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Bibliometric Analysis and Review of Recent Literature on Flood Susceptibility and Trends in Forecasting Methods

Prerak Pathak[1]* and K Muralidharan[2]

[1]*Department of Environmental Studies, The Maharaja Sayajorao University of Baroda, India*

[2]*Department of Statistics, The Maharaja Sayajirao University of Baroda, India*

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***Corresponding author:** Prerak Pathak, Department of Environmental Studies, Faculty of Science, The Maharaja Sayajirao University of Baroda, Vadodara, Gujarat (390002), India, Email: prerak.pathak-envphd@msubaroda.ac.in

Abstract

Global environmental issues like Climate change has contributed to the increased frequencies and intensity of hydrological disasters like floods. Using a bibliometric methodology, this article presents a comprehensive analysis of flood susceptibility and forecasting. The study investigates the historical trends and patterns of research on flood susceptibility and forecasting. The analysis examines a variety of factors, such as the number of publications, countries, institutions, and journals that have made contributions to this field. The study emphasizes the significance of flood susceptibility and forecasting as essential elements of disaster management and the need for sustained research in this field. In addition, the article examines the publications by various authors on statistical, spatial, and machine-learning approaches utilized in flood susceptibility and forecasting. The conclusion of the article identifies research gaps and prospective directions for research on flood susceptibility and forecasting.

Keywords: Bibliometric; Flood susceptibility; Forecasting; GIS; Statistical analysis; Machine learning

Introduction

Several environmental challenges are being witnessed by people globally. Most of these challenges are rooted in our resource-intensive urban lifestyle. Some of these challenges are reversible and some are irreversible like Climate change. As a consequence of human-caused Greenhouse Gas (GHG) emissions, both biotic and abiotic components of natural ecosystems are under growing stress [1]. A number of the recent natural disasters may be traced back to a modification or shift in the climate of the entire planet. The term “flood” refers to a type of hydro-meteorological disaster that occurs when an abnormally large volume of water suddenly covers a portion of land that is not typically submerged in water within a relatively short length of time. Floods are a major contributor to the destruction of property, the loss of biodiversity, and the loss of human lives. Rainfall totals that are excessive, together with subsequent runoff volumes that are greater than the carrying capacities of natural channels and borders, are the root causes of floods. Heavy precipitation and surface runoff are the main hydrological processes that are considered in watershed management planning [2]. As a result of climate change, floods have gotten significantly more severe and have occurred with greater frequency all around the world [3]. In India, an area of around 40 million hectares has been identified as flood-prone area [4]. The world, including India, has witnessed some of the deadliest hydro-meteorological disasters including floods since the year 2019 [5]. The recent report on mortal losses from disasters caused by natural hazards, grounded on the EM-DAT data from 2000 to 2019 [6] includes flooding within the hydrological hazards- type, along with landslides and surge action. Several approaches are grounded on the traditional and current understanding of the threat conception [7] and define the threat as a product of hazard, exposure, and vulnerability. Other methods conduct a statistical analysis of the patterns of flood tide damages, as well as the characteristics of the hazard and the exposure [8]. Flood susceptibility analysis and the prognosis of such disasters can help us in explaining damage patterns, population exposures, and other risk patterns in the region [9]. Hence, governments are trying to develop reliable maps and models of flood risk areas and plans for sustainable flood risk management focusing on prevention, mitigation, and preparedness [10]. For hazard vulnerability assessment and severe event management, flood prediction and simulation models are of critical relevance. Accurate and authentic models for predictions can contribute highly to water resource management strategies, policy-making, and further mitigation planning [11]. Hence, it is important to use advanced modelling systems for a short and long-term prognosis for floods and other hydro-meteorological events to reduce the extent of damage [12]. Currently, there are so many watershed models available to predict different hydrological events [13-15]. However, it is complex to predict the flood lead time and occurrence location due to the dynamic climate system. Important elements to take into account are the amount of data required, how user-friendly the system is, and the number of resources needed. Different researchers have identified different methods and techniques to prepare a model that can predict flood events in their respective study locations in the short-term and long-term future. Some of the methods are based on Geographical Information System (GIS), some are solely based on statistical analysis, and some are physically based models or Artificial Intelligence/Machine Learning (AI-ML). To make the predictions and analysis more accurate, researchers have tried to develop hybrid models. GIS and statistical hybrid models can predict hydro-meteorological disasters such as urban floods more effectively [16]. GIS and Remote sensing methodologies have been used to predict flood-prone areas and the extent of floods for a long time. A significant number of approaches to flood hazard mapping utilize Digital Elevation Modelling (DEM), water discharge data, and flood frequency data such as remote sensing, GIS, and hydrological data [17]. However, traditional techniques to predict such high-intensity hydrological disasters have some limitations regarding data and variables like precipitation and flow levels [18]. Thus, so many hybrid approaches have been introduced to increase the accuracy of the models. Such hybrid models include climatic data, topographic and elevation data, land use (LU) and proximity information, the artificial neural network (ANN), and logistic regression (LR) models [19]. Such hybrid models of ML techniques and GIS can also be utilized for urban management and planning concerning climate resiliency. This method can identify practical contributing factors and risk indices for the occurrence of floods at the municipal level, which can be important for outlining a long-term Smart Cities plan [20].

The major flood modelling systems that are available today are data-specific and they involve various simplified assumptions [21]. Thus, newly invented techniques like Artificial Intelligence and Machine Learning are important techniques to predict hydrological as well as hydro-meteorological events for dendritic watershed systems. Some models were used to predict hydrological processes of extreme weather events like run-off of rainwater during storms and cyclones [22-25], hydraulic models of flow [23,26], global circulation [27], shallow water conditions [28]. Physical based models show high capabilities for predicting flood scenarios. Although physical models demonstrated significant skills for forecasting a broad variety of flooding scenarios, they frequently require various forms of hydro-geomorphological monitoring information. This necessitates costly computing, which prevents short-term prediction from being possible [29]. In addition, the construction, training, and validation of such models sometimes demand in-depth knowledge and experience related to hydrological as well as climatic parameters, which has been noted to be a very difficult task mentioned by Kim et al. [30]. Furthermore, several studies point to a gap in the efficiency of short-term prediction of physical models [31]. As an illustration, such models were frequently incapable of making accurate forecasts. In their research, Van den Honert & McAnerney [32] studied the failure of flood forecasting that occurred in Queensland, Australia in the year 2011. In a similar vein, numerical prediction models were described in the development of deterministic computations; nevertheless, these models lacked dependability due to the presence of systematic errors [33,34]. Despite this, it was stated not too long ago that physically based flood models have lately seen significant advancements due to the hybridization of models [35] and more powerful flow simulations [36,37]. Recently, a considerable amount of studies have been carried out on the prognosis of severe hydro-meteorological events using hybrid models which are more efficient and powerful towards long-term predictions.

Methodology and Data Collection

Bibliometric analysis is effective for tracing the evolution of a research area and identifying research hotspots. It quickly identifies the coupling relationship between published articles and the cooperation relationship between authors because it combines mathematics, statistics, and philology to assist researchers in conducting quantitative analysis and visual research on literature. It allows us to explore the subtle evolutionary aspects of a particular discipline while illuminating its frontiers. The most prevalent methods of analysis are core author analysis, co-citation analysis, and co-word analysis.

For this study, research articles and research papers related to flood predictions were searched and collected from the Web of Science portal's core collection database. The database was searched through keywords such as, "Flood predictions using GIS tools", "Flood predictions through statistical analysis", "Flood predictions by AI-ML" and "Flood predictions through hybrid models of ML" and sorted the database for literature types-Articles, papers, and review. Through this, we collected a dataset of 1389 research papers from the period of 1999 (January)-2023 (March). We then sorted all the papers based on their relevance to the research topic. After the final sorting and filtering process, 769 papers remained.

A detailed bibliometric analysis has shown further in the third section along with different cooperation networks and co-citation networks. Different techniques and sources have been discussed in different sub-sections. In fourth section, a technical review is

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presented in terms of advanced hybrid models and methodologies used in different hydrological processes like Rainfall-runoff analysis and flood susceptibility modelling. The review concludes with further research directions and limitations of using different advanced modelling technologies in this field.

