



Improving flood forecasting capability of physically based distributed hydrological model

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Improving flood forecasting capability of physically based distributed hydrological model by parameter optimization

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Abstract

Physically based distributed hydrological models discrete the terrain of the whole catchment into a number of grid cells at fine resolution, and assimilate different terrain data and precipitation to different cells, and are regarded to have the potential to improve the catchment hydrological processes simulation and prediction capability. In the early stage, physically based distributed hydrological models are assumed to derive model parameters from the terrain properties directly, so there is no need to calibrate model parameters, but unfortunately, the uncertainties associated with this model parameter deriving is very high, which impacted their application in flood forecasting, so parameter optimization may also be necessary. There are two main purposes for this study, the first is to propose a parameter optimization method for physically based distributed hydrological models in catchment flood forecasting by using PSO algorithm and to test its competence and to improve its performances, the second is to explore the possibility of improving physically based distributed hydrological models capability in catchment flood forecasting by parameter optimization. In this paper, based on the scalar concept, a general framework for parameter optimization of the PBDHMs for catchment flood forecasting is first proposed that could be used for all PBDHMs. Then, with Liuxihe model as the study model, which is a physically based distributed hydrological model proposed for catchment flood forecasting, the improved Particle Swarm Optimization (PSO) algorithm is developed for the parameter optimization of Liuxihe model in catchment flood forecasting, the improvements include to adopt the linear decreasing inertia weight strategy to change the inertia weight, and the arccosine function strategy to adjust the acceleration coefficients. This method has been tested in two catchments in southern China with different sizes, and the results show that the improved PSO algorithm could be used for Liuxihe model parameter optimization effectively, and could improve the model capability largely in catchment flood forecasting, thus proven that parameter optimization is necessary to improve the flood forecasting capability of physically based distributed hydrological model. It also has been found that the appropriate

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particle number and the maximum evolution number of PSO algorithm used for Liuxihe model catchment flood forecasting is 20 and 30, respectively.

1 Introduction

Improving flood forecasting capability has long been the goal of the global hydrological communities, and catchment hydrological models are the main tools for flood forecasting. The first model used for flood forecasting is commonly referred to as the Sherman's unit hydrograph method (Sherman, 1932). Early catchment hydrological models are usually referred to as lumped conceptual models (Refsgaard et al., 1996; Chen, et al., 2011), and a large number of this kind of models have been proposed, such as the Stanford Model (Crawford et al., 1966), the Xinanjiang Model (Zhao, 1977), and many other lumped models included in the the book of Computer Models of Watershed Hydrology (Singh et al., 1995). Lumped conceptual models usually aggregate the hydrological forcings, state variables and model parameters over the whole catchment, so could not represent the spatial distribution of the terrain characteristics and hydrological forcings finely, thus impacting their flood forecasting capabilities. With the development of remote sensing and GIS techniques, high resolution terrain data such as the Shuttle Radar Topography Mission DEM database (Falorni et al., 2005; Sharma et al., 2014), the USGS land use type database (Loveland et al., 1991, 2000), the FAO soil type database (<http://www.isric.org>), and precipitation estimated by digital weather radar (Fulton et al., 1998; Chen et al., 2009) have been prepared and freely available globally, this largely facilitated the development of physically based distributed hydrological models (here after refers to as PBDHMs). PBDHMs discrete the terrain of the whole catchment into a number of grid cells at fine resolution, and assimilate different terrain data and precipitation to different cells, thus having the potential to improve the catchment hydrological processes simulation and prediction capability (Ambroise et al., 2006). Dozen of PBDHMs have been proposed since the blueprint of PBDHMs had been published by Freeze and Harlan (1969), the first full PBDHM is regarded

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as the SHE model published in 1987 (Abbott et al., 1986a, b), the others include WAT-
 TERFLOOD 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), Liuxihe model (Chen
 et al., 2011), and more. While at the same time, the so called semi-distributed hydrolog-
 ical models have also been proposed, such as the SWAT model (Arnold et al., 1994),
 TOPMODEL model (Beven et al., 1995), HRCDHM model (Carpenter et al., 2001), and
 others, with model complexity between the lumped model and distributed model.

Model parameters are very important to all kind of models as they will determine
 the models performances in flood forecasting. Most of the model parameters could
 not be measured directly, therefore need to be estimated by some kind of model pa-
 rameter estimation techniques (Madsen, 2003; Laloy et al., 2010; Teta et al., 2015).
 As the lumped model has limited model parameters, the optimization techniques has
 long been employed to calibrate the model parameters to improve the model's per-
 formance. For example, Dowdy et al. (1965) conducted a preliminary research on the
 parameter automatic optimization, Nash et al. (1970) and O'Connell et al. (1970) put
 forward a method to evaluate the accuracy of model simulation by utilizing efficiency
 coefficient, Ibbitt et al. (1971) design a conceptual watershed hydrological model pa-
 rameters fitting method, Duan et al. (1994) proposed the Shuffle Complex Evolution
 Algorithm, Eberhart et al. (2001) proposed the Particle Swarm Optimization method,
 Jasper et al. (2003) proposed the SCEM-UA method, Chu et al. (2011) proposed the
 SP-UCI method, among others. Now lots of parameter optimization methods for lumped
 hydrological models have been developed.

There are also many studies to parameter optimization to semi-distributed hydro-
 logic models, among them the most studied model is SWAT due to its open assess
 codes and simple model structures. For examples, the SCE-UA method was used
 to calibrate SWAT model for streamflow estimation (Ajami et al., 2004), the remote
 sensing derived evapotranspiration is used to calibrate the SWAT parameters by us-

ing Gauss–Marquardt–Levenberg algorithm (Immerzeel et al., 2008), and a multi-site calibration method with GA algorithm is also proposed for calibrating the SWAT parameters (Zhang et al., 2008). For estimating the parameters of Hydrology Laboratory Distributed Hydrologic Model, the regularization method was studied (Pokhrel et al., 2007).

PBDHMs usually have very complex model structures, and the hydrological processes are calculated by using physical meaning equations, so to run a PBDHM is very time consuming compared with the lumped model. In addition, PBDHM sets different model parameters to different cells, so the total model parameters of a PBDHM is huge even for a small catchment, this makes it difficult to calibrate the PBDHMs parameters like that widely exercised in lumped models. In the early stage of PBDHMs, the PBDHMs are assumed to derive model parameters from the terrain properties directly, so there is no need to calibrate model parameters. This is true and all the proposed PBDHMs could determine the model parameters with their own methods (Refsgaard, 1997; De Smedt et al., 2000; Vieux et al., 2002; Chen, 2009). It is fair when they are used to study the future impacts of the hydrological processes caused by climate changes, or by terrain changes due to human activities, in which there is no observation data to evaluate the model performance or to calibrate the model parameters, and the hydrological processes simulation/prediction accuracy is not so important, while detecting the changing trends is the key issue. But like the lumped model, parameter uncertainty still exists in PBDHMs, and parameter optimization is still needed to reduce this uncertainty (Gupta et al., 1998; Madsen, 2003; Vieux and Moreda, 2003; Reed et al., 2004; Smith et al., 2004; Pokhrel et al., 2012), particularly for those application with high prediction accuracy requirement, such as the catchment flood forecasting. The scalar method (Vieux et al., 2003; Vieux, 2004) proposed to adjust Vflo model parameters in its application to flood forecasting could be regarded as the first exploration of PBDHMs parameter optimization. In this method, every parameters are adjusted manually with a factor or a multiplier (scalar) based on the initially derived parameters from the terrain properties, and the scalars for the same parameter in dif-

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ferent cells are taken the same values, in this way, the parameters to be adjusted are only a few, so it is feasible in running time, and proven to be effective. For MIKE SHE model, an automatic parameter optimization method with SCE algorithm was proposed in simulating catchment runoff (Madsen, 2003), which considers two objectives, one is fitting the surface runoff at the catchment outlet, another is minimizing the error on simulated underground water level at different wells. In Liuxihe model, a half automated method was proposed to adjust the model parameter (Chen, 2009; Chen et al., 2011). In simulating a medium-sized catchment runoff processes with WetSpa Model, a multi-objective genetic algorithm was used to optimize the WetSps parameter (Shafii et al., 2009). Compared with lumped model and semi-distributed model, studies to parameter optimization of PBDHMs are very few, particularly for their uses in flood forecasting, further works needs to be done.

Current optimization methods are mainly used in lumped hydrological model parameter calibration, and could be divided into two categories, including global optimization and local optimization (Sorooshian et al., 1995). Local optimization method search the parameter starting from a given initial parameter value with a fixed step length step by step, such as the simplex method (Nelder et al., 1965), Rosenbrock method (Rosenbrock, 1960), Pattern search method (Hooke and Jeeves, 1961), among others. Local optimization methods are widely applied in early stage (Sorooshian et al., 1983; Hendrickson et al., 1988; Franchini et al., 1996), but local optimization method is difficult to find the global optimum parameters. Lots of global optimization methods have been proposed since then for lumped models in the past decades after realizing the disadvantages of the local optimization method, such as the Genetic Algorithm (Holland et al., 1975; Goldberg et al., 1989), Adaptive Random Search (Masri et al., 1980), Simulated Annealing (Kirkpatrick et al., 1983), Ant Colony System (Dorigo et al., 1996), Shuffle Complex Evolution Algorithm (SCE) (Duan et al., 1994), Differential Evolution (DE) (Storn and Price, 1997), Particle Swarm Optimization algorithm (PSO) (Eberhart et al., 2001), SCEM-UA (Jasper et al., 2003), SP-UCI (Chu et al., 2011; Li et al., 2007), AMALGAM (Vrugt and Robinson, 2007), among others. Global optimization methods

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have been widely studied and applied in lumped model parameter calibration, with SCE and PSO the most widely used algorithms. SCE has been used for parameter optimization of Mike SHE (Madsen, 2003; Shafii et al., 2009), but PSO has never been used for PBDHMs parameter optimization. PSO algorithm has the advantages of flexibility, ease implementation and efficiency (Poli et al., 2007; Poli, 2008), it has the potential to be employed to optimize the PBDHMs parameters.

