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A review of recent advances in urban flood research

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ABSTRACT

Due to a changing climate and increased urbanization, an escalation of urban flooding occurrences and its aftereffects are ever more dire. Notably, the frequency of extreme storms is expected to increase, and as built environments impede the absorption of water, the threat of loss of human life and property damages exceeding billions of dollars are heightened. Hence, agencies and organizations are implementing novel modeling methods to combat the consequences. This review details the concepts, impacts, and causes of urban flooding, along with the associated modeling endeavors. Moreover, this review describes contemporary directions towards urban flood resolutions, including the more recent hydraulic-hydrologic models that use modern computing architecture and the trending applications of artificial intelligence/machine learning techniques and crowdsourced data. Ultimately, a reference of utility is provided, as scientists and engineers are given an outline of the recent advances in urban flooding research.

1. Introduction

Urban flooding is a disaster with severe consequences. In urban areas, with limited infiltration, rainfall events may instigate a rapid ascent of floodwaters. Human mortality, injury and long-term health effects are possible outcomes as a result of drownings, vehicular accidents, or collapsed structures. In addition, adverse economic impacts transpire, as transportation services and businesses are damaged and disrupted [80]. Due to increases in urbanization and severe weather events, urban flood occurrence and intensity is expected to increase in the future. Urban flooding has been studied extensively, and in recent years, there has been an increased momentum. Indeed, the United States (U.S.) Department of Energy has dedicated $66 million towards combating climate change-induced extreme events, such as urban flooding [198], and the National Academy of Sciences organized an ad hoc committee of scientists to conduct case studies and explore urban flood occurrences [128]. The urgency of research is therefore clear, and as a response, the scientific community has investigated causes, created models, and implemented mitigation techniques, generating a rich catalog of urban flood studies.

The goal of this paper is to review the fundamental aspects of urban flooding and provide a synthesis of contemporary interests and modern approaches. In the process, the paper attempts to synthesize urban flood studies, primarily with a United States (U.S.) focus. Fig. 1 depicts a chart outlining the elements of this review. There are a number of flood-related reviews. For instance, *An Overview of Flood Concepts, Challenges, and Future Directions* by Mishra et al., analyzes the phenomena of flooding, outlining risks, modeling, and suggestions for optimal resolutions [119]. However, all types of floods are covered in the review; hence, the analysis particular to urban flooding is brief. Likewise, Teng et al., [175] and Fenton, [61] provide overviews of flooding and methods to assess risk, yet specifics on urban flooding are described minimally [61,175]. Distinctively, the current review is solely dedicated to urban flooding, probing specific driving factors and modeling challenges unique to urban flooding.

There have also been previous reviews addressing aspects of urban flooding. In *Urban flood impact assessment: A state-of-the-art review* by Hammond et al., the impacts of urban flooding are examined, predominantly, from an economic viewpoint [80]. The theme of the Hammond et al paper is that urban flood occurrence is devastating, and there is a need for improved methods of estimating the associated direct and indirect financial losses. By contrast, this paper presents a more

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comprehensive discussion, where urban flood definitions, influences on flood severity, and current modeling undertakings are additionally explored. Also, in *Advances in Urban Design and Engineering*, Karmaker et al. dedicates a chapter, "Urban Flood Risk Mapping: A State-of-the-Art Review on Quantification, Current Practices, and Future Challenges", to urban flooding [94]. While the chapter outlines urban flood risk and vulnerability; the discussion on modeling techniques is exclusively limited to physical models. Similarly, Bates, Bulti and Abebe, and Cea and Costabile also abridge the modeling discussion of flood risk and prediction to the physics-based modeling methodologies [16,29,32]. Physical modeling is highly significant in urban flood research; nevertheless, the utilization of statistical and machine learning models is also on the rise [123]. The inclusion of these contemporary techniques is essential to provide a holistic view. Accordingly, this review concerns recent advances, and there is also an in-depth discussion on data driven methods, specifically those incorporating Artificial Intelligence and Machine Learning (AI/ML) algorithms. There have been urban flood modeling reviews which have mentioned AI/ML methods [77,116]; yet, there is brevity in the descriptions of their implementations. Notably, in this review, there is a larger discussion on AI/ML methods. There is also a cohesive presentation of urban flood research, including the causes and impacts, where an understanding of the phenomena of urban flooding may be achieved, and the modeling endeavors, such as physical models and the newer, more trending, data-driven models are presented.

2. Need for urban flood research

Urban floods may occur when a pluvial flood occurs in built environments where the natural landscape has been altered by the creation of sidewalks, buildings, and roads [66,161]. In these environments, impervious surfaces disrupt the absorption of rainwater into the ground. Consequently, instead of natural processes, sewer system becomes the central mode for stormwater removal. Highlighting the role of the sewer network, FEMA allows for urban flood characterization to include flooding by sewer back-ups (water entering properties from internal drains), clogged catch basins (blocked inlet drains of the stormwater infrastructure), manhole overflows (water flowing from sewer connection through the covers), and water seepage from walls and floors [66]. Moreover, the National Academy of Sciences describes urban flooding as floodwaters exceeding the stormwater capacity [128]. An urban flood may also be labeled as a flash flood. When high-intensity precipitation events occur in an urban environment, flood levels may rapidly arise as the sewer system struggles to remove the continuous downpour of water. Accordingly, in this incident, the categorization of the event would be that of an urban flash flood.

Due to increased urbanization and the effects of climate change, the threat of urban flooding is evermore present. The proceeding subsection will detail these challenges. The impacts in regard to health and safety, economic consequences, and the effect of urbanization and climate-related intense rainfall events are discussed.

2.1. Impact of flooding towards health and safety

There is not extensive literature on deaths directly from urban flooding as most literature compiles statistics on deaths for all flooding incidents, including coastal and riverine floods. However, a glimpse of the urban flood danger may be revealed by specific events. For instance, in September of 2021, there were a total of 44 New York City (NYC), New Jersey, and Westchester County deaths from the urban flood event resulting from the Hurricane Ida-induced torrential rainfall [59,142]. Overall, it has been reported that there are approximately 100 flood related deaths in the U.S. annually [13,89]. Internationally, Jonkman and Kelman found that 175,000 flooding deaths had occurred over a period from 1975 to 2001[90], and Paterson and Harris estimated approximated 4,700 flood deaths in the year 2016[138].

