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Published in: Journal of Hydrology

Link to article, DOI: 10.1016/j.jhydrol.2018.07.064

Publication date: 2018

Document Version Peer reviewed version

Link back to DTU Orbit

Citation (APA): Jamali, B., Löwe, R., Bach, P. M., Ulrich, C., Arnbjerg-Nielsen, K., & Deletic, A. (2018). A rapid urban flood inundation and damage assessment model. *Journal of Hydrology*, *564*, 1085-1098. https://doi.org/10.1016/j.jhydrol.2018.07.064

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1 A Rapid Urban Flood Inundation and Damage Assessment Model

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14 Abstract

15 Urban pluvial flooding is a global challenge that is frequently caused by the lack of available 16 infiltration, retention and drainage capacity in cities. This paper presents RUFIDAM, an urban 17 pluvial flood model, developed using GIS technology with the intention of rapidly estimating 18 flood extent, depth and its associated damage. RUFIDAM integrates a 1D hydraulic drainage 19 network model (SWMM or MOUSE) with an adapted version of rapid flood inundation 20 models. One-metre resolution topographic data was used to identify depressions in an urban 21 catchment. Volume-elevation relationships and minimum elevation between adjacent 22 depressions were determined. Mass balance considerations were then used to simulate 23 movement of water between depressions. Surcharge volumes from the 1D drainage network 24 model were fed statically into the rapid inundation model. The model was tested on three 25 urban catchments located in southeast Melbourne. Results of flood depth, extent and damage costs were compared to those produced using MIKE FLOOD; a well-known 1D-2D hydrodynamic model. Results showed that RUFIDAM can predict flood extent and accumulated damage cost with acceptable accuracy. Although some variations in the simulated location of flooding were observed, simulation time was reduced by two orders of magnitude compared to MIKE FLOOD. As such, RUFIDAM is suitable for large-scale flood studies and risk-based approaches that rely on a large number of simulations.

32 Keywords

33 Flood damage cost; Geographic Information Systems (GIS); hydrodynamic modelling;

34 MIKE FLOOD; MOUSE; SWMM

35 **1.** Introduction

36 Global climate is changing with increases in the frequency and intensity of extreme events, 37 such as coastal flooding, extreme precipitation and heat waves already observed (IPCC, 38 2014). This, together with urbanisation and land use change, will cause even more severe 39 floods and damage to urban areas in the near future. However, it is neither practically nor 40 economically feasible to make urban areas completely free from flooding (CSIRO, 2000; 41 Zhou et al., 2012). For example, it is difficult to protect against minor frequent floods, although we know that the cumulative cost (over time) of these small events might be 42 43 comparable to, or even larger than, extreme yet infrequent floods (Moftakhari et al., 2017). 44 Adaptation has seen a shift towards implementing a range of novel solutions, (e.g. green infrastructure or real-time control solutions), rather than "fighting" against the forces of nature 45 46 by building traditional large structures (Mimura et al., 2014). That said, it has been speculated that while potentially beneficial for minor frequent floods, novel measures might not be 47 48 suitable for the mitigation of extreme cases. Consequently, water utilities and local 49 municipalities are recognising the need to develop "integrated" flood management plans and strategies to minimise flood hazard and build flood resilience (e.g. Melbourne Water, 2007)
by evaluating both traditional and novel flood protection solutions.

52 To support this process, the utilisation of computer models to simulate flood extent, depth, 53 duration and flow velocity and their associated damages, as well as effectiveness of different 54 solutions, is paramount. Ideally, planning for flood risk mitigation should be supported by many flooding scenarios (i.e. future climates and urbanisation rates) and alternative solutions 55 56 (traditional and novel) with respect to uncertain future conditions, as well as their possible 57 consequences and damages (Apel et al., 2006). For example, exploratory modelling (Bankes, 58 1993), is used for analysing many scenarios with a high level of future uncertainties (e.g. 59 Löwe et al., 2017; Urich et al., 2013). To ensure accuracy in the modelling, we need to 60 continuously simulate these selected scenarios over time - e.g. continuous simulation is 61 crucial for the assessment of green infrastructure flood benefits since they mainly protect 62 against minor but frequent flooding episodes. This approach should consider a whole range 63 of storm types (in terms of magnitude, intensity and duration) over a long time period (e.g. 50 64 to 100 Years). Additionally, it is able to see the effect of antecedent conditions, such as the 65 retention/detention storage available prior to a storm, an important consideration in capacitive catchments (Kuczera et al., 2006; Rahman et al., 1998; Rahman et al., 2002). 66

67 Urban pluvial floods are generally caused by a lack of drainage capacity. This is especially 68 true during high intensity rainfall where free flow to the underground drainage network 69 (typically called the "minor system") becomes pressurised and the water level rises above-70 ground causing surcharge in manholes or sewer inlets. The surcharged flow subsequently 71 spreads across the surface flow network, called "major systems", which usually includes 72 roads, footpaths, ground depressions and small water courses (Maksimović et al., 2009). The dynamic interaction of minor and major systems, known as the "dual-drainage concept" 73 74 (Djordjević et al., 1999; Djordjević et al., 2005), is represented in urban flood models in 75 various ways and with different levels of complexities. The most detailed representation of 76 this interaction belongs to 1D-2D models, where a one dimensional (1D) drainage network 77 model is coupled with a two dimensional (2D) overland flow model. MIKE FLOOD (DHI, 78 2013), SOBEK (Deltares, 2017), XPSWMM (XPSolutions, 2017) and TUFLOW (WBM, 79 2008) are examples of commercially available models. These detailed flood models can 80 simulate flood characteristics with great intricacy, however they are often computationally 81 intensive and, occasionally, numerically unstable (Leandro and Martins, 2016; Lhomme et 82 al., 2006; Teng et al., 2017; Zhang and Pan, 2014).

