

February 17, 2017

Dr Marie-Claire ten Veldhuis
Editor
Hydrology and Earth System Sciences (HESS)

RE: hess-2016-530

Dear Editor,

Please find enclosed the revised manuscript: "Partitioning the impacts of spatial and climatological rainfall variability in urban drainage modelling" by Nadav Peleg, Frank Blumensaat, Peter Molnar, Simone Fatichi and Paolo Burlando. The manuscript has been revised according to the comments of the Editor. We would like to thank the Editor for her efforts and constructive comments.

Editor:

General

The authors have replied to all the reviewers' comments in their rebuttal and made changes to the manuscript accordingly. However, some of the comments merit a more substantial and critical discussion than is currently provided.

Specific comments

1) The authors conclude that climatological variability contributes more to flow variability than spatial rainfall variability. This makes sense for the relatively small catchment they investigated, as 30 years of rainfall are likely to represent more variability than rainfall over a domain of only 77 ha (or less, the subcatchments are max 30 ha). Still, the results on spatial rainfall variability obtained in this study are strongly dependent on the choices that have been made in the rainfall downscaling procedure (see also comment nr2 by reviewer 2), since the original spatial scale of the rainfall data is larger than the catchment scale (2x2km). For example, it is assumed that the wet area ratio is always equal to one during storms (and zero in between storms), which strongly limits the degree of spatial variability that can occur. In reality, even if the scale of a storm is typically larger than a few km², more and more zero rainfall pixels would occur within the storm domain as one scales down to smaller scales. The impact of the assumptions made for the downscaling procedure on the partitioning results should be more critically discussed.

We agree with the Editor statement that the results on spatial rainfall variability obtained in this study are dependent on the choices that have been made in the rainfall downscaling procedure. However, the suggestion of the Editor that we are underestimating the rainfall spatial variability in small urban catchments with a wet area ratio equal to one is generally not true, especially when high rainfall intensities are considered. This has been shown using a dense rain-gauge network for a different location but with a similar spatial characteristics in past studies of the authors (Peleg et al., 2013; 2016). There we have found that convective events (rainfall intensity >10 mm h⁻¹) were characterized with a mean wet area ratio of 0.88 for a much larger domain (4 km²) than the domain that was analyzed in this study (2.25 km²). It is important to realize that our downscaling methodology generates a spatial distribution of rain intensities which cover a large range, many pixels having extremely low intensity which would not even be detected by a typical rain-gauge. For example, 29% of the rainfall intensities simulated for Case 4 (chosen as an example) were lower than 0.1 mm h⁻¹ (and 39% were <0.2 mm h⁻¹), which can be considered as insignificant, practically zero, rainfall. As a result we do not think that the degree of spatial variability in our downscaling is limited (underestimated) due to the fact that the wet area ratio was fixed.

We also agree with the Editor that the assumptions made for the downscaling procedure are to be discussed, and in fact most of the relevant assumptions made for the downscaling were mentioned in the discussion part at the manuscript. The paragraph dealing with the rainfall generator in the discussion section was modified to include additional aspects that were not discussed before: "The rainfall generator was used to simulate rainfall for the weather radar subpixel scale, i.e. in a finer spatial resolution than can be estimated using the MeteoSwiss radar. The rainfall

data required for a complete validation of the rainfall generator for this resolution can be obtained from a dense rain-gauge network (for networks examples see Muthusamy et al., 2016; Peleg et al., 2013) but such a network is not available in the analyzed region. **Four aspects** are discussed in the light of missing information for the subpixel scale (**i.e. rainfall downscaling process**): (i) the rain fields are simulated following a lognormal distribution. We assume that the non-zero part of the subpixel spatial rainfall distribution follows the observed lognormal distribution that is recorded by the weather radar for this region (as in Paschalis et al., 2014; Peleg et al., 2016). A different spatial rainfall distribution will significantly affect the results of the extreme rainfall; (ii) we assume that occurrence and intensity statistics are equal for each of the grid cells, i.e. no spatial correlation is applied for the rainfall occurrence or intensity. This means that orography, distance from the lake, and urban micro-climate effects are not considered; (iii) **we assume that the rainfall spatial correlation structure for this region follows the average structure obtained from estimates made in dense rain-gauge networks in Poland, Germany and Israel (Moszkowicz, 2000; Müller and Haberlandt, 2016; Peleg et al., 2013). The exact impact of the spatial correlation structure at the radar subpixel scale in urban drainage studies is yet to be determined; and (iv) we assume that the power-law used for the scaling of the rainfall coefficient of variation is continuous from the weather radar to its subpixel scale, and it is not affected by a scale-break. Overestimation of the rainfall coefficient of variation will affect the rainfall spatial variability and therefore impact the partitioning results**".

2) Another point that requires more discussion is how the uncertainty of the model used in this study might influence the results (see also comment reviewer 2 regarding use of 10 minute temporal resolution). The authors refer to Tokarczyk et al. (2015) for information about model calibration. In this paper, Nash-Sutcliffe efficiency values of 0.70-0.75 were reported and simulated versus observed hydrograph results show relative errors in peak flow estimates of over 25%, for flows up to about 300 l/s. The range of flows that is analysed in the partitioning study is far outside this range (1000-3000 l/s), while variability associated with rainfall climatology and spatial variability is of the same order of magnitude as the model uncertainty (~25%).

We agree with the Editors' opinion that limitations due to the comparatively coarse temporal rainfall resolution (10 min) can be discussed more in depth. We furthermore discuss the relevance of the overall model accuracy (relative error for peak flows of 25%, NSE ~0.7) in the light of the evaluated rainfall variability:

1a) We agree that using a 10 min rainfall input represents a critical point, in particular when the average response time in the considered catchment is in the order of minutes (see Tokarczyk et al., 2015; Fig. 8). Still, we achieve a reasonable hydraulic model performance when validating the model results against flow observations at the catchment outlet (Location B in the present manuscript – the same, but not labelled, in Tokarczyk et al., 2015). As shown in Appendix A (at the end of this letter), the original calibration was focused not just on peak-flow performance, but also on the performance of time-to-peak and runoff balance. With this we follow recommendations given in Krause et al. (2005). The calibration for flows at location B yielded in NSEs >0.8 for individual events; overall performance for longer periods was estimated with NSE ~0.7 (see Appendix A and Tokarczyk et al., 2015). We consider the calibration procedure as adequate and accept the model performance as reasonable.

1b) To further justify the use of 10 min rainfall data, we carried out additional benchmark simulations with partial data from a rain-gauge recording rainfall at finer temporal resolution (1 min). In Appendix A, we show that both rainfall records, being independently measured and of different temporal resolution, are similarly adequate to reproduce flow dynamics in the considered catchment. However, the rather vague meta-information on the 1 min rainfall record (measurement accuracy, gauge type, mode of operation) does not suggest the use of this fine temporal resolution data in a scientific publication. We are fully aware of the relevance of an adequate temporal rainfall resolution for urban drainage modelling studies, but here we do not want to dilute the focus of the study (spatial and climatological variability) by including a controversial issue, which ultimately cannot be clarified on the basis of available data. Overall, we believe that based on the results of this benchmark and the more-than-average model validation (1-year field observations as reference; not just one event; various performance criteria) we show that flow dynamics can be adequately reproduced, even though we feed the model with a 10 min rainfall input.

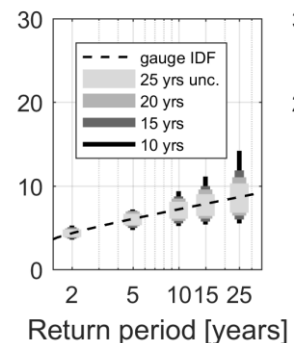
2) The fact that the NSE for flows observed/simulated at Location B is 0.7-0.75 for the validation period, and that peak flows at the same location were deviate up to 25% can be attributed to several different sources, e.g. model structure uncertainty, inadequate model calibration, measurement error in the flow reference, and model input data uncertainty.

We further agree that the range of peak flows that were analyzed in this study varies within two orders of magnitude (300–3000 ls^{-1}) whereas the model validation was only conducted for location B, at which peak flows hardly exceed 300 ls^{-1} . At this particular location, modelled peak flows have been assessed, i.e. deviate up to 25% (positive and negative) compared from observed flows. Locations A and C show higher peak flows, but the model performance at these locations can only indirectly be evaluated through location B. Assuming similarly high deviations (~25%) at locations A and C would be a first assumption, but it cannot directly be verified. However, considering the fact that the same hydrodynamic model (inherent with the same deficiency) has been used for all simulations, we assume that the error due to the model structure and calibration equally influences each single simulation. Since the focus of the study had not been at the quantification of absolute peak flows for this particular catchment in Lucerne, but on a relative contribution of different rainfall variabilities to flow variations, any other realistic urban catchment could have been used. We chose the Lucerne catchment as real-life case because it is representative and it had been thoroughly researched and verified, including the quantification of an overall modelling error based on measured observations. We will make this model error, quantified for location B, transparent in the revised version of the manuscript, but we are confident that the conclusions regarding spatial and climatological rainfall variability do not become invaluable because peak flow deviations are in the same order of magnitude as researched rainfall variabilities.

Consequently, a new paragraph was added in the “results and discussion” section, summarizing the above points and main message from Appendix A below: **“Rainfall records were obtained from a rain-gauge that is located about 2 km west of the case study catchment. It was chosen for three main reasons (i) its proximity to the catchment; (ii) it has a sufficiently long record (34-year) that is adequate for statistical climatology analysis; and (iii) records have been verified by MeteoSwiss ensuring sufficient consistency. In contrast to these advantages, the 10 min temporal resolution of the rain data requires critical consideration when simulating the dynamics of the flow response (e.g. Ochoa-Rodriguez et al., 2015), particularly as the average flow response in the investigated catchment is in the order of minutes. However, we achieve a reasonable hydraulic model performance when validating the model against flow observations at the catchment outlet (location B), considering peak flow, time-to-peak and flow balance (see Tokarczyk et al., 2015). Low flow volume errors ($\pm 5\%$) and Nash-Sutcliffe-Efficiencies of >0.8 for individual events, i.e. >0.7 for longer periods, support the fact that the flow dynamics are reproduced adequately. Remaining peak flow errors of up to 25% reflect existing deficiencies stemming from multiple sources, e.g. inadequate model structure, insufficient model calibration, measurement errors in flow reference data and model input data uncertainty. Considering that the same hydrodynamic model has been used for all the simulations, it is likely that the error due to model structure and calibration do not introduce a consistent bias to the variability partitioning. A complete investigation of the model hydrodynamic uncertainties will provide additional insights but it will be difficult to constrain with the current length of available flow data”.**

3) A final point the authors could discuss more critically is the fact that they use data over a period of 30 years and draw conclusions for return periods up to 30 years. In particular, they conclude that the contribution of spatial rainfall variability becomes more important for larger return periods (> 10 years), but statistics beyond 10 years are quite unreliable for a 30 year time series, given the small sample sizes in the extreme tail of the statistical distribution.

