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Advances and challenges in modelling and prediction of urban flooding: a comprehensive review on recent progresses

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Abstract

Urban flooding has been an increasingly significant challenge for many cities due to rapid urbanization and climate change, leading to more frequent and intense of extreme events. Recent advances in modelling and prediction of urban flooding have focused on application of machine learning and other AI-oriented methods in modelling and prediction of urban flooding. This paper is a review of the recent development trends and results in modelling and prediction of urban flooding, categorizing them into four sub-topics: 1). Coupled Hydrological-Hydraulic Models, 2). Integration of High-Resolution Data and Remote Sensing in the model simulations, 3). AI-based Flood simulation and Prediction and 4). Climate Adaptation and resilient approaches. These new or improved approaches have been developed and demonstrated in the real case studies internationally. It is concluded that the recent development in urban flooding modelling reflects a shift towards more integrated, data-driven, and climate-resilient approaches. The combination of advanced machine learning and other AI technologies with coupled 1D& 2D hydrological-hydraulic models, high-resolution data can improve the flood simulation accuracy and computation efficiency, and further, the community involvement is enhancing the ability of cities to predict, mitigate, and adapt to urban flooding challenges.

Highlights

- This paper is a review of recent development in modelling and prediction of urban flooding.
- Integration of machine learning (ML) and AI-oriented new solutions with physically based 1D and 2D hydrological and hydraulic modelling is showing one of the major improvements over the past ten years.
- Lack of high resolution terrain data and measured flood data during extreme events is still a bottleneck for calibration of the physical models, thus affecting the accuracy of model simulations and for AI based analysis.

Introduction

Under the dual pressures of global climate change and rapid urbanization, urban pluvial flooding has become an increasingly severe issue, posing significant threats to the safety of residents, their properties and the sustainable development of cities (Fowler et al., 2021; Henan flood, 2021; Tellman et al., 2021). On the one hand, global warming has led to a remarkable increase in the frequency and intensity of extreme precipitation events globally (IPCC, 2022; FinansNorge, 2023; UNDRR, 2023). On the other hand, the rapid expansion of urban areas has resulted in a substantial rise in impervious surfaces, reducing the infiltration capacity of the land surface while overburdening the limited capacity

of stormwater drainage systems—thereby significantly elevating the risk of urban flooding (Tellman et al. 2021; Gao et al. 2023; Kaspersen et al. 2017).

Over the past 20 years, the typical method for simulation and prediction of urban flooding has been mainly the coupled 1D & 2D hydrological-hydrodynamic models based on physical processes (Nie, 2004; Djordjevic *et al.*, 2005; ...; Leitão *et al.*, 2016, Guo *et al.*, 2021; Zhang *et al.*, 2022). However, due to the complexity of the physical processes, it requires iterative method to solve the complex equations, making it difficult to meet the critical requirements for emergency management and decision making. Machine learning (ML) algorithms, Deep Learning (DL) methods and AI-oriented advanced data treatment technologies have been, on the other hand, convincing a substantial approach to overcome the bottlenecks in urban flood simulation, due to their advantages in fast extracting and analysing the data and running computations, therefore, combining the advantages of machine learning and other AI-based deep learning approaches have been a trend of recent development (Shen *et al.*, 2018; Kabir *et al.*, 2020; Li and Liu *et al.*, 2021b; Fu *et al.*, 2022; Jiang *et al.*, 2022 and Wang *et al.*, 2024). This paper aims to review the recent development, both advances and limitations in modelling and prediction of urban flooding, using it as a guide for improvement in this topic area.

