

Meteorological - Hydrological Coupling Flood Forecast and Error Propagation Characteristics Based on Radar Data Assimilation in Small- to Medium Sized River Basin—A Case Study of Zhanghe River Basin in China

Yufang Gao

Nanjing University of Information Science and Technology

linyi cong

1992508761@qq.com

Nanjing University of Information Science and Technology

Tao Peng

China Meteorological Administration Wuhan Institute of Heavy Rain

Xin Sun

Inner Mongolia Meteorological Observatory

Tong Nie

Nanjing University of Information Science and Technology

Yigchun Hu

Nanjing University of Information Science and Technology

Research Article

Keywords: radar data assimilation, meteorological - hydrological coupling model, rainfall-runoff forecast, Zhanghe River basin, error propagation

Posted Date: March 1st, 2024

DOI: <https://doi.org/10.21203/rs.3.rs-3924553/v1>

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Version of Record: A version of this preprint was published at Natural Hazards on October 21st, 2024.
See the published version at <https://doi.org/10.1007/s11069-024-06944-z>.

Meteorological - Hydrological Coupling Flood Forecast and Error Propagation Characteristics Based on Radar Data Assimilation in Small- to Medium Sized River Basin: A Case Study of Zhanghe River Basin in China

Yufang Gao ^{1,3}, Linyi Cong ^{1,4*}, Tao Peng ^{2,3}, Xin Sun⁵, Tong Nie ¹ and Yingchun Hu ¹

^{1*} Key Laboratory of Meteorological Disaster of Ministry of Education / Joint International Research Laboratory of Climate and Environment Change / Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters / School of Applied Meteorology, Nanjing University of Information Science & Technology, Nanjing 210044, China.

² China Meteorological Administration Basin Heavy Rainfall Key Laboratory / Hubei Key Laboratory for Heavy Rain Monitoring and Warning Research, Institute of Heavy Rain, China Meteorological Administration, Wuhan 430205, China.

³ Three Gorges National Climatological Observatory, Yichang 443099, China.

^{4*} Jilin Province Technology Center for Meteorological Disaster Prevention, Changchun 130062, China.

⁵ Inner Mongolia Meteorological Observatory, Inner Mongolia Meteorological Service, Hohhot 010051, China.

*Corresponding author(s). E-mail(s): 20201208004@nuist.edu.cn;

Abstract

In small- to medium-sized river basins, flood forecast accuracy and adequate lead times are especially important for the scheduling of catchment management decisions, involving flood prevention measures and disaster mitigation. For this study, the Zhanghe River basin in China was selected as the study area. A meteorological–hydrological coupled model, which linked the Weather Research and Forecasting (WRF) model to the WRF-Hydro model, was used with radar data to explore the influence of data assimilation frequency on rainfall and runoff forecasts, as well as the differences in error propagation characteristics between meteorological and hydrological models. The results were as follows: (1) Doppler radar data assimilation has the ability to improve the temporal and spatial variability of rainfall forecasts. Appropriate data assimilation show positive effect on improving the rainfall forecast. 3h assimilation intervals data assimilation may result in over-estimating under the influence of complex topography in Zhanghe River Basin. The rainfall forecast results based on 6 and 12 h assimilation intervals were more accurate than those derived from a 3 h interval, with the average cumulative rainfall errors being reduced by 44.86% and 53.26%, respectively. (2) Rainfall forecasts have a significant impact on the accuracy of subsequent runoff forecasts. The runoff results showed that the assimilation of radar data at higher frequencies does not guarantee the further improvement of the runoff simulations due to the overestimation of forecast rainfall. The average flood peak error under the 6 and 12 h assimilation intervals was 27.52% and 20.0%, respectively, less than that using the 3 h interval. Therefore, the effective information contained in the assimilation data is more important than the amount of data. (3) Error propagation between models differs with the changing assimilation frequency of the radar data and the consequent effect of the rainfall forecast. With the increase in assimilation frequency of the radar observations, the error

range increases. Compared with the rainfall errors, the runoff errors show greater variability. Through quantitative analysis, it was found that there is no well-defined linear relationship between the rainfall and runoff errors. At the same time, the potential of radar data assimilation is discussed, and some suggestions for improvement are put forward.

Keywords: radar data assimilation; meteorological - hydrological coupling model; rainfall-runoff forecast; Zhanghe River basin; error propagation

1. Introduction

Global climate change, frequent extreme weather events, and flooding caused by heavy rainfall are extremely harmful to the residents of affected areas [1,6]. Traditional hydrological forecasts take conventional observational data as the input to a hydrological model, and the lead time depends on the confluence time of the basin [2,4,43]. However, the low density and likelihood of damage associated with station networks in small- and medium-sized river basins in mountainous areas leads to a lack of observational data; e.g., precipitation and runoff amounts. Combined with the rapid confluence of such watersheds, this lack of data means that forecast lead times are short and prediction accuracy is low. One approach to generating longer-term flood forecasts, and thereby improving flood control and disaster mitigation in small- and medium-sized rivers basins, is by introducing precipitation forecasts during the lead time and using high-precision meteorological and hydrological information to carry out flood forecasting and early warning work [2-9]. Therefore, increasing attention has been paid to flood forecasting based on the coupling of numerical prediction models with hydrological models.

In recent years, the development of Numerical Weather Prediction (NWP) models and distributed hydrological models has provided technical support for coupled meteorological-hydrological flood forecasting [2-24]. NWP models can provide quantitative precipitation forecast (QPF) products with long lead times [2-3]. The lead times associated with the latest weather prediction models fall within the range of 1–15 days. At the same time, distributed hydrological models describe a catchment's topographic features and streamflow formation processes based on a grid, which can simulate hydrological processes effectively and couple with NWP models conveniently [9,16]. However, it is still challenging to forecast rainfall and runoff using a coupled NWP and hydrological model for small- and medium-sized river basins. The primary reasons are as follows: (1) Due to the nonlinearity and complexity of the atmosphere, numerical weather forecasting is less precise for small to medium-sized river basins compared to larger basins [4,25-27]. (2) With the increase in resolution, it is more difficult to match meteorological and hydrological coupling in scale [6-8]. (3) Due to geographical conditions, the distribution of rainfall is uneven, and the time of concentration has a greater influence on small to medium basins than in larger basins. Consequently, any errors associated with the meteorological and hydrological data collection are not as readily smoothed out by the river network, which greatly increases the difficulty of hydro-meteorological forecasting in smaller basins [27].

As an important model input for watershed runoff forecasting, the quality of rainfall data directly affects the accuracy of the flow forecasting results [2-4,10-12]. The temporal distribution of rainfall can lead to differences in the flood flow, total flood volume, and timing of the peak flood occurrence. Meanwhile, the uneven spatial distribution of rainfall will increase the uncertainty associated with the parameters in the hydrological model. Therefore, accurate acquisition of the regional spatial and temporal distribution of rainfall is the key to coupled meteorological-hydrological flood forecasting [10-12]. Numerical weather forecasting is a method used to predict future weather conditions by solving dynamic and thermodynamic equations through numerical calculation using specified initial conditions based on existing weather conditions [20-24]. Accurate initial values are key to successful numerical weather forecasting. Data assimilation can be used to improve the forecasting ability of NWP models by combining observation data and numerical models to provide more accurate initial values for numerical weather prediction models [13,19]. However, conventional observations are far from sufficient for convective-scale data assimilation (DA), which requires information with a high temporal and spatial resolution. Thus, as a useful remote sensing instrument, radar can probe inside clouds to provide data regarding convective-scale phenomena and rainfall structure information with a high level of spatial and temporal precision [28]. Radial velocity assimilation can change the wind field and affect water vapor transport, and radar reflectivity assimilation is essentially a correction of the humidity field, which directly affects the formation of rainfall. Hence, to enhance the

precision and reliability of the numerical rainfall forecast, it is advantageous to assimilate high-resolution radar observations and regularly adjust the initial field and lateral boundary conditions of the NWP models [4,21-23].

Liu et al. [21] designed 11 data assimilation models to reproduce 24-hour rainfall in the Zijianguan Basin and compared the performance of different data assimilation schemes. They found that the assimilation of radar reflectivity data generated the most accurate results. Gu et al. [4] conducted several case studies in the Qingjiang Basin in Hubei Province to examine the effects of conventional observation data and radar data assimilation on QPF and flood forecasting. Their results showed that radar data assimilation made the time distribution of the rainfall more accurate and the peak error smaller. Liu Y et al. [22] explored the potential influence of data assimilation frequency, indicating that a high assimilation frequency can better predict the temporal and spatial distribution of convective torrential rain. It can be seen that radar data assimilation can improve the initial conditions and short-term predictions for NWP models. However, the related studies mentioned that assimilating radar observations into a numerical prediction model may produce spurious precipitation and large errors in the position and magnitude of precipitation, and high-frequency cyclic assimilation may exacerbate this problem [65-70]. Thus, the accuracy of the rainfall forecasts differs for different river basins, different types of rainfall processes, and different radar data assimilation schemes. The influence of data assimilation frequency on rainfall and runoff forecasts requires further investigation.

