1   Extending flood forecasting lead time in large watershed by coupling WRF QPF with

2   distributed hydrological model

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14   **Abstract**. Long lead time flood forecasting is very important for large watershed flood

15   mitigation as it provides more time for flood warning and emergency responses. Latest

16   numerical weather forecast model could provide 1-15 days quantitative precipitation

17   forecasting products at grid format, by coupling this product with distributed

18   hydrological model could produce long lead time watershed flood forecasting products.

19   This paper studied the feasibility of coupling the Liuxihe Model with the WRF QPF for

20   a large watershed flood forecasting in southern China. The QPF of WRF products has

21   three lead time, including 24 hour, 48 hour and 72 hour, with the grid resolution being

22   20kmx20km. The Liuxihe Model is set up with freely downloaded terrain property; the

23   model parameters were previously optimized with rain gauge observed precipitation,

24   and re-optimized with WRF QPF. Results show that the WRF QPF has bias with the

25   rain gauge precipitation, and a post-processing method is proposed to post process the

26   WRF QPF products, which improves the flood forecasting capability. With model

27   parameter re-optimization, the model's performance improves also. This suggests that

28   the model parameters be optimized with QPF, not the rain gauge precipitation. With the

29   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

54   lead time for the latest weather prediction model could be as long as to 1~15 days

55   (Buizza, 1999, Ahlgrimm et al., 2016). By coupling the weather prediction model QPF

56   with flood forecasting model, the flood forecasting lead time thus could be extended.

57   This provides a new way for large watershed flood forecasting (Jasper et al., 2002,

58   Zappa et al., 2010, Giard and Bazile, 2000). Many numerical weather prediction models

59   have been proposed and put into operational use, such as the European Centre Medium-

60   Range Weather Forecasts (ECMWF) Ensemble Prediction System (EPS) (Molteni et

61   al., 1996, Barnier et al., 1995), the weather research and forecasting (WRF) model

62   (Skamarock, 2005, 2008, Maussion, 2011), the numerical weather forecast model of

63   Japan Meteorological Agency (Takenaka et al., 2011, Gao and Lian, 2006), the

64   numerical forecast model of China Meteorological Agency (Li and Chen, 2002), and

65   others.

66

67   Watershed flood forecasting relies on a hydrological model for computation tool, while

68   the precipitation is the model's driving force. The earliest hydrological model is

69   regarded as the Sherman unit-graph (Sherman, 1932), which belongs to the category of

70   lumped hydrological model. Many lumped hydrological models have been proposed,

71   such as the Sacramento model (Burnash, 1995), the NAM model (DHI, 2004), the

72   Xinanjiang model (Zhao, 1977), among others. The lumped hydrological model regards

73   the watershed as a whole hydrological unit, thus the model parameter is the same over

74   the watershed, but this is not true, particularly for a large watershed. The precipitation

75   the lumped hydrological model uses is averaged over the watershed also. This further

76   increases the model's uncertainty in large watershed flood forecasting as it is well

77   known that the precipitation distribution over the watershed is highly uneven. The QPF

78   produced by numerical weather prediction model forecasts precipitation at grid format,

79 which provides detailed precipitation distribution information over watershed. This is

80 another advantage of QPF. The lumped hydrological model could not take the

81 advantage of gridded WPF products.

82

83 The latest development of watershed hydrological model is the distributed hydrological

84 model (Refsgaard et al., 1996), which divides the watershed into grids, and different

85 grids could have their own precipitation, terrain property and model parameter. Hence

86 a distributed hydrological model is the ideal model for coupling WRF QPF for

87 watershed flood forecasting. The first proposed distributed hydrological model is SHE

88 model (Abbott et al.1986a, 1986b), and now many distributed hydrological models

89 have been proposed, and a few have been used for watershed flood forecasting, such as

90 the SHE model (Abbott et al.1986a, 1986b), the WATERFLOOD model (Kouwen,

91 1988), the VIC model (Liang et al., 1994), the WetSpa model (Wang et al., 1997), the

92 Vflo model (Vieux et al., 2002), the WEHY model(Kavvas et al., 2004), the Liuxihe

93 model (Chen et al., 2009, 2011), among others.

94

95 As distributed hydrological model calculates the hydrological process at grid scale, so

96 the computation time needed for runing the distributed hydrological model is huge even

97 for a small watershed. This limits the model's application in watershed flood forecating,

98 particularly in large watershed. Model parameter uncertainty related to distributed

99 hydrological model also impacted its application. But with the development of parallel

100 computation algorithm for distributed hydrological model and its deployment on

101 supercomputer (Chen et al., 2013), the computation burden is not a great challenge of

102 distributed hydrological modeling anymore. Also with the development of automatical

103 parameter optimization of distributed hydrological model in flood forecasting (Madsen

104 et al., 2003, Shafii et al., 2009, Xu et al., 2012, Chen et al., 2016), the model parameters

105 could be optimized, and the model's performance could be improved largely. With these

106 advances, now distributed hydrological model could be used for large watershed flood

107 forecasting.

108

109 In this paper, the WRF QPF is coupled with a distributed hydrological model-the

110 Liuxihe model for a large watershed flood forecasting in southern China. The spatial

111 and temporal resolution of WRF QPF is at 20km*20km and 1 hour respectively with

112 three lead times, including 24 hour, 48 hour and 72 hour. The WRF QPF has a similar

113 precipitation pattern with that estimated by rain gauges, but overestimates the averaged

114 watershed precipitation, and the longer the WRF QPF lead time, the higher the

115 precipitation overestimation. Since WRF QPF has systematic bias compared with rain

116 gauge precipitation, a post-processing method is proposed to post process the WRF

117 QPF products, which improves the flood forecasting capability. The Liuxihe Model is

118 set up with freely downloaded terrain property. The model parameters were previously

119 optimized with rain gauge observed precipitation, and re-optimized with WRF QPF.

120 With model parameter re-optimization, the model's performance improved. Model

121 parameters should be optimized with QPF, not the rain gauge precipitation. Flood

122 forecasting products produced by coupling Liuxihe Model with WRF QPF provide

123 good reference for large watershed flood warning due to their long lead time and

124 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,

147 non-hydrostatic, fully compressible, and has the terrain-following sigma coordinate

148 system. The model is considered as the next generation's medium range weather

149 forecasting model, and can simulate different weather processes from cloud scale to

150 synoptic scale, especially in horizontal resolution of 1 ~ 10 km. The model also

151 integrates the advanced numerical methods and data assimilation techniques, a variety

152 of physically process schemes, and multiple nested methods and the capability of being

153 used in different geographical locations. WRF-ARW model satisfies the needs of

154 scientific research and practical applications for this study.

155

156 Prior studies have been shown in quantitative precipitation forecasting by using WRF-

157 ARW model. For instance, Pennelly et al. (2014) employed the WRF model to predict

158 three precipitation events of Alberta, Canada, and compared the precipitation with 48

159 hour leading time predicted by the model with rain gauges. The results showed that

160 Kain-Fritsch cumulus parameterization overestimated the value of precipitation

161 invariably. Eiserloh and Chiao (2015) used WRF-ARW with data assimilation to

162 investigate an Atmospheric River event over Northern California. Maussion et al. (2011)

163 compared the capability of WRF model in retrieving monthly precipitation and

164 snowfall at three different spatial resolution including 30, 10 and 2 km domains over

165 Tibet. Their results showed that the model was able to recapture monthly precipitation

166 and snowfall. Pan et al. (2012) used two WRF simulation groups between pre-process

167 and post-process in Heihe river basin, and compared and analyzed the mean bias error,

168 root mean square error and correlation coefficient of the two WRF groups. Huang et al.

169 (2011) found that variations in the microphysical process parameterization schemes

170 had much more influence on precipitation than that of cumulus parameterization

171 schemes, especially for a torrential rain attributed to large-scale forcing that mainly

172 resulted from stratus clouds. Kumar et al. (2008) used WRF model to study a heavy

173 rain in 2005, their results showed that WRF model could reproduce the storm event and

174 its dynamical and thermo-dynamical characteristics. Hong and Lee (2009) conducted a

175 triply nested WRF simulation for convective initiation of a thunderstorm. Givati et al.

176 (2012) predicted the hiemal precipitation event of 2008 and 2009 based on WRF model

177 in upstream of the Jordan River, and coupled WRF model with hydrological model-

178 HYMKE to simulate the velocity and discharge of Jordan River. Sensitivity experiment

179 of WRF microphysical schemes by Niu et al. (2007) have shown the adequate

180 performance of precipitation predicted associated with region, center location and

181 rainfall intensity. Xu et al.(2007) compared the hiemal continuous precipitation process

182 predicted with the estival results by WRF model, the results showed that the KF scheme

183 was better than BM scheme in summer. Hu et al. (2008) found that the parameterization

184 scheme of WRF model was related to the model resolution, and the parameterization

185 scheme should be selected by the resolution of WRF model.

186 3.2 Configuration of WRF for LRB B

187 The WRF-ARW was applied to LRB following the configurations by Li et al. (2015).

188 More information about LBR can be found in Li et al. (2015) and Chen et al. (2017).

189 The model domain is centered at 23.8N, 109.2W with the Lambert conformal projection.

190 The vertical structure includes 28 levels with the focus on the lower-levels of

191 troposphere.   The initial and time-dependent lateral boundary conditions are supplied

192 from NCEP Global Forecast System (GFS) 3-hourly global analysis at 0.5 °horizontal

193 resolution. The model domain has a 20 km grid resolution. The single-moment 3-class

194 microphysics (WSM3) parameterization (Hong and Lim, 2006) is adopted for this study.

195 Kain-Fritsch cumulus parameterization (Kain, 2004) as well as the YSU boundary layer

196 microphysics scheme (Hong et al., 2006) are used. Other physics   schemes   used

197   include the NOAH scheme for the land surface physics (Ek et al., 2003), the Goddard

198   scheme for the shortwave radiation physics (based on Chou and Suarez,1994), and

199   Rapid Radiative Transfer Model (RRTM) scheme for the longwave radiation physics

200   (Mlawer et al., 1997).

201

202   The spatial and temporal resolution of WRF is at 20km x 20km and 1 hour, respectively.

203   The entire Liujiang River Basin is covered by total 156 grid points of the WRF model.

204   The simulated QPF for flood events in years 2011 to 2013 were produced with three

205   different lead time (i.e., 24 hours, 48 hours and 72 hours), respectively. As shown in

206   Figs. 2-4, the WRF QPF products in in three different years, while (a) is the rain gauge

207   precipitation, (b) is the WRF QPF with 24 hour lead time, (c) is the WRF QPF with 48

208   hour lead time, and (d) is the WRF QPF with 72 hour lead time.

209   Fig. 2 is here

210   Fig. 3 is here

211   Fig. 4 is here

212   3.3 Evaluation of WRF QPF and rain gauges precipitation

213   Comparisons of WRF QPF and rain gauge precipitation are performed. From the

214   simulated results, as shown in Figs. 2, 3 and 4, it appears that the temporal

215   precipitation pattern of both products is similar, although there are some insignificant

216   differences. To make further comparison, the accumulated precipitation of the three

217   flood events averaged over the watershed are calculated and listed in Table 1.

218

219   Table 1 is here

220

221 As summarized in Table 1, it could be found that the WRF QPF accumulated

222 precipitation has obvious bias with rain gauge accumulated precipitation. For all the

223 three flood events, the WRF QPF accumulated precipitation are higher than those

224 measured by rain gauges. In other words, the WRF QPF overestimates the

225 precipitation. For flood event 2011, the overestimated watershed averaged

226 precipitation of WRF QPF with lead time of 24 hour, 48 hour and 72 hour are 23%,

227 32% and 55% respectively. For the flood event in 2012, they are 16%, 37% and 71%

228 respectively. They are 50%, 73% and 95% respectively from the event in 2013. The

229 results suggest that longer the WRF QPF lead time, the higher chance of

230 overestimation.

