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Article

The Suitability of the Satellite Metrological Inputs Source on the Hydrological Model in a Small Urban Catchment

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Abstract: Distributed/semi-distributed models are considered to be sensitive to the spatial resolution of the data input. In this paper, we take a small catchment in high urbanized Yangtze River Delta, Qinhuai catchment as study area, to analyze the impact of spatial resolution of precipitation and the potential evapotranspiration (PET) on the long-term runoff and flood runoff process. The data source includes the TRMM precipitation data, FEWS download PET data, and the interpolated metrological station data. GIS/RS technique was used to collect and pre-process the geographical, precipitation and PET series, which were then served as the input of CREST (Coupled Routing and Excess Storage) model to simulate the runoff process. The results clearly showed that, the CREST model is applicable to the Qinhuai catchment; the spatial resolution of precipitation had strong influence on the modelled runoff results and the metrological precipitation data cannot be substituted by the TRMM data in small catchment; the CREST model was not sensitive to the spatial resolution of the PET data, while the estimation fourmula of the PET data was correlated with the model quality. This paper focused on the small urbanized catchment, suggesting the influential explanatory variables for the model performance, and providing reliable reference for the study in similar area.

Keywords: spatial resolution; interpolation method; CREST model; Qinhuai catchment

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1. Introduction

With the social and economic development in recent decades, floods and droughts prediction, water resources management, and water supply/control infrastructure construction have been the prime focus of hydrology (Barua et al., 2013; Brown et al., 2015; Kalbus et al., 2011). Watershed models describing the metrological parameters and the surface hydrological process precipitation were widely applied to the achieve the new goals of the modern hydrological research and investigations (Henriksen et al., 2003; Jakeman and Hornberger, 1993; Kvočka et al., 2015; Sivapalan et al., 1996). Accurate metrological data reflecting the spatial and temporal variability are crucial for reliable hydrological modeling (Strauch et al., 2012). Previous researches have pointed out that the resolution, of precipitation data can cause serious errors in model outputs (Andréassian et al., 2001; Bárdossy and Das, 2008; Lopes, 1996). The diversity of commonly used potential evapotranspiration (PET) estimations indicates a variation of almost an order of magnitude and predicts a wide range

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of runoff changes applied in hydrologic model (Boughton and Chiew, 2007; Ekström et al., 2007; Milly, 2015; Oudin et al., 2005a).

Predicting precipitation based on satellite images has been widely discussed, and several prediction methods were proposed corresponding to various electromagnetic spectrum (Dingman, 2002). Among them, the Geoestationary Operational Environmental System (GOES) series (Vincente et al., 1998) and the Tropical Rainfall Measuring Mission (TRMM) were adopted mostly (Kummerow et al., 2000). TRMM was launched in November 1997 and works as precipitation monitor in the tropical area for the joint project between the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploratory Agency (JAXA) (Kummerow et al., 2000; Rozante et al., 2010). It can provide precipitation products with temporal resolution of 3h and spatial resolution of $0.25° \times 0.25°$ for large-scale distributed hydrological models. numerous attempts to validate TRMM retrievals with ground-based estimates are performed and excellent agreement with gauge measurements on monthly to seasonal timescales at continent/sub-continent or regional scale were recognized (Nair et al., 2009; Nicholson et al., 2003; Stisen and Sandholt, 2010). Successful application of TRMM precipitation data in distributed hydrological models of large-scale or data scarcity basin has been witnessed (Meng et al., 2014; Rozante et al., 2010; Xue et al., 2013), while its suitability in the small basin is not reported yet. Another conventional estimation of daily areal rainfall can be obtained by spatial interpolation of rain gauges' data. Direct interpolation techniques has been pointed out to neglecting the topographical variation and limited by the distribution of the available of precipitation stations (Taesombat and Sriwongsitanon, 2009).

To represent the potential evaporative demand introduced into a model often poses a dilemma to the scientist and engineers in the past decades, due to its agronomic concept and sampling scarcity (Oudin et al., 2005a). A wealth of studies adopted the empirical (Chiew and Mcmahon, 1992; Chiew and McMahon, 1991; Tait and Woods, 2007) or estimated PET input, which contains only mean values but deviated from the real climatic condition. The Famine Early Warning System (FEWS) projected by the U.S. Agency for International Development (USAID) originally for food security analysis for extensive areas of sub-Saharan Africa, provides PET data globally with spatial resolution $0.25° \times 0.25°$, and has been adopted in various hydrological models (Liu et al., 2005; Verdin et al., 2000). Validation studies disputed about the appropriate data source of PET. Although many hydrologists have seen no output difference between the models driven by mean PET and PET reflected spatial and temporal variations (Burnash, 1995; Fowler, 2002), PET estimations based on temperature and solar radiation tend to provide the best streamflow simulations in other researches (Oudin et al., 2005a, 2005b). Finding the most adequate PET input to distributed rainfall–runoff models to improve the streamflow simulations would be an interesting issue.

In addition to the data inputs, the model structure is considered to be one source of uncertainty in hydrological simulation (Butts et al., 2004; Montanari and Di Baldassarre, 2013). Plenty of distributed and half distributed have been constructed and applied in multi-scale basins or regions globally, and each of them has advantages. The distributed and semi distributed hydrological models, HBV (Lindström et al., 1997), TOPMODEL (Valeo and Moin, 2000), Mike SHE (Im et al., 2009), SWAT (Franczyk and Chang, 2009), HEC-HMS (Lin et al., 2009), DHSVM (Chu et al., 2010), HGS (Brunner and Simmons, 2012) and GR (Ficchì et al., 2016), for example, have been extensively used to assess the hydrologic processes. How to select the model, to sufficiently reflect the real situation of the catchment and focus on the selected scientific question, is essential in the application of the new powerful research tool.

The objective of this paper is to describe and discuss the reliability of TRMM precipitation and estimated PET data in the hydrological modeling in a small urbanized catchment in comparison with the gauged data, based on CREST model (Coupled Routing and Excess Storage model). Special attention was paid to the resolution and estimation method of the input metrological data. Finally, based on the metrological input with highest efficiency, the applicability and accuracy of the CREST model in small urbanized catchment was discussed.

2. Material and methods

2.1 Study area

Qinhuai River basin is located in the lower part of Yangtze River delta, 118°39′-119°19′E and 31°34′-32°10′N. It covers and area of 2631 km² with elevation varies from sea level to 417 m.a.s.l.. The main Qinhuai River flows 110 km, across Jurong and Nanjing city, and emptying into Yangzte River. The study area is an intermountain basin, with low-lying polders 6-8 m.a.s.l. along the main river, but surrounded by the low mountain and hills with elevation around 300 m.a.s.l.. Meteorologically, the basin has cold dry winter and hot humid summer, due to the control of the marine monsoon subtropical climate. The mean annual temperature is about 15.4 °C. The mean annual precipitation is approximately 1047 mm with high seasonal and annual variation. The concentrated precipitation in summer, combined with the frequently extreme storm caused by the tropical cyclone and subtropical high press belt, has severely increased flood disaster, especially in the downstream. The main soil types includes yellow-brown soil, purple soil, limestone soil, paddy soil, and gray fluvo-aquic soil. The paddy filed and dry land occupy most area of the basin, while the woodland, impervious surface, water cover the rest. Data collected from the seven rain gauging stations and two stream flow gauging stations at the outlets of the basin were adopted for the current study. The location of the study area and gauge stations, elevation, and river network pattern are given in Fig. 1.

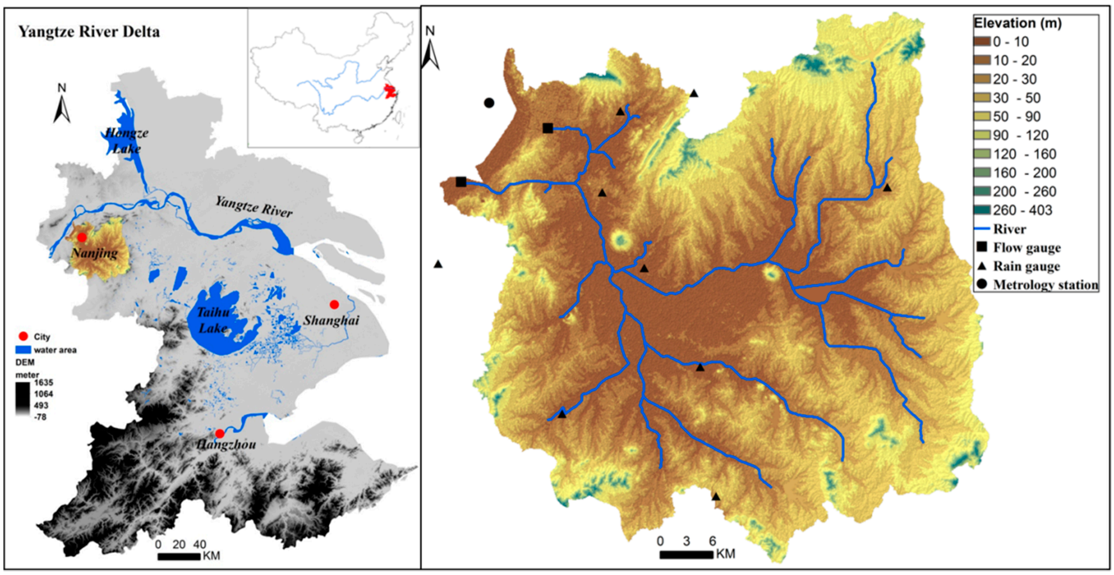

Fig. 1. Location of the Qinhuai basin and the distribution of hydrological stations

