Large watershed flood forecasting with high resolution distributed hydrological model

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Abstract. Distributed hydrological model has been successfully used in small watershed flood forecasting, but there are still challenges for the application in large watershed, one of them is the model's spatial resolution effect. To cope with this challenge, two efforts could be made, one is to improve the model's computation efficiency in large watershed, another is implementing the model on high performance supercomputer. This study sets up a physically based distributed hydrological model for flood forecasting of Liujiang River Basin in south China. Terrain data DEM, soil and land use are downloaded from the website freely, and the model structure with a high resolution of 200m*200m grid cell is set up. The initial model parameters are derived from the terrain property data, and then optimized by using the PSO algorithm, the model is used to simulate 29 observed flood events. It has been found that by dividing the river channels into virtual channel sections and assuming the cross section shapes as trapezoid, the Liuxihe Model largely increases computation efficiency while keeping good model performance, thus making it applicable in larger watersheds. This study also finds that parameter uncertainty exists for physically deriving model parameters, and parameter optimization could reduce this uncertainty, and is highly recommended. Computation time needed for running a distributed hydrological model increases exponentially at a power of 2, not linearly with the increasing of model spatial resolution, and the 200m*200m model resolution is proposed for modeling Liujiang River Basin flood with Liuxihe Model in this study. To keep the model with an acceptable performance, minimum model spatial

resolution is needed. The suggested threshold model spatial resolution for modeling Liujiang River Basin flood is 500m*500m grid cell, but the model spatial resolution at 200m*200m grid cell is recommended in this study to keep the model a better performance.

Key words: watershed flood forecasting, distributed hydrological model, Liuxihe Model, parameter optimization, model spatial resolution

1 Introduction

Flooding is one of the most devastating natural disasters in the world, and huge damages has been caused (Krzmm, 1992, Kuniyoshi, 1992, Chen, 1995, EEA, 2010). Flood forecasting is one of the most widely used flood mitigation measurements, and watershed hydrological model is the major tool for flood forecasting. Currently the most popular hydrological model for watershed flood forecasting is still the so-called lumped model (Refsgaard et. al., 1996), which averages the terrain property and precipitation over the watershed, so do the model parameters. Hundreds of lumped models have been proposed and widely used, such as the Sacramento model proposed by Burnash et. al. (1995), the Tank model proposed by Sugawara et. al. (1995), the Xinanjiang model proposed by Zhao (1977), and the ARNO model proposed by Todini (1996), only naming a few among others. It is widely accepted that the precipitation for driving the watershed hydrological processes is usually unevenly distributed over the watershed, particularly for the large watershed, so the lumped model could not easily forecast the watershed flooding of large watersheds. Furthermore, due to the inhomogeneity of terrain property over the watershed, which is true even in very small watershed, so the watershed flood forecasting could not be forecasted accurately if the model parameters are averaged over the watershed. For this reasons, new models are needed to improve the watershed flood forecasting capability, particularly for large watershed flood forecasting.

Development of distributed hydrological model in the past decades provides the potential to improve watershed flood forecasting capability. One of the most important features of the distributed hydrological model is that it divides watershed terrain into grid cells, which are regarded to have the same meaning of a real watershed, i.e., the grid cells have their own terrain properties and precipitation. The hydrological processes are calculated at both the grid cell scale and the watershed scale, and the parameters used to calculate hydrological processes are also different at different grid cells. This feature makes it could describe the inhomogeneity of both the terrain property and precipitation over watershed. The distributed feature of the distributed hydrological model is a very important feature compared to lumped model, which makes it could better simulate the watershed hydrological processes at all scale, small or large. The inhomogeneity of precipitation over watershed could also be well described in the model, this is very helpful in modeling large watershed hydrological processes, particularly in the tropical and sub-tropical regions where the flooding is driven by heavy storm. For this reason, distributed hydrological model is usually regarded to have the potential to better simulate or forecast the watershed flood (Ambroise et. al., 1996, Chen et. al., 2016). Employing distributed hydrological model for watershed food forecasting has been a new trend(Vieux et. al., 2004, Chen et. al., 2012, Céline Cattoën et. al., 2016, Witold et. al., 2016, Kauffeldt et. al., 2016).

The blueprint of distributed hydrological model is regarded to be proposed by Freeze and Harlan (1969), the first distributed hydrological model was the SHE model proposed by Abbott et. al. (1986a, 1986b). Distributed hydrological model requires different terrain property data for every grid cells to set up the model structure, so it is data driven model. In the early stage of distributed hydrological modeling, this posted great challenge for distributed hydrological model's application as the data was not widely available and inexpensively accessible. With the development of remote sensing sensors and techniques, terrain data covering global range with high resolution has got readily available and could be acquired inexpensively. For example, the DEM at 30m grid cell resolution with global coverage could be freely downloaded (Falorni et al., 2005, Sharma et. al., 2014), which largely pushes forward the development and application of the distributed hydrological models. After that, many distributed hydrological models have been proposed, such as the WATERFLOOD model (Kouwen, 1988), THALES model (Grayson et al., 1992), VIC model (Liang et. al., 1994), DHSVM model (Wigmosta et. al., 1994), CASC2D model (Julien et. al., 1995), WetSpa model (Wang et. al., 1997), GBHM model (Yang et. al., 1997), WEP-L model (Jia et. al., 2001), Vflo model (Vieux et. al., 2002), tRIBS model(Vivoni et. al., 2004), WEHY model (Kavvas et al., 2004), Liuxihe model (Chen et. al., 2011, 2016), and more.

Distributed hydrological model derives model parameters physically from the terrain property data, and is regarded not need to calibrate model parameter, so it could be used in data poor or ungauged basins. This feature of distributed hydrological model made it applied widely in evaluating the impacts of climate changes and urbanization on hydrology(Li et. al., 2009, Seth et. al., 2001, Ott, et. al., 2004, Vanrheenen et. al., 2005, Olivera et. al., 2007). But it also was found that this feature caused parameter uncertainty due to the lack of experiences and references in physically deriving model parameters from the terrain property, so could not be used in fields that require high flood simulated accuracy, including watershed flood forecasting. It was realized that parameter optimization for distributed hydrological model is also needed to improve the model's performance, and a few methods for optimizing parameters of distributed hydrological model have been proposed. For example, Vieux et. al. (2003) tried a so-called scalar method to adjust the model parameters, and the model performance is found to be improved largely. Madsen et. al. (2003) proposed an automatic multi-objective parameter optimization method with SCE algorithm for SHE model, which improved the model performance also. Shafii et. al. (2009) proposed a multi-objective genetic algorithm for optimizing parameters of WetSpa model, the improved model result is regarded to be reasonable. Xu et. al. (2012) proposed an automated parameter optimization method with SCE-UA algorithm for Liuxihe Model, which improved the model performance in a small watershed flood forecasting. Chen et. al. (2016) proposed an automated parameter optimization method based on PSO algorithm for Liuxihe Model watershed flood forecasting, and tested in two watershed, one is small, one is large. The results suggested that distributed hydrological model should optimize model parameters even if there is only little available hydrological data, while the derived model parameters physically from the terrain perperty could serve as an initial parameters. The above progresses in distributed hydrological model's parameter optimization has matured, and will largely improve the performance of distributed hydrologcial model, thus pushing forward the application of distributed hydrologcial model in real-time watershed flood forecasting.

Spatial resolution is a key factor in distributed hydrological modeling. Theoretically if the spatial resolution of a distributed hydrological model is higher, i.e., the grid cell size is smaller, the terrain property could be described finer, and the hydrological processes could be better simulated or forecasted, so the model spatial resolution should be as high as possible. But on the other hand, higher model spatial resolution requires higher resolution terrain property data for model setting up which may not be available in some watersheds. But the most important is that distributed hydrological model uses complex equations with physical meanings to calculate the hydrological processes, so it needs much more computation resources than that of lumped model, and the required computation resources increases exponentially with the increasing of the model spatial resolution. So in modeling flood processes of a large watershed, the computation time needed for running the distributed hydrological model will be huge if the model spatial resolution is kept high, which may make the model application impractical due to high running cost. So if distributed hydrological model is needed to be applied in large watershed, a coarser resolution is the only choose, and the model's capability will be impacted with less satisfactory results. This is also called the scaling effect of distributed hydrological modeling. For this reason, current application for watershed flood forecasting either limited to small watershed with higher resolution or coarser resolution in large watershed, i.e., a trade-off between the model performance and running cost.

Nowadays forecasting large watershed flooding has been in great demands as it impacts peoples and their properties at large range, but due to the scale effect, current distributed hydrological models employed for large watershed are at coarser resolution, which lowers its capability for flood forecasting and warning. For example, past application of distributed hydrological model for large watershed flood forecating are at the resolution coarser than 1km grid cell (Lohmann et. al., 1998, Vieux et. al., 2004, Stisen et. al., 2008, Rwetabula et. al., 2007), the models employed in the pan-European Flood Awareness System (EFAS; Bartholmes et. al., 2009, Thielen et. al., 2009, 2010, Sood et. al., 2015, Kauffeldt et. al., 2016) are at 1-10km grid cell, which makes the result only applicapble for flood warning.

Challenge for distributed hydrological model application in large watershed flood forecasting is its need for huge computation resources, to cope with this challenge, two efforts could be made. One is to improve the computation efficiency of the distributed hydrological modeling in large watershed, another is implementing the model on high performance supercomputer so in the cases that the users are willing to pay a high computation cost, the flood forecasting of large watershed with high resolution could be done. In this study, the Liuxihe Model (Chen et. al., 2011, 2016), a physically based distributed hydrological model proposed for watershed flood forecasting, has been tried for flood forecasting of a large watershed in southern China to validate the feasibility of distributed hydrological model's application for large watershed flood forecasting.

2 Method and data

2.1 Liujiang River Basin

The river basin studied in this paper is the Liujiang River Basin(herein after referred to as LRB) in south China, which is the first order tributary of the Pearl River. LRB originates from Village Lang in Guizhou Province, and drains though Guizhou Province, Guangxi Zhuang Autonomous Region and Hunan Province with 72% of its drainage area in Guangxi Zhuang Autonomous Region. The length of its main channel is 1121 km, the total drainage area is 58270 km^2 that marks it a large river basin in China.

Fig. 1 sketch map of Liujiang River Basin(LRB)

LRB is a mountainous watershed. There are high mountains in the north and northwest of the watershed with high elevation, while in its south and southeast area, the elevations are relatively low. This topography helps forming severe flooding in the middle and downstream. The basin is in the sub-tropical monsoon climate zone with an average annual precipitation of 1800 mm, and the precipitation distribution is highly uneven both at spatial and temporal with 80% of its annual precipitation occurs in the summer. LRB is in the center of storm zone of Zhuang Autonomous Region, heavy storm was very frequent in the past. There are 59 disastrous flooding in the past 400 years with recording since 1488, which makes LRB the tributary with most disastrous flooding among all the first order tributaries of the Pearl River. In the watershed, there is no significant reservoirs to store flood runoff, so flood forecasting is one of the most effective ways for the flood management.

2.2 Liuxihe Model

Liuxihe Model is a physically based distributed hydrological model proposed mainly for watershed flood forecasting (Chen, 2009, Chen et. al., 2011, 2016). Like other distributed hydrological models, Liuxihe Model divides the watershed into grid cell based on the DEM of the studied watershed. To keep a reasonable model performance, in the past experiences of Liuxihe Model research and application, the model resolution is limited to 90m*90m or 100m*100m, but only used in small watersheds (Chen, 2009, Chen et. al., 2011, 2013, 2016, Liao et. al., 2012 a, b, Xu et. al., 2012 a, b). Precipitation, evaporation and runoff production are calculated at cell scale, runoff routes first on cell, then along the cell to river channel, and finally to the watershed outlet. As Liuxihe model is mainly used in the sub-tropical regions, so the runoff production is calculated based on the saturation-excess mechanism(Zhao, 1977). The runoff routing is classified as hill slope routing, river channel routing, subsurface routing and underground routing. The hill slope routing is regarded as the one-dimensional unsteady flow, and the kinematical wave approximation is employed to do the routing. The river channel routing is also regarded as the one-dimensional unsteady flow, but the diffusive wave approximation is employed to do the routing. The above methods are widely used in the dominated distributed hydrological models.

