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Leveraging AI for Natural Disaster Management

Takeaways From The Moroccan Earthquake

Morocco Solidarity Hackathon

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Leveraging AI for Natural Disaster Management : Takeaways From The Moroccan Earthquake

Morocco Solidarity Hackathon *
Organizers, Speakers, Mentors and Participant teams

Abstract

The devastating 6.8-magnitude earthquake in Al Haouz, Morocco in 2023 prompted critical reflections on global disaster management strategies, resulting in a post-disaster hackathon, using artificial intelligence (AI) to improve disaster preparedness, response, and recovery. This paper provides (i) a comprehensive literature review, (ii) an overview of winning projects, (iii) key insights and challenges, namely real-time open-source data, data scarcity, and interdisciplinary collaboration barriers, and (iv) a community-call for further action.

1 Introduction

Natural disasters, including earthquakes, wildfires, and floods first impact the most vulnerable populations. On September 8th, 2023, a 6.8-magnitude seism hit Al Haouz, Morocco, causing 2,946 fatalities, 5,674 injuries, 50,000 damaged homes, in particular in the most vulnerable regions of the Atlas Mountains, and damaged heritage sites in the region (International Medical Corps, 2023; Center for Disaster Philanthropy, 2023; Britannica, 2023). A group of students and researchers felt compelled to act, and they organized a hackathon one week later. They invited the broader community to deliberate on the use of Artificial Intelligence (AI) to monitor and mitigate such natural disasters. A unifying theme emerged: the importance of obtaining extensive, real-time, and open-source data to amplify their societal impact.

2 Literature Review

In what follows, we delve into AI's role, particularly machine learning (ML), in natural disaster management, drawing from numerous studies (Tan et al., 2021; Kuglitsch et al., 2022b,a; Snezhana, 2023; Chamola et al., 2020), insights from hackathon speakers, and suggesting potential directions for future mid- to long-term research. This review does not encompass all aspects or areas addressed by winning hackathon teams, which focused on more pressing and immediate needs in response to the community's call. Instead, it serves as an initial snapshot of existing work, with a comprehensive and systematic review to be conducted in the future. AI algorithms improve forecasting, early warnings, and disaster response, assisting decision-making and resource allocation through comprehensive data analysis for natural disaster risk assessment, and climate change adaptation and mitigation. ML techniques are used to analyze large datasets and make accurate predictions for effective disaster management. However, challenges persist, including diverse AI methods and hazards, intricate data collection and handling, and decision-makers' willingness to act. AI approaches for natural disasters aligns with several United Nations Sustainable Development Goals (SDGs), including SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land) (Snezhana, 2023; Yigitcanlar, 2021; Kuglitsch et al., 2022b). These approaches enhance prediction and resource distribution reducing disaster's impacts (Snezhana, 2023; Chamola et al., 2020; Kuglitsch et al., 2022a). Green AI contributes to intelligent, sustainable urban ecosystems, i.e. SDG 11 (Yigitcanlar, 2021; Verdecchia et al., 2023). AI's climate science explorations, driven by ML, bolster adaptation and mitigation strategies related to SDG 13 (Snezhana, 2023; Yigitcanlar, 2021). AI's

*Web site: Morocco Solidarity Hackathon

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impact is also significant in health and well-being (SDG 3), minimizing disaster-related health consequences (Chamola et al., 2020). However, AI's effectiveness varies among disaster types (Snezhana, 2023), deployment requires strict governance and regulation to manage risks (Yigitcanlar, 2021), and joint multi-stakeholder efforts are required for responsible AI use.

