Accounting for correlated observation error in the assimilation of high resolution sounders

Peter Weston, James Cameron and Laura Stewart

1) Introduction

Currently data from high resolution sounders, such as AIRS (Atmospheric Infrared Sounder on the NASA satellite Aqua) and IASI (Infrared Atmospheric Sounding Interferometer on the EUMETSAT satellite Metop-A), are used with diagonal observation error covariance matrices (**R**) within the Met Office 4D-Var assimilation scheme, assuming no correlation between channels. This is inadequate due to the presence of errors of representativeness, forward model error and errors associated with the pre-processing of the data. Previous work both at the Met Office (Stewart et al. 2009) and ECMWF (Bormann et al. 2010) has demonstrated that correlations exist in IASI data particularly for channels sensitive to water vapour. It is likely that a better description of the error correlations in 4D-Var will allow for improved use of the water vapour channels. This poster shows the results of performing a diagnostic technique described by Desroziers [2005] on AIRS and IASI data to estimate the true structure of the **R** matrices. Initial tests using the full matrices resulted in the 4D-Var minimisation becoming unstable leading to non-convergence and increased computational cost. To counter this, the raw matrices have been reconditioned. Results from trialling these matrices in the Met Office assimilation scheme are also shown.

2) Desroziers Diagnostic

To estimate the structure of the full **R** matrix I have used the diagnostic procedure introduced by Desroziers et al. (2005). This uses observation minus background (O-B) and observation minus analysis (O-A) statistics to produce observation error variances and covariances. The formula is:

$$\mathbf{R} = E((y - H(x_a))(y - H(x_b))^T)$$

A key assumption which is used in the derivation of the above formula is that the **R** and **B** matrices used in the assimilation to produce the O-A and O-B stats are exactly correct. However in this project we know that the **R** matrix is not correct initially. Therefore the results should not be entirely trusted. However it has been shown, in very simple examples, that iterating the Desroziers diagnostic after starting with incorrect errors can lead to convergence to the true errors which is encouraging.

3) IASI channels used

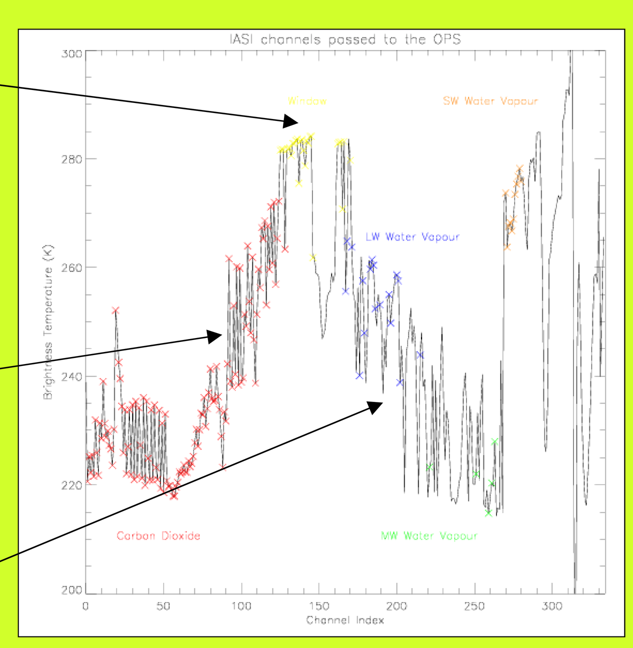


Figure 1 – Sample brightness temperatures measured by each of the IASI channels assimilated

