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2 High-resolution interactive global flood forecast for past, 3 present, and future

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9 *Abstract*

10 Globally operating modelling approaches for flood dynamics have shown significant increases in usage, quality
11 and availability in recent years. Flood modelling at global scale stretches the computational demand, due to
12 combinations of spatial scale and resolution, limiting to static pre-computed maps and prohibiting interactivity.
13 Particular high-resolution global models are only available as static information layers, whereas dynamic models
14 operate at lower resolution to address operational shortcomings. In this article, a novel system is described that
15 links a state-of-the-art efficient flood modelling core with an automated global parameterization scheme based on
16 global, bias-corrected and space-based datasets. This combined approach delivers a first-generation, zero
17 configuration flood modelling system capable of producing high-resolution, interactive flood maps. It supports a
18 highly efficient global early warning system for both flash and fluvial floods and enables the generation of historic
19 flood map time series for any location worldwide. The utilized event-based simulation approach has some
20 limitations in applicability to continuous modelling, the system shows major speed increases at near-identical
21 accuracy with global availability.

22 Keywords: flood, climate, hazard, risk

23 *Highlights*

- 24 - Real-time global flood map forecasts for flash and fluvial floods at high resolution.
- 25 - Global out-of-the-box interactive flood hazard maps.
- 26 - An additional 10x speed improvement for larger areas over the previous FastFlood model.

27

28 Introduction

29 Flood modelling can be a time-consuming exercise, requiring vast computational resources and significant
30 expertise on the various interplays between data quality, detail, and the numerical solutions deployed within a
31 particular model. High-applicability flood modelling approaches have emerged in the past decade to provide
32 enriched information layers for various types of applications (e.g. trend analysis, historic baselines, climate
33 analysis, efficient large-scale hazard and risk mapping, portfolio risk management).

34 Despite the availability of powerful flood-hazard mapping products like JBA's high-resolution flood
35 maps (Bradbrook, 2006), CAMAFlood (Yamazaki et al., 2018), Fathom (Bates et al., 2018), the Copernicus-based
36 Global Surface Water Explorer (Pekel et al., 2016), DFO Flood Observatory (Kettner et al., 2021), GLOFAS
37 (Harrigan et al., 2020), and Google's Global Flood Mode (Nearing et al., 2025), these systems typically generate
38 static flood hazard layers or daily-subdaily inundation maps for predefined scenarios. These outputs, while widely
39 used across applications such as trend analysis, historical baselines, climate assessments, large-scale risk mapping,
40 and portfolio risk management, are not designed as interactive or adjustable simulation platforms. Due to the
41 complexity of their modeling pipelines and the substantial computation required, live parameter tuning or scenario
42 editing in real time is generally not feasible. As a result, these systems excel at producing ready-to-use hazard
43 maps but rarely support on-the-fly adjustment of inputs or real-time exploration by non-expert users (Alfieri et al.,
44 2013; Cohen et al., 2024; Google Research, 2024).

45 ~~These models are used widely, as a means of creating flood maps, but predominantly through their primary output~~
46 ~~products; flood hazard maps or daily maps. These are static layers generated once for various scenarios, or at a~~
47 ~~daily or sub-daily timestep, and have been used in wide ranges of application. However, due to their complicated~~
48 ~~systems and sometimes large computational requirements, they do not provide a practically adjustable or~~
49 ~~interactive simulation tool.~~

50 The steady improvements in the past decades in this field have been largely supported by a consistent effort to
51 enrich Earth Observation datasets (space-based) and other global datasets to produce consistent global data layers
52 of physically-based variables. These layers are useful for the parameterization of physically-based models. Key
53 datasets include elevation data, which gained a massive boost with the release of Copernicus30, and the various
54 refinements on this (Ho et al., 2025), as well as numerous national high-quality datasets. Similarly, land cover,
55 soil, and water levels are now mapped from space more frequently and in more detail than ever before (e.g.
56 SoilGRIDS v2, Poggio et al., 2021; and WorldCover 10m, Venter et al., 2022), allowing for higher quality
57 modelling setups anywhere in the world.

58 Besides these improvements, a global parameterization scheme remains lacking. Using these global and EO
59 datasets often remains a labor-intensive undertaking requiring particular expertise on the interplay between the
60 model and the data quality and limitations. Few models (e.g. LisFlood, SFINCS, LISEM) incorporate these
61 datasets as automatically available options, and all require code setups, installation and some configuration. The
62 common need to provide local higher-quality datasets could play a big role here, although some tools provide the
63 global data as a supplementary or default layer, with an option to use custom datasets through a common format.

64 Additionally, some of the parameterization required for a versatile flood modelling system requires datasets not
65 yet produced; in particular, event-based simulation often makes use of design storms or IDF curves. While these
66 inputs can be a tool for localized analysis of precipitation-driven floods, their application to larger areas encounters
67 fundamental issues with the assumptions underlying the design storm analysis (e.g. homogeneous applicability of
68 point statistics to larger areas). Area reduction factors can be used to scale design events, but no globally covering,
69 consistent dataset exists, and implications in their usage for hydrological modelling are far-reaching. Even lowered
70 homogeneous intensities cannot be used in physically-based infiltration models due to their nonlinearity. Localized
71 variability within events dominates real-world infiltration signals. Another solution, like IDF-curve Extensions,
72 has been suggested based on Intensity-Frequency-Duration-Space-curves (IDFS curves), but a global analysis for
73 such statistics is required to effectively apply and use them on a wider scale (Nabukulu et al., 2025).

74 Finally, existing systems nearly completely lack true interactivity, meaning that user-provided changes through
75 simple input, preferably made without requiring GIS manipulation of data or particular expertise with other

76 software, are not possible. Some systems support these types of changes to scenarios by the user, but the flood
77 modelling methods underlying it are not fast enough to support true interactivity on larger scales, even with vast
78 compute resources.

79 True low-code and no-code solutions would allow for a completely new type of application of flood models, and
80 bring the capacity to implement and test adaptation and mitigation, at the building level or otherwise, to serve
81 completely new sectors.

82 *Problem Statement*

83 Flood modelling systems that provide high-applicability flood maps have advanced in recent decades, but a system
84 with rapid, interactive (one that rapidly provides new output based on selected alternative scenarios), zero
85 configuration automated global parameterization (without requiring extensive setup and modelling expertise),
86 global coverage (with pre-processed data for model setup and scenarios) and high resolution (at global scale using
87 20, 10 or smaller grid cell sizes) does not exist. Several key components are currently missing to facilitate such a
88 system, among which are

- 89 - Global model parameterization supporting past, present, and future scenarios
- 90 - Automated boundary condition placements and model setup
- 91 - Space-appropriate design precipitation and snowmelt scenarios
- 92 - Rapid flood model core that allows for interactive changes by users

93 *Objective*

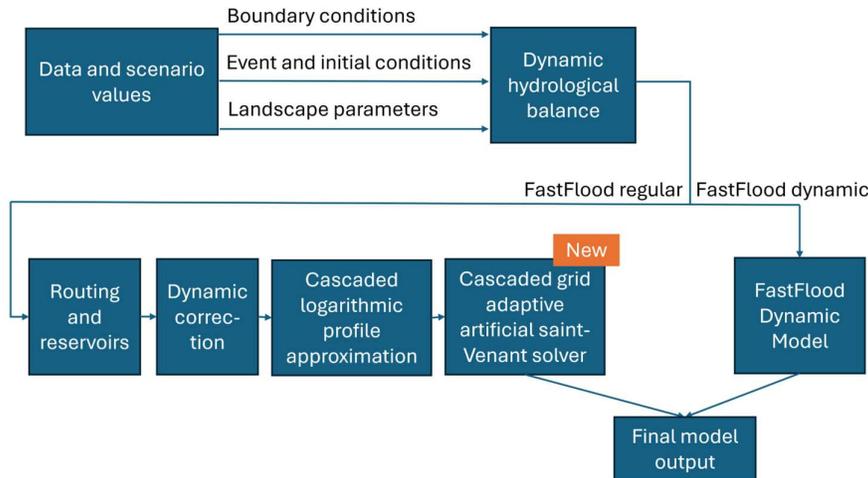
94 In this paper, we introduce and describe the workings of the FastFlood Global system, a novel zero-configuration,
95 global, high-resolution flood model for past, present, and future forecasts. Next, we give a short description of the
96 flood model at the core of the system, which can utilize either the FastFlood rapid time-implicit model or a more
97 traditional saint-venant solver. Additionally, an overview is provided of the various types of events that can be
98 simulated, and how these are then parameterized for historic, present and future periods. The last section describes
99 several case studies of the system, for both past, present and future application of the model, as well as comparative
100 analysis with observations and other modelling systems.

101 The focus of this article is expressly not on the technical details underlying the various data preprocessing and
102 simulation steps, as other works will be cited to expand in more detail on those (see also Bout et al., 2024). Here
103 we are presenting the general system as something that we believe to be a crucial development direction that will
104 allow a new type of usage for flood models.

105 *Methods*

106 *FastFlood Global System Schematic*

107 A schematic overview of the FastFlood global system is provided in Figure 1. This system, itself contained within
108 a single executable code, hosted as an API to provide geotiff output to user requests. The data parameterization
109 and boundary conditions are provided, by default, based on a collection of numerous pre-processed global datasets.
110 Then, the FastFlood model can be used to simulate the actual flow processes, which will return the final output
111 layers.

