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Editors

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Editors
Prashanth Janardhan
Department of Civil Engineering
National Institute of Technology Silchar
Silchar, Assam, India

Parthasarathi Choudhury
Department of Civil Engineering
National Institute of Technology Silchar
Silchar, Assam, India

D. Nagesh Kumar
Department of Civil Engineering
Indian Institute of Science Bangalore
Bangalore, Karnataka, India

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Contents

Surveying Flash Floods in Urban Indian Environment: A Review of Machine Learning Applications

Sardar Rechel Blessy, Balerao Supraja, Kushal Rathi, Kamalini Devi, K. Vasanth, and Pulipati Srilatha

Abstract This survey paper conducts a thorough examination of the global challenge posed by urban flash floods, analyzing the intricate factors influencing the occurrence and severity of these events. Drawing on a diverse array of literature and case studies, the study delves into the complex dynamics of urban flash floods and their far-reaching impacts on human populations, infrastructure, and the natural environment. Highlighting the imperative for proactive flood risk management and resilient urban planning, the research puts forth actionable recommendations to bolster urban resilience in the face of mounting flood risks. In addition to evaluating machine learning algorithms like Iso clustering and ensemble classifiers for rapid flood mapping and precise flood susceptibility assessment, the study also explores the utilization of satellite imagery for enhanced flood monitoring and analysis. By integrating insights from both machine learning techniques and satellite imaging, the research aims to provide a comprehensive understanding of urban flash floods and offer practical strategies to mitigate their adverse effects. The study underscores the critical importance of implementing robust flood management measures, advanced early warning systems, and sustainable urban development practices to address the escalating threat of flash floods in urban areas and safeguard vulnerable communities, critical infrastructure, and ecological systems from the devastating consequences of these events.

Sardar Rechel Blessy, Balerao Supraja, Kushal Rathi—These Authors Contributed equally.

S. R. Blessy · B. Supraja · K. Rathi (✉) · P. Srilatha
Department of Artificial Intelligence and Data Science, Chaitanya Bharathi Institute of Technology, Hyderabad 500075, Telangana, India
e-mail: kushalrathi02@gmail.com

K. Devi
Department of Civil Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad 500075, Telangana, India
e-mail: kamalinidevi1@gmail.com

K. Vasanth
Department of Electronics and Communications Engineering, Chaitanya Bharathi Institute of Technology, Hyderabad 500075, Telangana, India

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Keywords Urban flash floods · Flood risk management · Resilient urban planning · Machine learning algorithms · Satellite imagery

1 Introduction

Urban areas worldwide face an increasing threat from flash floods, a phenomenon characterized by sudden, intense rainfall leading to rapid and potentially devastating inundation. As cities grow and climate patterns shift, the risk of flash floods in urban areas becomes more pronounced, demanding comprehensive strategies for mitigation and preparedness. Understanding the factors that contribute to flash floods is fundamental in developing effective flood risk management practices and urban planning.

This survey paper aims to provide an extensive analysis of the various factors affecting flash floods in urban settings. The study presents a comprehensive review of the existing literature, exploring both natural and anthropogenic elements that influence the incidence, severity, and consequences of urban flash floods. By synthesizing the collective knowledge from past research, we seek to contribute to a better understanding of the complex interplay of factors in urban flood risk.

Urban flash floods not only pose threats to human lives and property but also have far-reaching economic and environmental consequences. The implications of poorly managed flood risk can be severe, with implications for urban resilience, infrastructure integrity, and community well-being. As such, this survey paper aims to offer insights and recommendations that can inform urban planners, policymakers, and disaster management authorities in their efforts to reduce the vulnerability of urban areas to flash floods.

Through an analysis of the current state of research, we aim to highlight gaps in our understanding and provide a foundation for future studies and the development of urban flood risk management strategies.

1.1 Previously Majorly Affected Cities

In 2019, the Patna floods wreaked havoc with over 30 casualties and extensive damage due to heavy monsoon rains. Triggered by the overflowing Ganga River, the flash floods submerged Patna for days, reaching 6–7 feet in some areas, marking the worst flood since 1975. Meteorological records revealed a record-breaking 177 mm of precipitation in 48 h, accompanied by a historic September rainfall of 430 mm, worsening the crisis. The National Disaster Response Force (NDRF) deployed five teams, rescuing around 5,000 people, while property damage, structural destruction, and waterborne diseases escalated. From September 28 to October 1, torrential rainfall persisted, accumulating 400 mm, worsened by non-functional sump houses until October 1, leaving 60% of Patna waterlogged for ten days, particularly in low-lying areas. Figure 1, sourced from the referred paper, highlights that the devastation in Patna serves as a stark reminder of the immense damage floods can cause [1].