There are two main purposes of this study, the first is to propose a parameter optimization method for PBDHMs in catchment flood forecasting by using PSO algorithm and to test its competence and improve its performances, the second is to explore the possibility of improving PBDHMs capability in catchment flood forecasting by parameter optimization, i.e. if PBDHMs parameter optimization can improve model performance significantly and achievable. In this paper, based on the scalar concept, a general framework for parameter optimization of the PBDHMs for catchment flood forecasting is first proposed that could be used for all PBDHMs. Then, with Liuxihe model as the study model, which is a physically based distributed hydrological model proposed for catchment flood forecasting, the improved Particle Swarm Optimization (PSO) algorithm is developed for the parameter optimization of Liuxihe model in catchment flood forecasting. The method has been tested in two catchments in southern China with different sizes, and the results show that the improved PSO algorithm could be used for Liuxihe model parameter optimization effectively, and could improve the model capability largely in catchment flood forecasting.

2 Methodology

Based on the scalar concept, a general methodology for parameter optimization of the physically based distributed hydrological model for catchment flood forecasting is proposed, which is applicable to all physically based, distributed hydrological models. This methodology has 3 steps, including parameter classification, parameter initialization and normalization, and automated parameter optimization.

2.1 Parameter classification

In physically based distributed hydrological model, the whole terrain is divided into large numbers of grid cells, and the model parameters in each cell is different, so the total parameter number is huge. The methodology proposed in this paper classifies the parameters into a few types, so to reduce the parameter numbers need to be optimized.

If we assume that all model parameters of a PBDHM are related and only related to one physical property of the terrain they belong, including the topography, soil type and vegetation type, then the parameters of a PBDHM could be classified as 4 types, i.e. the climate related parameters, the topography related parameters, the vegetation(land use) related parameters and soil related parameters, this classification could be used for all PBDHMs. With this classification, the parameters in different cells will have the same values if they have the same terrain properties, and the independent parameters are defined based on this classification, i.e. the independent parameters are the parameters with the same terrain properties in each cells, and only the independent parameters need to be estimated and optimized. With this treatment, the number of model parameters with their values need to be estimated will be largely reduced, i.e. from millions to tens, so the independent parameters could be optimized by employing optimization methods.

2.2 Parameter initialization and normalization

After classified the model parameters into independent parameters, the feasible values of all the independent parameters will be derived from the terrain properties directly, these values, in this paper, are called the initial values of the model parameters. As mentioned above, all proposed PBDHMs have their own methods to determine the initial model parameters.

Then the parameters are normalized with the initial values as follow:

$$x_i = x'_i / x_{i0} \quad (1)$$

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where x'_i is the original value of parameter i , x_{i0} is the initial value of parameter i , x_i is the normalized value of parameter i . With this normalization, all parameters become no-unit variables.

2.3 Automated parameter optimization

The normalized independent parameters will be automatically optimized with optimization methods. To do this, two important things need to be determined, the first one is to choose an optimization technique, in this study as mentioned above, the PSO algorithm will be employed. The second thing is to choose the optimization criterion (objective function), different objective function will result in different model parameters, thus different model performances. There are two main practices, including the single objective function and multiple objective functions (Tang et al., 2006). Single objective optimization uses one objective function in the parameter optimization, and is the prevailing practice for both lumped model and distributed model parameter optimization. Multiple objective optimization considers simultaneously two or more objective functions, the different objectives could have same measures quantitatively, such as to minimize the model efficiency and model efficiency for logarithmic transformed discharges simultaneously (Shafii et al., 2009), or even have different measures quantitatively, such as to minimize the streamflow simulation error and the well water level simulation error simultaneously (Madsen, 2003). Not producing one set of optimal parameters like in single objective optimization, multiple objective optimization produces pareto-optimal parameter sets, each pareto-optimal parameter is a feasible parameter, which provides the user the opportunity to trade off among different simulation purposes. For example, if the user want to have a better simulation to the high flow of the streamflow, then the high weight will be given to the model efficiency, but if a better simulation to the low flow is expected, then the priority should be put on the model efficiency for logarithmic transformed discharges (Shafii et al., 2009). Multiple objective optimization is more flexible than single objective optimization, but requires much more computation, so if the model simulation purpose is determined, i.e. the objective is known, then the

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single objective optimization is enough. In this study, the purpose is to optimize the model parameter for flood forecasting, so the purpose is obvious, the one objective function to minimize the peak flow relative error of the catchment discharge at outlet is chosen, and the single objective optimization is carried out.

2.4 Liuxihe model and parameter classification

Liuxihe model (Chen, 2009; Chen et al., 2011) is a physically based distributed hydrological model mainly for catchment flood forecasting. In Liuxihe model, the studied area is divided into a number of cells horizontally by using a DEM, the cells are called a unit-basin, and are treated as a uniform basin in which elevation, vegetation type, soil characteristics, rainfall, and thus model parameters are considered to take the same value. The unit-basin is then divided into three layers vertically, including the canopy layer, the soil layer and the underground layer. The boundary of the canopy layer is from the terrain surface to the top of the vegetation. The evapotranspiration takes place in this layer, and the Evapotranspiration Model is used to determine the evapotranspiration at the unit-basin scale. In the soil layer, soil water is filled by the precipitation and depleted via evapotranspiration. The underground layer is beneath the soil layer with a steady underground flow that is recharged by percolation. All cells are categorized into 3 types, namely hill slope cell, river cell and reservoir cell.

There are 5 different runoff routings in Liuxihe model, including hill slope routing, river channel routing, interflow routing, reservoir routing and underground flow routing. Hill slope routing is used to route the surface runoff produced in one hill slope cell to its neighbouring cell, and the kinematical wave approximation is employed to make this runoff routing. For the river channel routing, the shape of the channel cross-section is assumed to be trapezoid, which makes it estimated by satellite images, and the one dimensional diffusive wave approximation is employed to make this routing.

The parameters in Liuxihe model are divided into unadjustable parameters and adjustable parameters. The flow direction and slope are unadjustable parameters which are derived from the DEM directly and remain unchanged. The other parameters are

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adjustable parameters, and could be adjusted to improve the model performance. The adjustable parameters are classified as 4 types, including climate based parameters, topography based parameters, vegetation based parameters and soil based parameters. Currently in Liuxihe model, there is method for determining initial values of adjustable parameters, and then the adjustable parameters are optimized by a half-automated parameter adjusting method, i.e. based on the initial parameter values, the parameter values are adjusted by hand to improve the model performance, and the parameter adjusting is done one parameter by one parameter. In this way, it is very tedious and time-consuming, and takes months to adjust the parameters even in a very small catchment, so it is not highly proficiency though it could improve the model performance, and is also not a global optimization method. An automatic, global optimization method of Liuxihe model is needed. In this study, the Liuxihe model will be employed as the representing PBDHM.

2.5 Improved PSO algorithm for Liuxihe model

2.5.1 Principles of Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) algorithm was first proposed by American psychologist, James Kennedy and electrical engineer, Russell Eberhart (1995) during their studying to the social and intelligent behaviors of a school of birds in searching for food and better living places, now it is widely used in parameter calibration of lumped hydrological model. Resffa et al. (2013) used the PSO algorithm to optimize strategies for designing the membership functions of Fuzzy Control Systems for the water tank and inverted pendulum, Mauricio et al. (2013) used the PSO Optimisation software for SWAT model calibration, Zambrano-Bigiarin et al. (2013) developed a HydroPSO software for model parameter optimization, Bahareh et al. (2013) used single-objective and multi-objective PSO algorithms to optimize parameters of HEC-HMS model, Leila et al. (2013) employed a multi-swarm version of particle swarm optimization (MSPSO) in connection with the well-known HEC-Res PRM simulation

model in a parameterization–simulation–optimization (parameterization SO) approach, Richard et al. (2014) compared the PSO algorithm with other algorithms in Hydrological Model Calibration, Jeraldin et al. (2014) used PSO in the tank system, these PSO applications are for lumped models only.

PSO is a global searching algorithm, in which, each particle represents a feasible solution to the model parameters, and usually an appropriate number of particles is chosen to act like a school of birds, the appropriate number of particles is a very important PSO parameter that will impact the PSO's performance. In the optimization process, these particles move forward over the searching space at the same time following certain rules, which include each particle's moving direction and moving speed, that could be determined with the following equations.

$$V_{i,k} = \omega \times V_{i,k-1} + C_1 \times \text{rand} \times (X_{i,l\text{Best}} - X_{i,k-1}) + C_2 \times \text{rand} \times (X_{g\text{Best}} - X_{i,k-1}) \quad (2)$$

$$X_{i,k} = X_{i,k-1} + V_{i,k} \quad (3)$$

where $V_{i,k}$ is the moving speed of i th particle at k th step, $X_{i,k}$ is the position of i th particle at k th step, $X_{i,p\text{Best}}$ is the best position of i th particle at k th step (current), $X_{g\text{Best}}$ is the best position of all particles at k th step, ω is inertia acceleration speed, C_1 and C_2 are learning factors, rand is a random number between 0 and 1, here ω , C_1 and C_2 are also important PSO parameters that will impact the PSO's performance.

