Short-Term Numerical Forecasting of a Shallow Storms Complex Using Bistatic and Single-Doppler Radar Data

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(Manuscript received 3 October 2001, in final form 18 June 2002)

ABSTRACT

A new method based on four-dimensional variational radar data assimilation into a cloud-resolving model has been developed for nowcasting purposes. This method allows for the retrieval of the model prognostic variables that compose the initial state of the simulation. 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, which provides a realistic mesoscale flow that is in better agreement with the air circulation retrieved from dual-Doppler observations within the precipitating regions. Furthermore, the near-ground refractivity index of air derived from ground targets is used to diagnose a high-resolution and two-dimensional distribution of relative humidity in the mixed layer. Two experiments are performed: one uses multiple-Doppler information coming from McGill University’s bistatic radar network and the second considers only single-Doppler observations. This updated algorithm has been applied to a shallow hailstorm and shows very encouraging skill in predicting the short-term evolution of this convective system. The time evolution of the storm is captured well, and a significant improvement is noticed when compared with the nowcasting method based on Lagrangian persistence. When compared with the results obtained with the bistatic network, results when a single-Doppler radar is used show weaker capability to forecast the radial velocity than the precipitation pattern but still give a better forecast than the Lagrangian persistence method does.

1. Introduction

The assimilation of radar data into a numerical prediction model presents a great challenge. The effectiveness of that kind of assimilation in predicting convective-scale features using a mesoscale cloud model is still not obvious. The determination of the error structure of this information and the kind of radar-derived information that should be assimilated are two of the main problems.

By assimilating successive observations of radial velocities from a multiple-Doppler radar network in a cloud model, Sun and Crook (1997) have retrieved unobserved dynamical and microphysical fields using a four-dimensional variational data assimilation (4D-var) adjoint technique. They more recently made a successful attempt at nowcasting low-level wind and temperature for a line of storms by integrating a cloud-resolving model after having assimilated successive single-Doppler observations (Sun and Crook 2001). Their results are confined, however, to the low troposphere and thus are not yet applicable to the quantitative precipitation forecast (QPF) problem.

Montmerle et al. (2001, hereinafter MCZ01) use the forward assimilation method, first attempted by Lin et al. (1993) and more recently by Weygandt et al. (2002a,b) using single-Doppler observations, to reproduce a realistic time evolution at high resolution of three different convective cells composing a midlatitude storm, leading to a better QPF than did the persistence of the initial precipitation field. Although successive dual-Doppler observations of the explicit structure of a convective storm are still assimilated, this method does not use an adjoint model, and thus the model solution at a previous time is not reestimated using new observations. However, a retrieval algorithm that uses the model as weak constraints permits the retrieval or estimation of the initial state of all the prognostic fields of the model.

In the current study, two notable improvements have been added to this technique. First, the echo-free regions

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are henceforth filled by a linear wind (i.e., a wind that varies linearly in the horizontal direction) that gives a mesoscale environmental flow in better agreement with the radar data than does a single sounding, as used in MCZ01. The method of Caye et al. (2002, hereinafter CLZM02), which can be considered to be a combination of the volume velocity processing (VVP) analysis and a synthetic dual-Doppler approach, has been used for that purpose. The linear wind analysis is deduced using a time series of single-Doppler observations that describe the movement of a convective system with respect to the radar. The different viewing angles, coupled with the frozen turbulence assumption and the constraint of the continuity equation, permit the retrieval of a linear wind that fits the observed radial velocities in the least squares sense. The second improvement concerns the use of the air refractivity index deduced from ground targets (Fabry et al. 1997), which is available for the case presented herein. This index is used here as a diagnostic tool to estimate the two-dimensional distribution of humidity in the mixing layer, which is a crucial parameter in the problem. Furthermore, to quantify the added value provided by bistatic-Doppler radar data information for nowcasting, a single-Doppler experiment is undertaken for comparison.

This paper is organized as follows: the different datasets that have been assimilated in the retrieval process are presented in section 2, and the computation of the linear wind is further developed in section 3. An insight into the method that allows assessing the initial field of every prognostic variable of the model is then detailed in section 4, and the result of the forecast initialized with the latter is presented in section 5.

