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Use of EDA-based background error variance in 4D-Var

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Use of EDA-based background error variance in 4D-Var

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Atmospheric data assimilation schemes work by combining a 6–12 hour forecast (the background) with observations. The background essentially contains the information from all previous observations propagated by the forecast model. To a large extent, the skill of an assimilation system is determined by how accurately we can describe the errors in the background and the observations. The weight given in the analysis to observations depends on the ratio of background error and observation error variance. In addition, the spatial and temporal structures of the background error covariance are very important for the assimilation scheme.

4D-Var is the four-dimensional variational data assimilation technique used at ECMWF. It performs a statistical interpolation in space and time between observations and an estimate of the model state (i.e. the background). Standard 4D-Var implicitly evolves the background error covariance over a (12 hour) assimilation window, but is not able to use this information in the next analysis. This implies that the background error covariance at the beginning of the assimilation window is almost isotropic and the background error variance is largely homogeneous. It has long been recognised, however, that the spatial and temporal variability of the background errors can be large. This implies that background error estimates need to be flow-dependent and evolving in order for the assimilation system to be able to extract the maximum amount of information from the observations.

It is possible to estimate flow-dependent background error covariance. This can be done through an ensemble of perturbed data assimilations (Ensemble of Data Assimilations, EDA; *Isaksen et al.*, 2010); i.e. an ensemble of independent data assimilations where the main error sources (observation, model and boundary conditions errors) are properly represented. The EDA has been used in two main ways.

- ***Integrated Forecasting System (IFS).*** To specify the static background error statistics for 4D-Var and, since May 2011 (cycle 37r2), to provide flow-dependent estimates of background error variances.
- ***Ensemble Prediction System (EPS).*** To provide EDA analysis variances that have been used since June 2010 (cycle 36r2) for the estimation of the initial errors (*Isaksen et al.*, 2010, *Buizza et al.*, 2010).

A schematic representation of the EDA and its interaction with 4D-Var and the EPS is shown in Box A.

In this article we describe the scientific issues involved in the implementation of flow-dependent background error variance derived from the EDA, and their impact on the ECMWF deterministic analysis and forecast. This is the first step towards a fully flow-dependent representation of background errors where the correlation structures will also be estimated from the latest available EDA.

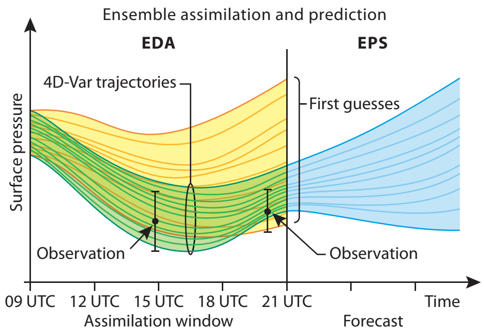
How the EDA works

A

The EDA is an ensemble of independent 4D-Var data assimilations where the main analysis error sources (observation, model and boundary conditions errors) are represented by perturbing the relative quantities (observations, forecast model and sea surface temperature, respectively) according to their estimated accuracy.

In the idealized schematics below, one can see how the 4D-Var 12-hour assimilation window (left part of the diagram) modifies the initial trajectories of the EDA members (in yellow) to reflect the information from the assimilated observations (black dots with error bars). The analysis trajectories (in green) show the impact of the new observations on the ensemble: the spread of the ensemble has been reduced and the centre of mass of the ensemble has been shifted.

At the end of the assimilation window the EDA is used to provide (a) background error information for the successive deterministic analysis update and (b) the initial perturbations of the Ensemble Prediction System (EPS) around the control analysis.



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Controlling sampling noise in the EDA variances

The background error estimates derived from the EDA are themselves affected by estimation errors which have to be dealt with, and if possible reduced.

