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Parameter dynamics of distributed hydrological model in simulating or forecasting flood processes of urbanizing watersheds

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Abstract: In the past decades, the world has experienced rapid urbanization and observed the appearances of large amount urbanizing watersheds with enhanced flooding, which has a constant changing land use/cover(LUC) types as the most significant feature. Simulating and forecasting urbanizing watershed flood processes faces great challenges, one is how to relate model parameters with the changing LUCs to secure an accurately and reliable simulation and forecasting results. In this study, a methodology for simulating and forecasting urbanizing watershed flood processes is proposed, which employs Liuxihe model as the watershed hydrological model. This methodology sets up the Liuxihe model with latest terrain properties, then derives initial parameter look-up table based on terrain properties, and optimizes it if there is observed hydrological data. If there is LUC changes, then the parameters are updated with the changed LUCs based on the optimized parameter look-up tables. Case study in a highly urbanizing watershed in the Pearl River Delta Area in southern China has shown that this method acquires accurate and reliable flood processes simulation results. Further more, this study has proven an assumption that the hydrological model parameters are LUC stationary, i.e., with the LUC changes, the parameter look-up table will not change, parameter look-up table optimized in a specific time with current LUCs will not change even the LUCs changed. With this assumption, the parameter look-up table only needs to be optimized once. This is a science question that has not been not well answered yet by the scientific communities.

Keywords: Flood simulation, flood forecasting, land use/cover change, Liuxihe model, parameter optimization

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1 Introduction

In this study, an urbanizing watershed is referred to a watershed with constant land use/cover (LUC) changing, and has urban land (impervious surface) as its major or significant LUC type. Urbanizing watersheds usually locate in the rapidly developing or urbanizing area. For the past century, the world is in constant urbanization (He et al., 2021; Addae and Dragicevic, 2023), and its urban population reached 50% in 2007 (United Nations, 2014). While for the developing countries, the urbanization trend is still rapidly going (Huang et al., 2022; Xue et al., 2022). For example, intense urbanization has occurred in India and Nigeria from 1970-2010, where 85% and 30% of cropland area within ten km of urban areas converted to urban land respectively (Guneralp et al., 2020). China also experienced a rapid urbanization since 1978, with its urban population reached 55% in 2018 (Zhao et al., 2023; Fang and Wang, 2011). China's urbanization is still going on and quick in some regions (Yu, 2021), with its urban population projected to be 68% in 2050 (Development Research Foundation of China, 2010). During this world urbanization process, lots of urbanizing watersheds appeared worldwide, some of them already have very high urban land percentage over 50% (Wang and Chen, 2019), while others are still in its growing stage. For example, in China's Pearl River Delta Area (PRDA) where the rapidest regional urbanization was observed in China (Li et al., 2011), most of the watersheds have a higher than 30% urban land rate, with some over 50% already (Chen et al., 2015, Zhang et al., 2015).

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For an urbanizing watershed, rapid land use/cover (LUC) change, particularly the converting of vegetated area (pervious surface) into urban land area (impervious surface), is the most observed direct change caused by human activities. This change induces increased surface runoff and peak flow, which was well observed and analyzed (Leopold, 1968; Hollis, 1975; Rose et al., 2001; Yang et al., 2016; Wang et al., 2022; Zhao et al., 2023). Simulating watershed flood processes has long been the goal of the world hydrological communities, it is the prerequisite for flood mitigation project design and flood forecasting. But for an urbanizing watershed, how to consider the LUCs change in the simulation is still a great challenge.

Watershed hydrological models are the most employed tools for watershed flood processes simulation and forecast, lumped models are widely used in the early stages (Refsgaard et al., 1996; Chen et al., 2011), such as the Stanford model (Crawford et al., 1966), the Xinanjiang model (Zhao, 1977) and the ARNO model (Todini, 1996), only list a few. Lumped models calibrate model parameters by using series hydrological data observed in the past, and the LUC change could not be reflected with model structure or parameter, thus can only be used for simulating the past hydrological processes, not the changing one. For this reason, lumped hydrological models are not the appropriate models for simulating or forecasting urbanizing watersheds flood.

Physically based distributed hydrological models (PBDHMs) are the new development of watershed hydrological models, as the terrain is divided into grid cells (Freeze and Harlan, 1969; Abbott et al., 1986a, 1986b) and the runoff production and routing are calculated cell by cell, thus having the potential to better simulate

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hydrological processes (Ambroise et al., 1996). Dozens of PBDHMs have been proposed and widely used in scientific studies, including the SHE model (System Hydrologue Europeen model) (Abbott et al.,1986a, b), the VIC model (variable infiltration capacity model) (Liang et al., 1994), the WEP model (Water and Energy transfer Process model) (Jia et al., 2001) and the Liuxihe model (Chen et al., 2011), and many others. The most outstanding feature of PBDHMs is that model parameters have physical meanings, and can be directly derived from the watershed terrain properties, such as the elevation, soil type and LUC. A table is usually set up to define the relationship between the parameters and the terrain properties, which is referred to as the parameter look-up table. This gives PBDHMs potential to simulate or forecast urbanizing watershed flood as it can relate model parameters with LUC changes.

In the early study, look-up table is proposed based on limited local experiences and laboratory experiments, which shows big uncertainty and impacts the model's performance. Recent studies have shown that parameter optimization can improve PBDHMs performances (Madsen, 2003; Smith et al., 2004; Pokhrel et al., 2012; Chen et al., 2016), which was assumed previously that parameter optimization is not needed for PBDHMs. Several methods have been proposed, such as the scalar method (Vieux et al., 2003; Vieux, 2004) for Vflo model, the SCE algorithm for MIKE SHE (Madsen, 2003), the multi-objective genetic algorithm for WetSpa model (Shafii et al., 2009), the SCE-UA algorithm (Xu et al., 2012) and the Particle Swam Optimization (PSO) algorithm (Chen et al., 2016) for Liuxihe model. But these efforts were mainly carried out in simulating or forecasting flood for natural watershed, i.e., watershed with little LUC changes.

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For simulating or forecasting urbanizing watershed flood processes by using a PBDHM, big challenges still exist. The biggest one is how to acquire a reliable and accurate look-up table, so to adjust parameters with changing LUCs. The second is a science question, i.e., if a reliable and accurate look-up table could be set up, then should it be LUC stationary? I.e., with the LUC changing, the look-up table should be changed accordingly or not? There are two purposes for this study, the first is to propose a methodology for simulating or forecasting urbanizing watershed flood processes by using a PBDHM with satisfactory model performances, which can relate the model parameters with the changing LUCs. This methodology employs Liuxihe model as the PBDHM, and sets up the Liuxihe model with latest terrain properties; then proposes an initial parameter look-up table based on current parameterization experiences, and optimizes it if there is observed hydrological data. With parameter look-up table optimization, the parameter look-up table is reliable and accurate. This methodology solves the first challeng and has been tested in a highly urbanized watershed in southern China.

The second purpose is to answer the science question of parameter stationary. The authors assume that the model parameters are LUC stationary, i.e., with the LUC changing, the parameter look-up table will not change, i.e., a parameter look-up table optimized in a specific time with current LUCs will not change after the LUCs changed. With this assumption, the parameter look-up table only needs to be optimized once. This assumption has been proven by the simulation results in the case study, so to solve the second challenge. The remaining parts of this article are organized into 4 sections. Section 2 introduces the study watershed, the hydrological data, LUC change data and terrain property data. Section 3 introduces the methodologies, including Liuxihe model and its parameter look-up table determination. Section 4 introduces the results in the case study watershed, and section 5 provides a discussion.

