Error characterisation of atmospheric motion vectors

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(Manuscript received June 2003; revised February 2004)

From the middle 1990s local high density atmospheric motion vectors (AMVs) began to be generated from geostationary satellite imagery and to be used operationally in the Australian Bureau of Meteorology. It was soon realised that their benefit to numerical weather prediction (NWP) was dependent on quality control, error characterisation and data selection. Here, by comparing the AMVs with collocated radiosonde data, we show that quality control (QC) considerably reduces vector error. In many cases, QC also reduces the correlated error and its associated length scale. Modern operational data assimilation schemes require estimation of observation errors, and they assume either that the errors are uncorrelated or require knowledge of their correlated error and length scale. A new construct, the expected error (EE) now employed at the Bureau, has been introduced to assist in quality control and error characterisation of AMVs. In this approach each vector is characterised by an expected error value, the correlated error and the related length scale, in addition to the set of currently available error indicators . The expected error allows direct comparison of the accuracy of vectors, based on different image types, or from different producers. At present, comparison of accuracy error is a more difficult process. Provision of the correlated error and length scale permits better use of the vectors in data assimilation, and provides a firm basis for data thinning.

Introduction

Since the operational use of locally generated atmospheric motion vectors (AMVs) by the Bureau of Meteorology began in 1992 (Le Marshall et al. 1992), it has been known that careful quality control of the winds is required to ensure a positive impact in regional and global data assimilation. Their 'optimal' use is particularly dependent on the characterisation of errors associated with particular vector types.

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During production, vectors with unacceptably large (gross) errors are typically removed by examining the temporal consistency of the vectors (the acceleration check), the spatial consistency of the vectors (buddy checks) and by error estimates, based on comparison with the forecast model background field (Le Marshall et al. 1994, 2003). The AMVs are expected to have spatially correlated errors because of the methods used in their generation and quality control. For example, errors in image navigation can give rise to spatially correlated velocity errors. A forecast background field with spatially correlated errors is often also used for cloud and water vapour feature height assignment and can lead to correlated error. Correlated error may also be produced by similar errors in height assignment of fleets of vectors associated with a given cloud area of uniform type. In such cases, height assignment and quality control are both dependent on a forecast model with correlated errors. Determining these gross and correlated errors is crucially important in data assimilation and NWP.

Here, we examine the quality control, error characterisation and assimilation of atmospheric motion vectors generated at the Australian Bureau of Meteorology (ABM). We demonstrate that the judicious application of quality control and error estimation can improve the accuracy and error characterisation of the AMVs.

The atmospheric motion vectors (AMVs)

The methods used for AMV estimation in the ABM are described in full by Le Marshall et al. (1999, 2000). Three sequential infrared (IR), visible (VIS) or water vapour (WV) band images (known as a triplet), typically separated by an hour or half an hour, are used to provide tracers which are used for velocity estimation. High density winds are generated continuously at these half hourly or hourly intervals. Selected targets are tracked automatically using model forecast winds, followed by a lagged correlation technique, which minimises root mean square (rms) differences in brightness from successive images to estimate the vector displacements. Cloud height assignment uses forecast temperature profiles. The cloud height assigned for the low-level winds is that of the cloud base (Le Marshall et al., 1992), following the field work of Hasler et al. (1976, 1977). The benefit of height assignment to the cloud base has been documented in Le Marshall and Pescod (1994). Upper level AMVs are assigned to the cloud-top altitude which is estimated using 11 and 12 μm split window observations (Le Marshall et al. 1998). For water vapour motion vectors, height assignment of the upper-level cloud vectors and middle-level vectors in clear conditions is described in Le Marshall et al. (1999).

An example of the wind vectors, obtained from the ABM's operational system is shown in Fig. 1, over the Tasman Sea (around 20°S, 160°E).

Accuracy of AMVs

The accuracy of AMVs is determined by several factors. The resolution and navigation of the imagery used for tracking clearly determines the accuracy in measuring displacement of targets. The time between images is also important in that it needs to be short enough to allow features to be tracked while being long enough that the inherent errors in measuring displacement (due to image resolution) do not lead to large velocity errors. The number of vectors generated also depends on these factors. A summary of these influences may be seen in Jedlovec and Atkinson (1998) and Le Marshall et al. (2000).

