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A space-time hybrid hourly rainfall model for derived flood frequency analysis

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Abstract

For derived flood frequency analysis based on hydrological modelling long continuous precipitation time series with high temporal resolution are needed. Often, the observation network with recording rainfall gauges is poor, so stochastic precipitation synthesis is a good alternative. Here, a hybrid two step procedure is proposed to provide suitable space-time precipitation fields as input for hydrological modelling. First, a univariate alternating renewal model is presented to simulate independent hourly precipitation time series for several locations. In the second step a multi-site resampling procedure is applied on the synthetic point rainfall event series to reproduce the spatial dependence structure of rainfall. The alternating renewal model describes wet spell durations, dry spell durations and wet spell amounts using univariate frequency distributions separately for two seasons. The dependence between wet spell amount and duration is accounted for by 2-copulas. For disaggregation of the wet spells into hourly intensities a predefined profile is used. In the second step resampling is carried out successively on all synthetic event series using simulated annealing with an objective function considering three bivariate spatial rainfall characteristics. In a case study synthetic precipitation is generated for two mesoscale catchments in the Bode river basin of northern Germany and applied for derived flood frequency analysis using the hydrological model HEC-HMS. The results show good performance in reproducing average and extreme rainfall characteristics as well as in reproducing observed flood frequencies. However, they also show that it is important to consider the same rainfall station network for calibration of the hydrological model with observed data as for application using synthetic rainfall data.

1 Introduction

Efficient flood protection measures require a good knowledge about 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 and Wallis, 1997; Stedinger et al., 1993). If those data are not available or if impacts of climate or land use change are to be investigated derived flood frequency analysis is a good alternative. In this latter approach a rainfall-runoff model is used to provide simulated flows either in form of single flood events or as continuous time series. Disadvantage of the event based simulation is the required assumption about equal probabilities of the design rainfall and the resulting flood runoff. With continuous rainfall-runoff simulation this problem can be avoided and the design flood is derived by flood frequency analysis of simulated flows. However, this kind of hydrological modelling requires long continuous rainfall series with high temporal and sufficient spatial resolution. Given the restricted availability of those observed data, synthetic precipitation is utilised with increasing frequency for this purpose (Aronica and Candela, 2007; Blazkova and Beven, 2004; Cameron et al., 1999; Moretti and Montanari, 2008).

Over recent years, several stochastic precipitation models for short time step rainfall have been proposed. To the early approaches belong the alternating renewal models which are based on event series of wet-dry spells (Acreman, 1990; Grace and Eagleson, 1966; Haberlandt, 1998; Pegram and Clothier, 2001). Those models have a simple structure, the estimation of parameters from point observations is straightforward and the models can easily be applied for rainfall synthesis at single locations. However, they are usually not able to simulate space-time rainfall for several stations in a catchment. Less important here and more suitable for daily rainfall are the classical time series models because of difficulties with modelling the high intermittence of short time step rainfall and the large number of required parameters (Haan et al., 1976; Wilks, 1998). Advanced approaches for rainfall modelling with sub-daily time steps are the point process models like Newman-Scott or Bartlett-Lewis rectangular pulse models (Cowpertwait, 2006; Onof et al., 2000; Rodriguez-Iturbe et al., 1987), which can also be extended to simulate space-time rainfall. They are based on the physical structure of the rainfall process and describe probabilistically arrival times of storms and cells within storms as well as cell intensities and durations. Often they assume independence between cell intensities and durations. One recent exception is described in Evin and Favre (2008) where cubic copulas are used to model this relationship. A difficulty with point process models arises from the parameter estimation which requires usually observed radar data or relies on optimisation which may lead to some kind of parameter equifinality (Beven and Freer, 2001). The latter makes a conditioning of the model parameters on climate difficult. Other models for synthetic rainfall generation which can be applied for derived flood frequency analysis include different disaggregation approaches (Koutsoyiannis et al., 2003; Lu and Yamamoto, 2008; Olsson, 1998) and various resampling methods (Bárdossy, 1998; Lall and Sharma, 1996).

Objective of this study is to provide a simple parsimonious space-time model for the synthesis of hourly rainfall which can especially be used as data generator for flood frequency analysis. The idea is to use a hybrid or two-step approach. First, an alternating renewal model is used to simulate independently precipitation time series for several locations. In the second step, a resampling procedure is applied on the generated event time series to reproduce the spatial dependence structure of the rainfall process. The approach is validated using observed rainfall characteristics and simulated flood frequencies. The paper is organised as follows. In Sect. 2 the methodologies for the alternating renewal model and the resampling approach are developed. Section 3 discusses a case study with rainfall modelling and derived flood frequency analysis for two mesoscale catchments in northern Germany. Finally, in Sect. 4 conclusions and an outlook are given.

2 Methodology

2.1 Single-site temporal rainfall synthesis

In the first step of the rainfall generation process single site precipitation synthesis is carried out using an alternating renewal model (ARM). Alternating renewal models describe the precipitation process by dividing the time series into dry and wet spells. The entire precipitation process is separated into an external and an internal structure. The external structure characterises the occurrence and the amount of the precipitation events, as explained by the variables dry-spell-duration (*dsd*), wet-spell-duration (*wsd*) and wet-spell-amount (*wsa*) or wet-spell-intensity (*wsi*). Figure 1 shows a scheme of the rainfall event process. The internal structure describes the precipitation distribution within the wet-spells. The precipitation occurrence process is completely determined by establishing probability distribution functions for the variables *dsd* and *wsd*. A basic condition is the independence and identical distribution of the durations of the wet and dry spells. The precipitation amount *wsa* or the intensity $wsi=wsa/wsd$ can also be modelled using probability distributions. However, *wsa* or *wsi* cannot be treated as independent of *wsd*.

