



1 Targets-specified grids-tailored sub-model approach for fast large-scale high-resolution 2D 2 urban flood modelling

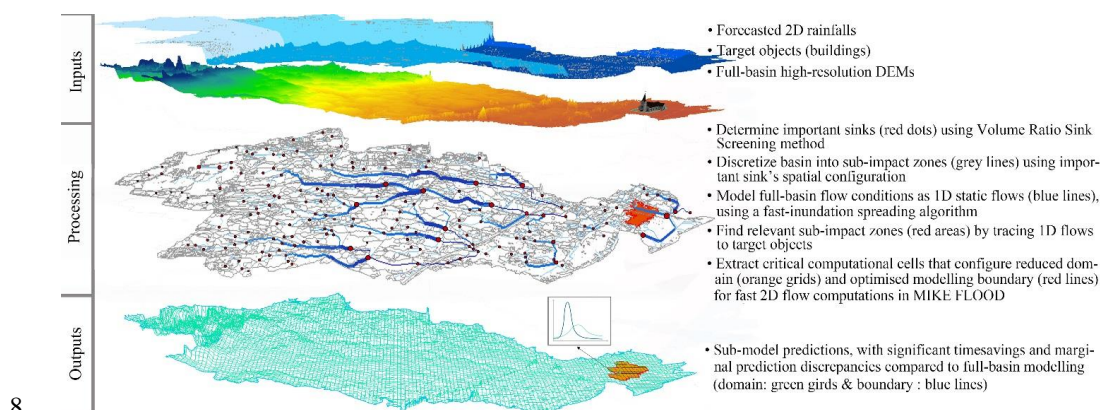
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7 Graphic abstract



9 Abstract

10 The accuracy of two-dimensional urban flood models (2D models) is improved when high-resolution Digital
 11 Elevation Models (DEMs) is used, but the entailed high spatial discretisation results in excessive
 12 computational expenses, thus prohibiting the use of 2D models in real-time forecasting at a large scale. This
 13 paper presents a sub-model approach to tailoring high-resolution 2D model grids according to specified targets,
 14 and thus such tailor-made sub-model yields fast processing without significant loss of accuracy. Among the
 15 numerous sinks detected from full-basin high-resolution DEMs, the computationally important ones are
 16 determined using a proposed Volume Ratio Sink Screening method. Also, the drainage basin is discretised into
 17 a collection of sub-impact zones according to those sinks' spatial configuration. When adding full-basin
 18 distributed static rainfall, the drainage basin's flow conditions are modelled as a "1D static flow" by using a
 19 fast-inundation spreading algorithm. Next, sub-impact zones relevant to the targets' local inundation process



20 can be identified by tracing the 1D flow continuity, and thus suggest the critical computational cells from the
21 high-resolution model grids on the basis of the spatial intersection. In MIKE FLOOD's 2D simulations, those
22 screened cells configure the reduced computational domains as well as the optimised boundary conditions,
23 which ultimately enables the fast 2D prediction in the tailor-made sub-model. To validate the method, model
24 experiments were designed to test the impact of the reduced computational domains and the optimised
25 boundary conditions separately. Further, the general applicability and the robustness of the sub-model
26 approach were evaluated by targeting at four focus areas representing different catchment terrain morphologies
27 as well as different rainfall return periods of 1-100 years. The sub-model approach resulted in a 45-553 times
28 faster processing with a 99% reduction in the number of computational cells for all four cases; the predicted
29 flood extents, depths and flow velocities showed only marginal discrepancies with Root Mean Square
30 Errors (RMSE) below 1.5 cm. As such, this approach reduces the 2D models' computing expenses
31 significantly, thus paving the way for large-scale high-resolution 2D real-time forecasting.

32 **Keywords:** Targets-specified modelling, tailored grids, sub-model generation, large-scale high-resolution
33 flood modelling, real-time forecasting.



34 **1. Introduction**

35 Urban floods pose escalating threats to human settlements in times of continued urbanisation and climate
 36 change (Bernstein et al., 2008). In order to mitigate the flood risks and the related consequences, a flood
 37 forecasting system that complies with two criteria: i) accurate spatial and temporal flood predictions and ii)
 38 sufficient lead time between rainfall predictions and flood predictions, is considered as a prerequisite to provide
 39 precise early warnings for decision makers. Therefore, with the purpose of identifying an accurate and timely
 40 urban flood model to configure such a system, we review two types of models: i) 2D hydrodynamic models
 41 (Section 1.1) and ii) 1D static models (Section 1.2). After summarising the strengths and potentials for the two
 42 models, the scientific innovation of the proposed approach is outlined by identifying a 1D/2D complementary
 43 solution that adapts a 1D static model to tailor a 2D model grids based on specified targets, thus achieving fast
 44 and accurate predictions in large-scale high-resolution 2D urban flood modelling (Section 1.3).

45 **1.1 2D hydrodynamic models (2D models)**

46 By enabling more realistic 2D dynamic flows across regular grids, 2D models are advocated as a preferential
 47 approach to other alternatives for urban flood simulations (Maksimović et al., 2009; Mark et al., 2004; Mark
 48 and Parkinson, 2005; Schmitt et al., 2004; Leandro et al., 2009). However, 2D models tend to be
 49 computationally expensive. When numerical solvers (implicit/explicit solvers) are executed in a high spatial
 50 discretisation based on a fine grid, to stabilise the models, the optimum time steps must be decreased
 51 accordingly, which boost processing time considerably. Although applying a coarse grid is considered a
 52 straightforward way to reduce computing time, it turns out that the extra details inherent in high-resolution
 53 DEMs can benefit simulation accuracy substantially (Fewtrell et al., 2008; Yu and Lane, 2006a). Particularly
 54 when micro-topography dominates the direction of flood propagation, grid coarsening may smear critical
 55 elevation information resulting in imprecise inundation distributions (Fewtrell et al., 2011; Jensen et al., 2010).
 56 Recently, the occurrence of decimetric DEMs allows for the inclusion of more detailed micro-topographies in
 57 urban flood models, which initiates a new high-resolution simulation era. However, due to the prohibitive
 58 processing time, high-resolution applications have been limited to small scale modelling only (Fewtrell et al.,
 59 2011; Sampson et al., 2012). For the same reason, the use of high-resolution grids in real-time forecasts



60 (nowcasting) is impractical. Consequently, applying high-resolution DEMs to large-scale modelling and real-
 61 time forecasts remains a challenge.

62 To improve the 2D models' computational efficiency, four speed-up approaches may be employed: i)
 63 parallelization technology taking advantage of Graphics Processing Units (GPUs), multi-core Central
 64 Processing Units (MCs), remotely distributed computers and cloud computing such as JFLOW-GPU (Lamb
 65 et al., 2009), OpenMP (Neal et al., 2009), MPI libraries (Neal et al., 2010), FloodMap-Parallel model (Yu,
 66 2010) and CityCAT (Glenis et al., 2013); ii) a simplified hydrodynamic model approach that solves simplified
 67 governing equations, whereby reasonable flood extents and depths can be yielded quickly although the
 68 momentum conservation is less emphasized, e.g. inertial LISFLOOD-FP (Bates et al., 2010) and Quasi 2D
 69 (Kuiry et al., 2010); iii) a coarse-grid approach, where computational time is reduced by increasing the grid
 70 size (Yu and Lane, 2006a); to compensate for loss of accuracy due to smearing of details, especially around
 71 buildings, various improvements have been introduced, including sub-grid treatment (Chen et al., 2012a; Yu
 72 and Lane, 2006b; Yu and Lane, 2011), the multi-cell approach (Hénonin et al., 2015), the multi-layered
 73 approach (Chen et al., 2012b) and the porosity parameter (Bruwier et al., 2017; Guinot and Soares-Frazão,
 74 2006; McMillan and Brasington, 2007; Sanders et al., 2008); and iv) the Cellular Automata (CA) approach,
 75 where a universal transition rule is coded for spatial discretization in the simulation, thus achieving a reduced-
 76 complexity procedure in 2D models (Dottori and Todini, 2010; Dottori and Todini, 2011; Ghimire et al., 2013;
 77 Guidolin et al., 2016). Whereas these technologies may reduce computational costs to some extent, new fast-
 78 approaching remote sensing technologies delivering enhanced data accuracy in tremendous volumes are even
 79 more difficult for them to handle (Bates et al., 1997; Barnea and Filin, 2008; Cobby et al., 2003; Fewtrell et
 80 al., 2011; Leitão, 2016; Lichti et al., 2008; Marks and Bates, 2000; Mason et al., 2003; Mason et al., 2007;
 81 Meesuk et al., 2015; Sampson et al., 2012; Schubert et al., 2008; Tokarczyk et al., 2015). Especially, the use
 82 of a high-resolution modelling grid is the precondition to explicitly include all detailed spatial representations
 83 of datasets into 2D simulations. Thus, the computational efficiency of 2D models remains a challenge in the
 84 high-resolution data context.



85 1.2 1D static models (fast-inundation spreading models)

86 Although 2D hydrodynamic models still dominate, increasing attention is paid towards fast-inundation
 87 spreading models due to their fast computing speed. Noteworthy examples include RFIM (Krupka et al., 2007;
 88 Liu and Pender, 2010, Jamali et al., 2018), RFSM (Bernini and Franchini, 2013; Gouldby et al., 2008; Lhomme
 89 et al., 2008), ISIS-FAST (Shaad, 2009), FCDC (Zhang et al., 2014), GUFIM (Chen et al., 2009), SCALGO
 90 (Arge et al., 2010), USISM (Zhang and Pan, 2014) and Arc-Malstrøm (Balstrøm and Crawford, 2018). A
 91 conception of “hydrostatic condition” (Bernini and Franchini, 2013), also known as the “flat water assumption”
 92 (Zerger et al., 2002) is commonly embedded as the underlying algorithm in these models. With mass
 93 conservation as the only governing law and disregarding temporal evolution, the fast-inundation spreading
 94 models present a filling/spilling process within the predefined flow patterns thus resulting in predictions
 95 rapidly. Here, we name the process “1D static flow” in this research. These models are divided into two types
 96 (Zhang and Pan, 2014): one is used for point-source triggered floodings like dam breaching and riverbank
 97 overflow (RFIM, RFSM, ISIS-FAST, FCDC); the other (non-point source models) is more directly relevant
 98 to stormwater-inundations in urban areas (GUFIM, USISM, Arc-Malstrøm). By using 1D static flows instead
 99 of 2D dynamic flows the fast inundation spreading models gain computational efficiency substantially, and
 100 thus a fast-processing speed is obtained particularly when dealing with large-scale high-resolution DEMs.
 101 However, there are two notable drawbacks: first of all, due to their intrinsic neglect of time evolution, they
 102 cannot reproduce flow dynamics (i.e. hydrographs), and peaks may be miss-captured in such static simulations.
 103 Secondly, they do not account for the conservation of momentum and, therefore, cannot provide flow
 104 velocities, which is essential to flood risk assessments.

105 1.3 Hypothesis and research objectives

106 The simplified urban flood models can be designed to perform specific modelling tasks by deliberately
 107 ignoring the representation processes deemed incidental to the defined modelling purpose (Hunter et al., 2007).
 108 If we adapt a 1D static model to exclude 2D model grids that are irrelevant to specified targets (i.e. specified
 109 buildings and specified precipitations), then 2D dynamic flows would avoid the prohibitive processing time



110 when dealing with large-scale high-resolution DEMs, while compensating for the drawbacks of 1D static flows
 111 used, which results in cost-efficient tailor-made sub-models.

