# IMPACTS OF MODEL ERROR AND ENSEMBLE INITIATION ON MESOSCALE DATA ASSIMILATION WITH AN ENSEMBLE KALMAN FILTER

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## 1. Introduction

The ensemble Kalman filter (EnKF; Evensen 1994) has recently been implemented in various atmospheric and oceanic models. The potential of using the EnKF to assimilate simulated sounding and surface observations for regional-scale numerical weather prediction with a perfect model and perfect initial statistics is recently explored in Zhang et al. (2004). The EnKF has been shown to be very successful in various perfect model experiments. Here we explore the impacts of model error and ensemble initiation on the EnKF performance.

## 2. The reference simulation and ensemble forecasts

The study uses the PSU-NCAR mesoscale model MM5 (Dudhia 1993). The model domain has 190x120 horizontal grid points with 30-km grid spacing and covers the continental United States. There are 27 layers in the terrain-following vertical coordinate with model top at 100 hPa and more grids placed at the boundary layers. The reference initial analyses at 00Z 24 January 2000 are generated using the real-time operational Eta model as the first guess. Details and references on model configurations can be found in Zhang et al. (2004).

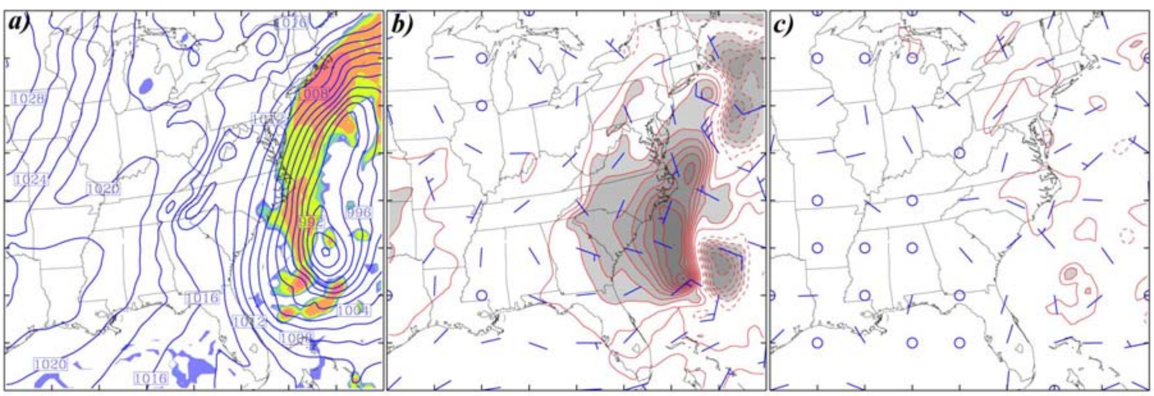

**Figure 1.** (a) MSLP (every 2hPa) and reflectivity from reference simulation; (b) wind and MSLP difference (every 0.5 hPa) between reference simulation and ensemble forecast and (c) between reference simulation and EnKf analysis at the 36-h forecast times.

The ensemble forecasts are produced by randomly selecting initial perturbations from the background error covariance used by the MM5 three-dimensional variational (3DVAR) data assimilation system developed at NCAR (Barker et al. 2003). The MM5 3DVAR system was performed on a transformed geostrophically balanced streamfunction field. Twenty of such random but balanced initial perturbations of the streamfunction were thus created and then transformed to derive the wind, temperature and pressure perturbations. These perturbations are then added to the reference NCEP analysis at 0000 UTC 24 January 2000 to generate a 20-member ensemble that is integrated for 36 h. For the control experiment ("CNTL"), the reference simulation is generated the same manner as one of the ensemble members but with different realizations of the balanced random perturbations. The reference simulation is used to generate observations and is also used as the truth to evaluate the performance of the EnKF. The analysis domain covers an area of 2400km x 2400km, a subset of model domain which has no significant influence from the lateral boundaries.