What makes Liuxihe Model unique is that the river channel cross section shape is assumed to be trapezoid. With this assumption, the river channel size could be represented with 3 dimensions, including the bottom width, side slope and bottom slope. One of the advantages with this assumption is that the river channel cross section size could be estimated with remotely sensed data(Chen, et.al, 2011), so Liuxihe Model could do river channel runoff routing real physically, thus making Liuxihe Model a fully distributed hydrological model. As there are too many river channel cross sections, and many of them are in the upstream of the watershed where it is not easily accessed, so in real hydrological modeling, directly measuring the river channel cross section sizes are impractical considering the high cost. For this reason, most of the distributed hydrological model could not be applied in real applications, or simply route the runoff with lumped methods which makes the model not a fully distributed hydrological model, thus lowering the model's capability in simulating or forecasting the watershed flood processes. Another advantage of this assumption is that it also simplifies the runoff routing, thus improves the model's computation efficiency. For this reason, even Liuxihe Model has a very high resolution, it still could be used in real-time flood forecasting. This feature of Liuxihe Model in estimating river channel cross section sizes makes it has the potential to be used in large watershed flood forecasting.

Like other distributed hydrological model, when used in ungauged or data poor watershed flood forecasting, Liuxihe Model derives model parameters physically from the terrain property data. But if there is observed hydrological data, automatic parameter optimization methods could been tried. But as automatic parameter optimization needs thousands model runs, that makes it difficult to be used widely due to huge computing source requirement, which also make it taking long time in setting up the model. For this reason, a public computer cloud was set up for optimizing the parameters of Liuxihe Model which employs parallel computation techniques and was implemented on a supercomputer system(Chen et. al., 2013). With this development, Liuxihe Model could easily optimize its model parameters.

Above advancements of Liuxihe Model in estimating river channel cross section sizes with remotely sensed data, automatic parameters optimization and supercomputing makes it has the potential to be used in large watershed flood forecasting, so in this study, the Liuxihe model is employed to study the LRB's flood forecasting.

2.3 Hydrological data

There are 66 rain gauges installed in the watershed. In this study, hydrological data of 30 flood events has been collected, including the precipitation of the rain gauges and the river discharge of Liuzhou river gauge that locates in the downstream of the watershed and closes to the outlet as shown in Fig. 1 with a hourly step, brief information of these flood events is listed in Table 1.

Table1 Brief information of flood events with data collected in LRB

2.4 Terrain property data

Terrain property data includes DEM, land use/cover map and soil map, which are used for setting up the distributed hydrological model for flood forecasting. In this study, the DEM was downloaded from the SRTM database (Falorni et al., 2005, Sharma et. al., 2014), the land use type was downloaded from the USGS land use type database (Loveland et. al., 1991, Loveland et. al., 2000), and the soil type was downloaded from FAO soil type database (http://www.isric.org). The downloaded DEM has a spatial resolution of 90m*90m, considering LRB is large, the running load for the model with a resolution of 90m*90m may be too heavy to run in this study, so the DEM is rescaled to the resolutions of 200m*200m, as shown in Fig. 2(a). The downloaded land use and soil type were at 1000m*1000m resolution, so there are rescaled to the same resolution of DEM, as shown in Fig. 2(b) and Fig. 2 (c) respectively.

Fig. 2 Terrain properties of LRB

The highest elevation and the lowest elevation of LRB are 2124 m and 42 m respectively. There are 9 land use types, including evergreen needle leaved forest(18.1%), evergreen broadleaved forest(31.0%), shrubbery(32.5%), mountain and alpine meadow(0.1%), slope grassland(13.7%), urban area(0.1%), river(0.2%), lakes(0.3%) and cultivated land(4%).

There are 11 soil types, including Humicacrisol(0.8%), Haplic and high activitive acrisol(1.5%), Ferralic cambisol(5%), Haplicluvisols(3.5%), Dystric cambisol(2.8%), Calcaric regosol(45.5%), Dystric regosol(2.9%), Haplic and weak active acrisol(18%), Artificial accumulated soil(1.5%), Eutricregosols and Black limestone soil(3.5%), Dystric rankers(15%).

3 Results

3.1 Liuxihe Model set up

Considering LRB is large, so the DEM with 200m×200m resolution is adopted to set up the model structure, not at the original 90m×90m resolution. The whole watershed is first divided into 1469900 cells by the DEM horizontally, which were further categorized into hill slope cells and river cells. By using Strahler method (Strahler, 1957), the river channel is divided into 3 order system as shown in Fig. 3, which divides the whole cells into 1463204 hill slope cells and 6696 river cells.

Fig. 3 Liuxihe Model structure set up for LRB (200m×200m resolution)

To estimate the river channel sizes, 178 virtual nodes were set on the river channel system, and 225 virtual channel sections were formed as shown in Figure 3. As in Liuxihe Model, the shape of the virtual channel sections is assumed to be trapezoid, so the cross section size is represented by three dimensions, including bottom width, side slope and bottom slope. As proposed in Liuxihe Model, the bottom width is estimated based on the satellite remote sensing imageries. For the side slope, it is a low sensitive data, so it could be estimated based on local experiences. For the bottom slope, it is calculated with the DEM along the virtual channel section.

3.2 Parameter optimization

In Liuxihe Model, an initial parameter set was derived first based on the terrain properties, including the DEM, soil type and land use/cover type, then the parameters will be optimized. In this study, for the insensitive parameter of the land use/cover related parameters, which is the evaporation coefficient, the initial value is set to be 0.7 for all cells based on the experiences. The initial value of roughness, i.e., the Manning's coefficient, which is the sensitive parameter of the land use/cover related parameters, is derived from the land use/cover type based on references (Chen et.al., 1995, Zhang et.al., 2006, 2007, Shen et.al., 2007, Guo et.al., 2010, Li et.al., 2013, Zhang et.al., 2015), and listed in Table 2.

Table 2 The initial values of land use/cover related parameters

For the soil related parameters, including the water content at saturation condition, the water content at field condition, the water content at wilting condition, hydraulic conductivity at saturation condition, soil thickness and soil porosity characteristics coefficient b. Based on past modeling experiences and references (Zaradny, 1993, Anderson et al., 1996), a value of 2.5 is set to b for all soil type, and the water content at wilting condition is set to be 30% of the water content at saturation condition. The soil thickness is estimated based on local experiences and listed in Table 3 for all soil types. The initial values of the water content at saturation condition, the water content at field condition and hydraulic conductivity at saturation condition are estimated by using the Soil Water Characteristics Hydraulic Properties Calculator (Arya et al., 1981) based on soil texture, organic matter, gravel content, salinity and compaction. The estimated initial values of soil-related parameters are listed in Table 3.

Table 3 The initial values of soil related parameters

In this study, PSO algorithm is employed to optimize the initial model parameters as PSO algorithm has been integrated into the Liuxihe Model Cloud (Chen et. al., 2013, Chen et. al., 2016). The number of particles of PSO algorithm is set to 20, while the value range of inertia weight ω is set to 0.1 to 0.9, the value range of acceleration coefficients C1 is set to 1.25 to 2.75, and C2 to 0.5 to 2.5, and the maximum iteration is set to 50. Flood event of 20080609 is selected to optimize the parameters of Liuxihe model, and Fig. 4 shows the result of the parameter optimization. Among them, Fig. 4(a) is the parameters evolving process, Fig. 4(b) is the changing curve of objective function which is set to minimize the peak flow error, Fig.4(c) is the simulated hydrograph of flood event 20080609 with the optimized parameters.

Fig. 4 Parameter optimization results of Liuxihe Model for LRB with PSO algorithm

From the results in Fig. 4, it could be found that after 14 evolutions, the parameters optimization process converges to its optimal values, and the optimal parameters are achieved, the simulated hydrological process of flood event that is used for parameter optimization is quite good fitting the observed hydrological process, it could be said that the parameter has a good optimization effect.

As mentioned above, the automatic parameter optimization of the distributed hydrological model is very time consuming. In this study, even supercomputer is employed with parallel computation techniques, the time used for this parameter optimization is overwhelming, the total time used for achieving the above optimal parameters of Liuxihe model for LRB flood forecasting is 220 hours, more than 9 days. Considering several runs are usually needed before achieving the final results, so the parameter optimization procedure may take a few months, this run time is really a good investment, but the validation results proves this is worth.

3.3 Model validation

The other 29 flood events were simulated by using the Liuxihe model with the above optimized parameters, and the simulated hydrographs of 8 flood events are shown in Fig. 5, the simulated hydrographs of 8 flood events with initial parameters are also shown in Fig. 5.

Fig. 5 Simulated flood events by Liuxihe Model with optimized parameters

From the result of Fig. 5, it has been found that the simulated flood processes fits the observation reasonably well, particularly the simulated peak flow is quite good, and the simulated hydrological processes with optimized model parameter improved the simulated hydrological processes largely. To further analyze the effect of parameter optimization on model performance improvement, five evaluation indices of the simulated flood events, including the Nash–Sutcliffe coefficient, the correlation coefficient, the process relative error, the peak flow error and water balance coefficient are calculated from the simulated results. Table 4 listed the 5 indices for both the simulated results with the initial parameters and the optimized parameters.

Table 4 Evaluation indices of the simulated flood events

From Table 4, it could be seen that the five evaluation indices are quite good for the simulated hydrological processes with the optimized model parameters. The average peak flow error is 5% with 14% the maximum. The average Nash–Sutcliffe coefficient, correlation coefficient, process relative error and water balance coefficient are 0.82, 0.83, 0.22 and 0.87 respectively, that are also quite good for large river basin flood simulation. Five evaluation indices of the simulated hydrological processes with the optimized model parameters are also good improvements to those simulated with the initial parameters, those are 0.64, 0.62, 0.37, 0.29 and 0.78. There are excellent improving in all five indices, with the average increases of 0.18, 0.21 and 0.09 of the average Nash–Sutcliffe coefficient, correlation coefficient and water balance coefficient respectively, and the average decreases of the peak flow error and process relative error are 24% and 15% respectively. So it could be concluded that the Liuxihe Model set up in LRB with optimized parameters are reasonable and could be used for flood forecasting of LRB. This also implies that parameter optimization of distributed hydrological model could improve model performances, and it should be done when it is possible.

4 Discussions

4.1 Computation time vs model resolution

To evaluate the spatial resolution scaling effect of distributed hydrological modeling in LRB, the DEM with 90m*90m resolution is rescaled to the resolutions of 400m*400m, 500m*500m, 600m*600m and 1000m*1000m respectively, the land use and soil type at 1000m*1000m resolution are also rescaled to the same resolutions of the DEM used. Liuxihe models for LRB flood forecasting at the above resolutions are then set up with the above methods, and the model structures are shown in Fig. 6.

Fig. 6 Liuxihe Model structure set up for LRB with different resolution

With different spatial resolution, the numbers of grid cells, hill slope cells and river cells are different, but the river channel order are all set to 3, the numbers of virtual channel nodes for 400m*400m, 500m*500m, 600m*600m and 1000m*1000m resolution models are 100, 68, 46 and 33 respectively, numbers of grid cells, hill slope cells and river cells with different model resolution are listed in Table 5. , the sizes of every virtual cross sections are measured with the above method.

Table 5 Grid cell numbers with different model spatial resolution

From Table 5, it could be seen, number of grid cells of the model with 200m*200m resolution is 4 times of that with 400m*400m resolution, 6.25 times of that with 500m*500m resolution, 9 times of that with 600m*600m resolution, and 25 times of that with 1000m*1000m resolution, it increases at an approximate exponential of power 2, not linearly with the model resolution.