In 2015, the Chennai floods, triggered by heavy northeast monsoon rains, devastated the Coromandel Coast, causing over 500 deaths and displacing 1.8 million people. With economic losses ranging from ₹200 billion to ₹1 trillion, it ranked among the costliest disasters in 2015. Unprecedented rainfall of 1,218.6 mm in November, coupled with El Nino conditions and Bay of Bengal warming, contributed to the catastrophe. The flooding resulted from a combination of factors, including inadequate infrastructure, unplanned urbanization covering natural drainage areas, aging civic structures, and upstream reservoir water release. These floods highlighted the pressing need for improved preparedness in the face of such complex challenges. Figure 2, sourced from the referred paper, provides a visual representation of precipitation levels across the country, potentially including Chennai during this period [2].

In 2018, Kerala faced its worst floods in nearly a century, beginning in July. The region experienced an extraordinary 2346.6 mm of rainfall from June 1, 2018, to August 19, 2018, surpassing the normal by 42%. Specifically, the rainfall in June, July, and the first 19 days of August exceeded normal levels by 15%, 18%, and a staggering 164%, respectively. On the evening of August 8, heavy rainfall, 116% above average, filled dams to their maximum capacities, leading to a subsequent 310 mm (12 in) of rain within the following 48 h. The primary factors contributing to the floods included intense rainfall in a short duration, insufficient drainage capacity, unregulated reservoirs, and the failure of flood control structures. Figure 3, sourced from the referred paper, visualizes this data, showing the areas that received the highest amount of precipitation [3].

Previously, majorly affected Indian cities stand as stark reminders of India's vulnerability to floods. Mumbai's 2005 deluge, the wettest day ever recorded in the city, caused widespread destruction with over 300 lives lost due to heavy rainfall exceeding 944 mm in just 24 h [4]. Gujarat's 2006 catastrophic floods were triggered by overflowing rivers like Narmada, Tapi, and Mahi, which breached embankments and inundated entire towns and villages. Millions were displaced, critical infrastructure like roads, bridges, and communication networks were severely damaged, and agricultural lands were destroyed, highlighting the immense economic and social costs of such events [5]. Similarly, Kolkata's 2007 battle with the overflowing Ganges River and its tributaries highlighted the disruption floods bring to daily life. Millions faced disruptions as essential services like electricity and water supply were compromised, transportation networks were paralyzed, and homes and businesses were flooded [6]. These events expose India's vulnerability to extreme weather events and underline the need for robust flood management strategies across the country.

