A critical review of real-time modelling of flood forecasting in urban drainage systems

Journal of Hydrology 607 (2022) 127476

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Review papers

A critical review of real-time modelling of flood forecasting in urban drainage systems

Farzad Piadeh, Kourosh Behzadian [*], Amir M Alani

School of Computing and Engineering, University of West London, St Mary's Rd, London W5 5RF, UK

ARTICLE INFO

This manuscript was handled by A. Bardossy, Editor-in-Chief, with the assistance of Jozsef Szilagyi, Associate Editor

Keywords:
Artificial intelligence-based models
Data-driven models
Real-time flood forecasting
Urban drainage systems
Urban flood

ABSTRACT

There has been a strong tendency in recent decades to develop real-time urban flood prediction models for early warning to the public due to a large number of worldwide urban flood occurrences and their disastrous consequences. While a significant breakthrough has been made so far, there are still some potential knowledge gaps that need further investigation. This paper presents a comprehensive review of the current state-of-the-art and future trends of real-time modelling of flood forecasting in urban drainage systems. Findings showed that the combination of various real-time sources of rainfall measurement and the inclusion of other real-time data such as soil moisture, wind flow patterns, evaporation, fluvial flow and infiltration should be more investigated in real-time flood forecasting models. Additionally, artificial intelligence is also present in most of the new RTFF models in UDS and consequently further developments of this technique are expected to appear in future works.

1. Introduction

Climate change has likely consequences in hydrology including extreme rainfall and changing precipitation patterns that both result in more urban floods and adverse effects on existing urban infrastructure (Rubinato et al., 2019; Balistrocchi et al., 2020). These effects result in loss of property particularly utility infrastructure and household assets, human and economy especially income in industries and transport interruption in trades (Miller and Hutchins, 2017; Konami et al., 2021). Fig. 1 shows the geographical spread of flood occurrences and associated losses by country over the recent 30 years based on the data collected from CRED (2021). The figure shows developing countries especially in Asia and Africa have been dealing mainly with social damages i.e. human losses and affected populations while developed countries in Europe and North America have been mainly suffering from economic loss. For example, China and India as countries mainly affected by flood events in Asia are ranked first in the world for the average affected people per event whereas the top ranking of average human loss and economic loss are reported for Venezuela and Denmark, respectively. This unequal distribution of impacts shows the diverse effects of flood occurrence. Besides, in recent 30 years, floods have caused more than US $1,280 billion for the world economy, affected nearly 2 billion people around the world and killed about 214,000 (UNDRR, 2019). Therefore, it is of paramount importance for all involved parties including stakeholders, communities, and researchers to take proper actions and mitigate the risk of flood occurrence. Furthermore, the increasing need for new developments and urbanisation will probably exacerbate these consequences as natural drainage and open spaces in urban areas are routinely being modified or replaced with impervious drainage channels, paved and impermeable areas (Han and He, 2021).

Numerous structural measures have been developed such as blue-green infrastructure and stormwater management facilities to decline the adverse effects of floods (Li et al., 2020). However, non-structural approaches especially early flood warning systems have attracted more attention in recent decades due mainly to the time saving for development and operation, cost-effectiveness and no extra space or facilities required for new construction or physical modification (Berndtsson et al., 2019; Hadi pour et al., 2020). Early flood warning systems have been widely used for real-time forecasting of flood in the case of river basins, reservoirs, lakes, stream flows, mountainous areas, prairies, urban surface runoff and urban flooding in coastal cities (Hadid et al., 2020; Meyers et al., 2021). However, unique features of floods in urban and non-urban areas as listed in Table 1 need to be realised for any planning of real-time forecasting. These features can be used to determine the requirements for spatial and temporal data, types of flood modelling, the inclusion of potential flood impacts and key performance indicators. More specifically, real-time flood forecasting (RTFF) in urban drainage systems (UDS) typically requires modelling of distributed

* Corresponding author.
E-mail addresses: kourosh.behzadian@uwl.ac.uk (K. Behzadian), amir.alani@uwl.ac.uk (A.M. Alani).

https://doi.org/10.1016/j.jhydrol.2022.127476
Received 10 October 2021; Received in revised form 7 January 2022; Accepted 14 January 2022
Available online 22 January 2022

systems with high spatial and temporal complexity, which is overstressed by spatial limitation as well as short preparation time (Zhao et al., 2019a; Mullapudi et al., 2020).

A significant breakthrough has been made over the recent decades to overcome some major challenges in the main steps of RTFF meaning "data collection and preparation", "model development" and "performance assessment". Multiple attempts have been made in the research works that focused on at least one of these three main areas of RTFF modelling. However, there are still some potential knowledge gaps that need further investigation. To address this, a few recent reviews given in Table 2 show thorough literature from various perspectives of concepts, models and tools for real-time forecasting of urban flooding. Data collection and preparation have been critically analysed by several researchers in recent years. McKee and Binns (2015) suggested some applicable data merging methods within the scope of hydrological models of urban flooding. Furthermore, Ochoa-Rodriguez et al. (2018) evaluated the capability of different data merging methods in the context of data resolution only. Daal *et al.* (2017) and Thorndahl et al. (2017) linked the data resources to "performance assessment" of urban flood forecasting without supporting model development. Daal *et al.* (2017) argued high demand for the model performance assessment is heavily affected by the lack of uncertainty analysis of input data. Thorndahl et al. (2017) pointed out the accuracy of radar data through numerous examples of only hydrological models. Salvadore et al. (2015) critically analysed various modelling of urban hydrological processes and mapped the future trends of model development based on only data resolutions. García et al. (2015) and Nkwunonwo et al. (2020) reviewed several real-time control strategies and listed relevant models and software tools. Finally more recently, Kourtis and Tsihrintzis (2021) analysed the impacts of climate change on UDS design and reviewed the associated challenges. In summary, these reviews have mainly focused on urban flood forecasting with the aid of describing data requirements, developing models and measuring model performance, rather than discussing real-time forecasting models in the context of urban drainage systems. As a result, to the best of our knowledge, there is a lack of a critical and comprehensive review to provide knowledge on this context to enable the field of research and provide the articulation of current and

Table 1
Main features of flood in urban and non-urban areas*.

Characteristics	Drainage systems	
	Urban areas	Non-urban areas
Flood description	- Overflow of urban drainage infrastructures due to lack of proper drainage in an urban area	- Overflow or rise of water bodies such as rivers, streams, sea level and reservoirs
Flood causalities	- Mainly fast surface runoff generated by rainfall	- Mainly high intensity of rainfall or accumulation of surface runoff
Flood duration	- Between a few minutes to a couple of days	- Part of days to a week
Spatial flood impacts	- Small areas i.e. streets to neighbourhoods, can be extended to all urban areas, but highly distributed	- Large scale such as vulnerable zones, and river riparian zones
Spatial restrictions for flood management	- No flexibility in land surfaces or underground modification as previously occupied - Fast variation in land use	- High flexibility in non-urban areas
Main types of impacts	- Economic loss and business interruption - Human loss, Mental and social problems - Urban structure and infrastructure damages	- Soil erosion - Wasting crops and livestock - Natural habitat loss - Water pollution - Reservoir or water infrastructure damages

*: Inspired by Cools et al. (2016), Zhao et al. (2019b), Dao et al. (2020a).

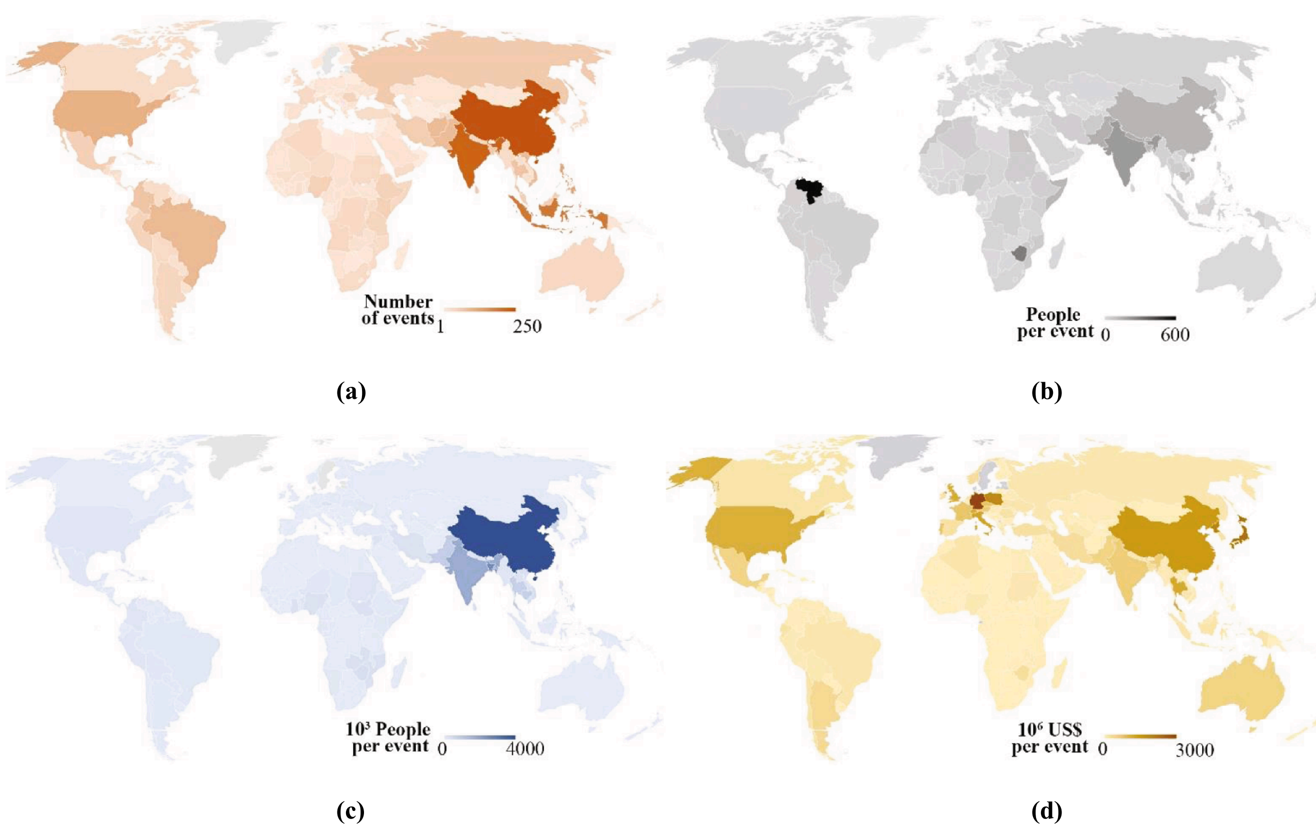


Fig. 1. Geographical occurrences of flood events (1990–2021): a) number of flood events, b) average human loss, c) average affected people, d) average economic loss.

Table 2
Recent literature reviews of urban flood forecasting and modelling.

Review topic	Covered issues based on main steps of urban flood forecasting models			Reference
	Data collection and preparation	Model development	Performance assessment	
	Specifying required data, providing recorded data, preparing the model input from collected data	Developing the model, training/setting up, and testing	Model validation and evaluating the efficacy of the model performance	
Identifying urbanised catchments' hydrological modelling to map future modelling development	NF[1]	Presenting urban hydrological processes, models based on only temporal and special resolutions of data	NF	Salvadore et al., (2015)
Reviewing approaches of real-time control and flood modelling in UDS	NF	Presenting several real-time control strategies, common relevant models and software tools	NF	García et al., (2015)
Describing diverse methods for merging data, recorded by rain gauges and radar stations in the case of urban flooding	Reviewing available data types and data merging for hydrological models	NF	NF	McKee and Binns, (2015)
Inspecting impact of removing uncertainty analysis and limited size of data in evaluation periods for the performance of real-time control in UDS	Interpreting uncertainty analysis of input data and their role in model performance	NF	Demonstrating demands for model performance assessment dealing with long-term historical data in one case study	Daal et al., (2017)
Explaining the application of radar data for the enhancement of rainfall estimation in the concept of urban hydrology	Describing characteristics of radar data, in numerous UDS modelling examples	NF	Presenting the accuracy of radar data as the input data of urban hydrological models demonstrated on some specific models	Thorndahl et al., (2017)
Discussing challenges and potential of different merging strategies in the concept of urban hydrology	Describing both rain gauge and radar data and evaluating merging methods based on data resolution only.	NF	NF	Ochoa-Rodriguez et al., (2018)
Discussing urban flood risk management for developing countries	NF	Providing significant materials in flood modelling, their status, as well as their strengths and weaknesses, Discussing uncertainties and their role in the model calibration	NF	Nkwunonwo et al., (2020)
Challenge aspects of adapting UDS to climate change were defined, including hydrologic-hydraulic design.	Investigating the impact of climate change on data sources	Reporting modelling approaches and applied software statistically	NF	Kourtis and Tsihrintzis, (2021)

NF: Not focused.

future directions.