Parameters of the models with 400m*400m, 500m*500m, 600m*600m and 1000m*1000m resolutions are optimized with PSO algorithm by using the same flood event data, and listed in Table 6. From the results it could be seen that some parameters are significantly different with resolution variation, but some changes little, this implies that the model parameters are resolution-dependent.

Table 6 Optimized parameters with different model spatial resolution

Computation times required for parameter optimization are quite different. For the model with 200m*200m resolution, the time for parameter optimization is 220 hours, while that for models with 400m*400m, 500m*500m, 600m*600m and 1000m*1000m resolutions are 80, 55, 35 and 12 hours respectively. The times needed for parameter optimization of the model at 200m*200m resolution is 2.75 times of that for 400m*400m resolution model, 4 times of that for 500m*500m resolution model, 6.3 times of that for 600m*600m resolution model, and 18.3 times of that for 1000m*1000m resolution model respectively. Considering the time needed for model run, the 200m*200m model resolution is regarded as appropriate for LRB.

5.2 Model performance vs model resolution

The other 29 flood events are also simulated with the models at 400m*400m resolution, 500m*500m resolution, 600m*600m resolution, and 1000m*1000m resolution. Simulated hydrograph of 5 flood events, including 2 big, 2 medium and one small ones are shown in Fig. 7.

Fig. 7 Simulated results with different model resolutions

From the results it could be seen that the simulated hydrological processes with 5 different spatial resolutions are quite different. The result simulated with 1000m*1000m resolution is not so good, although the flood shapes are simulated well, but the peak flow are much lower than that of the observation, so the result is not acceptable, and could not be recommended. The result simulated with 600m*600m resolution is better than that of 1000m*1000m resolution, but there is still big peak flow error, so the result with 600m*600m resolution is also not recommended. The result simulated with 500m*500m resolution model is a big improvement to those simulated with 600m*600m resolution and 1000m*1000m resolution model, the flood shapes are more similar to the observation, and the peak flow is also get closer to the observation, so it could be recommended for flood forecasting if the spatial resolution could not be much finer. The result simulated with 400m*400m resolution has some improvements to that of 500m*500m resolution, but it is not significant, so it is not recommended to replace that at 500m*500m resolution. The result simulated with 200m*200m resolution model is a big improvement to those simulated with 400m*400m resolution and 500m*500m resolution model, the flood shapes fits the observation much better, and the peak flows are much closer to the observation also, it is a good simulation result and could be recommended for flood forecasting of LRB. As the results are good enough so there is no need to further explore the finer model resolution.

5 Conclusions

By employing Liuxihe Model, a physically based distributed hydrological model, this study sets up a distributed hydrological model for the flood forecasting of Liujiang River Basin in southern China that could be regarded as a large watershed. Terrain data including DEM, soil type and land use type are downloaded from the website freely, and the model structure with a high resolution of 200m*200m grid cell is set up, which divides the whole watershed into 1469900 grid cells that is further divided into 1463204 hill slope cells and 6696 river cells. The initial model parameters are derived from the terrain property data, and then optimized by using the PSO algorithm with one observed flood event, which improves the model performance largely. 29 observed flood events are simulated by using the model with optimized parameters, the results are analyzed, and the model scaling effects are studied. Based on these studies, following conclusions are suggested.

1. In Liuxihe Model, the river channels are divided into virtual channel sections, and the cross section shapes are assumed to be trapezoid and the size is the same within the virtual channel section. The size of the virtual channel section is simplified to three indices, including bottom width, side slope and bottom slope, those are estimated by using remote sensing imageries. This method not only makes the distributed model application practical, but also simplifies the river channel routing method. This significantly increases the model computation efficiency, and makes it could be used in larger watersheds. Results in this study shows the model setting up with this method has a reasonable performance, i.e., this simplification has not sacrificed the model's flood simulation accuracy significantly, so this simplification could be used in large watershed distributed hydrological modelling, including Liuxihe model and other models.

2. Uncertainty exists for physically derived model parameters. Parameter optimization could reduce parameter uncertainty, and is highly recommended to do so when there is some observed hydrological data. In this study, the simulated hydrograph with optimized model parameters is more fitting the observed hydrograph in shape than that simulated with initial model parameters, the 5 evaluation indices are improved also. The average increases of Nash–Sutcliffe coefficient, correlation coefficient and water balance coefficient are 0.18, 0.21 and 0.09 respectively, the average decreases of the peak flow error and process relative error are 24% and 15% respectively, this implies that the model performance is improved significantly with parameter optimization.

3. Computation time needed for running a distributed hydrological model increases exponentially at an approximate power of 2, not linearly with the increasing of model spatial resolution. In this study, the computation time required for parameter

optimization for the model with 200m*200m resolution is 220 hours, that is 4 times of that of the model at 500m*500m and 18.3 times of that of the model at 1000m*1000m resolution respectively. Based on the Liuxihe Model cloud system implemented on the high performance supercomputer, the 200m*200m model resolution is the highest resolution that could be fulfilled in modeling Liujiang River Basin flooding with Liuxihe Model considering the computation cost. This also means that if the user could pay high computation cost, then larger watershed could also be modelled with Liuxihe Model by implemented the Liuxihe Model cloud system on a much more advanced high performance supercomputer, this could be easily done nowadays if the user thinks this investment is a worth doing.

4. In forecasting watershed flood by using distributed hydrological model, minimum model spatial resolution needs to be maintained to keeping the model an acceptable performance. Usually if the model spatial resolution increases, i.e., the grid cell gets smaller, the model performance is better, but this will increase the run time significantly, so there is a threshold model spatial resolution to keep the model performance reasonable while keep the model run at the least time. In this study, the threshold model spatial resolution is at 500m*500m grid cell, but the resolution at 200m*200m grid cell is recommended by trading-off between the computation cost and the model performance. This conclusion may be different in different watersheds for Liuxihe Model, or even different in the same watershed for different models.

5. Terrain data downloaded freely from the website derived the river channel system that is very similar to the natural river channel system after it is rescaled from its original spatial resolution of 90m*90m to 200m*200m, 500m*500m and 1000m*1000m, but the higher resolution DEM describes the river channel more in details. This means that the freely downloaded DEM could be used to set up the Liuxihe Model for Liujiang River Basin flood forecasting.

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Figures

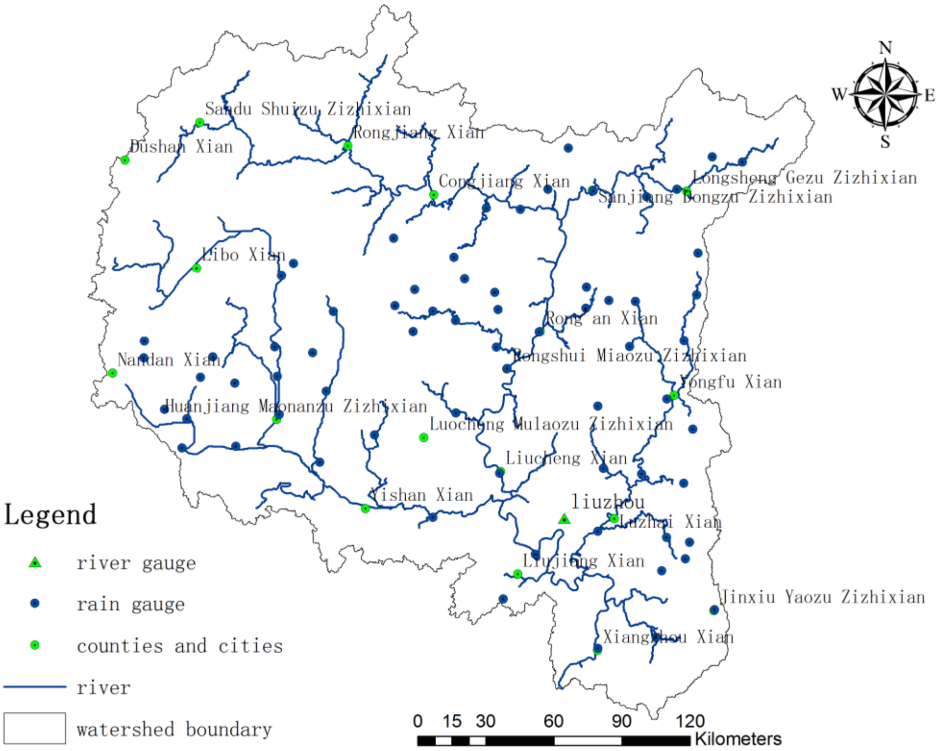
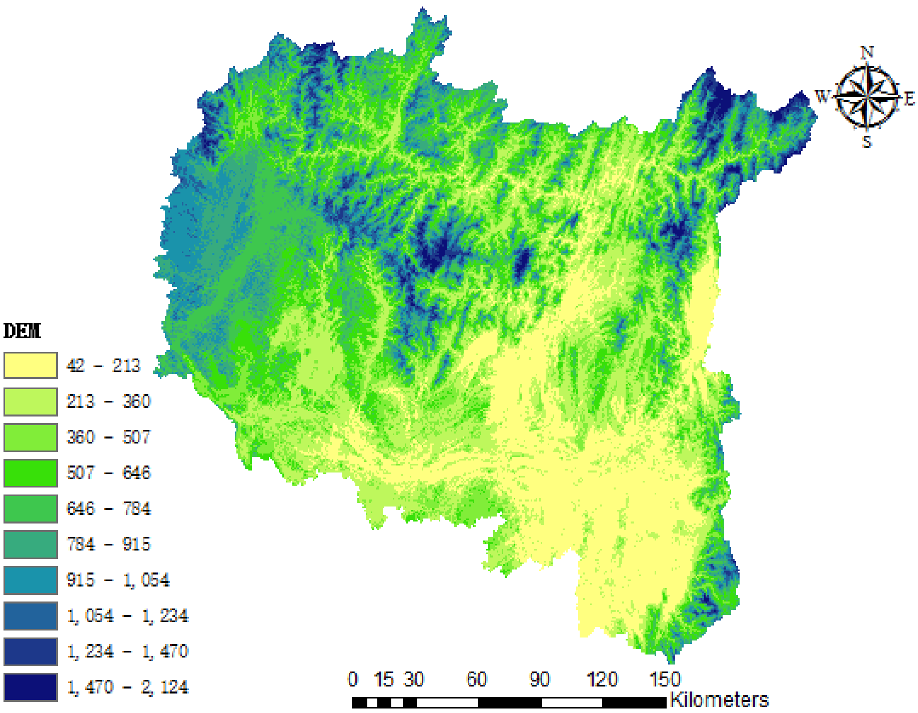
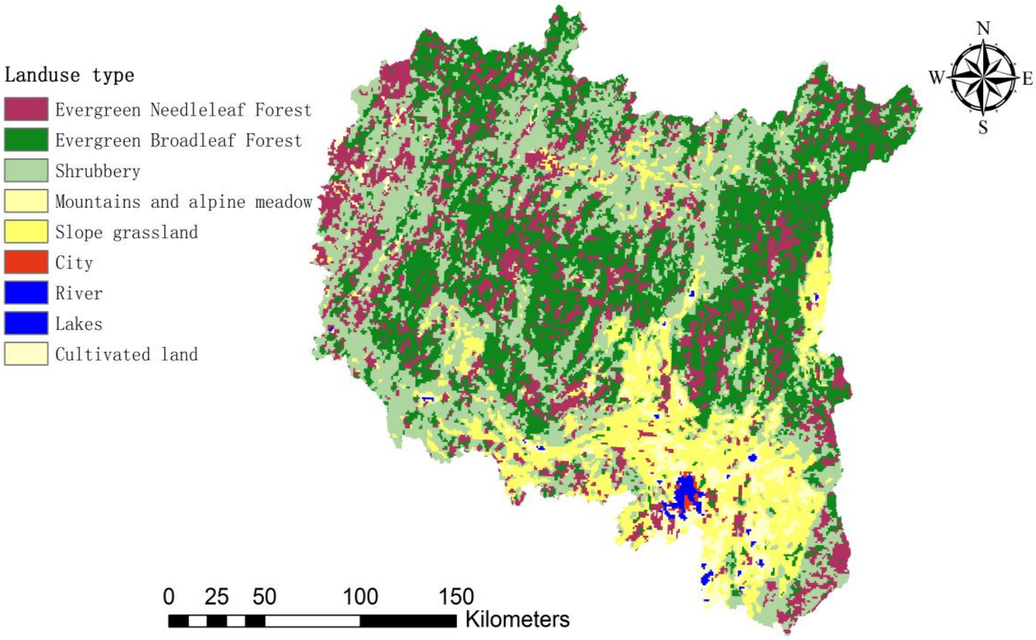


