Improved Prediction of Landfalling Tropical Cyclone in China Based on Assimilation of Radar Radial Winds with New Super-Observation Processing

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ABSTRACT: This work explores the impact of assimilating radial winds from the Chinese coastal Doppler radar on track, intensity, and quantitative precipitation forecasts (QPF) of landfalling tropical cyclones (TCs) in a numerical weather prediction model, focusing mainly on two aspects: 1) developing a new coastal radar super-observation (SO) processing method, namely, an evenly spaced thinning method (ESTM) that is fit for landfalling TCs, and 2) evaluating the performance of the radar radial wind data assimilation in QPFs of landfalling TCs with multiple TC cases. Compared to a previous method of generating SOs (i.e., the radially spaced thinning method), in which the density of SOs is equal within the radial space of a radar scanning volume, the SOs created by ESTM are almost evenly distributed in the horizontal grids of the model background, resulting in more observations located in the TC inner-core region being involved in SOs. The use of SOs from ESTM leads to more cyclonic wind innovation, and larger analysis increments of height and horizontal wind in the lower level in an ensemble Kalman filter data assimilation experiment with TC Mujigae (2015). Overall, forecasts of a TC’s landfalling position, intensity, and QPF are improved by radar data assimilation for all cases, including Mujigae and the other eight TCs that made landfall on the Chinese mainland in 2017. Specifically, through assimilation, TC landing position error and intensity error are reduced by 33% and 25%, respectively. The mean equitable threat score of extreme rainfall [>80 mm (3 h)−1] forecasts is doubled on average over all cases.

KEYWORDS: Precipitation; Tropical cyclones; Nowcasting; Numerical weather prediction/forecasting; Data assimilation; Ensembles

1. Introduction

On average, seven tropical cyclones (TCs) make landfall in China every year. According to the Chinese Meteorological Administration (CMA 2014, 33–39), landfalling TCs in 2013 claimed direct economic losses of up to 126 billion CNY, which is equal to 0.21% of China’s gross domestic product (GDP) in that year. About 66.7% of China’s GDP (7.8 trillion U.S. dollars) was concentrated in TC-prone areas in 2015, and this is increasing annually (Ye et al. 2019). Inaccurate forecasts of TC track, intensity, and especially heavy rainfall after landfall are detrimental to people’s lives and the nation’s development. However, the official forecast ability of TC rainfall is still limited, partly because of the large error in the initial conditions of numerical weather models (Rogers et al. 2013). Thus, proper TC initialization with multiple observations in Numerical Weather Prediction (NWP) is of great importance (Pu et al. 2009; Li and Pu 2014; Li et al. 2014; Zhang and Pu 2014; Honda et al. 2018; Lee et al. 2018; Kumar and Shukla 2019; Lu et al. 2019; Zhang et al. 2019; Zhang and Pu 2019).

Doppler radar can observe the fine structure of a TC’s inner core and outer rainband prior to landfall and many methods or systems of assimilating radar observations have been developed, i.e., such as the WRFDA system (Wang et al. 2013a,b), PSU WRF-EnKF system (Zhang et al. 2006; Meng and Zhang 2007, 2008a,b) and advanced regional prediction system, ARPS (Xue et al. 2000, 2001, 2003). Recently, the impact of assimilating the radial velocity (Vr) of airborne (Zhang et al. 2011; Weng and Zhang 2012; Zhang and Weng 2015) or ground-based (Zhang et al. 2009; Weng et al. 2011; Dong and Xue 2013) Doppler radar in the United States through an ensemble Kalman filter (EnKF) has been widely verified. The result of a 5-yr real-time forecast experiment (Zhang and Weng 2015) with the PSU WRF-EnKF system demonstrated that airborne radar Vr assimilation reduced the intensity error of landfalling hurricanes by 25%–28% for a 2–4-day lead time. Zhu et al. (2016) first assimilated Chinese ground-based Doppler radar data with the PSU WRF-EnKF system. They pointed out that assimilating Chinese Guangzhou radar radial wind observations could significantly enhance the performance of TC Vicente’s (2012) initialization and the forecast of its rapid intensification, as well as the associated rainfall prediction after landfall. Following Zhu et al. (2016), the impact of assimilating velocity observations of Taiwanese Doppler radar on the forecast of heavy rainfall induced by TC Morakot (2009) was examined (Yue and Meng 2017;
Encouragingly, rainfall forecasts in both Taiwan (Yue et al. 2017) and the Chinese mainland (Yue and Meng 2017) were improved, showing the potential value of ground-based Doppler radar radial wind observations in official TC forecasts. With the development of the China Meteorological Administration (CMA), the mean distance between two neighboring Doppler weather radars is about 180 km along the coast of China (Zhu et al. 2016). Although the detection area of a coastal radar stretches 230 km offshore and the time available to forecast landfalling TCs is limited, it still provides a reliable way to observe the fine structure of landfalling TCs in China. The influences of radar data assimilation on landfalling TC forecasts, particularly heavy rainfall nowcasts, need further examination with multiple cases.