Data collection and preparation. Data collection and processing are crucial for AI-based natural disaster management relying on ML techniques. High-quality datasets encompass diverse data sources, including satellite imagery, remote sensing (Ivić, 2019), seismic activity, meteorological (Velev and Zlateva, 2023), and geospatial data (Kia et al., 2012) for natural disaster risk assessment. Data fusion techniques integrate multiple sources for a comprehensive view of disaster-related factors (Arfanuzzaman, 2021). Preprocessing and feature engineering are vital for cleaning, transforming, and extracting relevant features (Sun et al., 2020), ensuring data quality for ML model effectiveness (Kuglistsch et al., 2022). Data quality and quantity pose numerous challenges, including issues with satellite imagery resolution, meteorological data gaps during rare extreme weather events, and absence of historical data (Ivić, 2019). Addressing said challenges calls for data calibration, correction, resolution improvements, sufficiency, and representation (Kuglistsch et al., 2022). Integrating satellite and drone imagery, mobility, and social media data can improve hazard models, enabling accurate predictions for disasters like floods, fires, and earthquakes (Gevaert et al., 2021; GFDRR, 2018; Burke et al., 2019; Syifa et al., 2019; Duarte et al., 2018).

Natural disaster preparedness. Natural disasters cause significant damage; accurate forecasting is crucial for establishing preparedness strategies and efficient disaster response plans. ML improves earthquake prediction and post-disaster assessment. Random forests (RFs) outperform physics-based modeling (Zhu et al., 2023), while geophysical indicators support seismic activity predictions using decision trees and SVM (Chelidze et al., 2022). Multi-layer perceptrons (MLP) predict earthquakes based on geophysical laws (Reyes et al., 2013), and recurrent neural networks (RNN) refine predictions with GPS data (Narayan, 2021). Adaptive neuro-fuzzy inference systems (ANFIS) analyze seismic patterns, providing competitive results (Al Banna et al., 2020; Rana et al., 2022). A hybrid one-week-ahead prediction model achieves 70% accuracy (Saad et al., 2023). In (Mignan and Broccardo, 2020), a meta-analysis emphasizes the need for transparent ML models. Integrating varied datasets, rigorous validation, and interdisciplinary collaboration are pivotal for grounding ML's potential in earthquake prediction.

Climate change necessitates improved flood forecasting methods, considering rainfall-runoff, flash flood, streamflow, storm surge, precipitation, and daily outflow (Mosavi et al., 2018). Traditional ML algorithms, such as RFs and SVM, are used for rainfall prediction and flash flood mitigation (Yu et al., 2017). ANFIS is prevalent in flood risk management, estimating peak flow and water levels (Jimeno-Sáez et al., 2017; Chang and Chang, 2006). MLP and RNN models are widely applied in flood risk management and rainfall-runoff forecasting using rainfall, runoff, and evapotranspiration data (Rezaeian Zadeh et al., 2010; Xiang et al., 2020). Moreover, deep learning models trained on radar-data, with physics assimilation, successfully forecasted rainfall 12–24 hours ahead (Sønderby et al., 2020; Espeholt et al., 2022; Andrychowicz et al., 2023).

In wildfire management, fuzzy clustering and ANFIS forecast wildfires using meteorological data (Jayakumar et al., 2020), while logistic regression, RFs, and convolutional neural networks (CNN) predict wildfire spread with weather and historical fire records (Huot et al., 2022; Radke et al., 2019). A comprehensive study used RFs, SVM, and MLP for detecting high-probability large wildfire events (Pérez-Porras et al., 2021). For hurricane management, a multimodal approach using XGBoost and encoder-decoder architecture was developed for 24-hour intensity and track forecasting (Boussioux et al., 2022). In (Gao et al., 2023), a Hybrid methodology combines k-means and ARIMA models to capture hurricane trends, and an autoencoder architecture simulates hurricane behavior. Recently, purely data-driven weather prediction models (Pathak et al., 2022; Lam et al., 2022; Bi et al., 2023), have demonstrated remarkable skill in multi-day comparisons to state-of-the-art numerical weather prediction and hurricane trajectory forecasts. See (Chen et al., 2020) for a review on ML models for cyclone forecasting.

