

Review

Machine Learning for Flood Resiliency—Current Status and Unexplored Directions

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Abstract

A systems-oriented review of machine learning (ML) over the entire flood management spectrum, encompassing fluvial flood control, pluvial flood management, and resiliency-risk characterization was undertaken. Deep learners like long short-term memory (LSTM) networks perform well in predicting reservoir inflows and outflows. Convolution neural networks (CNNs) and other object identification algorithms are being explored in assessing levee and flood wall failures. The use of ML methods in pump station operations is limited due to lack of public-domain datasets. Reinforcement learning (RL) has shown promise in controlling low-impact development (LID) systems for pluvial flood management. Resiliency is defined in terms of the vulnerability of a community to floods. Multi-criteria decision making (MCDM) and unsupervised ML methods are used to capture vulnerability. Supervised learning is used to model flooding hazards. Conventional approaches perform better than deep learners and ensemble methods for modeling flood hazards due to paucity of data and large inter-model predictive variability. Advances in satellite-based, drone-facilitated data collection and Internet of Things (IoT)-based low-cost sensors offer new research avenues to explore. Transfer learning at ungauged basins holds promise but is largely unexplored. Explainable artificial intelligence (XAI) is seeing increased use and helps the transition of ML models from black-box forecasters to knowledge-enhancing predictors.

Keywords: flood resiliency; artificial intelligence; XAI; flood forecasting; flood life cycle; deep learning; recurrent learning



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1. Introduction

Floods are said to occur when flows occur on an otherwise dry land or when the flow in a water body is well above normal values. There are many types of flood, defined as per when and where they occur. Fluvial floods are known to occur when water levels in the channel flow over the banks and spill into the floodplain. Pluvial floods are caused by water directly accumulating on land surface that is not necessarily near a river. Coastal floods are caused when seawater is pushed onto land by high tides, storm surges, and tsunamis. Urban floods are a type of pluvial flooding where flooding occurs in urban areas, mainly due to an excessive amount of impervious surfaces, sealed soils, and insufficient drainage systems. Flash floods occur when a large amount of rain falls over a short period of time. The high intensity of rainfall reduces the amount of infiltration and quickly leads

to runoff. While not very common, a rise in groundwater levels in low-lying areas can also lead to flooding, referred to as groundwater floods [1].

Flooding is a common natural disaster that affects every part of the Earth and causes billions of dollars of damage and even loss of life in many parts of the world. The US Department of Homeland Security states that 90% of the natural disasters in the US involve flooding [2]. Climate change models indicate that floods will become more intense and also increase in frequency in many parts of the world [3,4]. Increased urbanization to accommodate a growing global population and heterogeneous economic growth is also diminishing natural infiltration capacity and increasing runoff and flooding in many areas [5]. In addition, improper construction of flood mitigation structures, dam breaks, and other engineering failures can also lead to flooding [6]. Given the large-scale economic and environmental damage, and health hazards, and loss of life, the deleterious impacts of floods must be prevented when possible, or at least minimized to reduce damage.

It is important to ensure that the impacts of flooding on humans are either fully eliminated or controlled to the greatest extent possible. Developing such strategies to combat flooding is not easy as the main drivers of flooding—(1) weather and climate, and (2) land-use alterations—cannot be predicted with a high degree of certainty and are prone to change. The impacts of floods must be managed so that the community can rebound back to normalcy as soon as possible. As societies continue to learn from flooding disasters, the following questions arise: How have flood management paradigms changed over time? What are the current approaches with regards to managing flooding risks?

Flood management requires decision-makers to have reliable data on various aspects. These data include, flooding characteristics such as peak flows, flood duration, flood volume, flood inundation depths. Factors causing flooding such as precipitation and land-use alterations must be known as well. In addition, information on population distribution, social characteristics, and economic assets that are directly in the line of flooding hazards must also be mapped. Such data are not only useful for immediate flooding emergency response operations, but also to guide the development of new flooding infrastructure to absorb the shocks of flooding or at least mitigate their impacts to an acceptable level. In the case of riverine flooding, the impacts on aquatic and riparian habitats and ecosystems are also of concern. Much of these data are hard to obtain and are not deterministic in nature. Therefore, decisions regarding flooding have to be made under considerable uncertainty. The European Flood Awareness System (EFAS) provides an excellent example of such a decision support system on a continental scale [7].

Mathematical models have been used to support flood decision making. Models can be used to translate rainfall into runoff (for a given type of land use) and estimate the dimensions of a flood such as peak flows in rivers, the area likely to be inundated, and the depth of water on urban transportation infrastructure. These models are used not only for quantifying flooding related hazards, but also used to design flood control and flood mitigation structures, assess risks to humans and the environment due to flooding, and to develop new policies and guidelines that help in proactively combating the effects of flooding.

A wide range of tools and techniques have been proposed, using a variety of different mathematical strategies. Mathematical models built using conservation principles of physics and at varying levels of spatial and temporal complexity have been available for some time now and continue to be widely used [8]. In a similar manner, a broad range of statistical tools have been used for flood estimation and forecasting [9,10], and multivariate flood risk assessment frameworks [11,12]. In recent times, the use of machine learning (ML) methods has been gaining ground [13]. ML methods are universal approximators that can capture highly nonlinear relationships. As such, their utility for flood forecasting has

garnered much interest in recent times. The literature identified using a simple search in Google Scholar of “Flood and Machine Learning” has more than doubled from 19,000 documents retrieved in 2015 to over 40,000 documents in 2024. This change is indicative of the growing interest in using ML for flood forecasting and management studies.

The proliferation of machine learning methods in flood prediction applications has also led to several review papers in recent years [14,15]. However, the emphases of these reviews have largely been on prediction aspects. While predicting floods is indeed an important task, flood management also entails many other tasks such as ranking and prioritization of sites and susceptibility mapping. A review of machine learning usage in the context of flood management practices has not been undertaken to the best of the authors’ knowledge. The main goal of this paper is to fill this important gap that currently exists in the literature.

The lack of a suitable review of machine learning methods for flood management also suggests that there are likely several unexplored directions of research. Identifying these unexplored directions will stimulate new avenues of research and address those aspects where machine learning methods can offer benefits that have not yet been brought to fruition. In a similar vein, newer studies will also make machine learning models more congruent with the needs of flood risk management.

To achieve the above-mentioned goals, the rest of the paper is organized as follows: (1) The methodologies adopted in this review are presented; (2) a brief review of flood management paradigms is undertaken to help readers understand how flood management has shifted from a more command–control approach to a more holistic resiliency paradigm that not only seeks to mitigate flooding hazards but also to help areas to bounce back to the original (or a better) state upon the cessation of flooding. To properly evaluate the benefits of machine learning it is also important to assess the strengths and limitations of physics-based models, which have been used in flood studies over a longer period of time. The main physics-based modeling tools available today are briefly reviewed, along with their strengths and limitations, next. This evaluation seeks to set the stage for evaluating machine learning models. For the sake of completeness, machine learning models are briefly described and their role in flood management is explored in greater detail.

2. Methodology

While the primary focus is on machine learning applications over the entire gamut of flood management, presenting a brief evolution of risk management frameworks, from command–control-type approaches to a community-focused resiliency approach, was deemed necessary to place the review in the proper context. Physics-based models provide a theoretically rigorous approach to flood modeling and continue to be used today. Figure 1 depicts the resiliency paradigm adopted in this study. Resiliency here is viewed as an umbrella of tools, technologies, and policies that contribute towards a common goal of withstanding flooding threats or improving the ability of communities to quickly bounce back to normalcy or better after the flood.

Physics-based methods and machine learning methods are not competitors and can be used in a synergistic manner. Therefore, some commonly used machine learning codes are briefly reviewed here. While machine learning methods have gained popularity and widespread usage, these tools and methods are not routinely taught in water-related curricula. Many decision-makers may be unaware of different types of learning algorithms that machine learning offers. Therefore, machine learning methods are also briefly reviewed for the sake of completeness. A narrative review approach is adopted for these topics as the goal is to summarize key concepts and provide context and structure for a more comprehensive machine learning models across the flooding life cycle [16].

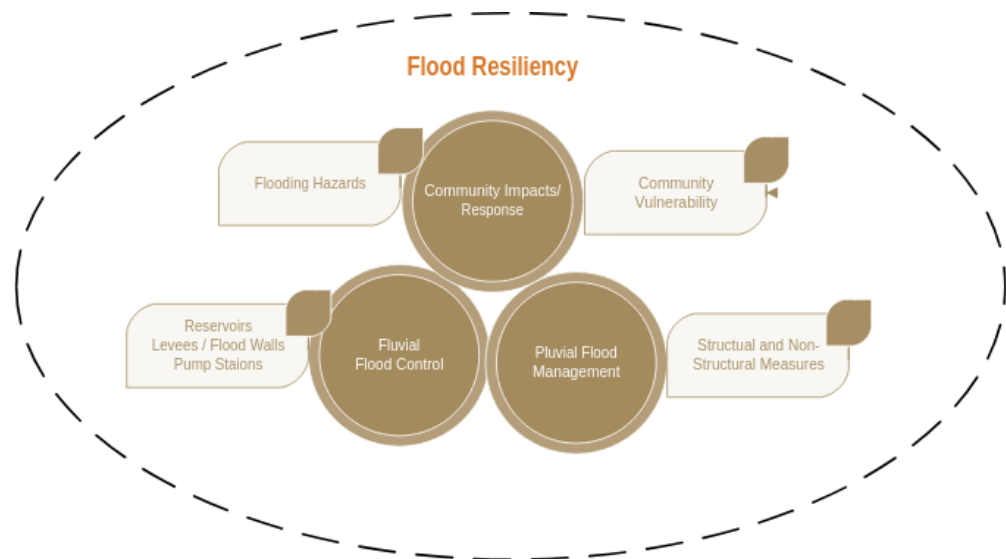


Figure 1. Resiliency framework adopted for structuring the review.

Having presented the conceptual life cycle of flooding, a detailed systematic review of the literature pertaining to each topic was undertaken [17]. Major bibliographic databases—(1) Web of Science Core Collection, (2) Scopus, and (3) Google Scholar—were utilized to identify over 5,000 references, using a suite of keywords such as—“flood reservoir inflows + Machine learning” “Flood reservoir outflows + Machine Learning”; “Flood Resiliency + Machine learning”. The search was constrained to a custom range of 2019–2025 (both inclusive), as the number of publications focused on machine learning has increased exponentially over this period, with many new advancements. The literature was mostly trimmed down to studies presented in Q1 and Q2 journals and conference proceedings, such as IEEE conferences, which undergo peer review. The inclusion of conference proceedings was deemed necessary as some newer innovations, particularly using sensors and ML, appeared in such publications. Other journals were utilized when the paper had something unique to offer. The focus was largely on those publications that provided methodological advancements, rather than those which simply presented newer case studies without any significant methodological contributions.

