Effects of digital elevation model resolution on topography-based runoff simulation under uncertainty

L. Cui, Y. P. Li, G. H. Huang and Y. Huang

ABSTRACT

Topography plays a critical role in controlling water dispersion and soil movement in hydrologic modeling for water resources management with raster-based digital elevation model (DEM). This study aims to model effects of DEM resolution on runoff simulation through coupling fuzzy analysis technique with a topography based rainfall–runoff model (TOPMODEL). Different levels of DEM grid sizes between 30 m and 200 m are examined, and the results indicate that 30 m DEM resolution is the best for all catchments. Results demonstrate that the DEM resolution could have significant influence on the TOPMODEL rainfall–runoff simulation. Fuzzy analysis technique is used to further examine the uncertain DEM resolution based on considering Nash, sum of squared error, and sum of absolute error values of TOPMODEL. The developed model is calibrated and validated against observed flow during the period 2010–2012, and generally performed acceptably for model Nash–Sutcliffe value. The proposed method is useful for studying hydrological processes of watershed associated with topography uncertainty and providing support for identifying proper water resources management strategy.

Key words | DEM resolution, hydrologic modeling, TOPMODEL, topographic, uncertainty

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INTRODUCTION

Currently, one-third of the world's population is living in countries and regions with water resources' limitation (Bates *et al.* 2008). Due to limited water availability, the management of water resources has become an increasingly pressing issue for decision-makers (e.g., China) (Li & Huang 2009, 2010; Meng *et al.* 2013; Suo *et al.* 2013; Yang & Chen 2013; Ma *et al.* 2014). Hydrologic models are particularly useful tools in that they are frequently used for water balance analysis, extending and infilling stream flow records, flow forecasting, reservoir operation, water supply, and watershed management (Misgana & John 2005; Li *et al.* 2013; Nederkoorn *et al.* 2013; Su *et al.* 2013). Topography is a significant control on the spatial distribution of hydrological variables, which exerted by topography on the movement of water within the landscape is fundamental to the prediction of hydrologic models. Topography is an important land-surface characteristic that affects the transport of chemicals and sediment from the land surface into and through the stream-channel system (Moore *et al.* 1991). Topography also affects most aspects of the water balance in a watershed, including the flow path followed by water as it moves down and through hill slope and the rate of water movement (David & Gregory 2000). Moreover, a digital elevation model (DEM) can provide fundamental information for understanding the topographic control on the movements of water, sediments, and contaminants over a watershed. The general approach is to use topographic indices calculated from the DEM to measure the flow of water controlled by topography. Thus, the availability of a DEM is of great importance in the spatial extent of a hydrological model.

Previously, a number of algorithms were developed for performing various standard hydrological models using the DEM (Luo *et al.* 2012; Alvisi *et al.* 2013; Yan *et al.* 2013). The popularity of the DEM in water resources applications stemmed from both its applicability to landscape-based

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runoff modeling and its practicability of utilization together with other data layers such as land use and soil type (Bhattarai & Dutta 2007; Bahremand & De 2008). For decades, a number of studies have shown that hydrological models are sensitive to DEM horizontal resolution, especially due to its influence on computed slopes and related model-derived quantities such as surface saturation extent and some DEM resampling methods were used in hydrologic models (Wolock & Price 1994; Zhang & Montgomery 1994; Peters *et al.* 2003). For example, Chaubey *et al.* (2005) described the effect of DEM data on predictions from the Soil and Water Assessment Tool (SWAT) model for Moores Creek watershed, and their results implied that the choice of input DEM resolution depended on the watershed response of interest. Chaplot (2005) studied the impact of the mesh size of DEM (from 20 to 500 m) within the SWAT model to simulate runoff, sediment, and NO_3-N loads at the outlet of an agricultural watershed. DEM at lower resolutions was obtained by resampling the DEM data at 30 m resolution using bilinear interpolation. Results showed that an upper limit to DEM mesh size of 50 m is required to simulate watershed loads. Decreasing the mesh size beyond this threshold does not substantially affect the computed runoff flux but does generate prediction errors for nitrogen and sediment yields. Wu *et al.* (2007) showed that DEM grid size had significant influence on the topographic index distribution which represented the effect of topography on watershed hydrology in topography based rainfall–runoff model (TOPMODEL), and the simulated discharges and model efficiencies using the same set of TOPMODEL parameters were sensitive to DEM grid size especially at coarse resolutions. Vázqueza & Feyen (2007) assessed the effects of DEM gridding on the predictions of Gete watershed runoff using MIKE SHE and a modeling resolution of 600 m. It was found that the independent calibration of the assembled hydrologic models was revealed as a function of the different DEM grid sizes. Lin *et al.* (2010b) evaluated the impact of DEM on SWAT predictions for runoff, and the results indicated that the predictions of TP and TN decreased substantially with coarser resampled resolution. In general, these studies were effective for investigating the effects of DEM resolution on hydrological models.

However, in real-world problems, uncertainties commonly exist in topography and their interrelationships could be extremely complicated in hydrological modeling (Arnold & Fohrer 2005; Huang *et al.* 2010). For example, uncertainties involved in hydrological modeling could be related to the land surface and aquifer heterogeneity, physical properties of the geology system, and the interaction between surface and subsurface water systems. In fact, TOPMODEL is a rainfall–runoff model that bases its distributed predictions on the analysis of watershed topography. Compared with other distributed hydrological model such as SWAT, MIKE SHE, DEM has significant influence on the topographic index which represents the effect of topography on watershed hydrology in TOPMODEL; any DEM uncertainties can be propagated into the output of hydrologic model prediction, causing inaccuracies. The conventional methods often have difficulties in addressing such uncertainties, resulting in information loss or distortion in DEM-based hydrological simulation. An issue with the topography-based runoff modeling was that at what spatial resolution a model would perform optimally. Any uncertainties in the DEM would propagate into the output of hydrologic model prediction, leading to inaccuracies of prediction results (Wolock & McCabe 1995). Bruneau *et al.* (1995) conducted a sensitivity analysis on the space and time resolutions of DEM and showed that the modeling efficiency was fairly high inside a relevant domain of space and time resolutions and that working outside this domain induced a strong decrease of modeling efficiency. Wilson & Gallant (2000) provided a summary on topographic properties where direct surface derivatives from DEM were categorized as primary topographic attributes; this work examined DEM resolution uncertainty in watershed terrain representation with the four important variables (slope, aspect, and plan and profile curvature). Wu *et al.* (2008) examined the effects of DEM resolution on a set of important topographic derivatives, including slope, upslope contributing area, flow length, and watershed area, and analyzed how sensitive each of the attributes is to the resolution uncertainty by considering the effects of overall terrain gradient and bias from resampling.

Although a DEM was a model of the elevation surface, it was often not treated as a model, but was accepted as a true representation of the earth's surface (Suzanne & Charles 2006). The effects of DEM error on elevation and derived parameters were often not evaluated by DEM users

(Wechsler 2003). Consequently, to more effectively reflect the real-world system, it is necessary to research the effect of DEM resolution on the efficiency of the hydrological model. However few previous studies have examined the relationship between the hydrological model efficiency and multiple DEM resolutions (Tripathi *et al.* 2006; Rasmus & Jan 2007). In fact, low DEM resolution ignores the tiny topography which affects pathways of surface water movement and the model efficiency. Ignoring this tiny topography could affect the modeling accuracy. Appropriate DEM resolution could contribute to the run time and efficiency of hydrologic models.

