2B.6 LATEST DEVELOPMENT OF 3DVAR SYSTEM FOR ARPS AND ITS APPLICATION TO A TORNADIC SUPERCELL STORM

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1. INTRODUCTION

In our previous research, we developed a 3DVAR system within the ARPS framework and applied it to the assimilation of WSR-88D radar and other data (e.g., Gao et al. 2002a, 2004, 2006b; Hu et al. 2006a, b, Hu and Xue 2006). The radar data analysis component in this 3DVAR system has so far been focusing on radial velocity data due to our emphasis on analysis of wind fields. Reflectivity data are used, in combination with surface and satellite cloud observations, in a physics-based complex cloud analysis scheme as a follow-on step to 3DVAR (Brewster et al. 2005; Hu et al. 2006a).

Through experiments for the prediction of the Fort Worth, Texas, tornadic thunderstorms, Hu et al (2006) found that "this 3DVAR system is capable of successfully analyzing observations from different sources, including those from radiosonde, wind profilers, surface stations, and Doppler radars". When cloud analysis procedure is also included in the assimilation, the individual storm cells can be predicted for up to 2h. In the study of 8 May 2003 Oklahoma City Tornadic Thunderstorm case, Hu and Xue (2007) also got some interesting results by assimilating the data from a single Doppler radar with some properly chosen parameters within complex cloud analysis. All these results illustrate the obviously positive impact of assimilating radar data into storm-scale NWP model through this 3DVAR system. And applying a mass divergence constraint in the cost function (Gao et al 1999) can further increases the positive impact of radial velocity data on the storm forecast (Hu et al, 2006).

But at the same time, some issues come up with the 3DVAR system. For some cases, if the radial velocities are assimilated alone without cloud analysis procedure, the model fails to produce the storms in the analysis and ensuing forecast. This is because the other

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model variables except the three components of wind fields are not properly retrieved. One way to retrieve other model variables is through complex cloud analysis. In it, the temperature and model hydrometer variables can be estimated from radar reflectivity and satellite data. For example, in-cloud temperature adjustment, or latent heat release nudging are used to obtain temperature variables in the cloud analysis. But the resultant temperature field may not be consistent with other model dynamic fields because other dynamic variables are not adjusted accordingly. The alternative is to couple the thermodynamic information with the dynamic field through momentum equations which is first proposed by Gal-Chen(1978). Weygandt (2002) used this method to retrieve the perturbation pressure and potential temperature fields and justified that the results agree qualitatively with expectations for a deep-convective storm. But to accurately estimate the time tendencies in three momentum equations is sometimes very difficult. So other information is needed.

In this paper, we report the latest development of 3DVAR system in light of the above issues. We then apply the new system to a tornadic supercell storm.

2. THE UPDATED ARPS 3DVAR SYSTEM

In the 3DVAR system, the cost function, J, is written as the sum of the background and observational terms plus a penalty or equation constraint term (J_c):

$$J(x) = \frac{1}{2}(x - x^b)^T B^{-1}((x - x^b) + \frac{1}{2}\left[H(x) - x^o\right]^T R^{-1}\left[H(x) - y^o\right] + J_c \tag{1}$$

Following the standard notion of Ide et al (1997), x and x^b are the analysis and background state vectors, and y^o is the observation vector. B and R are the background and observation error covariance matrices, respectively. H(x) is the observation operator. To improve the conditioning of the cost function minimization problem and avoid the need for the inverse of B, a new control variable v is introduced, which is related to the analysis increment according to

$$\mathbf{x} - \mathbf{x}^b = \mathbf{B}^{1/2}\mathbf{v} \tag{2}$$

In terms of v, the background term becomes

$$J_b = (1/2)\mathbf{v}^T\mathbf{v} \tag{3}$$

Consequently, the minimization is performed in the space of v. The recursive filter proposed by Purser et al. (2003a, b) is used to model the effect of the background error covariance, or more precisely the square root of B. Currently in our 3DVAR system, the background field is provided by a previous ARPS model forecast, or other large scale models' forecasts. The observations include Doppler radar radial velocity and reflectivity, single-level surface data (such as Mesonet), multiple-level observations (such as rawinsondes and wind profilers).

