



**HAL**  
open science

## Evaluating terrain-based HAND-SRC flood mapping model in low-relief rural plains using high resolution topography and crowdsourced data

Hassan Sabeh, Chadi Abdallah, Nanée Chahinian, Marie-George Tournoud, Rouya Hdeib, Roger Moussa

### ► To cite this version:

Hassan Sabeh, Chadi Abdallah, Nanée Chahinian, Marie-George Tournoud, Rouya Hdeib, et al.. Evaluating terrain-based HAND-SRC flood mapping model in low-relief rural plains using high resolution topography and crowdsourced data. *Journal of Hydrology*, In press, 10.1016/j.jhydrol.2024.132649 . hal-04872427

**HAL Id: hal-04872427**

**<https://hal.science/hal-04872427v1>**

Submitted on 9 Jan 2025

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

# Journal Pre-proofs

## Research papers

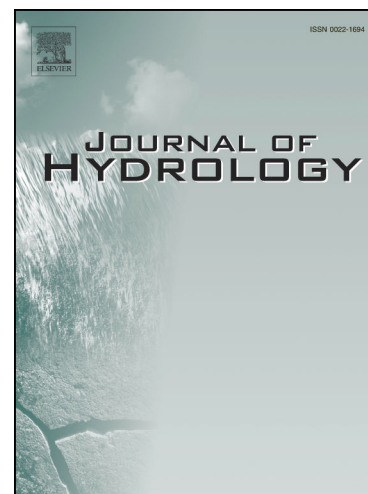
Evaluating terrain-based HAND-SRC flood mapping model in low-relief rural plains using high resolution topography and crowdsourced data

Hassan Sabeh, Chadi Abdallah, Nanée Chahinian, Marie-George Tournoud, Rouya Hdeib, Roger Moussa

PII: S0022-1694(24)02045-6  
DOI: <https://doi.org/10.1016/j.jhydrol.2024.132649>  
Reference: HYDROL 132649

To appear in: *Journal of Hydrology*

Received Date: 17 July 2024  
Revised Date: 5 December 2024  
Accepted Date: 9 December 2024



Please cite this article as: Sabeh, H., Abdallah, C., Chahinian, N., Tournoud, M-G., Hdeib, R., Moussa, R., Evaluating terrain-based HAND-SRC flood mapping model in low-relief rural plains using high resolution topography and crowdsourced data, *Journal of Hydrology* (2024), doi: <https://doi.org/10.1016/j.jhydrol.2024.132649>

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

# 1 Evaluating Terrain-Based HAND-SRC Flood Mapping Model in Low-Relief 2 Rural Plains Using High Resolution Topography and Crowdsourced Data

## 3 **Keywords:**

4 Height above nearest drainage; Synthetic rating curve; Low-complexity model; DEM resolution; Hydro-  
5 conditioning; HEC RAS

## 6 **Authors and affiliations:**

7 Hassan Sabe<sup>a,b,\*</sup>, Chadi Abdallah<sup>a</sup>, Nanée Chahinian<sup>b</sup>, Marie-George Tournoud<sup>b</sup>, Rouya Hdeib<sup>c</sup>, Roger  
8 Moussa<sup>d</sup>

9 <sup>a</sup> *National Center for Natural Hazards and Early Warning, CNRS-L, Beirut, Lebanon*

10 <sup>b</sup> *HSM Montpellier, Univ Montpellier, CNRS, IRD, Montpellier, France*

11 <sup>c</sup> *Department of Civil and Architectural Engineering, Applied Science University, Manama, Kingdom of*  
12 *Bahrain*

13 <sup>d</sup> *LISAH, Univ Montpellier, INRAE, IRD, Institut Agro, Montpellier, France*

14 *\* Corresponding author*

15 *E-mail address: [hassan.sabea@cnrs.edu.lb](mailto:hassan.sabea@cnrs.edu.lb)*

16

17

18

19

20

21

22

23

24

25

## 26 **Abstract**

27 Low-complexity terrain-based models are increasingly utilized for their rapid simulation time and low  
28 data requirements. The Height Above Nearest Drainage terrain index coupled with Synthetic Rating

29 Curves (HAND-SRC) emerges as a prominent model for mapping floods from a digital elevation model  
30 (DEM). However, the DEM requirements for its implementation remain unclear in many geographic  
31 settings. In this study, we evaluate the terrain conditions necessary for HAND-SRC flood mapping in  
32 rural low-relief terrain. This was investigated in the Ostouane River, Northern Lebanon, where an  
33 intensive field investigation was conducted to collect a high-resolution DEM (25 cm), bathymetric cross-  
34 sections, and a crowdsourced dataset reconstituting the January 2019 flood event. Specifically, we  
35 scrutinize both the terrain's geometric representation and its resolution. An adapted hydro-conditioning  
36 process was introduced to assess flood mapping performance. This process integrated surveyed and  
37 theoretical bathymetry, enforced drainage into both bathymetry and floodplain and removed levees in an  
38 unorthodox approach. The generated terrain was then tested after resampling it into coarser DEM  
39 resolutions. The hydro-conditioned terrain with integrated surveyed bathymetry demonstrated reliable  
40 flood mapping accuracy against crowdsourced data (CSI = 0.64 and RMSE = 0.54 m) and HEC-RAS  
41 extents (CSI = 0.66). Introducing a theoretical trapezoidal bathymetry based on hydraulic geometry power  
42 laws produced improved metrics due to enhanced drainage continuity between the channel and  
43 floodplains. Analysis of the resampled terrains highlights a random loss of terrain convergence and  
44 geometric accuracy, disrupting the model's implementation and accuracy at coarser resolutions (> 1 m).  
45 Overall, the comprehensive hydro-conditioning approach allows the model to depict the full inundation  
46 extent and retain the topographic accuracy in the HAND index raster. A sufficient grid resolution that  
47 maintains terrain convergence and drainage continuity is essential to overcome the challenges of low-  
48 relief topography. While the model admits limitations in cell-by-cell flood depth estimations, we suggest  
49 that it can be highly beneficial for rapid and accurate flood mapping.

## 50 1. Introduction

51 Floods are one of the most threatening natural hazards, imposing significant risk on exposed populations.  
52 Every year, around 83 million humans are impacted by floods, causing billions of dollars in losses and  
53 thousands of casualties (CRED, 2022; Rentschler & Salhab, 2020). Driven by the need for comprehensive  
54 flood risk management, floods have become a major focus of scientific research aimed at improving  
55 methods that facilitate hazard modelling, inundation mapping and emergency response (Jafarzadegan et  
56 al., 2023; Teng et al., 2017).

57 The distinctive flooding problems encountered in various basins worldwide triggered the synthesis of a  
58 multitude of adapted modelling techniques during the past decades. Yet, finding an approach that best fits  
59 the modelling problem and purpose is still a challenge in the field (Jafarzadegan et al., 2023). Factors  
60 such as data availability, flood response time, computational requirements, basin characteristics and the  
61 desired level of accuracy define these problems and dictate the choice and complexity of the approach.  
62 The availability and reliability of gauged rainfall and discharge data needed for model optimization,  
63 remain a major concern in ungauged and data-scarce basins around the globe (Grimaldi et al., 2013).  
64 Nevertheless, the integration of remote sensing and crowdsourcing as alternative sources of information  
65 has contributed to improving modelling accuracy despite their constraints in temporal domains (Notti et  
66 al., 2018; Sy et al., 2019). Topographic data remain the main input in any type of flood modelling and  
67 have become highly accessible providing extensive coverage at global scale. Simultaneously, topographic  
68 surveying techniques can now provide accurate, high resolution and low-cost products (Tamminga et al.,  
69 2015). This transformation and expansion in input data, be it in quality, quantity, scale or coverage  
70 presents an opportunity to assess new generations of well adapted inundation mapping approaches.

71 In general, three classifications of flood mapping methods can be identified: empirical methods, hydraulic  
72 models, and simplified conceptual methods (Teng et al., 2017). Empirical methods directly rely on  
73 statistical approaches and on observational data (Mudashiru et al., 2021). However, they can be limited in  
74 their spatio-temporal domains and constrained by engineering, financial and environmental factors.  
75 Hydraulic models are the most utilized approach for replicating flow dynamics based on shallow water



76 equations. They require many inputs, including channel and floodplain geometries, surface roughness  
77 coefficients and hydraulic structures dimensions, necessitating substantial computational resources. In  
78 contrast, simplified conceptual models, also referred to as “low-complexity models”, adopt simplified  
79 physical concepts that rely mainly on topographic information for flood delineation. Many of these  
80 models are based on the manipulation and analysis of digital elevation models (DEMs) through various  
81 techniques such as filling and spilling (Lhomme et al., 2008; Jafarzadegan et al., 2023) or by integrating  
82 power laws of hydraulic geometry such as the hydro-geomorphic method and the geomorphic flood index  
83 method (Annis et al., 2019; Deiana et al., 2023; Nardi et al., 2006). These models have become more  
84 prominent driven by the advantages they offer despite lacking accurate representation of overland flow  
85 physics (Afshari et al., 2018; Dhote et al., 2023; McGrath et al., 2018).

86 Terrain based flood mapping approaches were initially driven by the widespread availability of satellite-  
87 based DEMs covering many ungauged basins around the globe. The concept behind their development  
88 asserts that floodplains can be distinguished relying on the geomorphic footprint that remains embedded  
89 in the terrain even in altered and urbanized areas (Annis et al., 2019; Nardi et al., 2006). This has led to  
90 the emergence of several terrain-based models that extract the topographic properties of rivers and  
91 floodplains in the form of synthetic and composite indices (Lioi et al., 2020) such as the geomorphic  
92 flood index (Samela et al., 2017), the topographic index (Beven & Kirkby, 1979; Manfreda et al., 2011)  
93 and slope position (Dhote et al., 2023). Because of their low-complexity, low data requirement and rapid  
94 simulation time, these methods have been adopted for flood forecasting and large-scale flood inundation  
95 mapping. Despite that, their accuracy has been hampered by the coarse resolutions of DEMs (Manfreda et  
96 al., 2014), which are unable to capture flood controlling features (Schumann et al., 2013). However, the  
97 increasing availability of high-resolution digital elevation models (HRDEM) may provide new avenues in  
98 this field as they have undeniable advantages in terms of vertical accuracy and detection of detailed  
99 features. Finer resolutions were found to improve the performance in low-complexity terrain-based  
100 approaches (Aristizabal et al., 2024; Garousi-Nejad et al., 2019). However, such level of detail can  
101 introduce additional errors and require supplementary processing caused by artificial structures and  
102 topographic depressions that influence the flow direction and accumulation patterns especially in complex  
103 low-relief terrains (Woodrow et al., 2016; Zheng et al., 2018a). Furthermore, terrain representation within  
104 a DEM is another concern in flood modelling. Features such as bathymetry and levees are critical  
105 components that influence the performance and accuracy of various models (Afshari et al., 2018;  
106 Ghanghas et al., 2022; Wing et al., 2019a).

107 Height Above Nearest Drainage or HAND is a terrain index defined as the height of a DEM grid cell  
108 above the nearest drainage flow line into which the cell drains. The concept of HAND was first  
109 introduced by Rennó et al. (2008) based on initial attempts by Rodda (2005) to map floods on a cell-by-  
110 cell basis. The approach utilizing HAND index use a stage height representing a water level above a  
111 reference drainage line. Subsequently, all DEM grid cells hydrologically connected to the drainage line  
112 are classified as either flooded or non-flooded cells based on the HAND value of each cell. The literature  
113 on HAND highlights several developments aimed at overcoming the limitations of the method. The main  
114 novelty in the approach is the introduction of synthetic rating curves (SRCs) by Zheng et al. (2018b),  
115 which allow estimating a stage height from normalized hydraulic geometry over a river reach. HAND-  
116 SRC as a parsimonious hypsometric model has shown to be reliable for flood inundation mapping when  
117 tested against established flood maps, gauged observations and remote sensing data (Aristizabal et al.,  
118 2024; Garousi-Nejad et al., 2019; Johnson et al., 2019; Zheng et al., 2018b). The National Water Center  
119 (NWC) in the US implemented the model for continental-scale flood inundation mapping and integrated it  
120 into operational forecasting (Li et al., 2023; Liu et al., 2018). Nevertheless, its applications extend to  
121 hydrological landscape classification (Gharari et al., 2011), detection of groundwater potential areas  
122 (Hamdani & Baali, 2019) and in correlating soil-water gradients (Schietti et al., 2014).

123 Within flood modelling domain, crowdsourced data has been increasingly integrated as it has emerged as  
124 a supplementary low-cost source of information. Such data are a product of the participatory contribution  
125 of the general public in generating and developing new knowledge that can be beneficial in a scientific  
126 context (Buytaert et al., 2014). The integration usually exploits photographic records, videos, texts and  
127 measurements collected through different means such as interviews, applications and social networks.  
128 Furthermore, it relies on eyewitness accounts to characterize and extract geo-tagged information on past  
129 flood events (Paul et al., 2018; Sy et al., 2019, 2020). Such observations have also been assimilated into  
130 hydrological and hydraulic models with the objective of enhancing flood forecasting (Mazzoleni et al.,  
131 2017; Songchon et al., 2023) or to calibrate and validate inundation models (Dasgupta et al., 2022;  
132 Gitundu et al., 2023; Malgwi et al., 2021). Crowdsourced data proves to be advantageous compared to  
133 satellite imagery by providing dense and detailed information of flood depths in urban settings. This data  
134 can be particularly useful in small ungauged basins whose flood response is faster than the satellite revisit  
135 interval.

136 Most recent research on the HAND-SRC flood hazard mapping scrutinized large scale applications,  
137 where coarse satellite-based DEMs enable the operational use of the model at regional and national scales  
138 (Liu et al., 2018; Yamazaki et al., 2019). Nevertheless, a comprehensive assessment of HAND-SRC at  
139 smaller scales is still very limited (Li et al., 2023) and its adaptation in different geographies remains  
140 scarce (Wing et al., 2019b). Furthermore, combining high resolution DEMs with bathymetric surveys is  
141 absent in the literature, while crowdsourced data remain largely untested for assessing terrain-based  
142 models (Zheng et al., 2022). Despite the advancements in the HAND-SRC approach, low-relief terrains  
143 have been found to present a challenge due to the inherent problems in the DEMs and the modelling  
144 implementation (Afshari et al., 2018; Godbout et al., 2019; Hocini et al., 2020; Jafarzadegan et al., 2022;  
145 Johnson et al., 2019). A literature review on HAND-SRC in low-relief regions revealed two key aspects  
146 that could potentially enhance the model's performance. These were: (1) the terrain setup, including  
147 feature representation and DEM preparation through hydro-conditioning and (2) the DEM resolution and  
148 accuracy.

149 The main objective of this study is to evaluate the conditions necessary for effective fluvial flood  
150 mapping using the HAND-SRC model in a low-relief setting. It also aims to assess the opportunities from  
151 using high-resolution DEM based on a series of tested configurations that scrutinize the terrain and its  
152 resolution. For this purpose, a high-resolution digital elevation model, a bathymetric survey, and a dataset  
153 of crowdsourced past flood water levels were utilized. The study was conducted in a low-relief rural  
154 floodplain with anthropogenic features, comprising a mixed urban and agricultural landscape within a  
155 small Mediterranean basin. This work encompasses an intensive field investigation to collect a detailed  
156 spatial and topographic dataset in addition to a crowdsourcing campaign of a past event.

157 The paper is divided into four sections. The first section describes the study area and its hydrological,  
158 morphometric and physical characteristics as well as the acquisition of the topographic, spatial,  
159 hydrometric and crowdsourced datasets. The second section presents the methodology followed to  
160 develop the HAND-SRC terrain-based model and a HEC RAS hydraulic model. The proposed steps for  
161 preparing the DEM by creating terrain setups are then outlined along with the parameters, resolutions and  
162 metrics used for evaluation. In the results section, the terrain hydro-conditioning processes and parameter  
163 choices are first evaluated, followed by the flood mapping performance and finally the effect of varying  
164 DEM resolution. Thereafter, the findings are discussed in light of the tested processes and configurations.  
165 Finally, conclusions are drawn on the capabilities and limitations of the HAND-SRC with  
166 recommendations for future work.

## 167 **2. Study area and data**

### 168 **2.1. Ostouane basin in North Lebanon**

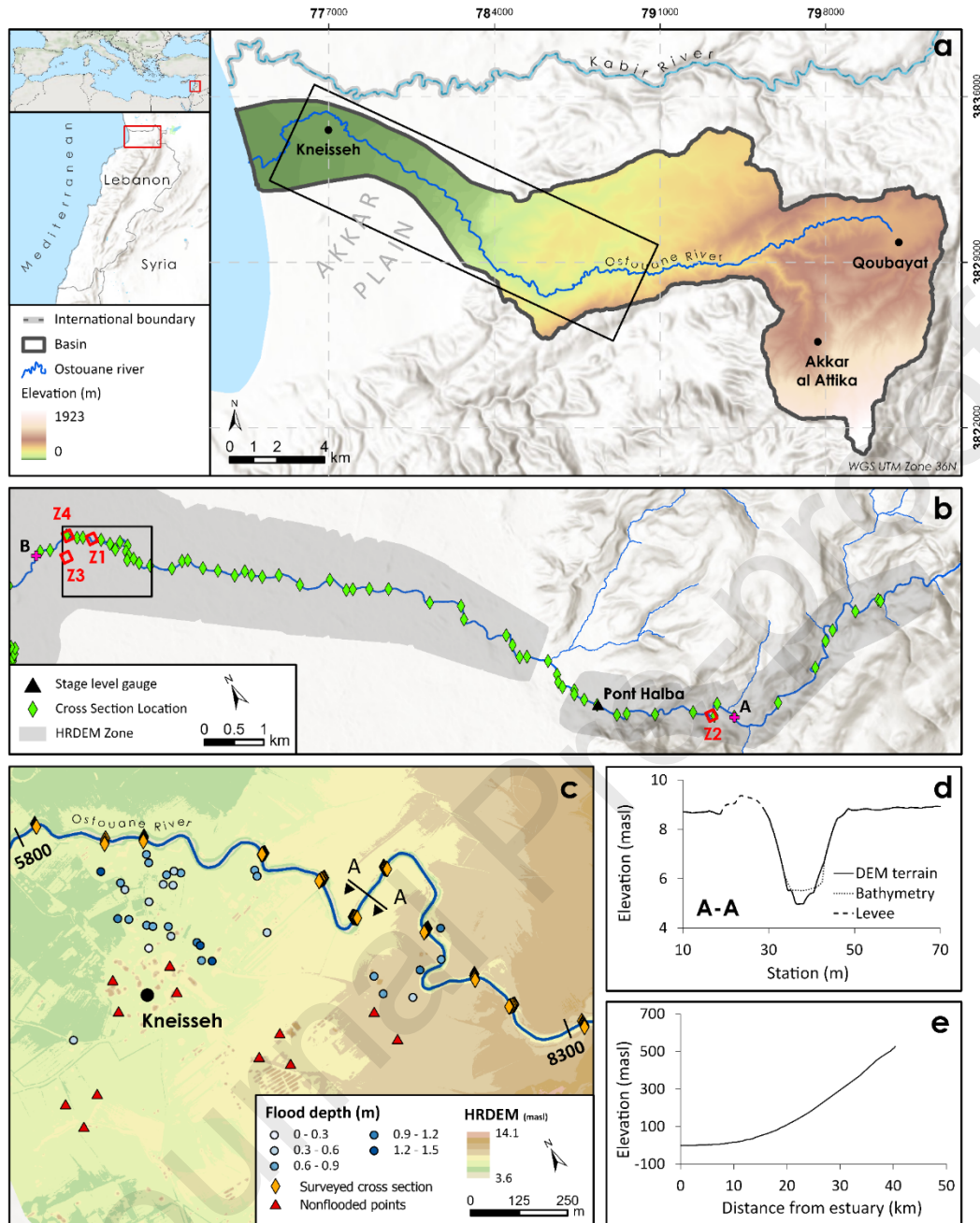
169 The study is conducted in the Ostouane River basin located in Northern Lebanon in the region of Akkar  
170 (Fig. 1a). The basin is one of the country's coastal catchments along the eastern Mediterranean. The  
171 river's headwaters originate from the northernmost section of the Mount Lebanon range near Akkar al-  
172 Attika. The river drains an area of approximately 144.1 km<sup>2</sup> and flows in a western direction down to its  
173 estuary. The maximum altitude in the basin is 1923 meters, with an average land slope of 25.6%.

174 The basin has a Mediterranean climate, characterized by cool rainy winters and dry hot summers. The  
175 annual rainfall ranges from 667 mm/yr near the coast up to 1040 mm/yr over the high mountainous areas,  
176 with an average of 861 mm/yr. The average discharge of the river is 2.2 m<sup>3</sup>/s, with a maximum monthly  
177 flow of 7.9 m<sup>3</sup>/s during February. For a 100-year return period, a peak flow of 118.5 m<sup>3</sup>/s is estimated at  
178 Pont Halba gauge station. However, the basin lacks reliable long-term precipitation records that can  
179 capture the intensity of sub-daily rainfall events. Despite the existence of three rainfall stations, issues  
180 such as recurrent failures, non-coinciding records and the absence of sub-daily measurements prevent a  
181 comprehensive hydrological assessment.

182 The basin's topography can be divided into a mountainous relief with steep regions on the eastern and  
183 central parts, and a flat floodplain terrain that is most susceptible to inundation near the estuary. The  
184 river's slope decreases from 2.09% near the headwaters to 0.08% as it flows into the Akkar Plain. Its  
185 average width varies between 8 and 12 meters along its course, widening up to 42m upstream of Kneisseh  
186 village. The river then flows into a series of meanders in a deep and narrow channel that varies between 6  
187 and 10 meters in width, with low slope and densely vegetated banks.

188 The land cover in the basin is dominated by agricultural areas (44.2%), followed by wooded lands (26%),  
189 and urbanized areas (5%). The scrutinized rural floodplain (Fig. 1c & Figs. 2a,2b,2c) is mainly  
190 agricultural with dispersed urbanization, and is characterized by anthropogenic features such as canals,  
191 ditches and levees. These were developed to support local agricultural practices and for flood mitigation  
192 purposes. The levees present are small soil embankments individually developed by local farmers. They  
193 are not optimized or built per engineering standards, with gaps and breaches, and are scattered along  
194 different segments of the river.

