A Simulated Radar Reflectivity Calculation Method in Numerical Weather Prediction Models

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ABSTRACT: The simulated radar reflectivity used by current mesoscale numerical weather prediction models can reflect the grid precipitation but cannot reflect the subgrid precipitation generated by a cumulus parameterization scheme. To solve this problem, this study developed a new simulated radar reflectivity calculation method to obtain the new radar reflectivity corresponding to the subgrid-scale and grid-scale precipitation based on the mesoscale Global/Regional Assimilation and Prediction System (GRAPES) model of the China Meteorological Administration. Based on this new method, two 15-day forecast experiments were carried out for two different time periods (11–25 April 2019 and 1–15 August 2019), and the radar reflectivity products obtained by the new method and previous method were compared. The results show that the radar reflectivity obtained by the new simulated radar reflectivity calculation method gives a clear indication of the subgrid-scale precipitation in the model. Verification results show that the threat scores of the improved experiments are better than those of the control experiments in general and that the reliability of the simulated radar reflectivity for the indication of precipitation is improved. It is concluded that the new simulated radar reflectivity calculation method is effective and significantly improves the reflectivity products. This method has good prospects for providing more information about forecasting precipitation and convective activity in operational models.

KEYWORDS: Convective parameterization; Mesoscale models; Numerical weather prediction/forecasting; Subgrid-scale processes

1. Introduction

Modern numerical weather prediction (NWP) models offer capabilities to simulate radar reflectivity from the output of NWP models, such as single-level radar reflectivity and composite reflectivity (CR) (the maximum reflectivity in a grid column). These simulated radar reflectivity products are not only a means to display more details of the temporal and spatial characteristics of convective weather systems (Koch et al. 2005) and the thickness and height of clouds but also an important reference to estimate the occurrence and intensity of heavy rainfall events (Kain et al. 2008). By direct comparison with the observed radar reflectivity in real time, these simulated radar reflectivity products from NWP models can help people to better understand mesoscale processes (Koch et al. 2005). Therefore, these simulated radar reflectivity products from NWP models are becoming increasingly popular among weather forecasters.

How is simulated radar reflectivity determined from NWP outputs? Actually, the moist physical process, which is used to describe the mutual conversion between water vapor and various hydrometeors and the corresponding dynamic and thermal impacts in NWP models (Kuo and Reed 1988; Sheng et al. 2003), plays a key role in the calculation of simulated

radar reflectivity. The moist physical process can be described by grid-scale cloud microphysics parameterization schemes and subgrid-scale cumulus parameterization schemes. Grid-scale cloud microphysics parameterization schemes directly forecast the various hydrometeors of clouds and precipitation and describe the mutual conversion between them (Molinari and Dudek 1992). Subgrid-scale cumulus parameterization schemes are an implicit parameterized description and describe the total influence of the convective clouds and their precipitation in the grid on the model atmosphere (Arakawa and Chen 1987; Molinari and Dudek 1992; Chen et al. 2004). Generally, simulated radar reflectivity is computed from the forecast mixing ratios of grid-resolved hydrometeor species of a grid-scale cloud microphysics parameterization scheme, assuming Rayleigh scattering by spherical particles of known density and an exponential size distribution (Smith et al. 1975). Several methods have been developed over the years. Smith et al. (1975) simulated radar reflectivity using some parameters related to precipitation, such as the intercept parameter, the density of water and the rainwater concentration. The simulation of radar reflectivity of realistic rainfall events was performed by Krajewski et al. (1993) and in a complex extension by Anagnosto and Krajewski (1997). They simulated three-dimensional radar reflectivity using a stochastic space–time

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FIG. 1. (a) Forecast 1-h precipitation (mm). (b) Forecast simulated radar composite reflectivity (dBZ).

model of rainfall events and a statistically generated rain drop size distribution (DSD). Haase and Crewell (2000) used mesoscale model output fields of all meteorological parameters, including different types of hydrometeors, to simulate radar reflectivity based on the Lokal-Modell weather forecast model. Koch et al. (2005) simulated radar reflectivity using some model parameters, such as the model forecasting hydrometeor mixing ratio and the density of dry air from the WRF single-moment 5-class microphysics scheme (WSM5) in the Weather Research and Forecasting (WRF) Model, and used the simulated radar reflectivity to analyze mesoscale weather systems.

Rosenthal (1970) pointed out that when the resolution of NWP models reached 5–10 km, then the demand for subgrid-scale cumulus parameterization schemes would be reduced. At present, researchers generally believe that an NWP model in which the horizontal resolution of the grid reaches 3 km or higher can recognize convective-scale precipitation without a cumulus parameterization scheme (Molinari and Dudek 1992; Adlerman and Droegeleier 2002). Therefore, the simulated radar reflectivity from these 3-km or higher horizontal resolution NWP models in which only a grid-scale cloud microphysics parameterization scheme is used plays well.

However, in recent years, a grid resolution of 9–20 km has been widely and commonly used by mesoscale regional NWP models and global NWP models in many countries and research centers. These mesoscale regional and global models cannot directly identify convective-scale precipitation due to their coarse grid resolution. They have to jointly use cloud microphysics and cumulus parameterization schemes to forecast precipitation.

