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Focus Paper

# Artificial Intelligence: A new era for spatial modelling and interpreting climate-induced hazard assessment

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ABSTRACT

The application of Artificial Intelligence in various fields has witnessed tremendous progress in the recent years. The field of geosciences and natural hazard modelling has also benefitted immensely from the introduction of novel algorithms, the availability of large quantities of data, and the increase in computational capacity. The enhancement in algorithms can be largely attributed to the elevated complexity of the network architecture and the heightened level of abstraction found in the network's later layers. As a result, AI models lack transparency and accountability, often being dubbed as "black box" models. Explainable AI (XAI) is emerging as a solution to make AI models more transparent, especially in domains where transparency is essential. Much discussion surrounds the use of XAI for diverse purposes, as researchers explore its applications across various domains. With the growing body of research papers on XAI case studies, it has become increasingly important to address existing gaps in the literature. The current literature lacks a comprehensive understanding of the capabilities, limitations, and practical implications of XAI. This study provides a comprehensive overview of what constitutes XAI, how it is being used and potential applications in hydrometeorological natural hazards. It aims to serve as a useful reference for researchers, practitioners, and stakeholders who are currently using or intending to adopt XAI, thereby contributing to the advancements for wider acceptance of XAI in the future.



## 1. Introduction

The UN Office for Disaster Risk Reduction (UNDRR) defines modelling as a "qualitative or quantitative approach to determine the nature and extent of disaster risk, including identifying potential hazards and their characteristics like location, intensity, frequency, and probability". In the context of natural hazards, modelling can be construed as a non-structural measure contributing to risk management. The global population is estimated to grow more than 11 billion by 2100 (United Nations, 2019). This increase will lead to tectonic shifts in the number of people living in the cities, which could reach 75% (Angel et al., 2012). Growing evidence of global climate change, driven by rising greenhouse gas emissions (Hallegatte, 2009), will have profound impacts on natural hazards, potentially increasing their occurrences and causing severe economic and human losses. It is estimated that by 2030, the total urban land in high-frequency flood zones will rise by 33% compared to 2015 (Güneralp et al., 2015).

For a long time, researchers have aimed to examine the impact of climate change and natural hazards, considering various characteristics such as frequency, duration, severity, spatial extent, and timing, among other parameters. Such analysis aims to examine past observations and analysing possible future occurrences. The techniques employed can be broadly categorised into physical models, statistical models, or a combination of both. Various research articles have addressed different aspects of climate

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change and natural hazards characteristics. As an example, Schneiderbauer et al. (2021) reviewed studies related to natural hazards risk perception in mountain regions related to climate change. The study identified critical gaps in current research and emphasized the need for more multidisciplinary research, along with risk characterisation over space and time. Gariano and Guzzetti (2016) reviewed landslide-climate studies and noted a geographical bias in their distribution, with large parts of the world remaining uninvestigated. One key finding highlighted the importance of focussing on emission scenarios, and downscaling techniques, rather than solely describing the controlling factors when examining worst-case scenarios. This approach could potentially overestimate or underestimate landslide hazards and risk. However, among the various research articles on climate change and natural hazards modelling, no study has investigated Explainable Artificial Intelligence (XAI).

In simple terms, XAI refers to the AI models whose output can be understood by humans. In the past two decades, machine learning has played a pivotal role in advancing climate change studies in the field of natural hazards. Numerous studies have extensively explored the applications of machine learning, leading to a better understanding of natural hazards and its characteristics. However, there is now a growing consensus within the scientific community and practitioners that relying solely on machine learning may not be adequate for effective mitigation strategies. As a result, XAI is gaining prominence to enhance the acceptance of ML approaches in decision-making purposes and improving modelling outcomes. Although focussed on machine learning applications have gained wide acceptability in recent years, we now recognize a gap in the transparency of these models, driving the timely need to shift the focus towards XAI. This study focuses on hydro-meteorological natural hazards, specifically on droughts, floods, landslides, and extreme events. We perform an overview of XAI studies for the above-mentioned natural hazards, highlights key findings, and provides a pathway for future course of actions required to ensure wider acceptability of XAI among both the scientific community and practitioners.

## 2. How climate change is impacting natural hazard events

According to the latest findings from the Intergovernmental Panel on Climate Change (IPCC), each of the past four decades has been consecutively warmer than any preceding decade dating back to 1850. Quantitatively, the global surface temperatures have seen a rise of 0.84 °C to 1.1 °C in the first two decades of this century compared to 1850–1900. And the IPCC is "unequivocal" in saying: "humans are to blame for this global warming". The Paris Agreement of 2015 set out a goal of limiting global temperature rise to 1.5 °C. After a major setback in 2020, when the United States withdrew from the climate accord (Schiermeier, 2020), things are back on track and necessary steps are being taken to limit the temperature rise. Although, this is not a perfect measure to tackle global warming, this was the major step taken by global leaders, like the Antarctic ozone hole debacle. A study by Farinosi et al. (2020) analysed how a decrease in global warming, achieving the targets set out in Paris Agreement would affect the exposure of global population to droughts, floods, and heatwaves. The results indicate that limiting the temperature increase to <2 °C would lead to a 50% reduction in exposure to these events in Africa, Asia, and the Americas, and a 40% reduction in Europe and Oceania. If the temperature rise is limited to 1.5 °C, further decrease of 10%–30% is expected across the globe. Additional efforts to limit it to 1.5 °C would further reduce the exposure by about an additional 10%–30% in all the areas considered.

The economic losses due to climate change are staggering, with estimated daily loss of US$202 million, killing 115 people over the last 50 years, according to a report from the World Meteorological Organization (WMO). The frequency of disasters has also increased five-fold during this period, with more extreme events being reported. However, an improvement in early warning systems and disaster management has led to decrease in casualties by a factor of 3. Fig. 1 shows a broad overview of natural hazards in 2022 captured by NatCatSERVICE.

The impacts of climate change on the Earth's atmospheric conditions is due to an increase in greenhouse gas emissions that contribute to a warmer atmosphere capable of holding more moisture. As per the Clausius–Clapeyron equation, a 1° increase in atmosphere warming can hold 7% higher moisture content, potentially leading to more intense rainfall in a shorter time, provided if the conditions are right (Coumou and Rahmstorf, 2012; Cattiaux and Ribes, 2018; Dikshit et al., 2022a,b). This leads to increase in hydrometeorological hazards like landslides and flash floods. On the other hand, warmer temperatures enhance evaporation, which reduces surface water, alters the timing of water availability, and dries out soils and vegetation (Coumou and Rahmstorf, 2012). This leads to periods of low rainfall drier than they would be in cooler conditions leading to drought like conditions. Additionally, the rise in atmospheric moisture content results in an increased supply of latent energy that fuels storms. This leads to a higher potential intensity of tropical storms as sea surface temperatures increase (Coumou and Rahmstorf, 2012).