Disaster relief logistics and response In the aftermath of disasters, crucial logistics decisions are needed. Mathematical optimization is a pivotal tool for guiding these decisions. We outline the most important types of relief decisions and refer readers to further studies (Klibi et al., 2018; Gholami-Zanjani et al., 2019; Bertsimas et al., 2021; Banomyong et al., 2019; Gupta et al., 2019b; Kundu et al., 2022).

Evacuation is a vital strategy to protect people from the impacts of disasters. (Bayram, 2016) surveys optimization and simulation methods for fast and smooth evacuations. *Timely delivery of relief supplies* like food, water, medicine, and tents is essential to assist the victims. Numerous papers propose optimization methods for operational decisions (Ben-Tal et al., 2011; Avishan et al., 2023) and strategic positioning of humanitarian logistics centers (Stienen et al., 2021). In particular, optimizing the location of supply facilities to ensure robustness and to hedge against all uncertainties is of paramount importance (Balcik and Beamon, 2008; Döyen et al., 2012). Various *medical aid optimization* approaches have been suggested. For instance, (Jia et al., 2007) propose a temporary medical aid facility location model. See (Boonmee et al., 2017) for more examples. Rapid transportation of casualties to emergency facilities is crucial, and many optimization addressing this need have been proposed in the literature (Farahani et al., 2020).

While numerous optimization methods for disaster relief exist in literature, only a few have been practically implemented due to data uncertainty and scarcity (Kunz et al., 2017). Acquiring accurate, real-time information from disaster areas is challenging. To address these uncertainties, various stochastic and robust data-driven decision models have been proposed (e.g., (Ghasemi et al., 2020; Avishan et al., 2023)). We advocate a better integration of AI and optimization: the data needed by relief optimization models can be obtained by AI in a much faster and more efficient way (Boccardo et al., 2015). Satellite or drone images, combined with DL-based models (e.g., CNNs, transformers), provide valuable information on **accessible roads** (Zhao et al., 2022; Wu et al., 2021) for route planning and resource allocation (Daud et al., 2022; Commission, 2023), flood inundation (Munawar et al., 2021b), and **building and health care infrastructure damage** (Su et al., 2020; Bouchard et al., 2022; Cheng et al., 2021), guiding relief optimization models such as resource allocation and relief planning (Munawar et al., 2021a). Social media data, combined with AI-driven solutions such as ML and natural language processing, can also enhance input data for disaster relief optimization models (Gupta et al., 2019a).

Communication and sensing technologies In the absence or destruction of infrastructure, communication and multimodal sensing technologies are instrumental in enabling a swift response in post-earthquake management, notably for remote areas and villages. Specifically, aerial platforms can collect sensitive data on the fly and prioritize the deployment of emergency response units. Drones can be remotely controlled over ultra-reliable 5G wireless link, while taking into account harsh weather conditions, intermittent loss of connectivity or loss of line of sight visual from remote operators. In the fully autonomous setting when remote control operations are not possible, self-organizing drone swarming solutions using various sensors (LiDAR; cameras, thermal sensors, etc.) can help sense and fuse information from distributed geographical areas. This challenging problem mandates effective ways of sampling important sensory information, optimal path planning and communication over the air (Shiri et al., 2020). In these settings, inter-UAV communication can be enabled via various interfaces such as WiFi, free-space-optics and a network of orbiting satellites, e.g., the recent Starlink satellite used in the aftermath of the Moroccan earthquake to re-establish connectivity. For high situational awareness, immersive technologies such as VR/AR over low-latency and highly reliable 5G multi connectivity can boost network coverage and facilitate the communication and sharing of high-definition sensing information to medics or other emergency teams (Correia et al., 2021). Among the plethora of sensing modalities, wireless (RF) sensors have several advantages as they can see through walls (Adib and Katabi, 2013) for rubbles by detecting reflected RF waves. Likewise, sensing and localization can be enabled by transmitting low-powered microwave/RF signals through rubble to look for reflection changes as deployed by NASA, using its FINDER program, during the Nepalese 7.8 magnitude earthquake (DHS Science & Technology Press Office, 2022; of Homeland Security, 2022).