112 This paper presents a sub-model approach to reducing 2D models' computing time in case of large-scale high-
 113 resolution urban flood modelling. The reduction is done by two phases (I/II) distinguished by multiple scales
 114 (i.e. basin/local catchment), see Fig. 1: i) aiming at identifying reduced domains, the 1D static model (Arc-
 115 Malstrøm) is adapted to trace the relevant sub-impact zones based on specified target objects and specified
 116 precipitations; ii) aiming at the highest precise flow predictions, the full 2D dynamic model (MIKE FLOOD)
 117 is used based on the reduced domain intersected with sub-impact zones. To investigate the influence of the
 118 domain reductions, the MIKE FLOOD predictions based on the sub-model domain is benchmarked against the
 119 one of the full domain, and further compared to the one defined from municipality borders. Meanwhile, to
 120 investigate the validity of the suggested boundary conditions, the discrepancies of optimal boundary condition
 121 is compared to the ones of uniform closed-/open-boundary conditions. Finally, to prove general applicability
 122 and robustness, performances of four sub-models are benchmarked and compared using different terrain
 123 morphologies as well as different rainfall return periods.

124 **2. Methodology**

125 The program of the sub-model approach is adapted from the prototype of Arc-Malstrøm and consists of five
 126 modules (Modules I-V, as illustrated in Fig. 1), where Module II is essentially following the Arc-Malstrøm
 127 and Modules I, III-V is added for the sub-model tailoring purpose. The general procedure is programmed and
 128 wrapped up with ArcGIS' Python interface (ArcPy). To address the distinctions between Arc-Malstrøm and
 129 the sub-model approach, further comparisons and associated tests are inclosed as Supplementary Document
 130 S1, S2 and S3.

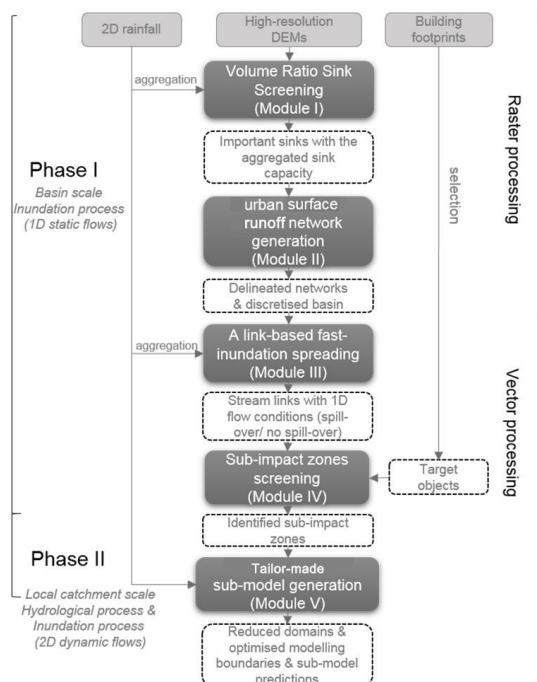


Fig. 1. Illustration of the suggested method. In the central column, shaded boxes represent major modules; light grey boxes are required input data; dashed-line boxes are intermediate data between different modules and the final outputs. Phase I and Phase II (left side) represent the two major phases, where an appropriate level of modelling complexities (hydrological/inundation process) is addressed at each modelling scale (basin/local catchment scale) to achieve a holistic computational efficiency in multiple-scale simulations. The right side represents the GIS processing environment that shifts from raster (computationally expensive) to vector processing (computationally cheap) for the sake of the general computational expense reduction.

2.1 Volume ratio sink screening (Module I)

When creating an urban surface runoff network, the numbers and spatial configuration of sinks are critical factors concerning network delineations (stream links) and discretisation of the drainage basin. To avoid spurious network components due to an increasing number of sinks detected from high-resolution DEMs (i.e. 0.4 m/1.6 m), a Volume Ratio Sink Screening method (VRSS) is proposed as presented in Fig. 2a. This module screens for computationally important sinks to generate relevant networks (Section 2.2) and adequate volumes involved in subsequent computations (Section 2.3).

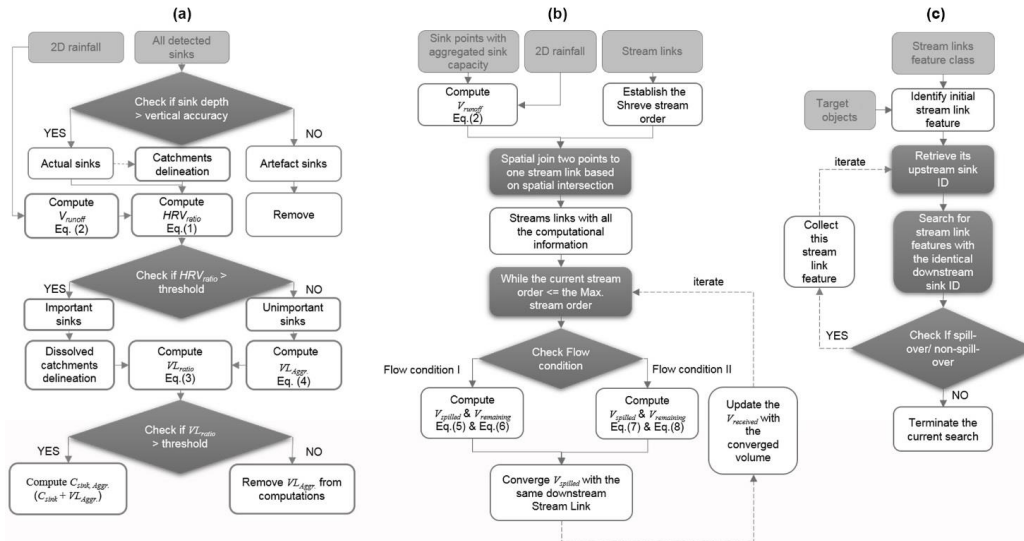


Fig. 2. (a) The Volume Ratio Sink Screening method; (b) The link-based fast-inundation spreading algorithm; (c) The sub-impact zones screening method, where the dark grey shaded boxes represent major steps and light grey boxes are input data. Note: V_{runoff} – Runoff Volume, HRV_{ratio} – Hydrological Retention Volume ratio, $VL_{Aggr.}$ – Aggregated Volume Loss, VL_{ratio} – Volume Loss ratio, $C_{sink, Aggr.}$ – Aggregated Sink Capacity, $V_{spilled}$ – Spilled Volume, $V_{remaining}$ – Remaining Volume, $V_{received}$ – Received Volume.

In general, sinks are classified into two categories: actual sinks and artefacts (Lindsay and Creed, 2006). To preserve the actual sinks only, the DEM's vertical accuracy is used, whereby artefact sinks shallower than or equal to this threshold value are removed. Other sink artefacts, such as detected inside enclosed building blocks or on rooftops, are deleted (see Fig. 3a). Nevertheless, the inclusion of all actual sinks as computational nodes may lead to massive computational costs while improving minor modelling accuracy for network-based computations (i.e. 1D static/dynamic modelling). To further differentiate “important” from “unimportant” sinks in light of the computational efficiency, the Hydrological Retention Volume Ratio (HRV_{ratio}) is defined as the ratio between a sink's capacity (volume) and the runoff volume generated from its associated contributing catchment, which reflects the sink's runoff retention performance (strong/poor) relative to rainfall amounts, see Eq. (1) and (2). So, if we consider the spill-over as a transition moment when a sink uses up all retention capacities and generates runoff only, then “unimportant” sinks that make quicker spill-over during a rain event should be modelled as part of catchments rather than having retention capacities. To substitute those catchments from screened “unimportant” sinks, “important” sinks should initiate another round of catchment delineation (drainage basin discretisation) resulting in “dissolved catchments”, see Fig. 3b.



$$164 \quad HRV_{ratio} = \frac{C_{sink}}{V_{runoff}} = \frac{S_1}{S_1 + S_2} \quad (1)$$

$$165 \quad V_{runoff} = R_{cellsize}^2 \times \sum_{i=1}^n A_i \quad (2)$$

166 where C_{sink} is the sink's capacity; $R_{cellsize}$ is the cell size of the 2D rainfall (distributed dynamic rainfall) that has
 167 the commensurate cell size of DEMs; A_i is the total rainfall contained by cell i in the total rainfall raster
 168 (distributed static rainfall) that is aggregated from the 2D rainfall, and n is the total number of rainfall cells
 169 within each sink's catchment. S_1 and S_2 are the accumulated rainfall from the hyetograph before and after the
 170 unimportant sinks start spilling over. This means that an equivalent proportion is shared between this volume
 171 ratio and the percentile of the rainfall hyetograph. Therefore, to determine such a parameter, the accumulated
 172 rainfall amount that indicates a spilling moment for the unimportant sinks can act as a reference.

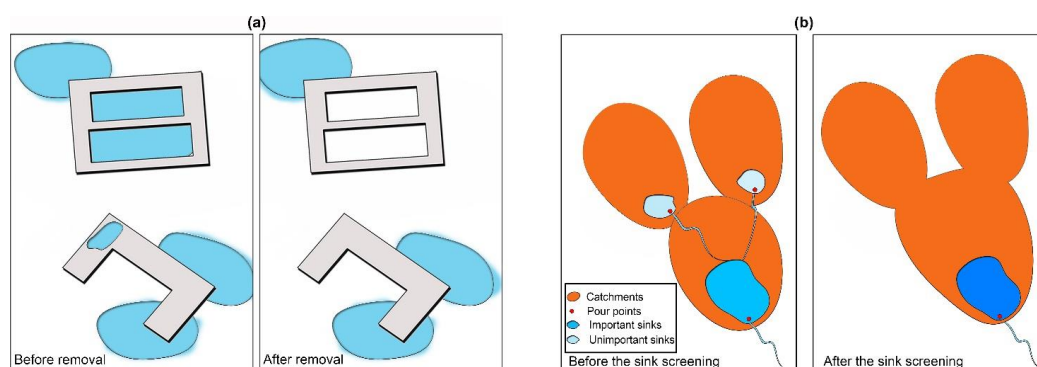
173 Since volume losses associated with removed “unimportant” sinks may accumulate to significant volume due
 174 to stream branch convergences, the Volume Loss Ratio (VL_{ratio}), see Eq. (3), is introduced. This ratio is defined
 175 as the aggregated volume loss in removed sinks vs. the downstream “important” sinks' retention capacities.
 176 The aggregated volume loss is calculated as shown in Eq. (4) and depends on the volume and number of
 177 “unimportant” sinks. If the aggregated volume loss is relatively high compared to the important sinks included,
 178 it cannot be ignored but is added to the downstream important sinks' capacities. Otherwise, insignificant
 179 volumes are removed. In this way, the computationally important number of sinks and their aggregated sink
 180 capacities ($C_{sink, Aggr.}$) are determined with VRSS.

$$181 \quad VL_{ratio} = \frac{VL_{Aggr.}}{C_{sink}} \quad (3)$$

$$182 \quad VL_{Aggr.} = \sum_{i=1}^n V_i \quad (4)$$



183 where $VL_{Aggr.}$ is the aggregated volume losses; V_i is the volume loss from the identified “unimportant” sink i ,
 184 and n is the number of sinks located within the dissolved catchment (see Fig. 3b).



185 Fig. 3. (a) Artefact sinks on roofs and within enclosed buildings (left), and after removal (right); (b) Sink screening process where
 186 unimportant sinks (light blue, left) are removed and important sinks (dark blue, left) are selected to delineate one dissolved catchment
 187 (right). Besides, volumes from unimportant sinks (removed, right) are summarized as the $VL_{Aggr.}$ to be added to the capacity of the
 188 important sink (dark blue, right) downstream. Finally, the important sink with $C_{sink, Aggr.}$ (dark blue, right) is generated. Note: pour
 189 points (red) denote the starting points of concentrated flow from sheet-flow (orange area) to channel-flow (blue line); the gradually
 190 darker blue colour (right) represents the enlarged capacity due to the volume aggregation.
 191

192 The suggested VRSS method offers several advantages over other alternatives (Maksimović et al. 2009,
 193 Balstrøm and Crawford, 2018). First, instead of conventional screening criteria (i.e. depth and volume) which
 194 reflects a geometric distinction between “small” and “big”, sinks’ runoff retention performance (poor/strong)
 195 is assessed to determine sinks’ computational importance in network-based computations. Second, unlike
 196 absolute screening criteria, introducing the relative variable V_{runoff} computed from the distributed total rainfall
 197 raster allows an adaptive sink screening criterion to be scaled with the spatially varying magnitude of
 198 precipitation, thus adding an effect of rainfall heterogeneity to the sink screening process. Third, sinks’ pour
 199 points can denote a starting point of concentrated runoff, thus distinguishing runoff transition processes from
 200 sheet-flow to channel-flow, see Fig. 3(b). With an adaptive threshold value to differentiate these two flow
 201 conditions, a more precise hydraulic representation of catchment processes in 1D hydrodynamic models can
 202 be obtained. Fourth and finally, the volumes from screened sinks are not neglected. Instead, a criterion is
 203 applied to control the volume loss independent from the screening process of sink numbers. This can minimize
 204 the accumulated effect of volume losses throughout a basin-wise hierarchical network.