We do agree that rainfall uncertainties become important when the record length is similar, or smaller, than the estimated return period. Marra et al. (2016) recently demonstrated how uncertainties increase with return period and with smaller record length for different climate regions and durations (a snapshot taken from Figure 9 in Marra et al. is given at the right, illustrating this point). We acknowledge the need to notify the readers of this point, stating that our results represent the climate uncertainties derived from a 30-year data period. This point in fact strengthens the results of this study, as with a larger sample period the climate uncertainties for a longer return period are expected to decrease, implying that the contribution of the spatial rainfall variability for longer return period may be even higher than reported in this study.



The following changes to the text were made in the discussion section: “While the use of spatially distributed rainfall data can supply valuable information for sewer network design (based on rainfall with return periods from 5 to 15 years), it will become even more important when performing flood risk assessments of

extreme events (larger return periods). **A 30-year record was used in this study, which can be regarded as the minimum period for IDF/FDF analysis. Since uncertainties in climate statistics decrease with a longer observational record (e.g. Marra et al., 2016), the contribution of the additional spatial variability for larger return periods might be even greater than presented here. However, a longer period of observation is required to confirm this assertion“.**

A few comments with respect to the figures the authors have provided in the supplement to the paper:

4) Figures S6 and S7: these are very insightful figures presenting the main results of the partitioning study. It is not clear why the authors have chosen to show results for location B, where flow is controlled by a throttle, in the main body of the paper, while they present results for locations A and C in the supplement. I would suggest to present and discuss all 3 figures in the main body of the paper.

Location B has initially been selected to be shown in the main part of the manuscript, because the model had been validated against field data at this particular point. Figures S6 and S7 were moved to the main manuscript, as suggested.

5) Figure S1: this figure presents parameters used for the spatial downscaling procedure, but the interpretation of the figure isn't entirely clear. In the caption: "For the case study, rainfall was generated over an area of 2.25 km² using grid size of 100 m, thus a CV of 1.5 was used." Yet in the figure, the domain area seems to span 64-1024km² (doesn't go down to 2.25 km²) and the grid size 2-16km. Where do we read the CV value of 1.5 for domain size 2.25 km² and grid size 100m from the figure?

The surface in Figure S1 presents the rainfall coefficient of variation that was estimated using MeteoSwiss weather radar system (i.e. for domain areas of 64-1024 km² and grid cell length of 2-16 km). The surface was computed using a two-parameter power function with R² of 0.99. The rainfall CV used in this study is an extrapolation of the surface, calculated using the two-parameter function, as the domain size and grid cell length are much finer than the observed data. To better explain this in the text, the figure caption was modified as follows: "A surface representing the rainfall coefficient of variation (CV) for temporal resolution of 5 min as analyzed using MeteoSwiss weather radar system over the study area. X-axis refer to the domain area (64–1024 km²), Y-axis refer to the dimension of the rainfall grid cell (2–16 km) and Z-axis represent the rainfall CV. The surface was generated using a two-parameter power function that was fitted to the data $[Z(X,Y)=0.54X^{0.18}-51.57Y^{0.007}+51.63]$ with a coefficient of determination of 0.99. For the case study, rainfall CV was extrapolated from the observed surface using the above function as follows: X=2.25 km² (area of the case study for which rainfall was simulated), Y=100 m (simulate rainfall grid cell length) and Z= 1.5 (simulated rainfall CV)".

We would like again to express our thanks to the Editor and we look forward to hearing from you regarding our submission. We would be glad to respond to any further questions and comments that you may have.

Sincerely,

Nadav Peleg, Frank Blumensaat and Peter Molnar on behalf of the authorship

References

- Krause, P., Boyle, D. P., and Bäse, F. (2005). "Comparison of different efficiency criteria for hydrological model assessment." *Advances in Geosciences*, 5, 89-97.
- Marra, F., Morin, E., Peleg, N., Mei, Y., and Anagnostou, E. N.: Comparing Intensity–Duration–Frequency curves derived from CMORPH and radar rainfall estimates over the Eastern Mediterranean, *Hydrol. Earth Syst. Sci. Discuss.*, doi:10.5194/hess-2016-597, in review, 2016.
- Tokarczyk, P., Leitao, J. P., Rieckermann, J., Schindler, K., and Blumensaat, F. (2015). "High-quality observation of surface imperviousness for urban runoff modelling using UAV imagery." *Hydrol. Earth Syst. Sci.*, 19(10), 4215-4228.

Appendix A - Influence of temporal rainfall resolution on hydraulic simulations

Motivation

To research the influence of the temporal resolution of rainfall input data on the representation of flow dynamics we compare results of hydrodynamic simulations with different rainfall inputs (1 and 10 min temporal resolution).

Rainfall data

Case study simulations were carried out with a rainfall record from the MeteoSwiss rain—gauge station ‘*Allmend*’ (10 min temporal resolution). The same series had been used for research outlined in Tokarczyk et al. (2015). This rainfall record had been chosen for several reasons: (i) the gauge is in close proximity to the catchment (2 km); (ii) rainfall records are sufficiently long (more than 30-year) and are consistent; and (iii) rainfall data were thoroughly verified by MeteoSwiss and by the authors. Seen in the light of these advantages, we accepted that the available temporal resolution of this data is only 10 min. By doing so we also assumed that the 10 min rainfall input for the hydrodynamic model would be adequate to capture short-term flow dynamics observed in the case study catchment.

This assumption is justified through a thorough model calibration/validation procedure (split-sample approach) described by Tokarczyk et al. (2015). For more than 40 different rainfall events in 2014/2015, model performance has been validated for the criteria peak flow, time-to-peak and runoff balance. Performance has been rated adequate since flow volume balance (Bias) error was consistently below 5% and Nash-Sutcliffe-Efficiency (NSE) for individual events was always higher than 0.7 (often higher than 0.8); for longer periods somewhat lower due to inclusion of dry weather periods.

In addition to this, we carried out benchmarking simulations using the 10 min rainfall and rainfall records from two nearby stations (‘*Eichhof*’, ‘*Matthof*’) in 1 min resolution. This data stems from a less systematically organized regional rain—gauge network (manual digitalization; no automatic data transfer; no central data management; see rain—gauge locations in Fig. A1). Furthermore, this record only contains data for selected periods (May - June 2015), partly in fragments (Fig. A2). Based on the *comparing analysis of rainfall* illustrated in Fig. A2 the following conclusions can be drawn:

1. 1 min and 10 min data show similar dynamics, whereas for the considered period (01-May-2015 until 25-June-2015) the ‘*Allmend*’ station records show lower rainfall heights than the ‘*Matthof*’ and ‘*Eichhof*’ records (Fig. A2). For the abovementioned period the full deviation between ‘*Eichhof*’ and ‘*Allmend*’ data is 5.7%. It can be considered small, i.e. within the range of a typical rainfall measurement error.
2. For further analysis (to what extent temporal resolution will influence hydraulic modelling results) we only use records from ‘*Eichhof*’ (1 min) and ‘*Allmend*’ (10 min); ‘*Matthof*’ (1 min) data are excluded due to missing data.
3. Events which are considered in detail are: (A) 01-May-2015 – 06-May-2015 and (B) 14-Jun-2015 – 25-Jun-2015.

Hydraulic modelling benchmark using the calibrated SWMM model

Figures A3—A6 illustrate the model performance for hydraulic simulations driven by two different rainfall inputs of different temporal resolution (MeteoSwiss station ‘*Allmend*’: 10 min; ‘*Eichhof*’ station: 1 min). Similar values for the performance measures *NSE* and *Bias* suggest that in this particular case, temporal rainfall input resolution does not significantly influence the hydraulic model performance (see Fig. A3-A6 for measured hydrographs at location B; Fig. A7-A8 simulated flow series are compared among each other for two different locations A and B). This is, indeed, contrary to what had been expected (and reported elsewhere). Numerous previous studies underline the relevance of an adequate temporal resolution for urban hydrology applications (typically ≤ 5 min and in accordance with average response time of the catchment) but the expected deviations for different rainfall inputs could not be observed in the present case.