Therefore, the objective of this study is to model the effects of DEM resolution on topography-based watershed runoff simulation under uncertainty for the Xiangxi River watershed, China. The TOPMODEL is used for simulating water movement in the entire land phase of the hydrological cycle. Four experimental catchments with hydrological and meteorological data are selected to carry out the research, and in each catchment a hydrological station has been built to provide the detailed hydrological and meteorological data. Different levels of DEM grid sizes are studied, and parameter calibrations are conducted at each level. Fuzzy analysis technique is also used for analyzing the relationships between the DEM resolution and TOPMODEL efficiency through considering Nash, sum of squared error (SSE), and sum of absolute error (SAE) values. The results obtained will be useful for helping planners to establish effective water utilization and allocation policies and thus improve the local ecosystem sustainability.

STUDY AREA

The Xiangxi River watershed is located between latitudes 31.0 °N and 31.5 °N as well as longitudes 110.4 °E and 111.0 °E, with a drainage area of 3,213 km². It is one of the largest tributaries in the Three Gorges Reservoir region. The topography is dominated by mountains with elevation ranging from 60 m to 3,087 m. The basin is situated in a humid region in western Hubei province in China, with an average annual temperature of 16.6 °C and an average annual flow of 40.18 m³/s (Li *et al.* 2008; Yang *et al.* 2010). It is characterized by high rainfall, and it is

one of the rainiest centers in the west of Hubei province with an average annual precipitation of 1,015.6 mm. More than 70% of the total annual precipitation falls from April to September and hence the water resource is subject to large variability (Li *et al.* 2012). The length of the main stream of Xiangxi River watershed is 94 km, and the distance between the estuary and the Three Gorges Dam is about 34.5 km.

The importance of this river basin lies in the fact that the Xiangxi River watershed is the headwater of the Three Gorges Reservoir region, bearing the heavy responsibility for the water supply for the Yangtze River. Floods are often atmospherically driven in the catchment caused by excessive precipitation and water resource management is critical in this river basin. For the management of the watershed, it is very important to explore the relationship between the dynamic variations of water resources and seasonal changes. Also, the topography of the Xiangxi River watershed is dominated by mountains, and only one hydrological station was built in the outlet of the watershed in the main stream. The hydrological characteristics of the tributary were neglected due to the lack of hydrological data. In order to establish the applicability of the runoff simulation model, the watershed was divided into four categories with 45 sub-catchments through the step-wise clustering method based on the natural environmental characteristics of the catchment, such as topography, vegetation, soil, micro-climate, and traffic conditions. Four experimental catchments were selected from the sub-catchments among the four categories. In each experimental catchment, hydrological and weather stations were established to monitor the hydrological and meteorological data of the experimental catchment in the Xiangxi River watershed; the area of the experimental catchments is bigger than 50 km². Therefore, the Xiangxi River watershed is partitioned into four experimental catchments in the upstream middle reaches and downstream of the watershed in terms of stream networks, geology, physiognomy, and administrative boundaries (as shown in Figure 1). The weather stations and hydrological information is shown in Table 1. In this watershed, runoff shows significant intra-annual variations and is dominated by event flows from summer storms; such hydrological regime provides an opportunity to examine the time dynamics of the subtropical watershed system.
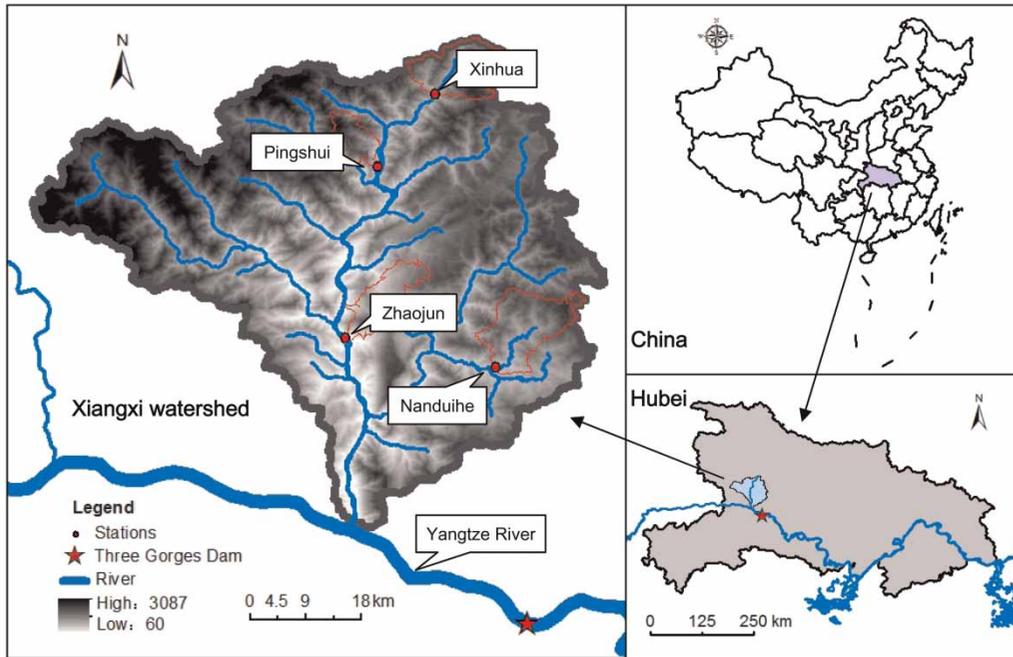
Figure 1 | The location of Xiangxi watershed and the spatial pattern of the experimental catchments.

Table 1 | Detailed information of the experimental catchments

Catchment	Latitude	Longitude	Altitude
Nanduihe	31°11′28″N	110°57′54″E	553
Pingshui	31°29′5″N	110°47′52″E	404
Xinhua	31°31′19″N	110°52′43″E	713
Zhaojun	31°14′15″N	110°44′36″E	180

Also, land cover and soil have been relatively stable in the watershed during the past half century, such that the steady surface and subsurface conditions are helpful in highlighting the driving forcing of the watershed system.

METHODOLOGY

Topography-based rainfall–runoff model

TOPMODEL is a semi-distributed catchment hydrology model that predicts storm runoff from a combination of saturated surface contributing area and subsurface runoff. TOPMODEL is not a traditional model package, but more a collection of concepts. There have been many revisions

to the original version to adapt to specific circumstances (Beven 1997, 2001). Based on the concept of runoff generation, the basic model assumptions are: (1) the dynamics of the saturated zone can be approximated by uniform subsurface runoff production per unit area over the area, a, draining through a point; and (2) the hydraulic gradient of the saturated zone can be approximated by the local surface topographic slope, $\tan\beta$; groundwater table and saturated flow are parallel to the local surface slope.

On the basis of these two assumptions, a short description of the basic modeling concepts is given. The down slope subsurface flow rate per unit contour length at any location i in the watershed q_i (m²/h) is approximated as

$$q_i = T_o e^{-S_i/m} (\tan\beta_i) \tag{1}$$

where T_0 (m²/h) is the lateral down slope transmissivity when the saturated zone reaches the ground surface, S_i (m) is the local soil moisture deficit, and m (m) is a scaling parameter controlling the rate of decrease in soil hydraulic conductivity with depth.

As the water table recharge and the soil transmissivity are assumed to be spatially constant, S_i (m) can be

expressed as

$$S_i = \overline{S} + m(\overline{\lambda} - \ln(\alpha_i / \tan\beta_i)) \qquad (2)$$

where S_i (m) is mean soil moisture deficit of the watershed, λ is the watershed average of the topographic index $\ln(\alpha/\beta)$. Unsaturated and saturated zone fluxes q_v (m/h) are simulated as

$$q_v = \frac{S_{uz}}{SD_i t_d} \qquad (3)$$

where S_{uz} (m) is the storage in the unsaturated zone, SD_i (m) is the local saturated zone deficit due to gravity drainage which is dependent on the depth of the local water table, and t_d (h/m) is a time delay constant expressed as the mean residence time for vertical flow per unit of deficit.

