A mesoscale convective system (MCS) over East China on June 5, 2009 was thoroughly analyzed using an Advanced Regional Prediction System (ARPS) ensemble square root filter (EnSRF) system. The analyzed reflectivity structure, location and intensity compared well with observation, and were substantially better than an experiment without radar data assimilation. The cold pool and wind speed in the convective regions were strengthened. With improved initial conditions, the impact of single-moment (SM), double-moment (DM) and triple-moment (TM) microphysics parameterization (MP) schemes on ensemble forecasts of MCSs was evaluated. The use of multi-moment (MM) MP schemes showed some improvements in neighborhood ensemble probability for reflectivity and precipitation. Quantitative reflectivity and precipitation forecast skills were also improved in MM forecasts, with those of the TM forecast the best.

**KEYWORDS**
ensemble forecast, EnSRF, microphysical parameterization scheme, radar data assimilation

1 | INTRODUCTION

Mesoscale convective systems (MCSs) are severe convective storms often accompanied by disastrous weather conditions, such as dangerous lightning, strong winds, flash floods, large hail and even tornadoes. Thus, accurate prediction of MCSs is crucial for saving lives and property. With increasing computational power, it is possible to analyze and forecast MCS features using numerical weather prediction (NWP) models. One major challenge of storm-scale NWP is the accuracy of initial conditions. Doppler radar observations with high temporal and spatial resolution make them the best platform to probe MCS structure. However, optimal incorporation of such useful data into NWP initialization to minimize errors in initial conditions for MCS investigation is challenging.

The ensemble Kalman filter (EnKF) technique has seen increasing interest in operational centers and research communities because it can dynamically evolve flow-dependent background error covariance and be implemented relatively easily.

For convective-scale radar data assimilation, that covariance, especially cross-covariance produced by EnKF, is important. This is because model state variables not directly observed can be retrieved. During recent years, this approach has been successfully implemented and tested through simulated and real storm cases (Dowell, Wicker, & Snyder, 2011; Johnson, Wang, Carley, Wicker, & Karstens, 2015; Snyder & Zhang, 2003; Tong & Xue, 2005; Wheatley, Knopfmeier, Jones, & Creager, 2015; Yussouf, Mansell, Wicker, Wheatley, & Stensrud, 2013; Zhang, Snyder, & Sun, 2004). EnKF is capable of automatically providing an ensemble of initial conditions that at least theoretically have the proper characteristics for initializing ensemble forecasts. Recently, experimental real-time ensemble predictions based on cycled EnKF data assimilation analyses have also been performed by the Center for Analysis and Prediction of Storms (Xue et al., 2008) during the National Oceanic and Atmospheric Administration (NOAA) Hazardous Weather Testbed Spring Experiments. A storm-scale radar and satellite data assimilation system developed as
part of the warn-on forecast project was also run in real time (Jones et al., 2016; Wheatley et al., 2015).

Although EnKF can provide accurate initial conditions, deficiencies in the NWP model are important in the prediction of convective systems. Model error can become dominant in the integration, even if it begins with accurate initial conditions. One of the difficulties of simulating convective systems is microphysics parameterization (MP) schemes that crucially depend on the assumption of the particle size distribution (PSD) of hydrometeors (Gilmore, Straka, & Rasmussen, 2004). The common bulk-microphysics scheme assumes that PSDs of hydrometeors have a specified functional form during simulation. The function commonly used is the generalized gamma distribution \( N(D) = N_0 D^{\alpha} e^{-\lambda D} \). Here, \( N(D) \) is the number density related to particle diameter \( D \). The intercept \( N_0 \), shape \( \alpha \) and slope parameter \( \lambda \) are parameters that control the distribution shape. Subscript \( x \) represents a specific hydrometeor. In a typical single-moment (SM) MP scheme, \( \alpha \) is often fixed and \( N_0 \) fixed or diagnosed (Wainwright, Dawson, Xue, & Zhang, 2014), whereas mass content is predicted. Double-moment (DM) MP schemes also predict total number concentration (zeroth moment), so both \( N_0 \) and \( \lambda \) can be updated. \( \alpha \) is specified as a constant or diagnosed value (Milbrandt & Yau, 2005a). Triple-moment (TM) MP schemes predict the additional sixth moment of the distribution, which effectively allows \( N_0 \), \( \alpha \) and \( \lambda \) to vary independently.

