An integrated modelling approach for flood simulation in the urbanized Qinhuai River basin, China

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Declarations

Funding

This work was supported by the National Natural Science Foundation of China (No. 41771029 and No. 41371044), the Research Council of Norway (FRINATEK Project

274310) and the Strategic Priority Research Program of the Chinese Academy of Sciences (No. XDA23040202)

Conflicts of interest

The authors declare that they have no conflicts of interest.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability

The code that supports the findings of this study is available from the corresponding author upon reasonable request.

Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Runjie Li, Guodong Bian and Jinkang Du. The first draft of the manuscript was written by Runjie Li, and all authors commented on previous versions of the manuscript. The modified manuscript was completed by Jinkang Du, Runjie Li and Long Yang. All authors read and approved the final manuscript.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 41771029 and No. 41371044), the Research Council of Norway (FRINATEK Project 274310), and the Strategic Priority Research Program of the Chinese Academy of Sciences (No. XDA23040202), whose support was greatly appreciated.

Abstract

The accurate simulation and prediction of flood response in urbanized basins remains a great challenge due to the spatial and temporal heterogeneities in land surface properties. We hereby propose an integrated modelling approach that consists of a semi-distributed conceptual hydrological model and a novel parameterization strategy. The modelling approach integrates the Xinanjiang (XAJ) model, Taihu Basin (TB) model, and Nash instantaneous unit hydrograph (IUH) into a framework. Model parameters are calibrated by optimizing their relationships with corresponding physical factors. The proposed modelling approach is applied in the Qinhuai River basin (QRB), China. The modelling approach shows satisfactory performance in flood simulation both for calibration and validation of flood events in the QRB. The approach has temporal and spatial prediction capability by using the established relationships between parameter values and physical factors. Robustness analysis reveals that the different sets of flood events used for parameter relationship calibration led to similar model performance. Numerical experiments show that impervious coverage poses strong influences on the model performance and needs to be considered in flood routing simulations for small- or medium-intensity flood events.

Keywords

Urbanization, Hydrological model, Model calibration, Flood response, Parameter estimation

1. Introduction

As one of the most extensive anthropogenic activities, urbanization has triggered a variety of environmental issues (Booth and Jackson 1997; Patra et al. 2018; Zhang et al. 2018), among which hydrological alterations have attracted increasing concern in the past several decades. Urban development increases impervious surface area and artificial drainage systems, which dramatically alter hydrological processes (Braud et al. 2013; Oudin et al. 2018; Schueler et al. 2009), such as an increase in surface runoff, a decrease in infiltration and changes in groundwater discharge (e.g., Burns et al. 2005; Salvadore et al. 2015). Previous studies have shown that disastrous flood events have become more frequent due to urbanization (Hu 2016; Hundecha and Bardossy 2004).

Hydrological modelling is the most useful and effective tool to examine the impacts of urbanization on hydrological processes (Jacobson 2011; Trinh and Chui 2013). Hydrological models can be typically divided into three categories: lumped, semi-distributed and distributed models (Arnold and Gibbons 1996; Bach et al. 2014; Salvadore et al. 2015). Of all three categories, semi-distributed models reasonably consider the spatial heterogeneity of subcatchments or hydrologic units compared with the lumped model. In addition, semi-distributed models are superior to distributed models in terms of reducing computational complexity and the number of parameters. Therefore, semi-distributed hydrological models are broadly employed in urban hydrological studies, e.g., the Storm Water Management Model (SWMM), Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS), Soil and Water Assessment Tool (SWAT), and so on (e.g., Abbaspour et al. 2015; Arnold and Fohrer

2005; Lee and Heaney 2003; Lhomme et al. 2004; McColl and Aggett 2007; Valeo and Moin 2000; Zhao 1992).

In this study, we propose a semi-distributed conceptual modelling approach that combines the Xinanjiang (XAJ) model (Zhao 1992), Taihu Basin (TB) model (Cheng et al. 2006), and Nash instantaneous unit hydrograph (IUH) method (Nash 1960). The modelling approach uses spatially variable parameters and adopts conceptual methods to calculate runoff generation and routing. It has relatively feasible parameterization and high computational efficiency. Model calibration based on the observed hydrological data is necessary for obtaining better model performance. To reduce the number of calibrated parameters for semi-distributed models, parameters with low sensitivities or direct physical meanings can be assigned to their 'typical' value from current literature or field measurements. For example, hydraulic properties of soil can be obtained from the literature and from field measurements (Refsgaard 1997; Rodriguez et al. 2008). The ratio and connectivity of impervious surfaces can be obtained using remote sensing products (Lee and Heaney 2003). Parameters with high sensitivities are calibrated based on observed data. However, the observed data are usually scarce and unavailable for the calibration of parameters in each sub-basin. To determine the values of some highly sensitive parameters (especially for process-related parameters), one solution is to use regression equations to calculate those parameters based on physical data as independent variables (Xu 1999, 2003; Yang et al. 2018). For instance, Bedient and Huber (1992) presented regression equations for determining the time of concentration and the storage coefficient of the Clark unit hydrograph for each sub-basin. These equations represent relationships between parameters and other easily measurable physical factors, such as channel length, channel slope, and percentage of developed land. However, parameter estimations using these relationships are not always accurate because different basins or sub-basins may have different relationships; thus, the estimated values might be used only as initial values of the parameters for further calibration (USACE-HEC 2000). Ideally, these equations should be rebuilt or calibrated for each individual sub-basin. However, it is almost impossible to rebuild the equations due to the lack of observed data for each sub-basin. To address this problem, a parameterization scheme was proposed in this study by directly building unified equations to calculate parameters for each sub-basin, and the coefficients in the equations can be calibrated based only on the streamflow data at the basin outlet. In this way, the limitation of a lack of observation data for sub-basins can be solved, the number of calibrated model parameters can be reduced, and the calibration efficiency can be improved.

Therefore, the objectives of this study are to (1) propose a framework that uses a semi-distributed rainfall-runoff model for simulating flood processes in a mesoscale urbanized basin; (2) propose a parameterization scheme by establishing relationships between model parameters and potential driving factors; and (3) evaluate the simulation and prediction capacity of the integrated modelling approach.

