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, with the grid resolution being 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. This 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 are useful as they 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 models 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 extended. This provides a new 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 on a hydrological 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 uses is averaged over the watershed also. This 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. This 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. Hence a 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. This 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 great 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 a 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 precipitation 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. Since 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 provide good reference for large watershed flood warning due to their long lead time and rational results.

2 Study area and data

2.1 Study 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., 2017). LRB is in the monsoon area with heavy storms that induced 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 are 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 QPFs and their post-processing

3.1 WRF model

All simulations for this study were conducted with the Advanced Research WRF (WRF-ARW) model version 3.4 (Skamarock et al. 2008). WRF-ARW model is 3-D, non-hydrostatic, fully compressible, and has the terrain-following sigma coordinate system. The model is considered as the next generation's medium range weather forecasting model, and can simulate different weather processes from cloud scale to synoptic scale, especially in horizontal resolution of 1 ~ 10 km. The model also 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. WRF-ARW model satisfies the needs of scientific research and practical applications for this study.

Prior studies have been shown in quantitative precipitation forecasting by using WRF-ARW model. For instance, Pennelly et al. (2014) employed the WRF model to predict three precipitation events of Alberta, Canada, and compared the precipitation with 48 hour leading time predicted by the model with rain gauges. The results showed that Kain-Fritsch cumulus parameterization overestimated the value of precipitation invariably. Eiserloh and Chiao (2015) used WRF-ARW with data assimilation to investigate an Atmospheric River event over Northern California. 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 domains over Tibet. Their results showed that the model was able to recapture monthly precipitation and snowfall. 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. 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. Kumar et al. (2008) used WRF model to study a heavy rain in 2005, their results showed that WRF model could reproduce the storm event and its dynamical and thermo-dynamical characteristics. Hong and Lee (2009) conducted a triply nested WRF simulation for convective initiation of a thunderstorm. 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. Sensitivity experiment of WRF microphysical schemes by Niu et al. (2007) have shown the adequate performance of precipitation predicted associated with region, center location 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.

3.2 Configuration of WRF for LRB B

The WRF-ARW was applied to LRB following the configurations by Li et al. (2015). More information about LBR can be found in Li et al. (2015) and Chen et al. (2017). The model domain is centered at 23.8N, 109.2W with the Lambert conformal projection. The vertical structure includes 28 levels with the focus on the lower-levels of troposphere. The initial and time-dependent lateral boundary conditions are supplied from NCEP Global Forecast System (GFS) 3-hourly global analysis at 0.5 $^{\circ}$horizontal resolution. The model domain has a 20 km grid resolution. The single-moment 3-class microphysics (WSM3) parameterization (Hong and Lim, 2006) is adopted for this study. Kain-Fritsch cumulus parameterization (Kain, 2004) as well as the YSU boundary layer microphysics scheme (Hong et al., 2006) are used. Other physics schemes used include the NOAH scheme for the land surface physics (Ek et al., 2003), the Goddard scheme for the shortwave radiation physics (based on Chou and Suarez,1994), and Rapid Radiative Transfer Model (RRTM) scheme for the longwave radiation physics (Mlawer et al., 1997).

The spatial and temporal resolution of WRF is at 20km x 20km and 1 hour, respectively. The entire Liujiang River Basin is covered by total 156 grid points of the WRF model. The simulated QPF for flood events in years 2011 to 2013 were produced with three different lead time (i.e., 24 hours, 48 hours and 72 hours), respectively. As shown in Figs. 2-4, the WRF QPF products in 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 Evaluation of WRF QPF and rain gauges precipitation

Comparisons of WRF QPF and rain gauge precipitation are performed. From the simulated results, as shown in Figs. 2, 3 and 4, it appears that the temporal precipitation pattern of both products is similar, although there are some insignificant differences. 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

As summarized in 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 measured by rain gauges. In other words, 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 the flood event in 2012, they are 16%, 37% and 71% respectively. They are 50%, 73% and 95% respectively from the event in 2013. The results suggest that longer the WRF QPF lead time, the higher chance of overestimation.

3.4 WRF QPF statistical calibrations

From the simulated results (c.f., Fig. 2, 3 and 4, and Table 1), the WRF QPF has significant bias compared to rain gauge precipitation. Assuming the rain gauge precipitation is correct, the WRF QPF needs to be further calibrated. In order to do so, the WRF QPF is further post-processed based on the rain gauge precipitation to correct the systematic error of WRF QPF. The principle of WRF QPF statistical calibrations proposed in this study is to keep the areal averaged event accumulated precipitation from both model and rain gauge products to be equivalent. In other words, the statistical approach is to nudge the WRF QPF precipitation to rain gauge results.

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 events over the watershed as 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 surface area of WRF grid i divided by the whole watershed drainage area, 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 grids 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 statistical calibration methods, the WRF QPF of flood event 2011, 2012 and 2013 are post-processed, and will be used to couple with the Liuxihe Model for flood simulations.

4 Hydrological model

4.1 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 watersheds for 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 hill slope 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. (2017) 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 was found 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 was set up in LRB and the optimized model parameters were be used in this study as the first attempt. Fig. 5 shows the model structure.

Fig.5 is here

4.2 Liuxihe Model parameter optimization

While the model parameters optimization by Chen et al. (2017) is done by using the rain gauge precipitation, this study uses the WRF QPF as the precipitation input. So the parameters of Liuxihe Model that were set up in LRB may not be appropriate for coupling the WRF QPF. For this reason, considering Liuxihe Model is a physically based distributed hydrological model, the parameters were optimized again by using the WRF QPF flood event in 2011. Hence, the WRF QPF is the post-processed one, not the original one. Results of parameter optimization are shown in Fig. 6. Among 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 may be seen that the optimized model parameters with WRF QPF improved the flood simulation when compared to the corresponding flood simulation based on gauge precipitation. This means parameter optimization with

WRF QPF is necessary.

4.3 Coupling WRF QPF with Liuxihe Model for LRB flood forecasting

When the Liuxihe Model set up for LRB flood forecasting (Chen et al., 2017) was employed to couple with the WRF QPF, the model spatial resolution remained 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.

5 Results and discussions

5.1 Effects of WRF post-processing

The original WRF QPF and the post-processed QPF were used to couple with the Liuxihe Model. In this simulation, the original model parameters that were optimized with the rain gauge precipitation were employed, not the re-optimized model parameters. The 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 are much lower than the observed ones. But with post-processed WRF QPF used, the simulated flood discharge increased and became much more close to the observation. This 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) were 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, 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. It is obvious that with the post-processed WRF QPF, the evaluation indices are improved substantially. These results show that WRF QPF post processing could improve the flood forecasting capability because the WRF QPF is more close to the observed precipitation after post-processing. So it should be practiced for real-time flood forecasting.

5.2 Results comparison for different model parameters

The model parameters optimized with rain gauge precipitation and WRF QPF are different; so different parameter values will result in different model performance. To analyze this effect, the flood events of 2012 and 2013 with two different sets of model parameters values 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 figures it may be 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 matches. 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 is found that the results of flood simulation based on the re-optimized model parameters have better evaluation indices. All evaluation indices for those 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 need to be re-optimized with the WRF QPF. This finding implies that the precipitation pattern has obvious impact on model parameters. It should be considered, and model parameter optimization is a rational way for considering this effect.

5.3 Flood simulation accuracy with different lead time

To compare the model performance with different lead time, the flood events with 3 different lead times are simulated and shown in Fig. 12. The 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 result get 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 to 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) were calculated and listed in Table 4.

Table 4 is here

From the results of Table 4, it is found that the simulated flood events with 24 hour lead time have best evaluation indices, and are 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, while 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, while 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 lead time, the practical value of WRF QPF gets lower.

6 Conclusion

In this study, the WRF QPF was 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 performances 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 for the event accumulated total precipitation. 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 times 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 need to be re-optimized using the post-processed WRF QPF, this improves the model performance significantly. That is, in coupling the distributed 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 are rational and could benefit the flood management communities due to their longer lead times for flood warning. They provide 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, while 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, while 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.

7 Data availability

The Rain gauge precipitation and river flow discharge data were provided by the Bureau of Hydrology, Pearl River Water Resources Commission, China exclusively used for this study. The WRF QPF results were provided by Yuan Li, and has been published and cited in this paper (Li et al. 2015). The Liuxihe Model used in this study are provided by Yangbo Chen, and has been published and cited in this paper (Chen et al. 2017).

Competing interests. The authors declare that they have no conflict of interest.