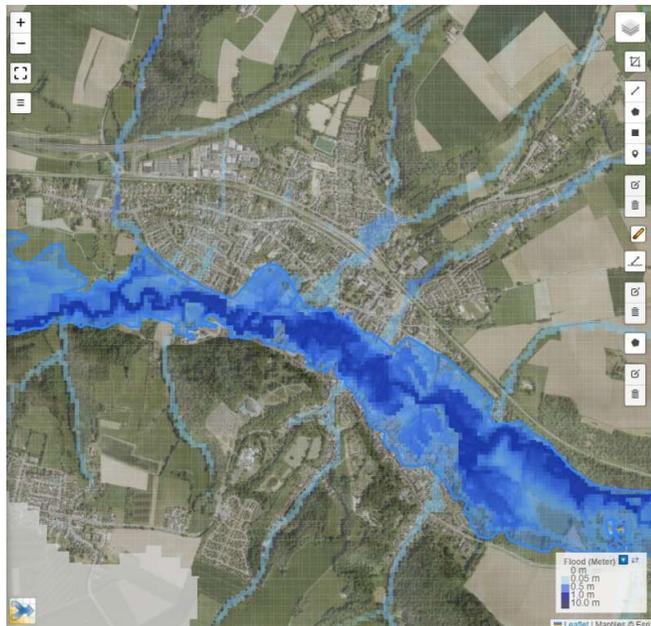


112

113 *Figure 1 FastFlood Global system schematic*
 114 *view.*

115 **FastFlood Model**

116 The core of the system is the time-implicit
 117 FastFlood model, a recent innovation in flood
 118 modelling approaches. At its core, it by-passes
 119 explicit time-stepping in regular solutions to
 120 flood dynamics by solving immediately for
 121 peak-of-intensity during the event. This
 122 leverages an adapted physically-based solver
 123 that allows for super-fast simulation of flood
 124 hazard maps. It achieves a speed increase of
 125 over 20 thousand times on average compared to
 126 a traditional flood model (see Appendix A,
 127 including the changes presented in this methods
 128 section). This speed increase derives
 129 predominantly from the manner in which the
 130 model directly computes the peak flood depths,
 131 peak velocities, and durations. As a trade-off in
 132 not carrying out explicit time-stepping, some
 133 limitations are present in the case of temporal
 134 dynamics that deviate from real solutions, in
 135 particular for events with dominant wave dynamics.



136 *Figure 2 FastFlood.org model applied to the floods in the Geul river,*
 137 *South-Netherlands, 2021*

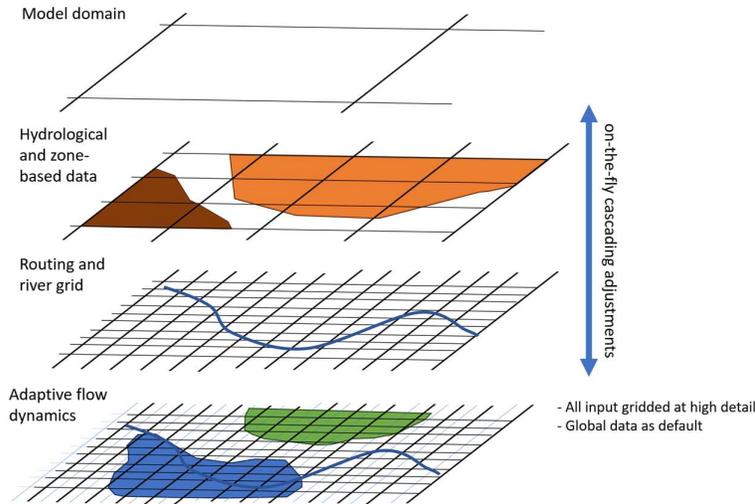
136 Several aspects of the model have been adjusted, with a focus on combined accuracy and efficiency. Each of these
 137 will be further detailed in the sections below.

- 138 - Process-dependent grid adjustment
- 139 - A cascaded grid for the final artificial Saint-Venant solver

140 *Cascaded-grid adaptive artificial Saint-Venant solver*

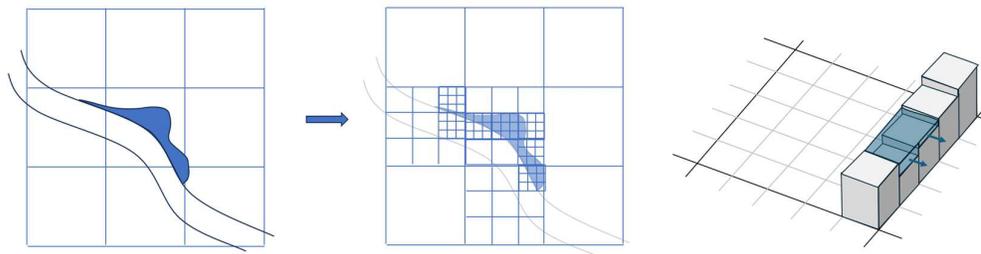
141 The first adaptation to the FastFlood model is the usage of process-dependent grids. Input layers, while provided
 142 at high resolutions to make parameterization uniform and consistent, are reprocessed to lower resolutions on-the-
 143 fly. These lower-resolution grids are then used to solve processes that do not require the full resolution demanded
 144 by the final flow dynamics solver. Currently, hydrological and zone-based processes (soil zones, for example) are
 145 calculated at the lowest resolution, a factor 9 lower, and river routing and reservoir calculations are carried out at

146 a factor 3 lower resolution. The factors 3 and 9 are used here as a consequence of the factor-3 scaling and
 147 interpolation that is used. For most required variables, averaging is carried out as an interpolation operation, but
 148 particular variables involved in non-linear processes can not be averaged, as it would alter the effective outcomes
 149 of the model¹. Then, instead, averaging of later variables is used, which are linear with respect to the model output,
 150 or alternatively, the process is maintained at high resolution instead.



151
 152 *Figure 3 Grid adjustments for various processes as used by FastFlood*

153 The final step of the FastFlood model is an artificial adaptation of the Saint-Venant. This step is carried out after
 154 the initial floodplain water distribution by means of the logarithmically cascaded profile approximations. This
 155 solver, for which details can be found in earlier work, has been adapted to function on an adaptive cascading
 156 grid.



157
 158 *Figure 4 Adaptive nootree grid refinement scheme (left) and the need for estimation of partial flow through*
 159 *boundaries at the edge of a group of grid cells (right)*

160 The final artificial Saint-Venant solution is carried out on an adaptive grid, before finally being refined for the
 161 full domain to full resolution as to provide full output file resolution and consistent file formatting.

¹ The elevation data is re-interpolated for river routing using a particular geometric consideration. Two effects can be important here, as the flow routing needs to follow channels with lower elevation values, but using minimum interpolation might remove obstacles from the data, while maximum interpolation might remove the actual flow paths. We take out of each 3x3 gridcell group that 3rd value, which is based on a geometric consideration. Any consistent high elevation feature that blocks water flow, must either have 2 pixels within the 3x3 cell group, and requires to be blocked, or alternatively, the feature will instead have 2 pixels with higher elevation in the neighboring 3x3 cell groups, and the water or routing will instead be blocked there.

162 Landscape parameters

163 *Elevation and DTM Filtering*

164 Our elevation dataset is a reprocessed version of Copernicus30, with a custom DTM filter that removes
165 buildings and vegetation

166 We implement a new DTM filter particularly meant to remove buildings and vegetation from the elevation models,
167 as these can effectively prevent water flow through urban and forested areas, and cause erroneous artefacts to
168 develop in the final flood maps. These kind of data filters are known as DTM filters, which have been applied
169 widely in various forms, in particular for the application of flow modelling (Hawker et al., 2022, Pronk et al.,
170 2024). The approach shown here provides a novel implementation based on the sweeping algorithmic structure as
171 deployed by FastFlood for hydrological correction of terrain. The sweeping algorithms, with simple but well-
172 chosen update rules, can often provide useful processing steps with minimal compute requirements.

173 Here, two sweeping algorithms are developed, first, an isolated obstacle sweep filter. Here, sweeps move into the
174 grid and update according to the rule (applied separately for each cardinal direction in the grid):

$$175 \quad z_{i+1} = \max(z_{i-1} + \min(0, z_i - z_{i-1}), z_{i+1} + \min(0, z - z_{i+1}))$$

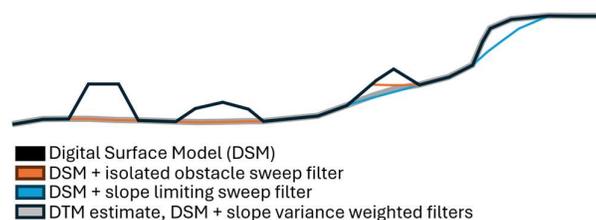
176 Secondly, a slope limiting sweep filter is implemented, with an update rule define as

$$177 \quad z_{i+1} = \min(z_i + \min(S_{max}, (1.0 - w_{i+1})(z_{i+1} - z_i)), z_{i+1})$$

178 Both filtering algorithms are combined with a weighted value based on a more typical slope-based object detection.
179 Considering the abrupt changes in elevation caused by vegetation or buildings due to, often vertical, gradients
180 along their edges, the variance of the slopes relative to the regional slopes are used to create a weighting factor for
181 the filters.

$$182 \quad w = \min\left(1.0, c_1 \frac{WindowVariance(DEM - WindowAverage(DEM, s_1))}{WindowAverage(Slope(DEM), s_1)}\right)$$

183 Final height adjustments, during the algorithms, are limited to estimates of maximum viable building and
184 vegetation height from the Global Building Height dataset (JRC) and the global canopy height raster data
185 (NASA) to provide some guidance in terrain where isolated features are part of the landscape, but no buildings
186 or vegetation is present.



187

188 *Figure 5 DTM filter as deployed through FastFlood*

189 Example output of the filter is provided in appendix B.

190 Landscape parameterization

191 **LandCover**

192 Land cover information is provided through classified Sentinel-2 data, in particular the Copernicus WorldCover
193 10m dataset. Each class is linked with Manning's surface roughness value based on literature values. The
194 presence of vegetation, supplemented with global forest cover and canopy height data, are in addition used to
195 estimate leaf area index for interception estimations during the hydrological component of the model.

