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"Urban flood prediction and mapping using Machine Learning and Deep Learning"

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Abstract
Floods, which are becoming more frequent due to climate change, are potentially threatening to the high population density areas and complex infrastructures in urbanized zones and cause huge social, economic and environmental damages. The most significant challenge with the traditional methods (physics-based) of flood prediction is their speed of simulation, which makes it difficult to provide timely predictions for the occurrence of urban flood events. Recently, by analyzing big datasets such as weather patterns, terrain characteristics and historical flood records, machine learning (ML) models have shown promising results in improving the accuracy of flood predictions and flood maps. This work presents metadata analysis aiming to understand recent efforts using ML and specifically, deep learning (DL) approaches (e.g., Decision Trees, Support Vector Machines, Convolutional Neural Networks, Long-Short Term Memory, etc.) to predict timing, extents, and urban damages caused by flash floods. The literature highlights a wide range of input data, but the most common are rainfall, slope, elevation and distance from river and roads. Model performance metrics, that have been used the most are precision (0.7-0.98), accuracy (0.64-0.98) and AUC (0.69-0.99). Additionally, out of 112 research papers, 40 are from China, reflecting the country's significant focus to improving flood prediction models.

Highlights
- ML and DL techniques can improve the accuracy of urban flood prediction.
- Random Forest (RF) is the most commonly used machine learning method.
- ML models are feasible for flood mapping in countries where access to hydrologic and hydraulic modelling data is limited.

Introduction
Urban flooding, driven by rapid urbanization, aging infrastructure and climate change, is one of the biggest challenges faced by modern civilization. It is very important to predict the possibility of flooding in urban basins in advance. Hazardous flooding events may take many forms and occur at high frequencies, leading to considerable damage to residential and commercial property.
In recent years, a wide range of different machine learning (ML) (more than 35) and deep learning (DL) (more than 19) methods have been applied to urban flood prediction and flood mapping. It is unclear how different studies have selected appropriate ML models, input parameters for them, and what are the common metrics to which the results are compared. In order to move forward with new research

on ML and DL applications in urban flood management, we need comprehensive understanding of challenges (and inadequate pathways) and opportunities (successful demonstrations) in up-to-date literature.

The main objective of this study is to understand metadata of current studies covering ML and DL techniques used in urban flood predictions. To overcome this objective, the review will address the following: (i) trends and characteristics of ML and DL, applied in urban flood predictions, (ii) performance levels of ML/DL algorithms in urban flood predictions, (iii) common indicators and influential factors in urban flood assessment, (iv) strengths and limitations of current studies that could improve future urban flood predictions and maps.

Methodology

The metadata extraction was conducted from studies available from the scientific database Scopus, focusing on different search terms, like "flood prediction" OR "flood forecasting" OR "flood mapping" AND "urban flooding" AND "machine learning" OR "deep learning". The analysis focused on finalized papers written in English. The publication in languages other than English were not translated and were excluded. The country of origin was not considered when searching for publications.

Total of 160 research papers were found using the previously described method. When we removed the research papers that were not related to urban floods, 112 research papers were obtained. All these papers were categorized into two groups: flood prediction (61 research papers) and flood mapping (51 research papers). After that, all papers were divided based on techniques that were used in papers (machine learning or deep learning). This division is shown on Figure 1. Metadata on model inputs, parameters, model rating, outputs, etc., were extracted from each paper, and grouped into categorical and scale factors.

