# Early Flood Warning for Linyi Watershed by the GRAPES/XXT Model Using TIGGE Data

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**ABSTRACT**

Early and effective flood warning is essential for reducing loss of life and economic damage. Three global ensemble weather prediction systems of the China Meteorological Administration (CMA), the European Centre for Medium-Range Weather Forecasts (ECMWF), and the US National Centers for Environmental Prediction (NCEP) in THORPEX (The Observing System Research and Predictability Experiment) Interactive Grand Global Ensemble (TIGGE) archive are used in this research to drive the Global/Regional Assimilation and PrEdiction System (GRAPES) to produce 6-h lead time forecasts. The output (precipitation, air temperature, humidity, and pressure) in turn drives a hydrological model XXT (the first X stands for Xinanjiang, the second X stands for hybrid, and T stands for TOPMODEL), the hybrid model that combines the TOPMODEL (a topography based hydrological model) and the Xinanjiang model, for a case study of a flood event that lasted from 18 to 20 July 2007 in the Linyi watershed. The results show that rainfall forecasts by GRAPES using TIGGE data from the three forecast centers all underestimate heavy rainfall rates; the rainfall forecast by GRAPES using the data from the NCEP is the closest to the observation while that from the CMA performs the worst. Moreover, the ensemble is not better than individual members for rainfall forecasts. In contrast to corresponding rainfall forecasts, runoff forecasts are much better for all three forecast centers, especially for the NCEP. The results suggest that early flood warning by the GRAPES/XXT model based on TIGGE data is feasible and this provides a new approach to raise preparedness and thus to reduce the socio-economic impact of floods.

**Key words:** TIGGE, GRAPES, flood warning, XXT, rainfall-runoff process

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## 1. Introduction

Early and effective flood warning is essential for reducing loss of life and economic damage. The availability of several global ensemble weather prediction systems through THORPEX (The Observing System Research and Predictability Experiment) Interactive Grand Global Ensemble (TIGGE) archive provides an opportunity to explore new dimensions in early flood forecasting and warning (Pappenberger et al., 2008). As an important data supporting system, TIGGE has made a great contribution to correction of systematic errors from different sources such as uncertainties of observation, initial value problems, and imperfect models. He et al. (2010) used the TIGGE data to drive the Xinanjiang model to forecast discharges and flood events in the upper Huai catchment. Their results demonstrated satisfactory flood forecasting

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skills with clear signals of floods up to 10 days in advance. Froude (2010) analyzed the prediction of Northern Hemisphere extratropical cyclones by nine different ensemble prediction systems (EPSs) archived as part of the TIGGE project. He found that the European Centre for Medium-Range Weather Forecasts (ECMWF) ensemble mean and control have the highest level of skill for all cyclone properties. Moreover, the TIGGE database has also been extensively used in the studies by Yamaguchi and Majumdar (2010) and Keller et al. (2011).

The Global/Regional Assimilation and PrEdiction System (GRAPES) is an important operational numerical weather prediction system in the China Meteorological Administration (CMA). This model adopts a structure of standardized and module-based software in accordance with the strict requirements of software engineering. A preliminary study (Wu et al., 2005) shows that the application of GRAPES meets the requirement for sustainable development of the numerical prediction system of China. Nowadays, GRAPES has been developed in various fields, such as GRAPES-Meso for mesoscale weather prediction, GRAPES-TCM for typhoon prediction, GRAPES-SDM for sandstorm forecast, and GRAPES-SWIFT for short-time weather forecast (Zhao and Li, 2006; Zhu et al., 2007). Further development of the GRAPES is undergoing. So far, however, the operational GRAPES in the CMA has not yet been able to directly predict runoff and hence flood events.

