IMPROVING AMV IMPACT IN NWP

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Abstract

Atmospheric motion vectors (AMVs) provide a high temporal frequency near-global coverage wind product, which will continue to play a role in constraining numerical weather prediction (NWP) analyses for many years to come. However, realising the full potential of AMVs for NWP remains a challenge, partly due to the complicated nature of the AMV errors and the ever-increasing requirements for high quality observations as NWP models improve.

In recent years we have seen improvements in forecasts from assimilating AMVs in the polar regions, from assimilating new better quality datasets (e.g. from Meteosat Second Generation) and from adjustments to quality control and the way we represent observation errors in the assimilation. Looking ahead, where may we benefit from further developments?

In this paper, we will consider (i) how new datasets may help to improve data coverage, (ii) the role of AMVs in high resolution NWP and (iii) options for improving quality control and assimilation.

IMPROVING AMV DATA COVERAGE

The largest gaps in AMV data coverage are seen in the mid-latitude bands, highlighted in Figure 1, which separate the geostationary and polar AMVs.

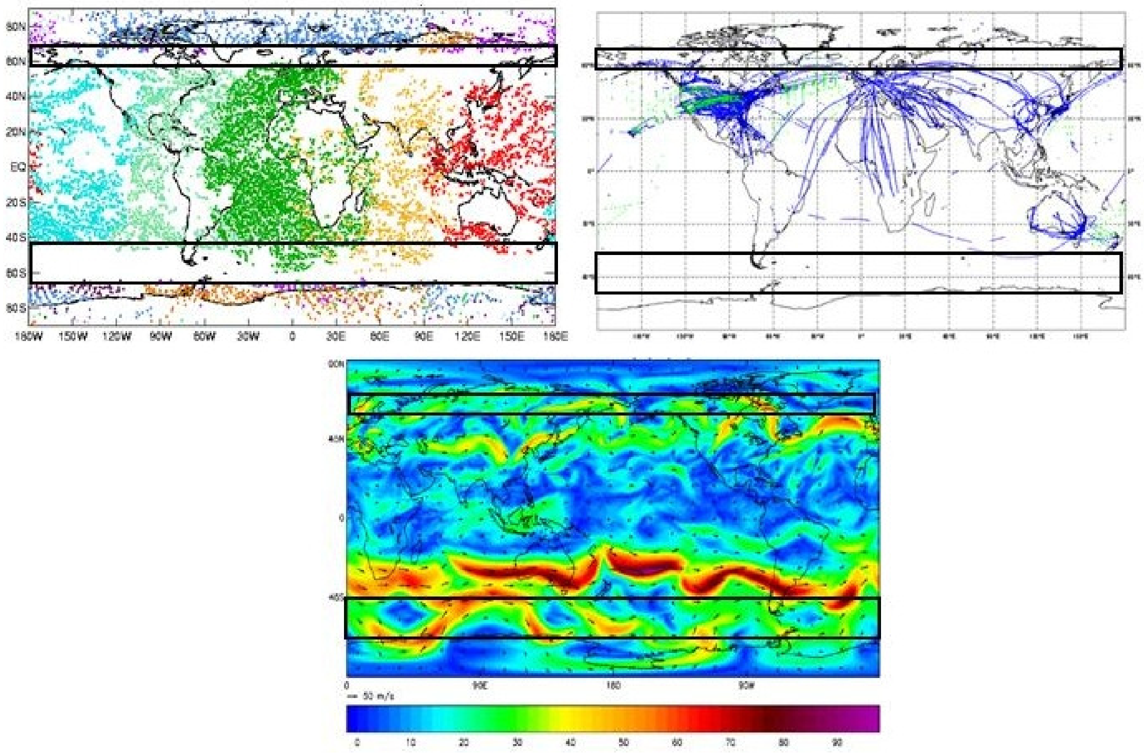

Figure 1: **(top left) AMV coverage for 1500-2100 UTC on 8 July 2008, (top right) example aircraft coverage and (bottom) example 250 hPa model wind field showing the location of the jets. The boxes mark the main gaps in AMV coverage.**

The AMV data gaps are generally not well covered by other wind datasets (e.g. aircraft data shown in Figure 1 top right). We can see from the model wind field (Figure 1 bottom) that the data gaps are located in meteorologically interesting areas. Improving wind coverage could, in particular, help to constrain the polar front jets.

