A Compilation of Benchmark Pluvial Flood Datasets

Sara Ghalandari

Department of Earth Sciences, Islamic Azad University, Iran.
(ghalandari.sa@gmail.com)

The paper is Accepted in a peer-review journal named
'European Journal of Development studies'.

Accepted in the European Journal of Development Studies
www.ej-develop.org

A Compilation of Benchmark Pluvial Flood Datasets

Sara Ghalandari

ABSTRACT

Urban pluvial flooding is a dangerous natural hazard that has become more common in recent years, making it a global threat to metropolitan areas. Surface water floods and flash floods are two common types of pluvial flooding. The second one is extremely hazardous and damaging due to both the power of the water and the debris that is frequently swept up in the flow. Buildings and their contents are damaged by pluvial floods, which also disrupt stormwater drainage, transportation, and electrical supply. Future flood risks are anticipated to rise because of urbanization, climate change, and global warming. Many essential features of urban flood hazards are still poorly understood due to the complex nature of the relevant processes and the paucity of long-term field observations. Therefore, in this paper, we have collected different sources of data that are used for flood forecasting. Satellite data, gauge measurements, and citizen observations are the most important sources of precipitation and flood data. Conducting a global case study review also showed that the Digital elevation model (DEM) and rainfall are the most crucial variables when it comes to floods, and they are nearly universally employed in all models. The discussion suggests that soil moisture conditions are likely to be the predominant mechanism causing the observed flood trends.

S. Ghalandari*
Department of Earth Sciences, Islamic Azad University, Iran.
(ghalandari.sa@gmail.com)

Corresponding Author

Keywords: citizen flood observations, gauge data, pluvial flooding, satellite data.

I. INTRODUCTION

Flood is a prevalent natural hazard (Wilby & Keenan, 2012), leading to substantial property losses and Worldwide fatalities (Doocy *et al.*, 2013). For instance, between 2004 and 2015, flooding events in the US caused an average of $9.1 billion in losses each year and 71 deaths. (National Academies of Sciences, Engineering, and Medicine, 2019). Climate change, recognized as a significant threat to humanity (Arjomandnia *et al.*, 2023) and addressing their fundamental necessities like energy provision (Nematirad & Pahwa, 2022), is anticipated to lead to more frequent heavy precipitation ((Prein *et al.*, 2017; Wilby & Keenan, 2012), increasing the risk of devastating natural disasters like floods. The effects of flooding are more severe in urban areas due to population growth (Hossain *et al.*, 2015) and changes in land cover that increase surface imperviousness (Zhang *et al.*, 2018). Urban areas may be affected by pluvial, fluvial, and coastal flooding. In this research, we focus on urban pluvial flooding, a phenomenon that is a substantial contributor to urban floods but has received little systematic measurement and modeling. (Rosenzweig *et al.*, 2018).

Pluvial flooding seems to be dominant in numerous regions across the world (Wu *et al.*, 2012), and it poses increasing and significant social and economic impacts (Llasat *et al.*, 2016; Yin *et al.*, 2016). These floods, known as surface-water floods, are brought about by Intense precipitation when the urban environment is unable to adequately absorb the water and the drainage system's capacity is surpassed (The Scottish Government, 2013). Unlike fluvial and coastal floods, pluvial floods are typically caused by localized convective weather patterns, which are marked by swift-moving storm cells. These weather systems may occur almost anywhere and anytime, and their severity varies greatly because of the urban environment. (Borga *et al.*, 2011). As a result, significant damage typically occurs on a local scale in certain urban areas (Nicklin *et al.*, 2019).

Pluvial flooding is on the rise in developed nations. In the UK, pluvial flooding accounts for roughly 40% of damages along with economic losses in cities (Douglas *et al.*, 2010). A government-commissioned report found that most of the damage caused by the 2007 floods in the United Kingdom resulted from overwhelmed storm sewer systems in urbanized regions (Pitt, 2007). In China, 98% of cities are exposed to or vulnerable to regular flooding (Jiang *et al.*, 2017). A survey conducted from 2008 to 2010 revealed that about 200 Chinese cities experienced significant urban pluvial flooding at least once, with over 100 cities experiencing such events on more than three occasions. (Jiang *et al.*, 2018). Due to the significant damage caused by floods, accurate prediction and forecasting are crucial for effective flood management.

In this paper, we aim to introduce the generally diverse sources of data employed in flood forecasting and to conduct a global case study review to understand the most prevalent factors utilized in flood forecasting models.

II. Different Sources of Data Used for Flood Forecasting

The capacity to anticipate the likelihood of floods based on current stormwater infrastructure and precipitation inputs is still a major problem for flood risk management (Jiang *et al.*, 2018). Accordingly, a significant amount of research has been conducted to determine the specific rainfall levels considered critical for the likelihood of pluvial flooding (Martina *et al.*, 2006). The thresholds are expressed either in terms of rainfall intensities or total accumulations (Montesarchio & Ridolfi, 2011). The inferred thresholds can be utilized to forecast local floods or create early warning systems (Martina *et al.*, 2006). To identify the essential rainfall values, two basic methods have been proposed: (i) physically-based hydrological modeling (Norbiato & Borga, 2008; Yang *et al.*, 2016) and (ii) statistical, data-driven analyses (Golian *et al.*, 2010). For both methods, extensive archives of regionally dispersed, high-quality hydrometeorological observations at multiple spatial and temporal scales are necessary. This data can be accessed using different sources mentioned below:

A. Gauge Measurements

To depict the rainfall and flooding data in studies, rain gauges, and simulated inundations were employed. For monitored areas, stream gauges offer in-situ, nearly real-time flooding data (such as streamflow). For instance, the majority of USGS stream gauges collect data every 15 minutes (USGS, 2016). However, because rain gauges are sometimes relatively sparsely distributed throughout catchments, it is challenging to fully understand the spatial variability. Urban locations are particularly affected by this issue because of how sensitive the hydrological response may be to changes in rainfall patterns over time (Cristiano *et al.*, 2017; Schellart *et al.*, 2012). Additionally, hydraulic inundation models have their own difficulties since Calibrating and validating these systems requires a substantial amount of field observations, many of which may not be readily accessible or available for practical use. (Eggimann *et al.*, 2017).

B. Satellite Data

Remote sensing techniques provide a valuable means for ongoing monitoring of various hydrometeorological data, including precipitation. For hundreds of satellite sensors with various geographical resolutions, temporal frequencies, and optical or radar signal capabilities, inundation detection techniques have been developed. Utilizing the pronounced absorbent characteristics of water in the short-wave infrared spectrum compared to other objects or the near-infrared (NIR) spectrum relative to the visible spectrum are common approaches to map inundation with MODIS (Feng *et al.*, 2012; Islam *et al.*, 2010). Similar methods to MODIS algorithms may be used to detect flooding in medium-resolution sensors like Landsat and Sentinel-2. Synthetic Aperture Radar (SAR) sensors' capacity to see through clouds makes them useful for flood detection. Water, which often has lower backscatter values compared to other features, has been utilized to map inundation by SAR sensors like Sentinel-1.

