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Temporal rainfall disaggregation using a multiplicative cascade model for spatial application in urban hydrology

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SUMMARY

Rainfall time series of high temporal resolution and spatial density are crucial for urban hydrology. The multiplicative random cascade model can be used for temporal rainfall disaggregation of daily data to generate such time series. Here, the uniform splitting approach with a branching number of 3 in the first disaggregation step is applied. To achieve a final resolution of 5 min, subsequent steps after disaggregation are necessary. Three modifications at different disaggregation levels are tested in this investigation (uniform splitting at Δt = 15 min, linear interpolation at Δt = 7.5 min and Δt = 3.75 min). Results are compared both with observations and an often used approach, based on the assumption that a time steps with Δt = 5.625 min, as resulting if a branching number of 2 is applied throughout, can be replaced with Δt = 5 min (called the 1280 min approach). Spatial consistence is implemented in the disaggregated time series using a resampling algorithm. In total, 24 recording stations in Lower Saxony, Northern Germany with a 5 min resolution have been used for the validation of the disaggregation procedure. The urban-hydrological suitability is tested with an artificial combined sewer system of about 170 hectares.

The results show that all three variations outperform the 1280 min approach regarding reproduction of wet spell duration, average intensity, fraction of dry intervals and lag-1 autocorrelation. Extreme values with durations of 5 min are also better represented. For durations of 1 h, all approaches show only slight deviations from the observed extremes.

The applied resampling algorithm is capable to achieve sufficient spatial consistence. The effects on the urban hydrological simulations are significant. Without spatial consistence, flood volumes of manholes and combined sewer overflow are strongly underestimated. After resampling, results using disaggregated time series as input are in the range of those using observed time series.

Best overall performance regarding rainfall statistics are obtained by the method in which the disaggregation process ends at time steps with 7.5 min duration, deriving the 5 min time steps by linear interpolation. With subsequent resampling this method leads to a good representation of manhole flooding and combined sewer overflow volume in terms of hydrological simulations and outperforms the 1280 min approach.

1. Introduction

Rainfall time series of high temporal resolution and sufficient station density are crucial for urban hydrology (Schilling, 1991). Bruni et al. (2015) analyzed the influence of spatial and temporal resolution of rainfall on intensities and simulated runoff. With decreasing resolution, the variability of rainfall intensities was reduced and the runoff behavior changed regarding maximum water depth and runoff peaks. Emmanuel et al. (2012) extracted different types of rainfall from radar data in Western France with 5 min-resolution and analyzed their spatial extension with variograms. They found that for an adequate spatial representation, rainfall gauges should have a maximum distance of 6.5 km for light rain events and 2.5 km for showers. Berne et al. (2004) found similar values by an investigation of intensive Mediterranean rainfall events. They recommended temporal resolutions of 3–6 min and a station density of 2–4 km for urban catchments with an area of 1–10 km^2. Ochoa-Rodriguez et al. (2015) analyzed the effect of different combinations of temporal (1–10 min) and spatial (100–3000 m) resolutions for different catchments (up to drainage areas of 8.7 km^2). They found that for drainage areas greater than 100 ha spatial resolution of 1 km is sufficient, if the temporal resolution is fine enough (<5 min).

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Radar-measured rainfall data would meet these requirements. Unfortunately, the direct measurement with a radar device is not possible, only reflected energy from hydrometeors at a certain height above the ground can be measured. Thus, radar data can be affected by different sources of errors, e.g. variations in the relationship between reflected energy and rainfall intensity depending on rainfall type, changes in the precipitation particles before reaching the ground, anomalous beam propagation and attenuation (Wilson and Brandes, 1979). Hence, it could be expected that the use of uncorrected radar data is not acceptable for many hydrological applications. However, after correction radar data can be an useful input for e.g. urban hydrological applications (Ochoa-Rodriguez et al., 2015).

On the other hand, direct rainfall measurement is possible with rain gauges. The measurement is also affected by errors, e.g. wind induced errors, losses from surface wetting or evaporation from collectors, but these can be quantified and corrected (Richter, 1995; Sevruk, 2005).

However, the availability of observed time series for rain gauges meeting the aforementioned requirements concerning temporal and spatial resolution is rare. On the contrary, time series with lower temporal resolution (e.g. daily measurements) exist for much longer periods and denser networks. Disaggregation of the time series from these non-recording stations using information from the recording stations is a possible solution to this data sparseness problem.

Several methods are available that can be used for this disaggregation e.g. method of fragments (e.g. Wójcik and Buishand, 2003), Poisson-cluster models (e.g. Onof et al., 2000), cascade models or a combination of different methods (e.g. Paschalis et al., 2014).

For a theoretical introduction to cascade models and the underlying theory of scale-invariance the reader is referred to Serinaldi (2010) and the reviews of Veneziano et al. (2006), Veneziano and Langousis (2010) and Schertzer and Lovejoy (2011). An advantage of micro-canonical cascade models is their exact conservation of rainfall volume of the coarse time series at each disaggregation step (Olsson, 1998). The total rainfall amount of each coarse time step is distributed on the number of finer time steps, whereby the number of resulting wet time steps and their rainfall amount (as fraction of the total rainfall amount of the coarser time step) depends on the cascade generator. An aggregation of the disaggregated time series results in exactly the same time series that was used as a starting point for the disaggregation. Accordingly, all required parameters for the disaggregation process can also be estimated from the aggregation of the recording time series (Carsteanu and Foufoula-Georgiou, 1996) and can then be applied to the disaggregation of time series from surrounding non-recording stations (Koutsoyiannis et al., 2003).

Cascade models are widely applied in urban hydrology. One structural element of the cascade models is the branching number b, which determines the number of finer time steps generated from one coarser time step. In most cases $b = 2$, which means that a starting length of 24 h will result in an inapplicable temporal resolution of 11.25 or 5.625 min. So a direct disaggregation from daily values to 5- or 10-min values is not possible. One established solution is to preserve the rainfall amount of a day, but the length is reduced to 1280 min, instead of 1440 min (Molnar and Burlando, 2005, 2008; Paschalis et al., 2014; Licznar et al., 2011a,b, 2015). Under this assumption, temporal resolutions of 5- or 10-min can be achieved. However, this is a very coarse assumption and missing time steps have to be infilled with dry intervals for applications such as the continuous modeling of sewer systems. If b is changed during the disaggregation process, other temporal resolutions can be achieved. Lisniak et al. (2013) introduce a cascade model with $b = 3$ to reach the first and $b = 2$ to reach all further disaggregation levels, which leads to time steps with 1 h duration. A parameter sparse version of their model is applied in Müller and Haberlandt (2015).

The application of cascade models for generation of high-resolution time series is recommended by several authors. Segond et al. (2007) suggest a cascade model for the disaggregation of hourly time series, although other methods were also tested in their investigation. Onof et al. (2005) disaggregated hourly values with $b = 2$ to 3.75 min intervals and transformed them into 5 min intervals by a linear interpolation (similar to the diversion process to achieve hourly resolutions described in Güntner et al., 2001). Hingray and Ben Haha (2005) tested several models for disaggregation from 1 h to 10 min. Micro-canonical models have shown best performance regarding rainfall statistics, but also for modeled discharge results.

Considering these previous studies, the testing of different cascade model variations for the disaggregation of daily values is the first novelty of this investigation. The impact on time series characteristics like average wet spell duration and amount, dry spell duration, fraction of dry intervals, average intensity, autocorrelation function and also extreme values will be analyzed.

Furthermore, the impact on overflow occurrence and volume within an artificial sewer network will be analyzed. Although rainfall time series are often disaggregated for this purpose, analyzes of the impact on runoff in sewer systems are rare. An artificial sewer system in combination with real recording rainfall gauges will be used for this study. As time series of different stations are disaggregated without taking into account time series of surrounding stations, this per station or single-point procedure results in unrealistic spatial patterns of rainfall. Since the spatial resolution is also important for high-resolution rainfall (Berne et al. 2004; Emmanuel et al. 2012), the spatial distribution of rainfall has to be considered. Müller and Haberlandt (2015) introduced a resampling algorithm to implement spatial consistence into time series after disaggregation for hourly resolutions. A similar procedure will be used in this study for the first time to the author's knowledge for 5 min values. Also, it will be analyzed if there is a necessity for spatial heterogeneous rainfall (resulting from more than one station) to represent extreme events in such a small catchment, or if uniform rainfall resulting from one station is sufficient.

The paper is organized as follows. In the "Data" section the investigation area, the rainfall stations and the artificial sewer system are described. In the next section the applied methods are discussed in three parts. In the first part different possibilities for the rainfall disaggregation are explained. The second part concerns the implementation of spatial consistence in the disaggregated time series. The implementation in the sewer system and the analysis of the model results are described in the third part. In the "Results and Discussion" section the results for all three parts are shown and discussed. A summary and outlook are given in the final section.

2. Data

2.1. Rainfall data

The stations used for this investigation are located in and around Lower Saxony, Germany (47 614 km^2, see Fig. 1). The investigation area can be divided into three different regions, the Harz middle mountains with altitudes up to 1141 m in the south, the coastal area around the North Sea in the north and the flatland around the Lüneburger Heide in between. Some areas of the Harz mountains have average annual precipitation greater than 1400 mm. Furthermore, the study area can be divided climatologically according to the Köppen–Geiger classification into a temperate climate in the north and a cold climate in the mountainous region. Both climates exhibit hot summers, but no dry season (Peel et al., 2007).

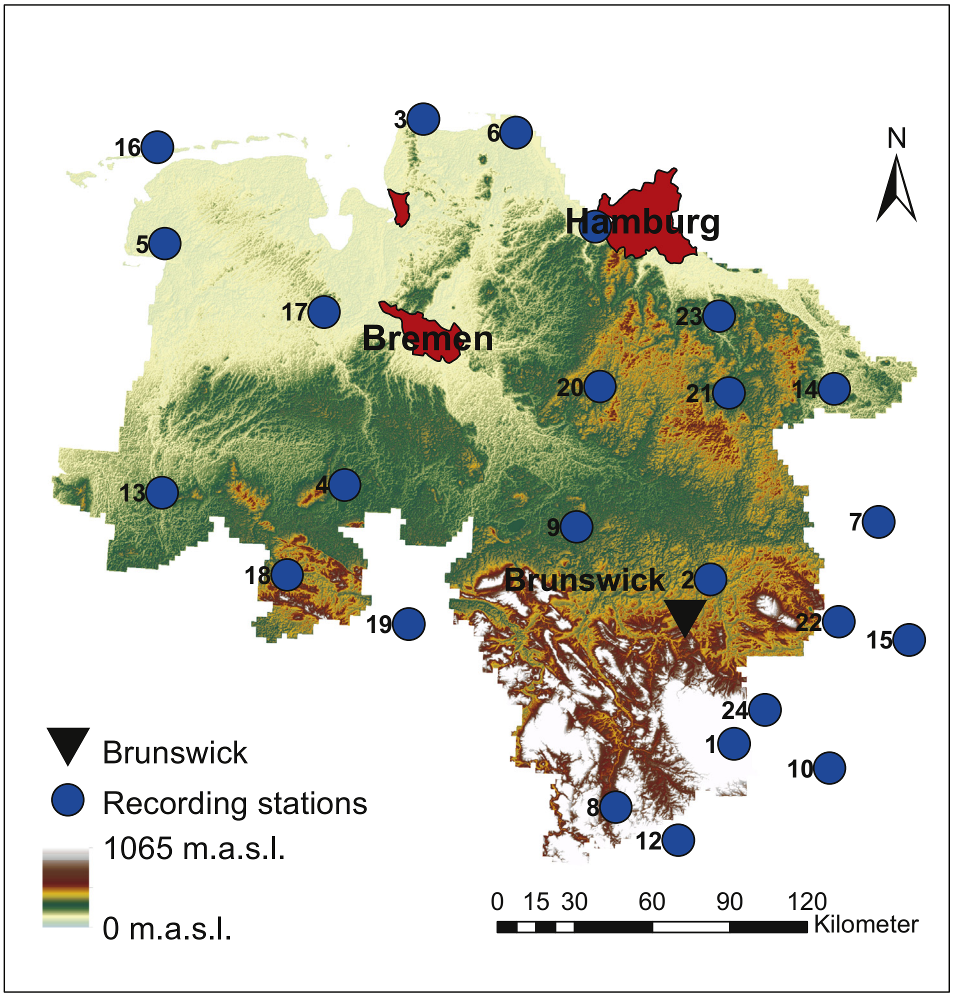

Fig. 1. Recording stations in and around the federal states of Lower Saxony, Hamburg and Bremen. The city of Brunswick is also shown.

In Fig. 1, 24 recording stations from the German Weather Service (DWD) with long term time series (9–20 years) are shown. These stations are used for the validation of the cascade model variants, concerning the representation of different rainfall characteristics. These are overall characteristics like average intensity and fraction of wet hours, but also event characteristics like dry spell duration, wet spell duration and wet spell amount as well as extreme values. Events are defined as having a minimum of one dry time step before and after the rainfall occurrence (after Dunkerley, 2008). A dry time step is defined with a rainfall intensity of 0 mm/5 min. The measurement devices are either tipping buckets, drop counters or weighting gauges, with accuracies of 0.1 mm or 0.01 mm. Time series of single stations from different data bases with different temporal resolutions (1 and 5 min) have been combined to extend their time series length, so the resulting temporal resolution is 5 min. This enables also comparisons with previous microcanonical cascade studies (see discussion in Licznar et al., 2015) These characteristics and further information of the rainfall stations are given in Table 1.

