Application of Physical Filter Initialization Scheme on WRFVAR

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1. Introduction

In variational data assimilation scheme, usually, the analysis fields are not in balance because of poorly defined background error covariance, insufficient observations, imperfect modal, and observation errors.

Some researches have been focused on using weak constraints to reduce the dynamic imbalance between model variables based on the idea that unbalanced initial conditions often generate high-frequency oscillations with amplitude larger than those observed in nature. One of the approaches is digital-filter initialization (DFI) proposed by Lynch and Huang (1992). Another approach is to use some physical constraint such as temporal and spatial smoothness penalty functions, mass continuity and smoothness, steady advective-diffusive equation, or dynamical constraints etc.. Liang et al. (2007) proposed a model constrained 3DVar (MC-3DVar) technique to apply the full physics and dynamics of numerical model as constraints in 3DVar. The MC-3DVar can dramatically reduce the high frequency oscillations in the analyses fields.

In this study, the MC-3DVar technique is extended to 4DVar scheme and implemented in WRF-4DVar (Huang et al. 2009) system.

2. Method

In MC-3DVar (Liang et al. 2007), the analysis field of the initial conditions is obtained to minimize a cost function as

$$J_3=[\mathbf{x}-\mathbf{x}_b]^T\mathbf{B}^{-1}[\mathbf{x}-\mathbf{x}_b]+[\mathrm{H}(\mathbf{x})-\mathbf{y}]^T\mathbf{O}^{-1}[\mathrm{H}(\mathbf{x})-\mathbf{y}]+\sigma\left[\frac{\Delta\mathbf{x}}{\Delta t}-\frac{\Delta\mathbf{x}_b}{\Delta t}\right]^T\mathbf{R}^{-1}\left[\frac{\Delta\mathbf{x}}{\Delta t}-\frac{\Delta\mathbf{x}_b}{\Delta t}\right] \quad (1)$$

where **X** the analysis field, $\mathbf{X}_b$ the background, **B** the background error covariance, **O** the observation error covariance, **R** the time tendency error covariance of the model variables, **y** the observation, *T* the observation operator and the transfer operator, **σ** is a given positive weighting factor.

For 4Dvar, the cost function can be defined in a time window as

$$J_4=[\mathbf{x}-\mathbf{x}_b]^T\mathbf{B}^{-1}[\mathbf{x}-\mathbf{x}_b]+\sum_{i=1}^{N}[\mathrm{H}(\mathbf{x}_i)-\mathbf{y}_i]^T\mathbf{O}^{-1}[\mathrm{H}(\mathbf{x}_i)-\mathbf{y}_i]+\sigma\sum_{j=1}^{M}\left[\frac{\Delta\mathbf{x}_j}{\Delta t}-\frac{\Delta\mathbf{x}_{bj}}{\Delta t}\right]^T\mathbf{R}^{-1}\left[\frac{\Delta\mathbf{x}_j}{\Delta t}-\frac{\Delta\mathbf{x}_{bj}}{\Delta t}\right] \quad (2),$$

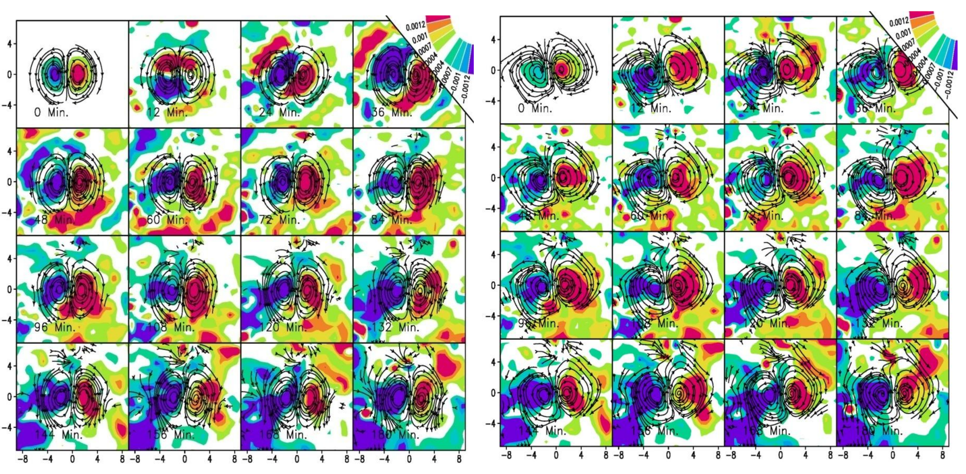
where the first term is as same as that in 3DVar, the second term for distance between analysis and observations at time *i* , the third term the penalty defined at time *j*.