2. Data available

a. Doppler data

The case studied herein is a shallow hailstorm sampled by the McGill University bistatic multiple-Doppler radar network on 26 May 1997 [a complete description of this network, composed of one S-band Doppler radar and two low-gain nonscanning receivers, can be found in Kilambi et al. (1997)]. This storm, extensively studied by Protat et al. (2001, hereinafter PZC01), was at 0029 UTC composed of two main shallow convective cells (depth around 5 km) aligned along a NE–SW axis developing in an environmental air circulation characterized by a moderately strong low-level shear. Reflectivities up to 45 dBZ were observed within these two cells, whereas the northern part of the system is characterized by more-stratiform precipitation.

Because of the weak advection speed of that hailstorm, dual-Doppler observations of the precipitating area from the S-Band scanning radar and one of the passive receivers were available for more than 1 h, from 0024 to 0129 UTC. Two successive volumetric scans beginning at 0029 UTC are assimilated in the retrieval process. To avoid ground clutters, which are unavoidable at low levels, a cleanup of the data based on the reflectivity pattern is performed.

b. Refractivity

In contrast with MCZ01, the refractivity index $N$ was available for the case presented here. This index is extracted from radar phase information of ground echoes and gives valuable information about the two-dimensional structure of the temperature and the moisture field (Fabry et al. 1997). At microwave frequency, its formulation is

$$N = \frac{77.6 P}{T} + 373000 \frac{e}{T^2}$$

(1)

where $P$ is pressure (hPa), $T$ is the temperature (K), and $e$ is the water vapor pressure (hPa). To improve the understanding of this formula, the variation of the refractivity index with respect to given temperature and humidity for a pressure of 1000 hPa is shown in Fig. 1. It shows that the dynamical range of refractivity in the atmosphere is strongly dependent on temperature: when the air is cold, variations of refractivity are limited to a few tens of $N$ units by the low saturation vapor pressure. On the other hand, as the temperature increases, the potential magnitude of the second term of (1) increases. More water vapor can reside in the air, allowing the range of possible refractivity values to expand to nearly 200 $N$ units at 30°C. Hence, in the atmosphere, the refractivity is mainly a function of mois-
ature above about 0°C and of temperature below 0°C. In our case, the mean temperature near the ground is 13.2°C, which indicates that \( N \) is more linked to the humidity field because the pressure is quasi-constant near the ground. Thus, high values of \( N \) correspond to more-humid conditions.

At 0029 UTC, the refractivity pattern displayed in Fig. 2 shows that the mesoscale condition at low levels in the region located west of the storm is drier than the area situated below the precipitation where \( N \) is maximum. The strong gradient of \( N \) between these two regions indicates that the surface moisture is obviously modified by the passage of precipitation. These simple behaviors are of a great interest for nowcasting purposes, because thunderstorm initiation is very sensitive to small-scale moisture variability in the boundary layer. In comparison with the use of convectional surface data, high-resolution moisture information from ground targets could indeed significantly improve the initial conditions. The use of \( N \) for the calculation of humidity in the boundary layer will be described in section 4d.

c. Sounding

A nearby sounding is required to specify the vertical distribution of humidity in the region surrounding the precipitating system and to give the hydrostatic profile from which the thermodynamic perturbations are computed. A composite sounding deduced from a regional analysis of the Canadian Meteorological Center (CMC) and from in situ measurements by the McGill UHF profiler is used. The latter gives a better estimation of the temperature in the mixed layer.

This composite sounding was weakly unstable (with a CAPE of around 134 J kg\(^{-1}\)) and indicated a cloud top around 650 hPa, which is lower than what we get from the radar (~500 hPa). To simulate a convective system whose cloud-top level is comparable with what was observed, the initial sounding should carry enough available energy to raise particles to that altitude. Thus, it has been necessary to modify this sounding to get environmental conditions in better agreement with the radar observations. Therefore, the cloud top has been raised to the observed value and the resulting CAPE has increased up to 340 J kg\(^{-1}\), which indicates a moderate instability (Fig. 3).

3. Retrieval of the mesoscale circulation

In MCZ01, the air circulation of the echo-free region (referred to hereinafter as the background field) was characterized by a horizontally homogeneous wind field deduced from a large-scale analysis because the flow surrounding the storm was relatively uniform. In the
current study, we use the method developed in CLZM02, which permits the computation of a linear mesoscale environmental flow from a time series of volume scans performed by a single-Doppler radar. The background field is thus composed of two different regions: one described by at least one single-Doppler scan during the successive single-Doppler observations and the echo-free area in which the wind circulation is deduced from linear extrapolation. The reader is referred to CLZM02 for a discussion of the limitations and potential problems with the method of linear wind retrieval when the size of the echo-free regions is large or when the actual flow is nonlinear. In the current work the method was improved to include an adaptive procedure for the selection of the weights associated with each observation (details of this new procedure are given in section 3b).

