# Are we going towards "no-brainer" risk management? A case study on climate hazards

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**Abstract:** The overall risk management domain is stepping into its 4.0 phase by implementing and increasingly relaying on cyber-technological systems. Enhanced computational power provides the capability of processing collected databases for prediction and preparation purposes. In fact, early warnings can lead to suggestion for proactive strategies, or directly initiate the action of autonomous actuators ensuring the required level of system safety. But have we reached the promises of digital risk management yet, or will we ever reach them? A traditional view on safety defines it as the absence of accidents and incidents. A forward-looking perspective on safety affirms that it involves ensuring that "as many things as possible go right". However, in both the views there is an element of uncertainty associated to the prediction of future risks and, more subtle, to the capability of possessing all the necessary information for such prediction. This uncertainty does not simply disappear once we apply advanced Machine Learning (ML) techniques to the infinite series of possible accident scenarios, but it can be found behind modelling choices and parameters setting. In a nutshell, "there ain't no such thing as a free lunch", i.e., any model claiming superior flexibility usually introduces extra assumptions. This contribution will illustrate a case on climate-driven disaster data extracted from the Emergency Events Database (EM-DAT) where ML techniques are used to understand natural disaster mortality and unravel underlying causes and influential factors that can inform decision-making and be relevant for risk reduction efforts. This manuscript may allow to affirm with certain confidence that present risk management systems are not even close to a "no-brainer" condition in which the responsibility for human and system safety is entirely moved to the machine. However, this shows that such advanced techniques are progressively providing a reliable support for critical decision making and guiding society towards more risk-informed and safety-responsible planning.

**Keywords:** Risk management, Climate hazards, Natural disasters, Machine Learning, Clustering

## 1. INTRODUCTION

At the beginning of the 90s, Prof. Diekmann [1] stated the following: "New analysis tools are emerging, which have the potential to allow complex risk analyses to be performed simply. These new tools, which are underpinned by decision analysis and, lately, expert-systems technology, may lead to powerful, yet simple, approaches to the representation of risky problems." Such optimistic prediction on the future of risk analysis was also accompanied by the suggestion of a possible interdisciplinary direction. "Future approaches to risk analysis will certainly rely more on the advances being made in Artificial Intelligence (AI) and cognitive sciences. New computer tools and knowledge-representation schemes will unquestionably lead to new techniques, insights and opportunities for risk analysis."

In the same decade (1997), the Russian chess grandmaster Garry Kimovich Kasparov (former World Chess Champion, ranked world No. 1 from 1984 until his retirement in 2005) lost a chess game with the chess playing computer Deep Blue by IBM, which was an example of Good Old-Fashioned Artificial Intelligence (GOFAI) [2]. On that game, Kasparov later stated the following: "Deep Blue was intelligent the way your programmable alarm clock is intelligent [3]. Not that losing to a 10-million-dollar alarm clock made me feel any better."

In general, risk management has tried to make use of AI, but it has unevenly progressed since the mentioned events. It neither respected Diekmann's prediction (methodological gaps are still present [4]), nor turned into "programmable-alarm-clock intelligence" thanks to the progressive refinement of Machine Learning (ML) models and the increase in available computing power [5].

This contribution aims to outline what AI, and in particular ML techniques, can bring to risk analysis and management by illustrative examples related to climate-driven events (e.g., storms, floods, drought, heatwaves) . ML techniques are used to understand natural disaster mortality and unravel underlying causes and influential factors that can inform decision-making and be relevant for risk reduction efforts.

### 1.1. Machine Learning and Big Data

AI is intelligence demonstrated by machines and it is divided into sub-fields based on technical considerations, such as particular goals (e.g., "robotics" or "machine learning"), the use of particular tools ("logic" or artificial neural networks), or deep philosophical differences.

This contribution focuses on the sub-field of Machine Learning (ML). ML refers to techniques aiming to program computers to learn from experience [6]. ML is known for providing meaning to raw data and solving practical problems in a reliable and efficient way. These problems require machine assistance since the amount of data and the complexity of the statistical patterns imply that humans would not be able to solve them via traditional techniques [7].

