Journal of Hydrology: Regional Studies 61 (2025) 102583

Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

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

Integrated flood modelling and risk assessment in urban areas: A review on applications, strengths, limitations and future research directions

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ARTICLE INFO

Keywords:
Disaster and risk management
Hazard assessment
Inundation simulation
Remote sensing

ABSTRACT

Study region: Global scale.
Study focus: The purpose of this study is to provide a comprehensive global assessment of urban flood modelling by: (i) critically reviewing the most widely used flood models in urban settings; (ii) synthesizing their operational mechanisms, including the integration of diverse data types and validation techniques; and (iii) evaluating each model's strengths and limitations in simulating flood dynamics and assessing urban flood susceptibility. Furthermore, the paper establishes a framework for selecting acceptable modelling methodologies for successful flood risk management in real-world urban scenarios.
New hydrological insights for the region: Hydraulic-hydrological models, and cloud-based geospatial platforms have been widely applied in flood modelling and risk and vulnerability assessment. Despite these advancements, accurate flood modelling remains a challenge due to limitations in input data quality. Among earth observation tools, radar satellite data was identified as the most effective due to its reliability under cloudy and rainy conditions. Enhancing model accuracy and validation remains possible through the integration of both optical and radar data with hydraulic and hydrological models. For example, radar backscatter intensity can be used to estimate flood depths. However, key research gaps remain, notably, the integration of high-resolution climate projections and socio-economic factors into flood risk models, and the application of modelling tools in poorly planned urban areas to assess real-time changes in land use following flood events.

1. Introduction

Floods are one of the most frequent and prevalent natural disasters worldwide (Agonafir et al., 2023; Iliadis et al., 2023). Between 1990 and 2020, statistics indicate that floods constituted more than 50 % of all natural disasters globally (Avila-Aceves et al., 2023). However, predicting their reoccurrence remains challenging due to their inherently stochastic nature. For instance, in the summer of 2022, the United States experienced four distinct flooding events, each classified as a 1-in-1000-year flood (Ermagun et al., 2024). In contrast, Southeast Asia exhibited different temporal patterns, with major flood events recorded in 2000, 2011, 2013, and 2016 (Ahamed and Bolten, 2017). Africa is no exception to this, as more than 16 countries were affected by widespread flooding in 2009 (Di

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https://doi.org/10.1016/j.ejrh.2025.102583
Received 20 January 2025; Received in revised form 1 July 2025; Accepted 2 July 2025
Available online 24 July 2025

Baldassarre et al., 2010).

Their increasing severity in the preceding decades has significantly impacted national and global economies, infrastructure, demography, and ecosystems (Avila-Aceves et al., 2023). For example, floods in North America caused billions of dollars' worth of damage, while in Europe, they led to £ 3.2 billion in economic losses, including a disruption in infrastructural networks (Adeel et al., 2020; Pregnolato et al., 2016). Thailand's severe floods in 2011 affected over 13 million people and led to 680 deaths (Seemuangngam and Lin, 2024). On the other hand, Parasiewicz et al. (2019), denoted that flood occurrence instigates concurrent post-disturbance effects such as habitat composition. Similarly, in sub-Saharan Africa, significant livestock and crop losses were reported (Balgah et al., 2023), with regions in the Nyabugogo catchment suffering from extensive farm damage, spanning over 1000 ha during the 2012 floods (Icyimpaye et al., 2022)

Human activities such as rapid urbanization exacerbate flood occurrence. For example, rapid urban urbanization combined with changes in land use, has limited the presence of permeable surfaces thus causing amplified runoff (Agonafir et al., 2023; Dharmarathne et al., 2024). In large countries like China, this has led to changes in river systems and environmental degradation (Deng et al., 2015). Sea level rise in Florida increased the magnitude and intensity of urban floods (Wdowinski et al., 2016). This, therefore, renders them susceptible to rapid, severe, and short-lived flooding events when compared to inland areas (Dharmarathne et al., 2024; Wdowinski et al., 2016). Additionally, in response to these escalating challenges, research has shown that with global warming and climate change; 100-year flood flows will increase (Islam et al., 2024), further increasing flood risk of areas that are already susceptible. To address these issues, it is essential to gather comprehensive information about flood events and at risk areas to create or refine strategies for mitigation and response (Shoko and Dube, 2024).

Flood modelling reduces flood risk by simulating and understanding flood dynamics using one and two-dimensional flood models (Mind'je et al., 2019). These offer the intricate simulation of river channels and the spatial distribution of water flow across the floodplain, respectively (Mudashiru et al., 2021). Thus, integrating these two types of models offer significant advances to model flood dynamics in real-time. On the other hand, empirical models like statistical and machine learning assist in flood prediction and susceptibility, supporting long-term planning and decision-making (Kumar et al., 2023).

Furthermore, the availability of remote sensing and Geographical Information Systems (GIS) provide a platform to (i) monitor and predict potential floods for both seasonal and long term (ii) conduct flood hazard maps (iii) ensure effective emergency responses (iv) examine land and society flood susceptibility using high spatial and temporal resolution at little to no cost (Manandhar et al., 2023; Mind'je et al., 2019). While there exist, other reviews related to flood modelling and risk assessment, some are rather selective and less extensive. For example, Mind'je et al. (2019) reviewed flood susceptibility and hazard in the context of Rwanda. Tom et al. (2022) presented a review on flood modelling in developing cities. Mosavi et al. (2018) conducted a review on flood prediction methods using machine learning. Sun et al. (2024) provided a comprehensive review of compound flood risk mapping for urban resilience in coastal areas. Elmer et al. (2012) conducted a review on the drivers of flood risk at a catchment scale.

The study therefore attempts to provide an overview at a global scale by (i) examining the different and commonly used urban flood models (ii) synthesize how these models operate and applied in urban environments by the use of different data types and techniques to monitor and validate flood models (iii) consider their strengths and limitations in modelling floods and assessing flood susceptibility. Additionally, it offers preliminary guidance on selecting a suitable technique for addressing practical flood-related events.

2. Method and materials

2.1. Literature search and database

The research focused on flood modelling techniques and the aftermath of assessing floods. To gather the information; different search engine strategies were used i.e. dynamic search and non-dynamic search from Google Scholar, Science Direct, Scopus and Web of Science database from 2009 to 2024 to account for the most relevant literature. The dynamic search used a search engine code as

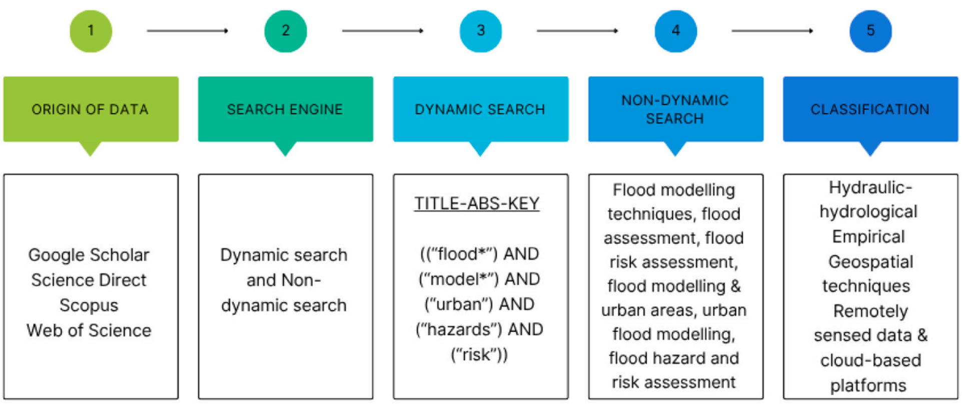

Fig. 1. An overview of the literature search description.

follows: TITLE-ABS-KEY ((“flood*”) AND (“model*”) AND (“urban”) AND (“hazards”) AND (“risk”)). This consisted of journal articles, conference papers, reviews, conference reviews, and book chapters. These included 10,200 from Google Scholar, 4564 from Science Direct, 497 from Scopus, and 878 from Web of Science. From the literature database retrieved, flood modelling methods were then classified (Fig. 1). Furthermore, the search engine terms from the retrieved literature database used a non-dynamic search which included: flood modelling techniques, flood assessment, flood risk assessment, flood modelling and urban areas, urban flood modelling, flood hazard and risk assessment, flood/hazard/inundation, numerical modelling/hydraulic modelling/hydrodynamic modelling/physically based modelling, flood modelling in cities/urban areas, flood modelling/MCDA/empirical modelling, flood modelling/machine learning techniques, flood modelling and risk assessment, flood hazard/remote sensing/, water resource mapping/flood mapping. A total of 3720 from Google Scholar, 618 from ScienceDirect, 443 articles were retrieved from Scopus, 459 from Web of Science. After applying the inclusion criteria, a final total of 470 articles were selected for this review.

