Ensemble flood forecasting based on ensemble NWP and the GMKHM distributed hydrological model

Lili Wang, Hongjun Bao

National Meteorological Center, China Meteorological Administration, Beijing, 100081, P. R. China

Abstract The incorporation of numerical weather predictions (NWP) into a flood forecasting system can increase forecast lead times from a few hours to a few days. A single NWP forecast from a single forecast centre, however, is insufficient as it involves considerable non-predictable uncertainties and lead to a high number of false alarms. The availability of global ensemble numerical weather prediction systems through the THORPEX Interactive Grand Global Ensemble' (TIGGE) offers a new opportunity for flood forecast. The GMKHM distributed hydrological model, which is based on a mixed runoff generation model and overland flow routing model based on kinematic wave theory, and the topographical information of each grid cell extracted from the Digital Elevation Model (DEM), is coupled with ensemble weather predictions based on the TIGGE database (CMC, CMA,ECWMF,UKMO,NCEP) for flood forecast. This paper presents a case study using the coupled flood forecasting model on the Xixian catchment (a drainage area of 8826 km²) located in Henan province, China. A probabilistic discharge is provided as the end product of flood forecast. Results show that the association of the GMKHM model and the TIGGE database gives a promising tool for the anticipation of flood events several days ahead,, comparable with that driven by raingauge observation.

1 Introduction

Flood protection and awareness have continued to rise on the political agenda accompanied by a drive to “improve” flood forecasts (Demeritt et al., 2007; DKKV, 2004; Parker and Fordham, 1996; Pitt, 2007; van Berkomp et al., 2007; Cloke and Pappenberger, 2009). Giving flood forecasting services, civil protection authorities and the public adequate preparation time and thus reducing the impacts of the flooding (Penning-Rowsell et al., 2000). Many flood forecasting models rely on precipitation inputs, which come initially from observation networks (rain gauges) and radar.

Actually, the incorporation of numerical weather prediction (NWP) into a flood forecasting model can increase forecast lead times from a few hours to a few days. Single deterministic weather forecast from NWP can't take uncertainties and systematic biases into consideration and hence often fail to replicate weather variables correctly. Ensemble Prediction Systems (EPS) have evolved over the last decade to simulate the effect on weather forecasts of observation uncertainties, model uncertainties (e.g. due to a lack of resolution, simplified parameterization of physical processes and effect of unresolved processes), imperfect boundary conditions and data assimilation assumptions (Park et al., 2007). An EPS is interpreted by Buizza as a system based on a finite number of deterministic integrations and regarded as, so

far, the only feasible method in meteorology to predict probability density function beyond the range of linear error growth. EPS forecasts from a single weather centre only account for part of the uncertainties originating from initial conditions and stochastic physics (Roulin, 2006). Other sources of uncertainties, including numerical implementations and/or data assimilation, can only be assessed if a grand ensemble (GE) of EPS from different weather centres are combined (Goswami et al., 2007). When various models that produce EPS from different weather centres are aggregated, the probabilistic nature of the ensemble precipitation forecasts is better retained and accounted for (He et al., 2009, 2010; Bao,2009;Bao and Zhao, 2012). An ensemble of weather forecasts can be used on catchment hydrology and provide improved early flood forecasting as some of the uncertainties can be quantified (Cloke and Pappenberger, 2008).

To this end, a case study was carried out using five TIGGE forecast centres. The GMKHM model (Bao et al. 2017a,2017b) was used to simulate the discharge. The study area is the Xixian catchment, located upstream of the Huaihe River. The aims of this paper are to (1) develop atmospheric-hydrologic flood forecasting model cascade driven by TIGGE ensemble forecasts, and (2) apply the model cascade to the Xixian catchment and compare the simulation results driven by TIGGE forecasts and raingauge observation.

*Correspondence to: Hongjun Bao (baohongjun@cma.gov.cn)

2 Case study area and Data

The Huaihe River is located between latitudes 31°N and 35°N and longitudes 112°E and 121°E. It originates in the Tongbai Mountains of Henan Province, and flows over four provinces in east-central China. The length of the main channel of the Huaihe River is 1000 km and the total catchment area is 1.912×10^5 km². Its mean annual precipitation and runoff depth is approximately 888 and 240 mm respectively. The runoff coefficient ranges from 0.1 (northeast) to 0.6 (southwest). The Xixian catchment,

located between latitudes 31.5°N and 33.0°N and longitudes 113.0°E and 115.0°E in the upstream of the Huaihe River, has a drainage area of 8826 km² and is situated in the south of Henan province, China. The catchment average annual precipitation is 1145 mm, 50% of which is within the period of the flood season (June–September). Ten rainfall stations and one hydrological station are available in the Xixian catchment. Fig.1 shows the location of Xixian catchment in China and the sketch of the upper reaches of Huaihe River above Xixian station.

