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1 Identifying fit-for-purpose lumped surrogate models for large urban drainage systems using

2 GLUE

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10 Abstract

11 Distributed physically based models (DPMs) have become the standard tool for urban drainage modelling.
12 However, high computational demands limit these in applications where fast or multiple simulations are
13 needed. This paper presents simple fit-for-purpose cheaper-to-run surrogate models (SMs) for pipe
14 network simulations which are validated against a DPM. The SMs are set up by lumping the DPM network
15 into compartments in which the volume of water is governed by mass balances. Outgoing discharges to
16 downstream compartment(s) and surcharging are computed from unambiguous volume-discharge curves.
17 The SMs are applied on a 45 km² catchment, Elster Creek in Melbourne, Australia. The number of simulated
18 states and simulation times are reduced by approximately 3 and 6 orders of magnitude, respectively.
19 Different SM complexities are examined. The simplest SM using steady state training data performed well
20 with NSE of 0.98 for volume in the most upstream compartment. When emulating the aggregated
21 surcharge from that compartment, the SM captured all surcharge events correctly. NSE improved from 0.35
22 to 0.84 when subdividing the compartment into 17 subcompartments. Uncertainty of SM parameters was
23 examined using the Generalized Likelihood Uncertainty Estimation (GLUE) methodology. Two different
24 sampling methods were applied. Limits of acceptability for real-time control, warning and planning,

25 resulted in many accepted models upstream and few to none in downstream backwater-prone areas. All
26 applications showed SM uncertainty bands within expected uncertainty bands for DPM, supporting the use
27 of a simpler conceptual model in fit-for-purpose modelling in urban water systems when computational
28 demands of DPMs are prohibitive.

29 Keywords: Hydraulic modelling, surrogate models, urban drainage, computational time, uncertainty, GLUE

30 **1 Introduction**

31 Projections of climate change show an increase in frequency and magnitude of extreme rainfall. Coupled
32 with rapid urbanization, this will lead to increased loading of urban storm- and wastewater systems,
33 thereby increasing the risk of pluvial flooding and combined sewer overflows (IPCC, 2012; Semadeni-Davies
34 et al., 2008). To mitigate this risk, adaptation measures can be implemented by changing the infrastructure,
35 in the form of, e.g. bigger pipes, installation of basins, including local infiltration measures etc. (Zhou et al.,
36 2012). Designing adaptation measures requires models, typically in the form of distributed physically-based
37 models (DPMs). Dynamic adaptation using Model Predictive Control to optimize the use of the existing
38 systems storage capacity can also be applied (Lund et al., 2018). Real-time applications require models that
39 in seconds or minutes can produce forecasts of selected hydraulic states several hours into the future,
40 which is not feasible with DPMs, and the usage of DPMs for scenario development and design
41 optimization is also impeded due to the high computational time of the models (Henonin et al., 2013). As
42 reported in (Leitão et al., 2010), the computational time for this model type is typically longer than real
43 time, making them unfit for real-time modelling, questionable for warning purposes, and also prohibitive
44 when exploring many planning scenarios, although a few examples are available (Löwe et al., 2017; Rauch
45 et al., 2017). Hence many applications need a fast and numerically stable model with sufficient accuracy at
46 key locations in the catchment, and even though the development in computers computational speed
47 continues, this will not provide the orders of magnitude speed-up required in the foreseeable future. This

48 applies for planning purposes in at least two typical situations: 1) where city-scale planning purposes often
49 focuses on certain parts of the city while other parts are less interesting and hence DPM results are never
50 needed nor interpreted for many parts of the system, and 2) where calculation of pollution loads can be
51 done with sufficient accuracy using simplified hydraulic models (Vaes and Berlamont 1998, Johansen et al.,
52 1984). It also applies to forecast and control situations, where the uncertainty of the forecasts makes the
53 use of DPM models obsolete because the improved calculation accuracy does not lead to improved results
54 (Lund et al 2018).

55 Because many applications of urban flood models require multiple fast simulations, several attempts have
56 been made to reduce the computational time of the DPMs. One approach is to enhance computational
57 performance by optimising the usage of computational resources through e.g. parallelisation (Leandro et
58 al., 2014; Neal et al., 2010), but this requires that sufficient computational resources are available. Another
59 approach is to reduce computational costs by means of simplification. Simplified models will, however, not
60 be able to emulate the entire model space of the original models. Model errors are thus introduced when
61 going from the original High-Fidelity (HiFi) model to a simpler model. Choosing the level of simplification is
62 a trade-off between accuracy, acceptance of errors and computational time. This decision should be based
63 on the type of process simulated and the objective of the problem to define the level of details needed in
64 the required model output, the acceptable error margin and computational time allowed also known as fit-
65 for-purpose modelling (Beven, 2015; Blazkova and Beven, 2009; Haasnoot et al., 2014; Jamali et al., 2018;
66 Wright and Esward, 2013). Furthermore, the acceptable level of error introduced during a model
67 simplification process should be seen in relation to the typically rather large uncertainties in the model
68 input, such as rainfall data, and the errors between reality and the original model.

69 The methods of going from a HiFi model to a LoFi model can be divided into two main categories: LoFi
70 DPMs and conceptual models. LoFi DPMs are also physically-based but less detailed compared to the
71 original models (Razavi et al., 2012). Methods for going from a HiFi DPM to a LoFi DPM vary through

72 literature. Some methods reduce the numerical accuracy, i.e. use a coarser spatial/temporal grid size
73 (Fewtrell et al., 2011) or apply steady state (Jamali et al., 2018). Other reduce the number of physical
74 processes in the model e.g. by reducing the Saint-Venant equations to either the diffusive or kinematic
75 wave formulation (Fewtrell et al., 2011; Neal et al., 2010; Neelz, S. & Pender, 2013). Another approach is to
76 simplify the system itself via pruning, trimming and merging rather than the model formulation. Davidsen
77 et al. (2017) and Leitão et al. (2010) applied a combination of the above and conducted a 35 and 42 %
78 reduction of the network elements resulting in a 70 and up to 61 % reduction in computation time,
79 respectively. This method may, however, not be sufficient for a large number of applications, where a
80 speed-up of several orders of magnitude is needed.

81 Another branch of model simplification is to use a cheaper-to-run conceptual model (Razavi et al., 2012; Ye
82 et al., 2014). Results from the original model or measurements can be used to calibrate the conceptual
83 model and in some cases validate it if no measured data are available. This is a data-driven approach and
84 therefore the model does not need to consider any physical processes. These models are denoted
85 surrogate models (SMs) (Razavi et al., 2012; Meirlaen et al., 2002). Most conceptual models apply the
86 storage principle (Chow et al., 1988; Vaes, 1999; Vanrolleghem et al., 2009; Wolfs et al., 2013). The simplest
87 model assumes that there is a linear and unambiguous relationship between the storage and the discharge,
88 which is the dominating model component for flow routing for real-time control applications (e.g. Löwe et
89 al., 2016; Joseph-Duran et al., 2014; Ocampo-Martinez, 2013). However, as pointed out in Chow et al.
90 (1988), Vaes (1999) and Wolfs et al. (2013) the relationship between the storage and the discharge might
91 be influenced by a lot of factors, such as attenuation and backwater, resulting in a non-linear ambiguous
92 relationship. Coping with this has been handled by using different methods from the static-dynamic storage
93 principle (Cunge, 1969; Vaes, 1999) relating the dynamic storage to the inflow, the combiner-splitter
94 approach (Solvi et al., 2005), retention capacity and storage method in the SMUSI model (Muschalla et al.,
95 2006), a combination of the two (Vanrolleghem et al., 2009) and multiple linear segments combined with
96 transfer functions (Wolfs et al., 2013). The surrogate models in the current study are primarily based on the

97 use of non-linear unambiguous storage-discharge relationships as previously used by Vaes (1999) and Wolfs
98 et al. (2013). This routing concept, as well as the model engine used in the current work, is already being
99 used in real time applications for forecasting flows in the drainage system (Borup et al., 2017). As opposed
100 to the previously mentioned studies, we expand the model to also include surcharging to the surface. For
101 access to the code of the model engine see (Borup, 2018).

102 Hence the aim of this study is to test surrogate models of varying complexity for urban drainage networks
103 (pipe, channels, etc.) hydraulic modelling with the objective of identifying suitable models for real time
104 control, warning and planning purposes. First the surrogate model setup is examined and benchmarked
105 against the original 1D HiFi network model. Then the uncertainty of the surrogate model parameters, i.e.
106 the variability of the storage-discharge relationship, is examined by using the General Likelihood
107 Uncertainty Estimation (GLUE) methodology and the results of the surrogate models are evaluated from a
108 limit of acceptability approach for different application areas.

109 **2 Methodology**

110 **2.1 Surrogate model formulation**

111 The surrogate models are set up by lumping big parts of the distributed drainage system into
112 compartments, as illustrated in Figure 1. Compartments are delineated areas in which the volume of water
113 is modelled with a mass balance by the in- and outgoing discharges. Each compartment can receive water
114 from multiple upstream compartments and discharge to multiple downstream compartments, outlets and
115 surface locations. The division of compartments are subjective and the surrogate models can thus be set up
116 to fit the given modelling purpose. The main guideline used for the compartment delineation in the current
117 work is to place flow-limiting or altering structures, such as throttle pipes, weirs and nodes from which the
118 water can flow in multiple directions along compartment boundaries, since this helps to ensure some

119 causation between the volume of water in the compartment and the discharges out of this. This minimum
 120 requirement can then be supplemented with states that have particular importance for the modeller.