Currently, operational model resolutions are still too coarse compared to the density of raw radar observations, leading to much of the information in raw data creating noise for model backgrounds (Janić et al. 2018). To properly assimilate these high-spatial-resolution observations, a key technique called super-observation (SO) processing has been widely used in radar data assimilation, in which raw observations are smoothed and aggregated into a similar density compared to the model grid interval. Generally, SO processing can 1) reduce the random instrumental error of raw observations, 2) partly remove representative error (Janić et al. 2018) by decreasing the volume of observations as well as by balancing the spatial distribution of observations and the model background, and 3) lessen the computational expense (Alpert and Kumar 2007). Various methods to create Vr SOs have been discussed in the literature, and they can be roughly divided into two categories (Waller et al. 2019): one involves calculating innovation in the model background to modify raw observations, after which these modified raw data are applied in a specific small region (Daley 1993; Simonin et al. 2014); the other, which is more commonly used, simply averages the observations under some conditions (Xiao et al. 2008; Salonen et al. 2009; Zhang et al. 2009; Weng and Zhang 2012; Bick et al. 2016; Lippi et al. 2019; Waller et al. 2019). Although algorithms of the second type share a similar general design, they differ considerably in detail (e.g., various delta azimuths and delta ranges to create SOs). Via statistics of observation minus background (OMB) values with a 1-month experiment, different parameter settings in radial wind SO processing were evaluated by Salonen et al. (Salonen et al. 2009). They demonstrated that averaging the spacing of range bins was not critical to the result, while various azimuthal angle averaging settings could not show a consistent performance in both statistics at different ranges from the radar. The default SO processing (Alpert and Kumar 2007) in the Gridpoint Statistical Interpolation system (Shao et al. 2016) was refined by Lippi et al. (Lippi et al. 2019). They revealed that the operational thinning settings somehow oversmoothed the observations and discarded potentially valuable information, and a precipitation prediction was enhanced by averaging observations over a smaller spatial box.

The literature above indicates that different SO-generating parameters may lead to different SO characteristics and rainfall forecasts after the assimilation of radial wind. However, up to now, whether or to what degree SO processing can affect landfalling TC analysis and forecasts has remained unclear. The SO processing with a radially spaced thinning method (RSTM) used in the PSU WRF-EnKF system (Zhang et al. 2009) has been widely adopted in many studies related to TC forecasts (Weng and Zhang 2012; Zhu et al. 2016; Yue and Meng 2017; Yue et al. 2017). However, the unevenly distributed SOs generated by this method are a weakness for assimilating ground-based Doppler radar. In this study we first use a new SO processing method to generate evenly distributed SOs. Then, the differences between the two methods regarding the SO characteristics and their impacts on track, intensity, and rainfall forecasts are analyzed. Moreover, we also investigate the impact of assimilating Chinese Doppler radial wind observations with the new SO processing on landfalling TC rainfall forecasts with multiple TC cases. With this, we can obtain robust results and eliminate the randomness of conclusions from a single case study, in contrast to many previous studies (Zhu et al. 2016; Yue and Meng 2017; Yue et al. 2017). The effectiveness of the radar data assimilation combined with the new SO processing algorithm in the numerical prediction of landing TCs is extensively evaluated.

Since a preoperational or operational radar radial wind data assimilation framework has been implemented in numerous official centers including NOAA (Gustafsson et al. 2018), the Met Office (Simonin et al. 2014), Météo-France (Montmerle and Faccani 2009), JMA (Hara et al. 2013), and KMA (Xiao et al. 2008), we anticipate that this work could lay the foundation for the application of Chinese Doppler radial wind observations in the real-time numerical forecasts at the CMA and provide useful guidance for rainfall nowcasts of landfalling TCs in China. The rest of the paper is organized as follows. The details of the new radar SO processing method, model configuration, and experimental design are introduced in section 2. Section 3 uses super landfalling TC Mujigae (2015) as an example to illustrate the effects of the new radar SO processing method. In addition, all cases of TCs making landfall on the Chinese mainland in 2017 are examined with the assimilation of radar radial wind observations in section 4. A brief summary is given in section 5.

2. Methods
   a. Model and data assimilation configuration

The forecast model used is an advanced research version of the Weather Research and Forecasting model (i.e., WRF-ARW) version 3.8.1. The initial and boundary conditions were derived from NCEP final analyses (FNL) at 1° × 1° with a 6-h interval. Three two-way nested domains were used with 43 vertical levels and a model top at 50 hPa; 120 × 100, 151 × 151, and 169 × 169 horizontal grid points; and grid spacing of 40.5, 13.5, and 4.5 km for d01, d02, and d03, respectively. This resolution configuration follows that of many previous works (Zhang et al. 2009, 2011; Weng and Zhang 2012; Zhu et al. 2016; Yue and Meng 2017; Yue et al. 2017),...
and some (Zhang et al. 2009, 2011) have pointed out that forecasts at 1.5-km grid spacing have similar performance to forecasts at 4.5-km resolution. The WRF single-moment six-class microphysics (WSM6) scheme (Hong et al. 2004), Yonsei University (YSU) scheme (Noh et al. 2003), Dudhia shortwave radiation physics scheme (Dudhia 1989), and Rapid Radiative Transfer Model (RRTM) longwave radiation physics scheme (Mlawer et al. 1997) were used in all three domains. For the outer domain (d01), the Kain–Fritsch cumulus scheme was used (Kain 2004).

