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

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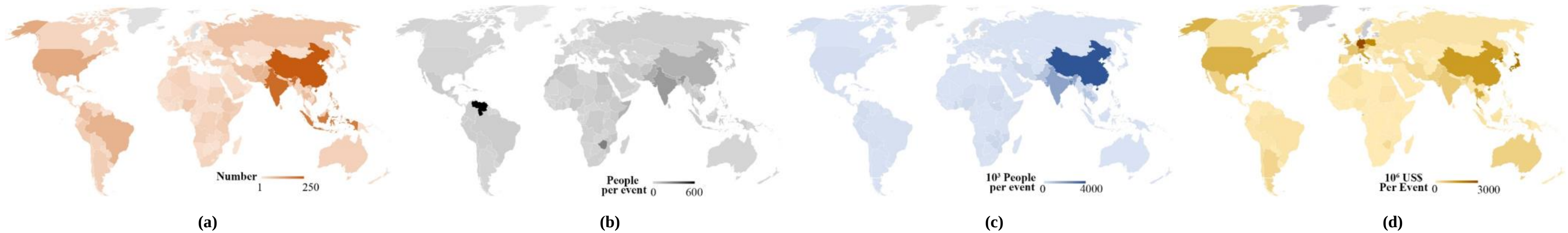
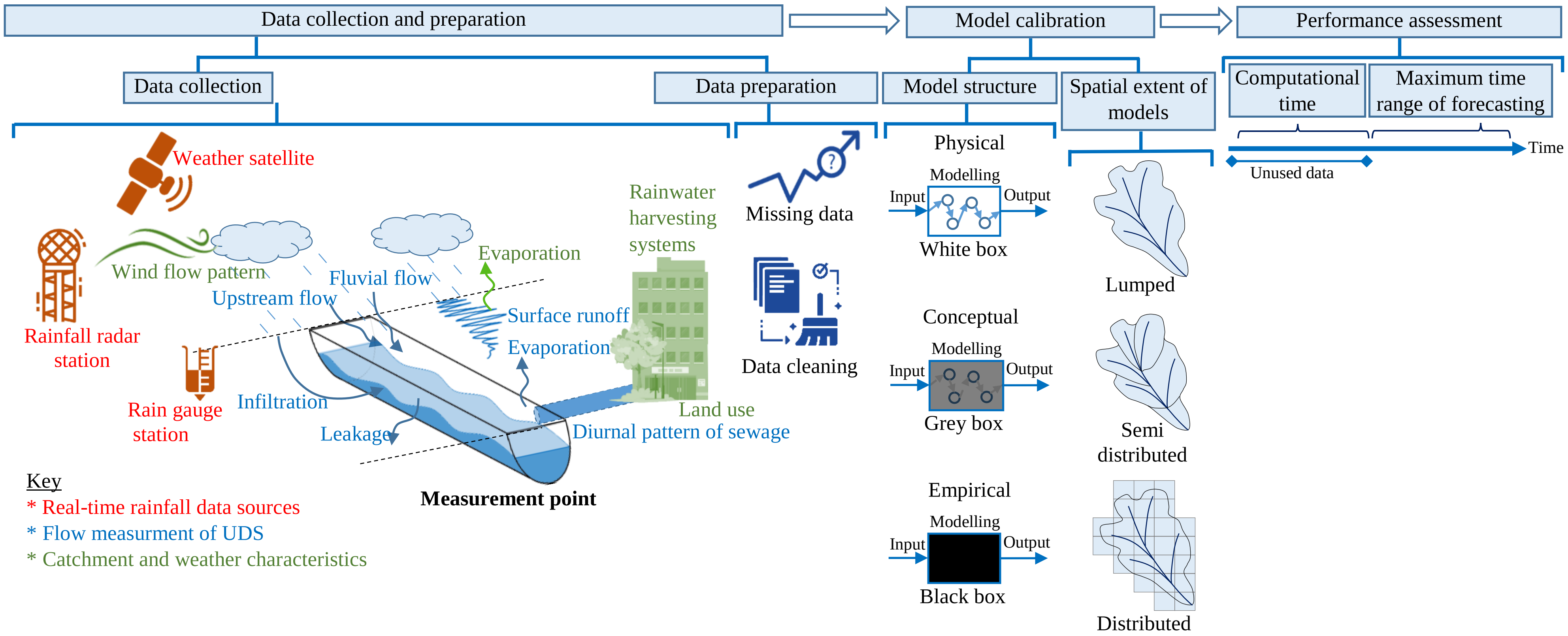
Graphical Abstract (for review)



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

Real-time flood forecasting in urban drainage systems
(Non structural approach to mitigate the flood damages)



A Critical Review of Real-Time Modelling of Flood Forecasting in Urban Drainage Systems

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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 real-time flood forecasting models in UDS and consequently further developments of this technique are expected to appear in future works.