231 3.4 WRF QPF statistical calibrations

232 From the simulated results (c.f., Fig. 2, 3 and 4, and Table 1), the WRF QPF has

233 significant bias compared to rain gauge precipitation. Assuming the rain gauge

234 precipitation is correct, the WRF QPF needs to be further calibrated. In order to do so,

235 the WRF QPF is further post-processed based on the rain gauge precipitation to

236 correct the systematic error of WRF QPF. The principle of WRF QPF statistical

237 calibrations proposed in this study is to keep the areal averaged event accumulated

238 precipitation from both model and rain gauge products to be equivalent. In other

239 words, the statistical approach is to nudge the WRF QPF precipitation to rain gauge

240 results.

241

242 Based on this principle, the WRF QPF post-processing procedure is summarized as

243 follows:

244

245   1) Calculate the areal average precipitation of the WRF QPF for each flood events

246   over the watershed as following equation.

247   $\bar{P}_{WRF} = \dfrac{\sum\limits_{i=1}^{N} P_i F_i}{N}$ (1)

248   Where, $\bar{P}_{WRF}$ is the areal average precipitation of WRF QPF of one flood event, P_i is

249   the precipitation on WRF grid i, F_i is the surface area of WRF grid i divided by the

250   whole watershed drainage area, N is the total number of WRF grids.

251

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

253   equation.

254   $\bar{P}_2 = \dfrac{\sum\limits_{j=1}^{M} P_j}{M}$ (2)

255   Where, $\bar{P}_2$ is the areal average precipitation of the rain gauges network, P_j is the

256   precipitation observed by jth rain gauge, M is the total number of rain gauges.

257

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

259   following equation.

260 $$P_i^{'} = P_i \frac{\overline{P_2}}{\overline{P_{WRF}}} \quad (3)$$

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

262 With the above WRF QPF statistical calibration methods, the WRF QPF of flood

263 event 2011, 2012 and 2013 are post-processed, and will be used to couple with the

264 Liuxihe Model for flood simulations.

265 **4 Hydrological model**

266 4.1 Liuxihe Model

267 Liuxihe model is a physically based fully distributed hydrological model proposed

268 mainly for watershed flood forecasting (Chen, 2009, Chen et al., 2011), and has been

269 used in a few watersheds for flood forecasting(Chen, 2009, Chen et al., 2011, 2013,

270 2016, Liao et al., 2012 a, b, Xu et al., 2012 a, b). In Liuxihe Model, runoff components

271 are calculated at grid scale, runoff routes at both grid and watershed scale. Runoff

272 routing is divided into hill slope routing and river channel routing by using different

273 computation algorithm. Liuxihe Model proposed an automatic parameter optimization

274 method using PSO algorithm (Chen et al., 2016), which largely improves the model's

275 performance in watershed flood forecasting. Now Liuxihe Model is deployed on a

276 supercomputer system with parallel computation techniques (Chen et al., 2013) that

277 largely facilitates the model parameter optimization of Liuxihe Model.

278

279 Chen et al. (2017) set up Liuxihe Model in LRB with freely downloaded terrain

280 property data from the website at a spatial resolution of 200m*200m, and optimized

281 model parameters with observed hydrological data. The model was validated by

282 observed flood events data, and the model performance was found rational and could

283   be used for real-time flood forecasting. The model only uses rain gauge precipitation,

284   so its flood forecasting lead time is limited. In this study, the Liuxihe Model was set up

285   in LRB and the optimized model parameters were be used in this study as the first

286   attempt. Fig. 5 shows the model structure.

287

288   Fig.5 is here

289

290   4.2 Liuxihe Model parameter optimization

291   While the model parameters optimization by Chen et al. (2017) is done by using the

292   rain gauge precipitation, this study uses the WRF QPF as the precipitation input. So the

293   parameters of Liuxihe Model that were set up in LRB may not be appropriate for

294   coupling the WRF QPF. For this reason, considering Liuxihe Model is a physically

295   based distributed hydrological model, the parameters were optimized again by using

296   the WRF QPF flood event in 2011. Hence, the WRF QPF is the post-processed one, not

297   the original one. Results of parameter optimization are shown in Fig. 6. Among them,

298   (a) is the objective function evolution result, (b) is the parameters evolution result, and

299   (c) is the simulated flood process by using the optimized model parameters. To compare,

300   the simulated flood process of flood event 2011 was also drawn in Fig. 6(c).

301

302   Fig. 6 is here

303

304   From the result of Fig. 6(c), it may be seen that the optimized model parameters with

305   WRF QPF improved the flood simulation when compared to the corresponding flood

306   simulation based on gauge precipitation. This means parameter optimization with

307   WRF QPF is necessary.

308   4.3 Coupling WRF QPF with Liuxihe Model for LRB flood forecasting

309   When the Liuxihe Model set up for LRB flood forecasting (Chen et al., 2017) was

310   employed to couple with the WRF QPF, the model spatial resolution remained to be

311   200m*200m. As the spatial resolution of WRF QPF is at 20km*20km, the WRF QPF

312   was downscaled to the resolution of 200m*200m by using the nearest downscaling

313   method, the same spatial resolution of the flood forecasting model.

314   **5 Results and discussions**

315   5.1 Effects of WRF post-processing

316   The original WRF QPF and the post-processed QPF were used to couple with the

317   Liuxihe Model. In this simulation, the original model parameters that were optimized

318   with the rain gauge precipitation were employed, not the re-optimized model

319   parameters. The simulated results are shown in Fig. 7, 8 and 9.

320

321   Fig. 7 is here

322   Fig. 8 is here

323   Fig. 9 is here

324

325   From the above results, it could be seen that the simulated flood discharges with the

326   original WRF QPF are much lower than the observed ones. But with post-processed

327   WRF QPF used, the simulated flood discharge increased and became much more close

328   to the observation. This implies that the flood forecasting capability has been improved

329 by post-processing of WRF QPF. To further compare the three results, 5 evaluation

330 indices, including Nash-Sutcliffe coefficient(C), correlation coefficient(R), process

331 relative error(P), peak flow relative error(E) and water balance coefficient(W) were

332 calculated and listed in Table 2.

333

334   Table 2 is here

335

336 From the results of Table 2, it has been found that all the 5 evaluation indices have been

337 improved by coupling the post-processed WRF QPF. For example, for flood event 2011

338 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation coefficient/R,

339 process relative error/P, peak flow relative error/E and coefficient of water balance/W

340 with original WRF QPF are 0.65, 0.88, 35%, 14% and 1.44 respectively, but those with

341 the post-processed WRF QPF are 0.75, 0.93, 23%, 8% and 1.15 respectively. For flood

342 event 2012 with 48 hour lead time, the above 5 evaluation indices with original WRF

343 QPF are 0.63, 0.75, 48%, 12% and 1.43 respectively, and are 0.75, 0.84, 26%, 8% and

344 1.32 respectively with the post-processed WRF QPF. For flood event 2013 with 72 hour

345 lead time, the above 5 evaluation indices with original WRF QPF are 0.44, 0.75, 129%,

346 45% and 1.66 respectively, and are 0.55, 0.82, 98%, 23%, 1.25 respectively with the

347 post-processed WRF QPF. It is obvious that with the post-processed WRF QPF, the

348 evaluation indices are improved substantially. These results show that WRF QPF post

349 processing could improve the flood forecasting capability because the WRF QPF is

350 more close to the observed precipitation after post-processing. So it should be practiced

351 for real-time flood forecasting.

352

353   5.2 Results comparison for different model parameters

354   The model parameters optimized with rain gauge precipitation and WRF QPF are

355   different; so different parameter values will result in different model performance. To

356   analyze this effect, the flood events of 2012 and 2013 with two different sets of model

357   parameters values are simulated, and are shown in Fig. 10 and Fig. 11 respectively.

358   Only the post-processed WRF QPF are coupled in this simulation.

359

360   Fig. 10 is here

361   Fig. 11 is here

362

363   From the above figures it may be that the simulated flood results with re-optimized

364   model parameters are better than those simulated with the original model parameters.

365   The simulated flood discharge with the re-optimized model parameters matches. To

366   further compare the two results, 5 evaluation indices, including Nash-Sutcliffe

367   coefficient(C), correlation coefficient(R), process relative error(P), peak flow relative

368   error(E) and water balance coefficient(W) are calculated and listed in Table 3.

369

370   Table 3 is here

371

372   From the results of Table 3, it is found that the results of flood simulation based on the

373   re-optimized model parameters have better evaluation indices. All evaluation indices

374   for those based on re-optimized model parameters are improved. For example, for flood

375   event 2012 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation

376   coefficient/R, process relative error/P, peak flow relative error/E and coefficient of

377   water balance/W with original model parameters are 0.58, 0.82, 35%, 12% and 1.08

378   respectively, but those with the re-optimized model parameters are 0.74, 0.86, 28%, 8%

379   and 0.95 respectively. For flood event 2013 with 48 hour lead time, the 5 indices with

380   the original model parameters are 0.62, 0.86, 22%, 13% and 1.24 respectively, and are

381   0.68, 0.89, 18%, 9% and 1.06 respectively for those with re-optimized model

382   parameters. So it could be said that in coupling the WRF QPF with distributed

383   hydrological model, the model parameters need to be re-optimized with the WRF QPF.

384   This finding implies that the precipitation pattern has obvious impact on model

385   parameters. It should be considered, and model parameter optimization is a rational way

386   for considering this effect.

387   5.3 Flood simulation accuracy with different lead time

388   To compare the model performance with different lead time, the flood events with 3

389   different lead times are simulated and shown in Fig. 12. The model parameters are the

390   re-optimized ones, and the QPF is the post-processed QPF.

391

392   Fig. 12 is here

393

394   From the results of Fig. 12, it could be seen that the flood simulation result get worse

395   as the lead time increases, i.e., the model performance with 24 hour lead time is better

396   than that with 48 hour lead time, and the model performance with 48 hour lead time is

397   better than that with 72 hour lead time. The simulated hydrological process with 24

398   hour lead time is very similar to that simulated with rain gauge precipitation. To further

399   compare the results, 5 evaluation indices, including Nash-Sutcliffe coefficient(C),

400   correlation coefficient(R), process relative error(P), peak flow relative error(E) and

401   water balance coefficient(W) were calculated and listed in Table 4.

402

403   Table 4 is here

404

405   From the results of Table 4, it is found that the simulated flood events with 24 hour lead

406   time have best evaluation indices, and are very close to those simulated with rain gauge

407   precipitation. For flood event 2012, the Nash-Sutcliffe coefficient/C, correlation

408   coefficient/R, process relative error/P, peak flow relative error/E and coefficient of

409   water balance/W with rain gauge are 0.82, 0.89, 20%, 5% and 0.8 respectively, while

410   those with 24 hour lead time are 0.74, 0.86, 28%, 8% and 0.95 respectively, those with

411   48 hour lead time are 0.63, 0.84, 48%, 12% and 1.32 respectively, and are 0.56, 0.56,

412   56%, 18% and 1.54 respectively for 72 hour lead time. For flood event 2013, the Nash-

413   Sutcliffe coefficient/C, correlation coefficient/R, process relative error/P, peak flow

414   relative error/E and coefficient of water balance/W with rain gauge are 0.95, 0.92, 8%,

415   6% and 1.08 respectively, while those with 24 hour lead time are 0.87, 0.87, 9%, 12%

416   and 1.02 respectively, those with 48 hour lead time are 0.62, 0.86, 22%, 13% and 1.24

417   respectively, and are 0.61, 0.87, 75%, 17% and 1.66 respectively for 72 hour lead time.