The study of climate change impacts on natural hazards has largely focussed on two broad aspects. The first group of studies has focussed on analysing the climate model outputs under different scenario and studying its characteristics at different spatial scales. Although model outputs have their fair share of success, care must be taken when examining and interpreting the outputs. The classical case of computational simulations failing short was during the ozone hole crisis. In this instance, the models failed to account for the activation of ozone-depleting chlorine species, a process that takes place on and within polar stratospheric cloud particles at exceptionally low temperatures. Whereas, the second group of studies has focussed on examining the likelihood of extreme events, which have garnered more attention in recent times due to their rising occurrences. The catastrophic 2019/20 Australian bushfires known as "Black Summer" event have been linked to flash drought, an extreme event which has been gaining prominence in the last two decades. Such events have both short-term impacts like air quality, health, loss of human and animal lives and long-term impacts including vegetation structural changes, ecohydrological damages and several others.

Although the trend of rising global temperatures is quite apparent, it is harder to gauge the precise impact of climate change on specific extreme weather events – including hurricanes, typhoons, floods, wildfires, and heat waves. The studies on climate model outputs is straightforward, and its analysis provides an outlook towards the future of natural hazards, which typically shows a greater number of such incidences with increased risk and vulnerability. The next section focusses on these aspects providing a broader idea of the impact of climate change on different hydro-meteorological natural hazards.

### 2.1. Droughts

Droughts are episodic water deficient conditions prevailing in an area for shorter and/or longer durations (Dai, 2013). Several studies show an increase in global warming may lead to more droughts in this century, as a result of low rainfall in the subtropics

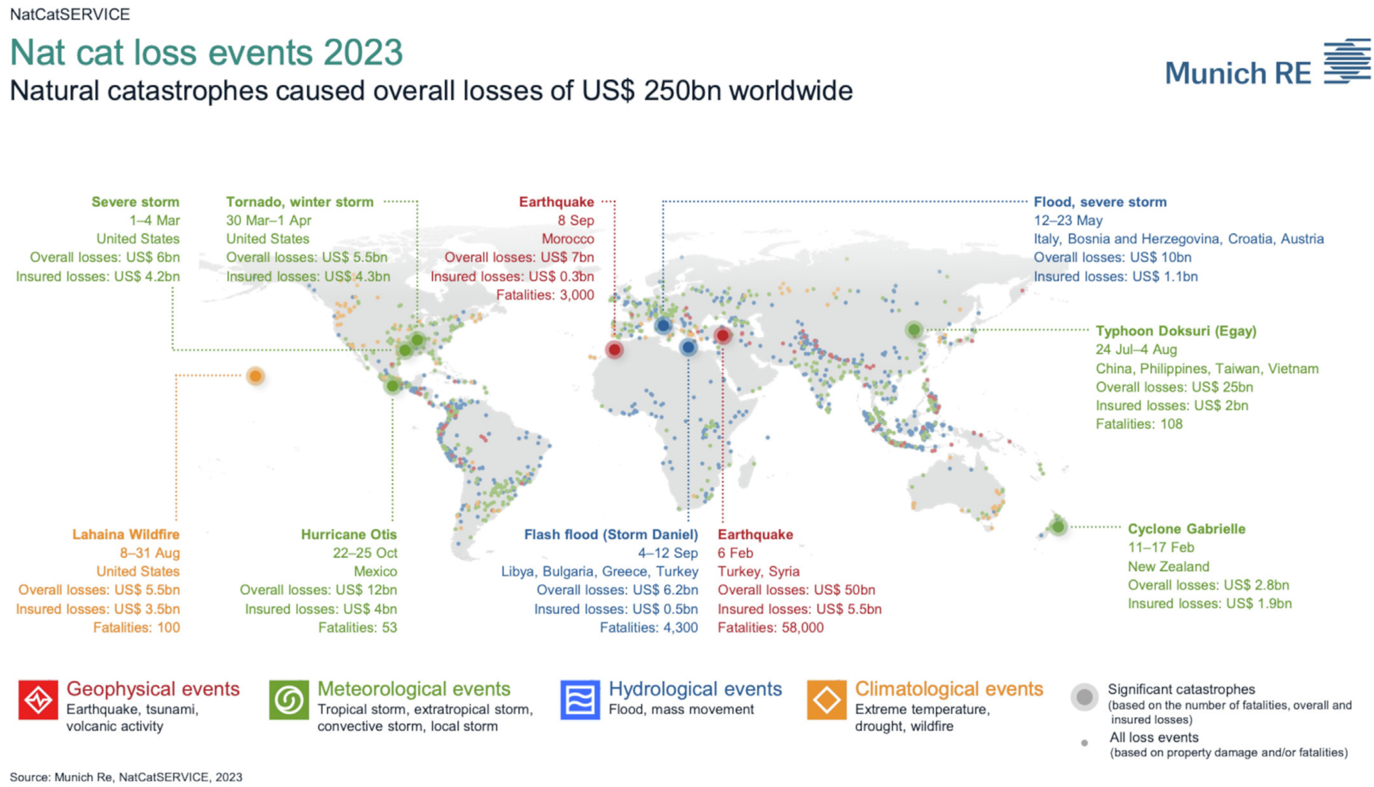


**Fig. 1.** An overview of global natural hazards that occurred in 2022 (Source: NatCat Services).

and the warmer temperatures leading to increase in evaporative demand (Dai et al., 2018). Vicente-Serrano et al. (2020) argued that heightened water uses efficiency of plants in response to rising $CO_2$ levels might decrease the evaporative demand, thus potentially alleviating drying. However, ascertaining a direct correlation between droughts and global warming can be tricky as they are variable and can occur every year or every few years, lasting for years or even decades, causing different levels of dryness. This complexity makes droughts difficult to discern random events from events caused by human-induced warming. In a recent work, Williams et al. (2020) studied human-induced climate change contribution to 21st century megadrought in the Western USA and northern Mexico using rainfall data, modelled temperature, and relative humidity, and found human-induced warming to contribute about 46% to the severity of drought.

The study by Cook et al. (2015) suggested the likelihood of megadroughts (droughts lasting for 10 years or more, such as the Australian Millennium Drought) – is projected to increase from the present 12% to 60%–80% dependent on different climate scenarios. There have been numerous studies showcasing the variation of drought characteristics across the globe for different climate scenarios. Such analysis is largely dependent on the drought indices, region and time period used to examine future drought scenario. Chiang et al. (2021) used drought indices, Standardised Precipitation Index (SPI) and Standardised Precipitation Evaporation Index (SPEI) at 6-month scale and highlighted a shift in drought frequency, drought duration and drought intensity distributions due to anthropogenic forcing. Cook et al. (2020) examined drought dynamics (rainfall, soil moisture and runoff) from the outputs of Coupled Model Intercomparison Project (CMIP6). The study found a significant increase in drying response in soil moisture and runoff compared to rainfall during the warm seasons (April–September) in Northern Hemisphere.

