Improving the Model Convective Storm Quantitative Precipitation Nowcasting by Assimilating State Variables Retrieved from Multiple-Doppler Radar Observations

YU-CHIENG LIOU, JIAN-LUEN CHIOU, WEI-HAO CHEN, AND HSIN-YU YU
Department of Atmospheric Sciences, National Central University, Jhongli City, Taiwan

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ABSTRACT

This research combines an advanced multiple-Doppler radar synthesis technique with the thermodynamic retrieval method, originally proposed by Gal-Chen, and a moisture/temperature adjustment scheme, and formulates a sequential procedure. The focus is on applying this procedure to improve the model quantitative precipitation nowcasting (QPN) skill in the convective scale up to 3 hours. A series of (observing system simulation experiment) OSSE-type tests and a real case study are conducted to investigate the performance of this algorithm under different conditions.

It is shown that by using the retrieved three-dimensional wind, thermodynamic, and microphysical parameters to reinitialize a fine-resolution numerical model, its QPN skill can be significantly improved. Since the Gal-Chen method requires the horizontal average properties of the weather system at each altitude, utilization of in situ radiosonde(s) to obtain this additional information for the retrieval is tested. When sounding data are not available, it is demonstrated that using the model results to replace the role played by observing devices is also a feasible choice. The moisture field is obtained through a simple, but effective, adjusting scheme and is found to be beneficial to the rainfall forecast within the first hour after the reinitialization of the model.

Since this algorithm retrieves the unobserved state variables instantaneously from the wind measurements and directly uses them to reinitialize the model, fewer radar data and a shorter model spinup time are needed to correct the rainfall forecasts, in comparison with other data assimilation techniques such as four-dimensional variational data assimilation (4DVAR) or ensemble Kalman filter (EnKF) methods.

1. Introduction

During the past few decades, numerous methods have been developed for the purpose of improving the accuracy of convective-scale nowcasting (0–3h) by assimilating radar data into a high-resolution numerical model. The pioneer work of Gal-Chen (1978, hereafter G78) showed that the thermodynamic parameters (i.e., pressure and temperature perturbations) can be inferred from the radar-derived three-dimensional winds, and these fields play an important role in correctly initializing a numerical model. Lin et al. (1993) first applied the concept of G78 to initialize a numerical model using radar-synthesized winds and retrieved thermodynamic fields. In their work, efforts were made to design a procedure by which one can smoothly fill in missing wind data. Their simulated storm shows good agreement with the observations. Crook (1994) developed two methods to initialize the flow in the data-void area and tested the sensitivity of the G78 method to the tendency terms, time smoothing, length of assimilation window, errors in the velocity fields, sloping terrain, and the non-hydrostatic terms. The retrieval and data-filling methods developed in Crook (1994) were applied to observed gust-front cases in Crook and Tuttle (1994), but the wind fields were obtained through a less accurate reflectivity-based Tracking Radar Echos by Correlation (TREC) technique. They found that the numerical forecast of surface winds, surface convergence, and temperature fields can be improved over persistence forecast (meaning a forecast in which the wind field is assumed to be constant in time) by 30%, 25%, and 28%, respectively. Weygandt et al. (2002) adopted the G78 method in conjunction with a single-Doppler velocity retrieval scheme developed by Shapiro et al. (1995) to initialize a numerical model. Their study...
indicated that the general storm evolution could be well predicted within a period of 35 min. Zhao et al. (2006) presented that significant improvements can be achieved in the three-dimensional wind forecasts by assimilating the flow field obtained from a three-and-a-half-dimensional variational data assimilation (3.5DVAR) system (Xu et al. 2001), along with the thermodynamic variables retrieved by a scheme similar to G78 into the U.S. Navy’s Coupled Ocean–Atmosphere Mesoscale Prediction System (COAMPS).

Recently, the first author of this manuscript designed a variational-based multiple-Doppler three-dimensional wind synthesis method (Liou and Chang 2009; Liou et al. 2012), which possesses several advantages over the traditional geometric approach (see section 2a). To fully explore the potential of the G78 thermodynamic retrieval technique in improving the model rainfall now-cast, this study combines the aforementioned advanced wind analysis method and a moisture/temperature adjustment scheme with the G78 algorithm, and formulates a sequential process by which the meteorological state variables can be either observed or retrieved and then utilized to reinitialize a high-resolution model. The aim is to evaluate the impact of this process on the model prediction, focusing particularly on the improvement of the short-term (~3 h) quantitative precipitation now-casting (QPN) skill in the convective scale. In addition, since the solution from G78 is subject to a horizontal constant, which can be determined by an in situ measurement of the pressure or temperature at each altitude, experiments with this additional information available through sounding observations in the analysis domain are conducted. When the in situ observations are not available, the feasibility of using the model outputs as an alternative is investigated. The unobserved model state variables, based on the design of the G78-type assimilation system, are retrieved instantaneously from the Doppler radar wind measurements—they are not obtained by assimilating the radar data into a model—then generated through model internal adjustment over a period of time integration. Thus, the model spinup time can be greatly reduced. For this reason, it will be demonstrated in this study that fewer model spinup time can be greatly reduced. For this reason, it will be demonstrated in this study that fewer