205



2.2 Urban surface runoff network generation (Module II)

To assemble the urban surface runoff network (Fig. 4), we used the GIS-based method developed by Balstrøm and Crawford (2018), including four hydro-objects: blue spots (sinks), their sub-impact zones (catchments), their pour points, and stream links. “Blue spots” referring to all surface depressions (Hansson, 2010) are generated by subtracting the original DEM from the filled DEM. “Sub-impact zones” describes the blue spots’ catchments identified by the ArcGIS’ Watershed tool, where the discretization of the drainage basin is obtained by the flow direction raster derived from the “8N approach” (Baker and Cai, 1992; Greenlee, 1987; Jenson and Domingue, 1988). Pour points denote the overflow positions along the blue spots’ rims, and their locations are determined by searching for the highest flow accumulation cell value within each blue spot region as well as the lowest elevation cell value along the rim. “Stream links” describes the topological connectivity between blue spots, i.e. flow paths, and are delineated based on ArcGIS’ Cost Path tool. Notably, the flow direction and flow accumulation raster required by ArcGIS tools in this section are derived on the basis of the filled DEM. Accordingly, the different drainage basin discretisation and network delineations are identified in relation to the rainfall’s spatial variation based on VRSS (the comparison test regarding network generations between the sub-model approach and Arc-Malstrøm are provided in Supplementary Document S2).



Fig. 4. The Greve basin’s urban surface runoff network, where blue polygons represent blue spots (sinks) and blue lines represent stream links (flow paths). (Map data: © 2017 Google, Digital Globe)

2.3 Link-based fast-inundation spreading (Module III)

In order to quickly estimate flood volumes across the basin-wise network, we developed a link-based fast-inundation spreading algorithm (Fig. 2b). First it should be noted that, as seen from Eq. (2), rainfall-runoff conversion on catchments is assumed as 100%. Given a specific modelling purpose – identifying simple



Boolean flow conditions (spill-over/non-spill-over), the spatially-varying magnitude of rainfalls and the complexity of terrains are considered as dominant factors affecting overland flow in case of large-scale inundation. Therefore, detailed hydrological losses (i.e. evaporation and infiltration) and the presence of underground drainage systems are deliberately disregarded to obtain the minimum computational efforts exclusively accounting for the minimum necessary representation process.

The suggested algorithm uses stream links as computational objects. Therefore, all computational information related to sink features (points), i.e. $C_{sink, Aggr}$, V_{runoff} , $V_{received}$, $V_{spilled}$ and $V_{remaining}$, is joined onto their intersected stream links (edges). This allows for the subsequent fast-inundation calculation to be exclusively based on one stream link feature class' attribute table (see Fig. 5b). The Shreve stream order (Shreve, 1966) is used to determine the correct computational order of stream links and the convergence order of excess flows. By governing the conservation of mass balance within each stream link, flood volumes are computed according to two flow conditions:

If $V_{received} + V_{runoff} > C_{sink, Aggr}$. (Flow condition I)

$$V_{spilled} = V_{runoff} + V_{received} - C_{sink, Aggr}. \quad (5)$$

$$V_{remaining} = C_{sink, Aggr}. \quad (6)$$

Else $V_{received} + V_{runoff} \leq C_{sink, Aggr}$. (Flow condition II)

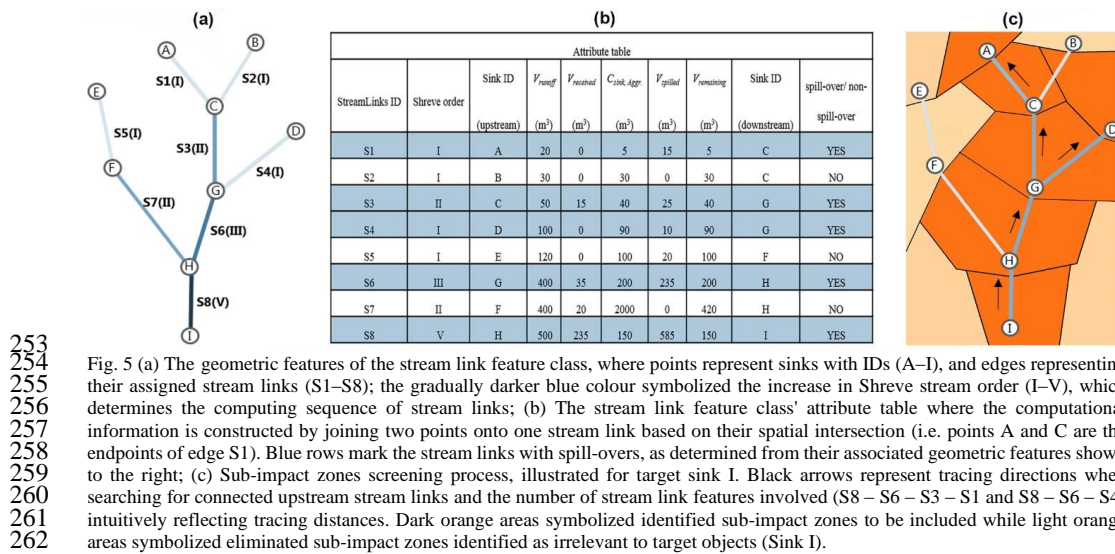
$$V_{spilled} = 0 \quad (7)$$

$$V_{remaining} = V_{received} + V_{runoff} \quad (8)$$

where $V_{spilled}$ represents excess volumes once the spill-over level is reached and $V_{remaining}$ is the actual volume retained locally, and $V_{received}$ represents the converged flow volumes received from upstream connecting links. $C_{sink, Aggr}$ is obtained from Section 2.1. After enabling this algorithm, a stream link feature class incorporating



geometric features and their associated attribute table is produced (Fig. 5a and b). Notably, in addition to the computed results of $V_{spilled}$ and $V_{remaining}$, topological connectivity identifying the next downstream stream link is also self-established in the same table (upstream & downstream sink ID, see Fig. 5b), which is now ready for the upstream tracing operation as illustrated in Fig. 5c and explained further in Section 2.4.



Whereas a fast-inundation computation was presented by Balström and Crawford (2018) previously, the essential difference of these two algorithms comes at the different approaches configuring the data structures for computations. Arc-Malström's data structure is built on ArcGIS' geometric networks (Esri, 2019). The computational information (i.e. C_{sink_agg} , $V_{received}$, V_{runoff} , $V_{spilled}$ and $V_{remaining}$) is coded in the point (junction) class's attribute table, and the topological connectivity (e.g. points-to-points) are identified in a separate table (i.e. geometric network's relation class) during the set-up of ArcGIS's geometric network. Thus, this data structure formulates a point-based fast-inundation routing, where the mass conservation is computed exclusively based on the point class objects and the computing order is referred by the points-to-points relationship in the geometric network's relation class. In contrast, this new algorithm self-establishes the data structure that configures computational information as well as the self-identified topological connectivity into the stream link feature class' attribute table thus facilitating efficient data storage and retrieval from one source. More importantly, unlike Arc-Malström's accessing the geometric network's internal function and class



objects via the ArcObjects SDK, this new algorithm is programmed based on ArcGIS' Python interface (ArcPy) only, which facilitates the automation and wrap-up of all modules in a consistent programming environment.

2.4 Sub-impact zones screening (Module IV)

With the aim of identifying the relevant sub-impact zones, a screening algorithm is programmed to perform upstream tracing tasks based on the stream link feature class (Section 2.3). As suggested by Fig. 2c, when introducing the target objects among urban infrastructures (i.e. buildings, parks and roads) as input variables, the intersecting stream link features are first selected (i.e. S8 as it intersects with Sink I) representing local inundations as well as their associated inflow paths. Here, although spill-overs - due to the possible high-momentum flows - may impact all the neighbourhood flow conditions, their significant volumes would follow the preferential paths indicated by stream links, thus affecting the downstream flow conditions primarily. Meanwhile, a sink could receive multiple inflows. To fully expose multiple inflow paths, the procedure continuously matches all the stream links by indexing the current upstream sink ID until all the upstream stream links being identical downstream sink ID were included (Fig. 5b). More importantly, in order to reflect the actual flow continuity beyond flow paths (simply indicating flow directions), flood volumes along the stream links are taken into account by conserving the mass balance during the whole tracing procedure. Here, based on $V_{spilled}$, we introduce a Boolean flow condition property (spill-over/non-spill-over, see Fig. 5b) as a search termination criterion. So, stream links associated with non-spilled-over sinks (i.e. tracing-brake features) are excluded from the search list, which results in optimal stream links (i.e. S8-S6-S3-S1 or S8-S6-S4, see Fig. 5c). In case of heavy rainfall, the tracing distance would increase with more involved stream links due to the more densified spilling configurations and vice versa (Fig. 6). This thereby avoids a substantial risk of tracing all connected flow paths basin-wise, such as Arc-Malstrøm's upstream tracing function and ArcGIS' Watershed tool. Finally, since these identified stream links represent all main flows related to specified inundation modelling, their intersected sub-impact zones would suggest suitable modelling areas (domains) covering relevant runoff generations (sheet-flow) as well as flood propagations (channel-flow).

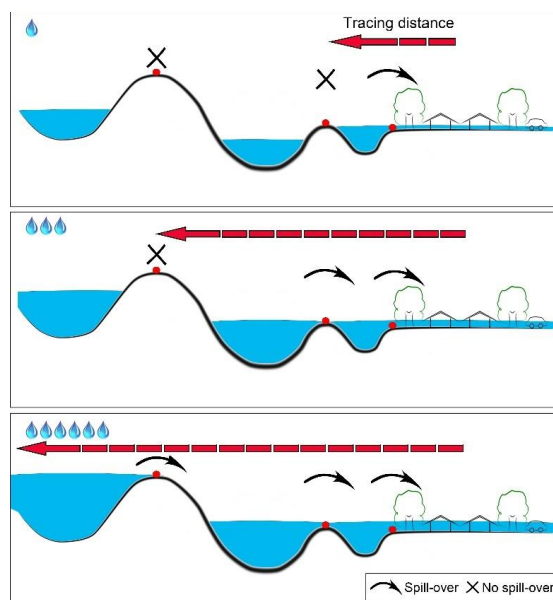


Fig. 6. Search procedure along stream links at various uniform rainfall scenarios, where the optimal tracing distance (red arrow) is determined from the continuity of overland flow based on spill-over and non-spill-over properties. Note: The number of raindrops (blue) represents the rainfall's magnitude and No spill-over refers to the termination criterion to stop further upstream tracing. In case of distributed rainfall, various optimal tracing distance in relation to target objects should be determined.