The most important factor influencing the accuracy of the AMVs is height assignment. It is well established that low-level vectors should be assigned to the level of the cloud base. On the other hand, upper-level targets travel at the speed of the wind at cloud top and therefore need to be associated with the cloud-top altitude. The assignment of low-level AMVs to cloud base was first described by Le Marshall et al. (1992) and later in Schmetz et al. (1996). Different methods employed for the height assignment for upper-level vectors are described in Le Marshall et al. (2003). These methods are designed to take into account variations in cloud emissivity in the estimation of cloud-top altitude by using multi-pixel, statistical and multi-channel approaches. Typical verification results from

Fig. 1 GMS-5 cloud and water vapour motion vectors over the Tasman Sea for 2300 UTC 24 July 2002.

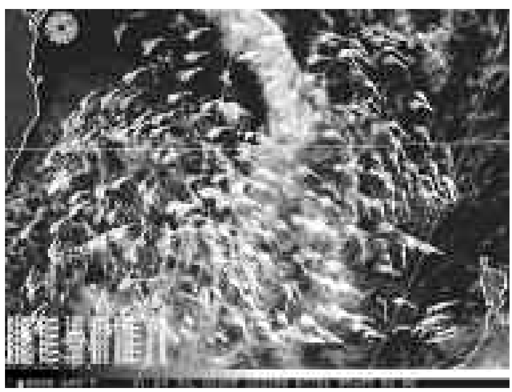


Table 1. Comparison of radiosonde winds and GMS-5 based AMVs (available for selection for operational use) collocated within 150 km over the Australian region, January to June 2002 inclusive. [IR1 = 11 μm imagery based winds, VIS. = low resolution (5 km) visible winds, HR VIS = high resolution (1.25 km) visible winds, WV = water vapour based winds and MMVD = mean magnitude of vector difference (m s^{-1})]

Types		*IR1*	*VIS*	*HR VIS*	*WV*
Low (950 – 700 hPa)	No. of obs.	3722	923	3134	---
	MMVD (m s^{-1})	3.32	3.26	3.33	---
Middle (699 – 400 hPa)	No. of obs.	26	3	8	513
	MMVD (m s^{-1})	5.26	3.31	4.99	4.75
High (399 – 150 hPa)	No. of obs.	2327	472	1258	9511
	MMVD (m s^{-1})	5.57	5.75	4.88	5.23

the application of these multi-channel height assignment methods to IR (IR1), low resolution (5 km) VIS and high resolution (1.25 km) visible (HRVIS) imagery over the Australian region are seen in Table 1, which shows the vectors available for selection for operational use. Note that the numbers in Table 1 are indicative only, as fewer vectors can be made available for operational use and this will result in smaller differences/errors.

AMV quality control and assimilation

Error determination and rejection in most real-time AMV estimation systems are generally based on several elements. These include the correlation between the brightness temperature arrays of the search and target areas, the difference in meridional and zonal wind components of the two vectors from a tracer tracked in adjacent pairs of images, and the deviation of the calculated wind vectors from the first-guess field.

For data assimilation, data thinning is often required when using high density AMVs. In practice, thinning is achieved by reducing data density to a separation suggested by the length scale of the correlated error (typically around 100 km). This is usually achieved by preferentially selecting vectors of higher accuracy. The selection generally involves use of the quality indicator (QI), expected error (EE), recursive filter flag (RFF), error flag (ERR) or other indicators of error level available with the vectors, and should result in an observational error level close to that of the background field. It is noted that the error level on which the data selection is based, as well as the error of the background field, are both estimated from data at radiosonde sites, where short-term forecast errors are usually lower because of the proximity of sonde data. Overall, error levels of the data to be assimilated are generally chosen to be close to or lower than the background errors, particularly away from conventional observations, thereby facilitating improved prognosis. It is also important in the analysis process to exercise judicious quality control (such as gross error checks) to prevent poorly characterised vectors degrading the analysis.