Data assimilation is performed using a multiscale ensemble-based data assimilation and application system (Duan et al. 2019). The process is shown in Fig. 1, as well as the associated noDA experiment for comparison in this paper. Following the method used in Zhang et al. (2009), the balanced initial and boundary perturbations are generated and added to NCEP FNL with ensemble perturbations derived by drawing random perturbations from a 3DVAR built with WRF (WRF 3DVAR; Barker et al. 2004). First, a set of random perturbations with normal distribution is added to the control variables (streamfunction, unbalanced potential velocity, unbalanced temperature, pseudo relative humidity, unbalanced surface pressure) in the WRF 3DVar package under the “cv3” background error covariance setting. Then, the perturbation increment vector is transformed back to model space via an EOF transform, a recursive filter, and physical transformation. By tuning the variance factors of five control variables, we get a set of ensembles with a suitable spread. The final perturbed variables include pressure, horizontal wind components, potential temperature, and water vapor mixing ratio, and their standard deviations averaged over all domain grids are about 0.4 hPa, 1.6 m s\(^{-1}\), 0.7 K, and 0.75 g kg\(^{-1}\), respectively. The spread is similar to that in previous studies (Zhang et al. 2009; Yue and Meng 2017). The lateral boundary perturbations are created by FNL data using the same method as the initial ensembles, and this treatment is the same as in Zhang et al. (2009). Because of the limited quantity of members, variables of perturbed members are likely to have a skewed distribution. To generate 60 members with a mean equal to the original IC, the mean of members is replaced by the original IC in each member. After downsampling to d02 and d03, members are integrated for 6–12 h to develop a high-resolution, flow-dependent background error covariance structure. Radial velocity data are assimilated 4 times at 1-h cycling intervals within a lead time of 4–9 h before TC landfall, depending on the time the TC moves into the scanning range of Doppler radar. After cycling the radar data assimilation, an 18-h forecast is initiated with the mean of updated ensemble members. To preserve the estimation of background error covariance, all three domains were fixed in both the ensemble spinup and cycling DA periods. In the forecast stage, d02 and d03 were configured as storm-following, allowing a fine inner-core structure to be simulated wherever the TC moved.

Covariance inflation is proposed as in Zhang et al. (2004). After sensitivity tests, a relaxation coefficient of 0.5 was adopted. Because radar observations have a limited range of 230 km, radar observation data may not affect the background field of an area other than 1000 km. Therefore, 20% and 80% of the total radar data are randomly selected and assimilated in d02 and d03 with a localization radius of 450 and 150 km, respectively. Meanwhile, no observation is assimilated in d01 because high-spatial-resolution radar observations are thought to represent only the local atmospheric state, in contrast to many previous works (Zhang et al. 2009; Weng and Zhang 2012; Zhu et al. 2016; Yue and Meng 2017; Yue et al. 2017). All data assimilation and forecast processes have been established on a TianHe-1(A) high-performance supercomputer with 312 computer processors. The result of the 18-h TC forecast is available 1.5 h after the latest Doppler radar observation is collected.

b. Radar velocity data of the evenly spaced thinning method (ESTM)

Before generating SOs, we use a fully automatic Doppler radar velocity observation de-aliasing software (Xiao et al. 2016) to “correct” speed-folded observations in raw Vr volumes. Many studies (Zhang et al. 2009; Zhu et al. 2016; Yue and Meng 2017; Yue et al. 2017) have generated SOs by horizontal averaging in polar space of the raw polar volume, which is called the radially spaced thinning method (RSTM)

![FIG. 1. Schematic flowchart for the EnKF (EnKF-ESTM and EnKF-RSTM share the same experiment setting, except for SO processing) and noDA experiments. The three blue parallel arrows represent ensemble spinup before the DA cycles. The three red arrows show four radar data EnKF assimilation cycles at 1-h intervals. The blue arrows present forecasts with the ensemble mean of FNL or noDA experiment. The black line represents the time of TC landfall. The time labels in brackets indicate the time points for TC Mujigae.](image-url)
In RSTM, radar $V_r$ observations are thinned layer by layer. The following measures are implemented to generate an SO with RSTM (Zhang et al. 2009): 1) discount any raw observations with values smaller than $2\text{ m s}^{-1}$ or greater than $70\text{ m s}^{-1}$ or a distance from the radar of less than 4 km, 2) if a raw $V_r$ observation deviates from the average of all raw observations within a bin up to 2 times the standard deviation, discount it, 3) there should be at least four valid $V_r$ raw observations in an averaging bin, 4) there will be no SO for a bin whose standard deviation is twice the average of the standard deviations in all bins, and 5) the final SO value of the bin will be the average of at most 10 raw observations closest to the center of the bin. However, RSTM has two shortcomings. First, the density of SOs is almost equal in radial space, while in model grid space, the data density decreases from the radar center outward, meaning that the TC inner core is always in a region with lower observation density (Fig. 2b). Second, raw data in different directions will be averaged quantitively, leading to additional error. In light of these shortcomings, a new thinning method, called the evenly spaced thinning method (ESTM), is designed in this study, in order to make good use of TC inner-core observations.