2.5 Tailor-made sub-model generation (Module V)

Urban flow is usually characterised by numerous transitions of supercritical flows and numerical shocks (Hunter et al., 2008). Full 2D models are considered as best candidates to expose the complicated flow dynamics. Thus, MIKE FLOOD's rectangular cell solver, which solves alternating direction implicit schemes on inertia wave equations (ADI), is used in this module to obtain dynamic 2D flow predictions (DHI Water & Environment, 2017). More importantly, by accounting for identified sub-impact zones, critical computational grid-cells (dark orange cells) intersecting them are extracted from the high-resolution DEM's grid. Thus, a reduced modelling grid extent is identified simultaneously, resulting in efficient computational costs for MIKE FLOOD's 2D simulations, see Fig. 7a. Besides, the suggested 1D flow patterns (blue edges) define that runoffs generated within the identified sub-impact zones must exit at downstream terminal pour points (i.e. Sink I's pour point), only. To be consistent with these described 1D flow conditions, the irrelevant grid-cells (light orange cells) within the reduced modelling grid extent should be assigned the Nodata value to prevent outwards 2D flow leakages along the upstream edges. 2D weirs should be established by pulling up the terminal pour



point's surrounding elevation values (marked ↓ in Fig. 7b) to the spilling level, while sufficient retention
 volumes $> V_{\text{spilled}}$ should be accommodated to the downstream side of the 2D weirs by decreasing the associated
 grid-cell elevations (marked × in Fig. 7b). For the grid-cells intersecting the internal subtracted areas or
 buildings, their elevation values should be substituted by a specified value (e.g. 100) to be excluded from the
 final 2D flow computations. Based on the reduced domain (dark orange cells) and the optimised boundary
 conditions (the red outline) determined above, additional complexities (e.g. hydrological losses, distributed
 roughness surface values, impervious surface types and hydraulic behaviours concerning rooftops) may be
 involved subsequently at the local catchment scale. Thus, this GIS-based method ultimately produces tailor-
 made sub-models providing fast 2D flow predictions.

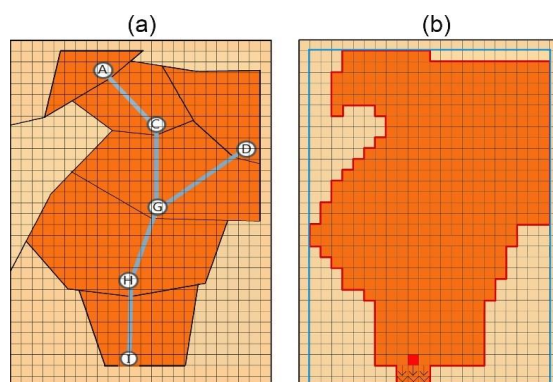


Fig. 7 (a) The intersection between sub-impact zones and the high-resolution DEM's grids; (b) The computational domain determination for MIKE FLOOD's 2D simulation, where dark orange grid-cells represents critical computational cells configuring the reduced computational domain, the blue frame represents the reduced rectangular modelling grid extent and the red frame represents the reduced computational domain and the optimised boundary conditions. The red grid-cell represents the location of terminal pour points, and the grid-cells marked ↓ configure the 2D weir having the spilling elevation level. Furthermore, the grid-cells marked × configure retention volumes based on decreased elevations.

2.6 Model experiments

The sub-model approach suggests two outcomes: i) reduced computational domains and ii) optimised boundary conditions. To clarify the individual effect, their validities were investigated separately as two-folds:
 On one hand, the suggested domains can lead to fast 2D predictions in MIKE FLOOD. Yet, their prediction accuracy may be affected as well. To quantify the influence of domain reductions, tests using consistent boundary conditions were conducted to validate this method against benchmark results, and the other domain reduction approach (Municipality domain approach, Section 2.6.1) was used for comparison purposes. On the



341 other hand, optimised boundary conditions may lead to prediction discrepancies along the boundary areas. To
342 evaluate the influence of the various boundary conditions adopted, tests using the consistent domain were
343 conducted to compare benchmarking discrepancies in different boundary conditions. Furthermore, as
344 according to Leitão et al. (2009) different types of terrain morphology may impact overland flow patterns
345 significantly, tests (Section 2.6.3) were carried out on different catchments (within the Greve basin described
346 in Section 3.1) under different associated regional rainfalls (Section 3.2) to validate the general applicability
347 and the robustness of the sub-model approach.

348 **2.6.1 Domain reduction tests (sub-model approach vs. municipality domain approach)**

349 We identified the full-basin domain approach, where the entire drainage basin area has flow directions pointing
350 towards the outlet (i.e. ArcGIS' Basin/Watershed tool). Further, this approach converts the whole area into the
351 full 2D domain in the MIKE FLOOD (Fig. 10a). As we enable 2D dynamic flows at the full-basin domain,
352 this approach reproduced the most accurate flow dynamics thus taken as the benchmark solution. Yet, without
353 having any specified targets, this approach reflects general modelling targets. In contrast, taking the buildings
354 within focus area A as the specific target objects (Map A, Fig. 8), we identified two different reduced domains
355 following two approaches: i) the sub-model approach, where the sub-model domain (Fig. 10b) was delineated
356 as the suggested approach; ii) the municipality domain approach, where a reduced domain was delineated
357 simply based on municipality borders including all target objects (Fig. 10c).

358 In order to ensure the consistent starting point for comparisons, the same inputs – i.e. DEMs Section 3.2 and
359 Rainfall Section 3.3 – were used for the three approaches. Yet, due to the different domains determined from
360 the different approaches, the two inputs for the sub-model approach and the municipality domain approach
361 were tailored by having a mask operation (i.e. ArcGIS' Extract by Mask tool) based on their suggested domain,
362 respectively. Finally, the predictions of the sub-model approach and the municipality domain approach were
363 both validated against the benchmark solution within the same extents of the masks, and discrepancies of the
364 two approaches were further compared regarding flood extents, flood depths internal points' hydrographs and
365 computational efficiencies. In this test, to exclude the influence of the inconsistent boundary conditions,



uniform closed-boundary conditions were adopted for all three approaches (the test based on uniform open-boundary conditions are provided in Supplementary Document S4).

2.6.2 Boundary condition comparison tests (optimised boundary conditions vs. uniform closed-boundary conditions vs. uniform open-boundary conditions)

We identified the optimised boundary conditions as suggested by the sub-model approach. With the same sub-model domain, the simulations based on uniform closed-boundary conditions and the uniform open-boundary conditions were carried out for comparison purposes. Like Section 2.6.1, the same rainfall input was used for the three approaches. All these results were validated against the benchmark solution within the same extent of the sub-model domain respectively, and their discrepancies were compared regarding flood extents and flood depths. Finally, the internal points that illustrated significant discrepancies in hydrographs (Section 2.6.1) were investigated further.

2.6.3 General applicability tests (Sub-model A vs. B vs. C vs. D)

We selected four focus areas (Map A, B, C and D, Fig. 8) representing various typical topographies from the three regions described in Section 3.1, and buildings (orange polygons in Map A, B, C and D) were in turn listed as specified target objects. Four sub-models and their predictions were generated by targeting different flooded objects as well as their associated rainfalls representing return periods of 1-100 years (detailed rainfall inputs were provided in Supplementary Document S5). Likewise, the benchmark solution was used to validate their discrepancies within the same extents of the four sub-models' domains. To pursue the most accurate sub-model predictions, their identified optimised boundary conditions were adopted in this test.

3. Case-studies

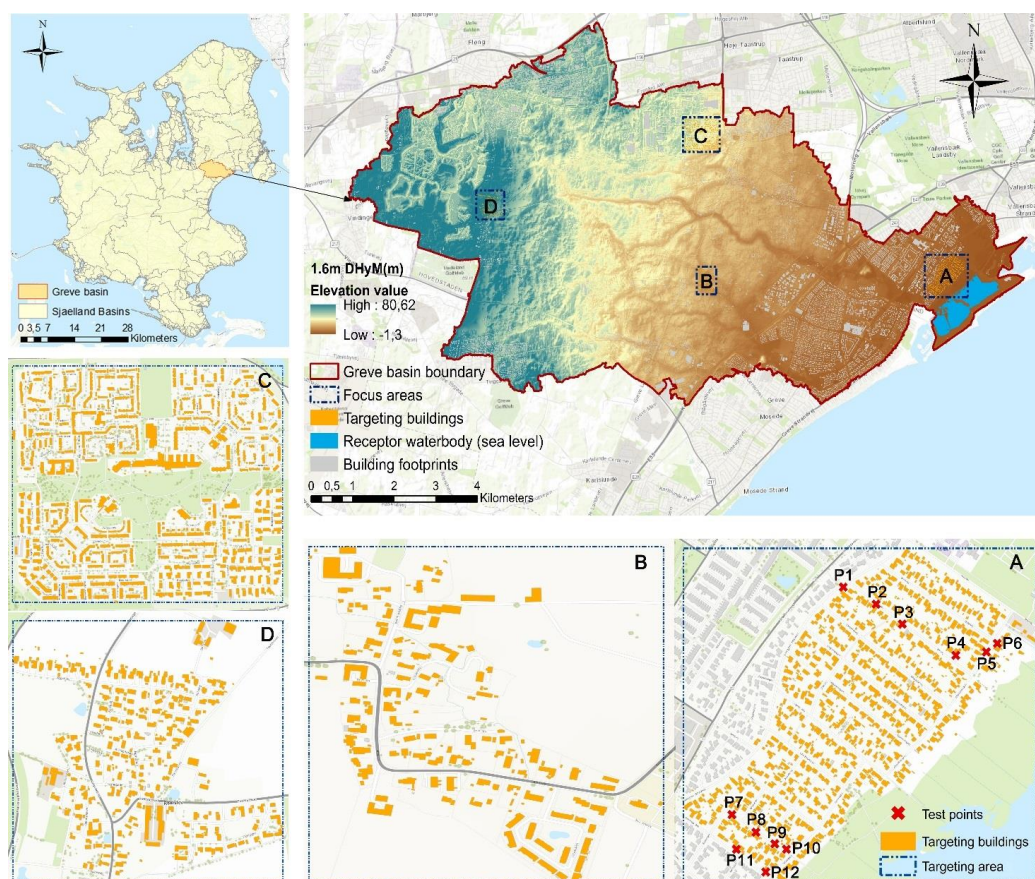
3.1 Study site

The study area is “the Greve basin” located on Zealand, Denmark, approximately 30 km SW of Copenhagen, that includes both rural and urban areas. The study basin's extent of 73.8 km² was determined from a Danish nationwide hydrologic conditioned elevation model (DHyM) using ArcGIS' Basin tool. With reference to Fig. 8, the eastern urbanised region's terrain (dark orange) is low-lying and flat (Avg. elevation of 3.81 m with St.



dev. of 1.85 m), the central region (light orange) is slightly undulating (Avg. elevation of 14.74 m with St. dev. of 5.44 m) while the westernmost region (yellow to green) is the highest-lying with the steepest gradients within the basin (Avg. elevation of 37.4 m with St. dev. of 8.84 m). Thus, the basin's topography demonstrates complications regarding the spatial variation of terrains. In addition, a receptor waterbody (blue polygon, Fig. 8) representing sea level elevation is located towards east/southeast acting as the basin's outlet collecting all runoffs.

397



Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, 724 Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community
 Fig. 8. Case study area: Basin divisions for Zealand and location of the Greve basin (upper left); the hydrologically conditioned elevation model (1.6 m resolution) covering the Greve basin (upper right). Map A, B, C, and D show four selected focus areas and their target objects (buildings) that were hit by the extreme rainfall event on July 2nd, 2011. Areas marked with a red X represent locations where water depths and velocity hydrographs are extracted (L-shaped in the northeast, F-shaped in the south).