2. Methodology

a. Multiple-Doppler wind synthesis method

The Doppler-radar-observed radial velocity is merely the projected component of the wind field along the radar beam. Techniques of using single-Doppler radar to recover the unobserved cross-beam wind components have been developed since the 1990s (e.g., Sun et al. 1991; Shapiro et al. 1995; Xu et al. 1995; Liou and Luo 2001). On the other hand, when data from more than one radar are available, numerous methods of using multiple-radar (usually two) measurements to reconstruct a full three-dimensional wind field have also been developed since the late 1960s by adopting the traditional geometric approach (e.g., Armijo 1969; Ray et al. 1975; Doviak et al. 1976; Brandes 1977; Ray et al. 1978), or more recently the variational approach (e.g., Scialom and Lemaitre 1990; Protat and Zawadzki 1999; Shapiro and Mewes 1999; Gao et al. 1999, 2004). Through a special treatment of the mass continuity equation immediately above the topography, techniques for recovering wind fields over terrain can be found in Georgis et al. (2000), Chong and Cosma (2000), Chong et al. (2000) and in Bousquet et al. (2007, 2008a,b) using airborne or ground-based radars.

In this research, we employ a variational-based multiple-Doppler three-dimensional wind synthesis method from Liou and Chang (2009) and Liou et al. (2012). The wind fields are obtained by variationally adjusting the solutions to satisfy a series of constraints, which include the geometric relation between the Cartesian winds and the multiple-radar radial velocity observations, anelastic continuity equation, vertical vorticity equation, background wind, and spatial smoothness terms. The primary advantages of this method are as follows: (i) the winds along the radar baseline can still be well recovered; (ii) the resulting three-dimensional flow fields satisfy a simplified vertical vorticity equation, and thus can be used directly for diagnosing vorticity budget, and optimizing the thermodynamic retrieval (Protat and Zawadzki 2000); (iii) data from any number of radars can be easily merged; (iv) the immersed boundary method (Tseng and Ferziger 2003) is incorporated to take into account the topographic forcing, so the wind fields can be synthesized over complex terrain; and (v) the background wind field, which can be obtained from a combination of the sounding observations, outputs from another mesoscale model, and/or the reanalysis data from operational centers, is used to fill in the areas where no radar data are available. This is an effective way to resolve the problems associated with radar data-void regions, which are often present near the ground and outside the storm boundary.
b. A modified thermodynamic retrieval algorithm

The traditional thermodynamic retrieval scheme proposed by G78 is adopted but with the contributions from vapor, cloud, and rainwater included in the buoyancy computation. The algorithm uses the momentum equations:

\[
\frac{1}{\theta_{v0}} \left[ \frac{D\theta}{Dt} - f u + \text{turb}(u) \right] = \frac{-\partial \pi'}{\partial x} = -F, \tag{1}
\]

\[
\frac{1}{\theta_{v0}} \left[ \frac{D\theta}{Dt} + f u + \text{turb}(u) \right] = \frac{-\partial \pi'}{\partial y} = -G, \tag{2}
\]

\[
\frac{1}{\theta_{v0}} \left[ \frac{D\theta}{Dt} + \text{turb}(w) + g q_r \right] = \frac{-\partial \pi'}{\partial z} + g \frac{\theta'}{\theta_0 \theta_{v0}} = -H. \tag{3}
\]

The subscript “0” represents a horizontally homogeneous basic state, from which the nonhydrostatic perturbations are expressed by variables with a single prime. In (1)–(3), \((u, v, w)\) stand for three Cartesian wind components, \(f\) refers to the Coriolis parameter, \(g\) is the gravity, and \(\text{turb}(\cdot)\) denotes a subgrid-scale turbulence parameterization operator that can be parameterized using a simple first-order closure scheme. A normalized pressure \((\pi)\) called the Exner function is employed. It is defined as

\[
\pi = C_p \left( \frac{p}{p_0} \right)^{R/C_p} \tag{4}
\]

where \(p\) is the pressure, \(p_0 = 100\) kPa, \(R\) is the gas constant, and \(C_p\) is the specific heat capacity at a constant pressure. The potential temperature, virtual potential temperature, and virtual cloud temperature perturbation are represented by \(\theta, \theta_{\text{vir}},\) and \(\theta'_c\), respectively. The latter two quantities are defined by

\[
\theta_{\text{vir}} = \theta(1 + 0.61q_{\text{ws}}), \tag{5}
\]

\[
\theta'_c = \theta' + (0.61q_{\text{ws}} - q_c)\theta_0, \tag{6}
\]

where \(q_{\text{ws}}\) stands for the perturbation of the water vapor mixing ratio from its basic state \((q_{\text{w0}})\), and \(q_c\) is the cloud water mixing ratio. In (3), \(q_r\) refers to the rainwater mixing ratio. According to Sun and Crook (1997), it can be estimated using the relationship with radar reflectivity \((\eta\) in dBZ) by

\[
\eta = 43.1 + 17.5\log(\rho q_r), \tag{7}
\]

where \(\rho\) is the air density (replaced by \(p_0\) in this study). Once the three-dimensional air motion is known through a multiple-Doppler radar synthesis, the values of \(F, G,\) and \(H\) can be obtained. It should be pointed out that only a warm rain process is considered in the thermodynamic retrieval and moisture/temperature adjustment scheme. The computation can be improved by taking into account the cold rain process using the hydrometeor classification algorithm suggested in Gao and Stensrud (2012).

