AMV errors: a new approach in NWP

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ABSTRACT

NWP forecast skill is partly controlled by the quality of the initial state, or analysis. In variational data assimilation schemes the analysis is derived by minimizing a cost function made up of a departure from the background and a departure from the observations. How close the analysis pulls towards the observations is determined by the balance of observation errors and model background errors. If the observation errors are set too low the observations are given too much weight which can have a detrimental impact on the quality of the analysis, too high and the observations are less able to correct errors in the background. The observation errors are therefore a fundamental and very important part of the assimilation.

AMVs have complicated error characteristics. Despite this most NWP centres, including the Met Office, only allow the errors to vary with pressure. Can we do better? One option is to generate individual observation errors for each wind using information on the quality of the AMV vector and height assignment.

In this paper we will describe the proposed approach to generate individual observation errors, show initial impact trial results and discuss options for how to take this work forward.

AMV ASSIMILATION AT THE MET OFFICE

The Met Office global NWP model uses a 4D-Var data assimilation scheme (Rawlins et al., 2007). At the Met Office we assimilate IR, cloudy WV and VIS winds from Meteosat-9, Meteosat-7 and MTSAT-1R; IR and cloudy WV winds from GOES-11 and GOES-12 and IR, cloudy WV and clear sky WV winds from Terra and Aqua (NESDIS and direct broadcast). For more details see the Met Office AMV usage page on the NWP SAF website.

The AMV assimilation approach at most NWP centres involves applying quality indicator thresholds, spatial and temporal blacklisting, thinning the data (typical scale of one observation per 200 km by 200 km by 100 hPa box) and removing data which deviate too far from the background. The AMVs are generally treated as point observations in space and time, although neither assumption is true. The observation errors typically vary only with pressure (those used at the Met Office are shown in table 1) and are calculated from O-B statistics, but inflated to alleviate problems with correlated error (e.g. Butterworth et al. 2002). The result of the quality control is to remove the majority of the observations. At the Met Office typically only 2% remain (e.g. Figure 1).

Level (hPa)	1000	850	700	500	400	300	250	200	150
Error (m/s)	3.6	2.8	4.0	4.8	6.2	6.2	5.6	5.8	6.6

Table 1: ***AMV observation errors used in the Met Office models.***

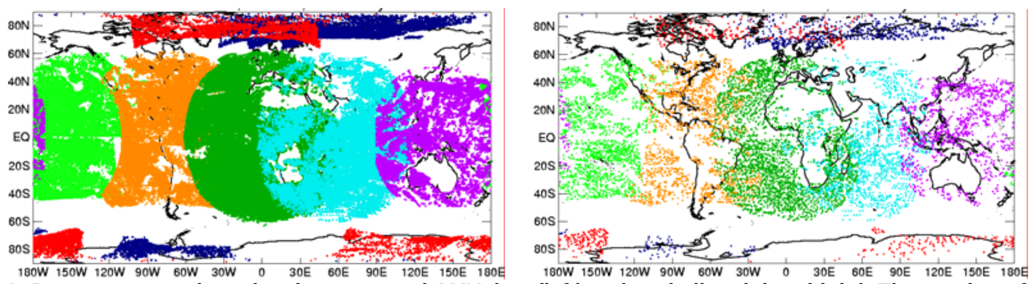


Figure 1: ***Data coverage plots showing extracted AMV data (left) and assimilated data (right). The number of winds assimilated is only 80602 for this 6 hour assimilation cycle, just 2% of the 460641 winds received.***

The current strategy is clearly very wasteful. There is also evidence to suggest that, although most of the poor quality winds are removed, some are assimilated, in some cases leading to detrimental impact on forecast quality (e.g. Forsythe & Saunders 2006).

How can we improve our approach? Aside from tweaking the existing set-up by modifying the spatial blacklisting, quality indicator thresholds and background check criteria, three areas that may be particularly important to consider are the observation errors, the observation operator and whether there is a better way to handle the spatially and temporally correlated errors. In this paper we focus on the observation errors.

