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Typhoon rainstorm simulation with radar data assimilation in southeast coast of China

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Abstract. As an effective technique to improve the rainfall forecast, data assimilation plays an important role in meteorology and hydrology. The aim of this study is to explore the reasonable use of Doppler radar data assimilation to correct the initial and lateral boundary conditions of the Numerical Weather Prediction (NWP) systems. The Weather Research and Forecasting (WRF) model is applied to simulate three typhoon storm events in southeast coast of China. Radar data from Changle Doppler radar station are assimilated with three-dimensional variational data assimilation (3-DVar) model. Nine assimilation modes are designed by three kinds of radar data (radar reflectivity, radial velocity, radar reflectivity and radial velocity) and three assimilation time intervals (1h, 3h and 6h). The rainfall simulations in a medium-scale catchment, Meixi, are evaluated by three indices including relative error (*RE*), critical success index (*CSI*) and root mean square error (*RMSE*). Assimilating radial velocity with time interval of 1 h can significantly improve the rainfall simulations and outperforms the other modes for all the three storm events. Shortening the assimilation time interval can improve the rainfall simulations in most cases, while assimilating radar reflectivity always leads to worse simulation as the time interval shortens. The rainfall simulation can be improved by data assimilation as a whole, especially for the heavy rainfall with strong convection. The findings provide references for improving the typhoon rainfall forecasts in catchment scale and have great significance on typhoon rainstorm warning.

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1 Introduction

Although the resolution of numerical weather prediction (NWP) system is increasing with the improvement of computational efficiency and abundance of observation data, the rainfall is still one of the most difficult meteorological factors to forecast (Lu et al., 2017; Avolio and Federico, 2018). Typhoon always comes along with heavy rainfall, which lead to great loss. However, due to the uncertainty of the rainfall and the imperfect generation of NWP system, rainfall forecast with severe convection is unsatisfactory in medium and small catchment scale (Tian et al., 2017a). Data assimilation plays an important role in NWP and is always applied to correct the initial and lateral boundary condition of NWP system, which can effectively improve the rainfall forecast (Mohan et al., 2015; Liu et al., 2018).

Various kinds of observation data have been tested and assimilated by different assimilation methods. Wan and Xu (2011) simulated a heavy rainstorm by Weather Research and Forecasting (WRF) model with Gridpoint Statistical Interpolation (GSI) data assimilation (DA) system in the central Guangdong Province of south-east China. The rainfall simulation error was reduced at 4-km grid scale by assimilating satellite radiance data, which helped to analyse rainfall causes accurately. Giannaros et al. (2016) evaluated a lightning data assimilation (LTNGDA) technique over eight rainfall events occurred in Greece. The verification score of the rainfall simulation were significantly improved by the employment of WRF-LTNGDA, especially for heavy rainfall. Zhang et al. (2016) presented a regional ensemble data assimilation system that assimilated microwave radiances into WRF model. The rainfall simulations were improved in terms of the accumulated rainfall and spatial rainfall distribution for hydrological applications in the southeastern United States. In order to increase the rainfall simulation accuracy in catchment scale, Yucel et al. (2015) assimilated conventional meteorological observations by three-dimensional variational data assimilation (3-DVar) model in large scale meteorological fields. As the inputs of the hydrological model, the improvement of rainfall simulations reduced the errors of runoff simulation in the western Black Sea Region of Turkey.

Due to the high spatiotemporal resolution, radar data are assimilated to correct the NWP system for mesoscale and microscale weather prediction (Milan et al., 2008; Zhao and Jin, 2008). Wang et al. (2013) tested the radar data assimilation system by simulating a midlatitude squall-line case in the U.S. Great Plains, and the results indicated that radar data assimilation was able to improve rainfall forecasts at the convective scale. Liu et al. (2013) selected 4 storm events in a small catchment (135.2 km^2) located in southwest England to explore the effect of data assimilation for rainfall forecasts, and assimilating radar reflectivity can significantly improve the forecasting accuracy for the events with one-dimensional evenness in either space or time. Hou et al. (2015) improved the short-term forecast skill up to 9 hours by assimilating radar data in southern China.

However, the mode of radar data assimilation has not been investigated in depth, and the consistent conclusions have not been obtained for time interval setting of data assimilation and the option of radar reflectivity and radial velocity. Tian et al. (2017b) found that radar reflectivity assimilation led to better rainfall simulation than radial velocity assimilation with the time interval of 6 h. Maiello et al. (2014) assimilated both radar reflectivity and radial velocity with 3 h assimilation cycle to improve the WRF high resolution initial condition, and the rainfall forecast became more accurate for several experiments in the urban area

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of Rome. Bauer et al. (2015) indicated that radar data assimilation significantly improved the rainfall simulation by a 1-hour Rapid-Update Cycle with the high resolution of 3 km in Germany.

China suffers approximately nine tropical cyclones (TCs) each year in average (Shen et al., 2017). Most TCs develop into typhoons which always bring huge economic losses and a great number of casualties. Fujian is one of the most regularly affected provinces in the coastline of southeast China. Heavy rainfall caused by typhoon and complex terrains lead to severe flood disasters in Fujian Province. The rainfall forecasts play an important role to prevent the flood disasters, while the rainfall caused by typhoon with severe convection is still difficult to predict (Li et al., 2019). There are eight Doppler radar stations to obtain full coverage for meteorological monitoring in Fujian province. The plentiful radar data provide convenience and basis for the exploration of radar data assimilation in catchment scale.

In this study, Meixi catchment located in Fujian province is chosen as the study area. Due to the frequent heavy rainfall, the flood disasters have attacked the Meixi catchment more than 20 times since 1949. In order to explore the reasonable use of Doppler radar data assimilation to correct the initial and lateral boundary conditions of the NWP systems, the WRF model is applied to simulate three typhoon storm events affecting the Meixi catchment and 3-DVar model is used to assimilate the radar data to improve the typhoon rainstorm simulations. Nine assimilation modes are designed by three kinds of radar data (radar reflectivity, radial velocity, radar reflectivity and radial velocity) and three assimilation time intervals (1h, 3h and 6h). The rainfall simulations are evaluated by three indices including relative error (*RE*), critical success index (*CSI*) and root mean square error (*RMSE*).

2 Model and evaluation method

2.1 WRF model and configurations

As the latest-generation mesoscale NWP system, the WRF model in version 4.0 is used to simulate the three typhoon storm events. Three nested domains with two-way nesting are designed and centered over Meixi catchment. The grid spacings are set at 4 km, 12 km and 36 km for the three nested domains from inside to outside (Chen et al., 2017). The grid numbers for the nested domain sizes are 100×100 for Dom 1, 210×210 for Dom 2 and 300×300 for Dom 3 (Fig. 1). Meixi catchment can be completely covered by the innermost domain. All domains are comprised of 40 vertical pressure levels with the top level set as 50 hPa (Maiello et al., 2014). The NCEP Final (FNL) Operational Global Analysis data with 1°×1° grids are used to drive the WRF model and provide the initial and lateral boundary conditions. The time step is set to be 1 h for the WRF model output. The spin-up period of 12 h is applied to obtain a more accurate rainfall simulation. The option of physical parameterisations has significant effect on the rainfall simulations, especially for microphysics, planetary boundary layer (PBL), radiation, land-surface model (LSM) and cumulus physics (Otieno et al., 2019). Considering the application effect and frequency in southeast coast of China, WRF Single-Moment 6 (WSM 6) for microphysics, Yonsei University (YSU) for PBL, Rapid Radiative Transfer Model for application to GCMs (RRTMG) for longwave and shortwave radiation, Noah for LSM

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and Kain-Fritsch (KF) for cumulus physics are adopted in this study (Srivastava et al., 2015; Hazra et al., 2017; Cai et al., 2018).

