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Methods and models to assess the effectiveness of hydraulic risk mitigation
measures

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Abstract

Floods are among the most dangerous natural disasters, affecting thousands of people worldwide every year. Their frequency and intensity are expected to increase due to climate change and ongoing urbanization, making the identification of effective mitigation strategies increasingly important. However, flooding includes different types of events, such as pluvial, fluvial, and coastal floods, which differ in their governing physical processes and in the current level of scientific understanding. Mitigation strategies must therefore be developed with reference to the specific type of flooding considered. This thesis focuses on fluvial and pluvial flooding from different perspectives. For fluvial flooding, the study investigates simplified methodologies for the preliminary assessment of mitigation measures, avoiding the need for computationally expensive hydrodynamic models. The proposed approach was tested on two case studies in Sardinia and yielded promising results. For pluvial flooding, the research initially focused on two urban basins in New York City, represented using high-resolution geospatial data and a 2D shallow-water-equations (SWE) model. Three real flood events were simulated to compare different approaches for representing the influence of the sewer system when detailed drainage data are unavailable. Model performance was evaluated using street-level water-depth observations collected through the FloodNet sensor network. The results showed that the proposed approach, based on representing sewer outflow at inlets through weir/orifice equation, outperformed the other simplified methods considered. The validated modelling framework was then extended to assess the effectiveness of Nature-Based Solutions for pluvial flood mitigation. Green roofs and permeable pavements were included in the model and tested, both individually and in combination, under design storms with different return periods and coverage scenarios. The results indicate that, under the adopted simplified schematization, these measures can effectively reduce both flood depth and flood extent, particularly for events with low to medium return periods (10–25 years). Finally, the thesis proposes a new building representation for 2D SWE models applied to urban flooding. The approach is designed to include, in a simplified way, the influence of water storage within buildings and basements. Water is allowed to enter buildings through openings, while basements are represented through a storage-based formulation.

The method was first evaluated on a simplified test case and then applied to an urban basin in London under a design storm. Despite its simplified formulation, the proposed approach produced realistic results, with magnitudes consistent with those reported for real flood events.

Chapter 1

Introduction

Floods are the most frequent natural disasters, causing significant socioeconomic, health, and environmental impacts (*CRED and UNDRR*, 2020; *NCEI (NOAA National Centers for Environmental Information)*, 2025). Flood risk arises from the complex interaction among three main components: hazard, exposure, and vulnerability. In the context of flooding, hazard refers to the frequency and/or magnitude of flood events that may cause adverse impacts, exposure to the presence of people, infrastructure, and assets located in areas potentially affected by flooding, and vulnerability to the susceptibility of those exposed elements to suffer damage when a flood occurs (*UNDRR*, 2017; *Tsakiris*, 2014; *Reisinger et al.*, 2020). From this perspective, flood mitigation strategies may act on one or more of these three components. Some measures aim to reduce hazard, for example by lowering flood extent, water depth, or flow velocity (*Di Baldassarre et al.*, 2009; *Heine and Pinter*, 2012). Others act on exposure, for instance by limiting the presence of people and assets in flood-prone areas (*Bower et al.*, 2024; *Ajibade et al.*, 2022; *Wolff et al.*, 2023), while others reduce vulnerability by increasing the resistance, preparedness, or resilience of exposed elements (*Ringo et al.*, 2025; *Kreibich et al.*, 2017).

Both climate change and urbanisation are expected to intensify flood hazard and risk: climate change can increase the frequency and intensity of extreme precipitation (*Tabari*, 2020) while ongoing urbanization leads to larger runoff coefficients and, by reducing terrain roughness, can favour high flow velocities and reduce the time-to-peak (*Feng et al.*, 2021; *Hollis*, 1975; *Jacobson*, 2011). The identification of effective mitigation strategies is therefore a priority. However, the term “flood” encompasses a variety of phenomena that differ in their causes, physical mechanisms, temporal evolution, and spatial occurrence (e.g. river corridors, coastal zones or urbanised areas). The main drivers of flooding are fluvial, which occurs when water flowing in a river overtops the

levees; coastal, which is due to ocean tides and storm surges; and pluvial, which results from intense precipitation that exceeds the drainage capacity of the natural landscape (e.g., interception, infiltration) and stormwater infrastructure (*Rosenzweig et al.*, 2018). As a result, particularly when considering flood hazard reduction, mitigation strategies differ according to the type of flooding involved and must reflect the specific physical processes governing each phenomenon. For this reason, a clear regulatory and planning framework to define the main elements involved in flood risk assessment and management is required.

1.1 Flood risk mitigation and management

Flooding is a worldwide hazard and, as such, its management can be framed within broader disaster risk reduction strategies. At the global level, the *United Nations Office for Disaster Risk Reduction*, (UNDRR), promotes disaster risk reduction worldwide and supports the implementation of the *Sendai Framework for Disaster Risk Reduction 2015-2030* (UNDRR, 2015). The Sendai Framework aims to prevent the creation of new disaster risk, reduce existing risk, and strengthen resilience through a set of general priorities for action. Within this perspective, the principles of disaster risk reduction are intended to be translated into more specific frameworks and actions at continental, national, and local scales.

1.1.1 European and Italian framework for flood risk management

At the European level, the Directive 2007/60/EC, known as the Floods Directive (FD) (*European Parliament and Council of the European Union*, 2007), establishes a common framework for flood risk assessment and management across Member States, with the aim of identifying areas at risk of flooding and supporting the planning of mitigation measures. Although specifically focused on flood events and their management, the FD builds on the basin-scale approach previously introduced by the Water Framework Directive (WFD, 2000/60/EC), which established a common framework for the protection and management of water resources and required Member States to identify river basin districts and prepare River Basin Management Plans, to be periodically reviewed and updated. In particular, the FD requires Member States to carry out a preliminary flood risk assessment, prepare Flood Hazard and Flood Risk Maps (FHRMs) for areas of potentially significant flood risk, and subsequently develop Flood Risk Management Plans (FRMPs), with the aim of

reducing the adverse consequences of flooding for human health, the environment, cultural heritage and economic activity. Flood hazard maps must be produced for three scenarios, namely floods with a low probability or extreme events, floods with a medium probability, and floods with a high probability, where appropriate. For each scenario, the maps should show at least flood extent and water depth or water level and, where appropriate, flow velocity or the relevant water flow. On the basis of these maps, Member States must then prepare management plans addressing prevention, protection and preparedness, including flood forecasting and warning systems.

An important feature of the Floods Directive is its six-year planning cycle. Preliminary assessments, maps and management plans must be periodically reviewed and, where necessary, updated, making the Directive a dynamic framework. This aspect is particularly relevant in a context where data availability, modelling tools and scientific knowledge are continuously evolving. In its practical implementation, the FD has been applied to five main flood sources: fluvial, pluvial, groundwater, seawater, and floods from artificial water-bearing structures. However, the first cycle of implementation showed a clear predominance of fluvial flooding in Member States' mapping activities. By 2019, 26 Member States had prepared FHRMs for fluvial flooding, compared with 17 for seawater flooding, 14 for pluvial flooding, 9 for floods from artificial water-bearing structures and only 4 for groundwater flooding (*European Commission*, 2019). This highlights how fluvial flooding has remained the main focus of flood hazard and risk mapping across Europe. In Italy, the WFD was transposed through Legislative Decree No. 152/2006, which identified river basin districts as the reference territorial units for water management and confirmed the central role of basin planning. Subsequently, the FD was transposed through Legislative Decree No. 49 of 23 February 2010, which introduced the national framework for flood risk assessment and management and led to the preparation of the Flood Risk Management Plans (Piani di Gestione del Rischio di Alluvioni, PGRA). Reporting on the implementation of the procedures required by the FD involves both the competent basin authorities and ISPRA (Istituto Superiore per la Protezione e la Ricerca Ambientale). In addition, ISPRA also prepares a publicly available national report; for the first planning cycle, the most recent version is that of *Lastoria et al.* (2021).

1.1.2 United States framework for flood risk mitigation and management

In the United States, the *Federal Emergency Management Agency* (FEMA) is responsible for mapping flood risk across the country. To support this activity, FEMA developed the *Risk Mapping, Assessment and Planning* (Risk MAP) programme, through which flood

maps, including the *Flood Insurance Rate Maps* (FIRMs), are produced and updated in cooperation with participating communities. These maps identify the areas exposed to flood hazard and provide one of the main technical and cartographic bases for the *National Flood Insurance Program* (NFIP). The NFIP is one of the main instruments through which FEMA addresses flood risk management at the national scale. The programme aims to reduce flood risk by combining flood insurance with floodplain management standards adopted at the community level. Participation in the NFIP is voluntary for communities, but only properties located in participating communities can access NFIP flood insurance. In practice, communities that join the programme must adopt and enforce minimum floodplain management regulations, while residents and property owners may then benefit from access to federally backed flood insurance (FEMA, 2021; Horn, 2021).

1.2 Thesis structure

The work presented in this thesis was funded by the NRPP within the Geosciences IR project coordinated by ISPRA.

In the thesis, the focus is on fluvial and pluvial flooding, which differ not only in their governing mechanisms but also in the current state of the art in terms of hazard characterization and modelling. Until relatively recently, pluvial flooding has often been regarded as a comparatively minor hazard, partly because stormwater systems were assumed to be properly designed to limit its occurrence and impacts, and partly because its consequences were often perceived as relatively limited in terms of both economic losses and risk to human life (Rosenzweig *et al.*, 2018). By contrast, fluvial flooding has been the subject of decades of research, resulting in a comparatively mature knowledge base that spans both process understanding and flood inundation prediction (Bates, 2022) as well as the design and evaluation of mitigation strategies within flood risk management (Merz *et al.*, 2010). In real events, however, fluvial and pluvial flooding may also happen simultaneously and interact in compound flooding conditions (Guan *et al.*, 2023b). In such cases, attributing the resulting inundation pattern to the different contributing processes may be challenging. Recent studies have therefore proposed methods to distinguish the relative contribution of different flood sources. For example, Perrini *et al.* (2025) used tracer-aided 2D numerical modelling to separate fluvial and pluvial components in compound pluvial-fluvial flooding. Since these two flood sources may require different mitigation strategies, disentangling their relative contribution and identifying the areas mainly affected by each source is particularly important for flood risk mitigation and management and should be further investigated. In the present thesis, however,

the two flood types are analysed separately and compound flood conditions are not explicitly considered. Consistent with the different maturity of the two research fields, this thesis addresses fluvial and pluvial flooding from distinct perspectives. For fluvial flooding, the focus is on developing simplified, computationally efficient methods to quantify the influence of mitigation measures without the need for fully resolved hydrodynamic modeling. Although the simplified method proposed is not able to represent the full dynamics of the process, it can be used for a rapid assessment of the effectiveness of mitigation measures during the initial stages of the design process. In this sense, the proposed approach is consistent with the *fit-for-purpose* approach for model development (Merz *et al.*, 2024).

For pluvial flooding the emphasis is on identifying and investigating key factors that play an important role in inundation dynamics, with the aim of strengthening process understanding and supporting more reliable modeling. Within this framework, the influence of mitigation measures in reducing the adverse effects of pluvial flooding in urban areas is also investigated. More specifically, one contribution focuses on the use of street-level water depth observations during pluvial floods to develop a framework for the accurate simulation of such events when detailed data on the urban drainage system are not available. This framework was subsequently used to assess the effectiveness of Nature-Based Solutions for urban pluvial flood mitigation. Finally, a new storage-based representation of buildings in 2D SWE models was proposed to represent the effects of floodwater intrusion into buildings.

The work is structured as following:

- **Chapter 2 - On the use of simplified approaches for assessing fluvial flood mitigation measures.**

This chapter reviews the state of the art and introduces the proposed simplified approach to evaluate the effectiveness of fluvial flood mitigation measures. The method is based on the HAND (Height Above the Nearest Drainage) index and extends the approach to include the influence of mitigation measures that can be represented as terrain modifications. The approach is then applied to the selected case studies and the results are discussed.

- **Chapter 3 - Increasing the fidelity of hyperlocal simulations of urban pluvial flooding through street flooding observations.**

This chapter focuses on pluvial flooding in urban areas and proposes a new approach to account for the effects of the sewer system where detailed data are not available. The method consists of modifying the widely used 2D SWE model LISFLOOD-FP

to represent the sewer system by modeling an outflow at inlets using a weir/orifice equation and is compared with other simplified approaches. The results are evaluated considering two urban basins in New York City, for which street-level flood observations during real events were available thanks to the FloodNet network.

- **Chapter 4 - Assessing Nature-Based Solutions for urban pluvial flood mitigation.**

This chapter use the modeling framework validated in Chapter 3 and, focusing on one of the two urban basins in New York City, assess the influence of Nature Based Solutions in pluvial flood mitigation. Green roofs with different coverage and permeable pavements are simulated both individually or in combination considering design storms with multiple return periods, for a total 35 simulations.

- **Chapter 5 - A new storage based representation of buildings and basement in urban flooding.**

This chapter presents a new building representation method to account, in a simplified manner, for the storage effects of buildings and basements in urban flooding. The approach allows the water to enter buildings through openings, and represents the influence of basements by implementing a storage-based method in a well known 2D SWE model. The method is then tested using a design storm and considering an urban basin in London.

Chapter 2

On the use of simplified approaches for assessing fluvial flood mitigation measures

As previously discussed, flooding is not a single, uniform phenomenon, but rather a broad category that includes different flood types, each governed by distinct physical processes and thus requiring different analytical approaches. Among the different flood types, this part of the thesis focuses on fluvial (or riverine) flooding, i.e. flooding that occurs when water overflows the normal boundaries of watercourses (*UNDRR and ISC, 2025*).

2.1 Introduction

Fluvial flooding is one of the most common types of flooding. According to data available from the EM-DAT dataset for the period 2000–2025, about 43% of recorded flood events are classified as having riverine origin (*Delforge et al., 2025, 2024*). However, this proportion should be interpreted with caution, as the relative representation of flood types in available databases may be affected by reporting practices, including the historical underreporting of some events such as pluvial flooding. In addition, the inclusion criteria adopted in EM-DAT tend to favour the reporting of larger and more severe events, since an event is recorded in the database only if at least one of the following conditions is met: (1) at least 10 deaths, (2) at least 100 people affected, or (3) a call for international assistance or the declaration of a state of emergency.

Nevertheless, these uncertainties do not reduce the relevance of fluvial flooding, which remains one of the most important flood types in terms of human and economic impacts. For this reason, considerable effort has been devoted to the assessment of fluvial flood hazard which constitutes a key step for both flood risk analysis and the design of mitigation measures.

2.1.1 Methods for flood hazard mapping

Several methods are available in the literature for the identification of areas exposed to fluvial flood hazard for a given discharge value. Following the classification proposed by *Teng et al.* (2017) three groups can be identified: empirical methods, hydrodynamic methods, and simplified methods. Empirical methods are based on the analysis of information from past flood events; hydrodynamic methods rely on the numerical solution of the equations governing fluid motion and may be one-, two-, or three-dimensional; simplified methods, by contrast, do not explicitly simulate the underlying physical processes, but instead rely on simplified hydraulic relationships. Among these approaches, hydrodynamic methods generally provide the most detailed physical representation of flood propagation, although at the expense of higher data requirements and computational cost. Owing to the increasing availability of high-resolution topographic data, for example from LiDAR (Light Detection and Ranging) and remote sensing, together with the growth of computational power, one- and two-dimensional hydrodynamic models have become the standard tools for flood extent mapping (*Rosenzweig et al.*, 2021; *Teng et al.*, 2017). Simplified methods, on the other hand, identify flood extent for a given discharge by using simplified representations of the physical processes involved. Many of these methods, for example, rely on the topographic and geomorphological characteristics of the study area, combined with simplified relationships linking such characteristics to hydraulic variables. Although they provide a less physically detailed representation of the phenomenon (*Sanders et al.*, 2024), these methods have often been shown to produce satisfactory results, especially considering their much lower data requirements and computational cost. Owing to their short computation times, simplified methods are often used for preliminary assessments at national or continental scale, as well as in operational applications such as early warning systems, as shown, for example, by *Piacentini et al.* (2020) and *Li and Demir* (2022). Although simplified and geomorphological methods have been widely used for flood hazard mapping, when the focus shifts to the assessment of mitigation measures, the available literature is dominated by studies based on hydrodynamic methods, such as *Castellarin et al.* (2011), *Viero et al.* (2013), *Dazzi et al.* (2019), and *Shustikova et al.* (2020). This is mainly due to the complex flow behaviour in the presence of obstacles or hydraulic structures, which generally requires advanced mod-

elling approaches for a detailed representation. As a result, the use of simplified methods to estimate the effects of mitigation measures remains a relatively underexplored topic, despite their potential advantages in terms of computational efficiency. In this context, identifying the situations in which simplified methods can be used instead of hydrodynamic models is of fundamental importance and should follow a *fit-for-purpose* approach (Merz *et al.*, 2024). In other words, when the objective is to obtain an initial simplified estimate, a simplified method may be sufficient, whereas more detailed analyses generally require methods that better represent the underlying physical processes.

2.1.2 Simplified methods

Among simplified flood-hazard mapping methods, a relevant subgroup is represented by geomorphological approaches, which identify flood-prone areas using terrain descriptors and relationships based on the topographic structure of the basin. Examples include the GFPLAIN method developed by Nardi *et al.* (2006, 2013, 2019), which identifies flood-prone areas by comparing the elevation of each cell with an estimated water depth along the drainage network and the Geomorphic Flood Index (GFI) method (Manfreda *et al.*, 2008, 2011; Samela *et al.*, 2017; Manfreda and Samela, 2019), in which flood-prone areas are identified through a topographic index derived from contributing area and local slope, using a modified version of the equation originally proposed by Kirkby (1975). In both cases, a key step is the estimation of water depth through relationships linking it to geomorphological characteristics. Deiana *et al.* (2023) compared these methods using alternative rating relationships and, based on six case studies in Sardinia and Sicily, found that stage–discharge relationships provided the best overall performance.

A related and widely used family of methods is based on the HAND (Height Above the Nearest Drainage) index (Rennó *et al.*, 2008; Nobre *et al.*, 2011), which represents the vertical distance of each DTM cell from the nearest cell belonging to the drainage network. The index was later proposed as a proxy for flood inundation mapping by Nobre *et al.* (2016) and the method has subsequently been investigated and applied at different spatial scales. Given an estimated water depth, h , cells with HAND values lower than h are classified as flooded, whereas cells with higher values are considered non-flooded for the given discharge. The estimation of water depth is therefore a key step and, in order to avoid numerical simulations, it is commonly obtained through relationships linked to the geomorphological characteristics of the basin. For example Zheng *et al.* (2018b) used the HAND descriptor to obtain Synthetic Rating Curves (SRCs), which allow for the identification of a relation between the discharge Q and the water depth h from Manning’s equation. These curves can then be used to assess the h corresponding to a given

discharge (for example, a design discharge). The derivation of the curve is therefore of great importance considering that errors in its identification can lead to errors in the delineation of the flood inundated area (*Johnson et al.*, 2019). To improve the estimation of SRCs, *Zheng et al.* (2018b) used Manning’s roughness as a calibration parameter to identify the HAND-derived SRCs that were closest to those obtained using HEC-RAS 1D. The identification of accurate SRCs also depends on terrain characteristics, such as channel slope. *Yu et al.* (2025) compared SRCs obtained through the HAND-based approach with those derived from HEC-RAS 1D against field data, showing that hydrodynamic models can improve SRC estimation, although at a higher computational cost. They also found that the two approaches provide similar results in areas with medium- to high-slope channels, whereas the differences are greater in low-slope channels. Another important factor affecting SRC evaluation is the resolution of the DTM (*Ghanghas et al.*, 2022). However, this aspect is also relevant for other geomorphological approaches (*Annis et al.*, 2019) and for hydrodynamic models (*Ozdemir et al.*, 2013; *Horritt and Bates*, 2001). The areas subject to flood hazard for that discharge are therefore the cells with a HAND value lower than the assessed h . The methodology based on the HAND index provides an indication of the flooded area with a low computational cost and for this reason these methods have also been adopted within the United States National Water Model (NWM) for rapid Flood Inundation Mapping (FIM) (*Johnson et al.*, 2019; *Aristizabal et al.*, 2023). The methodology has been tested in several case studies (*Garousi-Nejad et al.*, 2019; *Gordon et al.*, 2023; *Hu and Demir*, 2021; *Li and Demir*, 2022; *Liu et al.*, 2018; *Zheng et al.*, 2018a; *Li et al.*, 2023) showing satisfactory performance, especially when considering its much lower computational cost compared with hydrodynamic models.

Although one of the first case studies in which the HAND index was used to identify flooded areas was a basin in Brazil (*Nobre et al.*, 2016), the method was later widely applied in the United States, as discussed above. However, its application has also been extended to other parts of the world. For example, case studies have been reported in Brazil, Canada, France, and Taiwan (*Gordon et al.*, 2023; *Scriven et al.*, 2021; *Yu et al.*, 2025; *Carvalho et al.*, 2020; *Hocini et al.*, 2020). In addition, *Arcorace et al.* (2024) proposed a modified HAND-based methodology aimed at improving the physical consistency of estimated flood volumes, and tested it on one basin in Italy and another one in southern Africa. These studies show that the HAND approach has been investigated under a variety of climatic, geomorphological, and geographical settings, beyond its widespread application in the United States. Although the methods reviewed above have mainly been applied to flood hazard mapping, the present work focuses on their possible extension to the assessment of mitigation measures within the Italian planning and funding framework. In this context, the water depths obtained from the HAND-derived SRCs may also be used to support a simplified, first-order assessment of direct flood damage,

for instance through depth–damage curves (*Scorzini and Frank, 2017*). By applying the same damage function to the ante-operam and post-operam configurations, the potential reduction in damage can be estimated consistently across the considered mitigation scenarios. Although such an approach remains simplified and does not aim to provide a detailed monetary assessment, it can provide useful preliminary information for comparing alternative mitigation measures and identifying the most promising solutions at an early planning stage.

2.2 ReNDiS and the RaStEM framework

In Italy, flood hazard and flood risk maps are delineated in accordance with the EU Floods Directive (*European Parliament and Council of the European Union, 2007*) and its national transposition through Legislative Decree No. 49/2010, as discussed in Section 1.1.1. The same framework also regulates the preparation of Flood Risk Management Plans (FRMPs), which are developed at the scale of the Units of Management and then coordinated at the River Basin District level. At the national scale, Italy is divided into 47 Units of Management grouped within 7 River Basin Districts (*Lastoria et al., 2021*), which correspond to the 7 Italian Flood Risk Management Plans, known as *Piani di Gestione del Rischio di Alluvioni* (PGRA). FRMPs are required to include measures aimed at reducing both the potential adverse consequences of flooding for human health, the environment, cultural heritage and economic activities and, where appropriate, the likelihood of flooding itself (*European Parliament and Council of the European Union, 2007*). In practice, however, while the PGRA provides a detailed delineation of flood hazard areas (classified into three levels associated with different return periods) and of flood risk areas, the description of mitigation measures is usually more general, partly because of the large spatial scale considered. The results of the PGRA are publicly available and are also summarised by ISPRA in national reports. For the first planning cycle, the main reference is the report by *Lastoria et al. (2021)*, which shows that almost 2.5 million people (4.1% of the total population) live in areas characterised by high flood hazard, corresponding to return periods between 20 and 50 years. More than 6.8 million people (11.5% of the total population) live in areas characterised by medium flood hazard, corresponding to return periods between 100 and 200 years, while more than 12.2 million people (20.6% of the total population) live in areas characterised by low flood hazard, corresponding to return periods between 200 and 500 years. These data highlight the need for accurate planning and for the implementation of both structural and non-structural measures aimed at mitigating flood risk. Within this context, ReNDiS (*Repertorio Nazionale degli interventi per la Difesa del Suolo*) plays a central role as a

platform used to collect, store and manage information on soil-defence interventions and hydrogeological risk-mitigation measures. Developed by ISPRA as part of its monitoring activities on behalf of the Ministry for the Environment and Energy Security (MASE), ReNDiS was initially designed to track interventions financed through plans and programmes under the responsibility of the Ministry. It has subsequently been expanded to include interventions financed by other public administrations as well, thereby strengthening its role as a national reference database for the planning, funding and monitoring of mitigation measures.

The procedure through which funding for mitigation measures is allocated by MASE is regulated by the Prime Minister’s Decree of 27 September 2021 (commonly referred to as the “Decreto Criteri”) (*DPCM*, 2021). According to the Decree, funding requests must be uploaded to the ReNDiS web platform by each Region and are subsequently evaluated by the relevant River Basin District Authority. After this evaluation, the system automatically assigns a score to each request on the basis of the criteria defined in the Decree. These scores are then used to establish a ranking of the proposed interventions, which forms the basis for the allocation of available funding. These criteria require information describing both the ante-operam and post-operam conditions, including, among other elements, the number of people exposed to the hazard before the intervention and the percentage reduction expected after its implementation. However, funding requests are usually submitted at an early stage of project design, when several of the data required for score assignment are still difficult to obtain. To support the representation of mitigation measures through a common, standardised, transparent, and spatially explicit framework, ISPRA developed the web-GIS platform RaStEM (*Rappresentazione Standardizzata degli Effetti di Mitigazione*) (*Dessi et al.*, 2025). RaStEM requires information on the ante-operam and post-operam conditions, including the extent of flood-hazard areas. While this information may be available for the ante-operam case (for example within the PGRA), it is often difficult to estimate for the post-operam scenario at the early design stage. Within this context, the Geosciences IR project, funded under NextGenerationEU, provided the resources needed to improve the RaStEM platform and to develop tools able to support the assessment of the information required for post-operam evaluation. The work presented in this thesis is one of the activities made possible within the Geosciences IR project¹, and is aimed at identifying and developing simplified, data-scarce methodologies to assess the influence of mitigation measures on flood-hazard areas at early stages of the design process. The approach relies on the HAND methodology, described in 2.1.2, and extends the method to account for the presence of mitigation measures.

¹<https://www.geosciences-ir.it/>

2.3 The proposed approach

The proposed method builds on approaches available in the literature, and aims to extend HAND-based methodologies to the assessment of the effect of mitigation measures on the reduction of flood-hazard areas.

2.3.1 Data

The approach is intended to perform a simplified study at the early stages of the mitigation measure design process; therefore, applicability using data freely available across the entire national territory was considered a key requirement. The HAND methodology is a geomorphological method and, as such, requires mainly geomorphological data, in particular a Digital Terrain Model (DTM), i.e. a raster file representing the elevation of each cell, and the position of the stream network. The DTM is particularly important for describing the study area and for deriving other variables (*Tarboton, 2003*). In Italy, the *Piano Straordinario di Telerilevamento* (PST) was developed with the aim of increasing the availability of environmental data and improving knowledge in support of management and risk-mitigation activities². At present, the plan has led to the availability of LiDAR derived DTMs with a spatial resolution of 1 or 2 m. However, these data are available mainly for riverine and coastal areas and do not cover the whole country, as shown in Figure 2.1. To overcome this limitation, the theoretical framework and the tool were developed using data from the Tinitaly dataset (*Tarquini et al., 2007, 2023*). This dataset, made available by the *Istituto Nazionale di Geofisica e Vulcanologia* (INGV), provides a DTM covering the entire country, with a resolution of 10 m. The other information required to apply the approach consists of geospatial data describing the stream network. The requirement of using data available for the whole national territory still applies; therefore, the stream network provided by the *DataBase di Sintesi Nazionale* (DBSN), produced by the *Istituto Geografico Militare* (IGM) (*IGM, 2025*), was adopted. The dataset is freely available as a geodatabase file and also includes several other vector layers, such as building footprints and infrastructures.

2.3.2 Theoretical framework and tool implementation

The proposed approach aims at representing the flood hazard area, for a given design discharge, in both the ante-operam and post-operam conditions. However, most of the

²<https://gn.mase.gov.it/portale/piano-sstraordinario-di-telerilevamento>

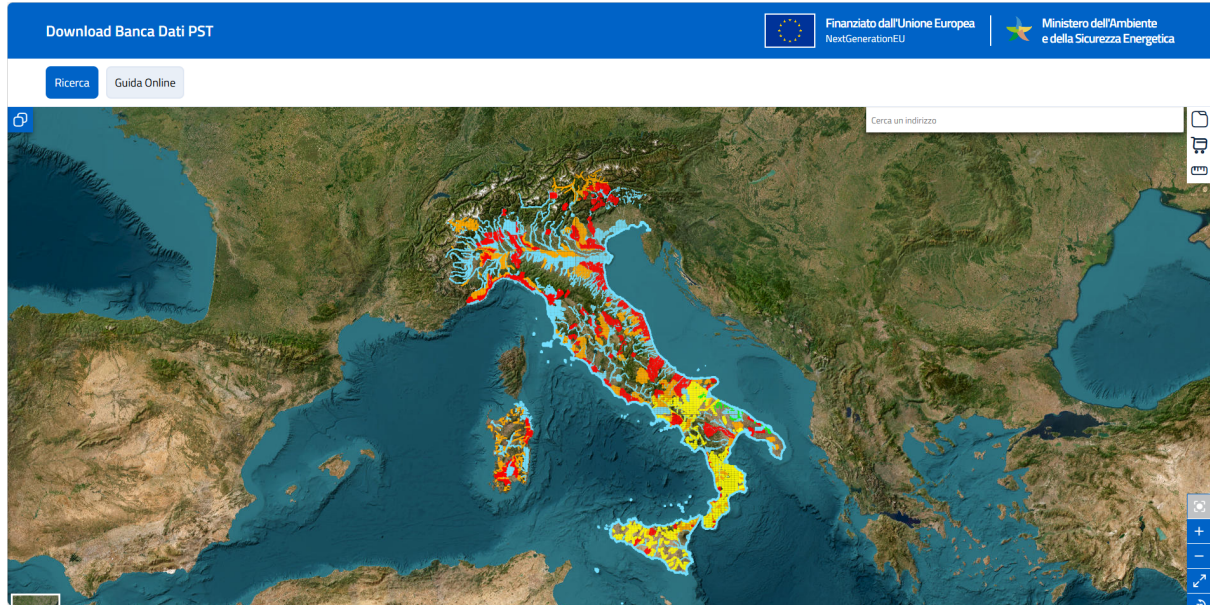


Figure 2.1: Web platform developed within the NextGenerationEU plan for accessing and downloading PST data. Areas shown in cyan, yellow, red, orange and green correspond to datasets currently available for download. The different colours indicate data acquired in different phases and years.

process is common to both cases. The procedure implemented is described step by step in the following. To increase the accessibility of the tool for non-expert users, the procedure was implemented within the QGIS software (*QGIS Development Team*, 2019), which is an open-access GIS platform widely used for applications in hydrology and risk mitigation studies. Following the approach adopted by (*Zheng et al.*, 2018b) and (*Garousi-Nejad et al.*, 2019) the first step consists of hydrologically conditioning the DTM and obtaining the HAND map; then the SRCs are calculated using the Manning equation (Eq. 2.1), and finally, for a given discharge, the hazard areas are delineated. In the development of the tool, several of the functions adopted for DTM conditioning are available through the WhiteBox Open Core (*Lindsay*, 2024) library within the corresponding QGIS plugin. The procedure for deriving SRCs was implemented as a python script.

DTM hydro-conditioning and HAND map

The HAND raster map represents the vertical distance of each cell of the DTM with respect to the closest cell of the stream network, considering the drainage direction; therefore, the identification of the drainage direction is a key step in the process. However, when a DTM and stream-network data obtained from different sources and with different resolutions are used together, their spatial correspondence may be imperfect. To enforce consistency between the DTM and the stream network used as input, and thus force

the representation of flow direction to be in accordance with the stream shapefile, the stream was burned into the DTM by lowering the corresponding cells. For this purpose, *Garousi-Nejad et al.* (2019) suggest to burn the stream using an high value (in their study about 1000 m). The resulting raster is hereafter referred to as the burned DTM (BDTM). Moreover, channel burning, as shown by *Garousi-Nejad et al.* (2019), allows for a better estimation of the HAND values and thus for a better representation of the SRCs.

The BDTM obtained using the FillBurn algorithm (*Lindsay, 2016*), was subsequently used to identify the drainage direction using the D8 method (*O'Callaghan and Mark, 1984*) and to extract the stream in raster format (which is required for the subsequent operations). This file is a binary raster, in which a value of 1 is associated with cells belonging to the stream, while a value of 0 is set for cells outside it. In parallel, the original DTM was conditioned using the fill-depressions algorithm available in the WhiteBox QGIS plugin to remove artificial void or local depressions created by DTM errors.

The HAND map was then calculated using the "ElevationAboveStream" function available in the WhiteBox QGIS plugin. As input, the function uses the filled original DTM together with the stream raster derived from the BDTM. The BDTM was not used directly for the calculation of the HAND map because of the artificially lowered elevation along the stream network. The entire workflow was implemented within a function developed in the QGIS Graphical Modeler.

Synthetic Rating Curves derivation

To derive the SRCs, the Manning equation is used:

$$Q(h) = \left(\frac{1}{n}\right) \cdot A(h)R(h)^{2/3}i^{1/2} \quad (2.1)$$

Where $Q(h)$ is the discharge, n is the Manning's roughness, $A(h)$ is the cross-section wetted area, $R(h)$ is the hydraulic radius and i is the bed slope.

The equation is based on the assumption of uniform and stationary flow, which represents an important simplification of real flow behaviour. To reduce the errors associated with this assumption, the stream under study is divided into smaller portions, hereafter referred to as reaches, and the equation is applied separately to each of them. In this way, the hydraulic variables used to derive the SRCs are evaluated over shorter river segments and their associated surrounding areas, for which the assumption of hydraulic homogeneity, although still a strong simplification, becomes more reasonable.

In the tool, the subdivision of the stream, together with the identification of the corresponding reaches and of the surrounding areas associated with them, is performed through a specifically developed module within the QGIS Graphical Modeler, that requires as input the length of each reach (assumed constant throughout the study area) and the width of the area to be considered. In practice, this identification is carried out by tracing sections orthogonal to the river and by considering the area between two consecutive sections as hydraulically homogeneous. The section length and the distance between two consecutive sections depend on the river characteristics and, at the moment, must be specified by the user as numerical values. A separate SRC is then derived for each of these areas using the calculations described below.

The SRCs are derived using the methodology and applying Eqs. 4–10 used by *Zheng et al.* (2018b), which are reported here for completeness. For a given value of water depth h , the set of cells with HAND values lower than h is considered inundated and identified as I . The surface water area of the inundated zone, $S(h)$, is then computed using Eq. 2.2 as the sum of the areas of all cells belonging to I .

$$S(h) = \sum_{n \in I} a_n \quad (2.2)$$

Where a_n is the area of the n -th cell in the inundated area I .

The channel bed area of the inundated zone is computed using 2.3

$$B(h) = \sum_{n \in I} a_n \cdot \sqrt{1 + s_n^2} \quad (2.3)$$

Where a_n and s_n are the area and slope, respectively, of the n -th cell in the inundated area I .

The flood volume of the inundated zone, $V(h)$ is computed using Eq. 2.4

$$V(h) = \sum_{n \in I} a_n \cdot h_n \quad (2.4)$$

Where a_n and h_n are the area and the water depth respectively of the n -th cell in the inundated area I .

The reach-averaged channel width is then calculated using Eq. 2.5:

$$W(h) = S(h)/L \quad (2.5)$$

Where $S(h)$ is the surface water area and L is the reach length.

The reach-averaged cross-sectional area is computed in a similar way using Eq. 2.6

$$A(h) = V(h)/L \quad (2.6)$$

Where $V(h)$ is the flood volume and L is the reach length.

The reach-averaged wetted perimeter is computed with Eq. 2.7

$$P(h) = B(h)/L \quad (2.7)$$

Where $B(h)$ is the inundated channel bed area and L is the length of the reach.

Finally, the hydraulic radius is obtained using Eq. 2.8

$$R(h) = A(h)/P(h) \quad (2.8)$$

Where $A(h)$ is the reach average wetted area and $P(h)$ is the reach average wetted perimeter.

The procedure is automatically performed by considering a range of water-depth values, h , from 0 up to a user-defined maximum value, with increments of 0.15 m. For each value of h , the corresponding discharge Q is calculated in order to derive the SRC. An interpolation method is then applied to obtain a polynomial equation describing the curve.

For a given discharge, this equation allows the corresponding value of h to be estimated; flood hazard areas are then delineated by identifying all cells with HAND values lower than or equal to h . However, because of the way the HAND index is defined, and also because of local topographic complexity and the modified drainage direction derived from the BDTM, some cells located relatively far from the stream may still exhibit HAND values lower than or equal to h , even when they are separated from the stream by natural or artificial barriers. This situation may occur, for example, in the post-operam case. Although these cells satisfy the HAND threshold, they are not necessarily hydraulically connected to the flooded stream network and therefore should not be considered flooded. To overcome this limitation, while also allowing a correct representation of linear barriers

such as levees, all cells with HAND values lower than or equal to h are grouped into clusters. In practice, a binary raster file is created, where to each cell c_{ij} is assigned a value:

$$\begin{cases} c_{ij} = 1 & \text{if } h \geq HAND_{ij} \\ c_{ij} = 0 & \text{if } h < HAND_{ij} \end{cases} \quad (2.9)$$

Cells with a value of 1 that are spatially connected are identified as clusters, however only clusters connected to the stream cells are retained as flooded areas, whereas disconnected clusters are excluded.

To apply the Manning equation (Eq. 2.1) a value of the roughness coefficient, n must also be specified. This parameter is of great importance for the derivation of the SRCs and, consequently, for the delineation of flood-hazard areas, as stated by *Zheng et al. (2018a)* and *Garousi-Nejad et al. (2019)*. *Scriven et al. (2021)* tested different approaches to account for roughness variability within the method. By comparing the results with observations from a real flood event, they obtain good results using a minimum–median approach, in which the discharge is computed using both the minimum and the median values of n derived from land cover. This allows two different discharge values Q to be associated with the same value of h , representing best-case and worst-case scenarios.

However, the work of *Scriven et al. (2021)* was aimed at developing a tool for rapid, on-the-fly flood mapping in Canada, based on measured or estimated river discharge. In the present case, the method is instead intended to assess the influence of mitigation measures that may be funded according to the rules defined by the Italian Prime Minister’s Decree of 27 September 2021. These rules also require that the proposed mitigation measures be located within areas identified as flood-hazard areas in the PGRA, within areas included in ongoing PGRA updates, or within areas affected by recent flood events (*DPCM, 2021*). Because an ante-operam delineation of flood-hazard areas is usually already available for the same site, and is often derived from hydrodynamic models providing a more physically accurate representation of the process, the proposed approach uses Manning’s roughness coefficient n as a calibration parameter. As shown by *Garousi-Nejad et al. (2019)* the use of known flooded areas to calibrate n can substantially improve the reliability of the results. Consistent with both the institutional framework and the available literature, the proposed approach therefore calibrates Manning’s roughness in the ante-operam condition by identifying the value that best reproduces the known flood-hazard area, and then applies the same calibrated value to the post-operam analysis. At present, the calibration procedure is performed manually by the user.

Post-operam

After the calibration of n , and the corresponding delineation of the ante-operam flood-hazard area, the post-operam situation can be analysed. As explained above, the proposed methodology does not explicitly simulate fluid motion; therefore, it can only represent mitigation measures whose effects can be approximated through modifications of the terrain model, such as levee construction or river-bed deepening. A first modification of the DTM is carried out using a relatively large elevation increase, with the sole purpose of forcing the derived flow direction to deviate according to the presence of the levee. The original DTM is then modified again, this time by increasing the elevation by a value equal, or close, to the actual levee height, in order to represent the mitigation measure itself. The workflow previously described is then repeated, and the hydroconditioning procedure is followed by calculating the modified HAND raster using the DTM with the actual levee height, while adopting the flow direction obtained from the DTM modified with the larger elevation increase. The need to use a higher elevation increase to derive the deviated flow direction is due to the fact that the actual levee height alone may not be sufficient to reproduce the intended deviation of the flow paths. The modification of the flow paths is highlighted in Fig. 2.2a,b.

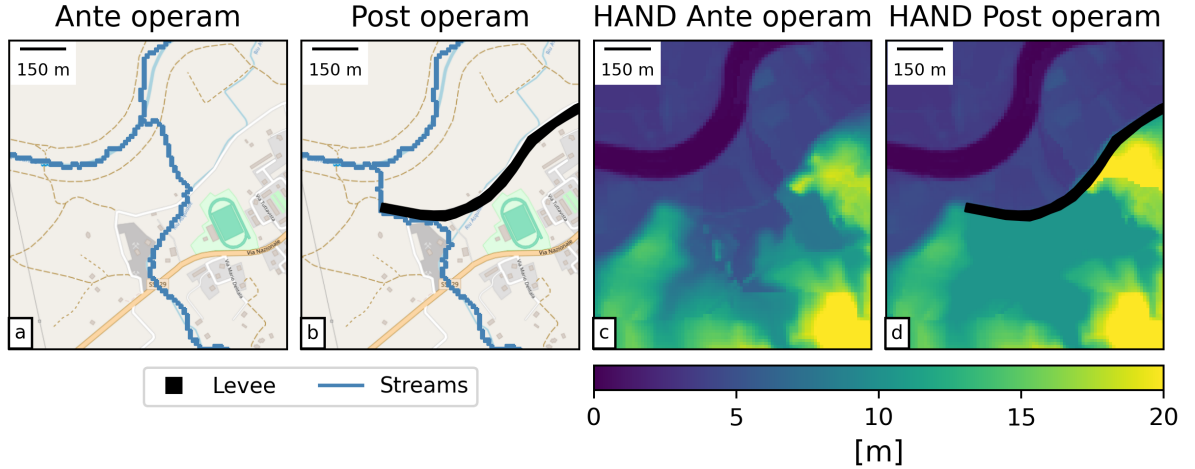


Figure 2.2: (a) Example of a stream in the ante-operam condition. (b) Stream modification caused by the local increase of the DTM used to represent the levee. (c) HAND map for the ante-operam condition. (d) HAND map obtained for the post-operam condition, with deviated flow paths and a DTM increase equal to the levee height.

