Assimilation of Reflectivity Data in a Convective-Scale, Cycled 3DVAR Framework with Hydrometeor Classification

JIDONG GAO AND DAVID J. STENSRUD
NOAA/National Severe Storms Laboratory, Norman, Oklahoma

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ABSTRACT

The impact of assimilating radar reflectivity and radial velocity data with an intermittent, cycled three-dimensional variational assimilation (3DVAR) system is explored using an idealized thunderstorm case and a real data case on 8 May 2003. A new forward operator for radar reflectivity is developed that uses a background temperature field provided by a numerical weather prediction model for automatic hydrometeor classification. Three types of experiments are performed on both the idealized and real data cases. The first experiment uses radial velocity data only, the second experiment uses both radial velocity and reflectivity data without hydrometeor classification, and the final experiment uses both radial velocity and reflectivity data with hydrometeor classification. All experiments advance the analysis state to the next observation time using a numerical model prediction, which is then used as the background for the next analysis. Results from both the idealized and real data cases show that, assimilating only radial velocity data, the model can reconstruct the supercell thunderstorm after several cycles, but the development of precipitation is delayed because of the well-known spinup problem. The spinup problem is reduced dramatically when assimilating reflectivity without hydrometeor classification. The analyses are further improved using the new reflectivity formulation with hydrometeor classification. This study represents a successful first effort in variational convective-scale data assimilation to partition hydrometeors using a background temperature field from a numerical weather prediction model.

1. Introduction

The operational Weather Surveillance Radar-1988 Doppler (WSR-88D) network is a valuable source of data for storm-scale numerical weather prediction (NWP). However, the assimilation of radar reflectivity into storm-scale NWP remains a challenge. One of the greatest difficulties is the uncertainty in the reflectivity forward operators that link model hydrometeor variables with radar reflectivity observations. These uncertainties occur because of the complexity of numerical model microphysical schemes. Another difficulty is the highly nonlinear nature of the reflectivity forward model, which often leads to violating some basic assumptions of data assimilation (Daley 1991).

Four approaches to the assimilation of radar reflectivity data into storm-scale NWP models are currently used. The first approach is a four-dimensional variational data assimilation (4DVAR) technique. Sun and Crook (1997) compare several ways to assimilate reflectivity data in their 4DVAR scheme using observing system simulation experiments. They find that the best way to assimilate reflectivity data is to transform the reflectivity data into rainwater mixing ratio and then assimilate the rainwater into the cloud-scale model. This can be easily done in their 4DVAR framework because only warm rain microphysics is used and only one hydrometeor variable—the rainwater mixing ratio—contributes to reflectivity, as the ice-related hydrometeors are neglected. Sun and Crook (1997) also show that the computational cost and strong nonlinearities with model microphysics, including ice microphysics, often causes difficulties in the 4DVAR assimilation of radar data.

The ensemble Kalman filter (EnKF) is another approach for directly assimilating reflectivity data into an NWP model (Tong and Xue 2005; Dowell et al. 2011). Results show that the assimilation of reflectivity data into a storm-scale NWP model with EnKF generally improves the quality of the analysis and forecast if radial
velocity data are also used. Dowell et al. (2011) find that when a reflectivity observation is assimilated, bias errors in the model fields associated with reflectivity (rain, snow, and hail–graupel) can be projected onto other model variables through the ensemble covariances, leading to temperature analyses being very sensitive to ensemble spread and low-level cold pools being unreliable when obtained through reflectivity data assimilation.

The third approach for the assimilation of radar reflectivity data uses a cloud analysis to specify hydrometer variables and adjust in-cloud temperatures (Albers et al. 1996) and is often used for real-time applications and related research. In these procedures, the reflectivity information is mainly used indirectly. Zhang et al. (1998), Hu et al. (2006a,b), and Schenkman et al. (2011) have shown success in simulating and forecasting convective storms with a cloud analysis scheme, when radial velocity data are also assimilated in a three-dimensional variational data assimilation (3DVAR) system (Gao et al. 1999, 2004). The adjusted in-cloud temperature from the cloud analysis also can initialize an NWP model with a digital filter technique (Weygandt and Benjamin 2007). This approach has been successfully applied to the National Weather Service’s operational rapid update cycles for mesoscale analysis. Advantages of the cloud analysis method include its simplicity, ease of implementation, and computational efficiency. However, cloud analyses by necessity include a number of empirical relationships between the hydrometer variables and observed reflectivity. Many uncertainties exist in these parameter settings that may limit its value for storm-scale NWP (Gao et al. 2009).

