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Effect of varying calibration scenarios on the performance of a hydrodynamic sewer model

F. Tscheikner-Gratl[1*], P. Zeisl[2], C. Kinzel[2], J. Leimgruber[3], T. Ertl[4], W. Rauch[2] and M. Kleidorfer[2]
[1] *Sanitary engineering, Delft University of Technology, P.O. Box 5048, 2600 GA Delft, The Netherlands*
[2] *Unit of Environmental Engineering, University of Innsbruck, Technikerstrasse 13, Innsbruck 6020, Austria*
[3] *Institute of Urban Water Management and Landscape Water Engineering, Graz University of Technology, Stremayrgasse 10/I, Graz 8010, Austria*
[4] *Institute of Sanitary Engineering and Water Pollution Control (SIG), University of Natural Resources and Life Sciences, Muthgasse 18, Vienna 1190, Austria*
[*] *e-mail: F.Tscheikner-Gratl@tudelft.nl*

Abstract: Case studies concerning urban water management tend to be large, prestigious cities which have the financial and human resources to participate in research projects. This bears the risk that research outcomes are biased towards large municipalities. Consequently, the aim of this paper is to discuss calibration of a hydrodynamic model for the representative example of a small municipality. To exemplify the uncertainties immanent to the calibration process 17 scenarios - differing in assumptions for calibration - were estimated. The performance of the different scenarios was assessed using a hydrodynamic sewer model. The occurring flooding volume from the urban drainage system elicited by the rainfall data sets used as well as the combined sewer overflow was compared for the different scenarios and rain measurements. The different calibration scenarios proved to result in high deviations in the performance of the hydrodynamic model. It can be seen, that the selection of the applied calibration data is a very sensitive decision in the modelling process. The variations show that model calibration is of utmost importance. The differences in performance can lead to different outcomes design and decision-making processes possibly leading to higher volumes, which is not cost-effective, or to underestimation of the needs that will result in lacking robustness and malfunctioning of the network.

Key words: calibration, urban drainage, uncertainties

1. INTRODUCTION

Discrepancies between the simulated and the measured system behaviour of urban drainage models are unavoidable, due to unavoidable uncertainties. These can be caused by the simplification of the real physical interrelationships inherent to modelling as well as by difficulties to identify the necessary model parameters. Hence, the calibration process is a crucial and fundamental component of the model development process, unquestioned from a scientific point of view (Muschalla et al., 2009).

However, in engineering practice uncalibrated or insufficiently calibrated models are still used, with data availability often being the limiting factor. Calibration usually requires sampling campaigns, which in turn can increase the economic cost of the projects up to an unachievable level (Freni et al., 2009). Calibration uncertainties relate to the data used for calibration and their selection, and to the calibration methods (Leonhardt, 2015). They source in measurement errors for both, inputs and outputs, the selection of appropriate calibration input and output datasets, the applied calibration algorithms and the objective functions used in the calibration process (Deletic et al., 2012).

Case studies of urban water management studies in scientific literature are often large, prestigious cities, which have the financial, and human resources to participate in research projects. They are selected for providing a good data background as e.g. measurement data over the last years and/or the required infrastructure for further data collection and management. Such case studies are not always representative for the entire situation of the living environment in a country. At least, there is the risk that research outcomes are biased towards large municipalities (Tscheikner-Gratl et al., 2016a).

Consequently, the aim of this paper is to discuss calibration of a hydrodynamic model for the representative example of a small Austrian municipality (15,000 inhabitants). For this purpose, the hydrodynamic drainage model of this case study was calibrated based on different calibration scenarios (different number of calibration events, different rainfall input). Additionally, varying precipitation data of the surrounding area using an uncalibrated model plus the various calibrated models was used to analyse influences of input data uncertainties.