2.2 CREST Model

The Coupled Routing and Excess Storage model (CREST), developed by the University of Oklahoma (http://hydro.ou.edu) and NASA SERVIR Project Team (www.servir.net), is a distributed hydrological model aims at surface and subsurface runoff and storages simulation in a cell-to-cell

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algorithm (S. I. Khan et al., 2011; S.I. Khan et al., 2011). The core principle of CREST includes the surface runoff generation processes, the cell-to-cell runoff routing, and the coupling of runoff generation and routing scheme. Variable infiltration capacity curve (VIC) based on kinematic wave assumption is adopted in the surface runoff generation calculation. Multi-linear reservoirs are used to simulate cell-to-cell routing of surface and subsurface runoff separately. Finally the coupling mechanism reconstruct the surface and subsurface water flow process cell-to-cell (Meng et al., 2014; Xue et al., 2013). The grid based structure of CREST enables multi-scale modeling research, as well as detailed and realistic treatment of hydrological variables, e.g. soil moisture (Meng et al., 2014). The framework of CREST model is shown in Fig. 2.

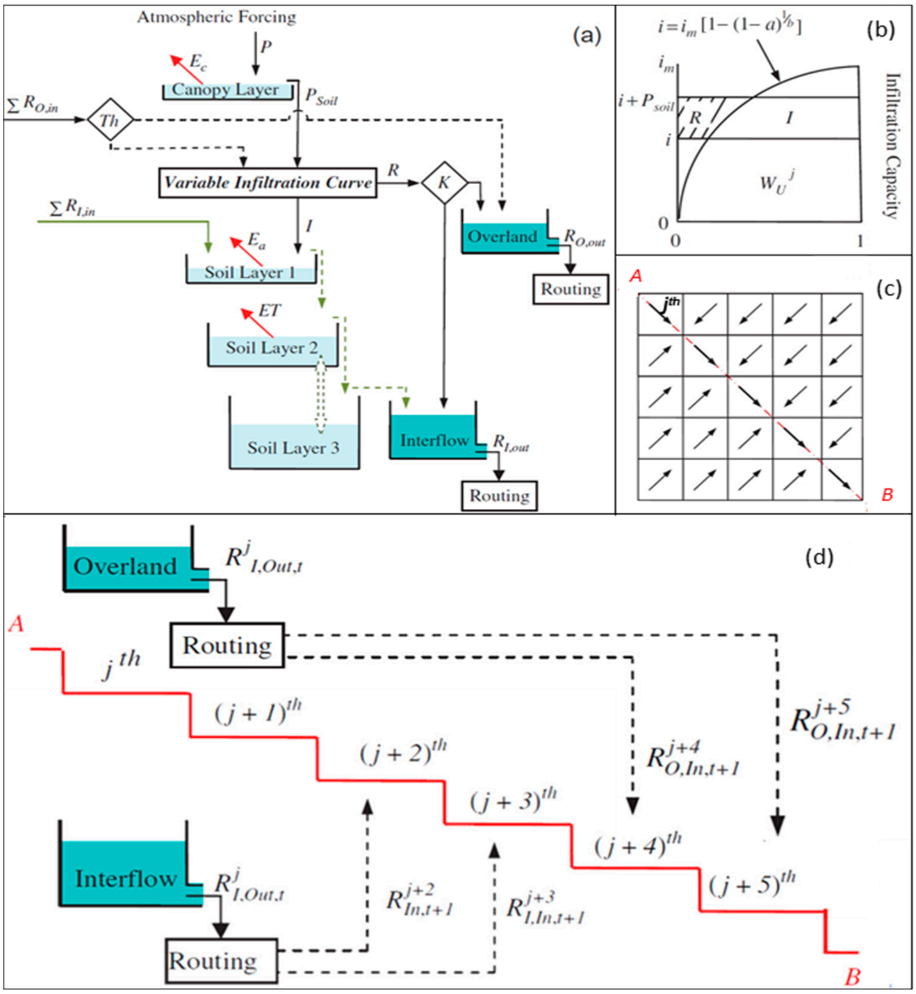

Fig. 2. Core components of CREST: (a) vertical profile of a cell including rainfall–runoff generation, evapotranspiration, sub-grid cell routing and feedbacks from routing; (b) variable infiltration curve of a cell; (c) plane view of cells and flow directions; and (d) vertical profile along several cells including sub-grid cell routing, downstream routing and subsurface runoff redistribution from a cell to its downstream cells.

2.3 Kriging interpolation

Kriging interpolation technique, named after the South-African mining engineer who developed this method in the 1950s, was adopted in our research (Matheron, 1963). It was originally proposed to evaluate the natural resources storage, and recently are widely used in constructing grid data from point data series, or predicting data at location with no data based on the spatial autocorrelation of observed data after improvement (Aalto et al., 2012; Zhu and Li, 2009). The basic formula are as follows,

$$F（x,y） = \sum_{i=0}^{n} w_i z_i \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j \gamma(x_i, x_j) + \mu = \gamma(x_i, x) \tag{2}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{3}$$

$$\sigma_k{}^2 = \sum_{i=1}^{n} \lambda_i \gamma(x_i, x) - \gamma(x, x) + \mu \tag{4}$$

here, F(x,y) refers to the estimated value on the point with cooridination (x,y), n represents the number of discrete points, z_i is the value of each point, $w_i$means the weight of the points, $\lambda_i$is the weight coefficient, μ menns lagrange multiplier, γ is the variation coefficient, and σ_k refers to the variance.

2.4 Data acquisition and preparation

2.4.1 Elevation and river data

The basic elevation data of the catchment were downloaded from the hydrologic data center of the United States Geological Survey (USGS, http://hydrosheds.cr.usgs.gov/dataavail.php). The original digital elevation model (DEM), flow area chart (FAC) and the river flow direction (FDR) data were corrected and rectified in Arcgis 10.1, and finally tailored according to the border of study area (Fig. 3).

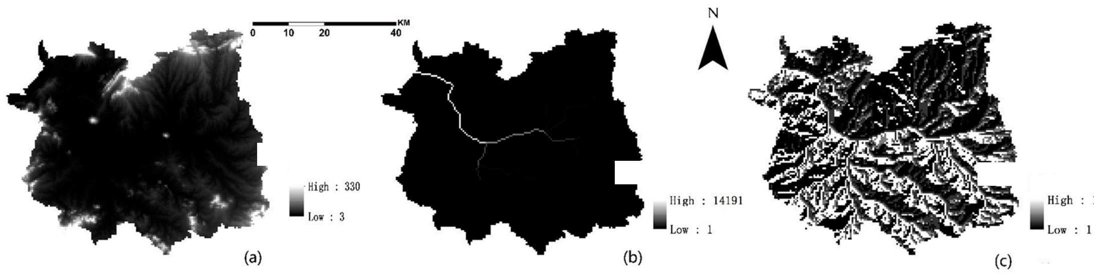

Fig. 3. The basic geographical information of the study area, (a) DEM, (b) FAC, (3) FDR.

The river network data were abstract from the 1:50000 digital topographic map (DGM), with the help of thematic map (TM image) with the resolution of 30 m from 2008. Finally 724 rivers were abstracted, among which, Jurong river and Lishui river are the main branch rivers of the catchment, with drain area of 1280 km^2 and 902 km^2 respectively.

2.4.2 Metrological data

2.4.2.1 Precipitation

The daily TRMM precipitation data from 2001 to 2006, and daily station precipitation data from Jurong, Qianhancun, Tianshengqiao, Zhaocun, Dongshan, Qilin, Wudingmen and Jiangning stations of the same period were collected. Due to the driven data of CREST model is required in grid format, interpolation processing to the point station precipitation data was carried out in Arcgis 10.1 based on Kriging interpolation technique. Actually we also made the interpolation based on other methodology, for example, inverse distance weighted method (IDW). However, no clear evidence that the Kriging interpolation has lower accuracy. Finally, the spatial distribution of the Kriging interpolated annual precipitation is shown in Fig. 4 (left).