Following the widely adopted practice, TOPMODEL calculates the actual evapotranspiration E_a (m/h) as a function of potential evapotranspiration E_p (m/h) and maximum root zone moisture storage deficit, $S_{r\,max}$ (m) in the case E_a is not available directly, where S_{rz} is the root zone moisture deficit

$$E_a = E_P\left(1 - \frac{s_{rz}}{S_{r\,max}}\right) \qquad (4)$$

Basic inputs in TOPMODEL involve precipitation, potential evapotranspiration, and digital elevation data for channel routing and topographic index calculation. As discussed above, four important parameters present in the model, m, T_0, t_d, and $S_{r\,max}$, need to be calibrated with observed discharge data.

The performance of TOPMODEL simulation is usually represented by the Nash and Sutcliffe efficiency coefficient (Nash) (Nash & Sutcliffe 1970) as it remains the most commonly used in assessing hydrologic modeling efficiency. The SSE and SAE are the other two indices used to represent the performance of TOPMODEL. The coefficient standing for the goodness of fit between observed and simulated hydrographs can be defined as follows:

$$\text{Nash} = 1 - \frac{\sum_{i=1}^{n}(Q_{simi} - Q_{obsi})^2}{\sum_{i=1}^{n}(Q_{obsi} - Q_{avg})^2} \qquad (5)$$

$$\text{SSE} = \sum_{i=1}^{n}(Q_{simi} - Q_{avg})^2 \qquad (6)$$

$$\text{SAE} = \sum_{i=1}^{n}(Q_{simi} - Q_{obsi}) \qquad (7)$$

where n is the number of time steps, Q_{simi} and Q_{obsi} are the simulated and observed discharges at time i, respectively, and Q_{avg} is the average observed discharge over the simulation period.

Fuzzy analysis

Fuzzy set optimization can be extended to situations involving subjective uncertainty. The value of membership function u (membership grade) describes the degree of acceptability from 'bad' to 'good' and varies from 0 to 1. An optimal choice can be considered as pattern recognition between an 'ideal alternative' and 'anti-ideal alternative'. Pattern recognition is a problem typical of fuzzy sets (Cheng 1999). An optimal alternative is a satisfactory solution not an optimum solution restricted to a finite set of alternatives, and optimal rank of alternatives can be obtained by the membership degree of alternative.

In this study, it is supposed that the total number of objectives for model efficiency is m, and the total number of feasible alternatives under different DEM resolutions is n. The finite alternative sets consisting of n candidate alternatives are $A\{A_1, A_2 \ldots, A_n\}$ and each alternative is described by the objective set $B\{B_1, B_2 \ldots, B_m\}$. The decision matrix is represented by $X = (x_{ij})_{m \times n}$, where x_{ij} is the ith objective value of alternative A_j $(j = 1, 2, \ldots, n)$. In determining satisfactory decisions among n alternatives, the decision matrix X should be transformed into a matrix of membership degree, such as the model efficiency. Thus, different types of objectives can be calculated using the following formula:

$$r_{ij} = (x_{ij} - x_{i\,min})/(x_{i\,max} - x_{i\,min}) \qquad (8)$$

$$r_{ij} = (x_{i\,max} - x_{ij})/(x_{i\,max} - x_{i\,min}) \qquad (9)$$

where $x_{i\,max} = \vee_{i=1}^{n} x_{ij}$, $x_{i\,min} = \wedge_{i=1}^{n} x_{ij}$. For the 'high value' type of objective, the larger its value the greater is its membership degree relative to 'optimal' and it should be adopted with

Equation (8), otherwise for the 'low value' type of objective one should use Equation (9). After transformation the matrix of membership degree is represented as: $R(r_{ij})_{m \times n}$. For the multi-objective decision-making problem with limited alternatives, the optimal alternative is relative and thus the ideal alternative is defined as: $G(g_1, g_2, \ldots, g_m)^T$. The 'anti-ideal' alternative is defined as $B(b_1, b_2, \ldots, b_m)^T$, where $g_i = \vee_{j=1}^{n} r_{ij}$, $b_i = \wedge_{j=1}^{n} r_{ij}$, $i = 1, 2, \ldots, n$.

The optimal relative membership degree of each alternative can be obtained by minimizing the sum of its squared distances to ranking centers (Chen & Fu 2005). The weighted distances is used to represent the distance between G to ranking B, and defined as

$$D_j(w) = \sqrt{\sum_{i=1}^{m} [w_i(g_i - r_{ij})]^2} \qquad (10)$$

$$d_j(w) = \sqrt{\sum_{i=1}^{m} [w_i(r_{ij} - b_i)]^2} \qquad (11)$$

In Equations (10) and (11), w is a weight vector $= (w_1, w_2, \ldots, w_m)^T$, $\sum_{i=1}^{m} w_i = 1$, $w_i > 0$, and $i = 1, 2, \ldots, m$. If the membership degree of alternative A_j relative to G is denoted by u_j, then the one relative to B is $1 - u_j$, which gives the definition of synthetically weighted distance

$$F_j(u_j) = u_j^2 \sum_{i=1}^{m} [w_i(g_i - r_{ij})]^2 + (1 - u_j)^2 \sum_{i=1}^{m} [w_i(r_{ij} - b_i)]^2 \qquad (12)$$

To obtain the optimal solution, the synthetically weighted distance is minimized (Lee & Li 1993): $\text{Min}\{F_j(u_j)\}$, where $j = 1, 2, \ldots, n$. Let d $F(u_j)/du_j = 0$ ($j = 1, 2, \ldots n$), giving n equations

$$w_i = \left[\sum_{k=1}^{m} \frac{\sum_{j=1}^{n} \{[u_j(g_i - r_{ij})]^2 + [(1 - u_j)(r_{ij} - b_i)]^2\}}{\sum_{j=1}^{n} \{[u_j(g_k - r_{kj})]^2 + [(1 - u_j)(r_{kj} - b_k)]^2\}} \right]^{-1} \qquad (13)$$

$$u_j = \left[1 + \frac{\sum_{i=1}^{m} [w_i(r_{ij} - g_i)]^2}{\sum_{i=1}^{m} [w_i(r_{ij} - b_i)]^2} \right]^{-1} \qquad (14)$$

From Equation (13), u_j can be obtained. According to the definition of membership grade, one knows that the bigger u_j, the better the alternative is. Thus, the relatively optimal DEM resolution of TOPMODEL can be obtained.

DATA COLLECTION AND ANALYSIS

The experimental catchments are divided by DEM at 30 m resolution through the hydrology tools of geographic information system (GIS) software. The area of each catchment is more than 50 km^2 with the altitude from 200 m to 1,000 m. Geographical properties of these four experimental catchments are shown in Figure 1, and the topographical properties are characterized by low hills with moderate slope. The vegetation coverage of these catchments is good and soil erosion is not serious. Consequently, in the outlet of the watershed in the main stream only one hydrological station was built. The properties of the hydrologic records are often neglected owing to the lack of hydrological data, such as rainfall and river flow. All these unique features make it very difficult to develop a favorable hydrological model.