As a result, two types of precipitation, grid-scale precipitation and subgrid-scale precipitation, are forecasted by these models. As mentioned by Anagnosto and Krajewski (1997), their simulated radar reflectivity ignored the variability of subgrid-scale rainfall, which is a nonignorable problem in radar rainfall estimation. Haase and Crewell (2000) also mentioned that their simulation lacked some subgrid-scale rainfall due to the coarse model resolution, and the impact could be quite significant for convective situations. Previous calculation methods of simulated radar reflectivity were mostly based on cloud microphysics theory and resolvable grid-scale precipitation; these methods did not consider subgrid-scale precipitation and could not reflect subgrid-scale precipitation information. Figure 1 shows a forecasting result from the GRAPES model on 18 April 2019. A comparison of the hourly accumulated precipitation forecast 27 h after the initial time (Fig. 1a) with the composite reflectivity (CR) (the maximum reflectivity in a grid column) (Fig. 1b) shows that the model forecasts large amounts of precipitation in Guangdong, China. However, the simulated CR does not match well with the forecasted precipitation, which leads to difficult application of the simulated CR by forecasters. This is a common problem in most models using cumulus parameterization schemes.

To solve this problem and improve the simulated radar reflectivity, we designed a new simulated radar reflectivity calculation method based on the 10-km GRAPES-MESO regional model and obtained a new diagnostic field of radar reflectivity corresponding to grid-scale and subgrid-scale precipitation.

This paper is organized as follows. Section 2 introduces the method, the design of the experiments and the model data. Section 3 analyzes the experimental results, and section 4 presents the conclusions.

2. Methods, experimental design, and model data

a. Forecast model

A regional mesoscale model of GRAPES (GRAPES-MESO) developed by the Numerical Weather Prediction Center of the China Meteorological Administration (Chen et al. 2008) is used in this study. Table 1 shows the configurations of this model. The main features of GRAPES-MESO include a fully compressible dynamic core with nonhydrostatic approximation, a semi-implicit and semi-Lagrangian scheme for time integration, and height-based terrain-following coordinates. The forecast region covers China (15°–65°N, 70°–145°E), and the horizontal resolution of the model is $0.10^\circ \times 0.10^\circ$ (10 km) with 51 vertical levels (the model top is at 10 hPa). The model runs once a day (initialized at 0000 UTC) out to a 48-h forecast length. The lateral boundary conditions and initial conditions of GRAPES-MESO are provided (directly downscaled) from the Global Forecasting System (GFS) developed by the National Centers for Environmental Prediction (NCEP) and the National Oceanic and Atmospheric Administration (NOAA).

b. New radar reflectivity calculation method

Previously, the simulated radar reflectivity calculation method proposed by Koch et al. (2005) was used in the GRAPES-MESO

TABLE 1. Parameter configuration of the GRAPES-MESO model.

Parameter terms	Parameter configurations
Model version	GRAPES-MESO 4.3.0.0
Horizontal resolution	$0.10^\circ \times 0.10^\circ$
No. of vertical levels	50
Initial conditions	NECP Global Forecasting System
Lateral boundary conditions	NECP Global Forecasting System
Model region	$15^\circ\text{--}65^\circ\text{N}$, $70^\circ\text{--}145^\circ\text{E}$ (mainly for the area of China)
Forecast length and start time	48 h, 0000 UTC
Start method	Cold start, and the assimilated cloud initial data are applied
Physical parameterization scheme	Kain–Fritsch (new Eta) (Kain 2004), WSM6 (Hong and Lim 2006), MRF (Hong and Pan 1996), Monin–Obukhov (Beljaars 2010), RRTM (Mlawer et al. 1997), Dudhia (Dudhia 1989), Noah (Wang and Chen 2013)

model. This method uses some cloud microphysics parameters (e.g., the particle intercept, the rainwater mixing ratio and the slope factor) to calculate the radar reflectivity factor as follows:

$$Z_{\text{micro}} = \frac{\lambda_r (\rho q_r)^{1.75}}{N_{0r}^{0.75}} + \frac{\lambda_s (\rho q_s)^{1.75}}{N_{0s}^{0.75}} + \frac{\lambda_g (\rho q_g)^{1.75}}{N_{0g}^{0.75}}, \quad (1)$$

where Z_{micro} is the radar reflectivity factor calculated in the cloud microphysics scheme. The terms λ_r , λ_s , and λ_g represent the slope factors of rain, snow, and graupel particles, respectively; q_r , q_s , and q_g represent the rainwater, snow, and graupel mixing ratios, respectively, all obtained from the model predictions. The terms N_{0r} , N_{0s} and N_{0g} represent the rain, snow, and graupel intercept parameters, respectively; ρ is the density of dry air. After the reflectivity factor Z_{micro} is obtained and transformed using Eq. (2), the equivalent reflectivity Z_e (dBZ) is obtained as follows:

$$Z_e = 10 \log(Z_{\text{micro}}). \quad (2)$$

However, this radar reflectivity does not consider the subgrid-scale precipitation generated by the cumulus parameterization scheme. Therefore, based on the Kain–Fritsch (new Eta) scheme (Kain 2004), we try to design a new simulated radar reflectivity calculation method for subgrid-scale and grid-scale precipitation. According to the Kain–Fritsch (new Eta) scheme, the value of $R_{(ij)}$, which represents the amount of convective subgrid precipitation in an air column at one model integration step, is calculated as

$$R_{(ij)} = Dt \left[\left(\sum_{k=\text{bottom}}^{k=\text{top}} \text{TR}_{(ij,k)} - \sum_{k=\text{bottom}}^{k=\text{top}} \text{TD}_{(ij,k)} \right) \text{Ainc} \right] \frac{(1 - \text{Fb})}{\text{SQ}}, \quad (3)$$

where Dt is the model integration step, Fb is the judgment coefficient (equal to 0 or 1), SQ is the area of one horizontal grid space interval, $\text{TR}_{(ij,k)}$ is the condensation precipitation rate produced by the updraft in each layer of the model, and $\text{TD}_{(ij,k)}$ is the evaporation rate produced by the downdraft in each layer of the model. Here, top is the top layer of the updraft or downdraft, bottom is the bottom layer of the updraft or downdraft, and Ainc is the adjustment coefficient. The value of $R_{(ij)}$ is calculated from the total condensation precipitation rate accumulated from the updraft minus the total evaporation

rate accumulated from the downdraft in an air column and then multiplied by time and the related parameters.

Then, we assume that the subgrid precipitation generated in the cumulus parameterization scheme is similar to that in the real atmosphere. The raindrops in the cloud cannot be held by the updraft and fall when convection develops to a certain height. On the way down, they decrease in size, disappear by evaporation or collide with other raindrops to form large raindrops in the underlying clouds before finally reaching the ground. These assumptions mean that there is also a corresponding single-layer precipitation rate in each layer of the cumulus parameterization scheme. Based on this single-layer precipitation rate, we can obtain the three-dimensional distribution of subgrid precipitation. We refer to this as $R_{\text{cu}(ij,k)}$, which is calculated as follows:

$$R_{\text{cu}(ij,k)} = Dt[(\text{TR}_{(ij,k)} - \text{TD}_{(ij,k)})\text{Ainc}] \frac{(1 - \text{Fb})}{\text{SQ}}. \quad (4)$$

The total precipitation $R_{\text{total}(ij,k)}$ is obtained by the addition of the subgrid precipitation $R_{\text{cu}(ij,k)}$ and grid precipitation $R_{\text{micro}(ij,k)}$ as follows:

$$R_{\text{total}(ij,k)} = R_{\text{cu}(ij,k)} + R_{\text{micro}(ij,k)}. \quad (5)$$

Multiplying the total precipitation $R_{\text{total}(ij,k)}$ by the time t (in this research, one integration step is 60 s; therefore, the time $t = 60$) will obtain the three-dimensional distribution of the hourly total precipitation $R_{\text{total}_h(ij,k,t)}$ as follows:

$$R_{\text{total}_h(ij,k,t)} = R_{\text{total}(ij,k)} t. \quad (6)$$

TABLE 2. Experimental settings for three different Z – R relationships.

Expt name	Setting
crctl	Control experiment, the old calculation method based only on a microphysics scheme
cr200	Improved experiment, the new calculation method, empirical formula: $Z = 200R^{1.6}$
cr300	Improved experiment, the new calculation method, empirical formula: $Z = 300R^{1.4}$
cr355	Improved experiment, the new calculation method, empirical formula: $Z = 355R^{1.26}$

TABLE 3. Summary of deterministic forecasts of binary event sequences (the numbers of observations and forecasts are represented by a , b , c , and d).

Forecast event	Observation events		
	Happen	Not happen	Amount
Happen	a (hit)	b (false alarm)	$a + b$
Not happen	c (miss)	d (negative correct rejections)	$c + d$
Amount	$a + c$	$b + d$	$a + b + c + d = n$

It is assumed that the distribution of the total forecasted precipitation is the same as the distribution of the raindrop spectrum in the actual precipitation. According to the theory of radar quantitative precipitation estimation and the Z - R relationship (Bent 1943; Marshall and Palmer et al. 1948; Morin et al. 2005), the empirical formula is obtained as follows:

$$Z_{\text{total}} = AR_{\text{total}_h(i,j,k,i)}^b \quad (7)$$

where Z_{total} is the new radar reflectivity factor calculated by the above method (units: $\text{mm}^6 \text{m}^{-3}$), and A and b are empirical parameters. Based on Eq. (2), a new equivalent reflectivity factor $Z_{e(\text{new})}$ is given as

$$Z_{e(\text{new})} = 10 \log(Z_{\text{total}}). \quad (8)$$

The new equivalent reflectivity factor $Z_{e(\text{new})}$ calculated in this way not only reflects information on grid-scale precipitation but also reflects information on subgrid-scale precipitation.