[Figure 1]

2.2 3-DVar data assimilation

The fundamental of 3-DVar data assimilation is to produce an optimal estimate of the true atmospheric state by the iterative solution of a prescribed cost function (Ide et al., 1997):

$$J(x)=\frac{1}{2}(x-x^b)^T B^{-1}(x-x^b)+\frac{1}{2}(y-y^0)^T R^{-1}(y-y^0) \tag{1}$$

where x is the state variable, x^b is the first guess or background, y is the observation space, and y^0 is the observation. y=H(x) is the model-derived observation that is transformed from x by the observation operator H for comparison against y^0. B is the background error covariance matrix, and R is the observation error covariance matrix. The background error covariance has significant impact on the performance of data assimilation. Due to the wide applicability, the matrix of CV3 is adopted in this study to simplify the data assimilation procedure (Meng and Zhang, 2008). Equation (1) shows that the assimilated observation has significant effect on the performance of data assimilation. Therefore it is particularly important for time interval setting of data assimilation and the option of radar reflectivity and radial velocity.

2.3 Observation operator for radar data

The observation operator H in Eq. (1) links the model variables to the observation variables. For radar reflectivity, the observation operator is shown as (Sun and Crook, 1997):

$$Z = 43.1 + 17.5\log(\rho q_r) \tag{2}$$

where Z is the radar reflectivity in dBZ, ρ is the density of air in kg m^{-3}, and q_r is rainwater mixing ratio in g kg^{-1}. Equation (2) is derived by assuming a Marshall-Palmer raindrop size distribution and that the ice phases have no effect on reflectivity.

For radial velocity, the model-derived radial velocity V_r can be calculated as (Tian et al., 2017b):

$$V_r = u\frac{x - x_i}{r_i} + v\frac{y - y_i}{r_i} + (w - v_t)\frac{z - z_i}{r_i} \tag{3}$$

where (u, v and w) is the three-dimensional wind field, (x, y, z) represents the location of the observation point and (x_i, y_i, z_i) represents the location of the radar station. r_i is the distance between the location of a data point and the radar station, v_t is the hydrometer fall speed or terminal velocity. According to Sun and Crook (1998), v_t can be given by:

$$v_t = 5.40a(\rho q_r)^{0.125} \tag{4}$$

$$a=\left({p_0}/{\overline{p}}\right)^{0.4} \tag{5}$$

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where a is the correction factor, $\overline{p}$ is the base-state pressure and p_0 is the pressure at the ground.

2.4 Rainfall evaluation statistics

The relative error (RE) is used to evaluate the total rainfall amount simulation:

$$RE = \frac{P' - P}{P} \times 100\% \tag{6}$$

where P' is 24-h accumulated areal rainfall simulation, which is averaged from all grids inside the Meixi catchment; and P is 24-h accumulated areal rainfall observation, which is calculated by the Thiessen polygon method with observations of the 8 rain gauges in Meixi catchment (Sivapalan and Blöschl, 1998).

The spatiotemporal patterns of the rainfall simulation are evaluated by the critical success index (*CSI*) and root mean square error *(RMSE)*:

$$CSI = \frac{1}{N}\sum_{i=1}^{N}\frac{NA_i}{NA_i + NB_i + NC_i} \tag{7}$$

$$RMSE = \frac{\sqrt{\frac{1}{M}\sum_{j=1}^{M}\left(P'_j - P_j\right)^2}}{\frac{1}{M}\sum_{j=1}^{M}P_j} \times 100\% \tag{8}$$

In order to evaluate the simulation of spatial rainfall distribution, *NA*, *NB* and *NC* at each time step i are calculated by comparing the rainfall simulation with observation at the rain gauge locations as shown in Table 1, and 24 for N is the number of total time steps. For temporal dimension evaluation, *NA*, *NB* and *NC* are calculated based on the time series data obtained for the simulated and observed areal rainfall at each rain gauge i, and 8 for N is the number of rain gauges in Meixi catchment. The perfect score of *CSI* is 1.

[Table 1]

For spatial distribution of rainfall simulation, P'_j and P_j refer to the simulation and observation of 24-h accumulated rainfall at rain gauge j, respectively. M is the total number of rain gauges. For temporal dimension evaluation, P'_j and P_j are the areal rainfall simulation and observation at each time j. Total number of time steps is 24 for M. The perfect score of *RMSE* is 0.

3. Study area and data

3.1 Meixi catchment and storm events

The Meixi catchment lies in east-central of Fujian province with subtropical monsoon climate. The drainage area is 956 km2. The average annual rainfall is approximately 1560 mm in Meixi catchment and most storm flood disasters are caused by typhoon generated in Western Pacific. The most destructive flood occurs on 9 July, 2016 in this mountainous catchment and causes many casualties and huge economic losses. The 24 h accumulated rainfall is 242 mm and peak flow reaches 4710 m^3/s. The previous history of heavy rainfall and flood, indicates that accurate rainfall forecasts appear to be particularly important for Meixi catchment.

Three typhoon storm events, including Saola, Hagibis and Nepartak, are chosen to investigate the appropriate radar data assimilation modes in Meixi catchment. Saola formed on July 28, 2012 while landed Fuding, Fujian until August 3. With moving inland slowly, Saola weakened into a tropical storm at Jiangxi. In the whole process, Saola never had a direct impact on Meixi catchment and the accumulated 24-h rainfall was only 84 mm. Hagibis landed Shantou, Guangdong on June 15, 2014 and then moved toward north with a fast-moving speed. Fortunately, Hagibis weakened into a tropical depression quickly during moving to northeastern Fujian on June 17. Therefore, Hagibis also had limited impact in Meixi catchment and the accumulated 24-h rainfall was only 66 mm. Nepartak reached Fujian on July 9 and strengthened at Putian. Then Nepartak moved towards the northwest with a fast-moving speed and affected Meixi catchment directly. During the period, Nepartak reached its peak intensity and led to heavy rainfall in Meixi catchment. Three rainfall storms are shown in Table 2.

[Table 2]

3.2 Radar data and assimilation modes

In the 8 radar stations, S-band Doppler weather radar located at Changle can completely cover Meixi catchment. The observation radius of Changle radar reaches 250 km and the distance between Meixi catchment and radar station is less than 100 km (Fig. 2), which makes the quality of radar data credible. The assimilated data, radar reflectivity and radial velocity, can be obtained once every 6 min continuously. All the radar data with quality control are provided by the newest generation weather radar network of China (CINRAD/SC). The observation error standard deviations of radar reflectivity and radial velocity are set 2 dBZ and 1 m s^{-1} in the 3-DVar model, respectively (Caya et al., 2005). The radar data assimilation modes are designed by three kinds of radar data (radar reflectivity, radial velocity, radar reflectivity and radial velocity) and three assimilation time intervals (1h, 3h and 6h). The rainfall simulation without data assimilation is used as control mode. Nine modes are shown in Table 3.

[Figure 2 and Table 3]

3.3 WRF cycling runs for data assimilation

In order to obtain the whole process of the rainfall simulation, the running time is set as 36 h, 42 h and 36 h for storm event I, II and III, respectively. As shown in Fig 3, the cycling runs are set according to the time interval of data assimilation and run 1 can be regarded as the WRF run without data assimilation. The dashed line segment represents the model spin-up. The first-guess generated by run 1 is applied to drive run 2. As time progresses, the first guess file generated in the previous run is used to provide the initial conditions for the following run. For storm event I, data assimilation starts on 3 August 2012 at 00:00

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and occurs with intervals of 6 h, 3 h and 1 h. The start time of data assimilation is 18:00 on 17 June 2014 and the end time is 00:00 on 18 June 2014 for storm event II. Data assimilation takes place on 8 July at 18:00 and ends on 9 July at 18:00 with intervals of 6 h, 3 h and 1 h for storm event III.