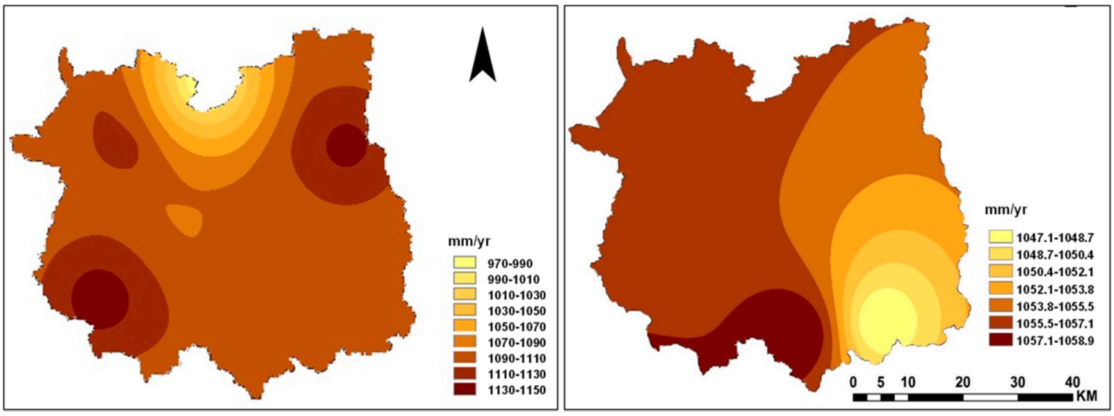

Fig. 4. The distribution of interpolated annually precipitation (left) and evapotranspiration (right).

In order to test the accuracy of Kriging interpolation. The data from the eighth precipitation station, Xiajiabian were adopted. We abstracted the interpolated precipitation data from the distribution map according to the coordination of Xiajiabian, and then compared it with the gauged precipitation. The mean absolute error and relative error were around 1 mm/day and -1.84% respectively. This proved the high reliability of the Kringing interpolation. In addition, comparison between the averaged station precipitation and the TRMM precipitation were made and the results were shown in Fig. 5. The TRMM data tends to overestimated the storm volume in general. The relative error between the two series was around 68.79%.

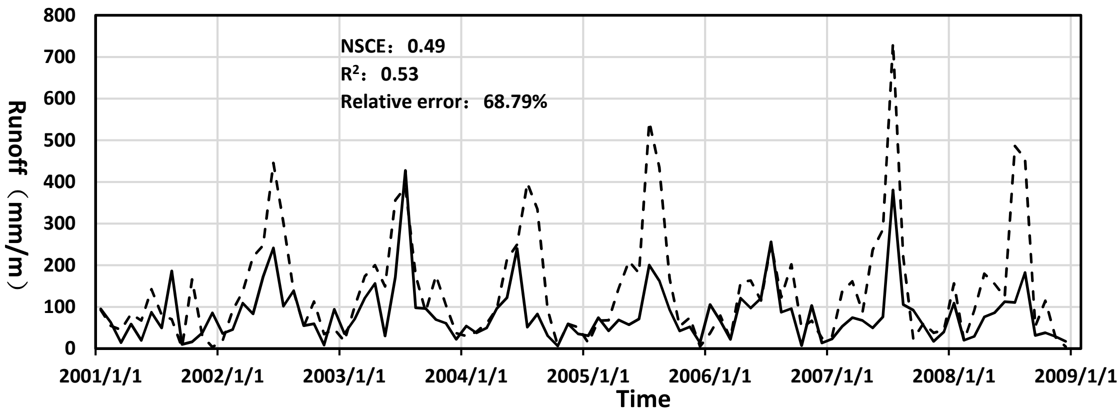

Fig. 5. The monthly averaged station gauaged precipitation (solid line) and the TRMM precipitation (dashed line)

2.4.2.2 Evapotranspiration (PET)

Three series of PET data during the study period were available in Qinhuai catchment, the gauged date from Nanjing metrology station, the estimated data based on empirical formula, and the FEWS downloaded data (http://earlywarning.usgs.gov/fews/datadownloads/Global/PET). The gauged PET data was the only real measured data based on one evaporating dish inside the station. It was a single point data which was not sufficient to drive the model, but was a reliable reference in evaluating the other two series. The PET data can be estimated by the empirical formal, based on the energy and temperature (Hargreaves and Allen, 2003; Hargreaves and Samani, 1985). Estimation based on Blaney-Criddle method, Abtew method and Hargreaves were carried out, and the results indicated that the Hargreaves estimation shows the highest agreement with the gauged data. Therefore, we mainly focus on the explanation of Hargreaves method.

Hargreaves methodology was first proposed in 1975, further developed in 1985, and has been proven to be very efficient and accurate in PET estimation (Archibald and Walter, 2014; Klein et al., 2015). The formula is as follows,

$$PET = K_{ET} S_P \Delta T^{0.5} (T + 17.8) \tag{5}$$

where PET is the daily evapotranspation mm/day; S_P is the potential solar radiation (kJ/m²/day); K_{ET} is the calibration coefficient; ΔT is the daily temperature range (T_{max}-T_{min}) (°C); T is the daily averaged temperature (°C).

A modification was made to the synthetic PET based on the empirical coefficient correction method, to get the final daily PET of the current study area. Fig. 6 gives the trend lines of the three PET series. The estimated and downloaded data fit the gauged data well in the troughs time period. Pervading over estimation occurred at the peak value position, especially from 2002 to 2007. The Hargreaves estimated data has relatively higher quality, compared with the downloaded one.

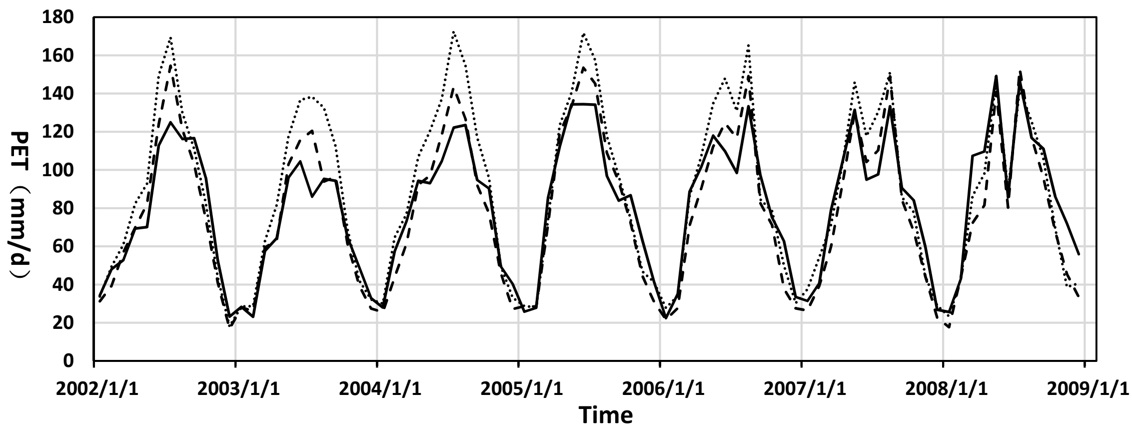

Fig. 6. The PET data from gauage station (solid line), Hargreaves estiamtion (dashed line) and FEWS downloaded (dotted line).

The interpolation processing based on the IDW The source, resolution, interpolation method and the number of the data source about the precipitation and PET data used to drive the model were summarized in table.

Tab. 1. The detail information about precipitaiton and PET data

Data	**Source**	**Resolution**		**Number of data source**	**Models**		
		Spatial (m)	Temporal		T1	T2	S
Precipitation	TRMM	30000	Monthly	4	√		
	Station	450	Monthly	7		√	√
PET	FEWS	110000	Daily	1		√	
	Station	450	Daily	6	√		√

2.5 Model construction and calibration

Based on the satellite remote sensing data, the CREST model was designed to enable multi-scale hydrological modeling. The key remote sensing data can be interpolated to the suitable resolution. This study applies the CREST model to the Qinhuai basin with metrological data of different spatial resolution, to investigate the sensitivity of the model. In addition to the topography related data and metrological date mentioned in the former part, the land cover, vegetation coverage and soil distribution were necessary and determined by field survey. The input data has strict format requirement in CREST model. Tab. 2 gives the format and resolution of each input data.

Tab. 2. The input information of CREST Model

Modules	**Input data**	**Resolution (m)**	**Format**
Basics	DEM (Degital elevation model)	450	ASC
	FAC (Flow area)	450	ASC
	FDR (Flow direction)	450	ASC
	Slope	—	DEF
	Stream (River network)	450	ASC
Calib	Calbirated parameters	—	TXT
ICS	Initial condition setting	—	TXT
OBS	The obverserved flow series	—	CVS
	The outlet location	—	Shpfile
Param	Hydrological parameters	—	TXT
Metro	PET external file	450/110000	ASC
	PET internal file	—	MAT
	Precipitation external file	450/30000	ASC
	Precipitation internal file	—	MAT

The study period was divided into calibration period from 2001 to 2005, and validation period from 2006 to 2008. The warm-up period required by the CREST model was included in the calibration period, from Jan. 1st to Jan 31st 2001. Instead of manual calibration with higher uncertainty due to the man-induced factor, CREST model allows automatic calibration based on the embedded adaptive random search method (ARS). This study adopted four commonly used statistical criteria, the Nash–Sutcliffe Coefficient of Efficiency (NSCE), the relative bias ratio (BIS), the mean absolute error (MAE) and the correlation coefficient (r) to evaluate the hydrological model performance. The definition of each criteria are defined in Tab. 3.

