Reducing uncertainty in derived flood frequency analysis related to rainfall forcing and model calibration

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Abstract Hourly precipitation data sets are generated with a stochastic rainfall model and using a statistic disaggregation approach. The synthetic rainfall data are used as input for a continuous hydrological model applied to a mesoscale catchment in the Bode River basin in Germany. The simulated flows are analysed regarding the derived probability distributions of annual peak flows. The results show significant differences in flood probabilities for using spatially random rainfall, homogeneous rainfall or spatially structured rainfall. The direct calibration of the hydrological model using stochastic rainfall on flood probability distributions generally reduces both the bias and the variability in the simulated flows compared to the standard procedure using observed rainfall and runoff time series for calibration.

Key words derived flood frequency analysis; continuous hydrologic modelling; stochastic rainfall; rainfall disaggregation; model calibration; uncertainty

INTRODUCTION

Reliable flood risk assessment and the development of effective flood protection measures require a good knowledge of flood frequencies at different points in a catchment. The classical approach to obtain design flows is to carry out local or regional flood frequency analysis using long records of observed discharge data (e.g. Hosking & Wallis, 1997). If flow data are not available or if impacts of climate or land-use change are to be investigated, rainfall–runoff modelling is a good alternative, using either event-based or continuous simulation.

A disadvantage of the event-based simulation is the required assumption about equal return periods for the design storm and the resulting design flood. This is usually not given, considering e.g. the initial soil moisture conditions in the catchment, which may lead to different floods for the same storm. With continuous rainfall–runoff simulation this problem can be avoided and the design flood is derived by flood frequency analysis of long series of simulated flows. However, such kinds of hydrological modelling require long continuous rainfall series with high temporal and sufficient spatial resolution. Given the restricted availability of those observed data, synthetic precipitation is often used for this purpose (Cameron *et al.*, 1999; Blazkova & Beven, 2004; Aronica & Candela, 2007; Haberlandt *et al.*, 2008; Moretti & Montanari, 2008).

Still, one challenge with this approach is to provide space–time consistent rainfall fields for distributed hydrological modelling. Another problem is the optimal calibration of the hydrological models considering flood frequencies as simulation target and the dependence of the parameterization on the input data (e.g. Bárdossy & Das, 2008). In this paper, these two special problems will be addressed. First, the uncertainty related to using spatially random synthetic rainfall *versus* spatially consistent synthetic rainfall for hydrological modelling is assessed. Second, different calibration strategies are compared, based on either observed precipitation or synthetic rainfall and using either observed hydrographs or observed probability distributions of peak flows as target variables.

METHODOLOGY

Stochastic rainfall model

A hybrid stochastic precipitation model is applied to provide continuous hourly space–time rainfall series consisting of two components (Haberlandt *et al.*, 2008). The first component is a classical alternating renewal model used to simulate independent precipitation event time series for several locations (Fig. 1).

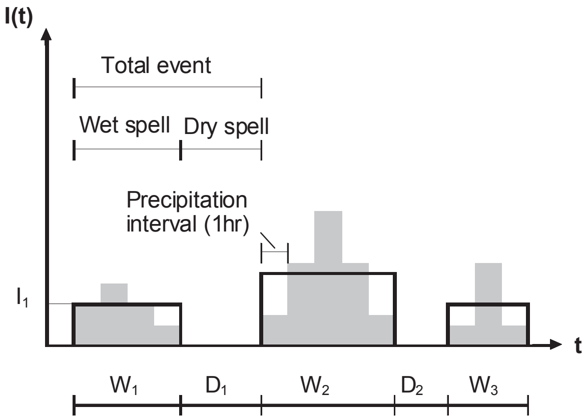

Fig. 1 Scheme of the precipitation event process.