A NEW APPROACH TO SETTING AMV ERRORS

Two options

There are two main approaches to estimating errors in the AMV data. The first is a statistical approach where factors that may affect the errors, e.g. wind speed, are identified and used as predictors. This is the basis of the current formulation of the Expected Error (EE), initially designed at the Bureau of Meteorology (Le Marshall et al., 2004). Linear regression against AMV-radiosonde differences is used to create regression coefficients, which are then used to estimate the AMV errors. The main advantage of this approach is that it is easy to implement. The EE shows a good relationship with O-B statistics (e.g. Berger et al., 2006) and has been used at the Bureau of Meteorology for thresholding and thinning selection. The second approach is physically-based and involves identifying and quantifying the error sources in the AMV data. Statistics may still be useful, for example in understanding the relative contribution of the different error sources, but the important difference is that the approach ties back to a physical understanding of the errors in the AMV data. It is a tougher proposition, but ultimately should lead to better results and is our preferred approach. Additionally because it encourages a better understanding of the limitations of the derivation, it may highlight areas of the AMV derivation which could be improved.

The proposed approach

The first step in designing physical estimates of the AMV errors is to distinguish two parts, one linked to an error in vector derivation and one to an error in height assignment. The latter is more problematic in regions of large vertical wind shear, but will not matter where there is little variation in u and v with height. Some sources of error in the AMV vector and height are listed in Forsythe & Doutriaux-Boucher (2005).

One idea for developing estimates of u and v errors is to use the correlation surface from the tracking step. Intuitively there are two things to look for: firstly, a high maximum correlation coefficient and secondly, a clear single maximum. The tracking accuracy is less certain in cases where there are no locations in the search window with good correlation values or where the maximum in correlation is broad or there are multiple maxima. Navigation error could also be incorporated in the final estimate of u and v error.

The height error estimate is likely to be harder to do well as there are a number of sources. Ideally biases in the radiance data should be corrected prior to the height assignment step (e.g. Daniels et al., 2004). The remaining sources of height error include noise in the observed radiances, limitations of the height assignment techniques (e.g. emissivity and single cloud layer assumptions etc.), errors in the forecast model (used for temperature and moisture profiles), errors in the radiative transfer model and identification of the appropriate pixels in the target box to use for the height assignment. Figure 2 illustrates how the spread of cloudy radiances can be used to provide an estimate of height uncertainty (approach applied in the EUMETSAT MSG derivation scheme). Minimum residual methods can also provide estimates of height uncertainty. Investigations are required to assess how useful these measures are and whether they can be further developed over time to capture the main sources of error in the AMV heights.

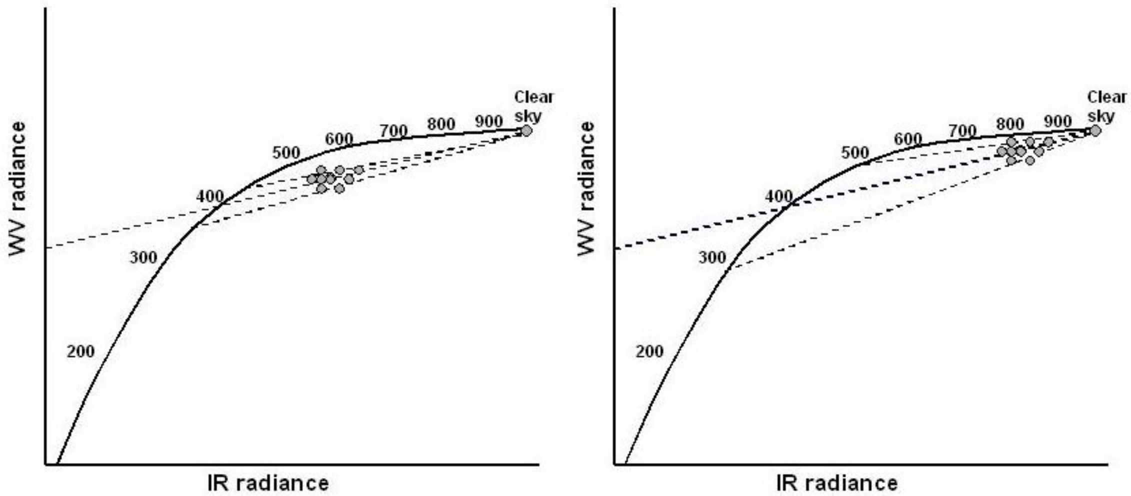


Figure 2: ***Schematic cartoon to illustrate how the uncertainty in height can be estimated from the spread of observations. The uncertainty is greater for thinner cloud (as shown on right).***