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

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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). Figure 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 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, affect nearly 2 billion people around the world and kill 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).

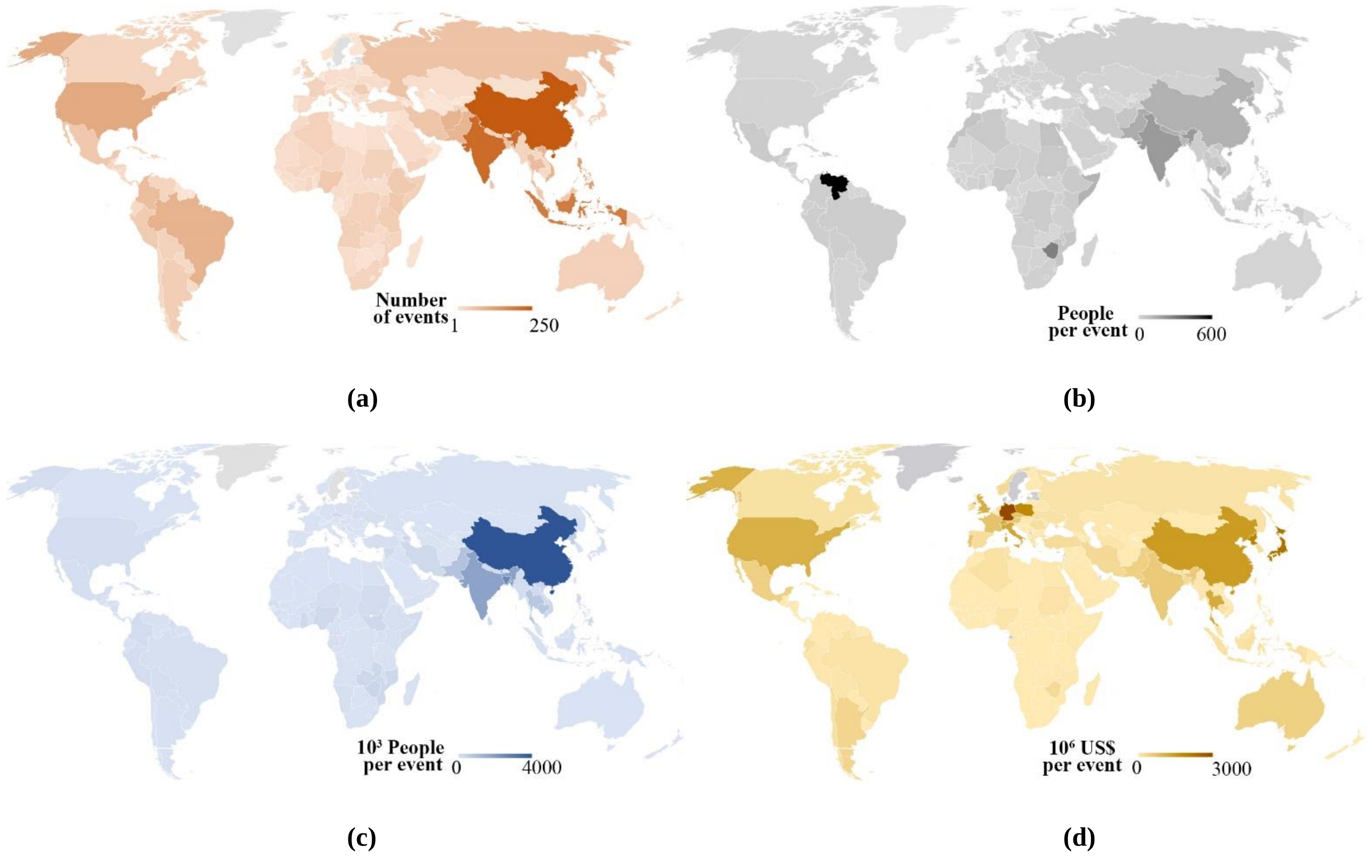


Figure 1. Geographical occurrences of flood events (1990-2021): a) number of flood events, b) average human loss, c) average affected people, d) average economic loss

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 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).