Hydrological models have been widely used as the significant tools to simulate the runoff process in catchments of different dimensions for runoff forecasting. The rainfall-runoff process is filled with extremely complex physics. As conceptual models such as TOPMODEL (a topography based hydrological model), SWAT (Soil and Water Assessment Tool), and SHE (Système Hydrologique Européen) consider both hydrologic and climatologic variables, such as precipitation, runoff, temperature, and evaporation, they have always been widely used to transform rainfall into runoff (Beven and Kirkby, 1979; Beven et al., 1984; Zhang et al., 2006; Vazquez and Feyen, 2007; Demirel et al., 2009). Aiming at more precise prediction results, some hybrid models have been developed, such as the XXT (the first X denotes Xinanjiang, the second X denotes hybrid, and T denotes TOPMODEL) model proposed by Xu (2010) and Xu et al. (2010, 2012). Due to its simplicity in model structure and efficient computation, it is suitable for use in the ensemble prediction by GRAPES based on the TIGGE data.

Although there is an increasing amount of literature on the use of TIGGE data in hydrological models for flood forecast, the use of a hydrological model and GRAPES driven by TIGGE is rarely addressed. The objective of the present work, therefore, is to predict runoff based on the simple but efficient hydrological model XXT with GRAPES driven by the TIGGE data.

## 2. Data description and methods

### *2.1 TIGGE data and the study area*

In this paper, TIGGE data in July 2007 from three numerical weather prediction (NWP) centers, i.e., the CMA, the ECMWF, and the National Centers for Environmental Prediction (NCEP), were obtained from the CMA and were used to drive the operational GRAPES. The outputs in turn drive the hydrological model XXT.

The Linyi hydro-station gauged watershed at the upstream of the Yishusi catchment in Shandong Province, China was selected as the study watershed for flood prediction in July 2007. The Linyi watershed with a drainage area of 10040 km$^2$ lies in the semi-arid area of eastern China (Fig. 1).

### *2.2 The hydrological model XXT*

TOPMODEL is a physically based watershed model that simulates the stream flow generation based on the variable-source-area concept (Beven and Kirkby, 1979; Bouilloud et al., 2010; Liu et al., 2009; Wolock, 1993). TOPMODEL has been widely used to study a variety of research topics, including synthetic flood-frequency derivation, model-parameter calibration, carbon budget simulation, and spatial scale effects of hydrologic processes. The Xinanjiang model

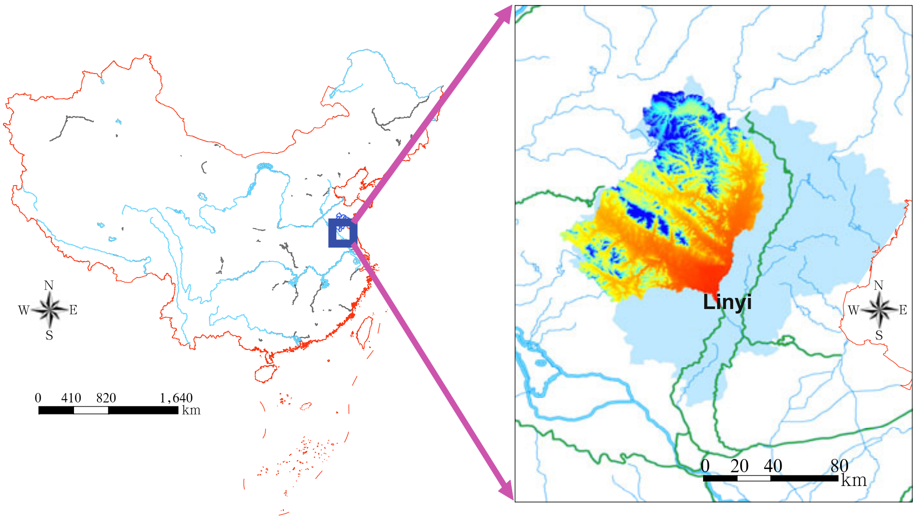


**Fig. 1.** The study area: left for China and right for Yishusi catchment in which the area in red and blue represents the Linyi watershed.