83 Due to this practical limitation, flood mitigation studies that use detailed 1D-2D models are 84 often reduced to a limited number of simulations, with performance of each measure 85 evaluated against predefined storm events (i.e. design rainfall) and future conditions. 86 Conversely, simplified models reduce flood simulation time in different ways. However, this 87 speed-up usually comes at the expense of accuracy loss. According to the concept of "fit for 88 purpose model", we should be pragmatic when selecting a model for flood simulation: a fit 89 for purpose model is a model that predicts the required results within the desired level of 90 accuracy and manageable amount of time and computational expense (Guillaume and 91 Jakeman, 2012; Haasnoot et al., 2014; Wright and Esward, 2013).

Attempts to improve the computational performance of flood models can be classified intothe following three categories:

Model simplification: reducing model structural complexities by incorporating simpler
 representations of processes. Examples include: Simplifying 2D shallow water equations
 by omitting certain terms such as inertia (Bates and De Roo, 2000; Bates et al., 2010;
 Seyoum Solomon et al., 2012); replacing complex 2D surface flow models with 1D
 models composed of surface depressions and overland flow paths (known as 1D-1D
 models) (e.g. Maksimović et al., 2009; Mark et al., 2004); using Cellular Automata (CA)

100 approaches instead of solving shallow water equations in the modelling of 2D overland 101 flows (Dottori and Todini, 2011; Ghimire et al., 2013; Guidolin et al., 2016) as well as 102 their application in 1D drainage networks (Austin et al., 2014) and 1D-2D dual drainage 103 systems such as CADDIES model (Guidolin et al., 2012); using highly simplified 104 conceptual models known as rapid inundation models (Bernini and Franchini, 2013; 105 Krupka, 2009; Lhomme et al., 2008) or sometimes considered as 0-term models (Néelz 106 and Pender, 2013); and using empirical/data driven surrogate models (Wolfs and 107 Willems, 2013).

Detail reduction: using less detailed data or bigger time steps, reducing model input
 details and/or simulation time-step, e.g. using lower resolution topographic data (Cook
 and Merwade, 2009; Fewtrell et al., 2008; Savage et al., 2016) or simplified drainage
 networks (Davidsen et al., 2017).

Maximum use of computational resources: parallel computing, code parallelisation, and
 utilising graphics processing units (GPU) in 1D (Burger et al., 2014) and 2D models
 (Kalyanapu et al., 2011; Leandro et al., 2014; Vacondio et al., 2014; Zhang et al., 2014b)

and using remote distributed computers or Cloud computing (Glenis et al., 2013).

One method can be implemented independently or together with methods in other categories.
The reduction in simulation time can vary by orders of magnitude depending on the method
used. Among others, rapid flood inundation models and empirical models generally have
lower simulation time, in the order of seconds or a few minutes (Bernini and Franchini, 2013;
Krupka, 2009; Néelz and Pender, 2010; Néelz and Pender, 2013), which makes them a
potential choice when many simulations are required.

Rapid inundation models divide the 2D surface domain into elementary areas called *Impact Zones* (IZs) (Lhomme et al., 2008) representing local depressions. Flood water fills these
depressions and spills towards neighbouring depressions until all flood water is spread over

125 the ground surface. These models provide more computational speed by disregarding the 126 temporal evolution of the flood hydraulic process (Bernini and Franchini, 2013; Gouldby et 127 al., 2008; Krupka et al., 2007; Lhomme et al., 2008). These models are solely based on solving 128 water balance equations and only predict the final and maximum flood extent and its 129 associated depth. These indicators nevertheless represent the most important characteristics 130 that are used for flood risk assessment (Bernini and Franchini, 2013; Krupka, 2009; Lhomme 131 et al., 2008). Rapid inundation models are particularly suitable for large study areas and/or 132 stochastic modelling for probabilistic flood risk assessment (Néelz and Pender, 2013; Teng et 133 al., 2017). Examples of these models developed for simulating fluvial flooding (where the flood source is from a river or dike-breach) are: RFIM¹ (Krupka et al., 2007), RFSM² 134 135 (Gouldby et al., 2008) and its modified versions (Bernini and Franchini, 2013; Lhomme et al., 2008), and FCDC³ (Zhang et al., 2014a). Models that are developed for simulating pluvial 136 flooding (where flooding is mainly triggered by the lack of storm drainage network capacity) 137 include: GUFIM⁴ (Chen et al., 2009) and USISM⁵ (Zhang and Pan, 2014). GUFIM and 138 139 USISM have a storm runoff model to estimate surface runoff, which is the cumulative rainfall volume in excess of infiltration and the drainage network's capacity. This runoff then serves 140 141 as input to the inundation model.