C. Citizen Observations

The growing use of weather radar in hydrology in recent years has resulted in a significant improvement in rainfall readings. A study focused on obtaining precise precipitation data for Iran using a generalized regression neural network model. The findings indicated that satellite products corrected with gauge data are more effective than products solely based on gauges or satellites. Consequently, by combining the strengths of various precipitation data sources, such as satellites and gauges, it becomes feasible to achieve accurate and comprehensive characterization of rainfall patterns over time and space (Mohammadpouri *et al.*, 2023), resulting in an enhanced comprehension of flood responses (Thorndahl *et al.*, 2017; Wang *et al.*, 2015; Wright *et al.*, 2014; Zhu *et al.*, 2013).

The lack of high-resolution hydrological measurements continues to be a significant constraint. Several studies have suggested using citizen observations in place of professional hydrological measures to close this gap (Overeem *et al.*, 2016; Smith *et al.*, 2017; Weeser *et al.*, 2018; Yang & Ng, 2017). Previous research has demonstrated that such a strategy may be advantageous for hydraulic and hydrological modeling (Herman Assumpção *et al.*, 2017; Starkey *et al.*, 2017) as well as Monitoring and managing the risks associated with flooding (Wang *et al.*, 2018). For a more thorough examination of how citizen observations might be used to study hydrology and water resources, see (Buytaert *et al.*, 2014; Muller *et al.*, 2015).

III. THE GLOBAL STUDY REVIEW

In the second part of the paper, we examine several case studies and datasets related to pluvial flooding from different regions around the world, including Asia, Europe, and the Americas. The goal is to gain insight into the commonly used data in flood forecasting models.

A. Europe

Pina *et al.* (2014) present a 1D/2D urban drainage model with a comparison of semi-distributed and fully distributed rainfall-runoff modules. The "Zona Central" catchment, a 1.5 km2 region in the center of Coimbra, Portugal, was the subject of the research. The digital terrain model (DTM) data was derived from a LIDAR model with a 1-m regular cell resolution, while the network data was given by the water utility AC, guas de Coimbra, EM. The land use data necessary for the hydrological characterization of models was obtained using building polygons and Open Street Maps data. (Simoes, 2012) conducted a monitoring effort between 2010 and 2012 to assess water depth at key locations in the sewage network and estimate rainfall in the watershed. This information was utilized to compare and calibrate the output of both models. To compare the performance of both models, rainfall data and images from one flood event (June 9, 2006) were also employed.

Tuyls *et al.* (2018) assessed the surface flood return period using a 35-year rainfall dataset and a coupled 1D/2D surface and network model. The study was carried out in Lystrup, near Aarhus, Denmark, where the urban drainage system, specifically the stormwater system, covers an area of approximately 875 × 104 m^2 and serves a population of around 10,300 residents. To conduct their analysis, the researchers compiled a dataset containing rainfall measurements spanning 35 years (1979–2015 with minor disruptions) collected from two distinct rain gauges. These rain gauges are managed by the Danish Wastewater Pollution Committee in collaboration with the Danish Meteorological Institute (DMI) and are part of a broader network of approximately 150 rain gauges dispersed throughout the country.

Gaitan *et al.* (2016) explored the possibilities of using accessible geographic datasets to explain the occurrence of flood occurrences that people report to the government during a period of heavy rain. According to an evaluation made by the Netherlands Royal Meteorological Institute in 2014, this event, which was marked by very localized torrential rainfall, produced variable total rainfall values ranging within the range of 125 to 140 mm in numerous rain gauges, with an estimated return time of 2000–5000 years. Several citizen reports on the sites of flooding incidents—which acted as indicators of urban flooding—were sparked by the occurrence, which happened in Amsterdam in 2014. The study accessed meteorological, socioeconomic, and cadastral geographical data from publicly available sources. Rainfall intensities for 15- and 60-minute duration, as well as information on the population density per square kilometer and the typical building age per square kilometer, were collected from various sources. Using ArcGIS, its spatial analyst tools, and QGIS, data processing was carried out, including data clipping, digital elevation model filtering, and the identification of watersheds and overland flow pathways. Table I gives an overview of the data.

TABLE I: DATA SOURCES AND VARIABLES UTILIZED IN GAITAN ET AL. (2016)

Data source (s) or variable (v)	Spatial, temporal resolutions	Metric or unit
Max. rainfall intensity (s)	1km^2, every 5 min	mm/h × km2
Interpolated digital elevation model (s)	0.5 × 0.5 m grid	m
Maximum rainfall intensity at 15 min (v)	1km^2 cells	mm/h × km2
Maximum rainfall intensity at 60 min (v)	1km^2 cells	mm/h × km2
Impervious ratio (v)	1km^2 cells	Ratio (dimensionless)
Average distance to outflow point (v)	1km^2 cells	m
Average catchment size (v)	1km^2 cells	m^2

Tian *et al.* (2019) explored the prospect of utilizing citizen flood observations to learn new information on urban pluvial flooding. To predict the likelihood of floods based on peak rainfall intensities over various temporal scales, three binary decision trees have been trained. The study focuses on Rotterdam, a Dutch city situated in a low-lying region of the Rhine and Meuse river delta. More than half of the city's land is covered in paved or semi-paved surfaces. To enhance the monitoring of urban sewage and drainage systems, the municipality created a citizen observatory database in 2001. In subsequent years, a system was implemented to collect reports via telephone, email, mobile application, and website. Each report's date, location, and a brief summary of the incident were entered into a database. Five of the seven categories, out of which each citizen report was assigned, are associated with floods. The authors employed a dataset of over 70,000 citizen reports that were gathered between 2008 and 2017. After quality check and weekend elimination, there were around 38,300 reports submitted over a period of 2609 days. The vast number of complaints amply demonstrates the severity of Rotterdam's water-related nuisance problem and the frequency of these occurrences. The Royal Netherlands Meteorological Institute (KNMI) provided information on the volume of rainfall on days when there was pluvial flooding. Rainfall estimates were derived from radar reflectivity measurements. Using the whole rain gauge network from KNMI, all radar composites are corrected and confirmed at both hourly and daily time intervals. The Climate4Impact website and KNMI's FTP server both offer free access to data in netCDF4 or HDF5 formats.