196 **Precipitation**

197 We use ERA5- Land, the fifth-generation global reanalysis from ECMWF, offering hourly global estimates of

198 atmospheric and land-surface variables on ~10 km grid from 1940 to near real-time (Muñoz-Sabater et al., 2021;
199 ECMWF, 2017). GPM IMERG provides blended multi-satellite precipitation retrievals at 0.1° (~10 km)
200 resolution every 30 minutes, including early, late and final runs calibrated against ground observations (Huffman
201 et al., 2019; Zhou et al., 2023). This is used as the basis for the analysis of the spatial component of the rainfall
202 statistics. ERA5 furthermore delivers surface temperature, humidity, soil moisture and radiation forcing.

203 **Climate**

204 The climate scenarios are based on a General-Extreme-Value analysis of the CMIP6 NASA downscaled climate
205 model ensemble (Thrasher et al., n.d.). A total of 20 models were used to carry out segmented-window GEV
206 analysis, obtaining ratios between extreme precipitation of each return period for each time period (current,
207 2030, 2045, 2060, 2075, 2090, 2100). Based on these ratios, current period design events are adjusted using the
208 bicubically interpolated relative changes most closely related to the actual return period and duration of the
209 design event.

210 **Soil and infiltration**

211 We integrate SoilGrids v2.0, a global machine-learning soil mapping system at 250 m resolution, predicting
212 properties like texture, organic carbon, density, pH and depth to bedrock, based on >230 000 soil profiles and
213 environmental covariates (Hengl et al., 2017; ISRIC, 2017). Based on these soil characteristics, pedotransfer
214 (Saxton et al., 2006) functions are utilized to predict soil physical parameters. SMAP provides spaceborne
215 L-band microwave retrievals of near-surface soil moisture. Together, these inform soil infiltration parameters
216 and initial moisture state in subsurface and hydrological modeling.

217 **Rivers and hydraulic structures**

218 River discharge and hydraulic routing are informed using GLOFAS, the global flood forecasting system run by
219 Copernicus Emergency Management Service and ECMWF, providing ensemble streamflow forecasts at ~0.05°
220 resolution and flood hazard maps (Alfieri et al., 2013; ECMWF/Copernicus, 2022). GRDC datasets supply
221 in-situ river discharge observations utilized for bias-corrected of the GLOFAS re-analysis datasets. Global
222 Surface Water Explorer (GSWE) and Global Flood Database layers supply historical flood extents. These are
223 used to calibrate and validate hydraulic and flood-routing components of the model.
224 Global riverine shapes are derived from combined Hydrobasins and Global River Mask From Landsat data. The
225 OpenStreetMaps database is sampled for the location of culverts, and automatically placed in the local drainage
226 grid.

227 **Stormwater drainage capacity**

228 For many areas around the world, protection against flood impact is in place. This can take many forms, but
229 commonly feature either levee systems or urban stormwater drainage systems. Both are estimated here using the
230 FLOPROS global protection level database, as well as the urban regions derived from OSM data as well as
231 WorldCover 10m built-up classification. A stormwater drainage system is added to the setup for urban regions,
232 with a capacity that equals the design event of the protection level specified in FLOPROS. In a similar approach,
233 the width and depth of rivers are adjusted to implement the influence of levee systems in regions with a high
234 protection level. The empirical power laws linking drainage area to river depth for each region of the globe are
235 rescaled according to the protection level, with an empirical scaling derived from a subset of river depth samples
236 under various protection levels.

237 **Buildings**

238 Building and roads are used to influence infiltration processes, as well as flow, through surface roughness, and
239 provide exposure output. Both elements are obtained through the OpenStreetMaps dataset, in vectorized format.
240 For modelling input, these are first rasterized before infiltration capacity of the regular soil is reduced to zero,
241 and only stormwater drainage capacity is left for urban areas.

242

243

244 **Overview**

Domain	Dataset(s)	EO Sources / Usage	Satellite platforms
meteorological	ERA5, GPM IMERG	ERA5 for atmospheric/land surface forcing; IMERG for precipitation inputs	GPM sensors, satellites via ERA5 assimilation
Sub-surface and soil	SoilGrids, SMAP	SoilGrids for soil physical properties; SMAP for soil moisture state	SMAP soil moisture; SoilGrids based on in situ
Rivers & hydraulic structures	GLOFAS, GRDC, GSWE, Global Flood DB	GLOFAS for ensemble streamflow forecasts; GRDC for calibration; GSWE/flood DB for historical inundation, OpenStreetMaps data for culverts and local drainage routes	ERA5-forced GLOFAS; satellite imagery underlying GSWE
Surface and cover	Copernicus DEM (GLO-30, EEA-10), national DEMs , World cover	DEM data for elevation/surface slope; flood layers and Worldcover used to derive surface roughness	TanDEM-X derived Copernicus DEM; World cover based on Sentinel-1 and 2
Buildings and roads	Sentinel-2 imagery plus canopy/building height,	Sentinel-2 for mapping impervious urban infrastructure; ancillary EO for 3D modeling and hydraulic routing	Sentinel-2 (and optionally Sentinel-1 SAR fused)
Urban stormwater capacity & protection	FLOPROS	FLOPROS, river width, reservoir capacity, lake altimetry and IMERG precipitation feed urban drainage models	FLOPROS global database

245

246 *Table 1 Overview of utilized datasets to carry out parameterization of the FastFlood model*247 **Event scenarios**248 *Multi-scale design storms for precipitation and snowmelt*

249 Design events, when selected by the user, are derived from global re-analysis data (ERA5- Land). To address
 250 the generalized application of design events, either for precipitation or snowmelt, we introduced the usage of
 251 IDFS curves (Nubakulu et al., 2026) as a major extension of the idea of Area Reduction Factors (ARF)
 252 (Svensson & Jones, 2010; Wright et al., 2014). These are analogous to traditional IDF curves, but instead feature
 253 a variation of spatial sizes used for the analysis. Additionally, this multi-dimensional analysis approach aids in
 254 preventing some of the pitfalls in generalizing the multitude of potential storm events within the historical
 255 records (Wright et al., 2014). The analysis for the spatial component was carried out on GPM IMERG, a 20-year
 256 3-hourly record. Based on this, a series of unique IDF curves was fitted for windows of 1 gridcell, 3 gridcells, 9
 257 gridcells, 27 gridcells and 81 gridcells, with a gridcell size of ~11 km for GPM data. Finally, based on the
 258 required size for the design event, bicubic interpolation is carried out in the spatial dimension to obtain the IDF
 259 curves for the exact size, and then continue to generate Hyetographs as would usually be done using IDF curves.
 260 A highly useful property of these spatial scaling components is that they furthermore reflect how the averaging
 261 taking place for large-region design events reduces the intensity compared to the actual localized extreme
 262 precipitation that is part of the event. Real events for larger basins, while having significantly lower extreme
 263 precipitation on average, have localized extremes significantly higher, which limits the fraction of infiltration
 264 taking place. The spatial scaling resulting from the IDFS curves characterize the relative difference between the
 265 large-scale lower average extremes and localized values that would be part of the same event. We utilize these
 266 relative changes to provide a virtual precipitation value to the infiltration calculations. This means we in fact
 267 deal with infiltration as if the event had the locally expected precipitation, while the large-scale routing and
 268 accumulation to the river system, as well as the final fluvial floods, still get the correct total design precipitation
 269 for the basin.

270 *Baseflow, soil moisture*

271 Soil moisture is initialized using historical data, utilizing NASA SMAP layers to ensure global coverage. For
 272 design events, monthly statistics derived from SMAP are employed. These events are situated within the median

273 soil moisture value of the wettest month to reflect the high frequency of flash flood occurrences during annual
274 wet periods. The maximum moisture value is excluded to avoid overestimation; as peak moisture levels typically
275 manifest post-flood, utilizing these values as initial conditions would result in a compounding of extreme
276 precipitation effects.

277 Baseflow is derived from GLOFAS re-analysis data, calculated as the moving-window average of discharge
278 values for the week preceding the event's onset (Feizi et al., 2022). In hazard map scenarios (design events),
279 discharge is incorporated directly into the boundary conditions for river flow rates. This discharge is assumed to
280 accumulate linearly per unit of drainage area upstream of the largest outlet within the model domain, thereby
281 allowing the model to be warm-started with pre-existing discharge in the river system. For extended simulations,
282 soil moisture content in riverine grid cells is linearly reduced by the baseflow.

283 *Boundary conditions and placement*

284 *Placement and routing adjustment for large rivers*

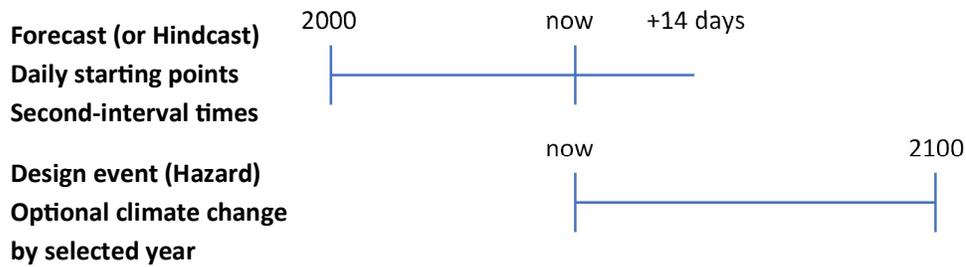
285 Discharge boundary condition placement is carried out starting with the incoming routes as taken from
286 HydroBasins river lines (Lehner & Grill, 2013). These river lines, while available globally, feature a deviation
287 from actual river center lines up to several Kilometres, and do not feature splitting rivers. We perform a series of
288 search and match algorithms within nearby elevation data to find optimal placement pixels with lower elevation,
289 indicating the riverbed is found. Discharge values are linked to GLOFAS pixels using a similar search and match
290 based on drainage area, with a final correction applied for minor mismatches in terms of drainage area. The
291 GLOFAS design values, as well as forecasts, are corrected with a bias correction using scaling factors based on
292 return period values (a full extreme-value focused histogram transform).

293 A routing adjustment is carried out based on detected river splitting within the network. This is only required for
294 the FastFlood static model, as the dynamic model will split river flow naturally based on the Saint-Venant
295 equations. For the static model, river sections that deviate from main river lines are detected, and flow is split
296 based on the proportional river branch widths.

