# Introduction of Spectral Localization to Ensemble-based Variational Assimilation for a Cloud-Resolving Model

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## 1. Introduction

To address the nonlinearity of MWR TBs and the flow-dependency of the Cloud-Resolving Model (CRM) forecast error, ensemble-based variational data assimilation (EnVA) method has been proposed (Zupanski 2005, Aonashi and Eito 2011). Though, there often exist serious sampling errors of the CRM ensemble forecasts. In order to solve this problem, some error-damping methods have been proposed. We analyzed CRM ensemble forecasts to check the validity of presumptions of these methods, and applied the error-damping methods to our EnVA scheme.

## 2. CRM ensemble forecasts

CRM: JMANHM with horizontal resolution of 5 km (Saito et al. 2006).

Ensemble forecasts: We performed 100-member 7-hour forecasts that started with initial values with geostrophically-balanced perturbation (Mitchell et al. 2002) plus humidity perturbation.

Cases: Typhoon ('04/6/9/15 UTC ), Extra-tropical low ('03/1/26/21UTC), and Baiu front ('04/6/1/00 UTC)

## 3. Analyses of CRM Ensemble forecast error

3.a Horizontal correlation of ensemble forecast error

1) Precipitation-related variables (precip, W) had narrow correlation scales (~ 15 km). 2) Horizontal correlation scales of other variables (U, V, PT, RH) decreased (160 km -> 40 km) with precipitation rate.



3.b Power spectral of horizontal ensemble forecast error

1)Diagonal modes are dominant for precipitationrelated variables. Offdiagonal modes are negligible. 2) Other variables had



significant amplitudes for low-frequency, off-diagonal modes

3) The presumption of the spectral localization "Correlations in spectral space decreases as the difference in wave number increases" is valid for the CRM ensemble forecast error.

3.c Cross correlation of CRM variables in the vertical

- 1) Cross correlation between precipitation-related variables and other variables increases with precipitation rate.
- 2) Variables can be classified in terms of precipitation rate.



#### 4. Assimilation method

4.a Neighboring ensemble

Spectral Localization (Buehner and Charron, 2007)  $\hat{C}_{sl}(k1,k2) = C(k1,k2)\hat{L}_{sl}(k1,k2)$ 

When transformed into spatial domain

 $C_{st}(x1, x2) = \int C(x1 + s, x2 + s)L_{st}(s)ds$ 

Spectral-Localized correlation is a weighted, spatiallyshifted average of correlation over the neighboring points.

We used spatially-shifted average of Ensemble forecast error correlation over the neighboring points (Neighboring Ensemble).

4.b Classification of variables

We classified variables in terms of precipitation rate: Rain-free areas: (U,V,PT,RHw2) (W, Pr) Weak precip areas: (U,V,PT) (W,Pr, RHw2) Heavy precip areas: () (W,Pr, RHw2, U,V,PT)

We assume zero cross correlation between different classes.

## 4.c EnVA using the classified NE

We assumed that the analysis increment belongs to subspace spanned by the classified NE:  $(\delta \overline{X}^a)_{lc} = (P_{NE}^{f/2})_{lc} \circ \Omega_{lc}$ 

Cost function of EnVA:  $J: \frac{1}{2}\sum (\delta \overline{X}^a)'_{lc} P_{lc}^{-f} (\delta \overline{X}^a)_{lc} + \frac{1}{2} (H(\delta \overline{X}^a) - d)' R^{-1} (H(\delta \overline{X}^a) - d)$ 

$$\int \frac{1}{2} \sum_{k}^{lc} trace(\Omega_{lc} S_{lc} \Omega_{lc}) + \frac{1}{2} (H(\Omega_{lc}) - d)' R^{-1} (H(\Omega_{lc}) - d)$$

Background terms can be approximated with SVD principal modes:

$$J: \frac{1}{2} \sum_{lc} \chi_{lc} ' \chi_{lc} + \frac{1}{2} (H(\chi_{1}, .., \chi_{LC}) - d)' R^{-1} (H(\chi_{1}, .., \chi_{LC}) - d)$$
$$\chi_{lc} = (\Lambda^{1/2} V \Omega)_{lc}$$

5. Summarv

We analyzed CRM ensemble forecasts to check the validity of presumptions of the sampling damping methods, and applied the damping methods to the EnVA scheme.

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