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Data Assimilation – progress and plans
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1. Introduction

Improvements to observation pre-processing and data assimilation algorithms have traditionally provided significant improvements in weather forecast skill. This trend has continued since the last MOSAC data assimilation report in 2009, with a number of significant upgrades:

a. The resolution of the global four-dimensional variational (4D-Var) incremental data assimilation algorithm was increased from 90km to 60km in November 2010, providing a global NWP index improvement of $+0.37/1.50$ verified against observations/analyses respectively.

b. A world-first hybrid variational/ensemble data assimilation algorithm was implemented in July 2011, introducing two-way coupling between the global 4D-Var and the Met Office Global Regional Ensemble Prediction System (MOGREPS). Combined with a package of additional data assimilation and satellite changes, the July 2011 package provided one of the largest improvements in global NWP index seen in recent years: $+2.44/1.67$ verified against observations/analyses respectively. The improvement broken down for the various components of the index is shown in Fig. 1, clearly indicating that, with the exception of tropical wind verification against analyses, the PS27 DA/SA upgrade was beneficial across the entire range of global NWP index parameters.

c. A variety of improvements to 3/4D-Var’s forecast error covariance model have been introduced to make better use of humidity observations, especially near saturation, and in areas of high static stability.

d. The direct assimilation of radar radial velocity observations has been introduced into the convective-scale (1.5km) UKV 3D-Var system with significant benefit.

In addition to the above implementations, strategies and implementation plans for NWP-nowcasting, ensemble data assimilation, coupled ocean-atmosphere initialization, and land data assimilation have been developed and initiated. In the following sections, further details of the above key implementations and strategic frontiers are briefly outlined.
2. Coupled Variational/Ensemble Data Assimilation

Ensemble forecasts provide objective estimates of forecast uncertainty for use in an increasing range of probabilistic NWP products. In addition, short-range ensemble perturbations can provide detailed information on the flow-dependent, multivariate nature of forecast errors for data assimilation. The data assimilation and ensemble prediction efforts are therefore intricately linked. At the Met Office, 4D-Var provides the ‘control analysis’ for the Met Office Global/Regional Ensemble Prediction System (MOGREPS). Ensemble initial condition perturbations are updated separately via an Ensemble Transform Kalman Filter (ETKF) algorithm (Bowler 2008), and added to the control 4D-Var analysis to provide the initial conditions for the next cycle of ensemble forecasts. A previous MOSAC paper (Barker 2009) described plans to feed the MOGREPS short-range forecasts back into 4D-Var via a ‘hybrid’ variational/ensemble data assimilation algorithm. The hybrid approach is attractive scientifically because it elegantly combines the benefits of ensemble data assimilation (flow-dependent covariances) with the known benefits of 4D-Var (full-rank covariances, simultaneous treatment of all observations, etc) within a single data assimilation system. The hybrid approach provides a seamless transition between current variational and future ensemble data assimilation approaches through a limited number of tuning parameters that set the relative weight given to traditional (climatological) and ensemble covariances.

Initial hybrid performance described in Barker (2009) indicated a significant improvement versus 3D-Var, but was essentially neutral when applied in 4D-Var. Since 2009, further development and testing has been performed, leading to the world’s first implementation of a hybrid 4D-Var/ETKF data assimilation algorithm for global NWP in July 2011. A number of improvements to the original hybrid algorithm have been made, including a) Introduction of vertical localization for the ensemble perturbations within 4D-Var, b) Improved balance through the removal of scales significantly larger than the covariance localization radius from the ensemble perturbations, c) Relaxation to standard climatological covariances in the upper stratosphere and mesosphere to avoid anomalous ensemble perturbations near the model top, and d) Internal hybrid tunings to adjust the relative weight of climatological/ensemble components of forecast error to preserve the overall fit of the analysis to observations, and a slight reduction in horizontal covariance localization lengthscale to 1200km, etc.

**Plans:** The implementation of the global hybrid variational/ensemble algorithm represents only the latest stage in the coupling between data assimilation and ensemble prediction systems. Short-term development plans for the global hybrid include increased ensemble size and a more sophisticated covariance localization. In 2012, a new, 2.2km component of the ensemble (MOGREPS-UK) will be implemented, thus permitting the testing of hybrid variational/ensemble data assimilation for the convective-scale 1.5km UKV data assimilation system.