The key to successful meteorological-hydrological coupled flood forecasting also lies in matching the temporal and spatial resolution between the models. The WRF-Hydro model is an extension of the mesoscale numerical weather prediction model WRF (which focuses on land surface hydrological processes). It was primarily developed mainly by the National Center for Atmospheric Research (NCAR) in 2013. This high-resolution distributed hydrological model can simulate runoff and related hydrological processes based on river grids, so it can better match the WRF model in time and space resolution, and be more effectively coupled with the WRF model by using one-way and two-way couplings, resulting in improved runoff forecasting [29]. WRF-Hydro has been applied to river basins in many countries and has achieved good simulation results [29-39]. However, the impact of improving radar data assimilation on WRF rainfall forecasts and its propagation characteristics in the coupled WRF/WRF-Hydro meteorological-hydrological model needs further study [40-42].

Therefore, it is important that we study the influence of radar data assimilation on rainfall forecasts and meteorological-hydrological forecast error propagation characteristics, and also to improve the effectiveness of meteorological-hydrological forecasts in small- to medium-sized river basins. A typical small- to medium-sized basin in the southern regions, the Zhanghe River basin in Hubei Province, China, is prone to flooding. This study focuses on the Zhanghe Basin utilising Doppler radar data and a three-dimensional variational data assimilation method to construct the coupled WRF/WRF-Hydro meteorological-hydrological model. The effects of different frequencies of radar data assimilation on rainfall accumulation processes, as well as the temporal and spatial distributions, are investigated for four different types of storm event that occurred in the Zhanghe Basin in 2017 and 2018. The effectiveness of using Doppler radar data for rainfall-runoff forecasting, and the transmission characteristics of errors in the coupled meteorological-hydrological process, are also explored.

2. Study area and data

2.1 Zhanghe River Basin

The Zhanghe River Basin is located in Hubei Province, China (30.9 °N ~ 31.7 °N, 111.4 °E ~ 112.2 °E) (Figure 1). The area of the basin is about 2228km². The topography is mainly mountainous and hilly. The average length and width of the basin is about 100km, the width is about 30km, the elevation range is 65m ~ 1583m [43].

There are mainly six types of land use in the river basin, with the highest forest coverage, followed by cultivated land (Figure 1b). The main soil types are clay loam and clay (Figure 1c). The mountain climate has remarkable characteristics, and it is a typical small and medium-sized river basin in the humid mountain area of the south of China. The average annual rainfall is 1003.6mm, the rainfall is abundant, and the annual distribution of precipitation is extremely uneven, mainly from May to September, with the characteristics of short duration, high intensity, concentrated rainfall [43].

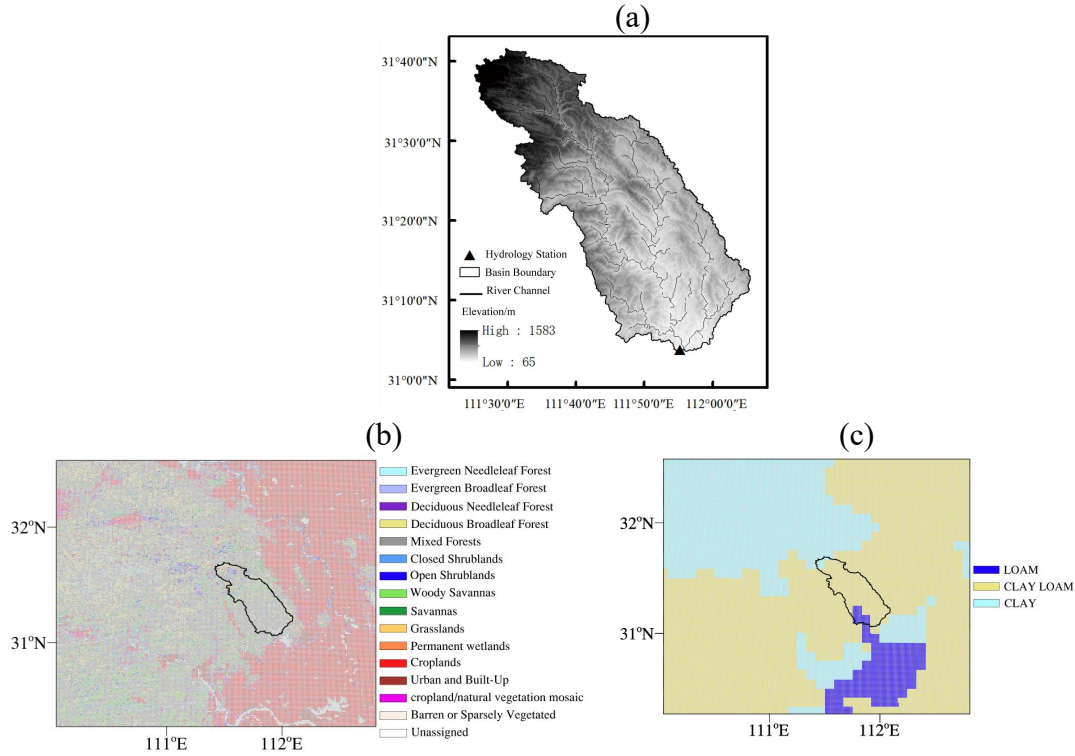


Figure 1. Geographical characteristics of the study area

Elevation, stream network and hydrological station of Zhanghe River Basin; (b) land use; (c) soil category.

2.2 Meteorological and hydrological datasets

The the China Meteorological Administration Multisource Precipitation Analysis System (CMPAS) product is a three-source data fusion of satellite, radar and ground station data. For this study, we used CMPAS to analyze and evaluate the rainfall forecast results of WRF model in different assimilation frequencies, and as the forcing data of atmospheric precipitation for WRF Hydro model in uncoupled mode [44-45]. CMPAS is available at spatial and temporal resolutions of 0.05° and 1 h, respectively.

The radar data in the S-band are assimilated to correct the initial state of the numerical prediction model.

DEM data comes from SRTMDEM 90m resolution raw elevation data (<http://www.gscloud.cn/sources>). The data of landuse type and soil type are from the MODIS (Moderate-resolution Imaging Spectroradiometer) dataset, which the resolution is 30 s. DEM data, landuse types and soil types are used to generate hydrological information files by the GIS pre-processing tools of WRF-Hydro model.

Based on the hourly runoff data of Guanyinsi hydrological station, the parameters of WRF-Hydro hydrological model are calibrated, and the runoff forecast results under different assimilation frequencies are evaluated. In this study, four typical flood events in Zhanghe River Basin from 2017 to 2018 were selected as a case study (Figure 2). The flood process and peak runoff of each event are shown in Table 1. Among the four typical rainfall events, 20170708 has a short duration and high intensity; 20171001 has a long duration and weak intensity; 20180505 has a long duration and strong intensity, and 20180704 is a bimodal event. The characteristics of the four rainfall processes are different, so the rainfall and runoff processes with different characteristics are simulated and reproduced to explore the effect of meteorological-hydrological coupling forecast based on radar data assimilation.

170

Table 1. The characteristics of four typical storm events between 2017 and 2018.

