Typhoon rainstorm simulations with radar data assimilation on the southeast coast of China

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Received: 29 April 2020 – Discussion started: 6 July 2020
Revised: 1 January 2021 – Accepted: 16 January 2021 – Published: 23 February 2021

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 on the southeast coast of China. Radar data from a Doppler radar station in Changle, China, are assimilated with three-dimensional variational data assimilation (3-DVar) model. Nine assimilation modes are designed by three kinds of radar data and at three assimilation time intervals. 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 at a time interval of 1 h can significantly improve the rainfall simulations, and it 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 simulations as the time interval shortens. The rainfall simulations 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 at catchment scale and have great significance on typhoon rainstorm warning.

1 Introduction

Although the resolution of numerical weather prediction (NWP) systems is increasing with the improvement of computational efficiency and abundance of observation data, rainfall is still one of the most difficult meteorological factors to forecast (Lu et al., 2017; Avolio and Federico, 2018). A typhoon always comes with heavy rainfall which leads to great loss. However, due to the uncertainty of the rainfall and the imperfect generation of NWP systems, rainfall forecast with severe convection is unsatisfactory in medium and small catchment scales (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 systems, 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 using the Weather Research and Forecasting (WRF) model with the Gridpoint Statistical Interpolation (GSI) data assimilation (DA) system in the central Guangdong Province of southeast China. The rainfall simulation error was reduced at 4 km grid scale by assimilating satellite radiance data, which helped to analyze rainfall causes accurately. Giannaros et al. (2016) evaluated a lightning data assimilation (LTNGDA) technique over eight rainfall events occurring in Greece. The verification scores of the rainfall simulations were significantly improved by the employment of the WRF-LTNGDA scheme, especially for heavy rainfall. Zhang et al. (2013) presented a regional ensemble data assimilation system that assimilated microwave radiances into the WRF model for hydrological applications.
The rainfall simulations were improved in terms of the accumulated rainfall and spatial rainfall distribution in the southeastern United States. Yucel et al. (2015) assimilated conventional meteorological data by a three-dimensional variational data assimilation (3-DVar) model into the coupled atmospheric–hydrological system. The rainfall simulations, as well as the runoff simulations, improve significantly in large basins in the western Black Sea region of Turkey.

Due to their 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 four-dimensional variational data assimilation (4-DVar) system by simulating a midlatitude squall-line case in the US Great Plains, and the results indicated that radar data assimilation was able to improve rainfall forecasts from the WRF model at the convective scale. Liu et al. (2013) selected four storm events in a small catchment (135.2 km$^2$) located in southwest England to explore the effect of data assimilation for rainfall forecasts based on the WRF model, and assimilating radar reflectivity by the 3-DVar model can significantly improve the forecasting accuracy for the events with one-dimensional evenness in either space or time. By using the WRF model and Advanced Regional Prediction System (ARPS) 3-Dvar, Hou et al. (2015) improved the short-term forecast skill by up to 9 h by assimilating radar data in southern China.

Most studies focus on the assimilation algorithm and data selection. However, consistent conclusions have not been obtained for the option of radar reflectivity and radial velocity, and few studies pay attention to the time interval setting of data assimilation. Based on the WRF and 3-DVar models, Tian et al. (2017b) found that radar reflectivity assimilation led to better rainfall simulations than radial velocity assimilation at the time interval of 6 h. Maiello et al. (2014) assimilated both radar reflectivity and radial velocity by the 3-DVar model with a 3 h assimilation cycle to improve the WRF high-resolution initial conditions, and the rainfall forecast became more accurate for several experiments in the urban area of Rome. Bauer et al. (2015) used the WRF model in combination with the 3-DVar scheme to estimate the rainfall simulations, and the results showed that radar data assimilation significantly improved the rainfall simulations by a 1 h Rapid Update Cycle at the high resolution of 3 km in Germany.