4) 4D-Var Results

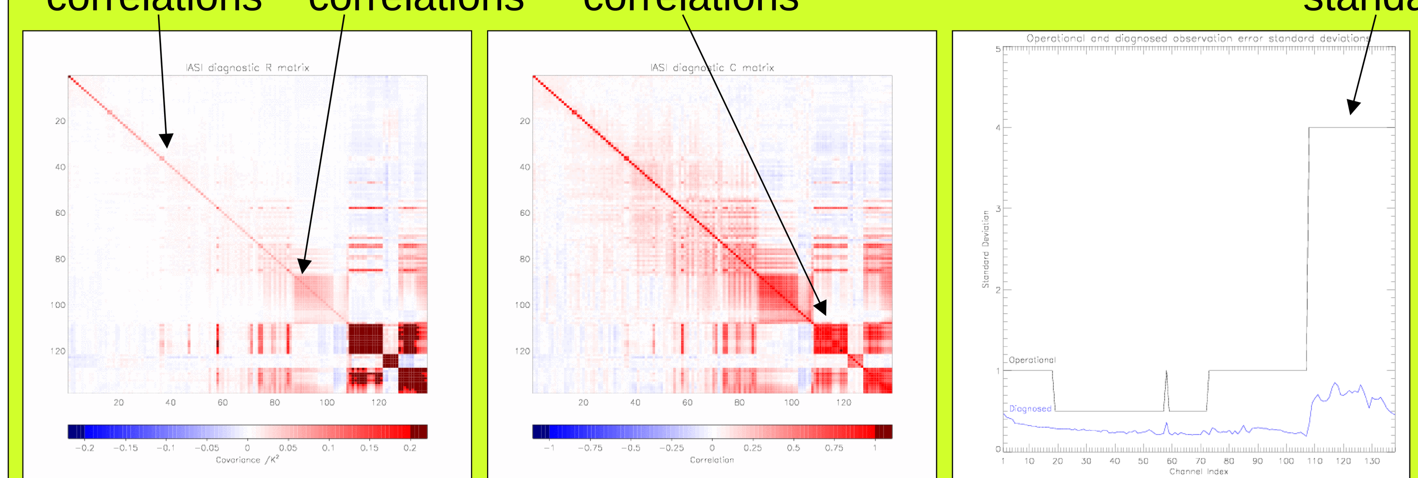


Figure 2 – Desroziers' diagnostics produced using output from the Met Office's 4D-Var system. The **R** matrix is on the left, the correlation (**C**) matrix is in the middle and the diagnosed and operational standard deviations are on the right, all for IASI data

Figure 2 shows that there are weak error correlations between temperature sounding channels, slightly stronger correlations between window channels and very strong correlations between water vapour channels.

The diagnosed standard deviations are much smaller than the currently used operational ones. The water vapour sensitive channels have the largest standard deviations due to larger representativeness errors for these channels.

5) Conditioning

Figure 3 shows the results of testing the matrices, once they'd been made symmetric and positive definite, in the 4D-Var system. A suggested reason for the increased number of iterations was that the matrices had high condition numbers. The condition number of the **R** matrix directly affects the condition number of the Hessian which impacts on how quickly 4D-Var converges.

Full **R** used for	Overall time (s)	Time per iteration	Number of iterations
No obtypes	3605	91.16	39
AIRS & IASI	127.02%	0.42%	128.21%

Figure 3 – Table showing the increase in time, processing time and iterations when using the full **R** matrices for IASI and AIRS in 4D-Var

Matrix used	Sub matrix condition number (IASI, AIRS)	Iterations	Cost function value (IASI, AIRS)
Diagonal	64.0, 256.0	39	39252, 68895
Full	1956.6, 12187.5	89	242020, 269904
Full	67,66.9	60	128448, 133220

Figure 4 – Table showing the results of using full matrices with different condition numbers in the assimilation

Figure 4 shows that reducing the condition numbers of the matrices results in a decrease in the number of iterations. Operationally at the Met Office a conjugate gradient based minimisation is now used where a fixed number of 60 iterations are performed. This minimisation fails when using the raw matrices, but using the reconditioned matrices results in a successful convergence of the minimisation. Figure 5 compares the standard deviations from the raw matrices and the reconditioned ones.

