

What can we learn from a 500-year event? Experiences from urban drainage in Austria

Manfred Kleidorfer, Franz Tscheikner-Gratl, Tanja Vonach and Wolfgang Rauch

ABSTRACT

Urban drainage systems are designed to capture the runoff for a certain return period of a design rainfall event. Typically, numerical models are used, which are calibrated by comparing model response and measured system performance. The applicability of such models to predict the system behaviour under extreme events is unclear, as usually then no data are available. This paper describes the analysis of an extreme rainfall event in the year 2016. The event is characterized by a very short duration and very high rainfall intensities. The maximum-recorded rainfall peak was 47.1 mm rainfall within 10 min, which corresponds to a return period of 500 years. The event caused local flooding on streets, interruptions of traffic and damages in buildings. In order to improve the flood resilience of the city, the event was analysed with an existing 1D hydrodynamic model of the sewer system. Model results were compared to water level measurements in the drainage system and citizen observations of surface flooding (gathered from social media and citizen reports). Although the hydrodynamic model could reproduce water level measurements in parts of the system, the plausibility check using descriptive data showed that the model failed to predict flooding in some areas.

Key words | extreme rainfall event, hydrodynamic model, social media, stormwater management model, urban flooding

Manfred Kleidorfer (corresponding author)

Franz Tscheikner-Gratl

Tanja Vonach

Wolfgang Rauch

Environmental Engineering,

University Innsbruck,

Innsbruck,

Austria

E-mail: manfred.kleidorfer@uibk.ac.at

Franz Tscheikner-Gratl

Sanitary Engineering,

Delft University of Technology,

Delft,

The Netherlands

INTRODUCTION

One of the key tasks of urban drainage systems is the safe disposal of stormwater runoff in order to protect the urban environment from flooding. Urban drainage systems are designed to comply with this requirement for a specific design rainfall event and a certain return period. Typical return periods for the design, i.e. the sizing of pipe diameters and storage volumes, in Austria are in the order of 1 to 10 years (depending on the land-use and the related damage potential) (ÖWAV RB II 2009; CEN 2017). Typically, hydrodynamic models of the drainage systems are used to evaluate if the drainage infrastructure is designed such that no flooding occurs for a certain design return period. These are typical 1D applications of a hydrodynamic model only modelling the subsurface infrastructure without considering the surface conditions. Accordingly, events with higher rainfall intensities, i.e. higher return periods, happen infrequently but lead to an overload of the drainage system and consequently to flooding and potentially to damage. Coupled 1D drainage network and 2D surface models enable the

prediction of inundation depths on the surface and hence can be used to assess the actual flood risk (Schmitt *et al.* 2004; Leandro *et al.* 2009; Simões *et al.* 2011; Fraga *et al.* 2017).

Models of urban drainage systems are usually (or at least should be) calibrated (Tscheikner-Gratl *et al.* 2016). For this task, model predictions (e.g. water levels, flow, etc.) are compared to corresponding measurements in the system and model parameters are optimized in a way that the deviation between measured and simulated time series is minimized. Calibration data are either collected in measurement campaigns or are available from routine measurements in the system. However, data for rare (extreme) events are hardly ever available. While rainfall recordings for extreme events might be available (rainfall measurements are often available from meteorological services), measurement data of the corresponding system response in the drainage systems are seldom reliable (runoff, water depth) for such extreme events, as this would require a measurement campaign taking place during such an event. Especially calibration

of coupled 1D/2D models is difficult, as measurements of water levels on the surface usually do not exist (Leitão *et al.* 2013). Han *et al.* (2014) showed an example of estimating model parameters by comparing modelled and observed flood extent instead of water levels. However, this still requires an accurate description of the flooding, which is often not available. An additional difficulty is introduced by the point that the relationship between rainfall intensities and flooding is non-linear (Kleidorfer *et al.* 2009; Leandro *et al.* 2016). One reason for this behaviour is pervious surfaces connected to the drainage system which generate runoff only for high precipitation rates, when the infiltration capacity is exceeded (Davidsen *et al.* 2017). Hence, parametrization of rainfall/runoff models for pervious surfaces is difficult and usually based only on literature values of soil characteristics.

Consequently, hydrodynamic models of drainage systems are often used outside their calibration range. This is model extrapolation exercise. For plausibility of model results (water levels, flows, flooded nodes), it is important that existing hydrodynamic models are validated/checked for plausibility of results whenever such events are recorded. For this task, all available information sources should be used. Apart from direct measurements (if available) other potential sources are observations provided by citizens or damage reports of emergency services or insurance companies. This incorporation of 'soft data', i.e. qualitative descriptions of citizens is a novel method to check the plausibility of model results. For example, Smith *et al.* (2015) presented an approach that demonstrated how social media data (in this case geocoded Twitter data) can be used in real time to validate flooding predictions of a hydrodynamic model. Similarly, Brouwer *et al.* (2017) presented a method to elicit flood maps from Twitter messages and concluded that these uncertain data still contain valuable information to derive the required information.