has been successfully applied in humid and semi-humid regions in China since its development (Zhao et al., 2011; Zhao, 1980, 1992). Gan et al. (1997) pointed out that the Xinanjiang model did consistently better, even in dry catchments, compared with the Pitman model of South Africa, the Sacramento model of the US, the NAM model of Europe, and the SMAR (Soil Moisture Accounting and Routing) model of Ireland. The Xinanjiang model uses a single parabolic curve to represent the spatial distribution of soil moisture storage capacity over a catchment, where the exponent parameter $b$ measures the non-uniformity of this distribution (Jayawardena and Zhou, 2000).

Based on the soil moisture storage capacity distribution curve (SMSCC), the Xinanjiang model, together with the simple model structure of TOPMODEL, a new rainfall-runoff model named XXT was developed (Xu, 2010; Xu et al., 2012). The vertical structure of this newly developed model consists of three parts: the interception zone (including vegetation layer and root zone of soil), the unsaturated zone, and the saturated zone. In the XXT model, the water table is incorporated into SMSCC and it connects the surface runoff production with base flow production. This improves the description of the dynamically varying saturated areas that produce runoff and also captures the physical underground water level. Xu et al. (2010, 2012) demonstrated that XXT is a simple and efficient hydrological model and performs better than Xinanjiang, TOPMODEL, and SWAT in daily runoff prediction and flood forecasting. In the present work, it is therefore selected as the flood forecasting model using rainfall data from GRAPES as the inputs.

## 3. Experiments and results

### *3.1 Rainfall forecast by GRAPES using TIGGE data*

Three global ensemble weather prediction systems of the CMA, ECMWF, and NCEP in the THORPEX TIGGE archive are used in this research to drive the GRAPES model. Figures 2–4 show the observed rainfall versus forecasted rainfall by GRAPES using the TIGGE data of CMA, ECMWF, and NCEP, respectively, for 6-h rainfall forecasts from 0000 UTC 18 July to 1200 UTC 20 July 2007 in the Linyi watershed. From Fig. 2 to Fig. 4, it is easily seen that observed rainfall starts from 1200 UTC 18 July and reaches the maximum of around 40 mm at a mean speed of about 7 mm h$^{-1}$ at 1800 UTC 18 July, and then decreases to zero at 1200 UTC 19 July. In Fig. 2, the differences among all the members of CMA are extremely large. Furthermore, from 1200 UTC 18 to 1200 UTC 19 July, all the members hold very low values close to 0, far less than the observed one. In the end of the forecast period, all members overestimate the observed rainfall.

