Third International Winds Workshop
10-12 June 1996

NORMALISED QUALITY INDICATORS FOR EUMETSAT CLOUD MOTION WINDS

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The transfer of METEOSAT operations from the European Space Operations Centre to EUMETSAT provided an opportunity to include several new features in the extraction of meteorological products. One of the most significant changes was conceived in the automatic quality control of the cloud motion winds. The new scheme is composed of several quality functions that all provide a continuous quality indicator. These functions utilise hyperbolic functions that enable the system to return normalised quality indicators between 0 and 1. This enables a final assessment of the quality of each individual vector. The assessment is based on the weighted mean of the normalised indicators and is also performing a pre selection of the most suitable winds for dissemination. This is important as the new Cloud Motion Wind derivation scheme is simultaneously providing a wind vector in all three METEOSAT spectral bands and without the pre selection the manual quality control would be overwhelming.

The new automatic quality control also forms the foundation of providing the users with not only the fraction of best winds accepted by the quality control procedures but a more complete wind field with a final quality mark. This new information can then be utilised by the end user to select the wind field most appropriate for his application or as a direct weight in an assimilation scheme. A higher level of automation will also enable a higher frequency of disseminated wind fields.

1. Introduction

The derivation of accurate Atmospheric Motion Vectors (AMVs) from satellite observations has proven to be an indispensable source of data, especially over the data void ocean areas. The operational production of these vector fields is at present confined to data from the geostationary satellites, namely Meteosat (EUMETSAT/Europe), GOES (NOAA/Nesdis/USA), GMS (JMA/Japan) and Insat (IMD/India) (e.g. CGMS XXIII, 1995). Other geostationary systems are also planned, but have not yet reached an operational status. During the past years the instrumentation on board these spacecraft has improved, particularly on GOES and GMS, providing extended capabilities for the wind derivation process. Already wind fields are derived not only from the infrared window channels (CMWs, Cloud Motion Winds), but also from the visible (VWs, Visible Winds) and water vapour (WVWVs, Water Vapour Wind Vectors) channels. Since the extraction frequency is continuously increasing in response to the improved assimilation schemes, the amount of disseminated vectors will in the near future be manifold as compared to previous years. This implies that the traditional approach to quality control of the derived vectors including a manual intervention has to be reconsidered. In the USA (Nieman et al, 1996) the manual quality control has been completely abandoned since the advent of GOES-8 and GOES-9, and also in Europe efforts are concentrated in improving the automatic quality control procedures. At present the derived Atmospheric Motion Vectors (AMVs) are mainly used as single level point observation. Even though the introduction of new assimilation schemes will change the use of the data to be more realistic it is still important in the future to describe how well the derived vectors are representative of a scale, e.g. a scale similar to radiosonde observations.

In November 1995 the operational derivation of wind vector fields using Meteosat imagery data was transferred from MIEC (Meteorological Information Extraction Centre) at ESOC (European Space Operations Centre) to the MPEF (Meteorological Products Extraction Centre) at EUMETSAT. This provided an opportunity to include several new features in the extraction of meteorological products. One of the most significant changes was conceived in the Automatic Quality Control (AQC) of the wind vector fields. This paper will present the current approach for the automatic quality control at EUMETSAT, which attempts to assign a reliability estimate to each individual wind vector and which can be used as an indication of the expected RMS error if the vectors are used as point measurements.

