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

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Abstract

Physically based distributed hydrological models(here after refers to as 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, 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 uncertanties associated with this model 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 cathcment flood forecating 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 improverd 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 particle number and the maximum evolution number of PSO algorithm used for Liuxihe Model catchment flood forcasting is 20 and 30 respectively.

Key words： Flood forecasting, physically based distributed hydrological model, Liuxihe Model, parameter optimization, Particle Swarm Optimization

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 reducing 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, Loveland et. al., 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 facilited the development of physically based distributed hydrological models. 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 as the SHE model published in 1987 (Abbott et. al., 1986a, 1986b), the others include 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), *WEHY model* (*Kavvas et al., 2004, 2006*), Liuxihe model (Chen et. al., 2011), and more. While at the same time, the so called semi-distritubed hydrological 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 parameter 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 performance. 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 parameters fitting method, Duan et. al. proposed the Shuffle Complex Evolution Algorithm(SCE) (1994), Eberhart et.al proposed the Particle Swarm Optimization method (2001), Jasper et.al proposed the SCEM-UA method (2003), Chu et.al proposed the SP-UCI method (2011), among others. Now lots of parameter optimization methods for lumped hydrologcial models have been developed.

There are also many studies to parameter optimization to semi-distributed hydrologic models, among them the most studied model is SWAT due to its open assess codes and simple model sturctures. 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 using 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 diffucult 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 requirment, 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 multiplicator(scalar) based on the initially derived parameters from the terrain properties. The scalars for the same parameter in different cells are taken the same values, so the parameters to be adjusted are only a few. This is feassible computationally, and proven to be effective. For MIKE SHE model, an automatic parameter optimization method with SCE (Duan et.al, 1994) was employed 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 WetSpa 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 optimizaton methods 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, easy 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 for 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 cathcment flood forecating by parameter optimization, i.e., if PBDHMs parameter optimization could improve model performance significantly and achiverable. 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 improverd 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 hydrolgocial 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 hydrolgocial 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. It is assume that all model parameters of a PBDHM are related and only related to one physical property of the terrain they belong, including the topgraphy, 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 paramerers, 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 independant parameters are the parameters with the same terrain properties in each cells, and only the independant 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:

$$x_i = x_i' / x_{i0} \tag{1}$$

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 multilpe 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 lever 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 feassible 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 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 choosen, 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 evaportranspiration takes place in this layer, and the Evaportranspiration Model is used to determine the evaportranspiration 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 routes the surface runoff produced in one hill slope cell to its neighbouring cell, and the kinematic wave approximation is employed to make this 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 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 determing 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 parametere 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 lumpled hydrological model. Resffa et. al. (2013) used the PSO algorithem 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 algorithem with other algorithems 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.

$$V_{i,k} = \omega \times V_{i,k-1} + C_1 \times rand \times \left(X_{i,lBest} - X_{i,k-1} \right) + C_2 \times rand \times \left(X_{gBest} - X_{i,k-1} \right) \quad (2)$$

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

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, $X_{i,pBest}$ is the best position of i^{th} particle at k^{th} step(current), X_{gBest} is the best position of all particles at k^{th} step, ω is inertia acceleration speed, C1 and C2 are learning factors, *rand* is a random number between 0 and 1, here ω, C1 and C2 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 approched, 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.

2.5.2 Improved PSO algorithm

In the early PSO algorithm, particle number, ω, C1 and C2 are fixed, studies showed that changing the values of ω, C1 and C2 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 empoyed in changing ω, C1 and C2 are stated below, and will be tested in the studied catchments. In this paper, the appropriate PSO particle number, ω, C1 and C2 are called PSO parameters.

(1) 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（FIW）(Eberhart and Shi, 2001). In this study, the LDIW strategy is employed to dynamically determining the value of ω with the following equation.

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

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.

(2) Acceleration coefficients C1 and C2

Acceleration coefficients C1 and C2 also impact PSO's performance. In early studies, acceleration coefficients C1 and C2 usually take the same value of 2, and are fixed in the evoluion process. Studies show that dynamically adjusting C1 and C2 and take different values for C1 and C2 could improve PSO′s performances, and a few methods have been proposed, such as the linear strategy (Ratnaweera et. al., 2004), concave function strategy (Chen et. al., 2006), arccosine function strategy (Chen et. al., 2007). In this study, the arccosine function strategy is employed to determine the values of C1 and C2, the equations are listed below.

$$c_1 = c_{1\min} + \left(c_{1\max} - c_{1\min}\right)\left(1 - \frac{\arccos\left(\frac{-2\times i}{MaxN} + 1\right)}{\pi}\right) \qquad (5)$$

$$c_2 = c_{2\max} - \left(c_{2\max} - c_{2\min}\right)\left(1 - \frac{\arccos\left(\frac{-2\times C_i}{MaxN} + 1\right)}{\pi}\right) \qquad (6)$$

Where C_{1max}, C_{1min} are the maximum and minimum value of C_1, and the values of 2.75 and 1.25 are recommended, C_{2max}, C_{2min} are the maximum and minimum values of C_2,and the values of 2.5 and 0.5 are recommended, i is the current evolution number.

2.5.3 PSO procedure

The parameter optimization method based on PSO is summaried below.

1) Choose the independent parameters to be optimized. In the case that the computation load is a great challenge, only highly sensitive parameterwill be optimized, otherwise, all parameters could be optimized;

2) Initialize independent parameters to be optimized and normalize them;

3) Choose optimization criterion, particle number, maximum evolution nember, ω, C1 and C2;

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 postions of all particles, then calculate the moving directions and speeds of every particles at current evolution by using equation (2) and equation (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 511km^2 and channel length of 70km, which is a typical mountainous catchment with frquent 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 runing time in a feassible limit. There are 50 rain gaugues within the catchment and one river flow gaugues 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 1(a) is the sketch map of Tiantoushui Catchment with locations of rain gauges and the tributaries.

Figure 1 is here

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 Thisseon Polygon method(Derakhshan et. al., 2011).

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 3622km^2, 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 1(b) 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 90mX90m, but the other two data are at the 1000mX1000m spatial resolution, so they are rescaled to the spatial resolution of 90mX90m. Figure 2 and Figure 3 show the property data of DEM, land use types and soil types of the two catchments respectively.

Figure 2 is here

Figure 3 is here

In the Tiantoushui Catchment, the highest, lowest and average elevation are 1874 m, 174 m 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 accumulated 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 m, 170 m 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 catchemt into grids with DEM. In this study, the Tiantoushui Catchment is divided into 65011 grid cells using the DEM with grid cell size of 90mx90m, 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 63647 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 Figure 4(a).

