Does distributed monitoring improve the calibration of urban drainage models?

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Highlights

- Distributed reference data impove our understanding of spatiotemporal flow dynamics and correlation patterns in drainage networks.
- However, improvements in parameter inference can end up being only marginal when switching from single to multiple data sources.
- This can happen due to: a) close proximity of multiple sensors b) constrained sensitivty caused by throttles, and d) observational errors.

Introduction

Collection of accurate observations - discharge using conventional flow meters and water quality using grab samples – has been laborious and costly; only a small number of such devices can be operated at reasonable expenses. However, with the advancements in sensor and data communication technology (e.g. Blumensaat et al., 2018; Ebi et al., 2019), we can now deploy a larger number of sensors across the entire drainage network (Eggimann et al., 2017). But there is a paucity of research on the marginal returns of increasing spatially distributed data in the context of model improvements. Wani et. al., 2017 demonstrated the usability of binary data from nonconventional sensors deployed in CSO tanks. They devised a likelihood function for hydraulic urban drainage models, which can infer the parameters of the model within the Bayesian framework, and thus provide improved model predictions and a faithful quantification of uncertainty. Nevertheless, the value of such inference for geographically dispersed data hasn't been extensively researched. In this study, we therefore aim to analyze the value of distributed sensing in the context of urban drainage modeling.

Methodology

Paramter inferece: For parameter inference in the Bayesian framework, we need to first statistically define the observation generating process (Y), which can be seen as the sum of the deterministic model (SWMM in this case) and a stochastic error term. $Y = f(x, \theta) + E(\psi)$ Where f is the deterministic model, E is a random variable to account for the error in the deterministic model, (θ, ψ) are parameters and Y is what we expect our observations to be like. Calibrating a model within the Bayesian framework comes with two main benefits: A) The calibration procedure yields a posterior distribution of parameter values, and not just a single optimal value. This captures the parameter uncertainty. B) Once these posterior parameter samples are run through the model, we also get the predictive uncertainty in the forward simulation.

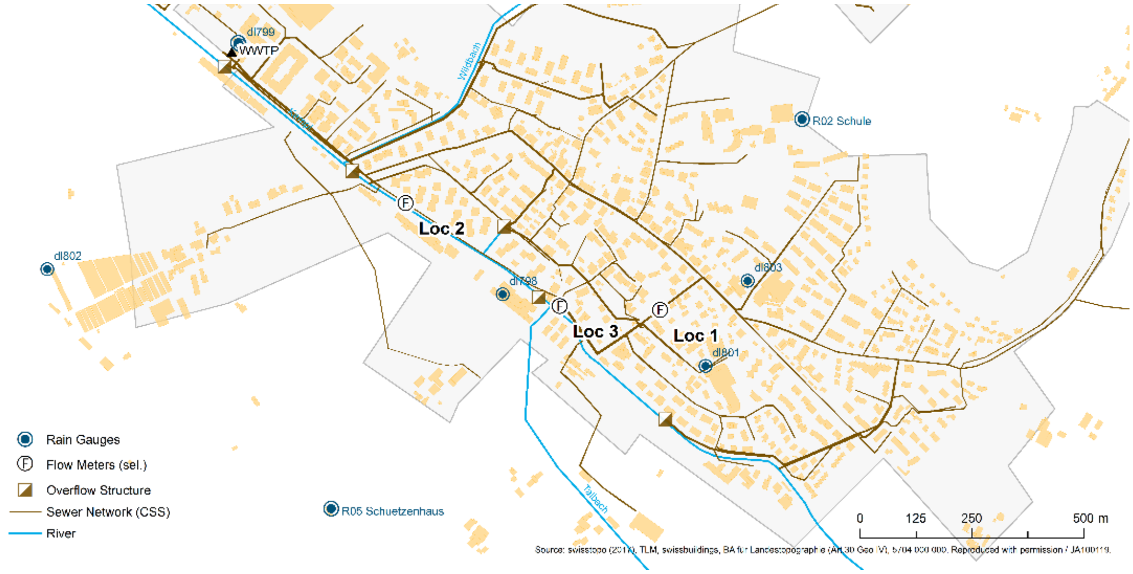

Figure 1: Layout of the case study in Fehraltorf, Switzerland. Sewer network, rain gauges and corresponding flow monitors (loc 1, loc 2, loc 3) are indicated.