Guerreiro *et al.* (2017) attempted to model pluvial flooding at a continental scale and determine the percentage of flooded areas for all European cities, considering a 10-year return period for hourly rainfall. Data used in this study are the Digital Elevation Model over Europe, Urban Morphological Zones 2000, a European daily gridded data set for precipitation as well as maximum and mean surface temperature at a 0.25-degree resolution covering the period 1950–2013, along with several observed sub-daily rainfall datasets. A total of 38 gauges across Europe, providing time-series data for annual maximum hourly rainfall, were contributed by Dr. Panos Panagos of the Joint Research Centre as part of the REDES project. Additionally, there were 192 gauges in the UK, with time-series data on annual maximum hourly rainfall provided by Dr. Stephen Blenkinsop from Newcastle University as part of the CONVEX project. These datasets were compiled from three main sources: the UK Met Office Integrated Data Archive System (MIDAS), the Scottish Environmental Protection Agency (SEPA), and the UK Environment Agency (EA). To maintain consistency with the gauge density across Europe and avoid potential biases in the analysis, not all of these gauges were utilized. Data were obtained from SEPA, EA, and MIDAS.

Löwe *et al.* (2021) explored the configuration of deep learning techniques to enhance the accuracy of predicting 2D maximum water depth maps during urban pluvial flood events. They trained a neural network model to identify patterns in hyetographs (rainfall data) and topographical information, with the specific goal of swiftly predicting flood depths for rainfall events that were not part of the training dataset and for different geographical locations. Their investigation focused on Odense City, located in Denmark. They obtained terrain and land use data from the Danish geodata portal called Kortforsyningen as their primary data sources. Furthermore, they took into account rainfall observations collected at a 1-minute interval from ten rain gauges strategically placed throughout Denmark. These gauges had been in continuous operation for a minimum of 40 years. The entire study area was covered by a grid comprising 3,740 × 4,273 pixels at a 5-meter resolution, which they deemed adequate for the purpose of screening floods. Their dataset comprised a total of 53 flood maps that encompassed the study area. In this research, the most effective model was achieved by combining five datasets that described terrain aspects, curvature, terrain depression depth, imperviousness, and flow accumulation.

B. Asia

Noymanee *et al.* (2017) investigated the potential of utilizing machine learning techniques to predict flooding occurrences in the Pattani River, employing openly available data. The study considers various factors, including the time of data collection, the geographical location, and the configuration of prediction models. They assess the quality characteristics of multiple machine learning algorithms and examine a series of flood models for both upstream and downstream scenarios across different forecast timeframes. The Pattani basin has implemented a telemetry project aimed at monitoring and collecting data. Flooding in the Pattani region primarily arises from heavy rainfall and flash floods originating in the Titiwangsa mountains. The Pattani Basin telemetry project's website serves as a valuable resource for monitoring the basin's situation, offering crucial data such as hourly water level records, daily peak water levels, and stationary data related to the riverbed. Hydroinformatics data for the Pattani basin is provided in a semi-open format and can be accessed upon request. In the context of their study, the authors utilize two datasets sourced from the Pattani Basin telemetry project: a training dataset containing hourly data from 2015 to 2016 and a testing dataset comprising hourly data from January to February 2017.

Yin *et al.* (2016) conducted a numerical analysis to examine pluvial flooding and assess how land subsidence impacts flood risks within urban areas utilizing a hydraulic model. They utilized data from the pluvial flood incident that occurred in Shanghai, China, to calibrate and simulate their model. The study aimed to understand how flooding patterns evolved over four different time intervals (1991, 1996, 2001, and 2011) in downtown, considering changes in local topography and substantial land subsidence rates, which reached up to 27 mm/year. The chosen watershed was within central Shanghai, specifically in the North Huangpu District, with boundaries along the Huangpu River to the east and Suzhou Creek to the north. Precipitation data in 15-minute intervals were collected from 12 meteorological stations placed across the study area and nearby regions during the event on August 12, 2011. To estimate precipitation amounts across the study area for each period, the researchers used ordinary kriging interpolation between the meteorological stations. The study benefited from the presence of an up-to-date high-resolution topographic dataset and data on land subsidence rates over time, allowing them to reconstruct elevation changes at various time points. The study obtained Airborne LiDAR data from 2006 through the Shanghai Survey Bureau, featuring an average image separation of 0.6 meters. The initial LiDAR dataset underwent precise processing and segmentation utilizing TerraSolid software. They created a Digital Elevation Model (DEM) by employing classification algorithms within the TerraScan module, effectively removing non-topographic elements such as trees, cars, and buildings. Additionally, land subsidence contours were established using an extensive array of subsidence monitoring data sources. These sources included leveling points, GPS measurements, CCD hydrostatic leveling systems, and 4675 Liquid Level Sensors. The data collection spanned various time intervals, including 1991–1995, 1996–2000, 2001–2005, and 2006–2010, encompassing Shanghai.

Ke *et al.*, (2020) conduct a study with the aim of preparing urban areas for frequent pluvial flood events. They employed machine learning techniques to establish a rainfall threshold for distinguishing between flood and non-flood events. This approach involved ML models that could identify multiple rainfall threshold lines plotted in a two-dimensional space defined by two principal components, ultimately providing a binary classification (flood or no flood). Over the past few decades, Shenzhen, a city in Southern China, has experienced rapid growth, transitioning from a rural area to a thriving economic hub and a significant industrial city. Positioned on the central coast of Guangdong Province, Shenzhen serves as a vital gateway from mainland China to Hong Kong and holds strategic importance within the Pearl River Delta region. Rainfall data for the study was collected from 25 rainfall gauges between 2014 and 2017, sourced from the SMB. Areal average rainfall intensity was used as a representation for the entire study area, indicating the mean rainfall intensity across all sub-areas or districts. The initial dataset contained 1-minute rainfall intensity measurements, which were aggregated into longer temporal scales, including 5, 10, 15, 30, 60, 120, 360, 720, and 1440-minute intervals.

Lin *et al.* (2021) conducted an analysis to examine the linear relationship between the density of flooding hotspots and various potential influencing factors within a heavily urbanized city. They employed Pearson correlation analysis for this purpose. Furthermore, they developed two random forest-based models to assess the significance of different building metrics. The initial model focused solely on common influencing factors, while the second model incorporated a broader range of building metrics into its analysis. The data employed in this study is shown in Table II.

TABLE II: COMPREHENSIVE DETAILS REGARDING THE DATA EMPLOYED BY LIN ET AL. (2021)

Data	Detail	Source
Flooding hotspots	Point	Water Resources Bureau of Shenzhen.
DEM	30 m resolution	National Geomatics Center of China.
Observed Land cover data	10 m resolution, classified as green space, water, impervious surface, barelands	Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC10) (Gong *et al.*, 2019).
Precipitation	1000 m resolution	Meteorological Bureau of Shenzhen.