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Figures

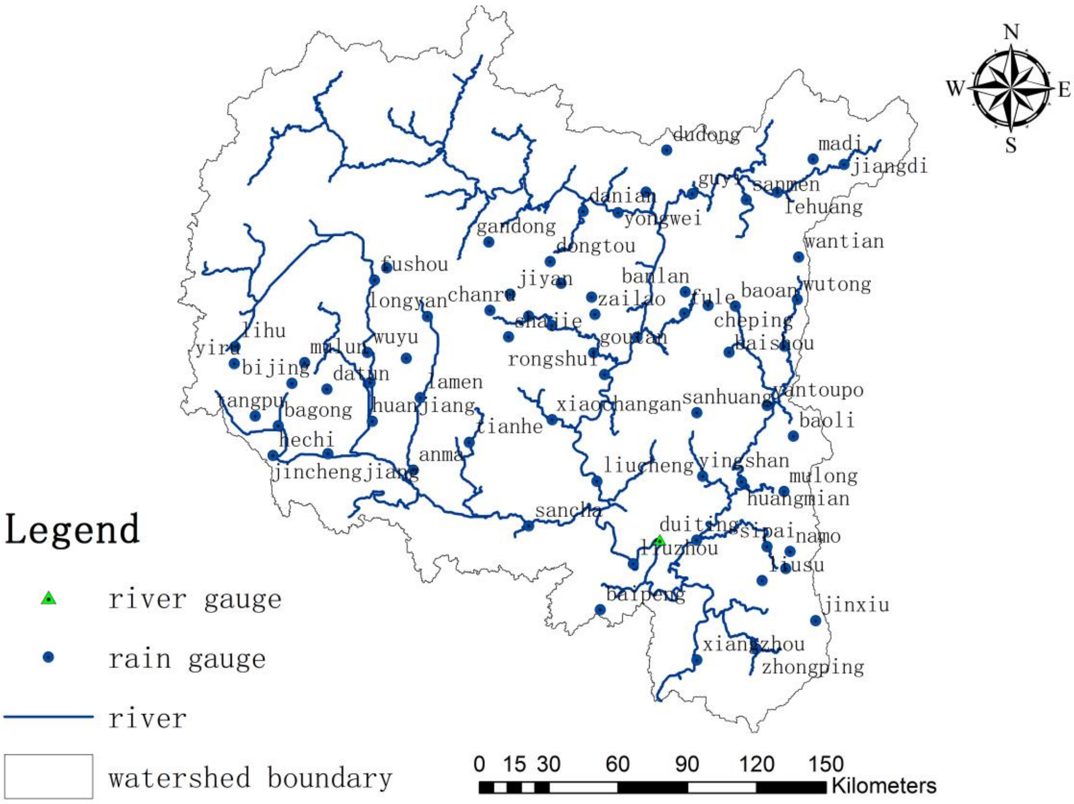
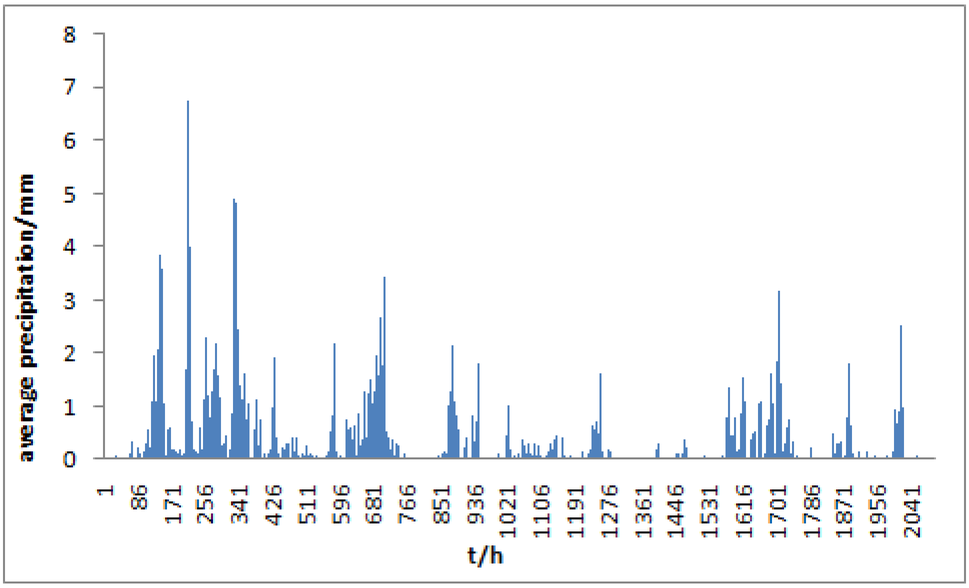


Fig. 1 Sketch map of Liujiang River Basin(Chen et al., 2017)


average precipitation/mm
0
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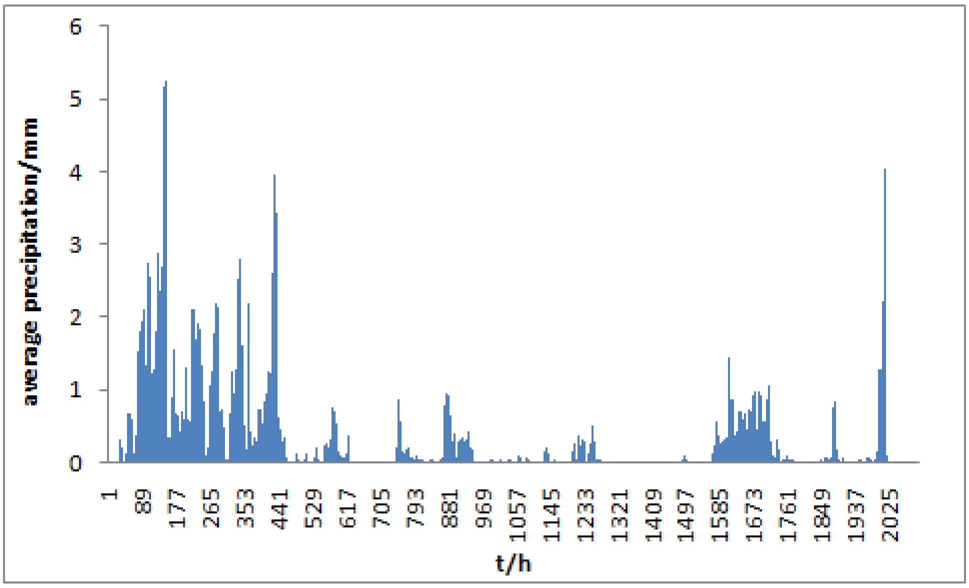
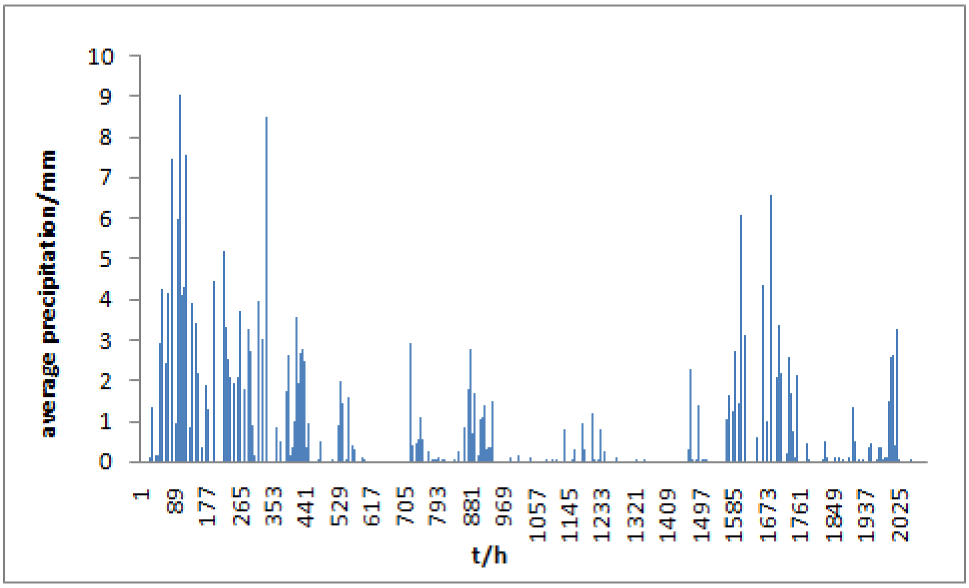
t/h

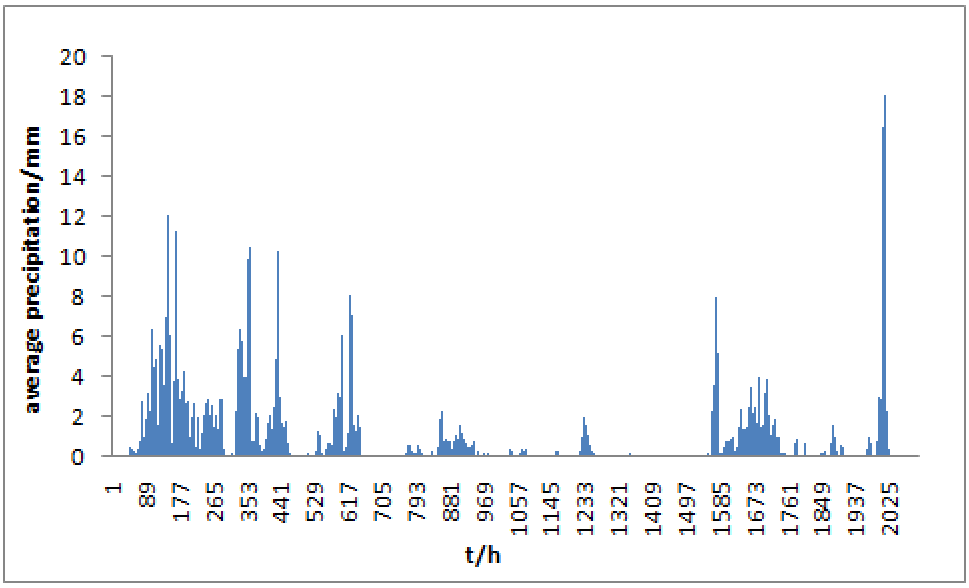
(a)


average precipitation/mm
0
1
2
3
4
5
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)