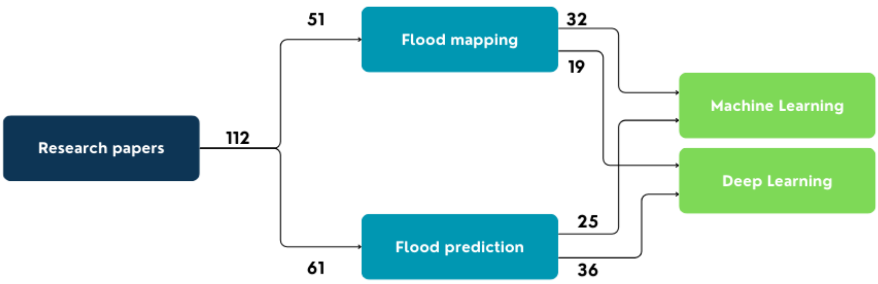


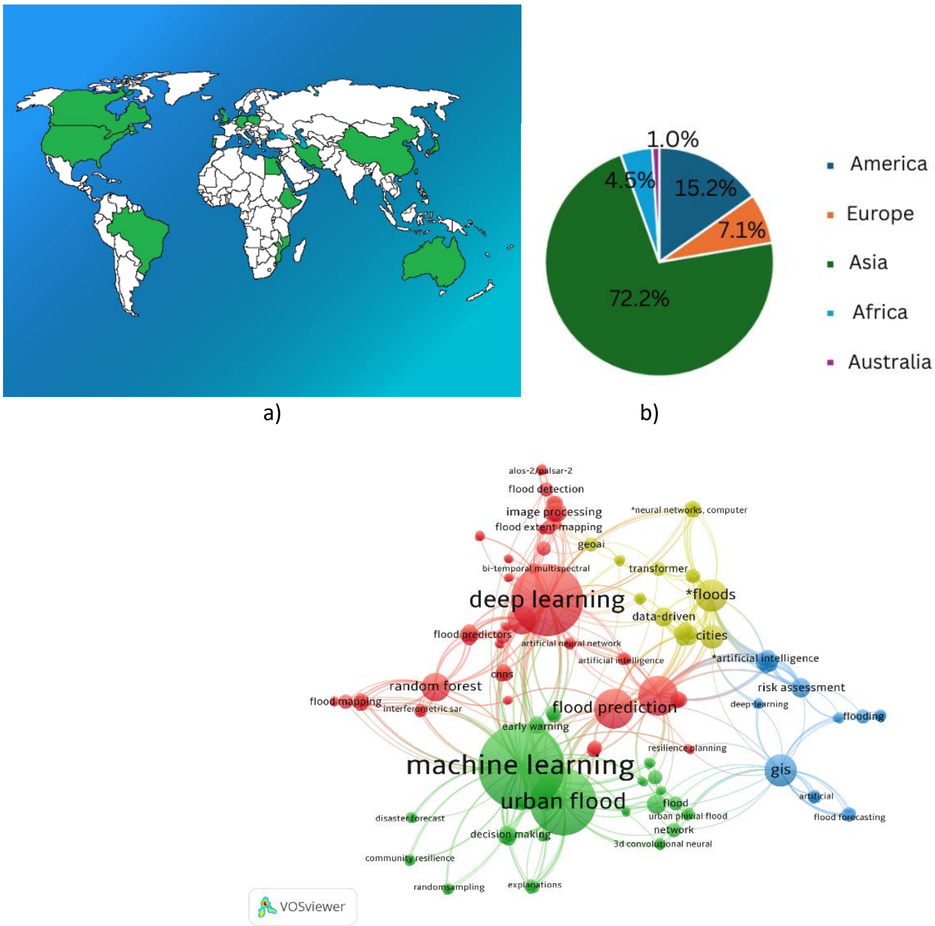
Figure 1. Division of research papers

Bayesian Linear Mixed Model (BLMM) was used to predict ML models' efficiency across diverse input (training) conditions (parameters). Drawing from both literature insights and model results, the influence of each model input factor on the urban flood prediction is further explored in this work.

Results and discussion

Bibliometric analysis for the collected research papers is presented in Figure 2. The 72.2% of research papers are from Asia continent, while 15.2% are from America, 7.1% are from Europe, 4.5% are from Africa and 1% are from Australia. 40 research papers come from China, which should not be surprising, as China is one of the leaders in technology and research, with major investments in artificial intelligence, machine learning, and deep learning. They have also recognized the potential of using ML and DL models in areas where there is no observed data. The oldest research paper is from 2018 and the most recent is from 2025.

A cluster of keywords in visualization is important because it allows to identify and group similar or related concepts, which helps to better understand thematic connections and patterns in data. Node size representing the frequency of co-occurrence, links representing co-reference and colours representing different clusters. Figure 2c shows that all keywords are divided in 4 clusters (red, green, blue and yellow) with the most frequent keywords: "deep learning", "machine learning and urban flood", "gis" and "floods".



a) b)

c)

Figure 2. Bibliometric analysis for the collected research papers based on a), b) geographical distribution, c) cluster of keywords

DL methods, such as Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM), allow for the analysis of complex patterns from satellite images and time series, while ML algorithms often use regression and classification for faster and more efficient forecasts. RF and CNN are the most commonly used ML and DL methods (Löwe *et al.*, 2021), (Li *et al.*, 2021), (Darabi *et al.*, 2019), (Rafiei-Sardooi *et al.*, 2021).
The use of street camera images as input to models is becoming increasingly common (Zhong *et al.*, 2023), (Chen *et al.*, 2024).
The performance of ML/DL methods in urban flood prediction and mapping varies (F1 score, Kappa, recall, etc.), but the most commonly used model rating are precision (0.7-0.98), accuracy (0.64-0.98) and AUC (0.69-0.99), where the methods show effectiveness in urban flood modeling.
Common indicators and influential factors in urban flood assessment include rainfall, topography, land use, distance from rivers and roads, drainage systems, etc. Slope, elevation and land use are used as input data in more than 35 research papers, while distance to river is input data only used in flood mapping (Zhao *et al.*, 2021), (Darabi *et al.*, 2020). Distance to rivers, elevation, and distance to drainage

emerge as crucial variables for accurate flood inundation modeling in urban areas (Leggesse *et al.*, 2024).
Limitations of flood records reduce the performance of the CNN method, that requires a large amount of data for training (Wang *et al.*, 2023). One of the strengths of ML and DL over traditional methods (physics-based) is the speed of prediction in urban areas, which was demonstrated in a research paper where the speedup was 2618 (Berkhahn and Neuweiler, 2024).

Conclusions and future work

Recently, ML and DL models have been increasingly used in flood prediction and flood mapping, which have shown really good results (precision (0.7-0.98), accuracy (0.64-0.98) and AUC (0.69-0.99)). Bayesian Linear Mixed Model would highlight the importance of certain input parameters in relation to the model's rating parameters, providing valuable insights and guidelines for future research.
For future work recommended to include the intrinsic uncertainty of the rainfall forecast in the predictions i.e., determining how such uncertainty propagates to the outputs of the model (Chaudhary *et al.*, 2022). As part of the performance assessment, computational time and prediction range should be more highlighted in future studies. Also, there is no theoretical framework for the selection of input parameters for ML models yet.

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