The proposed approach for estimating the total AMV observation error allows for both an error in the u/v vector components and an error in the u/v vector components due to a height assignment error. If we assume the AMV vector and height errors are independent (reasonable assumption), the total AMV error can be calculated by combining the two parts as shown below.

$$(\text{Total u/v error})^2 = (\text{Error in u/v})^2 + (\text{Error in u/v due to error in height})^2$$

The error in u/v due to the error in height (E_{vp}) can be calculated using the model background wind profile and an estimate of the height error. The formulation below assumes a Gaussian distribution of height error, which seems a reasonable assumption for much of the AMV data based on best-fit pressure statistics. In cases where AMV data shows a marked height bias it may be better to consider blacklisting.

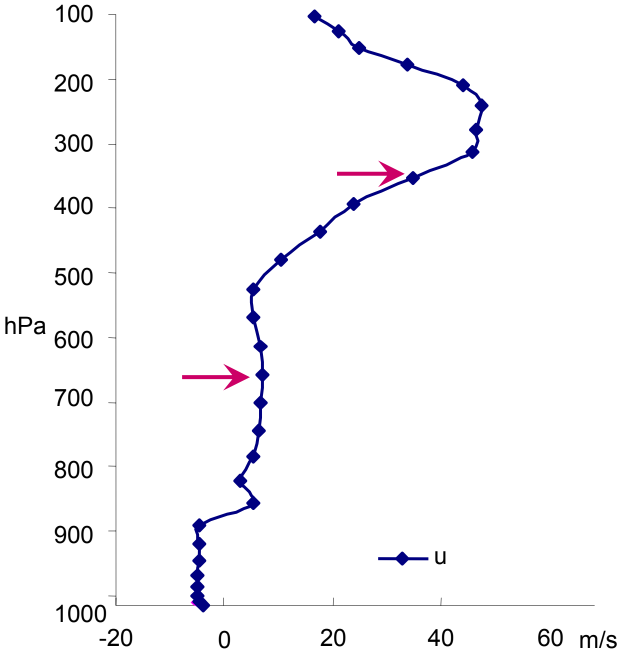
$$E_{vp} = \sqrt{\frac{\sum W_i (v_i - v_n)^2}{\sum W_i}}$$

$$\text{where } W_i = e^{-((p_i - p_n)^2 / 2E_p^2)} * dP_i$$

i = model level
v_i = wind component on model level
v_n = wind component at observation location
p_i = pressure on model level
p_n = pressure at observation location
E_p = error in height assignment
dP_i = layer thickness

The error in vector due to the height error is calculated separately for the u and v components giving separate u and v component errors.

With this approach, the same height error will yield a bigger observation error in regions of high vertical wind shear (see examples in Figure 3). It therefore allows us to down-weight winds where a height error would be problematic and allows us to give greater weight to winds where the height assignment is less critical.



P hPa	E_u m/s	E_p hPa	Total u error m/s
350	2	60	11.1
	2	80	12.9
	2	100	14.3
660	2	60	2.2
	2	80	2.6
	2	100	3.6

Figure 3: ***Examples of total u error for a case in a high shear region (350 hPa) and a case in a low shear region (680 hPa) with varying height error inputs.***

The inputs required for this approach are estimates of the error in the height assignment and in the u and v wind components. It is hoped that these will be provided routinely with the AMVs by the data producers using information available during the derivation. As these are not yet available, we need to consider alternatives.

Recent studies investigating the seasonal and geographic distribution of O-B statistics and comparisons of AMV pressure to model best-fit pressure have highlighted some general trends in the AMV errors (e.g. Forsythe & Saunders, 2008). We may be able to use this enhanced knowledge to estimate suitable values for the u, v and height errors. We know, for example, that the error in the height assignment is likely to be bigger at mid level than high and low level and is likely to be different dependent on the height assignment method (e.g. equivalent black-body temperature (EBBT) versus CO_2 slicing).

