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RESEARCH ARTICLE

Parameter transferability across spatial resolutions in urban hydrological modelling: a case study in Beijing, China

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Abstract This study examined the influence of spatial resolution on model parameterization, output, and the parameter transferability between different resolutions using the Storm Water Management Model. High-resolution models, in which most subcatchments were homogeneous, and high-resolution-based low-resolution models (in 3 scenarios) were constructed for a highly urbanized catchment in Beijing. The results indicated that the parameterization and simulation results were affected by both spatial resolution and rainfall characteristics. The simulated peak inflow and total runoff volume were sensitive to the spatial resolution, but did not show a consistent tendency. High-resolution models performed very well for both calibration and validation events in terms of three indexes: 1) the Nash-Sutcliffe efficiency, 2) the peak flow error, and 3) the volume error; indication of the advantage of using these models. The parameters obtained from high-resolution models could be directly used in the low-resolution models and performed well in the simulation of heavy rain and torrential rain and in the study area where sub-area routing is insignificant. Alternatively, sub-area routing should be considered and estimated approximately. The successful scale conversion from high spatial resolution to low spatial resolution is of great significance for the hydrological simulation of ungauged large areas.

Keywords SWMM, high resolution, low resolution, rainfall characteristics, parameter transferability

1 Introduction

Landscape modifications associated with urban sprawl have dramatic impacts on catchment hydrology and cause increases in the peak flows and runoff volumes (Shen et al., 2014). The use of urban hydrological modelling increases our understanding of hydrological processes and related storm water management issues and has been widely used as a research method for storm water management (Blöschl and Sivapalan, 1995; Peel and Blöschl, 2011; Zhang et al., 2014). Rainfall runoff modelling is dependent on an understanding of the real world system and the physical representation of the catchment, which is generally influenced by data resolution and the subjective experience of the researcher (Park et al., 2008; Chow et al., 2012). Therefore, spatial heterogeneity of the urban landscape is still a major challenge in urban hydrologic modelling (Leandro et al., 2016).

High-resolution (HR) modelling could potentially replicate the hydrological process more precisely and further provide important information on effective storm water management problems, such as low-impact development (LID) practices (Krebs et al., 2014). HR modelling is required for properly assessing the LID performance at the catchment scale (Palla and Gnecco, 2015). However, the accompanying high spatial resolution digital elevation models (DEMs) and network data with smaller diameters are impractical for larger urban areas, particularly in China. Consequently, a model structure with a lower spatial resolution and lumped parameters (LR model) is generally used for urban models because it requires fewer input data and is more computationally efficient than HR models (Zaghloul, 1981; Zhao et al., 2009; Chow et al., 2012). Understanding the influence of reduction in spatial resolution and further exploring the transferability of parameters from the HR model to the LR models are thus extremely important for applying the model in ungauged or poorly gauged areas (Melsen et al., 2016). If the probability of parameter transferability among different resolutions is proven to be high, HR models could be built for a representative small area. The parameters of LR

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models for this area (obtained from parameter transferability) could be applied to the large ungauged areas.

The effects of spatial resolution on model output have been well established in previous studies and papers focused on rural hydrology compared with urban areas (Elliott et al., 2009; Ghosh and Hellweger, 2012; Shen et al., 2013). The general approach has been to either vary the number of watershed subdivisions or the input data resolution, or both, and then to observe the effect on model output (Ghosh and Hellweger, 2012; Melsen et al., 2016). Both the watershed subdivision and the parameters should represent the high resolution in the HR models. However, the parameter sets were kept constant across several spatial resolutions, and the impact of spatial resolution on model performance was ambiguous in previous studies. The parameter sets transferability from HR to LR models, yet the possibility of limits is still lacking in the research.

The large amount of water generated in a short period of time and the limited capacity of sewer systems have placed increasing pressure on the existing infrastructure and water supply in the municipality of Beijing. However, the lack of network data, high-quality DEMs, and monitoring data have greatly limited urban hydrological modelling and affected storm water management planning to some extent. Management of the storm water runoff from urban areas is a complex task and has become an increasingly important environmental issue. Building the HR models with limited data and studying the parameter transferability among different resolutions is an effective method under the current circumstances. The two primary objectives of this study were (i) to evaluate the effect of spatial resolution on simulation output and parameterization for a highly urbanized catchment and (ii) to explore the probability and limits of parameter transferability from HR models to LR models.

2 Materials and methods

2.1 Study area and input data

The study catchment is located on a typical campus with a long history, located in the Haidian District of Beijing between the northern second ring and the third ring. The catchment occupies an area of 58 ha, which includes approximately 31.69% of the area for green spaces and 30.29% of the area for buildings. The existing storm water management system has characteristics of the old town, such as old sewer networks and inadequate drainage capacity, but it also has some new storm water management measures, such as permeable pavements that occupy only 1.94% of the total area. The Haidian District, located in the northwestern region of the city, is one of eight districts in the urban area of Beijing, China. The mean annual temperature of Haidian is 14.0°C, and the average annual rainfall is 570 mm. The district has an area of 430 km^2, a population of 2.81 million, and contains more than 80 higher education institutions and 213 research institutions. Colleges, residences, and main traffic roads were the three typical impervious types of land use in the Haidian District.

The land use data, in .mxd format, were obtained from the regulatory agency on application. The data included detailed information about the land use classification, the coordinates, and the block of the study catchment. A sewer network map, obtained from the relevant regulatory agency, was complemented with detailed information acquired from a professional surveying and mapping company. The catchment is served by a separate storm sewer system consisting of sewer pipes that range in size from 0.1 to 0.9 m (97% are made of concrete and 3% of PVC). Runoff generated from the catchment discharged into the drainage network of the city via 5 outlets (Fig. 1). Storm water outflow was recorded at five-minute recording intervals from July to September 2014 at outfall3 by an installed automatic flow-monitoring device (HACH FL900).

A rain gauge was installed in the catchment to obtain rainfall data at five-minute intervals. A total of eight rainfall event datasets were used in this study. These rainfalls were representative of the storms occurring in Beijing, ranging from single to multiple peaks and from short to long durations. Events were distinguished by inter-event periods $\geqslant 6$ h to ensure that the selected events were considered independent from one another. Four events were selected for calibration purposes, and the remaining four rainfall events were used for validation. Detailed information about the hydrometeorological characteristics displays the typical comprehensiveness of the selected rainfall events. Hydrometeorological data were analyzed for each storm event, and the following parameters were determined: rainfall duration, rainfall peak intensity, rainfall depth, rainfall type, runoff duration, peak flow rate, runoff volume, and time to peak (Table 1).