Figure 4 is here

The Liuxihe Model is also set up in UMWC, the Catchment is first divided into 460695 grid cells using the DEM with grid cell size of 90mx90m. The river channel system is treated as a 3-order channel system, and 3295 river channel cells and 457400 hill 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 Figure 4(b).

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 Figure 1(a), 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 5mm/d 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 Table 1 and table 2 respectively for the two catchments.

Table 1 is here

Table 2 is here

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 Table 3 and Table 4 respectively.

Table 3 is here

Table 4 is here

4. Discussions and results

4.1 Impacting of particle number to PSO performance and the determination of appropriate particle number

Particle number is an important parameter of PSO, to understand the impact of the particle number to the PSO performance and to determine the appropriate particle number, 6 values of particle number, including 10, 15, 20, 25, 50 and 100 have been used to optimize the model parameters of Liuxihe Model setting up in Tiantoushui Catchment, while maximum evolution number is set to 50, ω, C1 and C2 are dynamically adjusted with equation (4), equation (5) and equation (6), and flood event flood2006071409 is used to do this calculation. 5 evaluation indices, including Nash-Sutcliffe coefficient C, correlation coefficient R, process relative error P(%), peak flow relative error E(%) and The coefficient of water balance W(%) have been computed, and listed in Table 5, the computation times for each optimization also have been listed in Table5.

Table 5 is here

We first analysis the impact of particle number to the computation time. From the results of table 5 we found that with the increasing of the particle number from 10 to 100, the computation time used decreases first, but when the particle number is bigger than 20, the computation time increases then, and when the particle number is 20, the computation time is 12.1 hours, which is the shortest among others. This means that particle number impacts the computation time used in optimization, the small and big particle number is not the best particle number, there exist an appropriate particle number to make the optimization at the least time. In the Tiantoushui Catchment, 20 is an appropriate particle number from the view of computational efficiency.

We further analysis the impact of particle number to the model performances by comparing the 5 evaluation indices. From the results, obvious trend could be found that with the increasing of the particle number, the Nash-Sutcliffe coefficient C, the correlation coefficient R and water balance coefficient increase first, but when the particle number reaches 20, the three indices decrease. While for the process relative error W and peak flow relative error E, the trend is inversed, i.e., with the increasing of the particle 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.

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

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 convengence, we first draw the optimization evolution process of PSO in Tiantoushui Catchment in Figure 5, both the objective and parameter evolution processes are included.

Figure 5 is here

From Figure 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 Figure 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 Figure 6, the objective evolution process of PSO in UMWC is similar with that in Tiantoushui Catchment.

Figure 6 is here

From Figure 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 Figure 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 Figure 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 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 hours, this is acceptable. The time needed for parameter optimization in UMWC is about 82.6 hours, 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, C1 and C2 are dynamically adjusted with equation (4), equation (5) and equation (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, Figure 7 shows 4 of the simulatd hydrographes, the hydrographes simulated by the model with initial parameter values are also drawn in Figure 7.

Figure 7 is here

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.

Table 6 is here

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 evaluation 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 necerssary.

4.6 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, C1 and C2 are dynamically adjusted with equation (4), equation (5) and equation (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, Figure 8 shows 4 of the simulatd 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 Figure 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.

Figure 8 is here

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.

Table 7 is here

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 optimiztion 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.

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 requirrment 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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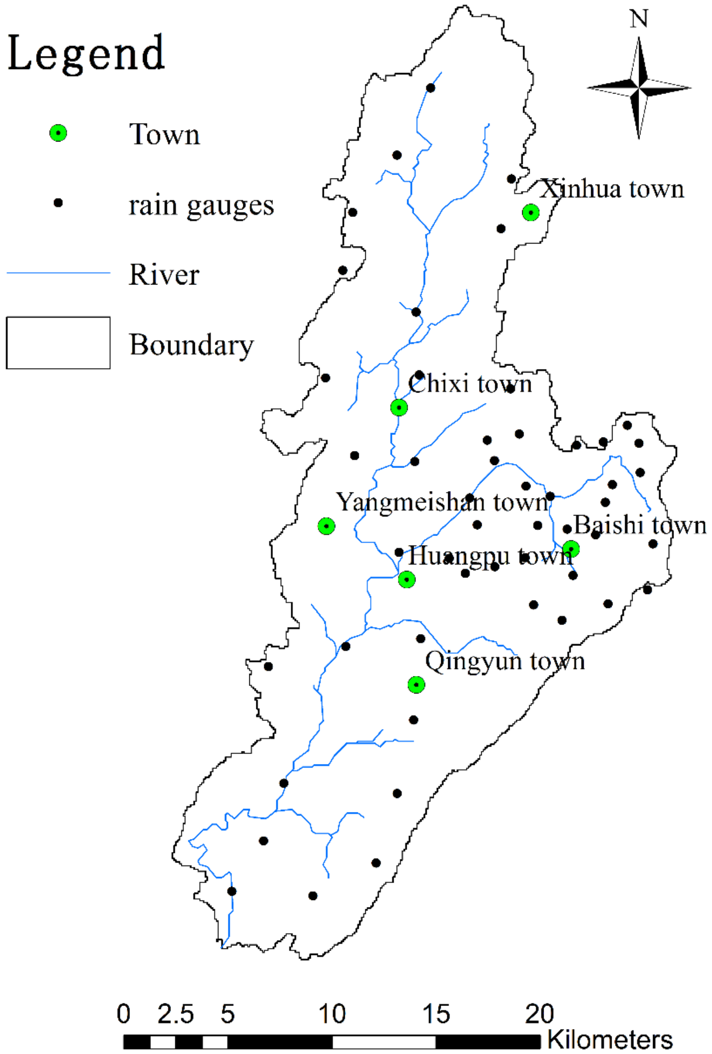
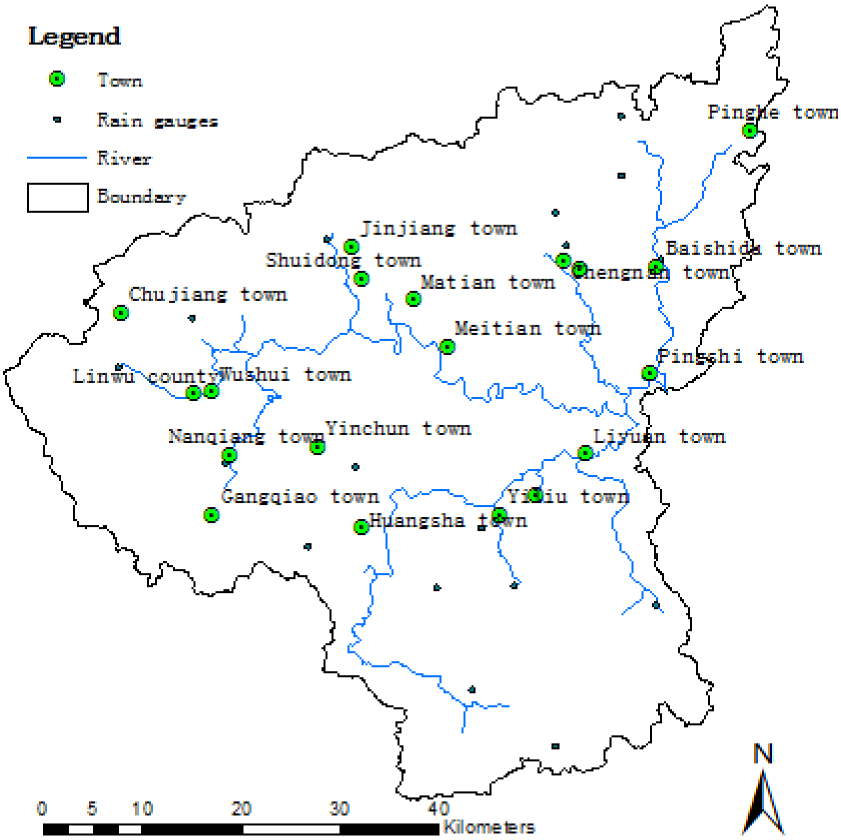
Figures

