Improving calibration of two key parameters in Hydrologic Engineering Center hydrologic modelling system, and analysing the influence of initial loss on flood peak flows

Musheng Lin, Xingwei Chen, Ying Chen and Huaxia Yao

ABSTRACT

Parameter calibration is a key and difficult issue for a hydrological model. Taking the Jinjiang Xixi watershed of south-east China as the study area, we proposed methods to improve the calibration of two very sensitive parameters, Muskingum *K* and initial loss, in the Hydrologic Engineering Center hydrologic modelling system (HEC-HMS) model. Twenty-three rainstorm flood events occurring from 1972 to 1977 were used to calibrate the model using a trial-and-error approach, and a relationship between initial loss and initial discharge for these flood events was established; seven rainstorm events occurring from 1978 to 1979 were used to validate the two parameters. The influence of initial loss change on different return-period floods was evaluated. A fixed Muskingum *K* value, which was calibrated by assuming a flow wave velocity at 3 m/s, could be used to simulate a flood hydrograph, and the empirical power-function relationship between initial loss and initial discharge made the model more applicable for flood forecasting. The influence of initial loss on peak floods was significant but not identical for different flood levels, and the change rate of peak floods caused by the same initial loss change was more remarkable when the return period increased.

Key words | calibration, HEC-HMS model, initial discharge, initial loss, Jinjiang Xixi Watershed, Muskingum *K*

Musheng Lin
Xingwei Chen (corresponding author)
Ying Chen
School of Geographic Science,
Fujian Normal University,
Fuzhou,
Fujian, 350007,
China
E-mail: *cxwchen215@163.com*

Huaxia Yao
Dorset Environmental Science Centre,
Ontario Ministry of the Environment,
1026 Bellwood Acres Road,
Dorset,
Ontario, P0A 1E0,
Canada

INTRODUCTION

The Hydrologic Engineering Center hydrologic modelling system (HEC-HMS), a HMS developed by the HEC of the US Army Corps of Engineers (2003), was used for modelling of flood events, stormflow forecasting and other purposes by many researchers or water resources engineers (Anderson *et al*. 2002; Knebl *et al*. 2005; Amengual *et al*. 2007; Yusop *et al*. 2007; Chen *et al*. 2009; Verma *et al*. 2010). We chose the model for our study, based on three reasons: its distribution structure is able to consider spatial variations in watershed condition and rainfall; its applications to flood modelling or forecasting have been increasing recently; and its parameter number is comparatively small, suitable to our study area.

Parameter calibration is important to successfully model storm events and provide flood predictions. Major parameters of the model include initial loss, *CN* (SCS curve number), basin lag time, Muskingum *K*, recession constant, and Muskingum *X*. Based on studies of parameter sensitivity (Sardoii *et al*. 2012; Tahmasbinejad *et al*. 2012), major sensitive parameters are identified as the *CN*, Muskingum *K*, initial loss and basin lag time. The Muskingum *X*, or the weight of inflow versus outflow (0–0.5) is not sensitive and not discussed in our study. Among the four sensitive ones, *CN* can be determined from land use and soil property data by using empirical tables established in the model system; basin lag time can be calculated via a GeoHEC-HMS component (USACE 2003); and therefore the Muskingum *K* and initial loss become a focus for calibrating the model. The initial loss means the lost precipitation during a stormflow event, prior to the onset of flood runoff. The loss is caused by plants' interception of precipitation in the watershed, depression storage on the watershed surface, initial infiltration into soil and evaporation loss. The Muskingum *K* is interpreted as the travel time of a flood wave along the channel reach. It is the ratio of river length to flood wave velocity, but the velocity is usually not measured.

doi: 10.2166/wst.2013.562

The HEC-HMS system provided two calibration methods for the users: a trial-and-error method and an automated optimisation (Skahill 2006). Both these methods have been used the initial loss in the literature to calibrate. There were also two situations when the initial loss was calibrated by the trial-and-error method: the initial loss was empirically fixed as 20% of the maximum soil water content in the watershed (Mashayekhi *et al*. 2010), or the initial loss was given different values for different rain events, and consequently it varied in a range (Lin & Chen 2010).

