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Application of AI in Urban Flash Flood Risk Assessment: From Real-time Warning to Resilience Planning

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Abstract: The rapid advancement of artificial intelligence (AI) has revolutionized urban flash flood risk assessment, offering transformative solutions from real-time warning systems to long-term resilience planning. Coastal and low-lying urban areas, housing over 40% of the global population, face escalating flood risks due to climate change, sea-level rise, and intensified extreme weather. Traditional flood modeling, reliant on physical parameters, struggles with computational inefficiency and data scarcity. AI-driven approaches, particularly deep learning (DL) and neural networks address these gaps by leveraging multi-source data fusion, dynamic prediction, and reinforcement learning (RL) to enhance accuracy and efficiency. Techniques such as convolutional neural networks (CNNs) and U-Net architectures enable automated flood mapping using satellite and sensor data, while hybrid models integrating hydrodynamic simulations with machine learning (ML) improve inundation forecasting. Despite progress, challenges persist, including data quality in developing regions, model generalizability, and ethical concerns in AI deployment. This review highlights AI's potential to bridge technical gaps, optimize emergency responses, and inform resilient urban planning while underscoring the need for robust datasets, interdisciplinary collaboration, and ethical frameworks to ensure equitable and sustainable flood risk management.

Keywords: AI, urban sustainable development, storm surge, risk assessment

1. Introduction

The increasing effects of climate change are putting further strain on coastal areas, which are socially and economically significant and heavily inhabited. The coastline is within 100 km of approximately 60% of cities with populations over 5 million, which means that approximately 40% of the global population (approximately 2.4 billion people) resides within this range. Of these, 250 million individuals reside beneath the yearly coastal flood threshold [1]. The economic development and social stability of coastal regions are negatively impacted by the frequent extreme weather events that result in severe flooding in low-lying coastal areas, putting residents' lives and property at risk.

Global climate change is resulting in an increase in temperatures, which in turn is raising sea levels. The movement of tropical cyclones is slowed, and their intensity increases. The intensity and frequency of extreme rainfall events are increasing. Coastal areas will be more prone to flooding due to climate change and the concentration of people and economic activity there [2].

This implies the need for a reliable flood modelling system, which is critical. At the same time, the conventional model is predicated on physical processes and parameters that are challenging to

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accurately measure. Through the implementation of deep learning in data-driven flood simulation, this disparity is gradually being closed. Deep learning models look at past flood data to understand and accurately show how floods spread and change, providing a method that doesn't rely on physical conditions and often results in more accurate simulation results [3].

This research attempts to examine advancements in machine learning and neural networks in addressing the computational inefficiencies and stringent data precision requirements that have historically constrained hydrological and hydraulic methodologies. A substantial aspect of modern research on flood warnings focuses on enhancing water level prediction algorithms to provide dependable models for precise flood forecasts, typically grounded in rainfall-water level correlations. This study enables a qualitative assessment of the magnitude and risks of floods, hence improving the efficacy of early warning systems for flooding and associated calamities [4].

2. Application of AI in flood forecasting and risk assessment

Many researchers have successfully applied artificial intelligence to flood prediction and early warning systems. As an illustration, Tang et al. [5] carried out an exhaustive research project on flood forecasting by employing machine learning pattern identification and dynamic migration of parameters. Adhikari et al. [6] revealed that Convolutional Neural Networks (CNN) performed the best in flood forecasting using wavelet decomposition functions. This was the case regardless of the climate in the location that was tested. Flood risk categorisation was accomplished by Jin Dongxuan et al. [7] by utilizing extreme gradient boosting, random forest, and decision tree models, which demonstrated the highest level of accuracy. This research has demonstrated that artificial intelligence has a significant amount of potential in the field of urban flood management in various locales.

2.1. Data Level Application: Multi-Source Heterogeneous Data Fusion

The imaging capabilities of the Landsat satellite are crucial for mapping and understanding the dynamics of surface water. Typically, a method for comprehensive flood mapping and monitoring is provided by the combination of optical and synthetic aperture radar (SAR) data. Commercial Earth observation satellites generate huge amounts of data, which exceed the capacity of manual interpretation within the limited time frames required for effective flood response. Machine learning is essential for disaster response, environmental monitoring, and land management, as it facilitates more automated and efficient data analysis. These strategies can deliver relevant information rapidly, facilitating improved decision-making and more effective answers to diverse issues [8].

Unlike traditional methods that mainly use spectral indices, convolutional neural networks (CNNs) effectively gather both spectral and spatial information at the same time from training data. To recognize flooded-area boundaries and patterns and to capture spatial details, they are frequently built using architectures such as U-Net or FCN for semantic segmentation. Semantic segmentation on remote sensing imagery has been extensively employed in various applications, including environmental monitoring, land cover mapping, flood detection, and disaster management, with CNNs serving as a significant component of machine learning techniques [9].

