

Article

A Sink Screening Approach for 1D Surface Network Simplification in Urban Flood Modelling

Guohan Zhao ^{1,*}, Ole Mark ², Thomas Balstrøm ¹ and Marina B. Jensen ¹¹ Department of Geoscience and Natural Resource Management, University of Copenhagen, Rolighedsvej 23, 1958 Frederiksberg C, Denmark; tb@ign.ku.dk (T.B.); mbj@ign.ku.dk (M.B.J.)² Krüger A/S, Søborg, 2860 Hovedstaden, Denmark; oma@kruger.dk

* Correspondence: zhaoguohan2014@hotmail.com

† Current address: Department of the Built Environment, Aalborg University, Thomas Manns Vej 23, 9220 Aalborg Øst, Denmark.

Abstract: Sinks configure the surface networks for overland flow processes representations during 1D hydrodynamic modelling. The excessive number of sinks detected from high-resolution DEMs can boost 1D computational costs significantly. To pursue optimal sink numbers and their optimal spatial distribution, a Volume Ratio Sink Screening (VRSS) method was developed to screen for computationally important sinks, while compensating for volume losses from removed (unimportant) sinks, such that 1D hydrodynamic modelling yields faster computing times without significant loss of accuracy. In comparison with an existing geometry-based sink screening method, we validated this method by conducting sensitivity analyses for the proposed screening criteria in three Danish case areas of distinct topographies. Two iterative procedures were programmed to assess and compare their sink screening performances in terms of sink number reductions and volume loss reductions, and a volume loss solver was developed to quantify catchment-wide volume losses in the 1D surface network. Compared to a geometry-based sink screening method, the VRSS method performs more robustly and produces more efficient reductions in the number of sinks, as well as efficient reductions in volume losses.



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Keywords: sink screening methods; 1D surface network simplification; volume ratio sink screening method; 1D hydrodynamic modelling; urban flood modelling

1. Introduction

Climate change and increased urbanization have made urban floods a frequent environmental threat, causing human, societal and financial losses [1]. To support the planning and design of mitigation measures, a range of urban flood inundation models have been documented in the current scientific literature.

Two-dimensional (2D) hydrodynamic models discretize the rainfall-runoff process across 2D rectangular grids, where volume interactions are considered as fluxes between cells determined from 2D Shallow Water Equations (SWEs). These models intrinsically integrate a large magnitude of spatially varying parametrization (i.e., precipitations, topography and surface roughness) with a single-cell response function in a fully distributed manner, and therefore yield high spatial precision [2–9]. However, such accuracy comes at a prohibitive computational cost of solving the full 2D SWEs. To reduce computing time, a range of 2D speed-up approaches including the coarse-grid approach [10–13] along with sub-grid treatments [14–17] and porosity treatments [18,19], simplified 2D hydrodynamic model [20–22], Cellular Automata (CA) approach [23–25] and the sub-model approach [26] have been developed. Aside from the above-mentioned, parallelization technologies based on multicore Central Processing Units (i.e., OpenMP and MPI libraries) [27–29], Graphics Processing Units [30–32] and cloud computing [33] also demonstrate a considerable performance improvement for 2D models. In addition, attempts have been made to explore the static model approach [34–38] and the machine learning approach [39–52]. Yet,

as they either partially or fully neglect the physical process, these two approaches are both challenged by providing the detailed flow dynamics (e.g., flow velocity). Especially for the latter, the challenges inherent in black box models, concerning their data-consuming nature, inductive biases from training data, explainability, learning transferability across multiple cases, still require further research effort for in-depth investigation.

Nowadays, the applications towards high-resolution simulations [53], large-scale simulations [54], real-time simulations [3,55], continuous simulations, flood control optimisation and uncertainty analysis [56] make substantial demands on the computational efficiency of the urban flood models. As opposed to computationally prohibitive 2D surface flood models, 1D surface flood models are also advocated as fast and cost-efficient alternatives due to their spatial representation approximation when using a 1D surface network [3–5,57–62]. In these models, a 1D surface network is used to spatially discretize the rainfall-runoff processes into topographically distinguishable units (referred to as “subcatchments”), and the hydrological responses of each subcatchment is modelled as homogeneous units using conceptual models (e.g., linear/nonlinear models). From the subcatchments’ exit points, the generated hydrographs are linked to a 1D hydraulic wave routing the flows into delineated preferential flow paths (i.e., stream links). In this way, 1D surface models represent the flow dynamics of the entire catchment, ultimately obtaining flow predictions within 1D surface networks.

To configure a 1D surface network, a definitive point that distinguishes two processes, i.e., subcatchment delineations (discretisation) and stream link delineations, is required. Following different approaches in defining this point, two network extraction technologies have been categorized [63]: (i) cell-based surface network extractions; (ii) feature-based surface network extractions. From defining a specific cell (pixel) value as the definitive point on a flow accumulation raster, the cells with values greater than this threshold value configure the networks [64–68]. Whereas this accumulation threshold value is adequate to denote the “start” of concentrated flow in river networks, the definitive threshold of the channel flow concentration may not suit urban flood modelling since the primary modelling focus has shifted from conveyance flooding (aiming at describing the vulnerability along stream links) to ponding flooding (aiming at describing the vulnerable sink areas). Therefore, taking the topographic features of sinks as the indicator, the authors of [62] introduced the sinks’ pour points as the points denoting the runoff transition process from sheet-flows into channel-flows, and thus a 1D surface network was identified exclusively for urban flood modelling. As such, sinks are considered as the critical topographic features that configure the 1D surface network in urban flood modelling. The number of sinks detected from high-resolution DEMs are enormous [69–71], and if all were included, then the complexity of the 1D surface network configured may boost the computing expenses substantially while yielding minor modelling accuracy improvement. To simplify the 1D surface network, in the way of reducing the computational cost, a sink screening method leaving out sinks based on a combination of two geometry-based criteria (sinks’ maximum depths and volumes) was proposed [62,69,72]. The geometry-based sink screening method considers two geometric features of detected sinks: maximum depth and volume. If the maximum depth and volume of a sink are both smaller than the set threshold values, it is considered to be an artefact sink, thus being filtered out from further computations. This method leads to over 90% reduction in the number of sinks. Nevertheless, issues of (i)–(iv) persist:

- (i) The criteria reflecting the “small/big” conception concerning the sinks’ geometry may ignore the sinks’ primary subcatchment behaviour (“strong/poor”) of retaining runoffs in relation to flood inundations, and therefore may lead to the removal of strong runoff retention sinks, while saving poor ones, and vice versa;
- (ii) Due to the accumulated effect of the converging networks, negligible small volume losses from excluded sinks may upscale to substantial amounts, leading to massive overestimated flood volumes concentrated at a specific spot;

- (iii) The method tends to be case-dependent and thus challenged by identifying an optimal combination of these two criteria, i.e., a balanced result that achieves the maximal number of removed sinks and the minimal volume losses, simultaneously, across various landscapes;
- (iv) Treating the sink screening process homogeneously, the use of uniform criteria may overlook the spatial variability in case of large-scale areas (e.g., basins), where the intensified heterogeneity may affect the final screening results significantly.

To address these issues, we propose a Volume Ratio Sink Screening method (VRSS) using two criteria: (i) Hydrologic Retention Volume Ratio (HRV_{ratio}) and (ii) Volume Loss Ratio (VL_{ratio}). Furthermore, we compare the VRSS method to the geometry-based sink screening method. This was achieved by sensitivity analyses of different criteria for the screening processes in terms of sink reductions and volume loss reductions. With the aim of testing the general applicability and the robustness, the two methods were tested and compared in three Danish basins (Greve, Copenhagen City Center and Amagerbro) of distinct topographies.

2. Methodology

2.1. The Volume Ratio Sink Screening Method

The VRSS method conducts the sink screening process from following the three steps, I–III, see Figure 1. According to [71], the general sinks detected from DEMs are classified into two categories: actual sinks and artefacts. To preserve the actual sinks only, the first screening criterion, i.e., the vertical accuracy of the DEMs referring to the Root Mean Square Error (RMSE), was applied. This value is computed by considering the average of the squared differences between the elevation value of the DEMs and the one of co-located points determined from the ground survey. Here, the sinks shallower than the vertical accuracy are considered as artefacts, thus, they are removed in Step I. Nevertheless, the number of remaining actual sinks may still be substantial. From a perspective of the hydrological performance for each sink in urban flood modelling, i.e., runoff retentions and runoff interceptions, two volume-ratio-based screening criteria, i.e., HRV_{ratio} and VL_{ratio} , are proposed and used for the further screening in Steps II and III.

In order to identify the computational importance of each sink in relation to the specific urban flood inundation simulation, the sinks' runoff retention performance (poor/strong) relative to the specific rainfall amounts is evaluated based on HRV_{ratio} computed as a volume ratio between the sink's capacity (C_{sink}) and the received total runoff volumes (V_{runoff}). Thus, if we consider the spillover as a transition moment (t_i) indicating when a sink uses up all its retention capacity and generates runoff only—performing like subcatchments, then these “unimportant” sinks that cause quicker spillover during a rain event should be modelled as part of the subcatchments for runoff generation rather than retention storage units. To substitute those subcatchments from screened “unimportant” sinks, “important” sinks should initiate another round of catchment delineation resulting in “dissolved subcatchments”, i.e., an updated subcatchment delineation (discretisation) (Figure 1b):

$$HRV_{ratio} = \frac{C_{sink}}{V_{runoff}} \times 100\% = \frac{S_1}{(S_1 + S_2)} \quad (1)$$

$$C_{sink} = R_{cell}^2 \times \sum_{i=1}^m D_i \quad (2)$$

$$V_{runoff} = R_{cell}^2 \times \sum_{i=1}^n A_i \quad (3)$$

where R_{cell} is the resolution of the employed DEMs; D_i is the sink depth value represented in $Cell_i$, and A_i is the total rainfall depth value contained by $Cell_i$ in distributed rainfall raster datasets; m is the total number of cells for each sink and n is the total number of cells

in each sink's subcatchment; S_1 and S_2 are the accumulated rainfalls in the hyetograph, see Figure 1c, and t_i indicates the time when the unimportant sink starts spilling. Therefore, the sinks with poor runoff retention are filled up quickly before t_i , and their dynamic filling process is considered insignificant. Thus, such representations are disregarded.

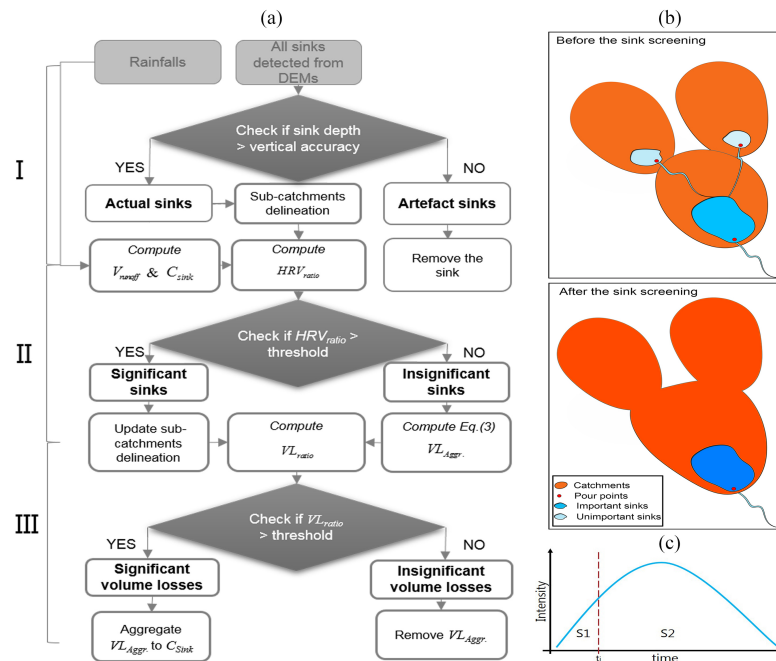


Figure 1. (a) The workflow behind the VRSS method, where light grey boxes represent input data; Step I represents the removal of artefact sinks; Step II represents a computationally significant sink selection; Step III represents the control of volume losses. (b) The sink screening process: before and after, where pour points denote a transition point indicating runoff converted from sheet flow (orange) to channel flow (blue lines). (c) Rainfall hyetograph, where the poor runoff retention sinks tend to be filled up rapidly before the time of t_i , and a smaller HRV_{ratio} indicates a smaller proportion of S_1 with earlier t_i in relation to the temporal variation of a rainfall event. Notes: increasing blue colouring for sinks symbolizes larger volumes.