Additionally five recording stations from the city of Brunswick are used (see Table 1, station I–V). These stations are not shown in Fig. 1 due to their proximity with distances to each other less than 5 km. However, the city of Brunswick is shown. The time series lengths of these stations are shorter (02.01.2000–24.12.2006), so that they have not been used for the validation of the cascade model variants. Due to their proximity, these stations are used for the estimation of the bivariate characteristics, for the validation of the resampling algorithm and as input for the validation within an urban-hydrological model. The measurement devices are tipping buckets with accuracies of 0.1 mm and temporal resolutions of 1 min. However, to enable comparisons to the aforementioned stations the time series are aggregated to 5 min.

2.2. Combined sewer system

An artificial combined sewer system was constructed in order to compare the different disaggregation approaches (Fig. 2). The application of artificial systems is a common approach for the validation of synthetic rainfall (Kim and Olivera, 2012). The sewer system consists of 22 sub-catchments with a mean area size of 7.6 ha, ranging from 1.1 ha to 16 ha (with a standard deviation of 4.6 ha), and a cumulative total of 168.1 ha. Each catchment has a fraction imperviousness of 65%. A uniform slope of 0.25 is used for all pipes. A tank before the outfall of the sewer system was implemented. It has a storage capacity of 2184 m^3, equal to 20 m^3 per hectare of impervious area and is a typical value after Imhoff and Imhoff (2007).

Three rain gauges are implemented. They have been arranged with the same distances to each other as three rain gauges in the city Brunswick (station I, II and IV). This allows a direct comparison between simulated discharges and flood volumes resulting from observed and disaggregated time series. With a maximum distance of about 3 km for these three stations, the rainfall data meets the requirements suggested by Berne et al. (2004) and Emmanuel

Table 1
Attributes of rainfall stations for a temporal resolution of 5 min.

ID	Name	Altitude (m.a.s.l.)	Mean annual precipitation (mm)	Fraction of wet 5 min-intervals (%)	Average wet spell duration (min)	Average wet spell amount (mm)	Average dry spell duration (min)
1	Braunlage	607	1397	8.1	15.5	0.51	175.3
2	Braunschweig-Voel.	81	638	4.4	15.7	0.43	336.8
3	Cuxhaven	5	869	6.2	19.1	0.51	291.9
4	Diepholz	39	690	4.6	15.2	0.43	314.8
5	Emden	0	825	5.2	15.5	0.47	281.2
6	Freiburg/Elbe	2	888	6.4	18.5	0.49	272.9
7	Gardelegen	47	581	6.2	22.7	0.40	340.2
8	Göttingen	167	631	4.3	14.1	0.40	315.3
9	Hannover	55	641	3.9	13.2	0.41	323.0
10	Harzgerode	404	612	7.3	23.9	0.38	304.3
11	Jork-Moorende	1	727	5.7	18.4	0.44	302.0
12	Leinefelde	356	942	8.0	25.5	0.57	291.1
13	Lingen	22	789	5.5	16.6	0.46	286.6
14	Lüchow	17	569	3.9	14.3	0.39	349.3
15	Magdeburg	76	496	5.5	22.1	0.38	373.3
16	Norderney	11	744	4.5	14.6	0.46	309.5
17	Oldenburg	11	809	6.4	18.1	0.43	263.1
18	Osnabrück	95	874	5.4	14.8	0.45	258.3
19	Bad Salzuflen	135	825	5.0	13.5	0.42	253.0
20	Soltau	76	804	5.3	15.4	0.44	274.1
21	Uelzen	50	643	5.5	17.5	0.39	300.1
22	Ummendorf	162	549	5.9	23.6	0.41	367.2
23	Wendisch Evern	62	686	5.8	18.0	0.40	290.2
24	Wernigerode	234	625	7.1	23.6	0.39	305.1
I	Prinzenweg	77	628	3.3	11.0	0.39	318.4
II	Bürgerpark	77	606	3.1	11.1	0.41	344.1
III	Fremersdorfer Straße	83	577	3.0	10.9	0.39	347.9
IV	Weststadt	91	597	3.1	11.1	0.41	346.9
V	Grünewaldstraße	76	623	3.4	10.9	0.38	310.5

et al. (2012). Additionally, each of the rain gauges influences similar fractions of the sewer system (station I: 32.7%, station II: 31.2%, station IV: 36.0%), whereby to each subcatchment only the one rain gauge is assigned, which is closest to the centroid of the subcatchment (see Fig. 2). If one of the rain gauges would be situated more central than the other two, it would affect a higher fraction of the area due to a higher distance of other stations. If so, the rainfall input would be uniform for also a higher fraction of the area. So due to the central position of all three rain gauges the effect of the spatial consistence will be emphasized.

3. Methods

In this section, the cascade model for the disaggregation of the rainfall time series will be described first. Afterwards, the implementation of the spatial consistence and the application to an artificial urban hydrological case are explained.

3.1. Cascade model

The principle of a multiplicative micro-canonocal cascade model, as it was introduced by Olsson (1998) for temporal rainfall disaggregation, is illustrated in Fig. 3. One coarse time step is split into b finer time steps of equal duration, where b is the branching number, with $b = 2$ in Fig. 3. For the splitting, the weights W_1 and W_2 are used to determine the rainfall volume in the two finer time steps. The sum of W_1 and W_2 is 1 in each split, so that the rainfall volume is conserved exactly. An aggregation of the disaggregated rainfall would result in the same time series that has been used for the disaggregation. Possible combinations of W_1 and W_2 are given in (1), the so-called cascade-generator:

$$W_1, W_2 = \begin{cases} 0 \text{ and } 1 \quad \text{with } P(0/1) \\ 1 \text{ and } 0 \text{ with } P(1/0) \\ x \text{ and } 1-x \text{ with } P(x/(1-x)); 0 < x < 1 \end{cases} \quad (1)$$

where P is the probability of each combination of weights. The probability $P(0/1)$ denotes a splitting with no rainfall volume assigned to the first time step (W_1) and 100% of the rainfall volume ($W_2 = 1 - W_1$) in the second time step. The probability $P(1/0)$ causes a vice versa result. The rainfall volume could also be distributed over both time steps with a $x/(1-x)$-splitting. The relative fraction x of rainfall assigned to the first time step is defined as $0 < x < 1$. Considering x as a random variable for all disaggregation steps, a probability density function $f(x)$ with the empirical probabilities for each value of x is estimated. Theoretical density functions are not fitted.

It has been shown by several authors that the parameters are volume and position dependent (Olsson, 1998; Güntner et al., 2001; Rupp et al., 2009). For the cascade model in general, four different positions in the time series (starting, enclosed, isolated, ending) and two volume classes for each position are used. Güntner et al. (2001) analyzed different thresholds for the differentiation of the two volume classes. They proved that the mean rainfall intensity of all rainfall intensities of the actual cascade level for one position is an acceptable threshold for this differentiation. It has therefore also been applied in this study. The probabilities are shown exemplary for rain gauge Göttingen in Appendix A for aggregation steps from 5 min to 1280 min.

Marshak et al. (1994) analyzed estimated parameters based on different aggregation levels and compared them. Differences between the parameter sets are significant and should be taken into account, especially if the disaggregation process is carried out over a high number of cascade levels. Furthermore, it can be distinguished between unbounded and bounded cascade models. In unbounded cascade model the parameters are assumed to be scale-independent, which means that the same parameter set is applied over all disaggregation levels. However, it was found that the cascade-generator exhibits a scale dependency (see Serinaldi, 2010, and references therein), so for each disaggregation step a different parameter set has to be applied. It should be mentioned, that

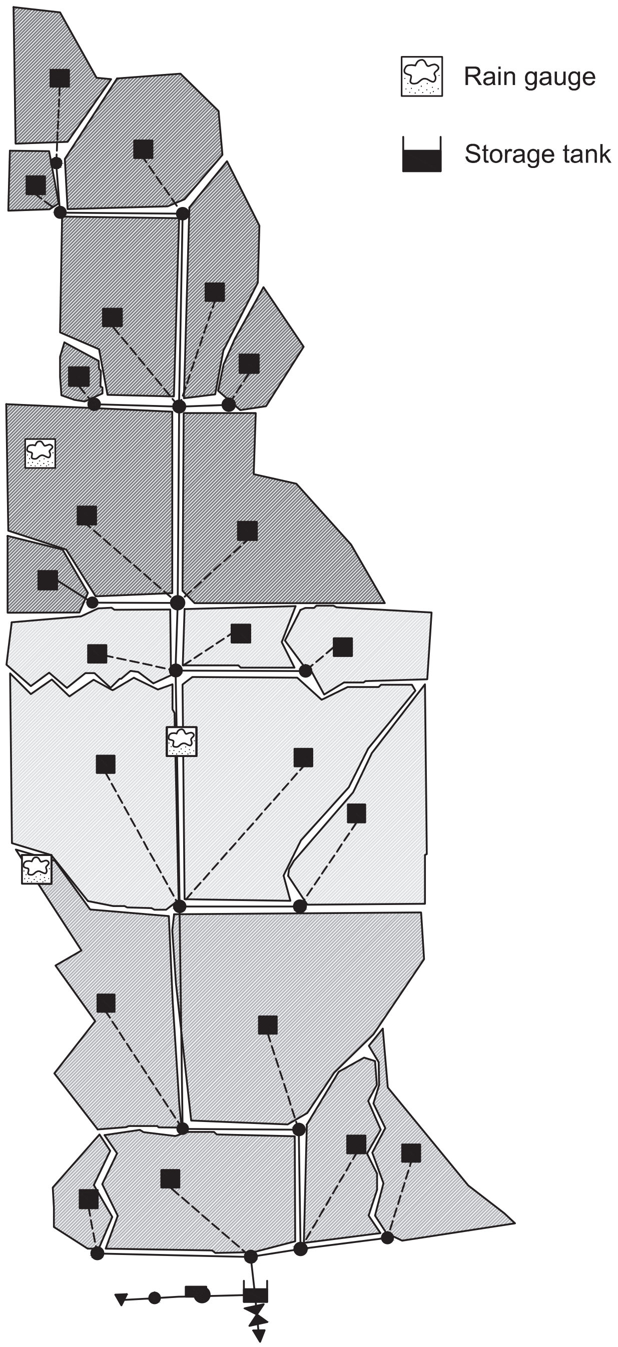

Fig. 2. Map of the sewer system (168.1 ha) with three implemented rain gauges. The affected sub-catchments for each station are illustrated by different shades (Weststadt, upper part; Bürgerpark, lower part; Prinzenweg, middle part).

Rupp et al. (2009) found only minor improvements using scale-dependent parameter sets by an application over a small range of time scales (daily to hourly). Although unbounded cascade models are still used (Jebari et al., 2012), bounded cascade models can be found more frequently in the recent literature (Rupp et al., 2009; Licznar et al., 2011a,b; Lombardo et al., 2012; Lisniak et al., 2013). This increases the amount of parameters with each disaggregation level. The similarity of $P(0/1)$ for starting boxes and $P(1/0)$ for ending boxes (and vice versa) as well as $P(0/1) \approx P(1/0)$ for enclosed and isolated boxes (Güntner et al., 2001) could be used to reduce the parameter count in order to keep the model as parameter parsimonious as possible. However, to isolate the effects of the approaches described below, this was not applied in this study. For the sake of completeness it should be mentioned, that other cascade models less parameters exist, e.g. universal multifractals with three parameters valid on various successive cascade steps (the interested reader is referred to the review of Schertzer and Lovejoy, 2011). However, a multiplicative micro-canonical, bounded cascade model is applied for this study.

In most cases, disaggregation starts with daily values from time series of non-recording stations, since the network density is higher and time series are longer for these types of stations in comparison to recording stations. However with the method explained above, a final resolution of 5 min cannot be achieved directly. One day lasts per definition 24 h, which is 1440 min in total. Using a branching number of $b = 2$ throughout the whole disaggregation process results in temporal resolutions of 5.625 min after eight disaggregation steps. This is not a very useful resolution if these time series are to be used for further applications such as urban water management models. Different alternatives to reach a 5 min resolution are explained and discussed in the following two subsections.

Method A – 1280 min approach

One possibility is to assume, that the complete daily rainfall amount occurs in only 1280 min. Using this assumption, a final resolution of 5 min can be achieved by a complete conservation of the rainfall amount. This assumption is common for generating rainfall for urban applications (Licznar et al., 2011a,b; 2015; Molnar and Burlando, 2005; Serinaldi, 2010; Paschalis et al., 2014). However, the final time series length is reduced due to this underlying assumption. There exist different possibilities how to avoid this reduction, e.g. inserting missing time steps as dry time steps in each day or only between two successive dry days. However, each of these methods would directly influence the time series characteristics. For further processing the disaggregated, shortened time series was used without any changes. Another alternative would be a disaggregation down to a very fine scale and then aggregate time steps to the temporal resolution most similar to 5 min. Possible disaggregation levels would be 42.2 s (11 disaggregation steps), respectively 5.3 s (14 disaggregation steps), which can be aggregated to 4.922 min, respectively 5.01 min. However, the scale-dependent parameters cannot be estimated from observations for this high resolution, so this alternative could not be applied in the investigation.