Ahmed Imran et al. [10] have created a comprehensive flood monitoring framework that combines multimodal data inputs, such as meteorological prediction models and terrestrial sensor networks, with deep learning-based inundation detection to create a reliable early warning system for flood risk mitigation. The implementation of a novel image segmentation architecture, DeepLabv3, was achieved through the supervised learning of multispectral satellite imagery, which was supplemented with manually annotated flood extent labels. By conducting a comparative evaluation against benchmark segmentation methods, the proposed system demonstrated superior performance, attaining an overall segmentation accuracy of 87% across various hydrological scenarios.

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Quantitative validation confirms the framework's efficacy in facilitating timely emergency preparedness through high-temporal-resolution flood forecasting and also confirms its suitability for real-time disaster management applications by maintaining computational efficiency.

2.2. Model Level Application: Dynamic Prediction and Vulnerability Analysis

Recent research has shown that machine learning and deep learning methods can identify implicit patterns and trends in data without understanding the physical mechanics governing hydrological processes. They offer considerable potential for overcoming the limitations of hydrological models and fulfilling the objective of dynamic prediction. Hou et al. [11] created a swift prediction model for urban flood inundation by combining high-precision hydrodynamics with machine learning methods. The hydrodynamic model was integrated with the random forest (RF) and k-nearest neighbour (KNN) algorithms to establish a correlation between rainfall characteristics and inundation results. This methodology removed the necessity for iterative calculations of intricate equations, thereby facilitating the rapid prediction of urban flood inundation. Combining these two models improves prediction stability and shows that the model can correctly predict urban flood inundation brought on by rainstorms. The developed model can generate the forecast results within one minute. This expeditious output offers decision-makers ample time to facilitate emergency decision-making, thereby enabling them to implement more appropriate anti-inundation measures.

In comparison to the hydrological model, Konapala et al. [12] developed a hybrid model that combines machine learning and hydrological modelling. This model has the potential to enhance the stream flow simulation results of various basins in the United States. The "meteo-hydro-AI" method, which combines weather forecasts for rainfall, models that consider both surface water and groundwater, and AI to correct forecast errors, has become more popular for predicting floods. From 2010 to 2017, Liu et al. [13] assessed this meteo-hydro-AI approach for the prediction of extreme floods in the Luohe Basin, yielding a 7-day advance time. They employed CSSPv2 land simulations, ECMWF ensemble forecasts, and LSTM deep learning. The integrated approach demonstrated its potential in ensemble forecasting of extreme floods by increasing Nash-Sutcliffe efficiency by 0.27–0.82 and cutting root mean square errors by 22–49% at three outlets, in contrast to the traditional ESP method.

2.3. Decision-making Level: Emergency Response and Resilience Planning

In several poor nations or areas, the use of AI in flood management can alleviate a deficiency of labour. [7] employ deep learning models to forecast flood water levels in the CarayCaray Basin located in eastern Visayas. The accuracy of the DNN model was deemed superior to all other flood-level forecast models. They employed high-gradient boosting, random forests, and decision tree models for flood categorisation. The extreme gradient boosting model had the greatest accuracy. We anticipate that AI-driven prediction models will diminish losses from natural disasters and improve mitigation methods as flood management becomes increasingly necessary. Explicit flood warnings can be sent based on established flood level patterns, enabling preemptive actions to be implemented before flood catastrophes.

Reinforcement Learning (RL) excels in addressing the dynamic complexities of urban flood management and the necessity for sequential decision-making in contexts with several potential solutions [14]. Reinforcement learning can be taught using simulation environments or historical data, facilitating real-time flood forecasting to swiftly respond to changing flood circumstances and enhancing comprehension of the intricate interactions between flood dynamics and intervention options [15].

Furthermore, flood mitigation is an essential element of urban flood risk assessment and prevention. The primary objective of pluvial flood mitigation is to reduce the possible damage and threats to humans and their property. This idea directs the formulation of mobile pump deployment techniques. Limited research has incorporated human aspects into flood prediction and the scheduling of mobile pumps. The Coupled Human and Natural Systems (CHANS) modelling framework, introduced by Qin et al. [16], employs reinforcement learning (RL) to investigate mobile pump placement and scheduling for efficient urban pluvial flood control. It employed advanced hydrodynamic modelling for real-time, precise flood inundation forecasts, delivering high-resolution data for reinforcement learning training. The framework skilfully includes human factors related to floods, like how many people live in an area and the damage to buildings, which improves the data used for scheduling pumps and allows for a direct look at the social and economic effects of floods. This approach offers a comprehensive tool and critical insights for policymakers to formulate more efficient pluvial flood management plans, thereby reducing the impact of flooding on urban inhabitants and their properties.

3. Technical challenges

3.1. Data Bottleneck and Model Generalization

Obtaining high-quality datasets continues to be a considerable issue in many developing nations. Despite the prevalent usage of open-access satellite data, issues such as data latency, data loss, and low resolution may result in imprecise flood susceptibility maps.