2. The MPEF Automatic Quality Control

2.1 Background

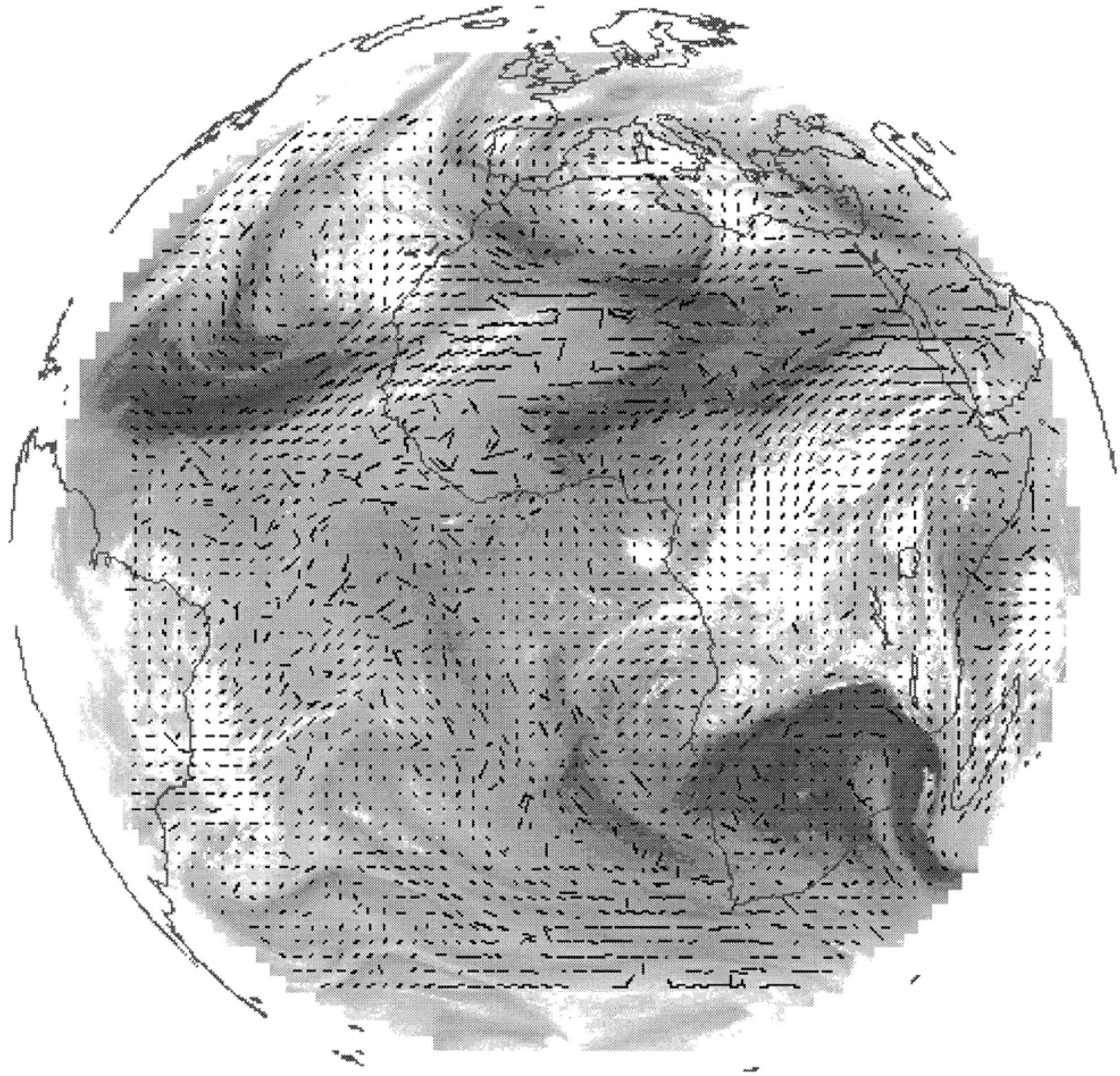

Figure 1. A typical Water Vapour Wind Vector field (22 January 1992).

The introduction of a sophisticated automatic quality control (AQC) scheme is essential in many ways. Figure 1 presents a typical vector field derived from consecutive water vapour images for which no quality control (QC) has been applied. The derivation scheme and the quality control applied at MIEC/ESOC has extensively been described in Schmetz et al (1993) and the extension to WV winds in Laurent (1993) and Holmlund

(1994). Furthermore the implementation at EUMETSAT has been described in Buhler and Holmlund (1994). The derived field is in large areas consistent and representative of the flow at the level of the measured radiances, but a large number of completely misleading vectors are also present. It is therefore imperative to perform a pre-screening of the data and to remove vectors which are apparently wrong or not representative of the flow at the time and space scale suitable for data assimilation or interpretation. Furthermore a successful AQC scheme will limit the necessity of manual quality control (MQC), hence providing the opportunity to disseminate wind at a higher frequency and for several channels.