Methodology

Aim and scope of the review

Urban flooding has become an increasingly critical challenge for cities worldwide, driven by the intensifying impacts of climate change and rapid urban expansion. In response to this pressing issue, the present review aims to provide a comprehensive synthesis of recent advances and development trends in the modelling and prediction of urban flooding. Specifically, the review addresses the following research questions: (1) What are the state-of-the-art of UFM, the advances and challenges? (2) How have artificial intelligence (AI), machine learning (ML), and other data-driven approaches enhanced the speed and accuracy of flood prediction? (3) What roles do the hybrid models that combine physical principles with data-driven techniques play in advancing simulation efficiency and accuracy? (4) How are climate adaptation strategies—including nature-based solutions (NBSs) and urban planning tools—being integrated into flood modelling frameworks to improve long-term preparedness and decision-making?

To answer these questions, a systematic literature search was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009). Relevant literature was retrieved from the Web of Science Core Collection database, covering the period from 2000 to 2024. According to Figure 1, the search strategy utilized Boolean combinations of terms related to urban flooding, hydrological and hydraulic modelling, simulation and prediction, machine learning, and climate adaptation. An initial pool of 929 articles was identified. To ensure high scientific quality and relevance of the reviewed literature, a set of well-defined eligibility criteria was applied during the screening process. First, the selection was limited to studies published in English to maintain consistency in language interpretation and avoid potential translation bias; Secondly, the title, abstract and key words, and thirdly, only peer-reviewed articles, proceedings papers, and review articles were considered for full-text analysis. 784 peer-reviewed articles were selected for further studies.

Trend of development of urban flood modelling

784 articles were selected relevant for review according to the eligibility criteria described in above section. According to the result, a trend of development of the scientific publications was plotted in Figure 2, showing that there were a small number of publications in the early years, and after a gradual rise from 2008 to 2017, turned to a significant growth in the later period, and it reached the peak in 2024. This trend mirrors the growing academic focus on urban flood modelling as research efforts and interest in addressing related challenges have intensified over time. In addition, not all the publications in the early stage around the year 2000 have been included in the

scientific database, thus publications searching in other sources according to the title and key words have been identified and reviewed.

