Improving the Ensemble Covariances used in hybrid-4DVar & 4DEnVar.

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Andrew Lorenc, Mohamed Jardak, and others CERFACS, Toulouse. June 2017.

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- □ Hybrid-4DVar & 4DEnVar
- \Box Current Met Office strategy \Rightarrow this work.
- □ Exploratory toy & hybrid-4DEnVar experiments (Lorenc 2017)
- Choosing settings
 - Ménétrier diagnostics
 - Tuning experiments
- □ Results from hybrid-4DVar trials currently in progress
- Provisional Summary and Perspectives

Met Office Ours are incremental, with no outer-loop and no model error terms. Each gives a 4D best-fit to prior & observations in a 6 hour window. Use underline to denote 4D variables and operators:

Four-Dimensional Variational DA Methods

$$\mathbf{x}^{b}$$
 background trajectory

$$\mathbf{P}$$
 4D error covariance of \mathbf{x}^{b}
 $\delta \mathbf{x}$ 4D analysis increment

$$\mathbf{y} = H\left(\mathbf{x}^{b} + \delta \mathbf{x}\right)$$
 model estimate of obs

$$J\left(\delta \mathbf{x}\right) = \frac{1}{2}\delta \mathbf{x}^{T} \mathbf{P}^{-1}\delta \mathbf{x} + \frac{1}{2}\left(\mathbf{y} - \mathbf{y}^{o}\right)^{T} \mathbf{R}^{-1}\left(\mathbf{y} - \mathbf{y}^{o}\right)$$
 penalty function

4DVar uses linear model $\delta \mathbf{x} = \mathbf{M} \delta \mathbf{x}_0$

4DEnVar uses a linear combination of perturbation trajectories $\delta \mathbf{x} = \Sigma_{k=1}^{N} \mathbf{\alpha}_{k} \circ \mathbf{x}'_{k}$ hybrid \Rightarrow a combination of climatological and localized ensemble covariances.



hybrid-4DVar

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

Localised 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

$$\mathbf{v}^{T} = \left[\mathbf{v}^{cT}, \mathbf{v}_{1}^{\alpha T} \cdots \mathbf{v}_{N}^{\alpha T}\right]$$

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

Uses extended control variable;

– a non-quadratic *J* prevents us easily using other minimisation algorithms. Transforms ensemble **X** to variables used in balance transform: Ψ , *X*, ^{*a*}*P*, μ .



hybrid-4DEnVar

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

Localized 4D covariance $\mathbf{P} = \beta_c^2 \mathbf{IBI}^T + \beta_e^2 \mathbf{C} \circ \mathbf{XX}^T$

hybrid-4DVar

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

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



Met Office trial of 4DEnVar Lorenc et al. (2015)



- We expected hybrid-3DVar and hybrid-3DEnVar to perform equally.
- Adding the time-dimension in hybrid-4DVar made a big improvement,
- whereas adding it in hybrid-4DEnVar gave much less benefit.



- **1. B**^c was given large weight (80%) and treated differently: propagated by model in 4DVar, persisted in hybrid-4DEnVar.
- 2. Non-propagation of localisation.
- 3. Initialisation: 4DVar's J_c ensured that its increment was a balanced trajectory of the PF model.
- Insufficient degrees of freedom: more are needed before increasing weight on B^e, even more for <u>B^e</u>.
- Something else?
 Why did hybrid-4DVar beat hybrid-3DVar by so much?



Met Office R&D Strategy for global DA

- Concentrate on improving ensemble covariances
- Implement these first in hybrid-4DVar
 - only later will we revisit 4DEnVar option.
- Bigger & better ensemble generation using En-4DEnVar (Bowler et al. 2017)
- 2. Consistent climatological \mathbf{B}_c & related diagnostic studies (Wlasak, *work in progress*)
- **3.** Improving diagnosed ensemble covariances (Lorenc 2017)



Poster at ISDA Reading 2016: "Generalised Localisation -Improving ensemble-based covariance estimates for use in hybrid variational assimilation"

Lorenc (2017): Improving ensemble covariances in hybrid-variational data assimilation, without increasing ensemble size. *Q.J.R.Meteorol.Soc.* **143**, 1062-1072, doi:10.1002/qj.2990

- Tested, in a simple toy problem, methods which had been proposed in literature: Horizontal localisation, Spectral Localisation using Wavebands, Scaledependent localisation, Variance filtering, Hybridisation.
- Tested in hybrid-4DEnVar trials a combination of these, plus use of time-lagged and time-shifted ensemble perturbations.