Figure 1 shows the mean sea-level pressure (MSLP) and model-derived reflectivity at 36-h forecast times from the reference simulation (Fig 1a). The maximum differences of MSLP associated with the surface cyclone between the ensemble mean and the reference simulation is about 8.5 hPa (Fig. 1b) at 36h.

The evolution of the forecast error growth revealed from the difference between the reference simulation and ensemble mean can be best summarized in terms of difference total energy: $\mathrm{DTE}=0.5(U'U'+V'V'+kT'T')$ (Zhang et al. 2002). The map distribution of the root mean square (RMS) of the vertically-averaged DTE at 36 h are displayed in Fig. 2a. The maximum error growth occurs near the surface cyclone.

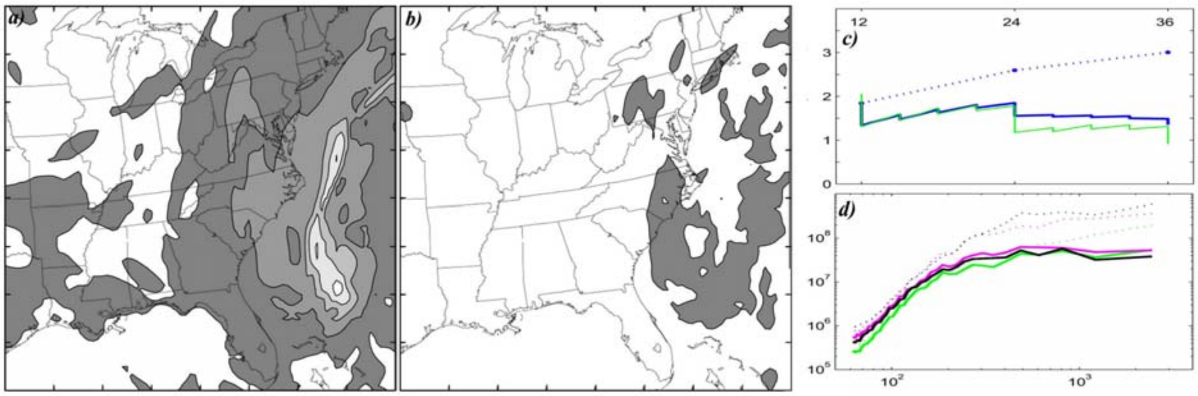


**Figure 2.** RMS DTE (every 2m/s) between the reference simulation and (a) ensemble forecast mean, (b) EnKF analyses mean at 36h as well as (c) the evolution of the domain-averaged root mean square of DTE and corresponding STD (gray) of analysis ensemble spread and the DTE between reference and ensemble mean, and (d) the power spectrum analysis of the DTE between reference simulation and ensemble mean (dashed) and between reference simulation and EnKF analyses mean (solid) at 12h(light), 24h (medium) and 36h (black).

## 4. EnKF experiments

*4.1 Perfect-model perfect-initiation experiment*

Formulation of the EnKF used can be found in Zhang et al. (2004), which follows closely that of Snyder and Zhang (2003). Observations are taken from the reference simulation. Typical of standard sounding and surface observations network, the sounding observations are spaced every 300km by 300km horizontally and at every sigma level; the surface observations are spaced every 60km by 60km available at the lowest model level. We assume that the observations have independent, Gaussian random errors of zero mean and variance of 1m/s for u and v, and 0.5 K for T. Sounding and surface observations are assimilated every 12 and 3 h, respectively.

In the perfect model experiment (CNTL), the same model configuration is used to produce ensemble forecasts and the reference simulation from which observations are taken. We begin assimilating observations at 12 h. Differences in MSLP between ensemble mean analyses after 24-h EnKF assimilation and the reference simulation (truth) at 36-h is displayed in Fig. 1c. It is found that, the EnKF with 20 members is very effective in keeping the analysis close to the reference simulation. The analysis error of MSLP is reduced by as much as 80%.