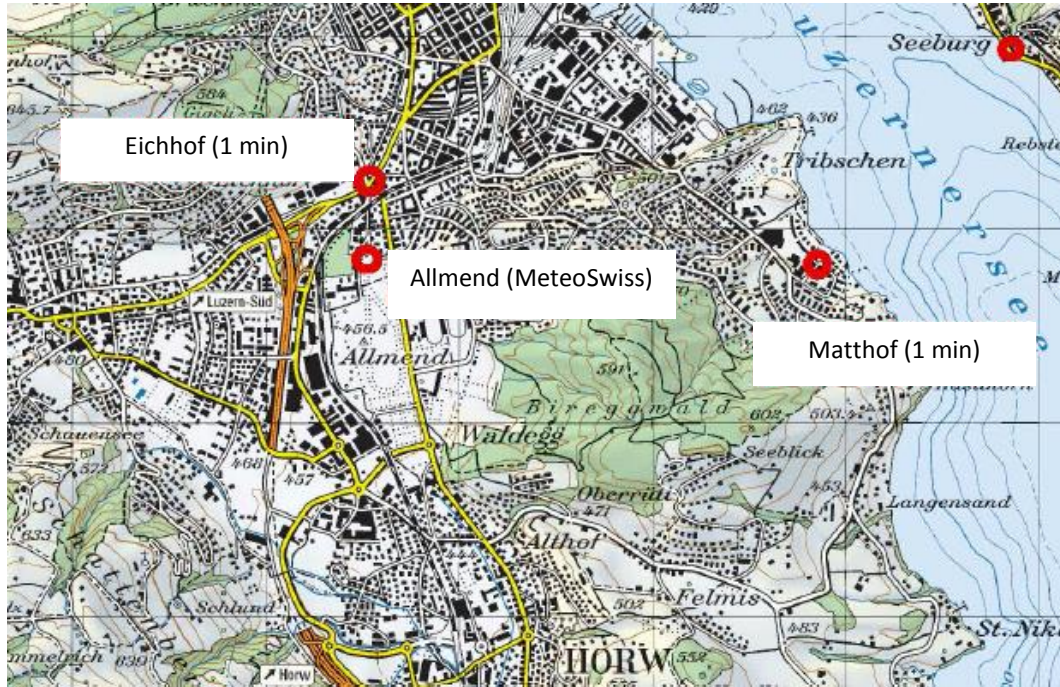


Figure A1: Locations of different rain—gauges used in this analysis

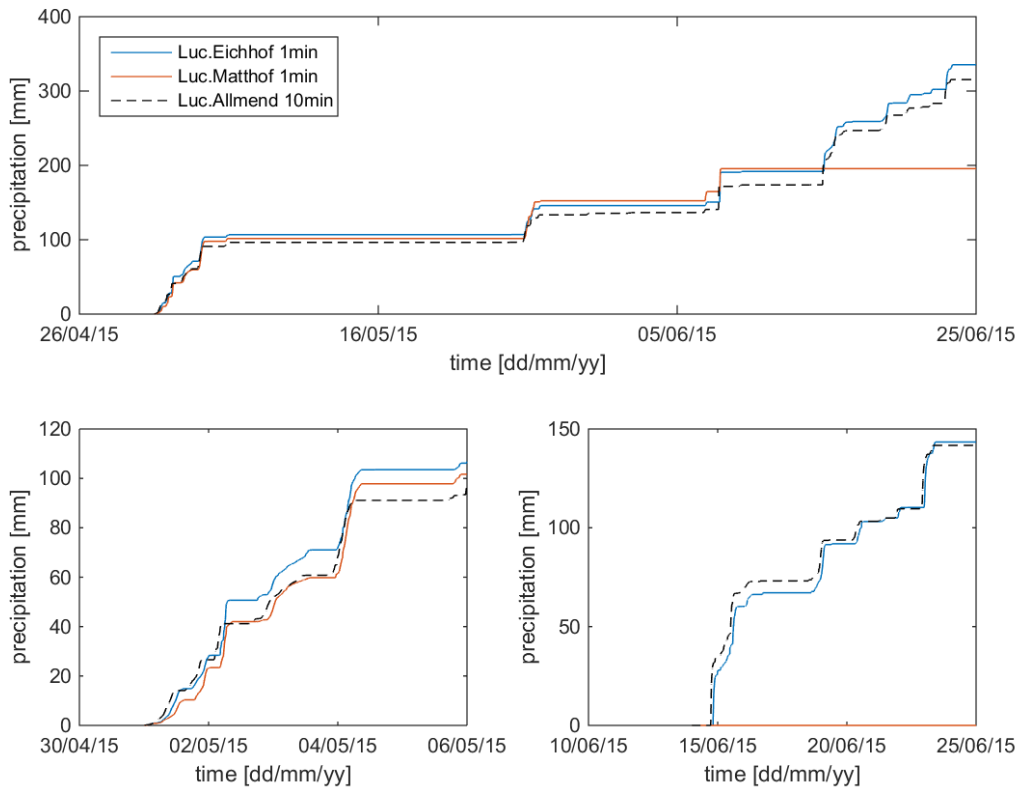


Figure A2: cross-comparison between 1 min (Eichhof, Matthof) and 10 min (Allmend – MeteoSwiss station) rainfall data. Upper chart shows full period for which 1 min data are available. Lower charts show events A and B.

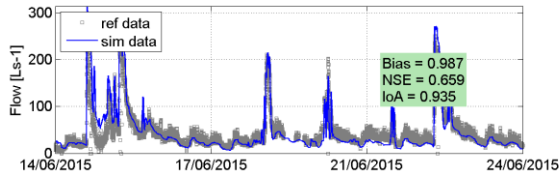


Figure A3: simulated vs. observed hydrographs at location B for a selected period at which rainfall data from different gauges were available. Here rain input is taken from MeteoSwiss rain-gauge ‘Allmend’ (10 min).

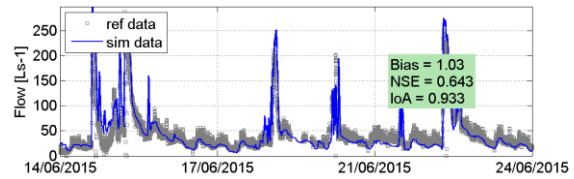


Figure A4: simulated vs. observed hydrographs at location B for a selected period at which rainfall data from different gauges were available. Here rain input is taken from rain gauge ‘Eichhof’ (1 min).

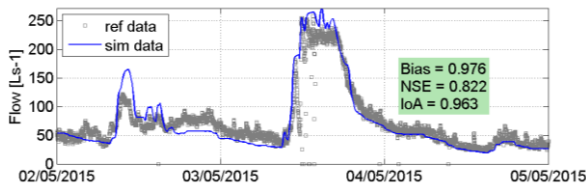


Figure A5: simulated vs. observed hydrographs at location B for a selected period at which rainfall data from different gauges were available. Here rain input is taken from MeteoSwiss rain-gauge ‘Allmend’ (10 min).

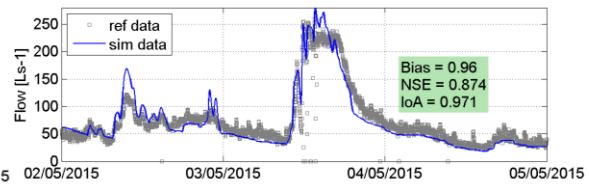


Figure A6: simulated vs. observed hydrographs at location B for a selected period at which rainfall data from different gauges were available. Here rain input is taken from rain gauge ‘Eichhof’ (1 min).

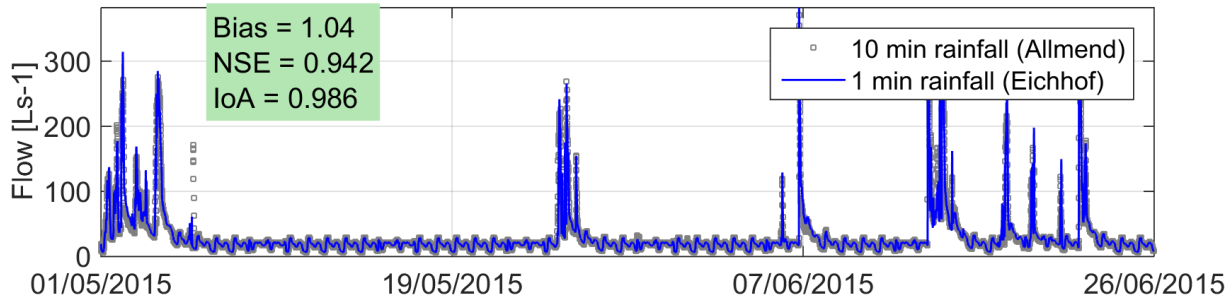


Figure A7: cross-comparison of two *simulated* hydrographs at location B. Simulations are driven by rainfall data from different sources and with a different temporal resolution (Allmend - MeteoSwiss: 10 min; Eichhof: 1 min).

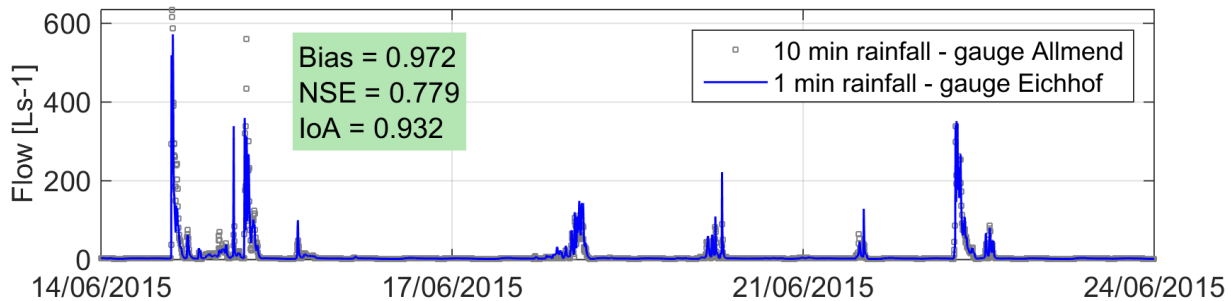


Figure A8: cross-comparison of pipe flow at the inner catchment node, i.e. location A. Simulations are driven by rainfall data from different sources and with a different temporal resolution (10 min: Allmend - MeteoSwiss; 1 min: Eichhof). Deviations is more obvious than for constraint flow at the catchment outlet (location B – see Figure A7).

Limitations

Additionally acquired 1 min rainfall data must be considered with care for two reasons: (i) little information is available on monitoring devices, i.e. measurement principle, mode of operation and maintenance intervals; and (ii) despite the fact we received the data from a trustworthy source (retired urban drainage engineer who maintains rain—gauges voluntarily), we were not able to fully verify this data. Measurement accuracy remains difficult to assess. We compared the daily sum of the two gauges with the data from the MeteoSwiss station '*Allmend*' with very little deviation, but doubts remain regarding the reliability of the 1 min records, particularly for the sub-10 min scale.

To Conclude

Analyses explained above lead to the conclusion that the 10 min rainfall data from the MeteoSwiss station '*Allmend*' used for the analysis in the paper can be considered as representative, despite the fact that flow time in the catchment is in the same order of magnitude as temporal resolution of rainfall data used.

The comparison of simulations run with different rainfall input shows a high degree of agreement despite the temporal resolution of rainfall input data differs by factor 10 (10 min – 1 min). Flow dynamics at location B (location at which flow reference data had been available) are sufficiently well reproduced by either of the rainfall inputs.

However, final doubts remain regarding the measurement accuracy of rainfall records from the 'Eichhof' station on sub-10min scale. This is the reason why we prefer not to include this additional data source in the original manuscript, nor in the supplementary material.

Partitioning the impacts of spatial and climatological rainfall variability in urban drainage modelling

Nadav Peleg¹, Frank Blumensaat^{2,3}, Peter Molnar¹, Simone Fatichi¹, and Paolo Burlando¹

¹ETH Zurich, Institute of Environmental Engineering, Hydrology and Water Resources Management, Zurich, Switzerland

²Swiss Federal Institute of Aquatic Science and Technology, Eawag, Dübendorf, Switzerland

³ETH Zurich, Institute of Environmental Engineering, Urban Water Systems, Zurich, Switzerland

Correspondence to: Nadav Peleg (nadav.peleg@sccer-soe.ethz.ch)

Abstract. The performance of urban drainage systems is typically examined using hydrological and hydrodynamic models where rainfall input is uniformly distributed, i.e. derived from ~~one single or a single or from~~ very few rain-gauges. When models are fed with a single uniformly distributed rainfall realization, the response of the urban drainage system to the spatio-temporal variability of rainfall rainfall variability remains unexplored. ~~High-resolution stochastic rainfall generators allow studying the response and sensitivity of urban drainage networks to these spatial and temporal rainfall variabilities. The goal in~~ The goal of this study was to understand how climate variability and spatial rainfall variability, jointly or individually considered, affect the response of a calibrated hydrodynamic urban drainage model. A stochastic ~~high-resolution spatially distributed~~ rainfall generator (STREAP) was used to simulate many realizations of rainfall for a ~~period of 30 years~~ 30-year period, accounting for both climate variability and spatial rainfall variability. The generated rainfall ~~was then ensemble~~ was used as input into a calibrated hydrodynamic model (EPA SWMM) for simulating surface runoff and channel flow in a small urban catchment in the city of Lucerne, Switzerland. The variability of peak flows in response to rainfall of different return periods was evaluated at three different locations in the urban drainage network and partitioned among its sources. ~~We found that the~~ The main contribution to the total flow variability was found to originate from the natural climate variability (on average over 74%). In addition, the ~~contribution of~~ relative contribution of the spatial rainfall variability to the total flow variability was found to increase with longer return periods. This suggests that while the use of spatially distributed rainfall data can supply valuable information for sewer network design (typically based on rainfall with return periods from 5 to 15 years), there is a more pronounced relevance when conducting flood risk assessments for larger return periods. The results ~~clearly~~ show the importance of using ~~stochastic rainfall generators~~ multiple distributed rainfall realizations in urban hydrology studies to ~~not only~~ capture the total flow variability in the response of the urban drainage systems to heavy rainfall ~~but also to identify the origin of this~~ variability events.