Hence, extending the aforementioned works, the overall objective of this paper is to review all advances of the real-time data-driven forecasting models of urban flooding and thereby demonstrating a comprehensive picture of the present approaches and highlighting future directions of real-time control of urban flooding. The current review is organised in the following four sections. The research design structure with the relevant bibliometric analysis used to select the peer-reviewed papers is first described. Data types and available data sources for developing RTFF models in UDS is then presented along with reviewing data merging techniques. Hydrological and hydraulic models for RTFF in UDS and their performance assessment are then analysed in the next section. Finally, conclusions are drawn by summarising key findings and making recommendations for future studies on RTFF in UDS.

2. Research design and bibliometric tracking

RTFF in UDS can be used for a wide range of assessments and applications such as risk assessment, deep-learning visual assessment and GIS-based flood monitoring. The current review mainly focuses on scientific peer-reviewed papers studying real-time forecasting of water depth/ discharge in the urban sewer chambers over the last decade between 2011 and 2021. This is because this area of research has been advancing in recent years and is now placed as a central concern in many mitigation flood hazard attempts.

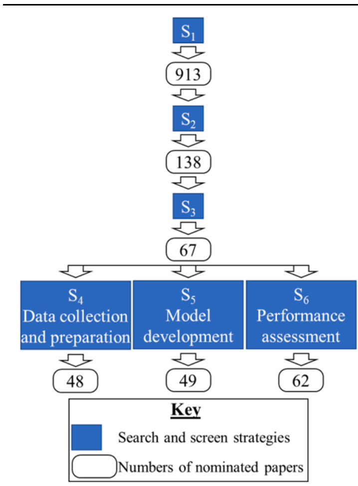
Appropriate research works were collected from the Scopus search engine according to the guideline suggested by Moher et al. (2009). They were refined by a set of six search and screen strategies (S1-S6) demonstrated in Table 3. The search results started from 913 publications in S1 and were gradually narrowed down through the following steps S2-S3 and finally limited to a total of 67 studies that were then classified under three categories of studies as 48 for data collection (S4), 49 for model development (S5) and 62 for performance assessment (S6). Note that although the main focus of this review is flood forecasting in urbanised areas, non-urbanised flood forecasting is also reviewed to capture recently developed concepts in the field that can be used for future directions.

2.1. Bibliometric analysis

Bibliometric analysis (BA) was first conducted for the collected publications as shown in Fig. 2 for the geographical distribution of case studies and clustering analysis, density and timeline of keywords. The BA shows most of the relevant studies RTFF are from Europe (66%) and the three highest countries for these publications are the UK (17.5%), China (15.5%) and Denmark (10.5%). By comparing this with Fig. 1, it relatively agrees with geographical locations of flood events generally for countries in Europe and America although it is only 7% in Asia mainly from China. Evidently, more studies related to RTFF in UDS may be required from Southeast Asia and South America to have a better balance between geographical locations of flood events and relevant publications.

Analysis of knowledge domain bibliometric track (Fig. 2b-d was conducted by VOSviewer software for the collected publications based on co-occurrence of key terms for a specific unit of analysis (keywords,

Table 3
Flowchart of the search strategies in the study



Code	Search and screen strategy	Keywords
S1	Finding publications studying flooding in urban drainage systems	(Urban OR city OR Domestic) AND (flood OR pluvial OR fluvial OR storm) AND (runoff OR overflow OR discharge OR inundation) AND (drainage AND system OR network OR sewage OR wastewater OR separate OR combined OR Catchment)
S2	the results were limited to the last decade, English language articles, and journal papers only with searching under titles, keywords, and abstracts.	–
S3	The results were screened for RTFF papers	(Forecast OR predict OR estimate OR assess OR real-time OR monitor OR susceptibility OR analysis)
S4	The results were screened for rainfall data sources, and rainfall-runoff parameters and key variables.	(Rainfall OR rain OR storm OR precipitation) AND (satellite OR gauge OR radar OR station) OR (merge OR integration OR assimilation OR interpolation OR bias adjustment) OR (land AND use) OR (evaporation OR evapotranspiration) OR (soil AND condition OR moisture OR layer) OR (infiltration OR leakage OR dry AND weather AND flow) OR (data AND missing OR filling Or cleaning OR imputation OR completion OR event AND identification)
S5	The results were divided and screened for modelling types	(Physical OR empirical OR conceptual) AND (lump OR semi-distribute OR distribute) AND (model OR method OR data-driven OR algorithm) AND (hydrological OR Hydraulic) OR (water AND level AND depth) OR (discharge OR flow OR quantity)
S6	The results were screened for performance assessment approaches	(Performance OR Sensitivity OR efficiency OR indicator) AND (assess OR test OR coefficient)

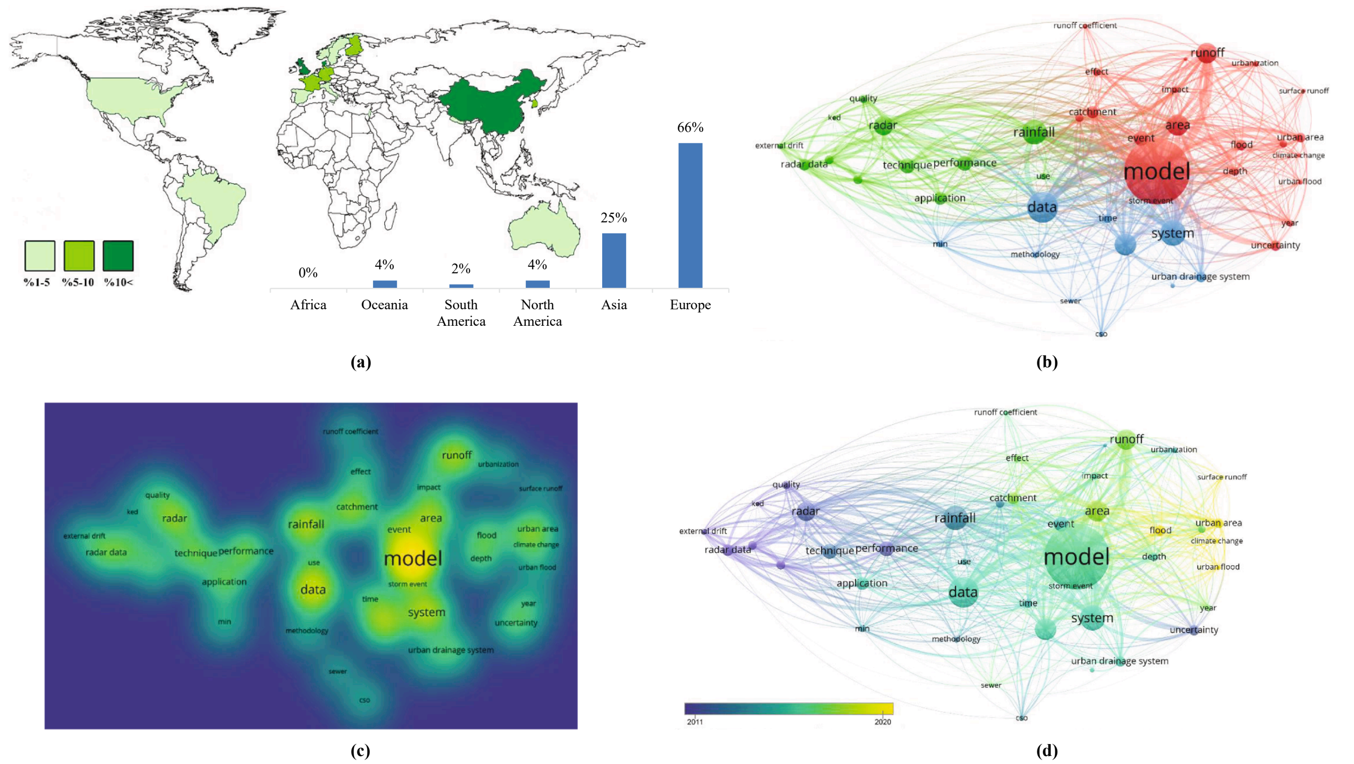


Fig. 2. Bibliometric analysis for the collected papers based on a) geographical distribution, b) cluster of keywords, c) density of keywords, d) timeline of keywords.

titles and abstracts), type of analysis (co-occurrence) and counting method (full counting). The findings of this analysis can support researchers to appraise close relationships between the frequency of co-occurred keywords in the publications and determine the directions of future studies by highlighting the core content of specific subjects (Goh and See, 2021). More specifically, three types of analysis were carried out here based on the methodologies introduced by Ding et al. (2014) and Perianes-Rodriguez et al. (2016): (1) cluster analysis in Fig. 2b: grouping a collection of keywords into multiple classes in which node size representing the frequency of co-occurrence, links representing co-reference and colours representing different clusters, (2) density analysis in Fig. 2c: extraction of the number of times that keywords appear in the publications; (3) timeline analysis in Fig. 2d: mapping keywords onto the colour coded timespan of studies within the last decade.

The three major clusters (green, blue and red) identified in Fig. 2b show strong connections of keywords in those publications. More specifically, the green cluster mainly represented by "rainfall" is strongly connected with "radar" in the same cluster and is also related to data sources, data quality and data preparation techniques. The blue cluster recognised by "data" is connected with "time steps" and the main characteristics of "system" such as UDS, combined sewer systems. Both clusters are strongly connected to the "model" in the red cluster as the major focus of all papers. In other words, "Model" as the largest keyword represents the leading research area for RTFF in UDS. Similarly, the density of keywords in Fig. 2c also confirms the majority of research topics in the last decade are mainly scattered around "data" and "model". This is also in line with the two main steps of modelling in Tables 2 ("data collection and preparation" and "model development"). The colour coded visualisation of the keywords in the studies in Figurer 2d shows how the research focus of frontiers of knowledge has changed over the past decade. More specifically, the research works were mainly dealing with rainfall data sources such as radar data at the beginning of the decade while exploring model and system were the primary focus in the middle of the decade and finally the studies were concentrated on specific issues such as climate change and urban flooding and the role of urbanisation in recent years.

3. Data collection and preparation

RTFF models heavily rely on the types and quality of data collection and preparation for model development and performance assessment. Therefore, available data and measurements have a major impact on RTFF models in UDS. These data may be unavailable or inaccessible mainly due to the restriction in both temporal ad spatial gaps. The typical data required in RTFF modelling include "rainfall data", "flow measurement of UDS" and "catchment and weather characteristics" (Thrysøe et al., 2019; Li, 2020). Rainfall depth and chamber water depth in UDS are the main data required whereas others are alternatively used for modelling when needed to enhance the model performance. These data are not necessarily the same as used in flood forecasting models that are applied for designing UDS. For example, some conventional parameters like land use, slops angles, catchment area, vegetation ratio, installed sustainable urban drainage systems and surface roughness which are routinely used for modelling UDS (Hamil, 2011), may not be required to capture as real-time data. Otherwise, some other variables need to be recorded and used in the real-time flood forecasting models which are the focus of this section.

3.1. Real-time rainfall data sources

Three main sources of real-time rainfall data widely used in hydrological science include telemetry ground rain gauges, rainfall radar data, and weather satellites, with the key features shown in Table 4. Rain gauge data are the most applicable and primary source of rainfall estimation and installed rainfall stations are currently spread all over the world (Fig. 3). Rain gauges measure the accumulative depth of rainfall over a specific period (e.g. 15 min) for a given location to obtain representative rainfall measurements over the area. While rain gauge stations can provide an accurate point of measurement, they are subject to numerous sources of uncertainty that can limit their exclusive

Table 4
Key features of main rainfall data sources for RTFF*.