In G78, (1) and (2) are first employed to variationally search for a set of \(\pi'\), which minimize the difference between \(\partial \pi'/\partial x\) and \(F\), as well as \(\partial \pi'/\partial y\) and \(G\). This is equivalent to solving a Poisson equation for \(\pi'\):

\[
\frac{\partial^2 \pi'}{\partial x^2} + \frac{\partial^2 \pi'}{\partial y^2} = \frac{\partial F}{\partial x} + \frac{\partial G}{\partial y} \tag{8}
\]

subject to the Neumann boundary conditions \(\partial \pi'/\partial x = F\) and \(\partial \pi'/\partial y = G\) along the east–west and north–south boundaries, respectively. Owing to the use of the Neumann boundary conditions for solving (8), the unique solution from (8) is \(\pi' = \langle \pi' \rangle\), where angle brackets represent a horizontal average. G78 pointed out that, from a purely mathematical point of view, a single point of independent in situ observation of the pressure at each horizontal layer is sufficient to determine the vertical profile of \(\langle \pi' \rangle\), from which the three-dimensional \(\pi\) can be derived. Once \(\pi\) is obtained, it is substituted into (3) to calculate \(\theta'_c\) directly. Note that this procedure is different from what was originally proposed in G78, in which the computation involved the horizontally averaging of (3). In G78, aircraft observations are suggested as a choice for providing the in situ measurement over the region overlapping with radar signals. Since aircraft missions are not always available in daily operations, in this study we assess the impact of applying the extra information obtained from sounding measurements on the retrievals and the following model forecast. When in situ observations are not available, the feasibility of utilizing the model forecast results instead is also examined.

It is worth mentioning that there are a number of studies that have attempted to overcome the problem associated with this unknown horizontal constant. For example, in Roux (1985) and Roux (1988), a simplified thermodynamic equation is employed by neglecting the evolution and subgrid-scale diffusion of the potential temperature. In their methods, the heat source/sink term is estimated based on certain assumptions. As a result, the pressure and potential temperature perturbations are solved up to a volumewide constant, which can be deduced from a single point of independent observations somewhere in the retrieval domain. In Liou (2001) and Liou et al. (2003), the heat source/sink term is considered as a retrievable variable so that the pressure
gradients and temperature perturbations can be inferred from the wind measurements.

It should also be pointed out that Weygandt et al. (2002) applied the Dirichlet condition by setting the pressure perturbation along the boundaries to be zero while solving (8). This assumption is, however, suitable only when the precipitation system is well inside the analysis domain. It is also noticed that the thermodynamic retrieval scheme introduced in this section establishes a direct linkage between dynamic and thermodynamic fields. The same purpose is achieved in Xiao et al. (2005) through a so-called Richardson equation. However, the derivation of the Richardson equation involves the assumption of hydrostatic balance, which may not be appropriate for the convective-scale data assimilation as presented in this study. Ge et al. (2012) also incorporated a diagnostic pressure equation into a storm-scale three-dimensional variational data assimilation (3DVAR) system to couple different model variables so that a more dynamically consistent analysis can be obtained. Their studies revealed that the use of this pressure equation can reduce the spinup time of the precipitation and improve the model forecast of the storm evolution.

c. A moisture/temperature adjustment scheme

It was shown in Crook (1996) that the development of convection is highly sensitive to the moisture amount and structure in the boundary layer. Hu et al. (2006) developed a sophisticated cloud analysis procedure by which one can retrieve the amount of the hydrometeors and adjust the in-cloud temperature and moisture. This procedure, in conjunction with a 3DVAR scheme for analyzing the radial velocity data, allowed the model to accurately capture the key characteristics of the main tornadic thunderstorm taking place during the 28 March 2000 Fort Worth, Texas, tornado outbreaks. In this study, a simple and yet effective moisture/temperature adjustment scheme is designed based on the concept similar to that suggested in Lin et al. (1993) and Weygandt et al. (2002). That is, we saturate those areas where certain thresholds are satisfied. An iterative approach is formulated to adjust both the temperature and moisture fields. The procedure can be described as follows:

(i) Set \( q'_{\text{wv}} = 0 \) in (6).
(ii) Use the thermodynamically retrieved \( \theta'_c \) from section 2b and the simulated \( q_c \) from a model (this model will be used as the data assimilation platform), one can compute \( \theta' \) from (6), then convert it to temperature \( T \).
(iii) Use the retrieved pressure and temperature at the surface (or lowest level) from section 2b to estimate the dewpoint temperature \( (T_d) \) at the surface, as

\[
T_d = \frac{B}{\ln(Ae/q_{\text{wv}}^0 P)_{\text{sfc}}},
\]

where \( A = 2.533 \times 10^8 \) kPa, \( B = 5.417 \times 10^3 \) K, \( e = 0.622 \), and \( q_{\text{wv}} = q_{\text{wv}}^0 + q_{\text{wv}}' \).