### a. Method

This method can be seen as a combination of the VVP analysis (Waldteufel and Corbin 1979), the synthetic dual-Doppler concept, and the constraint of the continuity equation. Here, with $z$ being height, the two linear horizontal components of the wind ($u$ and $v$), the vertical velocity $w(z)$, the vorticity $\xi(z)$, stretching $\chi(z)$, and shearing $\tau(z)$ are retrieved in a moving frame of reference, given an assumption of frozen turbulence in the stratiform part of the radar echoes. The horizontal wind field is expressed as follows:

$$ u(x, y, z, t) = u_r(z) + \frac{D(z) - \tau(z)}{2} [x - u'(t - t_r)] + \frac{\chi(z) - \xi(z)}{2} [y - v'(t - t_r)] $$

and

$$ v(x, y, z, t) = v_r(z) + \frac{D(z) + \tau(z)}{2} [x - u'(t - t_r)] + \frac{\chi(z) + \xi(z)}{2} [y - v'(t - t_r)], $$(2)

where

$$ D(z) = u_r(z) + v_r(z), $$

$$ \tau(z) = v_r(z) - u_r(z), $$

$$ \chi(z) = v_r(z) + u_r(z), $$

and

$$ \xi(z) = v_r(z) - u_r(z). $$

Subscripts $x$ and $y$ indicate spatial derivatives, $(u_r, v_r)$ are the mean wind, $(u', v')$ are the moving frame velocity components, $t$ is the time in the assimilation period, and $t_r$ is the initial time. A first guess of the moving-frame velocity is estimated from the translation of the reflectivity pattern (Gal-Chen 1982). The control variables, including the moving-frame translation velocity components $(u', v')$, are adjusted so as to obtain the best fit through the radial velocity observations (see CLZM02 for more details). The analyzed radial velocity $V_r$ is expressed as a function of the linear wind parameters.

$$ V_r(x, y, z, t) = X_{\theta_p} = $$

$$ \begin{bmatrix} 
\sin(\beta) \cos(\phi) \\
\cos(\beta) \cos(\phi) \\
\frac{r}{2} \cos(\phi) \\
\frac{r}{2} \sin(2\beta) \cos(\phi) \\
\frac{r}{2} \cos(2\beta) \cos(\phi) \\
(t - t_r) \sin(\beta) \cos(\phi) \\
(t - t_r) \cos(\beta) \cos(\phi) \\
\sin(\phi)
\end{bmatrix} \begin{bmatrix}
\frac{D(z) - \tau(z)}{2}
\frac{\chi(z) - \xi(z)}{2}
\frac{D(z) + \tau(z)}{2}
\frac{\chi(z) + \xi(z)}{2}

\end{bmatrix}.$$  (4)

where $\beta$ is the azimuth measured from the north and clockwise, $\phi$ is the elevation angle, $r$ is the slant range from the radar, $V_r$ is the terminal fall velocity of precipitating hydrometeors, and $X$ is the operator acting on the vector $\theta_p$ of $p$ parameters to be estimated. By scanning the precipitating system as it moves with respect to the radar, the complete circulation is revealed by the effect of the different viewing angles.

To retrieve the vertical motion $w(z)$, the anelastic continuity equation is used as an additional strong constraint, zero vertical motion being imposed at the ground and at the top of the vertical domain. The latter cor-
responds broadly to the maximum altitude of radar echoes, which is 6 km for the case of shallow storms presented herein. The linearity of the horizontal wind implies that $w(z)$ is constrained at each level by a constant form, because the horizontal convergence is constant. The linear wind field is obtained by minimizing the following cost function:

$$J = J_o + J_s,$$

where

\[ J_o \]
The measurement error $\sigma^2_{m,i}$ is in general a function of space and time. To simplify, here it is reduced to a constant by considering the statistical properties of the radar signal (Doviak and Zrnic 1993). The representativeness error $\sigma^2_{r,i}$ also depends on the spatiotemporal location of the measurement. When the linear wind model is used to assimilate Doppler data, the representativeness error can dominate the total observational error, especially in regions for which the wind field is strongly nonlinear, which is often associated with convection. In other words, the Doppler measurements where the wind is nonlinear must be given less weight than measurements elsewhere. In the limit, the regions of nonlinear wind field should be excluded from the linear wind analysis. On the other hand, the residuals $\hat{r}_i$ at the end of the minimization should be close to the variances $\sigma^2_i$ chosen for the estimation of the weights. This leads to the following relationship:

$$\hat{r}_i = (V_{ri} - V'_{ri})^2 = \sigma^2_i,$$

(10)

where a caret over a variable denotes its value at the minimum of the cost function. The most intuitive way to solve (10) is by an iterative method because the left-hand side depends implicitly on the right-hand side. Thus, the algorithm is as follows:

1) set $\sigma^2_i = 1$,
2) minimize the cost function to get $\hat{r}_i$,
3) $\sigma^2_{r,i} = \max(\hat{r}_i - \sigma^2_{m,i}, 0)$, and
4) repeat steps 2 and 3 until the $\hat{r}_i$ converges.

This adaptive method for the weights used here for the linear wind analysis was studied by Holland and Welsch (1977). The solution for the final weights unfortunately might not be unique. This method has been applied to 10 successive volume scans of radial velocity from 0024 to 0109 UTC, with one complete volume scan lasting 5 min. Figure 4 displays the horizontal mean of the retrieved linear circulation at different vertical levels in comparison with in situ measurements provided by McGill’s UHF profiler located in downtown Montreal, Quebec, Canada, in the first 3 km of the troposphere. It shows that the low-level vertical shear of the horizontal wind from south to east is captured well by the algorithm and that the intensity of the wind is consistent with what was observed. Above 4 km, the mean retrieved linear wind intensifies and blows in a more southeasterly direction (we note, however, that less confidence should be put in the retrieved linear flow at these heights because fewer radial wind observations are available).

4. Computation of the initial fields

The cloud-resolving model used in this study is the Canadian Mesoscale Compressible Community (MC2) model (Laprise et al. 1997). This model is based on a semi-implicit semi-Lagrangian algorithm and a com-
ple complete warm and cold microphysical parameterization (Kong and Yau 1997).

To initialize this mesoscale cloud model, the initial state of its prognostic variables needs to be estimated. The wind circulation and its associated thermodynamic variables are retrieved from Doppler measurements. The humidity field near the ground is computed from refractivity. Where refractivity measurements are not available, the humidity is deduced from an empirical formulation that relates the vertical motion and the humidity. The liquid rain and the ice crystals are diagnosed from the reflectivity, and the liquid cloud and graupel mixing ratios are taken to be equal to zero.

To retrieve the dynamical and the thermodynamical components from Doppler observations and background fields, we use an assimilation method that consists of variationally adjusting the model dynamical fields to a time series of observations under physical constraints. To obtain an initial state most compatible with the parameterizations of the forecast model, these dynamical fields must satisfy the model physical equations using the same discretization schemes. A staggered and vertically stretched Arakawa-C grid type (Arakawa 1966) is used here. For the studied case, a horizontal spacing of 500 m has been chosen with a 60 km horizontal domain, and the vertical grid interval extends from 120 m near the ground to 800 m at the top of the domain. The details of the retrieval have been set out in MCZ01. Hence, only the broad outline of the method is presented below.

a. Retrieval of the air circulation

Measurements of the radial velocities from the bistatic radar network and from the background field are assimilated as weak constraints in the precipitating region and in the echo-free region, respectively. This leads to the following cost functions to be minimized:

\[ J_1 = (V_i - V_i')^T W_i (V_i - V_i') + \sum_{p=1}^2 (V_p - V_p')^T W_p (V_p - V_p') + (V_b - V_b')^T W_b (V_b - V_b), \]

where primes denote observations; vectors \( V_i, V_p, \) and \( V_b \) represent the analyzed radial velocities in space seen by the transmitter, the \( P \) bistatic passive receivers, and the background, respectively; and \( T \) stands for the transpose; \( W_i, W_p, \) and \( W_b \) are weighting matrices.