The overall improvement after 24-h EnKF assimilation in terms of RMS DTE is shown in Fig. 2b. Compared to ensemble forecast without EnKF (Fig. 2a), the improvement is most pronounced in the vicinity of the surface low, consistent to Fig. 1b and c. The performance of the EnKF in this perfect-model experiment is best summarized in Fig. 2c, which shows the evolution of the domain-averaged RMS DTE (black) and the corresponding STD (gray) of analysis ensemble spread. Compared to the reference ensemble forecast with no observations assimilated (dashed), over the 24-h assimilation period, the overall error reduction is ~60%.

Difference in degree of error reduction of DTE is examined through comparison of the power spectra of analysis and forecast errors at different times (Fig. 2d). The EnKF is very efficient in reducing the growing structure, especially at larger scales, which tend to have better and more reliable covariance and to be influenced by a larger number of observations. The EnKF is less effective in reducing errors at smaller, marginally resolvable scales, likely due to poor representation of background error covariance and limited predictability at these scales.

*4.2 Sensitivity to model errors*

An important source of model error for this event comes from insufficient model resolution (Zhang et al. 2002). In experiment "Tru10KM", the same initial condition as in CNTL is used to generate the reference simulation but the model includes a two-way nested 10-km domain. The DTE evolution, horizontal distribution and power spectrum analysis are shown in Fig. 3. We can see that, although there is a bigger error at 12 h before assimilation, the EnKF analysis at 36 h can still decrease the error by as much as 50% (Fig.3a). Similar to CNTL, most of the error reduction comes from large scales (Fig. 2c). The DTE is generally larger than that of CNTL (Fig.2a) but are greatly smaller than the ensemble forecast without EnKF (Fig.2b). There is far less improvement at the intermediate scales than the CNTL (Fig. 3b), suggesting inadequacies in representing background error covariance at those scales with a coarser resolution model. The problem could potentially get worse when real-data observations are used, which contains information at all scales.

Another source of model error comes from subgrid-scale parameterizations. In experiment "TruKF", the same initial condition as in CNTL but the KF cumulus parameterization scheme (instead of the Grell scheme in CNTL) is used to generate the reference simulation. The overall improvement in analysis error through the EnKF is ~30% (all at larger scales), significantly less that in Tru10KM, although the reference ensemble forecast error is smaller at 36h (Fig. 4). The biggest difference in analysis error between CNTL and TruKF is just near the near the surface cyclone especially offshore where cumulus parameterization is likely to be active.

Both experiments suggested that, while the performance of EnKF can be degraded with an imperfect model, the filter can still reduce the analysis error significantly. The analysis error tends to saturate at a higher level than the perfect CNTL experiment.

*4.3 Sensitivity to ensemble initiation*

When the real-data observations are assimilated, the initial ensemble may not contain perfect statistics (uncertainty) for the true atmosphere. Here we examine the impact of imperfect ensemble initiation in simulated data experiments when the reference simulation is initiated differently from one of the ensemble members. Experiment "TruRDM" use the same ensemble forecast as in CNTL, but the reference simulation is generated with initial conditions used in the CNTL reference further perturbed with grid-point random perturbations (with STD of 3 K for temperature, 3 m/s for winds). The new reference contains not only balanced but also unbalanced initial perturbations different for the balanced 3DVAR perturbations assumed in the ensemble forecast. The DTE evolution, horizontal distribution and power spectrum analysis are shown in Fig.5. Even though the initial error is much larger than CNTL, the overall improvement in analysis error is over 50%, only slightly larger than the CNTL (Figs.5a, b); again most of the improvements come from large scales (Fig.5c).