For one step optimization, it is also called one evolution, all particles move forward one step, all particles will then have their best positions up to now, and the best position of all particles represents the global optimal positions of all particles. With step by step evolution, the global positions of all the particles will be approached, and the corresponding parameter values are the optimal parameters values. In the evolution process, a maximum number of evolution is usually set to keep the optimization process in a reasonable time limit.

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2.5.2 Improved PSO algorithm

In the early PSO algorithm, particle number, ω , C_1 and C_2 are fixed, studies showed that changing the values of ω , C_1 and C_2 in the PSO search process will improve the PSO's performance (El-Gohary et al., 2007; Song et al., 2008; Acharjee et al., 2010; Chuang et al., 2011). In this study, current research progress in improving PSO's performance will be introduced to improve PSO algorithm, the strategies employed in changing ω , C_1 and C_2 are stated below, and will be tested in the studied catchments. In this paper, the appropriate PSO particle number, ω , C_1 and C_2 are called PSO parameters.

Inertia weight ω

The inertia weight ω is a PSO parameter impacting the global search capability (Shi and Eberhart, 1998). In the early study, ω takes a fixed value of less than 1, current studies show that changing ω could improve the PSO performance, and a few methods for dynamically adjusting ω have been proposed, such as linear decreasing inertia weight strategy (LDIW) (Shi and Eberhart, 2001), adaptive adjustment strategy (Ratnaweera et al., 2004), random inertia weight (RIW) (Shu et al., 2009), fuzzy inertia weight (Eberhart and Shi, 2001). In this study, the LDIW strategy is employed to dynamically determining the value of ω with the following equation.

$$\omega = \omega_{\max} - \frac{t(\omega_{\max} - \omega_{\min})}{T} \quad (4)$$

where, t is the current evolution number, T is the maximum evolution number, ω_{\max} takes the value of 0.9, ω_{\min} takes the value of 0.1.

Acceleration coefficients C_1 and C_2

Acceleration coefficients C_1 and C_2 also impact PSO's performance. In early studies, acceleration coefficients C_1 and C_2 usually take the same value of 2, and are fixed

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4. Initialize every particles, i.e. determine their initial positions, and calculate the value of the current objective function.
5. Evolution calculation: for every evolution, first determine the best position of every particle and the global positions of all particles, then calculate the moving directions and speeds of every particles at current evolution by using Eqs. (2) and (3), finally check the optimization criterion, if it is satisfied, then the optimization end, otherwise, continue to the next evolution.

3 Studied catchment and Liuxihe model set up

3.1 Studied catchment and hydrological data

Two catchments in southern China have been selected as the case study catchments. The first catchment is Tiantoushui catchment in Lechang County of Guangdong Province, it is a small watershed with a drainage area of 511 km² and channel length of 70 km, which is a typical mountainous catchment with frequent flash flooding in southern China. Tiantoushui catchment will mainly be used to test the PSO parameters impacts to the algorithm performance, so to propose the optimal PSO parameters for the Liuxihe model parameter optimization. As this work needs lots of model runs, so a small catchment helps to keep the running time in a feasible limit. There are 50 rain gauges within the catchment and one river flow gauges in the catchment outlet, the high density rain gauge network is built not only for flash flood forecasting, but also for some kinds of scientific experiments, this will also help to reduce the uncertainties caused by the uneven precipitation spatial distribution. Figure 1a is the sketch map of Tiantoushui Catchment with locations of rain gauges and the tributaries.

Hydrological data of 9 flood events has been collected for this study, including the river flow at the catchment outlet and precipitation at each rain gauges at an hourly interval. The precipitation measured by the rain gauges will be interpolated to the grid cells by employing Thiessen Polygon method (Derakhshan et al., 2011).

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The second studied catchment is the upper portion of Wujiang catchment in southern China, and is called in this paper the upper and middle Wujiang catchment (UMWC). UMWC is in the upper and middle stream of Wujiang catchment with a drainage area of 3622 km², flooding in the catchment is also very frequent and heavy. The purpose of studying this big catchment is to show that PSO could still work in large catchment. There is one river flow gauge in the outlet of UMWC, and 17 rain gauges within the catchment. Figure 1b shows the sketch map of the catchment with locations of rain gauges and the tributaries. Hydrological data of 14 flood events from UMWC has been collected, including the river flow at the catchment outlet and precipitation at each rain gauges at one hour interval, the precipitation measured by the rain gauges will also be interpolated to the grid cells employing Thisseon Polygon method.

3.2 Property data for Liuxihe model setting up

Catchment property data used for model set up in this study are DEM, land use types and soil types, these data of the studied catchments are downloaded from the open access databases. The DEM is downloaded from the Shuttle Radar Topography Mission database at <http://srtm.csi.cgiar.org>, the land use type is downloaded from <http://landcover.usgs.gov>, and the soil type is downloaded from <http://www.isric.org>. The downloaded DEM is at the spatial resolution of 90 m × 90 m, but the other two data are at the 1000 m × 1000 m spatial resolution, so they are rescaled to the spatial resolution of 90 m × 90 m. Figures 2 and 3 show the property data of DEM, land use types and soil types of the two catchments, respectively.

In the Tiantoushui Catchment, the highest, lowest and average elevation are 1874, 174 and 782 m, respectively. There are 4 land use types, including evergreen coniferous forest, evergreen broadleaved forest, bush and farmland, accounting for 27.6, 36.5, 25.5, and 10.4 % of the total catchment area, respectively. There are 10 soil types, including water body, Humicacrisol, Haplic and high activitive acrisol, Ferralic cambisol, Haplic luvisols, Dystric cambisol, Calcaric regosol, Dystric regosol, Artificial accumu-

lated soil and Dystric rankers, accounting for 4.8, 56.5, 1.7, 3.4, 6.5, 4.5, 0.7, 5.6, 9.8 and 6.5% of the total catchment area, respectively.

In the UMWC catchment, the highest, lowest and average elevation are 1793, 170 and 982 m, respectively. There are 8 land use types, including evergreen coniferous forest, evergreen broadleaved forest, shrub, sparse wood, mountains and alpine meadow, slope grassland, lakes and cultivated land, accounting for 26.4, 24.3, 35, 2.1, 0.1, 2.6, 0.5 and 9.1% of the total catchment area, respectively. There are 12 soil types, including water body, Humicacrisol, Haplic and high activitive acrisol, Ferralic cambisol, Haplic luvisols, Dystric cambisol, Calcaric regosol, Dystric regosol, Haplic and weak active acrisol, Artificial accumulated soil, Eutricregosols and Black limestone soil and Dystric rankers, accounting for 4.8, 56.5, 0.5, 3.4, 6.5, 4.5, 0.7, 5.6, 9.8, 6.6, 1.0 and 0.2% of the total catchment area, respectively.

3.3 Liuxihe model set up

To set up the Liuxihe model in the studied catchments is to divide the whole catchment into grids with DEM. In this study, the Tiantoushui Catchment is divided into 65 011 grid cells using the DEM with grid cell size of 90m × 90m, then they are categorized into reservoir cell, river channel cell and hill slope cell. In the studied catchments, there are no significant reservoirs, so there are no reservoir cells set. Based on the method for cell type classification proposed in Liuxihe model, the river channel system is treated as a 3-order channel system, and 1364 river channel cells and 63 647 hill slope cells have been produced in Tiantoushui Catchment, respectively. Futher, 10 nodes have been set on the Tiantoushui Catchment, and the river channel system is divided into 14 virtual sections, and their cross-section sizes have been estimated by referencing to satellite remote sensing images. The Liuxihe model structure of Tiantoushui Catchment is shown in Fig. 4a.

The Liuxihe model is also set up in UMWC, the Catchment is first divided into 460 695 grid cells using the DEM with grid cell size of 90m × 90m. The river channel system is treated as a 3-order channel system, and 3295 river channel cells and 457 400 hill

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slope cells have been produced, respectively. 32 nodes have been set on UMWC, and their cross-section sizes have been estimated by referencing to satellite remote sensing images. The Liuxihe model structure of UMWC is shown in Fig. 4b.

3.4 Determination of initial parameter values

In Liuxihe model, the flow direction and slope are two unadjustable parameters which will be derived from the DEM, and will remain unchanged. Based on the DEM shown in Fig. 1a, the flow direction and slope of the studied catchments are derived. The other parameters are adjustable parameters, which need initial values for further optimization. Evaporation capacity is a climate based parameter, and its initial value is set to 5 mm day⁻¹ at both catchment based on the observation near the catchment outlet. Evaporation coefficient and roughness are land use based parameters, and are less-sensitive parameters in Liuxihe model, the initial values of evaporation coefficient are set to 0.7 at both catchments as recommended by Liuxihe model (Chen, 2009), while the initial values of roughness are derived based on reference (Wang et al., 1997) and are listed in Tables 1 and 2, respectively for the two catchments.

The other parameters are soil based parameters. In Liuxihe model, b is recommended to take the value of 2.5, soil water content at wilting condition takes 30% of the soil water content at saturated condition, the initial values of other soil based parameters are calculated by using the Soil Water Characteristics Hydraulic Properties Calculator (Arya et al., 1981) that calculates soil water content at saturation and field condition and the hydraulic conductivity at saturation based on the soil texture, organic matter, gravel content, salinity, and compaction. The initial values of soil based parameters are determined by using the program developed by Keith E. Saxton that could be downloaded freely at <http://hydrolab.arsusda.gov/soilwater/Index.htm>, the initial values of the soil based parameters at the two studied catchments are listed in Tables 3 and 4, respectively.