The current approach is to set the u and v errors using the model independent QI (see Figure 4).

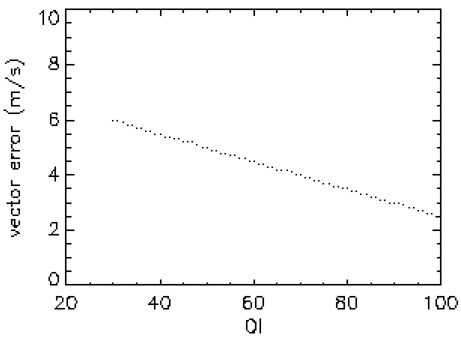


Figure 4: ***Plot showing relationship between the u/v error estimates used in the new Met Office observation error scheme and the model independent QI.***

The height error estimate is set using a look up table, dependent on satellite, channel, pressure level, surface type, height assignment method and latitude band. The values are based on the root mean square difference between the model best-fit pressure and AMV observed pressure. These have been calculated for a month of data at various times of the year. An example of the height error estimates for Meteosat-9 IR 10.8 winds is shown in Figure 5.

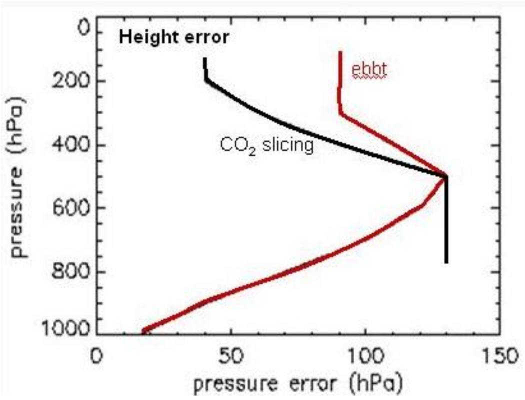


Figure 5: ***Plot showing an example of the height error estimates as a function of pressure and height assignment method for the Meteosat-9 IR 10.8 winds.***

ASSESSING THE NEW SCHEME

New errors versus old errors

The distribution of old errors, defined in Table 1, and new errors are shown in Figure 6. The new errors peak at lower values than the old errors and have a tail extending to higher values. The long tail is due to AMVs in regions of high vertical wind shear being assigned large error estimates (e.g. example shown in Figure 3).

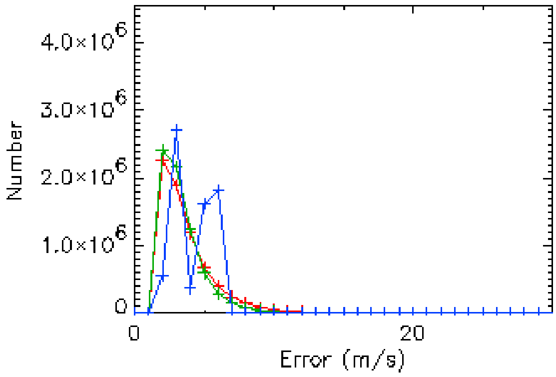


Figure 6: ***Distribution of the old (blue) and new errors (red and green for u and v components respectively) for 2 weeks of data after blacklisting is applied.***

Figure 7 compares the old (left) and new (centre) errors for the Meteosat-9 IR 10.8 winds for the 18 UTC run on 24 February 2008.