By exclusively involving the computationally important sinks, the 1D surface network can be simplified substantially due to the reduced sink numbers. However, as reported by [60], the removed computationally unimportant sinks may illustrate a runoff interception effect that attenuates the flow propagation. Thus, neglecting the volume may result in higher surface flow peaks (i.e., flood depths and flood volumes), faster flow velocity, as well as shorter peak time in the subsequent 1D hydraulic computations. Furthermore, although such volume losses may be insignificant for the 1D surface network at the small catchment scale, the convergence of streams may trigger the accumulation and the concentration of the erroneous volumes, thus causing significant overestimations in some specific downstream areas. Therefore, in order to limit such impacts of volume losses in the 1D surface network, VL_{ratio} compares the aggregated volume losses ($VL_{aggr.}$) to the downstream important sink's retention capacities (C_{sink}).

$$VL_{ratio} = \frac{VL_{aggr.}}{C_{sink}} \times 100\% \quad (4)$$

$$VL_{aggr.} = \sum_{i=1}^n V_i \quad (5)$$

where V_i is the volume loss from the computationally unimportant $sink_i$ (i.e., light blue sinks, Figure 1b) that were removed in Step II, and n is the number of computationally unimportant sinks located within the subcatchment's updated sub-catchments (i.e., dark

orange subcatchment) from the computationally significant sink (i.e., the dark blue sinks, Figure 1b). Thus, VL_{ratio} assesses the computational significance of volumes for the VL_{aggr} concerning the runoff interception effect. If such an aggregated volume loss is relatively high compared to the important sinks included, then it cannot be ignored but it can be added to the downstream important sinks' capacities. Otherwise, insignificant volumes can be removed.

2.2. Sink Screening Experiment Design

In general, the VRSS method first removes artefact sinks using the vertical accuracy criterion, then determines sink reduction (i.e., the computationally important sinks) using the HRV_{ratio} and further deals with the volume losses of the removed computationally unimportant sinks based on the VL_{ratio} . In contrast, the geometry-based sink screening method determines the sink reductions using the criteria of the maximum depth and the volume concurrently, while the volume losses are controlled by the volume criterion. As such, sink reductions and volume losses are identified as the two common outcomes for both sink screening methods. From following those two aspects, we conducted the sensitivity analysis for their proposed criteria and compared their discrepancies.

For sink reduction tests (Section 2.2.1), as the topological complexity of the 1D surface network is based on the number of sinks as well as their spatial configuration, the sink reductions unfolded thus: (i) the total number of sink reductions (Section 2.2.1-(i)) and (ii) the spatially varying reduction of sinks (Section 2.2.1-(ii)), where their individual effects were investigated individually.

For volume loss tests (Section 2.2.2), in order to address the influence of volume losses, a volume loss spreading solver that quantifies the volume losses in the 1D surface network was developed (Section 2.2.2-(i)), and the reduction of the volume losses is further investigated (Section 2.2.2-(ii)).

2.2.1. Sink Reduction Tests

(i) The total number of sink reductions.

To quantify the reduction effect of the two approaches in the total number of sinks, an iteration procedure was programmed to obtain the sensitivity analysis results (the detailed workflow is illustrated in Figure A1a, Appendix A). By adopting stepwise incremental threshold values, this procedure was executed using different criteria (i.e., maximum depth, volume and HRV_{ratio}) within their predefined iteration ranges. For the geometry-based approach, a concatenation of the maximum depth and volume based on the logic operator "AND" is used. In order to clarify their individual reduction effect, each criterion was investigated in an independent iteration. Next, their combined effect was analysed and discussed to address their mutual interference. The detailed parameter settings for the sensitivity analysis are elaborated in Appendix B. To compare the results derived from different criteria, the obtained results were interpreted and analysed by: (i) the curves for the sink reduction reflecting the total number of the reduced sinks in relation to the change of the threshold values, and (ii) boxplots illustrating the distribution of the results. Here, the reduction rate ($reduction\ rate = reduced\ number\ of\ sinks / origin\ number\ of\ sinks \times 100\%$) was taken as the indicator. Six accumulated rainfalls of 30 mm, 50 mm, 70 mm, 90 mm, 110 mm and 130 mm covering rainfall return periods of 10–100 years were used to explore the HRV_{ratio} 's responses to various rainfall variations.

(ii) Spatially varying reduction of sinks.

The use of HRV_{ratio} enables adaptive reductions over the variation of rainfalls. To invoke a spatially varying reduction based on rainfall heterogeneity, a rainfall recorded from a radar source (also referred to as "radar rainfall") was used to compute each sink's HRV_{ratio} , and the matching HRV_{ratio} -derived curves were produced from the same iteration procedures (Figure A1a, Appendix A). For comparison, other HRV_{ratio} -derived curves, disregarding the rainfall heterogeneity, were generated by assuming

statistic values (i.e., maximum, mean and minimum) of associated radar rainfall cells as accumulated rainfalls. In addition, threshold values of 5%, 15% and 25% were selected as representatives of HRV_{ratio} , and the spatial variations of the removed sinks were summarized cell-wise (1000 m resolution) based on the radar rainfall grids of each of the three cases. Finally, the sink reduction rate was used as the indicator to maintain the comparison consistency for all three case areas.

2.2.2. Volume Loss Reduction Tests

(i) Quantification of volume losses (the volume loss spreading solver).

In order to evaluate the volume loss accumulations over the convergence of stream branches, a volume loss spreading solver was developed to quantify the volume discrepancies in the 1D surface network. As suggested by Figure A1c in Appendix A, the general workflow illustrates two successive computations: (i) flood volume computations (i.e., blue zones, Figure A3c) and (ii) volume loss computations (i.e., red zones, Figure A3c). In order to quantify the flood volumes for each sink (i.e., $V_{spilled}$), a link-based fast-inundation spreading algorithm, as reported by [26], was used to enable a filling-and-spilling routine that distributes flood volumes to all sinks rapidly from following the sequence of the Shreve stream order [73]. Furthermore, the removed sinks contain volumes for storing of water, so an exclusion hereof may result in identical volumetric overestimations at downstream via the spillover (Figure A3a). Therefore, we modelled the overestimated volumes as the oil liquids following a spilling-and-remaining routine. Detailed computational equations, processes and the computation example are provided in Appendix C.

(ii) The reduction of volume losses.

In order to quantify impacts of the volume losses, which in turn proves the sensitivity of VL_{ratio} , the redistributed volume losses were computed by using the volume loss spreading solver and an iterative procedure was programmed to conduct sensitivity analysis using different VL_{ratio} threshold values (see Figure A1b). Thus, the stepwise reductions in volume losses were investigated from the curves for the volume loss reduction, and were further discussed from the perspectives of (i) the source volume losses, (ii) the spilled volume losses and (iii) the remaining volume losses, where the $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n VL_i^2}$ is taken as the indicator, and n is the total number of streams (polylines) or sink polygons. The detailed parameter settings for the sensitivity analysis are elaborated in Appendix B. To retrieve the consistent source volume losses for each case, the screening results based on HRV_{ratio}^{Radar} of 15% were used. The spatially varying reductions in volume losses were investigated from maps, and VL_{ratio} values of 50%, 20% and 5% were considered as representative threshold values. Once again, identical grid meshes (Section 2.2.1-(ii)) were used to sum up the VL_{source} for each cell, while networks (polylines) and sink polygons were applied to explore the redistributed volume losses in $VL_{spilled}$ and $VL_{remaining}$.

3. Case Studies

Three Danish case areas (Greve, a town in Greater Copenhagen; City Center of Copenhagen; Amagerbro, a city district in Copenhagen) were selected to validate the robustness and general applicability of the two sink screening methods in landscapes with different topographies. All three areas suffered from urban floods during the extreme rainfall event on 2 July 2011. Both the City Center of Copenhagen and Amagerbro are heavily urbanized, while Greve is a suburb of Copenhagen, characterized by a combination of urban and rural areas. As shown in Figure 2, case boundaries were delineated by the Basin tool and sink detections were determined by the Fill tool in ArcGIS Desktop 10.6 [74]. A high-resolution 1.6 m digital hydrologically conditioned elevation model, DHyM [75], was used as input in the analyses. However, in order to avoid underestimations in sink volumes and in the number of sinks, a method was used where building elevations were extracted from the commensurate digital surface model (DSM) substituting the DHyM's ground elevations to

ensure precise representations of building topographies [69]. A summary of topographic characteristics and sink statistics for the three case areas is presented in Table 1. The radar rainfall (see Figure 2) recorded from the extreme event on 2 July 2011 was selected for the analyses. A summary of the radar rainfalls' cell values (mm) for the three cases is presented in Table 1.

Table 1. Topographic overviews, sink statistics and radar rainfall statistics for the three case areas on 2 July 2011.

			Greve	Copenhagen City Center	Amagerbro
Topographic overviews	Elevation (m)	Min.	−1.29	−0.89	−5.16
		Max.	80.62	98.55	87.8
		Mean	22.37	12.87	4.26
		St. dev.	15.08	7.91	4.99
	Slope (%)	Mean	9	30	17
		St. dev.	19	49	36
Sink statistics	Total number		30,556	13,899	7356
	Max. depth (m)	Min.	0.05	0.05	0.05
		Max.	20.6	22.27	26.3
		Mean	0.18	0.28	0.22
		St. dev.	0.48	1.26	0.95
	Volume (m ³)	Min.	0.13	0.13	0.13
		Max.	5,027,476	602,870	564,441
		Mean	485	210	278
		St. dev.	33,930	6200	9976
		Sum.	14,819,660	2,918,790	2,044,968
Radar rainfall statistics	Rain amounts (mm)	Min.	23.6	77.4	88.09
		Max.	109.19	147.5	133
		Mean	58.97	104.68	111.46
		St. dev.	26.82	12.2	14.69

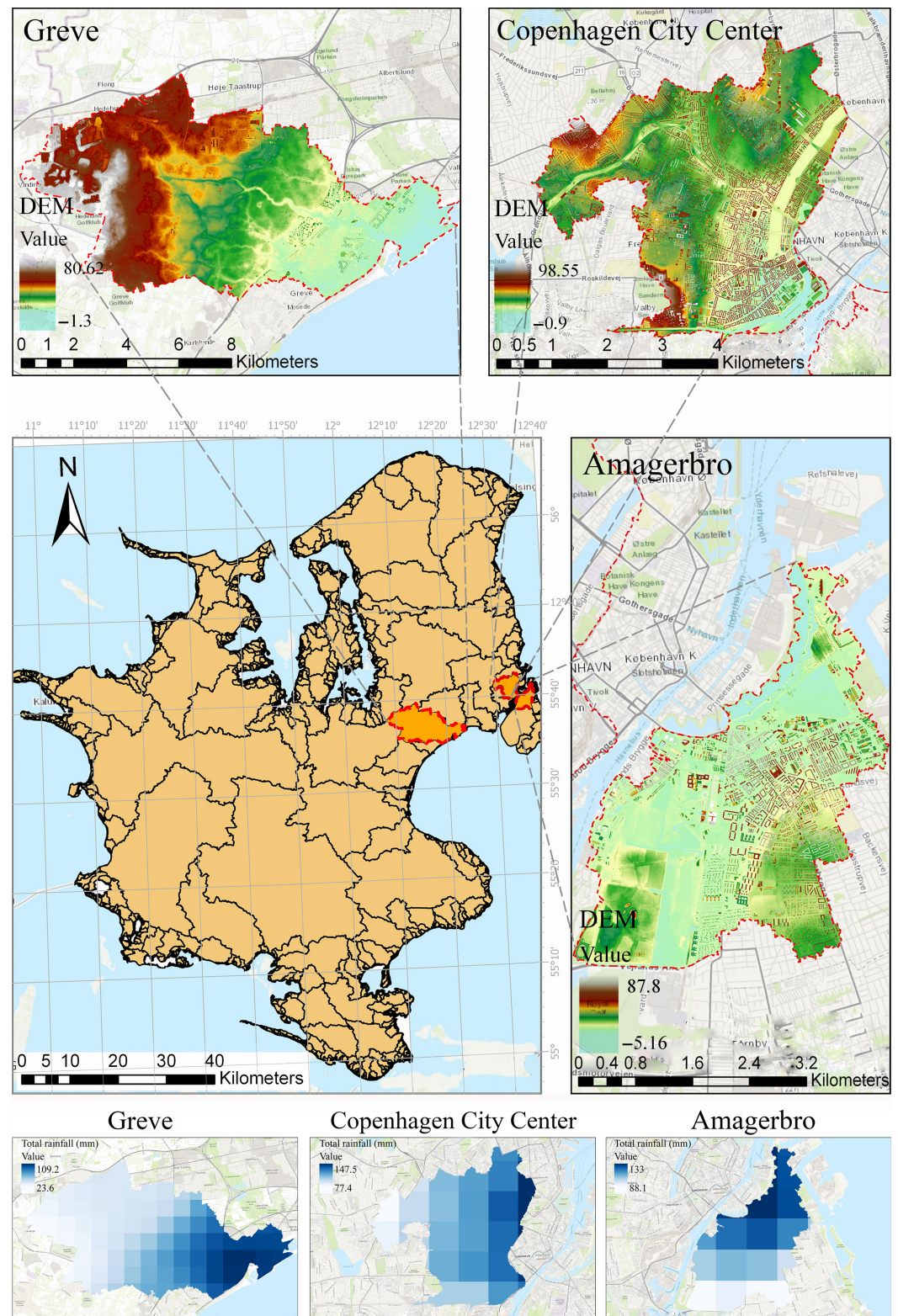


Figure 2. Locations and radar rainfall datasets for the three case areas: Greve, Copenhagen City Center and Amagerbro. Each radar rainfall cell represents the accumulated rainfall for an area of 1000 m × 1000 m. Base map shown in this paper is from source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