Six steps are implemented sequentially to generate one SO with ESTM: 1) discount any raw data within 10 km of the radar center or with a value smaller than $4\text{ m s}^{-1}$; 2) split one azimuth direction scanning range into many bins whose length is 5 km in the radial direction; 3) discount any bin whose valid raw data number is less than 4; 4) sweep out any raw observation if its deviation from the mean of the data in one bin is greater than twice the standard deviation of all raw valid observations in that bin; 5) calculate the mean of all raw observations now left in the bin; 6) project the averaged observations vertically onto a grid with 5 km resolution, and the observation closest to the median of all data in one grid is treated as the SO. The relevant schematic diagram of RSTM and ESTM is shown in Fig. 3. By averaging raw observations in one azimuth direction, the random instrument error can be reduced (Salonen et al. 2009) without introducing additional error. To reduce representation error (Janjić et al. 2018), the bin length in the radial direction and the size of grid mentioned in the 6th step are set deliberately close to the model resolution (i.e., 4.5 km). The error of SO is set to $1\text{ m s}^{-1}$, which is consistent with many works (Dong and Xue 2013; Chen et al. 2017). A sample distribution of the raw observations and SOs generated by the two methods at 0000 UTC 4 October is shown in Fig. 2. The SO generated by ESTM is uniformly distributed, while the SO obtained by RSTM is uniform in radial space, which leads to a lack of observations at the edge of scanning region. The exact location of the TC center is unclear in the SO obtained by RSTM (Fig. 2b), which makes the fine structure of the TC inner core hard to obtain. In contrast, the observations at the edge of the radar scanning region can be effectively used with ESTM, and this can supplement the wind information from the TC inner core that is very important for obtaining fine structure of the TC. The characteristic differences between RSTM and ESTM are further detailed in section 3b.

Because many ground clusters are not easy to remove in some cases, all observations in the first layer are not used. In addition, because the scope of the radar’s seventh–ninth elevation layers is inadequate to represent the TC inner core, these observations are also removed. Only the observations in the second–sixth elevation layers are assimilated.

c. Experiment design and data description

To compare the effect of the two thinning methods on radar assimilation and TC forecasts, two data assimilation experiments, ESTM-EnKF and RSTM-EnKF, with the same model configuration except for different thinning methods are conducted. In addition, a noDA experiment without any data assimilation is performed, initialized with the same FNL data to compare with the two EnKF experiments, as shown in Fig. 1.

The radial velocity observations assimilated are from S-band coastal Doppler radar, which is similar to the WSR-88Ds of the United States (Zhu and Zhu 2004). The rainfall observations we select are $0.1^\circ \times 0.1^\circ$ satellite precipitation products (Shen et al. 2014) merged with Chinese hourly rain gauge data, which
are called the CPC Morphing technique (CMORPH) precipitation product. TC track and intensity information are from the CMA best track dataset.

3. Results of the case study—TC Mujigae

a. Case overview

TC Mujigae (2015) is taken as an example to analyze the capacity of the two SO processing methods to predict its landfall. Mujigae made landfall in Zhanjiang Province at 0500 UTC 3 October 2015 after rapid intensification offshore. At landfall, the maximum surface wind speed was up to 52 m s$^{-1}$ and central sea level pressure was 935 hPa, according to the best track data of the CMA’s Shanghai Typhoon Institute. Mujigae caused severe flooding and direct economic losses of more than 25 billion Chinese yuan (RMB). There were 7.479 million people affected by Mujigae, including 19 fatalities. The Doppler radar at Haikou (site No. Z9898) observed the rapid intensification of Mujigae. Four cycles of radar data assimilation were performed from 0000 UTC 4 October before the forecast initialized at 0300 UTC 4 October.

b. SO characteristics of RSTM and ESTM

The effects of the radar Vr observation thinning methods can be captured by visualizing the observation minus background (OMB) distribution of four assimilation cycles (Fig. 4). The overall patterns with the two methods are similar (particularly in the first cycle, because they share the same background field); however, due to specific characteristics of the SO generating method, the OMB for RSTM (Figs. 4a,c,e,g) is too dense near the radar site and too sparse at the edge of the scanning volume, where the center of the TC is located. There is very little fine structure of the TC inner core in FNL data due to their coarse resolution, causing a larger OMB. This indicates that the model inner-core observations are crucial to TC initialization. Much more cyclonic wind innovation in the TC inner-core region and a more specific TC location are produced by ESTM. Both algorithms thin raw observations to a resolution relative to the model grid interval (4.5 km), resulting in approximately equal SO counts, whereas SOs within 100 km of the TC center are quite different (Fig. 5a). The number of SOs generated by ESTM is almost twice that of RSTM in the TC’s innermost region (0–50 km). In addition, averaging the winds from different directions in RSTM may induce artificial biases (Salonen et al. 2009). Also, ESTM has a smaller OMB bias and RMS at different distances (Fig. 5b), showing its better performance on the SO statistical characteristics.