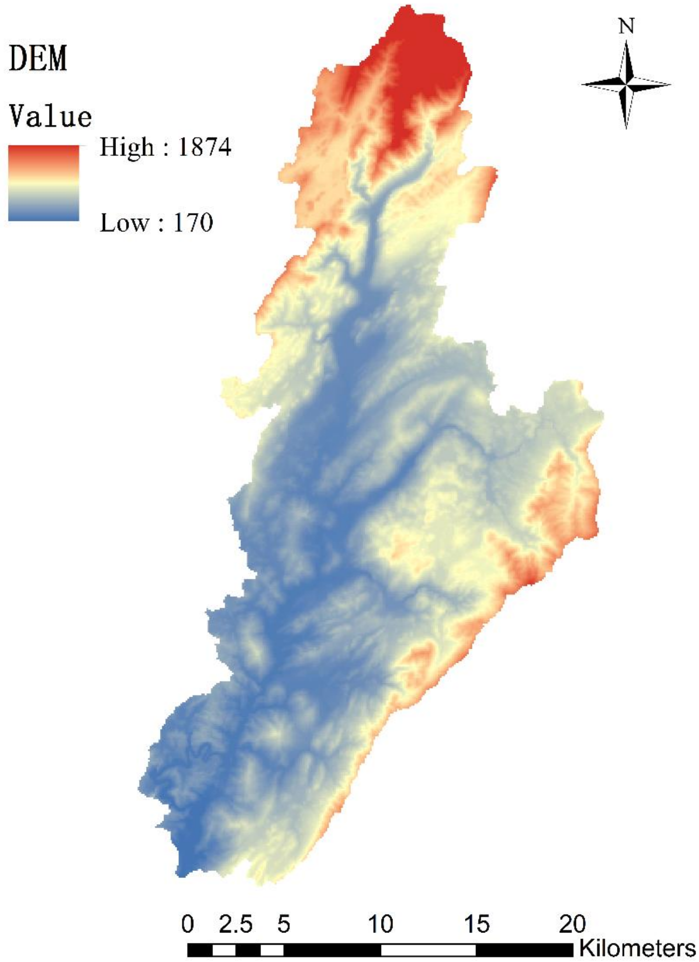


(a) Tiantoushui Catchment

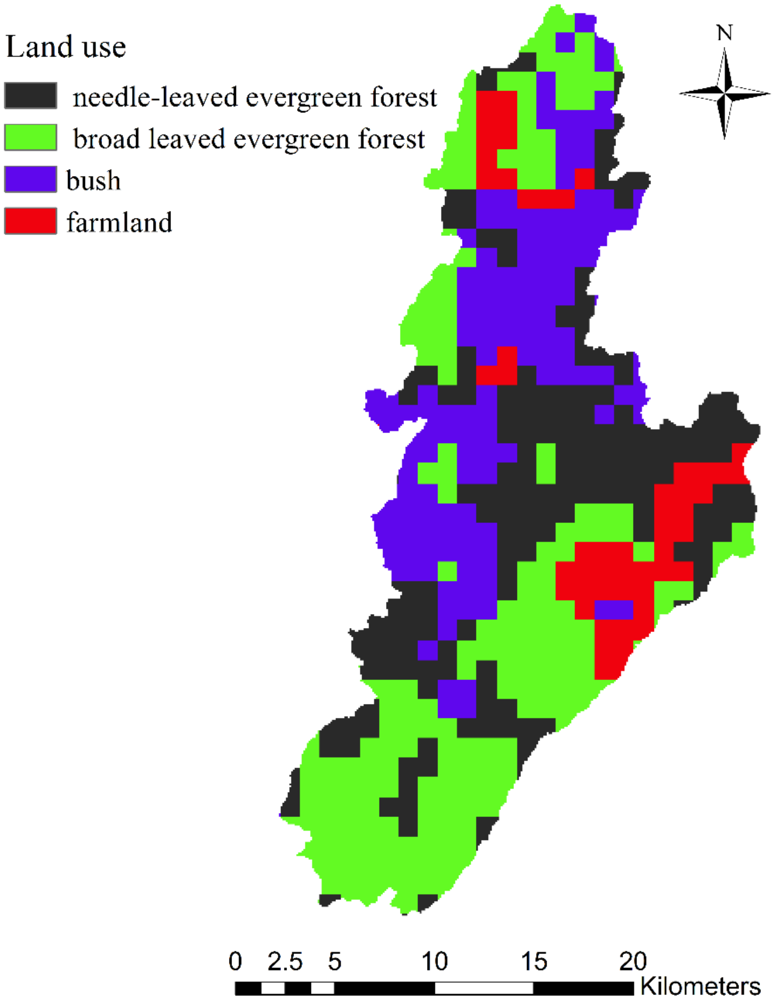


(b) Upper and middle Wujiang Catchment(UMWC)

