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Hydro-Meteorological Hazards Extremes Events modeling Using GeoAI: A Review and Case Study

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ABSTRACT
The existing standard methodologies in Hydro-meteorological hazards events modeling pertaining to early warning systems, prediction, simulation, susceptibility mapping, mitigation, and assessment are crucial for understanding climate dynamics, forecasting potential climate-related hazards, and developing strategies to reduce risks and enhance resilience. These methodologies integrate various data sources, including atmospheric, oceanic, and terrestrial observations, to simulate future climate scenarios and inform policymaking and disaster preparedness efforts. The emerging Geospatial Artificial Intelligence (GeoAI) methodologies are established techniques that have continually excelled in addressing some of the above scenarios efficiently. Nevertheless, as GeoAI is in the nascent stage of study, it presents unresolved in-quiries concerning model interpretability, explainability, model generalization, and the en-hancement of its longevity (predictability). This paper thoroughly reviews the application of deep learning techniques in modeling many facets of hydro-meteorological hazards supported by a case study.

KEYWORDS
GeoAI, GeoDL, Hydro-Meteorological, Deep Learning, HMH-GeoAI, Shelf life

1. Introduction

The erratic behavior of the atmosphere has led to numerous climate change and challenges, culminating in a rise in the frequency of extreme events in recent times Ahmed and Güneyli (2023). Figure 1 comprehensively summarizes these numbers. Natural hazards, encompassing geophysical, meteorological, climatological, and hydrological occurrences, have resulted in extensive devastation worldwide Debele et al. (2019). Hydro-meteorological hazards, including floods, droughts, and extreme weather events, are among the most devastating natural disasters affecting communities worldwide. These occurrences are increasing in frequency and intensity as a result of climate change, posing significant threats to human life, infrastructure, and economies. Hydro-meteorological hazards have had profound impacts globally, with significant loss of lives and property. For instance, floods affected over 1.65 billion people globally, resulting in approximately 104,614 deaths and economic losses exceeding $651 billion Lima and Rezende (2023). Similarly, droughts during the same period affected 1.43

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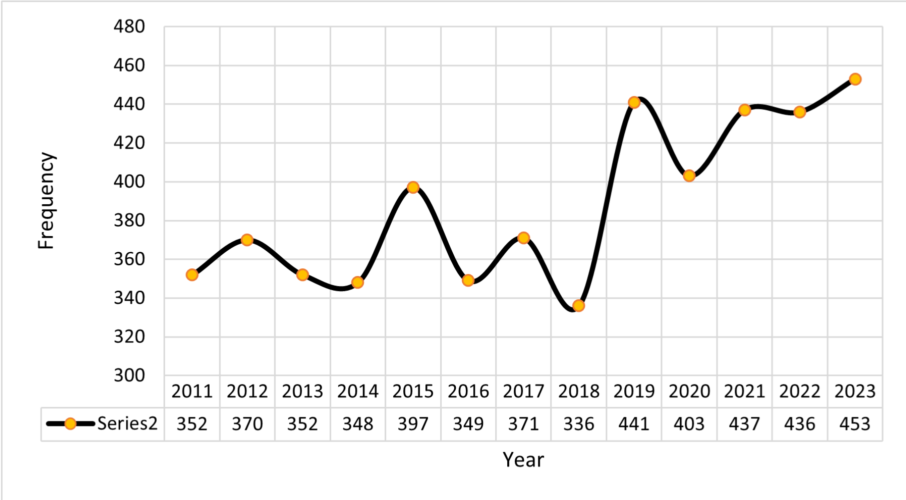


Figure 1. Number of natural hazards events occurred from 2017 to 2024

billion people and caused economic losses of around \$124 billion. Drought in year 2011 led to a severe food crisis, affecting over 13 million people Brown and Sovacool in East Africa continent. Landslides have caused significant fatalities and damage, particularly in mountainous regions. 2013 Uttarakhand floods and landslides in India resulted in over 5,700 deaths and extensive infrastructure damage Gill (2022) . Cyclones have been responsible for substantial loss of life and property in the coastal areas. Cyclone Nargis in 2008 caused over 138,000 deaths in Myanmar and economic losses of around \$10 billion. More recently Doan and Mark (2008), Cyclone in 2019 affected over 3 million people in Mozambique, Zimbabwe, and Malawi, causing over 1,300 deaths and significant infrastructure damage Deprez and Labattut (2020) . The Indian Ocean tsunami in 2004 is believed to be one of the deadliest natural disasters in recent history, causing approximately 230,000 deaths across 14 countries and economic losses estimated at \$10 billion Bernard (2012). The 2011 Tōhoku tsunami and earthquake in Japan resulted in over 15,000 deaths and economic losses of around \$235 billion Weitzdorfer and Beard (2021). Avalanches, while less frequent, have also caused significant fatalities and damage. Hydro-meteorological extreme events have threaten civilization, eliciting concern and necessitating the pursuit of remedies to these dangerous circumstances. Numerous research has investigated diverse elements, including the simulation of extreme events Tan et al. (2020), early warning systems Rim et al. (2022), risk assessment Xi et al. (2023), and nature-based solutions (NBS) Debele et al. (2019). Previously proposed traditional models encountered difficulties, including substantial computational resource demands, restricted data availability, and subpar data quality. Nonetheless, because to developments in high-intensity computing technology and enhanced access to data on hazard events, novel models employing innovative methodologies are being developed rapidly. The advent of artificial intelligence (AI) and its subfields has rendered computational limitations obsolete.

Artificial Intelligence (AI) is a phrase usually given to machine learning (ML) or deep learning (DL) algorithms aimed at stimulating the intellectual processes of humans; for instance, the capability of reasoning, meaningful discoveries, generalization, or learning from previous experiences, etc. Liu et al. (2022). This field has drastically changed the perspective of looking at challenges that have remained unanswered for many years. Decision Tree, Random Forest, Support Vector Machine (SVM), k-means clustering, and Naïve Bayes are a few of the frequently used and known algorithms of ML that help the machine to learn and train itself from the data that is provided to the system to accomplish the assigned task of classification or prediction. Deep Learning (DL) is a subfield of Machine Learning (ML) that is inspired by the structure and function of the human brain Choi (2023). They consist of interconnected components, termed artificial neurons, and are systematically arranged in several layers, therefore referred to as "deep," allowing them to get hierarchical representations of information. LeCun et al. (2015): Putri and Athoillah (2024). Frequently used techniques to obtain the desired results include Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Long-Short Term Memory (LSTM), Natural Language Processing (NLP), Large Language Model (LLM), and so on. Review studies related to deep learning models Alzubaidi et al. (2021)in the context of application, challenges, and future work in deep learning, as well as the ability to solve complex problems, have made DL stand out from other techniques. Further, innovative approaches have demonstrated remarkable potential with promising results in diverse fields to which humans are exposed in this twenty-first century Fan et al. (2023). Terrain feature extraction and detection Li and Hsu (2022), land use land cover classification Zhong et al. (2019), urban environment assessment Mirowski et al. (2018), image geolocalization Weyand et al. (2016), toponym recognition and disambiguation Wang et al. (2020), geographic knowledge graph completion Qiu et al. (2019); Yan et al. (2019), and traffic forecasting Li et al. (2017). The latest DL approaches have achieved exceptional performance across numerous applications. comprising audio and speech processing and visual data processing Young et al. (2018), among other trends in deep learningLeCun et al. (2015).