In reality, the operational forecasts from meteorological departments are guidance forecasts with a large forecasting area. It is impossible to focus on the accuracy of the rainfall in small and medium catchment scales. Limited computing power means that the number of restarting times for the forecasting system is only 2–4 times per day (Xie et al., 2016). The forecasting accuracy descends gradually as the run time goes on because the data assimilation is not in real time. Due to the poor accuracy at small scales and low resolutions, the rainfall forecasting from the meteorological department cannot be used directly as the input for hydrological forecast-
landed at Fuding, Fujian, by 3 August. Then Saola weakened into a tropical storm at Jiangxi. With the movement of Saola, Meixi catchment was not directly affected, and the accumulated 24 h rainfall was only 84 mm. Hagibis landed at Shantou, Guangdong, on 15 June 2014 and then moved toward the north at a fast-moving speed. Fortunately, Hagibis weakened into a tropical depression quickly while moving to northeastern Fujian on 17 June. Event II occurred after the typhoon passed Meixi catchment, and the accumulated 24 h rainfall was only 66 mm. Nepartak reached Fujian on 9 July 2016 and strengthened at Putian. Then Nepartak moved towards the northwest at a fast-moving speed, and event III occurred when Nepartak was close to Meixi catchment. During the period, Nepartak reached its peak intensity. The 24 h accumulated rainfall was 242 mm, which led to a high peak period, Nepartak reached its peak intensity. The 24 h accumulated rainfall was 242 mm, which led to a high peak period. The evaluation needs an additional forward operator that associates the observational and representative error covariance matrix. The fundamental aim of the 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):

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

where $x$ is the vector of the analysis, $x^b$ is the vector of first guess or background, $y$ is the vector of the model-derived observation that is transformed from $x$ by the observation operator $H$, i.e., $y = H(x)$, and $y^0$ is the vector of the observation. $B$ is the background error covariance matrix, and $R$ is the observational and representational error covariance matrix. Equation (1) shows that the 3-DVar is based on a multivariate incremental formulation. Velocity potential, total water mixing ratio, unbalanced pressure, and stream function are all preconditioned control variables. Radial velocity has already been derived into component winds that are the same as the analysis variables; hence, radial velocity can be assimilated directly by Eq. (1). However, radar reflectivity assimilation needs an additional forward operator that associates the model hydrometeors with the radar reflectivity. Due to the wide applicability, the matrix of CV3 is adopted in this

3 Model description and numerical experiments

3.1 Model description

3.1.1 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 (Dom 1, Dom 2, and Dom 3) with two-way nesting are designed and centered over Meixi catchment. The grid spacings are set at 4, 12, 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 \times 100 for Dom 1, 210 \times 210 for Dom 2, and 300 \times 300 for Dom 3 (Fig. 1). Meixi catchment is completely covered by the innermost domain. All domains are comprised of 40 vertical pressure levels with the top level set at 50 hPa (Maiello et al., 2014). The NCEP Final (FNL) Operational Global Analysis data with $1^\circ \times 1^\circ$ 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 parameterizations has a 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). According to the previous studies on physics options selection, WRF Single-Moment 6 (WSM 6) for microphysics, Yonsei University (YSU) for PBL, the Rapid Radiative Transfer Model for application to GCMs (RRTMG) for longwave and shortwave radiation, Noah for LSM, and Kain–Fritsch (KF) for cumulus physics are adopted in this study (Srivastava et al., 2015; Hazra et al., 2017; Cai et al., 2018; Tian et al., 2021).

3.1.2 The 3-DVar data assimilation and observation operator

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Figure 1. The location of the Meixi catchment and three nested domains.
study to simplify the data assimilation procedure (Meng and Zhang, 2008).

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

$$Z = 43.1 + 17.5 \log (\rho q_r),$$

(2)

where $Z$ is the radar reflectivity (in dBZ), $\rho$ is the density of air (in $\text{kg m}^{-3}$), and $q_r$ is rainwater mixing ratio (in $\text{g kg}^{-1}$).

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 follows (Tian et al., 2017b):

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

(3)

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

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

(4)

$$a = \left( \frac{p_0}{\bar{p}} \right)^{0.4},$$

(5)

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

3.2 Numerical experiments

3.2.1 Assimilation modes

An 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 the radar station is less than 100 km.
Table 2. Physical parameterizations used in the WRF model.

| Physical parameterization          | Scheme                                      |
|-----------------------------------|---------------------------------------------|
| Microphysics                      | WRF Single-Moment 6 (WSM 6)                 |
| Planetary boundary layer (PBL)    | Yonsei University (YSU)                    |
| Longwave and shortwave radiation  | Rapid Radiative Transfer Model for application to GCMs (RRTMG) |
| Land surface model (LSM)          | Noah                                        |
| Cumulus                           | Kain–Fritsch (KF)                           |

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 |

(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, and radar reflectivity and radial velocity) and at three assimilation time intervals (1, 3, and 6 h). The rainfall simulation without data assimilation is used as the control mode. Nine modes are shown in Table 3.

