Journal of Flood Risk Management

WILEY | CIWEM Chartered Institution of Water and Environmental Management

SPECIAL ISSUE PAPER OPEN ACCESS

Approaching Urban Flood Modelling According to Available Data: A State-of-the-Art Review and Future Challenges

Dina Pirone | Roberta Padulano | Giuseppe Del Giudice

Department of Civil, Architectural and Environmental Engineering, University of Naples Federico II, Napoli, Italy

Correspondence: Dina Pirone (dina.pirone@unina.it)

Received: 9 July 2025 | **Revised:** 9 December 2025 | **Accepted:** 19 January 2026

Keywords: data collection | flood hazard mapping | preliminary flood susceptibility assessment | urban flood modelling

ABSTRACT

Urban flood modelling allows for developing effective strategies for mitigating flood risks and improving urban resilience. Different urban models can be selected according to the desired objective, ranging from simplified frameworks to more sophisticated numerical models. While several studies explored the advantages and limitations of existing model types, very few publications address the urban flood modelling issue based on data availability and data collection. Urban data regarding digital elevation models, sewer networks, and small-scale features can vary significantly. Thus, the availability and resolution of available data strongly influence urban flood modelling. This study reviews existing approaches to achieve satisfactory urban flood modelling according to the available data and desired objectives. We explored the advantages and limitations of data-rich environments and the benefits of the simplifications. We identified two primary objectives most concerned with ongoing urban flood simulation research: flood modelling for preliminary flood susceptibility assessment and flood hazard mapping. For each category, we investigated how previous authors approached data collection tasks and which resolution they considered sufficiently high to retain their objectives achieved. This study provides valuable guidance for scientists, engineers, and decision-makers, promoting a more informed and mindful approach to urban flood modelling.

1 | Introduction

Urban flooding refers to the inundation of land or property in urban areas due to excessive rainfall, poor drainage systems, or a combination of factors preventing water from being absorbed or drained. Due to impervious surfaces like roads, pavements, and buildings, rainwater runs off quickly, overwhelming drainage systems. Urban flooding can have severe consequences, including damage to property, disruption of transportation systems, and threats to public safety. It can also lead to the contamination of water supplies, posing health risks to residents.

Compared to flooding in natural basins, the consequences of urban flooding may become more severe in urban areas due to the higher population density and concentration of economic resources such as infrastructure and public buildings. In urban areas, floods exhibit more diverse and complex processes, as the water follows multiple flow paths, such as crossroads, sewers, underpasses, courtyards, and parks, and flows around or within buildings and urban furniture. Consequently, the high heterogeneity and variability in urban areas are a challenge associated with several urban flood modelling projects that aim at acquiring precise and reliable high-resolution topographic, hydrological, and hydraulic data.

Data survey is the first step to implementing urban flood modelling, and knowing which data is available and which data the study requires is crucial to achieving the study's objective. While several studies explored the advantages and limitations of existing model types (Mignot and Dewals 2022; Mignot et al. 2019; Bulti and Abebe 2020; Guo et al. 2021; Mudashiru et al. 2021; Luo et al. 2022), very few publications address the urban flood modelling issue based on data availability and data collection. The lack of data is a crucial challenge in developing and validating urban flood modelling (Luo et al. 2022). Indeed, urban flood modelling dramatically relies on the selection of input parameters; thus, several authors suggest meticulously investigating the resolution and quality of each input parameter before implementing any urban flood model (Barco et al. 2008; Apel et al. 2009; Guo et al. 2021; Savage et al. 2016; Yang et al. 2018). Moreover, the accuracy of hydrologic and hydrodynamic models used to study and predict urban flooding depends on the availability of high-resolution terrain and infrastructure data (Bermúdez et al. 2018; Bhuyian and Kalyanapu 2018; Bruwier et al. 2018; Shrestha et al. 2022). Thus, without valid input data, the simulation accuracy and transferability of a model could be questionable (Lin et al. 2023).

On the one hand, a data-rich environment encourages the development of models that can produce predictions that align with the available data while staying within acceptable margins of error. However, advanced modelling approaches supported by detailed spatial information are not always the answer (Xafoulis et al. 2023). Indeed, even though high-resolution digital elevation models (DEM) describing urban surface patterns are increasing and have been applied for urban hydrological modelling, small-scale urban landscape features, such as curbs, remain challenging to detect and are often poorly represented. This small-scale information is required to describe surface flow patterns for high-resolution hydrological models in urban areas (Song, Guan, Guo, and Yu 2025). While these limitations can be complemented for small catchments via thorough on-site visits, such detailed investigations are often impractical for large areas (Krebs et al. 2014). Moreover, sewer network data are usually of good quality only for primary public stormwater collectors but become increasingly incomplete for conduits with smaller diameters, usually adopted to drain private parcels. Once again, individuals can manually supplement this information for small urban catchments, but this process is impractical for parameterising large urban areas. In practice, urban flooding systems involve several variables. Therefore, one suggested approach to tackling this problem could be by hierarchical simplification of the system, with an initial screening to identify the most critical variables (Dawson et al. 2008).

Previous studies have underscored the critical role of data quality, resolution, and completeness in achieving robust urban modelling outcomes. However, while these studies have provided valuable insights and recommendations, a gap remains in synthesising their suggestions into a unified approach that addresses the multifaceted aspects of data surveys and resolution in urban flood modelling. Therefore, this study seeks to formulate comprehensive research questions that build upon previous authors' findings and integrate their suggestions into a cohesive framework. Specifically, the research questions this study attempts to answer are:

- How can urban flooding objectives be achieved according to available data?
- What is the suitable spatial resolution for urban flood modelling?

This paper aims to demonstrate that the suitable spatial resolution depends on the objective of the model application and the area of application. Thus, existing approaches to achieving satisfactory urban flood modelling are reviewed according to the available data and desired objectives. Then, the advantages and limitations of data-rich environments and the benefits of the simplifications are explored. This study identified two main objectives that are the most concerned with ongoing urban flood modelling: flood risk mapping for preliminary assessment and flood risk mapping for flood hazard mapping. For each of them, this study investigates how previous authors approached data collection tasks and which resolution they considered sufficiently high to retain their objectives achieved.

This study first presents the methodology for selecting literature in Section 2, laying the foundation for a comprehensive review. Then, Section 3 describes the identified objectives and sub-objectives of urban flood modelling. Section 4 provides practical guidance and insightful suggestions from the reviewed literature, offering valuable insights for practitioners engaged in urban flood modelling. Section 4 also discusses future research needs and challenges. Finally, Section 5 draws conclusions.

2 | Methodology—Paper Selection Criteria

This study systematically searched the urban flood modelling approach in peer-reviewed articles, reviews, and reports based on the Scopus—Document Search (as of 31 October 2024). The approach is inspired by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for a systematic and transparent approach (Page et al. 2021). According to the different levels of keywords mentioned in Table 1, the collection of papers involved a structured, iterative approach where keywords were categorised into various levels to refine the search. Initially, Level 1 (primary) keywords, representing broad, core concepts, were used to gather

TABLE 1 | Review keywords, organised into levels offering increasing details and specificity.

Level 1	Level 2	Level 3
– Urban flooding – Urban flood modelling – Flood risk mapping – Pluvial flood risks – Flood susceptibility	– Urban areas/urban basin – Flood risk assessment – Flood hazard mapping – Flood prone areas – Conditioning factors	– DTM/DSM – Sewer networks/drainage networks – Dual drainage concept – Preliminary flood susceptibility assessment

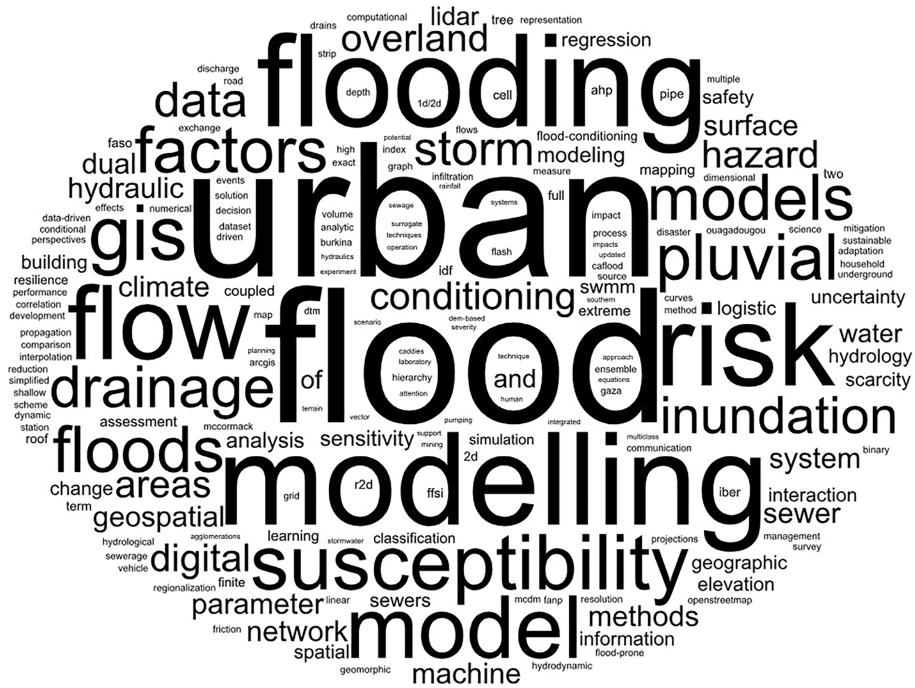

FIGURE 1 | Word cloud of cited paper's keywords co-occurrence. The size of the words represents the frequency of the keywords, with a larger size indicating higher frequency.

a wide range of documents. Then, Level 2 (secondary) keywords, focusing on related subtopics, were applied to refine the search results further, typically combined with Boolean operators like "AND" and "OR." Lastly, Level 3 (tertiary) keywords, which include more specific terms, were used to fine-tune the search, excluding irrelevant papers or addressing more specialised areas. The search strategy progressively narrowed the scope, and the papers retrieved were then analysed for relevance, with the keywords from each level helping to filter the literature systematically. Based on the search results obtained in many attempts and adjustments, this study determined the final search strategy and identified 70 papers.

