Extending flood forecasting lead time in large watershed by coupling WRF QPF with distributed hydrological model

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Abstract. Long lead time flood forecasting is very important for large watershed flood mitigation as it provides more time for flood warning and emergency responses. Latest numerical weather forecast model could provide 1-15 days quantitative precipitation forecasting products at grid format, by coupling this product with distributed hydrological model could produce long lead time watershed flood forecasting products. This paper studied the feasibility of coupling the Liuxihe Model with the WRF QPF for a large watershed flood forecasting in southern China. The QPF of WRF products has three lead time, including 24 hour, 48 hour and 72 hour, the grid resolution is 20kmx20km. The Liuxihe Model is set up with freely downloaded terrain property, the model parameters were previously optimized with rain gauge observed precipitation, and re-optimized with WRF QPF. Results show that the WRF QPF has bias with the rain gauge precipitation, and a post-processing method is proposed to post process the WRF QPF products, which improves the flood forecasting capability. With model parameter re-optimization, the model's performance improves also. It suggests that the model parameters be optimized with QPF, not the rain gauge precipitation. With the increasing of lead time, the accuracy of WRF QPF decreases, so does the flood forecasting capability. Flood forecasting products produced by coupling Liuxihe Model with WRF QPF provides good

reference for large watershed flood warning due to its long lead time and rational results.

Key words： WRF, Liuxihe Model, Flood forecasting, lead time, parameter optimization

1 Introduction

Watershed flood forecasting is one of the most important non-engineering measures for flood mitigation(Tingsanchali, 2012, Li et al., 2002), significant progresses in watershed flood forecasting have been made in the past decades(Borga et al., 2011, Moreno et al., 2013). Lead time is a key index for watershed flood forecasting, especially for large watershed (Toth et al., 2000, Han et al., 2007). Only flood forecasting products with long lead time is useful as it could provide enough time for flood warning and flood emergency responses. In the long practice of flood forecasting, ground based rain gauge measured precipitation is the main input for flood forecasting model, but as this kind of precipitation is the rainfall falling to the ground already, so it has no lead time. This makes the watershed flood forecasting with very short lead time (Jasper et al., 2002), and could not satisfy the requirement of flood warning (Shim et al., 2002) in lead time, particularly in large watershed, thus reducing the value of the flood forecasting products in watershed flood mitigation.

The developed numerical weather prediction model in the past decades could provide longer lead time quantitative precipitation forecast(QPF) product at grid format, the lead time for the latest weather prediction model could be as long as to 1~15 days

(Buizza,1999, Ahlgrimm et al., 2016). By coupling the weather prediction model QPF with flood forecasting model, the flood forecasting lead time thus could be extende this provides w way for large watershed flood forecasting (Jasper et al., 2002, Zappa et al., 2010, Giard and Bazile, 2000). Many numerical weather prediction models have been proposed and put into operational use, such as the European Centre Medium-Range Weather Forecasts (ECMWF) Ensemble Prediction System (EPS) (Molteni et. al., 1996, Barnier et. al.,1995), the weather research and forecasting (WRF) model (Skamarock, 2005, 2008, Maussion, 2011), the numerical weather forecast model of Japan Meteorological Agency (Takenaka et al., 2011, Gao and Lian, 2006), the numerical forecast model of China Meteorological Agency (Li and Chen, 2002), and others.

Watershed flood forecasting relies o ydrological model for computation tool, while the precipitation is the model's driving force. The earliest hydrological model is regarded as the Sherman unit-graph (Sherman, 1932), which belongs to the category of lumped hydrological model. Many lumped hydrological models have been proposed, such as the Sacramento model (Burnash, 1995), the NAM model (DHI, 2004), the Xinanjiang model (Zhao, 1977), among others. The lumped hydrological model regards the watershed as a whole hydrological unit, thus the model parameter is the same over the watershed, but this is not true, particularly for a large watershed. The precipitation the lumped hydrological model u l is averaged over the watershed also his further increases the model's uncertainty in large watershed flood forecasting as it is well known that the precipitation distribution over the watershed is highly uneven. The QPF produced by numerical weather prediction model forecasts precipitation at grid format, which provides detailed precipitation distribution information over watershed is another advantage of QPF. The lumped hydrological model could not take the advantage of gridded WPF products.

The latest development of watershed hydrological model is the distributed hydrological model (Refsgaard et. al., 1996), which divides the watershed into grids, and different grids could have their own precipitation, terrain property and model parameter, distributed hydrological model is the ideal model for coupling WRF QPF for watershed flood forecasting. The first proposed distributed hydrological model is SHE model (Abbott et. al.1986a, 1986b), and now many distributed hydrological models have been proposed, and a few have been used for watershed flood forecasting, such as the SHE model (Abbott et. al.1986a, 1986b), the WATERFLOOD model (Kouwen, 1988), the VIC model (Liang et. al., 1994), the WetSpa model (Wang et. al., 1997), the Vflo model (Vieux et. al., 2002), the WEHY model(Kavvas et al., 2004), the Liuxihe model (Chen et. al., 2009, 2011), among others.

As distributed hydrological model calculates the hydrological process at grid scale, so the computation time needed for runing the distributed hydrological model is huge even for a small watershed, which limits the model's application in watershed flood forecating, particularly in large watershed. Model parameter uncertainty related to distributed hydrological model also impacted its application. But with the development of parallel computation algorithm for distributed hydrological model and its deployment on supercomputer (Chen et. al., 2013), the computation burden is not a challenge of distributed hydrological modeling anymore. Also with the development of automatical parameter optimization of distributed hydrological model in flood forecasting (Madsen et. al., 2003, Shafii et. al., 2009, Xu et. al., 2012, Chen et. al., 2016), the model parameters could be optimized, and the model's performance could be improved largely. With these advances, now distributed hydrological model could be used for large watershed flood forecasting.

In this paper, the WRF QPF is coupled with the distributed hydrological model-the Liuxihe model for a large watershed flood forecasting in southern China. The spatial and temporal resolution of WRF QPF is at 20km*20km and 1 hour respectively with three lead times, including 24 hour, 48 hour and 72 hour. The WRF QPF has a similar pattern with that estimated by rain gauges, but overestimates the averaged watershed precipitation, and the longer the WRF QPF lead time, the higher the precipitation overestimation. As WRF QPF has systematic bias compared with rain gauge precipitation, a post-processing method is proposed to post process the WRF QPF products, which improves the flood forecasting capability. The Liuxihe Model is set up with freely downloaded terrain property. The model parameters were previously optimized with rain gauge observed precipitation, and re-optimized with WRF QPF. With model parameter re-optimization, the model's performance improved. Model parameters should be optimized with QPF, not the rain gauge precipitation. Flood forecasting products produced by coupling Liuxihe Model with WRF QPF provides good reference for large watershed flood warning due to the long lead time and rational results.

2 Studied area and data

2.1 Studied area

Liujiang River Basin(LRB) is selected as the studied area, which is the largest first order tributary of the Pearl River with a drainage area of 58270 km^2(Chen et. al., 2016). LRB is in the monsoon area with heavy storms that induces severe flooding in the watershed, and caused huge flood damages in the past centuries. Fig. 1 is a sketch map of LRB.

Fig. 1 is here

2.2 Rain gauge precipitation and river flow discharge

Precipitation of 68 rain gauges within the watershed in 2011, 2012 and 2013 was collected and used in this study to compare with the WRF QPF. Precipitation data is at one hour interval. River discharge near the watershed outlet is collected also for this same period. As this study focuses on watershed flood forecasting, so only the precipitation and river discharge during the flood events are prepared. There is one flood event in each year. The flood events are numbered as flood event 2011, flood event 2012 and flood event 2013 respectively.

3 WRF QPF and post-processing

3.1 WRF model

The WRF model (Skamarock et. al., 2005, 2008) is considered as the next generation's medium term weather forecasting model, and can simulate different weather processes from cloud scale to synoptic scale, especially in horizontal resolution of 1 ~ 10 km. Also, it integrates the advanced numerical methods and data assimilation techniques, a variety of physically process schemes, and multiple nested methods and the capability of being used in different geographical locations. The development of WRF model satisfies the needs of scientific research and practical application, and could be further improved and strengthened. Now WRF model has replaced the previously used MM5 model.

Many studies have been carried out in quantitative precipitation forecasting by using WRF model. For example, Kumar et al. (2008) used WRF model to study a heavy rain in 2005. The result showed that WRF system could reproduce the storm event and its dynamical and thermo-dynamical characteristics. Hong and Lee (2009) set up a triply nested WRF model to simulate the initiation of a thunderstorm, conducted the sensitivity test. Maussion et. al. (2011) compared the capability of WRF model in retrieving monthly precipitation and snowfall at three different spatial resolution including 30, 10 and 2 km. The result showed that WRF model had a good performance in simulating monthly precipitation and snowfall in Tibet. Givati et al. (2012) predicted the hiemal precipitation event of 2008 and 2009 based on WRF model in upstream of the Jordan River, and coupled WRF model with hydrological model-HYMKE to simulate the velocity and discharge of Jordan River. Pennelly et. al. （2014）employed WRF model to predict three precipitation events of Alberta, Canada, and compared the precipitation with 48 hour leading time predicted by WRF model and the precipitation observed by rain gauges. The result showed that Kain-Fritsch scheme overestimated the value of precipitation invariably. Zhang (2004) introduced the WRF version 2 and grapes 3d variation assimilation. The simulation and real-time forecasting results of weather conditions showed that WRF model had a good performance in forecasting all kinds of weather conditions and had the ability to predict the air quality. Niu et. al.（2007）tested the sensitivity of microphysical scheme to a typical heavy rain based on WRF model, and analyzed the performance of precipitation predicted from the precipitation region, center position and rainfall intensity. Xu et. al.（2007）compared the hiemal continuous precipitation process predicted with the estival results by WRF model. The results showed that the KF scheme was better than BM scheme in summer. Hu et. al.（2008）found that the parameterization scheme of WRF model was related to the model resolution, and the parameterization scheme should be selected by the resolution of WRF model. Huang et. al.（2011）found that variations in the microphysical process parameterization schemes had much more influence on precipitation than that of cumulus parameterization schemes, especially for a torrential rain attributed to large-scale forcing that mainly resulted from stratus clouds. Wang and Ma (2011) introduced the application of WRF model from the physics parameterization scheme, real-time simulation study and the comparison with MM5 model in China in recent decade. Pan et. al.（2012）used two WRF simulation groups between pre-process and post-process in Heihe river basin, and compared and analyzed the mean bias error, root mean square error and correlation coefficient of the two WRF groups.

3.2 WRF Q of LRB

The WRF model（version 3）was set up in LRB by Li et. al. (2014). The model domain is centered at 23.8N, 109.2W, and the projection is Lambert conformal projection. The vertical structure includes 28 layers covering the whole troposphere. The WRF single-moment 3-class microphysics parameterization, ~~i.e.,~~ the Kain-Fritsch (Kain, 2004) ~~and~~cumulus parameterization (Hong and Lim, 2006) were adopted for precipitation simulation. The parameterization scheme of WRF is more than that of other mesoscale numerical weather prediction (NWP) which includes 5 kinds of physical parameterization schemes: microphysical process, cumulus, land surface processes, atmospheric radiation and planetary boundary layer. There are 13 microphysical process parameterization schemes. Purdue Lin scheme was used in this study as microphysical process. The parameterization scheme of precipitation was improved based on the scheme of Lin et al. (1983) as well as Rutledge and Hobbs (1983), which is more mature than other schemes and is suited to simulate the high resolution real time data.

The spatial and temporal resolution of WRF is at 20km*20km and 1 hour respectively, so there are 156 WRF grids in LRB. QPF products in 2011, 2012 and 2013 were produced at 3 different lead times, respectively 24 hours, 48 hours and 72 hours. Fig. 2, 3 and 4 are WRF QPF in three different years, while (a) is the rain gauge precipitation, (b) is the WRF QPF with 24 hour lead time, (c) is the WRF QPF with 48 hour lead time, and (d) is the WRF QPF with 72 hour lead time.

Fig. 2 is here

Fig. 3 is here

Fig. 4 is here

3.3 Comparison of WRF QPF and rain gauges precipitation

WRF QPF and rain gauge precipitation are compared in this study. From the results of Fig. 2, 3 and 4, it could be found that the temporal precipitation pattern of both products are similar. There are some kinds of differences, but the difference is not significant. To make further comparison, the accumulated precipitation of the three flood events averaged over the watershed are calculated and listed in Table 1.

Table 1 is here

From the results of Table 1, it could be found that the WRF QPF accumulated precipitation has obvious bias with rain gauge accumulated precipitation. For all the three flood events, the WRF QPF accumulated precipitation are higher than those estimated by rain gauge, i. e., the WRF QPF overestimates the precipitation. For flood event 2011, the overestimated watershed averaged precipitation of WRF QPF with lead time of 24 hour, 48 hour and 72 hour are 23%, 32% and 55% respectively, for flood event 2012, they are 16%, 37% and 71% respectively, for flood event 2013, they are 50%, 73% and 95% respectively. This also means that the longer the WRF QPF lead time, the higher the overestimation.