Deterministic model and urban drainage data: We used data from the Urban Water Observatory, an initiative that provides long-term observations on rainfall/runoff processes with a very high spatial and temporal resolution in a real-life urban wastewater system of Fehraltorf, Zurich, Switzerland (Blumensaat et al. 2018). In Fehraltorf, storm and wastewater collection is realised through a gravity-driven, combined sewer system (27.1 km sewers; 10’600 inhabitants; 80 ha connected catchment area). Four non-controlled CSO structures with an area-specific storage capacity of 36.1 m^3 ha^{-1} discharge to a sensitive creek in case of hydraulic system overload (see Fig. 1). The plots for this abstract are created using the flow data generated by two rainfall events (over a 50 hr duration) collected at three locations.

Results and discussion

In this study, we find that calibration using spatially distributed data does not necessarily lead to better parameter estimates and consequently better model predictions (Figure 2b). We find that the parameters do not get constrained substantially when calibration is performed using multi-site flow observations. This, we show, can happen due to several compounding factors:

a) distributed water level measurements used as reference are mostly taken along the main collector, thus providing marginal added information in the context of upstream subcatchment behaviour in particular for moderate rain events that are not relevant for CSO activity;
b) there are throttle structures in the considered network which muzzle rainfall-runoff signals from upstream (constrained sensitivity);
c) there are large observational uncertainties, that can sometimes provide conflicting signals to the parameter inference procedures.

But, we do note that the multi-site data allow studying the correlation between observations and model errors at various location in order to understand whether this spatial dependence needs to be incorporated in the likelihood function (Figure 2a).

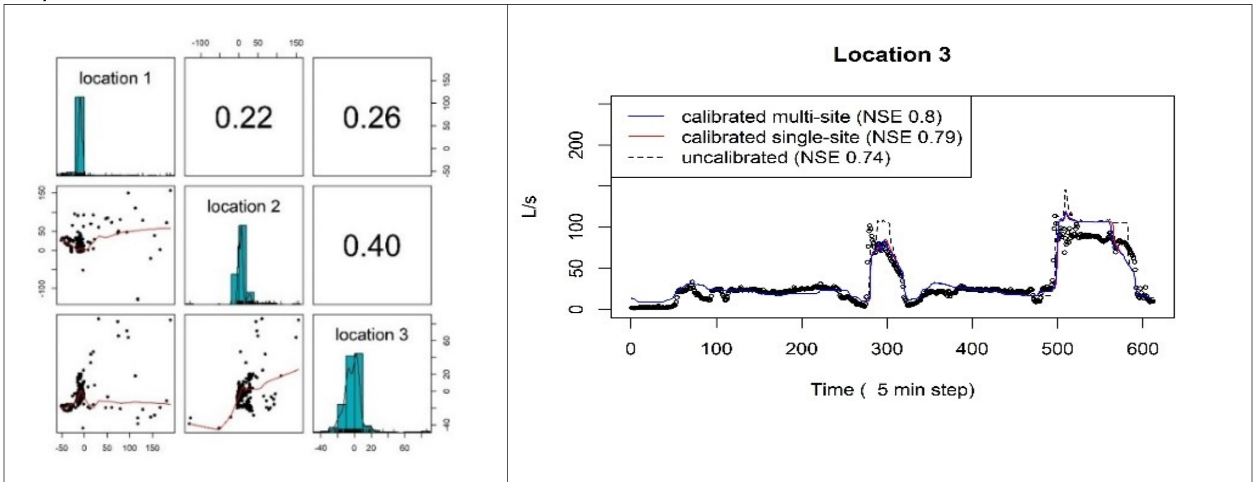

Figure 2a: Correlation between model errors. While one expects a strong correlation between *observations* (flow in L/s) at adjacent locations, we find there is only weak correlation between *model errors* (in L/s). Therefore we assume the errors to be spatially independent during inference. 2b: Model performance (here shown at location 3) does not show any significant improvements when parameters infered using data from multiple locations.

Conclusions and future work

We conclude that while distributed sensing of discharge and water level helps understanding the dynamics of the stormwater runoff, it is not always straightforward to make better predictive models of complex urban drainage networks using this data. This analysis - by delineating the bottlenecks towards informative inference - provides via-negativa recommendations for the placement of distributed sensors, when improved model performance is also one of the motivating factors for such data collection campaigns.

References

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