*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)

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 and finally more recently, Kourtis and Tsihrintzis (2021) analysed the impacts of climate change on UDS design and reviews 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 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.

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)

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	
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)

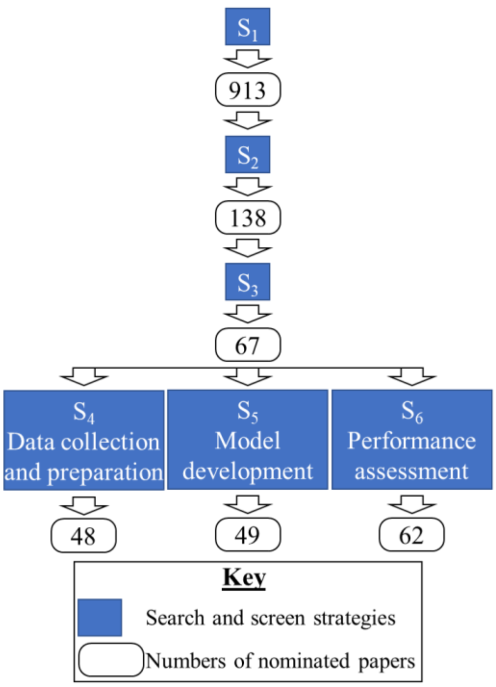
NF: Not focused

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.

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)

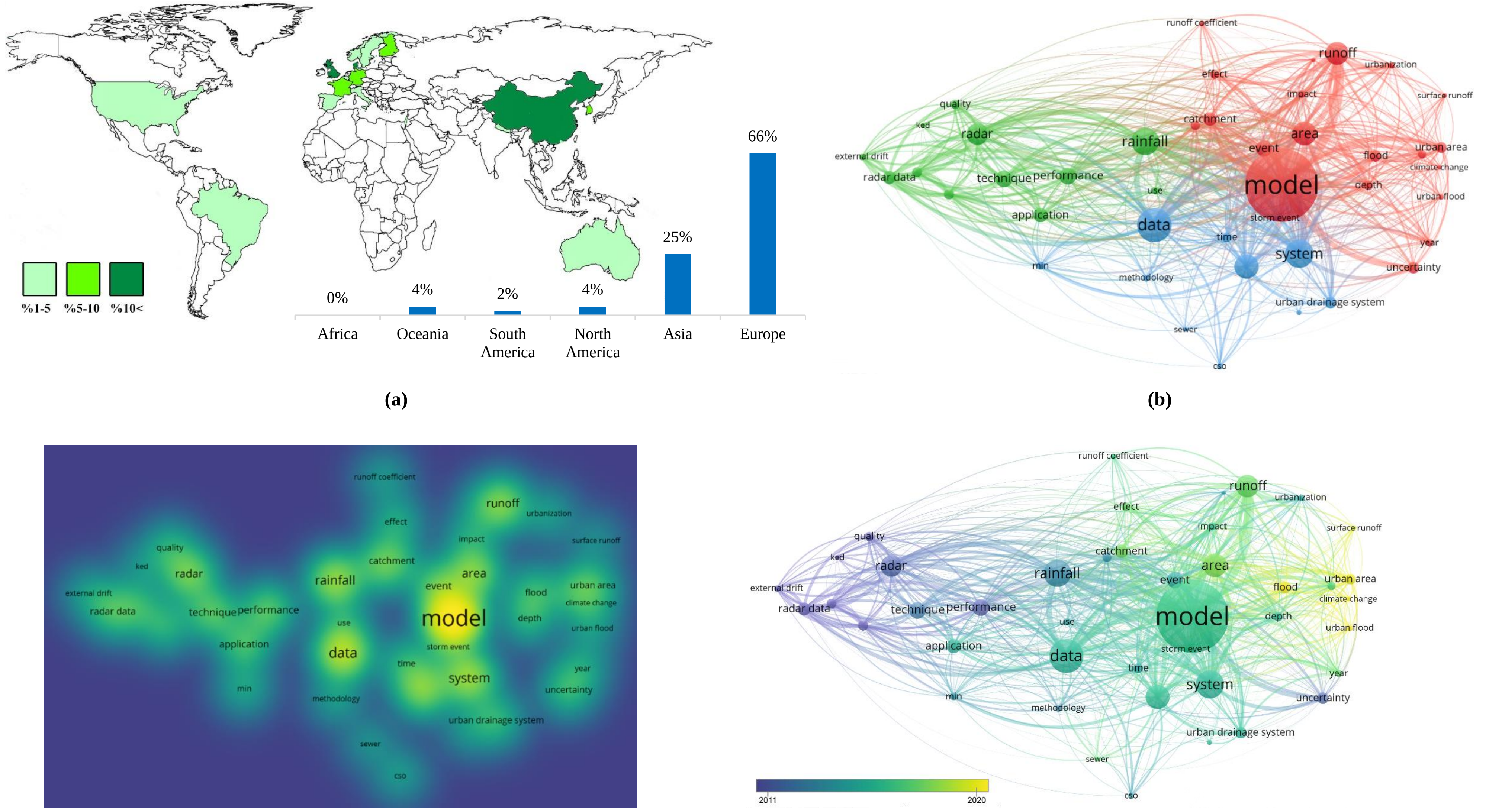
		OR (soil AND condition OR moisture OR layer) OR (infiltration OR leakage OR dry AND weather AND flow) OR (data AND missing OR filling Or cleaning OR imputation OR completion OR event AND identification)
S5	The results were divided and screened for modelling types	(Physical OR empirical OR conceptual) 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)