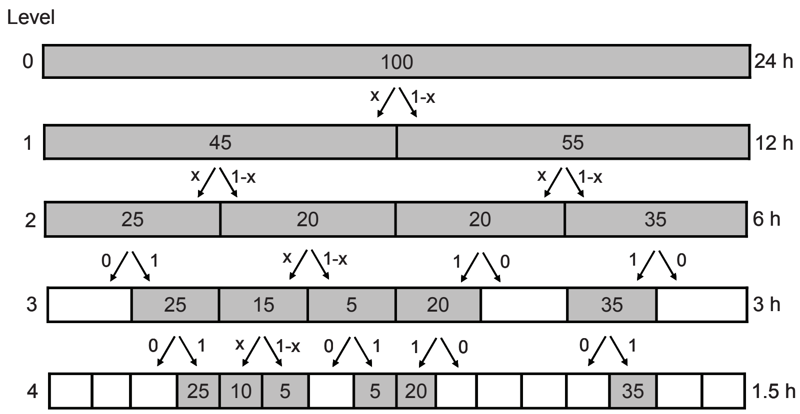

Fig. 2 Scheme of a multiplicative random cascade model.

Wet and dry spell durations are modelled by general extreme value and Weibull distributions, respectively. Wet spell intensity is modelled using a Weibull distribution. The dependence between wet spell intensity and duration is described by a 2-D copula (De Michele & Salvadori, 2003). For disaggregation of the wet spells into hourly intensities a special profile with random peak time is used. The second component uses simulated annealing for resampling the univariate event time series (Bárdossy, 1998) to reproduce the spatial dependence structure. The objective function includes three bivariate criteria: (a) the probability of rainfall occurrence, (b) Pearson's correlation coefficient, and (c) the expected rainfall amount conditioned on rainfall occurrence at a neighbouring station. The parameters of the rainfall model are estimated for summer (May–October) and winter (November–April) seasons separately.

Rainfall disaggregation model

Usually the availability of daily precipitation data is much better than for hourly data. Thus one interesting alternative is the disaggregation of daily rainfall into smaller time steps. For disaggregation a multiplicative random cascade model with exact mass conservation is applied here (Güntner *et al.*, 2001) (Fig. 2).

The model divides the observed 24 h precipitation subsequently into two equal size non-overlapping boxes, having one of the three possible states with certain transition probabilities P: wet/wet with $P(x/1–x)$, wet/dry with $P(1/0)$ or dry/wet with $P(0/1)$. Here, the divisions are carried out from level zero (24 h) up to level five (45 min). Hourly rainfall is finally estimated by dividing the 45 min rainfall boxes into three uniform 15-min blocks and re-aggregating four blocks each from the time series back to 60 minutes. The parameters for the model are each estimated from the nearest hourly neighbour station. The main problem here is the conservation of the space–time structure of precipitation.

Hydrological modelling

For runoff simulations the conceptual hydrological model HEC-HMS (Scharffenberg & Fleming, 2005) is used. The model is operated continuously on an hourly time step. It uses the soil moisture accounting (SMA) algorithm for runoff generation, the Clark Unit Hydrograph for the transformation of direct runoff, two linear reservoirs to consider interflow and baseflow transformation, and a simple river routing where the flows are only lagged in time. Snowmelt is calculated externally using the degree-day method. Potential evapotranspiration is also computed externally using the method proposed by Turc-Wendling (Wendling *et al.*, 1991).

For model calibration five sensitive parameters of HEC-HMS are selected and estimated in lumped mode for the catchment under investigation using the PEST algorithm (Doherty, 2004). Employing different calibration strategies three versions of "optimal" parameter sets are determined using the different input and output data. Table 1 indicates how the three parameter sets have been estimated. To obtain parameter set I, observed continuous time series of rainfall and runoff are used for classical calibration, minimizing the sum of squared deviations between observed and simulated runoff. Half of the observation period is used for calibration and half for validation. For parameter set II, several realisations of disaggregated rainfall from daily observations are used to simulate continuous runoff time series. Flood frequency analysis is applied on annual maximum series derived from the simulated flows. For the observed series and for each simulated realisation the general extreme value distribution (GEV) is fitted. The sum of squared weighted deviations between a set of "observed" quantiles and the median of "simulated" quantiles from all realisations is used here as objective function for calibration. The same procedure is also applied using stochastic rainfall to obtain parameter set III. For both parameter sets II and III only half of the generated realisations are used for calibration, but all realisations are used later for validation and application.