c. Track and intensity analysis and forecast

Figure 6 shows the simulated cyclone position and minimum sea level pressure (minSLP) of every posterior EnKF mean analysis field with four cycles of data assimilation (dashed line), and forecasts initialized with the final cycle analysis (solid line). The noDA experiment initialized from the FNL analysis without any data assimilation fails to capture Mujigae’s rapid intensification offshore. Both of the EnKF experiments improve the initial position and minSLP to varying degrees, and also result in improved track and intensity forecasts (Figs. 6a,b). Because radar observations in the TC’s inner-core region contain a more precise structure than the FNL background field, the increase in observations to be used in ESTM leads to a decrease in minSLP of 12 hPa after only one volumetric Doppler velocity observation is assimilated, while the decrease in minSLP is only 4 hPa in RSTM. With all four cycles, the initial position and
FIG. 4. The observation minus background (OMB; m s$^{-1}$) distribution of layer two (elevation angle = 1.4°) radar Z9898 SO observations created by (left) RSTM and (right) ESTM for the (a),(b) first; (c),(d) second; (e),(f) third; and (g),(h) fourth DA cycle. The black dot represents the TC location at the corresponding time.
minSLP error of ESTM are smaller, 15 km and 11 hPa, compared to RSTM (Figs. 6c,d). In addition, the forecast of ESTM gives a better prediction in the first 9 h after TC landfall as well as a lower minSLP error. Mujigae's landing position error in the noDA, RSTM, and ESTM forecasts is about 70, 50, and 25 km, respectively (Fig. 6c). Thus, the percentage improvement is 64% in ESTM-EnKF, which is much higher than that of RSTM-EnKF (~29%). This shows that although traditional RSTM can correct Mujigae's forecast, ESTM has a better ability to reduce the track and intensity error.

d. Analysis increments

To further explore the difference between the ESTM and RSTM experiments, Fig. 7 shows their analysis increments in the first data assimilation cycle, in which the background members (the guess fields) in the two experiments are the same. Due to more strong wind observations in the TC inner
core, wind velocity increments of up to 70 m s\(^{-1}\) are found in the ESTM experiment, which is 22 m s\(^{-1}\) larger than in the RSTM experiment. In addition, the 850 hPa height increment near the TC location in ESTM is about 20 gpm, which is much lower than in RSTM (≈11 gpm), indicating a stronger TC after assimilation (Fig. 6b). In total, there is a larger difference in the increment of the TC inner core than in the outer region. Despite much more observations near the radar site in RSTM, the increment in that region is almost equal to that in ESTM. There are two main reasons for this: 1) The SO density near the radar site is much higher than the model grid, indicating that the background field cannot absorb this information and some data are rejected directly by the assimilation system in order to reduce computing time. 2) Because the background does not contain small-scale information in the TC inner core, observations in TC inner core are more important for making corrections to the background vortex structure. Although the observations near the radar site (in the outer region of the TC) is increased in RSTM, they are less useful in updating the vortex structure in the analysis. In total, RSTM has a much larger increment and ingests more precise dynamic and thermodynamic information in the inner-core region, leading to a better analysis result of Mujigae’s track and intensity.

With all four cycles of radar velocity data assimilation, the dynamic structure of Mujigae in noDA, RSTM-EnKF, and ESTM-EnKF is shown in Fig. 8. The azimuthal mean
tangential wind and radial inflow are strengthened significantly in both EnKF experiments. The maximum tangential wind (low-level inflow) of ESTM-EnKF is greater than 55 m s\(^{-1}\) (20 m s\(^{-1}\)), which is 5 m s\(^{-1}\) (2 m s\(^{-1}\)) larger than in RSTM-EnKF. Also, the maximum wind radius of Mujigae in the three experiments is 55, 40, and 30 km, respectively. The eye size (where tangential wind speed is less than 10 m s\(^{-1}\)) of the vortex in ESTM-EnKF is the smallest, and the large tangential wind region is the greatest (greater than 30 m s\(^{-1}\)). Also, much stronger outflow in the upper layers and stronger inflow immediately beneath the upper-level outflow layer are found in ESTM-EnKF, indicating a stronger TC secondary circulation than in RSTM-EnKF. One benefit of the flow-dependent background covariance of EnKF is that the upper level downstream within the eyewall is much strengthened in ESTM-EnKF compared to RSTM-EnKF, though most of the additional observations are in the lower radar scanning volume. In total, this shows that the additional inner-core observations in ESTM-EnKF have a significant impact on building a compact and strengthened TC vortex.