Tab. 3. The evaluation parameters and their definitions

	NSCE	**Explaination**
NSCE	$\mathrm{NSCE} = 1 - \frac{\sum_{i=1}^{n}(\mathrm{OBS_i} - \mathrm{SIM_i})^2}{\sum_{i=1}^{n}(\mathrm{OBS_i} - \overline{\mathrm{OBS}})^2}$	SIM and OBS are the simulated and observed runoff , mm/d; $\overline{\mathrm{SIM}}$ and $\overline{\mathrm{OBS}}$ present the average value of SIM
MAE(mm/d)	$MAE = \frac{\sum_{i=1}^{n}\lvert OBS_i - SIM_i\rvert}{n}$	
Bias (%)	$Bias = [\frac{\sum_{i=1}^{n} SIM_i - \sum_{i=1}^{n} OBS_i}{\sum_{i=1}^{n} OBS_i}] \times 100$	

r	$r = \left(\frac{\sum_{i=1}^{n}(OBS_i - \overline{OBS})(SIM_i - \overline{SIM})}{\sqrt{\sum_{i=1}^{n}(OBS_i - \overline{OBS})^2 \sum_{i=1}^{n}(SIM_i - \overline{SIM})^2}} \right)^2$	and OBS, mm/d; n is the number of sample; i refers to the ith simulated of observed value

3. Results and analysis

3.1 Model results

3.1.1 Model with TRMM precipitation (T1)

TRMM precipitation data was used to drive the Test model 1 (T1). The NSCE, R and Bias of the calibration period for monthly runoff were 0.39, 0.59 and 14.31%, in calibration period, respectively; while during validation period, the NSCE and r declined to 0.38 and 0.41, the Bias, on the contrary increased to 19.51% (Fig. 7). The simulation quality with the TRMM precipitation data was low calibration period and was even lower in calibration period. The total simulated and observed runoff of the study period were 13778.46 mm and 7885.76 mm, with a MAE of 194.51 mm/m. The simulation based on TRMM precipitation tended to over estimate the runoff series, especially during storm event, which is in accordance with the variation trend of the TRMM precipitation data.

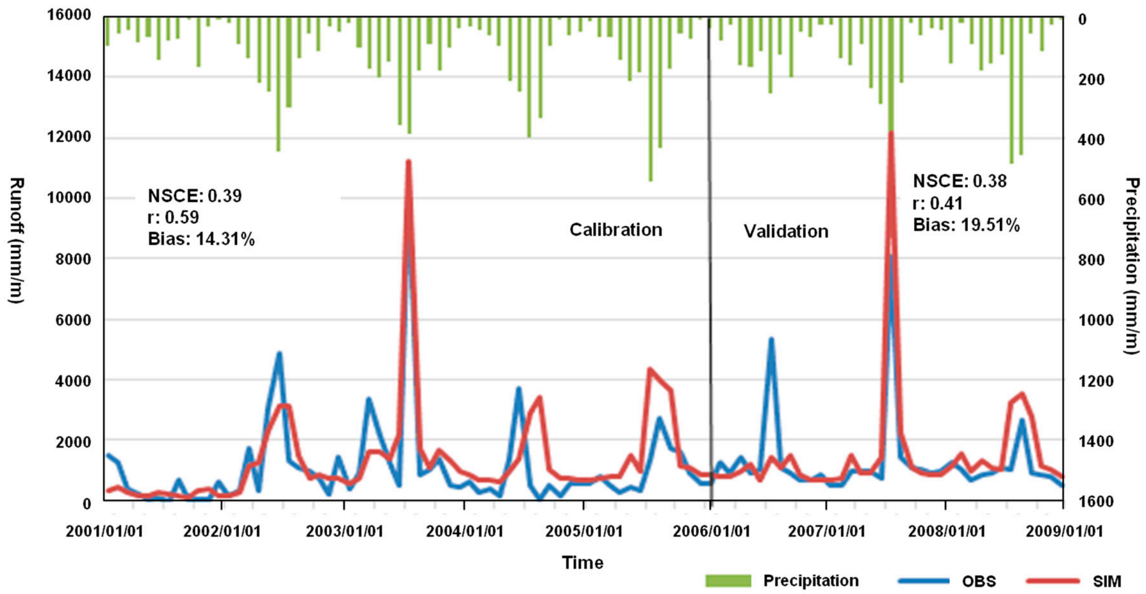

Fig. 7. Comparision of the monthly observed and simulated runoff series of the Model-T1.

3.1.2 Model with FEWS PET (T2)

Test model 2 (T2) simulated daily runoff series based on the FEWS PET and the results were show in Fig. 8. The simulation quality was relatively high compared with that of T1, with NSCE of 0.85 and 0.78, and r of 0.90 and 0.82 in calibration and validation term. The negative value of Bias, -9.38% and -25.99% suggested the under estimation of the T2 model, and the under estimation trend was even stronger in the validation term. The average AME of the estimated runoff in former and later

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term were 17.39 mm/d and 25.30 mm/d. According to Fig. 8, under estimation occurred not only during storm event, but also in the wet days.

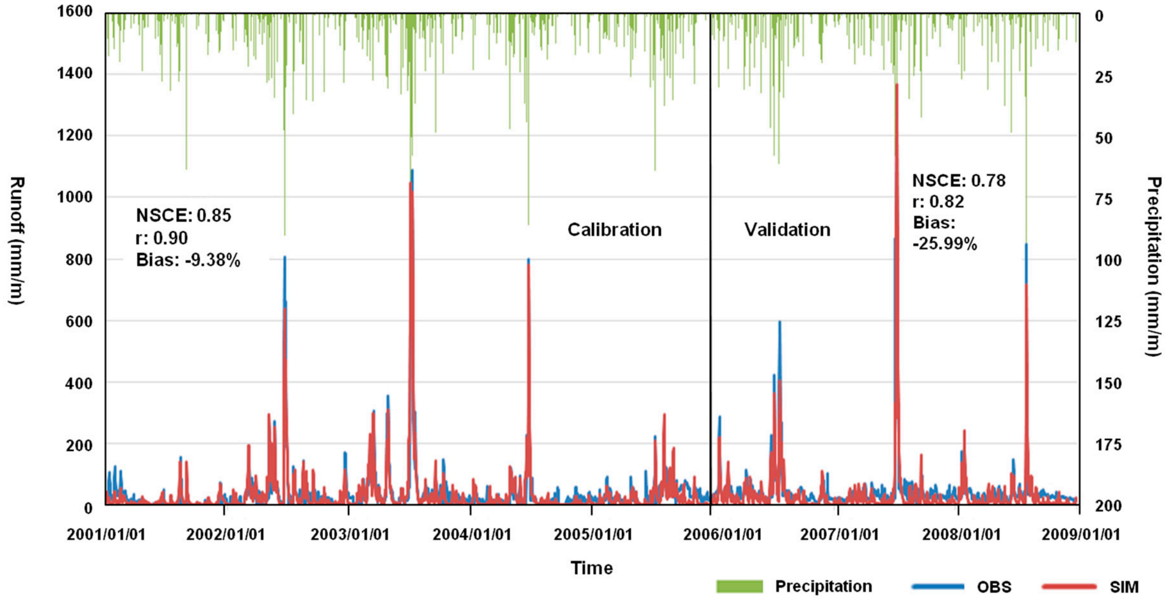

Fig. 8. Comparision of the daily observed and simulated runoff series of the Model-T2.

3.1.3 Model with gauged precipitation and estimated PET (S)

The standard model (S), driven by the interpolated gauged precipitation and PET data produced best results compared with T1 and T2. As shown in Fig. 9, the NSCE, r increased to 0.91 and 0.79 in calibration and validation process. Although the absolute Bias increase to -19.28% and -32.73%, the MAE had a slight decrease, to 16.85 and 24.29 mm/day, in former and latter period respectively. Moreover, the simulated date shows understand estimation trend in general, despite the results of storm events were in relatively better accordance.