2 Study watershed and data

2.1 Study watershed

Songmushan Watershed(SW) is the upstream of Hanxishui River Basin(HRB) locating in Dongguan City in southern China. Songmushan Reservoir(SR) was built in the middle stream of SW, and the watershed area controlled by SR is called as Songmushan Reservoir Watershed (SRW) in this study. Originating from the Lotus Mountain, SRW has a drainage area of 54.2 km^2, and a river length of 11.19 km. SRW was selected as the study watershed bacause it is a typical urbanizing watershed in China, and hydrological data in recent years for this study is also available. Fig. 1 shows the location of SRW.

Fig. 1 is here

The major topography of SRW is gentle hills. This area enjoys a subtropical monsoon climate with frequent storms in the summer monsoon season. Average annual precipitation of SRW is 1674 mm, which caused serious flooding in the past. SRW has observed rapid urbanization in the past decade, which has created a high percentage of urbanized land. It is a typical watershed in the Pearl River Delta area that experiences considerable increasing both in flooding and urbanization.

Songmushan Reservoir was initially built for irrigation in 1958 as Dongguan City was

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primarily an agriculture area at that time, and there was no systematical hydrological observation until 2008. With China's reforming and opening, Dongguan City has been developing very fast since 1987, and become an international metropolitan. Dongguan City has been a highly urbanized area since then, and there is almost no agriculture anymore. For this reason, irrigation is not needed, and the reservoir has the new roles of flood mitigation and water supply after a heavy flooding in 2006. In 2008, an automatic hydrological data collecting system was built which includes 6 rain gauges (Fig. 1) and 1 water level gauge at the dam site.

2.2 Hydrological data

In this study, hydrological data of 13 flood events between 2008 and 2015 was obtained, including precipitation of the 6 rain gauges and the reservoir inflow at one hour interval. Table 1 shows the basic information of these flood events.

Table 1 is here

2.3 LUC change data

Chen et al. (2017) prepared a LUC dataset of the whole Dongguan City using the Landsat series satellite remote sensing imagery (Irons et al., 2012, Tang et al., 2013). A total of 12 imageries from 1987 to 2015 at an average 3-year interval were obtained, and the SVM classifier algorithm (Vapnik, 1995) was employed to estimate the LUCs accordingly. LUC data at 1987, 1990, 1993, 1996, 1999, 2001, 2003, 2005, 2008, 2011, 2013 and 2015 were prepared for the whole Dongguan City. There are six LUC types, including urban land (impervious surface), water body, forestry land, farmland, grassland and bare land. LUCs of SRW in 2008, 2011, 2013 and 2015 were extracted from this dataset, Fig. 2 shows these results.

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Fig. 2 is here

Urban land area of SRW was 18.62% in 2008, but reached 23.40%, 26.24% and 30.37% in 2011, 2013 and 2015 respectively, this is a significant increasing in urban land under urbanization, and this watershed could be regarded as an urbanizing watershed as its LUCs was in constant changing from 2008 to 2015.

2.4 Terrain property data

Terrain property data is mainly used for model set up and initial model parameter deriving, includes DEM, soil type and LUC type. DEM was prepared based on the topography map surveyed recently by the local government agency, the spatial resolution is at 30 m grid cell (Fig. 3(a)). The highest, lowest and mean elevation of the watershed are 489 m, 9 m and 38.1 m respectively.

Soil map was downloaded from the FAO world soil map dataset (www.isric.org) as shown in Fig. 3(b). There are 4 soil types in the watershed, including urban land, water body, ferric acrisols and cumulic anthrosols, with areal percentages of 1.0%, 14.0%, 67.0% and 18.0% respectively.

Fig. 3 is here

In this study, a new soil type, the urban land soil type is defined. For which, its land use/cover is the urban land, but its real soil type beneath the surface could be any type. In fact, it is a virtual soil type proposed to facilitate the runoff production. So the soil type data in Fig. 3(b) needs to be adjusted based on this definition. Besides, the urban land data in Fig. 3(b) was prepared by FAO in 1990, so it is out of date, and have been updated with the results of Fig. 2 in this study. The final soil types of SRW, adding the urban land soil type, is produced and shown in Fig. 4, the soil types in 2018, 2011, 2013 and 2015 are different.

Fig. 4 is here

3 Methodology

3.1 Liuxihe model

The PBDHM employed in this study is the Liuxihe model, which is a physically based, distributed hydrological model proposed for watershed flood forecasting (Chen, 2009; Chen et al., 2011; Chen, 2017). But any PBDHMs which could relate its parameters with LUCs could be employed.

Liuxihe model divides the watershed surface into grid cells, which are categorized as hill slope cells, river channel cells and reservoir cells. For river channel cells and reservoir cells, the watershed surface is water, runoff produced in these cells are equal to the net precipitation. The surfaces of hill slope cells are covered with different land use/cover (LUC) types, so each hill slope cell has its unique LUC. Currently in Liuxihe model, there is no urban land LUC type, only vegetated LUCs. Each hill slope cell also has its own soil type and elevation. LUC type, soil type and elevation are called watershed terrain properties in Liuxihe model. Runoff is produced first on cells, and then routed to the watershed outlet via a routing network. Runoff production is governed by the infiltration, and the soil type is the controlling terrain property for runoff production. Runoff routing is categorized as hill slope routing, river channel routing and reservoir routing. The kinematical wave approximation is employed for hill slope routing, while the diffusive wave approximation for river channel routing.

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For Liuxihe model, there is no way to make runoff production and routing calculation for the urban land grid cells, so in this study, a module that can make this calculation is added. The urban land surface is impervious, the precipitation falls to this ground surface is regarded completely converted into surface runoff, and no precipitation is infiltrated to the soil beneath it. Runoff produced on cells with urban land surface is equal to precipitation fallen to the surface. The approach used to calculate runoff production is as below.

$$R_{i,t}=P_{i,t}-E_{i,t} \tag{1}$$

Where $R_{i,t}$, $P_{i,t}$ and $E_{i,t}$ are surface runoff, precipitation and actual evaporation produced on cell i at time t respectively, and the evaporation could be regarded as water surface evaporation if there is surface runoff, otherwise it is zero.

As only the hill slope cell may have urban land surface, so the runoff routing on urban land cell is hill slope routing. In Liuxihe model, hill slope routing is solved by using kinematic wave approximation. For hill slope routing, the governing factors are the slope of the cell and the roughness coefficient of the surface. For the hill slope routing on urban land surface, the same approach is used but using different roughness coefficient. The above approaches for runoff production and routing on urban land cell has been developed and embedded into the currently used Liuxihe model software tool.

3.2 Liuxihe model parameter look-up table determination

Liuxihe model is a distributed hydrological model, so each grid cell has its own parameters, i.e., 13 parameters (Chen et. al, 2011). The parameters in each grid cell are divided into 4 categories, including climate-based parameters, topography-based parameters, vegetation-based parameters and soil-based parameters (Chen et. al, 2016). The parameters' values are related to only one category terrain property of its grid cell,

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i. e., climate-based parameters are only related to the climate condition, the topography-based parameters are only related to the topography, vegetation-based parameters are only related to the land use/cover types, and the soil-based parameters are only related to the soil types. There is only one climate-related parameter, i.e., the reference evaporation which is regarded as the same for all grid cells. There are two topography-based parameters, including flow directions and slopes for hill slope cells and river channel cells. There are also two vegetation-based parameters, the evaporation coefficient and roughness. There are 8 soil-based parameters, including soil property coefficient, soil thickness, hydraulic conductivity under saturated condition, soil water contents under saturated condition, field condition, and wilting condition. There is one parameter for underground water routing which is regarded as the same for all grid cells, and is also a soil-based parameter.