3 Moroccan Solidarity Hackathon: General Vision, Timeline & Results

The Moroccan Solidarity Hackathon was initiated in response to the seismic event in Morocco on September 8th, 2023, that revealed a recurring pattern characterized by significant loss of life. This pattern predominantly stemmed from inadequate pre-disaster preparedness and the complexities surrounding effective relief and rescue operations. While the hackathon's inception was motivated by the necessity to provide tangible contributions to earthquake risk mitigation, its scope rapidly expanded to encompass the broader domain of natural disaster management.

The fundamental vision of the hackathon was to establish a collaborative platform for individuals driven by their commitment to mitigating the risks associated with natural disasters. To fulfill

this vision, the hackathon focused on three distinct tracks: **(1) Natural Disaster Preparedness.** Strategies and solutions to enhance preparedness measures for future natural disasters. This encompassed the improvement of forecasting capabilities for various natural events, such as hurricanes, floods, volcanic eruptions, and earthquakes. Additionally, it involved strategically placing critical infrastructure, such as hospitals and police stations, to optimize their resilience in the face of such disasters. **(2) Relief Rescue Efforts.** Optimization of relief and rescue operations during and after natural disasters, emphasizing overcoming logistical challenges. **(3) Data Curation.** The curation and utilization of crucial datasets are imperative; these datasets include for example satellite and drone imagery used for damage assessment and individually collected data employed to identify distressed communities.Teams recognized that the raw data alone was insufficient, so they also labeled data (manually or using ML), including road detection, to facilitate effective on-ground rescue efforts.

Hackathons, though valuable for generating innovative ideas quickly, often have limited impact due to their short duration. To overcome this limitation, our hackathon aimed to extend its impact beyond the event itself. It sought to engage winning teams and interested participants, nurturing the development of their ideas for real-world implementation. During the event, each team created a 3-minute presentation and a one-page report. Mentors provided guidance, and a post-hackathon jury selected winners based on a set of predefined criteria (detailed in Appendix A).

4 A Summary of Spotlight Projects & Directions

We identify promising contributions for practical implementation, assessed by the jury based on criteria inspired by the UN's solution quality evaluation metrics (detailed in Appendix A).

4.1 DeepAster

DeepAster aims to leverage satellite imaging data to provide a real-time assessment of the impact of natural disasters, enabling precise resource allocation based on immediate needs.
Contribution. The solution offers an interactive map showing emergency levels, including building detection, emergency degree calculation, and estimating affected population. It was fine-tuned to recognize North African-style roofs, showcasing its feasibility and potential impact.
Challenges. Limited access to real-time satellite images and initial challenges with model generalization due to the architectural peculiarity of Moroccan buildings. To overcome the latter, alternative data sources were used, for instance, Maxar's Morocco Earthquake Open Data Program (Maxar.com, 2023), along with a manually labeled dataset specific to Moroccan buildings.
Key Takeaways and Future Work The team envisions refining the model's adaptability to different building structures and leveraging meta-learning to address data scarcity.

4.2 SOS Drone

The SOS Drone project explores the use of *Unmanned Aerial Vehicles* (UAVs) for post-disaster response and impact on infrastructure assessment.
Contribution. The project had three key impacts: analyzing the effects on strategic routes, locating and estimating survivor numbers, and evaluating the impact on buildings. A pre-trained YOLOv6 (Li et al., 2022) variant (Huggingface.co, 2023) was fine-tuned for enhanced human detection in disaster scenarios, while a model inspired by MSNet architecture (Zhu et al., 2021) augmented building damage assessment capabilities. The route analysis combined image classification and object detection, with the integration of RDD2022 data (Arya et al., 2022) anticipated to further refine road damage assessments due to earthquakes.
Challenges. Limited training data and regulatory drone constraints in Morocco meant that substantial computational resources were required for real-time algorithm development.
Key Takeaways and Future Work The ultimate goal of the team is to ensure that the systems remain at the forefront of disaster management strategies, safeguarding lives and minimizing the disasters' impact on communities, by refining the AI algorithms and broadening the project's scope to cover various disaster scenarios and geographies.

