Diagnostics for the Assimilation of Observations in the Boundary Layer in 4DVAR

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Abstract

We present a method that allows the separation of the relative contributions of the background error covariances and the linear model in spreading information from observations in 4DVAR. The motivation for this work has been the sometimes poor assimilation of observations in the boundary layer of the Met Office's 4DVAR data assimilation system. We explore the role of the physical parameterisations in the 4DVAR linear model in spreading the information from observations. We have generated two sets of background error covariance statistics using the National Meteorological Center (NMC) method: a control set and a modified set. The control set are derived from the NMC method in the usual way. For the modified covariance statistics the model errors of the moisture control variable at different levels are set to be artificially uncorrelated. Thus spreading of information will be due mainly to the physics thereby allowing us to see more clearly the influence of the physics. We perform a set of single observation tests for a range of cases. Analysis increments are created from the insertion of a single observation of moisture. These diagnostics show that the background error covariance matrix tends to dominate the spreading of the information compared with the physical parameterisations. Therefore, the priority of further work is to improve the covariance statistics before we can gain the full potential from the linear model physical parameterisations, particularly in the boundary layer.

1. Introduction

Many observations are not being correctly assimilated into the current Met Office operational NWP 4DVAR data assimilation system, particularly in the boundary layer. In 4DVAR information from observations can be spread by the background error covariance matrix **B**, the dynamics and the physical parameterisations in the linear model. We present diagnostics that allow us to separate the relative contributions of spreading by background error covariances and the linearised physics. The motivation for this work has been the sometimes poor assimilation of observations in the boundary layer, particularly in temperature inversions and stratocumulus cloud cases. These problem cases have principally been attributed to inappropriate vertical background error covariances that have a tendency to spread the information from observations too much (Lorenc, 2007), thus overwhelming spreading by the linear physics.

We explore the role the physical parameterisations of the boundary layer in the Met Office's 4DVAR linear model in spreading the information from observations. In particular we evaluate a newly developed method for boundary layer parameter estimation. To aid us in our diagnosis of the system, we generate a modified set of background error covariances that do not spread information vertically for moisture. This allows us to decouple the spreading of information by the background error covariances and the linear physics. By removing the contribution of the background error covariances we can see more clearly the influence of the linear physics in single observation experiments. To observe the structure function of the background error covariance we can use 3DVAR to generate the analysis increments for the corresponding run. Thus we can compare the spreading by the background error covariances and the linear physics.

The paper is structured in the following way. Section 2 gives an overview of the linear boundary layer scheme in the Met Office 4DVAR system. Section 3 describes how the background error covariances were generated and how the single observation tests were performed. Section 4 discusses the results, and in Section 5 we give a summary and provide suggestions for further work.

2. Boundary layer scheme

The physical parameterisations in the linear model of the Met Office incremental 4DVAR scheme, allow us to more closely match the perturbations from the nonlinear forecast runs. Linearisations tests are a well established tool that allows us to diagnose the performance of our linear model. In linearisation tests we examine the difference in the geophysical increments between the linear forecast model M', and the difference of a pair of nonlinear model M runs. One model is run from the background and the other run from the analysis (strictly background plus analysis increment) generated from the preceding cycle. We want

$$M'\delta x-(M(x)-M(x+\delta x))$$

to be as small as possible. Here x is a vector of geophysical quantities of wind speed, temperature, pressure, air density and moisture over all grid points and levels. An issue with the linearisation tests is that the linear model is only as good as the non-linear physics that it linearises. That is to say this diagnostic may tell us nothing about the forecast scores that we seek to improve. In the Met Office scheme, the nonlinear model is the Unified Model (UM) and linear model in 4DVAR is known as the perturbation forecast (PF) model. We note that while the PF model is linear it is not tangent linear to the nonlinear model.

The Met Office 4DVAR scheme contains several linearised components of physics including convection, microphysics, and surface drag and diffusion in the boundary layer. In this paper we are concerned with the linear boundary layer scheme, so we provide a brief review here.

The linear model in the Met Office 4DVAR system uses a scheme similar to Buizza (1994) for parameterising the vertical diffusion and surface drag for momentum in the boundary layer. A full account of the Met Office scheme is given in Payne (2006).

The vertical diffusion of momentum is

$$\frac{\partial\psi}{\partial t}=\frac{1}{\rho}\frac{\partial F_{\psi}}{\partial z},$$

where ψ is either zonal U or meridional V wind speed, ρ is air density, F_{ψ} is the flux and z is height. The surface fluxes for U and V are

$$F_U=\rho_0 u_*\frac{k(U_L-U_0)}{\ln\left(\frac{z_L+z_0}{z_0}\right)}$$

and

$$F_V=\rho_0 u_*\frac{k(V_L-V_0)}{\ln\left(\frac{z_L+z_0}{z_0}\right)}$$

respectively, where k is 0.4, ρ_0 is reference pressure, u_* is wind velocity scale factor, z_0 is the roughness length, and z_L is the height of the lowest model level above the surface. The upper-level flux is

$$F_\psi = \rho_0 u_* \frac{kz}{1 + kz/80k} \exp\left(\frac{z}{h_0}\right) \frac{\partial \psi}{\partial z},$$

where h_0 is a constant.