121

122 *Figure 1: Example of dividing distributed physically-based model into compartments.*

123 Figure 2 shows two compartments in series. Here compartment n can discharge water to the downstream
 124 compartment $n+1$. As opposed to (Borup et al., 2017) water can also surcharge to the surface, Q_{spill} . The
 125 model boundaries are set so that this surcharged water cannot re-enter the compartments but simply
 126 disappears out of the model. Therefore this surcharging is referred to as the spilling discharge as water
 127 *spills* out of the model (DHI, 2014a). Moreover, the SMs only represent the drainage network while the
 128 rainfall runoff entering the SMs (Q_{run} on Figure 2) is obtained from the rainfall runoff simulations of the
 129 original HIFI model. This choice has been made to keep the focus on the simulation of the drainage network
 130 since this is the time consuming part of a 1D network DPM simulation. The discharges out of each
 131 compartment are only dependent on the storage volume in the compartment, which means that backwater
 132 from downstream compartments cannot be taken explicitly into account.

133 *Figure 2: Conceptual setup of surrogate model compartments n and $n+1$. The figure illustrates a setup*
 134 *where each compartment has exactly one discharge to the downstream compartment and one spilling*
 135 *discharge, but multiple connections are possible.*

136 The discharges out of a compartment are governed by volume-discharge curves which are generated from
 137 the SM parameters. A total of $2 \times L \times m$ parameters are used to describe one SM compartment, where L is
 138 the number of volume-discharge parameter pairs and m is the number of connections out of the
 139 compartment. Each volume-discharge parameter pair consists of a volume parameter and a discharge
 140 parameter. In-between the volume-discharge pairs the SM interpolates using piecewise linear functions, f ,
 141 to create continuous volume-discharge curves for each connection. The term connection is used to describe
 142 outflows in the form of compartment-to-compartment, $Q_{out,n}$ or compartment-to-surface, $Q_{spill,n}$. $Q_{spill,n}$ can
 143 both be in terms of spill to the surface and combined sewer overflows (CSOs). Spill to the surface, weirs and
 144 CSOs will have similar volume-discharge curves as they need to exceed a certain threshold of volume
 145 before the discharge begins. The piecewise linear approach has the advantage that non-linearities due to,
 146 e.g. overflows and flow constraints can be taken into account. In this study we derive the volume-discharge
 147 parameter pairs that are required to estimate the various f 's from DPM result files. This process will be
 148 referred to as the training of the surrogate model. The expression for storage for compartment n , S_n , from
 149 Figure 2 is given as:

$$\frac{dS_n}{dt} = Q_{run,n}(t) + Q_{in,n}(t) - Q_{out,n}(t) - Q_{spill,n}(t) \quad (1)$$

150 where t is the time. $Q_{run,n}$ is the water routed to the sub-surface system, i.e. identical for the DPM and the
 151 surrogate model, and $Q_{out,n}$ and $Q_{spill,n}$ are calculated as function of the volume in compartment n , S_n , using
 152 their own individual piecewise linear function as illustrated in next the next paragraph.

153 2.1.1 Training of the surrogate model

154 The training data are produced by applying rain data to a DPM and then extracting the resulting volumes
 155 and discharges from the model results. This process is illustrated in Figure 3(a-c) when using a constructed
 156 staircase rain as rainfall data, and Figure 3(d-f) when using a historical rain series instead.

157

Figure 3: Process of extracting steady state training data (a-c) and dynamic training data (d-f): (a) Input data to the DPM: a staircase rain, (b) DPM resulting volume over time with volume steady state points, (c) steady state volume-discharge points produced by the DPM and equivalent volume-discharge parameter pairs with linear interpolation performed by the SM. (d) Input data to the DPM: a series of historical rain events, (e) DPM resulting volume over time, (f) Cloud of volume-discharge points produced by the DPM and equivalent 3 volume-discharge parameter pairs fitted to represent the shape of the cloud with linear interpolation performed by the SM.

Using a constructed staircase rain for producing the training data allows for the system to reach close to steady-state conditions at the end of each step of the staircase. This allows for extracting un-ambiguous volume-discharge relationships with just a single simulation. The drawback of using these steady state data points is that the steady state conditions are only reached when backwater reaches its maximum, which

169 implies that the discharge out of a compartment might be underestimated for rain events that do not cause
170 backwater in the system. If, on the other hand, historical rain series are used, the dynamic storage and
171 discharge responses are represented in the training data. But in this case much more data needs to be
172 produced and these training data will show a volume-discharge relationship that is far from un-ambiguous,
173 as illustrated on Figure 3(f). Since we are only dealing with model-to-model simulations and not real
174 observations, any ambiguity caused by uncertainties of the input data e.g. distribution of rainfall is not
175 included.

176 The number of volume-discharge parameter pairs, L , can be varied. Since the steady-state data points in
177 Figure 3(c) describe an un-ambiguous volume-discharge curve, these steady state volume-discharge points
178 can be used directly as parameter pairs for the SM. Often the shape of the curve can, however, be
179 described sufficiently accurate with much fewer points. In this study this reduction is made using a generic
180 optimizer, *fmincon*, from (MATLAB and Statistics Toolbox Release 2015b, 2015) to search for the L volume-
181 discharge pairs that leads to the lowest squared difference between the full set of training data points and
182 the linear interpolation between the reduced number of points.

183 2.1.2 Surrogate model setups

184 When setting up a SM decisions need to be made on the coarseness of compartment resolution, the
185 number of volume-discharge parameter pairs for each connection out of the compartments, what input
186 data to use for the DPM to compute the training data and if any additional functions or parameters should
187 be included to describe, e.g. attenuation and other hydraulic constraints. The importance of these decisions
188 is explored in the following using five different SM setups:

- 189 • $SM_{\text{steady},20}$ uses $L=20$ and steady-state training data.
- 190 • $SM_{\text{steady},4}$ uses $L=4$ and steady-state training data.
- 191 • $SM_{\text{steady},4,\text{div}}$ uses $L=4$ and steady-state training data. One compartment is further divided into 17
192 subcompartments to study the influence of compartment resolution.

- $SM_{\text{steady},4+\text{UH}}$ uses $L=4$ and steady-state training data and additionally, to capture the dynamic behaviour seen in Figure 3, we also apply a unit hydrograph (UH) as a post-processing step. The concentration time is fitted manually to each compartment by applying a pulse to the DPM and estimating the travel time of the peak.
- $SM_{\text{dynamic},4}$ uses $L=4$ and historical events as training data. This consists of multiple volume-discharge points as illustrated in Figure 3(f). The parameters are found by using the same volume parameters as for $SM_{\text{steady},4}$ and then calculating the corresponding discharge parameters as the mean of the discharge points of the dynamic training data with approximately the same volume.

2.2 MIKE URBAN model formulation

The HiFi DPM used in this study is a MIKE URBAN model (DHI, 2014a). This software from DHI simulates unsteady flows in a pipe network with altering free surface and pressured flow conditions. The hydrodynamic computation is based on an implicit, finite difference numerical solution of the 1D Saint-Venant equations. The computational grid in MIKE URBAN consists of alternating Q - and h - points in each pipe, i.e. points where the discharge, Q , and water level, h , are computed at each time step. There is a minimum of three computational points in each pipe and h is furthermore computed for each node. The model automatically generates the computational grid based on the velocity condition (DHI, 2014a). To get an overview of the amount of surcharged water from the drainage network, all nodes in the models are set to spilling nodes, i.e. water can spill to the surface from the drainage network, but it cannot re-enter the drainage system. MIKE URBAN rainfall runoff computation is a separate simulation from where the hydrologic load is used as input to the pipe network. The rainfall runoff simulations are several orders of magnitude faster than the network simulations. The rainfall runoff model applied in this study is model type B – kinematic wave (DHI, 2014b).

215 **2.3 Uncertainty analysis**

216 Every time we apply a model and go from reality to a model space we introduce uncertainties (Refsgaard et
217 al., 2006). In this project there are uncertainties both related to the DPM and the SM. The three major
218 sources of uncertainties in the surrogate models are the model formulation, structure and parameters.
219 Especially the model structure as the SM is highly simplified compared to the DPM. This is both in terms of
220 the equations used to describe the movement of water in the network and also the delineation of the
221 compartments. The training data used can also be a large source of uncertainty as this determines the
222 volume-discharge parameters in the SM and sometimes the structure of the SM. To assess the possible
223 errors introduced by these uncertainties the Generalized Uncertainty Estimation (GLUE) methodology is
224 applied (Beven and Binley, 1992).

225 GLUE is a methodology to identify models that are acceptable or *behavioural* model setups from a set of all
226 possible models based on user defined limits of acceptability. It thus deals with the problem of multiple
227 acceptable models (the equifinality thesis). In GLUE the model errors are handled implicitly by assuming
228 similar characteristics of errors in calibration and in prediction. According to Beven (2009) the decisions
229 required to apply the GLUE framework involve the following: (i) Define model structure(s) (ii) Decide which
230 model parameters should be varied (iii) Define prior distribution of model parameters (iv) Decide method
231 for sampling the model space (v) Define likelihood measure (vi) Decide limit of acceptability. After this a
232 large sample of model realizations can be generated with Monte-Carlo simulations.

233 The most common application of GLUE is to condition models on measured observations (Aronica et al.,
234 2005; Beven and Binley, 2013; Thorndahl et al., 2008). However, in this study we will condition the
235 surrogate models on the original HiFi DPM instead of observations as also done by e.g. Meirlaen et al.,
236 (2002), Vaes (1999) and Wolfs et al. (2013).