In July 2016 in the southeast of Innsbruck (Austria) an extreme event took place, which was characterized by a very short duration and very high rainfall intensities. The event caused local flooding on the streets, interruptions of traffic and damage to buildings. In this paper, the event is evaluated in order to improve the understanding of the system's ability to handle extreme events and to learn for the future on how to improve flood resilience. Therefore, the rainfall data were statistically analysed, results of a hydrodynamic model were compared to available water level measurements in the system and the flooded areas predicted by the model were compared to descriptions of citizens and reports in newspapers and social media. It was found that model predictions were accurate for parts of the system

(expressed as agreement between measured and simulated water level time series), while in other locations, the model failed to predict flooding. Probable reasons for this deficit are insufficient representation of spatial rainfall distribution, and insufficient representation of runoff from permeable areas, as well as overloaded stormwater treatment facilities, which were not included in the model but contributed to surface flooding. Additionally, the recorded event can be used in scenario analyses to improve the system resilience to extreme events.

METHODS

Innsbruck (Austria) is located in Central Europe. The climate is Alpine, which is characterized by cold winters and strong precipitation events during the summer period. The city is drained by a combined sewer system of approximately 240 km network length. The total catchment area is approximately 2,500 ha; the connected impervious area amounts to 800 ha. A detailed hydrodynamic model consisting of 5,000 nodes and 2,500 subcatchments, which was calibrated on water level measurements for rainfall events of medium intensity (partly filled pipes), is available in the software SWMM (Gironás *et al.* 2010; Burger *et al.* 2014). The model of this case study was extensively tested in different applications (Kleidorfer *et al.* 2014; Tscheikner-Gratl *et al.* 2014; Mikovits *et al.* 2015; Möderl *et al.* 2015; Mikovits *et al.* 2018) including an analysis of the impact of climate change and urban development on the flood risk of the city (Mikovits *et al.* 2017). The last study also included a coupled 1D/2D simulation, although the used approach was a simplified 2D simulation according to James *et al.* (2013).

Six rain gauges (squares) and 35 ultrasonic water level sensors (dots) are located in the city (see Figure 1). The general flow direction is from west (left) to east (right) to a central wastewater treatment plant (see Figure 1). The rainfall data were analysed and compared to historical rainfall records and their statistical evaluations, respectively.

Additionally, the hydrodynamic 1D model was used to investigate the system's response to the 2016 extreme event. Therefore, two different types of spatial rainfall representation were tested:

- SRR1: Each subcatchment was connected to the nearest rain gauge (Figure 2, left). This corresponds with a division of the catchment area according to a Voronoi decomposition (also called Thiessen Polygon Method – see Tabios & Salas 1985).

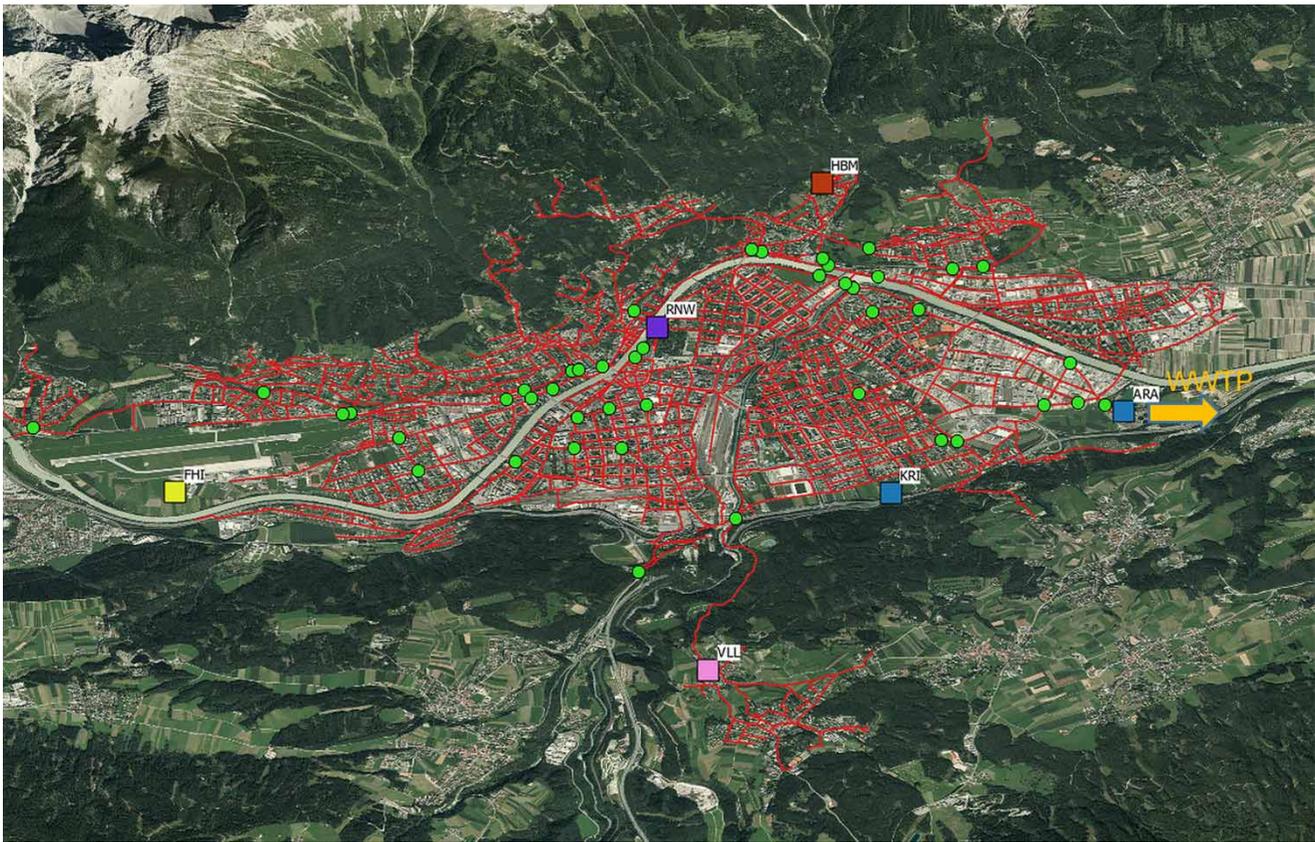


Figure 1 | Location of rain gauges (squares) and water-level measurements (circles) in the drainage system.