Events	Start time	End time	Peak flow (m ³ /s)	Cumulative rainfall (mm)
20170708	08/07/2017 06:00	10/07/2017 06:00	939.37	62.34
20171001	01/10/2017 06:00	08/10/2017 06:00	566.5555556	65.10
20180505	30/06/2018 00:00	03/07/2018 00:00	374.59259	51.77
20180704	04/07/2018 04:00	07/07/2018 00:00	384	35.06

171

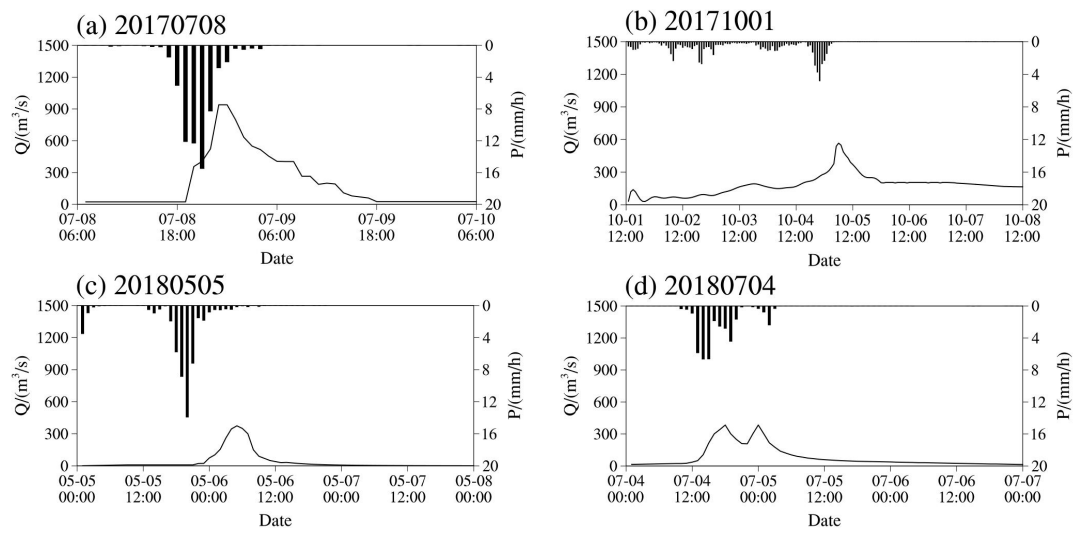


Figure 2. Rainfall-runoff process lines for four typical storm events.

172

3. Research method

173

3.1 Mode Setting

174

3.1.1 WRF mode setting

175

In this study, the Weather Research and Forecasting (WRF V4.1.1) model is selected to forecast rainfall. Taking 33.20°N and 111.80°E as the center, the three-layer nesting scheme is adopted. The horizontal resolutions of d01, d02 and d03 are 15km, 5km and 1km respectively, which can cover the whole Zhanghe River basin (Figure 3). The NCEP GFS prediction data with a horizontal resolution of 0.25 °× 0.25 ° are used as the initial and boundary fields of the WRF model. The main parameterization schemes adopted in WRF model refer to Gao's research results [43]. Microphysical process scheme Thompson scheme, land surface scheme Noah, cumulus convection scheme KF, boundary layer MYJ, long wave radiation RRTM and short wave radiation Dudhia are set as the physical parameterization scheme of WRF model in this study.

182

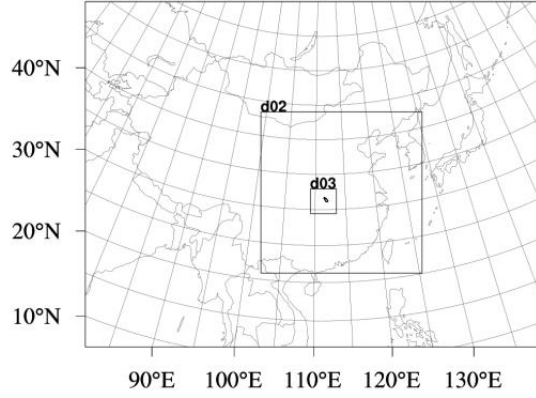


Figure 3. The WRF domain. Zhang River basin is indicated by black polygons.

3.1.2 Assimilation method of WRF-3DVAR

In order to obtain more accurate rainfall forecast results, the three-dimensional variational assimilation (3DVar) technique with high computational efficiency and strong stability is selected in this study [22,24,46]. The background field error and observation data are used to modify the background field of the atmospheric model to make the background field of the model closer to the actual meteorological situation, so as to adjust and improve the background field of the model [47].

The main objective of the 3DVar method is to obtain a statistically optimal estimate of the true atmospheric state by minimising a cost function in an iterative manner over a given analysis time, which can also be interpreted as solving for an analytical variable, which makes an object function to measure the distance reach the minimum among the analysis variable (corrected initial field and lateral boundary conditions), the background field (initial field and lateral boundary conditions) and the observation field (meteorological observation information)]. The cost function can be expressed as the distance between x weighted by the inverse matrix of the background error covariance and the background field x^b plus the distance between x weighted by the inverse matrix of the observation error covariance and the observation y_0 [51,61-62]. The objective functional can be expressed by the following expression:

$$J(x) = \frac{1}{2} \left\{ (x - x^b)^T B^{-1} (x - x^b) + [y_0 - H(x)]^T R^{-1} [y_0 - H(x)] \right\} \quad (1)$$

Where x is expressed as an N -dimensional analytical field (including temperature, pressure, humidity, wind). x_b is the background field of N -dimensional vector. B is the error covariance matrix of $N \times N$ -dimensional background field. N refers to the degree of freedom of the analytical field. y_0 is the M -dimensional observation vector and H is the observation operator, which projects the pattern variables from the model space to the observation space. R is the $M \times M$ dimension observation error covariance matrix, $R = E + F$, E is the instrument observation error covariance matrix, F is the observation representative error covariance matrix. M refers to the degree of freedom of the observation field. After the background field, observation data and background error covariance are inputted into the system, the analytical field of the model can be obtained by iterative processing of the assimilation system. Finally, the assimilated boundary conditions need to be updated for further simulation or prediction.

3.1.2.1 Selection of background error covariance

In the assimilation system, the background error covariance matrix is an important parameter, which not only represents the background error characteristics of large-scale circulation, but also contains mesoscale disturbance information, and largely determines the error correlation between different variables [47]. Through the NMC (National Meteorological Center) method widely used in the assimilation system, the

background field error covariance selected in this paper is calculated by using the control variables based on CV7 (u, v, T, RH_s, P_s) [56]. The prediction errors of the regional samples of the 12h prediction effectiveness WRF model at the same time in July 2018 are counted as the background error covariance during assimilation, which can be calculated by the following expression:

$$\mathbf{B} = \overline{(\mathbf{x}^{24} - \mathbf{x}^{12})(\mathbf{x}^{24} - \mathbf{x}^{12})^T} \quad (2)$$

Among them, $\mathbf{B}$ is the background error covariance matrix. For the regional numerical model, $\mathbf{x}^{24}$ and $\mathbf{x}^{12}$ in equation (2) are two prediction fields which are predicted to the same time but the prediction time is 24 hours and 12 hours respectively. The prediction error samples can be obtained by making the difference between the two prediction fields.

3.1.2.2 Assimilation data

The assimilation data used in the study are derived from the SA band Doppler weather radar reflectivity and radial velocity data installed in Yichang, Hubei Province, China (111.296 °E, 30.702 °N). The temporal resolution is 6min, the scanning height is 13km, the scanning radius is 230km, the scanning range can completely cover the Zhanghe River basin, and the spatial resolution is 1kmx1km. The quality control procedures include removing ground clutter, radial interference echo, non-meteorological echoes, speckles, and so on. The relationship between radar coverage and watershed location is shown in Figure 4.

Considering the discontinuity of wind speed analysis field and the inability to effectively exclude observations with large wind update vectors in the near-surface layer during the quality control process, the radial wind is directly assimilated in this study [28,48,63]. On the other hand, the direct assimilation method in the process of variational minimization, the linearization of nonlinear reflectivity forward operator may introduce error, convergence and stability problems. Therefore, we adopt the method of indirectly assimilating radar reflectivity, that is, assimilating four kinds of hydrometeor from radar reflectivity factors: rain (qr), snow (qs), graupel (qg) and water vapor (qv) [46,50]. The forward model for equivalent radar reflectivity factor (Ze) is the sum of the contribution of qr, qs and qg to radar reflectivity. The reflectivity and radial wind data of Doppler weather radar in Yichang station are transformed into WRF-3DVar assimilable data format (ob.radar) through the program, which is used as the input file of the observation field.

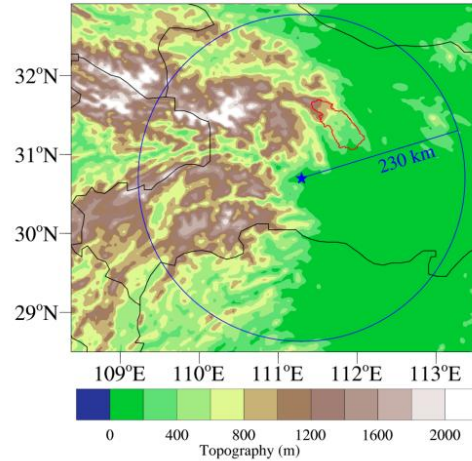


Figure 4. Scanning range of Doppler radar and geographical location of river basin. The blue star is the radar position of Yichang Station, the blue outline is the radar scanning range, the red outline is the Zhang River basin, and the shadow is the altitude

3.1.2.3 Assimilation test design.

According to the spatial scale and characteristics of radar data, this study assimilates the inner grid d02 region based on WRF model. Experiments with different time intervals are designed to assimilate Doppler radar data, and four individual rainfall forecasts are carried out. Previous studies have shown that for

short-term heavy rainfall events, assimilating radar radial wind and reflectivity at the same time is better than assimilating radial wind or reflectivity alone [49]. In this study, radar radial wind and reflectivity are assimilated at the same time for different assimilation frequencies in d02 region. Among them, the cycle prediction test (cycle) did not carry out data assimilation, and the model carried out 24-hour cycle prediction after 6 hours of spin-up. Assim_03h, assim_06h and assim_12h represent the assimilation test schemes of radar radial wind and reflectivity at 3h, 6h and 12h intervals in d02 area, respectively.