Table 1 Parameter sets for HEC-HMS calibrated using different input and output data.

Parameter set	Input data (rainfall)	Output data (runoff)	Calibration period
I – OBS	Observed rainfall 13 years	Observed discharge 7 years	4 years
II – DISAG	Disaggregated rainfall from daily observed data 20 realisations × 36 years	Probability distribution of annual peak flows 36 years	36 years observed peak flow using 10 realisations rainfall
III – STOCH	Stochastic rainfall 20 realisations × 100 years	Probability distribution of annual peak flows 56 years	56 years observed peak flow using 10 realisations rainfall

STUDY REGION AND DATA

The investigations are carried out for the mesoscale Selke catchment up to the gauge Silberhütte belonging to the Bode River basin in northern Germany (Fig. 3). The Bode region has elevations between 1140 m a.s.l. at the top of the Brocken Mountain and about 80 m a.s.l. Mean annual rainfall varies between 1700 mm/year and 500 mm/year. Floods are generated either by frontal rainfall, frontal rainfall on snowmelt or convective storms.

Figure 3 shows also the locations of the precipitation stations and the sub-catchments. The lengths of the observation periods for rainfall and streamflow data are indicated in Table 1. Because of the sparse network of recording hourly rainfall gauges, daily stations are also included for simulations with observed and stochastic rainfall. For the former, daily rainfall totals are

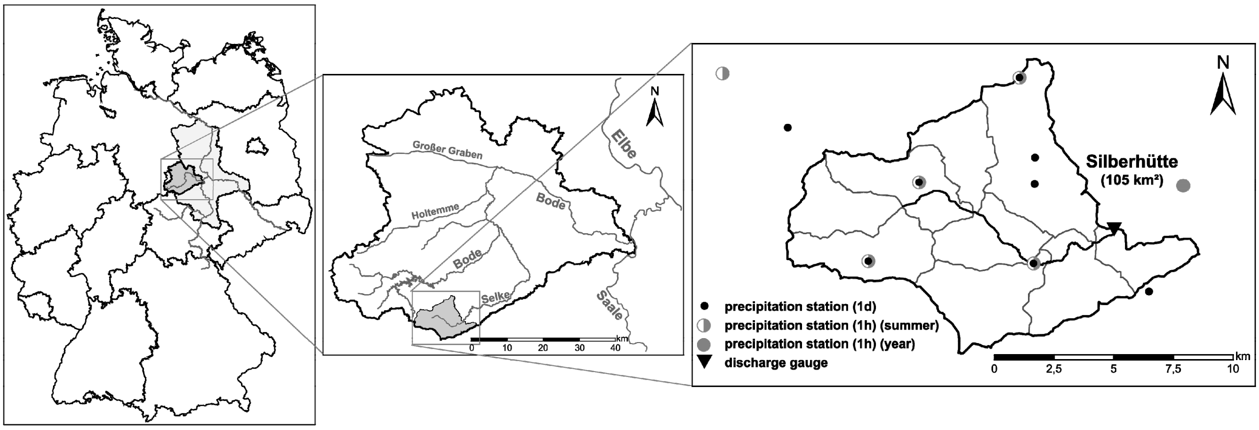

Fig. 3 Locations of the Selke catchment with precipitation stations, streamflow gauge and sub-catchment delineation.

disaggregated into hourly data using the intensity profile from the nearest station with high resolution data. For the latter, stochastic rainfall is transferred to the daily station locations by scaling the time series with the long-term rainfall ratio between the two locations. Finally, areal rainfall for sub-catchments is calculated by Thiessen interpolation from all daily and hourly station locations.