(iv) Estimate the height \( (H) \) of the lifting condensation level (LCL) using the following relation suggested in Rogers and Yau (1989):

\[
H(\text{km}) \approx (T - T_d)_{\text{sfc}}/8.
\]

(v) Saturation is assumed to take place when the radar reflectivity is greater than 10 dBZ, and the height is above LCL. For those saturated grid points, the saturation water vapor mixing ratio is computed. By subtracting the basic state, a new \( q_{\text{wv}}' \) can be obtained, followed by an update of \( \theta' \) in (6).

(vi) If \( \Delta q_{\text{wv}}' \) and \( \Delta \theta' \), the differences between the old and updated \( q_{\text{wv}}' \) and \( \theta' \), are both smaller than prescribed thresholds (in this study, \( |\Delta q_{\text{wv}}'| < 5 \times 10^{-5} \text{kg kg}^{-1} \) and \( |\Delta \theta'| < 1 \times 10^{-2} \text{K} \)), the iteration stops. Otherwise, steps (ii)–(vi) are repeated.

The aforementioned procedure forms an iterative loop. Our tests show that, for any given grid point where the moisture/temperature adjustment is required, the solution can be converged within 10 iterations.

Starting from the radial velocities and reflectivity measured by multiple-Doppler radars, the sequential procedure introduced in this section provides a set of three-dimensional winds, thermodynamic parameters (i.e., pressure and temperature), rainwater, and water vapor within the analysis domain. A model can be initialized based on this set of data and then continue its time integration.

3. Results from OSSE experiments (experiments TRUE and BKGD)

In this section a series of OSSE-type tests is used to study the influence of applying Doppler radar observed and derived parameters on the model’s QPN capability. Table 1 gives a description of the design of each experiment. The Weather Research and Forecasting (WRF) Model is utilized for the simulation and data assimilation experiments. The model domain contains \( 41 \times 41 \) grid points along the horizontal, and 40 \( \sigma \) layers along the vertical direction. The horizontal resolution is 2.0 km. The background field is determined according to Weisman and Rotunno (2000), with the thermodynamic profile characterizing an environment of moderate instability, and the
hodograph representing a quarter-circle shear profile. A warm bubble with the maximum temperature perturbation reaching 3.0 K is superimposed on the background field. Warm rain microphysical process is used in all OSSE experiments.

Figure 1 shows the evolution of this storm. It splits into a right- and a left-moving storm at about $t = 50$–$60$ min, owing to the interaction between the mean wind shear with the updraft (Rotunno and Klemp 1982). The surface rainfall begins at about $t = 60$ min, as illustrated by the 5-min accumulated precipitation in Fig. 2. At $t = 140$ min, both storms appear about to leave the analysis domain (Figs. 1e and 2c). The evolution of this splitting storm is used as the “true” natural atmosphere (named experiment TRUE). A second simulation (experiment BKGD) is conducted by reducing the maximum temperature perturbation to 0.5 K and the moisture to half that of TRUE. It should be pointed out that by applying these changes, the convective available potential energy (CAPE) dropped from 2300 J kg$^{-1}$ in the TRUE run to 80 J kg$^{-1}$ in experiment BKGD. Owing to the weak initial perturbation and drier environment, the storm does not grow until a very late stage in the simulation ($t \sim 85$ min, see Fig. 7). Experiment BKGD represents an unsuccessful simulation of the storm, but it can still provide certain background information (e.g., cloud water mixing ratio) for the retrievals.

a. Testing of the retrieval and initialization procedure (experiment CNTL)

The purpose of the OSSE experiments introduced in this and sections 3b and 3c is to examine the accuracy of the sequential retrieval/reinitialization procedure introduced in section 2, and explore the impact on the rainfall forecast of initializing the model using retrieved parameters under different situations. Thus, the values of $F$, $G$, and $H$ in (1)–(3) are estimated based on the TRUE-generated three-dimensional wind field throughout the analysis domain. In experiment CNTL, an in situ sounding measurement is also assumed to be available inside the domain to determine the value of $\langle p' \rangle$ at each horizontal plane. Figure 3 compares the true and retrieved pressure, potential temperature, and water vapor perturbations at $z = 4.75$ km and $t = 60$ min. It is obvious that at this moment, the precipitating system has split into two storms, where one finds relatively lower pressure, warmer potential temperature, and higher moisture. These features are successfully recovered by the retrieval algorithm. It is noticed that the retrieved moisture field illustrates an evident boundary (Fig. 3f). This is because the adjustment scheme involves a set of thresholds, which in principle does not activate the moisture modification immediately outside the storms where the radar reflectivity is too low.

Owing to the availability of the in situ sounding measurement of the pressure at each altitude, the vertical structure of the pressure, potential temperature, and water vapor fields can be retrieved without ambiguity. Figure 4 displays the true and retrieved results over a north–south-oriented vertical cross section along $x = 28$ km. The retrieved fields are in good agreement with their true counterparts. The right-moving storm locating at $y \sim 36$ km, characterized by an air column of stronger updrafts (not shown) than the left-moving one, is associated with lower pressure and warmer potential temperature. The true moisture fields (Figs. 4e,g) from