There are a variety of ways urban flood fatalities occur. Considering the September 2021 post-tropical depression Ida event, 11 of the 13 NYC deaths were caused by basement flooding [192], where floodwaters entered the basement units of multi-family homes via windows and openings, trapping the residents inside and resulting in drowning. The

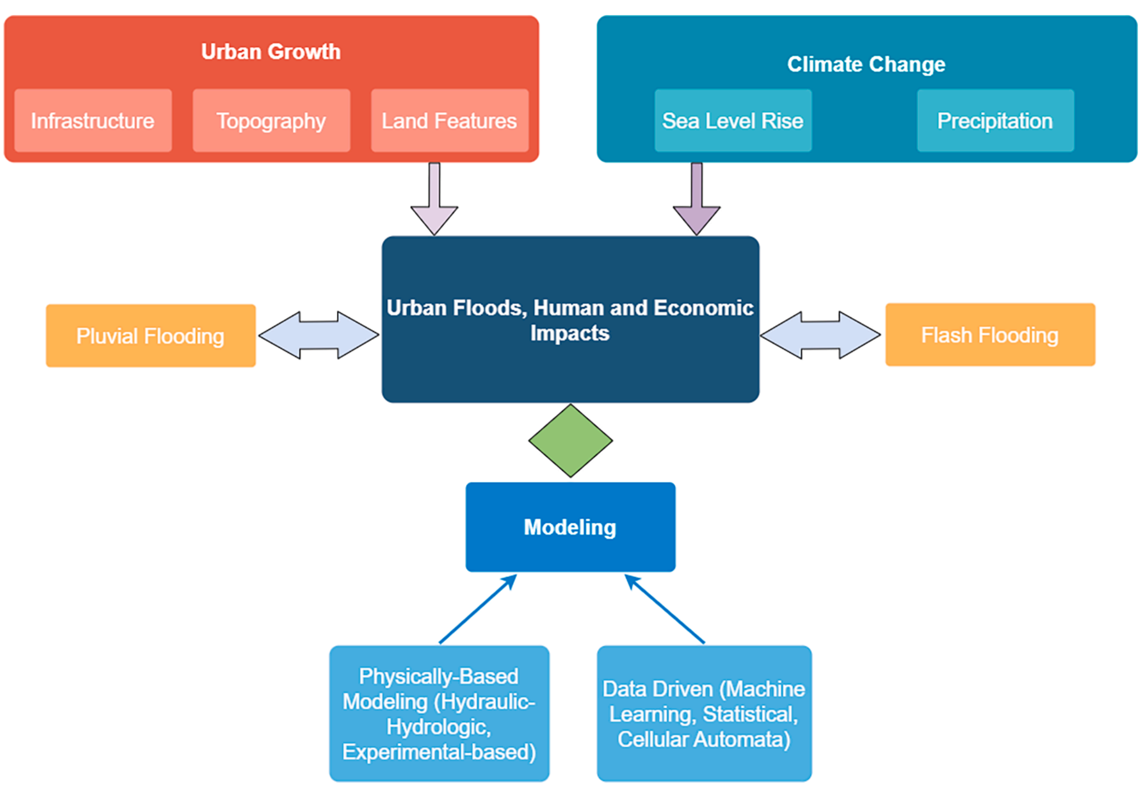

Fig. 1. A flow chart outlining the key elements of the review.

data encompassing all flooding classifications also shows that drowning deaths are most frequently caused by vehicular flooding, as opposed to those who die within their homes [13,63,193]. Vehicle-related deaths comprising a large portion implies that the deceased may have been unaware of the imminent flooding danger, as the person would have otherwise taken cover in a shelter. Besides basement drownings and vehicular deaths, sources of flood fatalities include pedestrian crossings, collapsed buildings, and electrocution [13,14,191].

Aside from death, there are additional safety and health concerns associated with flooding. For one, non-fatal injuries, such as blunt trauma, contusions, lacerations, animal bites, and puncture wounds may be sustained [166,191]. Indeed, flooding events resulting in non-fatal damages are seven times more likely to occur than those resulting in death [91]. Moreover, these injuries are often brought about by downed power lines, debris, broken windows, falling trees, stray animals (snakes, rodents, etc.), and building collapses, which occur during floods [31,166]. While preventive measures such as boarding windows and seeking safe shelter may alleviate the occurrence of injuries, it has also been found that many of flood damages occur during transport or evacuation [166]. Therefore, earlier warning alerts would be beneficial as to allow more time for safety preparations. Another health concern of flooding is contaminated water. Ten Veldhuis et al demonstrated urban flood waters to contain elevated amounts of fecal matters. By studying three flooding incidents in Hague, the Netherlands, the intestinal enterococci and E.coli levels were found to be one to three times greater than the levels in European bathing quality water [174]. This finding indicates that the floodwaters posed unacceptable risk to human health [174]. Furthermore, the Center of Disease Control (CDC) states that floodwaters may contain human waste, industrial hazardous waste, and carcinogenic compounds, such as arsenic, chromium, and mercury, where exposure to the waters may cause skin rash, gastrointestinal illness, wound infections, tetanus, and leptospirosis [31]. Thus, floodwaters pose physical danger with immediate effects, such as injuries or death, in addition to accompanying health risks, which may lead to disease and illness.

2.2. Economic impacts of urban flooding

There are substantial economic costs associated with urban flooding catastrophes. During an urban flooding event, destruction to the infrastructure, such as power failures, interrupted transportation services, and structural damages to the buildings and vehicles, is possible. Given the dense population and infrastructure of cities, the financial loss in urban flooding is expected to be greater than that for a rural flood of similar magnitude [163]. Exemplifying the expense of flooding in urban areas, FEMA data shows that there were $10 billion in payouts, loans and grants to NYC and New Orleans over a 10-year period from 2004 to 2014 [128]. Also, over a five-year period, it is estimated that there were more than $750 million in urban flooding costs for the Chicago metro area [42], and in Detroit, a single urban flooding incident of 2014 resulted in approximately $2 billion of loss [134]. Finally, the post-tropical depression Ida mass casualty event of 2021 incurred $7.5 to $9 billion in expense to New York and $8 to $10 billion in New Jersey. The overall estimated economic loss to the U.S. from the Hurricane Ida incident is greater than $75 billion [21].