Four representative meteorological and hydrological stations located in the upper, middle, and lower Xiangxi River watershed were built to monitor the hydrological and meteorological data for the four experimental catchments. The detailed information of the experimental catchments can be referred to in Table 1. The available hydrological data of the four hydrological stations and weather stations include rainfall, evaporation, and discharge, and each hydrological and meteorological record was measured by hours. Discharge records and meteorological records at these four stations cover July 1, 2010 to February 1, 2012. Continuous precipitation and discharge data have been collected from the four stations from October 1, 2010 to September 30, 2012. Figures 2 and 3 show the observed daily runoff, rainfall, and evaporation records during the period October 1, 2010 to September 30, 2012 for the four stations.

In this study, the DEM data for the Xiangxi River watershed are obtained from NASA via the internet, and they are selected as the base resolution. GIS software is used for analyzing and displaying DEM data, and the watershed is delineated and extracted with the hydrology tools of GIS
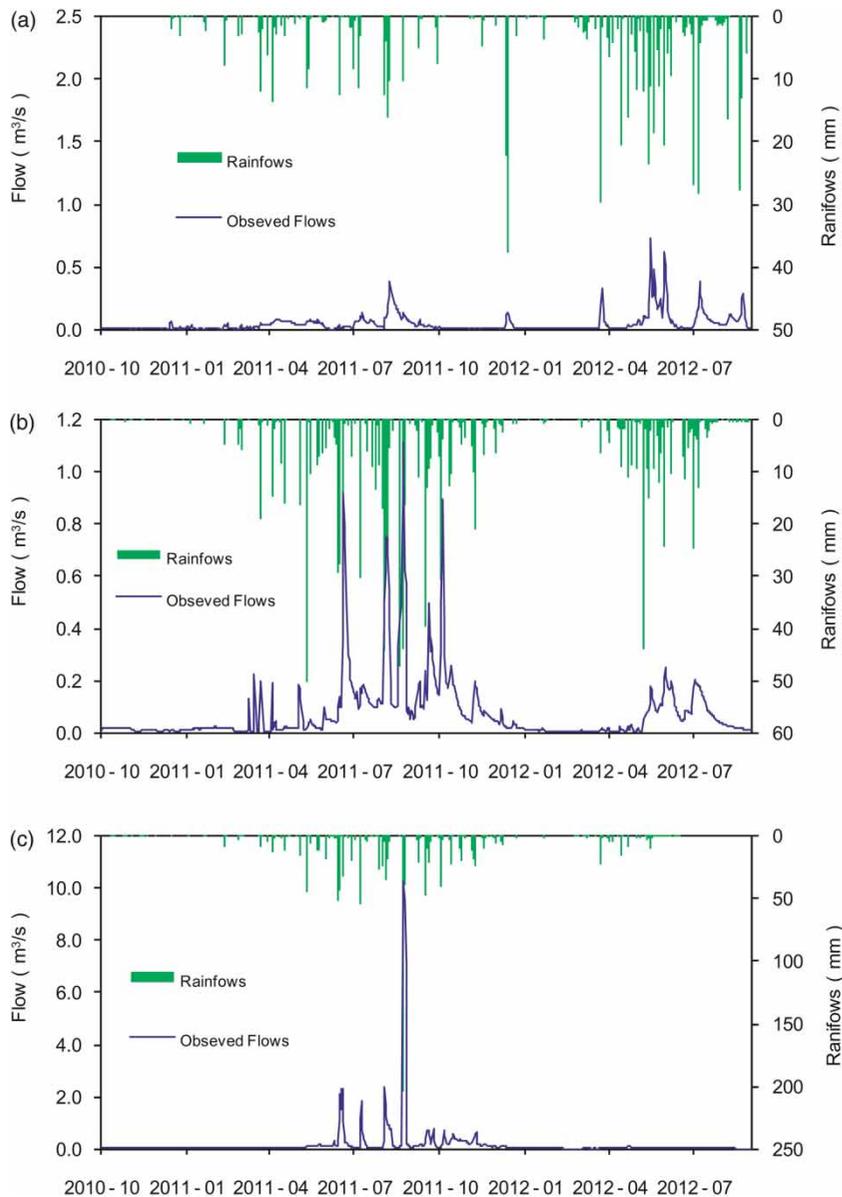
Figure 2 | The daily runoff and rainfall records for (a) Nanduihe catchment, (b) Xinhua catchment and (c) Zhaojun catchment during the period October 1, 2010 to September 30, 2012.

spatial analyst. The quality of a DEM is affected by many factors, such as terrain roughness, sampling density, elevation data collection method, interpolation algorithm, and grid resolution. In fact, errors exist both in original low and high resolution DEMs. Masataka (1998) proved that the nearest neighbor resampling method showed the highest accuracy. Nearest neighbor interpolation method finds the closest subset of input samples to a query point and applies weights to them based on proportionate areas; the method does not require input from the user and works equally well for regularly as well as irregularly distributed data (Watson 1992). The flow directions on each grid change with different DEM resolutions, having impacts on the flow concentration paths on grids. Decreasing DEM resolution can affect the average slopes, surface area/2D area, and volume/2D area, which is attributed to the loss of detailed topography characteristics as a result of decreasing DEM resolutions (Lin *et al.* 2010a). The 30, 60, 100, 150, and 200 m DEM resolutions are examined in this study. Each DEM at all five resolutions in the four experimental
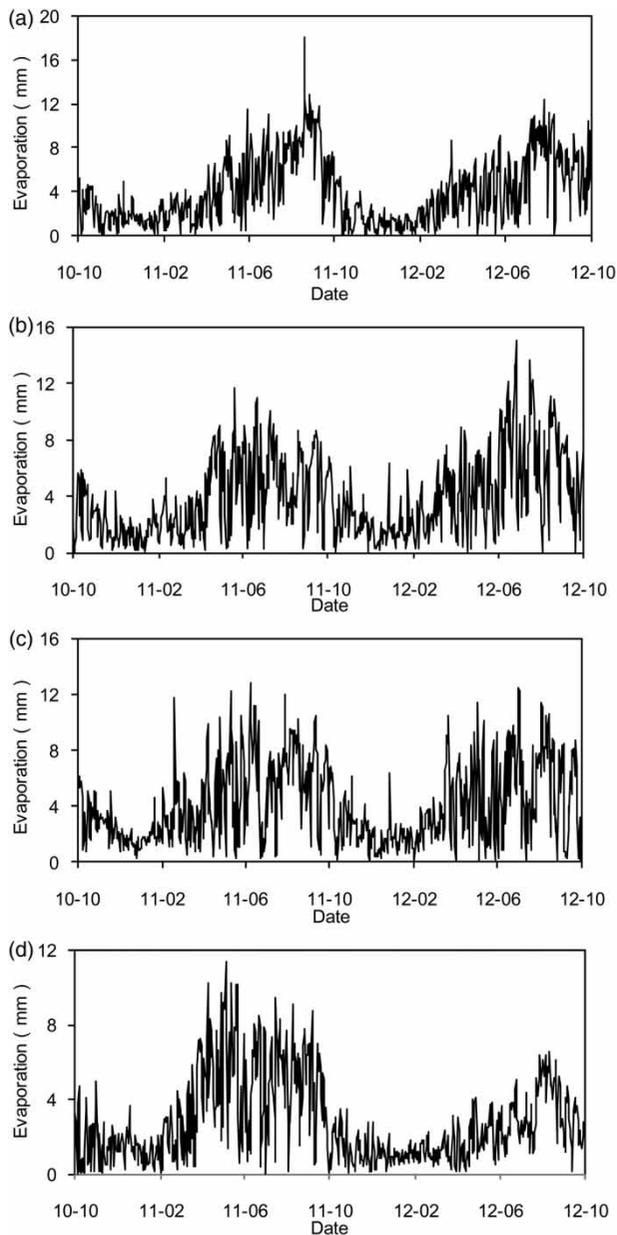
Figure 3 │ The daily evaporation records for (a) Pingshui catchment, (b) Zhaojun catchment, (c) Nanduihe catchment and (d) Xinhua catchment during the period October 1, 2010 to September 30, 2012.

catchments is used to generate the topographic index distribution required by TOPMODEL for the comparative study. The five applied DEM resolutions were divide into two categories, 'fair resolution' category and 'coarse resolution' category, to better present the study results. The grid sizes less than 90 m belong to the former, while 150 m and above belong to the latter.

