Assimilation of Doppler Radar Observations with a Regional 3DVAR System: Impact of Doppler Velocities on Forecasts of a Heavy Rainfall Case

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ABSTRACT

In this paper, the impact of Doppler radar radial velocity on the prediction of a heavy rainfall event is examined. The three-dimensional variational data assimilation (3DVAR) system for use with the fifth-generation Pennsylvania State University–NCAR Mesoscale Model (MM5) is further developed to enable the assimilation of radial velocity observations. Doppler velocities from the Korean Jindo radar are assimilated into MM5 using the 3DVAR system for a heavy rainfall case that occurred on 10 June 2002. The results show that the assimilation of Doppler velocities has a positive impact on the short-range prediction of heavy rainfall. The dynamic balance between atmospheric wind and thermodynamic fields, based on the Richardson equation, is introduced to the 3DVAR system. Vertical velocity (w) increments are included in the 3DVAR system to enable the assimilation of the vertical velocity component of the Doppler radial velocity observation. The forecast of the hydrometeor variables of cloud water (qc) and rainwater (qr) is used in the 3DVAR background fields. The observation operator for Doppler radial velocity is developed and implemented within the 3DVAR system. A series of experiments, assimilating the Korean Jindo radar data for the 10 June 2002 heavy rainfall case, indicates that the scheme for Doppler velocity assimilation is stable and robust in a cycling mode making use of high-frequency radar data. The 3DVAR with assimilation of Doppler radial velocities is shown to improve the prediction of the rainband movement and intensity change. As a result, an improved skill for the short-range heavy rainfall forecast is obtained. The forecasts of other quantities, for example, winds, are also improved. Continuous assimilation with 3-h update cycles is important in producing an improved heavy rainfall forecast. Assimilation of Doppler radar radial velocities using the 3DVAR background fields from a cycling procedure produces skillful rainfall forecasts when verified against observations.

1. Introduction

Doppler radar observation is an important data source for mesoscale and microscale weather analysis and forecasting. Early work on Doppler radar data analysis mainly focused on the following two aspects: rainfall R analysis, using radar reflectivity Z via the Z–R relation (Jorgenson and Willis 1982; Fujiyoshi et al. 1990), and the synthesis of two independent Doppler velocities (Ray et al. 1980, 1981). Techniques to estimate the velocity field by objectively determining the motion of radar echo patterns have also received much attention (Tuttle and Foote 1990). In recent years, assimilation of Doppler radar data for short-term numerical weather forecasting or nowcasting has become a focal point of research (Sun and Crook 2001; Weygandt et al. 2002a,b).

Doppler radial wind observation is usually assimi-
lated in the form of the velocity–azimuth display (VAD) wind profiles in real-time applications (Lindskog et al. 2002; Benjamin et al. 2004). On the research front, more sophisticated techniques have been applied to the assimilation of high-resolution raw radar observations rather than radar-estimated fields, such as VAD wind profiles. Sun and Crook (1997, 1998) reported a study in which Doppler radial velocity and reflectivity observations were assimilated into a cloud-scale numerical model using the four-dimensional Variational Doppler Radar Assimilation System (VDRAS). Gao et al. (1999) developed a three-dimensional variational data assimilation (3DVAR) Doppler radar analysis system for the Advanced Regional Prediction System (ARPS). Weygandt et al. (2002a) used a technique that combines a single-Doppler wind retrieval algorithm in a study to initialize an observed supercell storm. Although these studies have shown promising results, their applications are limited to isolated convective systems that have relatively weak synoptic-scale forcing. In this paper, we examine the impact of radar data on convective systems that are associated with significant synoptic-scale forcing.

In recent years, the National Center for Atmospheric Research (NCAR), in partnership with the Korea Meteorological Administration (KMA) and Seoul National University (SNU), has developed and implemented a regional 3DVAR system (Barker et al. 2003, 2004) at KMA, in an attempt to replace KMA’s optimal interpolation (OI)-based Regional Data Assimilation and Prediction System (RDAPS). The fifth-generation Pennsylvania State University–NCAR Mesoscale Model (MM5) is the forecast component of RDAPS. In this study, we assimilate Doppler radial velocities from KMA’s Jindo Doppler radar data using the 3DVAR system. There are several technical and scientific challenges in such an undertaking. First of all, the radar data are normally at the resolution of 1 km or higher. Yet, at this time, the highest grid resolution of the current KMA’s RDAPS system is 10 km. A technique of data thinning (with the radar observations at a reduced resolution, compatible with the analysis system) has to be developed. Second, achieving data quality control is a very important step before radar data are assimilated into a 3DVAR system. Some undesired radar artifacts, such as ground clutter and anomalously propagated (AP) clutter, sea clutter, range folding, velocity folding, and other noise have to be removed or corrected. These errors are embedded in the normal weather returns, so properly recovering or removing them is essential to the success of the data assimilation. Third, the error variance of the Doppler radar data needs to be determined and specified in order to assimilate the radar data observations effectively, together with other sources of information.

Although there are challenges, radar data assimilation could be very promising for short-range numerical weather prediction. The purpose of this study is to examine whether Doppler radar data assimilation in MM5’s 3DVAR has the potential to increase the accuracy of mesoscale analysis and numerical weather prediction over the Korean Peninsula. A prefrontal rainband observed by the Jindo radar on 10 June 2002 is used for the investigation. There are two major objectives in this study: one is to further develop the MM5 3DVAR system by assimilating Doppler radar observations, and the other is to investigate the impact of radar observations on the prediction of a mesoscale precipitation system.

To assimilate Doppler radar observations, a number of modifications to the existing 3DVAR system need to be made. 1) The 3DVAR has been modified to include vertical velocity (w) increments in the 3DVAR analysis. This is important when radar data are included in the analysis and for small-scale convective weather systems. 2) Mixing ratios of cloud water (q_c) and rainwater (q_r) are included in the background fields of the modified 3DVAR system. When the 3DVAR system is run in cycling mode, passing q_c and q_r to the next cycle can alleviate the spinup problems for the subsequent forecast. 3) The observation operator for Doppler radial velocity has been developed and tested independently and as part of the 3DVAR system. A series of experiments assimilating KMA’s Jindo radar data for the 10 June 2002 case were carried out. The 3DVAR radar data assimilation system is stable and robust in the cycling mode, and the results from the 10 June 2002 case study are positive.