While all rapid inundation methods utilise the same concept in their routine for generating IZs, there are variations in their flood spreading routines. For example, the RFIM (Krupka, 2009) and the earlier version of RFSM (Gouldby et al., 2008) implemented a one-directional spilling flood inundation routine in which an IZ with excess volume only spills towards the neighbouring IZ(s) that have the lowest communication level. By incorporating more physical

¹ Rapid Flood Inundation Model (RFIM)

² Rapid Flood Spreading Model (RFSM)

³ Flood-Connected Domain Calculation (FCDC)

⁴ GIS-based Urban Flood Inundation Model (GUFIM)

⁵ Storm Inundation Simulation Method (USISM)

147 processes into RFSM, Lhomme et al. (2008) introduced a multi-directional spilling routine. 148 In their new method, spilling towards neighbouring IZ(s) is determined by comparing the 149 communication levels to a calculated water level, which considers the effect of IZ shape on 150 the speed of filling and impact of surface friction on the spilling dynamics. Thus, water can 151 spill towards more than one neighbouring IZs.

Current rapid inundation models are used to simulate fluvial flooding, where the flood source 152 153 is from a river or dike-breach. The flood inundation routine in these models starts with 154 spreading flood from the specified breach point and estimates its extent. However, the 155 application of the rapid inundation models for urban pluvial flood inundation (where flooding 156 is mainly generated by surcharges from the drainage network manholes) has not yet been 157 investigated. In the case of urban pluvial flooding, surcharges from drainage network 158 manholes can occur at many locations and surface inundation generated by different manholes 159 can meet each other in several locations. ISIS FAST model (CH2M, 2013) is a commercial 160 package that was developed based on the concept of rapid flood inundation models. The 161 'Dynamic Linked' version of ISIS FAST model is able to simulate urban pluvial flooding by 162 creating a dynamic linking with a 1D drainage network model. The rapid flood inundation model implemented in the dynamic mode however, solves the Manning's equation (and 163 164 therefore the temporal evolution of flooding) instead of using simple volume balance 165 methods. The Dynamic Linked ISIS FAST model therefore represents a dynamic 1D-2D 166 model that uses a more complex rapid flood inundation model. To our knowledge there are 167 no other rapid inundation models that attempt to couple a 1D drainage network model to 2D 168 rapid inundation model.

169 This study aims to develop and validate an urban pluvial flood inundation model that is fast, 170 yet accurate enough for predicting maximum flood extents (and depths) and their associated 171 damage costs. We named it RUFIDAM - Rapid Urban Flood Inundation and Damage

172 Assessment Model. The main novelty of this study is its advancement of rapid inundation 173 models for applications urban pluvial flood assessment. Unlike existing rapid inundation 174 models, RUFIDAM adopts a modified rapid inundation routine and couples it to a 1D 175 drainage network model in a static way, allowing simulation of inundation caused by surcharging drainage manholes. In other words, we tested the hypothesis that the surcharges 176 177 predicted by a 1D drainage network model can be fed to a rapid flood inundation model (to 178 reliably characterise the location and magnitude of pluvial flooding in minor-major drainage 179 systems) without considering bi-directional dynamics between the two models. We test the 180 validity of this hypothesis by comparing RUFIDAM against a well-known 1D-2D 181 hydrodynamic urban flood model in series of simulation experiments. Our model was found 182 to predict flood inundation and damage costs with sufficient accuracy, while being 183 considerably faster than existing hydrodynamic models.

184 **2.** Methods

185 **2.1. Model formulation**

The RUFIDAM model structure (see Figure 1) has four main modules: (M1) IZs generation;
(M2) 1D drainage network model; (M3) rapid flood inundation model; and (M4) damage
assessment block. These four blocks are conveniently integrated with a graphical user
interface (GUI) developed using the Python Toolbox in ArcGIS.

190

191 FIGURE 1 APPROXIMATELY HERE

192

193 The IZs generation module (M1) is responsible for creating the input data for the rapid 194 inundation model. The 1D drainage network model (M2) simulates the rainfall-runoff process

195 and estimates the amount of water that enters the pipe network, then uses a hydraulic 196 simulation engine to calculate surcharges from the subsurface drainage network. These 197 surcharge volumes are imported as input to the rapid flood inundation model (M3). The 198 current version of RUFIDAM is able to use either SWMM (Rossman, 2015) or MOUSE (DHI, 2003); two well-known and well-tested packages. The linkage between 1D drainage 199 200 network model and rapid flood inundation model is 'static' (c.f. Section M2). The damage 201 assessment module (M4) uses the depth-damage curve method to calculate residential, 202 commercial-industrial and road damage costs based on the inundation depths produced by the 203 rapid inundation model. The next section explains each module in detail.

204 M1. Impact zones generation

205 Rapid inundation models divide the 2D surface domain into elementary areas called *Impact* 206 Zones (IZs) (Lhomme et al., 2008), representing local depressions. All impact cells within a 207 particular IZ flow towards the accumulation point of that IZ (see Figure 2). The 208 communication point of an IZ determines the communication level at which water spills into 209 the neighbouring IZ (Lhomme et al., 2008). Flood water fills these cells and starts to overflow 210 to adjacent IZs according to the elevation of communication points between two or more 211 neighbouring IZs (Figure 2). An example of the generated IZs from a 1m resolution DEM 212 before and after elimination process is illustrated in the supplementary document S1.