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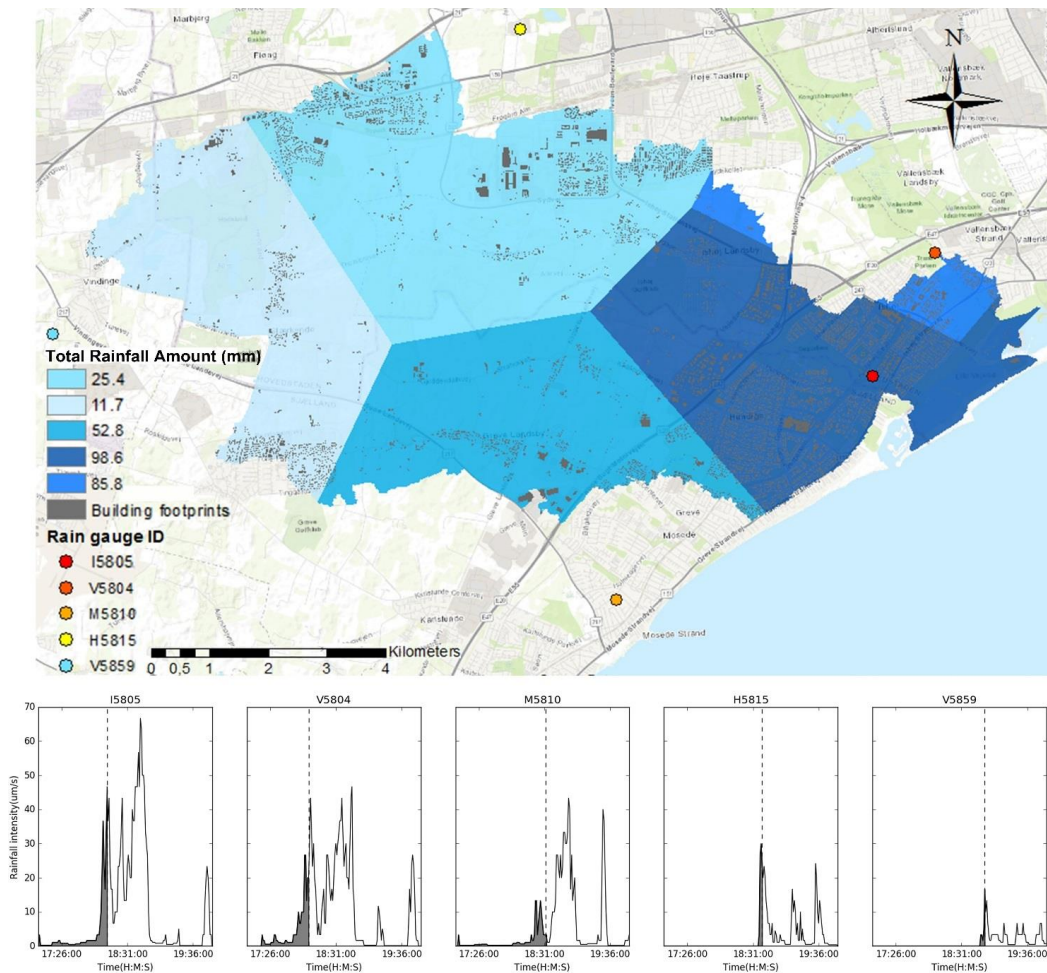


404 **3.2 Input DEMs and pre-processing enhancements**

405 The generation of the urban surface runoff network (Section 2.2) benefits from the quality of the DEM
406 regarding grid size, data accuracy (horizontal/vertical), DEM generation technologies and data sources
407 (Adeyemo et al., 2008; Leitão et al., 2009; Leitão, 2016). To avoid massive computational expenses while
408 incorporating sufficient precision to reflect micro-topographies such as road curbs, the DHyM with a resolution
409 of 1.6 m and a vertical accuracy of 0.05 m was selected (Data Supply and Efficiency Board, 2013). However,
410 since this DHyM excludes roof elevations and contains ground elevations only, an urban surface runoff
411 network analysis based exclusively on a DHyM may lead to miss-reflections of localised floods and an
412 underestimation of total sink volumes (Jensen et al., 2010; Leitão et al., 2009). If instead, a Digital Surface
413 Model (DSM) is used, this may include noises from, for example, tree canopies and parked cars. Sensitive to
414 these issues, building elevations from a DSM was fused with the DHyM, thus obtaining a “combined” DEM
415 as input to the sub-model approach.

416 **3.3 Rainfall**

417 An extreme precipitation event on July 2nd, 2011 was selected. Due to the large extent of the Greve basin, we
418 used data from five available rain gauges to cover the basin-wise rainfall heterogeneities (see Fig. 9). The
419 Thiessen polygon approach was applied to distribute precipitation data from these rain gauges onto their
420 nearest neighbourhoods (Fig. 9), simulating the pattern of the progressively decreasing rainfall from the eastern
421 coastline towards western inland. According to the time-series of I5805 (shown as hyetographs in Fig. 9), the
422 overall simulation time of 172 minutes was used for MIKE FLOOD, where the simulation continued for 97
423 minutes after the main peak, allowing for the sufficient time for flood peaks to flow through the landscape.



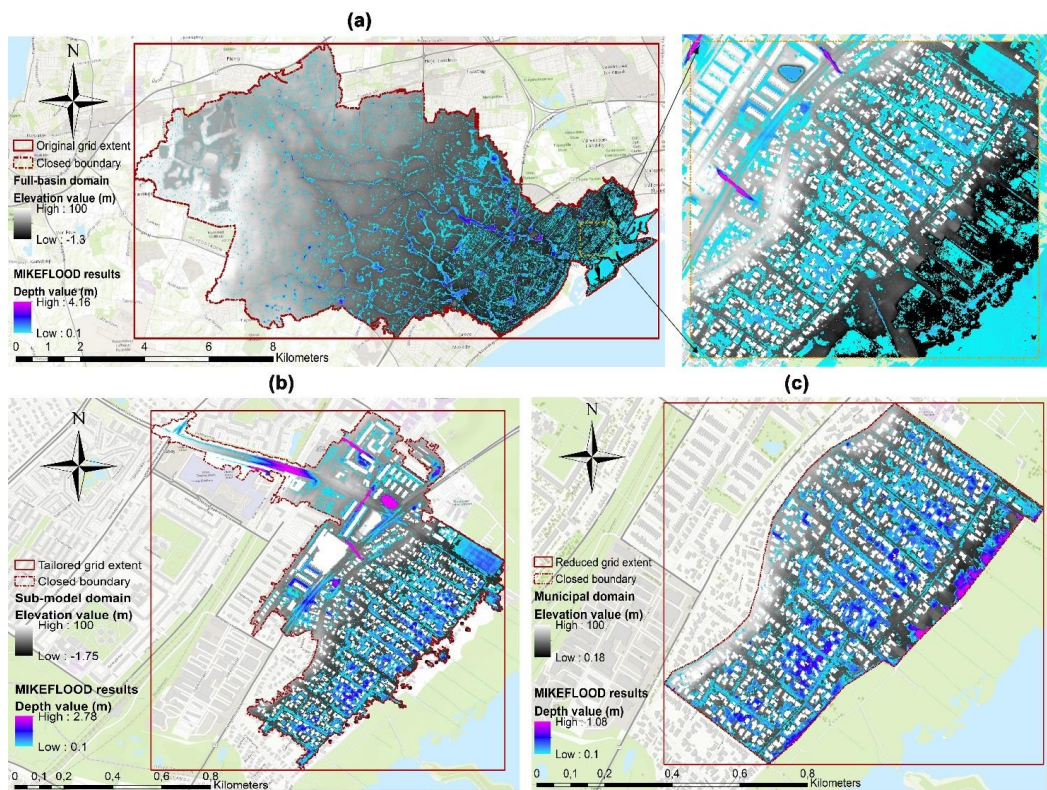
Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, 724 Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community
Fig. 9. Spatial rainfall distribution based on Thiessen polygons and corresponding time-series rain gauge data. (shaded areas of rain gauge data represent the accumulated rainfall when the unimportant sinks start spilling over in five areas)

3.4 Modelling parameters

The HRV_{ratio} parameter was set to 15%, considering that the corresponding accumulated rainfall (i.e. 14.8 mm = 15% \times 98.6 mm, gauge I5805) is relatively small compared to the total. Next, a VL_{ratio} of 5% was applied to decide upon the final removal of VL_{Aggr} . For the MIKE FLOOD computations, default parameters were used for the 2D engine (DHI Water & Environment, 2017). A uniform surface friction value (Manning Roughness Coefficient, $M = 32$) was assumed, and a dry surface was defined as the initial condition. In case of the insignificant influence of evaporation and infiltration and drainage systems during the rainfall event, the 100%



rainfall-runoff conversion was assumed, and drainage systems were excluded for MIKE FLOOD’s 2D flow computations.



Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, 724 Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Fig. 10. 2D flow domains determined by three approaches and their associated predictions based on MIKE FLOOD: (a) The full-basin domain determined from the full-basin high-resolution DEM. Notably, since the downstream receptor water body is involved as one part of the computation domains to collect the basin runoffs, the predictions on land areas can be considered as benchmark results, whereas the uniform closed boundary was adopted; (b) The sub-model domain, where the sub-model approach delineates the reduced domain accounting for the basin-wise 1D static flows; (c) The municipality domain determined from municipality borders. The red frame represents the extent of 2D model grids, the dotted frame defines the external modelling boundary, and the transparent spaces in-between two frames define the Nodata grid-cells. The grid-cells with the value of 100 define the excluded internal domain (i.e. buildings and non-spilling sub-impact zones) in MIKE FLOOD. Note: The figure on the right side of Fig. 10a shows benchmark results zoomed in the same extent as the other approaches for easy comparisons.

4. Results

4.1 Domain reduction tests

4.1.1 Maximum depth flood extent

MIKE FLOOD’s 2D prediction results produced from the three different domains are presented in Fig. 10a, b and c, where a 10 cm flood depth was adopted as the threshold defining critical flood depths. To demonstrate



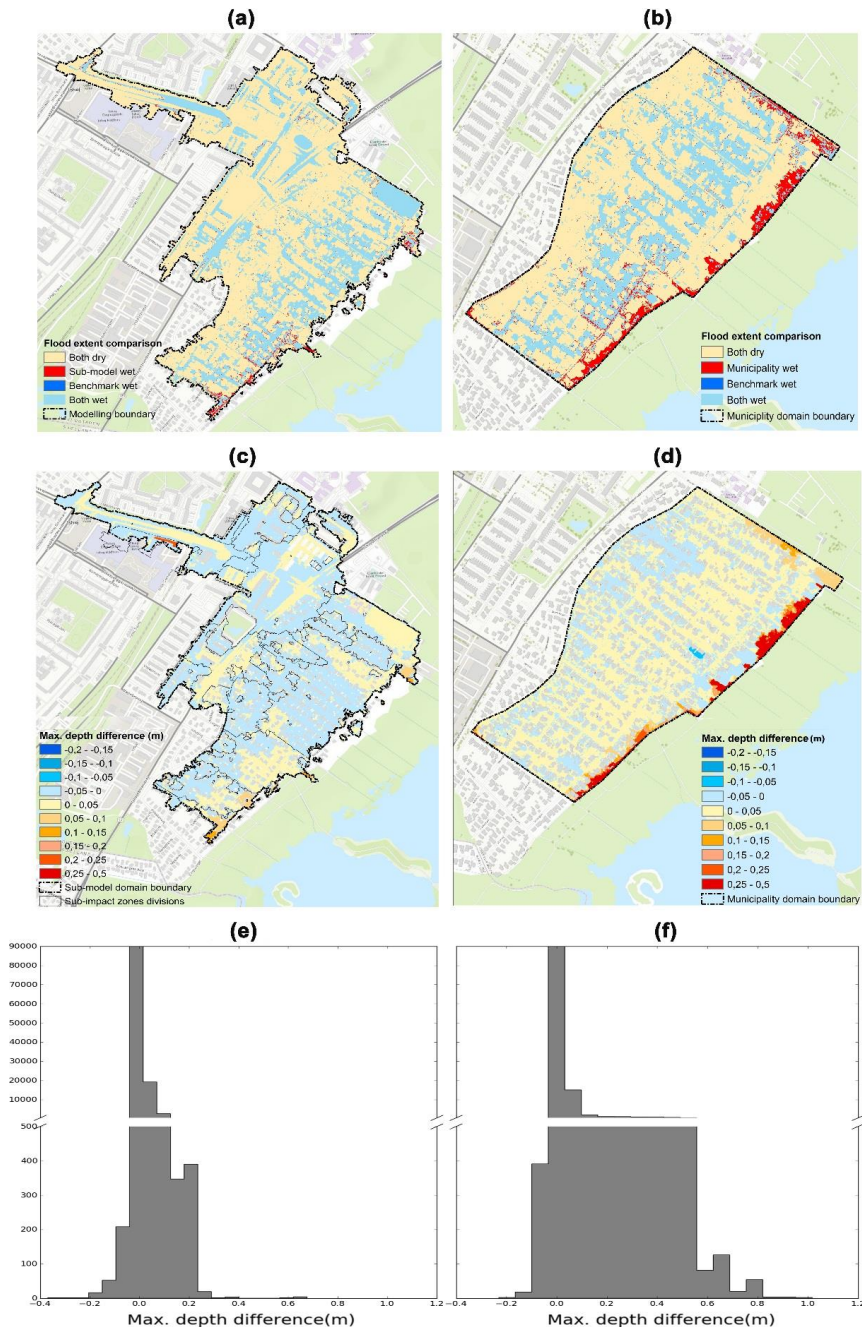
the discrepancies of maximum depth flood extents, binary analyses (dry/wet) from the status of the flooded cells were conducted (Fig. 11a and b). The predicted inundation extents were in good agreement in most areas, while overestimations occurred along the downstream edge as expected from using the closed boundary. In contrast to the municipality domain approach, the sub-model approach returned fewer overestimations that tended to occur near terminal pour points only.