Global problems and events that occur around us directly or indirectly possess geospatial and spatiotemporal patterns Li (2020); these patterns have a lot of potential to unveil interesting facts and relations. Realising the potential of geospatial data, big tech companies are now using this in their own way for personal benefit or for society's welfare. Geospatial data Ndu and Shoko (2024)and geographical components are also usually referred to as coordinates. These data take a central position in mapping and tackling critical phenomena Li (2020). Spatiotemporal patterns can be analyzed and visualized using various techniques, allowing for a better understanding of the complex relationships between global and local problems and events. Advancement in technology and promotion of interdisciplinary research introduced the cutting-edge field to the world in 2017. Geospatial Artificial Intelligence, abbreviated as GeoAI, is usually famous among researchers and industry communities. The term was first coined at the 2017 ACM SIGSPATIAL Conference. This is the conjunction of two distinct areas: geospatial science and artificial intelligence. GeoAI is an upcoming and exciting area for research that has provided prominent solutions with a significant level of accuracy. For instance, in environmental epidemiology VoPham et al. (2018), health care sector Ahmad et al. (2024), in subdomains of human geography such as cultural, economic, and urban geography, among others, to monitor complex human behaviors and examine non-linear relationships between human activities and their drivers Wang et al. (2024a). Additionally, GeoAI has been instrumental in optimizing urban development, environmental monitoring, and disaster management, leveraging improved data acquisition and management capabilities. However, the field also faces challenges, including non-standardized AI tool development, data privacy, security concerns, and potential biases in algorithms Gao and Wang (2023); Hosena et al. (2024); Lunga et al. (2022). Despite these challenges, GeoAI research continues to evolve, with recent advancements in spatial representation, learning, spatiotemporal prediction, and semantic analysis of geotext data Gao (2020). Moreover, GeoAI has demonstrated strengths in large-scale image analysis, automation, high accuracy, and rapid technological advancement, which are particularly evident in applications involving satellite and drone imagery Li and Hsu (2022). In summary, GeoAI's applications are vast and impactful, ranging from human geography studies to environmental and urban planning. The field's evolution is marked by both its potential to address complex spatial problems and the challenges that necessitate ongoing research and interdisciplinary collaboration. Future research directions include the development of user-friendly tools, privacy-preserving models, and the integration of non-technical aspects in explainable AI Gao and Wang (2023); Hosena et al. (2024); Xing and Sieber (2023). The continued growth of GeoAI is likely to further its contributions to various fields, fostering sustainable and intelligent development Gao (2020); Lin (2022) and Pierdicca and Paolanti (2022) of systems and so on.

The work holds significant academic value, as it consolidates existing research on the GeoAI applications and deep learning algorithms in modeling hydro-meteorological hazards, providing a comprehensive overview of the present state of the field and highlighting key advancements and methodologies. This fosters a holistic understanding of the subject and encourages interdisciplinary collaboration. The review's findings have practical implications for disaster risk management and mitigation, emphasising the potential of GeoAI to inform policy and decision-making processes. It underscores the importance of incorporating advanced modeling techniques into policy frameworks to enhance early warning systems and disaster preparedness strategies. Additionally, by outlining future research directions, the review sets an agenda for ongoing and upcoming studies, identifying gaps and opportunities for new researchers. The article aims to provide a holistic review of the work done in modeling hydrometeorological hazards using GeoAI, encompassing ML and DL algorithms, aiding researchers in understanding the current status and discovering avenues for advanced research. The conceptual framework of the proposed study focuses on investigating, categorizing, and summarizing hazard deep learning models, addressing existing forecasting issues, and comparing the long-term dependency of LSTM model variants. Figure 2 depicts the conceptual framework of the proposed study.

The rest of the paper is further organized into six sections. Section 2 presents the bibliometric analysis of the current topic undertaken for study to get an overview of the present scenario in terms of publication number over the years, contribution with respect to extreme events, and collaboration of countries and institutes. Section 3 discusses the work done in the subdomains of hydrometeorological hazards modeling by summarizing tasks, problem statements, algorithms, and datasets used. In Section 4, a case study is discussed in the context of future research in reltion to the concept of shelf-life of the model. Section 5, emphasis on limitations and future scope, can be addressed in the upcoming years by critical thinking and proposing novel techniques and approaches, ending with Section 6, which contains concluding remarks in the field of Hydro-meteorological Hazards-GeoAI in the context of status and future use and expansion.

2. 2. Data extraction methodology

Research in the field of modeling hydrological hazards with a set of DL algorithms in association with geographical location has substantially increased. With diverse topics in hazards and dataset availability, it is challenging to carry out a systematic review. However, in this context, a scoping review methodology was adopted Gonzales-Inca et al.