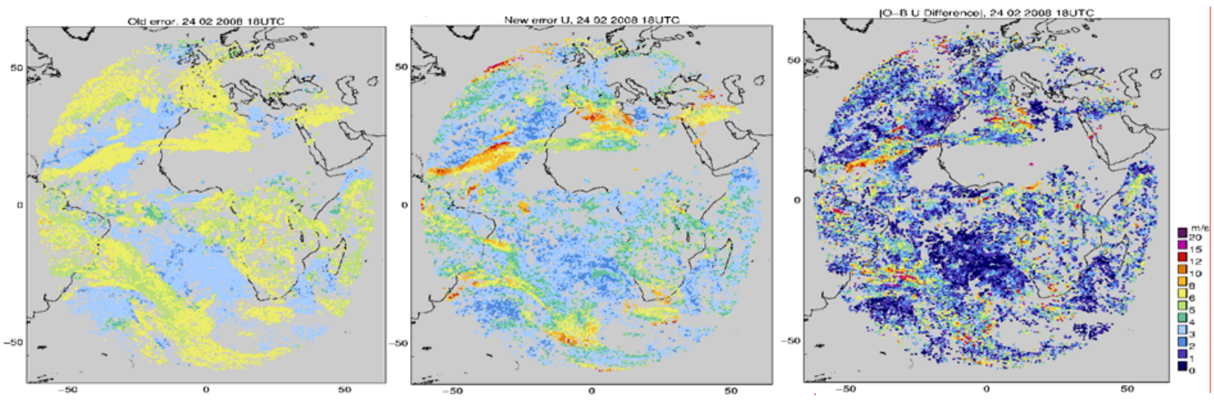


Figure 7: ***Plots showing the old (left) and new (middle) u component AMV observation errors for Meteosat-9 IR winds for the 18 UTC run on 24 February 2008. Also shown is the absolute observation minus background u component (right) for that run.***

The new errors are more variable in value, with the biggest values located in the jets, where the vertical wind shear is largest. Also shown is the absolute observation minus background u component difference (right), which can be used as a proxy for the error (also contains a contribution from error in the background). We don't expect a 1:1 relationship, but we would hope that most of the largest O-B differences correspond to AMVs with larger assigned errors. The relationship looks promising and provides some confidence in the skill of the new approach.

Relationship to O-B root mean square difference

We expect to see a positive correlation between the observation errors and root mean square difference values between the observation and background u and v components. In an idealised situation we might expect the points to lie on a straight line above the x=y line as the O-B root mean square difference contains a contribution from the background error. However, we know that it is better to use inflated errors for the AMVs to compensate for spatially and temporally correlated errors so in reality it may be better for the points to lie in a line on or below the x=y line. Figure 8 shows an example for 2 weeks of AMV data after blacklisting is applied. The results are encouraging.

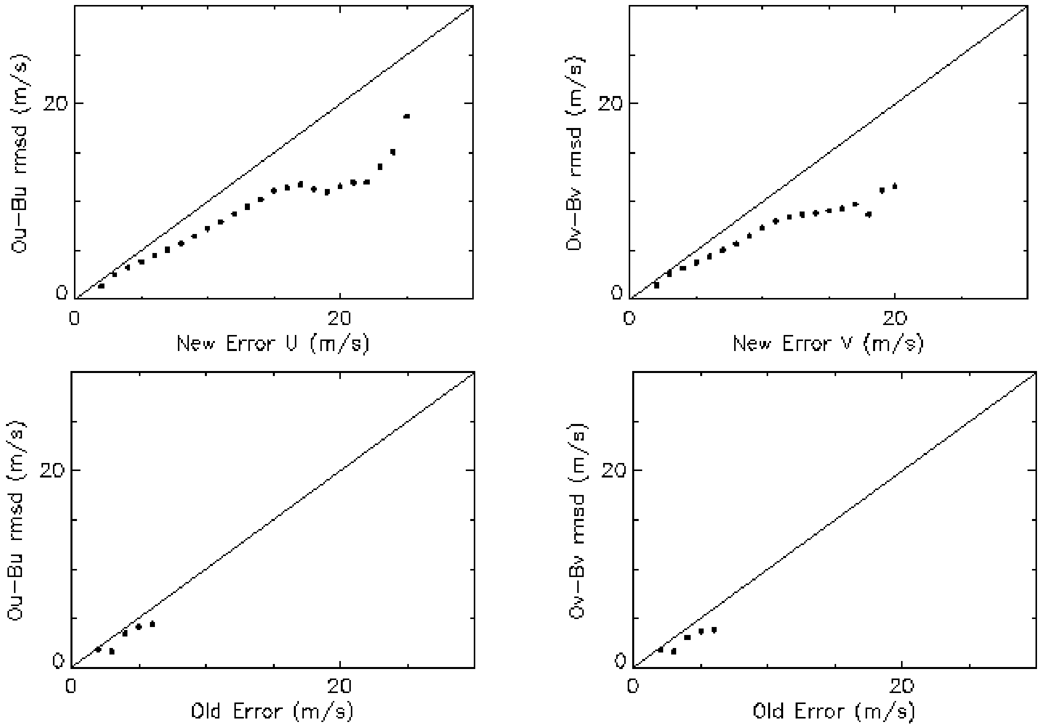


Figure 8: ***Plots comparing the new u and v errors and the old errors to the observation-background root mean square vector difference for 2 weeks of data after blacklisting is applied.***