Here, the ARM developed by Haberlandt (1998) for urban hydrologic applications has been adapted and is modified for the purpose of rainfall generation for flood frequency analysis. Table 1 shows the components of the external model structure.

Wet and dry spell durations are modelled by the general extreme value and Weibull distribution functions, respectively. Considering the fitting performance for the marginal distributions and the low serial correlation of events the required minimum time without rain for the separation of two events has been set to one hour and two hours for the summer and winter seasons, respectively. The wet spell intensity is modelled using a Kappa distribution function. The dependence between wet spell intensity and duration is described by a 2-copula. A 2-copula is a bivariate distribution function on the unit square with uniform marginals (see e.g. Nelson, 2006):

$$C\left(u,v\right) = \mathrm{Prob}\left(U \le u,\ V \le v\right) \quad \text{with} \quad C=[0,1]\,,\ u=[0,1]\,,\ v=[0,1]\,. \tag{1}$$

Thus, the 2-copula can be used for describing the dependence structure between two arbitrary marginal distributions:

$$C\left(F(x_1), F(x_2)\right) = F\left(x_1,\ x_2\right)\,. \tag{2}$$

HESSD

5, 2459–2490, 2008

A space-time hybrid hourly rainfall model

U. Haberlandt et al.

Here, the Frank copula has been chosen which has been successfully applied for linking rainfall duration and intensity before (De Michele and Salvadori, 2003):

$$C(u,v) = -\frac{1}{\alpha}\ln\left[1 + \frac{\left(e^{-\alpha u}-1\right)\left(e^{-\alpha v}-1\right)}{\left(e^{-\alpha}-1\right)}\right] \quad \text{with} \quad C[0,1],\ u[0,1],\ v[0,1]. \tag{3}$$

The Frank copula has only one parameter α, describing the dependence between u and v. The parameter α can be approximated from Kendall's Tau (De Michele and Salvadori, 2003) with:

$$\tau(\alpha) \approx \frac{1}{9}\alpha - \frac{1}{900}\alpha^3 + \frac{1}{52920}\alpha^5 - \frac{1}{2721600}\alpha^7 + \ldots. \tag{4}$$

The alternating renewal model part describing the external structure of the rainfall process has 11 station specific parameters in total, which are estimated for summer (May to October) and winter seasons (November to April) separately (see Table 1).

For the simulation of the internal precipitation structure, a simple profile model is adapted (Haberlandt, 1998), disaggregating the wet-spell-amount into a special predefined pattern. A symmetric "double exponential function" describes the rainfall intensity within a wet spell (Fig. 2). The precipitation intensities can be calculated from

$$PI = wsp \cdot \exp\left[c \cdot \lambda(t - wspt)\right], \tag{5}$$

where *wsp* is the wet spell peak, *wspt* is the wet spell peak time, c=(+1) for $t \leq wspt$ and c=(−1) for $t > wspt$ and λ is a event specific parameter, which can be calculated from the external variables and the peak. So, the internal rainfall model is completely defined by the variables *wsd*, *wsa*, *wsp* and *wspt*. Since the variables *wsd* and *wsa* are already given by the external model, only *wsp* and *wspt* have to be specified here. The wet spell peak *wsp* is estimated by a simple regression to the wet-spell-intensity *wsi* using all stations in the study region:

$$wsp = a \cdot wsi^{\beta}. \tag{6}$$

HESSD

5, 2459–2490, 2008

A space-time hybrid hourly rainfall model

U. Haberlandt et al.

The wet-spell-peak-time *wspt* is generated from a uniform distribution. The main advantage of this simple profile model is that it needs no station specific parameters. This approach is obviously a strong simplification of the internal rainfall process. However, from the internal structure only a sufficient approximation of the peak intensity is expected. The detailed internal rainfall variability is assumed to be of minor importance compared to the external one for the generation of extreme flow events (see also Haberlandt, 1998).

2.2 Synthesis of the space-time rainfall structure using resampling

In this second step of the rainfall generation process the synthetic precipitation event time series for several locations in the study region will be resampled in order to reproduce the spatial dependence structure of the rainfall process. It is important to note, that for resampling not the hourly data are used but the event time series. This is in accordance with the basic idea of the alternating renewal process from step one, which assumes the independence of events. Thus, the resampling on the event time series does not destroy the temporal rainfall structure for single time series and does not need not to consider any autocorrelation. The resampling is carried out using simulated annealing (Aarts and Korst, 1989), which has been used for rainfall generation before (Bárdossy, 1998). Simulated annealing can be considered as a non-linear discrete optimisation method which minimises a certain objective function.

In our case the objective function should reflect the spatial dependence structure of the rainfall process. Three bivariate criteria have been defined for this purpose and are to be calculated from the hourly rainfall time series. The first criterion describes the probability of bivariate rainfall occurrence at two stations *i* and *j*:

$$P_{ij}\left(z_i > 0 | z_j > 0\right) = \frac{n_{11}}{(n_{01} + n_{10} + n_{11} + n_{00})}, \tag{7}$$

where z is the hourly rainfall intensity and n_{kl} is the number of hours with simultaneously occurring rainfall state k at station i and rainfall state l at station j. The possible rainfall states of occurrence are 1 for rainfall and 0 for no rainfall. The second criterion describes the interrelation between two stations i and j regarding their rainfall intensities. Here, Pearson's coefficient of correlation is applied:

$$\rho_{ij} = \frac{cov\left(z_i, z_j\right)}{\sqrt{var(z_i) \cdot var(z_j)}} \forall z_i > 0, z_j > 0. \tag{8}$$

The last criterion is a continuity measure proposed by Wilks (1998), which describes the interrelation between two stations i and j regarding the combined effect of rainfall occurrence and amount:

$$C_{ij} = \frac{E\left(z_i | z_i > 0, z_j = 0\right)}{E\left(z_i | z_i > 0, z_j > 0\right)}, \tag{9}$$

where E is the expectation operator. The ratio C_{ij} will become smaller with increasing interrelation between the two stations, and it will become a value of about 1 for independent stations.