Given the vast and growing literature in this area, no claims of completeness are being made here. However, the review comprehensively captures major strands of research inquiry. The primary focus of this systematic review was to identify common themes and patterns in the literature. Figure 1 presents the definition of resiliency and major themes around which the review is organized, giving insights with regards to ML algorithms used and factors influencing their performance. As performance metrics tend to be site-specific and affected by the quality of data, the focus was not on quantitative evaluations but on how the models performed overall, what challenges were faced across different aspects of the flood management life cycle, and what the unexplored directions were. The focus was on identifying themes and creating a general framework that will enable decision-makers, researchers, and practitioners to evaluate future studies using the framework and insights presented here.

3. Evolution of Flood Management Practices

3.1. Fluvial Flood Control

Early flood mitigation efforts were largely focused on controlling the harmful effects of flooding on humans and were based on the notion that flooding, while inevitable, could be fully controlled. Flood control projects were largely structural in nature and involved

building large-scale facilities to store flood waters and both delay and attenuate the flood wave to protect downstream communities. Even today, riverine flood-control structures provide the first line of defense against flood waters arising from upstream areas. These structures include reservoirs, levees, flood walls, and pump stations.

Reservoirs are constructed across a river and usually have extra free-board and sluice-and-gate mechanisms to control flooding. Levees are earthen embankments built alongside rivers to prevent water from overflowing. River walls serve the same function as levees but are often built from concrete. Pump stations are used to pump excess water that is flowing out of the levees or flood walls and pump that water back into the river.

Despite several flood control projects being undertaken, flooding continues to be a problem in many parts of the world [18]. Building new or scaling up existing flood control infrastructure is cost prohibitive and highly dependent upon the quality of hydrologic information that is available at the site [19,20]. Increased climate variability also adds uncertainty with regards to hydrological information and makes scale-up of existing projects challenging [21].

3.2. Pluvial Flood Management

With increased urbanization, the impacts of pluvial flooding became significant. There was growing recognition that controlling fluvial flooding alone was insufficient and humans and the environment must be protected from pluvial flooding. Flood management now sought to create an environment where humans could learn to live with floods. Retention and detention basins, culverts and green infrastructure such as rain gardens, bioswales, blue roofs, and enhanced infiltration systems (e.g., permeable pavement) prevent flood water from accumulating in residential areas [22,23]. In a similar vein, non-structural measures, such as zoning laws that restrict development in flood-prone areas, increasing public awareness, and employing early-warning systems to evacuate people to safer areas are also utilized [24–26]. Rather than keeping the flood waters away from humans (as is the case with flood control), flood management also sought to keep humans away from flooding hazards. This approach of flood management was largely based on the notion of identifying the susceptibility of a land parcel to flooding (e.g., 100-year floodplain) and using that information to keep people away from flooding impacts through structural and non-structural measures [27].

While coastal and riparian areas are prone to flooding, they also offer several other significant opportunities, such as access to water-based trade routes, fishing and aquaculture operations, and enhanced recreation activities. The number of people living in coastal areas has increased substantially over the last few decades, with nearly 40% of the world's population residing within 100 km of the coast [28] and over 50% of the population within a few kilometers of a water body [29]. Flood insurance programs provide safety net for people susceptible to flooding damages. These programs rely on risk assessments to evaluate the probability of a flood hazard that a person and/or infrastructure is exposed to in developing insurance policies and setting premiums.

While flood risks have been defined in multiple ways, using both qualitative and quantitative measures, a widely used definition views flooding as a product of hazard, value, and vulnerability [30]. Hazard characterizes the threatening event, including its probability of occurrence; the values (or values at risk) denote humans, infrastructure, and other assets that are present at a location; and vulnerability is the lack of resistance to damaging forces of the hazard-causing event. Flood risk management uses the risks of flooding hazards as the basis for management and seeks to develop structural and non-structural measures that mitigate the effects of hazards to acceptable levels of risk [25].

3.3. Resiliency-Based Flood Management

While floods cause damage to both humans and the environment, they are important for sustaining river and floodplain ecosystems. Floods transport fine sediment and energy, required for riverine flora and fauna. In addition, the disturbances created by flood and droughts are essential for fostering ecological biodiversity [31,32]. The ecological importance of floods is no longer a theoretical construct but has been integrated with reservoir operations for flood control [33]. Flood management is transitioning from human-centric approaches towards more holistic frameworks [34].

The recognition of the importance of flooding for the functioning and sustainability of vibrant riparian ecosystems coupled with the inadequacy of flood control strategies, and the movement of flood mitigation from being a command–control-type engineering endeavor to a more stakeholder-driven, participatory, community-based effort has brought to light the concept of flood resiliency. While the definitions of flood resiliency continue to evolve [35], the synthesis of resiliency definitions from a wide range of disciplines provided in [36] has seen widespread usage in resiliency-based flood management studies [37,38]. In this approach, flood resiliency approaches are categorized into three types: (1) Engineering resiliency; (2) ecological resiliency; and (3) socio-ecological resiliency (see Figure 2). While the words engineering, ecological, and socio-ecological are used in this approach, they are not domain-specific and have been used in diverse systems and applications [37].

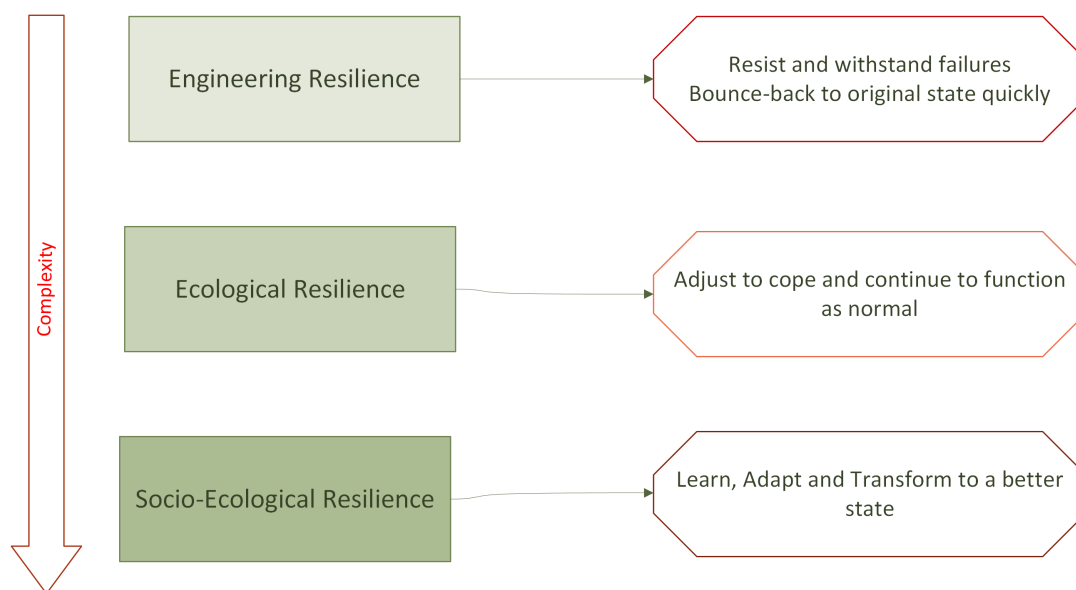


Figure 2. Common definitions of resiliency.

The main idea of engineering resilience is to create systems that can withstand hazards and not fail. If and when failure occurs, these systems need to bounce back to their original (pre-flooding) stage quickly. The traditional design of hydraulic infrastructure is based on the idea of engineering resiliency. The concept of the return period (or the average time of recurrence of a flooding event of a certain magnitude or higher) is used for design of structures that aim to control floods (dams and levees), mitigate their effects (detention and retention basins), or otherwise interact with floods (e.g., bridges), and it is suitable for use in single systems [39].

The ecological resilience is typically applied to a system with multiple interconnecting parts. This allows the system to adjust and cope with flooding hazards. For example, early-warning systems allow people to procure supplies in advance and take other precautionary measures (e.g., evacuate to a higher elevation) to cope with short-term floods. Socio-

ecological resilience focuses on complex adaptive systems (or a system of systems). Here the system may not come back to its original state but adapts and transforms to a better state. For example, relocation of people out of the floodplains to areas with lower inundation risks is often undertaken after devastating hurricanes [40].

It is important to recognize that flood resiliency is not independent of flood control and flood risk management approaches. Rather, the resiliency paradigm subsumes both the flood control and flood risk management concepts. From this viewpoint, the resiliency provided by flood control and risk-based structural and non-structural alternatives is evaluated and improved upon in most flood resiliency endeavors so as to benefit from past investments in flood planning and course-correct in light of new information [38]. While the goal of any flood planning endeavor is to minimize the risks of flooding to humans and the environment, socio-ecological resiliency-based planning and management challenges one to think outside the box and evaluate whether converging to a new equilibrium is better (or worse) than trying to return to the original state.

Regardless of the methodology adopted, flood management is a costly endeavor that requires considerable investments in infrastructure, and a time-consuming process, where diverse and often conflicting views and values have to be reconciled effectively.

4. Physics-Based Models for Flood Management

Quantitative information is paramount to flood management. Estimates of runoff, streamflows, the nature and extent of inundation, and the frequency and magnitudes of extreme rainfall are therefore a major component of flood management endeavors. It is not only important to analyze historical floods but also develop robust estimates for future conditions, especially given the recognition that past climate is not necessarily a good indicator of future flooding events [41].

Mathematical models used for flooding can be categorized as (1) white-box models, (2) gray-box models, and (3) black-box models. White-box models are the most rigorous and employ mass, energy, and momentum conservation principles. Gray-box models are based on the conservation-of-mass principle, along with empirical laws to describe flooding. Black-box models are completely empirical and built on site-specific data.

Both white-box and gray-box models are referred to physics-based models as they are based on physical principles. The development and application of these models dates back at least 100 years [42]. Physics-based models can be developed for a wide range of systems, such as streams and rivers, watersheds, reservoirs, and wetlands. In addition, they can be developed to study combined interactions like climate–hydrology dynamics [43], human–water linkages [44], and the food–energy–water nexus [45].

Flood planning studies often employ more than one model. For example, a conceptual hydrological model can be used to model fluvial flood discharges into a stream, while a hydraulic routing model can be used to study fluvial flooding. When multiple models are used, they can be loosely coupled (meaning the two models are separately run) or tightly coupled (one software allows running of all the models with seamless data transfer between them). The application of physics-based models entails many aspects. Salient modeling considerations are presented in Table 1.

Several software simulators have been developed by various agencies to support flood management. Widely used software simulators are presented in Table 2. A wide range of engineered and natural systems pertaining to flood control can be modeled using these software at varying levels of complexity.