Liuxihe model takes two steps to determine model parameters, firstly deriving initial parameter look-up tables from the watershed terrain property data, and then optimizing them. For a specific watershed studied, Liuxihe model first proposes parameter look-up tables, which are two-dimensional tables referring the values of parameters with the terrain properties, for example, with soil type Ferric Acrisols, the parameter value of soil water content under saturated conditions is referred to as 46.1%. Based on these parameter look-up tables, the parameters of each grid cell could be determined according to the grid cell's terrain properties, including DEM, LUCs and soil types. As climate-based parameters take the same value for all grid cell, so there is no need for a look-up table for the climate-based parameters. While the topography-based parameters are calculated directly based on the DEM using the D8 method (O'Callaghan et al., 1984; Jensen et al., 1988), so there is no need for a look-up table for the topography-based parameters also. Therefor there are two parameter look-up tables, one is for vegetation-based parameters, and another is for soil-based parameters.

Liuxihe model proposed ways for determining the two parameter look-up tables. For the vegetation-based parameters look-up table, the referring values are decided from laboratory experiments and local experiences, or even from references or results from other watersheds. There are two vegetation-based parameters, the evaporation coefficient and roughness. For the soil-based parameters look-up table, Liuxihe model employs the Soil Water Characteristics Hydraulic Properties Calculator (Arya et al., 1981) to calculate the referring values based on the soil texture, organic matter, gravel content, salinity and compaction. With these parameters look-up table, based on its terrain properties, the initial parameters for each grid cell could be derived. With this way, if the terrain properties of each grid cell are available, then the initial parameters could be proposed.

As the initial parameters derived with the above method are highly experience-based, and current parameterization experiences are very limited, so the initial parameters have uncertainty, thus model performance could not be secured. To improve model performance, Liuxihe model optimizes the initial parameters by using optimization algorithm, this is the second step of Liuxihe model parameters determination. From past experiences of Liuxihe model parameterization, it has been found that parameter optimization could largely improve the model's performance. Besides, in optimizing model parameters, hydrological data from only one flood events is enough, not like lumped hydrological mode, series of hydrological data is requirred. This is very important for an urbanizing watershed as it usually has limited hydrological data, no

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long series of hydrological data.

Currently two algorithms have been proposed for Liuxihe model parameter optimization, one is SCE-UA algorithm (Xu et al., 2012), another is Particle Swam Optimization (PSO) algorithm (Chen et al., 2016). In optimizing parameters, Liuxihe model does not optimize all parameters of each grid cells, but optimizes the parameters look-up tables. I.e., an adjusting coefficient for each terrain property is proposed, so the optimized variables are limited, which makes the calculation practical, otherwise, even with the fastest computers in the world, the optimization is not feasible.

3.3 Dynamic parameter updating and parameter stationary

For an urbanizing watershed, the terrain properties, particularly the LUCs are in constant changes, so after parameter look-up table is optimized based on hydrological data from one specific flood event and terrian properties at a specific date, model parameters should be updated if the terrain properties changes, it is called in this study, dynamic parameter updating, it is also the core concept of this study, that the model parameters are dynamically changing with terrain property changes. Only with this dynamic parameter updating, the model performance can be secured. But this parameter updating is based on the assumption that the parameter look-up tables are LUCs stationary, i.e., the look-up tables are not changed with the terrain property changing. Otherwise, the updated parameters could not improve the model performance, or the parameter look-up table needs to be optimized again with the changed LUCs and new observed hydrological data.

Do the parameter look-up tables change with the watershed terrain property changing, it is a science question that has not been answered and fully studied by the scientific

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communities. The authors assume that the parameter look-up tables of Liuxihe model are LUC stationary, and the simulation results in the case study will validate this assumption.

4 Results

4.1 Liuxihe model set up

The DEM produced in this study with spatial resolution of 30 m is used to divide the studied watershed into 62942 grid cells, which are further divided into 658 river cells, 53435 hill slope cells and 8849 reservoir cells, based on the method employed in Liuxihe model. A 3-order river network is derived using the D8 method (O'Callaghan et al., 1984; Jensen et al., 1988) and Strahler river ordering method (Strahler, 1957) based on the DEM. The river network is further divided into 24 virtual sections based on 4 virtual nodes. In the Liuxihe model, the virtual river cross section shape is assumed trapezoidal, and the river size is estimated based on satellite remote sensing images. The structure of the Liuxihe model for SRW set up in this study is shown in Fig. 5. The time resolution of the Liuxihe model set up in SRW is 1 hour, the same with that of the observed hydrological data. Precipitation from rain gauges is interpolated to the grid cells by using the Thiesson Polygon method (Thiessen, 1911).

Fig. 5 is here

Flow directions and slopes are derived using the D8 method (O'Callaghan et al., 1984, Jensen et al., 1988) based on the DEM. The climate-based parameter, i.e., the potential evaporation is estimated as 5 mm/day for each grid cell according to daily evaporation observations in this region. According to previous studies of Liuxihe model

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parameterization and references (Chen et al., 1995; Zhang et al., 2006, 2007; Guo et al., 2010; Li et al., 2013), the initial look-up table for vegetation-based parameters is proposed and listed in Table 2.

Table 2 is here

Based on past modeling studies (Zaradny, 1993; Anderson et al., 1996; Shen et al., 2007; Zhang et al., 2015), the soil water content under wilting conditions takes 30% of the soil water content under field conditions, and the soil porosity coefficient takes the value of 2.5. Based on local experiences, the estimated soil layer thickness is listed in Table 3. The Soil Water Characteristics Hydraulic Properties Calculator proposed by Arya et al. (1981) is employed to calculate the soil water contents under saturation condition and field condition, and the hydraulic conductivity under saturation conditions, as listed in Table 3.

Table 3 is here

For grid cells with urban land soil type, all the soil-based parameters are set to zero. This reflects the hydrological response of urban land soil type, i.e., the precipitation falling onto urban land will be converted into surface runoff completely, no precipitation will be infiltrated to the soil or stored on the surface.

For Liuxihe model, hydrological data from only one flood event is needed for parameter optimization, and Particle Swam Optimization(PSO) is the official optimization algorithm, which has been tested and proven to be effective. In this study, hydrological

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data from flood event 20080625 is used for parameter optimization, and PSO algorithm is employed to optimize the parameters, while LUCs in 2008 is used. The optimized parameter look-up tables are called parameter-20080625-2008 to distinguish parameters optimized with different hydrological data and LUCs in different year. In parameter-20080625-2008, the first number is the flood event number with its hydrological data being used for parameter optimization, while the second one is the year of the LUCs which is used in the parameter optimization. I.e., Parameter-20080625-2008 is the optimized parameters by using hydrological data from flood event 20080625 and LUCs in 2008. Fig. 6 shows the evolution results of parameters, adaptive values and evaluation indices during the parameter optimization process.

Fig. 6 is here

With 9 evolution, the model parameters approached their optimal values, and the simulated hydrograph with optimized parameters fits the observed flood event well as shown in Fig 6(d), this means the PSO algorithm has good performance for Liuxihe model parameter optimization.

From the result of Fig 6(a), it has been found that the initial value of soil property coefficient is quite different from its optimized value, but with the optimization of PSO algorithm, its optimized value is obtained, this implies that the PSO algorithm has good convergence, and well suits Liuxihe model parameter optimization.

