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A Hybrid 3DEnVar Analysis System with WRF Model Interface for Storm-Scale Radar Data Assimilation

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1. Introduction

In the past 30 years, many studies have been conducted on the development of methods to initialize convective-scale NWP models. Now it has been well understood that the success of convective scale NWP is heavily depending on if we can effectively use the remote-sensing observations which can resolve internal storm structures. Currently there exists a national operational WSR-88D radar network which can be used to observe internal storm structures. However, these radars can only observe radial velocity which is related to three-dimensional wind fields and reflectivity which is related to hydrometer variables. There is no information about water vapor and temperature variables which are critical for initializing convective NWP. In order to initialize all model variables for the NWP model, other type of remote-sensing data should be used, or many model variables have to be retrieved from radar data. Future GOES-R may provide high-resolution data which can resolve internal storm structures, but still not all of model variables can be observed.

Among various advanced data assimilation techniques, four-dimensional variational data assimilation (4DVar) technique is ideal and can be used for the retrieval of the 3D wind and temperature from radar data. Such a system was first developed by Sun et al. (1991). , known as VDRAS (Variational Doppler Radar Analysis System), was later expanded to include microphysical retrieval, as well as short-term forecasts initialized by these retrieved fields (Sun and Crook 1997, 1998; Sun 2005; Sun and Zhang 2008). In the last two decades, a lot of studies about radar data assimilation were conducted using another advance data assimilation method - ensemble Kalman filter (EnKF) methods (Snyder and Zhang 2003; Zhang et al. 2004; Tong and Xue 2005; Dowell et al. 2004, 2010; Yussouf and Stensrud 2010). EnKF uses statistical information derived from ensemble forecasts in data assimilation analysis. The EnKF can easily retrieve unobserved model variables from radar radial wind and reflectivity. However, when model error is big, such as in convective scale NWP, this statistical information derived from ensemble forecasts may be not reliable. So hybrid methods which take advantages of both variational method and EnKF were proposed and developed recently by several institutes in meteorological community (Lorenc, 2003; Buehner 2005; Liu et al. 2008; Wang et al. 2007, 2008, 2013; Zhang et al. 2013).

In this study, we develop another type hybrid ensemble and variational data assimilation method for the WRF-ARW model. The background error covariances are derived from ensemble forecasts, so it is called 3DEnVar scheme. It is based on the 3DEnVar scheme developed for the ARPS model (Gao and Stensrud 2014). In the method, the 3DEnVar are performed many times same as the number of ensemble size (Fig. 1). The method is applied to assimilate simulated radar data for a supercell storm produced by WRF model. The results obtained by the hybrid method are better than the 3DVar method in wind field, temperature field and other hydrometeor-related variables.

In section 2, observing system simulation experiments (OSSE) is designed to examine the performance of the DA system. The experiment results are presented in section 3. The conclusion and future work is given in section 4.

2. Experimental design

a. Prediction model and truth simulation

The hybrid 3DEnVar DA system is tested with simulated data from an analytical sounding which is from Weisman and Klemp 1982 (“WK82”). A slightly modified version of the supercell simulation module in the WRF model is used as a forecast model to simulate the evolution of the storm. The prognostic variables in the modified WRF model includes three velocity components u, v, w; perturbation potential temperature θ; dry air mass in column μ; geopotential height ϕ; and six classes of hydrometeors: water vapor q_v, cloud water q_c, rain q_r, cloud ice q_i, snow q_s, and graupel q_g. However, the first version of ARPS 3DEnVar (Gao and Stensrud 2014) does not update the values of dry air mass in column and geopotential height. Therefore, a piece of code is added to compute these two missing variables after the analysis. The microphysical scheme used in this study is Purdue Lin scheme based on Lin et al. (1983) and Rutledge and Hobbs (1984) with some modification following Tao (1989). More details of this microphysics scheme can be found in Chen and Sun (2002).

In our experiments, the physical domain is 82 km × 82 km × 20 km. The model involves 82 × 82 × 40 grid points with 1 km horizontal resolution and about 0.5 km vertical spacing. The truth simulation is started from WK82 sounding. A 3-k ellipsoidal thermal bubble centered at $x = 20$, $y = 40$ and $z = 1.5km$, with radii of 10 km in x and y directions and 1.5 km in the z direction is added to the background to initiate the storm. Open conditions are used at the lateral boundary for this idealized case. The length of simulation is up to 2 h.

