4th NORDIC CONFERENCE ON CLIMATE CHANGE AND ADAPTATION

Identification and Application of Surrogate Models for Urban Drainage Modelling

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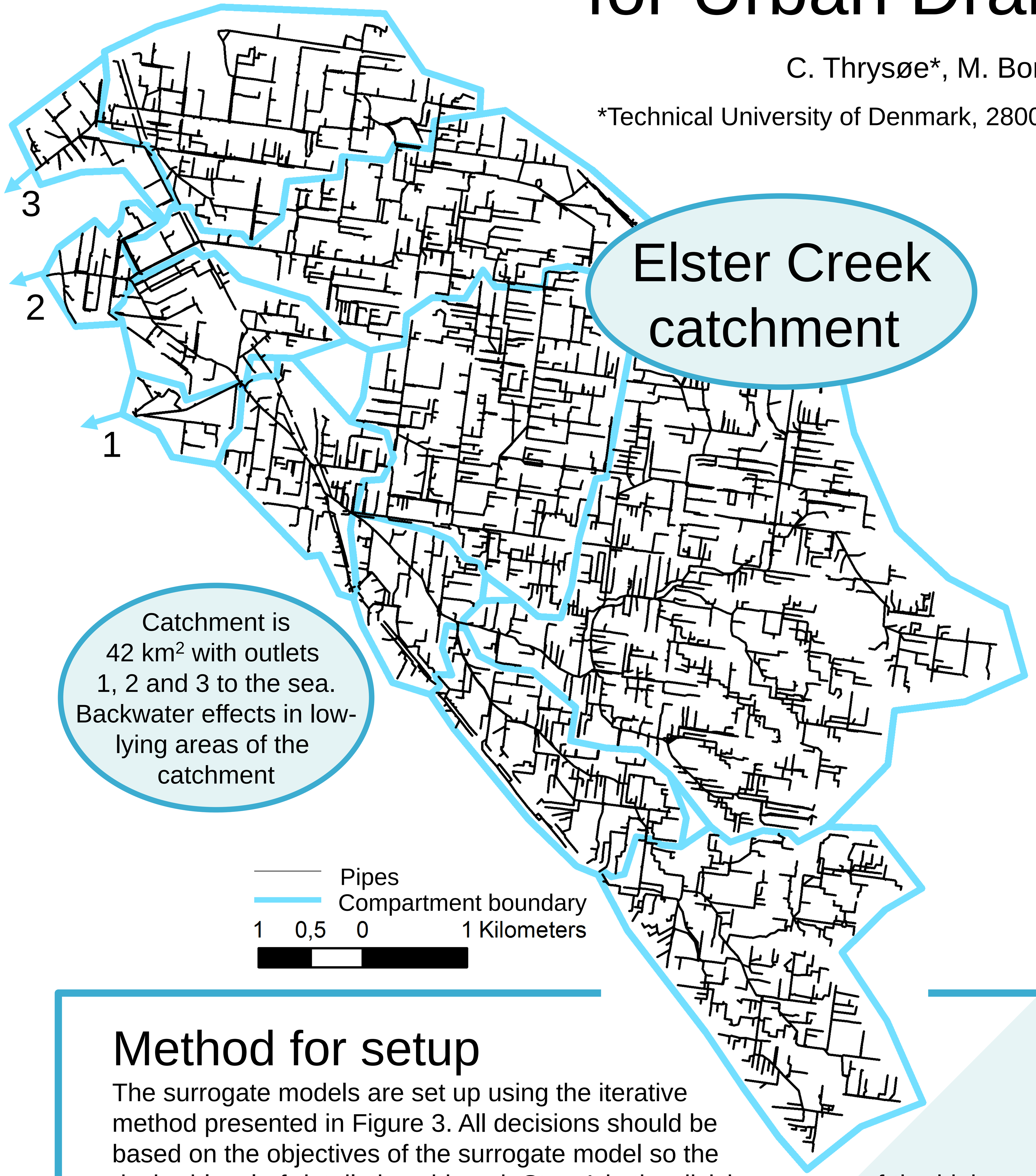

Background

Climate change and urbanization are expected to result in an increasing overloading of the urban stormwater systems in the future, leading to an increase in urban pluvial flood risk and combined sewer overflows[1]. To increase resilience, adaptation measures can be made. To test the feasibility of these, we need models. State-of-the-art flood models are distributed physically based models. However, these are impeded for some applications due to a high computational demand[2]. This study focuses on derivation and use of cheaper-to-run surrogate models, which can substitute high-fidelity models by mimicking the dynamic effects

Surrogate model structure

The high-fidelity model is lumped into compartments in which the volume of water is modelled as seen in Figure 1. The surrogate models will be based on a mass balance as illustrated in Figure 2. The volume within each compartment is governed by the in- and outgoing discharges[3,4].