Characteristics	Rainfall data source		
	Rain gauge station	Rainfall radar station	Weather satellite
Definition	A meteorological collection instrument positioned in an open space area. The precipitation is measured as the height of accumulated water per given time typically expressed in millimetres.	An echo-sounding system using the same arial transmitting signal and receiving the returned eco. The output is the pixeled image of a specific location with various indicated precipitation range.	Orbiting platforms with onboard instruments sensing data from the atmosphere and underlying surfaces
Common types	Weighing bucket, tipping bucket, floating or natural syphon, optical and acoustic gauge	Different maximum quantitative ranges of radars particularly X-band, C-band, and S-band	Geostationary and low earth orbiting
Strength	- Measuring accepted ground data - Providing real-time data	- Strong ability to show the location of precipitation - Providing near real-time areal rainfall estimates over a wide area	- Desirable spatial and temporal coverage
Weakness	- Inability to characterise the spatial distribution of rainfall - High systematic and calibration errors such as more sensitivity to strong winds, evaporation, splash-out, valley effect, tree cover, building cover - Required relatively opened flat area	- Fail to satisfy the accuracy and resolution requirements, especially for displaying rainfall at the surface - Risen errors from technical and meteorological related causalities such as weather shadowing or terrain barriers	- Inability to provide high-resolution data in small watersheds
Optimal practice	Points positioned near the stations or in the network of rain gauges	Areas on where there are no sufficient rain gauge stations to provide appropriate data	When there is a high demand to obtain data in high coverage areas which can be used for suitable rainfall prediction with enough lead time

*: Inspired by Acharya (2017), Maggioni and Massari (2018), AMS (2020), Met Office (2020), DEFRA (2021).

application in RTFF. Two main limitations of rain gauge data are: (1) the inability of point measurements to accurately characterise the spatial distribution of rainfall, and (2) high systematic and calibration errors (Dao et al., 2020a; Wu et al., 2020). To overcome this, a network of gauges constituting a series of gauges distributed throughout the area is recommended to provide a spatial distribution and approximate rainfall accumulations at ungauged areas (Jiang and Tung, 2013; Wu et al., 2020). However, there may be UDS with multiple sub-catchments covered by just a few rain gauges which are not sufficient enough to provide accurate forecasting (Borup et al. 2016).

In addition, the combination of more than one source of rainfall data can also be helpful to overcome the weaknesses and enhance the accuracy and confidence level of rainfall estimations. For example, rainfall radar estimates with the advantage of capturing the spatial distribution of rainfall and their variation in time were used to improve the accuracy of the data collected in rain gauge stations (Paz et al., 2017). Even with such a combination, they may still fail to satisfy the accuracy and resolution requirements for modelling urban hydrology (Wang et al., 2015). This is mainly because they are heavily dependent on radar environments such as visibility effects and variability in time and space (Pulkkinen et al., 2016; Cecinati et al., 2017). This situation can be improved by calibrating rain gauge stations through other sources especially the historic records of rainfall radar stations, which is known as merging techniques (McKee and Binns, 2015; Boudevillain et al., 2016).

Three basic techniques used for merging rain gauge and radar data are bias adjustment, interpolation and integration. Bias adjustment techniques are based on the correction of rain gauge data accumulations using radar data accumulations while interpolation techniques minimise the variance between the two measurement types. Furthermore, integration techniques proportionally combine rain gauge and radar data based on their relative uncertainty to minimise the overall estimation uncertainty. Table 5 lists recent applications of merging techniques with a dashboard summarised in Fig. 4. As can be seen, interpolation techniques were used in almost 68% of relevant studies in which the majority of cases (59%) applied kriging techniques followed by the conditional merging technique (18%).

While most of the studies used merging techniques for a single type of data source, only a few studies discussed a comparison of different merging methods. When using the Kriging method, Berndt et al. (2014) reported the measurement accuracy was increased by at least 14% and Nanding et al. (2016) showed measurement errors were cut down by half. However, Berndt et al., (2014) and Rabiei and Haberlandt (2015) proved conditional merging techniques outperformed other interpolation techniques. Besides, Delrieu et al. (2014) and Boudevillain et al. (2016) showed interpolation techniques can effectively increase the measurement accuracy when compared to bias adjustment for adjusting rain gauge precipitation estimates by radar data. Jewell and Gaussiat (2015) showed Kriging methods have more accuracy than Bias adjustment especially when long-term data are predicted. Finally, Wang et al. (2015) argued that while integration techniques have more capability to increase the model accuracy than interpolation and Bias adjustment techniques, their applications have no much interest due mainly to the requirements for more model complexity, data records and higher computational efforts.

While early flood warning systems need proper lead time (i.e. the time required for rain falling inside the catchment boundary to flow over the surface and discharge into the first entrance of UDS) to take the desired actions (Brunner et al., 2021), rain gauge and rainfall radar data may have limited special resolution of rainfall data, which results in the inability of models to provide accurate predictions for long-term ahead. To overcome this challenge, other studies on non-urban hydrology suggested exploiting new data sources especially weather satellites (Belete et al., 2020; Chen et al., 2021). The use of satellite products in urban rainfall estimates can support RTFF in UDS particularly in poorly gauged or radar areas and provide data with a higher range of spatial resolution (Islam et al., 2020; Kim et al., 2020). However, these data may suffer from a lack of high resolution for small watersheds such as urban areas, which may result in decreasing the accuracy of prediction (Azim *et al.*, 2020; Brunner et al., 2021). This can be mitigated by merging satellite products with rainfall data sources for future works on RTFF in UDS.

Other key factors of the rainfall data influencing the RTFF accuracy are temporal and spatial resolutions and historical duration/period of available data. Note that temporal resolution refers to the time between two subsequent data and spatial resolution particularly in rainfall radar refers to one side length of a single pixel in network data. Table 6 lists a summary of temporal and spatial resolutions for the two rainfall measurement sources including rain gauge and rainfall radar. It shows most

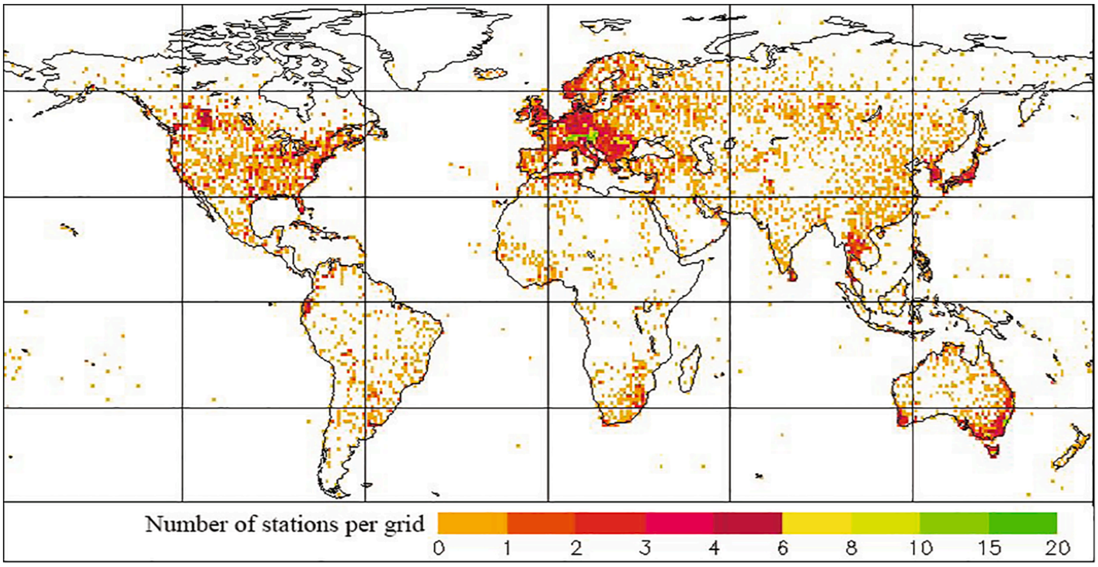


Fig. 3. Global distribution of installed rain gauge stations (NCAR, 2012).

rainfall radar data (73%) were used with a short (high) temporal resolution of fewer than 5 min for each timestep whereas various time steps were used for rain gauge data although 15-minute timesteps were slightly predominant (40%). As expected, many of the studies using radar data often take advantage of high temporal resolution due to more advanced technologies used in radar stations. Despite the availability of high-tech rain gauge stations to capture rainfall with high resolution, many countries are still using relatively old rain gauge stations (NCAR, 2012; Wu et al., 2020). Furthermore, the majority of the rainfall radar data (60%) had a spatial resolution of 1Km while 34% of radar data also had a finer resolution of less than 1 Km. A few studies recommended the most appropriate data resolutions for obtaining a satisfactory performance as temporal resolution of smaller than 15 min (Ochoa-Rodriguez et al., 2015) and spatial resolution of less than 1 Km (Ochoa-Rodriguez et al., 2015). Wang et al. (2019) also confirmed spatial resolutions greater than 1 Km can be unsuitable for urban flooding simulation.

Martens et al. (2013) also showed using the data with higher temporal resolution outperforms the data with the finer spatial resolution for obtaining more accurate estimates. However, Schaller et al. (2020) argued that using data with either higher temporal resolution or finer spatial resolution cannot necessarily result in more accurate flood predictions in comparison to when the resolution of different data resources are overridden. They argued that attempts to provide data resources with the same resolution may result in more achievement rather than trying to find data with better resolution.

3.2. Flow measurement of UDS

The flow of the surface runoff discharged into UDS is usually measured at gauging stations and expressed as either flow or chamber water depth. This measurement at multiple points of UDS is an essential variable used for RTFF (Swain *et al.*, 2018). The chamber water depth/flow measured in a conduit of UDS comprise various flows listed in Table 7. It can include surface runoff collected from the catchment and discharged into the UDS, sanitary sewage (if the sewer is combined), infiltration into the conduit, leakage/exfiltration into the ground and evaporation (Met Office, 2020; DEFRA, 2021).

Sanitary sewage typically with a diurnal pattern adds an extra load in combined sewer systems and reduces the capacity of UDS for carrying surface runoff during a flood (Troutman et al., 2017). This issue is suitably covered in CSO cases, especially in data-driven models. Fluvial flooding occurs when UDS's water flow spills onto the urban surfaces. These excessed flows have different hydrodynamic characteristics including (1) usually appearing earlier than surface runoff (pluvial flood) in UDS, and (2) failure in draining can happen everywhere of UDS length, whereas usually, UDS's drainage points are more vulnerable in surface runoff (Hamill, 2011; Tanaka et al., 2020). Selected studies have been focused on the prediction of pluvial flood in UDS and fluvial flood is indexed in the inundated urban flood maps or risk assessment of urban catchments (Shih et al., 2019; Geravand et al., 2020). Other flows such as leakage from conduits, evaporation from the water surface of open conduits and infiltration into conduits contribute to the total flow of conduits. These parameters are practised in physical models very well but are not focused on the data-driven models. However, While they can add noise on chamber water depth data without any uniform recognisable pattern and reduce the model accuracy, they have been not captured completely in the data-driven models (Ravazzani et al., 2016; Courdent et al., 2018; Fidal and Kjeldsen, 2020).

3.3. Catchment and weather characteristics

There are some key features in the catchment and weather such as soil moisture, evaporation of surface runoff, air temperature and moisture, and wind characteristics that have a key role on RTFF modelling in UDS. They are summarised in Table 8 and described below.

Soil moisture and its effects on soil infiltration is an important parameter required for the estimation of surface runoff (Li et al., 2018; Dao et al. 2020a). In the concept of data-driven models, only a few studies focus on this parameter. Courdent et al. (2018) argued that the soil moisture in rainfall-runoff modelling can be considered in two parts of fast and slow. While the fast part directly enters UDS, the slow one infiltrates with a considerable lag time. Fidal and Kjeldsen (2020) also showed the accuracy of rainfall-runoff simulation increases by 12% when the soil moisture is included.

Weather characteristics such as wind flow pattern (speed and direction), air temperature and air moisture regularly reported by weather stations (DEFRA, 2021) are considered as main weather parameters in RTFF. wind flow patterns can also affect the speed of rainfall movement and the direction pattern of rain (Figueroa et al., 2020; KC et al., 2021). Besides, high air temperature and low air moisture can prevent rainfall from reaching UDS by evaporation (Rubinato et al., 2019). The use of wind flow patterns for the estimation of surface runoff has almost been overlooked in RTFF modelling. Similarly, evaporation was not precisely be used for RTFF models although some studies used simple statical

Table 5
Recent Merging techniques of rain gauge and radar station data in recent studies.