237 2.3.1 Selection of model structure and parameters for GLUE

238 The DPM is run for a series of historical rain events resulting in a swarm of scattered volume-discharge
239 points due to the ambiguous volume-discharge relationships of a dynamical simulation, as shown in Figure
240 3(f). Note that for the highest values of volume and discharge there is a lower sample size due to the
241 rareness of these extreme events. In the GLUE analysis the discharge parameters are varied from the
242 distribution of discharge points for fixed volume parameters. The number of volume-discharge parameter
243 pairs will be $L=4$ for each connection. The volume-discharge pairs for surcharging and the volume
244 parameters will be fixed as the ones identified for $SM_{\text{steady},4}$.

245 2.3.2 Identifying prior parameter distributions

246 To identify the discharge parameter distributions, the volume axis is divided into ten equally sized bins. For
247 each of the four volume parameters in each connection, the suitable volume bin is identified. Hereafter a
248 vertical histogram showing the density of the discharge point variation in that bin is computed. These
249 histograms are used to estimate a triangular distribution for each discharge parameter by letting the mode
250 equal the median of the data and min and max values equal the corresponding smallest and largest value,
251 respectively.

252 2.3.3 Sampling methods

253 The histograms for each of the $L=4$ discharge parameters are used to estimate triangular distributions, from
254 where $L \times 500$ discharge parameters are sampled for each connection in each compartment. We apply two
255 different sampling types: *sampling type 1* and *sampling type 2*.

256 *Sampling method 1* allows for all $L=4$ discharge parameters to vary independently of each other. This entails
257 that the slope and shape of the volume-discharge curves will vary freely within the span of the training
258 data. For this sampling method It might occur that the n^{th} discharge parameter will be higher than the
259 lowest value for the $(n+1)^{\text{th}}$ discharge parameter, i.e. a negative slope in the volume-discharge curve. Such a
260 parameter constellation will imply that the discharge will decrease as a result of an increasing volume,

261 which conceptually is wrong for this type of model. Such a parameter constellation is thus rejected and not
262 included in the sample.

263 Attempting to explore the entire span of possible outcomes caused by variation of parameters, we
264 introduce *sampling method 2*. *Sampling method 2* applies the same discharge parameters as *sampling*
265 *method 1*, but sorts them from low to high. This means that for all compartments and compartment
266 connections, e.g. the smallest set of discharge parameters will be applied together for the same simulation.
267 By correlating all the discharge parameters in the system we aim to cover the largest possible variation of
268 discharge in the system for with a relatively small sample size. The two types of parameter sets are then
269 used in two separate Monte-Carlo simulations for the SM.

270 The two sampling methods are expected to provide an outlook on different types of uncertainties in the
271 system. *Sampling method 1* represents the full uncertainty of the SM parameters and parameter
272 constellation and is thus the most flexible in this regard. However, moving downstream errors due to
273 parameters might be cancelled through the system. Hence, applying this method would potentially
274 underestimate the variation observed if using actual measured data. *Sampling method 2* on the other hand
275 represents the largest possible difference in the discharge output at downstream compartments and thus
276 represents the other extreme. By applying both sampling methods we expect to cover the range of possible
277 outcomes arising if we had had actual measurement data available.

278 **2.3.4 Defining likelihood measure**

279 A uniform likelihood function is applied as seen in Equation (2). This implies that the likelihood or degree of
280 membership is equal for all models which are within the accepted range.

$$L(\theta|\psi_i^*) = \begin{cases} 1 & \text{if } a \leq \psi_i^* - \psi_i(\theta) \leq b \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

281 where $L(\theta|\psi_i^*)$ is the likelihood, θ are the model variables shown in Table 1, ψ_i^* is the probability of the
 282 observed value, $\psi_i(\theta)$ is the probability of the simulated value and a and b are lower and upper limits of
 283 acceptability.

284 2.4 Performance measures

285 We use the following measures to quantify the performance of the SMs: Nash-Sutcliffe Efficiency (NSE),
 286 Percent Error in Peak (PEP), Peak Difference (PDIFF) and Critical Success Index (CSI) (Bennett et al., 2013)
 287 (3-6). From this we further develop Peak Time Difference (PTDIFF) and Percent Error in Accumulated
 288 Discharge (PEAD) (7-8):

$$NSE = 1 - \frac{\sum_{t=1}^N (x_{DPM,t} - x_{SM,t})^2}{\sum_{t=1}^N (x_{DPM,t} - \bar{x}_{DPM,t})^2} \quad (3)$$

$$PEP = 100 \cdot \frac{\max(x_{DPM,i}) - \max(x_{SM,i})}{\max(x_{DPM,i})} \quad (4)$$

$$PDIFF = \max(x_{DPM,i}) - \max(x_{SM,i}) \quad (5)$$

$$CSI = \frac{\text{hits}}{\text{hits} + \text{missed} + \text{false positives}} \quad (6)$$

$$PTDIFF = t_{peak,DPM,i} - t_{peak,SM,i} \quad (7)$$

$$PEAD = 100 \cdot \frac{\sum_{t=1}^N (x_{DPM,t}) - \sum_{t=1}^N (x_{SM,t})}{\sum_{t=1}^N (x_{DPM,t})} \quad (8)$$

289 where $\bar{x}_{DPM,t} = \frac{1}{N} \sum_{t=1}^N x_{DPM,t}$, N is the length of the records, $x_{DPM,t}$ is the output from the HiFi DPM at time
 290 t , $x_{SM,t}$ is the output from the SM at time t , i is the peak number.

291 **3 Case study**

292 **3.1 Elster Creek Catchment**

293 The Elster Creek Catchment is located in Melbourne, Australia, and covers an area of approximately 45 km².
294 The area mainly consists of residential areas and has been subject to many large floods in recent years
295 (Olesen et al., 2017). A 1D drainage network DPM of the catchment area presented in (Davidsen et al.,
296 2017) is shown in Figure 4(a). The drainage network is a separate stormwater collection system and there
297 are therefore no CSOs in the catchment. The model consists of 10011 nodes, 10415 links and 12113 sub-
298 catchments, there are six weirs and no basins, pumps or control in the model. The weirs are internal
299 overflows over which the water flows when the system is under high hydraulic loading and thus
300 hydraulically speaking works just as a CSO. The network primarily consists of circular pipes. A large
301 rectangular open channel connects the mid-eastern part of the catchment to the main outlet to the sea.
302 The model contains three outlets to the sea. The main outlet is located in north-west and the two
303 additional outlets are located just north and south of the main outlet. The southern outlet is connected to
304 the open channel by a closed rectangular channel and the northern outlet is connected to the circular pipe
305 network by a closed rectangular channel. The given DPM consists of 44718 calculation points, i.e. states of
306 q and h .

Figure 4: (a) Map of the Elster Creek catchment in Australia with pipes from the MIKE URBAN model presented in (Davidsen et al., 2017) and division into 13 compartments (b) further subdivision of compartment SM1 to 17 subcompartments

The catchment is divided into 13 compartments as shown in Figure 4(a). When dividing the compartments it is ensured that all flow-limiting or altering structures (throttle pipes, weirs, pumps etc.) are placed on compartment boundaries. This is why compartment SM7 is very small; it has weirs both up- and downstream. The connections SM6-SM7 and SM7-SM8 are weir connections with the same hydraulic behaviour as CSO weirs in combined sewer systems. The computational grid has now been reduced from 44718 states to 13. Compartment SM1 represents 1009 nodes and 983 links and 4361 states in the DPM. If SM1 is further subdivided into 17 compartments as shown in Figure 4(b) additional 16 states are used. Hence the number of states in the SMs is close to 3 orders of magnitude lower than in the HiFi models and the computational scheme is reduced from iterative solution of partial differential equations to simple lookup in tables and interpolation.

320 **3.2 Rain data**

321 **3.2.1 Training data**

322 **Steady state data**

323 For identifying the volume-discharge parameter pairs for the steady state model a staircase rain as shown
324 in Figure 3(a) is applied with intensities ranges from 0.5 to 10 $\mu\text{m/s}$, corresponding to 1.8 to 36 mm/hour.
325 This range is defined for the catchment to cover system states from nearly empty to exceeding capacity i.e.
326 surcharging. For this catchment each step is set to 4 hours for achieving steady state conditions.

327 **Rain event data for $\text{SM}_{\text{dynamic},4}$ and GLUE**

328 37 years of rain data from a tipping bucket rain gauge is used (Madsen et al., 2017). From this series 45
329 events are extracted; the 15 events with the largest intensities recorded for durations of 30 and 180
330 minutes, respectively, and the 15 events with the largest depth. An event definition of a minimum of 10
331 hours of dry weather between events is used.

332 **3.2.2 Validation data**

333 For validation 52 year of rain data are applied (Australian Bureau of Meteorology, 2015). Similarly 3 x 15
334 events covering the largest depth, intensity over 30 min and 180 min are extracted. Two events were found
335 to be outside of the calibration range of the SMs and were discarded. This could have been avoided by
336 using higher rainfall intensities during the model calibration.