Estimation errors can formally be separated into random and systematic components. The random component is the part of the estimation error which will tend to zero if averaged over a very large sample of EDA members. In practice, for affordable ensemble sizes (10 in the current EDA configuration), this type of error is present and has to be addressed. It has been found that the size of the ensemble directly determines the range of spatial scales that can be robustly estimated from the EDA (*Bonavita et al.*, 2011).

Figure 1a shows the spread of the EDA background of the vorticity field at model level 64 (close to the 500 hPa isobaric surface), superimposed on the verifying 500 hPa geopotential height analysis, valid at 1200 UTC on 1 October 2011. The EDA estimates increased uncertainties in the accuracy of the background forecast on the cyclonic side of the 500 hPa trough approximately centred at (45°N, 22°W). This looks reasonable since this is an active weather system over an oceanic area which is not as well observed as Europe or North America. It is also apparent from Figure 1a that the EDA spread is spatially noisy and the significance of the small-scale details is doubtful.

The noisiness of the raw EDA spread is not surprising. The accuracy of error estimates sampled from the EDA can be expected to only increase proportionally to the square root of the ensemble size. Because only a small ensemble is currently affordable, the application of statistical post-processing techniques that allow the filtering of the sampling noise is required.

The filtering algorithm which has been implemented in the operational ECMWF analysis closely follows the pioneering work of *Raynaud et al.* (2009) at Météo-France, with the modifications described in *Bonavita et al.* (2011). This consists of applying different low-pass spectral filters for all the variables used in the analysis. The basis for this method is outlined in Box B.

The application of these low-pass filters in spectral space is similar to a weighted spatial averaging technique in grid-point space, which enables the large-scale signal of interest to be extracted while filtering out the small-scale sampling noise. This is apparent from Figure 1b (to be compared with Figure 1a) which shows the spread of the EDA background of the vorticity field at model level 64 (~500 hPa) after the application of a spectral filter and calibration step (that will be described below).

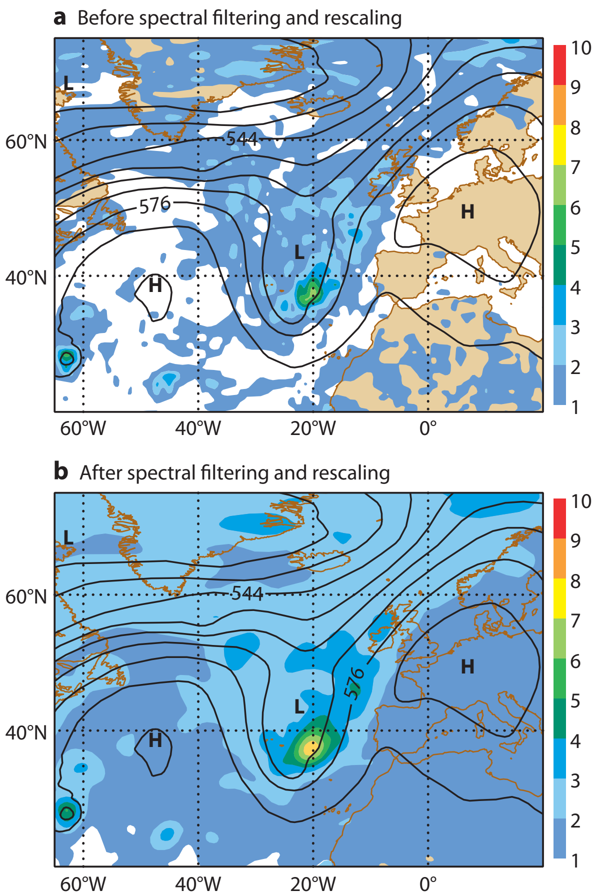
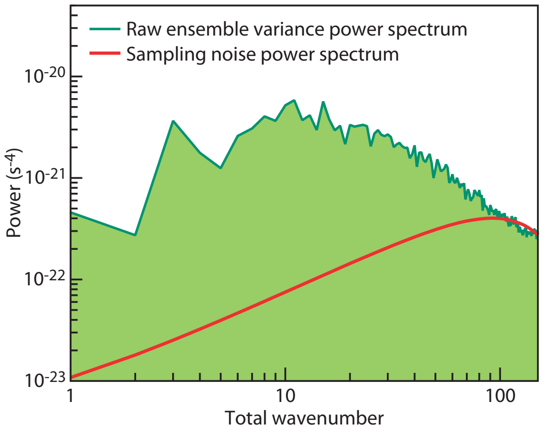


