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Improvement of flash flood modelling using spatial patterns of rainfall: a case study in southern France

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Abstract There is a need to improve rainfall–runoff modelling of flash floods in the Mediterranean region, in order to better predict these extreme hydrological events. In this study, the efficiency of the distributed SCS-LR rainfall–runoff model is evaluated, using either the mean areal rainfall or spatially distributed rainfall over the watershed as inputs of the model. The distributed SCS-LR model is an event-based model accounting for four parameters. The efficiency of the model using either averaged or spatial rainfall as inputs is considered through the simulation of flood events, with fixed or calibrated model parameters for each event. A total of 30 flood events that occurred in the Gardon River (525 km^2) located in the Cévennes region (southern France) were modelled. When both runoff and routing parameters are identical, the model is shown to underestimate the peak flows if using mean areal rainfall patterns instead of spatial rainfall patterns. Runoff volumes can also be underestimated in the case of highly variable rainfall occurring in dry soil conditions. The recalibration of the model is able to reduce some of the bias in the simulations. Nevertheless, as shown in the present study, not considering the spatial patterns of rainfall is leading to an increase in the variability of the model parameters. Thereby, the parameter estimation could be difficult with averaged rainfall in further applications of the model for operational purposes. The rainfall patterns have an impact on the parameterization of the model, depending on the rainfall spatial variation coefficient and the initial moisture of the soil. Accounting for the spatial pattern of the rainfall can improve the efficiency of the model, without increasing its complexity.

Key words flash floods; rainfall–runoff models; SCS; lag and route; spatial variability; rainfall

INTRODUCTION

Flash floods are a very destructive hazard in the Mediterranean region caused by intense rainfall events. Among other characteristics, the spatial distribution of rainfall and its intensity are known to influence the modelling of flooding events (Bárdossy & Das, 2008). Andreassian *et al.* (2001) indicated how crucial it is to test the sensitivity of rainfall–runoff models to different rainfall inputs, in order to assess their sensitivity and robustness. Arnaud *et al.* (2002) have shown that using spatially uniform rainfall instead of spatially distributed rainfall tends to underestimate the volumes and the peak flows when using the same calibration of the rainfall–runoff model. This underestimation mainly increases according to the spatial variation coefficient of rainfall. However, a different calibration of the model to reduce the bias in flood simulation when using spatially uniform rainfall instead of spatially distributed rainfall has not been tested.

The objective of this paper is to analyse how flash flood modelling can be sensitive to the spatial variability of the precipitation input. The impact of the spatial variability of rainfalls is analysed using an event-based rainfall–runoff model. Two questions were addressed: (i) what is the error of the model when using spatially uniform rainfall instead of spatially distributed rainfall, and when both runoff and routing parameters are identical? and (ii) how far is a recalibration of the model able to compensate for the error in flood simulation when using spatially uniform rainfall instead of spatially distributed rainfall? These questions were addressed in the Gardon catchment, which covers 545 km^2 (Fig. 1). Rainfall data were available from seven raingauges. The event-based model was considered as the distributed SCS-LR model, which combines the SCS runoff model and the Lag and Route routing model. The paper is organized as follows: the rainfall–runoff model is first presented, and then the study area and the datasets used are detailed. Then, the flood simulations were compared, using either spatial uniform or distributed rainfalls: first the comparison was performed with identical runoff and routing parameters; second, the comparison