337 **3.3 Limits of acceptability**

338 Limits of acceptability are set up to distinguish between behavioural and non- behavioural models based on
339 a (subjective) assessment of what is considered a well calibrated model. There are no formal guidelines on
340 how to evaluate models in urban drainage systems. However, a book on code of practice in urban drainage
341 modelling from (Wallingford Procedure Users Group, 1993) contains the following requirements for
342 verification of a model with flow survey data:

- 343 i. Peak flow rate from -15% to +25%
- 344 ii. Volume of flow from -10% to +20% over the period for which the observed flows are obtained
- 345 iii. Surcharge should be from -0.1 m to +0.5 m
- 346 iv. The general shape of the two hydrographs should be similar

347 Moreover models should pass a routine stability test including not exceeding an overall mass balance error
348 of 10% and flooding events that excess 25 m³ should be verified by evidence of an actual flooding. If all of
349 the above are valid for 2/3 of the events a model is considered validated. This evaluation scheme is, of
350 course, intended for model-to-observations comparisons but we can still use this as an initial guide for our
351 limits. We will include (i) with PEP for Q_{out} , (ii) is included with PEAD for Q_{out} , (iii) is not a direct output of the
352 surrogate models and hence PEP, PTDIFF, PEAD, CSI are used instead for the Q_{spill} and (iv) is included by
353 considering NSE. The limits will be conditioned on the DPM from the requirements of three different
354 applications; RTC, warning and planning, see Table 1. Since the conditioning is from model to model the
355 limits are set to be stricter than those for calibrating models to real observational data. Since the SM is only
356 able to model volumes and discharges, limits on pollutant loads, water levels, velocities etc. that might be
357 relevant is not included.

358 As previously discussed, models for RTC applications need to be able to predict the distribution of water in
359 the network at all times with sufficient accuracy, with high emphasis on catching the dynamical behaviour
360 of the system. Hence, limits of acceptability for this type of application are set for the discharge and volume
361 in the compartments. This can be used as input for developing a control strategy and to monitor the system
362 capacity during control. The spilling discharge is typically of less importance in RTC, although it is a focus of
363 current research efforts (e.g. Lund et al., 2018; University of Sheffield, 2018), and is therefore not included
364 in the present study. NSE is used as the performance measure for both discharge and volume while PEP is
365 used for the volume only.

Warnings can be important for the Waste Water Treatment Plant (WWTP) for, e.g. reducing the hydraulic loading before a storm and for flooding purposes for implementing adaptive measures to reduce damage costs. For the WWTPs it is important that the model is able to predict the magnitude and timing of the peak to the treatment plant and for flood warning, likewise the magnitude of the peak discharge to the surface and timing. Thus, the peak magnitude and timing are essential and hence PEP and PTDIFF are included for both the discharge and the spilling discharge in the limits of acceptability for this application.

For planning applications the models must be able to give an accurate prediction of the accumulated discharges to the treatment plant and the surface. Thus, limits of acceptability are set for PEAD for the discharge and surcharge. Moreover, the model must be able to give an accurate statistical representation of extremes and hence CSI for spilling discharge is applied. Since the DPM only covers a separate stormwater collection system, no limits will be set on CSOs as there are none of these in the system.

Table 1: Limits of acceptability for the three applications: RTC, Warning and Planning together with the number of accepted models for each limit and application for SM1 using sampling method 1 and 2, respectively.

		# accepted models					
	θ	Measure	Limit	<i>Sampling method 1</i>		<i>Sampling method 2</i>	
RTC	Q_{out}	NSE	>0.8	500	437/500	500	417/500
	S	NSE	>0.8	437		417	
		PEP	<30%	489		470	
Warning	Q_{out}	PEP	<25%	500	496/500	500	486/500
		PTDIFF	<15min	500		500	
	Q_{spill}	PEP	<50%	496		486	
		PTDIFF	<15min	500		500	
Planning	Q_{out}	PEAD	<25%	500	386/500	500	343/500
	Q_{spill}	PEAD	<25%	386		343	
		CSI	>0.90	500		500	

380 4 Results

381 4.1 Computational time

382 The DPM network simulations was performed with dynamically adjusted timesteps ranging from 1 second
383 to 1 minute and saving timestep of 1 min. The total number of outputs given by the DPM is nearly 55000
384 consisting of node water levels, weir discharges, node spilling discharges, link water levels, link discharges
385 and link velocities at the 44718 locations in the network. The SM was computed using fixed 1 min
386 calculation and saving timesteps. The total number of outputs given by the SM is 44 consisting of volumes,
387 discharges and spilling discharges at the 13 locations in the network.

388 A simulation of one event with three peaks and a duration of 31 hours took 3.3 hours to compute for the
389 DPM for the entire catchment. This was reduced to 8.5 milliseconds with the SM, which is a speedup of
390 $1.4 \cdot 10^6$. To estimate the influence of the amount of output data saved from the DPM the same simulation
391 was performed without saving any output data. This reduced the computational time for the DPM with
392 almost an hour and thereby reducing the SM speed-up to $9.9 \cdot 10^5$. Both models were run on the same PC
393 using a single core only.

394 4.2 Examination of Surrogate Model Structure

395 The five different surrogate model setups (presented in Section 2.1.2) are here tested on compartment
396 SM1 (see Figure 4). The spilling discharges from the 17 small new compartments in $SM_{steady,4,div}$ are
397 aggregated into a single time series to allow for a direct comparison with the other surrogate model setups.

398 Figure 5 shows the resulting volume, discharge and surcharge, respectively for the SMs and DPM for a
399 selected demonstration event (one of the validation events). $SM_{steady,20}$ is not shown for visual reasons as it
400 cannot be distinguished visually from the results from $SM_{steady,4}$. The top figure shows that all SMs except
401 $SM_{steady,4+UH}$ are emulating the DPM well in terms of volume in the compartment. The $SM_{steady,4+UH}$ is higher
402 in volume as water is retained in the compartment due to the unit hydrograph. Of all the surrogate models

403 $SM_{\text{steady},4,\text{div}}$ seems to have the best fit. For the discharge, the pink band shows a $\pm 23\%$ margin of the DPM
 404 results corresponding to the overall pipe discharge uncertainty found by Hansen and Liu (2004) by using
 405 Monte-Carlo simulations and a 84% confidence level. It is seen that all the SMs are within this uncertainty
 406 band and again $SM_{\text{steady},4,\text{div}}$ has the best fit. The surcharge is more difficult to model as it is a more dynamic
 407 and local process. All SMs are able to catch the overall behaviour, but only $SM_{\text{steady},4,\text{div}}$ is able to capture the
 408 peak with high accuracy.

409 — DPM, — $SM_{\text{steady},4}$, - - $SM_{\text{steady},4,\text{div}}$, - - $SM_{\text{steady},4+\text{UH}}$, - - $SM_{\text{dynamic},4}$, $\pm 23\%$ MU

410 *Figure 5: Resulting volume, discharge and surcharge over time for a selected demonstration event for the*
 411 *five different SM structures and DPM for compartment SM1.*

412 To further demonstrate the differences between the SMs, resulting volume-discharge curves for the SMs
 413 are plotted for the same demonstration event in Figure 6. Here the dynamic behaviour of the DPM is clear.
 414 Figure 6(a) shows the difference between $SM_{steady,4}$ and $SM_{dynamic,4}$ for Q_{out} . The SMs are very similar, so for
 415 this event it appears that one can use both steady state and event based training data. Figure 6(b) shows
 416 the DPM and $SM_{steady,4+UH}$. Here it is seen that the $SM_{steady,4+UH}$ volume-discharge curve is ambiguous, but
 417 the fit to the DPM curve is not good and results in larger volumes as also noted before. Figure 6(c) shows
 418 the volume-discharge curve for $SM_{steady,4,div}$ when all the 17 smaller compartments are combined into one
 419 graph. The behaviour of DPM is much better captured when increasing the compartment resolution as also
 420 seen in Figure 5. Figure 6(d) shows the volume-surge behaviour for all four models. $SM_{steady,4}$ and
 421 $SM_{dynamic,4}$ are both on the same line. $SM_{steady,4+UH}$ has a much larger volume for the surcharging. $SM_{steady,4,div}$
 422 is capturing the DPM well.

423 *Figure 6: Volume-discharge curves for the four different surrogate model structures for the same*
 424 *demonstration event as in Figure 5 for compartment SM1. (a-c) discharge (d) surge.*

425 Table 2 shows the performance measures presented in Section 2.3 for the five different SMs as the mean
 426 (and median) of all validation events. The column to the left shows the error statistics for the
 427 demonstration event shown in Figure 5 and 6 for comparison. Most error measures are similar to those of
 428 the single demonstration event, which indicates that this event is representative of the most of the
 429 features for all events. All SMs have a high NSE of 0.90 or above for volume and discharge except for

430 $SM_{\text{steady},4+\text{UH}}$ with a NSE of 0.86 for volume. For the aggregated surcharge only $SM_{\text{steady},4,\text{div}}$ performs well
 431 with a NSE of 0.84. Both mean and median are computed for PEP. The overall performance of volume and
 432 discharge is again better than for surcharging and again $SM_{\text{steady},4,\text{div}}$ performs the best. It is noticed that all
 433 SMs underestimates volume (except $SM_{\text{steady},4+\text{UH}}$) and discharge peaks. PDIFF shows that the absolute
 434 difference in peaks are $<0.4 \text{ m}^3/\text{s}$ for Q_{out} . For Q_{spill} mean PDIFF up to $-10 \text{ m}^3/\text{s}$ are noticed, but the median is
 435 typically much lower indicating some significant outliers. Only $SM_{\text{steady},4,\text{div}}$ performs very well here with a
 436 mean PDIFF of $1.1 \text{ m}^3/\text{s}$. The mean peak time difference for Q_{out} ranges from 11 to -0.21 min with
 437 $SM_{\text{steady},4,\text{div}}$ and $SM_{\text{steady},4+\text{UH}}$ with the smallest differences and for Q_{spill} from -11 down to -6.7 min for
 438 $SM_{\text{steady},4,\text{div}}$. CSI is 1 for all SMs meaning that the SMs has captured all the surcharge peaks of DPM and have
 439 no false positives. PEAD shows that all models except $SM_{\text{steady},4,\text{div}}$ underestimate the accumulated surcharge
 440 while $SM_{\text{steady},4,\text{div}}$ overestimates it.