c. Experimental design

We launched two 15-day comparative forecasting experiments for two different time periods. The first experimental period was from 11 to 25 April 2019, and the second was from 1 to 15 August 2019. Three different empirical equations were selected to verify the sensitivity of different Z - R empirical relationships. The first empirical relationship ($Z = 200R^{1.6}$) was proposed by Marshall and Palmer (1948). The second empirical relationship ($Z = 300R^{1.4}$) was derived from statistics of deep convective precipitation during the summer months in the United States and is used by weather radar precipitation algorithms in China (Fulton et al. 1998; Yao et al. 2007). The third empirical relationship ($Z = 355R^{1.26}$) considers the connection between different types of precipitation and different wave bands (Meneghini et al. 1989). A sensitivity experimental analysis is carried out separately, and its settings are shown in Table 2.

d. Verification method

Considering that radar reflectivity is a three-dimensional field with a complex structure, forecasters often choose the CR as a reference. The CR is the maximum value of the radar reflectivity of each layer and can reflect the characteristics of the entire three-dimensional radar reflectivity field in a simple and distinct way. Therefore, the CR is chosen

FIG. 2. Daily average precipitation (mm) during the experimental periods of (a) 11–25 Apr 2019 and (b) 1–15 Aug 2019.

as the verification variable in this research. The observed radar reflectivity is obtained from the three-dimensional network mosaic radar reflectivity data from the Doppler weather radar in China (1-km resolution; 72.5°–135.5°E, 18°–54°N) (Wang et al. 2009). Moreover, the observed precipitation data are multisource precipitation grid analysis data (10-km resolution; 69.975°–140.125°E, 14.975°–60.075°N) from the National Meteorological Information Center (Shen et al. 2013). These observed precipitation data are obtained by a two-step merging algorithm of the probability density function (PDF) and optimal interpolation (OI) based on the hourly precipitation observed by automatic weather stations (AWS) in China and retrieved from the CPC morphing technique (CMORPH) satellite data.

The following metrics were used in the verification: the threat score (TS) (Gilbert 1884), the hit rate (HR) (Swets, 1986), the miss ratio (MR) (Mason and Graham 2002), the false alarm ratio (FAR) (Donaldson et al. 1975), and the frequency bias (FB) (Donaldson et al. 1975). We verified the hourly forecast results for the 15-day experiments in two different time periods (11–25 April 2019 and 1–15 August 2019).

Many meteorological phenomena can be seen as a two-category event: either the event occurs, or it does not occur. Table 3 gives the (2×2) possible results of weather forecast events (Hogan and Mason 2012). For binary forecast data series, some metrics are required to verify the performance of the forecast. These indicators are hits (a), false alarms (b), misses (c), and negative correct rejections (d).

FIG. 3. The model region and verification regions.

The TS, HR, MR, FAR, and FB are calculated using the following equations:

$$TS = \frac{a}{a + b + c}, \quad (9)$$

$$HR = \frac{a}{a + c}, \quad (10)$$

$$MR = \frac{c}{c + d}, \quad (11)$$

$$FAR = \frac{b}{a + b}, \quad (12)$$

$$FB = \frac{a + b}{a + c}. \quad (13)$$

A radar reflectivity that reaches 30 dBZ represents a heavy precipitation process when used to estimate precipitation. It is unusual for the radar reflectivity to reach 40 dBZ in our experiment, and therefore, the thresholds of these verification metrics are set to 10, 20, and 30 dBZ. We count the hourly total indicators from the 15-day forecast results and then use these total indicators to calculate the TS, HR, MR, FAR, and FB.

Many precipitation processes occurred in the verification area in South China from 11 to 25 April 2019. This period represents the pre-rainy season or subtropical rainfall and usually marks the establishment of the East Asian summer monsoon (EASM) (Zhu et al. 2011; He and Liu 2016). The daily average observed precipitation from the multisource precipitation grid analysis data (National Meteorological Information Center) during the first experimental period (Fig. 2a) shows little precipitation in Northwest and North China. Most of the precipitation occurred in South China (Fig. 2a). The second experiment is from 1 to 15 August 2019. The EASM prevails during this period, the summer monsoon advances northward to northern China (Zhu et al. 2019), and there are many precipitation processes over all of China. The daily average observed precipitation during the second experimental period (Fig. 2b) shows that the regions of maximum precipitation are in the south, northeast and Central Plains regions of China.

FIG. 4. Radar reflectivity curve as a function of precipitation.

Therefore, different areas are selected for verification. In the first experimental period, the area (97.5°–123.5°E, 20°–40°N) is selected for verification. Considering that the subgrid precipitation generated by the cumulus parameterization scheme often occurred in South China during the experimental period, the verification area is divided into two regions: a southern region (20°–30°N) and a northern region (30°–40°N) (Fig. 3). There was abundant precipitation in the south, northeast and Central Plains regions of China in the second experimental period. Based on the verification region for the first experiment, a northeastern verification region is additionally added (109.5°–135.5°E, 40°–50°N) (Fig. 3).