Impact trial results

The new individual error scheme has been tested in two 4-week seasons in summer 2007 (24 May – 24 June) and winter 2007-8 (12 Dec – 12 Jan). Both trials were tested at N216 50 levels with 4D-Var using near-operational data usage and code.

One of the main measures at the Met Office for assessing whether an impact trial has improved the forecast compared with the control run is the NWP index. The global NWP index is produced from a weighted sum of the root mean square difference statistics for a range of forecast parameters (pressure at mean sea level, 500 hPa height, 850 hPa and 250 hPa wind fields) in different latitude bands and at different forecast ranges. The averaged results for the two seasons verified against observations and analyses is +0.2, which indicates a small positive impact of the AMV error change. To put this in perspective the two recent AMV denial trials at the Met Office in Dec 2005 and Dec 2007 have shown NWP index degradations of 1.5 and 0.6 respectively.

Figure 9 shows an example of the percentage forecast root mean square difference between the control and trial verified against observations for a range of forecast parameters (pressure at mean sea level, wind, geopotential height, temperature and relative humidity) at different levels and at different forecast range, separated by latitude band (north of 20N, 20N-20S, south of 20S). Anything below the line indicates a positive impact from the trial. Most benefit is seen at longer range, particularly in the northern hemisphere. The results in the tropics and southern hemisphere are more mixed.

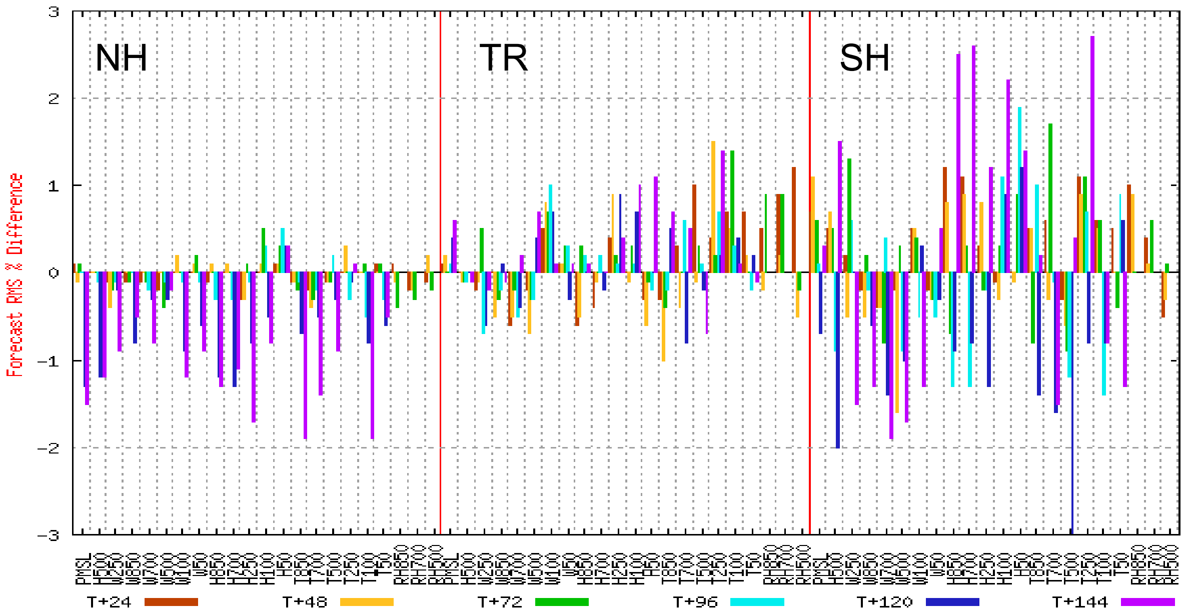


Figure 9: ***Change in percentage root mean square difference between the new error trial and control trial in the summer season verified against observations for a range of forecast parameters at different forecast range, separated into NH (north of 20N), TR (20N-20S) and SH (south of 20S). Anything below the line indicates a benefit from the experiment using new errors.***