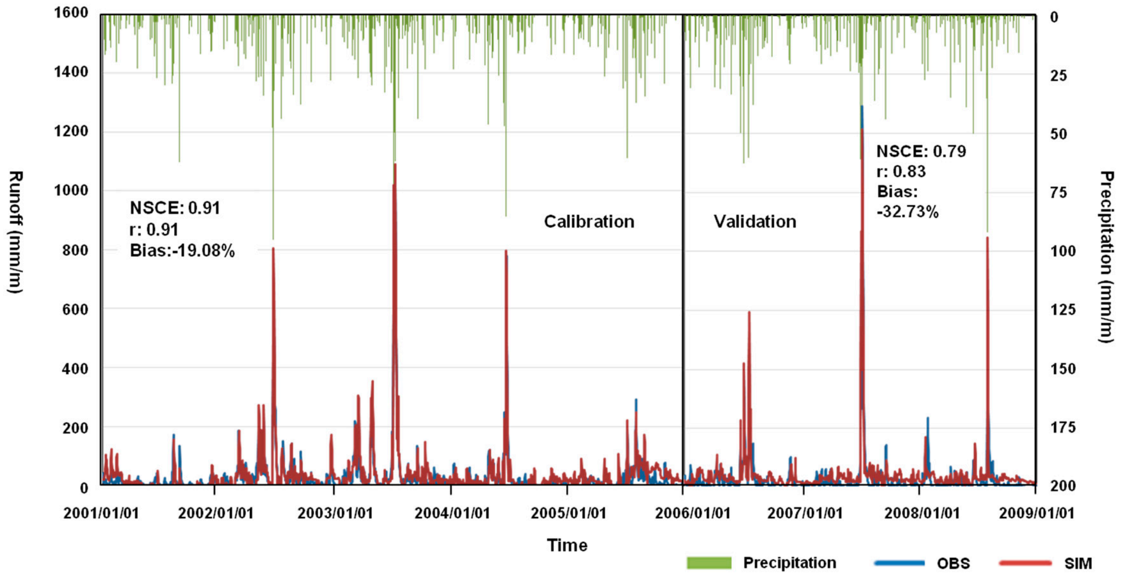

Fig. 9. Comparision of the daily observed and simulated runoff series of the Model-S.

Compared the three simulation, T1, T2 and S, the influence of the precipitation data source was much higher than that of the PET data. The low resolution and high over estimation of the TRMM precipitation data lead to the over estimation of the runoff. While the under estimation of the model T2 and S were resulted from the over estimation PET data. Although the FEWS PET data has lower spatial resolution and higher error combined to the gauged PET data, the model results were comparable to the model S. This indicated the insensitivity of the CREST model to the PET data source.

Both monthly and daily simulation were carried out to the three models. The daily simulated results of T1 model was hundreds times higher or lower than the observed value, indicating very less practical significance. Therefore it was not shown in this paper. The monthly simulation efficiency of T1 has been discussed in former part. For the reason of non-repetition, only the monthly simulation efficiency of model T2 and S were shown here (Tab. 4). Slightly superiority of models S was found according to Tab. 4.

Tab. 4. The efficiency of monthly runoff simulation

Model	Period	NSCE	MAE (mm/m)	R
T2	Calibration	0.93	299.63	0.93
	Validation	0.79	467.06	0.86
S	Calibration	0.93	300.18	0.95
	Validation	0.86	456.25	0.86

3.2 Storm simulation

The simulation during flood season or storm event is of great significance, especially for the small urban catchment confronting increasing flood risk. Six classical storm events, three of which were from calibration term and the other three from validation term, were picked up to test the simulation quality of model T2 and S in this part. The results were shown in Tab. 5 and Fig. 10. In general, the trend lines of T2 and S simulated runoff were nearly overlapped with each other, and reflected the trend of the observed data. The averaged NSCE and r of the six events were 0.84 and 0.89 for T2 model, and 0.86 and 0.90 for S model respectively. The averaged MAE were 67.30 and 62.09 mm/d, which confirmed the high quality of the FEWS PET data driven model. The estimated flood peak volume were lower than observed data, while the flood rising and recession process were mostly over estimated, which resulted in relatively short and wide flood hydrograph.

Tab. 5. The efficiency of storm runoff simulation

		Flood volume (mm)			Bias		MAE (mm)		NSCE		r	
		Observed	T2	S	T2	S	T2	S	T2	S	T2	S
Calibrated	2002 Jun	4914.56	4113.81	4191.74	-0.16	-0.15	62.57	61.74	0.88	0.89	0.97	0.97
	2003 Jul	10642.80	11795.10	11457.47	0.11	0.08	45.62	38.95	0.96	0.97	0.97	0.98
	2004 Jun	3872.26	4643.79	4549.33	0.20	0.17	49.68	46.58	0.90	0.91	0.92	0.93
Validated	2006 Jul	6063.66	5509.44	5342.55	-0.09	-0.12	40.81	41.12	0.83	0.83	0.93	0.94
	2007 Jul	7740.70	8218.59	8100.14	0.06	0.05	99.07	98.81	0.83	0.84	0.84	0.84
	2008 Aug	2153.00	3244.01	2748.07	0.51	0.28	106.08	85.35	0.63	0.72	0.74	0.76
Averaged		5897.83	6254.12	6064.88	0.10	0.05	67.30	62.09	0.84	0.86	0.89	0.90

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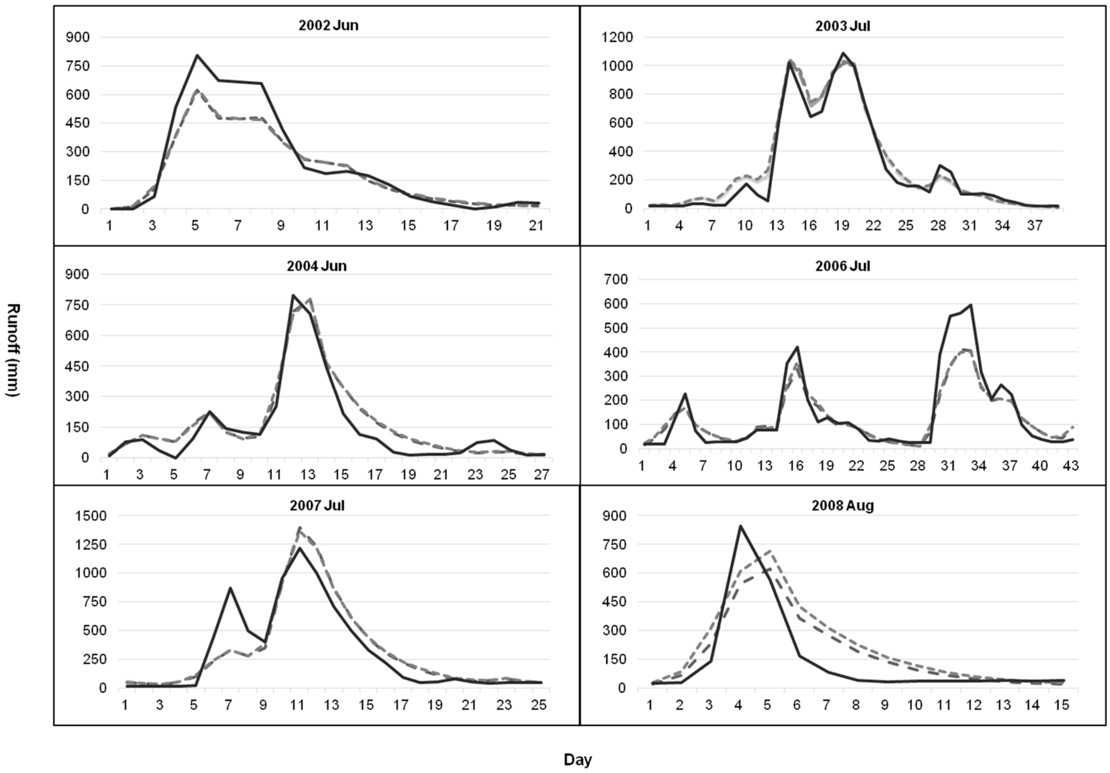

Fig. 10. The observed (solid lines) and simulated runoff series of model T2 (dotted lines) and S (dashed lines) during storm event.

The simulated and observed peak flow data were shown in Tab. 6. The FEWS PET driven model produced peak flow results with higher accuracy, with a MAE of 118.48mm, 23mm less that the error of model S. The simulated peak volume is -10.52% and -12.13% lower than observed data averagely, from model T2 and S respectively. The only over estimation occurred during the highest flood peak, with volume around 1214 mm in July 2007.

Tab. 6. The observed and simulated peak flow

		Peak volume (mm)			Bias (%)		MAE (mm)	
		Observed	T2	S	T2	S	T2	S
Calibrated	**2002 Jun**	806.00	636.61	623.42	-21.02	-22.65	169.39	182.58
	2003 Jul	1090.00	1046.27	1030.14	-4.01	-5.49	43.73	59.86
	2004 Jun	798.00	778.80	778.27	-2.41	-2.47	19.20	19.73
Validated	**2006 Jul**	595.00	400.87	412.01	-32.63	-30.75	194.13	182.99
	2007 Jul	1214.00	1366.35	1395.36	12.55	14.94	152.35	181.36
	2008 Aug	847.00	714.93	623.81	-15.59	-26.35	132.07	223.19
Averaged		891.67	823.97	810.50	-10.52	-12.13	118.48	141.62

As shown in Fig. 11, the Bias of the estimation have a clearly increase trend with the growing of peak volume, with the determination coefficient (R^2) of 0.78 and 0.69 for T2 and S. When the peak flow was under 1000 mm, the underestimation occurred, while over estimation happened only when the peak reach to the 1200 mm. The model seems to be more applicable to the medium peak event, with volume around 1000-1200 mm.