2.2. An analysis of research trends from the literature search

The dynamic search engine was used to study the network visualization using the title, abstract, and author keywords in VOSviewer software (version 1.6.20). The red cluster is the largest, which centers around the term ‘climate change’ and the types of flooding occurring in an urban area. This shows that climate variability is the main cause of flooding (Fig. 2) in all types of flood scenarios (e.g. storm surges and fluvial floods as a result of heavy rainfall). This cluster also contained keywords such as sea level rise, coastal flood, tropical cyclone, compound flooding, that exacerbate flood occurrence. The green cluster is the second largest cluster, with the representative term ‘flood’ and the associated methods used to simulate floods. This includes empirical modelling e.g. machine learning, hydraulic modelling and/or numerical simulation. Cluster 3 shown with a light blue colour consists of keywords such as flash floods, flood modelling, flood risk assessment, natural hazards, remote sensing, risk assessment, urban flood, and flood. This shows that remote sensing is an efficient used technique for monitoring floods and useful in providing quick short-term strategies in the event of sudden floods. The dark blue cluster shows a representative word ‘HEC-RAS’, followed by Geographic Information Systems (GIS) and HEC-HMS. This shows the significance of integration of hydrodynamic-hydrological models to study flood hazards by mapping their spatial distribution and dynamics of floods. The purple cluster is the least cluster, represented by the term ‘flood risk’, showing that it is determined by the relationship between flood hazard and vulnerability. Generally, flood risk is a function of flood hazard (e.g. frequency, flow velocity, extent, and depth) and vulnerability (the exposure and susceptibility of people and assets to floods) (Li et al., 2023; Ntanganedzeni and Nobert, 2021). Therefore, it can be concluded that cluster 1 consists of flood-influencing factors/driving forces, cluster 2 consists of data-driven approaches which are empirical modelling, cluster 3 can be categorized as geospatial techniques used for monitoring floods, cluster 4 can be recognized as hydraulic-hydrological models, whilst cluster 5 can be placed under flood risk assessment (Fig. 2).

To analyze the evolution of publications per year based on flood modelling and risk assessment, a scatter plot graph was used. The figure shows a relatively increasing number of publications with time, with the highest number recorded in 2024. This could be attributed to the growing concerns under climate change, flooding events and the resulting impacts thereby acknowledging advancements in modelling approaches and proactive measurements. Asia recorded the highest number of publications, followed by European countries (Fig. 4). This can be attributed to its rapid urbanization and population density. Fewer publications were shown in

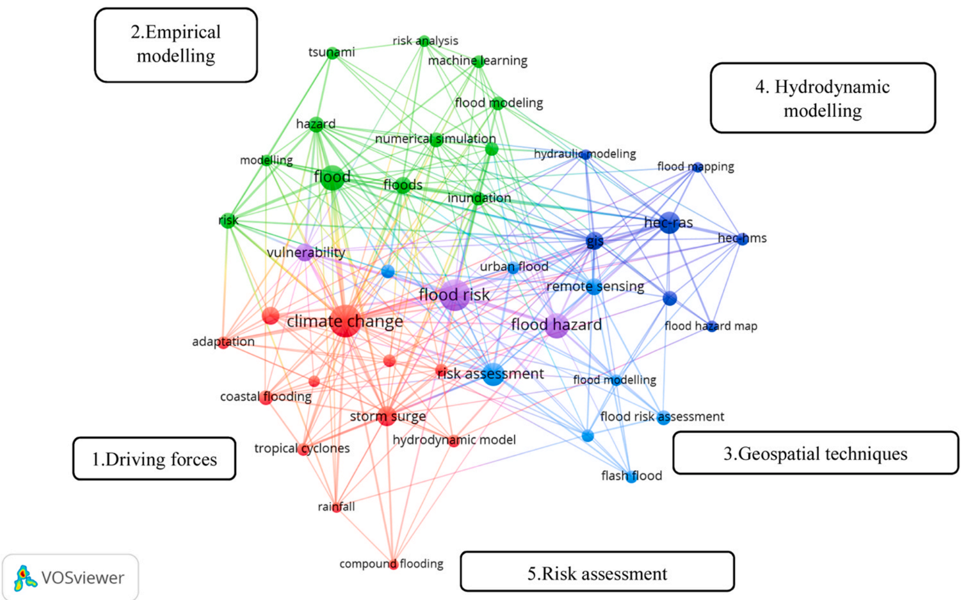

Fig. 2. An analysis of the dynamic search engine using title, abstract, and keywords.

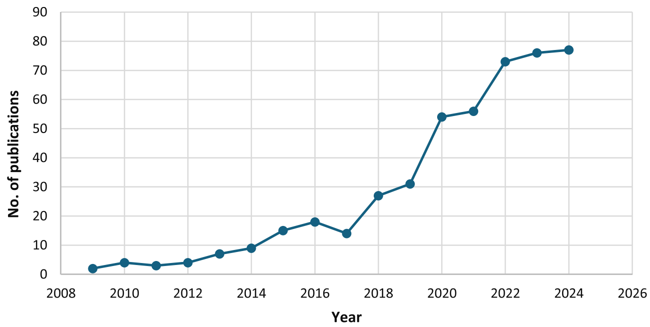

Fig. 3. Progression in the number of global publications on flood modelling and risk assessment.

South America and Africa, necessitating the need for more studies to be conducted to have a holistic understanding of flood dynamics and to help mitigate the increasing risks of flooding (Fig. 4).

3. Hydraulic-hydrological models

One of the predominant methods used in the assessment of flood hazards is the use of hydrodynamic and hydrological modelling. The runoff output data (e.g. as a response to rainfall) from the hydrological model is often integrated with the hydraulic model, facilitating their joint operation in understanding the scope of flood dynamics (Manandhar et al., 2023). These are mathematical representations of the physical processes that simulate fluid motion through various real data inputs; particularly in water systems such as a watershed. Furthermore, they involve solving equations in response to the laws of physics (e.g. the Partial Differential Equations of Navier-Stokes equations) to simulate water movement and its distribution through computing techniques (Mudashiru et al., 2021; Tom et al., 2022). Depending on the representation of spatial dimension or complexity of the floodplain, these models are then dimensionally categorized into 1D, 2D, 1D/2D, and 3D models (Kumar et al., 2023; Manandhar et al., 2023; Teng et al., 2017; Tom et al., 2022). With the use of meteorological, and watershed characteristics such as terrain, land use, soil composition, runoff, channel geometry & roughness input data; they are therefore capable of computing streamflow characteristics such as flow velocity, depth, and width/extent in space and time (Agonafir et al., 2023; Kumar et al., 2023). Most importantly they are widely employed for the deployment of flood prediction and scenario analysis, monitoring, risk assessments, and the evaluation of flood damage (Rathnasiri et al., 2023; Tom et al., 2022). Table 1 provides an overview of the different hydraulic-hydrological models and their applications.

3.1. One-dimensional (1D) model

The simplest approach to modelling floodplain flow involves assuming that the floodplain is represented as one-dimensional, focusing on the central axis of the river channel. The assumption is primarily made because the flow predominantly adheres to one dimension, as observed in confined channels or pipelines through the Saint-Venant equations (Teng et al., 2017). In this case, it is assumed that flow moves in a single direction parallel to the main channel, and a single cross-sectional average velocity is utilized to account for significant velocity discrepancies across the floodplain i.e. flow patterns are assumed to have a relatively stable, with little or no variation in velocity or direction. (Anees et al., 2016; Mudashiru et al., 2021; Teng et al., 2017).

The Hydrologic Engineering Centre for River Analysis System (HEC-RAS), is a typical example of a 1D software model that offers four primary river analysis functions: maintaining a consistent flow rate along the surface of a given river profile, simulating the dynamic flow of water, calculating sediment transport and riverbed modifications, and lastly examining water quality (Anees et al., 2016; Marina and Oana, 2015). For example, studies by Ahmad et al. (2016) and Ntanganedzeni and Nobert (2021) used the HEC-RAS model to compute water surface profiles in the Jhelum Kashmir, India and Livhuvhu River Catchment, South Africa respectively. The results by Ahmad et al. (2016) showed that to a greater extent, the area is likely to be flooded over a 50- and 100-year period and that there is a need to enhance and integrate forecasts of areas that are likely to be flooded during specific flood scenarios. Ntanganedzeni

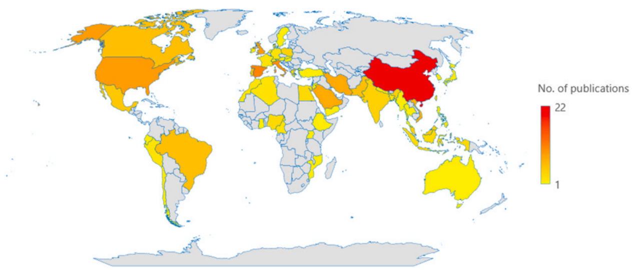

Fig. 4. Global distribution map of publications conducted on flood modelling and risk assessment.