This paper is organized as follows: Section 2 briefly introduces the Korean Jindo radar data and the preprocessing procedure, including data quality control, data thinning, and simple observation error statistics. In section 3, the 3DVAR system is reviewed and the technique for Doppler radial velocity assimilation in a cycling configuration is described. In section 4, an overview of the selected case is given. The design of the numerical experiments is summarized in section 5. Results from numerical experiments are diagnosed and discussed in section 6. A summary and concluding remarks are given in section 7.

2. KMA Jindo radar data and preprocessing

a. Jindo radar data

Jindo is located at the southwestern tip of the Korean Peninsula. The capability of the Jindo radar is compa-
rable to the Weather Surveillance Radar-1988 Doppler (WSR-88D) radar in the United States. It is an S-band radar manufactured by Gematronik in Germany. The radar has a dual-pulse repetition frequency (PRF) at a four-to-three ratio (600/400 s\(^{-1}\)). The Nyquist velocity (the maximum velocity that can be determined unambiguously) is 31.4 m s\(^{-1}\) and the maximum unambiguous range is 240 km. The data resolution of Jindo radar observations is high, with the gate size of 1 km and a beamwidth of 1°.

The raw radial velocity data are preprocessed before they are used in the 3DVAR system. Nine data levels (with elevations of 1°–9°) are included in the processing. The main steps include data quality control, data thinning, and estimating radar observation errors.

b. Data quality control

There are several commonly seen nonmeteorological returns in the Jindo raw radar data, including ground clutter, anomalously propagated ground clutter, second-trip echo, sea clutter, and other noise. For this study, we interactively edited the radar data using NCAR SOLO software (Oye et al. 1995) to conduct the data quality control. Each scan was carefully examined in order to identify unwanted radar echoes. These unwanted echoes were either recovered (e.g., velocity folding) or removed (all other unwanted returns).

Data quality control is an important step in data assimilation. Too many bad-quality data could ruin the 3DVAR analyses. We conducted 3DVAR experiments without removal of the unwanted radar data. As expected, the minimization of the 3DVAR system does not converge well. Information from the bad-quality data entered the 3DVAR minimization, which could make it fail to converge or produce large analysis departure from other good observations. In the operational environment, an objective approach for Doppler radar data quality control is necessary.

c. Data thinning

Radar data are sampled on radar spherical coordinates (range, azimuth, and elevation) with a resolution that is much higher than that of the KMA RDAPS system (10 km). One strategy is to process the data to a regular grid at a resolution that is compatible with the analysis system. In this study, the radar data are thinned to the Cartesian grids with the same map projection as the model before being injected into the 3DVAR system. This reduces redundant data (especially near the radar) and high-frequency features that cannot be resolved by the numerical model.

The thinning of Korean Jindo radar data is performed using NCAR’s Sorted Position Radar Interpolation (SPRINT) and Custom Editing and Display of Reduced Information in Cartesian Space (CEDRIC) software, developed by Mohr and Vaughan (1979) and Mohr et al. (1981). Data for each Cartesian grid are interpolated using the surrounding eight points from the four beams (two on either side, above, and below). Each volume of data is analyzed at the same time. To get rid of grid data that might be affected by noise during the interpolation, a local standard deviation of the eight points used in the interpolation is calculated and the radial velocity data with a standard deviation greater than 14 m s\(^{-1}\) are removed (The threshold of 14 m s\(^{-1}\) is chosen because the radial velocity histogram dips at 14 m s\(^{-1}\)). Spatial data filtering (with the influence radius of 2 km) is performed for the grid radar data to remove small-scale features that cannot be represented in the model analyses.

d. Estimate of the radar observation errors

We use the standard deviation calculated in SPRINT during the interpolation to represent the observation errors. Because the four adjacent data points, each representing a pulse volume, are used to perform the interpolation, the standard deviation computed in SPRINT represents the radial velocity errors in meters per second. The horizontal distribution of the standard deviation represents the error structure. However, larger values are found due to some voids of the raw radar data. Empirical rescaling of the calculated errors is done before the error statistics are used in 3DVAR. The Gaussian distribution of the errors is assumed at each level during rescaling, and the maximum error is set to 3 m s\(^{-1}\). The spatial observation error correlations that are possibly present in the raw data, and also are introduced during the data-thinning procedure, are ignored. We believe data thinning is necessary, which can result in a greater benefit even if the spatial error correlations are neglected. After the thinned observations and related errors are calculated, they are converted to the 3DVAR input format.

3. The 3DVAR system with Doppler radial velocity assimilation

a. Brief description of the 3DVAR system for use with MM5

The 3DVAR system developed by Barker et al. (2003, 2004) is used in this study. Its configuration is based on an incremental formulation (Courtier et al. 1994), producing a multivariate incremental analysis for pressure, wind, temperature, and relative humidity in
the model space. The incremental cost function minimization is performed in a preconditioned control variable space. The preconditioned control variables are streamfunction, velocity potential, unbalanced pressure, and humidity. The linearized mass–wind balance is used to define a balanced pressure. Following Lorenc et al. (2000), the background error covariance matrix allows for a separate definition of the vertical and horizontal correlation functions. Horizontal filter parameters are a function of the vertical eigenvector. The vertical modes are obtained from the decomposition in EOFs of statistical model forecast error covariance. Statistics of differences between 24- and 12-h forecasts are used to estimate background error covariances via the National Meteorological Center (NMC) method (Parrish and Derber 1992). In this study, the KMA operational forecasts in the month of July 2001 are used to perform the statistics. The typical correlation length scale for wind is about 55 km. After projection onto the vertical modes, three-dimensional fields are normalized by the square root of the eigenvalue of the relevant vertical mode. These normalized fields are then passed through a series of recursive filters that create the smoothing effect of a convolution with a covariance matrix. The current assumption under the application of the filter is that horizontal model forecast error correlations are homogeneous and isotropic. A detailed description of the MM5 3DVAR system can be found in Barker et al. (2003). Applications of the system have been reported in real-time analysis and forecasting (Barker et al. 2004).