Payne (2009) developed a methodology for parameter estimation in the boundary layer diffusion scheme of the 4DVAR linear model. The parameters form part of a component in the middle of the time-step and are selected by minimising the linearisation error. The UM diagnostic number of turbulent mixing layers (NTML) is used as the regression parameter for handling the different boundary layer situations.

3. Methods

For this study we generated new background error covariances and we use single observation experiments as our principal diagnostic. Here we describe how the background error covariances were generated and how the single observation tests were performed.

3.1. Generating the background error covariance matrix

We have generated two sets of background error covariances using the National Meteorological Center (NMC) method: a control set derived in the usual way and a modified set where the errors in the moisture control variable, μ, at different levels are set to be artificially uncorrelated (i.e. we use only diagonal vertical mode of moisture transformation, where off-diagonal elements of the model errors of μ at different levels are set to 0). We chose μ in this experiment because it is a fully decoupled control variable. Thus spreading of information will be due mainly to the physics and so we can more clearly see the influence of the linear model. The background error covariances were generated from May 2008 global runs of the UM at N216 (432 by 325 grid points) and 38 levels. We then performed a global to NAE (North Atlantic and Europe) LAM (local area model) conversion.

3.2. Single observation experiments

We perform a set of single observation tests for cases representing a range of meteorological situations, so that we can examine the performance of 4DVAR under different scenarios. Two cases are presented here: a winter anticyclone case on 19/12/2007 (Figure 1) and a summer convective case on 20/07/2007 (Figure 2). The analyses were run for the NAE LAM. Analysis increments in 4DVAR are created from the insertion of a single pseudo observation of μ and θ towards the end of the assimilation window at the surface at -4.3E, 51.9N using both sets of background error covariances and with and without the boundary layer diffusion filtering sub-step. Experiments were also run with the boundary layer filter for different values of NTML.

4. Results

The analysis increments for the single observation tests are displayed N-S cross-sectional plots at -4.3E, 51.9N. These are presented in Figures 3-7 for the two cases: 19/12/2007 and 20/07/2007.

The control experiments show typical structure functions for θ (Figure 3) and μ (Figures 4 and 6), where spreading is due to the background error covariances, dynamics and the linear physics. These analysis increments allow comparison with the single observation experiments run with the modified background error covariances, where the spreading of μ is artificially suppressed (Figures 5 and 7). We can see that the spreading of information is much less than with the control experiments. For the modified background error covariances, spreading is due to the physics and dynamics. When we apply the boundary layer diffusion filtering scheme we do get increased spreading, but it only makes a small contribution. In addition, we would expect more diffusion under unstable conditions compared with stable conditions, but this is not the case here. For both cases the boundary layer filtering scheme contributes similarly to the spreading.

To examine whether we could attain different degrees of spreading, we performed experiments using a different set of parameters by forcing the experiments to accept prescribed NTML values. Results showed that the spreading was largely insensitive to the parameters used. The difficulty is that the NTML diagnostic that is supplied through the linearisation states from the UM does not properly characterise the prevailing boundary layer conditions. Thus separability between boundary layer conditions during the training and testing phases of the scheme is poor.

