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Recovery of mesoscale covariance using time-phased ensembles

Kim, O.-Y[1]., C. Lu[1], J. McGinley[1], and J.-H. Oh[2]

[1]NOAA Earth System Research Laboratory, Boulder, CO 80305
[2]Department of Envi. and Atmos. Sci., Pukyong Nat'l Univ., Busan, Rep. of Korea

1. Introduction

One of the most important factors that determines meteorological analysis fields in a data assimilation system is the background covariance matrix. Not only do the correlations in this background covariance matrix perform the spatial spreading of information at the observation points throughout the model domain including data-sparse areas, but they also play a decisive role in how to smooth the analysis increments in data-dense areas.

One of the key issues for data assimilation is the specification of the background error covariance. There are classic methods to estimate the background error covariance mainly based on the study of forecasts started from the analyses, like the NMC method (Parrish and Derber 1992). Their theoretical foundation is now considered rather unclear.

In this research, we proposed a new method to estimate background error covariances, namely a time-phased ensemble forecast system, which was recently developed at NOAA's Global Systems Division (GSD) of the Earth System Research Laboratory (ESRL). In this research, we will examine how well this newly structured background error covariance can capture the flow dependent mesoscale features. We will also compare the covariance structure obtained from the time-phased ensemble method with that from NMC method.

2. Time-phased model ensemble system

The background error statistics are estimated from a set of model forecasts initialized at different times, but validated at the same time, forming a time-phased ensemble system (Lu et al. 2007). Because these initial perturbations are generated from different forecast initialization cycles, the background error covariance computed from such a statistical sample possesses flow-dependent information in the model. Mathematically, the background error covariance matrix from the time-phased ensembles can be expressed as

$$\mathbf{X}_{\tau}^{\mathbf{f}}(t) = M\left[\mathbf{X}(t-\tau)\right], \quad \tau \in \{1, 2, \cdots, N\}$$
$$\mathbf{B} = \left\langle (\mathbf{X}_{\tau}^{\mathbf{f}} - \mathbf{X}^{\mathbf{t}})(\mathbf{X}_{\tau}^{\mathbf{f}} - \mathbf{X}^{\mathbf{t}})^{\mathbf{T}} \right\rangle \tag{1}$$

where $\mathbf{X}_{\tau}^{\mathbf{f}}(t)$ is a forecast initialized at prior τ hour and M is a model propagation operator. The background error covariance is calculated with N member samples, denoted by the angle brackets.

3. Calculation of background error covariance using time-phased ensembles

Because of the huge dimension of error in a covariance matrix (on an order of $10^7 \times 10^7$ for realistic atmospheric application (Courtier 1997), two model-state vectors will be considered. Background error covariances (cross-covariance, spatial covariance, and cross-spatial covariance) as well as variance can be derived from these two model-state components (Zhang 2005),

$$Cov\{x_{i_1 j_1 k_1}, y_{i_2 j_2 k_2}\}$$
$$= \frac{1}{N-1}\sum_{n=1}^{N}(x_{i_1 j_1 k_1 n} - \overline{x_{i_1 j_1 k_1}}) \times (y_{i_1 j_1 k_1 n} - \overline{y_{i_1 j_1 k_1}}) \quad (2)$$

where x and y are two state variables at the grid-point $(i_1 j_1 k_1)$ and $(i_2 j_2 k_2)$. N is the total ensemble members, and n is each member in the time-lagged ensemble pool. These covariances and variance are related to each element in the background error covariance matrix. The diagnosis of the physical features of these two-dimensional background error fields will give us valuable insight into the behaviors of the background errors recovered from time-phased ensembles.

4. Physical diagnoses

The background error covariance typically reflects underlying background- balanced dynamics (Daley 1991). Special attention is focused on the discussion of this characteristic of background error covariance by comparing it with the diagnosis of potential vorticity (PV) from analyses. Typically the PV anomaly indicates an active weather event.

Fig. 1 shows the 300-hPa estimated background error covariance between U and T at every 6 hours for 24 hours. The covariance structure is consistent with the underlying background dynamics (PV) at respective times. The magnitude of the background error increases as the storm intensifies. The slight shift in the maximum of background error from the PV centers may be due to two factors: 1) the background errors tend to occur at locations where PV displays the greatest gradient; 2) the background errors recovered by the time-phased ensemble method contain a considerable amount of mesoscale motions, which tend to cause deviation from pure-balanced dynamics. It is suggested that covariances estimated from time-phased ensembles are flow-dependent. This follows the background-balanced dynamics at the relevant times. The cross-spatial covariance between U at point C (denoted in Fig. 1c) and T at any 300- hPa points valid at every 6 hours for 24 hours is shown in Fig. 2. One can see that the cross-spatial covariance also closely follows background dynamics, and its magnitude increases when as the storm intensifies.

5. Comparison of time-phased ensembles with NMC

The well-known NMC method is based on the assumption that the differences between a pair of forecasts valid at the same time, with different lead times, have a similar structure to those of the short-range forecast errors.