2.2 Storm water management model

The EPA's Storm Water Management Model (SWMM) was first developed in 1971 and has experienced several major upgrades since that time. SWMM tracks flow rate, flow depth, and water quality in each subcatchment, pipe and channel during a simulation period composed of multiple time steps (Huber et al., 1988; Vaze and Chiew, 2003). SWMM version 5.0 recently has been extended to model the hydrologic performance of specific types of LID controls (Rossman, 2010). As a dynamic hydrology-hydraulic water quantity and quality simulation model, SWMM has been used in thousands of sewer and storm water studies throughout the world (Zhao et al., 2009; Rosa et al., 2015; Tian et al., 2015). PCSWMM, developed by Computational Hydraulics International (CHI) and based

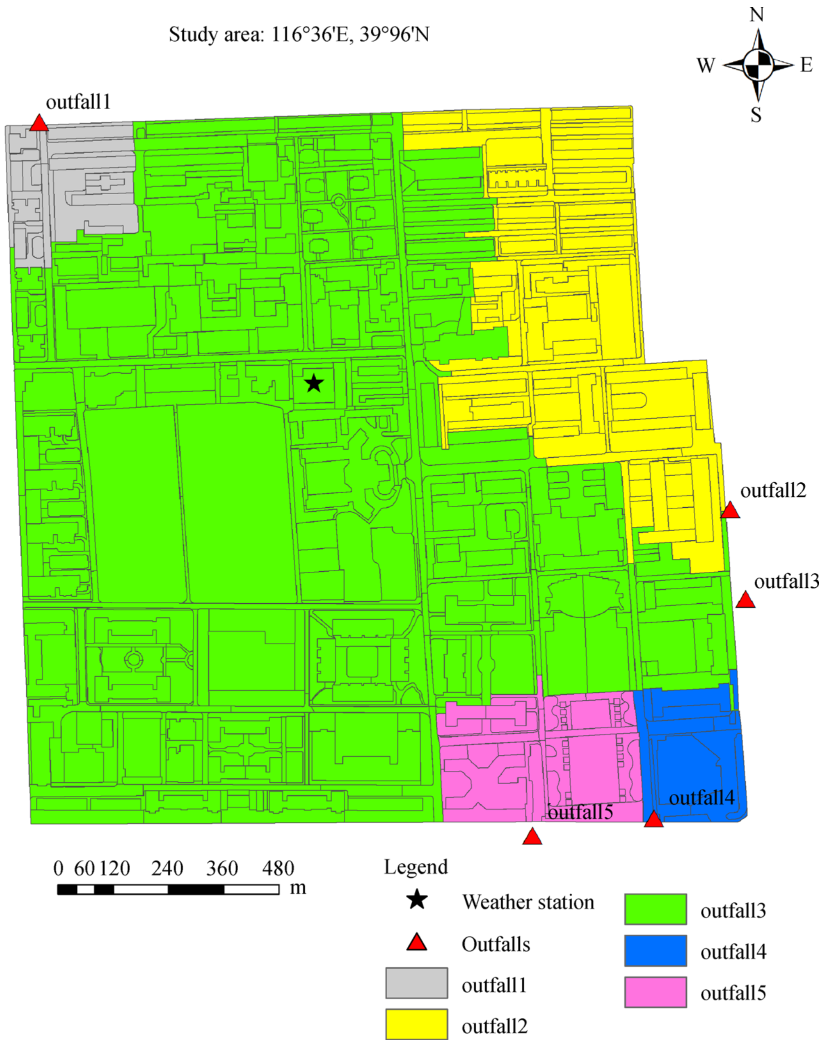

Fig. 1 Study area map showing the detailed upstream of five outfalls. Gray areas = the upstream of outfall1, yellow areas = the upstream of outfall2, green areas = the upstream of outfall3, blue areas = the upstream of outfall4, pink areas = the upstream of outfall5.

Table 1 Hydrometeorological data for the selected events

Event	y/mm/dd	Rainfall duration /min	rainfall peak intensity /$(mm\cdot h^{-1})$	Rainfall depth /mm	Rainfall type	Runoff duration /min	Peak flow rate /$(m^3\cdot s^{-1})$	Runoff volume /m^3	Time to peak /min
Calibration events	2014/07/29	400	43.28	35.7	Heavy rain	940	0.5375	4740	170
	2014/08/04	260	9.45	5.9	Light rain	595	0.06908	490.9	90
	2014/08/09	120	24.08	7.2	Light rain	275	0.1401	499.9	45
	2014/08/23	65	38.4	10.4	Moderate rain	235	0.5032	989.4	15
Validation events	2014/08/30	105	69.6	29	Heavy rain	200	1.022	3159	30
	2014/08/31	165	86.2	70.76	Torrential rain	330	0.9653	7205	15
	2014/09/01	1880	72	33.6	Heavy rain	1875	0.7034	4098	1745
	2014/09/26	20	50.4	7.8	Moderate rain	160	0.3958	783	10

on the full SWMM version 5.0 and other previous SWMM engines, was selected for this study. PCSWMM provides user-friendly pre- and post-processors that reduce errors in input and offers tools to improve understanding of results (James et al., 2003). The interface used in this study is PCSWMM 2014 with the engine SWMM 5.1.007.

Dynamic wave routing, which models backwater effects, flow reversals, pressurized flow, and entrance/exit energy losses, was selected for the routing method for this model (Huber et al., 1988). The infiltration loss from pervious areas was estimated by the Horton equation due to the availability of soil data.

2.3 Construction and calibration of high spatial resolution models

The catchment was first delineated according to the existing sewer network layer combined with the road layer. To reduce heterogeneity within each subcatchment and thus better represent the actual hydrologic behavior of the different surface covers, further micro-delineation was conducted based on the reclassified land use types (green space, asphalt area, roof, concrete block pavement, porous pavement, Sport I, Sport II, mixed land) and a detailed survey of flow paths. The HR discretization based on land use types results in subcatchments covered by a single land use type (Fig. 2). A total of 749 subcatchments were obtained, including 728 homogeneous subcatchments that

