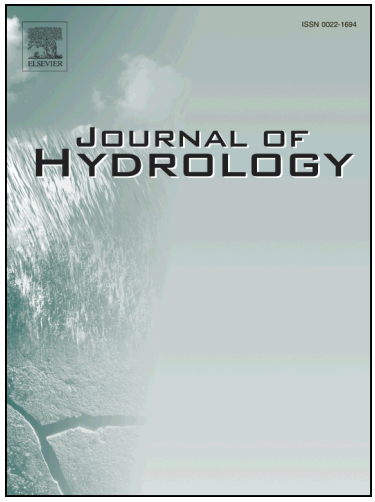

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A service-oriented architecture for ensemble flood forecast from numerical weather prediction

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SUMMARY:

Floods in mountainous river basins are generally highly destructive, usually causing enormous losses of lives and property. It is important and necessary to develop an effective flood forecast method to prevent people from suffering flood disasters. This paper proposed a general framework for a service-oriented architecture (SOA) for ensemble flood forecast based on numerical weather prediction (NWP), taking advantage of state-of-the-art technologies, e.g., high-accuracy NWP, high-capacity cloud computing, and an interactive web service. With the predicted rainfall data derived from the NWP, which are automatically downloaded, hydrological models will be driven to run on the cloud. Judging from the simulation results and flood control requirements offered by users, warning information about possible floods will be generated for potential sufferers and then sent to them as soon as possible if needed. Moreover, by using web service in a social network, users can also acquire such information on the clients and make decisions about whether to prepare for possible floods. Along with the real-time updates of the NWP, simulation results will be refreshed in a timely manner, and the latest warning information will always be available to users. From the sample demonstrations, it is concluded that the SOA is a feasible way to develop an effective ensemble flood forecast method. After being put into practice, it would be valuable for preventing or reducing the losses caused by floods in mountainous river basins.

Keywords: Ensemble flood forecast; Numerical weather prediction; Service-oriented architecture; Cloud computing; Web service

1. Introduction

Mountainous regions, where the natural conditions are extremely complicated, account for nearly two-thirds of the total land area in China. In such regions, high-intensity rainstorms occur frequently during the flood period, which can lead to serious flood disasters and cause enormous losses of lives and property to the inhabitants living in the villages at the riversides or near the outlets of rivers (Caruso et al., 2013; Mazzorana et al., 2013; Ruiz-Villanueva et al., 2013; Shi and Wang, 2015). According to the statistic, there are 29 provinces, 274 prefecture-level cities and 1,836 county-level cities that suffer from flood disasters in China, covering an area of 4.63 million km^2 and involving 0.56 billion people. The key prevention and control area is 0.97 million km^2, involving 0.13 billion people, among which 74 million people suffer a direct threat (Chen, 2010). Specifically, the death toll caused by flash flood disasters accounted for two-thirds of the total death toll caused by all flood disasters every year in China before the 1990s; the percentage has risen to 80% since 2000. Approximately 4,000 people, accounting for 90% of the death toll caused by all flood disasters, were dead or missing in the flash flood disasters in 2010. This indicates that the situation of flood prevention and control will still be severe in the future; more technical and financial support should be provided for these flood-prone regions. Consequently, it is important and necessary to develop an effective flood forecast method to prevent people from having to suffer flood disasters.

Generally, traditional methods for flood forecast include the following two types. The first type comprises those methods based on critical rainfall, including the static and dynamic critical rainfall methods (Carpentera et al., 1999; Georgakakos, 2006; Liu et al.,

2010). It is supposed that floods and some secondary disasters (e.g., debris flow and landslide) may occur in a river basin when the rainfall during a certain time interval reaches a certain amount or intensity (i.e., the static critical rainfall). Because the saturated degree of soil or the antecedent precipitation index has an important effect on the formation of floods, the critical rainfall should not be constant; thus, the dynamic critical rainfall method has been developed. Overall, the critical rainfall methods are easy to use, with no need for rainfall-runoff calculation; however, they cannot reflect the spatial variation of rainfall, making their applications in flood forecast limited. In contrast, the second type, which is applicable for river basins with sufficient, observed hydrological data, comprises those methods based on critical streamflow computed by using an empirical approach or hydrological models (Liu et al., 2005; Nayak et al., 2005; Cane et al., 2013; Moreno et al., 2013). Comparing simulation results against the flood control requirements, warnings concerning floods can be made early, if needed. Due to its high forecast accuracy, this type of method has been widely used; however, limited by the demand for massive observed data, it seems to be useless for river basins with poor data quality, especially for ungauged river basins.

China has dealt with the task of flood prevention and control for a long time. Moreover, more attention will be paid to floods in the future, and the construction of automatic weather stations, county-level data processing centers and early warning systems will be carried out in the near future. A number of provinces in China have set up their own flood warning systems; however, there are still gaps between the requirements for flood warning and reality. For example, a typical process of a flood warning system below the county level includes several levels (e.g., county, town, village, group and family). The

rainfall and hydrological regime is reported to the superior level by level, and the warning information is sent to the inferior level by level as well. Although such a process is in accord with the status quo in China, the lengthy information transmission may considerably affect the efficiency. Thus, it is important and necessary to develop a high-efficiency method for flood forecast.

To this end, this paper aims to propose such a flood forecast method. Currently, numerical weather prediction (noted as NWP hereafter), at the global scale, has developed rapidly with the development of science and technology (Demeritt et al., 2007; Pappenberger et al., 2008). Furthermore, service-oriented architecture (noted as SOA hereafter) has been successfully applied in a wide variety of fields (Erl, 2005; Bell, 2008; Linthicum, 2009); however, the application of SOA for ensemble flood forecast cannot be found in the literature. As a result, this paper proposes the general framework of an SOA for ensemble flood forecast based on the NWP for the first time, taking advantage of the high-accuracy NWP, high-capacity cloud computing and an interactive web service. On the one hand, NWP is introduced to increase the forecast lead time; on the other hand, SOA is introduced to improve the forecast efficiency. In this study, the major challenges in developing such a flood forecast method are i) automatically downloading and updating the predicted rainfall from the NWP in real time, ii) implementing multiple scenarios for flood forecast at the same time by using high performance computing (noted as HPC hereafter) job scheduling, and iii) transferring warning information efficiently by using an interactive web service. Due to these state-of-the-art technologies, this method would be useful for preventing or reducing the losses caused by flood disasters in mountainous river basins after being put into practice.

2. Methodology

A conceptual framework of the SOA for ensemble flood forecast based on the NWP, combining the advantages of the high-accuracy NWP, high-capacity cloud computing and an interactive web service, is proposed in this paper (Fig. 1). In the following, the basic structures of the SOA, NWP, hydrological model used for ensemble flood forecast, HPC job scheduling used for multiple scenarios, and interactive web service used for information transfer will be introduced in detail.

2.1. Service-oriented architecture

Service-oriented architecture (SOA) is essentially a software design methodology based on structured collections of discrete services that collectively provide the complete functionality of a complex application (Erl, 2005). Each service is a well-defined, self-contained set of functions and built as a discrete piece of code, which makes it possible to reuse the code by changing only the interactions of a certain service with other ones rather than the code of the service. Moreover, services communicate with each other closely, involving either simple data passing or complex coordination (Bell, 2008, 2010). Hence, SOA is considered as the infrastructure supporting communications between services, and some connecting services are required. Currently, web service, a set of protocols enabling services to be published, discovered and used in a technology neutral form, seems to be the most feasible way for developing the SOA (Benslimane et al., 2008). By using a web service, a service consumer (e.g., the user client) can send a request message to a service provider (e.g., the cloud server), and then the service provider can return a response message to the service consumer as soon as possible (Linthicum, 2009). It is worth noting

that the SOA is an architecture not only of services, as seen from a technology perspective, but also of policies, practices and frameworks, by which we can ensure that the right services are provided and consumed.