Term J_c in (1) includes any penalty or dynamic equation constraint terms that serve the important role of correlating the desired analysis variables. For initializing convective storms, we need to initialize all state variables from only the radial velocity and reflectivity observations; dynamic constraints that relate these two measurements to all state variables are critical for achieving the necessary balance between different model variables, unless flow-dependent background error covariances are derived from, for example, an ensemble.

One of the simplest, yet most important dynamic constraint is 3D mass divergence, as atmospheric flows, even at the convective scale, generally satisfy the anelastic mass continuity equation. The continuity constraint by itself is, however, insufficient, to uniquely determine the three wind components. In the light of this fact and the further need to couple the velocity fields and thermodynamic fields, additional constraints are supplied and discussed below.

We assume that the radial velocity and its time tendency are known, the latter is derived from successive radar scans. In our proposed 3DVAR framework, the three wind components u, v, w, potential temperature θ, pressure p, water vapor specific humidity q_v, are the analysis variables. The dynamic constraint term, J_c, is given by

$$J_c = P(x)^T C_P^{-1} P(x) + Q(x)^T C_Q^{-1} Q(x) + D(x)^T C_D^{-1} D(x) \tag{4}$$

The first term on the right hand side (R.H.S) of (4) is the pressure diagnostic equation constraint in which,

$$P \equiv \nabla \cdot \vec{E} \equiv -\nabla^2 p' - \nabla \cdot (\overline{\rho}\vec{V} \cdot \nabla \vec{V}) + g\frac{\partial}{\partial z}\left(\overline{\rho}\left[\frac{\theta'}{\overline{\theta}} - \frac{p'}{\overline{\rho}c_s^2} + \frac{q_v'}{\varepsilon + \overline{q}_v} - \frac{q_v'}{1+\overline{q}_v}\right]\right) \tag{5}$$

Where, vector $\vec{E}$ is the forcing term of the vector Euclidian momentum equations. The primed variables are perturbations from a base state, c_s is the acoustic wave speed, and ε is the ratio of the gas constants for dry air and water vapor. Other symbols follow convention. Setting P = 0 gives the elliptic diagnostic equation for perturbation pressure p' found in anelastic models. Minimizing the quadratic form of P provides an important coupling between different model variables, especially velocity and thermodynamic variables. The second term on R.H.S of (4)

$$Q = \frac{\vec{r} \cdot \vec{E}}{|\vec{r}|} - \left(\frac{\partial \overline{\rho} V_r}{\partial t}\right)_{ob}, \tag{6}$$

is the difference between the analyzed and observed time tendencies of radial velocity V_r (or, more accurately, radial momentum). The observed radial velocity time tendency can be estimated from two consecutive radar scans. This constraint allows the direct use of time tendency information contained in the radial velocity observations which is important for convective scale flows. The third term on R.H.S of (4) is intended to minimize the 3D anelastic mass divergence so as to provide the key coupling among three velocity Components.

The scheme outlined above emphasizes the use of dynamic constraints that are associated with small-scale nonhydrostatic flows, in particular when analyzing Doppler radar radial velocity data. In contrast to procedures that first perform (velocity and thermodynamic) retrievals, then get the final analysis in a stepwise manner (e.g., Weygandt et al 2002a, b), our proposed scheme utilizes data and dynamic equation constraints within a single minimization framework that includes direct analysis of all available data. Doing so allows for the incorporation of appropriate relationships among variables and the entire analysis can be performed on the native model grid. An idea similar to ours has recently been employed by Liang et al. (2007a, b), where shallow water equations or equations based on the MM5 model are used as weak constraints in a 3DVAR framework. The method was tested with tropical cyclone cases and the results show a significant decrease in track forecast errors. However, their system only minimizes the time tendencies of model equations, which is not suitable for convective scale problem. The three Cs in Eq. (4) are error covariances associated with the corresponding constraints, which are assumed to be diagonal matrices with empirically-defined constant diagonal elements. They determine the relative importance of each constraint and their optimal values can be determined through many numerical experiments in a trial-and-error fashion (Sun and Crook 2001).

The implementation of these constraints in 3DVAR will require the development of associated adjoints, expressed in the native terrain-following coordinates of ARPS, and most of this work has been completed, and currently we have finished the code development for constraint (3), and (4). The work is underway for updating the adjoints of these constraints for the new version of ARPS model.