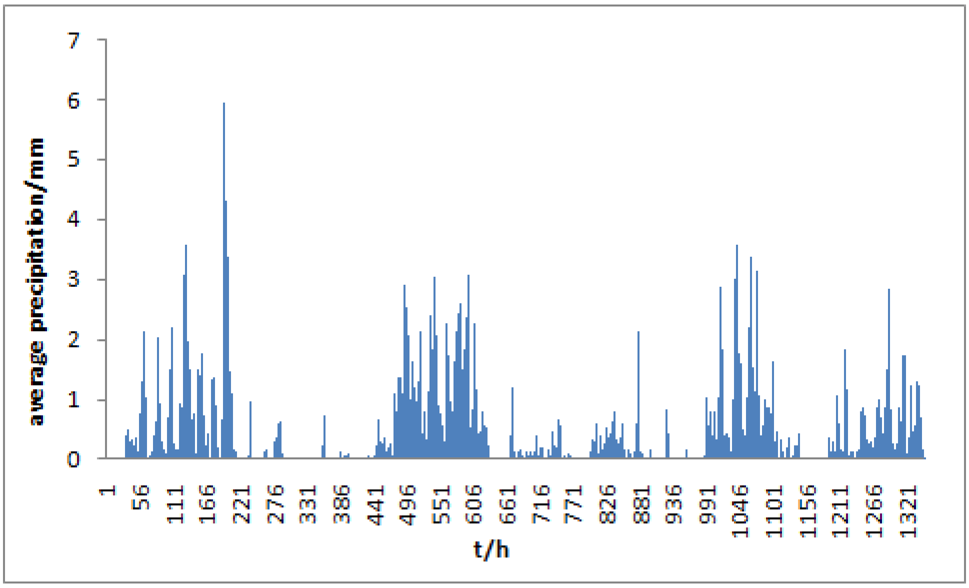


(c)

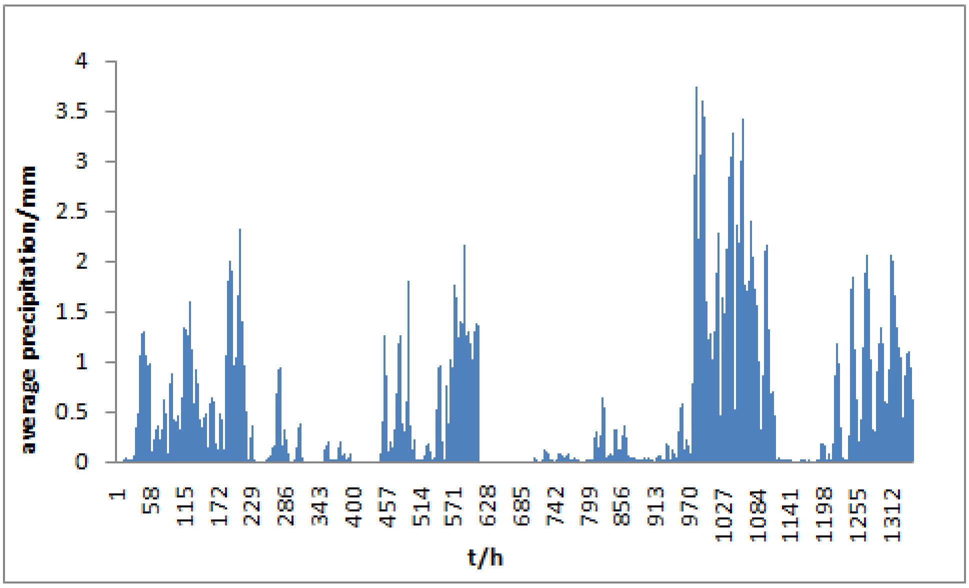


(d)

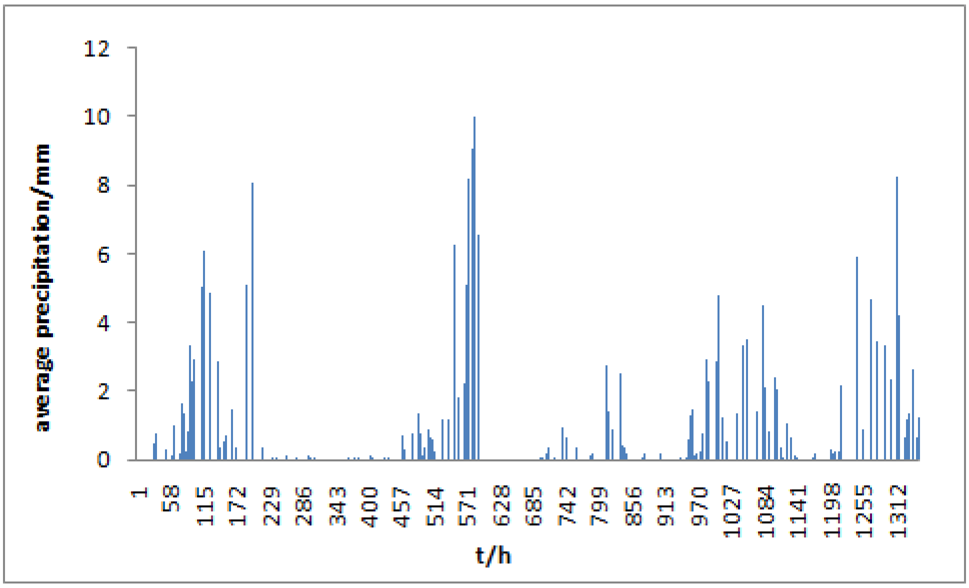
Fig. 2 Precipitation pattern comparison of two precipitation products(2011), (a) is the average precipitation of rain gauges, (b) is the average precipitation of WRF with 24 hour lead time, (c) is the average precipitation of WRF with 48 hour lead time, (d) is the average precipitation of WRF with 72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


average precipitation/mm
7
6
5
4
3
2
1
0
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
t/h

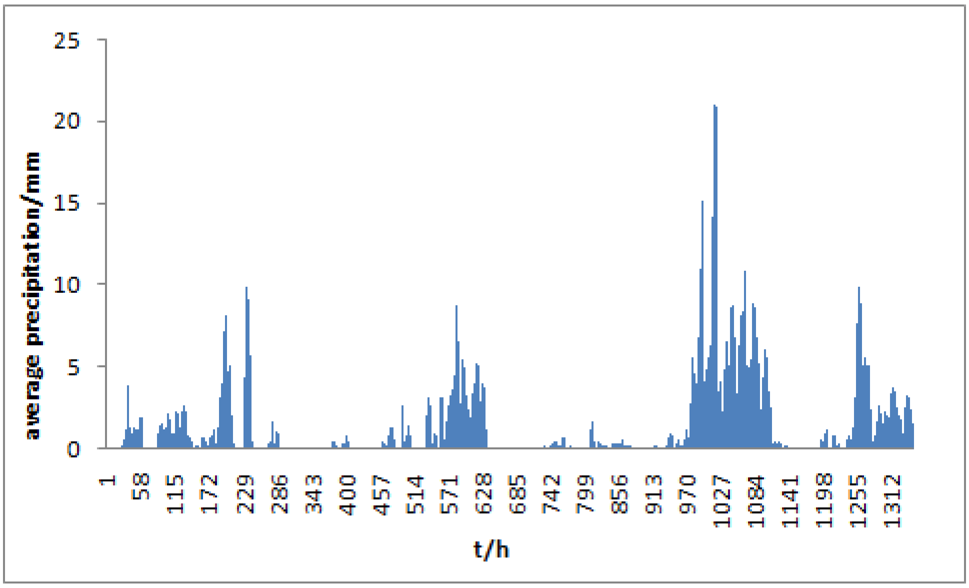
(a)


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

(b)

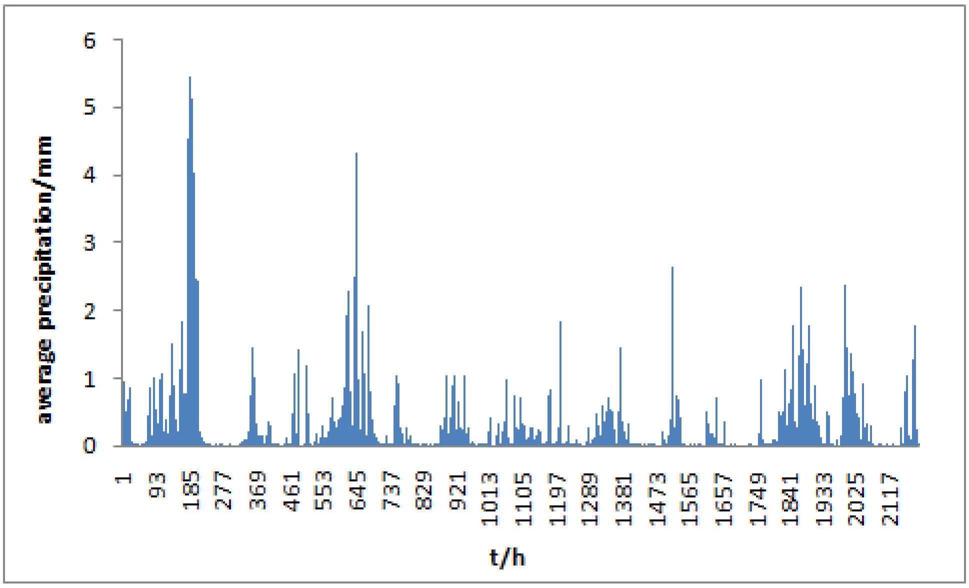


(c)