Figure 1. the location of Xixian catchment in China (left), and sketch of Xixian catchment (right)

Observed hydro-meteorological data were obtained from China Meteorological Administration (CMA), and TIGGE data were obtained from TIGGE-China. When the study was conducted, EPS data was available from five centres in the TIGGE database with the majority delivering EPS from January 2007 onwards. The flood

event taking place in July 2007 was selected as the flood event in the study area. The only five centres data is available in the TIGGE database during the studied flood occurring. Table.1 lists the five weather centres and their numbers of ensemble forecasts.

Table 1. List of the meteorological forecast centres used in the case study

Country/Region	Meteorological centre	Centre Abbreviation	Centre Code	Ensemble members
Canada	Canadian Meteorological Centre	CMC	BABJ	14+1
China	China Meteorological administrator	CMA	CWAO	14+1
Europe	European Centre for Medium-Range Weather Forecasts	ECWMF	ECMF	50+1
UK	Meteorological Office	UKMO	EGRR	23+1
USA	National Centres for Environmental Prediction	NCEP	KWBC	14+1

3 The GMKHM model

3.1 Introduction of The GMKHM model

The GMKHM model uses pixels for the DEM as the computational elements for rainfall-runoff modeling and each element consists of a water balance component and a cell-to-cell (30" × 30") flow routing component. The evapotranspiration, runoff production, and runoff separation in every pixel are calculated by the related modules of original Xinanjiang model (Zhao, 1992; Zhao and Liu 1995) and the Green-Ampt infiltration-excess model (Green and Apmt, 1911). The runoff yield of the computational element is composed of three components: surface, subsurface and groundwater, which are obtained from the value of tension water capacity and free water storage capacity of every cell. Outlet flow of each pixel to the outlet of the whole catchment is routed from cell to cell by using overland flow routing model based on kinematic wave theory with the computed order among the DEM grid cells. During the calculation of the runoff generation and runoff concentration in every computational element, the reinfiltration and influence of the river drainage network are taken into consideration (Band, 1986; Yao et al., 2009). The flow is partitioned into channel and downstream cell according to the channel inflow direction and channel outflow direction.

The application of DEM-based methods in this model provides catchment's basic features such as drainage network, flow length, catchment boundary and area for hydrologic simulations. Flow direction in every DEM cell was determined by using the D8 (deterministic eight neighbours) method (Fairfield and Leymarie, 1991) , as a consequence, the matrix of grid cells containing a channel (channel-cells) and computation order of each cell in the DEM were also obtained.

3.2 Calibration and Verification of The GMKHM model

In order to establish the reliability and applicability of the GMKHM model in the Xixian catchment, the model was calibrated. In this study, 20 flood events from 1990 to 2008 that took place in the Xixian catchment were used for model calibration and verification at a 6-hour time step. Because radar-based precipitation data sets are not available in the study sites at present, in order to obtain the rainfall input of each cell and consider the spatial variability of precipitation and its effect on catchment response, the Xixian catchment was divided into 10 sub-catchments by using Thiessen polygon method. The smallest sub-catchment was 4.7% in the Xixian catchment. There is only one rain gauge in each

sub-catchment by both division methods, so rainfall input of each cell can be obtained according to the gauged point value at the station in every sub-catchment. The GMKHM model is used with spatially uniform precipitation in every sub-catchment. According to the Accuracy Standard for Hydrological Forecasting in China (MWR (The Ministry of Water Resources of the People's Republic of China), 2000), the Nash Sutcliffe coefficient and the percent absolute error of peak flow, runoff volume and peak time are four important criteria to evaluate flood simulation and flood forecasting. In terms of peak flow, total runoff volume and peak time of each flood, the result of simulation or forecasting is satisfactory if the percent absolute peak error between the simulated and observed floods is less than 20%, if absolute error between the simulated and observed floods is less than 3 mm or percent absolute runoff error less than 20% and if the difference in peak time is within a routing period or three hours, respectively.