195 According to the FAO-UNESCO soil classification system, the basin is primarily covered by Cambisols  
196 (30.9%), Leptosols (22.5%), and Luvisols (21.5%) (Darwish et al., 2006). Surface formations of the  
197 Ostouane basin include the Cenomanian-Turonian (C4-C5) limestone which consists of limestone,  
198 dolomites and marly limestone. This formation outcrops in the eastern part of the basin (41.1%) and is the  
199 main contributor of spring discharge. A Pliocene basalt formation outcrops in the central and western  
200 regions of the basin (42.7%) whereas a Holocene formation of silt, sand and fluvial gravel covers the  
201 floodplain of the river (Dubertret, 1945). Moreover, several aquifer formations underly the basin,  
202 including the North Lebanon Cretaceous, Qammoua Cretaceous and the Akkar Neogene-Quaternary  
203 aquifers. The last two are separated by an unproductive Basalt aquiclude.



204

205 Figure 1: (a) Location of the Ostouane basin on the eastern Mediterranean in northern Lebanon showing  
 206 elevation, main river course and significant towns; (b) extent of the high-resolution DEM (HRDEM)  
 207 where the HAND-SRC model was implemented, the extent of HEC RAS model implementation (A-B),  
 208 location of the Pont Halba river gauge station, and zones Z1, Z2, Z3 and Z4; (c) test site showing  
 209 crowdsourced flood depths, locations of non-flooded point, surveyed cross-section points, and cross-  
 210 section A-A; (d) cross-section profile A-A showing the original terrain, surveyed bathymetry and levee  
 211 and (e) constructed longitudinal profile of the Ostouane river from surveyed cross-sections

## 212 2.2. Data acquisition



213 An intensive field investigation was conducted along the floodplains of the study area. This section  
214 describes the methods and tools used to acquire and develop the input datasets. A summary description of  
215 the collected datasets is shown in Table 1.

### 216 **2.2.1. High-resolution digital elevation model (HRDEM)**

217 A high-resolution digital elevation model (HRDEM) was produced using a fixed-wing drone  
218 photogrammetry over an area of 21.6 km<sup>2</sup> along the river floodplains (Fig. 1b). The process consisted in  
219 capturing a series of around 18,000 overlapping photos from which a 3D point cloud was generated. The  
220 point cloud derived from the Structure from Motion (SfM) technique was then transformed into space  
221 coordinates based on ground control points (GCPs) (Westoby et al., 2012). The digital terrain model was  
222 then processed by clearing all surfaces above the natural ground. The final resolutions of the DEM parts  
223 generated along different segments of the floodplains ranged between 10 and 20 cm. In order to  
224 standardize the resolution, all DEM parts were resampled using bilinear interpolation to a 25 cm  
225 resolution. One part of HRDEM was disregarded due to high vertical error resulting in two separate sub-  
226 parts. The interpolated DEM is denoted HRDEM in this study. A vertical accuracy assessment was  
227 conducted using a set of 19 ground truth points surveyed using an RTK GPS over the HRDEM of the  
228 study zone. The assessment showed a mean absolute error (MAE) of 3.4 cm and a root mean square error  
229 (RMSE) of 21.3cm. These values fall within the reported range of error in drone photogrammetry DEMs  
230 (Greenwood et al., 2019; Siebert & Teizer, 2014).

### 231 **2.2.2. River bathymetry**

232 The geometric data of the river channel were extracted through a series of cross-sections surveyed using a  
233 dual frequency RTK GPS (Fig. 2d). The spacing between consecutive cross sections was 220 meters on  
234 average, with a maximum spacing of 400 meters. A total of 58 collected cross-sections were utilized  
235 within the modelling domain (Fig. 1b). Figure 1d displays an example of a surveyed cross-section  
236 compared to the bathymetry of the DEM. The longitudinal profile of the river constructed using the  
237 surveyed cross sections is shown in figure 1e.

### 238 **2.2.3. Land use data**

239 The land cover dataset is based on digitizing GeoEye (2021) high-resolution imagery on a scale of 1/5000  
240 over the catchment and a 1/1000 scale within the floodplains (Abdallah et al., 2023). The land use/land  
241 cover corresponds to 34 different classes based on CORINE land classification adapted for Lebanon.

### 242 **2.2.4. River stage data**

243 Gauged water levels at the Pont Halba station and flow records were obtained from the Lebanese Litani  
244 River Authority. The gauge is located at an elevation of 76 masl and controls a draining area of 100 km<sup>2</sup>.  
245 The measurements are automated at a 15 or 45-minute interval. However, the flow records provided by  
246 the authority are of average daily discharge values. The stage-discharge relationship developed by LRA at  
247 the site relies on scarce in-situ flow measurements. During high flow conditions, these measurements are  
248 unavailable inducing large errors caused by the mere extrapolation of the rating curve. To address this, a  
249 theoretical rating curve was established using the topographic dataset and calibrated against the daily  
250 discharge. The rating curve was then used to convert the gauged water levels into more refined sub-daily  
251 flow estimates. The peak discharge of the January 2019 flood event was then estimated as  $Q_p=94.1 \text{ m}^3/\text{s}$   
252 at Pont Halba station.

### 253 **2.2.5. Crowdsourcing data on 2019 flood event**

254 The crowdsourcing of the past flood event was conducted in a similar approach to that of Sy et al. (2020).  
255 Due to the lack of an official census on flood events, the crowdsourcing campaign was conducted in 2023  
256 to collect eyewitness accounts and observations of past events at the flood impact locations. The most  
257 intense flood within the past 5 years, namely that of the 7<sup>th</sup> of January 2019 was scrutinized. The flood  
258 resulted in the inundation of both banks and the devastation of vast agricultural land and houses. The  
259 investigation targeted the inhabitants of this flood zone.

260 The main challenge faced during crowdsourcing inquiries is the elapsed time between the survey date and  
261 the flood event. Relying on eyewitness memory retrievals in describing flood events can induce  
262 uncertainties caused by memory distortions especially when a long time has passed since the event (Lacy  
263 & Stark, 2013). To minimize the impact of such distortion, the survey consisted of two phases. The first  
264 phase involved helping eyewitnesses recall the exact event by communicating the date, time, description,  
265 impact and proceedings of that event. The second phase included extracting observations by asking about  
266 the witnessed flood levels and extent. The enquiring of flood levels was repeated in a suggestive manner,  
267 with the respondents being asked to refer to a fixed object or a body part. Two coordinate points were  
268 then collected using a high-accuracy RTK GPS device: the maximum witnessed flood water elevation and  
269 the ground elevation below. Points that showed a significant error between the measured ground level in  
270 comparison to the DEM terrain levels were filtered out. Such discrepancies emerged from measurement  
271 errors or dense vegetation cover affecting the vertical accuracy of the DEM at a given location.

272 The final dataset comprised 33 peak flood levels and 12 non-flooded points. The average difference  
273 between the riverbed profile and the elevation of the crowdsourced flood points was 3.93 m. The vertical  
274 error between the HRDEM and the terrain elevation collected at the location of the crowdsourced flood  
275 depth measurements showed a MAE of 14.07 cm and a RMSE of 16.68 cm. The similar values of MAE  
276 and RMSE indicate a uniform distribution of error values. The majority of crowdsourced data were  
277 collected on the left bank of the Ostouane River where most houses and observations are found (Fig. 1c).  
278 Finally, a flood map was delineated using the collected extent and interpolated flood elevation points  
279 (Fig. SM1 in supplementary material).



280

281 Figure 2: Photos from field survey at Ostouane river: (a) a small breached levee developed by locals, (b)  
 282 river channel next to a non-engineered levee on one side, (c) ditches found around the agricultural lands  
 283 in the floodplain, and (d) river bathymetry survey

284 Table 1. Summary of surveyed, collected and developed datasets

Dataset	Source	Description/location	Scale/Resolution
Digital elevation model (DEM)	Drone Photogrammetry	DEM of floodplain	25 cm
Cross sections	Bathymetry survey	58 bathymetry cross sections	-
Land Use and Cover (LUC)	GeoEye (2020)	Digitized map with 35 classes	1/1000



River stage	Litani River Authority (LRA)	Pont Halba station	15 min
River flow	Litani River Authority (LRA)	Pont Halba station	daily
Crowdsourced flood levels	Field investigation	34 water levels & terrain elevation	-
Crowdsourced non-flooded locations	Field investigation	12 non-flooded points	-

285

286 **3. Methodology**

287 A terrain-based HAND-SRC model and a hydraulic-based HEC RAS model were developed here to  
 288 assess the performance of the former. This section describes (1) the implementation of the HAND-SRC  
 289 model, (2) the implementation of the HEC RAS model, (3) the approach and metrics used to evaluate  
 290 flood mapping, and (4) the workflow of the study.

291 **3.1. Terrain-based flood mapping: HAND-SRC**

292 The HAND-SRC model was implemented in two sub-parts of the study area, with areas of 15 and 6.6 km<sup>2</sup>  
 293 of the HRDEM (Fig. 1b).

294 **3.1.1. Model overview**

295 The implementation of HAND-SRC for flood mapping (fig. SM2 in supplementary material) consists of  
 296 three main steps: (a) calculation of the HAND raster, (b) extraction of hydraulic geometry and plotting  
 297 SRCs for each catchment and (c) flood mapping. The general approach adopted for the calculation of the  
 298 HAND raster and plotting of SRCs is similar to that found in previous literature (Aristizabal et al., 2023;  
 299 Garousi-Nejad et al., 2019; Zheng et al., 2018a, 2018b).

300 **a. HAND raster**

301 The HAND raster represents a grid of HAND index values denoted  $H$ . The index signifies the  
 302 hypsometric position of each DEM grid cell relative to a hydrologically connected reference drainage  
 303 line, denoted in this work as “flowline”. The HAND index value is calculated as the elevation difference  
 304 between the DEM grid cell and the flowline grid cell (Eq. 1).

$$305 \quad H = \text{elevation}_{DEM \text{ grid cell}} - \text{elevation}_{\text{connected flowline grid cell}} \quad (1)$$

306 The HAND raster grid is computed in five steps: (1) the river flowline is rasterized to match the grid size  
 307 of the DEM, (2) the pits are removed from the DEM using the *PitRemove* utility of TauDEM software  
 308 (Tarboton, 2024), (3) the D-infinity ( $D_{\infty}$ ) multiple flow direction model and the slope raster are calculated  
 309 using *DinfFlowDir* utility. Finally, (4) the HAND raster is generated using D-infinity distance down  
 310 *DinfDistDown* utility which provides  $H$  values referenced to the flowline.

### 311 **b. Hydraulic geometry and SRCs for a catchment**

312 A catchment is defined hereafter as an area draining into a specific river reach of length  $L$ , that is a  
 313 parameter in the HAND-SRC model. The catchment's hydraulic geometry for a given  $L$  is computed from  
 314 the HAND raster using predefined stage heights  $h$ . The process involves hypothetically filling the raster  
 315 up to a given stage height  $h$  and comprises the following six steps: (1) the flowline is discretized into a set  
 316 of reaches according to the reach length  $L$ , (2) the reaches are rasterized, (3) the catchment of each reach  
 317 is delineated using GRASS GIS *r.stream.basins* utility, (4) attributes of each reach (ID, slope, length and  
 318 area) are assigned to their corresponding catchment, (5) the reach scale hydraulic geometry (flood volume  
 319  $V$ , inundated surface area  $F$ , wetted riverbed area  $B$ , slope  $S$ ) are calculated using *catchhydrogeo* utility of  
 320 TauDEM, (6) these geometries are normalized against  $L$  to derive the wetted cross-sectional area  $A$ , top  
 321 width  $T$ , wetted perimeter  $P$ , and hydraulic radius  $R$ . Finally, a discharge ( $Q$ ) corresponding to a  
 322 catchment of a reach length  $L$ , at a stage height  $h$ , is determined using Manning's flow equation (Eq. 2):

$$323 \quad Q(h) = \frac{1}{n} A(h)^{2/3} R(h)^{1/2} = \frac{1V(h)^{5/3}S^{1/2}}{nLB(h)} \quad (2)$$

324 Manning's roughness coefficient  $n$  is the other parameter of the HAND-SRC model. For a fixed value of  
 325  $n$ , the calculation of the  $Q$  is repeated for each height  $h$  using Python™ scripts, which allow to plot a  
 326 synthetic rating curve (SRC) for each catchment.

### 327 **c. Mapping flooding areas and flood depths**

328 For a simulated discharge  $Q$ , a stage height  $h$  is extracted from the SRC at each catchment. This stage  
 329 height is used to generate flood inundation maps through binary classification (inundated vs. not  
 330 inundated) based on the HAND index values  $H$ . The stage height  $h$  is the HAND-SRC model variable.

331 The flood mapping is carried out by (1) denoting all grid cells with  $H$  value greater than  $h$  as non-flooded,  
 332 and (2) assigning the flood inundation depth as the difference between the  $H$  value at a grid cell and  $h$  at  
 333 its corresponding catchment ( $depth = h - H$ ). This procedure was performed using ArcHydro tools.

#### 334 **3.1.2. Model assumptions**

335 The implementation of the HAND-SRC model requires conforming to five key assumptions. These are:  
 336 (A1) All DEM grid cells susceptible to inundation must drain into the flowline. (A2) Within a processing  
 337 region the drainage must flow into a unique outlet. (A3) The stage height  $h$  is uniformly applied across  
 338 each catchment. (A4) Catchments are independent meaning no flow or volume exchange occurs at the  
 339 catchment boundaries. (A5) The filling volume is infinite. The first two assumptions (A1 and A2)  
 340 necessitate a hydro-conditioning process of the underlying terrain to: (a) enforce the drainage of flood-  
 341 prone areas into the river channel and (b) ensure a continuous decrease in elevations along the drainage  
 342 network and the flowline toward the outlet. Since DEMs do not necessarily adhere to these assumptions,  
 343 errors may arise from these processes depending on the region and methods used. The last three  
 344 assumptions (A3, A4 and A5) govern the application of stage height  $h$ , which may introduce errors and  
 345 limitations in the model.

#### 346 **3.1.3. Hydro-conditioning and definition of terrain setups**

347 Hydro-conditioning of the HRDEM was applied over the whole modelling domain prior to the  
 348 implementation of the HAND-SRC model. The hydro-conditioning processes account for the features  
 349 controlling the flooding processes while adhering to the model assumptions. Additionally, these processes  
 350 aim to mitigate and limit the impact of the inaccuracies resulting from the automatic HAND raster

351 calculation process (section 3.1.1) on terrain accuracy. Three types of hydro-conditioning are introduced  
 352 here: (a) integration of riverbed bathymetry, (b) enforcement of the floodplain drainage system, and (c)  
 353 removal of levees.

#### 354 **a. Integration of river bathymetry**

355 Riverbed bathymetry was integrated into the 25-cm HRDEM, incorporating either: (1) the surveyed  
 356 bathymetry, after an interpolation process or (2) a hypothetical trapezoidal cross-sectional shaped  
 357 bathymetry, based on hydraulic geometry power laws. In both cases, the bathymetric DEMs were  
 358 resampled into the 25-cm resolution and superimposed onto the HRDEM using ArcGIS Pro.

359 In the first case, the surveyed bathymetry was extracted from consecutive cross-sections through a  
 360 curvilinear interpolation along the river talweg. The interpolation is based on a string model that connects  
 361 successive cross-sections (USACE, 2020). To overcome the model's limitations in interpolating  
 362 floodplains and discontinuities in bank boundaries (Merwade et al., 2008), the interpolation boundary was  
 363 confined to the bathymetry zone delineated from drone imagery (Fig. SM3 in supplementary material).  
 364 This interpolation used cross-sections at 50-meter intervals. Three major cords connected both banks and  
 365 the minimum elevations of successive cross-sections, while minor cords connected the remaining points.

366 In the second case, the trapezoidal cross-section bathymetry was generated based on the local slope  
 367 bounded by the river width and the upstream and downstream cross-sections. Based on channel survey,  
 368 the cross-section geometry adopted a 1:2 ratio of horizontal to vertical side slopes. The top width of the  
 369 riverbed was then extracted from drone imagery along the river course. The depth  $D$  of the riverbed was  
 370 estimated from a power law expression of the top width  $W$  (Eq. 3) assuming a constant discharge at the  
 371 capture time:

$$372 \quad D = \alpha W^\beta \quad (3)$$

373 Regression of the surveyed bathymetric data resulted in values  $\alpha = 0.7609$  and  $\beta = -0.386$ .

374 After integrating the bathymetry into the HRDEM, an additional process was needed to ensure the  
 375 HRDEM adhere to the assumptions (A1) and (A2) of the model by enforcing a flowline in the bathymetry  
 376 (see section 3.1.2). The flowline is essential for HAND inundation mapping as it serves as a reference for  
 377 all HAND index calculations and is highly sensitive in low-slope rivers. To achieve a monotonically  
 378 decreasing flowline, the following method was applied: (1) drainage within the bathymetry DEM was  
 379 delineated based on the D8 flow accumulation grid (Lindsay, 2016). (2) The extracted flowline was then  
 380 burned into the original DEM using the AGREE-DEM method (Hellweger, 1997) which excavates the  
 381 DEM at the location of the flowline. Finally, (3) a fill-burn approach was applied to eliminate all  
 382 bathymetric inconsistencies, errors and multiple flowlines within the river bed. The "fillburn" tool of  
 383 WhiteboxTools was utilized (Lindsay, 2016; Saunders, 1999). This process enforced the flowline in the  
 384 bathymetry while maintaining a strictly decreasing path toward a singular outlet.

#### 385 **b. Floodplain drainage network enforcement**

386 DEMs of flat terrains, as in this study, usually lack the terrain convergence necessary in HAND-SRC  
 387 (Ghanghas et al., 2022; Godbout et al., 2019). Additionally, the presence of dense vegetation or artificial  
 388 structures, hinders the delineation of the floodplain drainage network in high-resolution DEMs.  
 389 Therefore, a hydro-conditioning process was implemented to enforce a micro-drainage network in the  
 390 floodplain. It consisted of:

391 (1) Detecting the inherent natural drainage network from the HRDEM using GeoNet tool (Passalacqua et  
 392 al., 2012). GeoNet, an open-source tool, is mainly used to extract hydrological and morphological data  
 393 from high-resolution DEMs to detect a network channel, even in the presence of engineered features such  
 394 as culverts. It was further tested in flat engineered landscapes and urbanized settings (Passalacqua et al.,  
 395 2010; Sangireddy et al., 2016). The tool detects channelized DEM grid cells based on a Laplacian  
 396 curvature computation and the flow accumulation area. The drainage network is then delineated based on  
 397 a geodesic least-cost path algorithm.

398 (2) Removing pits/sinks to prevent alterations in the flow direction grid.

399 (3) Enforcing the detected drainage network upon the DEM through a fill-burn tool to preserve the flow  
 400 direction (Lindsay, 2016; Saunders, 1999).

401 This process is necessary to: (a) conform to the assumption A1 of the model (see section 3.1.2), (b)  
 402 minimize the errors caused by the pit filling process in HAND raster calculation (see section 3.1.1) and  
 403 (c) eliminate drainage discontinuities that arise in the area separating the DEM and the superimposed  
 404 bathymetries.

#### 405 c. Removal of levees

406 In the Ostouane floodplain, levees disrupt the assumption that the floodplains should be draining into the  
 407 river channel (see section 3.1.2). The existing levee system, installed by locals, is discontinuous and  
 408 unregulated, failing to effectively mitigate floods. Previous studies have tried to enforce levees into  
 409 DEMs where the resolution failed to represent these features (Afshari et al., 2018; Aristizabal et al., 2023)  
 410 whereas here, their influence is investigated by removing the existing levees to restore the channel-  
 411 floodplain connection.

412 Levees were detected using an embankment mapping tool (Lindsay, 2016) based on a search distance  
 413 algorithm that requires the levee's centerline, side slope, height and width, to identify its extent. Due to  
 414 the variability of levee sizes in our DEM, a set of values covering the range of the measured dimensions  
 415 of existing levees were iterated (heights between 0.3 and 1.8 m; width between 3 and 10 m). The detected  
 416 embankments were then replaced by interpolated surfaces from the surrounding elevations.

#### 417 d. Definition of terrain setups

418 Several DEMs were developed to assess HAND raster and the HAND-SRC model. Terrain setup S1 is  
 419 based on the original 25-cm HRDEM. The other terrain setups (S1-rb, S1-fp, S2, S3) are based on the  
 420 same HRDEM but incorporate additional hydro-conditioning processes, as synthesized in Table 2.  
 421 Specifically, the surveyed river bathymetry and flowline enforcement are incorporated in terrain setups  
 422 S1-rb and S2, while the trapezoidal bathymetry is used in terrain setup S3. The floodplain drainage  
 423 network was enforced in terrain setups S1-fp, S2 and S3. Moreover, levees were removed to finalize  
 424 terrain setups S2 and S3.

425 Table 2. Terrain setups used for the assessment of hydro-conditioning and man-made features; × marks  
 426 the applied configuration in a setup

Terrain setup	River bathymetry	Levee removal
---------------	------------------	---------------

	Original 25-cm HRDEM	Surveyed cross-sections	Trapezoidal power law cross- sections	Floodplain drainage enforcement
S1	x			
S1-rb	x	x		
S1-fp	x			x
S2	x	x		x
S3	x		x	x

427

#### 428 3.1.4. Sensitivity analysis of reach length parameter

429 The reach length  $L$  and Manning's roughness coefficient  $n$  are the two parameters dictating the model  
 430 performance. Since Manning's roughness coefficient is established for different land cover types, the  
 431 reach length parameter was scrutinized as it can be more critical for the accuracy of hydraulic geometry  
 432 and SRCs (Gordon et al., 2023). A sensitivity analysis was performed using terrain setup S2 since it had  
 433 the highest level of hydro-conditioning while admitting a high terrain accuracy. Reach lengths adopted in  
 434 the literature ranged between 1 km and 3 km (Aristizabal et al., 2023; Garousi-Nejad et al., 2019; Hocini  
 435 et al., 2020; Rebolho et al., 2018; Zheng et al., 2018a, 2018b).  $L$  values tested here were 150 m, 300 m,  
 436 600 m, 900 m, and 1350 m and 2700 m.