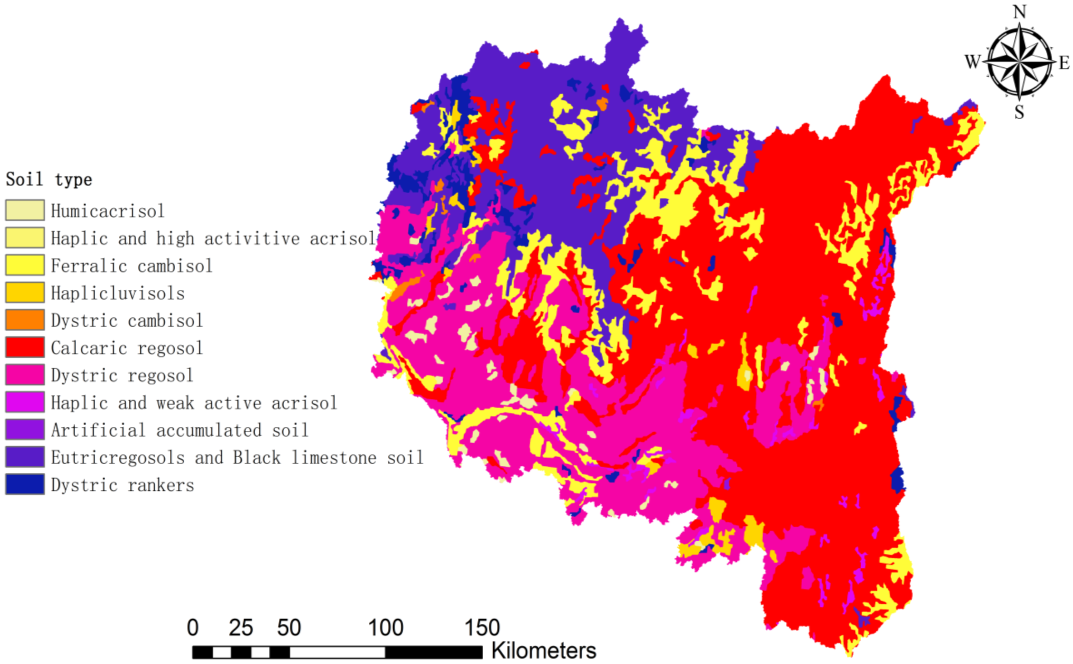
Fig. 1 sketch map of Liujiang River Basin



(a) DEM



(b) land use



(c) soil type

Fig. 2 Terrain properties of LRB

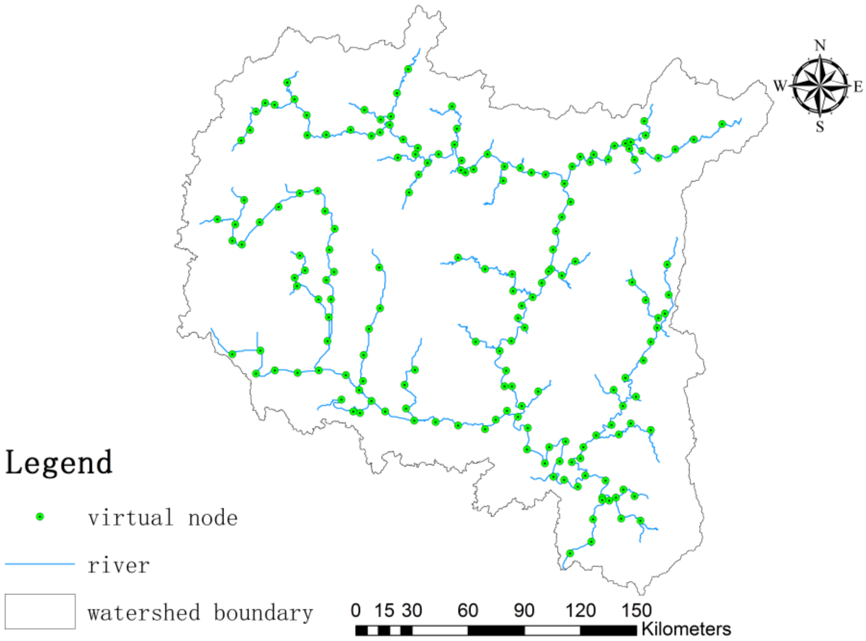
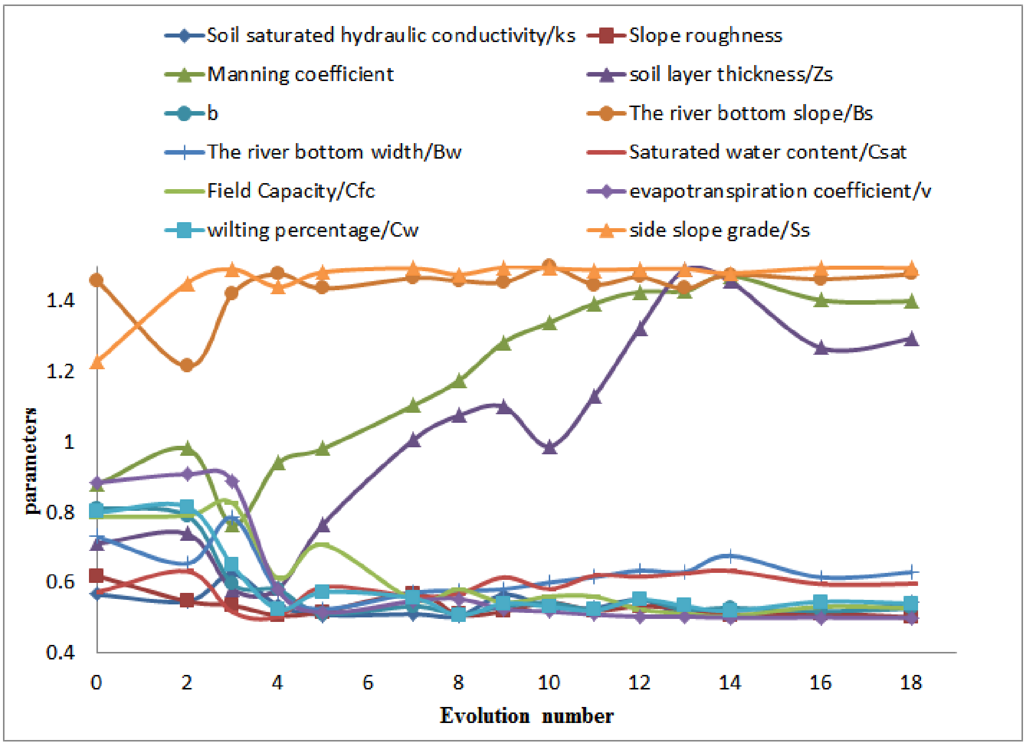
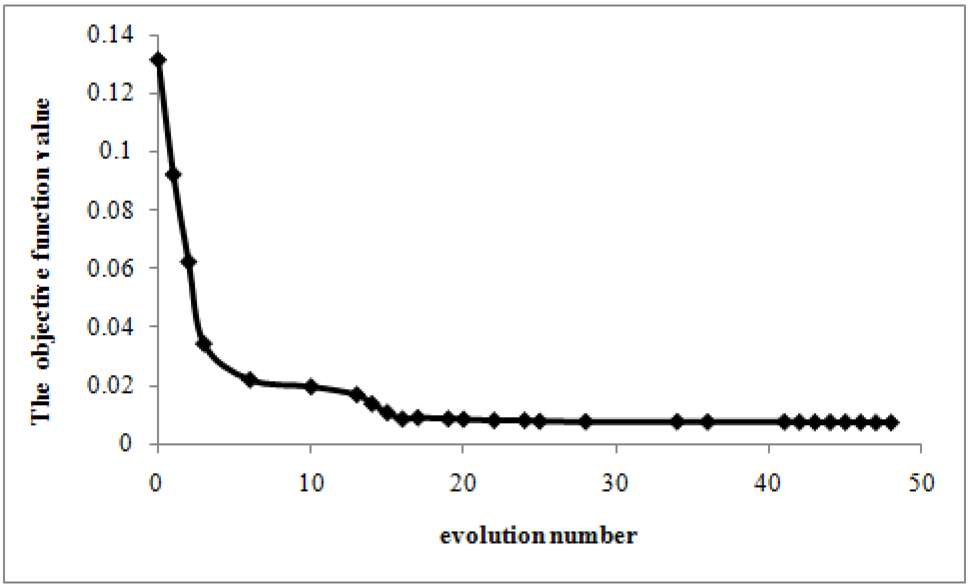


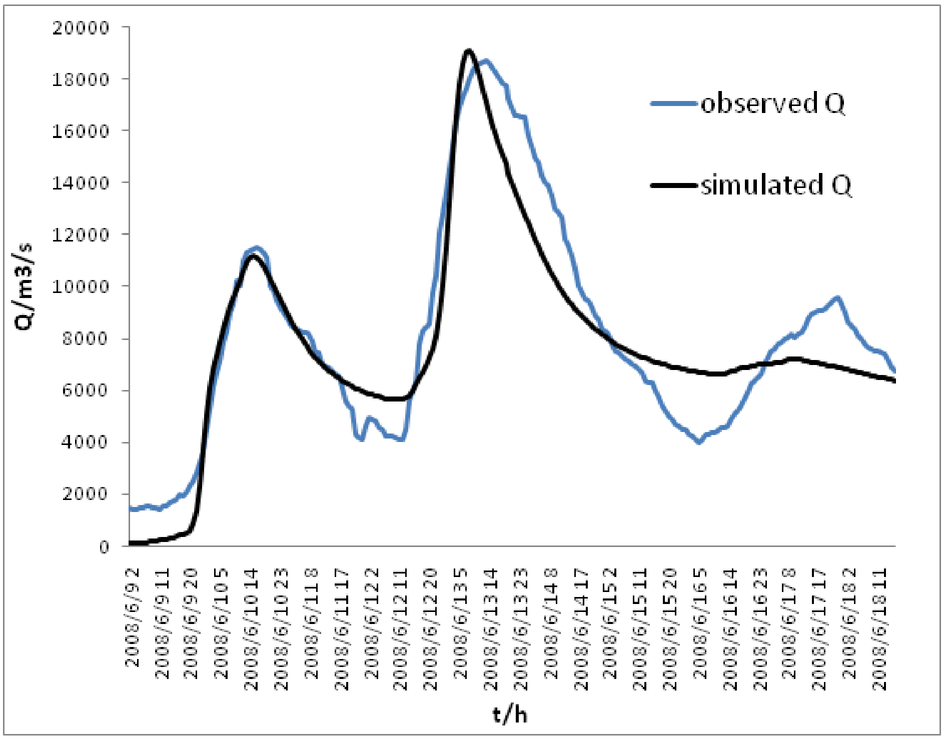
Fig. 3 Liuxihe Model structure set up for LRB (200m ×200m resolution)