2.1 Bibliometric analysis

Bibliometric analysis (BA) was first conducted for the collected publications as shown in Figure 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 Figure 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 (Figures 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, 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 methodologies introduced by Ding *et al.* (2014) and Perianes-Rodriguez *et al.* (2016): (1) cluster analysis in Figure 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 Figure 2c: extraction of the number of times that keywords appear in the publications; (3) timeline analysis in Figure 2d: mapping keywords onto the colour coded timespan of studies within the last decade.

The three major clusters (green, blue and red) identified in Figure 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 sewers. 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 Figure 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 the main steps of modelling in Tables 2 ("data collection and preparation" and "model development"). The colour coded visualization 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.



(a) (b)

(c) (d)

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

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 (Figure 3). Rain gauges measure the accumulative depth of rainfall over a specific period (e.g. 15 minutes) 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 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).

*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)

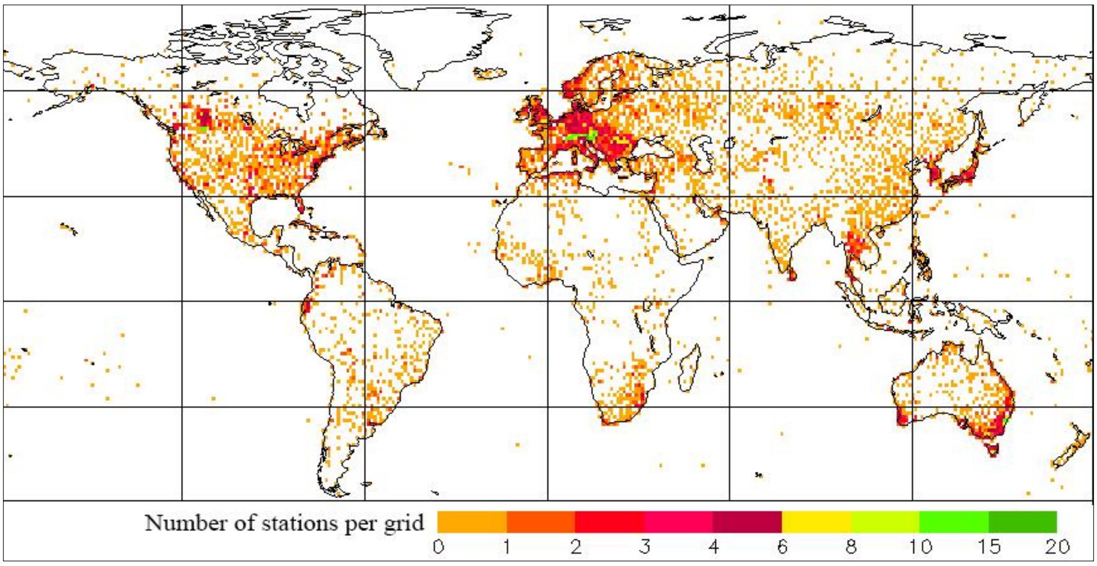


Figure 3. Global distribution of installed rain gauge stations (NCAR, 2012)

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 Figure 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 not much interest due mainly to the requirements for more model complexity, data records and higher computational efforts.