Table 1. Factors affecting the complexity of models used in flood risk management.

Concept	Types	Remarks
Model Spatial Dimensions	0D, 1D, 2D, 3D	0D models are also called lumped or box models.
Model Spatial Discretization	Lumped, semi-distributed, fully distributed	Semi-distributed models define the watershed using sub-watersheds. Fully discretized models use grids. Hundreds to thousands of grid cells are used to cover the watershed of interest.
Time Dimensions	Steady state, dynamic	Steady-state models are time-invariant, while dynamic models can vary in time (e.g., subhourly, hourly, daily, monthly, annually).
Event Type	Single event, continuous	Continuous models operate during wet and dry periods, while single-event models simulate flooding associated with single rainfall events.
Process Description	Linear, nonlinear	A model is nonlinear if even one of the processes is expressed using nonlinear equations
Solution Scheme	Analytical, numerical	Analytical models use exact solutions, while numerical schemes use approximate methods such as the finite-element or finite-difference schemes.

Table 2. Commonly used software for flood management.

Software	Type	Developer	Description	Major Outputs
HEC-HMS	Lumped and semi-distributed	USACE	Pluvial flood forecasting, river routing	Outflow hydrographs, peak flow
HEC-RAS	Fully distributed (1D/2D)	USACE	River hydraulics, dam breach	Water elevation, inundation mapping, velocity
SWMM	Semi-distributed	USEPA	Urban drainage, pluvial flooding, green infrastructure	Stormwater hydrograph, flood depth, sewer overflows
SWAT	Semi-distributed	Texas Agrilife/USDA	Watershed streamflow, sediment and pollutant transport	Streamflow, flooding, long-term hydrology, and water quality concentration
Mike 11	Lumped/semi-distributed	Delft Hydraulics Institute	1D river and channel modeling	Flood hydrograph, water level discharge
Mike 21 FM	Fully distributed (2D)	Delft Hydraulics Institute	2D model for urban flooding	Water depth, velocity fields, flood inundation maps
Mike Flood	Fully distributed (1D/2D)	Delft Hydraulics Institute	1D and 2D river and channel modeling. Integrates Mike 11 + Mike 21.	Flood hydrographs, discharge, inundation maps
Mike Urban	Semi-distributed	Delft Hydraulics Institute	Urban stormwater and pluvial flooding	Water levels, hydrographs, and sewer outflows
TUFLOW	Fully distributed (1D/2D/3D)	Tuflow.com	Stormwater, pluvial flooding, drainage networks	Water elevations, velocities, inundation extent
Flow-3D	Fully distributed 3D	Flow Science Inc., Santa Fe, NM, USA	Computational fluid dynamics model for dam break and complex urban flows	3D velocity profiles, water elevations, and flood propagation

Physics-Based Models—Pros and Cons

Physics-based models offer several advantages. They are built on well-established laws such as mass conservation, which are universally applicable. In addition, these principles

also offer numerical checks to ensure that the model has been coded correctly. Physics-based models have been in existence for several decades now and many studies have been carried out to evaluate the suitability of such models in simulating flood characteristics. In addition, there are several use cases and best practices related to their calibration and evaluation [46]. Software simulators such as HEC-RAS, HEC-HMS, and SWAT are well maintained and improved to exploit the benefits of current technologies, such as their integration with GIS and ability to pull in data from the web. The principles behind these models are also taught in fundamental engineering classes, along with software-specific training modules that are widely available. These models are known to capture major flooding characteristics and provide physically plausible explanations [47] and therefore have regulatory acceptance [48].

While physics-based models offer great theoretical rigor, their implementation is challenging on several fronts. Physics-based models contain model inputs that cannot be directly measured. These parameters have to be estimated indirectly from available observations. The process of obtaining unknown model inputs using observed outputs is called the inverse problem in mathematics or calibration in the hydrologic literature. The inverse problem is mathematically ill-posed and therefore does not yield unique solutions. In other words, different subsets of model inputs can result in similar output predictions [49]. Typically, available hydrologic records at most sites only allow reliable estimation of a few parameters [50]. Efforts to improve model calibration have focused on using expert knowledge to guide calibration [51] and/or regularization schemes that seek to restrict the number of calibration parameters during calibration [52,53], using other surrogate information [53] to guide calibration, and using ensemble methods [54] to construct confidence bounds by employing parallel computing approaches [55]. However, these improvements still largely remain in the theoretical regime and are not widely used in routine flood management studies. An analysis of the sensitivity and uncertainty of model outputs due to uncertainty and variability of inputs is recommended to understand the limitations of estimates of factors like inundation obtained from physics-based models [56].

As physics-based models require calibration, their usage in ungauged basins becomes even more challenging due to a lack of long-term output data [57]. Regionalization approaches are often employed to overcome this limitation. Calibrated data from nearby and/or similar systems are scaled for use in the ungauged basin [58,59]. Scaling of hydrological phenomena is however non-trivial and the success of regionalization depends upon the amount of informative content that is present to facilitate scaling [60]. Nesting ungauged watersheds within gauged watersheds is beneficial if the gauging density of the larger watershed is sufficiently high [61].

The ability of physics-based models to capture flood peaks is also of concern. This limitation stems from several factors: (1) Most flood models operate on a time-step of days or months due to availability of rainfall records at those scales. However, flooding is a much more dynamic phenomenon that causes changes in flows on the order of minutes to hours. The coarse temporal discretization limits the ability of the model to capture fine-scale changes [62]. Models make several other approximations to simulate various hydrological processes, these simplifications capture general trends well but cannot adopt to sudden changes in flow regimes [63]. (2) The root mean square error (RMSE), or its variant the Nash–Sutcliffe Efficiency (NSE), are widely used for model calibration. Minimization of this metric entails a trade-off in capturing a large number of low-flow events and relatively few high-flow events, which often leads to over-estimation of low flows and under-estimation of peak flows. The use of newer error metrics like the Kling–Gupta Efficiency (KGE) [64] can ameliorate this impact [65]. (3) The amount of data available also impacts the ability

to capture peak flows [66]. Clearly, errors in flood forecasts induce uncertainty in flood planning and management.

5. Machine Learning Modeling—Background

The limitations associated with physics-based formulations coupled with recent and rapid advancements in artificial intelligence (AI) and machine learning (ML) have increased the exploration of machine learning methods in applications focused on flood management. Machine learning models are not new, the term was coined by Arthur Samuel back in the year 1959 [67]. A timeline of major advancements in machine learning is presented in Figure 3. Algorithms developed in the 1960s, such as K-nearest neighbors (KNN), are in use even today [68].

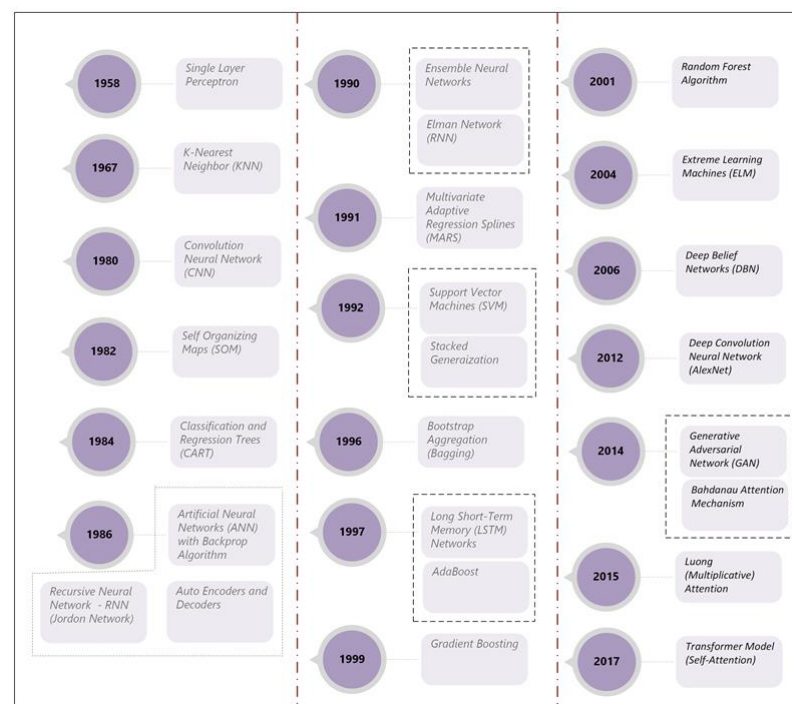


Figure 3. Timeline of major breakthroughs in machine learning.

Artificial neural networks (ANNs) have been around at least since the mid-1980s and some of the early applications of this technique for streamflow forecasting date back to the early 1990s [69,70]. In a similar vein, an early application of tree-based learners for flood studies can be traced all the way back to 1992 [71]. The number of applications of machine learning models steadily increased from the 1990s to the 2010s, congruent with algorithmic developments in this period.

In recent years, the number of papers has grown exponentially given the large-scale availability of data, general purpose libraries such as Scikit Learn [72] and Tensorflow [73], as well as many libraries such as caret [74], nnet [75], and randomforest [76] in R [77] and deep learning and reinforcement learning toolboxes in Matlab [78]. Computational power has also increased significantly in the last decade with the availability of graphical processing units (GPUs) and Tensor Processing Units (TPUs) on some platforms. Unlike conventional central processing units (CPUs), GPUs support parallel floating point operations (FLOPs), speeding up large-scale computations. TPUs utilize a grid of parallel processing elements through which computations are processed in a synchronous manner.

While the use of machine learning models is on the rise, it is important to note that they have their own set of limitations: (1) They are empirical and not generally not based on physical principles; (2) they are subject to overfitting, which means they can

learn the noise in the data and therefore cannot generalize the results; (3) some methods offer high predictive accuracy but do not explain the underlying processes (therefore are black-box models); (4) they often require large quantities of data, which may not be available at all sites; (5) their performance not only depends upon the available data, but also is influenced by parameters used in their parameter estimation methods (i.e., hyper-parameters). Therefore, prior to reviewing the use of machine learning for flood management, a brief overview of major learning strategies employed is presented to highlight important features and contextualize their utility in flood management studies.

5.1. Machine Learning Strategies

As shown in Figure 4, the four main types of ML are supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, an ML model is trained using a dataset that has both the inputs (features) and the output (labels). Outputs can be continuous or discrete. Supervised learning methods that employ discrete labels are referred to as classifiers, while those mapping continuous labels are called regressors. Unsupervised learning, on the other hand, is trained on a dataset that has no labels and is often used to cluster data. Semi-supervised learning uses a dataset where there are some data with labels and others without labels. This approach can be used for both classification and regression tasks. Reinforcement learning (RL) focuses on developing a long-term (operating) policy that maximizes long-term reward; while RL algorithms can in theory be used for classification, regression, and clustering tasks, they are not specifically designed with these applications in mind, but are better suited for decision making and control [79].