A fourth approach is a 3DVAR method developed by Xiao et al. (2005), with the model total water mixing ratio used as a control variable. They show the positive impacts of assimilating reflectivity data on short-range quantitative precipitation forecasts. However, only warm rain microphysics is used. This simplification may limit the value of this approach when applied to deep convective storms.

To effectively assimilate reflectivity data and radial velocity data into a storm-scale numerical model, microphysical variables for both liquid and frozen particles need to be included in the analysis variables, especially for deep moist convective storms where a large fraction of storm rainfall is produced via cold-cloud processes. As shown below, a hydrometeor classification that distinguishes between water and ice quantities is also necessary. In this study, ice microphysical variables (i.e., snow and hail mixing ratios) are included as control variables for the cost function defined in a 3DVAR method. A new forward operator for reflectivity is developed that uses a background temperature field from a NWP model as guidance for an automatic hydrometeor type classification. This is the first time a hydrometeor classification has been used in combination with storm-scale variational data assimilation. We choose a 3DVAR method instead of the more advanced 4DVAR and EnKF methods because of the high computational efficiency of the 3DVAR method. Efficient and fast analysis methods are essential for storm-scale phenomena where quick delivery of the analyses and forecasts is required to meet forecaster needs. Because the model equations are not used directly in the 3DVAR process, the nonlinearity of the reflectivity forward model may have a less negative impact on the minimization of the cost function than occurs in the 4DVAR problem shown by Sun and Crook (1997). We hypothesize that the inclusion of reflectivity data in a cycled 3DVAR data assimilation system will significantly reduce the severity of the spinup problem and can improve the short-range forecasts of thunderstorms. Experiments are performed in which synthetic radar data, sampled from an idealized model simulation of a supercell thunderstorm, and observed radar data from a tornadic supercell storm on 8 May 2003 are assimilated using the 3DVAR method. Three variants of the 3DVAR method are tested in both cases.

This paper is organized as follows: In section 2, a brief description of the data assimilation method (3DVAR) and the reflectivity forward operator is provided. In section 3, the proposed assimilation method is tested on a set of idealized data sampled from a simulated supercell storm for which the true wind field is known. In section 4, we further apply this method to a multiple-Doppler dataset for a tornadic supercell storm that occurred on 8 May 2003 near Oklahoma City, Oklahoma. Finally, summary and concluding remarks are given in section 5.

2. Assimilation method and radar observation forward operators

The details of the 3DVAR method are found in Gao et al. (2004). The analysis vector \( \mathbf{x} \) contains the three wind components \( u, v, \) and \( w \); potential temperature \( \theta \); pressure \( p \); and water vapor mixing ratio \( q_v \); also, the hydrometer variables are analyzed in a cloud analysis scheme (Hu et al. 2006a). For this study, however, the hydrometeor-related model variables, including the mixing ratios for rainwater \( q_r \), snow \( q_s \), and hail \( q_h \), are added to the analysis vector to assimilate reflectivity directly in a variational framework. The observation term in the cost function includes both radial velocity and reflectivity. The mass continuity equation is imposed as a weak constraint (Gao et al. 1999, 2004; Hu et al. 2006b).

The forward operator for simulated radar radial velocity \( v_r \) is calculated from
where $\mu$ is the elevation angle and $\phi$ is the azimuth angle of radar beams. The impact of the contributions from the hydrometeors to the radar radial wind measurements is not included in Eq. (1) because the radial velocity data are corrected based on Foote and du Toit (1969) before they are inserted to the variational method in the real data case. Another way is to include the terminal fall velocity formulation into the assimilation system, as discussed in Gao et al. (1999).