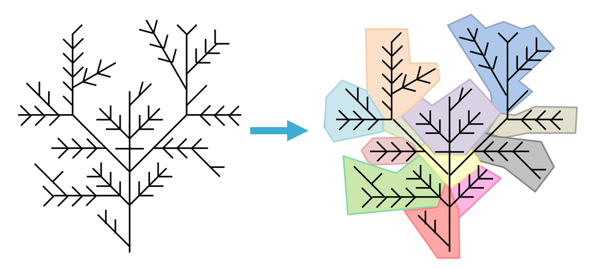

Figure 1: Principles of lumping distributed model into compartments

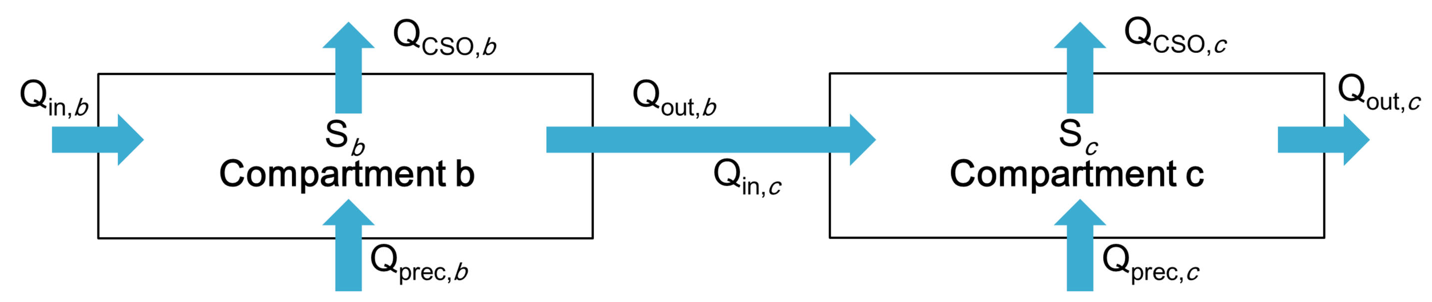

Figure 2: Conceptual drawing of surrogate model compartments

Method for setup

The surrogate models are set up using the iterative method presented in Figure 3. All decisions should be based on the objectives of the surrogate model so the desired level of details is achieved. Step 1 is the division of the high-fidelity model into compartments. This is done for the case study area Elster Creek catchment in Australia seen above. Step 2 is to create the training data for the surrogate models, this includes decisions on rain input to the high-fidelity model and the data types extracted. Figure 4 shows examples of input rain data to create the training data. Step 3 is to develop functions to describe the state of the compartments. If step 2 or 3 results in undesirable rating curves step 1 can be redone. Step 4 is to define the indicators and level of acceptability used to validate or reject the model in step 5.