b. Vertical velocity increments

To include a capability to assimilate Doppler radial velocity data, the regional 3DVAR system for use with MM5 was modified to include vertical velocity increments. Based on Richardson (1922) and White (2000), a balance equation that combines the continuity equation, adiabatic thermodynamic equation, and hydrostatic relation is derived (see the appendix) and expressed as

$$\gamma p \frac{\partial w}{\partial z} = -\gamma p \nabla \cdot \mathbf{V}_h - \mathbf{V}_h \cdot \nabla p + g \int_z^\infty \nabla \cdot (\rho \nabla h) \, dz, \tag{1}$$

where $w$ is vertical velocity, $\mathbf{V}_h$ is the vector of horizontal velocity (components $u$ and $v$), $\gamma$ is the ratio of specific heat capacities of air at a constant pressure/volume, $p$ is pressure, $\rho$ is density, $T$ is temperature, $c_p$ is specific heat capacity of air at constant pressure, $h$ is height, and $g$ is the acceleration due to gravity. For simplicity, hereinafter Eq. (1) will be referred to as the Richardson equation. Linearizing Eq. (1) by writing each variable in terms of a basic state (overbar) plus a small increment (prime) gives

$$\gamma p \frac{\partial w'}{\partial z} = -\gamma p' \nabla \cdot \mathbf{V}_h - \gamma p \nabla \cdot \mathbf{V}_h - \mathbf{V}_h \cdot \nabla p'$$

$$- \mathbf{V}_h \cdot \nabla p + g \int_z^\infty \nabla \cdot (\rho \nabla h) \, dz$$

$$+ g \int_z^\infty \nabla \cdot (\rho \nabla h) \, dz. \tag{2}$$

The basic state (overbar) variables satisfy Eq. (1). They also satisfy the continuity, adiabatic, and hydrostatic equations. The linear Eq. (2) is discretized, and its adjoint code is developed according to the code of the linearized equation. The correctness of the adjoint check following the method proposed by Navon et al. (1992) is verified.

The Richardson equation is chosen because of the following reasons: (a) It is a higher-order approximation of the continuity equation than the incompressible continuity equation or anelastic continuity equation, and the computation is affordable. (b) It can build an efficient linkage between dynamic and thermodynamic fields because the thermodynamic equation is directly involved in the derivation. The analysis fields should be more balanced than using a simple incompressible continuity equation or anelastic continuity equation. (c) In the Richardson equation, the local derivative of air density is dropped from the continuity equation by assuming a hydrostatic and adiabatic atmosphere. It, therefore, avoids the difficulties in the implementation of the continuity equation in the 3DVAR system, which is not designed to take local time derivates into account. Although the four-dimensional variational data assimilation (4DVAR) can handle the time derivates with integrations, it is much more expensive and complicates than 3DVAR. It must be noted that the Richardson equation (with adiabatic assumption) can still induce errors for a heavy rain event where latent heat release and evaporation are important. However, in the 3DVAR cycling procedure, the influence of latent heat release, evaporation, and other microphysical processes is reflected in the model forecast. The 3DVAR cycling uses the model forecast as the first guess for the next cycle. This can alleviate the problem. In the future, it is necessary to further assess the impact of the adiabatic assumption on the 3DVAR analyses by comparing the adiabatic and diabatic Richardson equations in the 3DVAR system.
c. Inclusion of background \( q_c \) and \( q_r \) in the 3DVAR system

In the regional 3DVAR system, the background fields can be MM5 input (analysis), or MM5 forecasts. Usually the MM5 input (analysis) does not contain cloud water and rainwater fields. However, if the MM5 3DVAR is set up for a continuous update cycle, the inclusion of cloud water and rainwater mixing ratios \( q_c \) and \( q_r \) in the analysis is possible. With cloud water and rainwater produced by the previous cycles, inclusion of background \( q_c \) and \( q_r \) in the 3DVAR system enables the information of these variables to be passed on to the next cycle. This can reduce the time that is required for cloud water and rainwater spinup when the model is integrated from the analysis as part of the cycling procedure. Moreover, observation operators for Doppler velocity and reflectivity require inclusion of cloud water and rainwater information. In the Doppler radial velocity operator, rainwater terminal velocity is included, and terminal velocity is calculated based on the rainwater mixing ratio (Sun and Crook 1998). In this paper, the regional 3DVAR system is modified to include background cloud water (\( q_c \)) and rainwater mixing (\( q_r \)).

d. Observation operator for Doppler radial velocity

The observation operator for Doppler radial velocity is

\[
V_r = \frac{u}{r_i} \frac{x-x_i}{r_i} + \frac{v}{r_i} \frac{y-y_i}{r_i} + (w-v_r) \frac{z-z_i}{r_i},
\]

where \((u, v, w)\) are the wind components, \((x, y, z)\) are the radar location, \((x_i, y_i, z_i)\) are the location of the radar observation, \(r_i\) is the distance between the radar and the observation, and \(v_r\) is the terminal velocity. For radar scans at nonzero elevation angles, the fall speed of precipitation particles has to be taken into account. There are different ways to calculate terminal velocity. Here, we use the algorithm of Sun and Crook (1998) to calculate terminal velocity \( V_r \) (m s\(^{-1}\)),

\[
v_r = 5.40 a q_r^{0.125},
\]

where \(q_r\) is the rainwater mixing ratio (g kg\(^{-1}\)). The quantity \(a\) is a correction factor defined by

\[
a = \left( p_0 \bar{p} \right)^{0.4},
\]

where \(\bar{p}\) is the base-state pressure and \(p_0\) is the pressure at the ground.