(a) Parameter evolution process

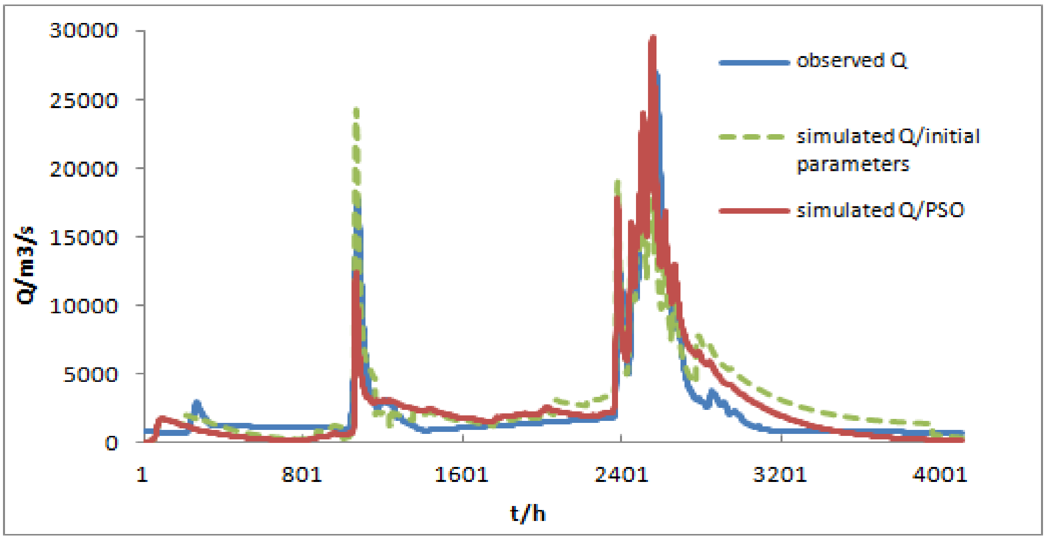


(b) Changing curve of objective function

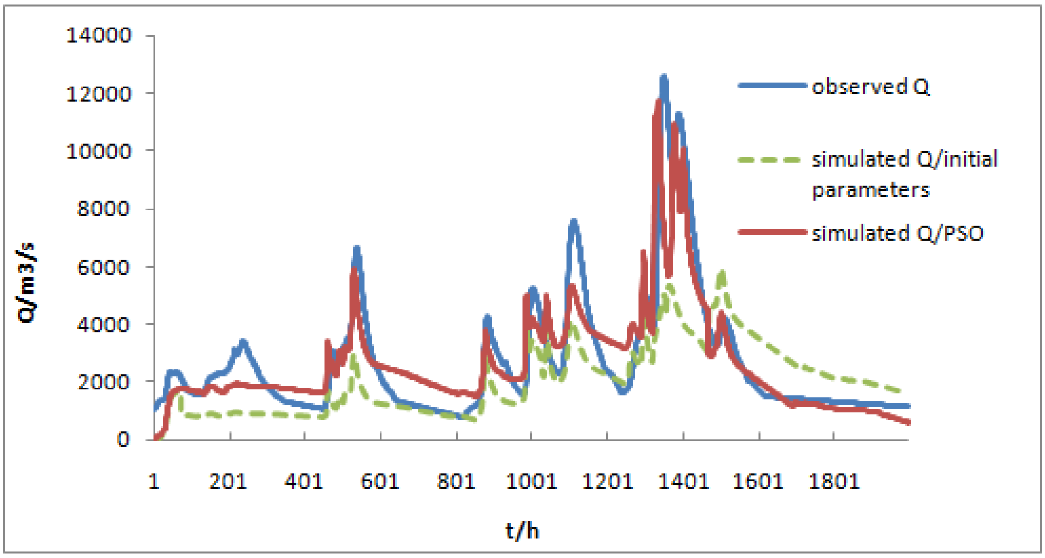


(c) Simulated flood process

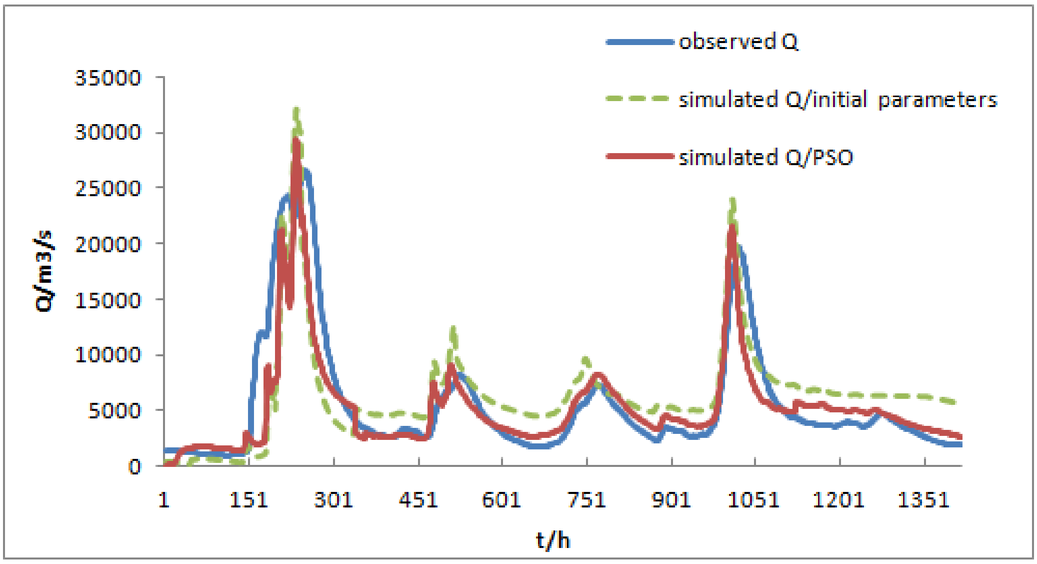
Fig. 4 Parameter optimization results of Liuxihe Model for LRB with PSO algorithm