Method B – Uniform splitting approach

The uniform splitting approach was introduced by Müller and Haberlandt (2015) and uses a branching number $b = 3$ only in the first disaggregation step, resulting in three 8 h-intervals. One, two or all three of these 8 h-intervals can be wet. The probabilities for the number of wet intervals can also be estimated from observations (see Table 2). The threshold for the volume classes in this first step is a quantile q chosen with respect to very high daily rainfall intensities ($q = 0.998$ as in Müller and Haberlandt, 2015). The probabilities in Table 2 show a clear dependency on the volume class. While for the lower volume class, the probability is highest for one wet 8 h-interval, for the upper volume class it is for three wet 8 h-intervals. Due to the chosen threshold, only a small number of wet days are used for the parameter estimation for the upper volume class. For the majority of those days all three 8 h-intervals are wet. Only a minority, if at all, shows just one or two wet 8 h-intervals. This confirms the findings of Müller and Haberlandt (2015) and underlines the importance of the implementation of an upper volume class.

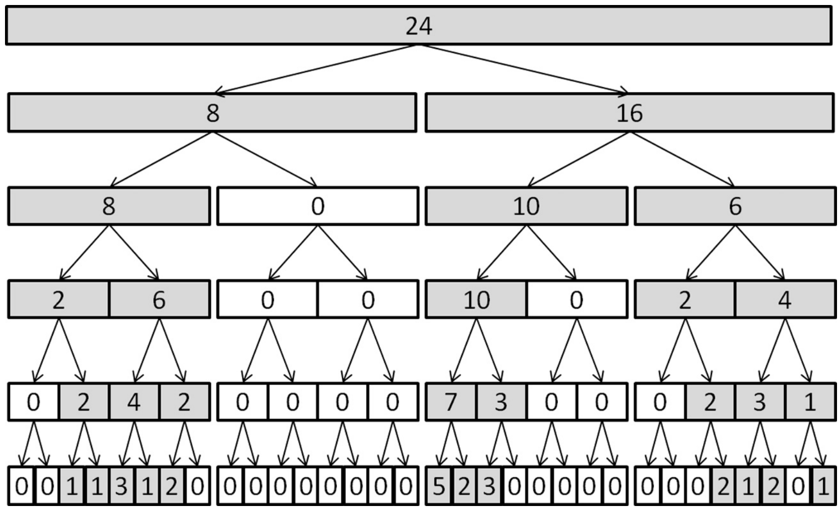

Fig. 3. Multiplicative cascade model scheme (adapted from Olsson (1998)), starting with a rainfall height of 24 mm.

Table 2
Probabilities for number of wet 8 h-intervals in the first disaggregation step using Method B for rain gauge Göttingen.

Volume class	Probabilities for number of wet 8 h-intervals		
	1	2	3
Lower	43%	35%	22%
Upper	25%	0%	75%

The application of $b = 3$ in the first disaggregation step has been done before by Lisniak et al. (2013) to achieve a target resolution of 1 h, which is a suitable temporal resolution as input for rainfall-runoff-models for rural catchments. The daily rainfall volume is distributed uniformly among the number of randomly as wet identified 8 h-intervals. This uniform distribution on the before chosen number of wet 8 h-intervals is a compromise between the parameter intensive approach proposed by Lisniak et al., who have used up to 8 empirical distribution functions to represent the splitting behavior from daily to 8 h-time steps, and the quality of the disaggregation results.

For the second and all following disaggregation steps, the branching number is reduced to $b = 2$. It is obvious that to achieve a target resolution of 5 min, additional modifications have to be introduced. The disaggregation levels delivering time steps of $\Delta t = 15, 7.5$ or 3.75 min therefore were used to introduce these modifications. It should be mentioned, that the parameters for the disaggregation steps for resolutions finer than 15 min with $b = 2$ cannot be estimated from observations directly, since only 5 min values are available. For disaggregations from 15 to 7.5 and consequently 3.75 min, the parameter set from the aggregation of 5 to 10 min was used throughout.

Method B1 – modification for $\Delta t = 15$ min

Similar to the first disaggregation step, a uniform splitting with a branching number $b = 3$ is applied. The threshold for the differentiation into two volume classes was chosen as the mean of all rainfall intensities at the 15 min-level. The parameters of the two volume classes differ significantly from each other.

Method B2 – modification for $\Delta t = 7.5$ min

Firstly, the rainfall volume of each time step is distributed uniformly on three time steps with 2.5 min. Afterwards, two non-overlapping time steps are aggregated always.

Method B3 – modification for $\Delta t = 3.75$ min

The applied method is similar to B2 and was used by Onof et al. (2005) and Onof and Arnbjerg-Nielsen (2009) for the disaggregation from 1 h down to 5 min. The rainfall volume is distributed uniformly on three finer time steps with 1.25 min duration, followed by an aggregation of four non-overlapping time steps.

The disaggregation is a random process, which leads to different results, depending on the initialization of the random number generator. This random behavior is covered by a certain number of disaggregation runs. It was found that after 30 disaggregation runs the average values of the main characteristics (see "Section 4.1 Temporal disaggregation") did not change significantly by an increasing number of disaggregation runs. Accordingly, 30 disaggregations were carried out for each method.

A comparison of the rainfall characteristics RC of disaggregated time series (Dis) with the observations (Obs) is carried out regarding the relative error rE. The objective criterion is calculated for each station i over all realizations n of the disaggregation and averaged afterwards over all stations:

$$rE = \frac{1}{n} \times \sum_{i=1}^{n} \frac{(RC_{Dis,i} - RC_{Obs,i})}{RC_{Obs,i}}, \quad (2)$$

For the investigation of the rainfall extremes resulting from the different methods partial duration series, also known as peaks-over-threshold, are extracted for all time series. The threshold is chosen in a way to obtain two values per year on average from each time series (DWA-A 531, 2012). Based on 30 realisations for each method, the median of the extreme values was determined for further processing. Since the time series lengths of the stations differ, also elements in the partial duration series and hence return periods are different. In order to include all stations in an objective comparison of extreme values, an exponential distribution was fitted to the medians. The exponential distribution, which is a standard distribution function in Germany for partial duration series of rainfall (DWA-A 531, 2012), was chosen for this purpose. The deviations of the fitted extreme values between disaggregated and observed rainfall are calculated using the relative root mean square error $rRMSE$. The deviations between disaggregated and observed rainfall intensities I for single return periods T of the fitted distribution function for each station i are calculated and averaged afterwards over all stations N:

$$rRMSE(T) = \frac{1}{N} \times \sum_{i=1}^{N} \sqrt{\frac{(I(T)_{Dis,i} - I(T)_{Obs,i})_2}{I(T)_{Obs,i}}} \text{ with}$$
$$T = 0.5, 1, 2, 5, 10 \text{ years}, \tag{3}$$

This criterion was used for the evaluation of rainfall disaggregation products before by Güntner et al. (2001) for single stations. They evaluate deviations of up to 10% as accurately generated, up to 15% as well reproduced and higher than 40% as overestimated, respectively more than 200% as severe overestimated. These values are based on the disaggregation results in their manuscript and are provided here to give a general feeling for the criterion as well as for the *rE*, whose absolute values are comparable to *rRMSE*.

3.2. Spatial consistence

The disaggregation of the rainfall time series is a pointwise procedure. This yields unrealistic spatial patterns of rainfall. A resampling procedure introduced by Müller and Haberlandt (2015) is applied to implement spatial consistence into the disaggregated time series z. Three bivariate characteristics are assumed to represent spatial consistence, namely, probability of occurrence, coefficient of correlation and continuity ratio (Wilks, 1998).

1. Probability of occurrence

The probability of occurrence $P_{k,l}$ describes the probability of rainfall occurrence at two stations k and l at the same time:

$$P_{k,l}(z_k > 0 | z_l > 0) \approx \frac{n_{11}}{n}, \tag{4}$$

where n is the total number of non-missing observation hours at both stations k and l, and n_{11} represents the number of simultaneous rainfall occurrence at both stations. A differentiation for convective and stratiform events as in Cowpertwait (1995) was not applied.

2. Pearson's coefficient of correlation

The Pearson's coefficient of correlation is used to describe the relationship between simultaneously occurring rainfall at two stations k and l. It is a measure of the linear relation between both rainfall time series (Eq. (4)). This coefficient was used previously for multisite rainfall generation by Breinl et al. (2013, 2014):

$$\rho_{k,l} = \frac{cov(z_k, z_l)}{\sqrt{var(z_k) x var(z_l)}}, z_k > 0, z_1 > 0. \tag{5}$$

3. Continuity measure

The continuity measure compares the expected rainfall amount at one station for cases with and without rain at the neighboring station (*E.* is the expectation operator):

$$C_{k,l} = \frac{E(z_k | z_k > 0, z_l = 0)}{E(z_k | z_k > 0, z_l > 0)}. \tag{6}$$

It is possible to estimate the prescribed values of these characteristics as functions of the separation distance between two stations from observed data (see Fig. 4). For the estimation, all stations from the city Brunswick are used (stations I–V from Table 1). The results for stations 1–24 are not shown here, because the spatial scale with distances up to 350 km is not useful for the aim of urban hydrologic modeling.

The resampling procedure involves a bivariate objective function $O_{k,l}$ that has to be minimized:

$$O_{k,l} = w_1 \times \left(P_{k,l} - P^*_{k,l}\right) + w_2 \times \left(\rho_{k,l} - \rho^*_{k,l}\right) + w_3 \times (C_{k,l} - C^*_{k,l}) \tag{7}$$

The parameters indicated by * are the prescribed values for two stations (resulting from the regression lines in Fig. 4), and the other parameters are the actual values. The fit of the regression lines to

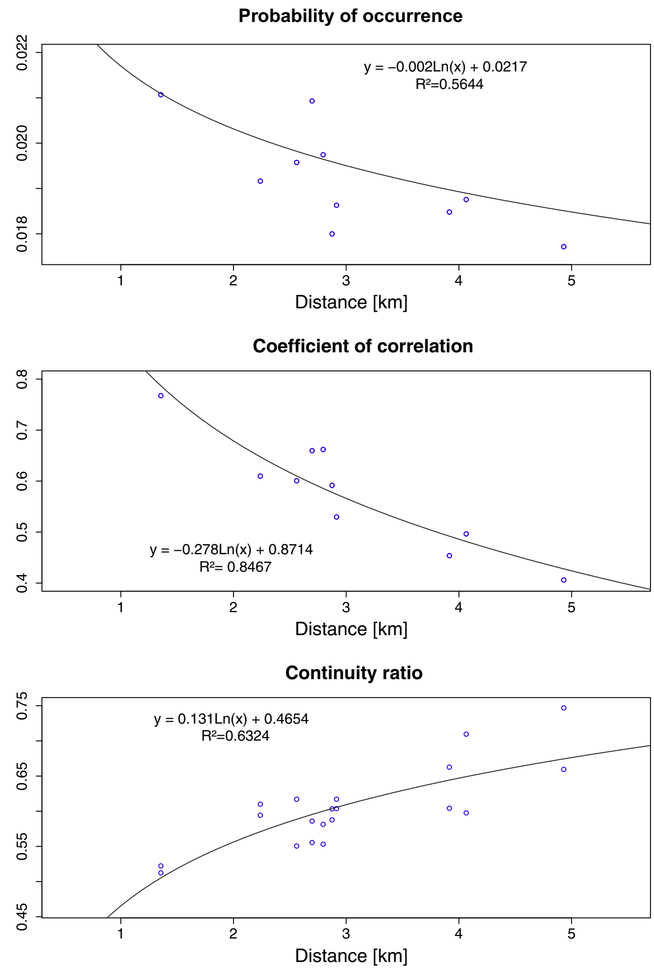

Fig. 4. Spatial bivariate characteristics for the city Brunswick, Lower Saxony.

the observations are also validated with Pearson's coefficient of correlation. To avoid confusion with the spatial characteristic, here the symbol R^2 is used for the goodness-of-fit. While for the probability of occurrence and the continuity ratio only a small R^2-value is achieved (due to the variation of these parameters), for the coefficient of correlation a R^2-value of 0.8462 is determined. However, the general behavior for all three characteristics (increasing or decreasing with increasing distance) can be represented by the regression lines. The weights w_1, w_2 and w_3 are necessary to adjust the scale of the rainfall characteristics and to consider their importance. The regression lines are necessary to determine prescribed values for distances not available from the recording rain gauges.

For the minimization a resampling algorithm, namely simulated annealing, is implemented (Kirkpatrick et al., 1983; Aarts and Korst, 1965). The algorithm has been used for rainfall generation processes before (Bardossy, 1998; Haberlandt et al., 2008).

For the resampling, two conditions are considered. The structure of the disaggregated time series (combination of position and volume classes) should not be changed. Also, the rainfall amount of each day should not be changed. Therefore, only the relative diurnal cycles of the disaggregated time series are resampled preserving the structure of the disaggregated time series described by position and volume class of the daily time step.

One disaggregated time series is chosen randomly as a reference time series. The relative diurnal cycles of a second randomly chosen time series will be resampled until the objective function is minimized, so it cannot be improved for a certain number of attempts. Swaps are only possible between days with the same position and volume class. At the beginning of the algorithm, also 'bad swaps' (worsening of the objective function) are accepted with a certain probability π. The parameter π decreases with the run time of the resampling algorithm. This allows to leave a local optimum to find the global minimum. After the resampling, the time series serves as a new reference station along with the first one. Further time series have to be resampled with respect to all reference time series and will be added afterwards to the set of reference time series. For detailed information on the applied resampling algorithm the reader is referred to Müller and Haberlandt (2015).