2. Study Area and Data

The Qinhuai River basin (QRB) is located in Jiangsu Province, south-eastern China

(Fig. 1). The drainage area is 2,631 km^2. The peak rainfall from June to August often leads to severe flood hazards. Fast urbanization further increases the frequency of floods in this region (Du et al. 2013). The main land-use types include water surface, paddy land, urban land, dry land, and woodland. There are seven reservoirs, four hydrological stations and seven rain gauges in the QRB. The Qinhuaixinhe and Wudingmen hydrological stations are located at the outlet of the basin (see Fig. 1 for locations).

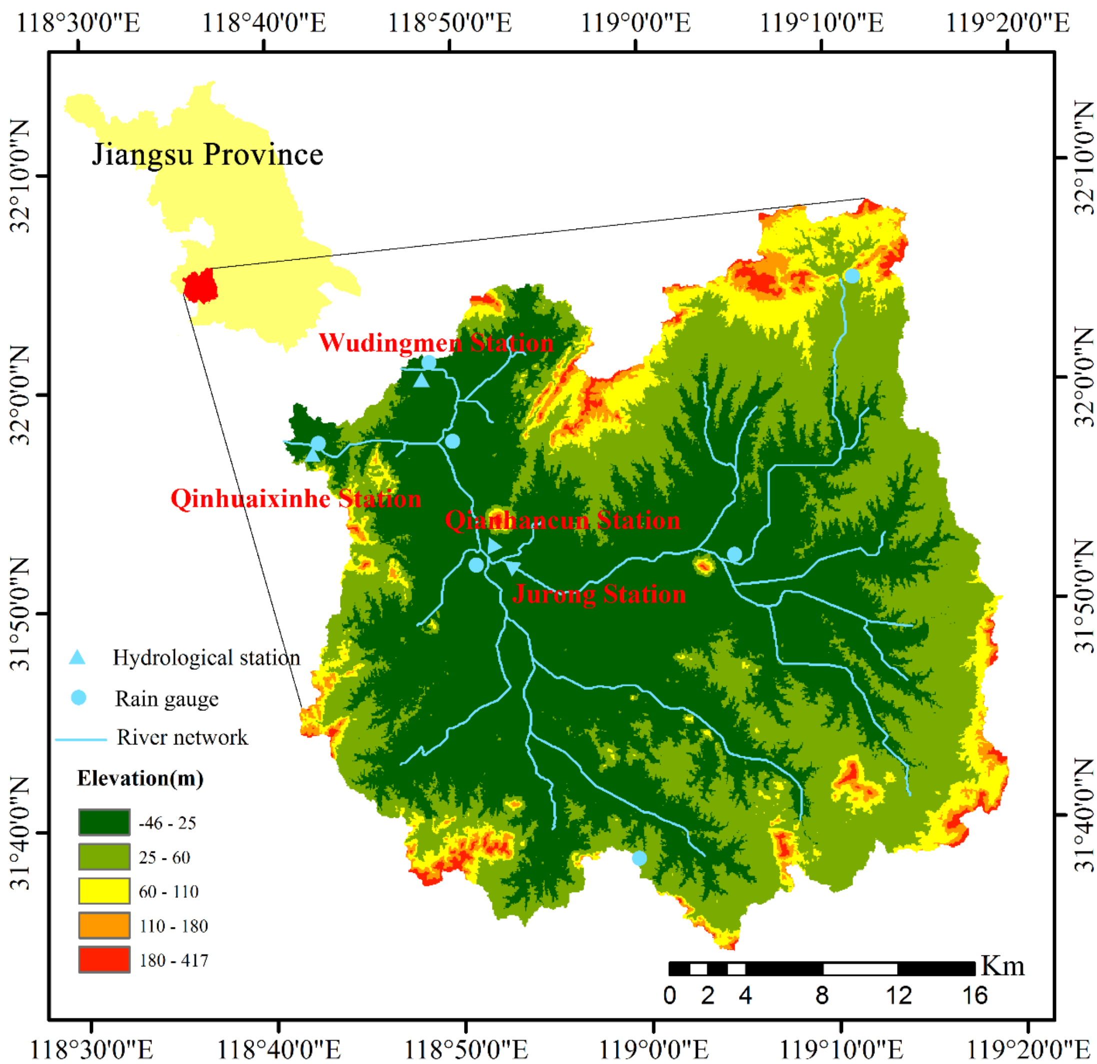

Fig. 1 Overview of the study area and location of hydrometeorological stations

Fourteen isolated flood events were selected from 1986 to 2015. The hourly rainfall data for the seven rain gauges, the hourly discharge data from Qianhancun Station and Jurong Station, and the instant peak flow and daily discharge data from Wudingmen Station and Qinhuaixinhe Station for the flood events were collected from the Nanjing Hydrological Bureau. The Thiessen polygon approach was used to interpolate rainfall. The hourly outflows of Wudingmen Station and Qinhuaixinhe Station were obtained by linear interpolation of the instant peak flow and the daily discharge of the stations. The summary of rainfall at the basin scale and runoff observed at Qianhancun station in the fourteen flood events is given in Table 1.

Table 1 Summary of selected rainfall and runoff events

		Basin-scale rainfall			**Streamflow at the Qianhancun Station**	
Storm no.	**Storm date**	**Depth (mm)**	**Duration (h)**	**Average intensity (mm/h)**	**Peak (m^3/s)**	**Time to peak (h)**
198707	July 2,1987	228.3	119	1.9	731	83
199106	June12,1991	333.9	115	2.9	964	81
199607	July 3, 1996	152.3	75	2.0	707	81
200607	July 19, 2006	171.4	91	1.9	513	79
200808	August 1,2008	115.3	32	3.6	654	37
200907	July 21, 2009	172.7	62	2.8	775	43
201007	July 12, 2010	153.2	32	4.8	491	34
201106	June 25, 2011	93.1	30	3.1	588	30
201107	July 18, 2011	95.6	56	1.7	517	30
201207	July 14,2012	62.8	17	3.7	380	20
201208	August 8,2012	78.3	37	2.1	667	47
201307	July 5,2013	125.9	62	2.0	497	37
201407	July 4, 2014	99.6	29	3.4	772	35
201506	June 16,2015	179.1	43	4.2	939	44

Fig. 2 shows changes in land use/land cover in the QRB during the period 1988-

2015. The land use/land cover was extracted from Landsat satellite images based on the rotation forest classifier method (Rodriguez et al. 2006; Bian et al. 2017). A noticeable change was found in the increase in impervious coverage from 3.92% to 19.76%, which was caused by the decrease in paddy field (from 50.09% to 29.94%) during the same period.