As shown in Fig. 1, the cloud server and user client are regarded as the two primary systems in the SOA. Data collection and management, hydrological simulation, flood forecast and early warning are achieved on the cloud server; meanwhile, messages of flood control requirements from different users and flood early warnings from the cloud server are transferred between the cloud server and user client by using a web service in a social network. Fig. 2 presents the flowchart of the SOA for ensemble flood forecast based on the NWP, and the details are introduced as follows.

First, the NWP data are downloaded automatically, in real time, from websites that provide relevant data and then stored in the database on the cloud server (see Section 2.2 for details); moreover, flood control requirements are provided by users on the clients and stored in the database as well. Second, a physically based hydrological model, the Digital Yellow River Integrated Model (noted as DYRIM hereafter) (Wang et al., 2007, 2015; Li et al., 2009a, 2009b), is adopted to compute the streamflow by using the NWP data; the simulation results are also stored in the database. Third, judging from the comparison of the simulation results against the flood control requirements from different users, flood early warnings are generated, if necessary; in addition, along with the real-time updates of the NWP data, the simulation results are refreshed in a timely manner so that the latest early warnings are always available. Finally, by using a web service, the flood forecast and early warning system on the cloud server can send warning information to the potential sufferers. Moreover, users on the clients can also run the DYRIM on the cloud server by

155 themselves at any time to acquire the simulation results within the forecast lead time of the
156 NWP data so that better preparation can be made for the possible flood disasters. Overall,
157 it is clear that such a process of flood forecast and early warning is quite different from the
158 current process and is useful to the potential sufferers, affording them much more response
159 time for flood disasters.

160 *2.2. Numerical weather prediction*

161 Normally, numerical weather prediction (NWP) can be divided into two categories:
162 single NWP and ensemble NWP. The single NWP is usually insufficient for flood forecast
163 because it involves considerable uncertainties that may lead to lots of errors (Demeritt et
164 al., 2007); meanwhile, the ensemble NWP may provide an opportunity to significantly
165 improve the quality of flood forecast, including not only accuracy but also lead time
166 (Pappenberger et al., 2008). It is believable that a more accurate prediction for atmospheric
167 conditions and meteorological phenomena (e.g., rainfall) in the near future can be obtained
168 from the ensemble NWP.

169 The THORPEX (i.e., The Observing System Research and Predictability Experiment)
170 Interactive Grand Global Ensemble (noted as TIGGE hereafter) dataset is one of the
171 acknowledged NWP datasets available at present (Richardson, 2005; Park et al., 2008).
172 This dataset has been available since 2006 from ten institutions worldwide, including the
173 Bureau of Meteorology (BoM, Australia), the China Meteorological Administration
174 (CMA), the Canadian Meteorological Center (CMC), the Center for Weather Forecast and
175 Climate Studies (CPTEC, Brazil), the European Centre for Medium-Range Weather
176 Forecasts (ECMWF), the Japan Meteorological Agency (JMA), the Korea Meteorological

Administration (KMA), the MeteoFrance (MF), the US NCEP, and the United Kingdom Meteorological Office (UKMO). All of these datasets have the same temporal resolution of 6 hours, while their horizontal resolutions are quite different (e.g., 9/16° for the CMA and 1° for the NCEP and CMC). Moreover, the forecast lead time of the TIGGE data can be 1-16 days, which indicates that the TIGGE data can be a promising tool for short- or medium-term flood forecast.

Due to the uncertainty of the NWP, this indicates that the TIGGE datasets from different institutions can provide a variety of alternatives and seem to be more suitable for this study. Generally, all of these TIGGE datasets can be downloaded for free from their respective official websites (e.g., *http://tigge.ecmwf.int/*). To acquire the newest rainfall data in time for flood forecast, a method to automatically download and manage the NWP data is proposed, taking advantage of the Htmlunit (2013) and Apache CFX web services (2014). Three steps are introduced in detail as follows.

Step 1: Download the NWP data from the websites. In this step, operations on the web browser are simulated and realized by using the Htmlunit; two tasks, including login authentication and data downloading, are realized by using the source codes given in Appendix A.

Step 2: Manage the NWP data on the cloud server. In this step, the downloaded NWP data are interpreted first and then stored in a specific database. Moreover, the NWP data are converted into visual images in the TIFF format (see Appendix B for the source codes).

Step 3: Make the above two steps autorun. In this step, the above two functions (i.e., data downloading and management) are packaged into a one by using the Apache CFX

199 web service. The program for downloading the NWP data is encapsulated as a service
200 component, which runs automatically at a fixed time interval in the background of a server;
201 moreover, this service is configured into the web server (i.e., Tomcat).

202 *2.3. Digital Yellow River Integrated Model*

203 Digital Yellow River Integrated Model (DYRIM) is a distributed model platform
204 developed by Tsinghua University for hydrological and sediment simulations in river
205 basins (Wang et al., 2007, 2015; Li et al., 2009a, 2009b). The DYRIM uses a high-
206 resolution digital drainage network that is extracted from a digital elevation model (noted
207 as DEM hereafter) (Bai et al., 2015) and coded using a modified binary tree method (Li et
208 al., 2010) to simulate runoff yield and flow routing on each hillslope-channel unit.
209 Moreover, dynamic parallel computing technology based on sub-basin decomposition has
210 been developed to speed up the simulation (Li et al., 2011; Wang et al., 2011, 2012; Wu et
211 al., 2013).

212 The DYRIM hydrological model is a physically based distributed model that
213 represents the infiltration-excess runoff yield mechanism. This model uses a hillslope-
214 channel as a basic hydrological unit because of the different hydrological response
215 mechanisms of hillslopes and channels. The runoff-yield model is established based on the
216 hillslope unit, where the soil mass is divided into topsoil and subsoil layers. A variety of
217 hydrological processes are simulated, including vegetation interception, evapotranspiration,
218 infiltration-excess runoff on the surface, subsurface flow in these two layers, and water
219 exchange between these two layers. In the DYRIM hydrological model, the temporal
220 resolution is six minutes and the rainfall data are uniformly assigned to each time step;

moreover, the rainfall data are spatially interpolated by using the inverse distance weighted method. It is worth noting that parameters in the DYRIM hydrological model can be divided into two types: (i) invariant parameters used for describing the properties of land use and soil type, influenced by the basic features of the river basin and determined from the literature, fieldwork and prior studies; and (ii) adjustable parameters that are calibrated and verified with the observed data.

2.4. HPC job scheduling

HPC is an important branch of computer science that focuses on the development of high performance computers and relevant software. It is a technology that can improve the capability of scientific computing through organizing a number of processors or computers as members of a cluster; it is based on parallel computing technology, a way of enabling an application to be divided into multiple parts that can be executed in parallel multiple processors. There are several types of HPC systems (e.g., large clusters and highly specialized hardware), most of which are based on clusters and interconnect with each other by using a high performance network, e.g., the Quad Data Rate (QDR) InfiniBand network. HPC allows scientists and engineers to solve complex scientific, engineering and business problems by using applications that require high bandwidth, low latency networking, and very high computing capability. In the future, HPC will be more networked, open, standard, structured and diversified in application. For example, in the field of hydrological simulation, HPC can be used when a parallel hydrological model (e.g., the DYRIM in this study) is applied in large-scale river basins.