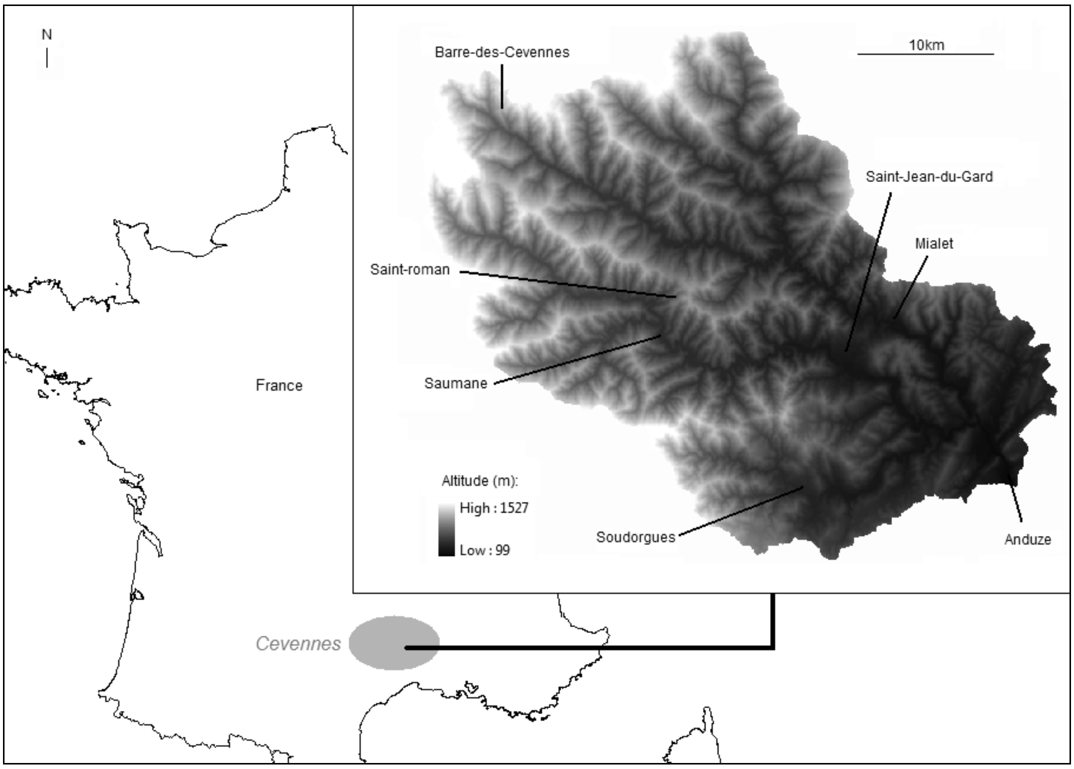

Fig. 1 The Gardon watershed and location of the raingauges.

was performed with calibrated parameters for each event. Finally there is a discussion about the capabilities of the model in flood simulation as well as the robustness of both runoff and routing parameters according to the rainfall input.

THE SCS-LR RAINFALL–RUNOFF MODEL

The hydrological model used here combines a GIS-based distributed version of the runoff model of the Soil Conservation Service (SCS) and a Lag and Route (LR) routing model. The SCS runoff model has been developed by the United States Department of Agriculture (Mishra & Singh, 2003) and has been widely used for flood modelling, partly because it performs efficiently while using a reduced number of parameters. SCS is commonly interpreted as modelling direct surface runoff, but it can also describe soil saturation processes (Steenhuis *et al.*, 1994). The Lag and Route routing model has also been widely used (Bentura & Michel, 1997). The model was implemented in the ATHYS modelling platform (http://www.athys-soft.org).

The distributed model is based on the following steps. First, the catchment was considered as a regular grid mesh of cells. A digital elevation model (DEM) was used to define a grid of cells of 500 × 500 m over the watershed. Rainfall was then computed for each cell at any time, considering either (i) an averaged uniform rainfall, (ii) a spatially interpolated rainfall, according to the method of the Thiessen polygons. Second, the runoff from each cell was calculated using a SCS runoff model. Third, each cell produced an elementary hydrograph at the outlet, using a Lag and Route routing model. Fourth, the complete hydrograph of the flood was obtained after the addition of the elementary hydrographs.