#### 437 3.1.5. Testing the effect of DEM resolution

438 In flood mapping, there are two key attributes of a DEM: the vertical accuracy and the horizontal  
 439 resolution. In flat terrains, the vertical accuracy can be more significant than the horizontal resolution,  
 440 with coarser DEMs still capable of reproducing the elevations accurately. However, both attributes are  
 441 necessary for accurate terrain representation. Using hydraulic models, fine resolution DEMs produce  
 442 more accurate flood maps and extents compared to coarser ones, even when admitting the same vertical  
 443 accuracy (Saksena & Merwade, 2015). Whereas using HAND-SRC model, it is generally found that finer  
 444 resolutions improve performance, however, no clear trend is established across different resolutions. An  
 445 improvement was found from increasing DEM resolution from 10 m to 3 m by Garousi-Nejad et al.  
 446 (2019). Conversely, no significant change in the accuracy of inundation extents was registered from  
 447 varying DEM resolution between 3 and 20 m, but a significant decline was found from using coarser  
 448 resolutions of 60 and 90 m by Aristizabal et al. (2024). Terrain-based models heavily rely on the DEM as  
 449 the main input, making them heavily prone to the DEM properties and errors. The variation in DEM  
 450 resolution leads to increased errors in the vertical accuracy, horizontal accuracy and the representation of  
 451 artificial features, albeit with lower computational demand. Typically, DEM errors arise from the  
 452 collection method, sampling methods, interpolation techniques and hydro-conditioning processes.

453 In this study, the errors stemming from DEM resampling were examined to determine their effect on  
454 HAND-SRC model performance. The HAND-SRC was simulated for resolutions of 1m, 3m, 5m, 10m,  
455 20m and 30m which correspond to the most commonly used DEM resolutions. The DEMs were  
456 resampled using bilinear interpolation technique from the HRDEM of terrain setup S2. For the sake of  
457 comparison between the various resolutions, a fixed reach length  $L$  of 1.35 km was used. This value was  
458 selected due to its suitability for coarser resolutions and as it falls within the adopted range in the  
459 literature. The resampled resolutions were evaluated in comparison to the 25-cm HRDEM of setup S2  
460 also using the same  $L$ .

### 461 **3.2. Hydraulics-based flood mapping: HEC-RAS**

462 A one-dimensional (1D) hydraulic model was used to develop reference flood maps using a more  
463 physically-based approach, for comparison against the low-complexity HAND-SRC model.

#### 464 **3.2.1. Model overview**

465 HEC-RAS (Hydrologic Engineering Center's River Analysis System) is a well-documented and widely  
466 used software in fluvial flooding simulation (USACE, 2020). In 1D configuration, the terrain is  
467 represented through a series of cross-sections and the flow is assumed to move in a longitudinal direction  
468 along the river.

469 Within a HEC RAS project file, three input files are needed: (1) a geometry file which includes the DEM,  
470 the surveyed cross-sections, and Manning's roughness coefficients, (2) a plan file specifying the  
471 simulation settings and (3) a steady/unsteady flow file containing the boundary conditions of the model.

#### 472 **3.2.2. Input data, parameters and boundary conditions**

473 The original 25-cm HRDEM was imported as the main input in the geometry file. The river centerline and  
474 bank lines were digitized using drone imagery within the RAS-mapper module of HEC-RAS. Cross-  
475 sections were then added at the locations of the surveyed ones. The cross-section elevations were  
476 corrected using the surveyed point measurements.

477 The channel Manning's roughness coefficients were determined for each cross-section according to the  
478 methodology described in (USDA, 2012), based on field observations, captured photos and drone  
479 imagery. For the floodplain, Manning's roughness coefficients were estimated based on the land  
480 use/cover maps. Furthermore, the upstream and downstream boundary conditions were set as the normal  
481 depth based on the average local slope. The flow file was designated to run the model in a steady state  
482 gradually varied flow simulation.

#### 483 **3.2.3. Flood mapping and aggregated rating curves**

484 The HEC RAS model was implemented over a 15 km length of the Ostouane River (see reach A-B in fig.  
485 1b) and simulated for the January 2019 flood. The model's Manning's roughness parameters were  
486 calibrated using the available flow records and crowdsourced flood depths. The flood maps at the peak of  
487 the January 2019 flood were generated.

488 A series of rating curves were extracted at all cross-sections. The HEC RAS generated rating curves are  
489 valid at the location of cross-sections whereas the SRCs are valid over a river reach. To facilitate  
490 comparison between both rating curves, those of HEC RAS were aggregated for cross sections within the  
491 same reach. This was achieved by extracting the median of heights at each reach to plot an aggregated  
492 rating curve (ARC).



### 493 3.3. Evaluation approach and metrics

494 The evaluation was conducted against: crowdsourced data and HEC RAS flood maps. The former  
495 consists of flood occurrences (flooded/non-flooded occurrences) and flood depths.

#### 496 3.3.1. Comparison of crowdsourced and simulated flood occurrences

497 To evaluate the model's accuracy in capturing crowdsourced flood occurrences, the contingency table  
498 metrics were utilized. The metrics rely on the true positives (TP), false positives (FP), false negatives  
499 (FN) and true negatives (TN) values. TP and TN refer to points correctly classified as flooded or non-  
500 flooded respectively. FP are non-flooded points falsely classified as flooded. Conversely, FN are flooded  
501 points falsely classified as non-flooded by the model.

502 The critical success index ( $CSI_p$ ) and Matthews correlation coefficient ( $MCC_p$ ) metrics were selected to  
503 assess the occurrence of flood at these locations. The CSI metric ranges between 0 and 1 while MCC  
504 ranges between -1 and 1. For both, a value of 1 represents a perfect match. CSI disregards true negatives  
505 and gives more significance to the ability of the model to avoid misses of flooded points or false alarms at  
506 non-flooded ones. However, CSI is sensitive to unbalanced datasets. MCC was thus introduced as it  
507 provides a balanced score that takes into account all instances of the confusion matrix regardless of their  
508 size.

$$509 \quad CSI_p = \frac{TP_p}{TP_p + FP_p + FN_p} \quad (4)$$

$$510 \quad MCC_p = \frac{TP_p \times TN_p - FP_p \times FN_p}{\sqrt{(TP_p + FP_p) \times (TP_p + FN_p) \times (TN_p + FP_p) \times (TN_p + FN_p)}} \quad (5)$$

#### 511 3.3.2. Comparison of simulated flood extents

512 The simulated flood extents of HAND-SRC and HEC RAS were also compared. CSI and MCC metrics  
513 were also utilized but for comparison of simulated areas. For this reason, the two metrics were denoted as  
514  $CSI_A$  and  $MCC_A$  for HEC RAS maps comparison as opposed to  $CSI_p$  and  $MCC_p$  used for crowdsourced  
515 points. Generally, while evaluating flood maps, CSI values below 0.5 are considered poor while ones  
516 above 0.65 are considered good, whereas MCC is considered satisfactory for values above 0.3 (Bernhofen  
517 et al., 2018; Fleischmann et al., 2019).

$$518 \quad CSI_A = \frac{TP_A}{TP_A + FP_A + FN_A} \quad (6)$$

$$519 \quad MCC_A = \frac{TP_A \times TN_A - FP_A \times FN_A}{\sqrt{(TP_A + FP_A) \times (TP_A + FN_A) \times (TN_A + FP_A) \times (TN_A + FN_A)}} \quad (7)$$

#### 520 3.3.3. Comparison of crowdsourced and simulated flood depths

521 The simulated flood depth and the crowdsourced flood depths were compared. The mean absolute error  
522 (MAE) and root mean square error (RMSE) were utilized for flood depth error evaluation. The two  
523 metrics were also used to calculate the error in DEM vertical accuracy and SRC accuracy.

$$524 \quad RMSE = \sqrt{\frac{\sum_{i=1}^n (depth_{HAND-SRC} - depth_{crowdsourced})^2}{n}} \quad (8)$$

$$525 \quad MAE = \frac{1}{n} \sum_{i=1}^n |depth_{HAND-SRC} - depth_{crowdsourced}| \quad (9)$$



### 526 3.3.4. Comparison between simulated flood depths

527 Flood depths simulated using HAND-SRC and HEC RAS were also compared. Three metrics were used  
 528 to assess the difference in the depth variable. The mean difference (MD), mean absolute difference  
 529 (MAD) and the root mean square difference (RMSD) were utilized in this assessment.

$$530 \quad MD = \frac{1}{n} \sum_{i=1}^n (depth_{HEC\ RAS} - depth_{HAND-SRC}) \quad (10)$$

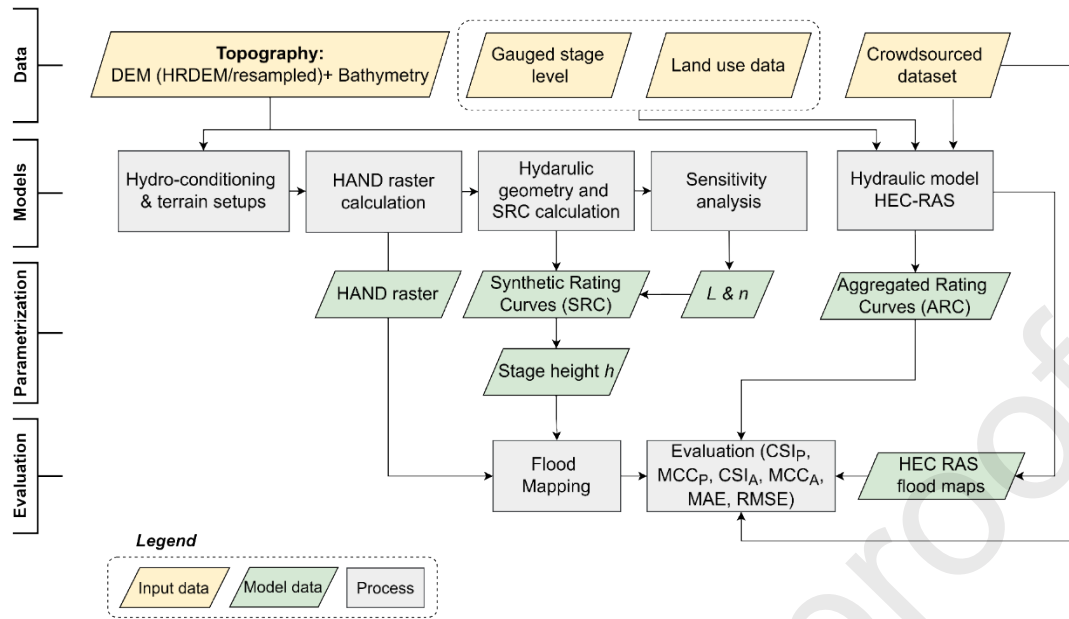
$$531 \quad MAD = \frac{1}{n} \sum_{i=1}^n |depth_{HEC\ RAS} - depth_{HAND-SRC}| \quad (11)$$

$$532 \quad RMSD = \sqrt{\frac{\sum_{i=1}^n (depth_{HEC\ RAS} - depth_{HAND-SRC})^2}{n}} \quad (12)$$

### 533 3.4. Workflow and analysis

534 In our workflow (Fig. 3): (1) the datasets were acquired, assessed and processed including topography  
 535 and crowdsourced data, (2) terrain setups were developed based on the chosen hydro-conditioning criteria  
 536 in Table 2 and the resolutions in selected in section 3.1.5, (3) the HAND raster files and SRCs plots were  
 537 calculated and flood maps were generated for the January 2019 event using the framework described in  
 538 section 3.1.1, (4) HEC RAS hydraulic model was set up and simulated to derive the flood maps and  
 539 ARCs, (5) the performance of the flood maps was evaluated against the crowdsourced data and HEC RAS  
 540 extents.

541 The methodology used to apply HAND-SRC models here is similar to the one used by (Zheng et al.,  
 542 2018a). However, several key modifications to the DEM preparation approach were introduced.  
 543 Specifically, two bathymetric inputs based on the surveyed riverbed and a hydraulic geometry power law  
 544 were integrated. In addition, a novel hydro-conditioning processes in the bathymetry and floodplain to  
 545 enforce drainage and remove levees were implemented. A sub-meter high-resolution DEM was utilized  
 546 for enhanced detection of the natural drainage patterns. This paper is set out to test HAND-SRC flood  
 547 mapping based on: the terrain representation enhanced by the hydro-conditioning processes and the  
 548 influence of the DEM resolution.



549

550 Figure 3: Workflow chart summarizing the main processes involved in the assessment of the HAND-SRC  
 551 model. The workflow begins with data acquisition followed by development of the terrain setups of  
 552 HAND-SRC and the HEC RAS model, then the calculation of the HAND raster and SRC plots. Finally,  
 553 flood maps are generated and evaluated against crowdsourced data and HEC RAS flood maps

## 554 4. Results

555 This section presents the outcome of the study from three aspects: (1) the evaluation of the model terrain  
 556 analysis and parametrization, (2) the HAND-SRC flood mapping performance compared to crowdsourced  
 557 points and HEC RAS, and (3) the effect of DEM resolution on flood mapping accuracy and computation  
 558 time.

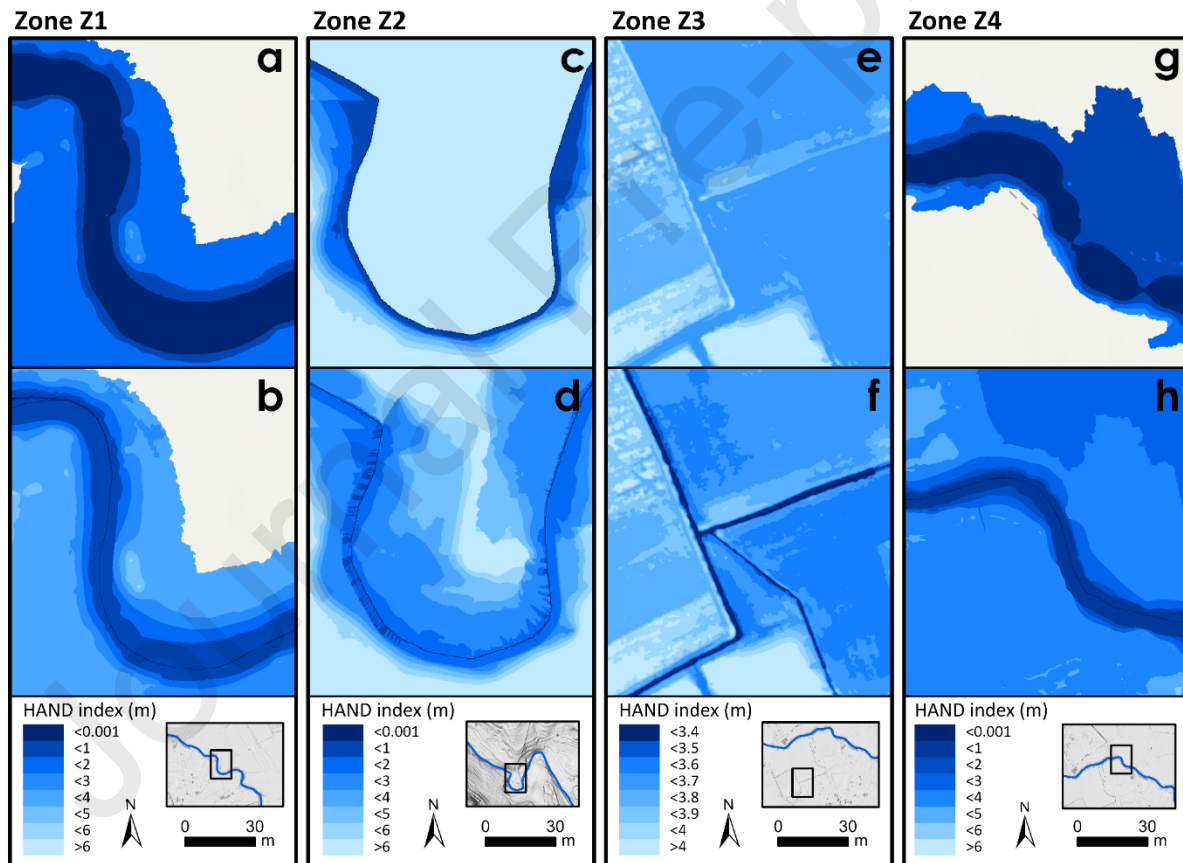
### 559 4.1. HAND-SRC model evaluation

#### 560 4.1.1. Effect of hydro-conditioning on HAND raster

561 The automatic pit filling and drainage delineation in the HAND raster calculation (described in section  
 562 3.1.1) can induce significant changes in the DEM. Prior to calculating the HAND raster, the hydro-  
 563 conditioning processes were applied to prepare the DEMs (see table 2). These processes are also  
 564 necessary to ensure that the DEM conforms to the assumptions of the HAND-SRC model, which is not  
 565 naturally achieved with fine resolution DEMs. Figure 4 illustrates the effects of hydro-conditioning  
 566 procedures on HAND raster (described in section 3.1.3) at four zoomed-in locations. In figure 4a, the  
 567 riverbed lacking an enforced flowline in terrain setup S1 was filled and flattened leading to the loss of  
 568 most bathymetric geometry. Enforcing a flowline as in the S1-rb setup (Fig. 4b) allowed retaining most of  
 569 the topographic details of the channel bathymetry at the expense of minor DEM alterations. Figures 4c  
 570 and 4d highlight the role of using a fill-burn approach after enforcing a flowline (ex. setup S1-rb),  
 571 particularly in locations where two or more parallel flowlines coexist leading to a ‘wall-effect’ in the  
 572 HAND raster (ex. setup S1). This problem is often found in reaches with wide and shallow channels and  
 573 where river islands are present. In addition, the hydro-conditioning of the floodplains by enforcing a  
 574 drainage network delineated using GeoNet improved the accuracy of the natural drainage that is  
 575 influenced by the existing canals and ditches. Consequently, this step reduced the impact of DEM pit

576 filling as shown in terrain setup S1-fp (figure 4e, 4f). Figures 4g & 4h demonstrate the effect of the  
 577 combined effect of the three applied processes including the removal of levees in setup S2. The effect of  
 578 the applied processes is reflected in the expansion of the extent of the HAND raster in addition to the  
 579 preservation of its terrain accuracy. The talweg profile in the bathymetry of both setups S2 and S3 showed  
 580 little difference in elevations (Fig. SM3 in supplementary material).

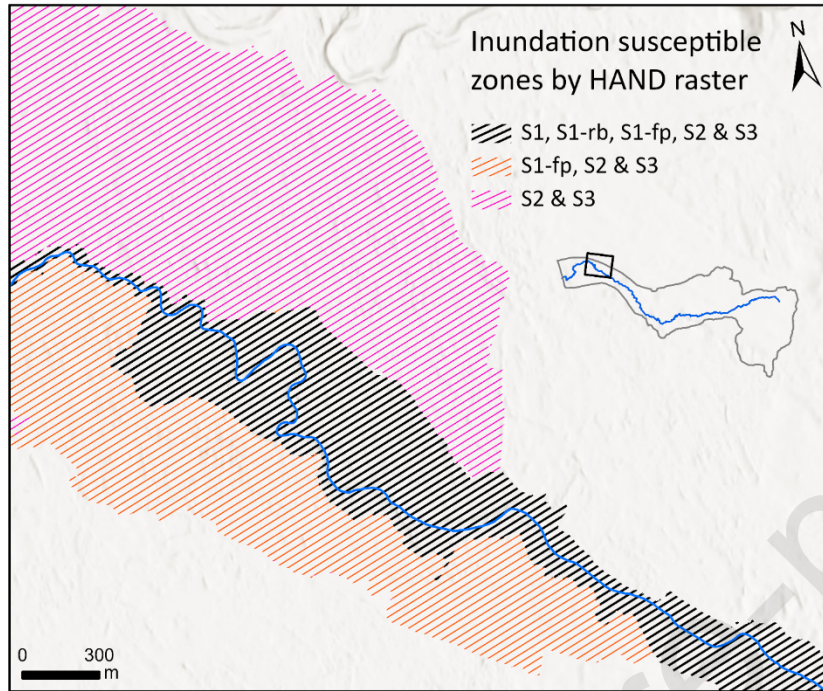
581 Based on different hydro-conditioning configurations, it was evident that combining all processes is  
 582 necessary at several locations along the river but especially at the model's test zone (Fig. 1c). Figure 5  
 583 illustrates the HAND raster extents using the various terrain setups. The HAND raster of terrain setup S1  
 584 (see Table 2) failed to extend over all inundation-prone zones within the floodplain due to the presence of  
 585 levees. However, hydro-conditioning the floodplain allowed the HAND raster to partially expand into the  
 586 full flood zone in setups S1-fp, S2 and S3. While integrating bathymetry did not affect the HAND raster  
 587 extents, removing levees enabled full hydrological continuity in the floodplains. By removing levees that  
 588 acted as drainage barriers, the HAND raster extended across the full floodplain area on both banks. This  
 589 comprehensive approach of hydro-conditioning by integrating bathymetry, enforcing floodplain drainage  
 590 and removing levees, allowed the model to accurately depict the full inundable extent of the terrain across  
 591 both banks. In the following sections, terrain setups S2 and S3 are scrutinized as they provided HAND  
 592 rasters with the most accurate representation of the topography and matched the full flood zone extents.