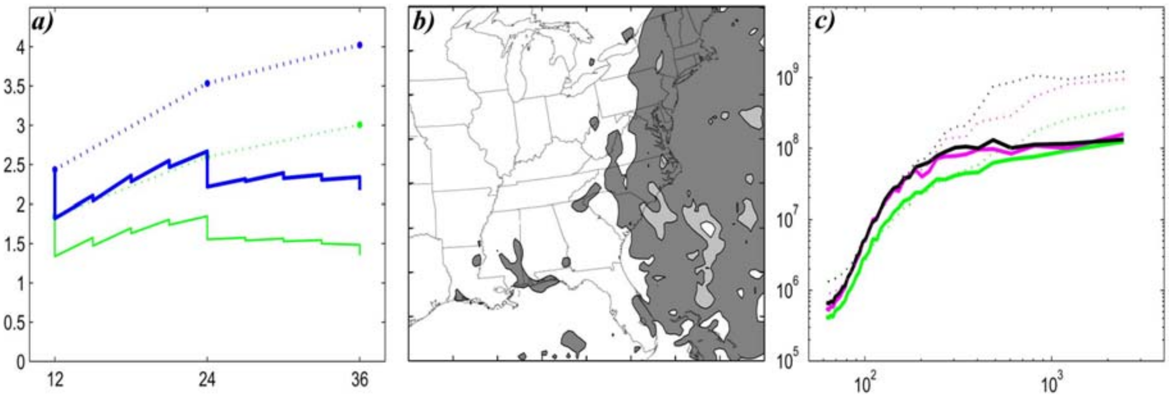


**Figure 3.** (a) As in Fig.2c, (b) as in Fig.2b and (c) as in Fig.2d but for the EnKF performance with a higher-resolution reference simulation. The light curve in (a) is the analysis error from the control experiment.