The forward model for equivalent radar reflectivity factor is obtained by summing the contributions from three hydrometeor mixing ratios—rain, snow, and hail—using the following formulation (Lin et al. 1983; Gilmore et al. 2004; Dowell et al. 2011):

$$Z_e = Z(q_r) + Z(q_s) + Z(q_h).$$

The rain component of the reflectivity is based on Smith et al. (1975) with

$$Z(q_r) = 3.63 \times 10^9 (\rho q_r)^{1.75},$$

where $\rho$ is atmospheric density. If the temperature is cooler than 0°C, then the reflectivity factor from dry snow is

$$Z(q_s) = 9.80 \times 10^8 (\rho q_s)^{1.75}.$$ (4)

For wet snow, which occurs at temperatures warmer than 0°C, the reflectivity is

$$Z(q_s) = 4.26 \times 10^{11} (\rho q_s)^{1.75}.$$ (5)

For hail, the reflectivity formulation based on Lin et al. (1983) and Gilmore et al. (2004) is used, with

$$Z(q_h) = 4.33 \times 10^{10} (\rho q_h)^{1.75}.$$ (6)

The last step converts equivalent reflectivity factor to the customary logarithmic scale (dBZ) using

$$Z_{dB} = 10 \log_{10} Z_e.$$ (7)

The assimilation of reflectivity observations using Eqs. (2)–(7) is less than ideal since the reflectivity factor is a function of all three hydrometeor variables (rainwater, snow, and hail). This leads to the solution being underdetermined, and it is possible to obtain a nonzero snow mixing ratio near the ground where only rainwater is expected because of the very warm temperatures at these levels. To solve this problem, the forward reflectivity operator [Eq. (2)] is modified such that

$$Z_e = \begin{cases} \frac{Z(q_r)}{Z(q_r) + Z(q_s)} \\ \alpha Z(q_r) + (1 - \alpha) \left[ Z(q_s) + Z(q_h) \right] \end{cases}$$

where $\alpha$ varies linearly between 0 at $T_b = -5^\circ$C and 1 at $T_b = 5^\circ$C, and $T_b$ is the background temperature from a NWP model. The equivalent reflectivity factors $Z_e$ calculated using Eqs. (2) and (8) are quite similar in terms of both precipitation pattern and reflectivity magnitudes. But the a priori partitioning of the hydrometeors variables in Eq. (8) allows the model background temperature to guide how much of the correction should occur in $q_r$ compared to how much correction should occur in $q_r$ and $q_b$. This point will be illustrated in the data assimilation experiments for both idealized and real data cases.

3. Experimental design and results for idealized case

The effectiveness of the 3DVAR for reflectivity and radial velocity data assimilation is evaluated using simulated Doppler radar data from a truth simulation of a supercell thunderstorm. The Advanced Regional Prediction System (ARPS; Xue et al. 2000, 2003) is used to generate the truth simulation. The environment from a well-documented supercell storm that occurred near Del City, Oklahoma, on 20 May 1977 is selected (Ray et al. 1981). Parameter settings for the ARPS model include $57 \times 57 \times 35$ total grid points with horizontal grid spacing $dx = dy = 1$ km with $dz = 500$ m in the vertical. The three-category ice microphysical scheme of Lin et al. (1983) is used. During the truth simulation, the initial cell develops and strengthens over the first 30 min. This cell splits at around 55 min, with the right-moving cell being dominant.

The 3D wind and hydrometeor fields from the truth run are sampled by two ground-based pseudoradars, located at the southwest and southeast corners of the model domain, to obtain synthetic radial velocity and reflectivity data using Eqs. (1)–(8). Random errors drawn from a normal distribution with zero mean and a standard deviation of 1 m s$^{-1}$ are added to the synthetic radial velocity data, and random errors with zero mean and a
A standard deviation of 3 dBZ are added to the reflectivity data.