297 *Final data pipelines and parameterization*

298 There are finally several primary options for using the FastFlood global system;

- 299 - Past
 - 300 ○ Hindcast
 - 301 ■ Using the data from the past to provide flood maps and information for any historic
 - 302 date since 01-01-2000.
- 303 - Present
 - 304 ○ Design event
 - 305 ■ Use design events, combining statistically representative input for precipitation,
 - 306 snowmelt and storm/tidal surge under current climate conditions
 - 307 ○ Forecast
 - 308 ■ Using the data from the past days to provide flood maps and information for the
 - 309 current day
- 310 - Future
 - 311 ○ Design event
 - 312 ■ Use design events, combining statistically representative input for precipitation,
 - 313 snowmelt and storm/tidal surge under climate change scenarios
 - 314 ○ Forecast
 - 315 ■ Use the latest snowmelt, precipitation and discharge forecast to predict flood maps
 - 316 and information for the coming two weeks relative to the current day.



317

318 *Figure 6 Schematic view of the time periods for which Fastflood Global can be used.*

319 Finally, each of these is interactive, meaning that when the user provides some alterations, including

- 320 - Elevation changes: Barriers or reservoirs constructed directly by means of an altered elevation model.
- 321 Can be provided as a vector dataset manipulated directly by the user.
- 322 - Flood protection: Alterations to channel dimensions and channel properties that can reflect potential
- 323 flood protection
- 324 - Drainage system: Alterations to the existence or capacity of stormwater drainage systems, or river and
- 325 channel routes.
- 326 - Nature-based solutions: Alterations to soil and vegetation information layers provided, with default
- 327 values based on recent literature for many common types of NBS.

328 [Results and analysis](#)

329 The following section showcases some of the applications of the model to extreme events around the world. The
 330 section outlines the model capabilities by providing an example use case how it can be used for different time
 331 periods like past present and future

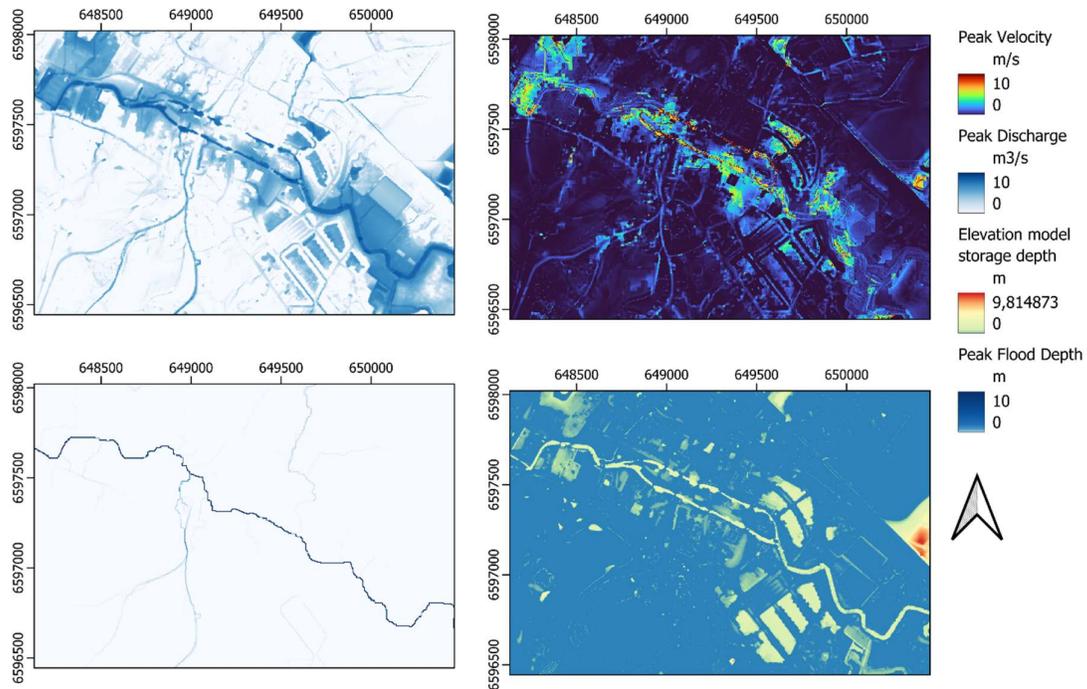
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333 **Past: Local flood time-series**

334 **Geul floods 2021**

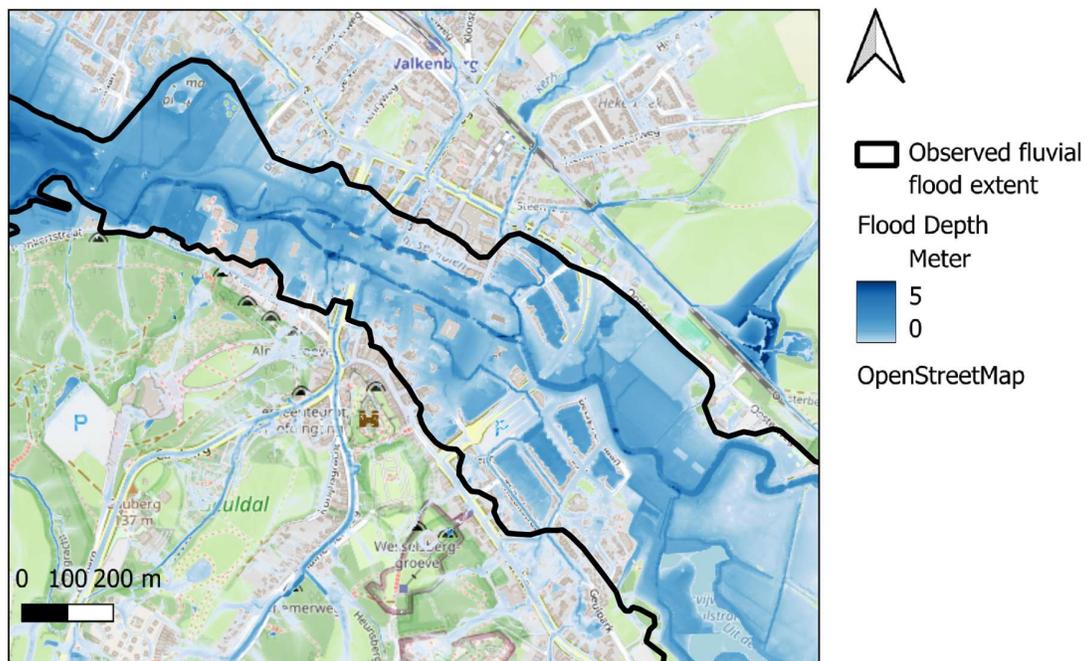
335 In June 2021, many parts of western Europe experienced severe flooding due to intense precipitation; one of the
 336 regions affected in the event was the city of Valkenburg in the Netherlands (Mohr et al., 2023). We used the
 337 FastFlood Global with its out-of-the-box parametrization to model the resulting flood for the event. Figure 7
 338 indicates the system's output, including the peak velocities and depths. The outputs show a good fit with the
 339 dron-based flood extent for the event, reaching a percentage accuracy of 94%.

340



341

342 *Figure 7 Flood modelling output for the city of Valkenburg, peak flood depth (Top left), peak velocity (Top right),*
 343 *peak discharge (Bottom left), and elevation depression storage (Bottom right). Note that these depressions are*
 344 *corrected for by the pre-processing algorithms (e.g. hydrocut/hydrofill/routing)*



345

346 *Figure 8 Comparison of the uncalibrated flood model output with the observed flood extent (observations where only*
 347 *mapped for the main Geul river in this region).*

348 The web-based tooling around the model allows the usage of the modelling system for interactive exploration of
349 alternative scenarios, visualized in Figure 14 for this region, with a 3D perspective view of the zero-
350 configuration available flood map output.



351

352 *Figure 9 The FastFlood global interactive features allowing users to add adaptations within the landscape and*
353 *explore in rapid fashion the consequences of these changes.*

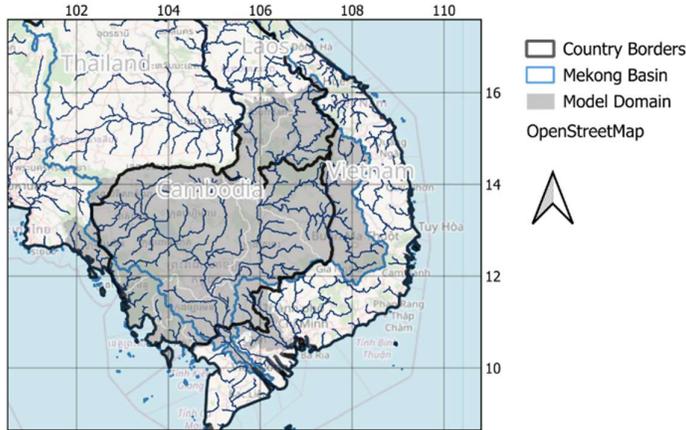
354

355 **Present: Hazard mapping**

356 **Cambodia flood hazard**

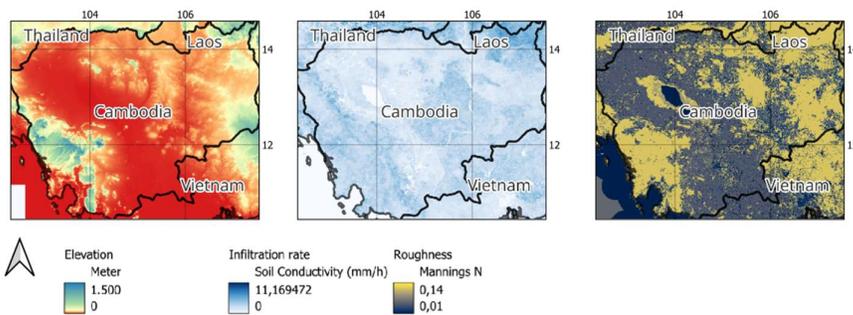
357 Another application of the model is presented here, for the country of Cambodia, utilizing the system for a
358 national flood hazard mapping effort. Figure 11 shows the input parameters including elevation data, surface
359 roughness and the infiltration rate. a hazard mapping example using the FastFlood global system at an
360 alternative scale. Predominantly, the out-of-the-box system is utilized here, with some key exceptions. Here,
361 special attention was given to the dynamics between the Mekong river and the Tonle Sap lake, where reverse
362 flow significantly increases flood extents around the lake. Here, the peak lake levels are based on satellite-
363 derived water surface altimetry, that captures the lake storage despite the pseudo-static nature of the FastFlood
364 model.