Research on the Overall Flood Prediction

Flood predictions using geographical information system (GIS)

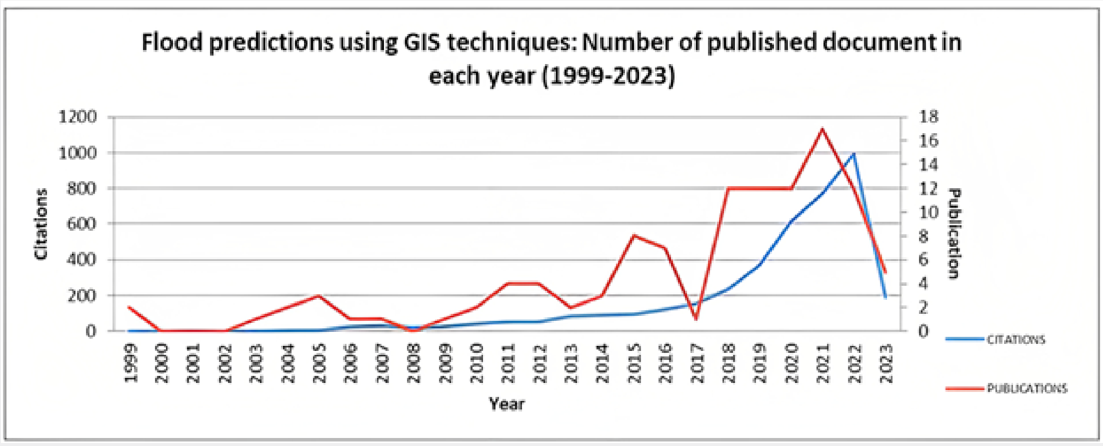

Figure 1: The number of published documents in each year (1999–2023).

The number of publications and citations in a field can indicate the level of scholarly interest in that area. Figure 1 shows that the literature on flood prognosis through GIS technologies has gradually increased since 2002 and has shown exponential growth after the year 2008. The literature related to flood prediction using Geographical Information System is highest in the year 2021 with 17 documents published in a single year.

The figure also shows the changing trends in the number of citations in different documents for the prediction of floods using recent and advanced technologies during the past 2.5 decades. The number of citations grew from 1 in 1999 to 993 in the year of 2022. Even in the year 2023, 193 citations have been observed till March. The most cited article is Tehrani's article (2015) on flood susceptibility assessment using GIS-based support vector machine models with different kernel types. This article has been cited 384 times with a mean citation value of 42.67 per year. This study was done based on different physical, geographical, and geological parameters and assessed through a support vector machine (SVM) model. This study has been a foundation research in the field of Flood prognosis through GIS and modelling.

Flood predictions using statistical analysis

Figure 2 demonstrates how the amount of research on flood prognosis using Statistical analysis and modelling has grown steadily since 2006 and exponentially since 2009. The number of publications for the literature on flood prediction using Statistical Analysis peaks in 2021 with 72 documents. The chart also displays the shifting patterns of the number of citations in various texts for flood prediction employing cutting-edge technologies during the previous 24 years. The number of citations has increased from 5 in 1999 to 3180 in 2022. Up until March of the year 2023, 675 citations have been recorded. This shows high demand for statistical Analysis in the field of disaster susceptibility modelling and disaster mitigation research. Tehrani's article [38] on Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS has been cited the most with a total of 499 citations and an average of 49.9 citations per year. In this study, the weights-of-evidence model (WoE) was initially applied to evaluate the effects of classes of each conditioning component on floods using bivariate statistical analysis (BSA). To assess the link between the likelihood of a flood occurring and each conditioning element, these factors were categorized using the acquired weights and added to the support vector machine (SVM) model.

Flood predictions using artificial intelligence and machine learning (AI-ML) technologies

Artificial intelligence and machine learning are relatively advanced technologies, and their use in flood prognosis just recently became popular. Figure 3 shows the number of publications and citations in the field of flood forecasting during the last 7 years i.e., from 2016 (January) to 2023 (March). The publications have exponentially increased after the year 2017. The highest number of publications can be observed during the year 2022 with 35 publications. Given the importance of

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such advanced technology in disaster vulnerability assessment and mitigation research, the number of citations has risen dramatically since 2018. The highest citation was recorded in the year 2022 with 1529 citations. Mosavi's [39] review article on flood predictions using Machine learning models has been cited the most with 490 citations in total and an average of 81.67 citations per year. This article reviews most of the research works in the field of flood prediction using physically based models as well as AI-ML techniques. The intense literature survey mentions limitations and gaps in different models which is important for further planning of such research works. This review has served as a foundation for future research in the field of flood prediction utilizing AI-ML technology.

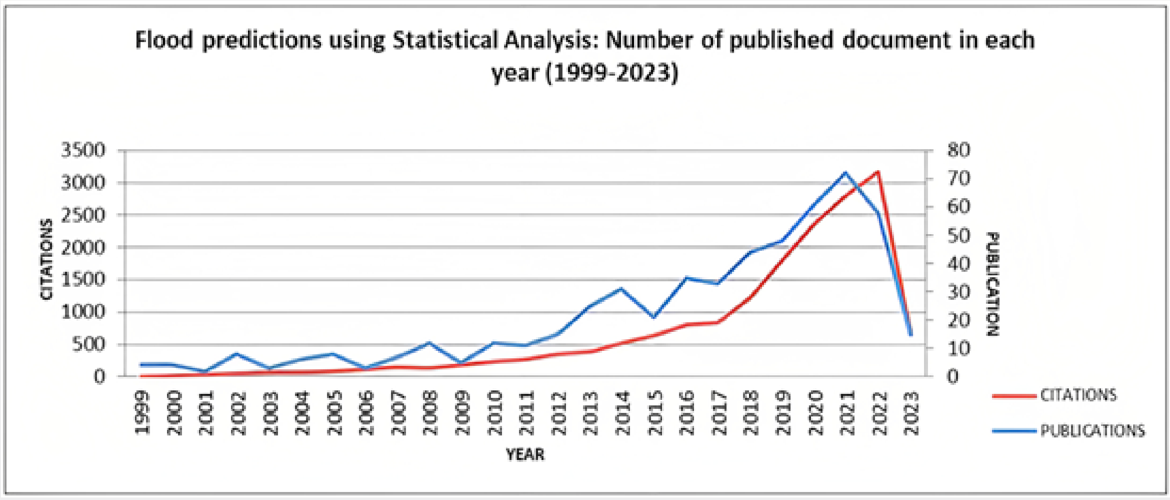

Figure 2: Number of published documents in each year (1999-2023).

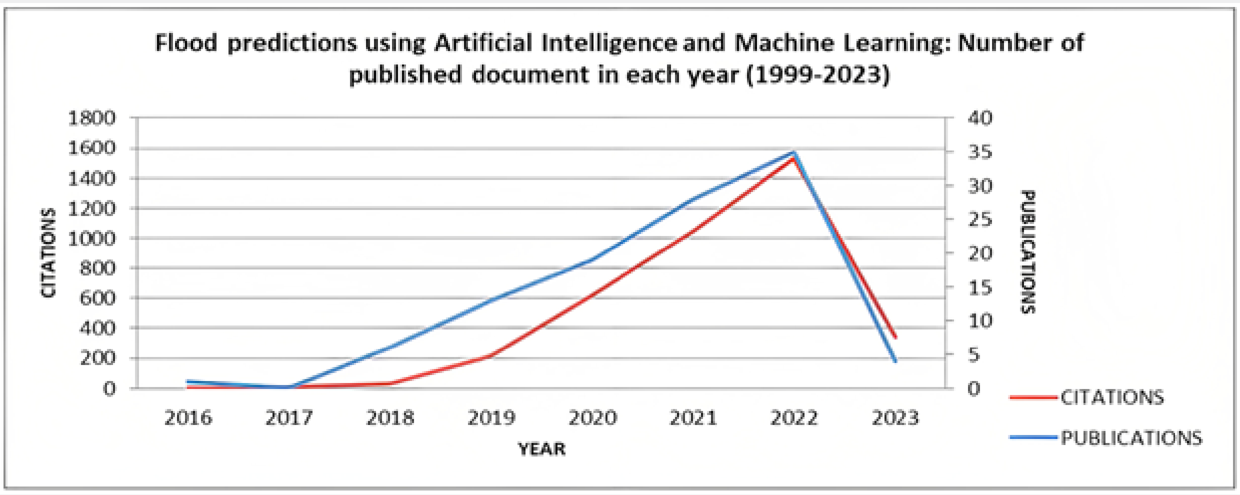

Figure 3: The number of published documents in each year (1999–2023).

Major research areas of the publication

Figure 4 displays the primary flood prediction research topics and their relative weights. The Web of Science database directs the flow of the research. It is evident that most of the study is focused on water resources, Environmental science, ecology, and geology, with a small amount of research concentrating on theoretical sciences.

Analysis of resources/journals

Figure 5 shows the number of documents published by a source or journal. The maximum number of research documents was published by the Journal of Hydrology with 46 articles about flood susceptibility and prognosis in different regions, followed by Water and Natural Hazards with 35 and 19 research publications respectively. These journals have a high number of citations and

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they form internal cooperation networks of citations with each other. This cooperation network of top journals is illustrated in Figure 6. Journal of Hydrology forms a large network with all the top journals and offers fundamental research documentation in the study field. Followed by Water and the Science of the Total environment.