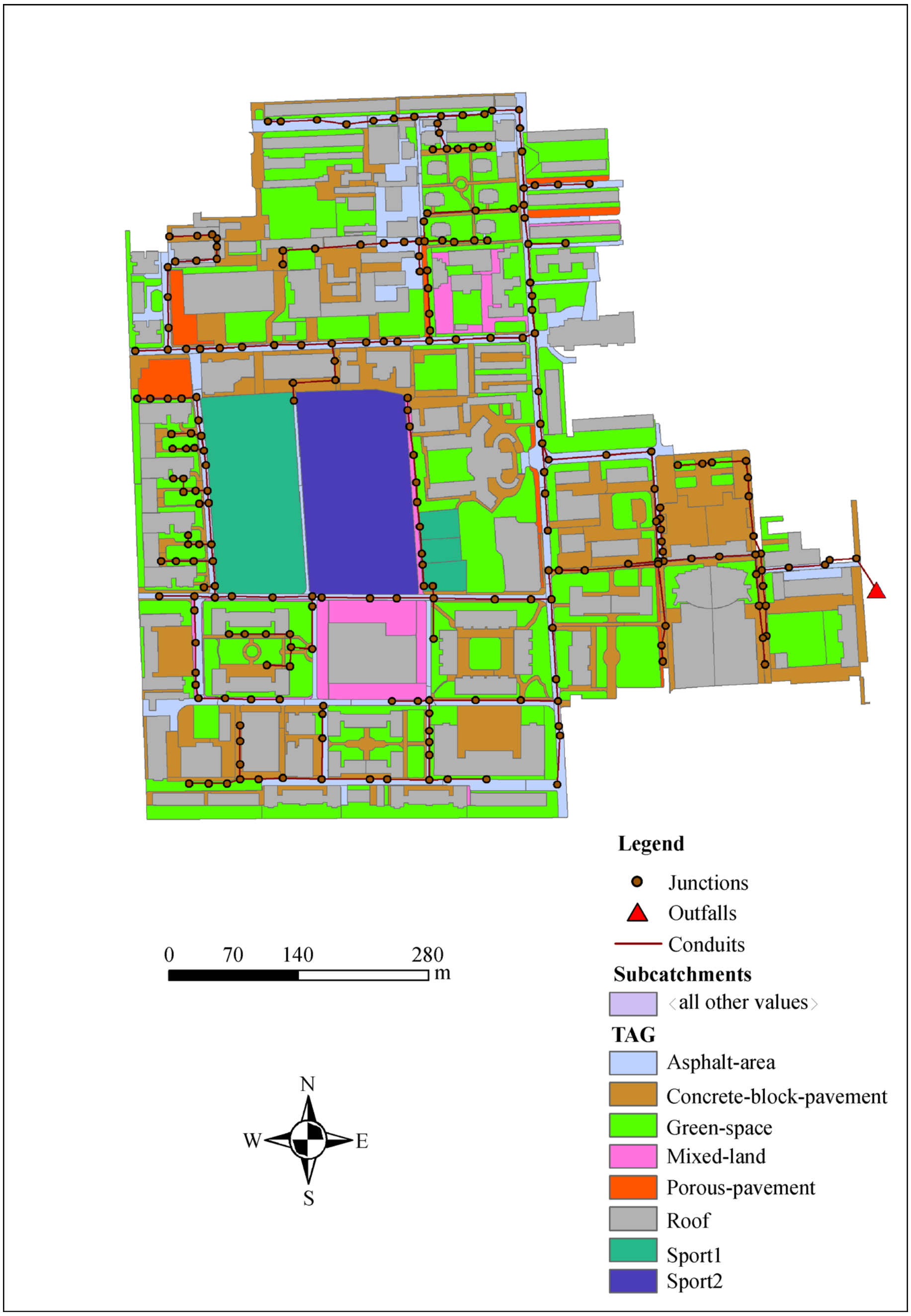

Fig. 2 The high resolution (HR) catchment discretization for the study area. Brown dots indicate the sewer inlets, wine red lines represent the storm water sewer network, and grey lines are subcatchment boundaries.

occupy 96.71% of the total area. The area of the subcatchments ranged from 0.0018 to 2.5739 ha, with an average of 0.0779 ha. The subcatchment runoff was assigned to the sewer system through the sewer inlet, which was the closest to the subcatchment area centroid (Borris et al., 2014). The flow directions between subcatchments were determined using topographical data and *in situ* observations.

Three major pieces of information were required for runoff quantity modelling in SWMM: physical catchment characteristics, rainfall, and infiltration. Most of the physical catchment data, such as catchment area and percentage of impervious area, were derived from land use data. The subcatchment slope was estimated by DEM derived from elevation data of all junctions, and the average slope was 1.7%. The other initial model parameter values were based on the literature, e.g., the Manning's roughness coefficient N for overland flow, surface depression storage, soil infiltration parameters, and the Manning's roughness for conduit (N-c) (Zhao et al., 2009). The parameter flow width (FW) is an important parameter closely related to subcatchment shape and area and was sensitive in most modelling. However, storm water flow paths in urban areas can be extremely complicated and equally unpredictable (Knighton et al., 2014). As a result, the FW was calculated using Eq. (1) and was regarded as a calibrating parameter in this study (Sun et al., 2014).

$$FW = k\sqrt{A}, \tag{1}$$

where FW is computed as a ratio of the square root of subcatchment area A (m^2), and k is a dimensionless coefficient range from 0.2 to 5.

The initial calibration between observed and computed rainfall-runoff events was conducted using the sensitivity-based radio tuning calibration (SRTC) function of PCSWMM, which works by designating uncertainty percent rankings for each parameter of interest. Subsequently, two scenarios, maximum and minimum value according to the uncertainty assigned, are simulated for each calibration parameter. Finally, the simulated flow is plotted along with the observed flow, and "tuning" levers can be turned to adjust the calibration parameters to suit the observed flows (Gooré et al., 2015). Therefore, the SRTC tool could be used to calibrate a model against observed data or test parameter sensitivity. The high and low percentage values are calculated using the following formulas:

$$V_{\mathrm{Low}} = V_{\mathrm{Current}} \times \left[\frac{1}{(1 + V_{\mathrm{f}})}\right], \tag{2}$$

$$V_{\mathrm{High}} = V_{\mathrm{Current}} \times (1 + V_{\mathrm{f}}), \tag{3}$$

where V_{Low} is the parameter value for the low end, V_{High} is the parameter value for the high end, V_{Current} is the parameter value used in the PCSWMM 5 model pre-calibration, and V_{f} is the fraction representing the percentage of the variability calculated for the range.

The SRTC tool was useful for fine-tuning the model, but not in gross adjustments (Gooré et al., 2015). The genetic multi-objective optimization algorithm NSGAII was used for further model calibration. The problem with the multi-objective calibration of a model can be generally stated as follows (Madsen, 2003):

$$\min_{\theta \in \Omega} f(\theta), \tag{4}$$

where f is the chosen objective function, θ is the model parameter set, and Ω is the parameter space. Two objective functions, $f1$ and $f2$, which need to be minimized, were adopted, which are shown as Eqs. (5) and (6)

$$f1 = \frac{\sum_{i=1}^{n} (Q_{\mathrm{o},i} - Q_{\mathrm{m},i})^2}{\sum_{i=1}^{n} \left(Q_{\mathrm{o},i} - \overline{Q}_{\mathrm{o}}\right)^2}, \tag{5}$$

$$f2 = \frac{(Q_{\mathrm{o,p}} - Q_{\mathrm{m,p}})}{Q_{\mathrm{o,p}}}, \tag{6}$$

where n is the number of observations, $Q_{\mathrm{o},i}$ and $Q_{\mathrm{m},i}$ [m^3/s] are the observed and modelled flow values, respectively, $\overline{Q}_{\mathrm{o}}$ [m^3/s] is the observed mean flow value, and $Q_{\mathrm{o,p}}$, $Q_{\mathrm{m,p}}$ [m^3/s] are the observed and modelled peak flow values, respectively.

The search space will expand in a geometric series with the increased number of calibrated parameters, and the calibration result will also be affected in the case of a large count of calibrated parameters. Thus, only the most sensitive parameters were submitted to the auto calibration. N-c and the depression storage for Asphalt, Roof, Gravel Road, Sport I, and Sport II were selected for further auto calibration according to the sensitivity analysis by SRTC.

