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CYCLE OF ASSIMILATION OF RADAR DATA IN A CLOUD RESOLVING MODEL

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1. INTRODUCTION

A 4D-Var cloud-scale radar data assimilation algorithm developed at the McGill University uses the dynamic core of the Canada Mesoscale Compressible Community (MC2) model with Kessler microphysics parameterization of as a weak constraint, to retrieve the different fields of the model prognostic variables from the S-band Doppler radar of McGill and its associated bistatic network (Caya, 2002). In this algorithm, the echo-free regions are filled by a 3D wind analysis from single-Doppler data based on linearity of the horizontal wind components in a moving reference frame (hereafter Linear Wind Analysis, Caya et al., 2002), which provides a realistic mesoscale flow that is in better agreement with the air circulation retrieved from dual-Doppler observations within the precipitating regions. The assimilation of the refractivity index, which is extracted from radar phase information of ground echoes (Fabry et al., 1997), leads an improvement in the humidity analysis in the boundary layer. Furthermore, the model error is taken into account in the cost function and the minimization is obtained by the conjugate gradient method. Applying this algorithm to summer storms, Montmerle et al. (2001 and 2002) have successfully initialized the MC2 model to produce a 1km resolution and 30 min forecast with skill better than the one obtained by the Lagrangian persistence method.

The cost function is defined by

$$J = J_0 + J_b + J_m + J_s \qquad (1.1)$$

in which J_0 represents the discrepancy from the radar observations, J_b the background error term, J_m the MC2 model error term, and J_s the three-dimensional smoothing spline constraint. A non-quadratic form of the cost function, caused by non-linearity of the observation operator and the model error term, could trap the minimization procedure into a local minimum. The results of retrieved experiments from dual-Doppler radar observations (Laroche and Zawadzki, 1994), in which the conservation equation for reflectivity is used as a weak constraint, show that the cost function has multiple minima and make the retrieved wind field sensitive to the initial guess. To enhance the ability to find the global minimum, a cycle of assimilation is designed in this study. It is performed with one additional radar volume scan introduced in each successive cycle. The analysis from the previous cycle is used as the background field and first guess of the minimization algorithm for the next cycle. The benefit of a forward-backward feedback loop from the first two consecutive cycles is examined by radar data of a shallow hailstorm.

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2. Cycle of assimilation of radar data

A schematic diagram of cycle of assimilation of radar data is in Fig. 1. It was performed by two successive assimilation cycles with four volume scans of radar data of a shallow hailstorm, sampled by the McGill University bistatic multiple-Doppler radar network on 26 May 1997. This storm (Protat et al., 2001) was composed of two main shallow convective cells (depth is around 5 km) aligned along a NE-SW axis at 0029 UTC, developing in an environmental air circulation characterized by a moderately strong low-level shear.

In a forward-backward feedback loop, the analysis

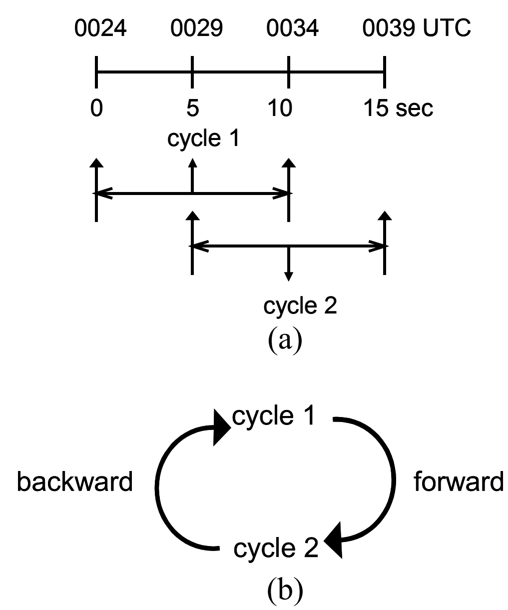

FIG. 1.- *A schematic diagram of cycle of assimilation of radar data. (a) Two successive assimilation cycles of the shallow hailstorm. (b) The forward-backward feedback loop of two assimilation cycles.*

of cycle 1 is used as the background field and the first guess in cycle 2. Then, the analysis of cycle 2 is used as the background field and the first guess in cycle 1. The loop is then repeated.

Figure 2 shows that the reduction of the cost function in cycle 1 is improved by the feedback loops. After three feedback loops, the cost function is reduced by one order of magnitude. On the other hand, by merely one feedback loop, root mean square (RMS) error of radial velocity drops dramatically (Fig. 3). With increasing the number of feedback loops the decrease of RMS error is limited. Furthermore, Fig. 3 shows the reduction of RMS error of radial velocity in high altitude is obviously much greater than that in low altitude.