During the truth simulation, the initial convective cell continually intensifies in the first 35 min. The cloud is starting to form at about 10 min. Rain water formed at about 15 min, ice phased field appeared at 15 min as well. The cell is splitting into two around 45 min. The right-moving cell (which moves to the southeast relative) tends to control the system with updraft reaching a maximum value 50 m s^{-1} at 75 min. The left-moving cell is also starting to split at this point.

b. Simulation of radar observations

The simulated radial velocity V_r is calculated from

$$V_r = u \sin\phi \cos\mu + v \cos\phi \cos\mu + w \sin\mu \quad (1)$$

where μ is the elevation angle and ϕ is the azimuthal angle of radar beams, and u, v, and w are the model-simulated wind components interpolated to the scalar points from the staggered model grid. The random errors for radial velocity are drawn from a normal distribution with zero mean and a standard deviation of 1 m s^{-1}. Since radial velocity is sampled directly from model wind field, the effect of hydrometeor sedimentation is not taken into account. The equivalent reflectivity factor is made up of three hydrometeor mixing ratios — rain, snow, graupel — estimating from the following equations:

$$Z_e = Z(q_r) + Z(q_s) + Z(q_g) \quad (2)$$

$$Z_{dB} = 10log_{10}Z_e \quad (3)$$

For reflectivity, random errors drawn from a normal distribution with zero mean and standard deviation of 3 dBZ are added to the simulated data (Gao and Stensrud 2012).

c. 3DEnVar data assimilation experiments design

We start the initial ensemble forecast at 30 min of model time when the storm cell is well developed. Random noises are added to the initially horizontally homogeneous background to generate the ensemble members. These noises are sampled from Gaussian distributions with zero mean and standard deviations of 5 m s^{-1} for wind components, and 3K for potential temperature. A 2D five-point smoother is applied to the perturbation fields, similar to the method used by Zupanski et al. (2006). The geopotential height, dry air mass in column and hydrometeor variables are not perturbed at the initial time. The simulated radar data are calculated and assimilated every 5 minutes with analysis-forecast cycle which begins at 30 min. In our 3DEnVar experiments, the correlation radius is 4 km in horizontal and 2 km in vertical.

Two sets of experiments are performed with the DA system. The first experiment is performed with no weighting for ensemble covariance which means that the assimilation is totally a pure 3DVar analysis. For the second experiment, the weighting for ensemble covariance is set to one that means only the ensemble-derived error covariance is used in the analysis. This method is similar to the EnKF but the minimization of ensemble of 3DVar cost function is used to solve the problem instead of EnKF method.

3. Results of OSSE experiments

In this section, we examine the effectivity of 3DEnVar by comparison of assimilation results with the truth simulation. As we discussed before, with zero weighting for ensemble covariance, this method can be treated as a traditional 3DVar method. While in the second experiment with full ensemble covariance, 50 ensemble members are used to provide the ensemble covariance. The analysis-forecast cycle procedure is shown as Fig. 1. The control member and 50 ensemble members assimilate the pseudo radar data at same time. The error covariance for control member is derived from these 50 ensemble members. However, for the 50 ensemble members, the error covariance is estimated according to the other 49 members except itself.

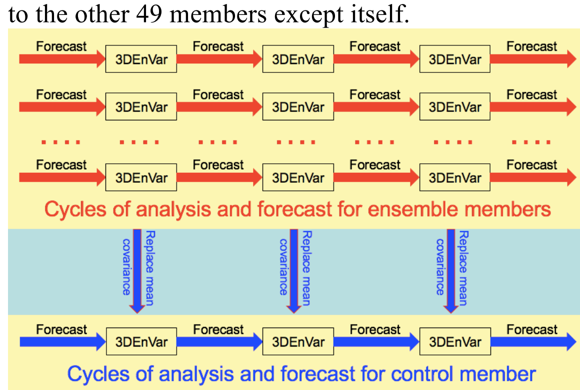

Fig. 1. The flow chart of 3DEnVar analysis-forecast cycle

To evaluate the analyses quantitatively, the root-mean-square (rms) errors of the analyzed fields are computed and compared to the truth. Similar to the study by Gao and Stensrud (2014), the rms errors are calculated over the domain where the reflectivity is larger than 10 dBZ. The rms errors for three com-