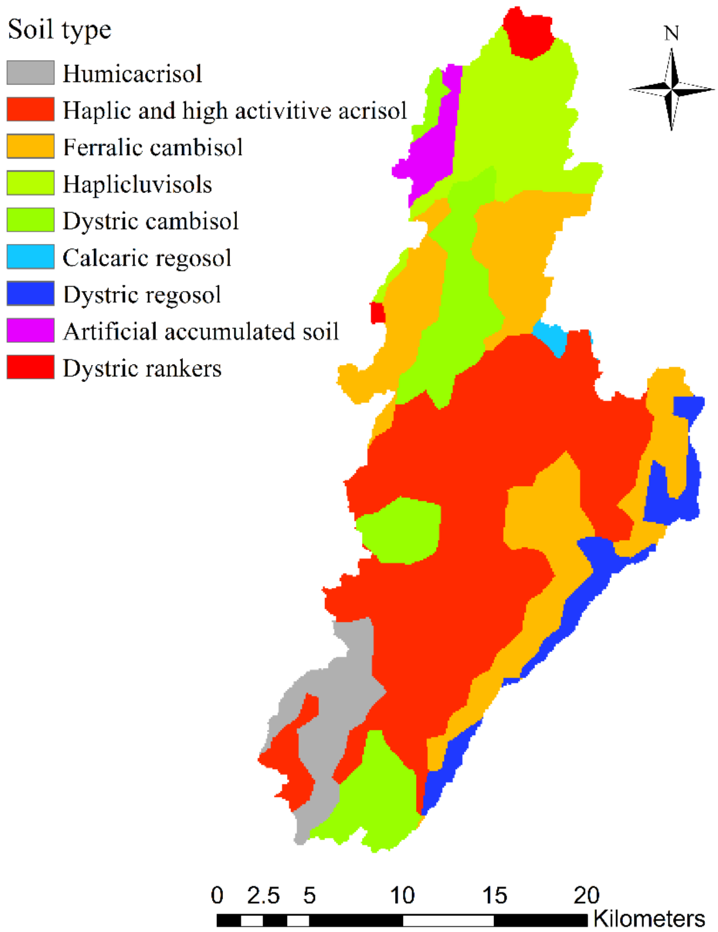
Figure 1 sketch map of the studied Catchments