Figure 1 (a) The EDA background ensemble spread for vorticity at model level 64 (shaded, units 10^{-5} s^{-1}) superimposed on the 500 hPa geopotential height analysis verifying 1200 UTC on 1 October 2011 at. (b) As (a), but after the application of the spectral filter and the calibration step, superimposed on the 500 hPa geopotential height analysis verifying on at 1200 UTC on 1 October 2011. Note that the rescaling changes the average values of the errors. Consequently the colour scale used for (b) is slightly different to that for (a) so as to highlight the main differences in the patters.

The basis for using a special filtering technique

B

There should be a significant scale separation between sampling noise and signal and this provides the basis for using a spectral filtering technique to separate the two components. In the figure the green line is the raw power spectrum of the 10-member EDA background forecast variance and the continuous line is the estimated power spectrum of the climatological sampling noise for vorticity at model level 64 (~500 hPa). The separation in spectral space of the signal (the EDA variance) from the random error power spectrum is clear up to approximately total wavenumber 80. This naturally leads to the definition of a low-pass spectral filter based on the signal-to-noise ratio defined by the two curves. The filters are separately computed for all the variables used in the analysis.



Basis of the definition of a low-pass spectral filter. Power spectrum of the 10-member EDA short-range (9-hour) forecast variance (green line) and power spectrum of the climatological sampling noise (red line) for vorticity at model level 64 (~500 hPa), as a function of total wavenumber.

Systematic errors in the EDA variances

The systematic error component is the part of the estimation error representing how much the EDA error estimates deviate, on average, from the truth. As such it reflects the deficiencies in the representation of the main sources of uncertainties in the analysis and background fields.

Errors in the deterministic background forecast can be considered to arise from three different sources: errors in the initial conditions, errors in the boundary conditions and errors in the model formulation. The ECMWF EDA tries to represent these sources of errors through the use of perturbed observations, perturbed sea surface temperature (SST) fields and perturbed model physical tendencies. Consequently any deficiencies or approximations in these errors will cause the sampled EDA variances to be sub-optimal estimates of the analysis and background errors. This type of estimation error will not be alleviated by an increase in ensemble size and will translate into systematic differences between the EDA sampled variances and the true analysis/forecast errors. This situation had been recognised at an early stage during the development of the ECMWF EDA (*Isaksen et al.*, 2007): globally averaged EDA spread values were diagnosed to be underestimated by approximately a factor of two, so that a global inflation factor of the same magnitude was applied to minimise the underestimation of errors. However the systematic errors of the EDA variances have a complex spatial and statistical structure which cannot be adequately represented by a global multiplicative inflation factor.

The relationship between EDA spread and analysis/background errors can be investigated in a quantitative manner by the use of spread-error plots, an example of which is given in Figure 2. For a statistically reliable EDA the spread-error curves (separately computed for the northern and southern hemispheres and the tropics) should lie on the diagonal (dashed black line). Their distance to the diagonal shows that the ensemble is under-dispersive (i.e. the root mean square error exceeds the spread) while their slope gives an indication of the bias of the ensemble spread. The slope of the calibration curves with respect to the diagonal suggests that different rescaling factors should be applied to the sampled EDA spread distribution. It is also apparent how tropical regions have, on average, different reliability characteristics than extra-tropical regions.

The rescaling does not change significantly on daily to weekly timescales. However it can be shown to have an appreciable seasonal drift (*Isaksen et al.*, 2010). This temporal drift is linked to time-varying model error characteristics and the ability of the current model error parametrization to properly describe their statistical effects. Irrespective of the physical causes of the drift of the rescaling factors, it is obvious that any statistical correction we might want to apply to the EDA spread must have a time-varying component.