There are a number of options which may help to reduce or remove these data gaps in the future:

1. **Increased geostationary coverage, in particular GOES coverage south of 40S.**
2. **Polar winds using image pairs.** This idea is being explored by EUMETSAT for Metop (see Dew et al., 2010).
3. **Multi-satellite polar winds.** Using alternate Metop-A/B image triplets reduces the time interval from 100 minutes to 50 minutes and increases the latitudinal range of overlap from polewards of ~65 N/S to polewards of ~45 N/S (see Figure 2 left). Using only image pairs would enable AMVs to be produced at all latitudes.
4. **Satellites in highly elliptical orbit (e.g. Figure 2 right).** A 2 satellite mission is being explored at Environment Canada (see Garand et al., 2010)
5. **Other wind datasets including ADM-Aeolus Doppler wind lidar and MISR follow-on.**

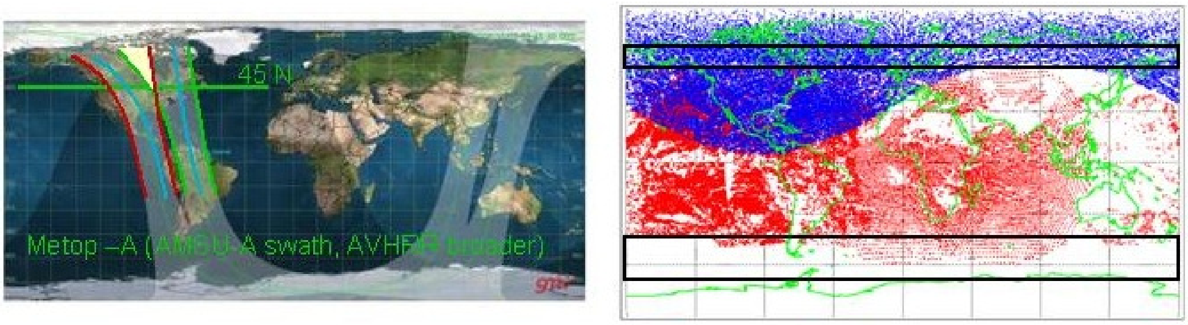

Figure 2: **(left) Example of improved coverage using image triplets from alternate Metop-A/B overpasses (Metop-A highlighted in green and red, Metop-B in blue). The yellow triangle shows the overlap between the three overpasses (area where AMVs can be produced with image triplets). Using only image pairs would provide coverage globally. (right) Example coverage from one satellite in highly elliptical orbit (blue) - from Riishojgaard, 2006.**

AMVS IN HIGH RESOLUTION NWP

Mesoscale wind data is of growing importance to NWP as models, in particular regional models, move to higher spatial resolutions e.g. Met Office global model at 25 km, regional at 12 km, UK moving to 1.5 km. An important focus of the higher resolution models is the improved prediction of high impact weather events. Work to develop mesoscale AMV products is ongoing at a number of centres (see mesoscale session of the IWW10 proceedings). However, it is still relatively early days in learning how best to produce and make use of these products.

The main challenges include:

1. Pixel resolution and time interval constraints on ability to resolve slower winds.
2. Increased tracking noise with smaller target boxes.
3. Current quality indicators (QIs) and NWP quality control may penalise good winds e.g. tight curvature around a low pressure system (spatial/temporal QI checks may score poorly).
4. How to make use of high resolution data in NWP (remove or reduce thinning box), without damaging the forecast due to spatially and temporally correlated errors.

Figure 3 shows a case study for 13 November 2009 comparing the mesoscale Meteosat-8 HRVIS AMVs (on the left) with the standard Meteosat-9 HRVIS AMVs (on the right). One notable feature is the improved representation of a region of faster winds (highlighted by the black circle) in the mesoscale AMVs.

Further work is required to develop high resolution AMV datasets and to learn how to use them optimally in NWP. The 10th International Winds Workshop recommended that centres should continue to share and discuss results to aid this process.