In this study, the background is not horizontally homogeneous as in MCZ01 but is represented by a linear wind that fits a time series of monostatic observations, as described in section 3. As we will see in the following, the use of that linear wind as a background shows great improvements in the forecast, because it better represents the mesoscale flow surrounding the storm. To perform a comparison with the multiple-Doppler retrieval, a single-Doppler analysis has also been undertaken. In this experiment, the term concerning the \( P \) passive receivers has not been taken into account and the linear wind has been applied everywhere, giving information about the tangential wind.

The anelastic continuity equation is used as a strong constraint, the discrepancies between the vertical velocities deduced from the upward integration and from the downward integration (denoted \( w_{\uparrow} \) and \( w_{\downarrow} \), respectively) being also minimized. This leads to an additional cost function:

\[ J_2 = \sum_{xyz} [(w - w_{\downarrow})^T W_{w}(w - w_{\downarrow})], \]

where \( xyz \) is the entire retrieval domain, \( w = w_{\uparrow} \), and \( W_w \) is the weighting diagonal matrix.

To remove data noise, a horizontal smoothing constraint is also applied on each of the three wind components (called \( J_3 \)). To avoid the propagation of information from the background through the multiple-Doppler areas by the smoothing constraint, the same method used in MCZ01 has been applied here (see their Fig. 4 associated with section 3b). This method is based on the properties of the conjugate gradient method for minimization: for all points in the observed area located near a grid point that belongs to the background, the gradient of the cost function associated with the smoothing constraint with respect to the control variables is neglected. The 3D wind field analysis is obtained by minimizing the total cost: \( J = J_1 + J_2 + J_3 \).

b. Contribution of the linear wind

Besides the fact that the linear wind analysis provides a realistic approximation of the mesoscale flow surrounding the system, its use as a background field in the dynamical retrieval shows a marked benefit when compared with the use of a horizontally homogeneous wind field derived from the multiple-Doppler areas by the smoothing constraint, the same method used in MCZ01 has been applied here (see their Fig. 4 associated with section 3b). As depicted in Fig. 5, the difference between the retrieved radial velocity as seen by the monostatic receiver and the observed one is by far better in the case where the linear wind is used as background field, with a maximum absolute difference in the main convective cell of 0.5 m s\(^{-1}\) versus more than 4 m s\(^{-1}\) in the sounding case. The regional analysis, from which the sounding was taken, is much less representative of the situation than is the linear wind obtained by the best least squares fit to 10 successive observations of radial velocity.

Furthermore, this linear wind coupled with single-Doppler information allows for the retrieval of a 3D wind flow, which is consistent with bistatic radar data. Figure 6 shows a horizontal cross section of the retrieved wind circulation for each case and shows that the algorithm used in single-Doppler mode permits the retrieval of convective activity within the cells of strong precipitation. However, the convection is less extensive.
Fig. 5. Horizontal cross sections of the difference field between the retrieved radial velocity and the radial velocity observed by the monostatic receiver (isocontour every 1.5 m s$^{-1}$, starting at −0.5 m s$^{-1}$ for negative values, which are plotted as dashed lines, and at 1 m s$^{-1}$ for positive values) and of the retrieved relative wind field (arrows every four grid points) for different backgrounds: (a) the hodograph plotted in Fig. 3b and (b) the linear wind analysis.
c. Thermodynamic retrieval

After having analyzed in time and smoothed the three wind components, the temperature perturbation $T'$ and the perturbation $q'$ of the nondimensional pressure $q = \ln(P/P_0)$ ($P_0$ is the reference pressure: 1000 hPa) are retrieved by minimizing an additional cost function with $(q', T')$ as the only control variables and with the three momentum equations used as weak constraints. These two thermodynamic variables are those used in MC2 and are expressed as follows:

$$
T(x, y, z, t) = T^* + T'(x, y, z, t) \quad \text{and} \quad (13)
$$
$$
q(x, y, z, t) = q^*(z) + q'(x, y, z, t). \quad (14)
$$

These three values are determined in section 2c and the hydrostatic profile $q'(z)$ defined by

$$
\frac{\partial q'(z)}{\partial z} = \frac{g}{R T^*} \left[ T^* + T'(z) \right]. \quad (15)
$$

where $R$ is the gas constant for air and $g$ is the acceleration caused by gravity.