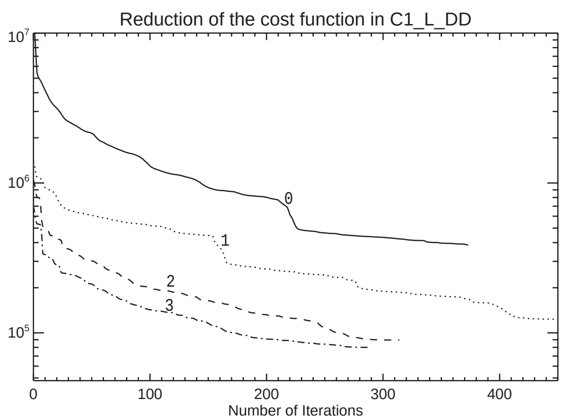

Fig. 2.- *Reduction of the cost function in cycle 1 of subsequent feedback loops (indicated by the numbers).*

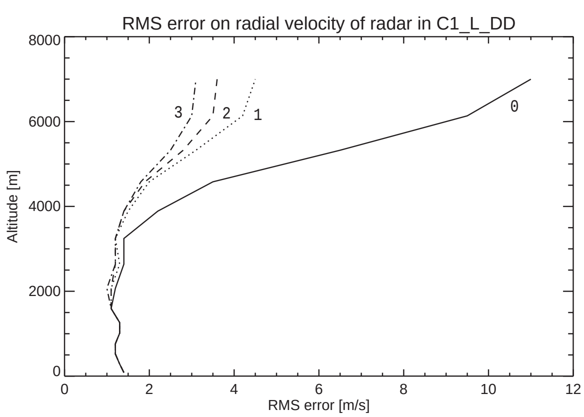

Fig. 3.- *Root mean square error of the radial velocity in cycle 1 of sequent feedback loops.*

The effect of feedback loops on the model error terms is similar to that on radial velocity, except that RMS error is increases after three feedback loops in cycle 2 (Fig. 6). The reduction of RMS on model error terms of cycle 1 in data voids is more evident than that in the data region during the assimilation cycle. Figures 4 and 5 show this in the x-momentum equation error in cycle 1.

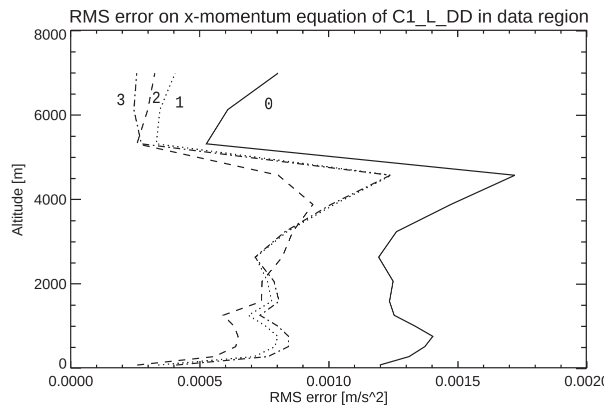

Fig. 4.- *Root mean square error of x-momentum equation of cycle 1 in data region.*

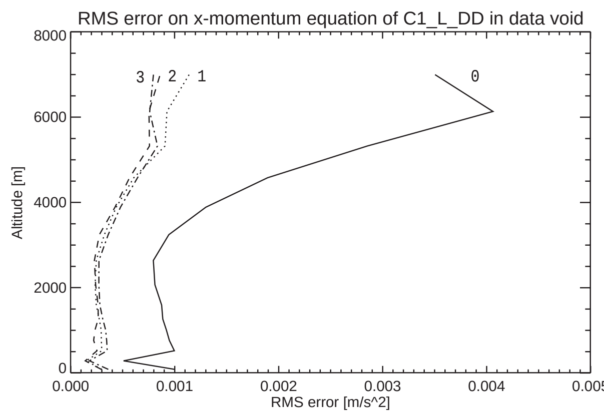

Fig. 5.- *Root mean square error of x-momentum equation of cycle 1 in data void region.*

Figure 7 and 8 show the retrieved vertical velocity field overlaid with the retrieved horizontal velocity vectors of cycle 1 at 2.1 km altitude in zero and in second feedback loop, respectively. The retrieved upward motion of convective cells from second feedback loop is stronger than that from without feedback loop. In the meantime, a newly developing cell in the SW part is analyzed. The retrieved horizontal wind field of data voids, the southeast part of Fig. 8, is more consistent with that of data region in second feedback loop.

A similar experiment was performed to test the sensitivity of the analysis with respect to the single-Doppler radar data. As shown by the retrieved horizontal velocity vectors in Fig. 9, the convective cells can't be retrieved until the second feedback loop. Furthermore, full velocity components can't be derived from single-Doppler radar data analysis even if feedback loops are performed. The retrieved upward motion from single-Doppler is obviously much weaker than that from multiple-Doppler radar data.