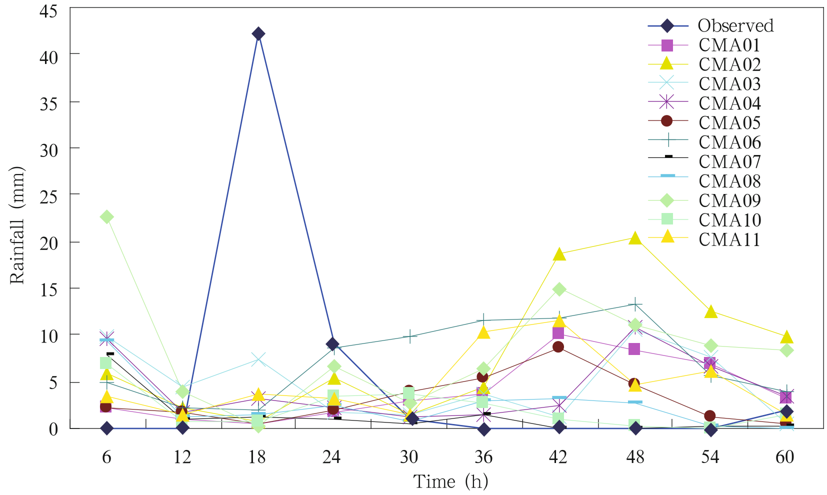


**Fig. 2.** Observed vs. forecasted rainfall by GRAPES using the TIGGE data from the CMA.

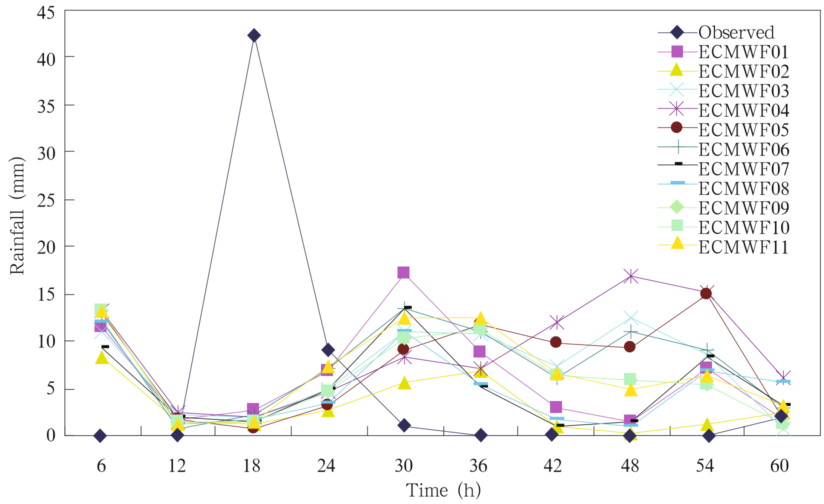


**Fig. 3.** As in Fig. 2, but for the ECMWF.

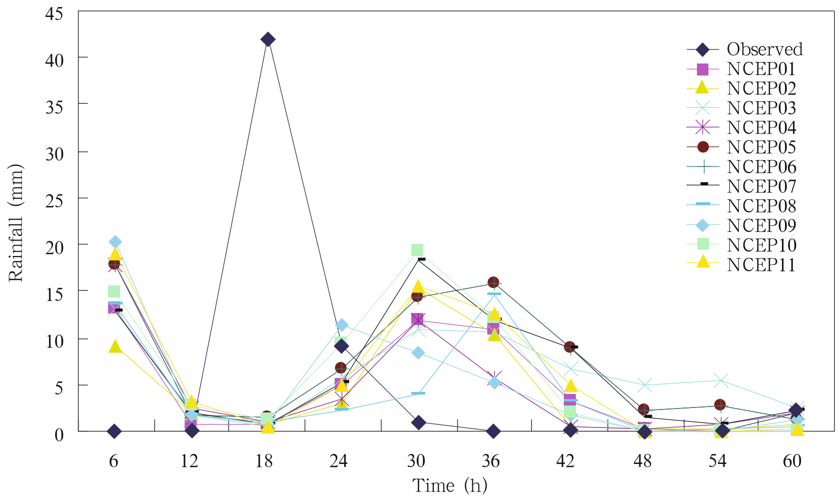


**Fig. 4.** As in Fig. 2, but for the NCEP.

Figures 2–4 also demonstrate that the rainfall curve forecasted by the CMA has one peak similar to that by NCEP. Figure 2 shows that the CMA forecasted precipitation peak lags 30 h behind the observation, while Fig. 4 shows that NCEP lags 12 h. The ECMWF forecasted precipitation curve has two peaks appearing around 30 and 54 h respectively from the prediction starting time, lagging 18 and 36 h behind the observed one. Although NCEP has an advantage over the other two EPSs for forecast of the precipitation peak, the rainfall forecast by any of the single EPS has missed the actual rainfall peak time almost entirely. The reason for this may be that the ability of the GRAPES model itself to forecast precipitation is not good enough. In addition, vertical and horizontal resolutions, and all kinds of physical process parameterizations have great effects on the performance of NWP models. Hence, applying the model of unchangeable resolution into different dimensions may result in some errors.