[Figure 3]

4 Results

4.1 Accumulated rainfall simulation of the nine data assimilation modes

Nine data assimilation modes for three storm events are evaluated by *RE* for 24 h accumulated rainfall. The average values of the *RE* (*ARE*) of three storm events for each mode is also calculated. As shown in Table 4, data assimilation modes make the rainfall simulation worse according to *RE*s of event I. Only mode 8 has the closest rainfall simulation to the observation in the nine data assimilation modes and the *RE* is below 1%. For event II, all data assimilation modes can improve the accumulated rainfall simulations, while for event III, most modes make the accumulated rainfall simulations better except for mode 2 and 3. Mode 8, i.e. assimilating radial velocity with time interval o 1 h, always has the lowest *RE* and performs the best. The improvement of the rainfall simulation is the most obvious for event III and the rainfall magnitude of mode 8 is close to the observation, which has important significance in torrential rainfall forecast and catastrophic flood forecast at medium and small basins.

[Table 4]

4.1.1 Evaluation of assimilating effects for the different kinds of radar data

The assimilating effects for three kinds of radar data are compared in different assimilating time intervals. Based on the *RE*s of mode 1, 2 and 3, assimilating radar reflectivity always leads to better simulations than assimilating other two kinds of radar data with time interval of 6 h. The worst mode for event I is assimilating both radar reflectivity and radial velocity while for event II and III is assimilating radial velocity. According to the *RE*s of mode 4, 5 and 6, assimilating radial velocity becomes the best choice with time interval of 3 h for the three storm events. Assimilating radar reflectivity has the worst performance in the three modes for event II and III, whereas assimilating radar reflectivity and radial velocity together performs the worst for event I. When the time interval of data assimilation becomes 1 h, the ranking of assimilation mode for accumulated rainfall simulation is assimilating radial velocity > assimilating radar reflectivity and radial velocity > assimilating radar reflectivity.

4.1.2 Evaluation of assimilation effects for the different assimilation time intervals

The influences of assimilating time intervals on rainfall simulation are analysed in this section. Comparing the *RE*s of mode 1, 4 and 7, shortening the time interval of radar reflectivity assimilation has no obvious improvement for rainfall simulation and even makes the rainfall simulation worse. For assimilating radial velocity, all the rainfall simulations of three storm events become more accuracy and the assimilation effects are significantly improved as the time interval shortens from 6 h to 1 h.

The *RE*s of the three storm events are all lower than 8% for the radial velocity assimilation with time interval of 1 h. According to mode 3, 6 and 9, shortening the assimilation time interval can improve the rainfall simulations in most cases for assimilating radar reflectivity and radial velocity at the same time, while only the *RE* of mode 6 is higher than the *RE* of mode 3.

4.2 Spatiotemporal distribution of rainfall simulation based on the nine data assimilation modes

The spatiotemporal patterns of the rainfall have significant effect on flood peek and peak time in medium and small catchments. The indices of *CSI* and *RMSE* are applied to compare the nine radar data assimilation modes. The average *CSI* values and the average *RMSE* values for the three storm events are also calculated for different assimilation modes.

4.2.1 Evaluation in spatial dimension

Table 5 indicates that most rainfall simulations with radar data assimilation are worse than the simulation without data assimilation for event I. Mode 8 with the highest *CSI* and lowest *RMSE* is the best choice in the nine data assimilation modes, which also leads to better rainfall simulation than no data assimilation. All *RMSEs* of the simulations with radar data assimilation are lower than the simulation without data assimilation, while only the *CSI* of mode 8 is higher than the simulation without data assimilation for event II. Combining the rainfall distributions shown in Fig.5, the falling areas of simulated rainfall without data assimilation are totally wrong. Although the spatial rainfall distributions have deviation compared with the observation, nine modes get better than the simulation without data assimilation as a whole, especially for mode 8 and 9. Based on the Table 5 and Fig.6, not all data assimilation modes help improve the rainfall simulation. Mode 4, 5 and 9 have just a little improvement on spatial distribution of rainfall simulation, and only the simulation of mode 8 is closed to the observation.

[Table 5 and Figure 4, 5, 6]

Based on the *CSI*s and *RMSE*s of mode 1, 2 and 3, assimilating radar reflectivity performs better than assimilating other two kinds of radar data in time interval of 6 h. Assimilating radar reflectivity and radial velocity at the same time always leads to the worst simulation. Comparing the two indices of mode 4, 5 and 6, assimilating radar reflectivity with time interval of 3 h can obtain the highest *CSI* for the three storm events, while assimilating radial velocity gets better performance than other two modes based on *RMSE* for event I and II. With the time interval of 1 h, the ranking of assimilation mode for spatial distribution of rainfall simulation is assimilating radial velocity > assimilating radar reflectivity and radial velocity > assimilating radar reflectivity.

Comparing the two indices of mode 1, 4 and 7, rainfall simulations become even worse as the time interval of radar reflectivity assimilation shortens. For the three modes of assimilating radial velocity, most simulations become more accuracy and the assimilation effects are significantly improved as the time interval shortens from 6 h to 1 h. The same conclusion can be obtained for assimilating radar reflectivity and radial velocity at the same time, while the improvement is not as obvious as assimilating radial velocity.

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4.2.2 Evaluation in temporal dimension

As shown in Table 6 and Fig. 7, the similar results can be found that most data assimilation modes cannot help the simulation of WRF model get better for event I. Mode 8 is outstanding with the highest *CSI* and lowest *RMSE*. According to the values of *CSI* and *RMSE*, only mode 8 and 9 are useful for the improvement of rainfall simulation and the increase of accuracy is obvious for mode 8 in event II. For event III, although most *CSI*s of the simulation with radar data assimilation are lower than the simulation without data assimilation, the *RMSE*s show the opposite conclusions. From the Fig. 9, mode 5, 8 and 9 improve the rainfall simulation of temporal distribution and the simulation of mode 8 is basically consistent with the observation.

[Table 6 and Figure 7, 8, 9]

According to the *CSI*s and *RMSE*s of mode 1, 2 and 3, assimilating radar reflectivity with time interval of 6 h performs better than assimilating other two kinds of radar data. Assimilating radial velocity performs the worst for event II and assimilating radar reflectivity and radial velocity at the same time always leads to the worst simulation for event I and III. Based on the two indices of mode 4, 5 and 6, assimilating radial velocity with time interval of 3 h can obtain the highest *CSI* and lowest *RMSE* for the three storm events, while assimilating radar reflectivity and radial velocity at the same time performs worse than other two modes. For the time interval of 1 h, the ranking of assimilation mode for temporal distribution of rainfall simulation is assimilating radial velocity > assimilating radar reflectivity and radial velocity > assimilating radar reflectivity.

Comparing the indices of mode 1, 4 and 7, rainfall simulations for temporal distribution become even worse as the time interval of radar reflectivity assimilation shortens from 6 h to 1 h. For mode 2, 5 and 8, shortening the time interval can significantly improve the rainfall simulation by assimilating radial velocity. Mode 3, 6 and 9 indicate that rainfall simulation is improved by shortening the time interval as a whole, whereas assimilating radar reflectivity and radial velocity at the same time with time interval of 3 h obtains the worst rainfall simulation for event II and III.

5 Discussion

Comparing the nine radar data assimilation modes, assimilating radial velocity with time interval of 6 h always performs the worst for rainfall simulation, while the rainfall simulation can be significantly improved by shortening the time interval of data assimilation. According to Eq. (3), although the physical process of the rainfall formation cannot be influenced by the radial velocity assimilation directly, the wind field and the water vapor transportation in initial and lateral boundary condition can be changed according to the wind information in radial velocity. However, the wind field is quite variable especially on the rainy days with typhoon. As the time interval becomes longer, the WRF model cannot be corrected by the radial velocity in time, whereas comparing with the simulation without data assimilation, the inevitable observation errors caused by atmospheric refractive in the radial velocity might lead to worse performance of the WRF model as the running time goes on (Montmerle and Faccani, 2009). That is the main reason that assimilating radial velocity with time interval of 6 h cannot obtain satisfactory simulations. Increasing the frequency of data assimilation, the effective information in radial velocity can correct the wind field and the water vapor transportation in the background field of WRF model timely, which is helpful to improve the rainfall simulation (Kawabata et al., 2014).