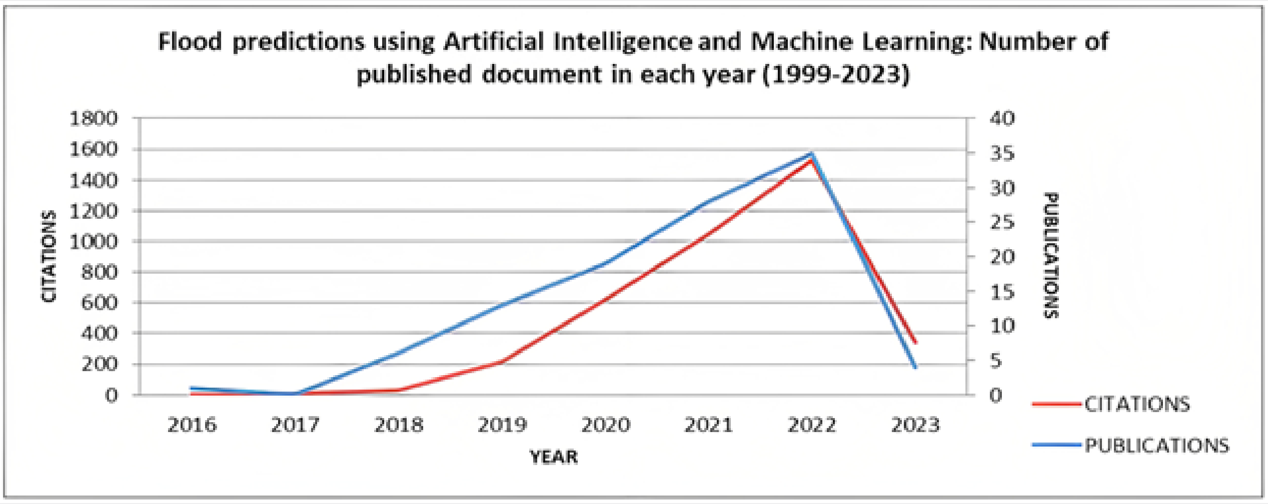

Figure 3: The number of published documents in each year (1999–2023).

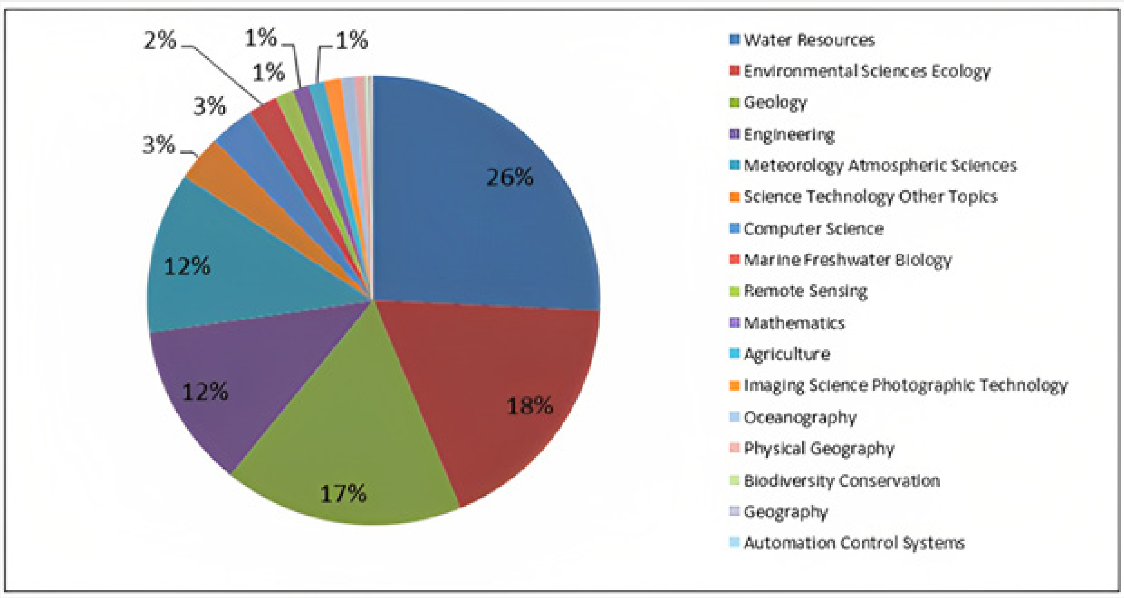

Figure 4: Main research areas and proportions.

Publication countries

Figure 7 shows the distribution of publications related to the prediction of a flood using different methodologies. A list was collected from the Web of Science (WoS) regarding countries of research. From this database, a map was prepared in ArcGIS. The map clearly shows that the United States of America has the greatest number of publications (143), followed by India (104) and the People's Republic of China/PRC (84). African countries have the least amount of published documents on this subject; however some African countries hit catastrophic flash floods almost every year which affects millions of people in those regions [40]. Researchers in these regions have focused more on the case studies of past flood events and trends of the flood occurrence.

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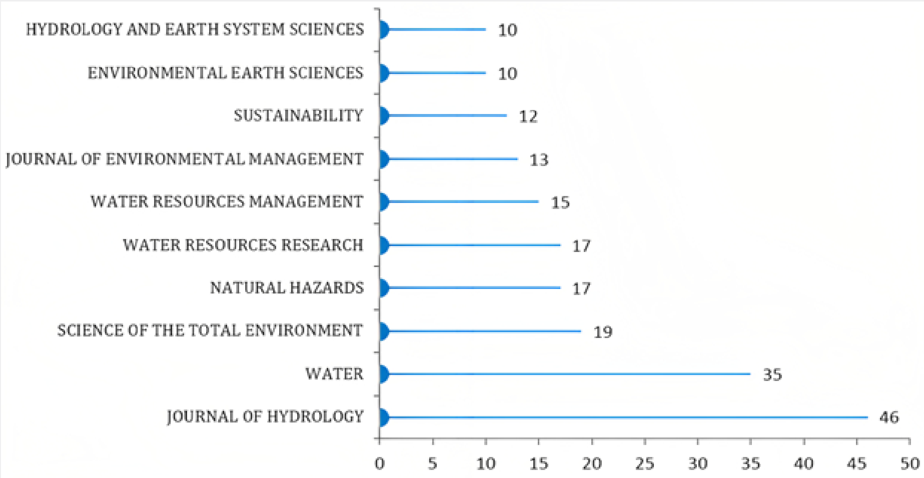

Figure 5: Top 10 journals with the highest published articles.

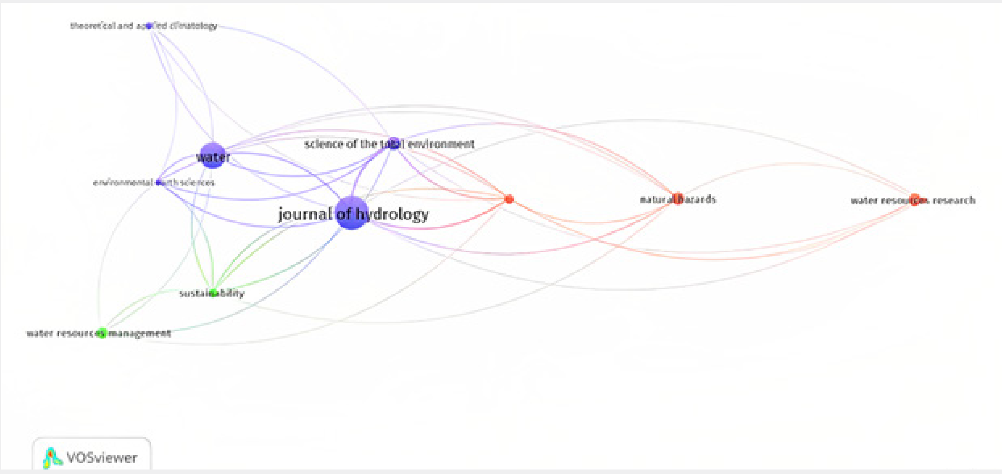

Figure 6: Cooperation networks of journals/sources.

Figure 8 shows bibliometric network visualization for the distribution of citations in different regions. The cooperation network shows 4 different clusters, each illustrating citations of documents from different countries and regions. USA, India, and China have offered a vast network of citations to other countries and regions in the field of Flood prognosis. These are also the countries with the highest number of publications. Thus, it can be inferred that these countries have done a considerable amount of quality research work which has served as a foundation for Disaster Mitigation and climate resilience studies. These are also the regions where floods are a huge threat to the living population as well as biodiversity. More than 20 million people are getting affected due to different types of a flood each year in these three countries. Hence, a high number of publications on Hydrological disaster mitigation from these regions can be justified.

