A SUPEROBBING SCHEME FOR ATMOSPHERIC MOTION VECTORS

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ABSTRACT

Experiments have been performed to test the effect of superobbing atmospheric motion vectors within the Met Office's global numerical weather prediction model. In superobbing, the difference between observations and co-located backgrounds within a given three dimensional box are averaged to create one superobservation. Like data thinning, superobbing lowers the effect of the correlated error by reducing the data density. Superobbing, however, has the added advantage over data thinning of reducing the uncorrelated error through averaging.

The results of these experiments, as compared to a system similar to the Met Office's operational system using data thinning, have been neutral. The forecast impacts are slightly positive in the northern hemisphere while slightly negative in the tropics and southern hemisphere reflecting the differing effects of alternative observations in the different hemispheres. This minor impact suggests that random error might not be the predominate error within atmospheric motion vectors.

1. INTRODUCTION

In order to simplify the calculations and reduce the computing resources in most modern data assimilation systems, the observations and background fields used in these systems are assumed to have uncorrelated errors. This assumption leads to potential problems with data types such as satellite winds for which correlated errors, both with each other and with the background fields, are significant. It has been suspected for some time that a sizeable component of the errors in atmospheric motion vectors (AMV)s are correlated in space and time, but it is only recently that an attempt has been made to test and quantify this idea. Bormann et al. (2002) carried out a collocation study of satellite wind – rawinsonde pairs and showed that if the sonde errors are assumed to be spatially uncorrelated, then the errors in satellite winds are significantly correlated for distances of up to 800 km. It is believed that this correlated error has limited the impact of satellite winds within most NWP models, particularly with the increasingly high resolution of the wind data.

Tests within the Met Office's global NWP system using high-resolution satellite wind data sets at full resolution led to poorer analyses and forecasts than the lower resolution data sets that preceded them. It was thought that the analysis was pulling too closely to the observations as their correlated errors would reinforce one another. These correlated errors are currently overcome within the Met Office observation processing system by data thinning. Thinning the data to 800 km, the resolution to which Bormann et al.'s work showed significant correlation, is an extreme measure and would lead to substantial loss of data and detail in the wind field. Instead, the winds are thinned to a box size of 2 degrees (~200 km). This resolution reduces the influence of correlated errors but does not solve the problem entirely. To further compensate for the error correlations, the observation errors for satellite winds were doubled from what was believed to be close to the true error in the observations, additionally reducing the impact of satellite winds on the analysis. The modification was shown to improve the forecast skill (Butterworth et al., 2002).

Although thinning and doubling the observation errors address the spatial correlation problem in a computationally inexpensive way, significant wind data are thrown away in the process. A more promising idea is to average the observations; observations within a given box are averaged to create one observation that is positioned at the average location. Like thinning, averaging will reduce the number and resolution of the data input into the data assimilation system and should therefore reduce the problems resulting from spatially correlated error. A major concern of this method, however, is that it could lead to the loss of some meteorological features. Consider a simple example in the region of a jet. If winds above and below a jet core are averaged and the resulting wind placed at the average location, there is a danger that the slower wind will be positioned in the high speed region of the jet core, weakening the analyzed jet. But can this problem be avoided? We propose a superobbing scheme as a solution. Instead of just averaging the observations, we will test a method to average the observation minus background difference, or innovation. This method should allow us to use more of the wind data, potentially reducing the observation error, while reducing the risks of smoothing atmospheric features.

2. SUPEROB OBSERVATION ERRORS

Before the superobbing method can be implemented, the way in which superobbing would affect how errors are treated in the data assimilation system must be understood. Most data assimilation systems produce their analyses through a complex weighted average between a model first guess, or background, and observations. The extent to which the background and observations influence the analysis is determined by their respective error value. Background errors are based on zonally and temporally averaged statistics from differences between 1- and 2-day forecasts valid at the same time for streamfunction, velocity potential, unbalanced pressure (ageostrophic pressure), and relative humidity. These background errors also contain a mass and wind balance constraint (Ingleby, 2000).