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5 title number, the process relative error W and peak flow relative error E decrease first, but when the particle number reaches 20, the two indices increase. This also means that with the increasing of the particle number, the model performance increases first and then decreases. So from the view of model performance, we could assume 20 is the appropriate particle number in Tiantoushui Catchment. So in this paper, from the results above, we could suggests that 20 is the the appropriate particle number of PSO algorithm for Liuxihe model in catchment flood forecasting in Tiantoushui Catchment.

10 The particle number of 20 is also used in the parameter optimization of UMWc catchment, and the model performance are also very satisfactory, and the computation time is acceptable, so in this study, we assume that 20 is the appropriate particle number for Liuxihe model parameter optimization when employing PSO algorithm for catchment flood forecasting nomatter the size of the catchment, this conclusion can also be derived from the results of PSO's convergence in next section.

4.2 PSO's convergence

15 PSO algorithm is an evolution algorithm, its searching process is an iteration process, so the convergence is a key issue, i.e. the algorithm should convergence to its optimal state in a limited iteration number, otherwise it could not be used practically. In PSO, the iteration is called evolution, one iteration is called one evolution. To explore PSO's convergence, we first draw the optimization evolution process of PSO in Tiantoushui Catchment in Fig. 5, both the objective and parameter evolution processes are included.

20 From Fig. 5 we found that during the evolution process, the objective function steadily decreases, that means the model performance is constantly improved. But for all the parameters, they do not change in the same direction, i.e. the parameters may increase in one evolution, and decrease in the next evolution, but after more than 25 evolutions, most of the parameters converge to their optimal values, with about 30 evolutions, all of the parameters converge to their optimal values, after that, there is almost no parameter

changes, this means 30 is the maximum evolution number for PSO in Tiantoushui Catchment.

From Fig. 5, we also found that the optimal parameter values of several parameters are quite different with the initial parameters, but some remain little changes, this also implies that the PSO algorithm has very good performance in convergence even the initial values of the parameters are far from its optimal values.

We further analysis PSO's performance in UMWC, but this time we only draw the parameter evolution process of PSO in UMWC in Fig. 6, the objective evolution process of PSO in UMWC is similar with that in Tiantoushui Catchment.

From Fig. 6 we also found that during the evolution process, the objective function steadily decreases, but the parameters do not increase or decrease in a constant way, the changing patten is similar with that shown in Fig. 5. After 25 evolutions, most of the parameters converge to their optimal values, with about 30 evolutions, all of the parameters converge to their optimal values. The patten in UMWC is the same with that in Tiantoushui Catchment.

From Fig. 6, we also found that the optimal parameter values of several parameters are quite different with the initial values, but some remain little changes, this patten in UMWC is the same with that in Tiantoushui Catchment also.

From the above results both in UMWC and Tiantoushui Catchment, we could assume that PSO algorithm has a very good performance in convergence in catchments with different sizes, and we could assume that the maximum evoluion number could be set to 30 no matter the size of the studied catchments. This conclusion also supports the conclusion that 20 is the appropriate particle number for Liuxihe model parameter optimization when employing PSO algorithm for catchment flood forecasting no matter the size of the catchment.

4.3 Computational efficiency

The computation time needed for physically based distributed hydrological model run is huge, for the parameter optimization, many many model runs are needed, so the

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computation time needed for the parameter optimization is also a key factor to impact the performance of the PSO. From Table 5, we know in Tiantoushui Catchment, the computation time for parameter optimization is about 12 h, this is acceptable. The time needed for parameter optimization in UMWC is about 82.6 h, it is also acceptable. The computer used for this study is a general server, but if use advanced computer, the time needed could be reduced largely.

4.4 Model validation in Tiantoushui catchment

The parameters of Liuxihe model in Tiantoushui Catchment have been optimized by employing PSO algorithm proposed in this paper, the particle number used is 20, maximum evolution number is set to 50, ω , C_1 and C_2 are dynamically adjusted with Eqs. (4)–(6), flood event flood2006071409 is used to optimize the parameters.

The other 8 observed flood events of Tiantoushui Catchment are simulated by the model with parameters optimized above to validate the model performance for catchment flood forecasting. To analysis the effect of parameter optimization to model performance improvement, Fig. 7 shows 4 of the simulatd hydrographes, the hydrographes simulated by the model with initial parameter values are also drawn in Fig. 7.

From the results, it has been found that the 8 simulated hydrographes fit the observed hydrographes well, particularly the simulated peak flow is quite good. From the results we also found that the model with initial parameter values do not simulate the observed flood events satisfactorily, i.e. the uncertainties are high.

To further analysis the model performance with parameter optimization, the 5 evaluation indices of the 8 simulated flood events have been calculated and listed in Table 6.

From Table 6 we found that the 5 evaluation indices have been improved by parameter optimization at different extent. For the results simulated by the model with initial parameters, the 5 evaluation indices, including the Nash–Sutcliffe coefficient, correlation coefficient, process relative error, peak flow relative error and water balance coefficient, have an average values of 0.66, 0.85, 72 %, 21 % and 1.03, respectively. While for the results simulated by the model with optimized parameters, the 5 evalua-

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tion indices have average values of 0.88, 0.939, 25 %, 6 % and 0.97, respectively. The average Nash–Sutcliffe coefficient has a 33 % increasing, the correlation coefficient a 9.6 % increasing, process relative error a 65.28 % decreasing, peak flow relative error a 71.43 % decreasing, and the water balance coefficient a 5.83 % decreasing. Among the 5 evaluation indices, the peak flow relative error and the process relative error have the biggest improvement.

The above results imply that with parameter optimization by using the PSO algorithm proposed in this paper, the model performance of Liuxihe model for catchment flood forecasting has been improved in Tiantoushui Catchment, optimizing parameters of Liuxihe model is necessary.

4.5 Model validation in UMWC

The parameters of Liuxihe model in UMWC have been optimized by employing PSO algorithm proposed in this paper, the particle number and maximum evolution number are also set to 20 and 50, respectively, ω , C_1 and C_2 are dynamically adjusted with Eqs. (4)–(6), flood event flood1985052618 is used to optimize the parameters.

The other 13 observed flood events of UMWC are simulated by the model with parameters optimized above, Fig. 8 shows 4 of the simulated hydrographes. To compare, the flood events also have been simulated with the parameters optimized with a half-automated parameter adjusting method (Chen, 2009), and the results are also shown in Fig. 8. From the simulated results, it has been found that the 13 simulated hydrographes fit the observed hydrographes well, particularly the simulated peak flow is quite good, this conclusion is the same with the results in Tiantoushui Catchment. From the results we also found that the model with initial parameter values do not simulate the observed flood event satisfactorily, the simulated results with parameters optimized with a half-automated parameter adjusting method is a big improvement to that simulated with the initial model parameters, but the simulated results with the PSO optimized model parameters are the best among the three results.

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To further analysis the model performance with parameter optimization, the 5 evaluation index of the 13 simulated flood events have been calculated and listed in Table 7.

From Table 7 we found that the 5 evaluation index have been improved by parameter optimization at different extent. For the results simulated by the model with initial parameters, the 5 evaluation indices, including the Nash–Sutcliffe coefficient, correlation coefficient, process relative error, peak flow relative error and water balance coefficient, have an average values of 0.757, 0.771, 38.8 %, 25.1 % and 0.924, respectively. While for the results simulated by the model with optimized parameters, the 5 evaluation indices have average values of 0.888, 0.960, 24.8 %, 2.4 % and 0.949, respectively. The peak flow relative error has been reduced from 25.1 to 2.4 % after parameter optimization, that is 90.44 % down and also the biggest improvement among the 5 evaluation indices. While the average Nash–Sutcliffe coefficient has a 17.31 % increasing, the correlation coefficient a 24.51 % increasing, process relative error a 36.08 % decreasing and water balance coefficient a 2.71 % increasing. The results have similar trend with that in Tiantoushui Catchment, this also implies that with parameter optimization by using the PSO algorithm proposed in this paper, the model performance of Liuxihe Model for catchment flood forecasting has been improved in UMWC Catchment, i.e. even for a larger catchment, PSO works well for Liuxihe model. Liuxihe model's capability for catchment flood forecasting could be improved by parameter optimization with PSO algorithm, and Liuxihe model parameter optimization is necessary.

5 Conclusion

In this study, based on the scalar concept, a general framework for automatic parameter optimization of the physically based distributed hydrological model is proposed, and the improved Particle Swarm Optimization algorithm is employed for the Liuxihe Model parameter optimization for catchment flood forecasting. The proposed method have been tested in two catchments in southern China with different size, one is small, one is large. Based on the study results, the following conclusions have been found.

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1. When employing physically based distributed hydrological model for catchment flood forecasting, uncertainty in deriving model parameters physically from the terrain properties is high, parameter optimization is still necessary to improve the model's capability for catchment flood forecasting.
2. Capability of physically based distributed hydrological model for catchment flood forecasting, specifically the Liuxihe model studied in this paper, could be improved largely by parameter optimization with PSO algorithm, and the model performance is quite good with the optimized parameters to satisfy the requirement of real-time catchment flood forecasting.
3. Improved Particle Swarm Optimization (PSO) algorithm proposed in this paper for physically based distributed hydrological model for catchment flood forecasting, specifically the Liuxihe model studied in this paper, has very good optimization performance, the optimized model parameters are global optimal parameters, and could be used for Liuxihe model parameter optimization for catchment flood forecasting at different size catchments.
4. The appropriate particle number of PSO algorithm used for Liuxihe model parameter optimization for catchment flood forecasting is 20.
5. The maximum evolution number of PSO algorithm used for Liuxihe model parameter optimization for catchment flood forecasting is 30.
6. The PSO algorithm has high computational efficiency, and could be used in large scale catchments flood forecasting.