The modified HAND raster consequently leads to a modified SRC with respect to the ante-operam case. Nevertheless, the cluster-based criterion described above remains necessary for the correct delineation of the flooded area. The area located behind the levee is affected only indirectly by the mitigation measure, through the modified flow paths, since the elevation of those cells is not directly changed by the levee height. As HAND

is defined with respect to the nearest stream cell along the flow directions, variations in HAND values behind the levee mainly reflect the modified drainage path rather than the hydraulic protection provided by the levee itself (see Fig. 2.2c,d). As a consequence, cells located landward of the levee may still satisfy the HAND threshold and be represented as flooded even in situations where overtopping should not occur. The cluster-based approach is therefore required to distinguish between areas that remain hydraulically connected to the stream network and areas that are effectively protected by the mitigation measure. If the levee is sufficiently high to prevent overtopping for the assigned discharge, the cells located behind it become disconnected from the clusters connected to the stream and are therefore excluded from the flooded area. By contrast, if the levee is too low and overtopping occurs, hydraulic continuity is restored between the river-side and landward areas, and the cells behind the levee are also classified as flooded.

2.4 Case Studies

The proposed procedure was tested on two different case studies located in Sardinia, Italy. The selection of these case studies was based on the availability of data within the PGRA. In particular, for some planned mitigation measures, the PGRA includes hydraulic studies carried out using HEC-RAS 1D. This is particularly valuable because flood hazard maps for both the ante operam and post operam scenarios are available from the same institutional source, thus ensuring a consistent and reliable basis for comparison. This makes the selected case studies especially suitable for testing the proposed approach. The case studies considered are the construction of two levees in the Cedrino Basin (*Autorità di Bacino Regionale della Sardegna, 2021a*) and the construction of one levee in the Posada Basin (*Autorità di Bacino Regionale della Sardegna, 2021b*). The position of the study basin in the national territory is shown in Fig 2.3a, while a zoom is shown in Fig 2.3b.

2.4.1 Cedrino Basin

The Cedrino basin (Fig. 2.4) is the basin drained by the Cedrino River, from which it also takes its name. The basin is located in the eastern part of the island and has an area of 1091 km^2 , while the Cedrino River has a total length of 80 km. A dam, the Pedra 'e Othoni Dam, is located along the river and forms Lake Cedrino. In the present analysis, only the part downstream of the dam is considered, for a total length of 23.9 km between the dam and the river mouth. In its downstream portion, the river

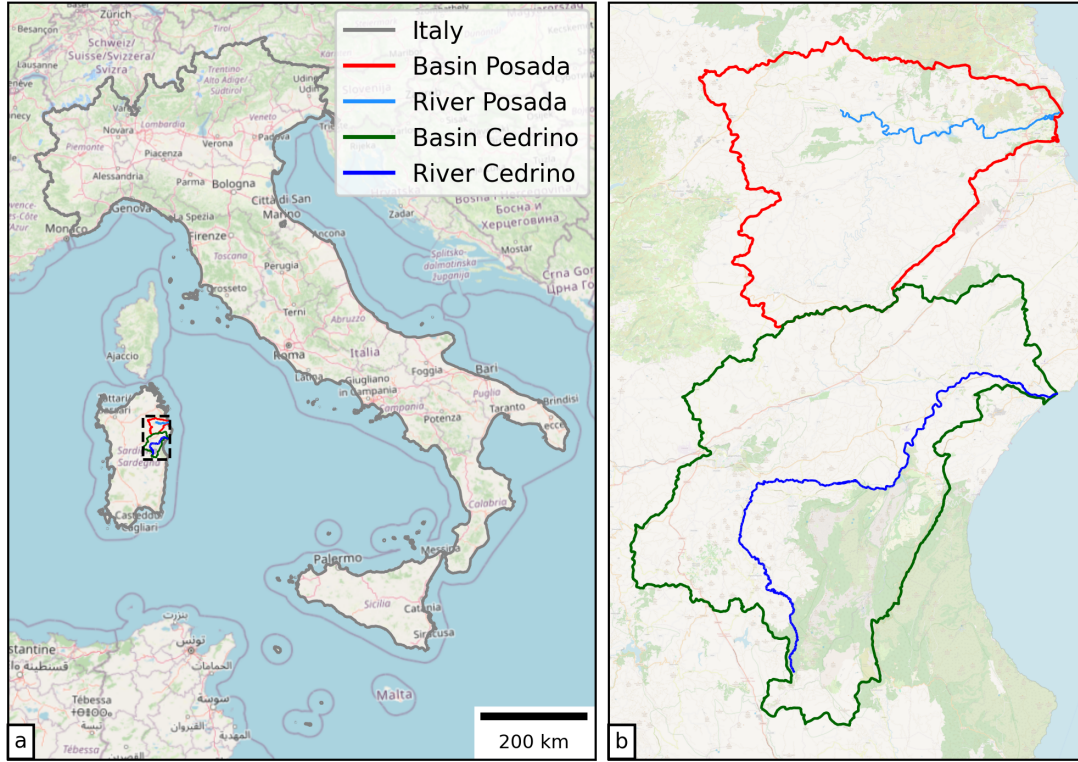


Figure 2.3: (a) Location of the study basins within the national territory. (b) Zoomed view of the study basins, showing their boundaries and the rivers considered. The background map is from OpenStreetMap.

flows near several towns: Galtelli and Orosei on the right bank, and Loculi, Irgoli, and Onifai on the left bank. Fig. 2.4 shows the ante-operam flood hazard areas for the three hazard levels, *High Probability Hazard*, HPH, *Medium Probability Hazard*, MPH and *Low Probability Hazard*, LPH. The dashed rectangle in Fig. 2.4 highlights the area of the river downstream of the dam, for which a zoomed view is reported in Fig. 2.5. Fig. 2.5 also shows the building footprint of Galtelli, from which it can be seen that part of the town lies within the flood hazard areas under all three hazard levels considered. For this reason, in the study of mitigation measures within the PGRA, Scenario 1 evaluates the implementation of a levee on the right bank of the river to protect the town. The study carried out in the PGRA considers the medium-hazard scenario, associated with an event with a return period of 200 years. Although other tributaries are present within the basin, the mitigation scenario examined here involves only a levee along the Cedrino River; therefore, only this river is considered in the application of the proposed approach.

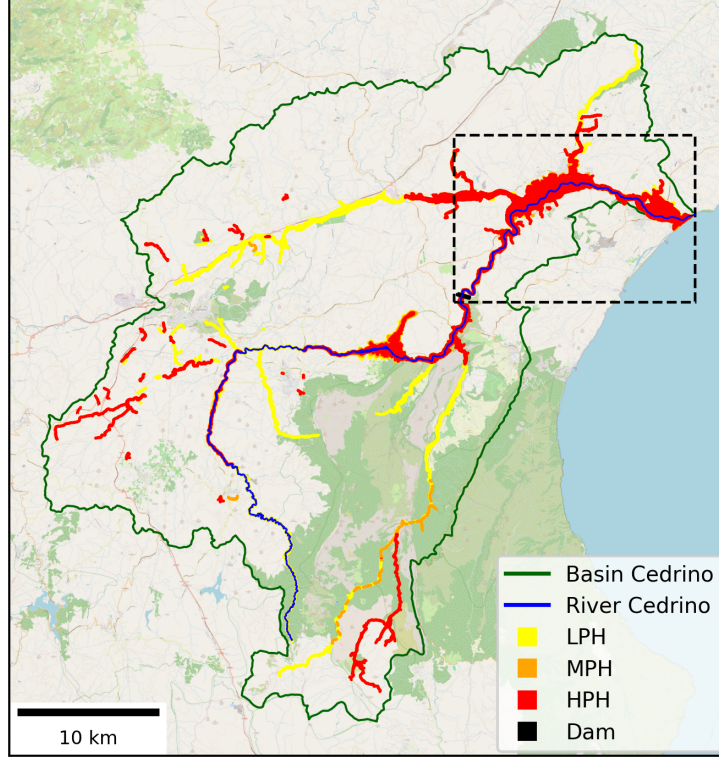


Figure 2.4: Map of the Cedrino Basin showing the flood-hazard areas identified in the PGRA for the three hazard levels. The Cedrino River and the basin boundaries are shown for reference. The background map is from OpenStreetMap.

Ante operam

The theoretical framework presented in Sec. 2.3.2 is then applied to the Cedrino River, considering as study area the part of the river downstream of the Pedra 'e Othoni Dam, shown in Fig. 2.5. The input data used are the 10 m resolution DTM obtained from Tinitaly (*Tarquini et al.*, 2023) and the shapefile representing the river obtained from the DBSN (*IGM (Istituto Geografico Militare)*, 2025). The first step consisted of hydro-conditioning the DTM, burning the stream network into the terrain model, and then computing the HAND map using the tool within the QGIS Graphical Modeler presented above. The DTM is shown in Fig 2.6a, while Fig. 2.6b shows the resulting HAND map together with the selected river reach and the surrounding areas associated with each reach, used for the derivation of the SRCs.

Once the SRCs had been derived for each area, flood-hazard areas were delineated for the MPH hazard level using the same discharge specified in the PGRA. As previously explained, Manning's roughness coefficient, n was used as a calibration parameter. To identify the most suitable value, flood-hazard areas were delineated using eight different values of n and the corresponding results were compared with the PGRA map by means

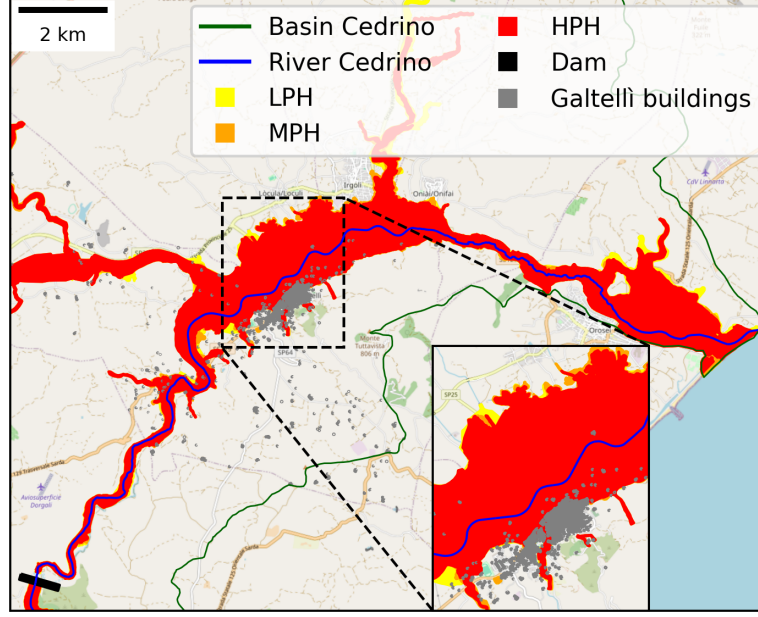


Figure 2.5: Zoomed view of the area downstream of the Pedra 'e Othoni Dam, corresponding to the dashed rectangle shown in Fig. 2.4. The map also shows the building footprints of Galtellì, the Cedrino River and the basin boundaries. The background map is from OpenStreetMap.

of the *Critical Success Index* (CSI), calculated as:

$$CSI = \frac{TP}{TP + FP + FN} \quad (2.10)$$

Where TP , FP and FN denote the true positive, false positive, and false negative areas, respectively. The CSI ranges from 0 to 1, with values closer to 1 indicating a better agreement between the simulated flood-hazard areas and those reported in the PGRA. In the present application, the CSI was computed over the entire study area, including the portions associated with tributaries that were not explicitly represented in the proposed modelling framework. Although the CSI, like other binary classification metrics, presents intrinsic limitations (*Stephens et al.*, 2014), it was considered an acceptable indicator for the purposes of the present calibration.

The results are reported in Table 2.1, and show that the best agreement is obtained for $n = 0.09$, which was therefore selected for the post-operam simulation. The results obtained with $n = 0.09$ are reported in Fig. 2.7. Overall, the CSI values are relatively high, supporting the feasibility of the proposed approach. As visible in the figure, however, some areas classified as flood-hazard zones in the PGRA are not reproduced by the proposed approach. These discrepancies are mainly associated with tributaries that were

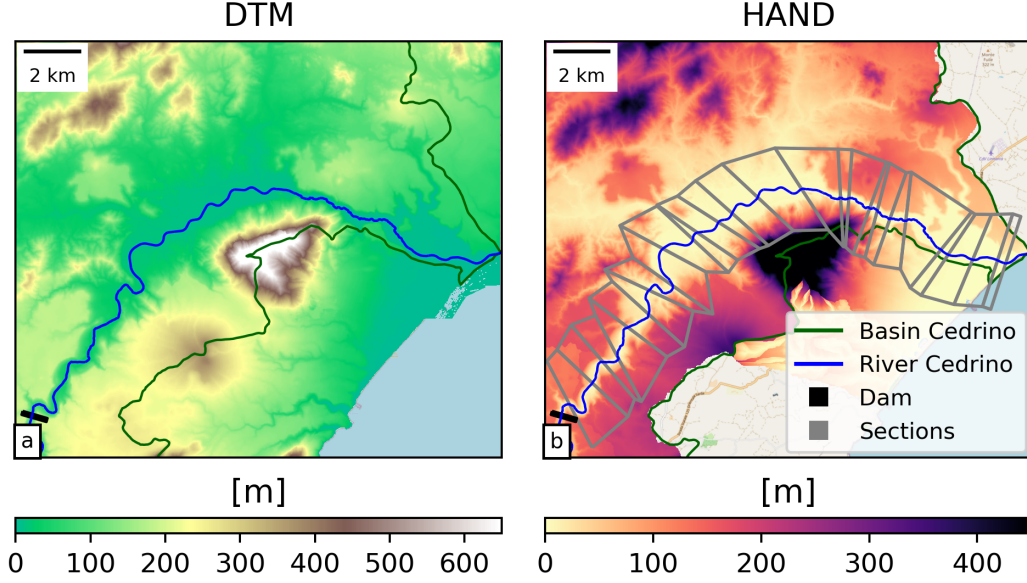


Figure 2.6: (a) DTM of the study area, showing the Cedrino River and the basin boundaries. (b) HAND map showing the subdivision of the stream into reaches and the surrounding areas used for the derivation of the SRCs. The Cedrino River, the basin boundaries, and the Pedra 'e Othoni Dam are also shown. The background map is from OpenStreetMap.

included in the PGRA modelling but not considered in the present study. This choice slightly penalises the CSI values; however, delimiting and excluding only those portions from the comparison would have required additional assumptions in defining the comparison domain. Nevertheless, since the primary objective of this stage was to identify the most suitable value of n , the tributaries were excluded from the modelling for simplicity.

Table 2.1: Scores obtained for different values of Manning's roughness coefficient, n , in the delineation of flood-hazard areas for the *MPH* level in the Cedrino Basin.

n	True Positive	False Positive	False Negative	CSI
$[s\ m^{1/3}]$	$[km^2]$	$[km^2]$	$[km^2]$	$[-]$
0.05	13.01	0.82	4.89	0.69
0.06	13.63	1.00	4.27	0.72
0.07	14.01	1.21	3.89	0.73
0.08	14.34	1.37	3.56	0.74
0.09	14.52	1.54	3.38	0.75
0.1	14.65	1.74	3.25	0.74
0.11	14.75	1.97	3.15	0.74
0.12	14.83	2.16	3.07	0.73

Ante operam

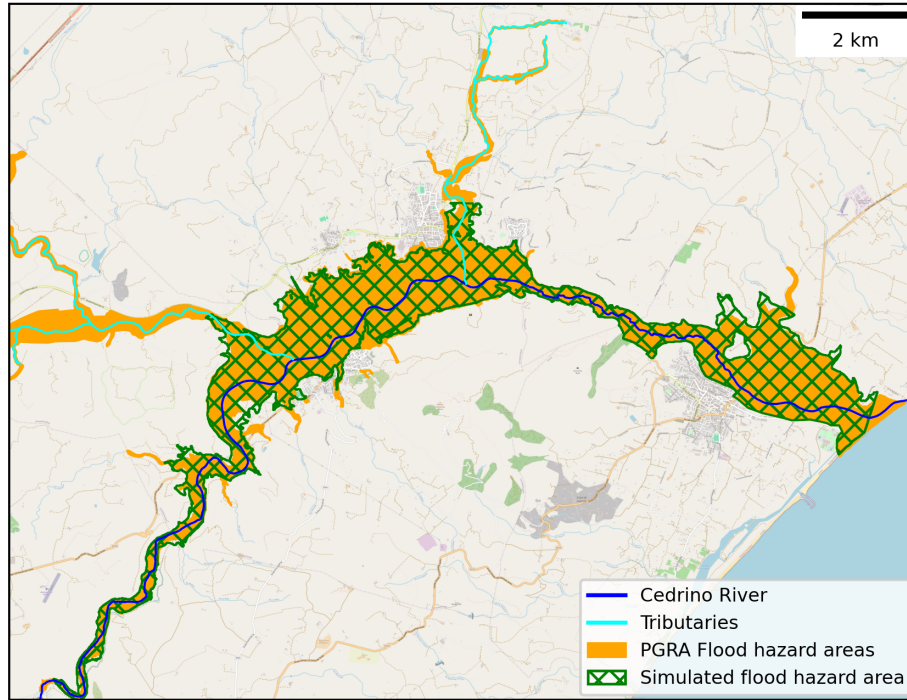


Figure 2.7: Flood-hazard area obtained with the proposed approach, superimposed on the corresponding PGRA results. The Cedrino River is also shown, together with the two tributaries not included in the use of the simplified approach. The background map is from OpenStreetMap.

Post operam

The post-operam configuration corresponding to Scenario 1 of the PGRA (*Autorità di Bacino Regionale della Sardegna*, 2021a), is shown in Fig. 2.8. The intervention consists of the construction of two levees aimed at protecting Galtellì and an industrial area, as well as the removal of an old bridge located between the two levees, and maintenance works within the river bed. Since the proposed simplified approach cannot represent the hydraulic effects associated with the presence or removal of structures such as bridges, this intervention was not included in the analysis. Although bridge removal could influence the downstream flow dynamics, and consequently the behaviour of the second levee, these effects cannot be captured without a hydrodynamic simulation. In the PGRA layout, the first levee also includes a branch that deviates from the main river alignment and extends into the urban area of Galtellì. However, due to the resolution of the DTM used in the present study, this urban branch could not be represented reliably. Therefore, in the simplified post-operam configuration adopted here, only the main portion of the first levee along the Cedrino River was considered, together with the second levee. The resulting scenario considered in the study is shown in Fig. 2.9, where the levees included

in the analysis are shown in black.

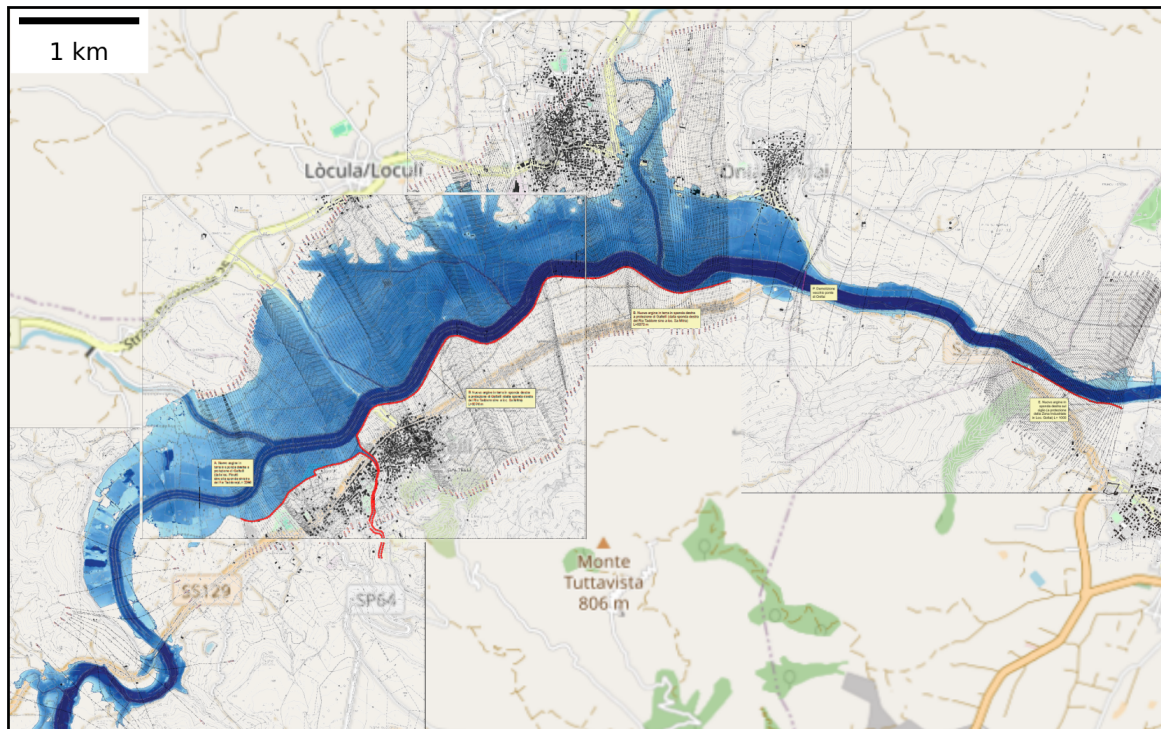


Figure 2.8: Scenario 1 considered in the PGRA (*Autorità di Bacino Regionale della Sardegna*, 2021a), showing the construction of two levees and the removal of a bridge. The interventions are shown in red, while water depth is shown in blue.

The levees were incorporated into the DTM using the tool described in Sec. 2.3.2. For both levees, the DTM was first modified by increasing the elevation of the corresponding cells by 15 m, in order to successfully alter the flow directions and the resulting HAND map. The DTM used for the actual analysis was then obtained by starting from the ante-operam DTM and increasing the cells within the levee footprints by the same height adopted in the PGRA, namely 2.5 m for the levee aimed at protecting Galtelli and 3 m for the downstream levee protecting the industrial area.

The results are shown in Fig. 2.10, where the flooded area derived using the proposed method (hatched green area) is superimposed on the maps obtained from the PGRA study (*Autorità di Bacino Regionale della Sardegna*, 2021a). The results show that the first levee performs overall well, being able to contain flooding except for a small portion located near its downstream end. In contrast, the second levee is not able to prevent flooding effectively.

A more detailed analysis of the results obtained for the second levee shows that all the cells within the levee are classified as flooded, indicating that the adopted levee height is not sufficient to prevent overtopping.

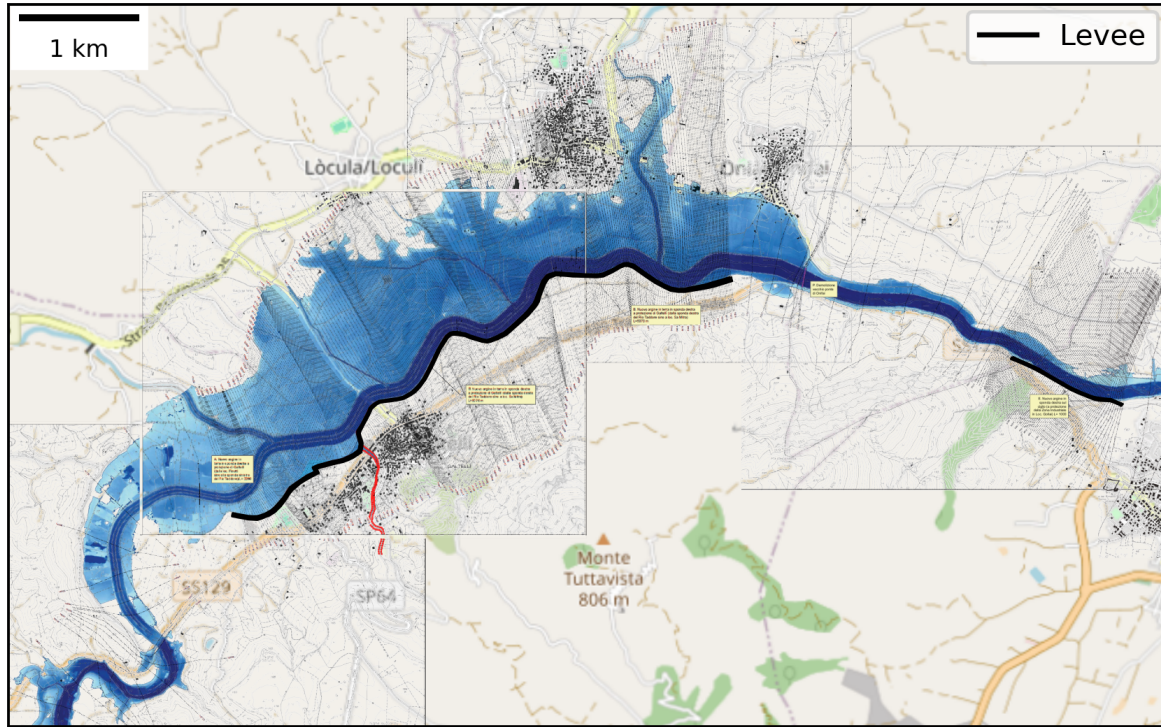


Figure 2.9: Levees implemented in the proposed approach, superimposed on the study plots from *Autorità di Bacino Regionale della Sardegna* (2021a).

The poorer performance obtained for the second levee can be explained by the simplifications adopted in the present approach. For example, the influence of bridge removal, which likely affects the downstream flow behaviour, is not taken into account. Moreover, inspection of the ante-operam DTM shows that the area where the levee is located is characterised by a relatively small elevation difference compared with the stream position. The adopted DTM is therefore probably not able to represent the local bathymetry in this area with sufficient accuracy. This may lead to a representation of the levee over cells that are lower than those corresponding to the actual terrain, thereby reducing its effective height in the model and its capacity to prevent overtopping.

The evaluation of the CSI score, as performed for the ante-operam configuration, could not be carried out for the post-operam case because the PGRA post-operam flooded area is available only as an image, whereas for the ante-operam case the flood-hazard perimeter is also provided as a shapefile. Fig. 2.11 shows the flood-hazard areas obtained using the proposed method in the ante-operam (Fig. 2.11a) and in the post operam (Fig. 2.11b) configurations. The comparison highlights the good performance obtained for the upstream levee designed to protect the town of Galtellì, whereas the downstream levee, aimed at protecting the industrial area, is not represented adequately and does not prevent flooding in the corresponding area. The delineated flood hazard maps (both ante- and post-operam) can successfully be uploaded in the RaStEM web-gis platform,

thus allowing for the estimation of the mitigation effects.

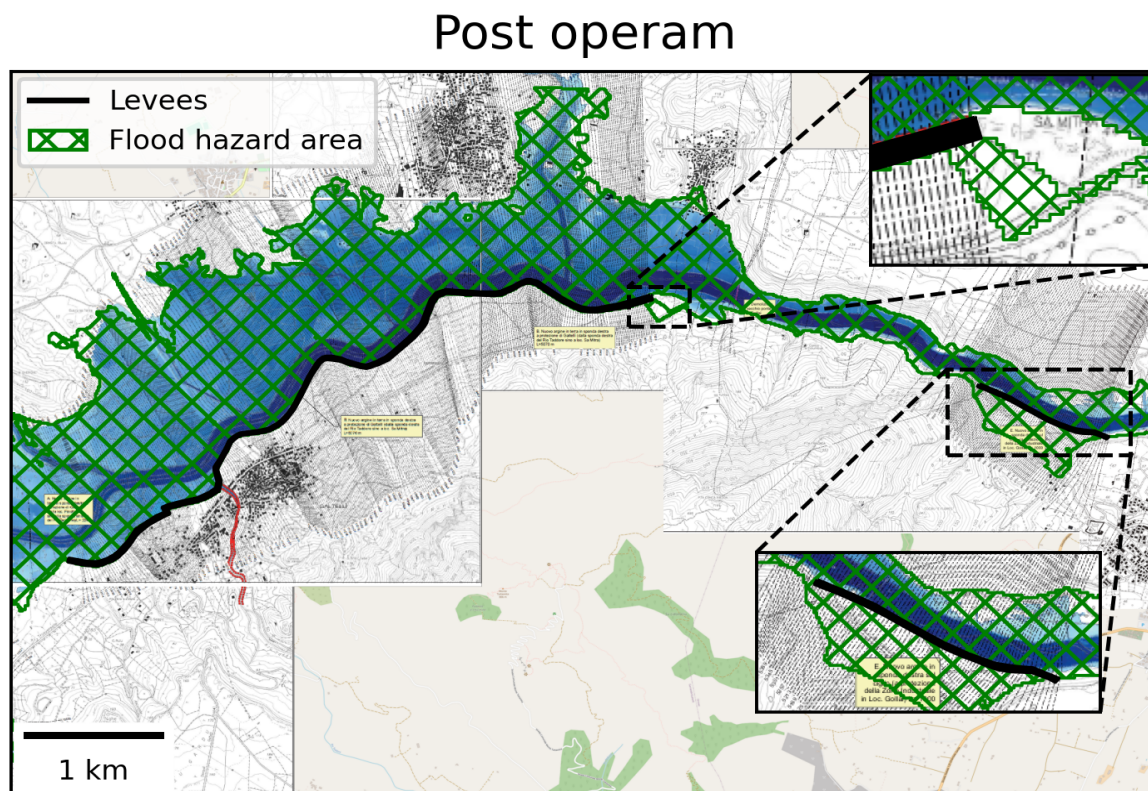


Figure 2.10: Flood-hazard areas obtained with the proposed approach (hatched green areas) after the inclusion of the levees (shown in black). The results are superimposed on the flood-hazard maps available in the PGRA for Scenario 1 (*Autorità di Bacino Regionale della Sardegna, 2021a*). Background map is from Openstreetmap.

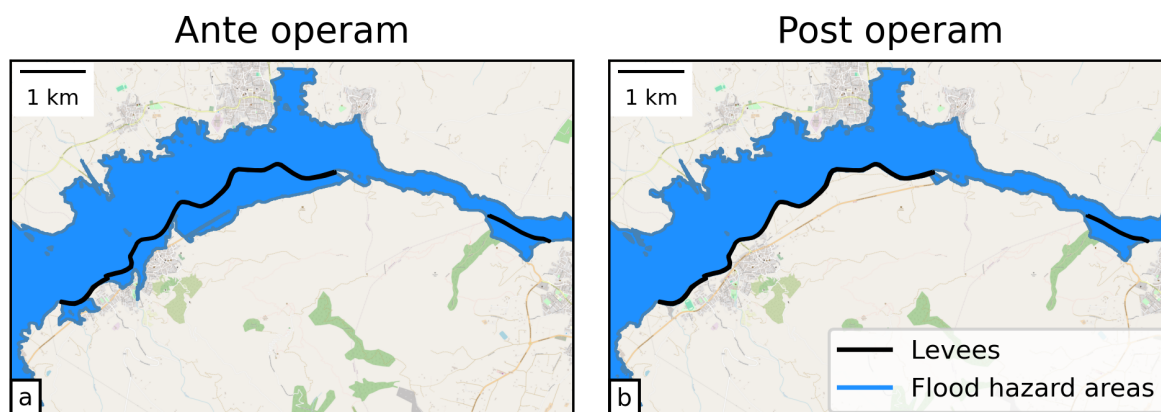


Figure 2.11: (a) Flood-hazard areas obtained with the proposed method for the ante-operam configuration. (b) Corresponding post-operam flood-hazard areas. Background map is from Openstreetmap.

Preliminary assessment of exposed elements

In addition to the comparison of flood-hazard extent, the delineated ante-operam and post-operam maps can also be used to support a preliminary assessment of the effectiveness of mitigation measures in terms of reduction of exposed elements. This step is particularly relevant within early-stage planning procedures, where the objective is often not to obtain a detailed estimate of economic losses, but rather to compare alternative interventions and identify those capable of producing the largest reduction in potential impacts. Although the HAND-based methodology can provide an estimate of water depth, spatially distributed water-depth values are not available in the PGRA maps for the study area. As a result, a monetary damage assessment based on commonly used depth–damage curves could not be consistently validated against the official reference data. For this reason, the analysis was limited to exposure-based indicators, which are more consistent with the type of information available for both the HAND-derived maps and the PGRA maps. This simplified assessment is also coherent with the information required by the Prime Minister’s Decree of 27 September 2021 (*DPCM*, 2021), where people and assets at risk are considered in the score assigned to each mitigation measure. For this purpose, the three flood-hazard maps available for the study area were considered: the ante-operam map from the PGRA, and the ante-operam and post-operam maps obtained through the proposed HAND-based methodology. These maps were used to estimate the number of exposed buildings and inhabitants by intersecting the flood-hazard areas with building data from the DBSN and census data from ISTAT (Italian National Institute of Statistics). The number of exposed buildings was determined by considering all buildings included in the DBSN, regardless of their building use class, and excluding only those classified as having poor structural conditions, namely those with the attribute ‘stato’ equal to ‘rudere’. Exposed buildings were then identified as those whose footprint lie within the flood-hazard area. The number of exposed inhabitants was estimated by redistributing the population reported in the official census data. In particular, the population of each census block was assumed to be uniformly distributed over the area covered by residential buildings located within that block. Based on this assumption, a number of inhabitants was assigned to each residential building proportionally to its area. The total number of exposed inhabitants was then obtained by summing the inhabitants assigned to the buildings located within the flood-hazard area. The analysis was carried out by comparing the reduction in exposed buildings and exposed population between the ante-operam and post-operam configurations obtained with the HAND-based methodology. The ante-operam values were also computed using the PGRA hazard map, in order to provide a reference for the exposure estimates.

The results of the exposure-based assessment are reported in Table 2.2. In the ante-

operam configuration, the HAND-derived flood-hazard area is slightly smaller than the corresponding PGRA area, with values equal to 16.1 km² and 17.9 km², respectively. However, this difference in flood extent does not directly translate into a lower estimate of exposed elements. On the contrary, the HAND-based map identifies a slightly higher number of exposed buildings and inhabitants, with 291 exposed buildings and 519 exposed inhabitants, compared with 281 buildings and 464 inhabitants obtained from the PGRA map. This result highlights that differences between flood-hazard maps may affect the estimation of exposed elements in a non-linear way. In fact, the impact of discrepancies in flood delineation depends not only on the total flooded area, but also on the spatial distribution of the exposed assets and population. Therefore, even relatively small differences in flood extent may lead to relevant differences in exposure estimates if they occur in densely populated areas. This aspect is consistent with the findings of *Molinari and Scorzini* (2017), who showed that the quality and resolution of input data, including building-footprint information, can significantly influence flood damage estimates. For this reason, the exposure-based indicators presented here should be interpreted as preliminary screening indicators, in line with the simplified nature of the approach used to delineate the flood-hazard areas. Within this limitation, these indicators can support a preliminary comparison of mitigation effectiveness. The HAND-based results show that the post-operam configuration reduces the flooded area by 11.2%. The reduction in exposed elements is more pronounced, with a 28.5% decrease in the number of exposed buildings and a 60.0% decrease in exposed inhabitants. This indicates that, although the reduction in flood extent is relatively limited, the results suggest a more substantial reduction in exposure, especially in terms of exposed population. Therefore, the exposure-based assessment provides information that is complementary to the simple comparison of flood-hazard extent and may be useful for the preliminary evaluation of mitigation effectiveness.

Table 2.2: Comparison of flood-hazard extent and exposed elements estimated for the Cedrina case study using the PGRA map and the proposed HAND-based approach maps.

Indicator	PGRA	HAND-based approach		
	Ante-operam	Ante-operam	Post-operam	Reduction
Flooded area [km ²]	17.9	16.1	14.3	11.2 %
Exposed buildings [-]	281	291	208	28.5 %
Exposed population [-]	464	519	208	60.0 %

2.4.2 Posada basin

The Posada basin is located in eastern Sardinia, immediately north of the Cedrina basin described above (Fig. 2.3). It is drained by the Posada River and covers an area of

697km^2 . The river has a total length of about 40 km, and along its course lies the Maccheronis Dam. In the present study, only the part of the river downstream of the dam is considered, corresponding to a total length of 15.5 km. Along this reach, the

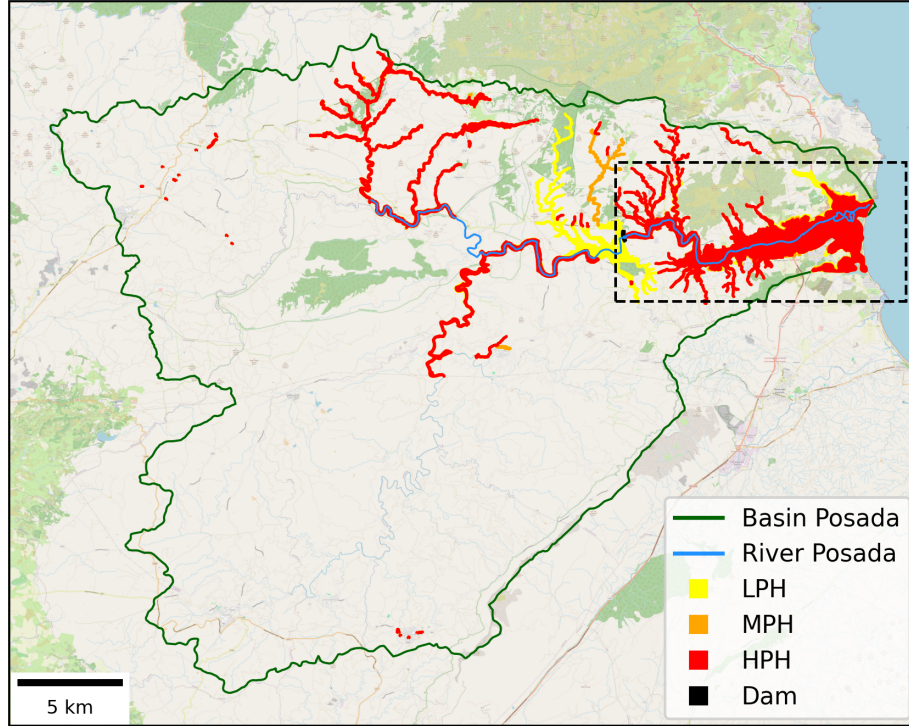


Figure 2.12: Map of the Posada Basin showing the flood-hazard areas identified in the PGRA for the three hazard levels. The basin boundaries and the Posada River are shown for reference. The dashed rectangle indicates the study area considered for testing the proposed method. The background map is from OpenStreetMap.

river flows near the towns of Torpè and Posada, both located on the right bank. Fig. 2.12 shows the flood-hazard areas identified by the PGRA for the three hazard levels (HPH, MPH, and LPH), while the dashed rectangle highlights the selected study area. In Fig. 2.13 a zoom on the area considered for the study is shown. The figure also shows that both towns are affected by the mapped flood-hazard areas. A levee is already present on the right bank. However, its existing height is sufficient to contain flooding only for events with relatively low return periods. For this reason, Scenario 1 proposed in the PGRA (*Autorità di Bacino Regionale della Sardegna, 2021b*) is aimed at protecting these two urban areas by increasing the levee height. The PGRA analysis refers to the medium-hazard scenario, associated with a 200-year return period event.

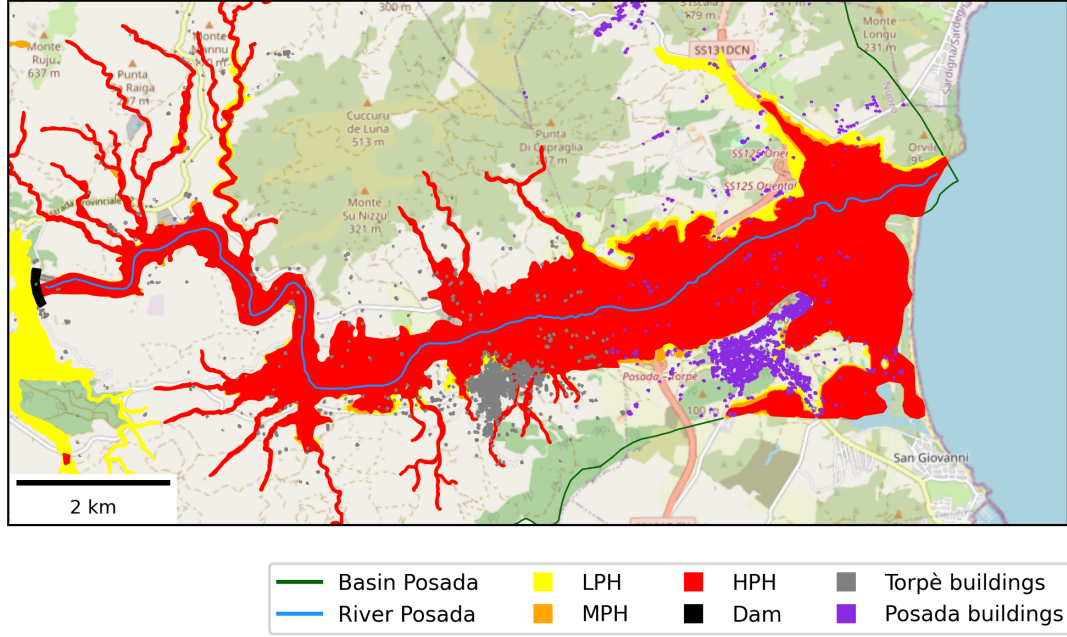


Figure 2.13: Zoomed view of the PGRA flood-hazard areas within the study area, corresponding to the dashed rectangle shown in Fig. 2.12. The map also shows the building footprints of Torpè and Posada, both of which are affected by flood hazard. The Posada river is also shown for reference. The background map is from OpenStreetMap.