In the ABM context, strict QC in the operational system was necessary, initially for upper-level winds and later for the mid-levels to ensure that GMS SATOBS improved operational regional forecasts. In a recent real-time regional high density AMV impact experiment from 12 September to 30 October 2000, local GMS-5 IR, VIS, HRV and WV image-based AMVs were assimilated into a test version of the ABM's operational regional forecast system (Puri et al. 1998). During the early part of the period, (12 to 24 September), the wind system provided mid-level WV vectors with error values near 6.4 m s^{-1}, considerably larger than that of the background field around 500 hPa. Table 2 shows mean skill scores (Teweles and Wobus 1954) for 500 hPa 24-hour forecasts for the Operational (Ops) and Ops + AMV systems and the mean magnitude of vector difference (MMVD) for the mid-level AMVs. It shows that the impact of these poor-quality winds was to degrade the forecast at 500 hPa in the first part of the assimilation experiment (12 to 24 September). After this period the wind

Table 2. Mean S1 skill scores at 500 hPa for Operations (Ops) and Operations plus AMVs (Ops+AMVs) (12 September to 30 October 2000) and mean magnitude of vector difference (MMVD) for mid-level AMVs compared to radiosondes for the same period.

	Mean S1		MMVD (m s^{-1}) mid-level
	OPS	OPS + AMVs	
12-24 Sept 2000	16.3	16.6	6.4
24 Sept-30 Oct 2002	16.7	16.4	4.2

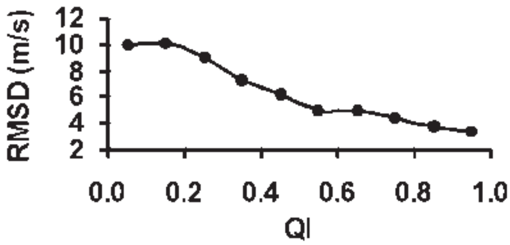
processing and QC was upgraded to reduce mid-level AMV errors, and from 25 September to 30 October, the impact of the AMV data was then to improve the 500 hPa forecasts. Note that the impact of the AMV data during the initial and final part of the experiment was to improve both the upper and lower-level forecasts. Other studies have also demonstrated the importance of QC and error characterisation in ensuring positive impact from data assimilation, both in Australia and elsewhere. Another example is the recently completed real time impact study in the ABM using locally retrieved GOES-9 AMVs.

The quality indicator

Recently, a quality indicator (QI) has been introduced to assist in data selection (Holmlund 1998) and Holmlund et al. (2001). A QI is associated with each AMV in the BUFR product from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) and the National Environmental Satellite, Data, and Information Service (NESDIS). The QI for each AMV is calculated by estimating direction consistency, speed consistency, vector consistency, spatial consistency and consistency with the operational forecast. The degree of compliance with these five tests is then used to form a single QI. The QI has been beneficial in the application of high-density winds, by providing a consistent estimation of the comparative accuracy associated with each vector. It is an essential error indicator for analysis using Global Telecommunication System (GTS) AMV BUFR data. The QI is being provided for all AMV types generated at the Bureau of Meteorology, using methods similar to those of Rohn et al. (1998) but without the additional (filter) checks now employed by EUMETSAT. Figure 2 shows QI against rms difference between low-level infrared AMVs and radiosonde winds located within 150 km, using the one-year period April 2000 to April 2001. The use of the QI for data selection and error estimation can be improved further by combining it with other quality measures such as the recursive filter flag (RFF) (Holmlund et al. 2001).

Note that, if QI is used rather than an expected error, then calibration curves similar to those of Fig. 2 need to be estimated for each vector type, for each wind producer. However, it may be simpler if data-producers provided an expected error with each AMV. In the ABM, expected error is calculated directly for all vectors. This direct measure of error obviates the need for multiple look-up tables to be constructed, for example, from Fig. 2, to estimate error from QI for each vector type for each producer. Currently for high density wind data available via the GTS, the QI, RFF etc. must be used for data selection and subsequent analysis.