Among the identified papers, this study identified two main objectives of flood risk mapping: preliminary flood susceptibility assessment (43% of the papers) and flood hazard mapping (57% of the papers). An illustrative diagram of the papers' keywords considered in the study is presented in Figure 1, while the Supporting Information summarises the papers used, indicating their keywords and the category they belong to.

Figure 1 provides a visual overview of the thematic structure of the literature: the largest and most frequent keywords (e.g., 'urban', 'flood', 'modelling', 'susceptibility', 'risk') reveal the dual focus of existing research on preliminary flood susceptibility assessment using GIS-based and data-driven approaches, and (ii) high-resolution flood hazard mapping relying on 1D/2D hydrodynamic models.

3 | Results—Objectives of Urban Flood Mapping

In this paper, urban flood mapping comprises two categories: preliminary flood susceptibility assessment and flood hazard mapping. Preliminary assessment provides a broad and initial evaluation of potential flood-prone areas, while flood hazard mapping involves a more thorough and precise analysis for comprehensive risk management (Cea and Costabile 2022).

3.1 | Preliminary Flood Susceptibility Assessment

According to the European Flood Directive, preliminary flood susceptibility assessment aims to evaluate the level of flood susceptibility in a river basin, district or unit of management to select those areas on which to undertake flood mapping and flood risk management plans (EU 2007). This approach allows for a first identification of critical areas, which can be the subject of more detailed analysis, leading to a better complementary understanding of the flood hazard.

Preliminary flood modelling usually formulates a binary pattern recognition problem in which areas are divided into prone and non-prone to flood, thus susceptible and non-susceptible to flood. Additionally, flood susceptibility can also be expressed in a more qualitative or graded manner, assigning levels such as low, moderate, or high susceptibility. Such approaches require further assumptions regarding threshold values, classification criteria, and often involve subjective judgement or expert-based interpretations. Different studies provide examples of methodologies for assigning and validating these susceptibility levels in different geographic contexts (Liuzzo et al. 2019; Santos et al. 2019).

Most studies avoid direct flood simulations and instead assess preliminary flood susceptibility by identifying areas most prone to flooding using a combination of flood-related conditioning factors, such as surface impervious ratio, land use,

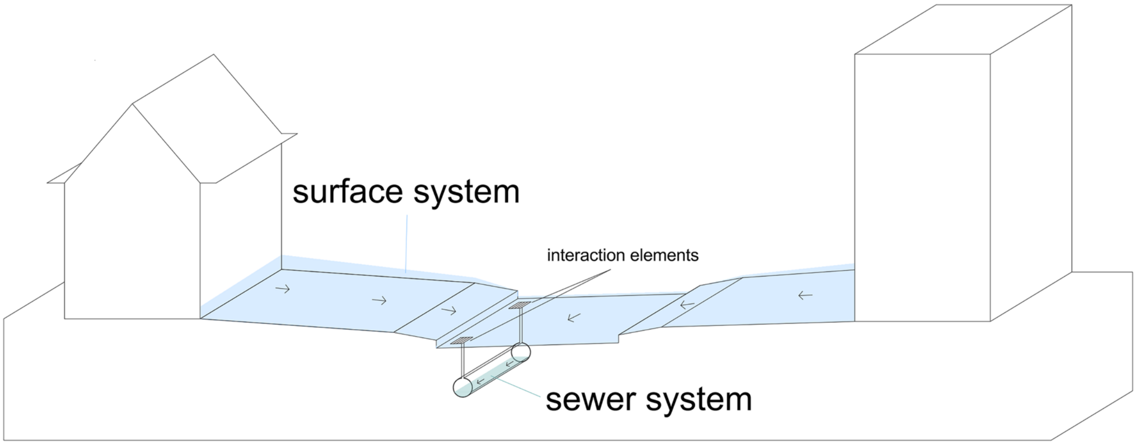

FIGURE 2 | Sketch of urban flooding over the surface and sewer systems, highlighting key components and possible interaction pathways.

or drainage network density. Since no universal guidelines exist for selecting flood conditioning factors in urban areas, previous studies usually combine globally collectable conditioning factors based on available data. Tehrany et al. (2019) highlighted that the most used factors are elevation, terrain slope, proximity to a river, geomorphology, drainage density, rainfall, land use/land cover, lithology, soil, and stream power index. However, these factors are mainly indicated for natural basins. In contrast, Darabi et al. (2019) further distinguished between conditioning factors and introduced some more related to urban areas. For example, they indicated that distance to channel, land use, and elevation played significant roles in flood hazard determination, whereas population density, quality of buildings, and urban density were the most critical factors regarding vulnerability. In both previous cases, as in other studies (Sarkadi et al. 2022; Wang et al. 2023; Nguyen et al. 2024; Song, Guan, and Yu 2025), authors use a grid-based approach to compute the conditioning factor. This grid-based approach usually exploits DEM with 5 m resolution (Darabi et al. 2019; Tehrany et al. 2019; Rahmati et al. 2020; Sarkadi et al. 2022) for areas of the order of 30 km^2 up to 150 km^2 or with 10–30 m resolution for areas of the order of 300–1000 km^2 (Lin et al. 2019; Parvin et al. 2022; Nguyen et al. 2024; Wang et al. 2024). Lower resolutions are neither commonly nor recommended for urban assessment because small-scale urban landscape features, such as curbs, remain challenging to detect and are often poorly represented, even with high-resolution DEM (Krebs et al. 2014).

Once the conditioning factors have been identified, their effectiveness in delineating flood-prone areas must be validated to ensure model reliability and practical applicability. Two main validation approaches are commonly adopted in the literature. The first relies on historical flood event data, such as flood extent data and creating a flood inventory map (Al-Juaidi et al. 2018; Wang et al. 2023; Nguyen et al. 2024; Traoré et al. 2024). By comparing the predicted flood extents with the observed ones from historical events, researchers can gauge the reliability of their models and conditioning factors in accurately predicting flood-prone areas. Therefore, this validating approach requires past events flood extension or point information that is usually converted into grid maps to match the DEM resolution of the conditioning factors (Al-Abadi and Pradhan 2020; Balestra et al. 2022; Panfilova et al. 2024). The second validation approach involves conducting detailed flood simulations on smaller zones and then extrapolating the findings to the entire study area. This approach allows researchers to assess the transferability and robustness of their models and conditioning factors across different spatial scales without conducting time-consuming and detailed simulations over the entire study area. In this way, some researchers first undertake detailed flood simulations on smaller areas and then use this partial result as validation for the entire study area. For example, some authors (Wang et al. 2019; Masoumi 2022) first run detailed models to simulate surface flooding and then compare the result of the simulation to preliminary flood maps obtained from conditioning factors. However, this latter validation approach is usually more suited for flood risk assessment in river basins (Manfreda and Samela 2019; Albertini et al. 2022). Indeed, river basins are usually larger than urban ones, and it is worth running detailed simulations that require long computational times only over smaller areas.

3.2 | Flood Hazard Mapping

Flood hazard is the probability that a flood of a given severity will occur at a site, with severity typically measured by hydraulic parameters. Flood hazard mapping aims to estimate those hydraulic parameters such as the maximum water depths, flow velocity, flow extensions, or a combination of them. To the reader's knowledge, this paper does not consider flood risk maps because it focuses on hydraulic parameters required for urban flood modelling. Thus, this study does not consider exposure nor vulnerability data (risk = hazard × exposure × vulnerability) but focuses on hazard ones.

In urban areas, approaching flood hazard modelling requires choosing how to model the surface system, the sewer system, and the interaction between them, where the surface system typically comprises overland flow over buildings, streets, and open spaces, while the sewer system represents underground stormwater conveyance (Figure 2). The approaches can be divided into three main groups: (1) modelling the sewer system without explicitly modelling the surface system; (2) modelling the surface system without explicitly modelling the sewer system and

(3) modelling both systems and the interaction of them, according to the dual drainage concept (Djordjević et al. 2005).