The framework of the SOA for ensemble flood forecast based on the NWP in this study tries to provide a two-layer parallelism (Fig. 3). The lower layer is the parallelism in the DYRIM hydrological model; the upper layer is the parallelism in the hydrological simulations with the NWP data from different institutions, which is realized by using a job scheduling function. Moreover, the Windows HPC Server 2012 used in this study has 24 compute nodes with 20 processor cores on each of them, i.e., 480 processor cores in total. Generally, one processor core can execute only one process each time; using more processor cores at one time means less time consumption. The number of processor cores used for hydrological simulation at one time can significantly affect the efficiency of the lower-layer parallelism and further affect the efficiency of the upper-layer parallelism. Namely, if N processor cores are used for hydrological simulation with the NWP data from one institution, then hydrological simulations with the NWP data from INT(480/N) (note: the symbolic function INT(X) means the integer part of a real number X) institutions can be carried out at the same time by using the HPC job scheduling.

2.5. Web service

An interactive web service is developed to receive the flood control requirements from the users and send early warnings to the users. Moreover, it is also used for queries on a variety of hydrological information (e.g., the digital drainage network, historical and predicted rainfall data, and streamflow predictions). All of the data are stored in the databases on the cloud server and can be inquired by the user clients at any time. For example, based on the global drainage network (Bai et al., 2015) extracted from the 30-m-resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)

Global DEM dataset (ASTER GDEM Validation Team, 2009, 2011), users can define a watershed by specifying the location of the watershed outlet (i.e., longitude and latitude) and the corresponding river reach. Then, the drainage network of the entire watershed will be selected for hydrological simulation (i.e., flood forecast).

3. Results and discussions

In this study, two river basins in China, including the Juma River basin in the southwest suburb of Beijing and the upper Baishui River basin in the north of Sichuan province, are regarded as the study areas for the application of the SOA for ensemble flood forecast based on the NWP. In the following, the available research data used for each case are introduced, and the results as well as discussions are presented.

3.1. Case study of the Juma River basin

The Juma River basin is located in the southwest of Beijing (114°27'-115°47' E, 39°12'-40°04' N). As shown in Fig. 4, there is only one hydrological station (i.e., the Zhangfang hydrological station) in this river basin; the drainage area in the upstream of this station is over 3,800 km^2. The high-resolution digital drainage network is also shown in Fig. 4; there are 25,833 river reaches and nearly 65,000 hillslopes in total in the extracted digital drainage network.

The Juma River basin was severely affected by the notorious rainstorm on July 21, 2012, in Beijing. This rainstorm was characterized by a large rainfall depth, long duration and high intensity. According to the information from the Beijing Water Authority, this rainstorm lasted for nearly 16 hours, and the mean rainfall depth of the whole city was 170

mm, with a significantly uneven spatial distribution. For example, the Fangshan District, in the southwest of Beijing, had the maximum rainfall depth of 301 mm, while Yanqing County, in the northwest, had the minimum rainfall depth of 69 mm. The area with a rainfall depth over 200 mm was approximately 6,000 km^2, covering 36% of the total area of Beijing, and the largest point rainfall (i.e., 460 mm, with a return period of 500 years) occurred in the Fangshan District. As a result, approximately 1.9 million people had property loss, and among them, 0.8 million were in the Fangshan District; furthermore, there were 79 persons killed due to this rainstorm.

To accurately forecast floods due to severe rainfall, the reliable estimation of rainfall is paramount; then, hydrological models can be used to forecast streamflow with more accuracy. In this case, the TIGGE data derived from six of the above-mentioned ten institutions (i.e., the CMA, CMC, CPTEC, ECMWF, NCEP and UKMO) are selected as the research data (i.e., the predicted rainfall data) because there was no data available from the other four institutions for the period of this rainstorm. After being downloaded automatically in real time from the official websites (see Section 2.2 for details), the NWP data are used as the basic input data for the follow-up streamflow simulation and flood forecast. The NWP data (i.e., the TIGGE data in this study) are considered to be an important factor that can affect the result of streamflow simulation; thus, it is possible that using the NWP data derived from different sources may lead to different flood forecast results.

To investigate the features of the various NWP data, the spatial distributions of total rainfall depth in Beijing and the surrounding area during the time period of 0:00-24:00 UTC, July 21, 2012, which were described by the TIGGE data derived from six institutions

(i.e., the CMA, CMC, CPTEC, ECMWF, NCEP and UKMO) released at 0:00 UTC, July 21, 2012, were shown in Fig. 5. Overall, the six TIGGE datasets have significantly different features for describing the spatial distribution of rainfall depth. On the one hand, the maximum values of total rainfall depth inside the Juma River basin during this period varied widely, e.g., 58.5 mm for the CMA data, 68.9 mm for the CMC data, 61.2 mm for the CPTEC data, 92.5 mm for the ECMWF data, 134.8 mm for the NCEP data and 151.9 mm for the UKMO data; the highest value was nearly three times as much as the lowest one. On the other hand, the rainfall centers described by these six TIGGE datasets during this period appeared in different locations. For example, the rainfall center described by the ECMWF data appeared in the downstream of the Juma River basin (Fig. 5d) but that described by the UKMO data appeared in the upstream of this river basin (Fig. 5f); moreover, for the NCEP data, heavy rainfall almost covered the entire river basin (Fig. 5e).

Furthermore, to evaluate the performances of the various NWP data in flood forecast, streamflow processes of the reach where the Zhangfang hydrological station is located were computed with these six TIGGE datasets by using the DYRIM hydrological model and HPC job scheduling. Because the features of these six TIGGE datasets for describing the spatial distribution of rainfall depth were significantly different, it is presumable that the simulation results would be different (see Fig. 6). In this study, the parameters derived from the previous study (Shi, 2013) were directly used, and Fig. 6 shows the comparisons of streamflows computed with the six TIGGE datasets against the observed data recorded at the Zhangfang hydrological station. Overall, all of the simulated values computed with these six TIGGE datasets were not close to the observed ones. Only by using the NCEP data or UKMO data could the peak flow be simulated; however, both the peak value and

appearance time were not accurate when they were compared with those presented by the observed data (approximately 2,500 m^3/s appeared at 23:00 UTC, July 21, 2012). By using the NCEP data, the computed peak value was approximately 3,800 m^3/s, 52% larger than the observed peak value, and the appearance time was six hours in advance; by using the UKMO data, the computed peak value was approximately 2,600 m^3/s, only 4% larger than the observed peak value, and the appearance time was only four hours in advance. It is inferred that the UKMO data showed much better performance than the NCEP data for this case. In addition, no peak flows could be simulated by using the other four TIGGE datasets (i.e., the CMA, CMC, CPTEC and ECMWF).

Furthermore, Table 1 lists the results of streamflow simulation by using these six TIGGE datasets. It is observed that the simulation results were markedly different as a whole. The values of flood volume were 3.92×10^6 m^3 (-95.27%) for the CMA data, 3.98×10^6 m^3 (-95.20%) for the CMC data, 3.94×10^6 m^3 (-95.26%) for the CPTEC data, and 3.92×10^6 m^3 (-95.27%) for the ECMWF data. For these four TIGGE datasets, the intensity of the predicted rainfall was not high enough for the runoff yield; the computed streamflow was actually the base flow, resulting in no peak flows appearing. If so, no floods would occur in the Juma River basin, which indicated that people living in this river basin would be safe. In contrast, the high intensity of the predicted rainfall for the other two datasets led to extremely large values of flood volume, e.g., 156.76×10^6 m^3 (88.98%) for the NCEP data and 112.17×10^6 m^3 (35.23%) for the UKMO data; moreover, as mentioned above, the peak values were very large as well (i.e., 3,800 m^3/s for the NCEP data and 2,600 m^3/s for the UKMO data); enormous losses of lives and property would be caused by such large floods if they came true.