213

214 FIGURE 2 APPROXIMATELY HERE

215

IZ generation involves generating a network of IZs and their characteristics (list of neighbours, communication points and levels, volume-elevation relationship) based on a digital elevation map using the following steps:

- 1. Compute flow direction for each cell of the DEM.
- 220 2. Identify sinks.
- 3. Identify watersheds for all sinks (confined areas where all points pour into the same sink).
- 4. Extract sink boundaries as lines and determine the minimal elevation between
 neighbouring IZs based on the digital elevation map.
- 5. Determine the volume stored for different water levels in each IZ based on the digitalelevation map
- Details of the procedure above is provided in the supplementary document S1. The results ofthe IZs generation step are output in the form of three tables, which characterise:
- Links between the different IZs, as well as the surface elevations above which water
 will be exchanged between IZs;
- Surface elevation-volume relationship for each IZ; and
- Links between IZs and nodes of the 1D network model.
- 233 M2. 1D drainage network model

234 The hydraulic simulation of the underground drainage network in this study was carried out 235 using MOUSE (DHI, 2003) although SWMM was also available. This model also includes a 236 simulation of the rainfall runoff process and thus, an estimation of the amount of surface 237 runoff water that is generated and must be managed by the pipe network and/or above ground. 238 RUFIDAM couples 1D drainage network models to the rapid flood inundation model in a 239 static way, where the 1D drainage network model simulation is carried out without a dynamic 240 interaction with the rapid inundation model. At the end of the 1D simulation, the predicted 241 surcharge volumes from each manhole are fed to the rapid inundation model. When the static 242 coupling method is used, the predicted surcharge volumes might differ from those predicted

243 by the dynamically coupled 1D-2D models. Our hypothesis is that urban pluvial flooding is a 244 local phenomenon, meaning the surcharges from the drainage network does not travel long 245 distances over the surface ground. The surcharge volume would rather pond above the 246 manholes and return to the underground network from the same node when there is available capacity (this is already modelled in the 1D drainage network model if the ponding option is 247 248 selected), or flow downstream and re-enter the drainage network within a short distance. 249 Therefore, it might be possible to simulate pluvial flooding without modelling these local 250 surface flows in detail while maintaining sufficient accuracy and gaining substantial speed-251 ups. Additionally, the rapid inundation model implemented in RUFIDAM does not represent 252 the temporal evolution of flooding and it cannot provide information on when the surface flow 253 might reach to a downstream intake nodes.

254 1D drainage network models (such as MOUSE and SWMM) commonly provide different 255 options to handle surcharges when used in a static simulation. In the so-called *ponding* 256 configuration, it is assumed that water ponds over the surcharging node and will return to the 257 network via the same node when the capacity exists to do so (DHI, 2003). Thus, the water 258 level in the manholes can rise above the terrain level. In the *spilling* configuration, it is 259 assumed that water leaves the pipe network once the terrain level is reached and not 260 reintroduced into the system. It is not immediately clear, which of these approaches is more 261 suitable as an input for the rapid inundation model. Therefore, both approaches were tested in 262 this paper, applying the standard configurations provided in MOUSE (DHI, 2003).

263 M

M3. Rapid flood inundation model

The rapid inundation model developed in this study, improves the RFIM algorithm (Krupka, 2009) by incorporating a simpler multiple spilling method used in RFSM (Lhomme et al., 2008) and further adapts it to represent the dynamics of overlapping inundations from multiple manholes. Our rapid inundation model takes the flood volumes from surcharging 268 manholes in the 1D model as input and spreads the flood volume among the IZs based on the269 elevation of communication points.

Figure 3 sequentially illustrates the inundation routine for three surcharging nodes and eight IZs in ten stages (labelled 1 to 10). The rapid inundation model spreads the surcharge volumes by first filling the IZs that are adjacent to surcharging manholes and spilling the excess water into the neighbouring IZs. The filling/spilling process continues until the surcharged volume from all manholes has been spread across the floodplain. A detailed flowchart of the algorithm developed is represented in the supplementary document S2.

The surcharges from different manholes are treated sequentially and the order of processing the different manholes does not affect the final flood map. Considering the surcharge volume from a single node, the containing IZ is filled up to the lowest communication point with a neighbouring downstream IZ, at which point the remaining surcharge volume is distributed into the downstream IZ, which is again filled up to its lowest communication point. If the water level in a downstream IZ rises to the same level as in a neighbouring upstream IZ, the two zones are merged and subsequently treated as one (Figure 3, subfigure 3).

283 Before an upstream IZ can overflow into a downstream IZ, which does not yet contain any 284 water, the water level in the upstream IZ needs to rise to a level Δz above the communication 285 point (Figure 3, subfigure 2, 4, 5 and 10). The extra driving head Δz represents friction losses 286 and it is treated as a parameter of the model (Krupka, 2009; Lhomme et al., 2008). The value 287 Δz is not considered in the computation of surcharge volumes as it is assumed that this water 288 will eventually spill to a downstream zone. However, Δz is considered when evaluating 289 maximal water depth in the IZs. If the level of the lowest communication point plus Δz is 290 greater than the level of other communication points, water will spill in multiple direction 291 (Figure 3, iteration 10).

294

295 M4. Damage assessment

296 The rapid flood inundation model produces a raster map, pixels of which represent water depths. 297 The damage assessment module translates these water depths into damage values. There are 298 various damage assessment frameworks of varying complexity developed internationally 299 (Hammond et al., 2015; Merz et al., 2010; Velasco et al., 2016) and in Australia (M.H., 2010; 300 Olesen et al., 2017). RUFIDAM assesses financial damage cost using the stage-depth damage 301 curve method in which cost is a function of flood depth and area. During the flood damage 302 assessment process, flood inundation maps are overlaid with building and road layers and 303 stage-depth damage curves are applied to estimate direct tangible flood damages RUFIDAM 304 uses stage-damage curves from Australian studies that were identified during a recent 305 literature review (Olesen et al., 2017). The implemented approach in this study uses three 306 curves for three types of land-uses: (1) residential buildings, (2) commercial and industrial 307 buildings and, (3) road areas. We implemented this approach because more detailed damage 308 curves were not available for Australia.