4.2 Flood simulation with Parameter-20080625-2008

With the above optimized Parameter-20080625-2008, the other 12 flood events were simulated, while in this sumulation, the LUCs in 2018 are used for all the 12 flood events, that means the parameters are regarded not changed during the watereshed urbanization, and the model parameters are not updated dynamically with the LUC changing. Four evaluation indices, including Nash-Sutcliffe coefficient, mean relative error, peak flow error and peak flow timing error, has been calculated and listed in Table 4, the simulated hydrographs are shown in Fig. 7.

Table 4 is here

Fig. 7 is here

From the results shown in Table 4 and Fig. 7, it has been found that for all the 12 flood events, the simulated hydrographs are similar with the observations in shape. In average for all the 12 flood events, the Nash-Sutcliffe coefficient is 0.79, the mean relative error is 63.91%, the peak flow error is 19.47%, while the peak flow timing error is -0.58 hour. From these results, the flood processes of SRW have been simulated reasonable by Liuxihe model set up in this study.

From the above results, we also find that the four evaluation indices get worse with time goes. For example, the average peak flow error for flood events in 2008 and 2009 is 6.7%, 35.88% in 2011, 17.15% in 2013 and 2014, and 27.87% in 2015, in general, the average peak flow error gets bigger as time goes. For the Nash-Sutcliffe coefficient, those in 2008 and 2009, in 2011, in 2013 and 2014, and in 2015 are 0.835, 0.775, 0.753 and 0.76, a similar trend with peak flow error. Based on these results, it can be proposed that the model parameters should have changed with time going, i.e., with LUC changes, and the model parameters need to be adjusted with the changing LUCs. To verify this opnion, the dynamical parameter updating is tested in the follow-up section.

4.3 Flood simulation with dynamic updating to parameter-20080625-2008

Based on the dynamic parameter updating method proposed in this study, parameters used for simulating flood events in 2011, in 2013 and 2014, in 2015 are updated with the LUCs in 2011, 2013 and 2015 respectively based on parameter-20080625-2008. The dynamically updated model parameters in 2011, 2013 and 2015 are different from each other, so are from parameter-20080625-2008, which is called parameter-20080625-2008-updated. With these parameters, 8 flood events(parameters for the flood events in 2008 and 2009 are not updated) are simulated again, the four evaluation indices have been calculated and listed in Table 5, the simulated hydrographs are shown in Fig. 7 also to make comparison with those results simulated with no parameter updating.

Table 5 is here

From the results shown in Fig. 7 and Tabel 5, it has been found that the model performance has been improved with dynamic parameter updating. For example, for all the 8 flood events, the simulated hydrographs fit those of the observations better than those simulated with no parameter updating. The Nash-Sutcliffe coefficients of all the simulated flood events with updated parameters gets higher, except those of flood event no. 20150520 and 20150720. The average Nash-Sutcliffe coefficient increasing is 0.764, a 0.3% incrasing. While for the peak flow error, all flood events have observed decreasing, the average decreasing is 66.81%, a very significant model performance imporvement. These results imply that with dynamical parameter updating, Liuxihe

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model has a much better performance in simulating the flood events of SRW, i.e., model parameters are in dynamic changing with the LUC changing, and dynamical parameter updating with the LUC changing is needed. This confirms the dynamic characteristics of model parameters.

5 Discussions

5.1 Effect of parameter optimization on model performance

To test the effectiveness of parameter optimization, the 12 flood events are simulated with the initial parameters, and the results are shown in Fig 8, to make comparision, the simulated hydrographs with dynamically updated parameters are also shown. From the results it could be found that the simulation results with initial and dynamically updated parameters are quite different. Though both the simulated hydrographs have similar patterns, but the flows simulated with the initial parameters are generally much lower than the observations, and those simulated with the dynamically updated parameters well fit the observation.

Fig. 8 is here

The four evaluation indices of the 12 flood events is calculated and listed in Table 6. Compared with the simulation with initial parameter, the simulation with dynamically updated parameters has been improved much based on these evaluation indices. Among them, the average Nash-Sutcliffe coefficient increased 68.2%, correlation coefficient increased 3.2%, peak flow error reduced 86.4%, water balance coefficient increased 45.8%. These results show that parameter optimization is needed and feasible even for distributed hydrological model.

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Table 6 is here

5.2 Parameter stationary

In above sections, the dynamic parameter updating was based on the optimized parameter look-up tables with LUCs in 2018. There appears a question, should the look-up table be optimized with the latest LUCs, not the LUCs at a specific time? I.e., is the look-up table no-stationary to LUCs during urbanization. If yes, then the look-up table needs to be optimized with the latest LUCs, and done again when there is significant LUC change. Otherwise, the look-up table can be optimized with LUCs at any time, and there is no need to optimize it very often. To answer this question, in this study, the parameters were optimized with LUCs in 2011, 2013 and 2015 also, and the hydrological data used for parameter optimization were from flood events 20110516, 20130815 and 20150520 respectively, these parameters are called parameter-20110516-2011, parameter-20130815-2013, and parameter-20150520-2015 respectively. Then the parameters are dynamically updated with latest LUCs, and are called parameter-20110516-2011-updated and parameter-20130815-2013-updated respectively, there is not parameter-20150520-2015-updated. I. e., dynamical parameter updating is time forward, not time backward. For example, parameter-20110516-2011-updated only update parameters with LUCs in 2013 and 2015, not in 2008 and 2011; parameter-20130815-2013-updated only update parameters with LUCs in 2015, not in 2008, 2011 and 2013, so there is not parameter-20150520-2015-updated. The dynamically optimized and updated parameters are then employed to simulate the flood events, and the results are shown in Fig. 9. The four evaluation indices are calculated and listed in table 7.

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Table 7 is here

Fig. 9 is here

Both the simulated flood hydrographs with and without dynamic parameters optimizing and updating have no obvious differences, so based on the above methods and results, it can be concluded that the parameters are stationary during the urbanization, i.e., during the LUC changing period. There is no need to optimize the look-up table very often with rapid LUC changing, parameter optimization and updating is most important.

5.3 Impact of LUC changes on flood responses

Based on the above results, it could be found that with the LUC changes, the flood response changes also. To quantitatively analysis this effect, the peak flow and urban land area rate of flood events from 2011 to 2015 are extracted from the above results and listed in Table 8. The values with no-update are the simulated values with parameter-20080625-2008, while the ones with update are the simulated values with parameter-20080625-2008-update.

Table 8 is here

From the results, it could be found that from 2008 to 2011, the SRW observed an urban land rate change from 18.62% to 23.4%, a 25.67% increasing. For flood event 20110516, with the same precipitaion, the peak flow will change from 87.08 m^3/s to 99.42 m^3/s, having a 14.2% increasing. While for flood event 201100808, the peak flow change is from 103.68 m^3/s to 117.21 m^3/s, having a 13.1% increasing. Both these events are light flood, the peak flow increasing has similar magnitude.

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But from 2008 to 2013, the SRW observed an urban land rate increasing of 40.92%. For flood event 20130815, which is regarded as a heavy flood event, the peak flow increasing is 9.0%, while for flood event 20140511, the peak flow increasing is 12.8%, for flood event 20140819, this is 14.6%. The latter two flood events are regarded as medium. With these results, it can be concluded that the much heavier of the flood magnitude, the more increasing of peak flow.

From 2008 to 2015, the SRW observed an urban land rate increasing of 63.10%. For flood event 20150520, which is regarded as a light flood event, and flood events 20150523 and 20150720, which are regarded as a medium flood event, the peak flow increasing are 56.3%, 18.5%, and 12.2% respectively. This implies that for the light flood event, the peak flow increases much more. Based on this analysis, with the increasing of the urban land area rate, the peak flow of a flood event will increase, and the light flood event has the most peak flow increasing, while the heavy one has the least peak flow increasing.

