# Recent Developments in Global Ensemble Prediction at the Met Office

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***Abstract***

**The Met Office has recently upgraded their global ensemble system (MOGREPS-G) to an ensemble of data assimilations (EDA). This new scheme uses a 4d ensemble variational scheme on an ensemble of 44 members which includes inflation schemes and a cost-efficient mean-pert minimization method. Static and flow-dependent background error covariances are combined in a hybrid approach. Model error is handled by SKEB and SPT stochastic physics schemes, and we introduce a new approach called Additive Inflation. This paper describes the new ensemble configuration and shows a comparison with the previous ETKF system.**

## 1 Introduction

The Met Office global ensemble (MOGREPS-G) was upgraded in late 2019 to replace the Ensemble Transform Kalman Filter (ETKF) scheme, which is responsible for creating its initial perturbations, with an Ensemble of Data Assimilations (EDA) scheme. This “ensemble of 4D-ensemble-vars” (En-4DEnVar) is essentially an ensemble of different initial conditions (i.e. analyses), each generated through its own data assimilation (DA) cycle; this allows the model to produce different forecasts for the same period, provide useful information about the uncertainty in the forecast, and to provide objective probabilities of specified events. The main advantage of En-4DEnVar is that it is more sophisticated than the ETKF scheme. It also uses similar code and scientific methodology to the deterministic forecast model’s data assimilation scheme. This change has led to more realistic initial ensemble perturbations and hence better probabilistic forecasts. The ensemble perturbations also better represent the flow-dependent background forecast errors used in the deterministic model’s hybrid-4dvar DA, leading to a better global analysis. With subsequent tuning (aimed at a later upgrade cycle) this is expected to further improve deterministic forecast skill.

## 2 Hybrid-4DEnVar

Full details of the En-4DEnVar scheme is described in [1]. Here we highlight just the key features of this implementation. The hybrid denotation clarifies that this variational data assimilation scheme is built from a combination of static and flow-dependent background error covariances, implemented with equal weighting to each. This retains the advantages of a deterministic 4dvar and an ensemble scheme and allows the scheme to function suitably with the relatively smaller number of 44 ensemble members. The handling of remaining unrepresented error sources is described below.

### 2.1 Additive and Multiplicative Inflation

To account for unrepresented error sources, we use both additive and multiplicative inflations. Additive inflation, along with physically based model uncertainty schemes is used to simulate and account for the effect of model error on the ensemble. Multiplicative inflation is used to account for unrepresented assimilation errors arising from observation-network errors including representivity errors. We have used a blend of the relaxation-to-prior perturbation (RTTP), a relaxation of the posterior ensemble (analysis) perturbations back to the prior (first guess) and the relaxation-to-prior spread (RTPS), which relaxes the posterior ensemble spread back to the prior. In our implementation we have an inflation factor of 0.5 for the RTPP and 0.8 for the RTPS.

### 2.2 Additive Inflation from analysis increments

MOGREPS-G now uses a novel approach to construct additive inflation increments based on an archive of deterministic data assimilation analysis increments [2]. In simple terms, a random draw from a historic archive of deterministic DA increments is done for every six hours of a forecast for each ensemble member in turn. The draws are limited to archived increments from the same season as the current forecast and any duplicates at the same forecast period are removed. The analysis increments, which represent an instance of model error at some point in the past, are converted to tendencies and then applied to the model forecast at every time-step. Every six hours this changes to the next analysis increment file. One of the advantages of this scheme is that the increments are structured by the data assimilation, which is designed to take account of model-error in a sophisticated way. The disadvantage is that this type of perturbation is not flow-dependent.

In addition to the additive inflation component we also apply a scaled (0.5) 3-month running average “bias-correction” component throughout the model forecast. This has been shown to be an effective way to address model forecast biases.

### 2.3 Stochastic Physics and surface perturbations

The EDA configuration continues to use the same stochastic perturbation schemes as before in the ETKF. Stochastic Perturbation of physics Tendencies (SPT) [3] applies perturbations to tendencies from the forecast model physics schemes that are controlled by a random Gaussian forcing pattern with a prescribed 500km decorrelation distance that evolves in time using an AR1 process with a 6-hour decorrelation period. Stochastic Kinetic Energy Backscatter (SKEB) [4] injects wind increments each time-step to account for missing kinetic energy sources from organised deep-convection and to offset a drain of energy through interpolation in the Semi-Lagrangian advection scheme. These increments are controlled by a similar random forcing pattern, but with a prescribed power-spectrum.