In general, it can be seen from Figs. 2–4 that there is high variability in the hydrograph of the rainfall forecasts by each member of the three global EPSs. They all have seriously underestimated the peak rainfall intensity. Trends of the time series of rainfall forecasts for different members of the same ensemble forecasting center are similar to each other. However, there is a large dispersion in forecasted rainfall values among the members. This indicates that the GRAPES model's ability to predict the precipitation intensity is relatively weak. Rainfall forecasts by GRAPES using the data from the NCEP forecast center are the closest to the observation while those from the CMA are the worst.

### *3.2 Runoff forecast by XXT using the output of GRAPES*

The forecasted rainfall data by GRAPES using the three global EPSs were input into the XXT model respectively in order to obtain runoff forecast for the Linyi watershed. The observed runoff (stream flow) and simulated runoff by XXT are shown in Figs. 5–7. Firstly, it is clearly seen from the three figures that before 1800 UTC 18 July, the observed discharge is very stable and below 100 $m^3$ $s^{-1}$. Afterwards, it reaches above 400 $m^3$ $s^{-1}$ at 1200 UTC 19 July, then decreases a little but still between 350 and 400 $m^3$ $s^{-1}$. To be specific, from 1800 UTC 18 to 0600 UTC 19 July, the growth rate of observed runoff is about 10 $m^3$ $s^{-1}$ $h^{-1}$ and it is nearly 33 $m^3$ $s^{-1}$ $h^{-1}$ from 0600 to 1200 UTC 19 July. In other words, flood peak occurs at 1200 UTC 19 July and the high flood process above 350 $m^3$ $s^{-1}$ lasts for the following hours. As a whole, the tendency of the forecasted runoff in Figs. 5–7 is generally consistent with that of the observed rainfall in Figs. 2–4. As for the XXT modeling results, forecasted runoff amounts derived from different datasets are significantly different.

In Fig. 5, all 11 members of the ensemble forecast cannot capture the runoff peak, not even the changing tendency of runoff. To go further, the runoff curves forecasted by members of CMA07, CMA08, and CMA10 hardly change with time. Before the runoff begins to increase rapidly, CMA03 and CMA09 overestimate the runoff while underestimate it during the period when the runoff is very large. And other members also perform unsatisfactorily. Nevertheless, CMA02, CMA06, and CMA09 successfully catch the flood at 0000 UTC 20 July. Generally speaking, forecasted runoff by XXT using the outputs of GRAPES driven by the CMA data hardly precisely agrees with the observed one.

In Fig. 6, almost all members have the similar trend to the observed one. None of the members of ECMWF precisely captures the peak either, just like the members of CMA in Fig. 5. However, before 0600 UTC 19 July, most members of ECMWF perform better than those of CMA. What is more, ECMWF03, ECMWF04, ECMWF05, ECMWF06, and ECMWF11 are also close to the observed one at 0000 UTC 20 July.

In Fig. 7, forecasted runoff by XXT using the outputs of GRAPES driven by the NCEP data is not very discouraging. As shown in Fig. 7, almost all members have the similar trend with the gauged runoff, and most members are able to model the runoff successfully before 0600 UTC 19 July. Among them, five members including NCEP05, NCEP06, NCEP07, NCEP10, and NCEP11 have relatively accurately depicted the runoff