The function of penalty term is to minimize the variance of the variables. The higher frequency oscillation is related to larger variance, therefore, the high frequency oscillation are eliminated by minimizing the variance of the variables. It act as a low-pass filter. Because the value of the penalty term is determined by the dynamic and physics of the model, this method is a physical filter.

A WRF-4DVar system with physical filter as Eq. (2) is developed in this study.

3. One-point observation in 3Dvar experiment

Appling Eq. (2) with one time step, it is a model constrained 3Dvar as shown in Liang et al. (2007). It is a 3Dvar when **σ**=0 (Control experiment). σ can be set to be different values to examine the performance of penalty term (i.e. **σ**=4e^{-1} **,σ** =4e^{-2} **,σ** =4e^{-3} , or **σ** =4e^{-4}**)** . A one-point observation of wind component v on 500hPa level is assimilated.



a b

Figure 1 The height and wind increment at initial time (0hr) and difference with the forecast of control experiment (without data assimilation) during 12~180min on 500 hPa in 3Dvar (a) and MC-3Dvar (b) experiments. In the forecasts of 3Dvar experiment, the high frequency oscillation is obvious.

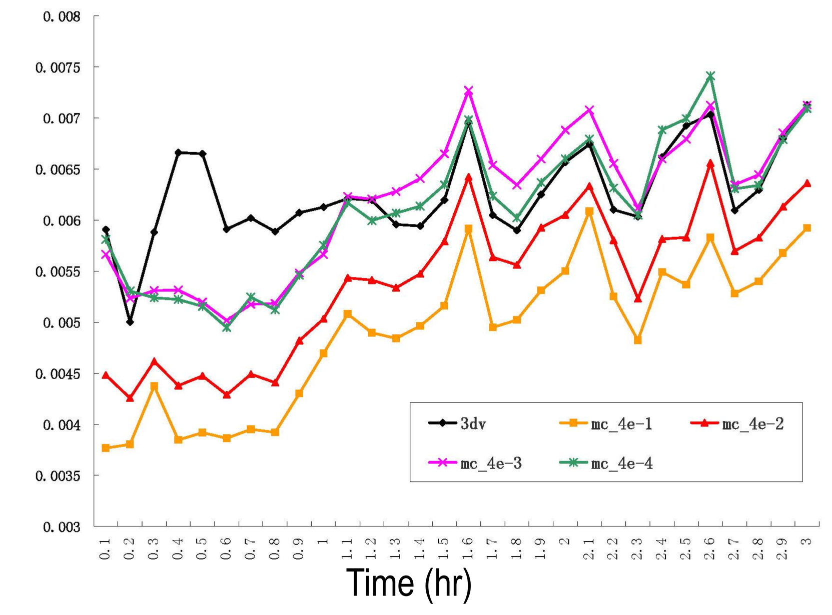


Figure 2 RMS of the sea level pressure difference between assimilation experiment and control experiment. It changes obviously from beginning of the integrating in 3Dvar experiment. It reaches a stable value after 36min. With the physical filter, the sea level pressure difference changes more slowly. The larger the weighting factor is, the more slowly the difference changes. It is obvious that the high frequent oscillation is reduced by the physical filter.

4. One-point observation in 4Dvar experiment

As shown in Eq. (2), the model constrains can be applied in 4Dvar.