In the traditional AQC, e.g. the AQC at MIEC/ESOC, a wind vector failing at least one of the applied quality tests was rejected. This approach rejected the major part of the wind field, including winds which were potentially good. Also the use of MQC to edit the actual components of the derived wind vectors is not practical for large amounts of data. The Recursive Filter (RF) analysis (Hayden and Purser, 1995) attempts to retain as much as possible of the pre existing information by automatically adjusting the derived components to be internally coherent and consistent with existing background fields. The RF has proven to be successful on a synoptic scale (Menzel, 1996). Also in cases where the background field is poor the RF is capable of maintaining the correct flow pattern, e.g. Velden (1996) showed the huge improvement in tropical storm tracking with WVWV fields. An alternative approach is based on the performance of the individual tests and estimates the reliability of the individual vectors and forms the foundation of the MPEF AQC. The derived reliability estimate can then be disseminated as a further parameter assign to each individual vector, giving the user the opportunity to select the vectors most suitable for his application or to assimilate the vector in his scheme with a weight related to or derived with the reliability estimate.

2.2 Normalised quality indicators

To define the probability of any vector to be of high or low quality one could use the general rules applicable to probability estimations. The probability for the simultaneous occurrence of n independent tests A_i can be expressed as

$$P(A_1 \cap A_2 \cap \ldots \cap A_n) = \prod_{i=1}^{n} P(A_i) \tag{1}$$

If the applied tests would have a Gaussian distribution, i.e. their distribution density function f(x):

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left(\frac{1}{2}\right)\left(\frac{x-a}{\sigma}\right)^2} \tag{2}$$

then the cumulative distribution function (CDF) of the tests can be defined as:

$$\Phi(x) = \int_{-\infty}^{x} f(t)dt\,, \tag{3}$$

which for the standardised normal Gaussian distribution is called the Gaussian error integral. In order to combine the results from different tests it is necessary that the test results would be normalised to deliver values within the same range for all tests. If the tests would have well defined distributions, the CDFs would provide the necessary normalisation. For correctly defmed tests, where the different levels relate to real quality, the CDFs can then be used to provide an estimation of the reliability of the individual vectors.

The distributions of meteorological parameters has extensively been investigated for climatological and statistical purposes (Berz, 1983). The distributions are often not Gaussian and therefore it is reasonable to assume that also the distributions of the tests applied in the AQC will have distributions which are non Gaussians. Figure 2 presents the distribution density of one of the tests applied, the speed symmetry tests. As a comparison also a Gaussian distribution for which the half width is roughly the same as for the observed distribution is included.

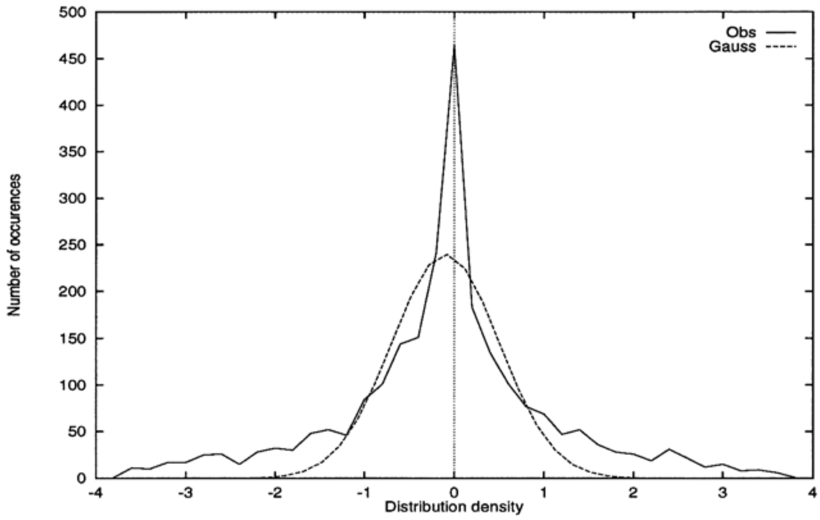

Figure 2. The distribution of the normalised speed differences.