Runoff model

For each cell of the catchment, the effective precipitation contributing to runoff at the time t, $Pe(t)$, is derived from the instantaneous precipitation $Pb(t)$, using a relationship based on the classical

SCS-CN model (Mishra & Singh, 2003) between the cumulative rainfall $P(t)$ at the time t and a reservoir capacity S (Gaume *et al.*, 2004):

$$Pe(t) = Pb(t)\left(\frac{P(t)-0.2.S}{P(t)+0.8.S}\right)\left(2-\frac{P(t)-0.2.S}{P(t)+0.8.S}\right) \tag{1}$$

A reduction of the cumulative rainfall has been considered, in order to simulate the decrease of the runoff coefficient in case of intermittent rainfall. This reduction was applied as a linear function of the cumulative rainfall at time t, according to the coefficient ds. The cumulative rainfall was calculated using the relation:

$$\frac{dP(t)}{dt} = Pb(t) - dsP(t) \tag{2}$$

with $P(0) = 0$ at the beginning of the event.

Thus, the runoff model accounts for two parameter, S and ds. S is the maximal soil water retention and can be considered as the initial water deficit at the beginning of each event. Therefore the S parameter is the initial condition of the event-based model (i.e. it depends on each event). The ds parameter can be derived from the observed recession curves of the flood hydrographs. In this application, the runoff parameters S and ds do not vary in space, but remains the same for all the cells.

Routing model

The effective rainfall is then routed from the cell to the outlet of the catchment. For each cell m, the model computes a propagation time at the outlet T_m and a diffusion time K_m:

$$T_m = \sum \frac{l_k}{V_0} \tag{4}$$

$$K_m = K_0 T_m \tag{5}$$

where l_k is the length of the flow path, V_0 the speed of propagation, and K_0 a coefficient without dimension. V_0 and K_0 are assumed here to be identical for each cell, and must be calibrated from rainfall and discharge data. The flow paths from the cell to the outlet are derived from the DEM.

The elementary discharge $q(t)$ due to the effective rainfall $Pe(t_o)$ of cell m at time t_o is given by:

$$q(t)=0 \quad \text{if } t < t_0 + T_m \tag{6}$$

$$q(t) = \frac{Pe(to)}{K_m}\exp\left(-\frac{t-(t_0+T_m)}{K_m}\right).A \quad \text{if } t > t_0 + T_m$$

where A is the cell size. Finally, all the elementary discharges provided from each cell at each time are added to obtain the complete hydrograph of the flood.

Model calibration and efficiency indicators

The calibration of the model was performed through an iterative process using the simplex method. The Nash-Sutcliffe (NS) efficiency coefficient was used to evaluate the agreement between the simulated and the reference runoff hydrograph:

$$NS = 1 - \frac{\sum_{t=1}^{n}\left(X_t - Y_t\right)^2}{\sum_{t=1}^{n}\left(X_t - \overline{X}\right)^2} \tag{7}$$

where X_t and Y_t are the observed and simulated discharge at time t.

In addition, the mean absolute relative error (*MARE*) between observed (Q_i) and modelled ($\hat{Q}_i$) peak flow or runoff volume for each event has been computed in order to compare the different approaches.

$$MARE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Q_i - \hat{Q}_i\right|}{Q_i} \tag{8}$$

HYDRO-METEOROLOGICAL DATASETS

The Gardon of Anduze (Fig. 1) is a 525 km^2 Mediterranean catchment located in the south of France, in the Cévennes mountain area. The catchment has a contrasted topography, with steep slopes, 10% on average. The maximal elevation is 923 m, and the outlet is located in Anduze (123 m). The geology consists of three main geological units; schist (dominant, 60%), granite and limestone. Soils are relatively thin, from 10 to 100 cm deep. The Gardon is mostly forested with a vegetation cover typical of the Mediterranean area (Moussa *et al.*, 2007). The climate is Mediterranean, with frequent heavy storms and intense rainfall in the autumn and winter seasons. Floods usually occur during very intense rainy events that may reach several hundred millimetres in 24 h. In September 2002, locally the daily rainfalls reached more than 600 mm. The flood rising times are short, ranging from 3 to 5 hours in this basin; runoff coefficients depend on the rainfall amounts, they can reach 0.5–0.6 in the extreme cases (Bouvier *et al.*, 2007).