3. Results

a. Z–R empirical relationship sensitivity experiments

As shown in section 2c, three types of Z–R empirical relationships were studied in this research. We calculated the theoretical radar reflectivity curves with precipitation for these three relationships to analyze the influence of precipitation on the simulated radar reflectivity. Figure 4 shows that the radar reflectivity calculated by $Z = 355R^{1.26}$ is slightly larger than the radar reflectivity calculated by the other relationships when the precipitation is low ($< 5 \text{ mm h}^{-1}$). The three types of radar reflectivity are equivalent when the precipitation reaches 6 mm h^{-1} . The radar reflectivity calculated by $Z = 200R^{1.4}$ is the largest of the three types when the precipitation is $> 6 \text{ mm h}^{-1}$. In general, the differences among the three types of radar reflectivity are subtle; even when the precipitation reaches 30 mm, the reflectivity calculated by $Z = 200R^{1.4}$ is only approximately 2.5 dBZ larger than that calculated by $Z = 355R^{1.26}$ (Fig. 4).

Figure 5 shows the evolution of the hourly TS with time in four forecasting experiments for the three groups of different Z–R relationships and a control group (a total of 15 days of statistical average results from 11 to 25 April 2019, divided into three thresholds). The left-hand column shows the results for the southern region, and the right-hand column shows the results for the northern region. The higher the TS is, the better the forecasting skills, and a perfect forecasting TS is equal to 1.

FIG. 5. Evolution of the TS over time in the improved and control experiments at three different thresholds (11–25 Apr 2019).

In the southern region, it is shown that the TS of the control experiment in the early stage of forecasting (before 6 h) is roughly better than the TSs of the three improved experiments, whereas the TSs of the three improved experiments are significantly better than that of the control experiment in the middle and late stages of forecasting, especially for the 20- and 30-dBZ thresholds (reflecting a heavy precipitation process). However, there is little difference among the TSs of the three improved experiments. In the northern region, the TSs of the three improved experiments are very similar to that of the control experiment, with no significant difference. Based on these verification results, it can be concluded that the impacts of the three different Z - R relationships are similar.

The results of a sensitivity experiment show that the choice of different Z - R empirical relationships has only a weak impact on the experimental results. Based on this conclusion, we selected the relationship $Z = 300R^{1.4}$ as the empirical relationship for the improved experiments and conducted follow-up experiments. This relationship is derived from statistics of deep convective precipitation during

the summer months in the United States (Fulton et al. 1998) and is used by the recent weather radar precipitation algorithms in China (Yao et al. 2007).

b. Case analysis

Two case studies of torrential rain were selected in South China from 18 to 20 April 2019, and 24 to 25 April 2019. We compared the results of the CR and three-dimensional radar reflectivity obtained by our new calculation method with the results obtained by the previous calculation method.

Figures 6a and 6c show the observed 24-h accumulated precipitation from 0000 UTC 18 April to 0000 UTC 19 April and from 0000 UTC 19 April to 0000 UTC 20 April 2019. Based on the distribution and evolution of the observed precipitation, a strong convective weather process occurred in South China from 18 to 19 April 2019, with a short-duration heavy rainfall event (Fig. 6b). The rainfall was relatively scattered, and multiple processes occurred. Torrential rain (maximum 3-h accumulated precipitation of 64 mm) (Fig. 6b) occurred in the south of Hunan Province, the center

FIG. 6. (a) Observed 24-h accumulated precipitation (mm) and (b) observed 3-h accumulated precipitation of the marked station from 0000 UTC 18 Apr to 0000 UTC 19 Apr, (c) observed 24-h accumulated precipitation (mm), and (d) observed 3-h accumulated precipitation of the marked station from 0000 UTC 19 Apr to 0000 UTC 20 Apr 2019.

and south of Jiangxi Province, the northeast of Guangxi Province, the center and north of Guangdong Province, the Pearl River estuary, and the south of Fujian Province. A strong convective weather process occurred again in South China from 19 to 20 April 2019, with a short-duration heavy rainfall event (Fig. 6d). Rainfall occurred in the center and southeast of Guangdong Province, northeast of Guangxi Province, east of Guizhou Province, southwest of Hunan Province, southwest of Chongqing Province, northeast of Sichuan Province, and southeast of Gansu Province.

Figures 7b and 7e–h show the forecasted precipitation, CR and vertical cross section of the three-dimensional radar reflectivity obtained from the 27-h model forecast initialized at 0000 UTC 18 April 2019, respectively. Figures 7a, 7c and 7d show the observed precipitation, CR and vertical cross section of the three-dimensional radar reflectivity for the same time period, respectively. We find that a heavy rain process occurred in Guangdong (Fig. 7a), and there were

many radar echoes (Fig. 7c) at that time. Figure 7d shows a strong convective cell structure in the vertical section of the observed three-dimensional radar reflectivity in the area with many radar echoes (Fig. 7d).