The errors in the observations and within the background make up the innovation: the difference between the observation and the background. The innovation statistics thus provide a measure of the upper limit of the observation errors. In calculating the operational observation error statistics, it is assumed that the background and observation errors are of similar magnitude. The observation errors can then be calculated using a year's worth of innovation variances at different pressure levels. These observation errors will be changed by superobbing, which changes the innovations. In this section, we will derive an expression for the new superob observation error.

Given a group of N observations (o_i) and corresponding background values (b_i) in a 3-dimensional box, a superob s can be formed as a weighted average of the observation minus the background. Namely:

$$s = b_o + \sum_{i}^{N} w_i (o_i - b_i) \qquad (1)$$

where b_0 is the background value at the superob location and w_i is the weight for each o – b pair.

By assuming that within a superob box: the observation and background errors are not correlated with each other, the background errors are fully correlated, the background errors have the same magnitude, all of the innovations are weighted equally (i.e. w_i is equal to the inverse of N), and the observation error correlations are constant, one can show that the Superob error e_s can be calculated by:

$$e_s^2 = W^T (\underline{D}\underline{C}\underline{D}) W \qquad (2)$$

where $\underline{C}$ is a correlation matrix and W is a vector of weights. $\underline{D}$ is a diagonal matrix of component observation errors within a box with the form:

$$D = \begin{pmatrix} \varepsilon_{oi} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \varepsilon_{on} \end{pmatrix}$$

where ε_{oi} represents the expected observation error of the *i*th component within the superob. The correlation matrix $\underline{C}$ is a square matrix with 1's along the diagonal and a constant correlation value on the off-diagonal. Based on values used in Bormann et al. (2002), a correlation value of 0.35 is used for the extra-tropics while 0.26 is used for the tropics (assuming a 2-degree by 2-degree box). For comparison, a correlation value of 1.0 would imply that the observation errors are fully correlated, while a value of 0.0 would imply fully uncorrelated error correlations.

3. EXPERIMENTAL DESIGN

To test the effect of superobbing on the model analyses and forecasts, a set of data impact experiments was run comparing forecasts and analyses of a control run without superobbing and a run with superobbing. The control run for these experiments is a low resolution (100 km) version of the Met Office's global NWP system with a forecast model described by Cullen (1997) and a 3-dimensional variational assimilation system described by Lorenc et al. (2000).

The control run assimilates all of the operational Met Office satellite data with the addition of the Binary Universal Form for the Representation of meteorological data (BUFR) GOES infra-red, water vapor and visible AMVs. Currently, the Met Office operationally assimilates only the older SATOB format infra-red winds. The satellite winds in the control run are thinned to 2-degree 100 hPa boxes. The observation errors and quality indicator thresholds are at their operational values. The experimental setup is identical to the control run, except that the winds are superobbed in 2-degree/100 hPa boxes rather than thinned. The data impact experiments are run from 12z 24 January 2004, through 12z 17 February 2004. Four analyses and 6-hr forecasts are produced each day throughout the period along with one long term forecast out to 144-hours. All of the forecasts are verified on this long range forecast initialized at 12z each day.

To conceptualize how much data is used in the thinning experiment versus the superobbing experiment, examine Table 1. The second column shows the number of available satellite winds (without quality control) for each experiment. The third column shows the number of winds that are assimilated (for thinning), and the total number of winds used as components for superobbing. The percentage of total winds is in parentheses. As the table shows, superobbing uses significantly more data. Keep in mind, however, that because the superobbing resolution is identical to thinning, the actual number of winds assimilated in the superobbing experiment (as superobs) is almost identical to thinning. The additional used winds are primarily used as components of each superob.