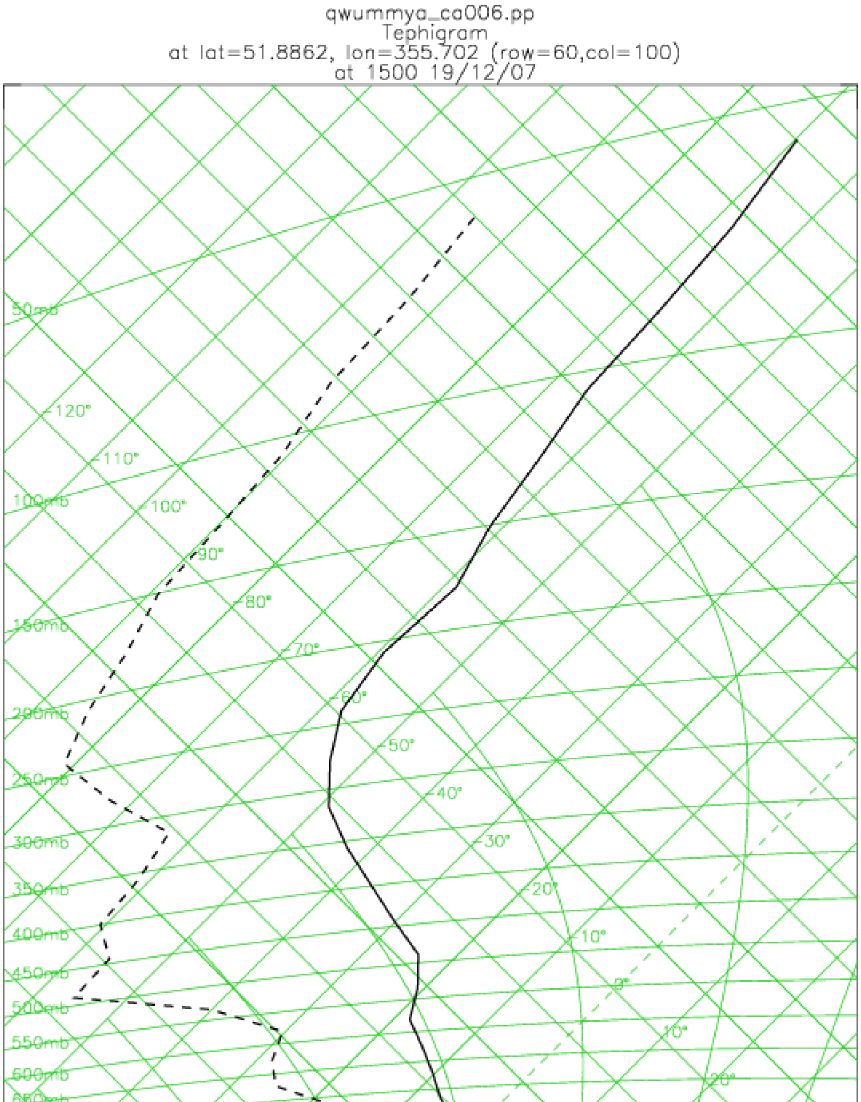


Figure 1: Tephigram from UM NAE LAM at 15Z on 19/12/2007 at -4.3E, 51.9N. Inversion in the boundary layer that persists throughout the analysis window. NTML diagnostic is 1.