As well as the large natural disasters, chronic smaller floods cause financial strain. Indeed, Merz et al had shown that higher probability, low damage events had enacted more strain in case studies of riverine flooding [114]. Regrettably, the costs of lower magnitude and frequent urban floods are not as well documented [128]. The reason may be that small urban floods, occurring during high intensity rainfall days or days with steady rainfall of long duration, are sporadically located throughout a city. This would make monetary quantification difficult, as only specific sections are affected at a time. In NYC, for instance, by the subway damage of Superstorm Sandy, the Metropolitan Transportation Authority (MTA) had estimated $5 billion in transit costs [56,113,122]; likewise, for post-tropical depression Ida, NYC MTA announced the flooding damage to be $75 to $100 million [79]. Yet, throughout the years, there have been chronic, much smaller subway flooding and infrastructural incidents in NYC, where minimal or no cost estimates were publicly disclosed. Examples include the subway flooding during Hurricane Henri in August of 2021[25,115], Hurricane Elsa in July 2021 [118,162], and Hurricane Florence in September of 2018 [57,64]. Additionally, news reports have depicted subway flooding on high rainfall days in the absence of tropical depressions, such as the subway flooding on May 5, 2017, where two services lines and a Penn Station entrance were shut down [149], yet no cost estimates were provided. The chronic urban flooding incidents carry a financial burden, including lower ticket sales (when a portion of transit is closed), increased cleaning fees, and critical costs of repair to electrical and plumbing systems. Yet, for these newsworthy events, documentation of the transit costs is undiscoverable. Therefore, there are economic stresses of urban flooding, of which are not fully quantified.

In addition to the primary impacts of urban flooding, there are also indirect costs. An indirect cost is considered an expense that is not immediate, and it may even occur years after the flood [5,80]. These types of costs include business interruption, loss of wages, long-term infrastructural damage, disruption of goods and services, tourism reduction, relocation expenses, and rental income loss [5,80,155]. In a United Kingdom study, Penning-Rowsell and Parker found that indirect expenses may be as high as 93% of direct flood losses [141], and in a Thailand based study, Tanoue et al found that indirect expenses represented two-thirds of the direct costs for a major flooding incident [172]. Thus, it is important to note that even in well-documented flooding expenses, there will also be a significant portion of indirect costs succeeding the aftermath.

2.3. Impact of climate change on urban flooding

Along with rapid urbanization, greater rainfall amounts or intensity as a result of a warming climate, will over stress the current drainage systems, thereby presenting an ever more severity of urban flooding [66,81]. In a 2019 U.S. climate report, NOAA shows that from September 2018 through August 2019, the precipitation mean of 37.55 in. (953.77 mm) was 7.61 in. (193.29 mm) above average (approximately 25% higher), making the year the fourth wettest period on record [130]. Further, it was found that for every 1.8 degrees Fahrenheit (1 degree Celsius) increase, the number of extreme storms increased by 21%, and by an analysis of climate change projections, it is estimated that the number of severe precipitation storms will grow 60% by the year 2100[28]. It has also been shown that storms have increased in areas where overall precipitation has decreased [11,12,177]. Thus, in these areas, when rainfall occurs, it is doing so at greater intensities [177]. Lastly, there is the effect of the urban heat island. By the increase of urban land use, such as building and concrete installations, convection is amplified, resulting in an increase in local precipitation follows [139].

An increase in extreme precipitation from tropical cyclones and other storms overtaxes the urban sewer network, as the capacities are designed to transport smaller volumes of stormwater [81,194,197]. This inadequate infrastructure is exemplified in the report, The New Normal: Combating Storm-Related Extreme Weather in New York City, which was created by the City of New York in response to the devastation of Hurricane Ida. During the tropical storm, the two-hour rainfall amounts surpassed the supposed 500-year storm in NYC [131], and the hourly rainfall was the greatest ever on record for the city [41]. The report states that the peak rainfall of 3.15 in. (80.01 mm) per hour exceeded the sewer system's current capacity of 1.75 in. (44.45 mm) per hour, and thus, it is recommended the drainage system undergo extensive renovation to double its capacity, at a project estimation of $100 billion [41]. Considering that the previous hourly record was set by Hurricane Henri a month prior [41], the suggested revision is an acknowledgement that there is an increasing risk of urban flooding and that design peak rainfall rates based on extrapolating past observations do not adequately account for the increasing rainfall intensity under a warming climate. Thus, due to a greater frequency of storms, specifically those of high rainfall intensity, urban flooding may become more severe, especially if the changes in the climate outpace the renovation of the sewer networks, which is likely considering the fiscal strains under which many cities labor.

3. Causes of urban flooding

Extreme precipitation, infrastructural factors such as the overloading of the sewer system or the blockage of inlet drains, topography, such as slope and elevation, and land features, such as buildings and impervious cover, play a major role in flooding risk. Geographic location may also determine flood risk; for example, areas located near the coasts are more vulnerable, where coastal waters overflow onto neighboring surfaces during rain events and are worsened by sea level rise and storm surge. As the list of possible urban flooding factors is extensive, this section puts forth some generally included variables and provides a foundational illustration of how different natural or engineering features affect water flow.

