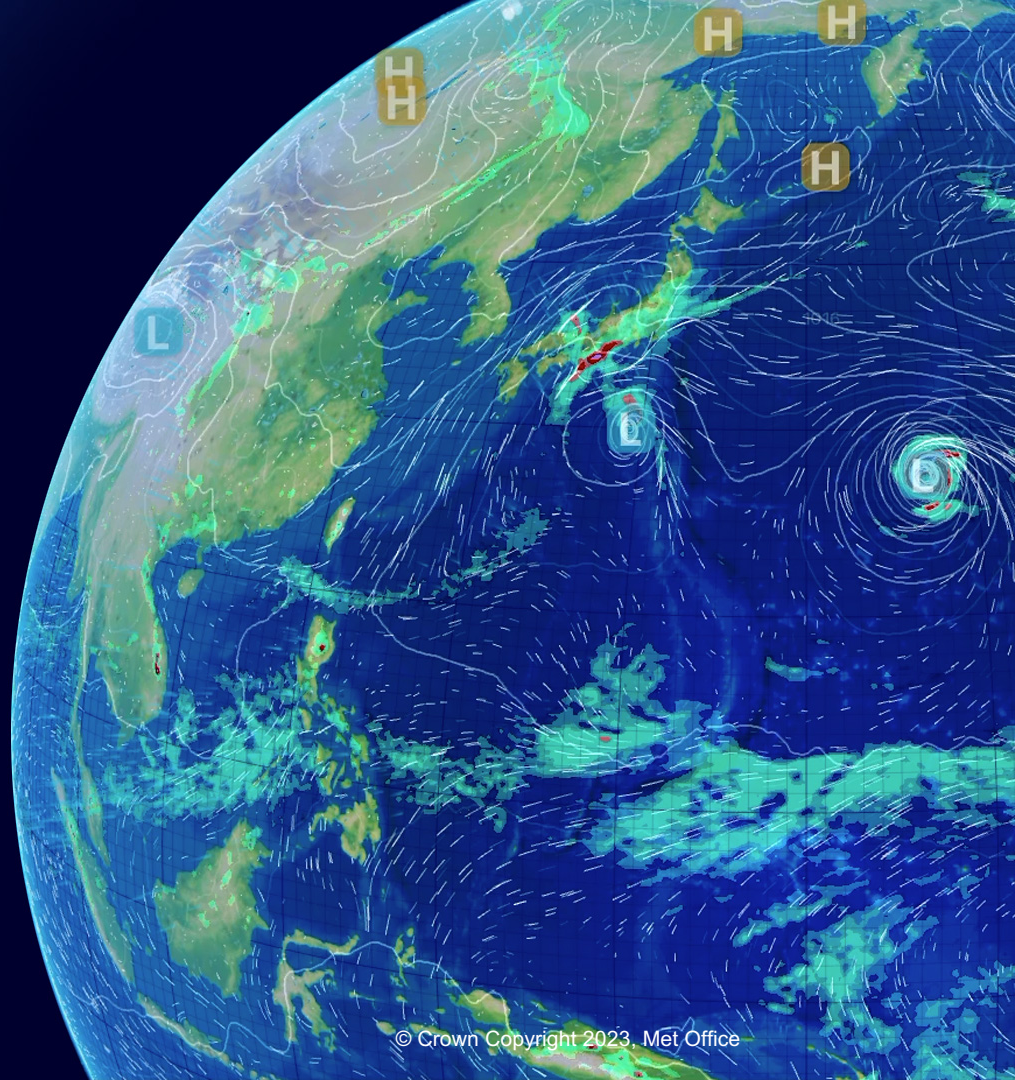


Designing new DA software for Operational Global NWP

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Met Office Next Generation Modelling System

The Met Office introduced its Unified Model in **1993** and a 4DVar DA system for it, in **2004**. The **UM** and **VAR** have for decades been the backbone of one of the best NWP systems.

In **2021** we started the NGMS Programme to *"Reformulating and redesigning our complete weather and climate research and operational/production systems, including oceans and the environment, to allow us to fully exploit future generations of supercomputer for the benefits of society"*



Momentum

The Unified Earth Environment
Prediction Framework

LFRic



NG-DA (a.k.a. NG-PAO)

Collaborative development: JEDI
Model-agnostic, Object Oriented.