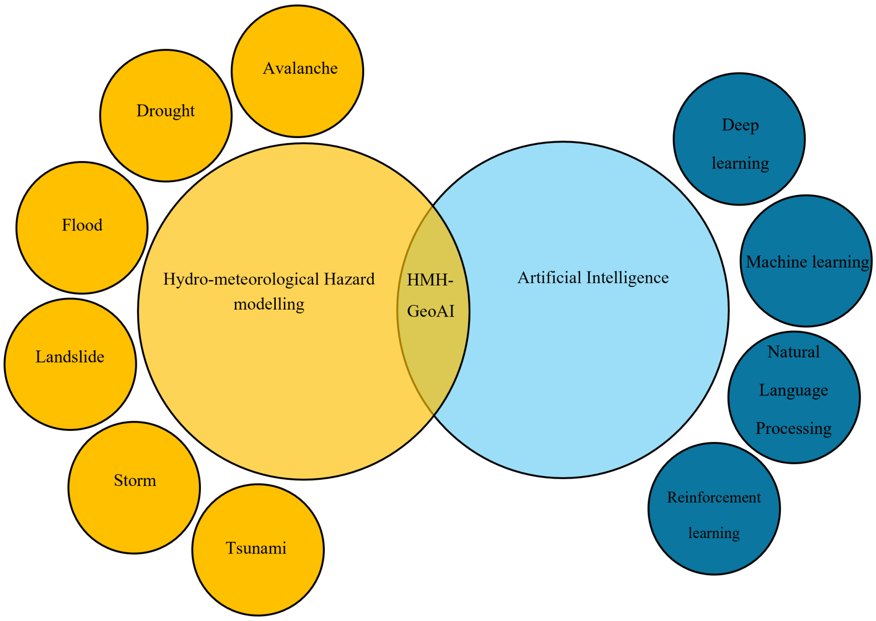


Figure 2. Conceptual framework of proposed review work

(2022); Pham et al. (2014); Sucharew and Macaluso (2019). A structured literature search was carried out to inculcate the relevant information and provide an overview of the application and research conducted to date. A literature search was carried out in a famous academic database, Web of Science (WOS). Based on the predefined keywords in the context of hydro-meteorological modeling, including “hydro-metrological hazards modeling,” “floods modeling,” “droughts modeling,” “storms modeling," “tsunami modeling," “landslides modeling," “avalanches modeling," “cyclones modeling," “tornadoes modeling," and “hurricanes modeling" combined with keywords relating to GeoAI, such as “Geospatial Artificial Intelligence,” “GeoAI,” “deep learning,” “artificial intelligence,” “LSTM,” “CNN,” “RNN,” “reinforcement learning,” and “ensembled modeling,” along with the boolean operators "OR" and "AND," publications listed in the database was 15091 publications. Further on, defining the time span of 2017 onwards with other initial keywords set in the search criteria of the WOS, 1487 articles were reported. In addition to the setting, manual screening of 1487 papers were done to ensure relevance to that of the topic. Finally, 835 (56%) got listed for further analysis.

3. Results

3.1. Analysis of GeoAI application in hydro-meteorological hazard modeling

It is very much needed to understand trends with respect to topics from distinct dimensions for good quality of research. A good bibliometric analysis facilitates researchers gettinhg a bird’s-eye view of the topic selected for research. Over the timespan of 2017 to 2024, it is clear from Figure 4 about work taken up in the field of hydro-meteorological event modeling using DL algorithms. It has exponentially grown with growing awareness about the outperformance of DL models. This rises at the annual percentage growth rate of 117%. In the year 2023, the scientific publications that were published were 227, while this year, in the middle of the year, it has reached 223.

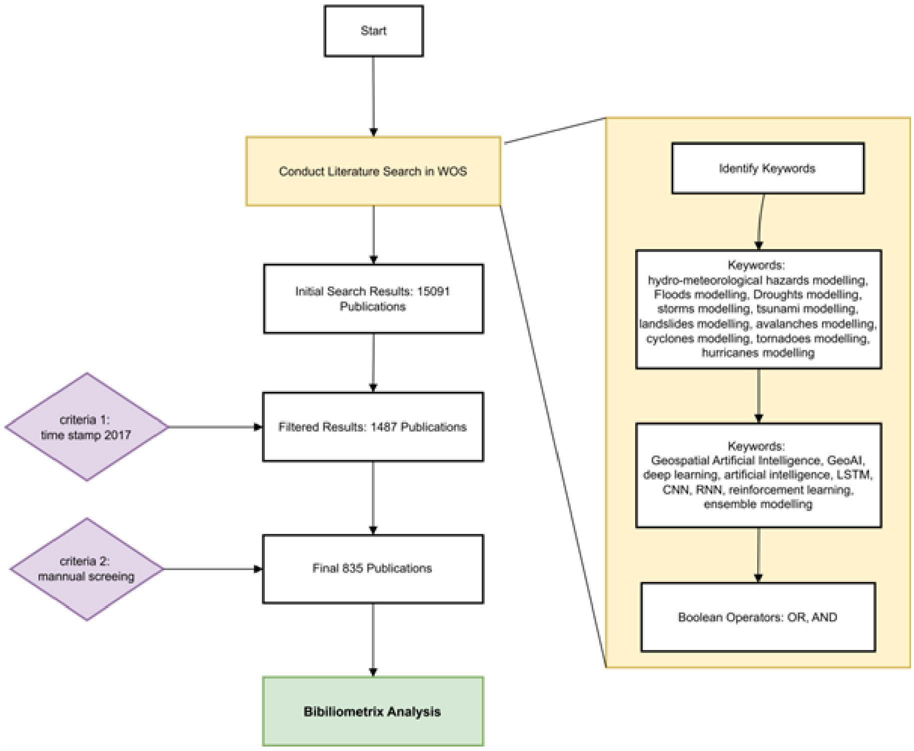


Figure 3. Data extraction methodology flow chart

With the defined growth rate, it is expected to reach 492 publica-tions. Looking at the sub-domains, 40%, i.e., 331 out of 835 finally found articles, are published related to flood. Followed by landslides 30% (239), 18% (150) Strom, while on the other hand, the least published articles were of avalanches and tsunamis, 9 and 8, respectively. Further to understand production of the scientific publications with respect to time, publica-tion data was plotted in figure 5. In 2017, one publication was reported related to avalanche, and another publication related to avalanches was reported from 2021 onwards. In 2018, papers published were of three major categories, namely flood, landslide, and storm. They have made a major contribution over the subsequent years. However, over the time pattern revised, a slight drop in the articles related to the storm is noticed. Drought has gained attention in the recent past, and as a result, publication in this year is more than 24 as compared to the last two years 2022 and 2023, with 18 articles.

To understand the main areas of focus and the technologies used in the field, a word-cloud diagram was obtained (see Figure 6 below) based on the 835 papers, where the words are clustered in two broad categories namely, domain and techniques. According to the frequency of usage of words like “landslide susceptibility,” “tropical cyclone,” “cyclone intensity,” “flood mapping,” “flood prediction,” and “drought prediction,” are more frequent, followed by the subtype of floods. While on the other hand “convolutional neural,” “machine learning,” and “artificial intelligence,” “deep learning,” “remote sensing” is common in the group of techniques.

Another aspect of the analysis was to understand which countries contribute significantly to this research domain. Figure 7 shows China was on top with 370 articles, which is closely 45% of the total articles. Followed by the USA 86 (10%) articles and at third place, India with 68 (8%). Further, these publications were categorized into