3.4 WRF QPF post-processing

From the results of Fig. 2, 3 and 4, and Table 1, the WRF QPF has significant bias with rain gauge precipitation. If the rain gauge precipitation is assumed correct, then WRF QPF has error. So in this study the WRF QPF is post-processed based on the rain gauge precipitation to correct the systematic error of WRF QPF. The principle of

WRF QPF post-processing proposed in this study is to keep the areal averaged event accumulated precipitation from both products ~~are~~ similar, i.e., to adjust the WRF QPF precipitation to make its event accumulated precipitation equal to that of rain gauge. Based on this principle, the WRF QPF post-processing procedure is summarized as follows:

1) Calculate the areal average precipitation of the WRF QPF for each flood event over the watershed with the following equation.

$$\bar{P}_{WRF} = \frac{\sum_{i=1}^{N} P_i F_i}{N} \quad (1)$$

Where, $\bar{P}_{WRF}$ is the areal average precipitation of WRF QPF of one flood event, P_i is the precipitation on WRF grid i, F_i is the drainage area of WRF grid i, N is the total number of WRF grids.

2) Calculate the areal average precipitation of the rain gauges with the following equation.

$$\bar{P}_2 = \frac{\sum_{j=1}^{M} P_j}{M} \quad (2)$$

Where, $\bar{P}_2$ is the areal average precipitation of the rain gauges network, P_j is the precipitation observed by jth rain gauge, M is the total number of rain gauges.

3) The precipitation of every WRF QPF grid then could be revised with the

following equation.

$$P_i^{'} = P_i \frac{\overline{P}_2}{\overline{P}_{WRF}} \quad (3)$$

Where, $P_i^{'}$ is the revised precipitation of ith WRF grid.

With the above WRF QPF post-processing method, the WRF QPF of flood event 2011, 2012 and 2013 were post-processed, and will be used to couple with the Liuxihe Model for flood simulation.

3 Hydrological model

3.1 Liuxihe Model

Liuxihe model is a physically based fully distributed hydrological model proposed mainly for watershed flood forecasting (Chen, 2009, Chen et. al., 2011), and has been used in a few watershed flood forecasting(Chen, 2009, Chen et. al., 2011, 2013, 2016, Liao et. al., 2012 a, b, Xu et. al., 2012 a, b). In Liuxihe Model, runoff components are calculated at grid scale, runoff routes at both grid and watershed scale. Runoff routing is divided into hillslope routing and river channel routing by using different computation algorithm. Liuxihe Model proposed an automatic parameter optimization method using PSO algorithm (Chen et. al., 2016), which largely improves the model’s performance in watershed flood forecasting. Now Liuxihe Model is deployed on a supercomputer system with parallel computation techniques (Chen et. al., 2013) that largely facilitates the model parameter optimization of Liuxihe Model.

Chen et. al. (2016) set up Liuxihe Model in LRB with freely downloaded terrain property data from the website at a spatial resolution of 200m*200m, and optimized model parameters with observed hydrological data. The model was validated by observed flood events data, and the model performance ound rational and could be used for real-time flood forecasting. The model only uses rain gauge precipitation, so its flood forecasting lead time is limited. In this study, the Liuxihe Model t up in LRB and the optimized model parameters wil e used in this study as the first attemp ig. 5 e model structure.

Fig.5 is here

3.2 Liuxihe Model parameter optimization

the model parameters opti ed by Chen et. al. (2016) is done by using the rain gauge precipitation, ~~but~~ this study uses the WRF QPF as the precipitation inpu the parameters of Liuxihe Model t up in LRB may not propriate for coupling the WRF QPF. For this reason, considering Liuxihe Model is a physically based distributed hydrological model, ~~one flood event could be used for parameter optimization,~~ the parameters were optimized again by using the WRF QPF in 2011 e WRF QPF is the post-processed one, not the original one. Results of parameter optimization are shown in Fig. 6 mong them, (a) is the objective function evolution result, (b) is the parameters evolution result, and (c) is the simulated flood process by using the optimized model parameters. To compare, the simulated flood process of flood event 2011 was also drawn in Fig. 6(c).

Fig. 6 is here

From the result of Fig. 6(c), it coul e found that the optimized model parameters with WRF QPF improved ~~uch than that simulated wit~~ n gauge precipitation is means parameter optimization with WRF QPF is necessary.

3.3 Coupling WRF QPF with Liuxihe Model for LRB flood forecasting

T Liuxihe Model set up for LRB flood forecasting (Chen et. al., 2016) mployed to couple with the WRF QPF, the model spatial resolution re s to be 200m*200m. As the spatial resolution of WRF QPF is at 20km*20km, the WRF QPF was downscaled to the resolution of 200m*200m by using the nearest downscaling method, the same spatial resolution of the flood forecasting model.

4 Results and discussions

4.1 Effects of WRF post-processing

The original WRF QPF and the post-processed QPF a used to couple with the Liuxihe Mode t simulation, the original model parameters that ptimized with the rain gauge precipitation employed, not the re-optimized model parameters e simulated results are shown in Fig. 7, 8 and 9.

Fig. 7 is here

Fig. 8 is here

Fig. 9 is here

From the above results, it could be seen that the simulated flood discharges with the original WRF QPF nuch lower than the observed one ut with post-processed WRF QPF used, the simulated flood discharge increased an uch more close to the observatio is implies that the flood forecasting capability has been improved by post-processing of WRF QPF. To further compare the three results, 5 evaluation indices, including Nash-Sutcliffe coefficient(C), correlation coefficient(R), process relative error(P), peak flow relative error(E) and water balance coefficient(W) a calculated and listed in Table 2.

Table 2 is here

From the results of Table 2, it has been found that all the 5 evaluation indices have been improved by coupling the post-processed WRF QPF. For example, lood event 2011 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with original WRF QPF are 0.65, 0.88, 35%, 14% and 1.44 respectively, but those with the post-processed WRF QPF are 0.75, 0.93, 23%, 8% and 1.15 respectively. T flood event 2012 with 48 hour lead time, the above 5 evaluation indices with original WRF QPF are 0.63, 0.75, 48%, 12% and 1.43 respectively, and are 0.75, 0.84, 26%, 8% and 1.32 respectively with the post-processed WRF QPF. lood event 2013 with 72 hour lead time, the above 5 evaluation indices with original WRF QPF are 0.44, 0.75, 129%, 45% and 1.66 respectively, and are 0.55, 0.82, 98%, 23%, 1.25 respectively with the post-processed WRF QPF. It is obvious that with the post-processed WRF QPF, the evaluation indices are improved much re. These results show that WRF QPF post processing could improve the flood forecasting capability because the WRF PF is more close to the observed precipitation after post-processing it should be d for real-time flood forecasting.

4.2 Results comparison for different model parameters

The model parameters optimized with rain gauge precipitation and WRF QPF are different. different parameter will have different model performance. To analyze this effect, the flood events of 2012 and 2013 with two different sets of model parameters are simulated, and are shown in Fig. 10 and Fig. 11 respectively. Only the post-processed WRF QPF are coupled in this simulation.

Fig. 10 is here

Fig. 11 is here

From the above ~~results it has been found~~ that the simulated flood results with re-optimized model parameters are better than those simulated with the original model parameters. The simulated flood discharge with the re-optimized model parameters ~~more fitting the observation~~. To further compare the two results, 5 evaluation indices, including Nash-Sutcliffe coefficient(C), correlation coefficient(R), process relative error(P), peak flow relative error(E) and water balance coefficient(W) are calculated and listed in Table 3.

Table 3 is here

From the results of Table 3, it has been found that the results of flood simulation based on the re-optimized model parameters have better evaluation indices. All evaluation indices for the based on re-optimized model parameters are improved. For example, for flood event 2012 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with original model parameters are 0.58, 0.82, 35%, 12% and 1.08 respectively, but those with the re-optimized model parameters are 0.74, 0.86, 28%, 8% and 0.95 respectively. For flood event 2013 with 48 hour lead time, the 5 indices with the original model parameters are 0.62, 0.86, 22%, 13% and 1.24 respectively, and are 0.68, 0.89, 18%, 9% and 1.06 respectively for those with re-optimized model parameters. So it could be said that in coupling the WRF QPF with distributed hydrological model, the model parameters ne[illegible] to be re-optimized with the WRF QPF. This finding implies that the precipitation pattern has obvious impact [illegible]model parameters,[illegible] should be considered, and model parameter optimization is a rational way for considering this effect.

4.3 Flood simulation accuracy with different lead time

To compare the model performance with different lead time, the flood events with 3 different lead tim[illegible] simulated and shown in Fig. 12[illegible]e model parameters are the re-optimized ones, and the QPF is the post-processed QPF.

Fig. 12 is here

From the results of Fig. 12, it could be seen that the flood simulation resul[illegible]ts worse as the lead time increases, i.e., the model performance with 24 hour lead time is better than that with 48 hour lead time, and the model performance with 48 hour lead time is better than that with 72 hour lead time. The simulated hydrological process with 24 hour lead time is very similar w[illegible]that simulated with rain gauge precipitation. To further compare the results, 5 evaluation indices, including Nash-Sutcliffe coefficient(C), correlation coefficient(R), process relative error(P), peak flow relative error(E) and water balance coefficient(W) are calculated and listed in Table 4.

Table 4 is here

From the results of Table 4, it has been found that the simulated flood events with 24 hour lead time has best evaluation indices, and is very close to those simulated with rain gauge precipitation. For flood event 2012, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with rain gauge are 0.82, 0.89, 20%, 5% and 0.8 respectively, those with 24 hour lead time are 0.74, 0.86, 28%, 8% and 0.95 respectively, those with 48 hour lead time are 0.63, 0.84, 48%, 12% and 1.32 respectively, and are 0.56, 0.56, 56%, 18% and 1.54 respectively for 72 hour lead time. For flood event 2013, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with rain gauge are 0.95, 0.92, 8%, 6% and 1.08 respectively, those with 24 hour lead time are 0.87, 0.87, 9%, 12% and 1.02 respectively, those with 48 hour lead time are 0.62, 0.86, 22%, 13% and 1.24 respectively, and are 0.61, 0.87, 75%, 17% and 1.66 respectively for 72 hour lead time. This finding means that the current WRF QPF capability is lead-time dependent, and with the increasing ~~of~~ lead time, the practical value of WRF QPF gets lower.

5 Conclusion

In this study, the WRF QPF coupled with a distributed hydrological model-the Liuxihe model for large watershed flood forecasting, and three lead times of WRF QPF products, including 24 hours, 48 hours and 72 hours are tested. WRF QPF post processing method is proposed and tested, model parameters are re-optimized by using the post-processed WRF QPF, model performance are compared among various conditions. Based on the results of this study, the following conclusions could be drawn:

1) The quantitative precipitation forecasting produced by WRF model has a similar pattern with that estimated by rain gauges temporally, but overestimated the averaged watershed precipitation (the event accumulated total precipitation), and the longer the WRF QPF lead time, the higher the precipitation overestimation. For flood event 2011, the overestimated watershed averaged precipitation of WRF QPF with lead time of 24 hour, 48 hour and 72 hour are 23%, 32% and 55% respectively. For flood event 2012, these are 16%, 37% and 71% respectively, while for flood event 2013, these are 50%, 73% and 95% respectively.

2. WRF QPF has systematic bias compared with rain gauge precipitation, and this bias could be reduced via post-processing. Principle used in this study for WRF QPF post processing is effective and could improve the flood forecasting capability. For flood event 2011 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with original WRF QPF are 0.65, 0.88, 35%, 14% and 1.44 respectively, but those with the post-processed WRF QPF are 0.75, 0.93, 23%, 8% and 1.15 respectively. For flood event 2012 with 48 hour lead time, the above 5 evaluation indices with original WRF QPF are 0.63, 0.75, 48%, 12% and 1.43 respectively, and are 0.75, 0.84, 26%, 8% and 1.32 respectively with the

post-processed WRF QPF. For flood event 2013 with 72 hour lead time, the above 5 evaluation indices with original WRF QPF are 0.44, 0.75, 129%, 45% and 1.66 respectively, and are 0.55, 0.82, 98%, 23%, 1.25 respectively with the post-processed WRF QPF.

3. Hydrological model parameters optimized with the rain gauge precipitation n[illegible]s to be re-optimized using the post-processed WRF QPF, this improves the model performance largely[illegible]., in coupling [illegible]stributed hydrological model with QPF for flood forecasting, the model parameters should be optimized with the QPF produced by WRF. For flood event 2012 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with original model parameters are 0.58, 0.82, 35%, 12% and 1.08 respectively, but those with the re-optimized model parameters are 0.74, 0.86, 28%, 8% and 0.95 respectively. For flood event 2013 with 48 hour lead time, the 5 indices with the original model parameters are 0.62, 0.86, 22%, 13% and 1.24 respectively, and are 0.68, 0.89, 18%, 9% and 1.06 respectively for those with re-optimized model parameters.