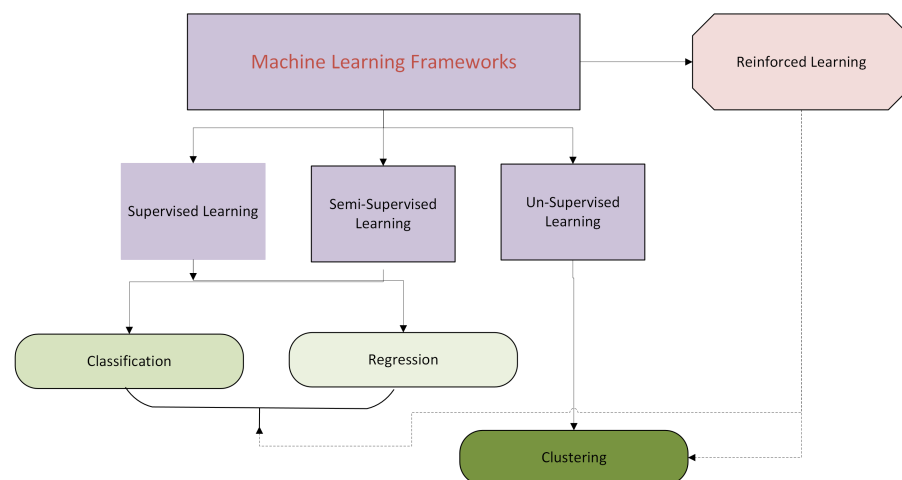


Figure 4. Major approaches to machine learning.

Humans use different approaches to learn information. Cognitive approaches focus on using past experiences and knowledge for making decisions and solving new problems. These strategies can range from simple memorization of facts to forming rules of thumb to guide decisions. In a similar vein, humans also decide when to learn what information, and evaluate competing pieces of information to make a decision based on the weight of the evidence provided by them. Human decision making is not always individualistic but involves collaboration (bagging) with peers and partners. Humans also exhibit the ability to build and improve on their previous experiences (boosting). Machine learning models that try and mimic the cognitive capabilities of humans can be categorized as cognitive-inspired machine learning (CIML) approaches.

Biological adaptations modify how stimuli (data) are sent to the brain (central processing unit) and how they are processed to create new information. Evolutionary changes

happen over longer time scales and change the biological makeup to improve survival. On shorter timescales, humans (living beings) also exhibit the ability to change their physical and neurological conditions to adapt to new conditions, learn new skills, or adapt to a new environment. In particular, the brain can reorganize and form new neural connections—this phenomenon is referred to as neuroplasticity and is a key mechanism by which the brain adapts to new information and environments.

Neuroplasticity plays a key role in memory and motor learning, helps in recovery from brain injuries, and is controlled by the nature of the stimuli [80]. Machine learning models that mimic evolution and/or the structure of the nervous system and the functioning of the brain can be categorized as biologically inspired machine learning (BIML) models.

A variety of machine learning models have been developed over the last seven decades (see Figure 4). Learning strategies provide a quick way to understand the broader ideas related to machine learning algorithms. Table 3 provides a grouping of machine learning algorithms based on their learning styles.

Table 3. Learning strategies of machine learning algorithms.

Learning Strategy	Learning Description	Style	Machine Learning Type	Example Method
Rule-based learners (a type of associative learning)	Codifies the relationship as IF-THEN rules	CIML	Supervised	Classification and Regression Tree (CART), Multivariate Adaptive Regression Splines (MARS)
Lazy learning	Memorizes data, defers learning until prediction time	CIML	Supervised	K-nearest neighbors (KNN), case-based reasoning (CBR)
Eager learning	Learns general function during training	CIML and BIML	Supervised	Support Vector Machines (SVMs), Naive Bayes (NB), artificial neural networks (ANNs)
Reinforcement learning	Learns by interacting with the environment with rewards and penalties	CIML	Reinforcement	Q-learning, policy gradients
Evolutionary learning	Learns using principles of genetic-encoding and survival-of-the-fittest paradigms	BIML	Supervised, unsupervised, and reinforcement learning	Supervised—symbolic regression; unsupervised—evolutionary clustering; reinforcement—symbolic policy learning
Hebbian learning	Learns by strengthening co-activating neurons	BIML	Unsupervised learning	Self-organizing maps (SOMs), neural Hebbian nets
Corrective learning (delta-rule learning)	Learns by minimizing errors of predictions	BIML	Supervised and unsupervised learning	Artificial neural networks (ANNs) using backpropagation or its variants
Greedy learning	Makes locally optimal decisions at each step rather than seeking a globally optimal solution	CIML and BIML	Supervised learning	Approach adopted by CART, deep neural nets, and other algorithms that have a large number of decision variables
Competitive learning	Competition helps select a winner	CIML and BIML	Unsupervised and supervised learning	Self-organizing maps (SOMs), ensemble classifiers

Table 3. *Cont.*

Learning Strategy	Learning Description	Style	Machine Learning Type	Example Method
Active learning	Model queries a human or a database for informative samples while learning	CIML and BIML	Mostly supervised learning	Diversity sampling (DS) and query by committee (QBC), uncertainty determination and minimization
Multi-task learning	Model learns more than one output from a set of inputs	CIML	Supervised	The idea of multi-tasking is cognitive, but BIML models can be used to achieve this cognition such as multi-input multi-output (MIMO) models—MIMO-ANN
Collaborative learning	Multiple models are developed and combined to improve predictions	CIML and BIML	Unsupervised and supervised	CIML and BIML models can be combined in this approach
Bagging	Trains different models using bootstrapped samples of data	CIML	Supervised	Random forest, bagging trees—a special form of ensemble learning
Boosting	Trains sequential models to correct previous errors	CIML	Supervised	AdaBoost, Gradient Boost, XGBoost; another form of ensemble learning
Deep learning	Typically a neural network model with multiple layers to handle big data	BIML	Supervised and Unsupervised	Deep belief networks and many variants
Attention learning	Focuses on most important data for prediction	BIML	Supervised	Commonly used in deep neural networks
Adversarial learning	Generator and discriminator compete to improve model; akin to predator–prey dynamics	BIML	Traditionally unsupervised, but can be modified for supervised learning	Generative adversarial network (GAN), a deep learning method; conditional GAN (cGAN) for supervised learning
Recurrent learning	Remembers previous data via memory cells or recurrent connections. Used with sequential data such as time series and text sequences	BIML	Supervised learning	Long short-term memory (LSTM) network, Elman machines; a form of deep learning
Convolutional learning	Uses moving windows to sample features, pool data to retain important features, and then perform nonlinear mapping	BIML	Supervised learning	Useful for gridded data. Convolution neural networks (CNNs); a form of deep learning
Encoder–decoder learning	Encodes and decodes data and useful for data compression, generation, and transformation	BIML	Supervised and unsupervised	Autoencoders and decoders; Transformer models; a form of deep learning
Self-supervised learning	Model creates ‘pseudo-labels’ from input data for training supervised models	BIML	Unsupervised/Hybrid	Used to fill missing values, particularly in images

More than one learning strategy presented in Table 3 can be adopted for a given task such as mapping nonlinear input–output relationships.

5.2. Calibration of Machine Learning Models

Machine learning models are empirical in nature, therefore the model parameters are unknown and have to be determined via calibration, particularly in the case of supervised learning. In unsupervised learning, there is no calibration per se, but distances between points within a cluster are minimized while the distance between two independent clusters is simultaneously optimized. While physics-based models are often calibrated using both automatic (optimization-based) and manual methods, machine learning models are calibrated almost exclusively using automatic optimization-based methods. In case of supervised classification, an error metric, such as the root mean square error (RMSE), is minimized. The objective function that is minimized is commonly referred to as the loss function in the machine learning literature. Similarly, the calibration of the supervised learning model is referred to as training the model.

Typically, the calibration of a supervised ML model is carried out by splitting the available dataset into two parts. The first part is called the training dataset, which is used to train the model, and the second part is the testing dataset. The training dataset is used to obtain unknown model parameters (e.g., weights of neural network) by minimizing a loss function. The performance of a model is then assessed by comparing the model predictions against the testing dataset that contains data that the model has not seen before. ML model algorithms also have a set of parameters that are necessary to define the structure of the model or to implement the optimization routines necessary for model calibration. These parameters are called ‘hyper-parameters’.

Hyper-parameters can be set based on previous studies, but most often are estimated (optimized) during the calibration process. When hyper-parameters are optimized as part of the training process, the training dataset is further divided into two parts: training dataset and validation dataset. The training dataset is used to train the model; the validation data is initially used to test the performance of the training under a given set of hyper-parameters and select their optimal values. Once the hyper-parameter values are identified, the validation dataset is subsumed into the training dataset and a final training is performed on the model. Validation datasets are also useful for early stopping (i.e., when the validation error increases even when the training error is decreasing as training progresses). Similarly, the validation dataset can be used to select the best model for a subset of models or use the validation error metrics to weigh different models within an ensemble.

Typically, the dataset is randomly split into training and testing subsets. In the case of sequential data (e.g., time series), the first part of the data is used for training while the latter part of the data is kept aside for testing. Train–testing splits of 70%–30% or 80%–20% are common. Typically, 10%–20% of the training data is used for validation.

Overfitting occurs when a model is able to predict the training data very well but demonstrates a rather poor performance on the testing (independent) dataset. Overfitting generally implies the model has more degrees of freedom (parameters) than necessary. Thus, the model is able to learn the noise in the data rather than focus on generalization. Overfitting can also occur with hyper-parameters. The validation dataset is used to avoid overfitting of hyper-parameters. Regularization methods are widely used to prevent overfitting: a regularization function adds a penalty with increasing weights, which causes the model to effectively drop some weights during the calibration to reduce the penalty on model performance. Overfitting is more likely in deep neural network models due to their complexity and more aggressive approaches such as dropout (where certain nodes are dropped from training with a certain probability) are used to prevent overfitting.

Training of supervised learning models typically occurs by sending small batches of data through the model to adjust weights. Each run with a model is called a training epoch. The stochastic gradient descent algorithm (SGD) is commonly used for model

calibration [81]. Automatic, or algorithmic, differentiation (AD) is widely used to compute gradients without significant numerical errors [82]. These gradients are used to identify newer estimates of parameters which reduce the loss function to the lowest possible value. However, in deep neural networks, the gradients of weights of early layers practically become zero (i.e., vanish), making training using conventional gradient descent ineffective. Greedy learning uses layer-by-layer training to eliminate the effects of vanishing gradients and effectively train deep networks. Greedy learning approaches are also used in other ML models such as random forests and gradient boosting methods [83].