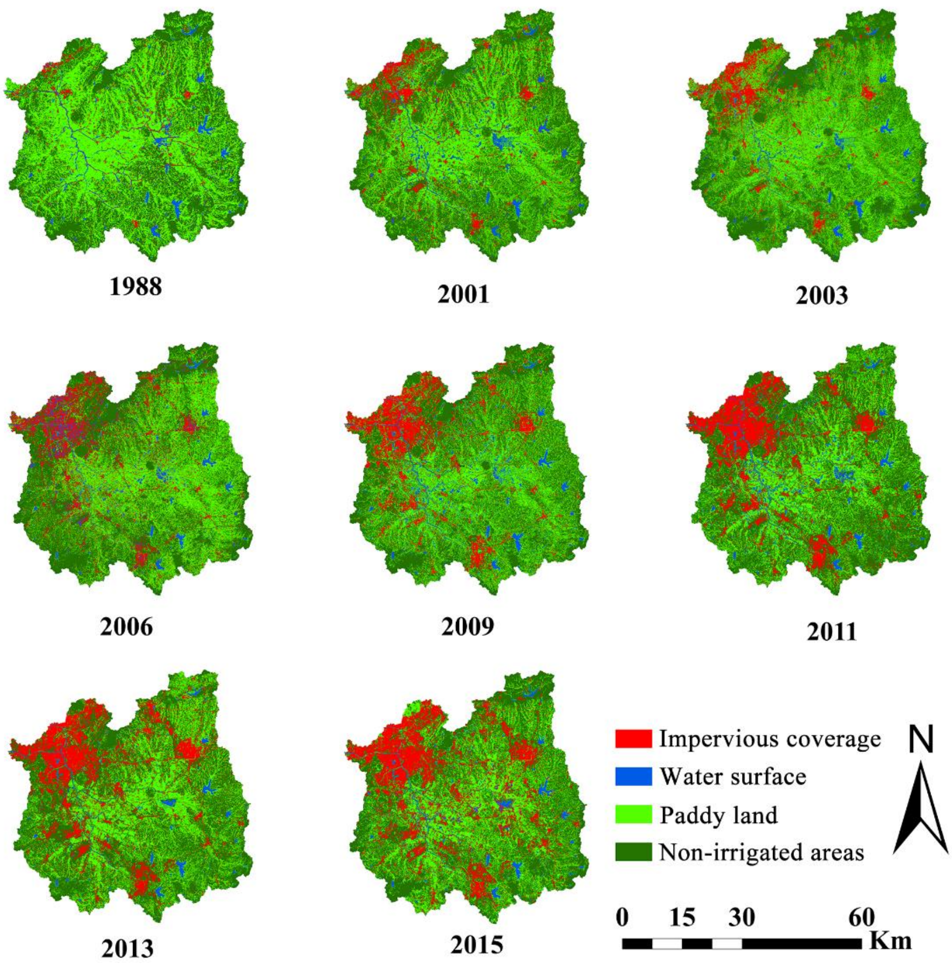

Fig. 2 Land use classification results of the Qinhuai River basin

3. Methodology

3.1 Overview of the modelling framework

The semi-distributed model has three individual modules: (i) runoff generation, (ii) runoff separation, and (iii) runoff routing. The runoff generation module is derived from the XAJ model and TB model; the runoff separation module is mainly adopted from the XAJ model; and the runoff routing module is established based on the XAJ model using the Nash IUH method (Nash 1957, 1960). The structure of the semi-distributed model is given in Fig. 3. The key feature of the XAJ model is that runoff is generated and calculated only when the soil moisture content reaches field capacity (Zhao et al. 1980). The TB model is a hydrological modelling system that considers the heterogeneity in runoff generation by categorizing land surfaces into four main categories, i.e., water surface, urban, paddy field, and non-irrigated farmland (Cheng et al. 2006). The QRB is divided into 18 sub-basins. The three modules were established for each of the sub-basins.

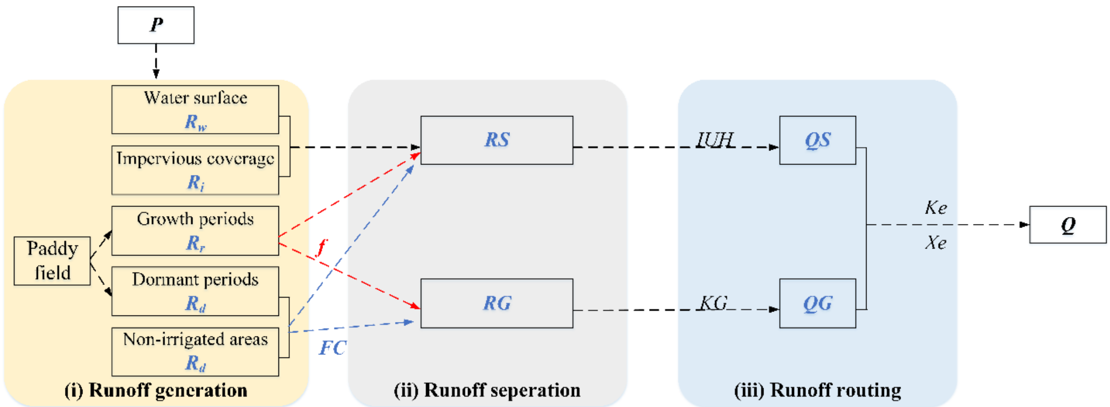

Fig. 3 The structure of the semi-distributed hydrological model

3.1.1 Runoff generation

In the runoff generation module, four types of land uses are considered: water surface, paddy field, impervious coverage, and non-irrigated areas.

The runoff generated from the water surface at each time interval is calculated as:

$$R_w = P - \beta \times E_p \tag{1}$$

where R_w is the runoff generated from the water surface (mm), P denotes the precipitation (mm), E_p denotes the potential evapotranspiration (mm), and β denotes the adjustment factor of E_p (-).