- SRR2: Each subcatchment has an individual rainfall time series which was assigned by applying an inverse distance weighted interpolation between the six rain gauges (Figure 2, right).

We used a hydrodynamic 1D modelling approach to simulate flow rates, water level hydrographs in drainage pipes and manholes, as well as flooding volume (i.e. ponded water at nodes). A 2D surface flood inundation model was not used.

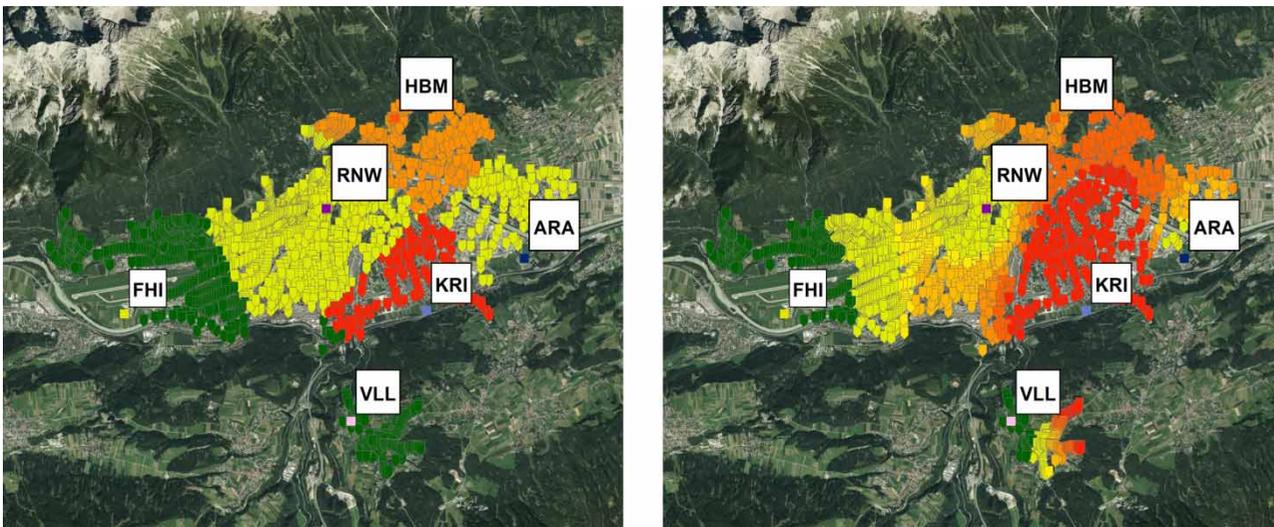


Figure 2 | Rainfall intensities (maximum value mm/min) for different subcatchments from low intensities (green 0.2 mm/min) to high intensities (red 8.5 mm/min) as examples for impact of spatial rainfall representation. Left: SRR1 - Allocation of subcatchments to rain gauges according to Voronoi decomposition. Right: SRR2 Spatial interpolation between rain gauges by using an inversed distance weighted method. Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wst.2018.138>.

Model results (predicted water level hydrographs and flooding volume) were compared to the water level measurements in the system and observations from citizens (gathered from social media platforms such as Twitter, Facebook or YouTube and from local media). For comparison of water level measurements, the Nash Sutcliffe Efficiency (NSE) (Nash & Sutcliffe 1970) was calculated. For comparison of flooding volume, no direct measurements of water volume or water depths on the surface were available. So citizen reports were used for qualitative comparison, i.e. it was analysed whether the model also reproduced flooding in areas where flooding was reported. This means that no detailed quantification of flood depth or extent of flooded areas, which would require a 2D surface-flood inundation model, was conducted. It is important to note that citizen reports can only be used for plausibility checks of observations, a falsification of wrong flood predictions is not possible (i.e. it is not possible to detect incorrectly modelled flooding locations as a 'missing' citizen report for a certain location does not mean that no flooding occurred in reality; maybe it was just not reported).

RESULTS AND DISCUSSION

Figure 3 shows the rainfall recordings of the event for the individual rain gauges (Figure 1). The total event duration was approximately 1 h. As visible here, the spatial variation of the rainfall intensities is very high. The intensity peak appeared a few minutes after the start of the event and

only at a locally limited area. The peak intensity for rain gauge KRI is 8.7 mm/min, whereas the peak intensity for rain gauge ARA (2 km distance) is only 4.0 mm. Although errors due to the measurement methods are possible (KRI uses a weighing precipitation gauge; ARA uses a tipping bucket rain gauge) the difference is realistic and fits observations of effects of the event. The total recorded rainfall at KRI was 52.5 mm, the recorded rainfall within 10 min was 47.1 mm, which corresponds to a return period of 500 years (Niedertscheider *et al.* 2016).