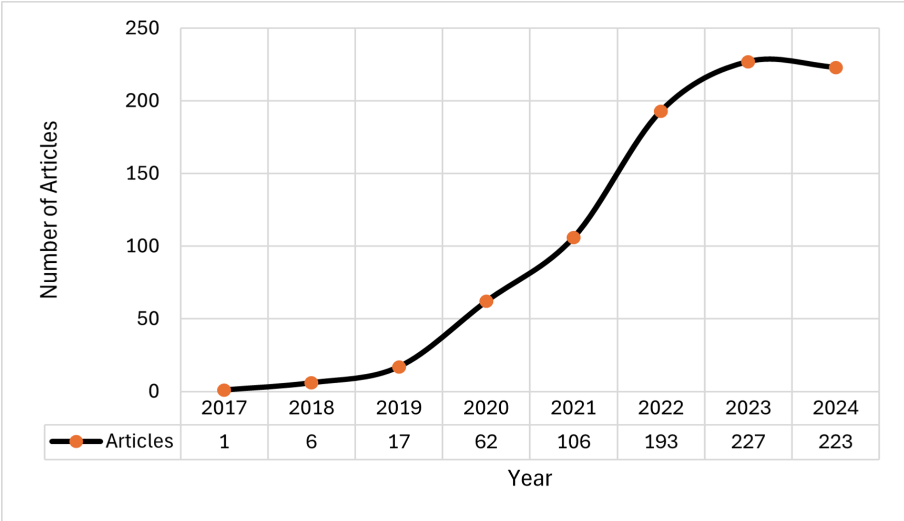


Figure 4. Number of publications per year

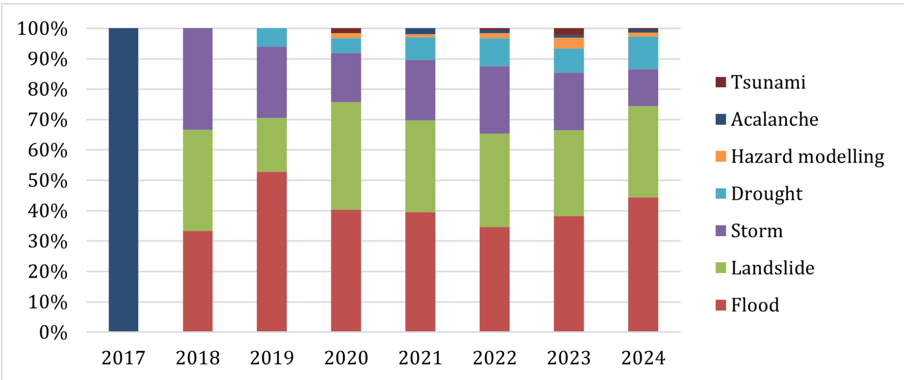


Figure 5. Publications of defined sub-domains with respect to time

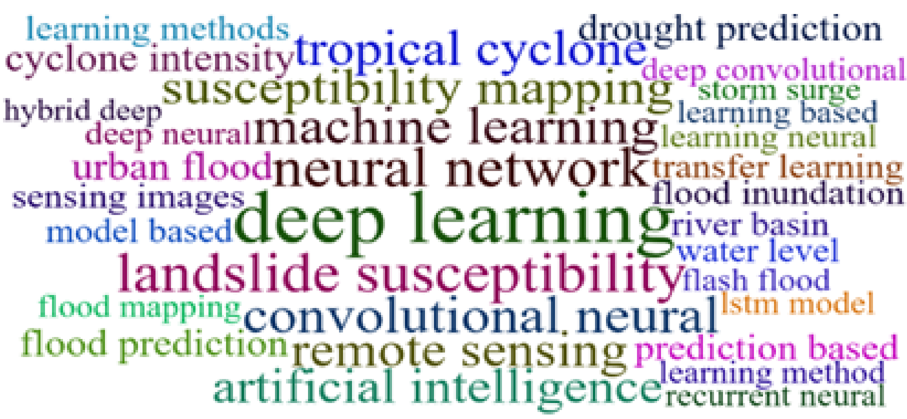
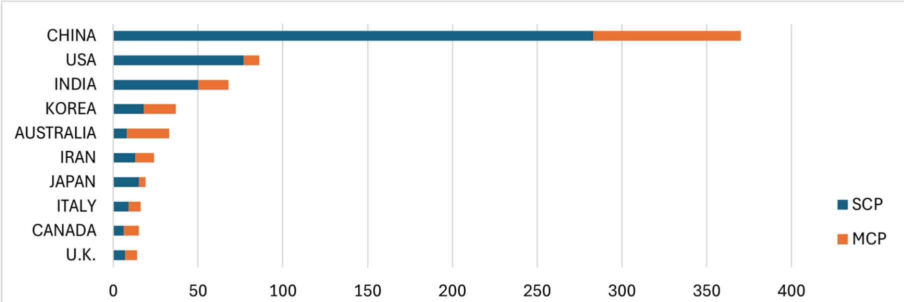


Figure 6. Word cloud of the words used in the title



	U.K.	CANADA	ITALY	JAPAN	IRAN	AUSTRALIA	KOREA	INDIA	USA	CHINA
SCP	7	6	9	15	13	8	18	50	77	283
MCP	7	9	7	4	11	25	19	18	9	87

Figure 7. Publication with respect to SCP and MCP

Single Country Published (SCP) and Multi Country Published (MCP) papers.

Collaboration between people, institutes, and country is another parameter of the potential of the research. As per the Chord diagram shown in Figure 8(a), China had large, diversified collaborations with countries like Japan, Italy, India, the USA, Australia, and many more in the GeoAI research. This network diagram has 9 clusters, of which two are major. Cluster in blue represent all countries which had high-frequency collaboration with China. The second largest cluster is contributed by other countries. However, the collaborations of other countries with China are also strongly interconnected in the same cluster.

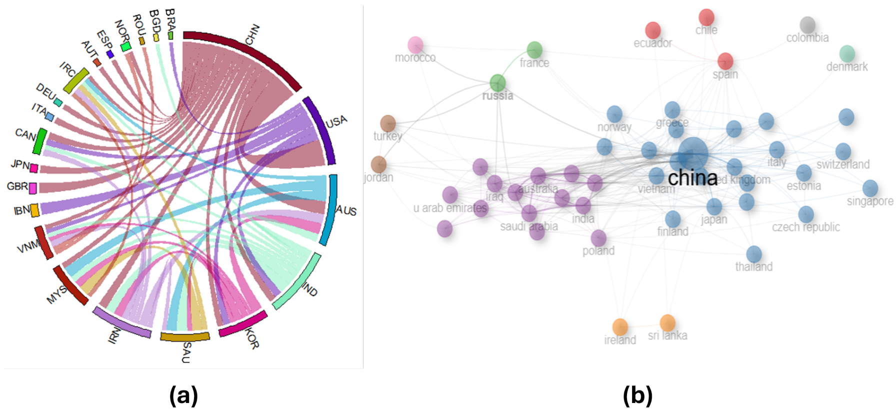


Figure 8. (a) Chord chart showing the collaboration among the countries; (b) Network chart showing the grouping (cluster) of the countries based on the collaboration done so far.

3.2. GeoAI applications in subdomain of hydro-meteorological hazards modeling

This section thoroughly summarizes the progress made in the specified subdomain of hydrometeorological hazards, focusing on the modeling of various activities at different stages that are directly or indirectly responsible for the occurrence of these events or serve as triggering factors. For example, prediction of weather in advance of hazards by nowcasting approaches, forecasting meteorological parameters Abitova et al. (2024), and hydrological parameters at a specified time, followed by post-hazard loss assessment Dikshit et al. (2024). As noted and emphasized previously, modeling extends beyond the prediction of extreme events. This discussion pertains to the hazards mentioned in relation to research conducted at various phases and degrees of events. This is crucial for identifying risk-prone locations, enabling the implementation of preventive measures in advance to mitigate economic and human losses.