Experiment	Available Winds	Used winds (Percent total)
Control-Thinning	200,000	8000 (4%)
Superobbing	200,000	48,000 (24%)

Table 1: Typical number of winds available and assimilated for a single run of the Control and Superob experiment. The majority of the increased number of winds for superobbing make up the components of the superob and are not assimilated directly.

4. RESULTS

The impact of the superobbing experiments is small and mixed. Figure 1 shows the root mean square difference (RMS) between the superob experiment and the control expressed as a percentage as compared to observations and analysis. In Figure 1, values that are below zero show fields that have improved the forecast. Percentages with absolute values higher than 2% are considered significant. As can be seen from the plots the results are mixed and mostly neutral. We see negative results for the 500 hPa 72-hour forecast (500 hPa) in the southern hemisphere and for the 96-hour forecast for PMSL in the southern hemisphere when evaluated against observations. We also see fairly positive results of PMSL at T + 72 in the northern hemisphere against observations. Most of the fields, however, produce small impacts on either side of neutral. The results are also neutral against the analysis with one notable exception: 250 hPa winds in the tropics. Otherwise some of the comparisons against analysis are better than those against observations and some are worse.

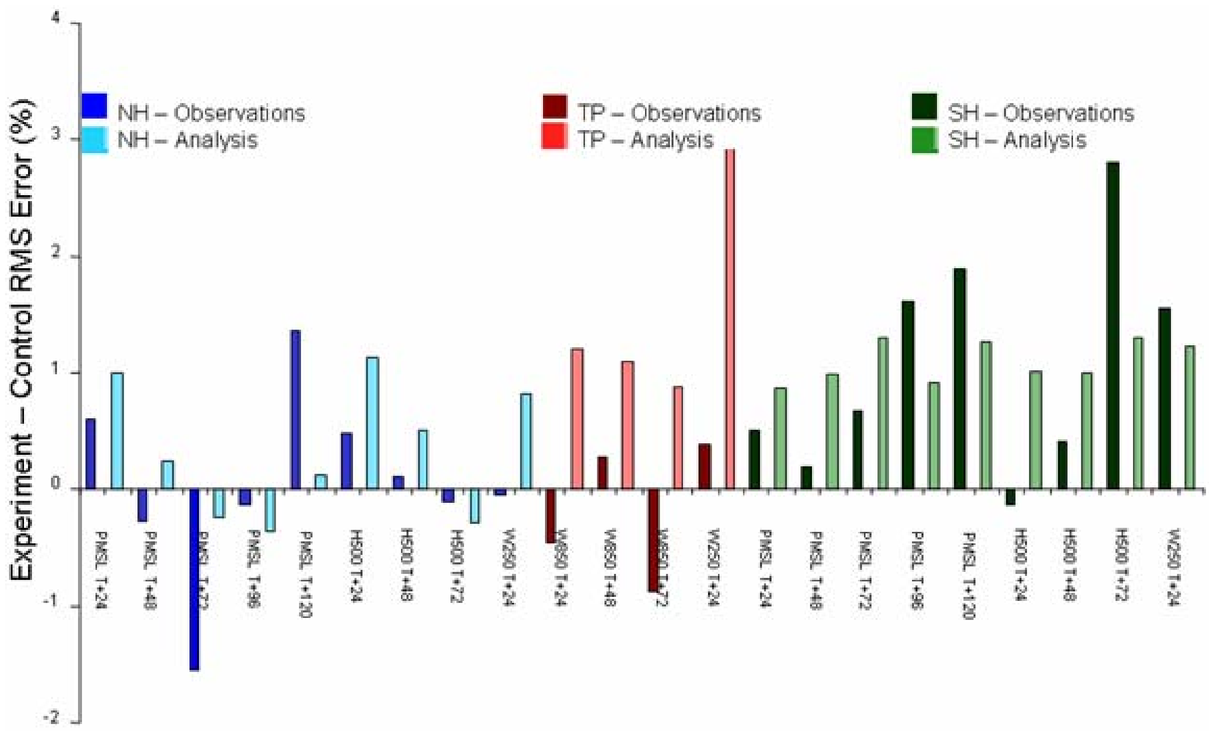

Figure 1: Root Mean Squared differences between the experiment and the control for the northern hemisphere (NH), the tropics (TP) and the southern hemisphere (SH) for mean sea level pressure (PMSL), 500 hPa geopotential height (H500) and 250 and 850 hPa winds (W250 and W850 respectively) with respect to analysis and observations. Negative numbers show improvement of the experiment over the control.