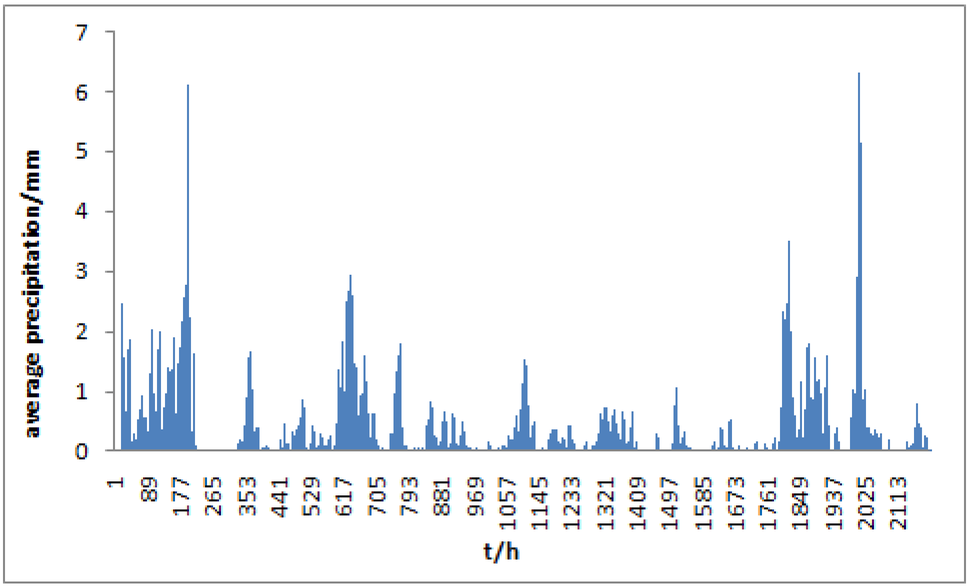


(d)

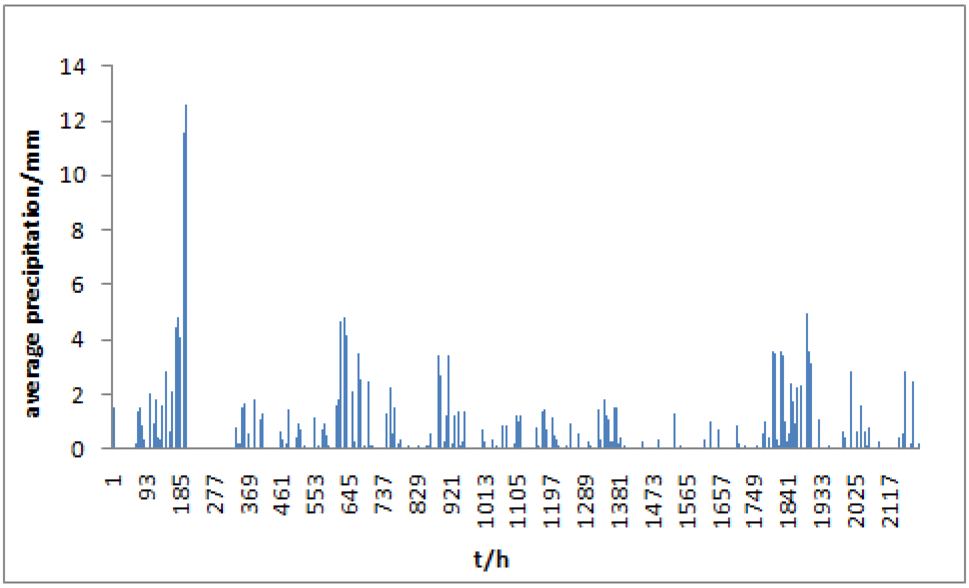
Fig. 3 Precipitation pattern comparison of two precipitation products(2012) , (a) is the average precipitation of rain gauges, (b) is the average precipitation of WRF with 24 hour lead time, (c) is the average precipitation of WRF with 48 hour lead time, (d) is the average precipitation of WRF with 72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

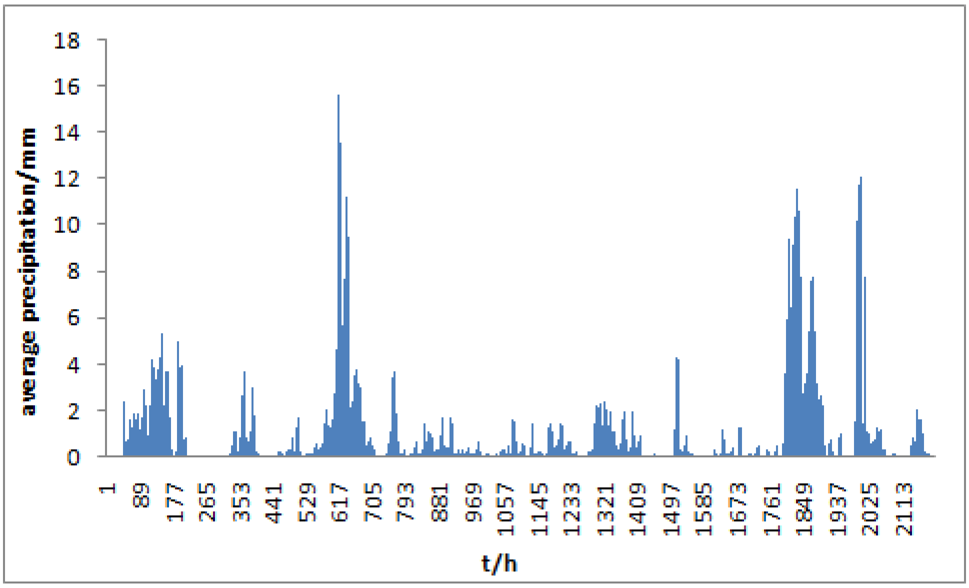
(a)


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.

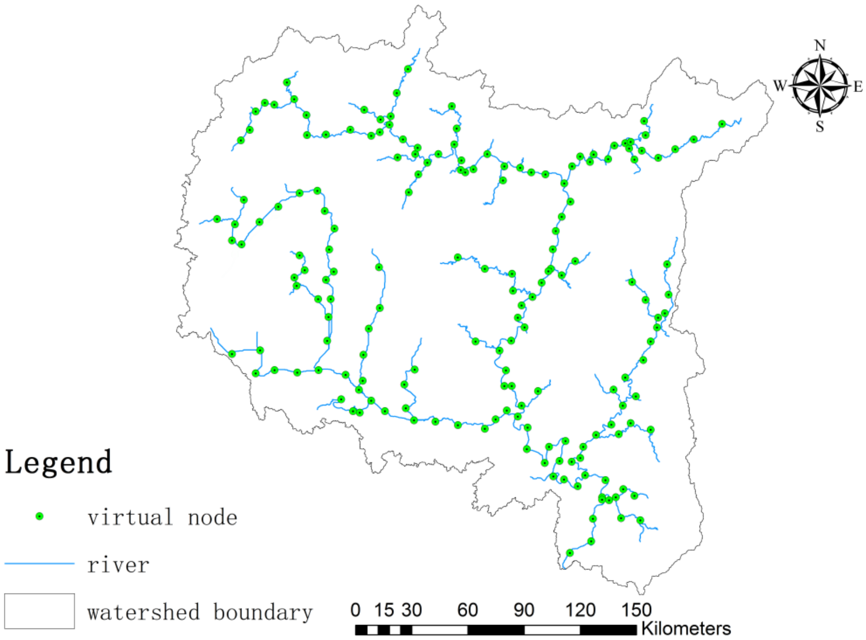
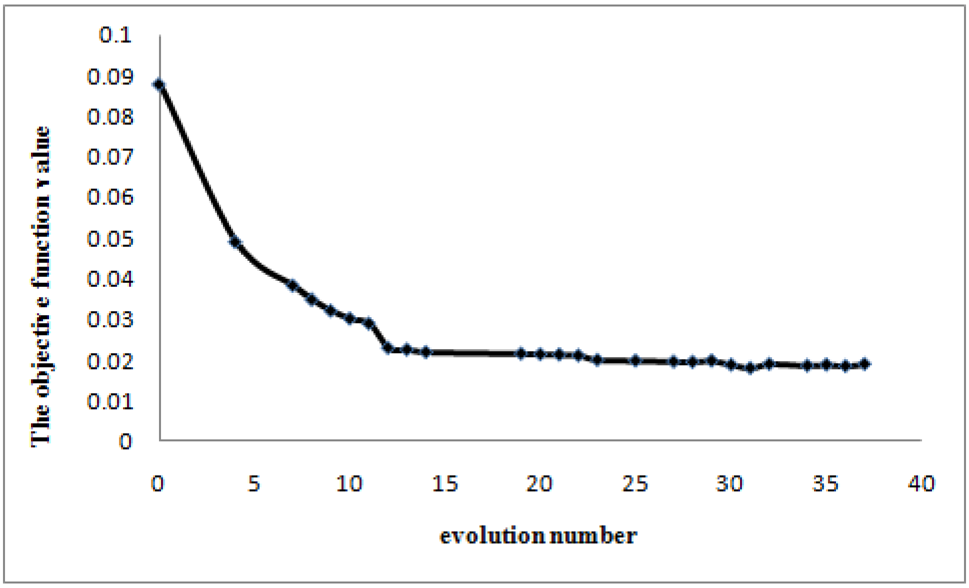
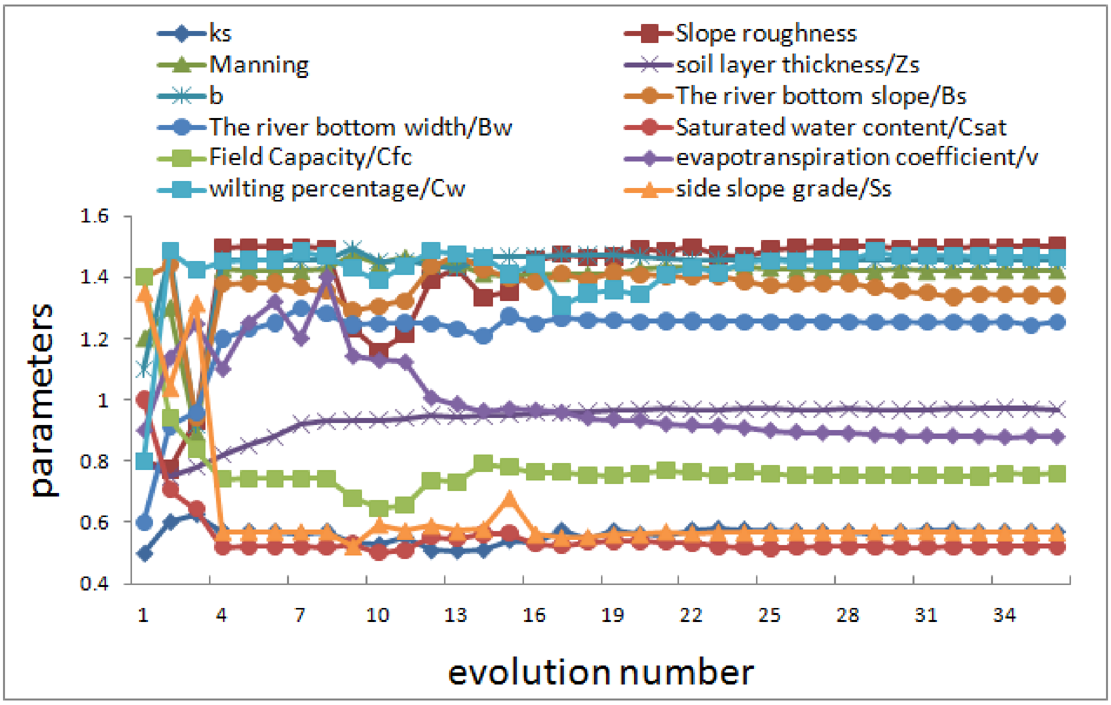