3.2.1. GeoAI for Tsunami

Tsunamis are significant natural disasters that arise from underwater disturbances, posing severe threats to coastal communities. This underwater disturbance can be typically caused by underwater earthquakes, volcanic eruptions, or landslides. Unlike regular ocean waves, tsunamis can travel across entire ocean basins at speeds exceeding 800 kilometers per hour (500 mph) and may reach heights of up to 30 meters (100 feet) upon arrival at coastal areas. Although this is not as frequent as other calamities, it can't be ignored, as it has enormous destructive capacity. As per the historical data from the database of the National Oceanic and Atmospheric Administration's (NOAA) Center, there were a total of 2400 events reported across the globe. One major event occurred in the Indian Ocean in the year 2004, resulted in over 230,000 fatalities across 14 countries with economic damage totaling roughly $13 billion (NOAA, 2020). Thus, emphasizing the critical need for models that can help in disaster pre-paredness and response strategies in tsunami-affected regions. The available models for tsunami are summarized in table 1.

Table 1. Proposed models for tsunami events using deep learning.

Task	Application	Method/dataset used	Reference
Inundation	Prediction from offshore observation	DL, LSTM	Mulia et al. (2022)
	High-Resolution Inundation Maps	Probabilistic model, CNN	Gibbons et al. (2023)
Ocean waves	Traveling ionospheric disturbance (TID)	back-propagation neural network (BPNN),Bilateral projection-based two-dimensional principal component analysis (B2DPCA)	Lin (2022)
	Prediction	LSTM, Bi-LSTM, CNN-LSTM	Xu and Wu (2023)
Assessment	Post-event assessment	Pre-trained neural network models (Vgg19, Inception, and Xception)	Ahmed and Güneyli (2023)
Detection	Road detection in affected area	YOLOv5	Sakamoto (2023)
Warning system	Using Global navigation satellite system Data	CNN	Rim et al. (2022)

3.2.2. GeoAI for Floods

Intensive continuous rainfall for hours or days generally leads to the situation of flooding. Flooding is recognized as one of the most frequent and costly natural disasters globally, necessitating robust flood management models Elyahyioui et al. (2020). Over the past years, flood events across the globe have increased substantially. Traditional flood modeling methods often face challenges related to computation complexity, prompting the exploration of more efficient alternatives, such as deep learning. Deep learning models can analyze extensive datasets rapidly, with simulation times significantly reduced compared to traditional hydrodynamic models. Thus, robust models are essential for predicting heavy rainfall leading to floods, identifying flood-affected areas Banupriya and Rajiv Kannan (2020), monitoring the streamflow Liu and Biljecki (2022), using satellite imagery to understand the flooding situation of large area Tang et al. (2021), and estimating the water level in the flood-affected areas Wu et al. (2024). Table 2 summarizes the application based on the task.

Table 2. Proposed models for flood events using deep learning.

Task	Application	Method/dataset used	Reference
Depth Forecasting	Stream flow prediction	variational mode decomposition (VMD), double-encoder Transformer, principal component, supervised encoder, and supervised variational encoder	Forghani et al. (2021);Liu and Biljecki (2022)
	Daily estimation	CNN, Random Forest (RF), GTB, AIC, BIC	Naganna et al. (2023)
	Automate flow estimation	RADARSAT-1 and -2, CNN, AI, and DL	Ziadi et al. (2024)
	Water level	SARIMA, RF, LSTM, LiDAR, Gradient Boosting (GB), SVM	Atashi et al. (2022);Hosseiny (2021); Kim and Ushio (2022); Muhadi et al. (2024); Wang et al. (2023)
Flood Forecasting	Depth under rainfall	GBDT	Wu et al. (2020)
	Spatial prediction of river flood potential	MLP-FR, RF-FR, CART-FR, MLP-WOE, RF-WOE, CART-WOE	Costache & Costache and Bui (2019)
	River flood forecasting	Conv-GRU	Miau & Huang et al. (2020)
	Real-time forecasting system	AI models, DSMs	Chitwatkulsiri and Miyamoto (2023)
	Optimizing LSTM for flash flood	LSTM, Genetic Algorithm (GA), NSE	Jhong et al. (2024)
	Spatiotemporal for urban flood	Graph convolution layers, GANs	Burrichter et al. (2023)
Warning System	Rapid urban flood prediction	U-Net, ResU-Net, CRU-Net	Shao et al. (2024)
	Flood water depth	U-NET, U-FLOOD	Löwe et al. (2021)
	Multi-stage LSTM for runoff prediction	ARIMA, Prophet, Neural Prophet, LSTM	Garg et al. (2023)
	Flash rainfall warning	LSTM	Lee et al. (2020)
	Reduce flood damage	ANN, LSTM, Stack-LSTM, BiLSTM	Won et al. (2022)
	Flash flood warning system	RTI, FFG, LSTM, FFW	Zhao et al. (2022)
Detection	Flood classification in urban areas	B-CNNSVM, RF	Banupriya and Rajiv Kannan (2020)
	Flood detection using traffic images	YOLOv4 dataset	Zhong et al. (2024)
	Flood detection using satellite images	PSO-PSO-UNET	Tuyen et al. (2021)
Susceptibility Mapping and modeling	Ungauged basin mapping	CNN, RF, MLP	Saha et al. (2022)
	DEM Upscaling for mapping	DEMs, IoU	Tan et al. (2024)
Assessment and Mitigation	Vulnerability & Exposure	ANN/MLP, Deep Learning	Pham et al. (2022)
Simulation	Smart flash flood assessment	DLNN-DL4j, BLR	Nakhaei et al. (2023)
	Urban flood diversion mitigation	DCNN-LSTM-Attention	Sun et al. (2024)
	Flood simulation	IFAS, LSTM	Chen et al. (2021)
	Spatiotemporal intelligent framework	BIC-GMM-Transformer-ANN, BGTA-FMM, NSE	Jin et al. (2024)
	Satellite precipitation simulation	IMERG, LSTM, HEC-HMS	Tang et al. (2021)

3.2.3. GeoAI for Drought

This event is entirely contrary to a flood. When a certain location experiences insufficient precipitation over an extended duration, leading to a decline in groundwater levels, the desiccation of water bodies becomes a natural occurrence, ultimately resulting in a condition of drought. Water shortages adversely impact agricultural activity, ecosystems, and human settlements. GeoAI integrates geospatial data and artificial intelligence, enhancing the capabilities of drought modeling by allowing real-time data analysis and predictive modeling. By analyzing various geospatial data sources, such as satellite imagery and ground-level measurements, GeoAI can capture the spatial dependencies affecting drought dynamics. This integration leads to more comprehensive assessments of drought risks and resource management strategies, particularly in regions vulnerable to climate change. Table 3 summarizes the work accomplished to date with AI and its subdomain algorithms.

Table 3. Proposed models for drought events using deep learning.