Case study	Merging techniques: Bias adjustment	Interpolation	Integration	Reference
Hong Kong	–	Plausible probability distribution	–	Jiang and Tung, (2013)
Flanders, Belgium	Multiquadric surface fitting	–	–	Martens et al., (2013)
Lower Saxony, Germany	–	Kriging with external drift, Conditional merging	–	Berndt et al., (2014)
Cévennes-Vivarais, France	Quantitative precipitation estimates	Ordinary Kriging, Kriging with external drift	–	Delrieu et al., (2014)
Copenhagen, Denmark	Time-dynamic adjustment	–	–	Lowe et al., (2014)
UK	Multiquadric surface fitting	Kriging	–	Jewell and Gaussiat, (2015)
North of England	–	Ordinary Kriging, Kriging, Kriging with external drift	–	Nanding et al., (2015)
Lower Saxony, Germany	–	Kriging with external drift, Conditional merging	–	Rabiei and Haberlandt, (2015)
North of England	Exponential correlations	–	–	Rico-Ramirez et al., (2015)
London, UK	–	–	Bayesian data merging	Wang et al., (2015)
Odense, Denmark	–	Static and dynamic	–	Borup et al., (2016)
Cévennes-Vivarais, France	Quantitative precipitation estimates	Ordinary Kriging, Kriging with external drift	–	Boudevillain et al., (2016)
Sydney, Australia	–	Nonparametric and Dynamic combinatorial	–	Hasan et al., (2016)
Northern Finland	–	Kriging	–	Pulkkinen et al., (2016)
Bethlehem, Jerusalem	–	Combination and Multiday aggregation	–	Bárdossy and Pegram, (2017)
Northern England	–	Kriging	–	Cecinati et al., (2017)
Helsinki, Finland	Mean-field bias	Advection	–	Niemi et al., (2017)
Catchment in Paris	–	Classical statistical analysis	–	Paz et al., (2017)
Busan, Korea	–	Conditional merging	–	Dao et al., (2020a)
Seoul, Korea	–	Ordinary Kriging	–	Dao et al., (2020b)
Zhengzhou, China	–	Kriging	–	Wu et al., (2020)

equations for calculating daily evaporation (Olsson et al., 2017; Courdent et al., 2018; Fidal and Kjeldsen, 2020).

3.4. Missing data

While the performance of the RTFF models depends on data availability, missing data that are a common occurrence can affect the model's performance significantly (Sharifi et al., 2016). Missing data occur when part of the data is not available mainly due to equipment failures, database loss, no data accessibility and no allowance to publicise (Kamwaga et al., 2018; Brunner et al., 2021). Aissia et al. (2017) recommended three approaches when dealing with incomplete or missing data as (1) selecting only continuous data records and neglecting events with missing data, (2) removing minor gaps from the dataset and considering the remaining data as a continuous dataset, (3) infilling gaps with suitable imputation techniques such as linear regression, double mass curve technique and subsidiary rainfall-runoff modelling. The first two approaches may either remove a large part of the dataset or be impossible when dealing with time-series data. However, the third one seems more efficient despite skewing the existing patterns recognised by original data (Aieb et al., 2019).

While there are no clear guidelines for data imputation in the context of UDS's missing data, infilling gaps have been widely used for rainfall prediction or non-urbanised flood forecasting (Aires, 2020; Kamkhad et al., 2020). Specific methods used for infilling missing data include the simple mean value of available data (Anbarasan et al. 2020), data mining techniques such as the K-Nearest Neighbours method (Motta et al. (2021) and empirical regression methods (Kamwaga et al. 2018). Dumedah et al. (2014) also applied 14 different artificial neural networks (ANN) and statistical methods for infilling missing soil moisture records in flood forecasting and showed ANN is the best suited infilling method. However, this issue needs to be more focused on RTFF in the UDS context.

3.5. Data cleaning

Data cleaning is defined as the process of identification and removal of irrelevant and outlier data to increase the accuracy of data-driven modelling (Brunner et al., 2021). Although hydrological data are usually collected continuously for both dry and wet weather (Fig. 5, rainfall and runoff data may only be needed during wet weather. Chamber water depth in the UDS conduits can change as a result of several reasons including (1) sanitary sewage discharged into combined UDS, (2) leakage/exfiltration or infiltration, and (3) flood from the UDS catchments. (Rahmati et al., 2020; Brunner et al., 2021). Hence, the time-series data during dry weather (i.e. 1 and 2 in Fig. 5) or wet weather with no changes on chamber water depth (i.e. 3 in Fig. 5) can be removed from the analysing period. Removal of irrelevant data can improve the computational time of building data-driven models and enhance the accuracy of estimations. Such data cleaning techniques have been considered in a few studies such as the warehouse method such as a data mining technique used to classify data in urban flood databases (Wu et al. 2020) and the surrogate model for data assimilation (Lund et al. 2019). While there is no general guideline for flood event identification specifically in urban areas (Darabi et al., 2019; Rahmati et al., 2020), classification techniques such as data mining methods and their application in event identification can be promising for future works.

When using flood events in the RTFF in UDS, other important factors for the prediction accuracy are the numbers of rainfall events and their return periods. Obviously, the more the number of rainfall events and the longer return periods in the dataset, the better model performance and accuracy we can expect. Analysis of the RTFF in UDS in Fig. 6 shows only a small proportion of studies (19%) benefited from a large number of events (i.e. over 1000 events) whereas the majority (73%) used less than 100 events in the RTFF. Furthermore, a similar proportion of the studies (17%) used rainfall with maximum return periods of over 10 years while almost half of the studies (48%) employed rainfall events with less than a one-year return period. While storms with a return period of over 5 years are used for UDS design (Hamil, 2011; DEFRA, 2021), the existing data-driven models for RTFF have mainly relied on events with short return periods as they may suffer from the lack of sufficient accessible or reliable data or alternatively prefer to focus on more frequent events.

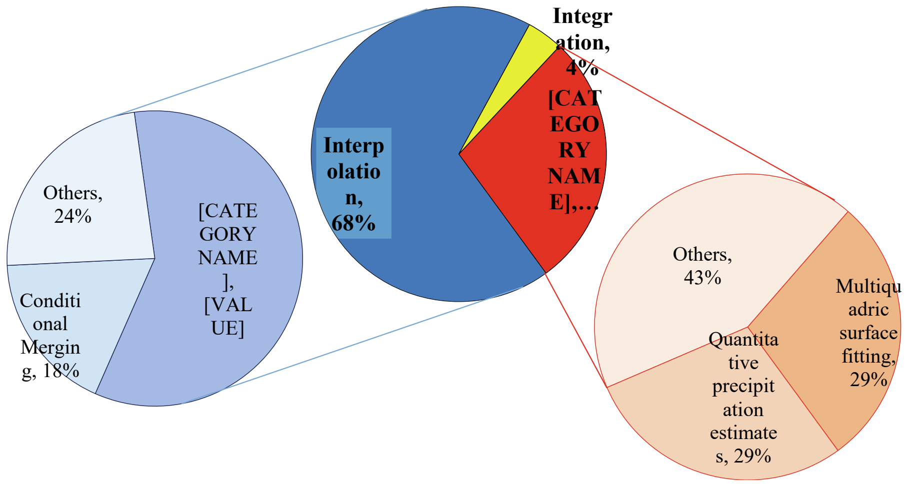


Fig. 4. Dashboard of techniques to merge rain gauge-radar data (out of 21 papers).

Table 6
Temporal and spatial resolutions of rainfall data in the collected studies (out of 48 papers).

Resolution classification	Rainfall source	
	Rain gauge	Rainfall radar
a) Temporal (minutes)		
<15	29%	**73%**
15	**40%**	17%
15 <	31%	10%
b) Spatial (Km)		
<1	–	34%
1	–	**60%**
1 <	–	6%

Table 7
Description and role of main elements of UDS's chamber water depth fluctuation*

Element	Definition	Effects on RTFF in UDS
Surface runoff	Flow, running off the land surfaces and finally is discharged into UDS.	The main cause of urban flooding
Diurnal pattern of sewage	A pattern of generated domestic wastewater, which recurs during day or month.	Plays a vital role in combined system overflow (CSO) by loading water during rainfall occurrence.
Fluvial flow	Flow, Transferred from direct raining over the UDS	Chamber water depth response to fluvial flow faster than surface runoff
Leakage	UDS flow transmitted to neighbouring soil layers due to structural failures.	Make noise on chamber water depth data because are completely variable and usually hardly can be captured.
Evaporation from the water surface of open conduits	The proportion of UDS's water turning into water vapour	
Infiltration	Slow response and lateral groundwater flow, infiltrated by neighbouring soil layers, loads to UDS, suffering from structural failures.	

*: Inspired from Lund et al. (2019), Fidal and Kjeldsen (2020), Wu et al. (2020), AMS (2020), Met Office (2020) and DEFRA (2021).

4. Model development

Models developed for urban flood forecasting are mostly classified based on the model structure and spatial extension (Salvadore et al., 2015; Sitterson et al., 2017). The three typical structures of urban flood forecasting models are physical, conceptual and empirical as defined and compared in Table 9. Physical models are basically hydraulic models that simulate flood events based on physical laws and theoretical principles with hydrological and hydraulic data (Muller and Haberlandt, 2018; Wang et al., 2019). Although these models have significant advantages, their disadvantages are known as requiring extreme detail and various data (Macchione et al., 2019; Li, 2020).

Table 8
Key features of catchment and weather characteristics in RTFF in UDS*

Parameters	Definition in flood forecasting community	Impact on RTFF
Soil moisture	The water content of the soil before flood occurrence	Conversion rate to surface runoff and lag time to reach the entry of UDS
Wind flow patterns	Speed and direction of the wind during rainfall	Influence rainfall estimates by specifying the direction and speed of raining
Air temperature, air moisture and Evaporation of surface runoff	The amount of water vapour in the air and the kinetic energy of air, which results in the specification of the proportion of surface runoff turning into water vapour before reaching UDS. It mainly depends on air temperature, air moisture and previous rainfall	Disappearing surface runoff before reaching UDS

*: Inspired by Hamil (2011), Yao et al. (2016), Zhu et al. (2016), Birkinshaw et al. (2020) and Liu et al. (2020).

Despite the physical models that are used mostly for UDS design, empirical models are mostly applied to RTFF in UDS. Using physical models in RTFF can be challenging due mainly to (1) high demand for geospatial data such as sewer networks and high-resolution topography for developing a numerical urban flood model which is constantly altered by intense human activities, (2) inability to simulate urban flood forecasting in a real-time or near real-time, and (3) poor performance in ungauged areas because the model parameters may not be well-calibrated or the calibration can be sophisticated when physical conditions change (Yin et al., 2017; Abou Rajeily et al., 2018; Yin et al., 2020) (4) lack of proper sampling design or strategy for collecting measurement data to be used for model calibration (Behzadian et al., 2009). Hence, the physical models have been mainly used for UDS design purposes under specific return periods of rainfall or certain predicted or historic rainfall data rather than real-time flood predictions based on

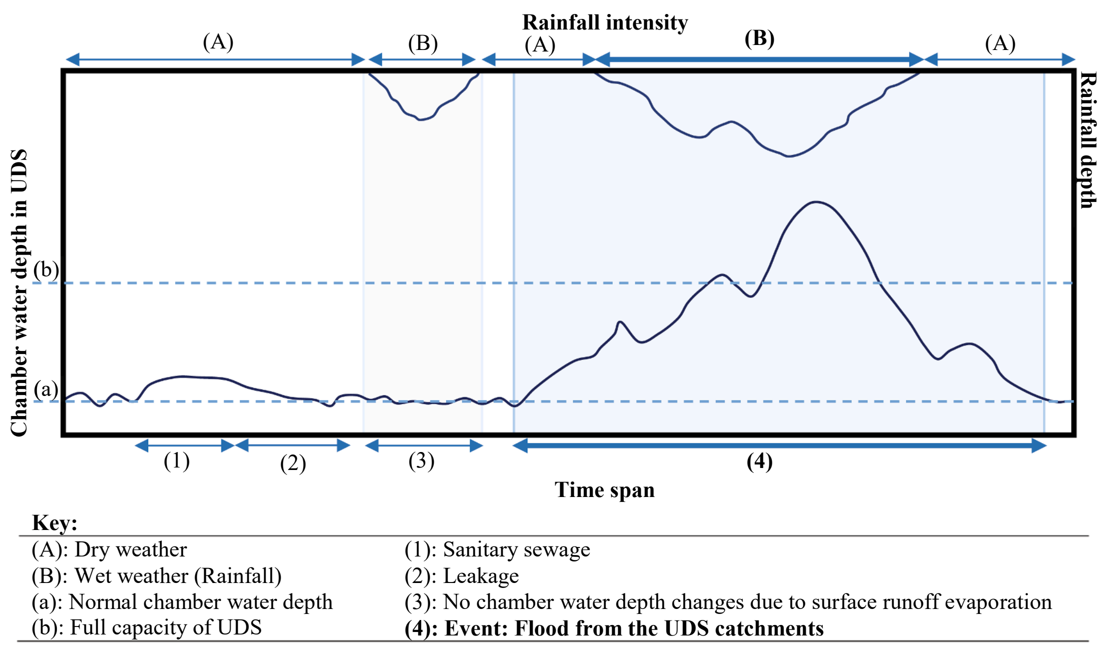


Fig. 5. The schematic variation of rainfall and chamber water depth in the UDS catchments.