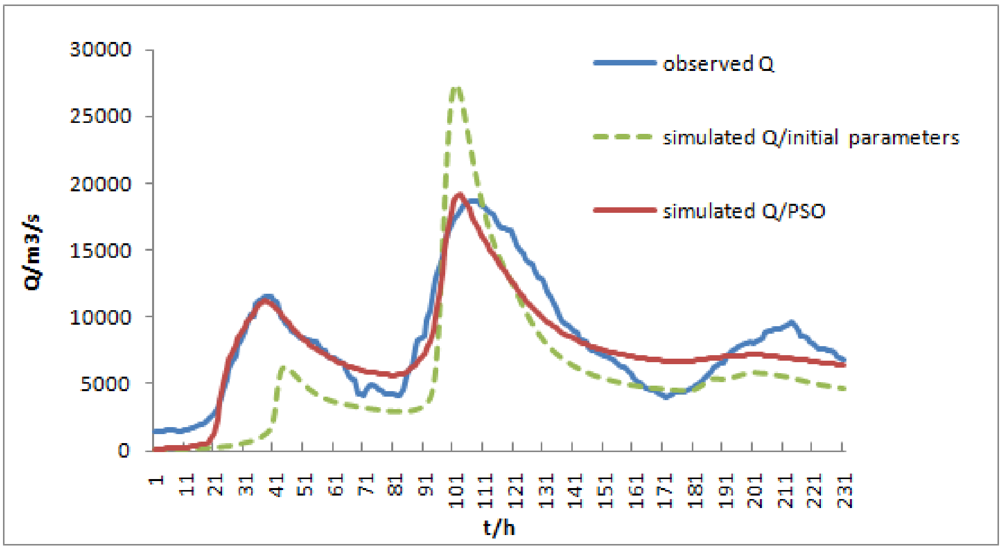
(a) flood event 1988051620



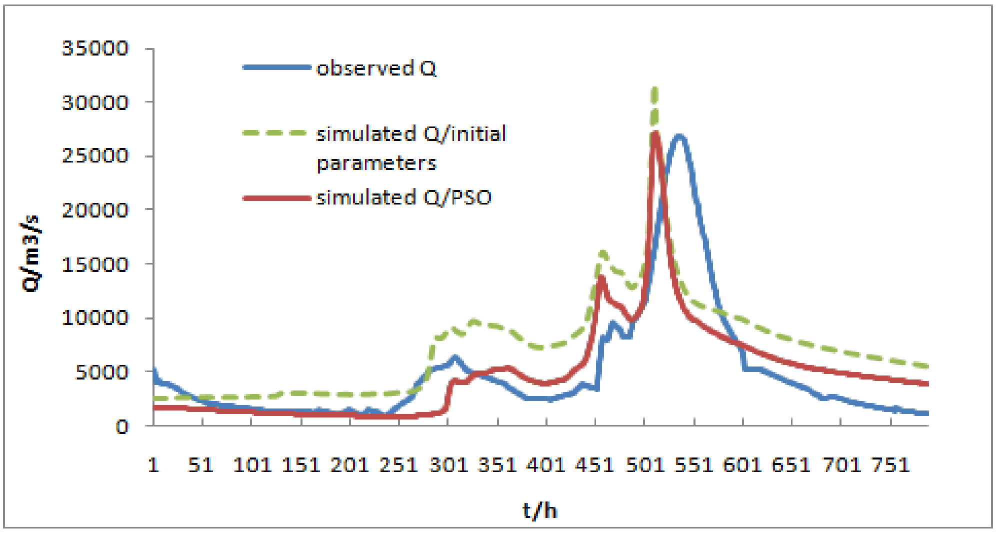
(b) flood event 1982042116



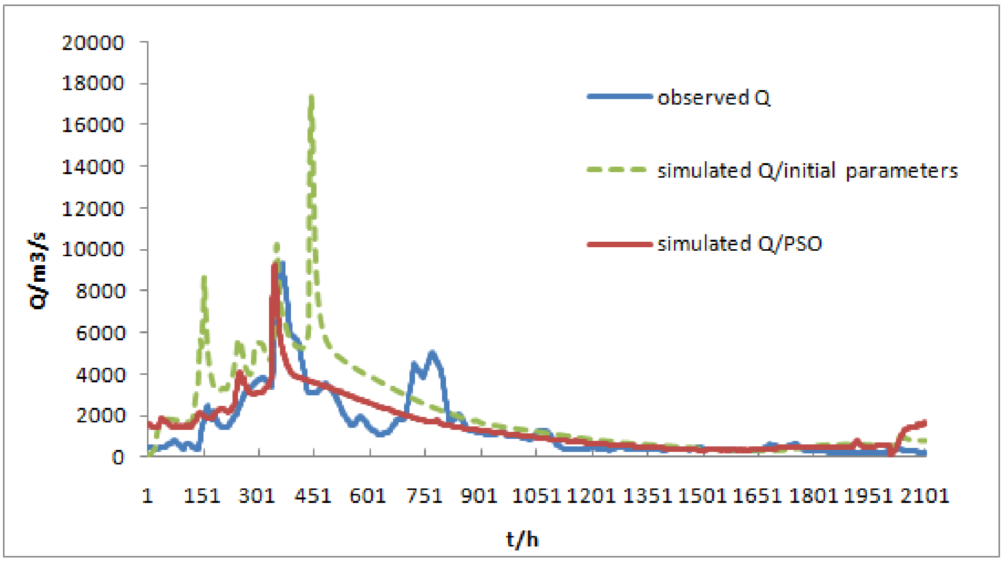
(c) flood event 1994060700



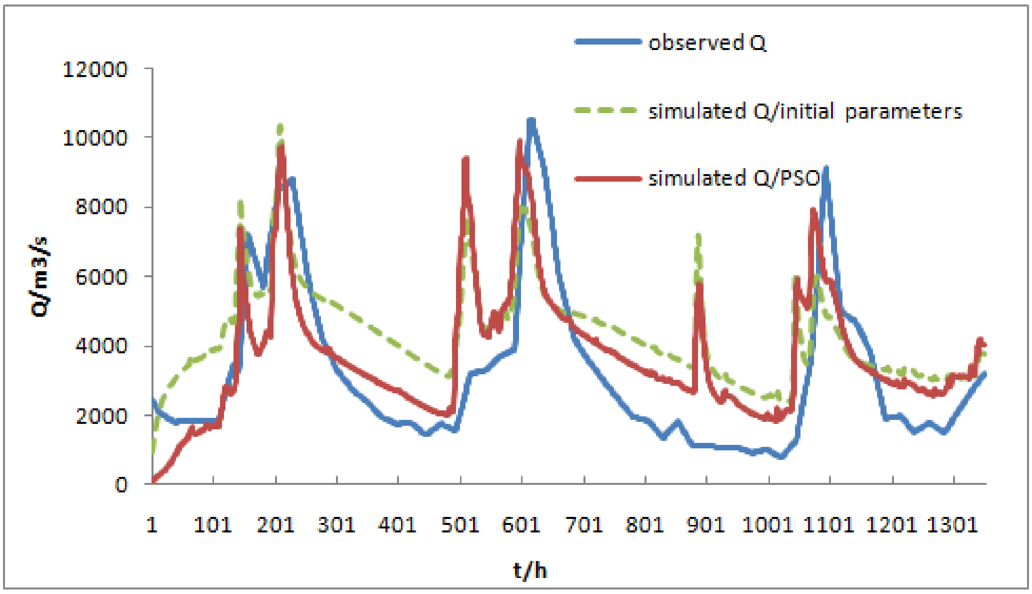
(d) flood event 2008060902



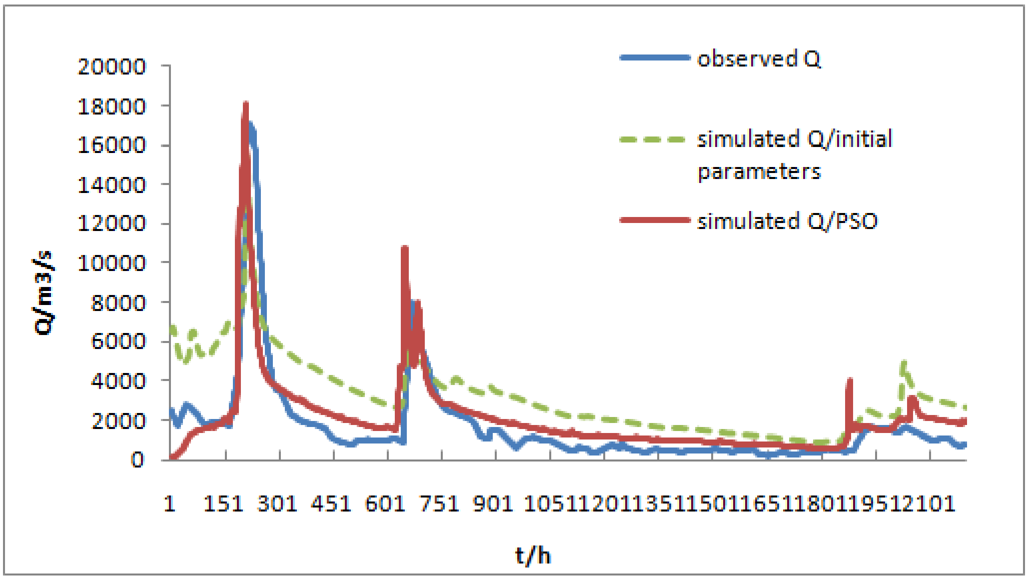
(e) flood event 200906090800



(f) flood event 201106010900

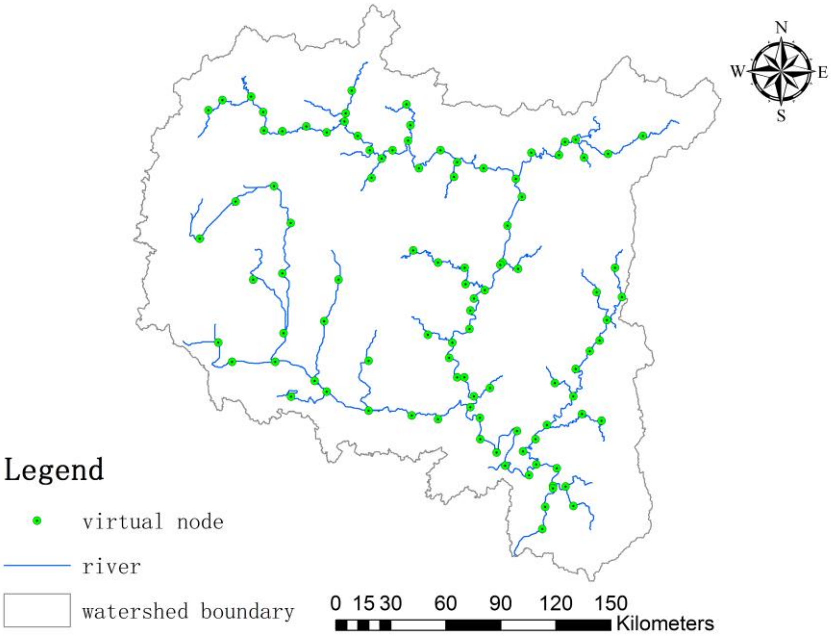


(g) flood event 201206022000

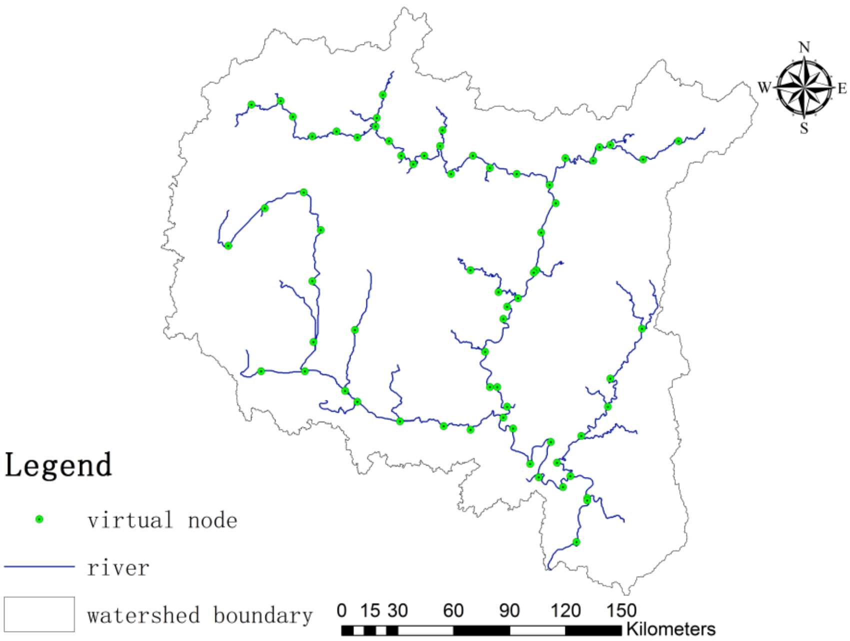


(h) flood event 201306011400

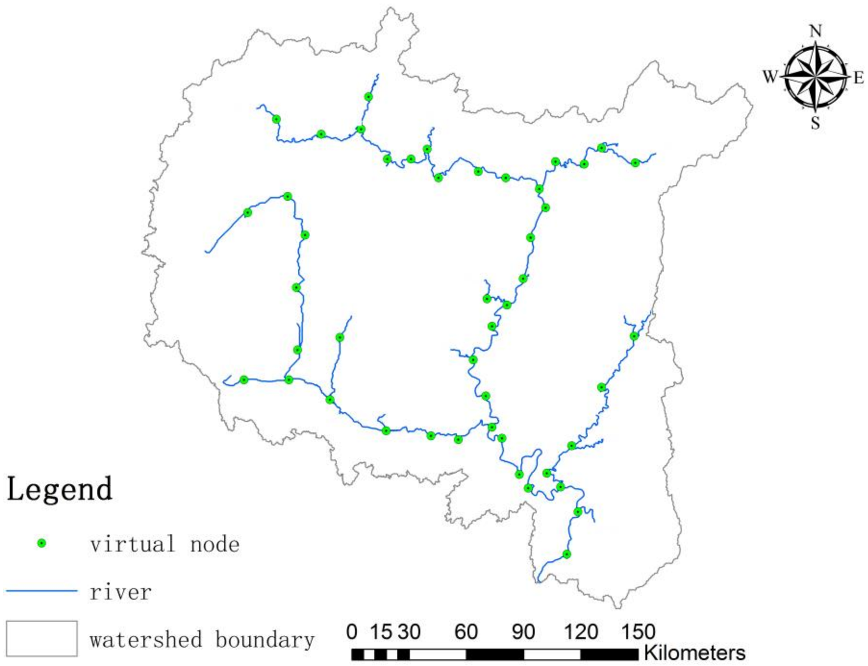
Fig. 5 Simulated flood events by Liuxihe Model with optimized parameters