ANALYSIS AND RESULTS

Relevance of spatially consistent rainfall

In order to assess the importance of spatially consistent rainfall for flood simulations, several precipitation data sets expressing different spatial rainfall consistence are generated. The model HEC-HMS is calibrated here using observed rainfall and runoff time series (parameter set I) and is then forced with the different precipitation time series. Flood frequency analysis is applied on the simulated runoff time series and compared against frequencies of observed peak flows.

Concerning rainfall disaggregation, two limiting cases are compared. In the first case, independent disaggregated rainfall for all stations involved is provided ("random rainfall"). The second consists of fully homogeneously disaggregated rainfall based on one dynamically selected pilot station showing the largest daily rainfall amount each ("uniform rainfall"). Figure 4(a) shows the results for summer maximum flow series. With randomly disaggregated rainfall the peak flows for return periods larger then 10 years are underestimated. The empirical distribution of peak flows resulting from uniformly disaggregated rainfall is higher than the distribution from random rainfall, as expected. The largest observed values are better reproduced, but smaller values are overestimated. The truth may be somewhere in between. So, in the absence of a capable method for temporal rainfall disaggregation considering spatial relationships, a pragmatic approach might be to use these two limiting cases as boundaries for estimating required design flows.

Concerning synthetic precipitation generated with the stochastic rainfall model, the effect of the resampling procedure on the simulated flood frequencies was of especial interest. Three rainfall scenarios are investigated: spatially random rainfall, spatially structured rainfall applying both components of the rainfall model and spatially uniform rainfall. For the random rainfall case the resampling procedure was omitted and for the uniform rainfall case only one rainfall station was used as homogeneous areal rainfall. In Fig. 4(b) the results for summer maximum flow series are shown. With random rainfall, floods are underestimated for return periods greater than 10 years, structured rainfall overestimated smaller floods and uniform rainfall largely overestimated floods. Structured rainfall leads to an increase of flood probabilities as expected. However, it does not fit to the observed values very well. One reason might be that the hydrological model is used here with parameter set I, calibrated on the 4 years of continuously observed streamflow (see also Fig. 5). The uniform rainfall simulates much too high peak flows. The difference with the corresponding case in Fig. 4(a) might result from using the same single station all the time here, and from the different type of synthetic rainfall data.

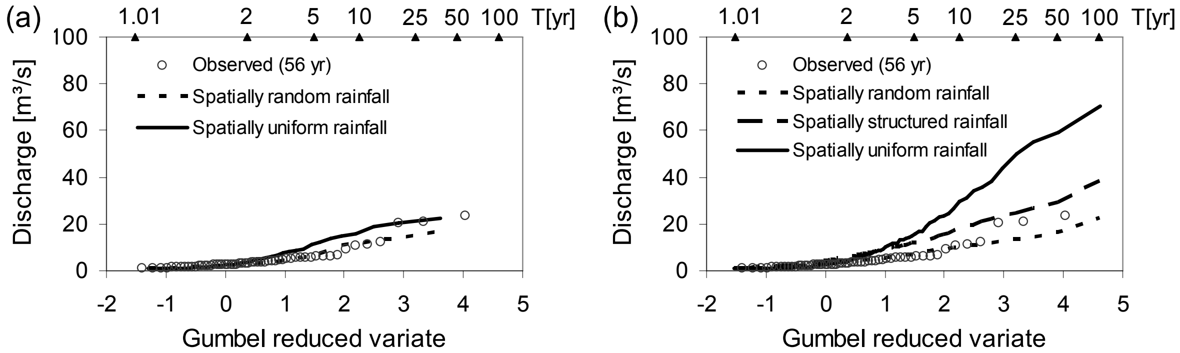

Fig. 4 Empirical probability distributions of summer peak flows for the Selke catchment derived from HEC-HMS simulations based on parameter set I (OBS): (a) using disaggregated rainfall (median of 10 realisations each 36 years), (b) using stochastic rainfall (median of 10 realisations each 100 years).