In light of the above diagnostic findings, a rescaling step is currently applied to the raw (unfiltered) EDA estimates of background error variances. This is aimed at enforcing approximate statistical consistency between the EDA variance estimates and the mean squared errors of the ensemble mean background (in the present case, the operational ECMWF analysis is taken as 'truth'). This statistical balance is enforced

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separately for each spread-error bin, variable and latitude band (northern hemisphere, tropics, southern hemisphere). The time-varying component is taken into account in the ECMWF implementation by computing a running mean of the scaling factors over the previous 5 days (e.g. the last available ten analysis cycles) from the nominal analysis date.

EDA variances in action: a case study

We illustrate the mechanisms through which the use of EDA variances impacts the ECMWF 4D-Var analysis with a case study. Tropical cyclone Aere affected the north-eastern part of the Philippines on the 8–9 May 2011, causing loss of lives and extensive damage due to the accompanying floods and landslides.

Figure 3 shows the mean sea level pressure evolution of the storm from the then operational ECMWF analysis (which at the time was still using climatological background error estimates) in the left column and from an experiment making use of the EDA error estimates in the right column. The diamond symbol locates the estimated position of the storm according to the Joint Typhoon Warning Center (JTWC) of the U.S. Air Force and Navy (Pearl Harbour, Hawaii). The experiment which makes use of the EDA variances is clearly more accurate in analysing the cyclone position.

What is more interesting in this case is the different use of the information from available observations (mainly surface pressure observations from land stations, shown as filled circles in bottom row of Figure 4). The top row of Figure 4 shows the estimated uncertainty of the background forecast of the logarithm of surface pressure and the background mean sea level pressure field. The bottom row shows the analysis increments for the mean sea level pressure field. As in Figure 3, the left column shows fields from the then operational ECMWF analysis and the right column has the corresponding fields from the experiment using EDA error estimates. It is clear that the estimated uncertainty in the then operational background is much smaller than in the EDA experiment and tends to be axis-symmetric with the predicted position of the cyclone. This reflects the limited flow-dependent effect in the old background error formulation. Besides, errors in the background state estimate will affect the background errors estimate. This is a fundamental limitation of the previous formulation of the background error variances.

On the other hand the errors diagnosed by the EDA are, by design, constructed to sample the real analysis errors, thus implicitly taking into account the observation network distribution and the model instabilities. In the present case they act to extrapolate the observational information from the land based stations into the more uncertain areas to the north-east of the cyclone, thus helping achieve a better positioning of the analysed storm.

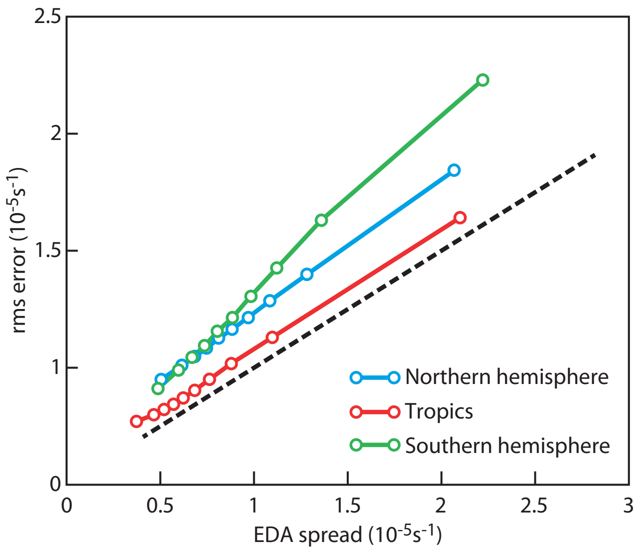

Figure 2 The spread-error diagram for vorticity at model level 81 (~900 hPa). Averaged over one month (August 2009). For a well balanced system all curves should be close to the diagonal indicated by the dashed line.