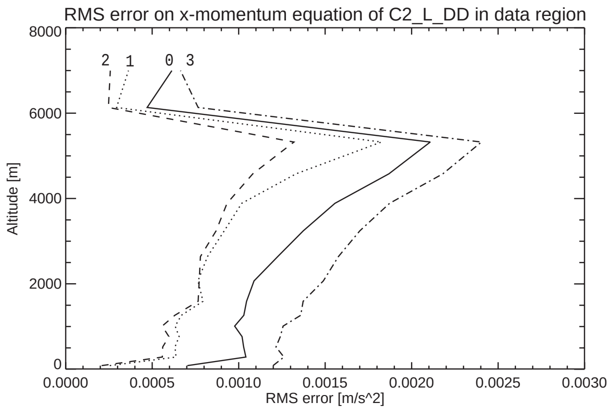

Fig. 6.- *Root mean square error of x-momentum equation of cycle 2 in data region.*

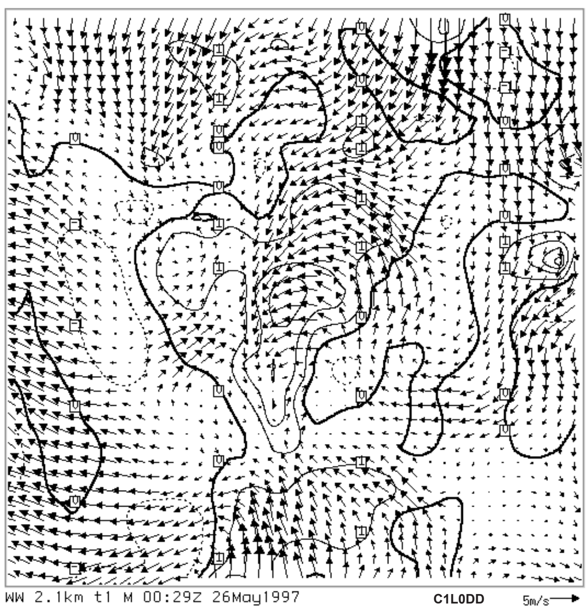

Fig. 7.- *The retrieved vertical velocity field overlaid with the retrieved horizontal velocity vectors of cycle 1 at 2.1 km altitude without a feedback loop. The contour interval is 1.0 m/s. Negative values are dashed lines and positive values are solid lines.*

3. Summary

The improvement of the background field from the first two feedback loops can dramatically reduce the root-mean square error of retrieved fields and model error terms. The background fields filled in data voids are adjusted to consistent with both of fields in data region and the dynamics of the MC2 model.

From the sensitivity experiment of single-Doppler radar data, the assimilation of multiple-Doppler radar data plays an important role in retrieval of full velocity components.

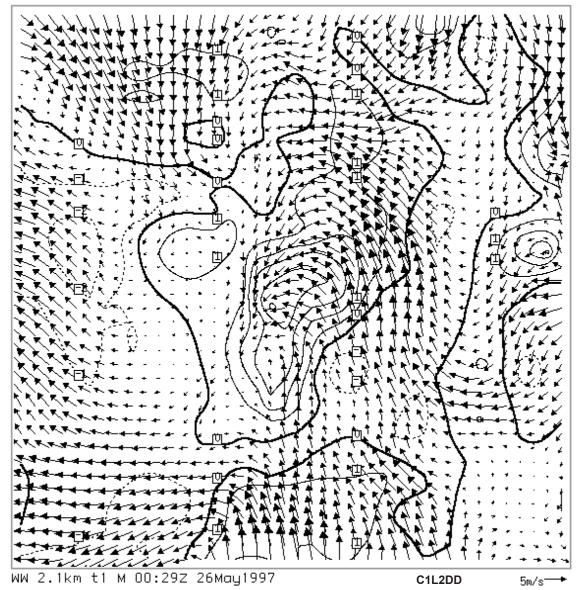

Fig. 8.- *As in figure 7 but retrieval from second feedback loop.*

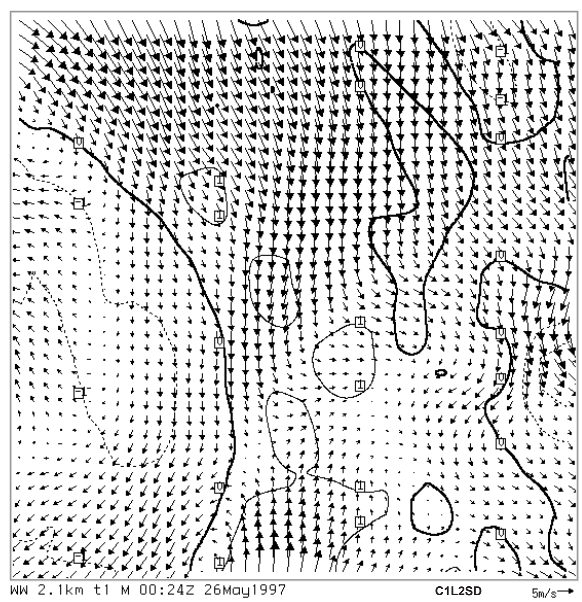

Fig. 9.- *As in fig. 8 but retrieved from single-Doppler radar data.*

The benefits of performing this looping appear only at the initial two cycles of the assimilation. When subsequent volume scans are introduced for further cycles in the assimilation the initial guess and background fields from the previous cycle are already sufficiently optimized. It appears that the looping is beneficial because of the imbalance introduced by the combination of the background filed obtained by the linear wind analysis in the data void regions and the analysis in the radar echo regions.

4. References

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