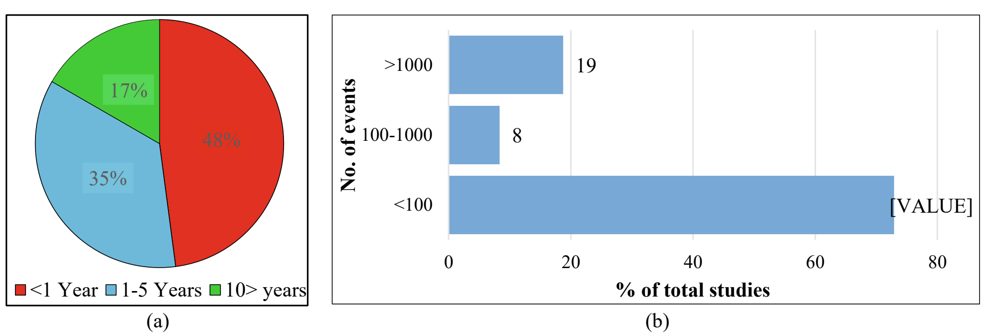


Fig. 6. % of frequency our of 48 papers related to RTFF studies for a) maximum return period of rainfall events b) number of rainfall events.

rainfall data records (García et al., 2015; Garofalo et al., 2017; Nkwunonwo et al., 2020). To overcome this, advanced empirical models with interconnected time-series data were developed (Tian et al., 2019; Xu et al., 2020). These models can be made by training through several observed input and output data without any restrictions of prior knowledge about hydrological processes and can be adapted by real-time data frequently (Ravazzani et al., 2016). However, the accuracy of these data-driven models heavily relies on the accuracy of input data (Zhang et al., 2018; Xu et al., 2020). Furthermore, estimations may be highly inaccurate for extrapolated events that were not used within the scope of input data of the model development (Zhao et al., 2019; Wu et al., 2020). Finally, as a trade-off between physical and empirical models, conceptual models were defined based on the knowledge and relationships of the hydrological processes without using physical data (Ben et al., 2019; KC et al., 2021).

Three main approaches found in the literature to improve the quality of the RTFF in UDS (A list of recently developed models used in real case studies of flood forecasting in UDS is shown in Table 10 with a dashboard summary in Fig. 7) are as follows: 1) optimisation methods for calibration of model parameters, 2) hybridisation approach by adding AI-based methods to existing physical models, and 3) alternative conventional or dynamic ANN models to predict longer steps ahead compared to physical models.

The vast majority of the optimisation models have been introduced recently such as Evolutionary Algorithms e.g. Memetic Algorithms and Particle Swarms Optimisation for calibration of model parameters in the other contexts rather than RTFF in UDS (Rajput and Datta, 2020; Raut et al., 2021). However, a few of them were used to advance physically based models in UDS. Genetic Algorithm and Particle Swarm Optimisation have been the most popular approaches that were used for optimal calibration, design and operation of UDS that were mainly simulated by Storm Water Management Model (SWMM).

Overall, urban flood forecasting Models have been developed for three main purposes, including flood inundation and understanding the surface runoff risk, design of UDS due to flood occurrence, and chamber water depth prediction. Most of the studies have relied on the first two purposes. Out of 35 studies published in the last decade, 77% were published in the recent five years showing great interest in urban flood forecasting in UDS. However, an increasing rate of studies for using data-driven methods indicate the special attention to these models due mainly to more availability of real-time data, improved computational efforts in the recent software and hardware and AI enhancement. This progress has also allowed researchers to use both data-driven and conceptual/physical models as a hybrid approach. For example, Bermúdez et al. (2018) coupled deep learning techniques such as gradient boosting decision tree (GBDT) to enhance the prediction of urban floods and concluded that hybrid methods can perfectly cover the drawback of both empirical and physical models.

Table 9
Classification of structure in the UDS flood forecasting models*

Characteristics	Type		
	Empirical	**Conceptual**	**Physical**
Definition	A data-driven model, making a non-linear relationship between inputs and outputs	Simplified equations interpret runoff processes by connecting components in the overall hydrological process	hydraulic models translating physical laws and theoretical principles on real hydrological responses.
Strengths	- Easy to develop - A small number of input parameters - More accurate outputs for short-time forecasting - Usually fast run time and short computational efforts	- Easy to calibrate - Simple model structure - More physical elements than empirical models - Fewer inputs than physical models	- Avoid non-physical outputs - Able to handle future long-term forecasting - Use of previous experienced knowledge
Weaknesses	- Unreasonable estimations for extrapolated events - Performance is highly dependent on the accuracy of input data - Capability limited to its development context	- Need training process - Spatial variation is not considered	- The required large number of input parameters for calibration and sometimes simplifying assumptions - Restricted to the degree of phenomena's understanding
Best use	- Ungagged locations - When only runoff output is required - When there is a lack of site-specific details - When the model is heavily independent of experimental data	- -When access to physical data is limited	- When physical data are available - When more detailed analysis and design are required - Where a high level of spatial resolutions is required
Representation of event	- Usually, black box1	- Mostly grey box2	- White box3
Spatial processes	- Lumped[4]	- Mostly semi-distributed[5]	- Mostly Distributed[6]

*: Inspired from Wagener et al. (2004), Gosain et al. (2009), Jajarmizadeh et al. (2012) and Sitterson et al. (2017).
1: Various data are transformed into predictions without understanding features and transparency in modelling processes.
2: A partial theoretical structure is combined with data for modelling.
3: Generated output and the relationship between variables can be physically demonstrated.
4: A model disregarding spatial variability and treats the entire UDS as one unit.
5: A model considering a series of lumped and distributed parameters.
6: A model accounting UDS with spatial resolutions.

Physical and empirical models account for the majority of those developed in the recent decade for forecasting urban flooding (Fig. 7a). The relatively equal usage of the three spatial resolutions (i.e. lump, semi-distributed and distributed models) in the developed models (Fig. 7b) can also indicate the importance and interest of all spatial resolutions for model developers. However, results show that empirical models are mostly developed by lumped spatial resolution, whereas physical models have used the distributed option.

Furthermore, in the past, academic research has favoured the development of physical and empirical models over data-driven ones, but this trend is changing now. Among empirical models developed recently for urban flood modelling as shown in Fig. 7d, Curved Number Method (CNM) and artificial neural network (ANN) are the most used methods in recent years (Yin et al., 2017; Dao et al., 2020a). The CNM techniques have been further advanced by including spatial variability, more accurate data collection, and hiring finer data resolution (Yin et al., 2020; Birkinshaw et al., 2020). Furthermore, ANN has been used to upgrade the physical models (Bermúdez et al., 2018; Li, 2020). Only about 20% of the 37 studies reviewed here applied AI for the RTFF in UDS. Those studies used deep learning models to find a relationship between time-series rainfall data and water depth of conduits in UDS for predicting the water depth in the future time steps. Mounce et al. (2014) used conventional ANN to predict water depth in sewer chambers up to 3h ahead using time-series of rainfall radar and gauging station data in UDS. Chang et al. (2014) used recurrent ANN for urban flood control and compared the performance of convolutional ANN with dynamic ANNs, particularly nonlinear autoregressive network with exogenous inputs (NARX). Their results showed NARX models outperform other models for prediction accuracy in longer periods due to the memory capability in processing the variable-length sequences of inputs and creating feedback connections enclosing several layers of the network. Abou rjeily et al. (2017) showed NARX model can effectively predict flood in a complex UDS for both minor and severe storm events. Finally, Zhange *et al.* (2018) applied a dynamic ANN method called long short-term memory (LSTM) for monitoring combined sewer overflow and showed conventional ANN models can only forecast one or two steps ahead accurately while LSTM has the capability for predicting multiple steps ahead especially for multivariate time series data.

Despite the promising results reported for applying the AI-based methods (e.g. ANN, support vector machine models, adaptive neuro-fuzzy inference system and decision tree method) to RTFF of non-urbanised areas (Mosavi et al., 2018; Zounemat-Kermani et al., 2020; Zounemat-Kermani et al., 2021), these applications are in the early stage of development for urban areas. Hence, the RTFF in UDS is expected to improve through any of the above approaches with significant research modelling methods and experimentation for further improvement.

4.1. Performance assessment

As part of the model development, its performance needs to be evaluated basically by comparing the model outputs with the corresponding measurements for the data not used for the model development (Dal et al., 2017). The performance assessment can also be along with adjusting the model parameters that are typically called model calibration and validation. After the model calibration, the model performance can be tested for future events and unseen data. Performance assessment can be carried out through key performance indicators (KPIs) represented as either model accuracy of predictions or computational effort (time).

Table 11 lists typical KPIs used in the recent studies of the RTFF in UDS. As the main goal of the RTFF is to give time for early actions to reduce the flood risks, the maximum time spent by the model to process the data and predict the flood is an important factor for relevant authorities to select the model for their operations. However, this issue is not focused very well in the papers. The first approach to measure is computational time, i.e. time spent on performing computational processes. However, this parameter highly depends on the characteristic of system configuration and cannot be compared for different developed models that are presented all around the world. Therefore, the number of iterations for iterative-based models is introduced as a surrogate KPI for the computational time by Abou Rjeily et al. (2017). In this approach, correlation between the model accuracy and the number of iteration was investigated to specify the model performance.

Prediction range is the other factor that shows the model performance. As the main goal of the RTFF is to give sufficient time for early actions to reduce the flood risks, the maximum prediction range is an important factor for relevant authorities to select the model for their

Table 10
Recent urban flood forecasting models applied for UDS.

Case study	Rainfall-runoff modelling method						Used AI models for real-time forecasting	Reference
	Model structure			Spatial resolution				
	Empirical	Conceptual	Physical	Lumped	Semi distributed	Distributed		
UK	ANN	–	–	●			●	Mounce et al., (2014)
Taipei, Taiwan	ANN	–	–	●			●	Chang et al., (2014)
Dongguan, China	–	–	SWM			●		Chen et al., (2015)
Beijing, China	–	–	SWMM	●				Yao et al., (2016)
Guangzhou, China	–	–	SWMM		●			Zhu et al., (2016)
Odense, Denmark		–	MIKE -Mouse			●		Borup et al., (2016)
Milano, Italy	CNM	–	–	●				Ravazzani et al., (2016)
Espoo, Finland	–	–	SWMM			●		Guan et al., (2016)
Cosenza, Italy	–	–	SWMM			●		Garofalo et al., (2017)
Malmo, Sweden	HYPE	–	–		●			Olsson et al., (2017)
Barcelona, Spain	CNM	–	–	●				Angrill et al., (2017)
Shanghai, China	CNM	–	–		●			Yin et al., (2017)
Helsinki, Finland	–	–	SWMM			●		Niemi et al., (2017)
Lille, France	ANN	–	SWMM			●	●	Abou Rjeily et al., (2017)
Brunswick, Germany	–	–	SWMM		●			Muller and Haberlandt, (2018)
Ghent, Belgium	ANN	Virtual storage	–			●	●	Bermúdez et al., (2018)
Copenhagen, Denmark	–	Nash linear reservoir cascade	–		●			Courdent et al., (2018)
Lille, France	–	–	SWMM			●		Abou Rajeily et al., (2018)
Drammen, Norway	LSTM, GRU	–	–	●			●	Zhang et al., (2018)
Melbourne, Australia	–	–	MIKE urban		●			Thrysøe et al., (2019)
Lafayette Parish, USA	–	–	SWM			●		Wang et al., (2019)
Northern China	Hebei	–	–		●			Tian et al., (2019)
Badalona, Spain	–	Virtual tank	–		●			Ben et al., (2019)
Copenhagen, Denmark	–	–	MIKE urban			●		Lund et al., (2019)
UK	LASSO, ANN	–	–	●			●	Zhao et al., (2019b)
Joao Pessoa, Brazil	–	–	SWMM		●			Silva and Silva, (2020)
Zhuhai, China	–	CaDDIES	SWMM, MIKE 21		●			Yin et al., (2020)
Salt lake, USA	–	–	RBC SWMM			●		Li, (2020)
Zhengzhou, China	GBDT, Data warehouse	–	–	●			●	Wu et al., (2020)
Seol, South Korea	CNM	–	–	●				Dao et al., (2020a)
Xiamen Island, China	–	–	SWM			●		Liu et al., (2020)
Munich, Germany	CNM, I-Tree Canopy method	–	–	●				Xu et al., (2020)
Great London, UK	URMOD	–	–	●				Fidal and Kjeldsen, (2020)
Newcastle, UK	–	–	Shetran		●			Birkinshaw et al., (2020)
Kathmandu, Nepal	–	–	PCSSWMM			●		KC et al., (2021)

AI: Artificial intelligence; ANN: Artificial Neural Network; CADDIES: Cellular Automata Dual DraInagE Simulation
CNM: Curve Number method; GBDT: Gradient Boosting Decision Tree; GRU: gated recurrent unit
LASSO: least absolute shrinkage and selection operator; LSTM: long short-term memory; NM: Not mentioned
SCEM-UA: Shuffled Complex Evolution Metropolis; SWM: Shallow Water Model; SWMM: Storm Water Management Model

operations. However, the number of time steps ahead for prediction of urban flood in recent studies has been limited to short-term mostly between 15 min to 90 min (See Table 11). These studies show that the accuracy of predictions made for periods longer than 60 min have been reduced significantly. Note that some physically based parameters such as catchment area and time of concentration can influence the performance of model predictions. For example, the accuracy of model predictions for larger catchment areas can be lower than those for smaller catchment areas. Also note that the impact of these parameters are likely to be negligible temporally and spatially for small catchment areas or short times of concentration. As a result, this poor performance can be translated as the deficiency of current RTFF in UDS to provide accurate predictions for longer periods, which need more attention in future works.