*2.2. Landslides*

Landslide is the movement of a mass of rock, debris, or earth under the influence of gravity (Hungr et al., 2013). The movement of these masses could be either flowing, sliding, toppling, falling, or spreading, or a combination of these (Gariano and Guzzetti, 2016). Mountains, where these hazards usually occur are called as "sentinels of changes" and respond quickly and effectively than any other geographical environments to climate changes (Beniston, 2003). The impact of climate change on landslides can be through multi-ways, an increase in rainfall and temperature would lead to increasing landslide incidences and in a form of consecutive events occurring post other natural hazards such as wildfires, heatwaves. Ravanel et al. (2017) revealed that the 2015 heatwaves in Western Europe leading to rockfalls was most likely a result of the warming of rock-wall permafrost from the 2003 summer heatwave. The sensitivity of landslides may also depend on landslide type, landslide size and its depth (Crozier, 2010). Shallow landslides which are mostly triggered by short-term rainfall can be more influenced by the parameter changes in short-term, like, rainfall intensity. However, deep-seated landslides would be affected by long-term hydrometeorological changes like changes in the monthly rainfall, groundwater, and seasonal snow cover (Bernardie et al., 2021).

Gariano and Guzzetti (2016) conducted an extensive examination of landslide research in the context of climate change. Their study performed an initial global evaluation of the prospective impact of landslides and revealed a rise in the occurrence and severity of rainfall-triggered landslides. This increase also translated to a higher number of individuals exposed to landslide risks. An interesting study on climate change impacts on landslides was conducted by Maraun et al. (2022), whereby the authors used a decade-old landslide event in Austria and simulated the event for a future climate scenario. The study focussed on four different scenarios under the possible regional hydrometeorological changes and found the landslide occurrence probability to increase by 66% in a worst-case scenario but could also decrease by 20% in a much drier soil condition and heavier rain scenario The suggestion was that if the Paris Agreement target were achieved, the associated alterations in land cover would effectively offset the consequences of climate change.

### 2.3. Floods

Floods are defined as the "overflowing of the normal confines of a stream or other body of water or the accumulation of water over areas that are not normally submerged". Floods can have multiple forms, including, river (fluvial) floods, flash floods, urban floods, pluvial floods, sewer floods, coastal floods, and glacial lake outburst floods (GLOF). Changes in rainfall (intensity, duration, timing, phase—rain or snow), and temperature patterns (impacting soil freezing, snow and ice melt and ice jam formation) can affect flood characteristics in a changing climate (Kundzewicz et al., 2014).

One of the first research works on global flood risk under climate change using outputs of 11 climate models was performed by Hirabayashi et al. (2013). The study showed an increase in flood frequency in some parts of the world (SE Asia, Peninsular India, east Africa), and decrease in flood frequency in other parts of the world for an ensemble of projections under high-concentration scenario. It also showed an increase in flood exposure would depend on the degree of warming. Arnell and Gosling (2016) studied the impacts of climate change on global river flood risk using a global hydrological model [Macro-scale—Probability-Distributed Moisture model.09 (Mac-PDM.09)] and 21 climate models at a spatial resolution of 0.5°. The estimates of the impacts vary across regions dependent on the use of climate models, however, generally, a consensus among the models was found. The results suggest an increase in flood magnitude across humid tropical Africa, south and east Asia, and consistent decreases around the Mediterranean, central America, central Europe.

### 2.4. Extreme events

The number of extreme weather events has surged dramatically in the past two decades, primarily due to increasing global temperatures and other climate shifts. Climate change will aggravate weather extremes, a uniform consensus among the scientific community. However, a fundamental issue with weather extremes is its definition, which has also been echoed by the National Academy of Sciences (2016) which argued a specific definition criterion along with a set of objective events to be used. Cattiaux and Ribes (2018) comprehensively discussed this important aspect and found a lack of spatiotemporal scale in extreme weather-related studies a major issue for defining such events. The authors proposed a four-pronged approach to define weather extremes, with a key focus on the specific event having a null probability of reoccurrence.

Extreme weather events are caused by strong and narrow bands of westerly winds known as jet streams, which flow above the Earth's surface. These currents are generated when cold air from the poles clashes against hot air from the tropics, leading to likelihood of hydrometeorological hazards. This leads to periods of unusual hot and cold weather patterns along the same latitude, and such precarious weather can remain for days or weeks leading to flash drought, heat waves and even fires (Chowdhary et al., 2019).

The impact of weather extremes on hydrological natural hazards is different across their characteristics. As an example, Sharma et al. (2018) found that despite increasing rainfall extremes, floods do not increase. An increase in rainfall should lead to more flooding is based on the fact of catchment specific conditions being invariant and streamflow is generated from rainfall alone. On the contrary, floods are dependent on various factors including location, rainfall duration, antecedent catchment conditions. Diffenbaugh et al. (2017) quantified the uncertainty associated with global warming impacts by calculating the severity and probability on four different metrics (hottest month, hottest day, driest year, and the wettest 5-d period) using the Community Earth System Model (CESM) Large Ensemble (LENS) dataset. The results suggest an increase in the severity and probability of the hottest month and hottest day of the year by more than 80%. Whereas the probability of the driest year has increased by 57% and the probability of the wettest 5-d period by 41%. Flash droughts (Otkin et al., 2018) which are extreme dry events affecting agriculture outputs, streamflow and reduction in soil moisture have also seen a rise over the past four decades. In a recent study by Christian et al. (2021), flash drought hotspots were identified with the highest frequency occurring in tropics and sub-tropics. Alizadeh et al. (2020) analysed the frequency of compound dry and hot extremes over the contiguous United States using ground-based observations in the last century and found an alarming rate of increase in rare dry-hot extremes.

#### 2.4.1. Understanding extreme events

The physical explanation of some extreme events is simple, for example, an increase in mean temperature will lead to increase in heat events and decrease in cold extremes, considering all the parameters to be same. But, if the distribution of temperature is shifted, similar to the concept of "Overton Window", the number of extremes (both hot and cold) will increase (Rahmstorf and Coumou, 2011). This simply means that the concept of "normal" weather conditions changes as extremes get more common. It means accurate predictions of such events are difficult, as other parameters change in the new normal weather condition and an in-depth examination is required.

