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Geology

FLOOD FORECASTING MODEL – A REVIEW

KEY WORDS: Flood forecasting, data-driven models, physically- based models, hybrid models

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ABSTRACT

Flood occurrences have persisted in India since ancient times. Certain regions in India frequently see devastating floods on an annual basis due to localised disparities in climatic patterns and precipitation levels. According to the Central Water Commission (2012), approximately 49.82 million hectares, equivalent to fifteen percent of India's land area, is susceptible to the risk of floods. The concept of "flood forecasting" refers to the systematic determination of the probability, magnitude, temporal occurrence, and duration of flood events within a designated geographical region. There are several methodologies available for flood prediction, including data-driven models, physically-based models, and hybrid models that combine elements of both approaches. When considering the suitable models to employ, it is crucial to consider factors such as the availability of data, the characteristics of the catchment area, and the required level of precision in forecasting. The efficacy of one's written work is in a literature review or a research piece and hinges upon the adeptness with which data is presented in a manner that exhibits the subject matter in a lucid and cohesive fashion. We have endeavoured to collate all the relevant research and discern any deficiencies in our comprehension.

1. INTRODUCTION:

Floods represent the most widespread and recurrent natural calamities resulting from meteorological conditions. According to Wilby and Keenan (2012), floods rank as the third most destructive natural phenomenon, following earthquakes and storms. According to Dilley et al. (2005), estimation suggests that about 33% of the global land surface is located in zones that are prone to flooding, serving as habitats for over 82% of the global population. India, like to other nations across the globe, exhibits a significant level of anxiety regarding the occurrence of flooding events. Floods are categorised as a natural catastrophe due to their extensive devastation, significant human toll, and substantial financial burdens they impose. The recent surge in the frequency of floods can be attributed to various variables, such as the escalation of global temperatures, occurrences of cloud bursts, tsunamis, inadequate river management practises, and sedimentation, among others. Floods are a commonly occurring and extensively prevalent form of natural disasters, resulting in substantial human casualties and property damage on an annual basis.

2. Flood Forecasting:

Flood forecasting (FF) is widely recognised as a significant issue within the field of Hydrology, despite its crucial role in mitigating property damage and human deaths. Flood forecasting stands as one of the limited resources available to address the challenges posed by floods. In recent times, the accuracy of forecasts has improved due to various factors. This includes the use of cutting-edge knowledge and algorithm techniques for the analysis and communication of uncertainties, advancements in data collection via satellite observations, and expertise in meteorological and hydrological modelling. This study offers a comprehensive overview of flood forecasting, encompassing many aspects such as the employed models, contemporary techniques for data collection and visualisation, as well as the associated hazards and warning systems. The subsequent bullet points delineate potential avenues for additional investigation and progress.

Flood forecasting is a methodology employed to ascertain the timing and magnitude of a flood event in a certain geographical region by the examination of hydrological, meteorological, and environmental factors. There are various approaches available for flood forecasting, encompassing both data-driven and physically-based models, as well as hybrid models that combine elements from both methodologies. The selection of the approach is contingent upon several aspects, such as the data's quality, the catchment area's characteristics, and the desired level of forecast accuracy.

In the study conducted by Kwesi Twum Antwi-Agyakwa *et al.* (2023), the conclusions were derived through the utilisation of machine learning, as well as probabilistic and numerical modelling techniques. The research encompassed various factors such as slope, profile curvature, river distance, river elevation, river density, population density, and road distance. Flood risk assessment first made use of probabilistic models like the Copula and the B.N. distribution to measure degrees of uncertainty. Furthermore, the advancement of deep learning technology resulted in the extensive implementation of Machine Learning Models for the purpose of flood prediction. Ultimately, their study successfully illustrated that the advancement of Geographic Information Systems (GIS) has facilitated the ability to forecast and anticipate flood occurrences in precise geographical areas.

In the study conducted by Lenise Farias Martins *et al.* (2023), the authors leveraged their expertise in utilising the Advanced Land Observing Satellite Digital Elevation Model. They focussed on four key variables: Latitude, longitude, altitude, and precipitation. This article proposes a novel approach to measuring flooding in semiarid areas. The research also introduces new techniques for assessing flood damage in unmeasured basins in semiarid locations with limited data availability.