4. Results

4.1. Total Number of Sink Reductions

The curves in Figure 3 compare the screening process using maximum depth, volume and HRV_{ratio} for the three case areas, and the boxplots represent the associated distributions. All HRV_{ratio} curves show up to 99% reduction ratio in the total number of sinks. In response to the variation of accumulated rainfalls (30–130 mm), the buffers enveloped by the curves for HRV_{ratio}^{30mm} and HRV_{ratio}^{130mm} cover all possible changes in the screening results. Notably, with increased accumulated rainfalls, a sharper rise of the reduction ratio was found with a more significant gradient indicating accelerated reductions in the total sink numbers, e.g., HRV_{ratio}^{30mm} of 40% reduction rate vs. HRV_{ratio}^{130mm} of 90% reduction rate, when HRV_{ratio} is 10% for Greve. In accordance with this, the decreased variance of distributions was identified as the squeezed boxes for HRV_{ratio} , suggesting more densified distributions of screening results. In addition, increased median values (red horizontal lines in Figure 3b) were identified, corresponding to an upward shift of the overall distributions for the reduction rate of sinks. In other words, a larger accumulated rainfall value triggers a more concentrated distribution of screening results towards the high reduction rate range, e.g., for HRV_{ratio}^{130mm} , the reduction rates are mostly squeezed into a range of 90–98%, thereby avoiding a screening effort (iteration times) for insignificant reductions in case of extreme rainfalls. Here, HRV_{ratio} demonstrated the adaptive reduction implying an efficient sink reduction in the total number of sinks. The curves based on the maximum depth present over 98% reduction ratio in the total number of sinks for the three cases. A sink reduction of >65% was obtained when the first threshold value of 0.1 m maximum depth was used. Although this significant reduction was yielded quickly, over half of it occurred merely using the first threshold value, which seems excessive. Likewise, the next reduction rate spiked 80% when using the second threshold value (maximum depth of 0.15 m), and more than 90% of the sinks were filtered away using the third threshold value (maximum depth of 0.2 m). Overall, for high reduction rates of >60% and substantial differences of reduction rates of >20 percentage points in all three cases, the curves based on the maximum depth illustrate a coarse (imprecise) screening process, as well as reflecting an oversensitive screening response, which is considered problematic, particularly when sink reductions of <65% are intended. In contrast, the curves based on the volume show more densified screening results due to the small increment value of 0.128 m^3 , constituting intuitively fine (detailed) curves. Here, a greater number of screening results (5–8 points, each represents one iteration) were seen before the number of sinks was halved, while minor differences of <20 percentage points were found between screening results. However, a ceiling effect was spotted for the three case areas' screenings, in which their maximum reduction rates were limited <85%. Due to considerable variation in sinks' volume values, e.g., the standard deviation of volumes = 33.9 m^3 for Greve (Table 1), the use of iteration ranges 0–10 m^3 is insufficient and covers only 85% of the total sinks. Whereas extending the iteration range may cover the remaining 15% of the sinks, the subsequent iteration works (iteration times) are tedious particularly when the incremental value of 0.128 m^3 is used to include several order of magnitudes higher volumes, e.g., $5,027,476 \text{ m}^3$ for Greve.

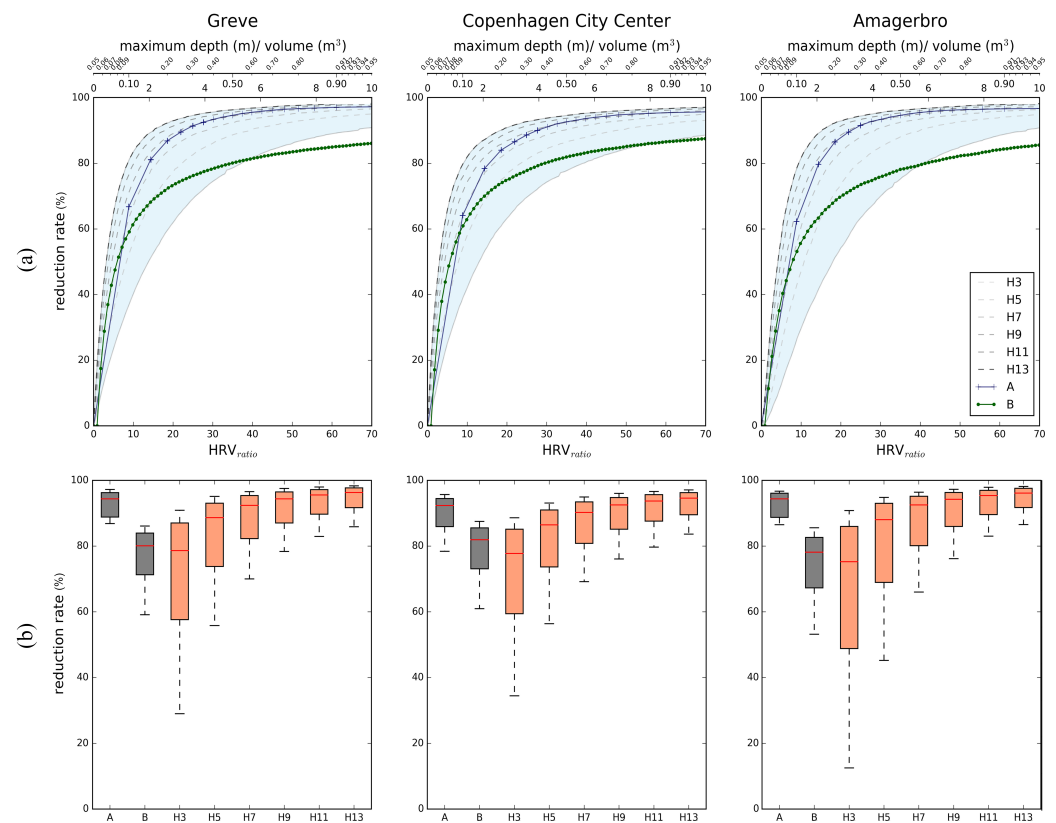


Figure 3. (a) Curves for sink reduction rate. The upper two x-axes represent the maximum depth and the volume; the lower x-axis stands for HRV_{ratio} . (b) Boxplots for the distribution of sink reduction rate. A and B belong to the geometry-based screening, with maximum depth and volume threshold values shown as grey boxes. H3–H13 belong to the HRV_{ratio} computed based on six accumulated rainfalls of 30–130 mm with threshold values shown as orange boxes. The upper and lower ends of the bars represent maximum and minimum value of sink reduction rate; the upper and lower ends of the boxes represent third quartile (0.25) and first quartile (0.75); the red lines represent the median value. Note: A = maximum depth; B = volume; $HR = HVR_{ratio}^{Radar}$; $H3 = HVR_{ratio}^{30mm}$; $H5 = HVR_{ratio}^{50mm}$; $H7 = HVR_{ratio}^{70mm}$; $H9 = HVR_{ratio}^{90mm}$; $H11 = HVR_{ratio}^{110mm}$; $H13 = HVR_{ratio}^{130mm}$.

4.2. Spatially Varying Sink Reductions

Figure 4 compares the HRV_{ratio} -derived curves (red) corresponding to radar rainfalls to the HRV_{ratio} -derived curves (dark blue, sky blue and green) corresponding to three accumulated (uniform) rainfalls, referring to the maximum, mean and minimum values of radar rainfall pixels in Table 1. Furthermore, the maps in Figure 4 depict detailed spatially varying reductions when using $HRV_{ratio} = 5\%$, 15% and 25% . Enveloped by curves based on maximum and minimum values, the light blue zones indicate possible deviations of the reduction rates in relation to the impact of rainfall heterogeneity for the three case areas. Compared with Copenhagen City Center and Amagerbro, Greve obtained the most significant deviations of the total number of sink reductions. This is ascribed to the different significances of rainfall heterogeneity reflected by the three cases' radar rainfalls, i.e., standard deviation of 26.8 mm for Greve vs. standard deviation of 12.2 mm and 14.7 mm for the other two case areas. As a result of the adaptive screening described in Section 4.1, the associated maps disclosed spatially varying reductions being scaled with accumulative rainfalls, as expressed by corresponding radar rainfall cells (Figure 2).

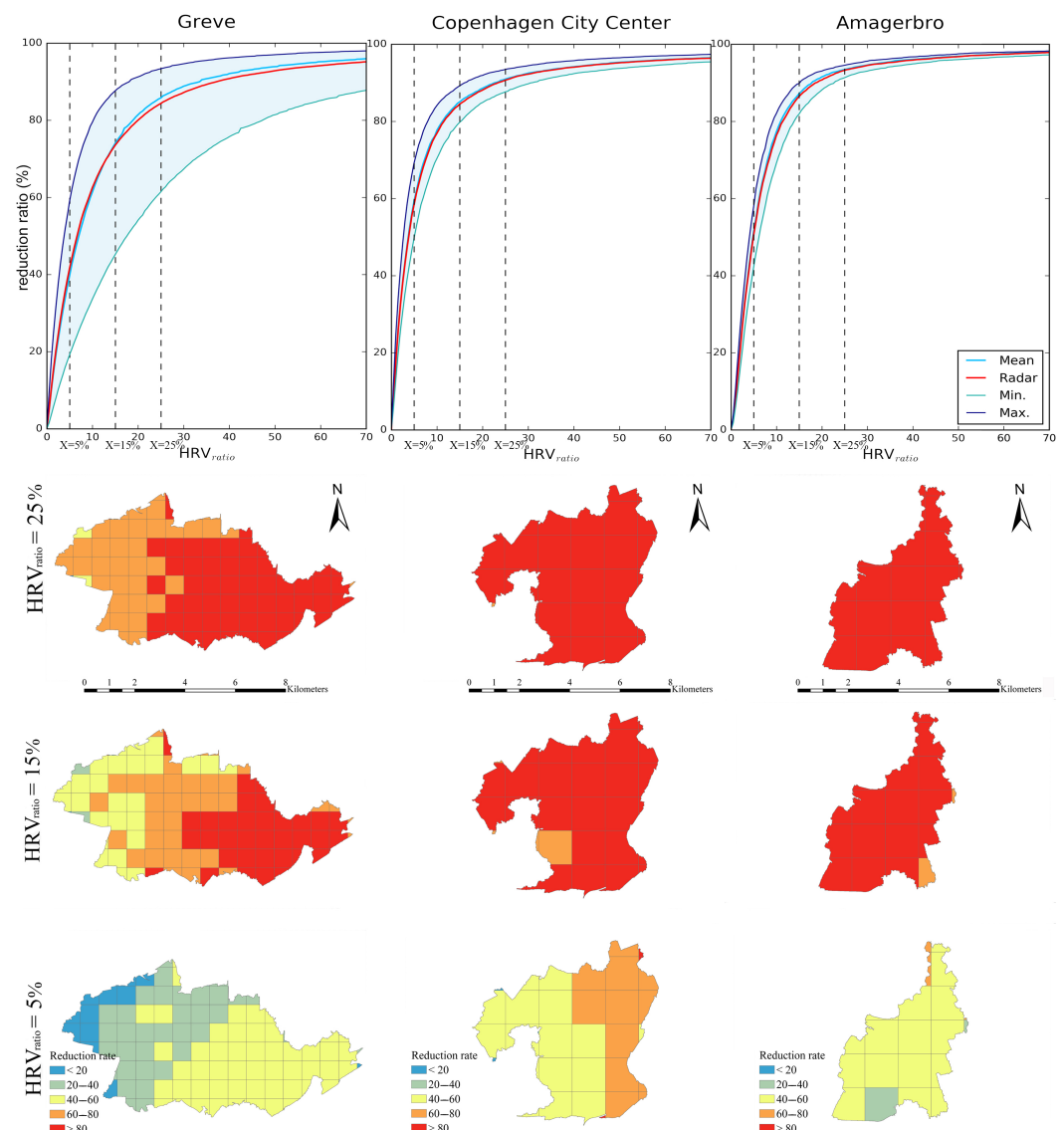


Figure 4. Spatially varying reductions of HRV_{ratio} computed based on the radar rainfalls of the three case areas. The curves present the deviation of the screening processes due to the impact of rainfall heterogeneity. The maps demonstrate how the reductions vary spatially for the three HRV_{ratio} of 5%, 15% and 25%.