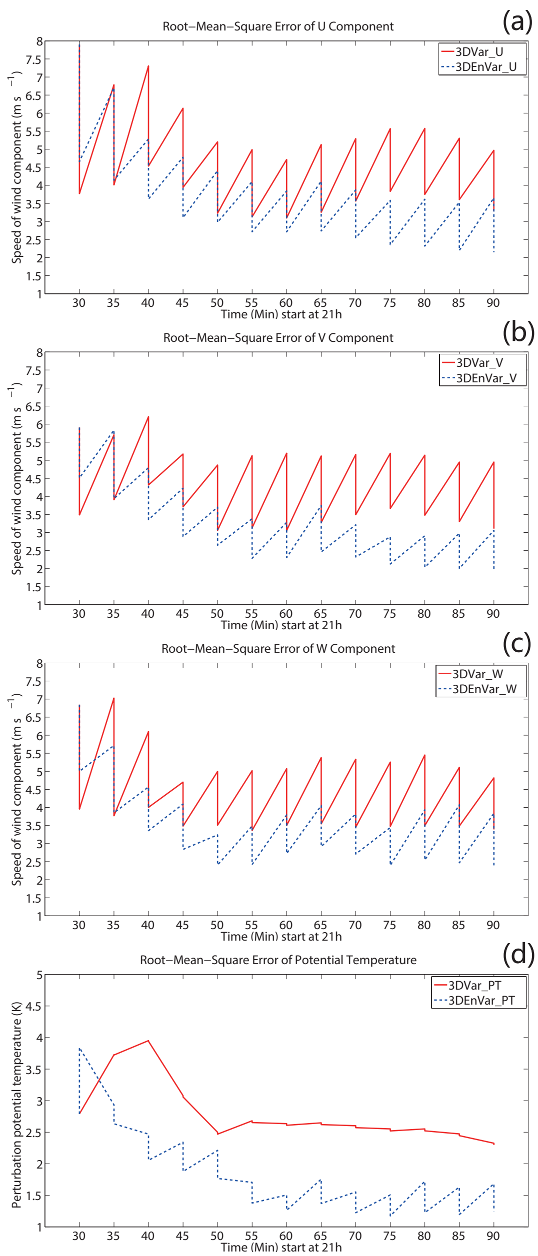

Fig. 2. The rms errors of the analysis and forecast for (a) horizontal wind component u (m s^{-1}), (b) horizontal wind component v (m s^{-1}), (c) vertical velocity w (m s^{-1}), and (d) perturbation potential temperature θ (K) with two different method: 3DVar (red solid line) and 3DEnVar (blue dashed line).

ponents of wind field and perturbation potential temperature of control member are shown in the Figure 2. Results show that the analysis of wind field is remarkable better when ensemble covariance is used in the analysis. The rms errors of analyzed wind components *u*, *v*, and *w* using 3DVar method are 3.28, 3.10 and 3.39 m s^{-1} at the of assimilation while rms errors for 3DEnVar are 2.15, 1.98 and 2.39 m s^{-1} respectively. The spread of forecast and analysis in wind field is decreasing as well which means that the skill of forecast is significant improved by applying 3DEnVar method. From Fig. 2d, we can clearly see that the 3DVar method barely improve the perturbation potential temperature. The comparison of these two method in temperature field also suggests that the performance of hybrid 3DEnVar with full ensemble-derived covariance is much better than the pure 3DVar method.

Figure 3 shows the comparison of the final assimilation results after 12 assimilation-forecasting cycles between the simulation with 3DVar analysis and 3DEnVar analysis with respect to the truth simulation. Although the low level wind and reflectivity from 3DVar method (Fig. 3e) and 3DEnVar method (Fig. 3i) are very similar to the truth simulation (Fig. 3a), the distributions of potential temperature field and the patterns of cold pool from 3DEnVar are better than the results using 3DVar method. The most notable differences appear near the location where the reflectivity is larger than 45 dBZ. While the minimum of potential temperature at surface from 3DEnVar is slightly warmer than simulated truth, the strength of the cold pool is closer to the truth run compared to the 3DVar method. The important storm structure is also captured in our experiments (Fig. 3 b-d f-h j-l). The analysis at 6 km above ground level (AGL) shows that 3DEnVar gives a better analysis in wind field, reflectivity patterns and potential temperature (Fig. 3j), especially at the center of the right-moving cell which is usually very strong and has potential to produce severe weather. The reflectivity pattern from 3DVar (Fig. 3f) is different from the truth (Fig. 3b). However, we can easily see that both of the reflectivity and potential temperature from 3DEnVar are nearly exactly same as the truth. The vertical structure of the storm is shown in the Figure 3c-d, 3g-h, 3k-l. The updraft core matches very well with the reflectivity observation in both analyses. However, we notice that there is a significant improvement in wind field by 3DEnVar in the domain without radar data.