2. METHODS

The analysed case study in this paper is a small municipality with 15,000 inhabitants in Tyrol, Austria (Kleidorfer et al., 2014; Muschalla et al., 2015; Tscheikner-Gratl et al., 2016a; Tscheikner-Gratl et al., 2016b). The urban drainage network consists of only 14 km of combined sewers, 67 km of wastewater sewers and 24 km of stormwater sewers. These stormwater sewers have 28 outfalls into the receiving water bodies, while in comparison only three combined sewer overflows (CSO) exist. In total, a catchment area of 95.31 hectare is connected to the combined sewer system. For model calibration and validation, precipitation was measured over the period of one year at three sites (rain gauges 1-3) in the catchment area and the water level at one site near the inflow to the wastewater treatment plant. This measurement setup also represents limited data availability, inherent to smaller operators due to limited budget.

The performance of different scenarios was assessed using the Storm Water Management Model (SWMM) software tool (Gironás et al., 2010). For the calibration of the hydrodynamic model a genetic algorithm implemented in PC-SWMM (James et al., 2002) was applied. For calibration data, measurements of rainfall at three locations within the municipality and water levels at the catchment outflow of the 10 strongest rainfall events, which occurred in the measurement period of one year, were chosen.

To exemplify the uncertainties immanent to the calibration process 17 scenarios - differing in assumptions for calibration - were used. The first scenario was the base scenario (00) without calibration. Then a calibration for each rainfall event took place individually (scenarios 01 – 10). Further, the model was calibrated using the entire rain series (11). For the next scenarios (12 -14) the rain series was used for calibration with only data from one of the three available rain gauges (1-3) respectively. Furthermore, the model was calibrated under the assumptions of a systematic 30% error of the water level monitoring data (+30% for scenario 15 and -30% for scenario 16) using again the entire rain series (like in scenario 11) to show the influence of measured calibration data uncertainties.

The Nash-Sutcliffe efficiency NSE (Nash and Sutcliffe, 1970) was chosen as the objective function to compare measured and predicted water levels. NSE is a measure to compare time series. It ranges from $-\infty$ to 1 (perfect match). After calibration, the remaining rainfall events were simulated and model performance for the individual calibration scenarios was evaluated. For this purpose, the absolute deviation of the NSE of each model (00 - 11) for every rainfall event to its best fit (which is always the scenario calibrated on that rainfall event) was calculated and summed up to get a cumulative measure. This verifies that scenario 11 (calibration on all ten events) shows the best overall performance and can therefore be used as reference scenario. For more details, see Tscheikner-Gratl et al. (2016a).

To show the influence of rainfall measurement uncertainties in comparison with the calibration scenario uncertainties, we compared the model results using two different precipitation data sets (1 year) of the Austrian Central Institute for Meteorology and Geodynamics (ZAMG) from the nearest measurement sites available (ZAMG1 10 km from the catchment and ZAMG2 30 km) with using our own measurements. Consequently, the occurring flooding volume from the urban drainage system elicited by the rainfall data sets used as well as the combined sewer overflow (CSO) was compared for the different scenarios and rain measurements.

3. RESULTS AND DISCUSSION

Figure 1 shows the variations of predicted flooding volume for the five measured rainfall series (RG 1 – 3 and ZAMG 1 and 2) when applying the 17 different calibration scenarios. It is notable that not all rain data sets (RG 1 and ZAMG 2) elicited flooding, while ZAMG 1 caused 3946 m³ of flooding for calibration scenario 15 in the observation period of 1 year. This illustrates also the variations in rainfall, even in a small though mountainous region. Even variations between the measurement points within a radius of 30 km are notable, hinting the variability of spatial precipitation distribution (Muthusamy et al., 2017). Furthermore, Figure 1 shows that for the rainfall data RG 2 in scenario 15, which elicits the most flooding, only 30% of the flooding occurs compared to the rainfall data of ZAMG 1 and in average over all scenarios only 8%. For RG 3 it is even less with 3% in average and 10% in scenario 15.