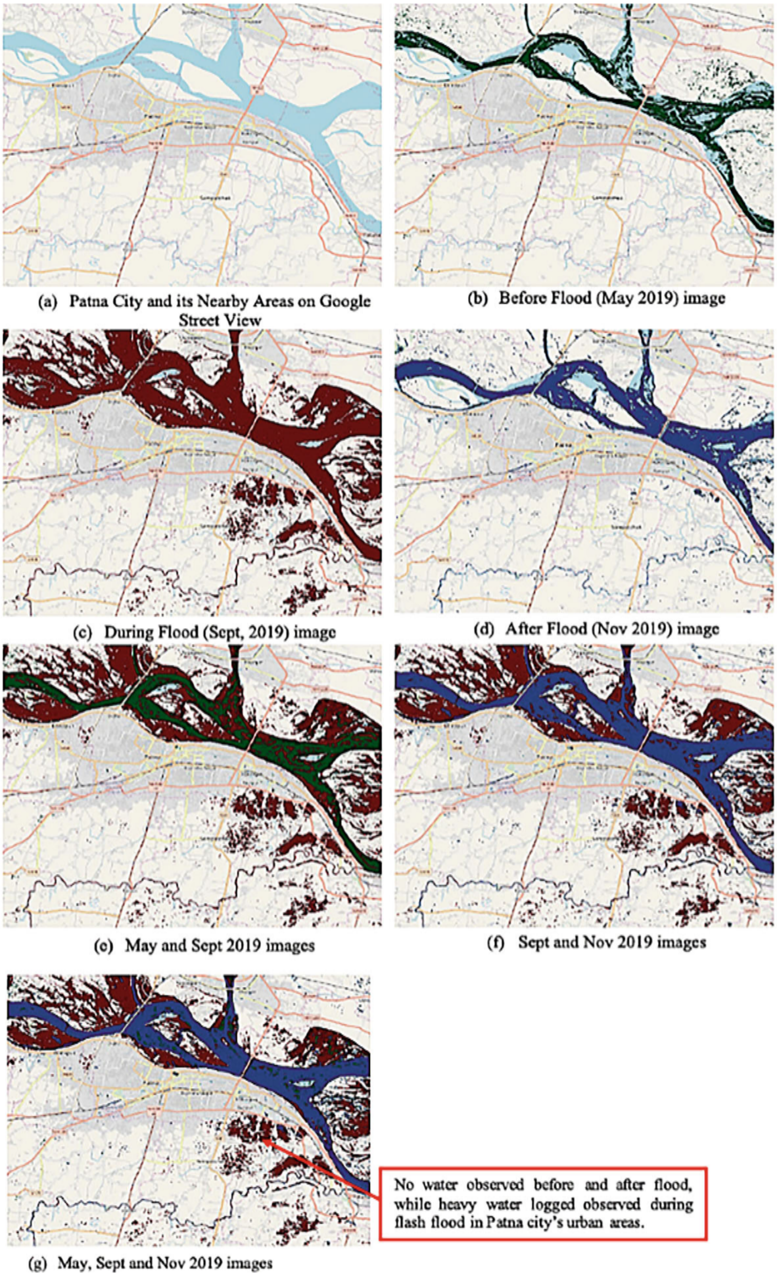

Fig. 1 Patna city: before, during, and after the flood (2019)