As stated in last section, the calculation of reflectivity using Eqs. (2) and (8) are quite similar in terms of both precipitation pattern and reflectivity magnitudes. Figures 1a and 1c show the reflectivity field calculated with Eq. (2) and Figs. 1b and 1d show the reflectivity field calculated with Eq. (8) using hydrometeor variables from truth simulation at 1 h of model integration. There are some differences in term of the maximum and minimum values, but the general reflectivity patterns match very well. Mathematically speaking, deriving three hydrometeo variables from only type of reflectivity observation is ambiguous, although the background term in the cost function reduces this ambiguity somewhat. In the low levels of the model, we know that the largest contribution to reflectivity is from rainwater, whereas in the upper levels the largest contribution to reflectivity is from ice-related variables. The partitioning in Eq. (8) simply addresses this fact and makes the forward operator for reflectivity more physically meaningful. Accordingly, when data assimilation or the inverse problem is performed, most of the correction occurs in the rainwater variable in the model low levels, whereas most of the correction occurs in the ice-related variables in the model upper levels. The relationship between model variables and reflectivity observation is more unique, or better defined, in the modified Eq. (8). This will be further verified in data assimilation experiments in both idealized case and real data cases.

The analysis starts from horizontally homogeneous fields as the first guess provided by the assumed

Fig. 1. The ARPS model–simulated reflectivity fields (dBZ). (a),(b) Horizontal cross section at \( z = 3.5 \) km and (c),(d) vertical slices through maximum vertical velocity, at \( y = 23.5 \) km; (a) and (c) are calculated using Eq. (2), while (b) and (d) are calculated using Eq. (8).
environmental sounding. Synthetic radar data are then assimilated using the 3DVAR to produce an analysis and a short 5-min forecast is made starting from this analysis using the ARPS model. This 5-min forecast then becomes the background for the next 5-min assimilation cycle. The analysis–forecast cycles are started at 20 min of the truth run integration time and extend over a 40-min period.

Three experiments are performed. In the first experiment VrOnly, only radial velocity data are assimilated. In the second experiment Vr&Z1, radial velocity data using Eq. (1) and reflectivity data using Eq. (2) are assimilated. In the third experiment Vr&Z2, radial velocity data using Eq. (1) and reflectivity data using the hydrometeor classification [Eq. (8)] are assimilated.

Results show that for VrOnly, the velocity structure around the storm is somewhat captured after three analysis–forecast cycles (Figs. 2f,g). The precipitation, as indicated by reflectivity, has not yet appeared. After two more cycles ($t = 40$ min), the precipitation reaches the

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**Fig. 2.** (a)–(e) Horizontal winds (vectors; m s$^{-1}$), perturbation potential temperature (contours at 1-K interval) and simulated reflectivity (shaded contours, dBZ) at 250 m AGL, for the truth simulation; (f)–(j) the cycled 3DVAR analyses with assimilating radial velocity only; (k)–(o) the cycled 3DVAR analysis with assimilating radial velocity and reflectivity without hydrometeor classification; and (p)–(t) the cycled 3DVAR analysis with assimilating radial velocity and reflectivity with hydrometeor classification. The times shown are 20, 30, 40, 50, and 60 min of model integration time. The assimilation interval is 5 min.
ground, but it is weaker and covers a much smaller area compared to the truth (cf. Figs. 2c,h). After seven analysis cycles \((t = 50 \text{ min})\), the right-moving storm cell is similar to the truth but the left-moving storm is still very weak. The extent of the cold pool is too small on the southwestern side of the storm even though its maximum intensity underneath the cells is close to the truth (cf. Figs. 2d,j). Only after 40 min of assimilation \((t = 60 \text{ min})\) do the overall storm structures become close to the truth, although the extent of the cold pool is still reduced (cf. Figs. 2e,j). In general, the development of precipitation is significantly delayed in VrOnly.

For Vr&Z1, the development of the storm is much faster. At the beginning of the analysis–forecast cycles, the precipitation already is reaching the ground and a wind perturbation is seen, with the patterns being weaker but quite similar to the truth (Fig. 2k). After two more cycles, the storm cell compares reasonably well with the truth (Fig. 2l) and a weak cold pool appears (Fig. 2g). With two more cycles completed \((t = 40 \text{ min})\), the overall storm structures begin to resemble the truth closely, although the extent of the cold pool is still smaller (Fig. 2m). After the final analysis cycle, the low-level flow and reflectivity patterns, as well as the strength and extent of the cold pool, are in very good agreement with the truth (cf. Figs. 2a,e) although some differences still exist in terms of the shape of the cold pool and reflectivity. These results suggest that the assimilation of both radial velocity and reflectivity in the cycled 3DVAR system help reduce the spinup time for developing hydrometeors in the analyses and forecasts.