RESULTS AND DISCUSSION

Performance of TOPMODEL

Although data collection was conducted over a period of several years, complete and continuous stream flow data were identified within the period 2010–2012. The data were split into two parts (split-sample calibration–validation method), with calibration performed for the period October 2010 to September 2011 and validation for the period October 2011 to September 2012. TOPMODEL was applied to simulate rainfall–runoff at each resolution in the four experimental catchments with parameter optimization for optimal performance. The hydrologic simulations of the four catchments were repeated using the same DEM resolution, 100 m. The results show that the Nash values of 0.849 at the outlet Pingshui catchment, and the SSE and SAE values are 0.082×10^{-3} and 0.089, respectively. Nash values in the other three experiment catchments are larger than 0.7 during model calibration. In the validation period, Nash values of all the four catchments also exceed 0.7 which means that TOP-MODEL performance is represented well in the Xiangxi River watershed. The calibrated value of main parameters under DEM 100 m are shown in Table 2. Figure 4 shows a comparison between the predicted and measured daily runoff at the four stations during the validation period at DEM resolution 100 m. It shows that the predicted values match the observed ones well at the four stations. Considering the DEM resolution uncertainties in the input data, the results are reasonable. TOPMODEL could reasonably simulate the rainfall–runoff in the Xiangxi River watershed, and it could be used for investigating the uncertainty of DEM resolution.

Comparison of modeling results

TOPMODEL is a rainfall–runoff model that bases its distributed predictions on the analysis of watershed topography. As a result, DEM is a significant influence on TOPMODEL efficiency. It is important to research the relationship between DEM resolution and model efficiency. General meteorological and hydrological data from the four stations comprising evaporation daily rainfall and discharge for the period 2010–2012 are used to simulate rainfall–runoff in the four experimental catchments at DEM resolutions

Table 2 | Calibrated value of main parameters of the model

Catchment	DEM	M (m)	ln(T$_0$) (m²/h)	Srmax (m)	Srinit (m)	Chvel (m/h)	Nash	SSE (10^{-3})	SAE
Nanduihe	30	0.014	1.5	0.008	0	1,400	0.855	0.012	0.045
	60	0.014	1.6	0.009	0	1,300	0.854	0.012	0.045
	100	0.015	1.3	0.006	0	1,600	0.845	0.013	0.046
	150	0.015	1.9	0.006	0	1,500	0.844	0.013	0.046
	200	0.017	2.2	0.005	0	1,500	0.820	0.015	0.049
Pingshui	30	0.017	1.9	0.006	0	1,100	0.862	0.075	0.082
	60	0.017	1.5	0.007	0	1,400	0.857	0.077	0.085
	100	0.019	1.7	0.005	0	1,700	0.849	0.082	0.089
	150	0.019	2.5	0.005	0	1,400	0.844	0.085	0.089
	200	0.019	2.4	0.006	0	1,200	0.842	0.086	0.086
Xinhua	30	0.020	0.5	0.009	0	1,300	0.790	0.192	0.127
	60	0.021	1.3	0.009	0	1,800	0.776	0.204	0.13
	100	0.023	1.4	0.008	0	1,500	0.766	0.213	0.135
	150	0.025	2.5	0.007	0	1,700	0.740	0.237	0.145
	200	0.023	2.2	0.008	0	1,400	0.720	0.21	0.132
Zhaojun	30	0.016	3.8	0.005	0	1,600	0.718	0.010	0.498
	60	0.018	3.5	0.001	0	1,300	0.711	0.010	0.571
	100	0.018	3.5	0.004	0	1,400	0.703	0.011	0.527
	150	0.019	3.4	0.003	0	1,500	0.677	0.011	0.527
	200	0.020	3.1	0.003	0	1,400	0.658	0.012	0.536

DEM, digital elevation model; M, exponential transmissivity function or recession curve; ln(T$_0$), natural logarithm of the effective transmissivity of the saturated soil; Srmax, soil profile storage available for transpiration; Srinit, initial storage deficit in the root zone; Chvel, effective surface routing velocity; Nash, Nash and Sutcliffe efficiency coefficient; SSE, sum of squared error; SAE, sum of absolute error.
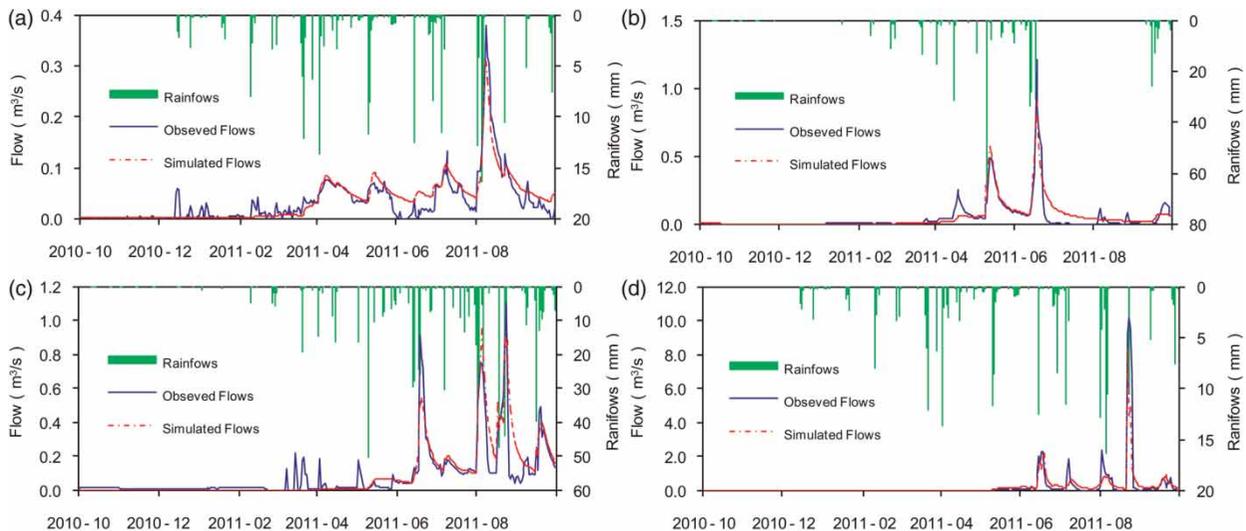
Figure 4 | Runoff simulation at DEM resolution 100 m during calibration period. (a) Nanduihe, (b) Pingshui, (c) Xinhua, (d) Zhaojun.