The three criteria are combined into one bivariate objective function as follows:

$$O_{ij} = w_1 \cdot \left(P_{ij} - P_{ij}^*\right)^2 + w_2 \cdot \left(\rho_{ij} - \rho_{ij}^*\right)^2 + w_3 \cdot \left(C_{ij} - C_{ij}^*\right)^2, \tag{10}$$

where the variables marked with * represent the prescribed values and the other ones are the simulated values. The weights ω are used to control the importance and to adjust the scale of the different criteria. The prescribed values need to be estimated from observed hourly data before they can be used in the objective function. If it is possible to express those bivariate statistics as functions of the separation distance between two stations i and j, the criteria could be used for resampling of time series between any two points in the study region no matter if observations are directly available at these locations.

The resampling algorithm using simulated annealing works then as follows:

HESSD

5, 2459–2490, 2008

A space-time hybrid hourly rainfall model

U. Haberlandt et al.

1. A rainfall station i with $i=2, N$ is selected for resampling. Note, the first station station $i=1$ is not resampled at all. A backup of the event time series from station i is made and the events are disaggregated into hourly values.

2. All neighbouring rainfall stations j with for $j=1, i-1$ are selected. These are the stations which have been resampled before including the first unresampled station $j=1$.

3. Two events are drawn at random from the resampling station i and swapped. A backup of the modified data from the time period between the two events is made and then the changed period is disaggregated into hourly values.

4. The value for the objective function O_{ij} (Eq. 10) is calculated/ updated using the data from the hourly series. An average objective function value O_i for station i considering all the neighbours $j=1, i-1$ is calculated:

$$O_i = \frac{1}{i-1} \sum_{j=1}^{i-1} O_{ij}. \tag{11}$$

5. The new value of the objective function O_{new} is compared with the old value O_{old}, which has been calculated before the last swap. If $O_{new}<O_{old}$ then the change is accepted.

6. If $O_{new} \geq O_{old}$ then the change is accepted with the probability:

$$\pi = \exp\left(\frac{O_{old} - O_{new}}{T_a}\right). \tag{12}$$

7. Steps 3 to 6 are repeated M times.

8. The annealing temperature T_a is reduced: $T_a=T_{a-1} \times dT$ with $0<dT<1$ and the work proceeds with step 3.

9. Steps 7 and 8 are repeated until the algorithm converges regarding resampling of the station i.

10. Then the algorithm is repeated for the next station (go to step 1).

Step 6 ensures that the optimisation does not stop at any local minima but will converge toward a global minimum. The annealing temperature T_a regulates the probability of negative changes. As lower T_a as less likely is the acceptance of a negative change. The convergence is ensured in reducing the temperature each time after M iteration steps. In order to speed up the algorithm for the resampling of long time series the hourly spatial dependence criteria are not recalculated for the whole time series but updated considering only the changed period between the two swapped events. In addition the distance between two randomly selected events for swapping can be restricted. The here described second step in the rainfall generation process yields rainfall time series with spatial dependence regarding the criteria in Eqs. (7)–(9) but preserves the temporal characteristics from the alternating renewal process.

3 Case study

3.1 Data and study region

The hybrid rainfall model is tested and applied for derived flood frequency analysis in two mesoscale catchments within the Bode river basin in northern Germany (Fig. 3). The considered 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/yr and 500 mm/yr. The two catchments Holtemme and Selke have drainage areas of 168 km^2 and 105 km^2, respectively. Floods are generated either by frontal rainfall, frontal rainfall on snow smelt or convective storms. Large floods in the Selke catchment occur mainly in the winter season while floods in the Holtemme take place mostly in the summer time. Figure 3 shows the rainfall gauges, which are used for hydrological modelling in both catchments. These comprise 19 non-recording rain gauges, 3 recording rain gauges operated all year and 8 recording rain gauges operated during the summer season only. In the following, these will be called daily stations, all year stations and summer stations, respectively. The length of the observation periods for the hourly stations which could be used for modelling here is between 12 and 14 years from 1993 to 2006. However, the number of hourly rain gauges is too small for the robust estimation of the spatial statistics (see Eq. 7 to 9) in relation to the separation distance. So, the study region has been extended for that purpose, providing then a total number of 23 hourly stations observed during summer and 15 stations observed during winter (not shown on Fig. 3).

3.2 Rainfall runoff model

For runoff simulations the hydrological model HEC-HMS (Scharffenberg and Fleming, 2005) is used, which has been applied successfully in the past for various purposes (see e.g. Fleming and Neary, 2004; Cunderlik and Simonovic, 2005; Neary et al., 2004; Maskey et al., 2004). HEC-HMS is a conceptual semi-distributed rainfall-runoff model and offers various tools for the description of the hydrological processes. Figure 4 illustrates the model structure which has been compiled from the available tools for this study. The model is operated continuously on a 1-h 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 base flow transformation and a simple river routing where the flows are only lagged in time. Snow melt is calculated externally using the degree-day method. Potential evapotranspiration is computed also externally using the method proposed by Turc-Wendling (Wendling et al., 1991) based on observed temperature and global radiation data from the three available climate stations. Potential evapotranspiration is the aggregated to monthly averages and fed into HEC-HMS. To account for spatial heterogeneity of precipitation and basin characteristics the two catchments are spatially divided into several subcatchments and river reaches (see also Fig. 3).