Table 1
An overview of hydraulic-hydrological models and their applications.

Model technique	Strengths & limitations	Access	Application of the model	References
HEC-RAS: 1D and 2D	Simulates both steady and unsteady flow but faces challenges in simulation of water quality in 2D flow.	Open source	Flood analysis and risk assessment	(Ahmad et al., 2016; Shahrim and Ros, 2020; Tom et al., 2022)
HEC-HMS	Integrates with other models but can be ineffective in simulating dynamic flood conditions.	Open source	Models rainfall-runoff dynamics and forecasts river behaviour for early warnings	(Manandhar et al., 2023; Nkwunonwo et al., 2020)
LISFLOOD	Intercepts with rainfall processes and integrates with GIS techniques, however, it cannot function independently	Open source	Assesses floodplain flooding & risk, and simulates flood dynamics for different return periods	(He et al., 2023; Nkwunonwo et al., 2020; Tom et al., 2022)
TELEMAC 2D	Suitable for both steady and unsteady flow but operates reliably under defined conditions.	Open source	Flood simulation of large-scale rivers, estuaries, and coastal areas.	(Seleem et al., 2021; Tom et al., 2022)
MIKE FLOOD: Couples Mike 11 1D and Mike 21 2D	Incorporates a large data set but requires extensive expertise and frequent calibration.	Commercial	Accommodates coastal, riverine floodplain, and urban drainage system simulation &assessment	(Anees et al., 2016; Liu et al., 2020; Manandhar et al., 2023; Nkwunonwo et al., 2020; Tom et al., 2022)
FLO 2D	Suitable for urban and riverine environments, however computing structures such as weirs and bridges separately is time-consuming.	Commercial	Addresses flood-related scenarios such as split channels and debris flows. Delineates flood hazard.	(Erena et al., 2018; Gao et al., 2023; Tom et al., 2022)
FINEL 3D	Time time-consuming but has high accuracy	Commercial	Accommodates coastal and riverine modeling and assessment	(Mudashiru et al., 2021)
SWMM 1D/1D	Adapts to diverse hydrodynamic processes but simplifies urban complexity to 1D.	Open source	Applications related to surface runoff, drainage, and groundwater. Flood hazard and risk assessment	(He et al., 2023; Manandhar et al., 2023)
JFLOW	High accuracy but has difficulty in simulating small scale effects.	Commercial	Hydraulic flood modeling	(Antwi-Agyakwa et al., 2023; Jodhani et al., 2023; Nkwunonwo et al., 2020)
Soil Conservation Service Curve Number (SCS-CN)	Requires minimal input data but excludes flow velocity simulations.	-	Simulates flood extent and depth	(He et al., 2023)
TUFLOW−2D	Slow but can simulate large-scale flood flow.	Commercial	Simulation of hydrodynamics complexities in 2D	(Jodhani et al., 2023; Nkwunonwo et al., 2020; Tom et al., 2022)
SWAT	Advantageous for continuous flood simulations but has difficulties in simulating extreme flood flows	Open source	Flood forecasting	(Devia et al., 2015; Chen et al., 2019)
Infloworks 1D	Adaptive to a broad spectrum of flood scenarios but simplifies urban complexity to 1D, it is also limited in simulating finer scale details.	Commercial	Drainage flood modelling, flood prediction, and mapping	(Agonafir et al., 2023; Gao et al., 2023)

and Nobert (2021) also revealed that in a 20-, 50- and 100-year flood, cultivated land and settlements will be the most susceptible to floods. On the other hand, Al-khafaji and Al-Merib (2024), Iraq, assessed flood risk by studying a river's capacity and predicted floods through various discharge scenarios. The study calibrated the model using adjusted manning's co-efficient factors and found that a roughness co-efficient of 0.023 was optimal for unstable conditions. This resulted in a least mean root square error of 0.053 between the simulated and observed discharge. Although the study was affected by uncertainties, it was observed that increasing flood scenarios in discharge would lead to 92.2 % flood susceptibility in the area, more especially in low-elevated regions.

While 1D models effectively simulate river and drainage systems as well as water resource structures (e.g. Bisht et al., 2016 and Gruss et al., 2018) like dam break flood analysis, their simplifying assumptions overlook important hydraulic factors necessary for accurately simulating urban flood dynamics (Anees et al., 2016; Teng et al., 2017). Consequently, they struggle to predict water surges necessary to visualize urban disaster floods precisely in terms of depth, velocity, and extent (Vojinovic and Tutulic, 2009). Additionally, the lack of information on flow conditions, river cross-sectional data or the existence of barriers such as wiers in river channels poses restriction for flood analysis (Avila-Aceves et al., 2023).

3.2. Two-dimensional (2D) models

The 2D models represent floodplain flow as a two-dimensional field (simulates water flow over a floodplain) assuming that water depth is shallow compared to the other dimensions such as width. The main equations used in these models are called two-dimensional Shallow Water Equations (2D SWE) which are based on the fundamental principles of physics describing how water and the forces/hydraulics driving it are conserved across an area (Teng et al., 2017; Tom et al., 2022). These equations are derived from the Navier-Stokes equations that describe flow in three dimensions, however, the SWE essentially simplifies the Navier-Stokes by averaging out the effects of depth thus making them work easier in two-dimensional scenarios (Mudashiru et al., 2021; Tom et al., 2022;

Vojinovic and Tutulic, 2009). For example, Abdelshafy and Mostafa (2021) in Asia, evaluated and identified flood-prone areas in urban coastal regions using the HEC-RAS 2D to simulate flood depth and velocity of the Wadi Reem basin. The results indicated that the model had difficulties in carrying a 100-year return period peak hydrograph, flood velocity and depth differences. On the other hand, Marina and Oana (2015) revealed that the model can predict water levels and flood-prone areas under extreme hydrological events.

Therefore, when considering flood models in terms of dimensionality and the use of these equations or how water will flow, implies that it is crucial to choose and assess how numerical schemes will enhance flood modelling. As a result, these models are classified based on numerical discretisation strategies, discretisation in time, physical and geometric aspects of flow, and spatial representation (Teng et al., 2017). Numerical discretisation strategies include finite element, finite difference, and finite volume methods. Discretisation in time can be implicit (the equation (s) governing fluid behaviour cannot proceed until the whole domain is solved) or explicit (independent; solved by the governing equation (s) using the current unit information at that given time step). Physical and geometric aspects of flow include kinematic and diffusion waves. Spatial representation can be done using structured mesh (rectangular grids), unstructured mesh (triangular grids), and most recently, flexible mesh (Avila-Aceves et al., 2023; Jodhani et al., 2023; Teng et al., 2017).

The strategies listed can therefore accurately model flood extent, predict flow depth and velocity across a grid delineating the topographic area under study, or conduct flood risk estimations. Talukdar et al. (2021) used the FLO2D flow model to map flood extent in Baitarani River, India, similar to Gharbi et al. (2016) that used TELEMAC 2D at Medjerda Riverin, Tunisia, and (Komolafe et al., 2021), Nigeria. Talukdar et al. (2021) used Shuttle Radar Topography Mission (SRTM) 90 m Digital Elevation Model (DEM), Land Use Land Cover (LULC), structured mesh, and soil texture data. Model validation produced high-performance metrics of 0.76 (Root Mean Square Error (RMSE)) and 0.87 (Nash-Sutcliffe Efficiency (NSE)). However, the study emphasized that, considering factors like model uncertainties, soil moisture conditions, and readily available remote sensing data (calibration and validation purposes) are some of the aspects needed for effective model simulations. On the other hand, Gharbi et al. (2016) noted that the reliability of the model highly depends on the quality of input data. The event-based flood modelling from FLO-2D results by Komolafe et al. (2021) showed flood depths ranging from 0 to 5.24 m, indicating severe flood hazards that could lead to significant damage, especially for low-lying regions. Furthermore, Yan et al. (2018) acknowledged that the use of a coarse grid resolution in urban areas may distort the representation of buildings, potentially leading to a loss in model performance. For example, Kalyanapu et al. (2013) conducted flood hazard on the American River, California using the Flood-2D GPU model, similar to the one presented by Teng et al. (2015) using MIKE 2D in Australia. This employed data such as the National Elevation Dataset (NED) and Light Detection and Ranging (LIDAR) DEM, flow hydrograph, and Manning's coefficients. The RMSE results using the LIDAR DEM and NED ranged from 1.31 to 9.1 and 1.74–11.75, respectively. The use of NED resulted in overestimations of flood depth and velocity.