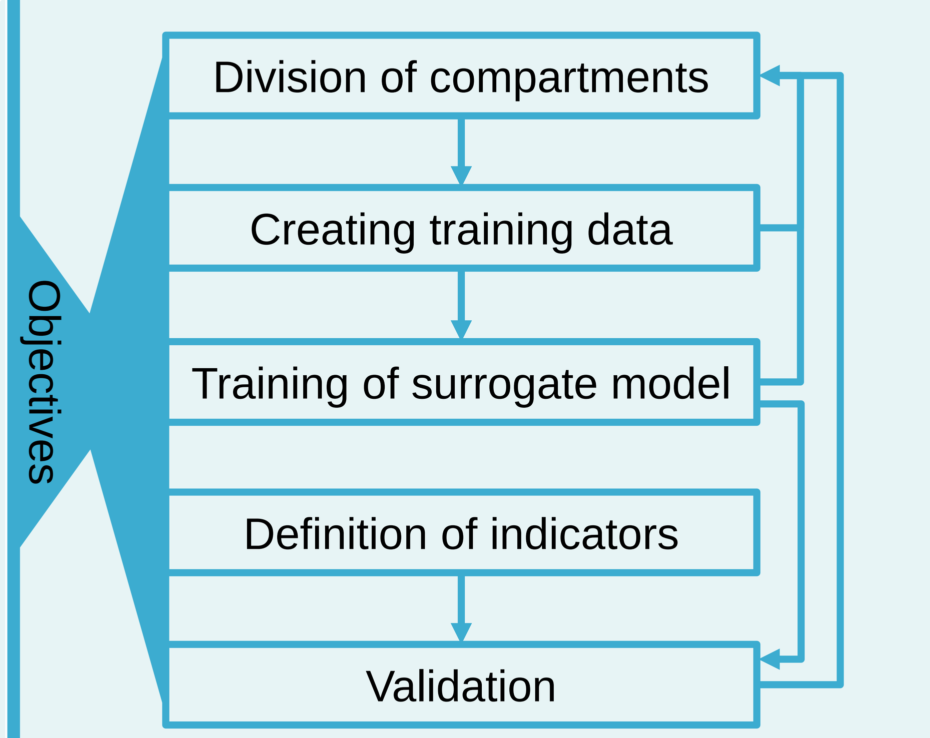

Figure 3: Procedure for setting up and testing surrogate models

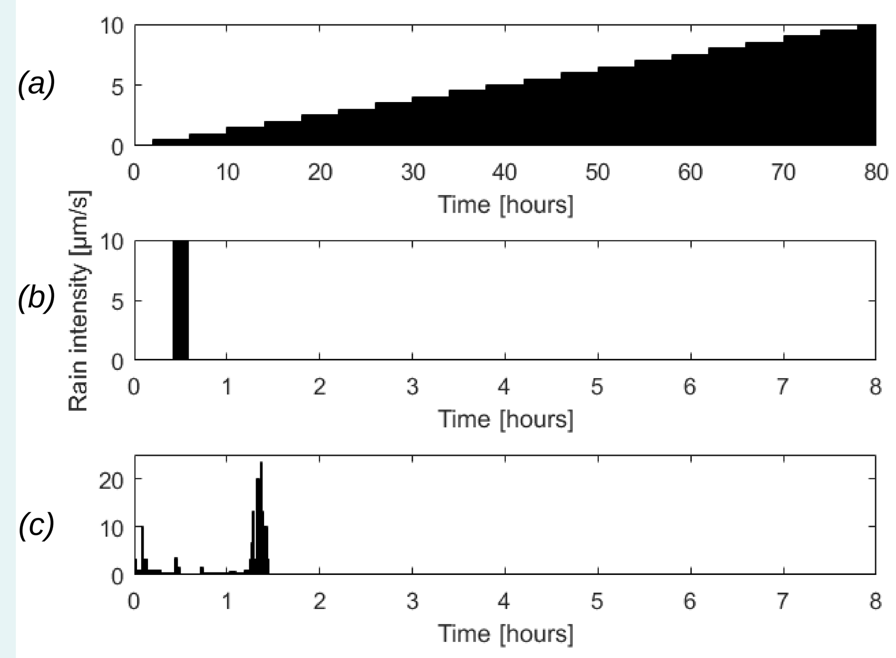

Figure 4: Example of different rain inputs to create training data. (a) staircase rain to extract steady-state points, (b) pulse rain (c) historical event