1 Introduction

Urban drainage systems are designed to ensure safe wastewater disposal (focus: dry weather) and adequate storm water handling (focus: wet weather). Whereas the variability of dry weather flows is rather low and well predictable, rain-induced flow dynamics scale over several orders of magnitude and require stochastic analysis due to the high variability of rainfall rainfall

variability. The latter is often addressed by summarizing the rainfall input in the form of Intensity–Duration–Frequency (IDF) curves (e.g. Guo, 2006; Yazdanfar and Sharma, 2015), which are essentially relating maxima of rainfall intensity for a given duration to their return period (Koutsoyiannis et al., 1998). For urban drainage system design, engineers choose return periods for which they expect the urban drainage system to perform with a certain reliability (e.g. an acceptable number of failures
5 such as overflows or flooding in a given return interval).

A common practice to evaluate the performance of urban drainage systems for different forcing situations is by using a model with a hydrological component to simulate the ~~transformation of rainfall into~~ runoff at the urban catchment scale, and a hydrodynamic component to simulate the flow in the drainage system itself. Rainfall is defined as the most important input required by these models (Vaes et al., 2001). It is recommended to use ~~high-resolution~~ high-resolution rainfall data in space
10 and time as an input because of the short concentration time of urban drainage systems, and because it reduces flow prediction uncertainty. The required spatial and temporal resolution depends on the size of the urban catchment, characteristics of the drainage system, and local climate. A general recommendation is to use rainfall data in a resolution similar to (or higher than) that produced by a typical X–band weather radar system, i.e. minutes in time and sub-kilometer in space (see discussion by Berne et al., 2004; Bruni et al., 2015; Ochoa-Rodriguez et al., 2015; Wright et al., 2014b).

15 Rainfall input may be given by observations of rain–gauges and weather radar; however this constrains the analysis to storms observed in a limited time period. ~~Stochastic~~ On the other hand, stochastic modeling of space-time rainfall fields ~~on the other hand~~ allows a full exploration of the potential impacts of space-time variability in rainfall on the urban drainage system. The *spatial rainfall variability* is defined as the variability derived from having multiple (stochastic) ~~spatial-rainfall distributions~~ spatially distributed rainfall fields for a given rainfall point in time. The temporal component, here referred to as
20 *climate variability*, is defined as the variability derived from having multiple (natural) climate trajectories generating different distribution of storms and rainfall intensities in time. It is also known as "internal variability" or "stochastic climate variability" (Deser et al., 2012; Fatichi et al., 2016; Hawkins and Sutton, 2009). The consideration is that observed rainfall represents only one trajectory of a given climate and producing stochastic rainfall based on observed rainfall statistics results in many realizations, each one equally probable (see for example Peleg et al., 2015).

25 The use of stochastic rainfall generators that account for ~~both spatial-rainfall distribution and temporal climatic~~ spatial rainfall variability and/or climate variability in urban hydrology applications is still rather new. Wright et al. (2014a) used stochastic storm transposition to synthesize long records of rainfall based on radar rainfall fields over the metropolitan area of Charlotte, North Carolina (USA), in order to estimate the discharge return periods for points inside the urban catchment. McRobie et al. (2013) extended the earlier Willems method (Willems, 2001) to generate spatially distributed Gaussian rainfall cells based
30 on weather radar data for the Counters Creek catchment sewerage system in London (UK). Simoes et al. (2015) produced stochastic urban pluvial flood hazard maps for the Cranbrook urban catchment (UK) using the McRobie et al. (2013) rainfall generator. Gires et al. (e.g., 2012, 2013) used a multifractal model to generate space-time rainfall fields for the same storm but with different spatial structures, to study their effect on the simulated flow in conduits in the Cranbrook catchment. The most recent stochastic rainfall generators that are able to produce rainfall fields in a high spatial and temporal resolution and may

be useful for urban applications are STREAP (Paschalis et al., 2013, 2014), HiReS-WG (Peleg and Morin, 2014) and STEPS (Foresti et al., 2016; Niemi et al., 2016).

The main objective of this paper is to investigate the relative contribution of the spatial versus climatic rainfall variability for flow peaks at different locations in the drainage network and for different return periods. We apply a new and advanced stochastic rainfall generator to simulate rainfall inputs for a small urban catchment in Lucerne (Switzerland) and simulate flow dynamics in the sewer system. ~~The stochastic rainfall generator is used to simulate multiple 30-year realizations of rainfall over the catchment, accounting for both climate variability and spatial rainfall variability.~~ This work demonstrates the potential of ~~high-resolution~~ using stochastic rainfall generators for urban applications and the benefits gained compared to other methods, such as bootstrapping rainfall events from a long rainfall series.

10 2 Case Study

The case study is an urban catchment located near the city center of Lucerne, Switzerland (Fig. 1). The catchment in total covers 77.0 *ha*, whereas 30.2 *ha* are connected to the combined sewer network: 11.5 *ha* of total area (5.3 *ha* impervious area) are connected to location A and 30.2 *ha* (13.6 *ha*) are connected to locations B and C. The catchment drains towards Lake Lucerne, with higher gradients at the upper part and moderate to low gradients in the lower part. The drainage system consists of separate and combined sewers (storm water and foul sewage share one pipe infrastructure) with a total network length of 11.2 *km*; hereinafter only combined sewers are considered. Both storm water and wastewater flows are solely driven by gravity. An overflow structure is built in the lower part of the catchment to alleviate network capacity excess during heavy rainfall (CSO location in Fig. 1). In this case, the carry-on flow towards the sewage treatment plant is hydraulically constrained (location B in Fig. 1), and excess water is spilled via a side-flow weir followed by a small retention tank (approximate 100 *m*³) into Lake Lucerne (location C in Fig. 1).

The flow rate at the outlet of the combined sewer system (location B) ~~is~~ was monitored for a period of 12 months from July 2014 to June 2015. In order to reduce measurement uncertainty, the water level and flow velocity was recorded using two different combi-sensors with different monitoring techniques (in-situ Doppler-ultrasound technique, ex-situ ultrasound-radar technique) in parallel. The recording interval was set to 1 *min* and 15 *min* for the Doppler-ultrasound sensor and the ultrasound-radar sensor, respectively.

3 Methods and Data

A stochastic ~~high-resolution~~ space-time rainfall generator was used to simulate multiple realizations of 2-D rain fields for ~~30 years~~ a 30-year period. The rainfall was generated for four distinct cases which were defined in order to explicitly account for the climate variability, spatial rainfall variability and total variability of the flow. The generated rainfall was used as an input into a hydrodynamic model. For each of the four cases, IDF curves were computed for the annual maxima of the mean areal rainfall and Flow–Duration–Frequency (FDF) curves were computed for annual flow maxima simulated at three different

network elements, representing different aspects in the assessing of the performance of urban drainage systems. The total flow variability was partitioned into the part originating from climate variability and the additional contribution due to spatial rainfall variability. The methods are illustrated in Fig. 2.

3.1 Rainfall Data

5 Rainfall data originate from two sources: a rain-gauge located about 2 km west to the ~~test-case study~~ catchment (Fig. 1) and a C-band weather radar composite. Both devices are operated by MeteoSwiss, the Swiss Federal Office of Meteorology and Climatology.

The tipping bucket rain-gauge records rainfall in 10 min intervals with a precision of 0.1 mm. A ~~34-year~~ 34-year record was used in this study, covering the period 1981–2014. High-resolution 10 min ~~min data~~ rainfall intensities were benchmarked
10 with hourly rainfall data (validated record provided by MeteoSwiss) and obvious deviations were corrected. The length of the observed record allows an adequate estimation of the statistical rainfall characteristics, especially regarding high rainfall intensities of short durations and with return periods up to 30 years. Climatological stationarity has been assumed for the observed record.

~~The high-resolution~~ High-resolution radar rainfall data (2 km and 5 min) for ~~the 8-year period~~ an 8-year period (2003–
15 2010~~are-~~) were derived from a third-generation weather radar system of MeteoSwiss (Gabella et al., 2005; Germann et al., 2006). Radar grid cells were examined for substantial ground clutter or beam blockage and errors were excluded. This data was only used for the study of the rainfall structure over the catchment and not for the calculation of IDF curves, as the accuracy of rainfall intensity recorded by the weather radar (binned data) is not sufficient to address extremes. Extreme rainfall intensity for a 1 km spatial resolution can be analyzed in Switzerland (e.g. Panziera et al., 2016) using the fourth-generation weather
20 radar system (Germann et al., 2015) or the gridded CombiPrecip products (Sideris et al., 2014). However, a longer period of ~~high-resolution~~ high-resolution rainfall from the latter mentioned products would be required in order to properly account for the climate variability discussed in this study.

3.2 Stochastic Rainfall Generator

Rainfall fields in a high spatial and temporal resolution were generated using the STREAP model (**S**pace-**T**ime **R**ealizations
25 of **A**real **P**recipitation). STREAP was presented by Paschalis et al. (2013) and used to generate rainfall over a large rural catchment for flood investigations (Paschalis et al., 2014) and to analyze the variability of extreme rainfall intensity over radar-pixel scales (Peleg et al., 2016). It is composed of three hierarchical modules describing: (i) the storm arrival process; (ii) temporal evolution of the mean areal intensity and fraction of wet area during a storm; and (iii) evolution of the space-time structure of rainfall during a storm.

30 For this analysis, rainfall was generated with a spatial resolution of 100 m x 100 m for a domain size of 1.5 km x 1.5 km (see mesh-grid in Fig. 1) and a temporal resolution of 10 min. For urban drainage applications 10 min can be considered a rather coarse temporal discretization, however we searched consistency with the observed rainfall record which is only available in 10

min resolution. The spatial resolution was chosen to roughly match the discretization required for the urban sub-catchments, i.e. about two sub-catchments per *ha* resulting in 158 individual sub-catchments within 77 *ha*.

3.2.1 STREAP Calibration

The calibration process of STREAP using weather radar products was discussed in detail by Paschalis et al. (2013). Some modifications were made to tailor STREAP to the specific case study presented here. Due to the short period of the weather radar records (8 years), the storm arrival process (first module) was calibrated using the rain-gauge data (34 years). That allowed a better representation of the statistics of storm probability of occurrence and duration.

Changes were also applied to the second module. Originally, mean areal intensity and fraction of wet area during a storm are simulated as a bi-variate auto-correlated stochastic processes that also depend on storm duration. Here, due to the small extent of the spatial domain, the wet area ratio was assumed to be equal to zero during intra-storm periods and assumed to be equal to one during storms, i.e. during storms all grid cells over the catchment are experiencing rainfall. The mean areal intensity is simulated using an AR(1) model which simulates a normalized quantile time series that is later inverted using a mixed-exponential function (Furrer and Katz, 2008; Smith and Schreiber, 1974), which parameters are computed using rain-gauge data.