Although, employing models with finer DEM offer greater precision, they significantly escalate computational time, posing a challenge for urban flood simulations, especially of large areas (Table 1). However, for the optimum representation of flood simulation in 2D SWE models; it is also essential to generate a finer numerical mesh, ideally less than 50 m that will also support the detailed 2D hydrological modelling (Avila-Aceves et al., 2023). Additionally, because the mesh layout is influenced by the topography, the mesh cell size should be no larger than the DEM's spatial resolution.

Furthermore, as urban floodplains are more complex than rural floodplains, they need integrated models to simulate surface water and rainfall-runoff dynamics. Additionally, they require consideration of parameters such as (i) data pertaining drainage network e.g. pipe characteristics and sub-catchment area, (ii) selection of the equations governing flow exchange at the inlet between 1D and 2D models (Kourtis et al., 2017; Vojinovic and Tutulic, 2009) and, (iii) the varying land use, spatio-temporal characteristics of flood levels, and finer details like paved roads (Agonafir et al., 2023).

Various studies (e.g. Fan et al., 2017; Hammami et al., 2022; Kourtis, 2017; Mitsopoulos et al., 2022) have adopted this technique not only to address issues associated with 1D models (including but not limited to solve some or all the one-dimensional Saint-Venant equations) but to also account for interactions between surface flow and underground drainage systems. For example; Barreiro et al. (2023) tested and developed an integrated 1D/2D urban flood model to a synthetic case study and of a real case study in Albufeira City, Portugal. This combined open-source 1D SWMM and 2D MOHID land models, which included manhole flow simulations. According to the model, the results were coherent with the observed past flood events which demonstrated promising implementations for decision making in terms of flood risk management. Due to increasing global climate variations, Iradukunda et al. (2024) in Rwanda, evaluated water structure responses to future climate change using the CMIP6 GCM projection model which was coupled with the SWAT and HEC-RAS. Interesting results revealed that under the ssp585 scenario, water structures might not be able to accommodate a 50-year return peak storm; necessitating the consideration of high greenhouse gas emission scenarios in the infrastructure development that are of high importance. In contrary, Chen et al. (2019) assessed climate change and land use impacts along the Jinsha River basin in China using meteorological data, the SWAT model, and GCM. The SWAT model yielded accurate high flow simulations (NSE value = 0.85 and Percent bias (PBIAS) < 10 %). Whereas, the downscaled GCM data effectively simulated extreme runoff indicators but had difficulties with flood frequency, duration and extreme low flows. Additionally, climate change emerged as the primary contributing factor than land use.

Despite the assumptions derived from the Navier-Stokes equations, the 2D hydrodynamic model has shown to be proficient in predicting flow dynamics across a grid that delineates the topographic domain being examined (Archer et al., 2024; Komolafe et al., 2021; Moghim et al., 2023; Teng et al., 2015). It offers significant advancements in assessing hydraulic parameters and identifying flood-prone areas, making it widely used in flood risk assessment and management (Teng et al., 2017). However, these models can require longer computational time due to the intricate evaluation process, and variations in cell sizes stemming from complex urban surfaces that can hinder efficiency by limiting the time step (Table 1). On the other hand, Rathnasiri et al. (2023) noted that the model's performance can also be limited by the simplification of real-time conditions and the fact that not all flood parameters are considered. Additionally, He et al. (2023), added that accurate simulation of floods remains a challenging issue because acquiring information about the drainage systems is still difficult and often overlooked. However, Jodhani et al. (2023) and Manandhar et al. (2023) acknowledged that there is no perfect model approach at present that comprehensively represents all facets of flood hydrodynamics but rather selecting an appropriate model should depend on the study interest, available data and quality of input parameters such as flow conditions. Consequently, the calibration and uncertainty of flood models is essential for addressing existing challenges in flood modelling as it still restricts the application of models.

3.3. Three-dimensional (3D) models

Three-dimensional models offer an improved accuracy, predictive capability, spatial visualization of complex hydraulic and environmental systems such as flooded areas through improved computing capabilities of 3D hydrodynamic models when compared to 1D and 2D models (Mudashiru et al., 2021). Furthermore, the models address solving the full Navier-Stokes equations and consider flood water flow in a fully 3-dimensional manner, including the incorporation of turbulent condition dataset (Mudashiru et al., 2021; Nkwunonwo et al., 2020). Embodying such models is deemed beneficial for accurately capturing flow dynamics, particularly in urban areas. For example, Rong et al. (2020) employed 2D and 3D hydrodynamic models to assess flood risk in an urban coastal city. The findings indicated that 2D models may lose accuracy in an urban environment with significant vertical fluctuations while 3D models coupled with high-resolution topographic data offered more realistic results.

However, it is suggested that even though these models offer (e.g. TELEMAC 3D and Delft 3D) precise solutions, their complexity might be unnecessary if simpler models based on certain assumptions can still provide a realistic outcome (Jodhani et al., 2023; Nkwunonwo et al., 2020). Furthermore, Tom et al. (2022) noted that employing 3D flood models for inundation over one kilometre was deemed impractical due to computational constraints, inaccuracies in the representation of free surface flows, and challenges with high-order turbulence. However, recent advancements in computing and the adoption of particle-based modelling have addressed some of these constraints as they enable the representation of micro-scale features, thus enhancing spatial resolution and eliminating spatial discretization issues (Mudashiru et al., 2021; Teng et al., 2017). Despite these new advancements, the application of 3D flood modelling remains relatively new, resulting in limited literature compared to 2D modelling (Teng et al., 2017; Tom et al., 2022).

4. Empirical models

Empirical models diverge from hydrodynamic models by utilizing parameters based on observational attributes data of the hydrological cycle rather than simulation thus allowing the model input-output to be near real-time patterns (Mudashiru et al., 2021). These models include statistical equations to establish relationships and predict the functional behaviour of flood occurrence probability between inputs and outputs (Mudashiru et al., 2021; Sindhu et al., 2024). Overall, empirical models are considered as accurate because flood events follow a historical cycle. Their accuracy heavily relies on the methods used for data collection, acquisition, and processing techniques (Tom et al., 2022). Because they solely rely on the input-output approach based on historical records, any errors introduced at any stage of the process can undermine the reliability of the outputs and the decision-making process (Mudashiru et al., 2021; Tom et al., 2022). Other limitations that should be considered in future studies include environmental challenges linked to weather conditions, sensor design, and the precision of algorithms used in data mining and processing (Rathnasiri et al., 2023; Tom et al., 2022).

However, the mentioned challenges have improved through integration of remote sensing data. Additionally, though empirical models lack a detailed representation of the hydrological processes in a basin, they are still valuable in predicting rainfall-runoff dynamics especially in the context of flood forecasting and hydrodynamic modelling through training and validation processes (Anees et al., 2016).

4.1. An overview of empirical models

4.1.1. Multi-criteria decision method

A multi-criteria decision method (MCDM) is a structured approach that is used to showcase flood-related decisions and helps in fostering a synthesized approach. MCDM, steps in as a method of integrating flood-influencing factors to make the decision-making process at ease (Mudashiru et al., 2021; Sahoo and Shubhra Goswami, 2023). The outcome typically contains a set of weights of the different flood-influencing factors based on their relative importance (Avila-Aceves et al., 2023). These weights can be determined by using different techniques. For example; the Multi-attribute utility theory decision-makers compare and use mathematical representations by assigning values to outcomes. This makes it easier to identify best strategies, especially that of flood management (De Brito and Evers, 2016). Pairwise comparisons involve evaluating two factors at a time (e.g. flood influencing factors) to determine which is more important based on a predefined scale. Methods like AHP and Fuzzy AHP help organize these comparisons to weigh the importance of each factor (Avila-Aceves et al., 2023; De Brito and Evers, 2016).