The distribution is based on the computed speed difference between the vector pair derived for each segment normalised by the mean vector speed. Even though the distribution density is symmetrical it shows a strong positive kurtosis as compared to the Gaussian distribution. Comparisons with other distributions (e.g. the Gumbel distribution) did not provide a higher degree of agreement. It is possible that the observed distribution is a combination of two types of distribution; a Gaussian distribution for random errors in the processing and a more general distribution applicable to meteorological phenomenon. Of more interest than the actual distribution is the cumulative histogram of the observations and the CDF. As the actual distributions of the tests is still to be clarified an alternative approach to the CDFs has been considered. A simple empirical function, based on the tanh function, has been used to normalise the individual quality tests (f(x)) to provide an estimate of the CDF:

$$\Phi_e(x) = \tanh(f(x))^c \quad (5)$$

Figure 3 presents a comparison between the cumulative histogram of the observed normalised speed differences, the integrated Gaussian error integral and the empirical normalisation function. All functions have been scaled to present the same range of values. Even though the three graphs show some similarity, there are also distinct differences. Figure 4 presents the differences between the three graphs.

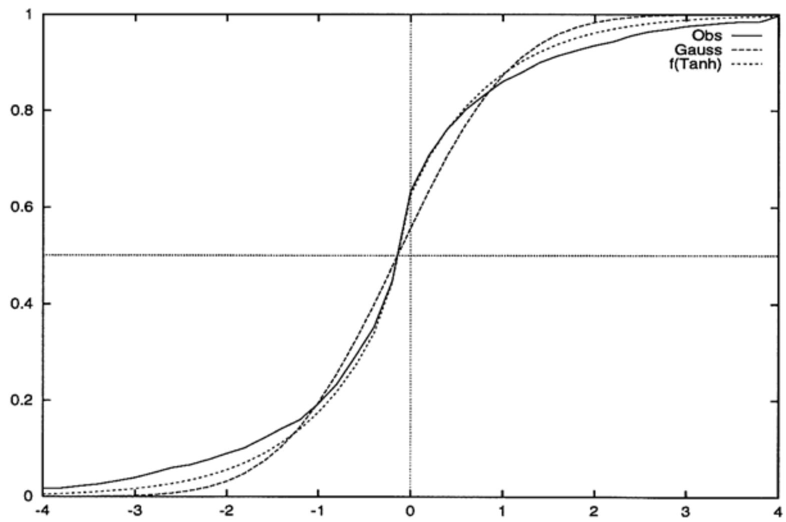

Figure 3. $\Phi_e(x)$, $\Phi_g(x)$ and the normalised accumulated histogram.

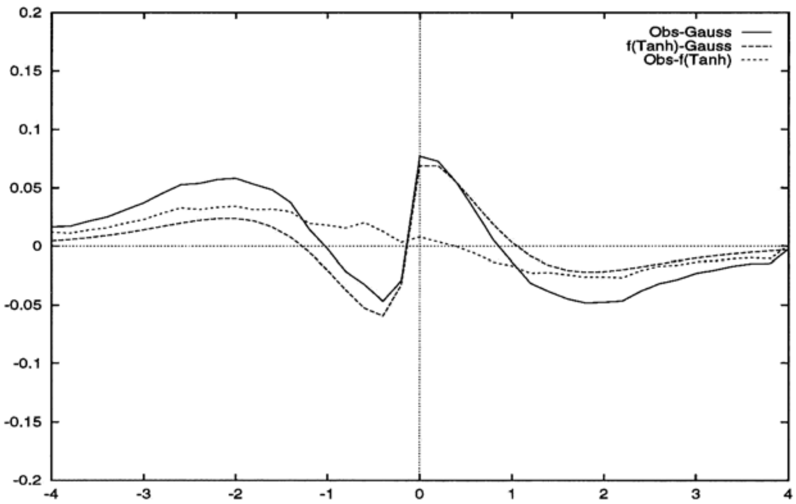

Figure 4. The differences between the functions in Figure 3.

The maximum difference between any two graphs is of the order of 8%. The difference between the tanh function and the observed cumulative distribution is however smaller, with a maximum difference of 3%. The approximation of the CDF using the tanh based function is of similar accuracy also for the other quality functions. The use of $\Phi_e(x)$ is therefore justified for the present investigations, but has to be recognised as a possible source of error during the interpretation of the results. As several of the quality control tests are tests on the vectors themselves, one cannot assume that the tests are independent. The dependence between the tests, and hence also $P(A_2/A_1)$, cannot easily be determined. Therefore instead of deriving the probability for a vector to be good, the estimated reliability (ER) of the individual vectors is defmed as the weighted average of the normalised quality indicator (NQI) delivered by the different tests $f_i(x)$:

$$ER = (1/\Sigma w_i)\sum w_i NQI(f_i(x)), \tag{6}$$

where the weight w_i enables the weighting of each of the individual tests according to their relative importance.