When initial loss was calibrated by the automated search method, its results varied with rain events used (Chen *et al*. 2009). Although the initial loss has been determined by the above two methods and the calibrated parameter could result in acceptable runoff modelling, concerns and questions do exist. If the initial loss is taken as a fixed number, this does not meet its physical definition as it does vary with time or events, and the fixation will impair the model's accuracy. If it is given as a changing range but the rule of change is unknown, it is still inconvenient to use the model for flood prediction (what value should be used for a certain rain-flood event?). Therefore, an important and necessary research is to improve the calibration of initial loss and provide a rule of how the initial loss should vary.

The Muskingum *K* is usually calibrated as a fixed value or a range (Rahajeng 2010), but the calibration procedure has not been described in detail and needs to be further studied. Further to the calibration of initial loss, the influence of initial loss on flood peak flows has not been well quantified.

Our research took the Jinjiang Xixi watershed as the study area, and calibrated Muskingum *K* by using flood wave speed, investigated the relationship of initial loss and initial discharge to regulate the changes in initial loss, and analysed the influence of initial loss on flood peak flows.

METHOD

Study site and data

Jinjiang Xixi basin is located in south-eastern Fujian Province of China (Figure 1) with an area of 2,466 km^2, and is characterised by a subtropical monsoon climate, average annual-mean temperature of 20.3 °C, and annual precipitation of 1,200 to 1,900 mm. The topography is dominated by mountains, hills and rangelands, higher on the north-west and lower on the south-east. Its major land use is forest (subtropical evergreen broadleaved forest) and cropland (tea garden and orchard), with the soil mainly being lateritic red soil.

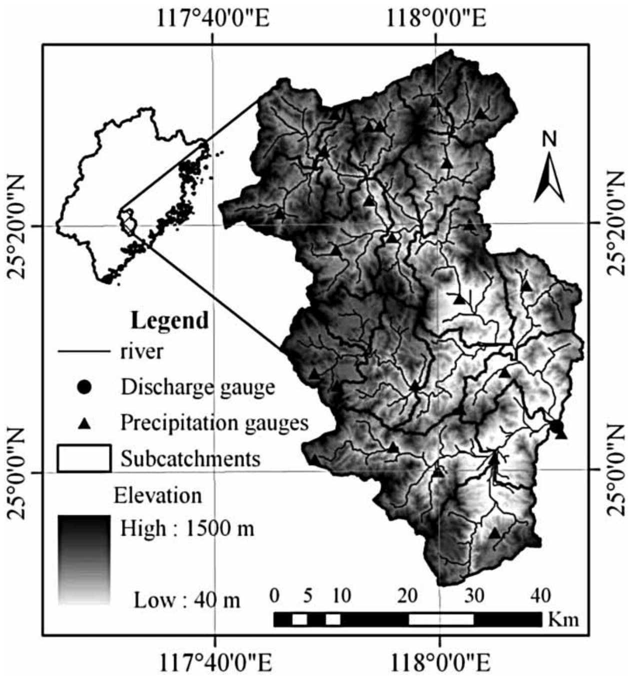

Figure 1 | Location of study watershed and its monitoring stations.

The datasets we used included a 30 m resolution digital elevation model, and the 1:100,000 land use data and soil information of 1985 provided by the provincial database. Hourly climate and hydrology data were available from 13–25 rain gauges and Anxi flow gauges (23°03′N, 118°10′E) in the Xixi watershed. Thirty storm events in the period 1972–1979 were prepared for model calibration. According to the China Department of Meteorology, a storm event is defined as its 24-hour rainfall being more than 50 mm. We chose 30 events from 1972–1979 based on the definition and the fact that the events represented various rain types in terms of their duration, rain volume and intensity. Selected events included all types of storms in our basin and ensured that the resultant analyses are robust to storm events and/or the study region.