4. Summary

A hybrid 3DEnVar DA system with WRF model interface has been developed based on ARPS 3DVAR (Gao et al. 1999, 2002, 2004; Hu et al. 2006; Gao and Stensrud 2014). In this study, this system is applied to assimilate radar data from a simulated supercell storm. The impact of ensemble covariance is examined in the experiment. The results show that the hybrid 3DEnVar method provides flow-dependent structures for variables which is not directly observed by radar and finally improve the forecast and analyses results. The 3DEnVar method which incorporate ensemble-estimated covariance into a three dimensional variational method is clearly

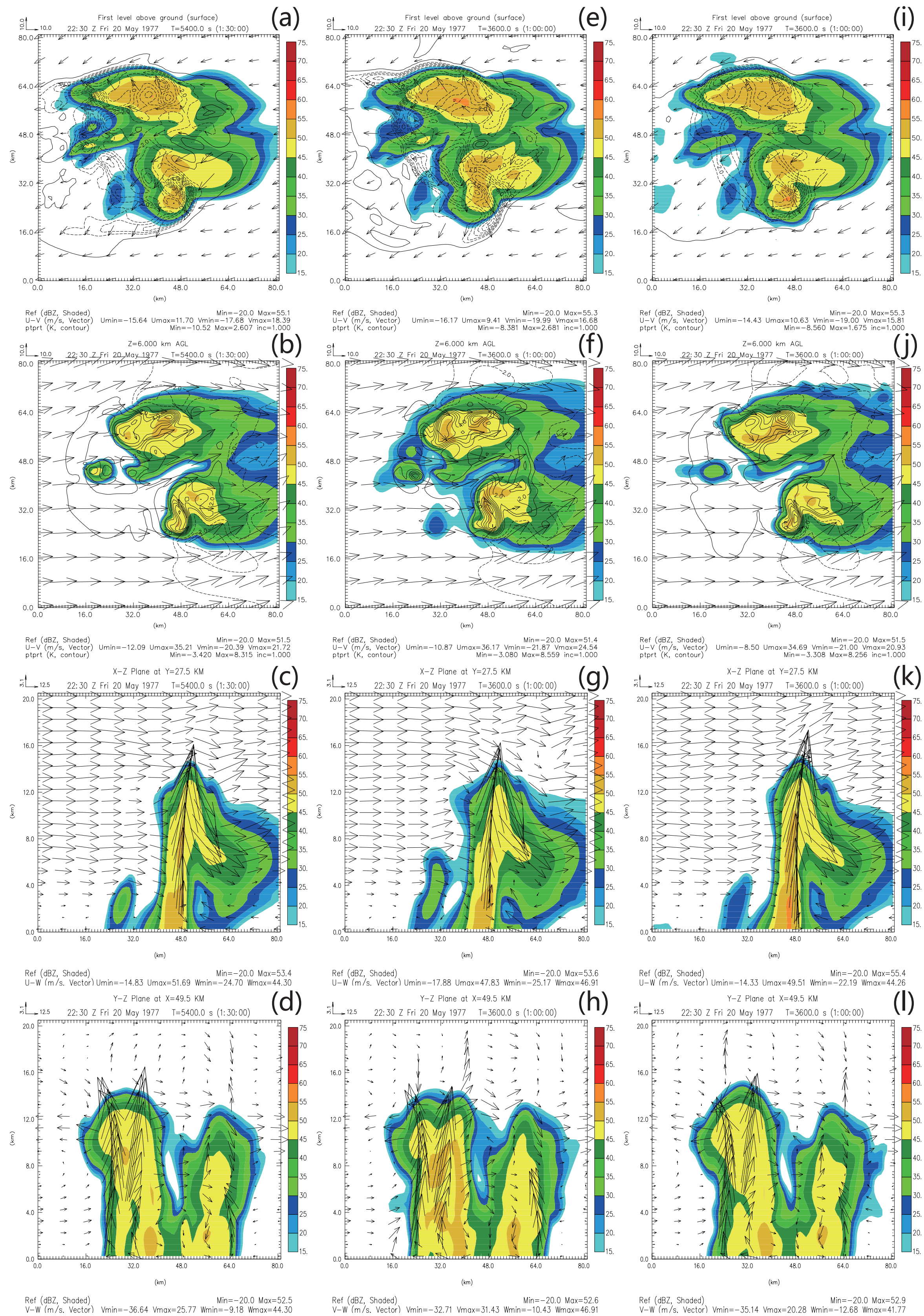

Fig. 3. The reflectivity, wind fields and perturbation potential temperature at the surface and 6 km above ground level, and the vertical section along the maximum vertical velocity for truth simulation (a-d), DA with static covariance (e-h) and DA with ensemble covariance (i-l)

demonstrated to have significant improvement for assimilation of radar data for thunderstorm forecasting by using WRF model. This technique can be effectively used for predicting the track and intensity of supercell thunderstorm.

Future work includes assimilating satellite data into this 3DEnVar DA system, such as lightning data, and testing the enhancements of satellite data assimilation. Ongoing work also includes investigating the possibility of this 3DEnVar system as a real-time analysis system.

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