Task	Application	Method/dataset used	Reference
Forecasting	Short-term drought index forecast	Random vector function link (RVFL), Convolutional neural network coupled with a bidirectional gated recurrent unit (CNN-Bi-GRU), feature selection (FS), Empirical Fourier Decomposition (EFD), and deep ensemble random vector functional link (Deep RVFL)	Jamei et al. (2024)
	Drought forecast	ARIMA, support vector regression (SVR), LSTM, ARIMA-SVR, least squares SVR (LS-SVR), ARIMA-LSTM, CNN-LSTM, Nash–Sutcliffe efficiency (NSE), artificial neural network (ANN), support vector regression (SVR), and explainable artificial intelligence (XAI)	Danandeh Mehr et al. (2023);Dikshit et al. (2021); Gorlapalli et al. (2022);Kang and Byun (2024); Katipoğlu et al. (2024); Tian et al. (2021); Xu et al. (2022); Zhang et al. (2024a)
Monitoring	Drought forecasting using lagged climate variables	Long short-term memory (LSTM), R2, Root Mean Square (RMSE)	Dikshit et al. (2021)
	Basin-Scale Daily Drought Prediction	CNN	Chen et al. (2024)
	Real-time monitoring	Generative Adversarial Network	Foroumandi et al. (2024)
	Monitoring	Convolutional Long Short-Term Memory (ConvLSTM), shallow learning Feed Forward Neural Networks (FFNN), Random Forest (RF), ROC-AUC, Silhouette, Chou Davies (SCD)	Foroumandi et al. (2023); Zhang et al. (2024b)
	Groundwater monitoring	Long short-term memory (LSTM) networks transfer learning (TL) = LSTM-TL	Ma et al. (2022)
	Construction of monitoring model based on multi-source remote sensing data	Moderate Resolution Imaging Spectroradiometer (MODIS) and tropical rainfall measuring mission (TRMM)	Shen et al. (2019)
Assessment	AI-based assessment and monitoring	AI models	Kikon and Deka (2022)
	DL driven	RNN, GRU, and LSTM, RMSE, MAE	Kadam et al. (2024); Maity et al. (2021)
Early warning	Cloud-based warning system	DataOps	Tamburri et al. (2022)

3.2.4. GeoAI for Landslides

Landslides are geological phenomena involving the movement of rock, earth, or debris down a slope. They occur due to numerous factors, including heavy rainfall, earthquakes, volcanic activity, and human activities, such as mining or construction. Landslides can have devastating effects, including loss of life, damage to infrastructure, and disruption of ecosystems. Landslides are a natural hazard that has substantially impacted ecosystems, communities, and infrastructure. Landslide modeling aims to assess susceptibility and predict potential occurrences. Landslides pose a significant threat to human life, infrastructure, and the environment, needing effective modeling tools to predict and manage their occurrences. The innovative approach of using deep neural networks (DNNs) and transfer learning, as discussed in Varshini and Sivadharshini (2024), has proven to be effective in geospatial analysis for landslide prediction. For instance, Yunus et al. (2022) discuss the use of DNNs in solving partial differential equations (PDEs), which could potentially be applied to geotechnical modeling aspects of landslides. Kiwelekar et al. (2020) also touch upon the use of deep learning for geospatial data analysis, which is relevant to landslide detection and monitoring. Tabel 4 summarizes the work done in the context of landslide activities.

Table 4. Proposed models for landslide events using deep learning.

Task	Application	Method/dataset used	Reference
Inundation	Prediction from offshore observation	DL, LSTM	Mulia et al. (2022)
	High-Resolution Inundation Maps	Probabilistic model, CNN	Gibbons et al. (2023)
Ocean waves	Traveling ionospheric disturbance (TID)	Bilateral projection-based two-dimensional principal component analysis (B2DPCA), back-propagation neural network (BPNN)	Lin (2022)
	Prediction	LSTM, Bi-LSTM, CNN-LSTM	Xu and Wu (2023)
Assessment	Post-event assessment	Pre-trained deep neural network models (Vgg19, Inception, and Xception)	Ahmed and Güneyli (2023)
	AI-based assessment and monitoring	AI models	Kikon and Deka (2022)
Detection	Road detection in affected area	YOLOv5	Sakamoto (2023)
	Automate using multi-source imagery	YOLOv5, YOLOv6, YOLOv7, and YOLOv8, precision, recall, f-score, and mean average precision	Chandra and Vaidya (2024)
	Detection	CNN, ResU-Net, LiDAR, LAU-Net, encoder U-Net, Swin Transformer, SeaFormer, ResNet-101, SEConvNet	Fang et al. (2022); Fu et al. (2022); Ghorbanzadeh et al. (2022); Janarthanan et al. (2023); Lu et al. (2023); Yang et al. (2022a)
Prediction	Earthquake triggered landslide	U-Net++, ResNet50, Random Forest	Yang and Xu (2022)
	Landslide target detection	R-CNN	Dianqing and Yanping (2022)
	AI integration into IoT cloud	IoT-edge-AI-cloud architecture	Joshi et al. (2023)
	Displacement using spatio-temporal approach	TGCN-LSTM, TGCN-GRU, FR, IoE	Xi et al. (2023)
	Landslide prediction using time-series SAR Dataset	RF, SVM	Al-Najjar et al. (2023)
	Soil depth	QRF, DNN	Pradhan et al. (2024)
	Land displacement	GTS, GNSS, EEMD, RNN	Niu et al. (2021); Yang et al. (2024)
Forecasting	Short-term drought index forecast	CNN-BiGRU, RVFL, FS, EFD, Deep RVFL	Jamei et al. (2024)
	Drought forecast	ARIMA, SVR, LSTM, ARIMA-SVR, LS-SVR, ARIMA-LSTM, CNN-LSTM, NSE, ANN, SVR, XAI	Danandeh Mehr et al. (2023); Dikshit et al. (2021); Kang and Byun (2024); Katipoğlu et al. (2024);Tian et al. (2024); Xu et al. (2022); Zhang et al. (2024a)
	Drought forecasting using lagged climate variables	LSTM, R2, RMSE	Dikshit et al. (2021)
	Basin-Scale Daily Drought Prediction	CNN	Chen et al. (2024)
	Real-time monitoring	GAN	Foroumandi et al. (2024)
	Monitoring	ConvLSTM, FFNN, RF, ROC-AUC, SCD	Foroumandi et al. (2023); Zhang et al. (2024b)
Monitoring	Remote sensing	DBN, CNN	Long et al. (2021)
	Hydrodynamic Landslide Evolution	VMD, SVR	Wang et al. (2022)
	Slope Monitoring	LSTM	Yang et al. (2022b)
	Automatic prediction	LR, ANN, LSTM, Bi-LSTM, Bi-LSTM-RF	Löwe et al. (2021)
	Model assessment	NB, RF, AB, MLP, CNN	Nguyen and Kim (2021)
Assessment	Hazard potential	CNN-SVM, CNN-LR, CNN-RF	Aslam et al. (2021)
	Landslide susceptibility	SSL-DNN, SVM, DNN, AUC, LR	Yao et al. (2022)
	Shallow landslide susceptibility mapping	Keras, SGD, root mean square propagation, AOM	Nhu et al. (2020)

3.2.5. GeoAI for Storm

Storms are complex meteorological phenomena characterized by violent atmospheric disturbances, which can include wind, rain, thunder, and lightning. They pose significant risks to human life, infrastructure, and ecosystems. Storm modeling using deep learning techniques is a subject of increasing interest within the field of meteorology, particularly due to the complex and dynamic nature of storm events. Deep learning, a subset of machine learning, has shown promise in capturing the intricate patterns associated with storm formation and progression. Neural Networks (RNNs), Conditional Restricted Boltzmann Machines (CRBMs), and Convolutional Networks (CNs) reveal varying levels of forecasting accuracy, suggesting that no single model is universally superior. Advancement that has taken place to model vari-ous activities in the storm see table 5.