To directly assimilate reflectivity into ARPS model, we have developed the adjoint operator for reflectivity. It adjusts the qr (rain water mixing ratio), qs (snow water mixing ratio), qh (hail mixing ratio) fields directly by minimizing the difference between the observed reflectivity and the calculated reflectivity from ARPS model using the forward operator of reflectivity based on Smith et al. (1975).

So far the ARPS3DVAR system uses the low-order recursive filter to model the effect of background error covariance (Purser 1982, Lorenc 1992, Huang 2000, Gao et al 2004). This filter is isotropic and not flow-dependent. For better assimilation and forecast, it is desirable to use an anisotropic spatial filter to model the background error covariance (Purser et al 2003). Liu and Xue (2006) have demonstrated the positive impact of flow-dependent background error covariances when assimilating the GPS slant-path water vapor observations using a simple but similar 3DVAR system. In their study, the anisotropic filter is just applied to one variable (water vapor specific humidity qv). It is desirable to extend the application of the anisotropic filter to all model variables (wind fields, thermodynamic fields and hydrometeor fields). For this purpose, a new version of anisotropic filter from Liu and Xue (2006) is implemented into the ARPS3DVAR system and applied to all model variables. Verification experiments have been conducted and the updating is justified to be reliable. But further experiments are still on the way.

3. A CASE STUDY

To test the performance of the variational method, we apply it to a case of the 3 May 1999 tornado outbreak in central Oklahoma. On that day, several supercell thunderstorms occurred in Oklahoma, and violent tornadoes were produced which caused considerable damages.

In this experiment, the ARPS model grid comprises 151 x 101 x 43 grid points. Horizontal resolution is 2km. The average grid spacing in the vertical direction is 400m and the minimum grid spacing is 20m. The boundary conditions is specified from a 12km ARPS model run initialized at 1600 UTC 3 May 1999. Only Level-II WSR-88D data from KTLX radar are used here to test impact of radar data. Figure 1a shows the composite reflectivity from observation by the KTLX radar (near Oklahoma City) at 2230 UTC.

In the experiment, both radial velocity and reflectivity data are assimilated to ARPS model, with mass continuity and eq. (5) as weak constraints. Here the direct assimilation of reflectivity data into model provides a simple and effective way to modify the three hydrometer variables of qr(rain mixing ratio),qs(snow mixing ratio) and qh(hail mixing ratio), It shows that the storm's location and pattern are well resolved (Fig 1c) when the reflectivity is used, much better than only assimilating radial velocity(Fig. 1b). It is noted that the intensity of the storm cell is not well resolved. This may indicate that the model variables are not well balanced. Further tunings of the system are needed. We will report the further testing of this case, the analysis and numerical forecasting will be reported in the conference.

4. CONCLUSION

Several new features including equation constraints, direct reflectivity assimilation, anisotropic filter have been incorporated to a 3DVAR system for a storm scale nonhydrostatic NWP model, the Advanced Regional Prediction System model (ARPS). The preliminary experiments have shown positive impact from the new features on the improvement of the storm-scale assimilation and forecast. These initial results will further be investigated after adding equation constraint (6) and with single and/or multi radar configurations. New development is underway for additional new observation operators, such as, differential reflectivity and specific differential phase from polarimetric radars. The completed system will then be applied to dual-polarization real radar cases, observed by KOUN, and 4-node CASA radars in the future.