Protat and Zawadzki (2000) have shown the robustness of this thermodynamical retrieval analysis for a comparable case of a shallow summer storm. The associated momentum checking parameters, which are commonly used as an indicator of the temperature and pressure perturbation quality, display excellent scores, with values below 0.015. This result indicates very low errors on the retrieved fields.

d. The humidity field

1) MIXING LAYER

In this region (below 750-m altitude), the relative humidity is calculated from the refractivity index $N$ deduced from ground targets. The three-dimensional thermodynamic fields are known as a result of the retrieval process. The water vapor pressure $e$ throughout the mixed layer is calculated from (1), and the saturated water vapor pressure $e_s$ is computed from Bolton’s (1980) formula:

$$
e_s = 6.11 \exp \left( \frac{17.27 T'}{T' + 235.86} \right). \quad (16)
$$

The relative humidity (RH) is then deduced from

$$
\text{RH} = 100\left(\frac{e}{e_s}\right). \quad (17)
$$

The values of RH are therefore subject to errors in the refractivity data themselves and in the retrieved thermodynamic fields. Errors in the refractivity measurement are mainly due to multipath propagation through refractivity contrasts, pulse delay trough hydrometeors, beam bending, and processing errors. However, Fabry and Creese (1999) have shown that these errors are nor-
Fig. 7. Retrieved ground-level relative humidity field (isocontours every 4%) and surface observations at 0100 UTC 26 May 1997 [the top number is the local temperature (°C), and the bottom one is the relative humidity (%)]. The second set of contours represent the geography of Montreal Island and the Saint Lawrence River.

mally small (except in the case of anomalous propagation), and the main source of error in the quantitative moisture estimate is the temperature variability. Protat and Zawadzki (2000) have used the momentum checking analysis to show that the thermodynamical retrieval method used herein leads to very weak errors in the retrieved fields, which indicates that the error in the diagnosed humidity field should be low.

To validate the retrieved RH values, comparisons at ground level with in situ measurements performed 30 min later can be seen in Fig. 7. These comparisons between the two datasets are very good: the strong gradient located west of the precipitating system (with values from 42% to more than 68%) is indeed observed with even stronger values (14%–60%). In the rest of the domain, the retrieved humidity overestimates the measurements by about 10%, which can be explained by the temporal gap between the two datasets. In the regions for which $N$ is unavailable, the relative humidity deduced from the environmental sounding is taken instead, with a value of 69.2%. The use of this index allows also for pockets that are more humid than the environment below the storm to be retrieved, with RH above 76%. By providing these more humid conditions, the measurements of $N$ increase the available potential energy of the precipitating system, which favors the triggering of the convection. This behavior leads in our case to a more realistic forecast, that is, a forecast in better agreement with the radar observations, as is shown in section 5c.

2) THE REST OF THE TROPOSPHERE

The same hypotheses as in MCZ01 are employed: in the precipitating regions above the level of free convection (LFC) every updraft is assumed to be saturated, whereas in the downdraft an empirical formulation between the downward motion $w$ (m s$^{-1}$) and RH is used:

$$\text{RH} = 10.9w + 91.8.$$  \hspace{1cm} (18)

Below the LFC and within the precipitating region, RH is computed by considering that a particle is following the dry adiabat. Elsewhere the humidity given by the nearby sounding is taken. The specific humidity is then deduced from RH and through the calculation of the specific humidity at saturation.
e. Initial fields of hydrometeors

The interpolated reflectivity between the two scanning times located in the bistatic coverage area is used to diagnose the liquid-rain \( q_r \) and ice-crystal \( q_i \) mixing ratios (g kg\(^{-1}\)) using the empirical formulations of Hane and Ray (1985) and Rogers and Yau (1989), respectively:

\[
q_r = 10^{(Z - 43.1)/17.5} / \rho \ 	ext{and} \ 
q_i = 0.26 \times 10^{(Z - 40)/16} / 0.45 / \rho
\]  

(19)  

(20)

where \( Z \) denotes the radar reflectivity (dBZ) and \( \rho \) is the air density.

MCZ01 have shown that very rapidly the model produces a reasonable amount of liquid cloud \( q_r \) and graupel \( q_g \) mixing ratios because the time constant of the associated microphysical processes is short. Thus, the need to initialize these two quantities may not be that critical. Their initial value is therefore taken as nil. However, the formation of ice crystals is a slow process, and consequently a simple computation of \( q_i \) from (20) shows great benefits for the forecast of stratiform precipitation.