Because of the sparse network for recording rainfall gauges also daily stations have been included in the model calibration. For that purpose daily rainfall totals are disaggregated into hourly data using the intensity profile from the nearest station with high resolution data. Areal rainfall for subcatchments is then calculated by Thiessen interpolation from all daily and hourly station locations.

The model HEC-HMS has been calibrated for the period from November 1997 to 2001 and validated for the subsequent period from November 2001 to October 2004 using the outlet streamflow gauges of the Holtemme and the Selke catchments. Figure 5 shows a comparison of observed and simulated streamflow during the validation period for the two catchments. The obtained model performance is sufficient with average Nash-Sutcliffe efficiencies of 0.81 and 0.86 for the Holtemme and Selke basins, respectively.

3.3 Synthesis and application of stochastic rainfall

The hybrid precipitation model is applied and validated for the study region in the following three step procedure:

1. Single site rainfall is generated for all hourly stations using the alternating renewal model.

2. The hourly rainfall series are resampled to generate the spatial rainfall structure, separately for the Holtemme and Selke catchments using simulated annealing.

3. Derived flood frequency analysis is carried out for both catchments using the rainfall-runoff model HEC-HMS and the synthetic rainfall data.

The parameters for the alternating renewal model have been estimated for the 3 all year and 8 summer stations for winter and summer seasons separately. Then several realisations a 100 years hourly rainfall data are generated for all stations. Table 2 shows a comparison between observed and simulated event characteristics exemplarily for three rainfall stations. The comparison shows sufficient agreement between observed and simulated statistics with a slight underestimation of mean rainfall and a somewhat larger deviation for the higher order moments, which is typical for this kind of models. Note, that only those features are used here for validation, which don't represent model variables in the precipitation model. In addition a frequency analysis is carried out on the annual maximum precipitation series for different durations. The results are presented in Fig. 6 for the station Harzgerode for both seasons and rainfall durations of 1 and 3 h. It can be seen, that the observed values are plotted mostly within the range of the simulated realisations. For larger return periods and durations a slight overestimation of the observed extreme values occurs. Considering the short observation periods it is difficult to validate the model regarding the synthesis of more extreme rainfall intensities. It is expected, that the hydrological validation, which comprises longer observed flow records, will allow an additional assessment of model performance regarding this issue.

Before in the next step the resampling can be carried out the spatial dependence criteria defined in Sect. 2.2 have to be estimated. Based on an extended data sample (cp. Sect. 3.1) different functions for the summer and winter seasons are fitted to the three statistics in relation to the separation distance between stations. Figure 7 shows the results exemplarily for the summer seasons. The relation between the criteria occurrence P_{ij} (Eq. 7), correlation ρ_{ij} (Eq. 8), continuity C_{ij} (Eq. 9) and the separation distance appear strong enough for the application of those relationships to derive the required statistics. The functions show the expected behaviour of the spatial rainfall expressing decreasing probability of simultaneous rainfall occurrence, decreasing correlation and increasing continuity with rising separation distance between two stations. From Fig. 7 a range between 150 km and 200 km can be estimated where the dependence between two stations disappears.

The resampling of the synthetic event series is carried out separately for the two catchments and the two seasons using simulated annealing for all available hourly rainfall gauges. Two stations for the winter season and four stations for the summer season are included for this procedure in the Holtemme basin. Concerning the Selke basin six stations are used for resampling of the summer data. However, in that basin no resampling for the winter time was necessary, because only one station is available. The performance of the simulated annealing algorithm depends on the number of rainfall stations included and on the specific criterion considered. The results are as better as smaller the number of included stations is. So, it is favourable to process the two neighbouring catchments separately here. Comparing the performance regarding the different criteria it is most difficult for the algorithm to simulate the prescribed probability of simultaneous rainfall occurrence P_{ij}, while it is easier to mimic the continuity measure C_{ij} and it is no problem to reproduce the correlation ρ_{ij}. On the whole the reproduction of the spatial dependence criteria was satisfactory for the two mesoscale catchments. Figure 8 shows a comparison of hourly rainfall time series before and after the resampling process for two neighbouring rainfall stations, which are located about 20 km apart. The effect of the resampling procedure becomes quite clear. Wet and dry spells as well as intensity peaks correspond much better between the two stations after the resampling process than before.

In the third step the stochastic rainfall data are used as input for the hydrological model HEC-HMS. The hydrological model has been calibrated using hourly and daily rainfall data, but synthetic precipitation is only generated for the hourly stations. It is known, that applying a hydrological model on rainfall data from a different station network as used in the calibration might produce biased runoff and the model parameters might need recalibration, which is difficult considering synthetic rainfall as input. Especially a model calibrated on denser precipitation information, as it would be the case here, might fail on sparser information (Bárdossy and Das, 2008). For that reason the generated hourly data are transferred also to the daily station locations, which have been utilised in calibration, using nearest neighbour interpolation and applying a correction factor taking into account the different mean seasonal precipitation amounts at the specific locations. Simulation experiments have shown that this simple method has improved results considerably regarding the simulation of flood frequencies in comparison to using only hourly station locations. For continuous hydrological modelling also temperature and radiation data are required for the calculation of potential evaporation. For this application of HEC-HMS with synthetic rainfall simply repetitions of 25 years blocks of observed hourly temperature and radiation data are used.