4. The simulated floods by coupling WRF QPF with distributed hydrological model [illegible] rational and could benefit the flood management communities due to [illegible]onger lead t[illegible] for flood warnin[illegible] provides a good reference for large watershed flood warning. But with the lead time getting longer, the flood forecasting accuracy is getting lower. For flood event 2012, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with rain gauge are 0.82, 0.89, 20%, 5% and 0.8 respectively, [illegible]se with 24 hour lead

time are 0.74, 0.86, 28%, 8% and 0.95 respectively, those with 48 hour lead time are 0.63, 0.84, 48%, 12% and 1.32 respectively, and are 0.56, 0.56, 56%, 18% and 1.54 respectively for 72 hour lead time. For flood event 2013, the Nash-Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow relative error/E and coefficient of water balance/W with rain gauge are 0.95, 0.92, 8%, 6% and 1.08 respectively, those with 24 hour lead time are 0.87, 0.87, 9%, 12% and 1.02 respectively, those with 48 hour lead time are 0.62, 0.86, 22%, 13% and 1.24 respectively, and are 0.61, 0.87, 75%, 17% and 1.66 respectively for 72 hour lead time.

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Figures

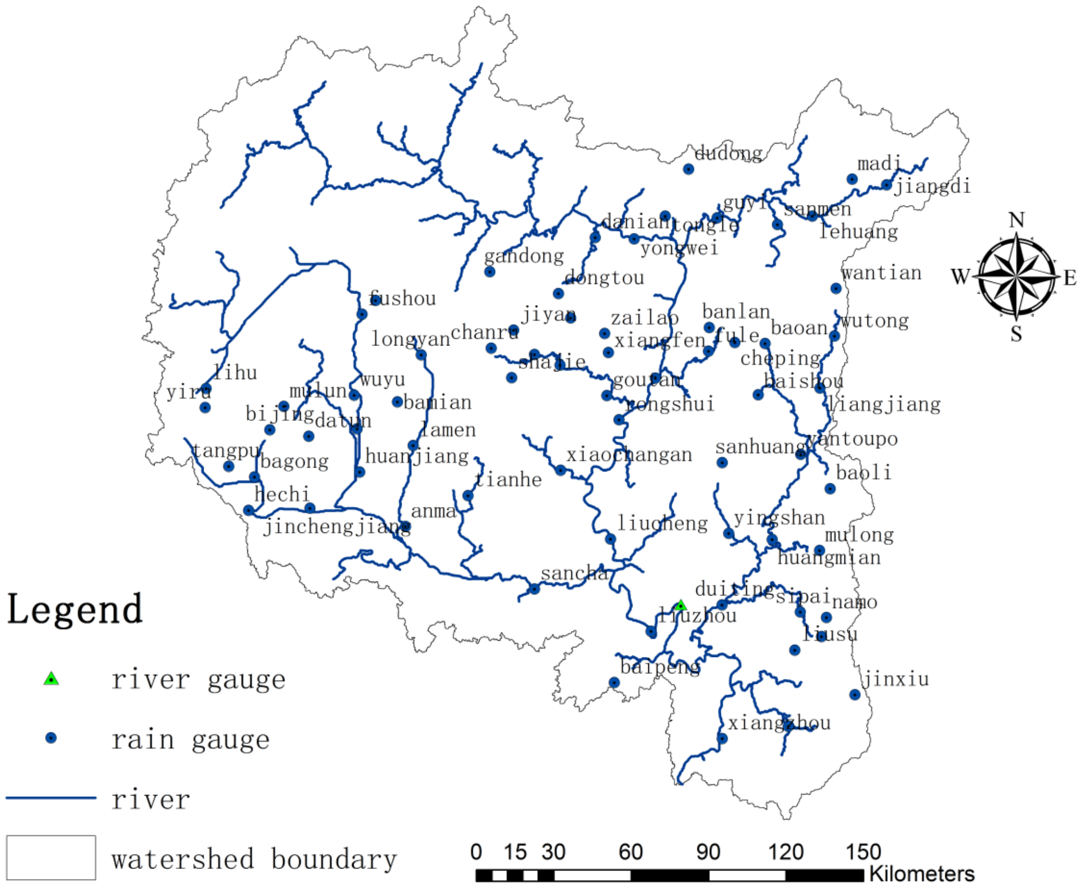
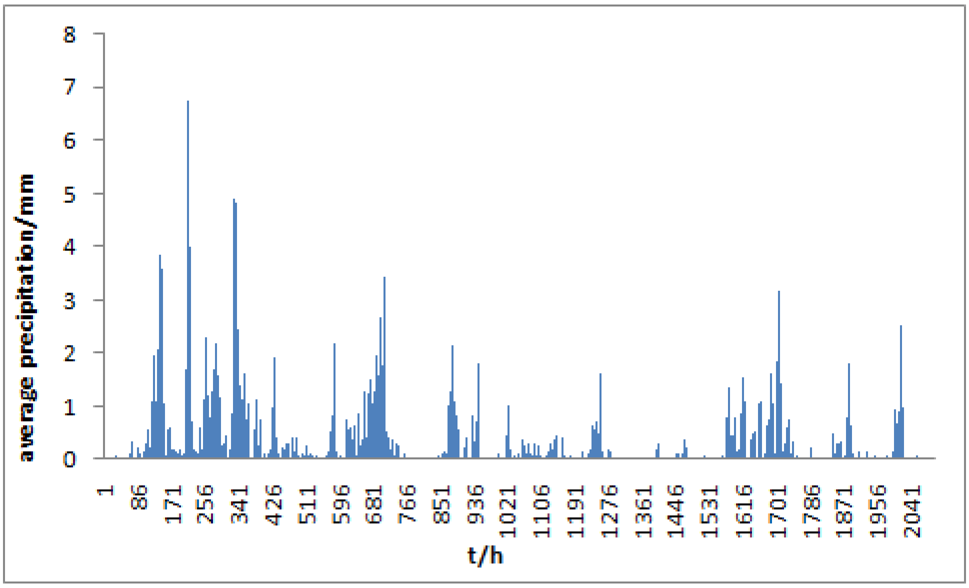


Fig. 1 Sketch map of Liujiang River Basin(Chen et. al., 2016)


average precipitation/mm
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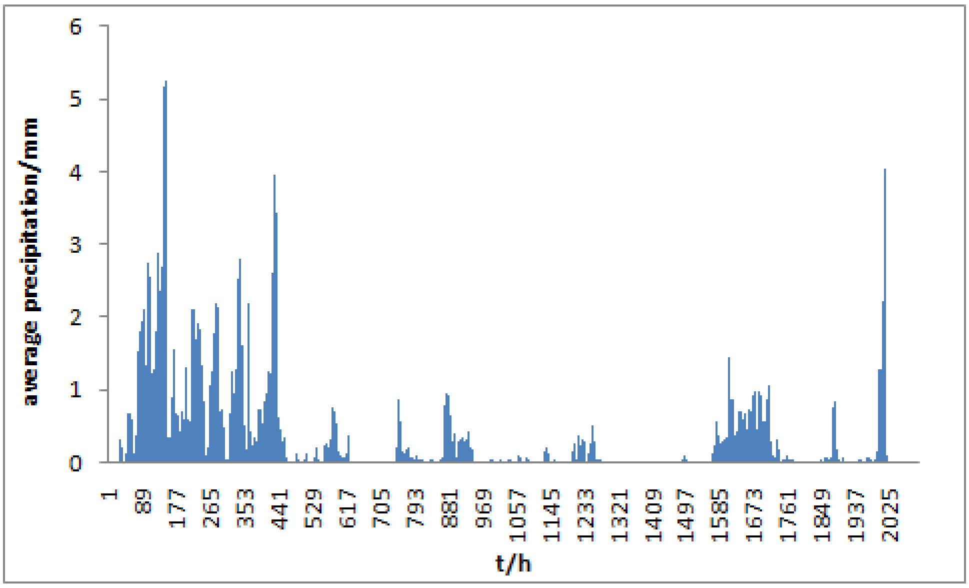
(a)


average precipitation/mm
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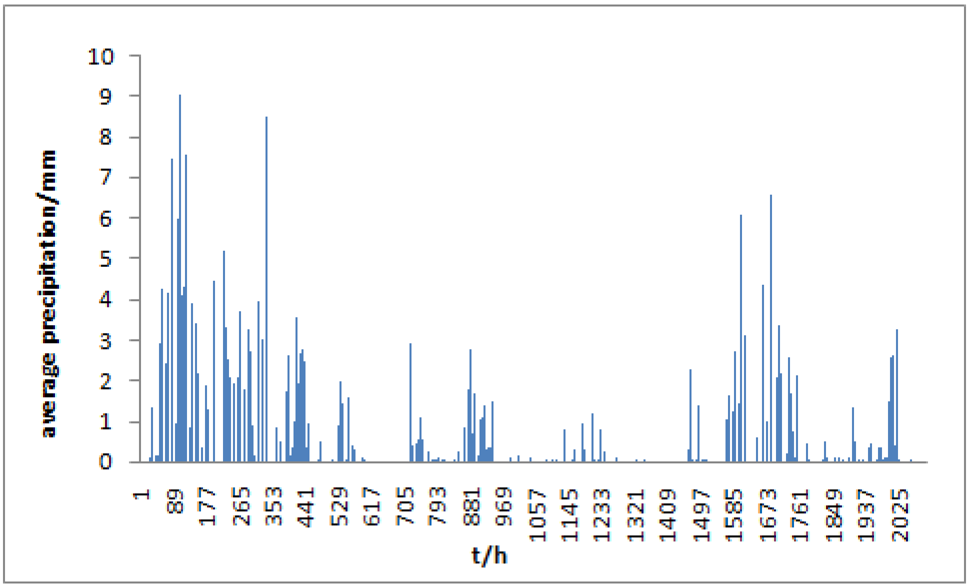
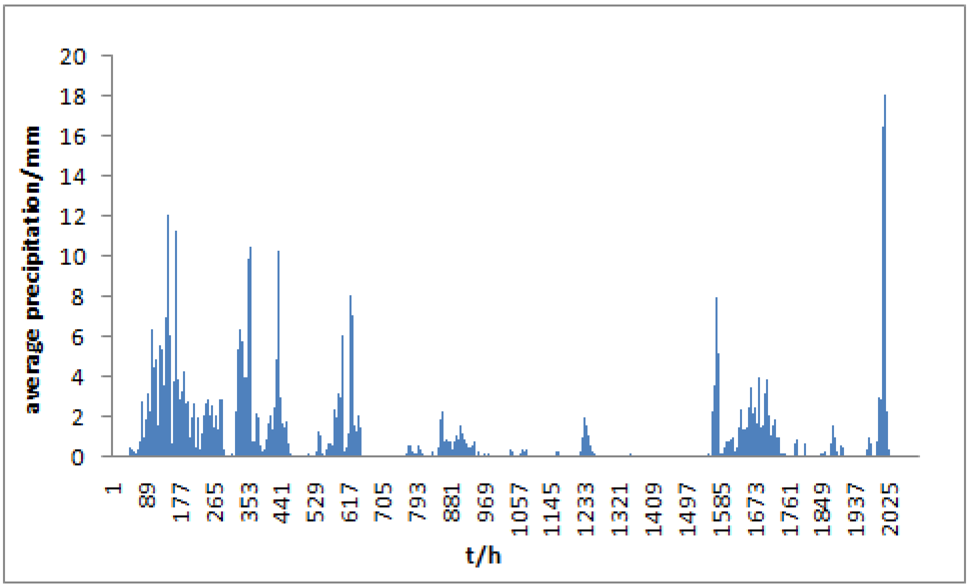
6
1 89 177 265 353 441 529 617 705 793 881 969 1057 1145 1233 1321 1409 1497 1585 1673 1761 1849 1937 2025
t/h

(b)