No modifications were needed for the last module. However, some model parameters (e.g. rainfall coefficient of variation) could not be directly estimated from the weather radar data as the spatial resolution of the radar product (2 *km*) is too coarse compared to the model resolution (100 *m*). Therefore the required parameters were first estimated using the weather radar data for a coarse spatial resolution and then downscaled to higher resolution using power law functions (Fig. S1 in the supplementary material) as described in Peleg et al. (2016). In addition, no direct measurements are available to estimate the small-scale rainfall spatial correlation structure for this region. The spatial structure was estimated using data from three dense rain-gauge networks (Moszkowicz, 2000; Müller and Haberlandt, 2016; Peleg et al., 2013), recording rainfall over small spatial distances (i.e. in the scale of 10^1 – 10^2 *m*) and temporal scales (i.e. 5–10 *min*). The data is presented in Fig. S2.

3.2.2 STREAP Evaluation

The evaluation of STREAP, its ability to reproduce the rainfall intensity over the domain (with emphasis on the high rainfall intensity), and its performance with regard to the natural climate variability of the annual maxima in rainfall intensity, are discussed below.

The ability of STREAP to reproduce the rainfall intensity over the domain is shown using the inverse cumulative distribution function for the 10 *min* mean areal rainfall intensity (Fig. 3). Up to the 0.95 quantile, STREAP consistently underestimates the rainfall intensity, but this underestimation is minor (maximum difference 0.052 *mm h*⁻¹) and is not expected to bias the flow in the catchment. When we focus on the 0.95–1 quantile range which reflects the heavy rainfall intensity, and especially on the upper 0.99–1 quantile range, which represent the extremes, STREAP performs very well, with small differences between simulated and observed values (maximum difference 1.177 *mm h*⁻¹). The maximum difference and the maximum error calculated for the 0.9995–1 quantile range, which covers entirely annual maxima rainfall intensities that were observed, are

as low as 1.072 mm h^{-1} and 1.54 % (respectively). An example of STREAP ability to simulate spatially distributed annual maxima rainfall intensity over the catchment is given in Fig. 4. The ability of STREAP to reproduce the natural climate variability in relation to the annual maxima rainfall intensity is discussed and presented in the Supplementary Material (Fig. S3).

5 3.3 Rainfall Cases Classification

Four rainfall cases were defined in order to account for climate variability and spatial rainfall variability and to allow the investigation of their effect on the urban drainage:

- Case 1: Consists of one time series of rainfall derived from the Lucerne rain-gauge (observed data, 34 years long). For this case, rainfall was not spatially distributed using STREAP but was uniformly distributed, i.e. same rainfall intensity was assigned to all sub-catchments for a given time step. In this case the rain-gauge time series represents also the mean areal rainfall over the catchment. This is a common and critical assumption in hydrological studies, where point rainfall is used to represent areal rainfall (Rodriguez-Iturbe and Mejia, 1974; Peleg et al., 2016; Sivapalan and Blöschl, 1998; Svensson and Jones, 2010).
- Case 2: consists of 30 realizations of the same time series (rain-gauge observations) that was used in case 1, but spatially distributed using STREAP. Cases 1 and 2 differ in the spatial configuration of the rainfall (uniformly distributed vs. spatially distributed) which will later allow to explicitly analyze how the spatial rainfall variability affects the flow.
- Case 3: consists of 30 realizations of 30 years generated by STREAP. For this case, STREAP was set to generate only the mean areal rainfall and to uniformly distribute it over the sub-catchments (similar to case 1). Comparing the urban drainage response to the rainfall given from cases 1 and 3 will allow us to account for the climate variability component directly, as case 3 represents 30 alternative and equiprobable trajectories of the rainfall series given in case 1.
- Case 4: consists of 900 realizations accounting for both the spatial rainfall variability and the climate variability. Each of the 30 realizations generated for case 3 were re-generated 30 times using STREAP. The forcing has a different spatial distribution of the rainfall over the sub-catchments for each re-generation. This allows computing urban drainage dynamics subjected to the total variability.

25 3.4 Hydrodynamic Model

Flow simulations were conducted using USEPA's Storm Water Management Model (EPA SWMM), a dynamic 1-D model coupling rainfall-runoff processes with hydrodynamic channel flow (Rossman, 2010). EPA SWMM was chosen as it represents a standard open-source application in urban drainage modeling (e.g. Hsu et al., 2000; Liong et al., 1995; Meierdiercks et al., 2010).

30 EPA SWMM is composed of two modules: the surface runoff (hydrological) and the in-sewer flow (hydraulic) model. The hydrological model calculates the direct runoff under consideration of initial precipitation losses (i.e. evaporation and wetting

losses) and soil infiltration (here using the Horton method). The resulting surface runoff is then used as input for the hydraulic model to simulate the pipe flow using the 1-D Saint-Venant equations. The diffusive wave approximation and a routing step of 10 s was applied for all simulations. Surface flooding is accounted for by allowing excess water to leave a manhole in case sewer capacity is exceeded. Due to the lack of detailed land use and surface topography data at meter scale it was found
5 inadequate to further define a manhole-specific "ponding area" allowing the water to spread at the surface around a manhole. Hence excess water leaving the manhole is routed into a virtual sink and does not re-enter the system even though sewer capacity is available again.

The sewer model application is based on infrastructure data from the municipality's cadaster database. The model has carefully been calibrated and validated (split-sample approach) using the above mentioned one-year flow data record. Flow
10 dynamics can be adequately reproduced throughout the year despite the rather coarse 10 min rainfall input data resolution. More details on the catchment, particularly on the urban land use characteristics, the monitoring set-up, model calibration procedure are given in Tokarczyk et al. (2015). The runoff-generating surfaces are distributed over the entire catchment. This is represented by 158 individual sub-catchment entities with an area ranging between 0.02 and 0.84 ha. The rainfall fields generated by STREAP were intersected with the sub-catchment areas and rainfall intensity was assigned for each sub-catchment
15 based on the weighted sum of the intersect area (cf. Gires et al., 2012). EPA SWMM was set-up for a continuous long-term simulation of 30 and 34 years, respectively, depending on the examined rainfall case. Unlike for the design-storm approach or the isolated analysis of single storm events as researched in many previous studies, antecedent hydrological conditions in the catchment and the drainage network are implicitly taken into account to fully address potential climatological changes also regarding dry spells.

20 3.5 Computation of IDF and FDF Curves

The Generalized Extreme Value (GEV) distribution (Jenkinson, 1955) is commonly used in hydrological studies to model extreme rainfall intensity (e.g. Koutsoyiannis and Baloutsos, 2000; Marra and Morin, 2015) (e.g. Koutsoyiannis and Baloutsos, 2000; Marra
flows (e.g Zaidman et al., 2003) since it covers the Gumbel, Fréchet and Weibull distributions (Katz et al., 2005). IDF and FDF curves were calculated by fitting a GEV distribution to the series of annual maxima of the mean areal rainfall intensity and the
25 conduit flow time series (respectively). The fitting of the parametric distribution is a required step for the partition analysis to be conducted (see next section) as it results in a continuous estimates of the curves quantiles (i.e. the return period).

IDF curves were calculated for two datasets: observed data derived from the Lucerne rain-gauge and simulated data that were generated using STREAP. For the observed dataset, one IDF curve was computed for the 34 years of records. For the simulated dataset, 30 IDF curves were calculated for the 30 stochastic realizations (of 30 years each). The curves were calculated for a
30 10 min duration.

FDF curves were calculated for the simulated flow at three locations which were chosen according to their function within the drainage network (see Fig. 1): (i) about 200 m upstream of the combined sewer overflows (CSO) structure in a sewer section that was previously identified as prone to pipe surcharge (location A - inner network node); (ii) about 200 m downstream of the CSO structure (location B – carry-on flow to sewage treatment works); and (iii) at the CSO outlet to lake (location C -

overflow). The number of derived FDF curves follow the rainfall cases as described in Section 3.3, i.e. 1 for the first case (34 years), 30 for the second and third cases (30 years each) and 900 for the fourth case (30 years each). FDF curves were calculated for a 5 min duration.

Note that no condition was imposed on the time concurrency of annual maxima of mean areal rainfall intensity and conduit flow, i.e. annual peak flow can precede, overlap or follow the annual maxima of mean areal rainfall intensity.

3.6 Variability Partitioning

The partition method used in this study follows the guidelines suggested by Fatichi et al. (2016). We assume that there are interactions between the two sources of variability, i.e. they cannot be treated independently, as the spatial pattern of the rainfall annual maxima is dependent on the extreme rainfall intensity that is driven by a given climate trajectory. [An illustrative example for the partition method described in the following is given in Fig. 5.](#)

The climate variability, CLM , is defined as the 5–95 quantile range of the flow that is calculated using the 30 spatial uniform climate realizations simulated for case 3 (i.e. the outcome is one flow range for a given return period). For each of the 30 climate realizations, the spatial rainfall-flow variability, SPT , is defined as the 5–95 quantile difference of the flow calculated using the spatially variable rainfall simulated for case 4. The outcome is 30 different flow ranges, $SPT_{RP}^1, SPT_{RP}^2, \dots, SPT_{RP}^{30}$, one for each climate trajectory and for a given return period, RP . The 5–95 quantile range was used because of the different sample sizes between case 3 (30 realizations) and case 4 (900 realizations). The ratio between the climate variability, CLM and the total variability, TOT , for each return period, RP , can then be estimated as:

$$\varphi_{CLM,RP} = \frac{CLM_{RP}}{TOT_{RP}} \quad (1)$$

where the total variability for a given return period is the difference between the maximum and minimum spatial variability simulated per return period from all climate trajectories:

$$TOT_{RP} = \max SPT_{RP} - \min SPT_{RP} \quad (2)$$

The total variability for a given return period, TOT_{RP} , will be always smaller than the sum of the flow variability from case 4, because there is a dependency between the two sources of uncertainty. Note that $1 - \varphi_{CLM,RP}$ is representing the unique contribution of spatial variability to the total variability for a given return period, however the total spatial variability, $\frac{\sum_{i=1}^N SPT_{RP}^i}{N}$, is larger or equal to $1 - \varphi_{CLM,RP}$ (see Fatichi et al., 2016). ~~An illustrative example for the partition method is given in Fig. 5.~~

4 Results and Discussion

In the following, we present computed IDF (rain) and FDF (flow) curves and discuss the contributions of individual rainfall variabilities to the modelled sewage flow variability at three different locations: A – inner network node (Fig. [S4 and S6](#) and [7](#) and

S4), B - carry-on flow (Fig. 6 and ??8), and C - combined sewer overflow (Fig. S5 and S79 and S5). The partitioning of the flow variability is presented for all three locations (Fig. 10).

