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Comparative experiments on the effect of several forms of background error covariance on 3DVar

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The background error covariance matrix (henceforth called as B matrix) plays an important role in the three-dimensional variational (3DVAR) data assimilation methods. However, it is very difficult to get B matrix accurately because the true atmospheric states is unknown. So far, various methods were developed to estimate B matrix (e.g. NMC method, innovation analysis method, recursive filters, and ensemble method such as EnKF). It will be worth studying that evaluating the function of different B matrix in 3DVar before further development and application of these methods.

In this paper, the several forms of B matrix are used to VAF (Variational Analysis using a Filter, one of 3DVar schemes to avoid the inversion of B matrix; Huang, 1999) and tested the effectiveness of these B matrixes with NCEP reanalysis and forecast data set. In our experiments the NCEP analysis is regarded as the true states. So the forecast error is known. The data from 2006 to 2007 is used as the samples to estimate B matrix and the data from 2008 is used to verify the assimilation effectiveness. The data used for NMC method to estimate B matrix is the 48h and 24h forecast valid at the same time.B matrix can be represented by a correlation part C and a variance part Σ^2 (B $=$ ΣCΣ). Here C is a non-diagonal matrix of correlations and Σ^2 is a diagonal matrix of variances. In numerous operational 3DVar system, Gaussian filter function as an approximate approach is used to represent the variation of correlation coefficients with distance. That is to say, the element of C can be described by $C_{i,j} = \exp[-(\frac{x_{i,j}}{L_x})^2 + (\frac{y_{i,j}}{L_y})^2]$. On the basis of the assumption, the following several forms of B matrix are designed in the comparative experiments: (a) Σ^2 and the characteristic length L_x, L_y are fixed and set to their mean values $\bar{L}_x, \bar{L}_y$ over the analysis domain; (b) similar to (a), but the mean characteristic lengths $\bar{L}_x, \bar{L}_y$ will reduce to 50 percent (for the height) or 60 percent (for the temperature) as opposed to the original; (c) similar to (b), but Σ^2 is space-dependence and calculated directly by the historical data; (d) Σ^2 and $\bar{L}_x, \bar{L}_y$ are all space-dependence and calculated directly by the historical data; (e) B matrix is estimated directly with the historical data; (f) similar to (e), but a localization process is performed; (g) B matrix is estimated by NMC method with the series of 48h and 24h forecasts and Σ^2 is reduced by 1.7 times in order to close to the value calculated from the true forecast error samples; (h) similar to (g), but the localization similar to (f) is performed.

By statistical analysis on the forecast error and the 3DVar experimental results, it is found that for the Gaussian-type B matrix, the use of the characteristic length calculated from the “true” error samples don’t bring a good analysis results for 3DVar. Even the samples used for data assimilation and estimating B matrix is exactly same. However, reduced characteristic length (about half of the original one) can lead to a good analysis. If the B matrix estimated directly from the data is used in 3DVar, the assimilation effect can not reach to the best. The better assimilation results can be obtained with the application of reduced characteristic length and localization. Even so, it hasn’t obvious advantage and costs more computational time compared with Gaussian-type B matrix with the optimal given characteristic length. Therefore, maybe the Gaussian-type B matrix, widely used for operational 3DVar system, is a good choice. In which, the crucial problem is how to determine the appropriate characteristic length.