Procedure of calibration

The distributed HEC-HMS model was firstly utilised in 2010 (Lin & Chen 2010) for the same study watershed, by using only eight storm events. Most calibrated parameters including the *CN*, recession constant, and Muskingum *X* did not change significantly when the storm events were increased, and therefore they are utilised for the present study without further corrections. Our focus is on the Muskingum *K* and initial loss. The 23 storm events in 1972–1977 are used to calibrate Muskingum K and initial loss, and the seven events in 1978–1979 are used to validate the calibration results.

The Muskingum K is calibrated by first calibrating the flood wave speed V, because the river length divided by the calibrated V value gives the Muskingum K value. The flood wave speed is determined with a trial-and-error method: adjusting its value from 1 to 7 m/s (a possible change range known from hydrological experience) and keeping all other parameters unchanged, running the model to get a flood hydrograph and comparing that to the observed one. The V value that gives the best agreement is chosen. Then the initial loss is calibrated for each of the 23 events, using the same trial-and-error method and objective function, producing various values. A relationship of initial loss to initial discharge is searched for and established based on the calibrated results, and the initial discharge is the one on the starting point of a flood hydrograph. According to the physical definitions of initial loss and initial discharge, they should be closely related. After the relationship of initial loss and discharge is expressed and all other parameters are calibrated from the 23 events, the model is further validated by using the remaining seven rain events which occurred in 1978–1979. For the assessment of model performance, five evaluation criteria were selected: relative error in flood peak flow (E_p), relative error in flood flow volume (E_v), error in peak flow time (E_t), the coefficient of determination (R^2), and the coefficient of efficiency (NS) (Nash & Sutcliffe 1970; Chen *et al*. 2009).

Analysing influence of initial loss

The influence of initial loss on flood peak flow is quantitatively analysed by designing storm-floods of different frequency and changing the initial loss value. At the hydrological monitoring station of the Xixi Watershed, the annual-maximum discharge has an average of 2,900 m^3/s, with a coefficient of variation 0.6 and a skewness coefficient 1.8 (Chen & Zhuang 1994). The station's flood peak flow of a 100-year return period is 8,990 m^3/s. An actual flood event (event number #730702) occurring on July 3 1973 is chosen for the analysis. It has a return period of 2.5 years in the flood record. The actual hourly rainfall time series is enlarged to produce two artificial storm events: one event generating a flood of 50-year return period and another generating a flood of 100-year return period. Then for each of the three cases (actual 2.5-year return, 50-year return, and 100-year return), the initial loss is supposed to change incrementally at 10 mm starting at 7 mm, as the initial loss varied between 7 and 68 mm (Figure 3). The 10 mm increment was good enough to find out the variation of peak flow with initial loss changes. The corresponding hydrograph is simulated by the model. The variations of the flood peak flow with the changes in initial loss can be displayed.

RESULTS AND DISCUSSION

Calibration of the Muskingum *K*

The trials for the Muskingum K are illustrated in Figure 2 (taking flood #720607 and #741017 as examples), with the flood wave speed V being tried from 1.0 to 7.0 m/s. It was found that $V = 3$ m/s could result in the best agreement between modelled and observed hourly discharges (see Table 1), for this and other flood events (similar results are not shown for other events because of limited page