Improved processing of the ensemble data **Waveband localisation**

- Suggested by Buehner and Charron (2207), Buehner (2012)
 - Correlations decrease with distance between horizontal wavenumbers, so split ensemble error modes into wavebands and assume they are uncorrelated.
 - Apply shorter localisation scales to shorter-scale bands.
 - Performance improvement in hybrid-4DEnVar with 48 members, similar to improvement from doubling the ensemble size to 96 members.Suggested BY
- 1. Split ensemble perturbations into horizontal spectral wavebands:



2. Localise each band with a suitable spatial localisation scale.

| For example: | Band: Scale (km |
|--------------|------------------|
| | — 1: 8115 |
| | — 2: 665 |
| | — 3: 230 |
| | — 4: 120 |
| | |



Good results in low-res hybrid-4DEnVar experiments.*



% change in RMSE vs. ECMWF analyses

Change \propto area of triangle



: at least 5% better

* Details in Lorenc (2017).



Improved processing of the ensemble data

Time-lagging and time-shifting



Current standard use of the ensemble.

Time-lagging: Add perturbations with longer lead-times, but correct validity times.
 Time-shifting: Add perturbations that are displaced in time.

(Equivalent to a smoothing in time.)



Good results in low-res hybrid-4DEnVar experiments.*



Change \propto area of triangle



: at least 5% better

* Details in Lorenc (2017).



- Number, size and shape of wavebands.
- Number of time-lags & time-shifts to use.
- Horizontal localisation scales for each waveband.
- Truncated eigen-expansion of vertical localisation matrix.
- Hybrid weights in $\mathbf{B} = \beta_c^2 \mathbf{B}_c + \beta_e^2 \mathbf{B}_e$

Cost (especially time in critical path) may be an issue.

Explore using the hybrid-diag method of Menetrier et al. (2015)



Wavebands copied from Lorenc (2017).



RMS zonal mean X-sections of u'



Raw ensemble



0.4 0.8 12 1.6 2.0 2.4 2.8 3.2 3.6 0.0

Sum of wavebands



waveband 4





covsampleen sampled background sigma in ar329n216nHnVwb3 u min=0.0549 mean=0.825 max= 3.93

1.6 2.0 0.8 1.2 2.4 2.8 3.2

waveband 3

covsampleen sampled background sigma in ar329n216nHnVwb2 u min=0.0765 mean= 1.1 max= 6.05



waveband 2

covsampleen sampled background sigma in ar329n216nHnVwb4 u min=0.0223 mean=0.454 max= 8.62



waveband 1

For a randomly chosen date in June

> 70 60

Aside: Wavebands & scale-dependent localisation can help with some tuning!



Changing localisation scale (from 600km to 800km) has mixed benefit when not using wavebands.

Changing all localisation scales (by factor 5/6) st has consistent benefit when using wavebands st with scale dependent localisation.



⇒ The regional variations in the split between wavebands take care of many regional variations in optimal tuning. (Lorenc 2017)



Ménétrier diagnostics

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- I used hybrid_diag_20160804 (not now the latest) from https://opensource.cnrm-game-meteo.fr/projects/hybrid_diag
- Diagnoses optimal filtering of ensemble covariances, to give best fit (Frobenius norm) to the covariance from a hypothetical infinite ensemble.
 - Frobenius norm "best" may not give best analysis.
 E.g. We localise Ψ, X, but want best analysis of their gradients u, v.
 - Assumes ensemble is perfect; often localisation and hybridisation are used to mask deficiencies in the ensemble.
 - Assumes ensemble members are independent; does not give correct results using lag-shift ensemble.
- I diagnosed optimal horizontal localisation for each waveband separately, then assumed these apply when they are combined.
 Because of this, I could not use the facility to diagnose hybrid β s.