Figure 9 compares observed and simulated flood frequencies from annual series for the two mesoscale catchments Selke and Holtemme at their outlet gauges. Simulated flows are shown based on the short observed rainfall time series and on 10 synthetic rainfall realisations a 100 years hourly data. Observed extreme values have longer records than the simulated ones using observed precipitation. The observed maximum flows and the simulated ones using observed rainfall data are laying mostly within the range of the simulated flows, which result from the stochastic precipitation data. Although the reference points are located somewhat more in the lower part of the synthetic range, the overall picture shows the ability of the precipitation model to provide suitable input for derived flood frequency analysis. Note, that in Fig. 9 the difference between the empirical distribution functions of observed and simulated flows using observed precipitation is indicating the model performance of HEC-HMS regarding the reproduction of the flood frequency. So, in the first instance the derived distribution functions using synthetic rainfall should cover the simulation results using observed rainfall.

In order to evaluate the importance of the spatial rainfall structure or more precisely the effect of the resampling procedure in addition hydrological modelling with HEC-HMS is carried out with spatially randomly and uniformly distributed synthetic rainfall data as input. For the former the resampling procedure has been omitted and for the latter only one rainfall station has been used as homogeneous areal rainfall for the two catchments, respectively. The results are illustrated for the Holtemme basin in Fig. 10 considering the summer season only, where the spatial dynamics are higher and more stations for resampling were available. It can be seen, that homogeneous rainfall leads to an overestimation of floods while spatial independent rainfall leads to an underestimation with respect to the simulated flows using observed rainfall. Forcing the hydrological model with resampled rainfall produces a more plausible flood frequency curve located in between the two marginal cases. This result encourages the application of the proposed resampling procedure to reproduce important characteristics of the spatial rainfall structure.

4 Conclusions

In this study a hybrid hourly rainfall model has been presented, which can be applied for derived flood frequency analysis. The model consists of two parts, an alternating renewal approach for the generation of point rainfall and a resampling procedure based on simulated annealing to reproduce the spatial statistics. Special attention was given to the derivation of a practical applicable parsimonious approach for precipitation synthesis. The performance of the rainfall model has been tested in three stages, for the simulation of temporal rainfall characteristics at single sites, for the reproduction of the spatial rainfall structure and for flood simulations in two mesoscale catchments in northern Germany. The results can be summarised as follows:

1. The single site rainfall model based on the alternating renewal approach allows a good reproduction of average event statistics and extreme value frequencies for short rainfall durations. This result could be achieved despite the parsimonious approach which uses only one probability distribution function for the whole range of wet spell intensities. The dependence between wet spell intensity and duration can easily be considered using a copula model. Still, improvements of this temporal model are desirable with regard to the overestimation of the extreme values for longer rainfall durations in the summer season.

2. With multisite resampling of the synthetic event series using simulated annealing the spatial rainfall structure could sufficiently be reproduced. The resampling of the events instead of the single hours preserves the temporal rainfall properties,

which has been prescribed in the first part of the model and, besides, it is computationally very favourable. It has been shown, that the consideration of the spatial rainfall structure in hydrological modelling has a significant effect on the derived flood frequencies.

3. The simulation results from rainfall runoff modelling have demonstrated the suitability of the synthetic precipitation data for derived flood frequency analysis in mesoscale catchments. However, it is important here to consider the same station network in calibration and application of the hydrological model. In future work the synthetic rainfall data might be included directly for the calibration of the hydrological model e.g. with the objective to minimize deviations to the observed flood frequencies.

Derived flood frequency analysis using synthetic precipitation data and rainfall-runoff modelling is becoming increasingly important in practical applications. This is especially the case for investigating the effect of complex flood protection measures and for analysing impacts of climate and land use changes. The presented model has also the potential to be used for statistical downscaling in climate impact studies, since its parameters can be related to larger scale climate characteristics which can be obtained from climate models. Also, an application for unsampled locations is possible through regionalisation of the model parameters. With such a method the hourly network density might be increased e.g. by including the daily station locations in a more sophisticated way as by simple data transfer.

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Table 1. External structure of the alternating renewal model.

Components of the rainfall event process	Description in the alternating renewal model framework	Number of parameters
Wet spell duration (*wsd*)	General extreme value distribution	3
Wet spell intensity (*wsi*)	Kappa distribution	4
Dependence between *wsd* and *wsi*	Frank copula	1
Dry spell duration (*dsd*)	Weibull distribution	3

HESSD

5, 2459–2490, 2008

Table 2. Event characteristics for the rainfall stations Harzgerode, Wernigerode and Braunlage (for location see Fig. 3) from 12 years observed and 200 years simulated rainfall data each.