The forecasted precipitation (Fig. 7b) is not accurate when compared with the observed precipitation (Fig. 7a), and there are some false alarms and misses. However, the distribution of the CR in the improved experiment (Fig. 7e) corresponds better to the forecasted precipitation than that of the control experiment (Fig. 7g), showing a good correspondence in Guangdong, Fujian, and other locations. Compared with the observed CR, the CR distribution of the improved experiment shows some similarities in the north of Guangdong, the coast of Guangdong, and the junction between Guangdong and Fujian. We could not find any radar reflectivity of the control experiment (Fig. 7h) in the vertical cross section of the three-dimensional radar reflectivity at the same location. However, the improved experiment (Fig. 7f) shows some radar

FIG. 7. (a) Observed 1-h precipitation (mm), (b) forecasted 1-h precipitation, (c) observed CR (dBZ), (d) vertical cross section of the observed radar reflectivity (dBZ), (e) forecasted CR (improved experiment), (f) vertical cross section of the forecast radar reflectivity (improved experiment), (g) forecasted CR (control experiment), and (h) vertical cross section of the forecast radar reflectivity (control experiment). (The observed precipitation is from 0200 to 0300 UTC 19 Apr 2019, and the observed radar reflectivity is from 0300 UTC 19 Apr 2019. The forecasted precipitation and radar reflectivity are from the 27-h model forecast initialized at 0000 UTC 18 Apr 2019.)

reflectivity and indicates a convective cell structure. The location of this convective cell structure is close to that in the observations, with a similar structure.

Figure 8a shows the observed 24-h accumulated precipitation from 0000 UTC 24 April to 0000 UTC 25 April 2019. A strong convective weather process occurred in Hunan and

Jiangxi provinces from 24 to 25 April. There was low-level vertical shear in this area, the atmosphere was very unstable, and water vapor was abundant. The precipitation was concentrated in Hunan, Jiangxi, and Fujian provinces. There was mainly moderate to heavy rain, with the extreme area reaching the magnitude of a rainstorm (Fig. 8b).

FIG. 8. (a) Observed 24-h accumulated precipitation (mm) and (b) observed 3-h accumulated precipitation of the marked station from 0000 UTC 24 Apr to 0000 UTC 25 Apr 2019.

Figures 9b and 9e–h show the forecasted precipitation, CR and vertical cross section of the three-dimensional radar reflectivity obtained from the 3-h model forecast initialized at 0000 UTC 24 April 2019, respectively. Figures 9a, 9c and 9d show the observed precipitation, CR and vertical cross section of the three-dimensional radar reflectivity for the same time period, respectively. Local precipitation occurred in the north of Jiangxi Province at this time (Fig. 9a), and the precipitation in the center reached >20 mm in 1 h (i.e., a short-duration heavy precipitation process). The observed CR also exhibited a large value in the same region (Fig. 9c). The vertical cross section of the observed three-dimensional radar reflectivity shows a strong convective cell near 28° – 29° N along the large-value area of the observed CR (Fig. 9d).

At this time, the forecasted precipitation area (Fig. 9b) is similar to the actual precipitation area (Fig. 9a); however, the magnitude of the forecasted precipitation is smaller than that in the actual situation, and there are also some false alarms. The distribution of the CR in the improved experiment (Fig. 9e) corresponds better to the precipitation than that of the control experiment (Fig. 9g). Moreover, compared with that in the control experiment, the CR in the improved experiment has a larger range of strong echo areas in the northwest of Jiangxi Province and the junction between Fujian and Jiangxi provinces, which is closer to the actual distribution of the CR (Fig. 9c). In the vertical cross section of the three-dimensional radar reflectivity at the same location, the radar

reflectivity of the improved experiment (Fig. 9f) is significantly larger than that of the control experiment (Fig. 9h) and forecasts a strong convective cell near 28° – 29° N, which is similar to the observations (Fig. 9d).

The above results show that the simulated radar reflectivity obtained by the new method clearly indicates the subgrid-scale precipitation in the model, and there is a significant improvement.

c. Analysis of the experimental results for the establishment periods of the EASM

The CR obtained by the improved and control experiments is verified in the first experimental period. The first experimental period is from 11 to 25 April 2019, when the EASM was established and many precipitation processes occurred in South China. Figures 10–12 show the hourly TS, HR, MR, FAR, and FB of the 15-day statistical averages at different thresholds (10, 20, and 30 dBZ), respectively, where cr300 represents the improved experiment and crctl represents the control experiment. The southern region is listed on the left-hand side of the figure, and the northern region is listed on the right-hand side. Both the TS and the HR are positive scores. A larger value for these scores means a more accurate forecast. By contrast, the MR and FAR are negative scores, and a smaller value means a more accurate forecast. In addition, a value of the FB that is closer to 1 means a more accurate forecast.

Figure 10 shows the verification results when the threshold is >10 dBZ. In the southern region, the TS of the crctl experiment is better than that of the cr300 experiment in the early forecasting stage (before 9 h), whereas the TS of the cr300 experiment is better than that of the crctl experiment at all other times. The HR and MR of the cr300 experiment are better than those of the crctl experiment at all times, but the FAR of the cr300 experiment is worse than that of the crctl experiment at all times. Compared with that of the crctl experiment, the FB of the cr300 experiment has no obvious advantage. In the northern region, the TS, HR, MR, FAR, and FB of the two experiments are quite similar.