The critical depth threshold value may affect the flood extent significantly. To fully expose the flood extent discrepancies of the two approaches, their results were further compared using different threshold values, adopting the F^2 statistic (Werner et al., 2005) as a performance indicator. In Table 1, high goodness of fit above 0.86 was observed in both approaches for either a depth threshold of 0.01 m or 0.05 m. However, following progressive increases of the threshold value, the sub-model approach showed a robust performance on flood extent predictions with F^2 values > 0.91 , while the F^2 value for the municipality domain approach started to drop sharply at the value of 0.15 m, indicating significant errors.

Table 1

F^2 values for the sub-model approach vs. the municipality domain approach.

Depth threshold (m)	0.01	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4
Sub-model approach F^2	0.970	0.956	0.941	0.928	0.923	0.917	0.913	0.914	0.911
Municipality domain approach F^2	0.913	0.861	0.808	0.765	0.734	0.689	0.603	0.504	0.323



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Fig. 11. Benchmarking discrepancies in Max. depth flood extents: (a) Sub-model approach's categorised map, (b) Municipality domain approach's categorised maps. Benchmarking discrepancies in Max. flood depths: (c) Sub-model approach's depth difference map, (d) Municipality domain approach's depth difference map, (e) Sub-model approach's histogram of Max. depth difference, (f) Municipality domain approach's histogram of Max. depth difference.



470 **4.1.2 Maximum flood depth**

471 Fig. 11c and d show the spatial distribution of the maximum flood depth differences (subtracting benchmark
 472 results from the sub-model domain's predictions and the municipality domain's predictions). Discrepancies of
 473 ± 0.05 m were seen in majority areas of the sub-model domains. Interesting, most underestimations of -0.05
 474 m were found to the upstream side of the sub-impact zones for the sub-model approach. This may be explained
 475 by the "8N approach" adopted when determining flow directions, where runoff is forced into one direction of
 476 eight adjacent cells. Thus, based on this "confined flow" algorithm, each sub-impact zone delineated was
 477 considered as the minimum contributing area only. If we refer to the flow direction along the steepest gradient
 478 as the major runoff (being fully harvested) and other directions as minor runoff, then the minor runoff,
 479 especially along defined upstream boundaries, may be miss-captured. Nevertheless, discrepancies of < 0.05
 480 m, compared to the vertical accuracy of the DEMs used, is considered insignificant. Close to the downstream
 481 boundary of the municipality domain, regional overestimations were observed in maximum flood depths.
 482 Because the closed boundary pulled up the spilling level limitlessly, the maximum differences > 1 m may be
 483 considered as problematic deviations from the benchmark. Notably, those red pixels indicating the highest
 484 flow accumulations suggest shifted terminal pour point positions as opposed to the sub-model approach.
 485 Apparently, for these positions, the sub-model approach produced significantly fewer over-predictions for the
 486 downstream boundary than did the municipality domain approach.

487 The histograms of maximum depth differences are displayed in Fig. 11e and f. A higher frequency of over-
 488 predictions occurred for the municipality domain approach's histogram, while a near-symmetric distribution
 489 of over- and under-predictions, approximately similar to the normal error distribution, was identified for the
 490 sub-model approach. The statistics for the maximum flood depth difference for both approaches were
 491 summarised in Table 2. Root Mean Square Errors (RMSE) of 0.02 m for the sub-model approach in the overall
 492 domain were below the vertical accuracy of the DEM. Also, to validate prediction discrepancies adjacent to
 493 targeted buildings, a targeting section was delineated by creating a buffer (3.2 m, the width of two grid cells)
 494 around them. In targeting sections, marginal discrepancies were observed both in benchmarking comparisons



495 and in comparisons of the two approaches. This is possibly due to the location of the buildings that is far away
 496 from impact areas caused by the backwater effect.

497 **Table 2**

498 Statistics of flood maximum depth difference for the sub-model approach vs. the municipality domain approach.

	Overall domain				Targeting section			
	Minimum (m)	Maximum (m)	Mean (m)	RMSE (m)	Minimum (m)	Maximum (m)	Mean (m)	RMSE (m)
Sub-model approach	-0.37	0.68	0.00	0.02	-0.22	0.36	0.00	0.02
Municipality domain approach	-0.23	1.02	0.02	0.08	-0.23	0.43	0.01	0.02

499

500 4.1.3 Internal points depths and velocity hydrographs

501 To clarify discrepancies in spatial-temporal flow developments, hydrographs including water depths and flow
 502 velocity in u- and v-directions were extracted for the three approaches (Fig. 12a and b). Two runoff patterns
 503 each containing 6 points were selected as a simplified representation of runoff dynamics in the focus area A
 504 (see Fig. 8, Map A), referred to as an L- and F-shaped flow pattern. In the L-shaped flow pattern, the selected
 505 positions are characterised by either conveyance flooding or ponding flooding (Allitt et al., 2009). Hence,
 506 points 1, 3 and 5 identify areas where surface depressions result in permanent ponding, whereas convergent
 507 and high-velocity flows occur near points 2, 4 and 6. The F-shaped flow pattern is primarily characterised by
 508 localised ponding flooding. Point 7 denotes the concentration of flows that collects runoffs from its north-
 509 westerly regions. This concentrated flow proceeds towards the southeast and intrudes into depression zones at
 510 point 8. Yet, at this point, two branch currents split from the origin, where one flows over point 9 and terminates
 511 at point 10 as permanent ponding, while the other branch hits point 11 and further flows towards point 12
 512 presenting ponding flooding in the southernmost corner.

513 Fig. 12a shows hydrographs for points 1–6 in terms of depths, u- and v-velocities for the L-shaped flow pattern.
 514 For points 1–5, good agreements with the benchmark regarding depths hydrograph's rising and falling limbs
 515 were obtained when using the sub-model approach. For points 1 and 2, in contrast to the municipality domain
 516 approach, average higher depth values accompanied by higher flow velocities for the sub-model approach were
 517 observed. Most likely, this happens because the extended regions restored the flooding propagation channel



518 allowing more water outside the targeted region to enter, which is consistent with findings by Yu and Coulthard
 519 (2015). Additionally, whereas over-predictions occurred at the downstream ponding area of point 6, this error
 520 of $< \sim 0.05$ m was considered insignificant. Apparently, u- and v-velocity hydrographs derived from the sub-
 521 model approach mostly replicated the predictions in the benchmark at points 1–5. Yet, an entirely different
 522 flow direction was identified at point 6 compared to the benchmark, whereas minor differences of < 0.02 ms⁻¹
 523 were found. As the consequence of the closed boundary, its hydraulic behaviour alters the actual runoff
 524 patterns, i.e. spilling to downstream, into a permanent ponding condition, and further inverse the flow direction
 525 due to the corresponding backwater effect.

526 Fig. 12b presents hydrographs of points 7–12 in terms of depths, u- and v-velocity for the F-shaped flow
 527 pattern. For points 7–9, overall goodness of fit with the benchmark was seen for the two approaches, suggesting
 528 marginal discrepancies of depths $< \sim 0.05$ m and velocities $< \sim 0.03$ ms⁻¹. In contrast, greater discrepancies of
 529 ~ 0.32 ms⁻¹ were identified for the u-velocity of point 10. Here, a southeast-directional flux was found for the
 530 municipality domain approach, while a permanent ponding suggested by near-zero flow velocities was seen
 531 for the sub-model approach. For points 11–12, depth overestimations of ~ 0.05 m were shown in the sub-model
 532 approach for the sake of the closed boundary. Although the municipality domain approach presents similar
 533 results to the benchmark, it is worthwhile noticing that an opposite flow direction was found for the u-velocity.
 534 At this point, the sub-model approach reproduces a more precise flow pattern compared to the municipality
 535 domain approach. Notably, for points 6, 10 and 12, whereas an agreement was found for depth hydrographs of
 536 three approaches, substantial divergences in flow directions were identified, which illustrates higher sensitivity
 537 in u- and v-velocities towards the alternation of the flow patterns. Hence, instead of flow depths, we consider
 538 that u- and v-velocities are more sensitive indicator implying whether the desired flow patterns are reproduced
 539 precisely.

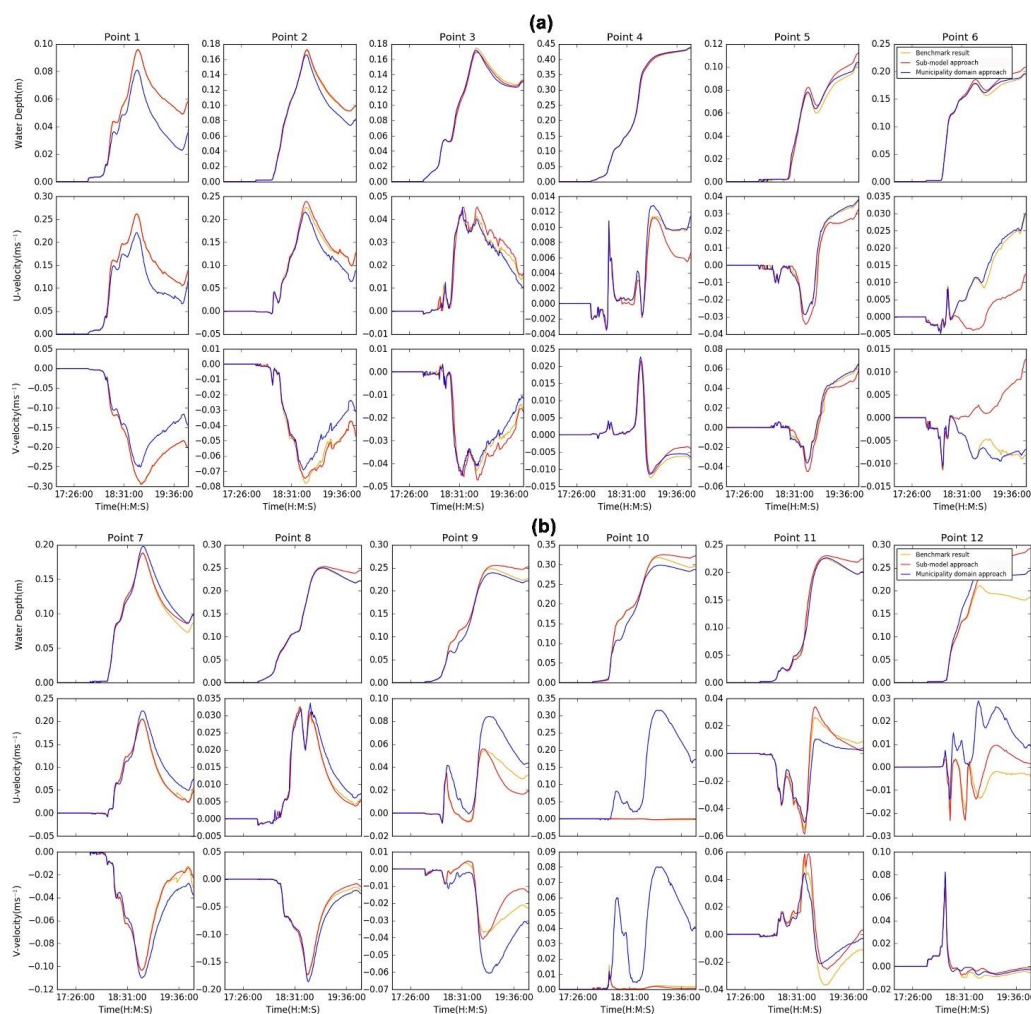


Fig.12. Flood depth, u- and v-velocity hydrographs for points 1-12: (a) The L-shaped flow pattern; (b) The F-shaped flow pattern.