On the contrary, assimilating radar reflectivity have little help for improving the rainfall simulation except for accumulated rainfall. However rainfall simulation become even worse as the time interval of radar reflectivity assimilation shortens from 6 h to 1 h. The background field of the WRF model has large difference with the actual weather situation, which can be reflected from the rainfall simulation without data assimilation against rainfall observation for the three storm events. As shown in Eq. (2), radar reflectivity is closely related to the humidity field and contains the information of rainfall hydrometeors (Wattrelot et al., 2014). That is to say the humidity information in radar reflectivity is quite different from the actual weather situation, which makes the 3-DVar data assimilation difficult to produce an optimal estimate of the true atmospheric state by the iterative solution of a prescribed cost function. It should be also mentioned that due to the unchangeable, the matrix of CV3 has wide applicability but is not practical for all cases (Kong et al., 2017). The inadaptation of CV3 in the typhoon synoptic system and the large differences between the humidity information in radar reflectivity and the actual weather situation might be the main reasons for poor performance of radar reflectivity assimilation (Sun, 2005). The more frequent the radar reflectivity assimilation, the greater the pressure on the 3-DVar data assimilation model. Other data assimilation model with variable background error covariance, such as the hybrid ensemble transform Kalman filter–three-dimensional variational data assimilation (ETKF-3DVAR), should be tested for radar reflectivity assimilation in further study.

For the even rainfall events in space and time, such as storm event I, data assimilation should be used carefully. The WRF model has good performance on even rainfall simulation, especially for accumulated rainfall. The errors in the assimilated data may have negative effect on the rainfall simulation. Additionally, assimilating other kinds of data and radar data together may help to improve the rainfall simulation. Though the conventional observations, such as upper-air and surface observations from meteorological station and sounding balloon, have low spatiotemporal resolution, the kinds of data are various and have wide coverage, which can help to improve the atmospheric motion in the WRF model at a large scale (Li et al., 2018). Yesubabu et al. (2016) indicates that assimilating the satellite observation also has positive effect on the rainfall simulation. Assimilating different data sources together with the radar data may further improve the rainfall simulation in catchment scale.

6 Conclusion

Data assimilation is an efficient technique for improving the rainfall simulation. In order to explore the reasonable use of Doppler radar data assimilation to correct the initial and lateral boundary conditions of the NWP systems, three typhoon storm events, including Saola, Hagibis and Nepartak, are chosen to be simulated by WRF model with the nine modes in Meixi catchment located in southeast coast of China. The FNL analysis data with 1°×1° grids are used to drive the WRF model, and radar data from Changle Doppler radar station are applied to correct the initial and lateral boundary conditions. Three evaluating indices *RE*, *CSI* and *RMSE* are used to evaluate the nine radar data assimilation modes, which are designed by three kinds of radar data (radar reflectivity, radial velocity, radar reflectivity and radial velocity) and three assimilation time intervals (1h, 3h and 6h).

Contrastive analyses of the nine modes are carried out from three aspects: accumulated rainfall simulation, spatial rainfall distribution and temporal rainfall distribution. Four main conclusions are obtained: (1) in the nine radar data assimilation modes, assimilating radial velocity with time interval of 1 h can significantly improve the rainfall simulations and outperforms the other modes for all the three storm events; (2) shortening the assimilation time interval can improve the rainfall simulations in most cases, while assimilating radar reflectivity always leads to worse simulation as the time interval shortens; (3) radar reflectivity is the best choice for the data assimilation with time interval of 6 h, while radial velocity performs best for the data assimilation with time interval of 1 h; (4) data assimilation can improve the rainfall simulation as a whole, especially for the heavy rainfall with strong convection, whereas the improvement for even distributed rainfall in space and time is limited. More numerical simulation experiments should be tested in other catchments at different climate conditions. Further studies also should be carried out to investigate the data assimilation techniques to improve the simulation ability of heavy rainfall in the study areas.

Author Contributions

All the authors contributed to the conception and the development of this manuscript. Jiyang Tian and Ronghua Liu contributed to radar data assimilation and manuscript writing. Liuqian Ding and Liang Guo assisted in the data assimilation modes design and analyses. Bingyu Zhang helped with the figure production.

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Table captions

Table 1: Rain-no rain contingency table for the WRF simulation against observation.

Table 2: Three storm events occurred in Meixi catchment.

Table 3: Radar data assimilation modes designed with data types and time intervals.

Table 4: Accumulated rainfall simulation (mm) and RE values (%) of the nine data assimilation modes for three storm events.

Table 5: *CSI* and *RMSE* for spatial distribution of rainfall simulation based on the nine data assimilation modes.

Table 6: *CSI* and *RMSE* for temporal distribution of rainfall simulation based on the nine data assimilation modes.

Figure captions

Figure 1: The location of the Meixi catchment and three nested domains.

Figure 2: The location of radar station and position relation between radar scan area and Meixi basin.

Figure 3: The time bars of the assimilation cycling runs for (a) storm event I, (b) storm event II and (c) storm event III.

Figure 4: Spatial distribution of the rainfall simulations with nine data assimilation modes for Event I.

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Figure 7: Time series bars of the rainfall simulations with nine data assimilation modes and the rainfall observation for Event I.

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Figure 9: Time series bars of the rainfall simulations with nine data assimilation modes and the rainfall observation for Event III.

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Table 1. Rain-no rain contingency table for the WRF simulation against observation.

Simulation/observation	Rain	No rain (<0.1 mm/h)
Rain	*NA* (hit)	*NB* (false alarm)
No rain (<0.1 mm/h)	*NC* (failure)	/

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Table 2. Three storm events occurred in Meixi catchment.

Event ID	Typhoon	Storm start time (UTC+8)	Storm end time (UTC+8)	24-h accumulated rainfall (mm)
I	Saola	03/08/2012 00:00	04/08/2012 00:00	84
II	Hagibis	17/06/2014 21:00	18/06/2014 21:00	66
III	Nepartak	08/07/2016 18:00	09/07/2016 18:00	242

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Table 3. Radar data assimilation modes designed with data types and time intervals.

Modes	Time intervals of data assimilation	Assimilated radar data
1	6 h	radar reflectivity
2	6 h	radial velocity
3	6 h	radar reflectivity and radial velocity
4	3 h	radar reflectivity
5	3 h	radial velocity
6	3 h	radar reflectivity and radial velocity
7	1 h	radar reflectivity
8	1 h	radial velocity
9	1 h	radar reflectivity and radial velocity

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Table 4. Accumulated rainfall simulation (mm) and *RE* values (%) of the nine data assimilation modes for three storm events.

Modes	Event I		Event II		Event III		*ARE* (%)
	Rainfall Simulation (mm)	*RE* (%)	Rainfall Simulation (mm)	*RE* (%)	Rainfall Simulation (mm)	*RE* (%)	
No radar data assimilation	85.16	0.88	43.16	34.32	64.20	73.47	36.22
1	61.74	26.86	70.37	7.09	66.79	72.40	35.45
2	60.97	27.77	80.88	23.09	58.59	75.79	42.22
3	35.44	58.02	70.85	7.83	61.11	74.75	46.87
4	41.49	50.86	79.69	21.29	71.75	70.35	47.50
5	66.16	21.63	72.19	9.86	101.23	58.17	29.89
6	37.10	56.05	77.49	17.94	151.64	37.34	37.11
7	61.12	27.60	80.64	22.72	104.28	56.91	35.74
8	83.65	0.91	70.67	7.55	227.96	5.80	4.75
9	82.50	2.28	71.31	8.53	188.01	22.31	11.04

Table 5. *CSI* and *RMSE* for spatial distribution of rainfall simulation based on the nine data assimilation modes.