Various rainfall events that can be used for calibration raise the issue of how to effectively explore all of the accessible information. Performing an independent calibration and combining the parameter sets obtained by the different calibrations is the method usually adopted (di Pierro et al., 2006). Another option includes creating a continuous sequence of calibration events to allow for multi-event evaluation (Krebs et al., 2014). However, the independence of the rainfall events was affected, and the related simulation results were influenced. To preserve the information for calibration provided through all rainfall events, multiple events were considered in the final objective functions:

$$\min \sum_{r=1}^{m} \left(f(\theta)\right)^2, \tag{7}$$

where m is the rainfall events, and other variables have previously been defined.

2.4 Development of low spatial resolution models

Considering the inlets, surface flow routing, and storm water network, subcatchments in the HR models were joined together and topologically assigned an outlet to the node closest to the centroid of the subcatchment (Fig. 3). Three scenarios were developed in the low-resolution models:

Scenario 1: Weighted average method – The subcatchments were aggregated according to the block boundaries obtained from the land use map. The subcatchment-related parameter values, such as imperviousness, Manning's roughness, and surface depression storage for pervious and impervious areas, were calculated by the weighted averages of the calibrated HR model using a "join" tool in PCSWMM. The subcatchment slope and flow width were determined using the same method as the HR model. The other parameters, such as Manning's roughness coefficient N for overland flow, soil infiltration parameters, and the Manning's roughness coefficient for conduit flow

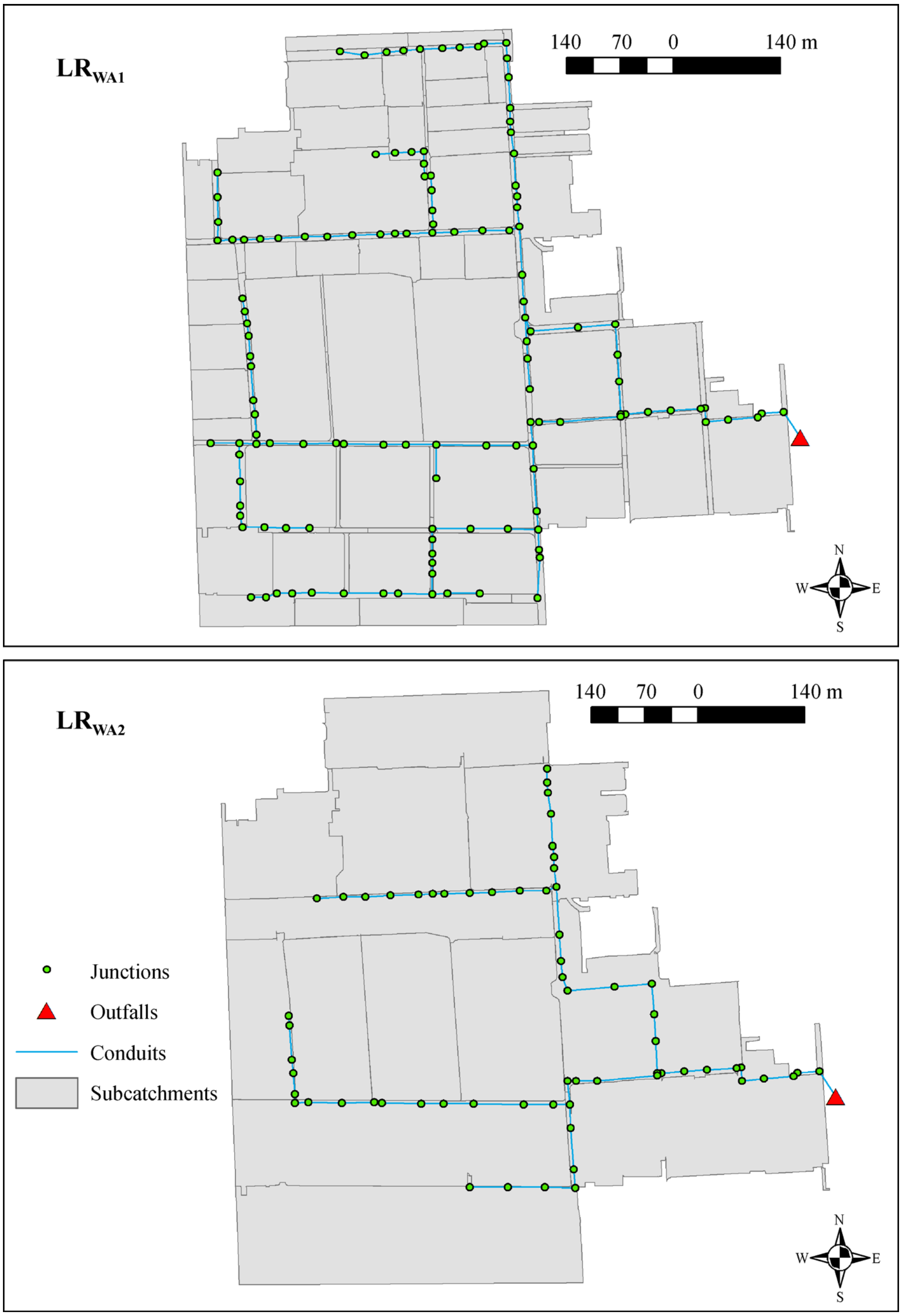

Fig. 3 The low resolution (LR_{WA1} and LR_{WA2}) catchment discretization for the study area. Green dots indicate the sewer inlets, blue lines represent the storm water sewer network, and grey lines are subcatchment boundaries.

N-c, adopted the same value as the HR model. Scenario 1 was established for exploring the possibility of direct application of the HR calibrated parameters in the process of scaling up. In scenario 1, to understand the scale conversion more specifically, two levels of aggregation were constructed, namely, LR_{WA1} and LR_{WA2}. Subcatchments aggregated in turn from HR to LR_{WA1} and subsequently to LR_{WA2} (Fig. 3).

Scenario 2: Sub-area routing consideration method-Based on Scenario 1 and considering the internal flow routing of runoff between pervious and impervious areas, 35% of runoff routed between sub-areas was established for all the subcatchments. LR_{SR1} and LR_{SR2} were named corresponding to LR_{WA1} and LR_{WA2} in Scenario 1, respectively.

Scenario 3: Recalibrated method – Maintaining only the spatial information for LR_{WA1}, the other parameters, particularly those most sensitive, were recalibrated. Models in this scenario were accordingly named LR_{RE}. This scenario was developed mainly to compare the performance of HR-based LR models (parameters obtained from application of HR models) to the common models (parameters by recalibration) other researchers used.

3 Results

3.1 Hydrometeorological characteristics

As shown in Table 1, a large variability was observed for the selected rainfall events, which represented the typical rainfall type for the study area. Rainfall depths varied from 5.9 mm to 70.76 mm. According to the China Meteorological Administration classification, two events were classified as light rain (0.1–9.9 $mm \cdot d^{-1}$ or 0.1–2.5 $mm \cdot h^{-1}$), two were classified as moderate rain (10.0–24.9 $mm \cdot d^{-1}$ or 2.6–8 $mm \cdot h^{-1}$), and four events were classified as heavy rain (25.0–49.9 $mm \cdot d^{-1}$ or 8.1–15.9 $mm \cdot h^{-1}$) or torrential rain ($\geqslant$50 $mm \cdot d^{-1}$ or $\geqslant$16 $mm \cdot h^{-1}$). Note that rainfall 0926, with a rainfall depth of 7.8 mm, was classified as moderate rain because of the very short duration (20 min). Rainfall durations ranged from 20 min to 1880 min and from single to multiple peaks. Rainfall peak intensities also showed a significant difference, varying from 9.45 $mm \cdot h^{-1}$ to 86.2 $mm \cdot h^{-1}$.