It is also instructive to examine how the forecast skill changes with time. Figure 2 shows the anomaly correlation of the model forecast of 500 hPa height as compared to its own analysis. From the plots, one can see that superobbing shows some skill (although probably not significant skill) against the analysis in the long range for the northern hemisphere, but is generally negative for long ranges in the tropics and the southern hemisphere. This result is consistent with the RMS in Figure 1.

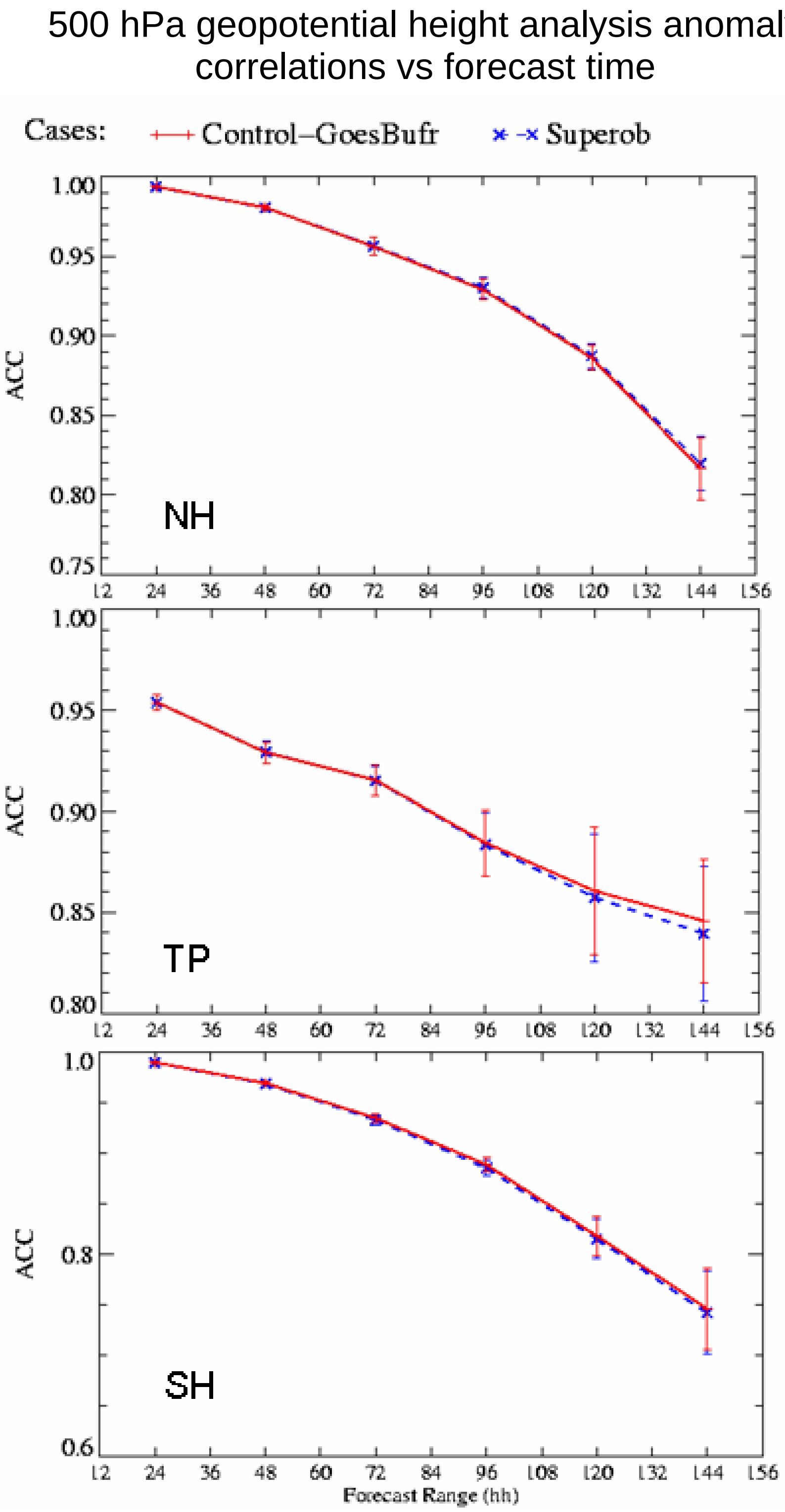

Figure 2: Anomaly correlations for the northern hemisphere (NH), tropics (TP), and southern hemisphere (SH) versus analysis. The solid red line represents the control run, while the dashed blue line represents the superob experiment. Superobbing shows positive results for long forecast times in the northern hemisphere, but is neutral or negative against the analysis in the southern hemisphere and the tropics.