Paddy fields can be divided into dormant periods and rice-growing periods. The runoff generated from paddy fields is calculated in different rice-growing periods and at each time interval, and it is described as:

$$H_2 = P - \alpha \times E_p + H_1 - f \tag{2}$$

When $H_2 > H_p$,

$$R_r = H_2 - H_p, H_1 = H_p \tag{3}$$

When $H_u < H_2 < H_p$,

$$R_r = H_2 - H_u, H_1 = H_u \tag{4}$$

When $H_d < H_2 < H_u$,

$$R_r = 0, H_1 = H_2 \tag{5}$$

When $H_2 < H_d$,

$$R_r = H_2 - H_d, H_1 = H_d \tag{6}$$

where R_r is the runoff generated from the paddy field in the rice-growing period (mm) at each time interval, a represents the water requirement coefficient of the paddy field (-), f is the infiltration in the paddy field (mm) at each time interval, and H_1 and H_2 are the depths of water in the paddy field at the beginning and end of each time interval (mm), respectively. H_p represents the depth of submergence tolerance (mm). H_u and H_d denote the suitable top and bottom depths of water needed at different growing periods (mm), respectively.

The runoff generated from impervious coverage at each time interval is calculated as:

$$R_{\mathrm{i}} = \varphi \times P \tag{7}$$

where R_i is the runoff generated from impervious coverage (mm), and φ is the runoff coefficient (-).

The runoff generated from non-irrigated areas and dormant paddy fields at each time interval is estimated based on the XAJ model. In the saturated area where the soil moisture content reaches field capacity, the runoff is calculated using Eq. (8). Otherwise, the runoff calculation can be found by referring to Zhao (1992).

$$R_{\mathrm{d}} = P - \left(WM - W_o\right) - E \tag{8}$$

where R_d represents the runoff generation (mm) in the time interval, WM is the areal mean tension water capacity (mm), W_0 is the initial soil water (mm), and E is the actual evapotranspiration (mm). Evapotranspiration is not considered in the runoff generation module due to its negligible contributions to flood simulation.

3.1.2 Runoff separation

Runoff separation aims to divide the generated runoff into two or more components according to land-use type. All the runoff generated from the water surface and impervious coverage would turn to surface runoff. The runoff from non-irrigated areas and dormant paddy fields is subdivided into surface runoff and groundwater runoff based on the free water capacity distribution curve (Li et al. 2018; Meng et al. 2016;

Zhao 1992), and the runoff in paddy fields calculated from Eqs. (2) to (6) turns to surface runoff; finally, infiltration at a steady rate contributes to groundwater runoff. For each sub-basin, the total surface runoff (groundwater runoff) is an area-weighted summation of runoff from the four land-use types (paddy land and non-irrigated areas).

3.1.3 Runoff routing

The surface runoff is routed directly to the outlet of each sub-basin by the Nash IUH method (Nash 1957, 1960), while the groundwater runoff is routed using the linear reservoirs method (Zhao et al. 1980; Zhao 1992). The discharge from the upper sub-basins is routed through the river network to the outlet of the sub-basin by the Muskingum successive-reaches model (Deng et al. 2009). The outflow at the outlet of each sub-basin is the summation of the surface runoff and groundwater discharge of the sub-basin and the river network routing discharge from the upper sub-basins.

3.1.4 Reservoir operation

Reservoirs can temporarily store flood water and release it later, which effectively lowers the magnitude and frequency of floods in downstream reaches. The changes in reservoir volume are simulated by the storage function approach as:

$$\frac{dV}{dt} = INF - OF \tag{9}$$

where V is the reservoir storage (m^3), t is the time (s), INF is the inflow (m^3/s), and OF is the release (m^3/s). The details on reservoir operation can be found in Du et al. (2016).

3.2 Model calibration strategy

To reduce the number of calibrated parameters and improve the calculation efficiency of the model, the following parameterization strategy is proposed. (1) Parameters with low sensitivities or direct physical meanings are set to their 'typical' values based on a literature review and expert experience. (2) Parameters with high sensitivity are estimated based on the proposed parameterization scheme: calibrating relationships between parameters and influencing factors, such as urbanization index (impervious ratio) and basin characteristics (i.e., area, slope and length). (3) Other parameters are determined through calibration.

The parameters with high sensitivity and the typical values of most parameters in the proposed model can be found in the literature (e.g., Li et al. 2018; Lin et al. 2011; Meng et al. 2016; Zhao et al. 1980; Zhao 1992). For the parameters with high sensitivity for groundwater routing, the Muskingum successive-reaches method and the runoff coefficient of the impervious surface are manually optimized based on the trial-and-error method. The parameters of the Nash IUH method for surface runoff routing for each sub-basin are calibrated by using the proposed parameterization scheme. To reduce parameter dimensions, we assume that the Nash IUH parameters of all sub-basins have the same functional relationships with sub-basin characteristics (e.g., area, slope and length of the river network) and urbanization index (i.e., impervious rate), and the relationships between the Nash parameters, urbanization index and basin characteristics can be expressed as follows:

$$n = f_1(A, SL, LE, IM, \ldots) \tag{10}$$

$$k = f_2(A, SL, LE, IM, ...) \tag{11}$$

where f_1 and f_2 are functions; n and k are the number and storage coefficient of linear reservoirs of the Nash IUH, respectively; and *A, SL, LE,* and *IM* denote the characteristics of the area, slope, length, and impervious ratio of a sub-basin, respectively. The Nash IUH parameters of each sub-basin can be calculated based on the relationships. Parameter optimization thus turns into the optimization of functions (10) and (11). The best mathematical forms of relationships f_1 and f_2 could be obtained by maximizing the average NSE for all calibrated flood events. The enumeration optimal method or other optimal methods could be implemented to find the optimal parameters for each relationship by maximizing the average NSE. The proposed parameterization strategy can improve model calibration efficiency by reducing the number of calibrated parameters.

3.3 Temporal and spatial prediction capabilities of the integrated modelling approach

To test the temporal prediction capability of the approach, six flood events from 1987 to 2009 were used for the relationship calibration, while eight flood events from 2010 to 2015 were used for model validation. Flood records from Qianhancun Station were used. The proxy-basin test was performed to verify the spatial prediction capability of the approach, i.e., calibrate flood events on one catchment and validate them on another catchment. The relationships of Nash IUH parameters were calibrated using the discharge data for fourteen flood events at Qianhancun Station. The calibrated relationships were then used to predict flood events for the entire QRB.