2.3 The MPEF tests

At MIEC/ESOC the operationally applied tests were either related to the symmetry of the vector pair or differences to the surrounding vectors. Similar tests are widely used as simple threshold tests at several wind derivation centre (e.g. Tokuno, 1996, Bhatia, 1996). Furthermore the inclusion of a test against the forecast vector interpolated to the location of the derived displacement vector has shown to be beneficial. The last test can be quite crucial, especially in the traditional approach were a wind has to survive all tests. In such a scheme manual intervention is imperative, otherwise significant true deviations from the forecast field would be filtered out. In the new approach the forecast test is included in the final ER value of the individual vectors, but even a complete failure against the forecast test will not exclude the derived vector from dissemination, providing that the other test turn out well. During the development phase several other tests were verified. Early investigations (Holmlund, 1991 and 1995), with verifications against the ECMWF first guess field, indicated that additionally two other types of test were potentially beneficial for the WVWV extraction. The tests related to the cloud configuration were important as an indication of the accuracy of the height assignment. In the new operational scheme the WVWV height assignment does not anymore depend on the cloud configuration and the IR EBBT. Instead the coldest identified WV layer is used to extract the heights and hence the cloud related tests are not implemented. As tests related to the maximum peak of the correlation surface also indicated a certain degree of skill a test related to the correlation computation was also included. The selected test attempted to verify the stability of the tracking by comparing the maximum value of the two derived correlation surfaces. This test had earlier (Holmlund, 1991) shown some skill, but during validation and tuning of the new scheme it did not perform as expected. Therefore this test is excluded from the present operational quality assessment scheme. At the moment five tests are applied within the MPEF AQC. Table 1 presents the tests, their relative weight (w) and the normalised test functions.

Table 1. The MPEF tests

N	Test name	w	Function
1	Direc. consistency	1	$QV = 1 - [\tanh[\lvert DIR_2(x,y)-DIR_1(x,y)\rvert/(A*e^{-(SPD/B)}+C)]]^D$
2	Speed consistency	1	$QV = 1 - [\tanh[\lvert SPD_2(x,y)-SPD_1(x,y)\rvert/(\max(A*vel,B)+C)]]^D$
3	Vector consistency	1	$QV = 1 - [\tanh[\lvert S_2(x,y)-S_1(x,y)\rvert/(\max(A*vel,B)+C)]]^D$
4	Spatial consistency	2	$QV = 1 - [\tanh[\lvert S(x,y)-S(x-i,y-j)\rvert_{min}/(\max(A*vel,B)+C)]]^D$
5	Forecast consistency	1	$QV = 1 - [\tanh[\lvert S(x,y)-F(x,y)\rvert/(\max(A*vel,B)+C)]]^D$

where DIR_i, SPD_i and S_i are the direction, speed and vector derived from the first image pair (i=1) or the second image pair (i=2). S(x,y) refers to the mean derived vector and F(x,y) to the interpolated forecast vector. S(x-i,y-j) refers to the vectors in the surrounding segments in the MPEF segment co-ordinates (Bühler and Holmlund, 1994).

3. Verification of the results

3.1 Subjective analysis of a typical case

The performance of the AQC can be evaluated subjectively by inspecting images together with the vector fields and their assigned quality. Figure 5 presents the derived wind vector field derived at 07.07.1996 from consecutive water vapour images.