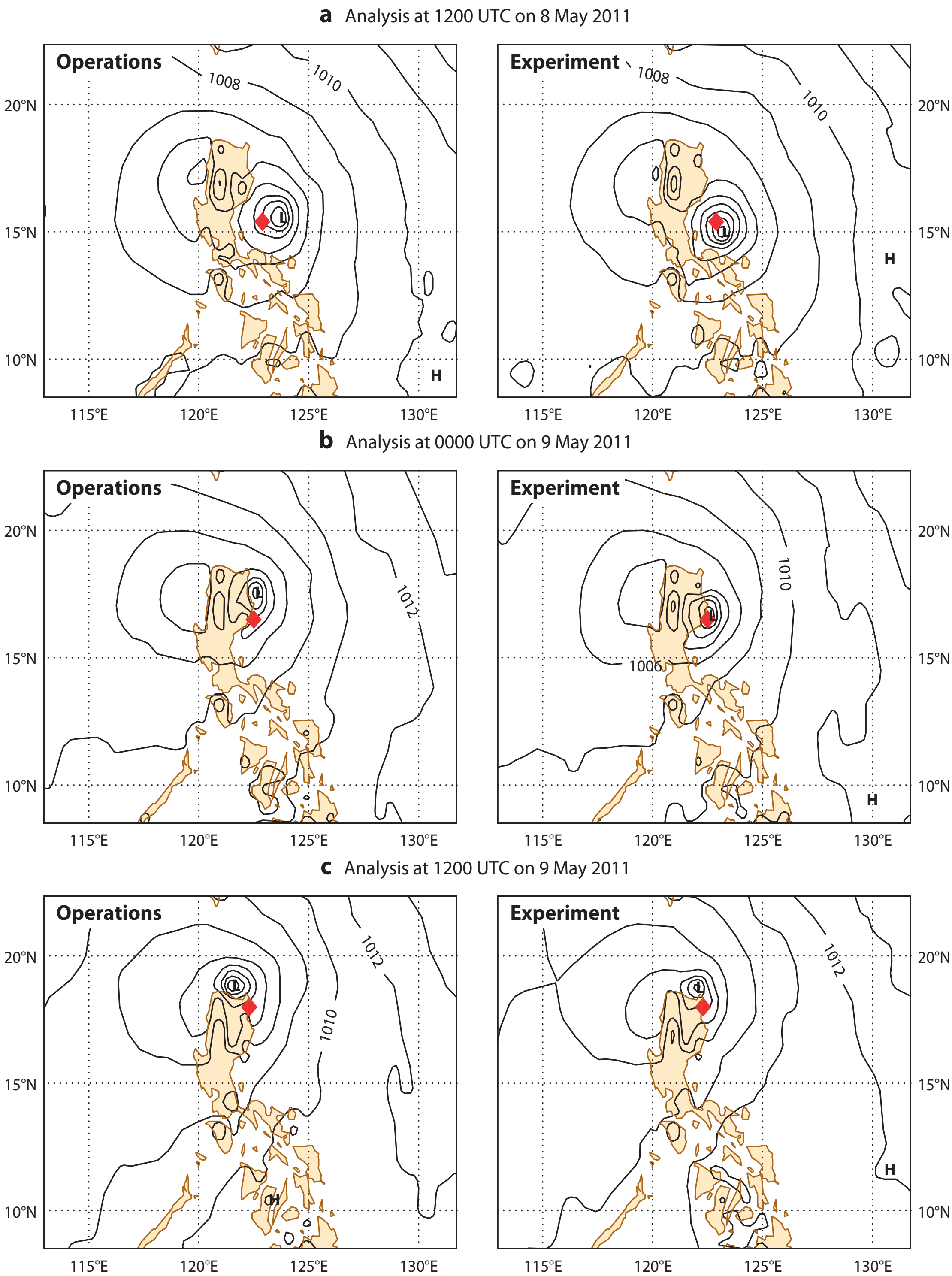

Figure 3 Analysed mean sea level pressure valid at (a) 1200 UTC on 8 May 2011, (b) 0000 UTC on 9 May 2011 and (c) 1200 UTC on 9 May 2011. Left column shows fields from the then operational ECMWF analysis and the right column has those from an experiment using EDA error estimates. The red diamond symbol denotes the independent best estimate of the position of Tropical Storm Aere.