The measured hydrological data also exhibited a large variation, which was not surprising due to the large variability in rainfall. Runoff durations ranged from 65 min to 1880 min, and the time to peak flow rate varied from 10 min to 1745 min. Notably, the rainfall 0831 lasted for only 165 min, but had the largest runoff volume (7205 m^3), indicating a short-duration, but continuous heavy rain. The above meteorological and hydrological data represent the diversity of our selected rainfall events, which makes the subsequent modelling more general and valuable.

3.2 Calibration and validation of HR model

Table 2 shows the parameters calibrated for the HR models. The parameter values identified from spatial data, the subcatchment slope and the impervious cover were thought to have small errors and thus were assigned a 10% uncertainty and first adjusted in the initial calibration. The porous pavement area, occupying only 1.94% of the total

Table 2 Parameter calibrated during parameter calibration for HR models

Calibration	Parameter	Calibration interval	Optimized value
Initial calibration based on SRTC	Width (*k* value)*	0.2–5	5
	Manning's roughness pervious	0.02–0.8	0.8
	Depression storage pervious/mm	3–10.2	10.2
	Horton's maximum infiltration rate/($mm \cdot h^{-1}$)	50–200	150
	Horton's minimum infiltration rate/($mm \cdot h^{-1}$)	0–20	20
	Horton's decay rate	2–7	2
	Manning's roughness impervious	0.011–0.033	0.012
Calibration based on genetic multi- objective optimization algorithm NSGAII	Manning's roughness conduit	0.011–0.024	0.015
Depression storage impervious/mm	Asphalt area (D1)	1–2.5	1.151
	Roof (D2)		1.225
	Concrete block pavement (D3)		1.344
	Sport I (D4)		1.77
	Sport II (D5)		1.684
	Mixed land (D6)		2.216

*$FW = k\sqrt{A}$, k as a calibrated value. Sources: Bedient and Huber (2002); Chow et al. (2012); Zhao et al. (2009).

area, was considered green area to simplify the analysis. Perturbations of FW with a *k* value ranging from 0.2 to 5 had some influence on the peak flow and runoff volume, and the *k* value was optimized as 5 for a better fit between the observations and simulations. However, perturbations of the subcatchment slope seemed to have no effect on the simulation output, possibly due to the flat characteristics of the study catchment. Manning's roughness for impervious areas (N-imperv) was also found to have a slight influence on the peak flow and runoff volume, which were also adjusted to better match the volume of the hydrograph. A value for N-imperv of 0.012 was adopted in the further optimization.

The sensitivity of the HR models for the parameters related to pervious surfaces, the Manning's roughness for pervious areas (N-perv), and the depth of depression storage on pervious area (Dstore-perv) appeared to vary with rainfall type. Unlike the models of the other three calibration events, the model of rainfall 0729, with the longest duration and highest peak rainfall intensity, was sensitive to these pervious associated parameters. In addition, the variation of the Horton infiltration parameters had a minor effect on the simulation output. The final values of the Horton maximum infiltration rate, the minimum infiltration rate, and the decay rate were 150 mm/h, 20 mm/h, and 2, respectively.

The depth of the depression storage on impervious areas (Dstore-imperv) was generally determined to be the most sensitive calibration parameter because it was the only parameter that determined losses from impervious areas when the percentage of imperviousness was known and fixed (Tsihrintzis and Hamid, 1998). In our study, Dstore-imperv also showed the most significant influence on the objective functions and therefore was separated into six parameters (D1–D6) based on the classified land use type. The hydrograph peak and shape were extremely sensitive to N-c, which is a key calibration parameter. In conclusion, both Dstore-imperv and N-c were identified as the key parameters that significantly affected the simulation output. These parameters were further optimized by the genetic multi-objective, multi-event optimization algorithm NSGAII (Table 2).

Figure 4 presents the typical measured and predicted hydrographs and corresponding evaluation indexes, one for each rainfall event, obtained from model calibration. Three indexes, the Nash-Sutcliffe efficiency (NSE), the peak flow error (PFE), and the volume error (VE) were used in our study for the convenience of comparison with other studies. Among the rainfall events, rainfall 0809 and rainfall 0823 had a single peak, rainfall 0804 had two peaks, and rainfall 0729 had multiple peaks. In general, the predicted rising limb was sharper than the measured limb, and the time to the peak occurred later. The simulated peak was slightly over-predicted, and the volume was similarly over-predicted. The calibrated model yielded an efficiency of NSE ranging from 0.842 to 0.905 and PFE ranging from −30.2% to −8.9% for individual rainfall events. The value of VE was between −36.5% and −6.8%. The prediction for the validated model also performed well with NSE ranging from 0.793 to 0.907, PFE ranging from −53.8% to −13.2%, and VE ranging from −25.6% to −2.3% (Fig. 4). The performance for the validation of event rainfall 0831 was lower than the other three validation events, possibly due to the short duration, but continuous heavy rain type, which was not included in the calibration sequence. Therefore, the calibrated parameter values did not fit well enough with the simulation of this rainfall type.

3.3 Performance of LR models and scale conversion

As shown in Fig. 5 and Fig. 6, the LR models performed differently from the simulated maximum inflow, the total runoff volume, and time to peak. There was great fluctuation in the performance of LR_{WA1} and LR_{WA2} models. For LR_{WA1}, the efficiency of NSE ranged from 0.135 to 0.913, PFE ranged from −100.9% to 16.59%, and VE ranged from −76.1% to 7.18%, varying with the individual rainfall events. After accounting for the internal routing of runoff between pervious and impervious areas, the overall performance of LR models was greatly improved with increased stability. The mean values of NSE for LR_{SR1} and LR_{SR2} were 0.878 and 0.903, respectively. Obviously, the simulated maximum inflow and total runoff volume of LR_{SR1} and LR_{SR2} were closer to the observation values. The mean PFE values reached −1.385% and −5.541% for LR_{SR1} and LR_{SR2} models. The mean values of VE were −3.567% and 2.138% for LR_{SR1} and LR_{SR2}, respectively. The results indicated the rationale for considering internal routing during the conversion between different resolutions.

Further analyses were conducted to better understand the effect of rainfall type on the performance of LR models (Fig. 6). HR models were also included for an improved comparison. Observably, in the process of upscaling from HR to LR_{WA}, the model performance was dependent on the rainfall type to a large extent. The LR_{WA} models performed better than the HR models for heavy rain and torrential rain. In this case, it seemed insignificant to consider the internal routing. The models for moderate and light rain events, however, were quite the opposite. The model performance decreased significantly from HR to LR_{WA1}, then to LR_{WA2}, and increased significantly after taking the sub-area routing into account. This change was particularly evident for light rain. For example, for rainfall 0804, the values of NSE improved greatly from 0.135 (LR_{WA1}) to 0.847 (LR_{SR1}) and from −0.181 (LR_{WA2}) to 0.879 (LR_{SR2}), respectively.