Analysis of high-level scientific research institutions

The top 10 journals in the field of flood susceptibility analysis and forecasting research are shown in Table 1 along with their main areas of publication. The Duy Tan University, which has published 25 articles overall, is the leading organization with the highest publication record in the field. Affiliations from Vietnam, China, and India are more focused on flood susceptibility analysis and mitigation studies. These tropical and subtropical countries witness different types of floods every year. The intensity of floods has increased in recent years and so do the fatalities. All the institutes and organizations have mainly focused on newly discovered advanced technologies like GIS and Machine learning for their studies.

Additionally, in Figure 9, we can see how these top ten institutions along with some other renowned affiliations work together effectively. Duy Tan University, Ton Duc Thang University, and The Chinese Academy of Sciences act as the hub of the current research's cooperating network. Maximum citation networks are formed by these 3 universities. Duy Tan University has formed a strong cooperative network with other universities of the same regions like Ton Duc Thang University and forms a cluster.

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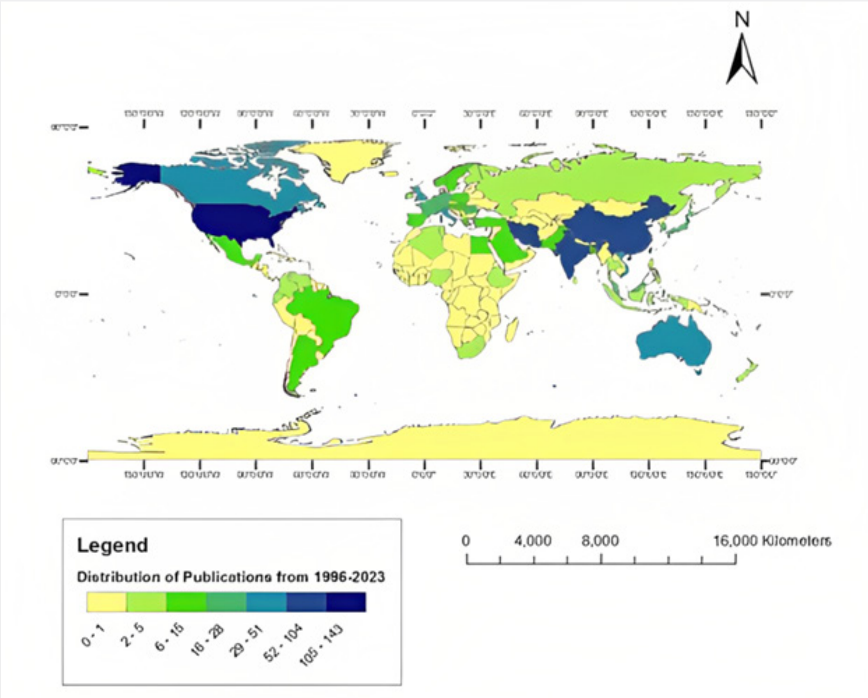

Figure 7: Global distribution of published documents (1999-2023).

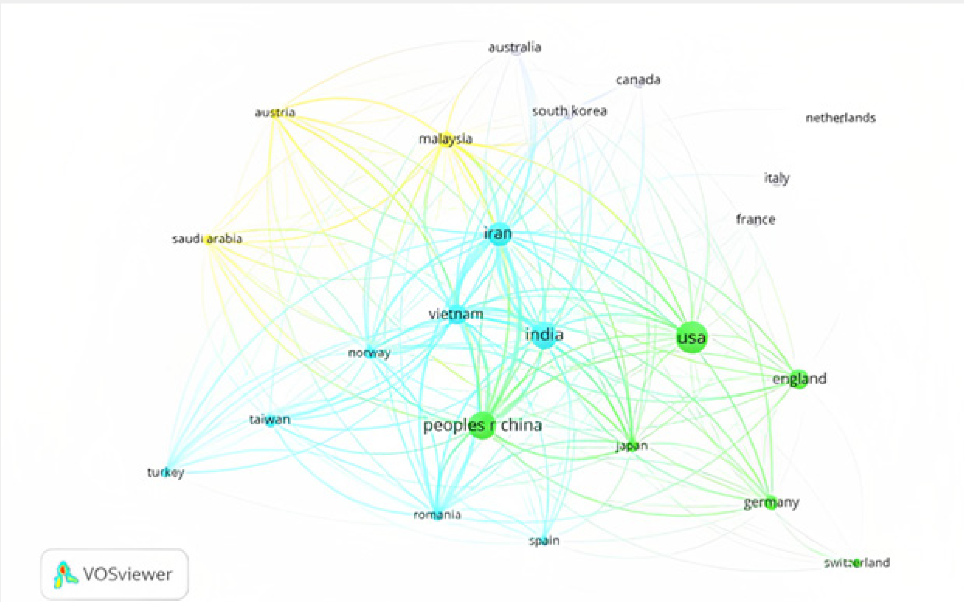

Figure 8: Cooperation network between countries.

Another cluster network was formed by The University of Bucharest and Tarbiat Modares University which form strong cooperative networks in their respective regions. Comparing the data of Table 1 & Figure 9, some affiliations like IIT and CNR which have a good amount of publications in this field, could not form a strong network in their respective regions. This also depicts a major research gap in these regions.

Analysis of authors and their highest cited publications

Table 2 shows the information about the top ten authors with the highest publications along with the documents that were cited the most. The research paper entitled, "A comparative assessment of decision trees algorithms for flash flood susceptibility modelling at Haraz watershed, northern Iran" has 353 citations which are highest among the other papers' citation ranks. 4 authors of this

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research paper, viz, Bui DT, Pham BT, Shahabi H, and Shirzadi A are also in this list of top ten authors who have published a considerable number of publications on Flood susceptibility and prognosis. Researchers evaluated four decision tree-based machine learning models for mapping the vulnerability to flash floods at the Haraz Watershed in northern Iran. These models were, Logistic Model Trees (LMT), Reduced Error Pruning Trees (REPT), Naive Bayes Trees (NBT), and Alternating Decision Trees (ADT). These methods are effective at identifying flood-prone locations.

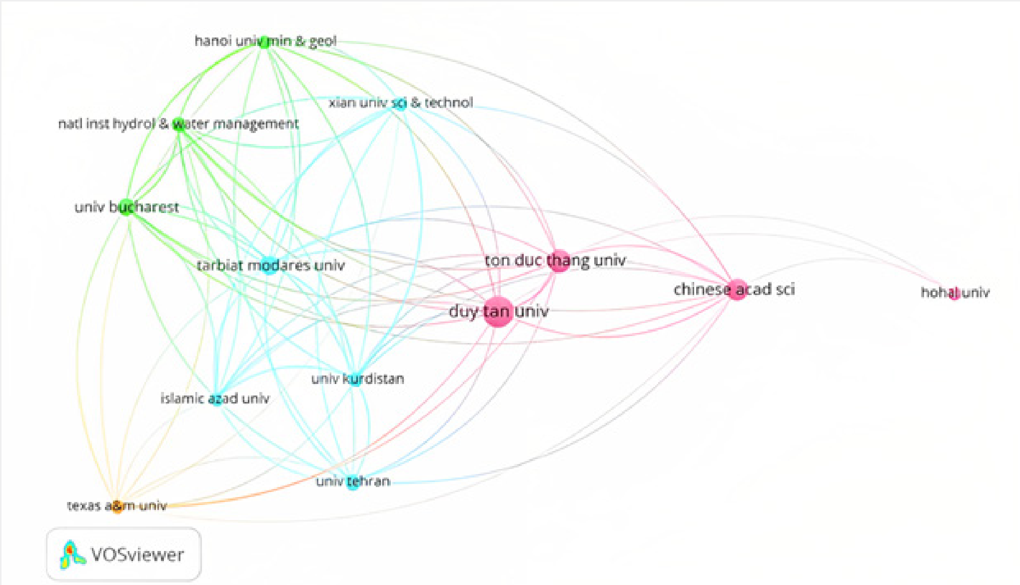

Figure 9: Institutional cooperation network.

Table 1: Top 10 affiliations based on the number of publications in flood susceptibility and forecast research.