5. Results

a. Simulation method

The same grid mesh and horizontal domain as were used for the retrieval are used here, with a time step of 6 s. Above the last vertical level used in the retrieval (7 km for the momentum level), the sounding defined in section 2c is applied uniformly up to the model lid, which is at 25-km altitude. We assume that the mesoscale flow in the region surrounding the storm does not present significant variations during the 1-h forecast, and consequently the lateral boundary conditions are kept constant. A band of five grid points in width along the lateral boundary is used to nest the model during the integration.

b. Forecast of the precipitation pattern

At the initial time (0029 UTC), the part of the system sampled within the bistatic coverage area is composed of three different cells (Figs. 8a,e). The two main cells, C1 and C2, are part of a convective line oriented along a SW–NE axis and are characterized by strong precipitation depicted by reflectivity values of up to 45 dBZ. As shown in PZC01, this system is very shallow, with the cloud tops reaching 5 km. The wind retrieval shows a greater convective activity within C1, which apparently is at its mature stage, with a maximum updraft of up to 6 m s\(^{-1}\) at 3-km altitude, whereas the developing C2 reaches one-half of this value in a much smaller area (Fig. 6a). A large region of more-stratiform precipitation extends northward of these cells. A third cell, C3, located in the eastern part of the sampled system, shows weaker convective activity (maximum updraft of 1.4 m s\(^{-1}\)) and moderate precipitation (around 35 dBZ). Monostatic radar observations show that this cell starts to dissipate at this moment. Thus, this system represents a great challenge for nowcasting purposes: two interacting cells, one developing and one in its mature stage, and a third isolated one, which is decaying.

During the first 30 min of the forecast, the simulated system bears a striking resemblance to the radar observations (Fig. 8). First, the advection speed of the simulated system is in agreement with the observed displacement of the system, which propagates approximately at 4.5 m s\(^{-1}\) in the southeast direction. That result shows that the mesoscale flow deduced from the linear analysis is in agreement with the displacement of the system. Moreover, C1 is progressively decaying and merges with C2 after 10 min of integration, the latter becoming wider, with reflectivity reaching 45 dBZ after 30 min. As explained in PZC01, this feature is due to the liquid precipitation within C1 that creates a cold downdraft through evaporation. This “rear-flank” downdraft produces a density current afterward that propagates toward C2, reinforcing the low-level convergence. The model also captures well the progressive decay of C3 and its slower movement relative to the convective line formed by C1 and C2. As a matter of fact, after 30 min of the forecast, C3 merges with the main system with the observed timing. Because the initial weak convective activity within C3 is quickly inhibited, the decrease in reflectivity is simply due to the fall of the initial liquid rain and ice crystals. Another interesting point is the slight increase of the stratiform precipitation (\( \sim 3 \) dBZ) throughout the simulation that is also observed. This stratiform precipitation is the result of the melting of ice crystals advected from the first two cells.

As already noticed in the case presented in MCZ01, the first 10 min of simulation are characterized by a slight decrease of precipitation before its reinforcement as the model generates new precipitation. This is linked to the relaxation time of the different microphysical processes.

The forecast initialized from the single-Doppler experiment shows interesting features (Fig. 9). The merging of C1 and C2 is less evident, but the simulation represents well the motion of C1 toward C2 and their gathering in the extreme southern part of the system. This is probably due to the fact that the retrieved updraft area within C1 is less extensive, less correlated with the reflectivity, and shows weaker intensity (Fig. 6b). Furthermore, C3 has in this case the same advection speed as the main system and does not merge as in the multiple-Doppler experiment.

c. Performances in terms of nowcasting

During the first 40 min of simulation, the performance of the forecast is evaluated by the normalized mean-square error \( E \):
which is the ratio of the mean-square difference between the forecast and the observation to the total variance of the observed data, and by the correlation coefficient $C$, which describes the proportion of the total variance in the observed data that can be explained by the forecast:

$$E = \frac{\sum (f - o)^2}{\sum (o - \bar{o})^2}, \quad (21)$$

$$C = \frac{\sum (o - \bar{o})(f - \bar{f})}{\sqrt{\sum (o - \bar{o})^2} \sqrt{\sum (f - \bar{f})^2}}. \quad (22)$$

Both parameters are computed on horizontal surfaces and an overbar indicates a horizontal average. The best forecast is obtained when $E$ is small and $C$ is close to 1. If the mean-square error is as large as the variance of the observed data, then $E = 1$. If $E > 1$, then the observations are better described by their mean than by the forecast. To quantify the contributions of the bistatic radar network and the refractivity index for the short-term forecast, those statistics are also applied to the single-Doppler experiment (referred to as SD in the following and which includes refractivity data), to the simulation initialized without the use of the refractivity index to diagnose the moisture in the boundary layer (NO-N and which includes bistatic data), and to a common nowcasting method, namely, the Lagrangian persistence (LP).