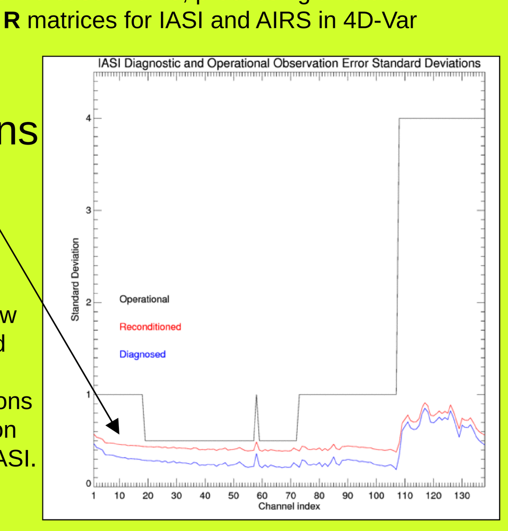


Figure 5 – Comparison between the raw diagnostic and reconditioned standard deviations (matrix condition number 67) for IASI.

6) Trial Results

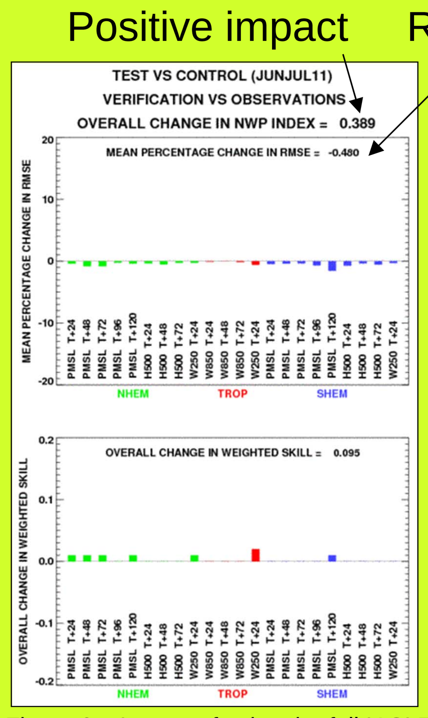


Figure 6 – Impact of using the full IASI **R** matrix in the Met Office forecast system

Two month long trials using just the full **R** matrix for IASI in the Met Office 4D-Var system have been run and compared against a control using the currently operational diagonal **R** matrix.

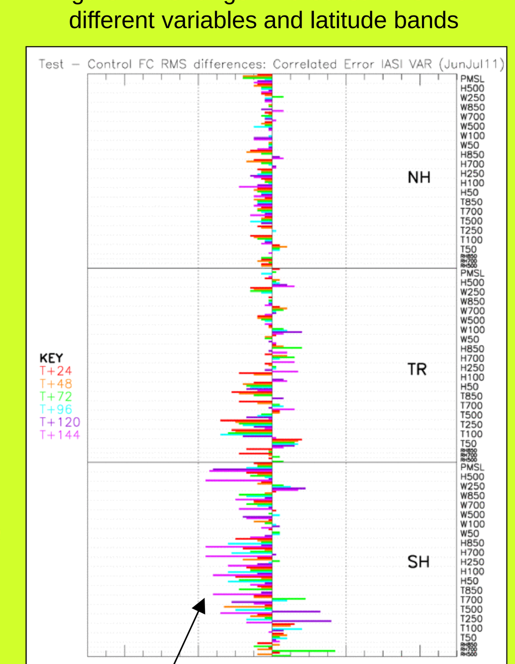
Figure 6 shows the reduction in forecast RMS error and increase in weighted skill resulting from this change. Figure 7 shows that the reduction in forecast RMS error is largest for geopotential height, pressure at mean sea level and temperature in the Southern Hemisphere. There are also smaller reductions in forecast RMS error for variables in both the tropics and the Northern Hemisphere.

Figure 8 shows the difference in background fit to IASI channels. There is a better fit for almost all channels but particularly in water vapour sensitive channels near the top of the figure. This is because using correlated errors allows the use of much smaller errors on the diagonal of the matrix so more weight is being given to these channels.