441 In conclusion, all the SM structures are able to sufficiently accurate describe the behaviour of the DPM. It
 442 does not seem to make a big difference if L is set to 4 or 20 volume-discharge parameter pairs, or whether
 443 steady state or dynamical training data are used. When trying to describe the ambiguousness of the
 444 dynamic volume-discharge curves shown in Figure 6, subdividing the compartments further proved to give
 445 the largest improvement. However, this increases the size and complexity of the SMs, and since the other
 446 SMs yield reasonably accurate results we proceed with the simplest of these models, $SM_{\text{steady},4}$.

447

Table 2: NSE, mean and median PEP, PDIFF, PTDIFF, CSI and PEAD for the volume over time, S , the outgoing discharge over time, Q_{out} , the spilling discharge over time, Q_{spill} , for compartment SM1 for the demonstration event from Figure 5 and 6 and the total 3x15 validation events. Numbers in bold and underline have the best score and numbers in bold italic the second best score.

Event			All events				
SM _{steady,4}			SM _{steady,4}	SM _{steady,20}	SM _{steady,4,div}	SM _{steady,4+UH}	SM _{dynamic,4}
NSE [-]	S	0.99	0.98	0.98	<u>0.99</u>	0.86	0.97
	Q_{out}	0.99	0.95	0.95	<u>0.99</u>	<u>0.99</u>	0.95
	Q_{spill}	0.55	0.33	0.35	<u>0.84</u>	0.33	0.32
PEP [%]	S	-4.2 / -4.2	4.1 / 1.6	5.0 / 4.5	<u>0.66 / 0.68</u>	-16 / -19	10 / 9.8
	mean/median Q_{out}	-2.5 / -2.5	7.6 / 4.3	<u>5.6 / 2.4</u>	5.8 / 4.3	7.4 / 4.3	7.3 / 6.4
	Q_{spill}	44 / 44	-2.1 / 24	<u>-0.2 / 27</u>	-1.6 / -2.0	-2.1 / 23	-5.0 / 17
PDIFF [m ³ /s]	Q_{out}	-0.37 / -0.37	0.23 / 0.27	<u>0.16 / 0.20</u>	0.31 / 0.37	0.22 / 0.27	0.36 / 0.30
	mean/median Q_{spill}	6.0 / 6.0	-9.8 / 2.4	-9.3 / 2.7	<u>1.1 / -0.50</u>	-9.8 / 2.4	-10 / 17
PTDIFF [min]	Q_{out}	18 / 18	10 / 13	11 / 13	<u>-0.21 / 2.0</u>	-0.28 / 2.0	8.8 / 13
	mean/median Q_{spill}	-8.0 / -8.0	-8.6 / -6.0	-8.3 / -6.0	<u>-6.7 / -2.0</u>	-8.6 / -6.0	-11 / -6.0
CSI [-]	Q_{spill}	1.0	<u>1.0</u>	<u>1.0</u>	<u>1.0</u>	<u>1.0</u>	<u>1.0</u>
PEAD [%]	Q_{out}	-0.39	-0.37	-0.57	1.9	-0.42	<u>-0.14</u>
	Q_{spill}	9.5	9.5	11	-9.7	9.5	<u>7.4</u>

4.3 Spatial performance

The performance for all 13 compartments is illustrated in Figure 7. This shows (a) NSE for volume and discharge and (b) NSE for spilling discharge. The arrows on Figure 7(a) are scaled according to the magnitude of the mean discharge and their colour show the SM performance for the discharges. Figure 7 (c-d) shows similar results for PEP.

458 *Figure 7: NSE (fig. a-b) and PEP (fig. c-d) for all Elster Creek compartments for $SM_{steady,4}$. Figure a and c show*
 459 *values for the volume (colour within compartment) and discharge between compartments (colours in*
 460 *arrows). Figure b and d shows values for the discharge to the surface from each compartment.*

461 Figure 7 shows that the SM performs well with regard to volume and discharge. The scaling of the arrows
 462 underlines that the SM performs the best for the major (and most important) discharges through the
 463 system. Furthermore, discharge performances for pure weir connections (SM6-SM7, SM7-SM8) are very

464 good indicating that the SM can easily be applied for modelling CSOs. In Figure 7 it is also clear that the SM
 465 has most difficulties in emulating the spilling discharge. The highest PEP values for the spilling discharge
 466 are found in compartments SM2, SM4, SM6, SM8 and SM11. There are several reasons for this behaviour.
 467 First, the topography of the area will have an impact as the area close to the shoreline is less steep. These
 468 compartments will thus be more prone to effects such as backwatering. Moreover, these shoreline
 469 compartments function both as storage and transportation, while upstream compartments with higher
 470 gradients only serve as transportation. Secondly, the compartments holding the highest PEP values are also
 471 some of the compartments with the smallest surcharge amounts. Table 3 shows the size of the
 472 accumulated spilling discharge for all compartments relative to the largest compartment, SM3.
 473 Compartments SM2, SM4, SM6, SM7, SM8 and SM11 are together with SM13 the compartments with the
 474 smallest accumulated spilling discharges. Thus the relative error will be larger for these compartments. In
 475 Table 3 the Peak Difference is also shown. These results underline that the PEP values by themselves do not
 476 necessarily give a good indication of the SM performance as the compartments with the highest PEP values
 477 do not have the highest PDIFF values. The CSI for the spilling discharge is also provided in Table 3. CSI
 478 values indicate that the SM is able to capture most peaks in the system. For compartment 7 the SM have six
 479 false positives and SM8, SM9 and SM13 all have one miss.

480 *Table 3: Relative size of the spilling discharge in relation to SM3 for all compartments and their PDIFF and*
 481 *CSI values.*

Compartment	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10	SM11	SM12	SM13
Relative size Acc Q_{spill} [%]	32	16	100	8.3	34	12	0.07	5.1	41	38	5.2	24	4.0
PDIFF [m^3/s] mean	-9.8	3.8	-0.37	2.8	-2.1	5.9	-5.9	1.8	3.3	-3.2	2.1	3.1	0.88
CSI [-]	1.0	1.0	1.0	1.0	1.0	1.0	0.82	0.97	0.97	1.0	1.0	1.0	0.97

482

483 **4.4 GLUE surrogate model evaluation**

484 **4.4.1 Defining prior distributions of surrogate model parameters**

485 Figure 8 shows the resulting dynamic volume-discharge curves for compartments SM1, SM2, SM6 and SM8
486 for all validation events. Each 2 min data point is coloured corresponding to the density of the volume-
487 discharge points. The mean and standard deviation of the discharge at varying volumes are also displayed.
488 We have chosen to apply $L=4$ volume-discharge parameter pairs as this number was found to be sufficient
489 for describing the shape of the volume-discharge curve.

490 A clear pattern is seen for all four compartments: The standard deviation increases with the volume up to a
491 certain point and then it decreases again. The small standard deviations for the larger volumes are due to
492 capacity limitations in the drainage system. At one point the maximum discharge capacity is reached and
493 this limits the variation of the discharge. Another clear pattern, which is observed for all four
494 compartments, is the skewed distribution around the mean.

495 The steady state points previously used for identifying the volume-discharge parameter pairs in the SM are
496 also shown. In all four compartments the steady state points are close to the and all within the standard
497 deviations. Vertical lines at the fixed volume parameters are shown and the discharge distributions will be
498 created at these cross-sections. The further downstream, the larger the discharge is through the
499 compartment and these compartments therefore have a smaller coefficient of variation. This observation is
500 in agreement with the findings in Section 4.2 when studying the behaviour for a given physical catchment,
501 i.e. that the dynamics are simulated more accurately when applying several SMs in series.

Figure 8: Volume-discharge curves generated with rain presented in Section 3.3.1 for four compartments: (a) SM1, (b) SM2, (c) SM6 and (d) SM8. The volume-discharge points from the DPM are marked with a colour corresponding to the density of points and connected with lines. The steady state points are given as well as the mean and standard deviation. The fixed volume parameters used are shown with vertical lines.

Histograms used for creating prior distributions for each of the four discharge parameters at the fixed volume parameters are shown in Figure 9 for the four compartments for SM1, SM2, SM6 and SM8. Again it is noticed that the sample size is much larger for the lower range and that some of the discharge parameters overlap with their min and max values.

Figure 9: Histograms for creating prior distributions for the discharge parameters for each of the four compartments: (a) SM1, (b) SM2, (c) SM6 and (d) SM8

4.4.2 Performance of surrogate model realizations

The simulation results for SM1 from 500 SM realizations created using *sampling method 1* are shown in Figure 10. The prediction bands are wider for the volume than the discharge. Some of the SM realizations take much longer to empty the compartments which results in extended tails for the volume plot. The DPM is within the SM band most of the time. However for the discharge and the spilling discharge the SMs appear to be too soon and too late, respectively.

Figure 10: Results for the DPM and the SM with 500 model realizations using sampling method 1 for the volume over time, S , the outgoing discharge over time, Q_{out} and spilling discharge over time, Q_{spill} for compartment SM1.

Similar resulting model simulations for the SM realizations for SM1 with *sampling method 2* can be seen in the supplementary material in Figure S.1. The main difference between the results are that when using *sampling method 2* the realizations are not intersecting due to the sorting of the parameters. This results in

526 slightly larger bands and less flexibility, indicating that the choice of sampling method does not have a
527 major role to play within a simple upstream compartment.