418   This finding means that the current WRF QPF capability is lead-time dependent, and

419   with the increasing lead time, the practical value of WRF QPF gets lower.

420   **6 Conclusion**

421   In this study, the WRF QPF was coupled with a distributed hydrological model-the

422   Liuxihe model, for large watershed flood forecasting, and three lead times of WRF QPF

423   products, including 24 hours, 48 hours and 72 hours are tested. WRF QPF post

424   processing method is proposed and tested, model parameters are re-optimized by using

425   the post-processed WRF QPF, model performances are compared among various

426 conditions. Based on the results of this study, the following conclusions could be drawn:

427

428 1) The quantitative precipitation forecasting produced by WRF model has a similar

429 pattern with that estimated by rain gauges temporally, but overestimated the averaged

430 watershed precipitation for the event accumulated total precipitation. The longer the

431 WRF QPF lead time, the higher the precipitation overestimation. For flood event 2011,

432 the overestimated watershed averaged precipitation of WRF QPF with lead times of 24

433 hour, 48 hour and 72 hour are 23%, 32% and 55% respectively. For flood event 2012,

434 these are 16%, 37% and 71% respectively, while for flood event 2013, these are 50%,

435 73% and 95% respectively.

436

437 2. WRF QPF has systematic bias compared with rain gauge precipitation, and this

438 bias could be reduced via post-processing. Principle used in this study for WRF QPF

439 post processing is effective and could improve the flood forecasting capability. For

440 flood event 2011 with 24 hour lead time, the Nash-Sutcliffe coefficient/C, correlation

441 coefficient/R, process relative error/P, peak flow relative error/E and coefficient of

442 water balance/W with original WRF QPF are 0.65, 0.88, 35%, 14% and 1.44

443 respectively, but those with the post-processed WRF QPF are 0.75, 0.93, 23%, 8%

444 and 1.15 respectively. For flood event 2012 with 48 hour lead time, the above 5

445 evaluation indices with original WRF QPF are 0.63, 0.75, 48%, 12% and 1.43

446 respectively, and are 0.75, 0.84, 26%, 8% and 1.32 respectively with the post-

447 processed WRF QPF. For flood event 2013 with 72 hour lead time, the above 5

448 evaluation indices with original WRF QPF are 0.44, 0.75, 129%, 45% and 1.66

449 respectively, and are 0.55, 0.82, 98%, 23%, 1.25 respectively with the post-processed

450 WRF QPF.

451

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.

464

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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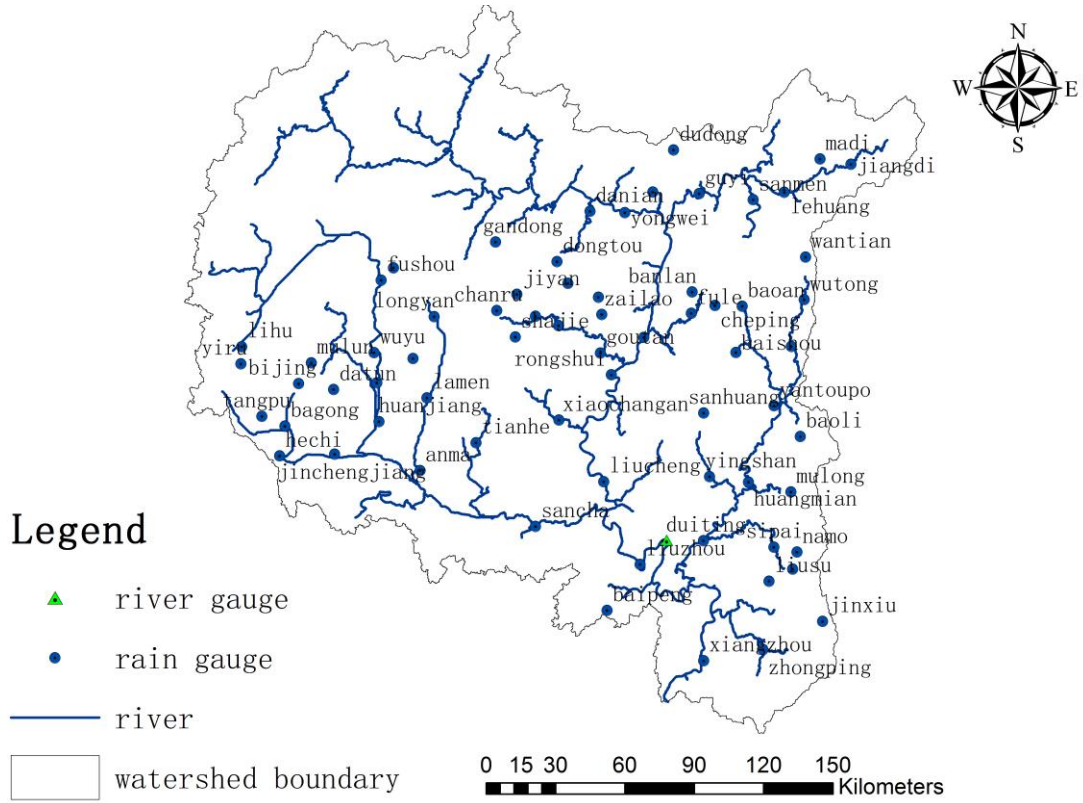
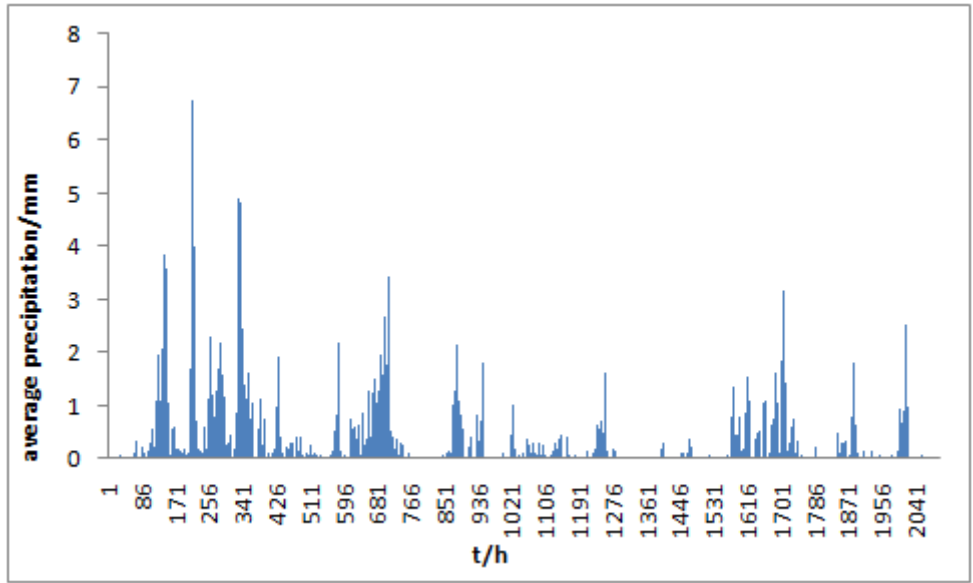
50479033), and the Basic Research Grant for Universities of the Ministry of Education

of China (fundingno.13lgjc01).

496

Figures

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

500

501

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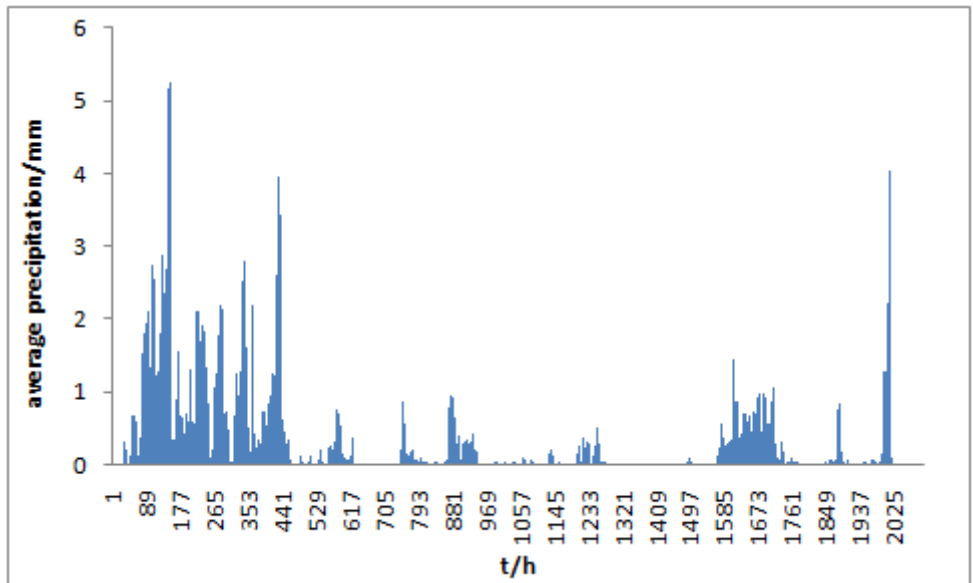
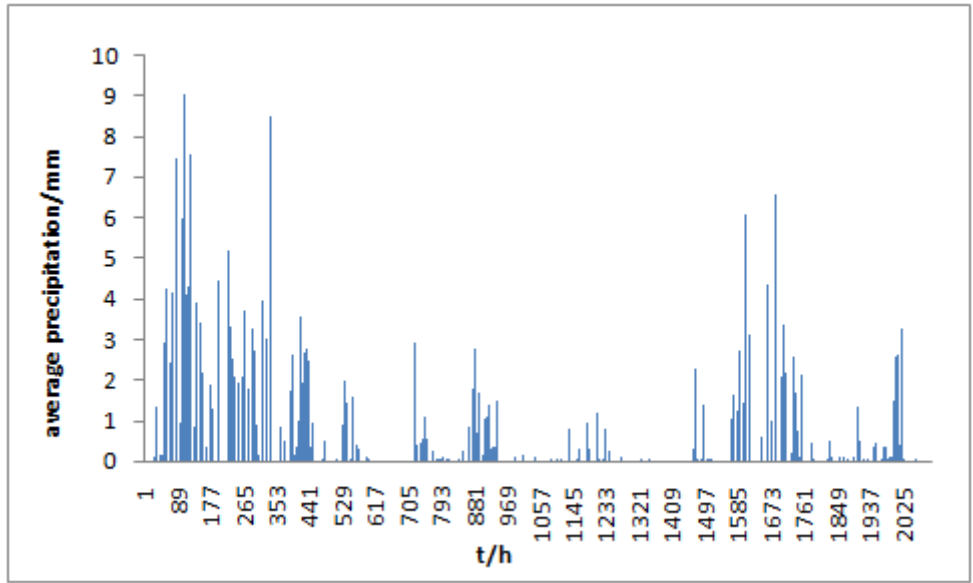
503   (a)

504

505   (b)