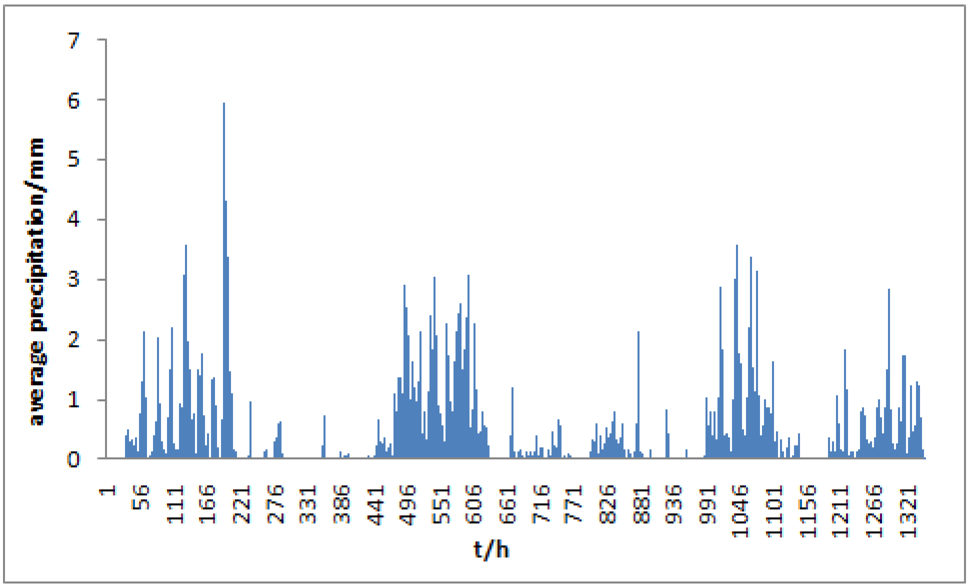


(c)

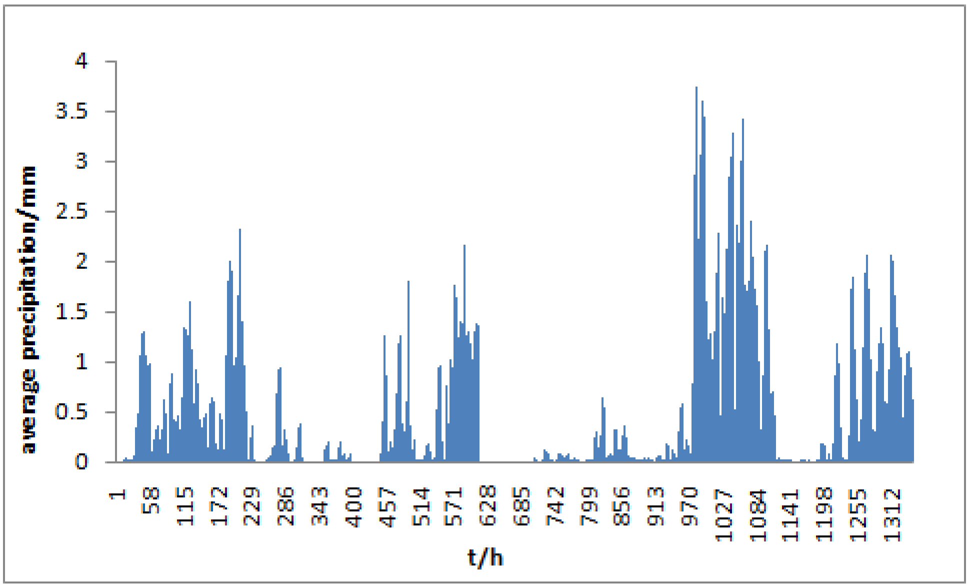


(d)

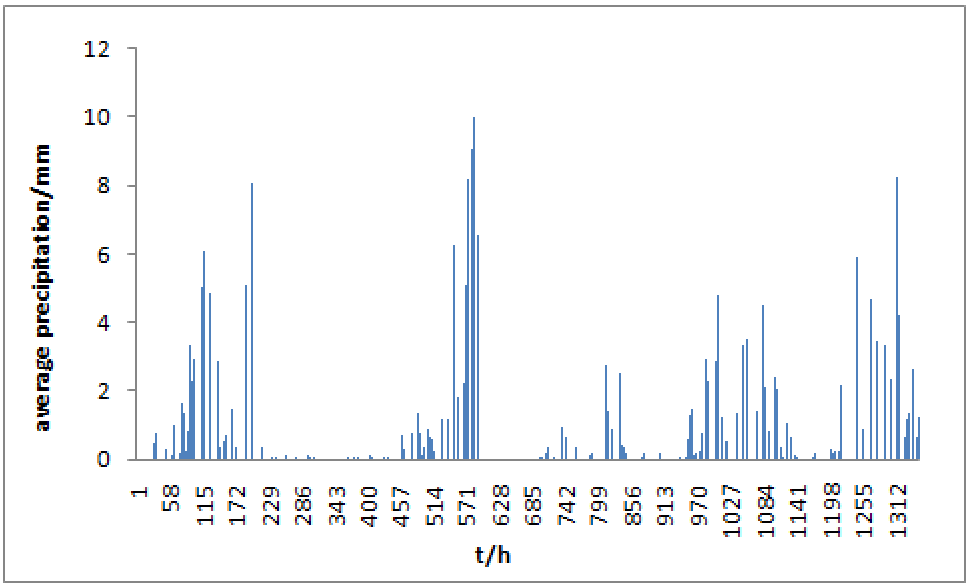
Fig. 2 Precipitation pattern comparison of two precipitation products(2011), (a) is the average precipitation of rain gauges, (b) is the average precipitation of WRF with 24 hour lead time, (c) is the average precipitation of WRF with 48 hour lead time, (d) is the average precipitation of WRF with 72 hour lead time.


average precipitation/mm
t/h
0
1
2
3
4
5
6
7
1
56
111
166
221
276
331
386
441
496
551
606
661
716
771
826
881
936
991
1046
1101
1156
1211
1266
1321

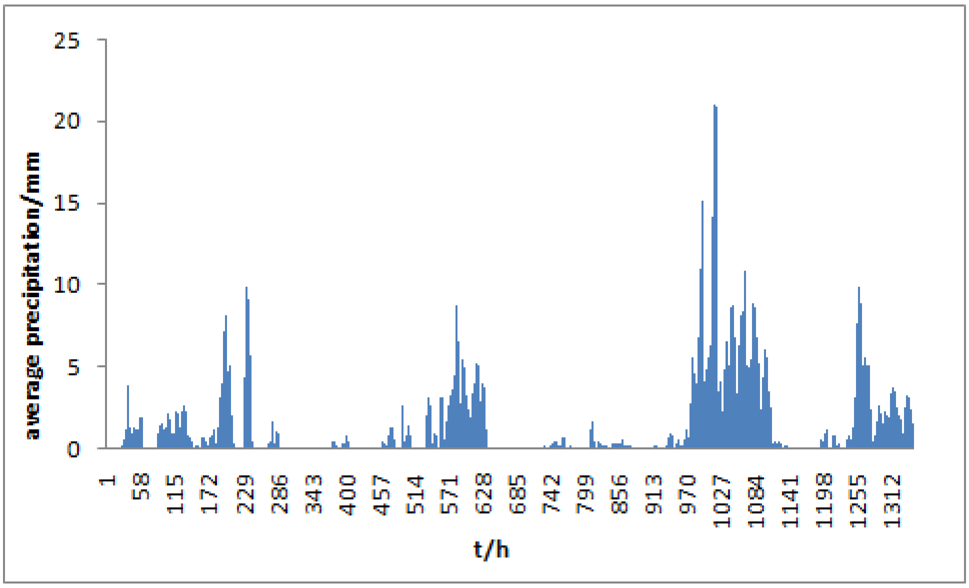
(a)


average precipitation/mm
t/h
0
0.5
1
1.5
2
2.5
3
3.5
4
1
58
115
172
229
286
343
400
457
514
571
628
685
742
799
856
913
970
1027
1084
1141
1198
1255
1312

(b)

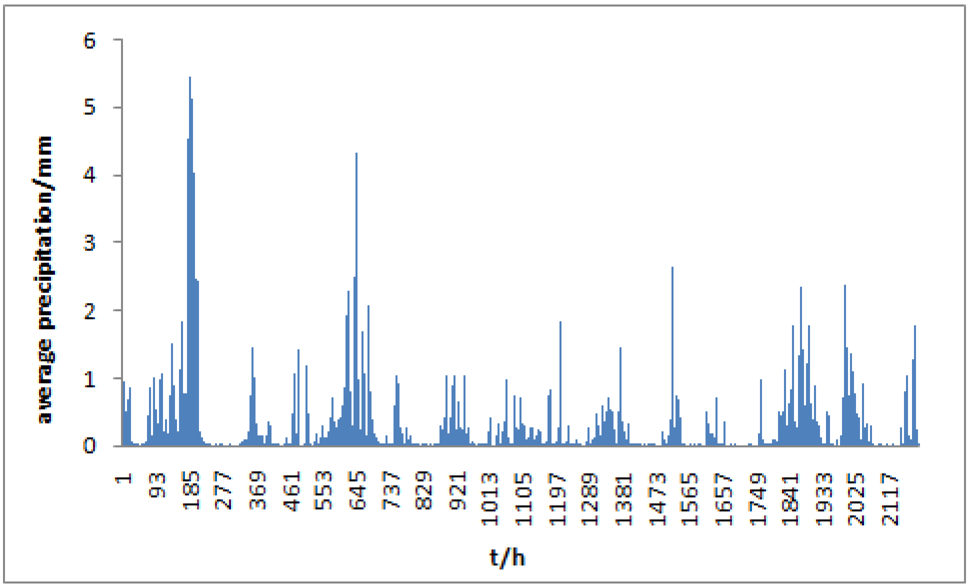


(c)

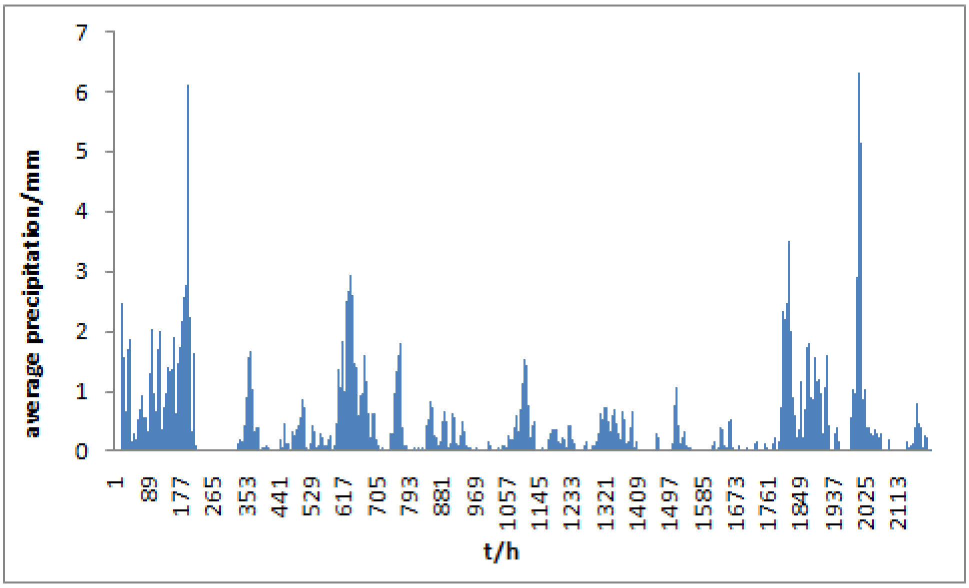


(d)

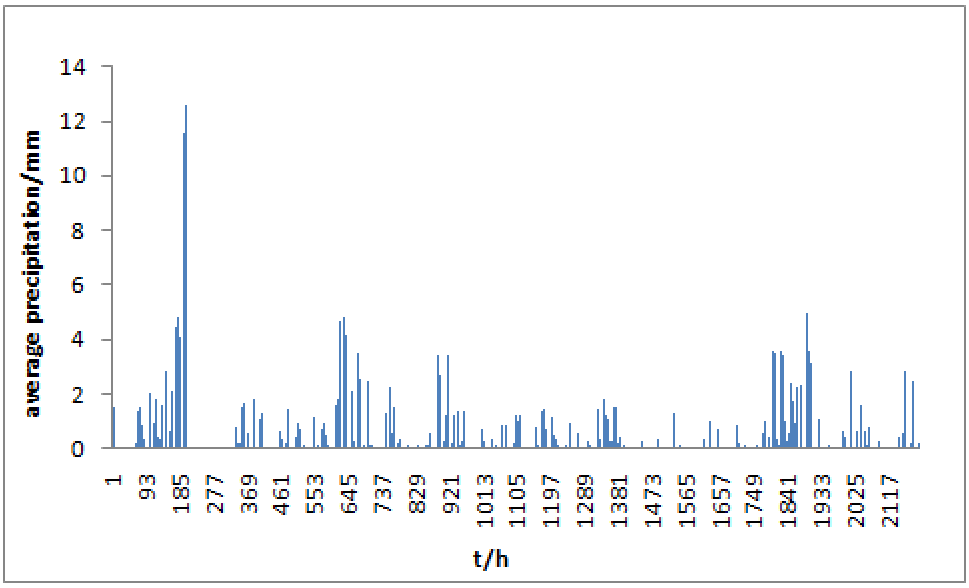
Fig. 3 Precipitation pattern comparison of two precipitation products(2012) , (a) is the average precipitation of rain gauges, (b) is the average precipitation of WRF with 24 hour lead time, (c) is the average precipitation of WRF with 48 hour lead time, (d) is the average precipitation of WRF with 72 hour lead time.