Modes	Event I		Event II		Event III		Average values for the three events	
	CSI	*RMSE*	*CSI*	*RMSE*	*CSI*	*RMSE*	*CSI*	*RMSE*
No radar data assimilation	0.7368	0.1535	0.4479	0.5635	0.6146	0.7482	0.5998	0.4884
1	0.7614	0.4524	0.3587	0.4070	0.6154	0.7841	0.5785	0.5478
2	0.6925	0.4967	0.2829	0.4771	0.6154	0.7844	0.5303	0.5861
3	0.6865	0.6907	0.3346	0.4618	0.6154	0.8147	0.5455	0.6557
4	0.7436	0.6261	0.3561	0.4359	0.6154	0.7905	0.5717	0.6175
5	0.7358	0.5341	0.3195	0.4170	0.6096	0.7123	0.5550	0.5545
6	0.7143	0.6614	0.2212	0.4783	0.5909	0.6285	0.5088	0.5894
7	0.5337	0.4275	0.3949	0.4896	0.5938	0.8004	0.5075	0.5725
8	0.7395	0.1505	0.4504	0.3589	0.6287	0.1643	0.6062	0.2246
9	0.7368	0.4211	0.3168	0.3152	0.6146	0.4519	0.5561	0.3961

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Table 6. *CSI* and *RMSE* for temporal distribution of rainfall simulation based on the nine data assimilation modes.

Modes	Event I		Event II		Event III		Average values for the three events	
	CSI	*RMSE*	*CSI*	*RMSE*	*CSI*	*RMSE*	*CSI*	*RMSE*
No radar data assimilation	0.6875	0.6018	0.3718	1.3131	0.6146	1.9223	0.5580	1.2791
1	0.6830	1.0351	0.3069	1.3843	0.6034	1.8138	0.5311	1.4111
2	0.6458	1.1787	0.2483	2.0950	0.6034	1.8232	0.4992	1.6990
3	0.6421	1.2414	0.2969	1.4631	0.6034	1.8318	0.5141	1.5121
4	0.6674	1.1411	0.2902	2.2037	0.6034	1.8153	0.5203	1.7200
5	0.6796	1.1115	0.2969	2.0414	0.6145	1.7793	0.5303	1.6441
6	0.6667	1.2878	0.2031	2.6387	0.5851	2.0122	0.4850	1.9796
7	0.4549	1.5132	0.3125	2.3337	0.5938	1.8452	0.4537	1.8974
8	0.6877	0.3822	0.3969	0.7015	0.6221	0.8459	0.5689	0.6432
9	0.6875	1.3862	0.2663	1.1180	0.6146	1.1699	0.5228	1.2247

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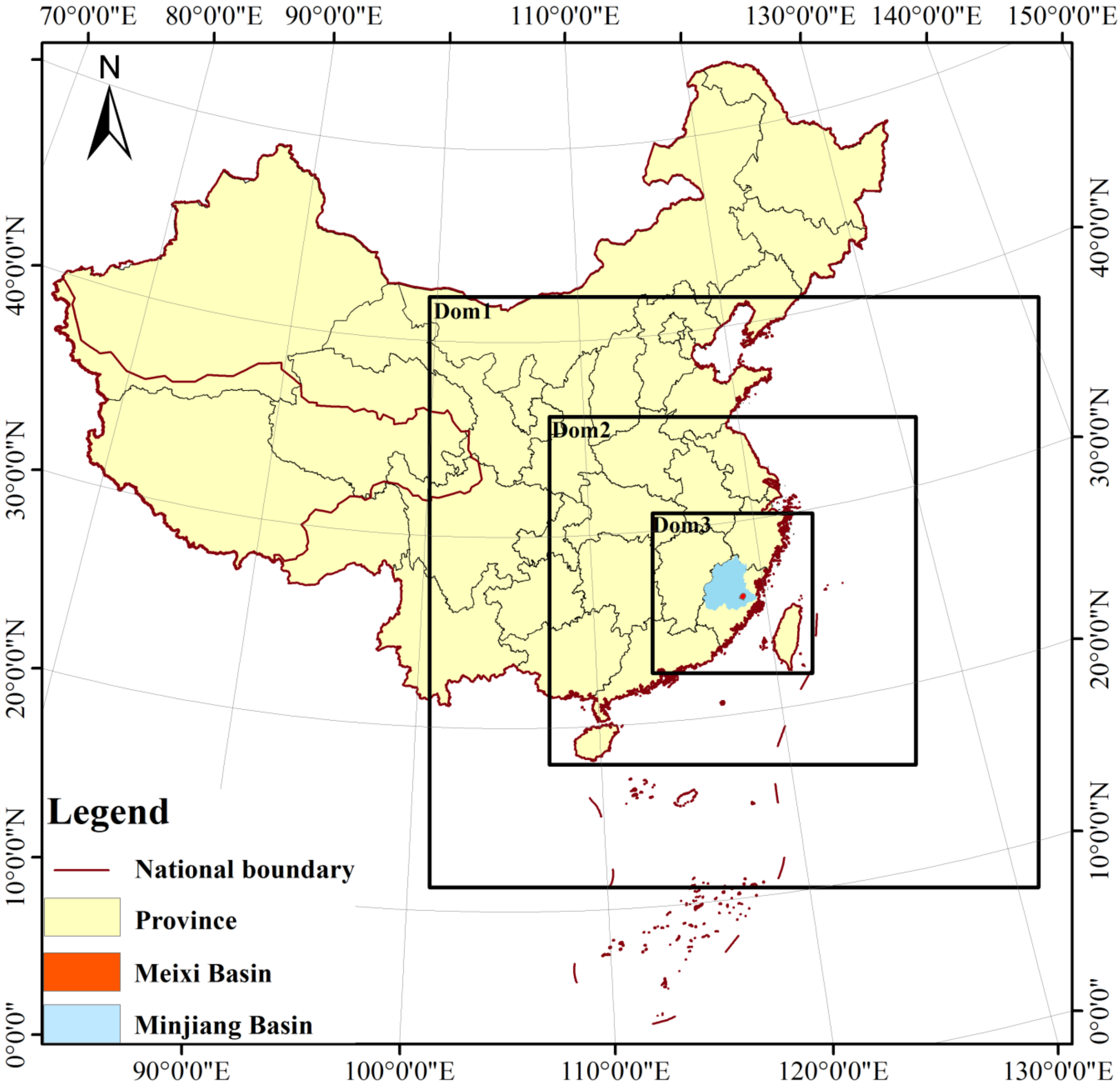

Figure 1. The location of the Meixi catchment and three nested domains.