Miao *et al.* (2016) established a strategy for issuing flash flood alerts in ungauged mountainous catchment areas Situated in areas of China characterized by humidity, semi-humidity, and semi-aridity. Their approach involved implementing a geomorphology-based hydrological model (GBHM) in four distinct mountainous catchments, each possessing drainage areas ranging from 493 to 1601 square kilometers. One of these areas was the Suichuan catchment, characterized by a drainage area of 910 square kilometers and an average annual rainfall of 1637 mm, situated within the Ganjiang River basin. Topographical data for these catchments were represented using a digital elevation model (DEM) having a 90-meters spatial resolution, sourced from the SRTM Database. Soil information was acquired from the China Dataset of Soil Properties for Land Surface Modeling. Land use and land cover information were procured from the Environmental and Ecological Science Data Center of West China with a resolution of 100-meter resolution. Rainfall data, including both daily and event-based records, were sourced from gauges and observed discharge data from the Hydrological Bureau, Ministry of Water Resources of China. Event-based rainfall data were particularly accessible during flood seasons, with temporal resolutions varying from 6 hours to 1 hour, depending on rainfall intensity.

C. Americas

Hjelmstad *et al.* (2021) assessed the effectiveness of three radar-derived quantitative precipitation estimates (QPEs), namely Stage IV, Multi-Radar Multi-Sensor (MRMS), and gauge-corrected MRMS (GCMRM), along with the Storm Water Management Model (SWMM) hydrologic-hydraulic model for modeling pluvial flooding incidents during the North American monsoon in Phoenix. Their study focused on a specific urban catchment spanning 2.38 km^2, and for four distinct storm events, they conducted simulations using both the original QPEs and an ensemble of 100 QPEs that accounted for radar uncertainty by incorporating a statistical error model. Phoenix, Arizona's metropolitan area, has experienced rapid growth, becoming one of the swiftest-growing urban regions in the United States. Its population increased from 1.86 million in 1985 to more than 4.7 million in 2018 (Guan *et al.*, 2020). The researchers incorporated three radars-derived QPEs into their study: Stage IV, MRMS, and GCMRMS. Stage IV QPEs are generated by processing and merging reflectivity data from the NEXRAD network. Subsequently, rainfall rates are corrected based on gauge and satellite observations and undergo manual quality control, as explained by Lin (2020). MRMS products, on the other hand, are generated by integrating radar data from both the NEXRAD and Canadian networks, incorporating atmospheric environmental data, satellite data, and information from lightning and rain gauge observations (Zhang *et al.*, 2016). The researchers obtained

Stage IV and MRMS QPEs for the summers spanning from July to October during the years 2015 to 2019. Regarding MRMS, they specifically acquired version 11 of the radar-only and gauge-corrected (GCMRMS) data. The QPEs from Stage IV and MRMS, including GCMRMS, were accessible in polar stereographic coordinates at resolutions of 4 kilometers and 1 hour (1 kilometer and 2 minutes for some cases; 1 kilometer and 1 hour for others).

Chagas *et al.* (2020) have introduced a novel catchment dataset tailored for comprehensive hydrological investigations in Brazil. The dataset comprises daily time series data of observed streamflow obtained from more than 3500 measurement points, along with essential meteorological data encompassing precipitation, evapotranspiration, and temperature for 897 carefully picked catchment areas. In addition, it encompasses a rich set of 65 attributes that span various aspects, including topography, climate, hydrology, land cover, geology, soil composition, human intervention factors, and indicators reflecting data quality. The paper provides an in-depth account of the processes used to generate these hydrometeorological time series and associated characteristics, discusses their limitations, and highlights their key spatial characteristics. They observed streamflow, precipitation, evapotranspiration, temperature, and land cover.

Bonafilia *et al.* (2020) have introduced Sen1Floods11, a dataset dedicated to surface water information, comprising unprocessed Sentinel-1 images along with categorized data on permanent water bodies and areas affected by floods. This dataset encompasses a total of 4,831 individual 512x512 image chips, collectively covering an area of 120,406 km^2. Sen1Floods11 was utilized for the training, validation, and testing of fully convolutional neural networks (FCNNs) designed for the segmentation of permanent water and flooded areas. To facilitate the model's training, they drew on two primary sources of data. First, they utilized the JRC (European Commission Joint Research Centre) surface water dataset, which offers monthly surface water observations at a 30-meter resolution using Landsat satellite imagery. The second data source was derived from 11 flood events detected within a global flood event database maintained by the Dartmouth Flood Observatory. The selection of these events required that they had coverage from Sentinel-1, along with coinciding Sentinel-2 imagery captured either on the same day as the Sentinel-1 image or within a 2-day timeframe. Furthermore, two flood events occurring in Cambodia and Spain were included to introduce more geographic diversity and variability into the dataset.

Table III is the summary of selected studies that are presented above.

TABLE III: Summary of selected studies that are discussed in section 2

Paper	Area	Data	Model	Target
Pina *et al.* 2014	Europe	-DTM -OSM -Water depth -Rainfall -Photographs of the flood event	1D/2D urban drainage model	Assessment of semi-distributed versus fully distributed rainfall-runoff modules
Tuyls *et al.* 2018	Europe	-35 years rainfall dataset	1D/2D surface and network model	Surface flood return period assessment
Noymanee *et al.* 2017	Asia	- water level data measured on an hourly basis -water level recorded at daily peak -stationary data related to the riverbed -Hydroinformatics data	Machine learning method (Bayesian linear model)	Forecasting of flooding phenomena
Bonafilia *et al.* 2020	All	-surface water data set, including raw Sentinel-1 imagery and classified Permanent water and flood water	(Sen1Floods11) Train, validate, and test fully convolutional neural networks (fcnns) to segment permanent and floodwater	Operationalize deep learning algorithms for flood mapping
Gaitan *et al.* 2016	Europe	- Max. Rainfall intensity - Interpolated DEM - Maximum rainfall intensity at 15 min and 60 min - Impervious ratio - Average distance to the outflow point - Average catchment size	Using multivariate analysis techniques	The potential inherent in open spatial datasets to explain the occurrence of citizen-reported flood occurrences during a heavy rain event.