MCDM methods have demonstrated relevance in delineating flood hazards even in data-scarce environments (Abdrabo et al., 2020; Lin et al., 2019; Torresan et al., 2016), where the application of hydraulic-hydrological models would be difficult. Additionally, they do not demand technical extensive expertise and, therefore can be integrated with other concepts such as GIS to meet specific decision-making needs (Avila-Aceves et al., 2023). For example, Lin et al. (2019) in Zhengzhou City, China and Abdrabo et al. (2020) in Hurghada, Egypt used a GIS-MCDM (AHP) model to assess the potential flood extent and scale in data-scarce areas. This incorporated a composite urban flood risk index derived from flood influencing factors, where LULC and physical vulnerability were the primary contributors of floods. Although the study by Abdrabo et al. (2020) was not validated, validation by Lin et al. (2019) received an Area Under the Curve (AUC) of 74.27 %. However, both studies recommended more applications of MCDM, especially in larger regional scale areas to determine model reliability. Gaya and Cherrared (2023) conducted a hazard and vulnerability assessment in Algiers City, Algeria to identify vulnerable points of the storm sewer network using FMECA model, MIKE Urban and AHP method. Despite limitations caused by the lack of data, the models produced a Lin's CCC value of 0.88. The study recommended that, obtaining specific degree of affected areas, state of infrastructure, and damaged items would improve the accuracy and practicality of flood simulations.

Studies by Pathan et al. (2022), India and Karami et al. (2024), Iran also leveraged the integration approach of using MCDA methods such as AHP and TOPSIS to delineate flood zones. Both studies indicated that TOPSIS was a superior method compared to AHP. However, the study of Abdrabo et al. (2020) had noted that; using statistical techniques such as AHP fuzzy logic and Principal Component Analysis could enhance the AHP method. Additionally, the study by Karami et al. (2024) was limited by the lack of access to data (accurate land use and soil maps) and deficiencies in long-term climatic data.

4.1.2. Statistical models

Statistical methods use flood-influencing factors to predict the likelihood of flood occurrence or risk within a study area, expressed in mathematical terms. They are mostly useful in providing flood hazard indices using weighted indices (Kaya and Derin, 2023; Mudashiru et al., 2021). Despite their linear assumptions which may not reflect the nonlinear nature of floods, they still provide efficiency and accuracy with the aid of GIS and remote sensing data. They can effectively be utilized in flood analysis, yielding more adaptable, impartial, and accurate decisions in evaluating relevant factors influencing floods (Kaya and Derin, 2023; Tehrany et al., 2014). Furthermore, that they can quantify issues related to uncertainties in a set of data (Yang et al., 2018a). However, this set of data consists of a large preexisting dataset that can be quite complex for interpretation and statistical analysis. Moreover, they can be ineffective in understanding how individual factors contribute to flood occurrence (Mudashiru et al., 2021; Wubalem et al., 2021).

The most common statistical models include bivariate and multivariate. Bivariate model studies the relationship of each flood influencing factor to the probability of flood occurrence (Tehrany et al., 2014; Wubalem et al., 2021). Examples include Frequency Ratio (FR), Weight of Evidence, Statistical Index, and Certainty Factor. Multivariate models facilitate the exploration of the regression relationship between dependent variable (flood occurrence) and multiple independent variables (flood influencing factors) (Wubalem et al., 2021). Examples include Logistic Regression (LR) models (Bayesian, Kernel, binomial, and multinomial), multivariate regression (Partial Least square), discriminant analysis, Shannon entropy, and techniques that include Bootstrapping (BT) and Random Subsampling (RS).

Often, FR and bayesian models are employed. For example, Ali et al. (2019) in India, assessed the capability of GIS, integrating it with AHP and FR for identifying areas at risk of flooding. FR was used to determine the relationship between previous flood instances and the likelihood of future flood events, drawing from a dataset of 200 points where flooding occurred. The results indicated a success rate of 81.42 % and 84.50 % for the FR model using the training (75 %) and testing (25 %) datasets, respectively. AHP revealed that the most influential factors was proximity to rivers, land use land cover, and precipitation. In another study, Wubalem et al. (2021) compared the effectiveness of bivariate (FR), multivariate (LR), MCDA (AHP), and GIS in flood susceptibility approach in Lake Tana basin, Ethiopia. The results showed that bivariate models outperformed (AUC = 99.1 %) MCDA (AUC = 86.9 %) and LR (AUC = 81.4 %). The study recommended the importance of incorporating hazard and risk analysis in flood-prone areas. Dodangeh et al. (2020) in Ardabil Province, Iran, integrated RS and BT techniques with machine learning algorithms (GAM, MARS, BRT) for flood prediction. RS improved the performance of the models while BT showed a better performance. The BT-GAM model showed the highest statistical metrics (AUC = 98 %, TSS = 0.93, COR = 0.91), followed by the BT-MARS model (AUC = 97 %, TSS = 0.91, COR = 0.91) and the BT-BRT model (AUC = 95 %, TSS = 0.79, COR = 0.79). In a different study, Saad et al. (2015) in Canada evaluated the mechanisms behind spring floods, focusing on factors like occurrence, duration, frequency, and intensity of precipitation using a multivariate copula model, frequency analysis as well as hydrometeorological indices for both pre and post-flooding. Findings demonstrated that the 90th percentile of spring rainfall significantly influences extreme spring peak flow. The study also reported that the joint and conditional return periods derived could offer valuable insights into adaptation and flood risk management strategies when suitable indicators are selected. Similarly, Wu et al. (2019) in Zhengzhou City, China assessed urban flood risk using a Bayesian Network model and GIS application techniques (e.g. kringing interpolation and multiple buffer operator for spatial analysis of rainfall and river network, respectively) to study the relationships of factors impacting on flood disaster. Although key factors were identified with minimal relative errors, the study noted that the model was not comprehensive enough thus recommended the inclusion of more factors such as drainage network and improved data quality such as rainfall and DEM. Besides these approaches, traditional methods have proven reliability. In a different study, Yiiong and Bundan (2018) used a linear regression method for river flood prediction with the use of water level and rainfall intensity parameters. A second-order polynomial function showed a strong correlation ($y = 1.0269x + 148.75$) between the two parameters which demonstrated precise results for possible river floods in the near future.

4.1.3. Machine learning algorithms

Machine learning algorithms employ computers to learn the underlying patterns and relationships from historical data without being explicitly programmed to predict future occurrences (Agonafir et al., 2023; Kumar et al., 2023; Mudashiru et al., 2021). They have the advantage of being able to predict where data is missing and to take large and unstructured data sets ranging from topographical, meteorological, and hydrological aspects (Rathnasiri et al., 2023). The data can be used to assess the performance, train, test, and validate the model's accuracy or reliability through metrics (Kumar et al., 2023; Mosavi et al., 2018).

Various machine learning models have been applied in the aspect of flood susceptibility, categorize vulnerability, and flood damage assessment thus demonstrating encouraging predictive abilities (Rathnasiri et al., 2023). Such models include (i) Decision Trees (e.g. Random Forest (RF), Classification and Regression Trees (CART), Logistic Model Tree, (ii) Ensembles (e.g. Boosted Regression Tree, Bayesian Logistic Regression Tree), (iii) K-nearest neighbour (Naïve Bayes Tress), (iv) Neural Networks (Artificial Neural Networks (ANN), Deep Learning Neural network (DLNN), Convolutional Neural Network) and (v) Support Vector Machine (SVM)/Support Vector Regression (SVR) (Linear, Multiple, and Polynomial) vi) Unsupervised K-means clustering methods (Kaya and Derin, 2023; Mosavi et al., 2018).

Supervised learning algorithms such as the SVM rely on statistical theories and minimization principles and are one of the popular applied classification and regression complexities. Its superior empirical performance positions it advantageously relative to other algorithms (Tehrany et al., 2015). For example, Nhangumbe et al. (2023) in Beira City, Mozambique, monitored floods and conducted damage assessment using Sentinel 1-SAR and Sentinel 2, supervised SVM and unsupervised K-means machine learning methods. The study highlighted that although both methods performed equally well; the supervised method had a higher accuracy (IoUs ranging from 0.86 to 0.84) compared to unsupervised method (IoUs ranging from 0.83 to 0.82). Costache (2019) in Romania, Zhao et al. (2019), Beijing, as well as Moradian et al. (2024), Ireland; conducted similar studies by comparison of machine learning algorithms. The studies used WELLSVM, SVR, fuzzy SVM, ANN, LR, Radial Basis Function (RBF), and DT for urban flood susceptibility and compound flooding. According to Zhao et al. (2019), the WELLSVM demonstrated a stronger fit and prediction capability in both training (AUC = 0.98 %) and testing (AUC = 0.82 %) of datasets compared to the other models and showed a better-quality susceptibility map, whilst Costache (2019) had a fuzzy SVM (AUC=

0.91 %) and Moradian et al. (2024) showed a correlation coefficient of 1.00 for RBF. Ganjirad and Delavar (2023) in the United States, conducted flood risk maps using RF and SVM. It was confirmed that slope, plan curvature, and elevation had the greatest impact on flood risk, with importance scores of 0.135, 0.123, and 0.197, respectively. Furthermore, the study recommended the use of advanced data fusion and combining machine learning or rather deep learning data with physical models.