Looking further ahead, more radical changes to the basic data assimilation algorithm are envisaged. Apart from the use of hybrid covariances, the global 4D-Var algorithm is essentially unchanged. Thus, although the hybrid permits a smooth transition to ensemble-based flow-dependent covariances, the long-term challenges for 4D-Var scalability, maintainability and flexibility remain. A review of alternative ensemble-based data assimilation algorithms has been undertaken in 2010/2011 to assess potential alternatives to 4D-Var. This activity has included a series of scientific seminars, strategy meetings, and consultation with external experts (Hamill/Whitaker – NOAA, Fisher/Tremolet – ECMWF, Houtekamer/Buehner – EC, Auligne – NCAR). A next-generation data assimilation strategy document is currently in preparation as an initial milestone towards the strategic key deliverable:

**February 2016: Operational Implementation of next-generation global/convective-scale ensemble/variational data assimilation system.**

In summary, the strategy involves a) Continuing efforts to further improve the efficiency of 4D-Var in the short/medium-term (described in 2.1 above), and b) The development of a ‘4D-Ensemble-
Var’ algorithm for the medium/long-term that removes the need for the expensive linear PF-model and its adjoint completely. The new algorithm is a natural successor to the current hybrid, by extending the use of ensemble perturbations to model the evolution of forecast error throughout the 4D-Var time window (Fig. 2).

Figure 2: Schematic relationship between a) Traditional 4D-Var (top black arrow, making no use of the ensemble, modelling covariance evolution via the linear PF model, using static initial covariance), b) Hybrid-PF-Var (middle black arrow - uses ensemble perturbations at the start of the time window in combination with the PF model), and c) 4D-Ensemble-Var (lower black arrows – using the ensemble throughout the time-window instead of the PF model).

As in all ensemble data assimilation algorithms, the bulk of the computational cost of 4D-Ensemble-Var is in the integration of the ensemble forecasts. The analysis step (assimilation) is relatively cheap - a similar number of operations to 3D-Var, although with significantly increased memory and I/O costs. The computational cost savings from removing the PF/adjoint model can be reinvested in a larger ensemble to reduce ensemble sampling error. Results from a similar technique in Buehner (2010) indicate an ensemble size of 100-200 members may be sufficient to match 4D-Var performance.

Ensemble data assimilation algorithms are typically less tied to particular models than their variational counterparts. Increased flexibility will be strategically important during the development of the next-generation dynamical core within the GungHo project. Reduced model/application-dependence also opens up the possibility of truly coupled data assimilation between earth system model components (i.e. cross-covariances between atmosphere, land, ocean, etc). Over the next two years, the 4D-Ensemble-Var algorithm will be developed and tested within the current VAR software framework. This permits both a clean intercomparison between alternative techniques, as well as ensuring that general developments benefit all flavours of 4D-Var under consideration within a single software system.

It should be noted that the 4D-Ensemble-Var algorithm still requires a separate mechanism to update the ensemble perturbations, separately from the data assimilation. In the current hybrid, this role is performed by the ETKF. This separation is suboptimal because the ensemble mean (data assimilation) and perturbations (ETKF) are updated using different covariance models. In the
4D-Ensemble-Var project, an ‘Ensemble of 4D-Ensemble-Vars’ will be developed to address this inconsistency, in a similar way to the ECMWF’s strategy to develop an ‘Ensemble of traditional 4D-Vars’. The 4D-Ensemble-Var approach promotes increased flexibility, relying on covariance localization techniques and larger ensemble sizes to make maximum use of the raw ensemble covariances. The ECMWF approach requires fewer ensemble members, instead relying on the continued use of sophisticated (but more core-specific) linear/adjoint/covariance models to treat sampling error, allowing the ensemble to define only a subset of flow-dependent forecast error parameters (e.g. variances, lengthscales, etc).

3. 4D-Var Improvements: Increased Resolution and Algorithmic Changes

As part of the November 2010 global data assimilation upgrade, the resolution of the four-dimensional variational (4D-Var) assimilation incremental analysis was increased from N144 (~90km) to N216 (~60km). The improved resolution provided a significant boost to global NWP index scores (+0.37/1.5 versus observations/analyses respectively). It is noteworthy that the upgrade was achieved through focussed efforts to improve the scalability and algorithmic efficiency of 4D-Var, rather than via additional HPC nodes or additional delays to operational products. In particular, the introduction of an initial, low-resolution 4D-Var ahead of the critical observation cut-off time now provides a Hessian preconditioning that reduces the cost of the later time-critical, high-resolution 4D-Var (see Fig. 3).

Figure 3: Schematic of the dual N108/N216 (120/60km) 4D-Var approach implemented operationally in November 2010. The initial low-resolution ‘VAR N108’ is run ~15 minutes ahead of the main 4D-Var start time to provide Hessian eigenvectors and an initial guess for the later higher-resolution, time-critical ‘VAR N216’. This Hessian preconditioning leads to quicker convergence of the 4D-Var algorithm, and a significant reduction in N216 4D-Var run-time.