Statistical analysis of extreme climate events in the tail of the distribution is a go-to approach to study these events. For instance, Cattiaux and Ribes (2018) used a traditional return period approach focussing on the probability of an extreme event to be null compared to the commonly used risk-based approach which uses conditioning to the concurrent climate state. As these events are, by definition, rare, such events are characterised by a small sample leading to an uncertain analysis of such events. Therefore, statistical analysis of extreme events can be challenging. Naveau et al. (2020) provided details of the different statistical methods for extreme event likelihoods in climate science. Although different statistical approaches can help to understand if a recent extreme event has significant difference than expected in an unchanging climate. However, this has two key problems: (i) Statistics can explain if a recent extreme event was significantly different from stationary or previous extreme events. But it does not address the causative variable, such as human-induced or natural factors or a combination of both. (ii) The statistics of extreme events are difficult to execute, given a lack of definition. As a consequence, the tails of the probability density function become ill-defined, and assuming a Gaussian distribution is not valid. Moreover, there exist numerous potential extreme events across diverse regions, timeframes, and weather variables (Ren et al., 2018). Coumou and Rahmstorf (2012) suggested three important requirements to carry out a comprehensive statistical analysis of extremes, which are: (i) single, comparable extreme type; (ii) time-series selection based on objective criteria, and (iii) a long-running high-quality data.

## 3. What is XAI

The exact definition of Explainable AI (XAI) is debatable and is often underspecified (Guidotti et al., 2019). XAI broadly refers to the ability to explain a process in understandable terms to a human (Doshi-Velez and Kim, 2017). When using XAI, two terms are frequently used, interpretability and explainability, which are often used interchangeably. Interpretable models refer to the use of a single model capable of comprehending the internal mechanisms of a model, whereas explainable models involve the use of a secondary model to explain the outcomes of the primary model (Rudin, 2019). Despite arguments against the use of explainable models, citing potential biases and misleading outcomes (Rudin, 2019), some instances show minimal errors. These errors can be mitigated by scrutinizing the impact of explanations on algorithmic aversions and avoiding an over-reliance on algorithmic advice (Balagopalan et al., 2022).

XAI can enhance the understanding of causation by providing insights into the internal workings of complex models. Unlike purely correlational approaches, that identify associations between variables, XAI methods, such as model-agnostic techniques or transparent model architectures, can reveal the causal relationships embedded within the data. For example, by visualizing feature importance or highlighting decision pathways, XAI allows researchers to identify and interpret factors contributing to specific outcomes. This transparency aids distinguish between mere correlations and causal factors, empowering users to make informed decisions and gain a deeper understanding of the underlying mechanisms governing a system.

In the context of hydro climatic natural hazards, we define interpretability or explainability as the ability to understand the underlying processes of different variables directly or indirectly leading to its occurrence. Google's whitepaper suggests the use of explainability for the following purposes:

- Improvement in transparency via shared understanding between the human and AI.
- Making more informed human decision when AI is used as a decision aid.
- Allow debugging if and when system behaves unexpectedly.
- Supporting fair auditing for regulatory requirements.
- Supporting generalization ability and trust to significant levels.

As there is an increasing use of machine learning (ML) approaches to better understand different aspects of natural hazards, XAI is an important catalyst in advancing our comprehension of ML uses in this field. Often, ML models can lead to incorrect conclusion, as the underlying mechanism is not very well-studied. Broadly, the use of ML models in natural hazard modelling involves selecting multiple factors (also known as controlling factors) which are fed into the model for regression or prediction purposes (Fig. 2).

### 3.1. Input variables

The choice of the predictors as input variables for any ML model is arguably the first and most important step in its application. The input variables generally have four 'V' characteristics, which are volume, velocity, variety, and veracity (Reichstein et al., 2019). Volume refers to the massive amounts of data that are generated, while velocity refers to the speed at which the data is produced and changes. Variety highlights the diverse sources of data, which can include climate data, vegetation data, and other data types. Veracity refers to the uncertainty associated with the data, which can pose challenges for accurate analysis and decision-making.

The volume and variety of data can be overwhelming. In natural hazard modelling, as a variety of factors can influence the severity and impact of these hazards. For example, rainfall data from a single flood event could generate data from multiple weather stations and create a data volume challenge. Similarly, water scarcity data can generate a considerable volume of information from different sources. The 'variety' aspect refers to the diverse types and sources of data, which could be divided into three: satellite imagery, climate models and ground-based observations (Dikshit et al.,