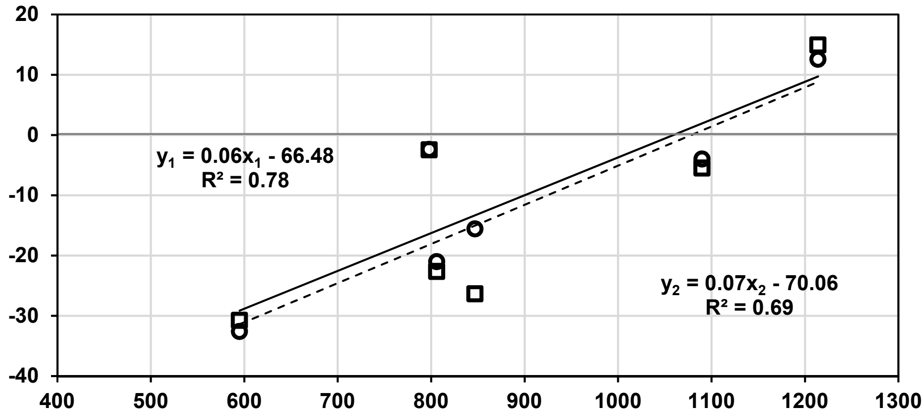

Fig. 11. The estimated errors and trend lines of simulated peak flow of model T2 (round dot, solid line) and S (square dots, dashed line).

4. Discussion

4.1 Relibality of CREST model

The SWAT (Soil and Water Assessment Tool, developed by the US Department of Agriculture and the Texas Experimental Station) and HEC-HMS (developed by the US Army Corps of Engineers Hydrologic Engineering Centre (HEC)) model of Qinhuai catchment has been constructed and applied years ago (Du et al., 2013, 2012). The long-term flow simulation quality of the three models were summarized in Tab. 7. As shown in Tab. 7, the NSCE and R of CREST and HEC-HMS model were the highest and lowest among the three models. The Bias indicated that SWAT model produced results with best quality, while CREST model showed worst quality results. The high value of NSCE and R suggested the efficient performance of CTRST model, while the high Bias represented the under estimation of the model. One possibility of the high Bias of CREST might lie in the frequent under estimation during the study period. The HEC-HMS and SWAT simulated were, on the contrary, sometimes higher than the observed value, and in some other time lower than the real condition. The balance of positive error and negative error lead to the relatively low Bias.

Tab. 7. The observed and simulated long-term flow series of three models

	Calibrated			Validated		
	CREST	HEC-HMS	SWAT	CREST	HEC-HMS	SWAT
NSCE	0.93	0.78	0.85	0.86	0.77	0.78
R	0.95	0.79	0.85	0.86	0.79	0.80
Bias (%)	-19.08	-13.03	6.52	-32.73	10.40	14.5

Only four same flood event simulation based on HEC-HMS and CREST were available, the volume and simulated error of which have been shown in Tab. 8. When we compared the Bias and MAE of each flood and the averaged condition, the CREST simulated volume is much closer to the observed data (Tab. 8). While during peak simulation, the HEC-HMS model presented higher accuracy (Tab. 8). Compared with the HEC-HMS, CREST model require less catchment underlying surface information and has superior efficiency in model construction and calibration. Despite the relative simpler of structure, the CREST model provide very high quality results in the flood simulation.

Tab. 8. The observed and simulated peak flow

Flood simulation	**Volume (mm)**			**error**			
	observed	CREST	HEC-HMS	Bias (%)		MAE (mm)	
				CREST	HEC-HMS	CREST	HEC-HMS
2002.06	4914.56	4191.74	6683.80	-14.71	36	722.82	1769.24
2003.06	10642.80	11457.47	14687.06	7.65	38	814.67	4044.26
2004.06	3872.26	4549.33	3446.31	17.49	-11	677.07	425.95
2006.07	6063.66	5342.55	5457.29	-11.89	-10	721.11	606.37
Averaged	6373.32	6385.27	7568.62	-0.37	13.25	733.92	1711.46
Peak simulation	**Volume (mm)**			**error**			
	observed	CREST	HEC-HMS	Bias (%)		MAE (mm)	
				CREST	HEC-HMS	CREST	HEC-HMS
2002.06	806	623.42	979.00	-22.65	21.46	182.58	173.00
2003.06	1106	1030.14	1115.00	-6.86	0.81	75.86	9.00
2004.06	798	778.27	871.00	-2.47	9.15	19.73	73.00
2006.07	595	412.01	556.00	-30.75	-6.55	182.99	39.00
Averaged	826.25	710.96	880.25	-15.68	6.22	115.29	73.50

4.2 TRMM data and its suitability

Plenty of literature about the suitability of TRMM precipitation data in hydrologic models are available. The TRMM data were normally adopted in large scale catchment and TRMM-based calculated hydrographs are comparable with those obtained using station data, with better monthly performance and discounted daily performance (Collischonn et al., 2008; Huffman et al., 2007; Meng et al., 2014; Nicholson et al., 2003). In our study, the TRMM data driven CREST model reflected the runoff process in rather poor quality in monthly scale, which become worse in daily scale. According to the comparison TRMM data tend to over estimated the precipitation, especially during the storm event in this area. The substitution of gauged data with TRMM data is proven to be impractical in this small catchment, despite the relatively homogeneity of topography and climate condition inside the catchment.

4.3 PET data and its uncertainty

Various estimation of PET based on metrological parameters were proposed by previous researchers. The referenced data from evaporating dish was a point data, and is not able to describe the spatial variation of the catchment. The wide applied one based on temperature and solar radiation, such as Hargreaves estimation, was proven to be more reliable. On the contrary, the estimation based only on temperature, for example Blaney-Criddle PET data showed lower agreement with real data (Fig. 12). When we drove the CREST model with the Blaney-Criddle PET data, the efficiency declined compared with the Hargreaves and FEWS based model, especially during the storm event simulation. In conclusion, despite the spatial distribution of PET data was revealed in the interpolated-estimated data, the simulated results from these data were not improved much. The model was more responsive to the PET from different estimation method, instead of the spatial resolution of PET.

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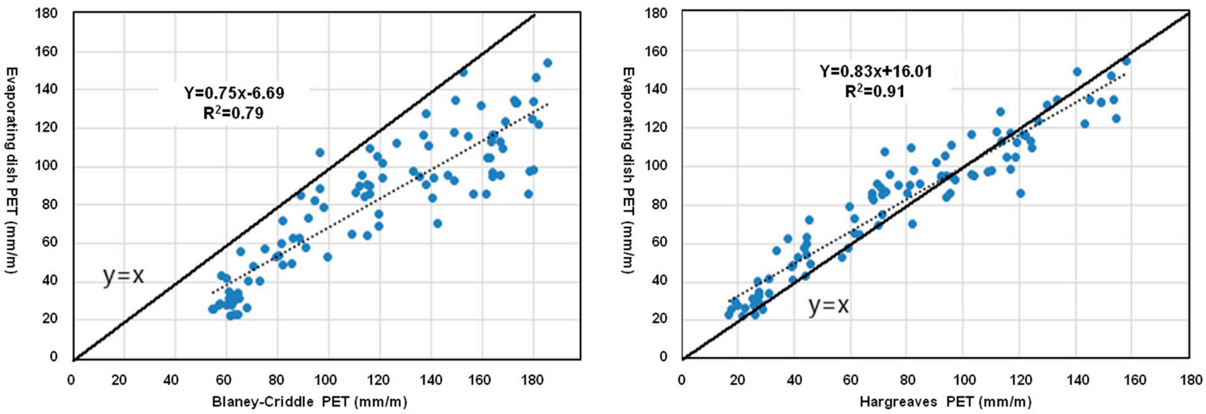

Fig. 12. The evaporating dish PET against Blaney-Criddle and Hargreaves estimated PET, the solid line is the ideal fitting line, and the dotted line is the real fitting line.

5. Conclusion and outlook

This research focus on the influence of the metrological inputs from different source on the performance of the CREST model. The model driven by the satellite precipitation TRMM plus gauge-estimation PET (model T1), the gauged precipitation data plus the FEWS PET data (model T2), and the gauged precipitation data plus gauged based precipitation (model S) were constructed and separately. The models feeding by TRMM and FEWS were evaluated and the applicability of CREST model in small urbanized catchment, Qinhuai catchment located in the lower part of Yangtze River Delta, was evaluated. The results revealed that,

The sensitivity of CREST model to precipitation data was strong. TRMM precipitation was not sufficient to substitute the station gauged data in Qinhuai catchment even in simulation with monthly step.
CREST model was not responsive to the spatial resolution of PET data. Both FEWS and gauge-estimated PET data input provided satisfied runoff output. Instead, the estimation method of the PET data was influential to the model performance.
Compared with other distributed/semi-distributed models, CREST produced acceptable long-term runoff series, and high accurate flood runoff simulation.