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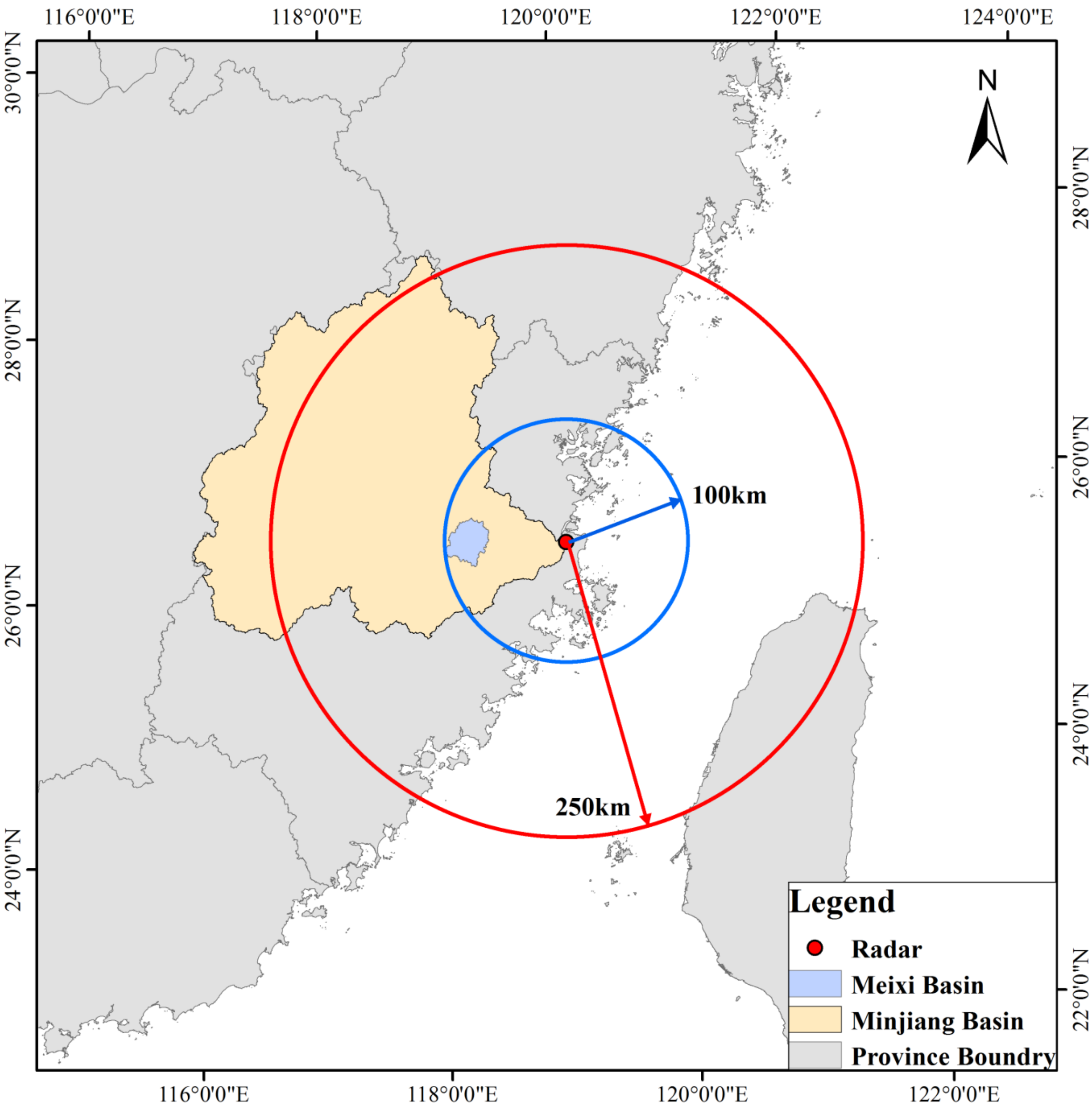

Figure 2. The location of radar station and position relation between radar scan area and Meixi basin.

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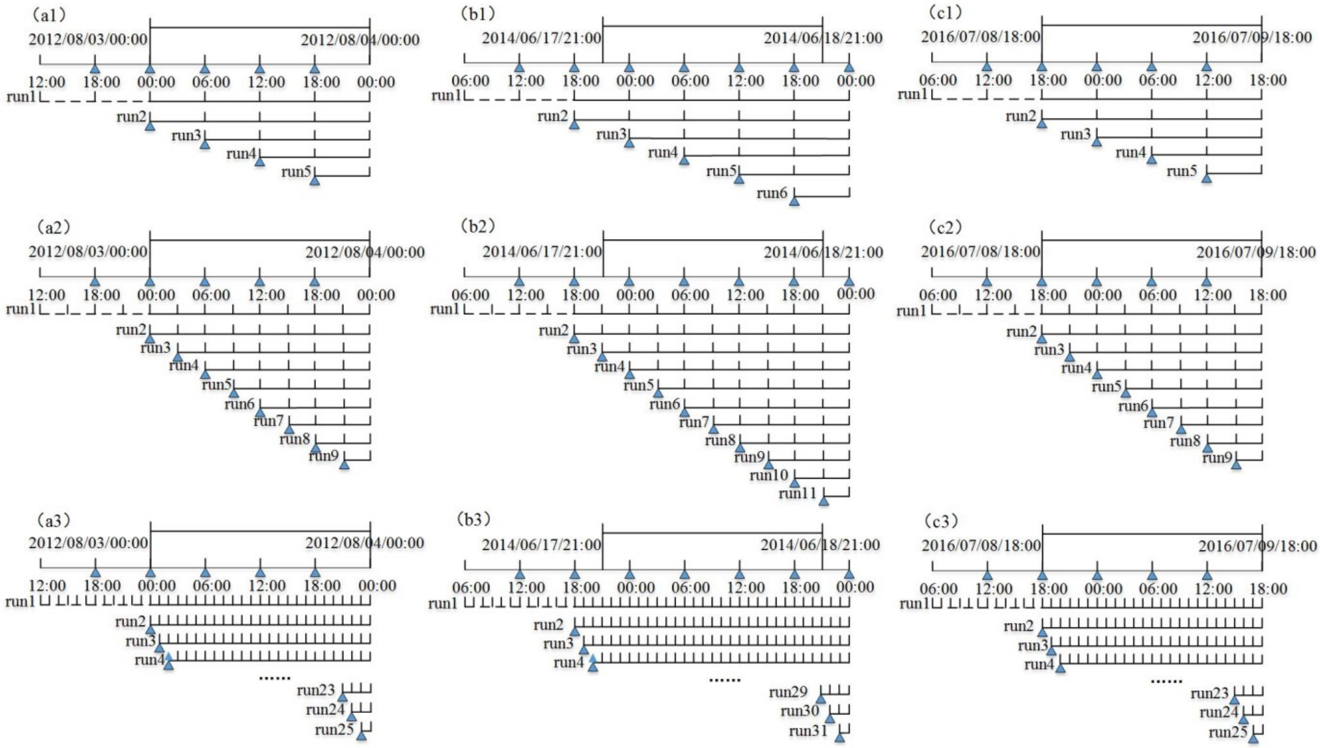

Figure 3. The time bars of the assimilation cycling runs for (a) storm event I, (b) storm event II and (c) storm event III.