528 Additional simulation results for the SM realizations for discharge and spilling discharges for compartments
529 SM1, SM2, SM4 and SM8 can be seen in the supplementary material in Figures S.2-S.3 and S.4-S.5 for
530 *sampling method 1* and 2, respectively. As we move downstream in the system, the difference between the
531 two sampling methods becomes larger in two ways: *Sampling method 2* gets a wider band of models
532 downstream for discharge compared to *sampling method 1* as expected due to the discharge parameter
533 correlation. However, *sampling method 1* results in a larger band of models for the spilling discharge
534 downstream than *sampling method 2*. This might seem surprising as the motivation behind using *sampling*
535 *method 2* was to create the largest model span. The narrow bands for the spilling discharge is because the
536 largest spilling discharge for a compartment is obtained when the water is held back in the given
537 compartment, i.e. low discharge parameters, while discharge(s) to the given compartment from upstream
538 compartments are high, i.e. high discharge parameters. Such a constellation of parameters between
539 compartments is not possible for *sampling method 2* since all parameters within and between the
540 compartments are correlated. Therefore we actually get the largest band of models for the spilling
541 discharge when allowing parameters to vary freely as in *sampling method 1* for the downstream
542 compartments.

543 To further investigate the influence of the discharge parameters, the four different discharge parameters
544 are plotted with their resulting error in dotted plots. First the discharge parameters from *sampling method 1*
545 are plotted with the limits of acceptability from Table 1 for compartment SM1 in Figure 11.

546 For RTC the limits of acceptability for NSE for both volume and discharge and PEP for volume appear to
547 accept most of the SM realizations with NSE for the volume being the strictest requirement. For warning
548 limits all models, except for very few models in PEP for spilling discharge, appear to be accepted. For
549 planning limits the PEAD for the spilling discharge is the strictest requirement.

— RTC limit, — Warning limit, — Planning limit

Figure 11: NSE, PEP, PTDIFF, PEAD and CSI values as functions of density of discharge parameters 1, 2, 3, 4, respectively, for sampling method 1 with limits of acceptability for the three applications from Table 1. The top 3x4 figures show NSE for the volume, discharge and spilling discharge. The next 3x4 figures similarly show the PEP values. The next 2x4 figures show the PTDIFF values for the discharge and spilling discharge.

The next 2x4 figures show the PEAD values similarly. The final 1x4 figures show the CSI values for spilling discharge. It should be noted that the y-axis for the same error measures might vary for visual ability.

For the entire discharge parameter spectrum there appears to be an upper limit for the performance for NSE for Q_{out} and Q_{spil} and PTDIFF for Q_{out} preventing a perfect error score. All other measures show close to perfect fits somewhere in their range of parameters. This is a result of the model structure and not the parameter ranges. As also seen in Figure 10 none of the SM realizations excel in capturing the behaviour of DPM results for spilling discharge regardless of the discharge parameters. Thus to improve these, the model structure would have to be improved as described in Section 4.2.

Taking a closer look on each of the four discharge parameters, for discharge parameter 1 the NSE plots show an optimum of $\sim 2\text{-}3 \text{ m}^3/\text{s}$ for volume and discharge, while for spilling discharge the opposite pattern is seen. For PEP for discharge parameter 1 a "V" shape for the volume is seen peaking at $\sim 3 \text{ m}^3/\text{s}$, the opposite shape is seen for the discharge while the spilling discharge appears more random. For PTDIFF the lower parameter ranges result in the smallest errors while it for PEAD appears to be the upper range. For discharge parameter 2 and 3 a trend towards the higher values is obtained in NSE, PEP and PEAD. Discharge parameter 4 does not show an optimal range of values as low errors are present in the entire parameter spectrum. This is also the discharge parameter with the smallest range.

For the discharge parameters from *sampling method 2* similar dotty plots are shown in Figure 12. Since the sampling is done systematically, the four plots for the four discharge parameters will be the same when regarding the percentiles. Instead we show dotty plots for four compartments: SM1, SM2, SM6 and SM8. Here the same pattern for SM1 is observed as in Figure 12. However, as a result of the sampling method, the SM realizations are now much more bound. This is reflected in the graph as one model realization with a specific discharge parameter cannot have different error measures for that same discharge parameter, and therefore the patterns become much clearer.

579 It is seen that especially the PEP limit for Q_{spill} for the warning applications reject all models in SM6. As
580 discussed earlier, this error measure might be too strict on these compartments, due to their low surface
581 discharge amounts. No model realizations in the entire parameter range can meet this criterion. It might be
582 that these compartments are highly governed by the larger upstream compartment. Compartment SM8,
583 however, appears to be more sensitive to the discharge parameters, but this compartment also fails for the
584 PTDIFF criterion for warning with SM2 and SM6.

585 Results for $SM_{steady,4}$ are also shown to evaluate the volume-discharge parameter pairs found using the
586 steady state method. It is seen that the $SM_{steady,4}$ is mostly in the good range of the plot indicating that this
587 method for finding volume-discharge parameter pairs is decent.

588

— RTC limit, — Warning limit, — Planning limit, — SM_{steady,4}

Figure 12: NSE, PEP, PTDIFF, PEAD and CSI values as functions of density of percentile discharge parameters for compartments SM1, SM2, SM6, SM8 respectively, for sampling method 2 with limits of acceptability for the three applications from Table 1. The top 3x4 figures show NSE for the volume, discharge and spilling discharge. The next 3x4 figures similarly show the PEP values. The next 2x4 figures show the PTDIFF values

595 for the discharge and spilling discharge. The next 2x4 figures show the PEAD values similarly. The final 1x4
596 figures show the CSI values for spilling discharge. It should be noted that the y-axis for the same error
597 measures might vary for visual ability.

598 **4.4.3 Rejection of non-behavioural models**

599 Table 1 shows number of accepted models for compartment SM1 for each of the three applications and for
600 each of the limits of acceptability within each application for both sampling methods. For RTC the
601 restricting limit is NSE for volume which yields an overall acceptance of 437 and 417 models for method 1
602 and 2 respectively. For warning, all models are accepted for all limits except PEP for spilling discharge which
603 gives an overall acceptance of 496 and 486 models for method 1 and 2, respectively. For planning, again all
604 models are accept for all other limits than PEAD for spilling discharge, which yields a number of 386 and
605 343 accepted models for *sampling method 1* and 2, respectively. The warning application has the highest
606 number of accepted models for compartment 1 while planning has the lowest number of accepted models.
607 Generally, fewer models are accepted with *sampling method 2* than *sampling method 1* for the upstream
608 compartment.

609 Figure 13 shows the number of accepted models for all compartments in the catchment for the two
610 sampling methods. The red colour indicates than none of the 500 model realizations are accepted. Since
611 most compartments are connected to more than one compartment and the acceptance and rejection of
612 SMs depend on the performance of discharge between the compartments, only the largest connection is
613 considered if there are multiple connections. As expected, the downstream compartments along the shore
614 get none to very few accepted models due to severe backwater effects in this part of the catchment. The
615 RTC always have accepted models for all compartments. For the planning applications downstream
616 compartments near the shore have few to none accepted models. The difference between the two
617 sampling methods becomes more apparent as we move downstream. *Sampling method 2* generally results
618 in fewer accepted models than *sampling method 1*, primarily because spilling is not modelled with

619 sufficient accuracy. If the specific planning purpose was to dimension a downstream structure such as e.g. a
 620 treatment plant, one could choose to not include spilling in the conditioning, in which case there would be
 621 plenty of accepted models. If the low number of accepted models is not satisfactory different model
 622 formulations could be explored, including even simpler models where the compartments dominated by
 623 backwater is merged with their upstream compartments to avoid highlighting the problematic hydraulic
 624 features that may not be important in the actual use of the model.

625 *Figure 13: Number of accepted models for each of the three applications. Red colour indicates that none of*
 626 *the 500 SMs were accepted. First 1x3 figures shows the number of accepted models using sampling method*
 627 *1 and final figures 1x3 shows the number of accepted models using sampling method 2*

628 4.4.4 Prediction uncertainty for applications

629 Figure 14 shows the discharge prediction uncertainty bands for the same demonstration event as shown in
 630 Figure 5 and onwards for the three applications with *sampling method 1* for the four compartments SM1,
 631 SM2, SM6 and SM8. There are models accepted for all three applications in SM1, and hereafter only for
 632 planning and RTC as also seen in Figure 13. For SM1 the warning band is the widest, while for SM2, SM6

633 and SM8, RTC has the widest band with close to all models accepted. It is noticed that the planning
 634 application have the best fit around the DPM, but that all accepted applications bands capture the
 635 behaviour of the DPM. Furthermore it is observed that all accepted application bands are within the $\pm 23\%$
 636 DPM uncertainty bands visible in Figure 5. In the supplementary material in Figure S.7, the same figure can
 637 be seen for *sampling method 2*. Only for SM1 the bands are narrower, otherwise the bands are similar or
 638 wider. Figure S.6 and S.8 in the supplementary material shows the spilling discharge for the four
 639 compartments for *sampling method 1* and 2, respectively. Here it is seen that the bands from *sampling*
 640 *method 1* has a better coverage of the DPM than the narrower bands from *sampling method 2*.

— DPM

Figure 14: Results for the DPM (black line) and the SM with prediction uncertainty for the three applications using the limits of acceptability from Table 1 for the outgoing discharge over time, Q_{out} , for the four compartments SM1, SM2, SM6, SM8, respectively with sampling method 1.