In this paper, thirteen flood events were chosen to calibrate the GMKHM model parameters and seven flood events to verify the model in Xixian catchment. The results of verification are presented in Table 2; they are ordered by flood code of each flood event. The code of each flood event in column of Tables 2 stands for the start time of every flood event, for example, the event 20050820 was one that occurred on 20 August 2005. The statistical indices shown in Tables 2 include the relative peak flow error, relative runoff error, peak time error and Nash coefficient, i.e., the deterministic coefficient. The ratios of qualifying peak flow, flood runoff and peak time for the GMKHM model applied to the Xixian catchment are 100%, 90.0% and 95.0% respectively. The Nash coefficients of all of the events in Table 2 are greater or equal to 0.80 for the GMKHM model; the Nash coefficients of 12 floods are greater than 0.90 for the GMKHM model. The acceptable efficiency coefficients also indicate that the simulated flood hydrographs are conceptually reasonable for the model applied to the Xixian catchment. Tables 2 show that the simulation results of the GMKHM model can perform well in predicting flood runoff and outlet hydrographs. One factor may be that the effect of reinfiltration and drainage network on rainfall-runoff response considered by the gridded model is scale dependent; the response can be more accurately captured by the gridded model in larger catchments. Looking collectively at the calibrated and validated results for the Xixian catchment, the performances of the GMKHM model satisfy the first grade of flood forecasting calibration or validation (all of three ratios are more than 85%) in terms of the standard established by MWR, China. These analyses confirm the forecast robustness and reliability of the proposed GMKHM model.

Table 2. Calibration and validation results of the GMKHM model in Xixian catchment

Flood code	Peak flow	Runoff	Relative error	Relative error	Peak time	Nash Sutcliffe coefficient

		(m ³ /s)	(mm)	of Peak flow (%)	of runoff (%)	error (hour)	
Calibration	19910517	1670	100.4	5.0	15.1	-1	0.83
	19910629	4410	187.4	12.0	-0.5	0	0.95
	19910801	4420	108.3	0.3	-17.8	0	0.97
	19910901	524	41.3	0.8	1.1	-2	0.87
	19950705	2300	48.7	6.1	1.2	0	0.96
	19960619	4450	280.1	9.0	-1.0	0	0.95
	19980701	2510	60.9	0.4	-26.6	-1	0.89
	19980803	4800	323	-6.0	-14.7	0	0.91
	20000624	3150	145.8	5.1	-10.3	0	0.89
	20020621	5080	164.6	6.1	-7.8	0	0.92
	20030621	3900	143.9	11.5	5.2	0	0.96
	20030716	3800	114.7	-7.6	-3.3	0	0.94
	20040715	950	32.7	-7.3	7.8	0	0.90
Validation	20040728	2520	66.8	-8.7	1.4	1	0.84
	20050623	1560	34.9	-6.1	18.8	0	0.92
	20050704	6000	159.8	-14.5	-7.1	0	0.98
	20050820	3830	175.9	0.2	-8.5	-1	0.92
	20050828	3830	123.1	-5.4	10.0	1	0.92
	20070711	4330	107.2	11.3	-1.1	0	0.94
	20080722	3700	85.2	6.1	1.2	1	0.91
Absolute mean				6.5	8.0	0.35	0.92

4 Application and results

The majority of the weather centres delivered global EPS data from January 2007 onwards. This study focused on one flood event that took place in July 2007 (Fig.2). The

flood warning level at the Xixian station is 41.50 m and corresponds to a discharge of 4034 m³/s. The warning level was reached at 0000 (UTC) on 15 July 2007 for the studied flood event and exceeded in the subsequent one day.

Figure 2. Observed 6-hourly precipitation and discharge at Xixian catchment

4.1 Precipitation input evaluation

The precipitation forecasts P_f were retrieved from five weather centres in the TIGGE archive, namely Canadian Meteorological Centre (CMC), China Meteorological Administration (CMA), European Centre for Medium-Range Weather Forecasts (ECMWF), UK Met Office (UKMO), and National Centres of Environmental Prediction (NCEP). The forecasts of 11 July 2007 from NCEP were excluded from this study due to an error that occurred during data extraction. For the selected five centres, each provides one ‘central’ unperturbed analysis and a number of forecasts with perturbed initial conditions. All forecast members were assigned equal weights (Park et al., 2007). The consequent inference is based on the principle of equal probability of selection. The original medium-range forecasts are corrected in ca. 25×25 km resolution (He et al, 2009; 2010). They were interpolated to areal averages of ten sub-catchments to be used as inputs for the GMKHM model. Buizza (2008) pointed out that consistency between forecasts issued on consecutive days is a desirable property of a forecasting system, therefore we examined the feature by visually comparing

P_f of small, moderate and heavy precipitation with thresholds per day of 0.0~9.9mm, 10~24.9mm, over 25mm respectively. These thresholds are defined by the National Meteorological Centre of CMA. In this paper, the threat scores (TS) method (Zhao et al, 2010) was employed to evaluate the performance of the five weather centres and their grand ensemble. TS ranges from 0 to 1, with 0 indicating no skill and 1 perfect.