3.2.2 WRF cycling runs for data assimilation

In order to obtain the whole process of the rainfall simulations, the running time is set at 3, 42, and 36 h for storm events 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 (all times are UTC +8) and occurs at intervals of 6, 3, 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 at intervals of 6, 3, and 1 h for storm event III.

4 Rainfall evaluation statistics

In this study, the observation of areal rainfall in Meixi catchment is averaged by the eight stations with the Thiessen polygon method (Sivapalan and Blöschl, 1998), while the simulation of areal rainfall is averaged from all grids of the WRF model inside the Meixi catchment. The relative error (RE) is used to evaluate the total rainfall amount simulation:

\[
RE = \frac{P' - P}{P} \times 100\%,
\]

where \(P'\) is the simulation of 24 h accumulated areal rainfall, and \(P\) is the observation of 24 h accumulated areal rainfall.

The spatiotemporal patterns of the rainfall simulations are evaluated by the critical success index (CSI) and modified root mean square error (m-RMSE), which is defined as the ratio of root mean square error (RMSE) to the mean values of the corresponding observations (Liu et al., 2012; Prakash et al., 2014; Agnihotri and Dimri, 2015):

\[
CSI = \frac{1}{N} \sum_{i=1}^{N} \frac{NA_i}{NA_i + NB_i + NC_i},
\]

\[
\text{m-RMSE} = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \left( P'_j - P_j \right)^2} \left/ \frac{1}{M} \sum_{j=1}^{M} P_j \right. 
\]

The CSI is calculated based on the rain or no rain contingency table (Dai et al., 2019). Table 4 shows that rainfall...
0.1 mm h\(^{-1}\) as the threshold is regarded as no rain. In order to evaluate the simulation of spatial rainfall distribution by CSI, \(N_A\), \(N_B\), and \(N_C\) at each time step \(i\) \((i = 1)\) are calculated by comparing the rainfall observation with the simulation extracted at eight rain gauge locations, and then the values of \(N_A\), \(N_B\), and \(N_C\) at all time steps are averaged to produce the final verification results. Therefore, \(N\) refers to the total time steps \((N = 24)\). For temporal dimension evaluation, \(P'\) and \(P\) are the simulation and observation of areal rainfall at each time \(j\), respectively. \(M\) represents the total amount of time \((M = 24)\). The perfect score of RMSE is 0.

### 5 Results

#### 5.1 Accumulated rainfall simulations of the nine data assimilation modes

Nine data assimilation modes for three storm events are evaluated by RE for 24 h accumulated areal rainfall. The average values of the RE (ARE) of the three storm events for each mode are also calculated. As shown in Table 5, data assimilation modes make the rainfall simulations worse according to the REs 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 modes 2 and 3. Mode 8, i.e., assimilating radial velocity at a time interval of 1 h, always has the lowest RE and performs the best. The improvement of the rainfall simulations is the most obvious for event III, and the rainfall magnitude is quite close to the observation, which has important significance in torrential rain-
fall forecasts and catastrophic flood forecasts in medium and small basins.

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

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

5.1.2 Evaluation of assimilating effects for the different assimilation time intervals

The influences of assimilating time intervals on rainfall simulations are analyzed in this section. Comparing the REs of modes 1, 4, and 7, shortening the time interval of radar reflectivity assimilation has no obvious improvement for rainfall simulations and even makes the rainfall simulations worse. For assimilating radial velocity, all the rainfall simulations of the three storm events become more accurate, and the assimilation effects are significantly improved as the time interval shortens from 6 to 1 h. The REs of the three storm events are all lower than 8% for the radial velocity assimilation at a time interval of 1 h. According to modes 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.

5.2 Spatiotemporal distribution of rainfall simulations based on the nine data assimilation modes

The spatiotemporal patterns of the rainfall have a significant effect on flood peak and peak time in medium and small catchments. The indices of CSI and RMSE are also 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 modes.