6 Conclusions

In this study, a method is proposed for accurately simulating flood processes of urbanizing watersheds that appear during the world urbanization process, which employs the Liuxihe model, a physically based distributed hydrological model as the flood simulation tool. This method first derives initial parameter look-up tables, and then optimizes it, and dynamically updates the parameter with the changing LUCs to improve the model performance. A case study has been carried out in the Songmushan Reservoir Watershed, a highly urbanizing watershed in the Pearl River Delta Area in southern China which experienced rapid urbanization in the past decade. Based on the results, following conclusions have been proposed.

1. The methodology proposed in this study could be used for simulating and forcasting urbanizing watershed flood processes with good model performance.

2. For an urbanizing watershed, terrain properties are in changing, and model parameters are in changing also due to terrain properties changing, this is called model parameter dynamics. Model parameters should be updated with the LUC changes.

3. Parameter look-up table of physicall based distributed hydrological model is LUC stationary, i.e., the parameter look-up table only needs to be determined once during the watershed urbanization.

4. With same precipitation, flood peak flow will increase due to urban land rate increases. The much heavier the precipitation, the less increasing of the peak flow.

5. Parameter optimization is effective and needed in controlling parameter uncertainty for physically based distributed hydrological model.

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Figures

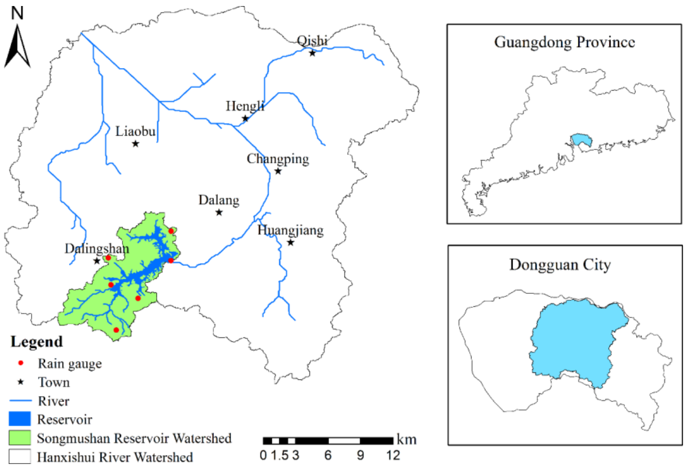

Fig. 1 Location of Songmushan Reservoir Watershed(SRW)

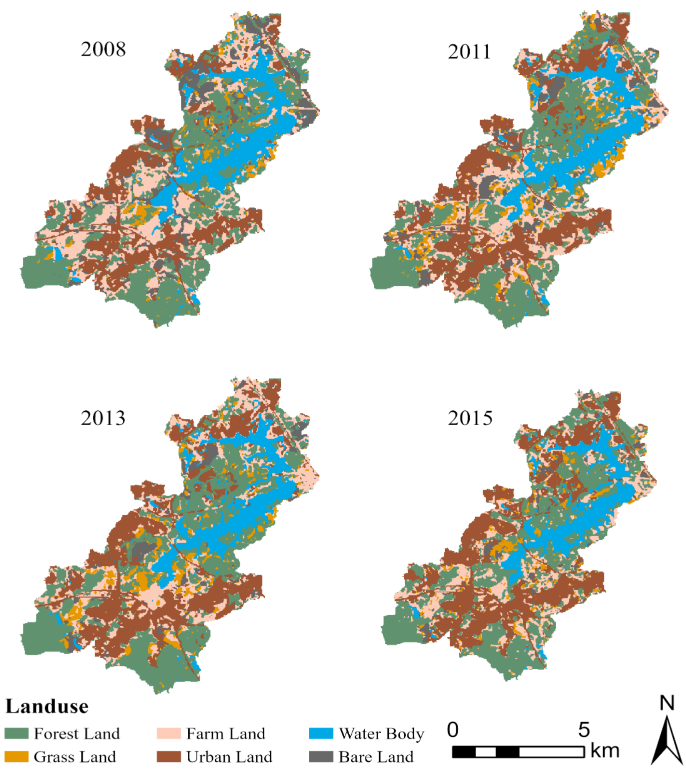

Fig. 2 LUCs of SRW

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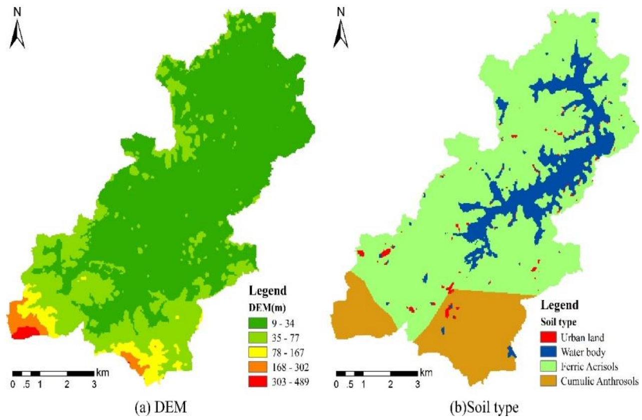