The above discussion and conclusions indicate the necessity of further develop of satellite precipitation monitor, both in spatial resolution and data precision, especially during storm event. The new generation of satellite product, GPM, is expected to improve the availability and accuracy of precipitation estimation (Wang, 2015). Accordingly, the hydrological simulation driven by GPM precipitation will be improved. The largely improvement of satellite precipitation would be combined with, but never completely replace the conventional precipitation data.
The data quality of PET series, mainly depend on the estimation formula and sample approach. Given most hydrological model is not responsive to the spatial resolution, but the data quality of PET, to improved the satellite monitor PET in the future would be sufficiently improve the performance of multi-scale hydrological simulation.

The limitations of the input data, the structure of the mathematical representation of hydrological processes, and the incomplete information of basin characteristics, result in the uncertainty in hydrological model calibration. Deciding the appropriate model and exploring for a unique set of model parameters of a given catchment which produce output with highest quality has been the topic of hydrologist since a long time. There always exist more than one model to accurately describe the hydrological processes of a certain catchment, each of which adept to present different lateral hydrological characteristic. CREST model, despite incapable of reflecting land use condition, has relatively simple structure reproduce high precise flood process. The scientific and practical significance of this is concentrate in the flood forecast and management. Combine with other hydrological models, more informative and accurate hydrograph of the study area can be provided, which will then improve the practical and predictive approaches of this area.

Author Contributions statement

Y.P. Xu, J.K. Du and S. Song designed the research. J.L. Wang and Q. Wang preprocessed the data and setup the model. S. Song conducted statistical analysis and drafted the manuscript. J.X. Zhang provided strategic advice and comments on the manuscript. All authors reviewed the manuscript.

Competing financial interests

The authors declare no competing financial interests.

Literature

Aalto, J., Pirinen, P., Heikkinen, J., Venäläinen, A., 2012. Spatial interpolation of monthly climate data for Finland: comparing the performance of kriging and generalized additive models. Theor. Appl. Climatol. 112, 99–111. doi:10.1007/s00704-012-0716-9

Andréassian, V., Perrin, C., Michel, C., Usart-Sanchez, I., Lavabre, J., 2001. Impact of imperfect rainfall knowledge on the efficiency and the parameters of watershed models. J. Hydrol. 250, 206–223. doi:10.1016/S0022-1694(01)00437-1

Archibald, J.A., Walter, M.T., 2014. Do Energy-Based PET Models Require More Input Data than Temperature-Based Models? — An Evaluation at Four Humid FluxNet Sites. JAWRA J. Am. Water Resour. Assoc. 50, 497–508. doi:10.1111/jawr.12137

Bárdossy, A., Das, T., 2008. Influence of rainfall observation network on model calibration and application. Hydrol Earth Syst Sci 12, 77–89. doi:10.5194/hess-12-77-2008

Barua, S., Muttil, N., Ng, A.W.M., Perera, B.J.C., 2013. Rainfall trend and its implications for water resource management within the Yarra River catchment, Australia. Hydrol. Process. 27, 1727–1738. doi:10.1002/hyp.9311

Boughton, W., Chiew, F., 2007. Estimating runoff in ungauged catchments from rainfall, PET and the AWBM model. Environ. Model. Softw., Special section: Environmental Risk and Emergency Management 22, 476–487. doi:10.1016/j.envsoft.2006.01.009

Brown, C.M., Lund, J.R., Cai, X., Reed, P.M., Zagona, E.A., Ostfeld, A., Hall, J., Characklis, G.W., Yu, W., Brekke, L., 2015. The future of water resources systems analysis: Toward a scientific framework for sustainable water management. Water Resour. Res. 51, 6110–6124. doi:10.1002/2015WR017114

Brunner, P., Simmons, C.T., 2012. HydroGeoSphere: A Fully Integrated, Physically Based Hydrological Model. Ground Water 50, 170–176. doi:10.1111/j.1745-6584.2011.00882.x

Burnash, R.J.C., 1995. The NWS river forecast system—catchment modeling, Computer Models of Watershed Hydrology, Water Resources Publications, V.P. Singh. ed. Highlands ranch, Co.

Butts, M.B., Payne, J.T., Kristensen, M., Madsen, H., 2004. An evaluation of the impact of model structure on hydrological modelling uncertainty for streamflow simulation. J. Hydrol., The Distributed Model Intercomparison Project (DMIP) 298, 242–266. doi:10.1016/j.jhydrol.2004.03.042

Chiew, F., Mcmahon, T., 1992. An Australian comparison of Penman's potential evapotranspiration estimates and class A evaporation pan data. Soil Res. 30, 101–112.

Chiew, F.H.S., McMahon, T.A., 1991. The Applicability of Morton's and Penman's Evapotranspiration Estimates in Rainfall-Runoff Modeling1. JAWRA J. Am. Water Resour. Assoc. 27, 611–620. doi:10.1111/j.1752-1688.1991.tb01462.x

Chu, H.-J., Lin, Y.-P., Huang, C.-W., Hsu, C.-Y., Chen, H.-Y., 2010. Modelling the hydrologic effects of dynamic land-use change using a distributed hydrologic model and a spatial land-use allocation model. Hydrol. Process. 24, 2538–2554. doi:10.1002/hyp.7667

Collischonn, B., Collischonn, W., Tucci, C.E.M., 2008. Daily hydrological modeling in the Amazon basin using TRMM rainfall estimates. J. Hydrol. 360, 207–216. doi:10.1016/j.jhydrol.2008.07.032

Dingman, S.L., 2002. Physical Hydrology. Prentice Hall, Boca Ratón.

Du, J., Qian, L., Rui, H., Zuo, T., Zheng, D., Xu, Y., Xu, C.-Y., 2012. Assessing the effects of urbanization on annual runoff and flood events using an integrated hydrological modeling system for Qinhuai River basin, China. J. Hydrol. 464–465, 127–139. doi:10.1016/j.jhydrol.2012.06.057

Du, J., Rui, H., Zuo, T., Li, Q., Zheng, D., Chen, A., Xu, Y., Xu, C.-Y., 2013. Hydrological Simulation by SWAT Model with Fixed and Varied Parameterization Approaches Under Land Use Change. Water Resour. Manag. 27, 2823–2838. doi:10.1007/s11269-013-0317-0

Ekström, M., Jones, P.D., Fowler, H.J., Lenderink, G., Buishand, T.A., Conway, D., 2007. Regional climate model data used within the SWURVE project ? 1: projected changes in seasonal patterns and estimation of PET. Hydrol. Earth Syst. Sci. Discuss. 11, 1069–1083.

Ficchì, A., Perrin, C., Andréassian, V., 2016. Impact of temporal resolution of inputs on hydrological model performance: An analysis based on 2400 flood events. J. Hydrol. 538, 454–470. doi:10.1016/j.jhydrol.2016.04.016

Fowler, A., 2002. Assessment of the validity of using mean potential evaporation in computations of the long-term soil water balance. J. Hydrol. 256, 248–263. doi:10.1016/S0022-1694(01)00542-X

Franczyk, J., Chang, H., 2009. The effects of climate change and urbanization on the runoff of the Rock Creek basin in the Portland metropolitan area, Oregon, USA. Hydrol. Process. 23, 805–815. doi:10.1002/hyp.7176

Hargreaves, G., Allen, R., 2003. History and Evaluation of Hargreaves Evapotranspiration Equation. J. Irrig. Drain. Eng. 129, 53–63. doi:10.1061/(ASCE)0733-9437(2003)129:1(53)

Hargreaves, G.H., Samani, Z.A., 1985. Reference Crop Evapotranspiration from Temperature. Appl. Eng. Agric. 1, 96–99.