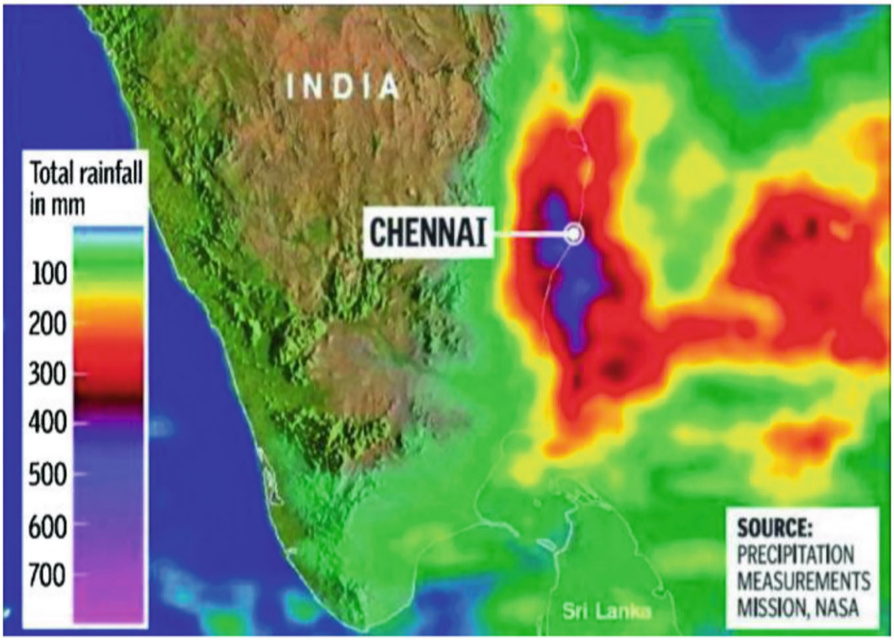

Fig. 2 Precipitation levels around India

2 Literature Review

The study by Lechowska [7] critically evaluates flood risk perception factors, distinguishing between rationalist and constructivist perspectives and examining their implications within existing literature. This analysis enhances our comprehension of flood risk and offers insights to enhance risk management strategies, stressing the significance of considering cultural, historical, and political contexts. Meanwhile, in flood prediction, Ghorpade et al. [8] provide a comprehensive overview of machine learning algorithms such as Support Vector Machines [9] (SVM is a method used for both classification and regression problems that seeks to find the best hyperplane to efficiently divide the data into classes.), Decision Trees [10] (They function as a supervised learning strategy for tasks involving regression and classification. To maximize information gain or reduce impurity, they partition the dataset iteratively based on feature values.), Artificial Neural Networks [11] (ANNs represent computational models which are utilized for various tasks such as classification, regression, and pattern recognition.), Ensemble Learning (integrates multiple models such as boosting, bagging to enhance predictive performance), and Long Short-Term Memory [11] (LSTM are a type of recurrent neural network architecture designed to capture long-term dependencies in sequential data.) models. SVM, for instance, shows notable efficiency in water level prediction, showing impressive R2 values ranging from 99.3 to 93.1% for lead times spanning one to seven days. R2 (or

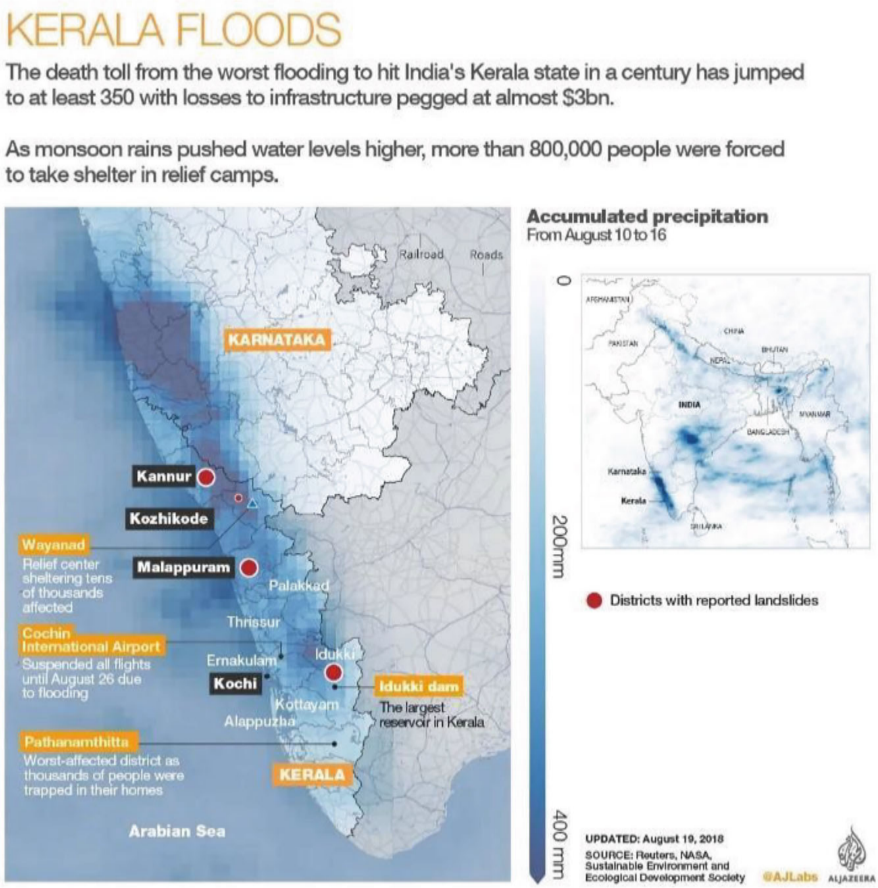

Fig. 3 Kerala: a visual look at the devastating rainfall

R-squared) is the percentage of the dependent variable's variability that the independent variables in a regression model can account for. While Decision Trees, find their application in flood mapping, with linguistic decision trees tailored for modeling river levels and ANNs have demonstrated prowess in flood event prediction, especially when dealing with multivariate long-term datasets. Ensemble learning techniques, such as random forest and boosting, have been employed to enhance prediction accuracy by emphasizing key features like cumulative rainfall, water flow, and humidity. Moreover, Long Short-Term Memory (LSTM) models have appeared as a promising avenue for flood prediction, particularly in regions with limited data availability. Finally, Hou et al. [12] explore the repercussions of flood disasters in China's Xixian New Area, focusing on agriculture, transportation, and human well-being. The study uses rainfall data and hydrodynamic models to simulate and forecast urban flood inundation. Evaluation of flood inundation predictions involves various performance metrics, yet specific accuracy outcomes are not disclosed. The research underscores the importance of further elaborating on the hydrodynamic model and accuracy metrics to deepen comprehension of flood management strategies in the Xixian New Area.