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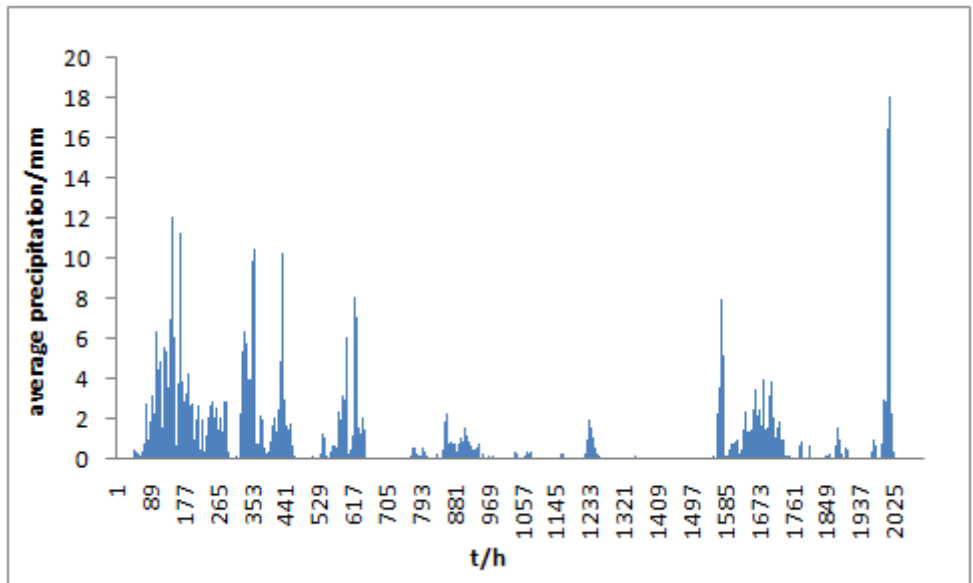
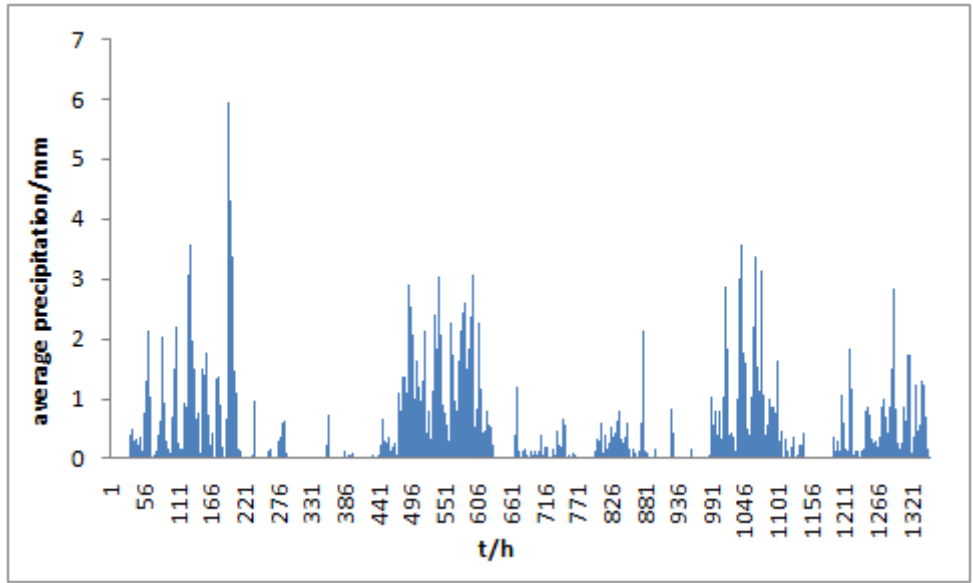
507   (c)

508

509   (d)

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

514

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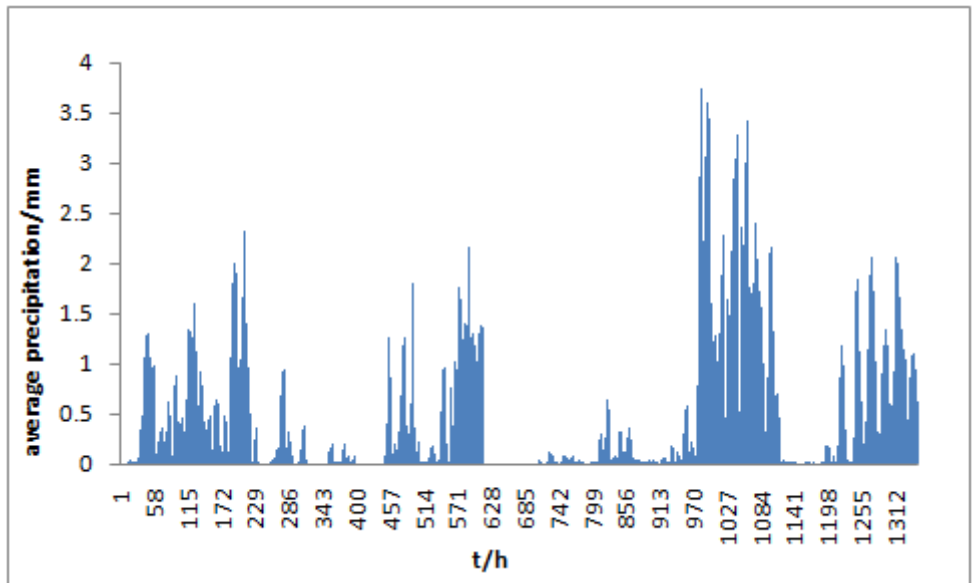
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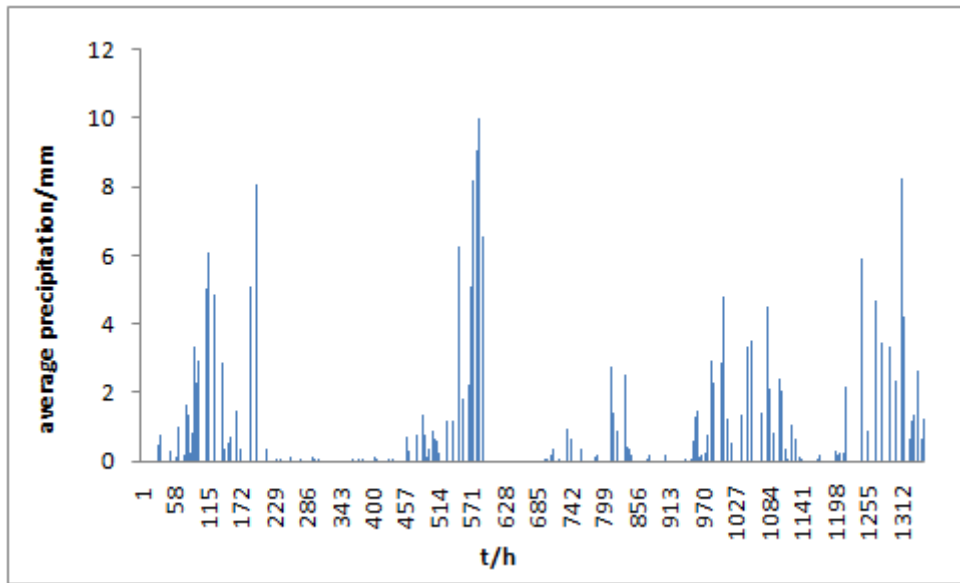
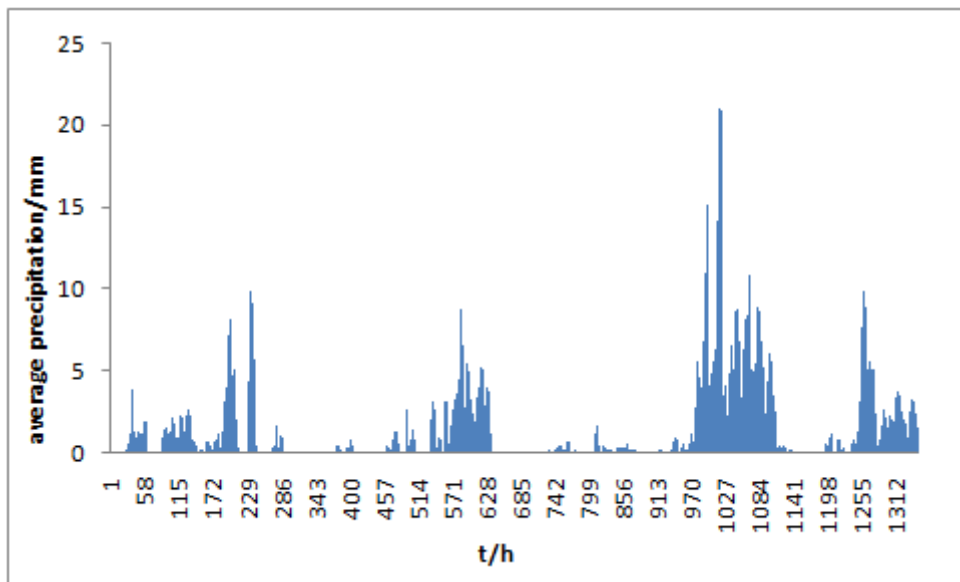
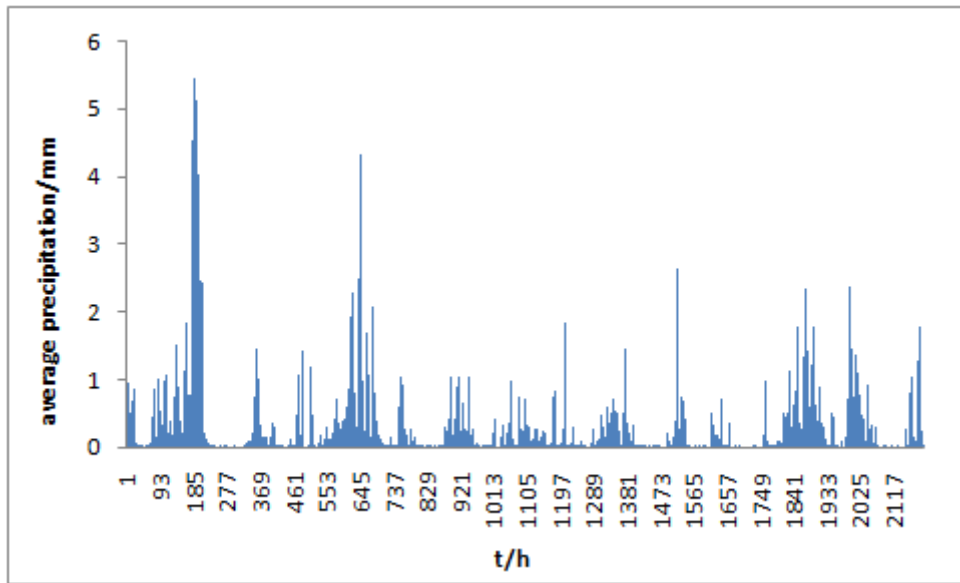
518   (b)

519

520   (c)

521

522   (d)

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

527

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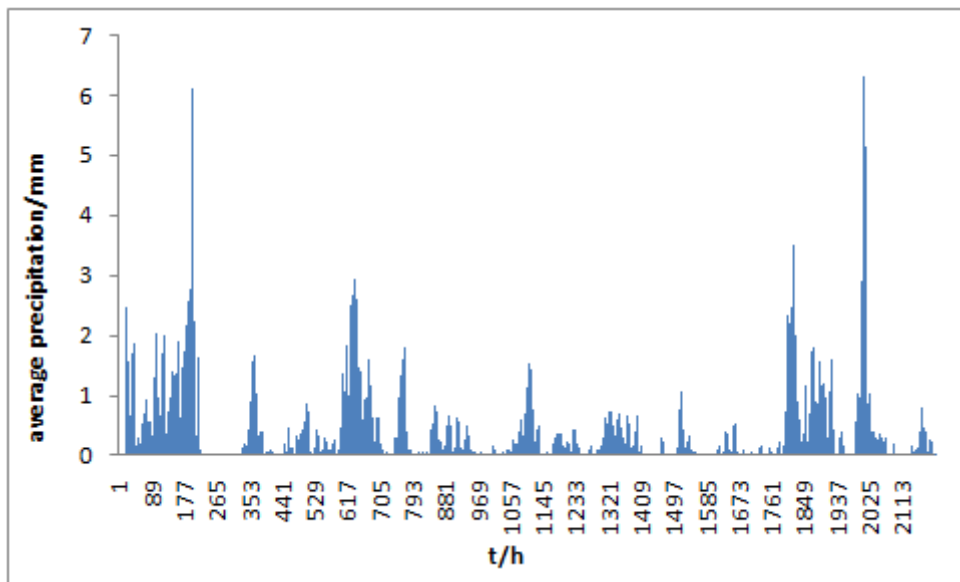
529   (a)