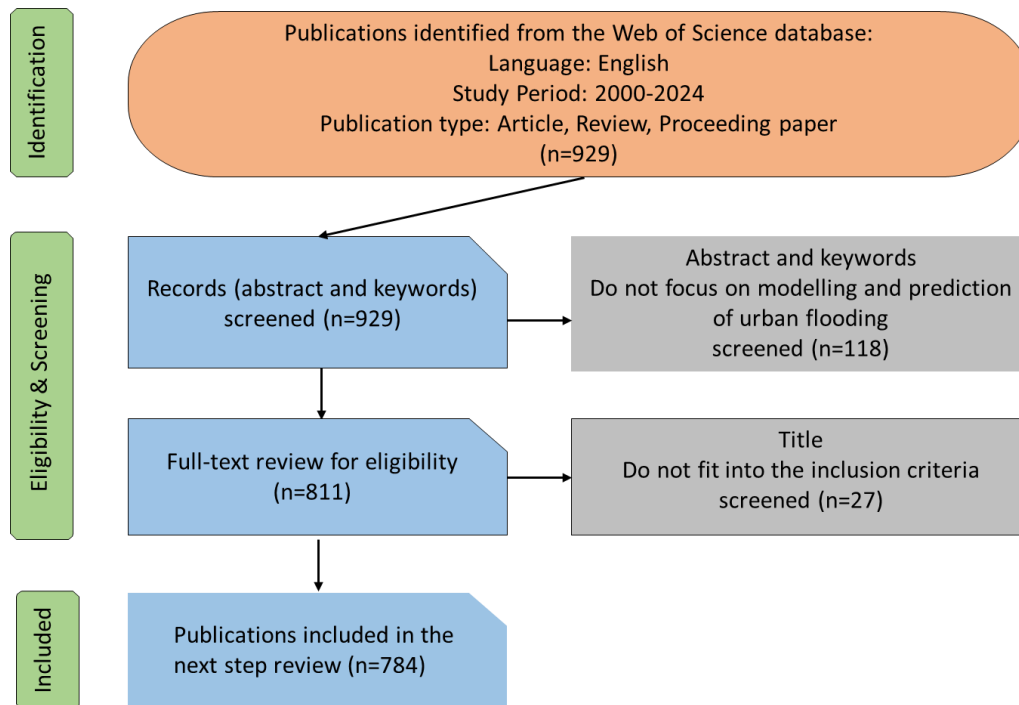


Figure 1. PRISMA flow diagram for literature selection

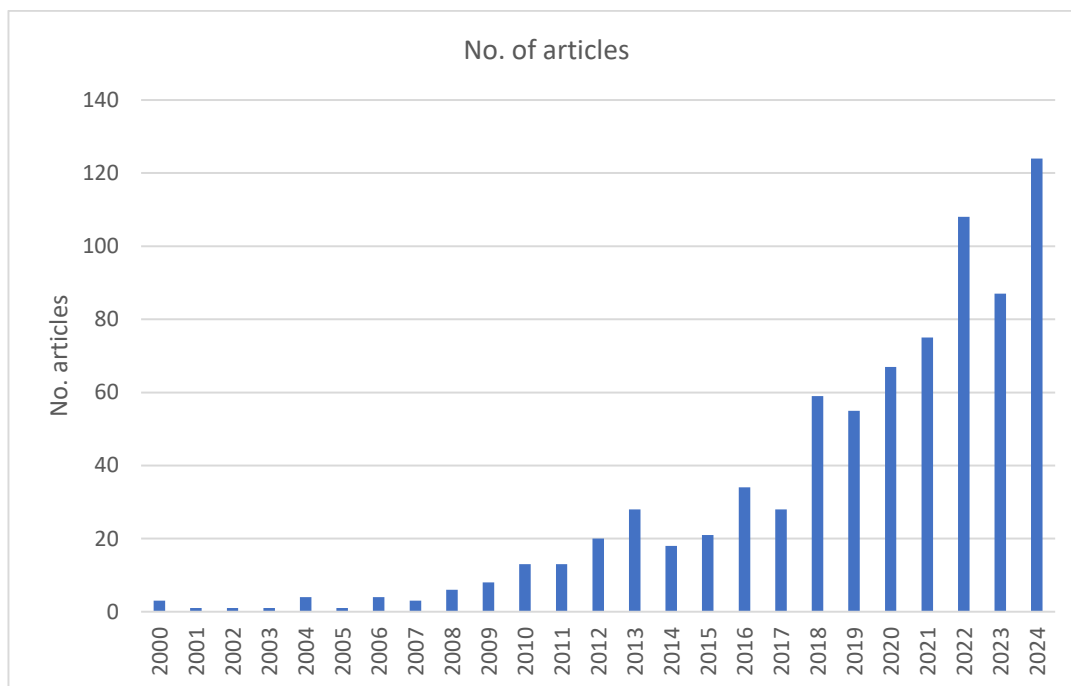


Figure 2. Identified scientific publications on urban flood models during 2000 – 2024

Thematic categorization of the literature

Of the identified 784 literature, 258 journal publications including research and review articles were selected for in-deep studies, including also literature from other scientific sources. According to the model approach and key research sub-areas, these articles are categorized in 5 sub-topic areas given in Table 1 below.

Table 1. Classification of the literature according to model approaches and subtopic areas.

Model Method	Number	Ratio	Key words
Coupled Hydrological-Hydraulic Models	77	29.84%	Urban flood models, coupled 1D&2D, MIKE URBAN, SWMM, HEC-RAS, integrated models.
High-resolution data & Remote Sensing	54	20.93%	high-resolution, Landsat-1 to Landsat-9, LiDARr, remote sensing, satellite imagery, Sentinel, spatial resolution, UAV
Risk Assessment & Resilience	49	18.99%	climate adaptation, flood hazard, flood risk, risk assessment, scenario analysis, vulnerability, sustainability, urban resilience.
AI-based Simulation & Forecast	46	17.83%	CNN, deep learning, early warning, forecasting, GRU (Gated Recurrent Unit), LSTM, machine learning, prediction, RNN, SVM, XGBoost.
Unclassified, including review	32	12.40%	Climate change, flood, model, water, inundation, flooding, flow, rainfall, extreme weather.
All literature	258		