Fig. 2 **Quality Indicator (QI) versus root mean square difference (rmsd) with radiosonde winds within 150 km for low-level GMS-5 infrared image based AMVs for 28 April 2000 to 29 April 2001.**



The expected error

The expected error (EE) is calculated from the wind speed, the wind and temperature shear, the pressure level and the elements that make up the QI. The elements of the QI have traditionally been used for QC of AMVs since the early 1980s and wind speed is known to be strongly related to AMV error. The vertical wind and temperature shear are also clearly related to AMV error, determining how height assignment errors influence AMV quality. Currently, least square regression is used operationally to compute the root mean square error in metres per second (m s^{-1}) from the EE components. That is, the five QI components, the wind speed, the vertical wind and temperature shear and the pressure level are used as predictands for root mean square error. Figure 3 (a) is a plot of the error calculated from the QI via a lookup table such as in Fig. 2. Figure 3 (b) is a plot of the EE versus measured error. As suggested from a comparison of Fig. 3 (a) and 3 (b), the EE is on average a more accurate means of determining the observed error.

Table 3 further summarises the results. In practice, the EE is also more efficient at data selection, for example, it provides well over 50 per cent more vectors at threshold error levels typical of operational data rejection and also well over 50 per cent more vectors at error levels associated with the background field.

The vastly improved coverage for a given error level or, equivalently, decreased error levels for the same AMV numbers, provides a much improved basis for analysis and prognosis. This result is expected as the weights used in EE have been determined specifically by regression to predict the root mean square error whereas those used in the QI were not. Other important aspects of the EE are that it can be used to compare AMVs from different producers and that it

Fig. 3(a) Predicted error using the QI lookup table.

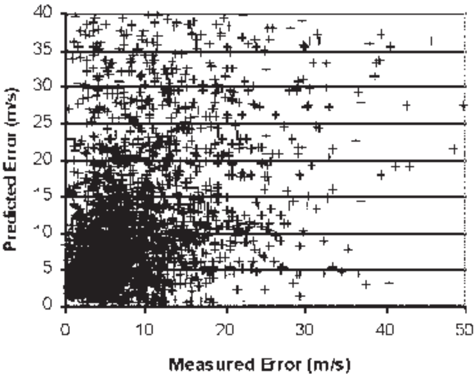
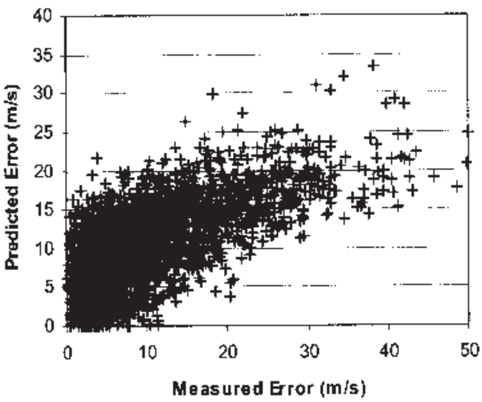


Fig. 3(b) Predicted error using the EE approach.



can be used quantitatively in conjunction with the correlated error and associated length scale in the analysis process, For example, the EE can be applied in conjunction with 3-D and 4-D VAR data assimilation techniques. Figures 4(a) and 4(b) give examples showing the QI and EE for AMVs over the Coral Sea on 7 November 2002. There is a clear relationship in this case, between the QI and EE, with, for example, QI values of around 0.92, implying RMSDs near 2.9 m s^{-1}.

Correlated error

In addition to the expected error, a correlated error (CE) and a length scale (L) are associated with the vectors. The CE has been computed using collocated, contemporaneous radiosonde and AMV observations from a match file. The approach used to derive the

Table 3. AMV numbers and comparative errors in predicted error when selecting upper-level WV AMVs (November, 2002) using EE and QI. (Here vector samples are chosen with av. MMVD equal to 5 and 6 m s^{-1} respectively)

	EE	*QI*	*EE*	*QI*
Threshold	EE<5.2	QI>.98	EE<8.5	QI>.89
No. of matches	3156	514	7265	2863
Av. MMVD	5.00	5.00	6.0	6.0
Av. err. in predicted err.	3.17	5.24	3.25	4.31

Fig. 4(a) The QI generated for AMVs over the Coral Sea on 7 November 2002.