4.3. Distribution and Redistribution of Volume Losses

Based on the sink removal at $HRV_{ratio} = 15\%$ (Figure 4), Figure 5a shows the distribution of volume losses, as illustrated by VL_{source} in radar rainfall cells (A), and the redistributed volume losses as illustrated by $VL_{spilled}$ in networks and $VL_{remaining}$ in sink polygons (B). In accordance with the map of Figure 4 at $HRV_{ratio} = 15\%$, the pattern similar to the rainfall spatial variation was observed for cells of VL_{source} , e.g., Greve. As the cell-based summarised volume losses rely on the number of removed sinks and their associated volumes, the distribution of VL_{source} , most likely, replicates the distribution of removed sinks. In the generated networks, the progressively darkened colours reflect the rise of $VL_{spilled}$ in relation to streams converging, and the highest $VL_{spilled}$ mounted at the termination point of networks, which suggests significant overestimations, i.e., 60,000 m³ for Greve, 20,000 m³ and 3000 m³ for the other two cases. In the generated sink polygons, $VL_{remaining}$ of 1200–1500 m³ were spotted in the westernmost upstream regions of Greve. With the small accumulated rainfall of 23.6 mm, the generated runoff volumes were insufficient to top the local VL_{source} over the spilling level. Thus, these VL_{source} were

retained locally and converted into equivalent $VL_{remaining}$. Likewise, Copenhagen City Center and Amagerbro obtained $VL_{remaining}$ of 1000–3000 m^3 and 1000–2000 m^3 in upstream regions. However, due to the progressively increased rainfalls for the central and downstream regions of Greve, most VL_{source} were carried away along with massive spillovers, and, therefore, marginal $VL_{remaining}$ were found in those areas. In contrast, for the other two cases, the immense capacity of downstream sinks took in the substantial $VL_{spilled}$ from upstream spillovers, and thus higher $VL_{remaining}$ (i.e., 6000–10,000 m^3 for Copenhagen City Center and 5000–6000 m^3 for Amagerbro) were identified for these areas.

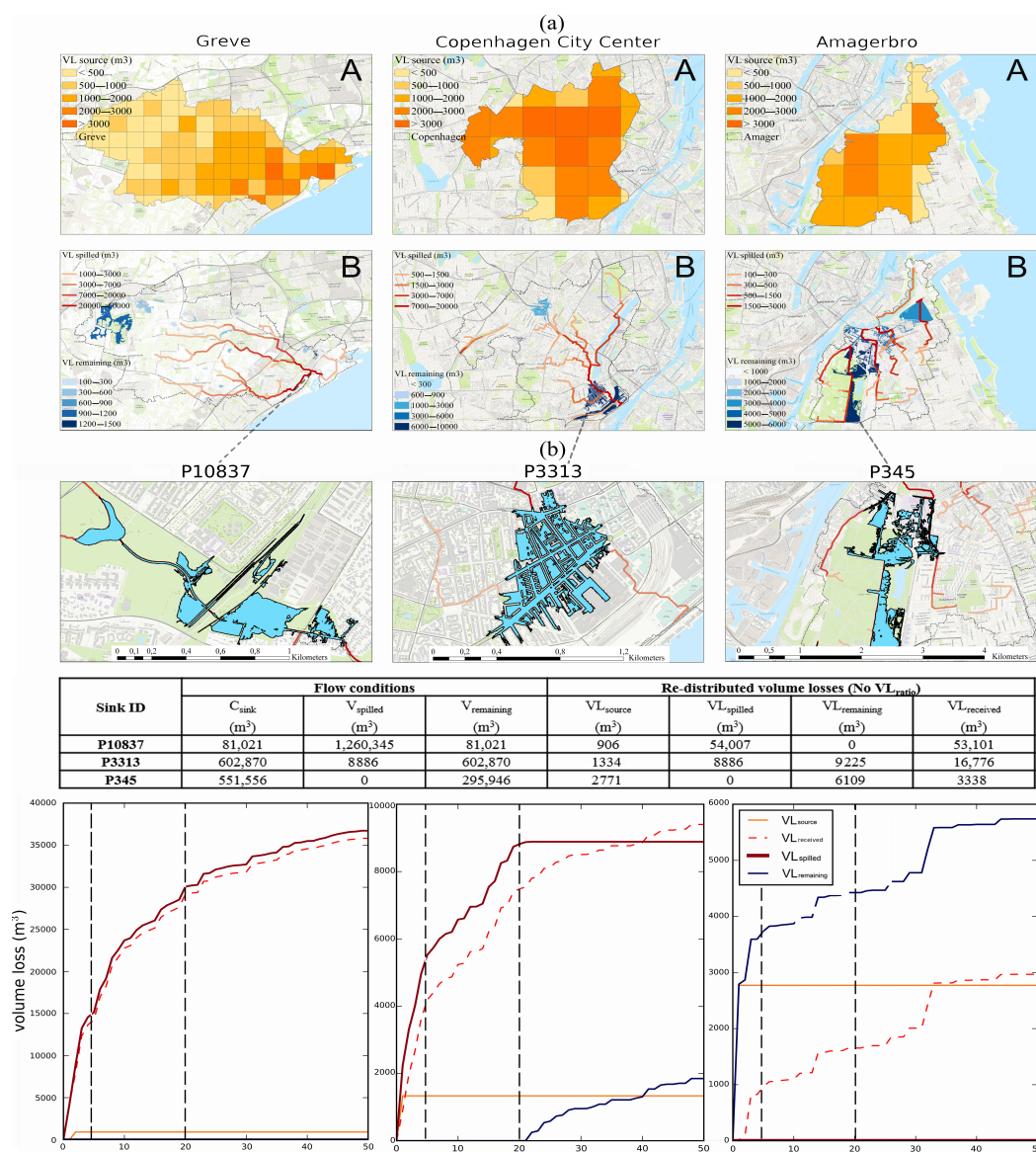


Figure 5. (a) Distribution and redistribution of volume losses for three case areas. A: Distribution of source volume losses. B: Re-distribution of volume losses illustrated as networks ($VL_{spilled}$) and sinks ($VL_{remaining}$). (b) Variation in volume losses of three selected sinks when using different VL_{ratio} threshold values, demonstrated for the three case areas. Above: Location of selected sinks. Below: Curves of volume losses. The associated table represents flow conditions for the three selected sinks (P10837: Greve; P3313: Copenhagen City Center; P345: Amagerbro) and their redistributed volume losses when no VL_{ratio} is used.

4.4. The Reduction of Volume Losses

The curves in Figure 6 show the reduction processes of RMSE for three cases over the decrease of VL_{ratio} from 50% to 0%. Particularly, when $VL_{ratio} = 0\%$ was used, all RMSE were eliminated due to the 100% inclusion (compensation) of volume losses in subsequent computations. Further, the maps depict detailed distributions and redistribution of volume losses at $VL_{ratio} = 50\%$, $VL_{ratio} = 25\%$ and $VL_{ratio} = 5\%$. In agreement with the curves, the diluted map colour of cells pointed to reductions of VL_{source} from the comparison of $VL_{ratio} = 50\%$ and $VL_{ratio} = 5\%$. Notably, a marginal $VL_{source} < 500 \text{ m}^3$ was identified for Copenhagen City Center with $VL_{ratio} = 5\%$. As a consequence of the reduced VL_{source} , the reduced networks and reduced number of sink polygons illustrate considerable reductions in terms of $VL_{spilled}$ and $VL_{remaining}$. Interestingly, as opposed to the RMSE of VL_{source} , higher sensitive changes were observed for $VL_{spilled}$ and $VL_{remaining}$, e.g., RMSE of $5\text{--}10 \text{ m}^3$ in VL_{source} vs. the RMSE of $600\text{--}1400 \text{ m}^3$ in $VL_{spilled}$, Greve. This suggests that the RMSE for VL_{source} may be too insensitive to indicate volume losses in 1D surface networks properly. Furthermore, given that the three cases were hit by extreme rainfalls, $VL_{spilled}$ performed relatively more responsive reductions in RMSE compared to $VL_{remaining}$ in response to the decrease of VL_{ratio} .

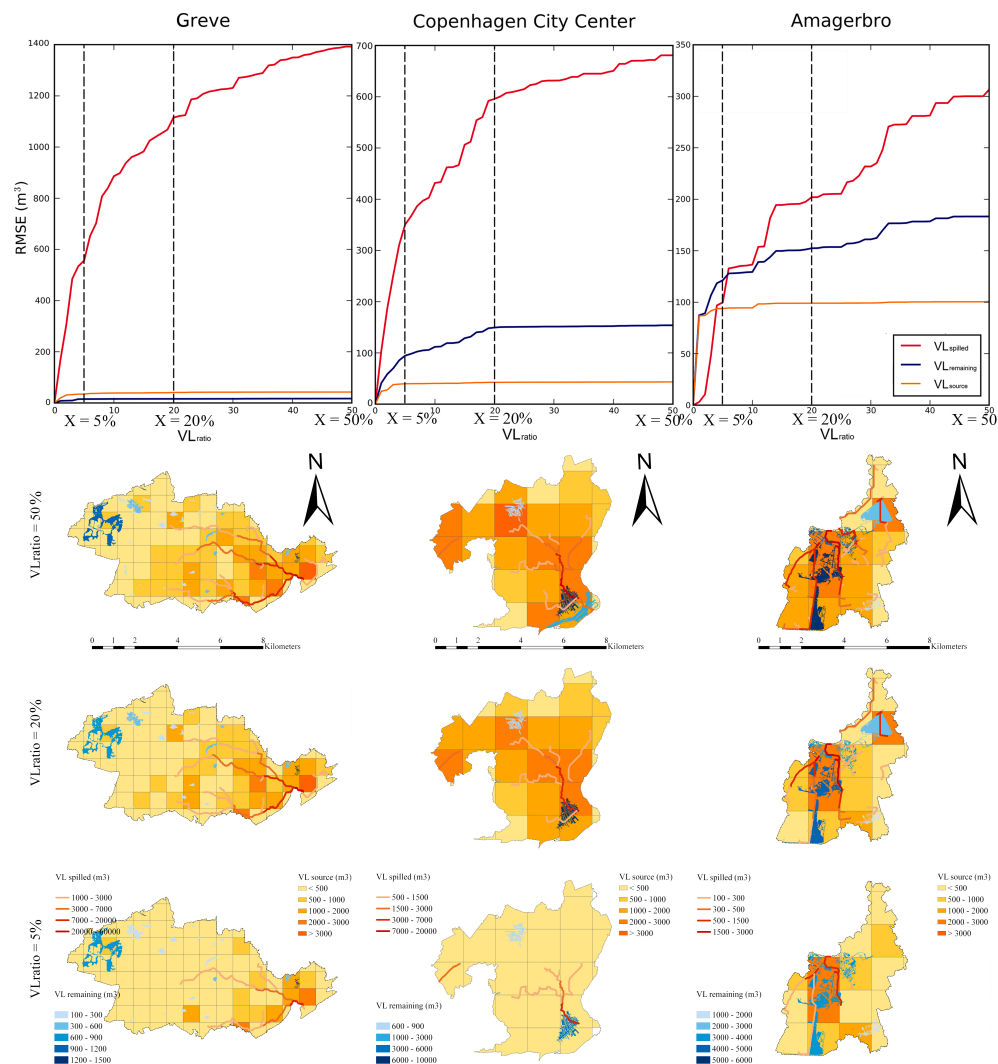


Figure 6. RMSE curves of volume losses and maps, where the general reduction in volume losses was demonstrated, and detailed spatial variations were presented from the perspective of spilled volume losses, remaining volume losses and source volume losses.

5. Discussion

The presented VRSS method can reduce sink numbers effectively whilst compensating for the volume loss accuracy. In contrast with the geometry-based sink screening method, its advantages, shortcomings and associated potentials are compared and discussed following from three aspects: (i) sink reductions (Section 5.1), (ii) volume loss reductions (Section 5.2) and (iii) computational efficiency and accuracy in 1D urban surface flood modelling (Section 5.3).