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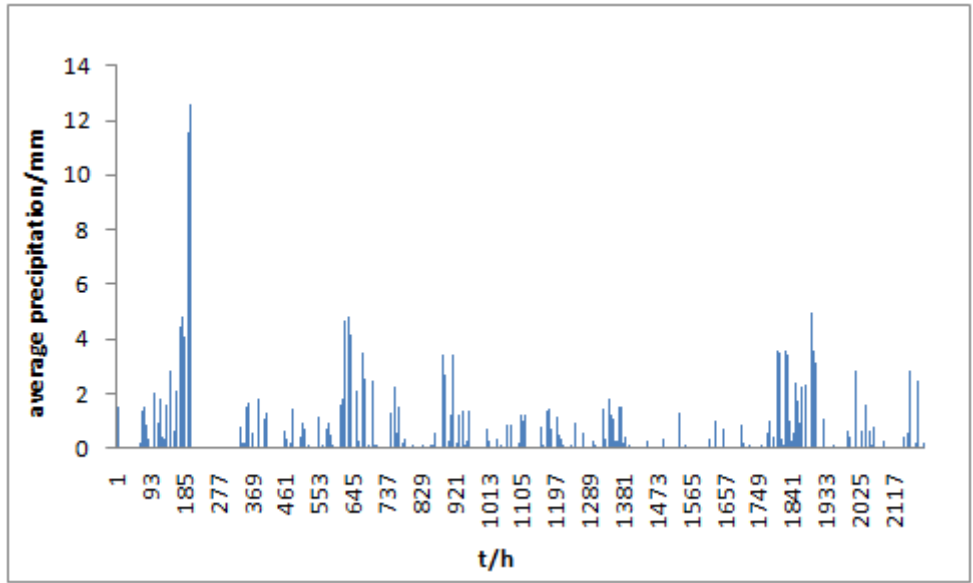
531   (b)

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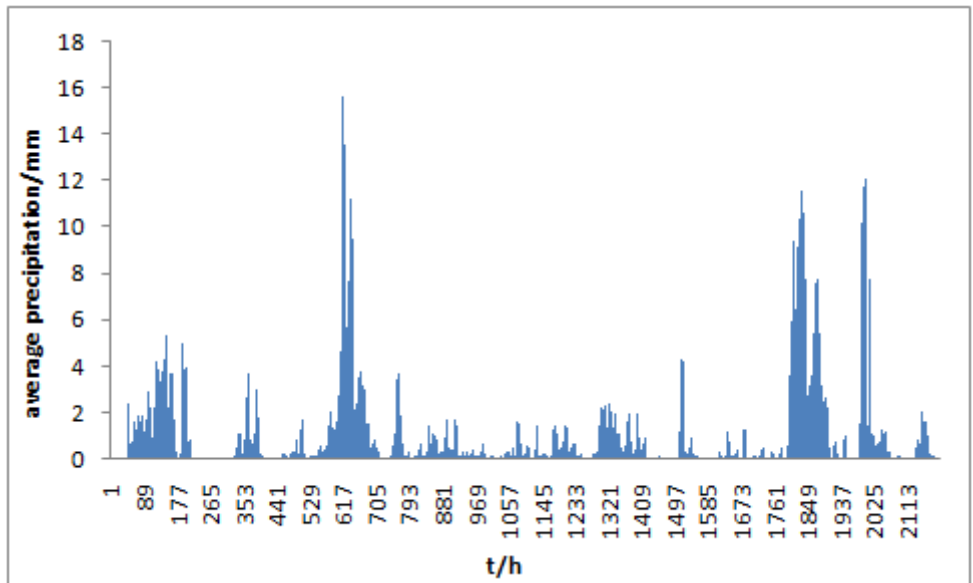
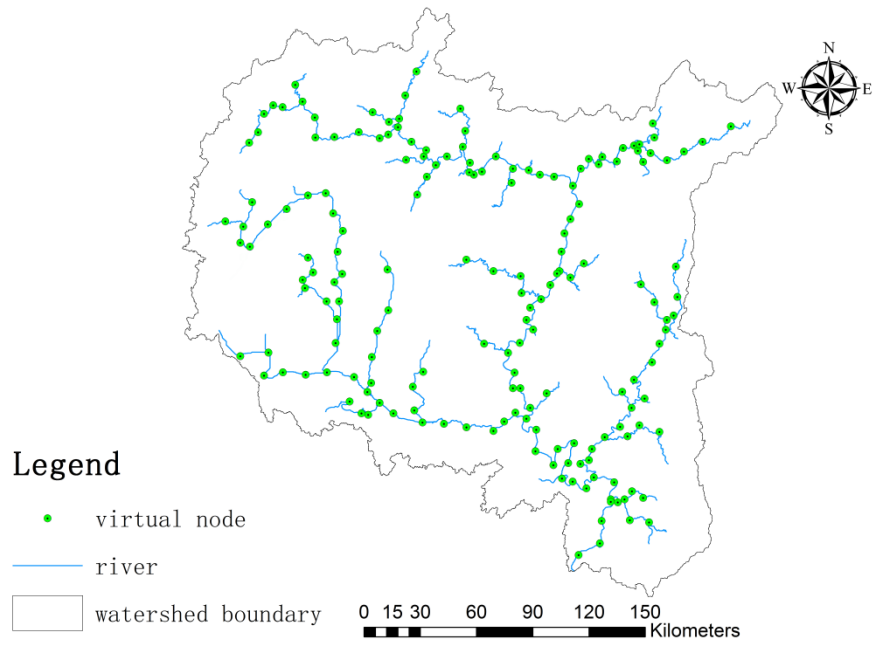

534

535   (d)

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

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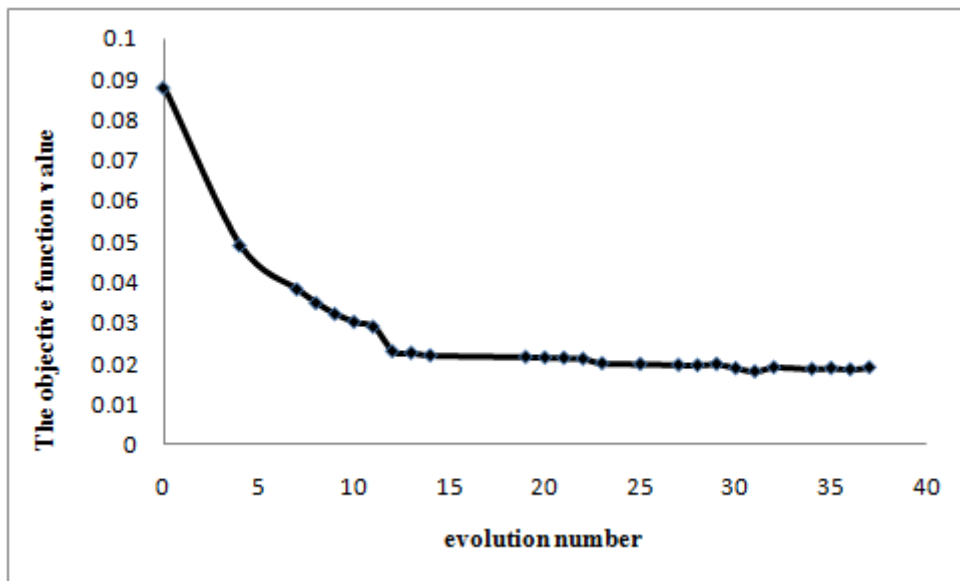
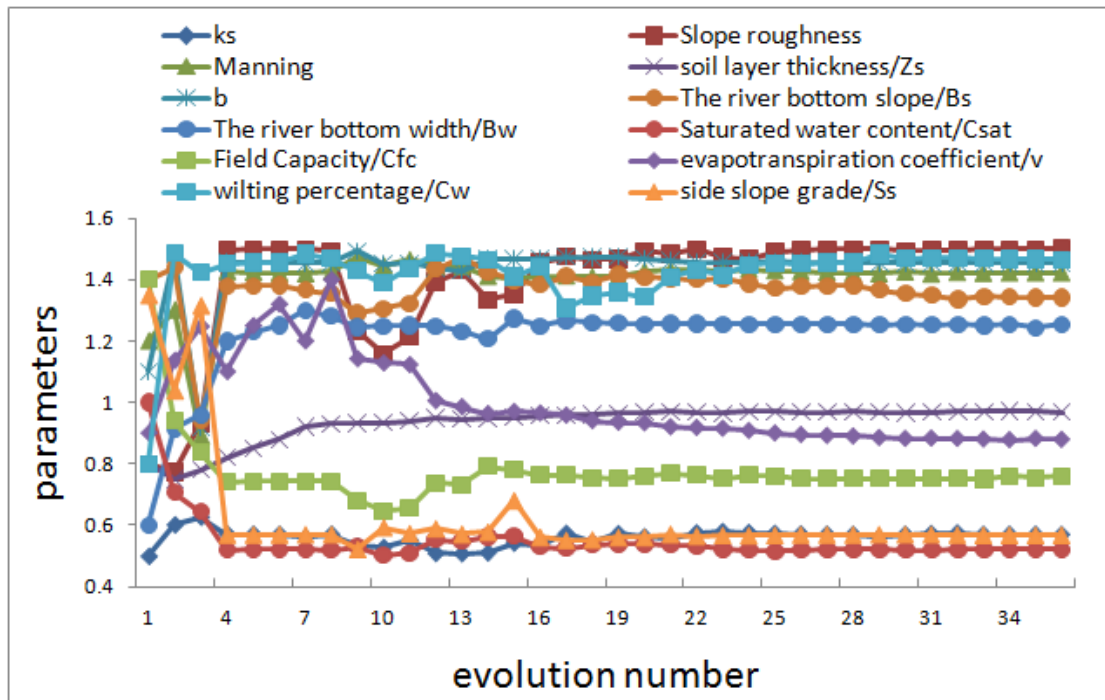
541   Fig.5 Liuxihe Model structure of LRB (200m×200m resolution, Chen et. al., 2017)