Yin *et al.* 2016	Asia	-precipitation data -topography & subsidence data -observed inundation data	Numerical analysis of pluvial flooding/ hydraulic model (floodmap-hydroinundation2d)	Assess the influence of land subsidence on flood risks within urban settings
Ke *et al.* 2020	Asia	-rainfall	Implement a traditional rainfall curve method or create several parametric and non-parametric machine learning models	Using a rainfall threshold to categorize events as either flood or non-flood occurrences,
Tian *et al.* 2019	Europe	- citizen flood observations - ten-year dataset of radar rainfall maps	Binary decision tree learning (DTL)	Predicting flood occurrences
Lin *et al.* 2021	Asia	- Precipitation - Observed land cover data - DEM - Flooding hotspots	Examined the linear correlation between the density of flood-prone areas and various potential factors/and formulated two random forest-based models to measure the significance of different building metrics.	Investigating the potential influence of three-dimensional building configuration on pluvial flooding
Guerreiro *et al.* 2017	Europe	-rainfall -DEM - mean surface temperature -maximum surface Temperature	Regression model	Calculate the percentage of the area flooded
Miao *et al.* 2016	Asia	- geographical Information - meteorological data -Hydrological data -DEM -Soil map -Land cover -rainfall -observed discharge	Geomorphology-based Hydrological model (GBHM)/ using frequency analysis and binary classification based on long-term GBHM simulations	Simulate flash floods/ determine the rainfall threshold for flood warning
Hjelmstad *et al.* 2021	Americas	-rainfall -soil data -percent imperviousness Terrain description	Assess the effectiveness of three radar-derived quantitative precipitation estimates (qpes), namely Stage IV, Multi-Radar Multi-Sensor (MRMS), and gauge-corrected MRMS (GCMRM), in combination with the Storm Water Management Model (SWMM) hydrologic-hydraulic mode/statistical error model.	Simulate pluvial flooding
Chagas *et al.* 2020	Americas	- observed streamflow -precipitation -evapotranspiration -temperature -land cover	Introduce a new catchment dataset	Acquire new perspectives on the factors influencing hydrological patterns, enhance the characterization of extreme hydroclimatic events, and investigate the effects of climate change and human activities on water resources in Brazil
Lowe *et al.* 2021	Europe	-rainfall -spatial inputs - topographic inputs	Convolutional neural network model	Examines the configuration of deep learning techniques to enhance the prediction accuracy of 2D maximum water depth maps for urban pluvial flood forecasting

IV. DISCUSSION

Based on the review of case studies, it is evident that rainfall and Digital Elevation Model (DEM) data are the most crucial variables when it comes to floods, and they are nearly universally employed in all models. Consequently, we will now delve deeper into these essential variables.

A. Digital Elevation Model (DEM)

Digital Elevation Model data play a crucial role in flood modeling by representing the physical land surface. The spatial resolution of a DEM pertains to the size of the area depicted by a single grid cell, which typically varies from 1000 meters to as small as 2 meters or less. High-quality DEM data are essential for estimating water interactions with the environment and identifying flood-prone areas. The precision of forecasts for water depth is directly associated with the accuracy and spatial resolution of the Digital Elevation Model (DEM) (Vaze *et al.*, 2010), with higher resolutions preserving topographical terrain features better. This enhanced resolution enables a more detailed definition of floodplains, streams, roads, and other narrow flow pathways, which significantly affect modeling results. In addition, topographic aspects influenced the fractal dimension of soil particle distribution, aiding in the modeling of soil properties like water distribution (He *et al.*, 2023). Fereshtehpour *et al.* (2023) demonstrate that the choice of DEM type and resolution significantly affects the accuracy of flood inundation predictions. Using a 30m Digital Terrain Model improves flood depth prediction by approximately 21% during peak stages, while a 15m resolution increases errors significantly.

B. Rainfall

There is a prevalent misconception regarding flooding, often assuming that being situated near a body of water is the sole risk factor. However, pluvial floods can manifest in any locale, be it urban or rural, even in regions devoid of nearby water bodies. Pluvial flooding transpires when an extreme rainfall event leads to flooding independently of any overflowing water source. Two prevalent types of pluvial flooding exist. Surface water floods transpire when urban drainage systems become overwhelmed, causing water to inundate streets and nearby structures. Surface water flooding typically unfolds gradually, affording people ample time to seek safety. The water levels are generally shallow, posing no immediate threat to lives but often resulting in significant economic damage. On the other hand, flash floods are characterized by sudden, intense torrents of swiftly moving water, typically triggered by heavy rainfall over a short timeframe or in nearby elevated areas. These flash floods can also occur due to the sudden release of water from an upstream levee or dam.

Although DEM and precipitation are crucial factors in flood prediction, the significance of soil data, particularly antecedent soil moisture, in flood magnitude should not be overlooked. Pluvial flooding is primarily driven by rainfall, but in some areas, increased rainfall intensities have not always led to higher flood magnitudes. A study conducted in Australia, utilizing gauged streamflow, catchment average rainfall, and modeled soil moisture data, emphasized that changes in flood intensity depend on both precipitation and antecedent soil moisture patterns. A decrease in soil moisture levels can lead to a reduction in flooding during more frequent events, but for the most infrequent events, changes in flow magnitude are more likely to align with trends in extreme rainfall (Wasko & Nathan, 2019). Therefore, Soil moisture plays a key role in flood formation (Karamouz *et al.*, 2019) by influencing rainfall-runoff processes (Hosseini *et al.*, 2023). Unlike precipitation and streamflow measurements, soil moisture data is often limited in availability, especially in developing areas, due to cost and custodian issues (Karamouz *et al.*, 2019). Nonetheless, it can be estimated using satellite data and citizen science-based methods. Karamouz *et al.* (2022) developed a data-driven model using artificial neural network kriging (ANNK) and ancillary data like NDVI, altitude, slope, Antecedent Moisture Condition (AMC), and precipitation. This approach increased soil moisture estimation resolution from SMAP's 36 km to 1 km, meeting SMAP's accuracy standards (Unbiased Root Mean Square Error < 0.04 m^3/m^3). It also holds promise for real-time soil moisture estimation in developing regions, enhancing high-resolution monitoring. Therefore, future research should concentrate on comprehending both variations in rainfall and soil moisture when forecasting floods.

V. Summary and Conclusion

Urban pluvial floods, also referred to as surface-water floods, pose a significant and widespread natural hazard in urban areas across the globe. These floods result from intense rainfall events that overwhelm the urban drainage system's capacity and hinder effective rainwater absorption. The extensive damage inflicted by pluvial floods, including harm to buildings and their contents, underscores the importance of precise prediction and forecasting in effective flood management. This paper introduces three primary sources of data commonly used in flood forecasting: Satellite data, gauge measurements, and citizen observations. It examines the advantages and disadvantages associated with each data source. The paper emphasizes that by combining the strengths of various precipitation data sources, such as satellites and gauges, it becomes possible to achieve accurate and comprehensive characterization of rainfall patterns over time and space, surpassing the capabilities of relying solely on gauge or satellite data.

Furthermore, through a case study review conducted in Europe, Asia, and America, the research reveals that among all data variables, Digital Elevation Models (DEMs) and rainfall are the most critical variables in flood forecasting. These variables are nearly universally employed in all models used for flood prediction. Notably, although most studies that explore trends in flooding primarily utilize precipitation, changes in soil moisture represent the dominant mechanism responsible for the observed trends in floods. Therefore, it is imperative to account for changes in soil moisture conditions when predicting catchment flood responses in the context of climatic change.