Table 5. Proposed models for storm events using deep learning.

Task	**Application**	**Method/dataset used**	**Reference**
Detection	Fast detection model	Convolutional-based cyclone detection framework, FastRR-R-CNN	Tian et al. (2024)
	Cyclone detection	Hurricane database HURDAT2, YOLOv3, Average Precision (AP) metric	Lam et al. (2023)
	Intensity detection using cloud images	CatBoost-Based Model (CMA-BST), convolutional neural network (CNN), root mean square error (RMSE)	Zhong et al. (2023)
Prediction	Path prediction	Long Short-Term Memory Networks (LSTM), Gated Recurrent Unit (GRU), auto-encoder (AE)	Lian et al. (2020); Sattar et al. (2023)
	Recurrent neural network models	Recurrent neural network (RNN), long short-term memory neural network (LSTM), gate recurrent unit network (GRU), and BiGRU	Wang et al. (2022)
	Time series-based image prediction	CNN and LSTM	Lu et al. (2022)
Nowcasting	High-impact weather	Self-attention-based gate recurrent unit (GaGRU)	Yao et al. (2022)
	Meso-γ Scale Convective Storms	Convolutional Long Short-Term Memory (LSTM), Encoder-Decoder Model (EDM), Critical Success Index (CSI) and Probability of Detection (POD)	Kim et al. (2022)
Intensity and tracking	Short-term prediction	Long Short-Term Memory (LSTM) network, Convolutional LSTM (ConvLSTM) network, Temporal Convolutional Network (TCN), and the recently developed Transformer model	Gan et al. (2024)
	Intensity estimation	Root Mean Square Error (RMSE), Mean Absolute Error (MAE)	Bansal et al. (2024)
Simulations	Low-intensity cyclone centers	Physics-enhanced deep convolutional neural network (CNN)	Wang et al. (2024b)
	Time-series image prediction using images	Convolutional neural networks and long short-term memory (LSTM)	Lu et al. (2022)
	Tropical cyclone intensification and boundary-layer winds	Deep learning, feature selection, 1D, 2D and 3D Navier-Stokes equations, deep transfer learning, generative adversarial networks	Song et al. (2023); Snaiki and Wu (2019)
Risk management	Assessing risk of storm surges	Bidirectional Attention-Based LSTM	Lan et al. (2023)
	Model for proactive hurricane response	Deep feedforward neural network (DFNN), local interpretable model-agnostic explanations (LIME)	Wang et al. (2023)

3.2.6. GeoAI for Avalanche

Avalanche hazards refer to the risks associated with the sudden release and flow of snow down slopes, which can lead to property damage, injury, or loss of life. These events can occur spontaneously due to natural conditions or be triggered by human activities, such as skiing or hiking. There are multiple factors responsible for the avalanche hazards, such as snowpack conditions, terrain features, and climatic conditions. They are also classified into two broad categories, such as slab avalanches and loose snow avalanches. Alph, one of the famous and suitable spots for skiing, faces the threat of avalanche. This can happen due to changes in the climate and disturbances occurring naturally or by activities performed by humans on the terrain. Traditional methods of avalanche modeling have utilized machine learning models such as SVM and MDA; there is potential for deep learning techniques to enhance the predic-tive capabilities given their success in various complex pattern recognition tasks Mellit and Kalogirou (2022);Mishra and Gupta (2017). Interestingly, despite the proven effectiveness of machine learning models in snow avalanche modeling, as demonstrated by the high AUC scores in Choubin et al. (2019), the literature, it does not extensively document the application of deep learning specifically to avalanche modeling. Some recent work on modeling of avalanches is shown in Table 6.

Table 6. Proposed models for avalanche events using deep learning.

Task	Application	Method/dataset used	Reference
Early prediction	monitoring snow on high altitude	Remote sensing and AI	Taylor et al. (2021)
	Early avalanche prediction	(CNN), grey wolf optimiza-tion (CNN-GWO) and im-perialist competitive algo-rithm (CNN-ICA)	Chen et al. (2022)
Ocean waves	Traveling ionospheric disturbance (TID)	Bilateral projection-based two-dimensional principal component analysis (B2DPCA), back-propagation neural network (BPNN)	Lin (2022)
	Prediction	LSTM, Bi-LSTM, CNN-LSTM	Xu & Wu et al. (2020)
Assessment	Post event assessment	Pre-trained deep neural network models (Vgg19, Inception, and Xception)	Ahmed and Güneyli (2023)
Detection	Road detection in affected area	YOLOv5	Sakamoto (2023)
Warning system	Using Global navigation satellite system Data	CNN	Rim et al. (2022)

4. Case Study

Here we propose a case study to compare some of the widely used deep learning models in terms of their reliability and adaptability. We focus more on the model's shelf life, which indirectly touches upon the concern of reliability about the model. Based on model shelf life research, one can know when to update the model parameters. So the prediction or forecasting done by the model is aligned to the real situation and is not deviated from the original event. This will have positive implications in various fields, like helping in taking swift decisions during extreme events, accurately estimating economic and environmental loss, risk assessment, and impact assessment. Further, at the time of model selection, this can become one of the most important measures to help researchers identify the best model along with other model validation measures. The concept and framework of shelf-life measure as an alternative measure for reliability are discussed in Das and Muralidharan (2024) article. Four models were compared based on model validation measures along with shelf life as one of the measures to get the best model.

For this case study we selected the data of Cyclone Biparjoy, categorized as an extremely severe cyclonic storm that occurred in India. It lasted for 13 days; as per the IMD reports it formed in the Arabian Sea on 6th June 2023 and lasted till 19th June 2023. This event had caused large devastation in the context of the economic and environment while the 12 life was lost due to hazard. A total of 83 observations on the speed of cyclone values are used for analysis. Further, we divide the data series into two separate sets namely training and testing, in accordance with convention ratio of 70:30, 70% of data used in training the model and 30% is used for testing, (y_1, y_2, $\ldots$,

y_m) and (y_{m+1}, y_{m+2}, ..., y_T), m = 58 data points and T = 25 data points. The m training points were used to train models, and the testing data was used to determine the Absolute Percent Errors (APE) for the $(T - m)$ predictions. Based on the APEs regression line was fitted on APE(t) and figuring out the value of t at which APE(t) hit 5% (Das and Muralidharan, 2024). For different variants of LSTM model shelf life in terms of days is summarized in table 7.

$$\text{APE} = \frac{|y_t - \hat{y}_t|}{y_t} \times 100; \quad t = m+1, m+2, \ldots, T \tag{1}$$

Table 7. Shelf life of different deep learning models.