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References

- Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'connell, P. E., and Rasmussen, J.: An Introduction to the European Hydrologic System – System Hydrologue Europeen, “SHE”, a: History and philosophy of a physically-based, distributed modelling system, *J. Hydrol.*, 87, 45–59, 1986a.
- 5 Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'connell, P. E., and Rasmussen, J.: An Introduction to the European Hydrologic System – System Hydrologue Europeen, “SHE”, b: Structure of a Physically based, distributed modeling system, *J. Hydrol.*, 87, 61–77, 1986b.
- Acharjee, P. and Goswami, S. K.: Chaotic particle swarm optimization based robust load flow, *Int. J. Elec. Power*, 32, 141–146, 2010.
- 10 Ajami, N. K., Gupta, H., Wagener, T., and Sorooshian, S.: Calibration of a semi-distributed hydrologic model for streamflow estimation along a river system, *J. Hydrol.*, 298, 112–135, 2004.
- Ambrose, B., Beven, K., and Freer, J.: Toward generalization of the TOPMODEL concepts: topographic indices of hydrologic similarity, *Water Resour. Res.*, 32, 2135–2145, 1996.
- 15 Arnold, J. G., Williams, J. R., and Srinivasan, R.: SWAT: soil water assessment tool, US Department of Agriculture, Agricultural Research Service, Grassland, Soil and Water Research Laboratory, Temple, Texas, USA, 1994.
- Arsenault, R., Poulin, A., Côté, P., and Brissette, F.: Comparison of Stochastic Optimization Algorithms in Hydrological Model Calibration, *J. Hydrol. Eng.*, 19, 1374–1384, doi:10.1061/(ASCE)HE.1943-5584.0000938, 2004.
- 20 Arya, L. M. and Paris, J. F.: An empirical model to predict the soil moisture characteristic from particle-size distribution and bulk density data, *Soil Sci. Soc. Am. J.*, 45, 1023–1030, 1981.
- Bahareh, K. S., Mousavi, J., and Abbaspour, K. C.: Automatic calibration of HEC-HMS using single-objective and multi-objective PSO algorithms, *Hydrol. Process.*, 27, 4028–4042, 2013.
- 25 Beven, K, Lamb, R., Quinn, P., Romanowicz, R., and Freer, J.: Topmodel, in: *Computer Models of Watershed Hydrology*, edited by: Singh, V., Baton Rouge, Florida, USA, 627–668, 1995.
- Carpenter, T. M., Georgakakos, K. P., and Sperflagea, J. A.: On the parametric and NEXRAD-radar sensitivities of a distributed hydrologic model suitable for operational use, *J. Hydrol.*, 253, 169–193, 2001.
- 30 Chen, G., Jia, J., and Han, Q.: Study on the strategy of decreasing inertia weight in particle swarm optimization algorithm, *J. Xi'an Jiantong Univers.*, 40, 53–56, 2006.

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Chen, S. L., Cai, G. R., Guo, W. Z., and Chen, G. L.: Study on the nonlinear strategy of acceleration coefficient in Particle Swarm Optimization (PSO) algorithm, *J. Yangtze Univers. (Nat Sci Edit)*, 1–4, 2007.

Chen, Y.: *Liuxihe Model*, Beijing, Science Press, Beijing, China, 198 pp., 2009.

Chen, Y., Zhu, X., Han, J., and Cluckie, I.: CINRAD data quality control and precipitation estimation, *Water Manage.*, 162, 95–105, 2009.

Chen, Y., Ren, Q. W., Huang, F. H., Xu, H. J., and Cluckie, I.: Liuxihe model and its modeling to river basin flood, *J. Hydrol. Eng.*, 16, 33–50, 2011.

Chu, W., Gao, X., and Sorooshian, S.: A new evolutionary search strategy for global optimization of high-dimensional problems, *Inform. Sci.*, 181, 4909–4927, 2011.

Chuang, L. Y., Hsiao, C. J., and Yang, C. H.: Chaotic particle swarm optimization for data clustering, *Expert Syst. Appl.*, 38, 14555–14563, 2011.

Crawford, N. H. and Linsley, R. K.: *Digital simulation in hydrology, Stanford Watershed Model IV*, Tech. Rep. 39, Stanford Univ. Dep. Civ. Eng, Stanford, 1966.

Dawdy, D. R. and O'Donnell, T.: Mathematical models of catchment behavior, *J. Hydraul. Div.-ASCE*, 91, 123–137, 1965.

Derakhshan, H. and Talebbeydokhti, N.: Rainfall disaggregation in non-recording gauge stations using space–time information system, *Sci. Iran.*, 18, 995–1001, 2011.

De Smedt, F., Liu, Y. B., and Gebremeskel, S.: Hydrological modeling on a watershed scale using GIS and remote sensed land use information, in: *Risk Analyses*, edited by: Brebbia, C. A., WIT press, Southampton, Boston, 10 pp., 2000.

Dorigo, M., Maniezzo, V., and Coloni, A.: Ant system: optimization by a colony of cooperating agents, systems, man, and cybernetics, Part B: Cybernetics, *IEEE T.*, 26, 29–41, 1996.

Duan, Q., Sorooshian, S., and Gupta, V. K.: Optimal use of the SCE-UA global optimization method for calibrating watershed models, *J. Hydrol.*, 158, 265–284, 1994.

Eberhart, R. C. and Shi, Y.: Tracking and optimizing dynamic systems with particle swarms, in: *IEEE Proceedings of the 2001 Congress on Evolutionary Computation*, Vol. 1, 94–100, 2001a.

Eberhart, R. C. and Shi, Y.: Particle swarm optimization: developments, applications and resources, in: *IEEE Proceedings of the 2001 Congress on Evolutionary Computation*, Vol. 1, 81–86, 2001b.

El-Gohary, A. and Al-Ruzaiza, A. S.: Chaos and adaptive control in two prey, one predator system with nonlinear feedback, *Chaos Soliton. Fract.*, 34, 443–453, 2007.

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- Falorni, G., Teles, V., Vivoni, E. R., Bras, R. L., and Amaratunga, K. S.: Analysis and characterization of the vertical accuracy of digital elevation models from the Shuttle Radar Topography Mission, *J. Geophys. Res. Ea. Surf.*, 110, 2003–2012, 2005.
- Franchini, M.: Use of a genetic algorithm combined with a local search for the automatic calibration of conceptual rainfall–runoff models, *Hydrolog. Sci. J.*, 41, 21–39, 1996.
- Freeze, R. A. and Harlan, R. L.: Blueprint for a physically-based, digitally simulated, hydrologic response model, *J. Hydrol.*, 9, 237–258, 1969.
- Fulton, R. A., Breidenbach, J. P., Seo, D. J., Miller, D. A., and O’Bannon, T.: The WSR-88D rainfall algorithm, *Weather Forecast.*, 13, 377–395, 1998.
- Goldberg, D. E.: *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, Reading, MA, 1989.
- Grayson, R. B., Moore, I. D., and McMahon, T. A.: Physically based hydrologic modeling: 1. A Terrain-based model for investigative purposes, *Water Resour. Res.*, 28, 2639–2658, 1992.
- Gupta, H. V., Sorooshian, S., and Yapo, P. O.: Toward improved calibration of hydrological models: multiple and non-commensurable measures of information, *Water Resour. Res.*, 34, 751–763, 1998.
- Hendrickson, J. D., Sorooshian, S., and Brazil, L. E.: Comparison of Newton-type and direct search algorithms for calibration of conceptual rainfall–runoff models, *Water Resour. Res.*, 24, 691–700, 1988.
- Holland, J. H.: *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, University of Michigan Press, Cambridge, MA, 1975.
- Hooke, R. and Jeeves, T. A.: “Direct Search” solution of numerical and statistical problems, *J. ACM*, 8, 212–229, 1961.
- Ibbitt, R. P. and O’Donnell, T.: Designing conceptual catchment models for automatic fitting methods, *IAHS-AISH P.*, 101, 462–475, 1971.
- Immerzeel, W. W. and Droogers, P.: Calibration of a distributed hydrological model based on satellite evapotranspiration, *J. Hydrol.*, 349, 411–424, 2008.
- Jasper, A., Vrugt, H. V., and Gupta, W. B.: A shuffled complex evolution metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters, *Water Resour. Res.*, 39, 1201, doi:10.1029/2002WR001642, 2003.