3.1. Precipitation

Precipitation is the main cause of urban flooding. While snowmelt holds contribution, particularly in urban areas of the northern hemisphere [159,180], rainfall is the driving factor [143,157,163,180]. In regards to rainfall, it is important to note that there are various expressions of the variable, such as rainfall intensity, storm duration, or total rainfall amounts, and, subsequently, there are studies where only one rainfall input is utilized, and some studies where a combination of rainfall parameters are applied. For example, Cea et al, only includes rainfall intensity in their numerical method-based rainfall-runoff model for urban areas [33], while Qin et al utilize rainfall amount, peak intensity, and duration in the investigation of low impact development techniques for urban stormwater management [143]. In another urban flood study, Liu et al employs rainfall intensity, while introducing an additional measure, rainfall movement direction [108]. Interestingly, in Liu et al, it is demonstrated that rainfall movement direction has up to a 20% effect on peak runoff in Shenzhen, China [108].

Arguably, rainfall intensity, as suggested by literature and fundamental hydraulic design, has the greatest impact on urban flooding. Urban drainage systems are designed for maximum rate of discharge (volume per time), which is an intensity-based metric [50,160,181]. Specifically, in flood protection hydraulic design, a vital parameter in the sizing of drainage structures is the design flow rate [85], and calculations of rainfall intensity are foundational for its determination [85,181]. Additionally, rainfall intensity for peak flow estimations is utilized within the U.S. Geological Survey (USGS) urban peak flow regression equations, where the 2-hour, 2-year occurrence rainfall intensity serves as an input [75], and in NYC, a 5-year return period is used with hourly rainfall intensity [40]. Also, by Emil Kuichling's rational method, average rainfall intensity is used, in conjunction with drainage area and the runoff coefficient, to determine the peak runoff rate [181]. While rainfall intensity is most significant, the element is oftentimes accompanied by storm duration values in formulations. Indeed, the intensity-duration-frequency curves, depicting the relationship between rainfall intensity, storm duration, and return period, are commonly used in peak flow methods for urban areas [85,181].

Along with the varying forms of rainfall variable estimations, there are also different methods of collecting the rainfall data. Mainly, there are two commonly used techniques, in-situ and remote sensing (radar and satellite), and, for urban flood applications, there are advantages and disadvantages of each. First, being direct measurement instruments, rain gauges have an advantage over remote sensing estimates, as common satellite issues, such as cloud top reflectance, thermal radiance, retrieval algorithm and overpass frequency do not apply [2], and although rain gauges, at times, suffer instrumental error [70], the error decreases with increased rainfall intensity [120]. On the other hand, an advantage of remote sensing data is its ability to provide adequate spatial distribution for rainfall estimations [176]. The distance between rain gauges is problematic for the hydrological model, particularly for small-scale urban drainages [126,184], and, in fact, some studies have shown it may account for as much as 20% of uncertainty [176,185]. Schilling suggested resolutions to be roughly 1 km for an urban area [156], and Berne et al. recommended a spatial resolution of 3 km for urban catchments of the order of 1000 ha [20]. As ground-based radar systems provide between 1-to-2 km resolution, the method is suitable [106]. In the U.S., 15 min and one hour rainfall gauge data may be obtained from the National Climatic Data Center NOAA [132], and a source of radar data is the Earth Observing Laboratory, where hourly, 6-hour, and 24-hour totals are available [54]. Hence, both methods of collecting rainfall data, remote sensing and rain gauges, have benefits and drawbacks, and in fact there are combined precipitation products that merge the different data sources in order to produce more accurate data.

3.2. Topography

The two main topographic flood factors are slope and elevation. First, slope, the incline of the ground surface, has effect on urban flooding, and similar to precipitation, many traditional hydraulic computations involve slope as a fundamental variable. For instance, in the analysis of urban runoff, the time of concentration (a necessary variable in hydrograph creations) calculations rely on surface slope values [85,161,181]. Also, slope is a necessary component of Manning's equation, which is frequently used to determine water velocity [85,161,181]. Larger slope angles lead to increases in velocity and discharge. Furthermore, studies have also illustrated the effect of slope on flooding. For instance, Bruwier et al demonstrated that mean water depth and peaks in stored runoff volume are lower in areas with greater slopes [27]. Thus, it seen that flatter surfaces are at higher flood susceptibility.

Elevation is also a commonly considered topographical factor in urban flooding. Indeed, numerous flood studies utilize a digital elevation model (DEM) as a basis in urban flood assessment [46,101,125,189]. Specifically, elevation influences flooding, as areas of low elevation are at an increased flood risk [15,135]. Demonstrating the effect, Kocornik-Mina et al show that for urban areas 10 m above sea level, the annual risk of flooding is 1.3%, while for urban areas 10 m below sea level, the risk is substantially greater, at 4.9%[97]. One reason for the impact is that lower elevated areas may be located at the bottom of a sloped surface, where water ponding is facilitated [183]. Areas close in elevation to the ocean or lake surface will also be vulnerable to rise in the water level due to regional precipitation, storm surge, or sea level rise. Hence, elevation is a topographical consideration when examining the flood risk of a city, particularly near a coast, where many large cities are located.

3.3. Land features

Land features, which may be considered engineered impervious surfaces, such as concrete sidewalks or asphalt streets, or man-made structures, such as buildings, have an impact on urban flooding. Firstly, acknowledged as significant, a variable representing the impervious cover of ground surfaces is utilized in many traditional hydraulic calculations. For instance, in the rational method, the runoff coefficient, a dimensionless number representing the infiltration ability of an area, is used to calculate the peak runoff volume in urban regions [181]. Specifically, the runoff coefficient has a direct relationship to the peak runoff rate, where higher values result in higher discharges, and impervious surfaces are assigned values ranging from 0.70 to 0.95, whereas green surfaces range from 0.05 to 0.35 values [181]. Also, in the Soil Conservation Service (SCS) method, cumulative runoff is calculated based on a direction relationship with curve number, where the curve number has greater values for urban districts and impervious surfaces, as opposed to open spaces with grass cover and meadows [85]. Additionally, as influences of increased flood risk, impervious cover is accounted for in multiple urban flood studies [48,58,168].