5.3. Explainable Machine Learning

While machine learning models can provide accurate predictions and map highly nonlinear input–output relationships, interpretability of the models is a major limitation. In this regard, physics-based models and statistical models (e.g., linear regression) perform much better as the model equations and parameters can be readily interpreted.

Explainable machine learning (XAI) is a rapidly emerging field of ML that seeks to improve the understanding of the inner workings of ML models. XAI provides several benefits, most important of which is the increased trust in using these models in mission-critical applications such as flood forecasting. XAI also helps evaluate if the model is based on biased data and helps debug the models and improve their work.

Some AI techniques such as CART, MARS, and genetic programming (GP) encode information in the data as rules and equations and therefore are readily interpretable. As boosting and bagging methods create multiple models with the same dataset, the relative importance of different parameters can be ascertained even if the model equations are not explicitly known per se. Tree-based algorithms are also used to explain other hard-to-interpret models [84].

Neural network models (particularly deep learners) encode the information in terms of weights that are hard to interpret. In such cases, the outputs obtained from the model are explained by fitting local (explainable) models around the predictions: Shapley Additive Explanations (SHAP), which uses game theoretic measures to explain the importance of different features on the output, and Local Interpretable Model-Agnostic Explanations (LIME), based on linear regression around the predictions, are commonly used to explain which inputs are important and how they affect a particular model output [85].

Having presented a broad overview of machine learning methods, the application of these techniques in flood risk management is explored next.

6. Machine Learning for Flood Resiliency

6.1. Machine Learning for Fluvial Flood Control

6.1.1. Machine Learning for Reservoir Operations

Reservoirs store excess water during high-flow events and release them during periods of high demand. The controlled release of flow out of the reservoir is to ensure there is minimal downstream hazards, but also is constrained by the capacity of the reservoir and associated infrastructure. Therefore, the outflow of the reservoir is a function of the water height in it. Reservoir operation rules (RORs) are used to define outflows. Operation rules tend to be complex, especially when there are multiple interconnected reservoirs, and they are only known to a few practitioners.

Machine learning models have been used to infer reservoir operating rules and predict outflows. A wide range of machine learning approaches, including artificial neural networks (ANNs), Support Vector Machines (SVMs), random forest (RF), deep neural networks (DNNs), and recurrent networks, especially the long short-term memory (LSTM) network, have been adopted for this purpose [86–93].

The main conclusion of these studies is that machine learning models provide better predictions than conventional tools (e.g., statistical models such as ARIMA or water-balance formulations). Deep learners, especially LSTM and GRUs (gated recurrent units) provide better predictions than other techniques in most, if not all, cases. However, there is no universal consensus on which model always provides the best results. Different models may perform well at different sites within a river basin. Therefore, assessment must always include multiple models to select the optimal model of those tested.

Reservoir inflows are a key input to these models and the quality of the output depends upon the quality of the inflow data. Note that reservoir inputs can be natural streamflows or controlled releases from an upstream reservoir (these reservoirs may or may not be explicitly modeled). While treating upstream reservoir releases as inputs simplifies the outflow predictions at a downstream reservoir, explicitly modeling the releases of these upstream reservoirs is shown to improve model predictions due to better accounting for lag times of flows [94].

Most studies focus on modeling monthly or daily outflows, although efforts are beginning to be made to develop sub-daily streamflow time series to improve streamflow forecasts [95]. Most models provide 1-step-ahead forecasting, with many providing 2-, 3-, and multi-step-ahead forecasts. Real-time forecasting is also being attempted using machine learning [96].

Statistical metrics such as the root mean square error (RMSE) are used as the objective (loss) function to minimize the errors between observed and modeled outflows. However, recent efforts have focused on including other information to help guide the calibration process. A mass-conserving LSTM (mc-LSTM) model has been presented as well [97]. Loss functions have been modified to include conservation relationships as well as other information such as reservoir operation rules [93,98].

While recurrent and non-recurrent neural networks (e.g., LSTM, GRUs, and ANNs) appear to provide better forecasts than most other models, the derived operational rules are abstracted as weights and thus not readily interpretable. This issue, if not of concern in forecasting, is the only goal of the model. However, interpreting the model results and which inputs have a bigger impact on the output is useful to evaluate the performance of ML models (especially those that behave like black boxes).

Scenario-based sensitivity analysis, and XAI methods like Shapley Additive Explanations (SHAP) are being employed to understand how ML model inputs affect reservoir outflows [98,99]. The results from these studies suggest that while XAI results make hydrological sense in most situations, there is no guarantee of this over the entire range of outputs [99]. An evaluation of whether ML models trained with physics-based or operation-based loss functions explain the results better is an interesting but unexplored direction of research.

Reservoir inflows are critical to properly predict outflows. In forecasting applications, reservoir inflows have to be estimated to make future predictive runs.

Therefore, considerable interest also exists in using machine learning for modeling reservoir inflows [100–116]. These models mainly focus on a daily time-step, but both monthly and sub-daily time-steps need also be predicted depending upon the requirements of the problem.

The modeling of reservoir inflows using machine learning bring about several distinct insights: (1) These models use meteorological variables such as precipitation, temperature, and wind speed and their lags. (2) Atmospheric teleconnections such as El Nino–Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO), the Pacific Decadal Oscillation (PDO), the Indian Ocean Dipole (IOD), and the Arctic Oscillation (AO) are also being employed. These teleconnections correlate with several reservoir inflow processes such as

rainfall, evapotranspiration, and snowmelt. (3) There is a greater propensity to combine multiple models rather than rely on a single algorithm such as LSTM. (4) Rather than utilize an ensemble mean (EM), most studies utilize a stacking ensemble (SE), wherein different parts of the dataset are predicted by different model subsets. This occurs because some models provide very high extreme values which bias the overall ensemble mean. (5) It is more common to see fused traditional and deep machine learning algorithms as well as statistical models such as ARIMA for reservoir inflow forecasts.

Reservoir inflow estimation is often fraught with uncertainty. These uncertainties can be random due to changing weather patterns, land-use alterations, and climate change. The ability of a model to capture extremely high inflows is critical in flood management applications. While ML models may perform better than traditional physics-based models for forecasting streamflows, they are not perfect nor without limitations. Model stacking and ensemble approaches may help with predictions, but also can potentially average down extreme forecasts. Explicitly capturing this uncertainty alongside point estimates adds value to the estimation process as it informs the decision-maker of which are more likely estimates and what are plausible values. Therefore, many studies have explored the use of uncertainty quantification methods such as Bayesian deep learning, Bayesian networks, fuzzy logic, and other heuristic models [51,89,100,114,115,117].

Despite a growing number of publications in this area, propagating uncertainties in reservoir inflows through single- and multi-reservoir operations is clearly a largely unexplored direction and of considerable practical significance.

6.1.2. Levees and Flood Walls

Levees and flood walls are structures built along a river to keep flood waters from flowing into the adjoining floodplain. While levees and flood walls serve similar purposes, the former are built using earthen materials, while the latter are built using concrete.

While applications of machine learning algorithms to study levees are limited (see Table 4), they have tackled the most challenging problems related to the resiliency of levees to withstand failure. Machine learning has been used to evaluate failure risk due to overtopping, compaction and liquefaction, and piping. Cracks and other early-warning signals, such as the formation of sand boils, which indicate piping due to liquefaction, have also been studied. Manual inspection and ground-penetrating radar (GPR) are two common approaches to evaluate hazards in these systems. Both of them are expensive and time-consuming; therefore automated detection using drones and transfer learning algorithms to enhance the value of limited GPR-based surveys have also been explored using machine learning methods. Deep neural networks such as convolution neural networks (CNNs) and the Viola–Jones object detection method, which is based on the boosting technique, have shown promise for evaluating drone-based surveys. Conventional neural networks such as ANN, SVM, Naive Bayes, and others have been useful to predict the risk of failures.

Table 4. Machine learning modeling focused on levees.

Focus	Method	Data	Reference
Levee overtopping	Logistic regression	Geometric, hydraulic geotechnical	[118]
Levee anomalies	AdaBoost; Viola–Jones detector	Field inspection data	[119]
Failure hazards	Deep learner	Electrical resistivity data	[120]

Table 4. *Cont.*

Focus	Method	Data	Reference
Hazard classification	Clustering	UAV, geophysical (shear velocity, EMI, apparent resistivity)	[121]
Levee compaction	Deep transfer learning, ANN, KNN, NB, LR for prediction	Transfer learning for feature dataset	[122]
Sand boils	Stack of ML algorithms (SVM, ANN, CNN)	Field surveys (images)	[123]

The United States alone has over 24,000 miles of levees and the average age of these levees is 51 years [124]. As such, many of the levees are in need of rehabilitation and most levees were not designed for modern climatic conditions. The review of the literature indicates that while attempts have been made to evaluate levee failure risks using machine learning, this is another largely unexplored area as far as flood resiliency is concerned.

The National Levee Database (NLD, 2025) [124] provides the best publicly available information to understand levee performance. Efforts to compile a larger dataset of images pertaining to levee failures, along with their hydraulic, geotechnical, and geophysical characteristics, would be a useful addition to facilitate further research in this area.

6.1.3. Pumping Stations for Flood Control

Pumping stations offer the third line of defense in flood control. Pumps are used to remove any excessive water and pump it back into the river. Machine learning has been utilized to model this system. Lee and Lee (2022) utilized multi-layer perceptrons (ANNs) to simulate the discharge from pumping stations using previous rainfall and discharges [125]. They concluded that while the method was useful, the study could have benefited from having inflow data into the pump stations as one of the inputs. Wang et al. (2023) [126] applied ANNs and SVMs with different evolutionary optimization techniques to study inflows into a pumping station for different time periods. They made use of water levels at other pumping stations, rainfall, and human factors to develop different models that showed a high degree of accuracy in their study area. Kow et al. (2024) [127] utilized a Transformer-based LSTM (T-LSTM) to abstract pump station operating rules using rainfall and flows from upstream stations. The use of Transformers assisted in capturing the seasonality in the operations and provided excellent results, both for typhoon and convective storm events. Joo et al. (2024) [128] combined gated recurrent units (GRUs) with deep-Q reinforcement learning to simultaneously minimize water levels in a retention basin and the number of pump switches over the entire storm duration. Their results indicate that this combination is useful to improve operations of pump networks used in flood control.

While traditional methods for operating pump stations using physics-informed models and traditional optimization routines continue to be used [129], efforts have started on exploring the use of machine learning models for predicting inflows, outflows, and the operation of these pumping stations. Pump stations help reduce flooding risks to humans and the environment but can also cause changes to local hydrology as well as affecting riparian and riverine habitats due to changes in dissolved oxygen [130]. Therefore, proper operation of these systems is critical. While the use of machine learning shows great promise, the lack of open-source datasets limits the number of researchers who have access to such data, which in turn hinders a deeper exploration of this topic.