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

Case study	Merging techniques			Reference
	Bias adjustment	**Interpolation**	**Integration**	
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)

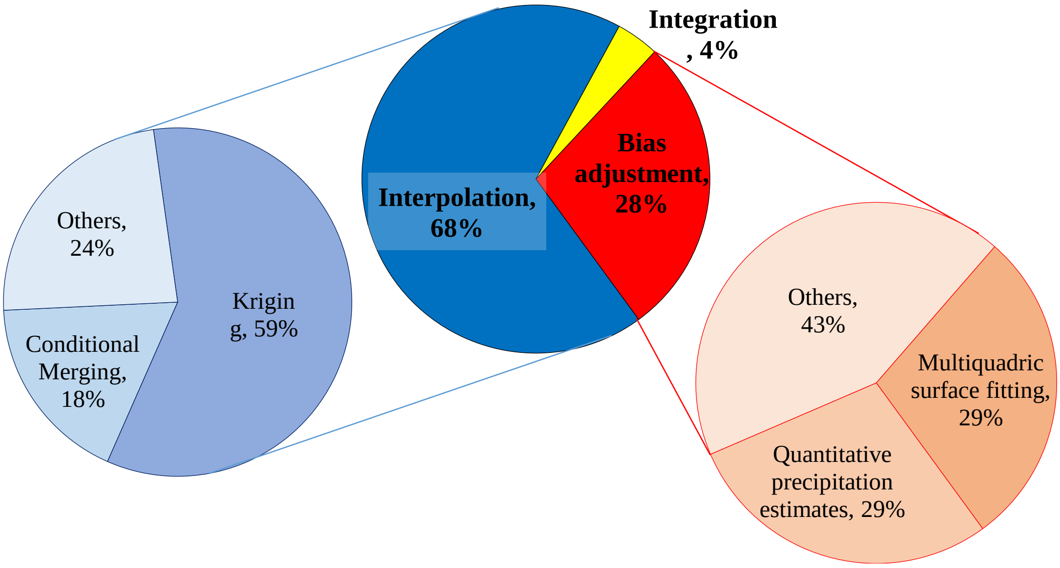


Figure 4. Dashboard of techniques to merge rain gauge-radar data (out of 21 papers)

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 suggest 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 rainfall radar data (73%) were used with a short (high) temporal resolution of fewer than 5 minutes 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 minutes (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.

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%

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).

*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)

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 has occurred when UDS's water 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 the 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.

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)

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 been almost overlooked in RTFF modelling. Similarly, evaporation was not precisely be used for RTFF models although some studies used simple statical 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 the 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 vastly 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 (Figure 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 Figure 5) or wet weather with no changes on chamber water depth (i.e. 3 in Figure 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.

