Enhancing Fluvial Modeling and Flood Prediction Accuracy through the Fusion of 3D Point Clouds, Multispectral, and RGB Data

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Abstract

Floods are among the most prevalent and devastating natural disasters, affecting over 2 billion people worldwide. The increasing frequency and intensity of extreme precipitation events, driven by climate change, increase the vulnerability of communities to flooding. This underscores the urgent need for more accurate and reliable flood prediction and risk assessment models to enhance preparedness and mitigation efforts. In this research, we investigate the critical role of Digital Elevation Model (DEM) resolution in fluvial flood modeling. DEMs are essential for representing the Earth's surface and are necessary in hydrodynamic simulations used to predict flood behavior. We employed a two-dimensional hydrodynamic model to simulate flood scenarios using DEMs of three different resolutions: 1 m, 5 m, and 25 m. The objective was to determine how variations in DEM resolution influence the accuracy of flood extent predictions. Our findings reveal that higher resolution DEMs, such as those with 1-meter resolution, provide a more precise and detailed representation of the terrain. This level of detail significantly reduces the predicted extent of flooding compared to lower resolution DEMs (5 m and 25 m).

1. Introduction

Floods represent a prevalent and profoundly impactful natural disaster worldwide. These catastrophic events lead to extensive loss of life, property damage, and economic disruption. According to (World Health Organization, 2020), from 1998 to 2017, over 2 billion people worldwide were impacted by floods, while the frequency and intensity increase in climate changeinduced extreme precipitation will lead to an increase in flood occurrences. In a similar context, National Flood Risk Assessment of (Environment Agency, 2009) reveals that 5.2 million properties in England, or one in six, are at risk of flooding, with annual damages exceeding £1 billion, and highlights significant vulnerabilities in critical infrastructure and public services, particularly water-related facilities. In a recent study, Feyen et al. (2020) suggested that a projected 3° C rise in global temperatures by 2100 would significantly increase river flood damage. The same researchers estimated that such a temperature increase could result in river flood losses within the European Union (EU) and the United Kingdom (UK) reaching six times the current annual figure of ϵ 7.8 billion, with the number of individuals exposed to river flooding annually rising to nearly half a million, compared to the current estimate of 170,000. These findings underscore the urgent need for robust adaptation strategies to mitigate the escalating risks posed by climate change-induced flooding.

The growing demand for enhanced flood prediction, risk assessment and the development of more effective flood mitigation and management strategies has highlighted the necessity for more accurate flood models. In recent years, the increased accessibility to supercomputers and advancements in high-resolution data collection have significantly contributed to the development of highly-detailed 2D flood models. For example, Zotou et al. (2020) tested the predictive performance of a hydraulic model using as reference the flood extent extracted through Sentinel - 1 imagery, while Saksena and Merwade (2015) tried to relate the errors arising from DEM properties, such as spatial resolution and vertical accuracy to flood inundation maps.

Extended research has been conducted on the effect of the DEM resolution on flood models. Indicatively, Saksena and Merwade (2015) applied a range of DEM resolutions from 6 m to 30 m on flood models and quantified the differences in several inundation parameters. Muthusamy et al. (2021) investigated the effect of DEM resolution in the characterization of the river channel and the consequences of this characterization on critical parameters of urban fluvial flood modelling, such as flood depth and flood extent. Ozdemir et al. (2013) in their study concluded that increasing the terrain resolution significantly affects modelled water depth, extent, arrival time and velocity and that the use of additional detail provided by terrestrial laser scanning data, as opposed to airborne sensors, will be beneficial for urban flood modeling. Peña and Nardi (2018) investigated the uncertainties of input parameters in 2D flood modelling and specifically the implementation of coarse simplified DEMs. Despite the extended related literature, Muthusamy et al. (2021) emphasized on the need to further investigate the effect of DEM resolutions on flood properties, to eliminate the inconsistencies of the results of previous studies.

In the present work, we assess the impact of Digital Elevation Model (DEM) resolution in fluvial flood modelling as well as the fusion of 3D point clouds derived from LiDAR data, multispectral and RGB images, employing a sophisticated twodimensional hydrodynamic model, in order to simulate different fluvial flood scenarios using DEMs with grid resolution ranging from 1 m to 25 m.