Table 2. Assimilation and forecast experiment design

Test Name	Assimilation Scheme
cycle	No assimilation
assim_03h	3 h interval assimilation radar reflectivity and radial velocity in the WRF d02 area.
assim_06h	6 h interval assimilation radar reflectivity and radial velocity in the WRF d02 area.
assim_12h	12 h interval assimilation radar reflectivity and radial velocity in the WRF d02 area.

3.1.3 WRF-Hydro mode settings

The WRF-Hydro model, as an extension of the widely used Noah and Noah-MP multi-parameter land surface models, is a physical, fully distributed and multi-parameter model that provides hydrologic processes with the land surface, subsurface, channel routing, underground, and base flow processes [29]. In this study, WRF-Hydro model version 5.0.3 was selected for runoff simulation, and the research process was carried out in d03 area, which the resolution of the coarse grid of the land surface model is 1km, the resolution of the fine grid of the confluence model is 100m, and the river density is 0.01 km². In this study, the WRF-Hydro model is driven by CMPAS and rainfall forecast data to simulate the runoff process. The WRF-Hydro model settings are shown in Table 3.

Table 3. The main parameterization schemes of the WRF-Hydro model

WRF-HydroV5.0.3	Option
Land surface model	Noah-MP model
Overland & subsurface flow routing	D8
Subsurface flow routing	Exponential bucket model
Channel routing	Wave-gridded method
Time step of forcing data	1 h
Time step of routing	6 s

3.2 WRFDA/WRF/WRF-Hydro coupling system

In this study, the initial field and lateral boundary conditions of the WRF model are derived from the GFS prediction data, and the radar reflectivity and radial wind data are assimilated by the WRF-3DVAR system, update the initial field and side boundary conditions to further run the WRF mode. The WRF-Hydro model is driven by the intermodal data interface to process the forecast rainfall data. The technical framework and forecast flow of the system is shown in Figure 5. The WRF model carries out a 6-hour spin-up before making rainfall forecast. The WRF-Hydro model uses CMPAS data for two months of “spin-up” before running run-off simulations.

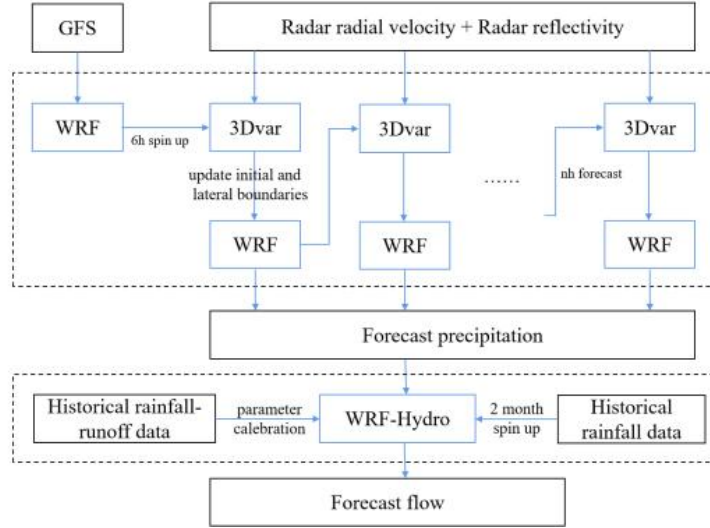


Figure 5. Construction of WRF/WRF-Hydro Meteorological-Hydrological Coupling system based on Radar data assimilation

3.3 Evaluation methods

Correlation coefficient (RR), flood peak present time difference (ΔT), absolute value of relative error of total discharge in runoff process ($|TE|$), absolute value of relative error of flood peak discharge ($|PE|$), Nash efficiency coefficient (NSE) were used as parameters of WRF-Hydro hydrological model calibration and runoff simulation [57-60], as shown in Formula (3-7).

Using the time difference of rainfall peak (ΔT_1 (h)), the hourly correlation coefficient of rainfall (RR_1), the absolute value of relative error of total rainfall ($|TE_1|$), the absolute value of cumulative relative error of rainfall at flood peak ($|PE_1|$), and the present time difference of flood peak (ΔT_2 (h)), the hourly correlation coefficient (RR_2) of runoff forecast, the absolute value of total runoff relative error ($|TE_2|$) and the absolute value of flood peak runoff relative error ($|PE_2|$) of runoff process, the results of rainfall-runoff forecast with different radar data assimilation frequency, and the error transfer between the models for quantitative comparative analysis, calculation formula see formula (3-6).

$$RR = \frac{\sum_{t=1}^{t=T} (A_{obs}^t - \bar{A}_{obs})(A_{sim}^t - \bar{A}_{sim})}{\sqrt{\sum_{t=1}^{t=T} (A_{obs}^t - \bar{A}_{obs})^2} \sqrt{\sum_{t=1}^{t=T} (A_{sim}^t - \bar{A}_{sim})^2}} \quad (3)$$

$$\Delta T = T^{A_{obs}^{max}} - T^{A_{sim}^{max}} \quad (4)$$

$$TE = \frac{\sum_{t=1}^{t=T} A_{obs}^t - \sum_{t=1}^{t=T} A_{sim}^t}{\sum_{t=1}^{t=T} A_{obs}^t} \times 100\% \quad (5)$$

$$PE = \frac{A_{obs}^{max} - A_{sim}^{max}}{A_{obs}^{max}} \times 100\% \quad (6)$$

$$NSE = 1 - \frac{\sum_{t=1}^{t=T} (A_{obs}^t - A_{sim}^t)^2}{\sum_{t=1}^{t=T} (A_{obs}^t - \bar{A}_{obs})^2} \quad (7)$$

In the formula, T is the duration of each runoff process, $T^{A_{obs}^{max}}$ 、 $T^{A_{sim}^{max}}$ represent the peak time of observation and simulation, respectively; A_{obs}^t 、 A_{sim}^t represent the observed value and simulated value of t time, respectively; $\bar{A}_{obs}$ 、 $\bar{A}_{sim}$ represent the average value of observed value and simulated value in T time, respectively.

4. Results

4.1 WRF-Hydro model parameter calibration

The main objective of the calibration is to ensure that the rainfall-to-runoff conversion of specific events will be as real as possible, with reducing the impact on error propagation analysis. In this study, three events (20150630, 20150714, 20160630) are selected for calibration, and the CMPAS data are

interpolated into 1km as the rainfall driver of the WRF-Hydro model. The stepwise approach is used to further calibrate the main parameters of the WRF-Hydro model on the basis of Gao, Y.F. et al [43]. Four events (20170708, 20171001, 20180505, 20180704) verify the parameter combination. The evaluation results of hourly simulated runoff of calibration and verification are shown in Table 4. It can be seen that the result of runoff simulation is good, and the parameter combination can be further applied to the study of flood forecasting in Zhanghe river basin.

Table 4. Calibration and verification of the evaluation results.

	case	RR	Relative error of flow/%		NSE	$\Delta T/h$
			PE	TE		
Calibration	20150630	0.88	14.61	14.28	0.75	0h
	20150714	0.94	18.16	11.07	0.87	0h
	20160630	0.91	17.75	16.71	0.78	0h
Verification	20170708	0.92	14.60	11.52	0.83	0h
	20171001	0.92	0.98	17.94	0.76	0h
	20180505	0.85	7.24	1.16	0.72	-2h
	20180704	0.88	15.26	6.94	0.77	1h

4.2 Rainfall forecast results based on radar data assimilation

In this study, four rainfall events with different characteristics from 2017 to 2018 were selected to simulate the rainfall process through different assimilation experiments. By analyzing the cumulative rainfall results of rainfall events in the basin, the temporal and spatial distribution characteristics of rainfall, this section will explore the influence of radar data assimilation on the forecast of rainfall results.