4. Synoptic overview of the rainfall case

The case used in this study is a rainfall event accompanying a cold front that moved southeastward and was associated with a cyclone. At 0000 UTC 10 June 2002, the cyclone was located in northeast China, with a central sea level pressure (CSLP) of 990 hPa. During the following 12 h, the cyclone moved southeastward slowly, with no change in its intensity (Fig. 1). The Ko-
The Korean Peninsula was in the warm sector of the cyclone, and the cold front was moving southeastward, approaching South Korea at 1200 UTC 10 June 2002 (Fig. 1). A prefrontal rainband accompanying the cold front caused heavy rainfall in South Korea.

The rainband moved over the KMA Automatic Weather Station (AWS) network at around 0600 UTC 10 June 2002. The KMA AWS network recorded maximum 1-h rainfall of 34 mm at 1500 UTC 10 June 2002. The observed maximum 3-h rainfall were 51.5 mm at 1500 UTC and 58.8 mm at 1800 UTC 10 June 2002 (Figs. 2a and 2b), respectively. Figure 2 shows that the maximum rainfall was located at the southwestern tip of Korea at 1500 UTC but moved inland to the northeast at 1800 UTC 10 June 2002. This rainband moved out of South Korea by 0000 UTC 11 June 2002.

The rainfall structure at 1500 UTC (Fig. 2a) indicates that there are two rainbands. This is supported by a radar reflectivity mosaic that was captured by the Korean radar network at 1200 UTC 10 June 2002 (Fig. 2c). The two-rainband structure is clearly identified in the radar observations. The southern rainband (with a maximum 3-h rainfall of 51.5 mm), located in the southwestern tip of Korea, is covered by the Jindo radar.
5. Experimental design

The KMA RDAPS system employs two domains (Fig. 3). The inner grid has a resolution of 10 km, while the outer grid has a resolution of 30 km. The number of horizontal grid points of the (inner) domain 2 is 160 × 178, covering the Korean Peninsula and surrounding area. The two-domain forecast models are one-way nested, with the boundary conditions of the inner domain provided by the forecast of the outer domain model. In the vertical, there are 33 sigma levels. The model top is at 50 hPa. Main model physics include the Kain–Fritsch cumulus parameterization (Kain and Fritsch 1993), Reisner-1 microphysics (Reisner et al. 1998), Dudhia’s radiation scheme, and the medium-range forecast (MRF) PBL parameterization (Hong and Pan 1996).

In the outer domain, initial and lateral boundary conditions are from the KMA global analysis with a 1.875° latitude × 1.875° longitude resolution as the first-guess field and are enhanced by the conventional observational data with 3DVAR. The initial conditions for the inner domain are analyzed using the 3DVAR system with the background fields nested down from the outer domain, and assimilating observations from conventional data plus the Jindo radar data. Boundary conditions are also nested down from the outer domain analysis. Our study used the exact same grid configuration as that of KMA’s RDAPS system.

A series of data assimilation experiments are designed and carried out in domain 2. The cold-start backgrounds for data assimilation experiments are nested down from domain 1. Table 1 summarizes the experiment designs. There are three basic experimental categories: the KMA operational run (RDAPS), 3DVAR experiments with only conventional Global Telecommunications System (GTS) data (3DV_C1000, 3DV_C0912, and 3DV_C0700), and 3DVAR experiments with conventional GTS data plus Doppler radar radial velocity data (RDR_C1000, RDRW_C1000, RDR_C0912, and RDR_C0700). The difference between RDR_C1000 and RDRW_C1000 is that no vertical velocity increments are included in RDRW_C1000 during assimilation. The conventions _C1000, _C0912, and _C0700 denote the 3DVAR cold-start times at 0000 UTC 10 June, 1200 UTC 9 June, and 0000 UTC 7 June 2002, respectively (see Table 1). All of the numerical forecasts (following the assimilation) start from 1200 UTC 10 June 2002.

![Fig. 3. Domain configuration for 3DVAR analysis and MM5 forecasting experiments. (Domain 1 has 171 × 191 grid points with a grid spacing of 30 km, and domain 2 has 160 × 178 grid points with a grid spacing of 10 km. The Korea Jindo radar station is shown with an asterisk.)](image)
The purpose of these experiments is to assess the impact of assimilating the Jindo radar radial velocity data on short-range rainfall prediction. Sensitivity experiments are also conducted to assess the impact of vertical velocity increments and the length of the total 3DVAR assimilation period (assimilation window, hereinafter) on the 3DVAR analysis and subsequent forecast.

6. Results

a. Test with a single radar observation

For understanding the propagation of Doppler radial velocity data in the 3DVAR analysis, a single observation test with the Doppler radial velocity at (35.20°N, 125.212°E; 3000 m) for the Jindo radar (located at 34.47°N, 126.33°E; 499 m) is performed. The innovation of this single radial velocity observation is assigned 1 ms

b. Statistics of the 3DVAR analyses with radial velocity assimilation

The 3DVAR system uses the quasi-Newton method (Liu and Nocedal 1989) for its minimization. The convergence criterion is a 99% reduction of the cost function gradient norm. To show the effectiveness of 3DVAR, Table 2 lists statistical root-mean-square errors of the radar data assimilation experiments (RDR_C1000, RDR_C0912, and RDR_C0700) verified against the Korean high-density AWS winds and Jindo Doppler radial velocities before (O-B) and after (O-A) 3DVAR minimization at 1200 UTC 10 June 2002. We can see that the 3DVAR analysis fits the observed radial velocities following the radar data assimilation. The rmses of radial velocities (RMSE_Doppler_R) are reduced by one-half after the minimization, relative to the background first guess. The statistics in Table 2 also show that the fitting to the surface AWS winds (cf. O-A with O-B in RMSE_AWS_u and RMSE_AWS_v) is also improved, especially for the v component.

c. Characteristics of the horizontal and vertical velocity analysis

In this section, we examine the wind and vertical velocity increments that are associated with Doppler radar radial velocity assimilation in order to understand the characteristics and influence of radial velocity on the regional 3DVAR analysis. Figures 5a and 5b show a comparison of 850-hPa wind speed and vector increments between 3DVAR without and with radial velocity assimilation at 1200 UTC 10 June 2002 (experiment 3DV_C1000 versus RDR_C1000). For these experi-
ments, the 3DVAR system was cycled 4 times at 3-h intervals over a 12-h assimilation window (from 0000 to 1200 UTC 10 June 2002). The results indicate that the location of the maximum wind increments occurs further south with the inclusion of the radial velocity data. Furthermore, the wind increment has a stronger northwesterly component in the vicinity of the cold front at 850 hPa. Assimilation of the Jindo Doppler velocities modifies the wind field and gives rise to the increase of the northwesterly wind in the front area. The vertical