593

594 Figure 4: HAND raster maps developed using the HRDEM at four locations: Z1, Z2, Z3 and Z4  
 595 highlighting different terrain setups: (a) S1, (b) S1-rb, (c) S1, (d) S1-rb, (e) S1, (f) S1-fp, (g) S1 and (h)  
 596 S2. (a) & (b) illustrate the impact of flowline enforcement in the bathymetry. (c) & (d) demonstrate the  
 597 impact of the fill-burn process in preventing a “wall-effect” in the HAND raster. (e) & (f) show the

598 impact of floodplain drainage enforcement. (g) & (h) illustrate the full impact of bathymetry integration,  
 599 drainage enforcement and removal of levees



600

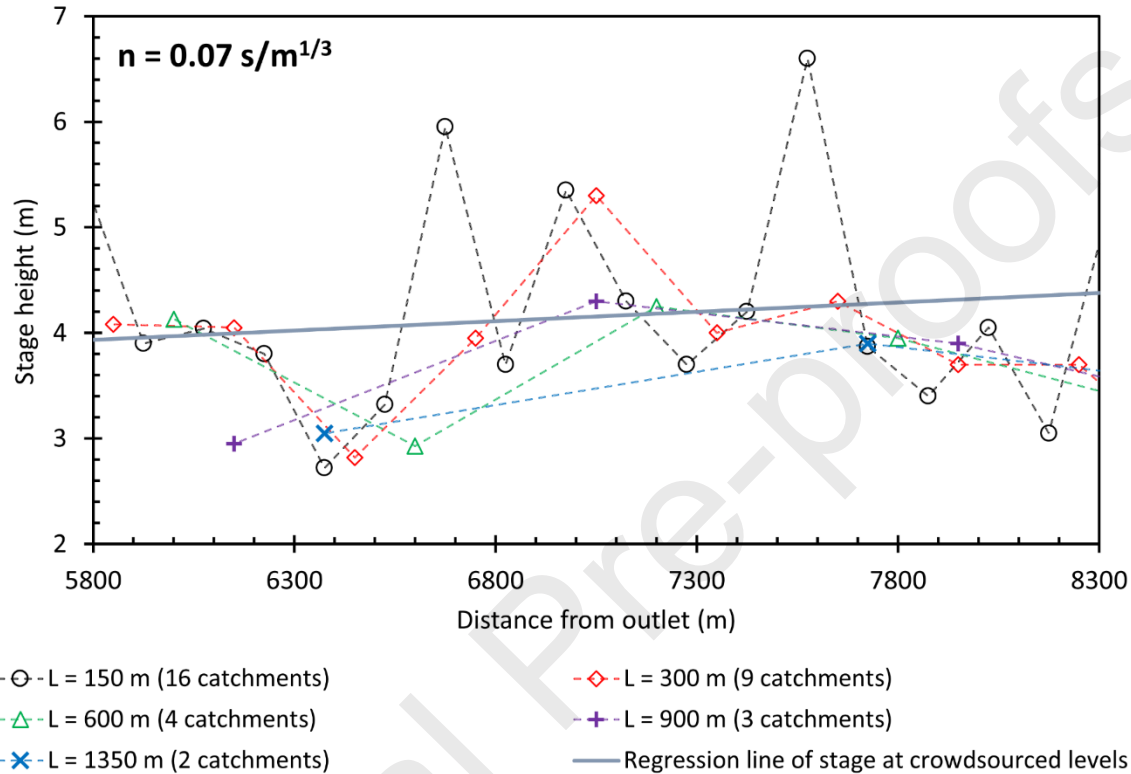
601 Figure 5: Inundation susceptible zones based on HAND raster extent under the five terrain-setups: S1, S1-  
 602 rb, S1-fp, S2 and S3 at the test site. S1 includes levees and lacks any hydro-conditioning process, S1-rb  
 603 includes bathymetry and levees, S1-fp includes levees with floodplain drainage enforcement, S2 includes  
 604 surveyed bathymetry with floodplain drainage enforcement and no levees, S3 includes surveyed  
 605 bathymetry with floodplain drainage enforcement and no levees

#### 606 4.1.2. Model parameterization and sensitivity analysis

607 Flood mapping using HAND-SRC is highly sensitive to the stage height in flat terrains (Johnson et al.,  
 608 2019; Jafarzadegan et al., 2022). The reach length  $L$  is usually fixed for the entire implementation domain  
 609 of HAND-SRC. It is generally recommended to use a moderate length between 1.2 and 5 km (Godbout et  
 610 al., 2019; Zheng et al., 2018a). This is to prevent the effects of local variability in slope and terrain in  
 611 smaller lengths and the loss of topographic details in lengthier ones. Similarly, Manning's roughness  
 612 coefficient is applied uniformly over the whole domain. The values are chosen either on the basis of other  
 613 model parameters or on the basis of land use. The range of this parameter varies between 0.05 and 0.08  
 614  $s/m^{1/3}$  (Aristizabal et al., 2023; Garousi-Nejad et al., 2019; Hocini et al., 2020; Johnson et al., 2019;  
 615 Zheng et al., 2018a). Based on this a Manning's roughness coefficient of  $0.07 s/m^{1/3}$  was selected for the  
 616 tested domain.

617 The role of reach length  $L$  was investigated by fixing Manning's roughness coefficient  $n$  to  $0.07 s/m^{1/3}$   
 618 and calculating stage heights for tested reach lengths of 150, 300, 600, 900 and 1350 m. The setup S2 was  
 619 chosen for the sensitivity analysis as it produced a HAND raster extended to the full floodplain area  
 620 unlike setups S1, S1-fp and S1-rb, while maintaining the highest topographic accuracy after implementing  
 621 the hydro-conditioning processes and integrating the surveyed bathymetry. Stage heights were derived  
 622 from SRCs of each catchment using the estimated peak discharge  $Q_p=94.1 m^3/s$  of the January 2019  
 623 event. Figure 6 shows the variation in stage value using various reach lengths. Stage heights for  $L$  of 150

624 m and 300 m demonstrated a good ability to capture the crowdsourced flood depths. However,  $L$  showed  
 625 little influence on the ability to correctly detect flooded and non-flooded crowdsourced occurrences. A  
 626 reach length  $L$  of 300 m was chosen for flood mapping purposes as it showed fewer outlier stage heights  
 627 arising from topographic heterogeneity compared to  $L = 150$  m. In addition, it yielded the lowest RMSE  
 628 (68.3 cm) compared to other  $L$  values.



629

630 Figure 6: Sensitivity analysis of reach length  $L$  in the HAND-SRC model. The stage heights ( $h$ ) were  
 631 calculated for five  $L$  values in the test site using a fixed Manning's roughness coefficient ( $n=0.07 \text{ s/m}^{1/3}$ )  
 632 and using the peak discharge of January 2019 flood,  $Q_p$ . The stage height is referenced to the flowline of  
 633 each reach and is added on the graph at the midpoint of the reach. A regression line was calculated from  
 634 the stage heights at which the crowdsourced flood levels are reached

## 635 4.2. HAND-SRC flood mapping

### 636 4.2.1. Flood depth and occurrence comparison against crowdsourced data

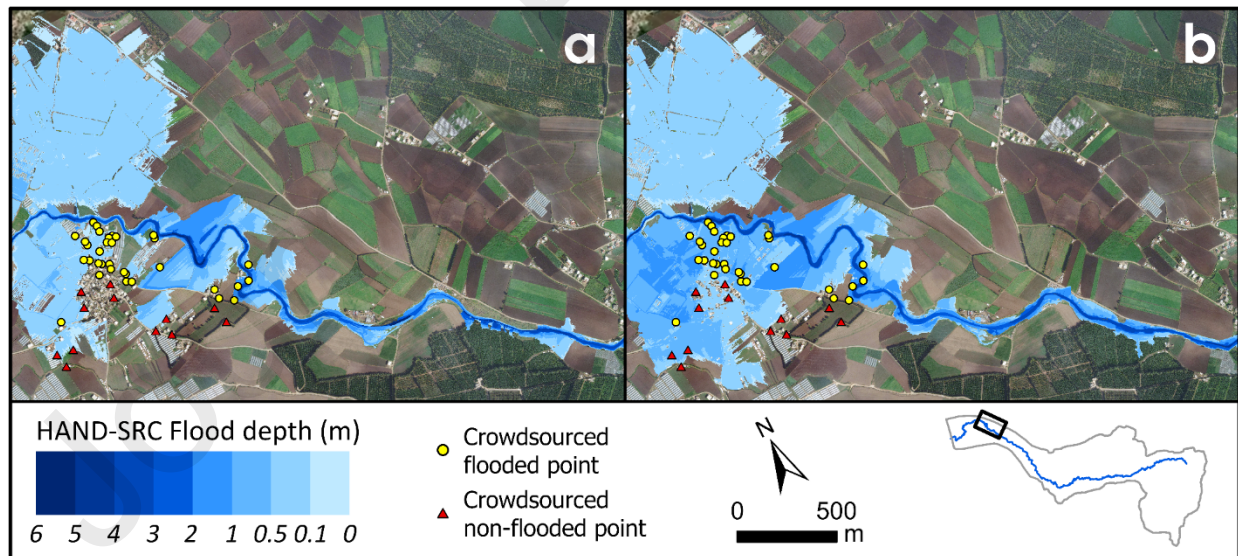
637 The performance of HAND-SRC flood mapping was investigated against crowdsourced data using the  
 638 two terrain setups S2 and S3 at the test site at the downstream part of the floodplain (Fig. 1c). The two  
 639 setups were selected for this assessment because they were the only ones to produce a HAND raster that  
 640 extends over the full floodplains and preserves a topographic consistency with the original HRDEM after  
 641 implementing the hydro-conditioning processes. The site has an average DEM slope of 6.7%, a standard  
 642 deviation of 1.34 m and a river gradient of 0.2%. A reach length of 300 m and a uniform Manning's  
 643 roughness coefficient  $n=0.07 \text{ s/m}^{1/3}$  were used. By using RMSE,  $CSI_p$  and  $MCC_p$  an evaluation form that  
 644 targets the depth and ability to capture the flooded crowdsourced points is elected rather than a flood area.  
 645 This allows for a more critical review of the model's ability to capture detailed locations within the



646 floodplain. The validity of crowdsourced data is thus relied upon rather than an established or simulated  
 647 flood map. The depth comparison made here is between the HAND-SRC flood depths and the  
 648 crowdsourced flood depths. The latter was calculated as the difference between the surveyed ground  
 649 elevation and the crowdsourced elevation of peak flood depth. The vertical elevation error was thus not  
 650 propagated throughout the rest of the calculations.

651 Figure 7 shows the flood maps generated for the different terrain setups. The figure was generated based  
 652 on stage heights derived from SRCs of each catchment for  $Q_p=94.1 \text{ m}^3/\text{s}$ . The maps have distinct patterns  
 653 and areas of inundation. The two setups S2 and S3 showed a balanced flooding area over the two banks of  
 654 the river. Differences between S2 and S3 can be identified where S3 showed higher flood levels and a  
 655 wider extent compared to S2. Both terrain setups were able to capture the flooded points to a good degree,  
 656 however S3 submerges several non-flooded points. Terrain setup S2 produced a  $CSI_p$  value of 0.64  
 657 compared to a  $CSI_p$  of 0.79 for S3. Whereas for  $MCC_p$ , the results showed values of 0.49 and 0.24  
 658 respectively. Additionally, both setups showed a RMSE of 70 cm and 54 cm respectively. Furthermore,  
 659 an intercomparison between the flood depths obtained with terrain setups S2 and S3 was performed. The  
 660 mean difference between both was 16 cm with S3 showing a higher flood depth. The mean absolute error  
 661 amounted to 31.1 cm. While varying level of differences could be observed along the different river  
 662 reaches, the difference throughout the floodplains was minimal.

663 The results of both scenarios using the various tested reach lengths are shown in table 3. For all lengths,  
 664 S2 showed higher RMSE compared to S3. Similarly, the  $CSI_p$  metric was also higher using S3. However,  
 665 for  $MCC_p$ , the results were variable with S2 showing higher value except for the 900 m and 2700 m reach  
 666 lengths. Considering that S2 is a better realization of the bathymetric geometry, S3 with a more simplified  
 667 geometry showed better metrics in capturing crowdsourced points compared to S2 under most  $L$  values.  
 668 This suggests that using a theoretical bathymetry instead of a surveyed one can be sufficient in such  
 669 applications with minimal difference in flood depths ( $< 25 \text{ cm}$ ).



670

671 Figure 7: Comparison between simulated HAND-SRC flood maps for the peak discharge  $Q_p$  of January  
 672 2019 flood event using the 25-cm HRDEM for the two terrain setups: (a) S2, which includes interpolated  
 673 surveyed bathymetry, flowline and floodplain drainage enforcement, and no levees; and (b) S3, which  
 674 includes trapezoidal power law cross-section bathymetry, flowline and floodplain drainage enforcement,  
 675 and no levees. For both setups a reach length of 300 m was used and a Manning's roughness coefficient  
 676 of  $n=0.07 \text{ s/m}^{1/3}$

677 Table 3: Terrain setups used for the assessment of hydro-conditioning and man-made features; × marks  
 678 the applied configuration in a setup

Terrain setup		Reach length L (m)					
		150	300	600	900	1350	2700
	RMSE (m)	0.64	0.70	0.71	0.65	0.62	0.61
S2	CSI <sub>p</sub>	0.48	0.64	0.54	0.56	0.63	0.55
	MCC <sub>p</sub>	0.38	0.49	0.40	0.41	0.47	0.41
	RMSE (m)	0.57	0.54	0.59	0.65	0.55	0.59
S3	CSI <sub>p</sub>	0.75	0.79	0.53	0.53	0.50	0.53
	MCC <sub>p</sub>	0.36	0.24	0.18	0.49	0.30	0.49

679

#### 680 4.2.2. Flood depth and extent comparison against HEC RAS

681 The comparison between HAND-SRC and HEC RAS flood maps was conducted for the peak discharge  
 682 value of the 2019 event for terrain setups S2 and S3 (fig. SM4 in supplementary material). It should be  
 683 mentioned that the DEM used in HEC RAS does not use the same hydro-conditioned terrain used in  
 684 HAND-SRC modelling. Instead, it relies on the original HRDEM with corrected cross sections (see  
 685 section 3.2). Initially, HEC-RAS flood maps were evaluated against crowdsourced points. HEC RAS  
 686 produced a CSI<sub>p</sub> value of 0.61 and the lowest RMSE in flood depth of 34 cm among all tested  
 687 simulations.

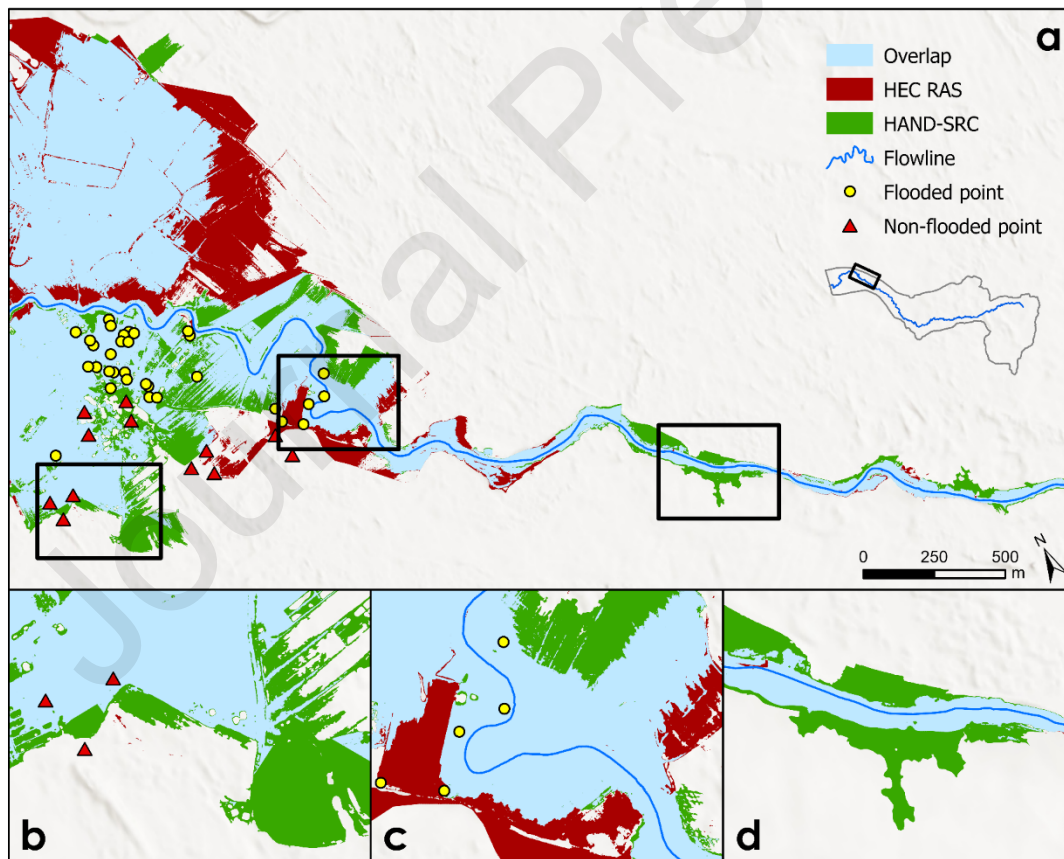
688 Figure 8 shows the comparison between HAND-SRC inundation maps using S3 setup with the HEC RAS  
 689 model. Evaluating setup S3 flood extents against HEC RAS extents produced a CSI<sub>A</sub> of 0.59 and MCC<sub>A</sub>  
 690 of 0.32. An overprediction by HAND-SRC was found on the left bank of the river contrary to an  
 691 underprediction on the right bank. For terrain setup S2, HAND-SRC gave a comparable pattern to that of  
 692 terrain setup S3, with a CSI<sub>A</sub> and MCC<sub>A</sub> of 0.66 and 0.35 between the two flooded extents. Moreover, the  
 693 flood depths simulated by HAND-SRC and HEC RAS were compared across overlapping flooded areas.  
 694 Figure 9 shows the comparison of HEC RAS and HAND-SRC flood depths using terrain setups S2 and  
 695 S3. In both cases, HAND-SRC underestimated the simulated flood depth. However, setup S2 showed  
 696 lower errors compared to S3. Terrain setup S2 revealed a MD of 0.15 m, MAD of 0.62 m, and a RMSD  
 697 of 0.72 m. Whereas under setup S3 a MD of 0.37 m was registered, a MAD of 0.66 m, and a RMSD of  
 698 0.98 m. The MD between S2 and S3 was 0.16 m.



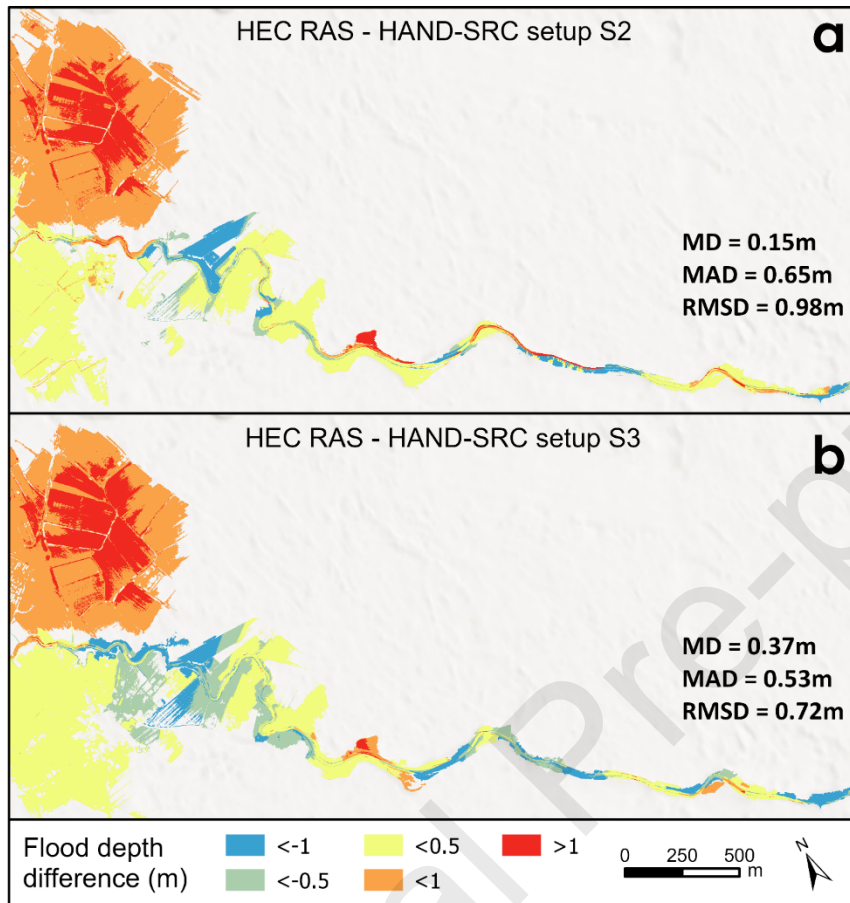
699 An alternative approach to simulate flood maps was then tested by using HAND raster of terrain setup S2  
 700 with ARCs instead of SRCs. The generated flood map showed the highest metric performances, with a  
 701  $CSI_A$  of 0.86 and  $MCC_A$  of 0.65. However, there was generally an overestimation in HEC-RAS depths  
 702 and extents compared to HAND-SRC. This test demonstrates that a hydro-conditioned terrain setup can  
 703 replicate the extents simulated by a hydraulic model more accurately by adjusting the reach length and  
 704 Manning's roughness coefficient parameters.

705 In the operational use of low-complexity models, correctly predicting flood occurrences with minimal  
 706 misses is essential, therefore, the model parameters were optimized using CSI metric. Testing this, an  
 707 optimal  $CSI_p$  value of 0.73 for crowdsourced data was obtained for a minimum stage height of 4.5 m  
 708 under all tested reach lengths. Back calculating Manning's roughness coefficient using this stage height  
 709 produced a corresponding value of  $n = 0.095 \text{ s/m}^{1/3}$ . Applying this value for all catchments in setup S2  
 710 improved the performance of the HAND-SRC extents compared to HEC RAS simulated extents by  
 711 10.6% ( $CSI_A$  score 0.66 to 0.73). In contrast, using a Manning's roughness coefficient based on fitting the  
 712 SRC to the ARC at the Pont Halba gauge station produced a value  $n = 0.062$  which hindered the model  
 713 prediction accuracy in the floodplains downstream.

714 Overall, both terrain setups S2 and S3 showed similar and good agreement with HEC-RAS flood maps.  
 715 These tests highlight the potential of HAND-SRC model, particularly with hydro-conditioned terrain and  
 716 optimized parameters. While HEC RAS produced the lowest RMSE in crowdsourced data, the HAND-  
 717 SRC model was capable of reproducing the HEC RAS extents sufficiently. This demonstrates that even in  
 718 challenging topographies, the HAND-SRC model can still be reliable for floodplain mapping.