<table>
<thead>
<tr>
<th>Expt</th>
<th>Description</th>
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<tbody>
<tr>
<td>TRUE</td>
<td>Simulation of a splitting storm; used as the true atmosphere</td>
<td>S</td>
</tr>
<tr>
<td>BKGD</td>
<td>Simulation of a weaker and drier storm, representing an unsuccessful model forecast; also used to provide background information for unretrievable parameters</td>
<td>S</td>
</tr>
<tr>
<td>CNTL</td>
<td>A control run with complete wind fields and sounding data available to estimate $\langle p' \rangle$; used as a verification of the retrieval/reinitialization procedure</td>
<td>S</td>
</tr>
<tr>
<td>NoSND</td>
<td>Similar to CNTL, but assuming no sounding data, and $\langle p' \rangle$ is provided by BKGD run</td>
<td>S</td>
</tr>
<tr>
<td>NoSND2</td>
<td>As in NoSND, but the retrieval/reinitialization procedure without sounding data is applied twice</td>
<td>S</td>
</tr>
<tr>
<td>NoQV</td>
<td>As in CNTL, but the moisture field is not adjusted</td>
<td>S</td>
</tr>
<tr>
<td>Err_wind</td>
<td>As in CNTL, but perturbations are implemented to imitate errors in wind fields</td>
<td>S</td>
</tr>
<tr>
<td>WRF_only</td>
<td>A pure model simulation of the SoWMEX IOP 8 heavy rainfall event; the model is initialized at 0600 UTC, followed by a 9-h simulation until 1500 UTC</td>
<td>R</td>
</tr>
<tr>
<td>WRF+rdr_MK</td>
<td>Simulation from WRF_only is updated at 1200 UTC by retrieved state variables using data from three radars; Ma-Kong sounding is also available for estimating $\langle p' \rangle$</td>
<td>R</td>
</tr>
<tr>
<td>WRF+rdr_PT</td>
<td>As in WRF+rdr_MK, but the Ping-Tong sounding is used for estimating $\langle p' \rangle$</td>
<td>R</td>
</tr>
<tr>
<td>WRF+rdr_MP</td>
<td>As in WRF+rdr_MK, but $\langle p' \rangle$ is estimated by averaging two $\langle p' \rangle$ profiles obtained from Ma-Kong and Ping-Tong soundings</td>
<td>R</td>
</tr>
<tr>
<td>WRF+rdr_NoSND</td>
<td>As in WRF+rdr_MK, but $\langle p' \rangle$ is provided using the pressure field from WRF_only</td>
<td>R</td>
</tr>
</tbody>
</table>
TRUE exhibit a “multiple cell” structure, which is effectively recovered in experiment CNTL (Figs. 4f,h) but with smaller amplitudes. From Fig. 4, it is realized that due to the use of a simple retrieval approach, the retrieved vapor field is not expected to reach a precision comparable to that of the retrieved pressure and temperature fields. Nevertheless, the information of the moisture is still very useful in rainfall forecasts, as will be demonstrated later in section 3c. The consistency between the true and retrieved fields also provides verification of the finite difference scheme used to compute $F$, $G$, and $H$ from wind measurements, the programming of the thermodynamic retrieval method, as well as the iterative procedure in the moisture/temperature adjustment algorithm.

In experiment CNTL, the winds from the TRUE simulation and the associated retrieved state variables from the aforementioned procedure are applied to reinitialize the model simulation from experiment BKGD at $t = 60$ min, followed by a 120-min time integration. Figures 5 and 6 depict the distribution of radar reflectivity at $z = 4.75$ km and 5-min accumulated rainfall at the surface, respectively. Compared to their true counterparts depicted in Figs. 1 and 2, the feature of the splitting storms is well captured. The rainfall forecast is also consistent with the true evolution, both quantitatively and qualitatively. Figure 7 illustrates the time variation of the averaged (over grid points) 5-min accumulated rainfall. It can be seen that experiment CNTL immediately captures the intensity and tendency of the precipitation after the first data assimilation. The rainfall produced by the CNTL experiment is close to the true simulation during the first 50 min, but a significant overforecast takes place after the first hour.

The spatial correlation coefficient (SCC) between the true and forecast precipitation pattern is calculated and displayed in Fig. 8a. Since the radar reflectivity is directly used to estimate the rainwater amount, the correlation reaches nearly one at the beginning, then gradually decreases with time, but remains at the level of 0.6 at $t \sim 160$ min, or approximately 100 min after the reinitialization. The commonly used equitable threat scores (ETSs) proposed by Schaefer (1990), with a threshold of 1.25 mm (5 min)$^{-1}$, is plotted in Fig. 8b. The ETS value decreases from 0.8 to 0.3 also at about

**Fig. 1.** Simulated radar reflectivity (dBZ, 15-dBZ interval) at $Z = 5.0$ km from experiment TRUE at (a) 60, (b) 80, (c) 100, (d) 120, and (e) 140 min.

**Fig. 2.** As in Fig. 1, but for the 5-min accumulated rainfall (5-mm interval) from experiment TRUE.
Figure 8c demonstrates that the rms error (RMSE in millimeters) of the model-forecast 5-min accumulated rainfall steadily grows with time. The decrease of the RMSE after $t \sim 150$ min might be attributed to the fact that at this moment the main precipitation systems have exited the boundaries, and most areas of the domain become free of rainfall. This can be illustrated by comparing Fig. 2e with Fig. 6e.

b. Without in situ sounding measurement
(experiments NoSND and NoSND2)

To obtain the thermodynamic field in a three-dimensional space, the G78 method requires at least a single point of in situ measurement of the pressure on each horizontal plane to determine the horizontal average of the pressure perturbation (i.e., $\langle p' \rangle$ or $\langle \pi' \rangle$). This is achievable by releasing a balloon sounding at or near the analysis time. However, in real cases, sounding
data may not be always available, owing to its sparse temporal resolution. Therefore, in this section, an attempt is made to use the outputs at the time of the re-initialization from a model simulation (i.e., experiment BKGD) to estimate \( p' \). This experiment, named NoSND, is equivalent to updating only the pressure perturbation part of the model forecast, while keeping its horizontal averages intact.