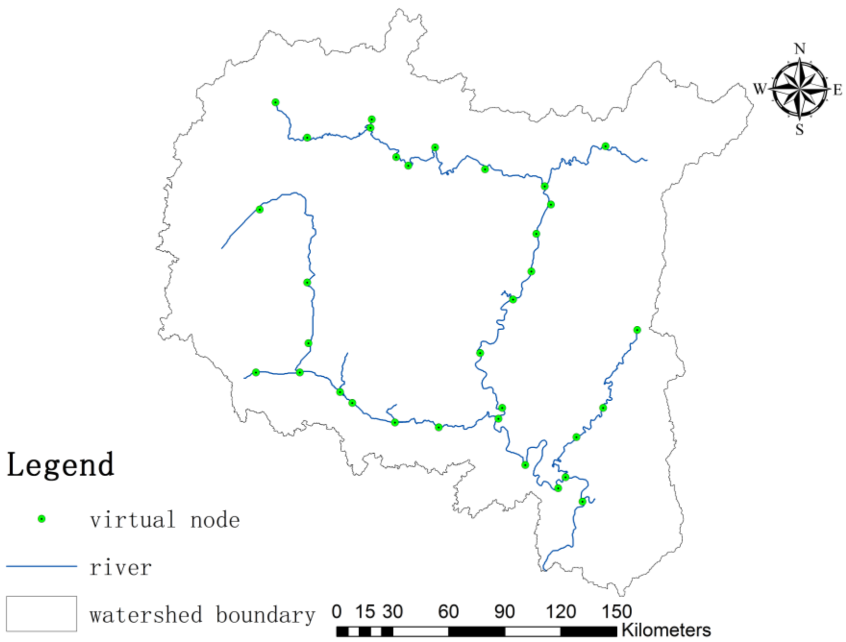
(a) 400m*400m resolution



(b) 500m×500m resolution

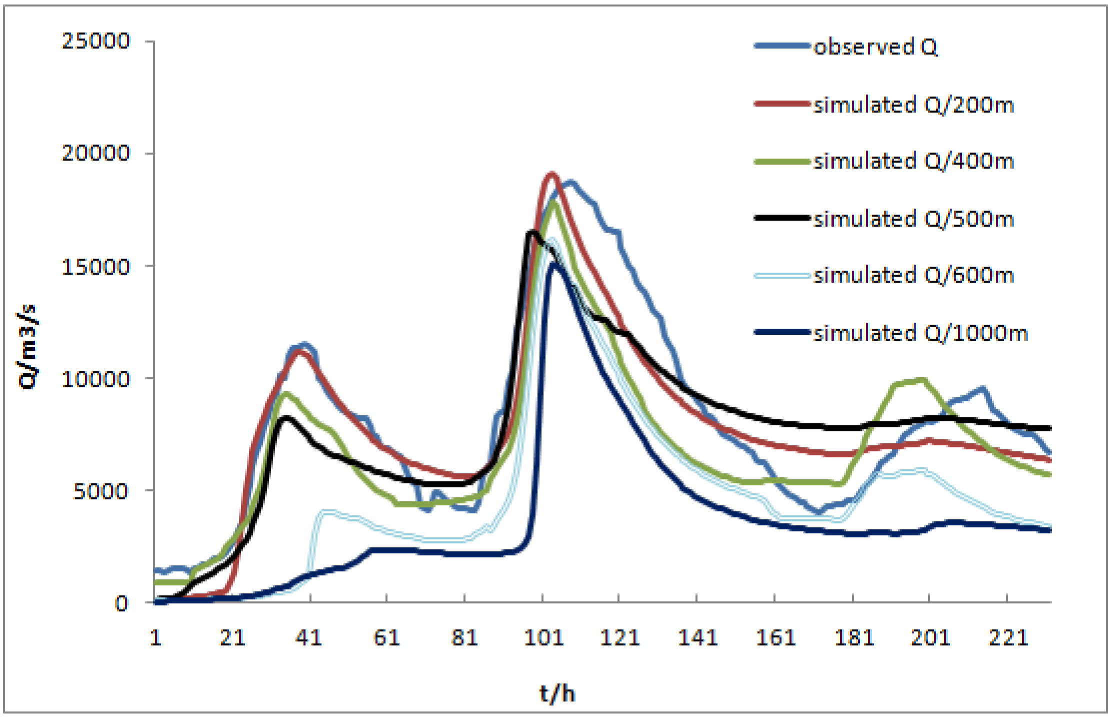


(c) 600m*600m resolution

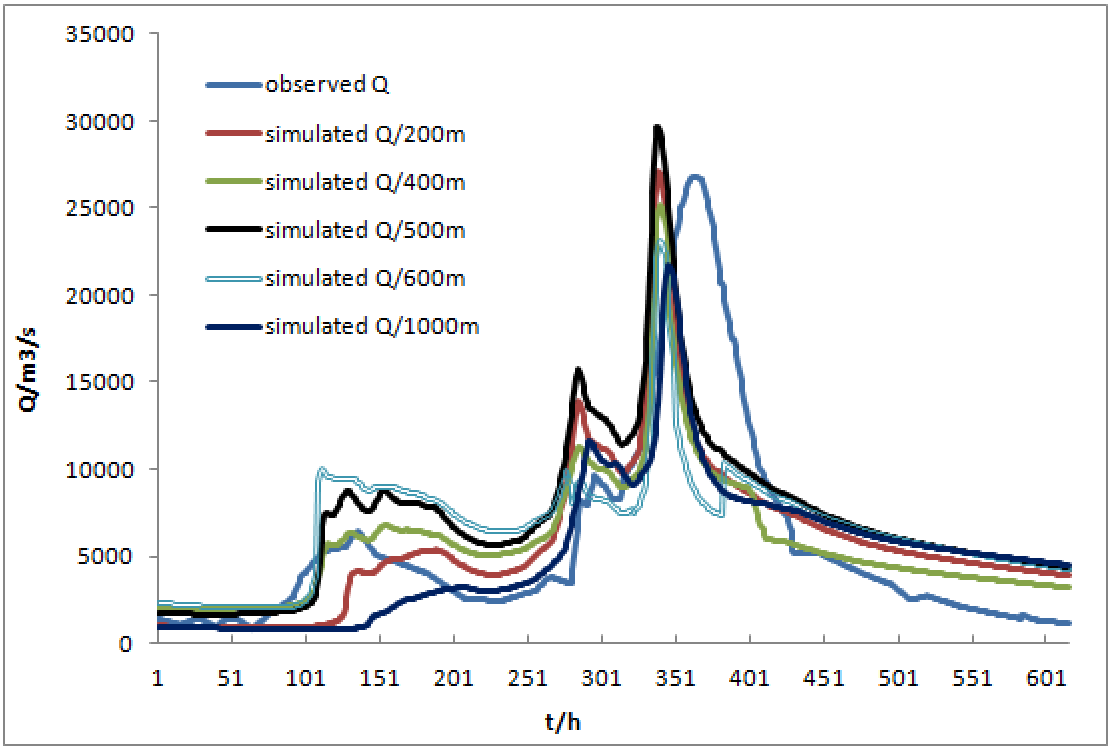


(d) 1000m×1000m resolution

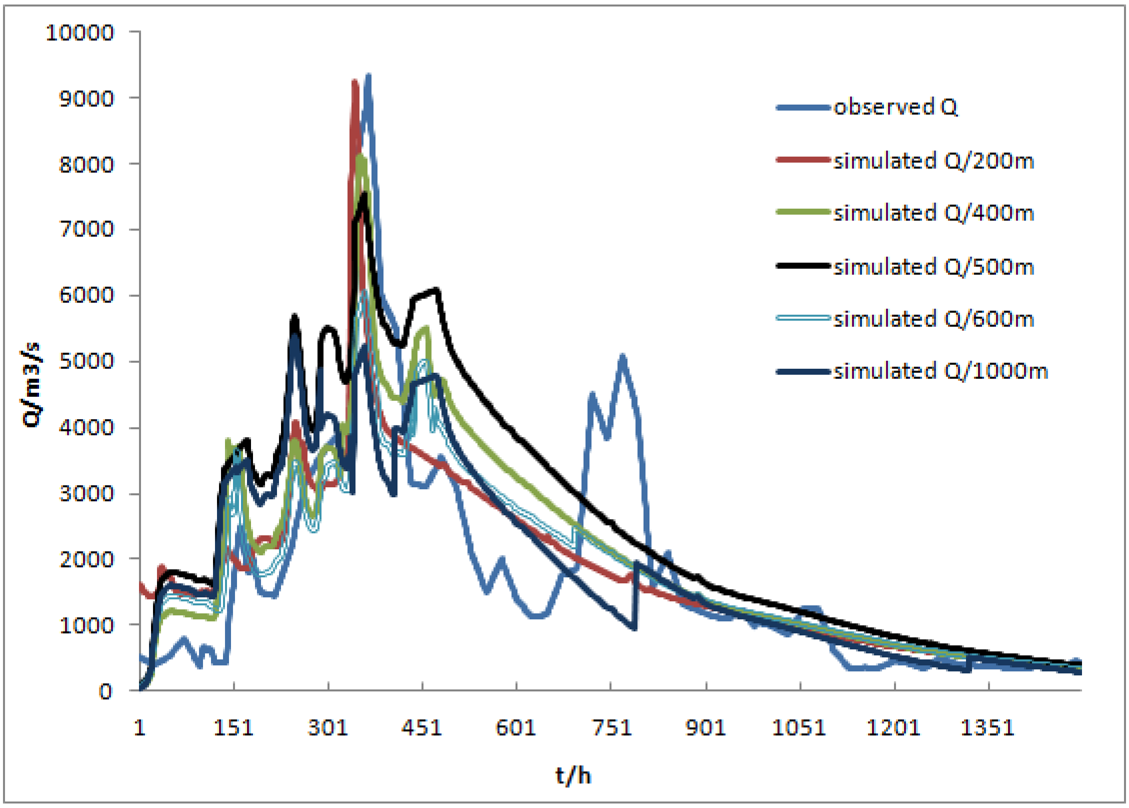
Fig. 6 Liuxihe Model structure set up for LRB with different resolution