354 *3.2. Case study of the upper Baishui River basin*

355 The upper Baishui River basin is located in the north of Sichuan province (103°22'-
356 103°47' E, 33°06'-33°40' N). The region in the upstream of the Batun hydrological station
357 with an area of 1,198 km^2 is considered in this study (Fig. 7). The four rainfall stations
358 with hourly observed data are also shown in Fig. 7. Moreover, there are 7,019 river reaches
359 and nearly 17,500 hillslopes in total in the extracted digital drainage network.

360 For this river basin, the flood occurred during July 16-23, 2010 is regarded as the
361 study case. The TIGGE data derived from four of the above-mentioned ten institutions (i.e.,
362 the CMA, CPTEC, ECMWF and UKMO) are selected as the research data (i.e., the
363 predicted rainfall data), as the data from the other six institutions are not available during
364 this period. Fig. 8 shows the comparison of the simulated streamflows calibrated with the
365 observed station rainfall against the observed streamflows recorded at the Batun station,
366 and the results were generally satisfactory when they were compared with those presented
367 by the observed data (approximately 75 m^3/s appeared at 3:00 UTC, July 17, 2010), with
368 peak value error of -17% and peak time error of six hours delay (Table 2). Fig. 8 also
369 shows the comparisons of streamflows computed with the four TIGGE datasets against the
370 observed data recorded at the Batun station. Overall, the results computed with these four
371 TIGGE datasets were not so close to the observed data. Only by using the ECMWF data or
372 CMA data could the peak flow be simulated; however, both the peak value and appearance
373 time were not accurate. Table 2 also lists the comparisons of streamflows computed with
374 the observed station rainfall and the four TIGGE predicted rainfall inputs against the
375 observed data recorded at the Batun station. Using the predicted rainfall, the simulated
376 peak value and time were 36.0 m^3/s (-52%) and six hours later for the ECMWF data and

377 30.4 m^3/s (-56%) and 7 hours later for the CMA data; no peak flow could be forecasted by
378 using the CPTEC and UKMO data.

379 *3.3. Discussions*

380 From the case studies, it can be seen that the results of flood forecast obtained by
381 using different NWP data can be markedly different, even completely opposite. To this end,
382 it is important and necessary to provide these various results of streamflow computation by
383 using different NWP data for users at the same time. In this study, implementing multiple
384 scenarios of flood forecast (i.e., streamflow simulations by using different NWP data) at
385 the same time can be realized by using the two-layer paralleled HPC job scheduling on the
386 cloud server (see Section 2.4 for details). Generally, these simulations can be completed
387 within a few minutes (e.g., 3 minutes for the first case and 2 minutes for the second case).
388 Thereafter, all of the simulation results will be compared with the flood control
389 requirements offered by users, and the probability of flood can be described by the
390 percentage of possible floods that are simulated with different NWP data (i.e., 2 in 6 for
391 the first case and 2 in 4 for the second case). If needed, relevant warning information of
392 floods will be generated and sent to potential sufferers immediately. In addition, users on
393 the clients can also acquire such warning information by using the web service in a social
394 network at any time.

395 Generally, methods for flood risk and vulnerability analyses have been proposed for
396 ensemble flood forecast (UNDRO, 1991; Willows and Connell, 2003; Wu et al., 2012).
397 For river basins with sufficient historical hydrological data, the frequency of the predicted
398 peak flow from each NWP data can be obtained from the probability distribution function

399 derived from the observed streamflow series. Meanwhile, the critical frequency of flood to
400 cause potential disaster can be determined for each NWP agency. Thereafter, through
401 comparing the forecasted frequency of peak flow from each NWP agency against its
402 critical frequency, flood risk degree can be evaluated separately. Finally, a method to
403 generate a synthetic warning from the separate risks, considering different weights
404 according to the historical performance of each NWP agency, is needed. This method is
405 hoped to be adopted in the proposed system in future work. However, for river basins with
406 no historical hydrological data, this method is still tough to succeed. Therefore, the
407 proposed system can only provide the various flood forecast results for users at this stage.
408 After being put into practice for years, accumulation of hydrological data may make a
409 result interpretation method more applicable to the proposed system, which is much more
410 useful to provide the decision-support for users.

411 Furthermore, it can be inferred that the discrepancies in peak values and times are
412 mainly caused by the low temporal-spatial resolution of the predicted rainfall data. For
413 flood forecast in any given river basin, the globally available predicted rainfall from the
414 NWP (e.g., TIGGE) data is not accurate enough. Nevertheless, the proposed system has
415 made the techniques and the platform ready for better flood forecast, when better predicted
416 rainfall data can be obtained from much finer national and regional NWP data.

417 ## 4. Conclusions

418 This paper proposed a conceptual framework for the SOA for ensemble flood forecast
419 from the NWP, combining the advantages of state-of-the-art technologies, e.g., high-
420 accuracy NWP, high-capacity cloud computing and an interactive web service. The

421 significance of this paper can be concluded as follows: first, a method to automatically
422 download and update the predicted rainfall derived from the NWP (e.g., the TIGGE data)
423 in real time was developed. Second, HPC job scheduling was adopted to implement
424 multiple scenarios of flood forecast at the same time; accordingly, various results of
425 streamflow simulation could be provided, and the latest warning information of floods
426 could be generated for potential sufferers. Third, by using the interactive web service in a
427 social network, users can either acquire such warning information on the clients at any
428 time or be informed to prepare for possible floods. It is concluded that the SOA will be a
429 feasible way for ensemble flood forecast based on the NWP, affording potential sufferers
430 much more response time when confronted with possible floods. After being put into
431 practice, the proposed system would be useful for preventing or reducing the losses caused
432 by flood disasters in mountainous river basins.

433

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Appendix A

Source codes for downloading the NWP data from websites are given as follows:

Login authentication:

```
WebClient client = new WebClient(BrowserVersion.FIREFOX_10);
HtmlPage  homePage = client.getPage("URL");
HtmlInput name = homePage.getInputByName("Name");
name.setValueAttribute("Value");
HtmlPage loginPage = homePage.getAnchorByText("Name of Link").click();
```

Data downloading:

```
URL url = new URL(downloadurl);
URLConnection conn = url.openConnection();
InputStream inStream = conn.getInputStream();
filestream = new FileOutputStream("@Path"+filename+".grib");
datewriter.write(filename);
datewriter.flush();
byte[] buffer = new byte[1204];
while ((byteread = inStream.read(buffer)) != -1){
        bytesum += byteread;
        filestream.write(buffer, 0, byteread);
}
```

Appendix B

Source codes for the NWP data interpretation are given as follows:

Data interpretation:

```
public class GridData; //the class of rainfall data
String filepath = "F:\\data.grib";
File fileptr = new File(filepath);
FileInputStream filestream = new FileInputStream(fileptr);
BufferedInputStream bufferstream = new BufferedInputStream(filestream);
private void GridSection(BufferedInputStream bufferstream, List<GridData> Points);
private void ProductSection(BufferedInputStream bufferstream);
private void DataSection(BufferedInputStream bufferstream, List<Double> PointsValue) throws
IOException {
        int Length = ConvertInt(4, bufferstream, "the total length");
        ConvertInt(1, bufferstream, "the serial number");
        bufferstream.mark(Integer.MAX_VALUE);
        for (int i = 0; i < TotalNumberofPoints; i++) {
            double PValue = ConvertPoint(24, bufferstream, "第" + (i + 1) + "点： ");
            PointsValue.add(PValue);
        }
        bufferstream.reset();
        bufferstream.skip(Length - 5);
}
```

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594

595

596 **List of figure captions**

597 **Fig. 1.** The framework of the service-oriented architecture (SOA) for ensemble flood forecast from
598 numerical weather prediction (NWP).

599 **Fig. 2.** The flowchart of the SOA for ensemble flood forecast from the NWP.

600 **Fig. 3.** The HPC job scheduling used in this study.