Affiliation	Fields	Publications	Region/Country
Duy Tan University	Flash floods, flood susceptibility mapping, Rainfall runoff modelling, ML models	25	Vietnam
Chinese Academy of Sciences	Runoff forecast, hybrid models to predict flood susceptibility	19	China
Indian Institute of Technology System (Iit)	Flash flood susceptibility, peak flow analysis, flood frequency estimation	19	India
Ton Duc Thang University	Flash flood potential index estimation, flood prediction using ensamble models, ML models	18	Vietnam
Tarbiat Modares University	Computational intelligence algorithm and Remote sensing in run-off mechanism	16	Iran
Consiglio Nazionale Delle Ricerche Cnr	Extreme hourly precipitation due to reverse orographic effect	14	Italy
University Of Bucharest	Flash flood potential assessment, Susceptibility assessment, spatial prediction of flood potential area	13	Romania
University Of California System	Stream prediction models, flood risk and impacts, nonstationary flood frequencies	13	USA
Texas A M University System	Flood risk prediction tools, flood mitigation strategies, climate change preparedness	12	USA
University Of Quebec	Global flood risk modelling, Hydro-climatic data analysis	12	Canada

Keywords co-occurrence analysis

To investigate the keywords co-occurrence network relevant to the research topic, a keyword density diagram is shown in Figure 10 based on the number of associations and the intensity of their relationships. Keywords like Machine learning, GIS, and Flood susceptibility have a large occurrence density. The research documents were chosen based on different methodologies to forecast flood and flood susceptibility thus the high density of such keywords depicting different techniques is explainable.

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Table 2: Top 10 authors with the highest publications and citations.

Rank	Author	Title of the Highest Cited Article	Citations of the Highest Cited Article	Total Publication of the Author
1	Bui DT	A comparative assessment of decision trees algorithms for flash flood susceptibility modelling at Haraz watershed, northern Iran [41].	353	20
2	Costache R	A novel deep learning neural network approach for predicting flash flood susceptibility: A case study at a high-frequency tropical storm area [42].	179	15
3	Pradhan B	Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS [43].	499	13
4	Chen W	Application of fuzzy weight of evidence and data mining techniques in the construction of flood susceptibility map of Poyang County, China [44].	203	10
5	Pham BT	A comparative assessment of decision trees algorithms for flash flood susceptibility modelling at Haraz watershed, northern Iran [41].	535	10
6	Shahabi H	A comparative assessment of decision trees algorithms for flash flood susceptibility modelling at Haraz watershed, northern Iran [41].	535	10
7	Arabameri A	Optimization of state-of-the-art fuzzy-metaheuristic ANFIS-based machine learning models for flood suscepti-bility prediction mapping in the Middle Ganga Plain, India [45].	58	9
8	Pham QB	Flood susceptibility modelling using advanced ensemble machine learning models [46].	134	9
9	Hong HY	Application of fuzzy weight of evidence and data mining techniques in the construction of flood susceptibility map of Poyang County, China [44].	203	8
10	Shirzadi A	A comparative assessment of decision trees algorithms for flash flood susceptibility modelling at Haraz watershed, northern Iran [41].	535	8

Figure 11 shows the co-occurrence network of these keywords during different periods in different documents related to flood prognosis. Here, Artificial Intelligence, ANN, and Machine Learning form a distinct cluster which shows these keywords were used in the documents which were published later after 2016. These techniques are quite new yet the co-occurrence of these words is high. Thus, we can infer that these are the techniques that are of more interest to the current authors and researchers. Also, these techniques are quite important in the field of flood predictions and disaster vulnerability assessment.

Through the bibliometric analysis, we have a wide range of datasets regarding top journals, pioneer institutes working in the field of flood susceptibility analysis and prediction sciences, highest cited documents and articles, authors with highest publication records and advanced technologies and models used by different researchers for different purposes. Further in the next section, a more technical review is given with respect to different methods used by different researchers and authors along with their limitations and research gaps.

Technical Review of Related Literature

It makes more sense to offer a comprehensive analysis on the basis of the bibliometric analysis, focusing on many approaches to research and writing employed by various authors and researchers, as well as the limitations and unanswered questions posed by those approaches. In recent years, the majority of authors have been concentrating their efforts on developing hybrid models that combine Artificial Intelligence and Machine Learning in order to analyse, investigate, and evaluate flood-prone locations as well as the intensity of floods along with short-term and long-term predictions.

The issue of urban flooding, which is a major worry in many cities throughout the world, is discussed in the article written by Motta et al. [20]. To forecast urban floods, the authors suggest a mixed methodology that incorporates machine learning and geographic information systems (GIS) rather than using only GIS methods. The hybrid method is tested on a case study of a flood-prone region in Brazil, and the results demonstrate that it

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is capable of making precise predictions about the frequency and intensity of floods. The study proposes an innovative approach that combines two potent technologies, machine learning and GIS, to increase the accuracy of flood predictions, which is a significant contribution to the field of urban flood prediction. As GIS enables the integration of many sorts of data such as topography elevation, land use, and rainfall intensity, the study also sheds light on the significance of adding spatial data into flood prediction models. The study does have certain restrictions, though. The study only employed a small number of variables; future research may look into using more variables to increase the precision of flood predictions. Finally, because the study concentrated on short-term flood prediction, future research might look into how the mixed approach might be utilised to assess the risk of long-term flooding.

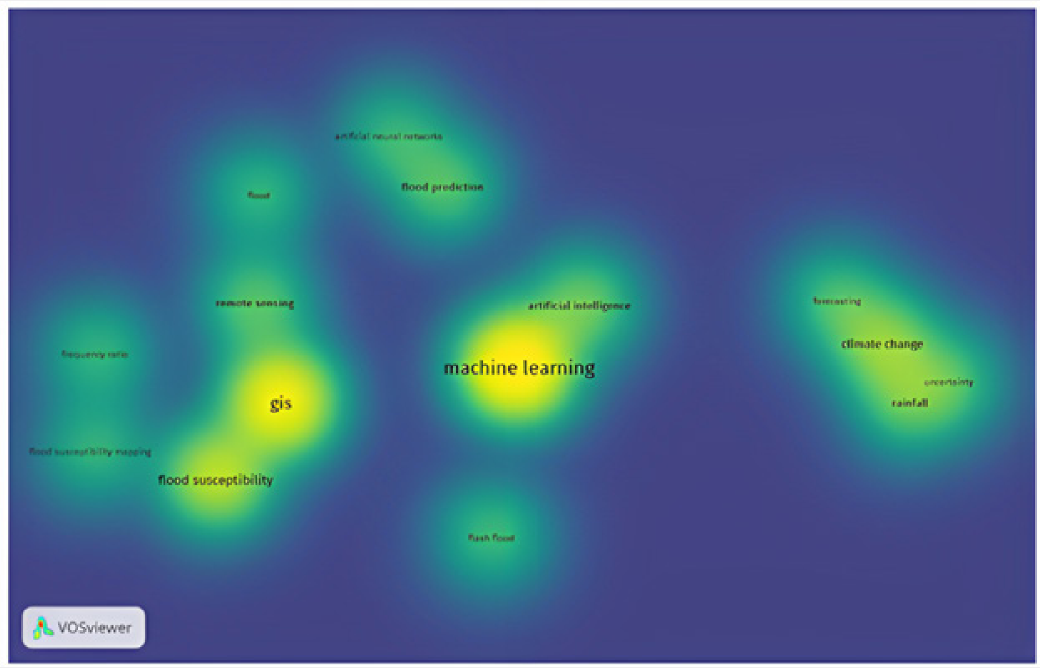

Figure 10: Density distributions of major keywords.

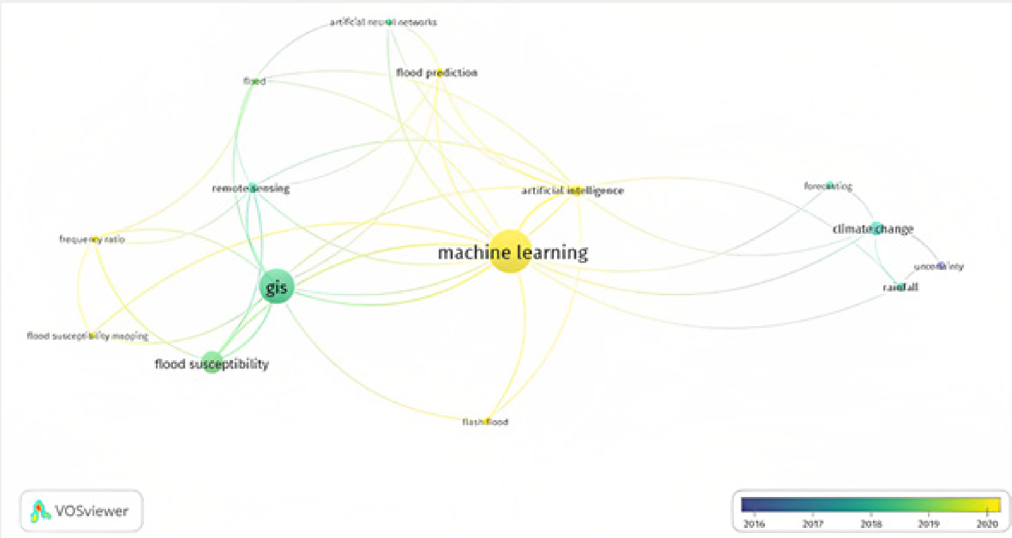

Figure 11: Co-occurrence networks of keywords.