average precipitation/mm
0
1
2
3
4
5
6
1
93
185
277
369
461
553
645
737
829
921
1013
1105
1197
1289
1381
1473
1565
1657
1749
1841
1933
2025
2117
t/h

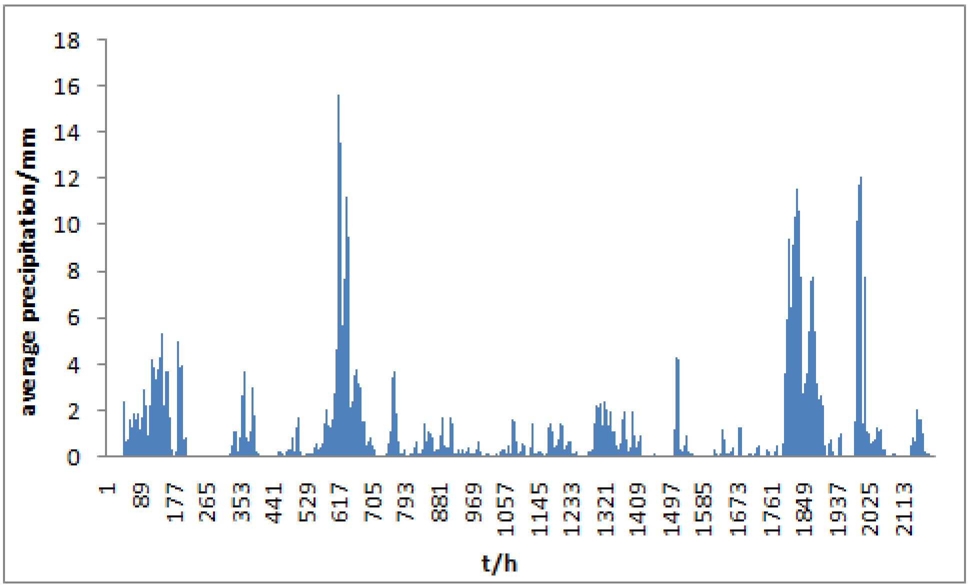
(a)


average precipitation/mm
0
1
2
3
4
5
6
7
1
89
177
265
353
441
529
617
705
793
881
969
1057
1145
1233
1321
1409
1497
1585
1673
1761
1849
1937
2025
2113
t/h

(b)



(c)



(d)

Fig. 4 Precipitation pattern comparison of two precipitation products(2013), (a) is the average precipitation of rain gauges, (b) is the average precipitation of WRF with 24 hour lead time, (c) is the average precipitation of WRF with 48 hour lead time, (d) is the average precipitation of WRF with 72 hour lead time.

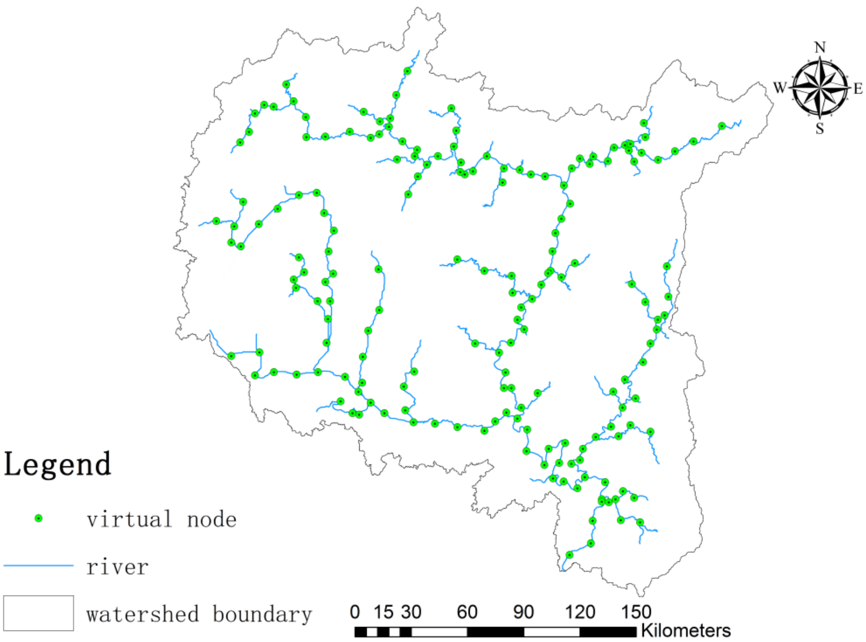
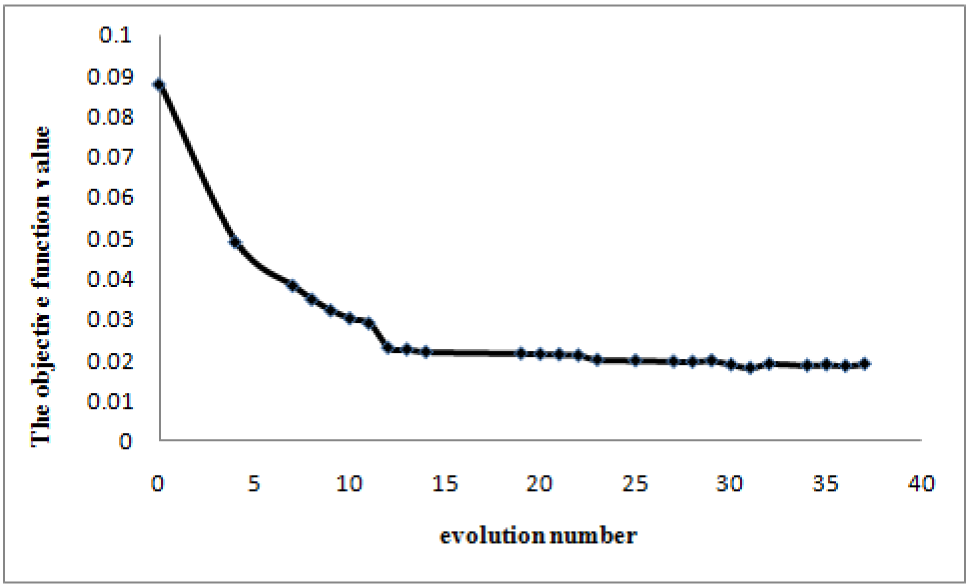
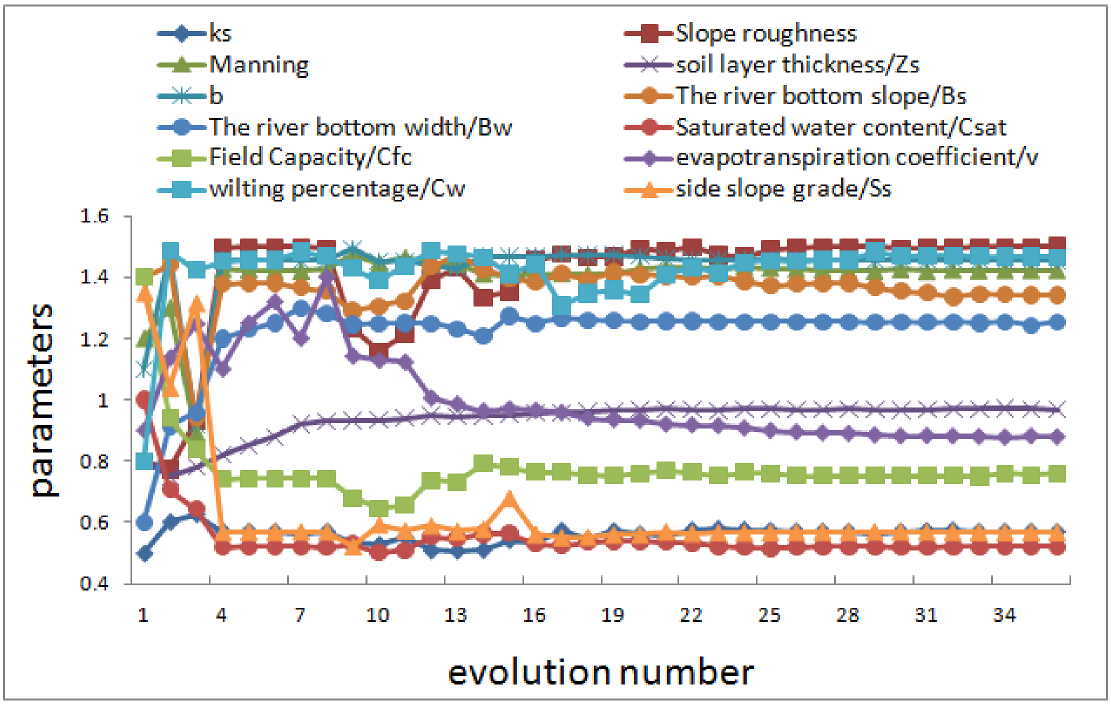


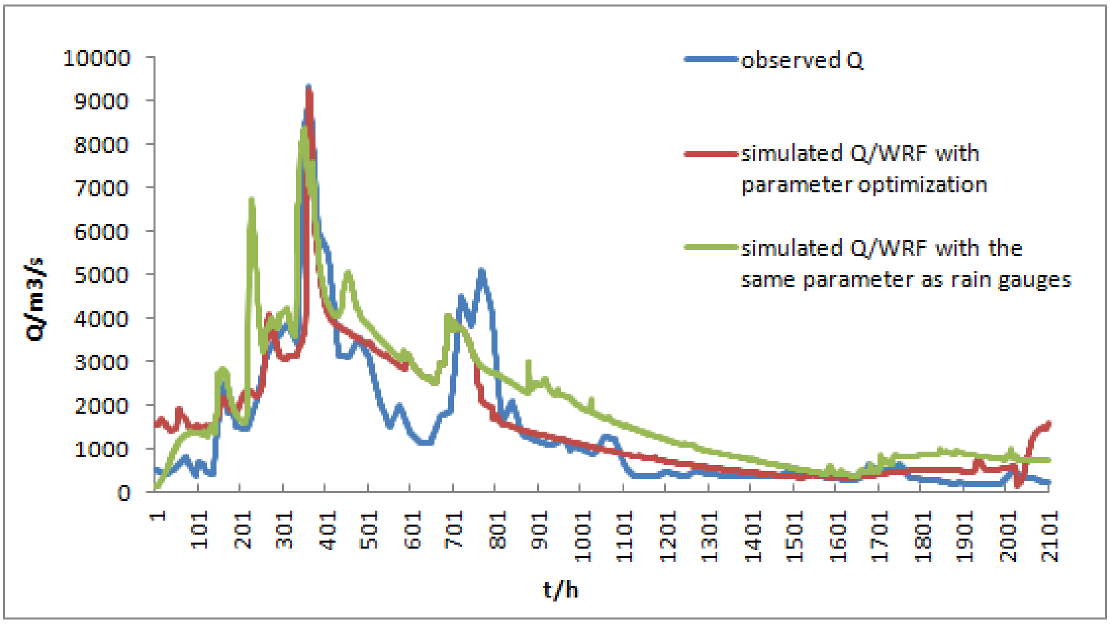
Fig.5 Liuxihe Model structure of LRB (200m×200m resolution, Chen et. al., 2016)