(a) DEM

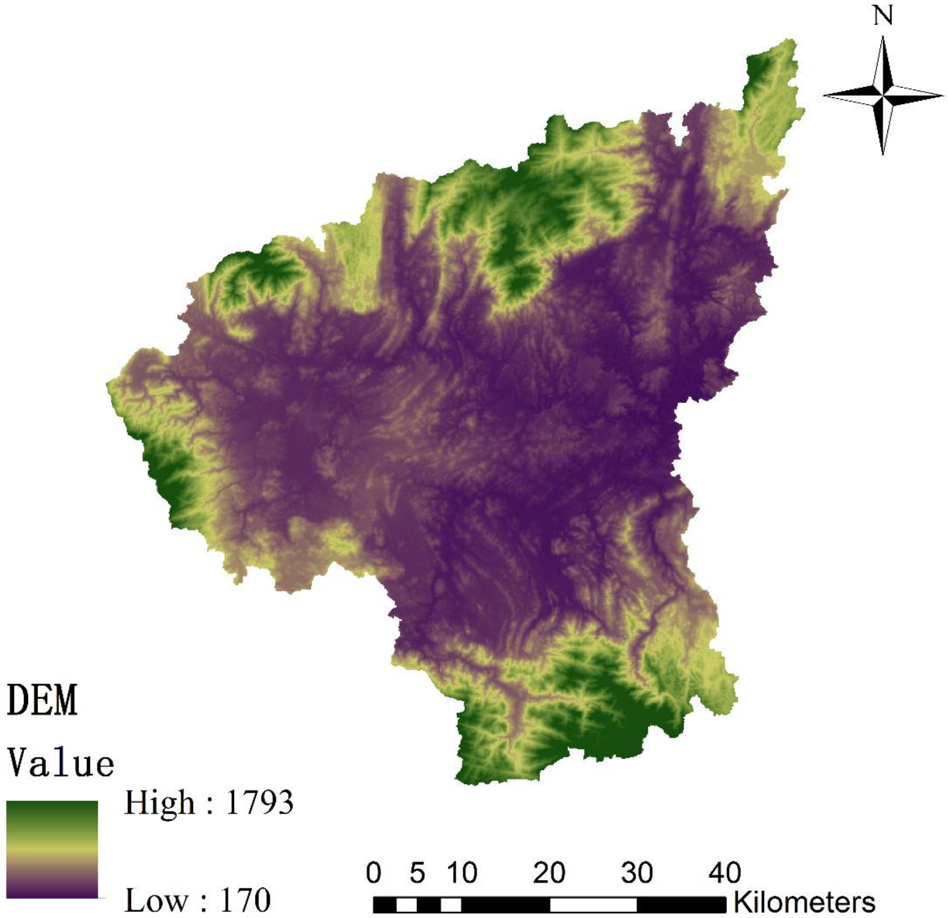


(b)Land use type

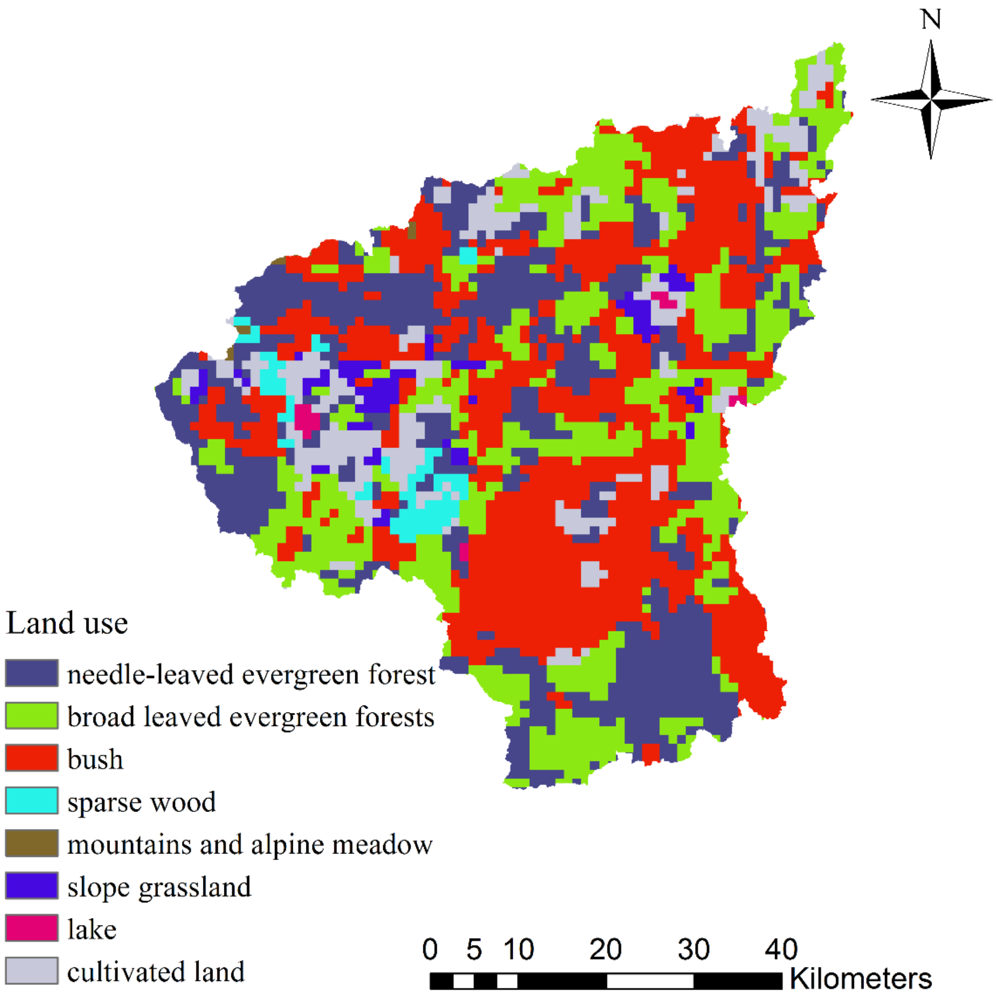


(c) Soil type

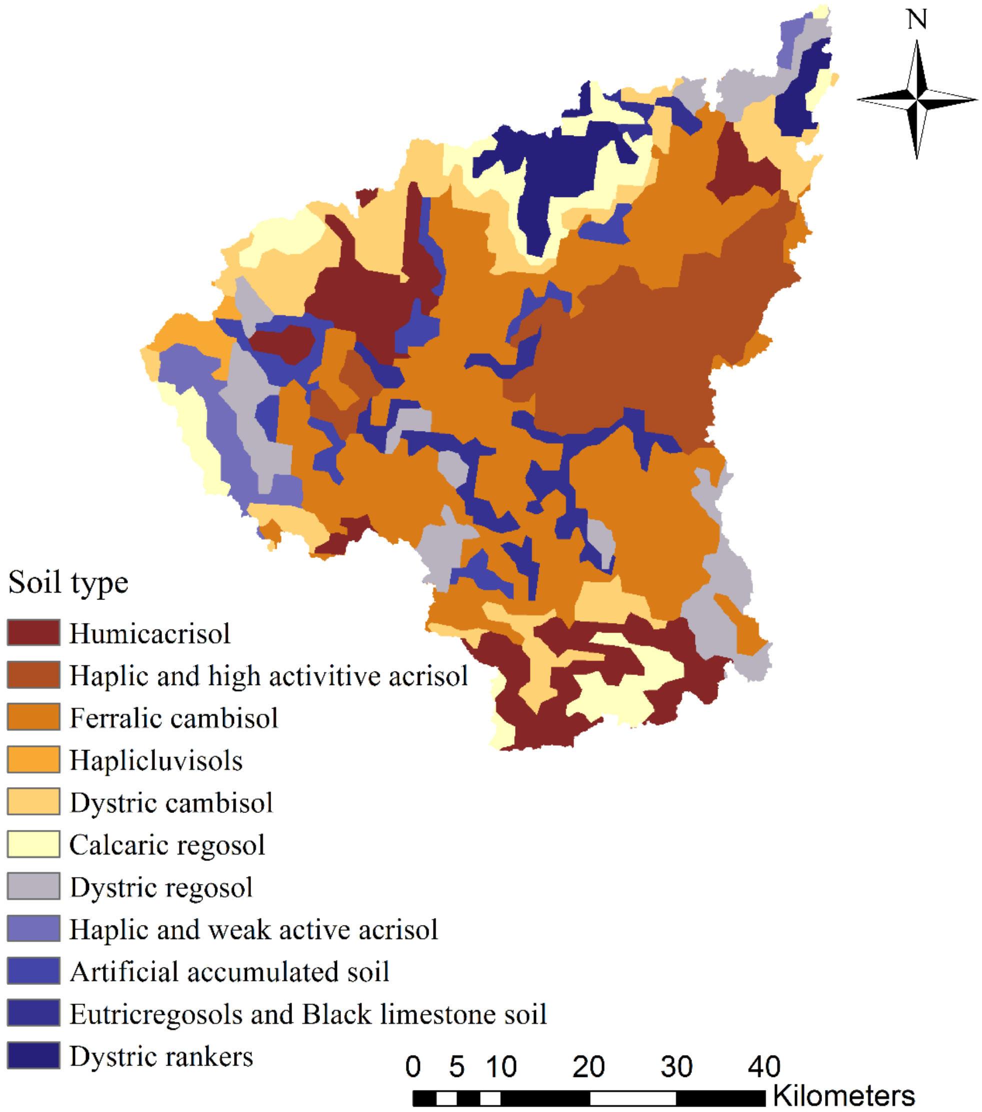
Figure 2 terrain property of Tiantoushui Catchment