Ante operam

The theoretical framework described in 2.3.2 and already applied to the Cedrino Basin in 2.4.1 was also applied to the Posada Basin. The DTM of the study area is shown in Fig. 2.14a, while Fig. 2.14b shows the corresponding HAND map and the sections used to derive the SRCs. As for the Cedrino Basin, eight simulations were performed using different values of Manning's roughness coefficient, n , in order to identify the value providing the best agreement with the PGRA map. The results are reported in Tab. 2.3 and show that the CSI score is the same for $n = 0.08$, $n = 0.09$ and $n = 0.1$. For the subsequent post-operam analysis, $n = 0.08$ was adopted. The flood-hazard areas obtained with this value are shown in Fig. 2.15, superimposed on the PGRA flood-hazard map.

Post Operam

After calibrating the most suitable value of n for the ante-operam configuration, the post-operam case was analysed. As discussed above, Scenario 1 in the PGRA study consists of increasing the height of an existing levee located along the right bank (*Autorità di Bacino Regionale della Sardegna*, 2021b), as shown in Fig. 2.16. The levee considered in the study is represented in Fig. 2.17. The PGRA scenario assumes a mean height

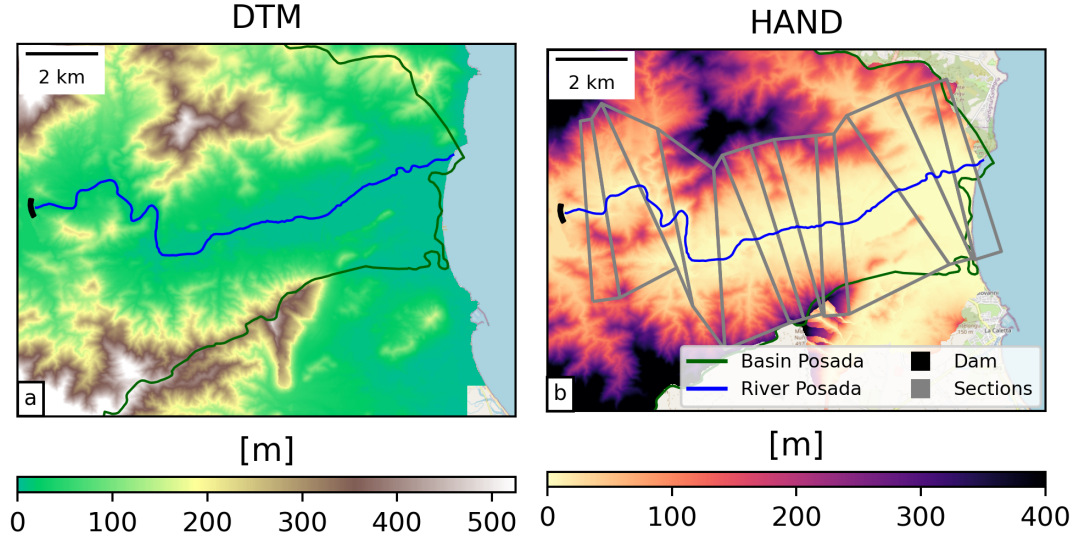


Figure 2.14: (a) DTM of the study area, showing the Posada River and the basin boundaries. (b) HAND map showing the subdivision of the stream into reaches and the surrounding areas used for the derivation of the SRCs. The Posada River, the basin boundaries, and the Maccheronis Dam are also shown. The background map is from OpenStreetMap.

increase of 2 m. However, in this situation the use of an higher elevation was required to correctly represent the levee. This requirement may be related to the fact that the existing levee is not fully represented in the DTM used for the ante-operam configuration, most likely because of its coarse resolution. This interpretation is further supported by the vertical accuracy of the DTM used in this work, which has an overall Root Mean Square Error (RMSE) of the order of 3.5 m (*Tarquini et al.*, 2007).

For the post-operam application, the DTM was therefore modified by introducing a localized terrain-height increase of 4.5 m along the levee alignment. With this value, the influence of the levee is represented satisfactorily, except for a small portion near the be-

Table 2.3: Scores obtained for different values of Manning’s roughness coefficient, n , in the delineation of flood-hazard areas for the *MPH* level in the Posada Basin.

n	True Positive	False Positive	False Negative	CSI
$[s\ m^{1/3}]$	$[km^2]$	$[km^2]$	$[km^2]$	$[-]$
0.05	10.67	0.49	4.70	0.67
0.06	11.20	0.66	4.17	0.70
0.07	11.53	0.83	3.84	0.71
0.08	11.74	1.01	3.63	0.72
0.09	11.96	1.19	3.41	0.72
0.1	12.10	1.38	3.28	0.72
0.11	12.21	1.57	3.16	0.72
0.12	12.31	1.77	3.07	0.71

Ante operam

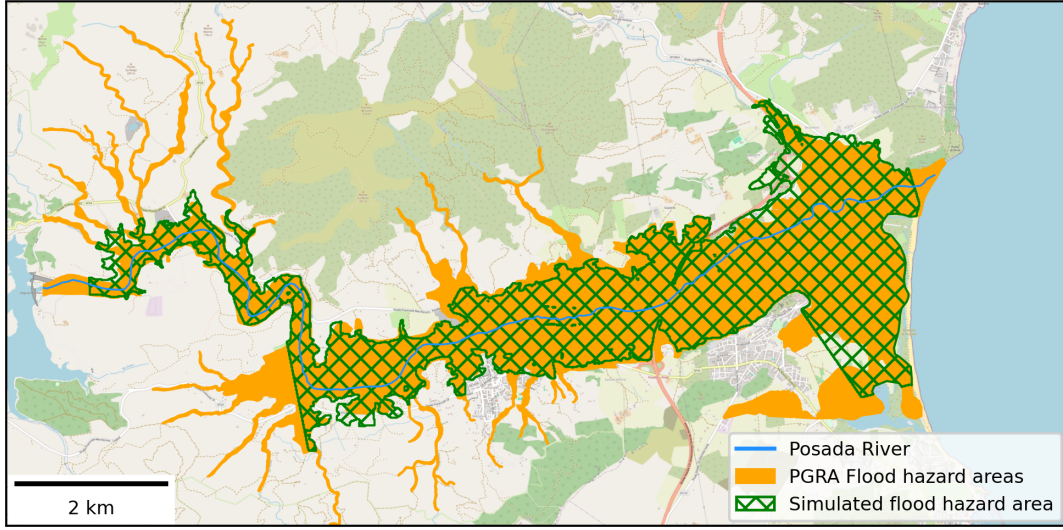


Figure 2.15: Flood-hazard area obtained with the proposed approach for the ante-operam configuration (hatched green area), superimposed on the flood-hazard area identified in the PGRA. The Posada River is also shown for reference. The background map is from OpenStreetMap.

ginning of the intervention (upstream) as shown in Fig. 2.18. The figure also shows that flooding still occurs near the end of the levee (downstream) under the design discharge. However, this area is also mapped as flood-prone in the PGRA study, probably because of a backwater effect.

2.5 Discussion

The results obtained in the two case studies suggest that the proposed HAND-based methodology can provide a useful simplified representation of the effects of mitigation measures on fluvial flood-hazard areas. In both basins, the ante-operam calibration produced a satisfactory agreement with the flood-hazard maps available from the PGRA, supporting the feasibility of the approach as a preliminary assessment tool. This result is particularly relevant considering that the method relies on limited input data, coarse-resolution topography, and simplified hydraulic assumptions. The low computational effort should also be considered: the identification of the ante-operam flood-hazard areas can be performed in less than 15 minutes.

Considering the theoretical basis of the method, which relies only on geomorphological characteristics, only mitigation measures that can be represented as modifications of the terrain model can be studied. For example, the case studies presented here considered

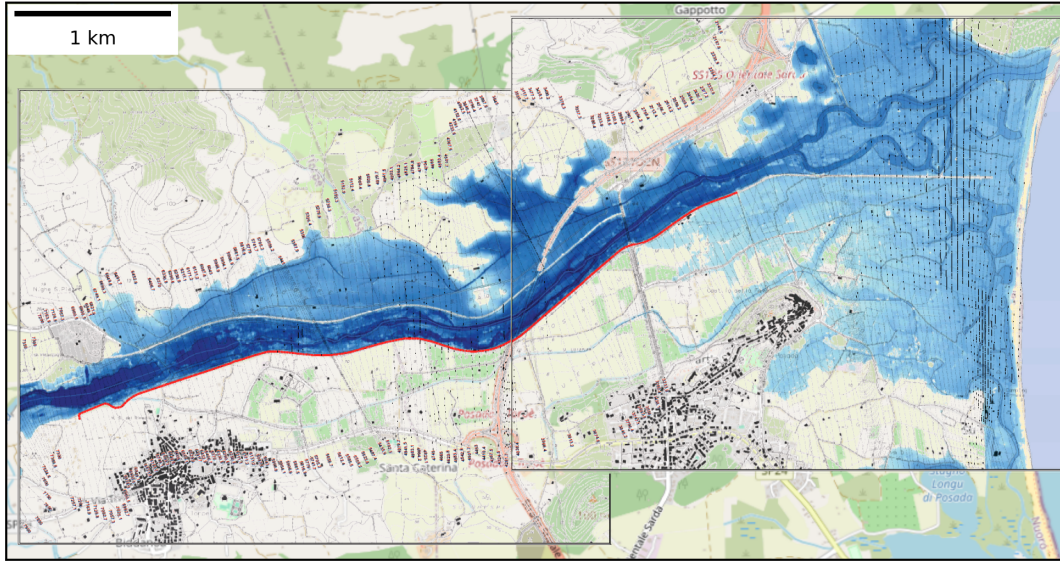


Figure 2.16: Scenario 1 proposed in the PGRA study, consisting of an increase in the height of an existing levee. The levee is shown in red in the figure taken from the PGRA study (*Autorità di Bacino Regionale della Sardegna, 2021b*). The background map is from OpenStreetMap.

the inclusion of levees aligned with the main river course and located in areas where the flood dynamics remain largely controlled by the topographic configuration captured by the DTM. Under these conditions, the cluster-based interpretation of HAND values allows the method to represent the disconnection of areas located behind the levee from the flooded river corridor, thus reproducing the expected reduction in flood-hazard extent.

At the same time, the case studies also highlight the main limitations of the approach. The methodology does not simulate flow dynamics explicitly and therefore cannot reproduce processes that depend strongly on local hydraulic interactions, such as the effects of bridges, local contractions, backwater, or complex urban flow patterns. This limitation was particularly evident in the Cedrino case study, where the PGRA Scenario 1 included both bridge removal and a more articulated levee layout, while the simplified representation adopted here could only include the portions of the intervention that were compatible with a terrain-based modification of the DTM. The poorer performance observed for the downstream levee in the Cedrino Basin is therefore consistent with the simplifications introduced and should not be interpreted as a failure of the general approach, but rather as an expected consequence of applying a simplified method to a hydraulically more complex configuration.

A second key issue concerns the influence of topographic data resolution. In the Posada river, the levee height adopted in the present application had to be increased with respect to those considered in the PGRA studies in order to produce an appreciable effect on the

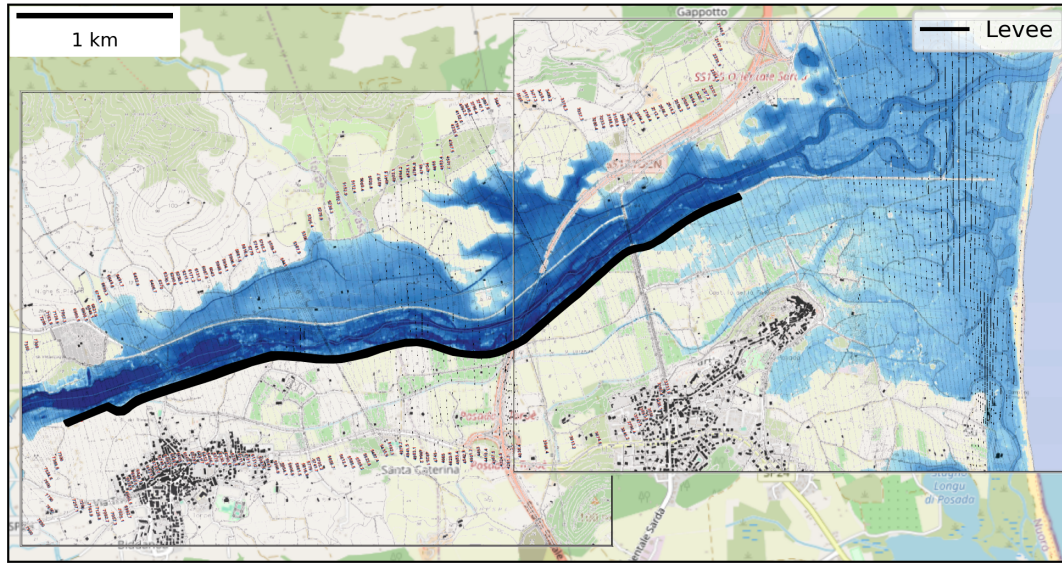


Figure 2.17: Levee implemented in the post-operam scenario using the proposed approach, superimposed on the study plots from the PGRA study (*Autorità di Bacino Regionale della Sardegna*, 2021b). The background map is from OpenStreetMap.

delineated flood-hazard areas. This aspect reflects the combined effect of two factors: the simplified nature of the proposed methodology and the use of a 10 m resolution DTM. At this resolution, the river bathymetry and the geometry of the banks are represented only approximately. Since in both case studies the levees are located close to the river channel, the simplified DTM may not correctly represent either the terrain elevation beneath the levee or the actual position of the river bank. As a result, a levee that in reality would be placed on the bank may be introduced in cells that are still part of the channel or of its immediate surroundings. This problem is particularly relevant where the banks are steep and narrow, and therefore only partially resolved in a 10 m DTM. Moreover, as described for the Posada Basin in Sec. 2.4.2, existing levees and other narrow linear structures may be only partially represented or even smoothed within the terrain model, thus leading to an underestimation of the effect of mitigation measures already present in the study area. By contrast, the PGRA studies used as reference relied on more detailed topographic information and on 1D hydrodynamic modelling, which allow a more physically consistent representation of both channel geometry and hydraulic structures. The need to adopt greater levee heights in the present work should therefore be interpreted as a scale and representation issue, rather than as a direct estimate of the actual structural dimensions required in reality.

This aspect is particularly relevant in applications where no reference PGRA map is available, i.e. in the situations where a simplified HAND-based approach would be most useful. In such cases, the terrain-height increase to be introduced in the post-operam

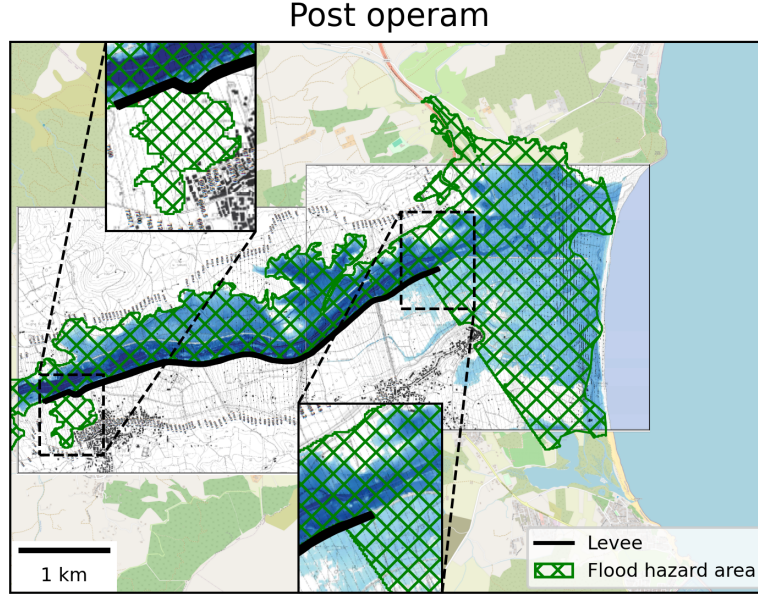


Figure 2.18: Flood-hazard areas (hatched green areas) obtained with the proposed method for the post-operam configuration representing Scenario 1 of the PGRA. The results are superimposed on the corresponding flood-hazard map reported in the PGRA (*Autorità di Bacino Regionale della Sardegna*, 2021b). The background map is from OpenStreetMap.

configuration should not be selected arbitrarily. A first estimate can be derived from the quantities already used in the ante-operam configuration. Since the HAND value represents the vertical distance between each terrain cell and the nearest drainage cell, while the SRC provides the water depth associated with the design discharge, the difference between the SRC-derived water depth and the local HAND value can provide an indication of the minimum terrain-height increase required for the area to be disconnected from the flooded corridor. This first estimate should also be interpreted in the light of the uncertainty and generalisation associated with the input DTM. Therefore, the effective terrain-height increase adopted in the simplified HAND-based representation may be considered as the combination of a hydraulic-topographic component, related to the difference between the estimated water depth and the local HAND value, and a topographic-uncertainty component, related to the accuracy and resolution of the DTM. Nevertheless, the height introduced in the DTM should not be interpreted as the actual design height of the levee, but as an effective representation height within the simplified terrain-based model. Its purpose is to test whether the mitigation measure is potentially capable of reducing flood-hazard extent under plausible terrain-correction assumptions.

The ante-operam calibration procedure also deserves discussion. In the present work, Manning's roughness coefficient was used as a calibration parameter in order to reproduce as closely as possible the flood-hazard extent available from the PGRA. This choice is

consistent with both the literature and the intended application of the method within the Italian planning framework, where ante-operam hazard maps are usually already available from more detailed studies. In this sense, the proposed approach is not intended to replace physically based hydrodynamic models where detailed analyses are needed, but rather to exploit existing information in order to derive a simplified and computationally efficient framework for post-operam screening. The calibration step is therefore a key part of the methodology, because it anchors the simplified approach to a locally known reference condition. However, if detailed land cover data are available, the adoption of a spatially varying Manning's roughness coefficient derived from actual land use could improve the physical realism of the method.

The results obtained in the Cedrino and Posada basins also suggest that the method is sensitive to the spatial context in which the intervention is located. In the Posada case study, the existing levee and its height increase could be represented in a more straightforward way, and the resulting post-operam behaviour was generally coherent with the scenario described in the PGRA. In the Cedrino case study, by contrast, the intervention involved multiple elements and a more complex hydraulic setting, including bridge removal and a levee branch extending into the urban area. These differences confirm that the method is more robust when applied to interventions whose effect can be approximated mainly through local topographic disconnection, and less reliable where the expected mitigation effect depends on detailed flow redistribution processes.

Overall, the proposed methodology should be interpreted as a screening-level tool for the early stages of mitigation-measure design. Its main strength lies in its ability to provide a first estimate of post-operam flood-hazard variations using limited data, open-source tools, and low computational cost. This makes it particularly suitable for contexts in which many candidate interventions must be evaluated in a standardised and transparent way, as expected within the Decreto Criteri framework. However, the results should always be interpreted in the light of the assumptions adopted and of the type of intervention considered. While the method can be used for a simplified assessment at the first stage of the planning and funding request procedure, the use of more advanced methods and more detailed data becomes necessary for the subsequent stages of design.

The proposed approach allows the effects of mitigation measures to be assessed in terms of reduction in flood-hazard extent, and does not provide a direct estimate of the expected damages associated with a flood event. Nevertheless, the delineated flood-hazard areas may be used as input for subsequent damage assessment, for example to estimate the monetary losses associated with the considered discharge through procedures such as MOVIDA (MOdello per la Valutazione Integrata del Danno Alluvionale) as applied in

the PGRA prepared by the Po River Basin District (*Autorità di Bacino Distrettuale del Fiume Po*, 2021; *Ballio et al.*, 2022; *Molinari et al.*, 2022).

2.6 Conclusion

This study presented a simplified methodology for assessing the effect of mitigation measures on fluvial flood-hazard areas at the early stages of design. The approach builds on the HAND framework and extends it in order to account for terrain modifications associated with mitigation measures, with particular reference to levees. The methodology was implemented within QGIS using openly available datasets covering the Italian national territory, with the aim of supporting data-scarce and standardised applications within the Italian planning and funding framework.

The results obtained from the two case studies in Sardinia indicate that the approach is capable of reproducing the ante-operam flood-hazard extent with satisfactory agreement after calibration of Manning’s roughness coefficient against the PGRA maps. This confirms that the HAND-based framework, although simplified, can provide a physically meaningful representation of flood-hazard areas, given the objectives of the present work, which are focused on preliminary assessment rather than on highly detailed analysis.

The post-operam applications showed that the methodology can also provide a useful first approximation of the effect of mitigation measures, especially when these can be represented as relatively simple modifications of the terrain model. In particular, the results highlighted a satisfactory representation of the effects of the upstream levee in the Cedrino Basin and of the levee-height increase in the Posada Basin. At the same time, the analyses also showed the limitations of the approach when the intervention involves more complex hydraulic effects, such as bridge removal, articulated levee layouts, or flow conditions influenced by local backwater effects.

The methodology does not explicitly simulate flow dynamics; as a consequence, its applicability is restricted to mitigation measures whose influence can be approximated through modifications of terrain elevation and the resulting topographic connectivity. In addition, the results are strongly influenced by the quality and resolution of the available topographic data. The need to adopt levee heights greater than those considered in the PGRA studies reflects this limitation and highlights the importance of scale effects in simplified applications based on coarse-resolution DTMs.

Despite these limitations, the proposed approach represents a useful contribution for

preliminary flood-hazard assessment in support of mitigation planning. Its low computational cost, reliance on freely available data, and implementation within an open-source GIS environment make it particularly suitable for the early evaluation of candidate interventions, especially where detailed hydraulic modelling is not yet available or is not feasible within available time and resource constraints.

Future work should focus on several aspects. First, the methodology could be tested on a larger number of case studies in order to better define the range of applicability of the approach and to identify the types of interventions for which it performs best. Second, the influence of higher resolution DTMs should be better studied. Third, the calibration procedure, which is currently performed manually, could be automated in order to increase reproducibility and facilitate operational use. Finally, further developments could explore the extension of the approach to additional types of mitigation measures beyond levees, provided that their effects can be represented within the same simplified conceptual framework.

In conclusion, the methodology proposed in this part of the thesis does not aim to replace hydrodynamic modelling, which is needed for a more reliable study of the overall flood dynamics, but rather to provide a simplified, transparent, and computationally efficient tool for the preliminary assessment of mitigation effects on fluvial flood hazard. In this role, it can support the standardised evaluation of interventions within the Italian planning context and contribute to bridging the gap between available territorial data and the information required at the early stages of decision-making.

Chapter 3

Increasing the fidelity of hyperlocal simulations of urban pluvial flooding through street flooding observations.

The study presented in this chapter led to the following publication:

Annis, S., M. Badas, and G. Mascaro, Increasing the Fidelity of Hyperlocal Simulations of Urban Pluvial Flooding Through Street Flooding Observations, *Advances in Water Resources*, p. 105223, doi:10.1016/j.advwatres.2026.105223, 2026.

3.1 Introduction

Pluvial flooding has been considered a relatively minor hazard for a long time because it was assumed that the stormwater infrastructure was properly designed to minimize its occurrence and impacts. For example, the U.S. Federal Emergency Management Service (FEMA) does not include pluvial flooding in its national directives (*FEMA (Federal Emergency Management Agency)*, 2023a). However, the stormwater infrastructure has been modified over time according to different design standards (*Underwood et al.*, 2020), and its layout and properties are often unknown. Therefore, every time the urban landscapes are altered and parts of the stormwater sewer are retrofitted, the performance of the entire sewer network cannot be accurately assessed, resulting in a possibly higher flooding hazard than what was assumed during design. The reviews by *Hammond et al.* (2013) and *Agonafir et al.* (2023) reported several studies highlighting that pluvial flood-

ing in urban regions causes direct tangible impacts by damaging buildings, infrastructure, and vehicles; indirect tangible consequences by interrupting businesses and infrastructure services; and intangible damages on health (casualties, injuries, mental health effects, floodwater pollution) and the environment, which can manifest close to and sometime after the event. Recent efforts have also emphasized the negative impacts of more frequent and less severe flood events, known as nuisance flooding (*Moftakhari et al.*, 2018). Despite pluvial flooding being increasingly recognized as a critical issue in urban stormwater management (*Rosenzweig et al.*, 2018), the knowledge of and the ability to accurately simulate this natural hazard are still limited largely because of the lack of continuous observations of street-level flood water variables at distributed locations (*Drews et al.*, 2023). Current simulation approaches relying on hydrologic and hydrodynamic models with varying levels of complexities have only been validated with alternative datasets including: water depth measurements in laboratory physical models (e.g. *Fraga et al.*, 2017; *Mignot et al.*, 2019; *Sañudo et al.*, 2025) ; outputs of numerical models that explicitly account for most physical processes and incorporate stormwater infrastructure, which are treated as “observations” (e.g. *Montalvo et al.*, 2024; *Oberauer and Lehmann*, 2024; *Xiang et al.*, 2024); sparse estimates of flood water depth from pictures published on social media platforms and news outlets (e.g. *Drews et al.*, 2023; *Guan et al.*, 2023a; *Guo et al.*, 2023); and proxies of flooding hotspots like insurance claims (*Gradeci et al.*, 2019). While these validation strategies have demonstrated value in improving flood models, they do not allow the quantitative assessment of their ability to capture the spatiotemporal dynamics of observed pluvial flood events in real-world urban catchments. In this study, we addressed this critical need, to our knowledge for the first time, using spatially distributed, continuous street-level water depth (h) data from the FloodNet network in New York City (NYC). FloodNet is a partnership between academic researchers and public agencies started in 2021, which has developed and installed ultrasonic sensors that continuously record the presence, depth, and duration of street-level floods in the five NYC boroughs (*Mydlarz et al.*, 2024). Currently, over 200 sensors have been deployed, and more are planned to be installed. Using these unique observations, we provided the first quantitative evaluation of commonly used pluvial flood modeling approaches based on direct, time-varying measurements of street-level h , thereby addressing the limitations of spatial-only or event-integrated validations approaches that are typically adopted. Specifically, we assessed three modeling approaches that are widely applied to simulate pluvial flooding with limited information on the stormwater sewer network (hereafter referred to as the sewer, for brevity), which is typical in most cities (see Section 3.4.1 for a brief literature review on flood modeling approaches). The methods rely on simulations with a rain-on-grid twodimensional (2D) hydrodynamic model where (1) the sewer is not considered, (2) the precipitation rate used to design the sewer is removed from the net precipitation input grids, and (3) distributed sinks are introduced at the stormwater inlet

locations using a single outflow relationship. We adopted the open-source LISFPLOOD-FP as the 2D rain-on-grid hydrodynamic model (*Bates and De Roo, 2000; Sharifian et al., 2023*) and applied it at the hyperlocal (meter-scale) resolution of 1 m, which is needed to quantify flood hazards for pedestrians, vehicles, and buildings (*FEMA (Federal Emergency Management Agency), 2025*). We initially provided methodological and practical insights for setting up and applying 2D hydrodynamic models in complex urban environments at hyperlocal scales. These include procedures to generate model domains that explicitly represent key urban landscape features affecting flow dynamics, such as buildings, streets, and local depressions; and to create net precipitation grids that account for building roofs and losses due to vegetation interception and infiltration in pervious areas. While these elements are often treated implicitly or in isolation in prior studies, here they were integrated into a coherent, observation-tested workflow. We used these insights to apply LISFPLOOD-FP in two urban catchments in the borough of Brooklyn using high-resolution geospatial data from the NYC OpenData public repository (*City of New York, 2025*). The catchments have areas of 10.9 km^2 and 0.8 km^2 and include six and two FloodNet sensors, respectively; they have similar building density and imperviousness but marked differences in steepness. No information on the sewer is available apart from the stormwater inlet locations. We then evaluated the three modeling strategies in the larger catchment for an intense event caused by Tropical Storm Ophelia in 2023 by comparing distributed model outputs with the sensors' measurements. Subsequently, we verified the robustness of the best-performing method, calibrated in the large basin, by applying it to a smaller and steeper catchment to simulate the same event and two additional floods generated by Tropical Storm Henri and Hurricane Ida in 2021. Finally, we showed that these hyperlocal simulations reproduce flood dynamics with high fidelity and enable the identification of basin areas experiencing varying levels of flood hazard, with the spatial and temporal resolution required for decision-making. This study demonstrates the value of street-level flood observations for quantifying the accuracy of pluvial flood models and guiding the selection of the most appropriate simulation approach under data constraints. The proposed framework advances current understanding of urban pluvial flood modeling and facilitates the application of hyperlocal simulations to support effective flood risk management and adaptation planning.

3.2 Study area and datasets

Our study sites are two urban watersheds of 10.9 km^2 and 0.8 km^2 in the borough of Brooklyn, New York City (NYC; Fig3.1a), selected because (1) they include six and two FloodNet sensors, respectively (Figs.3.1b-d), that detected pluvial flooding during

the analyzed storms (described in Section 3.3); (2) they are close to a high-resolution rain gauge of the New York State Mesonet network (*Brotzge et al.* 2020; Figs.3.1a,b); and (3) they have markedly different terrain properties, which makes them valuable case studies to assess model robustness. We tested all modeling approaches in the larger basin (hereafter, the calibration basin or CB) and evaluated the transferability of the best-performing method in the smaller catchment (hereafter, the validation basin or VB). The latter is in a historically flood-prone region where the first FloodNet sensors were placed, providing longer water depth records. To set up the model in the basins, we used several geospatial datasets from the NYC OpenData portal, listed in Table 3.1, along with key details, sources, and how they were utilized in this study. The datasets cover the entire city and were reprojected in UTM zone 18 N (EPSG code 26,918). The grids were aggregated at 1-m resolution; the same was done with the vector data after they were rasterized.

Table 3.1: Geospatial datasets obtained from the NYC OpenData portal used for the basin identification and the hydrologic-hydraulic simulations.

Dataset Name	Variable	Resolution	Year	Reference	Use
Topobathy LiDAR Hydroenforced Digital Terrain Model	Elevation with all vegetation and anthropogenic features removed	1 foot (0.3 m)	2017	<i>OCM Partners</i> (2017)	Basin delineation, terrain file for LISFLOOD-FP
Land Cover Raster Data	Eight land cover classes	6 inches (0.15 m)	2017	<i>New York City OTI</i> , 2017	Definition of (1) impervious areas and saturated hydraulic conductivity in the generation of effective precipitation, and (2) Manning’s roughness in LISFLOOD-FP
Building Footprints	Polygons with building footprints	NA	2016	<i>New York City OTI</i> , 2016	Terrain file for LISFLOOD-FP
Stormwater Inlets	Points with location of stormwater inlets	Point	2017	<i>New York City DEP</i> , 2017	Incorporation of stormwater infrastructure in the simulations
Tree Location	Points with tree location	Point	2015	<i>New York City DPR</i> , 2017	Identification of tree pits for the calculation of water infiltration into the soil

We delineated the basin boundaries from the Topobathy LiDAR Hydroenforced digital elevation model (DEM), which provides the surface elevation without vegetation and anthropogenic features (e.g., buildings) and includes hydroenforcement breaklines that allow water to flow through artificial pathways (e.g., culverts) that are not represented in the DEM (*OCM Partners*, 2017). The DEM was processed with Geographic Resources Analysis Support System (GRASS) libraries within the QGIS software (*QGIS Development Team*, 2019) to create the flow direction and accumulation grids and, subsequently,

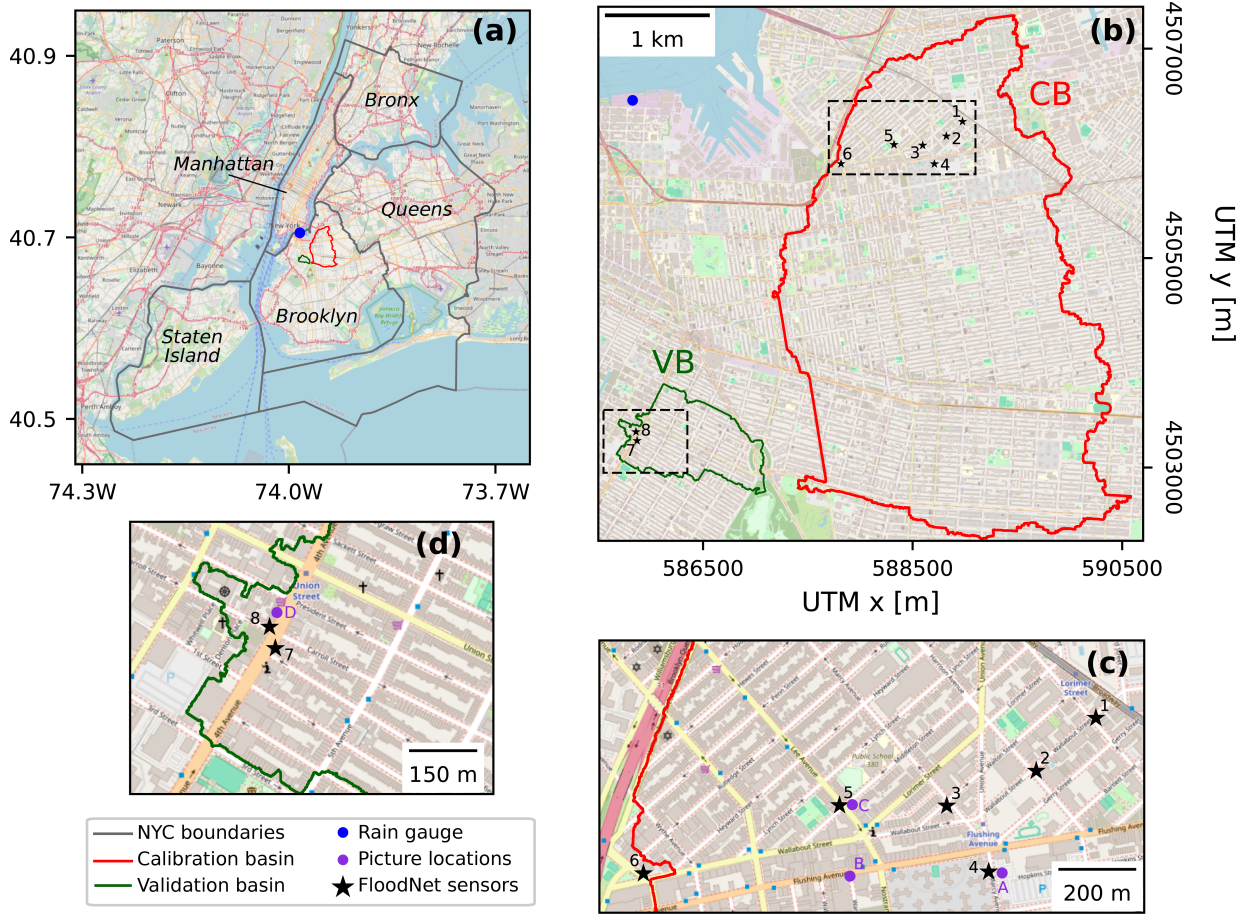


Figure 3.1: (a) Study basins in NYC in the borough of Brooklyn, along with the other four boroughs and the rain gauge of the New York State Mesonet network (latitude = 40.705° , longitude = 73.984°). (b) Basins' boundaries with the FloodNet sensors (numbered from 1 to 8; see Table B.1) reported in UTM zone 18 N (EPSG code 26,918); CB = calibration basin, VB = validation basin. (c)-(d) Zoom on the regions of the FloodNet sensors (dashed rectangles in panel (b)) in the two basins; panels (c)-(d) also show the sites A, B, C, and D of the pictures reported in Fig. 3.4. The base maps displayed in the panels are from OpenStreetMap.

the stream network using a threshold value of $200,000m^2$. We performed the latter task with the GRASS `r.watershed` module, which uses the least cost path algorithm to route flow out of depressions without applying any fill depression algorithm (Metz *et al.*, 2011). We retained these depressions to accurately represent localized flooding. To support this choice, we thoroughly inspected the depressions in the DEM and found that the vast majority correspond to realistic features (e.g., low-lying parking areas, railroads, and basements), with only a small number likely attributable due to DEM errors (see Sec. 3.6.3 and Figures C.1-C.9). The basins' DEMs are displayed in Fig. 3.2, along with a zoom on the area close to the outlet where the FloodNet sensors are installed and a three-dimensional view of such area. As expected for urban basins, the stream networks do not consist of actual channels but correspond to the road network paths with the highest flow accumulation values. In the CB (Fig. 3.2a-c), elevation declines steadily by

60 m over 4 km extending from the southern part to the outlet area, where the terrain is relatively flat. The VB (Fig. 3.2d-f) is much steeper, with elevation changing by 50 m in only 1.2 km. The three-dimensional views demonstrate that the high resolution of the LiDAR-based DEM captures small-scale elevation changes affecting local water flow. As reported in Table 3.2 and shown in Fig. 3.3, the basins are densely urbanized and largely impervious. Buildings, roads, and other impervious surfaces cover 75.3% (70.4%) of the CB (VB) area. Vegetation accounts for most of the remaining area, with trees covering 21.1% (27.0%) of the basin and being mostly placed in pits along streets, and grass/shrubs areas accounting for 3.0% (2.6%). Other land cover classes represent a negligible fraction of the basin area. To complete the basins' characterization and the model setup, we also acquired the building footprint and the stormwater inlets' location datasets from the city (Table 3.1). We obtained precipitation data at 5-minute resolution from a rain gauge of the New York State Mesonet network located on Gold Street, Brooklyn, just 2.1 and 3.0 km from the CB and VB outlets, respectively (Fig. 3.1b). We acquired water depth data from eight FloodNet sensors (Fig. 3.1b-d) at 1-minute resolution, with some gaps caused by issues in the data transmission network. Table B.1 in the Appendix B reports the sensors' location and the drainage area that ranges from 0.2 to 10.9 km² (0.15 to 0.79 km²) in the CB (VB).

Table 3.2: Land cover classes with their percentage in the calibration and validation basins and corresponding Manning's roughness derived from *Van Der Sande et al.* (2003).

Land cover class	Percent area in the calibration basin	Percent area in the validation basin	Manning's roughness, n
	(%)	(%)	(s m ^{1/3})
Tree canopy	21.1	27.0	0.05
Grass/shrubs	3.0	2.6	0.1
Bare soils	0.1	0.0	0.02
Water	0.0	0.0	0.03
Buildings	33.5	37.9	0.2
Roads	13.6	11.6	0.013
Railroads	0.5	0.0	0.033
Other impervious	28.2	20.9	0.05

3.3 The simulated pluvial flood events

We focused on three heavy precipitation events that caused widespread flooding in the basins. Two events occurred in 2021 as remnants of Tropical Storm Henri on August

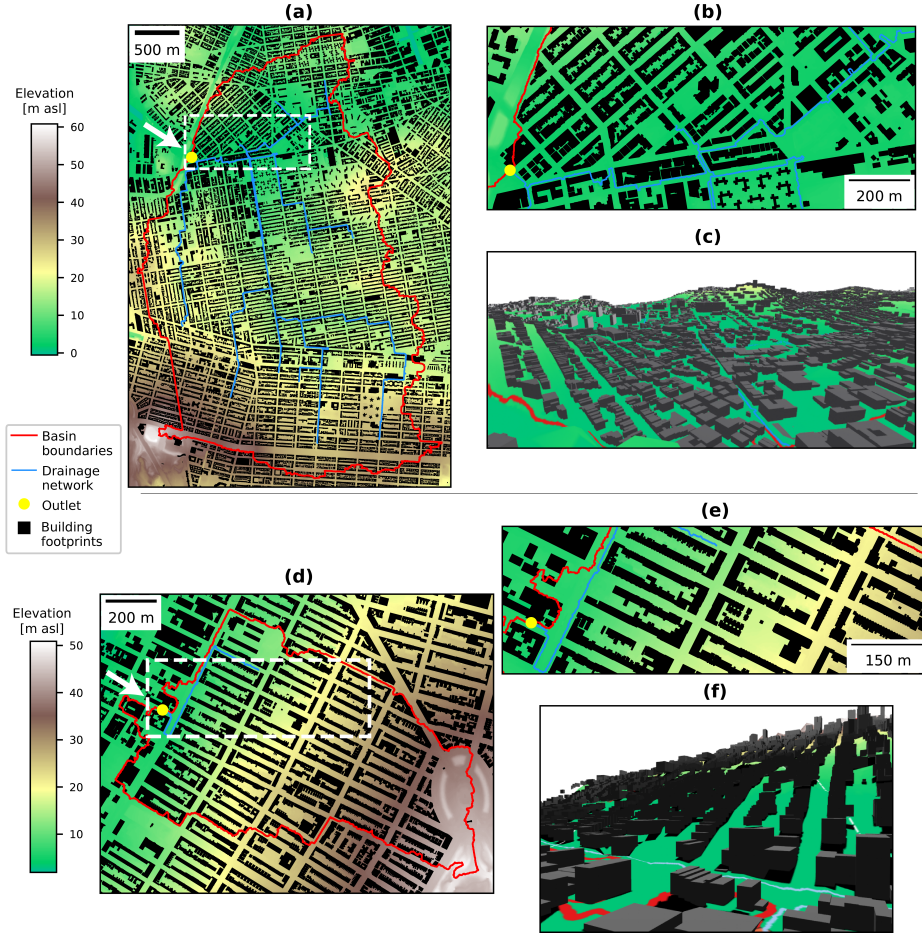


Figure 3.2: (a) DEM of the calibration basin (CB) with the building footprints, surface drainage network (i.e., roadways with the highest flow accumulation values), and outlet. (b) Zoom on the outlet region and the sensors (white rectangle in panel (a)). (c) Three-dimensional view of the area shown in (b) from an observer located just west of the outlet, with the viewpoint indicated by the arrow in panel (a). (d)-(f) Same as (a)-(c) but for the validation basin (VB).