In the study conducted by Dhumal, Hanumant Tukaram (2022), the authors relied on a dedicated HEC-RAS model for their predictions. External factors, namely rainfall, spillway flow, the river gauge readings, and river flow, all related to hydraulic considerations. The HEC RAS model, in particular, is versatile in assessing the range of dynamic flow characteristics. This model can be used locally to better understand local flood risks and develop strategies that are tailored to the area.

In the study conducted by Fernando Morante-Carballo *et al.* (2022), analysed a dynamic range of Land Use and Land Cover (LULC) features such as slope, profile curvature, distance from rivers, elevation, river network density, precipitation, stream power index, and LULC, NDVI (normalised difference vegetation index), soil type, and soil moisture. The research employed various tools including digital elevation modelling, GIS, remote sensing, and hydraulic and hydrodynamic flood simulations. The findings of the research are : In addition to increasing the reliability of findings and the breadth of the investigation, remote sensing is crucial for gathering information that would be inaccessible any other way. In order to simulate and assess phenomena like floods, important outputs include digital elevation models, soil type and land use maps, and hydraulic modelling environments.

In the study conducted by Georgios Mitsopoulos *et al.* (2022), utilised hydrological and hydrodynamic modelling techniques. They considered independent variables such as flood severity, flow rate, water depth, and average risk. The researchers identified vulnerable sites and concluded that the activities greatly reduced the predicted inundation areas.
In the study conducted by Mohammed-Ali, *et al*. (2022), utilised three models, namely MIKE model 11, an artificial neural network (ANN), and HEC-RAS SWMM with independent variables consisting of river flow, rainfall and water level. All of these models have demonstrated their capacity to provide comprehensive plans that contribute to the development and safeguarding of urban areas in close proximity to rivers.

In the study conducted by Wei Lun Tan *et at*. (2021), entailed the examination of rainfall data from ten sites in peninsular Malaysia using four different probability distributions, which encompass the Exponential, Generalised Extreme Value, and Weibull distributions. The data set covered a span of 33 years, from 1975 to 2008. In this comparison, both the descriptive and prescriptive analytics provided by the models are examined. The chi-square test, the Anderson-darling test, and the Kolmogorov-Smirnov test are the three statistical tests used to choose the optimal model. According to the statistics, the generalised extreme value model has proven to be the most reliable in predicting the occurrence of extreme rainfall in Peninsular Malaysia.

In the study conducted by Jun Liu *et al.* (2021), focused on developing three hybrid models: the support vector machine-flash flood hazard mapper, the cellular automata-flash flood hazard mapper, and the convolutional neural network-flash flood hazard mapper. Subsequently, an assessment was conducted to compare the efficacy of the aforementioned trio of hybrid models against three distinct machine learning models in the context of predicting flood susceptibility. Consequently, these hybrid models can be utilised as a fundamental basis for evaluating the likelihood of flooding and other natural hazards within a particular geographical region. The author opined that the current state of flash flood susceptibility mapping is insufficient in terms of assessing the effectiveness of flood management initiatives and offering detailed insights into flood characteristics, such as the area of inundation. They further added that additional investigation necessitates the development of a composite hydraulic model and that future studies should explore integrating machine learning techniques with physical simulation methodologies in order to enhance the precision of flood risk mapping.

In the study conducted by Nurul Fatihah Nor Azlan Shah1 *et al.* (2021), utilized independent variables such as study area, stream length, and stream slope were the independent variables employed alongside the Hydrologic Engineering Centre-Hydrologic Modelling System and the River Analysis System. The ability of a country to handle flood situations significantly impacts the outcomes. The NSM (Non- structural method) is superior to SM- (stormwater Management) due to its lower cost, better flood management, and fewer negative effects on the environment.

In the study conducted by Adannaya Simeon Ivo, *et al.* (2021), employed Artificial Neural Networks (ANNs) and Autoregressive Integrated Moving Averages (ARIMAs) to analyse weather records. The devastating effects of floods can be greatly mitigated with the aid of flood prediction models. This will allow the appropriate agencies to take preventative measures. Residents of flood-prone locations can receive advance warnings to prepare and evacuate as needed. These models can also be adapted for use in predicting various types of natural disasters, such as drought, by making slight adjustments to the key parameter.