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- Masri, S. F., Bekey, G. A., and Safford, F. B.: A global optimization algorithm using adaptive random search, *Appl. Math. Comput.*, 7, 353–375, 1980.
- Mauricio, Z. B. and Rodrigo, R.: A model independent Particle Swarm Optimisation software for model calibration, *Environ. Modell. Softw.*, 43, 5–25, 2013.
- 5 Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models Part I – A discussion of principles, *J. Hydrol.*, 10, 282–290, 1970.
- Nelder, J. A. and Mead, R.: A simple method for function minimization, *Comput. Journey*, 7, 308–313, 1965.
- O’Connell, P. E., Nash, J. E., and Farrell, J. P.: River flow forecasting through conceptual models Part II – The Brosna catchment at Ferbane, *J. Hydrol.*, 10, 317–329, 1970.
- 10 Pokhrel, P., Gupta, H. V., and Wagener, T.: A spatial regularization approach to parameter estimation for a distributed watershed model, *Water Resour. Res.*, 44, W12419, doi:10.1029/2007WR006615, 2008.
- Pokhrel, P., Yilmaz, K. K., and Gupta, H. V.: Multiple-criteria calibration of a distributed watershed model using spatial regularization and response signatures, *J. Hydrol.*, 418–419, 49–60, 2012.
- 15 Poli, R.: Analysis of the publications on the applications of particle swarm optimisation, *J. Artif. Evol. Appl.*, 2008, 1–10, 2008.
- Poli, R., Kennedy, J., and Blackwell, T.: Particle swarm optimization, *Swarm Intelligence*, 1, 33–57, 2007.
- 20 Ratnaweera, A., Halgamuge, S. K., and Watson, H. C.: Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients, *IEEE T. Evol. Comput.*, 8, 240–255, 2004.
- Reed, S., Koren, V., Smith, M., Zhang, Z., Moreda, F., and Seo, D.-J.: DMIP participants: overall distributed model intercomparison project results, *J. Hydrol.*, 298, 27–60, 2004.
- 25 Refsgaard, J. C.: Parameterisation, calibration and validation of distributed hydrological models, *J. Hydrol.*, 198, 69–97, 1997.
- Refsgaard, J. C. and Storm, B.: Construction, calibration and validation of hydrological models. in: *Distributed Hydrological Modelling*, edited by: Abbott, M. B. and Refsgaard, J. C., Springer, Netherlands, 41–54, 1996.
- 30 Resffa, F., O’ Castillo., Fevrier, V., and Leticia, C.: Design of Optimal Membership Functions for Fuzzy Controllers of the Water Tank and Inverted Pendulum with PSO Variants, *IFSA World*

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Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, Canada, 1068–1073, 2013.

Rosenbrock, H. H.: An automatic method for finding the greatest or least value of a function, *Comput. Journey*, 3, 175–184, 1960.

5 Shafii, M. and De Smedt, F.: Multi-objective calibration of a distributed hydrological model (WetSpa) using a genetic algorithm, *Hydrol. Earth Syst. Sci.*, 13, 2137–2149, doi:10.5194/hess-13-2137-2009, 2009.

Sharma, A. and Tiwari, K. N.: A comparative appraisal of hydrological behavior of SRTM DEM at catchment level, *J. Hydrol.*, 519, 1394–1404, 2014.

10 Sherman, L. K.: Streamflow from rainfall by the unit-graph method, *Eng. News-Rec.*, 108, 501–505, 1932.

Shi, Y. and Eberhart, R. C.: A modified particle swarm optimizer, in: *IEEE World Congress on Computational Intelligence, The 1998 IEEE International Conference on Evolutionary Computation Proceedings*, 69–73, doi:10.1109/ICEC.1998.699146, 1998.

15 Shi, Y. and Eberhart, R. C.: Fuzzy adaptive particle swarm optimization, in: *IEEE Proceedings of the 2001 Congress on Evolutionary Computation*, Vol. 1, 101–106, 2001.

Shu, X., Chen, Y., Huang, F., and Zhou, H.: Application of PEST in the parameter calibration of wetspa distributed hydrological model, *J. China Hydrol.*, 29, 45–49, 2009.

20 Singh, V. P.: *Computer Models of Watershed Hydrology*, Water Resources Publications, Colorado, 1995.

Smith, M. B., Seo, D.-J., Koren, V. I., Reed, S., Zhang, Z., Duan, Q.-Y., Cong, S., Moreda, F., and Anderson, R.: The distributed model intercomparison project (DMIP): motivation and experiment design, *J. Hydrol.*, 298, 4–26, 2004.

25 Song, S., Kong, L., Gan, Y., and Su, R.: Hybrid particle swarm cooperative optimization algorithm and its application to MBC in alumina production, *Prog. Nat. Sci.*, 18, 1423–1428, 2008.

Sorooshian, S. and Gupta, V. K.: Model calibration, in: *Computer Models of Watershed Hydrology*, edited by: Singh, V. P., Water Resources Publications, Colorado, 23–68, 1995.

30 Sorooshian, S., Gupta, V. K., and Fulton, J. L.: Evaluation of maximum likelihood parameter estimation techniques for conceptual rainfall–runoff models: influence of calibration data variability and length on model credibility, *Water Resour. Res.*, 19, 251–259, 1983.

Storn, R. and Price, K.: Differential evolution e a simple and efficient heuristic for global optimization over continuous spaces, *J. Global Opt.*, 11, 341–359, 1997.

HESSD

12, 10603–10649, 2015

Improving flood forecasting capability of physically based distributed hydrological model

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- Tang, Y., Reed, P., and Wagener, T.: How effective and efficient are multiobjective evolutionary algorithms at hydrologic model calibration?, *Hydrol. Earth Syst. Sci.*, 10, 289–307, doi:10.5194/hess-10-289-2006, 2006.
- 5 Vieux, B. E.: Distributed Hydrologic Modeling Using GIS, in: *Water Science Technology Series*, vol. 48, 2nd Edn., Kluwer Academic Publishers, Norwell, Massachusetts, 289 pp., 2004.
- Vieux, B. E. and Moreda, F. G.: Ordered physics-based parameter adjustment of a distributed model, in: *Advances in Calibration of Watershed Models*, edited by: Duan, Q., Sorooshian, S., Gupta, H. V., Rousseau, A. N., and Turcotte, R., Chapt. 20, *Water Science and Application Series*, vol. 6, American Geophysical Union, Washington, USA, 267–281, 2003.
- 10 Vieux, B. E. and Vieux, J. E.: VfloTM: a real-time distributed hydrologic model [A], in: *Proceedings of the 2nd Federal Interagency Hydrologic Modeling Conference*, 28 July–1 August, Las Vegas, Nevada, Abstract and paper on CD-ROM, 2002.
- Vieux, B. E., Cui, Z., and Gaur, A.: Evaluation of a physics-based distributed hydrologic model for flood forecasting, *J. Hydrol.*, 298, 155–177, 2004.
- 15 Vrugt, J. and Robinson, B.: Improved evolutionary optimization from genetically adaptive multi-method search, *P. Natl. Acad. Sci. USA*, 104, 708–711, 2007.
- Wang, Z., Batelaan, O., and De Smedt, F.: A distributed model for water and energy transfer between soil, plants and atmosphere (WetSpa), *J. Phys. Chem. Earth*, 21, 189–193, 1997.
- Wigmosta, M. S., Vai, L. W., and Lettenmaier, D. P.: A distributed hydrology-vegetation model for complex terrain, *Water Resour. Res.*, 30, 1665–1669, 1994.
- 20 Yang, D., Herath, S., and Musiak, K.: Development of a geomorphologic properties extracted from DEMs for hydrologic modeling, *Annu. J. Hydraul. Eng.*, 47, 49–65, 1997.
- Zhang, X., Srinivasan, R., and Liew, M. V.: Multi-site calibration of the SWAT model for hydrologic modeling, *T. ASABE*, 51, 2039–2049, 2008.
- 25 Zhao, R. J.: *Flood Forecasting Method for Humid Regions of China*, East China College of Hydraulic Engineering, Nanjing, China, 1977.

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Table 1. Initial values of land use based parameters in Tiantoushui Catchment.

ID	Name	Evaporation coefficient	Roughness coefficient
2	evergreen coniferous forest	0.7	0.4
3	evergreen broadleaved forest	0.7	0.6
5	shrub	0.7	0.4
15	cultivated land	0.7	0.35

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Table 2. Initial values of land use based parameters in UMWC.

ID	Name	Evaporation coefficient	Roughness coefficient
2	evergreen coniferous forest	0.7	0.4
3	evergreen broadleaved forest	0.7	0.6
5	shrub	0.7	0.4
6	sparse wood	0.7	0.5
7	mountains and alpine meadow	0.7	0.2
8	slope grassland	0.7	0.3
10	lakes	0.7	0.05
15	cultivated land	0.7	0.35

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Table 4. Initial values of soil based parameters in UMWC.

Soil type	Thickness/ mm	Saturated water content	Field capacity	Saturated hydraulic conductivity/mm h ⁻¹	<i>b</i>	Wilting percentage
Humicacrisol	700	0.515	0.362	3	2.5	0.2
Haplic and high active acrisol	1000	0.517	0.369	3	2.5	0.206
Ferralic cambisol	700	0.419	0.193	15	2.5	0.1
Haplicluvisols	1000	0.55	0.501	2	2.5	0.357
Dystric cambisol	820	0.385	0.164	34	2.5	0.076
Calcaric regosol	1000	0.5	0.324	3	2.5	0.172
Dystric regosol	950	0.388	0.169	33	2.5	0.077
Haplic and weak active acrisol	1000	0.55	0.501	2	2.5	0.357
Artificial accumulated soil	1000	0.459	0.25	8	2.5	0.121
Eutricregosols and Black limestone soil	430	0.495	0.312	4	2.5	0.156
Dystric rankers	150	0.43	0.203	10	2.5	0.113

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Table 5. Performances of PSO algorithm in Tiantoushui Catchment.