ML rely on a collection of examples of some phenomena, to be used for training and finding patterns that can help make decisions and predictions for new, unseen information [8]. ML has several practical applications in present industrial processes [9], and it may be the key to unlocking the value of safety data to perform novel risk management systems. Therefore, a computer may run a ML algorithm to assess risks for safety-critical industries (e.g., Oil and Gas). It would allow processing a large amount of information in the form of indicators from normal operations and past undesired events (from mishaps to major accidents), which would be used for training the algorithm. Due to the subjectivity of risk definition [10], risk level cannot be assigned to each event with certainty and a supervised approach may be needed. Practical examples of ML adoption in risk management refer to predict system losses and possible risks in undesired cases [4]. Among the most used ML algorithm, one can find the clustering, used to reveal (in an unsupervised way) meaningful groups within a dataset based on underlying patterns or structures [11].

Increasing attention has been dedicated to monitoring safety barrier performance through indicators, as a way to assess and control risk. Indicators may report a series of factors: physical conditions of a plant (equipment pressure and temperature), number of failures of an equipment piece, maintenance backlog, number of emergency preparedness exercises run, amount of overtime worked, etc. [12]. Øien et al. [12], Paltrinieri et al.[13], [14], and Landucci et al. [15] have produced several reviews on risk and barrier indicators. They show that definition and collection of risk indicators have become consolidated practices in "high-risk" industrial sectors. Such trend towards definition and collection of higher numbers of indicators [16] demonstrates the mentioned challenge on big data process for risk level assessment.

In recent years, several studies have focused on ML techniques to support natural disaster risk management. One widespread approach is the analysis of disaster databases and reports to extract relevant information and support risk-informed decision-making [17]. An exhaustive overview of ML applied to natural risk management may be found in [18], [19]. However, most of these investigations focus on illustrating the potential and effectiveness of their approaches. Still, little attention has been paid to the role of ML and whether its extensive use will lead to a condition where the responsibility for human safety is entirely moved to the machine. This study attempts to bridge this knowledge gap by illustrating an example of ML for natural disaster risk management and evaluating the need for human knowledge to interpret and contextualize the results.

### 1.2. Climate-driven natural disasters

Data analysis of climate hazards can aid risk management by shedding light on disaster characteristics, challenges, differences amongst regions, and similar events. Climate hazard management denotes the systematic actions focused on reducing the negative effects of disasters [20].

Mitigation measures contribute to climate hazard management by minimizing, monitoring, and reducing the probability of severe consequences, the corresponding avoidable impacts, and the unfortunate outcomes of natural hazards [21]. The risk for individuals inflicted by climate disasters differs based on societal vulnerability and exposure, and environmental conditions [22]. Climate change has forced more than 20 million people to move from their homes each year [23]. The development level of a country might affect the consequences of a natural disaster. It is often remarked how those living in poverty are hardest hit despite being the least responsible for climate change.

The increasing frequency of natural hazards led to greater attention worldwide devoted to mapping and reducing natural risks [24], unraveling and explaining potential impacts on societies. Vulnerability in this context can be a risk factor, but also an outcome: disaster exposure may lead to poverty causing damage to assets and livelihoods [25]. Besides, larger climate-driven disasters often cause extensive property damages and a high number of fatalities. Research has shown that natural disaster-related damages and mortality have increased in the past decades [23], [26].

Further research is needed to develop systematic approaches on disaster causes and impacts to improve responses, anticipation capacity, design risk prevention and mitigating interventions prior to or following major climate hazards. The International Disaster Database (EM-DAT) developed by the Centre for Research on the Epidemiology of Disasters (CRED) gathers data on natural disasters and maps them into different classification categories, impacts, and causes.

The study focuses on these climate-driven disasters in terms of societal impact, both on populations and properties, as they can be of relevance for industrial systems as well. EM-DAT is analyzed by using ML algorithm to investigate potential clusters of countries that show commonalities and subsequently can drive to common natural risk management mitigations.