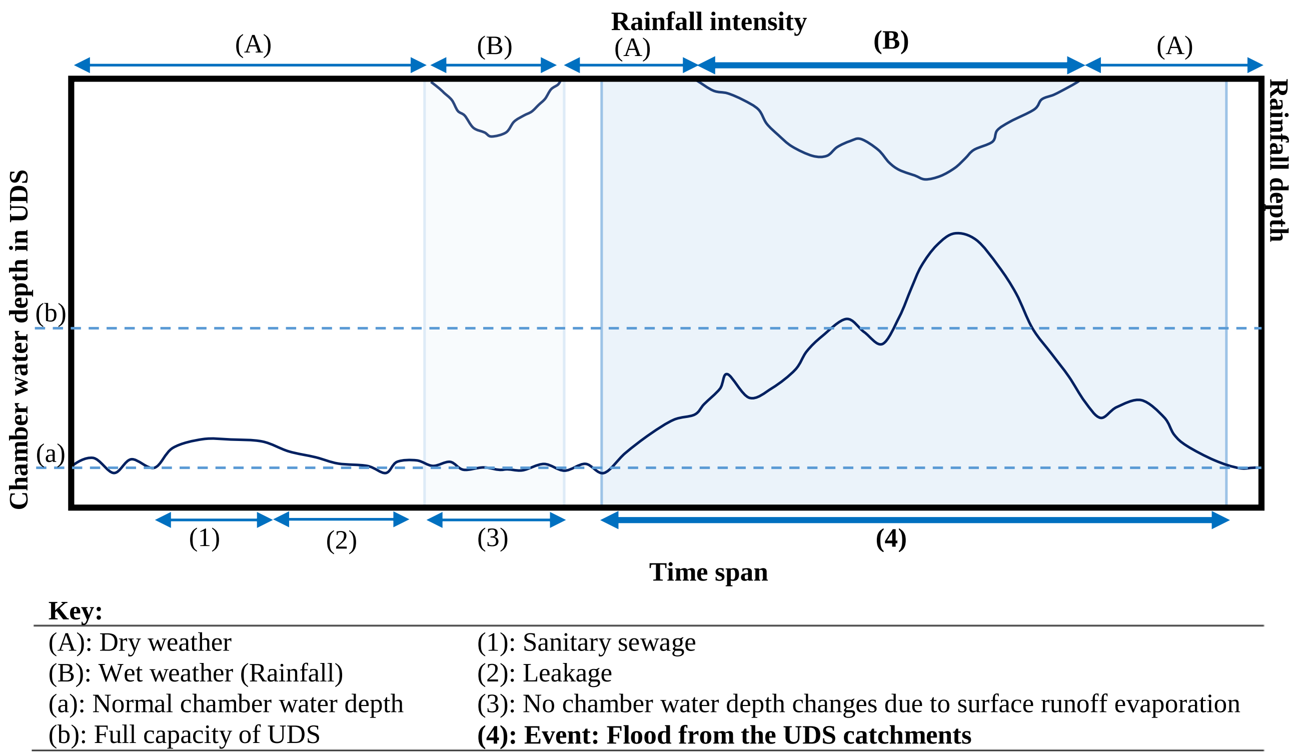
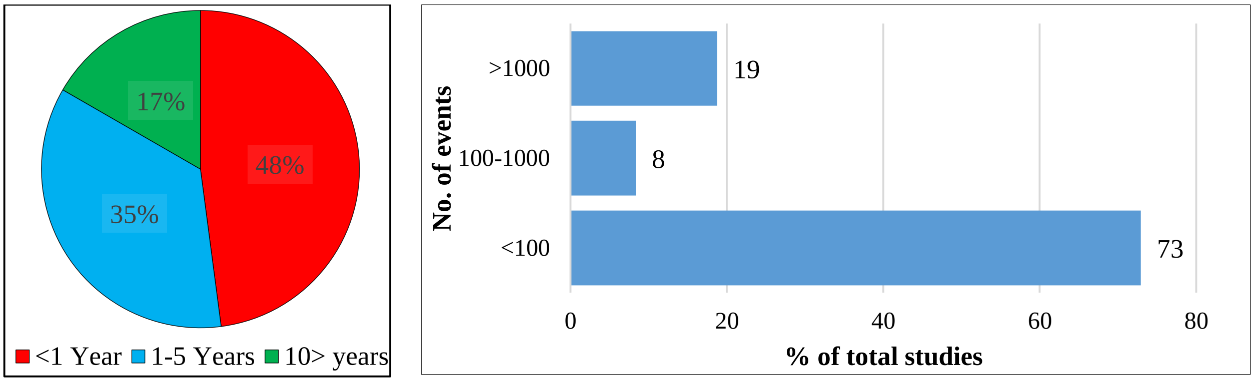


Figure 5. The schematic variation of rainfall and chamber water depth in the UDS catchments

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 Figure 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.



(a) (b)

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

4 Model development

Models developed for urban flood forecasting are mostly classified based on 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 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 box[1]	-Mostly grey box[2]	-White box[3]
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.

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 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 Figure 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 predicting urban flooding and concluded that hybrid methods can perfectly cover the drawback of both empirical and physical models.

Physical and empirical models account for the majority of those developed in the recent decade for forecasting urban flooding (Figure 7a). The relatively equal usage of the three spatial resolutions (i.e. lump, semi-distributed and distributed models) in the developed models (Figure 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 Figure 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 3 hours 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.