Since the cascade model is based on the scaling theory, it could be questioned if there is a discrepancy in the temporal dimension of the disaggregation process due to the spatial dimension of the resampling algorithm. Therefore, scaling behavior of the disaggregated time series is analyzed before and after the resampling with the relation described in Eq. (8)

$$M_q = \lambda^{K(q)} \tag{8}$$

with moments M, moments order q, the moments scaling exponent $K(q)$ and the scale ratio λ.

Analyzing the scaling behavior with log–log-plots of M_q and λ, indicating different durations, is a common method in the field of rainfall disaggregation with cascade models (see e.g. Over and Gupta, 1994; Svensson et al., 1996; Burlando and Rosso, 1996; Serinaldi 2010). The scale ratio represents a dimensionless ratio of two temporal resolutions of one time series. Dry time steps are neglected for the scaling analyzes. For the moments estimation probability-weighted moments (PWM) as in Yu et al. (2014) and Ding et al. (2015) are applied. An advantage of the PWM is their relative robustness against large rainfall intensities (Kumar et al., 1994; Hosking and Wallis, 1997). According to Kumar et al. (2014) and Lombardo et al. (2014) the investigation is limited to $1 \leqslant q \leqslant 3$. The PWM of different temporal resolutions will be compared before and after the resampling process.

3.3. Urbanhydrological modeling

3.3.1. Model SWMM

The sewer system has been constructed in the EPA Storm Water Management Model 5.1 (SWMM) (Rossman, 2010). With SWMM dynamic rainfall-runoff simulations can be carried out continuously or event-based to determine runoff quantity and quality from urban areas.

A constructed sewer system in SWMM is split horizontally into subcatchments. Each subcatchment is characterized by a number of parameters, e.g. total area, fraction of impervious area and slope. Connecting main pipes of the subcatchments are represented by 'links'. Furthermore, the sewer system can be complemented by storage/treatment devices, pumps and regulators.

The application of a semi-distributed model like SWMM limits the ability to reflect spatial variability due to the fact, that for each subcatchment the rainfall is assumed to be uniform for its area. However, since disaggregated time series from rain gauges are used in this study, there is no degradation of spatial variability. Nevertheless, it could be a negative aspect, especially when high-resolution spatial rainfall data is used (Gires et al., 2015).

For each subcatchment, flow is generated from both, dry weather flow (representing domestic and industrial wastewater flow) and rainfall runoff from pervious and impervious areas. Rainfall is assumed to be uniform for each subcatchment. For infiltration the equations of (modified) Horton, Green Ampt and Curve Number are selectable, here the Curve Number equation was used. The dynamic wave equation as approximation of the St. Venant-equations is used for the calculation of the flows through the sewer system. As forcing main equation for the dynamic wave, Hazen-Williams equation has been chosen. Pondage of flooded nodes can be allowed or not, here it was permitted. Overland flow does not occur.

3.3.2. Influence of number of recording stations

It could be questioned whether one station is enough to represent rainfall for such a small catchment (168.1 ha). So the impact of one or more implemented stations (we apply three stations) on the combined sewer system runoff has to be analyzed.

For this analysis the following procedure was applied, using observed data only. For three stations, the partial duration series of extreme values were derived (as described in Section 4.1 for the extremes of the other stations in Lower Saxony). This results in 14 total extreme values for each station using the time period 01.01.2000–24.12.2006 that is available for the stations Prinzenweg, Bürgerpark und Weststadt.

The return periods T_k of these extreme values can be calculated with the Weibull plotting position. Comparisons are carried out for extreme values with 30 min duration and for return periods of T_k = 4.4 years and T_k = 0.9 years, respectively. These are representative return periods for the dimensioning of sewer system elements (DWA-A 118, 2006; DIN EN 752-2, 1996).

If only one station is used, the extreme value is considered to be uniform throughout the whole catchment. This procedure is carried out for the extremes of each station, so in total three extreme values are analyzed for each return period.

If three stations are used, the time steps of an extreme value of one station (this station is the so-called master station) and the simultaneous time steps from the other two stations are used as spatial heterogeneous input. Again, the procedure is carried out for each station as a master station, in total three events are analyzed. Here 'events' are defined as an extreme value at the master station and simultaneous time steps at the other two stations.

3.3.3. Influence of disaggregation method

The aim of the second investigation based on the sewer system is to investigate, if there is a need for the implementation of spatial consistence using more than one station in addition to the choice of the disaggregation method. Therefore, three rainfall stations are implemented throughout.

For each disaggregation method the time series of all 30 realizations are resampled (*res*) to implement spatial consistence. For each method (A, A-res, B1, B1-res, B2, B2-res, B3, B3-res) and each realization (1–30), the partial duration series of extreme values were derived. Again, for one event the time steps of an extreme value of one station and the simultaneous time steps from the other two stations are used as spatial heterogeneous input (as carried out for three stations before, see Section 3.3.2). In total 90 events for each return period based on the 30 realizations of each method are used for simulation.

4. Results and discussion

The results section is organized as follows. The univariate rainfall characteristics of the disaggregation will be discussed in Section 4.1, while the multivariate characteristics will be analyzed in Section 4.2. All results of the urban hydrological modeling will be discussed in Section 4.3.

4.1. Temporal disaggregation

In total, four different variations of the micro-canonical cascade model were tested to disaggregate time series from daily to 5-min values. Seven basic rainfall characteristics were chosen for analyzes: wet spell duration and amount, average intensity, dry spell duration, fraction of dry intervals, autocorrelation and extreme values. A wet period is defined as the duration with rainfall volume continuously greater than 0 mm in each time step. The rainfall characteristics are illustrated in Figs. 5–8 and in Table 3 as observations vs. disaggregations for each station and as averages resulting from Eq. (2). Molnar and Burlando (2005) and Müller and Haberlandt (2015) identified a high fraction of rainfall intensities in the disaggregated time series smaller than the accuracy of the measuring instrument and hence the minimum resolution in the observed time series, which have been used for the parameter estimation. These time steps are from a hydrological point of view negligible. To reduce the impact on the results due to these small time steps, an additional analyzes of the rainfall characteristics with a minimum intensity of higher than 0.1 mm as threshold was introduced. This threshold value has additionally the advantage to exclude single tips from the measurement device. The results are shown in Fig. 6.

For stations with wet spell durations *wsd* shorter than 17.5 min (Fig. 5), method B2 and B3 show acceptable over- underestimations. The results are similar for B2 for wet spell durations shorter than 14 min, if a threshold is taken into account (Fig. 6). For stations with longer *wsd* all methods show underestimations, respectively. An underestimation of the *wsd* was identified before by Olsson (1998). This can be explained by the definition of a wet period. Every dry spell, regardless of its length, terminates a wet spell. So the reproduction of *wsd* becomes more and more complicated with an increasing length of observed *wsd*, because a single dry time step would divide a long wet spell into two shorter wet spells. The generation of dry intervals depends on the probabilities of $P(1/0)$ and $P(0/1)$. These probabilities are significant lower for all positions for the higher volume class in comparison to the lower corresponding volume class (see Appendix A). The influence of the rainfall intensity on the generation of dry intervals has been identified before by Rupp et al. (2009). It can also be confirmed, that the variation of the probabilities is higher between the volume classes in comparison to the variation between different scales.

The results for the average intensity also show a clear structure and trend, if no threshold is taken into account. All methods overestimate the intensities, with the largest deviations shown for method A (+63% on average). One reason for this lies in the reduction of the day duration by 160 min ~ 2.7 h (=1440 – 1280 min). If a threshold is introduced, deviations are smaller for all methods. Method B2 shows the smallest deviations for the average intensity in both analyzes.

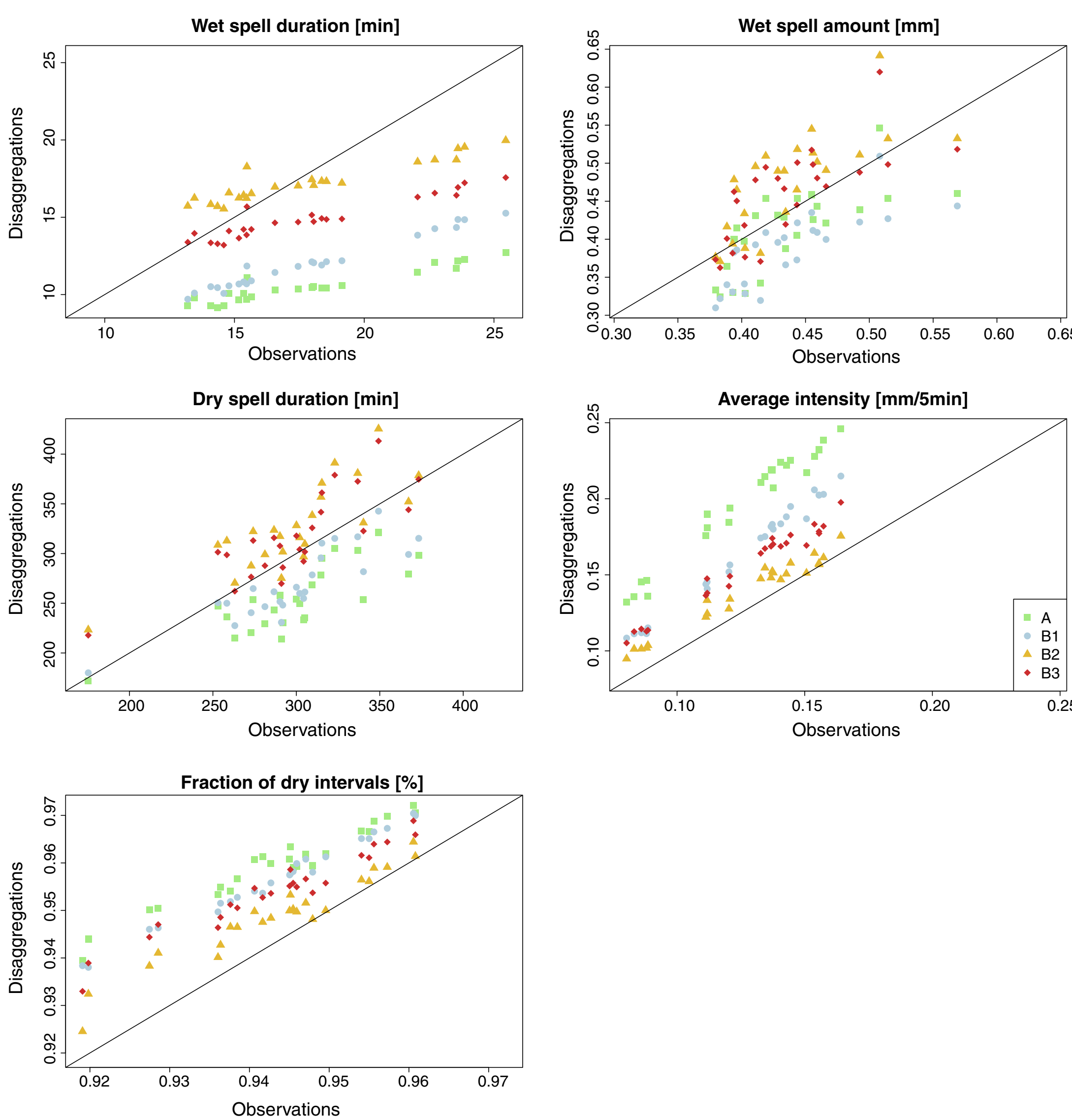

Fig. 5. Observed vs. Disaggregated rainfall characteristics for all 24 stations.

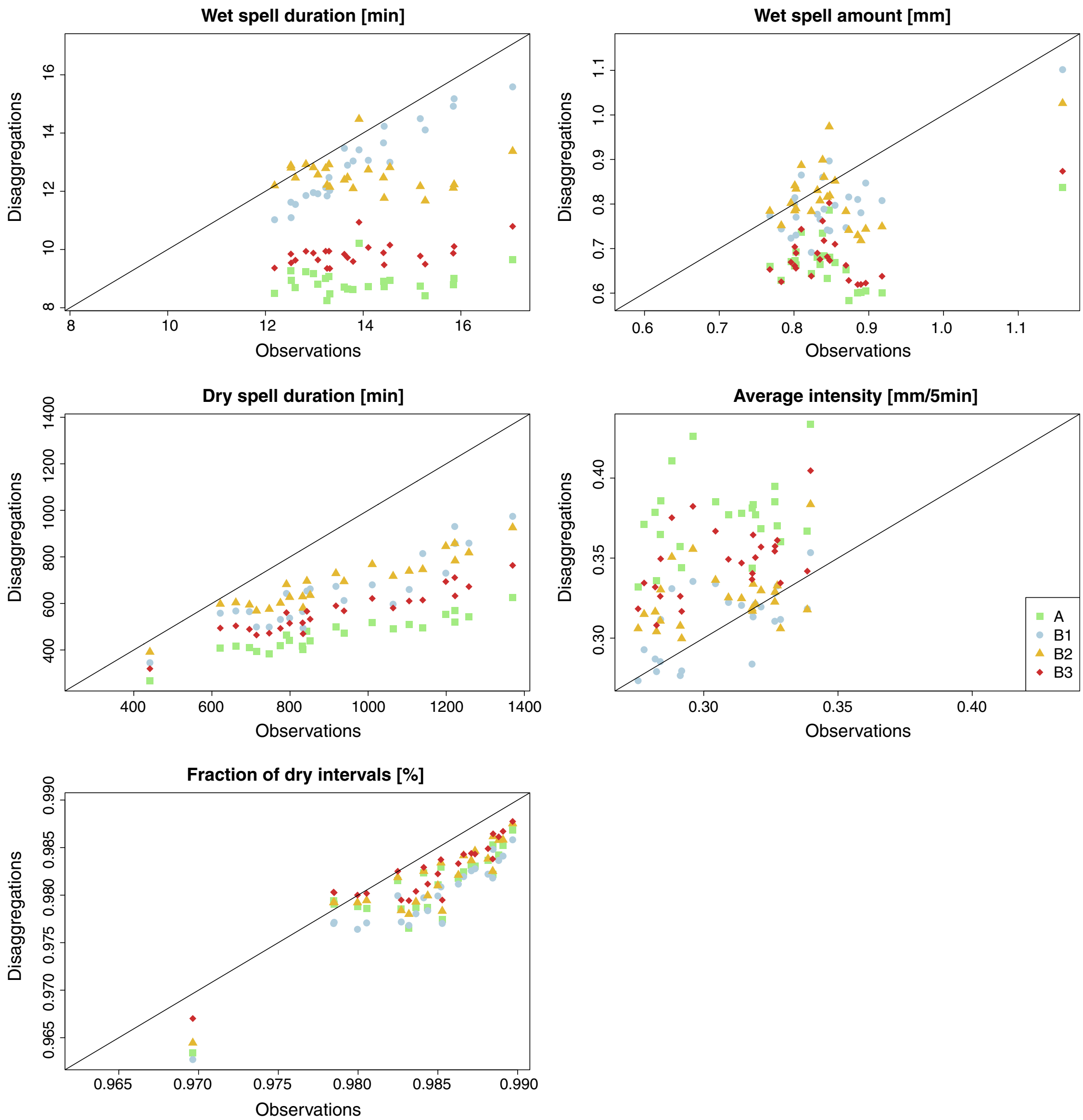

Fig. 6. Observed vs. Disaggregated rainfall characteristics for all 24 stations for all time steps with a rainfall intensity > 0.1 mm/5 min.