Fig. 3 Terrain property of SRW

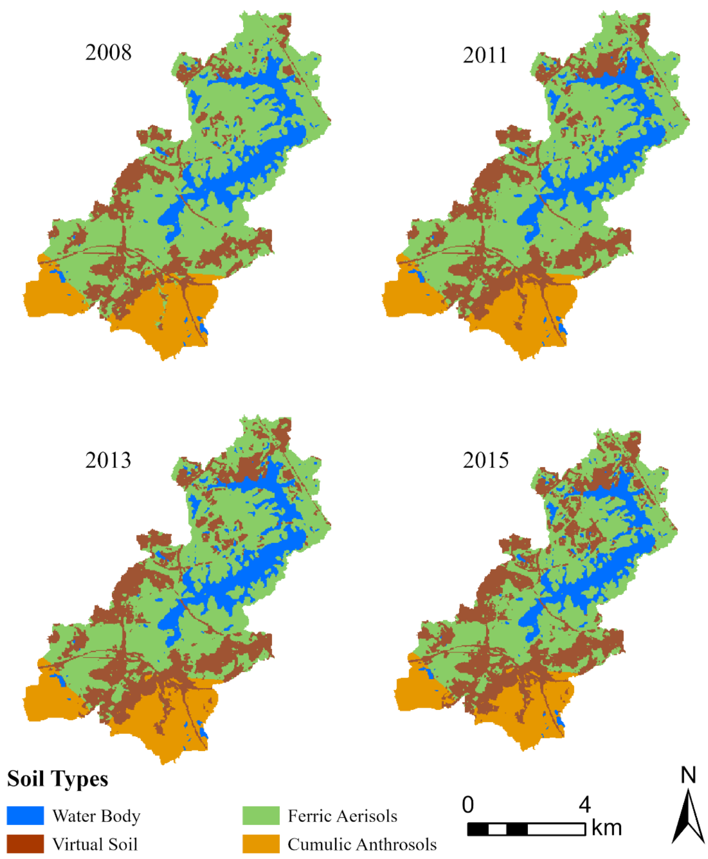

Fig. 4 Soil types of SRW adding urban land soil

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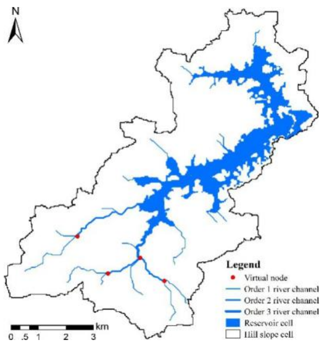
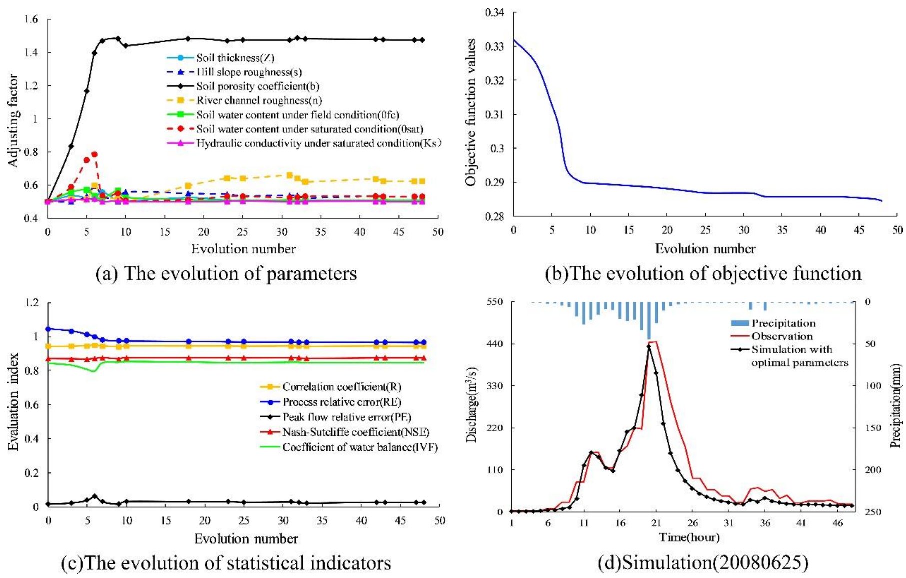


Fig. 5 Structure of the Liuxihe model of SRW



(a) The evolution of parameters

(b)The evolution of objective function

(c)The evolution of statistical indicators

(d)Simulation(20080625)

Fig. 6 results of parameter optimization

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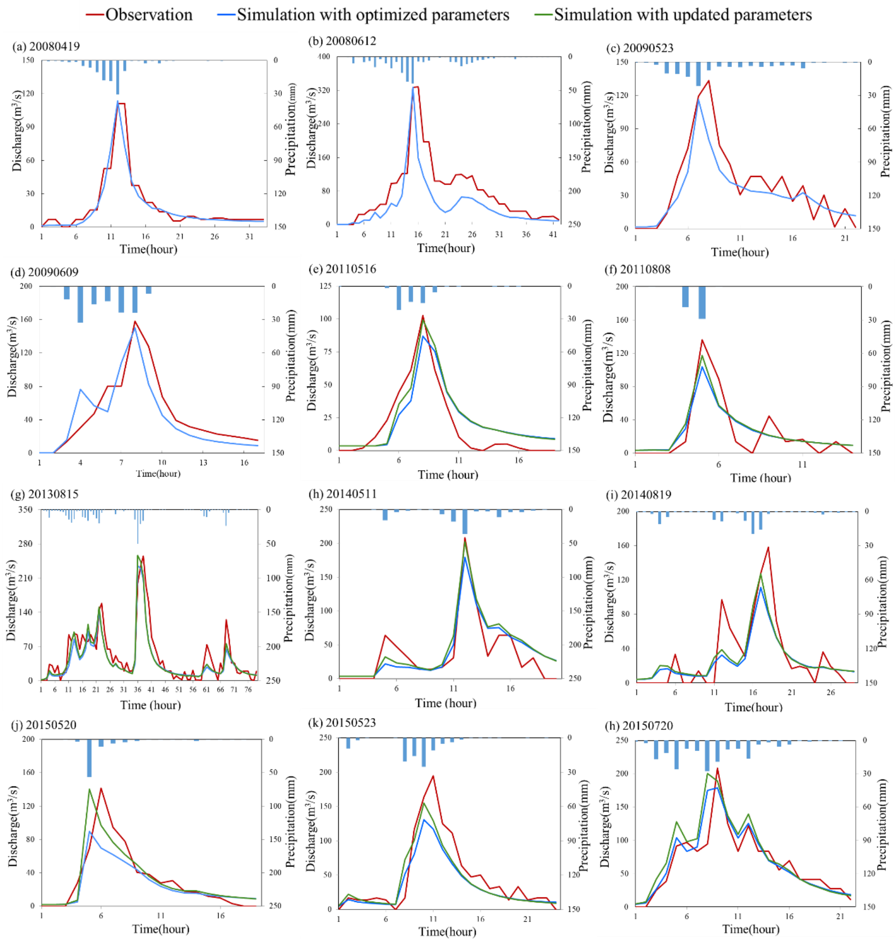

Fig. 7 Simulated flood hydrographs with Parameter-20080625-2008 and Parameter-20080625-2008-updated

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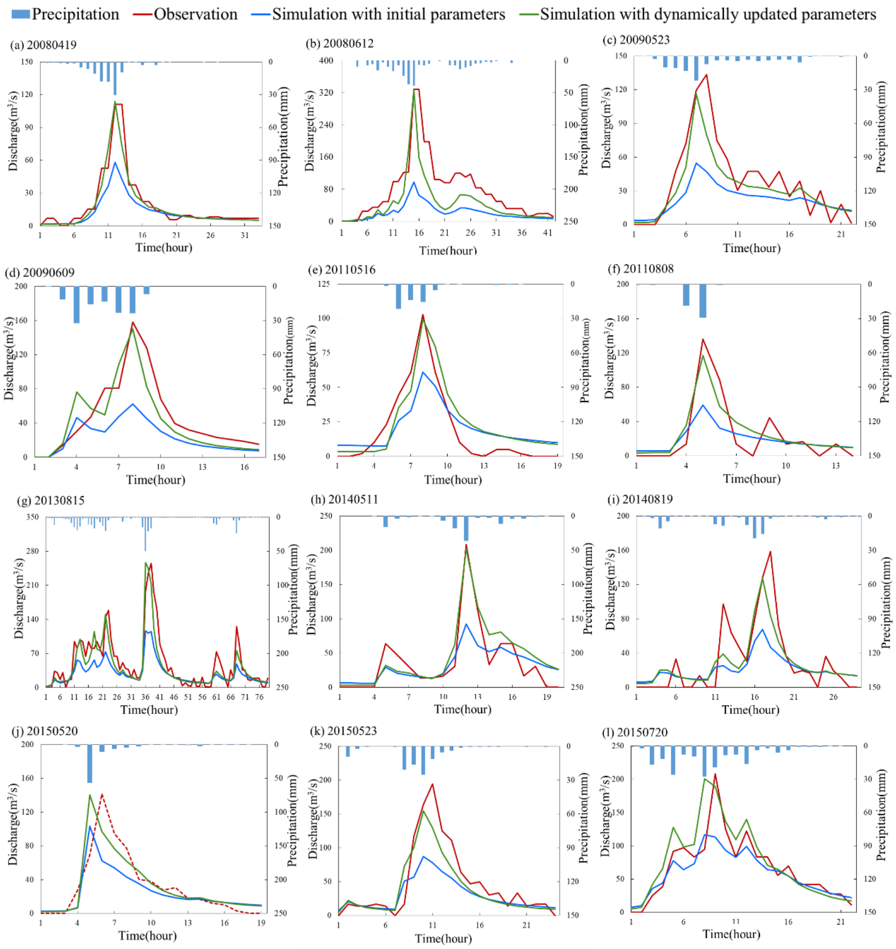