In addition to impervious ground surfaces, buildings contribute to urban flood occurrence. Buildings prevent infiltration, increase runoff, and affect the path and geometry of water flow [99]. Bruwier et al found that building factors, such building coverage, building size, and distance between buildings, dominated the other variables of the study, which had included street width and street curvature [27]. In another study of Szechuan, China, Lin et found that the density of buildings, building congestion, and the building coverage had more influence on pluvial flooding events than other variables, such as percentage of impervious surface, average roughness, average altitude, and average precipitation [107]. They demonstrated that the model incorporating building factors performed better (lower root relative squared error) than the model without inclusion [107]. Hence, building dynamics exert an appreciable influence on the occurrence of flooding in an urban area.

3.4. Infrastructure

The performance of the drainage infrastructure greatly affects urban flooding. The infrastructure, as related to urban flooding, includes all aspects of the sewer system imposed with the conveyance of stormwater. An inefficiency of a component adversely affects the removal of water from the surface. It is beyond the intent of this review to divulge into detailed aspects of engineering design, involving capacity calculations and pipe sizing methodologies; nevertheless, two main infrastructurally related factors are presented here: catch basin grate issues and the surcharged sewers. Both problem areas have been presented in prior studies as having noticeable impacts on flooding.

Catch basin blockages during a storm event is a significant contributor to urban flooding, as catch basins are the primary mechanisms for rainwater to enter the sewer system. As in many metropolitans, there are few alternative outlets; thus, when trash or other debris cover a catch basin drain, surface water, unable to permeate the streets, begins to pond and ascend to flood levels. The NYC Department of Environmental Protection (DEP) lists catch basing clogs as one of the three main causes of street flooding in NYC, aside from climate change and surcharged sewers [39]. Agonafir et al found that catch basin clogged complaints reported in the NYC 311 platform were a significant predictor of street flooding complaints in nearly half of all NYC zip codes [4], and had overwhelming percentage of importance in accounting for its spatial variability among neighborhoods [3]. Furthermore, Despotovic et al conducted laboratory tests, where it was shown that inlet coverings prevented the capture of water flow by as much as 60%[49]. Many urban flood studies include a clogging factor, which depicts the amount of runoff remaining on the surface for a given flow [49,71,76,150]. Hence, the blockage of catch basins has importance in urban flood risk assessment.

Surface water rises to flood levels in the advent of sewer surcharge. A sewer system is described as surcharged when the underground drainage network is at capacity, and rainwater is no longer able to enter the stormwater drains [39]. Moreover, there is the phenomena of extended surcharge, where the underground water, held under pressure, flows in reverse order, and exits onto the streets, usually via manholes or private drains [157]. Accordingly, sewer surcharge is accounted for in urban flood modelling [18,87,151,182]. Indeed, for adequate urban drain flow representation, Schmitt et al recommends a specific technique, dual drainage modelling, which accommodates the interaction between the surface flow and sewer flow during sewer surcharge [157]. Thus, to summarize, sewer surcharge and catch basin clogging issues depict a situation where rainwater gathers on the surface or streets, unable to be processed via the stormwater drains. With both flooding factors sharing the same outcome, a clogged catch basin illustrates problems within the external environment, where there is a blockage preventing connection to the underground system, and sewer surcharge and extended surcharge signify issues of the internal sewer system, where it is overloaded and poorly functioning.

3.5. Sea level rise

It has been shown that for the last 25 years, sea levels have been rising at an average rate of 3.3 mm/year [158]. Also, NOAA reports that water levels along the US coastline will rise an additional 10 to 12 in. (254 to 305 mm) by 2050, and flooding occurrence increase by 10 times the present frequency [133]. Therefore, for urban districts, located at a coast, there is increased potentiality, especially during extreme rain events, for the surrounding water bodies to overflow onto the land [72,165,171]. Griffiths et al had particularly shown that sea level rise of up to 47.2 in. (1.2 m) would result in higher volumes of overflow and longer times for stormwater removal [72]. In addition, Woodruff et al demonstrated that, due to sea level rise, flood levels previously associated with a 100-year storm are now taking place during three-to-20-year storms [186]. Thus, in certain urban areas, flooding is occurring more frequently due to the rising heights of the surrounding water bodies.

4. Recent advances in urban flood modeling

Urban flood models are often used to assess flood factors and determine risk zones. In an effort to protect life and property, urban flood modeling is a continuous endeavor. Highlighting both the traditional and recent advances, this review will discuss the main types of urban flood models: hydraulic-hydrologic models, cellular automata models, statistical models, and machine learning models.

4.1. Early hydraulic-hydrologic models

The hydraulic-hydrologic model, serving the purpose of simulating stormwater runoff, may be considered the standard approach in the assessment of urban flooding. Often referred to as dual drainage modeling, the hydrologic aspect concerns the water's behavior on the ground surface; whereas, the hydraulic portion regards the sewer network [99]. An early dual drainage model is the Storm Water management model (SWMM)[99]. Typical inputs for SWMM include detailed drainage plans, rainfall data, a mapping of impervious cover, and a DEM [55,112]. The model then incorporates hydrologic transactions, such as infiltration, interception and depression storage, and hydraulic processes, such as the routing of runoff through the system of piping, channels and storage, to simulate the behavior of stormwater under different climatic scenarios [55]. Thus, the SWMM model has many applications, including drainage design and sizing for flood control and the mapping of flood plains [55]. SWMM has been specifically applied towards urban flood estimation. For instance, Jiang et al utilized SWMM to estimate flood levels in Dongguan City, China for various return period precipitation [88], and Rabori and Ghazavi employed SWMM to simulate peak flows in the urban area of Zanjan City, Iran for 50-year return periods [145].