According to the chosen approach, data collection and requirements differ significantly. This difference depends on the typical observed behaviour of the sewer systems: when the drainage capacity of the sewer system is insufficient, it will reduce water collection capacity and eventually overflow through interaction elements (Cea et al. 2025). This behaviour usually happens when the flood event has a high return period (Lee et al. 2016). For example, Leandro et al. (2016) demonstrated that for low return period events (20 years), overland surface drainage is mostly restricted along preferential natural flow paths away from the building area, so sewer systems work. For higher return periods (100 years), when heavy flooding is observed across the natural flow paths and on the streets, the sewer system is usually overwhelmed and thus works outside its design range. This consideration is paramount because it determines which data is worth collecting to achieve the objective and which data can be ignored. For example, if the aim is to investigate flood hazard mapping with regard to a high return period (higher than 50 years), authors should evaluate whether collecting sewer network data is worth it or not.

3.2.1 | Sewer System Modelling

Among the approaches that only model the sewer system, one-dimensional (1D) sewer flow models claim a relatively simple model construction and a shorter runtime for simulations (Chang et al. 2015). Their implementation requires knowledge of the sewer pipes: materials, diameters, slopes, junctions, and elevations. Data collection for modelling storm sewer systems could face either a lack of data or an overwhelming volume of complex information to manage.

In the first case, authors usually implement urban flooding simulations only where data are of good quality by considering simplified network representations. Indeed, sewer network data become increasingly incomplete for secondary conduits, usually characterised by smaller diameters. Therefore, it is common to focus on sewer pipes, usually on the main roads, omitting minor drainage components due to unrecorded conduits or lack of information required for the model development (Krebs et al. 2014). Another approach to facing missing data involves approximating pipe details by considering constant properties—such as constant roughness coefficients—for the entire sewer network (Dong et al. 2022). Also, Li et al. (2025) proposed a graph reconstruction-based approach for generating physical sewer models from incomplete information, addressing the challenge of representing sewer drainage effect in urban pluvial flood simulation. Their approach utilises graph-based topological analysis and hydraulic design constraints to derive gravitational flow directions and nodal invert elevations in decentralised sewer networks with multiple outfalls. However, it should be considered that Shrestha et al. (2022) investigated how data completeness affects the accuracy of models by assuming different levels of availability of stormwater infrastructure data (ranging from 5% to 75% of attribute values missing). Their study found that the model overestimated flood depth and area, with different levels of missing data depending on the parameters—roughness and diameter primarily—and that model performance was more sensitive to missing data downstream and closer to the outfall than upstream missing data.

On the other hand, in cases of managing big data, some authors streamline it by focusing on critical network elements, such as primary streets, critical outfalls or conduits, to reduce preprocessing data treatments while preserving model accuracy. One suggested approach simplifies a sewer system hierarchically, with an initial screening to identify the most critical points (Dawson et al. 2008). For example, Ren et al. (2022) proposed a method that simplifies complex drainage networks by analysing network topology and generating subcatchments centred on outfall points. In this way, they reduced the issue of complex data (their total pipe length was almost 80 km) all over their study area (3.6 km^2) by isolating different sub-networks and highlighting critical paths. Also, Yang et al. (2018) analysed the impact of using a stroke scaling method to generalise a storm sewer network. Their approach proved that variations in sewer network complexity did not significantly affect flooding simulating for areas with a single drainage system, but they did for areas with multiple drainage systems. Indeed, most of the flood volume was primarily concentrated in the primary pipes, which could be identified using the simplified sewer network. Therefore, they also suggested isolating sub-networks and focusing on critical zones.

However, modelling only the sewer pipes allows for computing the water depths and velocities in the sewer pipes. Therefore, this approach is insufficient if the aim is to compute water depth over the surfaces, but additional information is required. For example, the water depths on the surface can be estimated by coupling the overflow from the pipes with a stage-storage relationship representative of the surrounding topography and, thus, based on water depth, geometric features, and clogging conditions. Therefore, beyond gaining information regarding the pipe network, if the aim is to obtain water depths over the entire study area, this approach requires the exact position of the points where the flow outcomes from the sewer pipes and information regarding the surrounding topography. For example, to estimate flood hazard hydraulic parameters beyond the sewer pipes and according to this approach, some studies first predicted the surcharge volume from the drainage system, which was then translated into the flood depth of a sub-catchment using a depth-volume or area-volume function (Hsu et al. 2000; Chang et al. 2015). Therefore, they acquired a detailed spatial DEM corresponding to the area to be investigated. However, it usually emerges that acquiring detailed data does not balance the inaccuracy of this simplified modelling. For example, according to this combined 1D sewer modelling and stage-storage relationships, flows can only outflow from the sewer pipes and cannot return, and information regarding the roughness of the surface is neglected. Therefore, this approach could lead to significant inaccuracies in the hydraulic parameters. An improved approach to estimating hydraulic parameters on urban surfaces from sewer system modelling consists of modelling the outflow from the pipes according to basic weir orifice formulas (Hakiel and Szydłowski 2017). In this case, according to an experimental test, previous authors highlighted that the only influence on exchange discharge value comes from the weir coefficient. Therefore, this approach requires collecting data and estimating the weir coefficient for the overflow points, adding another source of data collection.

Thus, if the aim of flood mapping according to sewer system modelling starts diverging towards computing flood depth over the study area, users should question whether switching to surface system modelling or opting for a dual drainage concept is worth it.

3.2.2 | Surface System Modelling

Several models exist to simulate detailed flood propagation only on urban surfaces to assess flood hazard. These models range from high-resolution simulations requiring extensive computational resources and detailed input data to simplified approaches that balance accuracy and computational efficiency. The suitable resolution for simulating detailed flood propagation on urban surfaces strongly depends on the type of model employed. The aim here is not to identify the best model for acquiring flood hazard information but to highlight the data types collected by previous authors as well as the most commonly used approaches for data acquisition. Urban data types in surface systems simulations include topological data, which provides elevation and contour information describing urban infrastructures such as buildings and streets, and land use data, which informs the model about the types of surfaces (Dasallas et al. 2024).

Topological data is usually obtained from DEM. A detailed DEM is essential for topography but can be challenging due to data scarcity or excessive information. Several studies investigated the effects of different DEM resolutions on flood hazard modelling results. In their study, Arrighi and Campo (2019) explored the implications of high-resolution DTM uncertainties on flood depth estimations by creating distinct terrain representations, varying from raw data to merged datasets incorporating building footprints and additional elevation points. Employing these representations, they simulated different inundation scenarios, addressing the challenges of merging elevation data sources and discussing the trade-offs in time and effort required to increase DTM detail. The comparative analysis of flood maps revealed significant discrepancies, with variations reaching 180% in densely urbanised areas depending on the terrain representation. Their findings underscored the critical role of accurate terrain representation in flood risk assessment, suggesting that DTMs should ensure an adequate spatial resolution, for example, of the order of 0.5–2 m for a study area of approximately 3 km^2 to correctly represent street and buildings' patterns. Bodoque et al. (2023) emphasised the importance of geometrically consistent DEMs and proposed a procedure to create robust ones using LiDAR data in an order of 2 m resolution. Their study highlighted that a lack of geometric coherence in DEMs causes detrimental errors in the distribution of depths, velocities, and flooded zones. Shen and Tan (2020) evaluated the influence of DEM resolution on urban inundation modelling to determine if high-resolution inundation simulations could be achieved using resampled DEMs, potentially reducing the data load without sacrificing accuracy. They noted that lower-resolution resampled DEMs (30 m) lead to substantial inaccuracies in inundation depth, underscoring the importance of carefully selecting DEM resolution (5 m for their study area of almost 2 km^2). Moreover, their study provided a valuable suggestion regarding the highest possible DEM resolution that should be considered. They suggested analysing building dimensions and density to determine the maximum possible DEM. Indeed, DEM grids with coarser resolution may smear flow paths in model terrain and subsequently change the hydraulic behaviour, thus leading to less accurate simulation results.

When detailed information from the DEM is unavailable, other approaches exist to represent the complex topography, including buildings, roads, and infrastructure. For example, Bellos and Tsakiris (2015), who studied flood simulation in urban areas to derive water depths, represented buildings by significantly increasing the friction source terms, a standard method, especially when the computational grid size is coarse (Varra et al. 2024). Indeed, in urban flood modelling, friction source terms act as a proxy for land use by representing how different surfaces resist; thus, higher friction values slow down the water flow, mimicking the effect of obstacles like buildings.

Land-use data, which allows for computing surface roughness and accurately representing the diverse and dense urban features, such as buildings, roads, and green spaces, should ideally match the resolution of DEMs to capture fine details of the urban basin. However, such detailed land-use data are often lacking; thus, coarser resolution can be considered. For example, Bodoque et al. (2023) exploited a national land cover mapping (scale of 1:25,000) to estimate the land use/land cover units and then matched it with the DEM resolution to run the flooding model. Löwe and Arnbjerg-Nielsen (2020) focused on the data resolutions that should be considered to characterise land use, thus imperviousness in aggregated form. For their case study (about 300 km^2), they found that a resolution of up to 400 m was optimal for modelling overall imperviousness (building, roads). When it came to building data specifically, they discovered that aggregating it to a resolution of 200 m was more effective than using finer data. This 200 m resolution was preferable because it smoothed out extreme variations in flood levels around buildings, making the model results more stable and reliable. In other words, finer data tended to exaggerate local flooding around individual buildings, while the 200 m resolution provided a more balanced and realistic view across the study area. Another approach for acquiring data to evaluate land use, thus roughness, was proposed by Leandro et al. (2016). They investigated the variability of buildings and the heterogeneity of land surfaces classified according to the online data on the Open Street Maps. Using Open Street Maps data allowed for identifying areas with different permeability and the location of ponding areas and naturalised surface flow paths.