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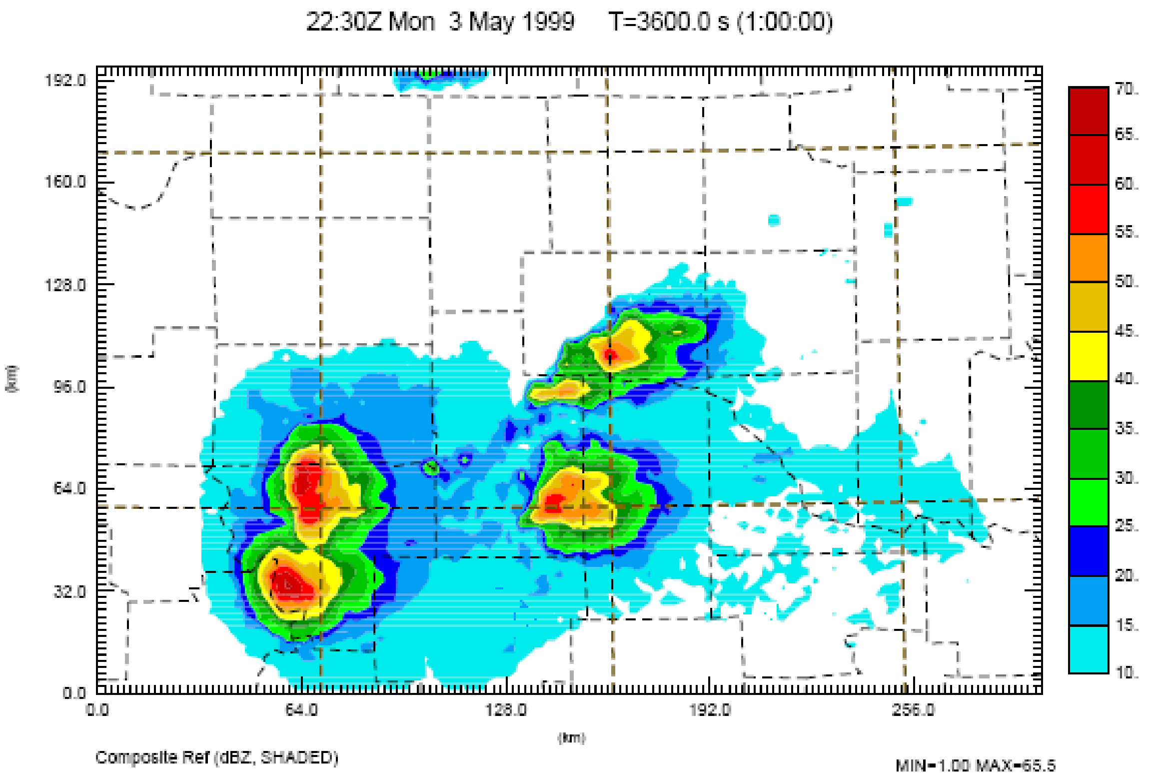