5.1. Sink Reductions

In general, according to the results from Section 4.1, the two sink screening methods perform valid sink reductions with at least 80% maximum reduction rate in the total number of sinks. However, due to the limitation of the DEM's vertical accuracy for sink maximum depths and the considerable dispersion for the distribution of sink volumes, the individual performance of the two criteria for the geometry-based sink screening method may illustrate either oversensitive screening responses or ceiling effects during the general sink screening process. At this point, HRV_{ratio} is unitless and thus its incremental value is not limited by the DEM's accuracy, which is a considerable advantage in case that a finer (more detailed) screening process is required. As for the geometry-based sink screening method, a logic operator "AND" concatenating the two criteria is used, thus enabling a combined reduction, where the final screening output is dominated by the criterion performing more significant reductions. Yet, sensitive to the distinct topographies, the combinations of the sink reductions based on the two criteria may differ from one case to another. As shown in Figure 5b, Greve and Amagerbro illustrate a situation where volume-derived results (distributions) were completely overruled by maximum-depth-derived results, i.e., the range of a volume-derived reduction rate 60–86% smaller than the one of maximum-depth-derived reduction rate 87–97%, which means, for this case, that the volume criterion did not perform sink reductions, but exclusively limited volume losses. In contrast, for Copenhagen City Center, an overlapping of 79–90% from the two ranges was identified. Here, when the combined threshold values were selected for this overlapped part, the mutual interference of the two criteria towards the final combined reduction is ambiguous. Due to such uncertainties, we conclude that the geometry-based sink screening method is case-dependent. Therefore, for the various landscapes applied, due attention should be paid to the selection of the two threshold values, as well as their combinations. In contrast, from the comparison of the three cases, HRV_{ratio} suggested stable outcomes regarding sink screening processes and screening result distributions, which proves the robustness and the general applicability of the proposed criterion (addressing issue (iii)). This is ascribed to the use of the accumulated rainfall in HRV_{ratio} , which undermines the dependency on topographies when using criteria exclusively based on the sinks' geometries. As opposed to the sink's geometric properties (big/small), HRV_{ratio} measures a sink's catchment behaviour (runoff retention performance, poor/strong) relative to distributed accumulated rainfalls. Here, by taking such a relative reference, HRV_{ratio} demonstrates an adaptive reduction in relation to rainfall scales, and thus is considered a more reasonable criterion than the geometry-based criteria in the context of 1D urban surface flood modelling (addressing issue (i)). Consequently, the use of radar rainfall enables a spatially varying sink reduction considering the spatial variation of rainfalls, and the curve deviations (Figure 6) for the three cases illustrate a significant impact of rainfall heterogeneity on the total number of sink reductions. Moreover, as noted in [69], as the sink is defined as the start point for flow paths, the number of the flow paths is highly dependent on the number of sinks. Thus, based on the spatially varying sink configurations in Figure 6, we infer that networks can be generated, illustrating spatially varying topological complexity in relation to the rainfall heterogeneity. In addition, due to the varying topographies in large-scale areas, optimal geometry-based criteria may differ from one region to another, thereby being challenged by covering such spatial complications with uniform threshold values. At this point, the spatially varying sink reduction of HRV_{ratio} appears advantageous as opposed to

the homogenous sink reduction, particularly in cases of large-scale study areas (addressing issue (iv)).

5.2. Volume Loss Reductions

The results of Section 4.3 suggest considerable volumetric diversions in terms of $VL_{remaining}$ and $VL_{spilled}$ for the three cases. Therefore, we conclude that it is essential to establish a control mechanism to confine the accumulation (i.e., $VL_{spilled}$) and the concentration (i.e., $VL_{remaining}$) of volume losses (issue (ii)). With the use of VL_{ratio} , the RMSE of $VL_{remaining}$ and $VL_{spilled}$ suggest significant reductions in the curves of Figure 6. Nevertheless, the RMSE of VL_{source} is insensitive as opposed to the RMSE of $VL_{remaining}$ and $VL_{spilled}$. Here, we consider that VL_{source} is a less adequate indicator of volume loss in the large-scale cases. Overall, the redistributed volume losses inside the three sinks demonstrate a significant case-dependency that relies on the computed flows, and therefore, their responses in relation to the variation of VL_{ratio} differ from one case to another. Therefore, to reduce volume losses to a desired level, modellers are recommended to quantify the volume losses ($VL_{remaining}/VL_{spilled}$) in the specific area of interest or to simply compensate for all the volume losses using $VL_{ratio} = 0\%$. In contrast, although the geometry-based sink screening method controls the volume losses at a negligible level by using the volume criterion to limit the amount of VL_{source} , two potential issues should be addressed with care. Firstly, the significance of the VL_{source} should be validated using $VL_{remaining}$ and $VL_{spilled}$ in case that the VL_{source} accumulates and is concentrated in some specific sinks up to a significant level. Secondly, the use of a volume criterion that controls volume losses may interfere with the number of sink reductions and in turn affect the final volume losses obtained, where such a loop effect is considered inappropriate. As with the lack of independence for the two screening processes, this may also bring up confusion regarding “to which extent which criterion works in which aspect”. As a consequence, unless the two screening processes perform independently in some specific cases, i.e., Greve and Amagerbro, it is difficult for modellers to identify a balanced result between sink reductions and volume losses by using only one screening process integrated from two criteria. At this point, the VRSS method uses two successive steps corresponding to two separate criteria that identify sink reductions and volume loss controls independently, which is considered a more accurate procedure (addressing issue (iii)).

5.3. Computational Efficiency and Accuracy in 1D Urban Surface Flood Modelling

As reported in [60], the simplified 1D surface networks yield extensive time reductions in subsequent 1D hydraulic computations. With the sink reductions triggered by HRV_{ratio} , it is anticipated that the VRSS method simplifies the complexity of 1D surface networks, thus reducing the computational costs significantly. Meanwhile, using adaptive boundaries distinguishing sheet-flows from channel-flows based on distributed rainfalls, such enhancements of the 1D surface network might be beneficial to the corresponding 1D hydraulic representations. Further, the VRSS method uses VL_{ratio} to differentiate the significance of the volume losses, and then determine either the compensation or the elimination of such volumes. As suggested by the results of Section 4.3 and (ii), we conclude that the volume losses in a 1D surface network can be reduced within a marginal level, and thus, the accuracy of the corresponding 1D urban flood modelling can be ensured properly with respect to surface flow peaks (i.e., flood depths and flood volumes), flow velocity, as well as peak time.

In addition to the sink reductions, an alternative solution to simplifying the networks (i.e., surface networks or sewer networks) are skeletonisation technologies, i.e., data scrubbing, branch pruning, trimming, and merging methods [76–78]. However, as noted in [79], such a simplification approach might be inadequate when dealing with a 1D surface network, and thus modellers are recommended to deploy the simplifications strategies onto the two networks (i.e., surface networks or sewer networks) separately, thus obtaining the most efficient element (i.e., sinks or manholes) reductions. Therefore, we believe that the

VRSS method is a feasible alternative to simplifying the 1D surface network. To extend its application to 1D–1D networks, we recommend using it as a post-processing step for the surface network simplification after enabling skeletonisation technologies for the sewer network simplification. In contrast to the geometry-based sink screening method, an additional variable of the total rainfall is required by the VRSS method. This may limit its application scope in case that the total rainfall is unknown, i.e., real-time flood forecasting. Here, we think a potential solution would be applying the numeric weather prediction to estimate the total rainfall ahead, but, for this case, the introduced input uncertainty of the total rainfall should be addressed with care. Furthermore, as for long-time continuous flood modelling, a threshold value that defines the dry and wet periods in historic rainfall data is required, in order to retrieve the total rainfall for each single event. However, long-term time-series rainfall data (e.g., 20-year continuous rainfall) could involve thousands of events, and it may sound like an excessive workload to generate a case-dependent network for every rainfall event. In this case, modellers may consider selecting more representative rainfalls by conducting rainfall statistics so that a balanced trade-off between the computational efficiency, workloads and enhanced accuracy is achieved.

6. Conclusions

This paper presents a VRSS method which yields effective sink reductions, whilst compensating for volume losses in the 1D surface network hydraulic computations. This method is validated and compared to the existing geometry-based sink screening method based on three case areas of distinct topographies. Two iterative procedures were programmed to conduct sensitivity analyses of the criteria proposed concerning screening effects in terms of sink reductions and the reduction of volume losses. Further, a volume loss spreading solver was developed to quantify the impact of volume losses in the 1D surface networks. Six accumulated rainfalls were used to analyse the screening response of HRV_{ratio} , and radar rainfalls of the three cases were applied to investigate the significance of the rainfall heterogeneity in the sink screening. The main findings are outlined as follows:

- Considering accumulated rainfalls as the relative reference, HRV_{ratio} performs an adaptive reduction in the total number of sinks, which indicates efficient reductions for extreme rainfalls. Based on the comparison of the three distinct cases, the sink screening performance of HRV_{ratio} is stable, thus proving the general applicability and robustness of this proposed criterion. Furthermore, the inclusion of a radar rainfall for the computation of HRV_{ratio} triggers spatially varying sink reductions. Based on the curve deviation deviations for the three cases, the significance of the rainfall heterogeneity affects the final sink screening result significantly. We therefore recommend the implementation of this method, especially for large-scale studies, in case that the significance of heterogeneity may intensify with the upscaled study area;
- In contrast, the geometry-based sink screening method is less adequate in sink reductions from four aspects: (i) the sink screening process based on the maximum depth is coarse, which reflects an oversensitive response in the total number of sink reductions (i.e., over 60% reduction rates and above 20 percentage points for stepwise changes of reduction rates); (ii) the screening process based on the volume indicates a ceiling effect, which results in incomplete screening results (i.e., covers 85% of sinks only); (iii) the combined reductions triggered by the concatenation of the two criteria are sensitive to distinct topographies, which may hinder its general applicability when dealing with various landscapes; iv) in the context of urban inundation simulations, sinks' catchment behaviours (runoff retention performance, strong/poor) are a more suitable criterion than the sinks' geometries (big/small);
- The volume loss spreading solver reveals a great degree of accumulation and concentration in volume losses over the converging network. The reduction process based on VL_{ratio} illustrates efficient reductions in volume losses with respect to the RMSE, as well as the specific sinks. However, the redistributed volume losses depend significantly on the computed flows for the individual case; thus, the corresponding

controlling process based on VL_{ratio} may vary from one case to another. Here, we recommend that the modeller consider the computed flows of focused sinks, as well as the tolerance level in relation to the specific modelling objective to determine an optimal VL_{ratio} . In contrast with the geometry-based sink screening method, the VRSS method shows a significant advantage by conducting sink reductions and the volume loss reduction separately from the two independent criteria.

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Appendix A

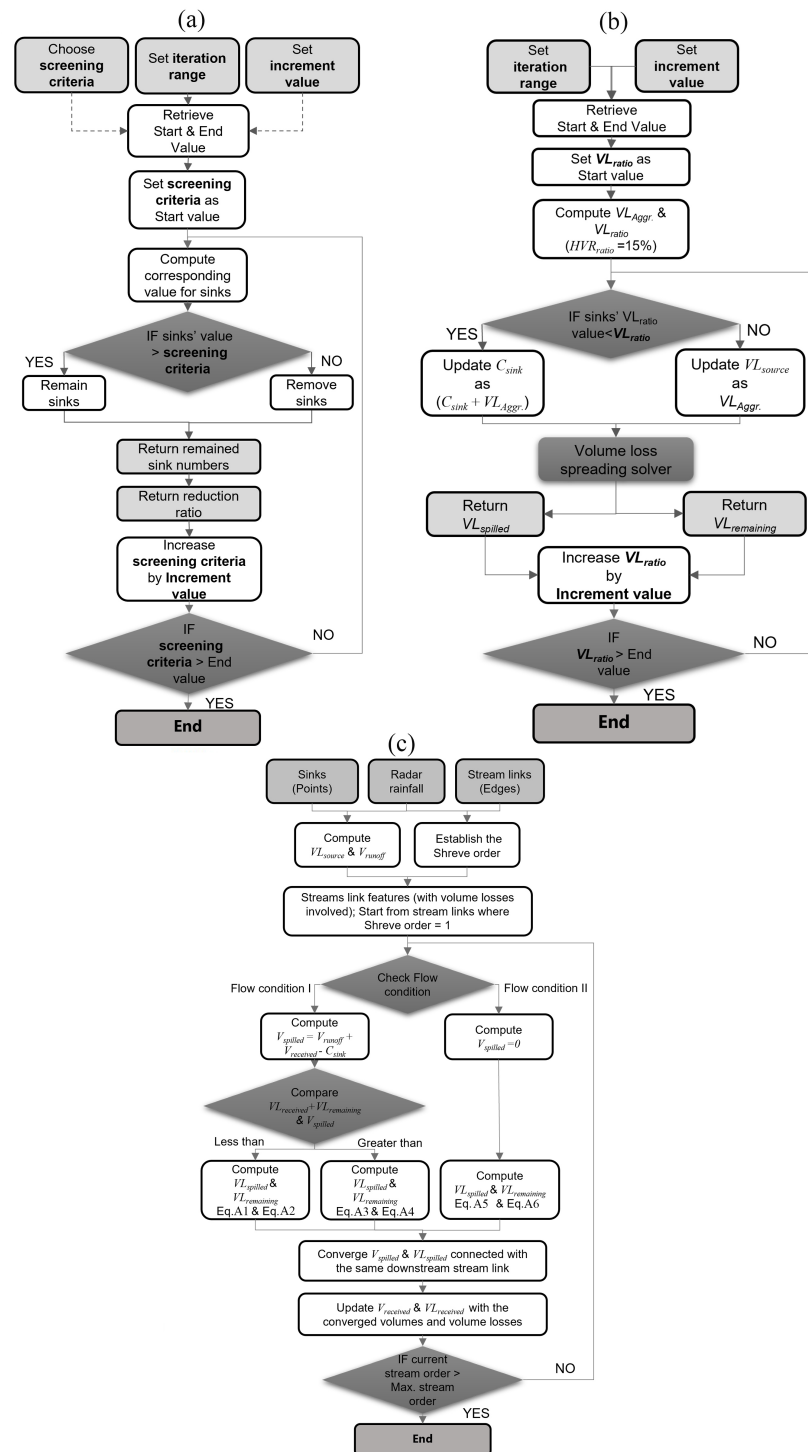


Figure A1. (a) Iteration procedures for the total number of sink reductions when using different screening criteria: (i) maximum depth, (ii) volume and (iii) HVR_{ratio} . (b) Iteration procedures of the volume loss reductions when using VL_{ratio} . (c) The volume loss spreading solver's workflow, where light grey boxes represent inputs and outputs of procedures; dark grey boxes stand for the major steps and bold fonts represent variables. Equations (A1)–(A6) are provided in Appendix C.