720 Figure 8: (a) Comparison of simulated HEC RAS and HAND-SRC extents for the January 2019 flood  
 721 event using terrain setup S3, (b) zoomed-in extent at the edge of the flood zone, (c) zoomed-in extent at a  
 722 river meander, and (d) zoomed-in extent in a reach with a deep straight channel



723

724 Figure 9: Comparison of simulated flood depths between HEC RAS and HAND-SRC at test site. The  
 725 maps were computed by subtracting HEC RAS flood depth from HAND-SRC flood depths for terrain  
 726 setups: (a) S2 and (b) S3. MD denotes Mean Difference; MAD denote Mean Absolute Difference; and  
 727 RMSE denote Root Mean Squared Difference

### 728 4.3. Resolution effect on HAND-SRC in low-relief areas

#### 729 4.3.1. Flood mapping using upscaled resolution

730 The analysis of the resampled DEMs focuses on the horizontal resolution impact, which is significant on  
 731 the computational burden and the adherence to the HAND-SRC assumptions. Obtaining high resolution  
 732 DEMs is still a challenge in many areas, therefore, testing whether coarser resolutions can reproduce  
 733 similar results is needed from an operational perspective. By resampling the HRDEM enables assessing  
 734 this effect.

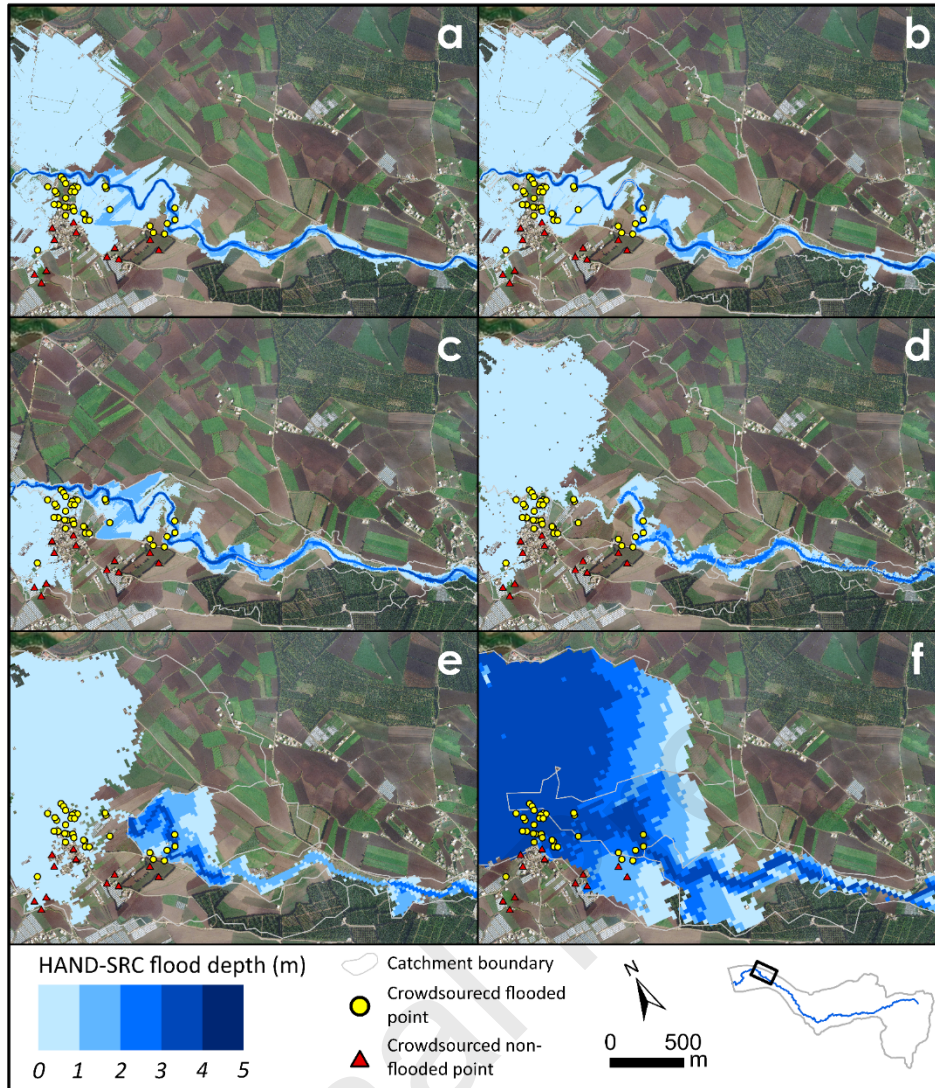
735 Figure 10 illustrates the flood maps at different resolutions. The 1 m resolution DEM produced a similar  
 736 flood extent and depth to that of the 25 cm HRDEM, yielding a balanced estimate of flood spatial extent.  
 737 However, the 3 m and 5 m resampled resolutions both showed flooding only on one side of the river. This  
 738 issue originated from the change in the flow direction grid caused by resampling. At a resolution of 5 m

739 and above the influence of the natural drainage in the floodplains becomes less significant as the drainage  
740 controlling features become dissolved within the grid cells whose size becomes larger than the width of  
741 the present ditches and canals. Contrarily, the delineated river flowline using a resolution of 30 m  
742 diverged away from the channel. This resulted in a clear overestimation of flood depth as the DEM turned  
743 into a completely flat area. The river's bank-full width varies between 8 and 15 meters and loses much of  
744 its elevation accuracy at resolutions of 20 and 30 m. At these two resolutions, SRCs showed higher errors  
745 and led to exaggerated stage heights. Consequently, the whole catchments were filled up to their  
746 boundaries. Generally, these results reflect how employing high-resolution DEMs is crucial for accurate  
747 flood modelling in flat regions, as coarser resolutions fail to capture critical drainage features and result in  
748 significant errors in flood extent and depth estimation mainly driven by the disruption of terrain  
749 convergence between the channel and floodplains.

750 Figure 11 shows the produced metrics of  $CSI_A$ ,  $CSI_P$ , and the RMSEs in the DEM vertical accuracy,  
751 SRCs, simulated flood depths, and flood surface water elevation (SWE) simulated using HAND-SRC  
752 under the selected DEM resolutions.  $RMSE_{DEM}$  refers to the DEM vertical accuracy that was calculated in  
753 comparison against the original HRDEM (before any resampling).  $RMSE_{SWE-CS}$  was calculated for the  
754 HAND-SRC surface water elevation compared to the crowdsourced flood SWE. Likewise, the  $RMSE_{FD}$   
755 was calculated between the HAND-SRC flood depths and the crowdsourced flood depths. Moreover,  
756  $RMSE_{SRC}$  was calculated against the ARC at each catchment. The evaluated terrain resolutions showed a  
757 consistent ability to simulate crowdsourced flooded depths except for the 30 m resolution. However, the  
758 tested resolutions showed a random ability to capture crowdsourced flood occurrences and HEC RAS  
759 flood extents. The 25 cm resolution yielded satisfactory values in all metrics.

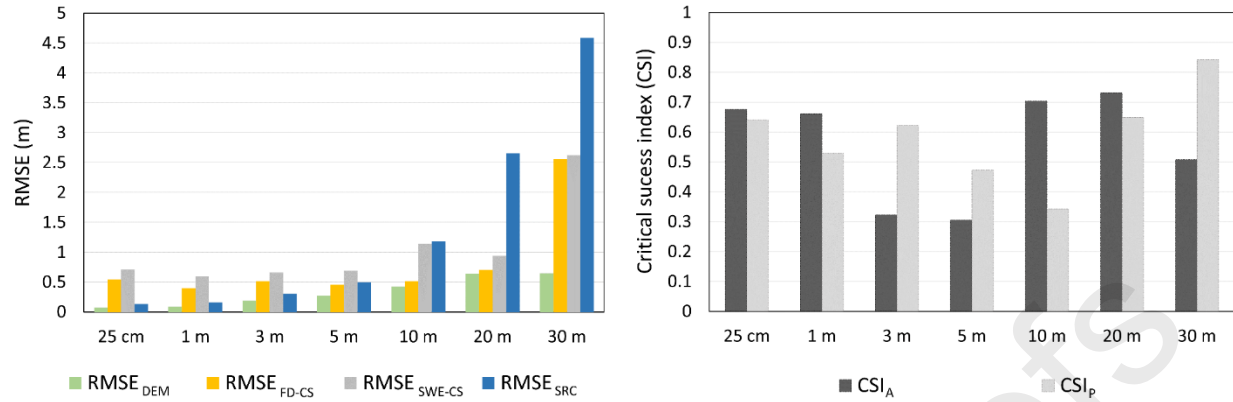
760 Contrary to expectations, a resolution of 20 m also demonstrated a satisfactory replication of HEC RAS  
761 extents and crowdsourced depths and occurrences despite the heightened errors in DEM accuracy. It  
762 should be noted that the errors in surface water elevations were more significant compared to the errors in  
763 flood depth which can be attributed to the heightened errors in DEM vertical accuracy. Furthermore, the  
764 resulting HAND rasters and flood maps failed to accurately capture the depth and hydraulic geometry of  
765 the river channel. No linear trend was observed from the resampled DEM flood mapping performance.  
766 However, some coarser resampled DEM resolutions could sufficiently capture the extent of flooding and  
767 crowdsourced occurrences or depths. Nonetheless, their inherent errors and compromised accuracy make  
768 them less ideal compared to finer resolutions with higher vertical accuracy.





769

770 Figure 10: Simulated HAND-SRC flood maps of the January 2019 flood event using terrain setup S2 at a  
 771 DEM resolution of (a) 25 cm, (b) 1 m, (c) 5 m, (d) 10 m, (e) 20 m and (f) 30 m. The DEMs were  
 772 resampled from the 25-cm HRDEM and the reach length used is 1350 m for a constant Manning's  
 773 roughness coefficient of 0.07



774

775 Figure 11: Evaluation of HAND-SRC model using root mean square error (RMSE) and critical success  
 776 index (CSI) across seven tested resolutions of terrain setup S2. RMSE is calculated for DEM vertical  
 777 accuracy (RMSE<sub>DEM</sub>), synthetic rating curves (SRCs) compared to ARC (RSME<sub>SRC</sub>), in addition to both  
 778 crowdsourced flood depth (RMSE<sub>FD-CS</sub>) and crowdsource ed water surface elevation (RMSE<sub>SWE-CS</sub>) that  
 779 were both against HAND-SRC simulations. CSI is calculated for crowdsourced points (CSI<sub>P</sub>) and HEC  
 780 RAS simulated flood extents (CSI<sub>A</sub>)

#### 781 4.3.2. Computation time

782 The computational time required to run the calculations/simulations showed a large difference between  
 783 the resampled DEM resolutions (Table 4). A personal computer was used for simulating the HAND-SRC  
 784 model equipped with an AMD Ryzen 5800h CPU with 8 cores (3.2 GHz and 16 logical processors) in  
 785 addition to a 16 GB of RAM. Parallel processing was adopted for simulating TauDEM utilities using 16  
 786 processes. The total time required to develop the HAND raster and the SRCs using the 25 cm HRDEM  
 787 with an area of 8 km<sup>2</sup> was 47.4 mins out of which 81% were dedicated for TauDEM utilities. In  
 788 comparison a 30 m resolution DEM required only 2.1 seconds. Generally, little difference was found  
 789 when simulating coarse resolutions above 5 m. The 3 m resolution required twice the time compared to  
 790 the 5 m DEM. Moving from a 3 m to 1 m resolution, a difference of two orders of magnitude in  
 791 simulation time was observed. An order of magnitude difference was also witnessed when changing the  
 792 resolution from 1 m to 25 cm resolution. The calculation of HAND raster and SRCs at high resolutions  
 793 can be of high computational requirement, however it is only needed once. Furthermore, there is no  
 794 significant computational cost when mapping floods which can be achieved in a matter of a few seconds.  
 795 In essence, setting up of HAND-SRC may be initially computationally demanding using high resolutions,  
 796 however, the model is highly efficient for repeated flood simulations required in operational forecasting  
 797 using all resolutions.

798 Table 4: The DEM resolutions tested using HAND-SRC, their raster size, uncompressed size and  
 799 computational time

DEM resolution (m)	Raster Size	Uncompressed size	Computational time (sec)
0.25	17488×15800	1.03 GB	2844.310

1	4372×3938	65.68 MB	100.331
3	1457×1313	7.3 MB	6.811
5	874×788	2.63 MB	3.349
10	437×394	672.57 KB	2.487
20	219×197	168.53 KB	2.158
30	146×131	74.71 KB	2.113

---

800

801 **5. Discussion**

802 This section presents the discussion of three aspects that highlights the importance of accurate terrain  
803 representation and the challenges of incorporating crowdsourced data sources for flood modelling.  
804 Specifically, it covers: (1) the hydro-conditioning processes and the effect of the reach length variation,  
805 (2) the flood mapping performance of the model, and (3) the DEM resolution effect on flood mapping.

806 **5.1. Terrain analysis: hydro-conditioning and reach length parameter**

807 Hydro-conditioning is an indispensable practice used to correct or improve the effectiveness of the  
808 geometric representation for modelling purposes. The hydro-conditioning processes applied here differ  
809 from (Garousi-Nejad et al., 2019; Zheng et al., 2018a) in four ways. First, two bathymetric DEMs were  
810 superimposed. The integration of bathymetry is an attempt to ensure topographic accuracy that is  
811 consistently absent in similar applications. Second, the enforced flowline was delineated using the D8  
812 approach. Third, the floodplain part of the DEM was hydro-conditioned by enforcing a drainage network  
813 delineated using GeoNet. Here, the drainage continuity into a singular flowline was ensured by two  
814 drainage enforcement processes, namely the AGREE-DEM and fill-burn processes. Fourth, levees were  
815 removed from the DEM to ensure full drainage continuity between the floodplains and river channel, in  
816 an unorthodox approach. These hydro-conditioning processes may seem unconventional in hydrological  
817 applications but are necessary to adapt to both the terrain's flat nature and the model's assumptions.

818 A key aspect of integrating interpolated bathymetry is that, unlike the trapezoidal cross-section  
819 bathymetry, it may admit multiple parallel flowlines. This generates inconsistencies in the HAND raster  
820 due to the increased downstream distance between a DEM grid cell and the flowline grid cell. The flow-  
821 burn approach that followed the AGREE DEM approach resolves this limitation, by leading the drainage  
822 within the bathymetry into the singular enforced flowline in the HAND raster.

823 Another pivotal impact of the hydro-conditioning processes is the alteration of the DEM. While this may  
824 introduce additional errors, it guarantees drainage continuity through the lowest elevations in the terrain.  
825 By enforcing drainage in the bathymetry and floodplain, these processes mitigate the effect of the  
826 automatic pit-filling and flow direction grid calculation while preparing the HAND raster. This approach

827 preserves the consistency between the original DEM and the HAND raster, which is essential for accurate  
828 mapping and for comparison with crowdsourced flood levels.

829 Levee representation within a DEM is highly significant since they act as a barrier against flow. In our  
830 study case, the high resolution of the DEM allowed detecting levees that act as a barrier despite their  
831 small size. These soil levees, developed through random efforts by local farmers, do not meet modern  
832 engineering design standards. They are also scattered along the river course with many gaps and breaches,  
833 rendering them non-optimal for flood mitigation. Unlike other studies (Afshari et al., 2018; Aristizabal et  
834 al., 2023) that tried to enforce levees into the DEM, we opted to remove them due to their lack of  
835 hydraulic significance. Our analysis revealed that removing these levees to allow floodplain drainage into  
836 the channel is crucial to producing coherent HAND raster that extend across the complete floodplains (see  
837 figure 5) and SRCs that accurately replicate ARCs by maintaining the hydrological connection.

838 It should be noted that levee presence in a DEM can be highly problematic in HAND-SRC model.  
839 Inundation in HAND-SRC is based on traced hydrological connection that drains the floodplains into the  
840 channel (assumption A1). These hydrological pathways require a monotonically decreasing flow direction  
841 grid that cannot occur in the presence of a levee. Since levees are raised structures that separate two  
842 regions in a DEM, no monotonic decrease will be found between the upstream and downstream sides of  
843 the levee. Therefore, any traced connection, if found, will be erroneous further contributing to errors in  
844 SRC and estimated stage heights. Furthermore, the HAND raster extent, in the presence of a levee, will be  
845 restricted to the levee location and will result in an infinite “wall effect” when the raster is filled up to the  
846 levee edge. Nonetheless, a stage height can be overlaid over the whole HAND raster regardless of a  
847 hydrological connection to overcome the levee problem, as in Afshari et al. (2018). This however, would  
848 lead to an overestimation of the flood extent, especially in flat terrains. Another possible workaround can  
849 be made by removing the levees and adjusting the SRC such that no floodplain inundation occurs until  
850 bank-full discharge is reached.

851 The two primary parameters of the HAND-SRC model are Manning's roughness coefficient and the reach  
852 length  $L$ . The former is dependent on the characteristics of the land surface and its features, while several  
853 terrain properties dictate the latter. The most commonly used  $L$  values in the literature are at least 1000 m.  
854 Here, reach lengths down to 150 m were tested. Our analysis revealed an increasing trend in the average  
855 stage height when reducing  $L$ . The outlier values that appear when using a reach length of 150 m can be  
856 attributed to either the delineated catchment's hydraulic geometry or the local slope heterogeneity.  
857 Catchments with lower  $L$  can be unbalanced, with a larger draining area on one bank of the river or  
858 different maximum fillable heights at each bank, leading to a strictly vertical filling of the catchment and  
859 consequently an increase in estimated stage heights. This is identified by sudden increasing shifts in  
860 SRCs. Reach slope outliers ranging from 0.01% to 0.7% were found in  $L=150$  m, contributing to the  
861 stage height variability in some catchments. (Godbout et al., 2019) found that decreasing  $L$  below 1.2 km  
862 or targeting low-slope reaches reduces SRC accuracy using a 10 m topographic dataset. In our study, the  
863 slope and reach length did not show any co-linearity, suggesting that stage height errors using shorter  $L$  (<  
864 1000 m) can be mitigated when robust bathymetric measures are available. The limitation on using  
865 shorter  $L$  remains from the effect of catchment geometry which mainly depends on the terrain  
866 connectivity and HAND raster quality.

## 867 **5.2. HAND-SRC flood mapping**

### 868 **5.2.1. Flood mapping performance**

869 HAND-SRC as a hydrological terrain filling technique coupled with Manning's flow equation lacks the  
870 physics of fluid mechanics in more complex hydraulic models using shallow water equations. Manning's  
871 flow equation certainly introduces a simplified flow hydraulics representation albeit the limitations



872 stemming from the uniformity assumption of water levels within a catchment (A3) their discretization  
 873 along catchments of a river reaches (A4) and the infinite water volume assumption (A5) (see section  
 874 3.1.2). These assumptions create a surface water elevation with a stepped curve along the river and fail to  
 875 conserve mass or momentum across consecutive river reaches. Nonetheless, a plethora of other simplified  
 876 low-complexity models can be used for rapid flood inundation mapping such as RFSM, TVD, AutoRoute,  
 877 planar surface, bathtub method, topographic wetness index, geomorphic flood index and slope position  
 878 (Dhote et al., 2023; Jafarzadegan et al., 2023; Teng et al., 2019). Yet, HAND tends to perform similarly  
 879 or better than other low-complexity models in terms of simulated extent and depth (Afshari et al., 2018;  
 880 Dhote et al., 2023; Lioi et al., 2020; McGrath et al., 2018). The model is an efficient and less costly  
 881 alternative to more physically-based models that admit higher ranges of uncertainty (Diehl et al., 2021).

882 Overall, the hydro-conditioned terrain setups were capable of capturing the extent and depths of  
 883 crowdsourced data ( $CSI_p$  of 0.64 and 0.79) and HEC RAS extents ( $CSI_A$  of 0.66 and 0.59). The presence  
 884 of crowdsourced points in rural areas may be subject to the influence of terrain features. The resulting  
 885 magnitude of RMSE errors compared to crowdsourced data was generally on the lower side ( $< 1\text{m}$ ), and  
 886 this can be attributed to the flat geomorphology of the terrain. While HEC RAS attained a lower RMSE  
 887 (34 cm), terrain setups S2 and S3 showed a low error as well (70 cm and 54 cm respectively). These  
 888 values are considered acceptable for flood modelling (Fleischmann et al., 2019).

889 Interestingly, the trapezoidal bathymetry in S3 produced some enhanced metric performances compared  
 890 to the surveyed interpolated one in S2 against crowdsourced data (table 3). A slight improvement was  
 891 also found in replicating HEC RAS extents. Flood depths using S3 were also overestimated against HEC  
 892 RAS but with similar hot-spots of overestimation and underestimation compared to S2. S3 had lower  
 893 MAD and RMSD compared to S2 but a higher MD indicating higher outliers than in S2. This implies a  
 894 greater bias toward underestimation of flood depth in setup S3 compared to setup S2. The average  
 895 trapezoidal bathymetry area is similar to that of the surveyed interpolated one while both terrains  
 896 produced similar rating curves. Yet, two main factors influencing this difference can be attributed. (1) The  
 897 enhanced drainage continuity between the channel with superimposed bathymetry and the floodplain  
 898 caused by reduced noise and errors resulting from bathymetric interpolation that may create obstructions  
 899 between both. (2) The reduced errors stemming from the internal drainage within the riverbed that can  
 900 lead to increased hydrological distance between the flowline and a DEM cell consequently leading to an  
 901 overestimation of HAND values and therefore reduced flood depths and extents. Such errors arise from  
 902 possible river islands or from the rectangular delineated drainage pattern within the surveyed interpolated  
 903 bathymetry. This suggests that a simplified geometry can be more favorable for terrain-based HAND-  
 904 SRC applications.

### 905 5.2.2. Underprediction in low-reliefs

906 In general, HAND-SRC maps underestimated the flood depths compared to crowdsourced data despite a  
 907 relatively high Manning's roughness coefficient ( $n = 0.07 \text{ s/m}^{1/3}$ ). Such a finding was also reported by  
 908 (Afshari et al., 2018; Hocini et al., 2020). Other works suggested a reduction of Manning's roughness  
 909 coefficient in high-stream order reaches and low-relief terrains (Johnson et al., 2019). Four factors can be  
 910 behind this difference. First, the hydro-conditioning can increase the fillable volumes and subsequently,  
 911 the cross-sectional area implying a higher  $n$  is needed as a result of assumption (A5). Second, errors in the  
 912 river slope in DEMs lacking bathymetry can lead to irregular slope estimates and increased height  
 913 differences especially in coarser resolutions adopted in the literature. Third, the underestimation of  
 914 hydraulic geometry due to the lack of bathymetry and the coarse resolutions in the different literature  
 915 (Godbout et al., 2019; Hocini et al., 2020; Johnson et al., 2019) result in a flat SRC with little sensitivity  
 916 to elevation. Lastly, the traced hydrological flow path along the flow direction between the flowline cell  
 917 and a DEM cell may not correspond to the actual distance in reality. This can be due to DEM errors or  
 918 incorrect drainage delineation resulting in increased distance along the hydrological flow path leading to

919 increased HAND index at a DEM cell that in reality should be lower. This may further contribute to the  
920 underprediction in flat areas.