Fig 1a Composite reflectivity from observation at 22:30UTC 3 May 1999

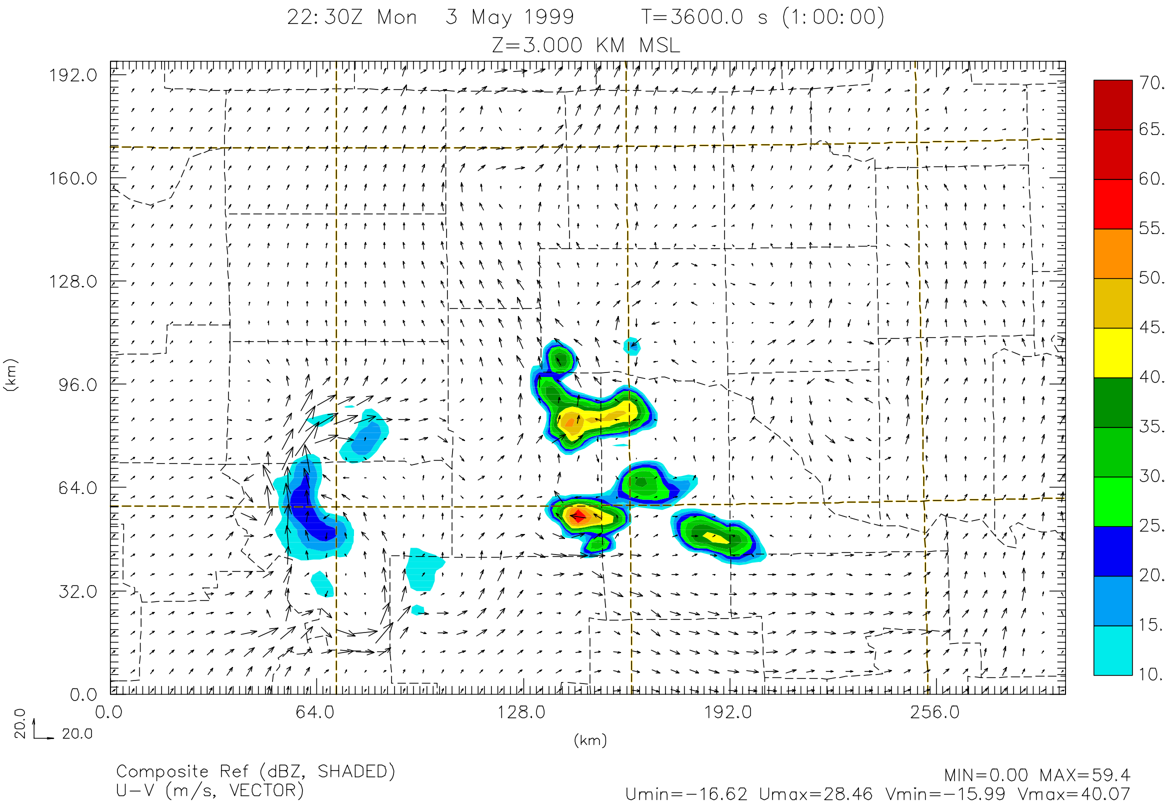

Fig 1b Composite Reflectivity after 1 hour assimilation without use of reflectivity data

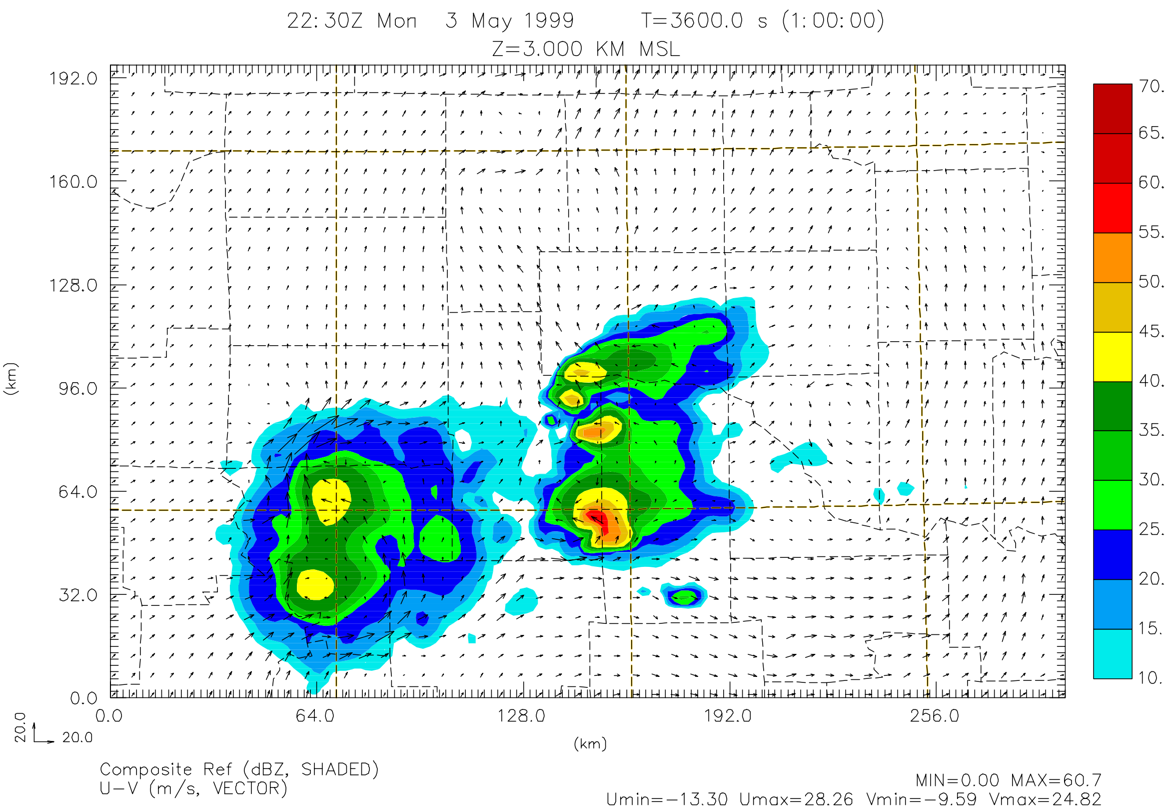

Fig 1c Composite Reflectivity after 1 hour assimilation with use of reflectivity data