Implementation of hybrid 3DVar in JMA's local analysis

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1. **Introduction**

Three-dimensional variational data assimilation (3DVar) with 5-km horizontal grid intervals are used in JMA's local analysis (LA) to create initial atmospheric analysis fields in local forecast model with 2-km horizontal grid intervals (Ikuta et al. 2021). In the assimilation reported here, the horizontally homogeneous and isotropic climatological background error covariance $\mathbf{B}_c$ is used (as of February 2022) for the background error covariance of the first guess, and the flow-dependent error covariance ($\mathbf{B}_e$) is not used. However, it is possible to implement hybrid 3DVar (Lorenc 2003) with the weighted average of $\mathbf{B}_c$ and $\mathbf{B}_e$ as the background error covariance, estimating $\mathbf{B}_e$ from the ensemble perturbations of the mesoscale ensemble prediction system (MEPS, Ono et al. 2021), as applied by JMA. This report outlines hybrid 3DVar implementation in LA and related effects.

2. **Hybrid 3DVar formulation**

In hybrid 3DVar, the analysis increment $\delta\mathbf{x}$ is determined by minimizing the cost function

$$J(\mathbf{v}) = \frac{1}{2}\mathbf{v}^T\mathbf{v} + \frac{1}{2}(\mathbf{H}\delta\mathbf{x} - \mathbf{d})^T\mathbf{R}^{-1}(\mathbf{H}\delta\mathbf{x} - \mathbf{d}) + J_{bc},$$

$$\delta\mathbf{x} \equiv \mathbf{B}^{1/2}\mathbf{v} \equiv \begin{bmatrix}\beta_c\mathbf{B}_c^{1/2} & \beta_e\mathbf{B}_e^{1/2}\end{bmatrix}\begin{bmatrix}\mathbf{v}_c \\ \mathbf{v}_e\end{bmatrix},$$

where $\mathbf{v} = [\mathbf{v}_c{}^T, \mathbf{v}_e{}^T]^T$ is a control vector, $\mathbf{d} = \mathbf{y}^o - H(\mathbf{x}^b)$ is the difference in observation $\mathbf{y}^o$ from the first guess $\mathbf{x}^b$, H and $\mathbf{H}$ are the observation operator and the related tangent linear version, $\mathbf{R}$ is the observation error covariance, and J_{bc} is a bias correction term. β_c and β_e are weights for the hybrid covariance, set as $(\beta_c^2, \beta_e^2) = (0.5, 0.5)$.

$\mathbf{B}_e$ is created from 100 ensemble perturbations using 5 lagged average forecasts (LAF) of MEPS with 20 members and spatial localizations with Gaussian functions (scales of $1/\sqrt{e}$ are set as 100 km horizontally and 0.5 km vertically) to reduce sampling errors. $\mathbf{B}_e$ is inflated by multiplying the factor, which is the ratio of $\mathbf{B}_c$ and the horizontal mean of $\mathbf{B}_e$ for potential temperature at 5.5 km above ground level, meaning that error variance is comparable to the magnitude of $\mathbf{B}_c$.

3. **Verification**

To verify the effects of hybrid 3DVar implementation, sensitivity experiments were conducted in 3-hour blocks for 2 – 15 July 2020 based on the CNTL experiment utilizing the configuration of JMA's operational local NWP system as of May 2021, with $\mathbf{B}_c$ updated using National Meteorological Center method (Parrish and Derber 1992). Here, sensitivity experiments with 20 and 100 ensemble perturbations (1 and 5 LAF, respectively) are referred to as M020 and M100, respectively.

In M020 and M100 root mean square errors in forecasts were smaller than those in CNTL, especially for surface temperature, specific humidity and horizontal wind (not shown). The equitable threat score (ETS) for precipitation was better in M020 and M100 than that in CNTL, especially with thresholds over 5 mm/h (Fig. 1). These improvements were greater in M100. In forecasts from analysis at 12 UTC on 3 July, the position of predicted heavy rain in M100 was closer to observation than M020 and CNTL (Fig. 2), which may relate to the flow-dependent analysis increment of low-level variables. Associated improvements were also observed in the boreal winter experiment for 11 – 21 January 2020 (not shown).

4. Summary

The implementation of hybrid 3DVar utilizing 100 ensemble perturbations of MEPS in LA improved forecasting of precipitation and surface variables. The update was applied to JMA's operational system in March 2022.

References

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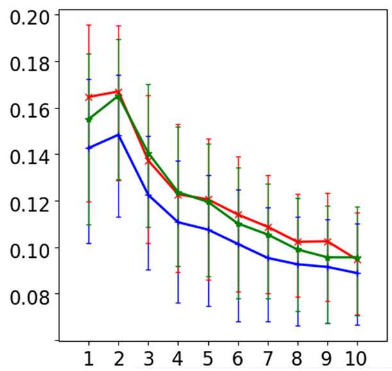

Figure 1. Equitable threat score for precipitation with a 10 mm/h threshold (vertical axis) at each forecast time [hours] (horizontal axis) in experiments for 2 – 15 July 2020 compared with JMA radar/raingauge analyzed precipitation (blue: CNTL; green: M020; red: M100). Error bars show 95% confidence intervals.

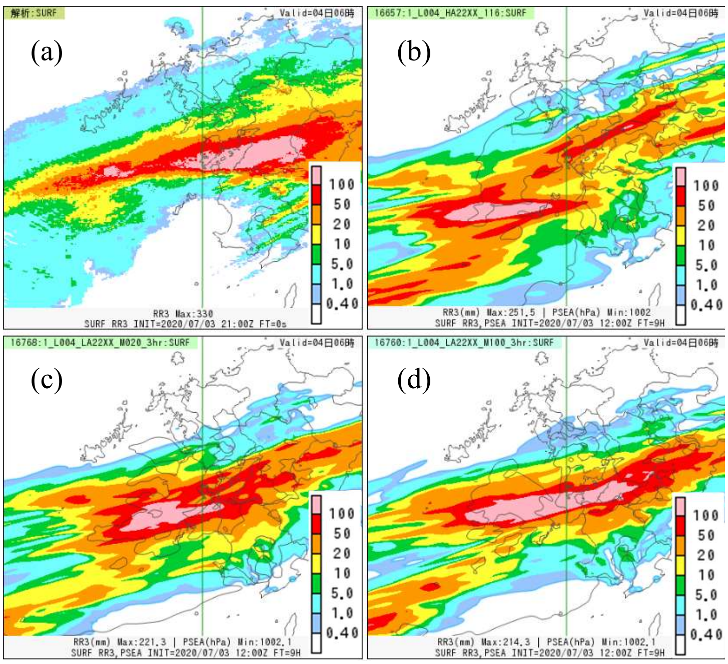

Figure 2. Three-hour precipitation (mm) for 18 – 21 UTC on 3 July 2020 in predictions from 12 UTC (a: JMA radar/raingauge analyzed precipitation; b: CNTL; c: M020; d: M100).