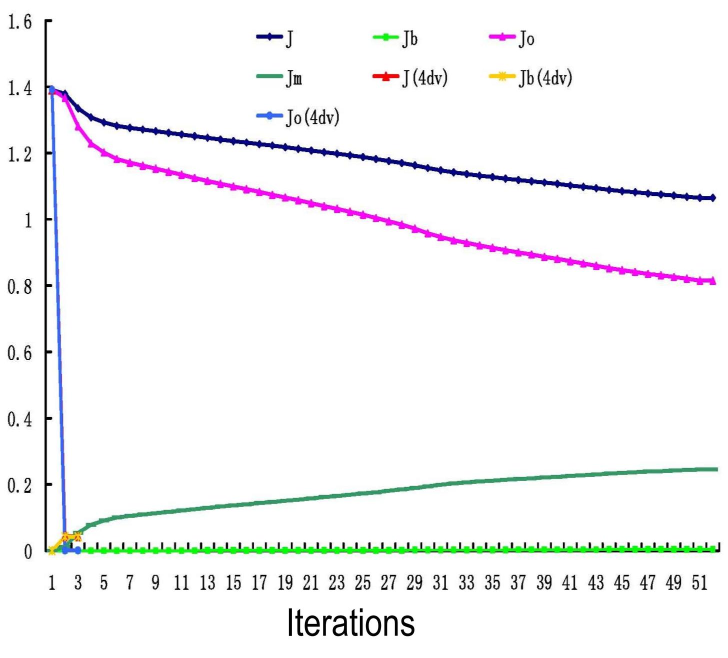
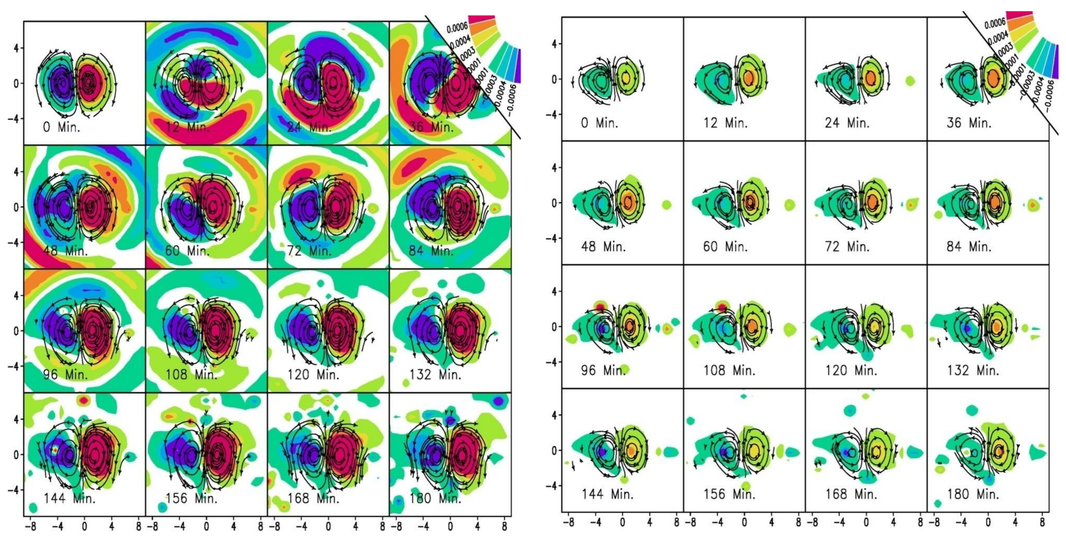


Figure 3 Change of each terms of the cost function of 4Dvar and MC-4Dvar experiment. In MC-4Dvar the cost function drops in a slower manner. Meanwhile, the penalty term increases slowly.



a b

Figure 4 Same as figure 1 except for 4Dvar (a) and MC-4Dvar (b) experiment. In the 4Dvar experiment, the high frequency oscillations are obvious compare to those in MC-4Dvar experiment

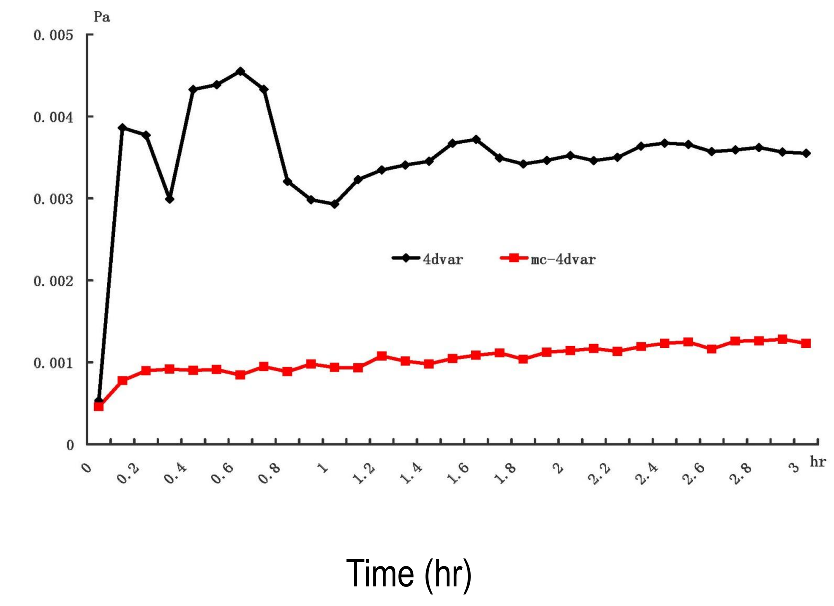


Figure 5The RMS of the sea level pressure difference in 4Dvar experiment (black line) and MC-4Dvar experiment (red line). It can be seen that the variance of the sea level pressure in 4Dvar experiment is larger than those in MC-4Dvar experiment and with obvious oscillations.