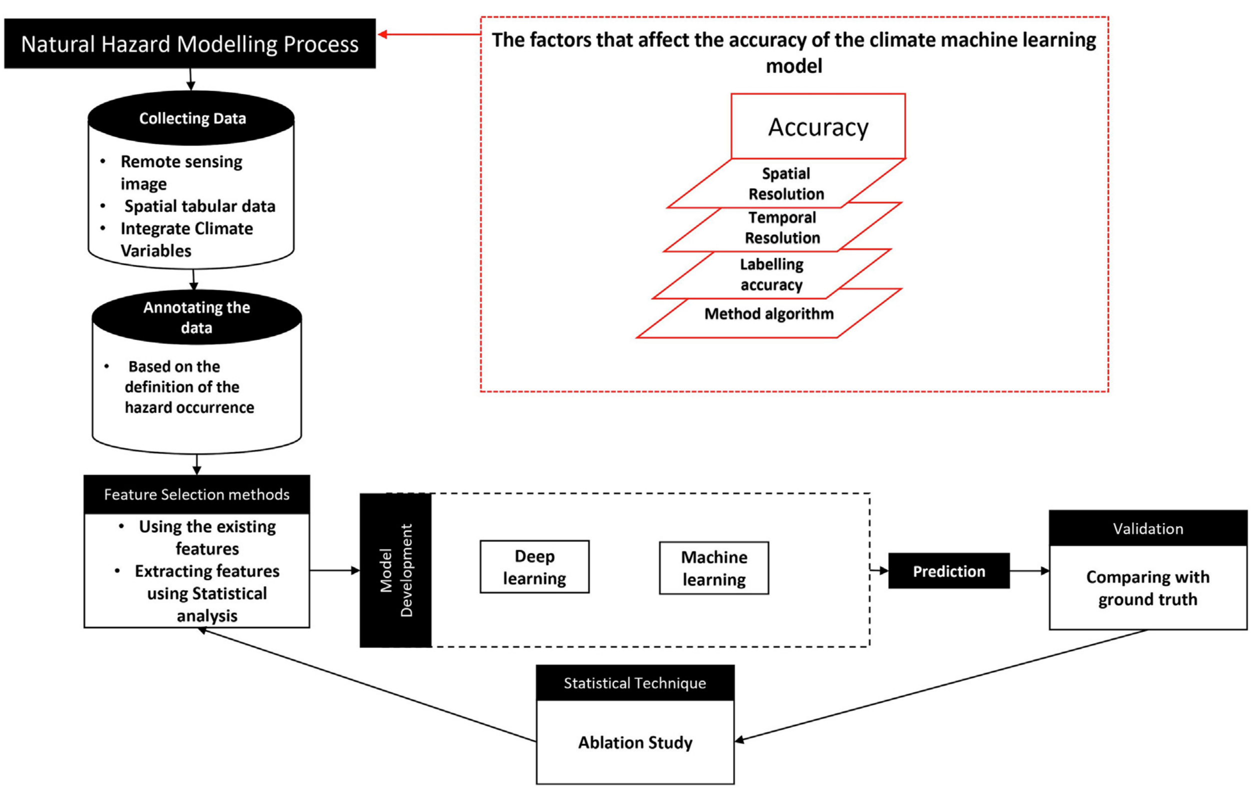


**Fig. 2.** General flowchart of the use of machine learning approaches for natural hazard modelling.

2022a,b). Climatic variables like temperature and precipitation, show high-volume and high-velocity changes, while remote sensing data, such as vegetation indices, exhibit high-volume and diverse data types. As an example, for landslides, data on topography, geology, precipitation, vegetation cover, and soil moisture are needed for effective analysis and prediction (Malamud et al., 2004; Guzzetti et al., 2006). For studying the floods, data from rain gauges, stream gauges, radar, and satellite remote sensing are used to estimate precipitation and water levels (Yang et al., 2021). In droughts, data on precipitation, temperature, soil moisture, vegetation indices, and streamflow are required for monitoring and forecasting (AghaKouchak et al., 2015; Ge et al., 2016). The variety of these data types and sources presents challenges in terms of data integration and compatibility, as well as quality control.

In the context of ‘velocity’ characteristic, examples include rapidly changing drought conditions which requires monitoring changing conditions in near real-time, particularly when frequent updates are needed to support informed decisions on crop irrigation by farmers. Similarly, floods generate vast amounts of data that need to be processed quickly to provide accurate information on the flood’s severity and risk. Finally, veracity which is arguably the most challenging part as data to analyse any hazard requires data from different sources and may have varying degrees of quality, completeness, and accuracy. As an example, global catalogues of landslides (Froude and Petley, 2018), floods (de Bruijn et al., 2019) and droughts (Spinoni et al., 2019) exist which primarily focus on major catastrophic events, albeit, small, non-catastrophic are often difficult to capture. Similarly, climatic and/or surface data may be incomplete or of varying quality dependent on the sources and various interpolation techniques (Dikshit et al., 2022a,b). Over the last decade, this aspect has seen tremendous progress, especially for remote sensing-based satellite data. Like, examining vegetation activity during extreme dry events necessitates the use of long-term fine spatio-temporal resolution vegetation indicators. Recent advances like, Europe’s S-5P satellite, carrying TROPOMI launched in 2017, providing daily Solar-Induced Chlorophyll Fluorescence (SIF) (Guanter et al., 2015) or the Advanced Himawari Imager (AHI) on board the Himawari-8 (Bessho et al., 2016) providing various vegetation data at 10-minute intervals are leading the front which would eventually support better understanding of various biomes as and when more data is available.

The selection of different variables among a myriad of available information can be tricky, and researchers often rely on assumptions, prior knowledge, and/or statistical techniques like correlation statistics, transforming variables, filtering approaches and several others. Although these approaches provide valuable information, often these approaches have major drawbacks, such as manual selection bias, computationally expensive, interactions among variables and lack of robustness. The involvement of XAI can significantly enhance the utility and reliability of ML models in natural hazard modelling.

### *3.2. Climate models*

The examination of future hazard scenarios relies on the results of Global Circulation Models (GCM), which represent the physical processes in the atmosphere, ocean, cryosphere, and land surface. GCMs are an integral part of the Coupled Model Intercomparison Project (CMIP) data archive (Taylor et al., 2012). Over the course of two decades, these CMIP projects have undergone iterative improvements, with each iteration proving to be better than its predecessor in terms of accuracy and reliability. However, some key issues with the use of these models exist:

(i) Distinguishing anthropogenic-induced climate forcing from internal variability – This represents a significant challenge when assessing the effects of global climate change at regional levels (Stocker et al., 2014). While General Circulation Models (GCMs) can distinguish between these two types of forcings, analyzing their intertwined interactions and the resulting impacts on climate variability remains challenging (Labe and Barnes, 2021). This issue is commonly referred to as a “signal-to-noise problem” within the climate research community. It is because the warming signs due to long timescales and the atmospheric concentrations of greenhouse gases due to anthropogenic activities is juxtaposed to the background noise of natural climate variability (Santer et al., 2011). Presently, distinguishing it involves the use of large ensembles of climate model simulations (Deser et al., 2020). Recently, researchers have attempted to use XAI to solve this challenge, like, Barnes et al. (2020) trained neural networks to predict the year using maps of annual-mean temperature or rainfall) from climate model simulations.

(ii) Climate prediction – One of the key challenges is climate prediction at different timescales, including subseasonal, seasonal and decadal. Typically, climate prediction utilises sea surface temperature (SST), which is the principal forcing variable of the atmospheric circulation that drives regional climate (Goddard et al., 2001; Hao et al., 2018). Neural networks have shown improvements in predictive skill across a range of scales (Ham et al., 2019). However, as Toms et al. (2020) aptly puts the current use of ML focusses on maximising the accuracy of the network’s output, while the interpretation is merely used in conjunction to confirm the high accuracy of the model with reasonable consistency from physical theory. The focus should be shifted to interpretation rather than output, as some of the recent works have shown (McGovern et al., 2019; Toms et al., 2020). The same can be applied to weather forecasting problems.

### *3.3. Examining the outputs*

The outputs are finally analysed based on various metrics, such as accuracy, precision, root mean squared error, variable importance plots and several others. Apart from examining statistical metrics, researchers attempt to understand the variable interactions using plots which determines the overall weights of the neural networks. Although these approaches provide key insights, it does not offer insights into model behaviour and identification of biases. XAI approaches can overcome this challenge by examining different aspects of model behaviour. Such as for prediction problems, which is usually a time-series data, it can provide key information on the importance of variable at different temporal lengths and explain how variables interact amongst themselves to reach a specific outcome. For classification problems, XAI models can spatially identify the relevance of variables and provide insights about any spatial differences.

However, due care must be taken when explaining a specific event from the characteristics of other variables. Although the explanation process can provide physical understanding (Trenberth et al., 2015; Vautard et al., 2016), a non-comprehensive understanding of the conditioning processes generally confuses or changes the relevant climate change questions. For a specific atmospheric circulation pattern, certain natural hazards can become less frequent, while being more frequent generally.

## 4. Using XAI effectively

Addressing the input data challenges requires integration of advanced data analytics techniques with traditional hydrological and meteorological data. Integrating XAI with traditional hydrological and meteorological data can offer promising opportunities for effective management of hydrometeorological natural hazards. XAI models can be broadly classified into two types: (i) Primary (Ad-hoc) and (ii) secondary (post-hoc) model.