**e. Rainfall forecast after TC landfall**

In addition to track and intensity, ESTM-EnKF also improves the forecast of heavy rainfall by Mujigae after its landfall. Figure 9 represents the 9-h accumulated rainfall forecast among CMORPH precipitation observations after Mujigae made landfall (from 0500 to 1400 UTC 4 October).

**TABLE 1. Spatial correlation coefficients of 9-h precipitation accumulation over land between the three model forecast experiments and CMORPH observations, calculated in radar observations for the directly affected region.**

<table>
<thead>
<tr>
<th>Time period</th>
<th>noDA</th>
<th>RSTM-EnKF</th>
<th>ESTM-EnKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>0500–1400 UTC 4 Oct 2015</td>
<td>0.5903</td>
<td>0.7102</td>
<td>0.7691</td>
</tr>
</tbody>
</table>
and the rainfall forecast error of noDA, RSTM-EnKF, and ESTM-EnKF. The results show that the area of extreme rainfall (greater than 51.2 mm) in noDA is much larger than that in the observations, leading to a large false alarm. The false alarm in Guangxi Province is lessened by radar data assimilation in both RSTM-EnKF and ESTM-EnKF. Moreover, the precipitation errors near two locations marked in Fig. 9 are decreased further in ESTM-EnKF, indicating the advantages of ESTM-EnKF over RSTM-EnKF in this case. To analyze the overall correlation between model precipitation and observations, spatial correlation coefficients of the region affected by radar observations are calculated (Table 1). This shows that precipitation forecasts with data assimilation have higher consistency. The coefficients of RSTM-EnKF and ESTM-EnKF are increased by 20.3% and 30.3% compared to noDA, respectively, which also shows that ESTM-EnKF has a greater ability to improve Mujigae’s rainfall forecast than RSTM-EnKF. Lippi et al. (Lippi et al. 2019) came to a similar conclusion in their heavy rainfall case study.

Fig. 10. Radar composite reflectivity of (a),(b) observations; (c),(d) RSTM-EnKF; and (e),(f) ESTM-EnKF at (left) 0700 UTC 4 Oct 2015 and (right) 1300 UTC 4 Oct 2015. The marked locations of A, B, and C marked with ⬤ are at same locations as in Figs. 9c and 9d. Because of the coarser resolution of the model compared to raw radar observations, the structure of RSTM-EnKF and ESTM-EnKF looks sparser.
In contrast to RSTM-EnKF, the false alarm rainfall in three areas is corrected in the ESTM-EnKF experiment. These three areas are marked by ⓧ in Figs. 9c, 9d, 10, and 11. It is also found that the false alarm in 9-h accumulated precipitation in these three areas is concentrated mainly in two different time periods. For areas of A and C, the false alarm occurs around 1300 UTC 4 October 2015, 8 h after Mujigae made landfall. Since the TC in ESTM-EnKF is located farther south in the first 10 h after landfall (Fig. 6a), the strong convection area near the typhoon center (near area A in Fig. 10f) is also southerly. Along with a weaker water vapor flux convergence (Fig. 11d) at 850 hPa, the false alarm rainfall in RSTM-EnKF (at area A) is corrected in ESTM-EnKF. In area C, a false convective cell (Fig. 10d) with high moisture convergence (Fig. 11b) appears in RSTM-EnKF. The location of the convective cell is close to the edge of the radar scanning area. Compared with RSTM, the spatial density of SOs in ESTM is much higher at the edge of the radar scanning area, enabling more observations with wind information to be assimilated. Thus, the analysis close to convective cell is corrected in ESTM-EnKF, leading to forecast improvement in area C. In area B, the false alarm occurs mainly around 0700 UTC 4 October 2015 and is located in a rainband of the TC. However, the reflectivity of the rainband in the RSTM-EnKF exceeds 50 dBZ, which is nearly 10 dBZ higher than the observation (about 40 dBZ). In the ESTM experiment, the divergence of the water vapor flux at 850 hPa is smaller (Fig. 11c) compared to RSTM-EnKF (Fig. 11a), implying that less water vapor is transported upward. Meanwhile, the convection of this rainband is weaker (Fig. 10e), leading to rainfall forecast improvement in area B.

4. Performance of ESTM-EnKF and RSTM-EnKF with nine landfalling TCs

a. TC cases and experimental design

In 2017, eight TCs (Merbok, Roke, Nesat, Haitang, Hato, Pakhar, Mawar, and Khanun) made landfall on the Chinese mainland. To evaluate the performance of the Vr observation assimilation without bias, data assimilation experiments are performed for these TCs in addition to the Mujigae case study in section 3. The configurations of these experiments are shown in Table 2, which included the radar

![Fig. 11. The 850-hPa water vapor flux divergence of (a),(b) RSTM-EnKF and (c),(d) ESTM-EnKF at (left) 0700 UTC 4 Oct 2015 and (right) 1300 UTC 4 Oct 2015. The locations of A, B, and C marked with ⓧ are at same locations as in Figs. 9c and 9d.](image-url)
assimilated, the assimilation period, and the forecast time. The tracks of all nine TCs (including Mujigae) and Chinese coastal Doppler radar distributions are shown in Fig. 12. The velocity data of the “first” radar that observes the TC inner-core region are assimilated.