542

543   (a) Evolutionary process of objective function

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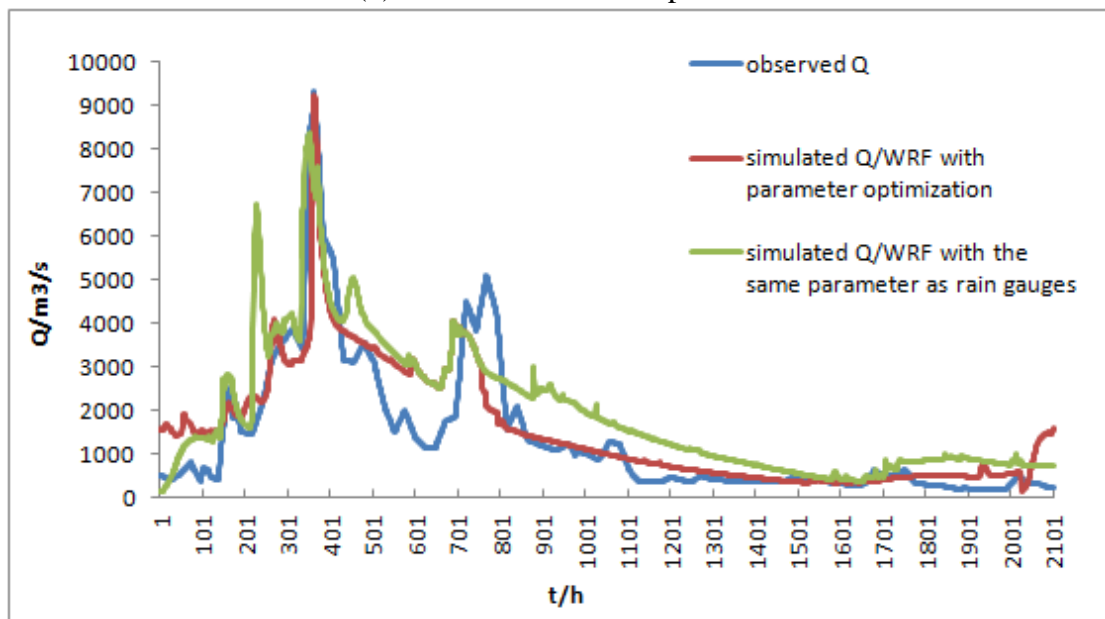
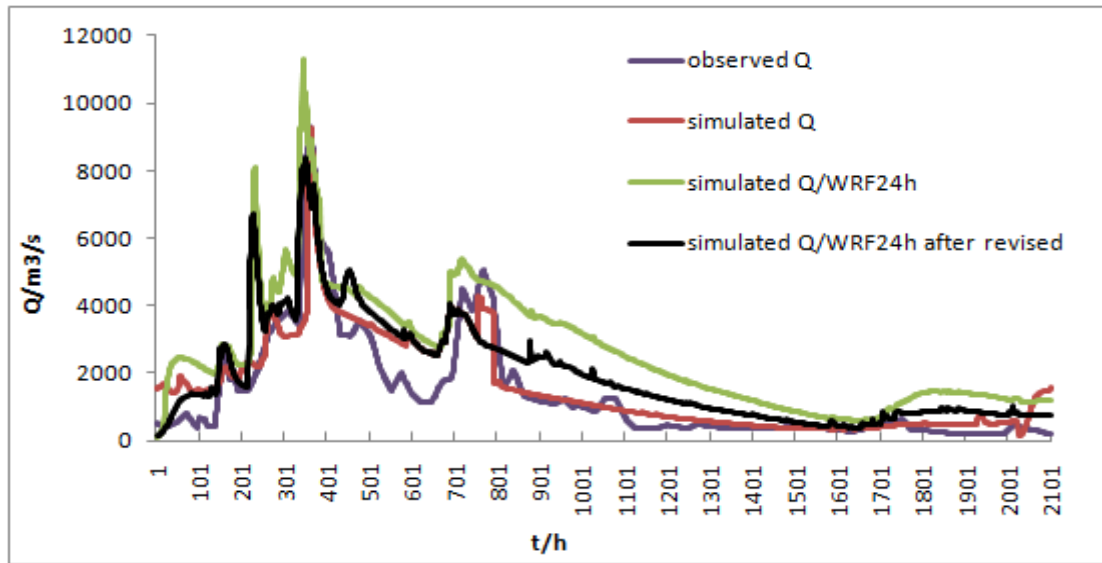
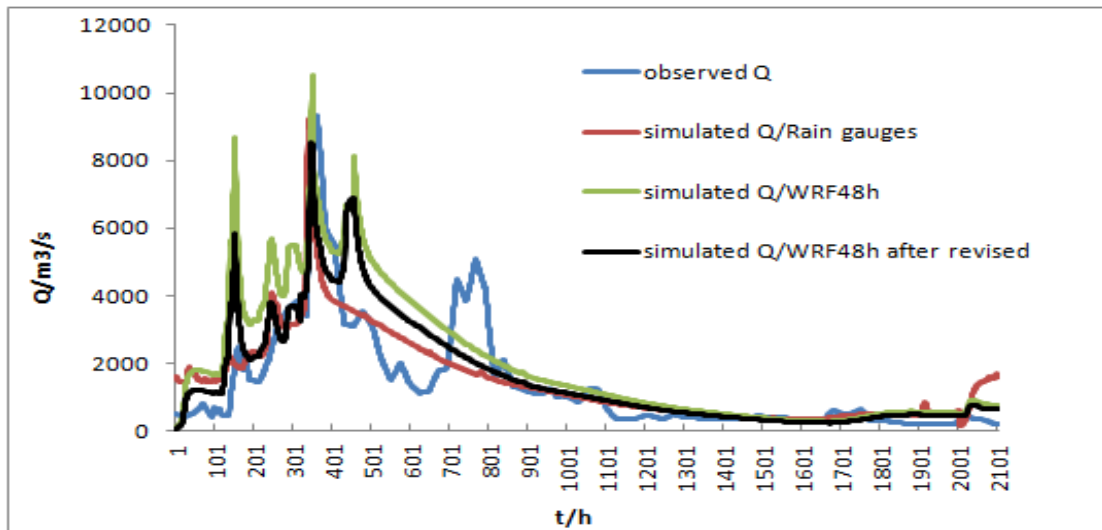
545   (b) Parameter evolution process

546
547   (c) Simulated flood process with optimized model parameters
548   Fig. 6 Parameter optimization results of Liuxihe Model for LRB with WRF QPF
549

550

551   (a) 24 hour lead time

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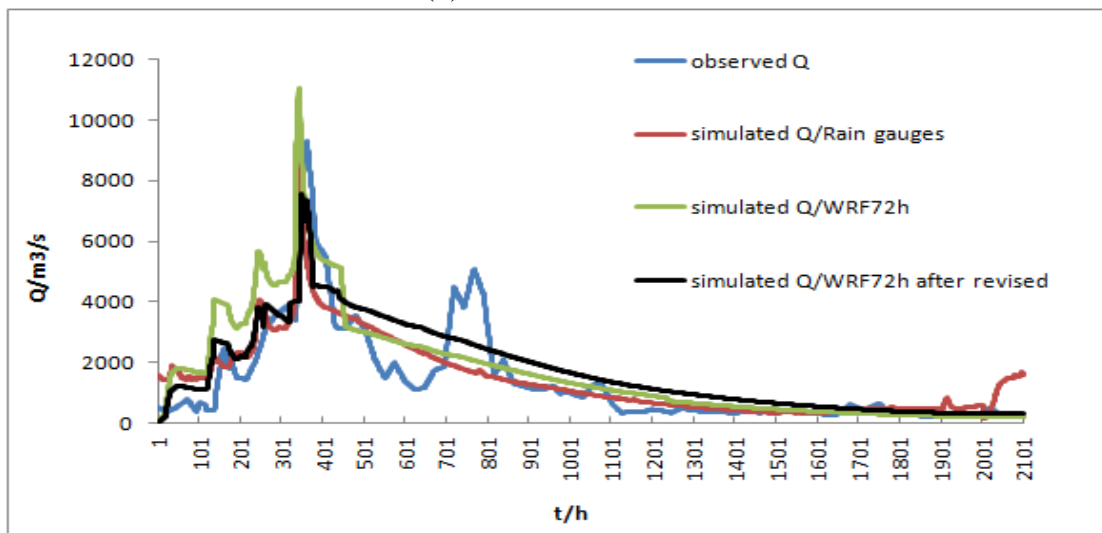
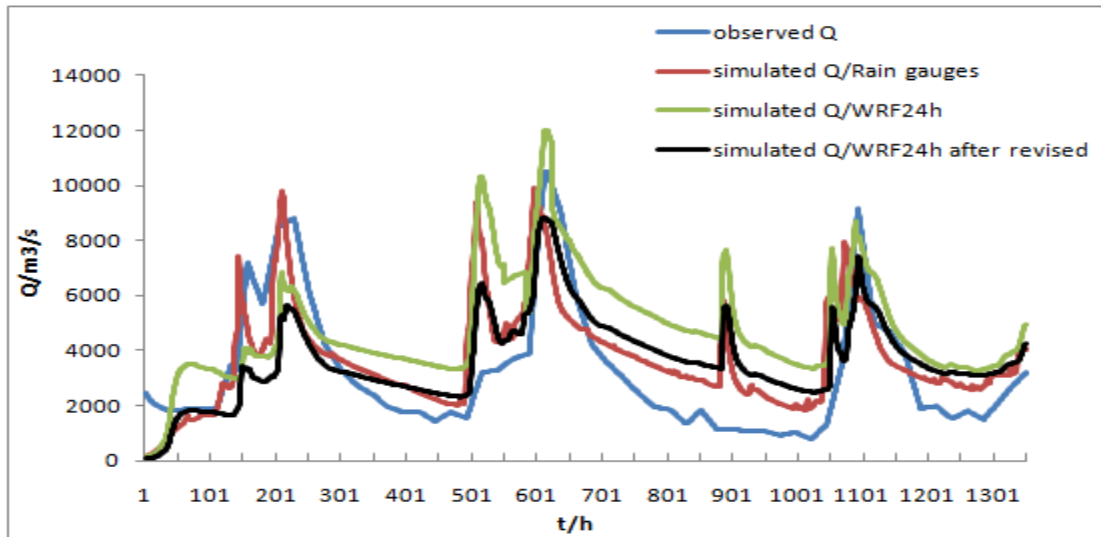
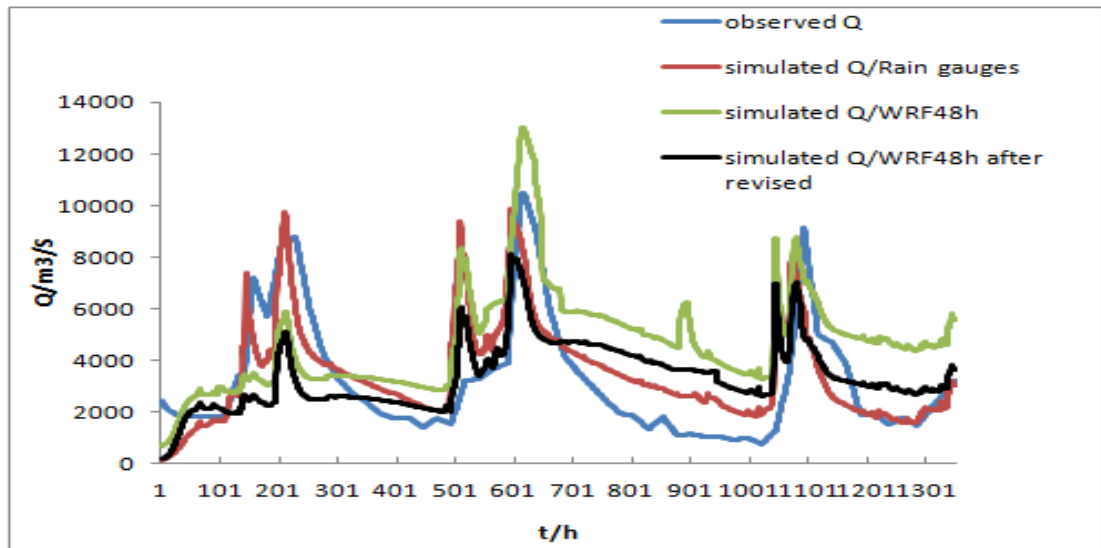
553   (b) 48 hour lead time