Fig.3 (a-b) shows the dichotomous forecast verification of the three category precipitation obtained from five EPSs and grand ensemble over Xixian catchment. TS (Fig.3(a)) shows that the five EPSs and grand ensemble have different performance. Scores of CMA, ECMWF and NCEP, ranged from 0.46 to 0.67 with TS and from 0.92 to 1.49 with bias score (B) with lead time ranging from 24hours to 240 hours, is slightly better than that of CMC and UKMO for small precipitation. In the range of moderate precipitation, UKMO performs better than other 4 centres. Five EPSs all have the TS value below 0.30 for heavy precipitation, which indicated that these events were rarely captured. Grand ensemble has a slightly better TS value than CMA and CMC.

a. Threat Score

b Bias Error

Figure.3 Yes/no forecast verification of the three category precipitation obtained from CMC, CMA, ECMWF, UKMO, NCEP and their grand ensemble (GrandE) over the Xixian catchment

4.2 Discharge simulation

Fig.4 shows the area mean P_f issued at 12:00 (UTC) 11 July 2007 and resulting Q_f at the Xixian station using ECMWF. All ECMWF forecast members issued on 12 July 2007 displayed the best agreement for the rainfall event occurred on 13 July 2007. Similarly, the amount and timing of the rainfall between 13 July 2007 and 15 July 2007 were best forecasted with 2-day lead time, i.e. from 14 July 2007 to 16 July 2007. For lead times longer than two day, the 51 ECMWF forecast members demonstrated a fairly consistent signal representing an intensive rainfall event but one could not tell the exact date and time it was to occur as the spread of forecast members was rather large. For example, forecasts issued on 11 July 2007 indicated a large precipitation event would possibly occur on 14 July 2007. Less than 10% of the forecast members

predicted it was to occur on 15 July 2007. The situation improved on 13 July 2007 when most forecast members clustered closer to each other than on the previous day of issue (over 70% members agreeing on 15 July 2007). Disagreements between probabilistic and single forecasts can be used as an indication of potentially low predictability (Buizza 2008) and vice versa. The progress of agreement amongst forecast members evolved from longer to shorter lead times demonstrates the EPS forecasts become more predictable as it is getting closer to the actual event. In comparison to the observed discharge, the ensemble of Q_f was underestimated by approximately 10-30% for all forecast members varying from day to day. In this study, Q_{50} is very comparable with the $Q_{sim-rain gauge}$ for ECWMF, and Q_{95} , Q_{50} , Q_{50} , Q_{95} for CMC, CMA, UKMO, NCEP respectively

Figure 4 Ensemble precipitation forecasts issued on 11 July, 2007 by “ECWMF” (lower) and ensemble forecast discharges (upper) in comparison with observation.

The ensemble of Q_f was evaluated using a warning table, where observations were compared with simulations. The warning table shows the forecasts ability to predict the individual events. The studied flood event is well predicted by all centres with a few days in advance (see Fig.5 for warning level). The percentages correspond to the percentage of members higher than the

alert threshold ($4034 \text{ m}^3/\text{s}$). However, making use of multiple centres from the TIGGE archive did not always show a better performance than using a single EPS centre. This indicates grand ensemble does not necessarily lead to a better performance than a single EPS. Techniques for combining multiple centres should be investigated in the future.

Figure 5 The warning table for the studied flood event. The six horizontal bars from bottom to top represent the five centers (CMC, CMA, ECWMF, UKMO, NCEP), and the ensemble of the five forecast centers.

5 Conclusion and outlook

A coupled atmospheric-hydrologic flood forecast model driven by the TIGGE ensemble forecasts is set up to study the potential benefits of using the TIGGE database in flood forecasting in the upper reaches of Xixian catchment during the 2007 flood seasons. GMKHM model is applied for forecasting rainfall-runoff process. The results demonstrate (1) the Grid-Xinjiang model can perform well for flood simulation and forecasting in the Xixian catchment. (2) The TIGGE archive is a promising tool for issuing a fairly reliable warning as early as 10 days in advance with producing forecasts of discharge comparable with the observed discharge. The reliability of the forecast can be improved at longer leadtimes, which holds great benefit for flood management and preparedness.

Techniques to deal with multi-model forecasts need to be developed. In this study, the principle of equal probability of selection was applied. Multiple EPS inputs should be used with great caution as they have different error structures and can't be easily combined (Cloke and Pappenberger, 2009; He et al, 2010). Different weather forecasts may be assigned a different weight coefficient, which might improve the performance of the grand ensemble.

A spatial and temporal correction to the ensemble weather predictions to resolve discrepancies in the spatial distribution and timing should be developed for flood forecast. The precision of rainfall forecast affects an offset of the peak in term of timing and magnitude that led to the partial failure in early flood warning in hydrological forecasting.

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