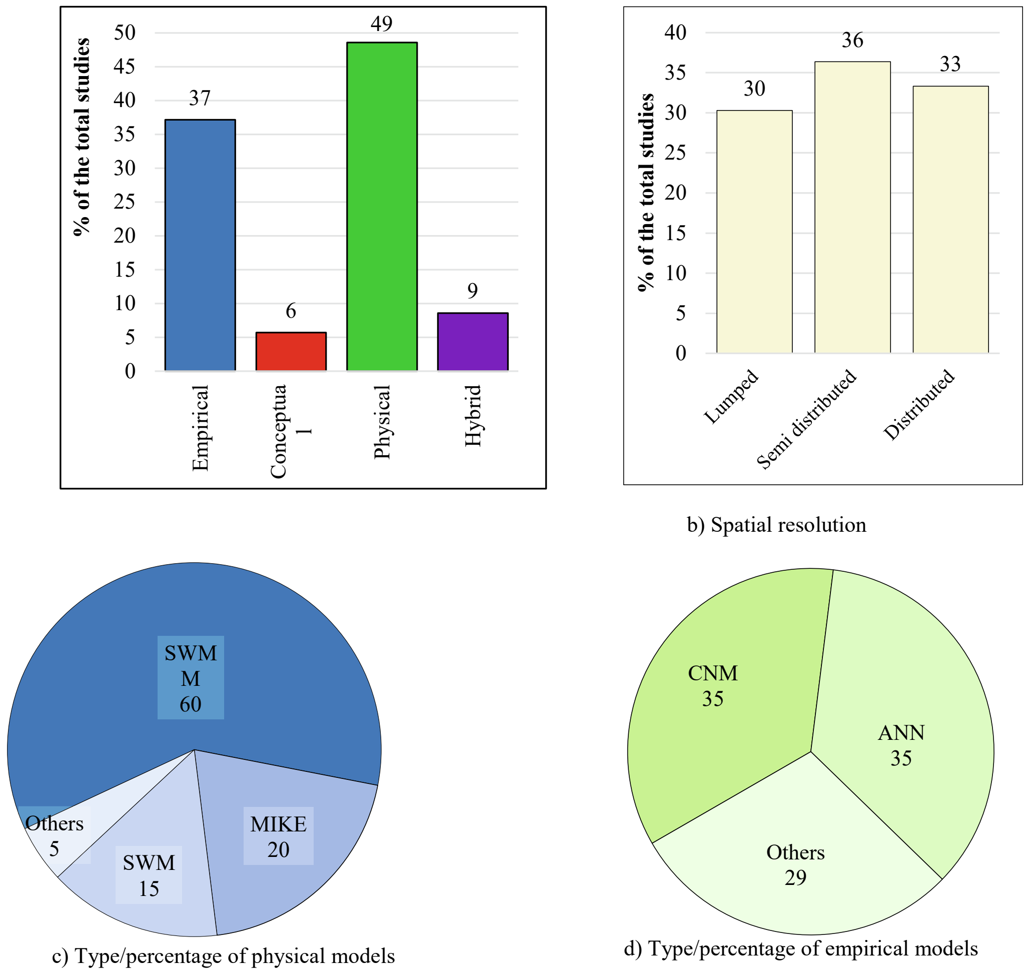


Fig. 7. Dashboard of recently developed rainfall-runoff models for flood forecasting in UDS (out of 37 studies).

Finally, although sensitivity analysis and uncertainty analysis methods have been widely used as an integral part of uncertainty assessments and accuracy of model calibration, their potential benefits have not been fully revealed in the concepts of RTFF in UDS (Razavi et al., 2021). Nkwunonwo et al. (2020) stated that parameterisation data and sensitivity analysis were usually overlooked in this concept and lack of uncertainty analysis is identified as the main deficiency in the performance assessment of real-time urban flood forecasting methods (Daal et al. 2017). As a result, the particular importance of including sensitivity analysis and uncertainty analysis in any RTFF in UDS should be incorporated in the model results.

5. Conclusions

This paper used a bibliometric approach to conduct a critical review of the recent developments of real-time flood forecasting models in urban drainage systems. The review evaluated all steps of the RTFF models in UDS including data collection and preparation, model calibration and performance assessment. The results demonstrated that there has been a surge of interest in the RTFF in UDS and this will continue to receive more attention in the future. The following points are concluded for future directions of the RTFF in UDS:

-Rain gauge-radar merging methods have been mainly employed in large scale non-urbanised applications. However, most literature worked on RTFF in UDS, have been used a single rainfall source for their modelling mainly because other rainfall sources cannot provide required data resolution or they are not compatible with the main rainfall data source which needs to be merged with. As a result, the literature on the performance assessment of using multiple rainfall resources is needed to specify the applicability of data merging in the context of RTFF in UDS.

-The rainfall merging techniques have been highly relied on the application of interpolation techniques, leading by kriging techniques and conditional merging techniques. However, there is a high demand to investigate the accuracy of integration techniques for urban data collection due to the successful application of this method in other hydrological applications.

-Using satellite products alone or by merging with a rain gauge or radar data should be more practised to take the opportunity of extending the valuable prediction range for early actions as a result of early flood warning.

-The effect of rainfall both spatial and temporal resolution on the accuracy of urban flood forecasting is recognised as an important research area that can be more focussed.

-Diurnal pattern of sewage for combined system cases, leakage, fluvial flow, UDS's infiltration and leakage rate, evaporation from the water surface of open conduits and should be dynamically accounted for building more accurate RTFF models. Furthermore, the dynamic role of soil moisture, wind flow pattern, air temperature and evaporation of surface runoff should be explored effectively to be included in these models.

-Providing effective imputation techniques to infill the missing data as a pre-processing step is significant to have reliable data for the RTFF models in UDS. Data cleaning especially event identification needs to be considered properly for developing RTFF models. More specifically, data classification techniques, particularly data mining techniques, should be used to remove unnecessary data.

Table 11
KPIs used in recent publications of the RTFF in UDS.

Reference	Computational time method	Prediction range (min)	Results
Mounce et al., (2014)	NM	15, 60, and 180	Acceptable performance for 15- and 60-minute prediction ahead. 180-minute ahead of prediction loses its accuracy.
Chang et al., (2014)	NM	10, 20, 30, 40, 50 and 60	The accuracy of the model for 60-minute ahead is significantly reduced in comparison to other prediction ranges.
Abou Rjeily et al., (2017)	Numbers of iteration	15	Regression results show nearly 100% of accuracy.
Abou Rajeily et al., (2018)	Numbers of iteration	15	Regression results show nearly 100% of accuracy.
Zhang et al., (2018)	NM	15, 30, 45, 60, 75 and 90	The accuracy of the model for longer than 60-minute ahead is significantly reduced in comparison to other prediction ranges.
Zhao et al., (2019b)	NM	15, 30, 45, 60, 75	The accuracy of the model for periods longer than 60-minute ahead is significantly reduced in comparison to other prediction ranges.

NM: Not Mentioned.

-Physical models have been mostly used for the UDS design and few cases focus on RTFF models in UDS. While AI models such as NARX and LSTM have been revitalised in recent years, it seems that they are taken into account as first steps in this context. Consequently, further progress in applying these models is an imperative demand as a momentous future direction.

-Computational time and prediction range should be more spotlighted in future studies as part of the performance assessment due to their role in offering sufficient lead time for taking preventive decisions by operators.