(a) Evolutionary process of objective function

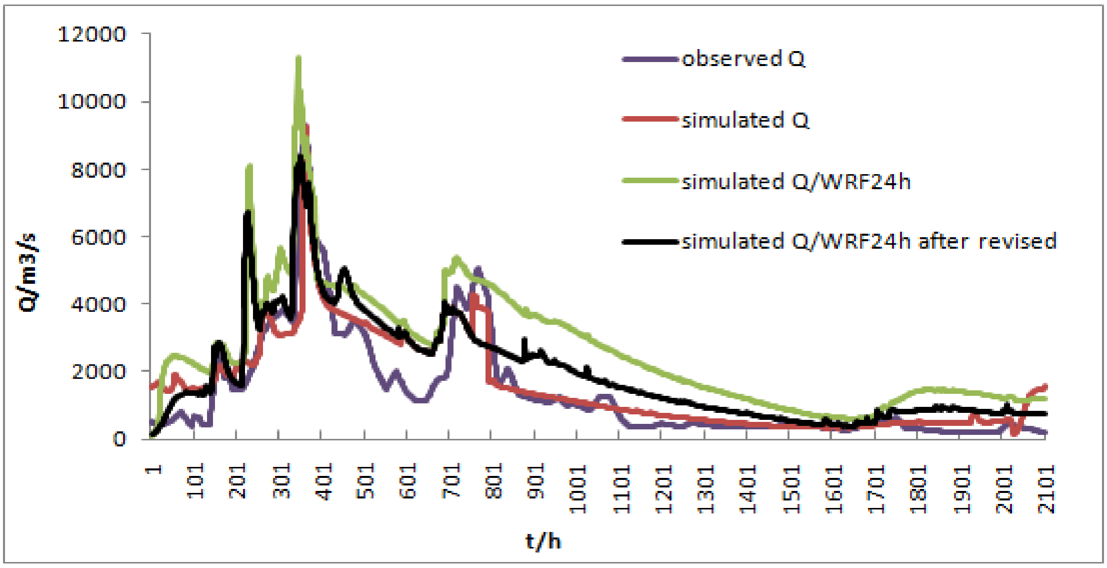


(b) Parameter evolution process

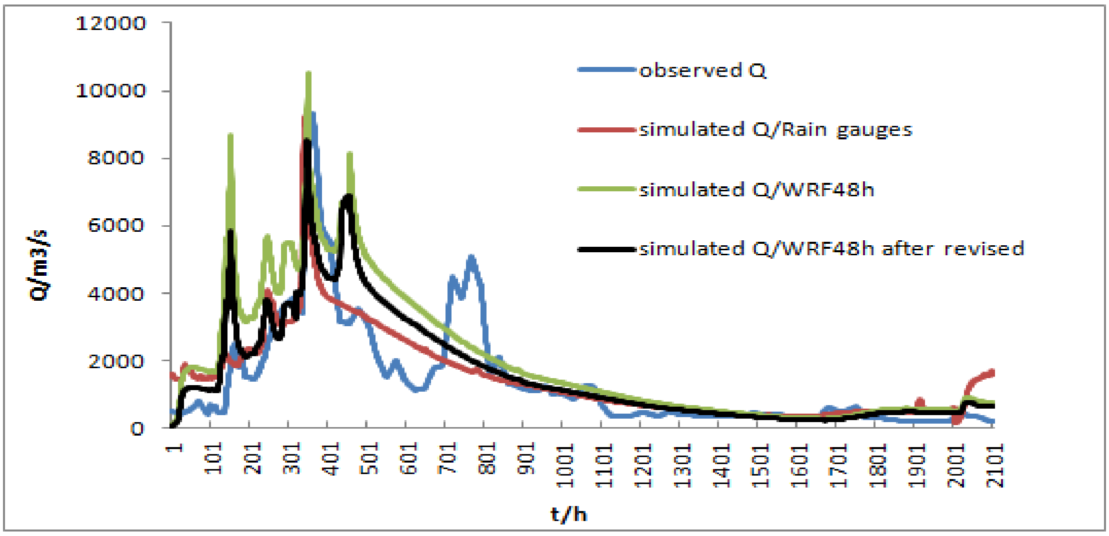


(c) Simulated flood process with optimized model parameters

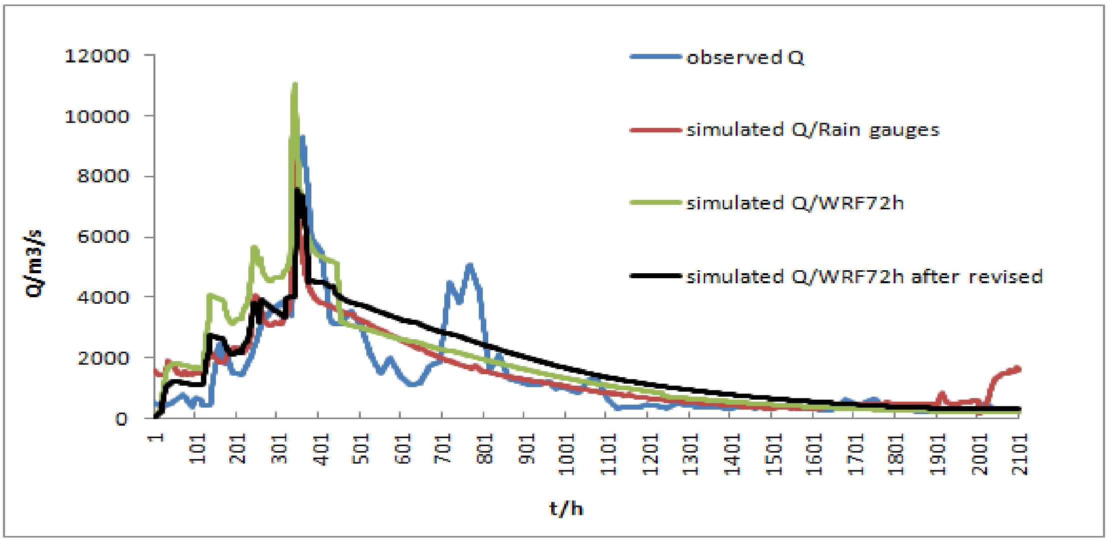
Fig. 6 Parameter optimization results of Liuxihe Model for LRB with WRF QPF



(a) 24 hour lead time

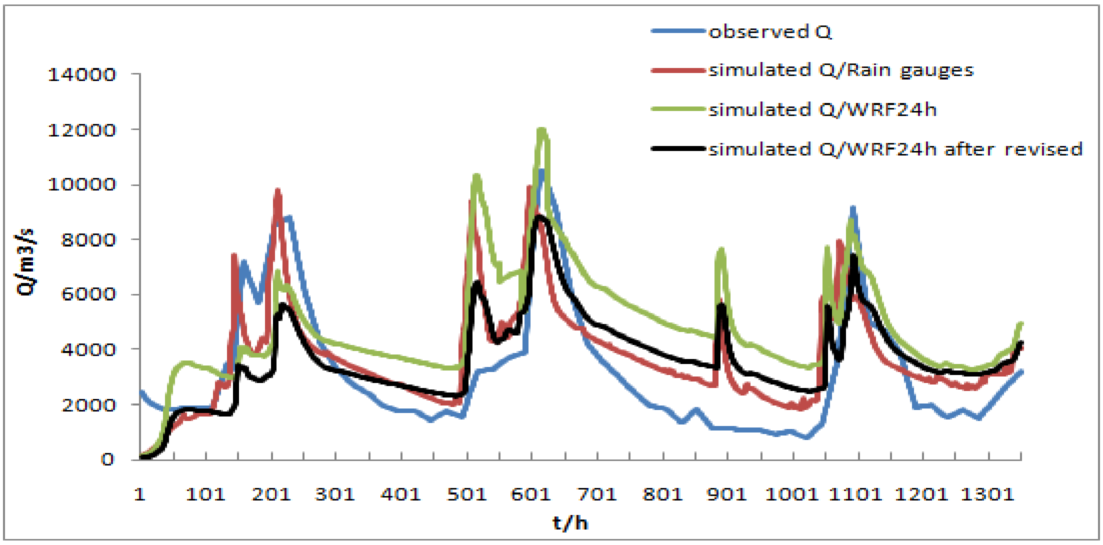


(b) 48 hour lead time

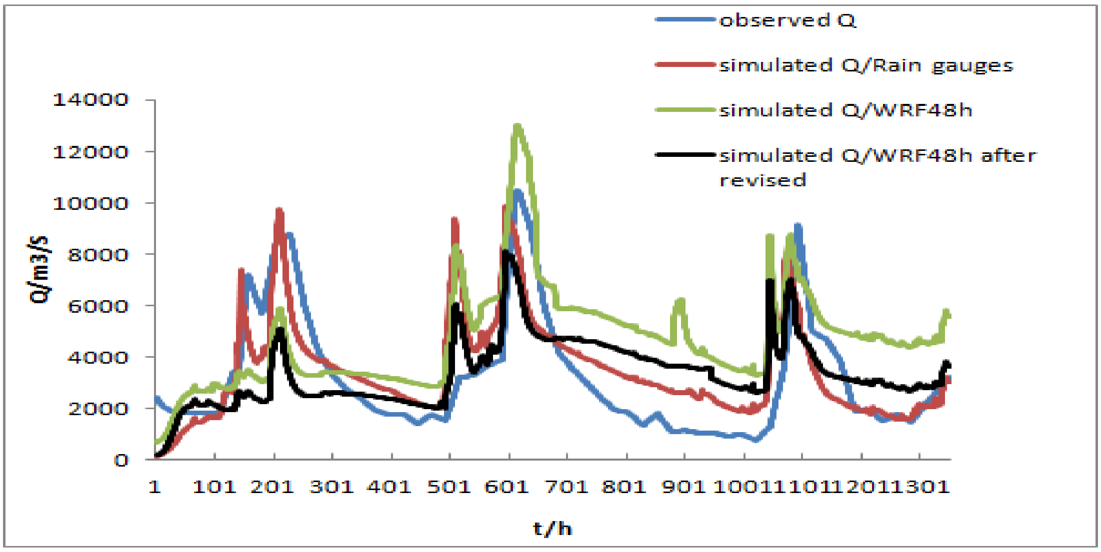


(c) 72 hour lead time

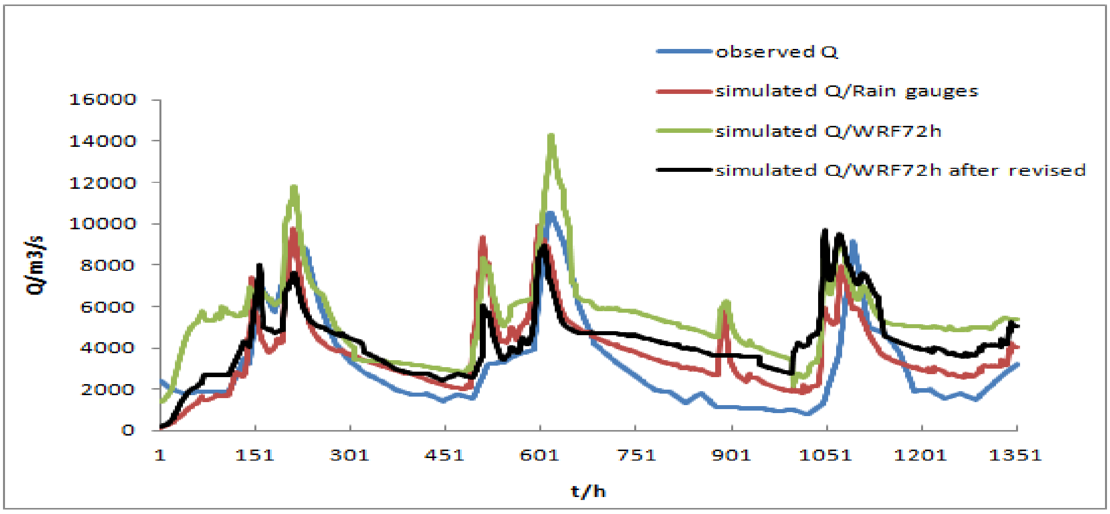
Fig. 7 Coupled flood simulation results with original model parameters (2011)