Figure 11 shows the verification results when the threshold is >20 dBZ. In the southern region, the TS, HR, MR, and FB of the cr300 experiment are better than those of the crctl experiment at most times, but the FAR of the cr300 experiment is worse than that of the cr300 experiment at all times. In the northern region, the HR and FAR of the cr300 experiment are better than those of the crctl experiment at most times, but the TS, MR, and FB of the two experiments are quite similar.

Figure 12 shows the verification results when the threshold is >30 dBZ, which generally represents a heavy precipitation process. The TSs in the early forecasting stage of the two experiments (before 3 h) are fairly similar in the southern region, but the TS of the cr300 experiment is better than that of the crctl experiment at all other times. The HR and FB of the cr300 experiment are better than those of the crctl experiment at most times. The MR and FAR of the two experiments are quite similar. In the northern region, the FAR of the cr300 experiment is better than that of the crctl experiment at most times, but the TS, HR, and MR of the two experiments are quite similar. Compared with that of the crctl experiment, the FB of the cr300 experiment has no obvious advantage at most times.

FIG. 9. (a) Observed 1-h precipitation (mm), (b) forecasted 1-h precipitation, (c) observed CR (dBZ), (d) vertical cross section of the observed radar reflectivity (dBZ), (e) forecasted CR (improved experiment), (f) vertical cross section of the forecast radar reflectivity (improved experiment), (g) forecasted CR (control experiment), and (h) vertical cross section of the forecast radar reflectivity (control experiment). (The observed precipitation is from 0200 to 0300 UTC 24 Apr 2019, and the observed radar reflectivity is from 0300 UTC 24 Apr 2019. The forecasted precipitation and radar reflectivity are from the 3-h model forecast initialized at 0000 UTC 24 Apr 2019.)

We introduced an evolution of the improved rate [$IR = (TS_{cr300} - TS_{ctrl})/TS_{ctrl}$] over time to better represent the changes in the TSs of the two experiments (Fig. 13). The IR in the early forecasting stage (before 6 h) is slightly negative or almost unchanged in the southern region but clearly positive at other times. There is a significant positive impact for large values of reflectivity with thresholds between 20 and 30 dBZ. This means that the ability of the CR in the improved experiment to reflect heavy precipitation processes has been significantly improved. In the northern region, although the improved experimental results have a small positive impact at the threshold of 20 dBZ, the TSs of the two experiments in the northern region are generally similar.

d. Analysis of experimental results for the prevailing periods of the EASM

Our analysis shows that during the periods when the EASM is becoming established, the results of the improved experiment

are significantly better than those of the control experiment in the southern region, but there are no obvious differences in the northern region. To explore whether the method or the rainfall weather system leads to these results, we conducted a second experiment from 1 to 15 August 2019, which is the prevailing period of the EASM, when there are many sources of water vapor in the atmosphere. Moreover, Super Typhoon Lekima passed through Shandong and Bohai Bay in China on 11 August 2019. Under this weather background, there were many precipitation processes in northern, southern, and northeastern China.

Figures 14–16 show the hourly TS, HR, MR, FAR, and FB of the 15-day statistical averages at different thresholds (10, 20, and 30 dBZ), respectively, with the southern region listed on the left-hand side, the northern region in the middle and the northeastern region on the right-hand side. Figure 14 shows the verification results when the threshold is >10 dBZ.

FIG. 10. Evolution of the TS, HR, MR, FAR, and FB over time for the improved and control experiments at a 10-dBZ threshold. (Initialized at 0000 UTC every day, forecast 48 h; 11–25 Apr 2019.)

FIG. 11. Evolution of the TS, HR, MR, FAR, and FB over time for the improved and control experiments at a 20-dBZ threshold. (Initialized at 0000 UTC every day, forecast 48 h; 11–25 Apr 2019.)

FIG. 12. Evolution of the TS, HR, MR, FAR, and FB over time for the improved and control experiments at a 30-dBZ threshold. (Initialized at 0000 UTC every day, forecast 48 h; 11–25 Apr 2019.)

FIG. 13. Evolution of the improved rate over time for the improved and control experiments at different thresholds. Blue indicates a negative impact compared with that of the control experiment, and red indicates a positive impact compared with that of the control experiment. (Initialized at 0000 UTC every day, forecast 48 h; 11–25 Apr 2019.)

In the southern region, the TS, HR and MR of the cr300 experiment are better than those of the crctl experiment, but the FAR and FB of the cr300 experiment are worse than those of the crctl experiment at most times. In the northern region, the HR of the cr300 experiment is better than that of the crctl experiment; however, the TS, MR, and FB of the two experiments are quite similar, and the FAR of the cr300 experiment is worse than that of the crctl experiment at most times. In the northeastern region, the HR and MR of the two experiments are quite similar, but the TS, FAR, and FB of the cr300 experiment are worse than those of the crctl experiment.