Figure 10 shows the T+48 hour forecast error difference between control and trial averaged over the course of the summer trial (verifying each trial forecast against its own analysis). The yellow-orange colours indicate degradation and the green-blue colours improvements. The differences are small and spread. There is a tendency for a slight degradation in the Indian Ocean.

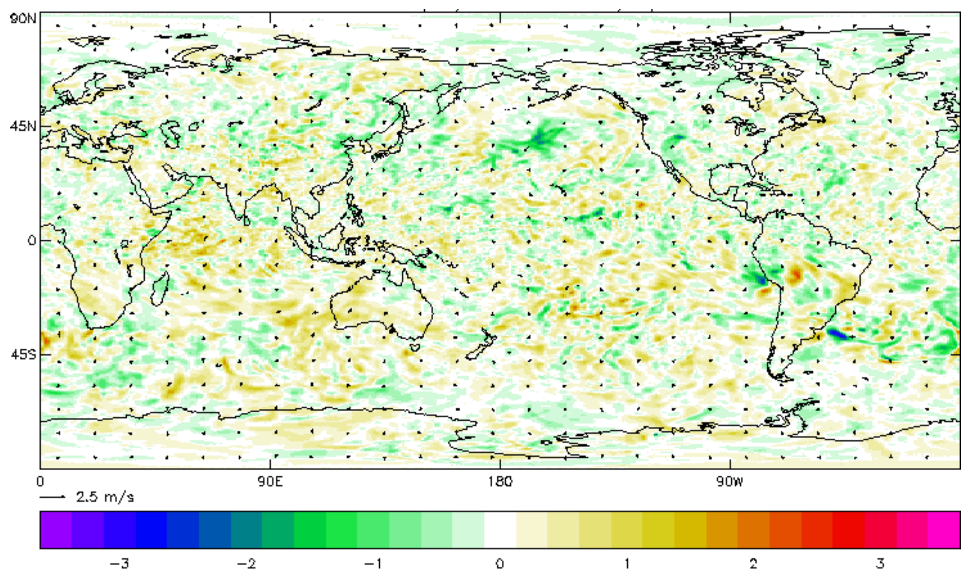


Figure 10: ***Difference in the 250 hPa wind field T+48 forecast error (each trial verified against its own analysis) for the new error and control trials for the summer season.***

WHERE TO GO FROM HERE?

The new AMV error scheme is recommended for inclusion in the next operational upgrade at the Met Office (due July 2008). Further investigations are planned to compare the height error estimates to the latest model best-fit pressure statistics and to consider other improvements to the strategy. A couple of areas which may be worth further consideration are the background check and the setting of u/v error estimates. The background check is affected by the change as the O-B threshold at which observations fail the check increases with the size of the observation error. One consequence of the new scheme is that very few AMVs fail the check.

Looking slightly further ahead we hope to be in a position to test u, v and pressure error estimates from the producers. As an example, at the moment all AMVs located at 200 hPa using the CO_2 slicing height assignment are assigned a height error of 40 hPa (based on best-fit pressure statistics). Information from the derivation step may give an indication of when this is a reasonable and when the height error should be more or less. Ultimately this should provide us with more realistic observation errors for use in NWP.

CONCLUSIONS

We have developed an approach to generate individual observation errors for each wind using information on the quality of the AMV vector and height assignment. It takes advantage of an increasing understanding of the sources of error and accounts for the height assignment error being more of a problem where the vertical wind shear is bigger. The new errors are more variable than the old errors and better reflect the O-B differences. The impact trial results show a small improvement and the change is recommended for operations. It is not trivial setting observation errors well, particularly as their success also depends on the appropriate setting of the background errors to ensure that the correct weighting is given to each. It is hoped that the impact of the scheme can be further improved through refinement of the existing set-up and, in particular, provision of u, v and height errors from the producers.

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