Table 1 summarizes estimated return periods after comparing the rainfall data with statistical rainfall characteristics of the region (Weilguni 2015) and the rainfall volume for the 10 min duration. At the rain gauge ARA (2 km distance), only a return period between 20 and 25 years was recorded, at a distance of 6 km (rain gauge FHI) the return period was only between 1 and 2 years. This confirms the knowledge that spatial rainfall variability is highly relevant in urban drainage modelling, especially for high return periods (Schilling 1984; Peleg *et al.* 2017).

The simulated water levels were compared to the data from the 35 water level measurements in the pipes/combined sewer overflow structures of the drainage system. The NSE for all measurement sites is shown in Figure 4 for both types of spatial rainfall representation and as a spatial representation in Figure 5 for SRR1. The comparison of measured and simulated water levels showed partly a surprisingly good agreement, in the best case an NSE of 0.966 (SRR1) and 0.958 (SRR2). The corresponding water level hydrographs are shown in Figure 6 (left). Here an ultrasonic

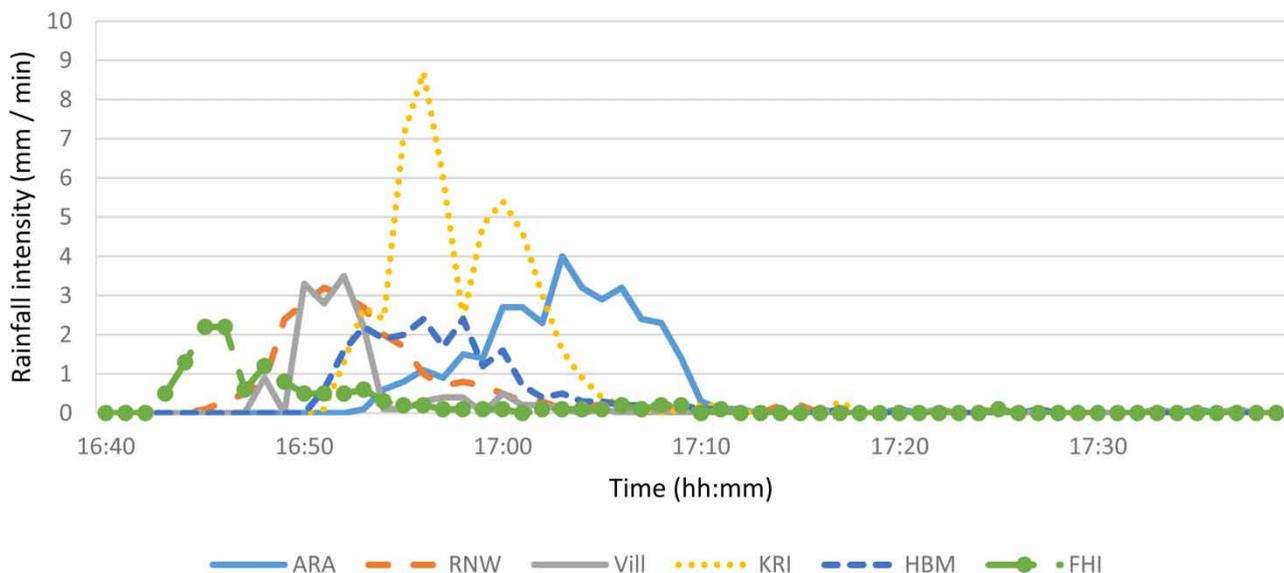


Figure 3 | Recorded rainfall data in mm/min for the six rain gauges.

Table 1 | Evaluation of return periods for the six rain gauges and rainfall intensity (mm/10 min)

Rain gauge	Return period (years)	Rainfall intensity (mm/10 min)	Total rainfall volume (mm)
ARA	20–25	27	47
VLL	5–20	14	30
RNW	5–20	20	36
KRI	500	47	65
HBM	3–5	18	32
FHI	1–2	10	26

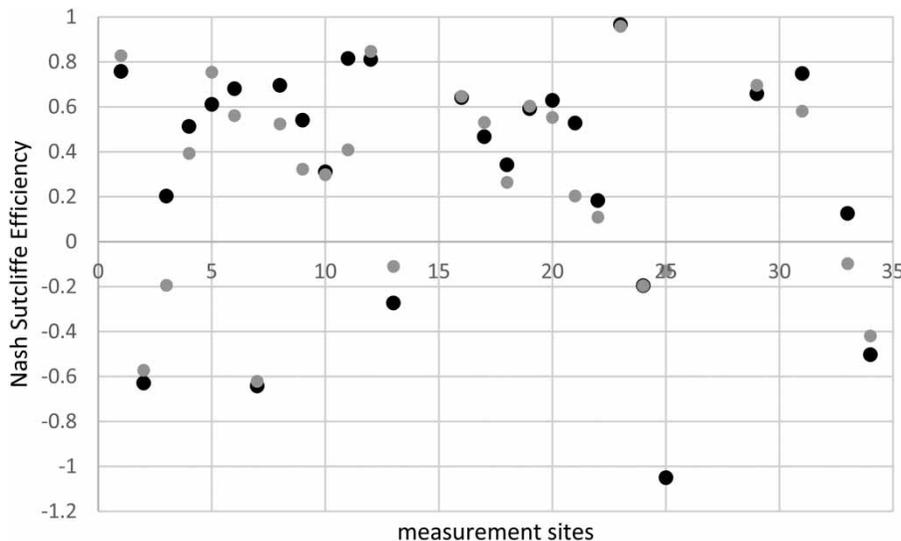
water-level sensor measures the water level from the pipe invert depth. The maximum depth in this combined sewer overflow structure would be 4.18 m. Such a good agreement was not expected as the model was never calibrated on data of such an extreme event.