The performance of recalibrated LR_{RE} models was not stable and showed significant variation among individual rainfall events. As a comparison scenario, models of LR_{RE} yielded an efficiency of NSE ranging from 0.498 to 0.927. Overall, the performance of LR_{RE} was inadequate

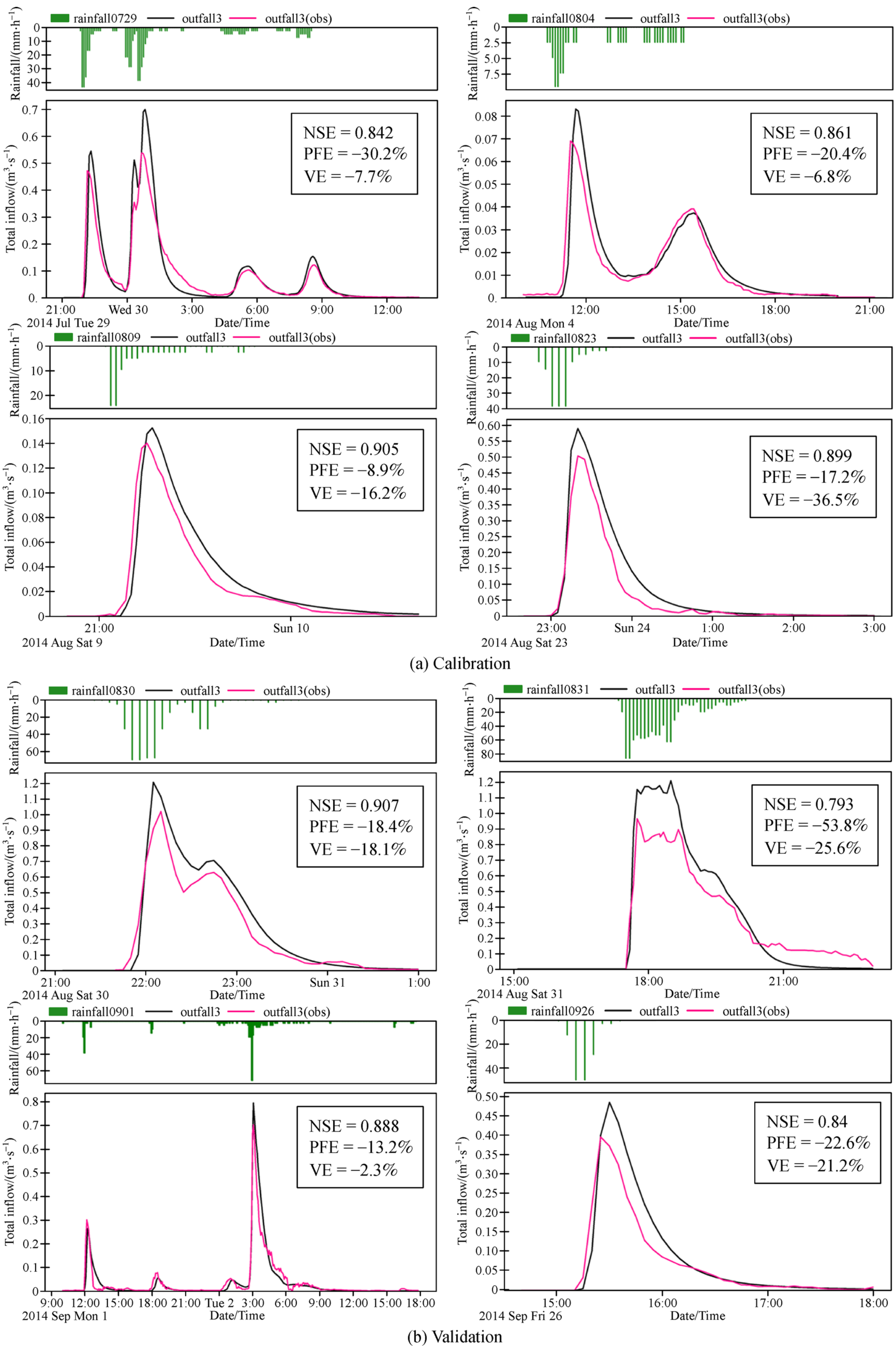

Fig. 4 Comparison of predicted and measured hydrographs of HR model from calibration and validation runs.