-Sensitivity analysis and uncertainty analysis should be more discovered for RTFF in UDS in order to cover the gap of calibration of model parameters and the uncertainty of model results.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abou Rjeily, Y., Abbas, O., Sadek, M., Shahrour, I., Chehade, F., 2017. Flood forecasting within urban drainage systems using NARX neural network. Water Sci. Technol. 76 (9–10), 2401–2412.
Abou Rjeily, Y., Abbas, O., Sadek, M., Shahrour, I., Hage Chehade, F., 2018. Model Predictive Control for optimising the operation of Urban Drainage Systems. J. Hydrol. 566, 558–565.
Acharya, R., 2017. Satellite Signal Propagation, Impairments and Mitigation, 1st Ed. Academic press, Cambridge, pp. 195–245.
Aieb, A., Madani, K., Scarpa, M., Bonaccorso, B., Lefsih, K., 2019. A new approach for processing climate missing databases applied to daily rainfall data in Soummam watershed, Algeria. Heliyon 5 (2), e01247. https://doi.org/10.1016/j.heliyon.2019.e01247.
Aires, F., 2020. Surface water maps de-noising and missing-data filling using determinist spatial filters based on several a priori information. Remote Sens. Environ. 237, 111481. https://doi.org/10.1016/j.rse.2019.111481.
American Meteorological Society (AMS). (2020). *Glossary of Weather, Climate and Ocean.* [online]. Available at: http://glossary.ametsoc.org, [Accessed12 Dec. 2020].
Anbarasan, M., Muthu, B., Sivaparthipan, C.B., Sundarasekar, R., Kadry, S., Krishnamoorthy, S., Jackson, D., Dasel, A.A., 2020. Detection of flood disaster system based on IoT, big data and convolutional deep neural network. Comput. Commun. 150, 150–157.
Angrill, S., Petit-Boix, A., Morales-Pinzón, T., Josa, A., Rieradevall, J., Gabarrell, X., 2017. Urban rainwater runoff quantity and quality – A potential endogenous resource in cities? J. Environ. Manage. 189, 14–21.
Ben Aissia, M.-A., Chebana, F., Ouarda, T.B.M.J., 2017. Multivariate missing data in hydrology – Review and applications. Adv. Water Resour. 110, 299–309.
Balistrocchi, M., Grossi, G., 2020. Predicting the impact of climate change on urban drainage systems in northwestern Italy by a copula-based approach. J. Hydrol. 28, 100670. https://doi.org/10.1016/j.ejrh.2020.100670.
Bárdossy, A., Pegram, G., 2017. Combination of radar and daily precipitation data to estimate meaningful sub-daily point precipitation extremes. J. Hydrol. 544, 397–406.
Behzadian, K., Kapelan, Z., Savic, D., Ardeshir, A., 2009. Stochastic sampling design using a multi-objective genetic algorithm and adaptive neural networks. Environ. Modell. Software 24 (4), 530–541.
Belete, M., Deng, J.i., Wang, K., Zhou, M., Zhu, E., Shifaw, E., Bayissa, Y., 2020. Evaluation of satellite rainfall products for modelling water yield over the source region of Blue Nile Basin. Sci. Total Environ. 708, 134834.
Ben, L.R., Sun, C., Palma, R.G., Duran, B.J., Meseguer, J., Cembrano, G., Puig, V., 2019. A Feedback Simulation Procedure for Real-time Control of Urban Drainage Systems. IFAC-Papers Online 52 (23), 101–106.
Bermúdez, M., Ntegeka, V., Wolfs, V., Willems, P., 2018. Development and Comparison of Two Fast Surrogate Models for Urban Pluvial Flood Simulations. Water Resource Manage. 32 (8), 2801–2815.
Berndt, C., Rabiei, E., Haberlandt, U., 2014. Geostatistical merging of rain gauge and radar data for high temporal resolutions and various station density scenarios. J. Hydrol. 508, 88–101.
Berndtsson, R., Becker, P., Persson, A., Aspegren, H., Haghighatafshar, S., Jönsson, K., Larsson, R., Mobini, S., Mottaghi, M., Nilsson, J., Nordström, J., Pilesjö, P., Scholz, M., Sternudd, C., Sörensen, J., Tussupova, K., 2019. Drivers of changing urban flood risk: A framework for action. J. Environ. Manage. 240, 47–56.
Birkinshaw, S.J., O'Donnell, G., Glenis, V., Kilsby, C., 2021. Improved hydrological modelling of urban catchments using runoff coefficients. J. Hydrol. 594, 125884. https://doi.org/10.1016/j.jhydrol.2020.125884.
Borup, M., Grum, M., Linde, J.J., Mikkelsen, P.S., 2016. Dynamic gauge adjustment of high-resolution X-band radar data for convective rainstorms: Model-based evaluation against measured combined sewer overflow. J. Hydrol. 539, 687–699.
Boudevillain, B., Delrieu, G., Wijbrans, A., Confoland, A., 2016. A high-resolution rainfall re-analysis based on radar–raingauge merging in the Cévennes-Vivarais region, France. J. Hydrol. 541 (A), 14–23.
Brunner, M.I., Slater, L., Tallaksen, L.M., Clark, M., 2021. Challenges in modeling and predicting floods and droughts: A review. WIREs Water 8 (3). https://doi.org/10.1002/wat2.v8.310.1002/wat2.1520.
Cecinati, F., Wani, O., Rico-Ramirez, M.A., 2017. Comparing Approaches to Deal With Non-Gaussianity of Rainfall Data in Kriging-Based Radar-Gauge Rainfall Merging. Water Resour. Res. 53 (11), 8999–9018.
Chang, F.-J., Chen, P.-A., Lu, Y.-R., Huang, E., Chang, K.-Y., 2014. Real-time multi-step-ahead water level forecasting by recurrent neural networks for urban flood control. J. Hydrol. 517, 836–846.
Chen, Y., Xu, M., Wang, Z., Gao, P., Lai, C., 2021. Applicability of two satellite-based precipitation products for assessing rainfall erosivity in China. Sci. Total Environ. 757, 143975. https://doi.org/10.1016/j.scitotenv.2020.143975.
Chen, Y., Zhou, H., Zhang, H., Du, G., Zhou, J., 2015. Urban flood risk warning under rapid urbanization. Environ. Res. 139, 3–10.
Cools, J., Innocenti, D., O'Brien, S., 2016. Lessons from flood early warning systems. Environ. Sci. Policy 58, 117–122.
Courdent, V., Grum, M., Mikkelsen, P.S., 2018. Distinguishing high and low flow domains in urban drainage systems 2days ahead using numerical weather prediction ensembles. J. Hydrol. 556, 1013–1025.
Centre for Research on the Epidemiology of Disasters (CRED). (2021). *Emergency Events Database.* [Online] The international disasters database. Available at http://www.emdat.be, [Accessed 09 Apr. 2021].
van Daal, P., Gruber, G., Langeveld, J., Muschalla, D., Clemens, F., 2017. Performance evaluation of real time control in urban wastewater systems in practice: Review and perspective. Environ. Modell. Software 95, 90–101.
Dao, D.A., Kim, D., Kim, S., Park, J., 2020a. Determination of flood-inducing rainfall and runoff for highly urbanized area based on high-resolution radar-gauge composite rainfall data and flooded area GIS data. J. Hydrol. 584, 124704. https://doi.org/10.1016/j.jhydrol.2020.124704.
Dao, D.A., Kim, D., Park, J., Kim, T., 2020b. Precipitation threshold for urban flood warning - an analysis using the satellite-based flooded area and radar-gauge composite rainfall data. J. Hydro-environ. Res. 32, 48–61.
Darabi, H., Haghighi, A., Mohamadi, M., Rashidpour, M., Ziegler, A., Hekmatzadeh, A., Kløve, B., 2020. Urban flood risk mapping using data-driven geospatial techniques for a flood-prone case area in Iran. Hydrol. Res. 51 (1), 127–142.
Delrieu, G., Wijbrans, A., Boudevillain, B., Faure, D., Bonnifait, L., Kirstetter, P.-E., 2014. Geostatistical radar–raingauge merging: A novel method for the quantification of rain estimation accuracy. Adv. Water Resour. 71, 110–124.
Department for Environment, Food and Rural Affairs (DEFRA). (2021). *DEFRA* Official Website [Online] Available at http://Environment.data.gov.uk, [Accessed 12 Jan. 2021].
Ding, Y., Rousseau, R., Wolfram, D., 2014. Measuring scholarly impact: Methods and practice, 1st Ed. Springer, London, pp. 285–320.

Dumedah, G., Walker, J.P., Chik, L.i., 2014. Assessing artificial neural networks and statistical methods for infilling missing soil moisture records. J. Hydrol. 515, 330–344.
Fidal, J., Kjeldsen, T.R., 2020. Accounting for soil moisture in rainfall-runoff modelling of urban areas. J. Hydrol. 589, 125122. https://doi.org/10.1016/j.jhydrol.2020.125122.
Figueroa, M., Armijos, E., Espinoza, J., Ronchail, J., Fraizy, P., 2020. On the relationship between reversal of the river stage (repiquetes), rainfall and low-level wind regimes over the western Amazon basin. J. Hydrol.: Reg. Stud. 32, 100752.
García, L., Barreiro-Gomez, J., Escobar, E., Téllez, D., Quijano, N., Ocampo-Martinez, C., 2015. Modeling and real-time control of urban drainage systems: A review. Adv. Water Resour. 85, 120–132.
Garofalo, G., Giordano, A., Piro, P., Spezzano, G., Vinci, A., 2017. A distributed real-time approach for mitigating CSO and flooding in urban drainage systems. J. Network Comput. Appl. 78, 30–42.
Geravand, F., Hosseini, S.M., Ataie-Ashtiani, B., 2020. Influence of river cross-section data resolution on flood inundation modeling: Case study of Kashkan river basin in western Iran. J. Hydrol. 584, 124743. https://doi.org/10.1016/j.jhydrol.2020.124743.
Goh, K.H., See, K.F., 2021. Twenty years of water utility benchmarking: A bibliometric analysis of emerging interest in water research and collaboration. J. Cleaner Prod. 284, 124711. https://doi.org/10.1016/j.jclepro.2020.124711.
Gosain, A., Mani, A., Dwivedi, C., 2009. Hydrological Modelling-Literature Review. Advances in Fluid Mechanics 339, 63–70.
Guan, M., Sillanpää, N., Koivusalo, H., 2016. Storm runoff response to rainfall pattern, magnitude and urbanization in a developing urban catchment. Hydrol. Process. 30, 543–557.
Pour, S.H., Wahab, A.K.A., Shahid, S., Asaduzzaman, M.d., Dewan, A., 2020. Low impact development techniques to mitigate the impacts of climate-change-induced urban floods: Current trends, issues and challenges. Sustain. Cities Soc. 62, 102373. https://doi.org/10.1016/j.scs.2020.102373.
Hadid, B., Duviella, E., Lecoeuche, S., 2020. Data-driven modelling for river flood forecasting based on a piecewise linear ARX system identification. J. Process Control 86, 44–56.
Hamil, L., 2011. Understanding Hydraulics, 3rd Ed. Macmillan Education, London, p. 507.
Han, J., He, S., 2021. Urban flooding events pose risks of virus spread during the novel coronavirus (COVID-19) pandemic. Sci. Total Environ. 755, 142491. https://doi.org/10.1016/j.scitotenv.2020.142491.
Hasan, M.M., Sharma, A., Mariethoz, G., Johnson, F., Seed, A., 2016. Improving radar rainfall estimation by merging point rainfall measurements within a model combination framework. Adv. Water Resour. 97, 205–218.
Kourtis, I.M., Tsihrintzis, V.A., 2021. Adaptation of urban drainage networks to climate change: A review. Sci. Total Environ. 771, 145431. https://doi.org/10.1016/j.scitotenv.2021.145431.
Islam, M.A., Yu, B., Cartwright, N., 2020. Assessment and comparison of five satellite precipitation products in Australia. J. Hydrol. 590, 125474. https://doi.org/10.1016/j.jhydrol.2020.125474.
Jajarmizad, M., Harun, S., Salarpour, M., 2012. A Review on Theoretical Consideration and Types of Models in Hydrology. J. Environ. Sci. Technol. 5 (5), 249–261.
Jewell, S.A., Gaussiat, N., 2015. An assessment of kriging-based rain-gauge–radar merging techniques. Q. J. R. Meteorolog. Soc. 141 (691), 2300–2313.
Jiang, P., Tung, Y.-K., 2013. Establishing rainfall depth–duration–frequency relationships at daily raingauge stations in Hong Kong. J. Hydrol. 504, 80–93.
Kamkhad, N., Jampachaisri, K., Siriyasatien, P., Kesorn, K., 2020. Toward semantic data imputation for a dengue dataset. Knowl.-Based Syst. 196, 105803. https://doi.org/10.1016/j.knosys.2020.105803.
Kamwaga, S., Mulungu, D.M.M., Valimba, P., 2018. Assessment of empirical and regression methods for infilling missing streamflow data in Little Ruaha catchment Tanzania. Phys. Chem. Earth. 106, 17–28.
KC, S., Shrestha, S., Ninsawat, S. Chonwattana, S. (2021). Predicting flood events in Kathmandu Metropolitan City under climate change and urbanization. *Journal of Environmental Management*, 281, 111894.
Kim, J., Han, H., Kim, B., Chen, H., Lee, J.-H., 2020. Use of a high-resolution-satellite-based precipitation product in mapping continental-scale rainfall erosivity: A case study of the United States. CATENA 193, 104602. https://doi.org/10.1016/j.catena.2020.104602.
Konami, T., Koga, H., Kawatsura, A., 2021. Role of pre-disaster discussions on preparedness on consensus-making of integrated flood management (IFM) after a flood disaster, based on a case in the Abukuma River Basin, Fukushima, Japan. Int. J. Disaster Risk Reduct. 53, 102012. https://doi.org/10.1016/j.ijdrr.2020.102012.
Li, C., Liu, M., Hu, Y., Shi, T., Qu, X., Walter, M.T., 2018. Effects of urbanization on direct runoff characteristics in urban functional zones. Sci. Total Environ. 643, 301–311.
Li, J., 2020. A data-driven improved fuzzy logic control optimization-simulation tool for reducing flooding volume at downstream urban drainage systems. Sci. Total Environ. 732, 138931. https://doi.org/10.1016/j.scitotenv.2020.138931.
Liu, J., Shao, W., Xiang, C., Mei, C., Li, Z., 2020. Uncertainties of urban flood modeling: Influence of parameters for different underlying surfaces. Environ. Res. 182, 108929. https://doi.org/10.1016/j.envres.2019.108929.
Lund, N., Madsen, H., Mazzoleni, M., Solomatine, D., Borup, M., 2019. Assimilating flow and level data into an urban drainage surrogate model for forecasting flows and overflows. J. Environ. Manage. 248, 109052.
Macchione, F., Costabile, P., Costanzo, C., De Lorenzo, G., 2019. Extracting quantitative data from non-conventional information for the hydraulic reconstruction of past urban flood events: A case-study. J. Hydrol. 576, 443–465.
Maggioni, V., Massari, C., 2018. On the performance of satellite precipitation products in riverine flood modeling: A review. J. Hydrol. 558, 214–224.
Martens, B., Cabus, P., De Jongh, I., Verhoest, N.E.C., 2013. Merging weather radar observations with ground-based measurements of rainfall using an adaptive multiquadric surface fitting algorithm. J. Hydrol. 500, 84–96.
McKee, J., Binns, A., 2015. A review of gauge–radar merging methods for quantitative precipitation estimation in hydrology. Can. Water Resour. J. 41 (1–2), 186–203.
Meteorological Office (Met Office). (2020). *Met office official website* [Online]. Available at http://Metoffice.gov.uk, [Accessed 10 Jan. 2021].
Meyers, S.D., Landry, S., Beck, M.W., Luther, M.E., 2021. Using logistic regression to model the risk of sewer overflows triggered by compound flooding with application to sea level rise. Urban Clim. 35, 100752. https://doi.org/10.1016/j.uclim.2020.100752.
Miller, J.D., Hutchins, M., 2017. The impacts of urbanisation and climate change on urban flooding and urban water quality: A review of the evidence concerning the United Kingdom. J. Hydrol.: Reg. Stud. 12, 345–362.
Moher, D., Liberati, A., Tetzlaff, J., Altman, D., 2009. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med. 6 (7), e1000097.
Motta, M., de Castro Neto, M., Sarmento, P., 2021. A mixed approach for urban flood prediction using Machine Learning and GIS. Int. J. Disaster Risk Reduct. 56, 102154. https://doi.org/10.1016/j.ijdrr.2021.102154.
Mounce, S., Shepherd, W., Sailor, G., Shucksmith, J., Saul, A. (2014). Predicting combined sewer overflows chamber depth using artificial neural networks with rainfall radar data. *Water Science & Technology*, pp. 69(6), 1326-1333.
Mosavi, A., Ozturk, P., Chau, K., 2018. Flood Prediction Using Machine Learning Models: Literature Review. Water 10 (11), 1536.
Mullapudi, A., Lewis, M.J., Gruden, C.L., Kerkez, B., 2020. Deep reinforcement learning for the real time control of stormwater systems. Adv. Water Resour. 140, 103600. https://doi.org/10.1016/j.advwatres.2020.103600.
Muller, H., Haberlandt, U., 2018. Temporal rainfall disaggregation using a multiplicative cascade model for spatial application in urban hydrology. J. Hydrol. 556, 847–864.
Nanding, N., Angel Rico-Ramirez, M., Han, D., 2015. Comparison of different radar-raingauge rainfall merging techniques. Journal of Hydro informatics 17 (3), 422–445.
National Centre for Atmospheric Research (NCAR). (2012). *Number of stations used by GPC for May 2012.* [Online]. Available at https://climatedataguide.ucar.edu, [Accessed 8 Jan. 2021].
Niemi, T.J., Warsta, L., Taka, M., Hickman, B., Pulkkinen, S., Krebs, G., Moisseev, D.N., Koivusalo, H., Kokkonen, T., 2017. Applicability of open rainfall data to event-scale urban rainfall-runoff modelling. J. Hydrol. 547, 143–155.
Nkwunonwo, U.C., Whitworth, M., Baily, B., 2020. A review of the current status of flood modelling for urban flood risk management in the developing countries. Sci. Afr. 7, e00269. https://doi.org/10.1016/j.sciaf.2020.e00269.
Ochoa-Rodriguez, S., Wang, L., Gires, A., Pina, R., Reinoso-Rondinel, R., Bruni, G., Ichiba, A., Gaitan, S., Cristiano, E., Assel, J., Kroll, S., Murlà-Tuyls, D., Tisserand, B., Schertzer, D., Tchiguirinskaia, I., Onof, C., Willems, P., Veldhuis, M., 2015. Impact of spatial and temporal resolution of rainfall inputs on urban hydrodynamic modelling outputs: A multi-catchment investigation. J. Hydrol. 531 (2), 389–407.
Ochoa-Rodriguez, S., Wang, L., Willems, P., Ono, C., 2018. Review of Radar-Rain Gauge Data Merging Methods and Their Potential for Urban Hydrological Applications. Water Resour. Res. 55 (8), 6356–6391.
Olsson, J., Pers, B.C., Bengtsson, L., Pechlivanidis, I., Berg, P., Körnich, H., 2017. Distance-dependent depth-duration analysis in high-resolution hydro-meteorological ensemble forecasting: A case study in Malmö City, Sweden. Environ. Modell. Software 93, 381–397.
Paz, I., Willinger, B., Gires, A., Ichiba, A., Monier, L., Zobrist, C., Tisserand, B., Tchiguirinskaia, I., Schertzer, D., 2018. Multifractal Comparison of Reflectivity and Polarimetric Rainfall Data from C- and X-Band Radars and Respective Hydrological Responses of a Complex Catchment Model. Water 10 (3), 269. https://doi.org/10.3390/w10030269.
Perianes-Rodriguez, A., Waltman, L., van Eck, N.J., 2016. Constructing bibliometric networks: A comparison between full and fractional counting. J. Informetrics 10 (4), 1178–1195.
Pulkkinen, S., Koistinen, J., Kuitunen, T., Harri, A.-M., 2016. Probabilistic radar-gauge merging by multivariate spatiotemporal techniques. J. Hydrol. 542, 662–678.
Rabiei, E., Haberlandt, U., 2015. Applying bias correction for merging rain gauge and radar data. J. Hydrol. 522, 544–557.
Rahmati, O., Darabi, H., Panahi, M., Kalantari, Z., Naghibi, A., Ferreira, C., Kornejady, A., Karimidastenaei, Z., Mohammadi, F., Stefanidis, S., Bui, D., Haghighi, A., 2020. Development of novel hybridized models for urban flood susceptibility mapping. Sci. Rep. 10, 12937.
Rajput, S.P.S., Datta, S., 2020. A review on optimization techniques used in civil engineering material and structure design. Mater. Today:. Proc. 26- Part 2, 1482–1491.
Raut, N.P., Kolekar, A.B., Gombi, S.L., 2021. Optimization techniques for damage detection of composite structure: A review. Mater. Today:. Proc. 45- Part 6, 4830–4834.
Ravazzani, G., Amengual, A., Ceppi, A., Homar, Víctor, Romero, R., Lombardi, G., Mancini, M., 2016. Potentialities of ensemble strategies for flood forecasting over the Milano urban area. J. Hydrol. 539, 237–253.
Razavi, S., Jakeman, A., Saltelli, A., Prieur, C., Iooss, B., Borgonovo, E., Plischke, E., Lo Piano, S., Iwanaga, T., Becker, W., Tarantola, S., Guillaume, J.H.A., Jakeman, J., Gupta, H., Melillo, N., Rabitti, G., Chabridon, V., Duan, Q., Sun, X., Smith, S., Sheikholeslami, R., Hosseini, N., Asadzadeh, M., Puy, A., Kucherenko, S., Maier, H. R., 2021. The Future of Sensitivity Analysis: An essential discipline for systems