The available data includes hourly discharge at Anduze and hourly rainfall data from seven gauges (Fig. 1) located in the basin (Anduze, Barre des Cévennes, Mialet, Saumane, Soudorges, Saint Roman and Saint Jean du Gard). A total of 30 flooding events were extracted between 1998 and 2008, with peak discharge ranging from 166 to 3130 m^3 s^{-1} and a median duration of 4.5 days. Most of the events (21) occurred during the months of September to December, and the remaining events during the months of February to May.

MODEL CALIBRATION AND EFFICIENCY

The rainfall–runoff model (SCS-LR) has been first calibrated using spatial rainfall input. First, the *ds* parameter was derived from the recession curves of the flood hydrographs and was set to the median value of 0.4 for all events. Second, the non-dimensional K_0 parameter was set to 1.5, based on previous model runs. Then, the calibration of V_0 and *S* was driven at the event-scale through the optimization of the NS coefficient, calculated from both observed and simulated discharges. The calibration domain is only the observed discharge above 40 m^3 s^{-1}, in order to only evaluate the model for the highest recorded discharges. The calibration of the model using spatial rainfall input led to a mean NS value = 0.86, mean *S* value = 151 mm, mean V_0 value = 2.2 m/s, MARE on peak flow = 0.13 and MARE on runoff volume = 0.27.

Flood modelling using the same calibration for averaged and spatial rainfall inputs

A first comparison was performed between the simulated floods using either spatial or averaged rainfall inputs. In this case, both S and V_0 parameters remained identical (i.e. calibrated parameters of the model using spatial rainfall input). When using the averaged rainfall input for flood modelling, the mean NS event value is 0.68, the MARE on peak flow is 0.30 and 0.34 for runoff volume. The comparison of simulated runoff and peak flows show that the simulated runoff volumes are not modified much (Fig. 2(a)), while the peak flows simulated with mean rainfall input appear to be underestimated from those simulated with spatial rainfalls input (Fig. 2(b)). The underestimation can be related to the spatial variation coefficient (i.e. ratio of the standard deviation and the mean values for each event at the seven raingauges) of the cumulated rainfall

(Fig. 2(c)): it can be seen that the maximal relative error on the peakflow corresponds to the maximal CV values, namely in both cases when CV exceeds 0.7.

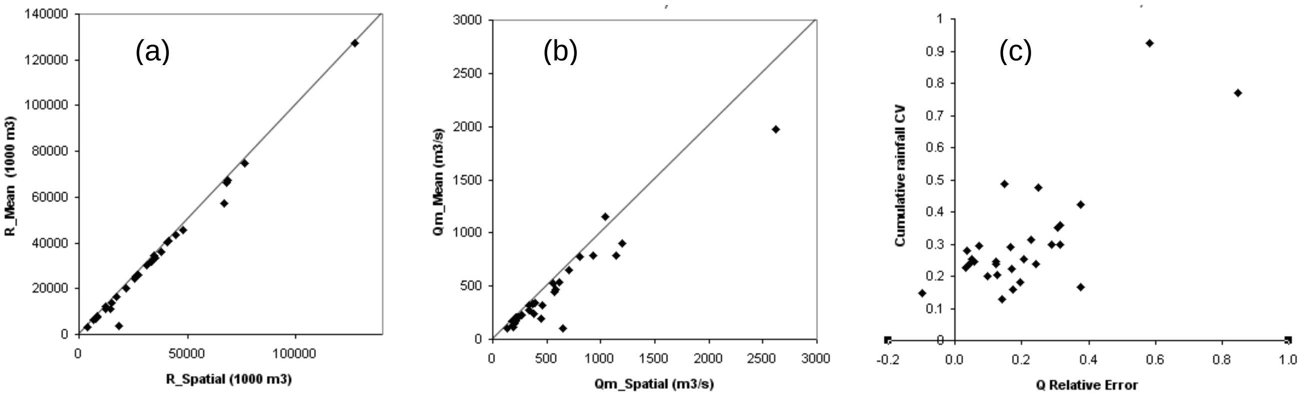

Fig. 2 Comparison of simulated runoff and peak discharge using spatial rainfall input and mean rainfall input, when parameters of the rainfall–runoff model are identical: (a) runoff volumes, (b) peak discharges, and (c) relationship between peak discharge relative error and the rainfall spatial variation coefficient.