4.2.1 Forecast results of cumulative rainfall

Figure 6 shows the forecasting process of four rainfall events under different data assimilation models. Compared with the CMPAS, it can be seen that different data assimilation models perform differently in different rainfall events. The cumulative rainfall forecast results of assim_03h, assim_06h, assim_12h were all overestimated in 20170708, 20171001 events, which the result of assim_03h test was overestimated the most and the cumulative rainfall of cycle test is closer to CMPAS. The prediction results of cycle and assim_12h test in 20180505 event were underestimated. The cumulative rainfall forecast results of assim_03h and assim_06h tests were both overestimated, which the assim_03h test was overestimated more seriously. For 20180704 event, the cumulative rainfall forecast results of the four schemes were all overestimated, with assim_03h overestimating significantly. Compared with the other three events, the cumulative rainfall forecast results were unsatisfactory.

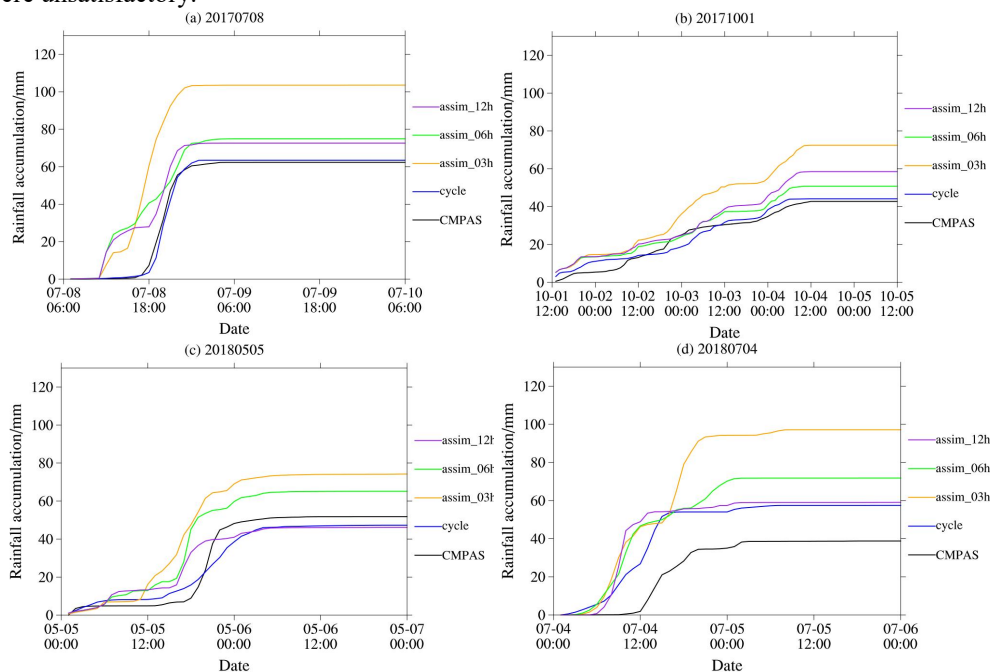


Figure 6. Variation curve of cumulative rainfall forecast results with time

According to the results of data assimilation at 3h intervals, it appears that all accumulated rainfall has been overestimated. The rainfall forecast results of assim_06h and assim_12h tests are better than those of assim_03h, with a reduction in the mean cumulative precipitation errors of 44.86% and 53.26%, respectively. Therefore, the appropriate assimilation frequency is more important for the rainfall forecast of Zhanghe River Basin. The reason may be that the significant adjustment during the initial forecast period, too frequent of an interval does not give the model enough time to adjust to the increments. And frequent stopping and restarting of the model with intermittent DA updates can potentially introduce imbalances and result in insertion noise in numerical models [68-70]. In addition to the error in boundary conditions, it can be seen that the assimilation of information related to water vapor will make the rain in the initial field easier to form rainfall [21,53-55,65-67], and high-frequency cyclic assimilation may exacerbate this problem. However, the cumulative rainfall results alone are not enough to analyze rainfall, and the temporal and spatial changes of rainfall need to be further analyzed.

4.2.2 Forecast the spatial and temporal distribution of rainfall

Forecasting the change of rainfall with time and rainfall areal is critical to understanding runoff generation, as it has a significant impact on the flood peak discharge, flood peak occurrence time and other related factors [15-16]. The spatial distribution of rainfall based on data assimilation and its variation with time are shown in Figure 7 and Figure 8 respectively. The spatial distribution and temporal variation of precipitation based on data assimilation show varying degrees of improvement, but a significant forecast error remains even after data assimilation.

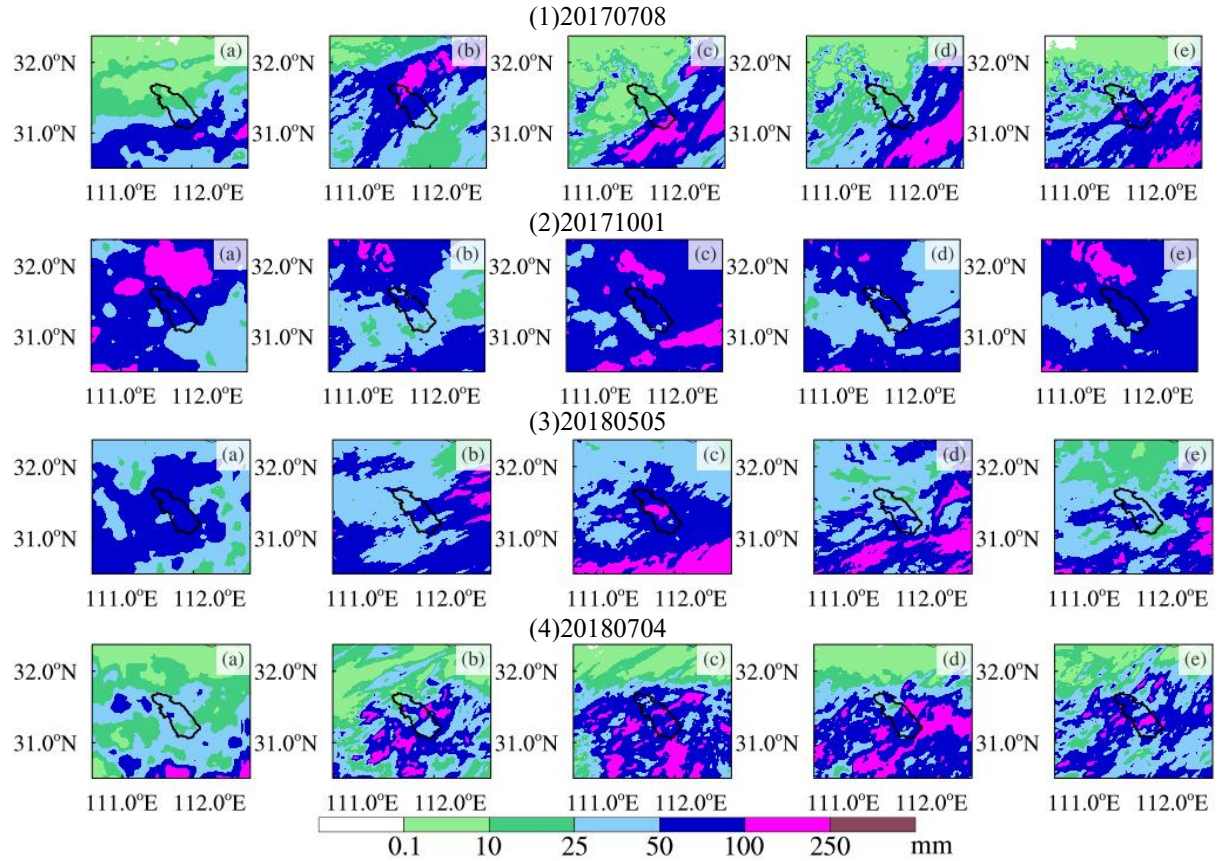


Figure 7. Spatial distribution of accumulated rainfall. (1)20170708; (2)20171001; (3)20180505; (4)20180704. (a-e) represent CMPAS、cycle、assim_03h、assim_06h、assim_12h

The spatial variations observed in event 20170708 show that both assim_06h and assim_12h improve the spatial distribution after data assimilation, mainly in the position of the rainfall centre. However, for the assim_03 results show a significant overestimation of rainfall In the lower reaches of the basin. For Event 20171001, the cycle experiment underestimated the amount of rainfall in the river basin downstream. However, the three remaining groups of assimilation experiments exhibited different levels of enhancement. Concerning the 20180505 event, except for the assim_03h test, the other tests undervalue the rainfall in the river basin. Especially the amount of rainfall in the upper reaches of the basin. For the 20180704 case,

regardless of the data assimilation method employed to predict rainfall, the outcomes are clearly overestimated. This may be due to the bimodal rainfall events are usually affected by the complex circulation situation, resulting in a secondary rainfall peak. As for 20180704 event, the short-term rainfall forecast can not capture the change of the circulation situation accurately. The four groups of experimental results show that the Doppler radar data assimilation method can improve the simulation results of the spatial distribution of precipitation, but with different degrees of improvement.