Used to develop **JADA**:

Flexible choice of DA method

Constraints on global JADA

Low risk:

use scientific design from current operational methods,
or developments we have tested and published.

New software:

neither possible, nor desirable, to copy details of VAR system.

Collaboration:

prefer approaches [which might be] used by JEDI collaborators.

New requirements: *ensemble-first* NWP system

more frequent “best estimate” analysis (**R**apid **U**ppdate **C**ycle).

Global DA assumptions

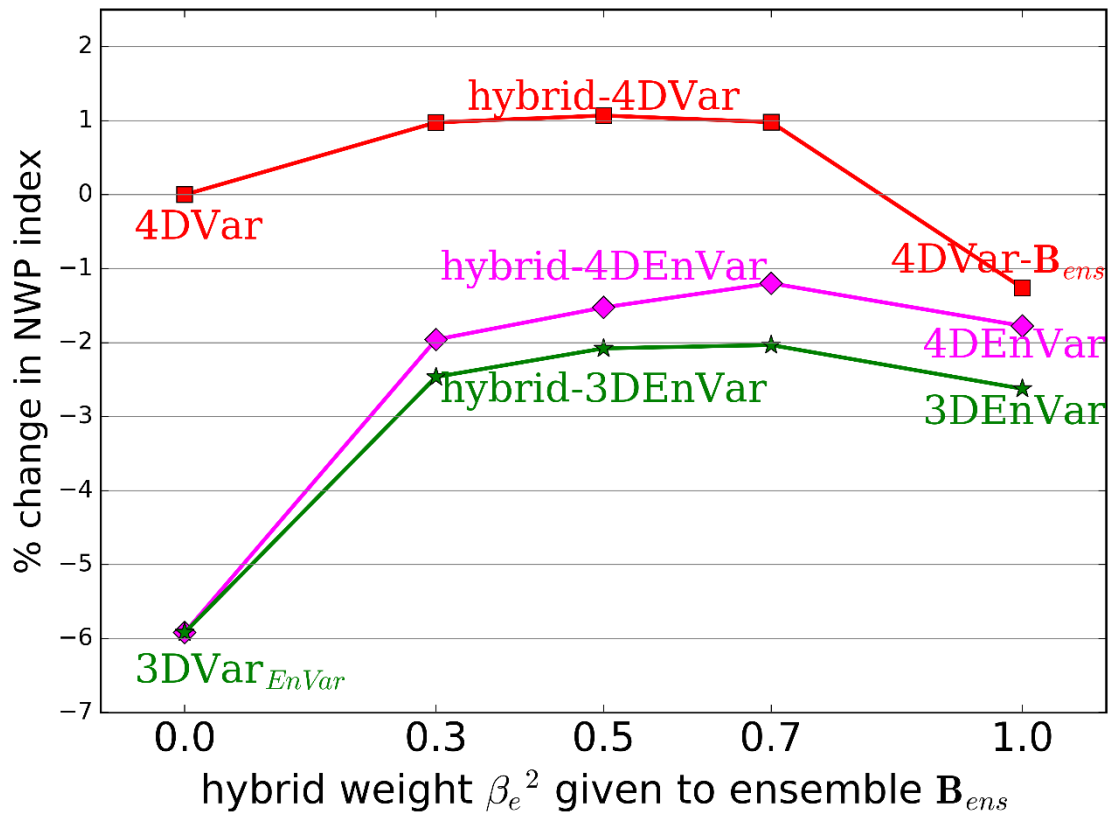
Despite strategy “*ensemble-based NWP system*”,
assume errors are quasi-Gaussian — a “*best estimate*” is useful.
This justifies use of Kalman-filter-based DA methods.

We will have an unperturbed *Control* member in the ensemble — “best estimate”.
We first consider the best DA method for this control.

N.B. For convective-scale regional NWP system,
we may not be making this assumption.