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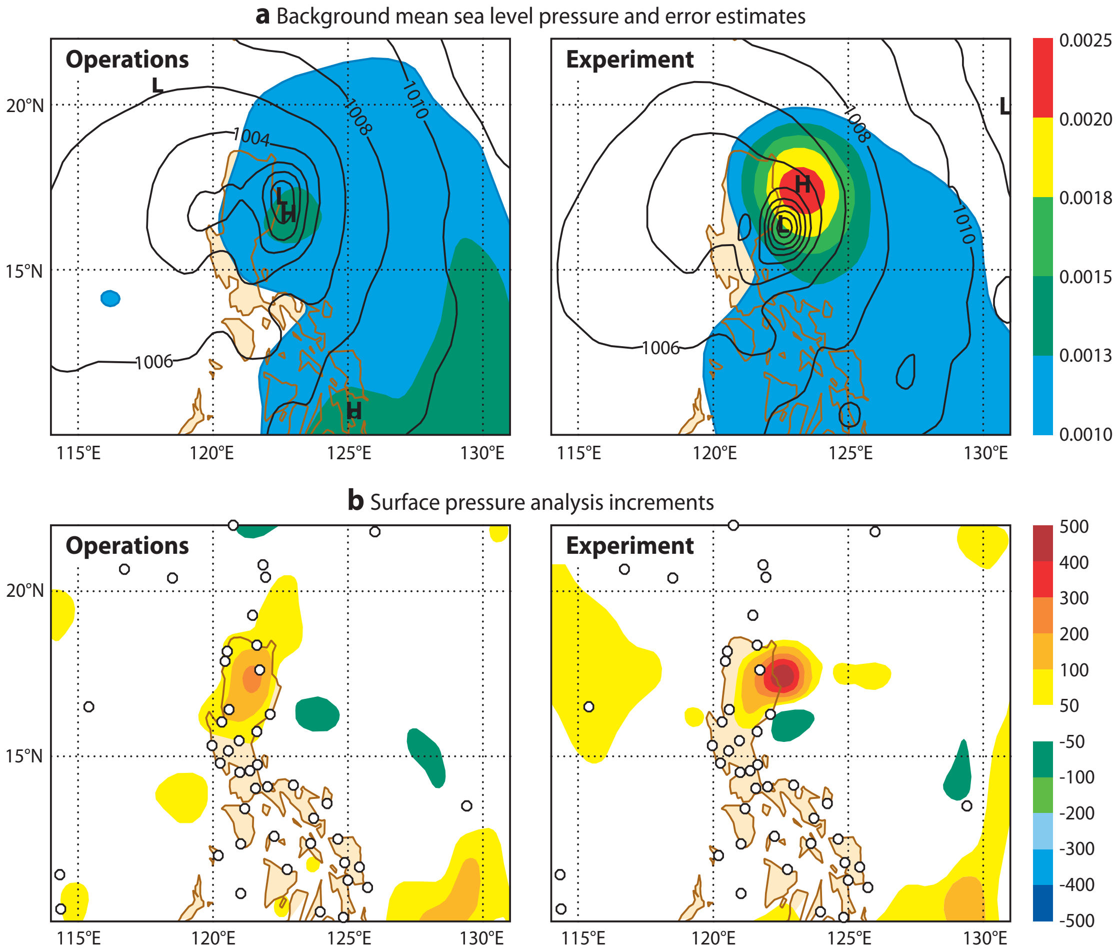

Figure 4 (a) Background mean sea level pressure valid at 0000 UTC on 9 May 2011 (solid line, units: hPa) superimposed on background error estimates for the logarithm of surface pressure (shaded contours). (b) Surface pressure analysis increments valid at 0000 UTC on 9 May 2011 (yellow-red shades indicate positive increments, green-blue shades negative increments, isolines of 50 Pa). Left column shows fields from the then operational ECMWF analysis cycle and the right column those from an experiment using EDA error estimates.