5. Case study

The primary study of the heavy rainfall case on 21st July 2012 in Beijing is carried out in this study. The assimilation time window is 1 hour. Only conventional radiometer and surface observations are assimilated in this study.

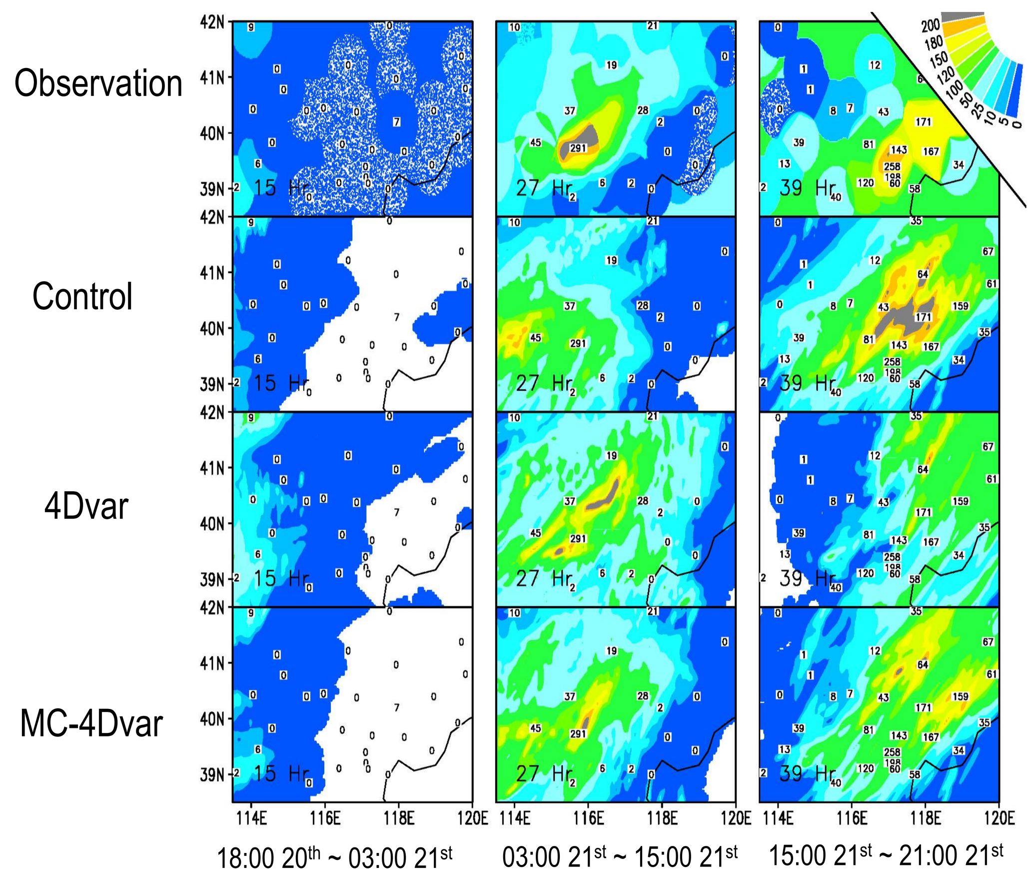


Figure 6 The 6hr accumulated precipitation observation and forecasting.

6. Conclusion and discussion

In variational data assimilation scheme, high frequency oscillations would be induced because of unbalance in the analysis fields while observation data are introduced. The physical filter scheme proposed by Liang et al. is used to minimize the time tendency of model variables, and thus eliminate the high frequency oscillations in the optimized initial conditions. In this study, the physical filter scheme is implemented in WRF-4Dvar system. The primary experiments show that the model constraints used in WRF-4DVar can eliminate the high frequency oscillations obviously.

More cases with detailed examination should be done in the future.

7. Reference

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