In Vr&Z2, hydrometeor classification is made through a background temperature field from the ARPS model. The analysis is noticeably improved compared to the other experiments. The precipitation is stronger from the very beginning of assimilation as compared with the previous experiments (cf. Figs. 2p,f,k). At 20 min into the assimilation \((t = 40 \text{ min})\), the cell splitting process has begun, and the cold pool is stronger and has larger extent than in the other experiments (cf. Figs. 2r,h,m). By 40 min \((t = 60 \text{ min})\), the structure of the storm is almost the same as in the truth (cf. Figs. 2l,e). Overall, the analysis converges much faster and the analysis errors are smaller. These results highlight the value of the partitioning of the hydrometeor types using the background temperature field.

To further illustrate why the third experiment yields an improved analysis, the values of \(q_r\), \(q_s\), and \(q_h\) after the first assimilation step are shown (Fig. 3). This time level is chosen because prior to this first assimilation step, the background fields for these hydrometeor variables are zero and the correction to these variables during the assimilation step is solely from reflectivity observations. For VrOnly, all hydrometeor variables \(q_r\), \(q_s\), and \(q_h\) are zero (not shown). For Vr&Z1, values of \(q_r\) after assimilation are small (Fig. 3a). Because the temperature exceeds 20°C at this level, the expected \(q_r\) after the assimilation is zero (Fig. 3b) and \(q_r\) should be zero except in a small region where hail is reaching the ground (Fig. 3c). However, relatively large values of \(q_r\) and \(q_h\) exist in Vr&Z1 (Figs. 3e,f) with the maximum value of \(q_r\) larger than the maximum value of \(q_r\). This is not a physically reasonable result. However, in Vr&Z2, we obtain a reasonable pattern for \(q_r\) (Fig. 3g) with near-zero values for \(q_s\) and \(q_h\) (Figs. 3h,i). In addition, \(q_r\) values are zero in the upper levels of the analysis where only snow and hail are expected because of the very cold temperatures at these levels (not shown); such behavior does not occur in Vr&Z1. These results indicate that the assimilation of reflectivity using Eq. (8) with hydrometeor classification is more reasonable and physically consistent with the truth run.

Root-mean-square (rms) errors of the analyzed fields are calculated against the truth by averaging over those grid points where the reflectivity is greater than 10 dBZ in the truth simulation. The rms errors generally decrease with each subsequent analysis–forecast cycle (Fig. 4). The rms errors decrease much faster for most of model variables (except \(w\)) when reflectivity is also assimilated. This rms error reduction is especially visible for later assimilation cycles. The improvements in \(w\) (Fig. 4a) and also for the horizontal wind components (not shown) are not large, since the assimilation of reflectivity has little direct impact on wind field. The rms errors for Vr&Z2 are smaller than for Vr&Z1, although the differences are not large. However, comparison of reflectivity and perturbation potential temperature against the truth (Figs. 2a,k,p) indicates that better analyses clearly are produced by Vr&Z2. This is not surprising given the strong influence of hydrometeors on the temperature field within thunderstorms and the more physically consistent analyses when hydrometeor classification is used. Since changes in cold pool strength influence thunderstorm updraft and evolution (Brooks et al. 1994; Gilmore and Wicker 1998), the importance of obtaining an accurate low-level temperature structure is hard to overstate.