Finally, it is worth noticing that often, surface models do not explicitly model the sewer systems in urban areas due to limited information or no data (Montalvo et al. 2024). However, simplified approaches exist to account for the sewer network without modelling it. For example, most studies accounted for the missing sewer system modelling by considering an equivalent infiltration capacity for the soil. Chang et al. (2015) estimated the equivalent infiltration by subtracting the sewer capacity of the preassigned return period. Similarly, Padulano, Costabile, et al. (2021) and Padulano, Rianna, et al. (2021) considered constant additional infiltration rates all over the

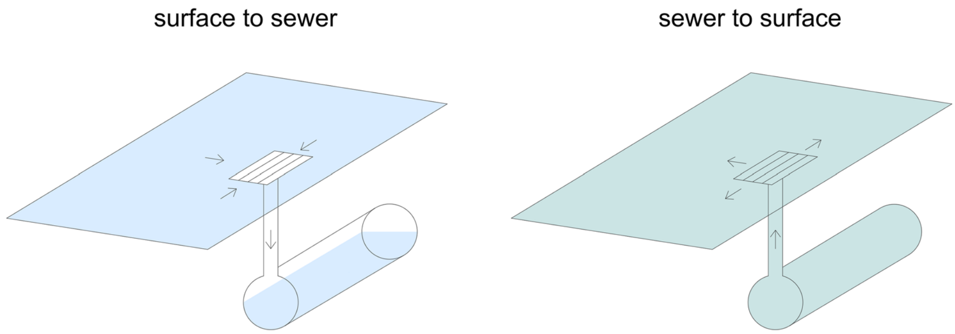

FIGURE 3 | Sketch of flow interaction between (left) from surface to sewer system; (right) from sewer to surface system.

domain to simulate the drainage effect of the sewer system. Other studies considered a reduction of net rainfall or the increase in infiltration rate over the domain by a factor proportional to the system's drainage capacity (Guo et al. 2021). Thus, several studies model only the surface system to acquire flood hazard information and still account for the sewer systems, which comprises knowing the infiltration capacity of the soil, the sewer systems' capacity or a percentage of rainfall reduction. While methods like rainfall reduction and fixed infiltration can reflect the pipe network's drainage capacity to a certain extent, they fail to correctly reflect the process of surface flooding receding and the flood risk transfer problem caused by the drainage pipe network, lacking a clear physical significance (Chen and Huang 2024). For example, Montalvo et al. (2024) assessed urban pluvial floods when detailed sewer network data is unavailable by generating a realistic virtual sewer network based on the high degree of topological correlation between street and sewer network layouts. Their approach reasonably represented a sewer network's drainage capacity during pluvial floods, especially compared with the above-mentioned simplified approaches, such as the rainfall reduction method, which in their study significantly underestimated the flood extent, especially in depressed areas. Therefore, the dual drainage concept, which requires acquiring information on the sewer systems, may seem more appropriate for this task. However, even though the dual drainage concept would provide a more accurate and holistic approach to flood modelling, the gap in implementing the dual drainage concept remains substantial, and users should fully understand the commitment required. For instance, Oberauer and Lehmann (2024) demonstrate that comparable outcomes can be achieved through the modification of 2D surface models, which require less data than the dual drainage concept.

3.2.3 | Dual Drainage Modelling

Coupled sewer and surface system models currently provide the most realistic representation of urban flooding, especially during extreme events (van Dijk et al. 2014). These models schematise the surface system as a grid or irregular mesh network, where cells exchange water with neighbouring cells and with the model of the sewer system by manholes and storm drains. Under normal conditions, storm drains intercept surface runoff and discharge into underground sewer pipes. However, if the sewer system is surcharged, its discharge capacity is reduced, and the flow could reach the surface. Therefore, an accurate characterisation of the flow exchange is essential in numerical models of urban flooding. For simplicity, the flow interaction between surface and sewer systems is usually called the surface-to-sewer and sewer-to-surface processes (Figure 3) (Noh et al. 2016; Dong et al. 2022). Surface-to-sewer exchange occurs when rainfall runoff enters the drainage system through inlets and manholes, whereas sewer-to-surface exchange represents surcharge, overflow, or backflow from the sewer network onto streets or ground depressions when the network becomes pressurised.

Considerations regarding data acquisition for the sewer and surface systems are the same as in the latter paragraphs. In this case, modelling the interaction between these systems necessitates extensive data on interaction points (e.g., manholes, storm drains) and the direction of these interactions (monodirectional—from the sewer system to the surface system or bidirectional—from the sewer system to the surface system and back again). Generally, storm drains are widely distributed on the road; thus, collecting their data distribution is mandatory to build a more realistic simulation model. However, collecting storm drain distribution data is almost impossible because of the shape diversity, welter of storm drains, and time limitations, especially over larger areas. A solution to this challenging task was suggested by Lee et al. (2016), who accurately simulated flooding in urban areas with a dual drainage concept by setting the number of storm drains on the ground surface based on a criterion (170 m^2/one storm drain) to avoid a non-equilibrium problem arising from a difference in the number of storm drains between the mesh generation methods. However, they suggested the urge need for further validation of their model with inundation survey data. Moreover, Liang and Guan (2024) found that inlet spacing plays a crucial role in affecting drainage efficiency. Also, Dong et al. (2022) proposed an integrated model to assess the flood risks to people and vehicles in urban areas. Their study assumed that street inlets intercepted the surface runoff, while the overflow process only occurred via manholes. However, their dataset included only the surface topography data, thus the sewer system data, such as sizes and locations of street inlets, manholes, and sewer pipes, was not covered. Therefore, to implement the dual drainage concept, they also used a hypothetical sewer drainage system to investigate the interaction between surface runoff and sewer pipe flow and the corresponding influence on hazard degrees of people and vehicles. Leandro et al. (2009) highlighted another vital concept for manhole data: they pointed out that manhole elevations should align with the surface elevations of the corresponding grid cells in the DEM. However, instead of merely adjusting the DEM elevations, they argued that incorporating virtual manholes based on their drainage areas is even more critical. To achieve this, they developed a trial-and-error technique to identify the optimal number and placement of these virtual manholes, ensuring that the model accurately represents surface flow dynamics and the interactions between the sewer system and the surface system. Jang et al. (2018) modelled different types of inlets to improve the accuracy of flood simulations: manhole-based approach, where surface water drains directly into manholes, ignoring street inlets; inlet-manhole approach, where surface water drains into manholes connected to multiple inlets; inlet-node approach, where surface water drains into sewer nodes connected to individual inlets. The study was developed in a data-rich environment: over an area of approximately 20 km^2, which comprises about 3500 manholes and more than 74′000 street inlets. They demonstrated that by draining surface water into distributed sewer nodes rather than manholes, flood extents can be predicted more accurately, and the fluctuation of sewer water level can be significantly reduced using the inlet-node approach. This method also minimised sewer water level fluctuations, demonstrating that accurate inlet modelling is crucial for effective flood management in urban drainage systems.

To sum up, previous studies have highlighted the importance of accurately modelling the interaction between sewer and surface systems, particularly when validation procedures or survey data are available. However, they also strongly recommend conducting systematic field data validation campaigns to enhance model reliability and applicability. These campaigns could involve the integration of high-resolution LiDAR data, GPS-based manhole elevation surveys, and the deployment of mobile sensors or UAVs during storm events to capture real-time surface inundation. For example, the inlet-node approach proposed by Jang et al. (2018), though developed in a data-rich environment, could be further tested in cities with limited sewer data by combining simplified synthetic sewer networks with targeted field validation in flood-prone zones. Such efforts would help assess the model's adaptability and identify critical parameters influencing performance under data-scarce conditions. Moreover, standardising validation methodologies across case studies could reduce inconsistencies in model assessment and promote broader adoption of dual drainage concepts in urban flood modelling.

4 | Discussion

According to previous studies, we highlight which data they used and which data they acquired to retain the objectives achieved.

4.1 | Preliminary Flood Susceptibility Assessment

For preliminary flood susceptibility assessment in urban areas, the prevailing standard resolution of 5 m emerges as a common denominator, balancing the need for sufficient detail with a broader perspective. This resolution provides the necessary level of detail during the initial stages of assessment for a preliminary understanding of flood-prone zones without overwhelming computational demands. This resolution is widely adopted across studies because it provides sufficient geomorphological information to delineate flow paths, depressions, and major urban structures while avoiding the computational and data-acquisition burdens associated with high-resolution DEMs. As several authors highlight, adopting submetric or LiDAR-based DEMs for susceptibility mapping often yields limited additional benefit relative to their cost and processing requirements; their full value is realised primarily in flood hazard mapping, where detailed hydraulics and building-scale processes are explicitly modelled.