## 2. EXAMPLE OF ML-BASED FOR RISK MANAGEMENT

### 2.1. EM-DAT database

The EM-DAT database was created following the 1980's investigation by CRED. The study was carried out to serve the purposes of humanitarian action at national and international levels. The initiative aimed to rationalize decision-making for disaster preparedness, as well as provide an objective base to assess vulnerability and set priorities.

The database is compiled from various sources, including United Nations agencies, non-governmental organizations, insurance companies, research institutes, and press agencies, e.g., United Nations Department of Humanitarian Affairs (UN-DHA), European Union Humanitarian Office (ECHO), International Federation of the Red Cross and Red Crescent, the Office of Foreign Disaster Assistance (OFDA-USAID), International Committee of the Red Cross and Red Croissant (ICRCRC, Switzerland), International Decade for Natural Disaster Reduction (IDNDR) [27].

Currently, EM-DAT collects more than 25000 disasters between 1900 - 2020. All the events in the EM-DAT database fulfill one or more of these entry criteria [27]:

- Deaths (10 or more people deaths)
- Affected (100 or more people affected, injuries or homeless)
- Declaration/Appeal (declaration by the country of a state of emergency and/or appeal for international assistance)

The reported incidents worldwide involve 189 countries, distributed as follows:
- About 15000 accidents are related to natural impacts (e.g., drought, extreme temperature, flood, landslide, storm, wildfire, etc.),
- About 10000 accidents refer to technological impacts (i.e., industrial, transport, and miscellaneous impacts).

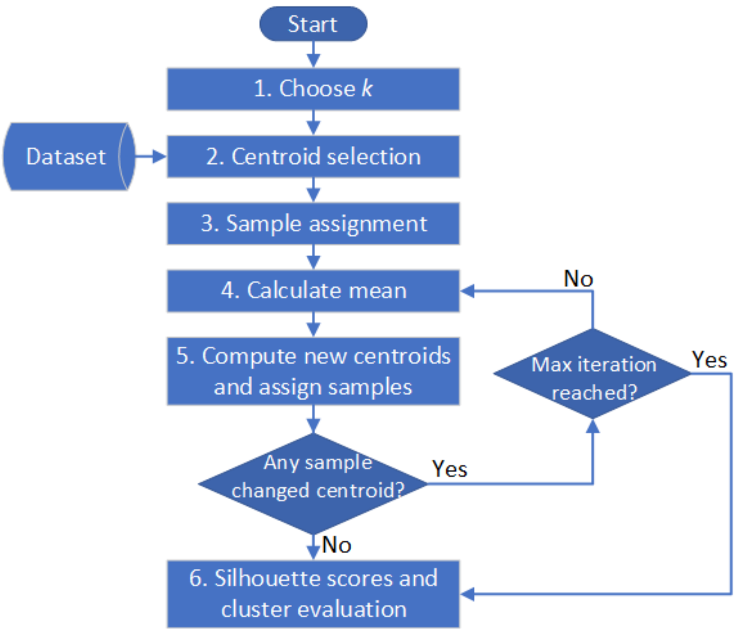
Technological events have not been considered in this study, and attention has been directed toward natural disasters. More specifically, only climate-driven disasters are examined (e.g., storms, floods, droughts, heatwaves). Other types of natural disasters (e.g., geophysical, biological, and extra-terrestrial) have been excluded from the analysis.

The database incorporates 43 parameters (e.g., location, date, damage, fatalities, disaster type, origin, reconstruction cost, insured damage, appeal, impacts) to fully detail the characteristics of the accident and allow its analysis [27].

## 3. METHOD

K-means is one of the most frequently used and effective clustering algorithms, as proved by results obtained in several diverse application contexts [28]. K-means has been used in this study to cluster countries found in EM-DAT, based on their similarity toward natural disaster exposure. The algorithm tries to group data by minimizing the within-cluster-sum-of-squares, which represents the distance between each data point and the cluster centroid [29]. Figure 1 depicts a flow chart in which explain the steps to perform a clustering algorithm.