### 4.1. Primary model

Primary models refer to a single model which can perform the necessary task and explain the model outcomes also known as interpretable models (Dikshit et al., 2022a,b). Without going into the detail of these examples, it focuses on scenarios where this approach can be useful. Some of the examples include,

Attention Models – Attention-based models are more appropriate which can identify important regions or features within images (Bahdanau et al., 2014). The attention mechanism of the model assigns weights to different regions, allowing the model to focus more on the most critical regions. In the context of climate change, attention-based models can be used to identify the regions where vegetation cover is most affected by climate change, or the areas where changes in soil moisture have the greatest impact on the occurrence of natural hazards.

Neural Backed Decision Trees (NBDT) – An interpretable model that combines the interpretability of decision trees with the power of deep neural networks can be better alternative for identifying the vulnerable regions by creating a heatmap (Wan et al., 2020). The NBDT model uses a decision tree to divide the input data into smaller sub-regions and then applies a deep neural network to each sub-region to make predictions. This can be particularly useful in situations where policymakers need to understand the underlying reasons for a model's predictions and allocate resources accordingly.

Generalized Additive Models (GAM) – These models can be used to identify non-linear relationships between input features and the target variable (Hasti and Tibshirani, 1995). This can help in better understanding the impact of climate change on natural hazards and their severity. One of the main challenges with the above-mentioned models is its ability to effectively incorporate both spatial and temporal information.

Graph Neural Networks (GNN) can prove to be an effective tool to exploit the interrelationships among the variables and predict the likelihood of natural hazards. For extreme dry events, like, flash droughts GNNs can exploit the complex relationships between multiple variable types which could be used to either develop a robust prediction model and/or distinguish flash drought events from heatwave events.

### 4.2. Secondary model

Secondary models explain the model outcomes using a different algorithm based on the outcomes of a primary model. Some examples include:

Shapley Additive Explanations (SHAP) – Th genesis of the model began in game theory with the aim to quantitatively calculate the contribution of single player in a multi-player game (Shapley, 1953). The aim was to objectively divide the total gain among the players based on individual's contributions to the outcome. The solution was to provide the fair reward to each player and assign a unique value using features like local accuracy, consistency, and null effect (Shapley, 1953). Lundberg and Lee (2017) used this simple concept in the field of ML and has significantly improved understanding of the model outputs. SHAP provides different explainers depending on the type of ML models used and these explainers can be interpreted using different plots, which are summary plot, dependence plot, individual force plot and collective force plot. The details of different explainers and plots were described in detail by Christoph (2019). It's use cases include selection of input variables to be fed into the model as well as examining the final outputs. The examination of the final outputs using SHAP plots are often used for different natural hazard problems, including landslide susceptibility modelling (Al-Najjar et al., 2022); drought prediction (Dikshit and Pradhan, 2021), flood susceptibility modelling (Pradhan et al., 2023).

Local Interpretable Model-agnostic Explanations (LIME) – It is a simple model which explains the model by focussing on the neighbourhood of the prediction as opposed to explaining the model globally (Ribeiro et al., 2016). The above are examples of specific models, and this is not an exhaustive list. There are several other models, like, layerwise relevance propagation (Toms et al., 2020) and more models will be developed overtime which will address the shortcomings of the available models.

## 5. XAI in different natural hazards

This section describes the different explainability studies conducted for hydrometeorological hazards, providing details on the processes used and the outcomes. For this, a Scopus based search with the terms "explainable*" OR "interpretable*" was used in conjunction with "landslide*", "flood*" and "drought*" from 1 January 2011 to 31 December 2022. Only journal articles written in English were considered for the review. A total of 3122 articles were identified and subsequently categorized based on the annual distribution of studies conducted for each hydrometeorological hazard. Fig. 3 shows the spatial map of different studies conducted globally along with the number of research articles for each hazard. The landslide studies have been marked as red circles, flood studies have been marked in blue and drought as light brown. The regions highlighting the country where XAI based study was conducted. It does not represent the actual study areas and is not a representative of different XAI based methods being used. This emphasises the rise in XAI based studies in the last decade, where the most-studied disaster is flood (53.3%), followed by landslide (25.9%) and drought (20.8%). As the figure shows the African continent has the least number of studies in this domain, prompting researchers to use XAI based approaches to study the continent.

The case studies have been divided into two categories: (i) XAI studies using a primary model, and (ii) XAI studies using a secondary model as described in the previous sections.

(i) XAI studies using primary model.

Maxwell et al. (2021) used Explainable Boosting Machines (EBM) to predict the probability of slope failure in West Virginia, USA. EBMs are a type of Generalized Additive Model (GAM). The model outputs provide information on how the model uses the predictors rather than providing estimations. Such an approach works well for regression purposes, however, for classification problems with EBM, the contributions of features are expressed as log odds and not probabilities. Dikshit et al. (2022a,b) used an attention-based model to forecast drought index for Eastern Australia. The results show the importance of including climatic variables as inputs along with the short-term and long-term dependencies of input variables for forecasting at different lead times, thereby providing a holistic view of interpretable models.