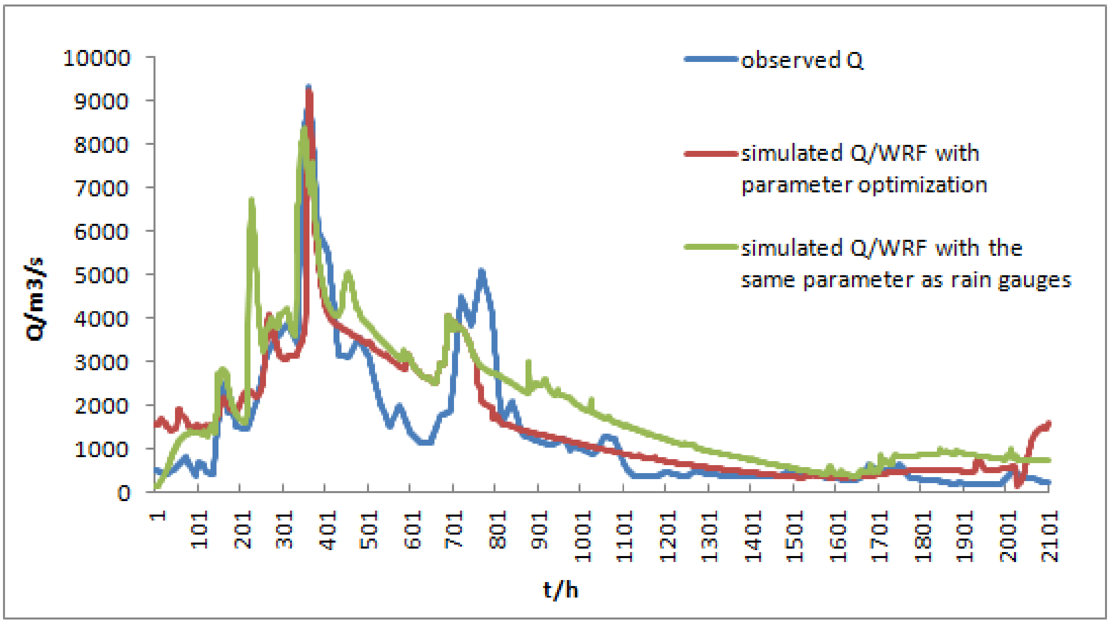
Fig.5 Liuxihe Model structure of LRB (200m×200m resolution, Chen et. al., 2017)



(a) Evolutionary process of objective function

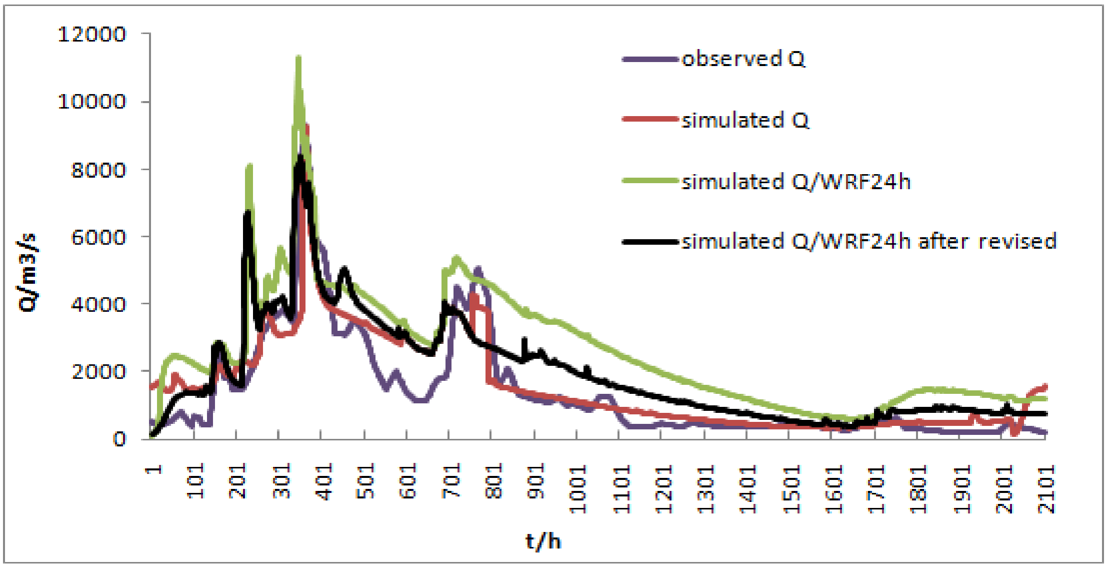


(b) Parameter evolution process

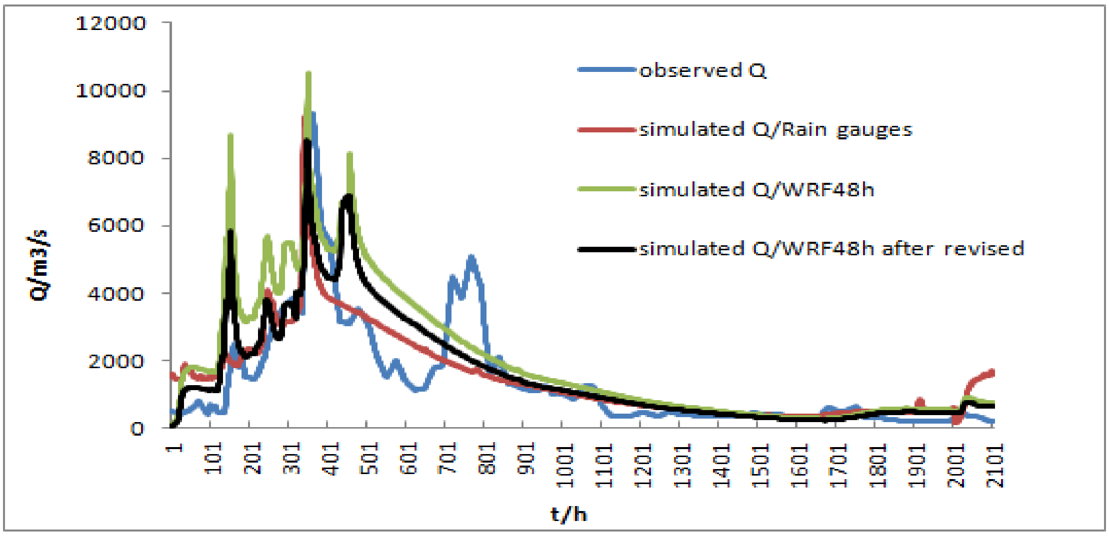


(c) Simulated flood process with optimized model parameters

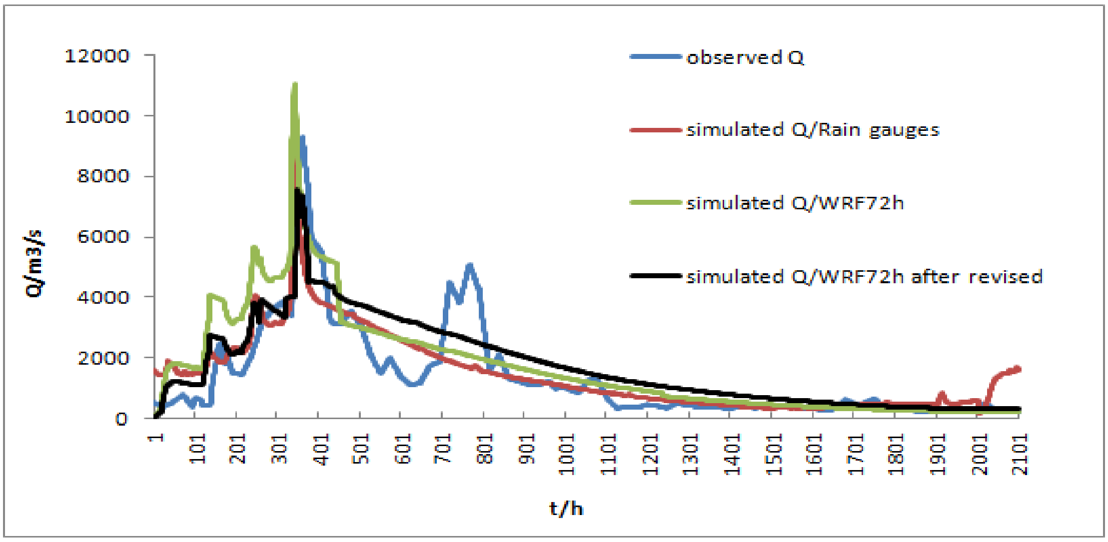
Fig. 6 Parameter optimization results of Liuxihe Model for LRB with WRF QPF