### 921 **5.2.3. Perspectives on crowdsourced data**

922 Crowdsourcing introduces a type of uncertainty that is complex to outline and constrain. The source of  
923 uncertainty varies according to the type of data, collection method and analysis approach. Yet, the  
924 approaches and protocols to understand them are still being developed (Assumpção et al., 2018; Nardi et  
925 al., 2022). In our study, the uncertainty in crowdsourced data manifests in the spatiotemporal  
926 characterization, originating from the timing of peak flood observation and the elevation errors.  
927 Evaluating this requires a transdisciplinary analysis incorporating demographic, social and psychological  
928 sciences to deal with the biases and randomness of human observations.

929 The validation of crowdsourced data relies on external inputs such as remote sensing or aerial imagery at  
930 the time of the flood which were not available in our study (Dasgupta et al., 2022; Nardi et al., 2022).  
931 Thus, crowdsourced data should adopt structured methods to validate and assess their interoperability  
932 without external inputs. The crowdsourced data used here consisted of 45 points of which 33 represented  
933 a peak flood water elevation distributed over an area of 0.45 km<sup>2</sup>. For rural streams, 5 to 10 high water  
934 marks are sufficient to characterize a flood, however, urban settings require a higher number (Koenig et  
935 al., 2016). Given the small area of the crowdsourcing survey, the density of the points was found to be  
936 sufficient to reduce the uncertainty and eliminate discrepancies. Furthermore, the crowdsourced points  
937 were classified into three reliability levels: low, medium and high based on demographic criteria and  
938 retrieval abilities of the eyewitness. High and medium reliability points showed a similar level of profile  
939 agreement contrary to low reliability points that exhibited a non-linear tendency with several outliers.  
940 Interestingly, the complete dataset was capable of providing sufficient information for model validation in  
941 the targeted areas. Moreover, the elevation profile from the surveyed flood levels matched the slope and  
942 flow direction of the river bed slope (0.16%), showing an agreement with basic hydraulic principles.  
943 Therefore, we suggest that an adequate density of crowdsourced points is essential to reduce their  
944 associated uncertainty and validate their accuracy.

945 A main limitation of crowdsourced data is their lack in uninhabited environments and covering urban  
946 environments where “sensors” whether human or technological are present. This can produce spatial  
947 biases derailing the overall accuracy of the approach in remote areas and agricultural plains. Our dataset  
948 admits an unbalance providing dense information only on the left bank of the river. This limitation was  
949 significant in the pre-processed terrain setups and tested DEM resolutions (3 m and 5 m) that showed  
950 good agreement in CSI<sub>p</sub> and RMSE metrics but failed to correctly capture the inundation extent of HEC  
951 RAS. Therefore, to overcome this limitation, hydraulic simulations or established flood maps are needed  
952 for an overall evaluation of the model on its full domain.

953 The implementation of HAND-SRC highly depends on the estimation of a stage height. In the literature,  
954 different approaches are used including gauged stage levels were used as input (Johnson et al., 2019;  
955 Zheng et al., 2018a). In regions suffering from low data availability, alternative sources of information  
956 can be used to establish a good range of stages such as remote sensing. In our case limiting the analysis to  
957 a single event at its peak can be restricting, however, integrating multiple events may enhance the model's  
958 robustness. Crowdsourced data are only fit for local enhancement of the HAND-SRC due to their spatial  
959 limitations. Nonetheless, the reliability of the model for a range of discharge values can be enhanced by  
960 adjusting the model parameters at each reach until SRCs match the ARCs of a hydraulic model.

961 The key advantage of using crowdsourced points is that they provide flood depth and extent estimates  
962 with minimal acquisition costs, at fine scales, and in urban environments. Yet, this can only be taken  
963 advantage of using a DEM with high resolution and accuracy. Integrating the crowdsourced flood depths

964 in calibrating the hydraulic HEC RAS model achieved a low RMSE (34 cm) illustrating the reliability of  
965 the dataset and its utility in the absence of other forms of observed data. In the future, crowdsourced data  
966 are expected to increasingly complement other forms of observed or remotely sensed data and in data  
967 assimilation in flood forecast models.

### 968 **5.3. DEM resolution requirement in low-reliefs**

969 Low-relief areas are highly prone to floods due to their inherent topographic characteristics. We tested a  
970 set of DEMs using HAND-SRC resampled using the bilinear interpolation method. This method was  
971 chosen because it preserves the smoothness of the DEM (Haile & Rientjes, 2005). The tests showed that  
972 only a 25 cm or a 1 m resolution DEMs can capture both flood depths and extents satisfactorily. The rest  
973 of the of coarser resolutions (3 m and above) all showed significant errors in water surface elevation,  
974 flood extents or flood depths in channel or floodplain. These errors can be attributed to several factors.  
975 First, the resampling of the DEM disrupts the terrain convergence leading to the formation of areas that  
976 do not drain into the river channel. This change arising from resampling usually follows no systematic  
977 trend (Wu et al., 2008). Second, the change in the drainage patterns results in the filling of the DEM  
978 leading to increased errors in the DEM and SRCs. Lastly, the reduction in DEM vertical accuracy is  
979 caused by the coarsening effect of the DEM. The first two factors are mostly present in low-relief terrain  
980 where resampling does not maintain the flow direction grid or drainage paths. The last factor consists of  
981 coarsening errors and errors from the interpolation method which are usually less significant (Muthusamy  
982 et al., 2021).

983 Several papers have demonstrated that varying the spatial resolution through resampling has a higher  
984 influence on flood depth predictions rather than the extent (Leskens et al., 2014; Saksena & Merwade,  
985 2015; Savage et al., 2016) in hydraulic modelling approaches. In our case, HAND-SRC as a terrain-based  
986 model showed a random pattern that influenced both the flood extents and depths in flat areas. However,  
987 a more comprehensive understanding of the DEM resolution impacts on HAND-SRC requires a broader  
988 assessment that includes other topographic settings.

989 Upscaled DEMs from higher resolution DEMs with high vertical accuracy can retain a high accuracy  
990 compared to global DEMs (Prakash Mohanty et al., 2020). Therefore, global DEMs may not be reliable  
991 for detailed assessment in low-relief sensitive terrains. Whereas, resampled DEMs from high resolution  
992 must be used with caution unless it conforms to two factors. (1) The resolution should allow the detection  
993 of the natural drainage pattern in the floodplains to achieve terrain convergence. (2) It should maintain  
994 enough topographic representation and accuracy in the DEM elevations for precise hydraulic geometry  
995 extraction. While an improvement in the performance of resampled DEMs is possible through additional  
996 hydro-conditioning, the approaches used in this study do not apply to all tested resolutions and are outside  
997 the scope of the study.

## 998 **6. Conclusion**

999 The purpose of this paper is to study the applicability of the low-complexity terrain-based HAND-SRC  
1000 model for flood mapping in a low-relief terrain with developed rural floodplains comprising channels,  
1001 ditches and levees. Due to the increasing demand for real time operational forecasting, testing adapted  
1002 approaches that provide efficient, rapid and accurate flood maps has become necessary. An application of  
1003 the HAND-SRC model using a complete geometric representation at a high resolution was presented. The  
1004 study further assessed the effective topographic representation required for HAND-SRC modelling in flat  
1005 areas through hydro-conditioning and upscaling DEM resolutions. The implementation was conducted in  
1006 the floodplains of the Ostouane catchment in Northern Lebanon. An intensive field investigation was  
1007 conducted to acquire a high-resolution DEM (25 cm), the bathymetry and a set of crowdsourced data on a  
1008 past flood event. Two sources of model validation were utilized: HEC RAS flood maps and crowdsourced

1009 data that consist of positive/negative flood occurrences and flood depths from a past event. While the first  
1010 provided a more comprehensive assessment of flood mapping, the latter scrutinized the accuracy of  
1011 prediction at detailed locations.

1012 Due to the sensitivity of flat terrains and the complexity of detailed floodplain features at high resolutions,  
1013 an adapted hydro-conditioning approach was introduced to restructure the terrain in preparation for  
1014 HAND raster and SRC calculations. This is also to adhere to the model assumptions and retain the DEM  
1015 accuracy. Overall, the terrain setups with the highest level of hydro-conditioning (S2 and S3) showed  
1016 reasonable prediction performance in capturing crowdsourced flood occurrences ( $CSI_p$  of 0.64 and 0.79  
1017 respectively), crowdsourced flood depths (RMSE of 0.7 and 0.54 m respectively) and HEC RAS extents  
1018 ( $CSI_A$  of 0.66 and 0.59 respectively). Both setups incorporated drainage enforcement in the bathymetry  
1019 and floodplain, levee removal, and bathymetric integration. These processes all served the goal of  
1020 achieving drainage continuity and terrain convergence between the floodplain and the channel.  
1021 Furthermore, adopting a theoretical bathymetry based on hydraulic geometry power law (S3) produced  
1022 similar predictions compared to the bathymetry interpolated from surveyed cross-sections (S2).  
1023 Therefore, a simplified representation of the terrain can still be effective for bathymetry representation.

1024 In addition to the representation of terrain features, the scalability of the hydro-conditioned terrain was  
1025 evaluated using resampled DEMs. Tested resolutions showed a variable performance mainly driven by  
1026 the effective topographic structure and properties of the DEM at the different scales. The highest  
1027 resolutions (25 cm and 1m) performed better in replicating correct flood extents and depths compared to  
1028 coarser resolutions where effective channel and floodplain features become dissolved. This leads to the  
1029 loss of drainage continuity and the alteration of terrain convergence in the DEM. Generally, coarser  
1030 terrains either resampled or from global DEMs should be used with caution due to their inherent structure  
1031 that does not necessarily conform to the model assumptions in flat terrains. Nonetheless, the utilization of  
1032 the sub-meter DEM resolution can be highly significant. This is demonstrated by permitting the detection  
1033 of the natural drainage through the detection of natural and artificial terrain features. The vertical  
1034 accuracy and fine resolution were both essential in avoiding the perfectly flat surface terrain problem that  
1035 is commonly found in coarser resolutions. Additionally, it permitted accurately identifying crowdsourced  
1036 locations and depths with high precision in the DEM. It is worth noting that the use of crowdsourced data  
1037 allows evaluating the model's ability to capture detailed locations but introduces significant uncertainty  
1038 and requires placing high credibility in eyewitness accounts. Despite that, such data may be the sole  
1039 source of model validation in ungauged areas. An adequate density has shown to be necessary for  
1040 validating the dataset itself without the need to introduce external inputs. The spatial bias of such data  
1041 however, renders it complementary for modelling validation.

1042 Our results also show that using the hydraulic model's aggregated rating curves (ARCs) instead of  
1043 synthetic ones (SRCs) demonstrated that the hydro-conditioned terrain can replicate the extents of HEC  
1044 RAS. Generalizing this finding however, require a more comprehensive review of SRC accuracy for all  
1045 discharge ranges. Nonetheless, the implemented approach required increasing Manning's roughness  
1046 coefficient to capture crowdsourced points levels. The fixed assumptions of this parameter can be a  
1047 limitation of the model but our analysis showed that it can still be locally optimized based on  
1048 crowdsourced observations.

1049 In conclusion, the HAND-SRC terrain-based model as a continental and regional scale flood mapping  
1050 approach was found to still be relevant at local scales and in flat terrains. Adopting a high-resolution  
1051 hydro-conditioned terrain that maintains terrain convergence and drainage continuity, can provide good  
1052 performance in a challenging low-relief topography. This can be achieved in a simple straightforward  
1053 fashion compared to hydraulic models that require a more intensive preparation process. The model can  
1054 be superior in terms of preparation effort and computational time. HAND-SRC cannot be relied on for  
1055 highly accurate cell by cell estimations of flood depth especially in terrains with anthropogenic features.

1056 However, as a rapid flood mapping model it is capable of providing reasonable satisfactory information  
 1057 on extent and depth. We thus suggest that the model can be beneficial for enhanced rapid identification of  
 1058 flood risk areas and for ensemble-based flood forecast mapping.

### 1059 **Acknowledgement**

1060 This research is conducted within a PhD thesis of the first author funded by a bourse from the National  
 1061 Council for Scientific Research in Lebanon (CNRS-L) and the University of Montpellier (UM). The work  
 1062 was conducted in cooperation between the national early warning system platform (NEWSP) in Lebanon,  
 1063 HydroSciences Montpellier (HSM) laboratory, and the laboratory for the study of Soil-Agrosystem-  
 1064 Hydrosystem interactions (LISAH).

### 1065 **Data statement**

1066 Data will be made available on request.

### 1067 **CRedit authorship contribution statement**

1068 **Hassan Sabeh:** Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing -  
 1069 Review & Editing. **Chadi Abdallah:** Supervision, Writing - Review & Editing, Funding acquisition,  
 1070 Project administration. **Nanée Chahinian:** Supervision, Writing - Review & Editing. **Marie-George**  
 1071 **Tournoud:** Supervision, Writing - Review & Editing. **Rouya Hdeib:** Supervision, Writing - Review &  
 1072 Editing. **Roger Moussa:** Conceptualization, Supervision, Writing - Review & Editing

### 1073 **Declaration of competing interest**

1074 The authors declare that they have no known competing financial interests or personal relationships that  
 1075 could have appeared to influence the work reported in this paper.

### 1076 **Supplementary material**

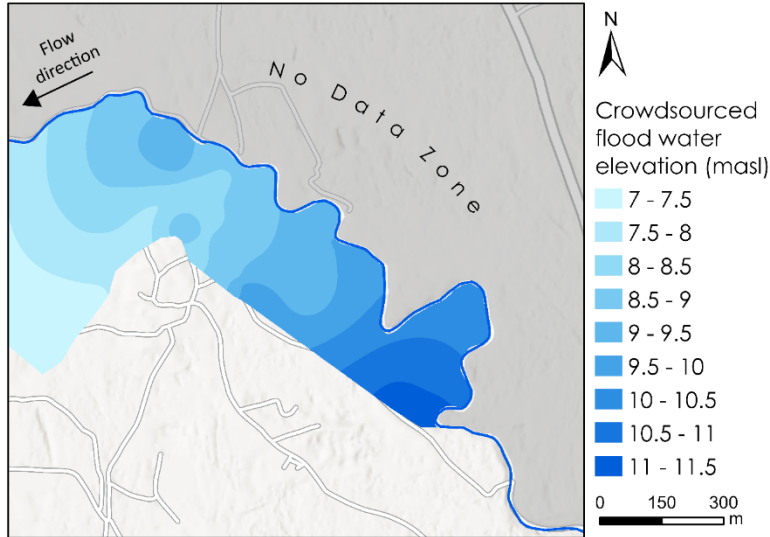
1077 Table A1. List of abbreviations

Abbreviations	Definition
ARC	Aggregated Rating Curve from HEC RAS model
CSI <sub>A</sub>	Critical Success Index used to compare with flood areal extent
CSI <sub>P</sub>	Critical Success Index used to compare with crowdsourced points flood occurrences
DEM	Digital Elevation Model
h	Height threshold used for flood mapping in HAND-SRC



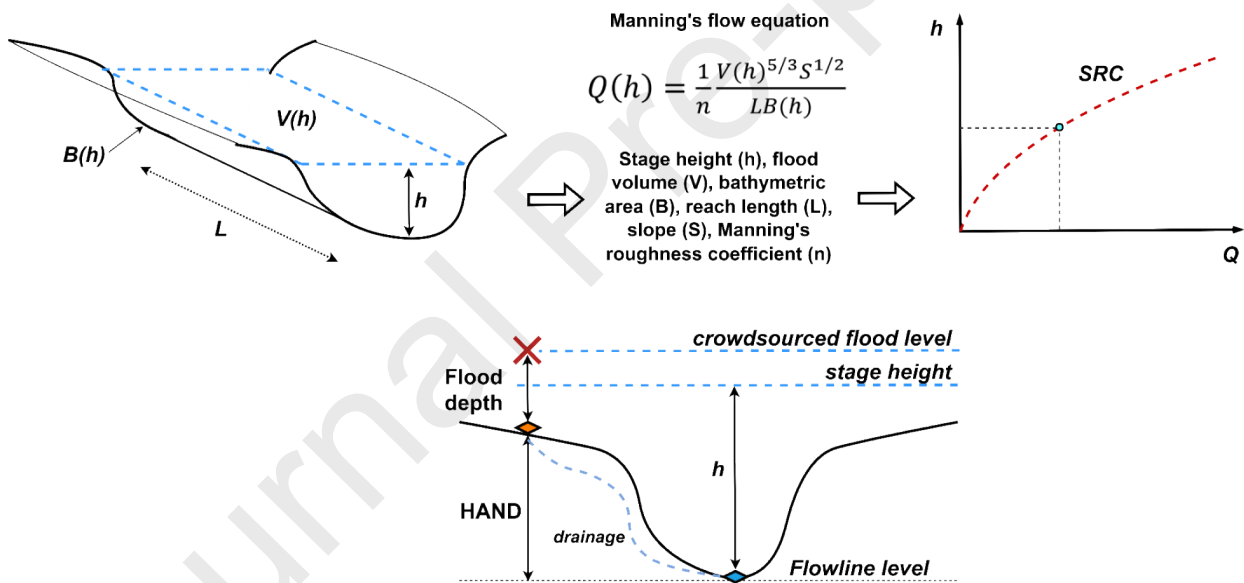
HAND	Height Above Nearest Drainage index
HAND-SRC	Flood mapping model based on utilizing HAND index and SRC
HEC RAS	Hydrologic Engineering Center's River Analysis System
HRDEM	High resolution digital elevation model
L	River reach length
$MCC_A$	Mathew's Correlation Coefficient used to compare with flood area
$MCC_P$	Mathew's Correlation Coefficient used to compare with crowdsourced points
n	Manning's roughness coefficient
$Q_p$	Peak flow estimated at Pont Halba (G1) station for 2019 flood event
RMSE	Root Mean Square Error
$RMSE_{DEM}$	Root Mean Square Error of DEM vertical accuracy
$RMSE_{FD-CS}$	Root Mean Square Error in simulated flood depth compared to crowdsourced flood depths
$RMSE_{SRC}$	Root Mean Square Error in synthetic rating curve
$RMSE_{SWE-CS}$	Root Mean Square Error in simulated SWE compared to crowdsourced flood SWE
SRC	Synthetic Rating Curve
SWE	Surface Water Elevation

---



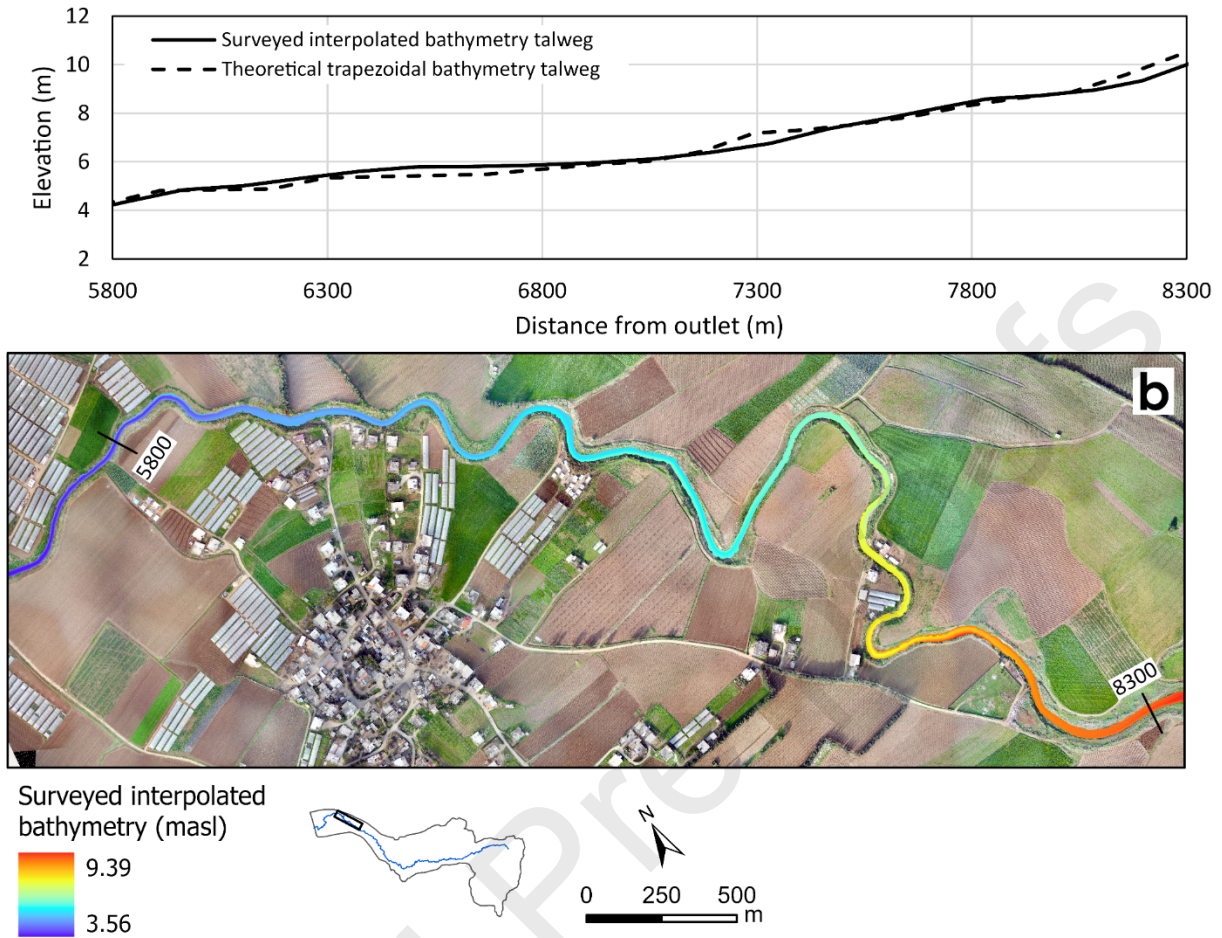
1079

1080 Figure SM1: Delineated flood map using crowdsourced flood depths, flood extent points and non-flooded  
 1081 point locations