3.4 Evaluation criteria

Four criteria were employed to evaluate the model performance (McCuen et al. 2006): the Nash-Sutcliffe efficiency (NSE), the coefficient of determination (R^2), the relative error of peak discharge (D_p) and the relative error of runoff volumes (D_v), and they are calculated as follows:

$$NSE = 1.0 - \frac{\sum_{i=1}^{n}\left[Q_c(i) - Q_o(i)\right]^2}{\sum_{i=1}^{n}\left[Q_o(i) - Q_o\right]^2} \tag{12}$$

$$R^2 = \frac{\sum_{i=1}^{n}[Q_o(i) - Q_o] \times [Q_c(i) - Q_c]}{\sqrt[2]{\sum_{i=1}^{n}[Q_o(i) - Q_o]^2} \times \sqrt[2]{\sum_{i=1}^{n}[Q_c(i) - Q_c]^2}} \tag{13}$$

$$D_{\mathrm{p}}(\%) = \frac{Q_{p,c} - Q_{p,o}}{Q_{p,o}} \times 100\% \tag{14}$$

$$D_{\mathrm{v}}(\%) = \frac{\sum_{i=1}^{n} Q_c(i) - \sum_{i=1}^{n} Q_o(i)}{\sum_{i=1}^{n} Q_o(i)} \times 100\% \tag{15}$$

where $Q_c(i)$ and $Q_o(i)$ denote the estimated and observed discharges for time period i (m^3/s), respectively; Q_c and Q_o represent the estimated and observed mean values (m^3/s), respectively; n is the total number of observed discharges; and $Q_{p,c}$ and $Q_{p,o}$ are the peak discharges of the estimated and observed hydrographs (m^3/s), respectively.

4. Results and Discussion

4.1 Model calibration and validation

4.1.1 Calibration of model parameters

The runoff generation parameters over paddy land were set to suggested values and are shown in Table 2 (Cheng et al. 2006). The parameters depend on different paddy growing periods. The daily infiltration capacity was set to 1 mm due to the high groundwater level and saturated soil during the growing season. The runoff coefficient of impervious coverage was set to 0.65 (-). The parameters *WM* and W_0 for non-irrigated areas were set to 120 (mm) and 30 (mm), respectively. The daily recession coefficient of groundwater in the linear reservoir method was set to 0.9, and the Muskingum time constant and weighting factor were calibrated to be 2 (h) and 0.2, respectively. The best relationships of the Nash IUH model parameters for all sub-basins were obtained by maximizing the average NSE of calibrated flood events using the optimal enumeration method:

$$n = 0.6 \times A^{0.05} \times IM^{-0.01} \tag{16}$$

$$k = 1.0 \times A^{0.27} \times IM^{-0.2} \tag{17}$$

where n and k are the number and storage coefficient of the Nash IUH of a selected sub-basin, A is the area of the sub-basin, and IM is the impervious ratio of the sub-basin.

Table 2 The runoff generation parameters of paddy land from Cheng et al. (2006)

Duration (day)	Depth of submergence tolerance (mm)	Top suitable water depth (mm)	Bottom suitable water depth (mm)	Coefficient of water requirement (-)	Daily infiltration capacity (mm)
5.16~5.25	20	10	5	1.00	1
5.26~6.23	30	20	10	1.00	1
6.24~6.30	50	30	20	1.35	1
7.1~8.4	50	30	20	1.30	1
8.5~9.3	50	40	30	1.65	1
9.4~9.16	50	30	20	1.76	1

9.17~10.20	20	10	0	1.50	1

4.1.2 Model performance

Table 3 indicates that the model achieves satisfactory performance during both calibration and validation periods, with the average values of R^2 and NSE exceeding 0.9 and the average values of D_P and D_V being lower than 5%. Fig. 4 demonstrates that the estimated results are well synchronized with the observed hydrographs in terms of both peak magnitudes and timing, indicating that the established model is applicable for flood simulation in the QRB. The parameterization strategy of calibrating relationships between model parameters and basin physical characteristics is also effective and suitable for the study basin.

Table 3 The statistics of the model calibration and validation results at Qianhancun Station

Period	**Flood code**	**Land-use pattern**	**Evaluation criteria**			
			R^2	**NSE**	**D_P (%)**	**D_V (%)**
Calibration	198707	1988	0.91	0.91	4.65	1.24
	199607	2001	0.86	0.84	12.84	5.75
	200808	2009	0.92	0.90	2.44	7.84
	201106	2011	0.95	0.95	3.74	1.15
	201207	2013	0.93	0.92	1.84	4.42
	201407	2015	0.93	0.93	2.14	3.85
	Mean value		0.92	0.91	4.61	4.04
Validation	199106	1988	0.92	0.91	0.90	3.51
	200607	2006	0.88	0.87	1.96	4.00
	200907	2009	0.97	0.94	2.34	9.29
	201007	2011	0.96	0.95	2.05	4.39
	201107	2011	0.77	0.76	1.90	4.04
	201208	2013	0.97	0.96	5.43	3.84
	201307	2013	0.97	0.96	1.43	4.94
	201506	2015	0.97	0.97	1.17	3.42
	Mean value		0.93	0.92	2.15	4.68