(a) DEM

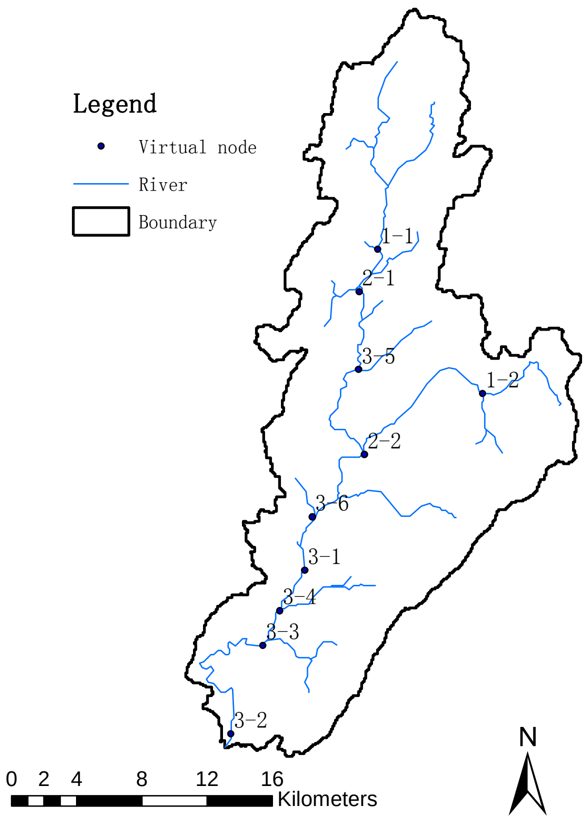


(b) Land use type

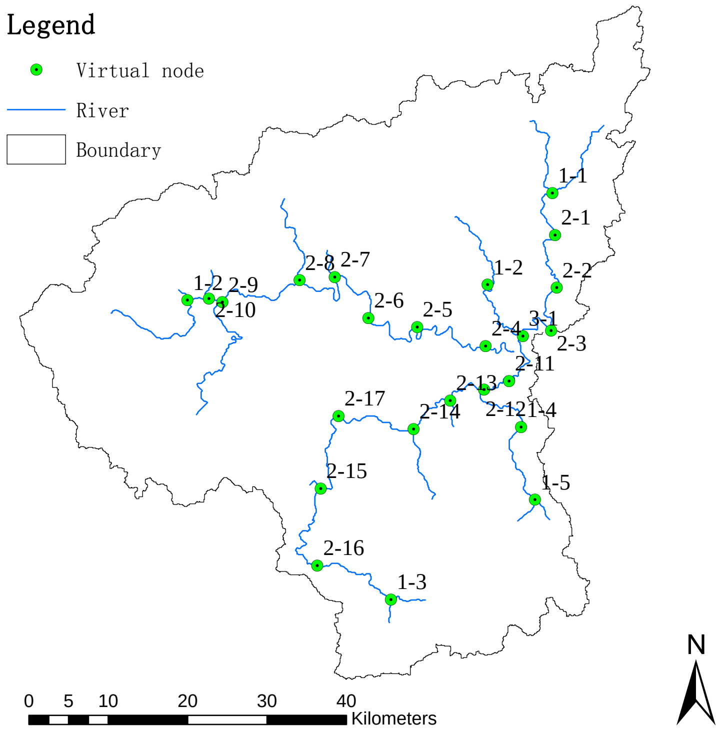


(c) Soil type

Figure 3 terrain property data of UMWC

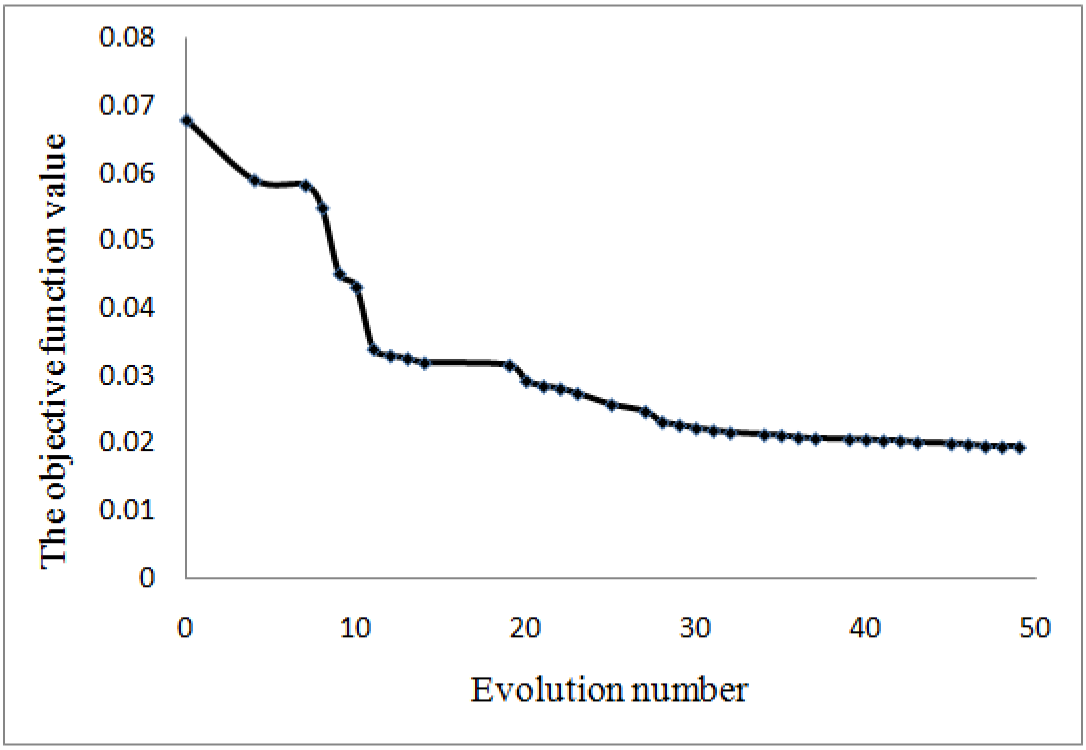


(a) Tiantoushui Catchment

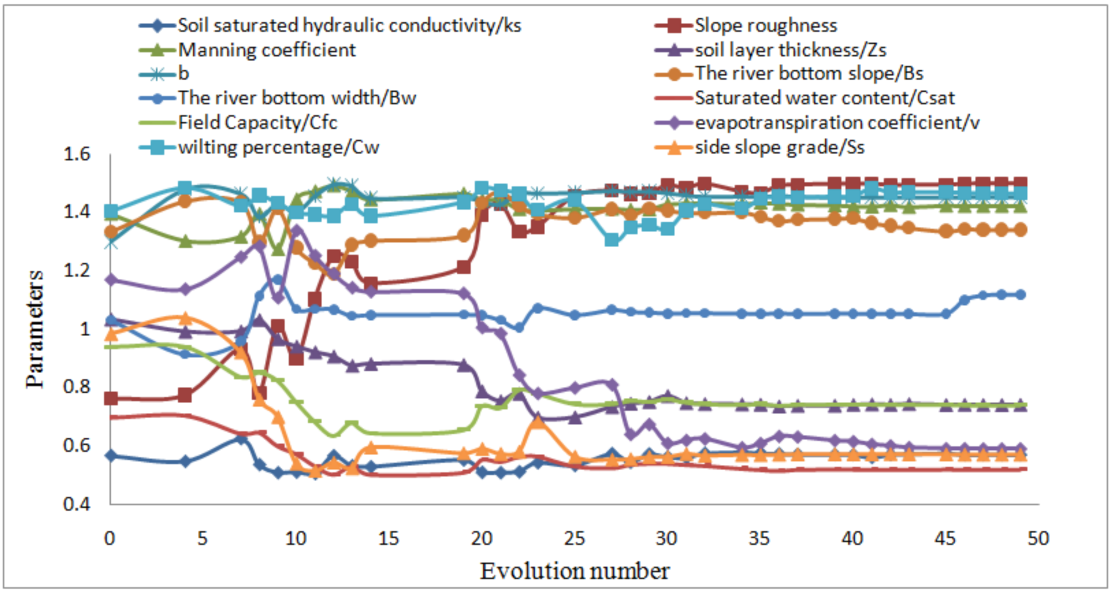


(b) UMWC Catchment

Figure 4 model set up results in Tiantoushui Catchment