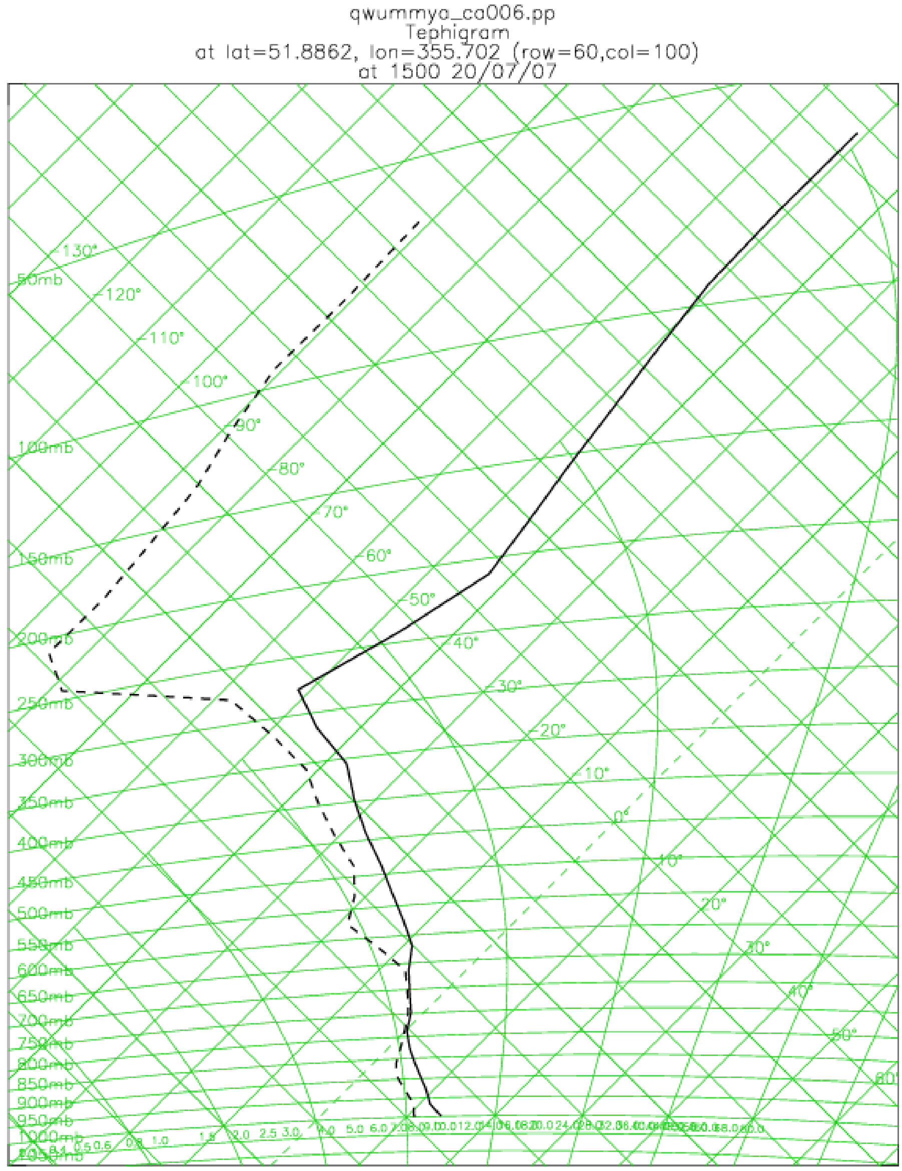
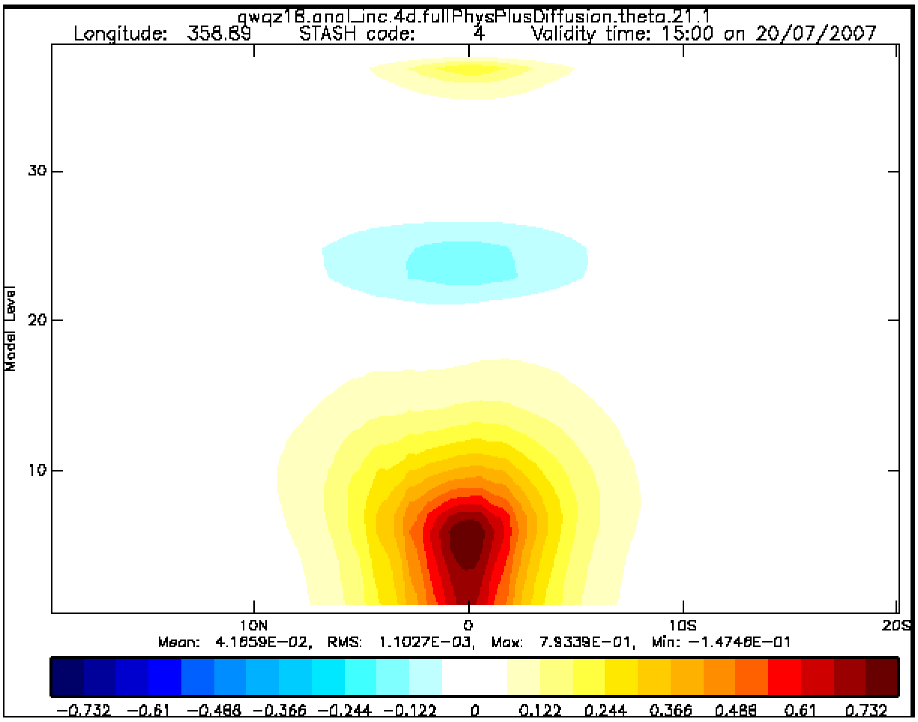
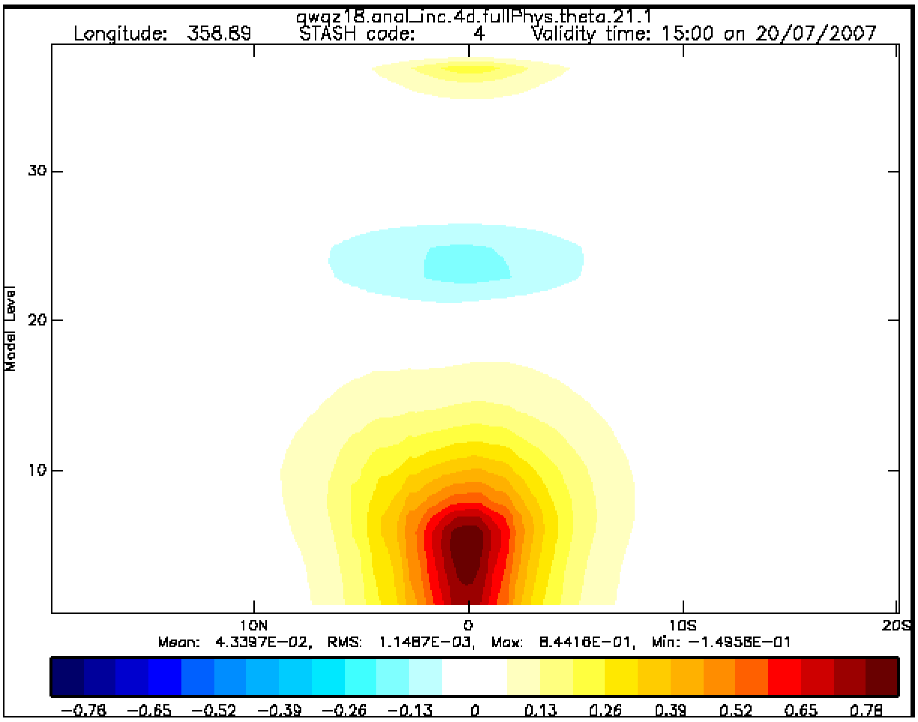


Figure 2: Tephigram from UM NAE LAM at 15Z on 20/07/2007 at -4.3E, 51.9N. At T+0 lowest level, temperature decreases adiabatically. In the layers above, the atmosphere is conditionally unstable. Clouds can form between 800-650mb. NTML diagnostic is 4.