The suggested resolution of 5 m for preliminary flood susceptibility assessment is suitable for relatively small to medium-sized catchments (10–40 km^2). Indeed, this resolution enables the extraction of geomorphological features using open-source tools within GIS software. For example, GIS techniques exploit DEM, providing insight into flow paths and depressions. Moreover, a resolution of 5 m allows for a reasonable distinction between urban infrastructure, such as buildings and streets.

For higher catchments (> 40 to 50 km^2), many studies employ coarser DEMs (10–30 m), which remain effective for capturing regional topographic gradients and broad-scale drivers of susceptibility. However, users opting for such a resolution or even lower should be aware that some critical urban details may be lost. Indeed, these resolutions could still represent broader topographical features such as building areas, parking, and parks, but they may miss finer details in densely built environments, such as narrow streets or passageways between buildings.

Thus, the evidence across studies, three consistent patterns emerged. First, coarse DEMs (10–30 m) offer adequate performance for broad-scale susceptibility assessments and large catchments, but they risk omitting fine-scale urban morphology. Medium DEMs (5 m) represent the most effective trade-off, providing actionable spatial detail without excessive computational burden; this is particularly true for neighbourhood-scale analyses and urban areas with moderate structural density. High-resolution DEMs (< 2 m) are generally unnecessary for susceptibility mapping; their benefits become evident only in hazard models with explicit representation of overland flow hydraulics and building-level interactions.

Similar considerations arise in the validation phase. Most susceptibility studies rely on flood inventory maps constructed from past flood reports, emergency records, or crowdsourced observations. Prevailing approaches exploit existing flood inventory maps, collecting reports of past severe flood events; thus, their spatial extension is usually provided in a vectorial formal form and then converted into a grid-based one that matches DEM resolution. Other approaches run urban flood simulations on a smaller part of the study area or use information from existing flood hazard maps, where available. In the second case, errors and uncertainties increase due to flood modelling simulations. Therefore, the first type of approach is preferred. Finally, considering these maps are usually provided in grid form, point information regarding past flood events is commonly used to validate them. In this way, users can geolocalise the points where past events occurred or where users reported flood events.

4.2 | Flood Hazard Mapping

For flood hazard mapping aiming to estimate key flood parameters such as flood extent, water depths, or flow velocity, the required data change according to the approach chosen to model the surface system, the sewer system, or both.

4.2.1 | Sewer System Modelling

The approach of modelling only the sewer system requires data of good quality regarding the characteristics of the sewer pipes to model. This data includes detailed information such as materials, diameters, slopes, and hydraulic properties of the sewer network. Acquiring this information for all the sewer networks over a case study is challenging because data is usually unavailable or difficult to obtain. Most approaches suggest focusing on critical zones and devolving the effort into acquiring and processing data near the outfall. Indeed, it was demonstrated that missing information far from the outflow does not significantly influence flood simulation. Approximation regarding missing features introduces uncertainties in the modelling; thus, strict simulation is preferable to those pipes with good-quality data. However, acquiring data for modelling only the sewer system is uncommon in extracting information regarding flood hazards in urban areas. Indeed, sewer pipe data is insufficient to estimate surface water depths and potential flood extents, but data on the surrounding topography, land use, and surface roughness are required. This additional data involves high-resolution elevation data with resolutions of less than 1 m, land cover maps, and information on drainage infrastructure beyond the sewer system, such as manholes or storm drains. Furthermore, this approach estimates water depths or flood extensions on the surface only when the sewer network overflows through such drainage infrastructure. It is worth highlighting that significant overflows occur when the water reaches such an energy that it flows up the storm drains or manholes to the surface. Therefore, since sewer overflow usually happens with high return periods, acquiring all this data for the sewer pipes and surrounding topography is not convenient when extracting crucial flood hazard information through modelling only the sewer pipes.

To conclude, even though it seems that modelling the sewer pipes requires information only regarding it, it appears that additional and detailed information is required to achieve crucial flood hazard information on the surfaces. Therefore, it is suggested that data for the sewer pipes and detailed information regarding surface topography be acquired only for specific points/zones of the study area where users are confident that sewer systems could overflow. Otherwise, considering the effort required to acquire detailed surface data, it would be wiser to model the surface systems and follow the data acquisition suggestion in its dedicated paragraph.

4.2.2 | Surface System Modelling

When modelling only the surface system to obtain flood hazard maps in urban areas, the importance of a topological representation cannot be overstated. While high-resolution data is valuable, the coherent integration of urban infrastructures within the DEM proves crucial for accurate flood hazard evaluations. Therefore, rather than identify an optimal resolution for urban flooding applications, it is worth highlighting that without a coherent representation, even the most detailed DEM can fail to predict floods accurately, leading to inadequate risk assessments and ineffective mitigation strategies. Therefore, prioritising a coherent DEM ensures that flood hazard maps are reliable and practical. Common approaches suggest starting from a DEM with resolutions ranging from 5 to 10 m to combine them with detailed information regarding streets and buildings.

On the other hand, for smaller urban area zones (i.e., districts or zones of the order of 3 km^2), resolutions of 1 to 5 m are more appropriate. Indeed, this finer resolution captures intricate terrain and urban infrastructure features. Thus, fine spatial resolutions (around 0.5–2 m) for densely built environments are ideal, while aggregated data can suffice in larger or less densely built regions. In any case, a variable that cannot be overstated is building density and distance. Indeed, it is suggested that DEM be avoided with resolutions lower than the distance; otherwise, they could not be adequately represented.

Finally, previous literature identified several approaches to account for the sewer systems. These approaches consider an equivalent infiltration capacity for the soil or a constant additional infiltration rate all over the domain to simulate the drainage effect of the sewer system. However, on one hand, it is not common to implement those approaches to derive flood hazard maps for higher return periods. During those events, previous authors demonstrated that the drainage systems' capacity is often insufficient; thus, they could be ignored without significant variation in the results. On the other hand, other authors highlighted that during intense events (with higher return periods), the sewer system significantly influences flooding in some areas because of the overflow through interaction points. However, a dual drainage concept is mandatory to account for this phenomenon.

4.2.3 | Dual Drainage Modelling

Considerations regarding the data required for modelling the sewer and surface systems through the dual drainage concept follow the suggestions above, while considerations regarding the data needed to model the interaction between them are provided below.

To accurately model the interaction between sewer and surface systems, extensive data collection and detailed characterisation of interaction elements are imperative. Interaction elements data are almost unavailable because of the shape diversity, non-uniform location along streets, and clogging status during their lifetime. Previous studies suggested setting a constant parameter for the number of interaction elements along the street. However, this suggestion derives from model stability issues rather than data collection suggestions. Moreover, most previous authors considered small areas (linear streets of about 100 m) and hypothetical or synthetic case studies built in the laboratory. Therefore, there is a pressing need within the scientific community to enhance methodologies to acquire interaction point data. More rigorous data collection strategies and refined parameters would significantly contribute to the accuracy of flood modelling through the dual drainage concept.

In the meantime, it is clear that significant effort and extensive field surveys are mandatory to implement the dual drainage concept for urban flood modelling accurately. Developing a reliable dual drainage model—which captures both the sewer system and the surface system and their interactions—is a complex task that demands considerable resources, time, and expertise. Unlike previous approaches that explicitly model one or the other system that may approximate some features, the dual drainage concept requires detailed mapping and assessment of infrastructure conditions and precise interaction points between surface and subsurface systems. The effort to gather these data is enormous, involving numerous challenges, including documenting the locations, dimensions, and operational conditions of inlets, manholes, and other interaction points. Furthermore, operational conditions can change frequently due to factors like clogging or wear over time, requiring surveys to be updated regularly to maintain data accuracy.

Finally, in many urban areas, data gathering is further complicated by limited accessibility to certain parts of the drainage network, requiring specialised equipment and techniques to conduct surveys effectively. As a result, accurately implementing a dual drainage concept demands both significant financial investment and dedicated personnel for on-ground data collection and processing. Additionally, since each urban area has unique drainage characteristics, site-specific customisation is often needed, further adding to the workload.

4.3 | Future Challenges

In urban flood modelling, future challenges in data acquisition pose significant obstacles as we confront the evolving dynamics of urbanisation. The need for more detailed data that accurately represents urban environments' complexities evolves through alternative data sources, such as remote sensing technologies, Internet of Things (IoT) sensors, and social media platforms. However, fusing heterogeneous datasets remains a substantial methodological challenge, requiring innovative models and standardised procedures for integration.