Particle number	Computation time/h	Nash–Sutcliffe coefficient/ <i>C</i>	Correlation coefficient/ <i>R</i>	Process relative error/ <i>P</i>	Peak flow relative error/ <i>E</i>	Water balance coefficient/ <i>W</i>
10	21	0.793	0.896	0.319	0.086	0.894
15	13	0.849	0.925	0.235	0.077	0.903
20	12.1	0.962	0.951	0.13	0.07	0.917
25	18.6	0.852	0.927	0.237	0.056	0.884
50	45	0.862	0.932	0.242	0.043	0.885
100	86.8	0.838	0.92	0.256	0.054	0.867

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Table 6. The evaluation index of the simulated flood events in Tiantoushui Catchment.

Flood events	Nash–Sutcliffe coefficient/ <i>C</i>		Correlation coefficient/ <i>R</i>		Process relative error <i>P</i> (%)		Peak flow relative error <i>E</i> (%)		Water balance coefficient/ <i>W</i>	
	(1) ^a	(2) ^b	(1) ^a	(2) ^b	(1) ^a	(2) ^b	(1) ^a	(2) ^b	(1) ^a	(2) ^b
flood1996071012	0.964	0.85	0.990	0.79	16.3	0.3	11.2	0.156	1.102	2.19
flood1998061811	0.862	0.613	0.930	0.876	21.4	1.946	20.8	0.397	0.963	1.194
flood2001061206	0.836	0.758	0.926	0.969	31.8	0.35	0.9	0.311	0.841	0.64
flood2007082100	0.866	0.343	0.942	0.775	13.9	0.409	0.7	0.329	0.966	0.581
flood2008061114	0.882	0.74	0.943	0.883	20.8	0.71	2.5	0.31	0.930	0.36
flood2012040607	0.792	0.766	0.893	0.891	27.0	0.764	5.0	0.115	0.913	1.058
flood2012060901	0.912	0.454	0.958	0.752	37.0	0.745	3.2	0.015	1.072	1.238
flood2012062113	0.91	0.778	0.955	0.896	0.301	0.498	0.005	0.084	0.972	0.987
average	0.88	0.66	0.94	0.85	0.25	0.72	0.06	0.21	0.97	1.03

^a Results simulated by model with optimized parameters.

^b Results simulated by model with initial parameters.

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Table 7. The evaluation index of the simulated flood events in UMWC.

Flood events	Nash–Sutcliffe Coefficient/ <i>C</i>			Correlation Coefficient/ <i>R</i>			Process relative Error/ <i>P</i>			Peak flow relative Error/ <i>E</i>			Water balance Coefficient/ <i>W</i>		
	(1) ^a	(2) ^b	(3) ^c	(1) ^a	(2) ^b	(3) ^c	(1) ^a	(2) ^b	(3) ^c	(1) ^a	(2) ^b	(3) ^c	(1) ^a	(2) ^b	(3) ^c
flood1980050620	0.906	0.610	0.810	0.958	0.831	0.931	0.168	0.480	0.288	0.004	0.230	0.013	0.913	0.760	0.796
flood1980042313	0.892	0.724	0.824	0.972	0.768	0.968	0.282	0.270	0.307	0.003	0.270	0.008	0.867	0.620	0.792
flood1981041014	0.917	0.700	0.451	0.967	0.830	0.883	0.141	0.417	0.317	0.043	0.180	0.185	0.973	0.729	0.729
flood1981040712	0.805	0.686	0.686	0.964	0.738	0.938	0.154	0.550	0.255	0.159	0.228	0.228	0.990	0.850	1.328
flood1981041310	0.739	0.796	0.796	0.938	0.758	0.958	0.221	0.260	0.265	0.006	0.146	0.146	0.830	1.160	1.061
flood1982051014	0.831	0.793	0.793	0.924	0.852	0.952	0.271	0.440	0.174	0.013	0.230	0.230	0.922	1.230	1.010
flood1983061513	0.904	0.810	0.839	0.954	0.850	0.925	0.327	0.530	0.363	0.007	0.350	0.072	0.944	0.680	0.967
flood1983022720	0.896	0.750	0.850	0.974	0.740	0.934	0.152	0.220	0.102	0.018	0.420	0.078	1.017	0.650	1.045
flood1984050310	0.971	0.800	0.816	0.989	0.684	0.980	0.085	0.380	0.388	0.010	0.210	0.010	0.951	0.720	0.820
flood1985092216	0.967	0.840	0.940	0.986	0.785	0.978	0.375	0.480	0.380	0.022	0.320	0.055	1.071	1.350	1.034
flood1987051422	0.961	0.853	0.913	0.986	0.731	0.973	0.266	0.241	0.281	0.012	0.280	0.013	0.925	1.510	0.892
flood1987052012	0.902	0.727	0.927	0.951	0.628	0.968	0.332	0.362	0.262	0.015	0.160	0.034	0.955	0.840	0.979
flood2008060902	0.850	0.756	0.800	0.923	0.825	0.820	0.140	0.414	0.214	0.004	0.240	0.104	0.985	0.910	0.850
average	0.888	0.757	0.8	0.960	0.771	0.94	0.248	0.388	0.28	0.024	0.251	0.09	0.949	0.924	0.95

^a Results simulated by model with optimized parameters.

^b Results simulated by model with initial parameters.

^c Results simulated by model with half-automated optimized parameters.

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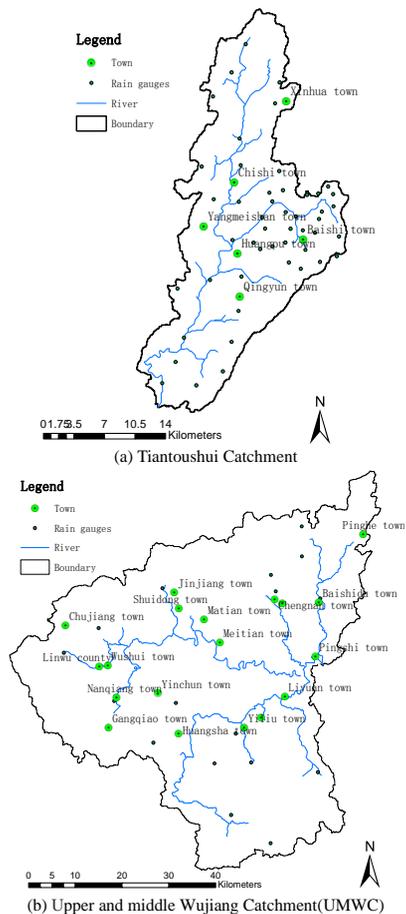


Figure 1. Sketch map of the studied Catchments.

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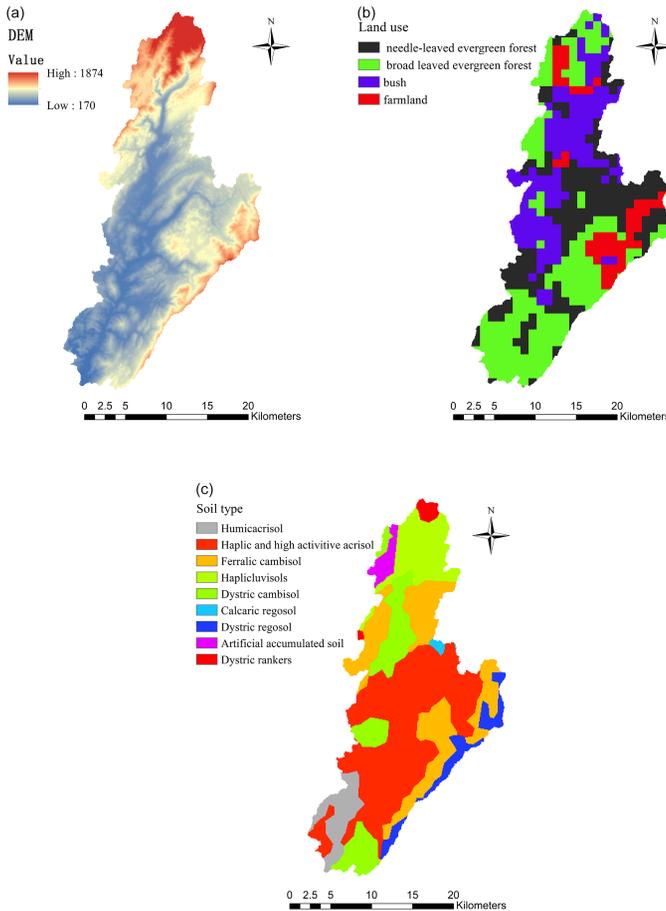


Figure 2. Terrain property of Tiantoushui Catchment.