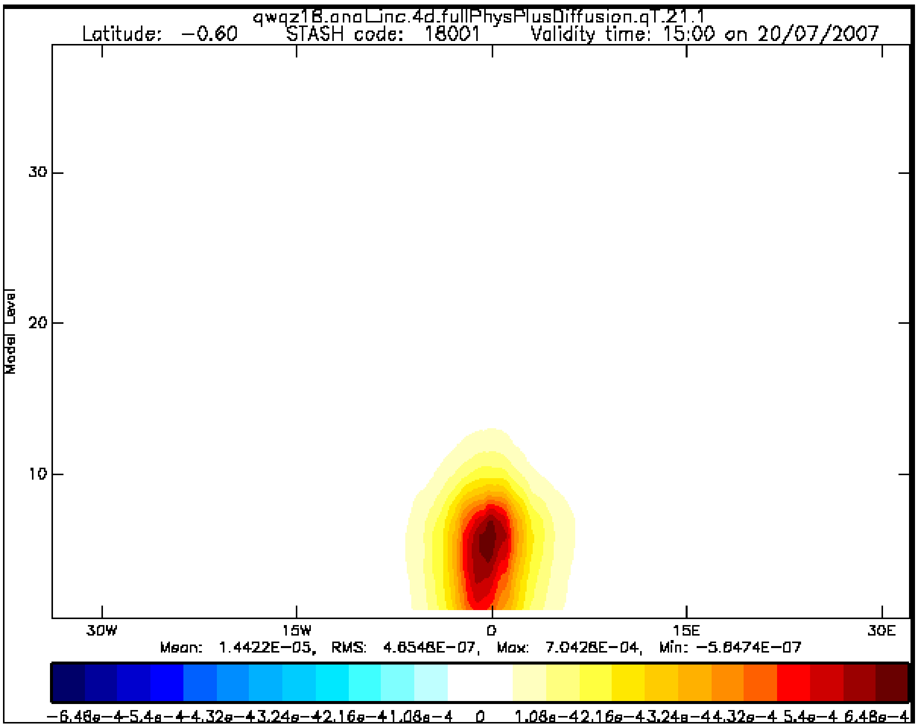


*(a) Analysis increment with vertical diffusion filter, control **B** and θ.*

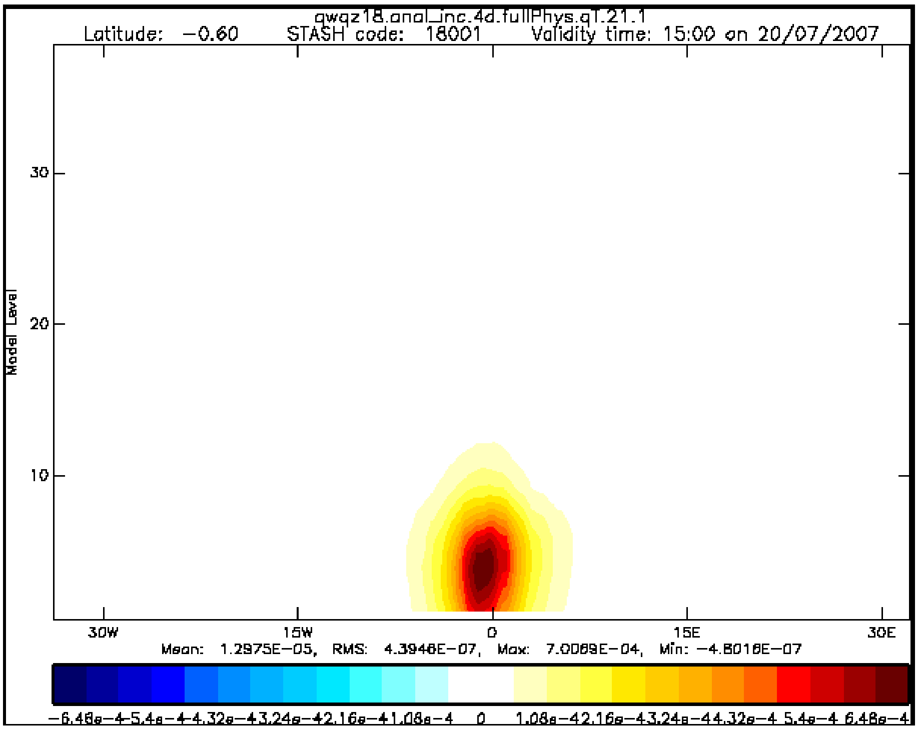


*(b) Analysis increment without vertical diffusion filter, control **B** and θ.*

Figure 3: N-S cross-sectional plots of single observation tests of θ showing θ for the NAE analysis increments at 18Z on 20/07/2007 at -4.3E, 51.9N.