Model evaluation and performance assessment

As stated in Table 1, the recent development in modelling and prediction of urban flooding has focused on improving the simulation accuracy and efficiency in different subtopic areas, e.g. coupling of the hydrological and hydraulic processes in urban environments, application of machine learning and AI-hierarchic deep learning and data-driven approaches. Moreover, the nature-based solutions (NBSs) implemented as mitigation measures in urban surface have modified the urban terrain and the hydrological -hydraulic processes, thus must be considered in the modelling development. This section has studied the literature in different sub-topic areas, provided a review on the advances and limitations of the recent processes.

Coupled Hydrological-Hydraulic Models

The coupled hydrological-hydrodynamic models based on physical processes has been the central method for simulating and predicting urban flooding over the past 20 years. A dual drainage urban flood modelling (1D&1D) was studied by Nie (2004), connecting a 1D sewer flow modelled run by MOUSE (DHI, 2000^a) and 1D surface channel flow generated from a digital terrain model, performed in MIKE 11 (DHI, 2011^b). The interaction of the two subsystems through artificial weirs at manholes. The study indicates a significant potential of using GIS in development of urban flood models and the essential in coupling with a 2D surface model in case of urban flooding. Djordjevic *et al.* (2005) presented a model approach SIPON – simulation of 1D pipe flow and 1D overland flow and the flow transitions between the two systems. Notably, Allitt *et al.* (2009) investigated the model approaches of 1D&1D and 1D&2D urban flood models and their performance in 3 case studies and concluded that to run a 1D&1D model is considerably faster than to run the simulation of a coupled 1D&2D by a factor of 10-100 times. It is estimated that the simulation time needed by a 2D surface flood model is approximately of x^3 times of a 1D model that has a simulation time of x minutes. The approach of the coupled 1D&1D and 1D&2D urban flood modelling have been further developed in several countries (such as Sănudo *et al.*, 2020; Zhang *et al.*, 2022 and Fappiano *et al.*, 2024), demonstrated the advances, suitability and limitations of the physical models. However, due to the complexity of the physical processes, it requires iterative solving of complex equations, making it difficult to meet the timeliness requirements for emergency decision making.

Advancements in application of high-resolution remote sensing data and images in UFM

Advances in satellite imagery, LiDAR data, and remote sensing technologies have enabled more detailed and accurate topographic models for flood prediction. This allows for better characterization of urban landscapes, including infrastructure, terrain, and drainage systems. The use of these high-

resolution data sources has improved the accuracy of flood maps and the detection of vulnerable areas in cities (e.g. Leitão *et al.*, 2016; Fappiano *et al.*, 2024).

The past five years have seen a remarkable step in the spatial, temporal, and thematic resolution of flood-relevant Earth-observation products. Baghermanesh *et al.* (2022) demonstrated a method employing simulated and PolInSAR features derived from TerraSAR-X images along with five auxiliary features, namely elevation, slope, aspect, distance from the river, and land-use that mostly contribute to flood mapping. The results indicated that an overall accuracy of 93.1% in urban areas was obtained, representing a 9.6% improvement over using the five auxiliary features alone. Several other studies have also concluded that SAR imagery can perform better than optical imagery in flood mapping (Chaabani *et al.*, 2018; Lin *et al.*, 2019). Moreover, Li *et al.* (2021) introduced a UAV platform, LiDAR sensor and data processing techniques for obtaining refined DEM for flood management. The results from case studies with two different types of the terrains: a small mountain area and a large urban area, show that the water depth and velocity affected by key micro terrain features, such as tiny channels and roads, can be captured and considered, indicating that LiDAR UAV techniques are an efficient and reliable method for surveying terrain, thus making high accurate flood simulation possible and reliable. Operational constellations such as Copernicus Sentinel-1 now deliver 10 m Synthetic Aperture Radar (SAR) acquisitions every 3–6 days over mid-latitudes, while commercial small-sat fleets achieve sub-metre repeats measured in hours. Studies by Trepekli *et al.* (2022) indicate these data streams, when fused with airborne or mobile LiDAR, allow construction of city-scale digital surface models (DSMs) with vertical accuracies < 15 cm, sufficient to resolve kerb heights and subtle flow paths between buildings. These research methods and outcomes indicate a great potential of recovery flood data and improving the modelling accuracy by application of high-resolution data and satellite images.