The primary issues in contemporary urban flash flood prediction are model dependability and data quality. Current models predict floods by looking at the straight-line relationship between input variables and the chance of floods happening, which may not accurately reflect more complex patterns. High-quality datasets are scarce. Open-access satellite data constitute the predominant data sources in these nations. Nonetheless, challenges such as current data availability, data loss, and low-resolution data represent significant potential issues. These flaws may lead to erroneous flood susceptibility maps in these nations [18].

Chen et al. [19] provide an extensive flood prediction for Hurricane Harvey with a 1-hour lead time, utilizing high-resolution quantitative precipitation predictions (QPFs) from operational Rapid Refresh (RAP) and High-Resolution Rapid Refresh (HRRR) models, in conjunction with deep learning nowcasts. The predictions of 2D flood extent utilising HRRR and AI hybrid forcings provide approximately 50% accuracy in forecasting future inundated regions. Conversely, AI nowcasts demonstrate negligible displacement errors; however, they underestimate precipitation intensity. These findings suggest that binary tests with low thresholds, frequently employed in this domain, overlook the significance of precipitation intensity mistakes in the analysis of exceptional events. The integration of QPFs and AI nowcasting methodologies does not enhance overall accuracy. When accurate forecasting is essential when observational data is unavailable, numerical weather prediction models are employed. Quantitative Precipitation Forecasts (QPFs) give basic information about how often floods might happen and how much flooding could occur, with the High-Resolution Rapid Refresh (HRRR) model performing slightly better than the Rapid Refresh (RAP) model. The AI nowcast fails to accurately depict Hurricane Harvey's precipitation intensity, highlighting the method's possible limitations and the inadequacy of standard machine learning performance evaluations to disclose such insights.

3.2. Ethical disputes

Al-Rawas et al. [17] fill this research gap by combining geospatial data, remote sensing, and AI to detect flood-affected areas in Tehran's Kan basin. They used deep learning methods, specifically

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U-Net and FCN algorithms, on optical and radar images from four flood events. The U-Net model's consistent superiority across diverse datasets and flood intensities, along with its ability to utilize data from multiple sources, makes it a potent tool for flood detection, assessment, and resource allocation in disaster management.

In urban planning, accurate flood zone delineation facilitates better risk assessment and mitigation strategies, enabling planners to formulate flood resilience plans, use zoning regulations to evaluate flood risks, and bolster community resilience for future floods. The research findings support immediate flood response and provide a foundation for long-term planning and policy development to protect communities and reduce the socioeconomic impacts of flooding. Future research could look at combining data from Sentinel-3, TerraSAR-X, LiDAR, and ground-based sensors to make segmentation more accurate; testing how well the U-Net model works in different geographic areas with various environmental conditions to see if it can be used widely; investigating improved deep learning models like U-Net++ and those that use attention mechanisms to boost segmentation results; and creating real-time early warning systems based on U-Net predictions to improve flood risk management and disaster response.

4. Significance of AI-Based Flood Management

AI applications for flood forecasting and risk management demonstrate advancements in data, modelling, and decision-making. Satellite imagery (e.g., Landsat, SAR) and IoT sensors, when processed using CNNs, attain 87% accuracy in real-time flood mapping at the data level. Hybrid models that combine hydrodynamic simulations with machine learning techniques reduce the forecast time from hours to minutes and enhance Nash-Sutcliffe efficiency from 0.27 to 0.82. Reinforcement learning enhances emergency responses by integrating socio-economic variables such as population density. Case studies, including Hurricane Harvey and Tehran's Kan Basin, illustrate AI's capacity to forecast flood extents (50% accuracy) and assess hazards (F1 score: 0.92).

Although AI revolutionised flood risk management, technological and ethical concerns persist. Numerous areas limit the availability of high-quality labelled data, a significant requirement for deep learning models. Hybrid approaches such as Meteo-hydro-AI integrate physical modelling with data-driven insights, yet they encounter challenges with real-time computational requirements. Ethical issues encompass algorithmic prejudice, as vulnerable populations frequently lack access to sophisticated monitoring systems, exacerbating disparities in disaster response. The opaque nature of neural networks impedes transparency in crucial decision-making processes. Future initiatives should prioritise interpretable models, the incorporation of human behavioural dynamics, and technologies like LiDAR and edge computing. Resolving these difficulties would enable AI technologies to attain both technical accuracy and social equality in climate resilience.

5. Conclusion

Artificial intelligence technologies are transforming flood risk assessment by facilitating expedited, more precise projections and data-informed resilience solutions. AI integrates multi-source data fusion and reinforcement learning for resource allocation, enhancing classical hydrological models, especially in dynamic metropolitan settings. Case studies highlight its capacity to reduce socio-economic losses via prompt alerts and enhanced mitigation strategies. Nonetheless, ongoing challenges—namely data scarcity, model universality, and ethical transparency—require immediate focus. To enhance AI's contribution to flood control, it is essential to prioritize high-resolution information, promote worldwide data-sharing activities, and incorporate ethical norms into algorithmic design. By integrating technology innovation with socio-environmental factors, AI can

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enable cities to address the challenges of climate change, protect at-risk people, and promote sustainable urban development amid increasing flood threats.

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