Name of rainfall station	Number of events [–]		Average *wsa* [mm]		Std. Dev. of *wsa* [mm]		Skewness of *wsa* [–]		Rainfall sum [mm]	
	obs	sim	obs	sim	obs	sim	obs	sim	obs	sim
Summer season (May to October):										
Harzgerode	89	86	3.68	3.56	5.36	5.68	4.81	7.73	328	308
Wernigerode	102	92	3.88	3.72	6.02	6.09	4.93	7.51	396	343
Braunlage	134	128	5.33	5.24	8.42	8.96	5.08	6.19	714	672
Winter season (November to April):										
Harzgerode	78	76	3.39	3.25	4.93	4.15	7.49	6.63	266	246
Wernigerode	102	88	3.77	3.53	5.21	4.47	3.85	5.28	382	312
Braunlage	115	110	7.44	7.02	11.5	10.1	3.91	4.21	854	768

HESSD

5, 2459–2490, 2008

A space-time hybrid hourly rainfall model

U. Haberlandt et al.

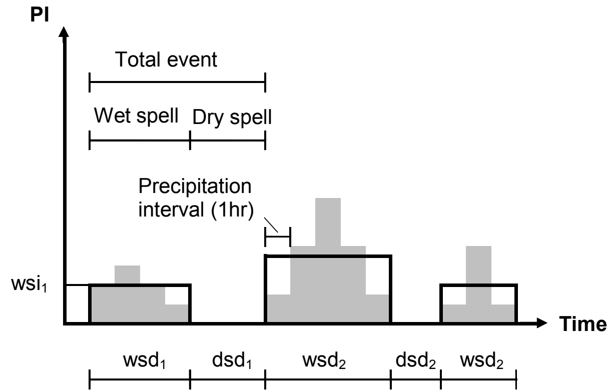

Fig. 1. Scheme of the precipitation event process.

HESSD
5, 2459–2490, 2008

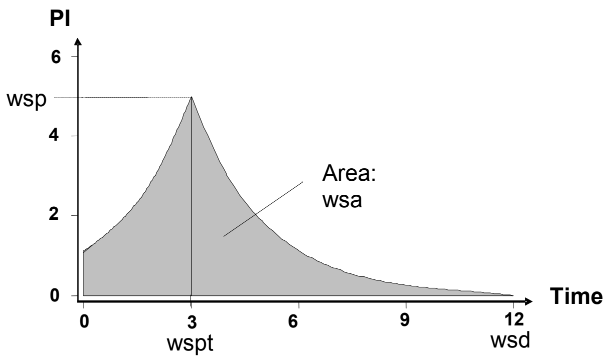

Fig. 2. Double exponential function for internal rainfall structure.

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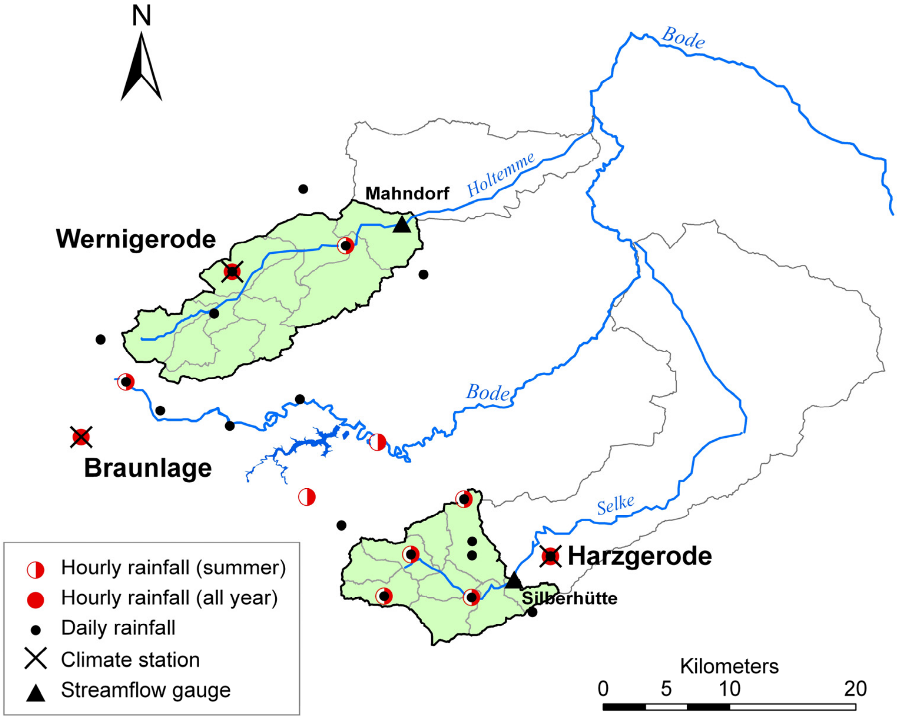

Fig. 3. Study region showing the two mesoscale basins Holtemme and Selke, their subcatchment delineation, used rainfall and climate stations as well as streamflow gauges.

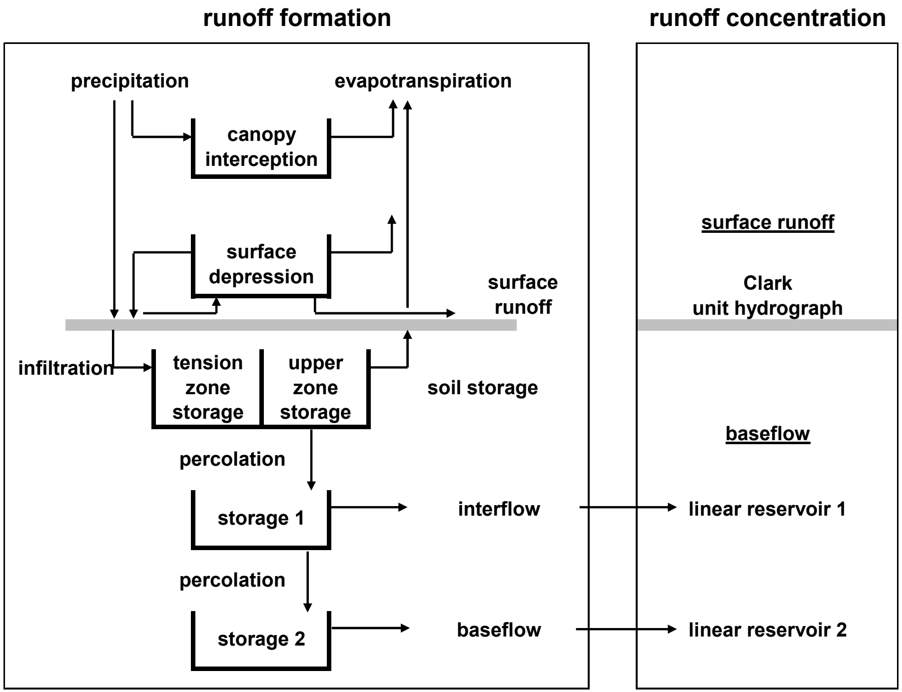

Fig. 4. Selected structure of the hydrological model HEC-HMS.