![Figure 4](image.png)

**Figure 4.** The 500-hPa 3DVAR analysis increment response of a single observation of radial velocity with 1 m s⁻¹ innovation at 35.20°N, 125.21°E (3000 m) for the Jindo radar site at 34.47°N, 126.33°E (499 m); (a) u, (b) v, (c) w, and (d) T (contour intervals are 0.1 m s⁻¹, 0.1 m s⁻¹, 0.05 cm s⁻¹, and 0.005 K, respectively; negative isolines are dashed).

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**Table 2.** Rmses of Korea AWS winds and Jindo Doppler velocities before (O-B) and after (O-A) 3DVAR analysis at 1200 UTC 10 Jun 2002.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>RMSE_AWS_u</th>
<th>RMSE_AWS_v</th>
<th>RMSE_Doppler_Rv</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>O-B</td>
<td>O-A</td>
<td>O-B</td>
</tr>
<tr>
<td>RDR_C1000</td>
<td>2.2464</td>
<td>1.8556</td>
<td>3.3504</td>
</tr>
<tr>
<td>RDR_C0912</td>
<td>1.9944</td>
<td>1.8632</td>
<td>3.6051</td>
</tr>
<tr>
<td>RDR_C0700</td>
<td>2.1438</td>
<td>1.8374</td>
<td>3.5829</td>
</tr>
</tbody>
</table>
velocity increments in RDR_C1000 show an increased upward motion from the lower to midlevel troposphere in the warm side of the front (Figs. 5c,d).

Figure 6 presents the total vertical velocity fields (background plus increments) at 1200 UTC 10 June 2002, analyzed by RDR_C1000. It can be seen that a zone of southwest–northeast upward motion is produced across the Korean Peninsula. The RDR_C1000 3DVAR vertical velocity analysis at 700 hPa (Fig. 6a) obtained the peak values of 93.75 cm s$^{-1}$ over the west coast of Korea. The peak values of the upward motion zone at 500 hPa (Fig. 6b) is shown over the west and east coasts of Korea (137.1 and 64.3 cm s$^{-1}$, respectively). The total vertical velocity is still dominated by the background field. However, the increments in Figs. 5c and 5d (which are about 10%–15% of the background field) added upward motions over the warm side of the front.
An important result from the assimilation of the radar data is the generation of a new rainband in the forecasts near the southwestern tip of the Korean Peninsula. Figure 7 shows the 3-h precipitation from experiments 3DV_C1000 and RDR_C1000 at 1500 and 1800 UTC 10 June 2002, respectively. Without radar data assimilation, experiment 3DV_C1000 produces a single rainband in the 3-h rainfall at both 1500 and 1800 UTC 10 June 2002 (Figs. 7a,b). As compared with the observations (Figs. 2a,b), the rainband of 3DV_C1000 is predicted too be farther north and much slower than the observations. On the other hand, the experiment RDR_C1000 generates a new rainband ahead at 1800 UTC (Fig. 7d). The newly generated rainband does not show very clearly (just a hint) at 1500 UTC (Fig. 7c), but it becomes stronger at 1800 UTC, while the old rainband behind it gradually diminishes (Fig. 7d). The main rainband of RDR_C1000 at 1500 UTC is still farther north. As the new rainband becomes the main rainband at 1800 UTC, it is closer to the observations (Fig. 2b) than the experiment 3DV_C1000. The rainband replacement process, which is not captured by 3DV_C1000, is simulated in the radar data assimilation experiment (RDR_C1000).

Figure 8 shows the 700-hPa vertical velocity fields of 3DV_C1000 and RDR_C1000 at 1500 and 1800 UTC 10 June 2002, respectively. The major difference between the experiments with and without Doppler radar radial velocity is that 3DV_C1000 predicts only one upward motion band (Fig. 8a), while two upward motion bands are predicted in RDR_C1000 at 1500 UTC (Fig. 8b). Recall that the vertical velocity at the model initial time (1200 UTC 10 June 2002) did not show two upward motion bands in the radar data assimilation experiments (Figs. 6a and 6b). The forecast vertical motion split up at 1500 UTC must result from the initial upward motion in the warm side of the front and horizontal wind modification after Doppler radial velocities are assimilated. The radar observation shown in Fig. 2c supports the two-rainband structure, which is reproduced by the radar data assimilation experiment.

Along the line AB shown in Fig. 8b, the cross section of the vertical velocity and velocity vectors of RDR_C1000 at 1500 UTC is shown in Fig. 9. It is indicated that the two upward motion bands are about 100 km apart at 1500 UTC. Between the two bands, there is a weak descent region. The maximum vertical velocity in the north band reaches 79.13 cm s\(^{-1}\). It is 38.36 cm s\(^{-1}\) in the south band. Both maximum vertical velocities are at around 700 hPa. From Fig. 9, we can also see that the depth of the upward motion for both bands is below 500 hPa. The high troposphere has flat velocity vectors, indicating that the rainfall system of this case is limited to the lower troposphere.

The 700-hPa vertical velocity fields of 3DV_C1000 and RDR_C1000 at 1800 UTC 10 June 2002 are shown in Figs. 10a and 10b, respectively. The two upward motion bands in RDR_C1000 develop into one band at 1800 UTC (Fig. 10b). Comparing Fig. 10a with Fig. 10b, it can be seen that the experiment with Doppler radial velocity assimilation (Fig. 10b) produces a faster move-
ment of the upward motion band than the experiment without radar data assimilation (Fig. 10a). The midpart of the upward motion band in RDR_C1000 is located about 50 km farther southeastward than that in 3DV_C1000 by 1800 UTC 10 June. In experiment RDR_C1000, Doppler velocity assimilation increases the northwesterly wind in the front area (Fig. 5b) and generates upward motion in the warm side of the front at model initial time of 1200 UTC 10 June (Figs. 5c and 5d). This flow pattern is the reason for the faster movement of the upward motion band in RDR_C1000.