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790 Fig. 8 Simulated flood hydrographs with initial parameter and dynamically updated

791 parameters

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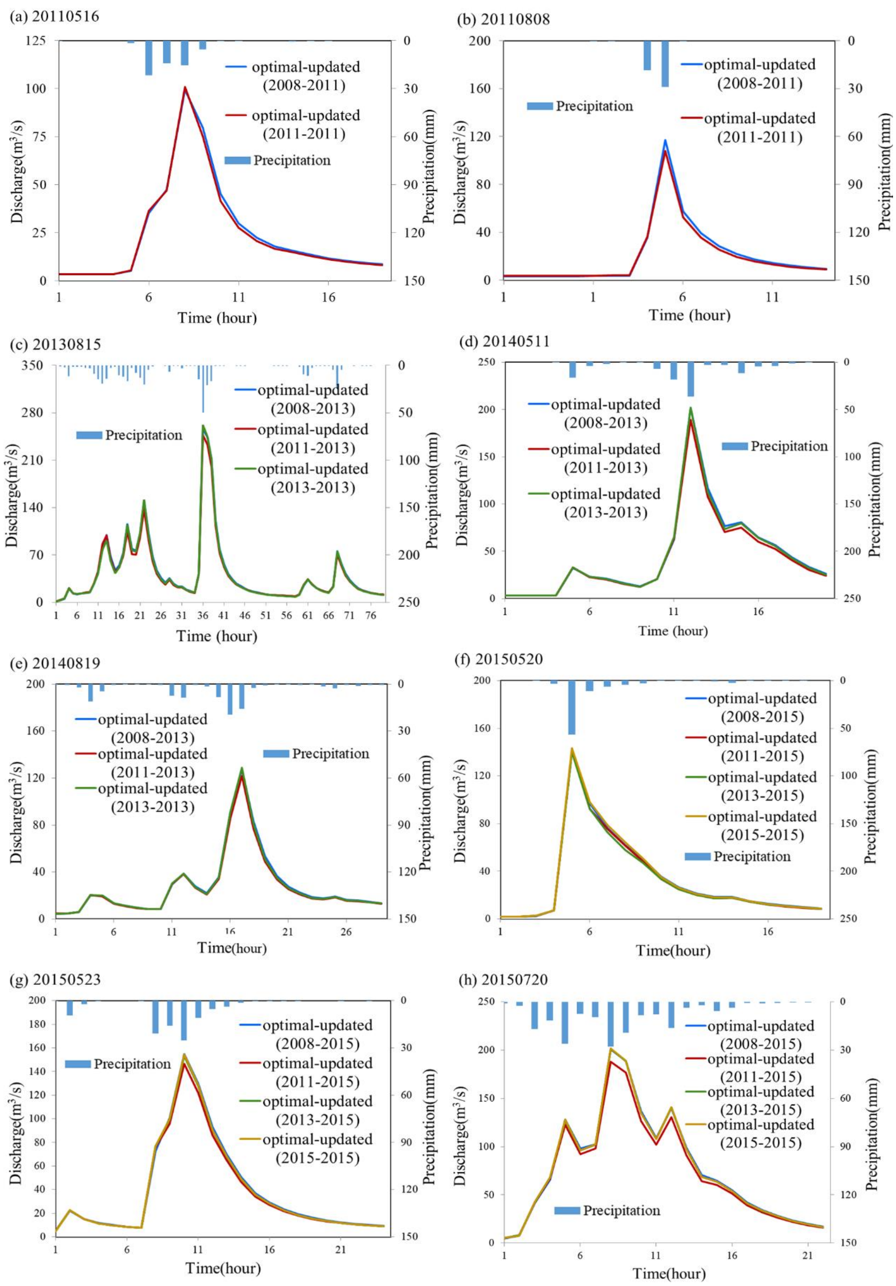

Fig. 9 Simulated flood hydrographs with dynamic parameter optimizing and updating.

* optimal-update (2008-2011) represents simulation results based on the 2008 LUC optimization parameters and the 2011 LUC updated parameters.

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Tables

Table 1 Brief information of flood events

Flood event no.	Start time (yyyymmddhh)	End time (yyyymmddhh)	Total rainfall (mm)	Peak flow (m^3/s)	Flood magnitude*
20080419	2008041910	2008042018	110.6	111.1	light
20080612	2008061219	2008061412	271.0	328.6	heavy
20080625	2008062500	2008062623	360.3	445.8	heavy
20090523	2009052304	2009052401	104.4	133.3	light
20090609	2009060900	2009060916	127.7	158.3	medium
20110516	2011051608	2011051702	60.1	102.8	light
20110808	2011080811	2011080900	48.6	136.1	light
20130815	2013081517	2013081823	351.3	254.7	heavy
20140511	2014051103	2014051122	110.7	208.3	medium
20140819	2014081914	2014082018	98.0	158.3	medium
20150520	2015052009	2015052103	90.1	141.7	light
20150523	2015052305	2015052404	100.9	194.4	medium
20150720	2015072022	2015072119	171.8	208.3	medium

* Flood magnitude is a qualitative measurement to the flood based on the peak flow of a flood event. I.e., for a flood event, if its peak flow is below 150 m^3/s, then it's flood magnitude is light. On the other hand, if its peak flow is over 250 m^3/s, it's flood magnitude is heavy. For other flood events, it's medium.

Table 2 Initial look-up table for vegetation-based parameters

Vegetation	Evaporation coefficient	Roughness
Forestry land	0.7	0.55
Grassland	0.6	0.18
Urban land	1.0	0.01
Bare land	0.4	0.12
Farmland	0.55	0.36

Table 3 Initial look-up table for soil-based parameters

Soil type	Soil water content under saturated conditions (%)	Soil water content under field capacity conditions (%)	Soil hydraulic conductivity under saturated conditions （mm·h^{-1}）	Soil layer thickness (mm)
Urban land	0	0	0	0
Ferric Acrisols	46.1	26.5	20.78	1500
Cumulic Anthrosols	45.8	35.3	2.81	850

Table 4 Evaluation indices of simulated flood events with Parameter-20080625-2008

Flood event no.	Nash-Sutcliffe coefficient	Mean relative error (%)	Peak flow error (%)	Peak flow timing error/hour
20080419	0.93	31.29	0.49	0
20080612	0.70	38.83	0.94	-1
20090523	0.81	144.10	23.96	-1
20090609	0.90	24.60	1.41	0
20110516	0.77	189.10	15.27	0
20110808	0.78	52.65	56.48	0
20130815	0.80	97.98	7.71	-2
20140511	0.80	48.54	13.99	0
20140819	0.66	36.06	29.75	-1
20150520	0.69	43.34	36.58	-1
20150523	0.78	39.52	32.85	-1
20150720	0.81	20.87	14.19	0
average	0.79	63.91	19.47	-0.58

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Table 5 Evaluation indices of simulated flood events with parameter-20080625-2008-updated