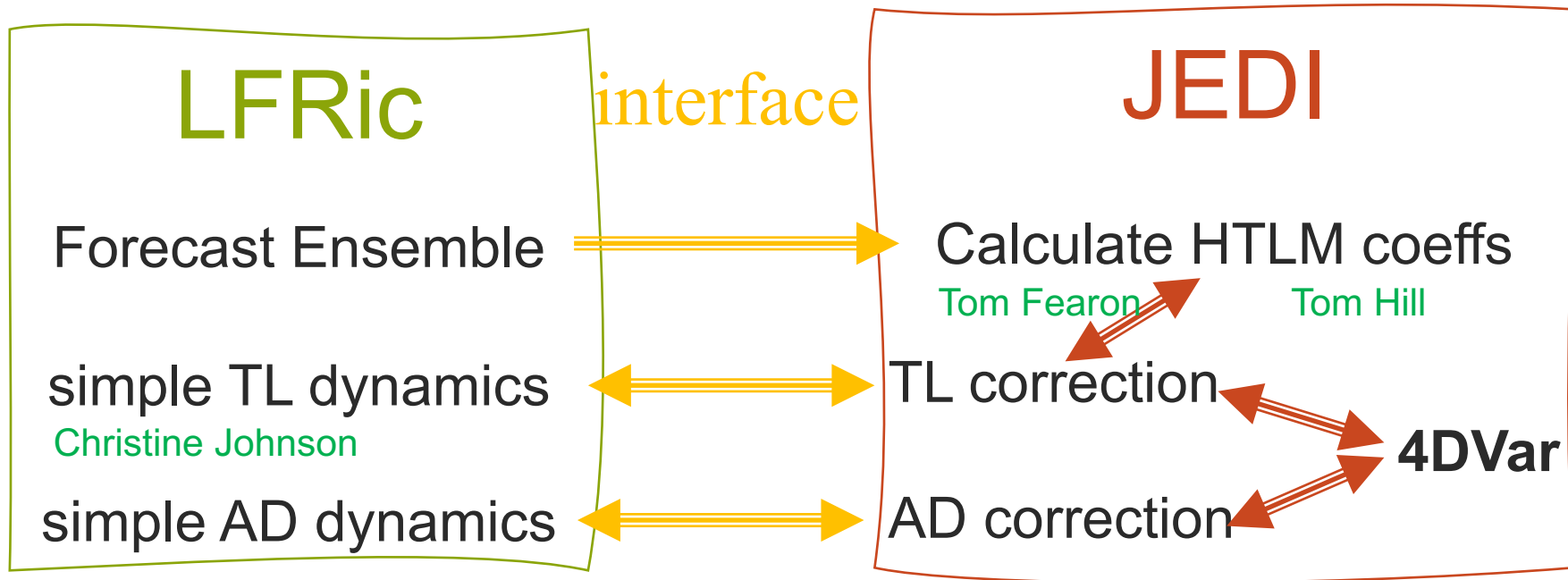
Lorenc & Jardak (2018): trials of global VAR DA & “deterministic” UM, using archived Ne=44 ensemble.

- Hybrid \mathbf{B} better than static \mathbf{B}_c or ensemble \mathbf{B}_{ens} alone.
- 4DVar (iterating linear model) better than 4DEnVar (using ensemble).
- Static \mathbf{B}_c used in 3DVar gave particularly poor results.