The effect of spatial rainfall variability on the flow can be directly estimated by examining the flow variability from case 2 (Fig. 6c, S2e and S4c and S5c). The effect of spatial rainfall variability is derived from the analysis of flow extremes occurring in a continuous time series of 30 years. The variability in annual flow maxima is computed from the spread in simulations for a given return period. This variability is expressed ~~here in its simplest form,~~ as the difference between the highest and lowest flows simulated for the 30 realizations for a given return period. The effect of spatial rainfall variability on urban hydrology was researched in the past (e.g. Bruni et al., 2015; Gires et al., 2012; Simoes et al., 2015; Willems and Berlamont, 2002) leading to the conclusion that this variability should be taken into consideration when running urban hydrological models. Indeed, for return periods between 2 and 30 years, the peak flow variability was found to vary between 18.3 and 55.1 $l s^{-1}$ at location A (Fig. S4c) and between 91.2 and 179 $l s^{-1}$ at location C (Fig. S6eS5c). At location B, peak flow variability was found to be lower (between 2.9 and 6.2 $l s^{-1}$, Fig. 6c) due to the fact that flow is hydraulically constrained by the upstream located throttle pipe.

The effect of the climate variability over the catchment is calculated from the 30 rainfall realizations stochastically simulated for cases 3 and 4 (left panel in Fig. ??7-9). Similar to the flow variability, the climate variability is expressed as the difference between the highest and lowest mean areal rainfall found for a given return period. In agreement with Peleg et al. (2016), the climate variability was found to increase with longer return periods, from 11.8 $mm h^{-1}$ for the two year return period to 47.2 $mm h^{-1}$ for the 30 year return period.

The individual effect of the climate variability on the ~~flows in the catchment flow~~ is estimated from case 3 (Fig. ??b, S3b and S5b7b, 8b and 9b). For the return periods of 2 to 30 years, the flow variability at location C, resulting only from climate variability, was found to be in the range 278.9–420.3 $l s^{-1}$. For most of the return periods this variability more than doubles the flow variability resulting from the spatial rainfall variability. The results for location C suggest that the role of climate variability is considerably more important than the role of spatial rainfall variability. The flow variability for the return periods 2–30 years for locations A and B were found to be in the range of 33.3–48.5 and 7.3–11.6 $l s^{-1}$ (respectively). As for location C, the flow variability resulting from climate variability is higher than the flow variability resulting from the spatial rainfall variability. However, the relative differences in variability around the median peak flow, calculated for the 30 years return period, reveal that the differences between the individual variabilities are much less pronounced for locations A and B (1.7% to 3.2% and 0.8% to 2.1%, respectively) in comparison to location C (3.5% to 10.7%). These differences regarding the absolute flow variability are expected as location B is located downstream of a hydraulic constraint (throttle pipe at CSO structure), thus flow is eventually levelled out, while at location A runoff is drained directly from its contributing sub-catchment without any buffering but still constrained due to surface flooding, i.e. excess flows leave the manhole through the lid and do not contribute to the actual peak flow.

The total flow variability is calculated using the data of case 4 (Fig. ??e7c, 8c and 9c). As expected, the total flow variability (e.g. location B: case 4, Fig. 8c) is larger than the flow variability resulting from either the spatial rainfall variability (case 2, Fig. 6c) or from the climate variability alone (case 3, Fig. ??8b). The partitioning of the total flow variability into its components

is presented for all three locations in Fig. 10. Results indicate that climate variability is the dominant contributor of the total variability of flow in the catchment. This applies to peak flows analyzed at all three locations in the urban drainage system. The highest ratio between climate variability and total variability is for location B, 83% for 2.2 years return period, and decreases for longer return periods to 57% for the 30 years return period. This decreasing trend was found to be less prominent for locations A and C, but statistically significant for all three locations as supported by a trend analysis using the Mann-Kendall test (Kendall, 1975; Mann, 1945). For location A, the relative mean ratio between the climate and the total variability was found to be around 81%. For location C, climate variability accounts for 75% for the 2 to 10 year return periods, decreasing to 62% for the 30 year return period. Averaged over all three locations and all return periods the mean ratio between the climate variability and the total variability is 74%, leaving 26% contribution due to the addition of spatial variability. The results of the partitioning ~~suggests~~ suggest that using traditional methods to quantify variability in urban drainage, such as bootstrapping, will likely result in an underestimation of the variability (and uncertainty) as only the climate variability will be represented. This is especially important for return periods that are longer than 10 years. While the use of spatially distributed rainfall data can supply valuable information for sewer network design (based on rainfall with return periods from 5 to 15 years), it will become even more important when performing flood risk assessments of extreme events (larger return periods). A 30-year record was used in this study, which can be regarded as the minimum period for IDF/FDF analysis. Since uncertainties in climate statistics decrease with a longer observational record (e.g. Marra et al., 2016), the contribution of the additional spatial variability for larger return periods might be even greater than presented here. However, a longer period of observation is required to confirm this assertion.

The rainfall generator was used to simulate rainfall for the weather radar subpixel scale, i.e. in a finer spatial resolution than can be estimated using the MeteoSwiss radar. The rainfall data required for a complete validation of the rainfall generator for this resolution can be obtained from a dense rain-gauge network (for networks examples see Muthusamy et al., 2016; Peleg et al., 2013) but such a network is not available in the analyzed region. ~~Therefore some assumptions were made. Two of those assumptions~~ Four aspects are discussed in the light of missing information for the subpixel scale (i.e. rainfall downscaling process): (i) the rain fields are simulated following a lognormal distribution. We assume that the non-zero part of the subpixel spatial rainfall distribution follows the observed lognormal distribution that is recorded by the weather radar for this region (as in Paschalis et al., 2014; Peleg et al., 2016). A different spatial rainfall distribution will significantly ~~affects~~ affect the results of the extreme rainfall ~~distribution~~; (ii) we assume that occurrence and intensity statistics are equal for each of the grid cells, i.e. no spatial correlation is applied for the rainfall occurrence or intensity. ~~That means that orographic~~ This means that orography, distance from the lake ~~or~~, and urban micro-climate effects are not considered; (iii) we assume that the rainfall spatial correlation structure for this region follows the average structure obtained from estimates made in dense rain-gauge networks in Poland, Germany and Israel (Moszkowicz, 2000; Müller and Haberlandt, 2016; Peleg et al., 2013). The exact impact of the spatial correlation structure at the radar subpixel scale in urban drainage studies is yet to be determined; and (iv) we assume that the power-law used for the scaling of the rainfall coefficient of variation is continuous from the weather radar to its subpixel scale, and it is not affected by a scale-break. Overestimation of the rainfall coefficient of variation will affect the rainfall spatial variability and therefore impact the partitioning results.

No automatic calibration process exists for STREAP. The model requires not only high-resolution rainfall data but also an expert user for the calibration process, as modifications to the calibration procedure (e.g. scaling at higher spatial resolution) are needed in order to tailor STREAP to a given application.

The three locations analyzed in this study were deliberately chosen according to their functional hierarchy within the combined drainage system (i.e. inner network node, carry-on flow and overflow). By doing so, we can clearly differentiate the effect of spatial and climatological rainfall variability on elements depending on their function within the network. On the other hand, previous studies showed a tendency that conduits located upstream, not affected by hydraulically constraining structures, are more sensitive to rainfall spatial variability in comparison to conduits located downstream (e.g. Gires et al., 2012). While it would be interesting to further investigate flow variability due to different spatial rainfall characteristics (e.g. the rainfall spatial correlation) at various upstream locations (similar as location A), this type of analysis would require larger drainage networks in comparison to the one presented here. Future studies will benefit from examining several different urban drainage systems with rainfall input from different high-resolution products to test the robustness of the findings.

Rainfall records were obtained from a rain-gauge that is located about 2 km west of the case study catchment. It was chosen for three main reasons (i) its proximity to the catchment; (ii) it has a sufficiently long record (34-year) that is adequate for statistical climatology analysis; and (iii) records have been verified by MeteoSwiss ensuring sufficient consistency. In contrast to these advantages, the 10 min temporal resolution of the rain data requires critical consideration when simulating the dynamics of the flow response (e.g. Ochoa-Rodriguez et al., 2015), particularly as the average flow response in the investigated catchment is in the order of minutes. However, we achieve a reasonable hydraulic model performance when validating the model against flow observations at the catchment outlet (location B), considering peak flow, time-to-peak and flow balance (see Tokarczyk et al., 2015). Low flow volume errors ($\pm 5\%$) and Nash-Sutcliffe-Efficiencies of >0.8 for individual events, i.e. >0.7 for longer periods, support the fact that the flow dynamics are reproduced adequately. Remaining peak flow errors of up to 25% reflect existing deficiencies stemming from multiple sources, e.g. inadequate model structure, insufficient model calibration, measurement errors in flow reference data and model input data uncertainty. Considering that the same hydrodynamic model has been used for all the simulations, it is likely that the error due to model structure and calibration do not introduce a consistent bias to the variability partitioning. A complete investigation of the model hydrodynamic uncertainties will provide additional insights but it will be difficult to constrain with the current length of available flow data

The computational cost of running a rainfall generator combined with an urban drainage model may constrain the use of the proposed approach for practical applications. But given the advances in the availability of computing capacity, also for non-scientific institutions, such application will ~~becomes~~ become feasible in the near future. We have used a powerful 20 core desktop machine (Intel Xeon CPU E5-2687W) to run the 961 stochastic rainfall realizations with STREAP in approximately 4 days. We estimated that the time needed to run SWMM using the same stand-alone machine would have been about 4 months, which is impractically long duration, ~~especially considering the small size of the urban catchment~~. Therefore, we have used a high performance computing (HPC) cluster with hundreds of computing nodes allowing SWMM simulations in less than 48 hours.

5 Conclusions

Output from a stochastic rainfall generator was used as input into an urban drainage model to investigate the effect of spatial rainfall variability and climate variability on peak flows in an urban drainage system located in central Switzerland. We found that the climate variability is the main contributor (74 % on average) to the total flow variability, but that the relative contribution of the addition of spatial rainfall variability increases with return period. This implies that the use of spatially distributed rainfall data can supply valuable information for sewer network design (based on return periods of 5 to 15 years), but it will become even more relevant when assessing the risk of urban flooding as a consequence of intense rain events of larger return periods.

The analysis presented in this study ~~was conducted at~~ focused on three different locations in the urban drainage system which reflect different system functions. Deviations in flow quantities and dynamics were expected and are, in fact, observed within the catchment depending on the corresponding location (i.e. up- or downstream of the overflow structure, or the overflow itself). Despite this, in agreement for all three locations we found that the climate variability is the dominant contributor to the flow variability for all return periods.

We present a single case study, a relatively small, but typical urban catchment located in the foothills of the Swiss Alps. ~~However, we~~ We argue that the variability partitioning is likely to be similar for most small- to medium-sized urban catchments. That is to say, the climate variability will constitute the largest contribution to the overall flow variability also in other urban catchments, and spatial variability will gain more importance as longer return periods are being considered. Further investigations are needed to examine the contributions of the variability components in larger catchments (potentially more prone to spatial rainfall variability) with a more complex drainage network (potentially with more flow attenuation) :-

~~Regarding the added value in using high-resolution stochastic rainfall generators for urban drainage applications, we conclude that not addressing the spatial rainfall variability will result in a considerable underestimation of the uncertainty in catchment response, especially for longer return periods which are likely of main interest. Stochastic rainfall generators and for different climates.~~

Stochastic spatially distributed rainfall generator should become an integral part of the urban hydrologist toolbox, particularly when estimating hazards of urban flooding. However, these ~~methods-models~~ are still not commonly used by planning engineers for designing and evaluating urban drainage systems. We identify four main aspects that contribute to the reluctant acceptance ~~among practitioners~~ in the field of urban drainage:

- High-resolution rainfall data are required (from a weather radar system or from a dense rain-gauge network) as well as an expert user for the calibration process. Setting up an automatic calibration process is unrealistic option due to the spatio-temporal differences between weather radar systems and the need to tailor the rainfall generator to specific locations.
- The high computational cost of running a rainfall generator combined with an urban drainage model may be prohibitive for common applications. Today the resources required for an efficient computation (e.g. HPC cluster) are often not ~~(yet) available~~ in the private sector available.