5.2.1 Evaluation in the spatial dimension

Table 6 indicates that although mode 8 with the highest CSI and lowest RMSE is the best choice in the nine data assimilation modes, rainfall simulations with data assimilation are always worse than without data assimilation for event I. Figure 4 shows that the observed rainfall center is located in the east of Meixi catchment, and it rains more in the upstream side than the downstream side. However, the spatial distribution of the accumulated 24 h rainfall with no data assimilation is even. Modes 1 and 2 simulate the rainfall on the east side of Meixi catchment accurately, while the simulated rainfall on the west side is much smaller than the observation. The rainfall simulations of modes 3, 4, 5, and 6 are all even in spatial dimension and lower than the observation. The simulation of mode 7 shows that the rainfall in the downstream side is less than the upstream side, whereas the different distribution in a east–west direction is not obvious, and the simulated rainfall is smaller than the observation. For mode 9, the spatial distribution of rainfall is also inconsistent with the observation. Only the simulation of mode 8 is close to the observed rainfall.

All RMSEs of the simulations with radar data assimilation are lower than without data assimilation, and only the CSI of mode 8 is higher than the simulation without data assimilation for event II. According to the rainfall distribution shown in Fig. 5, the falling areas of simulated rainfall without data assimilation are totally wrong. The observed rainfall center is located in the middle of the upstream and downstream catchment. However, the rainfall centers of modes 1, 4, and 7 are all located in the middle and lower region. The rainfall center is in the middle reaches for mode 2, while it is in the western catchment for mode 3. For modes 5 and 6, the spatial distributions of rainfall are also inconsistent with the observation. The simulated rainfall in the middle of the upstream catchment is close to the observation for modes 8 and 9 but in the downstream catchment is poor. Although the spatial rainfall distributions have deviations, nine modes get better than the simulations without data assimilation as a whole.

Based on Table 6, not all data assimilation modes help improve the rainfall simulations for event III. Modes 4, 5, and 9 have just a little improvement on rainfall simulations in spatial distribution, and only the simulation of mode 8 is close to the observation. The simulations of modes 1, 2, 3, 4, and 5 are much lower than the observation in the whole catchment. Most observed rainfall falls in the east of the catchment, while the simulated rainfall concentrates in the west for modes 6 and 9 and in the downstream catchment for mode 7.

Based on the CSIs and RMSEs of modes 1, 2, and 3, assimilating radar reflectivity performs better than assimilating the other two kinds of radar data at a time interval of 6 h. Assimilating radar reflectivity and radial velocity at the same time always leads to the worst simulations. Comparing the two indices of modes 4, 5, and 6,
Table 5. Accumulated rainfall simulation values (mm) and RE values (%) of the nine data assimilation modes for three storm events.

| Modes                  | Event I         | Event II        | Event III        | ARE (%)     |
|------------------------|-----------------|-----------------|------------------|-------------|
|                        | Rainfall RE (%) | Rainfall RE (%) | Rainfall 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 6. CSIs and RMSEs for the spatial distribution of rainfall simulations 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 |

Assimilating radar reflectivity at a time interval of 3 h can obtain the highest CSI for the three storm events, while assimilating radial velocity has a better performance than the other two modes based on RMSE for events I and II. For the time interval of 1 h, the ranking of assimilation modes for the spatial distribution of rainfall simulations is assimilating radial velocity > assimilating radar reflectivity and radial velocity > assimilating radar reflectivity. Comparing the two indices of modes 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 accurate, and the assimilation effects are significantly improved as the time interval shortens from 6 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.
5.2.2 Evaluation in the temporal dimension

As shown in Table 7, similar results can be found that most data assimilation modes cannot help the simulations of the WRF model get better for event I. Only mode 8 is outstanding with the highest CSI and lowest RMSE. Figure 7 shows that the rainfall is concentrated at 10:00–16:00 for the observation. However, the main rainfall processes occur at 03:00–05:00 for modes 3, 4, and 6, 03:00–05:00 and 14:00–15:00 for mode 1, 03:00–05:00 and 17:00–19:00 for mode 2, 03:00–05:00 and 09:00–10:00 for mode 7, and 03:00–05:00 and 20:00–24:00 for mode 9. The rainfall processes of modes 5 and 8 are similar with the observation, while the rainfall
Figure 6. Spatial distribution of the simulated 24 h rainfall accumulations with nine data assimilation modes for event III.

Table 7. CSIs and RMSEs for the temporal distribution of rainfall simulations 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     |
| 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                            | 0.6674   | 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   |

Simulations at 12:00–13:00 and 15:00 for mode 5 are worse than for mode 8.

According to the values of CSI and RMSE, only modes 8 and 9 are useful for the improvement of rainfall simulations, and obvious improvement can be found in mode 8 for event II. The actual main rainfall process occurs at 15:00–18:00, while the time is advanced by 3 h for modes 1, 4, 5, 6, and 7. There is a delay of 3 h for the main rainfall process of mode 3. Although the times of heavy rainfall for modes 2 and 9 are consistent with the observation, the areal rainfall at 18:00 is much higher than the observation.