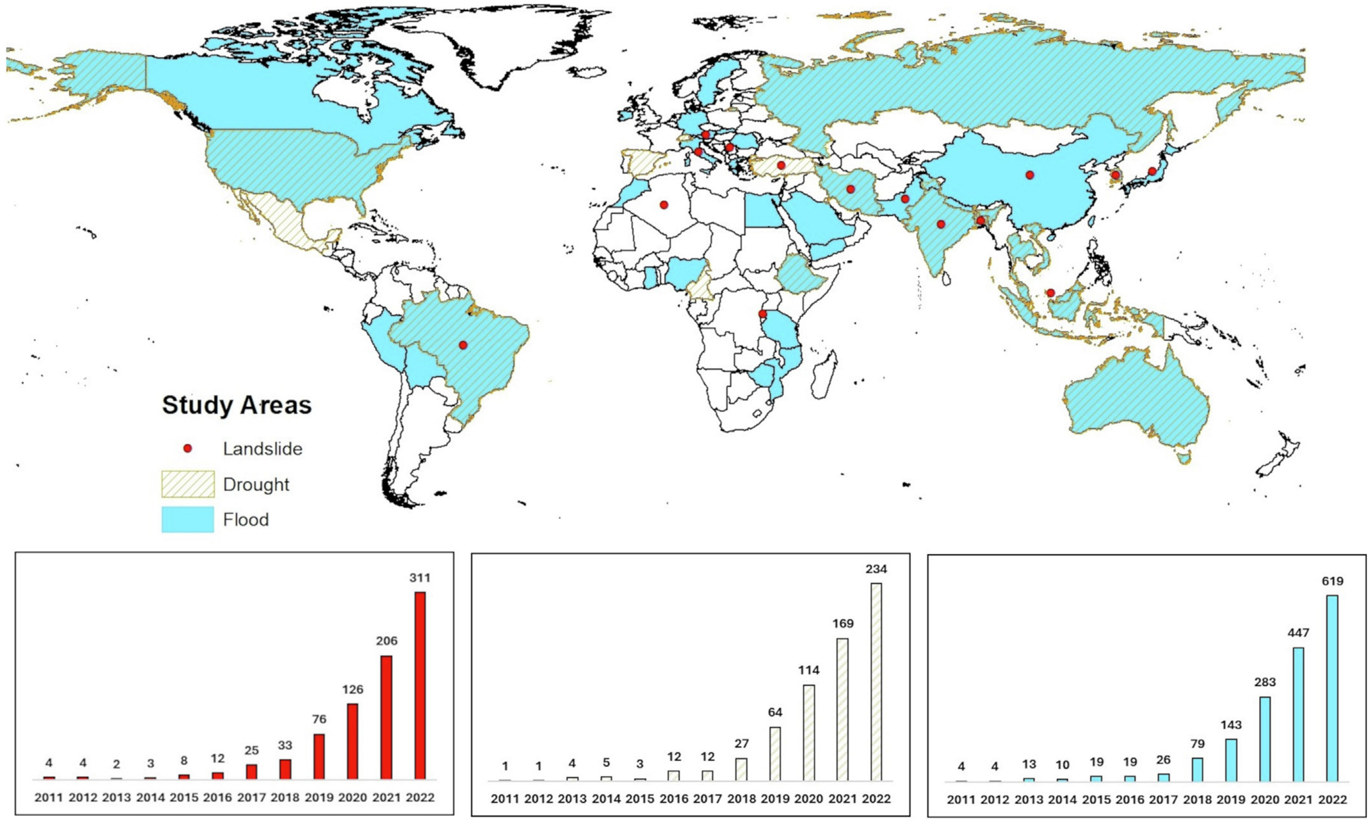


**Fig. 3.** Spatial distribution of the research papers for XAI-related studies for different hydrometeorological natural hazards.

(ii) XAI studies using secondary model.

Al-Najjar et al. (2022) used SHAP to examine the variable importance and impact of individual predictors for landslide susceptibility mapping in south-western Bhutan using two ML models (random forest and support vector machines). The study shows the difference in SHAP summary plots using RF and SVM, highlighting the benefit of using RF over SVM for the specific case study. Similar study for landslides and floods was also conducted by Ekmekcioğlu and Koc (2022), using Extremely randomized trees (ERT) coupled with the particle swarm optimization (PSO) model for Kentucky river basin, USA. However, individual force plots explaining the differences in variable interactions for a true and false landslide/non-landslide was not conducted in these studies. Collini et al. (2022) used different ML models to predict landslide evens using static and time-varying variables and later explained the model outcomes using SHAP. The model outcomes were interpreted for both global and local feature relevance, showcasing the variable importance and interdependencies to achieve the final output. Dikshit and Pradhan (2021) used SHAP to explain the model outcomes for drought forecasting in Eastern Australia. The results showcase how different input variables interact for known drought and non-drought conditions, replicating the behaviour found in physical-based models. Chakraborty et al. (2021) used XGBoost model in conjunction with SHAP to forecast the long-term groundwater level under different future climate scenario. The study showcases the dependencies and interactions among the variables, in a complex human-natural system, not captured well by linear models. Rampal et al. (2022) developed an interpretable deep learning model to improve rainfall downscaling over New Zealand and found the model capable of learning complex and physically plausible relationships.

## 6. Discussions and future directions

Machine learning has and will play a vital role in understanding the mechanisms of any hydrometeorological event. As available data and computational capacity improve, ML models including XAI models will play a central role in understanding and examining natural hazards. Over the last two decades, significant improvement has been achieved with the advancements in neural networks, thus enhancing our capability to understand natural hazards. However, policymakers and several researchers preferred to stay away from this technological advancement, as natural hazards are dynamic in nature and any action taken based on ML models will need transparency and accountability. Wrong prediction resulting from an output of a modelling study can be costly in real world decision making. Using XAI can assist in mitigating future events and develop strategies for effective natural hazard management, response, recovery, and resilience. However, there are key areas where the traditional ML modelling approaches can be benefitted with the use of XAI (Fig. 4).

(i) Data Availability and dimensionality reduction – A good ML model is hungry for data and the availability of high-quality data remains a challenge. There has been significant progress in the retrieval, storage, and use of different datasets, yet there exists incomplete, inconsistent, or outdated data, a common finding in developing and under-developed countries. This could also involve the need of domain expertise in certain situations, such as collection of landslide inventory data. The use of XAI approaches can help to remove the manual process involved.
The examination of natural hazards usually involves several input variables of varied types. Processing such a dataset is

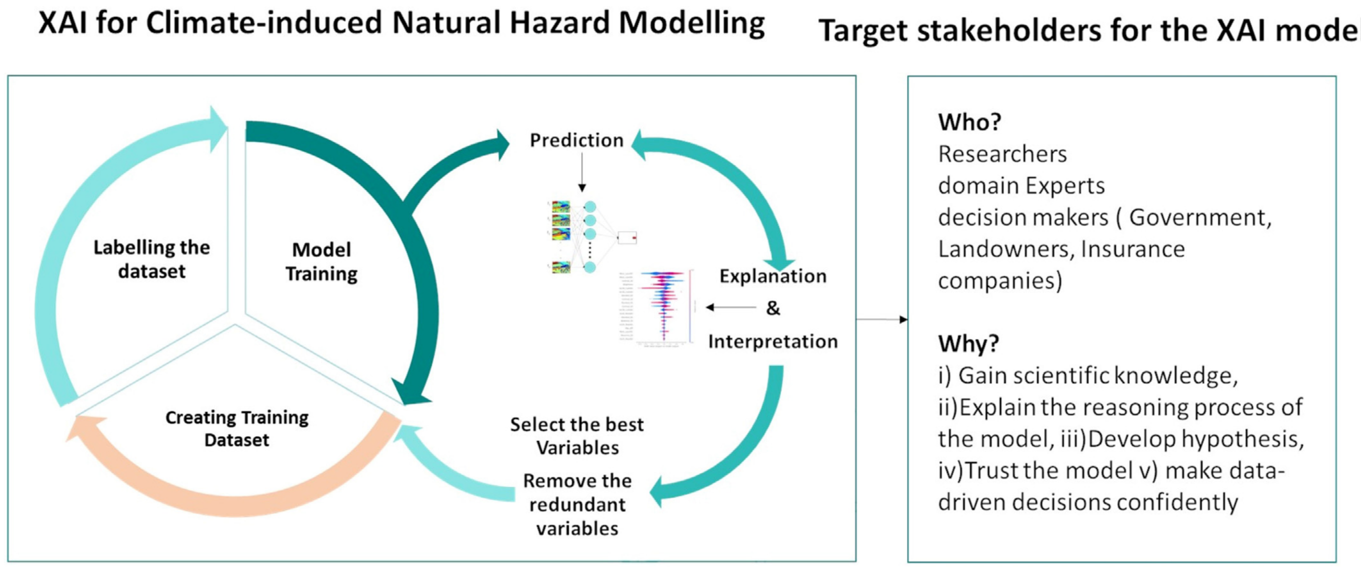


**Fig. 4.** Future directions of the use of XAI for climate-induced hazard assessment.

time-consuming and computationally expensive. Identifying the optimum predictors, along with removing the redundant variables, can reduce data dimensionality without a decrease in model performance. The selection of variables can involve statistical and/or expert knowledge. XAI can help to identify the key variables without any bias, such as studying susceptibility modelling for different hydrometeorological natural hazards include different variable types (e.g., geological, geomorphological, meteorological and vegetation) and feeding these variables into a ML model can lead to overestimation. Implementing XAI techniques, like SHAP can help to identify only the key variables and reducing the number of variables.