4DVar

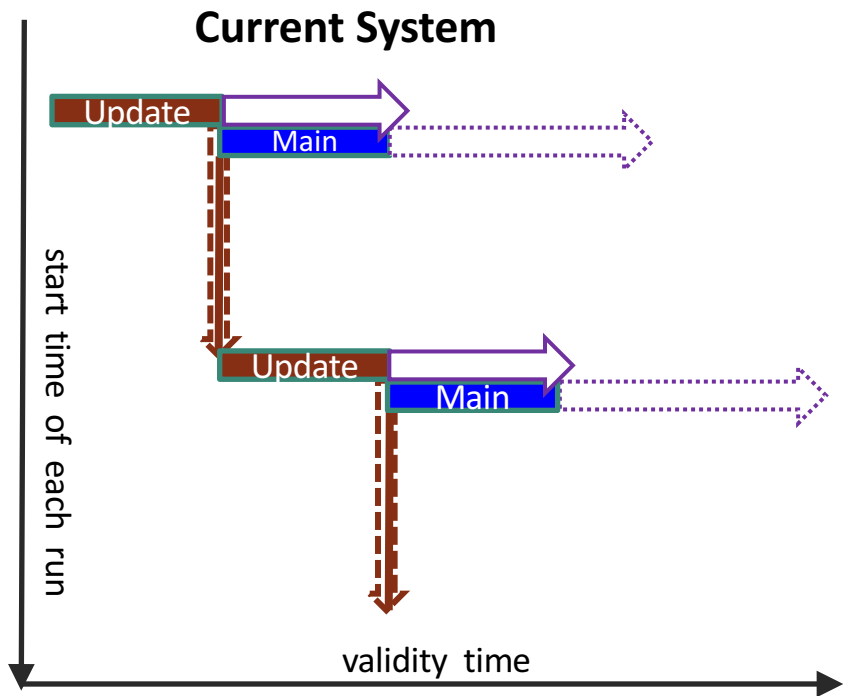
managed by Tim Payne





See poster by [Marek Wlasak](#), [Mayeul Destouches](#) and [Stefano Migliorini](#)

- Copied the science (but not the code) of the VAR static \mathbf{B}_c to JEDI software.
- Now working on software to calculate a flow-dependent \mathbf{B}_{ens} from a current ensemble. Plan to copy [some of] VAR techniques used to improve these (Lorenc 2017):
 - Time-lagged and time-shifted ensemble perturbations;
 - Split perturbations into wavebands, allowing spectral localisation, as well as scale-dependent spatial localisation.
- [3DVar being tested by Rick Rawlins](#)

- Payne (2018) demonstrated that a RUC is possible with our 4DVar system, and that its use for the global NWP significantly improved nested UK forecasts.

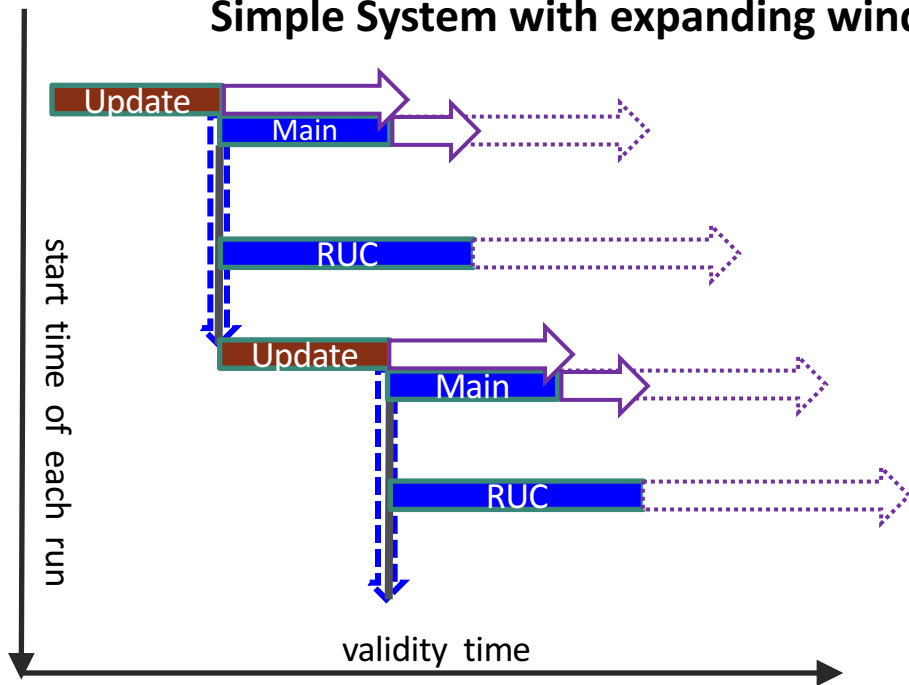


Filled blocks indicate 4DVar of all available obs for window.
 Solid arrows are forecasts used in the DA. 
 Dashed arrows are forecasts for general users. 

Update runs repeat **Main** including late observations.

- Payne (2018) demonstrated that a RUC is possible with our 4DVar system, and that its use for the global NWP significantly improved nested UK forecasts.

Simple System with expanding window RUC and Outer-Loop



Filled blocks indicate 4DVar of all available obs for window. Solid arrows are forecasts used in the DA. Dashed arrows are forecasts for general users.

RUC runs use **Main** as previous outer-loop iteration, and adds about 3 hours to the window.

Update runs use previous **RUC** as outer-loop, but restrict window to precisely 6 hours.