MM schemes that predict two or more moments can improve the simulation of convective systems compared to SM schemes. It has been shown that an advantage of the MM scheme is its size-sorting effect through different sedimentation of the predicted moments, which cannot be achieved by SM schemes because they use a single fall speed for the entire distribution of a given hydrometeor. Morrison, Thompson, and Tatarskii (2009) found that the DM scheme had better performance in simulating idealized squall lines, with a smaller \( N_0 \) in the stratiform region. Dawson, Xue, Milbrandt, and Yau (2010) showed in idealized simulations of supercells that storm structures and the cold pool were better predicted by the MM rather than SM scheme.

The present study uses the ensemble square root filter (EnSRF; Whitaker & Hamill, 2002) approach to assimilate radar data, for two purposes. First, it provides accurate initial conditions for ensemble forecasting of an MCS. Second, it helps to investigate the impacts of SM, DM and TM MP schemes on MCS prediction in eastern China. The paper is organized as follows. The experimental design is given in Section 2, analysis and various MP simulation results are discussed in Section 3, and summary and conclusions are presented in Section 4.

2 | DATA AND EXPERIMENTAL DESIGN

The Advanced Regional Prediction System (ARPS) EnSRF system (Xue, Tong, & Droegemeier, 2006) was used to analyze and simulate an MCS over east China on June 5, 2009. The MCS, between the Jiangsu and Anhui provinces (Figure A1), was initiated in an environment with a cold vortex over Northeast China. It developed into a long convective line of length 400 km at 0900 UTC. The system lasted for 7 hr and produced reports of frequent lightning, strong winds and large hail. The heaviest rainfall was observed in Jiangsu Province, with a maximum of 69.4 mm in a 3-hr period.

Lateral boundary conditions were provided by the National Centers for Environmental Prediction (NCEP) Global Forecast System, with a resolution of 0.5° × 0.5°. Three domains with one-way nesting were adopted, with horizontal resolutions of 6 (303 × 303 grid points), 2 (503 × 503 grid points), and 1 km (803 × 803 grid points). The model domain has 53 layers in vertical direction with an average vertical spacing of 425 m. The model top is located 22 km above the surface. Data of the S-band radars were subjected to preprocessing that included quality control (despeckling, ground clutter removal and velocity dealiasing; Brewster, Hu, Xue, & Gao, 2005) and horizontal interpolation onto the model grid before data ingest. Observations used for rainfall verification were from an hourly high-resolution (0.1° × 0.1°) merged precipitation product from the National Meteorological Information Centre of China. The model physics configuration included NASA (National Aeronautics and Space Administration) Goddard Space Flight Centre longwave and shortwave radiation parameterization, a two-layer soil model, and a 1.5-order turbulent kinetic energy-based closure scheme. The Kain-Fritsch (Kain, 2004) cumulus parameterization scheme was used only in domain 1. The MP scheme used in domains 1 and 2 was the Lin scheme (Lin, Farley, & Orville, 1983). Values of the fixed intercept parameters used in Lin scheme were \( 8 \times 10^3 \) m\(^{-1}\) for rain \((N_0)\), \( 3 \times 10^6 \) m\(^{-1}\) for snow \((N_0)\) and \( 4 \times 10^4 \) m\(^{-1}\) for hail \((N_0)\).

Two experiments, EXP_DA and EXP_ND, which only refer to the period leading up to the ensemble forecast, were conducted. In the EXP_DA experiment, radar data were assimilated with the EnSRF method. A schematic diagram is shown in Figure A2 to illustrate the assimilation and forecast setup for EXP_DA. In domain 1, the forecast was interpolated to 2 km to provide initial and lateral boundary conditions for the data assimilation cycles. In domain 2, random, smoothed and Gaussian perturbations were added to create a 40-member ensemble. The spatial scales of the perturbations were 8 km in the horizontal and 5 km in the vertical. The perturbations were added to the horizontal wind, perturbation potential temperature and water vapor mixing ratio, with standard deviations of 2 m s\(^{-1}\), 2 K and 1 g kg\(^{-1}\), respectively. Both radar velocity and reflectivity were assimilated every 6 min from 0900 to 1000 UTC on 5 June in domain 2. The observation operator used was that of Jung, Zhang, and Xue (2008). The observation error assumed for reflectivity and radial velocity are 3 dBZ and...
To maintain ensemble spread, multiplicative covariance inflation with a factor of 1.25 was used for the convective region with reflectivity >20 dBZ. Additive perturbations were also added to the ensemble analysis, with SD 0.5 m $s^{-1}$ for horizontal wind, 0.5 K for perturbation potential temperature and 0.5 g kg$^{-1}$ for water vapor mixing ratio. The variables updated in the EnSRF system consists of three velocity, potential temperature, pressure, the mixing ratios for water vapor, cloud water, rainwater, cloud ice, snow and hail, respectively. The second experiment, EXP_ND, was the same as EXP_DA except that no radar data were assimilated.