Flood event no.	Parameter	Nash-Sutcliffe coefficient	Correlation coefficient	Relative error (%)	Peak flow error (%)	Water balance coefficient	Peak flow timing error/hour
20110516	No-updated	0.769	0.889	189.10	15.30	1.17	0
	Updated	0.812	0.922	186.70	3.30	1.27	0
	Difference	0.043	0.033	-2.40	-12.00	0.10	0
	Increase(%)	5.600	3.700	1.27	-78.43	8.40	0
20110808	No-updated	0.784	0.919	57.30	23.80	1.01	0
	Updated	0.806	0.914	62.70	13.90	1.08	0
	Difference	0.022	-0.005	5.40	-9.90	0.07	0
	Increase(%)	2.800	-0.500	9.42	-41.60	7.10	0
20130815	No-updated	0.802	0.921	97.90	7.70	0.78	-2
	Updated	0.813	0.915	93.40	0.60	0.84	-2
	Difference	0.011	-0.006	-4.50	-7.10	0.05	0
	Increase(%)	1.400	-0.700	4.60	-92.21	6.90	0
20140511	No-updated	0.804	0.900	48.50	13.90	1.08	0
	Updated	0.819	0.921	52.40	3.00	1.20	0
	Difference	0.015	0.021	3.90	-10.90	0.11	0
	Increase(%)	1.900	2.300	8.04	-78.42	10.40	0
20140819	No-updated	0.659	0.865	36.10	29.80	0.83	-1
	Updated	0.689	0.849	33.60	19.50	0.92	-1
	Difference	0.030	-0.016	-2.50	-10.30	0.09	0
	Increase(%)	4.600	-1.800	6.93	-34.56	10.50	0
20150520	No-updated	0.691	0.873	43.30	36.60	0.80	-1
	Updated	0.683	0.837	46.20	0.90	1.01	-1
	Difference	-0.008	-0.036	2.90	-35.70	0.21	0
	Increase(%)	-1.200	-4.100	6.70	-97.54	26.40	0
20150523	No-updated	0.782	0.959	39.50	32.80	0.73	-1
	Updated	0.823	0.932	42.60	20.40	0.83	-1
	Difference	0.041	-0.027	3.10	-12.40	0.09	0
	Increase(%)	5.200	-2.800	7.85	-37.80	12.70	0
20150720	No-updated	0.810	0.914	20.90	14.20	1.05	0
	Updated	0.666	0.889	29.70	3.70	1.15	-1
	Difference	-0.144	-0.025	8.80	-10.50	0.10	-1
	Increase(%)	-17.800	-2.700	42.11	-73.94	9.70	0
average	No-updated	0.763	0.905	66.58	21.76	0.93	-0.63
	Updated	0.764	0.897	68.41	8.16	1.03	-0.75
	Difference	0.001	-0.008	1.84	-13.60	0.10	-0.13
	Increase(%)	0.313	-0.825	10.86	-66.81	11.51	20.00

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Table 6 The evaluation indices of simulated flood events with initial and dynamically updated parameters

Flood event no.	Parameter	Nash-Sutcliffe coefficient	Mean relative error (%)	Peak flow error (%)	Peak flow timing error/hour
20080419	initial	0.604	0.310	0.507	0
	updated	0.928	0.313	0.005	0
	difference(%)	53.6	1.0	-99.0	0.0
20080612	initial	0.010	0.559	0.708	-1
	updated	0.701	0.388	0.009	-1
	difference(%)	6910.0	-30.6	-98.7	0.0
20090523	initial	0.304	1.489	0.628	-1
	updated	0.809	1.441	0.239	-1
	difference(%)	166.1	-3.2	-61.9	0.0
20090609	initial	0.335	0.385	0.611	0
	updated	0.897	0.246	0.014	0
	difference(%)	167.8	-36.1	-97.7	0.0
20110516	initial	0.636	1.831	0.481	0
	updated	0.812	1.867	0.033	0
	difference(%)	27.7	2.0	-93.1	0.0
20110808	initial	0.482	0.526	0.568	0
	updated	0.806	0.627	0.139	0
	difference(%)	67.2	19.2	-75.5	0.0
20130815	initial	0.476	1.038	0.543	-2
	updated	0.813	0.934	0.006	-2
	difference(%)	70.8	-10.0	-98.9	0.0
20140511	initial	0.548	0.432	0.556	0
	updated	0.819	0.524	0.030	0
	difference(%)	49.5	21.3	-94.6	0.0
20140819	initial	0.398	0.412	0.573	-1
	updated	0.689	0.336	0.195	-1
	difference(%)	73.1	-18.4	-66.0	0.0
20150520	initial	0.576	0.513	0.269	-1
	updated	0.683	0.462	0.009	-1
	difference(%)	18.6	-9.9	-96.7	0.0
20150523	initial	0.518	0.413	0.550	-1
	updated	0.823	0.426	0.204	-1
	difference(%)	58.9	3.1	-62.9	0.0
20150720	initial	0.724	0.222	0.439	-1
	updated	0.666	0.297	0.037	-1
	difference(%)	-8.0	33.8	-91.6	0.0
average	initial	0.468	0.678	0.536	-0.667
	updated	0.787	0.655	0.077	-0.667
	difference(%)	68.2	-2.3	-86.4	0.0

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Table 7 Evaluation indices of simulated flood events with dynamic parameter optimizing and updating

Flood event no.	Optimizing year	Nash-Sutcliffe coefficient	Correlation coefficient	Relative error (%)	Peak flow error (%)	Water balance coefficient	Peak flow timing error/hour
20110516	2008	0.812	0.922	1.867	0.033	1.269	0
	2011	0.845	0.934	1.724	0.019	1.231	0
20110808	2008	0.806	0.914	0.627	0.139	1.076	0
	2011	0.780	0.909	0.621	0.206	0.997	0
20130815	2008	0.813	0.915	0.934	0.006	0.838	-2
	2011	0.789	0.909	0.962	0.032	0.799	-2
	2013	0.797	0.908	0.922	0.028	0.822	-2
20140511	2008	0.819	0.921	0.524	0.030	1.195	0
	2011	0.839	0.923	0.487	0.091	1.127	0
	2013	0.828	0.923	0.512	0.031	1.181	0
20140819	2008	0.689	0.849	0.336	0.195	0.918	-1
	2011	0.662	0.844	0.329	0.231	0.871	-1
	2013	0.675	0.841	0.332	0.186	0.904	-1
20150520	2008	0.683	0.837	0.462	0.009	1.006	-1
	2011	0.663	0.825	0.451	0.006	0.979	-1
	2013	0.658	0.821	0.455	0.009	0.966	-1
	2015	0.677	0.837	0.455	0.011	1.018	-1
20150523	2008	0.823	0.932	0.426	0.204	0.826	-1
	2011	0.776	0.918	0.465	0.246	0.784	-1
	2013	0.803	0.923	0.452	0.211	0.814	-1
	2015	0.806	0.923	0.449	0.207	0.816	-1
20150720	2008	0.666	0.889	0.297	0.037	1.151	-1
	2011	0.721	0.883	0.288	0.097	1.084	-1
	2013	0.659	0.885	0.304	0.033	1.144	-1
	2015	0.657	0.885	0.304	0.032	1.145	-1

Table 8 impact of urbanization on peak flow

Flood event no.	Peak flow (m^3/s)			Urbanization rate (%)*		
	no-update	update	increase(%)	no-update	update	increase(%)
20110516	87.08	99.42	14.2	18.62	23.4	25.67
20110808	103.68	117.21	13.1	18.62	23.4	25.67
20130815	235.08	256.19	9.0	18.62	26.24	40.92
20140511	179.18	202.07	12.8	18.62	26.24	40.92
20140819	111.23	127.43	14.6	18.62	26.24	40.92
20150520	89.85	140.44	56.3	18.62	30.37	63.10
20150523	130.58	154.72	18.5	18.62	30.37	63.10
20150720	178.78	200.59	12.2	18.62	30.37	63.10

*Urbanization rate is the rate of urban land area to the whole watershed area.