6.2. Machine Learning for Pluvial Flood Management

6.2.1. Pluvial Flood Estimation

Machine learning methods have been widely used in pluvial flooding studies [131–152]. Figure 5 explains the primary goals of these machine learning models in pluvial flooding studies. These studies either focus on predictions of flood characteristics or susceptibility mapping of flood-prone areas, mostly in urban environments.

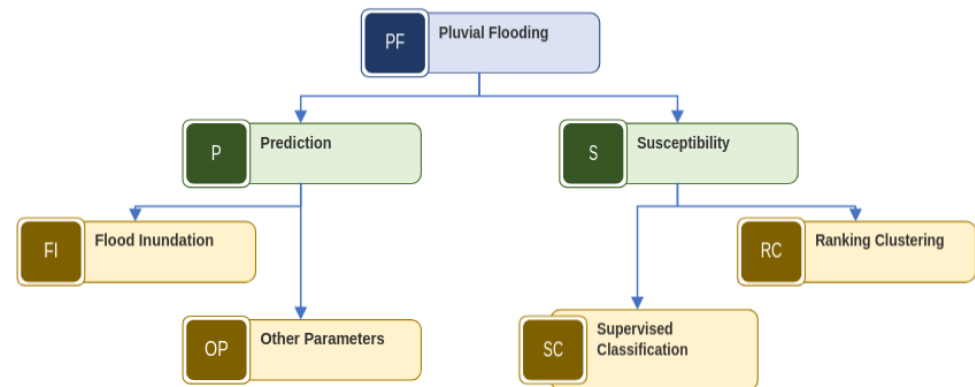


Figure 5. Classification of pluvial flooding studies.

The analysis of the literature pertaining to the use of machine learning for pluvial flooding demonstrates that a wide range of machine learning methods have been used in various applications. Among the traditional machine learning methods, the logistic regression (LR), artificial neural network (ANN), support vector machine (SVM), and K-nearest neighbors (KNN) algorithms show greater use. Ensemble methods such as random forest (RF) and XGBoost have also been used extensively. Among the deep learning algorithms, convolution neural networks (CNNs) stand out prominently. While all these models provide good results, there is no clear identification of which one is best.

ML based Classification methods are used to predict flood/no-flood zones using a suite of inputs such as precipitation, land-use type, elevation, and others. The labels (output) are obtained either from observed data within an urban area that is collected by municipalities and/or from those reported by citizens through navigation apps such as WAZE. The latter is useful for understanding flood-prone roads and other transportation infrastructure.

Unsupervised methods, such as fuzzy clustering, have been used to categorize an area's susceptibility to flooding. Such classifications can help data collection activities to develop supervised classifiers in the future. The depth of the water level in urban areas following a rainfall event as well as the extent of inundation in floodplains are also important aspects of pluvial flooding. As urban areas are typically ungauged, this information has to be obtained via simulation or using satellite remote sensing [153–155].

Machine learning methods have been widely used to abstract the results from physics-based models (i.e., flooding depth, inundation extent), using surrogate measures such as rainfall intensity, land elevation, and other characteristics. Again, a suite of conventional and deep learners have been employed for this purpose that have yielded good results. Once trained, machine learning models are easier to run and different scenarios can be evaluated to guide flooding planning and emergency management efforts. However, as ML models depend upon data from physics-based models, their accuracy cannot be greater than those obtained via physics-based simulators. Therefore, integrating physics-based simulations with satellite data can improve prediction methods, especially using interferometric synthetic-aperture radar (InSAR) and other remote sensing products. A case study of such integration is presented in [155].

One important aspect of pluvial flooding is the heterogeneity of datasets. For example, rainfall hyetographs are 1D temporal data, while digital elevation models are 2D (raster data), and high-water marks are points in 2D space (vector data). Simulation models can produce 1D or 2D data in space and over time. Transportation infrastructure is usually multi-line data (line vectors). Assimilation of such data from diverse sources is an important ancillary topic that is beginning to be explored [156,157].

Estimation of pluvial flooding characteristics, particularly inundation depth and extent, using physically based tools is rather difficult due to the paucity of data for model validation. While several studies have demonstrated that the output of such models can be captured using machine learning methods, the ability to transfer such learning to other sites via transfer learning approaches is another interesting area that has received little attention [158] and offers significant opportunities to improve flood risk management in other areas. In a similar vein, while the use of explainable artificial intelligence (XAI) methods such as SHAP has been demonstrated in the literature [141], their usage is still limited and offers significant potential to elucidate factors affecting pluvial flood risks.

6.2.2. Machine Learning Approaches for Low-Impact Development

Low-impact development (LID) aims to develop stormwater infrastructure within urban areas that largely mimic natural hydrology by enhancing infiltration, supporting vegetation, and enhancing water quality. In many US cities, it is part of the Municipal Separate Storm Water Systems (MS4) and permitted to discharge water from urban areas to natural water bodies. Environmental permits not only emphasize the rate and volume of discharges but also place restrictions on the quality of the discharged water. Therefore, contaminants of concern (CoCs) often control their design and operation even if their primary goal is to remove flood water from roads, residential neighborhoods, and business districts, and keep pluvial flood waters away from humans.

Machine learning models are being used to design and operate many LID features and understand their functioning. Complex physics-based formulations can be approximated using machine learning and used with multi-objective optimization for sizing LID practices [159]. This approach greatly reduces the computational time to obtain optimal solutions.

Deep reinforcement learning is widely being used to operate (control) stormwater treatment systems to mitigate flood flow rates and associated contaminant movement. Reinforcement learning is noted to help achieve real-time control under uncertainty [160–162].

Integration of machine learning with other ancillary technologies such as the Internet of Things (IoT), physical-model simulations, and remotely sensed datasets opens new avenues to model the performance of stormwater systems, develop better designs, and monitor LID systems [163,164]. Emerging studies indicate the promise of such integration, and this is another fertile area for further exploring the role of machine learning.

Predictions of water quality outflows from LID stormwater systems is of interest to decision-makers to ensure they are within compliance. Machine learning models have found uses in capturing and correlating highly complex water quality transformations occurring within LIDs to easily measured surrogate data such as rainfall, temperature, sunlight, and others. A variety of modeling algorithms have been evaluated and demonstrated to provide good results. The algorithms tested include, but are not limited to, ANN, SVM, KNN, random forest, generalized linear models (GLMs), partial least squares (PLS), and deep learners [165–169].

While ML models show high potential to predict water quantity and quality parameters in stormwater control and treatment systems, there is no single approach that stands out. The quality of predictions varies among models, so experimentation with a candidate set of models is often required. Conventional machine learning models (ANN, SVM) per-

form better than deep learners in some cases, especially when the amount of data available for calibration and testing is small. In addition to variability across models, a particular algorithm may be better suited for one water quality parameter but not another. This result indicates that some ML schemes are able to better assimilate certain processes that affect the quality of stormwater than others. However, the success of ML models in predicting emerging contaminants, such as microplastics, indicates their high potential to predict concentrations of contaminants for which the mechanisms of biochemical transformations are not completely known [169].

While ML algorithms show promise for modeling urban stormwater infrastructure, there are many unexplored research directions. The use of explainable machine learning (XAI) in understanding the predictions of ML models, especially to understand the fate and transport of emerging contaminants, has the potential to develop fundamental insights on pollutant behavior using machine learning. Evaluating the use of stacked and ensemble learning methods, and integrating physics-informed loss functions, are some easy implementations that have not been undertaken to date to the best of the authors' knowledge and offer some useful avenues to explore.

6.3. Machine Learning and Flood Resiliency

A significant amount of research focused on the resiliency of communities to flooding risks has begun to emerge in the last few years and a large sample of such studies, particularly those using machine learning approaches, is summarized in Table 5. The synthesis of these studies depicts common themes, which are presented in Figure 6.

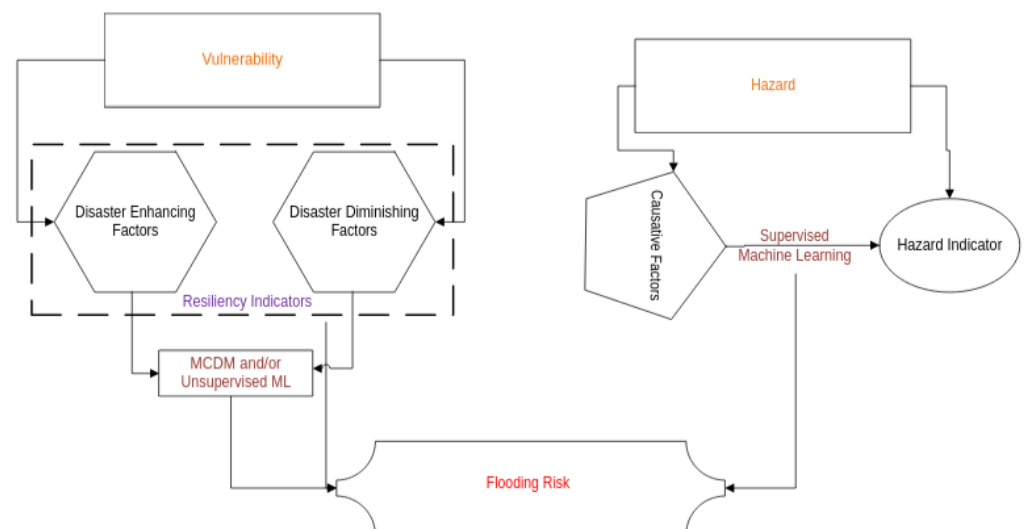


Figure 6. Overview of resiliency-risk modeling framework.

Resiliency is measured as the extent of vulnerability of a community to withstand a flooding hazard. The higher the vulnerability, the lower the resiliency of the community. Vulnerability captures demographic, economic, geographic, and engineering factors, such as the population density, the nature and extent of economic activity, land elevation, and distance from flooding features, such as streams, and engineering measures, such as pumping stations and other stormwater conveyance features.

Table 5. Summary of studies focused on flooding risk and resilience.