4. Application to a real data case

In the previous section, we discussed results from a set of three observing system simulation experiments that used model-generated pseudo observations. To demonstrate the effectiveness of the proposed assimilation method for a real data case, we apply our method to the 8 May 2003 Oklahoma City, Oklahoma, tornadic supercell storm. This case has high societal impact. The
storm spawned an F4 tornado that tracked through southern Oklahoma City causing $370 million (USD) in damage and 134 injuries. Four WSR-88D radars are located in this region: KTLX, located southeast of Oklahoma City in central Oklahoma; KVNX, located in northwestern Oklahoma at Vance Air Force Base; KINX, located just northeast of Tulsa, in northeastern Oklahoma; and KFDR, located in southwestern Oklahoma near the town of Frederick. However, only KTLX observed this storm closely and other three radars only
observed a small part of this storm at upper levels. Radar data from these four radars during the period from 2130 to 2200 UTC span the pretornadic phase of the storm. The environmental profile in the model is defined by the 0000 UTC 9 May 2003 Norman, Oklahoma, sounding, which was taken from very near the KTLX radar site. We employ a stationary grid consisting of 120 × 120 × 41 grid points. The horizontal grid spacing is uniformly 1 km, whereas the vertical grid spacing is 500 m. Since the storm motion is toward the northeast, the grid is positioned so that the initial storm development occurs in the southwestern part of the domain.

Before the analysis, the reflectivity observations from all four WSR-88D radars are synthesized to the model grid using a variational objective analysis method every 5 min within the same 40-min period as a reference for comparison. Figures 5a–e show that a strong hook echo is present in almost every reflectivity image. During the data assimilation process, however, both the radial velocity and reflectivity are used in their original radar polar coordinate.

The analysis and forecast cycles start from 2130 UTC and repeat every 5 min until 2210 UTC. Unlike the EnKF cycle analysis of Dowell et al. (2004), the initial 5-min forecast starts from the first analysis and no warm bubbles are used to initialize the storm. As in the idealized case, the three experiments VrOnly, Vr&Z1 and Vr&Z2 are performed.

Results show that for VrOnly, the velocity structure around the storm is analyzed very well after the first two analysis cycles (Figs. 5f,g), but precipitation has not yet appeared. The potential temperature is dominated by a strong warm center around the storm at 2140 UTC, whereas a cold pool is expected and indicated by observations from the Oklahoma Mesonet (not shown). At 2150 UTC, the precipitation reaches the ground, although it covers a much smaller area compared to the observed reflectivity (cf. Figs. 5c,h). After seven analysis cycles (at 2210 UTC), the storm cell begins to more closely resemble the observations. But the extent of the cold pool still appears too small and there is a strong positive temperature center north of the major storm cell that looks unreasonable (Figs. 5i,j). In summary, similar to results from the idealized case, the development of precipitation is significantly delayed in VrOnly.

For Vr&Z1, the development of the precipitation is much faster. At the beginning of analysis at 2130 UTC, light precipitation already is reaching the ground while the wind perturbation is similar to the VrOnly experiment (Fig. 5k). After two more cycles, the storm cell becomes stronger and a weak cold pool appears (Fig. 5l).
At 2200 UTC, the overall storm structure begins to resemble the observations in the core region, although the precipitation is weak in most of the area and the extent of the cold pool is very small (Fig. 5n). After the final analysis cycle, the storm core is small compared with the observations (cf. Figs. 5o,e), and the result looks even worse than that with only radial velocity assimilated (cf. Figs. 5o,j). These results suggest that while the assimilation of both radial velocity and reflectivity in the cycled 3DVAR system helps to reduce the spinup time for developing hydrometeors, some errors are also introduced and the storm is underdeveloped near the end of assimilation cycles.

In Vr&Z2, hydrometeor classification is made through a background temperature field from the ARPS model. This leads to the analysis of 8 May 2003 supercell being noticeably improved compared to the other two experiments. The reflectivity pattern matches much better with the observations throughout the assimilation cycles (Figs. 5p–t). The cold pool structure of the storm
develops earlier (cf. Figs. 5q,l,g) and spreads over a larger area than seen in the other experiments (cf. Figs. 5t,o,j). The large positive potential temperature center located to the north of storm cell in the VrOnly experiment has been corrected in Vr&Z2. Overall, the analyses are more reasonable and the analyses at the end of the assimilation period closely resemble the observations. Oklahoma Mesonet observations indicate that the cold pool to the northeast of the storm core is at least 2.4°C colder than the environment, while the 3DVAR analysis with hydrometeor partitioning indicates that the cold pool is about 2°C–4°C colder than the environment near that area, not warmer than the environment as indicated in the VrOnly experiment (cf. Figs. 5j,t). These results certainly illustrate the value of the partitioning of the hydrometeor types using the background temperature field as also found in the idealized case.