For event III, although most CSIs of the simulations with radar data assimilation are lower than the simulations without data assimilation, the RMSEs show the opposite conclusions. From Fig. 9, the observed rainfall is concentrated at 08:00–11:00. It can be easily found that modes 1, 2, 3, 4, 5,
Figure 7. Time series bars of observed and simulated areal rainfall with nine data assimilation modes and the rainfall observation for event I.

Figure 8. Time series bars of observed and simulated areal rainfall with nine data assimilation modes and the rainfall observation for event II.
and 6 cannot reproduce the heavy rainfall process in temporal dimension. The simulated rainfall is concentrated at 15:00–16:00 for mode 7. Only the simulation of mode 8 is basically consistent with the observation, while the simulation of mode 9 is worse than mode 8 at 08:00 and 10:00.

According to the CSIs and RMSEs of modes 1, 2, and 3, assimilating radar reflectivity at a time interval of 6 h performs better than assimilating the 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 simulations for events I and III. Based on the two indices of modes 4, 5, and 6, assimilating radial velocity at a 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 the other two modes. For the time interval of 1 h, the ranking of assimilation modes for the temporal distribution of rainfall simulations is assimilating radial velocity > assimilating radar reflectivity and radial velocity > assimilating radar reflectivity.

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

6 Discussion

In order to prove the accuracy of the assimilation results, typhoon paths for different assimilation modes are also simulated (Fig. 10). According to the simulations of Saola and Nepartak, the accurate typhoon path simulations always lead to accurate rainfall simulations. However, for typhoon Hagibis, the actual typhoon center is far away from the Meixi catchment during the assimilation process. Hence, only the actual typhoon path for Hagibis is added in Fig. 10. Comparing the nine radar data assimilation modes, assimilating radial velocity at a time interval of 6 h always performs the worst in rainfall simulations, while the rainfall simulations 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 conditions can be changed with the wind information in radial velocity. However, the wind field is quite variable, especially for stormy weather. As the time interval becomes longer, the WRF model cannot be corrected by the radial velocity in time, whereas compared to the simulations without data assimilation, the inevitable observation errors caused by atmospheric refractivity in the radial velocity might lead to worse performance in the WRF model as the running time goes on.
Figure 10. Typhoon path and simulations for (a) Saola, (b) Hagibis, and (c) Nepartak.

(Montmerle and Faccani, 2009). That is the main reason that assimilating radial velocity at a 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 the WRF model timely, which is helpful to improve the rainfall simulations (Kawabata et al., 2014).

The water vapor transportation increments and wind field for different modes at the rainfall concentrating time are used to show how assimilating radial velocity and radar reflectivity affects the WRF model’s initial and boundary conditions (Figs. 11–13). The shadows in Figs. 11–13 mean that water vapor transportation in the analysis field is more than in the background field. The darker the shadow in the figures is, the more the water vapor transportation increment
is, which is one of the most important factors that affects the amount of rainfall. For event I, counterclockwise wind field has contributed to the water vapor transportation from ocean to inland at 12:00 on 3 August 2012. Modes 1, 2, 5, 7, 8, and 9 all obtain the shadow area with the obvious water vapor transportation increment. However, according to the coverage area of the shadow, only modes 5 and 8 influence Meixi catchment directly, which is consistent with the result that rainfall simulations with modes 5 and 8 are higher than simulations with no data assimilation at 12:00, while the increment of simulated rainfall is quite obvious for mode 8. The differences of nine modes can be easily found in both the wind field and water vapor transportation increments for event II. The water vapor transportation increases significantly in modes 2, 3, 8, and 9 at 18:00 on 18 June 2014, which has a direct impact on the rainfall simulations.