Ménétrier et al. (2015); Ménétrier and Auligné (2015)



Horizontal localisation I diagnosed each variable, level independently.



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Horizontal localisation scales (km) for each waveband.

| | wb 1 | wb2 | wb3 | wb4 | |
|---------------------------------------|-------------|------|-----|-----|--------|
| Estimated & tuned by Lorenc (2017) | 6241 | 919 | 389 | 245 | BETTER |
| Diagnosed by hybrid-diag | 3039 | 1091 | 548 | 339 | |



Effect of horizontal localisation scales: Lorenc (2017) v hybrid-diag diagnosed

VERIFICATION VS OBSERVATIONS FROM 20150522 TO 20150626 **OVERALL CHANGE IN NWP INDEX = 0.120**

VERIFICATION VS ANALYSIS FROM 20150522 TO 20150626 OVERALL CHANGE IN NWP INDEX = 0.360

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T+120

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Γ+96

.

+72





Diagnosing vertical localisation

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- Only rather small differences between diagnosed localisation for different variables, or different wavebands.
- \Rightarrow Take mean over all variables, for unfiltered ensemble.
- Truncate to retain 90% variance, then renormalise.









Truncated and renormalised localisations





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- A. +6hr ensemble forecast, & IO to create perturbations Not on critical path.
- **B.** ×6 input of lag-shift ensembles into hybrid-VAR *Each ensemble is read in parallel, but different lag-shift are not.*
- **C.** ×**4** (wavebands) ×**6** (lag-shift) length of extended c.v. *Distributed over processors.*
- D. ×4 (wavebands) ×6 (lag-shift) transforms of control variables Distributed over processors.

High resolution 4DVar costs were dominated by PF and adjoint model forecast each iteration. It relies on low-res preconditioner to need fewer iterations. This doubles cost B.

The (~16) preconditioning vectors written and read have length **×24** (cost C), and IO is not currently parallel.



- Decision on next candidate upgrade (PS40) to be made in July, for final tests before implementation in Autumn.
- Costs of full wavebands + lag-shift package may rule it out. perhaps descope, e.g. wavebands + lag.
- Trials of revised **B**_e (Marek Wlasak) have shown benefit (and different optimal hybrid weights). This may be included.
- Coding to reduce critical costs can be done by PS41 in 2018.
- Ensemble of 4DEnVar (Ne=100) also candidate for PS41. This too increases costs.



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My poster at ISDA, Reading 2016



Generalised Localisation Improving ensemble-based covariance estimates for use in hybrid variational assimilation Andrew Lorenc



There are several methods, as well as the well known localisation, which can improve the covariance estimates from a small ensemble I demonstrate and tune them in a toy system and trial some in a full NWP system.

Toy Problem

256 points in a circle, with true error covariance B, a Gaussian-shaped function of distance, with large-scale variation in both the error variance and the correlation scale

Sample from B, of (N=10) perturbations with covariance Be. Errors in estimated B are measured using the RMS of elements of B-B. Freberius a

Improving the noisy B_e by:

 Horizontal localisation¹ applied using a Schur product B=LOB, where L is a localisation matrix of correlations with a specified scale.

Wavebands Spectral Localisation² A crude spectral localisation is achieved, projecting the ensemble onto wavebands and assuming independence. This has the effect of smoothing B

- Scale-dependent localisation. Use a different spatial localisation matrix for each waveband, with localisation scale increasing with wavelength.
- Variance filtering3. Smoothing with a specified scale is applied to the variance field - the correlations are unaltered.
- Hybridisation, A "climatological" B. used the same function as B., without the spatial variation of scale and variance. The hybrid combines \mathbf{B}_{c} (shown) with the localised B.