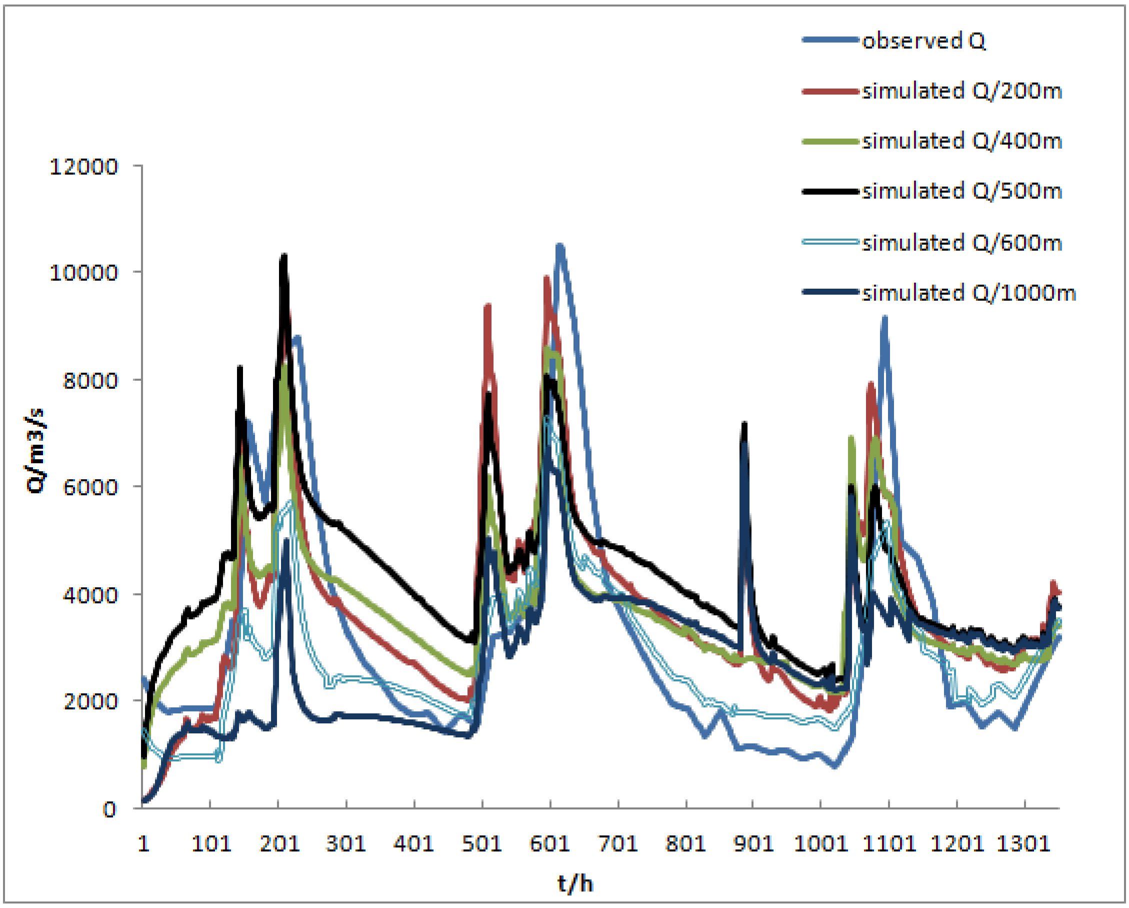
(a) flood event 2008060902



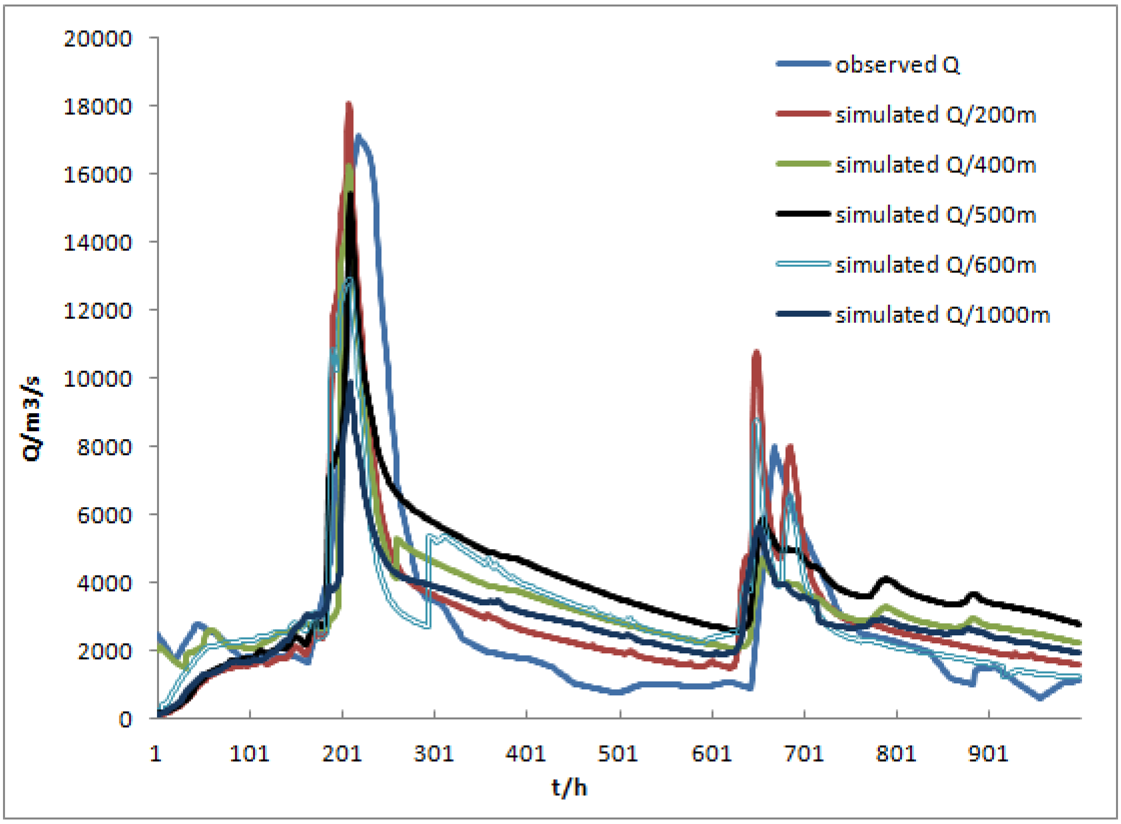
(b) flood event 2009060908



(c) flood event 2011060109



(d) flood event 2012060220

584 

585 (e) flood event 2013060114

586 Fig. 7 Simulated results with different model resolutions

587

588

Tables

Table1 Brief information of flood events in LRB

No.	*Floods No.*	*Start time （yyyymmddhh）*	*End time （yyyymmddhh）*	*length of time/h*	*peak flow (m^3/s)*
1	1982042116	1982042116	1982110216	4614	12600
2	1983020308	1983020308	1983021722	350	7880
3	1984021100	198402100	1984040105	1205	12900
4	1985011900	1985011900	1985021114	544	11400
5	1986022300	1986022300	1986042004	1334	12200
6	1987050100	1987050100	1987071700	1848	10800
7	1988070620	1988070620	1988100605	2915	27000
8	1989042600	1989042600	1989081009	2499	7500
9	1990050100	1990001000	1990072306	2006	11400
10	1991053118	1991053118	1991062806	686	14300
11	1992042900	1992042900	1992072107	1977	18100
12	1993060900	1993060900	1993082408	1818	21200
13	1994060700	1994060700	1994080706	1416	26500
14	1995052100	1995052100	1995071506	1296	17300
15	1996060600	1996060600	1996081808	1728	33700
16	1997060400	1997060400	1997062406	476	13600
17	1998051600	1998051600	1998090100	2520	19600
18	1990050100	1999050100	1999080404	1134	17800
19	2000052100	2000052100	2000061809	659	24100
20	2001051500	2001051500	2001062300	910	14200
21	2002042600	2002042600	2002081000	2520	17900
22	2003060600	2003060600	2003072103	843	11600
23	2004070300	200407000	2004081508	998	23700
24	2005061400	2005061400	2005070702	552	16400
25	2006060400	2006060400	2006071000	870	13200
26	2008060900	2008060900	2008061908	238	18700
27	2009060908	2009060908	2009071208	788	26800
28	2011061090	2011061009	2011090104	2004	9153
29	2012060220	2012060220	2012080101	1351	10500
30	2013060114	2013060114	2013090114	2200	17100

Table 2 The initial values of land use/cover related parameters

Land use/cover	*evaporation coefficient*	*roughness coefficient*
Evergreen needle leaf forest	0.7	0.4
Evergreen broadleaf forest	0.7	0.6
Shrubbery	0.7	0.4
Mountains and alpine meadow	0.7	0.2
Slope grassland	0.7	0.3
City	0.7	0.05
Cultivated land	0.7	0.35

Table 3 The initial values of soil related parameters

Soil Type	*soil thickness (mm)*	*water content at saturation condition*	*water content at field condition*	*hydraulic conductivity at saturation condition (mm/h)*
Humicacrisol	800	0.65	0.32	3.5
Haplic and high active acrisol	900	0.57	0.43	4.2
Ferralic cambisol	850	0.63	0.38	20.5
Haplicluvisols	980	0.46	0.15	2.6
Dystric cambisol	950	0.55	0.41	14
Calcaric regosol	1100	0.62	0.24	5.6
Dystric regosol	840	0.45	0.27	12.5
Haplic and weak active acrisol	1050	0.58	0.16	4.6
Artificial accumulated soil	1000	0.63	0.34	5.5
Eutricregosols and Black limestone	550	0.75	0.27	3.5
Dystric rankers	380	0.78	0.36	8

Table 4 Evaluation indices of the simulated flood events

ID	floods	parameters	Nash–Sutcliffe coefficient/C	Correlation coefficient/R	Process relative error/P	Peak flow relative error/E	Water balance coefficient/W
1	1982081219	initial	0.52	0.48	0.56	0.58	0.52
		optimized	0.84	0.75	0.30	0.01	0.83
2	1983020308	initial	0.60	0.55	0.45	0.26	0.65
		optimized	0.82	0.84	0.21	0.04	0.89
3	1984010100	initial	0.62	0.71	0.38	0.32	0.75
		optimized	0.75	0.89	0.26	0.14	0.96
4	1985010100	initial	0.58	0.57	0.35	0.33	0.85
		optimized	0.73	0.87	0.17	0.01	1.05
5	1986010100	initial	0.65	0.62	0.38	0.25	0.62
		optimized	0.83	0.85	0.23	0.04	0.94
6	1987050100	initial	0.76	0.45	0.35	0.36	0.58
		optimized	0.93	0.76	0.10	0.05	1.01
7	19880516200	initial	0.54	0.58	0.26	0.42	0.82
		optimized	0.84	0.80	0.15	0.04	0.90
8	1989042600	initial	0.52	0.55	0.55	0.25	0.62
		optimized	0.64	0.74	0.39	0.02	0.88
9	1990050100	initial	0.55	0.64	0.42	0.23	0.55
		optimized	0.85	0.87	0.14	0.03	0.85
10	1991053118	initial	0.63	0.62	0.40	0.18	0.68
		optimized	0.80	0.76	0.25	0.04	0.95
11	1992042900	initial	0.48	0.59	0.35	0.34	0.65
		optimized	0.66	0.84	0.20	0.11	0.89
12	1993060900	initial	0.75	0.65	0.38	0.28	0.84
		optimized	0.91	0.89	0.24	0.09	1.05
13	1994060700	initial	0.78	0.64	0.32	0.26	1.25
		optimized	0.93	0.85	0.14	0.04	0.85
14	1995052100	initial	0.68	0.48	0.42	0.35	0.65
		optimized	0.82	0.70	0.20	0.01	0.81
15	1996060600	initial	0.74	0.65	0.25	0.23	0.54
		optimized	0.90	0.93	0.18	0.02	0.86
16	1997060400	initial	0.65	0.51	0.23	0.26	0.65
		optimized	0.84	0.87	0.13	0.06	0.95
17	1998051600	initial	0.57	0.62	0.35	0.18	0.68
		optimized	0.83	0.85	0.30	0.01	1.05
18	1999061700	initial	0.48	0.59	0.33	0.15	0.55
		optimized	0.60	0.83	0.15	0.05	0.80
19	2000052100	initial	0.67	0.62	0.45	0.25	0.58
		optimized	0.79	0.89	0.26	0.06	0.83

20	2001051500	initial	0.62	0.56	0.32	0.22	0.68
		optimized	0.80	0.82	0.25	0.07	0.82
21	2002042600	initial	0.68	0.65	0.38	0.18	0.57
		optimized	0.86	0.90	0.24	0.02	0.87
22	2003060600	initial	0.75	0.55	0.25	0.26	0.55
		optimized	0.92	0.85	0.14	0.04	0.76
23	2004070300	initial	0.58	0.68	0.38	0.27	0.68
		optimized	0.78	0.82	0.23	0.08	0.85
24	2005061400	initial	0.65	0.62	0.52	0.32	0.65
		optimized	0.76	0.76	0.35	0.06	0.74
25	2006060400	initial	0.68	0.72	0.62	0.35	0.53
		optimized	0.82	0.83	0.30	0.10	0.86
26	2009060908	initial	0.75	0.78	0.25	0.23	1.22
		optimized	0.95	0.92	0.17	0.04	0.09
27	2011010100	initial	0.66	0.75	0.35	0.55	1.66
		optimized	0.80	0.84	0.26	0.03	1.02
28	2012010100	initial	0.63	0.68	0.34	0.22	1.42
		optimized	0.82	0.79	0.20	0.05	0.80
29	2013010100	initial	0.78	0.65	0.31	0.32	1.35
		optimized	0.95	0.82	0.20	0.06	0.92
average		initial	0.64	0.62	0.37	0.29	0.78
		optimized	0.82	0.83	0.22	0.05	0.87

Table 5 Grid cell numbers with different model spatial resolution

Model resolution	Number of grid cells	Number of hill slope cells	Number of river cells
200m*200m	1469900	1463204	6696
400m*400m	367475	365801	1674
500m*500m	235184	234113	1071
600m*600m	163322	162578	744
1000m*1000m	58796	58528	268

Table 6 Optimized parameters with different model spatial resolution*

Resolution	Soil saturated hydraulic conductivity/ks	Slope roughness	Manning coefficient	Soil layer thickness/Zs	b	The river bottom slope/Bs
200m	1.33	0.66	1.19	1.42	0.67	0.75
	The river bottom width/Bw	Saturated water content/Csat	Field Capacity/Cfc	Evapotranspiration coefficient/v	Wilting percentage/Cw	Side slope grade/Ss
	1.24	1.11	1.2	0.94	0.68	1.42
400m	Soil saturated hydraulic conductivity/ks	Slope roughness	Manning coefficient	Soil layer thickness/Zs	b	The river bottom slope/Bs
	0.75	1.12	1.23	1.4	1.25	0.65
	The river bottom width/Bw	Saturated water content/Csat	Field Capacity/Cfc	Evapotranspiration coefficient/v	Wilting percentage/Cw	Side slope grade/Ss
	0.89	1.02	1.22	1.18	1.15	0.76
500m	Soil saturated hydraulic conductivity/ks	Slope roughness	Manning coefficient	Soil layer thickness/Zs	b	The river bottom slope/Bs
	0.67	1.47	1.49	1.37	1.5	0.51
	The river bottom width/Bw	Saturated water content/Csat	Field Capacity/Cfc	Evapotranspiration coefficient/v	Wilting percentage/Cw	Side slope grade/Ss
	0.91	1.16	1.41	1.37	1.37	0.5
600m	Soil saturated hydraulic conductivity/ks	Slope roughness	Manning coefficient	Soil layer thickness/Zs	b	The river bottom slope/Bs
	1.02	0.98	1.24	0.95	1.21	0.86

	The river bottom width/Bw	Saturated water content/Csat	Field Capacity/Cfc	Evapotranspiration coefficient/v	Wilting percentage/Cw	Side slope grade/Ss
	1.12	0.87	1.28	1.08	1.16	0.95
1000m	Soil saturated hydraulic conductivity/ks	Slope roughness	Manning coefficient	Soil layer thickness/Zs	b	The river bottom slope/Bs
	0.5	1.43	1.17	1.11	1.47	0.57
	The river bottom width/Bw	Saturated water content/Csat	Field Capacity/Cfc	Evapotranspiration coefficient/v	Wilting percentage/Cw	Side slope grade/Ss
	1.1	0.76	0.53	0.6	1.5	0.54

*Values in the table are adjusting coefficient of the optimized parameters to the initial parameters, so values of the final optimized parameters are initial parameters time adjusting coefficient.

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