However, the analysis also revealed deficits in predicting water levels in some areas. While most of the poor agreements can be explained (e.g. inflow from other municipalities is only modelled as constant flow without temporal variation), this information was also used to improve the model representation. For example, Figure 6 (right) shows an over-estimation of the modelled runoff peak resulting in a NSE of -1.05 for SRR1. Here the water level is measured in a manhole; the maximum water level would be 4.83 m. It is likely that this is caused by an insufficient representation of spatial rainfall. The area of this measurement site is modelled with the rain gauge with the highest intensity (KRI), which might not express the real situation. In general, the

differences between the two methods for spatial rainfall representation SRR1 and SRR2 are small. No overall improvement by implementing the inverse distance weighted interpolation (SRR2) is visible. Although in the example shown in Figure 6 (right) NSE improves to -0.13 , the flow peak is still overestimated.

The collection of information from local newspapers and social media shows the effect of the event. Local flooding caused traffic interruptions and damages in garages and buildings. The emergency services received more than 700 calls and had more than 270 incidents. The descriptions in local and regional news and in the social media (including photos and videos) were helpful to identify areas of local flooding. This information was used for plausibility checks of the results of the hydrodynamic model. This was especially interesting as no water level measurement were available in the centre of the cloudburst cell or the flooded area.

Figure 7 shows the visualization of simulated flooded nodes as a heatmap (SRR1). This visualization technique is based on an interpolation between flooded nodes based on the flooding volume and does not represent real flooded areas (which would require a 2D surface model). The identified larger flooded area matches citizen reports. However, the model was not able to reproduce all flooding locations. For example, multiple citizen reports of flooding were collected near a shopping centre. In this area, the model failed to predict the effects of the event. This could also be caused by insufficient representation of spatial rainfall distribution but, here, also other reasons are possible. In the

**Figure 4** | NSE comparing simulated and measured water levels for SRR1 (black) and SRR2 (grey).

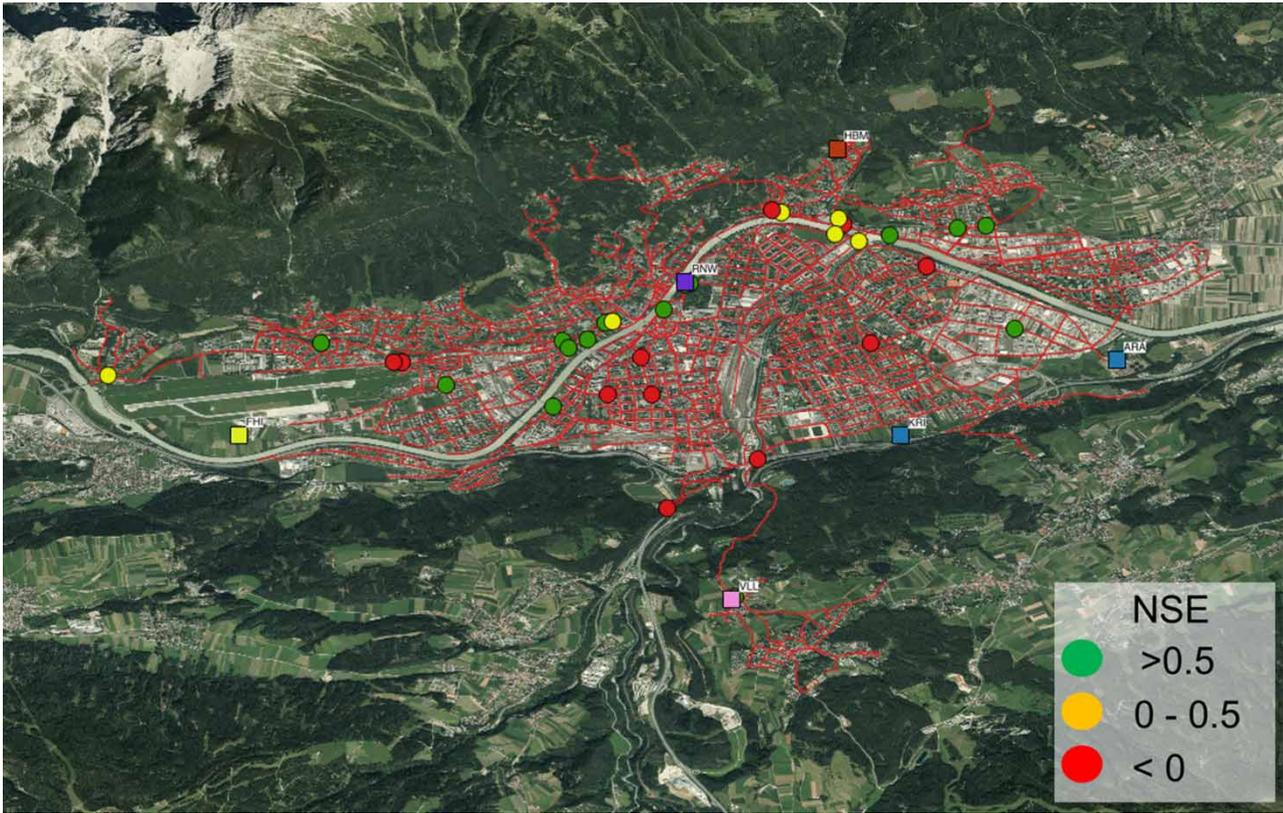


Figure 5 | Spatial representation of measurements locations with corresponding NSE for SRR1.

