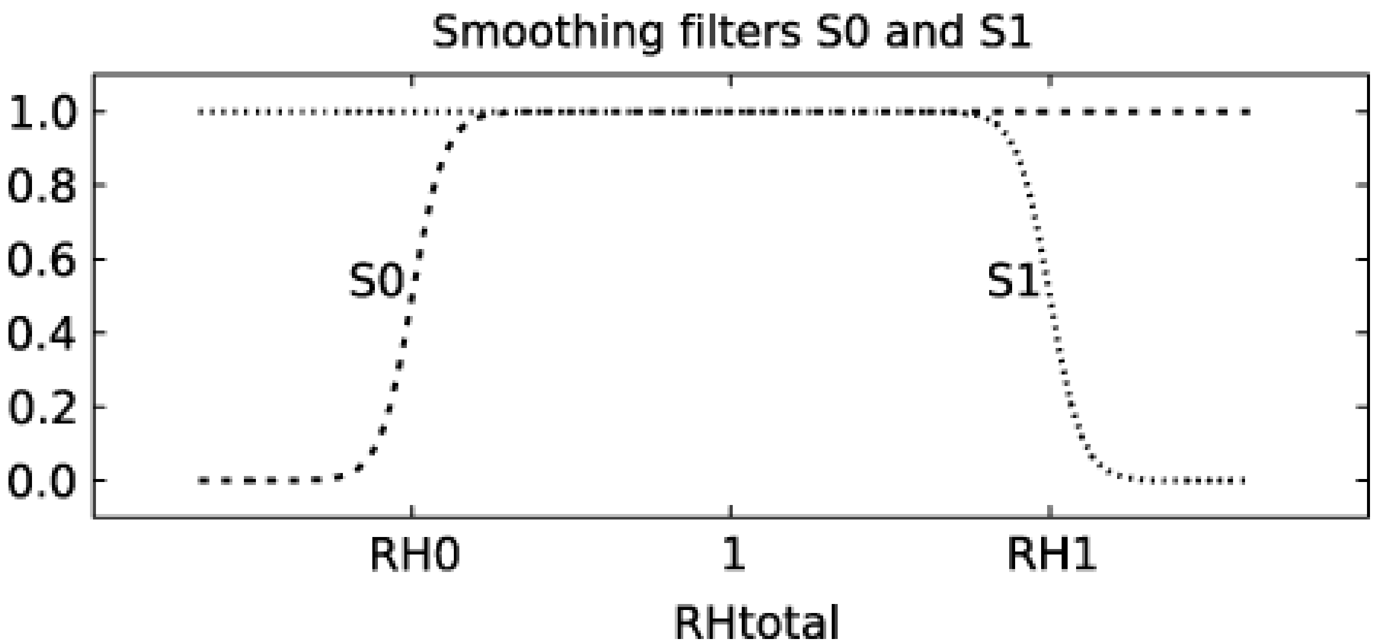
Forecast (u,v). sd(u)=sd(v)=2.

Analysed (u,v) for s=3, sd(s)=0.

Lorenc (2003)

Non-Gaussian cloud errors

(Renshaw and Francis 2011)