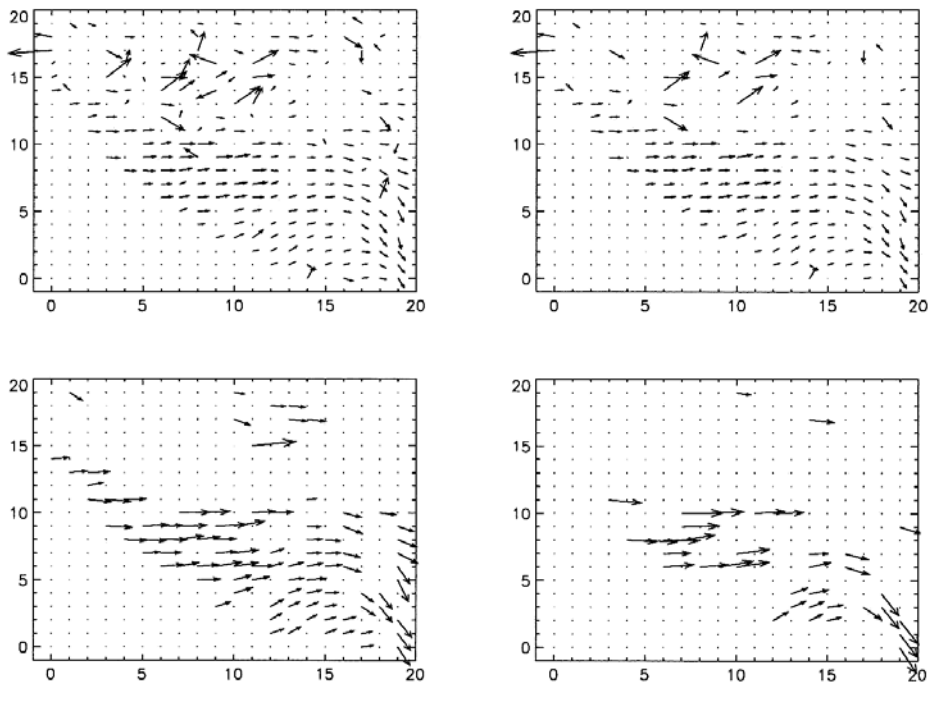

Figure 5. The impact of different AQC threshold levels for acceptance of WVWVs.

The four vector fields represent the same area over the South Atlantic region, filtered with the estimated reliability (ER), such that the presented vectors have a quality higher than the applied threshold value. The applied threshold for the upper left image is 0.0 (i.e. all vectors are displayed), for the upper right 0.25, for the lower left 0.5 and for the lower right 0.75. Already the reliability level 0.25 remove some of the vectors with gross errors but the most remarkable field is achieved with the level 0.5 As the screening gets tighter the coverage is decreasing and less than 20% of the original amount of vectors are left at the level 0.75. Already the subjective analysis indicates that the quality control is performing as expected, but in order to manifest this observation an objective analysis of the vector fields is also required.

3.2 Objective validation of the tests

To achieve a reliable estimate of the quality of the vectors a reference data set is required. At the moment the AMVs are mainly used as pseudo radiosonde measurements. It is therefore natural to use the radiosonde data for verification purposes, but it is important to recognise that also the radiosonde measurements contain errors and that they do not provide an absolute truth. Using long term statistics it is possible to show that the vector difference RMS error ($dvec_{RMS}$) between the satellite observed and radiosonde measurements and wind speed as measured by the radiosonde ($|vec|_{R/S}$) has a linear relationship (Schmetz et al, 1993). Their expression can be inverted to define the slope of the relationship:

$$A = (dvec_{RMS} - B)/|vec|_{R/S} \qquad (7)$$

The coefficients (A and B) can be derived during periods with no interventions in the extraction scheme. Table 2 presents the regression coefficients for the WVWV s derived during the derivation of WVWVs at ESOC.

Table 2. Regression coefficients for different periods of unmodified WVWV extraction at MIEC/ESOC.

	RMS slope	RMS Offset
December 92 - September 93	0.13	6.66
October 93 - January 94	0.19	5.06
February 94 - August 94	0.21	4.36
September 94 - November 95	0.23	3.92

The results presented in Table 2 are similar to those derived for high level CMWs indicating that these results are representative for the WVWVs. Therefore it is possible, despite the small number of periods, to roughly estimate B as:

$$B = B_{ave} \pm B_{\sigma} = 5.0 \text{ m/s} \pm B_{\sigma} \text{, where } b_{\sigma} = 1.0 \text{ m/s}$$
$$==>$$
$$A = (dvec_{RMS} - 5)/|vec|_{R/S} \pm B_{\sigma} /|vec|_{R/S} \qquad (8)$$