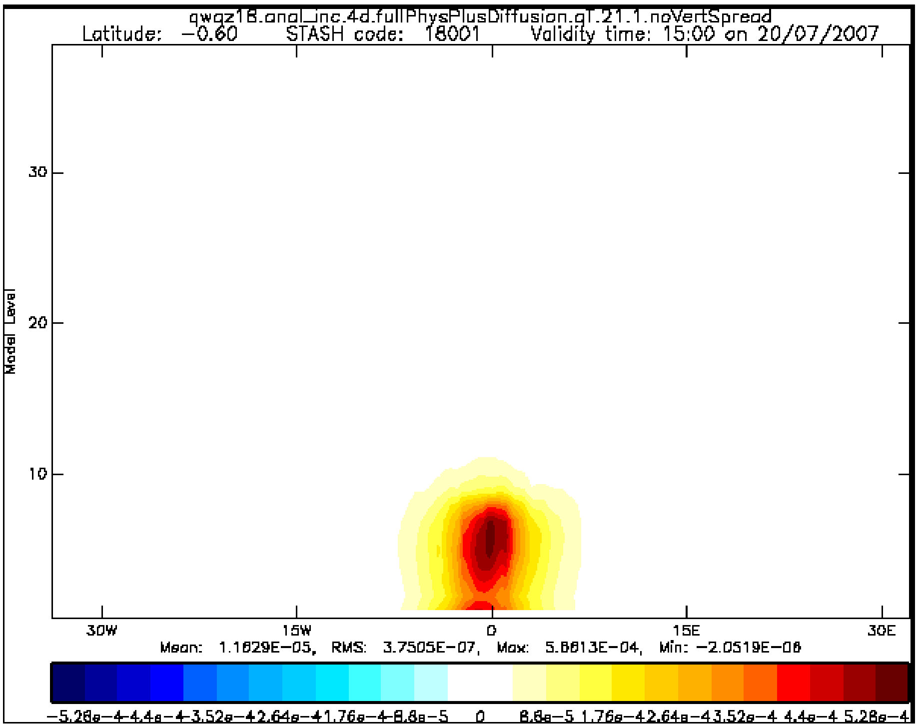


*(a) Analysis increment with vertical diffusion filter, control **B** and μ .*

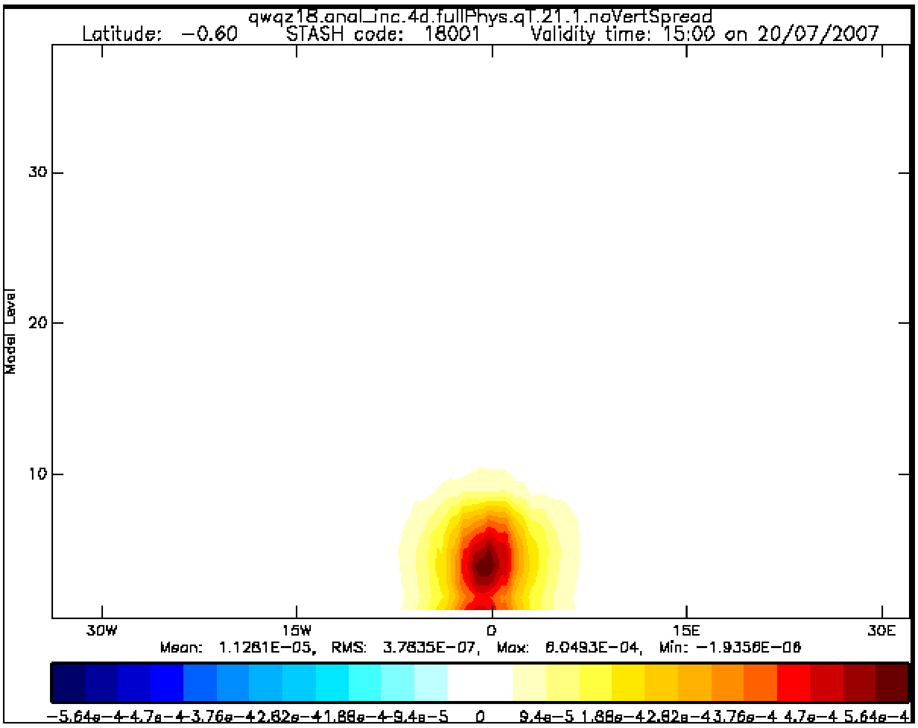


*(b) Analysis increment without vertical diffusion filter, control **B** and μ .*

Figure 4: E-W cross-sectional plots of single observation tests of μ showing moisture for the NAE analysis increments at 18Z on 20/07/2007 at -4.3E, 51.9N.