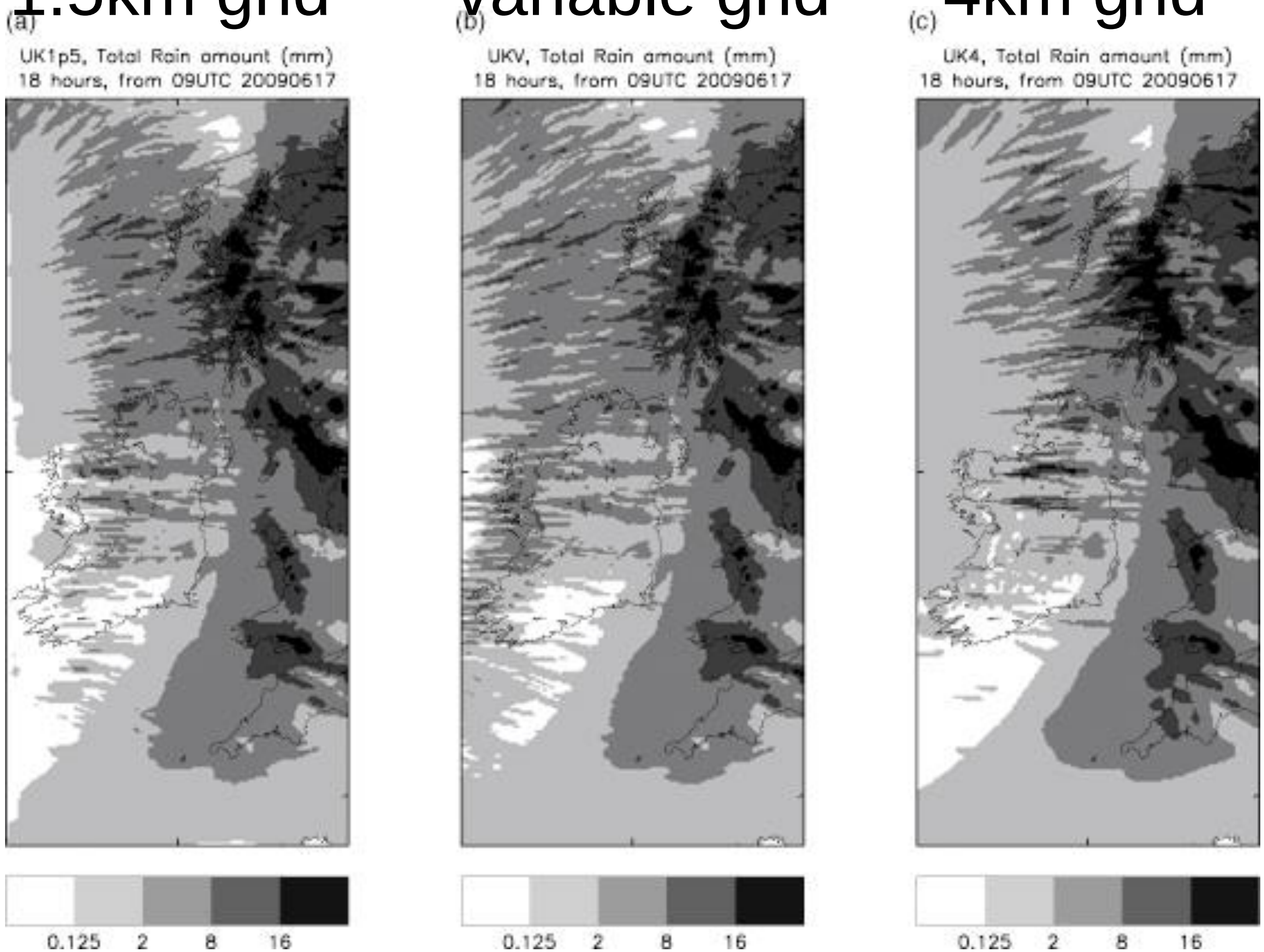
(Also VarQC, scatterometer de-aliasing, …)

Initialisation – Spin-up – Staying near the attractor

- In a linear world we would be blown away!
  We rely on nonlinear limits to growth of small perturbations,
- Resolution is increasing faster than observations,
  so the dependence on the model attractor is increasing.
  Diagnostic relationships are getting less useful.
- Technical fixes have been with us for years:
  - Incremental DA – leave the model alone if no obs!
  - Make increments smooth and balanced
  - Allow model to adjust when we add them:
    long enough window, 4DIAU, extra damping

Spin up of showery precipitation inside an inflow boundary

1.5km grid | variable grid | 4km grid



Tang et al. 2013

Vision – ideal Global DA
for NWP, using quasi-linear methods

- "Best estimate" DA of "known" scales (~12km), using 4D-Var because of:
  - Desire to treat all scales together;
  - Desire to make best use of satellite obs e.g. by bias correction, using high-resolution.
- Hybrid ensemble to carry forward error information from past few days.
- May still be scope for nested regional systems to give more rapid running and higher resolution.

N.B. This vision is good for perhaps a decade, while we are restricted to well known scales, so the KF theory of a "best estimate" + a covariance description of uncertainty is useful.

Some Personal Conclusions Long-term

- The scientific advantages of 4DVar are decreasing and will eventually not outweigh the increasing technical difficulties. (4DEnVar could be a replacement for 4DVar.)
- Convective-scale ensembles essential $\Leftarrow$ forecast uncertainty. Model dev, getting obs, & computational cost will dominate. Perhaps this militates in favour of the simple EnKF, but I prefer nested 4DEnVar, to handle all scales.
- Global NWP may fall further behind in computing, nevertheless, unless we get many more observations, convective−scale global NWP models will be available long before we know how to do their DA.

Question re global NWP

Met Office

- In 10~20 years we will be able to run global ensembles at resolutions such that the initial errors are non-Gaussian.
  - *If the ensemble mean is so smooth as to be significantly implausible as a real state, the errors are non-Gaussian.*
- Kalman Filter based methods (i.e. 4D-Var & EnKF) are not appropriate.
- [Nonlinear initialisation / the model attractor / spin-up] will be very important because of assimilation of imagery data and the desire for short-period precipitation forecasts.
- Models and observations will still be imperfect.
- Particle filters will be unaffordable.
- What will you do? (I will be retired ☺)

Questions?

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