During periods when no modifications to the extraction scheme is introduced A and B will remain constant. Analysing such a period it is therefore possible to estimate the performance during different sub sets of such a period without an accurate knowledge on the coefficients. For instance after the transfer of operations to EUMETSAT the system was frequently tuned and therefore no long time series were available for the determination of the coefficients. Assuming that A and B remain constant it is possible to define the normalised RMS vector difference as

$$NRMS = dvec_{RMS}/|vec|_{R/S} \qquad (9)$$

Using NRMS it is possible to get a rough indication of the performance of the system without knowing A and B. Comparing the NRMS for two sub periods (1 and 2) of a period with constant coefficients A and B we see that

$$\begin{aligned} NRMS_1 - NRMS_2 &= (dvec_{RMS1} - B)/|vec|_{R/S1} - (dvec_{RMS2} - B)/|vec|_{R/S2} + B/|vec|_{R/S1} - B/|vec|_{R/S2} \\ &= B/|vec|_{R/S1} - B/|vec|_{R/S2} \qquad (10) \end{aligned}$$

we see that the error in the factor is introduced through neglecting the variation in $B/|vec|_{R/S}$. For high level winds for which the mean wind speed generally varies between 20 and 25 m/s the relative error in comparing two periods with each other is then for typical values or RMS, mean wind speed and B of the order of 10% of the NRMS. Using the NRMS to compare different periods with different coefficients, but with the same mean wind speed the error can become larger. For tuning and monitoring purposes we have chosen to use the NRMS as a quick and simple tool to investigate the relative quality during periods of no changes to the derivation scheme or comparing consecutive periods with similar mean wind speed. Even though the NRMS is not an accurate measure of the true reliability of the winds, it provides a better indication of problems in the processing scheme than the pure RMS value.

To validate the derived ER values comparisons against collocated radiosonde measurements were performed. Figure 6 presents the relationship between the MPEF reliability estimate against the NRMS and against A for high level WV winds in June 1996.

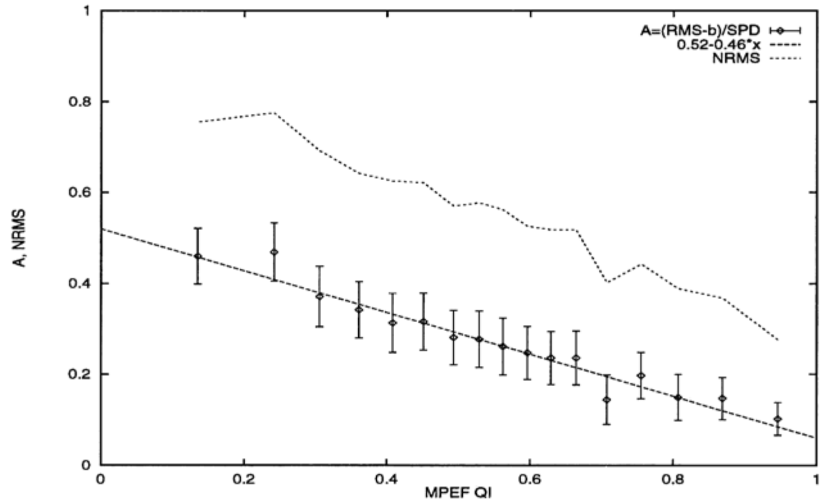

Figure 6. NRMS and regression coefficient A compared to the MPEF mean ER for high level WVWVs in June 1996.

The data presented in Figure 6 is based on R/S measurements collocated with MPEF WVWVs. The collocation data has been sorted according to the MPEF mean ER. The 3718 collocations were divided into 18 equivalent sized bins. The last 118 collocations with the lowest average ER were grouped together separately. For each bin the RMS vector difference as well as the mean ER has been computed. The derived RMS has then been used to compute the NRMS and A. The errorbars for A are estimated using b_{σ}. It should be noted that the used estimate of B is based on the MIEC derivation scheme and is therefore not fully reliable. To derive an accurate estimate of A and B long term statistics over several months are required. As the wind derivation scheme as well as other critical parts of the MPEF at MPEF/EUMETSAT has during the first months of operations been tuned and modified, there is at this stage no possibilities to derive a more accurate estimate of B.