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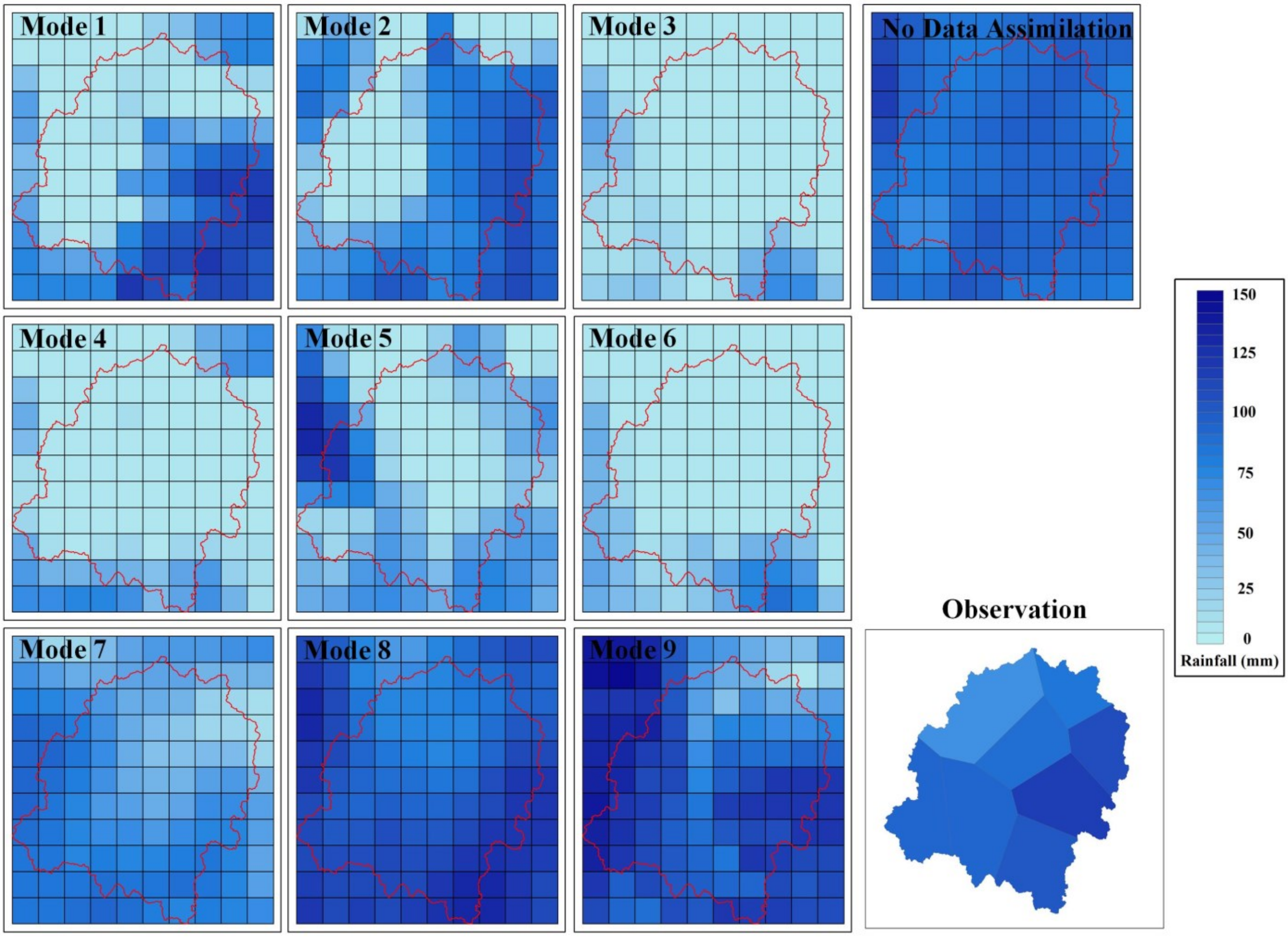

Figure 4. Spatial distribution of the rainfall simulations with nine data assimilation modes for Event I.

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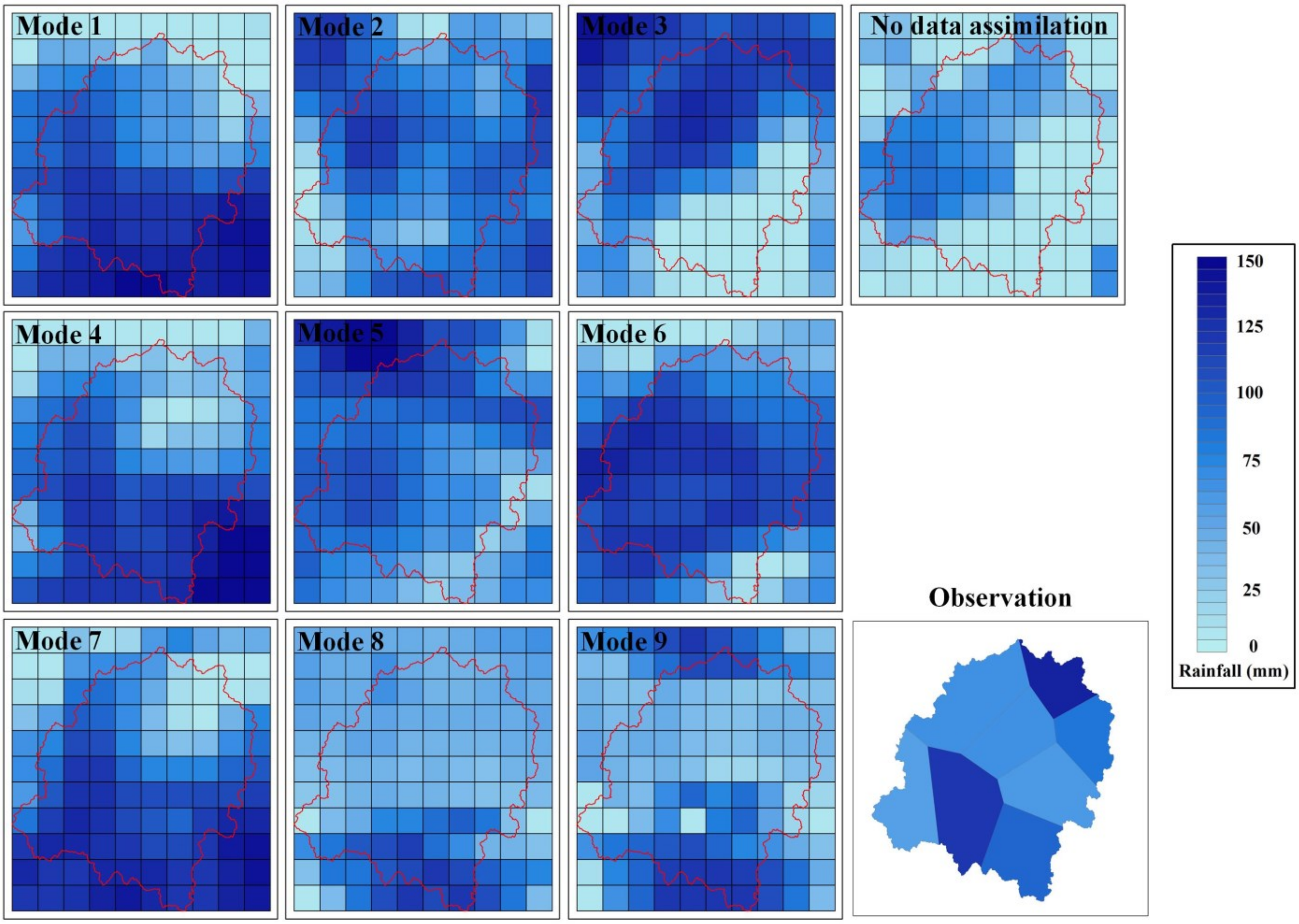

Figure 5. Spatial distribution of the rainfall simulations with nine data assimilation modes for Event II.