601 **Fig. 4.** The location and the digital drainage network of the Juma River basin.

602 **Fig. 5.** The spatial distributions of rainfall depth in Beijing and the surrounding area during 0:00-
603 24:00 UTC, July 21, 2012, which were described by six TIGGE datasets (i.e., the CMA,
604 CMC, CPTEC, ECMWF, NCEP and UKMO) released at 0:00 UTC, July 21, 2012.

605 **Fig. 6.** Comparison of the streamflows computed with the six TIGGE datasets against the observed
606 streamflow data recorded at the Zhangfang hydrological station.

607 **Fig. 7.** The location and the digital drainage network of the upper Baishui River basin.

608 **Fig. 8.** Comparison of the streamflows computed with the observed station rainfall and the four
609 TIGGE datasets against the observed streamflow data recorded at the Batun hydrological
610 station.

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612

Figure 1

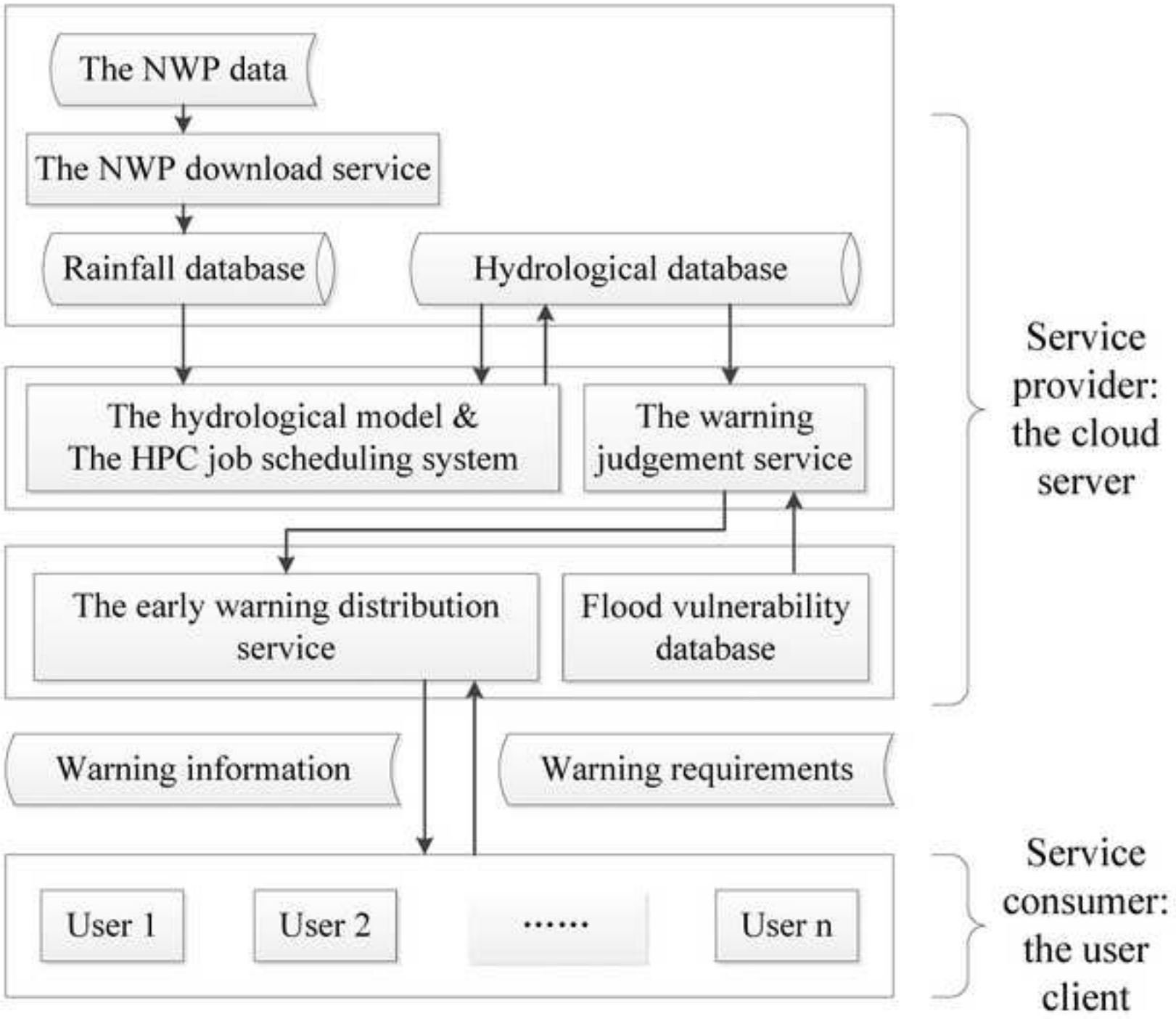


Figure 2

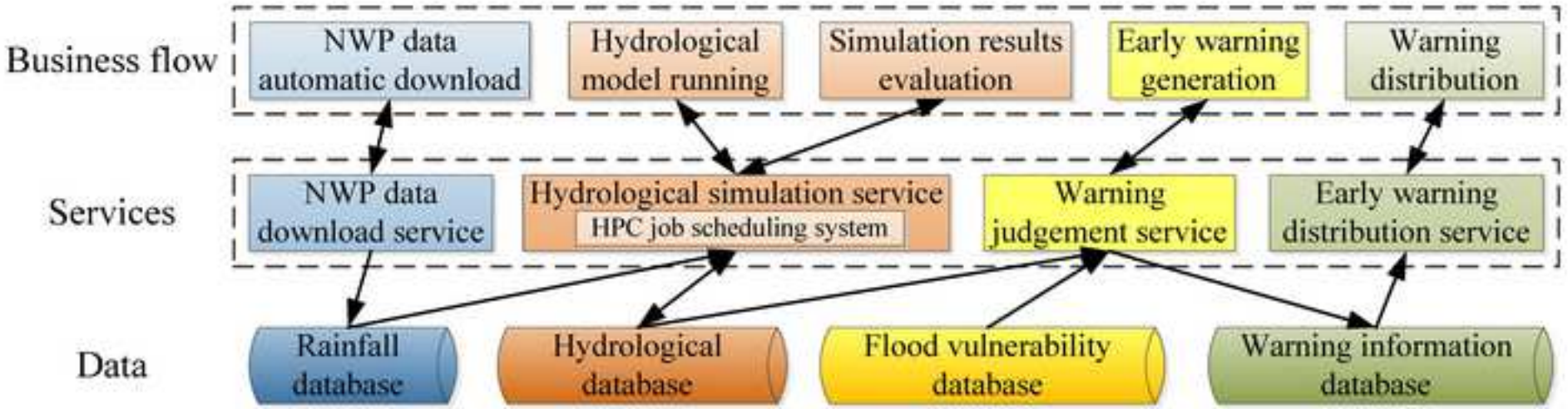


Figure 3

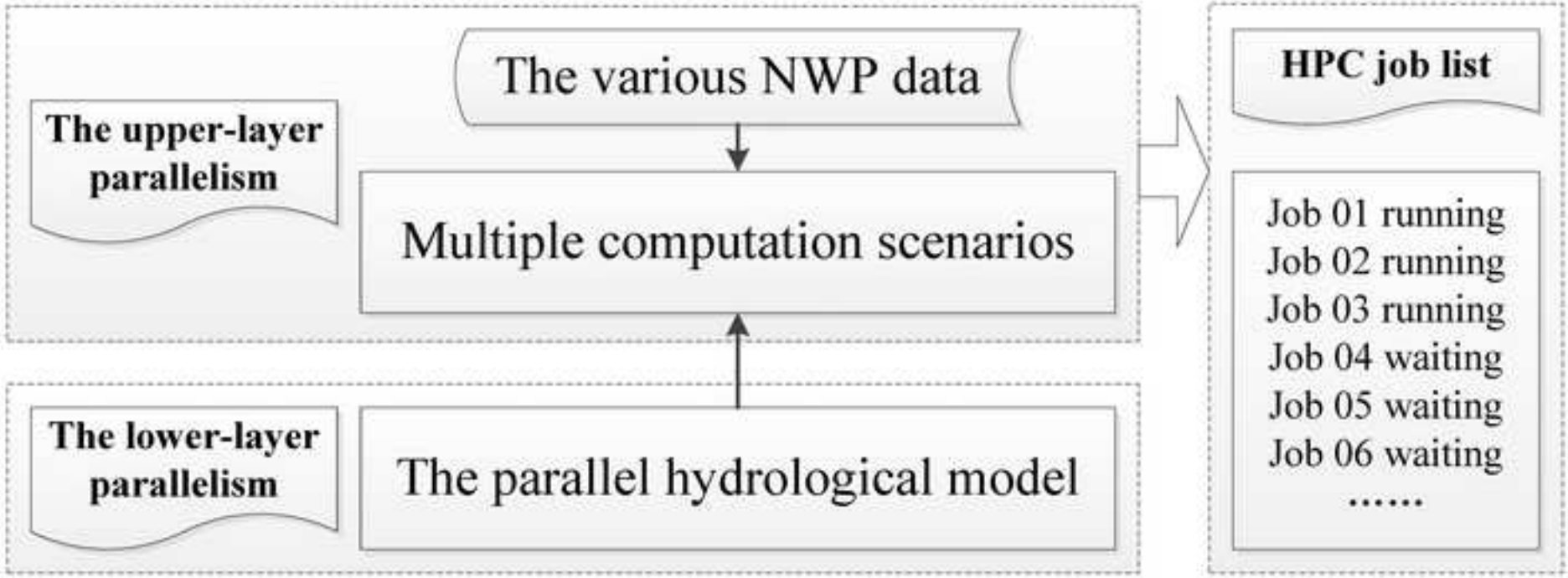


Figure 4

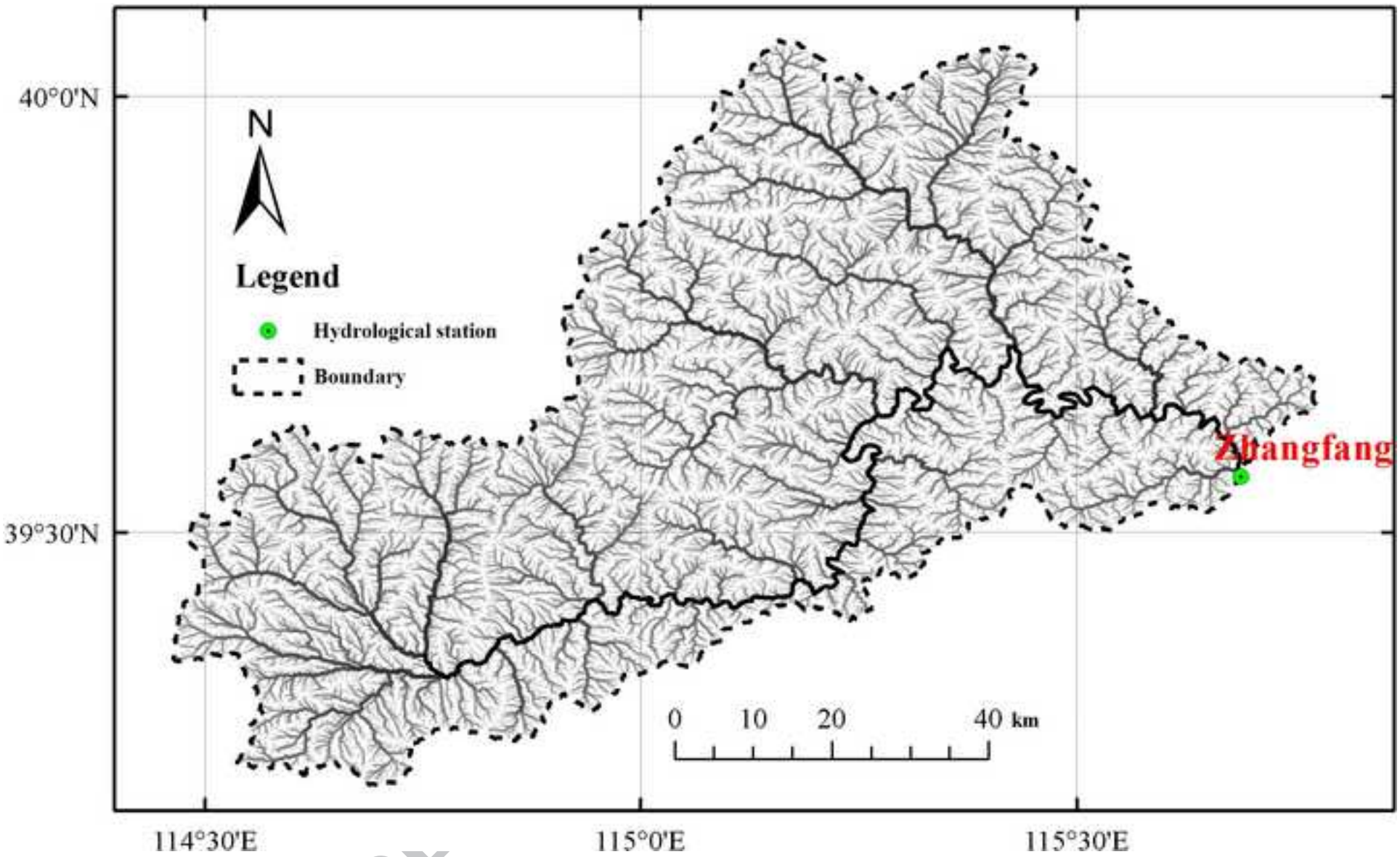


Figure 5

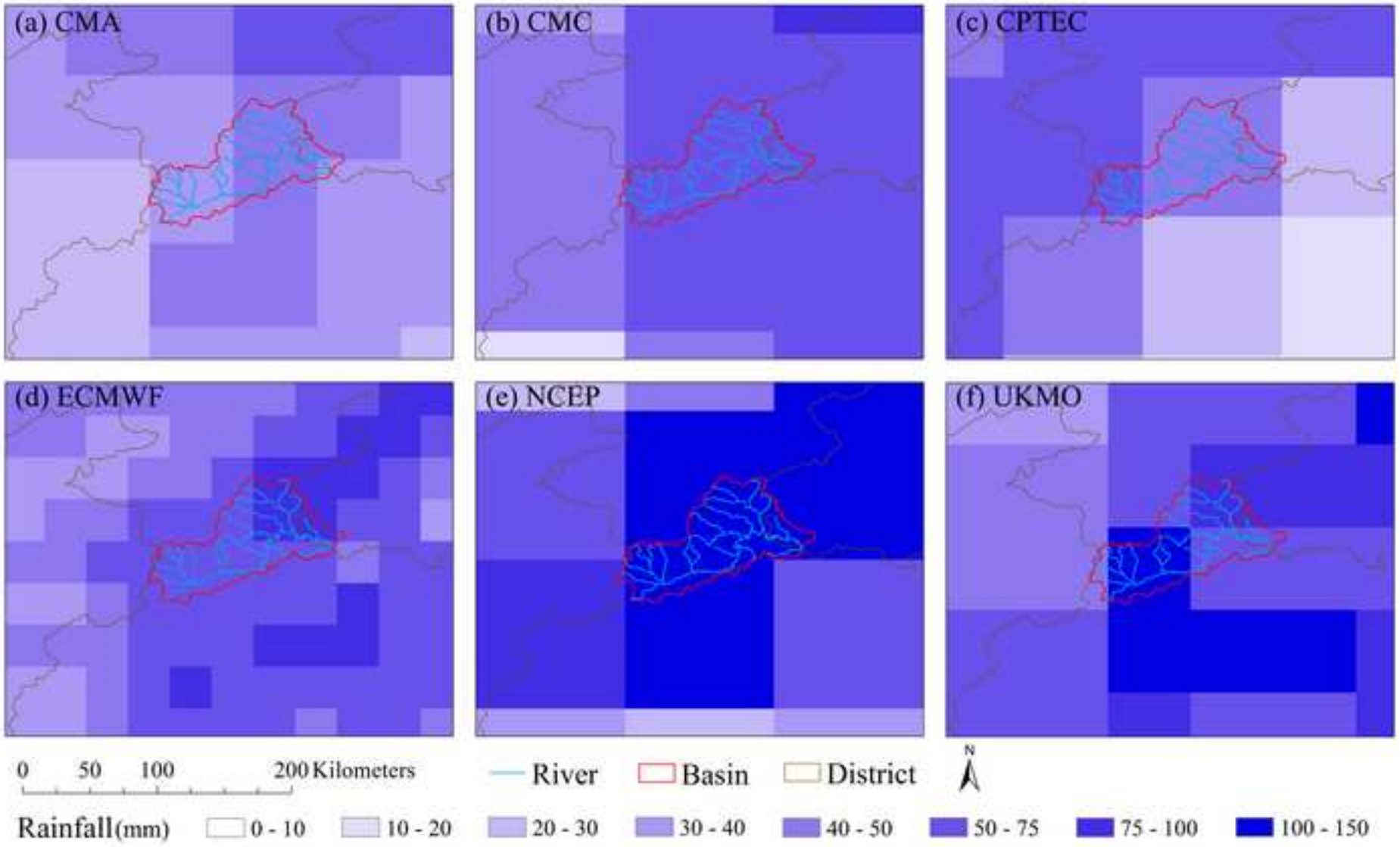


Figure 6

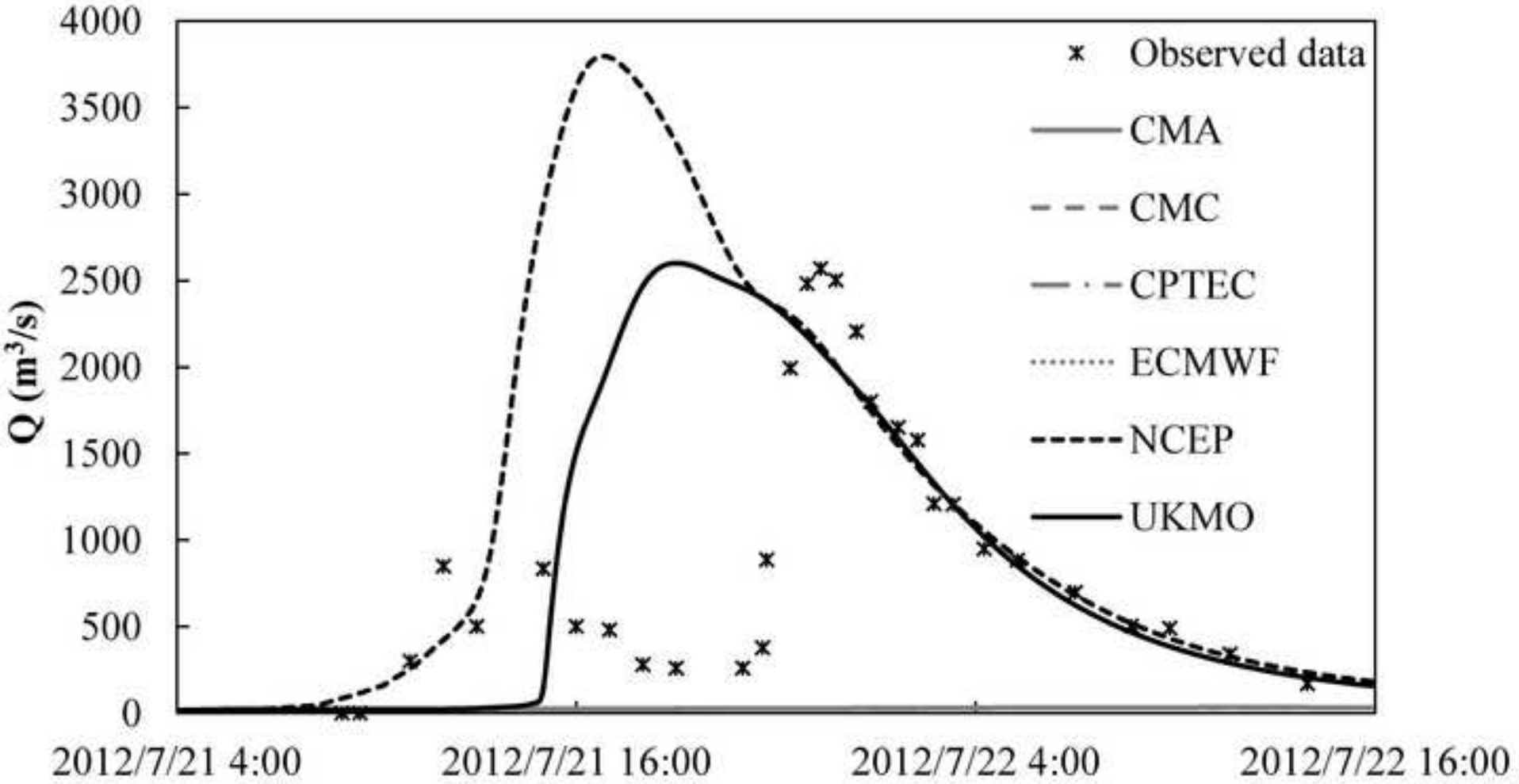


Figure 7

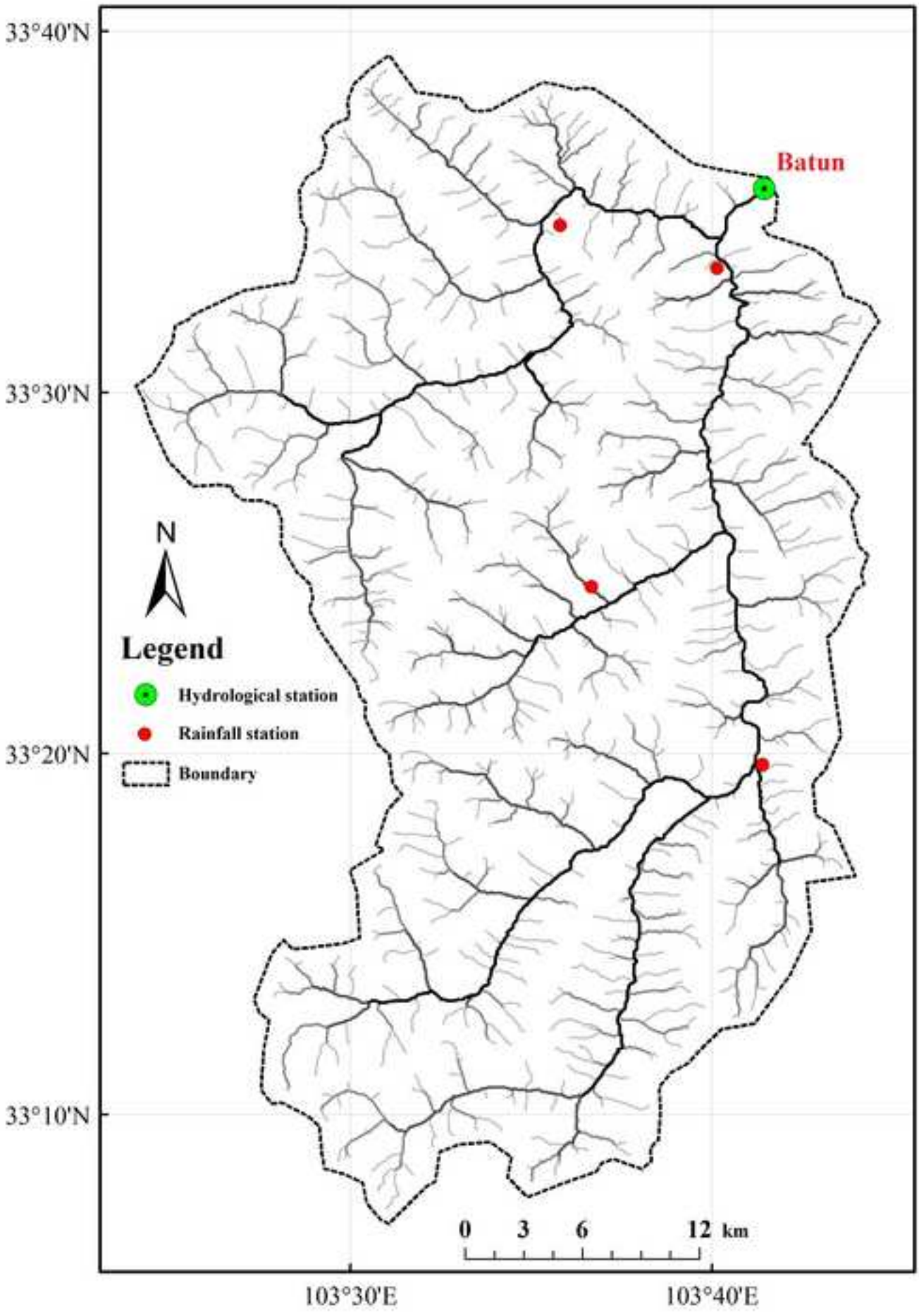
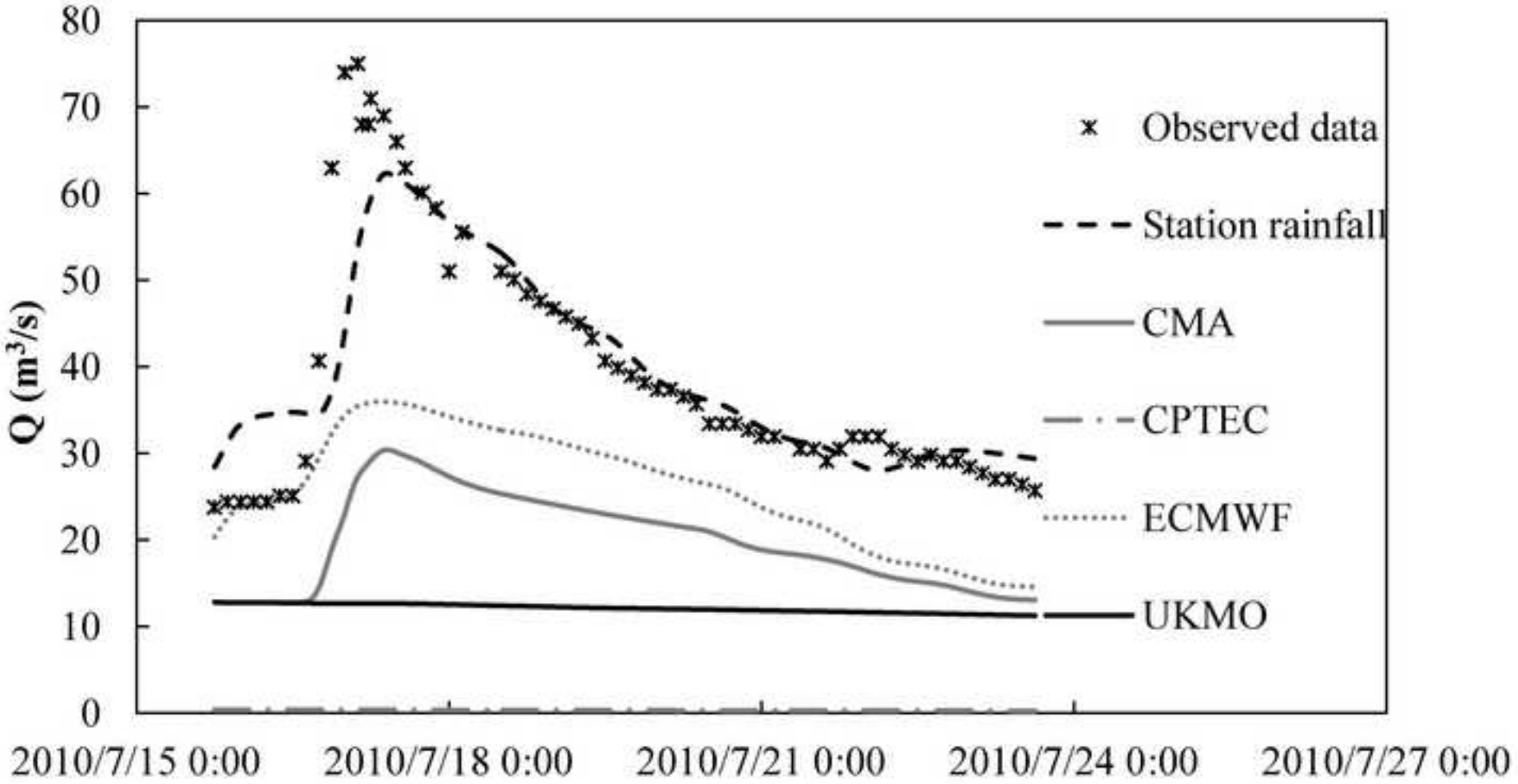


Figure 8



613

614 Table 1 Results of streamflow computation by using six different TIGGE data in the Juma River