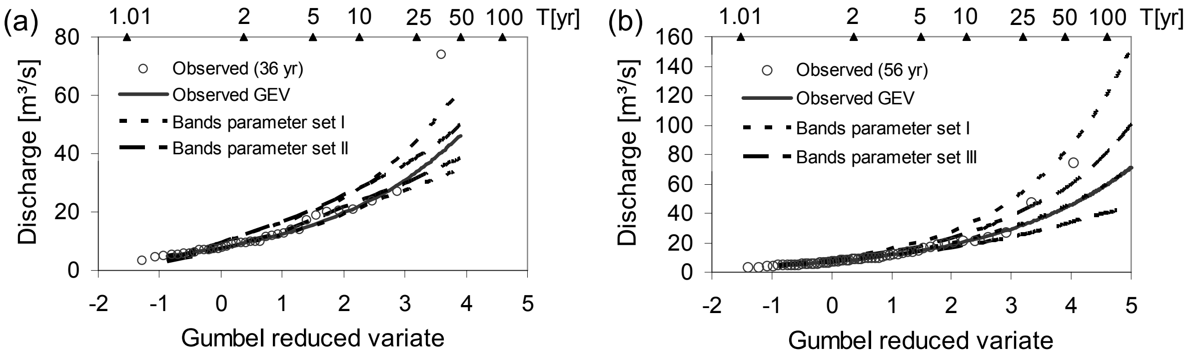

Fig. 5 Fitted GEV distributions for annual peak flows for the Selke catchment derived from HEC-HMS simulations comparing parameter sets I, II and III: (a) median and 90% confidence bands using disaggregated rainfall based on 20 realisations, (b) median and 90% confidence bands using stochastic rainfall based on 20 realisations.

Effect of calibration strategy

Next, the effect of different calibration strategies for HEC-HMS is analysed. Figure 5(a) shows the simulation results using disaggregated rainfall data as input. HEC-HMS has been calibrated here either based on observed precipitation and runoff time series (parameter set I), or directly based on disaggregated rainfall and a fitted probability distribution for peak flows (parameter set II). Targeting the observed GEV in calibration, both the bias and the variability of simulated peak flows using disaggregated rainfall data are smaller. However, the bandwidth of the simulated GEVs representing 90% of the realisations does not completely cover the observed GEV. Note that for disaggregated precipitation only 36 years out of the 56 years of observed peak flows could be used for calibration because of the restricted rainfall record length (see Table 1).

In Fig. 5(b) the results using the stochastic rainfall data as input for HEC-HMS are shown. Again, HEC-HMS has been calibrated here either based on observed precipitation and runoff time series (parameter set I), or directly based on stochastic rainfall and a fitted probability distribution for peak flows (parameter set III). Compared to using disaggregated rainfall to drive the hydrological model (Fig. 5(a)) the variability of simulated floods for both calibration strategies is larger here. This might be due to the higher variability of purely stochastic rainfall. However, using stochastic rainfall and the peak flow distribution for calibration of HEC-HMS instead of observed rainfall and runoff, the bias and variability of simulated floods with reference to the observed GEV can largely be reduced. In addition, the 90% confidence band nicely covers the observed peak flow distribution. Here, the full 56 year peak flow record could be used for calibration because of the unlimited length of stochastic rainfall.

SUMMARY AND CONCLUSIONS

In this paper, two special problems for derived flood frequency analysis have been investigated: (a) the uncertainty related to using spatially random synthetic rainfall *versus* spatially consistent synthetic rainfall, and (b) the effect of different calibration strategies for a hydrological model using observed or synthetic precipitation as input and observed time series of runoff or probability distributions of peak flows as output. The results show that:

(a) with disaggregated or stochastic rainfall a good reproduction of flood frequencies is possible;
(b) there are significant differences in derived flood probabilities depending on the degree of spatial rainfall consistence used to force the hydrological model;
(c) design flows might be estimated from two limiting cases of disaggregated rainfall data: spatially random and spatially uniform distributed precipitation;
(d) the spatial resampling component of the hybrid stochastic precipitation model increases the plausibility of simulated floods; and
(e) the calibration of hydrological models directly on stochastic rainfall and observed peak flow distributions reduces the uncertainty in derived flood frequency analysis.

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