**Figure 1. Flowchart of k-means-based clustering**




K-means is a partitioning algorithm that relies on the concept of distance and local optimization to perform clustering. One of the most common metrics to compute distances in k-means is the Euclidean distance, as it is flexible to accommodate different operational situations. Another characteristic of the algorithm is that it requires the user to specify the number *k* of clusters (step 1 in Figure 1). The algorithm will always converge, but it is vulnerable to local minima. This will depend on how centroids are initialized. By running the algorithm with a specified number of clusters $k$, $k$ random samples from the dataset are allocated as cluster centroids.

After the selection of $k$, the main steps of the k-means clustering algorithm are:

- Initialization: the step to choose k initial centroids (step 2 in Figure 1)
- Looping: iterative steps to stabilize centroids until reaching convergence or a maximum number of iterations (steps 3, 4, and 5 in Figure 1). This loop requires two sub-steps:
    - Assigning samples to their nearest centroid based on a selected distance measure.
    - Compute the mean of the assigned samples and create a new centroid.

K-means with Euclidean distance has been used to map countries' clusters as they appear in the EM-DAT database.

Clusters must be validated to check the logical cohesion between the clustered items and to compare the separation among them. A useful metric for validating the significance of clusters is the silhouette, whose scores represent the distance from one sample to the samples in the neighboring clusters [30]. Silhouette coefficients range between -1 and 1 where values close to 1 indicate high compactness within the cluster, which in turn implies longer distances among the sample and the neighboring clusters. Silhouette scores close to 0 indicate overlapping clusters, while negative values indicate a possible misplacement of the sample [31].

Within this case study, the algorithm runs on a set of selected features considered relevant for the scope of the analysis: World region, Disaster count, Missing data, Gross Domestic Product based on Purchasing Power Parity (GDP PPP), Population density, Disaster type, Total deaths. It is worth mentioning that GDP PPP and Population Density data are not available in EM-DAT and have been retrieved from external sources [32], [33]. In addition, categorical features have been converted into numerical features and standardized through z-score normalization.

## 4. RESULTS AND DISCUSSION

### 4.1. Clusters

The clustering algorithm allowed splitting the 189 countries involved in natural hazard accidents into 40 clusters of varied sizes. Considering the relatively large number of clusters, a complete review would be impractical. Therefore, a selection of the most interesting clusters is presented. Two criteria have been considered in the selection: cumulative number of fatalities and cluster compactness. Also, clusters that comprise only one country are treated separately.

The cluster with the highest cumulative number of fatalities and with more than two countries is:

Cluster 1. Bangladesh, France, Germany, Japan, Poland, South Korea, and Vietnam.

The cluster with the largest average intra-cluster silhouette score is:

Cluster 2. Cayman Islands, Saint Kitts and Nevis, and Turks and Caicos Islands.

On the other hand, the cluster with the smallest silhouette score is:

Cluster 3. Jamaica, Madagascar, Mauritius, Sint Maarten.

In addition, 11 clusters include only one country. Examples of these clusters are:

Cluster 4. China;
Cluster 5. India;
Cluster 6. USA.

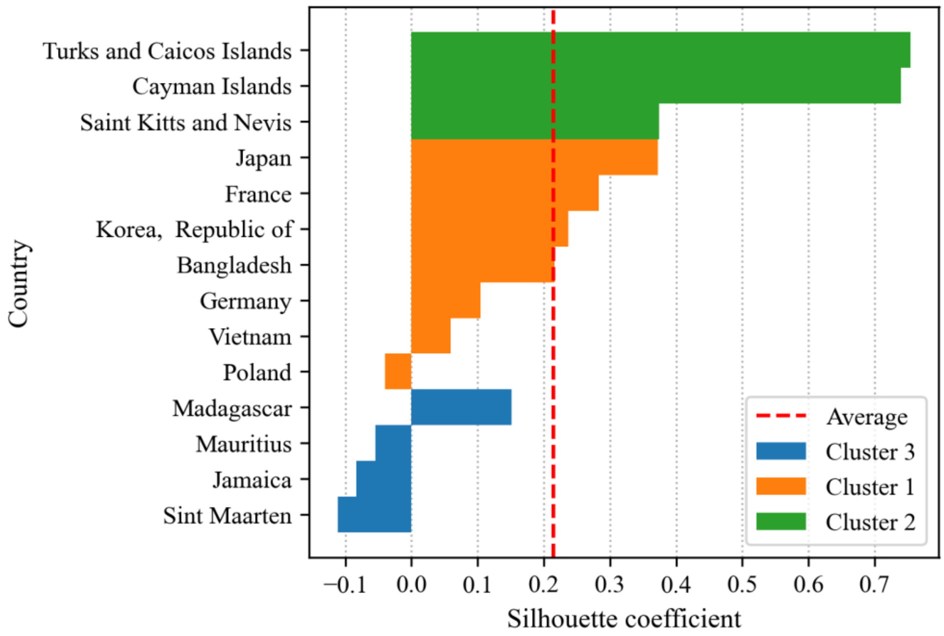
Relevant information about the countries in each cluster is summarized in Table 1. For each country, Table 1 displays the number of fatalities, the most frequent and severe natural disaster types, the location, and the income group [34]. Clusters and countries are displayed in descending order of number of fatalities.