In a system like the atmosphere, the actual background errors are expected to depend closely on weather situations. This is essentially the notion of flow-dependent background error covariances. The covariance structures from the NMC (Figs. 3b and d) are much smoother than those from the time-phased ensemble method (Figs. 3a and c). They may represent climatological features, rather than a particular weather system. The covariance structure from time-phased ensembles is not only fully dependent on the background-balanced dynamics, but they are also situational-dependent. However, those from the NMC method do not show any agreement with the situational background- balanced dynamics.
These analyses indicate that background error covariance constructed from time-phased ensembles may provide a better short-range NWP because they closely depict background weather situations as well as the time evolution of these weather systems.

6. Conclusions

In this research, we present a method using time-phased ensembles to estimate background error covariances. This method can not only be implemented effectively on-line (in the sense of parallel with model runs), but can also capture the detailed mesoscale structure in background error covariance.

The structure of mesoscale error covariance estimated from the time-phased ensemble method is flow-dependent and highly anisotropic, which is determined by the underlying governing dynamics and associated error growth. The mesoscale error covariance showed strong signals in the vicinity of the greatest PV gradient and active moist convection areas.

The NMC method renders a smoothed, large-scale structure in the background error covariance due to near-climatological averaging of day-to-day weather variability. On the other hand, the background error covariance recovered from time-phased ensembles is situational-dependent and keeps the variability in the atmosphere.

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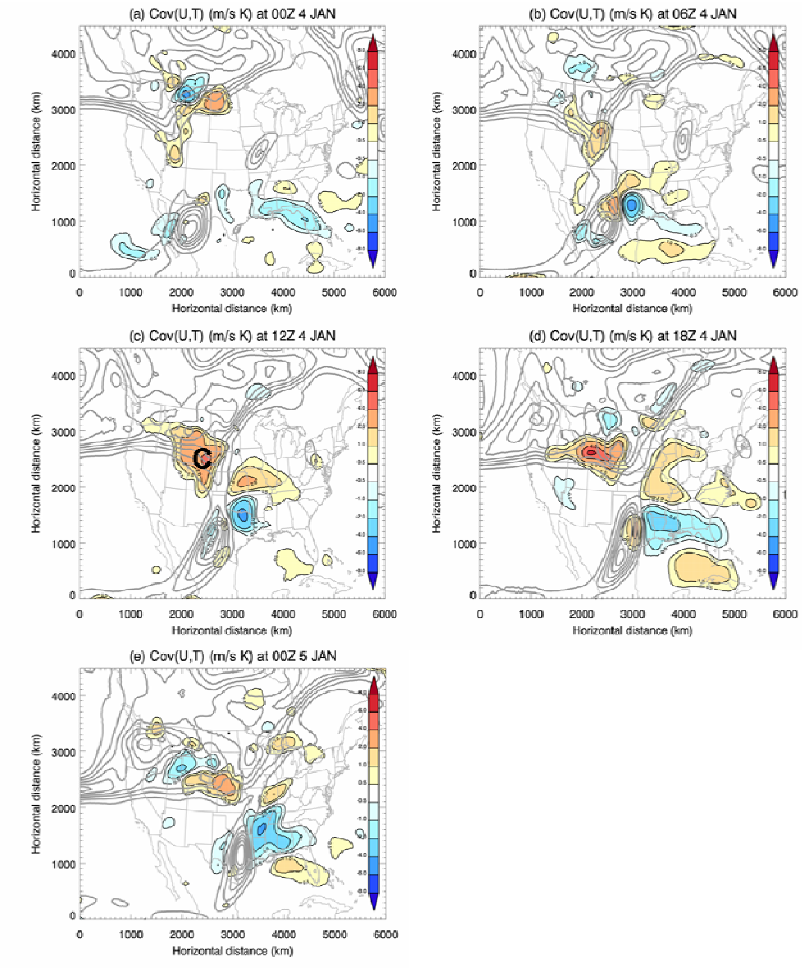

Fig. 1 The 300-hPa estimated background error covariance between U and T at (a) 00Z 4, (b) 06Z 4, (c) 12Z 4, (d) 18Z 4, and (e) 00Z 5 JAN. Positive values are shaded in red and negative values are shaded in blue. The covariance between -0.5 and 0.5 is not shaded. PV (gray solid line) is also plotted as a reference of the background balanced dynamics. Point C (maximum positive covariance) in (c) will be referred to in Fig. 2.