REFERENCES

Arjomandnia, R., Ilbeigi, M., Kazemidemneh, M., & Hashemi, A. N. (2023). Renovating buildings by modelling energy–CO 2 emissions using particle swarm optimization and artificial neural network (case study: Iran). Indoor and Built Environment, 1420326X2311512. https://doi.org/10.1177/1420326X231151244

Bonafilia, D., Tellman, B., Anderson, T., & Issenberg, E. (2020). Sen1Floods11: A georeferenced dataset to train and test deep learning flood algorithms for Sentinel-1. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 835–845. https://doi.org/10.1109/CVPRW50498.2020.00113

Borga, M., Anagnostou, E. N., Blöschl, G., & Creutin, J.-D. (2011). Flash flood forecasting, warning and risk management: The HYDRATE project. Environmental Science & Policy, 14(7), 834–844. https://doi.org/10.1016/j.envsci.2011.05.017

Buytaert, W., Zulkafli, Z., Grainger, S., Acosta, L., Alemie, T. C., Bastiaensen, J., De BiÃ¨vre, B., Bhusal, J., Clark, J., Dewulf, A., Foggin, M., Hannah, D. M., Hergarten, C., Isaeva, A., Karpouzoglou, T., Pandeya, B., Paudel, D., Sharma, K., Steenhuis, T., Tilahun, S., & Zhumanova, M. (2014). Citizen science in hydrology and water resources: Opportunities for knowledge generation, ecosystem service management, and sustainable development. Frontiers in Earth Science, 2. https://doi.org/10.3389/feart.2014.00026

Chagas, V. B. P., Chaffe, P. L. B., Addor, N., Fan, F. M., Fleischmann, A. S., Paiva, R. C. D., & Siqueira, V. A. (2020). CAMELS-BR: Hydrometeorological time series and landscape attributes for 897 catchments in Brazil. Earth System Science Data, 12(3), 2075–2096. https://doi.org/10.5194/essd-12-2075-2020

Cristiano, E., Ten Veldhuis, M.-C., & Van De Giesen, N. (2017). Spatial and temporal variability of rainfall and their effects on hydrological response in urban areas – a review. Hydrology and Earth System Sciences, 21(7), 3859–3878. https://doi.org/10.5194/hess-21-3859-2017

Doocy, S., Daniels, A., Murray, S., & Kirsch, T. D. (2013). The Human Impact of Floods: A Historical Review of Events 1980-2009 and Systematic Literature Review. PLoS Currents. https://doi.org/10.1371/currents.dis.f4deb457904936b07c09daa98ee8171a

Douglas, I., Garvin, S., Lawson, N., Richards, J., Tippett, J., & White, I. (2010). Urban pluvial flooding: A qualitative case study of cause, effect and nonstructural mitigation: Urban pluvial flooding. Journal of Flood Risk Management, 3(2), 112–125. https://doi.org/10.1111/j.1753-318X.2010.01061.x

Eggimann, S., Mutzner, L., Wani, O., Schneider, M. Y., Spuhler, D., Moy De Vitry, M., Beutler, P., & Maurer, M. (2017). The Potential of Knowing More: A Review of Data-Driven Urban Water Management. Environmental Science & Technology, 51(5), 2538–2553. https://doi.org/10.1021/acs.est.6b04267

Feng, L., Hu, C., Chen, X., Cai, X., Tian, L., & Gan, W. (2012). Assessment of inundation changes of Poyang Lake using MODIS observations between 2000 and 2010. Remote Sensing of Environment, 121, 80–92. https://doi.org/10.1016/j.rse.2012.01.014

Fereshtehpour, M., Esmaeilzadeh, M., Alipour, R. S., & Burian, S. J. (2023). Impacts of DEM Type and Resolution on Deep Learning-Based Flood Inundation Mapping. https://doi.org/10.48550/ARXIV.2309.13360

Gaitan, S., Van De Giesen, N. C., & Ten Veldhuis, J. A. E. (2016). Can urban pluvial flooding be predicted by open spatial data and weather data? Environmental Modelling & Software, 85, 156–171. https://doi.org/10.1016/j.envsoft.2016.08.007

Golian, S., Saghafian, B., & Maknoon, R. (2010). Derivation of probabilistic thresholds of spatially distributed rainfall for flood forecasting. Water Resources Management.

Gong. P., et al., 2019. Stable classification with limited sample: transferring a 30-m resolution sample set collected in 2015 to mapping 10-m resolution global land cover in 2017. Sci. Bull. 64, 370-373.

Guan, X., Mascaro, G., Sampson, D., & Maciejewski, R. (2020). A metropolitan scale water management analysis of the food-energy-water nexus. Science of The Total Environment, 701, 134478. https://doi.org/10.1016/j.scitotenv.2019.134478

Guerreiro, S., Glenis, V., Dawson, R., & Kilsby, C. (2017). Pluvial Flooding in European Cities—A Continental Approach to Urban Flood Modelling. Water, 9(4), 296. https://doi.org/10.3390/w9040296

He, F., Mohamadzadeh, N., Sadeghnejad, M., Ingram, B., & Ostovari, Y. (2023). Fractal Features of Soil Particles as an Index of Land Degradation under Different Land-Use Patterns and Slope-Aspects. Land, 12(3), 615. https://doi.org/10.3390/land12030615

Herman Assumpção, T., Popescu, I., Jonoski, A., & Solomatine, D. P. (2017). Citizen observations contributing to flood modelling: Opportunitiesand challenges [Preprint]. Rivers and Lakes/Instruments and observation techniques. https://doi.org/10.5194/hess-2017-456

Hjelmstad, A., Shrestha, A., Garcia, M., & Mascaro, G. (2021). Propagation of radar rainfall uncertainties into urban pluvial flood modeling during the North American monsoon. Hydrological Sciences Journal, 66(15), 2232–2248. https://doi.org/10.1080/02626667.2021.1980216

Hossain, F., Arnold, J., Beighley, E., Brown, C., Burian, S., Chen, J., Madadgar, S., Mitra, A., Niyogi, D., Pielke, R., Tidwell, V., & Wegner, D. (2015). Local-To-Regional Landscape Drivers of Extreme Weather and Climate: Implications for Water Infrastructure Resilience. Journal of Hydrologic Engineering, 20(7), 02515002. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001210

Hosseini, A. S., Asadi, D., mohammadzadeh, S., & Ghalandari, S. (2023). Exploring Spatial and Temporal Dynamics of Soil Moisture Using SMAP, Khorasan Razavi, Iran. Asian Journal of Social Science and Management Technology, 5(4).