Appendix B

It was found that the iteration ranges and increment values are sensitive to results obtained from the iteration procedures. In order to obtain representative results, iteration ranges (i.e., maximum depth [0, 1] m, volume [0, 10] m³ and HRV_{ratio} [0, 70]) were determined based on boxplots (boxplots are illustrated by Figure A2, Appendix B), which illustrate the distributions of these sink values. In addition, the principle of “as small as permitted” was applied in selections of increment values. Thus, an increment value of 0.05 m for the maximum depth was used corresponding to the DEM’s vertical accuracy, and an increment value of 0.128 m³ for volume was used corresponding to the volume accuracy computed as the vertical accuracy multiplied by the resolution squared (i.e., $0.05 \times 1.62 = 0.128$ m³). Considering that the HRV_{ratio} is unitless, and thus not limited by the DEM’s accuracy, an increment value of 0.5% was used for HRV_{ratio} to merely ensure a discernible resolution of the generated curves.

In accordance with the reason stated above, the iteration range of VL_{ratio} was determined as [0, 50]% based on the distribution of VL_{ratio} in boxplots (see Figure A2b), and the increment value of 0.5 was selected to ensure a discernible resolution for the curves.

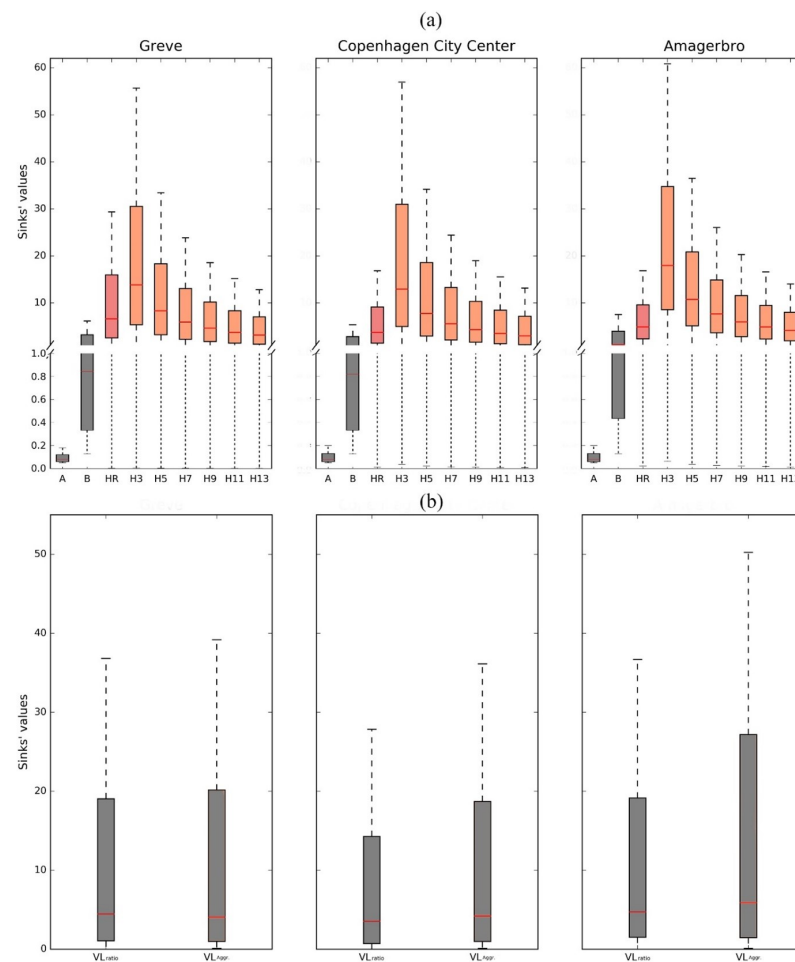


Figure A2. (a) Boxplots of maximum depth, volume and HRV_{ratio} , where iteration ranges were determined for three case areas. (b) Boxplots of VL_{ratio} and VL_{Aggr} (VL_{source}) when HRV_{ratio} of 15% was used, where iteration ranges of VL_{ratio} were determined for three case areas. Note: A = maximum depth; B = volume; HR = HRV_{ratio}^{Radar} ; H3 = HRV_{ratio}^{30mm} ; H5 = HRV_{ratio}^{50mm} ; H7 = HRV_{ratio}^{70mm} ; H9 = HRV_{ratio}^{90mm} ; H11 = HRV_{ratio}^{110mm} ; H13 = HRV_{ratio}^{130mm} .

Appendix C

Here, we model such overestimated volumes (VL) as the oils in the computed volumes (V), which means that its propagation follows two principles: First, overestimated

volumes (VL) are inherent in the computed flood volumes (V) and thus their volumes are not beyond the capacity available from the computed flood volumes (V); Second, overestimated volumes (VL) float above the actual flood volumes, thus spilling ahead. Therefore, by governing the mass conservation of volume losses, the redistribution of the volume losses follows a spilling-and-remaining routine based on two flow conditions (i.e., spil-over and non-spillover).

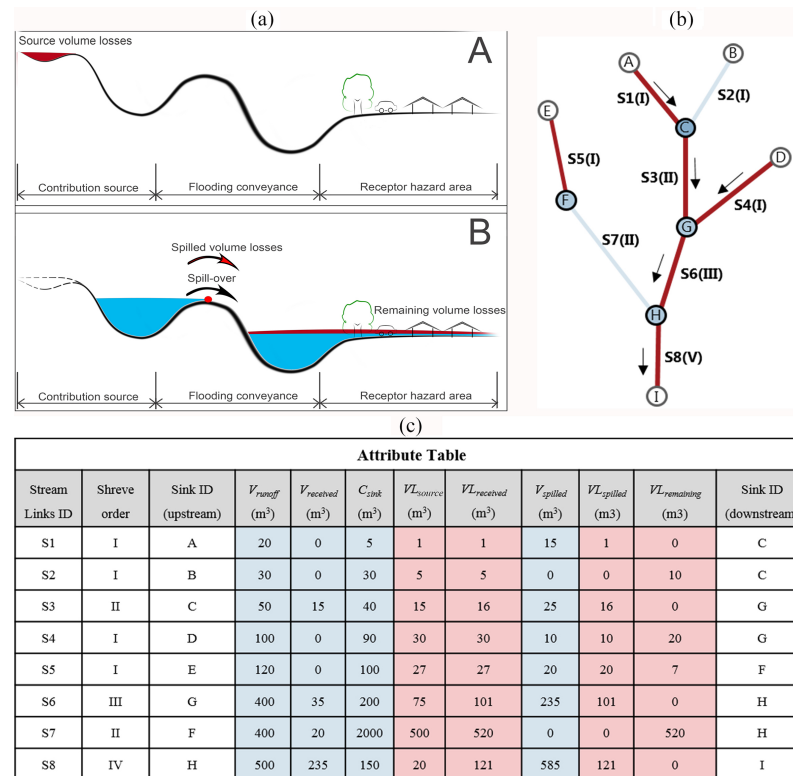


Figure A3. (a) The generation of source volume losses due to removed sinks (A) and the redistribution of volume losses (B). (b) Network geometry features, where Points A–I illustrate sinks, and blue points represent the sinks that contain $VL_{remaining}$. Edges S1–S8 stand for stream links and red edges represent the stream links that contain $VL_{spilled}$. (c) Attribute table containing the computational information corresponding to the geometry features, where blue zones represent link-based fast-inundation spreading computations, and red zones represent volume losses spreading computations.

For Flow condition I:

if $V_{received} + V_{runoff} > C_{sink}$, then $V_{spilled} = V_{runoff} + V_{received} - C_{sink}$,
and if $VL_{received} + VL_{source} \leq V_{spilled}$, then all volume losses pass through:

$$VL_{spilled} = VL_{received} + VL_{source} \quad (A1)$$

$$VL_{remaining} = 0 \quad (A2)$$

Else, if $VL_{received} + VL_{source} > V_{spilled}$, then volume losses partly pass through:

$$VL_{spilled} = V_{spilled} \quad (A3)$$

$$VL_{remaining} = VL_{source} + VL_{received} - V_{spilled} \quad (A4)$$

For Flow condition II:

Else, if $V_{received} + V_{runoff} \leq C_{sink}$, then $V_{spilled} = 0$ and no volume losses pass through:

$$V_{spilled} = 0 \quad (A5)$$

$$VL_{remaining} = VL_{source} + VL_{received} \quad (A6)$$

In addition, two variables, $V_{received}$ and $VL_{spilled}$, are updated for each iteration and are calculated as follows:

$$VL_{received} = \sum_{i=1}^n V_{spilled}^i \quad (A7)$$

$$VL_{spilled} = \sum_{i=1}^n VL_{spilled}^i \quad (A8)$$

where V_{runoff} stands for runoff volumes generated from each subcatchment and is calculated as Equation (3); $V_{spilled}$ represents the spilled volumes; C_{sink} is the sink's capacity; $V_{received}$ is the received volume converged from the $V_{spilled}$ of upstream sink i and n is the total number of upstream sinks; VL_{source} represents source volume losses within each subcatchment and is calculated as Equation (5); $VL_{spilled}$ is the spilled volume losses; $VL_{remaining}$ is the remaining volume losses; $VL_{received}$ is the received volume losses summed from the $VL_{spilled}$ of upstream sink i and n is the total number of upstream sinks. The relevant computation example is provided in Appendix D.

Appendix D

A computation example for the volume loss spreading computation in Figure A3: Stream order I: S1, S2, S4, S5.

For S1, $V_{runoff} = 20 \text{ m}^3$, $V_{received} = 0 \text{ m}^3$ and $C_{sink} = 5 \text{ m}^3$.

- (i) For flood volume computations (blue zones):
 $V_{spilled} = V_{runoff} + V_{received} - C_{sink} = 20 + 0 - 5 = 15 \text{ m}^3$;
- (ii) For volume loss computations (red zones):
 $VL_{source} = 1 \text{ m}^3$ and $VL_{received} = 0 \text{ m}^3$;
 Here, $VL_{received} + VL_{source} \leq V_{spilled}$;
 $VL_{spilled} = VL_{received} + VL_{source} = 1 \text{ m}^3$;
 $VL_{remaining} = 0 \text{ m}^3$.

For S2, $V_{runoff} = 30 \text{ m}^3$, and $V_{received} = 0 \text{ m}^3$, $C_{sink} = 30 \text{ m}^3$.

- (i) For flood volume computations (blue zones):
 $V_{received} + V_{runoff} = 30 \text{ m}^3 \leq C_{sink} = 30 \text{ m}^3$;
 $V_{spilled} = 0 \text{ m}^3$;
- (ii) For volume loss computations (red zones):
 $VL_{source} = 5 \text{ m}^3$ and $VL_{received} = 0 \text{ m}^3$;
 Here, $V_{spilled} = 0 \text{ m}^3$;
 $VL_{spilled} = 0 \text{ m}^3$;
 $VL_{remaining} = VL_{source} + VL_{received} = 5 \text{ m}^3$.