(a) 24 hour lead time

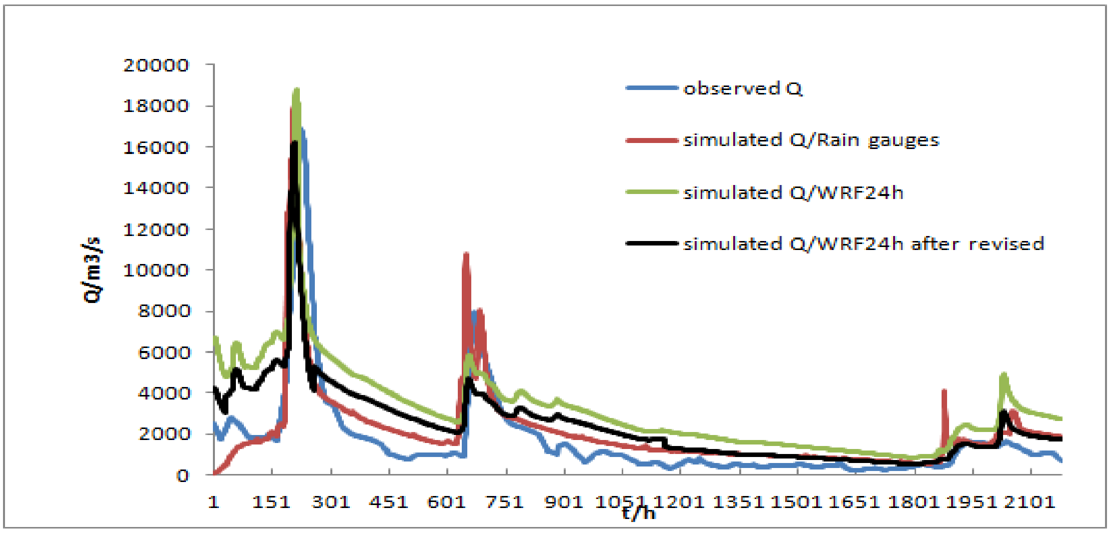


(b) 48 hour lead time

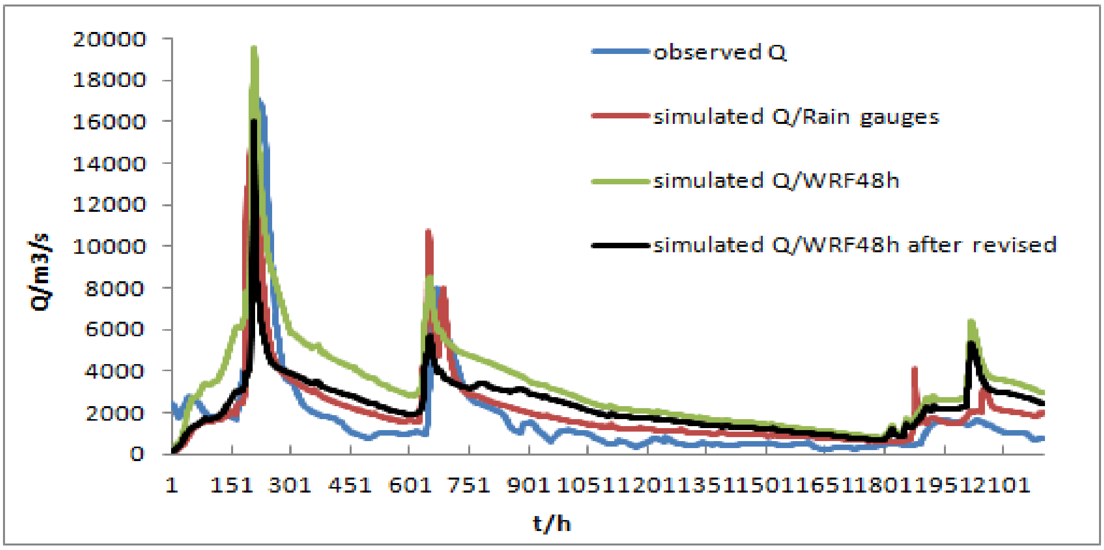


(c) 72 hour lead time

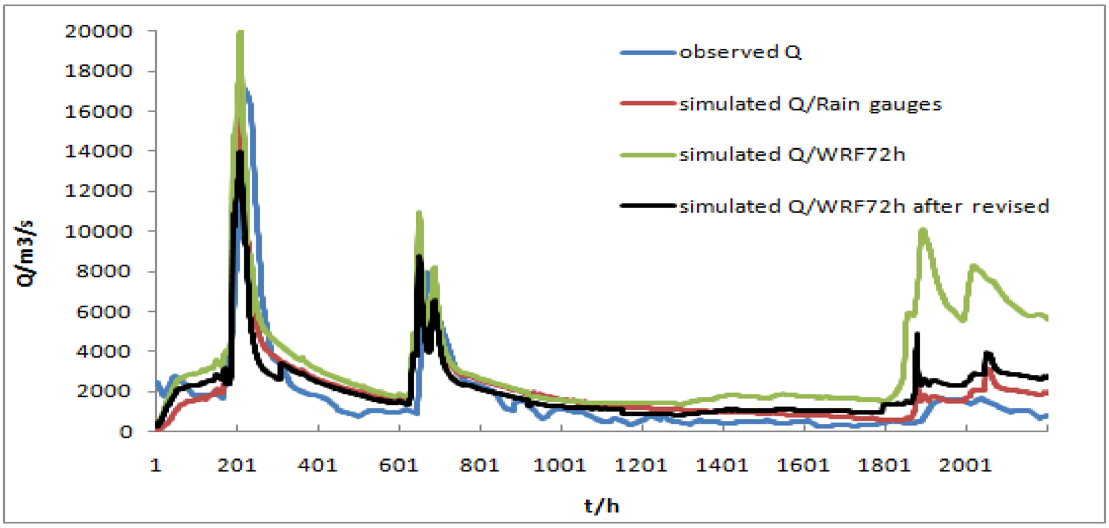
Fig. 8 Coupled flood simulation results with original model parameters(2012)



(a) 24 hour lead time

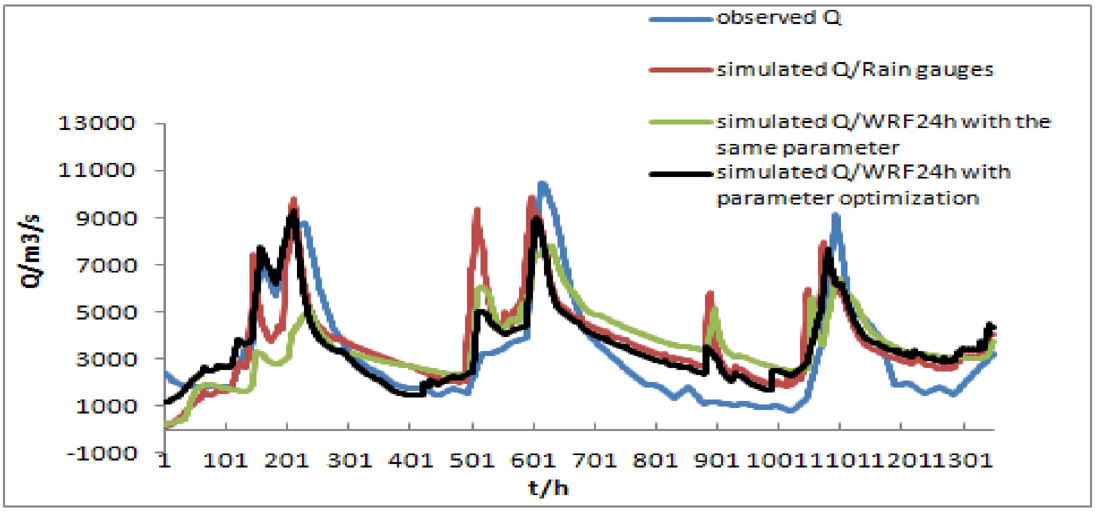


(b) 48 hour lead time

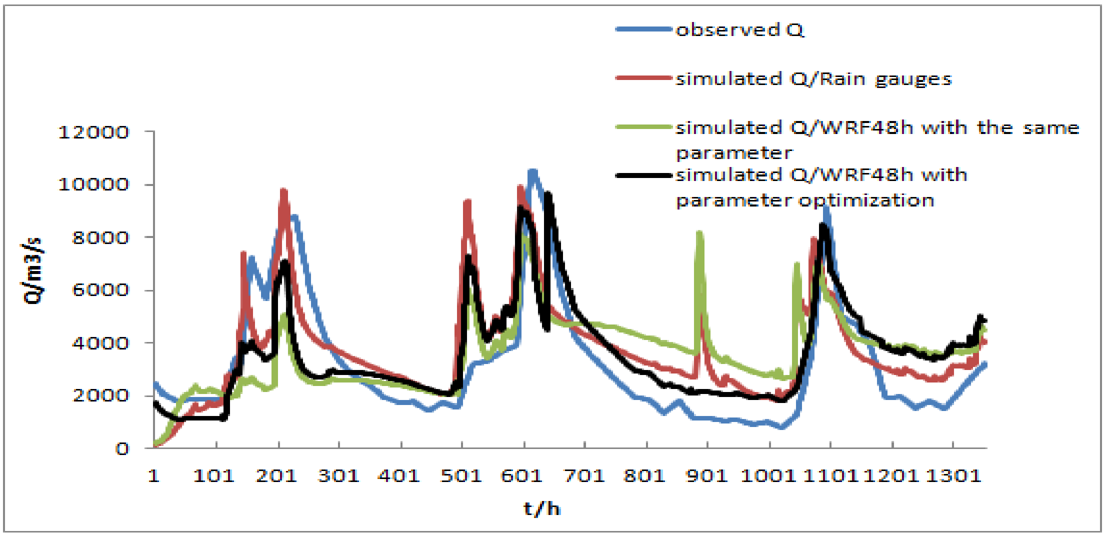


(c) 72 hour lead time

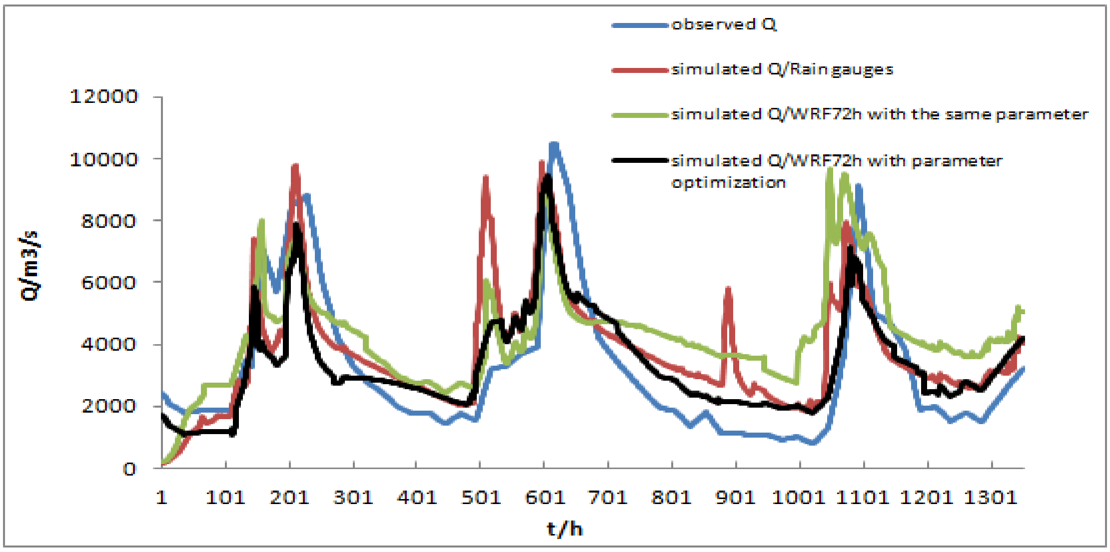
Fig. 9 Coupled flood simulation results with original model parameters (2013)