4.1.4 Computational efficiencies

The sub-model approach was executed in ArcGIS Desktop ver. 10.6. Table 3 shows the computational time tested on a laptop computer (Intel®Core™ i7-5600 CPU @ 2.60GHZ, 8GB of RAM). Based on GIS processing environments, phase I (see Fig. 1) is grouped into raster (Module I and II) and vector processing modules (Module III and IV), and their operational independency are maintained in the general workflow. That means, although the costly computational time (e.g. 2,321 seconds) is required for the raster processing, once accomplished, the sub-impact zone tracing tasks could be processed quickly and repetitively in the vector



549 processing environment, thus ensuring the fast generation of various sub-models when different target objects
 550 were specified.

551 By applying the sub-model approach, 99% of the computational cells were excluded from the full-basin
 552 domain for numeric computations of 2D flows, thus resulting in a factor 80 reduction with respect to elapsed
 553 time (calculated from Table 3). Although the municipality domain approach also harvested time reductions,
 554 prediction accuracy along the boundary areas was problematic due to the violation of the actual flow pattern
 555 (Section 4.1.1, 4.1.2 and 4.1.3).

556 **Table 3**

557 Comparison of computational efficiency when using different domain approaches.

		Full-basin domain approach	Sub-model approach	Municipality domain approach
Input DEM's grid extent (Columns × Rows)		10202 × 5263	10202 × 5263	10202 × 5263
Tailored grid extent (Columns × Rows)		×	903 × 967	701 × 612
Total No. of computational cells (wet)		27,124,785	263,278	148,258
Pre-processing time (s) (Phase I)	Raster processing	×	2,321	×
	Vector processing	×	111	×
MIKE FLOOD simulation time (Phase II)	Elapsed time (s)	482,412	6,090	2,903
	CPU time (s)	1,141,666	24,330	11,585
	Time step (s)	0.2	0.2	0.2

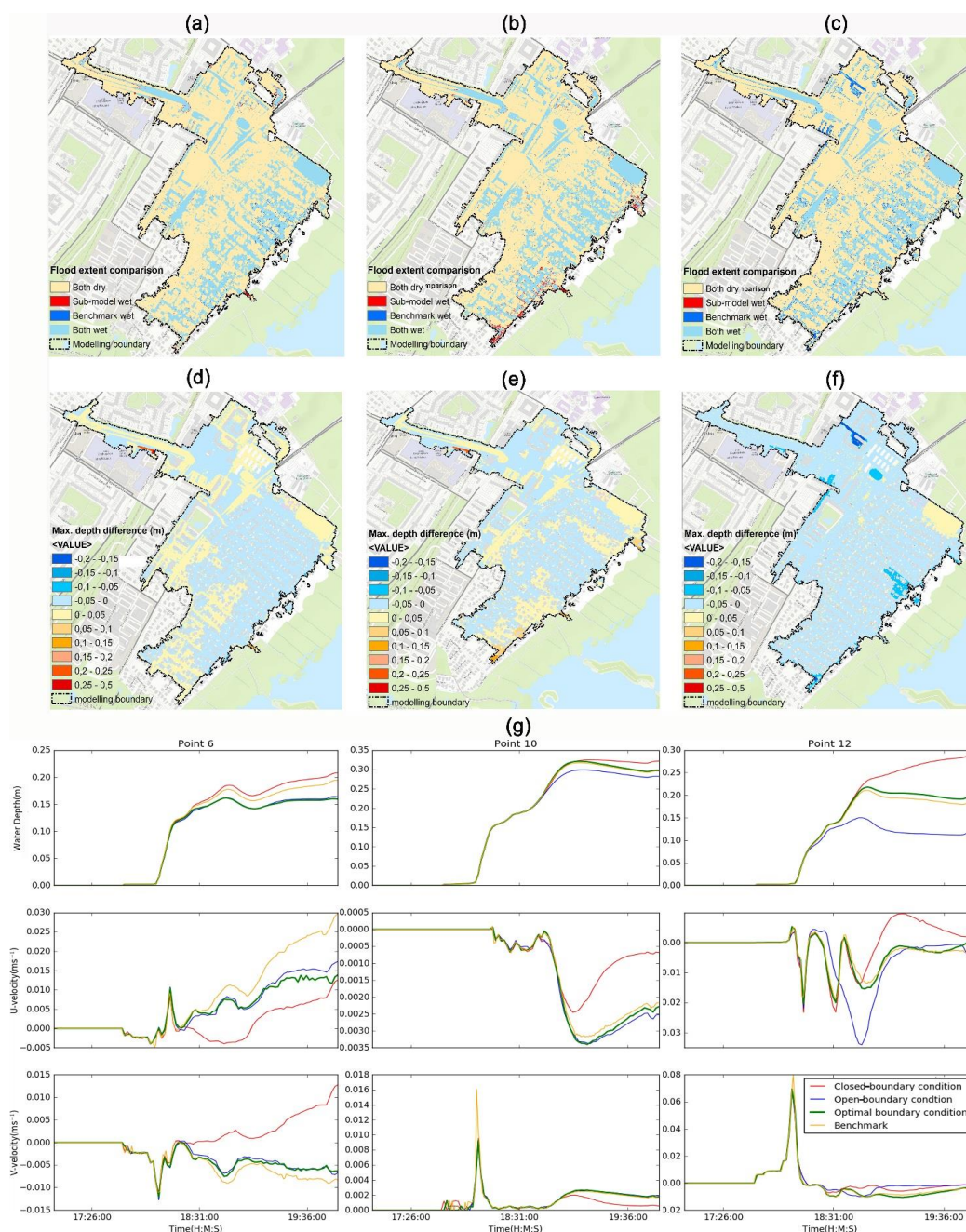
558

559 4.2 Boundary condition comparison tests

560 Fig. 13 shows the benchmarking discrepancies in terms of flood extents, flood depths and points' hydrographs
 561 when using different boundary conditions based on the same sub-model domain. In comparisons with three
 562 boundary conditions, the optimised boundary condition suggested by the sub-model approach presents the
 563 minimal predictions discrepancies of < ~0.5 m from the benchmark solution, particularly at the terminal pour
 564 point position. This is because the adopted 2D weir restores the actual flow pattern and thus allows the spill-
 565 over to take place at a constant elevation level. Further, other than the depth hydrographs, a goodness of fit
 566 against the benchmark solution was identified in u- and v-velocities when using the optimised boundary
 567 condition (Fig. 13g). As this stand, we conclude that the suggested algorithm resolves the overestimations in
 568 Section 4.1 properly and yields the highest accuracy in flow dynamics along the boundary areas. Yet, when



569 the uniform open-boundary condition was used, significant underestimations in maximum flood extents and
570 flood depths were seen along the edges of the sub-model domain, where unrealistic 2D flow leakages were
571 identified due to the lowered spilling level. As such, we consider the open-boundary condition inappropriate
572 since the 2D flows derived is inconsistent to the predefined 1D runoff conditions.

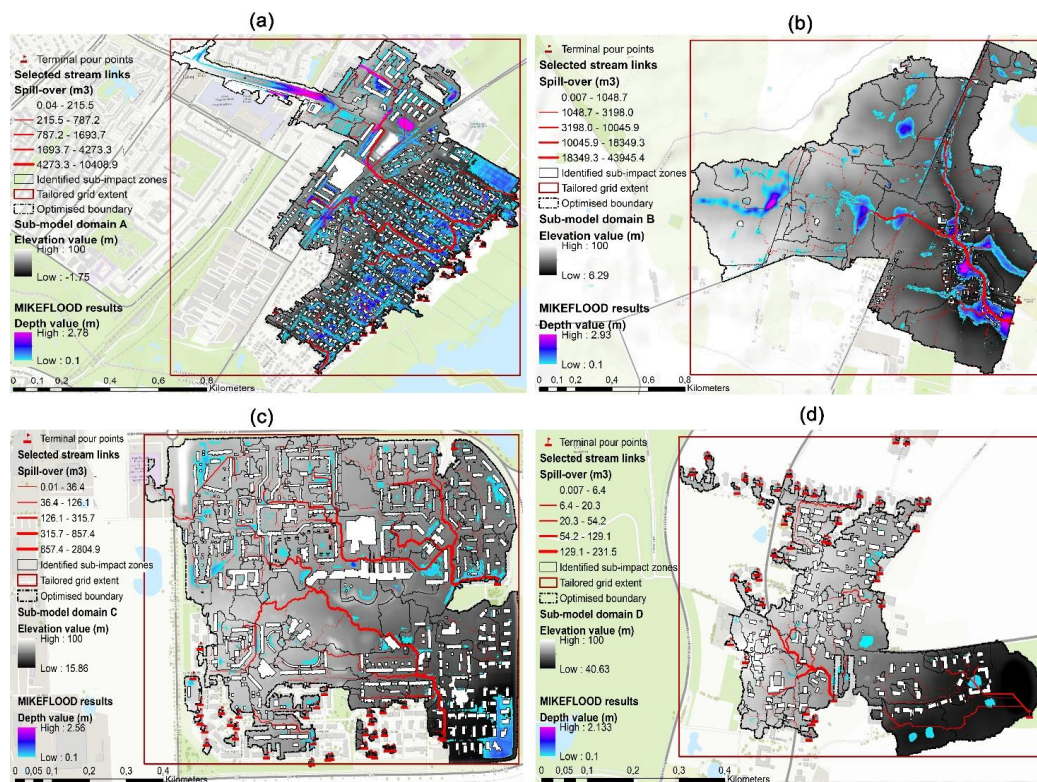


Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, 724 Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community
 Fig.13 Benchmarking discrepancies using different boundary condition strategies: (a) The optimised boundary condition's flood extent categorised map, (b) The uniform closed-boundary condition's flood extent categorised map, (c) The uniform open-boundary condition's flood depth difference map, (d) The optimised boundary condition's flood depth difference map, (e) The uniform closed-boundary condition's flood depth difference map, (f) The uniform open-boundary condition's flood depth difference map; (g) Flood depth, u- and v-velocity hydrographs for points 6, 10 and 12 using the different boundary conditions.



579 4.3 General applicability tests

580 Fig. 14 shows the outputs of four different sub-models (Sub-model A, B, C and D) in terms of 1D flow
 581 conditions, identified computational domains and corresponding MIKE FLOOD's 2D predictions. In
 582 accordance with Section 2.4, longer return period rainfalls resulted in longer maximum tracing distances.
 583 However, in response to the 50-year return period rainfall, Sub-model B identified the longest tracing distance
 584 of 2,535 m as well as the highest maximum spill-over volumes of 43,945 m³. The reason for this exception is
 585 due to its special catchment topographies, where only one flood propagation channel was identified discharging
 586 the substantial runoffs accumulated from the largest catchment area of 1,676,207 m². Conversely, as the result
 587 of substantial tracing-brake features identified during shorter return period rainfalls, scattered independent
 588 areas suggesting localised flooding phenomenon were found in the southern part of Sub-model C and the
 589 northern part of Sub-model D. As for 2D flow prediction accuracy, high goodness of fit with the benchmark
 590 was observed for all four sub-models. Notably, RMSE values suggested marginal discrepancies < 0.05 m
 591 compared to benchmark results. This is because the optimised boundary conditions achieve more precise peak
 592 level predictions in downstream regions as opposed to the uniform closed-boundary conditions (maps showing
 593 the detailed benchmarking discrepancies for the four sub-model predictions are provided in Supplementary
 594 Document S5). For computing time comparisons, similar vector processing time was observed for the sub-
 595 impact zones screening procedure when targeting the different number of buildings. Compared to the
 596 benchmark, significant time reduction factors of 45-553 were yielded for the four sub-models. Yet, due to the
 597 difference in the generation of reduced domains (e.g. modelling grid extent and total No. of computational
 598 cells), time-savings for each sub-model differ from one case to another, demonstrating the case dependency
 599 (targets-specified) of this approach. In general, the sub-model approach provides robust performance when
 600 processing onto different terrain morphologies as well as different rainfall return periods. Thus, it is a feasible
 601 approach to reducing the computing time for 2D models.