model runoff from natural (pervious) catchments, which do not drain to the sewer system under design conditions, is not considered. Furthermore, it is unclear how decentralized rainwater treatment facilities (infiltration trenches at large parking lots) responded to the event. As these facilities are designed for much smaller return periods and the status of their maintenance is questionable, it is likely that they are

overloaded and contributed to surface runoff (which is not considered in the model). Another potential reason might be clogging of sewer inlets and corresponding limited hydraulic capacity (Leitão et al. 2016).

Finally, the recorded extreme event was (and will be) used to analyse and improve the resilience of the system. Therefore, different rainfall scenarios were modelled and

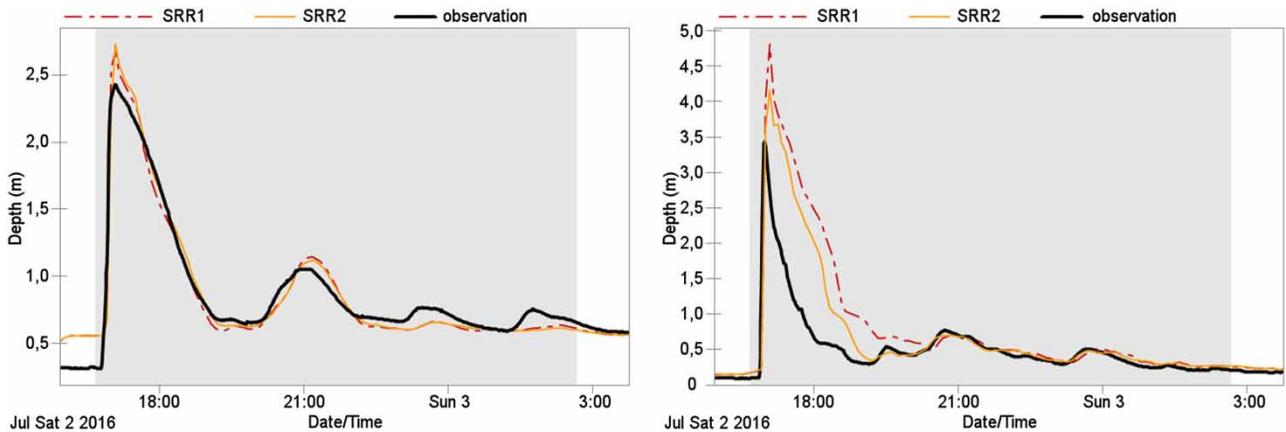


Figure 6 | Comparison of measured (thick line), simulated for SRR1 (dashed line), and simulated for SRR2 (thin line) water level in manhole. Left: Measurement site with NSE = 0.966 (SRR1) and NSE = 0.958 (SRR2), Right: Measurement site with NSE = -1.05 (SRR1) and NSE = -0.13 (SRR2); NSE is calculated for the range of the shaded area.