b. Track and intensity

By assimilating radar Vr observations, the position and maximum surface wind speed (maxWSP) error at a TC’s landing point are noticeably reduced apparently in both EnKF experiments (Fig. 13). The location (intensity) error at landfall of noDA, RSTM-EnKF, and ESTM-EnKF is 59.6 km (6.7 m s\(^{-1}\)), 47.0 km (5.8 m s\(^{-1}\)), and 39.8 km (5.0 m s\(^{-1}\)), respectively. Thus, compared with noDA, the location (intensity) error at landfall of ESTM-EnKF is reduced by about 33% (25%). And further compared with RSTM-EnKF, the location and intensity forecasts are also improved by 15% and 16%. With the forecasting range increasing and the TC moving inland, track error reduction in both EnKF experiments is not apparent, partly because the radar observational range is only 230 km and there is a lack of large-scale observations. Encouragingly, the averaged maxWSP error in both EnKF experiments is about 4.3 m s\(^{-1}\), which is reduced by about 1.5 m s\(^{-1}\) (about 25% reduction) most of the time through data assimilation. Radar SOs contain TC fine wind structure, and the background error covariance with flow-dependent characteristics in EnKF can accurately inject the observation information into the background field. These two points together cause the TC intensity and initial position error to be significantly reduced. Apart from the landing point, the performance of ESTM-EnKF is almost equal to that of RSTM-EnKF, which means that the different SO algorithms do not affect TC track and intensity forecasts when the prediction time is longer than 2 h.

c. Quantitative precipitation forecasting (QPF)

Mean spatial correlation coefficients of accumulated rainfall every 3 hours are calculated to compare the spatial consistency of the precipitation prediction experiments (Fig. 14). Except for the first 3 hours, ESTM-EnKF outperforms RSTM-EnKF, and as the forecast time increases, the improvement is more significant. Results of the EnKF experiment with ESTM show that the first 9-h precipitation forecast can be improved, and improvements are greater than 5% compared to noDA. As time after TC landfall increases, the corresponding improvement in the spatial correlation coefficient of the precipitation forecast decreases from 9.01% to 5.71%. The 3-h rainfall coefficient 10–12 h after TC landfall decreases slightly, to 2.33%. This phenomenon may be partly due to rapid error growth relative to the small-scale motion in the model and indicates that the life expectancy of radar velocity data in model rainfall prediction is up to about 9 h. The radar radial velocity assimilation with ESTM can improve the overall rainfall pattern with nowcasting lead times.

In addition to spatial correlation, the equitable threat score (ETS) is a point-to-point QPF verification statistic that is more rigorous in evaluating the skill of the precipitation prediction. The mean ETS of 3-h accumulated rainfall for four periods (1–3, 4–6, 7–9, and 10–12 h) is shown in Fig. 15. Because light rainfall prediction in the model has a certain randomness, and strong precipitation receives more attention in TC rainfall, only rainfall magnitudes larger than 15 mm (3 h)\(-1\) are verified. Much improvement occurs in moderate ($\geq 15$, $\leq 30$ mm) and heavy ($\geq 50$, $\geq 80$ mm) rainfall in all four periods through assimilation of Vr data. Especially, models without any data assimilation perform poorly in forecasting heavy rainfall greater than 80 mm. The ETS value of such extreme rainfall can be increased by more

![FIG. 12. Distribution of Chinese coastal Doppler radar and its observational range (colored cycle) and the track of all nine TCs (Merbok, Roke, Nesat, Haitang, Hato, Pakhar, Mawar, Khanun, and Mujigae, displaced in yellow line). Observations of radars noted by the solid red line (blue dashed line) are (not) assimilated in at least one (any) TC case.](image-url)
than 100% by rapid cycling of radar data assimilation with ESTM. Extreme precipitation is the main cause of damage in landfalling TCs and has always been a difficult point in official TC forecasts. Results prove that the data assimilation and forecast technique developed in this study meet the official needs of the CMA for TC forecasts.

Figure 16 displays the distribution of error difference (EnKF error minus noDA error) in all nine TC cases. Because TCs are too weak to identify their exact position in many cases, only the first two 3-h mean track errors and corresponding spatial correlation coefficients are shown in the scatterplot. There is an obvious decreasing Y (difference in 3-h accumulated rainfall forecast spatial correlation coefficients) with increasing X (track error difference) by linear regression analysis, with a significance greater than 95%. The correlation coefficient is -0.51. Both proofs show that the increase in track error is one reason why radar data assimilation leads to a negative impact on rainfall forecasts in some cases. It also indicates that observations with a broader range are needed to correct large-scale atmospheric fields, which are important to TC movement.