21 (*Pasch et al.*, 2022) and Hurricane Ida on September 1 (*FEMA (Federal Emergency Management Agency)*, 2023b), respectively. The third event happened on September 29, 2023, as a remnant of Tropical Storm Ophelia (*WPC*, 2023). Because of the time of FloodNet sensors' installation, flooding caused by Henri and Ida was only observed in the VB at one sensor, while all eight sensors measured street flooding caused by Ophelia in the two basins. The three events caused significant impacts in NYC, although with different severity, including disruptions in the transportation systems, road closures, power outages, roof collapses, and flooded basements. Ida resulted in 13 fatalities attributed to flooding. The precipitation hyetographs recorded by the gage close to the study basins are reported in Figs. 3.4a-c. Two main storms caused by Henri occurred over 5 h (labeled as St1 and St2 in Fig. 3.4a), a single storm concentrated in 8 h during Ida (St1 in Fig. 3.4b), and three main storms over 10.5 h (St1-St3 in Fig. 3.4c) within Ophelia. According to the intensity-duration-frequency curves at La Guardia Airport from NOAA

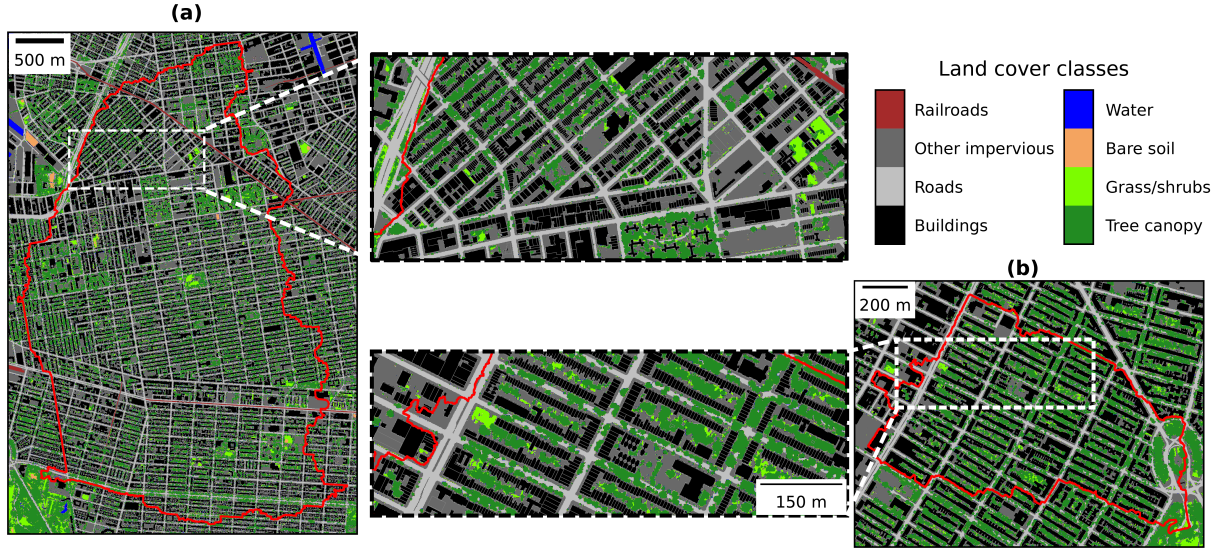


Figure 3.3: Land cover maps of the (a) calibration (CB) and (b) validation (VB) basins, along with a zoom on the outlet regions.

Atlas 14 (Fig. 3.4d; *Perica et al.*, 2015), the return periods of the maximum observed precipitation depths exceeded 10 years for durations above 1 h for all events and 100 years for some durations during Ida and Ophelia. Since the sewer has been largely designed for the 5-year return period, significant flooding conditions were observed in the study basins (Fig. 3.4d). This led to nonzero water depth recorded at the eight FloodNet sensors with peaks between 0.3 and almost 1 m (see Sec. 3.5.1).

3.4 Hydrologic-hydraulic modeling framework, setup, and simulations

3.4.1 Brief overview of current pluvial flood modeling approaches

Before describing the modeling approaches tested in this study, we briefly review the methods currently available for simulating pluvial flooding in urban areas. The most accurate simulations require the integration of a hydrologic model to reproduce rain-fall-runoff processes in pervious and impervious surfaces, a hydrodynamic model to represent overland flow routing of stormwater, and a hydraulic model to capture flow routing within sewer pipes. To our knowledge, no opensource modeling system currently represents all these processes in a fully coupled and highly detailed manner. A simpler version of this modeling scheme involves the use of coupled 2D-1D hydrologic-hydraulic models, which integrate a 2D “rain-on-grid” hydrodynamic model with a 1D pipe flow model

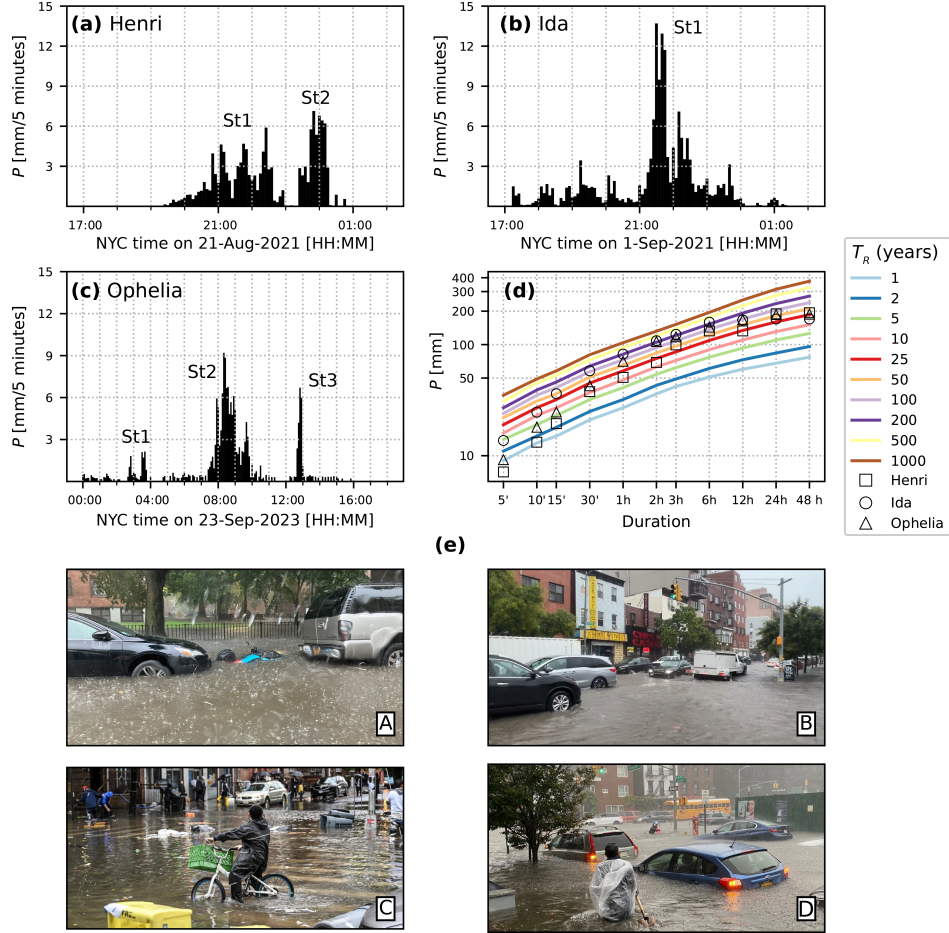


Figure 3.4: (a)-(c) Precipitation hyetographs observed by the NYS Mesonet rain gauge during Henri, Ida, and Ophelia with labels of the main storms. (d) Intensity-duration-frequency (IDF) curves at La Guardia Airport compared with the observed maximum precipitation depths; T_R is the return period. (e) Pictures of the event in locations A (Credits: Steve Kastenbaum), B (Credits: Liam Quigley), C (Credits: Fatih Aktas/Anadolu Agency via Getty Images), and D (Credits: Joann Amitrano) shown in Fig. 3.1c,d.

(Cea *et al.*, 2025; Rosenzweig *et al.*, 2021). The rain-on-grid feature expands the capabilities of traditional hydrodynamic models designed to simulate fluvial flooding by allowing the ingestion of spatially distributed net precipitation grids, which implicitly account for rainfall-runoff transformations. The rain-on-grid option is now available in several open-source 2D hydrodynamic models, including HEC-RAS (*Hydrologic Engineering Center*, 2021), TELEMAC-2D (Broich *et al.*, 2019; Hervouet, 2007), LISFLOOD-FP (Sampson *et al.*, 2013; Shaw *et al.*, 2021), PRIMo (Sanders and Schubert, 2019), and Iber (Bladé *et al.*, 2014; Sanz-Ramos *et al.*, 2025), among others. During the last few years, coupled 2D-1D models have been applied in urban areas worldwide (e.g. Bisht *et al.*, 2016; Chen and Huang, 2024; Montalvo *et al.*, 2024; Sañudo *et al.*, 2020, 2025; Wu *et al.*, 2018; Yang *et al.*, 2023). However, they still have significant drawbacks, including the need for extensive information on the sewer network, the high computational cost, and the

fact that they are mostly proprietary black-box software (*Agonafir et al.*, 2023) with only a few open-source exceptions (e.g., *Sañudo et al.*, 2025). An alternative simulation strategy that overcomes these limitations relies on 2D rain-on-grid surface hydrodynamic models with simplified methods to account for the underground sewer effect, including lowering the precipitation by the rainfall rate used to design the sewer pipes (e.g. *Carr et al.*, 2024; *Oberauer and Lehmann*, 2023; *Rong et al.*, 2024; *Singh et al.*, 2023; *Yu and Coulthard*, 2015) or increasing the infiltration rate artificially (*Wang et al.*, 2018). When the stormwater inlets’ locations were available, the sewer effect was also captured by creating distributed sinks at such locations where the outflow was considered either constant and equal to the maximum sewer capacity (*Xing et al.*, 2022) or variable and determined through simplified formulas for weir or orifice flow (*Chinchella et al.*, 2025; *Gallegos et al.*, 2009; *Palla et al.*, 2018). In both cases, the sewer capacity was assumed to be unlimited.

3.4.2 The LISFLOOD-FP hydrodynamic model

The hydrologic-hydraulic modeling framework adopted in this study is based on the LISFLOOD-FP 2D hydrodynamic model forced with net precipitation grids, along with different strategies to account for the sewer. The key elements of the framework and its application in the study basins are described in this and the following sections. LISFLOOD-FP simulates surface routing dynamics of fluvial and pluvial flooding by solving the 2D shallow water equations over a regular grid using several solution schemes with different mathematical and numerical complexities (*Bates et al.*, 2010; *De Almeida et al.*, 2012; *Hunter et al.*, 2005; *Shaw et al.*, 2021). Among these, we used the FV1 scheme in version 8.1, which solves the full system of equations using a first-order finite volume method with good accuracy and computational efficiency, also because it is parallelized for use in multi-core GPU and CPU (*Shaw et al.*, 2021). The model inputs can be time series of inflow hydrographs at specific locations and time-varying precipitation grids (*Sampson et al.*, 2013). Among the available boundary conditions, distributed sinks can be specified along with the corresponding time series of discharge leaving the domain. Model outputs include water depth and the two horizontal components of velocity and discharge. Buildings are key features affecting flood dynamics in urban environments; therefore, approaches with different complexities, computational cost, and accuracy have been proposed to incorporate their effect in 2D hydrodynamic models (*Mustafa and Szydlowski*, 2021; *Schubert and Sanders*, 2012). The main methods are summarized below.

- The Building Block (BB) method, in which buildings are treated as impermeable blocks by locally increasing the terrain elevation within each building footprint

(*Mustafa and Szydlowski, 2021; Schubert and Sanders, 2012*). This elevation increase may correspond to the actual building height; however, the presence of a sharp elevation step can introduce numerical instabilities, so smaller heights are often adopted. For example, an elevation increase of 30 cm as been used in technical reports (*SEPA (Scottish Environment Protection Agency), 2018*) (SEPA, 2018) and research papers (*Iliadis et al., 2023*) (Iliadis et al., 2023).

- The Building Hole (BH) method, where building footprints are removed from the computational domain, forcing flow to remain outside buildings (Schubert et al., 2008). Besides representing the blockage effect of building, the exclusion of building cells from the mesh reduces the computational cost.
- The Reflective Boundary (RB) approach, in which building walls are represented as reflective boundaries: the velocity component orthogonal to the wall is reversed, while the tangential component is preserved (Chaudhry, 2008)
- The Building Resistance (BR) method, which represents building effects by increasing surface roughness within the building footprint, thereby modelling the blockage effect of buildings as increased flow resistance (*Mustafa and Szydlowski, 2021*). The method allows flow to pass through building footprints and has been shown to perform well at coarser spatial resolutions, whereas for high-resolution DTMs the BB approach is generally expected to perform better (*Mustafa et al., 2023*).
- The Building Porosity (BP) approach, which treats buildings as porous media through which water can flow (Ferrari, 2024; Sanders et al., 2008). This approach is generally used to provide a simplified representation of sub-grid urban features, accounting for the combined effect of buildings and voids (e.g. streets) while using relatively coarse mesh resolutions (Dewals et al., 2021).

Among the available options in LISFLOOD-FP, we adopted the reflective-boundary approach, this method is accurate and computationally manageable compared to other simplified techniques. We implemented it by flagging the building footprints' cells as NODATA.

3.4.3 Generation of net precipitation grids

We accounted for the rainfall-runoff transformation by generating $1m$ grids of net precipitation every $\Delta t = 5min$, corresponding to the rain gauge resolution. Net precipitation was defined as precipitation minus the losses caused by canopy interception and soil infiltration. Given the relatively short duration of the storm, evaporation was considered

negligible. The net precipitation between $(t - \Delta t)$ and t , NP_t , was computed in each pixel as:

$$NP_t = P_t - V_t - I_t \quad (3.1)$$

where P_t is the precipitation measured by the rain gauge, V_t is the water intercepted by the tree canopy, and I_t is the water infiltrated in the soil. All fluxes are cumulative depths (in mm) within Δt . The two loss terms only exist for specific land cover classes, as described next. The losses due to canopy interception, V_t , were computed in the pixels classified as “tree canopy” (Fig. 3.3 and Table 3.2) based on the procedure of the i-Tree software suite from the U.S. Department of Agriculture Forest Service, described by Hirabayashi (2013) Hirabayashi (2013). The details are given in Appendix A. Infiltration losses, I_t , were calculated in the pixels classified as “bare soil” and “grass/shrub” (Fig. 3.3 and Table 3.2) and in the tree pits. The locations of the latter were estimated by (1) finding the coordinates of each tree from the 2015 Street Tree Census Data point file geodatabase (Table 3.1), (2) verifying that the land cover class in the co-located pixel was “tree canopy,” and (3) identifying three connected pixels including the pixel where the tree is located plus two of the eight adjacent pixels selected based on the orientation of the closest street. This mimics a $3 \times 1 \text{ m}^2$ rectangular tree pit typically adopted in NYC. The infiltration was computed using the Green-Ampt scheme (*Green and Ampt*, 1911) implemented in the Landlab open-source Python package (*Barnhart et al.*, 2020; *Hobley et al.*, 2017), assuming a saturated hydraulic conductivity of 10^{-6} m/s , which captures the average soil types of the region (*Soil Survey Staff*, 2025). For the tree pits, the infiltration was computed using precipitation that does not touch the canopy and directly reaches the ground, i.e., $(P_t - V_t)$. As mentioned above, the building pixels were flagged as NODATA. We accounted for the precipitation falling on the building roofs as follows. For each building, we identified the roof boundary from the building footprint dataset (Table 3.1) and computed the roof area, A_{roof} . For each time step, we calculated the precipitation volume fallen on the roof within Δt as $V_{BR,t} = P_t \cdot A_{BR}$ and assumed that this volume instantaneously falls on the n_{bound} pixels immediately outside the building perimeter. The latter were extracted by applying a buffer of 1 pixel to the roof boundary. We then assigned the same precipitation depth to each of the n_{bound} pixels computed as $P_{BR,t} = \frac{V_{BR,t}}{n_{bound} \cdot A_{pixel}}$, where $A_{pixel} = 1 \text{ m}^2$. This contribution from the roof was added to the net precipitation directly falling on the n_{bound} grid points. An example of a net precipitation grid under an input of 1 mm in 5 min is reported in Fig. 3.5. Note the larger intensities along the roof boundaries and the lower values in trees, tree pits, and pervious areas.

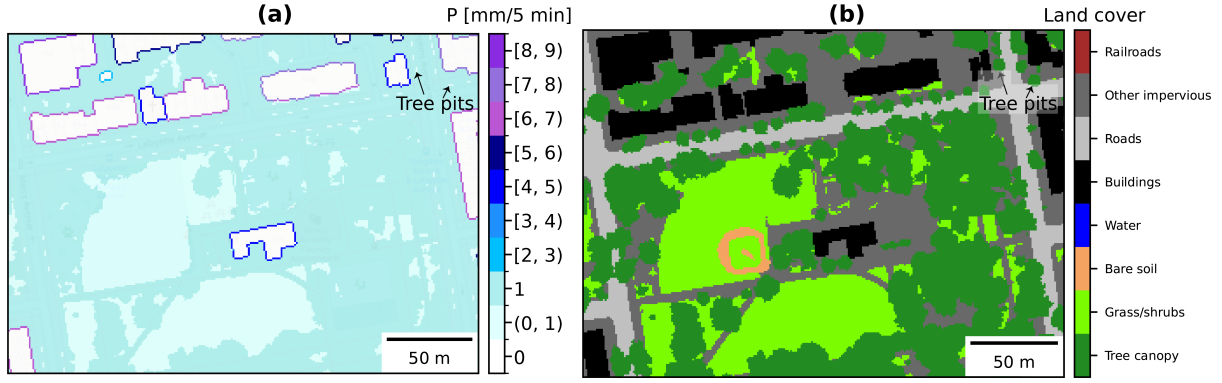


Figure 3.5: (a) Net precipitation grid under an input of 1 mm in 5 min in a portion of the domain including multiple land cover classes (shown in panel b) and tree pits. The tree pits are located at the sides of the streets; as an example, two of them are indicated with arrows in both panels.

3.4.4 Representation of the stormwater sewer network

We adopted two approaches to represent the effect of the sewer. The first assumes that the sewer can immediately absorb the runoff resulting from the precipitation intensity used to size its components, P_{design} . Its implementation involves replacing P_t in Eq. 3.1 with P_t^* , which is defined as:

$$\begin{cases} P_t^* = P_t - P_{design} & \text{if } P_t > P_{design} \\ P_t^* = 0 & \text{if } P_t \leq P_{design} \end{cases} \quad (3.2)$$

This method is used by governmental agencies in the U.K. (*UK Environment Agency*, 2019) and has been adopted in different studies when detailed sewer data were unavailable (*Carr et al.*, 2024; *Singh et al.*, 2023; *Yu and Coulthard*, 2015). For NYC, we assumed $P_{design} = 44 \text{ mm/h}$, corresponding to the 5-year, 1-hr storm (*NYC Mayor's Office of Resiliency*, 2021; Fig. 3.4d). The second approach is more sophisticated and represents the drainage from each stormwater inlet according to a simplified outflow equation. We were able to implement this method thanks to the availability of the stormwater inlet locations from the OpenNYC repository (Table 3.1). As an example, Fig. 3.6 shows the inlet locations close to three FloodNet sensors, along with pictures of the typical inlet types. As part of the available boundary conditions, LISFLOOD-FP allows the specification of distributed sinks with externally provided time series of outflows. When applying this method, the outflow time series are not known in advance because they depend on the local surface water depth and velocity, which are dynamic model variables. We then modified the *fv1.cpp* file of the source code to allow the computation of the outflow in each sink, Q_o , as a function of the water depth, h , and the 2D velocity vector

magnitude, u , in the co-located pixel at each time step. We adopted an experimental relationship among Q_o , h , and, u based on the experiments of *Xia et al.* (2022), which reasonably captured lab measurements under three flow behaviors, including weir flow for relatively shallow water, orifice flow for relatively high water, and a critical state in between. Such a relationship is:

$$Q_o = k \cdot u \cdot A_{inlet} \cdot Fr^\alpha \quad (3.3)$$

where u is the approaching flow velocity, A_{inlet} is the inlet area, and $Fr = u/gh$ is the Froude number, with g being the gravity acceleration, and k and α are empirical coefficients, estimated by *Xia et al.* (2023) as $k = 0.302$ and $\alpha = -0.816$. In the modified source code, we used the simulated h and u at each time step and inlet location to compute Q_o using Eq. 3.3, which allowed modeling stormwater removals. Given the variety of inlet types and clogging conditions in our basin (Fig. 3.6), which were unknown and whose heterogeneity could not be represented, we assumed a single set of parameters in Eq. 3.3 to represent all inlets. Specifically, we selected a mean value of 0.4 m^2 for A_{inlet} and the same value of -0.816 proposed by *Xia et al.* (2022) for α , while we calibrated k to simulate water depths that most closely match the FloodNet observations in the CB during Ophelia.

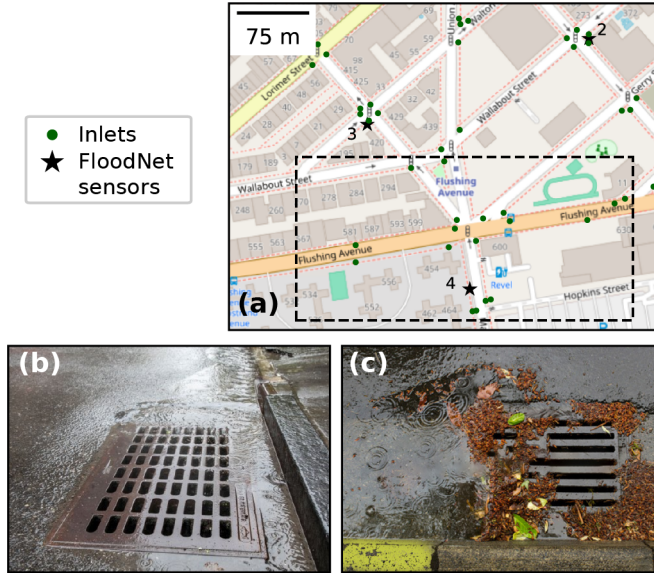


Figure 3.6: (a) Location of stormwater inlets from the OpenNYC dataset (see Table 3.1) close to some FloodNet sensors. The black dashed rectangle in (a) depicts the area shown in Fig. 3.10. The base maps displayed in the panels are from OpenStreetMap. (b)-(c) Pictures of typical inlets in NYC in clear (credit: *New York City DEP*, 2021) and partially clogged (credit: *NYC 311*, n.d.) conditions.

3.4.5 Model setup and numerical simulations

The LISFLOOD-FP computational domain for the CB consisted of a 5196×3620 grid centered on the basin and including a buffer of 100 cells in each direction. Elevation data provided by the LiDAR DEM (Table 3.1) were assigned to all grid cells except those corresponding the buildings, which were flagged as NODATA. This configuration resulted in 7,075,887 non-building cells within the basin. For the VB, the computational domain included a 1542×1174 grid with a buffer of 60 cells in each direction, resulting in 503,518 non-building cells within the basin boundaries. One of the model’s inputs is the grid of Manning’s roughness coefficients. These values were determined based on the look-up table for the land cover classes proposed by *Van Der Sande et al.* (2003), except for the “tree canopy” class, which we considered as “other impervious” since the trees are located mainly in the sidewalks (see Table 3.2). We assigned a zero-flux boundary condition to the northern, eastern, and southern domain borders, while we prescribed as open the western border containing the watershed outlet for both basins. We considered the basins initially dry, i.e., zero water depth everywhere. The outputs were generated every 5 min, consistent with the precipitation data. In the CB, we performed three simulations to reproduce flooding observed during Ophelia. In the first simulation, labeled No-SW, we did not represent the sewer effects and generated net precipitation grids every 5 min for 18 h (totaling 216 grids), as described in Section 3.4.3. We assumed the precipitation input was spatially constant within the basin using the records at the rain gauge in Fig. 3.1. We prescribed zero precipitation outside the basin to avoid unnecessary calculations and in agreement with the setup of zero-flux boundaries at three domain borders. In the second simulation, labeled Sim-SW, we accounted for the sewer through the simplified approach that subtracted the design storm from the observed precipitation. For this case, we created net precipitation grids as done for the No-SW experiment, with the subsequent application of Eq. 3.2. Finally, in the third experiment, we modeled the sewer impact using Eq. 3.3 with the modified LISFLOOD-FP code and the same net precipitation grids of the No-SW experiment. We conducted the third experiment, labeled Out-SW, multiple times with different values of k in the outflow Eq. 3.3 to identify its optimal value. We also performed a sensitivity analysis on the α exponent in Eq. 3.3, without achieving improved results (not shown). Hence, due to the inherent simplifications of the adopted approach, we deemed that assuming k as the only calibration parameter was adequate. As shown in the results, the third approach led to the best performance. We extensively assessed the robustness of the Out-SW approach with k determined at the CB by simulating all three precipitation events in the VB. The duration of these simulations was also 18 h. We assessed the model’s ability to capture the water depths at the FloodNet sensors by computing root mean square error ($RMSE$), mean bias error (MBE), and Pearson’s correlation coefficient (CC) between the simulated and observed

water depth time series. In addition, we calculated the difference between simulated and observed peaks (Δh_{peak}) and their occurrence times (Δt_{peak}). Multiple metrics were adopted to quantify distinct components of the model performance. Since the observed water depths are available at 1-minute resolution with some gaps and the simulations are every 5 min, we obtained the simulated values at the observation times via linear interpolation. All metrics are defined in Appendix B. We also computed basin flood metrics, including total fluxes; extent of flooded areas with different depth ranges; and flooding intensity for nuisance conditions (*Moftakhari et al.*, 2018), and low, moderate, significant, and extreme hazard levels for people, defined by the U.K. Department for Environment, Food & Rural Affairs (*DEFRA*, 2006; *Surendran et al.*, 2008) based on water depth and velocity, as described in Appendix B and shown in Fig. B.1.

3.5 Results

3.5.1 Assessment of the three modeling approaches in the calibration basin for the Ophelia event

In the current and following sections, the simulation results are presented by comparing the time series of water depth, h , observed by the FloodNet sensors and simulated in the co-located 1×1 m pixel, and displaying the map of the maximum h , h_{max} , across the simulation duration. The error metrics at each sensor are reported in Tables B.2 and B.3 for the CB and VB, respectively, while the basin flood metrics are presented in Table 3.3. We begin with the simulations of the Ophelia event in the CB. The h time series are shown in Fig. 3.7. The sensors (gray lines) did not measure any standing water caused by the first main storm St1, while they all reported a hydrograph with a nonzero h caused by storm St2. The increasing limb started at about 08:00, which is 30 min after the beginning of storm St2; the peak occurred between 08:51 and 09:27, depending on the sensor; and the falling limb ended at 09:25 at sensor 6 and between 10:00 and 12:08 at the other sensors. No standing water was observed after storm St3. The abrupt peak measured at sensor 2 might be due to debris floating on the water; disregarding this spike, the peaks ranged from 0.31 m to 0.65 m across the sensors. When compared to the observations, the hydrographs simulated neglecting the sewer (No-SW; black lines) are much longer and characterized by multiple peaks and rising and falling limbs with different slopes driven by the three main storms: h starts increasing early in the simulation, reaches the largest peak between 10:05 and 10:15 at all sensors, and slowly decays until the end of the simulation with a minor peak caused by storm St3 without returning to zero. The error

metrics indicate poor temporal correspondence ($0.2 \leq CC \leq 0.48$; Table B.2), a large overall error ($0.59\text{ m} \leq RMSE \leq 1.18\text{ m}$), and a severe overestimation of h across the entire time series ($+0.51\text{ m} \leq MBE \leq +0.93\text{ m}$) and of the peaks ($+0.53\text{ m} \leq \Delta h_{peak} \leq +1.48\text{ m}$), which are simulated with significant delays ($+43\text{ min} \leq \Delta t_{peak} \leq +83\text{ min}$). Before focusing on the simulated h_{max} , we note that, in all three simulation approaches, we found the presence of very high h (even exceeding 3 m) in a small number of isolated pixels in depressions that are either garages or low-lying areas most likely drained by pumps or caused by errors in the DEM (see discussion in Sec. 3.6.3). These outliers were identified and excluded from the flooded area computation with negligible effects on the results. The map of h_{max} for No-SW in Fig. 3.8a shows significant flooding in two large regions in the middle of the domain and close to the outlet, as well as in several streets. Specifically, h_{max} exceeded 0.3 m – the flooding threshold adopted by *FEMA (Federal Emergency Management Agency)* (2018) and *Schubert et al.* (2024) – in 13.3% of the basin and even 2 m in a non-negligible portion (Table 3.3). The combined analysis of h and u also revealed that neglecting the sewer led to the simulation of moderate-to-extreme flood hazard conditions in almost a third of the basin.

Table 3.3: Flood metrics for each simulation and basin, including storm durations, cumulative basin-averaged flows, and percent of the basin areas with maximum water depth (h_{max}) within several ranges and with different flood intensities occurring for >15 min. The latter are nuisance flooding and low, moderate, significant, and extreme hazards defined in Appendix B.

	No-SW	Sim-SW	Out-SW	Out-SW	Out-SW	Out-SW
Basin	CB (Area: 10.9 km ²)		VB (Area: 0.8 km ²)			
Precipitation event	Ophelia		Ophelia	Henri	Ida	
Approximate total duration of storms	10.4 h		10.4 h	5.1 h	7.75 h	
	Cumulative flows [mm]					
Net precipitation	173	75	173	172	140	164
Surface runoff	173	75	33	51	43	53
Outflow to stormwater	0	0	140	121	97	111
	Percent of the basin area in h_{max} map [%]					
0.03 m < h_{max} ≤ 0.1 m	10.28	9.82	11.56	15.00	13.75	16.25
0.1 m < h_{max} ≤ 0.3 m	7.89	6.79	6.70	5.00	5.00	8.75
0.3 m < h_{max} ≤ 2.0 m	12.11	7.98	4.86	3.75	3.75	5.00
h_{max} > 2.0 m	1.19	0.09	0.09	0.25	0.13	0.25
Nuisance flooding	26.88	18.35	20.83	25.00	21.25	30.00
Low hazard	18.17	10.92	10.46	10.00	7.50	11.25
Moderate hazard	11.74	6.06	5.05	3.75	2.50	5.00
Significant hazard	13.30	7.16	4.04	5.00	3.75	5.00
Extreme hazard	3.58	1.19	0.73	1.25	1.25	1.25

When the sewer is implicitly considered in the net precipitation (Sim-SW; red lines in Fig. 3.7), the simulation of the hydrographs' first part dramatically improves compared to the No-SW experiment, as it leads to significantly lower h before 8:00 while still capturing the observed steep increase occurring at that time. Despite these enhancements, h is still overestimated after 8:00, even if to a lower extent than No-SW, and remains practically constant after the peak caused by storm St2 due to the lack of water losses. This is reflected in lower mean errors ($0.32\text{ m} \leq RMSE \leq 0.89\text{ m}$) and biases ($+0.27\text{ m} \leq MBE \leq +0.62\text{ m}$) compared to No-SW; however, the temporal correspondence remains poor ($0.10 \leq CC \leq 0.39$; see Table B.2). For Sim-SW, the peaks are overestimated everywhere ($+0.13\text{ m} \leq \Delta h_{peak} \leq 1.05\text{ m}$) and are also modeled with a significant delay ($+262\text{ min} \leq \Delta h_{peak} \leq +297\text{ min}$), except for sensor 6 ($\Delta h_{peak} = 3\text{ min}$), because the highest simulated h occurs after storm St3 instead of storm St2. The map of h_{max} for Sim-SW in Fig. 3.8b shows lower values throughout the basins compared to No-SW, with $h_{max} > 0.3\text{ m}$ in 8.1% of the basin area and exceeding 2.0 m at a negligible number of pixels (Table 3.3). The areas under moderate to extreme hazard are about half the size of those simulated in the No-SW scenario.

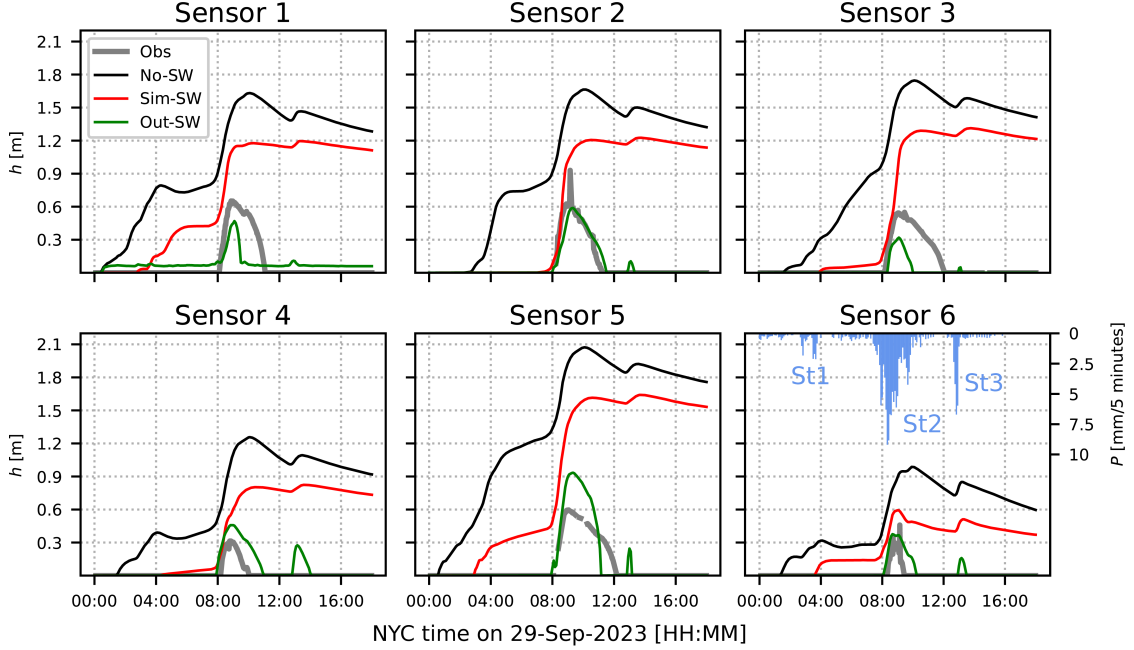


Figure 3.7: Time series of water depth, h , observed and simulated with the three approaches at six FloodNet sensors in the CB during Ophelia. For reference, the precipitation hyetograph is reported in the panel of sensor 6, along with the storms' labels.

To address the limitations of No-SW and Sim-SW, we modeled the sewer effect through distributed sinks located at the stormwater inlets (Out-SW). We preliminarily calibrated the parameter k of the outflow Eq. 3.3. Fig. 3.9 summarizes the error metrics for the simulations with four values of k at the six FloodNet sensors. We started with the same value of $k = 0.302$ used by Xia *et al.* (2022) Xia *et al.* (2022) and found that the

outflows from the basin were too high. We then repeated the simulations with k reduced by 20%, 25%, and 30% and found that $k = 0.226$ (25% reduction) led to the best performances at most stations. The Out-SW simulations with $k = 0.226$ (green lines in Fig. 3.7) capture the observed hydrographs remarkably well, including timing ($0.74 \leq CC \leq 0.92$; Table B.2), shape and magnitude of rising and falling limbs ($0.05 \text{ m} \leq RMSE \leq 0.13 \text{ m}$; $-0.001 \text{ m} \leq MBE \leq -0.05 \text{ m}$), and peaks ($-0.34 \text{ m} \leq \Delta h_{peak} \leq +0.34 \text{ m}$; $-23 \text{ min} \leq \Delta t_{peak} \leq +23 \text{ min}$). The only exceptions are a small minor peak following storm St3 at all sites. The map of h_{max} in Fig. 3.8c looks realistic, as this variable is mainly below 0.80 m, and the two large regions with widespread flooding simulated by No-SW and Sim-SW do not appear anymore. The areas under moderate and significant hazards are further reduced, while extreme hazard conditions are almost negligible (Table 3.3).

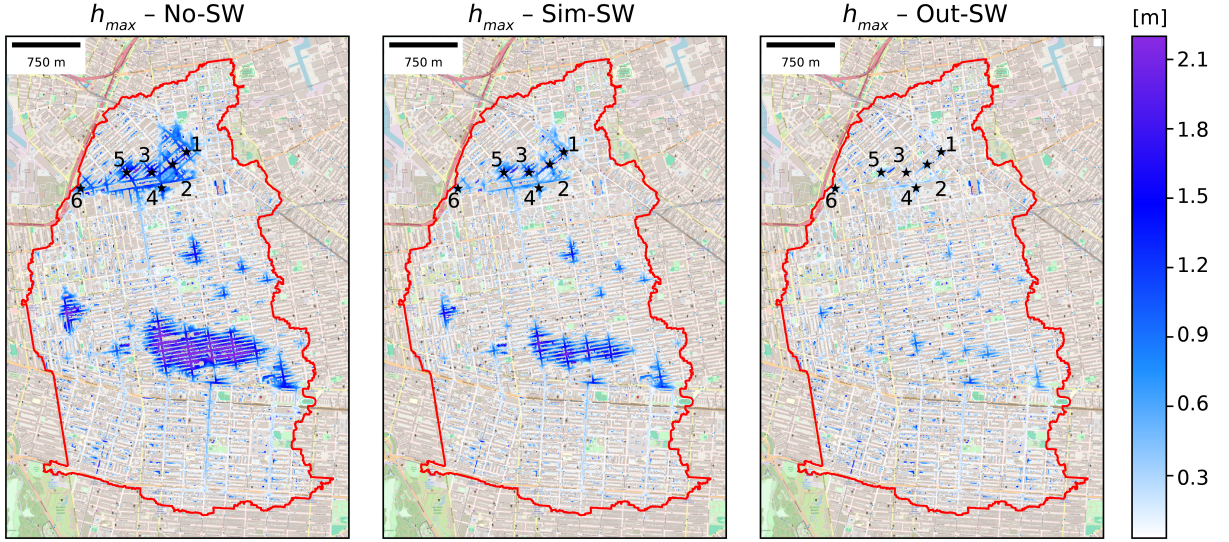


Figure 3.8: Maps of maximum h , h_{max} , with the sensors' location in the CB for the three simulation approaches. The base map is from OpenStreetMap.

3.5.2 Spatiotemporal dynamics of simulated water depths

We further demonstrated the fidelity and high level of detail of the Out-SW simulations by presenting in Fig. 3.10 maps of h in the vicinity of sensor 4 for six times from 8:00 to 10:30 on September 29, 2023, along with the stormwater inlet location. This is the area shown with a dashed rectangle in Fig. 3.6a, centered at the major intersection between Flushing Avenue and Union Avenue. At 8:00, the area is largely dry except for a few localized depressions where h exceeds 2 m, which are indicated to be basements according to visual inspection of satellite photos. After storm St2 begins, water starts ponding on the roadways, and the flooded areas expand from 8:30 to 9:00. As the precipitation intensity decreases after 9:00, the flooded areas recede because water enters

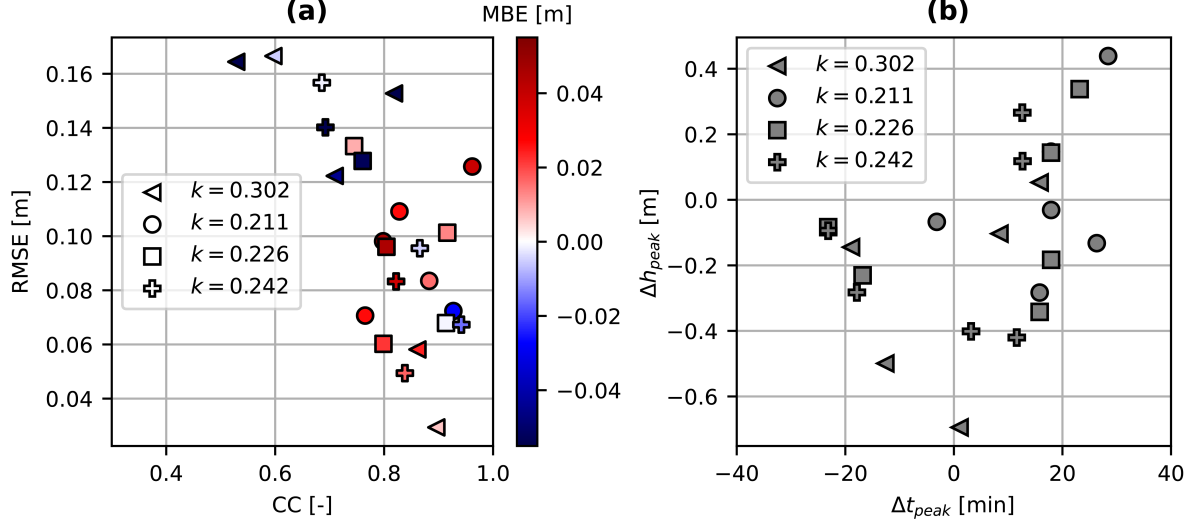


Figure 3.9: Scatterplots between the metrics quantifying the ability to simulate (a) the entire time series and (b) the peaks at the six FloodNet sensors for the Out-SW simulations in the CB with different values of the coefficient k in Eq. 3.3. The metrics are defined in Appendix B.

the stormwater inlets, as illustrated in the maps for 9:30, 10:00, and 10:30. Note how the larger number of inlets placed at the major intersection leads to a faster contraction of the flooded area compared to the regions located 50 m away that are drained by a smaller number of inlets, including where sensor 4 is located. The maps of Fig. 3.10 also demonstrate that the reflective-boundary method implemented in LISFLOOD-FP represents the water flow around the buildings very well.