(ii) Data explanation – Although, XAI models have opened new research directions, there are challenges with the widespread application of such models, especially for decision-making purpose. XAI has the capability to answer the questions like what data has been used to train the model and why that data was chosen. For example, by analysing data on past floods or droughts, an XAI model can determine the environmental variables (like, temperature, precipitation) impacting such events at various spatial (local to global) and temporal (daily to multi-year) scales. This meaningful information will help researchers and ML developers to build more robust models and assist with further AI system development. Similarly, it can also be applied for other research questions such as explaining individual predictions by identifying the key features in case of examining flood inundation depth for urban areas which could help to identify critical urban features like, proportion of impervious surface and the distance of drainage channel that contributes to increased flooding. Other cases of application include analysing spatial variable relationships between event and non-event locations in cases of drought and landslide. The examination of such interrelationships can help to understand why a region suffered from a natural hazard and other regions within a localised context did not. Similarly, the benefits of these models can also be replicated to other hazards, which would help to understand the importance of variables in a quantitative manner. These models can also be used to identify the most important features within dataset before serving as input to the model. This process would in turn help in removing redundant variables with a definite reason and not solely relying on multicollinearity tests like, variance inflation factor. However, there is need for interdisciplinary research involving deep understanding of the underlying science and data analysis to effectively understand the XAI outputs.

(iii) Intrinsically interpretable models and benchmarking – Rudin (2019) made an important distinction in the use of secondary and primary XAI models. The article emphasized the need to use intrinsically interpretable models for high-stakes decision making and avoid the use of post-hoc models for such purposes. Hence, some researchers are focusing on the development of self-explainable models, and examining the differences in the use of both these approaches would be key for the acceptance of XAI in the broader community.
In general, the utilization of XAI is often confined to applying these methods to benchmark problems, a common practice in the field of computer science, where users are expected to have a predefined understanding of what the outputs should resemble. However, this typically relies on an individual's subjective visual assessment of the output and their prior comprehension of the problem, both of which are susceptible to biases. To address this issue, Mamalakis et al. (2021) introduced the concept of "attribution benchmark datasets" with the aim of achieving comprehensive and interpretable XAI or falsifiable XAI research, as proposed by Leavitt and Morcos (2020). In these datasets, synthetic inputs and outputs are meticulously designed and generated in a manner that allows each input feature to be objectively derived, serving as a reliable benchmark for the evaluation of various XAI approaches.

(iv) Transparency – Another challenge revolves around ethical considerations, including issues of transparency and accountability. Like, XAI models should be developed with appropriate data collection and management practices to ensure that they do not reproduce or perpetuate existing biases. This could also include the use of ML models for predicting extreme events which would be biased given most of the extreme events do not have a definite definition. Although XAI has great potential to provide deeper insights on extreme events, it is important to understand it examines the relationship based on the data ignoring the underlying physical process. For an evolving concept, due care must be taken before applying an ML model to model or interpret the XAI outputs.

(v) Transferability – XAI can address a major problem in natural hazard modelling, which is model transferability. Often models are developed for specific natural hazards, which are not translated to other similar hazards. By providing insights to how a model reaches its decisions, XAI can be useful to adapt and apply in similar contexts, where the underlying triggering factor is common. It is crucial to acknowledge that comprehending the internal workings of a model can enhance its reusability. Nonetheless, making an incorrect assumption in this regard can have severe repercussions (Caruana et al., 2015). Transferability should consistently align with the inherent characteristics of an explainable model, but it's important to note that not every transferable model should automatically be deemed explainable (Arrieta et al., 2020).

## 7. Conclusion and way forward

The beginning of 21st century saw a boom in machine learning applications in geosciences and natural hazards modelling, which has improved our understanding of natural hazards and Earth system in general. As the acceptance of neural networks grew, questions began to arise around its black-box nature. Hence, a new field of study, known as Explainable Artificial Intelligence (XAI) has emerged in recent years, which focuses on understanding the model behaviour in a manner that humans do. Significant advances using XAI have been made in the field of computer science, medicine and more recently geosciences and natural hazard modelling is recognising its significance. This article is a comprehensive review of the nuances involved with XAI, providing details about different XAI approaches, case studies and future directions of work.

The future research directions for XAI in climate-induced hydrometeorological natural hazards should address limitations observed in traditional machine learning models. Key areas of focus include integrating XAI with decision support systems to enhance decision-making during hazardous events. Exploring causation within XAI is another avenue, aiming to develop models that not only predict climatic events but also illuminate intricate causal relationships between various factors. Real-time explainability is crucial, necessitating frameworks that offer transparent insights into AI model predictions promptly. Human-AI collaboration becomes paramount, exploring interfaces that facilitate meaningful interactions between AI systems and human experts. Given the complexity of extreme events, XAI can offer unique insights, such as identifying key variables leading to abrupt shifts in precipitation patterns. These research directions are pivotal for addressing challenges associated with data-driven models.

In summary, the key takeaways from this article are:

(i) XAI is gaining prominence and a potential solution to the "black box" problem in AI. Presently, the focus is on the application of different models to specific scenarios, which should be extended to improve the model accuracy, understanding and data handling challenges.

(ii) It highlights the various cases of application which could be explored using different XAI techniques and are yet to be explored, in the context of hydrometeorological natural hazards in the face of climate change.

(iii) Natural hazards have a unique problem of historic poor-quality data and a present rich-data quality, that can provide comprehensive insights into such events using XAI. Emphasizing more XAI studies can help tackle longstanding challenges effectively.

## CRediT authorship contribution statement

**Abhirup Dikshit:** Investigation, Data curation, Formal analysis, Modelling, Writing - original draft. **Biswajeet Pradhan:** Conceptualization, Supervision, Validation, Visualization, Resources, Project administration, Writing - review & editing, Funding. **Sahar S Martin:** Data curation, Writing - original draft. **Ghassan Beydoun:** Writing - review & editing. **M. Santosh:** Writing - review & editing. **Hyuck-Jin Park:** Writing - review & editing. **Khairul Nizam Abdul Maulud:** Writing - review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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