from 30 m to 200 m. The calibration was performed for the period October 2010 to September 2011 and validation for the period October 2011 to September 2012. Figure 5 shows for the four stations the predicted and observed

daily runoff during the calibration period at DEM resolution 30 m. The calibrated value of the main parameters of these four experimental catchments under different DEM resolution is demonstrated in Table 2. The predicted data
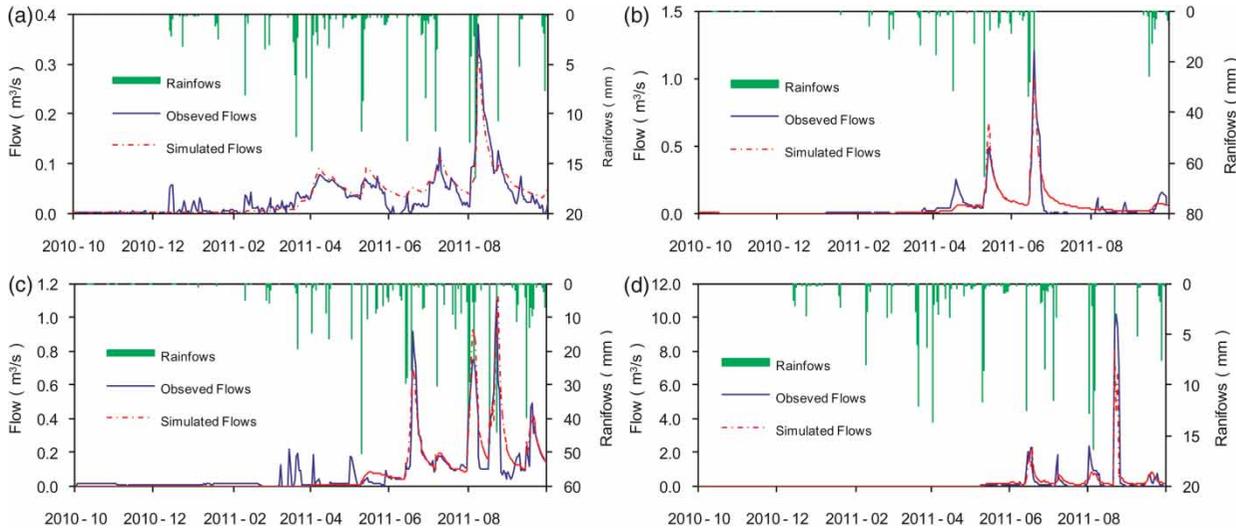
Figure 5 | Runoff simulation at DEM resolution 30 m during calibration period. (a) Nanduihe, (b) Pingshui, (c) Xinhua, (d) Zhaojun.

matched well the observed ones with the Nash value of 0.855 at the outlet of Nanduihe catchment, and the SSE and SAE values are 0.012×10^{-3} and 0.045, respectively. The Nash values at the outlet of the other three catchments range from 0.718 to 0.862 which means the model is performed well in the study system. The differences between measured and simulated runoffs under different DEM resolutions are analyzed as follows.

Figure 6 shows a comparison between the predicted and measured daily runoff at the four experimental catchments during the validation period at DEM resolution

30 m, and it shows that the predicted values match the observed ones well. The predicted runoff has significant correlation with the measured runoff. The Nash, SSE, and SAE for daily stream flow values are 0.76, 0.364×10^{-3}, and 0.167 at the Nanduihe catchment, and the results of other catchments during validation period are presented in Table 3. The timing and volume of the predicted peaks have a lower variance than the actual observation values in the Nanduihe catchment, Pingshui catchment, and Xinhua catchment, and have a higher variance than the actual observation values in the Zhaojun
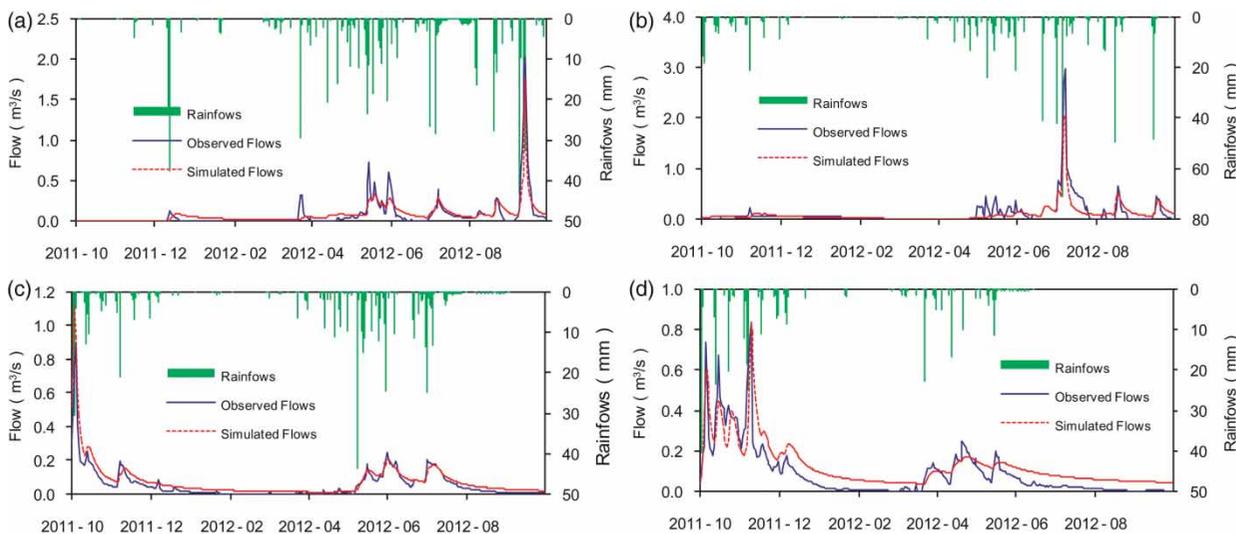

Figure 6 | Runoff simulation at DEM resolution 30 m during validation period. (a) Nanduihe, (b) Pingshui, (c) Xinhua, (d) Zhaojun.

Table 3 | Performance of the model in validation period

Catchment	DEM	Nash	SSE (10^{-3})	SAE
Nanduihe	30	0.760	0.364	0.167
	60	0.754	0.372	0.166
	100	0.742	0.330	0.173
	150	0.728	0.322	0.173
	200	0.713	0.379	0.187
Pingshui	30	0.792	0.535	0.235
	60	0.767	0.601	0.242
	100	0.746	0.656	0.242
	150	0.736	0.680	0.242
	200	0.716	0.654	0.243
Xinhua	30	0.790	0.063	0.091
	60	0.782	0.061	0.096
	100	0.753	0.071	0.109
	150	0.753	0.088	0.125
	200	0.696	0.071	0.107
Zhaojun	30	0.780	0.096	0.107
	60	0.775	0.109	0.161
	100	0.775	0.091	0.112
	150	0.773	0.091	0.119
	200	0.725	0.091	0.150

catchment. During the simulation of the Nanduihe watershed, the predicted dry season flows were underestimated by about 30%, compared with the measured flow. The wet season flow model is overestimated in Zhaojun catchment. The worst performance is in the dry season of 2012 in Nanduihe catchment. The Nash values of the four catchments are all above 0.75, implying that the TOPMODEL performs well at 30 m DEM resolution in each catchment.

The predicted and observed daily runoffs during the calibration period at DEM resolution 150 m are similar to the results of DEM resolution at 60 m, which were assumed to be constant throughout the entire simulation period. There was a statistically significant relationship between the predicted and the observed data, and the simulated river flow captured the interannual variations quite well in the four catchments. The predicted runoff reconstruction could be roughly compared with stream flow series of the records in the four catchments for the whole year, and the Nash values at DEM resolution 150 m are lower than at DEM resolution 60 m. The worst performance is Nanduihe catchment at the DEM resolution 150 m and the predicted peaks have a higher variance than the actual observation values. For the calibration period at DEM resolution 60 m, runoff simulations agreed well with observations in the four catchments. The Nash values of 0.854 at the outlet Nanduihe catchment, and the SSE and SAE values are 0.012×10^{-3} and 0.045, respectively. During the validation period at DEM resolution 150 m, all the Nash values are above 0.7 and lower than at DEM resolution 60 m and lower than the result at DEM 30 m.