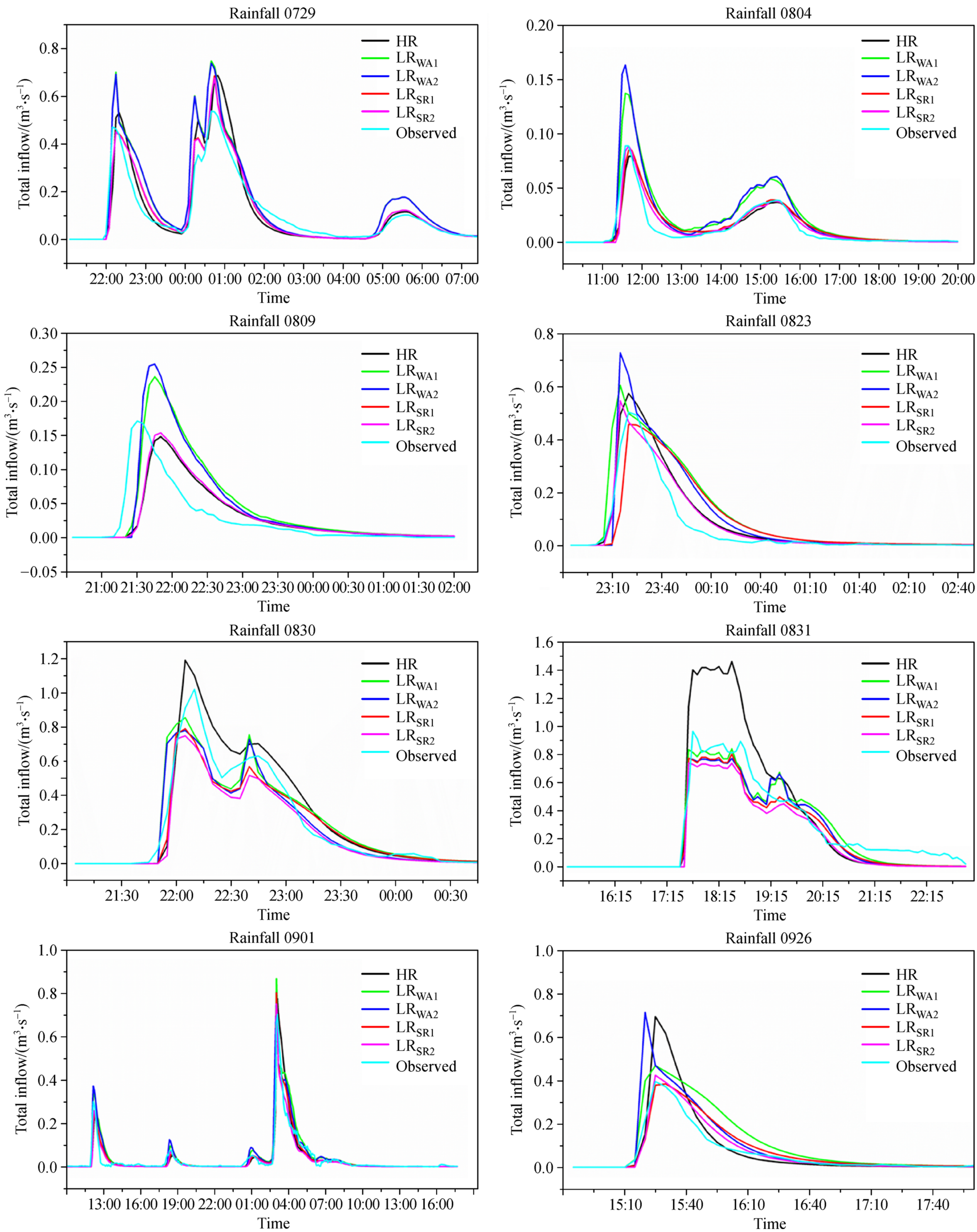

Fig. 5 Comparison of runoff process with different spatial resolutions.

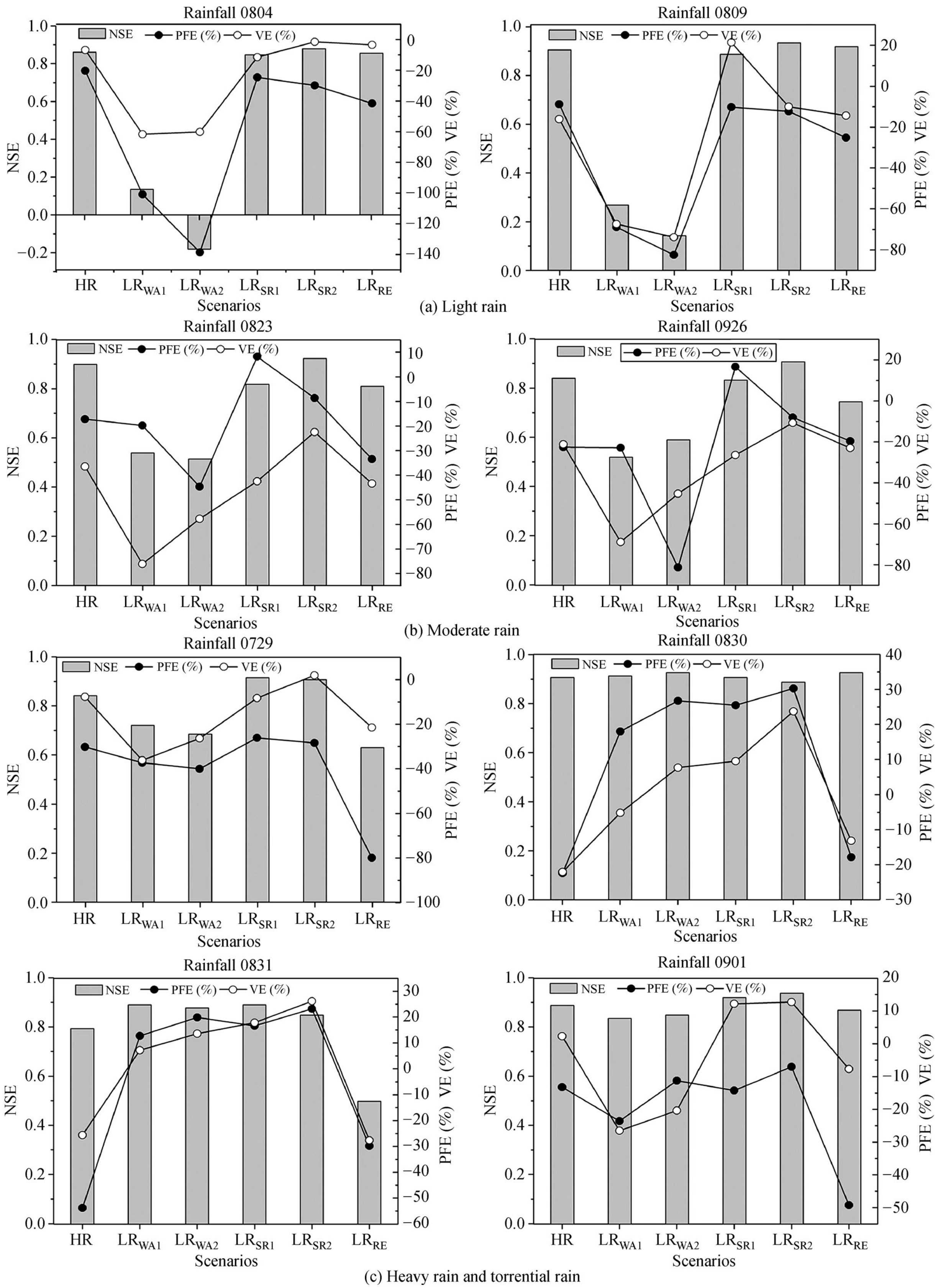

Fig. 6 Performances of three scenarios in the low resolution models and a comparison with the high resolution models.

compared to LR_{SR}, but better than LR_{WA}. From the perspective of parameter applicability, the parameters calibrated from HR models seemed to be better than the parameters from LR_{RE} models. According to the parameter sensitivity test by the SRTC tool, Dstore-imperv and N-c were still the most sensitive parameters affecting model performance of LR_{RE} models. Flow width had a significant effect on the peak flow and runoff volume. N-imperv had a slight influence on the model performance. These four parameters were submitted for the recalibration in the LR_{RE} models. Table 3 shows the values of the four parameters in both the LR_{WA}/LR_{SR} models and LR_{RE} models. Large differences were observed among the scenarios. The *k* values of the flow width were 4.35 in the LR_{RE} scenario and 5 in the LR_{WA}/LR_{SR} scenarios. The value of Dstore-imperv in the LR_{RE} scenario was 2.888, significantly higher than the value in the LR_{WA}/LR_{SR} scenarios, which ranged from 1.274 to 1.955. The value of N-c in the LR_{RE} scenario was 0.022, also higher than that in the LR_{WA}/LR_{SR} scenarios, which was 0.015. However, the value of N-imperv in LR_{RE} was the same as in the LR_{WA}/LR_{SR} scenarios.

4 Discussion

4.1 Sensitivity of model parameters

As a critical step in model implementation, parameter sensitivity may vary significantly, depending on the physical characteristics of the catchment. The parameter percent imperviousness was documented as the most sensitive parameter and used as the primary calibration parameter for volume computation (Tsihrintzis and Hamid, 1998; Barco et al., 2008; Palla and Gnecco, 2015). In this study, percent imperviousness was defined based on analyses of topographic maps with high spatial resolution, detailed field measurements, and surveying. Therefore, this parameter was considered relatively accurate and fixed, which generally is not possible for low spatial resolution models. The HR models performed notably well for the calibration and validation without a large perturbation of percent imperviousness, indicating the advantage of an HR model.