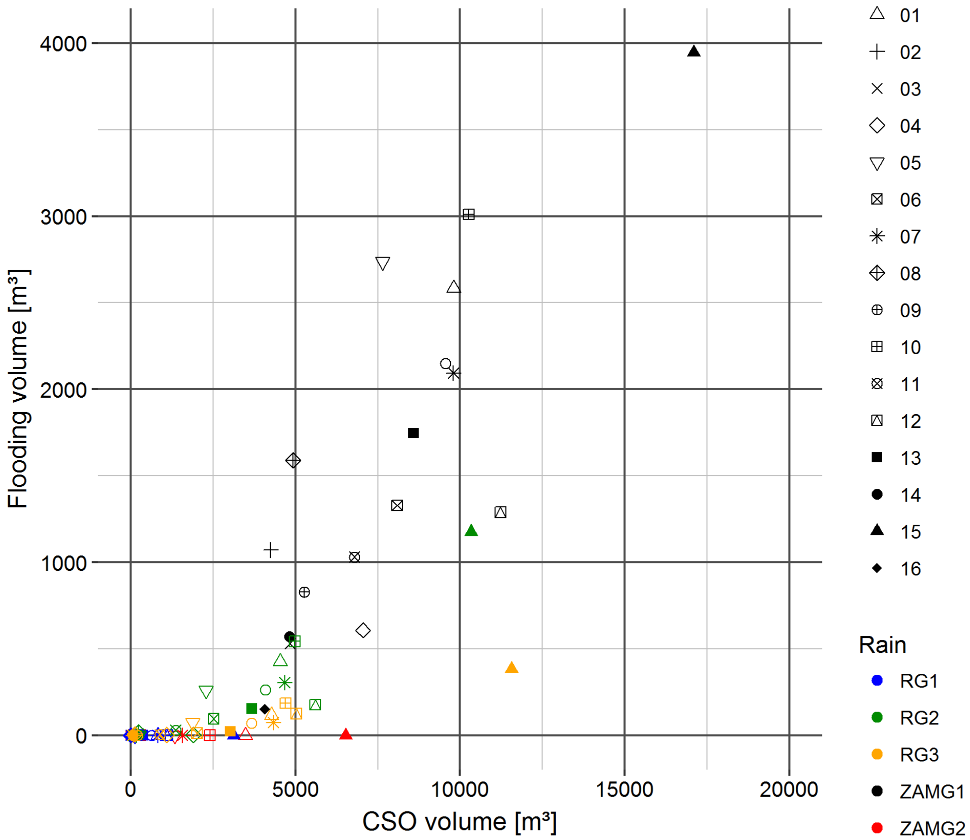

Figure 1. Flooding volume and CSO volume for measured 1 year rain series (RG 1 -3 and ZAMG 1 and 2) and the different calibration scenarios.

It also shows the variability of the results concerning the calibration scenarios, which are in the same scale as the before mentioned differences for rainfall data. For the same rainfall series (ZAMG 1) the scenarios can cause differences of up to 90%. Even if we neglect the obvious effect of a scenario assuming a systematic 30% error of the depth monitoring data (scenario 15 and 16), we can observe differences of up to 60% between calibration on one single rain event (e.g. between scenario 03 and 10). The flooding volume alone could however be misleading without taking into account other network data. The observed flooding volume can be regulated by combined sewer overflows (CSO).

By assuming scenario 11 to be the reference scenario (Tscheikner-Gratl et al., 2016a) and subdividing the scenarios in terms of deviation of the flooding and CSO volume for the rain set that elicits the most flooding ZAMG 1, the effect of calibration is easy to see (see Figure 2). The other rain series (RG 3 and RG 2) result in very low flooding volumes (5 and 30 m^3) for scenario 11 and the deviations are therefore even higher.