4.3 Team-of-5

Team-of-5's project highlights the vital role of real-time mapping in disaster management. They identified a crucial need for efficient route planning for emergency services in disaster-affected areas, such as Morocco's Atlas Mountains, which face challenges due to outdated mapping systems,

compromised road infrastructure, and uncoordinated volunteer efforts.
Contribution The project proposed a scalable solution combining high-resolution satellite imagery and crowdsourced data, focusing on identifying road damage or blockage. They explored data from many sources including Maxar Open Data Program (Maxar.com, 2023), DeepGlobe (Deepglobe.org, 2023), UNOSAT United Nations Satellite Centre (Unosat.org, 2023), and others, while also planning to incorporate information from "Aji Nt3awnou" Rescue Map (see section 4.5) and Waze. Implementation involved state-of-the-art deep learning architectures like YOLOv8 (GitHub, 2023) and aimed to develop a WhatsApp-based service to ensure accessibility and wider adoption, even under varying connectivities.
Challenges Throughout the project, the team navigated through the heterogeneous nature of geospatial data and the resource-consuming aspects of model training. These challenges highlighted the importance of cross-functional collaboration across different time zones and backgrounds, effective communication, goal setting, and applying technical skills in a new domain under time constraints.
Key Takeaways and Future Work The use of diverse data sources, advanced architectures, and the significant role of centralized entities were key insights. Looking ahead, addressing data heterogeneity, optimizing computational resources, and enhancing collaboration will be focus areas. The development of a user-centric WhatsApp-based service and the application of lessons learned in collaboration and communication will guide future work in real-world emergency scenarios.

4.4 Grooming in Darija

The Grooming in Darija project unveiled a critical concern regarding the increase in sexual predation on social media following natural disasters, particularly observed after the Moroccan earthquake (Lane and York, 2022). The team worked diligently to detect predatory content in Darija, a low-resource Moroccan Arabic dialect, emphasizing the urgency of enhanced data collection mechanisms and inclusive practices.
Contribution The team effectively employed pre-existing NLP models, fine-tuned on collected samples, yielding promising results; notably, DarijaBERT (Gaanoun et al., 2023) achieved an accuracy of 75% and an F1-score of 0.73. Their efforts highlighted the urgent need for enhanced data collection mechanisms and inclusive practices, especially for less prevalent languages and sensitive topics.
Challenges Addressing data scarcity and privacy in sensitive areas like abuse posed the primary challenge. The key takeaway underscored the grave reality of handling grooming and abuse data and the imperative need for innovative techniques that can generalize effectively with limited examples.
Key Takeaways and Future Work The project stressed the importance of AI reducing its reliance on extensive data. It advocated for methods that can perform well with limited data, fostering inclusivity and tackling issues tied to various languages, cultures, and sensitive topics.

4.5 Data Curation

Following the earthquake in Morocco, the team worked on enhancing the "Aji Nt3awnou" [†] ("Let's Help One Another") platform, a real-time interactive map fed by citizens' and NGOs' inputs.
Contribution Aji Nt3awnou aims to efficiently allocate resources and support by accurately mapping and prioritizing the evolving needs of victims. This project focused on improving map UI/UX, matching villages to coordinates, developing a ranking algorithm, and dealing with multiple dialects.
Challenges. The team overcame numerous obstacles, including linguistic diversity, lack of datasets for low-resource languages, computational constraints, and challenges in scaling, underscoring the essential role of meticulous data curation and cleaning.
Key Takeaways and Future Work Moving forward, the team plans to generalize their approach and create tutorials and guides, ensuring the adaptability and scalability of their solutions for future projects and diverse disaster scenarios.