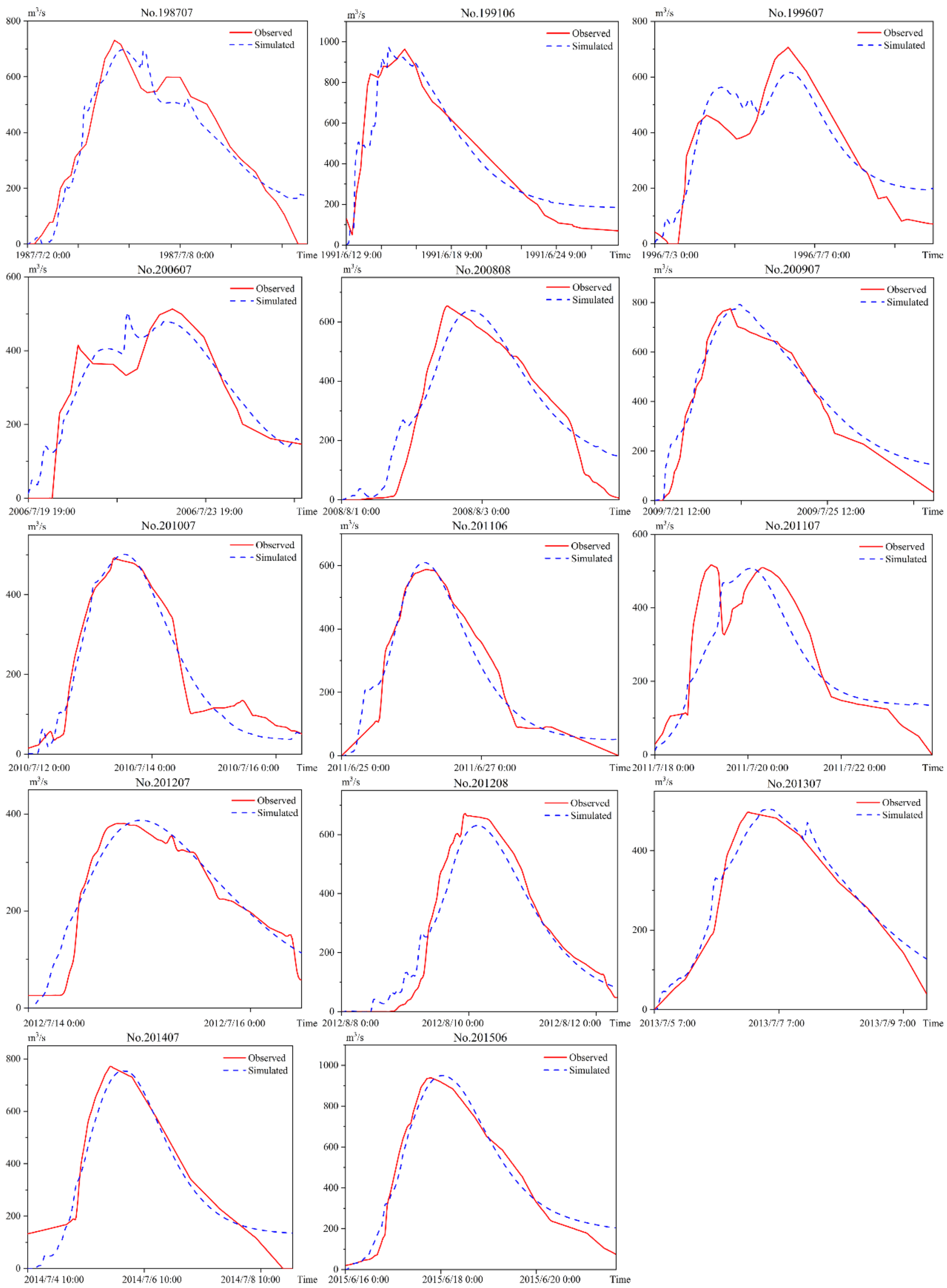

Fig. 4 Observed and simulated hydrographs of 14 floods at Qianhancun Station

Table 4 shows the temporal prediction results at Qianhancun Station. The average values of R^2 and NSE of all predictive flood events exceeded 0.9, while the average values of D_p and D_v were less than 5%, indicating that the proposed modelling approach can achieve good temporal prediction capacity. It also demonstrates that the relationships calibrated from the early period can be used for later or future flood event prediction.

The statistics of the spatial prediction performance of the approach are shown in Table 4. The results indicate satisfactory prediction results in terms of simulating flood events in the whole QRB, with the average R^2 and NSE exceeding 0.85 and the average values of D_p and D_v being lower than 10%, which demonstrate that the calibrated relationships over the upper and middle sub-basins can be transferred to the whole basin for flood simulation.

Table 4 The statistics of model temporal prediction results at Qianhancun Station and spatial prediction results in the whole QRB

Prediction capability	**Flood code**	**Land-use pattern**	**Evaluation criteria**			
			R^2	**NSE**	**D_P（%）**	**D_V（%）**
Temporal prediction results	201007	2011	0.94	0.94	0.82	1.26
	201106	2011	0.97	0.96	4.58	3.70
	201107	2011	0.78	0.77	2.10	3.60
	201207	2013	0.93	0.93	6.08	3.24
	201208	2013	0.98	0.98	1.37	2.05
	201307	2013	0.97	0.96	5.04	7.11
	201407	2015	0.94	0.93	3.38	2.31
	201506	2015	0.98	0.97	1.36	4.43
	Mean value		0.94	0.93	3.09	3.46
Spatial prediction results	198707	1988	0.94	0.94	3.76	2.03
	199106	1988	0.93	0.93	1.76	2.62
	199607	2001	0.84	0.82	4.88	7.27
	200607	2006	0.96	0.95	3.70	4.76
	200808	2009	0.92	0.92	6.73	4.24
	200907	2009	0.96	0.94	10.81	10.53
	201007	2011	0.96	0.96	13.72	1.47
	201106	2011	0.96	0.89	11.04	18.44
	201107	2011	0.85	0.79	10.85	15.00
	201207	2013	0.91	0.9	10.98	0.66
	201208	2013	0.96	0.99	1.22	8.68
	201307	2013	0.94	0.91	5.92	8.22
	201407	2015	0.89	0.76	19.72	19.82

201506	2015	0.82	0.78	14.09	0.88
Mean value		0.92	0.89	8.51	7.47

4.2 Impacts of building relationships with or without the consideration of impervious areas on model performance

The temporal and spatial variations of imperviousness should be considered in hydrological modelling for urbanized basins due to the role of impervious surface in influencing hydrological processes (Jacobson 2011; Praskievicz and Chang 2009). Previous studies have shown that an increase in impervious areas had large effects on the hydrological response for medium and small flood events but only small effects on extreme events (Braud et al. 2013; Kaspersen et al. 2015). To further examine the effects of impervious coverage on runoff generation and routing for flood events, the following test was conducted to determine the impacts of establishing the relationships of Nash IUH parameters with or without the consideration of imperviousness on model performances. Three scenarios were considered in the test: (1) flood simulation scenario; (2) temporal prediction scenario; and (3) spatial prediction scenario. The selected flood events for calibration and validation/prediction were the same as those described in Section 3.