Although the use of advanced machine learning has provided good performance with high accuracies, they are also associated with some challenges. For example, Munawar et al. (2022), noted that the classical machine learning methods such as SVM, Naïve Bayesian, and decision trees require thorough data labelling and feature selection processes for effective model training. Whilst Mosavi et al. (2018), revealed that ANN's major drawbacks are related to low accuracy due to poor data handling and interpretation of the modelled system, Avila-Aceves et al. (2023) noted that these models are commonly utilized for short-term flood prediction and alert systems.

In contrast, deep learning algorithms possess an innate ability to manage unstructured data that can automatically extract important features. Images can be used directly for training without the need of labelling. For example, Parvin et al. (2022) in Poland, compared the predictive performance of DLNN with Bayesian Logistic Regressions (BLR) and ANN to forecast flood vulnerability. The DLNN had the most predictive performance (87.70 %) than ANN (85.10 %) and BLR (69.70 %). Similarly, Youssef et al. (2022) in Ras Gharib, Egypt and Kotaridis and Lazaridou (2022), Italy reflected the similar results with the application of CNN in flood susceptibility, where Youssef et al. (2022) had an accuracy of 86.5 % and Kotaridis and Lazaridou (2022) with 95 %. Consequently, achieving time efficiency in flood susceptibility mapping for larger areas poses a challenge that must be addressed (Youssef et al., 2022). However, Kotaridis and Lazaridou (2022) recommended the use of artificial intelligence. This could involve the use of cloud computing methods and machine learning algorithms that leverages optical or radar imagery to detect and archive new flood events in a spatial database.

Furthermore, ensemble methods provide promising efficiency in forecasting floods as they employ several machine learning algorithms to enhance performance through automated evaluation and weighting system (Mosavi et al., 2018). For example, Doycheva et al. (2017) developed a methodology utilizing an ensemble learning method (COSMO-DE-EPS model) in Mulde river basin, Germany, to enhance flood forecasts by weighting ensemble members based on supervised machine learning. Thus, this approach tackled the uncertainties in numerical precipitation forecasts, as it had shown that 9778 COSMO-DE-EPS indicated good forecasts and an ensemble Rotation Forest accuracy of 93.54 %. The results proved to be beneficial for improving flood simulations and risk assessments thus recommended future research to expand the application of ensemble methods.

5. Geospatial techniques

Given the unpredictability of floods due to various climatic and environmental factors; enhancing the use of automated disaster prediction and forecasting technologies such as remote sensing is crucial in urban flood management (Munawar et al., 2022). These methods use fine spatial, temporal, and spectral resolutions to showcase potential flood zones, vulnerability impacts and monitor or delineate floods both for seasonal and long-term applications (Antwi-Agyakwa et al., 2023; Manandhar et al., 2023; Munawar et al., 2022). These technologies ranging from optical to microwave wavelengths and with the help of GIS, offer crucial data for flood mapping in adverse weather conditions (Manandhar et al., 2023). Table 3 summarizes some of the sensors used, which serve as input in flood-predicting models.

Geospatial flood modelling involves several key elements that are organized into distinct categories. These include hydro-meteorological factors, such as precipitation. Topographical elements, like DEMs, elevation, and slope; which play a crucial role in determining the speed of water (Avila-Aceves et al., 2023). Additionally, soil characteristics, including land use, geological maps, and soil texture, are important for assessing water absorption and runoff. Other relevant factors encompass proximity to water bodies, population density as well as various indices like Topographic Wetness Index and Standardized Precipitation Index (Avila-Aceves et al., 2023; Chikwiramakomo et al., 2021). Innovative remote sensing technologies such as multispectral satellites/platforms (e.g. MODIS, Landsat, ASTER, and Sentinel 2- MSI), LIDAR, and Radar (e.g. Sentinel 1-Synthetic Aperture Radar (SAR)) offer a broad area coverage and frequent revisit intervals, enabling the measurement of episodic urban floods at little to no cost (Aristizábal and Aristizábal, 2023; Manandhar et al., 2023; Munawar et al., 2022).

5.1. Intermediate multispectral sensors

Multispectral sensors collect data from a variety of wavelengths across the electromagnetic spectrum, ranging from visible light to various infrared wavelengths in passive mode. Their passive mode algorithm implies that they need daylight and clear skies to function effectively as cloud cover can weaken the signals received due to atmospheric attenuation (Aristizábal and Aristizábal, 2023; Tavares da Costa et al., 2019). This can cause difficulties in detecting floods because storms which often result in flooding are typically accompanied by clouds Sigopi et al., (2024) noted that clouds can cover large portions of the earth's surface (especially regions characterized with regular cloud cover, or during rainy seasons where areas experience increased cloudiness) further hindering the sensor's ability to capture data. For example, the cloud mask generated by MODIS covers approximately 67 % of the earth sky, while land areas have a cloud cover of around 55 %.

Despite the mentioned challenges associated with passive multispectral datasets; various studies (e.g. Fayne et al., 2017; Gumindoga et al., 2024; Huang et al., 2012) have provided invaluable use of these sensors for the detection and monitoring of flood dynamics, through the application of spectral indices, change detection, segmentation, and threshold techniques. Similar studies by

Table 2
Comparative assessment of flood modelling techniques.

Model/technique	Strengths	Limitations	Application of the model	Reference(s)
MCDA technique				
AHP (Analytic Hierarchy Process)	Organizes the issue at hand into a hierarchical framework for a better comprehension and communication.	Can be time-consuming for medium to high decision-making task. Recommended for regional scales	Flood susceptibility, flood-prone detection, risk assessment and impact assessment	(Abdullah et al., 2021)
ANP (Analytical Network Process)	Flexible to more complex structures, elements are interdependent and considered more accurate	Does not incorporate methods to address uncertainties, as it assumes that all inputs are known with certainty	Flood risk assessment, flood vulnerability	(Antwi-Agyakwa et al., 2023)
WSM (Weighted Sum Model)/Simple Additive Weighting	Easier comprehension as it involves basic arithmetic operations	Attributes must be converted into a consistent measuring unit for accuracy.	Flood risk analysis, disaster management	(Abdullah et al., 2021; Meral and Eroğlu, 2021)
TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)	Rapidly determines the best alternative with minimal involvement from the decision-makers.	Requires a significant amount of data	Flood prediction, flood forecasting, flood risk assessment	(Antwi-Agyakwa et al., 2023)
Statistical models				
Frequency ratio	Helps identify the strength and direction of correlation between variables	Necessitates on the use of preexisting flood data	Flood vulnerability assessment	(Akay, 2021; Al-Abadi and Al-Najar, 2020; Ali et al., 2020)
Statistical Index	An effective method to weigh the different factors, thus producing reliable results	Has the ability to overfit	Flood susceptibility	(Ali et al., 2020)
Certainty factor	Accommodates uncertainty and handles a large range of input data, including incorporation of GIS	Relies on accurate calculation of flood probabilities, which can be data intensive and sensitive to errors	Flood management, flood susceptibility	(Costache et al., 2020; Mudashiru et al., 2021)
Shannon Entropy	Ability to quantify issues related to uncertainties in a set of data	Sensitive to variability between input data	Flood vulnerability assessment	(Yang et al., 2018)
Logistic regression	Can analyze the relationship between different types of data i.e. including quantitative and qualitative	Can be quite complex and thus requires expertise in interpretation and statistical analysis	Flood susceptibility, flood forecasting	(Al-Abadi and Al-Najar., 2020, Wubalem et al., 2021. Tehrany et al., 2014)
Machine learning algorithms				
Support Vector Machine	Reduces overfitting, suitable for both linear and nonlinear relationships	Low accuracy and results may be hard to interpret	Flood susceptibility, hazard assessment, prediction of flood potential zones	(Mosavi et al., 2018)
Random Forest	Versatile and performs well	Time consuming when a large set of trees are used	Flood hazard assessment	(Avila-Aceves et al., 2023)
Classification and Regression Trees	Performs both classification and regression tasks, making predictions more accurate	Potential in flood prediction has not yet been fully explored	Flood susceptibility	(Al-Abadi and Al-Najar, 2020; Liu et al., 2020; Mosavi et al., 2018)
Naïve Bayes Tress	Commonly used and works well with limited data	Can produce low accuracies	Flood susceptibility assessment	(Rana and Mahanta, 2023)
Deep Learning Neural Network	Solves the problem of uncertainty and is adaptable	Quite complex to configure	Flood vulnerability assessment	(Parvin et al., 2022)
Artificial Neural Networks	Efficient in modelling complex scenarios	Poor data handling, complex and difficult to interpret	Flood vulnerability	(Sun et al., 2024; Ali et al., 2020, Mosavi et al., 2018)
Boosted Regression Tree	Enhances model accuracy while minimizing the risk of overfitting to the training data.	Limited speed processing	Mapping flood proneness, flood susceptibility assessment	(Al- Abadi & Al-Najar, 2020; Dodangeh et al., 2020)