3.5.3 Transferability of the best-performing simulation approach

The Out-SW modeling approach performed very well in the CB, after the k value in Eq. (3.3) was calibrated against the FloodNet h observations. We tested the robustness of this approach in the VB during all three precipitation events using k from the CB. Results are shown in Fig. 3.11, and the error metrics are reported in Table B.3. The Out-SW simulations reproduce very well the hydrographs' timing ($0.54 \leq CC \leq 0.98$), magnitude ($0.04\text{ m} \leq RMSE \leq 0.15\text{ m}$; $-0.002\text{ m} \leq MBE \leq -0.003\text{ m}$), and shape ($-0.35\text{ m} \leq \Delta h_{peak} \leq -0.09\text{ m}$; $+5\text{ min} \leq \Delta t_{peak} \leq +140\text{ min}$) for all three events. Notably, the model accurately captures the differences in h peaks measured at sensors 7 and 8 during Ophelia, which are significant despite the proximity of these sites. In addition, the model almost perfectly reproduces the hydrograph caused by Ida. There are two instances where the performance of Out-SW is lower: the model (1) cannot reproduce the first observed peak caused by storm St1 during Henri (note also the presence of a

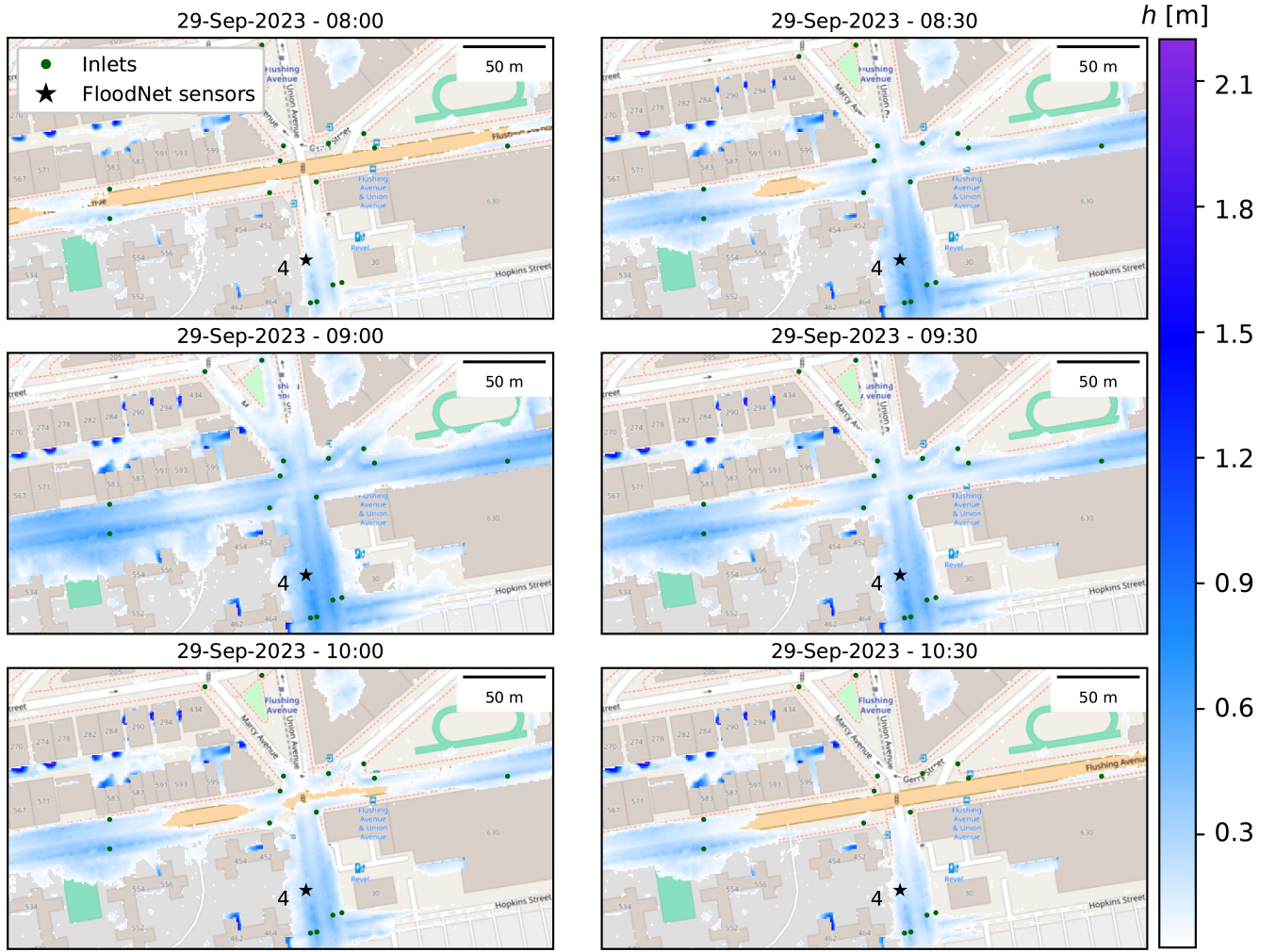


Figure 3.10: Maps of h simulated by Out-SW at six times between 8:00 and 10:30 on 29 September 2023 in the CB area depicted in Fig. 3.6a, with locations of the FloodNet sensor 4 and stormwater inlets. The base map is from OpenStreetMap.

spike likely caused by a floating object), and (2) simulates a second minor peak during Ophelia that was not observed. We carefully investigated the possible causes for these errors and concluded that the most plausible is the use of precipitation measurements from a rain gauge 3 km away from the basin, which may not accurately represent the precipitation that occurred in the basin during these times. Despite these two instances of lower performance, the comparisons with street flooding observations provide strong confidence in the robustness of the calibrated approach. As a final note, the maps of $h_{\max}$ are similar across all events (the map for Ida is shown in Fig. 3.11, the CC among the maps is > 0.99), with higher values in the back of the buildings and the downstream area close to the sensors. This is reflected in the close values across the three events of the flood metrics reported in Table 3.3. It is worth noting that, despite differences in terrains, the percentages of the basin area in different flooding conditions in the CB and VB are also quite similar. Figures 3.12-3.14 represent the corresponding of Fig. 3.10 for the VB.

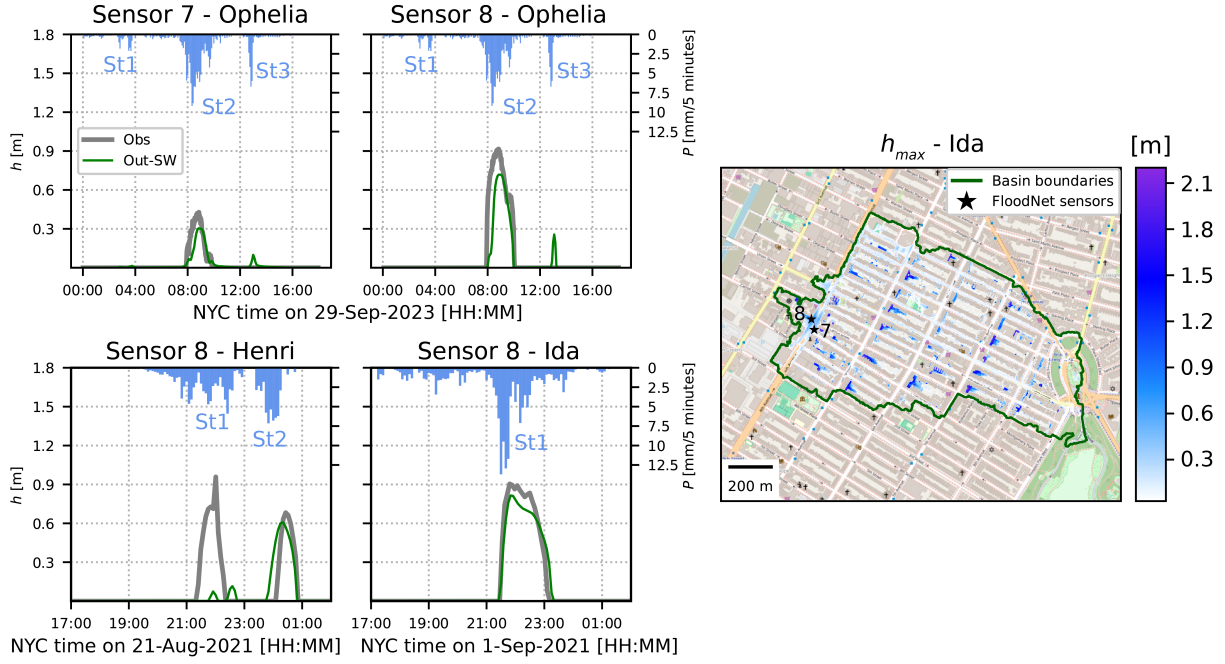


Figure 3.11: Results of the Out-SW simulations for the VB. Left panels: time series of observed and simulated h at the FloodNet sensors 7 and 8 during Ophelia and sensor 8 during Ida and Henri; the precipitation hyetographs and the storms' labels are also reported in each panel. Right panel: map of h_{max} during Ida. The base map is from OpenStreetMap.

3.6 Discussion

3.6.1 The value of street flooding observations to assess flood modeling approaches

The accurate simulation of pluvial flooding at hyperlocal scales is a challenging task influenced by several sources of uncertainty (Bates, 2023). A key step in reducing this uncertainty and building confidence in simulations of urban flood dynamics is their validation against distributed, continuous street flooding observations (Cea *et al.*, 2025; Molinari *et al.*, 2019; Schubert *et al.*, 2024). Such measurements are not yet routinely collected anywhere in the world, with the notable exception of the FloodNet network in NYC (Mydlarz *et al.*, 2024). Here, we used data from this observational network to perform what we believe is the first assessment of this kind for three popular modeling approaches used in the literature. To capture small-scale flood dynamics in heterogeneous urban regions and enable meaningful direct comparison with the sensor footprint, we applied the model at the hyperlocal resolution of 1 m^2 . The novelty of our assessment lies in the use of spatially distributed, continuous, street-level water depth observations to evaluate both the magnitude and timing of simulated pluvial flood dynamics. Previ-

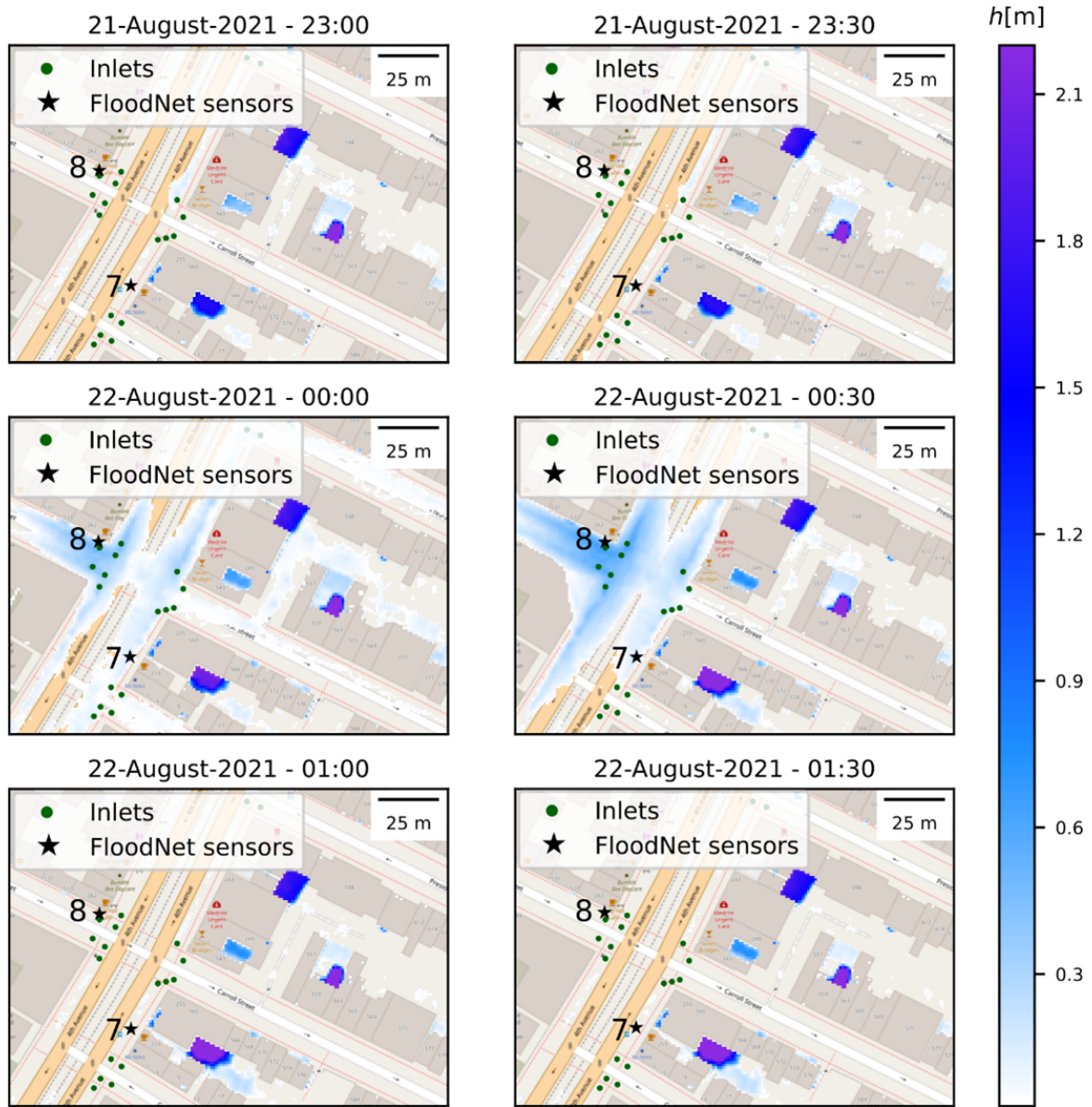


Figure 3.12: Simulated h during Tropical Storm Henri in VB, close to sensors 7 and 8 at six different times. Three spots with high water levels in depressed areas are visible from the first timestep chosen. The northernmost one is a parking area located below the surrounding areas, while the other two are visible only from satellite imagery, thus the actual presence of topographic depression is not verifiable. The base map is from OpenStreetMap.

ous validation efforts have typically relied on static indicators such as maximum flood extents or water marks, event-integrated metrics, or proxy datasets, which do not capture the temporal evolution of flooding and therefore limit the ability to discriminate among competing modeling approaches. By contrast, the FloodNet observations enable a quantitative, time-resolved evaluation of model performance at hyperlocal scales, allowing us to identify strengths and limitations of commonly adopted sewer-representation strategies that would not be evident from spatial-only validations. The study was conducted in two

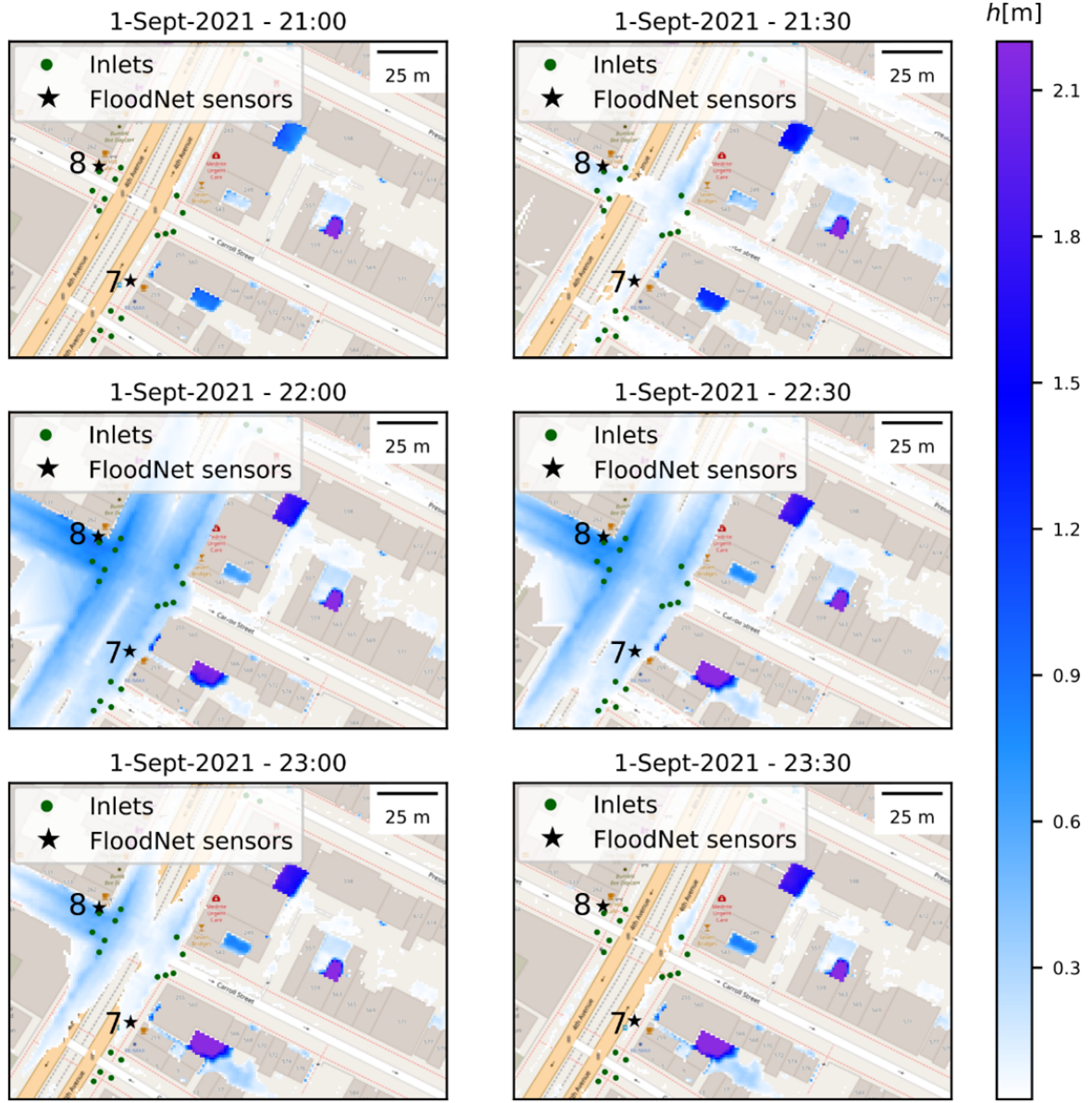


Figure 3.13: Same as Figure 3.12 but for Hurricane Ida.

flood-prone basins of different sizes and topographic features. The three simulation approaches were assessed in the CB against water levels from six FloodNet sensors observed during the Ophelia event. Some studies assumed that, under intense storms like Ophelia (Fig. 3.4d), the sewer network quickly reaches its capacity and does not significantly impact the extent and severity of flooding hazards (*Ivanov et al.*, 2021; *Schmitt and Scheid*, 2020). However, our simulations indicate that neglecting the sewer (No-SW) leads to severe overestimations of the extent and severity of flooding hazards (Table 3.3), which appear too large even for a conservative assessment. These findings align with *Kasaei et al.* (2025), who simulated pluvial and coastal flooding from Hurricanes Ida and Ophelia in Jamaica Bay, NYC, using the COAWST model at a moderate spatial resolution (50 m). Their simulations that did not account for the sewer system overestimated the

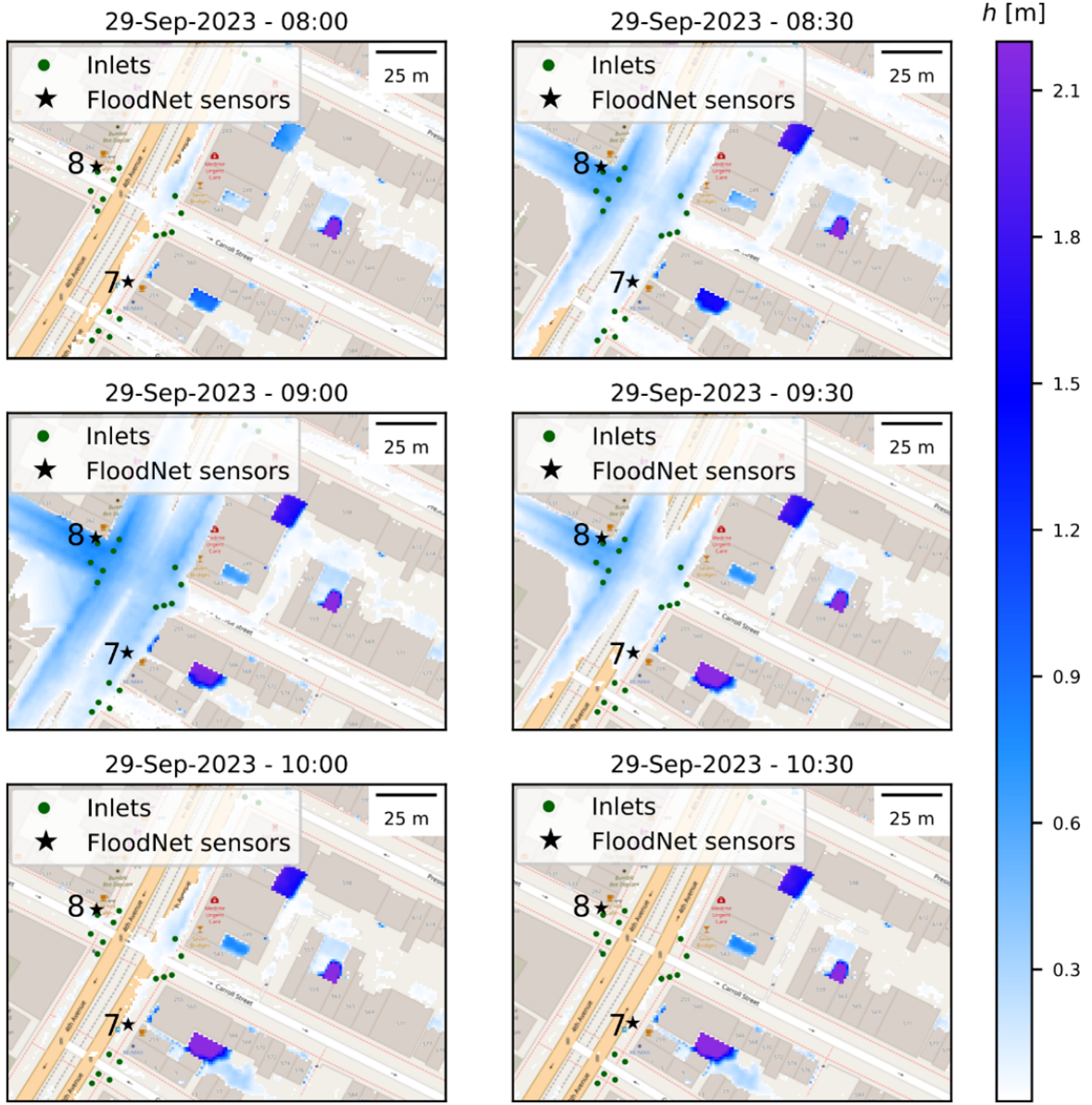


Figure 3.14: Same as Figure 3.12 but for Tropical Storm Ophelia.

observed high-water marks. Our overestimations are also consistent with other studies that compared a simulation without the drainage sewer against either h_{max} observations (Xing *et al.*, 2022), coupled 2D-1D simulations (Montalvo *et al.*, 2024), or 2D simulations with a simplified sewer, as in our Out-SW scenario (Schubert *et al.*, 2024). The simplified method that implicitly incorporates the sewer by reducing the net precipitation (Sim-SW) has been suggested by national design standards in the U.K. (UK Environment Agency, 2019) and applied in several studies with reductions that were either spatiotemporally constant (Montalvo *et al.*, 2024; Yu and Coulthard, 2015), spatially variable and temporally constant (Carr *et al.*, 2024; Singh *et al.*, 2023), spatially constant and temporally variable (Oberauer and Lehmann, 2023), or spatiotemporally variable (Li *et al.*, 2020). Our comparison with observed h in the CB reveals that applying a spatiotemporally con-

stant reduction has some skill in modeling the initial volume entering the sewer. This is consistent with the abovementioned study by *Kasaei et al.* (2025), where significant improvements were achieved by considering a spatially constant drain rate of 13 mm/h. However, this approach still importantly overestimates all flooding variables, leading to spatial patterns of h_{max} that are not too different from No-SW (Table 3.3). This outcome is opposite to what was found by *Xing et al.* (2022), who reported underestimations of the precipitation reduction method in a dense urban basin in Fuzhou, China. Focusing on a $0.6 - km^2$ basin in Spain, *Montalvo et al.* (2024) reported instead that reducing the precipitation rate led to both over- and under-estimations of h in different basin areas compared to a coupled 2D-1D simulation. In the future, the availability of longer records of street flooding observations could be very valuable in identifying and calibrating the optimal reduction of precipitation rates in space and time, eventually combined with increased infiltration rates. After proper calibration, this approach will likely be more data parsimonious and computationally efficient than other modeling techniques. The approach where the drainage system is modeled through distributed sinks at the stormwater inlet locations (Out-SW) led to very good performances at all sensors in the CB, after calibrating only one parameter (k in Eq. (3.3)) against the observations. The availability of h measurements in another basin (the VB) gave us strong confidence that this calibrated approach is robust and transferable in dense urban areas in NYC. We argue that the robustness observed across basins and events is primarily driven by the physically based structure of the model and its application at hyperlocal scales, which allow local water depth and flow velocity at stormwater inlets to be simulated with sufficient fidelity to reliably estimate inlet outflow. The identification of the specific value of the calibrated outflow parameter k plays a secondary role, but it remains necessary to successfully reproduce the observed hydrographs. The parameter k implicitly aggregates site-specific factors such as inlet geometry, maintenance condition, and partial clogging, which may vary across cities or even within a single urban area. As such, while the results indicate that the proposed approach is transferable within dense urban environments with broadly similar drainage characteristics, additional calibration may be required when applying the method to regions with substantially different inlet designs, maintenance regimes, or hydrologic conditions. These considerations are supported by *Schubert et al.* (2024), who demonstrated the superiority of a simplified inlet-based method in Los Angeles, a city that is significantly less dense than NYC. These authors performed regional flood simulations with a strategy, named PRIMo-Drain, where stormwater runoff was removed at over 150,000 inlets using a weir and orifice relationship based on a single coefficient, which was calibrated to contain flood inundation within street curbs for the 20-year storm. The PRIMo-Drain simulations were deemed more realistic than other modeling approaches that did not incorporate the sewer pipes. On the other hand, the abovementioned study by *Xing et al.* (2022) applied a method similar to Out-SW by assuming a constant outflow

based on local stormwater design standards at inlets identified from street view images. The simulations were compared against observations of h_{max} during two storms, finding only moderate improvements compared to a scenario that did not consider the sewer. The superior performance of the Out-SW simulations shown here could be attributed to (1) the use of dynamic outflow rates that change with the flow conditions and (2) the comparison against time-varying observed h .

3.6.2 Insights into model setup in complex urban basins

Our modeling effort provides valuable insights for setting up and applying flood models in complex urban regions at hyperlocal resolutions. Some of these details might have already been mentioned in the literature but relatively sparsely. Therefore, we believe that summarizing them is helpful for researchers and practitioners interested in applying flood models to advance the knowledge of pluvial flooding and design mitigation strategies. (1) Digital elevation models should be “hydroenforced”, i.e., modified to remove the effect of elevated infrastructure that could erroneously obstruct water flow. (2) Depressions in high-resolution DEMs should be kept when deriving the basin boundaries. However, as described in the next section, depression outliers should be inspected as they could be caused by errors in the DEM and might need to be removed while post-processing model outputs. (3) The reflective boundary method led to a realistic simulation of the water flow around buildings, a key modeling capability in dense urban regions. In LISFLOOD-FP, this method is applied by setting the building cells to NODATA. (4) Rain-on-grid hydrodynamic models might not include rainfall-runoff transformation. Here, we proposed a framework to generate net precipitation grids that account for the losses caused by canopy interception and soil infiltration and the precipitation redistribution around the building roofs.

3.6.3 Limitations and future work

Inevitably, our simulations also have limitations and inaccuracies. All modeling approaches tested here produced high water depths in localized areas, which were deemed to be unrealistic. These cases are primarily located in depressions, identified by subtracting the DEM from its filled version (Fig. C.1). We inspected satellite imagery and streetview pictures to verify the source of these depressions and found two main groups. The first includes cases where the depressions are playgrounds, parking areas, basements, and railroads located at lower elevations than the surrounding streets or sidewalks (see

examples in Figures C.2-C.6); in these cases, it might be possible that pumping stations or inlets not included in the city database drain these low-lying areas. In the second group of cases, the pictures did not reveal any important elevation differences, suggesting that the depression could be due to errors in the DEM or the absence of buildings that are present in the city database (see examples in Figures C.7-C.9). While precipitation spatial variability can influence urban flood dynamics, our modeling applications targeted only the uncertainties associated with hydraulic routing and sewer representation, rather than precipitation forcing. The net precipitation forcings of our runs were obtained assuming spatially uniform precipitation from a rain gauge outside the basins' boundaries. Since the catchments have small areas and are within 3 km from the gauge, this assumption led to good performance in most cases. The only exception was a missed peak caused by St1 during Henri in the VB, which we ascribed to the rain gauge records underestimating the actual precipitation in the basin. Future efforts should focus on generating more accurate precipitation fields that capture localized high rain rates and the spatial variability of intense storms that are often the main drivers of urban flash floods (*Ochoa-Rodriguez et al.*, 2015; *Peleg et al.*, 2022; *Zhou et al.*, 2021). Such an effort will require sub-kilometer and sub-hourly gridded precipitation fields, which in NYC could be obtained from weather radars (e.g., *Zhang and Gourley* (2018)) after accounting for their uncertainty, as done by *Hjelmstad et al.* (2021) in Phoenix, AZ. Given its good performance, the hydrologic-hydraulic model proposed here could also be used to investigate whether storms characterized by different precipitation spatiotemporal variability, either observed or simulated by stochastic models (*Hartke et al.*, 2022; *Mascaro et al.*, 2023; *Papalexiou et al.*, 2021; *Peleg et al.*, 2017), have distinct impacts on urban flooding. The approach adopted to account for the precipitation falling on the building roofs is simplified since it does not consider (1) the time lag in precipitation arrival from the roof to the ground, which is affected by building height and roof type; (2) the possible presence of downspouts, which implies a non-uniform contribution along the building perimeter; and (3) the direct discharge of precipitation water from the roof to the sewer via the downspouts, which occurs in several NYC buildings (*NYC Mayor's Office of Resiliency*, 2021). We believe these limitations are acceptable in this phase and should be addressed in future work, especially considering that the latter two could only be overcome by adopting a 2D-1D model that explicitly represents the sewer. All methods adopted here do not consider or strongly simplify the sewer effect. The best-performing Out-SW method assumes infinite sewer capacity and cannot represent surcharging and overflowing conditions. Therefore, the proposed approach is most appropriate for simulating events in which inlet capture dominates surface water removal, while it may underestimate flooding severity under conditions of sewer surcharge. Moreover, Out-SW also uses a single analytical form and parameterization of the outflow equation for all inlet types and clogging conditions. Future experimental work could enhance the physical

representation of inlet discharge under varying configurations and operating conditions. Moreover, recent aerial images could characterize the spatial heterogeneity of inlet types and correct possible inaccuracies in the city stormwater inlet dataset. Finally, future work should further assess the value of the simplified methods to represent the sewer, buildings, and rainfall-runoff transformations using coupled 2D-1D models validated against street flooding observations as the reference. On the one hand, coupled models are becoming increasingly available with open-source licenses (*Hydrologic Engineering Center*, 2024; *Sañudo et al.*, 2025) at lower computational costs, thanks to codes running on GPUs. On the other hand, sensors monitoring street-level flooding observations are starting to be installed at other sites (*Gold et al.*, 2023; *Son et al.*, 2023). Tests based on coupled models should be conducted primarily when information on the sewer layout is available. If this is not the case, like in NYC, these simulations could apply recent methods proposed to generate virtual sewer networks from terrain, building, and street information (*Chegini and Li*, 2022; *Montalvo et al.*, 2024).

3.7 Conclusion

The lack of street-level flooding data in urban areas has severely limited our ability to build confidence in hydrologic-hydraulic models that simulate pluvial flooding at hyperlocal resolutions, which are essential for accurately quantifying and mitigating flood hazards. In this study, we addressed this gap using continuous, spatially distributed water depth observations from the FloodNet network, which began operation in NYC in 2021. We first compared three modeling strategies using the LISFLOOD-FP two-dimensional, rain-on-grid hydrodynamic model applied at 1-m resolution to a $10.9 - km^2$ basin (CB) during Tropical Storm Ophelia in 2023. We showed that excluding the sewer network or simplifying its representation through reduced precipitation inputs resulted in significantly higher simulated water depths than observed at six sites. In contrast, the observed hydrographs were reproduced remarkably well when runoff removal at stormwater inlets was represented through an outflow relationship, with its single coefficient calibrated against the sensor measurements. We validated the robustness of this calibrated approach in a $0.8 - km^2$ basin (VB) with similar urban density but steeper terrain, using observations from two sensors during the same event and during Tropical Storm Henri and Hurricane Ida in 2021. Our results demonstrate that street-level flooding observations are essential for calibrating, testing, and improving existing and emerging methods to model urban flooding under varying levels of data availability. In addition, we developed methodological procedures and provided guidance for preprocessing geospatial data, setting up the model domain, and generating net precipitation forcings, which can

facilitate hyperlocal flood simulations in other urban landscapes. Overall, the findings of this study provide valuable insights for researchers and agencies seeking to apply hydrologic–hydraulic models to evaluate infrastructure and urban planning strategies for flood risk reduction.

Chapter 4

Assessing Nature-Based Solutions for urban pluvial flood mitigation.

4.1 Introduction

As already discussed in the Introduction (Chap. 1) and in Sec. 3.1, pluvial flooding in urban areas is an increasing risk, driven in part by climate change and continued urbanization. Within this context, assessing flood mitigation measures has become increasingly important for supporting an effective reduction of flood negative impacts. Mitigation measures can take different forms, and conventional interventions often rely on so-called grey infrastructure, such as sewer network upgrades, storage facilities, or deep tunnels *Chen et al.* (2021). However, these interventions require high construction and maintenance costs, making future adaptation more difficult, for example when accounting for climate change (*Esraz-Ul-Zannat et al.*, 2024). Moreover, grey interventions often provides negative impacts on ecosystem (*Onuma and Tsuge*, 2018). For this reason, in recent years *Nature-Based Solutions* (NBSs) have gained growing attention as a means of reducing runoff generation and attenuating pluvial flood hazard. In contrast to conventional grey infrastructure, NBSs can also deliver additional ecosystem benefits, including improved air quality and enhanced biodiversity (*Morketo et al.*, 2025). These solutions encompass a wide range of interventions, with the most common measures for pluvial flood management including green roofs, rain gardens, bioswales, retention ponds, infiltration trenches, and permeable pavements (*Alves et al.*, 2024).

New York City represents a particularly relevant case study for analysing the effectiveness of these solutions. The city is highly urbanised and has experienced several flood events

generated by different sources, including both coastal and pluvial flooding, as discussed in Chap. 3. In this context, the New York City Green Infrastructure Plan (*New York City DEP*, 2010) has identified NBSs as a key strategy for improving urban resilience and reducing pressure on the drainage network. Its implementation relies both on direct public investment and on economic incentives designed to promote private adoption. For example, at 2024 the NYC Department of Environmental Protection constructed more than 7000 m^2 of permeable pavements and finalised additional agreements for further construction in 2025 and 2026 (*New York City DEP*, 2024). At the same time, New York City also offers a Green Roof Tax Abatement, providing a one-time property tax reduction for buildings that install eligible green roofs (*New York City Department of Finance*, 2026).

The pluvial-flood modelling framework previously proposed, based on the use of LISFLOOD-FP with high resolution spatial data and including a simplified representation of the sewer system, was extensively validated against real street-level water-depth observations from three flood events (see Chap. 3). The satisfactory performance obtained supported the adoption of the same framework in the present chapter to assess the value of selected NBSs in reducing pluvial flood hazard. Among the different NBSs, the present modeling framework was extended to include the presence of *Green Roofs* (GRs) and *Permeable Pavements* (PPs).

A Green Roof is a multi-layer element positioned above the roof, whose upper layer is usually vegetated. Green Roofs can be extensive or intensive based on the thickness of the soil substrate: extensive GRs have a soil substrate with a thickness lower than 150 mm, while intensive GRs have a soil substrate with a thickness higher than 150 mm. The measure influences pluvial flooding by reducing the amount of water that reaches impervious surfaces due to soil retention and vegetation evapotranspiration, and by delaying the runoff of the water not retained by the system (*Kõiv-Vainik et al.*, 2022). Permeable pavements are paved systems designed to allow water to infiltrate through voids or permeable joints; therefore, their effectiveness strongly depends on the properties of the underlying material. By increasing local infiltration, PPs allow for flood peak reduction (*Kõiv-Vainik et al.*, 2022).

As a case study, the Validation Basin described in Chap. 3 has been considered, using the same high resolution geospatial data (1 m) and the same building representation (Reflective Boundary). Starting from the existing model setup, different scenarios were created by introducing alternative configurations of GRs and PPs. Simulations were then performed for rainfall events with different return periods, and the distributed outputs were analyzed to evaluate the ability of NBSs to reduce flood depth and flood extent.

The objective of the study consists of providing useful information on the potential contribution of GR and PP to urban stormwater management and in assessing the effectiveness of such measures to mitigate pluvial flood effects in highly urbanized environments.

4.2 Green roofs and permeable pavements representation in the proposed modeling framework

Existing studies investigating the influence of NBSs on the mitigation of pluvial flooding often rely on coupled hydrologic–hydraulic approaches, for example using the *Storm Water Management Model* (SWMM) (Rossman, 2016) to represent the hydrologic component and hydrodynamic models to simulate flow propagation (Cansian *et al.*, 2025; Griffiths *et al.*, 2024). In this framework, the effects of NBSs are usually represented in the hydrologic part of the study, often through the SWMM Low Impact Development (LID) elements implemented in the model. By contrast, the present study integrates the representation of NBSs directly within the high-resolution Rain-on-Grid hydrodynamic modelling framework previously described in Chap. 3. This approach allows the effects of NBSs on both runoff production and surface flood propagation to be evaluated within a single model.

In this study, extensive GRs and PPs are represented, and their inclusion in the modelling framework was achieved using two different approaches. To simulate the influence of PPs, a new function for calculating infiltration using the Green-Ampt model was added to the LISFLOOD-FP code, whereas GRs were represented by modifying the net precipitation used as model input.

4.2.1 Permeable Pavements simulation

The inclusion of PPs in the modelling framework was achieved by introducing a new function into the LISFLOOD-FP source code. As in Chap. 3 the study was carried out using the FV1 solver; therefore, the *fv1.ccp* file was modified. The new function computes infiltration by applying the Green-Ampt method (Green and Ampt, 1911) following the equations used for its implementation in SWMM (Rossman, 2016) and adapting the numerical implementation available in the OpenGeoSys code (OpenGeoSys Community, 2018). The equations used are reported below, starting from the integrated form of the Green-Ampt equation:

$$F_2 - F_1 - \Theta \ln \left(\frac{F_2 + \Theta}{F_1 + \Theta} \right) = K_s \Delta t \quad (4.1)$$

where F_1 and F_2 are the cumulative infiltration at the beginning and at the end of the time step, respectively, K_s is the saturated hydraulic conductivity, Δt is the computational time step and Θ is the capillary term computed as:

$$\Theta = \theta_d \psi_f \quad (4.2)$$

where θ_d is the soil moisture deficit, and ψ_f is the suction head at the wetting front.

To distinguish between unsaturated and saturated conditions, the cumulative infiltration required to saturate the soil surface layer, F_s was computed as:

$$F_s = \frac{K_s \psi_f \theta_d}{i_a - K_s} \quad (4.3)$$

where i_a represents the available water rate, defined as

$$i_a = i + \frac{d}{\Delta t} \quad (4.4)$$

including both the rainfall rate (i) and the ponded surface water depth (d).

If $i_a < K_s$, the infiltration increment over the time step is computed as

$$\Delta F = i_a \Delta t \quad (4.5)$$

where ΔF is the infiltration increment during the time step.

If $i_a > K_s$ but the soil remains unsaturated throughout the entire time step, the same expression is used provided that

$$F_1 + i_a \Delta t < F_s \quad (4.6)$$

If saturation is reached during the current time step, the saturated fraction of the time step is computed as

$$\Delta t' = \Delta t - \frac{F_s - F_1}{i_a} \quad (4.7)$$

where $\Delta t'$ is the fraction of the time step during which saturated conditions apply.

For this saturated fraction, the integrated Green–Ampt equation becomes

$$F_2 - F_s - \Theta \ln \left(\frac{F_2 + \Theta}{F_s + \Theta} \right) = K_s \Delta t' \quad (4.8)$$

Finally, the infiltration increment and the infiltration rate are computed as

$$\Delta F = F_2 - F_1 \quad (4.9)$$

$$f = \frac{\Delta F}{\Delta t} \quad (4.10)$$

where f is the infiltration rate.