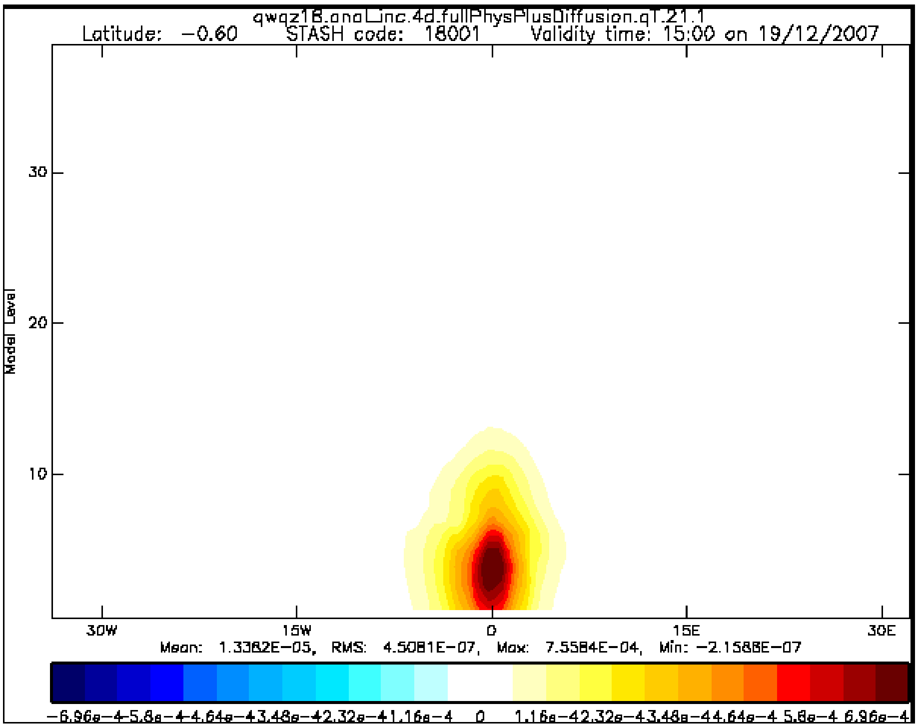


*(a) Analysis increment with vertical diffusion filter, modified **B** and μ .*

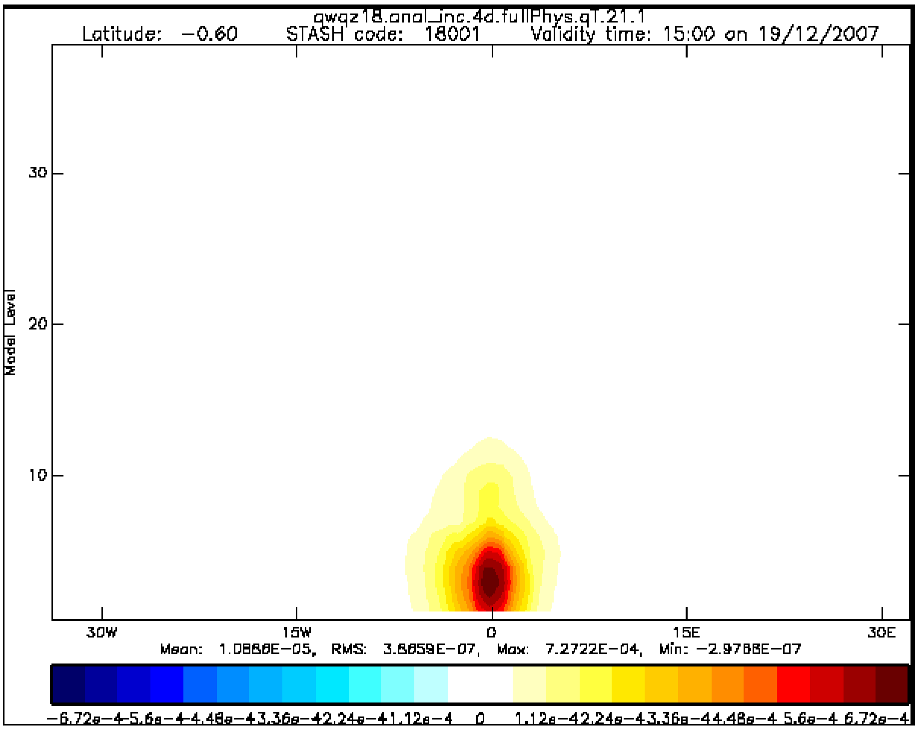


*(b) Analysis increment without vertical diffusion filter, modified **B** and μ .*

Figure 5: E-W cross-sectional plots of single observation tests of μ showing moisture for the NAE analysis increments at 18Z on 20/07/2007 at -4.3E, 51.9N.