Regardless of the HR or LR_{RE} models, two key parameters, Dstore-imperv and N-c, affected the model performance significantly. Manning's roughness, an indicator of the smoothness of the interior pipe walls, determined the hydraulic capacity of the pipe (Sun et al., 2014). These two parameters were unanimously considered the most sensitive parameters, and previous studies concluded the same regarding their sensitivity (Tsihrintzis and Hamid, 1998; Krebs et al., 2013, 2014). Flow width, representing the width of the downstream side of the idealized sloping rectangular subcatchment, was thought to have a strong influence on peak flow but a relatively weak influence on runoff depth (Huber et al., 1988; Chow et al., 2012). Thus, this parameter was always used for peak adjustment (Rosa et al., 2015). In our study, flow width was used as a calibration parameter, which slightly affected both the simulated volume and peak flow.

The sensitivity of the parameters related to the pervious area, including Manning's roughness (N-perv), the depression storage (Dstore-perv), and infiltration parameters, has not yielded a consensus (Liong et al., 1991; Tsihrintzis and Hamid, 1998; Peterson and Wicks, 2006; Barco et al., 2008; Wang and Altunkaynak, 2012; Baek et al., 2015). In this study, the sensitivity of these parameters was different for HR and LR models. The HR model for rainfall 0729 was sensitive to all of the parameters associated with pervious area, indicating that parameter sensitivity was affected by both the spatial resolution and the rainfall characteristics. The high spatial resolution and the use of homogenous subcatchments limited both the number of calibration parameters and narrower parameter ranges (Krebs et al., 2013). However, the importance of infiltration will be enhanced with larger and more frequent storm events, which could explain the sensitivity of the model for rainfall 0729 to these parameters.

4.2 The influence of spatial resolution on model performance

Previous studies have focused on the influence of spatial resolution on model output, primarily the simulated peak inflow and total inflow. The difference in output from models at different resolutions could be attributed to the nonlinearity of the model equations. The complicated models include numerous dynamic and interacting nonlinear processes and spatially varying parameters, which when averaged or aggregated are subject to this scale effect (Ghosh and Hellweger, 2012). Peak flow was found to increase or decrease with decreasing resolution (Zaghloul, 1981; Elliott et al., 2009). However, runoff volume was not impacted significantly by the spatial aggregation (Park et al., 2008; Ghosh and Hellweger, 2012). In our study, a dual scale effect was observed for peak flows. For the larger storms, peak flows were reduced in the process of

Table 3 Comparison of key parameter values between LR_{WA}/LR_{SR} and LR_{RE}

	Flow width- *k* value	Dstore-imperv/mm	N-imperv/mm	N-c
LR_{WA}/LR_{SR}	5	1.274–1.955	0.012	0.015
LR_{RE}	4.35	2.888	0.012	0.022

subcatchment aggregation from HR to LR_{WA1} and subsequently to LR_{WA2}. However, for the smaller storms, aggregation increased peak flows. Ghosh and Hellweger (2012) also reported a dual scale effect by varying the number of model subdivisions. Unlike other studies, the total runoff volume was also sensitive to spatial scale. The internal routing at different resolutions and the sewer network truncation resulted in the change of proportion of effective impervious areas (EIAs), which could affect the results of simulated runoff volume (Krebs et al., 2014).

Model performance is judged by various goodness-of-fit indexes. Among these indicators, NSE has received considerable attention in hydrological modelling and has become the most common evaluation coefficient (Ritter and Muñoz-Carpena, 2013). The HR models in our study, including data with high spatial resolution and separated sensitive parameters based on the land use type, might account more explicitly for the heterogeneity of surface properties (e.g., variation of land covers, soils, and slopes) that influence how water moves through the landscape. The HR models performed very well for almost all the rainfall types in terms of the NSE. The performance of LR_{WA1} and LR_{WA2} models, which adopted the average weighted parameters of HR models directly, varied with the rainfall types. After considering the sub-area routing, the models of LR_{SR1} and LR_{SR2} performed well for all the rainfall types. Note that the performance of recalibrated LR_{RE} models was not stable and showed significant variation among individual rainfall events, indicating the advantage of using HR models and HR-based LR models.

4.3 Parameter transferability in the process of scaling up

Generally, it is not easy to obtain basic data at high resolution for a large region; however, it is more feasible to obtain HR data for a specific small area within a large region. In this case, it is of significance to discuss the possibility of applying parameters calibrated from the HR models to the LR models. In this study, the performance of LR models using the weighted average method (LR_{WA1} and LR_{WA2}) was found to be dependent on the rainfall type. In our study catchment, many pervious areas are located next to buildings or other land use types, and flow routing occurs between these subcatchments during rainfall events. In the HR models, these flow paths could be described accurately for the homogeneity of each subcatchment and data with high spatial resolution. For LR_{WA1} and LR_{WA2} models, the surface runoff was routed directly to the sewer inlets, which resulted in the change of EIA (Krebs et al., 2014). Due to the limited storage capacity of the pervious area, the impact of this change was much greater for light rain than for heavy rain. Setting 35% runoff routing from impervious areas to pervious areas within subcatchments could weaken the effect, which was proven by the performance of LR_{SR1} and LR_{SR2} models.

Therefore, the HR-based parameters might be applied to the LR models directly for heavy rain (or above level) or in the study area where sub-area routing is not as significant. In other cases, sub-area routing should be considered and estimated to obtain ideal simulation results for using HR-based parameters. Sun et al. (2014) examined how the level of catchment discretization affected the model parameterization and output uncertainty of SWMM 5.0, indicating that the calibrated parameters obtained based upon micro-delineation would provide a higher confidence level in terms of parameter transferability for modelling other, particularly ungauged, sites. Our study has proved the possibility of upscaling from HR models to LR models in the same study area. Further validation study should be focused on the application of parameters from HR models to LR modelling in a larger area or other sites. Furthermore, as the risk of urban flooding has increased, integrated 1D-2D modelling has received greater attention to derive the detailed flow dynamics in local areas. However, the computational cost rises exponentially at finer resolutions (Vojinovic and Tutulic, 2009; Chen et al., 2012). Exploring the effect of spatial resolution on model performance and the possibility of parameter transferability across spatial resolutions in 2D hydraulic modelling could be the focus for further research.

5 Conclusions

This study investigated the effect of spatial resolution on hydrological modelling and the possibility of parameter set transferability in the process of upscaling in highly urbanized areas. Based on the results, the following conclusions are drawn:

- The spatial resolution not only affected the simulated peak inflow, but also the total runoff volume in our study catchment. Peak flows decreased in the process of subcatchment aggregation for the larger storms, yet increased for smaller storms. The simulated total runoff volume did not exhibit a consistent tendency.
- The parameterization was affected by both the spatial resolution used for catchment discretization and the rainfall characteristics.
- Scale conversion from HR models to LR models has proved to be possible by parameter transferability. The HR-based parameters could be applied to the LR models directly for heavy rain (or above level) or in the study area where sub-area routing is not as significant. Otherwise, sub-area routing should be considered and estimated to obtain ideal simulation results.

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