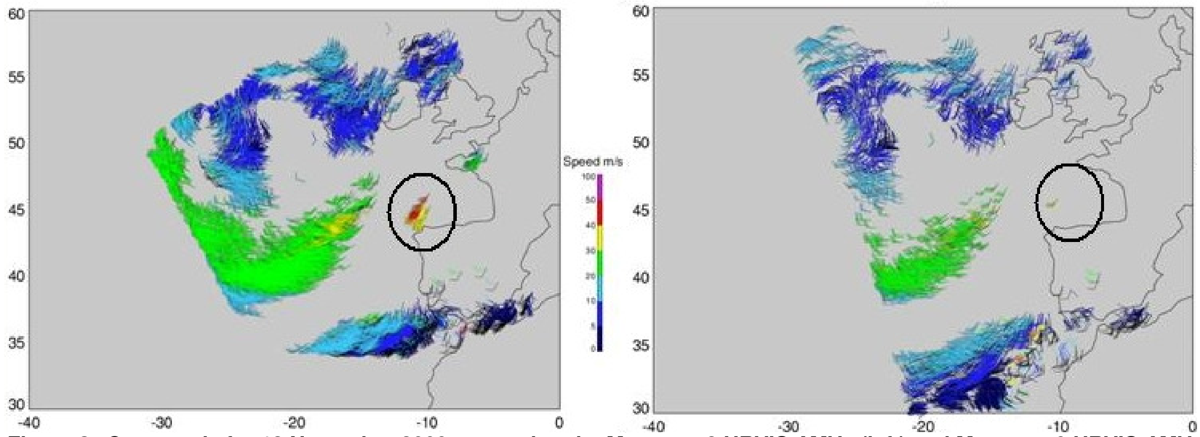

Figure 3: **Case study for 13 November 2009 comparing the Meteosat-8 HRVIS AMVs (left) and Meteosat-9 HRVIS AMVs (right). The black circle highlights a region of faster winds, which are much better captured in the Meteosat-8 AMVs.**

IMPROVING AMV QUALITY CONTROL AND ASSIMILATION

There are a number of elements to the AMV quality control and assimilation. These are discussed in the sub-sections below.

Blacklisting:

Blacklisting is the process where data is removed from the assimilation based on a number of criteria e.g. pressure level, surface type, observation time, observation speed, quality indicator etc. There is a balance within the assimilation between removing data through blacklisting and down-weighting data by increasing observation errors. As a rule of thumb, blacklisting is the preferred approach for subsets of data which are consistently of poorer quality. The main blacklisting options are shown in Table 1:

Type of blacklisting	**Based on….**	**Example**	**Decision Aids**
Spatial	Latitude, longitude, surface type, topography, AMV pressure, satellite zenith angle	e.g. all VIS winds above 700 hPa	Based on knowledge of AMV derivation limitations and O-B statistics
Temporal	Observation time	e.g. remove time slots affected by solar stray light	Based on known problems e.g. solar stray light and Hovmoeller O-B statistics plots
Speed	Observation speed	e.g. remove slow winds	Take into account navigation error and speed required to move target one pixel.
Quality Indicator (QI)	Choice of QI and threshold	e.g. remove all winds with QI<85	Based on statistics versus QI plots and data coverage plots to check retain coverage

Table 1: **A summary of different blacklisting options.**

Thinning:

Thinning has the affect of reducing data density and is the main approach used in NWP to alleviate problems with spatially and temporally correlated observation errors. An alternative is superobbing, where the O-Bs (innovations) for all observations within a box are averaged to create a superob (see Berger et al., 2004). In both cases, thought is required in setting suitable horizontal, vertical and temporal box dimensions (e.g. 200 km by 100 hPa by 3 hr). For thinning, there is an additional decision on how to select which observation to use (e.g. by closest to centre of box, highest QI, lowest observation error). For superobbing decisions are required on whether/how to weight the contributions from different observations to the superob and whether/how to reduce the observation error to reflect the reduction in random error through averaging.

Over the years many centres have shown improved forecast impact using a spatial box dimension of around 200 km, at least for global applications. The choice of optimal temporal box dimension for use with 4D-Var would benefit from further evaluation, particularly with the improving temporal availability of AMV datasets. It could also be interesting to investigate the idea of synoptic-dependent thinning, where the data is used at higher density in areas with greater variability in the wind field or where the forecast is most sensitive to analysis errors i.e. targeting

Background Check:

A background check is included in most NWP systems as a safeguard to avoid assimilating data that is very different from the background. Figure 4 shows an example of the data removed by the Met Office AMV background check.