Figure 15 shows the verification results when the threshold is >20 dBZ. In the southern and northern regions, the TS, HR, and MR of the cr300 experiment are better than those of the crctl experiment, but the FAR of the cr300 experiment is worse than that of the crctl experiment at most times. Compared with that of the crctl experiment, the FB of the cr300 experiment has no obvious advantage at most times. In the northeastern region, the HR of the cr300

experiment is better than that of the crctl experiment; however, the TS, MR, and FAR of the two experiments are quite similar, and the FB of the cr300 experiment is worse than that of the crctl experiment.

Figure 16 shows the verification results when the threshold is >30 dBZ. In the southern region, the TS, HR, and FB of the cr300 experiment are better than those of the crctl experiment; however, the MRs of the two experiments are quite similar, and the FAR of the cr300 experiment is worse than that of the crctl experiment at most times. In the northern region, the TS, HR, and FB of the cr300 experiment are better than those of the crctl experiment, but the MR and FAR of the two experiments are quite similar at most times. In the northeastern region, the TS and HR of the cr300 experiment are better than those of the crctl experiment; however, the MR and FAR of the two experiments are quite similar, and the FB of the cr300 experiment is worse than that of the crctl experiment. This means that the ability of the CR in the improved experiment to reflect heavy precipitation processes has been significantly improved.

FIG. 14. Evolution of the TS, HR, MR, FAR, and FB over time for the improved and control experiments at a 10-dBZ threshold. (Initialized at 0000 UTC every day, forecast 48 h; 1–15 Aug 2019.)

Figure 17 shows the evolution of the IR over time. The southern and northern regions show a significant positive impact, except when the IR (10 dBZ) in the northern region is neutral. In the northeastern region, the IR of the 10 and 20 dBZ thresholds is slightly negative or almost neutral, but the IR of the 30 dBZ threshold is slightly positive. According to Figs. 14–16 and the above analysis, we conclude that the hit of the improved experiment in the northeastern region is improved, but the number of false alarms increases at the same time. Then the

TS is not much improved for the cr300 experiment in the northeastern region.

These statistical verification results show that the results of the second experimental period are different from those of the first experimental period. In the period in which the EASM prevails, there is an improvement in the verification results of the improved experiment in both the southern and northern regions. This finding indicates that the impact of the new method is very sensitive to the rainfall weather system.

FIG. 15. Evolution of the TS, HR, MR, FAR, and FB over time for the improved and control experiments at a 20-dBZ threshold. (Initialized at 0000 UTC every day, forecast 48 h; 1–15 Aug 2019.)

There is a significant improvement for areas where plenty of subgrid model precipitation is generated, whereas the improvement is subtle when there is less precipitation or less subgrid precipitation. In addition, we find that the TSs of the two experiments are similar in the early forecasting stage. The reason is that the assimilated cloud initial data applied in the GRAPES model (Xue et al. 2001; Zhu et al. 2017) lead to more accurate radar reflectivity in the early forecasting stage. In addition, there is also less subgrid precipitation in the early forecasting

stage. Therefore, there is no obvious difference in the TSs of the two experiments in the early forecasting stage.

4. Summary and discussion

A new simulated radar reflectivity calculation method is designed based on the 10 km GRAPES-MESO model and applied to obtain a new simulated radar reflectivity corresponding to subgrid-scale and grid-scale precipitation. Two 15-day

FIG. 16. Evolution of the TS, HR, MR, FAR, and FB over time for the improved and control experiments at a 30-dBZ threshold. (Initialized at 0000 UTC every day, forecast 48 h; 1–15 Aug 2019.)

forecast experiments are carried out for two different time periods (11–25 April 2019 and 1–15 August 2019), and the radar reflectivity products of the two different calculation methods are compared. The results and conclusions are as follows:

- 1) Compared with those of the control experiment, the TS, HR, MR, FAR, and FB of the CR in the improved experiment are generally improved. This finding indicates the effectiveness of the new simulated radar reflectivity calculation method.
- 2) The analysis of two case studies and the verification results for the two experiments show that the reflectivity products calculated by the new method clearly indicate subgrid-scale precipitation and grid-scale precipitation in the model. These reflectivity products obtained by the new method are sensitive to the rainfall weather system; they exhibit a significant improvement for areas where plenty of subgrid model precipitation is generated, whereas the improvement is subtle when there is less precipitation or less subgrid precipitation.

FIG. 17. Evolution of the improved rate over time for the improved and control experiments at different thresholds. Blue indicates a negative impact compared with that of the control experiment, and red indicates a positive impact compared with that of the control experiment. (Initialized at 0000 UTC every day, forecast 48 h; 1–15 Aug 2019.)

This study verified the effectiveness of the new simulated radar reflectivity calculation method and the reliability of the new reflectivity products, especially for indicating subgrid-scale precipitation. However, there are still many problems and challenges in the application of this method in NWP models. First, we designed this method based only on the Kain–Fritsch (new Eta) scheme and the GRAPES-MESO 10-km model and did not consider any other cumulus parameterization schemes and models. The generalization of this method needs further verification. Second, the detailed impact of different Z – R empirical formulas on the simulated radar reflectivity needs further exploration.

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