The results show that the magnitude of the retrieved pressure (not shown) differs from the true solution generally by about 1–3 hPa. Nevertheless, the spatial distribution of the retrieved pressure still resembles the
“truth” quite well, as revealed in Fig. 9 by comparing the vertical gradient of the pressure perturbation, which is the quantity that is actually needed to compute the temperature [see (3)]. Consequently, as can be seen in Fig. 10, the retrieved potential temperature and water vapor fields are also in good agreement with the true solutions portrayed in Figs. 4c and 4e.

The performance of the model rainfall forecast after reinitialization is also illustrated in Fig. 7. The experiment NoSND immediately captures the intensity of the true precipitation. However, the overforecast of the rainfall amount becomes significantly worse than that in CNTL after \( t \sim 110 \) min. This leads to experiment NoSND2 in which the same retrieval/reinitialization procedure is repeated 30 min later at \( t = 90 \) min. Figure 7 shows that, by performing the same procedure one more time, even without the additional information from extra sounding observations, the overforecast of the rainfall is mitigated. Thus, the accuracy of the rainfall forecast can be effectively improved. Experiment NoSND2 suggests the use of a cycled retrieval/reinitialization procedure if future operational application is to be considered. In this cycled procedure, the outputs from the model forecast at the time steps for the second and following data assimilation can be retained for those parameters that cannot be retrieved by our algorithm, such as mixing ratios of cloud water, ice, snow, graupel, and hail. In addition, the wind field forecasted by the model can also serve as a background flow field to fill in the radar data-void regions.

For the spatial correlation between the true and forecast precipitation pattern, Fig. 8a reveals that in NoSND the SCC values drop to 0.6 at \( t = 135 \) min, approximately 75 min after the model reinitialization. In NoSND2, the SCC value is raised at \( t = 90 \) min. The additional data assimilation helps the model to prolong the similarity of the precipitation pattern between the forecast and the true solution. The same conclusion can be obtained by ETS scores and RMSE from experiment NoSND2 depicted in Figs. 8b and 8c, implying the feasibility and benefits of implementing additional retrieval/reinitialization when no sounding data are available.

Results presented in sections 3a and 3b demonstrate the importance of a reliable \( \langle p' \rangle \) profile in getting...
accurate retrievals. However, when observations are not available (or contaminated as discussed later in section 4), it is a feasible choice to use the model simulated \( \langle p' \rangle \) to replace the observations.

The overforecast of the rainfall, especially after the first hour, appears to be a common phenomenon for all data assimilation experiments (see Fig. 7). The authors have conducted several preliminary experiments in which the criterion to determine saturation is raised by increasing the threshold for radar reflectivity from 10 to 30 dBZ [see step (v) in the moisture adjustment procedure in section 2c]. It seems that the overforecast of the rainfall can be mitigated. It is also found that selecting a different microphysical scheme can affect the rainfall forecast. The investigation of this rainfall overforecast problem is under way, and a more complete discussion will be presented in a future paper.

c. Without moisture/temperature adjustment (experiment NoQV)

The design of experiment NoQV is the same as CNTL, except that the moisture/temperature adjustment scheme introduced in section 2c is turned off. The water vapor perturbation (\( q'_{sv} \)) is simply provided by the model simulation from experiment BKGD without any further modification. In other words, it is attempted to explore the influence of adjusting the water vapor on the model rainfall forecast. Figure 7 reveals that, without the moisture adjustment, the rainfall is significantly underforecast within the first 60 min, followed by an overforecast in the next 30 min. The SCC, ETS, and RMSE from NoQV (Fig. 8) reveal that without the moisture adjustment, the accuracy of the model rainfall forecast becomes inferior to that of experiment CNTL for approximately 40 min after the model reinitialization. The results from this experiment clearly demonstrate the importance of applying the moisture adjustment scheme to specify the water vapor field in the model initial state.

d. Imperfect wind field (experiment Err_wind)

The wind fields used in all experiments discussed in previous subsections are assumed to be perfect. However, due to the observational errors and the limitation of the retrieval technique, the wind fields retrieved by multiple radars would inevitably contain errors. To imitate a more realistic scenario, experiment Err_wind is designed such that it is the same as CNTL, except the wind fields from experiment TRUE are randomly perturbed before being applied for thermodynamic retrieval. The maximum perturbations added to the horizontal and vertical wind components are 1.0 and 0.2 m s\(^{-1}\), respectively. Figures 7 and 8 demonstrate that by using this set of contaminated wind fields, the model’s QPN skill is generally close or slightly inferior to that of experiment CNTL, and comparable to other experiments. Discrepancies between CNTL and ERR_wind in SCC, ETS, and RMSE become significant only after \( t > 140 \) min, or 80 min after the data assimilation. This result indicates that the assimilation procedure proposed in this study does have certain capability to tolerate errors embedded in the wind observations.