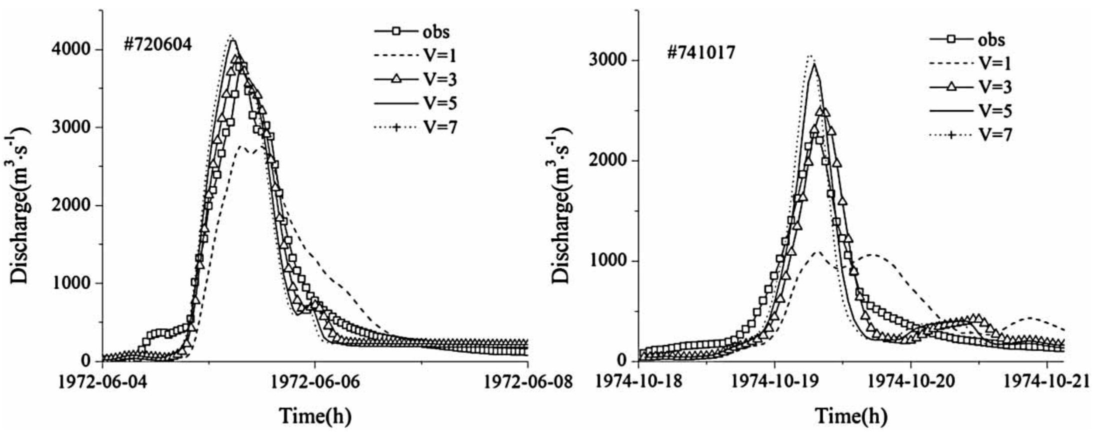

Figure 2 | Simulated floods at different flood wave speed.

Table 1 | Evaluations for simulated flood events, during both calibration and validation periods (obs is observed, mod is modelled, percent is percent error)

		Flood peak flow (m^3/s)			Flood volume (mm)					
Calibration or validation	Events	obs	mod	E_p (%)	obs	mod	E_v (%)	E_t[a] (h)	NS	R^2
Calibration	720604	3780	3864.7	2.24	117.31	112.34	– 4.24	– 1	0.94	0.96
	720709	2020	2255.7	11.67	68.14	74.29	9.03	2	0.85	0.96
	720807	1020	1124.5	10.25	30.06	27.08	– 9.91	– 1	0.89	0.94
	730401	1550	1858.4	19.90	54.97	57.89	5.31	8	0.88	0.85
	730406	1970	2051.3	4.13	70.86	63.87	– 9.86	– 1	0.90	0.88
	730702	3000	2696.2	– 10.13	47.82	48.34	1.09	1	0.95	0.96
	730716	3220	3449	7.11	126.49	131.13	3.67	1	0.94	0.95
	731009	3400	3048.7	– 10.33	58.33	57.84	– 0.84	2	0.91	0.89
	740524	1140	1161.8	1.91	16.65	14.24	– 14.47	1	0.88	0.91
	740622	1260	1560.3	23.83	46.41	43.47	– 6.33	– 1	0.70	0.85
	741017	2260	2479	9.69	63.29	63.9	0.96	1	0.89	0.90
	741108	1430	1557.8	8.94	57.15	57.01	– 0.24	1	0.89	0.94
	750610	1250	1307.9	4.63	48.09	42.29	– 12.06	– 2	0.65	0.74
	750923	2830	3048	7.70	77.38	72.8	– 5.92	3	0.80	0.87
	751005	2260	2082.5	– 7.85	73.11	72.31	– 1.09	0	0.90	0.82
	760526	1570	1518	– 3.31	22.12	22.14	0.09	0	0.89	0.91
	760810	1900	1829	– 3.74	33.28	28.95	– 13.01	2	0.89	0.89
	760825	2490	2687.5	7.93	75.68	65.18	– 13.87	1	0.76	0.83
	770527	1220	1381	13.20	43.91	43.82	– 0.20	6	0.86	0.89
	770601	1330	1471.6	10.65	20.61	19.28	– 6.45	0	0.76	0.84
	770801	1860	1746.8	– 6.09	38.76	33.78	– 12.85	2	0.86	0.88
	770815	1120	1132.3	1.10	30.54	29.86	– 2.23	0	0.94	0.96
	771001	1400	961.7	– 31.31	18.85	15.84	– 15.97	2	0.73	0.86
	Absolute mean			9.46	–	–	6.49	1.70	0.85	0.89
Validation	780616	1380	1578.5	14.38	22.92	22.21	– 3.10	1	0.80	0.93
	780622	1010	1079.7	6.90	27.14	25.74	– 5.16	0	0.87	0.89
	780822	824	920.4	11.70	45.87	53.33	16.26	0	0.79	0.87
	780828	1270	1230.9	– 3.08	26.77	23.47	– 12.33	0	0.89	0.91
	790402	843	689.5	– 18.21	18.44	13.64	– 26.03	– 2	0.69	0.74
	790610	2670	3766.2	41.06	94.99	106.43	12.04	0	0.75	0.97
	790822	929	894.6	– 3.70	19.24	13.92	– 27.65	0	0.83	0.91
	Absolute mean			14.14	–	–	14.65	0.43	0.80	0.89