Akram et al., (2024) in Pakistan and Fuentes et al. (2019) in Australia assessed flood extent, identified flood risk zones and spatio-temporal variations of flooded areas. This used MODIS and water-based detection algorithms such as Normalized Difference Indices (NDI), Open Water Likelihood, and Islam methodology. The results by Akram et al. (2024) indicated that areas near rivers were at significant risk of flooding, and lack of pre-disaster preparedness increased flood risk. On the other hand, Fuentes et al. (2019) demonstrated high spatial accuracy (Kappa coefficient = 0.57) when using the Islam method, while temporal flood dynamics were most effectively best derived by NDI and ensemble methods. In a different study, Silas et al. (2019) in Nigeria, assessed the sensitivity of NDVI, Enhanced Vegetation Index, Normalized Difference Water Index (NDWI), and Land Surface Water Index (LSWI) in detecting and mapping spatial flood extent using images derived from the MODIS Terra and Aqua. The results showed that all indices were sensitive to flood water detection.

The availability of historical data from a sensor such as MODIS and Landsat are well-suited for assessing trends over a longer period and for seasonal variations (Table 2; Sigopi et al., 2024). For instance, Skakun et al., (2014) in Namibia, conducted a time series over 30 years using Landsat data and a Shuttle Radar Topography Mission DEM 90 m resolution to map out flood hazard and risk assessment. These maps were fused to determine the relative frequency of inundation (RFI) and found that RFI values correlate with the relative water depth simulated by the hydrological model. However, the study recommended that a finer DEM be used as it limited the study to derive more accurate water depth results. For example, Mehmood et al. (2021) developed a flood mapping algorithm to delineate historical flood extents at a global scale. The approach utilized Landsat 5, 6, and 7 imagery, Height Above Nearest Drainage (HAND) for elevation data, along with indices such as the MNDWI and the NDVI. Although the results yielded high true positive rates ranging from 0.71 to 0.90, false positive rates were notably higher in urban areas. The study also highlighted limitations related to terrain-induced inaccuracies in the model outputs, an issue similarly reported by Jafarzadegan et al. (2022). However, these limitations can be addressed through calibration using additional event data and ground survey support. Likewise, studies by Bhatt and Srinivasa Rao (2018), Johnson et al. (2019), Komolafe et al. (2021), and Aristizabal et al. (2023) demonstrated the effectiveness of the HAND model in assessing urban flood risks, particularly in data-scarce regions. On the other hand, Demirkesen (2016) in Edine Province, Turkey acquired Landsat 7 ETM^{+} images and ASTER DEM to conduct flood hazard risk of the region. Some of the revealed results indicated that lower elevated regions were at risk of both coastal and fluvial flooding, whilst land use and landcover showed agricultural and forested areas would be the most affected areas. Additionally, flood waters inflict substantial damage to infrastructure, necessitating effective control management for economic growth. Al Faisal et al. (2018) in Bangladesh, demonstrated this by examining the extent of damage loss across various land uses, and subsequently calculating the proportion of losses before and after flood occurrence by using Landsat images. The proportion of vegetated areas decreased from 59.64 % to 48.17 %, followed by bare soil and built-up areas. While acquiring information in real-time provides significant benefits, it also presents challenges or time-consuming activities that necessitate validation processes to assess reliability. For example, Sivanpillai et al. (2021) in the United States, generated pre- and post-flood maps by identifying inundated areas through NDWI and Modified NDWI from Landsat images. These indices further needed validation processes such as determining kappa co-efficient and overall accuracy. The results showed that maps derived from NDWI had lower accuracy values due to misclassification than MNDWI with a producer accuracy > 90 %.

5.2. *High-precision multispectral sensors*

Sentinel constellation which was launched as part the Copernicus Program of European Space Agency provides Synthetic Aperture Radar (e.g. Sentinel 1-SAR) has a higher spatial and spectral resolution. This makes it a significant dataset for mapping flood events across the globe as it can collect data in areas of interest under cloud-free conditions (Munawar et al., 2022; Tavus et al., 2018). Studies (e.g. Ezzine et al., 2020 and Mason et al., 2014 have used Sentinel SAR to map flood hazard, extent, identify areas susceptible to floods, and for validation purposes. However, the study by Ezzine et al. (2020) suggested the use of forecasting methods and incorporation of socio-economic studies in flood risk assessment. In a different study, Mason et al. (2014) explored the possibility of detecting flood height in urban flooding layover regions (where floods might not be easily visible) by examining double scattering between the potential flooded ground and nearby building walls using SAR, change detection algorithms and LIDAR DEM data. Although the study demonstrated potential accuracies (recall rate ranging from 64 % to 72 %), it stated that the challenge of using Sentinel-SAR for urban flood detection is that its side-looking design can result in significant areas of the urban surface being obscured due to radar shadowing and layover from buildings. These shadowed regions may appear dark, resembling water, which could cause misclassification. Therefore, future work in analysing backscatter intensities for flood height measurements through SAR needs to be done more frequently as it can serve as a validation point. Sentinel 2 MSI provides an enhanced spatial and temporal resolution, making it particularly valuable for monitoring flood events including small water bodies and landcover changes with greater frequency (Table 3). In Malawi, Gumindoga et al. (2024) provided and integrated approach in modelling urban flash floods using hydrodynamic models, MODIS, and Sentinel-2 data. Although the satellite images portrayed effective ability in mapping the spatial distribution of flood events, the study further recommended the use of multiple satellite rainfall products for higher accuracy.

Additionally, the use of aerial drones has broadened the range of tools available for remote sensing in disaster management (Albertini et al., 2022; Manandhar et al., 2023). For example, aerial drones are reliable sources of data for delineating flood extent mapping, assessing impacts, and producing detailed digital terrain models for flood depth simulations (Kastridis et al., 2020; Shoko and Dube, 2024). Studies (e.g. Clasing et al., 2023, Wienhold et al., 2023; Yalcin, 2018) have demonstrated achievable results for flood depth simulation with the integration of UAV. However, its adoption is still an emerging sphere, especially for African countries (Sigopi et. al., 2024), with a few implemented case studies focusing on validation purposes for hydraulic-hydrological models. Moreover, its application in larger scale regions and cost-effectiveness still constraints the adoption (Bilașco et al., 2022; Sigopi et al., 2024).

Table 3
Summary of remote sensing technologies used for flood monitoring and prediction.

Platform/ Satellite	Swath width (km)	Spectral bands	Spatial (meters)	Wavelength (µm)	Temporal (days)	Strengths	Limitations	Reference(s)
MODIS (Terra and Aqua)	2330	36 bands (7 bands for land and cloud)	250 m (Red & NIR), 500 m (Blue, Green, IR) m and 1 km (Thermal)	0.405–14.385 µm	1–2	High temporal resolution	Low spatial resolution, and hindered by cloud cover	(Sigopi et al., 2024)
Landsat (OLI, TM, ETM)	185	7–11	30 m (from visible, near infrared, mid-infrared)	0.45 – 2.29	16	Has a broad range of historical data	Short temporal resolution	(Sigopi et al., 2024)
Sentinel 1-SAR	5.5*20, 20*40	4	20, 80,250,400	-	6–12	Captures data under various weather conditions.	Radar can fail to receive necessary values, causing false positives for flood detection	(Mashala et al., 2023 Munawar et al., 2022; Tavares da Costa et al., 2019)
Sentinel 2-MSI	290	13 bands Visible and NIR, Red edge, and SWIR, atmospheric bands	10 m, 20 m, 60 m	0.46–2.28	6	Provides higher accuracies	Susceptible to atmospheric attenuation	(Mashala et al., 2023; Petropoulos et al., 2024)
STRM DEM	233	-	-	-	-	Fast collection of data	Susceptible to noise and data gaps	(Tavares da Costa et al., 2019)
LIDAR	1–2	5	0.5	1.5–0.53	-	Operates during the day and night	Likely to be ineffective in adverse weather conditions	(Mashala et al., 2023; Tavares da Costa et al., 2019)
ASTER	60	14	15 m (near infrared) & 30 (short wave infrared) – 90 m (thermal infrared)	0.52–11.65	16	Its ability of obtaining high resolution, enables it to produce high accuracies	Timely collection of data is limited	(Mashala et al., 2023; Tavares da Costa et al., 2019)
NOAA/ AVHRR	2900	5	1100 (visible and infrared)	0.58 and 12.5	0.5	Has a broad range of historical data	Affected by cloud interference	(Sigopi et al., 2024)