- The struggle to overcome old engineering paradigms towards accepting variability ranges as useful information for design and performance assessment.
 - The difficulty of rainfall generators modelers to transparently convey the modeling chain, its results and uncertainties.
- 5 These aspects should be addressed in future applications of **high-resolution** stochastic rainfall generators in order to make them more accessible to the urban drainage community.

Acknowledgements. This project is partly funded by the Swiss Competence Center for Energy Research – Supply of Electricity. We are grateful to MeteoSwiss, the Swiss Federal Office of Meteorology and Climatology, and the city of Lucerne for providing us with precipitation and infrastructure data. We furthermore would like to thank the Engineering Consultants from HOLINGER AG, Bern for assisting us with
10 details on the hydraulic model and extracting operation data from the central data base. We thank the reviewers (Susana Ochoa-Rodriguez, Li-Pen Wang and an anonymous reviewer) and to Marie-Claire ten Veldhuis, the editor, for their contributions leading to a significantly increased quality of the paper.

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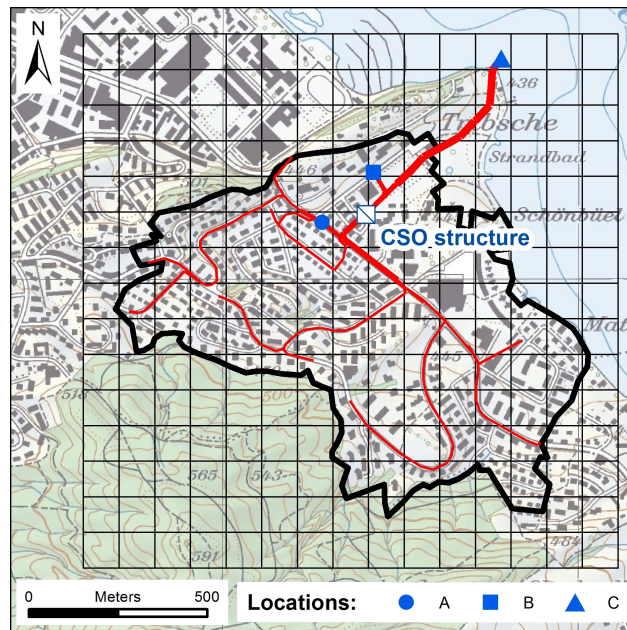


Figure 1. Location map of the case study catchment (bounded with black line). The black mesh represents the $1.5 \times 1.5 \text{ km}^2$ domain (grid cell resolution of $100 \times 100 \text{ m}^2$) for which stochastic rainfall was generated. The red lines represent the drainage system (thicker lines per pipe diameter) and the blue circle (inner network node), rectangle (carry-on flow) and triangle (combined sewer overflow) symbols represent the location for which the flow analysis was conducted. The combined sewer overflows (CSO structure, blue romb symbol) is located between locations A and B.

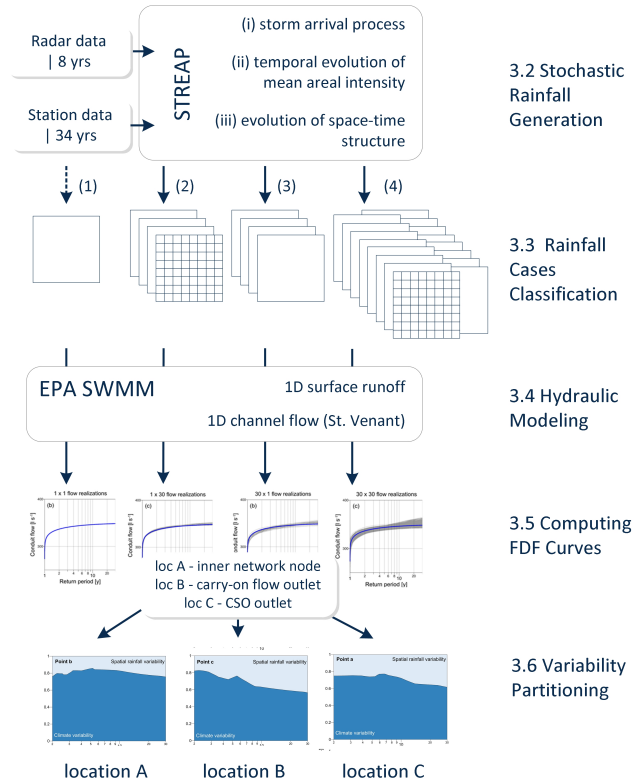


Figure 2. A schematic illustration of the methods used in this study: (i) STREAP model was used to simulate multiple realizations of 2-D rain fields based on radar and gauged data (Section 3.2); (ii) rainfall was generated for four distinct cases which were defined in order to explicitly account for the climate variability, spatial rainfall variability and total variability of the flow (3.3); (iii) EPA SWMM model was used to calculate the flow over the catchment (3.4); (iv) IDF and FDF curves were computed for the annual maxima of the mean areal rainfall and flow, respectively, at three different locations (3.5); and (v) the total flow variability was partitioned (3.6).

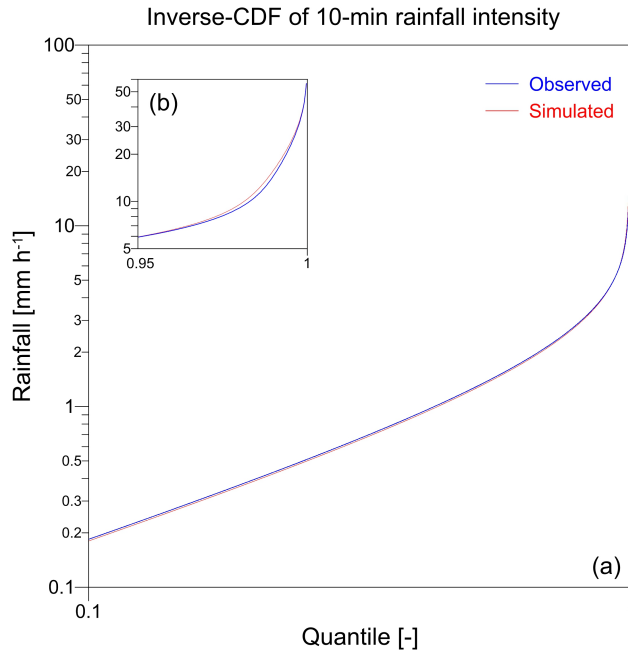


Figure 3. An inverse cumulative distribution function of the 10 *min* mean areal rain intensity over the catchment [The 0.1–1 quantile is presented in (a) and the 0.95–1 quantile range is zoomed in (b)]. Blue line represents 34 years of observed data (1981–2014) and red line represents the median of 30 realizations of 30 years. The simulated mean 5–95 quantile range of the rainfall intensity of the 30 realizations is also presented (shaded red).

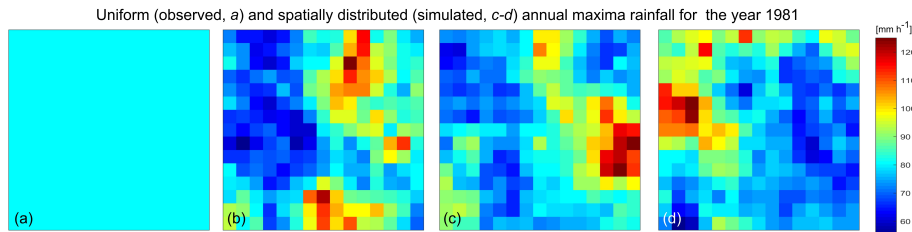


Figure 4. An example of STREAP ability to spatially distribute the annual maxima rainfall intensity over the catchment. The annual maxima recorded by Lucerne gauge for the year 1981 is 80.4 mm h^{-1} for duration of 10 *min*. Without STREAP, this value is assumed to be uniformly distributed over the domain (panel a). STREAP accounts for the spatial distribution of rainfall, thus while the areal average is preserved for each time step, some grid cells ($100 \times 100 \text{ m}^2$ resolution) will record higher rainfall intensity and some lower values. Example of the footprint of the annual maxima rainfall intensity for three random realizations of the year 1981 generated by STREAP are presented in panels b–d.

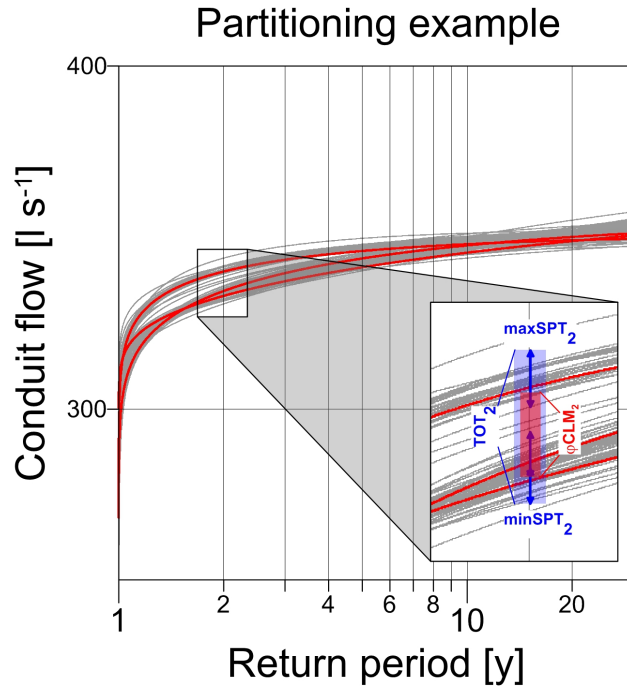


Figure 5. An example for the partition method (illustrative) for the 2 years return period (zoomed panel). 3 climate trajectories are plotted (red lines) for which the 5–95 quantile range is calculated ($\varphi_{CLM,2}$, red area). For each climate trajectory, 30 spatial realizations are plotted (grey lines). The 5–95 quantile range is then calculated for each of the 30 spatial realizations ($SPT_2^1, SPT_2^2, SPT_2^3$, plotted as blue arrows) and the total variability, TOT_2 (blue area), is defined by bounding the maximum and minimum flows defined by the spatial variability ($maxSPT_2$ and $minSPT_2$, respectively). The partition of the climate variability, $\varphi_{CLM,2}$, out of the total variability is then calculated as a simple ratio between the two.