2. Materials and Methods

2.1 DEM data acquisition for the study area

The DEM serves as a crucial input for 2D hydrodynamic models, significantly impacting the accuracy of flood extent predictions. To assess the influence of DEM resolution on fluvial modelling, we utilize DEMs with different resolutions within a 2D hydrodynamic model designed for a specific geographic area. For the present study, we identified a focal region located at the upstream region of the Scheldt River basin in Belgium, spanning an area of 1km by 320m (Figure 1). The specific area was selected due to its distinct geomorphological features that significantly increase the risk of severe flooding events.

Figure 1. This figure provides an overview of the study area, with the yellow frame indicating the specific region from which the point cloud data were collected.

For the coarse DEM, we utilised the freely available 25m DEM of the European Environment Agency (EEA). The topographic data used for the production of the high-resolution DEM were acquired using a Remote Sensing-based Multiscale Monitoring System that was developed according to the needs and specifications set by the EU-funded PLOTO project (Grant Agreement no 101069941) in order to monitor IWW corridors and wider areas. The RS-based multiscale monitoring system consists of the Ground Control Station (GCS) that includes two main components, (a) the Multi-satellite Ground Station (MsGS) and (b) the Generic Ground Station (GGS). The GCS is responsible for data acquisition by air and ground-based platforms and sensors. It aims at the acquisition of data for the IWW areas and corridors. Furthermore, satellite remote sensing data are being selected enabling the activation of the wider areas monitoring levels. Remote sensing data and Copernicus products are collected, processed, analysed and integrated into the Multisatellite Ground Station (MsGS). Advanced methodologies for a) 3D analysis using photogrammetric means and ML, mainly focusing on deep learning methodologies and tensor Algebra decomposition b) ground deformation assessment using SBAS approach, c) change detection using deep learning methodologies, and d) flood extent delineation based on Bayesian approach will be employed for generating the RS-MMS products. During the survey in Albert Canal, the DJI Matrice 300 RTK was used with the following sensors: (a) DJI Zenmuse L1, (b) Zenmuse P1 and (c) MicaSense RedEdge-P. Several flights at 50m, 60m and 90m were performed with the three sensors to acquire LiDAR data, RGB photos and multispectral ones (Table 1) covering the overall area and mainly focusing on the bank closer to Lanaye. In addition, 5 Ground Control Points were measured using a GNSS receiver to georeference the photogrammetric products.

The digital images were processed using the Image Based Modelling (IBM) software Agisoft Metashape v.1.8.3 following the common workflow as in every survey process. The captured images were loaded, examined, and evaluated and some of them were excluded. The next step was the detection of the marked targets (GCPs) to facilitate the alignment, scaling and georeferencing of the 3D point cloud and DEM. After the successful alignment of the images, the dense point cloud was generated and using that as source data the DEM was produced with a resolution of 2.78 cm/pix. Figure 2 illustrates a segment of the high-resolution DEM acquired using the methodology outlined in this section.

Table 1. Sensor, number and size of acquired data.

Figure 2. Segment of the high-resolution DEM of the study area.

2.2 2D Hydrodynamic modelling

In order to demonstrate the advantages of a detailed DTM in hydrodynamic simulations we used the well-known hydraulic software HEC-RAS (River Analysis System (HEC-RAS), 2024) software of the US Army Corps of Engineers Hydrologic Engineering Center. Specifically, we utilized the 2D mode, which solves a simpler form of the 2D Shallow Water

Scenario number	Resolution $(m \times m)$	Water Stage (m)	Number of pixels	Flood area (m^2)	% Flood area
	1×1	62	32.431.330	25.125	50
	1×1	63	35.628.162	27.601	55
3	1×1	64	39.130.769	30.315	61
	5×5	62	35.007.117	27.120	54
	5×5	63	38.472.509	29.805	60
	5×5	64	38.472.509	29.805	60
	25×25	62	35.106.538	27.197	54
	25×25	63	38.491.321	29.820	60
	25×25	64	42.050.751	32.577	65

Table 2. Comparison of the flooded area for the nine scenarios.

Equations, namely the 2D diffusion wave equations. The computational domain consists of the floodplain of a river system as depicted in Figure 3. When the water level exceeds the levees of the main channel, flood volume is propagated in the computational domain.

Therefore, the upstream boundary conditions consist of a water stage over the threshold which distinguishes the main river and the floodplains. Regarding the downstream and lateral boundary conditions, we assumed that water is propagated outside the computational domain while there is no backwater effect.