The prediction bands for the three applications are similar upstream for both the three applications and the two sampling methods. Downstream, the prediction bands differ for both applications and sampling methods. The large differences between the different applications are due to the fact that some of the applications are conditioned on spilling discharge which is difficult to model in downstream backwater-prone areas. Overall *sampling method 2* results in larger model bands downstream for discharge than *sampling method 1*. The bands for spilling discharge are in contrary to the discharge bands wider for *sampling method 1* due to the correlation of discharge parameters between compartments in *sampling method 2*. We would have expected the largest overall model span with sampling method 2 but the correlation of discharge parameters between the compartments hindered maximum variation of the spilling discharge. Hence, in this regard *sampling method 1* proved to be the best option with the largest span of models for the spilling discharge indicating that both the internal parameter constellation in a compartment and the parameter constellation between compartments need to be considered. However, the numbers of accepted models for each sampling method did not differ substantially due to the strict limit of acceptability for spilling.

659 **5 Discussion**

660 In recent years fit-for-purpose models in urban drainage modelling has received increased attention. Three
661 issues are prohibiting widespread application. First, no strict formal guidelines are found on how to
662 evaluate models and thus many different performance measures are found throughout literature varying
663 from statistical measures as NSE, RMSE etc. to visual inspection, e.g. (Vanrolleghem et al., 2009; Wolfs et
664 al., 2013). Secondly, the applications of the models are often not included in the choice of these error
665 measures. Finally, no limits are set for the different error measures to differentiate between acceptable
666 models and rejected models. All this means that it has been challenging to develop limits of acceptability
667 for the GLUE analysis both in terms of selection of indicators, the applications and the actual limits of
668 acceptability. These have thus only been made roughly for the three applications without further details on
669 e.g. lead time, and input data quality and uncertainty. Such factors may have a large influence on the model
670 criteria and these might vary greatly for different case study areas and projects. The SMs will have
671 limitations for all three applications areas, as the model criteria do not cover all possible sub-applications.
672 Hence, when modelling e.g. areas highly influenced by backwater, pollutant transport, velocity etc. other
673 more suitable models should be applied. For RTC, the SMs can be applied for static control as the model is
674 able to model flow gates, pumps etc. However, when implementing the control this might cause
675 backwatering and affect upstream compartments. In these situations, these compartments will either have
676 to be recalibrated for the given control strategy or to calibrate and employ several SM structures to
677 accommodate for different control strategies. For warning, the model criterion of peak spilling discharge
678 might be changed to a measure that is more easily interpreted like flood volume. For planning, specific
679 criteria for CSOs will be essential for combined sewer systems.

680 In many cases an iterative approach is needed to set up a SM given constraints of acceptability and
681 important locations in the system, i.e. the reverse work flow than we have applied in identifying a suitable
682 model structure. A key component in the work flow should be to choose the right compartment resolution
683 with respect to the applications and desired outcome. A simple approach will be to choose only the points

684 of interest as boundaries between compartments and supplement with compartments to describe key
685 disruptors (e.g. division of flows) and where a better description of complex flow patterns can be obtained
686 by using a finer compartment resolution. Currently the SM only models the aggregated surcharge from
687 each compartment, with no information on the spatial distribution of these flows to the surface within the
688 given compartment. To achieve more detailed spatial information, the compartment sizes may be reduced
689 or multiple connections to the surface from each compartment can be used. On the contrary, for
690 application where only the downstream point is considered, we have shown that the compartment
691 resolution can be very coarse and still provide sufficiently accurate discharges at the drainage outlet for
692 most applications. With the 13 compartments we have a good model for the overall state of the drainage
693 network of the considered domain, but as shown in compartment SM1, if this was increased to e.g. 100
694 compartments we would most likely have an even better model. Backwater effects represent a challenge,
695 though, and most likely the best way to circumvent it is to avoid a division into compartments where
696 backwater effects dominate the flows or include this in the SM structure. The process of setting up the
697 compartments and calibrating them is currently a manual process. It does require time to examine and
698 understand the network, deciding on compartment shapes and sizes and reporting links crossing the
699 compartment boundaries. Once a suitable compartment design has been obtained, the results of this paper
700 show that the surrogate model can be determined fairly easy and quick. We see a potential for
701 automatizing the workflow in the future.

702 We introduced two sampling methods to account for the shortcoming of using data from model-to-model
703 rather than model-to-observations, i.e. to account for model biases as well as model uncertainty. Although
704 the difference between the sampling methods were visible, especially downstream in the catchment, the
705 overall impact on accepted models were smaller than expected and it is doubtful that this procedure is
706 sufficient to account for all the variation that is present in actual measurement due to, e.g. spatial variation
707 of rainfall within each compartment.

Both the DPM and the SM introduce model errors. The high level of details in the DPM does not necessarily reduce the model uncertainty, but it prohibits us from exploring this uncertainty because of high computational costs. Compared to the expected uncertainty of the DPM, the uncertainty bands of the surrogate model are well within for the ranges of accepted models. From these reflections one can argue that surrogate models can be applicable for all three types of applications given that sufficient care is taken in setting up the model to the catchment in question. Hence the objectives of the modelling should always be taken into consideration to compute tailor-made fit-for-purpose modelling, including the cost of setting up the SM compared to using a HiFi model.

6 Conclusion

In this paper, lumped drainage surrogate models based on unambiguous volume-discharge curves from an original HiFi 1D network DPM are presented. The models are applied on the Elster Creek Catchment in Melbourne, Australia, with varying training data and model complexity. The key findings are:

- The proposed SMs are approximately six orders of magnitudes faster than the original DPM when reducing the number of states simulated by three orders of magnitude and the SM results are within expected uncertainty bands of results obtained by the HiFi DPM.
- The SMs are robust with respect to extraction of parameters, indicating that choice of training data seems to be of minor importance. The simplest SMs based on steady state training data perform well. We therefore recommend the usage of steady state data when training the SM.
- The results indicate that the most important factor is the compartment resolution. The selection of compartment size should be determined from the model objective as this is a trade-off between accuracy, computational time, and time to set up the SM.
- The SM structure is limited in predicting spilling in flat areas with backwater effects. In other areas the performance is sufficient. The spilling discharge is lumped for the compartments so it does not contain

any spatial information on how the flows to the surface are distributed within each compartment. For this, a finer compartment resolution or multiple surface connections can be applied.

- GLUE demonstrates that the SMs can be tailored to all major types of applications, e.g. RTC, warning and planning. Two sampling methods are applied to compensate for the model-to-model uncertainty. Upstream, different limits of acceptability result in similar prediction uncertainty bands for the three applications. For downstream applications the differences are higher, but probably none of the methods are able to cover the actual uncertainty when validating models against observations.

Despite their simplicity the presented SMs show great potential for usage in urban drainage modelling for various applications. The SMs proved to be within the overall uncertainty bands of the DPM supporting their usage in urban drainage modelling when computational demands of DPMs are prohibitive.

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References

- Aronica, G., Freni, G., Oliveri, E., 2005. Uncertainty analysis of the influence of rainfall time resolution in the modelling of urban drainage systems. *Hydrol. Process.* 19, 1055–1071. doi:10.1002/hyp.5645
- Australian Bureau of Meteorology, 2015. Rain data extracted from eWater MUSIC for Melbourne, Australia,

752 using the Pluviograph Rainfall Data Tool.

753 Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-Libelli, S.,
754 Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S.A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D.,
755 Andreassian, V., 2013. Characterising performance of environmental models. *Environ. Model. Softw.*
756 40, 1–20. doi:10.1016/j.envsoft.2012.09.011

757 Beven, K., 2015. Facets of uncertainty: epistemic uncertainty, non-stationarity, likelihood, hypothesis
758 testing, and communication. *Hydrol. Sci. J.* 6667, 150527103244004.
759 doi:10.1080/02626667.2015.1031761

760 Beven, K., 2009. *Environmental Modelling: An uncertain future?* Routledge, Oxon.

761 Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction.
762 *Hydrol. Process.* 6, 279–298. doi:10.1002/hyp.3360060305

763 Blazkova, S., Beven, K., 2009. A limits of acceptability approach to model evaluation and uncertainty
764 estimation in flood frequency estimation by continuous simulation: Skalka catchment, Czech Republic.
765 *Water Resour. Res.* 45, 1–12. doi:10.1029/2007WR006726

766 Borup, M., 2018. DtuSmModels Free software under the GNU General Public License v3 license, Technical
767 University of Denmark. [WWW Document]. URL <https://github.com/Moboha/DtuSmModels>

768 Borup, M., Thrysoe, C., Arnbjerg-Nielsen, K., Righetti, F., Mikkelsen, P.S., 2017. A fast surrogate model
769 tailor-made for real time control. 14th IWA/IAHR Int. Conf. Urban Drain.

770 Chow, V.T., Maidment, D.R., May, L.W., 1988. *Applied hydrology*. McGraw-Hill, US.

771 Cunge, J.A. On the subject of a flood propagation computation method (Muskingum method). *J. Hydraul.*
772 *Res.* 7: 205-230; 1969.

773 Davidsen, S., Löwe, R., Thrysøe, C., Arnbjerg-Nielsen, K., 2017. Simplification of one-dimensional hydraulic
774 networks by automated processes evaluated on 1D/2D deterministic flood models. J.
775 Hydroinformatics 19, 686–700. doi:10.2166/hydro.2017.152

776 DHI (Danish Hydraulic Institute), 2014a. MOUSE Pipe Flow Reference Manual 1–5. doi:10.1007/s13398-014-
777 0173-7.2

778 DHI (Danish Hydraulic Institute), 2014b. MOUSE Runoff Reference Manual

779 Fewtrell, T.J., Duncan, A., Sampson, C.C., Neal, J.C., Bates, P.D., 2011. Benchmarking urban flood models of
780 varying complexity and scale using high resolution terrestrial LiDAR data. Phys. Chem. Earth 36, 281–
781 291. doi:10.1016/j.pce.2010.12.011

782 Haasnoot, M., Van Deursen, W.P.A., Guillaume, J.H.A., Kwakkel, J.H., Van Beek, E., Middelkoop, H., 2014. Fit
783 for purpose? Building and evaluating a fast, integrated model for exploring water policy pathways.
784 Environ. Model. Softw. 60, 99–120. doi:10.1016/j.envsoft.2014.05.020

785 Hansen, A.C., Liu, L., 2004. Risk-Based Design of Drainage Systems Uncertainty Analysis. Technical
786 University of Denmark.