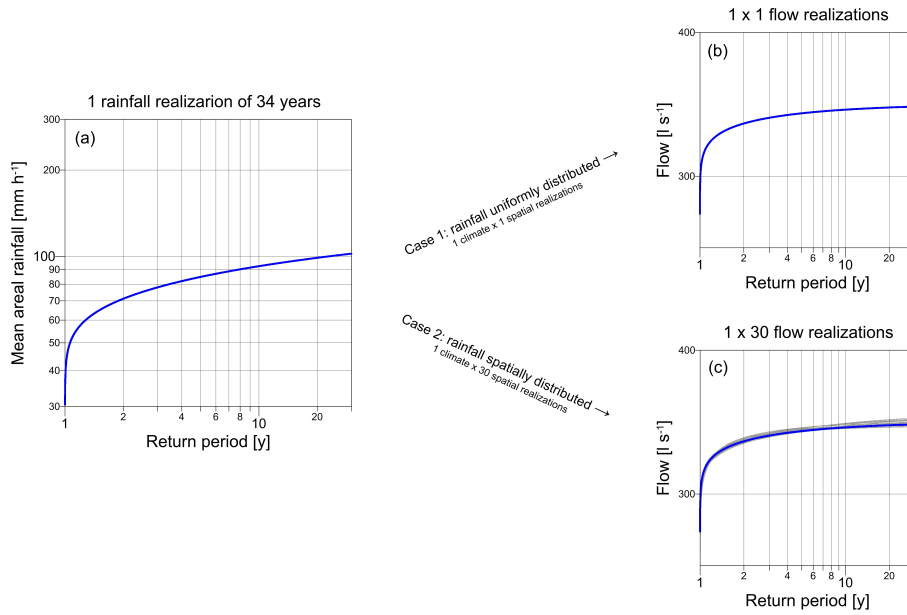


Figure 6. Rainfall and flow results for cases 1 and 2. In the left panel (a), the IDF curve computed for the mean areal rainfall over the catchment is presented. In the right panels, FDF curves for location B are presented [for uniformly distributed rainfall \(b\) and spatially distributed rainfall \(c\)](#). Blue line represents the IDF curve and the FDF curves computed from the observed uniformly distributed rainfall. Gray lines represent the FDF curves computed for the realizations with spatial rainfall variability.

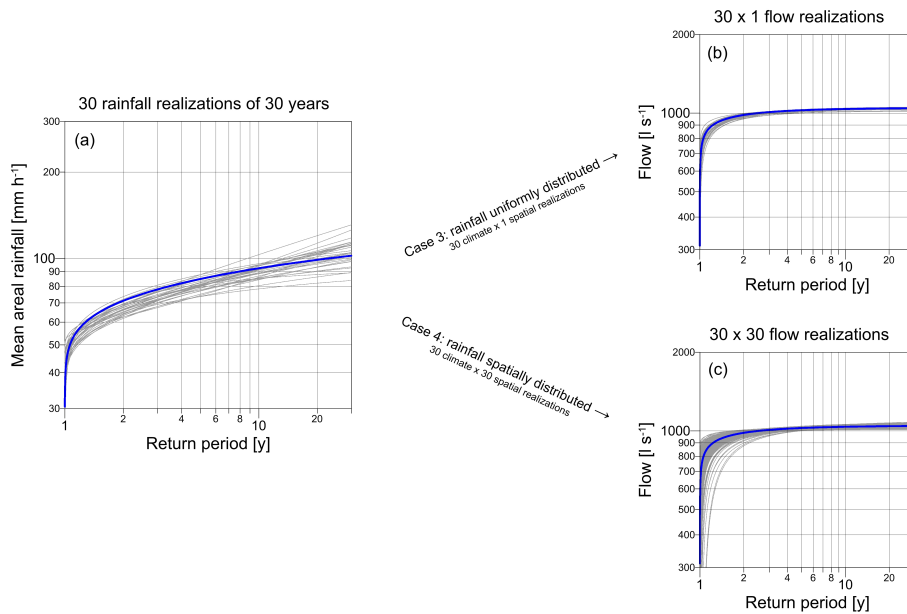


Figure 7. Same as Fig. 6, but for location A and cases 3 and 4.

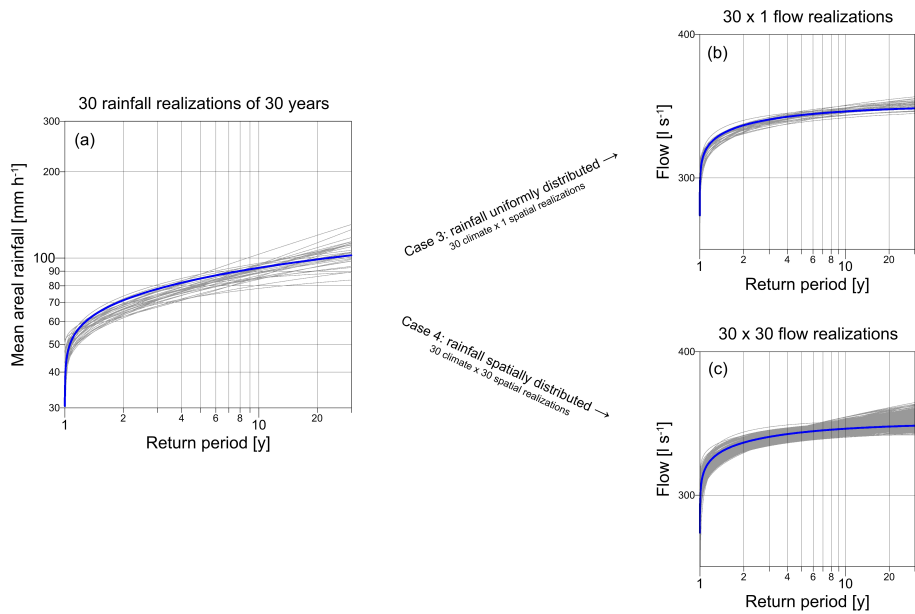


Figure 8. Same as Fig. 6, but for [location B](#) and cases 3 and 4.

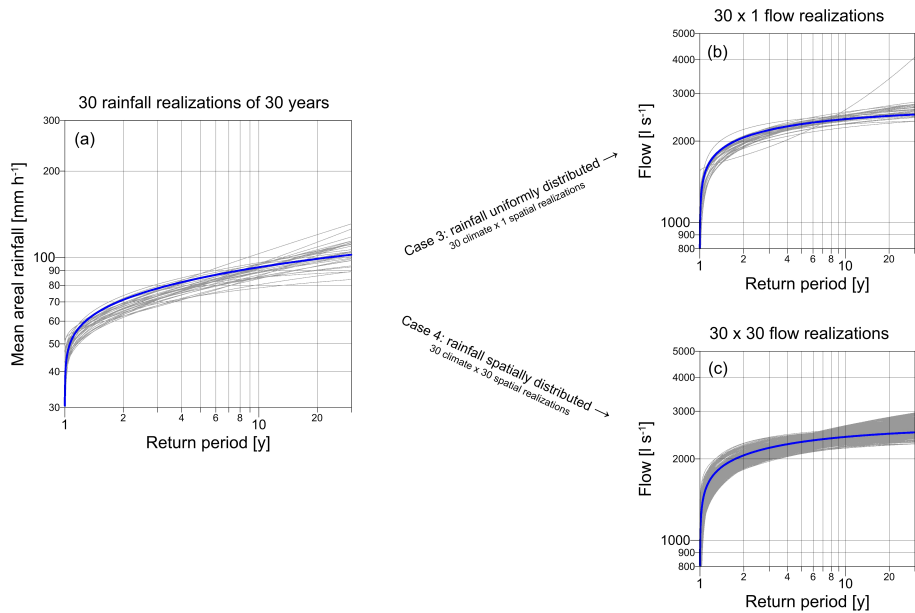


Figure 9. Same as Fig. 6, but for [location C](#) and cases 3 and 4. The poorly fitted GEV distribution for one realization presented in (b) was [excluded from the flow variability partitioning analysis](#).

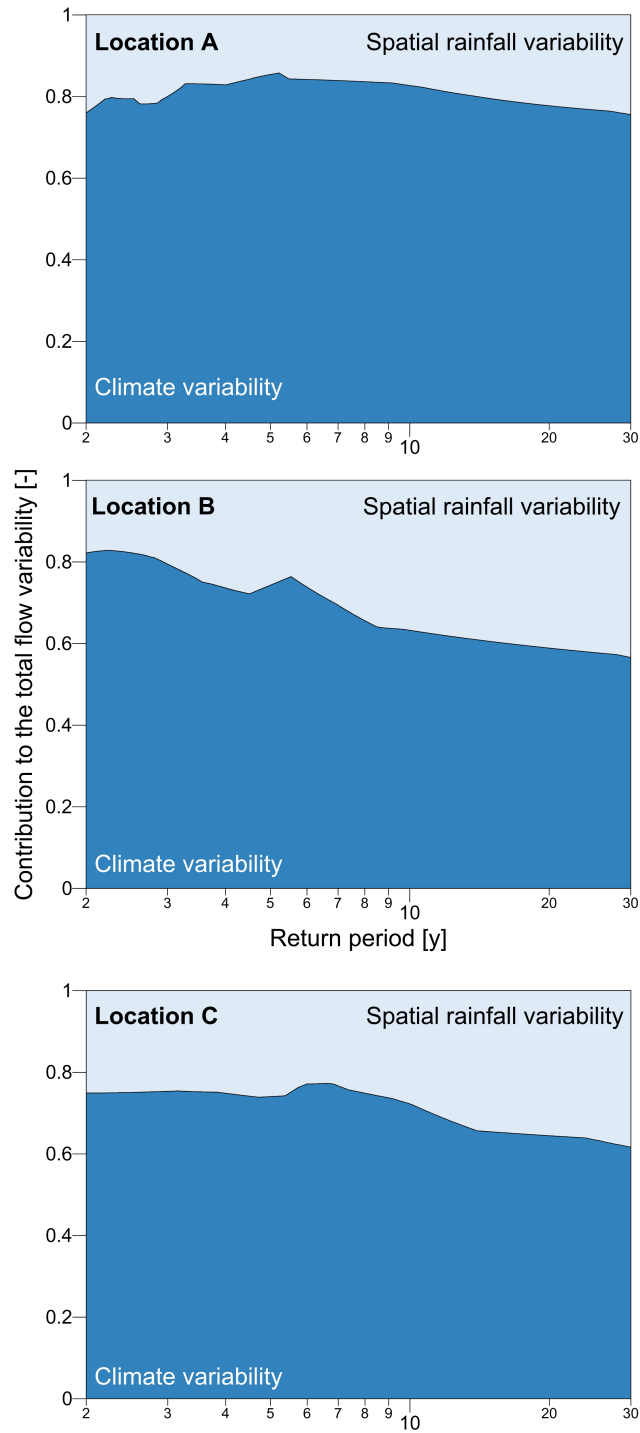


Figure 10. The ratio between the climate variability and the total flow variability for a given return period and for different locations within the urban drainage system is represented in dark blue. The remaining contribution is due to the addition of spatial rainfall variability (light blue).