Because precipitation is closely related to the upward vertical motion, the predicted rainband also moves faster in the experiment RDR_C1000 with Doppler velocity assimilation (Fig. 7d) than that of 3DV_C1000 without radar data assimilation (Fig. 7b). Although both 3DVAR experiments with (RDR_C1000) and without (3DV_C1000) the assimilation of radar radial velocity data predict that the rainband moves slower than the observations (Figs. 2a,b), the experiment with the radar data assimilation experiment more or less catches up with the speed of the observed rainband. As
a result, RDR_C1000 produces a better rainfall forecast than 3DV_C1000.

e. Assimilation of Doppler velocities without vertical velocity increments

To study the influence of the vertical velocity increments in the MM5 3DVAR system on Doppler radial velocity assimilation, an experiment RDRW_C1000 is carried out. In this experiment, no vertical velocity increments based on Richardson Eqs. (1) and (2) are included in 3DVAR. Therefore, the contribution from vertical velocity in observation operator (3) is removed. Assimilation of the Doppler radial velocity in RDRW_C1000 cannot adjust vertical velocity. There is also no feedback to the horizontal wind increments from the vertical velocity component in the observed radial velocity.

Figure 11 shows the 850-hPa wind speed and vector increments from RDRW_C1000 at 1200 UTC 10 June 2002. The distribution is similar to the experiment RDR_C1000 (Fig. 5b), but the magnitude of wind increments in RDRW_C1000 becomes smaller than in RDR_C1000 (Fig. 5b). The maximum wind speed increment in RDR_C1000 is 8.524 m s\(^{-1}\); it is 7.469 m s\(^{-1}\) in RDRW_C1000. From this comparison, we can conclude that the vertical velocity component in the Doppler radial velocity observation not only adjusts directly the vertical velocity in the analysis, but also influences the horizontal wind analysis. Without vertical velocity increments in 3DVAR, there is no adjustment of vertical velocity, and the influence from the vertical velocity component of the radial velocity on the horizontal wind analysis is ignored as well. The inclusion of Richardson’s equation in the MM5 3DVAR system builds a bridge between the 3DVAR analysis and the vertical velocity component of the radial velocity observations.

Furthermore, the rainfall forecasts from the RDRW_C1000 analysis have a different distribution from RDR_C1000. Figures 12a and 12b show 700-hPa vertical velocity and 3-h rainfall at 1500 UTC 10 June 2002 by RDR_C1000.
Unlike the distribution in Fig. 8b, vertical velocity does not show two bands of upward motion (Fig. 12a). The rainfall distribution at 1500 UTC 10 June 2002 (Fig. 12b) has only one band. There are mainly two differences in the 3DVAR analyses in RDR_C1000 and RDRW_C1000; one is the presence of vertical velocity in the warm side of the cold front (RDR_C1000 generates upward motion increments, but RDRW_C100 does not), and the other is that RDRW_C1000 produces smaller horizontal wind increments in the front area. These initial differences contribute to the forecast difference of vertical velocity and, hence, the rainfall distribution. The addition of the vertical velocity increments to the 3DVAR analyses produces a better short-range forecast as well.

The influence of background fields

The background field is a critical component of 3DVAR data assimilation. Background fields can have a profound influence on the resulting 3DVAR analyses and on the subsequent model forecast. Both MM5 input (cold start) and output (cycling) can be used as 3DVAR backgrounds. The cycling approach has an advantage in that the resulting analysis (which serves as the initial condition of the model) is more consistent with the forecast model. In this section, we will study the influence of background fields on the rainfall forecast by varying the length of the 3DVAR assimilation window.

We first conduct two experiments with a 24-h assimilation window—one with (RDR_C0912) and the other without (3DV_C0912) the use of radar velocity data. The cold-start time for both experiments is 1200 UTC 9 June 2002, and the 3DVAR cycling is applied every 3 h. The global analyses are used on the lateral boundaries for the forecast of each cycle. Figure 13 shows the 3-h precipitation results from the 3DV_C0912 (without the radial velocity) and RDR_C0912 (with the radial velocity)
ity) experiments at 1500 and 1800 UTC 10 June 2002. A stronger rainband is obtained when the assimilation window is extended to 24 h with or without the use of Doppler radial velocity. The rainband patterns resulting from the 3DVAR experiments with a 24-h assimilation window are closer to the observations than that of the experiments with a 12-h assimilation window. In addition, the rainfall amount in RDR_C0912 is increased with respect to 3DV_C0912. The rainfall intensity forecast is improved with Doppler radar data. The newly developed rainband in RDR_C0912 at 1500 UTC (Fig. 13c) is stronger than that of RDR_C1000 at the corresponding time (Fig. 7c). Without the use of radar data, the new rainband is not developed until 1800 UTC 10 June 2002 in the 3DV_C0912 experiment. However, the southern extent of rainfall at 1800 UTC is better in 3DV_C0912 (Fig. 13b) than in RDR_C0912 (Fig. 13d). Generally speaking, the Doppler radial velocity assimilation experiment RDR_C0912 improves the prediction of heavy rainfall (intensity and location) from the nonradar data assimilation experiment 3DV_C0912, which underestimates the rainfall amount and delays rainband development. The 3DVAR with 24-h continuous assimilation of observations gives a better rainfall forecast. With the Doppler radial velocity assimilation, the wind fields, as well as the vertical velocity (w) field, are reanalyzed in the 3DVAR cycling mode. As a result, the prediction of the rainband is improved. It should be noted that radar data are not continuously available within the 24-h assimilation window (from 1200 UTC 9 June 2002 to 1200 UTC 10 June 2002). In fact, for RDR_C0912, we only assimilate the radar data over a 3-h period from 0900 to 1200 UTC 10 June 2002. The key difference here is a longer 3DVAR assimilation window that allows the background fields to be better developed prior to the availability of the radar data.