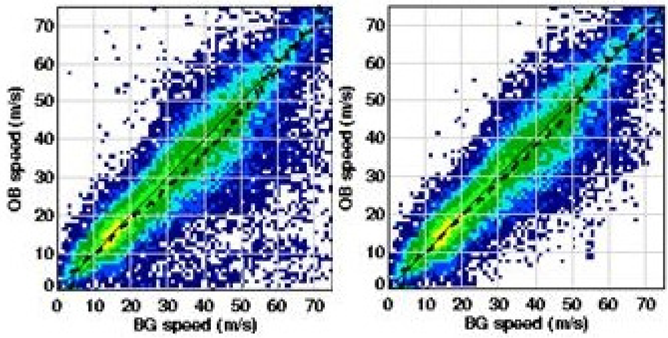

Figure 4: **Example speed bias density plots for a subset of AMVs. (left) all extracted AMVs and (right) all AMVs passing the Met Office AMV background check.**

The background check at the Met Office follows a Bayesian approach. Good observations and the model background are assumed to have normally-distributed errors and bad observations are assumed to have gross errors (see Ingleby and Lorenc, 1993, for more details). Until November 2009 we applied an asymmetric adjustment to penalise slower winds, but this was removed following improvements in AMV bias.

Within the Met Office system, the background check is carried out as part of the observation pre-processing. It may be beneficial to include an additional stricter check within the variational analysis.

Observation errors:

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.

We know from long experience that AMVs have complicated error characteristics, which depend on the quality of the vector and height assignment. In July 2008, the Met Office introduced a new error scheme where the error is set for each observation by combining an estimate of the error in u/v with the error in u/v due to an error in height. The latter is calculated using the model background wind profile and an estimate of the error in height (see Forsythe and Saunders, 2008, for more details).

The new scheme uses statistical estimates for the height error based on assigned pressure minus model best-fit pressure root mean square differences. In the future we hope to use physical u, v and height error estimates provided by the producers.

Work is ongoing to assess how well the scheme is working. Plots, such as the example shown in Figure 5, can be used to identify areas where there are large mismatches between the assigned u and v observation errors (top plots) and the O-B root mean square u and v differences (bottom plots).

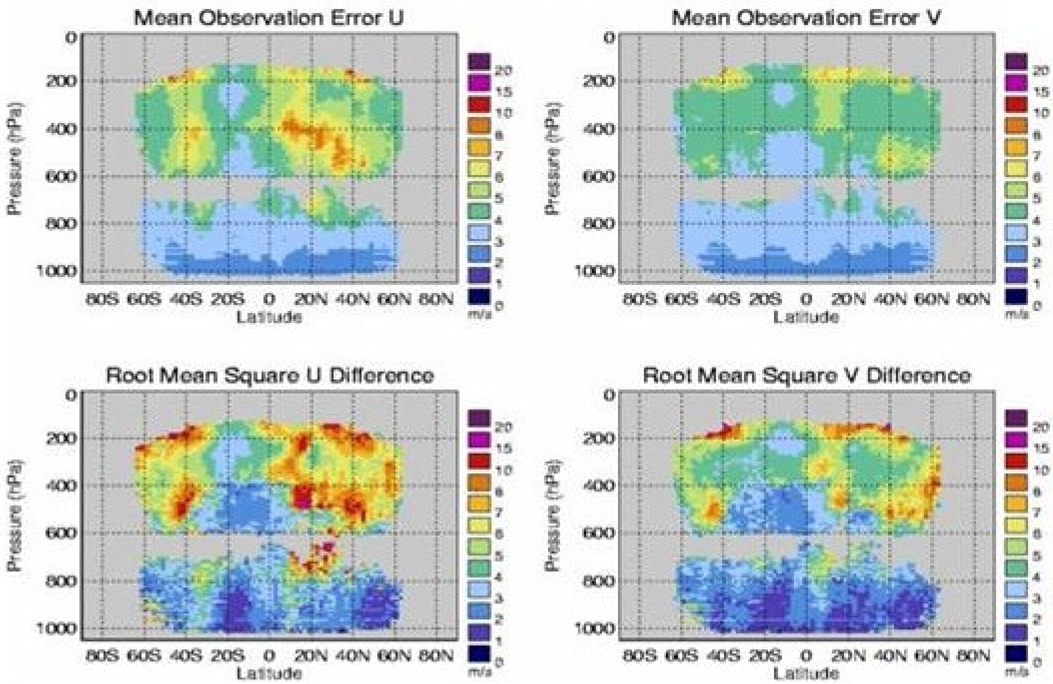

Figure 5: **Examples of plots which can be used to help assess the new AMV observation error scheme. If this is working effectively we would expect similarities between the mean observation error plots and the root mean square difference plots compared with the Met Office model background.**