For S4, $V_{runoff} = 100 \text{ m}^3$, $V_{received} = 0 \text{ m}^3$ and $C_{sink} = 90 \text{ m}^3$.

- (i) For flood volume computations (blue zones):
 $V_{spilled} = V_{runoff} + V_{received} - C_{sink} = 100 + 0 - 90 = 10 \text{ m}^3$;
- (ii) For volume loss computations (red zones):
 $VL_{source} = 30 \text{ m}^3$ and $VL_{received} = 0 \text{ m}^3$;
 Here, $VL_{received} + VL_{source} > V_{spilled}$;

$$VL_{spilled} = V_{spilled} = 10 \text{ m}^3;$$

$$VL_{remaining} = VL_{source} + VL_{received} - V_{spilled} = 20 \text{ m}^3.$$

For S5, $V_{runoff} = 120 \text{ m}^3$, $V_{received} = 0 \text{ m}^3$ and $C_{sink} = 100 \text{ m}^3$.

(i) For flood volume computations (blue zones):

$$V_{spilled} = V_{runoff} + V_{received} - C_{sink} = 120 + 0 - 100 = 20 \text{ m}^3;$$

(ii) For volume loss computations (red zones):

$$VL_{source} = 27 \text{ m}^3 \text{ and } VL_{received} = 0 \text{ m}^3;$$

$$\text{Here, } VL_{received} + VL_{source} > V_{spilled};$$

$$VL_{spilled} = V_{spilled} = 20 \text{ m}^3;$$

$$VL_{remaining} = VL_{source} + VL_{received} - V_{spilled} = 7 \text{ m}^3.$$

Stream order II: S3, S7.

For S3, $V_{runoff} = 50 \text{ m}^3$, and $V_{received} = V_{spilled}^{S1} + V_{spilled}^{S2} = 15 + 0 = 15 \text{ m}^3$, $C_{sink} = 40 \text{ m}^3$.

(i) For flood volume computations (blue zones):

$$V_{spilled} = V_{runoff} + V_{received} - C_{sink} = 50 + 15 - 40 = 25 \text{ m}^3;$$

(ii) For volume loss computations (red zones):

$$VL_{source} = 15 \text{ m}^3 \text{ and } VL_{received} = VL_{spilled}^{S1} + VL_{spilled}^{S2} = 1 + 0 = 1 \text{ m}^3;$$

$$\text{Here, } VL_{received} + VL_{source} \leq V_{spilled};$$

$$VL_{spilled} = VL_{received} + VL_{source} = 16 \text{ m}^3;$$

$$VL_{remaining} = 0 \text{ m}^3.$$

For S7, $V_{runoff} = 400 \text{ m}^3$, and $V_{received} = V_{spilled}^{S5} = 20 \text{ m}^3$, $C_{sink} = 2000 \text{ m}^3$.

(i) For flood volume computations (blue zones):

$$V_{received} + V_{runoff} = 420 \text{ m}^3 \leq C_{sink} = 2000 \text{ m}^3;$$

(ii) For volume loss computations (red zones):

$$VL_{source} = 500 \text{ m}^3 \text{ and } VL_{received} = VL_{spilled}^{S5} = 20 \text{ m}^3;$$

$$\text{Here, } V_{spilled} = 0 \text{ m}^3;$$

$$VL_{spilled} = 0 \text{ m}^3;$$

$$VL_{remaining} = VL_{source} + VL_{received} = 500 + 20 = 520 \text{ m}^3.$$

Stream order III: S6.

For S6, $V_{runoff} = 400 \text{ m}^3$, and $V_{received} = V_{spilled}^{S3} + V_{spilled}^{S4} = 25 + 10 = 35 \text{ m}^3$, $C_{sink} = 200 \text{ m}^3$.

(i) For flood volume computations (blue zones):

$$V_{spilled} = V_{runoff} + V_{received} - C_{sink} = 400 + 35 - 200 = 235 \text{ m}^3;$$

(ii) For volume loss computations (red zones):

$$VL_{source} = 75 \text{ m}^3 \text{ and } VL_{received} = VL_{spilled}^{S3} + VL_{spilled}^{S4} = 16 + 10 = 26 \text{ m}^3;$$

$$\text{Here, } VL_{received} + VL_{source} \leq V_{spilled};$$

$$VL_{spilled} = VL_{received} + VL_{source} = 26 + 75 = 101 \text{ m}^3;$$

$$VL_{remaining} = 0 \text{ m}^3.$$

Stream order IV: S8.

For S8, $V_{runoff} = 500 \text{ m}^3$, and $V_{received} = V_{spilled}^{S6} + V_{spilled}^{S7} = 235 + 0 = 235 \text{ m}^3$, $C_{sink} = 150 \text{ m}^3$.

(i) For flood volume computations (blue zones):

$$V_{spilled} = V_{runoff} + V_{received} - C_{sink} = 500 + 235 - 150 = 585 \text{ m}^3;$$

(ii) For volume loss computations (red zones):

$$VL_{source} = 20 \text{ m}^3 \text{ and } VL_{received} = VL_{spilled}^{S6} + VL_{spilled}^{S7} = 101 + 0 = 101 \text{ m}^3;$$

$$\text{Here, } VL_{received} + VL_{source} \leq V_{spilled};$$

$$VL_{spilled} = VL_{received} + VL_{source} = 101 + 20 = 121 \text{ m}^3;$$

$$VL_{remaining} = 0 \text{ m}^3.$$

References

- Bernstein, L.; Bosch, P.; Canziani, O.; Chen, Z.; Christ, R.; Riahi, K. *Climate Change 2007: Synthesis Report*; IPCC: Geneva, Switzerland, **2008**.
- Yu, D.; Coulthard, T.J. Evaluating the importance of catchment hydrological parameters for urban surface water flood modelling using a simple hydro-inundation model. *J. Hydrol.* **2015**, *524*, 385–400. [\[CrossRef\]](#)
- Henonin, J.; Russo, B.; Mark, O.; Gourbesville, P. Real-time urban flood forecasting and modelling—a state of the art. *J. Hydrol. Inform.* **2013**, *15*, 717–736. [\[CrossRef\]](#)
- Parkinson, J.; Mark, O. *Urban Stormwater Management in Developing Countries*; IWA Publishing: London, UK, **2005**.
- Schmitt, T.G.; Thomas, M.; Ettrich, N. Analysis and modeling of flooding in urban drainage systems. *J. Hydrol.* **2004**, *299*, 300–311. [\[CrossRef\]](#)
- Chang, T.J.; Wang, C.H.; Chen, A.S. A novel approach to model dynamic flow interactions between storm sewer system and overland surface for different land covers in urban areas. *J. Hydrol.* **2015**, *524*, 662–679. [\[CrossRef\]](#)
- Courty, L.G.; Rico-Ramirez, M.Á.; Pedrozo-Acuña, A. The Significance of the Spatial Variability of Rainfall on the Numerical Simulation of Urban Floods. *Water* **2018**, *10*, 207. [\[CrossRef\]](#)
- Courty, L.G.; Pedrozo-Acuña, A.; Bates, P.D. Itzi (version 17.1): An open-source, distributed GIS model for dynamic flood simulation. *Geosci. Model Dev.* **2017**, *10*, 1835–1847. [\[CrossRef\]](#)
- Guo, K.; Guan, M.; Yu, D. Urban surface water flood modelling—a comprehensive review of current models and future challenges. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 2843–2860. [\[CrossRef\]](#)
- Yu, D.; Lane, S.N. Urban fluvial flood modelling using a two-dimensional diffusion-wave treatment, part 1: Mesh resolution effects. *Hydrol. Process. Int. J.* **2006**, *20*, 1541–1565. [\[CrossRef\]](#)
- Fewtrell, T.; Bates, P.D.; Horritt, M.; Hunter, N. Evaluating the effect of scale in flood inundation modelling in urban environments. *Hydrol. Process. Int. J.* **2008**, *22*, 5107–5118. [\[CrossRef\]](#)
- Ramsauer, S.; Leandro, J.; Lin, Q. Inclusion of Narrow Flow Paths between Buildings in Coarser Grids for Urban Flood Modeling: Virtual Surface Links. *Water* **2021**, *13*, 2629. [\[CrossRef\]](#)
- Chen, A.S.; Evans, B.; Djordjević, S.; Savić, D.A. A coarse-grid approach to representing building blockage effects in 2D urban flood modelling. *J. Hydrol.* **2012**, *426*, 1–16. [\[CrossRef\]](#)
- Yu, D.; Lane, S.N. Urban fluvial flood modelling using a two-dimensional diffusion-wave treatment, part 2: Development of a sub-grid-scale treatment. *Hydrol. Process. Int. J.* **2006**, *20*, 1567–1583. [\[CrossRef\]](#)
- Chen, A.S.; Evans, B.; Djordjević, S.; Savić, D.A. Multi-layered coarse grid modelling in 2D urban flood simulations. *J. Hydrol.* **2012**, *470*, 1–11. [\[CrossRef\]](#)
- Yu, D.; Lane, S.N. Interactions between subgrid-scale resolution, feature representation and grid-scale resolution in flood inundation modelling. *Hydrol. Process.* **2011**, *25*, 36–53. [\[CrossRef\]](#)
- Henonin, J.; Hongtao, M.; Zheng-Yu, Y.; Hartnack, J.; Havnø, K.; Gourbesville, P.; Mark, O. Citywide multi-grid urban flood modelling: The July 2012 flood in Beijing. *Urban Water J.* **2015**, *12*, 52–66. [\[CrossRef\]](#)
- Bruwier, M.; Archambeau, P.; Erpicum, S.; Piroton, M.; Dewals, B. Shallow-water models with anisotropic porosity and merging for flood modelling on Cartesian grids. *J. Hydrol.* **2017**, *554*, 693–709. [\[CrossRef\]](#)
- Sanders, B.F.; Schubert, J.E.; Gallegos, H.A. Integral formulation of shallow-water equations with anisotropic porosity for urban flood modeling. *J. Hydrol.* **2008**, *362*, 19–38. [\[CrossRef\]](#)
- Bates, P.D.; De Roo, A. A simple raster-based model for flood inundation simulation. *J. Hydrol.* **2000**, *236*, 54–77. [\[CrossRef\]](#)
- Bates, P.D.; Horritt, M.S.; Fewtrell, T.J. A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *J. Hydrol.* **2010**, *387*, 33–45. [\[CrossRef\]](#)
- Hunter, N.M.; Horritt, M.S.; Bates, P.D.; Wilson, M.D.; Werner, M.G. An adaptive time step solution for raster-based storage cell modelling of floodplain inundation. *Adv. Water Resour.* **2005**, *28*, 975–991. [\[CrossRef\]](#)
- Ghimire, B.; Chen, A.S.; Guidolin, M.; Keedwell, E.C.; Djordjević, S.; Savić, D.A. Formulation of a fast 2D urban pluvial flood model using a cellular automata approach. *J. Hydroinform.* **2013**, *15*, 676–686. [\[CrossRef\]](#)
- Guidolin, M.; Chen, A.S.; Ghimire, B.; Keedwell, E.C.; Djordjević, S.; Savić, D.A. A weighted cellular automata 2D inundation model for rapid flood analysis. *Environ. Model. Softw.* **2016**, *84*, 378–394. [\[CrossRef\]](#)
- Gibson, M.J.; Savic, D.A.; Djordjevic, S.; Chen, A.S.; Fraser, S.; Watson, T. Accuracy and computational efficiency of 2D urban surface flood modelling based on cellular automata. *Procedia Eng.* **2016**, *154*, 801–810. [\[CrossRef\]](#)
- Zhao, G.; Balstrøm, T.; Mark, O.; Jensen, M.B. Multi-Scale Target-Specified Sub-Model Approach for Fast Large-Scale High-Resolution 2D Urban Flood Modelling. *Water* **2021**, *13*, 259. [\[CrossRef\]](#)
- Yu, D. Parallelization of a two-dimensional flood inundation model based on domain decomposition. *Environ. Model. Softw.* **2010**, *25*, 935–945. [\[CrossRef\]](#)
- Neal, J.C.; Fewtrell, T.J.; Bates, P.D.; Wright, N.G. A comparison of three parallelisation methods for 2D flood inundation models. *Environ. Model. Softw.* **2010**, *25*, 398–411. [\[CrossRef\]](#)
- Neal, J.; Fewtrell, T.; Trigg, M. Parallelisation of storage cell flood models using OpenMP. *Environ. Model. Softw.* **2009**, *24*, 872–877. [\[CrossRef\]](#)
- Lamb, R.; Crossley, M.; Waller, S. A fast two-dimensional floodplain inundation model. In *Proceedings of the Institution of Civil Engineers-Water Management*; Thomas Telford Ltd.: London, UK, 2009; Volume 162, pp. 363–370. [\[CrossRef\]](#)