(a) 24 hour lead time

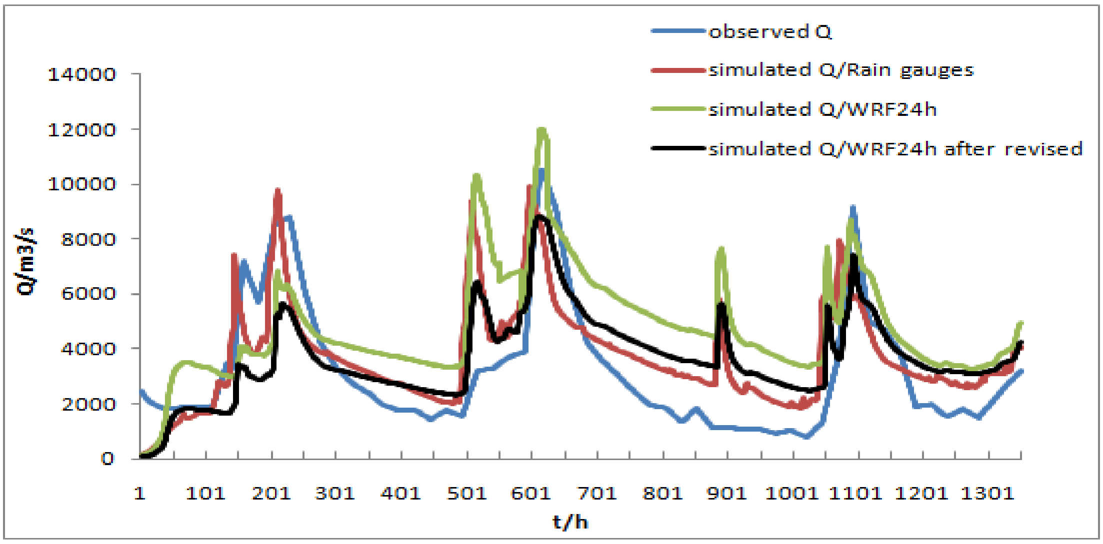


(b) 48 hour lead time

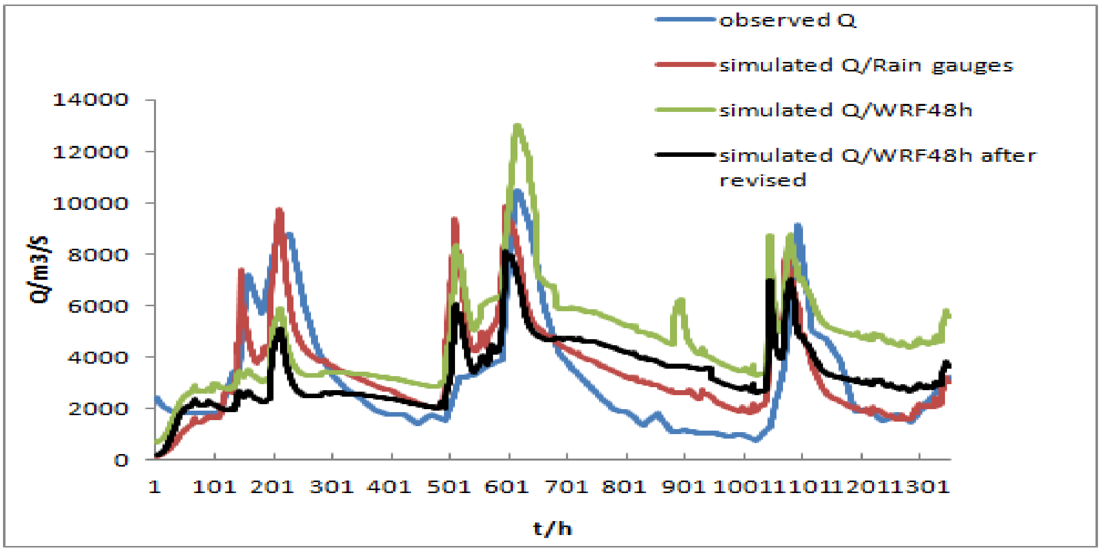


(c) 72 hour lead time

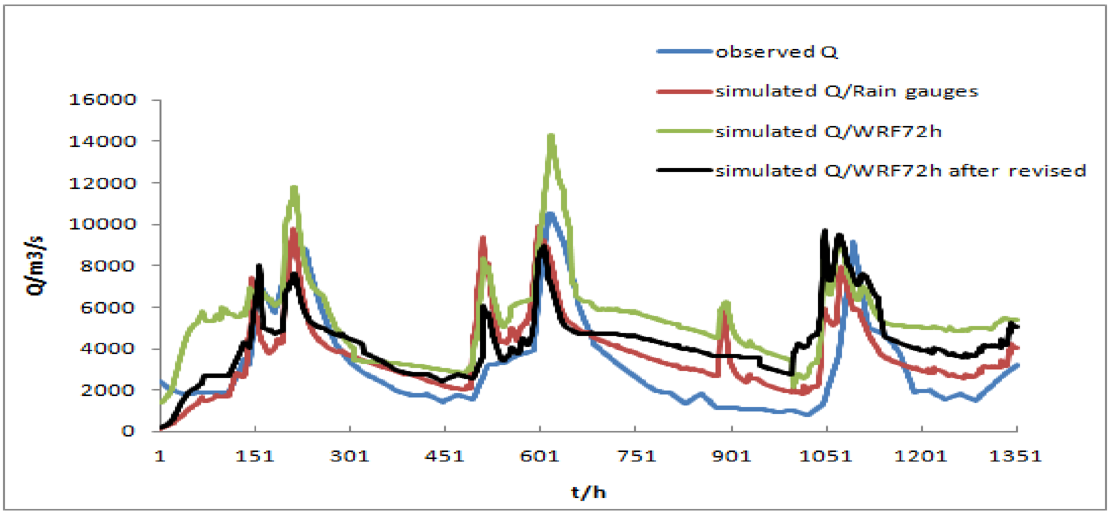
Fig. 7 Coupled flood simulation results with original model parameters (2011)