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Le et al. [47] examines flood forecasting using LSTM neural networks. South Korean river rainfall and water level data are used to create LSTM flood prediction models. LSTM models are compared to ANNs and SVMs. LSTM models exceed classic machine learning methods in accuracy and performance. For flood forecasting, LSTM models can incorporate data temporal dependencies, as shown in the study. In data with complicated temporal connections, LSTM models can predict floods, the scientists say. Despite the study's optimistic outcomes, research gaps remain. Firstly, the study only analyses data from one South Korean river, making it unclear if the conclusions can be applied elsewhere. Secondly, the study ignores meteorological and hydrological parameters that affect flood forecasting accuracy. Thirdly, the study ignores LSTM model drawbacks including over fitting and data requirements.

Till now many conventional methodologies have been used to make flood susceptibility maps, short-term and long-term prognosis of the hydro-meteorological disasters and to make a proper mitigation plan for the society. However, emerging technologies like Hybrid models, AI-ML and bivariate statistics are utilized by several researchers to prepare a proper Flood Susceptibility Map and to predict the events more accurately. In recent years, advanced technologies like Artificial Intelligence and Machine Learning models are being used to forecast the floods and related disasters. Different methods are discussed here.

Artificial neural network (ANN)

ANNs are efficient mathematical modelling systems with efficient parallel processing, allowing them to simulate biological neural networks with interconnected neuronal units. Among all the other AI-ML models, Artificial Neural Networks are quite popular to predict complex flood processes with an accurate approximation. There are a number of disadvantages related with the use of ANNs in flood modelling, such as the network architecture, data management, and physical interpretation of the modelled system. These disadvantages exist despite the fact that ANNs have a number of benefits. The use of artificial neural networks (ANNs) comes with a number of drawbacks, the most significant of which are the relatively low accuracy, the need for iterative parameter adjustment, and the delayed response to gradient-based learning processes [48]. A comprehensive review on major ANN techniques used for flood predictions and hydrological analysis is given in Table 3.

Table 3: Major ANN techniques used for flood predictions and hydrological analysis.

Author (s) & Year of Publication	Title of the Paper	Findings/Review
Jain et al. [49]	comparative analysis of event-based rainfall-runoff modelling techniques Deterministic, statistical, and artificial neural networks	ANN is one of the most applicable modelling techniques, as its generalisation capability and performance are comparable to those of the majority of conventional models.
Kisi et al. [50]	Streamflow forecasting using different artificial neural network algorithms	The study reveals how artificial neural networks and self-organizing map models can predict streamflow. The study only analyses data from one river basin, therefore more research is needed to validate the conclusions across locations and historical periods.
Li et al. [51]	Streamflow forecast and reservoir operation performance assessment under climate change	Compared to conventional statistical models, the ANN approach was used to make more accurate predictions.
Wu et al. [52]	Data-driven models for monthly streamflow time series prediction	Since their introduction in the 1990s, ANN algorithms are the most widely used for flood prediction modelling. Although FNN models turned out to be better in terms of data analysis and predictions of the streamflow.
Kar et al. 2010	Development of flood forecasting system using statistical and ANN techniques in the downstream catchment of Mahanadi basin, India.	ANNs are regarded as reliable data-driven instruments for developing black-box models of complex and nonlinear river flow and discharge forecasting.
Shamseldin et al. [53]	Artificial neural network model for river flow forecasting in a developing country	In a developing country, ANNs are used for river flow forecasting, which is important for disaster management and water resource planning. The author used an extended data period for model training and testing, which boosts model confidence.
Lohani et al. [54]	Hydrological time series modelling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques	ANN is an effective tool in flood prediction and susceptibility forecasting. However Neuro-fuzzy technique has some limitations in data analysis.
Taormina et al. [55]	Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice Lagoon.	High-frequency data helps estimate short-term groundwater level fluctuations in the article. The authors tested the ANN model in rainy and dry circumstances.

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Badrazeh et al. [56]	Impact of multi-resolution analysis of artificial intelligence models inputs on multi-step ahead river flow forecasting	The study uses multi-resolution analysis to better understand input variables and river flow dynamics. The authors also compared AI models for river flow forecasting, revealing their strengths and drawbacks.
Abbot et al. [57]	Input selection and optimisation for monthly rainfall forecasting in Queensland, Australia, using artificial neural networks.	Among all ML techniques, ANNs are the most prevalent learning algorithms, renowned for their versatility and effectiveness in modelling complex flood processes with a high defect tolerance and precise approximation.
Tanty et al. [58]	Application of artificial neural network in hydrology—A review	Artificial Neural network is one of the most effective tools to understand hydrological processes like streamflow, surface runoff and rainfall or precipitation data analysis.
Deo et al. [48]	Application of the artificial neural network model for prediction of monthly standardized precipitation and evapotranspiration index using hydrometeorological parameters and climate indices in Eastern Australia	The use of a complete set of input variables to the ANNs, which allowed the authors to study the relative value of various parameters in predicting the indices. The scientists also assessed the effectiveness of the ANNs using a range of measures, such as coefficient of determination (R2) and root mean square error (RMSE), which offers a thorough evaluation of the models' accuracy.
Panagoulia et al. [59]	multi-stage methodology for selecting input variables in ANN forecasting of river flows	The thorough analysis of ANNs in various climate regimes is one of the article's strongest points. According to the study, ANNs perform better than conventional approaches in most cases, and the authors go into great detail on why this is the case.
Sulaiman et al. [60]	Heavy rainfall forecasting model using artificial neural network for flood prone area	Instead of the tangible characteristics of a catchment, ANNs derive their meaning from historical data. Thus, ANNs are regarded as reliable data-driven instruments for developing black-box models of complex and nonlinear rainfall and flood relationships.

Multilayer perception (MLP)

MLP is composed of densely interconnected layers that transform any input dimension into the desired dimension. A perception with multiple layers is a neural network with multiple layers. In order to construct a neural network, neurons are combined such that the outputs of some neurons serve as inputs for other neurons. MLP models were shown to be more successful and to have more generalizability than ANN classes that are used in flood modelling. This was discovered through an evaluation of ANN classes that are used in the modelling of floods. Nevertheless, the MLP is typically more challenging to optimise [61]. Table 4 summarises the major MLP techniques used for flood predictions and hydrological analysis.

Table 4: Major MLP techniques used for flood predictions and hydrological analysis.

Author (s) & Year of Publication	Title of the Paper	Findings/Review
Riad et al. [62]	Rainfall-runoff model using an artificial neural network approach	The use of an ANN technique, which has been proven to be successful in modelling complex hydrological processes, is one of the article's strengths. The model was further assessed by the authors using a number of statistical metrics, such as the root mean square error, the Nash-Sutcliffe efficiency coefficient, and the coefficient of determination.
Senthil et al. [61]	Rainfall-runoff modelling using artificial neural networks: Comparison of network types.	Comprehensive comparison of various ANN models, which sheds light on the relative benefits and drawbacks of each architecture. The performance of the models was also assessed by the authors using statistical metrics including correlation coefficient and root mean square error, and the outcomes were contrasted with those of conventional hydrological models.

Adaptive neuro-fuzzy inference system (ANFIS)

It is a qualitative modelling technique employing soft computing and natural language. Fuzzy logic is a mathematical paradigm that incorporates expert knowledge into a fuzzy inference system (FIS). An FIS further imitates human learning via a less complex approximation function, which has enormous potential for nonlinear modelling of extreme hydrological events [63,64]. Table 5 shows the development in ANFIS techniques used for flood predictions and other hydrological analysis.

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Table 5: Major ANFIS techniques used for flood predictions and hydrological.

Author (s) & Year of Publication	Title of the Paper	Findings/Review
See et al. [65]	hybrid multi-model approach to river level forecasting	The hybrid technique is well-evaluated in the article. The hybrid technique was compared to separate models using RMSE, MAE, and correlation coefficient performance criteria. The hybrid model was more accurate and robust.
Bogardi et al. [66]	The fuzzy logic paradigm of risk analysis	The authors created a fuzzy logic model to assess flood risk in Hungary using multiple input factors. The fuzzy logic model was more realistic and thorough than probabilistic risk analysis.
Choubin et al. [64]	Drought forecasting in a semi-arid watershed using climate signals	Climate signals are critical for drought forecasting in semi-arid locations because climate variability greatly affects water availability. The neuro-fuzzy model surpassed MLR and ANNs in accuracy and the SPI and SPEI were major drought predictors.
Lohani et al. [21]	Improving real time flood forecasting using fuzzy inference system	Takagi–Sugeno (T–S) fuzzy models were used which is created through aneuro fuzzy interface or clustering. River flow forecasts can be improved by classifying rainfall–runoff data into frequent and unusual events and using TSC-T–S fuzzy model architectures.
Aziz et al. [67]	Application of artificial neural networks in regional flood frequency analysis: A case study for Australia	RFFA is commonly used to estimate flood quantiles in ungauged catchments. Quantile regression technique (QRT) and other popular RFFA approaches presume a log-linear connection between the dependant and predictor variables. ANN provides the most effective RFFA model.
Choubin et al. [63]	Multiple linear regression, multi-layer perceptron network and adaptive neuro-fuzzy inference system for forecasting precipitation based on large-scale climate signals	The models used large-scale climate signals including sea surface temperature and sea level pressure. MAE, RMSE, and R were used to assess model performance.