365 Figure 8 shows the global river network, based on a combination of Hydro Basins and Global River Centerlines
366 from LandSat.



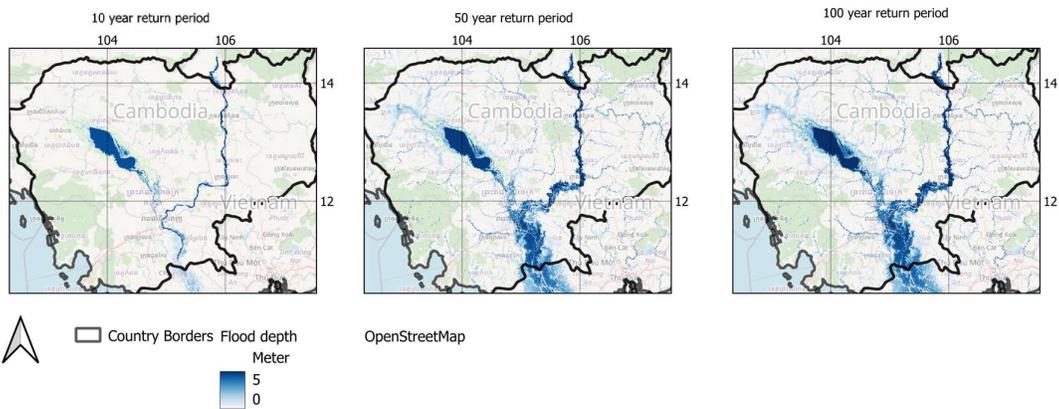
367

368 *Figure 10 The global river datasets, merging hydro basins and river centrelines from Landsat data, as used for*
 369 *the automated setup for Cambodia.*



370

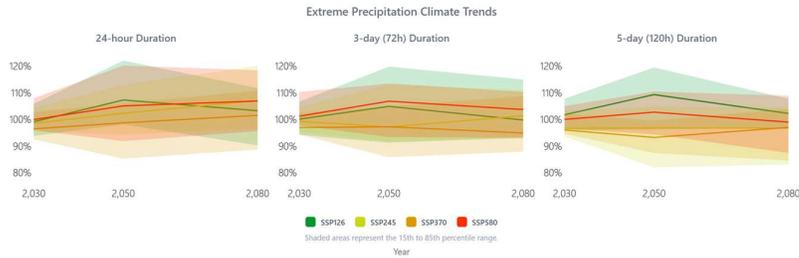
371 *Figure 11 Input parameters, landscape layers, for the Cambodia flood modelling; elevation data, infiltration*
 372 *rates for the second soil layer, and surface roughness.*



373

374 *Figure 12 Cambodia national-scale flood hazard maps at 20 meter resolution, visualized for 20, 50 and 100 year*
 375 *return periods.*

376 Climate change was addressed for the region, with additional flood simulations carried out with adjusted
 377 precipitation input. Figure 12 indicates the climate change trends on relative increases of extreme precipitation
 378 for various scenarios and durations of precipitation.



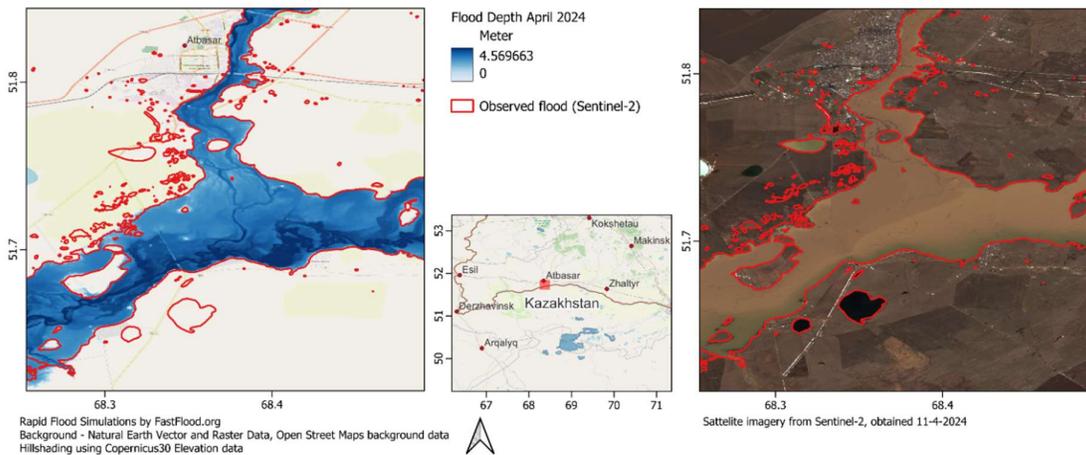
379

380 *Figure 13 Climate change scenarios, and their influence on extreme precipitation intensity in the region of Pnom Phen, with*
 381 *quantile 15 and 85 ranges within the CMIP6 NASA NEX-GDDP downscaled ensemble.*

382

383 **Future: Forecasting**

384 The model was applied for forecasting in the case of the 2024 Kazakhstan spring snowmelt floods. Figure 13
 385 shows the application of the automated parameterization of the FastFlood global system to the region around
 386 Atbasar, along the Ishim river. Discharge boundary conditions here are based on bias-corrected glofas forecasts,
 387 with automated placement and setup of appropriate mass and momentum flow boundary conditions for the
 388 advection calculations within the model. The model is applied here in an uncalibrated manner, and compared
 389 directly with sentinel-2 based flood extents, taken at the available date that most closely matches the peak of the
 390 flood extent in this region. The resulting modelled flood extents give a 99.4% accuracy compared to
 391 observations.



392

393 *Figure 14 Flood forecast results for the Ishim river, and the spring 2024 snowmelt driven floods in Kazakhstan*
 394 *around Atbasar.*

395 **Emergency Mapping**

396 Due to the calculation speed of the model, rapid application is possible in the context of emergency mapping.
 397 The provided figures illustrate the FastFlood Global system's critical utility in emergency response scenarios,
 398 specifically its capacity to generate immediate, accurate flood intelligence in data-scarce environments.

399 **Bangladesh 2024: Bridging Observational Gaps**

400 The first figure (Figure 15) presents a comparative analysis between post-event Sentinel-1 Synthetic Aperture
 401 Radar (SAR) imagery and FastFlood simulations for the June 2024 Bangladesh floods.

402 • **Observational Constraints:** While satellite-based tools like Sentinel-1 provide essential ground truth,
403 they are limited by satellite revisit times and data processing latency.

404 • **Predictive Value:** The FastFlood simulation (Right) demonstrates a high degree of spatial agreement
405 with the radar intensity observations (Left), accurately capturing complex inundation patterns across the
406 delta. In an emergency context, this allows responders to generate reliable inundation maps minutes to
407 hours before satellite imagery becomes available, filling critical information gaps during the initial
408 response phase.

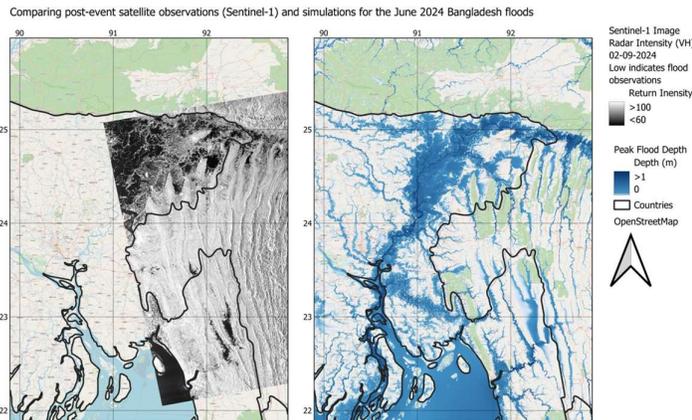
409 **Rapid Assessment and Calibration**

410 The second figure (Figure 16) highlights the system's speed during the immediate aftermath of a disaster,
411 visualizing a rapid simulation calibrated against high-resolution PlanetLabs optical imagery (12-09-2023).

412 • **Speed of Deployment:** This application demonstrates the ability to calibrate the model against space-
413 derived observations within a timespan of just a couple of minutes.

414 • **Operational Utility:** By rapidly assimilating available visual data to tune the model, the system
415 provides immediate estimates of flood depth and extent in complex urban environments. This capability
416 is vital for directing rescue operations to the most severely impacted zones when local ground data is
417 disrupted or non-existent.