Data source: USGS ASTEROverview: https://lpdaac.usgs.gov/data/get-started-data/collection-overview/missions/aster-overview/
LIDARExplorer: https://www.usgs.gov/tools/lidarexplorer

6. Remote sensed data and cloud-based platforms

There has been a notable increase in remote sensing datasets obtained from a variety of spaceborne and airborne sensors, each with distinct spectral, spatial, temporal, and radiometric resolutions. However, managing vast amounts of remotely sensed data; often amounting to petabytes, poses significant challenges. These challenges encompass common issues such as handling big data (big data methodologies and computing), and individual challenges specific to remote sensing applications such as data identification, fusion, interpretation, and visualization (Amani et al., 2020; Dube et al., 2023; Neves et al., 2016; Rathnasiri et al., 2023). To address these challenges comprehensively, there's a need for secure, efficient, and advanced cloud computing platforms tailored to remote sensing and GIS requirements (Amani et al., 2020; Zhao et al., 2021).

Cloud computing platforms therefore offer efficient solutions for storing, accessing, and analyzing datasets. They enable the accessibility, scalability, and fault tolerance of large-scale datasets, facilitating efficient management and processing of big data (Neves et al., 2016). Thus, providing a range of services such as virtualized computing services over the internet, and a platform that allows users to develop and run applications, storage, and software packages (Amani et al., 2020). Numerous cloud computing platforms such as Google Earth Engine, Amazon Web of Services, and Azure have been developed to date, offering various functionalities and services to support different applications and industries at a global scale (Amani et al., 2020; Zhao et al., 2021).

The development of Google Earth Engine (GEE) has generated significant engagement and interest in the field of remote sensing and geospatial data; especially that of scientific research. Additionally, the open-access GEE grants users to (i) publicly available remote-sensing and other pre-processed imagery (for topographic and atmospheric effects) through an internet-based Application Programming Interface and a web-based Interactive Development Environment. These tools effectively work with the prevalent coding languages such as Javascript and Python (ii) automatic parallel processing (to deal with big data processing challenges) and rapid computation; eliminating the need to download datasets or install software (iii) integration with other software packages and the use of private datasets. Lastly, the inclusion of built-in algorithms (e.g. machine learning) for data analysis and visualization without the need of the expertise of programming (Amani et al., 2020; Kumar and Mutanga, 2018).

Therefore, there has been an increasing interest in studies based on the GEE platform and for flood related events. For example, Mehmood et al., (2021), mapped significant flood extent in South Asia from 1980 to 2011 using Landsat series. Although the study showed high accuracy results ranging from 72 % to 90 %, it was however limited by the terrain input. Sellami and Rhinane (2024) in Tetouan, Morocco and Siddiq and Sejati (2023) in Pekalongan city, Indonesia conducted similar studies by modelling flood risk (flood extent and vulnerability). Siddiq and Sejati (2023) used Sentinel-SAR image for modelling flood extent, Landsat and World Pop data for flood vulnerability, and VIIRS night-time light for assessing capacity (via physical and economic capacity) of the study area. The overall flood risk revealed that the 43 % of the area had a moderate to high flood risk, with urban areas being affected the most. Although the study by Sellami and Rhinane (2023) offered insight on vulnerable areas, it was however limited by the low spatial resolution of satellites. However, Siddiq and Sejati (2023) recommended that the resolution of each component should be cross-checked for accuracy as well as incorporating field-based validation processes. Nhangumbe et al. (2023), in Mozambique used Sentinel-SAR, SVM and K-means machine learning algorithms in GEE to predict flood occurrence and flood damage assessment. Some results showed IoUs that are less than 0.5, which showed the importance of integrating DEM for accuracy improvements.

Moreover, most of these research efforts succeed in flood hazard in the extent of mapping the spatial inundated areas through the use of GEE; however, predominant attention addresses flood extent and do not emphasize on assessing the probability of flood occurrence, velocity, return period. For example, Mai Sy et al. (2023) stressed this importance as it was noted that as urbanization progresses and the interconnectivity among cities intensifies; the nexus between physical systems, economic systems, and the impact of human factors becomes a crucial component in flood management. Therefore, by providing a holistic approach provides the first step to flood mitigation measures. Additionally, Amani et al. (2020) highlighted that training machine learning algorithms are only limited to 100 GB, displaying large spatial extents can slow its performance and there are limited atmospheric correction algorithms. Nonetheless, the use of GEE empowers users to conduct more advanced spatial analyses than traditional methods as it possesses the capacity to incorporate extensive datasets into a single framework.

7. Future scientific research directions

Flood occurrence and the associated risk in urban areas continue to increase due to climate change, rapid urbanization and lack of resilient infrastructure, thus necessitating the need for robust flood modelling approaches. However, while current flood modelling has advanced in terms of spatial representation (1D to 2D or 1D/2D); data availability, methodological techniques, and data quality still remain practical limitations for improved accuracies, especially in developing countries. Addressing these limitations is essential for improving the relevance and usability of flood models. Key areas of focus include evaluating the resolution of the Digital Elevation Model (DEM), which is a critical factor in reducing model uncertainties; refining numerical schemes; conducting detailed topographical surveys; and incorporating high-resolution, readily available land use data for validation. Additionally, the integration of drainage system data and climate change projections is crucial. There is also a need for further exploration of 3D flood modelling approaches, as their application in current literature remains limited.

Machine learning approaches offer reliable flood prediction; however, their performance relies on large and labelled datasets. Future work should focus on data fusion, ensemble methods for forecasting, transfer learning techniques to minimize training of dataset, and imbedded artificial intelligence to detect, handle big data and archive new flood events in a spatial database. Although geospatial techniques proved as a great potential for flood mapping, particularly Sentinel 1-SAR; further recommendations lie on assessing its full potential in urban flood detection and the application of multiple high resolution rainfall products. Furthermore, socio-economic dimension efforts on flood risk are often overlooked, therefore further studies should adopt interdisciplinary approaches and participatory mapping to better inform-decision making and adaptation strategies for urban resilience planning.

8. Conclusion

Flood modelling and risk assessment are crucial elements in facilitating comprehensive management strategies. The current research has highlighted the different methods and techniques used in flood modelling and risk assessment. Although empirical models do not consider the physical processes and features of a hydrological system in a catchment and sometimes lack data availability; they still have high predictive analysis and accuracy as they have proven to understand non-linear relationships better. In contrast, hydraulic-hydrological models can delineate flood hazard zones and assess vulnerability providing information beyond. Open access of high-resolution DEM data, data quality input and access to underground pipe network is still a concern especially that of developing countries, this limits the delineation of floods in providing accurate results. However, there is no perfect model approach at present that comprehensively represents all facets of flood hydrodynamics, therefore ensuring the quality of input parameters should be efficient. Consequently, the calibration, sensitivity and uncertainty of flood models are essential for addressing existing challenges in flood modelling. Advancements such as the integration of remote sensing satellites operating in the optical and microwave region have provided that platform to move towards automated disaster prediction and forecasting, providing an improved processing capacity and thus increased speed compared to numerical models. Sentinel 1-SAR data has also shown achievable results, however, its validation methods using field-based methods is a common gap. Additionally, exploring the use of multibands or integration of different spectral bands from different satellite is still limited. Although cloud computing techniques are limited in delineating flood return period, depth and velocity; it has provided robust engagement especially that of scientific research in terms of efficiency. This empowers users to conduct more advanced spatial analyses than traditional methods as it possesses the capacity to incorporate extensive datasets into a single framework. Nonetheless, the respective strengths and limitations of these different flood modelling techniques still offer researchers and decision-makers insights, further improvements, and or potential opportunities for integration methods.

CRediT authorship contribution statement

Cletah Shoko: Writing – review & editing, Supervision, Methodology, Conceptualization. **Timothy Dube:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sibuyisele S. Pakati:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

Authors would like to thank the South African National Space Agency for funding this project.

Data availability

No data was used for the research described in the article.

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