Yan et al. [13] have presented a neural network-numerical simulation approach for urban flood inundation prediction. The model combines a statistical analysis model with a two-dimensional hydrological and hydrodynamic model. It learns and retains the mapping link between rainfall situations and maximum water depth using the Elman neural network. Data from 35 design rainfall scenarios in Tianjin, China, are used to train the model. Databases for rainfall and spatial point water depth prediction are also established by the project. The model can help with flood disaster management by giving prompt projections of standing water in metropolitan areas. While Ahmed et al. [14] have delved into the application of machine learning algorithms for generating multi-model ensemble predictions of precipitation and temperature. Their study explores various techniques including Artificial Neural Networks [11] (ANN), K-Nearest Neighbors [10] (KNN predicts the output of a new data point by averaging the outputs of its nearest neighbors.), Support Vector Machines [10] (SVM), and Relevance Vector Machines [11] (RVM extends Support Vector Machines by selecting a subset of training data points to define the decision function, providing sparse solutions and uncertainty estimates for predictions.). ANN stands out for its adaptability, not requiring prior knowledge of predictor importance. KNN particularly shines when employing 5 neighbors, relying on proximity-based learning for accurate predictions. SVM, commonly utilized in hydrology and climate change research, demonstrates robust performance. RVM, another machine learning approach, adopts a probabilistic framework for regression tasks, providing both predictions and uncertainty estimates. The research evaluates the performance of these algorithms in producing multi-model ensemble predictions, highlighting notable performance differences in ANN across diverse geographical regions. Whereas Nayak et al. [15] focus on flood forecasting using Deep Belief Network (DBN) for the Daya and Bhargavi rivers in Odisha, India. The study compares the performance of DBN with Teaching Learning-Based Optimization (TLBO) method, using parameters like Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The flood forecast is done for 1 day, 1 week, and 2 weeks. The results show that DBN performs better than TLBO, and further integration of complex networks with DBN can improve forecasting accuracy and extend the time period for issuing guidelines and evacuation measures.

The studies conducted by Sankaranarayanan et al. [16], Sati and Kumar [17], Martins et al. [18], and Surwase and Manjusree [19] collectively address diverse aspects of flood management and risk assessment. Sankaranarayanan et al. [16] developed an early flood warning system utilizing deep learning and machine learning, which predicts flood occurrences based on temperature and rainfall data spanning 13 years. Their comparison of various algorithms highlights the effectiveness of deep learning and underscores the importance of integrating these techniques into existing flood management strategies. Meanwhile, Sati and Kumar [17] analyzes the impact of cloudburst-triggered debris flow in Uttarakhand Himalayan villages, focusing on assessing debris volume, damage, and village susceptibility. Martins et al. [18] explores flood events in semi-arid watersheds, employing social perception data, field observations, and topography to estimate floodplain height and extent. They advocate for the use of non-conventional hydrological sources and open data on precipitation and flow. Surwase and Manjusree [19] investigates flood risk in Hyderabad city, emphasizing early warning systems for disaster risk reduction. Their study utilizes hydraulic calculations and sub-catchment analysis using PCSWMM (Personal Computer Storm Water Management Model) a Storm Water Management Model, a professional software tool specifically designed for modeling and simulating a variety of water-related systems in urban environments, for drainage system design and simulation, highlighting the importance of real-time flood risk management through a combination of modeling, forecasting, and alert systems. These studies collectively explore various aspects of flood management, ranging from early warning systems and flood prediction algorithms to the analysis of flood impacts and risk assessment methodologies. They underscore the importance of integrating data-driven approaches, using both traditional and non-conventional sources, to enhance flood management strategies and mitigate the impacts of flooding events.