The Met Office data assimilation scheme, like most centres, assumes uncorrelated errors to reduce computational cost. We know this is not true for the AMVs (e.g. Bormann et al., 2003). To address this most centres reduce the data density and inflate the observation errors. ECMWF have recently developed a system to allow for correlated error within the assimilation (see Isaksen and Radnóti, 2010). This requires a reasonable understanding of the AMV error correlations.

Observation operator:

Most NWP centres treat AMVs as point winds in space and time. Studies have been carried out to investigate the potential of modifying the observation operator to treat AMVs as layer observations (e.g. Rao et al., 2002; Bormann et al., 2002; Velden & Bedka, 2009). Some factors to consider are the shape, width and placement of the layer operator relative to the AMV assigned pressure. From an NWP perspective a weighting function that drops off smoothly from the assigned pressure level (e.g. a Gaussian) is preferred to a top-hat layer mean as this gives us a forward operator which is smooth and differentiable with respect to the assigned level. Within our tests, this was run with two settings: (1) centred on observation level and (2) offset (see Figure 6). In the offset case the weighting function is shifted either down (mid and high level winds) or up (low level winds) by one standard deviation. This reflects the single level height assignment being based on cloud top height for mid-high level winds and cloud base for low level winds.

Deciding what layer width to use is not trivial. In the future an estimate may be provided by the AMV producers using information on the variability of cloud top heights from the dominant cluster in the tracking and/or taking advantage of additional information on cloud optical thickness. Until then, we are dependent on a statistical approach. The main complication is that two issues are tied up together: (1) AMVs represent motion of a layer and (2) AMVs have height assignment errors. Both will affect the layer statistics.

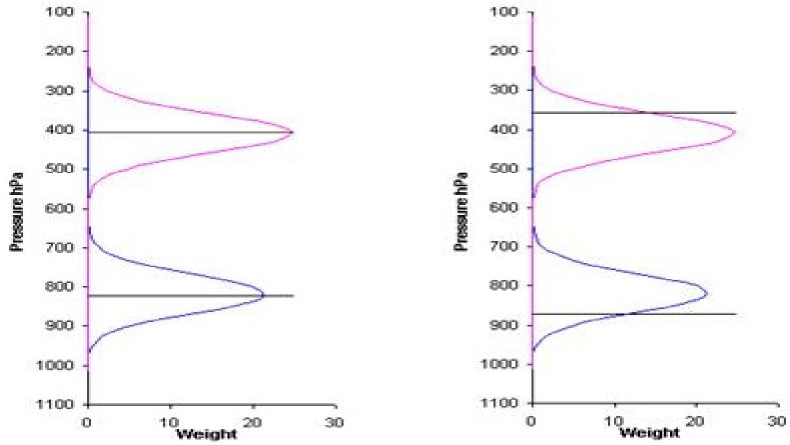

Figure 6: **Examples of Gaussian layer operators (left) centred and (right) offset.**

To get a feel for the impact, an initial test was done using fixed layer widths in 10 hPa steps from 10-200 hPa for all Meteosat-9 IR 10.8 observations. Figure 7 summarises the impact on (1) the mean vector difference between the observation and layer background and (2) the percentage of observations where treatment as a layer rather than a single level reduces the O-B vector difference.