Hydrologic-hydraulic modeling may apply two techniques, 1D/1D (one dimensional/one-dimensional) or 1D/2D (one dimensional/two-dimensional). The 1D/1D method models water flowing along surface streets. While it is apt at depicting the movement along one surface, it is limited in accounting for dynamic movement, such as the water overflowing curbs [99,111]. The 1D/2D model, on the other hand, simulates water movement that changes dimension, and it may also account for the infiltration of the permeable grasses or trees lining the sidewalks and surfaces [99,111]). While SWMM is considered a 1D/1D model, popular 1D/2D models are MIKE URBAN and InfoWorks ICM [22,154]. MIKE

URBAN utilizes the SWMM mechanism; additionally, it extends by simulating 2D overland flow and integrating GIS capabilities [22]). Also integrating GIS, InfoWorks ICM simulates the urban catchment, and it has been used for flood risk mapping and prediction [167]. In addition, cities, such as NYC use InfoWorks ICM in hydraulic modeling for drainage design [38]. Mark et al found that 1D/1D modeling performed well in evaluating the interaction between rainfall and the urban environment for larger flooding events; however, for the smaller, chronic urban floods, the 1D/1D models, unable capture the finer details, were limited in portraying accurate schematics [111]. Bisht et al found that the 1D/2D model, MIKE URBAN, performed better at modeling various levels of floods (large and small)[22]. There are, however, some drawbacks to the 1D/2D models. 1D/2D model requires extensive computational times, and the high costs associates due to this requirements. Further, they incur significant licensing and development expenses [84,100,111].

There is a significant barrier for both models (1D/1D and 1D/2D) in regards to the availability of the inputs. Specifically, the details of the underground sewer network may be difficult to obtains, as for many metropolitans, either due to age or security concerns, the drainage details are unavailable, incomplete, or inaccessible to researchers [6]. Therefore, while the dual-drainage model has useful applications, there are also accompanying challenges, such as cost, computational time, and data availability.

4.1.1. Advances in hydraulic-hydrologic models

There have been some 1D/2D models developed to overcome the time efficiency issues. Since the application of Shallow Water Equations (SWEs) has been a distinct cause for the slow processing speed of typical 1D/2D methods, there has been the introduction of models which employs Graphic Processing Units (GPUs) or omits less essential SWE calculations [74]. JFLOW, for instance, is a well-studied model, which has applied GPUs, to increase processing speed [44]. In addition, JFLOW simplifies the SWEs by a diffusive wave approximation, assuming gravitational force and resistance force are in equilibrium [170]. By the methodology of JFLOW, processing speeds may be as much as 100 times faster, with results comparable to the traditional 1D/2D models [98,121]. However, Morris et al notes that JFLOW is better suited for shallow water simulations [121]. Su et al also states that, since JFLOW is not adept at water flowing in both directions, the model is limited when modeling the complexities of the urban topography [170]. Another model, which uses the diffusive wave approximation is LISFLOOD-FP [17,164]. LISFLOOD-FP 8.0 has GPU solvers parallelized, resulting in substantial increase in computational speed [164]. However, some limitations include not accurately simulating flow under complex urban terrains [62]. Therefore, while there are 1D/2D models, which have been modified to reduce computational time, limitations remained, specifically towards accurately simulating flow in the urban environment.

In recent years models have been developed to improve the computational performance of the urban terrain. One such model is the Parallel Raster Inundation Model (PRIMo). Using a Godunov-type finite volume scheme for shallow water equations, PRIMo improves upon speed by limiting flux calculations and by parallel scaling [153]. Also, without drainage infrastructure information, PRIMo has been shown to predict flood inundation in the urban city of Los Angeles at a reasonable accuracy [153]. Another physical model, which has successfully modeled urban flooding without a map of the underground sewer system is FLURB-2D [136]. FLURB-2D, a hydrodynamic model utilizing a Galerkin finite element technique for solving shallow water equations, creates a mapping of the area based on observed inlets [136]. Also, a hydrodynamic model, RIM2D, alleviates data requirements, such as sewer plans, by rasterizing building locations [8]. With coding on CUDA and runs via GPUs, this model has a simplified build, quickened processing and the ability to forecast flooded areas, depths and velocities [8]. Thus, there are continuous adjustments in physical models to accommodate the urban area.

Furthermore, in regards to the data availability issues, experimental modeling with the application of numerical methods have been of aid. In this context, experimental modeling refers to conducting laboratory experiments to simulate urban flow, such as street flow and surface-sewer interactions [117]. Oftentimes, the experimental models are of benefit to hydraulic-hydrologic models by serving as validation sets. This is especially helpful in the field of urban flooding, where the incidence of flooding occurs quickly, creating difficulty in measuring extent. Moreover, when experimental models are used for validation, the models also detect areas of computational deficiencies. For example, in the Arrault et al study, an urban European experimental model not only evaluated the accuracy of a 2D shallow water hydraulic-hydrologic model; yet, it also showed issues within the Cartesian grid of the flow calculations [10]. Also, Li et al utilized experimental modeling to investigate the efficacy of the shallow water equations involved with a 2D computation model, where open areas were identified as a vulnerability in the model's prediction capability [104]. Therefore, experimental modeling provides a dataset for validation and serves as a troubleshooting mechanism for assumptions within equations of the hydraulic-hydrologic model. On a final note, regarding experimental modeling, the validation ability of experimental datasets have been of benefit to other models, in addition to the hydraulic-hydrologic. For instance, Dottori and Todini utilized an urban district experimental model to analyze the efficiency a 2D cellular automata model [52]. In the upcoming section, cellular automata modeling in urban flooding is described in more detail.

4.2. Cellular automata

Cellular automata (CA) is a grid-based approach that has been applied to urban flood modeling. With CA, detailed engineering plans of the drainage network are not required since simplifying assumptions are made, and pre-processing times are much lower than those of the physical 1D/2D models [69,129]. CA operates by discrete time/space steps, where a central cell is surrounded by a group of cells, defining an "area of influence"[37]. The area of influence at a time step will affect the cell at the subsequent time step [37]. In one of the first implementations of CA to simulate water spread, Cirbus and Podhoranyi utilized a DEM, where a cell would portray a water level; when the water level is flagged flooded, the water is shown as being transferred to a neighboring cell [37]. Then, in conjunction with hydrologic calculations and optimization techniques, this CA modeling approach was able to simulate runoff. In later years, the CA model has been improved and tailored toward urban flooding applications. For instance, Ghimire et al utilized rainfall data, a DEM, and a constant value for Manning's coefficient to develop a CA-based algorithm [69]. Water depth was able to be simulated, and the researchers found the results to be comparable to the physical model. In addition, Armal and Al-Suhili applied a modified CA model to a sub-catchment in NYC, which extended by accounting for the blockages of inlets [9]. They found that the water levels of the CA were consistent with the water levels measured by survey [9]. Also, Nkwunonwo et al had modified the CA model to incorporate semi-implicit finite difference numerical calculations (providing a physics-based component), and the results had shown to predict water depth in the urban area of Lagos, Nigeria at a Pearson correlation coefficient of 0.968 [129]. Nevertheless, there are limitations associated with CA models. For instance, CA neglects momentum conservation in its formulations, and consequently, velocity of flow estimations are adversely affected [86]. Nevertheless, CA is a widely implemented approach to simulate water flow, with lower costs and data requirements than hydrodynamic modeling techniques.