615 basin.

Data	Flood volume (10^6 m^3)	Relative error (%)	Peak value (m^3/s)	Relative error (%)	Peak time (UTC)	Peak time error
Observation	82.95	/	2,500	/	2012/7/21 23:00	/
CMA	3.92	-95.27	/	/	/	/
CMC	3.98	-95.20	/	/	/	/
CPTEC	3.94	-95.26	/	/	/	/
ECMWF	3.92	-95.27	/	/	/	/
NCEP	156.76	+88.98	3,800	+52	2012/7/21 17:00	-6 hours
UKMO	112.17	+35.23	2,600	+4	2012/7/21 19:00	-4 hours

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618

619 Table 2 Results of streamflow computation by using six different TIGGE data in the upper Baishui

620 River basin.

Data	Flood volume (10^6 m^3)	Relative error (%)	Peak value (m^3/s)	Relative error (%)	Peak time (UTC)	Peak time error
Observation	26.94	/	75.0	/	2010/7/17 3:00	/
Station rainfall (Calibration)	26.92	-0.06	62.3	-17	2010/7/17 9:00	+6 hours
CMA	13.55	-49.72	30.4	-56	2010/7/17 10:00	+7 hours
CPTEC	0.22	-99.17	/	/	/	/
ECMWF	17.68	-34.35	36.0	-52	2010/7/17 9:00	+6 hours
UKMO	8.25	-69.36	/	/	/	/

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623

624 # Research Highlights

625 1. Development of the framework of SOA for ensemble flood forecast from NWP

626 2. Development of a method to automatically download and update the NWP

627 3. Realization of implementing multiple scenarios of flood forecast at the same time

628 4. Validation of the new method through simulating flood flow at two river basins

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