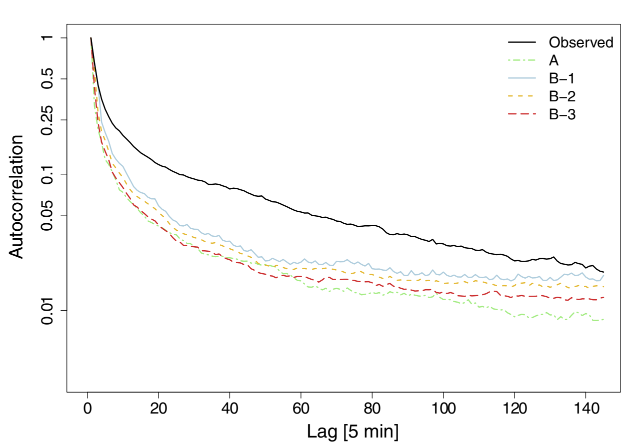

Fig. 7. Autocorrelation function of the observed and as median of 30 realisations from disaggregated time series for station Harzgerode.

The results for the wet spell amount *wsa* do not show a clear trend for all methods like that for *wsd* and average intensity (Fig. 5). The underestimation of *wsd* and the overestimation of average intensities compensate each other and lead to a deceptively good fit for method A with only slightly underestimations of *wsa*. Method B1 underestimates the observations more strongly, while method B2 and B3 overestimate *wsa* for most of the stations. If time steps with small rainfall intensities are neglected, different results can be identified (Fig. 6). Method A and B3 show strong underestimations, while B1 and B2 show acceptable agreements with 3% and 1%, respectively. It should be noticed that the absolute values of *wsd* are slightly decreasing with an introduction of the threshold, while *wsa* and average intensity are strongly increasing.

For the dry spell duration *dsd*, methods B2 and B3 show similar results, if all values are taken into account. Both overestimate the observations by 8% and 5%, respectively, while method A and B1 underestimate the observations by 13% and 10%, respectively. With the introduction of the threshold single tips of the measurement device are ignored, which increases the *dsd* significantly. All methods lead to underestimations, with the worst representation by method A.

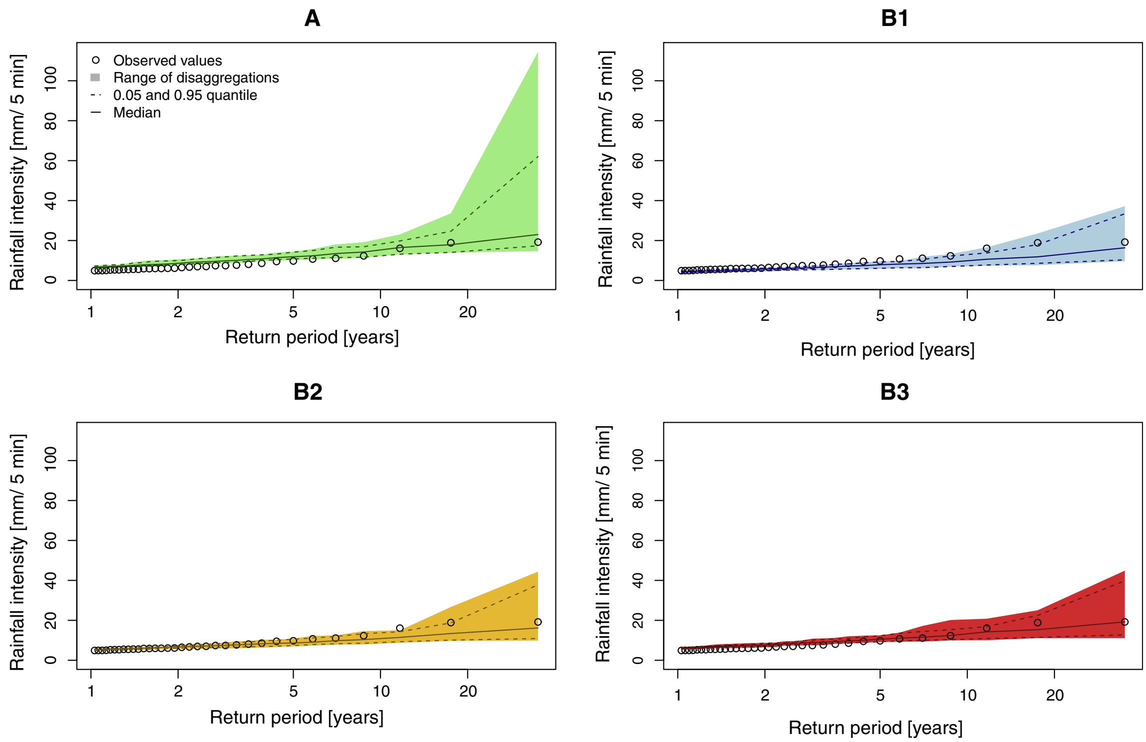

Fig. 8. Rainfall extreme values for a temporal resolution of 5 min for station Osnabrück resulting from method A, B1, B2 and B3 (January 1993 – November 2010).

Table 3
Relative error of rainfall characteristics between disaggregated and observed time series (mean for 24 stations).

Rainfall characteristic	Relative error (%)			
	A	B1	B2	B3
Wet spell duration (min)				
Average	−41	−32	−3	−16
Standard deviation	−66	−70	−52	−53
Skewness	−46	−59	−47	−49
Average intensity (mm/5 min)	63	30	11	23
Wet spell amount (mm)				
Average	−4	−11	8	4
Standard deviation	−24	−29	−19	−20
Skewness	3	−1	−12	−10
Dry spell duration (min)				
Average	−13	−10	8	5
Standard deviation	−18	−12	−3	−5
Skewness	10	15	5	7
Fraction of dry intervals (–)	2	1	1	1
Autocorrelation (–)				
lag 1	−50	−3	−4	−30
lag 12	−52	−42	−49	−56

The underestimation of both durations, *wsd* and *dsd*, by method A is a systematic error due to the shortening of the total length of the time series. The underestimation of *dsd* could be reduced by inserting dry intervals for the missing time steps of this method. However, the fraction of dry intervals is overestimated by method A as well as by the other methods, if all values are included. The differences between the methods are much smaller in comparison to *wsd* (see Table 3), since all dry days which are not influenced by the chosen disaggregation method, are also taken into account. With the threshold introduction the fraction of dry intervals is underestimated by all methods. However, the deviations between the methods themselves as well as in comparison to the observations are very small (>1%) and can be neglected.

Furthermore, the autocorrelation function is shown in Fig. 7 for the observed time series for station Harzgerode and as median of the autocorrelation functions resulting from 30 realisations for each method, taking into account all values of the disaggregated time series. The autocorrelation is underestimated by all methods. The relative errors are determined as average of all stations for lag-1 and lag-12, representing temporal shifts of 5 min and 1 h, respectively (see Table 3). The lag-1 autocorrelation is underestimated by method A with 50%, while method B1 (−3%) and B2 (−4%) show smaller underestimations. For lag-12, all methods show significant underestimation of the autocorrelation function of approximately −50%. The autocorrelation function for B1 shows peaks periodically in a 3-lags distance due to the applied uniform splitting approach for disaggregation of 15 min to 5 min. The underestimation of the autocorrelation function is a well-known problem and has been identified before by e.g. Olsson (1998), Güntner et al. (2001), Pui et al. (2012) and Paschalis et al. (2012, 2014).

A comparison of the observed empirical extreme values with the range, the 0.05% and 95% quantileand the median of the 30 disaggregations for station Osnabrück is given in Fig. 8. The median and both quantiles represent typical results for all stations. For the illustration the Weibull-plotting position was used. The medians of all 30 realisations for B2 and B3 show a good fit to the observed values, while the median for A tends to overestimate the observations. The range and quantiles of B2 and B3 are similar, while A shows strong overestimations and B1 underestimations, respectively. For the highest return period ($T = 35$ years), overestimations of the observed values can be identified by a factor of 6 for method A, if the range is taken into account. For other stations, overestimations for method B1 can be identified from the range as well (not shown here). The results shown regarding median and both quantiles are representative for most of the stations.

For comparisons exponential distributions were fitted to the median of all realizations for each station. Rainfall intensities are analyzed for the return periods of 0.5 (twice a year), 1, 2, 5 and 10 years and for durations of 5 min and 1 h. Fig. 9 shows the relative errors as box-whisker-plots for rainfall intensities of 5 min duration with return periods of 1 and 5 years for each method. Method A leads to the highest overestimation for both return periods. Hence the shortening of the day duration to 1280 min also affects the extremes with 5 min duration. Extreme values are also overestimated by B3. Due to the disaggregation down to a very fine temporal resolution of 3.75 min, the splitting of the daily rainfall amount can potentially be reduced onto only a small number of fine time steps. This leads to an overestimation of the extreme values.

Concerning the medians, B2 overestimates the observations slightly, while B1 underestimates them. In B1, rainfall at a temporal resolution of 15 min is split with one disaggregation step into three finer final time steps, while in B2, two disaggregation steps follow. This causes a higher intensity of rainfall (similar to the overestimation of B3). However, the range of rainfall quantiles with 5 year return periods resulting from B2 is much higher than for B1.

For longer durations, the differences between the methods decrease (see Fig. 10). For B1, B2 and B3 the results for 1 h are similar, because the disaggregation process is exactly the same until this duration. Minor differences are only caused by adjacent time steps of extreme events. For a return period of 1 year, the median of A, B1, B2 and B3 show the same slight overestimation of the observed values. For a 5 year return period, A also leads to a slight overestimation, while B1, B2 and B3 underestimate the extreme values of the observations. It should be noted that the deviations for 1 h rainfall duration are much smaller than for 5 min for all methods. However, the smallest ranges for both return periods result from A, which delivers the best performance for an hourly target time step.

The relative root mean square errors (*rRMSE*) for all rainfall quantiles and 5 min time step are given in Table 4. The *rRMSE* for all return periods is highest for method A, followed by B3. B2 is slightly higher than B1 for all return periods except 0.5 years. From a practical point of view, using the medians of B2 as design values would lead to a dimensioning 'on the safe side'.

4.2. Spatial consistence

Spatial consistence was assumed to be represented by matching three bivariate characteristics, namely probability of occurrence, Pearson's coefficient of correlation and continuity ratio. In Fig. 11, values for these characteristics resulting from the observations, after the disaggregation (without resampling) and after resampling are shown. For the coefficient of correlation, values similar to the observations could be achieved, although before resampling an underestimation independent from station distances could be identified.

For the continuity ratio, the results are more complex to interpret. Due to the definition of this characteristic (Eq. (6)), for each pair of stations two different values exist, depending on which station is defined as k and l. During the resampling only the time series combinations of the actual station k and the reference stations l are taken into account, not vice versa. The resulting values are the three well-fitted values from the resampled dataset for each distance in Fig. 11. For higher distances, values comparable to those from observations could be achieved. For a distance of 1.4 km, a slight worsening can be identified. Continuity ratios with values $C_{k,l} > 0.8$ represent the combinations that have not been considered during the resampling process. These values are worsening by the resampling for all distances. An omitting of continuity ratio would cause a worsening of all values for this characteristic (Müller and Haberlandt, 2015), so the continuity ratio remained included in the objective function.