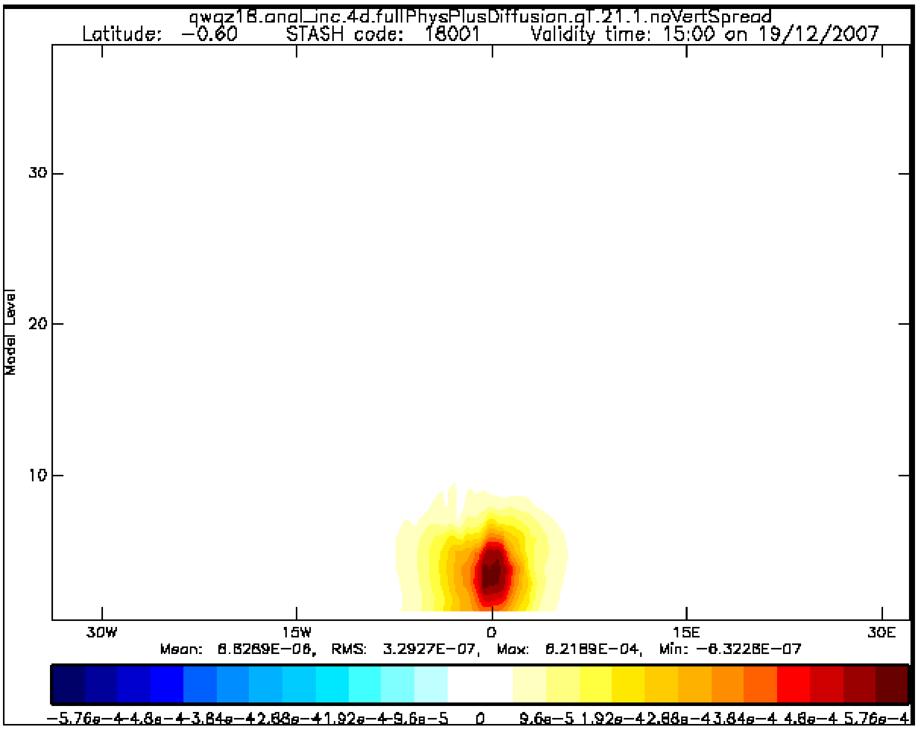


(a) Analysis increment with vertical diffusion filter, control **B** and μ .

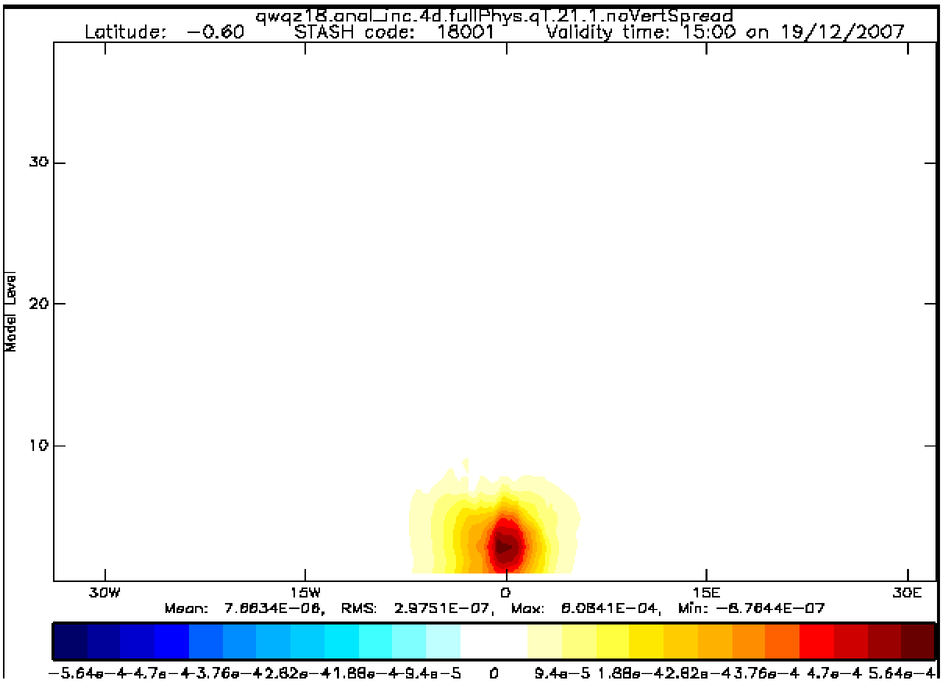


(b) Analysis increment without vertical diffusion filter, control **B** and μ .

Figure 6: E-W cross-sectional plots of single observation tests of μ showing moisture for the NAE analysis increments at 18Z on 19/12/2007 at -4.3E, 51.9N.



*(a) Analysis increment with vertical diffusion filter, modified **B** and μ .*



*(b) Analysis increment with vertical diffusion filter, modified **B** and μ .*

Figure 7: E-W cross-sectional plots of single observation tests of μ showing moisture for the NAE analysis increments at 18Z on 19/12/2007 at -4.3E, 51.9N.

5. Summary and further work

The physics is generally performing as expected in 4DVAR, but the background error covariances are spreading the information too much. Information is even being spread from the boundary layer into the free atmosphere by the background error covariances. The key findings are as follows:

- The background error covariances tend to dominate the vertical spreading of information.
- Boundary layer diffusion with filtering only provides a small increase in vertical spreading.
- Using uncorrelated vertical errors in background error covariances for μ reduces vertical spreading.
- Extent of spreading does not necessarily depend on prevailing boundary layer conditions. We get similar spreading under both stable and unstable conditions. Vertical spreading is largely insensitive to parameters (NTML).

The full potential of the PF physics cannot be realised until the background error covariances are improved. Therefore, the priority of further work is to improve the background error covariances before we can make further progress on the development of the physical parameterisations in linear model, particularly with respect to the boundary layer. Specifically we will set up a boundary layer control variable for humidity and temperature. We will also explore alternative diagnostics to NTML as full regression parameter, including boundary layer type, boundary layer height and turbulent mixing height.

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6. References

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