5. Conclusions and discussion

In this work, a new Doppler radar velocity observation super-observation processing method, the evenly spaced thinning method (ESTM), is demonstrated, in which the density of SOs is almost equal in one radar scanning volume and more information near the TC center is involved. TC location, intensity, and rainfall forecasts can be improved compared to the traditional thinning method [radially spaced thinning method (RSTM)]. In addition, the impact of assimilating Chinese coastal Doppler velocity observations for the track, intensity, and especially the associated precipitation of landfalling TCs is examined first using multiple cases.

The Chinese Doppler radar SO observations created by ESTM and RSTM are continuously assimilated during the rapid intensification of TC Mujigae (2015). Owning to more SOs located in the TC’s innermost region (0-50 km), much more cyclonic wind innovation in the TC inner-core region and a more specific TC location are produced by ESTM. Results show that the different thinning methods do significantly affect the results of assimilation. ESTM is more suitable for coastal radar assimilation in TC weather systems, with analysis location and intensity closer to best track observations. Mujigae’s landing position forecast error is reduced by 64% in ESTM EnKF compared to noDA, which is much higher than that of RSTM EnKF (~29%). In addition, both the rainfall prediction pattern and spatial correlation coefficients are improved compared with RSTM.
After four radar data assimilation cycles with ESTM thinning data, the maximum azimuthal mean speed of the tangential wind and low-level inflow is about 5 and 2 m s$^{-1}$ larger than in the experiment with RSTM, with a smaller maximum wind radius (~30 km) and a tighter inner-core vortex structure. The downdraft in the upper level of the TC eye is significantly strengthened, which is also a signal of a powerful TC. The structure difference is due to the different analysis increments in the two experiments. The increments in the TC eyewall are much larger in the ESTM-EnKF experiment, regardless of the mass and flow field in the lower level or the thermal field in the upper level, mainly because there are more SOs in the TC inner core, though the total number of SOs is almost equal. The problem of excess information for grids near the radar site and information lost at the rim of the scanning volume in RSTM is overcome. The TC location is clearer in the SOs thinned by ESTM, and large wind observations near the TC eye strengthen TCs with assimilation.

To examine the impact of assimilating Chinese coastal Doppler radar data through EnKF without bias, data assimilation, and forecast experiments for all eight landfalling TCs in 2017 are performed. By cycling assimilated Doppler velocity observations with ESTM, the mean landfalling location error of all nine TC cases (including Mujigae) is reduced by 33% compared with noDA. Although apparent improvement cannot be seen in the track forecast, the intensity error is steadily reduced by about 25% after TC landfall by radial wind assimilation with ESTM, which is owing to small-scale information in radar observations being injected into the model.

The results averaged over experiments with all nine TCs show good improvement with radar data assimilation in TC landfalling quantitative precipitation forecasting (QPF). The overall spatial correlation coefficients between model forecasts and CMORPH rainfall observations are enhanced by 9.0%, 6.8%, and 5.7%, respectively within 1–3, 4–6, and 7–9 h of TC landfall. The improvement is reduced with longer forecast lead times, which indicates that the error at small scales grows quickly and the “correcting effect” of radar observations in TC rainfall forecasts can be sustained for only about 10 h. Furthermore, the results of rainfall ETS show that radar assimilation can improve moderate [30 mm (3 h)$^{-1}$] and heavy [80 mm (3 h)$^{-1}$] rainfall forecasts in almost every period of the first 12 h after TC landfall. Specifically, the improvement rate of extreme precipitation [80 mm (3 h)$^{-1}$] is greater than 100%, which indicates that radar assimilation can double the forecast skill in such disasters and help reduce the associated damage.

We further found that there is a significant linear relationship between TC track forecasts and rainfall spatial correlation.

**FIG. 15.** ETS for different thresholds in RSTM-EnKF (green bar), ESTM-EnKF (yellow bar), and noDA (blue bar) forecasts of 3-h accumulated precipitation during (a) 1–3, (b) 4–6, (c) 7–9, and (d) 10–12 h after TC landfall. The number above each bar represents the ESTM-EnKF increment (reduction) percentage relative to noDA.
coefficients, and their correlation coefficient is $-0.51$. This result shows that a negative impact on rainfall forecasts in some cases may be derived from the track error. Certain other kinds of observations, such as radiosondes, surface stations, ships, and satellite radiances, may help correct large-scale environments for better performance of TC track and associated rainfall prediction.

Overall, this work demonstrates the potential benefits of assimilating ground-based Doppler radar radial wind data through EnKF with a new SO processing method. The assimilation of additional types of observations could be explored in the future. Radar reflectivity observation and radiosondes, surface stations, ships, and satellite radiances need to be assimilated jointly with Doppler radial winds from more than one radar. Impacts of data assimilation on precise forecasts of TC convection structure, large-scale environment, track, and associated rainfall prediction need more experimental validation. In the future, a rapid-cycling radar velocity data assimilation and TC nowcasting system based on the method outlined in this paper is expected to be finished and run in real time and is hoped to provide some reference for landfalling TC nowcasting for the CMA.

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