554

555   (c) 72 hour lead time

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

557
558   (a) 24 hour lead time

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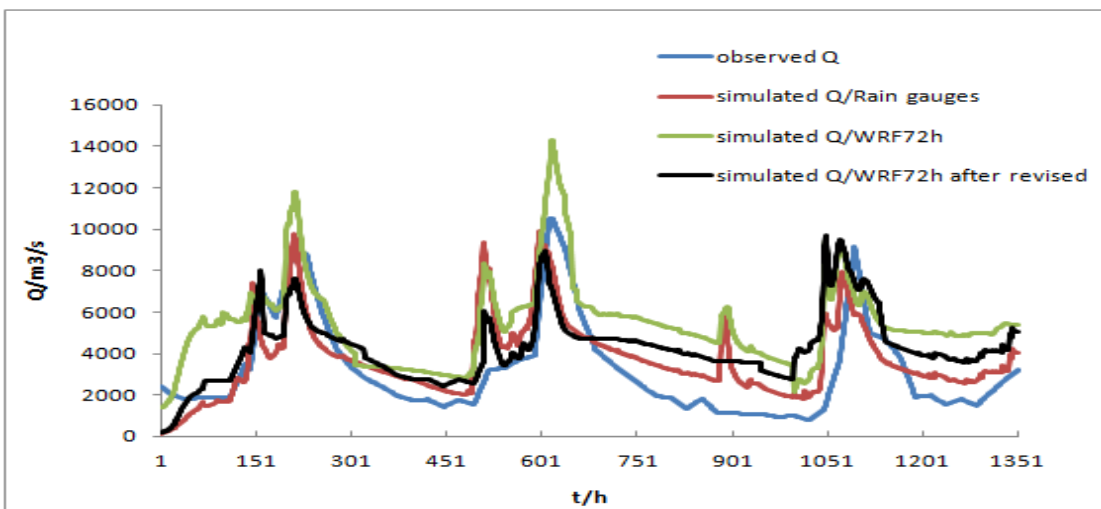
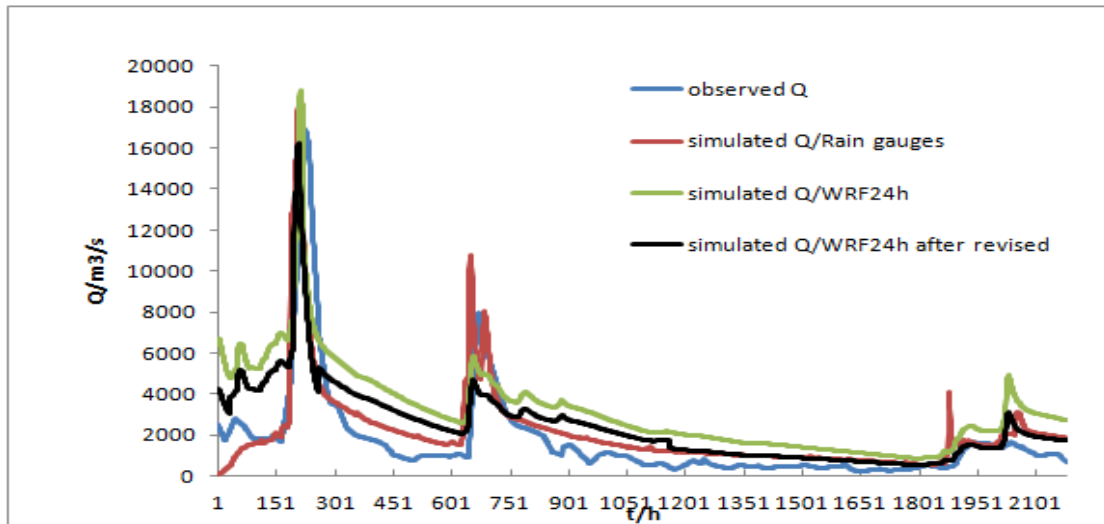
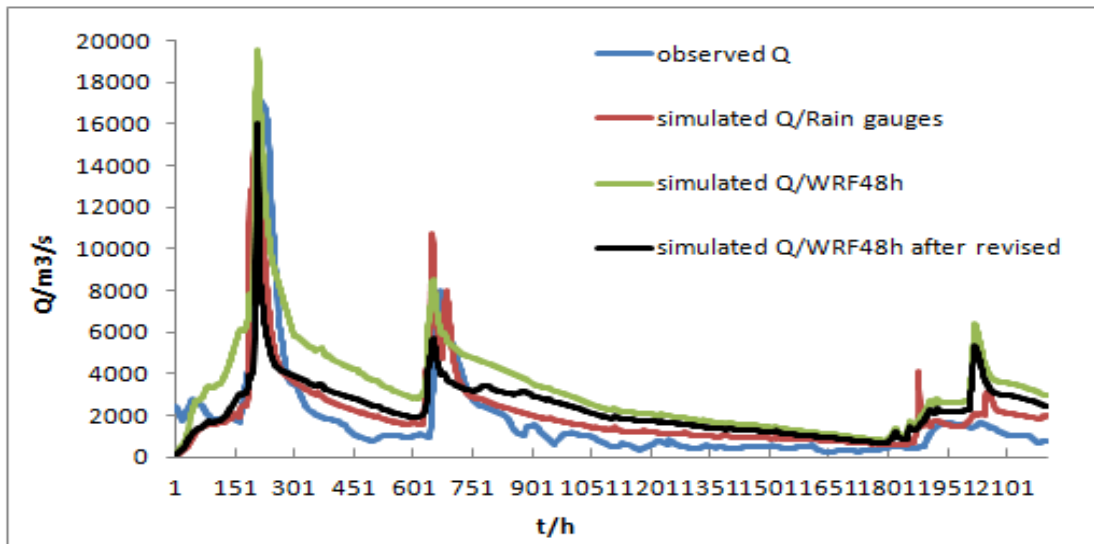
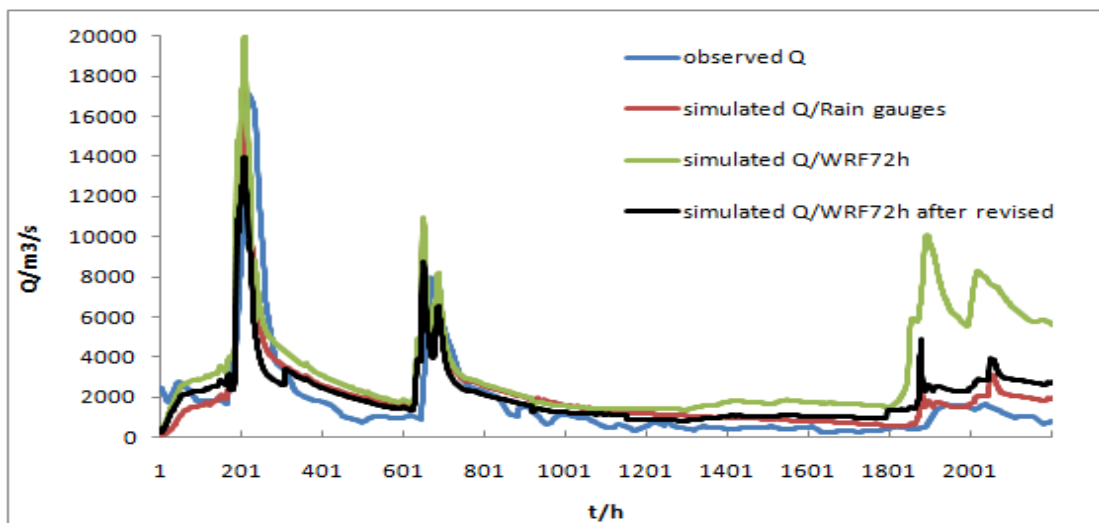
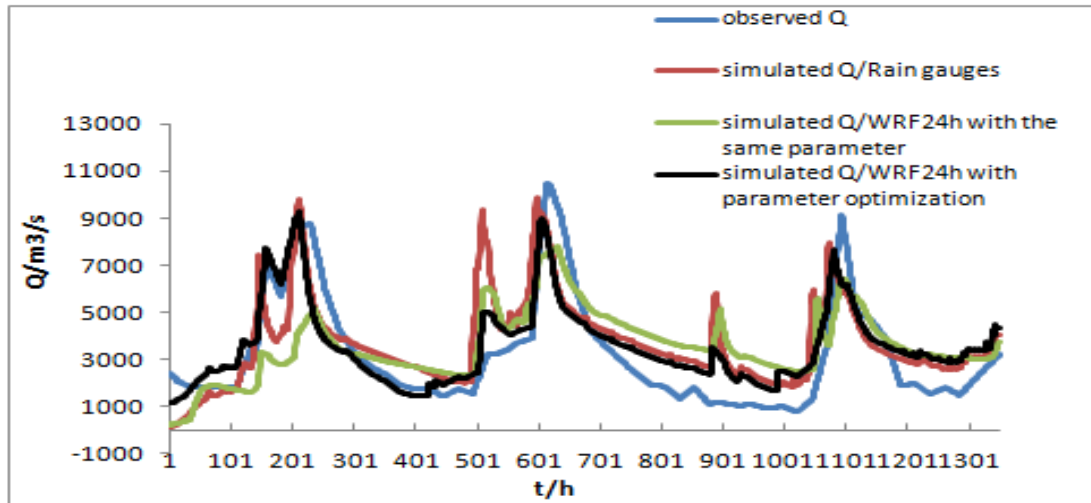
560   (b) 48 hour lead time

561

562   (c) 72 hour lead time

563   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)