In the study conducted by Mustamin *et al.* (2021), employed hydrological analysis using the HSS SCS method and the HEC-HMS programme. The author used data from the TRMM (Tropical Rainfall Measuring Mission) satellite, which measures rainfall and other variables such as land cover and soil composition. According to the results of the validation, the flood on June 12, 2020, might occur again in 20 years, whereas the storm on January 22, 2019 could occur again in 100 years.

In the study conducted by Filip Strnad *et al*. (2020), employed a combination of an L-moment based statistical model with an index flood method for this research. They used Gumbel plots and the Anderson-Darling test to analyse the model's outcomes and they applied Cluster analysis through K-means method. The study incorporated various independent variables, including degree of harm, degree of intensity, degree of duration, relative degree of harm, and temperature. The study found that regional frequency analysis was advantageous in minimising estimation errors related to drought characteristics and distribution parameters. In the context of describing volume shortfalls across most catchments, the Generalised Pareto Distribution was determined to be superior to the Generalised Extreme value Distribution. However, the extent to which this discovery is influenced by factors such as the characteristics of the research area and the drought diagnostic threshold remains unclear. The study also proposed that the subjectivity in identifying homogeneous regions, which is the most time-consuming and error-prone aspect of regional frequency analysis, could be reduced through application of techniques like the region of influence or Self Organising maps.

In the study conducted by Yirui Wu, Yukai Ding and Jun Feng (2020), incorporated an exceptionally computationally efficient sparse Bayesian model that they had developed in conjunction with the Synthetic Minority Over-sampling Technique (SMOTE). Their research focused on AdaBoost-based flood forecasting using this sparse Bayesian model. The study took into account factors such as rainfall, evaporation, and rain gauge placement of rain gauges. When combined with a Bayesian model, the AdaBoost training procedure demonstrated the capability to deliver precise and dependable flood forecasts, enhancing the overall accuracy and reliability of the predictions.

In the study conducted by Ximin *et al*. (2020), the researcher incorporated not just a BR-ANN, but also two other ANN-based flood forecasting models, namely, GRNN and an FFIN (General Regression Neural Network and Feedforward Neural Network). To characterise precipitation patterns in arid regions, they utilised parameters such as confluence length, slope, average confluence length, confluence accumulation, and confluence shape coefficient, in addition to area, precipitation, and antecedent precipitation. Among these models, the FFIN model emerged as the most superior choice for flood prediction, surpassing the performance of the BR-ANN, BP-ANN, GRNN, and Linear models. Particularly, in basins with limited runoff data, the FFIN model is recommended as a more effective alternative to the conventional forecasting method.

In the study conducted by Rabin Chakrabortty *et al.* (2019), the author ensured the reliability of the employed Artificial

Neural Network (ANN) models by incorporating Random Forest (RF) and Support Vector Machine (SVM) techniques. Various factors, including rainfall, river and road accessibility, drainage density, land use and land cover (LULC), geology, geomorphology, aspect elevation plan curvature and slope, and other similar factors were taken into account. As a result, the most critical factors contributing to flooding in low-lying areas were identified, specifically the intensifying changes in LULC and its expansion into a river basin. The application of ANN modelling to this subtropical river basin is highly pertinent. Through the use of this Flood Susceptibility Zoning Model (FSZM), the financial system can more effectively provide compensation to populations affected by floods and enforce essential land-use restrictions, thus reducing both human and financial losses.

In the study conducted by Vimal Mishra1 *et al.* (2018), the research employed the Generalised Extreme Value (GEV) distribution along with the Chi-square test. The goodness of fit of the GEV distribution was evaluated using QQ plots. Various independent factors, including dimensions, length, and shape, were taken into account. The study's findings utilised the GEV distribution to predict the likelihood of a recurrence of the extreme rainfall that occurred in Kerala in August 2018. It was estimated that the return period for a single day's worth of rain across the entire state in August 2018 was approximately 75 years. Furthermore, the maximum rainfall over two-day period was found to have a return time of about 200 years, while the maximum rainfall over three-day period had a return period of about 100 years.