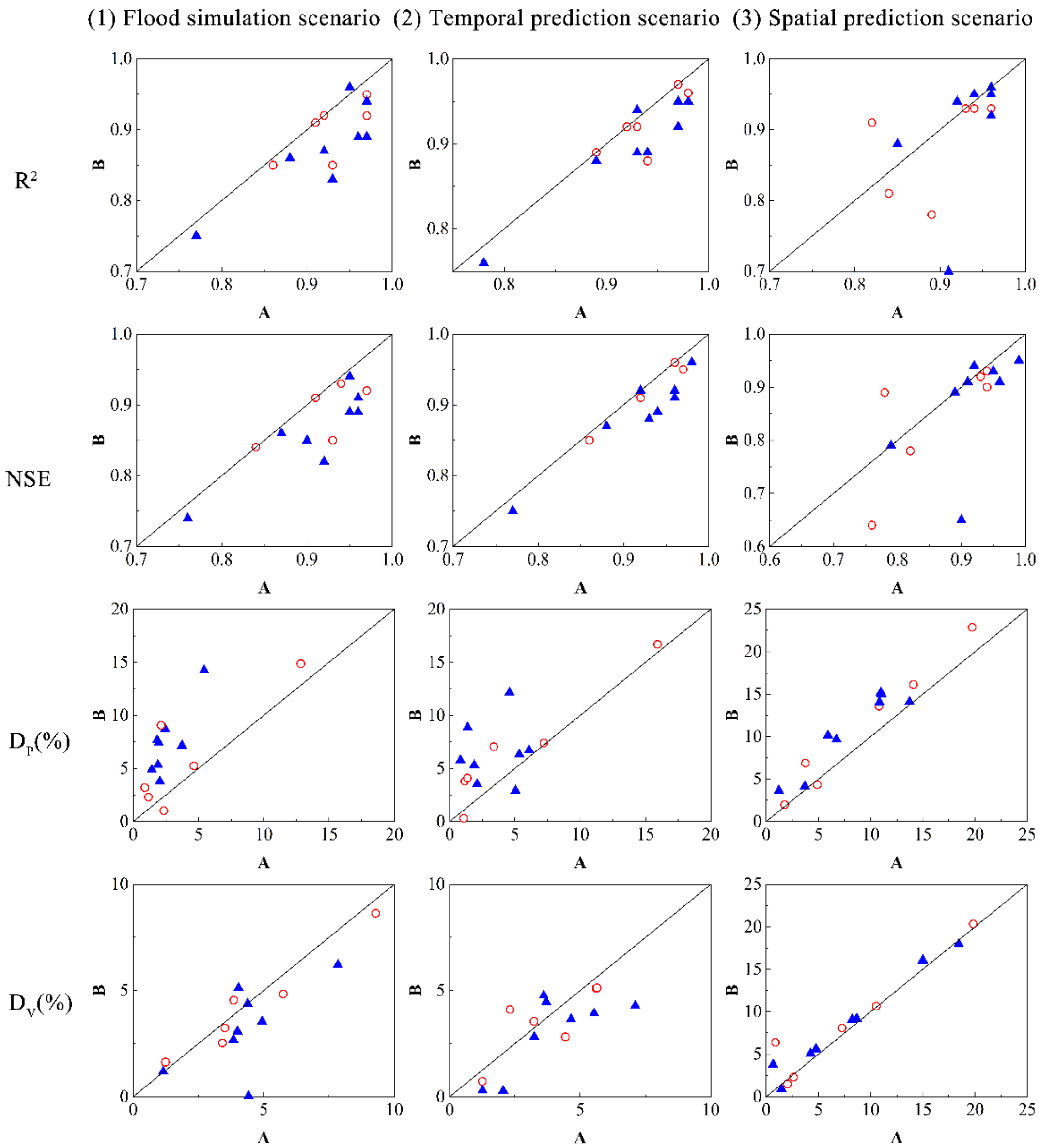

Fig. 5 Comparison of model simulation results, temporal prediction results and spatial prediction results with (A) and without (B) the consideration of imperviousness. Blue triangles represent small and medium floods (peak discharge lower than 700 m^3/s), red circles represent large floods (peak discharge higher than 700 m^3/s)

As seen from Fig. 5, almost all R^2 and NSE values for floods without the consideration of imperviousness in the surface runoff calculation are smaller than those that consider imperviousness, while the values of D_p that consider imperviousness are obviously smaller than those that do not consider imperviousness. For D_v values, all points are located near the 1:1 line, indicating that there is no distinct difference. This result is because impervious coverage only changes runoff-routing speed but not runoff volume. The volume of runoff generation remains the same for surface runoff routing regardless of whether imperviousness is considered.

For simulation and temporal prediction scenarios (Fig. 5), the values of R^2, NSE, and D_p for small and medium floods were considerably improved when imperviousness was considered compared to those that did not consider imperviousness, indicating that imperviousness has a pronounced impact on model simulation for small and medium flood events. For the spatial prediction scenario in the whole QRB (Fig. 5), the improvements in the R^2, NSE, and D_p values for most flood events were not as obvious as those in the first and second columns, which was likely because the impact of urbanization on the surface runoff process has been relatively weakened with the increase in basin size.

4.3 Impacts of flood event selection for calibrating the relationships on model performance

The effects of using different flood events for calibrating relationships of Nash IUH parameters on model performance were also analysed. Three scenarios were built: (1) flood simulation scenario: six flood events different from the ones in Subsection 4.1 were selected for relationship calibration, the others were used for validation, and the calibration and validation results were compared with those in Subsection 4.1; (2) temporal prediction scenario: three flood events from 1987 to 1996 were used for calibration and the others were used for validation, the results were compared with those calibrated by six flood events from 1987 to 2009 in Subsection 4.1; and (3) spatial prediction scenario: the prediction results of the whole basin using relationships calibrated by Qianhancun Station were compared with those calibrated by Jurong Station.