Wavelet neural network (WNN)

It is a mathematical method that can be used to extract information from a wide variety of data sources by doing an analysis of local variations in time series [68]. It is a hybrid tool of Wavelet Transform and Multilayer perceptron. In flood modelling, Decomposition of Wavelet Transform (DWT) can be widely applied for Rainfall Run-off analysis and prediction [69]. As shown in Table 6, Shafei et al. [76] have used Wavelet Neural Network techniques in river flow forecasting and other hydrological processes. They have also compared the performance of other models.

Table 6: Major WNN techniques used for flood predictions and hydrological analysis.

Author (s) & Year of Publication	Title of the paper	Findings/Review
Guimarâes et al. [70]	Daily streamflow forecasting using a wavelet transform and artificial neural network hybrid models	Based on the low-frequency components of the original signal, new wavelet and artificial neural network (WA) hybrid models are proposed in the literature for daily streamflow forecasting 1, 3, 5, and 7 days ahead. WA models also eliminated standard ANN model lags in daily streamflow estimates.
Nourani et al. [71]	Applications of hybrid wavelet–artificial intelligence models in hydrology: A review	Hybrid wavelet and AI-based models are promising hydrologic process simulators. This paper discusses hybrid modelling, its benefits, and the history and future of its usage in hydrology to anticipate key hydrologic cycle activities.
Kumar et al. [72]	Reservoir inflow forecasting using ensemble models based on neural networks, wavelet analysis and bootstrap method	This paper develops a reservoir inflow forecasting ensemble model using wavelet analysis, bootstrap resampling, and neural networks (BWANN). BWANN models outperform BWMLR models for uncertainty assessment, and range forecasts are more trustworthy, accurate, and useful for operational inflow forecasting than point predictions.
Seo et al. [73]	Daily water level forecasting using wavelet decomposition and artificial intelligence techniques	This research develops and tests two hybrid daily water level forecasting models. WANN and WANFIS are hybrid models. Wavelet decomposition and artificial intelligence algorithms can accurately anticipate daily water levels and be more efficient than conventional forecasting models.

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Sudhishri et al. [74]	Comparative evaluation of neural network and regression based models to simulate runoff and sediment yield in an outer Himalayan watershed	This work used a basic Non-Linear Dynamic (NLD) model to forecast daily runoff and sediment yield using watershed memory-based rainfall, runoff, and sediment yield. The results were compared with two commonly used Artificial Neural Network (ANN) and Wavelet-based ANN (WNN) models by obtaining maximum input parameters of temporal memory for rainfall, runoff, and sediment yield from the constructed NLD model by step-wise regression.
Kasiviswanathan et al. [68]	Potential application of wavelet neural network ensemble to forecast stream-flow for flood management	Long-term Streamflow forecasting is a challenging practice in hydrological modelling. Wavelet-based neural networks (WNNs) seem promise for long-lead-time forecasting.
Partal et al. [75]	Wavelet regression and wavelet neural network models for forecasting monthly streamflow	Wavelet transformation and multivariate linear regression (LR) form the wavelet-based regression model. Wavelet-based regression forecasts are compared to the wavelet-based neural network, which combines wavelet transformation and feed forward neural network.
Shafei et al. [76]	Predicting river daily flow using wavelet-artificial neural networks based on regression analyses in comparison with artificial neural networks and support vector machine models	This study examines wavelet-artificial neural networks (WANN) for short-term daily river flow forecast. Discrete wavelet transform and regression-based ANN improve the WANN model. WANN, ANN, and SVM models are evaluated using MSE, MAE, and R statistics. WANN outperforms ANN and SVM models in short-term daily river flow forecast.
Ravansalar et al. [69]	Wavelet-linear genetic programming: A new approach for modelling monthly streamflow	A hybrid wavelet-linear genetic programming (WLGP) model predicts monthly streamflow (Q) using DWT and LGP. The WLGP model considerably improved streamflow prediction accuracy in study area. The WLGP model can simulate one-month cumulative streamflow data forecast because it approximates peak streamflow values better.

Support vector machine (SVM)

A support vector machine (SVM) is a type of algorithm for deep learning that performs supervised learning for data group classification or regression. In artificial intelligence and machine learning, supervised learning systems provide labelled input and output data for classification. SVM is quite popular modelling method of futuristic data analysis. Due to the heuristic and semi-black-box nature of SVMs, their high computational cost and exaggerated outputs may be problematic; however, the least-square support vector machine (LS-SVM) significantly improved performance with acceptable computational efficiency [77]. Table 7 shows major SVM techniques used for flood forecasting and other hydrological process analysis by different researchers along with the model limitations.

Table 7: Major SVM techniques used for flood predictions and hydrological analysis.

Author (s) & Year of Publication	Title of the Paper	Findings/Review
Dibike et al. [78]	Model induction with support vector machines: Introduction and applications.	This paper reviews statistical learning theory and SVM and shows how the method can be used for feature classification and multiple regression (modelling) problems by applying it to two empirical data model induction scenarios. SVM performance is compared against ANNs on the identical data sets.
Sachindra et al. [79]	Least square support vector and multi-linear regression for Statistically downscaling general circulation model outputs to catchment streamflows	The best three standardised potential predictors were added to the LS-SVM-R and MLR models, followed by others depending on their correlations with streamflows, until model validation was maximised. Stepwise model development identified the optimal amount of possible variables for each month. MLR can be used to statistically downscale GCM outputs to streamflows, however LS-SVM-R is superior.
Nayak et al. [80]	Prediction of extreme rainfall event using weather pattern recognition and support vector machine classifier.	Research uses mesoscale (20–200 km) and synoptic scale (200–2,000 km) weather patterns to construct an SVM-based system to predict severe rainfall in Mumbai with a lead time of 6–48 h. The model forecasts all extreme events well in advance, despite false alarms. The fingerprinting approach performs better in false alarm and prediction than the state-of-the-art statistical technique.
Dehghani et al. [81]	Uncertainty analysis of streamflow drought forecast using artificial neural networks and Monte-Carlo simulation	Using a Monte-Carlo simulation technique, the uncertainty of SHDI and monthly streamflow discharge forecasts was studied. The Monte-Carlo simulations showed that all predicted values fall within the 95% confidence intervals.

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Bao et al. [82]	Multi-step-ahead time series prediction using multiple-output support vector regression.	This paper presents a novel multiple-step-ahead time series prediction method using M-SVR with MIMO prediction strategy. M-SVR with MIMO method provides the most accurate forecasts with low computational burden. The iterated SVR has the worst prediction accuracy but the lowest computational cost.
Tehrani et al. [38]	Flood susceptibility assessment using GIS-based support vector machine model with different kernel types	A probabilistic frequency ratio (FR) model was compared to the SVM model to evaluate its efficiency. The flood susceptibility maps were validated using AUC. Cohen's kappa index examined conditioning factors' effects on flood susceptibility mapping. In the current case study, all conditioning factors had a favourable impact on flood analysis except surface runoff, which reduced accuracy.
Gizaw et al. [83]	Regional flood frequency analysis using support vector regression under historical and future climate	Besides regression-based RFFA methods, machine learning algorithms like the artificial neural network (ANN) have shown promising results in regional flood quantile estimations. Support Vector Regression (SVR) is another machine learning method that is growing popular in hydrology. This study estimated regional flood quantiles for two study locations using an SVR-based RFFA model.
Granata et al. [84]	Support vector regression for rainfall-runoff modeling in urban drainage: A comparison with the EPA's storm water management model	Case studies include two northern Italian experimental basins. Two criteria are used to compare recorded and anticipated flow rates: RMSE and CoD. SVR has enormous potential in urban hydrology, however model calibration is limited.

Decision tree (DT)

Predictive modelling and flood simulation use the DT ML approach. DT employs a decision tree from branches to leaf targets. Classification trees (CT) have discrete final variables, where leaves represent class labels and branches represent feature label combinations. Researchers compared the efficacy of ANN, SVM, and RF in general flood applications, with RF delivering the best results [42]. Major Decision Tree techniques and their limitations in flood forecasting and hydrological process analysis is mentioned further in Table 8.