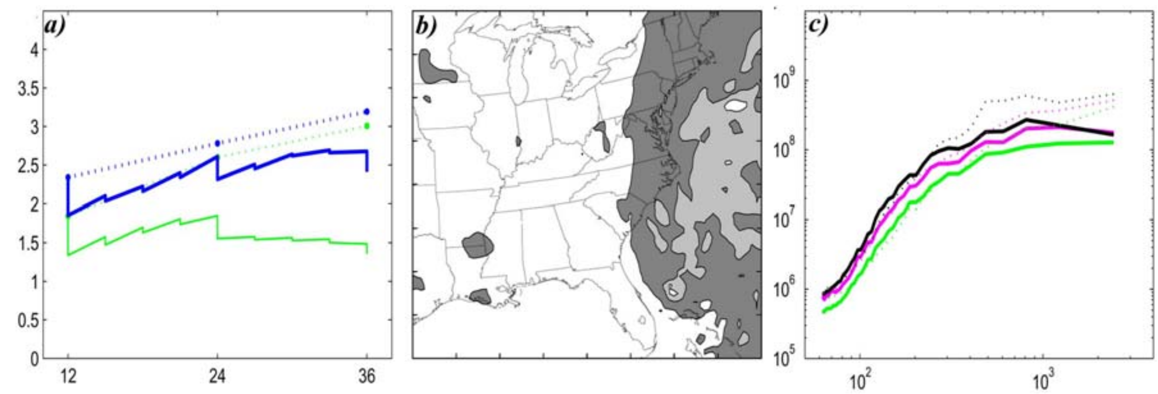


**Figure 4.** As in Fig.3 except for EnKF experiment with KF scheme in the reference simulation.

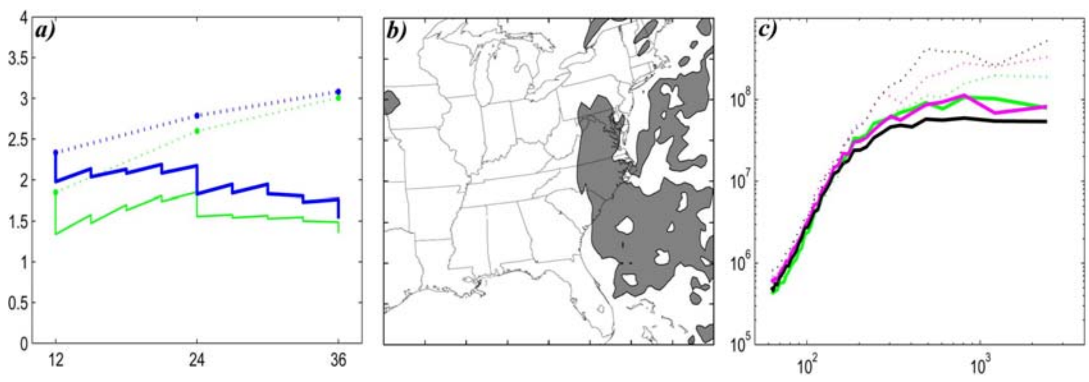


**Figure 5.** As in Fig.3 except that the reference simulation is further perturbed with random initial noises.

Experiment "EnsRDM" uses the same reference simulation used in TruRDM but the initial ensemble is generated by adding "grid-point", purely random noises (with STD of 3 K for temperature, 3 m/s for winds) to the reference NCEP analysis. Result shows that even though the initial ensemble has mostly unbalanced perturbations without the balanced statistics used to generate the truth, the EnKF still performs fairly well with the overall RMS DTE decreased 40% (Fig. 6a), also mostly at large scales (Fig.6c). Most of the difference between CNTL near the surface low area where there is active moist convection (with more active smaller scales) (Fig.6b).

These two experiments suggest that the EnKF is not very sensitive to the ensemble initialization, especially at larger scales. It appears that the initial ensemble statistics affects the overall EnKF less than imperfect models.

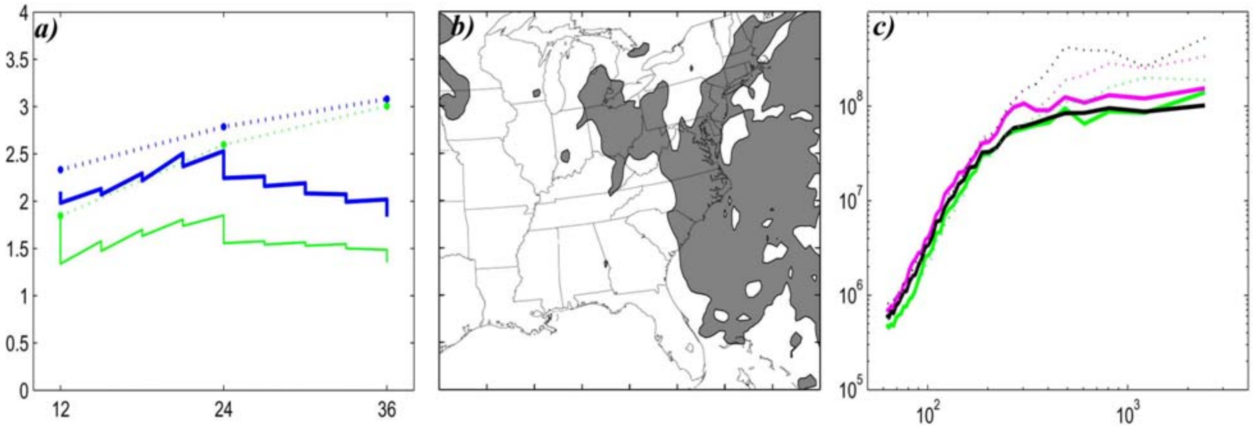


**Figure 6.** As in Fig.5 except for using totally random initial noise to initiate the ensemble.

## 5. Summary and conclusions

Through observing system simulation experiments, this study exploits the potential of using the ensemble Kalman filter for meso- and regional-scale data assimilation in some imperfect scenarios. The EnKF is implemented in a nonhydrostatic, mesoscale model (MM5) to assimilate simulated sounding and surface observations derived from reference simulations of the "surprise" snowstorm of January 2000. This is an explosive east coast cyclogenesis event with strong error growth at all scales as a result of interactions between convective-, meso- and subsynoptic-scale dynamics. Although the EnKF performance can be significantly degraded with an imperfect model and imperfect initial ensemble statistics, the EnKF is fairly successful for the limited imperfect scenarios tested; most of the improvements come from larger scales. The worst performance comes from experiments with physical parameterization error, which deserves explicit treatments of such errors in ensemble-based data assimilation systems. Current approaches include (1) simultaneous state and parameter estimation within the EnKF system (e.g., Aksoy et al. 2004) and (2) parameterization of model errors (e.g., Hammil and Whitaker 2004).

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