EDA variances in action: Impact on deterministic forecast scores

An assessment has been made of the impact of using online EDA variances in the deterministic analysis using an operational configuration of the ECMWF IFS (cycle 36r4), run at the operational resolution (T1279L91). The evaluation is performed for two long (~3 months) assimilation periods over the winter (11 January to 30 March 2010) and summer/autumn (2 August to 30 October 2010) seasons. In these experiments use is made of the variances computed from the ten member operational ECMWF EDA (as described in detail by *Isaksen et al.*, 2010), and the sample variances are filtered and rescaled as discussed above. Also the EDA error variance estimates are used as proxies of the background errors both in the 4D-Var minimization step (for vorticity and the balanced part of the other control variables) and in the observation background quality control check (for all variables). The controls differ from the experimental runs only in that they use the then operational quasi-static background errors estimates derived from the 'randomization' technique (*Fisher*, 2003).

Figure 5 presents vertical cross-sections of the twelve hours to eight days root mean square reduction of geopotential height errors for the winter EDA variance experiment against the control. The forecast experiment is verified against its own analysis. The improvement in forecast skill is apparent at most forecast ranges, latitude bands and pressure levels. It is interesting to note that improvements tend to be larger in the winter hemisphere. This is consistent with our understanding of the effect of EDA variances on the deterministic analysis as illustrated in the case study: in regions and times of the year where weather conditions are more active the impact of the use of EDA variances will be more significant.

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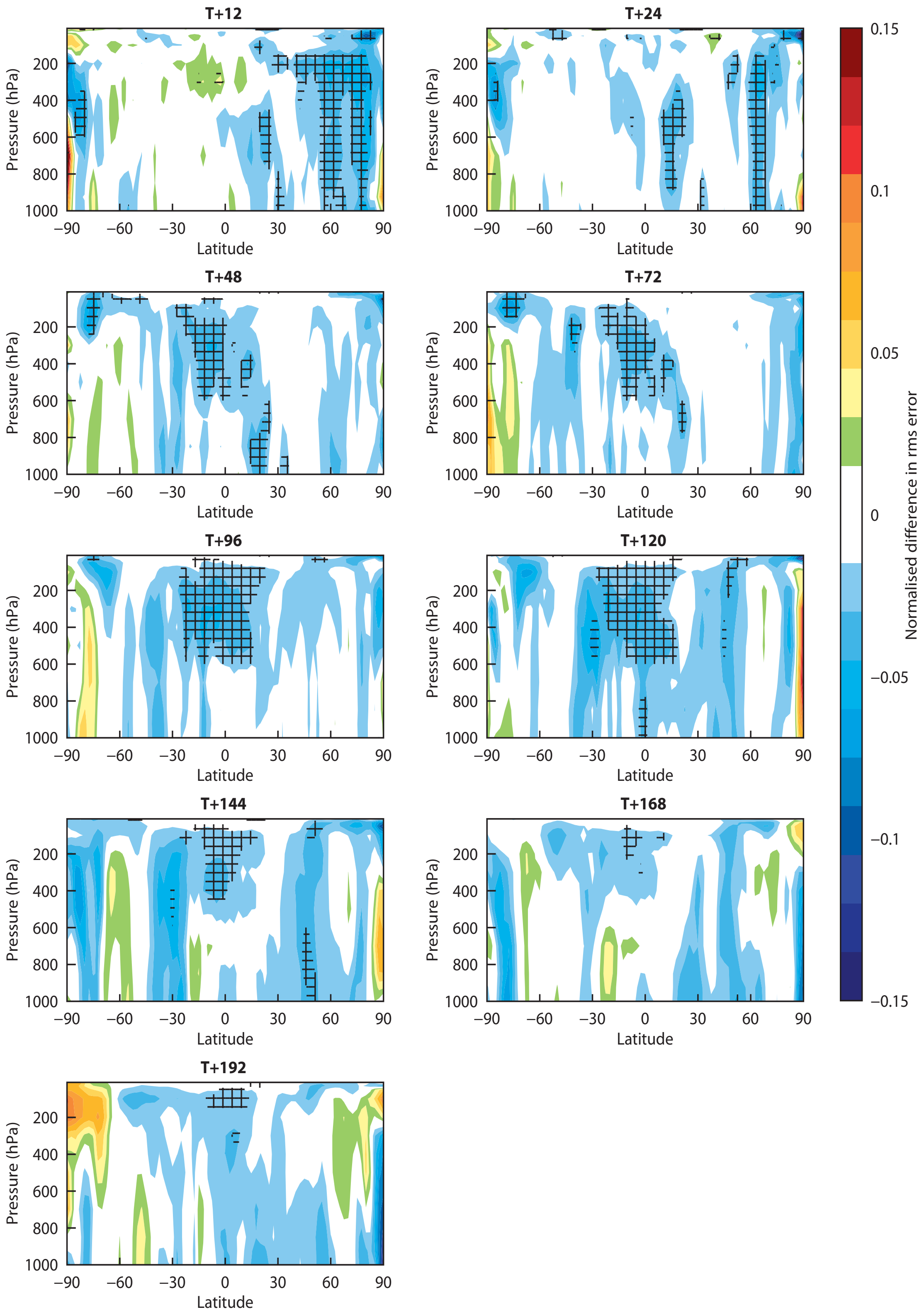