The studies by Madhuri et al. [20], Kumar and Sati [21], Rangari et al. [22], and Narayanan et al. [23] collectively focus on flood risk analysis and management. They utilize various methodologies such as machine learning, IoT-based reinforcement learning, geospatial analysis, and computer vision. Firstly, Madhuri et al. [20] analyzes flood risk in the Greater Hyderabad Municipal Corporation (GHMC) area using machine learning algorithms, focusing on factors like rainfall, elevation, slope, and distance from streams. They compare different algorithms and find XGBoost to be the most effective, with implications for predicting flood risk probabilities under future climate change scenarios. While Kumar and Sati [21] examines flash flood risk in Indian cities, particularly emphasizing IoT-based reinforcement learning. Their study collects extensive data on flood conditioning factors and validation points nationwide, addressing challenges in urban areas near rivers, seas, and hilly regions. They propose a method integrating reinforcement learning with IoT devices for effective flash flood management, highlighting the need for innovative techniques to minimize flood losses. Using geospatial data from publicly available internet sources, Rangari et al. [22] provide a quick assessment of the urban flood that occurred in Hyderabad in October 2020, analyzing the flooding event's intensity and spatial extent. They draw attention to the influence of increasing urbanization on the intensity of flooding and argue for better urban planning and drainage systems by contrasting this occurrence with one that occurred in August 2000. Whereas Narayanan et al. [23] analyzes flood risk in urban areas using a novel approach combining computer vision and participatory sensing. Participants capture and upload images of flooded structures using smartphones, and computer vision algorithms like SIFT are used to measure flood levels with high accuracy. The study highlights the potential of computer vision for effective flood monitoring, while also emphasizing the need for continual improvement in algorithms. These studies address the challenges posed by floods in urban areas and propose innovative solutions to mitigate risks and improve disaster response capabilities.

Rana et al. [24] delve into the geomorphological characteristics of the Rishi Ganga valley in the higher Himalayas, focusing on potential risks related to glacier-induced disasters like avalanches, glacial lake outburst floods (GLOFs), and debris flows. Their study underscores the significance of understanding hydrological processes and monitoring structural vulnerabilities in paraglacial zones to mitigate the magnitude of destruction. Additionally, they advocate for the development of robust early warning systems and the integration of disaster risk assessment into developmental planning for the Himalayan region. Syeed et al. [25] shift the focus to Bangladesh, analyzing flood risk using machine learning models based on a dataset spanning four decades. Their evaluation of various algorithms highlights the importance of accurate flood prediction models, suggesting the consideration of shorter periods for improved accuracy. Meanwhile, Karim et al. [26] provide an extensive review of flood inundation modeling methodologies across river basins, emphasizing the transition from traditional machine learning to advanced deep learning methods. They discuss challenges such as the integration of expert knowledge and the need for benchmark data for model evaluation. Furthermore, they advocate for the adoption of real-time flood simulation with machine learning and deep learning models, showcasing the potential for future research to enhance generalizability and address challenges in flood modeling with data-driven approaches. Collectively, these studies contribute to a comprehensive understanding of flood hazards and offer insights into enhancing disaster preparedness and response strategies through geomorphological analysis, machine learning modeling, and deep learning techniques.

The research conducted by Sadek and Li [27], Darbi et al. [28], and Rafiq et al. [29] covers a range of topics related to risk assessment and urban flood management. First, Rafiq et al. [29] emphasize how important it is to manage floods in cities, with a focus on how modeling must incorporate global topography data and rainfall-runoff dynamics. Their study supports comprehensive flood management plans with worldwide economic ramifications by highlighting the significance of taking tidal impacts and inundation estimates in low-lying areas into account. Whereas Sadek and Li [27] focuses on flash floods in urban areas, specifically in Ras Ghareb, Egypt, utilizing Sentinel-2 images, SRTM data, and helicopter photos for a low-cost impact assessment. They integrate FAHP and GIS to create a vulnerability map aiding decision-makers in flood preparedness, emphasizing the importance of social media imagery and geometric planning for enhanced flood mapping and mitigation. The FAHP model classifies flood vulnerability into four risk levels (low, moderate, high, very high) based on factors like land cover and slope. Lastly, Darbi et al. [28] conducted a study in Amol, Iran, utilizing various machine learning techniques to develop a highly accurate flood risk map. Their integrated approach incorporates geospatial variables and vulnerability assessment factors to pinpoint high-risk areas and recommend targeted flood risk reduction strategies. This research underscores the importance of integrating machine learning techniques for precise urban flood risk mapping and effective mitigation planning. These studies are connected by their common goal of improving urban flood management and risk assessment through the application of advanced modeling techniques, geospatial analysis, and machine learning algorithms. They aim to enhance flood preparedness and mitigation strategies in diverse urban environments.