The probability of occurrence was underestimated for the disaggregated, non-resampled time series for all distances. After the resampling all values could be improved significantly. However,

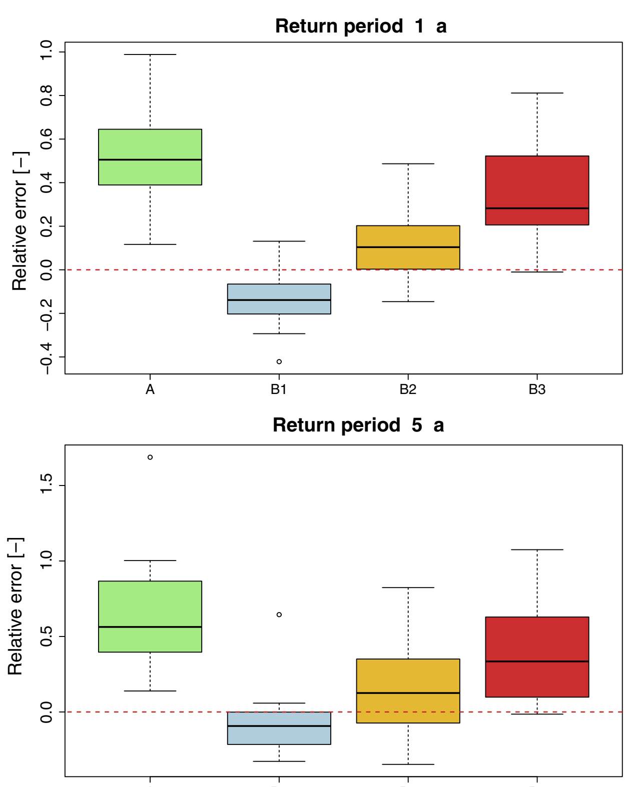

Fig. 9. Mean relative errors of simulated rainfall extreme values for 5 min durations for a return period of 1 year (upper part) and 5 years (lower part) for all stations, based on fitted exponential distributions. The dashed line marks a deviation of 0.

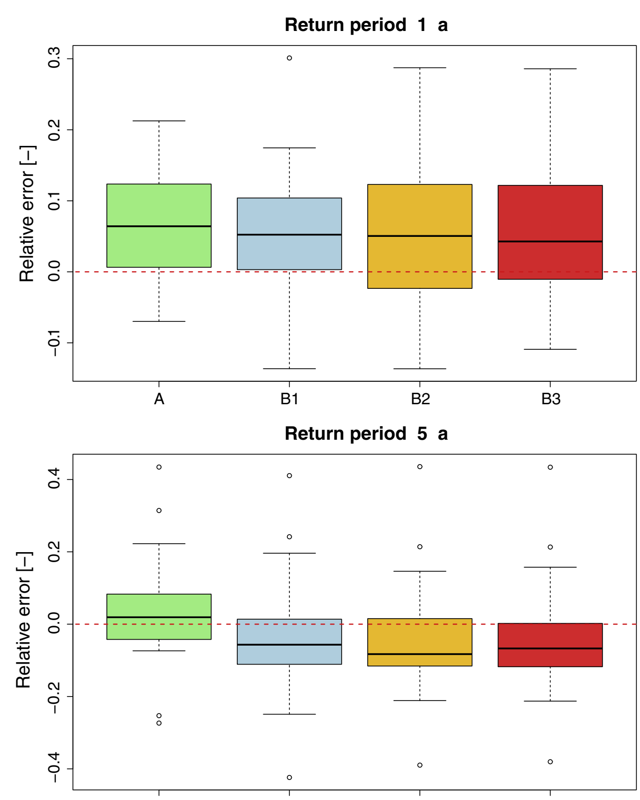

Fig. 10. Mean relative errors of simulated rainfall extreme values for 1 h durations for a return period of 1 year (upper part) and 5 years (lower part) for all stations, based on fitted exponential distributions. The dashed line marks a deviation of 0.

Table 4
Relative root mean square error *rRMSE* of rainfall extremes with 5 min durations based on all 24 stations.

Return period (a)	rRMSE (%)			
	A	B1	B2	B3
0.5	0.44	0.19	0.16	0.33
1	0.51	0.15	0.16	0.34
2	0.58	0.15	0.19	0.36
5	0.64	0.15	0.23	0.39
10	0.67	0.16	0.25	0.40

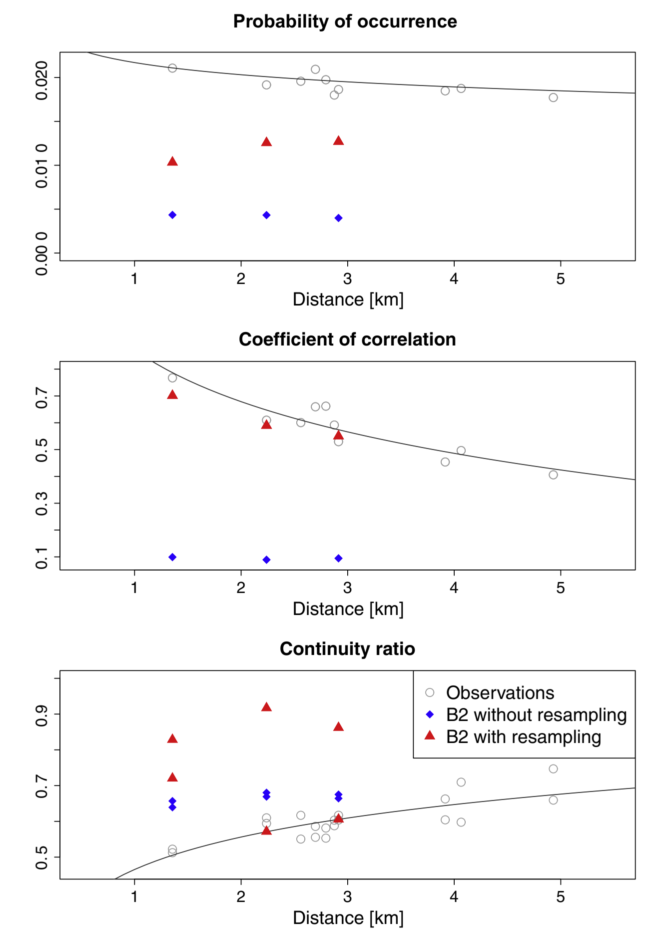

Fig. 11. Bivariate characteristics resulting from the observations (circles), the disaggregated but not resampled (diamonds) and disaggregated and resampled (triangles) time series.

values resulting from the observations could not be reached and are still underestimated. Due to the shortness of the time series only a limited number of relative diurnal cycles is available. The number is too small to find matching relative diurnal cycles, especially for a temporal resolution of 5 min with 288 time steps each day. Although a strong weighting of this characteristic in the objective function ($w_1 = 0.899$ in comparison to $w_2 = 0.002$ for Pearson's coefficient of correlation and $w_3 = 0.099$ for continuity ratio), a better fit was not possible. However, it can be assumed that this characteristic improves with increasing time series length.

It is further analyzed, if the resampling algorithm influences the scaling behavior of the disaggregated time series. Therefore the first three moments have been calculated for all realizations before and after the resampling. The means are shown in Fig. 12. The first probably-weighted moment represents the mean value of the time series. It is not changed by the resampling algorithm, since the total rainfall amount and the number of wet time steps are not changed. However, the second and the third moment show slight increases, indicating minor changes of the standard deviation and the skewness of the average intensity. The increases are stronger for finer temporal resolutions and can be identified for all methods. However, the deviations from the not resampled time series are smaller than 5% and hence accepted.

4.3. Urban hydrological modeling

For the urban model two investigations are carried out. In the first part the necessity for the implementation of more than one rainfall station will be analyzed. This investigation is carried out using observed time series only. Secondly, the benefit for the implementation of spatial consistence using more than one station in addition to the choice of the disaggregation method is analyzed. For both investigations two criteria will be used for the validation. The flood volume represents the water volume that leaves the sewage system temporary through manholes. The combined sewer overflow volume is the cumulative volume of the sewage system, which is released from the tank to the receiving water and not to the treatment plant.

It should be mentioned that a variation of the SWMM model parameter would influence the simulation results. As sensitive parameters have been identified the imperviousness and the surface depression storage (Barco et al., 2008; Goldstein et al., 2010). Also slope and the capacity of the main pipes would affect the resulting flood volumes and combined sewer overflow volume, a different tank volume would affect combined sewer overflow volume. For more information about the parameter sensitivity the reader is referred to Krebs et al. (2014).

4.3.1. Influence of number of recording stations

For this investigation only observed time series are used. In Fig. 13 the resulting flood volumes from using one (uniform rainfall) or three stations (heterogeneous rainfall) are shown for an observed extreme event at the master station with 30 min duration and a return period of $T_k = 4.4$ years. The heterogeneous case is assumed to represent the reference with small differences between results based on different extreme events. However, there are high deviations using uniform rainfall as input in comparison to spatial heterogeneous rainfall. The flood volume is overestimated by 143% on average if only one station is used as input in comparison to using all three stations (representing the reference through its spatial coverage). However, using only one station can lead to larger overestimations of 384% (station Bürgerpark), but also to underestimations (station Weststadt by 15%).

The same investigation was carried out for events with a return period of $T_k = 0.9$ years. For all three events, no flooding occurs

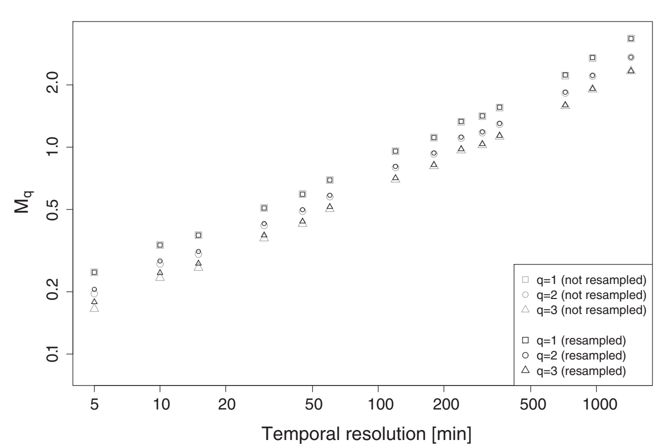

Fig. 12. Probability-weighted moments of disaggregated time series before and after the resampling for station Prinzenweg (mean values based on 30 realisations).

using three stations as input (not shown here). However, using one station leads to flooding for the station Weststadt, so again an overestimation of flooding volume occurs using spatial uniform rainfall.

The results for the combined sewer overflow volume (the overflow of the tank) are similar. It is overestimated by using only one station as input. Results are the same for both return periods (Fig. 14).

It can be concluded that one station is not sufficient to represent the rainfall behavior adequately, although only the effects for a small catchment (168.1 ha) are analyzed. This confirms the results of e.g. Schilling (1991), Berne et al. (2004), Emmanuel et al. (2012), Gires et al. (2015), Bruni et al. (2015) and Ochoa-Rodriguez et al. (2015), that for the representation of spatial variability of rainfall a high station network density is crucial.

These results are conformable to the theory of areal reduction factors, which should be mentioned in this context. The basic idea of this concept is that extreme point values cannot be used uniformly for applications requiring spatial rainfall. Therefore, the point values have to be reduced with an areal reduction factor. This is indicated by the results, since without a reduction of the point rainfall values overstimations of 67% ($T_k = 4.4$ a) respectively 71% ($T_k = 0.9$ a) of the combined sewer overflow volume occur comparing the average results of using 1 and 3 stations. Sivapalan and Blöschl (1998) found that these factors depend on the return period of the events and the applied catchment area. Veneziano and Langousis (2005) investigate the areal reduction factors in context of a multifractal analysis. For a critical review of areal reduction factors and methods to estimate them the reader is referred to Wright et al. (2013).

For further investigations spatial heterogeneous rainfall is applied throughout the study.

4.3.2. Influence of disaggregation methods and spatial consistence

For this investigation observed time series are used as reference for the validation of the disaggregated time series. For the comparison of the disaggregation methods before and after the resampling, the flood volumes of all nodes in the sewer system (Fig. 15) and the corresponding combined sewer overflow (Fig. 16) are analyzed event-based (see Section 3.3.3 for the event selection).

In Fig. 15 the total flood volume of each method is higher after resampling than before. First, the results for events with $T_k = 4.4$ years are discussed. After the disaggregation, but before the resampling, wet time steps are located "randomly" within the days of the time series. After resampling, the probability of simultaneously rainfall occurrence is much higher, which results in higher areal rainfall amounts and accordingly an increase in flood volume. Without resampling, the total flood volume is underestimated by

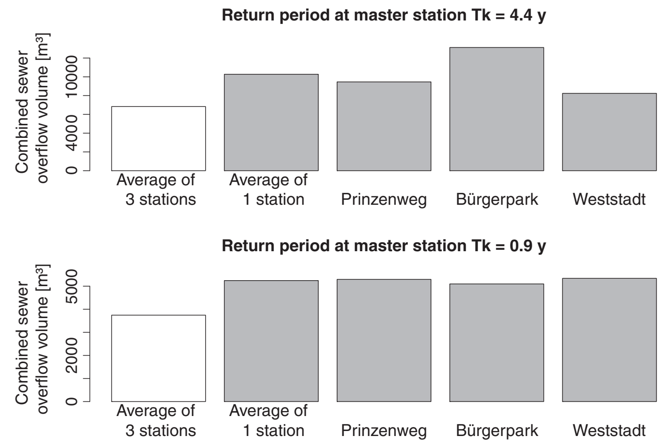

Fig. 14. Total volume of combined sewer overflow resulting from spatial heterogeneous (white) or uniform (grey) rainfall (return period at master station is $T_k = 4.4$ years and $T_k = 0.9$ years respectively, 30 min duration).

all methods. So if more than one station is used in the urban hydrological model, the disaggregated time series have to be resampled. Without resampling, unrealistic spatial patterns occur and the simulated flood volumes are not representable.