HESSD
5, 2459–2490, 2008

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◂ | ▸
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

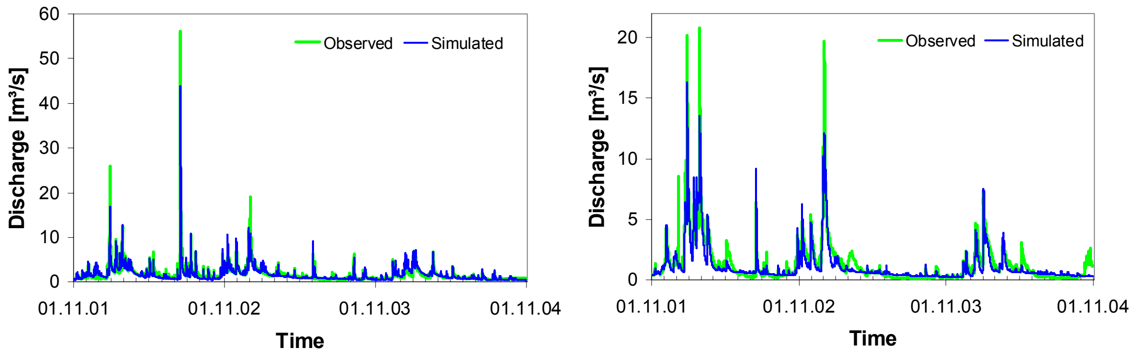

Fig. 5. Observed and simulated flows in the validation period for the Holtemme basin (left) and Selke the basin (right).

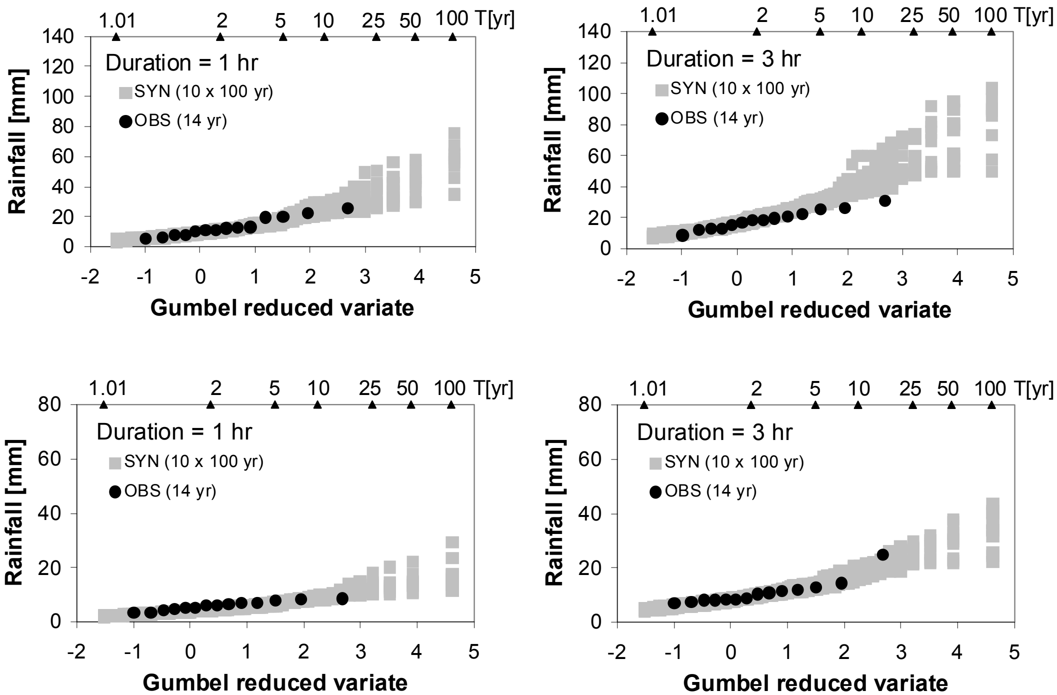

Fig. 6. Empirical probability distribution functions of observed (OBS) and synthetic (SYN) seasonal maximum rainfall for the station Harzgerode and two durations (top: Summer, bottom winter).