To compare the variation of rainfall predicted by WRF model with time under different assimilation tests, the hourly variation of QPF average rainfall is shown in Figure 8 by calculating the one-hour cumulative average rainfall of CMPAS and WRF QPF in Zhanghe river basin. For 20170708 event, the rainfall peak values of cycle test and assim_03 test were close to CMPAS, and the peak appeared 1 hour and 3 hours earlier respectively. However, the peak value of rainfall of assim_06h and assim_12h test is lower, and the error of the occurrence time is larger, which is up to 9 hours. The rainfall intensity of 20171001 event was weak and lasted for a long time, with a certain deviation in the peak value and peak time of all tests. Although the cumulative rainfall value of assim_03h test in 20180505 event is higher than CMPAS, the rainfall peak value and rainfall process of assim_06h test are closest to CMPAS for hourly area rainfall.

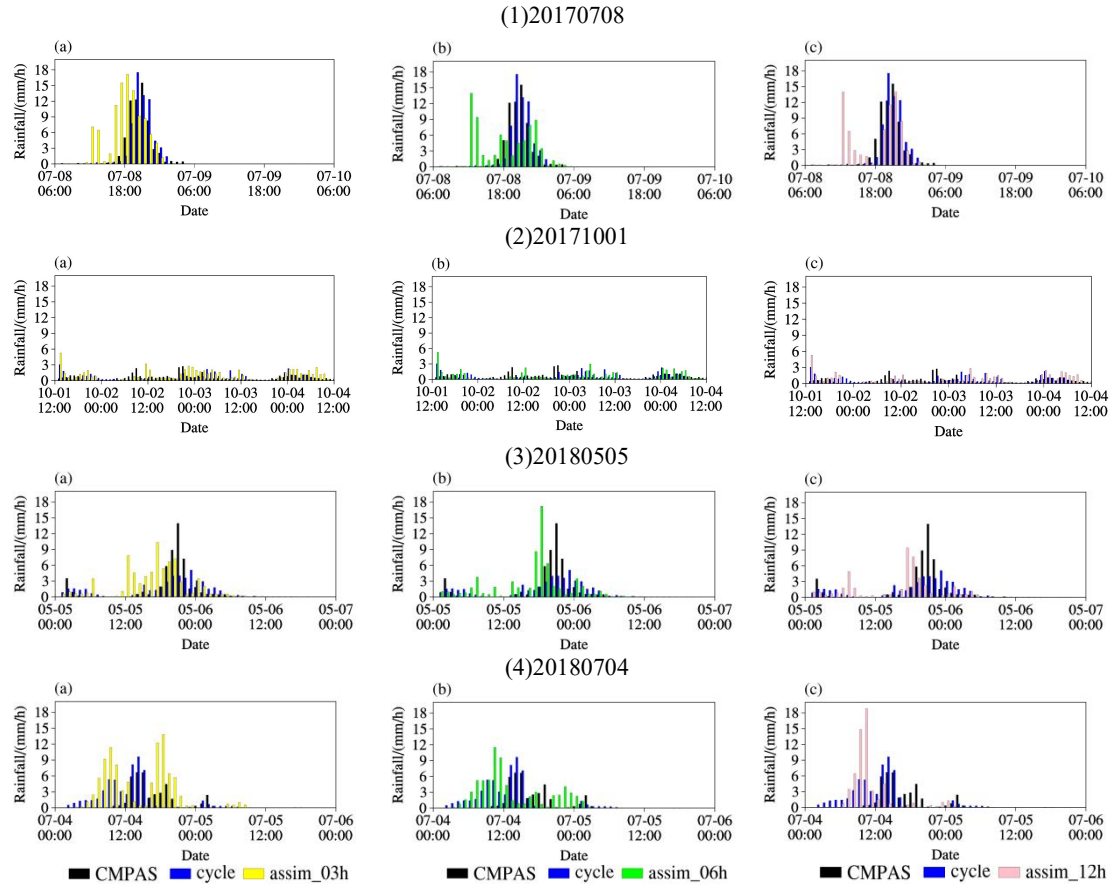


Figure 8. Time series charts of WRF predicted hourly precipitation versus CMPAS under different assimilation experiments: (1)20170708; (2)20171001; (3)20180505; (4)20180704

To further explore the impact of Doppler radar on time series of rainfall prediction, it was found that the peak rainfall time of the four events is earlier than CMPAS, except for the 20180505 cycle test. Currently, the analyses are performed only for the present study, this outcome may be attributed to the instability of the model's initial period, resulting in a better prediction effect of the WRF model in the spatial dimension of precipitation and a slightly worse prediction effect in the temporal dimension. The phenomenon that the predicted rainfall is earlier than the observation has a certain impact on the runoff simulation, such as flood rising time, peak time, and so on. Therefore, it is necessary to further explore the improvement degree of Doppler radar data assimilation on runoff forecast and the impact of rainfall forecast errors on runoff simulation results.

4.3 Error transfer characteristic

4.3.1 Runoff forecast result

Based on different radar data assimilation schemes, the runoff prediction results of WRFDA/WRF/WRF-Hydro coupling prediction of four events are shown in figure 9. It can be seen from Figure 9 that for different rainfall-runoff events, the flood peak occurrence time, flood peak discharge and total runoff deviation predicted by the coupled model under different assimilation frequency of radar data are different.

Among them, the cycle tests of 20171001 and 20180505 events did not predict the runoff process. Although the cumulative rainfall forecast error of the 20171001 event cycle test is very small, the corresponding runoff forecast error is large. The cumulative rainfall of the assim_06h test of this event is higher than that of the CMPAS, but the predicted flood peak discharge is relatively low. This phenomenon is mainly due to the fact that the formation of runoff is affected by the temporal and spatial distribution of rainfall. For the 20180505 event, although the rainfall accumulation value of assim_03h test is higher than that of assim_06h, the runoff forecast result of assim_06h test is higher. The reasons analysed may be that the peak rainfall for the assim_06h experiment was higher, the timing of the rainfall was more concentrated and the peak rainfall area was located in the lower part of the basin. The occurrence time of the peak rainfall is advanced, which leads to the occurrence time of the peak runoff predicted in advance.

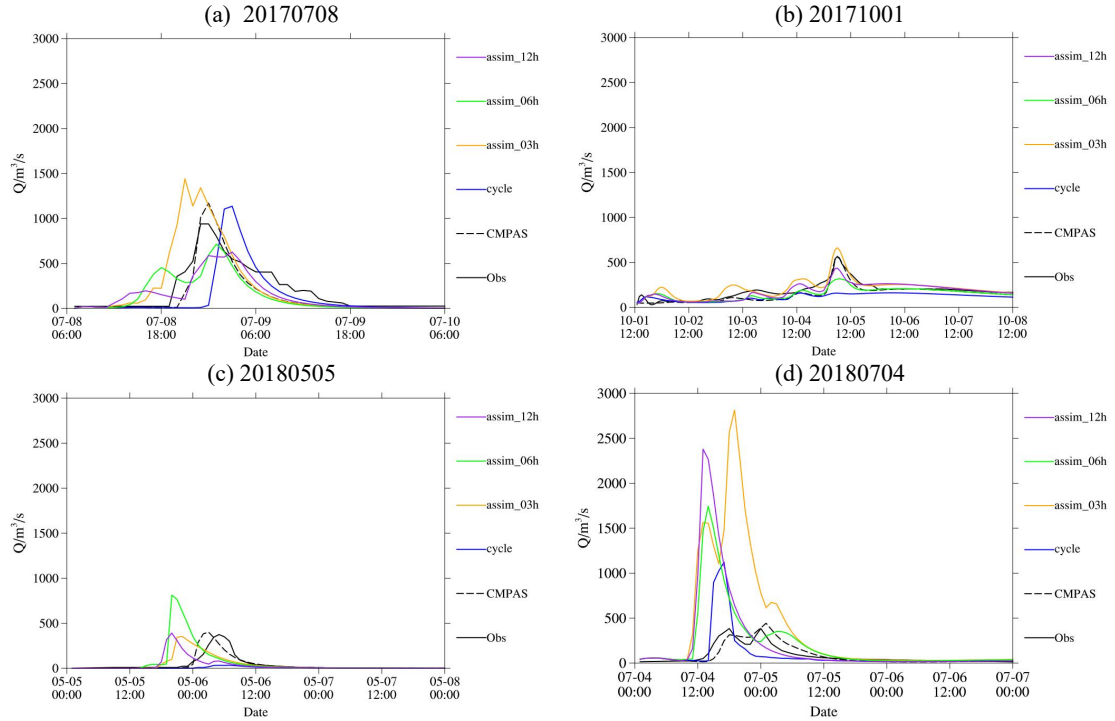


Figure 9. WRF-Hydro runoff forecast results based on rainfall forecasts from different radar data assimilation schemes: (1)20170708; (2)20171001; (3)20180505; (4)20180704

Although the cumulative rainfall forecast of the 20170708 event cycle experiment is relatively accurate, the occurrence time of the predicted flood peak is delayed due to the location of the rainfall centre in the upper reaches of the basin, which delays the entire hydrological process line towards the right. The prediction of runoff peak value of assim_03h test is overestimated, primarily due to the corresponding rainfall forecast being highly overestimated. Despite the assim_06h and assim_12h experiments are more accurate in predicting the location of the rainfall center, the rainfall center of this event is located in the lower reaches of the basin with a short confluence time. The final forecast for the peak discharge of the flood is underestimated due to the complex hydrological processes that amplify the impact of rainfall errors.