4.6 ML4Quake: Early Prediction & Warning

ML4Quake leverages INSTANCE (Italian Seismic Dataset (Michelini et al., 2021)) to improve earthquake early-warning alerts, aiming to predict quakes 10 seconds before they happen. Current alert systems trigger alerts 3 to 5 seconds post-quake[‡], underscoring the urgent need for life-saving technology advancements.

[†] `https://huggingface.co/spaces/nt3awnou/Nt3awnou-rescue-map`
[‡] `https://scienceexchange.caltech.edu/topics/earthquakes/earthquake-early-warning-systems`

Contributions Utilizing 3-channel waveform recordings from the dataset, which included both earthquake and noise, models were trained to focus on the first 10 seconds of each 120-second recording. The application of RFs and Neural Network models yielded promising results, with RF achieving 87% test accuracy and an F1-score of 84%.
Challenges Limited availability of comprehensive seismic waveform datasets and constraints in utilizing 120-second waveforms. Centralized entities are pivotal, providing access to extensive datasets and fostering collaborations among seismologists, emergency management organizations, and computer scientists, which is essential for building a comprehensive early warning system.
Key Takeaways and Future Work The collaboration of computer scientists and seismologists is crucial to gather comprehensive seismic datasets, enabling robust early warning systems, which are crucial to save lives and improve emergency response coordination.

5 Discussion & Takeaways

During the hackathon, speakers, mentors, and participants shared key insights, summarized in twofold.

(1) No Silver Bullet – Teamwork in Disaster Management: The hackathon experience emphasized the importance of a collaborative future, where AI/ML is employed in conjunction with expertise from climatology, engineering, data science, operations research and operations management. Partnerships among governments, NGOs, tech companies, and local communities, prioritizing robust, reasoning, and responsible systems, for social good, are essential. As Prof. Bengio highlights, "The AI people can't solve these problems by themselves; it's always a collaboration with many different expertise, ·, many different points of views." **(2) Real-time data-driven disaster management:** The importance of collecting and analyzing data in real-time cannot be overstated, as the most impact occurs in first 72 hours post-disaster. Developing resilient data acquisition systems, capable of withstanding adverse conditions, is essential. AI-assisted data labeling can further enhance risk mitigation strategies by transforming raw, unannotated datasets into valuable insights. Prof. Murphy's cautionary advice, "you've got to really think about the privacy and unanticipated ethical consequences," highlights responsible ethical AI, while addressing data fragmentation and scarcity of useful datasets.

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Morocco Solidarity Hackathon

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- Omar El Housni [11]

Judges and Mentors

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- Salim Chemlal [12]
- Wale Akinfaderin [13]
- Laurent Barcelo [14]
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- Jeremy Pinto [1]
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- Hamza Azzaoui [13]
- Dolly Akiki [13]
- David Min [13]
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   - Ayoub Loudyi [20]
   - Aymane El Firdoussi [21]
   - Achraf Sbai [22]
   - Sanae Attak [16]
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   - Yassine Squalli Houssaini [24]
   - Firdawse Guerbouzi [24]
   - Chaimae Biyaye [24]
   - Khadija Bayoud [24]
   - Ikram Belmadani [24]
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   - Charles Bricout [1]
   - Alex Maggioni [1]
   - Reyad OUAHI [25]
   - B.V. Alaka [26]
   - Kiruthika Subramani [27]
4. **Groomin in Darija**
   - Khaoula Chehbouni [1, 5]
   - Afaf Taik [1]
   - Kanishk Jain [28]
5. **Datacuration**
   - Hamza Ghernati [29]
   - Lamia Salhi [30]
   - Laila Salhi [31]
   - Jules Lambert
6. **ML4Quake**
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Supplementary Material