4.3. Statistical models

Statistical Models use probabilistic techniques to evaluate flooding risk or to forecast flood occurrences. Often using a Bayesian framework and/or including Poisson, or Negative Binomial (NB) statistical links, these models are employed, especially in newer studies, to remedy data availability and cost issues. For instance, Wu et al utilized a Bayesian framework to assess flood risk in the urban area of Zhengzhou City, China [188]. By assessing topography, rainfall, proximity and density to the river network, and land cover, influential factors were identified with low relative errors, and the mapping of predicted flooded areas were similar to the mapping of flooded areas based on historical events [188]. In another study, Li et al combined Bayesian methodology with Synthetic Aperture Radar observations to predict flood extent with an accuracy of 95%, when compared to the actual flooded conditions of the Houston, TX in 2017[105]. Aside from Bayesian frameworks, more traditional statistical regression techniques have also been used to examine flooding factors. For example, Agonafir et al utilized a negative binomial generalized linear regression technique to identify infrastructural and climatic factors affecting NYC street flooding complaints [4]. Additionally, Fang et al employed a Poisson-based generalized linear regression to identify and rank significant flooding factors for the Yangtze River in China [60]. Furthermore, Sadler et al found that the Poisson generalized linear regression model performed well in examining flooding influences in Norfolk, VA [152]. Therefore, data-driven models seem to hold promise for urban flood analysis.

4.4. Artificial intelligence and Machine learning (AI/ML)

Considerably one of the more modern approaches towards urban flood assessment and prediction, AI/ML techniques also have been implemented as a complement to physics-based models. AI/ML describes the programming of machines, using a set of training data, to learn and act without explicit step-by-step instructions, and predict future occurrences, or prescribe recommended actions [26]. Accordingly, due to the capabilities of these methods to learn from an environment, urban flood research has potential to benefit. Historical observations or documentations of flooding, in addition to data, such as topographical and land feature conditions, allow AI/ML methods to read the environment, learn the situation, and provide telling information, thereby attenuating reliance on the more inaccessible drainage data needed for physical modeling. AI/ML methods are lower in computational costs, while the possibility of maintaining accuracy and efficiency [45,123]. However, AI/ML methods may still be limited by the availability of a long and accurate historical record for training and may not perform well in simulating unprecedented conditions. Moreover, for accurate simulation of flood inundation, they would still need mapped inundation for training, which is still sparse in urban environments. With recent advances in unmanned air vehicles (UAVs) [103,178], and modern approaches to using processed images from public cameras and social media feeds (which in themselves are done using modern AI-based pattern recognition techniques)[53,95,124], inundation maps could be generated that can serve as training set for AI/ML-based flood simulation. This is still an emerging area of study.

There are multiple methodologies, including Fuzzy Logic, Genetic Algorithm for Rule Set Production, Support Vector Machine, and Multilayer Perceptron. However, the two techniques with the greatest upward trend in recent years are the Artificial Neural Network (ANN) and Decision Tree (DT) implementations, with ANN methods representing the vast majority of published articles [123]. Thus, this review will elaborate the ANN and DT techniques, with more detail given to ANN.

4.4.1. Artificial Neural network (ANN)

The ANN architecture, an interconnected network of nodes, or “neurons”, was created with the aim of imitating the biological nervous system, particularly the human-brain processes [110,173]. It has been considered the most prevalent of AI/ML techniques for flood analysis, and it has the ability to understand nonlinear relationships better [123]. By the complex comprehension of relationships and interactions, ANNs are able to simulate water behavior, such as evaporation, rainfall-runoff, and discharge [123,173]. Indeed, Karl and Lohani found ANN modeling to outperform traditional statistical methods at estimating peak flow [93], and Zhao et al found that the ANN model had higher precision and accuracy in detailing flood susceptibility than logistic regression and support vector machine models [195]. With increasing usage, researchers have also found utility in the application of ANN subsets, including the Convolutional Neural Network (CNN), the Feedforward Neural Network (FNN), and Recurrent Neural Network (RNN).

The CNN operates by three main layers: convolution, pooling, and fully connected [190]. The convolution layer extracts and learns from the inputs; the pooling layer, often set between convolution layers, enhances shift-invariance by reducing resolution; then, ultimately, the fully connected layers build upon the convolution and pooling layers to perform high-level interpretation and final output cataloguing [73,190]. Hence, based on this building block composition, an urban environment may be examined, without the need of detailed engineering plans. Particularly, CNN aids in the creation of flood risk zones. For instance, Zhao et all utilized a CNN model with nine input variables to predict flood occurrence and to map the areas of greater flood susceptibility in Beijing, China [196]. Also, Peng et al, with the use of satellite imagery, engaged CNN for the processing of high precision urban flood maps in Houston, TX [140]. In addition to risk zones mapping, CNN has been applied to forecasting. For example, Chen et al developed a CNN-based forecasting model to accurately predict flood peaks [34], and Guo et al employed a predictive CNN model, where the computation time was found to be 0.5% the time of the physical model [78]. However, while Guo et al determined that the accuracy of the CNN was sufficient, the CNN did not perform as well for areas with higher slopes and varying terrain inputs [78]. Finally, CNN has been widely applied to image processing. For example, Gebrehiwot et al utilized CNN to successfully extract and identify flooded areas from Unmanned Aerial Vehicles images [68]. Therefore, CNN techniques are shown to have vast applications.