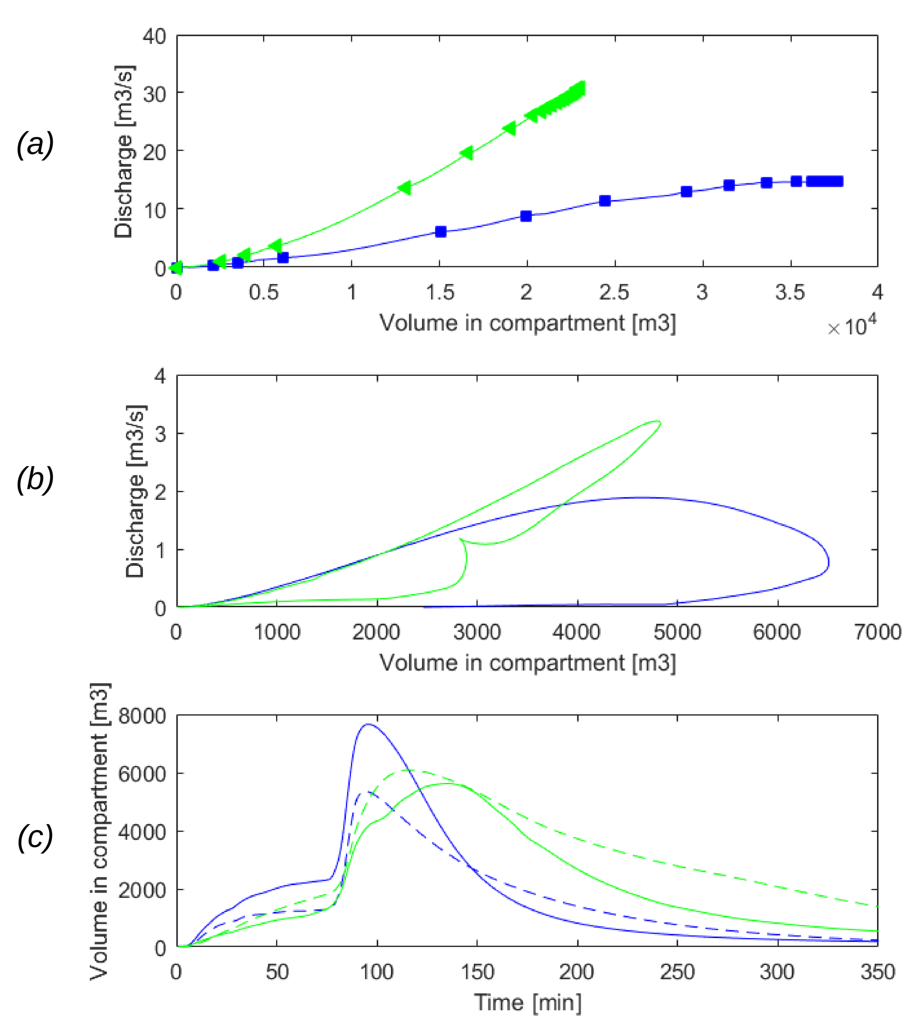

Figure 5: Step 3-7 (Fig. 3). (a) Rating curves created with rain in Fig. 4a, markers indicate steady-state points used for training data (b) Rating curves with rain in Fig. 4b. (c) Resulting discharges from high-fidelity model (full line) and surrogate model (dashed line) for rain in Fig. 4c using training data in (a).

	Time scale		
	Warning	Control	Planning
Application	- WWTP - Flood - …	- WWTP - RTC - …	- WWTP - Flood - …
Parameter	Surcharge discharge …	Volume Discharge …	Volume Discharge Surface discharge …
Indicator	Peak max Peak time …	Overall fit …	Surcharge frequency Annual loads …
Accept limit	NSE > $x_{threshold}$ PE < $x_{threshold}$ …	NSE > $x_{threshold}$ PE < $x_{threshold}$ …	NSE > $x_{threshold}$ PE < $x_{threshold}$ T_{diff} < $x_{threshold}$

WWTP Waste Water Treatment Plant
NSE Nash-Sutcliffe-Efficiency
PE Percentage Error
T Return period

Figure 6: Examples of Applications, with ideas for tested parameters, the indicators and limit of acceptability used for evaluation

Results

All steps in Figure 3 include some kind of decision making from the modeller. These choices are highly influential on output of the surrogate model. Preliminary key findings are:

- Step 1-3 are key in order to achieve the desired output of the study. In these steps the desired complexity of the surrogate model must be known to make fitting decisions. Selection of the suitable training data is difficult and the results vary as seen in Figure 5. All steps may have to be redone if no proper description can be made of the selected data.
- The indicators and level of acceptability in step 4 ultimately determine if the surrogate model should be rejected or accepted in step 5. These indicators should be highly determined from the intended application of the surrogate models as shown in the example given in Figure 6.

Preliminary results show great promise for the use of surrogate models in urban drainage modelling (e.g. Figure 5c applying the simple rating curves in 5a). It has been shown that the results of the surrogate models greatly depend on the choices made in the surrogate model setup. Thus it is important to clearly communicate the objectives and reasoning behind the model selection and setup. The author is currently working on developing methods for selection and definition of surrogate models based on application needs.

[1]Arnbjerg-Nielsen et. Al, (2015) Evaluating Adaption Options for Urban Flooding Based on New High-End Emission Scenario Regional Climate Model Simulations
[2]Wang et al, (2015) Urban Pluvial Flood Modelling; Current Theory and Practice
[3]Thrysøe et. al, (2016) Developing Fast and Reliable Flood models. Proceeding of the 9th NOVATECH Conference
[4]Wolfs et al, (2013) Development of a semi-automated model identification and calibration tool for conceptual modelling of sewer systems

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