The 20180704 event is multi-peak rainfall. Due to the complexity of rainfall and soil infiltration in the basin, all runoff forecasting results are unsatisfactory, which the forecast of flood peak discharge far exceeds the observation, regardless of the data assimilation method employed to predict rainfall. The error of flood peak discharge predicted by assim_03h test is the largest, followed by assim_12h and assim_06h. The assim_03h experiment can capture the multi-peak rainfall-runoff process, so the correlation coefficient (RR) between the forecast and the observation is higher (Table 5).

Through the simulation results of four rainfall processes, we find that the rainfall forecast results include cumulative rainfall, rainfall time and spatial distribution, which is very important for the formation process of runoff. The runoff results under different radar data assimilation frequencies show that the assimilation of radar data at higher frequencies can not guarantee the further improvement of runoff simulation for the Zhanghe River basin. The average peak flow error of assim_06h and assim_12h test is 23.97% lower than that of assim_03h test (Table 5). Therefore, the effective information contained in assimilation data is more important than the amount of data. For small- to medium-sized watersheds, rainfall intensity and falling area have great influence on runoff flood peak discharge and peak time. Rainfall in mountainous watershed presents high spatial variability due to elevation effects, which adds to the difficulty of numerical rainfall prediction in small and medium sized catchments. At the same time, the WRF forecast results themselves have a relatively large error, and the radar itself has a certain error and amplifies this error through assimilation. Small differences in amounts or shifts in time or space of modelled rainfall, in comparison with observed precipitation, can strongly modify the hydrologic response of small watersheds to extreme events [71-72].

4.3.2 Error transfer characteristics

The box chart of the evaluation results of rainfall and runoff forecast for four rainfall events is shown in Figure 10. It can be seen that with the increase of radar data assimilation frequency, the error range increases, and the variability of runoff error ($|PE_2|$, $|TE_2|$) increases significantly compared with rainfall error ($|PE_1|$, $|TE_1|$). However, the rainfall correlation coefficient and runoff correlation coefficient of assim_03 test (Table 5) are relatively higher.

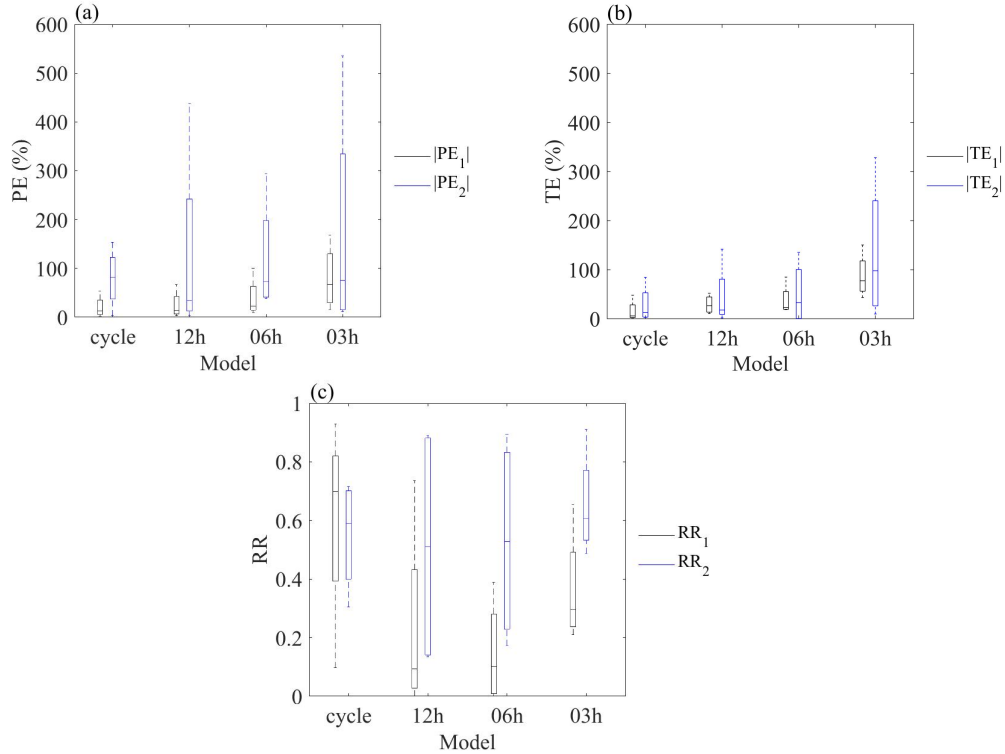


Figure 10. The statistical indexes of rainfall and runoff change with the frequency of radar assimilation data ($|PE_1|$ is the error of corresponding cumulative rainfall at peak time, $|PE_2|$ is the error of forecast of peak flood discharge; $|TE_1|$ is the forecast error of cumulative rainfall, and $|TE_2|$ is the forecast error of total runoff. RR_1 is the correlation coefficient between rainfall forecast results and fusion data, and RR_2 is the correlation coefficient between runoff forecast results and fusion data runoff simulation results.)

It can be found that the temporal and spatial errors caused by rainfall forecast will be magnified in different degrees when propagating to the hydrological process line by comparing the forecast results of rainfall and runoff. This phenomenon can be attributed to the increase of spatial variability of high-resolution rainfall products and the highly nonlinear conversion of rainfall and runoff, especially for typical small- to medium-sized watersheds such as the Zhanghe River Basin with highly complex topography [27].

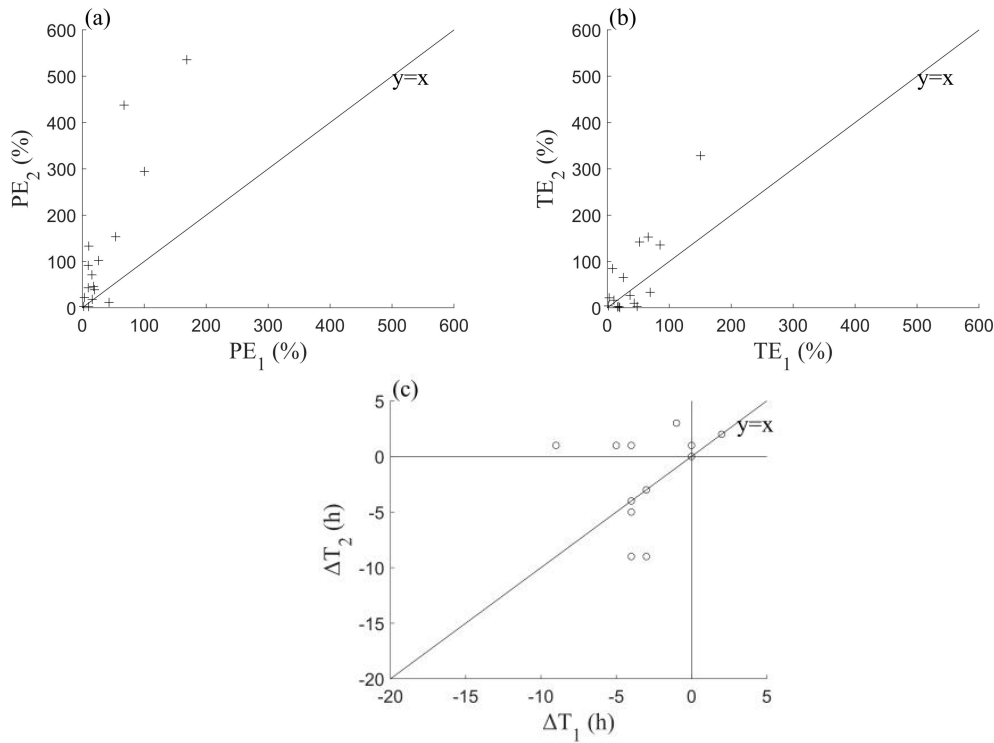


Figure 11. Scatter diagram of rainfall-runoff errors

(a) Cumulative rainfall error and peak runoff error corresponding to flood peak time (b) total rainfall error and total runoff error (c) current difference of rainfall peak and runoff peak