Sea-surface temperature (SST) perturbations [5] are applied once a day, at 06Z, to the analysed daily-mean OSTIA SST analysis. The SSTs then remain constant through the forecasts until the next day. Soil-moisture perturbations are currently provided by the soil-moisture analysis EKF scheme, but these are due to be replaced by the original soil-moisture perturbation breeding method [5].

## 3 Verification

Prior to implementation, this EDA scheme was tested in multiple configurations at different resolutions and over a range of periods. Typically, we run 3-month long trials at low (60km), medium (40km) and full-resolution (20km) for an extra-tropical summer and winter season. One key improvement relative to the previous ETKF scheme is seen in 850hPa temperature forecasts in the tropics, where there is a greatly reduced forecast error and increased ensemble spread, bringing the two lines closer together indicating more reliable probability forecasts (Figure 1). More generally, the scorecard in Figure 2, shows the improvement in CRPS values. These significant improvements are a combination of improved ensemble spread throughout, reduced error of the ensemble-mean forecast and in many cases improved systematic-error (bias).

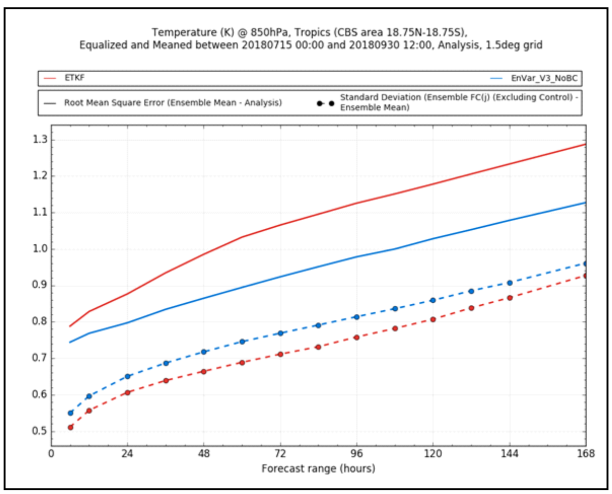


Figure 1. Root-mean-square error of the ensemble mean (solid) and ensemble spread (dashed) for tropical 850hPa temperatures of the ETKF (red) and En-4DEnVar (blue) systems verified against ECMWF analyses for trial over the period 15 July to 30 September 2018.


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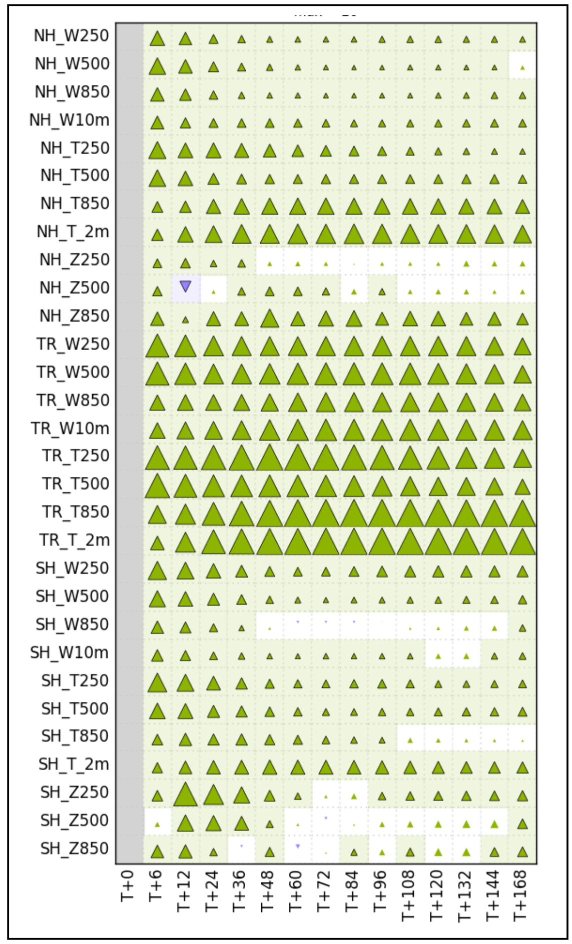


Figure 2. Scorecard of change in CRPS for En-4DEnVar vs ETKF verified against ECMWF analyses for the 40km trial 15 Jul–15 Oct 2018. Significant changes are shaded, with upward green (downward blue) triangles indicating a positive (negative) change, with maximum size of 20%.

## References


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