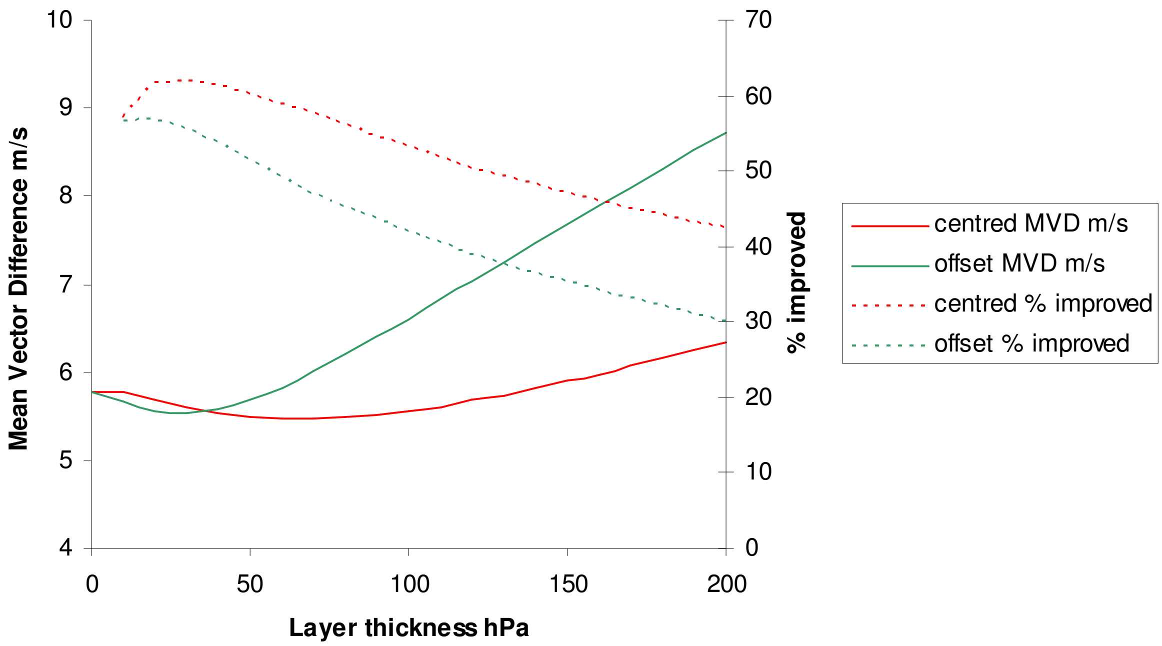

Figure 7: **Preliminary results investigating improvement in mean vector difference statistics as a function of layer width for Meteosat-9 IR 10.8 AMVs valid on 16 February 2010 00z run (2100-0300 UTC).**

The improvement is fairly limited (< 5%), peaking for layer widths in the range 30-90 hPa for the centred case and 20-40 hPa for the offset case. The centred case gives the best overall improvement.

Looking at this alone, we might conclude that there is little to be gained from treating the AMVs as layers. It should, however, be remembered that the same layer width is unlikely to be suitable for all Meteosat-9 IR 10.8 winds. Before separating further e.g. by pressure level or height assignment method, we decided to investigate the impact on mean vector difference statistics of allowing each observation to have its own best-fit layer width, defined as the layer in range 10-200 hPa giving the minimum O-B vector difference. Table 2 summarises the results.

	Mean Vector Difference (MVD) m/s	% reduction in MVD compared to single level
Single level	5.78	-
Best fixed layer – centred (70 hPa)	5.47	5
Best fixed layer – offset (30 hPa)	5.53	4
Best-fit layer - centred	4.07	30
Best-fit layer - offset	3.62	37
Best-fit single level	1.75	70

Table 2: **summarises the impact on mean vector difference for Meteosat-9 IR 10.8 AMVs valid on 9 February 2010 00 UTC run (2100-0300 UTC) when treating the AMVs as single level (at assigned or best-fit level) and layers (fixed layer width or best-fit layer width).**

Using the fixed layers gives only ~5% improvement; by contrast using the best-fit layers gives ~30% improvement. The latter gives us a guide to the upper limit of the O-B statistics improvements if the layer thickness is set optimally for each observation. However, it is important to remember that errors in AMV height assignment will also contribute to the results so a more realistic improvement may be closer to 10%. It is interesting to note that even using best-fit layers, the improvement is far less than that seen if we were to reassign the AMVs to the best-fit single level (~70% improvement).

Figure 8 shows the impact on the spatial distribution of O-B speed bias and standard deviation for 6 hr of IR AMVs when treated as: (1) single level, (2) 50 hPa centred layer and (3) best-fit centred layer.