309 **2.2.** Model testing and application

310 **2.2.1.** Case study description and data set

We tested RUFIDAM for three catchments (C1, C2, and C3 in bottom-right of Figure 4) of different sizes and average slopes, as presented in Figure 4. These catchments are located within the Elster Creek basin in South Eastern Melbourne, which has been subject to frequent pluvial and tidal flooding due to severe storms and urbanisation in low-lying areas. The catchment predominantly contains residential buildings and a small proportion of commercial and industrial buildings distributed across the area (Olesen et al., 2017). 317

318 FIGURE 4 APPROXIMATELY HERE

319

320 A 1D-2D hydrodynamic model for the catchment was available from a previous project 321 (Davidsen et al., 2017). This model was implemented in MIKE FLOOD (DHI, 2013) by replacing the 2D surface model with LiDAR DEM data of 1m horizontal resolution provided 322 323 by Geoscience Australia (GA, 2017). The same LiDAR DEM data was also used for 324 RUFIDAM modelling, to create IZs. Supplementary document S3 reports specification of 325 identified IZs for the three catchments. The 1D portion of this 1D-2D hydrodynamic model 326 was used as the 1D drainage network model in RUFIDAM to estimate input surcharge 327 volumes. It included a hydrologic runoff and hydraulic flow simulation engine. Runoff 328 simulations were performed using the so-called 'MOUSE model B'. In this approach, initial 329 losses are considered for runoff from impervious areas, while initial and infiltration losses are 330 considered for pervious areas. A modified Horton approach is applied for modelling 331 infiltration capacity. Runoff transformation is modelled using a kinematic wave approach and 332 all runoff is routed to manholes in the 1D network. Similar to the 1D-2D MIKE-FLOOD 333 model implemented in this study, RUFIDAM assumes that all the generated runoff enters the 334 drainage network.

Three design storms with duration of 4.5 hours and return period of 5, 10 and 100-years wereextracted from Australian guidelines and used in the simulation experiments.

337 2.2.2. Simulation experiments

As discussed in the following section, we performed a number of simulation experimentsusing the selected storms to develop and validate RUFIDAM.

340 1D drainage network simulation vs. 1D-2D simulation

341 We investigated the impact of implementing a static approach by comparing the results from 342 a 1D simulation of the network to a fully dynamic 1D-2D model. As mentioned in the model 343 description section, the 1D drainage network model can have two different configurations, 344 namely 'ponding' and 'spilling'. It was not obvious whether 1D simulations of the pipe 345 network should apply the spilling or ponding configuration when used in conjunction with the 346 rapid inundation model in a static way. To gain insight into these challenges, we compared 347 simulated total flows in links and maximum water levels in nodes for different static 1D model 348 configurations (ponding and spilling) against the results of the dynamic 1D-2D model (MIKE 349 FLOOD) in the three catchments and for all three storm events. Ideally, the comparison would 350 also consider the volume exchanged between 1D drainage network and surface in both 1D and 1D-2D simulations. However, this result was not readily available from MIKE FLOOD. 351

352 Sensitivity analysis of key model parameters

353 We conducted sensitivity analysis to investigate how RUFIDAM predictions varied based on 354 the 1D model setup (ponding and spilling) and to find the range of model parameters (constant 355 extra head Δz and minimum IZ area) for which the best performance indicators (see Section 356 2.2.3) were obtained. This analysis was carried out only in Catchment 1 for the 100-year 357 design storm. We used a grid-search approach with a total of 3000 simulations (2 drainage model setups i.e. spilling and ponding; 50 values for minimum IZ areas ranging between 10 358 to 2000 m²; and 30 values for Δz , ranging from 1 to 30 cm with 1 cm intervals). Our initial 359 360 investigation prior to the sensitivity analysis showed that there was no improvement in the 361 performance indicators for Δz within a 30 to 150 cm range and for minimum IZ area bigger 362 than 2000 m². Therefore, we limited our sampling to the range within which we expected to 363 find the best result and increased sampling frequency.

364 Surface inundation prediction

365 To evaluate how our simplified 2D simulation affects predictions of surface inundation, we 366 compared the 2D part of RUFIDAM (the rapid inundation model) against the 2D part of 367 MIKE FLOOD by providing them the same surcharge volumes as the boundary condition. 368 This helped remove the uncertainty of surcharge predictions caused by static simulation of 369 the 1D drainage network model when compared with the 2D surface models. In both model 370 simulations (rapid inundation model and MIKE FLOOD), 43 source points of inflows to the 371 surface model were considered as boundary conditions. These points and their flows were 372 derived by grouping the 380 nodes surcharging during a 1D network simulation of Catchment 373 1 for a T=100-year event. The inflow volume at each source point corresponded to the 374 aggregated surcharge volume of the nodes in each group. Since the rapid inundation model 375 does not consider the temporal evolution of flooding, it only requires the total surcharge 376 volumes as input, while we considered a typical surcharge hydrograph (represented in the 377 supplementary document S4) for all source points as input to MIKE FLOOD.

378 Damage cost prediction

We evaluated the overall performance of RUFIDAM in the three catchments and for all three storm events by comparing them against 1D-2D MIKE FLOOD results. We used the 1D model setup and rapid inundation model parameters that were suggested by the sensitivity analysis. We also compared total damage cost predicted by RUFIDAM to those predicted using MIKE FLOOD results. The damage cost of flooding were calculated using the stagedepth damage curves provided in Olesen et al. (2017).