**Table 1. Relevant information about the countries in the selected clusters**

| Cluster | Country | Fatalities | Threats (fatalities) | Location | Income [34] |
|---|---|---|---|---|---|
| 4 | China | 17.006.913 | Flood (10.321.805)<br>Drought (6.503.534) | East Asia | Upper-Middle |
| 5 | India | 4.515.665 | Cyclone (160.575)<br>Drought (4.250.320) | South Asia | Lower-Middle |
| 1 | Bangladesh | 2.590.573 | Cyclone (627.048)<br>Drought (1.900.018) | South Asia | Lower-Middle |
| | Japan | 50.565 | Cyclone (32.838)<br>Flood (13.513) | East Asia | High |
| | France | 28.793 | Heatwave (27.517) | Western Europe | High |
| | Vietnam | 26.025 | Cyclone (19.189)<br>Flood (3644) | Southeast Asia | Lower-Middle |
| | Germany | 10.213 | Heatwave (9361) | Western Europe | High |
| | South Korea | 8932 | Cyclone (3727) | East Asia | High |
| | Poland | 2378 | Cold wave (2085) | Central Europe | High |
| 6 | USA | 41.359 | Storm (30.942) | North America | High |
| 3 | Madagascar | 3161 | Cyclone (2834) | Sub-Saharan Africa | Low |
| | Jamaica | 1391 | Flood (730)<br>Cyclone (604) | Caribbean | Upper -Middle |
| | Mauritius | 81 | Cyclone (28)<br>Flash flood (11) | Sub-Saharan Africa | Upper-Middle |
| | Sint Maarten | 4 | Cyclone (4) | Caribbean | High |
| 2 | Saint Kitts and Nevis | 6 | Cyclone (6) | Caribbean | High |
| | Cayman Islands | 2 | Cyclone (2) | Caribbean | High |
| | Turks and Caicos | 0 | | Caribbean | High |

The silhouette plot of the selected clusters is displayed in Figure 2. Clusters that comprise only one country have not been included because their silhouette score equals zero.

**Figure 2. Silhouette plot of the selected clusters.**




The average silhouette score of the selected clusters (red vertical line in Figure 1) is equal to 0.21. Instead, the average silhouette score is 0.24 if all the 40 clusters are considered. It is also worth noting that Poland, Mauritius, Jamaica, and Sint Maarten show negative silhouette scores.

### 4.2. Discussion

Data in Figure 2 and Table 1 allows some observations on cluster composition, similarities and differences between members of the same clusters, and opportunities for inter-country knowledge sharing. In the remainder of this section, each cluster will be briefly commented, similarities and differences will be discussed in terms of fatalities, disaster type, development level, and economic possibilities. The discussion will focus on investigating whether the proposed method has effectively grouped countries that show similarities and subsequently can drive to common natural risk management mitigations.