In the study conducted by Muthusamy Seenirajan *et al.* (2017), the analysis was conducted using the following criterion and a Geographic Information System (GIS) coupled with Multicriteria Decision Analysis (MCDA). There was a lot of runoff water because of the heavy rainfall, the poor drainage, the kind of soil, and the river's catchment area. The research team relied on in-person interviews and field notes to draw their conclusions. The conclusion was that the situation was made worse by urbanisation and encroachments along river banks, swampy, low-lying areas, and the Adyar River in particular and since the river could no longer use the lowlands as flood plains, the water just flooded them.

In the study conducted by R D Singh (2012), the real-time flood forecasting is widely recognised as a very effective non-structural approach to flood management, garnering significant acclaim for its transformative potential. The finding of the study are: To ensure the accuracy and dependability of a forecast, it is imperative to continuously update the weather and flow data at the forecasting station in real-time. There is a pressing need for significant enhancements in the present level of real-time flood prediction. The establishment of a reliable automated communication system is crucial for the seamless transfer of real-time data. Proficiency across a diverse array of forecasting methods, including deterministic and stochastic models, artificial neural network (ANN) and Fuzzy logic techniques, among others, is of utmost importance. Performance indicators have the potential to provide recommendations for the implementation of field deployment strategies.

In the study conducted by M. Sulaiman *et al.* (2011), the researchers employed both artificial neural networks and the Zoning Matching Method. The results suggest that the proposed forecasting model may be useful in assisting the relevant water monitoring authorities in their efforts to anticipate and manage floods. Factors such as water level, rainfall, and river flow were considered among the variables. Further investigations involving the application of Zoning Matching Method to a larger dataset of 15 instances of low and normal water levels from the Rantau Panjang station could improve its capacity for real-time forecasting.

In the study conducted by D. De Wrachien, S. Mambretti & A. Sole (2010), a range of various methodologies were applied to analyze floods. These methodologies encompassed hybrid models, deterministic models, stochastic models, and frequency studies. The study examined the impacts of multiple factors, including precipitation, interception, infiltration, evaporation, soil moisture, and surface runoff, on overland and ground flows, as well as river channel hydraulics. The modelling tool aimed to assess risks and implement measures for mitigation, with the intension of providing benefits to various industrial zones, high-value urban floodplains and rural areas.

3. CONCLUSIONS:

This study aimed to integrate the previously distinct domains of flood risk assessment, flood hazard analysis, and flood vulnerability assessment. Previous instances of floods have exhibited the profoundly destructive consequences of this naturally occurring calamity. Researchers have explored and deployed various machine learning methodologies to forecast the occurrence of these floods and proactively undertake preventive measures. Linear regression, SVMs, DTs, CNNs, ensemble learning, and K-nearest neighbours are only some of the machine learning techniques presented here for flood prediction.

The most effective method for flood forecasting, according to the existing corpus of research, is the use of Long Short-Term Memory (LSTM) Recurrent Neural Networks. Artificial neural networks (ANNs) have been used to aid with flood prediction and risk assessment in recent scholarly research. The review highlights that the efficacy and precision of the trained model are significantly influenced by the dataset employed for its development.

A meteorological flood occurs as a result of extensive and severe precipitation that exceeds the average levels for a certain region. Delineating flood zones, creating flood hazard and risk maps, and evaluating flood dangers are all made much easier with the help of geographic information systems (GIS) and remote sensing. Together, vulnerability and exposure play a role in the development of flood risk. Flooding is the abnormal accumulation of water on normally dry ground, which is usually brought on by the frequency of flood incidents and the magnitude of the consequent damage are the two most important factors to consider when determining the severity of a flood threat. Both biological and social contexts must be taken into account when determining vulnerability. How vulnerable a person is can be gauged by how severely they are physically hurt.

In order to conduct a comprehensive examination of socioeconomic vulnerability, it is important to use a combination of qualitative and quantitative data pertaining to a society's adaptive potential and its existing economic endeavours. The evaluation of risk involves considering four potential outcomes: high, moderate, comparatively low, and low hazard, as well as high, moderate, and comparably low susceptibility.

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