The results for the multiple-Doppler experiment (CNTRL) displayed in Figs. 10 and 11 show good skill in the forecast and better scores for the four experiments. After 40 min of simulation, the reflectivity patterns at 800 and 650 hPa show a normalized error $E$ of less than 60% (>100% for LP) with a correlation index $C$ of around 75% (~40% for LP). The forecast of the radial wind is also good at 650 hPa with $E$ of less than 42% (135% for LP) and $C$ of around 80% (21% for LP), but it is poorer at 800 hPa. At this level, $E$ reaches 65% (102% for LP) and $C$ reaches 60% (28% for LP) at the end of the experiment, which is mainly related to the larger initial condition error from the retrieval.

At 650 hPa, ignoring the refractivity index leads to much lower scores for the reflectivity field when compared with CNTRL and SD, with $E$ being above 100% and $C$ being around 48% for NO-N, which is still better than LP. At 850 hPa, however, NO-N performs closer to CNTRL and is always better than SD ($E \sim 65\%$ and $C \sim 72\%$ for reflectivity; $E \sim 62\%$ and $C \sim 50\%$ for the radial velocity). It indicates that, for the NO-N experiment, the system is dissipating faster than for CNTRL and SD, a condition that is induced by the resulting lower available energy at low levels.

As expected, the SD experiment shows weaker capability than CNTRL in forecasting the radial velocity ($E = 78\%$ and $C = 42\%$ at 800 hPa), but it still gives better results than LP. The skill in precipitation pattern prediction is somewhat lower than for the multiple-Dopp-
**Fig. 10.** Time series of the (top) normalized mean-square error $E$ and (bottom) correlation $C$ between the monostatic observation and the reference simulation (solid line), the Lagrangian persistence (dashed line), the single-Doppler simulation (dotted–dashed line), and the "no-refractivity" simulation (dashed line) for the (left) reflectivity and (right) radial velocity at 800 hPa. The abscissa represents time (min).

**Fig. 11.** Same as in Fig. 10 but at 650 hPa.
6. Conclusions

The model initialization method of MCZ01 has been improved and was applied to a system of three intersecting convective cells. First, the environmental flow is now specified with a 3D linear wind estimated in a moving frame from several volume scans of single-Doppler data (CLZM02). In addition, the near-surface index of refractivity (Fabry et al. 1997) is used to initialize the humidity field near the ground.

The linear wind results in a much better matching between the environmental wind and the precipitating areas. The smoother transition between the environment and the convective cells avoids undesirable dynamic adjustment at the beginning of the forecast and contributes to a better prediction of the system.

The distribution of humidity in the boundary layer is known to have a great influence on the evolution of individual convective cells. In this study, the humidity field of the lowest model level has been initialized from refractivity measurements. This new information leads to an increase in low-level humidity, which permitted more vigorous storm development in better agreement with subsequent precipitation observations.

The numerical forecast outperformed the Lagrangian persistence method, in agreement with the earlier results of MCZ01. The combination of the linear wind in a moving frame and the monostatic radar radial velocity allowed a single-Doppler wind analysis to be compared with a multiple-Doppler bistatic wind analysis in terms of forecast skill. For the prediction of the radial wind pattern, the forecast with only single-Doppler data was not as good as the one using multiple-Doppler bistatic data, but it did have superior forecast skill over the Lagrangian persistence method. For the precipitation forecast, the difference between single- and dual-Doppler experiments is less significant.

The method is still undergoing refinement. Kessler warm microphysics is now being implemented to assimilated radar reflectivity and refractivity in the 4D-Var weak-constraint algorithm. This change will permit the analysis of 3D humidity and cloud fields consistent with the precipitation observations and can be considered to be a generalization of single-Doppler wind retrieval algorithms that use the conservation equation of reflectivity.

Acknowledgments. The authors are grateful to Rick Danielson from McGill University, who carefully reviewed the manuscript.

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