Sub-model ID		A	B	C	D
Focus areas	Total No. of targeting buildings	784	254	757	382
	Terrain morphologies				
	Avg. slope ± St. Dev. slope	2.52 ± 3.76	1.40 ± 1.32	3.14 ± 4.71	3.30 ± 4.78
Precipitations	Avg. EL ± St. Dev. EL (m)	2.19 ± 1.02	14.73 ± 2.75	24.92 ± 2.75	50.23 ± 4.63
	Rain gauges and total rainfall amounts	15804(85.8mm):34% V5805(98.6mm):66%	V5805(98.6mm):1% M5810(52.8mm):86% H5815(25.4mm):13%	H5815(25.4mm)	V5859(11.7mm)
	Return periods	100-yr	50-yr	10-yr	1-yr
1D flow conditions	Data volumes (MB)	579	909	210	130
	Longest 1D flow length (m) (Tracing distance)	1,641	2,535	1,324	405
	Max. spill-over volumes (m³)	10,408.9	43,945.4	2,804.9	231.5
	Total No. of identified sub-impact zones	188	154	273	121
Sub-model domains	Total areas of identified sub-impact zones (m²)	677,781	1,676,207	485,508	151,893
	Tailored grid extent (Columns × Rows)	906 × 969	1217 × 1129	632 × 505	499 × 403
	Total No. of computational cells (wet)	271,280	661,834	194,906	64,064
MIKEFLOOD's 2D prediction discrepancies	Max. depth flood extent (Depth threshold of 0.01m)	F²			
		0.980	0.990	0.966	0.880
	Max. flood depth (m)	Max.	0.433	0.098	0.106
		Mini.	-0.292	-0.420	-0.190
		Mean	-0.0002	0.0005	-0.001
Computational time		RMSE	0.015	0.003	0.008
					0.015
	Phase I (s)	Raster processing		2,321	
		Vector processing	111	146	181
		Elapsed time	6,196	10,654	2,413
Phase II (s)	Time reduction factor	78	45	200	553
	Time step			0.2	

Basemap source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, 724 Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Fig. 14. Four sub-models' 1D flow conditions, identified computational domains and their correspondent MIKE FLOOD predictions based on various types of terrain morphologies and rainfall return periods in 1-100 years: (a) Sub-model A, (b) Sub-model B, (c) Sub-model C and (d) Sub-model D. The optimised boundary conditions suggested by the sub-model approach are used for four sub-model simulations, where 2D outlets are established at the terminal pour points position that allows for water spilling at the pour point level. The detailed inputs, outputs, prediction validation and computational time information for each sub-model are provided in the table.



608 5 Discussion

609 The presented method can tailor 2D grids based on various specified targets, which results in cost-efficient
 610 tailor-made sub-models. The strengths, weaknesses and associated potentials are discussed as follows:

611 Firstly, as suggested by the domain reduction tests, the criteria determining critical cells may affect 2D flow
 612 patterns substantially. Here, the sub-model approach identifies critical cells that indicate main flow paths
 613 (channel-flows) and corresponding catchment areas (sheet-flows) explicitly, whilst multiple terminal pour
 614 points are sufficiently detected and accommodated with suitable hydraulic alternatives (i.e. 2D weirs). At this
 615 point, the domains ensure accurate 2D replications of actual flow patterns. Yet, when using the criteria based
 616 on municipality borders, this domain - due to the exclusion of the critical inflow path cell (upstream) and the
 617 inclusion of irrelevant catchment cells (downstream) – may result in flood underestimations, as well as shifted
 618 positions for the terminal pour points. In this sense, the inundation simulation has failed to reproduce the actual
 619 flow pattern in the first place, such that the subsequent 2D predictions are questionable. For the same reason,
 620 the reduced domains based on other criteria, i.e. cutting off elevation cells greater than a certain threshold or
 621 making a buffer at a certain spatial distance, may be problematic. Thus, we conclude that, without perceiving
 622 the surface runoff network from a broad basin perspective, the determined domains most likely alter the actual
 623 flow pattern to various extents. As opposed to other criteria exclusively based on flow directions (i.e. ArcGIS’
 624 Basin/Watershed tool or Arc-Malström’s tracing functions), the sub-model approach further includes new
 625 criteria of the mass balance by enabling the 1D static flow routing, thus facilitating more valid domain
 626 reductions for the large-scale case area. However, these two approaches may result in identical domains in
 627 case that catastrophic events pose basin-wise spilling configurations. Here, a GIS-based automated tool that
 628 determines an optimal 1D/2D hybrid surface modelling strategy by replacing secondary important 2D surface
 629 components (grids) with 1D surface hydraulic alternatives is considered as a future solution to reduce the
 630 computational time even further (Allitt et al., 2009).

631 Secondly, the sub-model approach yields substantial time-savings by eliminating the domain irrelevant to
 632 specific targets. To pursue the desired computational efficiency, modellers may sharpen their focus by



633 prioritising a few critical ones, as a limited number of target objects may result in more valid domain
 634 reductions, i.e. more time-savings. In contrast to the full-domain approach that implies general modelling
 635 targets, this targets-specified strategy may fail to provide the flood information outside the focus areas. Yet,
 636 based on distinct targets, the sub-model approach decomposes a large-scale model into many independent
 637 small sub-models (e.g. Sub-model A, B, C and D), and their computational independency would allow for
 638 parallel processing of multiple sub-models in a computer cluster environment without further accounting for
 639 flow interactions across their domain boundaries, thus reducing the computing time significantly. As another
 640 alternative solution, modellers may also adopt coarse-grids approach to fast complementing the predictions
 641 results other than the prioritised domains, and the final large-scale flood results fused from two parallel
 642 simulations (i.e. fine/coarse grids) should provide sufficient information whilst maintaining a marginal
 643 increase in overall computing time. Furthermore, due to the automation of the GIS-based procedure, the sub-
 644 model approach integrated with a real-time weather radar system may increase the possibility of applying 2D
 645 models into real-time forecasting applications in future. In this case, unlike a ‘one for all’ forecasting approach
 646 where predictive results of all possible future scenarios are provided based on one calibrated model, the sub-
 647 model approach would enable a more feasible forecasting solution in the adaption of real-world dynamics by
 648 reducing the scenario uncertainties through a real-time sub-model generation process.

649 Finally, the sub-model approach deploys a multiple-scale simulation strategy to obtain final predictions
 650 stepwise. From excluding different incidental representation processes according to the modelling purposes
 651 (i.e. aims i/ii, Section 1.3) specified for the two phases separately, sub-model approach uses different routings
 652 (i.e. 1D static/ 2D dynamic flows) with different complexities (i.e. hydrological/inundation process) at multiple
 653 scales (i.e. local catchment/ basin). Thus, the overall procedure achieves holistic computational efficiency
 654 compared to a single-time as-realistic-as-possible simulation for the large-scale inundation event. Further,
 655 without having additional efforts for code modifications in numeric engines, the implementation of the sub-
 656 model approach on other full 2D models should be straightforward. As most existing full 2D models perform
 657 similar peak water level predictions with marginal discrepancies in dense urban areas (Néelz and Pender,
 658 2010), it is anticipated that the obtained validation results (Section 4.1.1, 4.1.2) proven based on MIKE



659 FLOOD should fit for other full 2D engines – at least for the peak water levels. Yet, due to the various ways
 660 of coding velocity in full 2D models, the validation results for velocity hydrographs represent for MIKE
 661 FLOOD only. In addition, this approach is initially designed for dealing with flood inundation process
 662 dominated by overland flows. However, when rainfall amounts are low, the enhanced influence of the
 663 underground drainage system may affect the overland flow continuity, thus affecting domain reductions. For
 664 the sake of this limitation, adding a drainage component to represent the drainage system comprehensively
 665 could be an interesting future development, and further investigations on the significance of drainage systems
 666 regarding 1D flow continuity should be addressed. In addition, the sinks’ spill-overs in the current sub-model
 667 approach are simplified as “static” and single direction spilling. Therefore, incorporating a dynamic 1D routing
 668 (dynamic wave/kinematic wave) and a multiple-direction-spilling component would add more accuracy to
 669 flow pattern representations, thus ensuring more precise domain reductions. However, the trade-off between
 670 the modelling complexity, the computing time and the enhanced accuracy should be addressed and ultimately
 671 balanced based on the specified modelling purpose.

672 6. Conclusion

673 This paper presents a targets-specified grids-tailored sub-model approach to reducing the computing time for
 674 large-scale high-resolution 2D urban flood modelling. By utilising the enabled 1D static flows to trace sub-
 675 impact zones relevant to specific target objects, critical computational cells, that configure reduced
 676 computation domains as well as optimised boundary conditions, are extracted from a full-basin DEM’s high-
 677 resolution grids for MIKE FLOOD simulations. The outcome is tailor-made sub-models that require less
 678 computational efforts while avoiding significant losses in the prediction accuracy. The proposed method was
 679 tested for a basin area, the impacts of domain reductions and optimised boundary conditions on MIKE FLOOD
 680 were validated, and the general applicability and robustness of the suggested method were tested by targeting
 681 four focus areas accounting for different rainfalls as well as different terrain morphologies. The main findings
 682 are outlined as follow:

- 683 • The proposed sub-model approach performs 45-553 times faster processing in MIKE FLOOD by
 684 reducing 99% computational cells deemed to be irrelevant according to specified targets, i.e. specific



buildings and specified precipitations; Domain reduction tests reveal minor discrepancies against the benchmark (i.e. full-basin domain) concerning peak water levels when using the sub-model approach, and the general error deviations are within marginal level of < 0.05 m. The internal point hydrographs indicate general consistent spatial-temporal variations in water depths and flow velocities. Due to the violation of the actual flow pattern, differences were found in u- and v-velocities. However, the boundary condition comparison test reveals that the optimised boundary conditions resolve these potential errors properly. As suggested by the general applicability test, the performance of the sub-model approach is robust when dealing with different terrain morphologies as well as different rainfall return periods, whilst their RMSE are maintained at the marginal level of < 1.5 cm.

- Domains configured by critical cells impact the final 2D predictions substantially. The sub-model approach incorporates relevant flow patterns explicitly by tracing 1D static routing and accommodates commensurate hydraulic alternatives (i.e. 2D weirs) at terminal pour point positions, thus ensuring precise representations of actual flow patterns in configured 2D domain compared to other approaches. As opposed to the full-domain approach that implies general modelling targets, the sub-model approach provides no flood information outside the focus areas. However, the independency in-between various sub-models is a substantial advantage to parallel process many small sub-models in computer cluster environments without further considering information interactions across domain boundaries. Alternatively, modellers are recommended to use coarse grids to complement flood predictions beyond the prioritised domains. We see the two options as feasible solutions to improve computing time even further.

- With a multiple-scale simulation strategy, the sub-model approach decomposes a computationally expensive large-scale simulation process into two phases by emphasizing appropriate modelling complexities at multiple scales, which results in a holistic modelling efficiency. Besides, without reprogramming existing codes in numeric engines, the implementation of the sub-model approach on other full 2D models is straightforward. Furthermore, with the automation of the GIS-based procedure,



710 the sub-model approach is considered as a promising solution to the realisation of the 2D real-time
 711 forecasting system when integrated with a real-time weather radar system.

712 **Author contribution**

713 Guohan Zhao: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation,
 714 Visualization, Writing – Original Draft & Editing, Funding acquisition.

715 Thomas Balstrøm: Writing – Review & Editing, Resources, Supervision, Software.

716 Ole Mark: Writing – Review & Editing, Resources, Supervision, Validation.

717 Marina Bergen Jensen: Writing – Review & Editing, Resources, Supervision, Project administration, Funding
 718 acquisition.

719 **Competing interests**

720 The authors declare that they have no conflict of interest.

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