The three most populous countries in the world – i.e., China, India, and the USA – belong to stand-alone clusters and have not been considered similar to any other country in the dataset. This result is not surprising considering the unique characteristics of these countries in terms of location, area, exposure to natural threats, and economy. The number of fatalities in India and China is respectively one and two orders of magnitude larger than any other cluster. Also, China has a unique exposure to riverine floods and drought, which together caused 99% of the total number of fatalities (Table 1). India on the other hand is naturally exposed to severe droughts, which have caused more than 94% of the total deaths (Table 1). From an economic perspective, China has witnessed extraordinary growth in the last three decades and is currently the second-largest economy by GDP (Gross Domestic Product) in the world after the USA [35]. On the other hand, India is the sixth-largest economy, and its annual growth rate in terms %GDP has been larger than the USA but smaller than China since 1990 [36]. Geographically, China, India, and the USA are respectively the third, fourth, and seventh-largest countries by area [37], and they cross various climate zones [38]. In light of their unique characteristics, the grouping of these countries in stand-alone clusters appears reasonable. Also, a large body of research has focused on the study of climate-driven disasters in these countries [39]–[43]. Existing studies and governmental mitigation and response plans might be good opportunities to (i) share knowledge and lesson learned between these three countries and (ii) provide critical assistance to smaller, less-developed countries which have similar exposure to climate-driven events (e.g., Vietnam concerning flooding and Bangladesh concerning storms and droughts).

Regarding clusters with more than one country (i.e., clusters 1, 2, and 3), it can be observed that some clusters show apparent internal similarities while others are more difficult to interpret. For instance, cluster 2 was chosen because its members have the largest average similarity score (Figure 2), which indicates high compactness and separability [44]. Indeed, countries in this cluster, namely Saint Kitts and Nevis, Cayman Islands, and Turks and Caicos, are extremely similar: they all are archipelagos in the Caribbean Sea, classified as high-income countries, with a relatively low number of fatalities. Due to their location, the islands have been affected by several cyclones and storms. Nevertheless, the number of climate-related deaths is extremely low. Considering the already significant success of these countries in coping with tropical storms, there might be little scope for inter-country knowledge sharing. However, islands in different clusters with similar exposure to natural threats (e.g., Fiji Islands) may be inspired by the measures adopted by the countries in cluster 2. In other words, although knowledge transfer between countries in high-compact clusters may not appear interesting, there are still interesting learning opportunities for countries that have similar exposure but that were put in a different cluster due to significant differences in, e.g., the number of fatalities.

Cluster 3 was selected for the low silhouette score of its members, which are Madagascar, Jamaica, Mauritius, and Sint Maarten. Three out of four countries show a negative silhouette score, indicating low compactness and separability [44]. However, it is still possible to spot some similarities between the members of this cluster, which are islands or archipelagos, relatively close to each other in pairs. In spite of the differences, a more detailed analysis might reveal hidden similarities and interesting learning opportunities.

Cluster 1 was chosen because it shows the largest cumulative number of fatalities between clusters with more than two countries; therefore, it is definitely the most critical and interesting within the whole database. The cluster comprises Bangladesh, Japan, France, Vietnam, Germany, South Korea, and

Poland. Figure 2 shows that the members of this cluster have positive silhouette scores except for Poland, whose score is -0.04. Therefore, Poland may be considered an outlier and will not be considered further in the analysis. Interestingly, in spite of the relatively high compactness, cluster 1 appears rather heterogeneous. It comprises countries from different locations, with diverse socio-economic backgrounds and exposure to natural hazards. It is not trivial to identify similarities in this cluster. However, this should not be perceived as a limitation. On the contrary, comparing countries with both similarities and differences in disaster situations, demographics, and economy might be extremely interesting. It is not desirable to create 'perfect' clusters of countries for natural disaster comparison. A cluster of neighboring countries with the exact same possibilities and disaster situations is not advisable because there is little room for improvements and knowledge transfer. For cross-country learning to be relevant and helpful, it is beneficial that some countries are more exposed, developed, or prepared for disasters than others. However, countries should also exhibit some similarities in the disaster patterns and threats to facilitate comparison and the creation of actionable insights.
In light of these considerations, clustering algorithms must be considered tools to reveal similarities and guide the analysis towards countries that may be more interesting to compare. However, in-depth analyses are still needed to make sense of data, interpret clusters, discover hidden similarities, and enable cross-country learning and knowledge transfer. In other words, clustering algorithms have the potential to greatly simplify the analysis by removing the need for manual screening. However, human intervention and expert knowledge are needed to convert groups of related countries into actionable insights.