modeling and policy support. Environ. Modell. Software 137, 104954. https://doi.org/10.1016/j.envsoft.2020.104954.
Rico-Ramirez, M.A., Liguori, S., Schellart, A.N.A., 2015. Quantifying radar-rainfall uncertainties in urban drainage flow modelling. J. Hydrol. 528, 17–28.
Rubinato, M., Nichols, A., Peng, Y., Zhang, J.-min., Lashford, C., Cai, Y.-peng., Lin, P.-zhi., Tait, S., 2019. Urban and river flooding: Comparison of flood risk management approaches in the UK and China and an assessment of future knowledge needs. Water Sci. Eng. 12 (4), 274–283.
Salvadore, E., Bronders, J., Batelaan, O., 2015. Hydrological modelling of urbanized catchments: A review and future directions. J. Hydrol. 529 (1), 62–81.
Schaller, N., Sillmann, J., Müller, M., Haarsma, R., Hazeleger, W., Hegdahl, T.J., Kelder, T., van den Oord, G., Weerts, A., Whan, K., 2020. The role of spatial and temporal model resolution in a flood event storyline approach in western Norway. Weather Clim. Extremes 29, 100259. https://doi.org/10.1016/j.wace:2020.100259.
Sharifi, E., Steinacker, R., Saghafian, B., 2016. Assessment of GPM-IMERG and other precipitation products against gauge data under different topographic and climatic conditions in Iran: preliminary results. Remote Sensing. 8 (2), 135.
Shih, S., Kuo, P., Lai, J., 2019. A nonstructural flood prevention measure for mitigating urban inundation impacts along with river flooding effects. J. Environ. Manage. 251, 109553.
Silva, C.de.M., Silva, G.B.L.da., 2020. Cumulative effect of the disconnection of impervious areas within residential lots on runoff generation and temporal patterns in a small urban area. J. Environ. Manage. 253, 109719. https://doi.org/10.1016/j.jenvman.2019.109719.
Sitterson, J., Knightes, C., Parmar, R., Wolfe, K., Muche, M., Avant, B. (2017). An Overview of Rainfall-Runoff Model Types. *EPA/600/R-14/152 [Online]*, Available at http://epa.gov, [Accessed: 24 Jan 2021].
Tanaka, T., Kiyohara, K., Tachikawa, Y., 2020. Comparison of fluvial and pluvial flood risk curves in urban cities derived from a large ensemble climate simulation dataset: A case study in Nagoya, Japan. J. Hydrol. 584, 124706.
Thorndahl, Søren, Einfalt, T., Willems, P., Nielsen, J.Ellerbæk., ten Veldhuis, M.-C., Arnbjerg-Nielsen, K., Rasmussen, M.R., Molnar, P., 2017. Weather radar rainfall data in urban hydrology. Hydrol. Earth Syst. Sci. 21 (3), 1359–1380.
Thrysøe, C., Arnbjerg-Nielsen, K., Borup, M., 2019. Identifying fit-for-purpose lumped surrogate models for large urban drainage systems using GLUE. J. Hydrol. 568, 517–533.
Tian, J., Liu, J., Yan, D., Ding, L., Li, C., 2019. Ensemble flood forecasting based on a coupled atmospheric-hydrological modeling system with data assimilation. Atmos. Res. 224, 127–137.
Troutman, S.C., Schambach, N., Love, N.G., Kerkez, B., 2017. An automated toolchain for the data-driven and dynamical modeling of combined sewer systems. Water Res. 126, 88–100.
United Nations Office for Disaster Risk Reduction (UNDRR). (2019). *Annual report for the United Nations Office for Disaster Risk Reduction 2019*. [Online] Available at http://www.undrr.org, [Accessed 09 Apr. 2021].
Wagener, T., Wheater, H., Gupta, H., 2004. Rainfall-Runoff Modeling in Gauged and Ungauged Catchments, 1st Ed. Imperial College Press, London, UK, pp. 80–110.
Wang, L., Ochoa-Rodríguez, S., Van Assel, J., Daniel Pina, R., Pessemier, M., Kroll, S., Willems, P., Onof, C., 2015. Enhancement of radar rainfall estimates for urban hydrology through optical flow temporal interpolation and Bayesian gauge-based adjustment. J. Hydrol. 531 (2), 408–426.
Wang, X., Kinsland, G., Poudel, D., Fenech, A., 2019. Urban flood prediction under heavy precipitation. J. Hydrol. 577, 123984. https://doi.org/10.1016/j.jhydrol.2019.123984.
Wu, Z., Zhou, Y., Wang, H., Jiang, Z., 2020. Depth prediction of urban flood under different rainfall return periods based on deep learning and data warehouse. Sci. Total Environ. 716, 137077. https://doi.org/10.1016/j.scitotenv.2020.137077.
Xu, C., Rahman, M., Haase, D., Wu, Y., Su, M., Pauleit, S., 2020. Surface runoff in urban areas: The role of residential cover and urban growth form. J. Cleaner Prod. 262, 121421. https://doi.org/10.1016/j.jclepro.2020.121421.
Yao, L., Wei, W., Chen, L., 2016. How does imperviousness impact the urban rainfall-runoff process under various storm cases? Ecol. Ind. 60, 893–905.
Yin, D., Evans, B., Wang, Q., Chen, Z., Jia, H., Chen, A.S., Fu, G., Ahmad, S., Leng, L., 2020. Integrated 1D and 2D model for better assessing runoff quantity control of low impact development facilities on community scale. Sci. Total Environ. 720, 137630. https://doi.org/10.1016/j.scitotenv.2020.137630.
Yin, H.-long., Zhao, Z.-chao., Wang, R., Xu, Z.-xin., Li, H.-zheng., 2017. Determination of urban runoff coefficient using time series inverse modeling. J. Hydrodyn. 29 (5), 898–901.
Zhang, D., Lindholm, G., Ratnaweera, H., 2018. Use long short-term memory to enhance Internet of Things for combined sewer overflow monitoring. J. Hydrol. 556, 409–418.
Zhao, G., Pang, B., Xu, Z., Peng, D., Xu, L., 2019a. Assessment of urban flood susceptibility using semi-supervised machine learning model. Sci. Total Environ. 659, 940–949.
Zhao, W., Beach, T.H., Rezgui, Y., 2019b. Automated Model Construction for Combined Sewer Overflow Prediction Based on Efficient LASSO Algorithm. IEEE Trans. Syst. Man Cybernet.: Syst. 49 (6), 1254–1269.
Zhu, Z., Chen, Z., Chen, X., He, P., 2016. Approach for evaluating inundation risks in urban drainage systems. Sci. Total Environ. 553, 1–12.
Zounemat-Kermani, M., Matta, E., Cominola, A., Xia, X., Zhang, Q., Liang, Q., Hinkelmann, R., 2020. Neurocomputing in surface water hydrology and hydraulics: A review of two decades retrospective, current status and future prospects. J. Hydrol. 588, 125085. https://doi.org/10.1016/j.jhydrol.2020.125085.
Zounemat-Kermani, M., Batelaan, O., Fadaee, M., Hinkelmann, R., 2021. Ensemble machine learning paradigms in hydrology: A review. J. Hydrol. 598, 126266. https://doi.org/10.1016/j.jhydrol.2021.126266.