4.3.1 | Merging Remote Sensing Data

Recent developments in remote sensing technologies have significantly enhanced the capacity to support urban flood modelling, particularly in data-scarce environments (Teng et al. 2017). Optical, SAR, and LiDAR observations now provide increasingly detailed information on land cover, imperviousness, soil moisture, and surface water extent, which are essential for characterising urban hydrological processes. Numerous studies have demonstrated the value of satellite-derived flood maps for improving hydrodynamic simulations. For instance, SAR imagery has been shown to reliably identify inundated areas under a variety of atmospheric conditions, while high-resolution optical data support rapid flood mapping. At the same time, remote sensing-derived water levels and flood extents have become an important source of information for calibrating and validating hydraulic models, enabling improved representation of flow dynamics in urban settings. Collectively, this growing body of literature underscores the accelerating role of remote sensing in urban flood analysis and highlights its continued potential to complement traditional datasets used for hazard assessment and flood forecasting.

4.3.2 | Public Engagement for Acquiring Alternative Data

The increasing use of smartphones and videos by citizens is a new paradigm for harvesting urban flood data (Mignot and Dewals 2022). Because dense urban areas are rarely equipped with direct instrumentation for measuring inundation extent, water depth, or flow velocity, researchers increasingly rely on citizen-generated observations, including photos, videos, text reports, municipal call logs, and geotagged social media posts. Recent studies demonstrate that social media can serve not only as qualitative evidence but also as a quantitative source of flood information. Fohringer et al. (2015) showed how geolocated photos posted during the 2013 European floods could be processed to infer flood extent in near real time. Other works (Le Coz et al. 2016; Griesbaum et al. 2017) highlight that water depth can be estimated using reference objects (e.g., cars, buildings, street furniture), while videos uploaded during flood events can support velocity estimation through particle tracking or motion analysis. Additional research confirms the operational value of social-sensing-based flood mapping and its integration into emergency management workflows, underscoring the growing maturity of these techniques. These methods provide valuable calibration and validation data in locations where traditional sensors or ground surveys are lacking. Beyond social media, community mapping has proven highly effective in data-scarce settings. Petersson et al. (2020) developed a systematic framework for acquiring information on culverts, drains, ditches, and informal drainage pathways through community-led surveys. Their results illustrate that public engagement can generate reliable, high-coverage infrastructure datasets that are otherwise expensive or unavailable, making such approaches particularly suitable for resource-constrained environments. Finally, Lin et al. (2023) demonstrated the potential of large-scale 'social sensing' by producing near real-time flood risk maps through the automatic extraction of disaster information from online platforms. Their approach shows that user-generated content enables rapid situational awareness, providing spatially and temporally dense data within minutes of an event.

A key challenge associated with the use of citizen-generated flood information is the heterogeneous reliability of the observations. Unlike official monitoring networks, social-sensing data vary widely in terms of spatial accuracy, temporal consistency, and informational content. Several studies have therefore stressed the need to implement systematic procedures to verify and validate citizen-reported data before integrating them into urban flood models. In parallel, cross-validation against authoritative sources, such as municipal flood records, insurance claim databases, hydrodynamic model results, or remote sensing flood maps, has been shown to improve the robustness of extracted inundation information (Le Coz et al. 2016; Schumann et al. 2018).

Reliability can also be strengthened through multi-source triangulation, where observations are only retained if multiple independent posts, images, or reports corroborate the same inundation pattern, an approach commonly applied in social-sensing frameworks. Moreover, recent advances in machine learning have enabled automated filtering of crowdsourced content, helping identify implausible, duplicated, or irrelevant reports and assigning quality scores based on image clarity, presence of reference objects, or contextual metadata. Several authors have also emphasised that uncertainty should be explicitly acknowledged by deriving probabilistic descriptions of flood extent or depth when integrating crowdsourced information into models (See et al. 2018), making it possible to quantify the confidence associated with citizen-reported data.

While emerging sources such as social sensing and citizen-reported observations offer valuable opportunities to enrich urban flood modelling, their practical use is still limited by concerns regarding reliability and accuracy. Robust verification, filtering and cross-validation procedures therefore remain essential for transforming raw, opportunistic reports into trustworthy hydrological information that can be used confidently in modelling applications. The importance of establishing such validation frameworks becomes even more evident when examining the patterns shown in Figure 1, where keywords associated with alternative data sources are almost absent. Instead, terms related to terrain modelling and urban morphology—such as LiDAR, DTM/DSM and building representation—dominate the word cloud, highlighting the current dependence of the field on conventional, topography-driven datasets. This imbalance reinforces the need to enhance the credibility and integration of citizen-generated information so that it can complement traditional data sources and contribute to more spatially dense, timely and context-specific calibration and validation of urban flood models.

4.3.3 | Machine Learning Approaches

Data collection is critical even for modern machine-learning and deep-learning approaches in urban flood modelling. Although machine learning and deep learning methods can learn patterns and relationships directly from observed data, even when datasets are incomplete or heterogeneous, their predictive performance, generalisation, and reliability remain strongly dependent on the quantity, quality, and representativeness of input data (Wagenaar et al. 2020).

For instance, in a study by Zhou et al. (2023), a deep learning model combining a long short-term memory network with Bayesian optimisation and transfer learning was used to predict urban flood depths. Their results show that, when trained on appropriately collected data, the model achieved high accuracy and was many times faster than conventional hydrodynamic simulations. The authors also stress that data-driven model benefits greatly from well-sampled spatial and temporal data to learn flood dynamics robustly.

Supervised machine learning algorithms, such as Random Forest, Support Vector Machines, and gradient boosting, have been used to map urban flood hazard or susceptibility using observed geospatial data (e.g., land use, elevation, rainfall) (Li et al. 2025). Deep learning models, particularly convolutional neural networks and recurrent architectures, have further been applied to capture complex spatiotemporal flood behaviours using multi-source data. For example, convolutional neural networks–based flood-emulation models have been trained on digital elevation raster and rainfall inputs to generate flood inundation maps rapidly.

Despite such advances, there remain important challenges. Overfitting, limited interpretability, and difficulties in transferring models to new urban contexts are common when input data are sparse, noisy, or not representative (Bentivoglio et al. 2022). Moreover, data scarcity or poor resolution may prevent deep learning models from fully capturing key flood drivers in urban domains, limiting their utility for robust risk assessment. To address these limitations, hybrid frameworks that integrate artificial intelligence-based algorithms with physically-based hydrodynamic models have been proposed. Such combined approaches leverage the strengths of both data-driven learning (efficiency, pattern recognition) and process-based models (interpretability, physical realism), potentially improving generalisation and trust in predictions.

In conclusion, while machine learning and deep learning algorithms offer powerful, flexible tools to advance urban flood modelling, the importance of careful, systematic data collection cannot be overstated. Robust datasets, including high-resolution topography, sensor networks, remote sensing, and crowdsourced observations, remain foundational to maximise the potential of these techniques, particularly in real-world flood risk management.

5 | Conclusion

In conclusion, our paper investigated the data needed to achieve the identified urban flooding objectives. A thorough literature review has identified key objectives that drive urban flood simulation research and underscored the importance of tailoring spatial resolution to specific modelling goals and catchment scales. Our findings emphasise the nuanced relationship between data availability, model complexity, and the desired outcomes of urban flood modelling. We have elucidated that the suitable spatial resolution is contingent upon the objectives of the model application, with considerations for preliminary flood susceptibility assessment and flood hazard mapping. By synthesising previous approaches and recommendations, we have provided insights into researchers' strategies to navigate data-rich environments and the trade-offs associated with simplifications. We have highlighted the importance of understanding how different spatial resolutions impact the accuracy and applicability of flood models for various objectives. Ensuring data accessibility and interoperability across different platforms remains a persistent concern, hindering collaboration and comprehensive modelling efforts. Overcoming these challenges requires investing in advanced data collection technologies, establishing robust data-sharing protocols, and fostering collaborative partnerships among stakeholders. Even though the ongoing efforts to advance urban flood modelling techniques by integrating innovative methodologies, future research should focus on refining models through comprehensive sensitivity analyses and incorporating additional data sources addressing data availability and challenges related to model limitations.

Acknowledgments

Open access publishing facilitated by Universita degli Studi di Napoli Federico II, as part of the Wiley - CRUI-CARE agreement.

Funding

The “Inspiring” PRIN Project 2020, financed by the Italian MIUR (grant number: 2020NTSFXF), supported this work.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that supports the findings of this study are available in the Supporting Information of this article.

References

Al-Abadi, A. M., and B. Pradhan. 2020. “In Flood Susceptibility Assessment, Is It Scientifically Correct to Represent Flood Events as a Point Vector Format and Create Flood Inventory Map?” *Journal of Hydrology* 590: 125475.

Albertini, C., D. Miglino, V. Iacobellis, F. De Paola, and S. Manfreda. 2022. “Delineation of Flood-Prone Areas in Cliffed Coastal Regions Through a Procedure Based on the Geomorphic Flood Index.” *Journal of Flood Risk Management* 15, no. 1: e12766.

Al-Juaidi, A. E., A. M. Nassar, and O. E. Al-Juaidi. 2018. “Evaluation of Flood Susceptibility Mapping Using Logistic Regression and GIS Conditioning Factors.” *Arabian Journal of Geosciences* 11, no. 24: 765.

Apel, H., G. T. Aronica, H. Kreibich, and A. H. Thieken. 2009. “Flood Risk Analyses—How Detailed Do We Need To Be?” *Natural Hazards* 49: 79–98.