787 Henonin, J., Russo, B., Mark, O., Gourbesville, P., 2013. Real-time urban flood forecasting and modelling – a
788 state of the art. J. Hydroinformatics 15, 717. doi:10.2166/hydro.2013.132

789 IPCC, 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A
790 Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change.
791 Cambridge University Press, Cambridge, UK, and New York, NY, USA.

792 Jamali, B., Löwe, R., Bach, P.M., Urich, C., Arnbjerg-Nielsen, K., Deletic, A., 2018. A rapid urban flood
793 inundation and damage assessment model. J. Hydrol. 564, 1085–1098.
794 doi:10.1016/j.jhydrol.2018.07.064

795 Johansen, N.B., Harremoes, P., Jensen, M., 1984. Methods for calculation of annual and extreme overflow
 796 events from combined sewer systems, *Wat. Sci. .Tech.* doi:10.2166/wst.1984.0200

797 Joseph-Duran, B., Jung, M.N., Ocampo-Martinez, C., Sager, S., Cembrano, G., 2014. Minimization of Sewage
 798 Network Overflow. *Water Resour. Manag.* 28, 41–63. doi:10.1007/s11269-013-0468-z

799 Leandro, J., Chen, A.S., Schumann, A., 2014. A 2D parallel diffusive wave model for floodplain inundation
 800 with variable time step (P-DWave). *J. Hydrol.* 517, 250–259. doi:10.1016/j.jhydrol.2014.05.020

801 Leitão, J.P., Simões, N.E., Maksimović, Č., Ferreira, F., Prodanović, D., Matos, J.S., Sá Marques, a., 2010.
 802 Real-time forecasting urban drainage models: Full or simplified networks? *Water Sci. Technol.* 62,
 803 2106–2114. doi:10.2166/wst.2010.382

804 Löwe, R., Urich, C., Sto. Domingo, N., Mark, O., Deletic, A., Arnbjerg-Nielsen, K., 2017. Assessment of urban
 805 pluvial flood risk and efficiency of adaptation options through simulations – A new generation of
 806 urban planning tools. *J. Hydrol.* 550, 355–367. doi:10.1016/j.jhydrol.2017.05.009

807 Löwe, R., Vezzaro, L., Mikkelsen, P.S., Grum, M., Madsen, H., 2016. Probabilistic runoff volume forecasting
 808 in risk-based optimization for RTC of urban drainage systems. *Environ. Model. Softw.* 80, 143–158.
 809 doi:10.1016/j.envsoft.2016.02.027

810 Lund, N.S.V., Falk, A.K.V., Borup, M., Madsen, H., Steen Mikkelsen, P., 2018. Model predictive control of
 811 urban drainage systems: A review and perspective towards smart real-time water management. *Crit.*
 812 *Rev. Environ. Sci. Technol.* 48, 279–339. doi:10.1080/10643389.2018.1455484

813 Madsen, H., Gregersen, I.B., Rosbjerg, D., Arnbjerg-Nielsen, K., 2017. Regional frequency analysis of short
 814 duration rainfall extremes using gridded daily rainfall data as co-variate. *Water Sci. Technol.* 75(8),
 815 1971–1981. doi:10.2166/wst.2017.089

816 MATLAB and Statistics Toolbox Release 2015b, 2015. MATLAB and Statistics Toolbox Release 2015b.

817 Meirlaen, J., Huyghebaert, B., Sforzi, F., Benedetti, L., Vanrolleghem, P., 2001. Fast, simultaneous simulation
818 of the integrated urban wastewater system using mechanistic surrogate models. *Water Sci. Technol.*
819 43, 301–309

820 Muschalla, D., Reussner, F., Schneider, S., Ostrowski, M.W., 2006. Dokumentation des
821 Schmutzfrachtmodells SMUSI Version 5.0. Institut für Wasserbau und Wasserwirtschaft, Technische
822 universität Darmstadt, Germany.

823 Neal, J.C., Fewtrell, T.J., Bates, P.D., Wright, N.G., 2010. A comparison of three parallelisation methods for
824 2D flood inundation models. *Environ. Model. Softw.* 25, 398–411. doi:10.1016/j.envsoft.2009.11.007

825 Neelz, S. & Pender, G., 2013. Benchmarking the latest generation of 2D hydraulic modelling packages.
826 Technical report SC120002. Environment Agency, Bristol, UK.

827 Ocampo-martinez, C., Cembrano, G., Quevedo, J., 2013. Application of Predictive Control Strategies to the
828 Management of Complex Networks in the Urban Water Cycle. *IEEE Control Systems Magazine*, vol. 33,
829 no. 1, pp. 15-41, Feb. 2013. doi: 10.1109/MCS.2012.2225919

830 Olesen, L., Löwe, R., Arnbjerg-Nielsen, K., 2017. Flood Damage Assessment Literature Review and
831 Recommended Procedure. Cooperative Research Centre for Water Sensitive Cities, Melbourne,
832 Australia.

833 Rauch, W., Urich, C., Bach, P.M., Rogers, B.C., de Haan, F.J., Brown, R.R., Mair, M., McCarthy, D.T.,
834 Kleidorfer, M., Sitzenfrie, R., Deletic, A., 2017. Modelling transitions in urban water systems. *Water*
835 *Res.* 126, 501–514. doi:10.1016/j.watres.2017.09.039

836 Razavi, S., Tolson, B.A., Burn, D.H., 2012. Review of surrogate modeling in water resources. *Water Resour.*

837 Res. 48, W07401. doi:10.1029/2011wr011527

838 Refsgaard, J.C., van der Sluijs, J.P., Brown, J., van der Keur, P., 2006. A framework for dealing with
 839 uncertainty due to model structure error. *Adv. Water Resour.* 29, 1586–1597.
 840 doi:10.1016/j.advwatres.2005.11.013

841 Semadeni-Davies, A., Hernebring, C., Svensson, G., Gustafsson, L.G., 2008. The impacts of climate change
 842 and urbanisation on drainage in Helsingborg, Sweden: Combined sewer system. *J. Hydrol.* 350, 100–
 843 113. doi:10.1016/j.jhydrol.2007.05.028

844 Solvi, A.M., Benedetti, L., Gillé, S., Schosseler, P., Weidenhaupt, A., Vanrolleghem, P.A., 2005. Integrated
 845 urban catchment modelling for a sewer-treatment-river system. 10th Int. Conf. Urban Drain. 21–26.

846 Thorndahl, S., Beven, K.J., Jensen, J.B., Schaarup-Jensen, K., 2008. Event based uncertainty assessment in
 847 urban drainage modelling, applying the GLUE methodology. *J. Hydrol.* 357, 421–437.
 848 doi:10.1016/j.jhydrol.2008.05.027

849 University of Sheffield, 2018. Cost Effective Neural Technique for Alleviation of Urban Flood Risk - CENTAUR
 850 [WWW Document]. URL <https://www.sheffield.ac.uk/centaur> (accessed 10.24.18)

851 Vaes, G. 1999. The Influence of Rainfall and Model Simplification on Combined Sewer System Design. PhD
 852 Thesis, Hydraulics Laboratory, Department of Civil Engineering, University of Leuven, Belgium.

853 Vaes, G., Berlamont, J., 1998. Modelling of overflow emissions in Flanders. *Water Sci. Technol.* 38, 41–48.
 854 doi:10.1016/S0273-1223(98)07731-2

855 Vanrolleghem, P. a, Kamradt, B., Solvi, A., Muschalla, D., 2009. Making the best of two Hydrological Flow
 856 Routing Models: Nonlinear Outflow-Volume Relationships and Backwater Effects Model. *Proc. 8th Int.*
 857 *Conf. Xenobiotics Urban Water Cycle.*

858 Wallingford Procedure Users Group, 1993. Code of practice for the hydraulic modelling of sewer systems.
 859 Water Research Centre. ISBN: 0902156926.

860 Wolfs, V., Villazon, M.F., Willems, P., 2013. Development of a semi-automated model identification and
 861 calibration tool for conceptual modelling of sewer systems. *Water Sci. Technol.* 68, 167.
 862 doi:10.2166/wst.2013.237

863 Wright, L., Esward, T.J., 2013. Fit for purpose models for metrology: A model selection methodology, in:
 864 *Journal of Physics: Conference Series*. doi:10.1088/1742-6596/459/1/012039

865 Ye, Y., Song, X., Zhang, J., Kong, F., Ma, G., 2014. Parameter identification and calibration of the Xin'anjiang
 866 model using the surrogate modeling approach. *Front. Earth Sci.* 8, 264–281. doi:10.1007/s11707-014-
 867 0424-0

868 Zhou, Q., Mikkelsen, P.S., Halsnæs, K., Arnbjerg-Nielsen, K., 2012. Framework for economic pluvial flood
 869 risk assessment considering climate change effects and adaptation benefits. *J. Hydrol.* 414–415, 539–
 870 549. doi:10.1016/j.jhydrol.2011.11.031

871