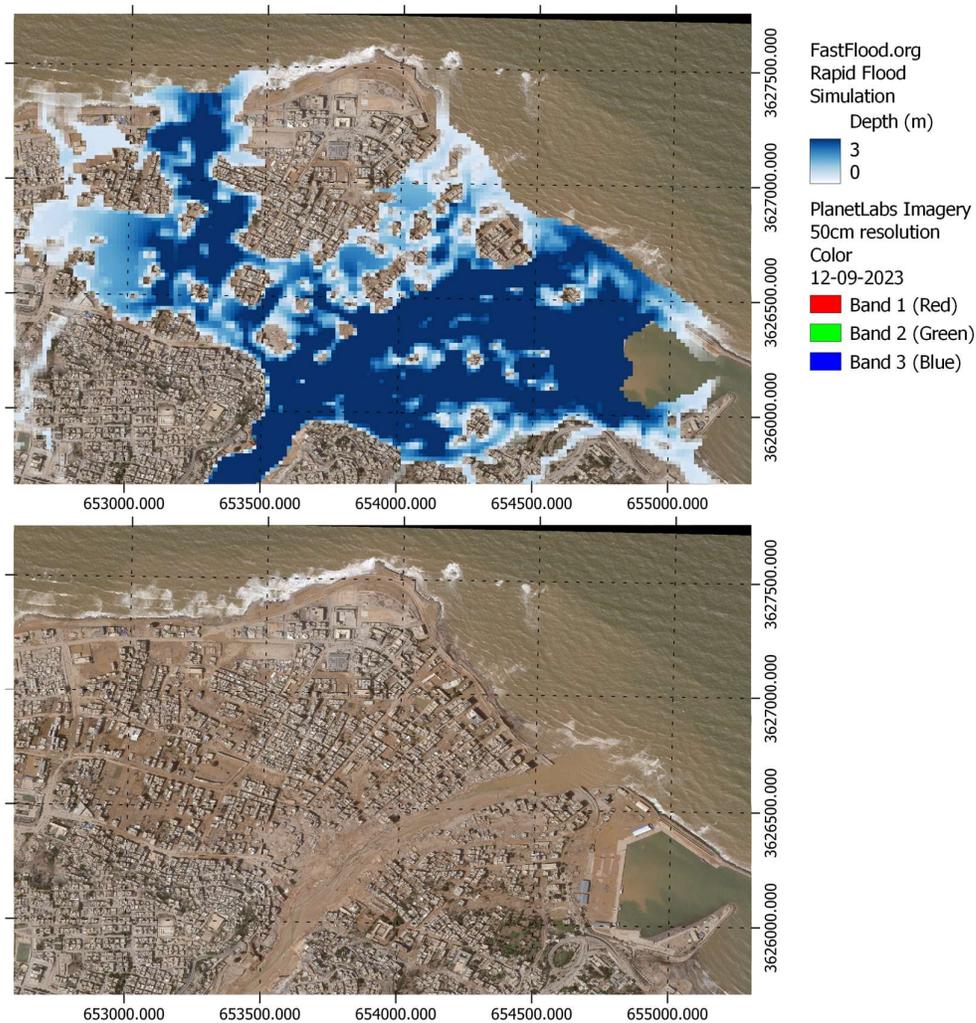
418 Together, these applications provide initial validation of the system's role in Emergency Mapping, where
419 calculation speed facilitates rapid situational awareness that static maps or slower traditional models cannot
420 provide.



421

422 *Figure 15 Flood modelling results, utilising the FastFlood Global system, for the Bangladesh floods in summer*
423 *2024 (Right), and Sentinel-1 VH intensity, where darker areas indicate water presence (Left).*

424



425

426 *Figure 16 Rapid flood modelling assessment, calibrating the FastFlood output within a time-span of a couple*
427 *minutes on space-derived observations.*

428

429 [Discussion](#)

430 **Comparative Review of FastFlood Global and Existing Flood Information Systems**

431 The FastFlood Global system integrates rapid hydrodynamic modelling with automated global parameterization,
432 distinct from existing static or operational frameworks. A comparative analysis against established categories
433 follows:

- 434 • **Global Hazard Information Layers (Fathom, JBA, FirstStreet):** These platforms provide high-
435 resolution, static hazard maps essential for risk baselines and trend analysis. However, they rely on pre-
436 computed scenarios, prohibiting real-time adjustment. In contrast, FastFlood Global utilizes a dynamic
437 core to allow interactive simulation of user-defined changes—such as new infrastructure or nature-
438 based solutions—facilitating immediate feedback on adaptation scenarios rather than static viewing.
- 439 • **Global Flood Forecasting Systems (JRC GloFAS, Google Flood Hub):** Operational systems like
440 GloFAS operate at coarse resolutions (~5 km) suitable for basin-scale discharge but limiting for local
441 impact assessment. Google Flood Hub improves locality but typically relies on AI or pre-calculated
442 libraries. FastFlood bridges this gap by downscaling coarse forecast data (e.g., GloFAS discharge) into

443 high-resolution (10 m) hydrodynamic inundation maps, maintaining physical consistency through
444 automated boundary condition coupling.

445 • **Real-time Response Tooling (Sentinel-based, ICEYE):** Satellite-based observation offers critical
446 situational awareness but is constrained by revisit times and cloud cover latency. FastFlood
447 complements these tools by providing predictive modelling to fill observational gaps. Validation against
448 Sentinel imagery for recent events (e.g., Kazakhstan 2024) demonstrates high spatial agreement
449 (99.4%), indicating its utility as a rapid proxy when direct observation is unavailable.

450 • **Adaptation Tools and Models (HEC-suite, MIKE, LISEM):** Traditional solvers provide high-fidelity
451 physics for engineering but require extensive manual setup and computational resources. FastFlood
452 reduces setup barriers via automated global parameterization (synthesizing ERA5, SoilGrids, etc.).
453 Benchmarking against the LISEM solver confirms comparable accuracy (~98% flood extent overlap)
454 with a computational speed increase of approximately three orders of magnitude (e.g., reducing runtime
455 from ~8 hours to 25 seconds for Dominica), enabling ensemble-based uncertainty analysis.

456 **Model Consistency and Uniformity**

457 The interactive nature of the FastFlood Global system precludes the use of static, pre-calculated data layers.
458 Consequently, maintaining consistency across variable spatial and temporal scales requires a targeted approach.

459 **Spatial Consistency** The spatial consistency of simulated flood intensities is of particular concern when altering
460 model domains (extent) or resolution. While the physically-based formulation of the FastFlood Global system is
461 designed to minimize resolution dependence, sensitivity to grid size is an inherent characteristic of numerical
462 flood models. Lower-resolution simulations inevitably degrade the representation of critical terrain features.
463 However, these effects are mitigated within the model through an automatic transition to a coupled 1D-2D
464 system, which ensures adequate throughflow even in complex terrain represented at coarser resolutions.

465 **Temporal Consistency** Temporal inconsistencies may arise from the divergence between the datasets used for
466 design events and real-time forecasting. Design events rely on Intensity-Duration-Frequency (IDF) curves
467 derived from 80 years of ERA5-LAND reanalysis data, whereas forecasts are generated using the ECMWF
468 ensemble. Although extreme precipitation statistics between these datasets are comparable, they are not identical.
469 It has been noted that ERA5 reanalysis data can underestimate precipitation extremes, particularly for small-
470 scale, high-return-period events. Future improvements to the model accuracy could be achieved through bias
471 correction of the IDF curves using global hourly precipitation station datasets.

472 **Boundary Condition Consistency** A specific challenge involves the parameterized consistency between a full-
473 basin hydrological simulation and a truncated domain (e.g., a river section) relying on external boundary
474 conditions. A full-basin domain generates discharge endogenously via the FastFlood hydrological computation.
475 Conversely, a truncated domain utilizes bias-corrected GLOFAS design discharge events. While conceptually
476 similar in terms of water balance, results from the internal hydrology are not guaranteed to match the bias-
477 corrected GLOFAS inputs used for river sections. The use of bias-corrected data allows the model to remain
478 linked to observational records, thereby maximizing accuracy. To address potential inconsistencies, the current
479 approach involves the automatic calibration of the inner model against global re-analysis design events. An
480 alternative method—developing fully consistent hydrology and routing between the inner model and the global
481 re-analysis model—remains a critical area for future development of the modelling system.

482 **Quality and Uncertainty**

483 The computational efficiency of the modelling approach facilitates the execution of ensemble simulations. This
484 capability is critical for capturing the range of potential flood scenarios resulting from uncertain meteorological
485 triggers. While limitations persist due to the global scope of the system—specifically regarding the incorporation
486 of local water management infrastructure—the presented work represents a significant advancement in the
487 coverage and feature set of global flood modelling. Furthermore, the integration of ensemble forecasts and
488 probabilistic hazard simulations enhances the quantification of model uncertainty.

489 **Global Forecasting and Early Warning Implications**

490 The implementation of this flood modelling system within a web-based platform provides access to detailed
491 global flood forecasts. By leveraging existing datasets and technologies, the system aims to maximize accuracy
492 and reliability while maintaining global coverage. However, the accessibility of such data raises ethical
493 questions regarding mandates, governance, and liability.

494 It is emphasized that the presented work is strictly distinct from an operational Early Warning System (EWS).
495 The platform is designed to provide detailed forecast information to users without issuing official warnings. The
496 operational objective is to supplement available information for users with specific technical requirements,
497 without interfering with the established protocols of water management agencies and mandated disaster response
498 bodies.

499 While there is functional overlap between the FastFlood Global system and an EWS—such as the forecast-based
500 calculation of expected flood intensity—fundamental differences remain. The technical modelling component
501 constitutes only a subset of a complete EWS, which fundamentally relies on institutional capacity, effective
502 dissemination channels, and community response mechanisms. With further validation across diverse sites and
503 evaluation over extended periods, the proposed approach could potentially be adapted to support official early
504 warning functions.