From the comparison of Figs. 7 and 13, we can see that continuous assimilation through cycling and the assimilation of radar radial velocity data have a significant impact on the rainfall forecast. We also carried out 3DVAR experiments (3DV_C0700 and RDR_C0700) with a 3.5-day assimilation window, cold starting at 0000 UTC 7 June with a 3-h cycling frequency. With the global analyses on the boundaries, a longer assimilation window resulted in a more intense precipitation forecast.

g. Forecast verifications

To further assess the impact of Doppler radial velocity assimilation on the forecast, we performed verifications against Jindo radar data (radial velocity) and KMA AWS rainfall observations.

Figure 14 is the verification of the first 9-h model forecasts against the Jindo Doppler radar radial velocity forecasts, starting at 1200 UTC 10 June 2002. At the model initial time, the rmse of radial velocity is reduced by more than one-half after assimilating the radial velocity data. During the subsequent 9-h forecast, the rmse of radial velocity for the experiments with radar data
assimilation (RDR_C1000, RDR_C0912, and RDR_C0700) are generally smaller than those without radial velocity assimilations (3DV_C1000, 3DV_C0912, and 3DV_C0700). Two exceptions are the comparisons of 3DV_C0700 with RDR_C0700 at 1800 and 2100 UTC 10 June 2002. As compared with Figs. 14a, 14b, and 14c, in general, the average rmse is reduced when a larger assimilation window is used.

Using KMA high-resolution AWS hourly rainfall observations, we calculated threat scores for the rainfall forecasts. The threat score is widely used to measure precipitation forecast skill. It is defined as

$$TS = \frac{C}{F + O - C}.$$  

where $O$ is the number of events that occurred, $F$ is the number of the events that are forecast, and $C$ is the number of the events that are correctly forecast. If the rainfall amount exceeded a certain threshold at any
AWS site, the AWS site is included in the counting of the number of the events that occurred. The calculation is applied to the AWS observed sites over South Korea. Therefore, the total number of events (including occurred and nonoccurred) is the number of the AWS observation sites \( T \) (\( T = 431 \) in the statistics). The calculation of threat scores was carried out with the same number of \( T \) over the AWS network in verifications.

Figure 15 shows the threat scores for 3-h-accumulated rainfall with thresholds of 5 and 10 mm for 3DVAR experiments with and without Doppler radial velocity assimilation. The threat scores for experiments with radar data assimilation are higher than those without radar data assimilation (RDR_C1000 versus 3DV_C1000; RDR_C0912 versus 3DV_C0912; and RDR_C0700 versus 3DV_C0700, respectively). The positive impact of Doppler velocity assimilation exists mainly in the first 6 h of the forecast. It is not clear if the positive impact can last longer than 6 h, because the main rainfall event moves to the sea and the AWS network captures far less rainfall after 2100 UTC 10 June 2002. However, the threat scores in the first 6-h forecasts clearly suggest that the Doppler radial velocity data assimilation is beneficial to short-range precipitation forecasts. The positive impact of Doppler velocity data assimilation on short-range rainfall forecasts can be seen in almost every pair of experiments with and without radar data assimilation.

Results from these experiments also show the impact of continuous assimilation through update cycles for the rainfall forecast. During the 3DVAR update-cycling procedure, the forecast from the previous cycle serves as the background for the next cycle when the AWS data and Jindo radar radial velocity data are assimilated. When the boundary conditions are specified as being correct, a better dynamic balance among the analysis variables can be achieved with continuous assimilation through the update cycles. The global analy-
ses are used on the lateral boundaries in this study. It is shown that a longer assimilation window can result in a higher threat score (Fig. 15). It must be pointed out that the results could be different in an operational environment when forecasts are used as lateral boundary conditions.

h. Comparisons with KMA operational forecast

The current KMA operational regional data analysis and prediction system (RDAPS) uses the KMA global analysis as the first guess, and is then enhanced by a three-dimensional OI-based objective analysis of the conventional observational data. A nudging technique (Newtonian relaxation) is used to gradually assimilate the analyses into the model over a 12-h period, starting from 12 h prior to the beginning of a forecast period. Figure 16 shows the 3-h rainfall forecasts at 1500 and 1800 UTC 10 June 2002 from KMA’s operational forecast (RDAPS) for the same case (period) with the same resolution and model physics. It can be seen that the predicted rainfall is much smaller than that of the observations (Fig. 2). By comparison, 3DVAR experiments either without or with radar data assimilation (Figs. 7 and 13) produce stronger rainbands, and the rainfall patterns are much closer to those of the observations (Fig. 2). In particular, the 3DVAR experiments with Doppler radial velocity assimilation and a longer assimilation window (Figs. 13c and 13d) produce better rainfall predictions, both in terms of the precipitation amount and the pattern. Results also indicate that the analysis with radar observational information produces sound wind fields, including vertical velocities. As a result, the pattern of the predicted rainband is improved after Jindo radar data are assimilated into the 3DVAR analysis.

Figure 17 presents the threat scores of RDAPS and 3DVAR experiments at 1500 UTC with thresholds of 1, 2.5, 5, and 10 mm. It is noticed that RDAPS demonstrates good forecast skill for light rainfall (thresholds of 1 and 2.5 mm). From Fig. 17, we can see that the predicted rainfall area in RDAPS is generally larger than that in the 3DVAR experiments. However, the rainfall forecast skills from the 3DVAR experiments with Doppler radial velocity assimilation are much better than the forecast skill of RDAPS for heavy rainfall (thresholds of 5 and 10 mm). Improving the heavy rainfall forecast is especially important for operational weather prediction. In this respect, 3DVAR, which can
incorporate unconventional observations (e.g., Doppler radar data), has an advantage.