(a) 24 hour lead time

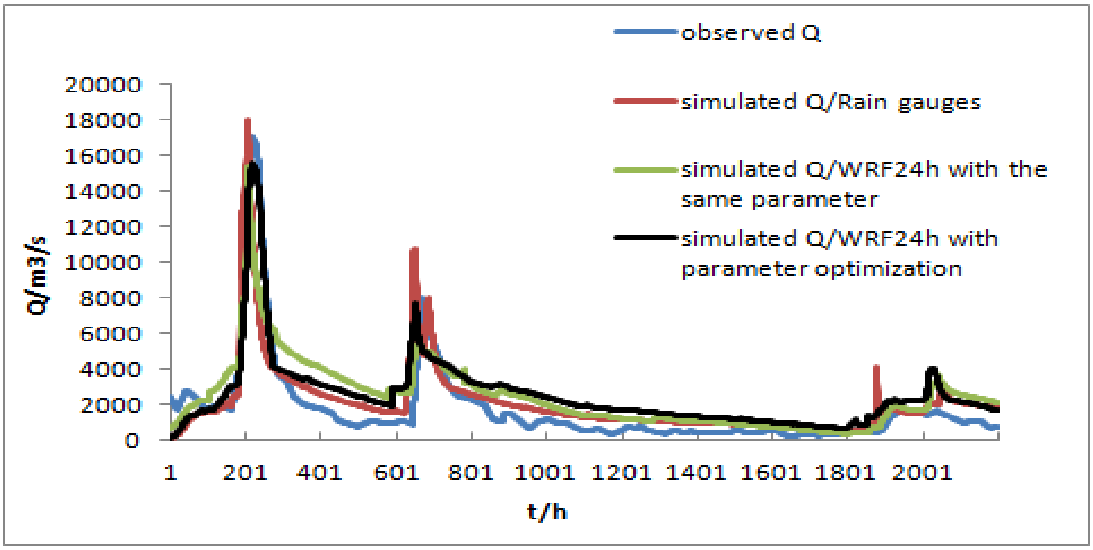


(b) 48 hour lead time

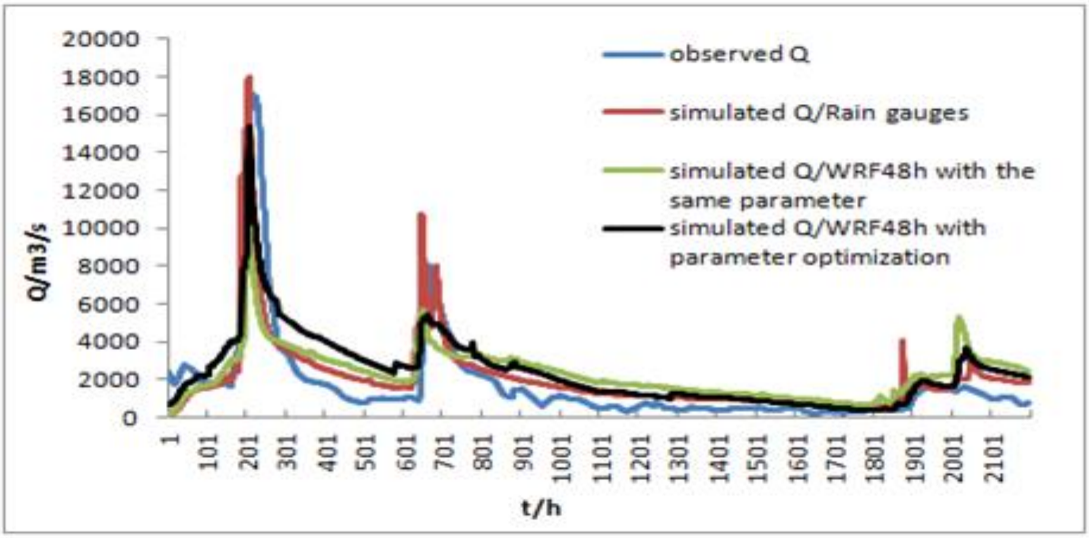


(c) 72 hour lead time

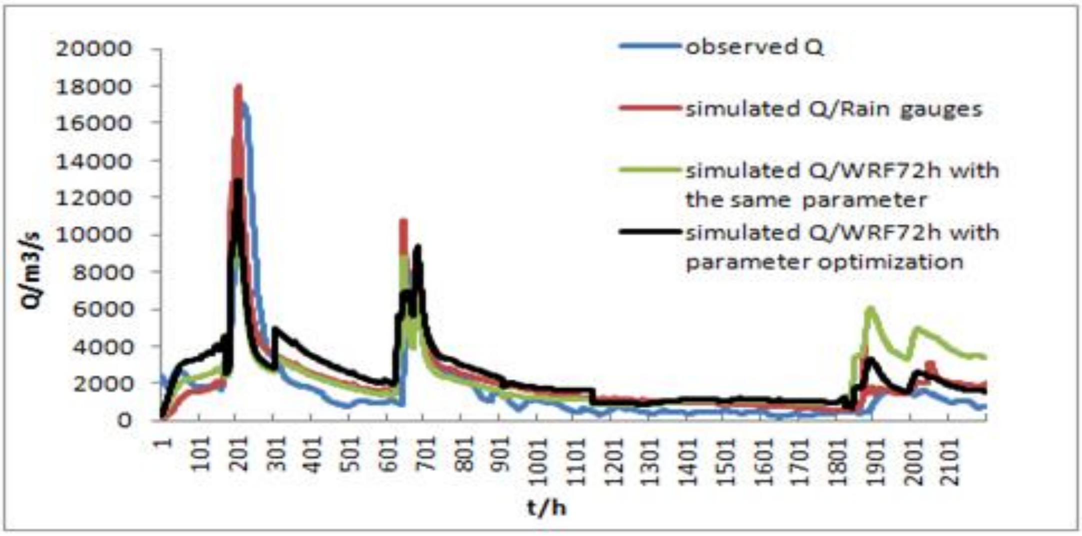
Fig. 10 Coupled flood simulation results with re-optimized model parameters (2012)



(a) 24 hour lead time

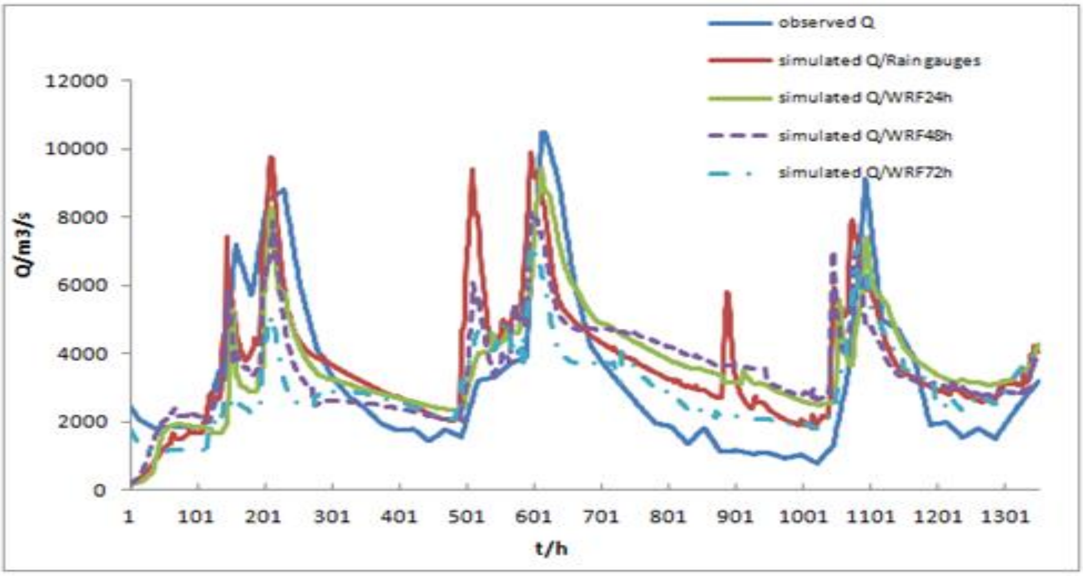


(b) 48 hour lead time

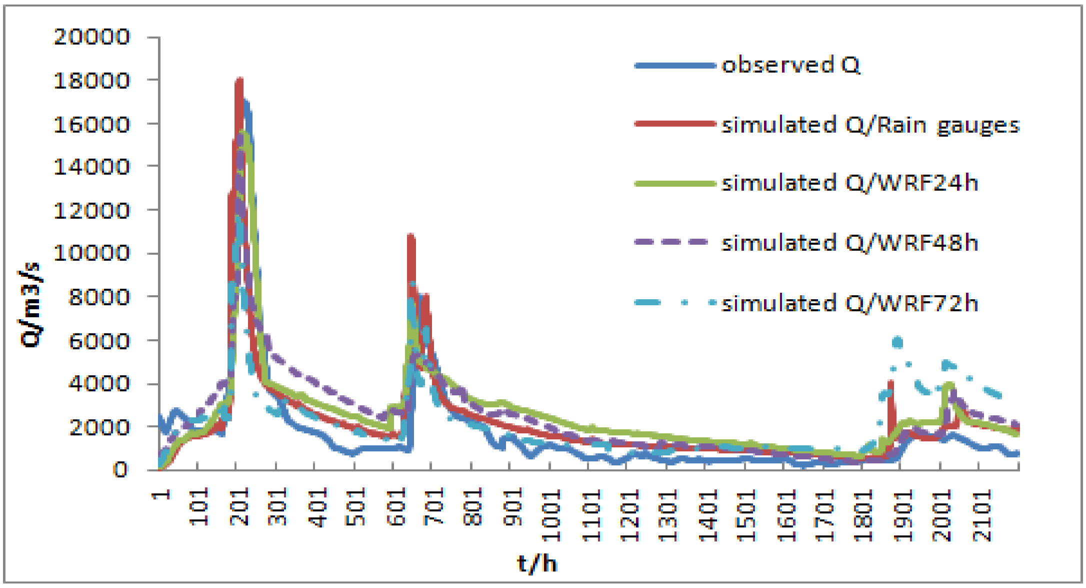


(c) 72 hour lead time

Fig. 11 Coupled flood simulation results with re-optimized model parameters (2013)



(a) Flood event 2012



(b) Flood event 2013

Fig. 12 Simulated results with different lead time

Tables

Table 1 Precipitation comparison of two products

Flood event no.	Precipitation products	average precipitation(mm)	relative bias %
2011	rain gauges	0.22	
	WRF/24h	0.27	23
	WRF/48h	0.29	32
	WRF/72h	0.34	55
2012	rain gauges	0.38	
	WRF/24h	0.44	16
	WRF/48h	0.52	37
	WRF/72h	0.65	71
2013	rain gauges	0.22	
	WRF/24h	0.33	50
	WRF/48h	0.38	73
	WRF/72h	0.43	95

Table 2 Evaluation indices of simulated flood events with post-processed WRF QPF

Rain type	statistical index	201101010	20120101	20130101
WRF/24h	Nash-Sutcliffe coefficient/C	0.65	0.48	0.65
	Correlation coefficient/R	0.88	0.73	0.83
	Process relative error/P	0.35	0.57	0.19
	Peak flow relative error/E	0.14	0.18	0.25
	The coefficient of water balance/W	1.44	1.35	1.38

WRF/24h after revised	Nash-Sutcliffe coefficient/C	0.75	0.58	0.75
	Correlation coefficient/R	0.93	0.82	0.85
	Process relative error/P	0.23	0.35	0.11
	Peak flow relative error/E	0.08	0.12	0.16
	The coefficient of water balance/W	1.15	1.08	1.12
WRF/48h	Nash-Sutcliffe coefficient/C	0.58	0.63	0.5
	Correlation coefficient/R	0.78	0.75	0.8
	Process relative error/P	0.52	0.48	0.34
	Peak flow relative error/E	0.41	0.12	0.24
	The coefficient of water balance/W	1.52	1.43	1.51
WRF/48h after revised	Nash-Sutcliffe coefficient/C	0.64	0.75	0.62
	Correlation coefficient/R	0.82	0.84	0.86
	Process relative error/P	0.45	0.26	0.22
	Peak flow relative error/E	0.34	0.08	0.13
	The coefficient of water balance/W	1.22	1.32	1.24
WRF/72h	Nash-Sutcliffe coefficient/C	0.45	0.66	0.44
	Correlation coefficient/R	0.68	0.36	0.75
	Process relative error/P	0.64	0.62	1.29

	Peak flow relative error/E	0.31	0.35	0.45
	The coefficient of water balance/W	1.67	1.54	1.66
WRF/72h after revised	Nash-Sutcliffe coefficient/C	0.52	0.75	0.55
	Correlation coefficient/R	0.75	0.45	0.82
	Process relative error/P	0.53	0.52	0.98
	Peak flow relative error/E	0.11	0.22	0.23
	The coefficient of water balance/W	1.15	1.14	1.25

Table 3 Evaluation indices of simulated flood event with different model parameters

parameter type	statistical index	201101010	20120101	20130101
Coupling model 24h/originally optimized model parameters	Nash-Sutcliffe coefficient/C	0.75	0.58	0.75
	Correlation coefficient/R	0.93	0.82	0.85
	Process relative error/P	0.23	0.35	0.11
	Peak flow relative error/E	0.08	0.12	0.16
	The coefficient of water balance/W	1.15	1.08	1.12
Coupling model24h /re-optimized model parameters	Nash-Sutcliffe coefficient/C	0.78	0.74	0.87
	Correlation coefficient/R	0.95	0.86	0.87
	Process relative error/P	0.19	0.28	0.09
	Peak flow relative error/E	0.06	0.08	0.12
	The coefficient of water balance/W	1.03	0.95	1.02

Coupling model 48h/originally optimized model parameters	Nash-Sutcliffe coefficient/C	0.64	0.75	0.62
	Correlation coefficient/R	0.82	0.84	0.86
	Process relative error/P	0.45	0.26	0.22
	Peak flow relative error/E	0.34	0.08	0.13
	The coefficient of water balance/W	1.22	1.32	1.24
Coupling model 48h /re-optimized model parameters	Nash-Sutcliffe coefficient/C	0.72	0.75	0.68
	Correlation coefficient/R	0.86	0.87	0.89
	Process relative error/P	0.32	0.22	0.18
	Peak flow relative error/E	0.21	0.06	0.09
	The coefficient of water balance/W	1.05	1.12	1.06
Coupling model 72h/originally optimized model parameters	Nash-Sutcliffe coefficient/C	0.52	0.75	0.55
	Correlation coefficient/R	0.75	0.45	0.82
	Process relative error/P	0.53	0.52	0.98
	Peak flow relative error/E	0.11	0.22	0.23
	The coefficient of water balance/W	1.15	1.14	1.25
Coupling model 72h /re-optimized model parameters	Nash-Sutcliffe coefficient/C	0.62	0.72	0.61
	Correlation coefficient/R	0.78	0.56	0.87
	Process relative error/P	0.38	0.32	0.75
	Peak flow relative error/E	0.09	0.18	0.17
	The coefficient of water balance/W	1.08	1.02	1.05

Table 4 Evaluation indices of simulated flood event with different lead time

Rain type	statistical index	20120101	20130101
Rain gages	Nash-Sutcliffe coefficient/C	0.82	0.95
	Correlation coefficient/R	0.89	0.92
	Process relative error/P	0.2	0.08
	Peak flow relative error/E	0.05	0.06
	The coefficient of water balance/W	0.8	1.08
WRF/24h	Nash-Sutcliffe coefficient/C	0.74	0.87
	Correlation coefficient/R	0.86	0.87
	Process relative error/P	0.28	0.09

	Peak flow relative error/E	0.08	0.12
	The coefficient of water balance/W	0.95	1.02
WRF/48h	Nash-Sutcliffe coefficient/C	0.63	0.62
	Correlation coefficient/R	0.84	0.86
	Process relative error/P	0.48	0.22
	Peak flow relative error/E	0.12	0.13
	The coefficient of water balance/W	1.32	1.24
WRF/72h	Nash-Sutcliffe coefficient/C	0.56	0.61
	Correlation coefficient/R	0.56	0.87
	Process relative error/P	0.56	0.75
	Peak flow relative error/E	0.18	0.17
	The coefficient of water balance/W	1.54	1.66

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