Flood modelling using a different calibration for averaged and spatial rainfall inputs

A second comparison of the simulated floods was performed, both S and V_0 parameters being calibrated for each event, using either spatial or mean rainfall inputs. When using the averaged rainfall input, the mean event NS value is 0.81 and the MARE is equal to 0.21 for peak flow, 0.26 for runoff volume. By comparing with the previous values which were obtained with identical model parameters, it was shown that calibration of the model is indeed able to reduce the bias resulting from different rainfall input data. The comparison of simulated values using either mean or spatial rainfall inputs show that the runoff volumes are quite similar (Fig. 3(a)), while the peak flow in some cases are still underestimated when using uniform rainfall input (Fig. 3(b)). Biases are, however, less than in the previous case, using identical parameters for both rainfall inputs (Fig. 3(c)).

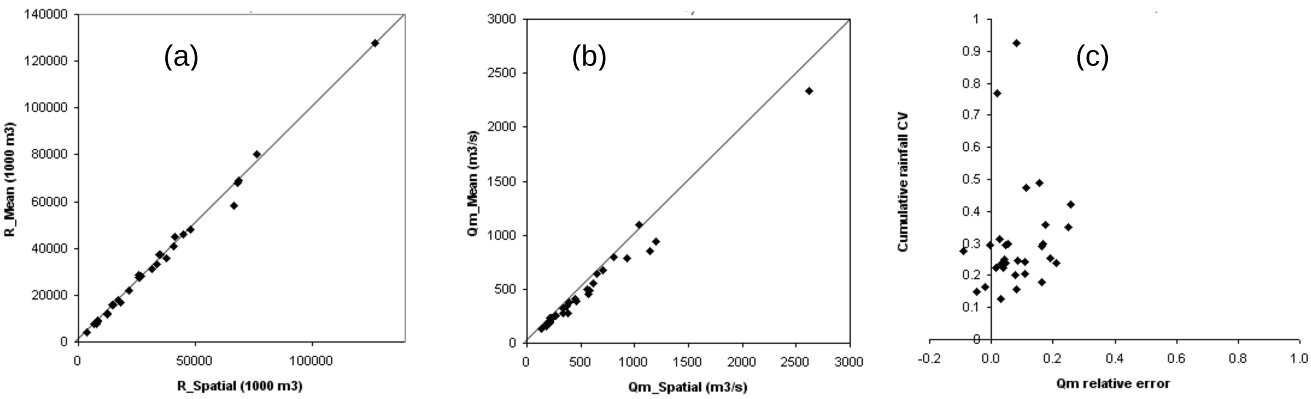

Fig. 3 Comparison of simulated runoff and peak discharge using spatial rainfall input and mean rainfall input, parameters being calibrated for each rainfall input: (a) runoff volumes, (b) peak discharges, (c) relationship between peak discharge relative error and the rainfall spatial variation coefficient.

Impact of averaged *vs* distributed rainfall inputs on model parameters

The comparison of the different calibration strategies shows that the rainfall input mainly impacts on the V_0 parameter. The *S* parameter does not show a great variation between the two approaches, except for the case of the 20 October 2008 event (Fig. 4(a)). This event corresponds to a highly variable (CV = 0.77) cumulated rainfall, occurring on dry soils (*S* = 436 mm). In this case, the rainfall input has a strong impact on the *S* parameter: using spatial rainfall input leads to S = 436 mm, while using uniform rainfall input leads to *S* = 247 mm. In contrast, the V_0 parameter tends to be overestimated when using uniform rainfall input (Fig. 4(b)). The overestimation can be strong, since V_0 values using uniform rainfall input may be twice the values obtained using spatial rainfall input. The overestimation can be related to the spatial rainfall variation coefficient (Fig. 4(c)). Thus, it is shown that recalibrating the rainfall–runoff model can reduce the bias in flood simulation, but makes the estimation of the parameters dependent on the spatial variation of the rainfall. This generates another bias, which can make further applications of the model for operational purposes difficult.