Islam, A. S., Bala, S. K., & Haque, M. A. (2010). Flood inundation map of Bangladesh using MODIS time-series images: Flood Inundation map of Bangladesh. Journal of Flood Risk Management, 3(3), 210–222. https://doi.org/10.1111/j.1753-318X.2010.01074.x

Jiang, Y., Zevenbergen, C., & Fu, D. (2017). Can “Sponge Cities” Mitigate China’s Increased Occurrences of Urban Flooding? Aquademia: Water, Environment and Technology, 1(1). https://doi.org/10.20897/awet.201703

Jiang, Y., Zevenbergen, C., & Ma, Y. (2018). Urban pluvial flooding and stormwater management: A contemporary review of China’s challenges and “sponge cities” strategy. Environmental Science & Policy, 80, 132–143. https://doi.org/10.1016/j.envsci.2017.11.016

Karamouz, M., Alipour, R. S., Roohinia, M., & Fereshtehpour, M. (2022). A Remote Sensing Driven Soil Moisture Estimator: Uncertain Downscaling With Geostatistically Based Use of Ancillary Data. Water Resources Research, 58(10), e2022WR031946. https://doi.org/10.1029/2022WR031946

Karamouz, M., Ghomlaghi, A., Saleh Alipour, R., Nazari, M., & Fereshtehpour, M. (2019). Soil Moisture Data: From Using Citizen Science to Satellite Technology. In World Environmental and Water Resources Congress, 85–95.

Ke, Q., Tian, X., Bricker, J., Tian, Z., Guan, G., Cai, H., Huang, X., Yang, H., & Liu, J. (2020). Urban pluvial flooding prediction by machine learning approaches – a case study of Shenzhen city, China. Advances in Water Resources, 145, 103719. https://doi.org/10.1016/j.advwatres.2020.103719

Llasat, M. C., Marcos, R., Turco, M., Gilabert, J., & Llasat-Botija, M. (2016). Trends in flash flood events versus convective precipitation in the Mediterranean region: The case of Catalonia. Journal of Hydrology, 541, 24–37. https://doi.org/10.1016/j.jhydrol.2016.05.040

Lin, J., He, X., Lu, S., Liu, D., & He, P. (2021). Investigating the influence of three-dimensional building configuration on urban pluvial flooding using random forest algorithm. Environment Research, 196, 110438.

Lin, Y., 2020. GCIP/EOP surface: precipitation NCEP/EMC 4KM Gridded Data (GRIB) Stage IV Data. Version 1.0 (1.0, p. 229482 data files, 2 ancillary/documentation files, 11 GIB) [GNU Zip Compressed (.gz) Gridded Binary (GRIB) Format (application/x-gzip), GN Zip (.gz) Format (application/x-gzip)]. UCAR/NCAR - Earth Observing Laboratory. doi: 10.5065/D6PG1QDD.

Löwe, R., Böhm, J., Jensen, D. G., Leandro, J., & Rasmussen, S. H. (2021). U-FLOOD – Topographic deep learning for predicting urban pluvial flood water depth. Journal of Hydrology, 603, 126898. https://doi.org/10.1016/j.jhydrol.2021.126898

Martina, M. L. V., Todini, E., & Libralon, A. (2006). A Bayesian decision approach to rainfall thresholds based flood warning. Hydrology and Earth System Sciences, 413–426.

Miao, Q., Yang, D., Yang, H., & Li, Z. (2016). Establishing a rainfall threshold for flash flood warnings in China's mountainous areas based on a distributed hydrological model. Journal of Hydrology, 541, 371–386. https://doi.org/10.1016/j.jhydrol.2016.04.054

Mohammadpouri, S., Sadeghnejad, M., Rezaei, H., Ghanbari, R., Tayebi, S., Mohammadzadeh, N., Mijani, N., Raeisi, A., Fathololoumi, S., & Biswas, A. (2023). A Generalized Regression Neural Network Model for Accuracy Improvement of Global Precipitation Products: A Climate Zone-Based Local Optimization. Sustainability, 15(11), 8740. https://doi.org/10.3390/su15118740

Montesarchio, V., & Ridolfi, E. (2011). Rainfall threshold definition using an entropy decision approach and radar data. Natural Hazards and Earth System Sciences, 2061–2074.

Muller, C. L., Chapman, L., Johnston, S., Kidd, C., Illingworth, S., Foody, G., Overeem, A., & Leigh, R. R. (2015). Crowdsourcing for climate and atmospheric sciences: Current status and future potential: CROWDSOURCING FOR CLIMATE AND ATMOSPHERIC SCIENCES. International Journal of Climatology, 35(11), 3185–3203. https://doi.org/10.1002/joc.4210

National Academies of Sciences, Engineering, and Medicine. (2019). Framing the challenge of urban flooding in the United States. National Academies Press.

Nematirad, R., & Pahwa, A. (2022). Solar Radiation Forecasting Using Artificial Neural Networks Considering Feature Selection. 2022 IEEE Kansas Power and Energy Conference (KPEC), 1–4. https://doi.org/10.1109/KPEC54747.2022.9814765

Netherlands Royal Meteorological Institute, Aug. 2014. Hoe vaak komt extreme neerslag zoals op 28 juli tegenwoording voor, en is dat anders dan vroeger? URL. http://www.knmi.nl/cms/content/120817/hoe_vaak_komt_extreme_neerslag_zoals_op_28_juli_tegenwoording_voor_en_is_dat_anders_dan_vroeger.

Nicklin, H., Leicher, A. M., Dieperink, C., & Van Leeuwen, K. (2019). Understanding the costs of inaction–an assessment of pluvial flood damages in two European cities. Water, 11(4), 1-18. https://doi.org/10.3390/w11040801

Norbiato, D., & Borga, M. (2008). Flash flood warning based on rainfall thresholds and soil moisture conditions: An assessment for gauged and ungauged basins. Journal of Hydrology.

Noymanee, J., Nikitin, N. O., & Kalyuzhnaya, A. V. (2017). Urban Pluvial Flood Forecasting using Open Data with Machine Learning Techniques in Pattani Basin. Procedia Computer Science, 119, 288–297. https://doi.org/10.1016/j.procs.2017.11.187

Overeem, A., Leijnse, H., & Uijlenhoet, R. (2016). Two and a half years of country-wide rainfall maps using radio links from commercial cellular telecommunication networks: TWO AND A HALF YEARS OF RADIO LINK RAINFALL MAPS. Water Resources Research, 52(10), 8039–8065. https://doi.org/10.1002/2016WR019412

Pina, R., Ochoa-Rodriguez, S., Simões, N., Mijic, A., Marques, A. S., & Maksimovic, Č. (2014). Semi-distributed or fully distributed rainfall-runoff models for urban pluvial flood modelling.

Pitt, S. M. (2007). The Pitt review: Learning lessons from the 2007 floods. Cabinet Office.