Then, 3-hr ensemble forecasts through 1300 UTC were conducted based on the final analysis ensemble of EXP_DA. Finally, the analysis and forecast ensemble was interpolated to 1 km to perform 3-hr ensemble forecasts in domain 3. To investigate the impact of various MP schemes on the MCS prediction, three ensemble forecast experiments

FIGURE 1 Composite radar reflectivity (dBZ; a, c, e) and vertical cross section of radar reflectivity (dBZ; b, d, f) along A–B for: observation (OBS, a, b), ensemble mean in domain 2 of EXP_ND (c, d), and EXP_DA (e, f) at 1000 UTC June 5, 2009
were run, using the SM Lin (hereafter referred to as EXP_DSM), DM Milbrandt and Yau (2005a) (MY) (EXP_DDM hereafter) and TM MY (Milbrandt and Yau (2005b) (EXP_DTM hereafter) schemes.

3 | RESULTS

3.1 | Analysis results

In this section, we first examine ensemble mean analyses of composite reflectivity from EXP_DA in domain 2 against EXP_ND and observations (Figure 1). At 1000 UTC, it is seen that the MCS had organized into two convective clusters over Jiangsu and Anhui provinces. At the same time, bow-shaped echoes had formed in southeast Jiangsu Province (Figure 1a). Convection in EXP_ND was not well organized and clearly weaker than observed reflectivity (Figure 1c). In EXP_DA, although the radar echo was slightly stronger than observed, major MCS features were generally captured at the correct location (Figure 1e). To reveal the vertical structure of reflectivity, cross sections along A–B in Figure 1a of observed and two analyzed reflectivities are presented in Figure 1b,d,f. EXP_ND almost completely missed the vertical MCS structure. EXP_DA captured two strong convective cells and stratiform precipitation, though with some underestimation in the height and width of reflectivity 20–30 dBZ. Root mean square innovations, spread of reflectivity and radial velocity are shown in Figure A3.

Surface potential temperature and wind speed differences between EXP_ND and EXP_DA in 1000 UTC analyses are pronounced (Figure 2). Bold black contours indicate reflectivity exceeding 20 dBZ.
The differences are about 4–6 K at the border of Anhui and Jiangsu provinces. The differences of EXP_DA versus EXP_ND are also evident in wind speed. EXP_DA produced stronger wind (maximum 14 m s$^{-1}$) and greater areal coverage of wind speed $>$12 m s$^{-1}$ in the convective regions.

3.2 | Comparison of SM and MM simulation results

Forecasts were first verified for radar reflectivity between 1030 and 1130 UTC using the neighborhood ensemble probability (NEP; Schwartz et al., 2010) method (Figure 3). The neighborhood radius was 6 km. Figure 3a–i shows NEP for reflectivity ($>$ 25 dBZ) at 1030, 1100 and...
1130 UTC for EXP_DSM, EXP_DDM and EXP_DTM. At 1030 UTC, all experiments gave similar patterns and probability, with shape and coverage similar to observed regions of high reflectivity. At 1100 and 1130 UTC, all experiments had some large values of probability away from the observed convective regions. However, EXP_DDM improved prediction of the northern part of the bow echo compared with the other two experiments. EXP_DTM predicted a larger area of high probability in northern Anhui Province than did the other experiments, especially at 1130 UTC (see the boxed area A). For reflectivity >45 dBZ (Figure 3j–r), associated with severe convection, all experiments exhibited larger errors than the 25 dBZ threshold, but EXP_DTM produced the most accurate prediction, particularly at 1100 and 1130 UTC (see the boxed area B).