Table 8: Major DT techniques used for flood predictions and hydrological analysis.

Author (s) Year of Publication	Title of the Paper	Findings/Review
Tehrani et al. [85]	Spatial prediction of flood susceptible areas using rule based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS	This study compares rule-based decision tree (DT) and frequency ratio (FR) and logistic regression (LR) statistical methods for flood susceptibility mapping. DT and integrated approach of FR and LR had success rates of 87% and 90% and prediction rates of 82% and 83%.
Wang et al. [86]	Flood hazard risk assessment model based on random forest	This study suggests an innovative and effective flood hazard risk assessment method of Random Forest. Evaluation results guide flood risk management, natural catastrophe avoidance, and reduction in the study basin through RF-DT.
Bui et al. [42]	Spatial prediction models for shallow landslide hazards: A comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree.	KLR and LMT models were promising for shallow landslip susceptibility mapping. This work shows that shallow landslip susceptibility mapping benefits from using the best machine learning approaches with correct conditioning selection.
Choubin et al. [87]	River suspended sediment modelling using the cart model: A comparative study of machine learning techniques	Nash-Sutcliffe efficiency (NSE), Kling-Gupta efficiency (KGE), and percent bias (PBIAS) were used to assess model performance. The CART model predicted SSL best (NSE = 0.77, KGE = 0.8, PBIAS < 15), followed by RBF-SVM. Thus, hydro-meteorological data-rich basins can benefit from the CART model.

Ensemble Prediction Systems (EPS)

Machine learning and Artificial Intelligence techniques are widely used for different purposes. The practise of making predictions using only one model rather than a collection of models tailored to a certain dataset, cost, and application is becoming less common as a result of a developing strategy. ML ensembles are made up of a limited number of different models,

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each of which can often accommodate a greater degree of flexibility than the alternatives. Zhang et al. [88] reviewed several Ensemble Machine Learning methods that were used to analyse and examine hydrological events, mainly floods. The other major studies in this area are given in Table 9.

Table 9: Major EPS techniques used for flood predictions and hydrological analysis.

Author (s) & Year of Publication	Title of the Paper	Findings/Review
Wang et al. [89]	Improving forecasting accuracy of annual runoff time series using ARIMA based on EEMD decomposition	This study forecasts annual runoff time series using the auto-regressive integrated moving average (ARIMA) model and ensemble empirical mode decomposition (EEMD). This study shows that EEMD improves forecasting accuracy and that the suggested EEMD-ARIMA model improves ARIMA time series techniques for annual runoff time series forecasting.
Ouyang et al. [90]	Monthly rainfall forecasting using EEMD-SVR based on phase-space reconstruction	Ensemble empirical mode decomposition (EEMD) preprocesses rainfall data. The phase-space reconstruction method designs forecasting model input vectors. As a case study, the hybrid model predicts monthly rainfall at a Changchun, China weather station. The hybrid model can anticipate monthly rainfall better than current methods.
Zhang et al. [88]	Operating characteristic information extraction of flood discharge structure based on complete ensemble empirical mode decomposition with adaptive noise and permutation entropy	Complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) entropy (CEEMDAN-PE) is proposed for the current study. Through this method, high frequency entropy noises were calibrated and analysed to examine the flood discharge structures.

Mosavi et al. [39] offers a summary of many machine learning models that have been applied to the task of flood prediction. These models include artificial neural networks, support vector machines, decision trees, and genetic algorithms. The writers explore the benefits and drawbacks of each model, as well as present instances of how each might be applied in a variety of geographic locations around the world. Machine learning models have demonstrated promising results in flood prediction, particularly when compared to classical statistical models, which is one of the major findings of the paper. However, the authors point out that there are a number of obstacles and research voids that need to be filled in. For instance, constructing reliable flood prediction models is made significantly more difficult by the dearth of data of a high quality and the restricted availability of data sets that cover a lengthy period of time. In addition, the authors stress that there is a need for additional study on the transferability of machine learning models across different locations, as well as research on the integration of diverse models for more accurate predictions [91-94].

Conclusion and Future Research Directions

The field of disaster susceptibility analysis, Prediction of severe weather events, and mitigation strategies have attracted a lot of scholarly attention recently, with both the number of publications and citations rising sharply. In this study, 769 publications on this subject were examined using bibliometrics, and statistical analysis was utilized to determine that the majority of the articles in the field were published in scientific journals like the Journal of Hydrology, Water, and Natural Hazards. The highest amount of research has been done for flood susceptibility modelling through statistical analysis. Technologies like Machine learning and Artificial intelligence are comparatively new modelling systems yet the publications in this field have exponentially risen in recent years which shows the high demand for such advanced technologies in the field of disaster susceptibility and mitigation. Hybrid modelling technologies also have higher efficiency in flood forecasting. The United States, India, and China were the top three countries for research in this area based on the number of publications. Duy Tan University in Vietnam has published the highest number of research documents along with a large number of citation networks in the study area. Bui D. T., Costache R., Pradhan B., and Chen W. have all made noteworthy contributions, according to our analysis of the publication authors, as identified in our study. Through keyword analysis and cooperation networks, it is clear that areas like AI-ML, GIS, and Flood susceptibility are emerging topics in recent times. Technical review shows that methods like Artificial Neural Network, Support Vector System and Decision Tree turned out to be the best possible techniques in flood prediction and susceptibility modelling. The interpretability of the results is one of the areas where artificial intelligence algorithms fall short in the field of flood forecasting. It is possible for these models to be quite complicated, making it challenging to comprehend how they arrive at their conclusions and forecasts. The inability to interpret the outcomes of these models can make it difficult for decision-makers to make good use of the information provided by these models. Predictions made by models are subject to a degree of uncertainty since AI models are built on statistical approaches, which by their very nature involve some degree of randomness. This uncertainty can be caused by a wide number of factors, such as mistakes in the data, restrictions

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imposed by the model's algorithms, or variations in the values used to define the input parameters. When utilising these models for the purpose of flood forecasting, it is therefore vital to keep in mind the degree of uncertainty associated with the forecasts that are produced by the models.

Increased focus on the significance of such studies

Research on flood susceptibility and flood prediction studies are essential for a variety of reasons:

a) Risk Reduction: Flood susceptibility research and flood prediction studies can aid in the identification of high-risk areas for flooding. This data can be used to develop effective flood risk reduction strategies, such as the construction of flood defences and the creation of flood warning systems.

b) Disaster preparedness: Accurate flood forecasts can assist emergency management authorities in preparing for and responding to potential flooding occurrences. This may involve evacuating affected residents, mobilizing emergency responders and resources, and coordinating relief efforts.

c) Environmental Management: Research on flood susceptibility can assist in identifying areas that are particularly susceptible to flooding due to environmental factors such as soil type, topography, and land use. This information can be used to inform decisions regarding land-use planning and environmental management, such as where to locate new development or how to manage wetlands and floodplains.

d) Planning and Design of Infrastructure: Flood prediction studies can also inform infrastructure planning and design. For instance, engineers can use flood forecasts to design structures such as bridges, culverts, and dams that can withstand expected flood events.

e) Economic Impacts: Significant economic effects can result from flooding, including property and infrastructure damage, disruption of business and industry, and loss of productivity. Flood susceptibility research and flood prediction studies can help identify the most vulnerable areas, thereby mitigating their effects.

Method innovation and selection of advanced technologies

GIS (Geographic Information System) and AI-ML (Artificial Intelligence and Machine Learning) techniques can be used to enhance the accuracy and timeliness of flood warnings by incorporating them into flood forecasting. GIS techniques can be utilized to acquire, manage, and analyze vast amounts of spatial data, such as river networks, elevation, land use, soil moisture, and precipitation data. This information may serve as input for AI-ML models. GIS can be used to extract features such as slope, aspect, and land use from spatial data for use as input for AI-ML models. Using historical flood data, AI-ML models such as neural networks, decision trees, and random forests can be trained to predict future flood events. These models can be combined with GIS data to generate flood forecasts that are spatially explicit. In multiple methods, AI and ML can be utilized in flood forecasting. Developing models that use historical data on rainfall, water levels, and other relevant factors to predict the likelihood and severity of floods is one of the most common methods. Using machine learning algorithms, these models can be trained to increase their accuracy and dependability over time.

Hybrid models of GIS and Artificial Intelligence/Machine learning can show high efficiency in flood predictions. GIS can be used to incorporate real-time data such as rainfall and river flow data with AI-ML models to generate real-time updates to flood forecasts. Through maps and other graphical interfaces, GIS software can be used to visualize and communicate flood forecasts to decision-makers and the general public. Big data concept is one such unexplored area, where the researchers can throw more light on the development of related models in terms of flood forecasting and susceptibility mapping.

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