31. Kalyanapu, A.J.; Shankar, S.; Pardyjak, E.R.; Judi, D.R.; Burian, S.J. Assessment of GPU computational enhancement to a 2D flood model. *Environ. Model. Softw.* **2011**, *26*, 1009–1016. [\[CrossRef\]](#)
32. Morales-Hernández, M.; Sharif, M.B.; Kalyanapu, A.; Ghafoor, S.K.; Dullo, T.T.; Gangrade, S.; Kao, S.C.; Norman, M.R.; Evans, K.J. TRITON: A Multi-GPU open source 2D hydrodynamic flood model. *Environ. Model. Softw.* **2021**, *141*, 105034. [\[CrossRef\]](#)
33. Glenis, V.; McGough, A.S.; Kutija, V.; Kilsby, C.; Woodman, S. Flood modelling for cities using Cloud computing. *J. Cloud Comput. Adv. Syst. Appl.* **2013**, *2*, 7. [\[CrossRef\]](#)
34. Balstrøm, T.; Crawford, D. Arc-Malstrøm: A 1D hydrologic screening method for stormwater assessments based on geometric networks. *Comput. Geosci.* **2018**, *116*, 64–73. [\[CrossRef\]](#)
35. Jamali, B.; Bach, P.M.; Cunningham, L.; Deletic, A. A Cellular Automata fast flood evaluation (CA-ffé) model. *Water Resour. Res.* **2019**, *55*, 4936–4953. [\[CrossRef\]](#)
36. Samela, C.; Persiano, S.; Bagli, S.; Luzzi, V.; Mazzoli, P.; Humer, G.; Reithofer, A.; Essenfelder, A.; Amadio, M.; Mysiak, J.; et al. Safer_RAIN: A DEM-based hierarchical filling-&-Spilling algorithm for pluvial flood hazard assessment and mapping across large urban areas. *Water* **2020**, *12*, 1514. [\[CrossRef\]](#)
37. Zhang, S.; Wang, T.; Zhao, B. Calculation and visualization of flood inundation based on a topographic triangle network. *J. Hydrol.* **2014**, *509*, 406–415. [\[CrossRef\]](#)
38. Jamali, B.; Löwe, R.; Bach, P.M.; Urich, C.; Arnbjerg-Nielsen, K.; Deletic, A. A rapid urban flood inundation and damage assessment model. *J. Hydrol.* **2018**, *564*, 1085–1098. [\[CrossRef\]](#)
39. Berkhahn, S.; Fuchs, L.; Neuweiler, I. An ensemble neural network model for real-time prediction of urban floods. *J. Hydrol.* **2019**, *575*, 743–754. [\[CrossRef\]](#)
40. Lin, Q.; Leandro, J.; Wu, W.; Bhola, P.; Disse, M. Prediction of maximum flood inundation extents with resilient backpropagation neural network: Case study of Kulmbach. *Front. Earth Sci.* **2020**, *8*, 332. [\[CrossRef\]](#)
41. Bermúdez, M.; Ntegeka, V.; Wolfs, V.; Willems, P. Development and comparison of two fast surrogate models for urban pluvial flood simulations. *Water Resour. Manag.* **2018**, *32*, 2801–2815. [\[CrossRef\]](#)
42. Guo, Z.; Leitao, J.P.; Simões, N.E.; Moosavi, V. Data-driven flood emulation: Speeding up urban flood predictions by deep convolutional neural networks. *J. Flood Risk Manag.* **2021**, *14*, e12684. [\[CrossRef\]](#)
43. Hofmann, J.; Schüttrumpf, H. floodGAN: Using Deep Adversarial Learning to Predict Pluvial Flooding in Real Time. *Water* **2021**, *13*, 2255. [\[CrossRef\]](#)
44. Liu, Y.; Pender, G. A flood inundation modelling using v-support vector machine regression model. *Eng. Appl. Artif. Intell.* **2015**, *46*, 223–231. [\[CrossRef\]](#)
45. Bermúdez, M.; Cea, L.; Puertas, J. A rapid flood inundation model for hazard mapping based on least squares support vector machine regression. *J. Flood Risk Manag.* **2019**, *12*, e12522. [\[CrossRef\]](#)
46. Jhong, B.C.; Wang, J.H.; Lin, G.F. An integrated two-stage support vector machine approach to forecast inundation maps during typhoons. *J. Hydrol.* **2017**, *547*, 236–252. [\[CrossRef\]](#)
47. Chang, L.C.; Amin, M.Z.M.; Yang, S.N.; Chang, F.J. Building ANN-Based Regional Multi-Step-Ahead Flood Inundation Forecast Models. *Water* **2018**, *10*, 1283. [\[CrossRef\]](#)
48. Chang, L.C.; Shen, H.Y.; Wang, Y.F.; Huang, J.Y.; Lin, Y.T. Clustering-based hybrid inundation model for forecasting flood inundation depths. *J. Hydrol.* **2010**, *385*, 257–268. [\[CrossRef\]](#)
49. Pan, T.Y.; Lai, J.S.; Chang, T.J.; Chang, H.K.; Chang, K.C.; Tan, Y.C. Hybrid neural networks in rainfall-inundation forecasting based on a synthetic potential inundation database. *Nat. Hazards Earth Syst. Sci.* **2011**, *11*, 771–787. [\[CrossRef\]](#)
50. Jamali, B.; Haghighat, E.; Ignjatovic, A.; Leitão, J.P.; Deletic, A. Machine learning for accelerating 2D flood models: Potential and challenges. *Hydrol. Process.* **2021**, *35*, e14064. [\[CrossRef\]](#)
51. Shen, H.Y.; Chang, L.C. Online multistep-ahead inundation depth forecasts by recurrent NARX networks. *Hydrol. Earth Syst. Sci.* **2013**, *17*, 935–945. [\[CrossRef\]](#)
52. Chang, F.J.; Chen, P.A.; Lu, Y.R.; Huang, E.; Chang, K.Y. Real-time multi-step-ahead water level forecasting by recurrent neural networks for urban flood control. *J. Hydrol.* **2014**, *517*, 836–846. [\[CrossRef\]](#)
53. Sampson, C.C.; Fewtrell, T.J.; Duncan, A.; Shaad, K.; Horritt, M.S.; Bates, P.D. Use of terrestrial laser scanning data to drive decimetric resolution urban inundation models. *Adv. Water Resour.* **2012**, *41*, 1–17. [\[CrossRef\]](#)
54. Mark, O. *Deterministic Modelling of Urban Stormwater and Sewer Systems*; Aalborg Universitetsforlag: Aalborg, Denmark, 2019.
55. Zhao, G. A Sub-Model Approach for Fast Large-Scale High-Resolution Two-Dimensional Urban Surface Flood Modelling. Ph.D. Thesis, Department of Geosciences and Natural Resource Management, University of Copenhagen, Copenhagen, Denmark, 2020.
56. Thorndahl, S.; Beven, K.; Jensen, J.; Schaarup-Jensen, K. Event based uncertainty assessment in urban drainage modelling, applying the GLUE methodology. *J. Hydrol.* **2008**, *357*, 421–437. [\[CrossRef\]](#)
57. Allitt, R.; Blanksby, J.; Djordjević, S.; Maksimović, Č.; Stewart, D. Investigations into 1D-1D and 1D-2D Urban Flood Modelling. In Proceedings of the WaPUG Autumn Conference 2009, Blackpool, UK, 11–13 November, 2009.
58. Pina, R.D.; Ochoa-Rodriguez, S.; Simões, N.E.; Mijic, A.; Marques, A.S.; Maksimović, Č. Semi- vs. fully-distributed urban stormwater models: Model set up and comparison with two real case studies. *Water* **2016**, *8*, 58. [\[CrossRef\]](#)
59. Salvatore, E.; Bronders, J.; Batelaan, O. Hydrological modelling of urbanized catchments: A review and future directions. *J. Hydrol.* **2015**, *529*, 62–81. [\[CrossRef\]](#)

60. Leitao, J.P.; Simões, N.; Maksimović, Č.; Ferreira, F.; Prodanović, D.; Matos, J.; Sá Marques, A. Real-time forecasting urban drainage models: Full or simplified networks? *Water Sci. Technol.* **2010**, *62*, 2106–2114. [\[CrossRef\]](#)
61. Leandro, J.; Chen, A.S.; Djordjević, S.; Savić, D.A. Comparison of 1D/1D and 1D/2D coupled (sewer/surface) hydraulic models for urban flood simulation. *J. Hydraul. Eng.* **2009**, *135*, 495–504. [\[CrossRef\]](#)
62. Maksimović, Č.; Prodanović, D.; Boonya-Aroonnet, S.; Leitao, J.P.; Djordjević, S.; Allitt, R. Overland flow and pathway analysis for modelling of urban pluvial flooding. *J. Hydraul. Res.* **2009**, *47*, 512–523. [\[CrossRef\]](#)
63. McCormack, J.; Gahegan, M.; Roberts, S.A.; Hogg, J.; Hoyle, B. Feature-based derivation of drainage networks. *Int. J. Geogr. Inf. Syst.* **1993**, *7*, 263–279. [\[CrossRef\]](#)
64. Hankin, B.; Waller, S.; Astle, G.; Kellagher, R. Mapping space for water: Screening for urban flash flooding. *J. Flood Risk Manag.* **2008**, *1*, 13–22. [\[CrossRef\]](#)
65. Jensen, S.K.; Domingue, J.O. Extracting topographic structure from digital elevation data for geographic information system analysis. *Photogramm. Eng. Remote Sens.* **1988**, *54*, 1593–1600.
66. O'Callaghan, J.F.; Mark, D.M. The extraction of drainage networks from digital elevation data. *Comput. Vis. Graph. Image Process.* **1984**, *28*, 323–344. [\[CrossRef\]](#)
67. Tarboton, D.G.; Bras, R.L.; Rodriguez-Iturbe, I. On the extraction of channel networks from digital elevation data. *Hydrol. Process.* **1991**, *5*, 81–100. [\[CrossRef\]](#)
68. Zhang, S.; Pan, B. An urban storm-inundation simulation method based on GIS. *J. Hydrol.* **2014**, *517*, 260–268. [\[CrossRef\]](#)
69. Leitão, J.P.; Boonya-Aroonnet, S.; Prodanović, D.; Maksimović, Č. The influence of digital elevation model resolution on overland flow networks for modelling urban pluvial flooding. *Water Sci. Technol.* **2009**, *60*, 3137–3149. [\[CrossRef\]](#) [\[PubMed\]](#)
70. Lindsay, J.B.; Creed, I.F. Sensitivity of digital landscapes to artifact depressions in remotely-sensed DEMs. *Photogramm. Eng. Remote Sens.* **2005**, *71*, 1029–1036. [\[CrossRef\]](#)
71. Lindsay, J.B.; Creed, I.F. Distinguishing actual and artefact depressions in digital elevation data. *Comput. Geosci.* **2006**, *32*, 1192–1204. [\[CrossRef\]](#)
72. Adeyemo, O.; Maksimović, Č.; Boonya-Aroonnet, S.; Leitão, J.; Butler, D.; Makropoulos, C. Sensitivity analysis of surface runoff generation for pluvial urban flooding. In Proceedings of the 11th International Conference on Urban Drainage, Edinburgh, UK, 31 August–5 September 2008.
73. Shreve, R.L. Statistical law of stream numbers. *J. Geol.* **1966**, *74*, 17–37. [\[CrossRef\]](#)
74. ESRI. ArcGIS Desktop 10.6. 2017. Available online: <https://desktop.arcgis.com/en/arcmap/10.6/get-started/introduction/whats-new-in-arcgis.htm> (accessed on 6 February 2022).
75. Data Supply and Efficiency Board, DHM/Nedbør, Copenhagen. 2013. Available online: <https://download.kortforsyningen.dk/> (accessed on 6 February 2022).
76. Hartell, W.; Cook, J.J.; Mankowski, R.; Herrin, G.; Wu, Z. *Automated Skeletonization Techniques*; Haestad Methods, Inc.: Waterbury, CT, USA, 2002.
77. WaPUG. *Code of Practice for the Hydraulic Modelling of Sewer Systems*; Wastewater Planning Users Group: London, UK, 2002.
78. Hartell, W.; Cook, J.J.; Mankowski, R.; Herrin, G.; Wu, Z. Method and System for Reduction of a Network Topology-Based System Having Automated Optimization Features. US Patent 7,054,799 B1, 8 July 2002.
79. Simões, N.; Leitão, J.; Maksimović, Č.; Sá Marques, A.; Pina, R. Sensitivity analysis of surface runoff generation in urban flood forecasting. *Water Sci. Technol.* **2010**, *61*, 2595–2601. [\[CrossRef\]](#)