4. Results from a real case study—IOP 8 of 2008 SoWMEX field experiment

The performance of the proposed retrieval/reinitialization procedure is further investigated using the data collected during the Southwestern Monsoon Experiment
This field experiment was conducted from May to June 2008 in Taiwan. Its scientific goal is to understand the mechanisms that trigger the intensive precipitations in the South China Sea and Taiwan during the Asian summer monsoon season and to improve the QPN capability in this area. The case selected for this study is intensive observing period (IOP) 8 on 14 June 2008. This particular IOP stands for a prefrontal squall line system, which produced more than 200 mm of rainfall within 24 h in some areas of the southern part of Taiwan island. Tai et al. (2011) pointed out that lack of in situ observations over the surrounding oceans poses great challenges to rainfall prediction in Taiwan. Given this limitation, Doppler radar became the most important data source.

Observational data from three S-band radars are utilized. They are the S-band dual-polarization Doppler radar (S-POL), operated by the National Center for Atmospheric Research, and RCCG and RCKT.
operated by the Central Weather Bureau (CWB) of Taiwan. Figure 11 portrays the geographic positions of these three radars, along with surface and radiosonde stations. Data from the latter two observation networks, combined with the reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF), are used to construct a background flow field. Details of the data interpolation can be found in Tai et al. (2011). This background wind field is needed in the multiple-Doppler velocity synthesis method for filling in the radar data-void regions, which often take place outside the storm boundaries or at the lower layers of the domain.

The configuration of WRF consists of two nested domains (D01 and D02). Both domains include $166 \times 184$ grid points in the horizontal and 46 σ layers in the vertical. The grid spaces are 6 and 2 km for D01 and D02, respectively. The pressure at the model top is 50 hPa. The D02 grid system overlaps the analysis domain to avoid additional interpolation. Five experiments are designed, with the description of each experiment listed in Table 1. In the first experiment (WRF_only), the WRF Model is initialized at 0600 UTC 14 June by the reanalysis data from the ECMWF, followed by a 9-h integration until $t = 1500$ UTC. This experiment, equivalent to the BKGD experiment in the OSSE tests, also provides information of the cloud water and water vapor mixing ratio. The latter is employed as the initial guess for the moisture/temperature adjustment procedure discussed in section 2c.

The in situ pressure observations needed for the thermodynamic retrieval are provided by radiosonde measurements. In this real case study, the soundings released at 1200 UTC at Ma-Kong and Ping-Tong stations (see Fig. 11) are available. In experiment WRF+rdr_MK, in conjunction with the data from the Ma-Kong sounding, the model state in D02 is reinitialized at $t = 1200$ UTC based on the radar observed and retrieved parameters, followed by a 3-h time integration.
until $t = 1500$ UTC. Experiments WRF+rdr_PT and WRF+rdr_MP are the same as WRF+rdr_MK except that they use sounding data provided by the Ping-Tong station and an average of both soundings, respectively. Finally, in experiment WRF+rdr_NoSND, the sounding data are assumed to be unavailable. Instead, the horizontally averaged pressure perturbation profile is obtained from the pure model simulation provided by WRF_only at $t = 1200$ UTC.

Figure 12 illustrates the observed radar reflectivity fields at $t = 1200$ and 1500 UTC, while the forecast fields from all five experiments are shown in Fig. 13. At $t = 1200$ UTC, two major rainbands, labeled by A and B in Fig. 12a, can be identified. Three hours later at $t = 1500$ UTC, rainband A has passed the southern tip of Taiwan, while rainband B stretches southwestward from the land to the ocean. However, it should be pointed out that in Figs. 12a,b, the radar reflectivity extends in the southwestern direction to a shorter distance than the one exhibited by the satellite imagery (not shown), indicating the radar observations of the squall lines are incomplete. This is caused by the limited range of detection of the radar, which also places a constraint on how long the influence from the radar data on the rainfall forecast can last. In a study of the same case, Tai et al. (2011) reported that in their research the positive impacts of assimilating radar data on model QPN can be maintained for about 2 h.

At $t = 1200$ UTC, it can be seen that the weather system in WRF_only is still at an early stage of development, with only a few scattered cells over the ocean (Fig. 13a). However, the system is growing rapidly and forms a major rainband spreading to a wide area with strong intensity at $t = 1500$ UTC (Fig. 13b). The rainbands A and B at $t = 1200$ UTC are better reproduced.
FIG. 13. The model-forecast composite radar reflectivity (max in a column) (dBZ, 15-dBZ interval) from experiments (a),(b) WRF_only; (c),(d) WRF+rdr_MK; (e),(f) WRF+rdr_PT; (g),(h) WRF+rdr_MP; and (i),(j) WRF_NoSND. Results are at (left) t = 1200 and (right) 1500 UTC.
in the other four experiments (WRF+rdr_MK, WRF+rdr_PT, WRF+rdr_MP, and WRF+rdr_NoSND in Figs. 13c, 13e, 13g, and 13i, respectively), which can be attributed to the direct assimilation into the model of the rainwater derived from the radar reflectivity measurements. At \( t = 1500 \) UTC, simulations from all five experiments show the major rainband B in southern Taiwan. However, in WRF+rdr_MK and WRF+rdr_PT (Figs. 13d and 13f), the rainband is broken in the coastal region. Furthermore, with the exception of WRF_only, stronger simulated radar reflectivity is found in the other four experiments, and it stretches farther northeast over the land, while the observed one does not. Rainband B is best simulated in experiment WRF+rdr_NoSND (Fig. 13j), which also turns out to be the only simulation that can reproduce rainband A to the southeast of Taiwan.