(a) evolution of objective function



(b)evolution of parameters

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

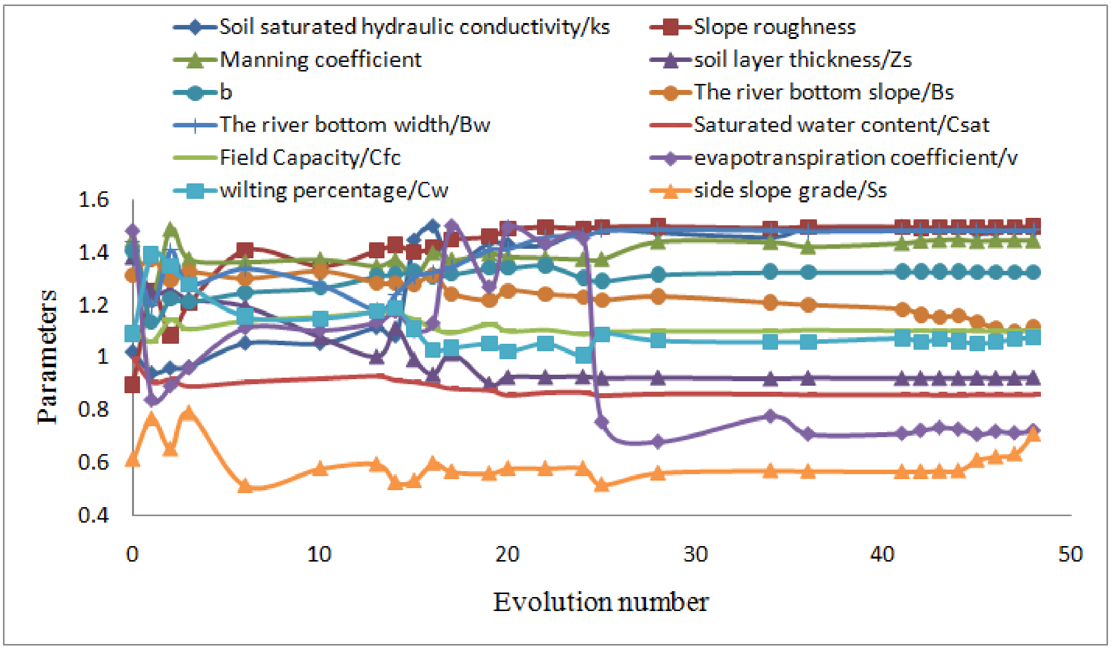
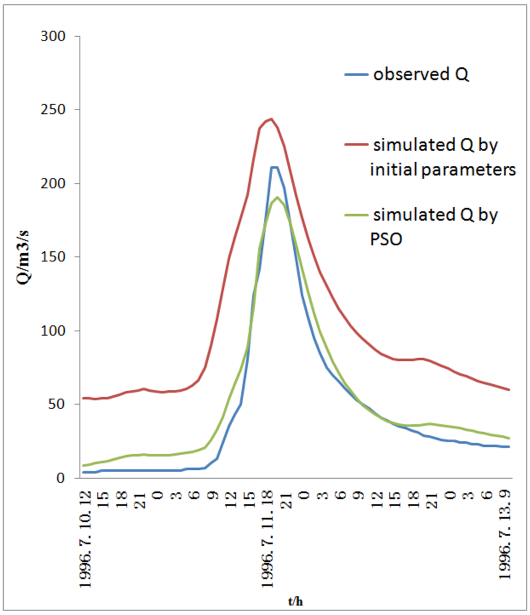
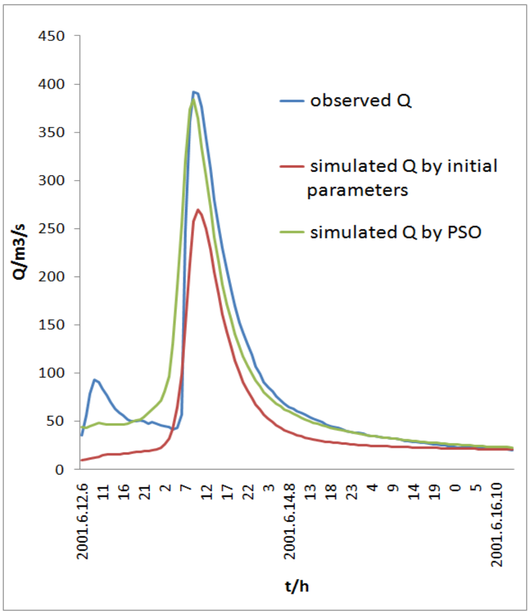


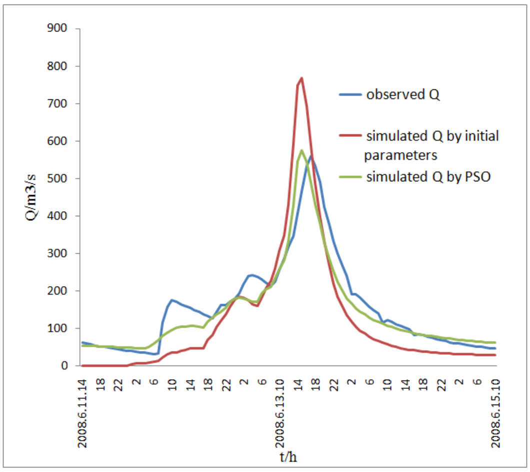
Figure 6 The evolution processes of parameter optimization with PSO in UMWC