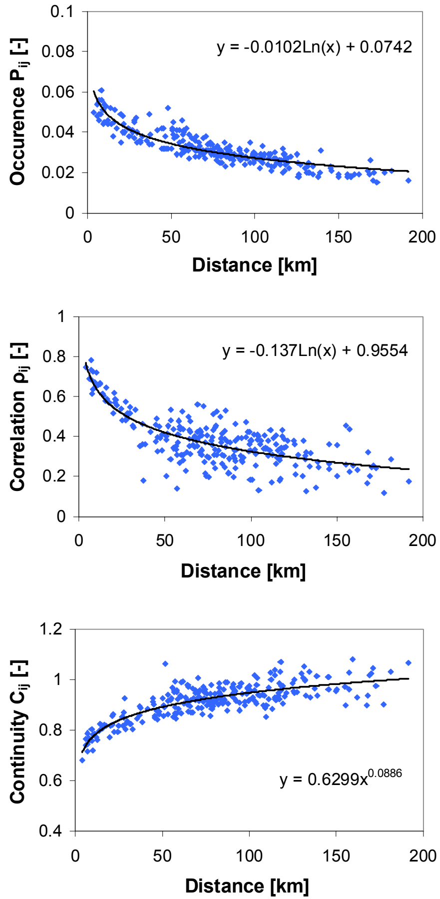

Fig. 7. Relation between the spatial dependence criteria which are used in the objective functions for simulated annealing and the station separation distance for the summer season.

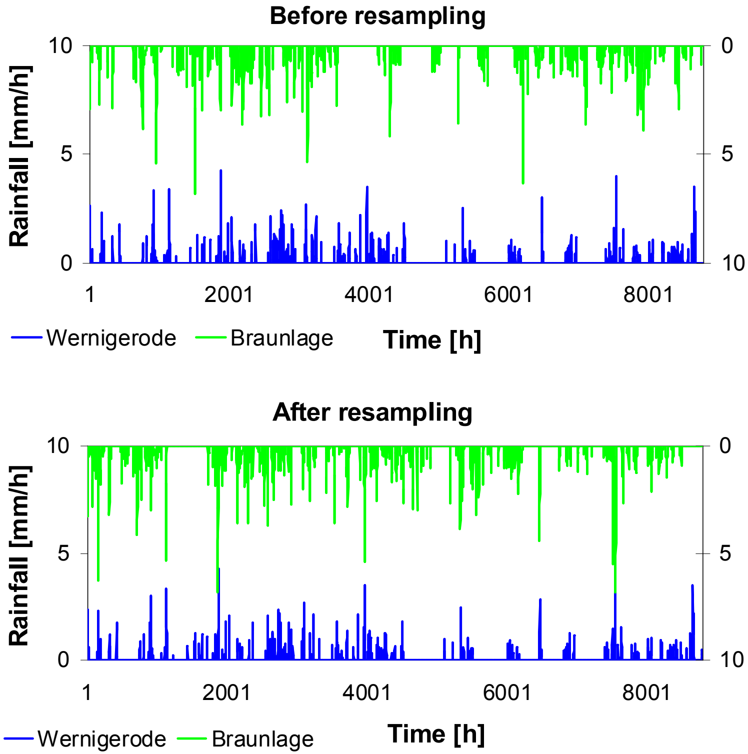

Fig. 8. Comparison of hourly precipitation time series for the stations Wernigerode and Braunlage before and after resampling the events of the latter station using simulated annealing.

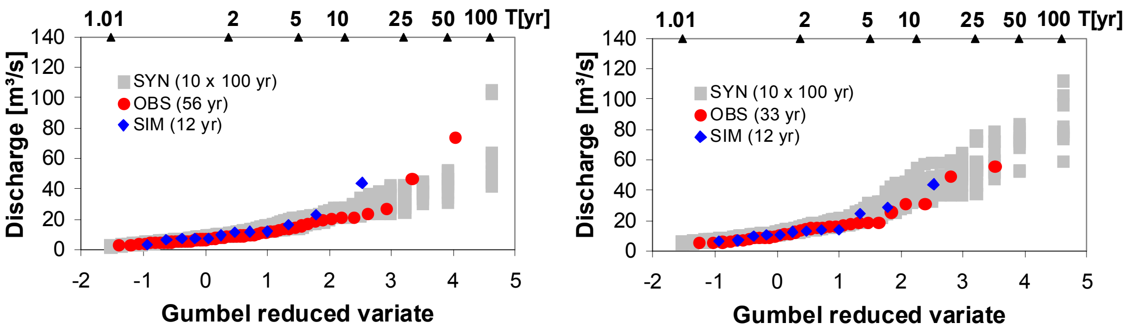

Fig. 9. Empirical probability distribution functions of observed discharge (OBS), simulated discharge using observed rainfall (SIM) and simulated discharge using 10 realisations a 100 years synthetic rainfall (SYN) for the Selke (left) and Holtemme (right) basins.

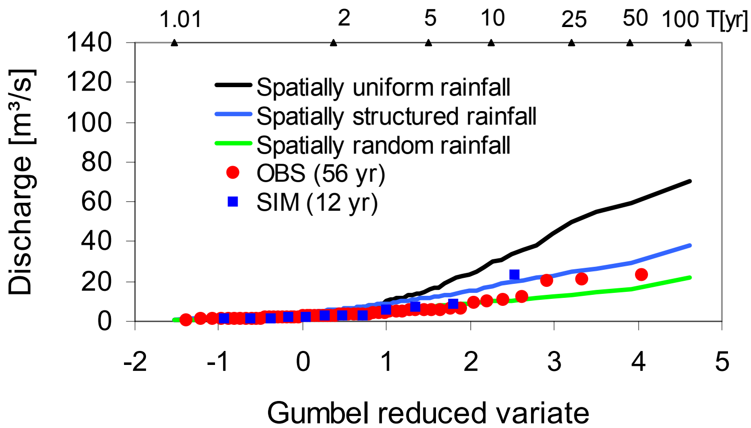

Fig. 10. Empirical probability distribution functions of observed discharge (OBS), simulated discharge using observed rainfall (SIM) and the median of 10 realisations a 100 years simulated discharge for three synthetic rainfall scenarios for the Holtemme basin in the summer season.