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)

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		
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

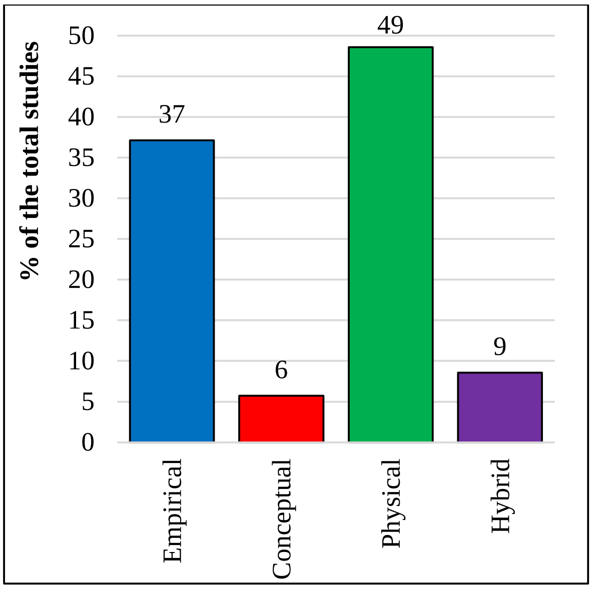
LSTM: long short-term memory

NM: Not mentioned

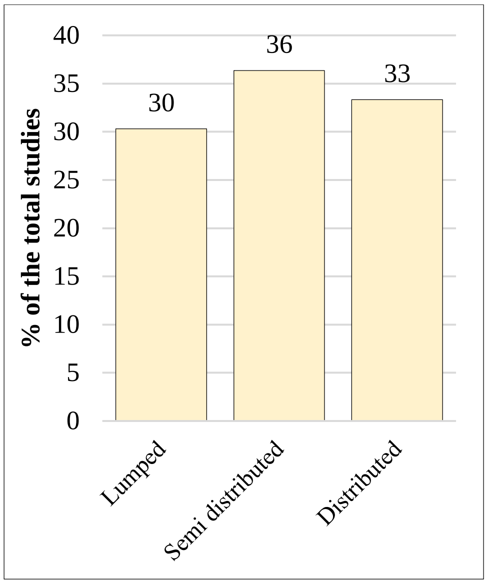
SCEM-UA: Shuffled Complex Evolution Metropolis

SWM: Shallow Water Model

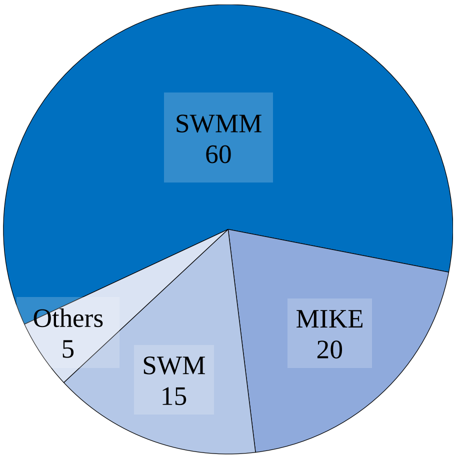
SWMM: Storm Water Management Model



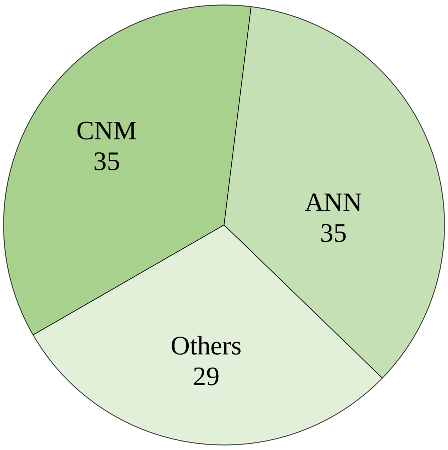
a) Model structure



b) Spatial resolution



c) Type/percentage of physical models



d) Type/percentage of empirical models

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

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 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 on very well in the papers. The first approach to measure spend time is considering 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 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 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 minutes to 90 minutes (See Table 11). These studies show that the accuracy of predictions made for periods longer than 60 minutes 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.

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 lose 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 near 100% of accuracy.
Abou Rajeily *et al*., (2018)	Numbers of iteration	15	Regression results show near 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 longer than 60-minute ahead is significantly reduced in comparison to other prediction ranges.

NM: Not Mentioned

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.
- 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 models has been revitalised in recent years and makes huge waves now, 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 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.

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