T+24 Forecast – Sonde RMS
Vector Error 250 hPa Wind

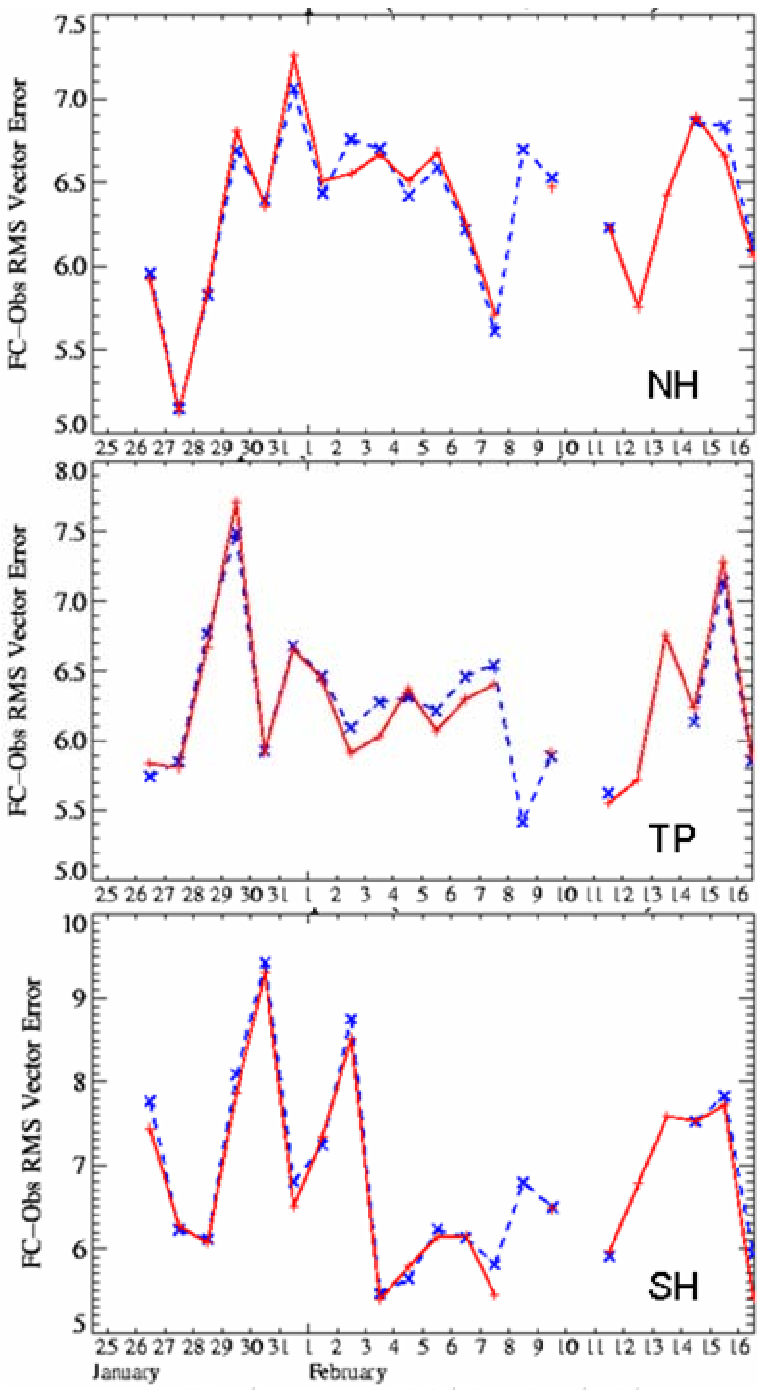

Figure 3: 24-hour Forecast – Sonde RMS 250 hPa wind vector error time series for the Control run (red solid line) and the superob experiment (blue dashed) line. The forecasts are evaluated at 12z from 25 January, 2004 through 12z 16 February. In all three regions superobbing both improves and degrades the control run, although the forecasts show the most improvement in the northern hemisphere.

It then becomes important to examine how the forecasts vary from day to day throughout the trial. Figure 3 is a time series of 24 hour forecast differences between radiosondes and the model 250 hPa wind. The RMS vector error is plotted as a function of day. The daily 12z forecast for superobbing (blue dashed line) and the control (red solid line) is plotted for the northern hemisphere, the tropics and the southern hemisphere. The missing values are due to missing radiosondes on the 10th. This problem does not affect the results shown.

Although the three regions shown in Figure 3 differ, all of them show both improved and degraded forecasts. The majority of the superob forecasts in the northern hemisphere are neutral or slightly positive as compared to the control. The forecasts on the 2nd and 3rd are consistently poor in all three regions, while the 12z forecast on the 4th is generally improved through superobbing. In general though, superobbing's effects are mixed and small at the 24 hour range. At longer ranges (not shown) the pattern continues with many mixed results, although they become slightly more extreme. The longer range is consistent with the 24 hour forecasts in that the northern hemisphere shows more forecast improvements than the southern hemisphere and the tropics.

5. CONCLUSIONS

As a whole, superobbing produced neutral and small impact as compared to its control. The impact was more positive in the northern hemisphere than in both the southern hemisphere and the tropics as compared to both observations and the corresponding analysis. A time series of individual forecasts also showed mixed results: some forecasts were positive, some negative, many were neutral.

A more difficult question to answer is why the results were so mixed. Theoretically superobbing should remove some of the random error in the satellite wind data and should reduce the correlated error by the same amount as thinning. Many assumptions were made, however, to calculate the new superob observation errors. In particular, the correlation values used, although based on the values calculated by Bormann, are still assumed to be constant throughout a superob box. A deeper understanding of the correlated and random error of satellite winds is crucial to data assimilation and is an ongoing area of research. A more optimal error and superobbing method, like that suggested in Lorenc (1981), combined with increased understanding of the errors, might improve the results as well.

It is also possible that we are not superobbing ideally. The choice of superobbing boxes is based on that of thinning: the same box size was chosen. Larger or smaller boxes might allow for more positive impact and is something that must be investigated. Vertical and temporal box sizes must also be considered and investigated more thoroughly.

The component observation errors and quality indicator flags also impact the assimilation process. These experiments used the operational observation errors and operational quality control. It is possible that these can also be better tuned to optimize superobbing over thinning.

Finally, these impacts were small enough to suggest that the random error reduced by superobbing is not a primary source of error for AMVs. The height assignment and areas where clouds are not moving with the average wind are both sources of error and are probably more significant than the random component of error. Understanding all of these sources of error will lead to more positive impacts from AMVs.

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