A Quality Evaluation Criteria of Proposals

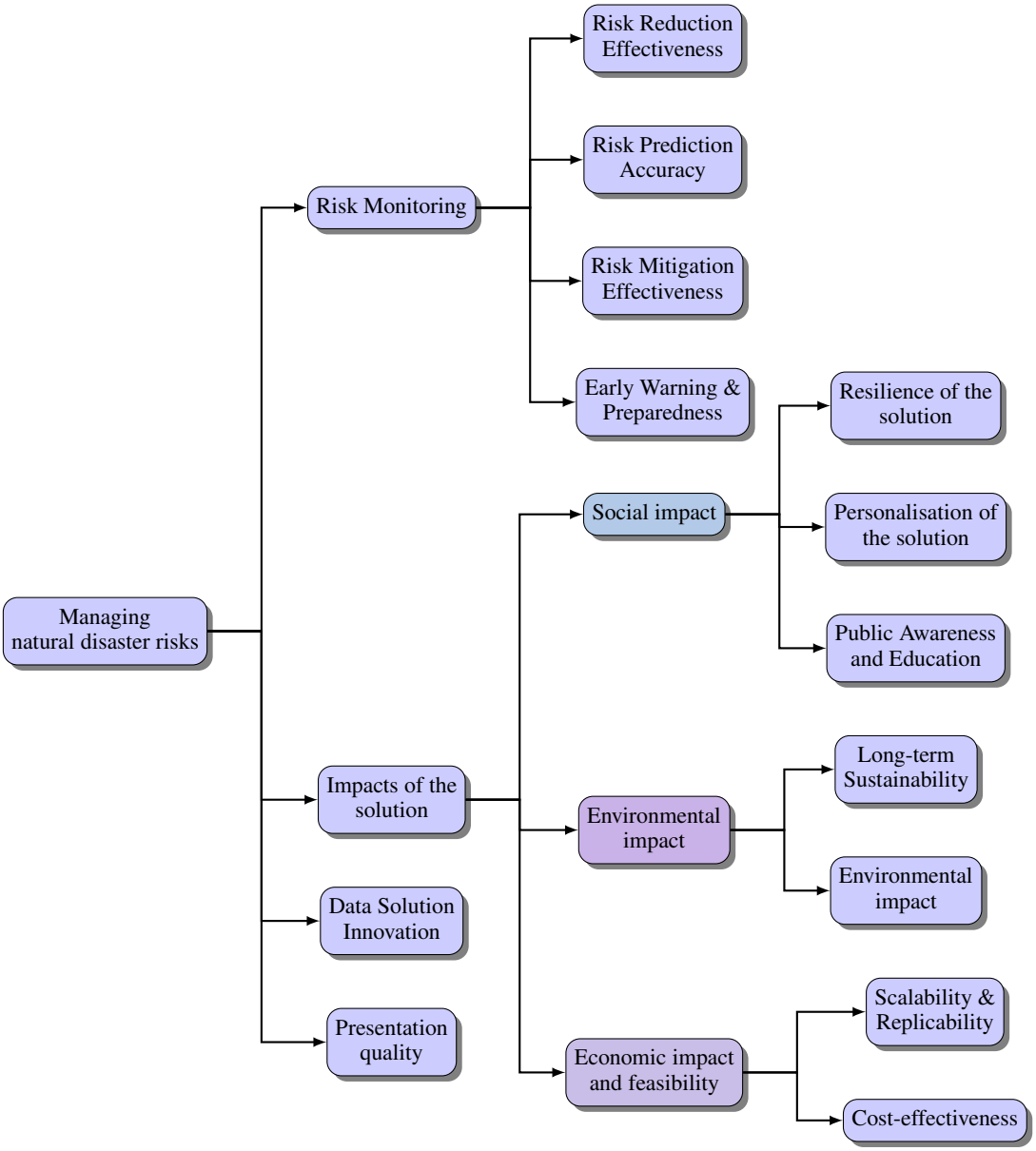

Figure 1: Criteria deployed during the Moroccan Solidarity Hackathon to assess the teams' proposals.