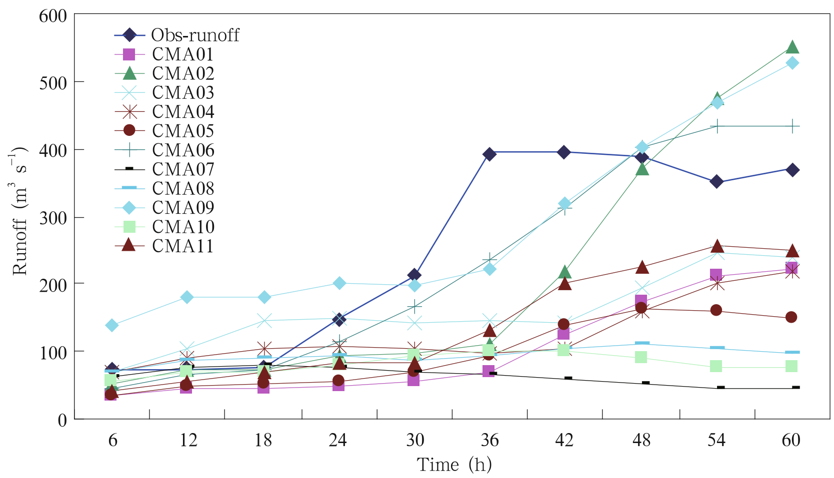


**Fig. 5.** Observed vs. forecasted runoff by XXT using the output of GRAPES driven by the CMA data.

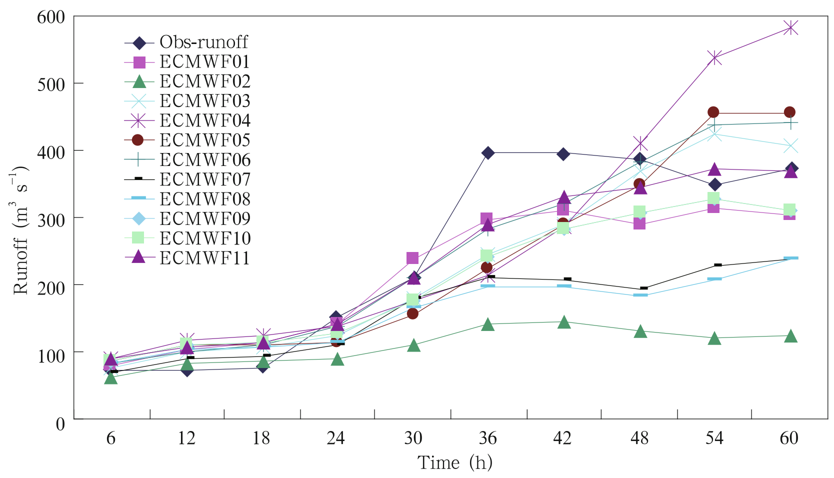


**Fig. 6.** As in Fig. 5, but for the ECMWF data.

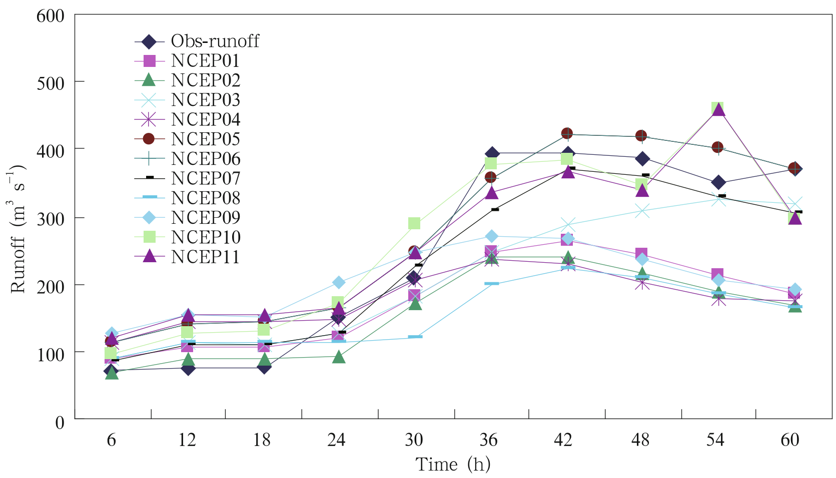


**Fig. 7.** As in Fig. 5, but for the NCEP data.

process in the whole case. The others underestimate it to some degree in the following two days, especially NCEP01, NCEP02, NCEP04, NCEP08, and NCEP09, which range between 150 and 250 $m^3 s^{-1}$ while the observed runoff fluctuates from 350 to 400 $m^3 s^{-1}$. Generally, forecasted runoff by XXT using the outputs of GRAPES driven by NCEP is relatively satisfactory compared with those by CMA and ECMWF.