385 **2.2.3. Performance indicators**

Ideally, RUFIDAM's performance should be tested using the measured data of an observedflood event. However, we did not have such a data and therefore compared our model with

MIKE FLOOD, a well-known 1D-2D hydrodynamic model. Since RUFIDAM only predicts the final and maximum flood extent and maps, we measured the performance of the model by comparing its results to the maximum flood depth map predicted by MIKE FLOOD model. Unlike RUFIDAM, MIKE FLOOD represents the temporal evolution of flooding, meaning a flood depth map can be reported at each time step of the simulation. The maximum flood extent map represents the highest water depth calculated for each pixel regardless of the time of occurrence.

For all the above scenarios, considering the maximum flood depth maps generated by the 1D-2D simulation in MIKE FLOOD as our *baseline*, we evaluated two different sets of indicators: (1) indicators for comparing model hydraulic behaviour and (2) indicators for comparing damage cost predictions. The hydraulic indicators, namely Root Mean Square Error (RMSE), Fit, and Bias, are calculated by pixel-by-pixel comparison of the flood depth in both models.

400 - RMSE for evaluating flood depth prediction performance is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_i^{RUFIDAM} - Y_i^{MIKE \ FLOOD})^2}{n}}$$
(1)

401 In which $Y_i^{RUFIDAM}$ and $Y_i^{MIKE FLOOD}$ are the maximum inundation depth of the *i*th cell 402 of the RUFIDAM and MIKE FLOOD results, and n is the number of cells that is wet 403 in at least one of the models. The closer the RMSE is to zero, the better the estimate 404 provided by the rapid model. We defined a pixel as wet if water depth was greater than 405 5 cm.

406 - *Fit* indicator (Lhomme et al., 2008) [%], was used to measure the agreement between
407 two models in predicating flood extent:

$$Fit = 100 \times \frac{B}{B + C + D}$$
(2)

where B represents the number of pixels inundated in both models, C is the number of
pixels inundated in RUFIDAM but dry in MIKE FLOOD, and D is the number of
pixels inundated in MIKE FLOOD but dry in RUFIDAM. A fit value closer to 100%
represents a better agreement in flood extent prediction.

Bias indicator represents the relative percentage error with respect to the final extent
of the flooded area. Positive values indicate overestimation of the extent compared to
the expected value, whereas negative values indicate underestimation. Values closer
to zero represent smaller errors in predictions (Bernini and Franchini, 2013).

$$Bias = 100 \times \left(\frac{B+C}{B+D} - 1\right)$$
(3)

416 The damage cost indicators include:

417 - *Percent Error (PE) of the total damage costs* [%] that measures the relative difference
418 between the total flood damage cost for a catchment (*Cost*) predicted by the models:

$$PE = 100 \times \frac{Cost_{MIKE-FLOOD} - Cost_{RUFIDAM}}{Cost_{MIKE-FLOOD}}$$
(4)

Fit indicator [%], was used to measure the agreement between two models in
predicting the number of flood damaged buildings at a location. This indicator was
calculated using Equation 2 where B is the number of damaged buildings in both
models, C is the number of damaged buildings in RUFIDAM but unaffected in MIKE
FLOOD, and D is the number of damaged buildings in MIKE FLOOD but unaffected
in RUFIDAM. A fit value closer to 100% represents a better spatial agreement in
damage prediction.

Bias indicator for number of flooded buildings [%], which evaluates the total number
of flooded buildings in a catchment, irrespective of their location. This indicator uses
Equation 3 with parameters defined for the damage cost fit indicator above. Positive

429 values indicate overestimation in the number of damaged buildings by RUFIDAM430 compared to MIKE FLOOD, whereas negative values indicate an underestimation.

431 **3. Results**

432 **3.1. 1D** drainage network simulation vs. **1D-2D** simulation

433 Figure 5 compares maximum water levels and total link flow volumes obtained in static 1D 434 drainage network simulations (with ponding and spilling configurations), against those 435 obtained from a dynamic (1D-2D MIKE FLOOD) simulation for a T=100-year event in 436 Catchment 3 (the results for Catchments 1 and 2 were similar as shown in the supplementary 437 document S5). In all three catchments, maximum water levels were positively biased for the 1D simulation with ponding configuration, while they vary around the values obtained from 438 439 the dynamic simulation when applying the spilling configuration. Link flow volumes were 440 overestimated by the 1D model with ponding configuration as compared to the dynamic 441 simulation and underestimated by the 1D model with spilling configuration. These trends 442 were consistent for all the considered catchments and rain events.

443

444 FIGURE 5 APPROXIMATELY HERE

445

Figure 6 shows a map of differences between maximum water levels (maximum water level in static 1D simulation minus maximum water level in dynamic 1D-2D MIKE FLOOD) and link flow volumes (total link flow in static 1D simulation minus total link flow in dynamic 1D-2D MIKE FLOOD) for a T=100-year event for Catchment 3. In upstream areas, the simulated levels and flows in the spilling method were very similar to the dynamic 1D-2D MIKE FLOOD model, while for the ponding method the upstream values were biased. As 452 water moves downstream, the difference in link flows aggregated, and resulted in a greater 453 difference in the main downstream links. Additionally, higher water levels in the ponding 454 simulation induced upstream pipe flows and thus led to reduced surcharge volumes in 455 upstream nodes.