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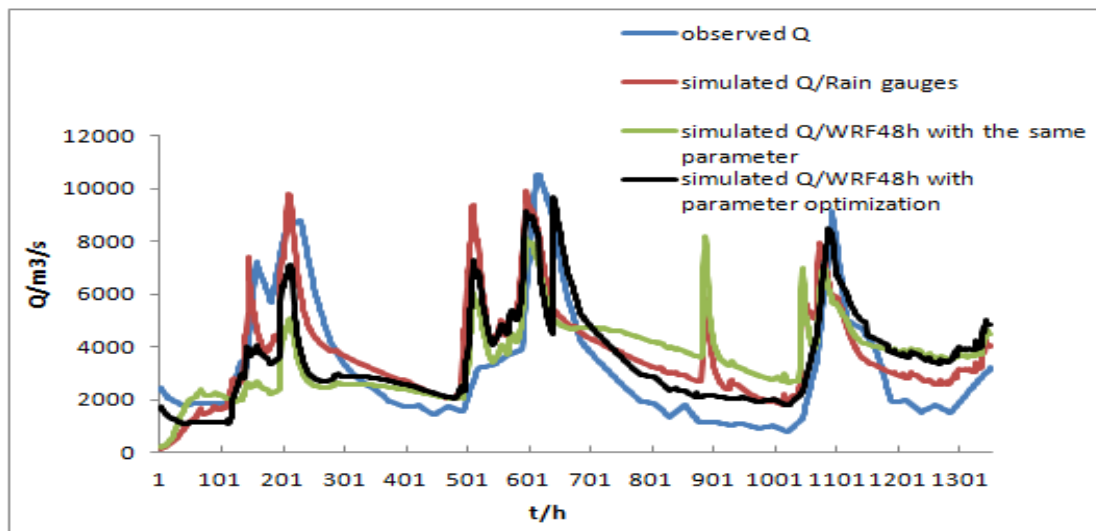
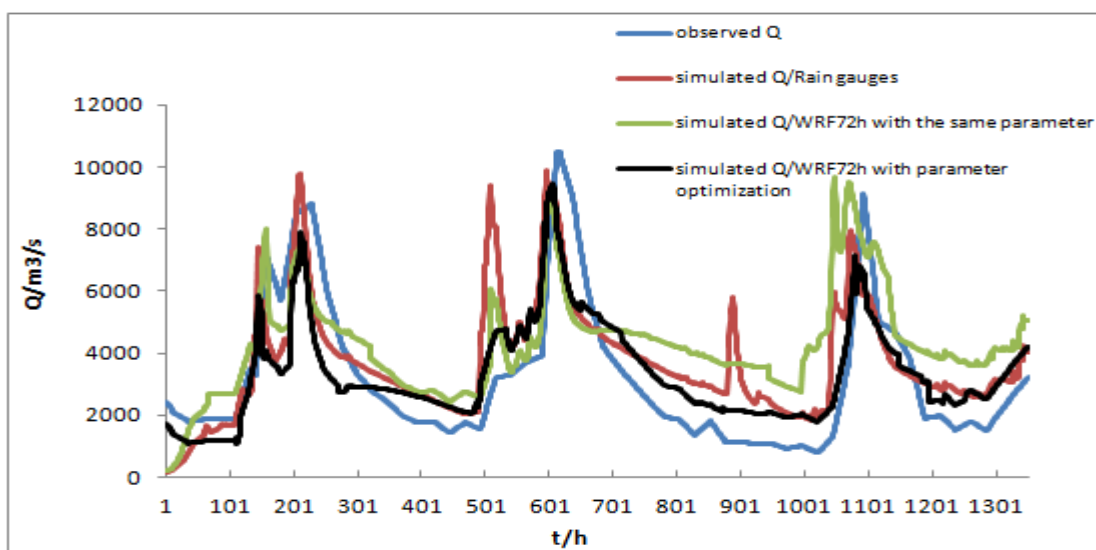
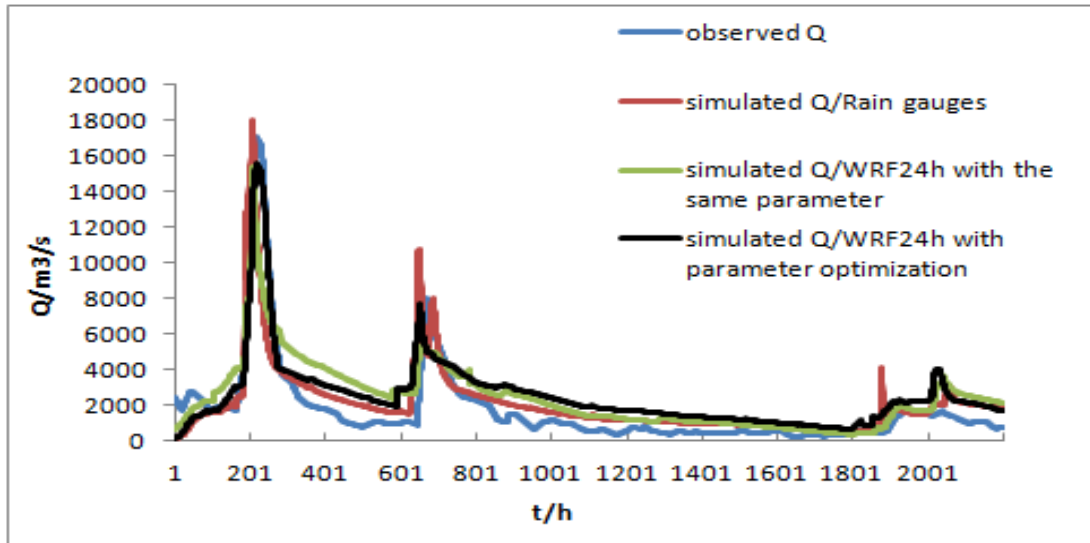
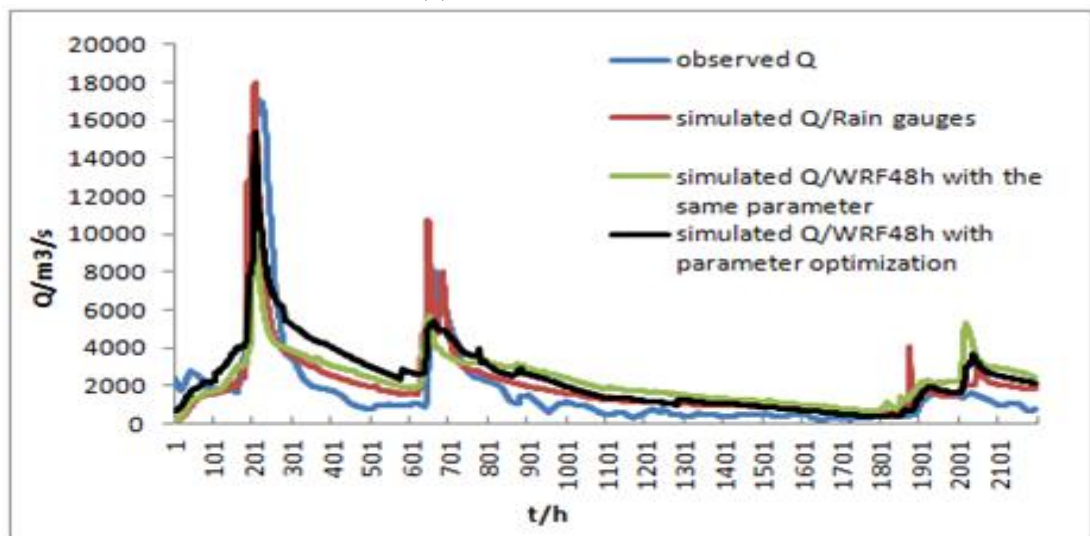
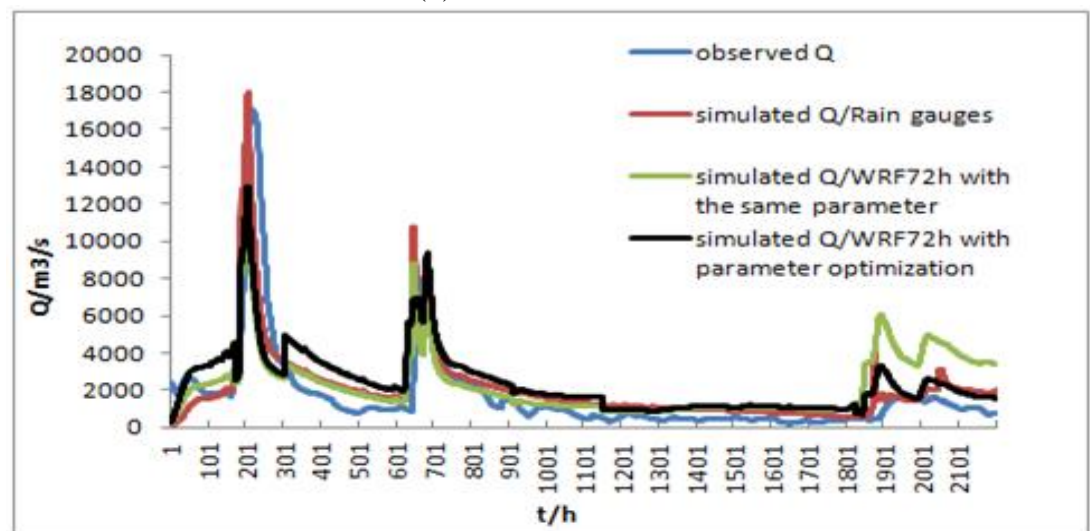
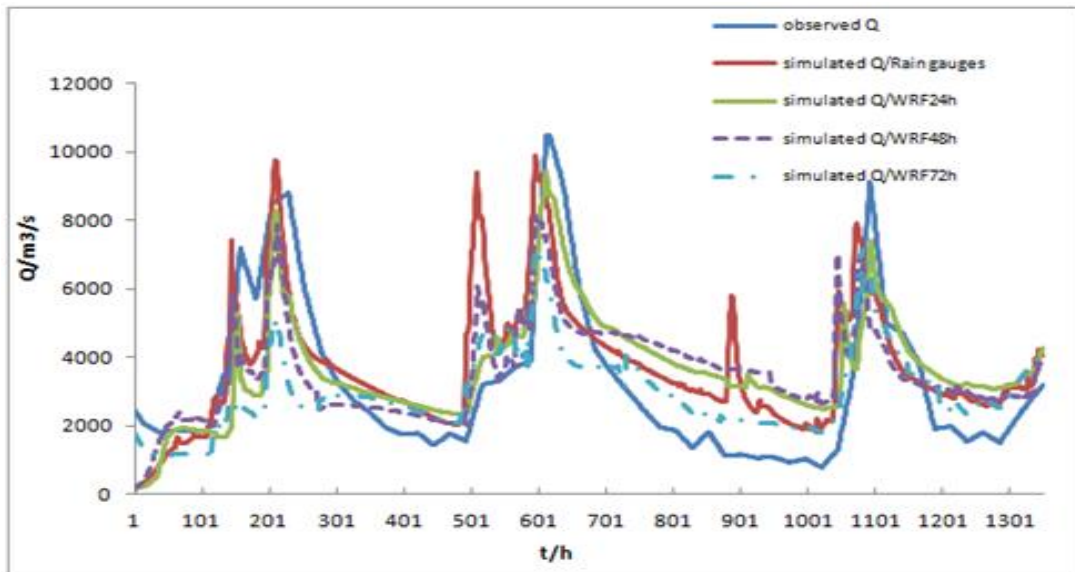
572 (a) 24 hour lead time

573
574 (b) 48 hour lead time

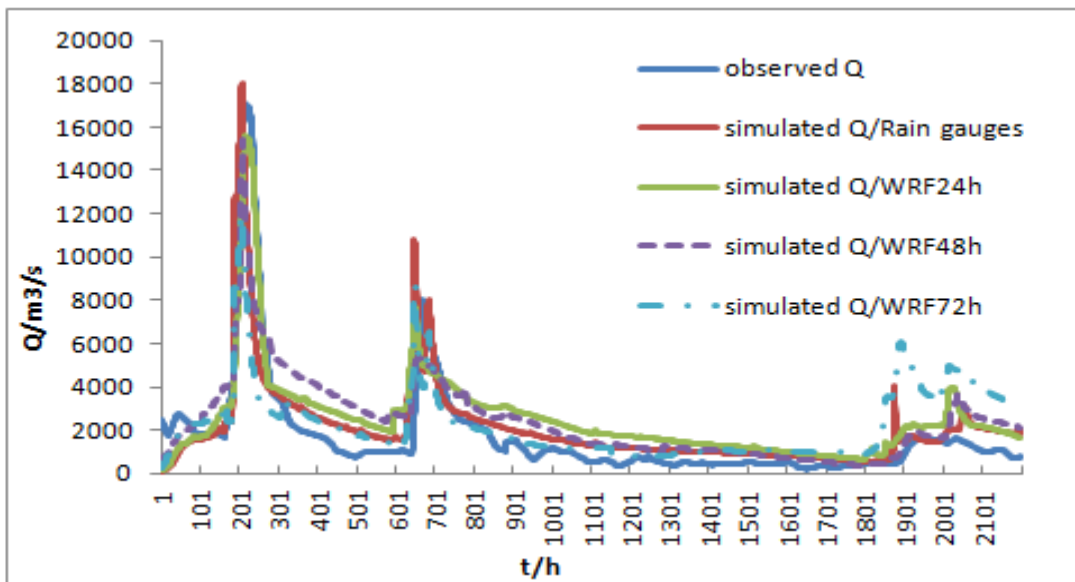
575

576 (c) 72 hour lead time

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

578

579   (a) 24 hour lead time

580
581   (b) 48 hour lead time

582
583   (c) 72 hour lead time

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

585

586   (a) Flood event 2012

587

588   (b) Flood event 2013
589   Fig. 12 Simulated results with different lead time
590

591 **Tables**

592 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

593

594

595 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

596

597 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

598

599 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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601

602

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