To further demonstrate the value of the partitioning of the hydrometeor types, Fig. 6 shows a vertical slice of analyzed rainwater ($q_r$) with wind vectors imposed and valid at first analysis time of 2130 UTC. For VrOnly, analyzed $q_r$ is zero everywhere so only the wind vectors appear (Fig. 6a). A strong updraft core (>25 m s$^{-1}$) is analyzed near the location of the storm. The strong downdraft (−18.72 m s$^{-1}$) is seen below the major updraft core behind the storm as often occurs in strong deep moist convection. For Vr&Z1, the analyzed $q_r$ appears weaker and extends to above 12 km AGL (Fig. 6b). Because the temperature is below freezing in the middle and upper levels of the model, this analysis looks suspicious and unreasonable. However, in Vr&Z2, we obtain a reasonable pattern for $q_r$ below 5 km AGL and with near-zero values for $q_r$ above this level (Fig. 6c). It is worth mentioning that the strength of the updraft core for all three experiments is quite similar. The results of our analysis of potential temperature after 10 min of cycling for 2140 UTC on 5 May are shown in Fig. 7. While the overall pattern looks similar at first glance, differences are seen in the low levels, where a cold temperature perturbation reaches ground level for the Vr&Z2 experiment (Fig. 7c). For other two experiments, the cold temperature perturbation is only beginning to

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**FIG. 6.** The $x$–$z$ vertical slice through maximum vertical velocity at $y = 23.5$ km for analyzed winds vectors (m s$^{-1}$), rainwater mixing ratio, (a) assimilating radial velocity only, (b) assimilating radial velocity and reflectivity without hydrometeor classification, and (c) assimilating radial velocity and reflectivity with hydrometeor classification, at initial analysis cycle 2130 UTC for the 8 May 2003 Oklahoma City supercell storm.
develop at low levels but does not reach to ground at this time (Figs. 7a,b).

5. Summary and concluding remarks

The assimilation of radar reflectivity into a storm-scale NWP model using a 3DVAR framework has not been thoroughly explored previously. This study is the first to include ice hydrometeors as analysis variables in variational storm-scale data assimilation, and also the first to partition hydrometeor variables using a background temperature field from a storm-scale NWP model.

The impact of assimilating both radar reflectivity and radial velocity data with intermittent 3DVAR analysis–forecast cycles is examined using both an idealized thunderstorm case and a real data case. A new forward operator for reflectivity is developed using the background temperature field from an NWP model to automatically classify hydrometeor types. Three preliminary experiments are performed. One experiment uses radial velocity data only, the second experiment uses radial velocity data and reflectivity data without hydrometeor classification, and the third experiment uses radial velocity data and reflectivity data with hydrometeor classification. It is found that by assimilating only radial velocity data, the model reconstructs the wind field of a supercell thunderstorm well within several assimilation cycles, but a spinup problem delays the development of precipitation. The spinup problem is reduced when assimilating reflectivity without hydrometeor classification. However, the analysis converges faster and the analysis errors are smallest when using the new reflectivity formulation with hydrometeor classification. The cold pool develops earlier and agrees better with the truth when using hydrometeor classification. The overall conclusion is that the assimilation of radar reflectivity and radial velocity data in the 3DVAR system significantly reduces the spinup problem and has the potential to improve short-range storm-scale analyses and forecasts. The partitioning of hydrometeors when assimilating reflectivity can be also used within other

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**FIG. 7.** The $x$–$z$ vertical slice for analyzed potential temperature through maximum vertical velocity at $y = 25.5$ km, (a) assimilating radial velocity only, (b) assimilating radial velocity and reflectivity without hydrometeor classification, and (c) assimilating radial velocity and reflectivity with hydrometeor classification at initial analysis cycle 2130 UTC for the 8 May 2003 Oklahoma City supercell storm.
advanced data assimilation methods, such as EnKF and 4DVAR.

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