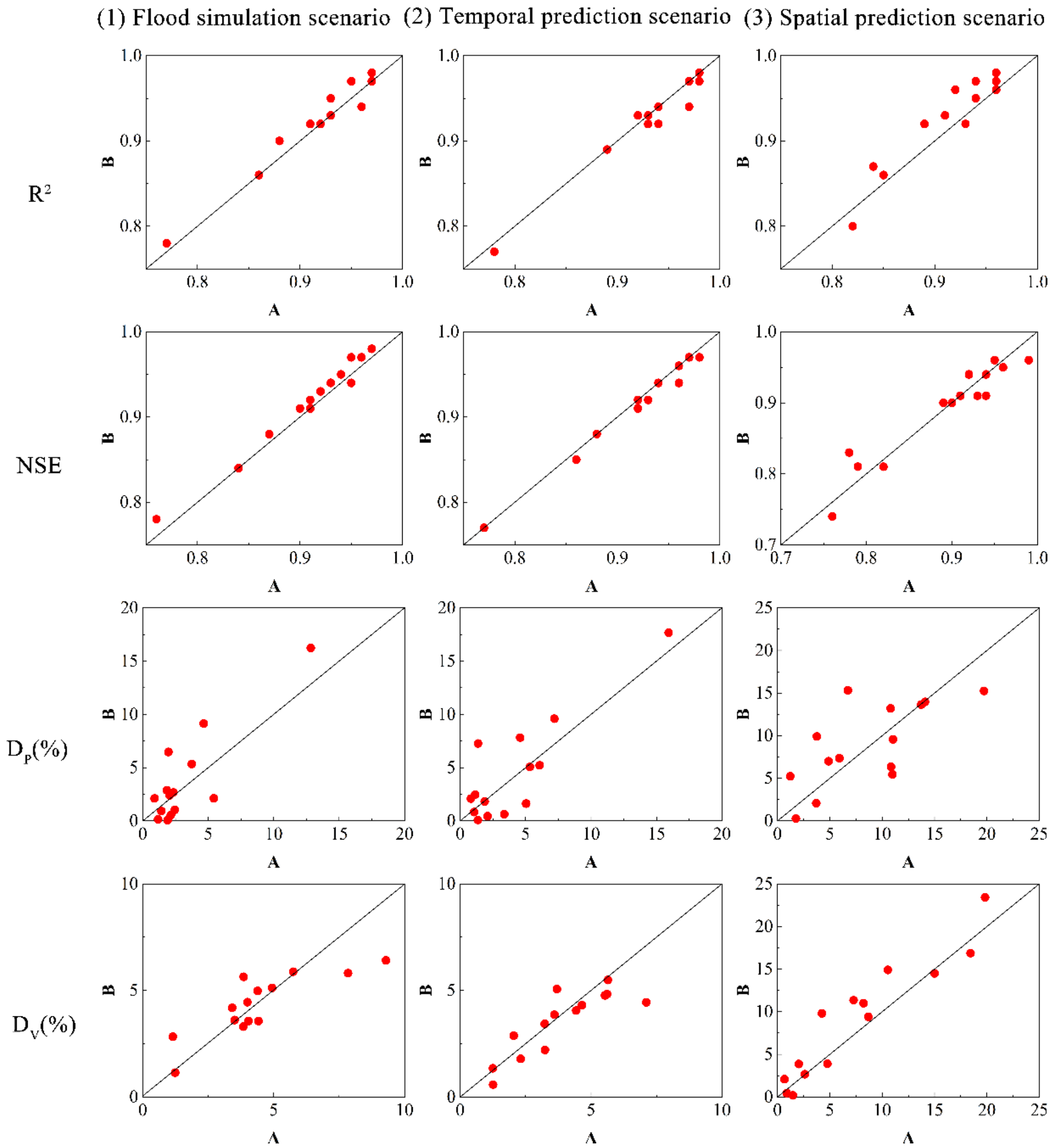

Fig. 6 Results of impacts of flood event selection for calibrating relationships on model performance. (1) Flood simulation scenario: comparison of calibration and validation results by selecting different flood events for calibration. *A* represents the previous flood simulations in

Subsection 4.1, and *B* represents flood simulations obtained by selecting the other six floods for relationship calibration; (2) Temporal prediction scenario: comparison of calibration and temporal prediction results obtained by selecting different flood events for calibration. *A* represents the previous calibration and temporal prediction results obtained by selecting the former six floods for relationship calibration in Subsection 4.1, and *B* represents those obtained by selecting the former three flood events for relationship calibration. (3) Spatial prediction scenario: comparison of spatial prediction results for the whole basin obtained by selecting different sub-basins for calibration. *A* represents the previous spatial prediction results with relationships calibrated by the discharge data of Qianhancun Station in Subsection 4.1, *B* represents the spatial prediction results with relationships calibrated by the discharge data of Jurong Station

As shown in Fig. 6, the R^2, NSE, D_p, and D_v values are located near the 1:1 line. The differences in the four criteria are statistically insignificant according to the *F*-test (α=0.05, Jamshidian et al. 2007), indicating that the use of different flood events for parameter calibration yielded similar results for simulation and temporal prediction. In terms of spatial prediction, the relationships calibrated from different sub-basins could be transferred to the whole basin and generated similar spatial prediction results. These results demonstrate that the impact of flood event selection on model performance is insignificant, indicating that the proposed parameterization scheme of establishing unified relationships between model parameters and driving factors of sub-basins is robust for hydrological modelling in basins with urbanization. Thus, the relationships calibrated based on flood events with the corresponding land-use patterns can be effectively used for flood simulation and prediction under urbanization with certain reliability.

5. Conclusions

In this study, we proposed an integrated modelling approach to simulate flood events in the QRB, an urbanized basin of south-eastern China. The impacts of imperviousness on runoff generation and runoff routing were both taken into account. Considering the lack of observed data in sub-basins, unified relationships between Nash IUH model parameters and driving factors for all sub-basins were established and calibrated with observed data at the basin outlet. The following conclusions were obtained: (1) the proposed semi-distributed modelling approach can produce reasonable flood simulation results, especially when parameters of the Nash model for any sub-basin are calculated based on calibrated unified relationships between parameters and sub-basin physical characteristics; (2) imperviousness is an important factor that should be considered in flood routing calculations, especially for simulating small or medium floods; (3) the integrated modelling approach is effective, robust and efficient for flood simulation in mesoscale basins and has prediction capability over time and space for future land-use changes and adjacent basins. Future studies need to be carried out to extend the application of the proposed modelling approach to other urbanized basins.

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