For method A, an overestimation of the average rainfall intensity and the extreme values has been identified before. Also, the total flood volume is overestimated after resampling by about. 240%. The overestimation of B1 and underestimation of B3 seem to be contrary to the findings of the extreme values (underestimation of B1 and overestimation of B3).

In B1, rainfall is split uniformly from time steps with 15 min duration to 5 min duration. This leads to an underestimation of the extreme values with 5 min duration, but results in continuous rainfall events. In B3, extreme values are overestimated, but rainfall events may be interrupted by dry intervals. Concerning the total flood volume, the continuity of extreme rainfall events seems to have a greater influence than short extreme values. The resampled time series of B2 show the best fit to the observations with an underestimation of 20%, but only slightly better than B3.

For the smaller events ($T_k = 0.9$ years), using observed rainfall does not lead to any flooding for all simulations. Also, for all non-resampled time series, no nodes are flooded. However, this should not be interpreted as being a good fit of all disaggregated time series without the subsequent resampling. An additional investigation of the combined sewer overflow volume is carried out to analyze this possible interpretation. Nevertheless, it should be noted that nodes are flooded after the resampling. The highest total volume occurs for A, the lowest for B2. A higher total flood volume of B3 in comparison

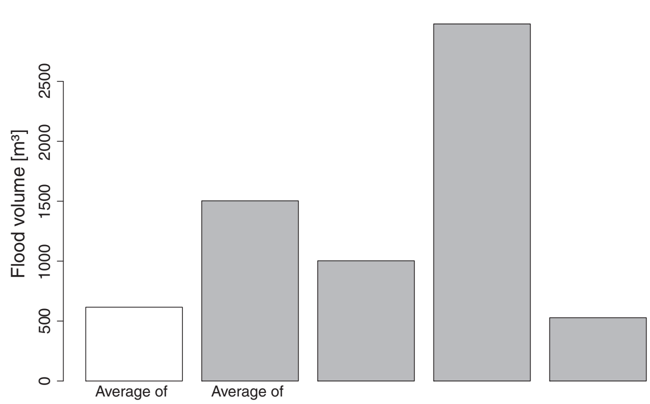

Fig. 13. Total flood volume resulting from spatial heterogeneous (white) or uniform (grey) rainfall (return period at master station $T_k = 4.4$ years, 30 min duration).

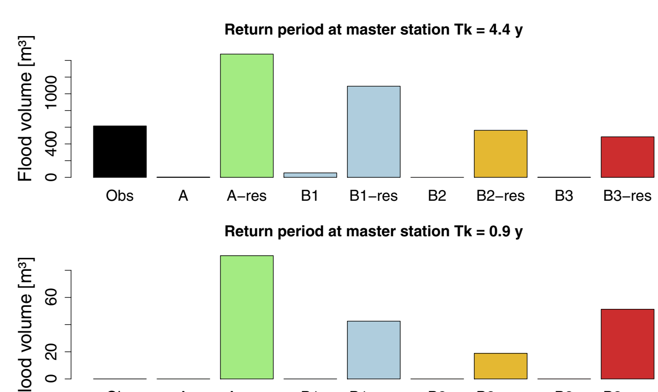

Fig. 15. Total flood volume for extreme values with two return periods with 30 min duration (average of 90 event-based simulations for A, B1, B2, B3 (and resampled analogues ("res")), 3 simulations for observations).

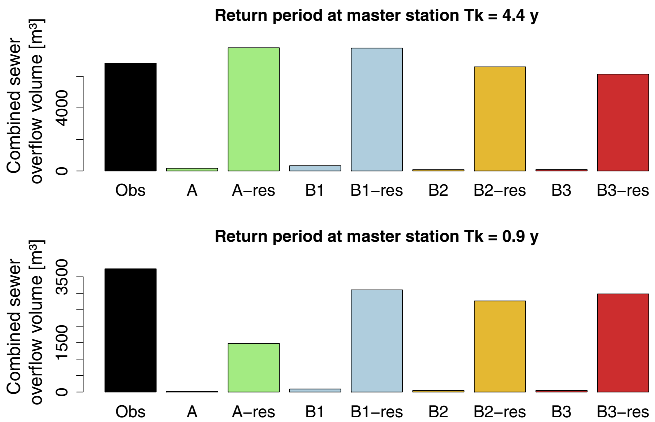

Fig. 16. Total volume of combined sewer overflow for extreme values with two return periods with 30 min duration (average of 90 event-based simulations for A, B1, B2, B3 (and resampled analogues ("res")), 3 simulations for observations).

to B2 can be identified for the smaller event, and vice versa for the higher event. This is consistent with the relationship of the extreme values for short durations (see Fig. 9).

In Fig. 16, the corresponding combined sewer overflow volumes during the events with return periods of $T_k = 4.4$ years and $T_k = 0.9$ years are shown. For the non-resampled time series almost no overflow occurs, which results in high underestimations in comparison to the observed time series. Concerning the resampled time series, for the event with $T_k = 4.4$ years, the results are quite similar to the total flood volumes of the nodes. A and B1 lead to overestimations, while B2 and B3 show underestimations. The best fit can be identified with a slight underestimation of 3.4% for B2.

For the smaller event ($T_k = 0.9$ years), all methods show underestimations. Again, combined sewer overflow volume cannot be reproduced by the time series without spatial consistence. After the resampling, A leads to the strongest underestimation, while the results for B1, B2 and B3 are similar (about 21% underestimation). It should be noted, that although no nodes were flooded by these events, an overflow volume of the tank occurs which is underestimated by all disaggregation methods. This can be explained by fraction of dry time steps during the event (Table 5). For the three observed extreme events, no dry time steps occur at the master station, while for the resampled time series the fraction ranges between 18% (B1) and 31%. For the other two stations the fraction of dry time steps are even stronger overestimated with 50–66% in comparison to 6% for the observations. So although the total rainfall amount of an extreme event is well-represented, the distribution of the rainfall amount in the event can have a significant influence on the modeling results. Hence the validation of applicability of extreme values from generated time series cannot be carried out without urban hydrological modeling.

The higher rainfall intensity of single time steps due to a higher fraction dry time steps in an extreme event leads to an overestimation of the flood volume for all disaggregation methods. For the observations, the water elevation in the system remains completely below the manhole cover level. Hence, no delayed flows occur and the whole water volume reaches the tank immediately, causing the combined sewer overflow.

Table 5
Fraction of dry intervals for the extreme events with return periods of $T_k = 0.9$ years with 30 min duration (average of 90 events for resampled, disaggregated time series; 3 events for observations).

Master station					Other stations				
Obs	A-res	B1-res	B2-res	B3-res	Obs	A-res	B1-res	B2-res	B3-res
Fraction of dry time intervals (%)									
0	31	18	20	21	6	66	50	56	58

5. Conclusions and outlook

In this study, two different investigations were presented to generate 5 min rainfall time series and apply them for urban hydrologic modeling. First, three modifications of the multiplicative random cascade model are introduced. All three modifications are further developments of the "uniform splitting"-approach introduced by Müller and Haberlandt (2015). A branching number $b = 3$ is applied in the first disaggregation step, while for all disaggregation steps $b = 2$ is applied. To achieve a final resolution of 5 min, different methods are tested, implemented at the disaggregation level 6 (called B1), 7 (B2) and 8 (B3), which represent 15, 7.5 and 3.75 min intervals, respectively. In B1 a uniform splitting is applied, while for the other two the final resolution is achieved by linear interpolation. The performance of the model was compared with observed values from Lower Saxony (Germany) and an existing modification of the cascade model, the so-called 1280 min approach (called A). Different criteria regarding time series statistics and extreme values were taken into account for the evaluation.

Molnar and Burlando (2008) analyzed the influence for parameter estimation using 1440 min (starting and ending of each day were discarded) or continuous usage of 1280 min and could find no large difference. However, it could be shown that for the disaggregated time series, differences are crucial. The investigations have been carried out twice, once taking all values of the time series into account and once including a threshold to neglect the influence of single tips in the observed time series and too small rainfall intensities in the disaggregated time series. The following conclusions can be drawn:

1. Method A is outperformed by B1, B2 and B3 regarding wet and dry spell duration, average intensity, lag-1 autocorrelation and fraction of dry intervals. For wet spell amount, A and B3 show better results than B1 and B2 taking into account all time steps. With the threshold-cleaned time series best results are provided by method B1 and B2.
2. Extreme values of 5 min duration are highly overestimated by A and B3. B1 shows slight underestimations, while B2 tends to overestimate the observations slightly. For extreme values of 1 h duration, only minor differences can be identified.
3. Altogether B2 shows the best performance. Most of the characteristics are only slightly overestimated (wet spell amount 8%, dry spell duration 8%, average intensity 11% and fraction of dry intervals 1%), wet spell durations are slightly underestimated (3%). The relative root mean square error for extreme values of 5 min duration is $rRMSE = 16\%$.

The overestimation for extreme values with 5 min duration can also be found by Onof et al. (2005) for B3. Molnar and Burlando (2005) show also overestimations resulting from A, while in Licznar et al. (2011a), extreme values of 5 min duration are underestimated.

The autocorrelation of the time series is underestimated by all methods. Lombardo et al. (2012) proved that the autocorrelation cannot be reproduced by the micro-canonical cascade model. An underestimation of the autocorrelation was identified before by e.g. Olsson (1998), Güntner et al. (2001), Pui et al. (2012) and Paschalis et al. (2012, 2014). Lisniak et al. (2013) show a good representation of the autocorrelation function for a validation period, while for the calibration period underestimations occur for all lags. Rupp et al. (2009) analyzed four different kinds of cascade models. Depending on the model choice, autocorrelation function was under- or overestimated.

One possibility to improve the results of method A could be a dressed cascade model (see Schertzer et al., 2002; Paulson and Baxter, 2007), which includes a continuation of the disaggregation process to very fine time scales and subsequently aggregation to the scale of interest. Another possibility would be to implement an additional disaggregation step from 5.625 min to 2.8125 min and subsequently an averaged weighting to achieve a final resolution of 5 min.

Since the disaggregation process is carried out station-based, spatial consistence is missing in between the disaggregated time series. The implementation of spatial consistence for 5 min rainfall is the second novelty of this study. A resampling algorithm is applied for the implementation of spatial consistence Müller and Haberlandt (2015), defined by the distance-dependent bivariate characteristics probability of occurrence, Pearson's coefficient of correlation and continuity ratio (Wilks, 1998). These characteristics have been analyzed before and after the resampling procedure.

4. The resampling algorithm is capable of implementing spatial consistence for time series with 5 min resolution.
5. The probability of occurrence and Pearson's coefficient of correlation could be improved significantly. Continuity ratio shows a slight worsening.

The disaggregated time series with and without spatial consistence as well as observed time series have been used as input for an artificial urban hydrological system. The main findings are:

6. Using spatial uniform rainfall (one station) as input does not ensure an adequate representation of node flooding and tank overflow, therefore spatial heterogeneous rainfall (three stations) has been applied for all further simulations.
7. The resampled time series lead to comparable results to those from the observations. Without resampling, unrealistic results regarding the volume of flooded nodes or combined sewer overflow volume occur.
8. The resampled version of B2 leads to the best fit to observations. Method A results in the worst representation among all resampled versions.

The overall performance of B2 was better in comparison to A, although the latter one can be seen as the standard disaggregation variant of the cascade model for urban-hydrological investigations (Licznar et al., 2011a,b; 2015; Molnar and Burlando, 2005; Serinaldi, 2010; Paschalis et al., 2014). The potential of the resampling algorithm has been proven for time series with 5 min resolution. However, the reproduction of bivariate characteristics can be improved. Further investigations of the proposed methods should be carried out for other regions with different rainfall characteristics and climate.

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Appendix A

See Table A1.

Table A1
The probabilities (%), resulting from the aggregation of the observed time series of rain gauge Göttingen, which were used for disaggregation in method A.

Aggregation (temporal resolution in min)	Position and volume class							
	Starting		Enclosed		Ending		Isolated	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
				$P(1/0)$				
5–10	36	3	22	1	48	20	46	45
10–20	20	2	16	1	57	27	46	21
20–40	14	2	16	1	60	27	44	22
40–80	14	4	19	2	60	29	42	24
80–160	13	4	23	3	59	29	45	24
160–320	15	4	26	6	59	28	43	21
320–640	18	6	29	8	58	31	38	25
640–1280	20	7	28	10	56	26	34	16
				$P(0/1)$				
5–10	49	27	21	1	40	2	46	44
10–20	56	30	16	1	28	3	47	19
20–40	57	32	14	2	18	3	43	21
40–80	58	33	17	4	16	6	44	23
80–160	58	31	21	4	17	7	41	23
160–320	60	28	23	6	18	8	40	25
320–640	55	32	27	10	19	8	40	18
640–1280	57	35	28	12	18	6	44	21
				$P(x/(1-x))$				
5–10	15	70	58	98	13	78	8	11
10–20	24	68	68	98	16	70	7	60
20–40	29	66	70	97	21	69	13	57
40–80	28	63	64	95	25	66	14	53
80–160	29	65	56	92	24	64	14	53
160–320	25	67	51	88	24	65	17	54
320–640	27	62	44	82	23	61	21	57
640–1280	23	58	44	78	26	68	23	63

References

Aarts, E., Korst, J., 1965. Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing. John Wiley & Sons, Chichester.