[a]A negative value of error in peak time indicates an earlier peak occurrence, and a positive value indicates a later peak occurrence.

space). We propose that a fixed number for Muskingum K can work well for the model's application to our study watershed.

Calibration of initial loss

A proper value for initial loss was found out by trial-and-error regarding one of 23 flood events. The individual values of initial loss and initial discharge are shown in Figure 3. A power equation was found suitable to express the relationship between these two variables:

$$Y = 420.78X^{-0.7717} \quad R^2 = 0.721 \tag{1}$$

where Y is the initial loss (mm) and X is the initial discharge (m^3/s).

Figure 3 shows that for a larger initial discharge, the antecedent soil moisture prior to the storm-flood event would be wetter and rain's infiltration loss would be less, resulting in a smaller initial loss. Vice versa, for a smaller initial discharge, the antecedent soil is drier and infiltration loss is greater, resulting in a greater initial loss. Equation (1) was applied later to predict the initial loss for seven storm-flow events during the model validation period, and the initial loss was used in the model to give flood processes.

Model evaluation

The five indexes for evaluation (E_p, E_v, E_t, R^2 and NS) are listed in Table 1 for the 23 events used for calibration. The E_p values have a mean of 9.5%, varying from –31.3% to 23.8%. Its absolute value is less than 20% for 21 events

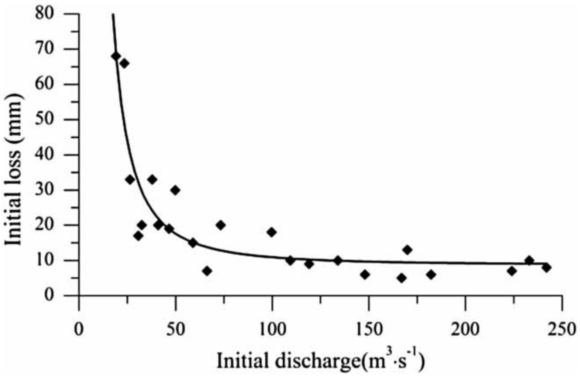

Figure 3 | Relationship between initial loss and initial discharge.

and larger than 20% only for two events (#740622, #771001). The values for E_v values have a mean of 6.5%, changing from −16.0% to 9.0%. Its absolute value is less than 15% except for event #771001. The values for E_t have a mean of 1.7 hours, changing from −2 to 8 h. It is less than 3 h for most events, but reached a greater error for event #730401 (8 h) and #770527 (6 h). The *NS* is averaged at 0.85, varying between 0.95 and 0.65, and is larger than 0.8 for 18 events, and less than 0.8 for only five events. R^2 has a mean of 0.89. These results indicated a reasonably satisfactory agreement between modelled and observed flood hydrographs.