Research projects undertaken by Hunt and Menon [30], Vemula et al. [31], and Bačová Mitková et al. [32] cover a variety of topics related to flood events and their effects. Using Weather Research and Forecasting (WRF) and WRF-Hydro models to simulate flood scenarios across various climatic variables, Hunt and Menon [30] analyzed the deadly 2018 Kerala floods. Similar to this, Vemula et al. [31] used the Storm Water Management Model (SWMM) to investigate the possible effects of upcoming extreme rainfall events on urban floods in Hyderabad, India. Bačová Mitková et al. [32] provided insights into flash flood occurrences in Slovakia's Malá Fatra National Park, contrasting different flood events and enhancing understanding of flash flood dynamics and historical perspectives in the area. Supriya et al. [33] and Keum et al. [34] offer valuable insights into flood risk management and real-time prediction systems. Supriya et al. [33] investigated urban flooding in Tamil Nadu's Vellar river basin, stressing proactive flood risk management strategies and employing the Storm Water Management Model (SWMM) for runoff simulation and flood flow estimation. Keum et al. [34] introduced a real-time flood prediction system for urban areas using machine learning techniques, demonstrating its accuracy, speed, and efficiency compared to commercial models. Bentivoglio et al. [35] and Tanim et al. [36] explored advanced flood mapping techniques using deep learning and satellite imagery. For a variety of flood mapping applications, Bentivoglio et al. [35] used Deep Learning (DL) models, showing improved accuracy and speed over conventional techniques. Using Sentinel 1 satellite data and police reports, Tanim et al. [36] developed a unique flood detection technique for urban regions that offers the possibility of quicker and more accurate flood mapping in urban settings.

The goal of Al-Abadi's study [37] was to use ensemble machine learning classifiers to map the susceptibility to flooding in a dry area of southern Iraq. Ground surface elevation, slope, plain curvature, topographic wetness index, stream power index, distance to rivers (Tigris and Gharraf), drainage density, lithology, soil, and land use/land cover were the ten significant flood factors considered in the study.

The study's conclusions showed that the Random Forest classifier was the most useful for determining the area's flood susceptibility. The mean decrease in accuracy and the mean decrease in Gini were used to calculate the significance levels of the factors. It was discovered that the distance to rivers (13.01%) was the most significant factor, followed by elevation (9.16%), drainage density (3.32%), soil (2.93%), geology (2.81%), stream power index (1.94%), and land use/cover (1.63%). The analysis revealed that factors such as topographic wetness index, slope, and profile curvature were the least significant.

The region was categorized into five susceptibility levels by the Random Forest model's flood susceptibility map: very low, low, moderate, high, and very high. The very low–low susceptibility classes accounted for 47% of the total area, the moderate zone for 18%, and the high–very high zones for 27%. Concentrations of high and very high susceptibility zones were found near Kut, at the mouth of the Gharraf River, and along the Tigris River.

Overall, the study demonstrated the effectiveness of ensemble machine learning classifiers, particularly Random Forest, in mapping flood susceptibility in the arid region of southern Iraq using the 10 influential flood factors identified in the analysis.

3 Conclusion

This survey paper sheds light on the critical need for effective flood risk management in urban areas facing increasing flash flood threats. By analyzing existing research, the paper provides a comprehensive understanding of factors influencing flash flood occurrence, severity, and consequences within urban environments. The integration of machine learning algorithms and satellite imagery shows promise for improved flood mapping, mitigation efforts, and disaster response, ultimately safeguarding urban populations.

Furthermore, the research emphasizes the importance of proactive measures like robust flood management protocols, advanced early warning systems, and sustainable urban planning practices. These measures are crucial for bolstering urban resilience and mitigating the impacts of flash floods on communities, infrastructure, and ecosystems. As urbanization intensifies alongside climate change and inadequate infrastructure, this survey serves as a valuable resource for researchers, practitioners, and policymakers. By promoting comprehensive flood risk management approaches and innovative technologies, the research contributes to building more resilient and adaptable urban environments capable of mitigating flash flood impacts. Future research holds the potential to further refine flood prediction models by incorporating additional data sources such as correlations between precipitation, soil moisture, relative humidity, cloud cover imagery, and even urbanization data. This could lead to more efficient models for flood mapping, susceptibility assessment, and damage estimation, allowing for the creation of accurate future trend graphs and ultimately more effective mitigation strategies.

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