Table 5. Evaluation index results of rainfall-runoff forecast

Event	test	$ PE_1 /\%$	$ PE_2 /\%$	$ TE_1 /\%$	$ TE_2 /\%$	RR ₁	RR ₂
20170708	cycle	12.95	2.93	1.84	4.20	0.93	0.50
	assim_03h	10.58	23.16	66.11	69.74	0.63	0.75
	assim_06h	10.21	38.93	20.19	0.54	0.39	0.77
	assim_12h	10.14	46.46	16.45	1.87	0.74	0.87
20171001	cycle	15.60	71.19	3.19	21.71	0.10	0.72
	assim_03h	15.98	18.10	69.36	42.91	0.26	0.91
	assim_06h	9.68	43.35	18.79	0.56	0.03	0.90
	assim_12h	3.43	22.27	36.80	19.52	0.06	0.89
20180505	cycle	9.65	91.64	8.65	84.49	0.71	0.69
	assim_03h	43.33	11.92	43.37	9.89	0.33	0.49
	assim_06h	26.35	102.17	25.80	65.45	0.17	0.17
	assim_12h	10.41	2.56	10.83	16.42	0.13	0.15
20180704	cycle	54.06	153.41	48.20	2.90	0.69	0.30
	assim_03h	168.69	535.70	150.52	328.48	0.21	0.63
	assim_06h	100.20	294.37	85.14	135.55	0.01	0.29
	assim_12h	67.39	437.58	52.26	142.03	0.00	0.13

The error scatter of rainfall and runoff under different assimilation frequencies of radar data are shown in Figure 11. It can be seen from Figure 11a that the peak error of runoff corresponding to the flood peak time is magnified after the hydrological model, but there is no clear linear relationship between rainfall error and runoff error. The main reason for the analysis is the complex structure of the hydrological model and the uncertainty of temporal and spatial errors in rainfall. It can be seen from Figure 11b and c that the error of total rainfall and the time difference of rainfall peak are magnified or reduced. Due to the uncertainty of rainfall area, there is no evident quantitative relationship between them [26-27].

5. Discussion

Runoff forecasts depend directly on the accuracy of the rainfall input. The coupling of NWP and distributed hydrological models can effectively extend the flood forecasting lead time. In addition, the Doppler radar data assimilation method also provides an effective way to improve the accuracy of the coupled model. However, experimental results show that the prediction accuracy is markedly different for different rainstorm events and different data assimilation models.

In this study, it is found that the appropriate assimilation frequency is more helpful for rainfall and runoff forecasting in Zhanghe River, a small and medium-sized watershed with complex terrain. Although many studies [21-23] have emphasized that shortening the time interval of assimilation, and increasing the assimilation frequency, help to improve accuracy in rainfall predictions. The rainfall and runoff forecast results of assim_03h are not significantly better than assim_06h and assim_12h for every for different events. It may be due to the fact that the more frequent assimilation may exacerbate model imbalances and lead to a decrease in forecast quality [68-70]. On the other side, Zhanghe River Basin, as a typical small and medium-sized basin in the humid mountainous areas of the south, is dominated by mountainous hills and complex topography, which reduces the accuracy of weather radar [64]. More observations must be assimilated, potentially resulting in the coupled model absorbing more observational errors. In future, we could attempt to to assimilate different types of information, including satellite observations, to enhance the validity of the observations. At the same time, it is important to take into account the relationship between reflectivity and rainfall intensity during assimilation, as it is one of the key factors that influences the effectiveness of the process. It should be noted that a single Z-R relationship is insufficient for all types of storms [52]. To enhance the impact of indirect radar reflectivity assimilation, a dynamic Z-R relationship specific to different rainfall types could be utilised in the future.

The significance of enhancing the precision of rainfall prediction is indisputable, and there is a need to enhance the efficiency of data assimilation as well. Generally speaking, the larger the amount of data assimilated by the numerical atmospheric model, the more complex the solution of the model, leading to longer operation times and decreasing computational efficiency. When exploring methods to enhance the accuracy of rainfall and runoff forecasts subsequent to data assimilation, it is crucial to also evaluate approaches for enhancing the efficacy of data assimilation to reduce its running time as much as feasible. In this study, for the multiple cases, a 24 hour forecast was undertaken on the primaryframe of the supercomputer employing 20 cores. The duration of assim_03h was greater than that of assim_12h, with a discrepancy of approximately 26-27 h. In practice, it is crucial to enhance the effectiveness of the combination of meteorological and hydrological forecasting to provide more time for decision makers to attempt to mitigate the serious impacts of heavy rainfall events.

The generation of rainfall and runoff is an intricate and nonlinear process. In small- to medium-sized river basins, rapid hydrological responses exacerbate the challenge of flood prediction. Therefore, the error propagation characteristics between meteorology and hydrology are of immense practical importance to understand the variation law of rainfall and runoff, and provide scientific and decision-making support. The experimental results of this study demonstrate that the runoff formation process will amplify the rainfall errors when the rainfall accumulation and temporal - spatial distribution errors are large. Additionally, due to the complex structure of the hydrological model and the uncertainty generated by rainfall errors in both time and space, there is no clear linear relationship between runoff and rainfall errors [39-42]. In the future, we aim to gather more observation data to further investigate the correlation between errors in rainfall and runoff.

6. Conclusions

This study takes Zhanghe River Basin as the study area, establishes WRF/WRF-Hydro meteorological-hydrological coupling model based on Doppler radar data assimilation, and selects four different types of rainfall events occurred in Zhanghe River Basin in Hubei Province from 2017 to 2018 as the research object. The results show that:

(1) Doppler radar data assimilation has the potential to enhance the accuracy of rainfall forecasting. For short rainfall duration and large intensity event (20170708), the temporal and spatial distribution is improved obviously. But for bimodal events (20180704), the enhancement effect is inadequate. The rainfall forecast of radar data assimilation at high frequency will be overestimated under the influence of complex topography in Zhanghe River Basin, and the result at 6 h and 12 h assimilation interval is better than 3h. Appropriate data assimilation show positive effect on improving the rainfall forecast.

(2) Radar data assimilation have direct benefits for runoff forecasts. For events 20171001 and 20180505, the flood process can not be simulated without radar data assimilation. After radar data assimilation, the coupling model can simulated accurate flood peak discharge. For event 20180704 with 03h assimilation frequency, the runoff forecast result is more consistent with the observed process than other prediction results, and can capture the bimodal process with higher correlation.

(3) Error propagation between models differs with the changing assimilation frequency of the radar data and the consequent effect of the rainfall forecast. Through the analysis of the box chart and scatter plot of rainfall and runoff forecast errors, the error range increases with the increase of radar data assimilation frequency. Compared with rainfall error, runoff error shows greater variability. Through quantitative analysis, it was found that there is no well-defined linear relationship between the rainfall and runoff errors.

The accuracy of radar data, the selection of assimilation methods and better hydrological model determination methods, and so on, still need to be further studied, which tailor the coupled atmosphere-hydrology system for the research area. Most of the small watersheds do not have enough rainfall and runoff data or belong to the area without data. The effectiveness of rainfall and runoff forecasting for small and medium-sized watersheds is limited due to the impact of human activities, rainfall, and other factors on flood forecasting in small watersheds. Therefore, the rainfall and runoff forecasting for small and medium-sized watersheds still need to be optimised.

Author Contributions: Conceptualization, Y.G. and L.C.; methodology, Y.G. and L.C.; software, Y.G. and L.C.; validation, Y.G. and L.C.; formal analysis, Y.G. and L.C.; data curation, Y.G. and L.C.; writing—original draft preparation, Y.G. and L.C.; writing—review and editing, Y.G., L.C., T.P., X.S., T.N., and Y.H.; visualization, Y.G. and L.C.; supervision, Y.G. and L.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was jointly sponsored by the National Key Research and Development Program of China (2022YFC3004003; 2023g029).

Acknowledgments: The numerical calculations in this paper have been performed on the supercomputing system in the Supercomputing Center of Nanjing University of Information Science and Technology. The authors are grateful to the two anonymous reviewers for their constructive comments and useful suggestions that helped significantly improve the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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