To prevent infiltration from exceeding the water available during the time step, thereby avoiding non-physical behaviour and numerical errors, the following additional constraint was imposed:

$$\Delta F \leq i_a \Delta t \quad (4.11)$$

To apply the code, the soil characteristics K_s (saturated hydraulic conductivity), ψ_f (suction head at the wetting front), and θ_d (soil moisture deficit) are required as input. These three variables should be provided as raster files with the same resolution as the DTM. The K_s input file also provides an activation flag, i.e. infiltration is computed using the described approach only in cells where $K_s > 0$. In LISFLOOD-FP, the flow equations are solved using a computational time step Δt typically shorter than 1 s, in order to satisfy the Courant–Friedrichs–Lewy condition and avoid numerical instability. Such a time step is not consistent with the characteristic time scale of the infiltration process. Therefore, to avoid unnecessary computations and reduce the overall computational cost, infiltration was updated every 30 s. The use of a different time step for infiltration is consistent with previous studies, for example in *Rong et al.* (2024) a Δt of 300 s was used.

4.2.2 Green Roofs representation

To include GRs in the simulations, we focused on their rainfall retention capacity, without considering the temporal delay associated with the measure. The mitigation measure was represented by modifying the precipitation input, specifically the algorithm used to redistribute the rainfall falling onto roofs. As explained in detail in Sec. 3.4.3, in the proposed approach buildings are represented using the Reflective Boundary method, and the corresponding DTM cells are therefore flagged as NODATA. Under this configuration, precipitation falling onto these cells cannot be directly included in the simulation; consequently, the rainfall volume falling onto building cells was uniformly redistributed along the building edges.

To account for the influence of GRs, a storage-based representation was adopted. For a given GR thickness, soil porosity, and antecedent moisture condition, the maximum water volume that could be stored, neglecting evapotranspiration, was estimated. During the precipitation redistribution procedure, the rainfall falling onto buildings was first assumed to be retained within the GRs, and redistribution along the building edges was applied only once the available GR storage capacity had been exhausted. The rainfall retained within the GRs was therefore excluded from the rainfall input, so that only the excess rainfall contributed to surface runoff in the simulation.

Pratically, for each timestep Δt the volume of net precipitation falling onto each building $V_{BR,t} = P_t \cdot A_{BR}$ (where $V_{BR,t}$ is the volume, P_t is the net precipitation and A_{BR} is the roof area, see Sec. 3.4.3) is compared with the storage available in the green roof $V_{GR,t}$. This comparison yields a modified rainfall volume $V_{BR,t}^*$ which is then redistributed along the building edges. If the storage available in the green roof is greater than or equal to the rainfall volume, the precipitation is assumed to be fully retained by the green roof and $V_{BR,t}^*$ is set equal to zero, while the corresponding amount is subtracted from the storage available in the green roof for the subsequent time step. If the available storage is lower than the rainfall volume, the storage for the next time step is set to zero and the modified rainfall volume is equal to the difference between the initial rainfall volume and the volume retained by the green roof, as described by the following equations:

$$\begin{cases} \text{if } V_{GR,t} \geq V_{BR,t} \rightarrow V_{BR,t}^* = 0 ; V_{GR,t+1} = V_{GR,t} - V_{BR,t} \\ \text{if } V_{GR,t} < V_{BR,t} \rightarrow V_{BR,t}^* = V_{BR,t} - V_{GR,t} ; V_{GR,t+1} = 0 \end{cases} \quad (4.12)$$

The computation was carried out using a specifically developed Python script.

4.3 Case study and modeling scenarios

The study was carried out considering an urban basin with an area of 0.8 km^2 located in Brooklyn, New York City correspondent to the Validation Basin previously introduced in Chap. 3, described in Sec. 3.2 and shown in Fig. 3.1. The basin is characterised by a highly urbanised land cover, with impervious surfaces such as roads, buildings and other impervious areas that represents the 70.4% of the basin (Tab. 3.2, Fig. 3.3b). The area is also historically prone to flooding and three major flood events occurred there in recent years, associated with Tropical Storm Ophelia on 29 September 2023, Tropical Storm Henri on 21 August 2021, and Hurricane Ida on 1 September 2021 (see Sec. 3.3). Owing to both its high level of urbanisation and its historical flood susceptibility, the basin was selected as the study area.

The simulations were carried out using the modelling framework described in Sec. 3.4, modified to include the representation of GRs and PPs as explained in Sec. 4.2. The simulation first considered a baseline configuration, representing the current land-cover and building treatment of the basin, including also the sewer representation validated in the previous chapter. This was used as the reference scenario for comparison with alternative mitigation configurations. Additional scenarios were then defined by assuming the implementation of PPs on all secondary roads and traffic islands, corresponding to $\sim 27\%$ of the basin surface (Fig. 4.1), either alone or coupled with different percentages of GR coverage. These configurations were tested under design storms with return periods T_R , ranging from 2 to 50 years, resulting in a total of 35 simulations.

PPs were represented using the following soil characteristics: $K_s = 8.3 \cdot 10^{-6} \text{ m/s}$, $\psi_s = 6.12 \cdot 10^{-2} \text{ m}$, $\theta_d = 0.33$. For GRs, the adopted setup considered a soil thickness of 8 cm, a porosity of 42%, and initially dry soil conditions, i.e. antecedent soil moisture equal to zero, which resulted in a maximum equivalent storage depth of $S_{GR} = 0.034 \text{ m}$ for each m^2 of green roof, these values are consistent with those reported in field studies (see for example *Cristiano et al. (2022, 2023)*). The buildings were assumed to be all technically suitable for the installation of green roofs. Multiplying the available storage depth by the building roof area, the storage volume described in the previous section was computed at the first time step as $V_{GR,start} = S_{GR,start} \cdot A_{BR}$. The value of $V_{GR,t}$ for the subsequent time steps is updated following Eq. 4.12. Different percentages of GR coverage were considered, ranging from 0% (no GRs) to 100% (all building roofs equipped with a green roof covering the entire available surface), with increments of 25%. Partial GRs coverage was not represented by explicitly modifying roof geometry, but by proportionally reducing the equivalent storage depth assigned to each building roof.

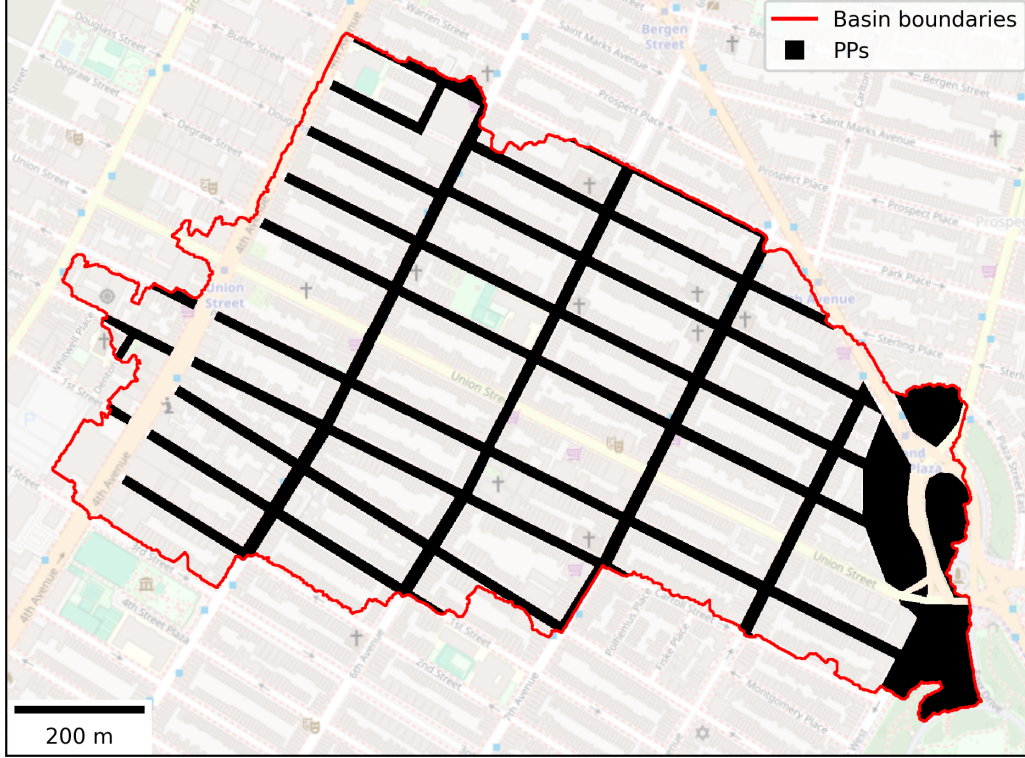


Figure 4.1: Secondary streets and traffic island in which the implementation PPs are considered. Background map is from Openstreetmap.

The design storms were defined assuming a constant precipitation intensity with a duration of 1 hour, and considering five different T_R : 2, 5, 10, 25 and 50 years. The rainfall characteristics were derived from the IDF curves at La Guardia Airport (*Perica et al.*, 2015).

4.4 Results

The simulations for the considered scenarios were designed to explore the effectiveness of NBSs under a range of rainfall severities, from more frequent events to less frequent but more intense storms. The results obtained under the NBS scenarios were compared with those of the baseline condition in order to quantify the mitigation effects. The analyses are based on maximum water depth, h_{max} and flood extent.

In Fig. 4.2 the maximum simulated water depth, h_{max} for the baseline scenario, i.e. without PPs and GRs, for $T_R = 25$ years is shown. The map highlights that, for an intermediate return-period event, flooding is generally characterised by relatively low water depths over most of the basin, while the highest values are limited to a small

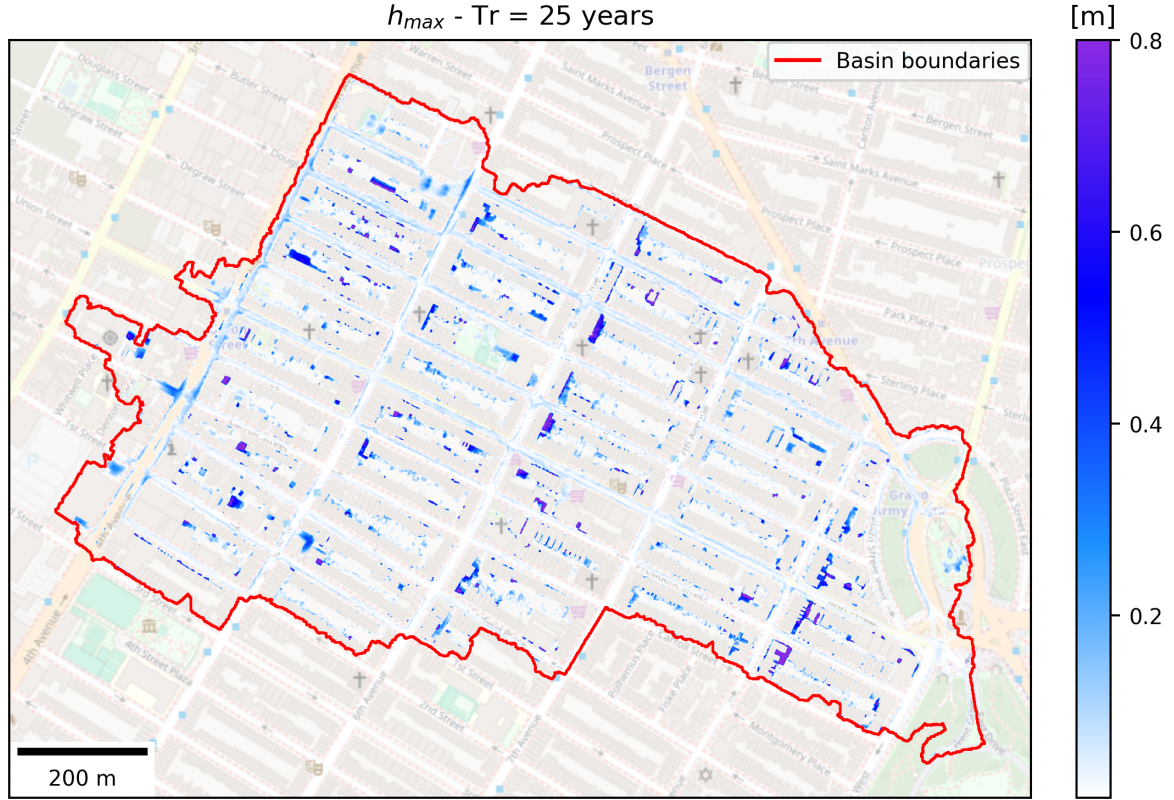


Figure 4.2: Map of the maximum water depth, h_{max} , for the baseline scenario considering a return period $T_R = 25$ years. The background map is from Openstreetmap.

number of areas, mainly in localised depressions (see Sec. 3.6.3, Fig. C.1 and Fig. C.6). In particular, 88% of the flooded pixels show $0.03 < h_{max} \leq 0.3 \text{ m}$ and the proportion increase to 99% for $0.03 < h_{max} \leq 1 \text{ m}$.

If GRs are implemented, the maximum water depth is reduced. Fig. 4.3 show the difference in maximum water depth Δh_{max} between the baseline scenario and the scenario that considers GRs installed on all the buildings, considering a coverage of 50% of the roof area. In the figure, values of $\Delta h_{max} = 0$ were masked to improve visualization. No PPs are implemented and a return period of $T_R = 25$ years is considered. The map highlights a spatial heterogeneity in the values of Δh_{max} despite GRs are implemented on all the buildings (with the assigned coverage). In particular, the largest reductions are observed in courtyards, which often have a lower terrain height compared to the surrounding streets, and close to the outlet, which represents an area historically prone to flooding. However, most of the differences in Δh_{max} are below 0.1 m. The relatively large difference observed near the outlet suggests that the effect of the considered measures is not purely local. Indeed, GRs are represented in a spatially homogeneous way within the basin boundaries. Therefore, the presence of higher Δh_{max} in this area indicates that interventions implemented upstream can also provide downstream benefits by modifying

the overall surface-flow propagation and reducing the runoff volume reaching flood-prone areas.

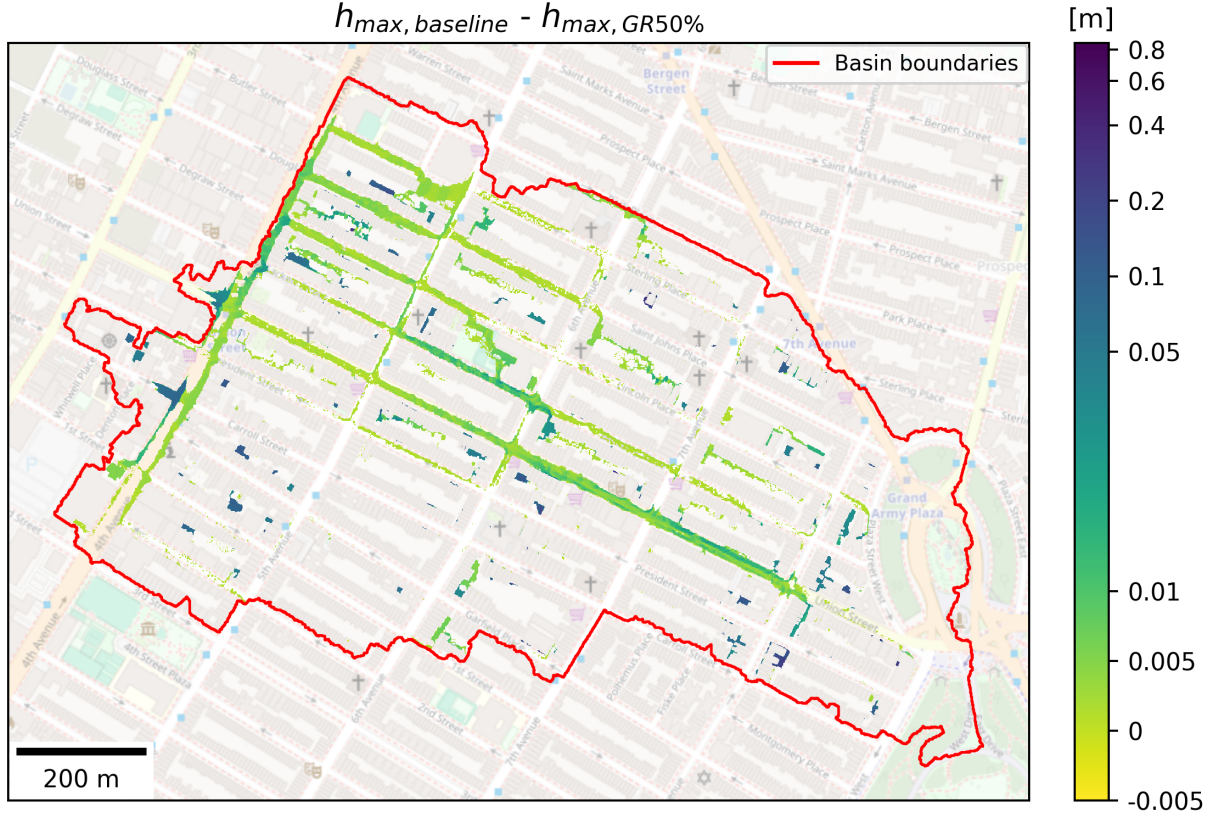


Figure 4.3: Map of the difference in maximum water depth, Δh_{max} , between the baseline scenario and the scenario that considers GRs implemented on all the buildings, with a coverage of 50%. No PPs are considered. The difference is computed considering a return period $T_R = 25$ years, and values of $\Delta h_{max} = 0$ were masked. The background map is from Openstreetmap.

The introduction of PPs in the baseline scenario also led to a reduction in the maximum water depth. Fig. 4.4 shows the difference in maximum water depth, Δh_{max} , between the baseline scenario and the scenario in which PPs are implemented in all the secondary streets and traffic islands for $T_R = 25$ years. The figure, with masked values of $\Delta h_{max} = 0$, shows widespread but generally moderate reductions in h_{max} and, compared to the 50% GR case, the effect of PPs appears slightly higher in magnitude, and affects a larger portion of the basin. Consistent with the results observed for GRs, the map of Δh_{max} also highlights the influence of the mitigation measures on streets not directly affected by the implementation of PPs, thus suggesting that the implementation of NBSs can provide positive effects in downstream areas of the basin as well.

Overall, these results suggest that both mitigation measures act by slightly lowering flood depths over a broad portion of the domain. To further evaluate the effectiveness of the

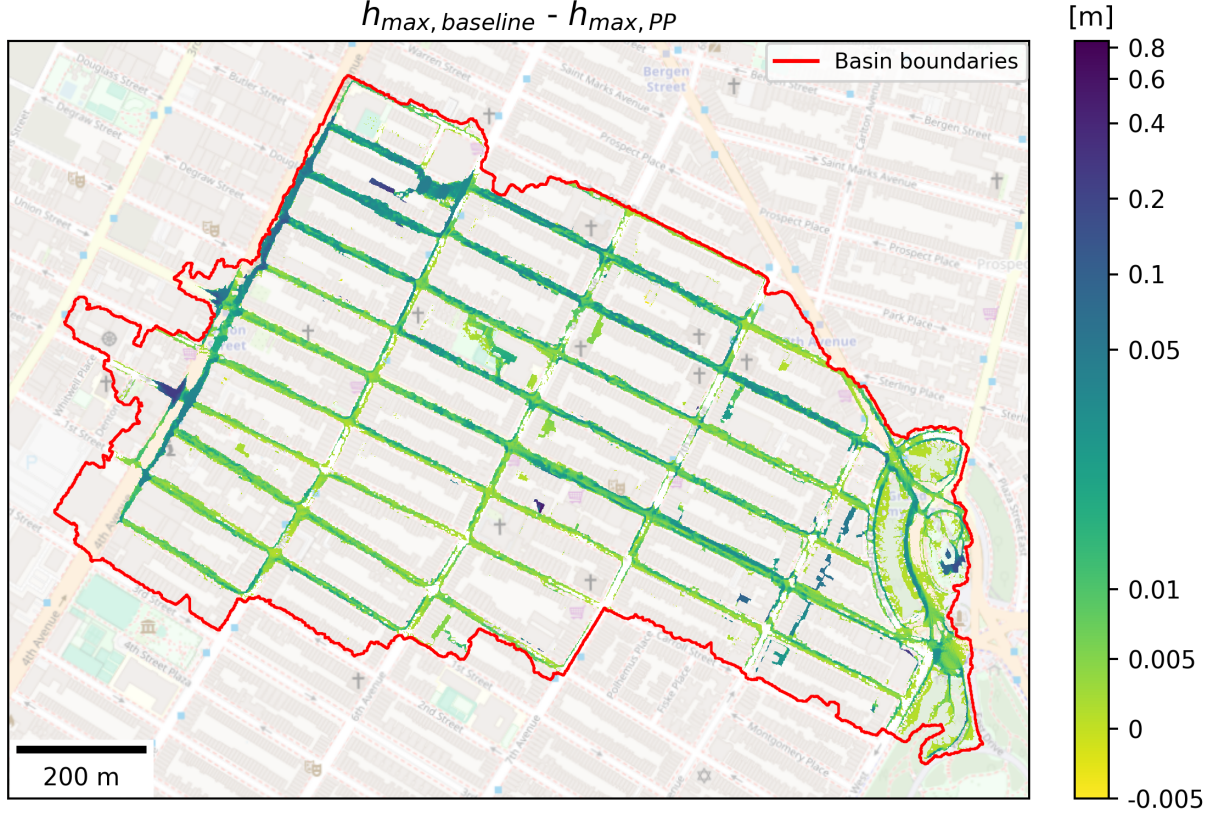


Figure 4.4: Map of the difference in maximum water depth, Δh_{max} , between the baseline scenario and the scenario that consider PPs in all the secondary streets and traffic islands. No GRs are considered. The difference is computed considering a return period $T_R = 25$ years. Background map is from Openstreetmap.

proposed mitigation measures, the flooded area was analysed by considering different values of h_{max} . The heatmaps in Fig. 4.6 show the percentage reduction in flooded area relative to the baseline scenario for the implementation of GRs (with GR coverage varying in the first four rows) and PPs (shown in the last row), under different rainfall return periods. Four panels are shown: one refers to the total wet area (i.e. with $h_{max} > 0.03 m$), while the other three refer to different water-depth ranges: $0.03 < h_{max} \leq 0.1 m$, $0.1 < h_{max} \leq 0.3 m$ and $h_{max} > 0.3 m$. Considering a $T_R = 2$ years, there are no cells with $h_{max} > 0.3 m$

Overall, GRs reduce the flooded area across all considered depth classes and for all return periods, although the magnitude of the reduction strongly depends on both GR coverage and flood depth. As expected, the mitigation effect generally increases with increasing GR coverage, while it tends to decrease as the return period increases.

For shallow flooding, i.e. for the total wet area and considering the first class with $0.03 < h_{max} \leq 0.1 m$, the reductions are generally limited when GR coverage is 50% or

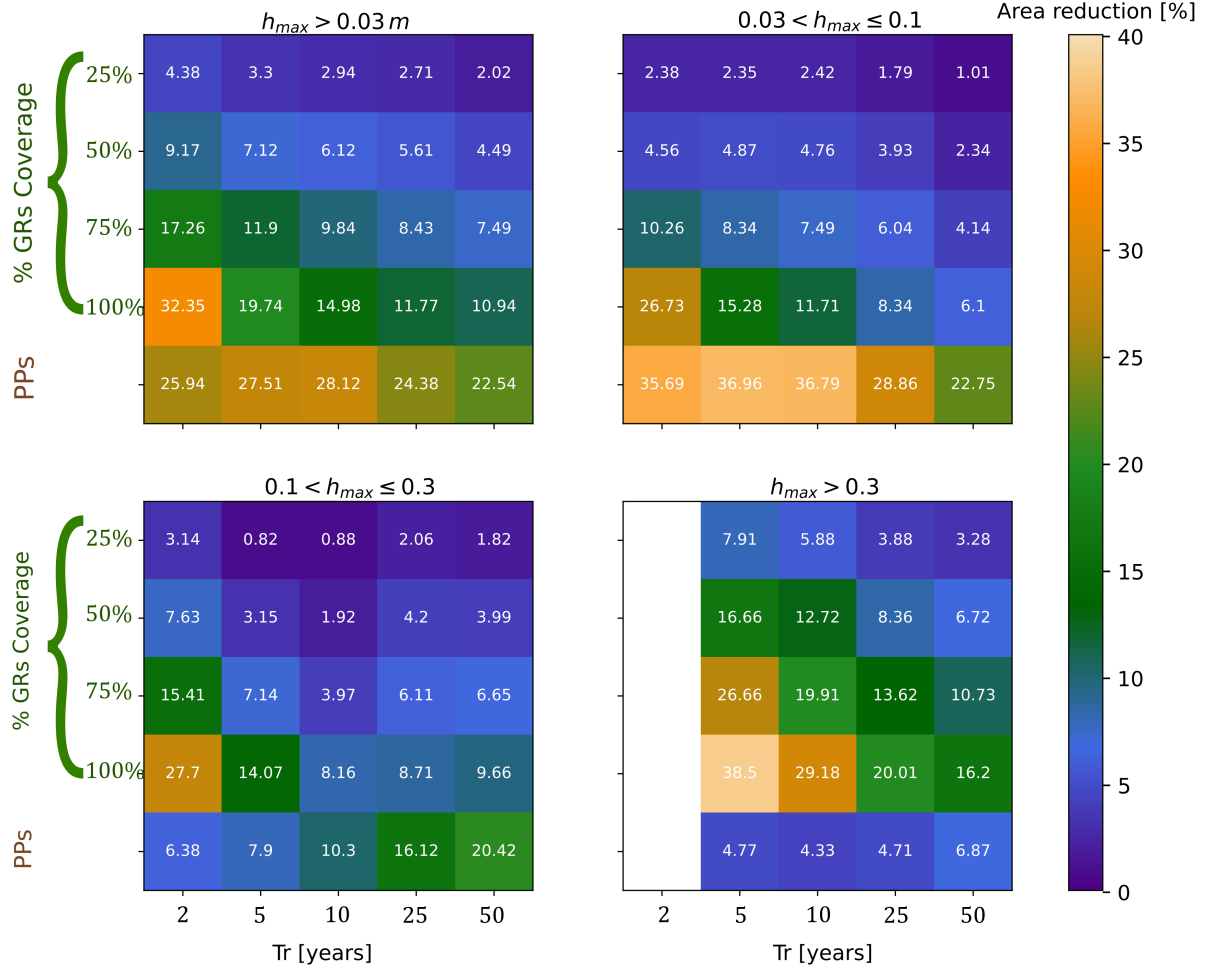


Figure 4.5: Heatmaps showing the area reduction for the 4 different water depth classes, in function of GRs coverage and for the scenario with PPs implemented

lower, and remain mostly below 10% for the higher return periods. In contrast, stronger effects are observed for higher GRs coverage, especially for the more frequent events. For 100% GRs coverage, the reduction in total wet area reaches about 32% for $T_R = 2$ years and remains around 11% even for $T_R = 50$ years. An higher influence is visible for the higher depth classes. For $h_{max} > 0.3 m$ the area reduction is from 20% to almost 40% for higher GRs coverage and lower return period. For this class benefits persisted even for $T_R = 50$ years for high GRs coverage. Overall, these results indicate that GRs provide a progressive mitigation effect, with benefits that increase with coverage and remain visible even for relatively severe rainfall events. However, for modest GR coverage scenarios, the effect is generally limited, particularly for shallow flooding and high return periods.

The results obtained for the PP scenario (last row of heatmaps in Fig. 4.5) show that permeable pavements can substantially reduce the flooded area, although the effect depends on both the water-depth class and the return period. For the total wet area (with $h_{max} > 0.03 m$) reductions remain consistently high across all the considered events, rang-

ing from about 22% to 28%. An even stronger effect is observed for shallow flooding (i.e. with $0.03 < h_{max} \leq 0.1 \text{ m}$) for which the reduction reaches values close to 37% for intermediate return periods and remains above 22% even for $T_R=50$ years. For intermediate depths (i.e. $0.1 < h_{max} \leq 0.3 \text{ m}$) the effectiveness of PPs increases with storm severity, reaching about 20% for $T_R=50$ years. In contrast, the reduction is much smaller for the highest depth class where values remain below 7% for all return periods.

A comparison between GRs and PPs highlights a different response depending on the considered depth class. PPs are generally more effective in reducing the overall flooded area and shallow inundation, often providing reductions comparable to or greater than those obtained with high GR coverage. On the other hand, GRs show a clearer benefit for the deepest flooded areas, especially when high roof coverage is considered. This difference suggests that the two measures act in a partly complementary way: PPs mainly reduce the spatial extent of widespread and relatively shallow flooding, whereas GRs are more effective in limiting the areas affected by higher water depths.

Given the promising results obtained for the individual measures, and considering their different effectiveness across the analysed water-depth classes, an additional combined scenario was tested, in which 50% GR coverage was coupled with PPs. Fig. 4.6 reports the results in terms of flooded area reduction for the 50% GR scenario, the PP scenario, and the combined scenario.

The combined scenario, in which PPs are implemented together with 50% GR coverage, shows a systematic increase in mitigation effectiveness compared with the two individual measures considered separately. In all the analysed depth classes, the flooded-area reduction obtained under the combined scenario is greater than that produced by either 50% GRs or PPs alone. This behavior is particularly evident for the total wet area ($h_{max} > 0.03 \text{ m}$) and for shallow flooding ($0.03 < h_{max} \leq 0.1 \text{ m}$) where the combined reductions reach about 33-40% for the more frequent events (i.e. $T_R=2-10$ years) and remain above 26% even for $T_R=50$ years.

Considering the intermediate depth class ($0.1 < h_{max} \leq 0.3 \text{ m}$) the combined scenario also provides consistently larger reductions, with values ranging from about 11% to 22%, depending on the return period. A similar pattern is observed for the deepest water depth class, where the combined scenario outperforms both individual measures for all the considered return periods. Although the absolute reductions remain smaller than those observed for shallow flooding, the combined effect is still substantial, reaching values above 17% for $T_R=2-10$ years. Overall, the results indicate that GRs and PPs provide complementary benefits when applied together. In particular, the reductions obtained in the combined scenario are very close to the sum of those produced by the two

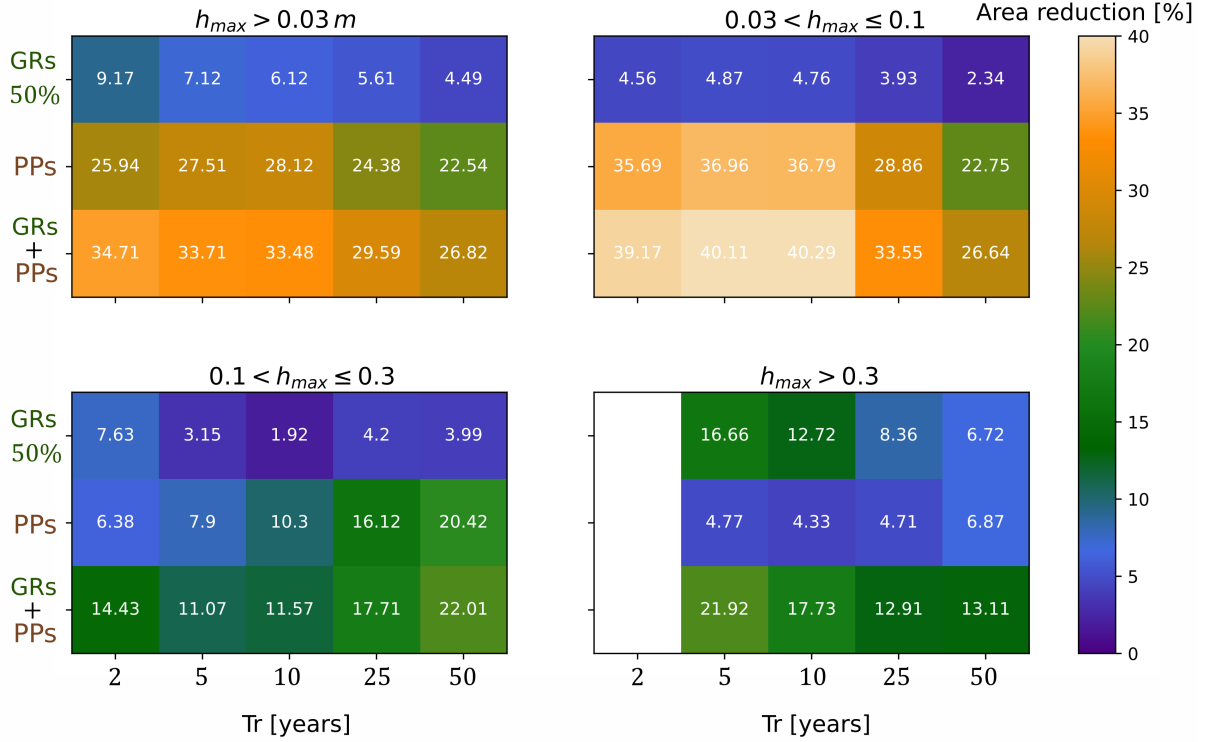


Figure 4.6: Heatmaps showing the area reduction for the 4 different water depth classes, for the implementation of GRs with 50% coverage alone, for the implementations of PPs alone, and for the combined scenario.

individual measures, suggesting an approximately additive effect. This indicates that the two NBSs mainly act through different but compatible mechanisms, so that their joint implementation can enhance the overall mitigation performance at the basin scale.

4.5 Discussion and conclusion

This study presented a preliminary assessment of the potential influence of two Nature-Based Solutions, namely green roofs (GRs) and permeable pavements (PPs), on pluvial flood hazard in a highly urbanised basin in Brooklyn, New York City. The analysis was carried out using the 2D hydrodynamic Rain-on-Grid modelling framework previously developed and validated for the study area, which was extended here to include simplified representations of both measures. A set of scenarios was considered by varying GRs coverage, introducing PPs on secondary roads and traffic islands, and combining the two measures under design storms with return periods ranging from 2 to 50 years.

The results obtained suggest that both GRs and PPs can contribute to reducing pluvial flood impacts at the basin scale, although with different effects depending on the consid-

ered water-depth class. As expected, GRs showed a progressive increase in effectiveness with increasing roof coverage. Moreover, the implementation of GRs appeared particularly beneficial in reducing the extent of deeper flooding. However, it should be noted that, in the baseline scenario, the areas affected by higher h_{max} values are often located in courtyards, close to building edges and therefore directly influenced by the representation of GRs. In contrast, PPs produced stronger reductions in the total flooded area and in shallow inundation, while being less effective for the highest water-depth class. When the two measures were combined, the results indicated complementary and approximately additive effects, suggesting that the simultaneous implementation of different NBSs may enhance the overall mitigation performance.

A relevant strength of the present study is that the assessment was carried out within a single 2D hydrodynamic Rain-on-Grid modelling framework, rather than relying only on simplified hydrological approaches. This makes it possible to evaluate the effects of the considered measures not only in terms of runoff generation, but also in terms of their influence on the spatial distribution and propagation of surface flooding. Moreover, the core of the adopted modelling framework was previously validated against real flood events in the same study area (see Chap. 3). Although this does not remove the uncertainties associated with the present NBS representations, it increases the credibility of the simulated flood response and supports the interpretation of the results as physically meaningful, including the non-local influence of NBSs. In particular, for both measures, reductions in maximum water depth are visible even in areas not directly affected by their implementation, due to the influence of upstream runoff reduction on downstream flood propagation. These findings should, however, be interpreted with caution. The analysis was designed as a simplified exploratory assessment, and several assumptions may lead to an overestimation of the achievable mitigation effect. In particular, GRs were represented through an equivalent storage approach, without explicitly accounting for their detailed hydraulic behavior or for delays in runoff generation. In addition, all buildings were assumed to be technically suitable for the installation of green roofs, which is unlikely to be realistic in practice. Similarly, the PP scenario assumed the implementation of permeable pavements on all secondary roads and traffic islands, likely overestimating the portion of the basin that could actually be interested by the measure.

Despite these limitations, the results remain useful in providing a first-order estimate of the potential benefits of the considered NBSs and in highlighting their different roles within the flood response. In this sense, the present analysis should be interpreted mainly as a comparative assessment of the relative influence of GRs and PPs under a consistent modelling framework, rather than as a definitive prediction of the absolute mitigation performance that could be achieved in the real basin. Future developments should therefore

focus on refining both the representation of the considered measures and the estimation of their realistically applicable extent within the study area, in order to provide a more realistic estimate of the achievable mitigation effect.

Chapter 5

A new storage based representation of buildings and basement in urban flooding.

5.1 Introduction

To accurately simulate flooding in urban areas, several components need to be represented, including the flood source (e.g. rainfall, river overflow, or tidal forcing), the interactions between overland flow and the sewer system, and the interaction between floodwaters and buildings and other urban obstacles (*Guo et al.*, 2021). The representation of sewer systems is one of the main modeling challenges; however, as discussed in Sec. 3.4.1, it has been investigated for many years and can be addressed using coupled surface-drainage models with real or synthetic sewer network data, or simplified approaches. The representation of buildings in urban flood models is crucial, as they can play a dual role during flood events: they act as impermeable obstacles that influence flow propagation, while also functioning as temporary storage when internal inundation occurs. This effect is especially relevant in the presence of basements, which are highly exposed to flooding because of their below-ground position and may provide additional storage volume. However, building representation in urban flood models is still often limited to the blockage effect, with facades treated as impervious boundaries, while the possible exchange of water between outdoor and indoor areas, as well as the storage effect of buildings and basements, is generally neglected (*Mignot et al.*, 2020). This is mainly due to data limitations and modelling complexity, which highlight the need for simplified approaches able to represent indoor flooding effects within 2D urban flood models

without the computational burden of detailed 3D simulations.

The most commonly used building representation approaches are described in Sec. 3.4.2 and mainly account for the effect of buildings through their blockage effect, while neglecting the potential intrusion of water. However, interest in this phenomenon has been increasing, and both experimental and numerical studies have investigated it. Experimental work has examined lateral flow intrusion through a single opening with different geometries and positions, as well as the influence of obstacles (*Mignot et al.*, 2020). In addition, experiments on porous urban blocks have been carried out under both steady and unsteady flow conditions (*Mejía-Morales et al.*, 2021; *Mejía-Morales et al.*, 2023). Numerical studies, on the other hand, have used 3D models to investigate flow intrusion into individual buildings and its effects on both flood dynamics (inside and outside the building) and the forces acting on the structure (*Gems et al.*, 2016; *Zhu et al.*, 2022), as well as to analyse groups of buildings or urban blocks (*Li et al.*, 2025; *Zhu et al.*, 2023). With specific reference to 2D SWE models *Dewals et al.* (2023) investigated the applicability of such models for representing flow exchanges between flooded streets and the interior of urban blocks through openings, by reproducing the physical experiments of *Mejía-Morales et al.* (2021) and *Mejía-Morales et al.* (2023) and testing different turbulence closures. Their results highlighted the ability of 2D models to simulate flow in complex urban settings, including configurations involving exchanges between external and internal areas, with satisfactory accuracy. The same experimental tests were later reproduced by *Li et al.* (2025) using a non-hydrostatic 3D model. Comparison with both the laboratory measurements and the results of *Dewals et al.* (2023) showed that the 3D model achieved higher accuracy than the 2D approach, although at a higher computational cost. Building on these studies, *Wu et al.* (2024) systematically analysed the influence of building openings across increasingly complex urban configurations, reproducing the single-building experiments of *Mignot et al.* (2020), the urban-block experiments of *Mejía-Morales et al.* (2021) and finally the flooding of an urban district composed of buildings through the reproduction of the inundation of the Toce River valley studied by *Testa et al.* (2007).

Evidence from real flood events has shown that internal flooding can affect a significant number of buildings. For example, the Greater Manchester area experienced two major flood events in 2004 and 2006, which led to about 90 buildings reporting internal flooding in one or both events (*Douglas et al.*, 2010). More recently, during the flooding that affected Newcastle on 26 June 2012, about 500 houses were internally flooded (*Bertsch et al.*, 2022). Overall, both numerical and experimental studies on idealised cases, together with evidence from real flood events, suggest that treating buildings as fully impervious during floods is an important simplification. At the same time, detailed

3D simulations of water intrusion are generally impractical for large study areas because of their high computational cost and the lack of detailed data. In this context, the proposed approach aims to bridge the gap between the common fully impervious representation of buildings and computationally demanding detailed simulations of indoor flow. The proposed method adopts a storage-based representation to account, in a simplified yet physically consistent way, for internal flooding at ground level and in basements within a 2D SWE framework. The chapter investigates the effects of a simplified treatment of indoor water storage on urban flood simulations while preserving applicability at large spatial scales. The methodology is first tested on a simplified case study (Sec. 5.2) and then applied to an urban basin in London as a case study (Sec. 5.3). Simulations are performed using both the fully impermeable building representation and the proposed approach and the results are subsequently shown (Sec. 5.4) and analysed (Sec. 5.5). Finally, the main conclusions are presented in Sec. 5.6.

5.2 Materials and methods

As discussed, buildings are usually considered fully impervious in urban flood models because of the limited availability of data on the location and geometry of openings, and because of computational limitations. However, data availability is increasing, and information on building opening locations and basement presence is becoming easier to obtain. In Great Britain, the Ordnance Survey National Geographic Database (OS NGD) (*Ordnance Survey*, 2026), available under license, provides building-level information on access locations and basement presence. In addition, the growing use of Volunteered Geographic Information (VGI) is improving the availability of similar data through open-access sources such as (*OpenStreetMap Contributors*, 2026). Moreover, when a detailed description of flow patterns within building interiors is not required, 2D SWE models have been shown to represent flow intrusion through openings with satisfactory accuracy (*Dewals et al.*, 2023; *Wu et al.*, 2024).