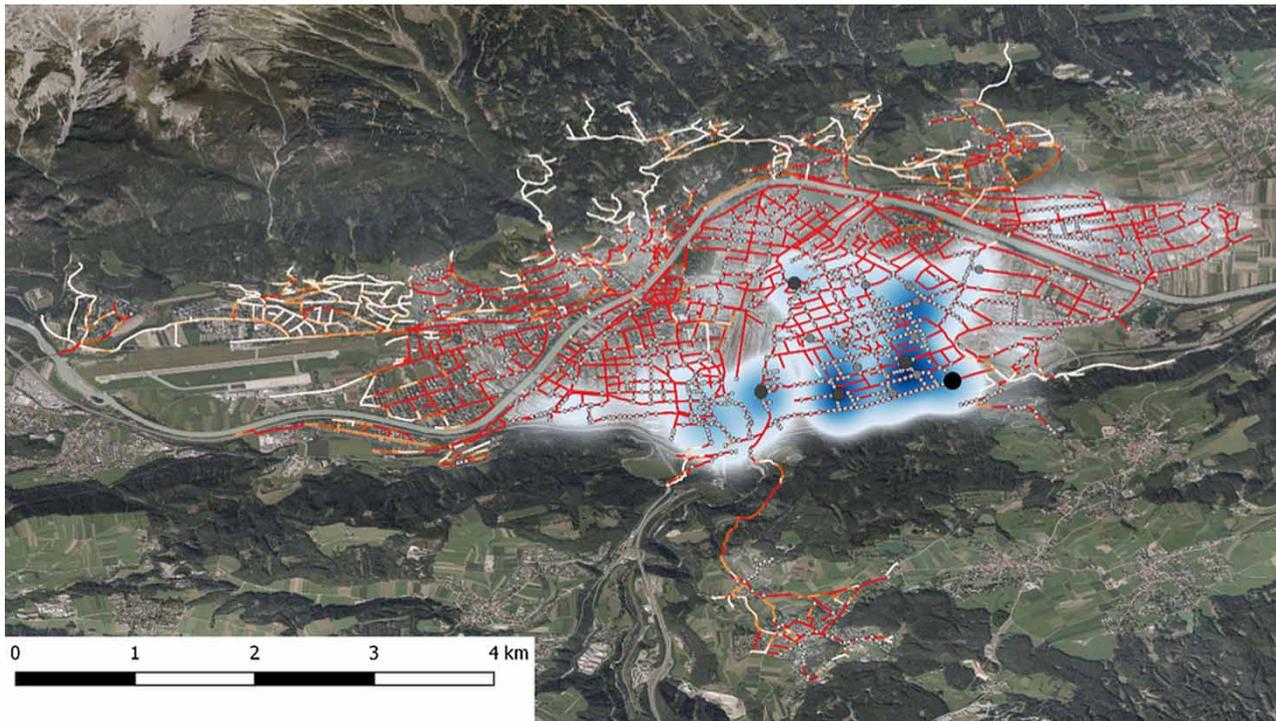


Figure 7 | Hydrodynamic model of the combined sewer system and visualization of flooding nodes as heatmap (SRR1).

the system response was analysed. Such simulations of scenarios of extreme events are a valuable source of information to test the effectiveness of different adaptation measures. In this context, especially the analysis of green infrastructure for stormwater treatment is interesting as such measures are often mentioned in the context of climate adaptation and flood mitigation (Lennon *et al.* 2014), but on the other side, seem to lose their effectiveness for very high precipitation intensities, especially if not well maintained.

CONCLUSIONS

The analysis of the extreme event with a return period of 500 years gave valuable insights for better understanding of the system under extreme conditions. Although the hydrodynamic model could accurately reproduce water level measurements in parts of the system, the plausibility check using flooding descriptions showed that the model failed to predict flooding in some areas. It was shown that the spatial rainfall variability was very high for the analysed event. This supports the knowledge that an appropriate representation in the model is necessary. In the presented case study, six rain gauges were available for an area of approximately 25 km², which seemed to be still not

enough to accurately describe this extreme event. A potential improvement, which still has to be analysed, is the consideration of radar rainfall data.

A further source of uncertainties may be the insufficient consideration of natural areas and decentralized stormwater treatment systems, which are not connected to the drainage system under normal operating conditions but which can contribute to surface flooding for very high precipitation rates. This opens not only the discussion of appropriate model representation but consequently also the discussion regarding responsibilities for the different authorities involved.

The collection and evaluation of citizen reports from (social) media gave valuable additional information for checking the plausibility of model results. Such descriptive information can be used to improve the model for future investigations. However, in this case study, this information alone does not seem to be sufficient to calibrate or validate the model. One reason for this is that adequate informative reports were rare, especially outside highly popular areas as shopping centres and that with current knowledge it is not straightforward to elicit quantitative information (e.g. water levels) from photographs. Furthermore, citizen observations only allow identification of false negative errors (flooding which is reported, but not predicted) but not of

false positive errors (flooding which is modelled, but not observed). Nevertheless, the involvement of people in citizen science projects to establish alternative information pathways to report observed flooding events is an interesting approach, which could improve the understanding of the system performance in the future.