Barco, J., Wong, K.M., Stenstrom, M.K., 2008. Automatic calibration of the U.S. EPA SWMM model for a large urban catchment. J. Hydraul. Eng. 134, 466–474.

Bardossy, A., 1998. Generating precipitation time series using simulated annealing. Water Resour. Res. 34 (7), 1737–1744.

Berne, A., Delrieu, G., Creutin, J.-D., Obled, C., 2004. Temporal and spatial resolution of rainfall measurements required for urban hydrology. J. Hydrol. 299, 166–179.

Breinl, K., Turkington, T., Stowasser, M., 2013. Stochastic generation of multi-site daily precipitation for applications in risk management. J. Hydrol. 498, 23–35.

Breinl, K., Turkington, T., Stowasser, M., 2014. Simulating daily precipitation and temperature: a weather generation framework for assessing hydrometeorological hazards. Meteorol. Appl. 22 (3), 334–347.

Bruni, G., Reinoso, R., van de Giesen, N.C., Clemens, F.H.L.R., ten Veldhuis, J.A.E., 2015. On the sensitivity of urban hydrodynamic modelling to rainfall spatial and temporal resolution. Hydrol. Earth Syst. Sci. 19 (2), 691–709.

Burlando, P., Rosso, R., 1996. Scaling and multiscaling of depth-duration-frequency curves for storm precipitation. J. Hydrol. 187, 45–64.

Carsteanu, A., Foufoula-Georgiou, E., 1996. Assessing dependence among weights in a multiplicative cascade model of temporal rainfall. J. Geophys. Res. 101 (D21), 26363–26370.

Cowpertwait, P.S.P., 1995. A generalized spatial-temporal model of rainfall based on a clustered point process. Proc. R. Soc. Lond. A. 450, 163–175.

Ding, J., Haberlandt, U., Dietrich, J., 2015. Estimation of instantaneous peak flow from maximum daily flow: a comparison of three methods. Hydrol. Res. 46 (5), 671–688.

Dunkerley, D., 2008. Identifying individual rain events from pluviograph records: a review with analysis of data from an Australian dryland site. Hydrol. Process. 22 (26), 5024–5036.

DIN EN 752, 1996. Drain and sewer systems outside buildings, German Institute for Standardization, Berlin.

DWA-A 118, 2006. Hydraulische Bemessung und Nachweis von Entwässerungssystemen, Arbeitsblatt der DWA, Hennef.

DWA-A 531, 2012. Starkregen in Abhängigkeit von Wiederkehrzeit und Dauer, Arbeitsblatt der DWA, Hennef.

Emmanuel, I., Andrieu, H., Leblois, E., Flahaut, B., 2012. Temporal and spatial variability of rainfall at the urban hydrological scale. J. Hydrol. 430–431, 162–172.

Gires, A., Giangola-Murzyn, A., Abbes, J.B., Tchiguirinskaia, I., Schertzer, D., Lovejoy, S., 2015. Impacts of small scale rainfall variability in urban areas: a case study with 1D and 1D/2D hydrological models in a multifractal framework. Urban Water J. 12 (8), 607–617.

Goldstein, A., DiGiovanni, K., Montalto, F., 2010. Resolution and sensitivity analysis of a block-scale urban drainage model. In: Palmer, R.N. (Ed.), World Environmental and Water Resources Congress 2010: Challenges of Change, Providence, Rhode Island, 16–20 May 2012. ASCE, Reston, VA, USA, pp. 4720–4729.

Güntner, A., Olsson, J., Calver, A., Gannon, B., 2001. Cascade-based disaggregation of continuous rainfall time series: the influence of climate. Hydrol. Earth Syst. Sci. 5 (2), 145–164.

Haberlandt, U., Ebner von Eschenbach, A.D., Buchwald, I., 2008. A space-time hybrid hourly rainfall model for derived flood frequency analysis. Hydrol. Earth Syst. Sci. 12 (6), 1353–1367.

Hingray, B., Ben Haha, M., 2005. Statistical performance of various deterministic and stochastic models for rainfall series disaggregation. Atmos. Res. 77, 152–175.

Hosking, J.R.M., Wallis, J.R., 1997. Regional frequency analysis. Cambridge University Press, Cambridge.

Kim, Dongkyun, Olivera, F., 2012. Relative Importance of the Different Rainfall Statistics in the Calibration of Stochastic Rainfall Generation Models. J. Hydrol. Eng. 17 (3), 368–376.

Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by simulated annealing. Science 220 (4598), 671–680.

Imhoff, K., Imhoff, K.R., 2007. Taschenbuch der Stadtentwässerung, Oldenburg Industrieverlag, 30. Auflage, 508 p.

Jebari, S., Berndtsson, R., Olsson, J., Bahri, A., 2012. Soil erosion estimation based on rainfall disaggregation. J. Hydrol. 436–437, 102–110.

Krebs, G., Kokkonen, T., Valtanen, M., Setälä, H., Koivusalo, H., 2014. Spatial resolution considerations for urban hydrological modeling. J. Hydrol. 512, 482–497.

Koutsoyiannis, D., Onof, C., Wheater, H.S., 2003. Multivariate rainfall disaggregation at a fine time scale. Water Resour. Res. 39 (7), 1173.

Kumar, P., Guttarp, P., Foufoula-Georgiou, E., 1994. A probability-weighted moment test to assess simple scaling. Stoch. Hydrol. Hydraul. 8, 173–183.

Licznar, P., Lomotowski, J., Rupp, D.E., 2011a. Random cascade driven rainfall disaggregation for urban hydrology: an evaluation of six models and a new generator. Atmos. Res. 99 (3–4), 563–578.

Licznar, P., Schmitt, T.G., Rupp, D.E., 2011b. Distributions of micro-canonical cascade weights of rainfall at small time scales. Acta Geophys. 59 (5), 1013–1043.

Licznar, P., De Michele, C., Adamowski, W., 2015. Precipitation variability within an urban monitoring network via microcanonical cascade generators. Hydrol. Earth Syst. Sci. 19 (1), 485–506.

Lisniak, D., Franke, J., Bernhofer, C., 2013. Circulation pattern based parameterization of a multiplicative random cascade for disaggregation of observed and projected daily rainfall time series. Hydrol. Earth Syst. Sci. 17 (7), 2487–2500.

Lombardo, F., Volpi, E., Koutsoyiannis, D., 2012. Rainfall downscaling in time: theoretical and empirical comparison between multifractal and Hurst-Kolmogorov discrete random cascades. Hydrol. Sci. J. 57 (6), 1052–1066.

Lombardo, F., Volpi, E., Koutsoyiannis, D., Papalexiou, S.M., 2014. Just two moments! A cautionary note against use of high-order moments in multifractal models in hydrology. Hydrol. Earth Syst. Sci. 18, 243–255.

Marshak, A., Davis, A., Cahalan, R., Wiscombe, W., 1994. Bounded cascade models as nonstationary multifractals. Phys. Rev. E 49 (1), 55–69.

Molnar, P., Burlando, P., 2005. Preservation of rainfall properties in stochastic disaggregation by a simple random cascade model. Atmos. Res. 77 (1–4), 137–151.

Molnar, P., Burlando, P., 2008. Variability in the scale properties of high-resolution precipitation data in the Alpine climate of Switzerland. Water Resour. Res. 44 (10), W10404.

Müller, H., Haberlandt, U., 2015. Temporal rainfall disaggregation with a cascade model: from single-station disaggregation to spatial rainfall. J. Hydrol. Eng. 20 (11), 04015026.

Ochoa-Rodriguez, S., Wang, L.-P., Gires, A., Pina, R.D., Reinoso-Rondinel, R., Bruni, G., Ichiba, A., Gaitan, S., Cristiano, E., Assel, J.v., Kroll, S., Murlà-Tuyls, D., Tisserand, B., Schertzer, D., Tchiguirinskaia, I., Onof, C., Willems, P., ten Veldhuis, M.-C., 2015. Impact of spatial and temporal resolution of rainfall inputs on urban hydrodynamic modelling outputs: a multi-catchment investigation. J. Hydrol. 531 (Part 2), 389–407.

Olsson, J., 1998. Evaluation of a scaling cascade model for temporal rainfall disaggregation. Hydrol. Earth Syst. Sci. 2 (1), 19–30.

Onof, C., Chandler, R.E., Kakou, A., 2000. Rainfall modelling using Poisson-cluster processes: a review of developments. Stoch. Env. Res. Risk. A 14 (6), 384–411.

Onof, C., Townend, J., Kee, R., 2005. Comparison of two hourly to 5-min rainfall disaggregators. Atmos. Res. 77 (1–4), 176–187.

Onof, C., Arnbjerg-Nielsen, K., 2009. Quantification of anticipated future changes in high resolution of design rainfall for urban areas. Atmos. Res. 92 (3), 350–363.

Over, T.M., Gupta, V.K., 1994. Statisitcal Analysis of mesoscale rainfall: dependence of a random cascade generator on large-scale forcing. J. Appl. Meteorol. 33, 1526–1542.

Paulson, K.S., Baxter, P.D., 2007. Downscaling of rain gauge time series by multiplicative beta cascade. J. Geophys. Res.-Atmos. 112 (D9), D09105.

Paschalis, A., Molnar, P., Burlando, P., 2012. Temporal dependence structure in weights in a multiplicative cascade model for precipitation. Water Resour. Res. 48 (1), W01501.

Paschalis, A., Molnar, P., Fatichi, S., Burlando, P., 2014. On temporal stochastic modeling of precipitation, nesting models across scales. Adv. Water Resour. 63, 152–166.

Peel, M.C., Finlayson, B.L., McMahon, T.A., 2007. Updated world map of the Köppen-Geiger climate classification. Hydrol. Earth Syst. Sci. 11 (5), 1633–1644.

Pui, A., Sharma, A., Mehrotra, R., Sivakumar, B., Jeremiah, E., 2012. A comparison of alternatives for daily to sub-daily rainfall disaggregation. J. Hydrol. 470–471, 138–157.

Richter, D., 1995. Ergebnisse methodischer Untersuchungen zur Korrektur des systematischen Messverfahrens des Hellman-Niederschlagsmessers. Berichte des Deutschen Wetterdienstes, 194, Selbstverlag des DWD, Offenbach a.M.

Rupp, D.E., Keim, R.F., Ossiander, M., Brugnach, M., Selker, J., 2009. Time scale and intensity dependency in multiplicative cascades for temporal rainfall disaggregation. Water Resour. Res. 45 (7), W07409.

Rossman, L.A., 2010. Storm water management model – User's manual version 5.0, Environmental Protection Agency, EPA/600/R-05/040.

Schertzer, D., Lovejoy, S., Hubert, P., 2002. An introduction to stochastic multifractal fields. In: Ern, A., Liu, W., (Eds.). Isfma Symp. Environmental Science and Engineering with related mathematical problems, High Education Press, Bejing, pp. 106–179.

Schertzer, D., Lovejoy, S., 2011. Multifractals, generalized scale invariance and complexity in Geophysics. Int. J. Bifurc. Chaos 21 (12), 3417–3456.

Schilling, W., 1991. Rainfall data for urban hydrology: What do we need? Atmos. Res. 27 (1–3), 5–21.

Segond, M.-L., Neokleous, N., Makropoulos, C., Onof, C., Maksimovic, C., 2007. Simulation of spatio-temporal disaggregation of multi-site rainfall data for urban drainage applications. Hydrolog. Sci. J. 52, 917–935.

Serinaldi, F., 2010. Multifractality, imperfect scaling and hydrological properties of rainfall time series simulated by continuous universal multifractal and discrete random cascade models. Nonlin. Processes Geophys. 17 (6), 697–714.

Sevruk, B., 2005. Rainfall measurement: gauges. In: M. G. Anderson (Ed.). Encyclopedia of Hydrological Sciences, Wiley & Sons Ltd., Chichester, pp. 529–535.

Sivapalan, M., Blöschl, G., 1998. Transformation of point to areal rainfall: Intensity-duration-frequency curves. J. Hydrol. 204 (1–4), 150–167.

Svensson, C., Olsson, J., Berndtsson, R., 1996. Multifractal properties of daily rainfall in two different climates. Water Resour. Res. 32 (8), 2463–2472.

Veneziano, D., Langousis, A., 2005. The areal reduction factor: a multifractal analysis. Water Resour. Res. 41 (7), W07008.

Veneziano, D., Langousis, A., Furloco, P., 2006. Multifractality and rainfall extremes: a review. Water Resour. Res. 42 (6), W06D15.

Veneziano, D., Langousis, A., 2010. Scaling and Fractals in Hydrology. In: Sivakumar, B., Berndtsson, R., (Eds.). Advances in Data-based Approaches for Hydrologic Modeling and Forecasting. World Scientific Publishing, Hackensack, 145p.
Wilks, D.S., 1998. Multisite generalization of a daily stochastic precipitation generation model. J. Hydrol. 210 (1–4), 178–191.
Wilson, J.W., Brandes, E.A., 1979. Radar measurement of rainfall – a summary. Bull. Amer. Meteor. Soc. 60 (9), 1048–1058.
Wójcik, R., Buishand, T.A., 2003. Simulation of 6-hourly rainfall and temperature by two resampling schemes. J. Hydrol. 273 (1–4), 69–80.
Wright, D.B., Smith, J.A., Baeck, M.L., 2013. A critical examination of area reduction factors. J. Hydrol. Eng. 19 (4), 769–776.
Yu, P.-S., Yang, T.-C., Lin, C.-S., 2014. Regional rainfall intensity formulas based on scaling property of rainfall. J. Hydrol. 295, 108–123.