Plans: Scalability remains a concern for both the nonlinear UM and the linear perturbation forecast (PF, and its adjoint) model used iteratively within the 4D-Var algorithm. Increased resolution provides both meteorological benefit as well as improved ‘weak’ scalability. However, further resolution upgrades will need to be accompanied by additional significant algorithmic changes if 4D-Var is to remain a viable option on future HPC platforms. In the short-term (2012/13), it is planned to upgrade 4D-Var resolution to N320 (~40km), making further use of early cut-off (T-30mins) N144/N320 4D-Var’s prior to the final N320 analysis. The cost of this configuration on 24 nodes of the current IBM P6 is 4.6/21.5/12.6mins respectively. A larger number (~x3) of nodes will
be available on the IBM P7 – exact timings will not be available until after P7 delivery (early 2012). It is anticipated that further significant computational savings can be made through improved GCR preconditioning within 4D-Var. More general solutions to the 4D-Var scalability challenge include weak-constraint 4D-Var and use of an ‘Ensemble of 4D-Vars’. Both these directions are under development at ECMWF, and remain possibilities for the Met Office in the medium/long-term. However, our central strategy going forward is to focus on the development of an alternative ‘4D-Ensemble-Var’ approach described in section 2 above.

4. Climatological Covariance Modelling

A nonlinear transformation of the humidity control variable has been successfully introduced into both global and regional data assimilation applications. Following ideas from Hólm (2002), the transformation allows for the different relationships between forecast errors in regions near saturation, so that the new variable’s errors are more nearly Gaussian. This means the error distributions can be properly represented by covariances in the variational cost function; implicitly accounting for the non-Gaussian distributions of humidity and cloud. Initial trials in the Met Office’s global and regional numerical weather prediction system have demonstrated a positive impact, both on forecast scores and on the ability to fit satellite data, as shown in Fig. 4. There is negligible change to the run time of the analysis system.

Figure 4: Percentage change in root mean square observation minus background forecast differences due to introduction of new moisture control variable in global 4D-Var’s covariance model. Selected moisture-sensitive satellite radiance channels from SEVERI, IASI, AIRS, SSMI/S, AMSU-A/B, and HIRS instruments shown.

The new moisture control variable was implemented operationally in global NWP in July 2011 at the same time as the hybrid 4D-Var/ETKF algorithm, and various improvements to the treatment and use of observations (additional surface observations, reduced spatial thinning for
ATOVS/SSMIS/IASI/AIRS/aircraft, GOES/Msat-7 clear-sky radiances, extra IASI radiances over land, and revisions to MSG clear-sky processing and GPSRO).

**Plans:** The initial focus for the climatological covariance modelling effort going forward is to refresh the software used to compute covariance statistics. Once this is complete (March 2012), the focus will move to a) Diagnosing and improving the representation of forecast errors from MOGREPS ensemble training data, b) Expanding the activity to include covariance localization modelling for ensemble data assimilation, and c) The assessment of a number of potential scientific improvements (e.g. reversing horizontal/vertical transforms, potential vorticity control variable, separation of large/small scale covariances, etc).

5. Convective-Scale Atmospheric Data Assimilation

Convective-scale data assimilation has received increased prominence in recent years, to the point where Met Office computer/human resources for convective-scale data assimilation research, development and implementation now surpass those devoted to the relatively mature global data assimilation effort. The field has evolved significant due to the availability of relatively mature convective-scale NWP models and advanced data assimilation techniques able to assimilate high-density, high time-frequency observations of high-impact weather from e.g. radar, ceilometers, wind profilers, etc. Progress has been made in initial implementations of 3D-Var for the 1.5km UKV model, and testing of 4D-Var for the London 2012 Nowcasting Demonstration Project. A previous MOSAC presentation (Ballard 2010) described the many remaining challenges in detail.

The new moist control variable described in section 3 above has been introduced into the convective-scale 3D-Var with a modest positive impact. A second improvement to the covariance model has been the development and implementation of a vertical adaptive grid, providing flow-dependent vertical error correlations. A grid transformation is performed which utilizes a ‘monitor function’ based on an estimate of static stability provided by the short-range ‘background forecast’. Fig. 5 shows vertical cross-sections of the potential temperature increment resulting from a single observation of specific humidity, placed just above a temperature inversion. With the new transform (right), the temperature response is confined to the region above the inversion, whereas in the standard case the impact of the humidity observation is seen (erroneously) as far away as the surface.

**Figure 5:** Vertical cross-section of potential temperature analysis increments due to a single specific observation near model level 10. Standard vertical coordinate (left) and new adaptive grid (right).
6. References

Ballard, 2010: Convective-Scale Data Assimilation. MOSAC Paper.