Figure 5 Meridional averages of normalised root mean square error reduction of geopotential forecasts. Blue shades indicate error reductions for the forecasts started from the experiment using EDA variances. Scores are averaged over the period 11 January to 30 March 2010. Crosses indicate regions having above 95% statistical significance. Note the improvement in skill at most forecast ranges.

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Future developments

The use of background error variance estimates sampled from an EDA was successfully implemented in the ECMWF 4D-Var (Cy37r2, May 2011), resulting in significant improvements in the skill of the ensuing deterministic forecast. This is the first important step towards the final goal of a hybrid assimilation system with a fully flow-dependent representation of background error covariance.

As explained above, filtering of sampling noise in the EDA variances is required. This has been implemented using a method developed at Météo-France. A refinement of the current spectral filter has been successfully tested and will be implemented in the next IFS release. Systematic estimation errors reflect, on the other hand, basic inadequacies of our modelling of the error sources in the EDA. An adaptive statistical rescaling technique is used to mitigate their impact. A more fundamental solution needs to be based on an improved representation of observation errors and model errors. In this respect it has already been shown (*Bonavita*, 2011) that more advanced model error parametrizations than the one currently used in the EDA, can provide more realistic and statistically consistent error estimates.

A number of further improvements and extensions to the current use of EDA variances in 4D-Var are envisaged. The increase of the EDA size has been shown by Bonavita et al. (2011) to be beneficial. Other developments currently pursued include the use of EDA variances for the first-guess check of radiances from satellite borne sensors, and the use of EDA variances to estimate the error variance of the unbalanced components of the ECMWF 4D-Var (along the lines discussed in *Raynaud et al.*, 2011).

The next big step will be directed towards the use of EDA information in the estimation of background error correlations. Being a much larger-dimensional problem, sampling issues will play an even bigger role than for the estimation of background error variance. This will probably imply the need to make use of a larger ensemble and to apply local spatial averaging techniques similarly to what has been implemented for the sampled EDA variances. This will be based on an extension of the wavelet approach (*Fisher*, 2003) already used in the ECMWF analysis.

Further reading

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