Deep learning Models	Model Shelf Life	MSE
Single Layer LSTM	8	14.00
Stacked LSTM	10	30.99
Bidirectional LSTM	11	18.15
Gated Recurrent Unit (GRU)	11	18.15

It is inferred that the single layer LSTM produces least MSE with lowest shelf life. However, the Bidirectional LSTM and Gated Recurrent Unit (GRU) produce a longer shelf life, although their MSE is slightly higher than the single-layer LSTM model. On considering the combination of model validation measures, the performances of both Bidirectional LSTM and GRU deep learning models are equally good and may be used for further prediction. However, it is recommended to run other more advanced and complex models for the same dataset for further validation and check considering more parameters like batch size, epoch value, optimization function and so on.

5. Discussion and Conclusion

Despite the promising result of GeoAI in the modeling of the various fields of hydrological hazards, there are certain areas for which justifiable connotations are sought for from research and application both. They include (i) availability and quality of data, (ii) use of multi-scale data, (iii) model complexity and interpretability, and (iv) model generalization, transferability and long-term dependency (self-lief of proposed or deployed model). Let us see how?

5.1. Availability and quality of data

In the present scenario, one is aware of the power of the data. For specific events like the above, it is challenging to get data. Few reasons can be as (a) data of already occurring events were not captured at the time point due to the unavailability of the tool and (b) an event that occurred was not reported or remained unobserved by anyone. Storms and avalanches are two such events that face challenges of data point availability and, at the same time, compromise with the quality of the data in terms of inconsistency and missing data, adversely affect the training model, and hamper the performance of prediction. Researchers are addressing this challenge by employing advanced data preprocessing techniques. Methods such as data augmentation, imputation for missing values, and filtering out noise are being utilized to enhance the quality of input data.

Additionally, there is a push for improved coordination among meteorological agencies to standardize data collection and reporting practices.

5.2. Use of multi-scale data

While dealing with the lone source data, it is easy and smooth to work with and get promising results, but to have a reliable and robust model that can outperform consistently, one needs to inculcate the concept of multiscale, also often known as multisource data. modeling data at different spatial and temporal scales adds another layer of complexity to hazard modeling. Inconsistencies in data availability across various scales can hinder accurate assessments. For instance, local data may not integrate smoothly with regional or national datasets, making it difficult to develop models that account for interactions at multiple scales. The lack of standardized methodologies for multi-scale data integration also exacerbates these issues. To address these limitations, adopting the best practices, such as leveraging machine learning techniques to improve data handling and enhancing collaboration across disciplines, is essential. These strategies can facilitate better data integration and improve the comprehensiveness of hazard assessments. Working on this will also open the door to transitioning from a single to a multi-hazard analysis framework to account for interrelations among different hazards effectively.

5.3. Model complexity and interpretability

There is no doubt about the performance of deep learning models, but the primary challenge is the complexity that is owned by these models. Due to which this is generally called a black box. While these models can capture intricate patterns in the data, they also require careful tuning of numerous hyperparameters and architectures. This complexity often results in over-fitting or underfitting, where the model performs well on training data but poorly on unseen data. This also leads to the problem of the so-called interpretability of deep learning models. The black-box nature of these models can make it difficult for meteorologists to understand how predictions are made, which is crucial for trust in forecasting systems. It is very much required to understand the functioning of the model that can help in tuning the hyperparameters and defined architectures of DL models. To address the problem and enhance performance, researchers are integrating interpretability techniques such as SHAP values (SHapley Additive exPlanations) and LIME (Local Interpretable Model agnostic Explanations). These tools help provide insights into which features significantly influence model predictions, fostering collaboration between data scien-tists and meteorologists to enhance decision-making.

5.4. Model generalization, transferability and reliability of performance over time

The problem of facing the challenge of fitting models across events is called generalization and transferability, and within events it is called reliability, often mentioned by shelf life on the model. Generalizing models in terms of different geographic areas or events is quite challenging. As models are built keeping in mind the focus of a specific event, often the data nature and structure vary from event to event, making it challenging in terms of generalizing the proposed models for all events. Also, over-period models exclude the patterns and insights obtained from the past and give more weight to the recent past, which sometimes gives rise to the problem of transferability from one model to another model or within a model. Once models are trained, tested, and deployed in real time, the question comes about the reliability of the model. The reliability is taken care of by the upcoming concept of the shelf life of the deployed model. For all these challenges, no standard methodologies are defined, and thus they remain open-ended.

The above discussed issues are mitigated by developing regularization techniques and leveraging transfer learning. These approaches allow models that have been pre-trained on large datasets to be fine-tuned for specific extreme events applications, saving time and computational resources. Researchers are also exploring the development of hybrid models that combine numerical weather prediction methods with deep learning techniques. These hybrid approaches aim to leverage existing meteorological knowledge while enhancing prediction capabilities through machine learning. The objective of this research was to determine the country with the highest number of publications, the most productive research institutes having collaboration within and across the countries, and research trends in align with the sub domain of the hydro-meteorological hazards using information from the web of science database. Therefore, the results section shows the temporal trend of publications and the most productive country and institutions. We witnessed numerous applications of GeoAI in hydro-meteorological modeling. As a result, it has undergone a transformative shift in recent years. This upward trend is majorly relying on spatiotemporal big data, remote sensing imagery, and GeoAI models to enhance research design and address the intricate, non-linear relationships between its potential drivers. The main applications of GeoAI models were in forecasting, nowcasting, detecting, simulation, and early warning systems. A wide range of GeoAI methods, e.g., CNN, RNN, SVM, RF, LSTM, Bi-LSTM, etc. algorithms, are used to facilitate this. The selection of a particular algorithm depends on the application objective, data availability, and user expertise. Although these methods have proven themselves by giving prominent results, leaving certain limitations and challenges like computation, complexity, transferability, interoperability, and generalizability of the models. Based on this literature review it is noticed that most of the current research trends focus on integrating the physical-based model with GeoAI methods to bridge data-driven and theory-driven knowledge generation. Several levels of model integration exist, but a fully developed physical-entity GeoAI model is still not available. However, the GeoAI models have shown high potential for autonomous hydrological prediction and forecasting and early warning systems. Since most of the problems discussed are complex in nature, an explicit solution may be served by using deep learning approaches, and hence, geospatial deep learning (GeoDL) may serve as an alternative for GeoAI models.

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