456

457 FIGURE 6 APPROXIMATELY HERE

458

459 3.2. Sensitivity analysis of key model parameters

460 Figure 7 shows the result of the sensitivity analysis by comparing results obtained from 461 RUFIDAM with different configurations, against a MIKE FLOOD simulation for a T=100-462 year event in Catchment 1. This figure used the damage cost prediction performance 463 indicators. Sensitivity analysis using the hydraulic performance indicators is provided in the supplementary document S6. These figures suggest that RUFIDAM was most sensitive to the 464 465 Δz parameter and minimum IZ area, while the choice of either ponding or spilling 466 configuration of the 1D model had minimal impact on model results. The spilling 467 configuration showed slightly better performance, which is in agreement with the already 468 presented results (section 3.1). In both spilling and ponding options, the impact of minimum 469 IZ area increased with Δz (up to around 10 cm), while the influence of Δz did not change with 470 an increase in IZ area. A parameter set should be selected by accounting for all performance indicators. The best PE and highest FIT values were observed for $\Delta z = 12$ to 15 cm, and 471 minimum IZ area between 150 to $250m^2$ in both spilling and ponding methods. Bias for the 472 473 same values were around -12 to 5 percent. As such, these parameter values in combination 474 with 1D model simulations using a spilling configuration were applied.

476 FIGURE 7 APPROXIMATELY HERE

477

478 **3.3.** Surface inundation prediction

479 Figure 8 shows the flood extent predicted by the rapid inundation model and MIKE FLOOD 480 for the scenario in which 43 nodes were surcharging. The flow paths predicted by the rapid 481 inundation model were very similar to those predicted by MIKE FLOOD. This highlights the 482 ability of the rapid inundation model in predicting the flooding pattern, even if it was over- or 483 underestimating local flooding. Figure 8 also shows a pixel-by-pixel comparison of flood 484 depth between both models. The rapid inundation model performed well in predicting higher 485 flood water depth (which can cause significantly higher damage costs). The Fit and Bias 486 values were 48.5% and -6%, respectively.

487

488 FIGURE 8 APPROXIMATELY HERE

489

490 **3.4.** Damage cost prediction

491 Figure 9 compares the flood damage cost for residential buildings, commercial/industrial 492 buildings and roads in all catchments, estimated using flood inundation maps produced by 493 MIKE FLOOD and RUFIDAM. Generally, RUFIDAM overestimated the total damage cost. 494 The predicted damage for residential buildings was similar across both models, while the 495 difference was higher for commercial/industrial damages. The reason for this discrepancy is 496 that the damage cost of these buildings was more sensitive to changes in water level. 497 Commercial buildings also incur a relatively high damage cost and represent a significant 498 proportion of the total damage costs even though the number of flooded buildings was lower. 499 As the number of commercial/industrial buildings decreases in a catchment, the total damage

500 cost predicted by RUFIDAM approaches the value predicted by MIKE FLOOD. In Catchment

501 3 no commercial/industrial building was flooded.

502

503 FIGURE 9 APPROXIMATELY HERE

504

Figure 9 also shows the Fit, Bias and PE indices for each catchment. The Fit index ranges around 40 to 50 percent while the Bias index was in the order of 10% or less in all cases. Hence, compared to a fully dynamic 1D-2D simulation, we concluded that RUFIDAM was able to reproduce the overall flood extent, while we observed quite widespread variation and errors in the locations where flooding was simulated. This is also evident from Figure 10, which compares flood depth and damage maps for the two different simulation methods.

511

512 FIGURE 10 APPROXIMATELY HERE

513

514 **4. Discussion**

515 **4.1. 1D** network model configuration as an input to rapid inundation model

516 Maximum water level and link flows were higher when the ponding configuration was applied 517 in the 1D simulation as opposed to the spilling configuration. The reason for this behaviour 518 is that higher water levels and thus higher pressure gradients were simulated in the 1D 519 configuration and that surcharged water will eventually enter the network from the same node 520 when the capacity becomes available. In the spilling configuration, all the surcharged volume 521 is assumed to be lost from the network and water levels cannot rise above the ground level. 522 In the 1D-2D MIKE FLOOD simulation, part of the surcharged volume will enter from the 523 same node, some will flow downstream and re-enter the network via other nodes and the rest 524 will exit the catchment as surface runoff. Surface water levels can affect the pressure gradients 525 in the pipe network, but the surface water levels above the manholes were usually low. Compared to 1D-2D simulation, the spilling method showed only small variations in water 526 527 levels and flows through upstream pipes, suggesting that surcharges should occur in a similar 528 location as in the 1D-2D simulation. During sensitivity analysis, slightly better results were 529 obtained for the spilling configuration than for the ponding configuration, while the 530 configuration of 2D parameters had greater impact on model results. This suggests that the 531 biggest potential for improving RUFIDAM should be found in the 2D surface model while a 532 static 1D model can describe the hydraulics of the pipe network with sufficient accuracy.

533 4.2. Predicting flood inundation

Overall, the maximum flood inundation extent predicted by the rapid inundation model were comparable with those predicted by the 1D-2D MIKE-FLOOD hydrodynamic model. The model performs better in areas that have natural depressions than flat topography and therefore tends to predict higher inundation depths better than lower depths (as high depth of flood water is usually formed in areas where there are natural depressions in the surface terrain and flood water can accumulate).