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REFERENCES

- Brouwer, T., Eilander, D., van Loenen, A., Booi, M. J., Wijnberg, K. M., Verkade, J. S. & Wagemaker, J. 2017 Probabilistic flood extent estimates from social media flood observations. *Nat. Hazards Earth Syst. Sci.* **17** (5), 735–747.
- Burger, G., Sitzenfrey, R., Kleidorfer, M. & Rauch, W. 2014 Parallel flow routing in SWMM 5. *Environmental Modelling & Software* **53**, 27–34.
- CEN 2017 EN 752 - Drain and sewer systems outside buildings. In: *EN 752*, European Committee for Standardization (CEN), Brussels, Belgium.
- Davidsen, S., Löwe, R., Ravn, N., Jensen, L. & Arnbjerg-Nielsen, K. 2017 Initial conditions of urban permeable surfaces in rainfall-runoff models using Horton's infiltration. In: *14th International Conference of Urban Drainage*. International Water Association, Prague, Czech Republic, pp. 26–34.
- Fraga, I., Cea, L. & Puertas, J. 2017 Validation of a 1D-2D dual drainage model under unsteady part-full and surcharged sewer conditions. *Urban Water Journal* **14** (1), 74–84.
- Gironás, J., Roesner, L. A., Rossman, L. A. & Davis, J. 2010 A new applications manual for the Storm Water Management Model (SWMM). *Environmental Modelling & Software* **25** (6), 813–814.
- Han, K., Kim, Y., Kim, B., Famiglietti, J. S. & Sanders, B. F. 2014 Calibration of stormwater management model using flood extent data. *Proceedings of the ICE-Water Management* **167** (1), 17–29.
- James, R., Finney, K., Perera, N., James, B. & Peyron, N. 2013 SWMM5/PCSWMM integrated 1D-2D modeling. In: *Fifty Years Of Watershed Modeling – Past, Present And Future Series* (A. S. Donigian, R. Field & M. Baker, eds.) ES Engineering Conferences International, New York, NY, USA.
- Kleidorfer, M., Möderl, M., Sitzenfrey, R., Urich, C. & Rauch, W. 2009 A case independent approach on the impact of climate change effects on combined sewer system performance. *Water Science and Technology* **60** (6), 1555–1564.
- Kleidorfer, M., Mikovits, C., Alrun-Jasper-Toennies, H. M., Einfalt, T. & Rauch, W. 2014 Impact of a changing environment on drainage system performance. *Procedia Engineering* **70**, 943–950.
- Leandro, J., Chen, A. S., Djordjević, S. & Savić, D. A. 2009 Comparison of 1D/1D and 1D/2D coupled (sewer/surface) hydraulic models for urban flood simulation. *Journal of Hydraulic Engineering* **135** (6), 495–504.
- Leandro, J., Schumann, A. & Pfister, A. 2016 A step towards considering the spatial heterogeneity of urban key features in urban hydrology flood modelling. *Journal of Hydrology* **535**, 356–365.
- Leitão, J. P., do Céu Almeida, M., Simões, N. E. & Martins, A. 2013 Methodology for qualitative urban flooding risk assessment. *Water Science and Technology* **68** (4), 829–838.
- Leitão, J. P., Simões, N. E., Pina, R. D., Ochoa-Rodriguez, S., Onof, C. & Sá Marques, A. 2016 Stochastic evaluation of the impact of sewer inlets' hydraulic capacity on urban pluvial flooding. *Stochastic Environmental Research and Risk Assessment* 1–16.
- Lennon, M., Scott, M. & O'Neill, E. 2014 Urban design and adapting to flood risk: the role of green infrastructure. *Journal of Urban Design* **19** (5), 745–758.
- Mikovits, C., Rauch, W. & Kleidorfer, M. 2015 A dynamic urban development model designed for purposes in the field of urban water management. *Journal of Hydroinformatics* **17** (3), 390–403.
- Mikovits, C., Tscheikner-Gratl, F., Jasper-Tönnies, A., Einfalt, T., Huttenlau, M., Schöpf, M., Kinzel, H., Rauch, W. & Kleidorfer, M. 2017 Decision support for adaptation planning of urban drainage systems. *Journal of Water Resources Planning and Management* **143** (12).
- Mikovits, C., Rauch, W. & Kleidorfer, M. 2018 Importance of scenario analysis in urban development for urban water infrastructure planning and management. *Computers, Environment and Urban Systems* **68**, 9–16.
- Möderl, M., Sitzenfrey, R., Lammel, J., Apperl, M., Kleidorfer, M. & Rauch, W. 2015 Development of an urban drainage safety plan concept based on spatial risk assessment. *Structure and Infrastructure Engineering* **11** (7), 918–928.
- Nash, J. E. & Sutcliffe, J. V. 1970 River flow forecasting through conceptual models part I – A discussion of principles. *Journal of Hydrology* **10** (3), 282–290.
- Niedertscheider, K., Neuner, M., Raffener, G., Mair, G. & Felderer, W. 2016 *Hydrologische Übersicht Juli 2016 (Hydrological Overview July 2016)*. Gruppe Bau und Technik, Abteilung Wasserwirtschaft, Sachgebiet Hydrographie und Hydrologie, Innsbruck, Austria.
- ÖWAV RB 11 2009 *Abwassertechnische Berechnung und Dimensionierung von Abwasserkanälen (Guidelines for the design of sewer pipes)*. Österreichischer Wasser- und Abfallwirtschaftsverband, Vienna, Austria.
- Peleg, N., Blumensaat, F., Molnar, P., Faticchi, S. & Burlando, P. 2017 Partitioning the impacts of spatial and climatological

- rainfall variability in urban drainage modeling. *Hydrology and Earth System Sciences* **21** (3), 1559.
- Schilling, W. 1984 Effect of spatial rainfall distribution on sewer flows. *Water Science & Technology* **16** (8–9), 177–188.
- Schmitt, T. G., Thomas, M. & Ettrich, N. 2004 Analysis and modeling of flooding in urban drainage systems. *Journal of Hydrology* **299** (3–4), 300–11.
- Simões, N., Ochoa-Rodriguez, S., Leitão, J., Pina, R., Sá Marquez, A. & Maksimović, Č. 2011 Urban drainage models for flood forecasting: 1D/1D, 1D/2D and hybrid models. In: *12th International Conference on Urban Drainage*, Porto Alegre, Brazil. <http://hdl.handle.net/10044/1/14681>.
- Smith, L., Liang, Q., James, P. & Lin, W. 2015 Assessing the utility of social media as a data source for flood risk management using a real-time modelling framework. *Journal of Flood Risk Management* **10** (3), 370–380.
- Tabios, G. Q. & Salas, J. D. 1985 A comparative analysis of techniques for spatial interpolation of precipitation. *JAWRA Journal of the American Water Resources Association* **21** (3), 365–380.
- Tscheikner-Gratl, F., Mikovits, C., Rauch, W. & Kleidorfer, M. 2014 Adaptation of sewer networks using integrated rehabilitation management. *Water Science & Technology* **70** (11), 1847–1756.
- Tscheikner-Gratl, F., Zeisl, P., Kinzel, C., Leimgruber, J., Ertl, T., Rauch, W. & Kleidorfer, M. 2016 Lost in calibration: why people still don't calibrate their models, and why they still should – a case study from urban drainage modelling. *Water Science & Technology*.
- Weilguni, V. 2015 *eHYD Bemessungsniederschlag (eHYD Design Rainfall)*. http://ehyd.gv.at/assets/eHYD/pdf/20150722_Bemessungsniederschlag.pdf.

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