Arrighi, C., and L. Campo. 2019. “Effects of Digital Terrain Model Uncertainties on High-Resolution Urban Flood Damage Assessment.” *Journal of Flood Risk Management* 12, no. S2: e12530.

Balestra, F., M. Del Vecchio, D. Pirone, et al. 2022. “Flood Susceptibility Mapping Using a Deep Neural Network Model: The Case Study of Southern Italy.” *Environmental Sciences Proceedings* 21, no. 1: 36.

Barco, J., K. M. Wong, and M. K. Stenstrom. 2008. “Automatic Calibration of the US EPA SWMM Model for a Large Urban Catchment.” *Journal of Hydraulic Engineering* 134, no. 4: 466–474.

Bellos, V., and G. Tsakiris. 2015. “Comparing Various Methods of Building Representation for 2D Flood Modelling in Built-Up Areas.” *Water Resources Management* 29: 379–397.

Bentivoglio, R., E. Isufi, S. N. Jonkman, and R. Taormina. 2022. “Deep Learning Methods for Flood Mapping: A Review of Existing Applications and Future Research Directions.” *Hydrology and Earth System Sciences Discussions* 2022: 1–50.

Bermúdez, M., V. Ntegeka, V. Wolfs, and P. Willems. 2018. “Development and Comparison of Two Fast Surrogate Models for Urban Pluvial Flood Simulations.” *Water Resources Management* 32: 2801–2815.

Bhuyian, M. N., and A. Kalyanapu. 2018. “Accounting Digital Elevation Uncertainty for Flood Consequence Assessment.” *Journal of Flood Risk Management* 11: S1051–S1062.

Bodoque, J. M., E. Aroca-Jiménez, M. Á. Eguibar, and J. A. García. 2023. “Developing Reliable Urban Flood Hazard Mapping From LiDAR Data.” *Journal of Hydrology* 617: 128975.

Bruwier, M., A. Mustafa, D. G. Aliaga, et al. 2018. “Influence of Urban Pattern on Inundation Flow in Floodplains of Lowland Rivers.” *Science of the Total Environment* 622: 446–458.

Bulti, D. T., and B. G. Abebe. 2020. “A Review of Flood Modeling Methods for Urban Pluvial Flood Application.” *Modeling Earth Systems and Environment* 6: 1293–1302.

Cea, L., and P. Costabile. 2022. “Flood Risk in Urban Areas: Modelling, Management and Adaptation to Climate Change. A Review.” *Hydrology* 9, no. 3: 50.

Cea, L., E. Sañudo, C. Montalvo, J. Farfán, J. Puertas, and P. Tamagnone. 2025. “Recent Advances and Future Challenges in Urban Pluvial Flood Modelling.” *Urban Water Journal* 22, no. 2: 1.

Chang, T. J., C. H. Wang, and A. S. Chen. 2015. “A Novel Approach to Model Dynamic Flow Interactions Between Storm Sewer System and Overland Surface for Different Land Covers in Urban Areas.” *Journal of Hydrology* 524: 662–679.

Chen, Z., and G. Huang. 2024. “Numerical Simulation Study on the Effect of Underground Drainage Pipe Network in Typical Urban Flood.” *Journal of Hydrology* 638: 131481.

Darabi, H., B. Choubin, O. Rahmati, A. T. Haghighi, B. Pradhan, and B. Kløve. 2019. “Urban Flood Risk Mapping Using the GARP and QUEST Models: A Comparative Study of Machine Learning Techniques.” *Journal of Hydrology* 569: 142–154.

Dasallas, L., H. An, and S. Lee. 2024. “Providing Solutions for Data Scarcity in Urban Flood Modeling Through Sensitivity Analysis and DEM Modifications.” *Journal of Hydroinformatics* 26: jh2024173.

Dawson, R. J., L. Speight, J. W. Hall, S. Djordjevic, D. Savic, and J. Leandro. 2008. “Attribution of Flood Risk in Urban Areas.” *Journal of Hydroinformatics* 10, no. 4: 275–288.

Djordjević, S., D. Prodanović, Č. Maksimović, M. Ivetić, and D. Savić. 2005. “SIPSON–Simulation of Interaction Between Pipe Flow and Surface Overland Flow in Networks.” *Water Science and Technology* 52, no. 5: 275–283.

Dong, B., J. Xia, M. Zhou, Q. Li, R. Ahmadian, and R. A. Falconer. 2022. “Integrated Modeling of 2D Urban Surface and 1D Sewer Hydrodynamic Processes and Flood Risk Assessment of People and Vehicles.” *Science of the Total Environment* 827: 154098.

European Union. 2007. “Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the Assessment and the Management of Flood Risks.” *Official Journal of the European Union* L288: chapter V.

Fohringer, J., D. Dransch, H. Kreibich, and K. Schröter. 2015. “Social Media as an Information Source for Rapid Flood Inundation Mapping.” *Natural Hazards and Earth System Sciences* 15, no. 12: 2725–2738.

Griesbaum, L., S. Marx, and B. Höfle. 2017. “Direct Local Building Inundation Depth Determination in 3-D Point Clouds Generated From User-Generated Flood Images.” *Natural Hazards and Earth System Sciences* 17, no. 7: 1191–1201.

Guo, K., M. Guan, and D. Yu. 2021. “Urban Surface Water Flood Modelling–a Comprehensive Review of Current Models and Future Challenges.” *Hydrology and Earth System Sciences* 25, no. 5: 2843–2860.

Hakiel, J., and M. Szydłowski. 2017. “Interaction Between Storm Water Conduit and Surface Flow for Urban Flood Inundation Modelling.” *International Journal of Sustainable Development and Planning* 12, no. 1: 133–143.

Hsu, M. H., S. H. Chen, and T. J. Chang. 2000. “Inundation Simulation for Urban Drainage Basin With Storm Sewer System.” *Journal of Hydrology* 234, no. 1–2: 21–37.

Jang, J. H., T. H. Chang, and W. B. Chen. 2018. "Effect of Inlet Modelling on Surface Drainage in Coupled Urban Flood Simulation." *Journal of Hydrology* 562: 168–180.

Krebs, G., T. Kokkonen, M. Valtanen, H. Setälä, and H. Koivusalo. 2014. "Spatial Resolution Considerations for Urban Hydrological Modelling." *Journal of Hydrology* 512: 482–497.

Le Coz, J., A. Patalano, D. Collins, et al. 2016. "Crowdsourced Data for Flood Hydrology: Feedback From Recent Citizen Science Campaigns." *Hydrology and Earth System Sciences* 20, no. 12: 4637–4655.

Leandro, J., A. S. Chen, S. Djordjević, and D. A. Savić. 2009. "Comparison of 1D/1D and 1D/2D Coupled (Sewer/Surface) Hydraulic Models for Urban Flood Simulation." *Journal of Hydraulic Engineering* 135, no. 6: 495–504.

Leandro, J., A. Schumann, and A. Pfister. 2016. "A Step Towards Considering the Spatial Heterogeneity of Urban Key Features in Urban Hydrology Flood Modelling." *Journal of Hydrology* 535: 356–365.

Lee, S., H. Nakagawa, K. Kawaike, and H. Zhang. 2016. "Urban Inundation Simulation Considering Road Network and Building Configurations." *Journal of Flood Risk Management* 9, no. 3: 224–233.

Li, G., W. Shao, X. Su, Y. Li, Y. Zhang, and T. Song. 2025. "Urban Flood Hazard Assessment Based on Machine Learning Model." *Water Resources Management* 39, no. 5: 1953–1970.

Liang, C., and M. Guan. 2024. "Effects of Urban Drainage Inlet Layout on Surface Flood Dynamics and Discharge." *Journal of Hydrology* 632: 130890.

Lin, L., C. Tang, Q. Liang, Z. Wu, X. Wang, and S. Zhao. 2023. "Rapid Urban Flood Risk Mapping for Data-Scarce Environments Using Social Sensing and Region-Stable Deep Neural Network." *Journal of Hydrology* 617: 128758.

Lin, L., Z. Wu, and Q. Liang. 2019. "Urban Flood Susceptibility Analysis Using a GIS-Based Multi-Criteria Analysis Framework." *Natural Hazards* 97: 455–475.

Liuzzo, L., V. Sammartano, and G. Freni. 2019. "Comparison Between Different Distributed Methods for Flood Susceptibility Mapping." *Water Resources Management* 33: 3155–3173.

Löwe, R., and K. Arnbjerg-Nielsen. 2020. "Urban Pluvial Flood Risk Assessment–Data Resolution and Spatial Scale When Developing Screening Approaches on the Microscale." *Natural Hazards and Earth System Sciences* 20, no. 4: 981–997.

Luo, P., M. Luo, F. Li, et al. 2022. "Urban Flood Numerical Simulation: Research, Methods and Future Perspectives." *Environmental Modelling & Software* 156: 105478.

Manfreda, S., and C. Samela. 2019. "A Digital Elevation Model Based Method for a Rapid Estimation of Flood Inundation Depth." *Journal of Flood Risk Management* 12: e12541.