Machine-learning in urban flood modelling and prediction

With the rapid advancements in data science and artificial intelligence, machine learning (ML) and deep learning (DL) techniques have demonstrated distinct advantages in urban flood modelling and forecasting (e.g. Shen 2018; Guo *et al.* 2020; Fu *et al.* 2022; Dang *et al.* 2024; Wang *et al.* 2024). Guo *et al.* (2020) presented a data-driven urban pluvial flood approach that is based on a deep convolutional neural network trained using flood simulation data obtained from three catchments and 18 hyetographs. The results show that flood prediction based on neural networks use only 0.5% of the time compared with that of physically based models, with promising accuracy and generalizability. A CNN model is utilised to estimate flood water depths (Kapir *et al.*, 2020). The model can predict water depths for over half of a million cells instantly in urban inundation areas. The pre-trained model is then applied to simulate the January 2005 and December 2015 floods in Carlisle, UK. The CNN model is highly accurate in capturing flooded cells as indicated by several quantitative assessment matrices. Li and Liu *et al.* (2021) investigates the use of machine learning for the assessment of surface water flood risks in urban areas. The factors that are considered in machine learning models include coordinates, elevation, slope gradient, imperviousness, land use, land cover, soil type, substrate, distance to river, distance to road, and normalized difference vegetation index, and several other recent developments and outstanding results (e.g. Chen *et al.*, 2024 and Khoshkonesh *et al.*, 2024).

These methods are capable of processing vast amounts of heterogeneous data and extracting complex spatiotemporal patterns with high efficiency. In contrast to physics-based models, ML algorithms do not require prior assumptions about the underlying processes, enabling rapid analysis and prediction (Kabir *et al.* 2020). Deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown strong capabilities in capturing nonlinear dependencies and dynamic changes during flood events (Gao *et al.* 2024; Situ *et al.* 2024). Nonetheless, data-driven approaches also present certain limitations. They require large volumes of high-quality, well-labelled data, and their performance may deteriorate significantly in scenarios with sparse, noisy, or imbalanced data (Zahura *et al.* 2020). Additionally, many deep learning models suffer from limited interpretability and high structural complexity, which can hinder their integration into operational flood management systems and policy-making processes (Gao *et al.* 2024; Zhou *et al.* 2024).

Nature-Based Solution, modelling and urban resilience approach

The climate change impacts on flood frequency and intensity, the role of Nature-Based Solutions (NBS) in urban flood management has gained remarkable attention. Models that integrate NBS alongside traditional engineering solutions are being explored to enhance flood resilience (Sang, 2020; Lama *et al.*, 2021, Ferreira *et al.*, 2022). Integrated modelling approaches have been developed to evaluate the impacts of NBSs on flood simulation and flood mitigation, evaluate also the impacts on urban ecology and urban resilience (Guido *et al.*, 2023)

Table 2 provides a summary of models, major achievements and limitation in modelling and prediction of urban floods with selected research publications.