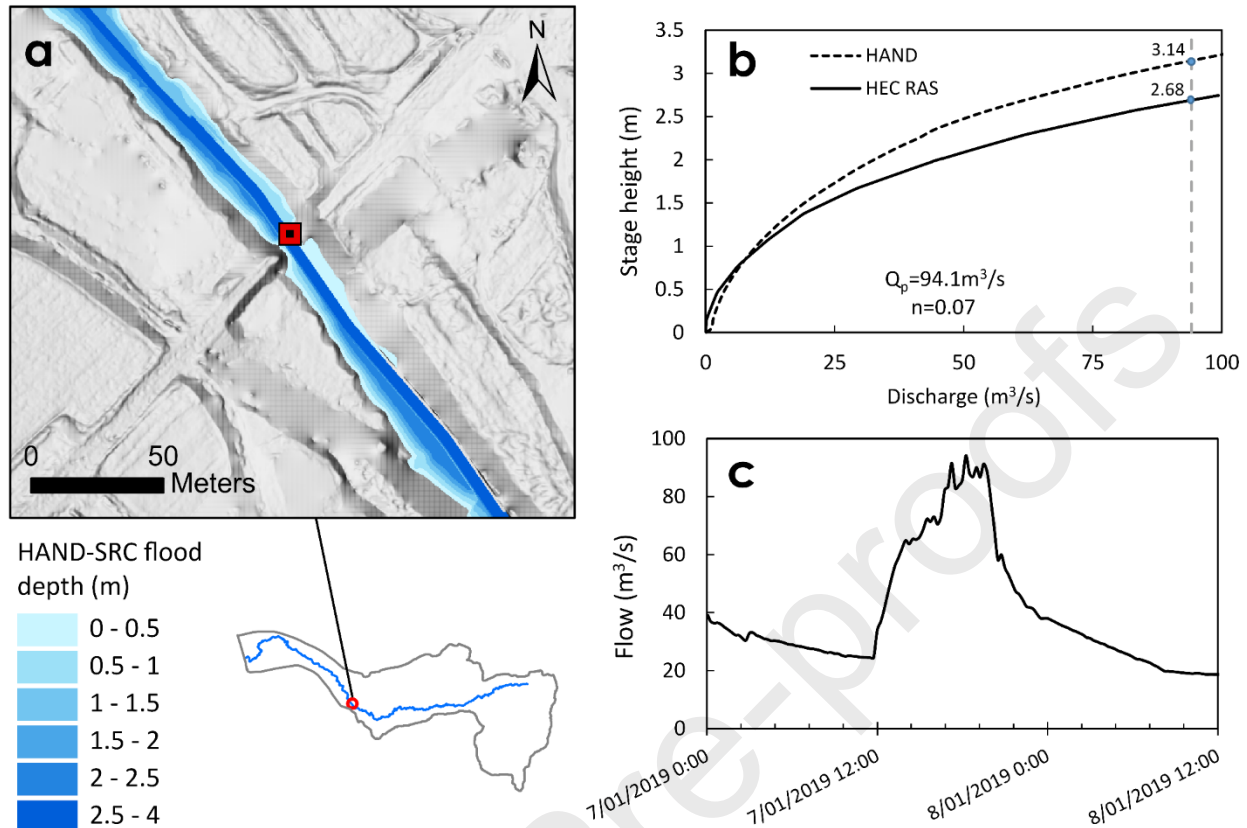
1082

1083 Figure SM2: Illustration of HAND-SRC conceptual model. The HAND raster is filled to a variable stage  
 1084 height  $h$  then the hydraulic geometries are extracted. Manning's flow equation is used to estimate the  
 1085 discharge and plot a synthetic rating curve for a Manning's roughness coefficient



1086

1087 Figure SM3: (a) Talweg elevation in the interpolated surveyed bathymetry and the theoretical trapezoidal  
 1088 geometry between stations 5300 and 8300 m measured from the river outlet, and (b) bathymetry zone and  
 1089 elevation across the test site



1090

1091 Figure SM4: The January 2019 flood event: (a) HAND-SRC flood depth at Pont Halba gauge station  
 1092 during peak flow; (b) Comparison between SRC and rating curve at the gauge; and (c) flow hydrograph  
 1093 during the event calculated based on the theoretical rating curve

#### 1094 References

- 1095 Abdallah, C., Hdeib, R., Al Sabeh, H., & Khatib, H. (2023). *FLOOD RISK ASSESSMENT FOR*  
 1096 *LEBANON "ROFAKA2 AL NAHER PROJECT"* (p. 128P). CNRS-L.
- 1097 Afshari, S., Tavakoly, A. A., Rajib, M. A., Zheng, X., Follum, M. L., Omranian, E., & Fekete, B. M.  
 1098 (2018). Comparison of new generation low-complexity flood inundation mapping tools with a  
 1099 hydrodynamic model. *Journal of Hydrology*, *556*, 539–556.  
 1100 <https://doi.org/10.1016/j.jhydrol.2017.11.036>
- 1101 Annis, A., Nardi, F., Morrison, R. R., & Castelli, F. (2019). Investigating hydrogeomorphic floodplain  
 1102 mapping performance with varying DTM resolution and stream order. *Hydrological Sciences*  
 1103 *Journal*, *64*(5), 525–538. <https://doi.org/10.1080/02626667.2019.1591623>
- 1104 Aristizabal, F., Chegini, T., Petrochenkov, G., Salas, F., & Judge, J. (2024). Effects of high-quality  
 1105 elevation data and explanatory variables on the accuracy of flood inundation mapping via Height  
 1106 Above Nearest Drainage. *Hydrology and Earth System Sciences*, *28*(6), 1287–1315.  
 1107 <https://doi.org/10.5194/hess-28-1287-2024>
- 1108 Aristizabal, F., Salas, F., Petrochenkov, G., Grout, T., Avant, B., Bates, B., Spies, R., Chadwick, N.,  
 1109 Wills, Z., & Judge, J. (2023). Extending Height Above Nearest Drainage to Model Multiple

- 1110 Fluvial Sources in Flood Inundation Mapping Applications for the U.S. National Water Model.  
1111 *Water Resources Research*, 59(5), e2022WR032039. <https://doi.org/10.1029/2022WR032039>
- 1112 Assumpção, T. H., Popescu, I., Jonoski, A., & Solomatine, D. P. (2018). Citizen observations  
1113 contributing to flood modelling: Opportunities and challenges. *Hydrology and Earth System*  
1114 *Sciences*, 22(2), 1473–1489. <https://doi.org/10.5194/hess-22-1473-2018>
- 1115 Bernhofen, M. V., Whyman, C., Trigg, M. A., Sleigh, P. A., Smith, A. M., Sampson, C. C., Yamazaki,  
1116 D., Ward, P. J., Rudari, R., Pappenberger, F., Dottori, F., Salamon, P., & Winsemius, H. C.  
1117 (2018). A first collective validation of global fluvial flood models for major floods in Nigeria and  
1118 Mozambique. *Environmental Research Letters*, 13(10), 104007. <https://doi.org/10.1088/1748-9326/aae014>  
1119
- 1120 Beven, K. J., & Kirkby, M. J. (1979). A physically based, variable contributing area model of basin  
1121 hydrology / Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin  
1122 versant. *Hydrological Sciences Bulletin*, 24(1), 43–69.  
1123 <https://doi.org/10.1080/02626667909491834>
- 1124 Buytaert, W., Zulkafli, Z., Grainger, S., Acosta, L., Alemie, T. C., Bastiaensen, J., De BiÃ"vre, B.,  
1125 Bhusal, J., Clark, J., Dewulf, A., Foggin, M., Hannah, D. M., Hergarten, C., Isaeva, A.,  
1126 Karpouzoglou, T., Pandeya, B., Paudel, D., Sharma, K., Steenhuis, T., ... Zhumanova, M. (2014).  
1127 Citizen science in hydrology and water resources: Opportunities for knowledge generation,  
1128 ecosystem service management, and sustainable development. *Frontiers in Earth Science*, 2.  
1129 <https://doi.org/10.3389/feart.2014.00026>
- 1130 CRED. (2022). *CRED - 2022—2021 Disasters in Numbers*. OECD. [https://www.oecd-](https://www.oecd-ilibrary.org/economics/inflation-cpi/indicator/english_eee82e6e-en)  
1131 [ilibrary.org/economics/inflation-cpi/indicator/english\\_eee82e6e-en](https://www.oecd-ilibrary.org/economics/inflation-cpi/indicator/english_eee82e6e-en)
- 1132 Darwish, T., Khawlie, M., Jomaa, M., Abou Daher, M., Awad, M., Masri, M., Shaban, A., Faour, G., Bou  
1133 Kheir, R., Abdallah, C., & Haddad, T. (2006). *Digital Soil Map of Lebanon 1/50,000. Monograph*  
1134 *Series 4. CNRS Lebanon*.
- 1135 Dasgupta, A., Grimaldi, S., Ramsankaran, R., Pauwels, V. R. N., & Walker, J. P. (2022). A simple  
1136 framework for calibrating hydraulic flood inundation models using Crowd-sourced water levels.  
1137 *Journal of Hydrology*, 614, 128467. <https://doi.org/10.1016/j.jhydrol.2022.128467>
- 1138 Deiana, C., Deidda, R., & Viola, F. (2023). Geomorphic floodplain mapping in small Mediterranean  
1139 catchments using LiDAR data. *Advances in Water Resources*, 178, 104493.  
1140 <https://doi.org/10.1016/j.advwatres.2023.104493>
- 1141 Dhote, P. R., Joshi, Y., Rajib, A., Thakur, P. K., Nikam, B. R., & Aggarwal, S. P. (2023). Evaluating  
1142 topography-based approaches for fast floodplain mapping in data-scarce complex-terrain regions:  
1143 Findings from a Himalayan basin. *Journal of Hydrology*, 620, 129309.  
1144 <https://doi.org/10.1016/j.jhydrol.2023.129309>
- 1145 Diehl, R. M., Gourevitch, J. D., Drago, S., & Wemple, B. C. (2021). Improving flood hazard datasets  
1146 using a low-complexity, probabilistic floodplain mapping approach. *PLOS ONE*, 16(3),  
1147 e0248683. <https://doi.org/10.1371/journal.pone.0248683>
- 1148 Dubertret, L. (1945). *Cartes géologiques du Liban à l'échelle de 1/50000*. [Dataset].



- 1149 Fleischmann, A., Paiva, R., & Collischonn, W. (2019). Can regional to continental river hydrodynamic  
1150 models be locally relevant? A cross-scale comparison. *Journal of Hydrology X*, 3, 100027.  
1151 <https://doi.org/10.1016/j.hydroa.2019.100027>
- 1152 Garousi-Nejad, I., Tarboton, D. G., Aboutalebi, M., & Torres-Rua, A. F. (2019). Terrain Analysis  
1153 Enhancements to the Height Above Nearest Drainage Flood Inundation Mapping Method. *Water  
1154 Resources Research*, 55(10), 7983–8009. <https://doi.org/10.1029/2019WR024837>
- 1155 Ghanghas, A., Dey, S., & Merwade, V. (2022). Evaluating the reliability of synthetic rating curves for  
1156 continental scale flood mapping. *Journal of Hydrology*, 606, 127470.  
1157 <https://doi.org/10.1016/j.jhydrol.2022.127470>
- 1158 Gharari, S., Hrachowitz, M., Fenicia, F., & Savenije, H. H. G. (2011). Hydrological landscape  
1159 classification: Investigating the performance of HAND based landscape classifications in a  
1160 central European meso-scale catchment. *Hydrology and Earth System Sciences*, 15(11), 3275–  
1161 3291. <https://doi.org/10.5194/hess-15-3275-2011>
- 1162 Gitundu, D. T., Gathenya, J. M., Raude, J. M., Sang, J., & Ngugi, H. N. (2023). Hydraulic analysis of  
1163 flash flood events using UAV based topographic data and citizen science in Enkare Narok river  
1164 basin. *Remote Sensing Applications: Society and Environment*, 30, 100977.  
1165 <https://doi.org/10.1016/j.rsase.2023.100977>
- 1166 Godbout, L., Zheng, J. Y., Dey, S., Eyselade, D., Maidment, D., & Passalacqua, P. (2019). Error  
1167 Assessment for Height Above the Nearest Drainage Inundation Mapping. *JAWRA Journal of the  
1168 American Water Resources Association*, 55(4), 952–963. [https://doi.org/10.1111/1752-  
1169 1688.12783](https://doi.org/10.1111/1752-1688.12783)
- 1170 Gordon, C. A., Foulon, E., & Rousseau, A. N. (2023). Deriving synthetic rating curves from a digital  
1171 elevation model to delineate the inundated areas of small watersheds. *Journal of Hydrology:  
1172 Regional Studies*, 50, 101580. <https://doi.org/10.1016/j.ejrh.2023.101580>
- 1173 Greenwood, W. W., Lynch, J. P., & Zekkos, D. (2019). Applications of UAVs in Civil Infrastructure.  
1174 *Journal of Infrastructure Systems*, 25(2), 04019002. [https://doi.org/10.1061/\(ASCE\)IS.1943-  
1175 555X.0000464](https://doi.org/10.1061/(ASCE)IS.1943-555X.0000464)
- 1176 Grimaldi, S., Petroselli, A., Arcangeletti, E., & Nardi, F. (2013). Flood mapping in ungauged basins using  
1177 fully continuous hydrologic–hydraulic modeling. *Journal of Hydrology*, 487, 39–47.  
1178 <https://doi.org/10.1016/j.jhydrol.2013.02.023>
- 1179 Haile, A. T., & Rientjes, T. H. M. (2005). *EFFECTS OF LIDAR DEM RESOLUTION IN FLOOD  
1180 MODELLING: A MODEL SENSITIVITY STUDY FOR THE CITY OF TEGUCIGALPA,  
1181 HONDURAS.*
- 1182 Hamdani, N., & Baali, A. (2019). Height Above Nearest Drainage (HAND) model coupled with  
1183 lineament mapping for delineating groundwater potential areas (GPA). *Groundwater for  
1184 Sustainable Development*, 9, 100256. <https://doi.org/10.1016/j.gsd.2019.100256>
- 1185 Hellweger, F. (1997). *AGREE-DEM surface reconditioning system.*
- 1186 Hocini, N., Payrastre, O., Bourgin, F., Gaume, E., Davy, P., Lague, D., Poinson, L., & Pons, F. (2020).  
1187 *Performance of automated flood inundation mapping methods in a context of flash floods: A*

- 1188 *comparison of three methods based either on the Height Above Nearest Drainage (HAND)*  
 1189 *concept, or on 1D/2D shallow water equations* [Preprint]. *Catchment hydrology/Modelling*  
 1190 *approaches*. <https://doi.org/10.5194/hess-2020-597>
- 1191 Jafarzadegan, K., Moradkhani, H., Pappenberger, F., Mofitakhari, H., Bates, P., Abbaszadeh, P., Marsooli,  
 1192 R., Ferreira, C., Cloke, H. L., Ogden, F., & Duan, Q. (2023). Recent Advances and New Frontiers  
 1193 in Riverine and Coastal Flood Modeling. *Reviews of Geophysics*, *61*(2), e2022RG000788.  
 1194 <https://doi.org/10.1029/2022RG000788>
- 1195 Jafarzadegan, K., Muñoz, D. F., Mofitakhari, H., Gutenson, J. L., Savant, G., & Moradkhani, H. (2022).  
 1196 Real-time coastal flood hazard assessment using DEM-based hydrogeomorphic classifiers.  
 1197 *Natural Hazards and Earth System Sciences*, *22*(4), 1419–1435. [https://doi.org/10.5194/nhess-22-](https://doi.org/10.5194/nhess-22-1419-2022)  
 1198 [1419-2022](https://doi.org/10.5194/nhess-22-1419-2022)
- 1199 Johnson, J. M., Munasinghe, D., Eyalade, D., & Cohen, S. (2019). An integrated evaluation of the  
 1200 National Water Model (NWM)–Height Above Nearest Drainage (HAND) flood mapping  
 1201 methodology. *Natural Hazards and Earth System Sciences*, *19*(11), 2405–2420.  
 1202 <https://doi.org/10.5194/nhess-19-2405-2019>
- 1203 Koenig, T., Bruce, J., O'Connor, J., McGee, B., Holmes, R., Hollins, R., Forbes, B., Kohn, M.,  
 1204 Schellekens, M., Martin, Z., & Peppler, M. (2016). Identifying and preserving high-water mark  
 1205 data. *U.S. Geological Survey, No. A-324*. <https://doi.org/10.3133/tm3A24>
- 1206 Lacy, J. W., & Stark, C. E. L. (2013). The neuroscience of memory: Implications for the courtroom.  
 1207 *Nature Reviews Neuroscience*, *14*(9), 649–658. <https://doi.org/10.1038/nrn3563>
- 1208 Leskens, J. G., Brugnach, M., Hoekstra, A. Y., & Schuurmans, W. (2014). Why are decisions in flood  
 1209 disaster management so poorly supported by information from flood models? *Environmental*  
 1210 *Modelling & Software*, *53*, 53–61. <https://doi.org/10.1016/j.envsoft.2013.11.003>
- 1211 Lhomme, J., Sayers, P., Gouldby, B., & Wils, M. (2008, October). *Recent development and application of*  
 1212 *a rapid flood spreading method*. [https://doi.org/DOI: 10.1201/9780203883020.ch2](https://doi.org/DOI:10.1201/9780203883020.ch2)
- 1213 Li, Z., Duque, F. Q., Grout, T., Bates, B., & Demir, I. (2023). Comparative analysis of performance and  
 1214 mechanisms of flood inundation map generation using Height Above Nearest Drainage.  
 1215 *Environmental Modelling & Software*, *159*, 105565.  
 1216 <https://doi.org/10.1016/j.envsoft.2022.105565>
- 1217 Lindsay, J. B. (2016). Whitebox GAT: A case study in geomorphometric analysis. *Computers &*  
 1218 *Geosciences*, *95*, 75–84. <https://doi.org/10.1016/j.cageo.2016.07.003>
- 1219 Lioi, B., Gioia, A., Totaro, V., Balacco, G., Iacobellis, V., & Chiaia, G. (2020). Coupled Use of  
 1220 Hydrologic-Hydraulic Model and Geomorphological Descriptors for Flood-Prone Areas  
 1221 Evaluation: A Case Study of Lama Lamasinata. In O. Gervasi, B. Murgante, S. Misra, C. Garau,  
 1222 I. Blečić, D. Taniar, B. O. Apduhan, A. M. A. C. Rocha, E. Tarantino, C. M. Torre, & Y. Karaca  
 1223 (Eds.), *Computational Science and Its Applications – ICCSA 2020* (Vol. 12252, pp. 607–619).  
 1224 Springer International Publishing. [https://doi.org/10.1007/978-3-030-58811-3\\_44](https://doi.org/10.1007/978-3-030-58811-3_44)
- 1225 Liu, Y. Y., Maidment, D. R., Tarboton, D. G., Zheng, X., & Wang, S. (2018). A CyberGIS Integration  
 1226 and Computation Framework for High-Resolution Continental-Scale Flood Inundation Mapping.