Considering the number of fatalities, Bangladesh can be regarded as an outlier due to its extreme history. The total number of climate-driven natural disaster fatalities in the country has been almost 2.6 million since the year 1900. Manual analysis of the EM-DAT database reveals that despite an increasing trend in the number of critical events, fatalities have decreased in recent times. Specifically, in the time period following 1992, the number of deaths has decreased, major outliers were less frequent, and resulted in fewer deaths. Nevertheless, tropical cyclones and storm surges have been particularly severe since 1900 [45]. The decreasing fatalities in spite of an increasing number and severity of cyclones suggest a significant improvement in mitigating measures. From an economic point of view, Bangladesh is relatively less developed than the other members of the cluster. GPD value is larger than Vietnam's but significantly lower than the other counties.

Vietnam is the fourth country in cluster 1 in terms of total fatalities. Similar to Bangladesh, the country is exposed to tropical cyclones and storms, although the number and severity of critical events are lower. Similar to Japan, a relevant part of the fatalities is caused by floods. Nevertheless, Vietnam has experienced a decreasing trend of fatalities in the past 20 years, although the decrease is less pronounced than in Bangladesh. From an economic point of view, Vietnam went from being one of the poorest countries in the world to becoming a lower-middle income country [35]. However, the development in Vietnam started later compared to other developed Asian countries like South Korea and Japan, but the growth rate has been faster than in Bangladesh [46].

Japan is the second country in cluster 1 in terms of total fatalities. Due to its location and geography, the country is particularly exposed to tropical cyclones, storms, localized rains, and floods [47]. However, the relatively large number of fatalities does not indicate unpreparedness or ineffective response to natural hazards. On the contrary, the continuous exposure to natural threats pushed the country towards increasingly effective mitigation measures [48], [49]. In fact, more than 82% of the total deaths were registered before 1960. After that year, the number of fatalities decreased drastically and has remained relatively stable. However, the trend has reversed during the last 20 years, and the number of fatalities has slowly returned to grow. This change may be related to the increasing frequency and severity of natural hazards. It is also worth mentioning that a relatively new type of event, namely heatwaves, has caused the most fatalities in the last ten years. Specifically, heat waves have caused 735 deaths since 2010, while tropical cyclones and floods caused 591 and 447 fatalities over the same period. Interestingly, heatwaves caused only 135 events from 1900 to 2010. The recent increasing trend in the number of fatalities differentiates Japan from Bangladesh and Vietnam. From an economic point of view, the Second World War had marked the beginning of extraordinary growth for Japan, which is currently one of the leading industrialized countries in the world.

Germany and France have significantly fewer fatalities than Bangladesh and Japan, and they are the only European countries in the cluster. Another difference is that most fatalities in Germany and France occurred after 2000 and were primarily caused by heatwaves. For instance, the heatwave of 2003 is responsible for 68% and 92% of the total deaths registered in France and Germany, respectively. This may indicate that rising global temperatures and climate change have affected countries that were not significantly exposed to natural threats in earlier times [50]. France and Germany have strong and stable economies and are respectively the seventh and fourth countries in the world in terms of GDP [35].

South Korea is the country with the least number of fatalities in cluster 1. Like Japan and Vietnam, South Korea is exposed to storms and floods, which are responsible for most deaths. However, extreme events are less frequent and intense in South Korea than in the other Asian countries in cluster 1. Also, the dataset analysis reveals a downward trend in the number of fatalities. Overall, South Korea is less exposed to natural hazards than Japan, Vietnam, and Bangladesh. However, more frequent and severe events are expected in the future to the effect of climate change [51]. From an economic point of view, the country grew from being a lower-income before 1980 to be a high-income economy in 1995 and currently the tenth country in the world in terms of GDP.