(a) 24 hour lead time

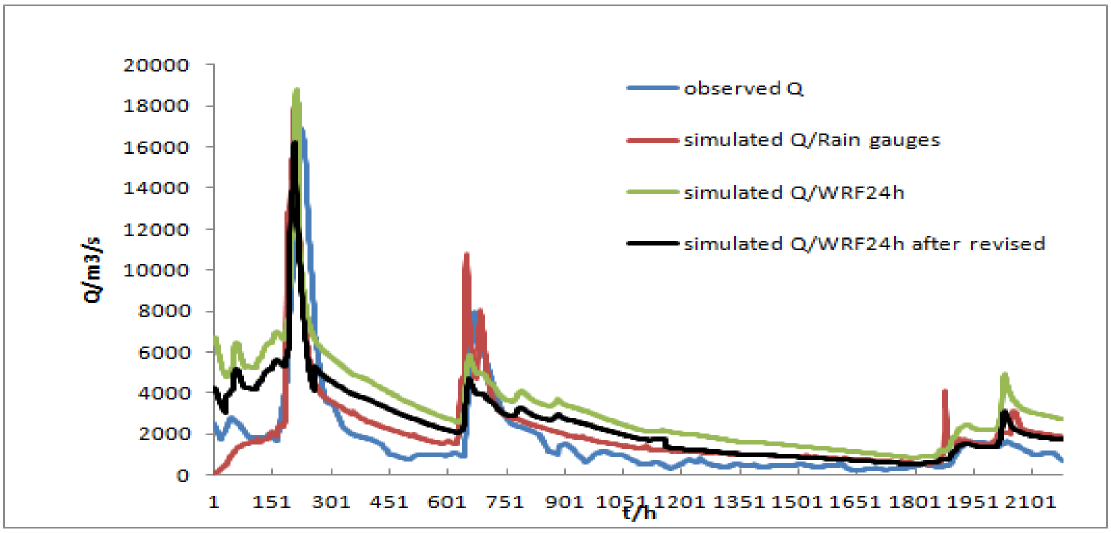


(b) 48 hour lead time

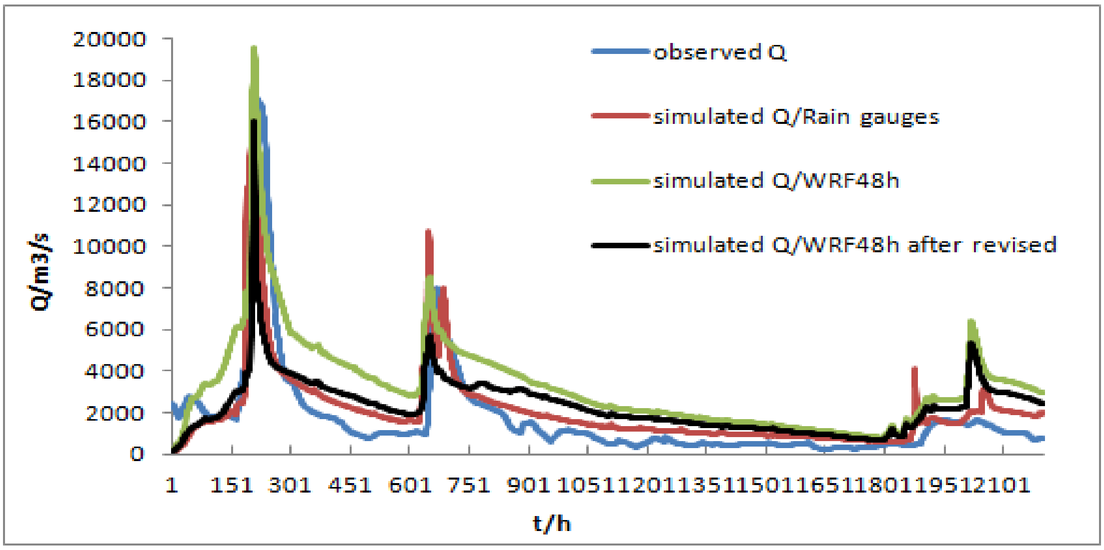


(c) 72 hour lead time

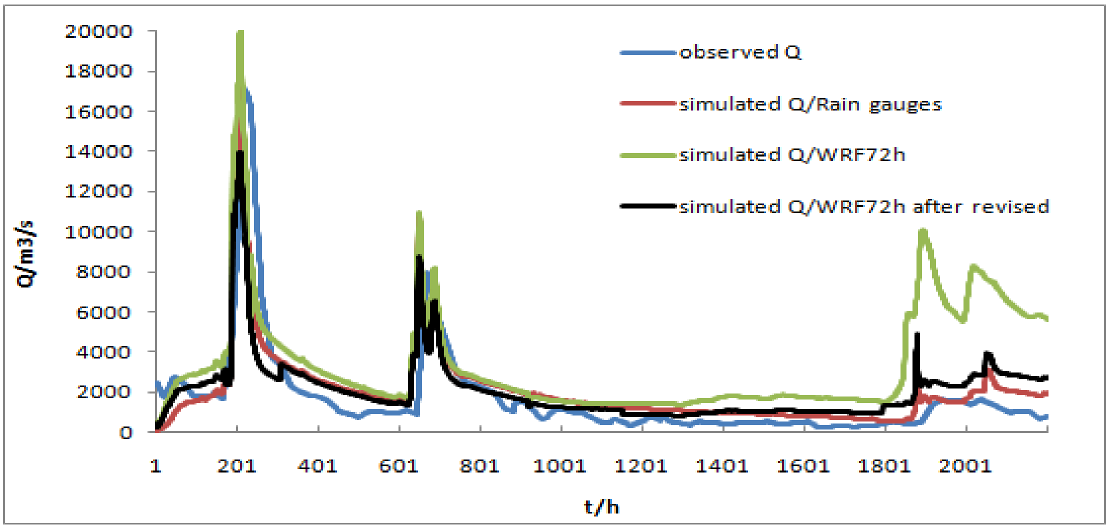
Fig. 8 Coupled flood simulation results with original model parameters(2012)



(a) 24 hour lead time

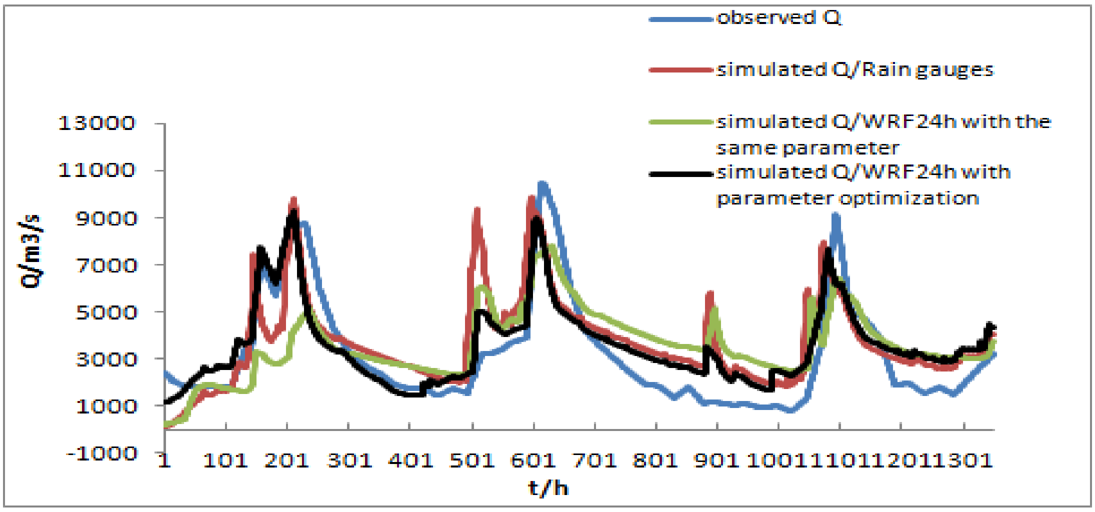


(b) 48 hour lead time

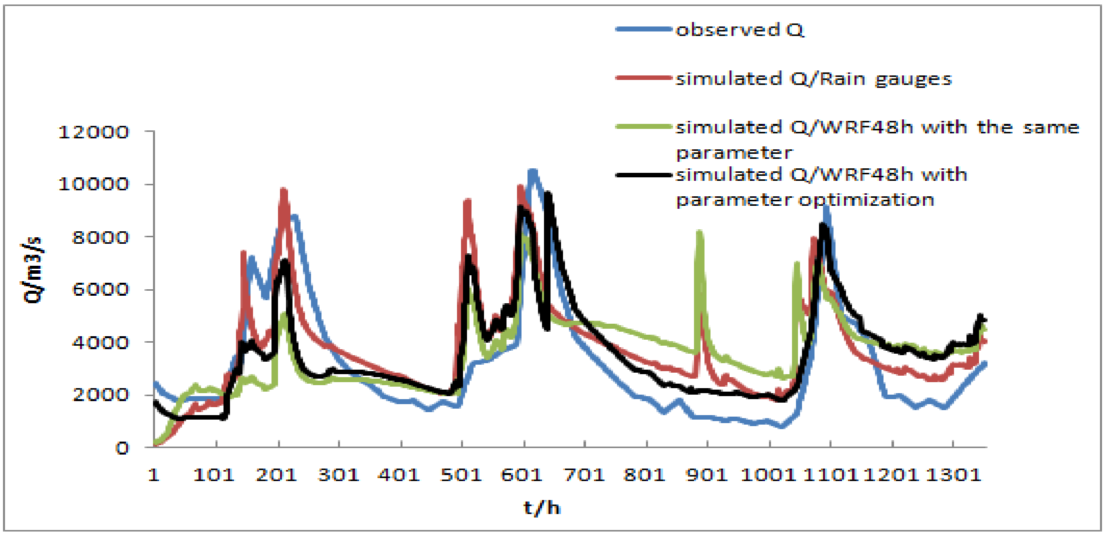


(c) 72 hour lead time

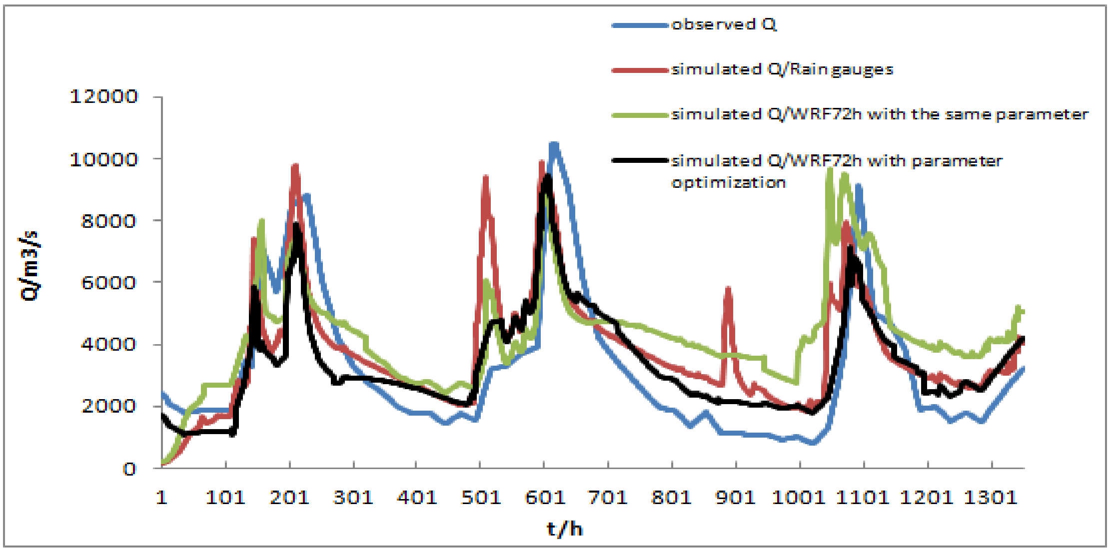
Fig. 9 Coupled flood simulation results with original model parameters (2013)