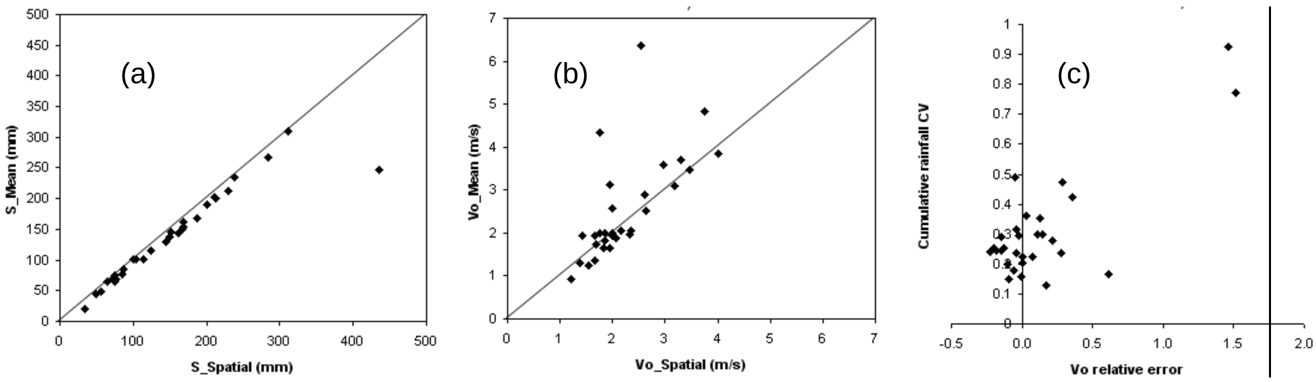

Fig. 4 Comparison of calibrated parameters using either spatial or mean rainfall: (a) S parameter, (b) V_0 parameter, (c) relationship between V_0 parameter relative error and cumulative rainfall spatial coefficient variation.

CONCLUSIONS

Flood simulations have been performed with a distributed event-based rainfall–runoff model using either mean rainfall or spatial rainfall input. The main objective was to estimate the bias on the simulations and on parameter estimation.

A first comparison of simulated runoff and peak flows was performed using identical parameters in the rainfall–runoff model. It shows that using mean rainfall generates a bias on the peak flows, which are underestimated compared to when using a spatial rainfall input. This underestimation can be related to the spatial variation coefficient of rainfall. For highly variable rainfall that occurs in dry soil conditions, volume runoff can also be biased.

A second comparison was performed using calibrated parameters for each rainfall input. The simulations are still better when using spatial rainfall input, but the efficiency differences between the two rainfall inputs are reduced. The routing parameter V_0 is sensitive on the rainfall input, and using the mean rainfall input led to overestimated V_0 values. The V_0 overestimation could be related to the CV of the cumulative rainfall. For highly variable rainfall that occurs in dry soil conditions, the runoff parameter *S* was also largely underestimated when using mean rainfall input. Thus, recalibrating the rainfall–runoff model can reduce the bias in flood simulation, but makes the estimation of the parameters dependent on the spatial variation of the rainfall.

Rainfall inputs have an impact on rainfall–runoff modelling, whether the parameters are identical or differently calibrated for each type of input. For the first comparison tested in the present study, the bias concerns the events peak flow and volume, whereas in the second comparison the bias concerns the parameter estimation.

As the results have been obtained for a given sample of floods and a specific model, it would be important to extend the scope of the study to a broader set of catchments and to consider other rainfall–runoff models, in order to provide a more general assessment of the impact of spatial rainfall on flood modelling.

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