In light of the considerations made for countries in cluster 1, the following suggestions and learning opportunities may be identified:

1. Vietnam and Bangladesh may be considered similar with respect to exposure to tropical cyclones. In addition, both the countries are low-middle income economies. Nevertheless, Bangladesh has been more successful in mitigating the effect of extreme events. Therefore, Vietnam could be inspired and learn from the affordable mitigating measures implemented in Bangladesh.
2. Japan offers significant learning opportunities for Vietnam and Bangladesh because it has similar exposure and has invested many resources into natural disaster prevention and mitigation policies. Less developed countries could greatly benefit from the lessons learned by countries with more financial resources.
3. The number of deaths in Bangladesh and Vietnam decreased during the last two decades, while the trend has inverted in Japan. This may be due to, e.g., increased elderly population, urbanization, and coastal moving, which all imply that more people are exposed to natural hazards. Future building and infrastructure plans should consider natural risks in order to avoid turning common hazards into major catastrophes due to demographic changes and population growth.
4. Considering the effect of climate change and the increasing global temperatures, it might be beneficial for the countries that have not experienced severe heat waves (e.g., Vietnam and Korea) to learn from countries that have been severely affected (e.g., France and Germany) in order to improve awareness and preparedness to possible extreme temperature events in the future.
5. Germany and Korea appear to be the less vulnerable countries in the cluster. Therefore, they should pay close attention to the current changes in trends and improve hazard preparedness. The less vulnerable, developed countries have economies that facilitate research on innovative mitigation measures. The focus should be to create low-cost, high-impact measures since natural disasters cause more harm to poorer countries and tend to worsen poverty and unemployment.

In general, the countries in cluster 1 offered interesting insights and discussion points. This suggests that the clustering procedure has successfully identified groups of countries that share similar characteristics and can benefit from each other's experiences and lessons. However, it must be recalled that the analysis of clusters requires manual intervention and expert knowledge to, e.g., interpret and evaluate the results of the clustering procedure, identify hidden similarities and differences between countries, analyze trends and recognize learning opportunities. Therefore, the results from this example of ML clustering for risk management purposes show how the techniques used require a deep understanding of their benefits, limitations, and application boundaries. For this reason, this contribution aims to convey the message that ML-based techniques must be considered as tools supporting and not substituting decision-making.

Awareness and knowledge of these tools properties by the user is essential to effectively exploit their results. The role of the human as user of these tools is even more central than before. ML should not be intended as a way to replace the human, but only as an improved approach assisting the human. This is conform with the concept of trustworthy AI by the European Commission [52] promoting explainable AI (XAI) human centrality by means of interpretability, info-besity (overload of information) avoidance, and transparency.

## 5. CONCLUSION

Considering the widespread adoption of AI and ML algorithms, many wonder whether we are proceeding toward a "no-brainer" era, where machines will be in charge of critical decisions, and human knowledge will have only a marginal role. This issue is especially important in the context of risk assessment and management, where errors may result in fatalities and significant economic losses. This study suggests that we are not yet close to such a condition since humans still play a key role in the decision-making process. In addition, we claim that ML algorithms may provide critical support and better-informed decision-making if certain conditions are met. These conditions include knowing (i) what the algorithm does, (ii) how it does it, and (iii) what the limitations are. We discuss this topic through an example of clustering of climate-driven natural disasters. EM-DAT dataset is used as the data source, and k-means is used to group countries that share similar characteristics with respect to exposure to natural disasters. The cluster analysis revealed underlying causes and influential factors that can inform decision-making and enable cross-country learning. However, the objective of this investigation is not to present and discuss an example of "perfect" clustering. On the contrary, the overall intent is to show that effective deployment of ML models must consider the role of humans in the design of the algorithms and interpretation of the results. This study shows that human knowledge still plays a pivotal role in developing and implementing ML algorithms. For example, expert knowledge is required for features selection, model hyperparameters tuning, evaluation strategy selection, and, more importantly, cluster analysis and interpretation. These steps involve human intervention and, therefore, heavily rely on human knowledge. In light of these considerations, ML algorithms are to be considered (advanced) tools, and like most tools, they are only as good as their users. Therefore, AI and ML must be considered powerful and reliable tools to extract hidden patterns from data and provide suggestions to decision-makers; however, humans are still essential to interpret those suggestions and, eventually, convert recommendations into actions.

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