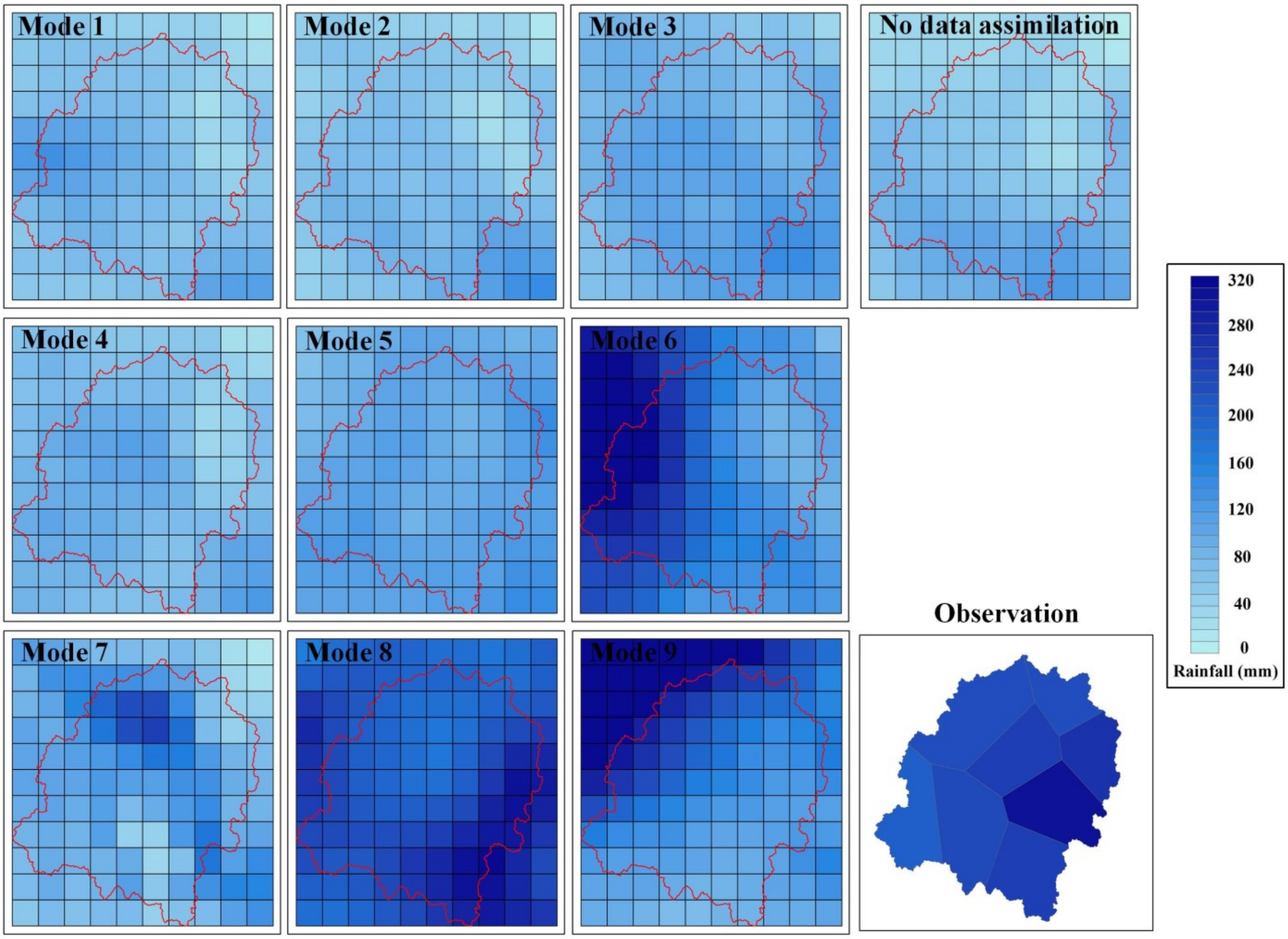

Figure 6. Spatial distribution of the rainfall simulations with nine data assimilation modes for Event III.

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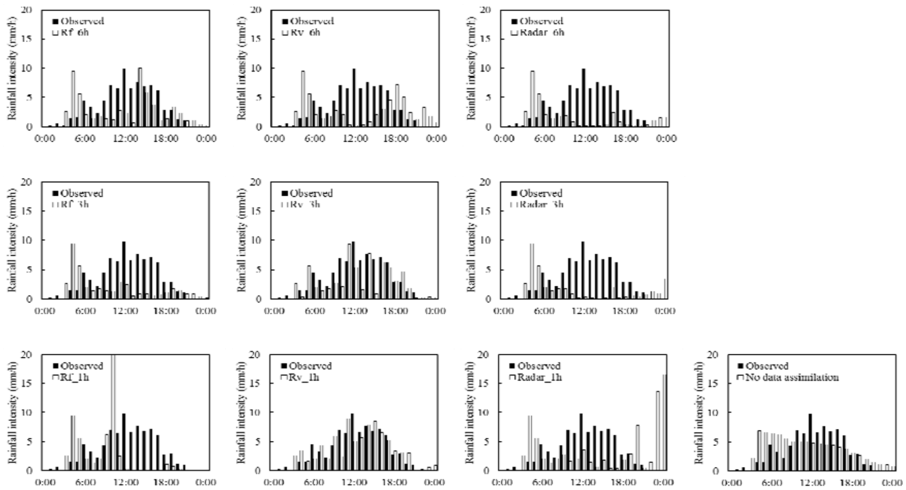

Figure 7. Time series bars of the rainfall simulations with nine data assimilation modes and the rainfall observation for Event I.

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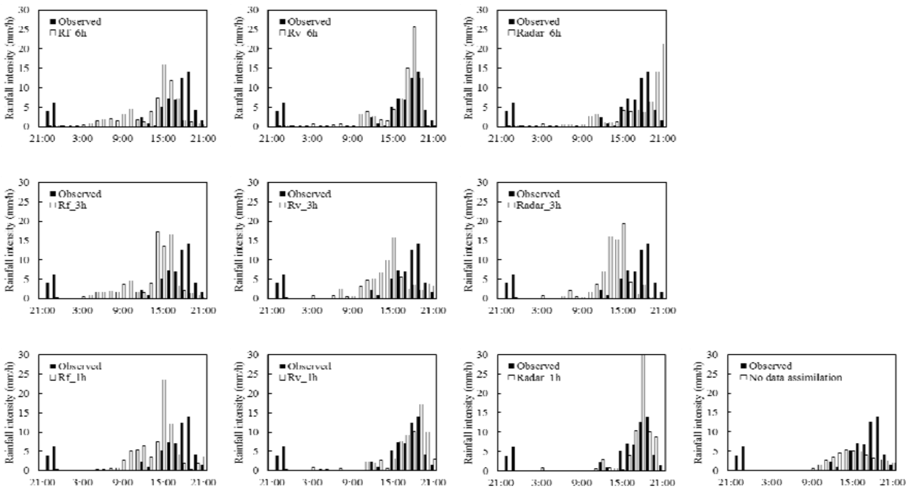

5 **Figure 8.** Time series bars of the rainfall simulations with nine data assimilation modes and the rainfall observation for Event II.

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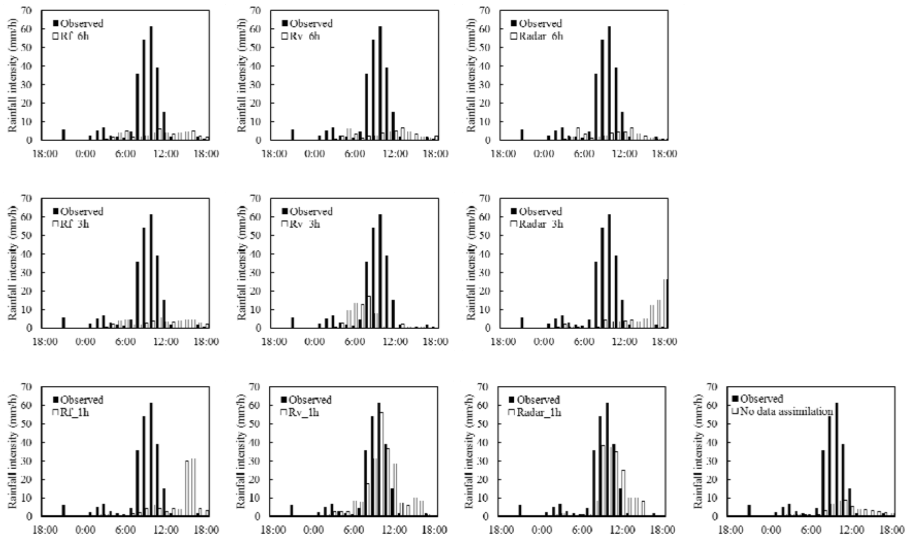

Figure 9. Time series bars of the rainfall simulations with nine data assimilation modes and the rainfall observation for Event III.