Figure 13 (Continued)

Figure 14 depicts the observed (by gauges) and predicted 3-h accumulated rainfall distributions from the five experiments. The observed precipitation is concentrated in two regions, marked by A and B in Fig. 14a, respectively. Precipitation in region B covers a larger area than in region A and exhibits a northeast–southwest-oriented pattern, extending from the center of the island to the coast. The topographic effect is evident, as the rainfall is confined mostly to the west of the north–south-oriented mountains over Taiwan (see Fig. 11). The simulated precipitation B, except in WRF_only, basically shows features similar to the observation near the center of the island but misses the rainfall maximum near the coastal area. In contrast, the precipitation in region A is better simulated in all four reinitialization experiments, although the intensity is overforecasted.
FIG. 14. The 3-h accumulated rainfall distributions over Taiwan from (a) observation, (b) WRF only, (c) WRF+rdr_MK, (d) WRF+rdr_PT, (e) WRF+rdr_MP, and (f) WRF+rdr_NoSND.
Hong and Lim (2006) pointed out that the WRF single-moment 6-class microphysics scheme (WSM6), which is the scheme adopted in this real case study, tends to increase the rainfall amount in high-resolution grid. To deal with this problem, different microphysics schemes will be tested in the future to study whether the overforecasting of the rainfall can be reduced.

A quantitative comparison of the accuracy of the rainfall forecast is shown in Fig. 15, in which the ETSs with thresholds of 6, 15, and 25 mm (3 h)$^{-1}$ are computed for all the experiments. This set of thresholds is approximately equivalent to the official definitions of heavy rain, torrential rain, and extremely torrential rain, respectively, given by the Taiwan CWB. The statistics indicate that the model QPN skill from those experiments equipped by radar data reinitialization outperforms that from the pure simulation WRF_only. The ETS scores from experiment WRF+rdr_NoSND with the 6 and 15 mm (3 h)$^{-1}$ thresholds reach the level of 0.4, and are generally higher than those obtained from WRF+rdr_MK, WRF+rdr_PT, and WRF+rdr_MP, and comparable to the results produced by a four-dimensional variational data assimilation (4DVAR) method reported in Tai et al. (2011). According to the study by Liou and Chang (2009), it is revealed that for pressure retrieval, if a sounding is used to estimate the average pressure perturbation at each altitude, then the accuracy becomes sensitive to the location of the in situ measurement. If the balloon sounding is released in an area of heavy precipitation, characterized by strong radar reflectivity and vertical motion, large errors can be introduced into the estimation. By examining Figs. 11 and 12a, it is found that at $t = 1200$ UTC, the Ma-Kong and Ping-Tong stations are indeed near or well within the principal raining areas. Thus, the observational error, which seems to be inevitable when the sounding measurements are taken in a highly unstable environment, may lead to the degradation of the accuracy of the retrievals, and lower the model QPN capability. Given this condition, a feasible alternative would be to use the model simulated results to replace the observational data and update only the perturbation part of the model simulation. Finally, it is also found that rainfall forecast can benefit from the adjustment of the moisture field, particularly at the early stage after model reinitialization.

Unlike other data assimilation techniques such as the 4DVAR method (e.g., Sun and Zhang 2008), and EnKF (e.g., Snyder and Zhang 2003; Dowell et al. 2004; Tong and Xue 2005; Xue et al. 2006), the proposed algorithm in this study retrieves the unobserved state variables instantaneously using the wind measurements, rather than requiring a long assimilation/adjustment process. As a result, the model spinup time can be effectively reduced. It is demonstrated that fewer radar data (e.g., two radar volume scans) are needed to achieve the purpose of improving the model short-term rainfall nowcast.

5. Conclusions

This study combines an advanced multiple-Doppler radar synthesis technique with the G78 thermodynamic retrieval method and a moisture/temperature adjustment scheme, and formulates a sequential procedure. The products of this procedure consist of the winds, pressure, temperature, water vapor, and rainwater mixing ratio in a three-dimensional space. By using the observed and retrieved state variables to reinitialize a high-resolution numerical model, its short-term quantitative precipitation nowcasting (QPN) skill in the convective scale can be significantly improved.

It is a practical choice to use a balloon sounding to provide the in situ measurements for determining the horizontal average properties of the weather system at each altitude in the G78 retrieval algorithm. However, error in the observations, which appears to be inevitable when the soundings are released in an unstable environment, may lead to a degradation of the accuracy of the retrievals, and lower the model QPN capability. Given this condition, a feasible alternative would be to use the model simulated results to replace the observational data and update only the perturbation part of the model simulation. Finally, it is also found that rainfall forecast can benefit from the adjustment of the moisture field, particularly at the early stage after model reinitialization.
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