Hybrid-4DVar & HTLM need an ensemble.

The current VAR system generates it using a low-resolution En-4DEnVar.

Now we want to unify the Control and ensemble system.

1. Use an ensemble of DAs, each running the Control DA method.

Expensive!

2. Use a Control-Pert method, which is derived from

Mean-Pert (Lorenc *et al.* 2017) & VarEnKF (Buehner *et al.* 2017)

Coded in JEDI by Tsz Yan Leung

Met Office Control-Pert

$$\Delta \mathbf{x}_k^a = \mathbf{B}\mathbf{H}^T \left(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R} \right)^{-1} \left(\mathbf{r}_k + \mathbf{y}^o - H \left(\mathbf{x}_k^b \right) \right)$$

Stochastic ensemble
of variational DA

$$\Delta \mathbf{x}_c^a = \mathbf{B}\mathbf{H}^T \left(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R} \right)^{-1} \left(\mathbf{y}^o - H \left(\mathbf{x}_c^b \right) \right)$$

Control DA

$$\Delta \mathbf{x}_k^a = \Delta \mathbf{x}_c^a + \Delta \mathbf{x}_k^{\prime a}$$

$\text{Inc}_k = \text{Control} + \text{Pert}_k$

$$\Delta \mathbf{x}_k^{\prime a} = \mathbf{B}\mathbf{H}^T \left(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R} \right)^{-1} \left(\mathbf{r}_k - \mathbf{H}\mathbf{x}_k^{\prime b} \right)$$

Pert_k is solution of a
variational minimisation

$$J \left(\Delta \mathbf{x}_k^{\prime} \right) = \frac{1}{2} \left(\Delta \mathbf{x}_k^{\prime} \right)^T \mathbf{B}^{-1} \left(\Delta \mathbf{x}_k^{\prime} \right) + \frac{1}{2} \left(\mathbf{r}_k - \mathbf{H}\mathbf{x}_k^{\prime b} - \mathbf{H}\Delta \mathbf{x}_k^{\prime} \right)^T \mathbf{R}^{-1} \left(\mathbf{r}_k - \mathbf{H}\mathbf{x}_k^{\prime b} - \mathbf{H}\Delta \mathbf{x}_k^{\prime} \right)$$

Met Office Control-Pert motivation

I have replaced N minimisations by $1+N$ minimisations – what's the point?

Pert increments depend on neither observed values nor ensemble fields (only perturbations). Their role is to adjust the ensemble spread (reducing it near observations).

$$\Delta \mathbf{x}'_k = \mathbf{B}\mathbf{H}^T \left(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R} \right)^{-1} \left(\mathbf{r}_k - \mathbf{H}\mathbf{x}'_k \right)$$

Since the background spread is not accurately known, it is sufficiently accurate to use simple **3DVar** to calculate the **Pert** increment.

The Control increment uses the observations and is added to all members. We plan to use the DA method outlined earlier:

hybrid-4DVar with a RUC and an outer-loop to calculate the **Control** increment.

Met Office So why is 3DVar now so bad?

In our trials in 2005, with static \mathbf{B}_c , 4DVar was only a little better than 3DVar.

Since then, there has been a **big increase in impact of all-sky radiances**.

E.g. Geer *et al.* (2017) showed that

“a 4D-Var system could extract dynamical information from humidity-sensitive radiances, and that this was achieved using the tracer-advection mechanism”

This depends on **cross-covariances between winds and tracers**, in regions of advection.

- ✓ 4DVar generates them implicitly (for obs later in the window)
- ✓ Ensemble covariances can sample them explicitly
- ✗ Isotropic [e.g. static] covariance models assume they are zero.

Convective-scale NWP strategy

0 to 3~6hrs **Nowcasting**

3 to ~24hrs **Ensemble DA, nested in global Control RUC, & short forecast**

Ensemble DA focusing on convective scales (e.g. Flowerdew 2017)

Synoptic-scales (for all members) blended in from global **control** RUC (Milan *et al.* 2023)

1 to ~5days **Longer ensemble forecast, nested in global ensemble**

Forecast ensemble, with each member downscaling a **different member** of global ensemble (MOGREPS-UK. Porson *et al.* 2020)

Met Office **References**

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