Finally, figure 9 shows the difference in background fit to AMSU-A temperature sounding channels. For most channels there is a better fit suggesting that accounting for correlated error in IASI observations is improving the model background.

Overall, the results show that accounting for correlated observation errors gives more weight to IASI observations and reduces forecast errors, especially in the Southern Hemisphere.

Figure 7 – Change in forecast RMSE for different variables and latitude bands



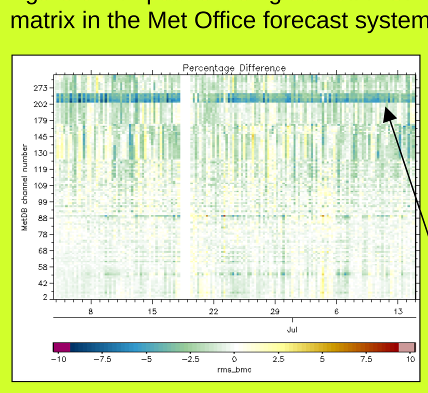


Figure 8 – Change in background fit to IASI channels

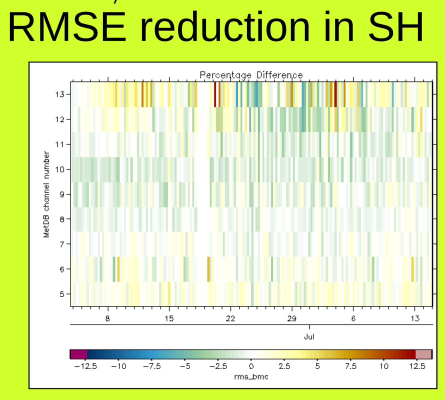


Figure 9 – Change in background fit to AMSU-A temperature sounding channels

7) Conclusions

The Desroziers diagnostic is not perfect but gives a good general idea of what the correlation structure is. Therefore the raw diagnostic matrices need to be modified to make sure they are symmetric and positive definite when being tested in the assimilation.

The inter-channel error correlations are largest in channels sensitive to water vapour and so, as predicted, the biggest positive impact of modelling the correlations should be in these channels.

Using the full **R** matrices in the assimilation scheme results in a very small increase in processing time but does result in the minimisation needing many more iterations to converge. Because of this the raw matrices need to be reconditioned before use operationally.

Results from trialling the use of these matrices show positive impact and an improvement in forecast accuracy. Therefore, correlated errors for IASI will be implemented operationally in November 2012.

8) Future Work

Once correlated observation errors have been implemented for IASI the aim is to implement them for the other high spectral resolution sounders, AIRS and CrIS.

Investigate the potential benefits of accounting for inter-channel error correlations for other instruments such as AMSU-A, MHS, SSMIS, ATMS and SEVIRI.

Further research into accounting for inter-channel error correlations in the 1D-Var pre-processor. A more accurate representation of the errors here should lead to better quality control and a more accurate retrieval of skin temperature, cloud parameters and emissivities.

Investigate the effect of accounting for correlated observation error on the optimal channel selection for high resolution sounders.

References

Desroziers G, Berre L, Chapnik B, Poli P. 2005. Diagnosis of observation, background and analysis-error statistics in observation space. Q. J. R. Meteorol. Soc. 131: 3385–3396.

Stewart L, Cameron J, Dance S, English S, Eyre J, Nichols N. 2009. Observation error correlations in IASI radiance data. Mathematics Report Series 1/2009, 26pp. Univ. Reading: Reading, UK.

Bormann N, Bauer P. 2010. Estimates of spatial and interchannel observation-error characteristics for current sounder radiances for numerical weather prediction. I: Methods and application to ATOVS data. II: Application to AIRS and IASI data. Q. J. R. Meteorol. Soc. 136: 1036–1063.

Met Office FitzRoy Road, Exeter, Devon, EX1 3PB United Kingdom
Tel: 01392 884049 Fax: 01392 885681
Email: peter.weston@metoffice.gov.uk