505 **Conclusion**

506 The presented FastFlood Global system provides a major step in the field of flood information technology, in
507 particular due to its global coverage, interactivity, ability to reach very high resolution where data is available,
508 and instant forecasting functionality. The model combines key parts of the rapid flood model FastFlood, with
509 even faster application due to the usage of cascading grids, and a automated parameterization scheme based on
510 numerous global and space-derived datasets. The quality of the models output

511 There are numerous limitations to the current methodology, which can be grouped in several categories

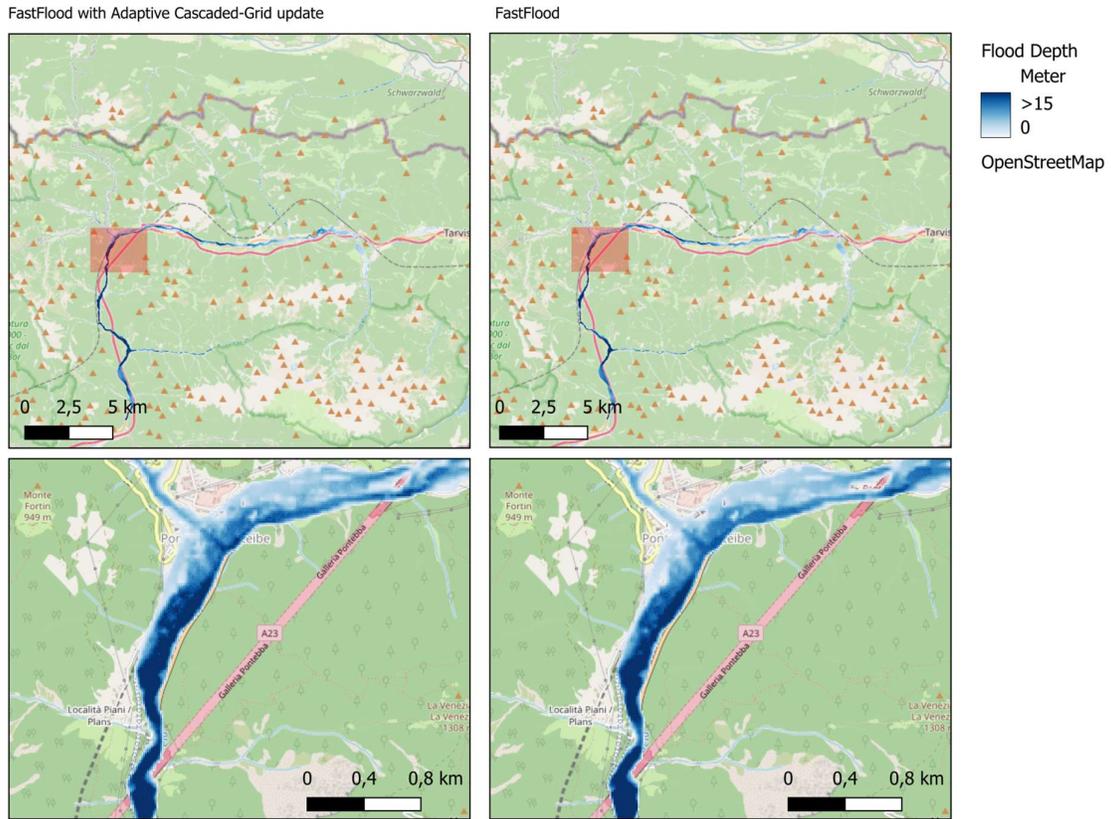
- 512 - Inconsistent output between past/future, design/forecast, due to the use of various datasets with
- 513 inconsistent biases and characteristics
- 514 - Out-of-the-box performance and calibration limitations might limit accuracy depending on the area.

515 Perhaps most important of all considerations is this; To users untrained in the usage of flood models, these kind
516 of systems can seem to offer a prediction that might be taken as “truth”, while containing limitations and
517 inaccuracies due to the underlying assumptions and data limitations associated to this or any other model. The
518 danger posed by inaccurate forecast without appropriate communication of limitations and uncertainties can erode
519 trust in these types of modelling tools. While these objections similarly can be true for static traditional flood
520 maps, the system presented here aims to provide close to expert-level interactive rapid tooling for a wide audience.
521 In industry applications, the reality is that a variety of subsidies, regulations, assessments, risk reduction and
522 management tasks require the use of flood models, often with highly limited resources, resulting in sub-standard
523 quality results. The presented tools can provide a major step forward in bringing more advanced flood technology
524 to new sectors, markets and communities.

525 **Appendix A: Comparison of the improved FastFlood performance**

526 To highlight the performance improvements, and the relative performance changes in terms of accuracy and
527 calculation speed, the FastFlood model was applied to two flood events with and without the used of the
528 cascading grid structure.

529 The first of these is the 2009 floods in the Fella basin, described in more detail by Bout & Jetten (2018) ,
530 together with a collection of reference simulation output utilizing traditional saint Venant solvers (as contained
531 in the model LISEM) The total computational grid for this region consists of 1716 x 1526 pixels at 10 meters
532 resolution. Simulation output is shown in Figure 15, with an observed FastFlood model runtime difference of
533 19.735 seconds vs 5.49 seconds.



534

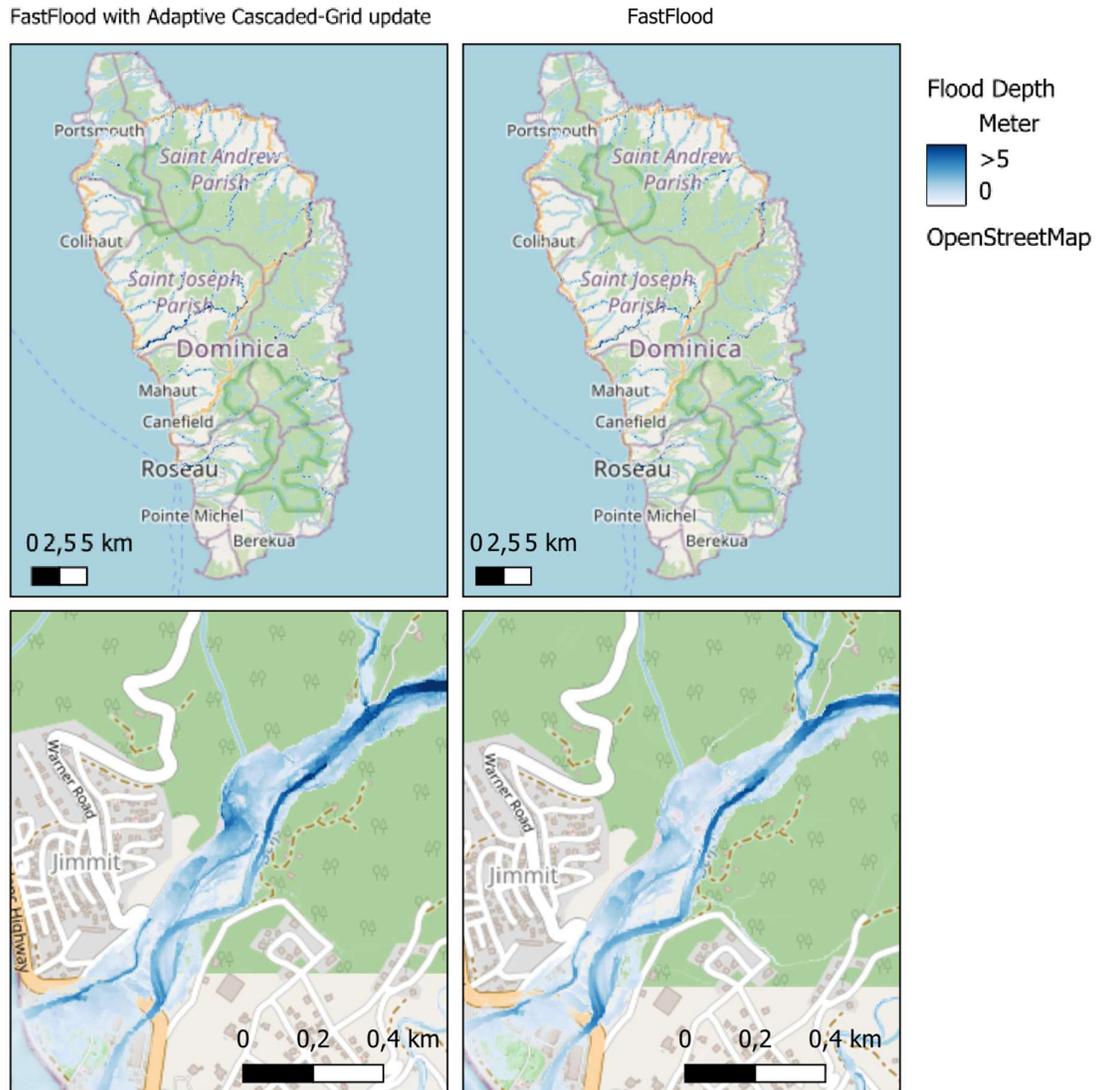
535 *Figure 17 Comparison of the FastFlood model with and without the usage of the cascading grid approach,*
 536 *applied to the 2009 floods in Fella basin, Italy.*

537 The pixel-wise percentage accuracy of flood extent between the usage of the cascaded grid refinement approach
 538 against a full traditional model is as follows

539 *Table 2 Relative comparison of the updated fastflood model, as well as compute time for the Fella basin.*

Fella	Flood Extent	Flood Depth	Compute time
Reference Saint Venant (LISEM)	100%	100%	29880
FastFlood	98.3%	98.1%	19.7
FastFlood GLocal	98.1%	97.3%	5.49

540 The second comparison case is the Caribbean island of Dominica. Here, the entire island with a 5 meter
 541 resolution DTM, and a grid resolution of 5211 x 9603 pixels was used. A final runtime difference was observed
 542 of 6444 seconds against 25 seconds.