For the simulations, we aggregated the detailed topographic information in three levels of accuracy to investigate the influence of the DTM space step in the hydrodynamic results: a) $\Delta x = 1$ m; b) $\Delta x = 5$ m; c) $\Delta x = 25$ m. The first level of accuracy is selected to take advantage from a detailed topography and in parallel to develop a simulation which is feasible to run in a conventional PC in terms of computational burden. The second level of accuracy is selected because this is the order of magnitude for typical DTM resolutions which are available in national level. Finally, the third level of accuracy is selected because this is the order of magnitude for global satellite-based DTM resolutions.

The Manning coefficient is defined equal to $n = 0.04 s/m^{1/3}$ in the entire computational domain, which is a typical value for rural floodplains. For the simulations, we assumed three scenarios which correspond in three water stages which exceed the main river boundaries: $H = 62 m$, $H = 63 m$, $H =$ $64 m$. It should be noted that the water level is not transient but constant, although 2D diffusion wave equations are capable to describe the dynamic of the flow over the time. The open boundaries are approached with the normal depth and a slope equal to $S = 1\%$. Finally, the time step is defined after a trialand-error procedure equal to $\Delta t = 1$ s.

3. Results and Discussion

As discussed in Section 2.2, this research examines three different DEM resolution scenarios. For each resolution scenario, three distinct water stages were applied to the HEC-RAS hydrodynamic models. Consequently, a total of nine scenarios were evaluated to determine the extent of inundation. Figures 4 to 6 illustrate the flood extent for all the 2D hydrodynamic models assessed. Each figure corresponds to a different water stage, namely 62 m, 63 m and 64 m. The comparison of the flooded areas reveals a clear trend: higher resolution DEMs result in smaller inundation extents. This finding underscores the importance of using high-resolution DEMs in accurately predicting flood extents and highlights the potential for more precise flood risk assessments. Table 3 presents the statistical results for the calculated flood depth for each scenario, specifically the minimum, maximum and mean values. Table 2 summarizes the results for the examined scenarios and quantifies the conclusions illustrated in Figure ??. The last column of the table shows the percentage of the flood area relative to the entire study area. The results indicate an approximate 5% increase in the inundation extent as the DEM resolution decreases.

Scenario	Resolution	Min	Max	Mean
number	$(m \times m)$	(m)	(m)	(m)
	1×1	0.01	10.49	1.10
2	1×1	0.01	10.91	1.21
3	1×1	0.01	10.91	1.21
4	5×5	0.01	11.49	1.97
5	5×5	0.01	11.91	2.06
6	5×5	0.01	11.91	2.06
	25×25	0.01	12.49	2.77
	25×25	0.01	12.91	2.84
	25×25	0.01	12.91	2.84

Table 3. Statistical results of the depth calculated by the 2D hydrodynamic simulations.

4. Conclusions

The study demonstrates that the resolution of Digital Elevation Models (DEMs) has a substantial impact on the accuracy of flood extent predictions in fluvial flood modeling. Higher resolution DEMs result in a smaller predicted inundation area, emphasizing the critical role of detailed topographic data in flood risk assessment. By employing a sophisticated two-dimensional hydrodynamic model, we were able to simulate various flood scenarios and confirm that the use of highresolution DEMs enhances the precision of flood predictions.

Overall, the findings highlight the importance of leveraging advanced data collection techniques and computational capabilities to address the growing challenges posed by climate change-induced flooding. Utilizing high-resolution topographic data enhances the accuracy of flood models, leading to betterinformed decisions regarding land use planning, infrastructure development, and emergency response strategies.

In conclusion, this study highlights the importance of DEM resolution in fluvial flood modeling and the necessity to adopt high-resolution topographic data in flood risk assessments. Future research should focus on the cost-benefit analysis of acquiring and processing high-resolution DEMs and explore their integration with other advanced hydrological and meteorological data to further improve flood prediction and management systems.

Figure 3. Graphical representation of the computational domain used in the current study from two points of view: a) cross-sectional view; b) top view

Figure 4. Aspects of the inundation area for 62 m water stage.

Figure 5. Aspects of the inundation area for 63 m water stage.

Figure 6. Aspects of the inundation area for 64 m water stage.

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