For each TIGGE center, 11 members produce a runoff forecast spread, which almost covers the observed runoff at a lead time of 6 h from 18 to 20 July 2007 and thus are suitable for predicting this flood event within the spread. The results are in agreement with some other studies (Xuan et al., 2009; Bao et al., 2011; He et al., 2010). Xuan et al. (2009) utilized the outputs of the fifth-generation Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model (PSU-NCAR MM5) to drive a grid-based distributed hydrological model for ensemble runoff forecast. Their work shows that ensemble hydrological forecasting driven by ensemble rainfall forecasts can produce comparable results with observations and the bias due to common underestimates of rainfall at fine scale can result in unrealistic low river flow forecasts. This is a possible reason for underestimates in the present study as well.

It can be seen from Figs. 2–7 that the forecasted runoff peaks greatly lag behind the observed one, partly because of the time lags of the forecasted rainfall peaks. Since the forecasted values driven by the TIGGE archive exhibit some spread, more weight should be given to the maximum curve when considering the flood peaks. Figure 5 illustrates that the XXT forecasted runoff peak is delayed for about 24 h, which may be due to the lagged temporal trend of rainfall forecasted by CMA. Therefore, if utilizing CMA data as the input into GRAPES for early flood warning, there would be a large bias. The runoff prediction results using the data from ECMWF contain two flood peaks, whose change tendency generally agrees with the forecasted precipitation. The flood peak forecasted by NCEP data is the closest to the observed one compared to those by the other two centers. Thus, the flood forecast based on the NCEP data is more usable in practice.

In general, the degrees of variation in Figs. 6 and 7 are both greater, especially in Fig. 7 whose curves of the simulated runoff are the closest to the observed one. In contrast to rainfall forecasts, the runoff forecasts are much better for all the three forecast centers, especially the NCEP. The reason is that the accuracy of hydrological model prediction depends on many factors, including precipitation and the model parameters. Runoff prediction is determined by previous precipitation in the watershed, previous runoff, previous evaporation, soil moisture storage capacity, and other information in the training period. The information is stored in the model parameters and model state variables. The hydrological model could perform better even though the input precipitation data are not accurate. In terms of early flood warning, the missed rainfall intensity peak will have more weight because missed events cause late preparation and can lead to doubts over the short-term forecast results when false alarms and hits are identified as the events draw nearer, hence reducing preparedness even more (Pappenberger et al., 2008). However, in this case it is suggested that early flood warning by the GRAPES/XXT model using the TIGGE data is feasible. Meanwhile, it provides a new method to raise preparedness and thus to reduce the socio-economic impact of floods.

## 4. Conclusions

In this paper, we utilize the operational NWP model GRAPES in the CMA together with the hydrological model XXT based on the TIGGE data from the CMA, ECMWF, and NCEP to predict a flood event. The results illustrate that rainfall forecasts by GRAPES using TIGGE data from the three forecast centers all underestimate heavy rainfalls, and rainfall forecast by GRAPES using the data from the NCEP forecast center is the closest to the observation while that from the CMA is the worst. Moreover, the ensemble is not better than individual member for rainfall forecasts. In contrast to rainfall forecasts, runoff forecasts are much better for all the three forecast centers, especially for NCEP.

TIGGE data have provided a good basis for probabilistic precipitation prediction, which facilitates the establishment of the hydrological ensemble prediction experiment. However, there could be some problems with this approach. For instance, the total number of members of TIGGE is large and excessive, and the operational systems involved may change any time. These may lead to unsatisfactory results if using TIGGE data as inputs to drive GRAPES. Therefore, special attention and effort must be paid in the future work in order to find a better way to combine ensembles from multiple centers.

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