7. Summary and conclusions

The regional MM5 3DVAR system is further developed to include the capability of assimilating Doppler velocities. The preprocessing of the Doppler radar data includes manual data quality control, data thinning to Cartesian grids, and the estimation of error statistics for the Doppler radar data. The 3DVAR system is modified to include vertical velocity \((w)\) increments in the analyses. The system is also modified to include background of cloud water \((q_c)\) and rainwater \((q_r)\), allowing information on these variables to be passed to the next update cycle when 3DVAR is applied in a cycling mode. The observation operator for Doppler radial velocity is developed and implemented with the 3DVAR system. A series of experiments assimilating KMA Jindo radar data for the 10 June 2002 heavy rainfall case are carried out. Numerical results lead to the following conclusions:

1) The modified 3DVAR system, which includes \(w\) increments and Doppler radial velocity assimilation, produces reasonable wind and vertical velocity analyses in the region where the Doppler velocity data are assimilated. When verified against high-resolution AWS wind observations and Jindo Doppler velocities, the root-mean-square errors (rmses) of the forecast winds (especially in the \(v\) component), initialized from radar data assimilation experiments, are reduced when compared with the experiments without radar data assimilation experiments.

2) The rainfall forecast in the first 6 h from 3DVAR analysis with Doppler velocity data is better than that without radar data when verified against the observed rainfall for all thresholds. When compared with the operational KMA regional forecasts, the 3DVAR experiments produce a better-defined rainband structure. The threat scores with thresholds of 5 and 10 mm in the 3DVAR radar data assimilation experiments are much higher than the KMA operational run. Moreover, 3DVAR experiments with radar data assimilation possess higher skill than experiments without radar data assimilation and KMA operational forecast in the prediction of heavy precipitation, illustrating the positive impact of radar data assimilation.

3) Sensitivity experiments with and without vertical velocity increments in the MM5 3DVAR system indicate that the inclusion of the Richardson equation in 3DVAR builds a bridge between analyses and the vertical velocity component of the Doppler radial velocity observations. Without this bridge, vertical velocity in the MM5 3DVAR could not be analyzed, and the influence from the vertical velocity component of the radial velocity on the horizontal wind analysis is ignored as well. The forecast of rainfall distribution is also degraded without vertical velocity increments in the 3DVAR analyses.

Although our initial attempt in mesoscale 3DVAR assimilation of single Doppler radar radial velocity is encouraging, a considerable amount of effort is required to further improve the system. This includes the development of reflectivity assimilation and refinement of the Doppler radar data quality, as well as the improvement and tuning of the error statistics. To take advantage of radar data at high temporal and spatial resolution, a 3DVAR system at a cloud-resolving resolution is needed, together with other improvements (digital filtering to avoid high-frequency noises, better dynamic balance, etc.). In particular, because of the univariate feature of the humidity analysis in the current 3DVAR system, a method should be developed to constrain the moisture analysis in the 3DVAR analysis.

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APPENDIX

Derivation of the Richardson Equation

The Richardson equation combines continuity, thermodynamic, and hydrostatic relations. From the continuity equation

\[
\frac{d\rho}{dt} + \nabla \cdot \mathbf{V} = 0,
\]  
(A1)

the adiabatic thermodynamic equation

\[
\frac{d\ln \theta}{dt} = 0,
\]  
(A2)
and the hydrostatic relation
\[ \frac{\partial p}{\partial z} = -\rho g, \quad (A3) \]
a balanced equation between dynamic and thermodynamic variables, can be derived according to Richardson (1922) and White (2000). In (A1)–(A3), \( \mathbf{V} \) is wind (components \( u, v, \) and \( w \)), \( p \) is pressure, \( \rho \) is density, \( \theta \) is potential temperature, and \( g \) is acceleration due to gravity.

According to the definition of potential temperature
\[ \theta = T \left( \frac{p_0}{p} \right)^{\frac{\gamma R}{C_p}}, \quad (A4) \]
and the equation of state, we can derive
\[ \frac{d}{dt} \ln \theta = \frac{C_v}{C_p} \frac{1}{\rho} \frac{dp}{dt} - \frac{1}{\rho} \frac{dp}{dt}, \quad (A5) \]
where \( c_v \) and \( c_p \) are specific heat capacities of air at a constant volume and pressure, respectively. For adiabatic atmosphere [(A2)], and with the aid of Eq. (A5), the continuity Eq. (A1) can be rewritten as
\[ \frac{\partial p}{\partial t} + \mathbf{V} \cdot \nabla p = -\frac{C_p}{C_v} \rho \mathbf{V} \cdot \nabla \mathbf{V}. \quad (A6) \]

From the hydrostatic Eqs. (A3) and (A1), we can have the following derivation:
\[ \frac{\partial}{\partial z} \left( \frac{\partial p}{\partial t} \right) = g \nabla \cdot (\rho \mathbf{V}_h) + g \frac{\partial}{\partial z} (\rho w), \quad (A7) \]
where \( \mathbf{V}_h \) is the vector of horizontal velocity (components \( u \) and \( v \)), and \( w \) is vertical velocity. Suppose at the model top (or \( z \approx 0 \)), \( w = 0 \) and \( \partial p/\partial t = 0 \). Integrating Eq. (A7), the hydrostatic equation becomes
\[ \frac{\partial p}{\partial t} = -g \int_{z}^{\infty} \nabla \cdot (\rho \mathbf{V}_h) \, dz + \rho gw. \quad (A8) \]

Substituting Eq. (A8) in Eq. (A6) and expanding the divergence term, we can obtain
\[ -g \int_{z}^{\infty} \nabla \cdot (\rho \mathbf{V}_h) \, dz + \rho gw + \mathbf{V}_h \cdot \nabla p + w \frac{\partial p}{\partial z} = \]
\[ -\frac{C_p}{C_v} \rho \mathbf{V} \cdot \nabla \mathbf{V}_h - \frac{C_p}{C_v} \rho \frac{\partial w}{\partial z}; \quad (A9) \]
that is, with the aid of hydrostatic relation (A3),
\[ \gamma p \frac{\partial w}{\partial z} = -\gamma p \mathbf{V} \cdot \nabla + \mathbf{V} \cdot \nabla p + g \int_{z}^{\infty} \nabla \cdot (\rho \mathbf{V}_h) \, dz, \quad (A10) \]
where \( \gamma \) is ratio of specific heat capacities of air at a constant pressure/volume \( (\gamma = c_p/c_v) \).

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