Figures 7 and 8 present a comparison between the predicted daily runoff at the four catchments during the calibration period and validation period at DEM resolutions 60 m and 200 m. The simulated stream flows are very similar to the two resolutions in both calibration and validation periods. The predicted runoff at the two DEM resolutions
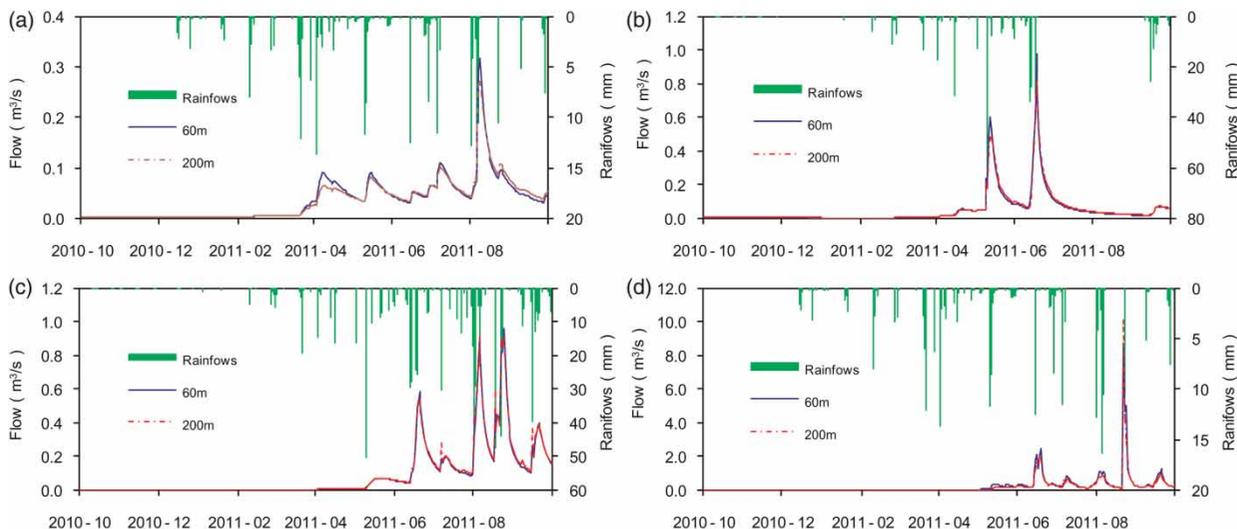
Figure 7 | Runoff simulation at DEM resolution 60 m and 200 m during calibration period. (a) Nanduihe, (b) Pingshui, (c) Xinhua, (d) Zhaojun.
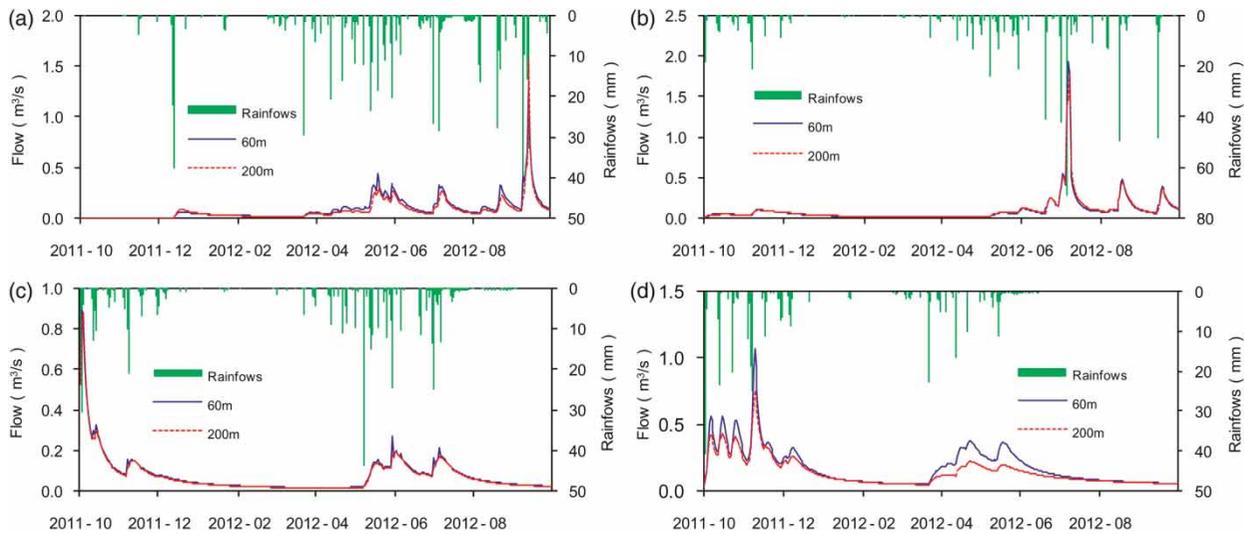
Figure 8 | Runoff simulation at DEM resolution 60 m and 200 m during validation period. (a) Nanduihe, (b) Pingshui, (c) Xinhua, (d) Zhaojun.

has significant correlation. The most noticeable difference between two DEM resolutions is that the discharge peaks of 60 m DEM resolution are higher than 200 m DEM resolution both in the calibration period and validation period at the four catchments, especially at Zhaojun catchment during the validation period. The model with 60 m DEM inputs performs slightly better than 200 m DEM. The results indicate that the model efficiency decreases as the DEM size increases.

In order to get a clear understanding of the Nash value trend with the increased DEM size, a line chart is created, as shown in Figure 9(a). The Nash value for the four watersheds keeps dropping when the DEM grid size increases throughout the entire study extent (30–200 m). The model performance keeps getting worse, gradually from the base 30 m resolution all the way to 200 m during the calibration period. The simulations with model calibration are performed at different DEM resolutions with an adequately wide range assigned to each parameter. For Pingshui watershed during calibration, to our surprise, the DEM resolution has little influence on the model performance except for a 2% Nash value decrease at 200 m, the maximum grid size in this study. It is believed that the sound performance of TOPMODEL at coarse DEM resolutions is due to the compensation effect of the saturated hydraulic conductivity parameter, T_0. The model performance with calibration maintained the same reduction over the study extents as
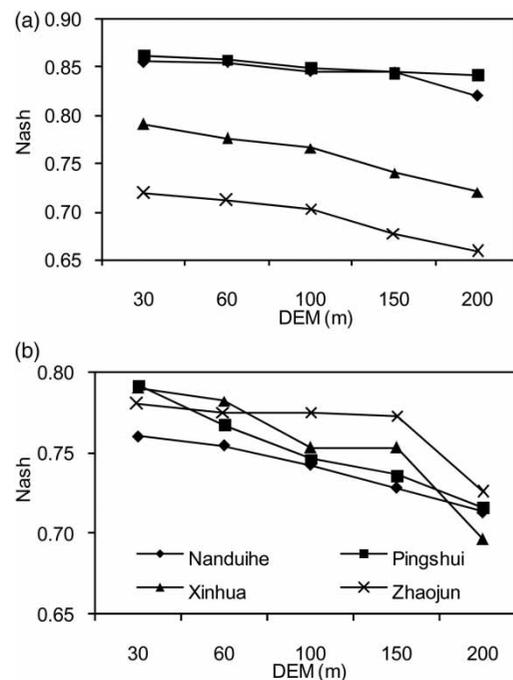

Figure 9 | Nash values under different DEM resolution during (a) calibration period and (b) validation period.