543

544 *Figure 18 Comparison of the FastFlood model with and without cascading grid, as applied to a hurricane event*
 545 *on Dominica.*

546 *Table 3 Relative comparison of the updated fastflood model, as well as compute time for the country of Dominica.*

Dominica	Flood Extent	Flood Depth	Compute time
Reference Saint Venant (LISEM)	100%	100%	122760
FastFlood	93.1%	98.1%	6444
FastFlood GLocal	98.1%	97.3%	25

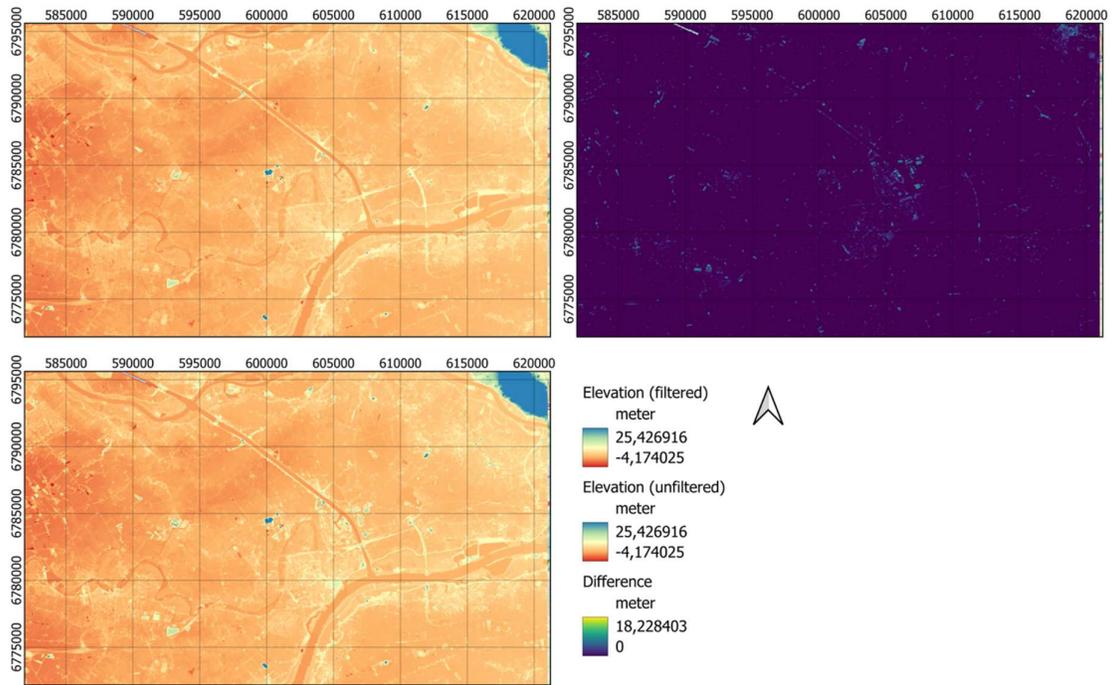
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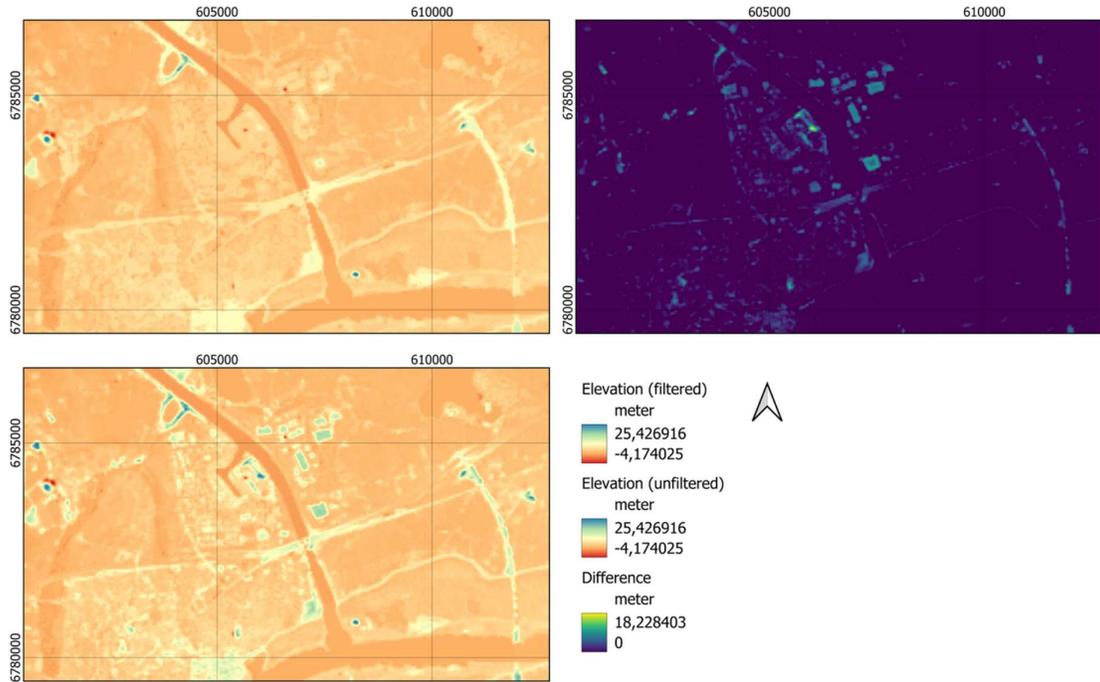
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550 Appendix B: DTM filter visualization

551 The elevation model filter results apply globally, and are visualized here for a region in the Netherlands and
552 United States of America (Chicago). Both cases the algorithms are applied to the Copernicus30 DSM data, with
553 input at approximately 30 meters resolution, and output at 20 meter resolution.



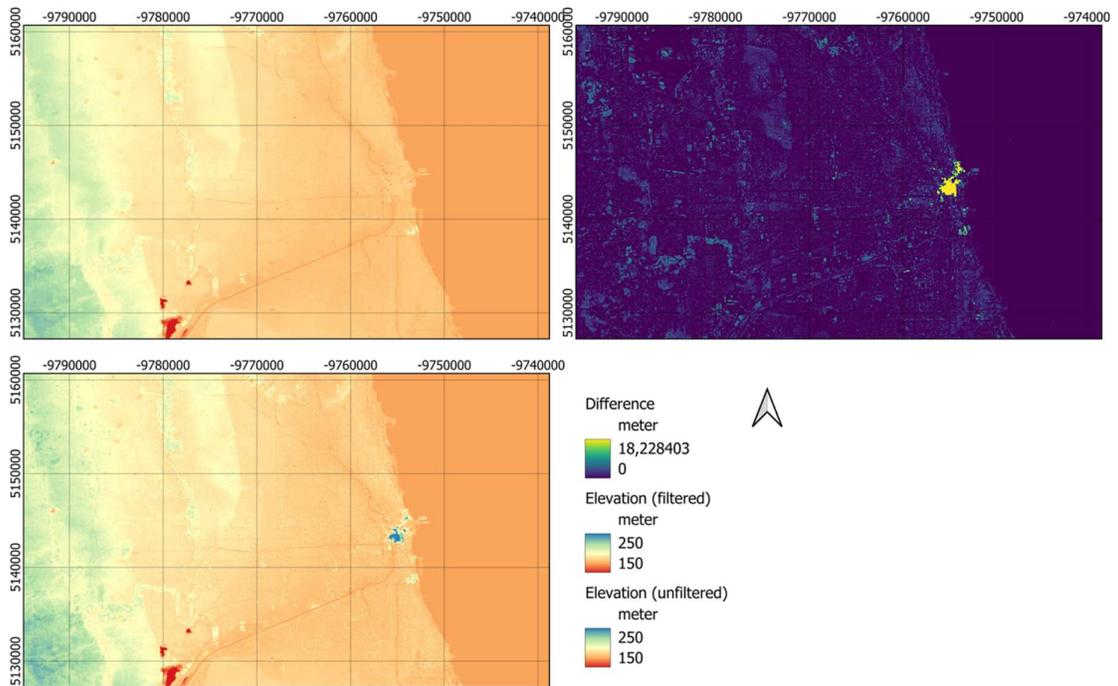


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Figure 20 DTM filter application, and elevation model differences for DTM and DSM, applied to Copernicus 30 data in the Netherlands.

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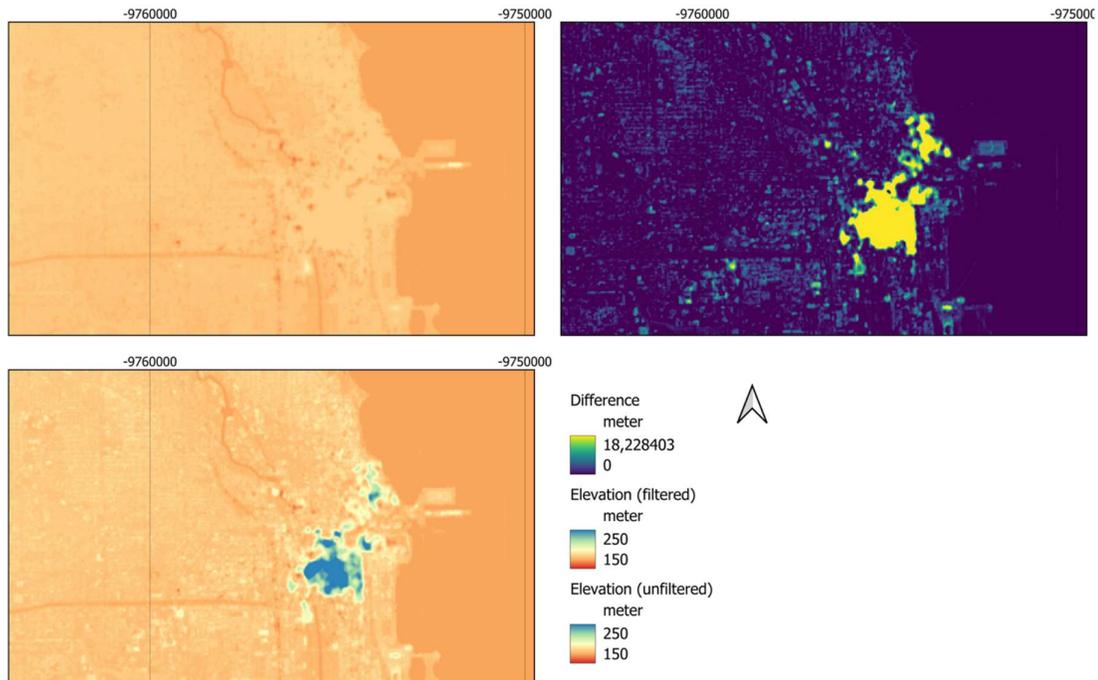


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Figure 21 DTM filter application, and elevation model differences for DTM and DSM, applied to Copernicus 30 data in the USA (Chicago).

562



563

564 *Figure 22 DTM filter application, and elevation model differences for DTM and DSM, applied to Copernicus 30 data in the*
 565 *USA (Chicago).*

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