Henriksen, H.J., Troldborg, L., Nyegaard, P., Sonnenborg, T.O., Refsgaard, J.C., Madsen, B., 2003. Methodology for construction, calibration and validation of a national hydrological model for Denmark. J. Hydrol. 280, 52–71. doi:10.1016/S0022-1694(03)00186-0

Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman, K.P., Stocker, E.F., 2007. The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. J. Hydrometeorol. 8, 38–55. doi:10.1175/JHM560.1

Im, S., Kim, H., Kim, C., Jang, C., 2009. Assessing the impacts of land use changes on watershed hydrology

 doi:10.20944/preprints201608.0134.v1

using MIKE SHE. Environ. Geol. 57, 231–239. doi:10.1007/s00254-008-1303-3

Jakeman, A.J., Hornberger, G.M., 1993. How much complexity is warranted in a rainfall-runoff model? Water Resour. Res. 29, 2637–2649. doi:10.1029/93WR00877

Kalbus, E., Kalbacher, T., Kolditz, O., Krüger, E., Seegert, J., Röstel, G., Teutsch, G., Borchardt, D., Krebs, P., 2011. Integrated Water Resources Management under different hydrological, climatic and socio-economic conditions. Environ. Earth Sci. 65, 1363–1366. doi:10.1007/s12665-011-1330-3

Khan, S.I., Adhikari, P., Hong, Y., Vergara, H., F Adler, R., Policelli, F., Irwin, D., Korme, T., Okello, L., 2011. Hydroclimatology of Lake Victoria region using hydrologic model and satellite remote sensing data. Hydrol Earth Syst Sci 15, 107–117. doi:10.5194/hess-15-107-2011

Khan, S.I., Hong, Y., Wang, J., Yilmaz, K.K., Gourley, J.J., Adler, R.F., Brakenridge, G.R., Policelli, F., Habib, S., Irwin, D., 2011. Satellite remote sensing and hydrologic modeling for flood inundation mapping in lake victoria basin: Implications for hydrologic prediction in ungauged basins. IEEE Trans. Geosci. Remote Sens. 49, 85–95. doi:10.1109/TGRS.2010.2057513

Klein, T., Randin, C., Körner, C., 2015. Water availability predicts forest canopy height at the global scale. Ecol. Lett. 18, 1311–1320. doi:10.1111/ele.12525

Kummerow, C., Simpson, J., Thiele, O., Barnes, W., Chang, A.T.C., Stocker, E., Adler, R.F., Hou, A., Kakar, R., Wentz, F., Ashcroft, P., Kozu, T., Hong, Y., Okamoto, K., Iguchi, T., Kuroiwa, H., Im, E., Haddad, Z., Huffman, G., Ferrier, B., Olson, W.S., Zipser, E., Smith, E.A., Wilheit, T.T., North, G., Krishnamurti, T., Nakamura, K., 2000. The Status of the Tropical Rainfall Measuring Mission (TRMM) after Two Years in Orbit. J. Appl. Meteorol. 39, 1965–1982. doi:10.1175/1520-0450(2001)040<1965:TSOTTR>2.0.CO;2

Kvočka, D., Falconer, R.A., Bray, M., 2015. Appropriate model use for predicting elevations and inundation extent for extreme flood events. Nat. Hazards 79, 1791–1808. doi:10.1007/s11069-015-1926-0

Lin, Y.-P., Verburg, P.H., Chang, C.-R., Chen, H.-Y., Chen, M.-H., 2009. Developing and comparing optimal and empirical land-use models for the development of an urbanized watershed forest in Taiwan. Landsc. Urban Plan. 92, 242–254. doi:10.1016/j.landurbplan.2009.05.003

Lindström, G., Johansson, B., Persson, M., Gardelin, M., Bergström, S., 1997. Development and test of the distributed HBV-96 hydrological model. J. Hydrol. 201, 272–288. doi:10.1016/S0022-1694(97)00041-3

Liu, Z., Martina, M.L.V., Todini, E., 2005. Flood forecasting using a fully distributed model: application of the TOPKAPI model to the Upper Xixian Catchment. Hydrol. Earth Syst. Sci. Discuss. 9, 347–364.

Lopes, V.L., 1996. On the effect of uncertainty in spatial distribution of rainfall on catchment modelling. Catena 28, 107–119. doi:10.1016/S0341-8162(96)00030-6

Matheron, G., 1963. Principles of geostatistics. Econ. Geol. 58, 1246–1266. doi:10.2113/gsecongeo.58.8.1246

Meng, J., Li, L., Hao, Z., Wang, J., Shao, Q., 2014. Suitability of TRMM satellite rainfall in driving a distributed hydrological model in the source region of Yellow River. J. Hydrol. 509, 320–332. doi:10.1016/j.jhydrol.2013.11.049

Milly, P., 2015. Potential Evapotranspiration as a Source of Uncertainty and Bias in Hydrologic Impact Analyses. Presented at the 2015 AGU Fall Meeting, Agu.

Montanari, A., Di Baldassarre, G., 2013. Data errors and hydrological modelling: The role of model structure to propagate observation uncertainty. Adv. Water Resour., 35th Year Anniversary Issue 51, 498–504. doi:10.1016/j.advwatres.2012.09.007

Nair, S., Srinivasan, G., Nemani, R., 2009. Evaluation of Multi-Satellite TRMM Derived Rainfall Estimates over a Western State of India. J. Meteorol. Soc. Jpn. Ser II 87, 927–939. doi:10.2151/jmsj.87.927

Nicholson, S.E., Some, B., McCollum, J., Nelkin, E., Klotter, D., Berte, Y., Diallo, B.M., Gaye, I., Kpabeba, G., Ndiaye, O., Noukpozounkou, J.N., Tanu, M.M., Thiam, A., Toure, A.A., Traore, A.K., 2003. Validation of TRMM and Other Rainfall Estimates with a High-Density Gauge Dataset for West Africa. Part II:

Validation of TRMM Rainfall Products. J. Appl. Meteorol. 42, 1355–1368. doi:10.1175/1520-0450(2003)042<1355:VOTAOR>2.0.CO;2

Oudin, L., Hervieu, F., Michel, C., Perrin, C., Andréassian, V., Anctil, F., Loumagne, C., 2005a. Which potential evapotranspiration input for a lumped rainfall–runoff model?: Part 2—Towards a simple and efficient potential evapotranspiration model for rainfall–runoff modelling. J. Hydrol. 303, 290–306. doi:10.1016/j.jhydrol.2004.08.026

Oudin, L., Michel, C., Anctil, F., 2005b. Which potential evapotranspiration input for a lumped rainfall-runoff model?: Part 1—Can rainfall-runoff models effectively handle detailed potential evapotranspiration inputs? J. Hydrol. 303, 275–289. doi:10.1016/j.jhydrol.2004.08.025

Rozante, J.R., Moreira, D.S., de Goncalves, L.G.G., Vila, D.A., 2010. Combining TRMM and Surface Observations of Precipitation: Technique and Validation over South America. Weather Forecast. 25, 885–894. doi:10.1175/2010WAF2222325.1

Sivapalan, M., Ruprecht, J.K., Viney, N.R., 1996. Water and salt balance modelling to predict the effects of land-use changes in forested catchments. 1. Small catchment water balance model. Hydrol. Process. 10, 393–411. doi:10.1002/(SICI)1099-1085(199603)10:3<393::AID-HYP307>3.0.CO;2-#

Stisen, S., Sandholt, I., 2010. Evaluation of remote-sensing-based rainfall products through predictive capability in hydrological runoff modelling. Hydrol. Process. 24, 879–891. doi:10.1002/hyp.7529

Strauch, M., Bernhofer, C., Koide, S., Volk, M., Lorz, C., Makeschin, F., 2012. Using precipitation data ensemble for uncertainty analysis in SWAT streamflow simulation. J. Hydrol. 414–415, 413–424. doi:10.1016/j.jhydrol.2011.11.014

Taesombat, W., Sriwongsitanon, N., 2009. Areal rainfall estimation using spatial interpolation techniques. ScienceAsia 35, 268–275. doi:10.2306/scienceasia1513-1874.2009.35.268

Tait, A., Woods, R., 2007. Spatial Interpolation of Daily Potential Evapotranspiration for New Zealand Using a Spline Model. J. Hydrometeorol. 8, 430–438. doi:10.1175/JHM572.1

Valeo, C., Moin, S.M.A., 2000. Variable source area modelling in urbanizing watersheds. J. Hydrol. 228, 68–81. doi:10.1016/S0022-1694(00)00153-0

Verdin, J., Lietzow, R., Rowland, J., Klaver, R., Reed, B., French, V., Lee, F., 2000. A comparison of methods for estimating start-of-season from operational remote sensing products: First results. USGS-EROS Data CenterSioux Falls Coll. Rep.

Vincente, G.A., Scofield, R.A., Menzel, W.P., 1998. The operational GOES infrared rainfall estimation technique. Bull. Am. Meteorol. Soc. 79, 1883.

Wang, J., 2015. Evaluation of GPM precipitation products using Q3 over the CONUS. Presented at the 2015 AGU Fall Meeting, Agu.

Xue, X., Hong, Y., Limaye, A.S., Gourley, J.J., Huffman, G.J., Khan, S.I., Dorji, C., Chen, S., 2013. Statistical and hydrological evaluation of TRMM-based Multi-satellite Precipitation Analysis over the Wangchu Basin of Bhutan: Are the latest satellite precipitation products 3B42V7 ready for use in ungauged basins? J. Hydrol. 499, 91–99. doi:10.1016/j.jhydrol.2013.06.042

Zhu, C., Li, S., 2009. Study on vertical velocity distribution with extra fine sediment. Presented at the International Conference on Test and Measurement, 2009. ICTM '09, pp. 260–263. doi:10.1109/ICTM.2009.5413058