Table 2. Overview of recent development in modelling and prediction of urban floods

Sub-topics	Model description	Advances and limitations	Selected publications
1. Coupled hydrological - hydraulic Models	The coupling of hydrological and hydraulic models has become more sophisticated, allowing for better prediction of stormwater runoff and the behaviour of floodwaters through urban environments. These models integrate 1D&2D surface water, stormwater systems, and sewer networks to simulate flood events under different precipitation scenarios.	The ability to model these systems simultaneously helps urban planners design more resilient infrastructure and optimize drainage systems.	e.g. Leitão <i>et al.</i> , (2016); Sãnudo <i>et al.</i> (2020); Jiang and Yu (2022); Fappiano <i>et al.</i> , (2024).
2. Integration of high-resolution data and remote sensing	Advances in satellite imagery, LiDAR data, and remote sensing technologies have enabled more detailed and accurate topographic models for flood prediction. This allows for better characterization of urban landscapes, including infrastructure, terrain, and drainage systems.	The use of these high-resolution data sources has improved the accuracy of flood maps and the detection of victims and vulnerable areas during floods.	e.g. Zhu <i>et al.</i> , (2017); Pollard <i>et al.</i> , (2018); Tellman, <i>et al.</i> (2021); Fappiano <i>et al.</i> , (2024).
3. AI based fast simulation, prediction and early warning of urban flooding	Machine learning and artificial intelligence (AI) are being increasingly incorporated into urban flood modelling to enhance predictive capabilities. AI-driven models can analyse large volumes of real-time data from sensors, weather forecasts, and social media feeds to provide early warnings.	AI-oriented approaches are largely data-dependent performance. Although it can accelerate the flood simulation efficiently. However, the simulation performance may be limited due to lack of high-resolution data.	Shen <i>et al.</i> (2018); Kabir <i>et al.</i> (2020); Guo <i>et al.</i> (2020); Li <i>et al.</i> (2021); Guo <i>et al.</i> , (2021); Fu <i>et al.</i> , (2022); Chen <i>et al.</i> (2024).
4. Climate Adaptation and urban resilience approach	Models that integrate NBS alongside traditional models are being explored to enhance flood resilience, including the changes in terrain, rainfall patterns, sea-level rise, and urban growth, to provide long-term flood risk assessment and management.	This forward-looking approach enables cities to prepare better for future challenges with an emphasis on sustainable urban planning and climate adaptation strategies.	Lama <i>et al.</i> , 2021; Ferreira <i>et al.</i> (2022); Zhang <i>et al.</i> (2022); Grigg (2023); Khoshkonesh <i>et al.</i> (2024)

Conclusions and future work

The recent development in urban flooding modelling reflects a shift towards more integrated, data-driven, and climate-resilient approaches. This review has drawn the following findings:

- The combination of advanced computational methods, real-time data integration, and climate resilient sustainable solutions is enhancing the ability of cities to predict, mitigate, and adapt to urban flood challenges. As the complexity of urban environments and the threat of climate change continue to grow, these innovations in UFM are crucial for building safer, more resilient urban spaces.
- The application of machine learning, as a part of AI advances for modelling and prediction of urban flooding provides an opportunity of fast simulation and prediction of urban flooding and flood risk analysis for emergency management and decision-making during hydroclimate extreme events. It is still a valuable focus for future development in modelling and prediction of urban flooding
- Monitoring and generation of the high-resolution digital terrain data and flood maps and flood data are valuable for flood simulation and prediction, while expensive, thus remain a bottleneck to improve the flood simulation accuracy.
- Beyond the importance of simulation accuracy, the simulation time is crucial in order to make precise flood forecasting, nowcasting and real time results, which are essential information for city managers and police officers to make efficient flood emergency management.
- Data ownership, algorithmic development, explainability and trustworthiness, multi-agent systems are identified as key areas to advance the application and implementation of deep learning in urban flooding simulation and prediction and flood risk management
- Community involvement in the scenarios and modelling can enhance the ability of cities to predict, mitigate, and adapt to urban flooding challenges.

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