(a) 24 hour lead time

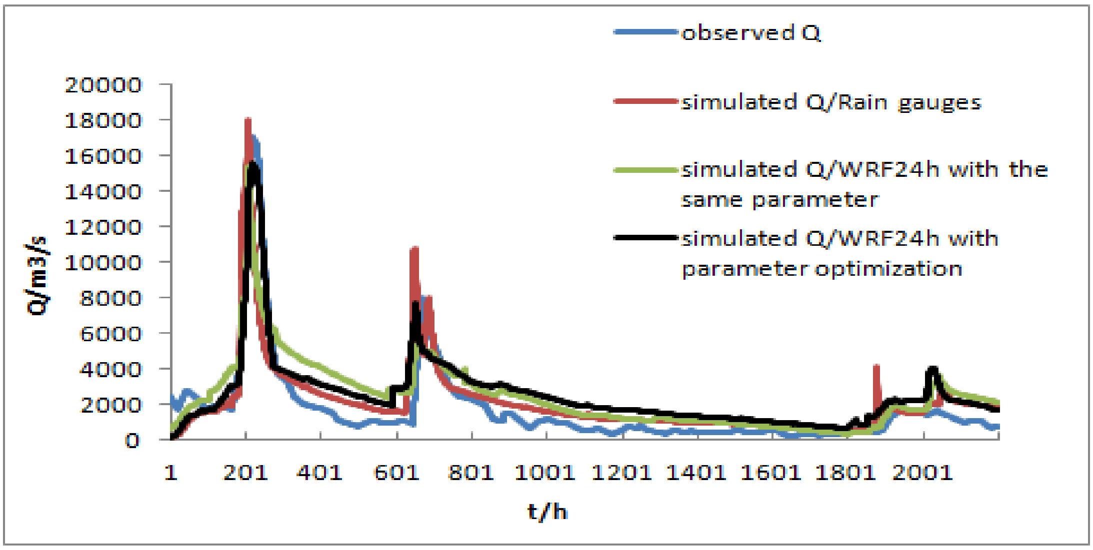


(b) 48 hour lead time

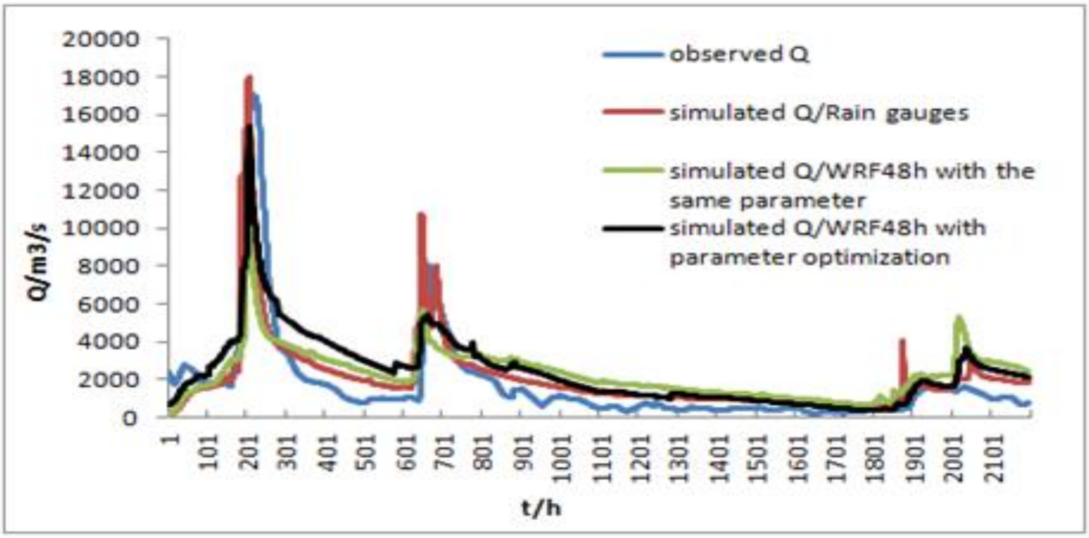


(c) 72 hour lead time

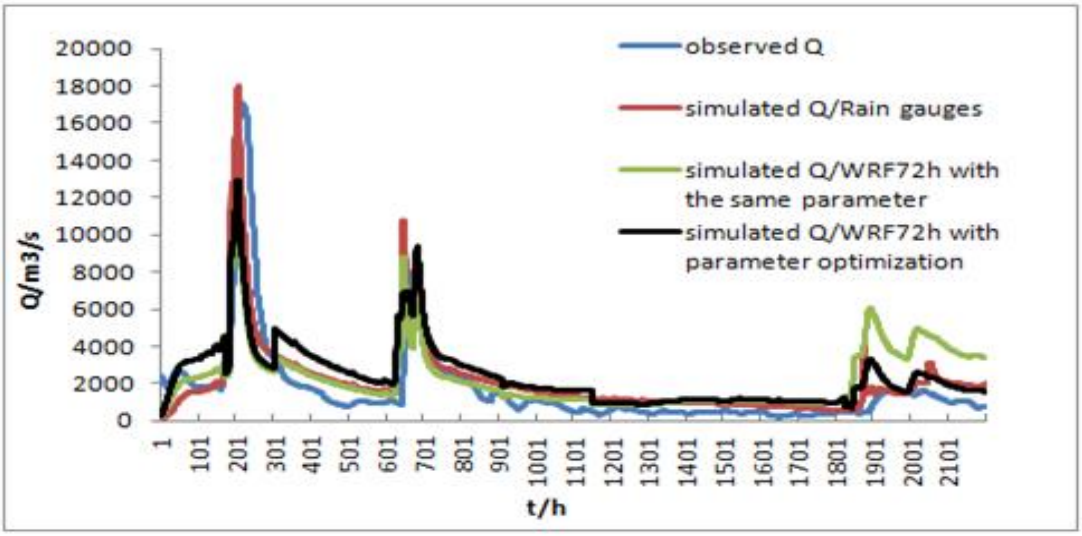
Fig. 10 Coupled flood simulation results with re-optimized model parameters (2012)



(a) 24 hour lead time

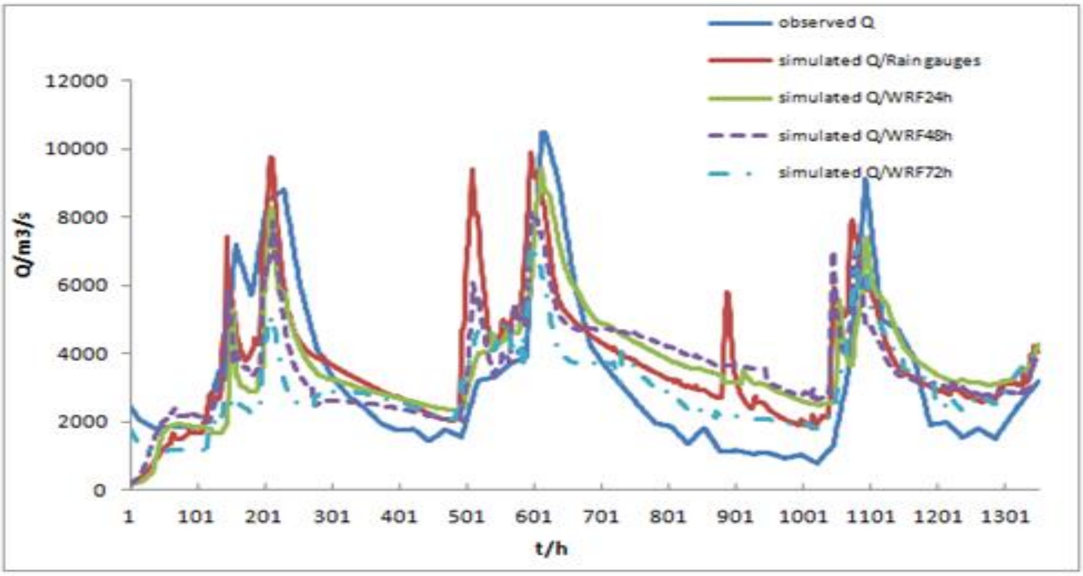


(b) 48 hour lead time

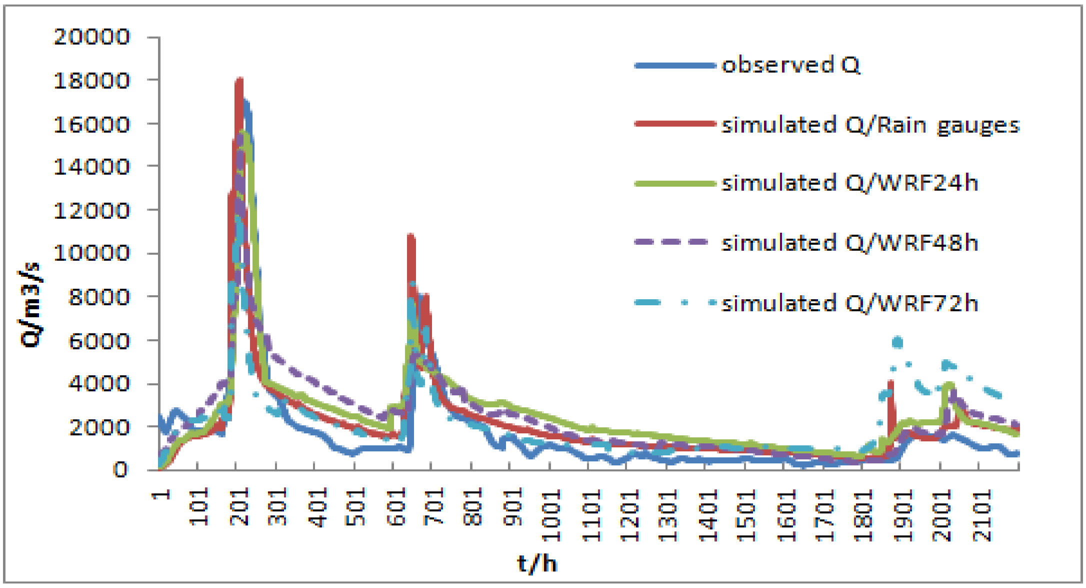


(c) 72 hour lead time

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	0.66	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	0.75	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	0.48	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	0.58	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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