Validation predictions were made for seven events, with the initial loss estimated from the initial discharge via Equation (1). Reasonable predictions of flood processes were achieved (Table 1). The predicted flood peak flow is within 20% of the observed with a mean error of 14.14%, except for one event (#790610, 41.1%). The flood volume is within 15% of the observed with a mean of 14.65%, except for two events (#790402, −26.0%; #790822, −27.7%). The peak time is well predicted, with a mean error of 0.43 hours and a maximum error of 2 h. The *NS* has a mean of 0.8. The coefficient of determination has the same average of 0.89. Therefore, the overall performance of HEC-HMS model is acceptable for the studied 30 flood events in 1972–1979.

In order to clarify what improvements have been achieved in flood modelling by introducing the initial loss–initial discharge relationship, a comparison was made between the hydrographs of seven 1978–1979 flood events predicted by the model with varying initial loss among events and the hydrographs predicted by the model with a constant initial loss. Part of the simulation results under varying initial loss have been shown in Table 1. The constant initial loss was determined as 15 mm by calibrating it against the 23 storm events, and its simulated results for the seven validation events are summarised in Table 2. It is evident that the simulation efficiency is higher with a varying parameter than with a constant value. Under the constant initial loss, E_p reached 51.1% (#790610) with an average of 17.73%, greater than the 14.1% in Table 1. The E_v reached 27.88% with an average of 19.79%, which is greater than the 14.7%, and it is more than 20% for four events. The E_t has the same average of 0.43 h. The *NS* has an average of 0.73, worse than the 0.8. R^2 has a mean of 0.88, and is slightly lower than the 0.89. As shown in Table 2, if the constant value is larger than the calibrated value (e.g. the initial loss simulated by Equation (1) for event #780828 is 9.46 mm), the simulated peak flow is less than the observed, and vice versa, if the constant value is smaller than the calibrated value (e.g. the initial loss simulated by Equation (1) for event #780822 is 25.0 mm), the simulated peak flow is larger than the observed. Therefore, the proposed initial loss varying with initial discharge outperformed the constant value treatment, and improved the accuracy of HEC-HMS.

Table 2 | Evaluations for simulated flood events when initial loss is constant

	Flood peak flow (m^3/s)			Flood volume (mm)					
Events	**Obs**	**mod**	**E_p (%)**	**obs**	**mod**	**E_v (%)**	**E_t (h)**	**NS**	**R^2**
780616	1380	1290.30	− 6.50	22.92	19.20	− 16.23	1	0.86	0.92
780622	1010	930.30	− 7.89	27.14	22.90	− 15.62	0	0.86	0.91
780822	824	1094.20	32.79	45.87	58.66	27.88	0	0.55	0.88
780828	1270	1012.10	− 20.31	26.77	20.87	− 22.04	0	0.83	0.92
790402	843	882.90	4.73	18.44	17.22	− 6.62	− 2	0.70	0.72
790610	2670	4034.50	51.10	94.99	118.67	24.93	0	0.56	0.92
790822	929	921.60	− 0.80	19.24	14.39	− 25.21	0	0.76	0.91
Absolute mean	–	–	17.73	–	–	19.79	0.43	0.73	0.88

Influence of initial loss on flood modelling

Three cases of storm size, having 2.5-year, 50-year and 100-year return period respectively, were simulated by the model for scenarios of different values of initial loss. For each case, the simulated flood peak flow decreased in a similar way when the initial loss, starting at 7 mm, increased by 10 mm increment (Figure 4). In the case of the 100-year return period, the peak flow decreased from 8,990 to 6,777 m^3/s nearly in a linear manner when the initial loss increased from 7 to 67 mm, and the decrease rate is 316.2 m^3/s per 10 mm change in initial loss. In other words, if the 100-year return period storm-rain occurred at a watershed condition with 67 mm initial loss, it would produce a much smaller flood which is equivalent to a flood of a 28-year return period. The significant influence of initial loss on floods indicated and confirmed the need for configuring the variation in initial loss for an improved prediction.