5.2.1 The proposed approach

The proposed approach aims to represent the blockage and storage effects of buildings during urban flooding in a simplified yet physically consistent way. Interior flooding and basement inundation are included using a storage-based representation, and for this reason the approach is hereafter referred to as the Building Storage (*BS*) approach. Flow obstruction is represented by treating external walls as impermeable, whereas openings

are introduced at external door locations to enable bidirectional flow exchange between the street and the building interior. Considering that basements are typically located below street level, any floodwater routed into these spaces is assumed to be unavailable for subsequent surface-flow propagation in the surrounding cells. This is achieved by removing the corresponding water depth from the computational domain and accounting for it as internal storage. For each building identified as having a basement, a storage height parameter h_s was defined, representing the maximum water depth that can be stored in each computational cell within the building footprint. At each timestep t , the water depth within basement cells (i.e. cells where $h_s > 0$), h_b^t , is compared with the available storage in the same cell, h_s^t . If the available storage is sufficient, all the water is removed from the cell, yielding a modified $h_b^{t*} = 0$. The corresponding amount is then subtracted from the available storage for the subsequent timestep h_s^{t+1} . Otherwise, the available storage is completely filled and only the excess water remains in the computational domain after the storage correction step. This mechanism is shown in the following equation:

$$\begin{cases} \text{if } h_b^t < h_s^t \rightarrow h_b^{t*} = 0 ; h_s^{t+1} = h_s^t - h_b^t \\ \text{if } h_b^t \geq h_s^t \rightarrow h_b^{t*} = h_b^t - h_s^t ; h_s^{t+1} = 0 \end{cases} \quad (5.1)$$

Where h_b^t and h_s^t represent, respectively, the water depth in a computational cell located within a building with a basement and the available storage height in the same cell at timestep t . The variable h_b^{t*} denotes the corrected water depth after application of the storage-based approach, whereas h_s^{t+1} represents the remaining storage height available at the timestep $t+1$. The *BS* approach was implemented using the 2D hydrodynamic model LISFLOOD-FP version 8.1 (*Bates and De Roo, 2000; Sharifian et al., 2023*). As in Chapters 3 and 4, the FV1 solver was used, thus the modifications were done in the *fv1.cpp* file. Building effects are usually represented through modification of the computational mesh, which coincides with the DTM used as input by the model. External building walls were treated as impermeable by assigning the corresponding cells as NODATA, which in LISFLOOD-FP is equivalent to imposing a reflective boundary (*Annis et al., 2026*). Flow intrusion at ground level was allowed by locally interrupting the walls at opening locations, where the original terrain elevation was retained. Water can thus flow inside and outside the building through the openings, according to the SWE solution. The initial storage height, h_s , was provided to the model as a raster grid aligned with the computational mesh, thus specifying for each cell the available basement storage height. The storage update in Eq. 5.1 is applied only to cells with $h_s > 0$ (i.e., basement cells), and the raster map of the remaining available storage h_s is written as output at user-defined intervals. Basement access was assumed to occur through the same openings used

for ground-level flow intrusion.

5.2.2 Simplified test case

To verify the conceptual consistency of the approach and the correctness of its implementation, a simplified test case was designed. The study domain consists of a 1 m resolution DTM with dimensions of 100×65 cells and a uniform longitudinal slope of 1%, with elevations ranging from 10 m above sea level on the left side (upstream boundary) to 9 m on the right side (downstream boundary). A single rectangular building was placed within the domain, with dimensions of 20 cells in the x-direction and 11 cells in the y-direction. A uniform discharge $Q_{in} = 5 \text{ m}^3/\text{s}$ was imposed at the upstream boundary. Three different building representations were tested: (1) fully impermeable (with the *RB* method), (2) *BS* with two opposite openings, (3) *BS* with two openings and basement storage; when present, openings were represented by a 1 m gap in the external walls. Using the *BS* approach, external walls were defined as impermeable and one cell thick. The building was positioned sufficiently far from the domain boundaries to avoid edge effects. To evaluate model behaviour, four monitoring points were defined at the centre of each building edge, located 2.5 m from the walls in the east, west, north, and south directions (E, W, N, and S, respectively). The simplified domain and the different building representations are shown in Fig. 5.1a-c, while Fig. 5.1d-f show the storage height, h_s , used (equal to 0 if no storage is considered or 1 m).

Each simulation had a duration of 1 hour and the outputs of water depth, h and velocity, u were saved every 30 seconds. The results at the four monitoring locations are shown in Figure 5.2. Fig. 5.2a-c depict the time evolution of water depth for the three configurations and Fig. 5.2d-f show the velocity response. Due to the symmetry of the simplified setup, points N and S exhibit identical behaviour in all simulations, and their hydraulic response is unaffected by the building representation. In contrast, points W and E, located upstream and downstream of the building, show a clear sensitivity to the building representation. In all cases, an initial rapid increase in u and h is observed due to the initially dry conditions. For the fully impermeable configuration, the water depth at all points remains approximately constant after the initial transient; the velocity also remains approximately constant at all points except at point W (upstream of the building) where the velocity initially increases and then suddenly decrease to a lower and constant value, close to the one at point E (downstream), once the flow interacts with the building. Introducing two opposite openings in the building walls produces a small increase in water depth upstream and a decrease downstream. Velocities increase relative to the fully impermeable case, and once the flow stabilizes the downstream velocity

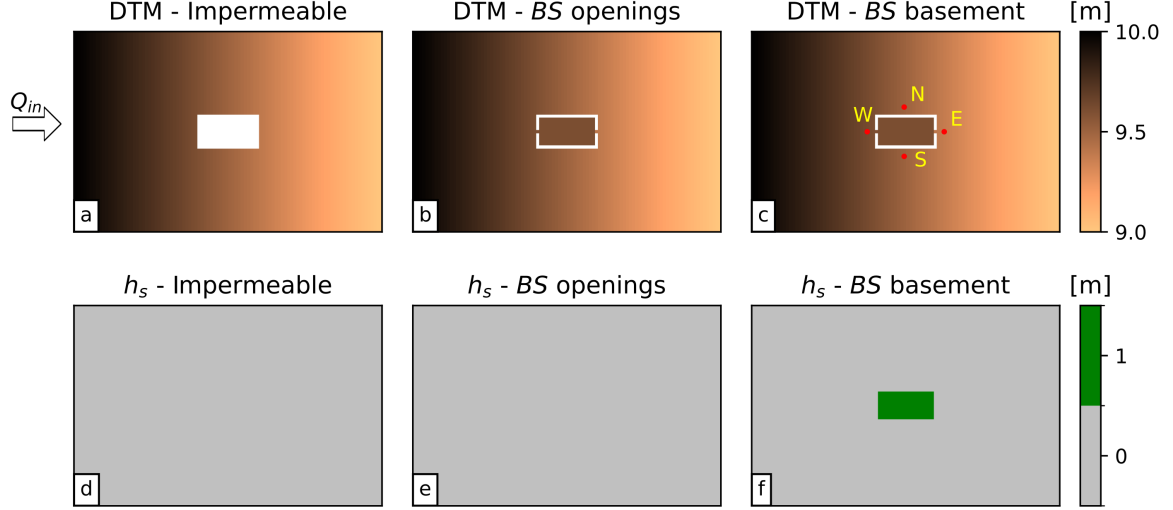


Figure 5.1: Representation of the simplified cases. (a) DTM for the impermeable representation; (b) for the *BS* approach without storage, and (c) with storage. (d) Storage height for the impermeable configuration; (e) for the *BS* approach without storage and (f) with storage.

exceeds the upstream value.

When basement storage is included, the results show a strong influence on the downstream flow characteristics: both h and u remain approximately constant while storage is still available and then increase to a higher constant value once the storage is fully used. The transition between the storage-available and storage-filled phases is visible as a small increase in downstream water depth and a more pronounced increase in flow velocity. This temporal behaviour confirms that the storage implementation acts as expected, removing from the computational domain the volume of water entering the basement until the storage is filled. Overall, the results of the simplified case indicate that the proposed building and basement representation yields physically consistent behaviour, supporting the correctness of the implementation and motivating its application to real urban flood simulations.

5.3 Realistic case study

The proposed *BS* approach was subsequently tested under a pluvial event driven by a design rainfall in a real case study area. The same event was simulated twice: in the first simulation all buildings were represented as fully impermeable using the *RB* approach, whereas in the second simulation the *BS* approach was used. All other input data and

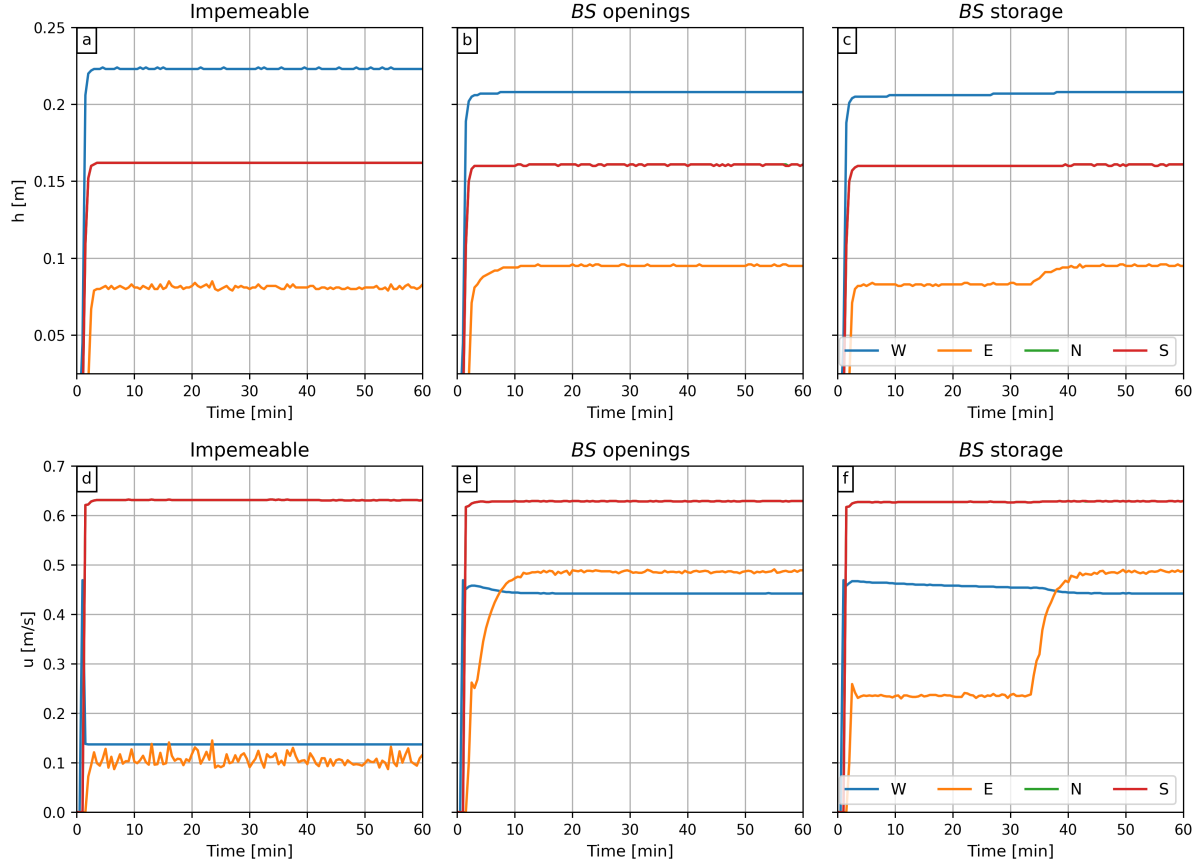


Figure 5.2: Results obtained for the simplified cases. (a) Water depth, h , for the impermeable configuration; (b) for the *BS* approach without storage, and (c) with storage. (d) Velocity, u , for the impermeable configuration; (e) for the *BS* approach without, and (f) with storage.

model parameters were kept identical in both simulations.

5.3.1 Model set-up

The selected case study was an urban basin in London with an area of 2.8 km^2 (Fig. 5.3a). The basin was delineated using the Geographic Resources Analysis Support System (GRASS) library within the QGIS software (*QGIS Development Team*, 2019). This procedure also provided the drainage direction and the flow accumulation for the study area. The identification was performed using the 1 m resolution LiDAR (Light Detection And Range) Composite Digital Terrain Model (DTM) available through the Department for Environment, Food & Rural Affairs (DEFRA) (*DEFRA (UK Department for Environment, Food & Rural Affairs)*, 2023). The computational domain extends beyond the basin boundary by an offset of 100 cells in each direction, resulting in a total of 3143×2381 cells. Building footprints within the study area were obtained from OSM, for a

total of 12502 buildings, of which 5521 are located within the delineated urban basin.

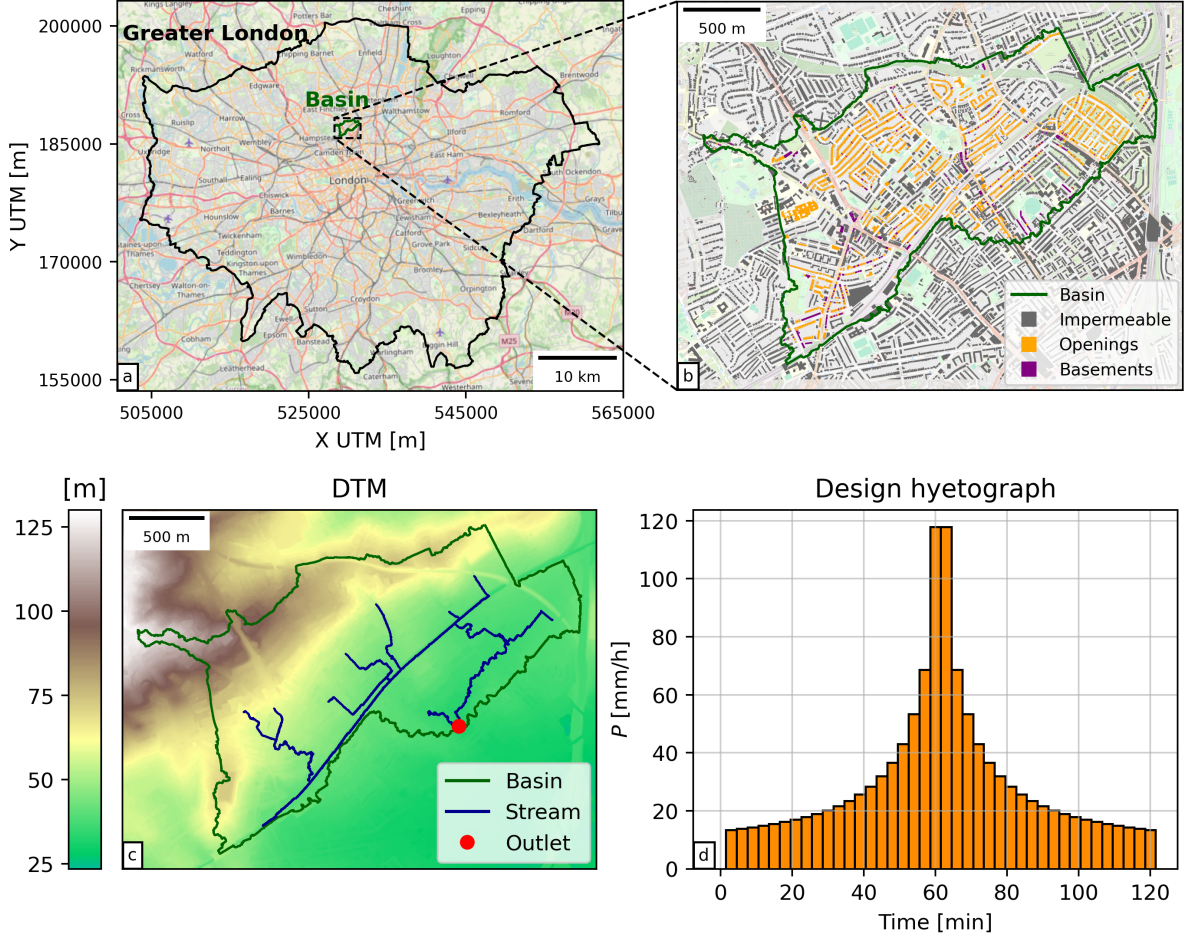


Figure 5.3: (a) Study basin within Greater London boundaries. (b) Zoom on the study basin with building footprints. The buildings are subdivided into impermeable, permeable with openings, and permeable with basements. (c) DTM of the study area, with the representation of Outlet and Stream network. (d) Design storm hyetograph.

The availability of data on building entrances has been increasing in recent years in OSM. Within the study basin, a total of 2310 points representing building openings were available. However, these openings were distributed in isolated clusters and were spatially incomplete. To improve the reliability of the results, the existing dataset was supplemented by manually adding 1545 additional opening points using Google Earth (*Google Earth*, 2025). These manual additions were intentionally limited to selected locations aimed at reducing spatial clustering, while a complete manual mapping of openings was avoided to preserve reproducibility and minimize subjective uncertainty. In total, 3855 openings were identified within the basin, associated with 2530 building footprints; the difference reflects that some footprints include multiple entrances and may aggregate multiple building units. Overall, the location of at least one opening was available for approximately 46% of the buildings. Buildings outside the basin, as well as buildings without identified openings, were represented as fully impermeable.

Information on basement presence was derived from the London Building Stock Model 2, available through the London Datastore (*London Datastore*, 2023). The dataset provides basement locations as point features without information on basement extent. Therefore, basements were assumed to have the same area as the corresponding building footprint in which the basement points are located; if more points lie in the same footprint, only one basement was considered. Given the lack of information on basement extent, this assumption provides an approximation of basement storage geometry. In the basin, 214 buildings have a basement and a known opening location (about 4% of the total and about 8% of the buildings with openings, Fig. 5.3b); for each one, a storage height $h_s = 2\text{ m}$ was assumed. This value was selected as a conservative basement height, consistent with the minimum headroom of 2.1 m reported in a residential basement study for the London Borough of Lambeth (*London Borough of Lambeth*, 2016). Given the 1 m grid resolution, this corresponds to a maximum storage volume of 2 m^3 per cell within basement cells.

The basin is characterized by a variable topography (Fig. 5.3c). In the north-western part, higher elevations are present, with a maximum value of $\sim 127\text{ m}$ (a.s.l.) while the south-western area exhibits lower elevations with a minimum of $\sim 32\text{ m}$ (a.s.l.). Fig. 5.3c also shows the outlet considered and the derived stream network which, in this urban basin, does not correspond to natural rivers but to high flow accumulation pathways, mainly coincident with major streets or railways. As explained in Sec. 5.2.1, the proposed approach requires modifying the DTM to represent external building walls as impermeable, while allowing flow through the identified openings. This process was implemented using a Python script. However, misalignment between the structured computational mesh and building walls prevents a perfect representation of openings along diagonal walls. As a result, openings are represented with a width of one or two cells, depending on wall orientation.

The DTM was further modified to avoid local depressions and elevation inconsistencies within building footprints by assigning a constant internal terrain elevation to each building, thereby preventing unrealistic internal ponding. This elevation was determined by calculating the median terrain elevation outside the building using a 3×3 cell window centered at the opening location (excluding the cells within the building footprint) and then increasing the value by 0.10 m to account for the typically higher internal floor elevation relative to the surrounding terrain. In the proposed approach, building openings were represented in a simplified manner, and the presence of doors or other physical barriers was not explicitly modelled. However, the 10 cm internal height increase can also be viewed as a threshold preventing the intrusion of shallow flow, consistent with the 0.1 m depth threshold adopted by SEPA for pluvial flood mapping, below which water depths are excluded (*SEPA*, 2018). Land cover data were used to assign spatially distributed

Manning roughness coefficients. The Land Cover Dataset with a spatial resolution of 10 m, available from the UK Centre for Ecology & Hydrology (*Rowland et al.*, 2025), was resampled to 1 m resolution to match the DTM. The correspondence between land cover classes and Manning roughness values was defined following the work of *Van Der Sande et al.* (2003).

In this study, the influence of sewer system, infiltration, interception, and evapotranspiration was not explicitly represented. Although these processes play an important role in the accurate simulation of pluvial flooding in urban areas, the aim of this work is to evaluate the proposed *BS* approach; their exclusion allows the analysis to focus specifically on the hydraulic response associated with building representation. The domain was assumed to be initially dry. Closed boundary conditions were imposed along the East, North, and South boundaries, while an open boundary condition was specified along the western boundary to permit free outflow, consistent with the location of the basin outlet in the western sector of the study area. Output variables (e.g., water depth, flow velocity, storage height) were saved every 1 minute.

5.3.2 Design rainfall

The simulations were performed using design rainfall as precipitation input, with a duration of 2 hours and a return period of 100 years. The temporal distribution followed a Chicago hyetograph derived from the Duration–Depth–Frequency (DDF) curves obtained by the Flood Estimation Handbook (FEH) (*UK Centre for Ecology & Hydrology*, 2022). The rainfall time series was discretized at a 3-minute temporal resolution and the resulting hyetograph is shown in Figure 5.3d. LISFLOOD-FP allows the use of spatially and temporally varying precipitation fields provided as NetCDF files (*Sampson et al.*, 2013). In the present case study, rainfall was assumed to be spatially uniform across the basin, and no precipitation was imposed outside its boundaries to isolate the basin response. For each time step, the precipitation value P was derived directly from the design hyetograph and a value of $P = 0$ was assigned to cells corresponding to building footprints. The volume of rainfall falling on building roofs was redistributed and assigned to the cells located along the external building boundary, following the procedure described in Sec. 3.4.3. The workflow followed for applying the *BS* approach to the real case study is shown in Fig. 5.4.

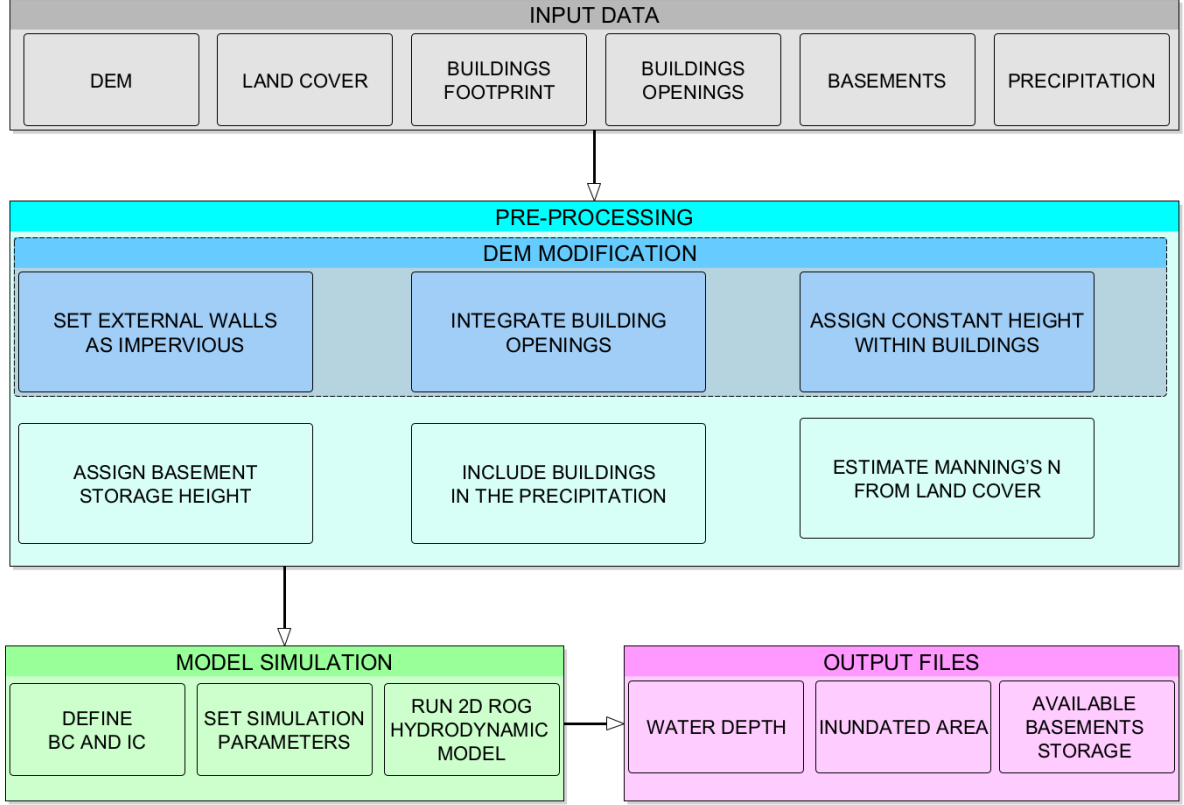


Figure 5.4: Flowchart representing the data used and the process followed to apply the study case.

5.4 Results

The results are first analysed through a domain-scale volume balance, and then in terms of water depth, h , both inside and outside buildings, as well as flooded-area metrics.

5.4.1 Volume balance and internal flooding

A volume balance for the whole domain was used to quantify how the total precipitation falling over the basin was partitioned among three components: surface water outside buildings, water present inside buildings, and water removed from the computational domain to represent basement storage. At the final time step, approximately 87.8% of the cumulative rainfall volume was outside buildings, 7.8% was inside buildings, and 4.4% was stored in basements. Overall, only $\sim 8\%$ of the available basement storage capacity in the study area was used. Analysing h within the building footprints, it was found that 160 buildings ($\sim 6\%$ of the buildings with openings) were classified as flooded, defined by a mean water depth within the building footprint of $h_{mean} \geq 0.3 \text{ m}$. This value was chosen

in line with the approach adopted by SEPA in pluvial flood mapping, where buildings are represented by increasing the DTM by 0.3 m, thereby introducing a comparable threshold for water to enter the building representation (SEPA, 2018). Among these, 28 buildings had basements that became completely filled during the event, resulting in flooding at ground level.

5.4.2 Spatial influence of the *BS* approach

Next, results were examined considering h_{max} , i.e. the maximum water depth reached during the entire simulation in each cell. Fig. 5.5 shows the spatial distribution of h_{max} for the fully impermeable representation ($h_{max,imp}$, Fig. 5.5 panels a,c) and for the *BS* approach ($h_{max,BS}$, Fig. 5.5 panels b, d). The maps highlight the different inundation patterns, with the *BS* approach allowing water to spread within buildings with openings. With both building representation approaches, the highest values of h_{max} are concentrated in depressions, particularly along the low-lying railway corridor that crosses the basin from south-west to north-east. To evaluate the impact of the *BS* approach, the difference in maximum water depth was computed as $\Delta h_{max} = h_{max,imp} - h_{max,BS}$ (Fig. 5.6). Considering the spatial distribution over the whole basin (Fig. 5.6a), Δh_{max} is predominantly negative within buildings (i.e. $h_{max,BS} > h_{max,imp}$), whereas positive values are mainly observed in their immediate surroundings and along streets. The highest absolute values of Δh_{max} occur mainly in cells where the largest $h_{max,imp}$ values are simulated. To describe the spatial variability of Δh_{max} in more detail, three representative areas were selected (Fig. 5.6b-d, Table 1). In the “I” area ($\sim 99\%$ impermeable buildings) Δh_{max} is close to zero over most of the domain, excluding the area close to the building with openings (Fig. 5.6b). In the “O” area ($\sim 83\%$ buildings with openings, $\sim 79\%$ without basements) Δh_{max} shows a more heterogeneous pattern, with negative values within several buildings and positive values mainly along adjacent streets (Fig. 5.6c). The “B” area ($\sim 21\%$ buildings with basements) exhibits the largest spatial contrasts, with more extensive areas affected by both negative values (within buildings) and positive values (in the street and close to buildings) (Fig. 5.6d). The area is located in a zone characterized by a larger contributing area than the other two zones (Figure 5.3c, Table 5.1).

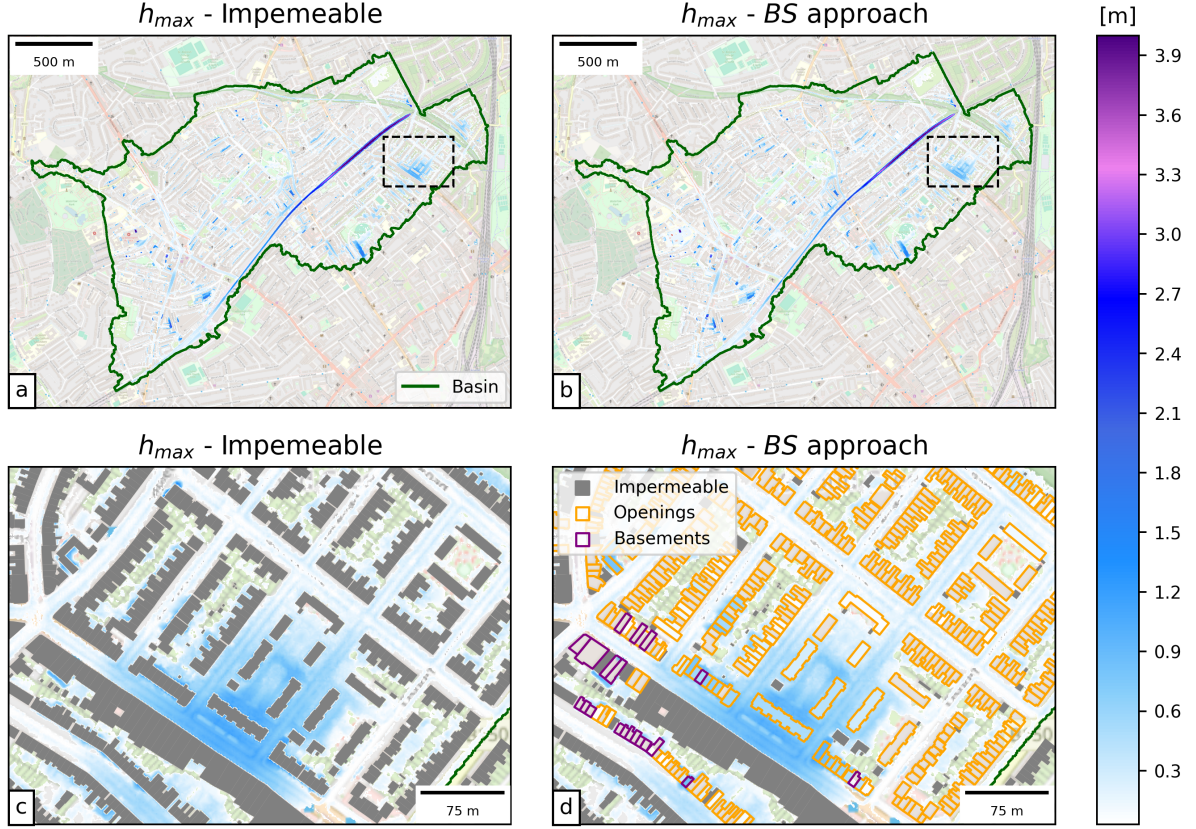


Figure 5.5: (a) Maximum water depth, h_{max} , obtained with the impermeable approach and (b) with the *BS* approach. (c) Map of h_{max} for the impermeable approach on the dashed area reported in panel a. (d) Map of h_{max} for the *BS* approach on the dashed area reported in panel b.

5.4.3 Temporal influence of the *BS* approach

Focusing on the same areas, the temporal evolution was also analysed considering only the cells outside buildings. Fig. 5.7 shows the flooded area, A , and the mean water depth, h_{mean} , computed from the simulated water depths obtained with the fully impermeable approach (red line) and with the *BS* approach (green line). The hyetograph is also shown for reference. The values are reported for the whole basin and for the three selected areas. The flooded area A is defined as the area where $h \geq 0.3m$. At basin scale, the *BS* approach reduces both the flooded area and the mean water depth relative to the fully impermeable representation. Considering the flooded area, the peak value for the whole basin (Fig. 5.7a) is reduced by $\Delta A_{peak} = 17\%$ and the differences between the two approaches remain visible also during the recession phase. The effects of the *BS* approach can be further analysed by considering the three areas separately. In the “I” area, the two curves almost overlap (Fig. 5.7b, $\Delta A_{peak} = 0.8\%$), the difference increases in area “O” (Fig. 5.7c, $\Delta A_{peak} = 17\%$) and is slightly larger in area “B” (Fig. 5.7d, $\Delta A_{peak} = 18\%$). A similar pattern is observed for h_{mean} (Fig. 5.7e-h). Differences are visible for the whole

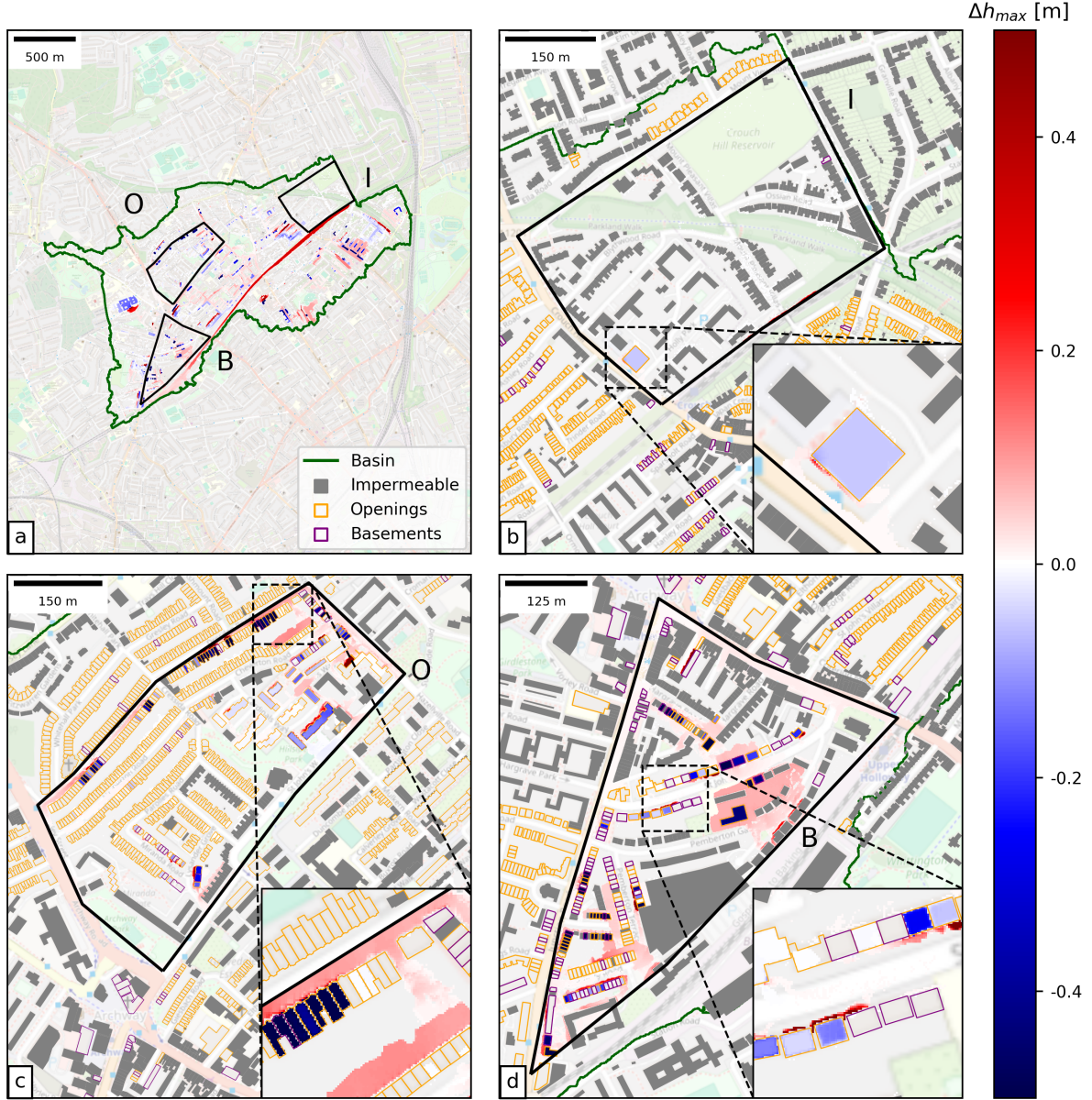


Figure 5.6: (a) Difference in maximum water depth between the impermeable representation and the *BS* approach, $\Delta h_{max} = h_{max,imp} - h_{max,BS}$ for the whole basin. In the map the three representative areas are also visible. (b) Detail on the I area, constituted by the majority of impermeable buildings along with a zoom of the dashed area. (c) Detail on the O area, constituted by the majority of buildings with openings, along with a zoom of the dashed area. (d) Detail on the B area, constituted by a relative high number of buildings with openings and basements along with a zoom of the dashed area.

basin (Fig. 5.7e), are almost negligible in area “I” (Fig. 5.7f), increase in area “O” (Fig. 5.7g), and further increase in area “B” (Fig. 5.7h).

Table 5.1: Buildings number and percentual for the whole basin and the three different areas considered.

Name	Area [km^2]	Total buildings [n°]	Impermeable buildings [%]	Permeable buildings [%]	Basements buildings [%]	Flow accu- mulation [m^2]
Basin	2.8	5521	49	46	6	2217
I	0.18	222	99	0.5	0.5	474
O	0.19	556	17	79	4	350
B	0.16	373	51	28	21	1538

5.5 Discussion

This study extends the conventional fully impermeable building assumption used in 2D SWE models for the study of urban flooding by introducing a simplified representation of indoor and basement storage. The *BS* approach is not intended as a detailed physical model of hydraulics within buildings, but it provides a simplified way to capture storage effects that can modify street-scale flood dynamics. This simplification is justified by the limited availability of data on building openings and the computational burden of more detailed building-scale simulations. The applicability of 2D SWE models to represent flow intrusion through building openings has been supported by the studies of *Dewals et al. (2023)* and *Wu et al. (2024)*. Here we discuss the mechanisms behind the observed differences relative to the impermeable approach and the implications for model interpretation and future developments.

5.5.1 Interpretation of the *BS* approach influence

The results show that, although the *BS* approach did not explicitly include the presence of doors or other obstacles and openings were assumed to be fully open, only a small proportion of buildings with openings ($\sim 6\%$) experienced internal flooding. The simulated number of buildings with internal flooding (160) is of the same order of magnitude as the numbers reported for real flood events in other parts of London. For example, during the flood that occurred on 25 July 2021 in the borough of Waltham Forest, 224 separate reports of internal flooding were received (*Resident Services, 2022*) and a further 54 were recorded in the London Borough of Redbridge (*Metis Consultants Ltd, 2022*). During the event of 12 July 2021, at least 340 properties were affected by internal flooding in the Royal Borough of Kensington and Chelsea (*JBA Consulting, 2022*). Similarly, basement storage remained limited: only 4.4% of the cumulative rainfall volume was stored in basements, corresponding to $\sim 8\%$ of the available basement storage capacity. However,

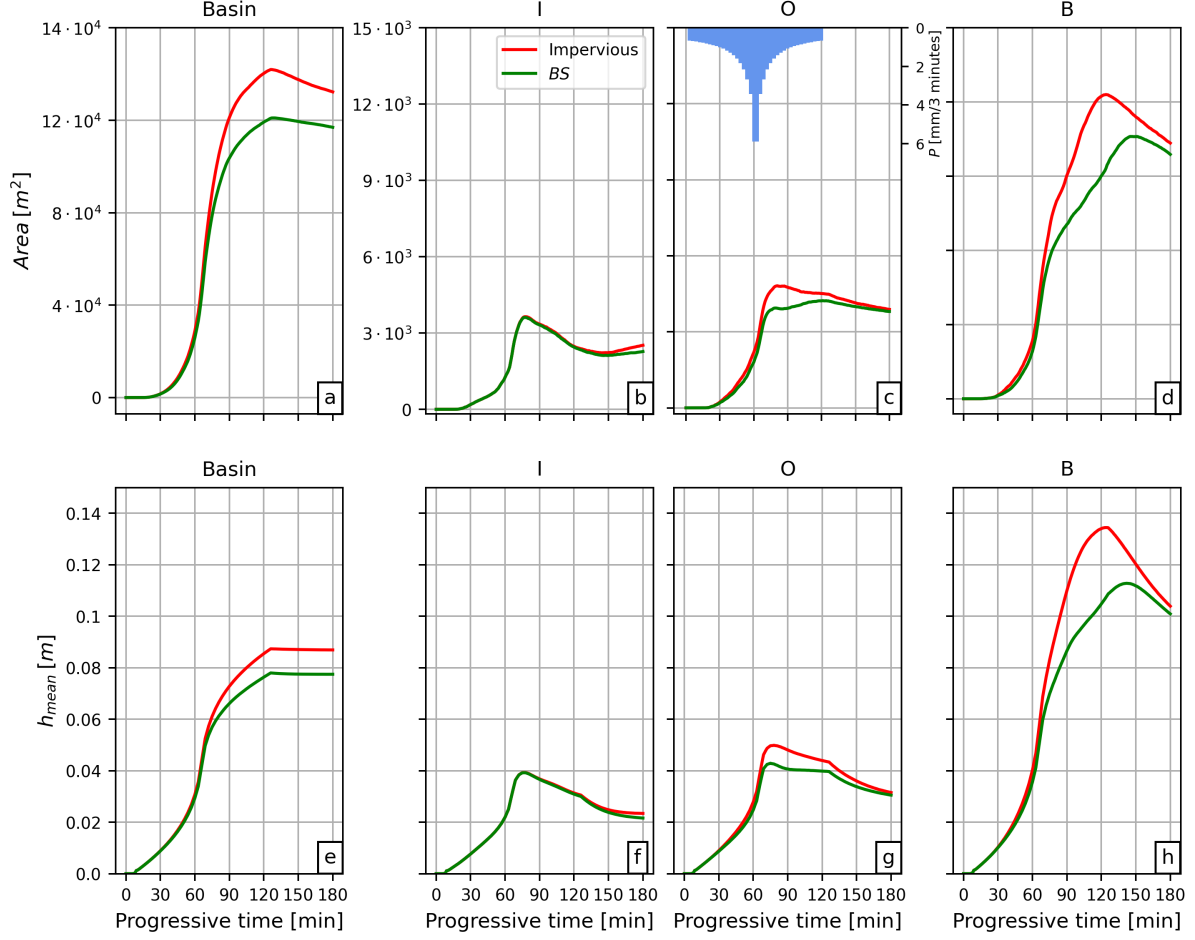


Figure 5.7: Time evolution of the flooded area, A , computed as the area interested by $h > 0.3\text{ m}$ for (a) the whole basin and (b), (c) and (d) for the three representative areas. Panel c report also the design hyetograph as a reference. Mean water depth, h_{mean} for (e) the whole basin and, (f), (g) and (h) for the three representative areas.

the simulated occurrence of 28 fully filled basements (i.e. with 2 m of water in each cell) may be overestimated and is likely influenced by the simplified representation of openings. Nevertheless, representing basement storage as a volume that is effectively removed from subsequent surface-flow propagation at street scale remains physically plausible. This interpretation is consistent with the results of *Gems et al.* (2016), who used a 3D model to simulate flow intrusion into a building during a fluvial flood. In their fully open configuration, both the ground floor and the basement became flooded during the rising limb of the hydrograph, with the water level in the basement reaching the ceiling level. During the recession limb, water depth outside the building and on the ground floor decreased, whereas the basement remained fully filled, indicating that once flooded it acted as trapped storage.