Citation	Methods Used	Focus/Findings
[170]	AHP, GIS, RS, and ML (random forest and SVM)	Community resilience of floods; ML for susceptibility analysis.
[171]	CNN to extract features for flood resilience + fuzzy logic for Resilience Index	Resistance, functional, and economic resilience explicitly modeled.
[172]	SOM compared with PCA	Economic, physical, and social dimensions of vulnerability considered.
[173]	SVM, ANN, RF, GBDT; stacking and ensemble not superior	Meteorological, geographic, and human resilience explicitly considered.
[174]	Unsupervised, supervised	Categorize resilience and predict using rainfall.
[175]	Different clustering	Resilience defined in terms of robustness and rapidity.
[176]	NB, LR, RF, Lazy Tree, ANN (RF provided the best results)	Predicts 4 classes—flood, flash flood, coastal flood, and lakeshore flood.
[177]	Ensemble methods, random forest	Flood risk is product flood susceptibility based on weights of evidence and flood hazard maps.
[178]	SVM, XGBoost, RF, MLP GBDT, 1DCNN	Disaster-inducing factor, disaster-breeding element, disaster-bearing bodies (input); deeper models not as useful as shallower models.
[179]	SVM + MCDM	SVM for flood susceptibility; MCDM for flood vulnerability.
[180]	Random forest was the best; SVM and boosted regression trees	TOPSIS for vulnerability; ML for hazard; output—various levels of risk.
[181]	Tree-based approaches with DEA	DEA for integrating socio-economic and adaptive capacity indicators (vulnerability); ML with geomorphology for susceptibility.
[182]	XGB, RF, CatBoost—RF was the best model	Susceptibility in riverbeds; geomorphology for mapping susceptibility.
[183]	GARP and MaxEnt	Hazard (flood, economic, social) x Hazard (flood hazard—based on field survey and ML).
[184]	ANN and linear regression	Landscape factors affecting flood susceptibility (satellite for flood hazards; role of LULC via regression).
[185]	Text mining, clustering and prediction	Role of big data, IoT, and social media data—flood risk mapping; rapid impact assessment on infrastructure failure; smart situational awareness; more conceptual study with application to Harris County.

Table 5. *Cont.*

Citation	Methods Used	Focus/Findings
[186]	Random forest and SVM; Multiple MCDM methods	Ensemble of MCDM and ML models for an aggregated Flood Susceptibility Index.
[187]	MCDM + deep neural networks; SHAP-based XAI	National flood risk insurance data, flood risk map. Improved risk at finer spatial levels.
[188]	CART, MARS, BRT, SVM, and linear discriminant analysis	Vulnerability using AHP (MCDM); flood hazards via ML. Different criteria used for vulnerability and hazards.

Multi-criteria decision-making (MCDM) approaches are used to aggregate such factors into a composite index. A suite of MCDM approaches, such as simple additive weighting (SAW), analytic hierarchy process (AHP), VIKOR, ELECTRE, and others have been utilized for this purpose (see [189,190] for an overview of these techniques). Briefly, MCDM aggregates ratings, which describe an alternative's concordance with a criterion, and criteria weights, which denote the relative importance of the criterion, and aggregates the scores over all selected criteria to rank and prioritize alternatives. Uncertainty is an integral component of such an analysis and therefore some studies have attempted to use fuzzy set theory to capture differences among decision-makers with regards to different criteria and ratings of alternatives.

Note that MCDM is an unsupervised approach wherein each alternative is ranked (so the number of initial clusters equals the number of alternatives). Once ranked, the grouping of these alternatives can be carried out subjectively or using unsupervised classification methods such as clustering and self-organizing maps (SOMs).

While vulnerability captures the likely impact (or lack thereof) of floods at a given location. The hazard posed by the flood also varies geographically. This risk arises because of hydrologic conditions, such as rainfall intensity, and also land-use land-cover (LULC) conditions that lead to runoff (flood) generation. The risk of flooding of a land parcel depends upon several factors including, but not limited to, rainfall intensity, duration, LULC, soil types, antecedent moisture conditions, and topographic slopes. Supervised machine learning models are used to develop relationships between flooded areas and other surrogate measures to model flooding hazards. A variety of approaches have been used to obtain flooded areas including, but not limited to, use of satellite imagery, household surveys, topography-based wetness indices, and subjective or anecdotal information of decision-makers. Clearly, the more direct the measurement, the more reliable the result. A suite of machine learning modeling including, but not limited to, ANN, SVM, CART, MARS, random forest, boosting methods (GBT, XGBoost, AdaBoost), and deep learning have been employed for these purposes and have been demonstrated to be able to model flood hazards with a high degree of accuracy.

The data volume available for modeling is often limited, which in turn favors conventional ML methods over deep learning paradigms. Some researchers have also utilized ensemble and stacking of algorithms, with varying degrees of success. The suitability of ensemble methods is hampered by the large predictive variability across different models. While most of the explanations of the ML modeling results are provided using tree-based approaches, Shapley Additive Explanations (SHAP) has also been used with deep learning models. While most models have focused on binary (flood/no flood) classification, multinomial models, to capture varying levels of hazard, have been explored to a limited extent.

Copula-based approaches are widely used to estimate joint and conditional risks of flood intensity, volume, and duration [191,192]. However, the integration of these approaches with machine learning is another poorly explored area of research. The coupling of ML and copula approaches to study droughts is demonstrated in [193], indicating the possibility of such an effort for flooding as well. Unlike droughts, which depend upon atmospheric variables (rainfall and temperature), estimation of flood duration, volume, and intensity is only possible in gauged catchments, and the flood indicators also depend on soil type, antecedent moisture, land use, and other factors, whose temporal variability is not known in many locations.

Flood hazard assessment in many areas is hampered by a paucity of data. This is particularly true not only in developing countries but also in rural and peri-urban areas of developed nations. Transfer learning provides one way to overcome this limitation, where a model trained over a larger dataset in a similar region is used to make predictions in another. In addition, several other emerging technologies provide useful information to understand flooding hazards and vulnerability. The Internet of Things (IoT) is bringing about new, low-cost technologies for monitoring both fluvial and pluvial floods [194–196]. Low-cost sensors have the potential to significantly increase the data that are available for flood mapping. While such sensors increase the data availability, they generally have poorer data quality and are prone to giving erratic results. Therefore, data cleaning becomes necessary and machine learning algorithms for detecting and removing outliers can be useful [197]. In addition, several machine learning models, both conventional and deep, can be used for real-time forecasting and enhancing the flood early-warning capabilities of downstream communities. While the integration of the IoT and machine learning or early-warning systems has been demonstrated in some areas [198], there is still considerable opportunity to explore this area, particularly in terms of data retrieval (using drones) when internet infrastructure may become non-functional due to floods.

7. Trends in Machine Learning Model Usage

The literature above indicates that machine learning models are being widely used across the spectrum of flood assessment and management applications. As machine learning models are empirical, most studies often assess two or more techniques to identify a suitable model. Sometimes the models are integrated into an ensemble and their average prediction is used as the most likely estimate. Regardless, understanding the trends in usage is important to identify whether some models are preferred over others or if some models are not being favored. To address this question, the number of peer-reviewed articles pertaining to each machine learning technique related to flood studies was obtained from the OpenAlex database [199].

The results, shown in Figure 7, reveal some interesting trends: The use of deep learning methods, particularly LSTM and CNN, has grown considerably. CNN is more widely used than LSTM because it can be used with both spatially and temporally structured sequences, while LSTM is specifically designed to deal with 1D datasets. There has also been a steady increase in the number of publications using other deep network (DNN) architectures such as autoencoders and decoders. Despite the growth in deep learning models, traditional neural networks (with a single hidden layer) are also used quite extensively. In particular, traditional neural methods integrate well with GIS and multi-criteria decision-making methods. Also, they serve as a useful benchmark to evaluate whether deep learners offer better results for a given flood application. In terms of tree-based learning, while the use of both random forest and boosting methods has increased in the last five years, random forest is slightly more preferred compared to boosting techniques. In particular, random forest algorithms have been used not just for predictions but also for feature

importance, although feature importance can be deduced from boosting methods as well. The preference for bagging methods likely arises from their simplicity and generalization ability. The random forest algorithm has only two hyper-parameters (number of trees and maximum depth). On the other hand, boosting methods have a greater number of hyper-parameters (e.g., shrinkage, regularization, and number of estimators) and therefore are harder to tune and more prone to overfitting. Bagging operations can be carried out in parallel while boosting methods are sequential in nature. Therefore, bagging methods can make use of multi-core and multi-threading capabilities when working with large datasets. These advantages explain the greater use of random forest over boosting techniques. Finally, Figure 7d shows the number of explainable AI (XAI) publications. As can be seen, this is a burgeoning area of research with a lot of potential for increased usage.

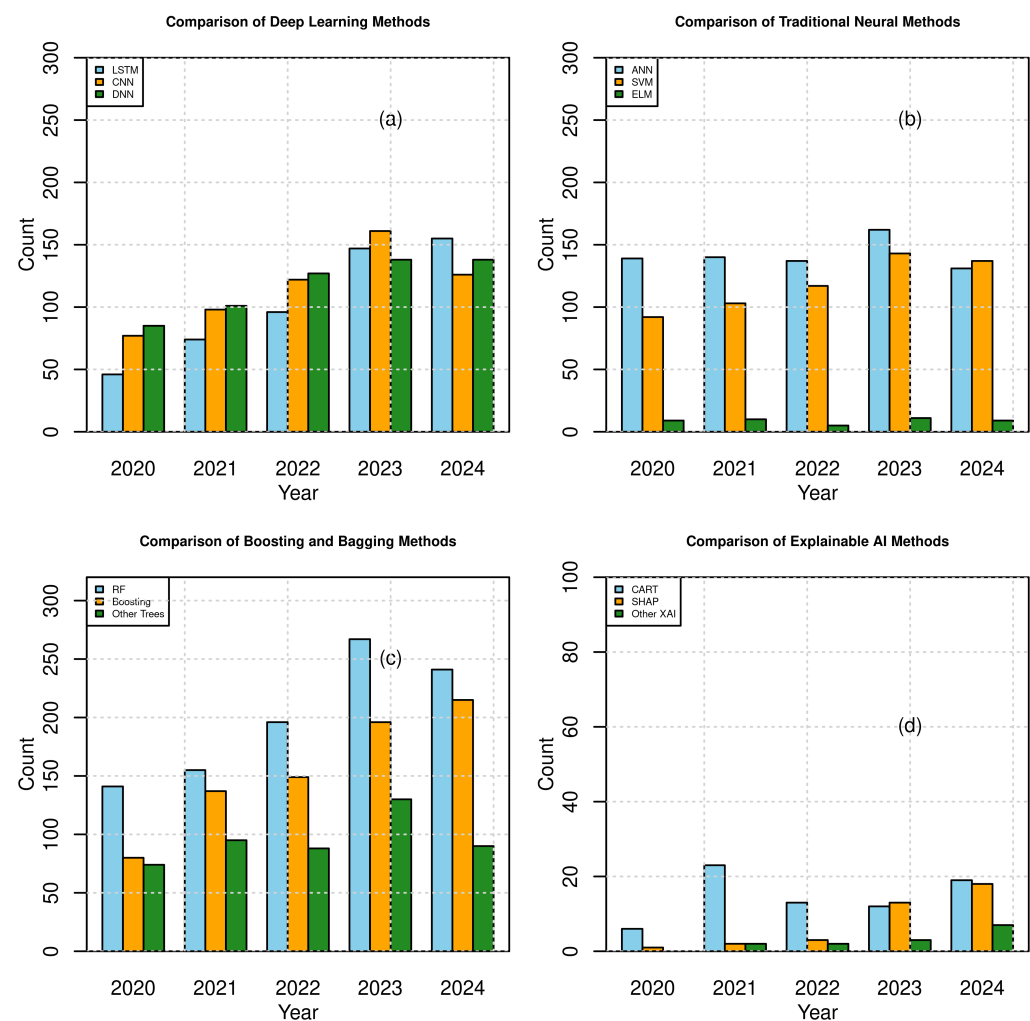


Figure 7. Counts of flood-related machine learning studies presented in peer-reviewed publications between 2000 and 2024: (a) Deep learners; (b) traditional neural networks; (c) tree-based learners; (d) explainable AI models. Data source: [199].