- 1227 *JAWRA Journal of the American Water Resources Association*, 54(4), 770–784.  
1228 <https://doi.org/10.1111/1752-1688.12660>
- 1229 Malgwi, M. B., Ramirez, J. A., Zischg, A., Zimmermann, M., Schürmann, S., & Keiler, M. (2021). A  
1230 method to reconstruct flood scenarios using field interviews and hydrodynamic modelling:  
1231 Application to the 2017 Suleja and Tafa, Nigeria flood. *Natural Hazards*, 108(2), 1781–1805.  
1232 <https://doi.org/10.1007/s11069-021-04756-z>
- 1233 Manfreda, S., Di Leo, M., & Sole, A. (2011). Detection of Flood-Prone Areas Using Digital Elevation  
1234 Models. *Journal of Hydrologic Engineering*, 16(10), 781–790.  
1235 [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000367](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000367)
- 1236 Manfreda, S., Nardi, F., Samela, C., Grimaldi, S., Taramasso, A. C., Roth, G., & Sole, A. (2014).  
1237 Investigation on the use of geomorphic approaches for the delineation of flood prone areas.  
1238 *Journal of Hydrology*, 517, 863–876. <https://doi.org/10.1016/j.jhydrol.2014.06.009>
- 1239 Mazzoleni, M., Verlaan, M., Alfonso, L., Monego, M., Norbiato, D., Ferri, M., & Solomatine, D. P.  
1240 (2017). Can assimilation of crowdsourced data in hydrological modelling improve flood  
1241 prediction? *Hydrology and Earth System Sciences*, 21(2), 839–861. [https://doi.org/10.5194/hess-](https://doi.org/10.5194/hess-21-839-2017)  
1242 [21-839-2017](https://doi.org/10.5194/hess-21-839-2017)
- 1243 McGrath, H., Bourgon, J.-F., Proulx-Bourque, J.-S., Nastev, M., & Abo El Ezz, A. (2018). A comparison  
1244 of simplified conceptual models for rapid web-based flood inundation mapping. *Natural Hazards*,  
1245 93(2), 905–920. <https://doi.org/10.1007/s11069-018-3331-y>
- 1246 Merwade, V., Cook, A., & Coonrod, J. (2008). GIS techniques for creating river terrain models for  
1247 hydrodynamic modeling and flood inundation mapping. *Environmental Modelling & Software*,  
1248 23(10–11), 1300–1311. <https://doi.org/10.1016/j.envsoft.2008.03.005>
- 1249 Mudashiru, R. B., Sabtu, N., Abustan, I., & Balogun, W. (2021). Flood hazard mapping methods: A  
1250 review. *Journal of Hydrology*, 603, 126846. <https://doi.org/10.1016/j.jhydrol.2021.126846>
- 1251 Muthusamy, M., Casado, M. R., Butler, D., & Leinster, P. (2021). Understanding the effects of Digital  
1252 Elevation Model resolution in urban fluvial flood modelling. *Journal of Hydrology*, 596, 126088.  
1253 <https://doi.org/10.1016/j.jhydrol.2021.126088>
- 1254 Nardi, F., Cudennec, C., Abrate, T., Allouch, C., Annis, A., Assumpção, T., Aubert, A. H., Bérod, D.,  
1255 Braccini, A. M., Buytaert, W., Dasgupta, A., Hannah, D. M., Mazzoleni, M., Polo, M. J., Sæbø,  
1256 Ø., Seibert, J., Tauro, F., Teichert, F., Teutonico, R., ... Grimaldi, S. (2022). Citizens AND  
1257 HYdrology (CANDHY): Conceptualizing a transdisciplinary framework for citizen science  
1258 addressing hydrological challenges. *Hydrological Sciences Journal*, 67(16), 2534–2551.  
1259 <https://doi.org/10.1080/02626667.2020.1849707>
- 1260 Nardi, F., Vivoni, E. R., & Grimaldi, S. (2006). Investigating a floodplain scaling relation using a  
1261 hydrogeomorphic delineation method. *Water Resources Research*, 42(9), 2005WR004155.  
1262 <https://doi.org/10.1029/2005WR004155>
- 1263 Notti, D., Giordan, D., Caló, F., Pepe, A., Zucca, F., & Galve, J. (2018). Potential and Limitations of  
1264 Open Satellite Data for Flood Mapping. *Remote Sensing*, 10(11), 1673.  
1265 <https://doi.org/10.3390/rs10111673>

- 1266 Passalacqua, P., Belmont, P., & Foufoula-Georgiou, E. (2012). Automatic geomorphic feature extraction  
 1267 from lidar in flat and engineered landscapes. *Water Resources Research*, 48(3), 2011WR010958.  
 1268 <https://doi.org/10.1029/2011WR010958>
- 1269 Passalacqua, P., Do Trung, T., Fofoula-Georgiou, E., Sapiro, G., & Dietrich, W. E. (2010). A geometric  
 1270 framework for channel network extraction from lidar: Nonlinear diffusion and geodesic paths.  
 1271 *Journal of Geophysical Research: Earth Surface*, 115(F1), 2009JF001254.  
 1272 <https://doi.org/10.1029/2009JF001254>
- 1273 Paul, J. D., Buytaert, W., Allen, S., Ballesteros-Cánovas, J. A., Bhusal, J., Cieslik, K., Clark, J., Dugar, S.,  
 1274 Hannah, D. M., Stoffel, M., Dewulf, A., Dhital, M. R., Liu, W., Nayaval, J. L., Neupane, B.,  
 1275 Schiller, A., Smith, P. J., & Supper, R. (2018). Citizen science for hydrological risk reduction and  
 1276 resilience building. *WIREs Water*, 5(1), e1262. <https://doi.org/10.1002/wat2.1262>
- 1277 Prakash Mohanty, M., Nithya, S., Nair, A. S., Indu, J., Ghosh, S., Mohan Bhatt, C., Srinivasa Rao, G., &  
 1278 Karmakar, S. (2020). Sensitivity of various topographic data in flood management: Implications  
 1279 on inundation mapping over large data-scarce regions. *Journal of Hydrology*, 590, 125523.  
 1280 <https://doi.org/10.1016/j.jhydrol.2020.125523>
- 1281 Rebolho, C., Andréassian, V., & Le Moine, N. (2018). Inundation mapping based on reach-scale effective  
 1282 geometry. *Hydrology and Earth System Sciences*, 22(11), 5967–5985.  
 1283 <https://doi.org/10.5194/hess-22-5967-2018>
- 1284 Rennó, C. D., Nobre, A. D., Cuartas, L. A., Soares, J. V., Hodnett, M. G., Tomasella, J., & Waterloo, M.  
 1285 J. (2008). HAND, a new terrain descriptor using SRTM-DEM: Mapping terra-firme rainforest  
 1286 environments in Amazonia. *Remote Sensing of Environment*, 112(9), 3469–3481.  
 1287 <https://doi.org/10.1016/j.rse.2008.03.018>
- 1288 Rentschler, J., & Salhab, M. (2020). *People in Harm's Way: Flood Exposure and Poverty in 189*  
 1289 *Countries*. The World Bank. <https://doi.org/10.1596/1813-9450-9447>
- 1290 Rodda, H. J. E. (2005). The Development and Application of a Flood Risk Model for the Czech Republic.  
 1291 *Natural Hazards*, 36(1–2), 207–220. <https://doi.org/10.1007/s11069-004-4549-4>
- 1292 Saksena, S., & Merwade, V. (2015). Incorporating the effect of DEM resolution and accuracy for  
 1293 improved flood inundation mapping. *Journal of Hydrology*, 530, 180–194.  
 1294 <https://doi.org/10.1016/j.jhydrol.2015.09.069>
- 1295 Samela, C., Troy, T. J., & Manfreda, S. (2017). Geomorphic classifiers for flood-prone areas delineation  
 1296 for data-scarce environments. *Advances in Water Resources*, 102, 13–28.  
 1297 <https://doi.org/10.1016/j.advwatres.2017.01.007>
- 1298 Sangireddy, H., Stark, C. P., Kladzyk, A., & Passalacqua, P. (2016). GeoNet: An open source software  
 1299 for the automatic and objective extraction of channel heads, channel network, and channel  
 1300 morphology from high resolution topography data. *Environmental Modelling & Software*, 83, 58–  
 1301 73. <https://doi.org/10.1016/j.envsoft.2016.04.026>
- 1302 Saunders, W. (1999). Preparation of DEMs for Use in Environmental Modeling Analysis. *In: ESRI User*  
 1303 *Conference*, pp. 24-30.

- 1304 Savage, J. T. S., Pianosi, F., Bates, P., Freer, J., & Wagener, T. (2016). Quantifying the importance of  
 1305 spatial resolution and other factors through global sensitivity analysis of a flood inundation  
 1306 model. *Water Resources Research*, 52(11), 9146–9163. <https://doi.org/10.1002/2015WR018198>
- 1307 Schietti, J., Emilio, T., Rennó, C. D., Drucker, D. P., Costa, F. R. C., Nogueira, A., Baccaro, F. B.,  
 1308 Figueiredo, F., Castilho, C. V., Kinupp, V., Guillaumet, J.-L., Garcia, A. R. M., Lima, A. P., &  
 1309 Magnusson, W. E. (2014). Vertical distance from drainage drives floristic composition changes in  
 1310 an Amazonian rainforest. *Plant Ecology & Diversity*, 7(1–2), 241–253.  
 1311 <https://doi.org/10.1080/17550874.2013.783642>
- 1312 Schumann, G. J.-P., Neal, J. C., Voisin, N., Andreadis, K. M., Pappenberger, F., Phanthuwongpakdee, N.,  
 1313 Hall, A. C., & Bates, P. D. (2013). A first large-scale flood inundation forecasting model: Large-  
 1314 Scale Flood Inundation Forecasting. *Water Resources Research*, 49(10), 6248–6257.  
 1315 <https://doi.org/10.1002/wrcr.20521>
- 1316 Siebert, S., & Teizer, J. (2014). Mobile 3D mapping for surveying earthwork projects using an Unmanned  
 1317 Aerial Vehicle (UAV) system. *Automation in Construction*, 41, 1–14.  
 1318 <https://doi.org/10.1016/j.autcon.2014.01.004>
- 1319 Songchon, C., Wright, G., & Beevers, L. (2023). The use of crowdsourced social media data to improve  
 1320 flood forecasting. *Journal of Hydrology*, 622, 129703.  
 1321 <https://doi.org/10.1016/j.jhydrol.2023.129703>
- 1322 Sy, B., Frischknecht, C., Dao, H., Consuegra, D., & Giuliani, G. (2019). Flood hazard assessment and the  
 1323 role of citizen science. *Journal of Flood Risk Management*, 12(S2), e12519.  
 1324 <https://doi.org/10.1111/jfr3.12519>
- 1325 Sy, B., Frischknecht, C., Dao, H., Consuegra, D., & Giuliani, G. (2020). Reconstituting past flood events:  
 1326 The contribution of citizen science. *Hydrology and Earth System Sciences*, 24(1), 61–74.  
 1327 <https://doi.org/10.5194/hess-24-61-2020>
- 1328 Tamminga, A. D., Eaton, B. C., & Hugenholtz, C. H. (2015). UAS-based remote sensing of fluvial  
 1329 change following an extreme flood event. *Earth Surface Processes and Landforms*, 40(11), 1464–  
 1330 1476. <https://doi.org/10.1002/esp.3728>
- 1331 Tarboton, D. G. (2024). Terrain Analysis Using Digital Elevation Models (TauDEM). *Utah Water  
 1332 Research Laboratory, Utah State University*. <https://hydrology.usu.edu/taudem/taudem5/>
- 1333 Teng, J., Jakeman, A. J., Vaze, J., Croke, B. F. W., Dutta, D., & Kim, S. (2017). Flood inundation  
 1334 modelling: A review of methods, recent advances and uncertainty analysis. *Environmental  
 1335 Modelling & Software*, 90, 201–216. <https://doi.org/10.1016/j.envsoft.2017.01.006>
- 1336 Teng, J., Vaze, J., Kim, S., Dutta, D., Jakeman, A. J., & Croke, B. F. W. (2019). Enhancing the Capability  
 1337 of a Simple, Computationally Efficient, Conceptual Flood Inundation Model in Hydrologically  
 1338 Complex Terrain. *Water Resources Management*, 33(2), 831–845.  
 1339 <https://doi.org/10.1007/s11269-018-2146-7>
- 1340 United States Department of Agriculture (USDA). (2012). *Part 630 Hydrology National Engineering  
 1341 Handbook Chapter 14: Stage Discharge Relations*.  
 1342 <https://directives.sc.egov.usda.gov/OpenNonWebContent.aspx?content=31844.wba>



- 1343 USACE. (2020). HEC-RAS River Analysis System Hydraulic Reference Manual version 6.0.  
1344 *Hydrological Engineering Center. US Army Corps of Engineers.*
- 1345 Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. (2012). ‘Structure-  
1346 from-Motion’ photogrammetry: A low-cost, effective tool for geoscience applications.  
1347 *Geomorphology*, 179, 300–314. <https://doi.org/10.1016/j.geomorph.2012.08.021>
- 1348 Wing, O. E. J., Bates, P. D., Neal, J. C., Sampson, C. C., Smith, A. M., Quinn, N., Shustikova, I.,  
1349 Domeneghetti, A., Gilles, D. W., Goska, R., & Krajewski, W. F. (2019a). A New Automated  
1350 Method for Improved Flood Defense Representation in Large-Scale Hydraulic Models. *Water*  
1351 *Resources Research*, 55(12), 11007–11034. <https://doi.org/10.1029/2019WR025957>
- 1352 Wing, O. E. J., Sampson, C. C., Bates, P. D., Quinn, N., Smith, A. M., & Neal, J. C. (2019b). A flood  
1353 inundation forecast of Hurricane Harvey using a continental-scale 2D hydrodynamic model.  
1354 *Journal of Hydrology X*, 4, 100039. <https://doi.org/10.1016/j.hydroa.2019.100039>
- 1355 Woodrow, K., Lindsay, J. B., & Berg, A. A. (2016). Evaluating DEM conditioning techniques, elevation  
1356 source data, and grid resolution for field-scale hydrological parameter extraction. *Journal of*  
1357 *Hydrology*, 540, 1022–1029. <https://doi.org/10.1016/j.jhydrol.2016.07.018>
- 1358 Wu, S., Li, J., & Huang, G. H. (2008). A study on DEM-derived primary topographic attributes for  
1359 hydrologic applications: Sensitivity to elevation data resolution. *Applied Geography*, 28(3), 210–  
1360 223. <https://doi.org/10.1016/j.apgeog.2008.02.006>
- 1361 Yamazaki, D., Ikeshima, D., Sosa, J., Bates, P. D., Allen, G. H., & Pavelsky, T. (2019). MERIT Hydro: A  
1362 High-Resolution Global Hydrography Map Based on Latest Topography Dataset. *Water*  
1363 *Resources Research*, 55(6). <https://doi.org/doi.org/10.1029/2019WR024873>
- 1364 Zheng, X., D’Angelo, C., Maidment, D. R., & Passalacqua, P. (2022). Application of a Large-Scale  
1365 Terrain-Analysis-Based Flood Mapping System to Hurricane Harvey. *JAWRA Journal of the*  
1366 *American Water Resources Association*, 58(2), 149–163. [https://doi.org/10.1111/1752-](https://doi.org/10.1111/1752-1688.12987)  
1367 [1688.12987](https://doi.org/10.1111/1752-1688.12987)
- 1368 Zheng, X., Liu, Y. Y., & Passalacqua, P. (2018a). GeoFlood: Large-Scale Flood Inundation Mapping  
1369 Based on High-Resolution Terrain Analysis. *Water Resources Research*, 54(12).  
1370 <https://doi.org/10.1029/2018WR023457>
- 1371 Zheng, X., Tarboton, D. G., Maidment, D. R., Liu, Y. Y., & Passalacqua, P. (2018b). River Channel  
1372 Geometry and Rating Curve Estimation Using Height above the Nearest Drainage. *JAWRA*  
1373 *Journal of the American Water Resources Association*, 54(4), 785–806.  
1374 <https://doi.org/10.1111/1752-1688.12661>

1375

1376 **Highlights:**

- 1377 • HAND-SRC applied in low-relief terrain with anthropogenic features in North Lebanon
- 1378 • Adapted hydro-conditioning necessary for HAND-SRC to replicate HEC-RAS flood extents
- 1379 • Crowdsourced depths are well captured by HAND-SRC (CSI = 0.64 and RMSE = 54 cm)

- 1380 • Integrated power-law bathymetry can reproduce flood maps of surveyed bathymetry
- 1381 • High DEM resolution  $\leq 1$  m maintains terrain convergence for HAND-SRC accuracy

1382

1383

## Evaluating Terrain-Based HAND-SRC Flood Mapping Model in Low-Relief Rural

1384

1385

1386

1387

1388

1389

1390

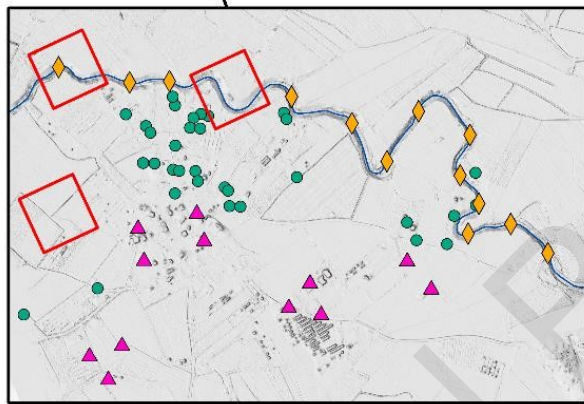
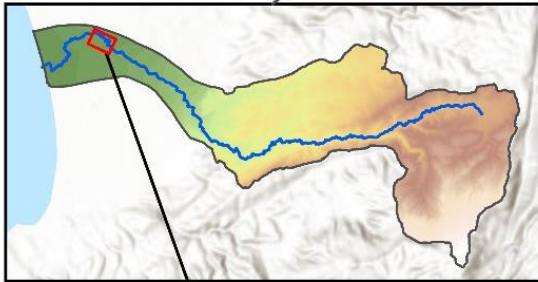
1391

1392

1393

1394 **Objective:** what is the effective representation of terrain for  
1395 HAND-SRC flood mapping in a low-relief terrain?

1396 **Study Area & Data      Methodology Effect of terrain**  
1397 **hydro-conditioning      DEM Resolution effect**



- ▲ Nonflooded point
- Flood depth point
- ◆ Cross-section

- Drone photogrammetry:  
25-cm DEM

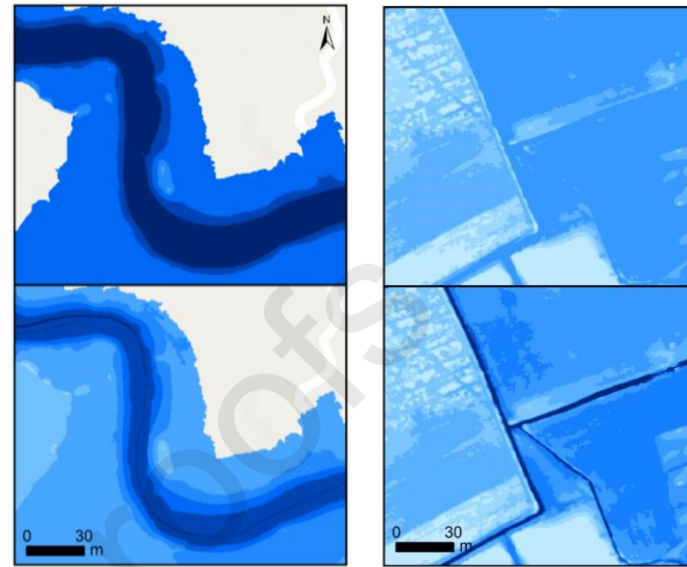
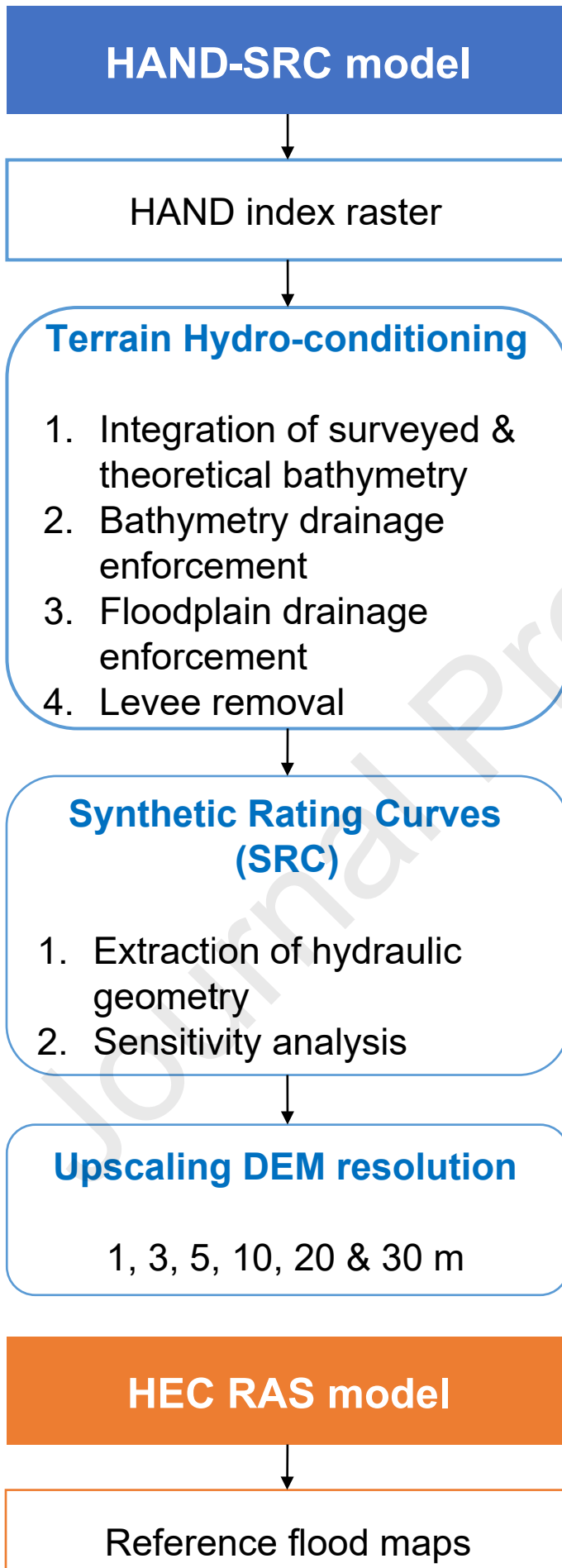
- Cross-sections

- Crowdsourcing of 2019  
flood event

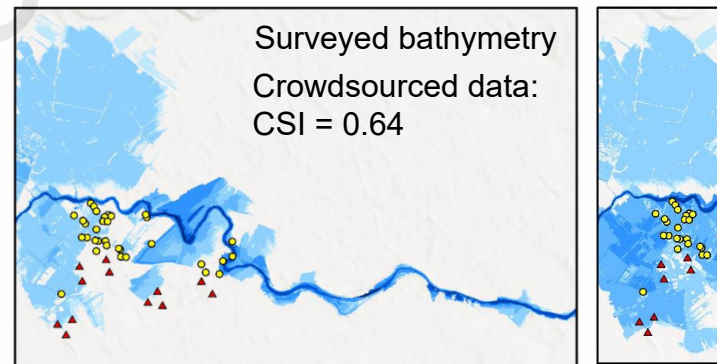
- Gauged water level

- Land use/cover

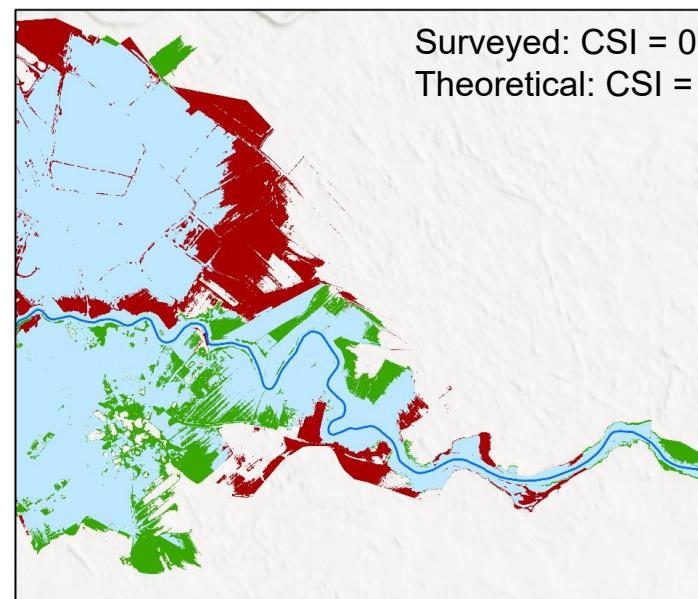
Journal Pre-proofs



### Effect of bathymetry



### Flood extent comparison





Journal Pre-proofs