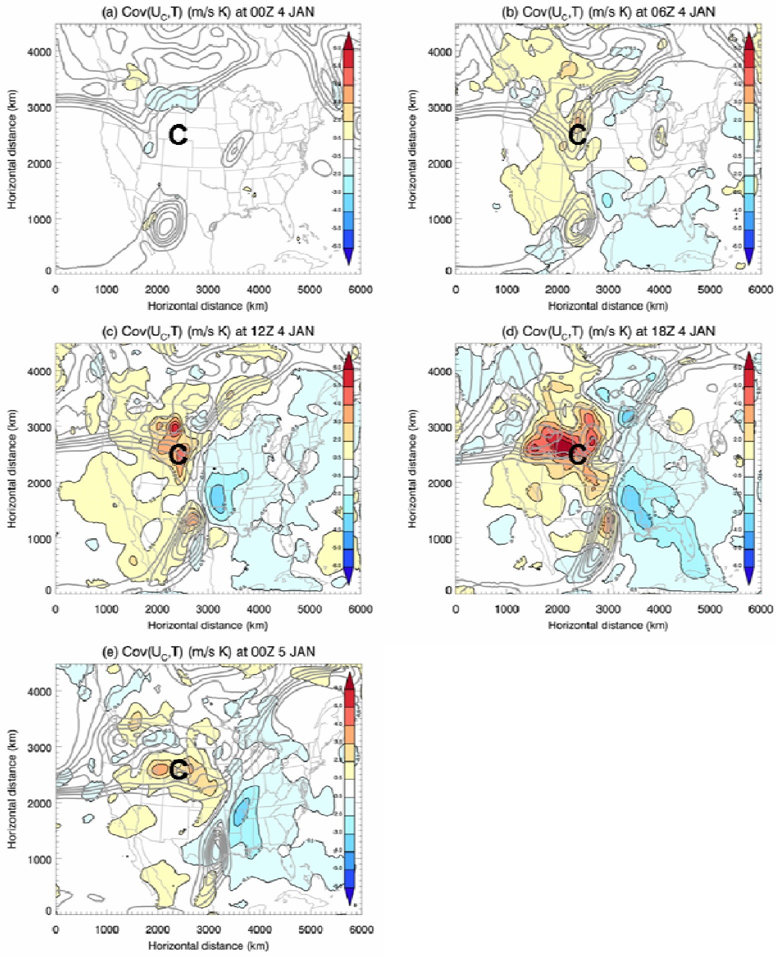

Fig. 2 The 300-hPa estimated background error cross-spatial covariance between U at point C and any T at (a) 00Z 4, (b) 06Z 4, (c) 12Z 4, (d) 18Z 4, and (e) 00Z 5 JAN. Positive values are shaded in red and negative values are shaded in blue. The covariance between -0.5 and 0.5 is not shaded. PV (gray solid line) is also plotted as a reference of the background balanced dynamics.

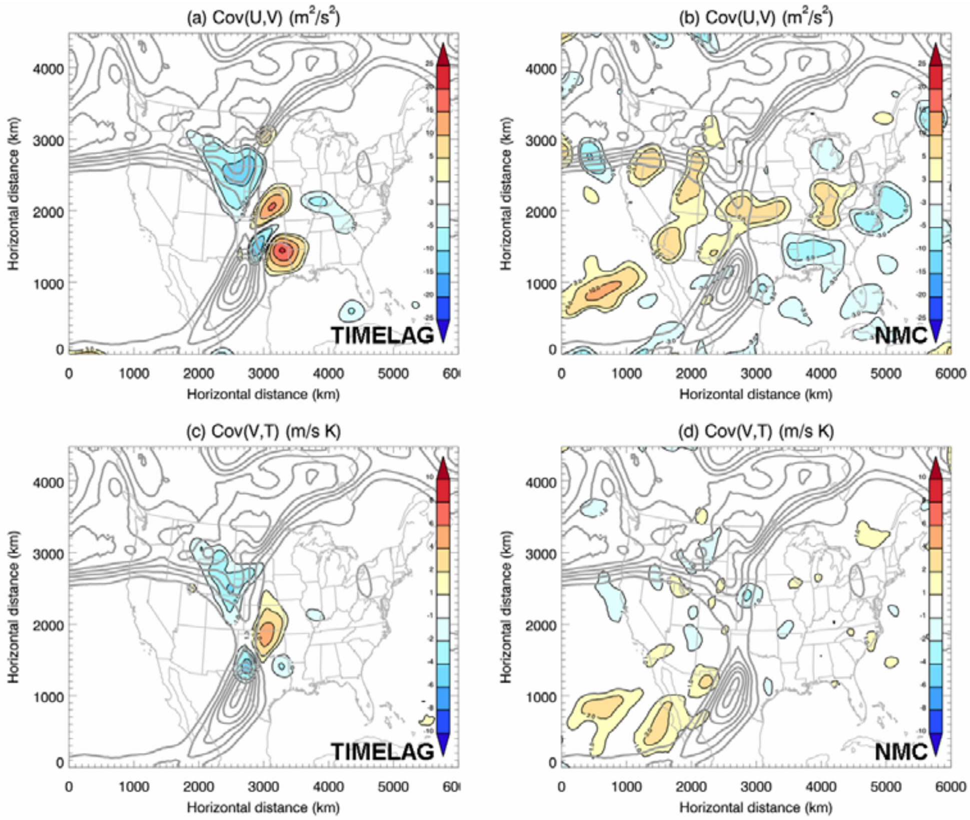

Fig. 3 The 300-hPa estimated background error covariance between U and V in (a), (b) and V and T in (c), (d) at 12Z 4 JAN. Left panel (a and c) is from the time-lagged ensemble method and the right panel (b and d) is from the NMC method. PV (gray solid line) is also plotted as a reference of the background balanced dynamics.