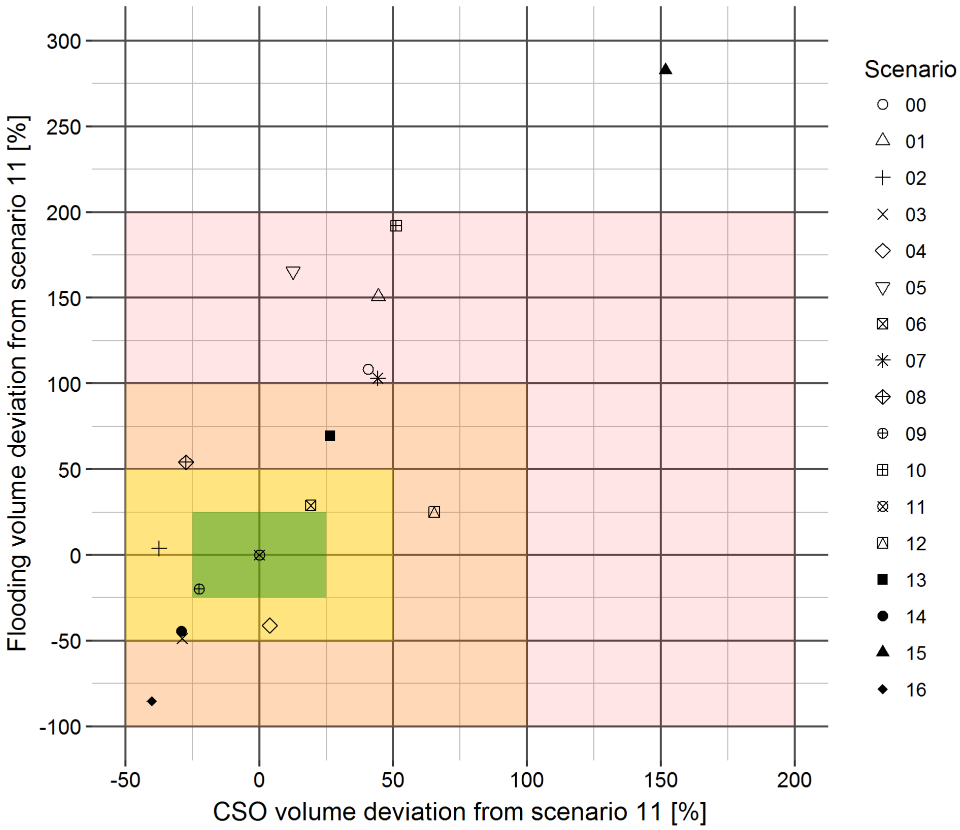

Figure 2. Flooding volume and CSO volume deviation from scenario 11 for measured 1 year rain series ZAMG 1

Only one scenario (09) shows low (less than 25%) deviation from the reference scenario in terms of flooding and CSO volume. Medium deviation (less than 50%) can be observed in 5 scenarios (02, 03, 04, 06 and 14). Other scenarios show high (up to 100% for scenarios 08, 12, 13 and 16) and very high (up to 200% for scenarios 00, 01, 05, 07, 10 and 15) deviations. Scenario 15 deviated even more. That shows that these scenarios with very high deviations perform even worse than an uncalibrated model (00) or at least not better for the rainfall ZAMG 1. Furthermore, it can be seen that these scenarios stem mainly from choosing an inappropriate rainfall event for calibration or from systematic errors in calibration data measurements. Interestingly the overestimation of these data (scenario 15) elicits a lot more effect on the flooding volume than the underestimation (scenario 16). This seems to be caused by plausibility restrictions in the calibration process (Tscheikner-Gratl et al., 2016a).

4. CONCLUSION

It can be seen, that the selection of the applied calibration data is a very sensitive decision in the modelling process. The variations show that model calibration is of utmost importance. The differences in performance can lead to different outcomes in design and decision-making processes. Subsequently this results in larger pipe diameters or higher storage volumes, which are not cost-effective, or in underestimation of the needs, which will result in lacking robustness and malfunctioning of the network (e.g. urban flooding).

The necessity of calibration also shows the importance of measurement data available in sufficient quantity and quality. It can be seen that spatial distributed rainfall measurement is advisable to minimize the uncertainties stemming from differences in rain intensities and distribution, which also occur in relatively small areas, especially in mountainous regions.

Further details can be found in Tscheikner-Gratl et al. (2016a) and Tscheikner-Gratl et al. (2016b).

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