540 One of the limitations of rapid inundation models is that their simple wetting/drying algorithm 541 tends to leave flooded areas in between IZs (which are natural flow paths) as dry areas. In 542 other words, only locations of ponding water will be reported as flooded areas and the flow 543 paths between two flooded neighbouring IZs will be reported as dry in the final inundation 544 map. As the size of IZs increases (the number of IZs decreases), the amount of dry areas 545 increases. This can be improved by finding possible connecting pathways between IZs using 546 the "rolling ball" technique suggested in the literature (CH2M, 2013; Leitão et al., 2009; 547 Maksimović et al., 2009; van Dijk et al., 2014). Water depth in these dry areas were usually 548 smaller than the minimum threshold level in our depth damage curves. Therefore, this 549 shortage did not significantly affect the total damage cost predictions.

550

4.3. Predicting flood damage cost

The total damage cost predicted by RUFIDAM had good agreement with those based on the MIKE-FLOOD inundation maps, for residential buildings and road areas. However, it was not comparable for commercial/industrial buildings because their damage cost is sensitive to flood depth. Estimated Fit index values for flood damage prediction were around 40 to 50 percent in different catchments, indicating RUFIDAM did not perform well in identifying the same buildings flooded in MIKE FLOOD, but was able to predict the overall damage cost within the study area.

558 In areas like Australian suburbs, where land-use usually does not vary a lot across small 559 distances, local variations in the prediction of flooding will have little impact on total flood 560 damage, particularly compared to the uncertainty from other model inputs such as damage 561 curves, the rainfall, etc. It is important to have a "balanced" level of complexity and 562 uncertainty among each modelling block (e.g. rapid inundation model and damage assessment 563 blocks). In particular, when comparing to the uncertainty resulting from depth-damage 564 functions (de Moel and Aerts, 2011), RUFIDAM provides estimates of total flood damage with sufficient accuracy and a minimum of simulation time and model complexity. de Moel 565 566 and Aerts (2011) states that while estimating the absolute flood damage cost, estimates for proportional changes in flood damages are much more robust. Therefore, we can expect more 567 568 confidence when we use RUFIDAM to compare the performance of different flood mitigation 569 measures, rather than predicting absolute damage cost reduction.

570 4.4. Computational requirements and simulation speed

571 In general, the simulation time of RUFIDAM was less than 15 minutes. This comprises the 572 total time spent for the 1D drainage network, rapid flood inundation model, damage 573 assessment processes and creation of output maps, but does not include the IZ generation 574 process (which we measured separately). Around 40 percent of this time was spent for 1D drainage network simulation (MOUSE simulation time for Catchments 1, 2, and 3 were 575 576 around 5, 6 and 1 minutes, respectively). The IZs generation process for catchments required 577 between 2 to 10 minutes depending on the catchment size. When running many simulations, 578 the IZs generation step need only be carried out once if the change in topography (e.g. city 579 development over time) is not considered.

Figure 11 compares the simulation time of RUFIDAM (excluding IZs generation) and MIKE FLOOD for all catchments and return periods in relation to catchment sizes. Unlike the rapid flood inundation model, MIKE FLOOD uses parallel processing (we used a 6-core CPU computer for MIKE FLOOD simulations). The total simulation time in RUFIDAM is a function of the study area (catchment size), number of IZs, and the amount of surcharge volume to be spread in the rapid inundation model. Figure 11 shows that in general, as the size of the catchment increases, the speed gain increases exponentially.

587

588 FIGURE 11APPROXIMATELY HERE

589

590 It should be noted that this analysis should also be carried out for DEMs with different 591 resolutions. It is expected that MIKE FLOOD would be significantly quicker when coarser 592 resolution DEMs are used.

593 **5.** Conclusion

This paper presented RUFIDAM, a GIS based rapid urban pluvial flood inundation and damage assessment model that was designed to run with very short computational and setup time to be used in exploratory modelling and continuous flood simulations. RUFIDAM integrates a 1D drainage network model with a simple and fast volume spreading routine based on only water balance and topography (local depressions).

Results showed that the spilling configuration of the 1D drainage network model (MOUSE) yields hydraulic results that are very similar to those obtain in a 1D-2D simulation. The surcharge volumes obtained from such a model are thus an appropriate input to a rapid flood inundation model when land use changes in the catchment are small and summary statistics are the key focus. Our hypothesis that using a 1D drainage network simulation are sufficiently accurate to simulate pluvial flooding without modelling these "local" surface flows in detail was proven to be valid.

The maximum flood inundation extents predicted by RUFIDAM were comparable with those predicted by the 1D-2D MIKE FLOOD especially in areas that have natural depressions and, hence, high water depths. However, local variations of flood areas were observed, leading to deviations about which buildings were considered flooded. However, comparable total flood damages are simulated by RUFIDAM and the 1D-2D model.

RUFIDAM is suitable for flood inundation and damage estimation when the study area is large or a large number of simulations are required (such as risk-based approaches for flood risk assessment or exploratory modelling) and where differences between calculations are more important than accurate calculations of each result.

Future research includes the sensitivity analysis of the model performance to the DEM grid resolution. The model has the potential to represent tidal floods and this capability will be introduced in the future to simulate tidal and pluvial flooding.

- 618 6. Acknowledgements
- 619 The Australia-Indonesia Centre (AIC) has financially supported this research. Melbourne
- 620 Water and City of Port Phillip kindly provided the catchment data. The authors would like to
- thank the anonymous reviewers for their valuable comments and suggestions to improve the
- 622 quality of the paper.

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