Prein, A. F., Liu, C., Ikeda, K., Trier, S. B., Rasmussen, R. M., Holland, G. J., & Clark, M. P. (2017). Increased rainfall volume from future convective storms in the US. Nature Climate Change, 7(12), 880–884. https://doi.org/10.1038/s41558-017-0007-7

Rosenzweig, B. R., McPhillips, L., Chang, H., Cheng, C., Welty, C., Matsler, M., Iwaniec, D., & Davidson, C. I. (2018). Pluvial flood risk and opportunities for resilience. WIREs Water, 5(6), e1302. https://doi.org/10.1002/wat2.1302

Schellart, A. N. A., Shepherd, W. J., & Saul, A. J. (2012). Influence of rainfall estimation error and spatial variability on sewer flow prediction at a small urban scale. Advances in Water Resources, 45, 65–75. https://doi.org/10.1016/j.advwatres.2011.10.012

Simoes, N. E. D. C. (2012). Urban Pluvial Flood Forecasting. https://doi.org/10.25560/10545

Smith, L., Liang, Q., James, P., & Lin, W. (2017). Assessing the utility of social media as a data source for flood risk management using a real-time modelling framework: Assessing the utility of social media for flood risk management. Journal of Flood Risk Management, 10(3), 370–380. https://doi.org/10.1111/jfr3.12154

Starkey, E., Parkin, G., Birkinshaw, S., Large, A., Quinn, P., & Gibson, C. (2017). Demonstrating the value of community-based ('citizen science') observations for catchment modelling and characterisation. Journal of Hydrology, 548, 801–817. https://doi.org/10.1016/j.jhydrol.2017.03.019

The Scottish Government. (2013, February 5). Surface water management planning: Guidance (2013). https://www.gov.scot/publications/surface-water-management-planning-guidance/.

Thorndahl, S., Einfalt, T., Willems, P., Nielsen, J. E., Ten Veldhuis, M.-C., Arnbjerg-Nielsen, K., Rasmussen, M. R., & Molnar, P. (2017). Weather radar rainfall data in urban hydrology. Hydrology and Earth System Sciences, 21(3), 1359–1380. https://doi.org/10.5194/hess-21-1359-2017

Tian, X., Ten Veldhuis, M., Schleiss, M., Bouwens, C., & Van De Giesen, N. (2019). Critical rainfall thresholds for urban pluvial flooding inferred from citizen observations. Science of The Total Environment, 689, 258–268. https://doi.org/10.1016/j.scitotenv.2019.06.355

Tuyls, D. M., Thorndahl, S., & Rasmussen, M. R. (2018). Return period assessment of urban pluvial floods through modelling of rainfall–flood response. Journal of Hydroinformatics, 20(4), 829–845. https://doi.org/10.2166/hydro.2018.133

USGS (2016). Flood Inundation Mapping (FIM) Program. http://water.usgs.gov/osw/flood_inundation/, last accessed on October 3, 2016.

Vaze, J., Teng, J., & Spencer, G. (2010). Impact of DEM accuracy and resolution on topographic indices. Environmental Modelling & Software, 25(10), 1086–1098. https://doi.org/10.1016/j.envsoft.2010.03.014

Wang, L.-P., Ochoa-Rodríguez, S., Van Assel, J., Pina, R. D., 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. Journal of Hydrology, 531, 408–426. https://doi.org/10.1016/j.jhydrol.2015.05.049

Wang, R.-Q., Mao, H., Wang, Y., Rae, C., & Shaw, W. (2018). Hyper-resolution monitoring of urban flooding with social media and crowdsourcing data. Computers & Geosciences, 111, 139–147. https://doi.org/10.1016/j.cageo.2017.11.008

Wasko, C., & Nathan, R. (2019). Influence of changes in rainfall and soil moisture on trends in flooding. Journal of Hydrology, 575, 432–441. https://doi.org/10.1016/j.jhydrol.2019.05.054

Weeser, B., Stenfert Kroese, J., Jacobs, S. R., Njue, N., Kemboi, Z., Ran, A., Rufino, M. C., & Breuer, L. (2018). Citizen science pioneers in Kenya – A crowdsourced approach for hydrological monitoring. Science of The Total Environment, 631–632, 1590–1599. https://doi.org/10.1016/j.scitotenv.2018.03.130

Wilby, R. L., & Keenan, R. (2012). Adapting to flood risk under climate change. Progress in Physical Geography: Earth and Environment, 36(3), 348–378. https://doi.org/10.1177/0309133312438908

Wright, D. B., Smith, J. A., Villarini, G., & Baeck, M. L. (2014). Long-Term High-Resolution Radar Rainfall Fields for Urban Hydrology. JAWRA Journal of the American Water Resources Association, 50(3), 713–734. https://doi.org/10.1111/jawr.12139

Wu, X., Yu, D., Chen, Z., & Wilby, R. L. (2012). An evaluation of the impacts of land surface modification, storm sewer development, and rainfall variation on waterlogging risk in Shanghai. Natural Hazards, 63(2), 305–323. https://doi.org/10.1007/s11069-012-0153-1

Yang, P., & Ng, T. L. (2017). Gauging Through the Crowd: A Crowd-Sourcing Approach to Urban Rainfall Measurement and Storm Water Modeling Implications. Water Resources Research, 53(11), 9462–9478. https://doi.org/10.1002/2017WR020682

Yang, T.-H., Hwang, G.-D., Tsai, C.-C., & Ho, J.-Y. (2016). Using rainfall thresholds and ensemble precipitation forecasts to issue and improve urban inundation alerts. Hydrology and Earth System Sciences.

Yin, J., Yu, D., Yin, Z., Liu, M., & He, Q. (2016). Evaluating the impact and risk of pluvial flash flood on intra-urban road network: A case study in the city center of Shanghai, China. Journal of Hydrology, 537, 138–145. https://doi.org/10.1016/j.jhydrol.2016.03.037

Zhang, J., Howard, K., Langston, C., Kaney, B., Qi, Y., Tang, L., Grams, H., Wang, Y., Cocks, S., Martinaitis, S., Arthur, A., Cooper, K., Brogden, J., & Kitzmiller, D. (2016). Multi-Radar Multi-Sensor (MRMS) Quantitative Precipitation Estimation: Initial Operating Capabilities. Bulletin of the American Meteorological Society, 97(4), 621–638. https://doi.org/10.1175/BAMS-D-14-00174.1

Zhang, W., Villarini, G., Vecchi, G. A., & Smith, J. A. (2018). Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston. Nature, 384–388.

Zhu, D., Peng, D. Z., & Cluckie, I. D. (2013). Statistical analysis of error propagation from radar rainfall to hydrological models. Hydrology and Earth System Sciences, 17(4), 1445–1453. https://doi.org/10.5194/hess-17-1445-2013