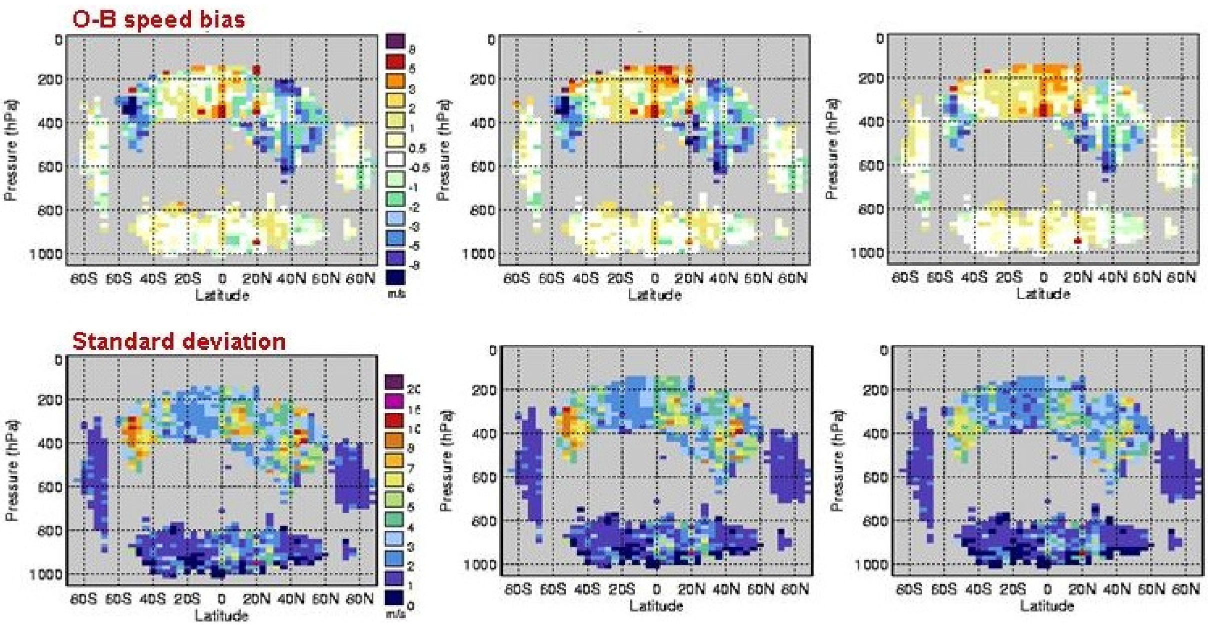

Figure 8: **Preliminary results investigating the impact on O-B speed bias and standard deviation for all IR AMVs valid for 16 February 00 UTC run (2100-0300 UTC) when treated as: (left) single level (middle) 50 hPa fixed centred layer and (right) best-fit centred layer.**

In most areas the standard deviation is improved; the improvement is greater using best-fit layers than a fixed 50 hPa layer. There is a tendency to reduce the slow bias in the jet regions, but increase the fast bias in the tropics. In this paper we have provided very preliminary results based on limited datasets. Further work is required to investigate the potential of this approach and the preferred operational set-up.

CONCLUSIONS

There are a number of areas to address in order to improve impact from AMVs on NWP forecasts. In many cases these rely on AMV producers and NWP centres working together to develop new products and to refine the derivation and assimilation of existing products.

Reducing the data gap between the current polar and geostationary datasets may help to constrain the polar front jets. A number of options may reduce or remove the gap including: polar winds using image pairs, multi-satellite polar winds, satellites in highly elliptical orbits, Doppler wind lidar and MISR follow-on missions.

Mesoscale AMV products have the potential to provide valuable information for high resolution NWP models, where a priority is the improved prediction of high impact weather events. It is anticipated that further work is required to refine the derivation of mesoscale winds and to adapt NWP assimilation and quality control to optimise impact in high resolution NWP.

The main elements of AMV quality control and assimilation are: blacklisting, thinning/superobbing, a background check, observation errors and an observation operator. In recent years we have made progress in the Met Office by implementing a new observation error scheme and refining our background check, but there is more work to be done. Some key areas include improving our use of AMVs through the time window (updating our temporal blacklisting and thinning) and evaluating changes to the observation operator.

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