Masoumi, Z. 2022. "Flood Susceptibility Assessment for Ungauged Sites in Urban Areas Using Spatial Modeling." *Journal of Flood Risk Management* 15, no. 1: e12767.

Mignot, E., and B. Dewals. 2022. "Hydraulic Modelling of Inland Urban Flooding: Recent Advances." *Journal of Hydrology* 609: 127763.

Mignot, E., X. Li, and B. Dewals. 2019. "Experimental Modelling of Urban Flooding: A Review." *Journal of Hydrology* 568: 334–342.

Montalvo, C., J. D. Reyes-Silva, E. Sañudo, L. Cea, and J. Puertas. 2024. "Urban Pluvial Flood Modelling in the Absence of Sewer Drainage Network Data: A Physics-Based Approach." *Journal of Hydrology* 634: 131043.

Mudashiru, R. B., N. Sabtu, I. Abustan, and W. Balogun. 2021. "Flood Hazard Mapping Methods: A Review." *Journal of Hydrology* 603: 126846.

Nguyen, H. N., H. Fukuda, and M. N. Nguyen. 2024. "Assessment of the Susceptibility of Urban Flooding Using GIS With an Analytical Hierarchy Process in Hanoi, Vietnam." *Sustainability* 16, no. 10: 3934.

Noh, S. J., S. Lee, H. An, K. Kawaike, and H. Nakagawa. 2016. "Ensemble Urban Flood Simulation in Comparison With Laboratory-Scale Experiments: Impact of Interaction Models for Manhole, Sewer Pipe, and Surface Flow." *Advances in Water Resources* 97: 25–37.

Oberauer, M., and B. Lehmann. 2024. "Enhanced 2D-Models as Alternative to Dual-Drainage Systems for Urban Flood Simulation." *Journal of Hydrology* 645: 132198.

Padulano, R., P. Costabile, C. Costanzo, G. Rianna, G. Del Giudice, and P. Mercogliano. 2021. "Using the Present to Estimate the Future: A Simplified Approach for the Quantification of Climate Change Effects on Urban Flooding by Scenario Analysis." *Hydrological Processes* 35, no. 12: e14436.

Padulano, R., G. Rianna, P. Costabile, C. Costanzo, G. Del Giudice, and P. Mercogliano. 2021. "Propagation of Variability in Climate Projections Within Urban Flood Modelling: A Multi-Purpose Impact Analysis." *Journal of Hydrology* 602: 126756.

Page, M. J., J. E. McKenzie, P. M. Bossuyt, et al. 2021. "Updating Guidance for Reporting Systematic Reviews: Development of the PRISMA 2020 Statement." *Journal of Clinical Epidemiology* 134: 103–112.

Panfilova, T., V. Kukartsev, V. Tynchenko, et al. 2024. "Flood Susceptibility Assessment in Urban Areas via Deep Neural Network Approach." *Sustainability* 16, no. 17: 7489.

Parvin, F., S. A. Ali, B. Calka, E. Bielecka, N. T. T. Linh, and Q. B. Pham. 2022. "Urban Flood Vulnerability Assessment in a Densely Urbanised City Using Multi-Factor Analysis and Machine Learning Algorithms." *Theoretical and Applied Climatology* 149, no. 1: 639–659.

Petersson, L., M. C. Ten Veldhuis, G. Verhoeven, Z. Kapelan, I. Maholi, and H. C. Winsemius. 2020. "Community Mapping Supports Comprehensive Urban Flood Modeling for Flood Risk Management in a Data-Scarce Environment." *Frontiers in Earth Science* 8: 304.

Rahmati, O., H. Darabi, M. Panahi, et al. 2020. "Development of Novel Hybridized Models for Urban Flood Susceptibility Mapping." *Scientific Reports* 10, no. 1: 12937.

Ren, H., S. Liu, M. Li, et al. 2022. "Topological Analysis and Application of Urban Drainage Network." *Water* 14, no. 22: 3732.

Santos, P. P., E. Reis, S. Pereira, and M. Santos. 2019. "A Flood Susceptibility Model at the National Scale Based on Multicriteria Analysis." *Science of the Total Environment* 667: 325–337.

Sarkadi, N., E. Pirkhoffer, D. Lóczy, et al. 2022. "Generation of a Flood Susceptibility Map of Evenly Weighted Conditioning Factors for Hungary." *Geographica Pannonica* 26, no. 3: 200–214.

Savage, J., F. Pianosi, P. Bates, J. Freer, and T. Wagener. 2016. "Quantifying the Importance of Spatial Resolution and Other Factors Through Global Sensitivity Analysis of a Flood Inundation Model." *Water Resources Research* 52, no. 11: 9146–9163.

Schumann, G. J., P. D. Bates, W. Buytaert, P. Matgen, and F. Pappenberger. 2018. "Progress in Integration of Remote Sensing–Derived Flood Extent and Free-Surface Water Elevations in Hydraulic Models." *Remote Sensing of Environment* 217: 500–516.

See, L., A. Comber, C. Salk, et al. 2018. "Comparing the Quality of Crowdsourced Data Contributed by Expert and Non-Expert Volunteers for Land Cover Mapping." *Remote Sensing* 10, no. 10: 1680.

Shen, J., and F. Tan. 2020. "Effects of DEM Resolution and Resampling Technique on Building Treatment for Urban Inundation Modeling: A Case Study for the 2016 Flooding of the HUST Campus in Wuhan." *Natural Hazards* 104, no. 1: 927–957.

Shrestha, A., G. Mascaro, and M. Garcia. 2022. "Effects of Stormwater Infrastructure Data Completeness and Model Resolution on Urban Flood Modeling." *Journal of Hydrology* 607: 127498.

Song, W., M. Guan, K. Guo, and D. Yu. 2025. "Rapid Flood Inundation Mapping by Integrating Deep Learning-Based Image Super-Resolution

With Coarse-Grid Hydrodynamic Modeling." *Engineering Applications of Computational Fluid Mechanics* 19, no. 1: 2481115.

Song, W., M. Guan, and D. Yu. 2025. "SwinFlood: A Hybrid CNN-Swin Transformer Model for Rapid Spatiotemporal Flood Simulation." *Journal of Hydrology* 660: 133280.

Tehrany, M. S., S. Jones, and F. Shabani. 2019. "Identifying the Essential Flood Conditioning Factors for Flood Prone Area Mapping Using Machine Learning Techniques." *Catena* 175: 174–192.

Teng, J., A. J. Jakeman, J. Vaze, B. F. Croke, D. Dutta, and S. J. E. M. Kim. 2017. "Flood Inundation Modelling: A Review of Methods, Recent Advances and Uncertainty Analysis." *Environmental Modelling & Software* 90: 201–216.

Traoré, K., T. Fowe, M. Ouédraogo, et al. 2024. "Mapping Urban Flood Susceptibility in Ouagadougou, Burkina Faso." *Environmental Earth Sciences* 83, no. 19: 561.

van Dijk, E., J. van der Meulen, J. Kluck, and J. H. M. Straatman. 2014. "Comparing Modelling Techniques for Analysing Urban Pluvial Flooding." *Water Science and Technology* 69, no. 2: 305–311.

Varra, G., V. Pepe, R. Della Morte, and L. Cozzolino. 2024. "A Novel Efficient and Robust Treatment of the Friction Source Term in 2D Shallow Water Inundation Models." *Journal of Hydrology* 634: 131045.

Wagenaar, D., A. Curran, M. Balbi, et al. 2020. "Invited Perspectives: How Machine Learning Will Change Flood Risk and Impact Assessment." *Natural Hazards and Earth System Sciences* 20, no. 4: 1149–1161.

Wang, Y., F. Meng, H. Liu, C. Zhang, and G. Fu. 2019. "Assessing Catchment Scale Flood Resilience of Urban Areas Using a Grid Cell Based Metric." *Water Research* 163: 114852.

Wang, Y., Q. Zhang, K. Lin, et al. 2024. "A Novel Framework for Urban Flood Risk Assessment: Multiple Perspectives and Causal Analysis." *Water Research* 256: 121591.

Wang, Z., H. Lyu, and C. Zhang. 2023. "Pluvial Flood Susceptibility Mapping for Data-Scarce Urban Areas Using Graph Attention Network and Basic Flood Conditioning Factors." *Geocarto International* 38, no. 1: 2275692.

Xafoulis, N., Y. Kontos, E. Farsirotou, et al. 2023. "Evaluation of Various Resolution DEMs in Flood Risk Assessment and Practical Rules for Flood Mapping in Data-Scarce Geospatial Areas: A Case Study in Thessaly, Greece." *Hydrology* 10, no. 4: 91.

Yang, Q., Q. Dai, D. Han, X. Zhu, and S. Zhang. 2018. "Impact of the Storm Sewer Network Complexity on Flood Simulations According to the Stroke Scaling Method." *Water* 10, no. 5: 645.

Zhou, Q., S. Teng, Z. Situ, et al. 2023. "A Deep-Learning-Technique-Based Data-Driven Model for Accurate and Rapid Flood Predictions in Temporal and Spatial Dimensions." *Hydrology and Earth System Sciences* 27, no. 9: 1791–1808.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** jfr370184-sup-0001-DataS1.xlsx.