Figure 11. Water vapor transportation increment and wind field (850 hPa) for event I at 12:00 on 3 August 2012.
Figure 12. Wind field and water vapor transportation increment (850 hPa) for event II at 18:00 on 18 June 2014.

in Meixi catchment. That is the main reason why simulated rainfalls with modes 2, 3, 8, and 9 are higher than the simulated rainfall with no data assimilation. However, the wind fields in these modes indicate a lack of warm and wet flow supply, and the rainfall weakening is almost inevitable after 18:00. Considering the wind field and the range of water vapor transportation increments, the rainfalls may continue for a period of time after 18:00 in modes 3, 8, and 9, which can also be reflected by hourly simulated rainfall shown in Fig. 8. For event III, the water vapor transportation increases significantly in modes 2, 3, 5, 6, 7, 8, and 9 at 06:00 on 9 July 2016, while only modes 8 and 9 affect Meixi catchment directly. The range of shadows in Fig. 13 is also consistent with the rainfall simulations. The wind field indicates that water
vapor transportation is sufficient for mode 8 at a later time, which leads to a significant increase in simulated rainfall.

Does further shortening the assimilation interval obtain better rainfall simulations? In terms of theory, the answer is yes because improving the assimilation frequency can correct the initial and lateral boundary conditions in a timely manner. However, the observation errors of radial velocity may be amplified with the high assimilation frequency in the WRF model. There may be an “inverted u” relationship between the accuracy of the rainfall simulations and the assimilation time interval (Myung et al., 2000). Further study should be carried out to investigate the optimal assimilation time interval.
On the contrary, assimilating radar reflectivity offers little help for improving rainfall simulations except for accumulated rainfall. Furthermore, rainfall simulations become even worse as the time interval of radar reflectivity assimilation shortens from 6 to 1 h. The background field of the WRF model has large differences from the actual weather situation, which can be reflected in the rainfall simulations without data assimilation against the rainfall observations 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 it difficult for the 3-DVar data assimilation to produce an optimal estimate of the true atmospheric state by the iterative solution of a prescribed cost function. It should also be mentioned that due to its unchangeability, the matrix of CV3 has wide applicability but is not practical for all cases (Kong et al., 2017). The inadaptability 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 the poor performance of radar reflectivity assimilation (Sun, 2005). The more frequent the radar reflectivity assimilation is, the greater the pressure on the 3-DVar data assimilation model is. Other data assimilation models with variable background error covariance, such as the hybrid ensemble transform Kalman filter–three-dimensional variational data assimilation (ETKF-3DVAR) (Wang et al., 2012; Shen et al., 2016), should be tested for radar reflectivity assimilation in future studies.

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 in rainfall simulations, especially for accumulated rainfall. The errors in the assimilated data may have a negative effect on the rainfall simulations. Additionally, assimilating other kinds of data and radar data together may help to improve the rainfall simulations. Though the conventional observations, such as upper-air and surface observations from meteorological stations and sounding balloons, 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 large scales (Li et al., 2018). Yesubabu et al. (2016) indicate that assimilating the satellite observation also has a positive effect on the rainfall simulations. Assimilating different data sources, together with the radar data, may further improve the rainfall simulations at catchment scale. In reality, ECMWF was also tested for the data assimilation before FNL was used in this study (Zhang et al., 2018; Zhao et al., 2012). Although the rainfall simulations show some differences based on the two kinds of boundary conditions, the patterns of improvements from different data assimilation modes are quite similar, and the same conclusions can be obtained.

7 Conclusions

Data assimilation is an efficient technique for improving rainfall simulations. 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 the WRF model with nine modes in Meixi catchment located on the southeast coast of China. The FNL analysis data with 1° × 1° grids are used to drive the WRF model, and radar data from the 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, and radar reflectivity and radial velocity) and at three assimilation time intervals (1, 3, and 6 h).

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

Data availability. The rainfall data from gauges used in this study were provided by the Fujian Institute of Water Resources and Hydropower. The radar data were provided by the newest-generation weather radar network of China (CINRAD/SC). The NCEP Final (FNL) Operational Global Analysis data are available at https://rda.ucar.edu/datasets/ds083.2/ (NCAR, 2020).

Author contributions. All the authors contributed to the conception and the development of this paper. JT and RL contributed to radar data assimilation and paper writing. LD and LG assisted in the design and analyses of the data assimilation modes. BZ helped with the figure production.

https://doi.org/10.5194/nhess-21-723-2021
Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. We thank the NHESS editor and two reviewers for constructive comments which improved the study.

Financial support. This research has been supported by the National Key R&D Program (grant nos. 2019YFC1510605 and 2018YFC1508105), the National Natural Science Foundation of China (grant nos. 51909274 and 51822906), and the IWHR Research & Development Support Program (grant nos. JZ0145B032020 and WRO145B732017).

Review statement. This paper was edited by Vassiliki Kotroni and reviewed by two anonymous referees.

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