The two graphs in Fig 6 show the same behaviour for the MPEF ER. The correlation between the mean ER and the NRMS was 0.97 and between the mean ER and A was 0.95. As also the derived regression line (against A) fits well to the data one can assume a monotone near linear dependence between the MPEF ER and A for high level water vapour winds. The signature for the high level IR CMWs is similar as for the WVWVs, but for low level winds the situation is different. Woick (1996) noted that the correlation for the regression analysis of low level winds was always low and hence a reliable estimate of the coefficient B cannot be derived. Figure 7 presents therefore only the results for NRMS instead of the coefficient A for two different periods, 15 Jan - 15 Feb. 1996 and June 1996.

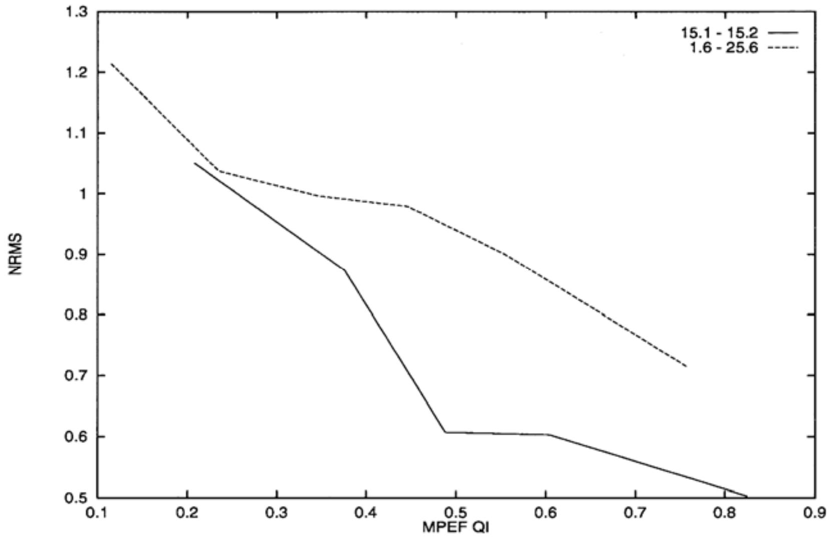

Figure 7. NRMS for low level winds during two different periods in 1996.

The change in the behaviour of NRMS is noticeable. This could be an indication of uncertainties in the presented approach or lack of data. For the first period in question only 200 collocations (divided to 5 bins) were available. It is also possible that the observed variation indicates a problem in the derivation scheme for low levels and further investigations are imperative.

4. Discussion and conclusions

The current operational AQC approach at MPEF/EUMETSAT has been presented. The strong relationship between the derived quality indicators and error in the derived wind vectors has been demonstrated. Based on these results the wind vectors will be disseminated with their respective QI value. This value can then be utilised by the users to define a coverage and level of quality tailored to their needs. The use of the tanh based function to normalise the quality tests seems to be adequate, especially for high level winds, but it could be improved by using a more accurate description of the accumulated distribution. There are several possibilities to derive a more complete description. The empirical approach would be based on long time periods and it would be possible to use the observed distribution to normalise the observations.

The accumulated observations could also lead to a better understanding of the real distributions of the tests. E.g. the distribution of the vector difference of the derived vector pair for one specific target is clearly not Gaussian. A more accurate description of the distribution could be given by e.g. the Gumbel or the binomial distribution, which often are used to describe the distribution of meteorological phenomenon (e.g. Berz, 1983). Also for the normalised speed difference test the observed distribution did not follow any simple single statistical distribution functions. It is possible that the observed distribution is actually a combination of two different types of distribution, i.e. one related to the meteorological phenomenon and the other to random errors in the processing. In such a case it could be possible to describe the meteorological distribution by e.g. the Gumbel distribution and the random error by a Gaussian distribution. This hypothesis need further investigations.

The present AQC is treating all vectors at all levels derived from the different spectral bands equivalently. It is likely, that due to the different characteristics of these winds, the AQC should be tuned separately for these different cases.

Acknowledgements

To my colleagues Mr H. Woick for providing the data for Table 2 and Dr S Elliott for providing figure 5.

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