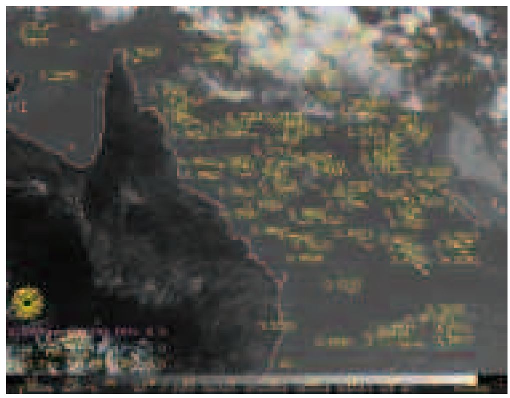
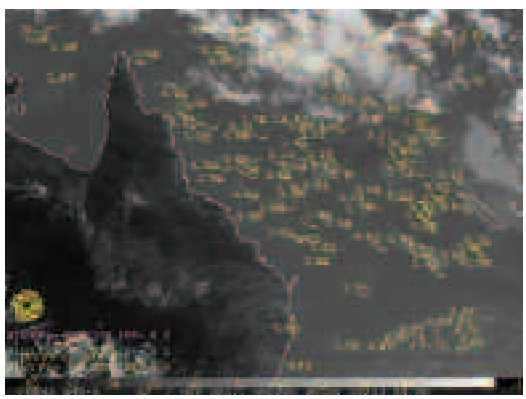


Fig. 4(b) The EE generated for AMVs over the Coral Sea on 7 November 2002.



spatial variation of correlated error from the match file assumes that the observation errors from radiosondes are spatially uncorrelated. In this case, any observed correlation between the AMV and radiosonde differences in the U or V wind components is attributed to spatially correlated AMV errors. Grouping errors, associated with radiosonde/AMV pairs at the same time, by using separation distance allows a characterisation of the average spatial structure of correlated errors for local GMS-5 AMVs. The method has been used widely and was discussed by Daley (1991). Extrapolation of the CE versus distance relationship to zero separation gives the magnitude of the spatially correlated AMV errors. The correlation function provides an estimate of the length scale of the CE. This length scale has been used as a basis for the thinning appropriate in regional data assimilation.

Analysis of correlated error

Here, we analyse observed data assuming an isotropic error correlation versus distance function, which is satisfactory for an initial application to data assimilation. The correlation function used to extrapolate to zero separation is the second order auto-regressive (SOAR) function (Daley 1991).

$$R(r) = R_{00} + R_0 \left(1 + \frac{r}{L}\right) e^{\frac{-r}{L}} \qquad \text{...1}$$

where *R(r)* is the error correlation, with fitting parameters R_{00}, R_0 (greater than 0), and L is the length scale, 'r' is the separation of the correlates.

Figure 5 and Table 4 show error correlation versus distance for local GMS-5 for AMVs in the Australian region. Figure 5(a) shows error correlation versus distance for high level WV vectors derived using 10 km distance separation category bins. The two distributions are for all vectors generated and those selected on error characteristics for use in operational NWP (Ops) in the Bureau. Figure 5(b) shows the same plot using 100 km separation for the bins. The effect of loss of resolution from binning is just discernible in the second distribution which is smoothed compared to that in Fig. 5(a). The parameters (R_0, R_{00}, L) of the related SOARs for the 10 km, and 100 km and bin cases are (0.91, 0.02, 84.8) and (0.73, 0.02, 101.1) respectively. Figure 5(c) shows the error correlation versus distance for IR1 high level vectors while Fig. 5(d) shows the distance correlation plot for mid-level WV AMVs. Figures 5(a), 5(b) and the noisy 5(d), show a reduction in CE and length scale from the quality control associated with the selection of vectors for use in the Bureau's operational regional data assimilation system. A similar reduction in CE length scale has also been noted through application of the EE and QI in data selection (see for example Figs 5(e) and 5(f)).

Fig. 5(a) Error Correlation versus distance (10 km bins) for all high level WV AMVs generated and those selected for NWP use (Ops).