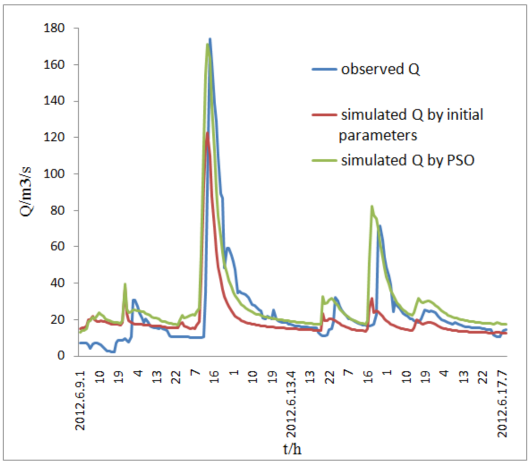
(a) flood1996071012



(b) flood2001061206

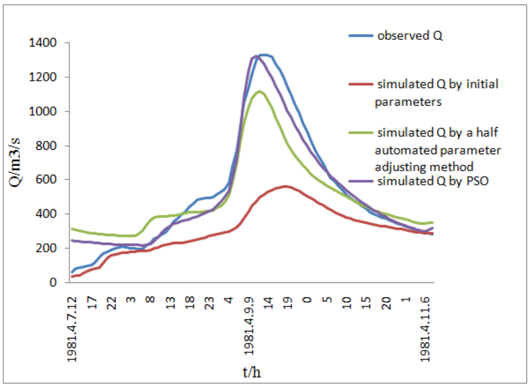


(c) flood2008061114

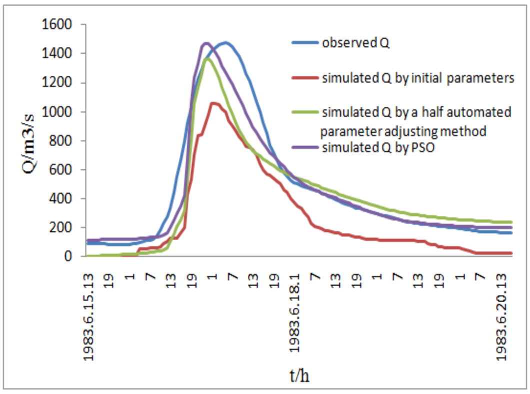


(d) flood2012060901

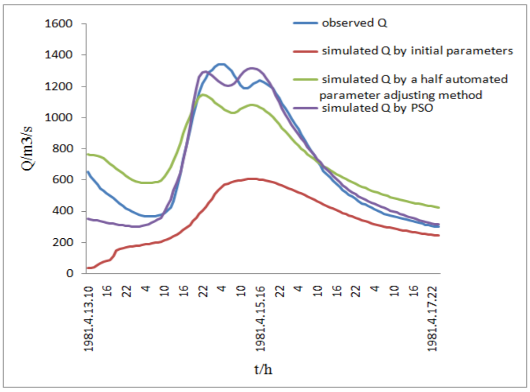
Figure 7 simulated flood events of Tiantoushui Catchment



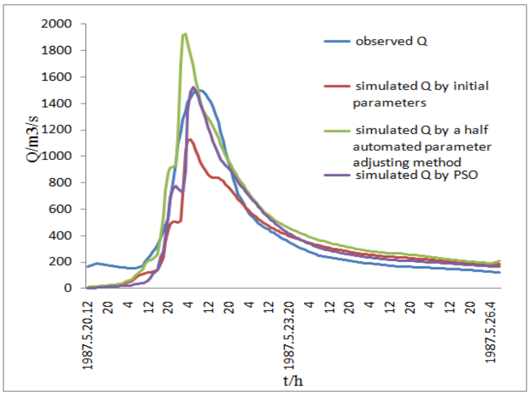
(a) flood1981040712



(c) flood1983022720



(b) flood1981041310



(d) flood1987052012

Figure 8 simulated flood events of UMWC

Tables

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

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

Table 3 Initial values of soil based parameters in Tiantoushui Catchment

Soil Type	Thickness/mm	Saturated water content	Field Capacity	Saturated hydraulic conductivity/mm/h	b	wilting percentage
Humicacrisol	700	0.515	0.362	3	2.5	0.2
Haplic and high activitive 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
Artificial accumulated soil	1000	0.459	0.25	8	2.5	0.121
Dystric rankers	150	0.43	0.203	10	2.5	0.113

Table 4 Initial values of soil based parameters in UMWC

Soil Type	Thickness /mm	Saturated water content	Field Capacity	Saturated hydraulic conductivity/mm/h	b	wilting percentage
Humicacrisol	700	0.515	0.362	3	2.5	0.2
Haplic and high activitive 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

Table 5 Performances of PSO algorithm in Tiantoushui Catchment

Particle number	computation time/hours	Nash-Sutcliffe coefficient/C	correlation coefficient/R	process relative error/P	peak flow relative error/ E	water balance coefficient/W
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

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

Flood events	Nash-Sutcliffe coefficient/ C		correlation coefficient/ R		process relative error P(%)		peak flow relative error E(%)		water balance coefficient /W	
	(1)*1	(2)*2	(1)*1	(2)*2	(1)*1	(2)*2	(1)*1	(2)*2	(1)*1	(2)*2
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

*1: results simulated by model with optimized parameters, *2: results simulated by model with initial parameters

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

Flood events	Nash-Sutcliffe coefficient/ C			correlation coefficient/ R			process relative error/ P		
	(1)*1	(2)*2	(3)*3	(1)*1	(2)*2	(3)*3	(1)*1	(2)*2	(3)*3
flood1980050620	0.906	0.610	0.810	0.958	0.831	0.931	0.168	0.480	0.288
flood1980042313	0.892	0.724	0.824	0.972	0.768	0.968	0.282	0.270	0.307
flood1981041014	0.917	0.700	0.451	0.967	0.830	0.883	0.141	0.417	0.317
flood1981040712	0.805	0.686	0.686	0.964	0.738	0.938	0.154	0.550	0.255
flood1981041310	0.739	0.796	0.796	0.938	0.758	0.958	0.221	0.260	0.265
flood1982051014	0.831	0.793	0.793	0.924	0.852	0.952	0.271	0.440	0.174
flood1983061513	0.904	0.810	0.839	0.954	0.850	0.925	0.327	0.530	0.363
flood1983022720	0.896	0.750	0.850	0.974	0.740	0.934	0.152	0.220	0.102
flood1984050310	0.971	0.800	0.816	0.989	0.684	0.980	0.085	0.380	0.388
flood1985092216	0.967	0.840	0.940	0.986	0.785	0.978	0.375	0.480	0.380
flood1987051422	0.961	0.853	0.913	0.986	0.731	0.973	0.266	0.241	0.281
flood1987052012	0.902	0.727	0.927	0.951	0.628	0.968	0.332	0.362	0.262
flood2008060902	0.850	0.756	0.800	0.923	0.825	0.820	0.140	0.414	0.214
average	0.888	0.757	0.8	0.960	0.771	0.94	0.248	0.388	0.28

Flood events	peak flow relative error/E			water balance coefficient/W		
	(1)*1	(2)*2	(3)*3	(1)*1	(2)*2	(3)*3
flood1980050620	0.004	0.230	0.013	0.913	0.760	0.796
flood1980042313	0.003	0.270	0.008	0.867	0.620	0.792
flood1981041014	0.043	0.180	0.185	0.973	0.729	0.729
flood1981040712	0.159	0.228	0.228	0.990	0.850	1.328
flood1981041310	0.006	0.146	0.146	0.830	1.160	1.061
flood1982051014	0.013	0.230	0.230	0.922	1.230	1.010
flood1983061513	0.007	0.350	0.072	0.944	0.680	0.967
flood1983022720	0.018	0.420	0.078	1.017	0.650	1.045
flood1984050310	0.010	0.210	0.010	0.951	0.720	0.820
flood1985092216	0.022	0.320	0.055	1.071	1.350	1.034
flood1987051422	0.012	0.280	0.013	0.925	1.510	0.892
flood1987052012	0.015	0.160	0.034	0.955	0.840	0.979
flood2008060902	0.004	0.240	0.104	0.985	0.910	0.850
average	0.024	0.251	0.09	0.949	0.924	0.95

*1: results simulated by model with optimized parameters, *2: results simulated by model with initial parameters, *3: results simulated by model with half-automated optimized parameters