The map of h_{max} shown in Fig. 5.5 for the fully impermeable approach (Fig. 5.5a,c) and for the *BS* approach (Fig. 5.5b,d), includes locally high and physically unrealistic

values. These values are mainly located in topographic depressions and are related to the omission of processes such as infiltration and the effect of the sewer system in the model set-up. Nevertheless, the focus of this study is on the relative differences between the two building representations. From this perspective, the proposed method behaves as expected, allowing surface water to enter buildings at ground level while accounting for the additional storage provided by basements. The spatial distribution of the Δh_{max} shown in Fig. 5.6 is consistent with expectations. Negative values of Δh_{max} are observed within buildings, where the *BS* approach allows water to enter, whereas positive values are generally found in the surrounding streets and areas adjacent to buildings, indicating lower maximum water depths outside buildings under the *BS* approach than under the fully impermeable representation. Considering the three representative areas, non-zero values of Δh_{max} affect progressively larger portions of the domain and reach higher absolute values when moving from “I” (largely impermeable) to “O” (with many openings but few basements) and “B” (with a relatively high number of basements). This pattern is also in line with the results of *Wu et al.* (2024), who used a 2D SWE model to investigate the influence of openings on flood dynamics within a building district and reported lower water depths in the streets close to buildings when openings were included. Considering the temporal evolution reported in Fig. 5.7, the flooded area A for the whole basin shows clear differences between the two approaches, with a peak reduction of $\sim 17\%$ using the *BS* approach. A similar effect is also visible for the mean water depth, h_{mean} , indicating that building representation affects not only the spatial distribution of flooding, but also its temporal evolution. This behaviour is consistent with the redistribution of surface water induced by flow intrusion through openings and basement storage. Direct comparison with previous studies remains difficult, because applications discussing the temporal evolution of aggregated metrics such as flooded area are still limited and often rely on different flooding thresholds. Nevertheless, a similar tendency was reported by *Choley et al.* (2021), who analysed street-scale variations in h_{max} and found that including building openings in a 2D SWE model reduced water depth in the street relative to a fully impermeable configuration. The comparison among the three representative areas further highlights the spatial heterogeneity of this effect. In the predominantly impermeable area “I”, the two approaches produce almost identical temporal responses, whereas the differences become evident in area “O” and are slightly larger in area “B”, where basement storage is more frequent. This confirms that the influence of the *BS* approach on temporal flood evolution is limited in predominantly impermeable areas but becomes progressively stronger where openings and basement storage are more widespread.

5.5.2 Limitation and future work

Although the proposed approach provides a useful framework for representing indoor and basement storage in large-scale urban flood simulations and yields promising results, it remains subject to several limitations that suggest directions for future work. A first limitation concerns the simplified representation of building openings. In the current implementation, openings can only be represented as either fully open or fully closed, and no account is taken of doors, barriers, or dynamic opening mechanisms. Moreover, only doors are explicitly represented, whereas other possible openings such as windows are neglected. Future developments could therefore explore more flexible opening representations, for example by introducing local elevation adjustments at openings to account for sills and other small barriers. A second limitation is related to the geometric representation of openings and walls on the structured computational mesh. The representation of opening geometry is constrained by grid resolution and becomes less accurate where walls are not aligned with the mesh, owing to the well-known staircase effect (*Kumar et al.*, 2009). This issue is not unique to the *BS* approach and also affects conventional impermeable building representations on structured grids; however, in the present case, inaccuracies in the representation of openings may directly affect the simulated water exchange with the building interior. The representation of basement storage is also highly simplified. In the proposed approach, water entering basement cells is removed from subsequent surface-flow propagation and treated as internal storage until the available storage is exhausted. This assumption is physically plausible and consistent with the behaviour reported by more detailed numerical studies (e.g. *Gems et al.* (2016)), but it neglects several potentially relevant processes, such as internal hydraulic connectivity and the presence of pumps that may contribute to emptying below-ground spaces toward the streets. In addition, basement extent was assumed to coincide with the corresponding building footprint, and a uniform storage height was assigned to all basement cells. These assumptions were necessary because of limited data availability, but they may influence the estimated storage capacity and its spatial distribution. Data availability is currently one of the main constraints for the wider application of the method. The location of building openings is particularly difficult to obtain: coverage in open-access datasets such as OpenStreetMap is still incomplete, while official datasets are often unavailable or restricted for privacy and security reasons. Similar limitations apply to basement data, which are rarely available with sufficient detail to describe their actual extent, geometry, and hydraulic characteristics. Nevertheless, the increasing availability of high-resolution imagery and LiDAR data is progressively improving the feasibility of identifying the location and geometry of openings, including through automatic detection techniques (*Feng et al.*, 2022; *Haghighatgou et al.*, 2022). Future work should therefore explore the integration of automated extraction methods and additional data sources

to improve the transferability of the approach. Another major limitation concerns validation. Validating urban flood models is difficult because of the limited availability of detailed, time-varying observed data (*Cea et al.*, 2025; *Molinari et al.*, 2019) and this challenge becomes even greater when considering data on building interiors. Although official reports may provide information on buildings affected by internal flooding, the exact locations are often not available for privacy reasons, and the definition of internal flooding is not always consistent across different reports. As a result, the present study can mainly assess the physical plausibility of the proposed representation and its effects on simulated flood dynamics, rather than fully validate indoor and basement water depths. Future work should therefore focus on applying the method to events for which more detailed post-event observations are available, including official reports and crowd-sourced information. Finally, the real-case application presented here was designed to isolate the influence of the *BS* approach on flood dynamics. For this reason, processes such as infiltration, interception, evapotranspiration, and the interaction with the sewer system were not explicitly represented. While this choice is useful for understanding the relative effect of building representation, it also limits the interpretation of the absolute values of simulated variables. Future applications should therefore investigate the performance of the *BS* approach within more complete modelling frameworks that include additional hydrological processes and the influence of the sewer system.

5.6 Conclusion

The present study proposed a new simplified approach to include building effects in urban flooding simulations using 2D SWE models. The approach, here referred to as the Building Storage (*BS*) approach, aims to represent both the blockage and storage effects of buildings during flood events in a computationally feasible way. The method allows flow intrusion at ground level and exchange between the building interior and the surrounding areas, while also representing the storage effect of basements where present. The simplified test confirmed the conceptual consistency of the implementation, and a realistic application in London showed that the proposed representation can modify both the spatial and temporal characteristics of simulated flooding. In particular, the *BS* approach resulted in a plausible number of buildings affected by internal flooding, of the same order of magnitude as those reported for real flood events in other parts of London. Compared with the fully impermeable approach, the *BS* approach causes a non-negligible reduction in both flooded area and mean water depth outside buildings at basin scale. Although the proposed approach does not aim to resolve detailed indoor hydraulics, the results indicate that it provides a physically plausible and practically applicable way

to include storage effects that are neglected in conventional urban flood modelling. At the same time, the study highlighted that basement storage remained limited at basin scale, while still affecting local water redistribution and some aggregate flood metrics. These findings suggest that simplified representations of indoor and basement storage can improve the interpretation of urban flood simulations, particularly when the objective is to investigate the role of building representation at neighbourhood or city scale. Future work should focus on improving the representation of openings and basements, increasing the availability and automatic extraction of relevant building data, and testing the approach by simulating well-documented flood events for which interior flooding data are available.

Chapter 6

Conclusions

The work presented here investigates different aspects of pluvial and fluvial flooding, with particular attention to the representation of risk mitigation strategies using simplified approaches. Compound flood conditions were not considered. The analysed topics differ in terms of physical processes, modelling frameworks, and case studies, but they share the common objective of improving the capability to assess mitigation strategies, even in situations where constraints are present in terms of data availability and computational cost. With regard to fluvial flooding, the work proposed a new HAND-based approach to allow the preliminary assessment of the effects of mitigation measures, particularly in the early stages of the design process, where the use of hydrodynamic modelling is usually not feasible. The results obtained for the Sardinian case studies showed that, despite its simplifications, the approach can provide a physically meaningful first-order estimate of the influence of mitigation measures when their effects can be represented through modifications of the terrain. The additional exposure-based analysis also showed that the method can provide preliminary information on the reduction of exposed buildings and population. This makes the method a useful tool for early-stage planning and screening analyses, coherent with the regulatory framework proposed by the European Union and implemented in Italy, where a simplified assessment of mitigation effects is required in the early stages of the process to support funding applications. With regard to pluvial flooding, the work focused on one of the main open challenges in the field: the limited availability of validation data for urban flood models. This issue is particularly relevant when evaluating the representation of the sewer system, which is a key component in urban areas but is often poorly described because detailed drainage data are not available. To address this problem, street-level water depth measurements collected by the FloodNet network during three real events in New York City were used to evaluate the proposed modelling framework. In particular, the observed data were used to test

a new approach for representing sewer outflow at inlets through a weir/orifice equation, and to compare its performance with that of other widely used simplified sewer representations. The results showed good performance for the proposed method. The same modelling framework was then extended to include the representation of two Nature-Based Solutions used to mitigate the effects of pluvial flooding: permeable pavements and green roofs. Considering several scenarios representing the measures both alone and coupled, with different coverage levels, the results highlight the beneficial effects of the proposed measures in reducing both the water depth and the flooded extent, although with results that vary depending on coverage and on the severity of the pluvial event. A further contribution concerned the representation of buildings in urban flood models. A new storage-based approach was proposed to account, in a simplified but physically plausible way, for the influence of building interiors and basements on flood dynamics. The approach does not aim to represent detailed interior hydraulics; rather, its purpose is to move beyond the common assumption of fully impermeable buildings, which contrasts with the numerous reports of interior flooding. The results showed that this representation can affect both local and basin-scale flood metrics, supporting the idea that building treatment is not only a geometric modelling choice, but also a relevant hydrodynamic component in urban flood simulations. Overall, the thesis highlights two broader conclusions. First, simplified approaches can provide useful and physically meaningful support for flood-hazard assessment and mitigation analysis, especially at the early stages of mitigation-measure design and planning, provided that their assumptions and range of applicability are clearly recognised. Second, improving the representation of key urban processes and components, such as sewer interactions, Nature-Based Solutions, and building storage, can significantly increase the reliability of flood simulations, even when some data are not available. Future work should therefore extend the proposed methods to additional case studies, refine the representation of the considered processes, and further exploit observational data for model development and validation.

Appendix A

Computation of canopy interception

We computed the losses due to canopy interception in the pixels classified as “tree canopy” by adapting the procedure of the i-Tree software suite from the U.S. Department of Agriculture Forest Service, which is described by *Hirabayashi* (2013). Let P_t be the precipitation depth fallen between $(t - \Delta t)$ and t . The method separates P_t as follows:

$$P_t = V_t + Pt_t \quad (\text{A.1})$$

where V_t is canopy precipitation or the fraction of P_t that falls on and touches the canopy, and Pt_t is the through canopy precipitation or the part of P_t that does not touch the canopy and reaches the ground directly. V_t contributes to filling the canopy storage, whose maximum value is estimated as:

$$Sv_{max} = S_L \cdot LAI \quad (\text{A.2})$$

where S_L is the specific leaf storage of water, assumed equal to 0.2 mm; and LAI is the leaf area index, taken as $2 \text{ m}^2/\text{m}^2$ based on the averages across tree types in NYC. We implemented an algorithm that keeps track of the water stored in the canopy over time, Sv_t , by applying the mass balance without including any evaporation term, given the short duration of the storm. When $Sv_t < Sv_{max}$, then $V_t > 0$. As the storage fills, we might have a time when $Sv_t \geq Sv_{max}$; then, Sv_t is set equal to Sv_{max} and $Vt = (Sv_{max} - Sv_{t-1})$. When the storage is full, $Sv_t = Sv_{max}$ and $V_t = 0$.

Appendix B

Error and flood metrics

The error metrics used to compare observed and simulated time series of water depth introduced in Sec. 3.4.5 are defined in the following equations:

$$CC = \frac{\sum_{j=1}^n (h_{s,j} - \bar{h}_s) (h_{o,j} - \bar{h}_o)}{\sqrt{\sum_{j=1}^n (h_{s,j} - \bar{h}_s)^2 \cdot \sum_{j=1}^n (h_{o,j} - \bar{h}_o)^2}} \quad (\text{B.1})$$

$$RMSE = \sqrt{\frac{\sum_{j=1}^n (h_{s,j} - h_{o,j})^2}{n}} \quad (\text{B.2})$$

$$MBE = \frac{1}{n} \sum_{j=1}^n (h_{s,j} - h_{o,j}) \quad (\text{B.3})$$

$$\Delta t_{\text{peak}} = t_{p,s} - t_{p,o} \quad (\text{B.4})$$

$$\Delta h_{\text{peak}} = h_{p,s} - h_{p,o} \quad (\text{B.5})$$

where $h_{s,j}$ and $h_{o,j}$ are the simulated and observed water depths, respectively, at time $j = 1, \dots, n$, with n being the total number of times when the observation was available; $\bar{h}_s$ and $\bar{h}_o$ are the corresponding averages; and $t_{p,s}$ and $t_{p,o}$ are the times of the simulated ($h_{p,s}$) and observed ($h_{p,o}$) peaks, respectively. We quantified flood conditions in the basin by computing the pixels under different conditions of water depth, h , and flow velocity,

u . These include nuisance flooding, defined as $0.03\text{ m} < h \leq 0.10\text{ m}$ and $u < 3\text{ m/s}$ following *Moftakhari et al.* (2018); and low, moderate, significant, and extreme hazards, which were computed based on the hazard rating (HR) formula proposed by *DEFRA*, 2006 and *Surendran et al.* (2008) as $HR = h \cdot (u + 0.5) + DF$, where DF is the debris factor assumed equal to 0.5 if $h < 0.25$ and 1 otherwise; the hazard is low when $HR < 0.75$, moderate when $0.75 \leq HR < 1.25$, significant when $1.25 \leq HR < 2$, and extreme when $HR \geq 2$ (see Figure B.1). Low hazard suggests that caution should be exerted for the presence of shallow flowing water or deep standing water, while moderate, significant, and extreme hazards refer to areas that are dangerous for children, most people, and all people (including emergency crews), respectively.

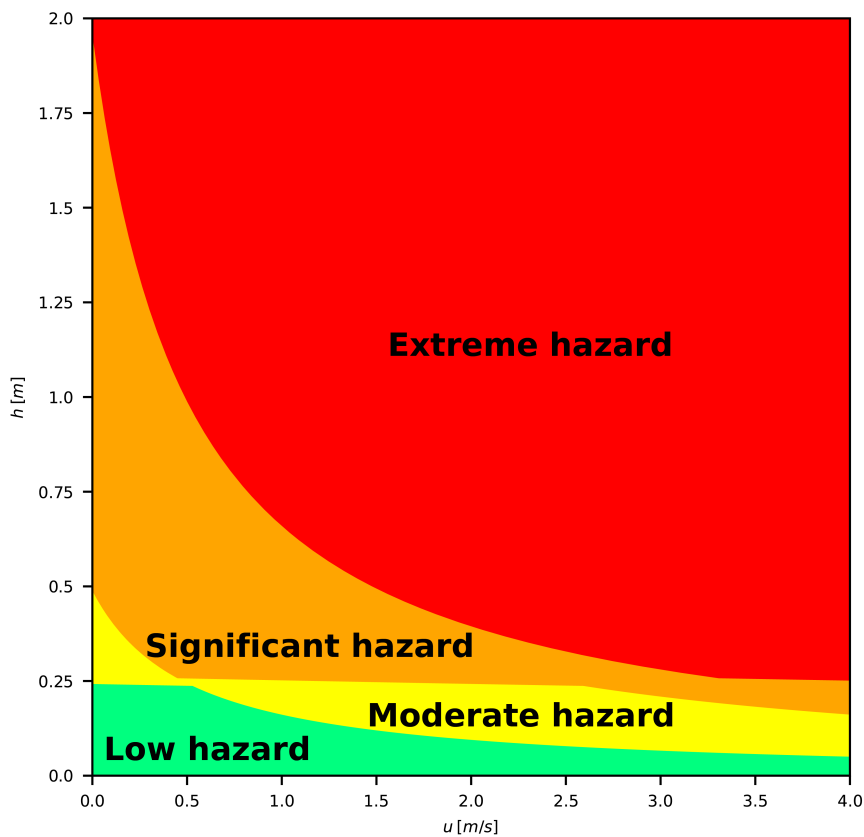


Figure B.1: Diagram reporting the hazard rating (HR) computed following the procedure described above. The hazard is low when $HR < 0.75$, moderate for $0.75 \leq HR < 1.25$, significant if $1.25 \leq HR < 2$ and extreme if $HR \geq 2$.

Table B.1: Numbers adopted in this study for the FloodNet sensors, corresponding cross streets and drainage area (see also Figure 3.1.)

FloodNet sensor number	Cross Streets	Drainage area [km^2]
1	Wallabout Street / Throop Avenue	0.75
2	Wallabout Street / Harrison Avenue	1.47
3	Walton Street / Marcy Avenue	1.58
4	Marcy Avenue / Flushing Avenue	1.17
5	Lee Avenue / Middleton Street	0.21
6	Kent Avenue / Wallabout Street	10.90
7	4th Av / Garfield Pl	0.15
8	Carroll St / 4th Av	0.79

Table B.2: Error metrics between the observed water depth time series at FloodNet sensors 1-6 in the CB during Ophelia and simulated in the co-located pixels with the three approaches (results for Out-SW are reported for $k = 0.226$).

		Sensor Number					
		1	2	3	4	5	6
CC [-]	No-SW	+0.40	+0.25	+0.48	+0.22	+0.45	+0.2
	Sim-SW	+0.32	+0.39	+0.33	+0.10	+0.38	+0.3
	Out-SW	+0.74	+0.91	+0.76	+0.80	+0.92	+0.80
RMSE [m]	No-SW	+1.04	+1.02	+1.01	+0.80	+1.18	+0.59
	Sim-SW	+0.78	+0.79	+0.75	+0.55	+0.89	+0.32
	Out-SW	+0.13	+0.07	+0.13	+0.10	+0.10	+0.05
MBE [m]	No-SW	+0.93	+0.75	+0.80	+0.68	+0.90	+0.51
	Sim-SW	+0.62	+0.56	+0.49	+0.40	+0.60	+0.27
	Out-SW	+0.01	-0.001	-0.05	+0.04	+0.01	+0.02
Δh_{peak} [m]	No-SW	+0.98	+0.73	+1.20	+0.94	+1.48	+0.53
	Sim-SW	+0.54	+0.30	+0.76	+0.51	+1.04	+0.13
	Out-SW	-0.18	-0.34	-0.23	+0.14	+0.34	-0.08
Δt_{peak} [min]	No-SW	+78	+61	+43	+83	+68	+51
	Sim-SW	+274	+276	+262	+297	+292	-3
	Out-SW	+18	+16	-17	+18	+23	-23

Table B.3: Error metrics between the observed water depth time series at FloodNet sensors 7-8 in the VB during all storms and simulated in the co-located pixels with the Out-SW approach with $k = 0.226$.

		Sensor Number			
		7	7	7	8
CC [-]	Out-SW	+0.54	+0.98	+0.84	+0.88
RMSE [m]	Out-SW	+0.15	+0.05	+0.04	+0.11
MBE [m]	Out-SW	-0.02	-0.003	-0.003	-0.02
Δh_{peak} [m]	Out-SW	-0.35	-0.09	-0.12	-0.20
Δt_{peak} [min]	Out-SW	+140	+5	+4	+13

Appendix C

DTM errors and local depressions in New York City

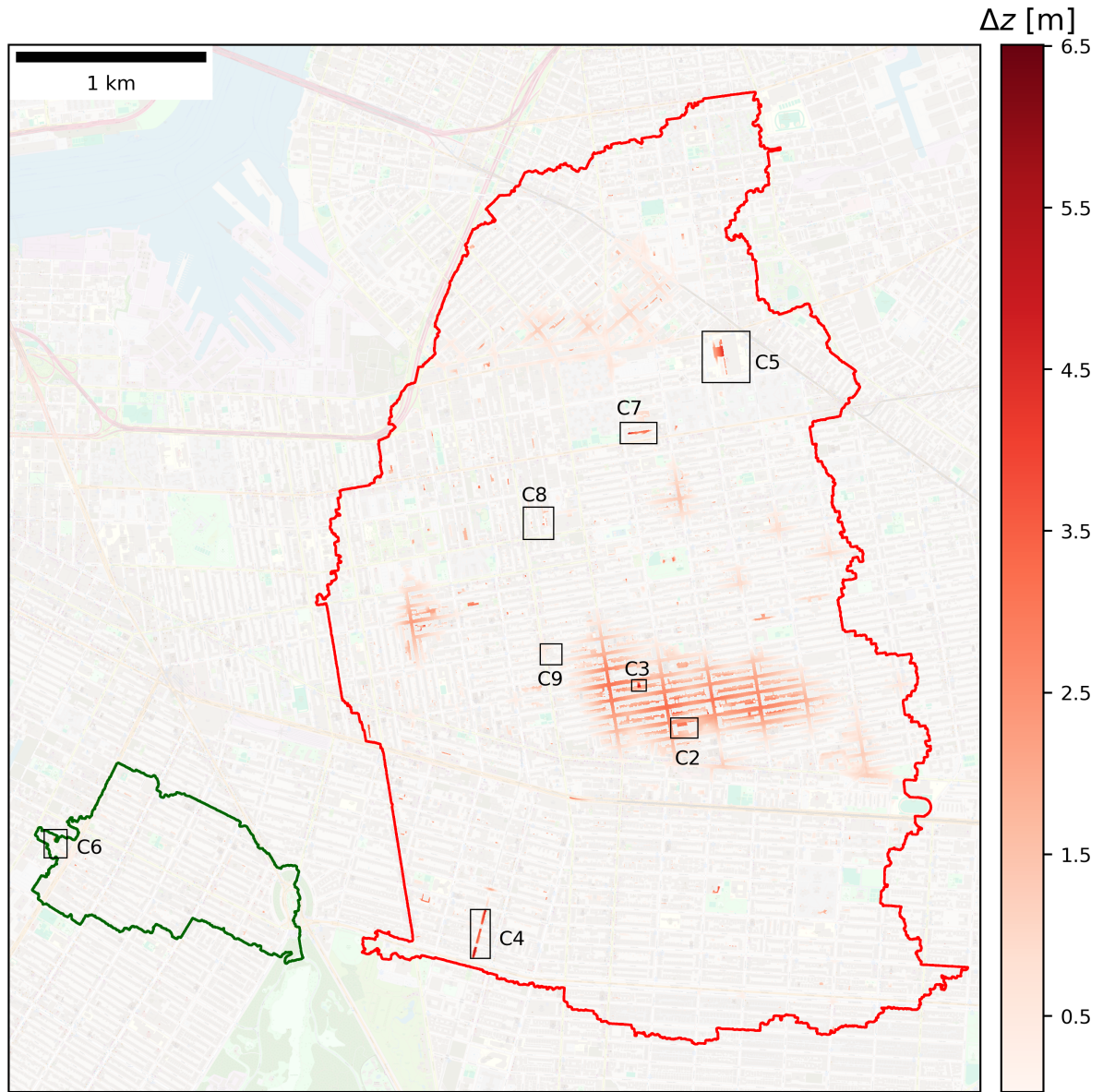


Figure C.1: Identification of depressions based on the difference between the filled digital terrain model (DTM) and the original DTM used in the simulations. Positive Δz values indicate depression. Rectangles highlight selected areas shown in Figures C.2-C.9. The base map is from OpenStreetMap.

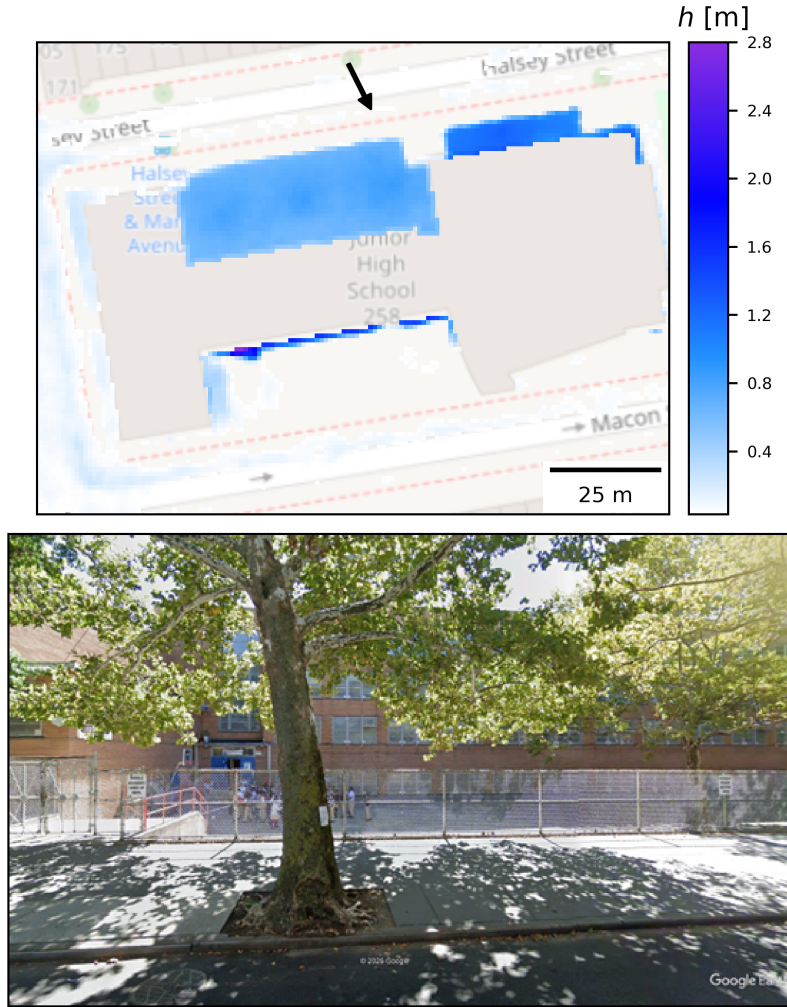


Figure C.2: Top panel: high water depth simulated with the Out-SW approach in the CB near a building in the terrain depression shown by rectangle C2 in Figure C.1; the base map is from OpenStreetMap. Bottom panel: view of the building as pointed by the black arrow on the top panel obtained from Google Earth, which indicates the presence of lower elevation than the sidewalk's, consistent with the DTM.

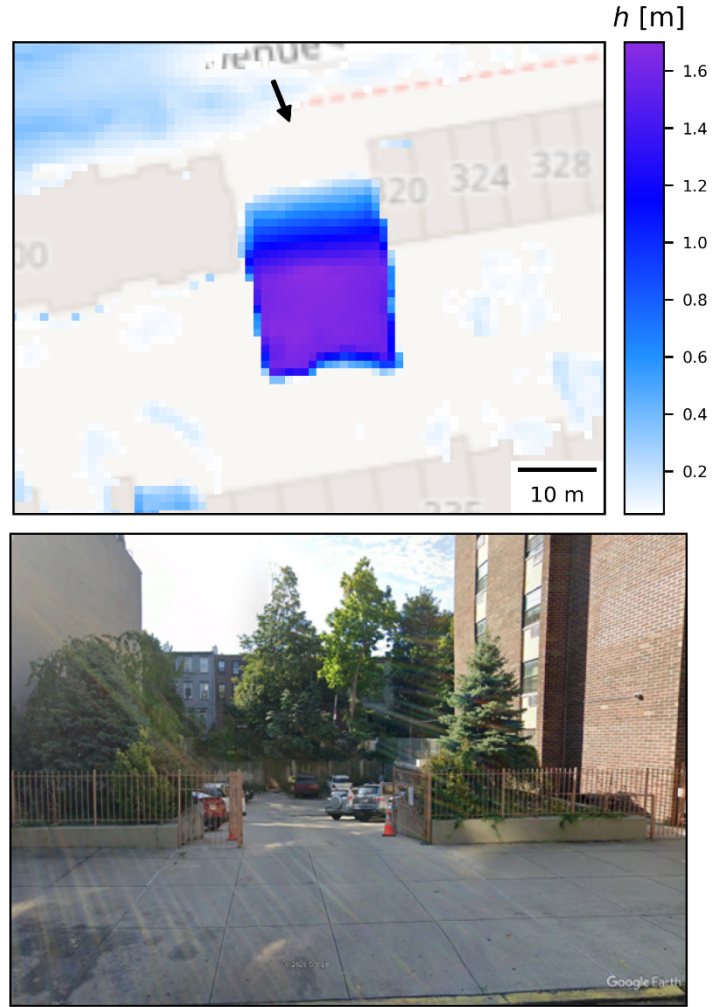


Figure C.3: Top panel: high water depth simulated with the Out-SW approach in the terrain depression in the CB shown by rectangle C3 in Figure C.1; the base map is from OpenStreetMap. Bottom panel: view of the buildings as pointed by the black arrow on the top panel obtained from Google Earth, indicating a parking area below street level, consistent with the DTM.

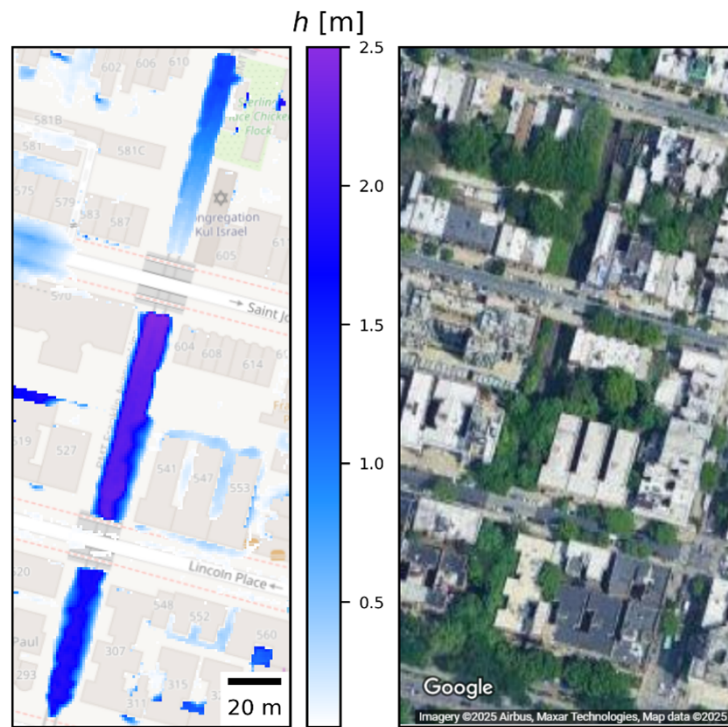


Figure C.4: Left panel: high water depth simulated with the Out-SW approach in the terrain depression in the CB shown by rectangle C4 in Figure C.1; the base map is from OpenStreetMap. Right panel: aerial view of the region from Google Satellite and Airbus, Maxar Technologies imagery, which indicates that the depression is along a railway. This case should have been treated while hydroconditioning the DTM by removing the roadway bridges.

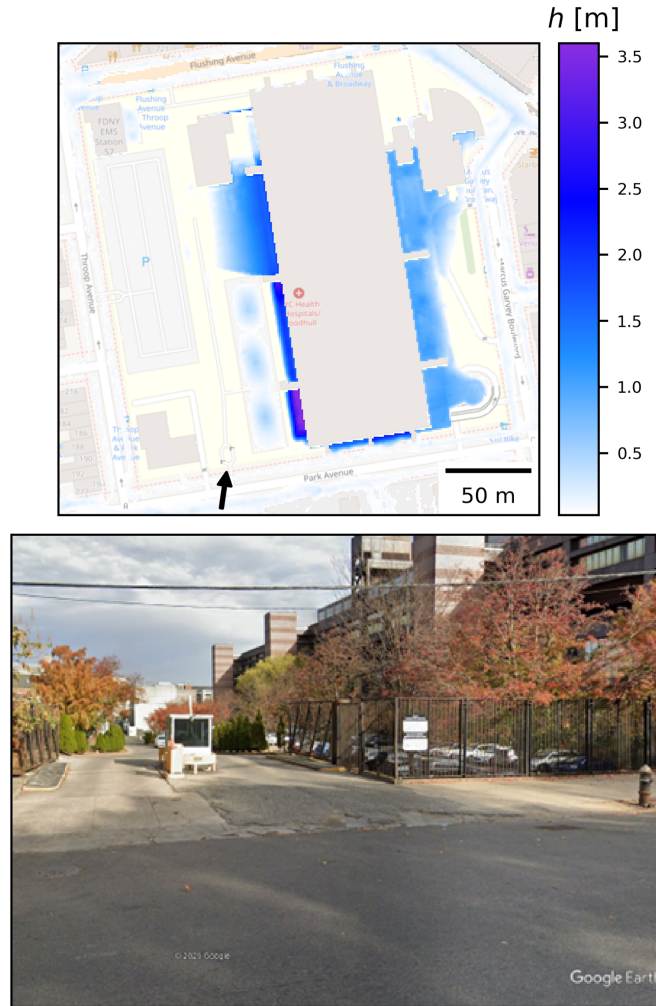


Figure C.5: Top panel: high water depth simulated with the Out-SW approach in the terrain depression in the CB shown by rectangle C5 in Figure C.1; the base map is from OpenStreetMap. Bottom panel: view of the buildings as pointed by the black arrow on the top panel obtained from Google Earth, which suggests that the areas around the building are at lower elevations than the street. Note that pictures closer to the building were not available.

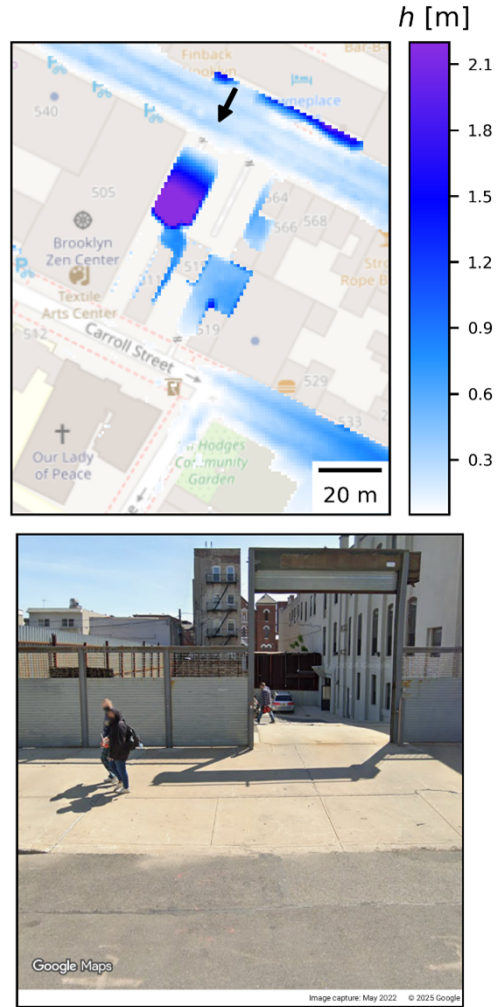


Figure C.6: Top panel: high water depth simulated with the Out-SW approach for the Ophelia storm in a terrain depression in the VB shown by rectangle C6 in Figure C.1; the base map is from OpenStreetMap. Bottom panel: view of the area pointed by the black arrow on the top panel obtained from Google Maps Street View, which shows the presence of a parking area on a level lower than the street, in accordance with the DTM.



Figure C.7: Top panel: high water depth simulated with the Out-SW approach in the terrain depression in the CB shown by rectangle C7 in Figure C.1; the base map is from OpenStreetMap. Bottom panel: aerial view of the buildings obtained from Google Satellite and Airbus, Maxar Technologies imagery, which does not seem to indicate the presence of depression. These might be due to inaccuracies in the DTM.

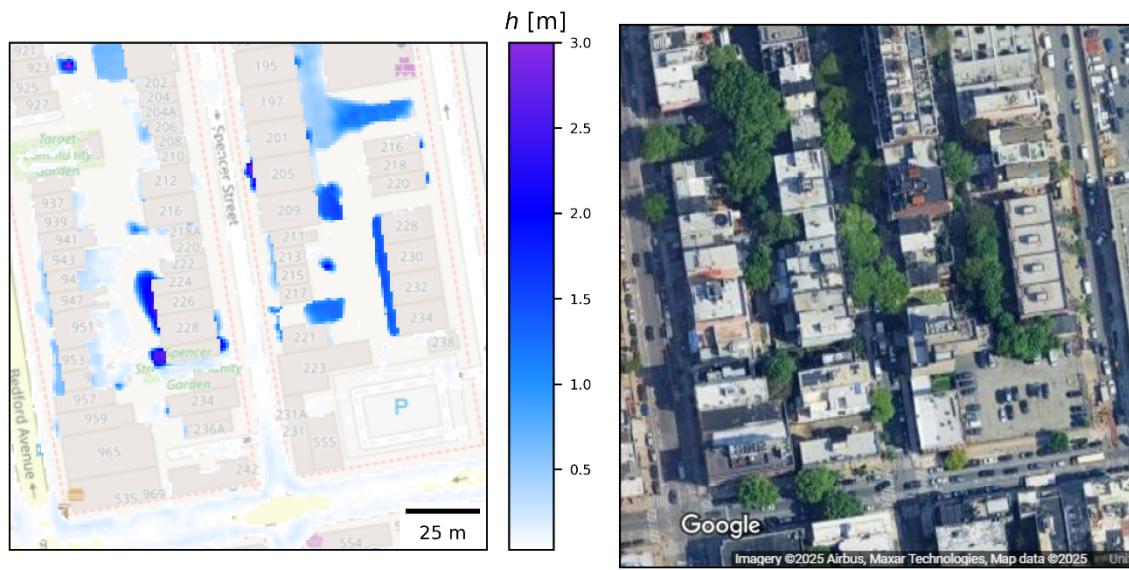


Figure C.8: Left panel: high water depth simulated with the Out-SW approach in the terrain depression in the CB shown by rectangle C8 in Figure C.1; the base map is from OpenStreetMap. Right panel: aerial view of the region from Google Satellite and Airbus, Maxar Technologies imagery, which does not suggest the presence of depressions. The absence of buildings in the DTM could likely cause the depression.

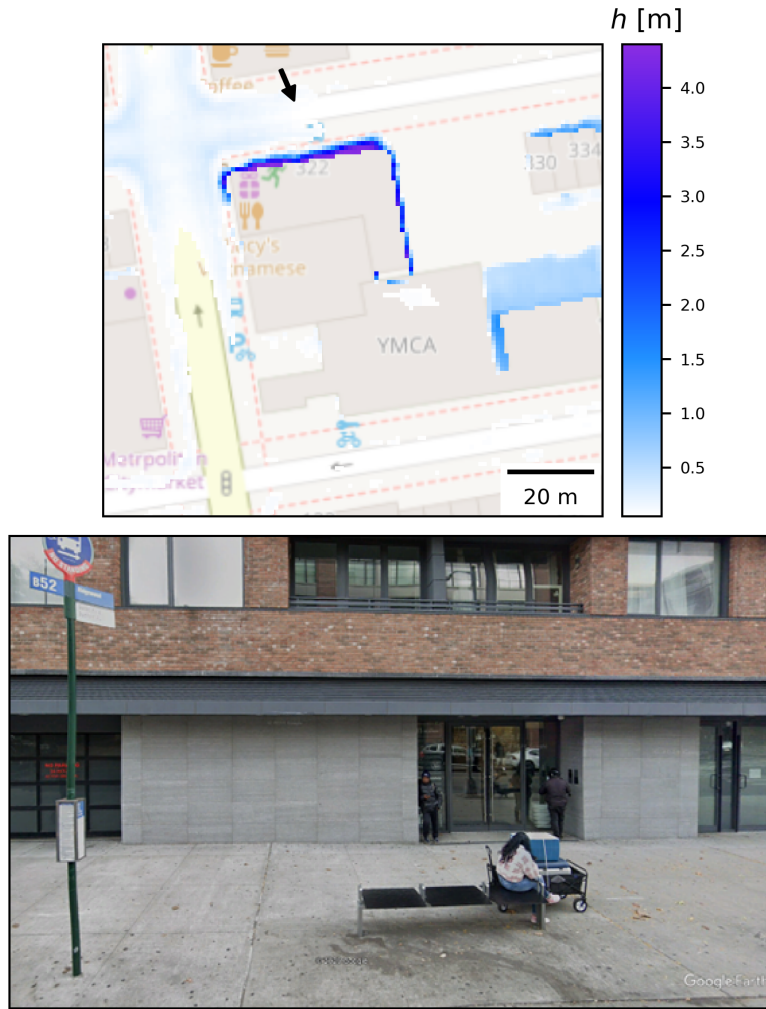


Figure C.9: Top panel: high water depth simulated with the Out-SW approach near a building in a terrain depression in the CB shown by rectangle C9 in Figure C.1; the base map is from OpenStreetMap. Bottom panel: view of the buildings as pointed by the black arrow on the top panel obtained from Google Earth, which shows the absence of depressions. These might be due to inaccuracies in the DTM.

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