FNNs and RNNs are related, as the RNN is a derivative of the FNN [51]. Concerning the FNN, it is one of the simplest forms of ANN, where, over the course of many cycles, the network acquires knowledge, as pairings of fixed-size inputs and outputs enter the first layer, feed into a middle layer, and moves forward through the last layer [123,169]. RNN extends the FNN by handling data of variable-length, thereby making it especially suitable for time-series analysis [51]. Thus, due to their simplicity, FNNs and RNNs have been applied in urban flood research. For instance, Berkhahn et al engaged an FNN-based urban forecasting model to predict flood water levels, where the FNN-based model’s accuracy was found to be comparable to the physical model [19]. Also, Abdellatif et al used FNN methodology to forecast flooding risk factors in an urban catchment in England, where infrastructural issues, such as surcharged sewers and manhole overflows, were predicted to become significant issues [1]. In regards to the RNN, multiple urban flood studies have implemented the technique, as well [7,30,137]. Indeed, Apaydin et al found that the RNN was an improved ANN version [7]. Moreover, similar to CNN, RNN has indirect applications towards urban flood understanding. Kang et al demonstrated that RNN may be used for precipitation forecasting, which may serve as a useful component in a dynamic urban flood prediction tool [92]. Hence, FNN and RNN, simple subsets of ANN, have a wide range of functionality within urban flood research.

4.4.2. Decision Tree (DT)

In addition to ANNs, the quantity of DT studies has been increasing at a high rate in recent years [123]. The DT, a hierarchical model, analyzes and discovers connections between data and the target variable to create decision rules [65,127]. Naïve Bayes (NB), Reduced Error Pruning (REP), logistic model trees (LM), alternating decision trees (AD), Classification and Regression Tree (CART) and the Random Forest (RF) techniques are some of the commonly used techniques [123]. In early machine learning developments, DT's have been used for classification and regression, where the classification aspect is applied to target variables with discrete values, and the regression is utilized for target variables with continuous values [47]. However, for modern urban flood studies, flexibility and innovation predominates, and particularly, the regression aspect is applied in either discrete or continuous cases. For instance, in the comparison of NB, REP, LM, and AD methods, Khosravi et al applied regression for each prediction model, where the target variables were discrete values representing flood locations [96]. In addition, algorithms, such as C4.5 and CART, which parcels continuous variables into discrete intervals, offer adaptability [82,144]. Thus, DTs are in constant development, with a flexibility that allows for tailored implementations towards flood prediction and susceptibility mapping.

Of the DTs, the CART and RF methods are most distinguished [123]. CART operates by a tree building mechanism, where the final output is an interpretable set of decision rules [43]. Since its inception in the 1980s, CART has been productively applied in numerous urban flood studies [35,36,147,187]. Indeed, Bouramtane et al had demonstrated that the prediction ability of CART surpassed support vector, logistic regression, and discriminant analysis models [23]. Further, the CART algorithm may serve as a foundational element for other algorithms. Specifically, the RF creates an ensemble of CART trees and fits each CART model to bootstrapped samples, thereby reducing the variance [83,102]. RF is able to handle large datasets, maintain robustness with noise, work with missing values, efficiently process outliers, and involve less overfitting than many other algorithms [24,109,148]. Subsequently, due to its diverse capabilities, RF models have been utilized in urban flood research. For instance, Wang et al used a RF model to map flood hazard zones in urban areas of Dongjiang River Basin, China [183]. In addition, Rafiei-Sardooi et al performed a comparison analysis of RF, support vector machine and logistic regression, and found that the RF produced the most accurate flood risk map [146]. Additionally, aside from flood hazard mapping, the RF has been applied to forecasting. For instance, Garcia et al implemented RF for flood forecasting in Manila, Philippines, and validation tests demonstrated that the flood estimations were accurate [67]. Therefore, urban flood researchers have found DT algorithms, such as CART and RT, to be of use in the understanding of urban flood occurrences.

5. Conclusion

With the main concepts, causes, impacts, and resolutions of urban flooding presented, this review may serve as a strategic starting point for researchers formulating additive ideas and methods, and it may assist as a guide or a primer of urban flood modeling approaches for scientists and engineers. Outlined below are the significant messages:

1. Urban flooding may produce fatalities and injuries, such as blunt trauma, contusions, lacerations, animal bites, and puncture wounds. In addition, floods in urban areas may lead to water contamination, causing long-term health effects.
2. Large-scaled, direct economic damages include destruction to the electrical systems, sewer network, plumbing infrastructure, transportation services, businesses, and residential homes. Single-occurring extreme events may enact damages exceeding billions of dollars. Smaller, chronic urban flooding also bring about financial strain; although, the monetary damages are not as well-documented. In addition, there are indirect costs, such as loss of wages, rental income and tourism revenue.
3. Extreme storms are projected to increase in occurrence due to climate change. Particularly, high intense rainfall events will adversely affect urban areas and induce more flooding happenstances. Moreover, urbanization is estimated to continue its growth; thus, there will be more people in the affected urban areas.
4. Influencing factors in urban flooding include the following: precipitation; topography, such as slope and elevation; impervious cover, such as buildings and concrete surfaces; clogged catch basins; insufficient capacity of the sewer network; sea level rising.
5. Early hydraulic-hydrologic based flood models while having good skill, often times deem impracticable due to issues involving data availability, costs, and computational time. Hence, in recent years, improved hydraulic-hydrological models have been created. These models are faster and utilize modern computing architecture and alternative forms of data.
6. Also, as a response to the issues of earlier models, recent research has proceeded with data-driven models, such as cellular-automata, statistical models, and AI/ML techniques. Studies have shown these models to be accurate and more computationally efficient.

With approximately, 55% of the world's population living in urban areas, the increase in extreme precipitation events will only exacerbate consequences [179]. From the severe storms of Germany and Belgium to tropical depression Ida in the eastern U.S., recent years marked an alarming rate of death and destruction by urban floods. Thus, more than ever, urban flooding poses a severe threat to the international community. As a response to the urgency, this review has presented a holistic view on the subject of urban flooding.

Declaration of Competing Interest

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

Data availability

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

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