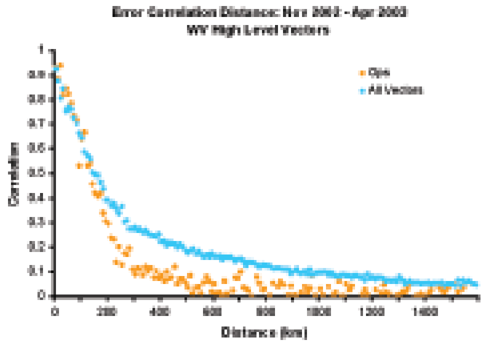


Fig. 5(b) Error Correlation versus distance (100 km bins) for all high level WV AMVs generated and those selected for NWP use (Ops).

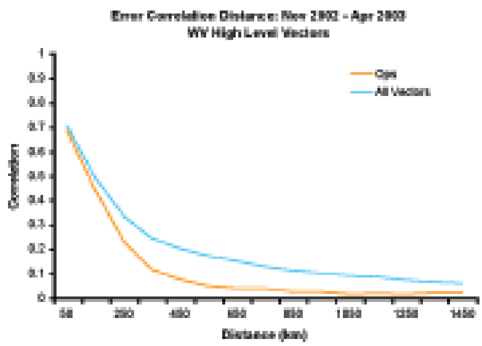


Fig. 5(c) Error Correlation versus distance (10 km bins) for all high level IR1 AMVs and those selected for NWP use (Ops).

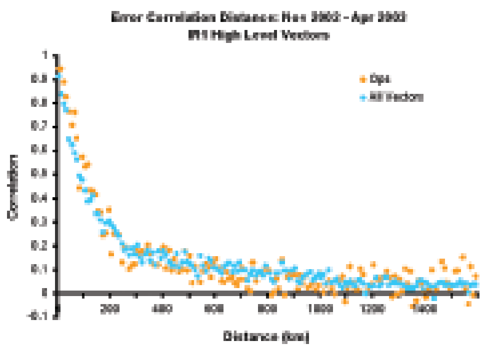


Fig. 5(d) Error Correlation versus distance (10 km bins) for all mid-level WV AMVs generated and those selected for NWP use (Ops).

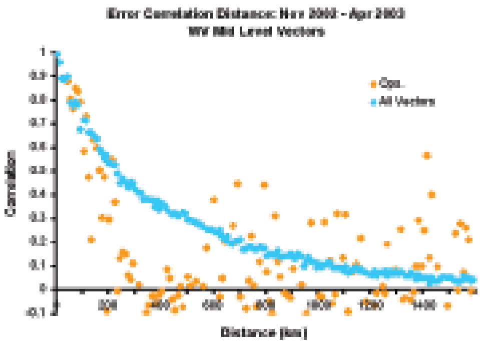


Fig. 5(e) Error Correlation versus distance for high level WV AMVs, EEmax = 3.0 and 9.0 m s^{-1} (100 km bins).

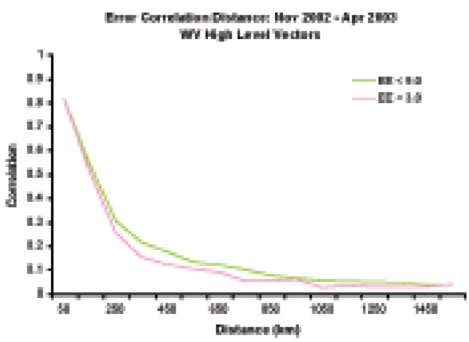
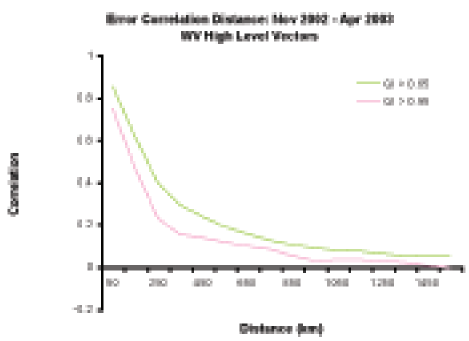


Fig. 5(f) Error Correlation versus distance for high level WV AMVs, QI = 0.65 and 0.95 (100 km bins).