Figure 4 presents the NEP for 1, 2 and 3-hr accumulated precipitation exceeding 2.5 mm starting at 1000 UTC. For 1-hr accumulated rainfall, all the experiments predicted a wide region of low probability in the observed convective region. The NEP forecast of each experiment was more accurate for 2 and 3-hr accumulated rainfall, EXP_DDM and EXP_DTM produced larger areas of probability than EXP_DSM in the bow echo region, with EXP_DTM being the best.

To quantitatively assess forecast performance for reflectivity in all experiments, four forecast metrics, fraction skill...
score (FSS; Roberts & Lean, 2008), equitable threat score (ETS), probability of detection (POD) and false alarm ratio (FAR) (Mashingia, Mtalo, & Bruen, 2014) were used to analyze results at different thresholds (Figure 5). The neighborhood size of FSS was 6 km.

Statistical verification was performed for reflectivity at 5, 15, 25 and 45 dBZ thresholds using the 3-hr forecast (Figure 5). EXP_DTM produced higher FSS, ETS and POD and lower FAR than the other experiments for all thresholds over the entire forecast period, especially for POD at threshold 15 dBZ. EXP_DDM generally had a slower decrease of FSS, ETS and POD and increase of FAR than EXP_DSM for all thresholds, except for POD at threshold 5 dBZ and t = 120–180 min and POD at threshold 15 and 25 dBZ in the first 10 min. The FSS, ETS and POD declined quickly in the first 40 min for threshold 45 dBZ. However, EXP_DTM still had slightly better scores than EXP_DDM, but much better scores than EXP_DSM, particularly for POD at t = 40–90 min. The highest skill of EXP_DTM for accumulated precipitation persisted for thresholds 1.0, 2.5 and 5 mm, followed by EXP_DDM and EXP_DSM (Figure A4).

### 4 SUMMARY AND CONCLUSIONS

An MCS over eastern China on June 5, 2009 was studied with an EnSRF radar data assimilation approach. The analyzed reflectivity structure from the EnSRF experiment compares well with observation in terms of intensity, coverage and location, and is markedly better than the experiment without radar data assimilation. The analysis shows that the radar assimilation with EnSRF invigorated the cold pool and surface wind in the convective region.

Based on the improved initial conditions, we investigated the impact of various MP schemes on short-term MCS forecasts. Three ensemble forecast experiments were conducted, using the SM MP (EXP_DSM), (DM) MP (EXP_DDM) and (TM) MP (EXP_DTM) schemes.
The neighborhood probability of reflectivity >25 dBZ revealed that EXP_DDM and EXP_DTM generated some improvement over other experiments in the 60–90 min forecast, in both the northern part of the bow echo for EXP_DDM and northern Anhui Province for EXP_DTM. EXP_DTM also yielded a wider area of high probability near observed strong reflectivities >45 dBZ relative to other experiments. High probabilities of EXP_DDM and EXP_DTM were also found in the bow echo region for 2 and 3-hr accumulated rainfall. Quantitative reflectivity and precipitation skills in terms of FSS, ETS, POD and FAR were maximum in EXP_DTM, followed by EXP_DDM and EXP_DSM.

The present study demonstrates the effectiveness of EnSRF in MCS analysis over eastern China using radar data and improvements of the MM MP schemes in ensemble forecasting. However, additional cases and longer forecast periods are necessary to reach more reliable conclusions. In addition, more mechanisms behind the contrasting results of forecasting. However, additional cases and longer forecast periods are necessary to reach more reliable conclusions.
APPENDIX

**FIGURE A1** Model domains and radar locations (black rectangle: area of simulation; circle: the coverage of radar observations; black dot: the four radar stations at Yancheng (9515), Nantong (9513), Nanjing (9250), Heifei (9551))

**FIGURE A2** Initial spin-up forecast, data assimilation cycles and subsequent forecast for the EXP_DA

**FIGURE A3** Root mean square innovations and ensemble spreads for EXP_DA for reflectivity (dBZ) (a) and radial velocity (m s\(^{-1}\)) (b) calculated against Nanjing radar (9250) during the assimilation period
FIGURE A4  FSS (a, e, i), ETS (b, f, j), POD (c, g, k) and FAR (d, h, l) of precipitation of EXP_DSM, EXP_DDM and EXP_DTM for threshold 1.0 mm (a–d), 2.5 mm (e–h) and 5.0 mm (i–l). x-axis is time in minutes, starting at 1000 UTC June 5, 2009. The shaded area is 95% confidence interval.