In the Ensemble Kalman Filter, only localisation is used. A potential advantage of ensemble-variational (EnVar) methods is that they can easily be combined, for example as in the plots below - the settings have been chosen to minimise |B-B.|



localisation & localisation & hvbrid variance filter & hybrid

Choosing the coefficients

Optimal settings depend on Ne and the methods used. I search parameterspace for the minimum (averaged over 512 samples) of |B-B.| or |A|-norms equal to the mean analysis error for one of 5 observation distributions.



Conclusions Toy Experiments

All the methods tested could make significant improvements to the sampled covariances

- The need for all the methods decreased with ensemble size and the optimal coefficients varied accordingly.
- [Waveband localisation + scale-dependent localisation] was better than [horizontal localisation + variance filtering] (both run without hybridisation).
- With hybridisation the difference was less. However the scale dependent localisation was more robust to the use of suboptimal localisation scales.
- The benefit of waveband localisation and scale-dependent localisation was not very sensitive to the algorithms used to define the bands and the scale dependence. The bands shown, with localisation scale increasing as wavelength^p with p=0.75, gave as good results as any tried.
- If not using wavebands, the variance filter was simple and beneficial. (It could also provide benefit in improved background variance fields for observation quality control.)
- The simple [B-B.] norm did not always give the same "optimal" settings as the analysis error norms. The latter halved the optimal localisation scales for dense observations.

Real NWP Experiments

- The best localisation scale increased with effective ensemble size, and varied with region (N.Hem., Tropics, S.Hem.).
- The use of 4 wavebands, with no change in localisation, consistently gave a small improvement (as predicted by the toy). Tuning scale-dependent localisation proved surprisingly difficult. My third try improved the Tropics and N.Hem., but degraded the S.Hem. Overall it was beneficial but more tuning is needed. (Probably the regional dependence of optimal scale is relevant.)
- The use of time-lagged ensemble perturbations consistently gave a small improvement.
- The use of time-shifted perturbations gave additional benefit But changing the shifts used from [3,6] hours to [1.2.3,4,5,6] hours did not
- Combining the best methods, it was possible to nearly match results from an Ne=200 ensemble, using only Ne=44.

Further Work

With all the methods (including the N_=200 ensemble) it proved difficult to improve all S.Hem. scores. Why?

The methods should be equally applicable to hybrid-4DVar (our current operational system) as to hybrid-4DEnVar tested here. Trials are needed – if successful, the methods can be implemented quickly.

We need better ways of choosing the correct settings. One hope is Ménétrier's method⁴, which calculates parameters to minimise |B-B_w| (B_w from a hypothetical infinite ensemble). This has two potential problems: it assumes that B,=B, and that minimising |B-B,| gives the best analysis. This can be illustrated by specifying B, to be different from B., Below B. & B., used different shaped covariances with the same variance and scale. In the top-righ plot, a short localisation is best, for the dense obs networks, for all N., correcting the Gaussian-shaped ensemble, which is too broad at short scales. Ménétrier's method should give the top-left Bnorm scales.



Real NWP System Experiments5 showed that hybrid-4DVar

or 4DEnVar, using simple spatial localisation, were significantly improved using N =200 instead of N =44. This improvement is my Can a similar improvement be obtained

by better estimation of covariances from a smaller ensemble?

target

target performance of an Ne=200

Methods for improving covariances

| | | mg cor | ana | | ~ | | | |
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| I ran hybrid-4DEnVar with a Ne=44 84 N512 forecasts against indepen | , N320 enser dent ECMWP | mble and verified F analyses. | NH ING | 1 | 1 | ÷ | | |
| A / ▼ indicate that the trial was better / worse than its control. | | | | 1 | ÷ | ÷ | 1 | 11 |
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| L=600km to L=800km | At Ne=4 | 44 that | 2 | ž | ž | 2 | 2.3 | 2.2 |
| change had mixed im | pact. (Fo | or the | NH PMS. | | | | | • * |
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