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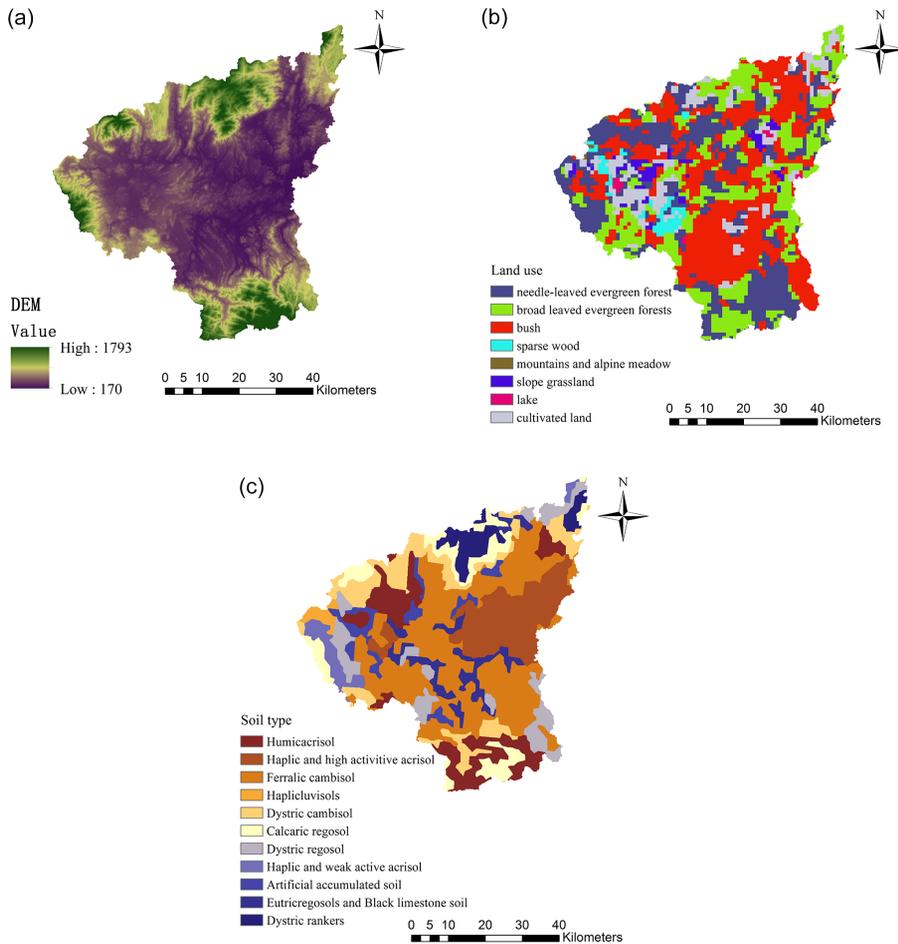


Figure 3. Terrain property data of UMWC.

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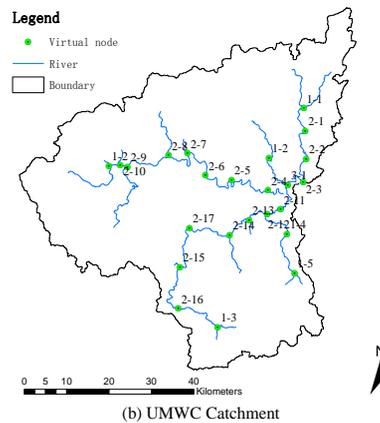
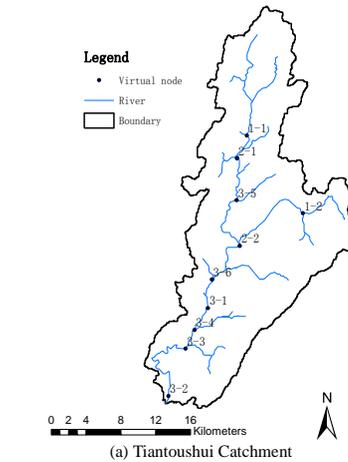


Figure 4. Model set up results.

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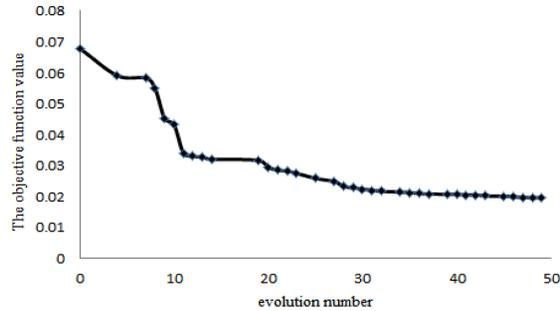
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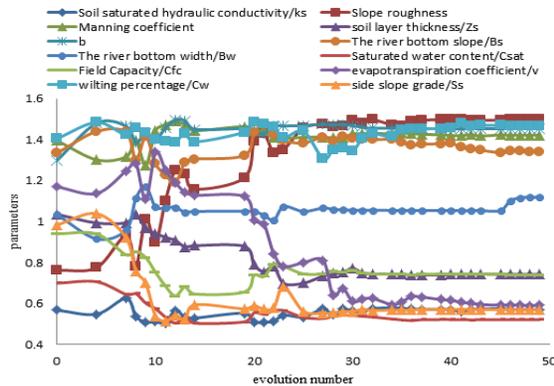
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(a) evolution of objective function



(b) evolution of parameters

Figure 5. The evolution process of parameter optimization with PSO in Tiantoushui Catchment.

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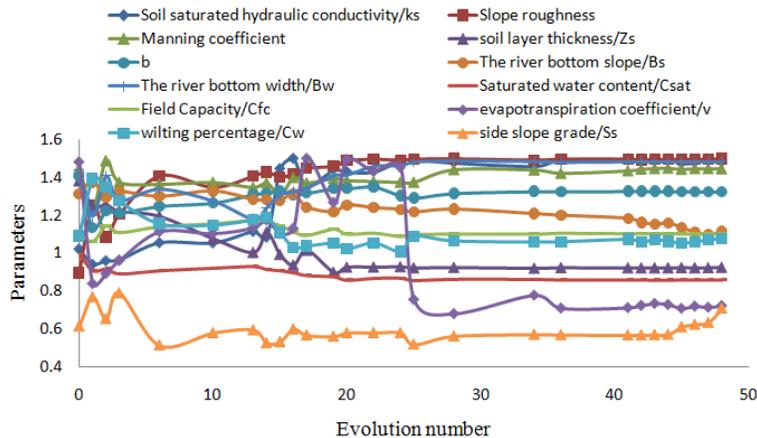


Figure 6. The evolution processes of parameter optimization with PSO in UMWC.

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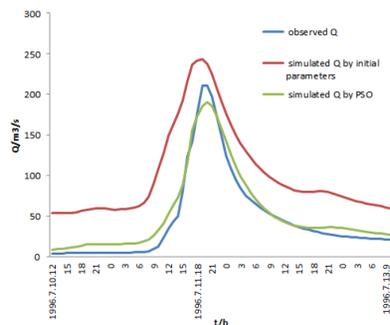
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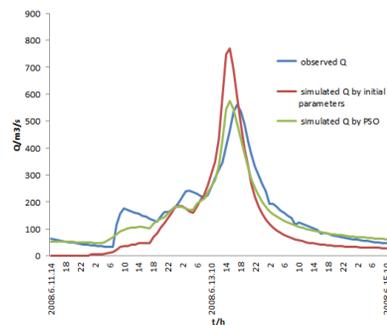


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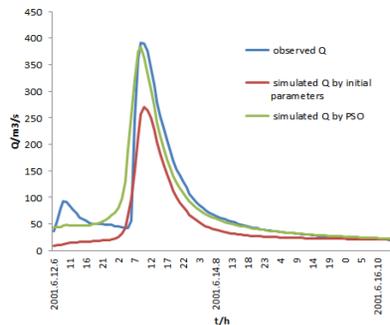
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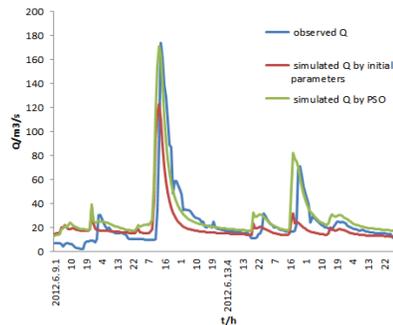
(a) Flood1996071012



(c) flood2008061114



(b) flood2001061206



(d) flood2012060901

Figure 7. Simulated flood events of Tiantoushui Catchment.

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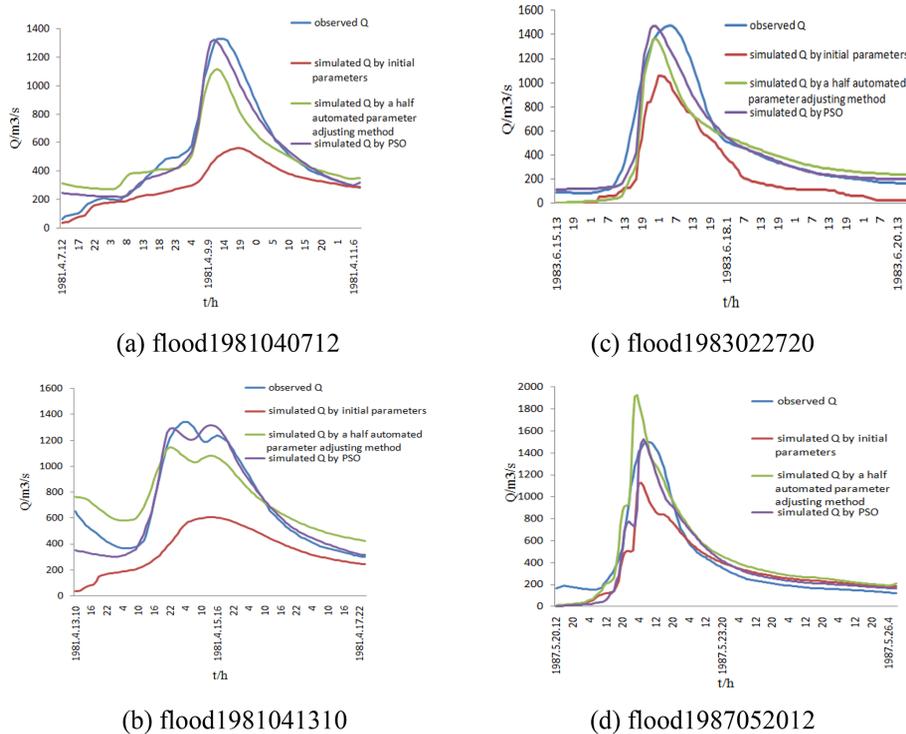


Figure 8. Simulated flood events of UMWC.

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