For the other two cases of 50-year and 2.5-year return period, the influence of initial loss on floods was similar to the first case: the peak flow decreased nearly in a linear manner with the increase of initial loss (Figure 4). However, the decrease rate is different; 304.4 m^3/s per 10 mm for the 50-year case and slightly smaller than the 316.2 for the 100-year return period, and 201.4 m^3/s per 10 mm for the 2.5-year case. Therefore, the influence enlarges when the storm size (or heaviness) increases.

Discussion

For a given flood event, a proper parameter value can be found to produce a reasonable fit to the flood hydrograph. The challenge comes with its application to operational flood prediction: which value should be used for specific events? For example, the same model (same treatments in runoff generation and flow routing) was used on the Taihu basin of China by Chen *et al.* (2009) and to the Xixi watershed in our present study, with different treatment of the initial loss. The automated search was applied to calibrate initial loss for the case of Taihu, an individual value was associated to each flood event, and the flood process was satisfactorily reproduced by the parameter value. However, no rule was provided to determine the variable initial loss for a prediction purpose: it is uncertain what kind of values will be chosen to run the model for making a reliable prediction. The proposed relationship of initial loss to initial discharge as tried in the Xixi case provided a possible solution to the challenge. When a prediction or forecasting is required, the event-specific initial loss value can be decided from the initial discharge, assuring a high level of accuracy and also with the convenience of easily setting up the parameter. However, the proposed relationship should not be applied to other watersheds with different watershed conditions. Similar relations could be obtained using our concepts or methods. A fixed value of Muskingum *K* can be used for other watersheds, but its value needs to be calibrated again.

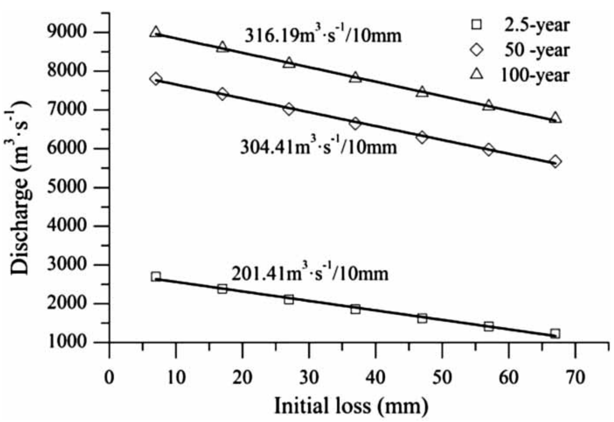

Figure 4 | Reduction of simulated flood peak flows along with increased initial loss.

We studied the relation of initial loss and discharge to provide assistance in flood prediction, but the physical mechanisms controlling initial loss have not been explicitly expressed. The relationships with antecedent rainfall, vegetation and soil condition should be studied in future, and the spatial distribution and variation of initial loss should be studied too. The influence of initial loss on different types of rain storms could be interesting. Finally, the HEC-HMS will need to be coupled with operational or real-time flood forecasting tools to promote forecasting efficiency.

CONCLUSION

A fixed and constant value of the flood wave speed was obtained to calibrate Muskingum *K* of HEC-HMS when applying it to the Xixi watershed of Jinjiang River in Fujian Province. Variability of initial loss was confirmed, and a varying rule was established by connecting it to the initial discharge, providing a useful method to calibrate the initial loss. The relationship between initial loss and initial discharge can be obtained from regular model calibration trials for selected flood events. The improvements made by the efforts in calibration of two key parameters have been demonstrated by model performance, prediction ability, and comparison to previous efforts without taking the variability into account. The significant influence of initial loss on flood processes or flood peak flows has been illustrated through simulations. These improvements to HEC-HMS calibration will benefit the model's application to watershed flood forecasting and water resource management.

ACKNOWLEDGEMENTS

The study was financially supported by the National Natural Science Foundation of China (No. 50979015). We thank Robert Girard for his suggestions. Three reviewers are thanked for their helpful comments.

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First received 8 April 2013; accepted in revised form 18 September 2013. Available online 22 October 2013