The parameters of the SOAR functions fitted to the distance correlation functions for GMS-5 IR1, HRVIS and WV image based AMVs are seen in Tables 4(a) and 4(b) which provide R_0, L, CE and root mean square difference (rmsd) compared to radiosondes using WMO Co-ordination Group for Meteorological Satellites (CGMS) criteria, for non-zero and zero R_{00}.

The above analysis shows length scales (L) to be larger at lower levels in this dataset. Upper length scales for a given R_{00} are similar while, at lower levels, HRVIS displays a larger length scale than those for IR1 and WV. In comparison with the lower resolution statistics (100 km bins) of Bormann et al. (2003), the length scales here are shorter and CE and R_0 are larger, a result aided by 10 km bins. Note that, in this study lower level vectors appear to have a larger average L and vectors selected via error using QC and EE (higher quality vectors) for NWP use, have shorter average length scales associated with their CE.

Discussion and conclusions

In this study we have described the methods used by the ABM in the production, quality control and error characterisation of local AMVs and have demonstrated that quality control (QC) and error characterisation are vital components of the AMV generation process. We have discussed the impact of QC on operational regional NWP and provided some examples. A new method of error characterisation, used in the ABM, which provides the error associated with each AMV has been introduced. The method predicts the errors associated with AMVs more accurately than other methods in common use. This is a distinct advantage for data selection and analysis. Use of the EE often results in improved data coverage at a given error level or the same data numbers with improved accuracy. In addition, the estimated error (EE) of each vector can be used directly in the analysis process and all AMVs can be treated in a similar fashion. Moreover, there is no need for all users to derive, or to receive QI calibration curves for each producer and for each wind type. The characteristic length scale (L) and correlated error (CE) have also been estimated and allow AMVs produced in the ABM to be characterised by EE, QI, RFF and also their CE and L. The EE, R_0 and L can be used directly in the analysis process.

In summary the QI and RFF play important roles in data selection and quality control when using high density winds available operationally via the GTS (a process necessary to ensure positive data impact), however the use of EE provides a more direct and accurate measure of AMV quality and can be used in

Table 4(a). Parameters of the SOAR function (Eqn 1) which best model the measured error correlations for the AMV types listed in the left-hand column.

	R_{00}		R_0		*L (km)*		*Corr. error* ($m\ s^{-1}$)		*RMSD* ($m\ s^{-1}$)	
Level	Low	High	Low	High	Low	High	Low	High	Low	High
IR1	0.04	0.06	0.82	0.83	123.3	73.1	3.23	5.21	3.94	6.28
HRVIS	0	0.01	0.96	0.70	127.2	82.9	3.54	3.82	3.69	5.46
Level	Mid	High	Mid	High	Mid	High	Mid	High	Mid	High
WV	0	0.02	0.67	0.91	95.1	84.8	3.49	4.39	5.21	4.82

Table 4(b). Parameters of the SOAR function (Eqn 1) which best model the measured error correlations for the AMV types listed in the left-hand column. R_{00} is assumed to be zero.

	R_{00}		R_0		*L (km)*		*Corr. error* ($m\ s^{-1}$)		*RMSD* ($m\ s^{-1}$)	
Level	Low	High	Low	High	Low	High	Low	High	Low	High
IR1	0	0	0.84	0.82	141.4	94.3	3.31	5.15	3.94	6.28
HRVIS	0	0	0.96	0.70	127.8	85.1	3.54	3.82	3.69	5.46
Level	Mid	High	Mid	High	Mid	High	Mid	High	Mid	High
WV	0	0	0.51	0.92	95.1	88.9	3.49	4.43	5.21	4.82

the analysis process to project analysis increments onto grid points. The improved AMV data base available through use of the EE provides an improved basis for analysis and prediction. This work has been a precursor to the generation of AMVs over the Indian Ocean, using data from the Geostationary Imaging Fourier Transform Spectrometer (GIFTS). When the GIFTS becomes available for operations, the EE, CE and L will be available for each AMV.

Acknowledgments

Thanks are due to T. Adair and I. Mouzouri for their help in preparing this manuscript. The authors also express their gratitude to R. Seaman for fruitful discussions in relation to this work. One of us (MD) acknowledges the support of an Australian Postgraduate award and a Victorian Government Information and Communication Technologies Postgraduate Scholarship.

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