8. Future Directions

The review demonstrates how machine learning (ML) is playing an important role across the gamut of flood applications. Not only are the number of papers published concerning it on the rise, but its applications are not limited to one type of problem. The review also highlights some key gaps and future research directions, which are enumerated below:

1. While the use of machine learning for pump station operations has been demonstrated, the number of studies is limited due to paucity of data. Efforts to develop other open-source datasets would be useful to further test the use of ML in real-time operations of flood control pumps.
2. With the advent of the Internet of Things (IoT), data will be collected at a much faster pace than before. However, the quality of data that many low-cost sensors provide may have a high degree of uncertainty. Therefore, the use of machine learning for data filtering (e.g., the use of autoencoders/decoders) and infilling of missing data needs to be evaluated.
3. Many sensors have enough computational power to not only collect data but also perform other computations. Edge computing approaches have a very important role in developing early-warning and real-time flood forecasting tools. Again, the integration of machine learning with hardware components for edge computing appears to be a promising area of research, particularly for pluvial flooding.
4. Flooding infrastructure such as levees spans over large distances. As these structures age, it is imperative to rehabilitate them before the occurrence of a catastrophic event. Expensive and error-prone human-based inspections are slowly being replaced by drone-based surveying. Large-scale image processing and anomaly detection are critical areas where machine learning use has been limited but has significant potential.
5. Advances in parallel and distributed computing services are expected to continue in the next few years. The potential of machine learning to serve as a backend for comprehensive visualizations based on virtual, augmented, and mixed realities offers significant potential to not only improve our understanding of floods but also help citizens and communities improve resiliency to better withstand flooding hazards and promote flood-informed development.
6. Machine learning models have a great role to play in assimilating data from general circulation models and downscaling them. ML approaches that can lead to more robust estimates and tackle non-stationarity need to be developed for climate-adaptive decision making.
7. The ability to generate synthetic datasets and augment limited measurements (e.g., high-water marks) provides new opportunities to utilize satellite, LiDAR, and visual observations to map pluvial flooding hazards. This requires integration of several machine learning technologies and assimilation of multiple datasets at various resolutions.
8. Ensemble models are often noted to have poor predictive capabilities due to large deviations in their predictions. Development of better tools to average ensemble models via integration of Bayesian and information-theoretic approaches could help develop new tool sets for flood applications.
9. Integrating machine learning methods with physics-based modeling can be doubly advantageous. Physics-based models can infuse theoretical underpinnings to ML models while machine learning algorithms can learn nonlinear processes not captured by physics-based formulations. Physics-informed machine learning can lead to solutions where the output is greater than the sum of the parts.
10. Soil moisture and land conditions play a very significant role in pluvial flooding. Machine learning approaches can play a significant role in predicting soil moisture due to its nonlinear dynamics. Machine learning models that help exploit available, albeit limited, soil moisture data in conjunction with physically based modeling is another largely unexplored direction that could help improve flood prediction and early warning.

11. The potential of reinforcement learning approaches has not been explored to the fullest extent. Reinforcement learning models can be used to manage flood control releases from flood detention basins by integrating both volume, flow rate, and water quality constraints.
12. Machine learning models have been widely used for predicting flood flows and volumes. Floods also cause changes to water quality, with grave ecological and environmental consequences. While some efforts to use machine learning for flood control have been undertaken, the development of multi-task machine learning models capable of predicting both flow and quality would be extremely beneficial but is largely unexplored at this stage.

9. Closing Remarks

Flooding is a complex problem that causes widespread damage across the world. It is now clear that flooding hazards cannot be completely eliminated using engineering measures alone. People have to live with floods. Flood control measures must not only focus on in-stream controls but also utilize structural and non-structural alternatives within an urban area to mitigate pluvial flooding to protect humans and also help mitigate downstream fluvial impacts. Despite keeping humans away from flood waters and managing them as necessary, the threats of flooding continue to grow unabated due to changes in climate, and population growth and concomitant urbanization. Therefore, the current thinking goes a step further and evaluates how humans and the environment of a region are at risk of flooding and what are the best strategies to absorb the shocks of flooding and rebound to a better (or at least to the pre-flooding) state. The idea of withstanding the harmful effects of flooding to the greatest possible extent (robustness) and rebounding back to a better state as quickly as possible (rapidity) is called resiliency-based flood management.

Resiliency-based flood management is not independent of flood control measures for minimizing fluvial and pluvial flooding, rather it takes a more holistic point of view in identifying the risks that exist within a region and using this knowledge to guide future growth that is flood-informed and also identify vulnerable targets that need immediate attention to bring the system back to normalcy. Thus, resiliency is not simply an engineering or land-planning and zoning endeavor but involves every one in the community contributing towards flood-proofing.

Machine learning models are widely used in flood studies, ranging from flood control to resiliency-based management. The usage is higher in those applications where data are readily available. Advances in remote sensing and drone-based data collection and the proliferation of low-cost sensors using the Internet-of-Things (IoT) will further expand its role in many other aspects of floods that are currently hampered by data limitations. While these technologies show promise, their full potential is yet to be explored [200]. While machine learning offers great prediction and forecasting abilities, there is no single universally acceptable method, so empirical experimentation with multiple models is necessary. This aspect should not be viewed as a weakness but exploited to learn more about the functioning of the models and what is making them better predictors (or not). Explainable AI (XAI) methods are useful in this regard and should be adopted to transition ML models from black-box forecasters to better-informed and knowledge-based predictors.

In closing, machine learning models offer exciting approaches to tackle the entire gamut of flood problems. They are useful supplements to traditional physics-based modeling tools. Efforts should be made to integrate these two techniques to improve our forecasting capabilities as well as interpreting flooding phenomena from multidimensional perspectives. Machine learning can be used to control and operate flood control and stormwater management infrastructure and improve understanding and the resiliency of

communities to flooding hazards. This requires close collaboration between flood managers, civil engineers, and hydrologists as well as the computer scientists and mechanical and electrical engineers who build sensor technologies. Machine learning offers a common language for bringing transdisciplinarity to flooding studies.

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Abbreviations

The following abbreviations are used in this manuscript:

No.	Abbreviation	Full Form
1	1D-CNN	One-dimensional convolutional neural network
2	AD	Automatic or algorithmic differentiation
3	AdaBoost	Adaptive Boosting
4	AHP	Analytic hierarchy process
5	AI	Artificial intelligence
6	ANN	Artificial neural network
7	AO	Arctic Oscillation
8	ARIMA	Autoregressive Integrated Moving Average
9	BIML	Biologically inspired machine learning
10	BRT	Boosted Regression Tree
11	CART	Classification and Regression Tree
12	CatBoost	Categorical Boosting
13	CBR	Case-based reasoning
14	cGAN	Conditional generative adversarial network
15	CIML	Cognitive-inspired machine learning
16	CNN	Convolution neural network
17	CoCs	Contaminants of concern
18	DBNs	Deep belief networks
19	DEA	Data Envelopment Analysis
20	DNN	Deep neural network
21	DS	Diversity sampling
22	ELECTRE	Elimination and Choice Translating Reality
23	ELM	Extreme Learning Machine
24	EM	Ensemble mean
25	EMI	Electromagnetic induction
26	ENSO	El Nino–Southern Oscillation
27	GAN	Generative adversarial network
28	GARP	Genetic Algorithm Rule-Set Production
29	GBDT	Gradient Boosting Decision Tree
30	GIS	Geographic Information System
31	GLM	Generalized linear model
32	GP	Genetic programming
33	GPR	Ground-penetrating radar
34	GRU	Gated recurrent unit
35	HEC-HMS	Hydrologic Engineering Center-Hydrologic Modeling System
36	HEC-RAS	Hydrologic Engineering Center-River Analysis System

37	InSAR	Interferometric Synthetic Aperture Radar
38	IOD	Indian Ocean Dipole
39	IoT	Internet of Things
40	KGE	Kling–Gupta Efficiency
41	KNN	K-nearest neighbors
42	LID	Low-impact development
43	LIME	Local Interpretable Model-Agnostic Explanations
44	LR	Logistic regression
45	LSTM	Long short-term memory
46	LULC	Land Use–Land Cover
47	MARS	Multivariate Adaptive Regression Splines
48	MaxEnt	Maximum entropy
49	MCDM	Multi-criteria decision making
50	mc-LSTM	Mass-Conserving long short-term memory
51	MIMO	Multi-input multi-output
52	ML	Machine learning
53	MLP	Multi-layer perceptron
54	MS4	Municipal Separate Storm Sewer System
55	NAO	North Atlantic Oscillation Index
56	NB	Naïve Bayes
57	NLD	National Levee Database
58	NSE	Nash–Sutcliffe Efficiency
59	PCA	Principal component analysis
60	PDO	Pacific Decadal Oscillation
61	PLS	Partial least squares
62	QBC	Query by committee
63	RF	Random forest
64	RL	Reinforcement learning
65	RMSE	Root mean square error
66	RNN	Recursive neural network
67	RORs	Reservoir operation rules
68	RS	Remote sensing
69	SAW	Simple additive weighting
70	SE	Stacking ensemble
71	SGD	Stochastic Gradient Descent
72	SHAP	Shapley Additive Explanations
73	SOMs	Self-Organizing Maps
74	SVMs	Support Vector Machines
75	SWAT	Soil and Water Assessment Tool
76	SWMM	Storm Water Management Model
77	T-LSTM	Transformer-based long short-term memory
78	UAV	Unmanned aerial vehicle
79	USACE	United States Army Corps of Engineers
80	USDA	United States Department of Agriculture
81	USEPA	United States Environmental Protection Agency
82	XAI	Explainable artificial intelligence
83	XGBoost	Extreme Gradient Boosting

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