DEM resolution. As mentioned before, Chang & Tsai (1991) and Gao (1997) showed that grid cell size determines minimum unit area for upslope contributing area and how its boundaries are defined with greater grid size leading to smaller calculated slope due to the smoothing effect of reduction in DEM resolution.

The simulations during validation exhibit a fair effect of the grid size on model efficiency as an identical set of parameters is used. As shown in Figure 9(b), Nash value keeps getting worse gradually when DEM size ranges from 30 m to 200 m. A significant drop in the performance for Zhaojun watershed occurs at 150 m where the Nash value falls to 0.725 from 0.773 at 100 m. The influence of DEM grid size on the topography is passed onto the TOPMODEL simulations. For the lowest efficiency at Xinhua catchment, its subsequent efficiency up to 200 m remains above 69.6%, which can still be regarded as satisfactory for continuous modeling with daily data. As regards to SSE and SAE, there is no significant increasing trend with DEM size. SSE and SAE are also two important indices for the efficiency of TOPMODEL. Therefore, it is important to examine the joint influence of all efficiency indices.

Assessment of modeling efficiencies

Nash, SSE, and SAE are three indices for representing TOPMODEL efficiency. However, few studies have focused on integrating multi-indices in assessing the impact of DEM resolution on the model efficiency. Although the Nash value at different DEM resolutions has a downward trend, the SSE and SAE values at different DEM resolutions did not have obvious features. In order to select the best fit DEM resolution, in this study, a multi-objective fuzzy optimal method was used to research the relationship between the DEM resolution and the TOPMODEL efficiency.

The fuzzy membership function used in this study indicates the relative importance of each DEM resolution. Nash, SSE, and SAE values of different DEM resolutions are shown in Tables 2 and 3. SSE is the sum of squares

error of the flows, and SAE is sum of absolute error. The low values of SSE and SAE represent the high efficiency of the model. After calculating the Nash SSE and SAE values with the use of Equations (8) and (9), the decision matrix X is obtained, and from Equations (11) and (12) the matrix of membership degree is obtained. Because Nash, SSE, and SAE are all the efficiency indices of TOPMODEL, the weight vector is set as $w = (1/3, 1/3, 1/3)$. From Equations (13) and (14), the membership grades under different DEM resolutions are represented in Table 4.

The optimum DEM resolution of TOPMODEL is obtained through the assessment of model efficiency (listed in Table 4). The results show that 30 m DEM resolution has the highest membership value during calibration and validation periods in all the four experimental catchments. Xinhua catchment has the worst membership value at 150 m DEM resolution both in the calibration period and validation period. In Zhaojun catchment, the worst membership grade emerges at 60 m DEM resolution during the validation period; however, in the other catchments all the worst membership grades appears at 200 m DEM. The results are different from those only using Nash value and do not show the pattern of the TOPMODEL performance getting worse gradually from the base 30 m resolution all the way to 200 m. The reason is that SSE and SAE do not show an obvious trend like the Nash value; Nash, SSE, and SAE have the same weights. In addition, Nash value cannot directly affect the simulation efficiency results, while SSE and SAE possess the same important roles compared with Nash value. The results are reasonable because changing grid size has significant effects on both the mean and local upslope contributing area as larger grid sizes bias in favor of large contributing areas.

Table 4 | The membership grade of different DEM resolutions

Catchment	Membership grade	30 m	60 m	100 m	150 m	200 m
Nanduihe	Calibration period	1.000	0.667	0.655	0.646	0.333
	Validation period	0.653	0.634	0.416	0.523	0.333
Pingshui	Calibration period	1.000	0.586	0.658	0.644	0.333
	Validation period	1.000	0.602	0.373	0.490	0.333
Xinhua	Calibration period	1.000	0.565	0.382	0.333	0.622
	Validation period	0.667	0.469	0.629	0.333	0.625
Zhaojun	Calibration period	1.000	0.637	0.465	0.555	0.333
	Validation period	0.667	0.333	0.337	0.471	0.598

The joint contributions from the slope and the contributing area are attributable to the increase of the topographic index with increasing grid size.

CONCLUSIONS

This study reported four experiments examining the effect of DEM resolution on TOPMODEL efficiency. Topography plays an important role in rainfall–runoff simulation, as described in this study, on spatial processing for hydrologic modeling. An original 30 m DEM for the study watershed was resampled to four lower resolutions of realizations that were then applied to a comparative study. Fuzzy analysis technique is used for analyzing the relationships between the DEM resolution and TOPMODEL efficiency in considering Nash, SSE, and SAE values. The Nash values of the four experimental catchments keep dropping when the DEM grid size increases throughout the entire experimental catchment extent, and the effect of the grid size change becomes weaker at lower resolution levels. It finds that 30 m DEM resolution is the best for TOPMODEL in the rainfall–runoff simulation of the Xiangxi River watershed among the five resolutions.

DEM resolution can cause larger surface roughness and elevation variations. The results have generally suggested that the selection of DEM resolution could have significant influence on the TOPMODEL rainfall–runoff simulation. This study used DEM-based hydrological model TOMODEL for simulating water movement in the entire land phase of the hydrological cycle, taking the Xiangxi River watershed as the experimental catchment. It is an attempt to examine the effect of the DEM resolution on TOPMODEL efficiency, and find out the best grid size for the formulation of the model. This work justifies the necessity of assessing uncertainties created by the DEM horizontal accuracy, and offers an initiation for such kind of analyses on empirical watershed modeling with GIS. This study modeled the effects of DEM resolution on topography-based watershed runoff simulation under uncertainty, and it was of theoretical and practical merit in obtaining deep insight into the causes behind the hydrological modeling uncertainty. The understanding would ensure that TOPMODEL uncertainty be rigorously assessed in terms of spatial data resolution with gaining integral insight into the association between watershed topography and hydrologic processes. The results obtained can be used for helping planners to establish effective water exploitation and allocation policies and thus improve the local ecosystem sustainability.

TOPMODEL is a semi-distributed catchment hydrology model that predicts storm runoff from a combination of saturated surface contributing area and subsurface runoff. TOPMODEL is not a traditional model package, but more a collection of concepts. In fact, TOPMODEL is a rainfall–runoff model that bases its distributed predictions on the analysis of watershed topography. Compared with other distributed hydrological models such as SWAT, MIKE SHE, DEM has significant influence on the topographic index which represents the effect of topography on watershed hydrology in TOPMODEL; any DEM uncertainties can be propagated into the output of hydrologic model prediction, causing inaccuracies. This study uses TOMODEL for simulating water movement in the entire land phase of the hydrological cycle, and takes the Xiangxi River watershed as the experimental catchment. The results showed that 30 m DEM resolution is the best for TOPMODEL in the rainfall–runoff simulation of the experimental catchments among five resolutions. The results obtained can be used for helping planners to establish effective water exploitation and allocation policies and thus improve the local ecosystem sustainability. Compared with other hydrological models, the results are similar to the results obtained by other models, as presented in the Introduction, and it also shows that DEM resolution has significant influence on hydrological models.

The developed system is limited by the hydrological data sources used, which have such short time series that are not sufficient for describing the long-term variation of the study area. Currently, the hydrological catchments cannot measure some peak flows caused by rainstorm. Consequently, future work can continue to focus on spatial calibration and validation of the modeling system. In addition, the DEM inputs may be associated with many uncertainties and biases, which may limit their applicability in a real-world hydrological context. The model solution would be more applicable if uncertainty analyses can be performed.

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