



## Review article

# A process-driven and need-oriented framework for review of technological contributions to disaster management



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## ABSTRACT

An escalation in the frequency and intensity of natural disasters is observed over the last decade, forcing the community to develop innovative technological solutions to reduce disaster impact. The multidisciplinary nature of disaster management suggests the collaboration between different disciplines for an efficient outcome; however, any such collaborative framework is found lacking in the literature. A common taxonomy and interpretation of disaster management related constraints are critical to develop efficient technological solutions. This article proposes a process-driven and need-oriented framework to facilitate the review of technology based contributions in disaster management. The proposed framework aims to bring technological contributions and disaster management activities in a single frame to better classify and analyse the literature. A systematic review of benchmark disruptive technology based contributions to disaster management has been performed using the proposed framework. Furthermore, a set of basic requirements and constraints at each phase of a disaster management process have been proposed and cited literature has been analysed to highlight corresponding trends. Finally, the scope of computer vision in disaster management is explored and potential activities where computer vision can be used in the future are highlighted.

## 1. Introduction

A disaster is defined as an event that occurs over a short or long period of time, affecting the entire community or society and wreaking havoc on people, the environment, infrastructure, wildlife, and the economy [1, 2, 3]. Hazard, vulnerability, and society's failure to deal with the disaster utilising the available resources are often the causes of disasters [4, 5, 6]. Disasters are broadly categorised as natural or man-made based on their origins. Natural disasters (e.g., earthquakes, floods, wildfires, landslides, liquefactions, volcanic eruptions, hurricanes, cyclones, tsunamis, tornadoes, pandemics, blizzards) are those caused by natural phenomena such as geophysical and hydrological processes [4, 7, 8, 9]. On the other hand, technological or man-instigated disasters (e.g., industrial accidents, transportation accidents, terrorist attacks, war, nuclear radiation, stampedes, social unrest, conflicts, oil spills, and fires) are caused by the direct or indirect intervention of humans [8, 9]. Another type of induced disasters is referred to as a cosmic disaster, which encompasses nuclear war, bioterrorism, and climate change [9, 10]. This article mainly focuses on natural disasters to restrict the scope and complexity of the performed review. A gradual increase in the oc-

currence and intensity of natural disasters is noted over the past few decades. According to Guha-Sapir [11], a fraction of the increase in occurrence is because of advances in reporting, communication and detection technologies. However, the increase in hydro-metrological disasters including floods and droughts is real, which is believed because of climate change and unplanned urbanization in disaster-prone regions [12, 13]. Increased intensity, urbanization, and population growth are the highlighted factors which increase the vulnerability and make natural disasters more damaging in terms of deaths and their effect on people [5, 6, 14]. From 2010 till 2021, a total of 4384 natural disasters occurred, which resulted in 0.5 million deaths, 1886 million affected and 1.89 billion US dollar damages [11]. The ratio of affected people is more in underdeveloped countries mainly because of lack of resources to deal with natural disasters [13]. These horrifying disaster statistics have raised concerns in the community forcing the development of innovative solutions and extension of existing methods to reduce the impact of disasters towards proactively protecting the community [15].

The occurrence of a natural disaster cannot be avoided; however, the response can be improved to reduce its impact on the community. Because of the unpredictable nature, only limited resources can be

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allocated in advance to deal with natural disasters. Disaster management is the institution that involves the systematic strategic planning and deployment of procedures towards reducing the impact of disasters by efficiently using the available limited resources [16]. It is a multidisciplinary field and involves the collaboration between people from a variety of domains such as environmental sciences, logistics, civil engineering and computer sciences. Therefore, it incorporates the contributions from multiple disciplines to improve the overall management process. In the context of disaster management, interpretation of natural disasters has changed over the years towards the vulnerability of people to a certain hazard [5] and multiple models have been developed for disaster risk reduction. Some common models of vulnerability and disaster risk reduction include the Pressure and Release (PAR) model [17], Hazards-of-place (HOP) model [18], Regions of Risk model [19], Integrated Assessment of Multi-Hazards model [20] and the UNISDR framework for disaster risk reduction [21]. Given the involvement of actors from various domains as evident from above-mentioned models, it is significant to have collaboration and interaction between involved groups to better understand the needs of the community and efficient disaster management. However, Seaberg et al. [22] highlighted the lack of any such comprehensive framework to connect the actors towards efficient disaster management. In this context, a common taxonomy and interpretation of disaster management related requirements are essential to develop the understanding of the problem to be addressed by a contributor (an integrator or technology provider).

In an effort to cope with disasters, academics and practitioners are developing different technology-oriented solutions [23]. Emerging disruptive technologies including Artificial Intelligence (AI) /machine learning/deep learning [24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46], social media/Big Data/crowd-sourced data [45, 47, 48, 49, 50, 51, 52, 53], computer vision [36, 43, 44, 51, 52, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71], Information Communication Technology (ICT)/mobile phone/Geographical Information System (GIS) [46, 72, 73, 74, 75, 76, 77, 78], virtual reality/augmented reality [79, 80, 81, 82] and robotics/Unmanned Aerial Vehicles (UAVs) [43, 57, 62, 71, 77, 83, 84, 85, 86, 87] are highlighted as potential tools that may significantly help in improving the disaster management practices. Recent technological advancements in computing hardware, communication infrastructure and cloud computing have made it possible to practically implement the technological solutions to real disaster situations. Computer vision and Intelligent Video Analytics (IVA) have emerged as trending and economical technologies to address complex real-world problems. There is the enormous potential of deploying state-of-the-art computer vision algorithms to address disaster management problems. A section at the end of the article presents the scope of computer vision in disaster management and highlights potential challenges.

A number of reviews already published related to the role of specific technologies (e.g., AI [88], ICT [2], Big Data [15, 89]) in the disaster management domain; however, no comprehensive literature entry was found where trending technologies are reviewed at the same time in the context of disaster management to demonstrate the patterns of technology shift over the years. Furthermore, the process-driven and need-oriented framework proposed in this article provides a unique perspective of literature where a common taxonomy is established between disaster management problems and technology providers.

This article proposes a framework for a process-driven and need-oriented review of the literature to help the contributors in a systematic classification of technological contributions to disaster management. The aim of the proposed review framework is to categorize the literature in a two-dimensional structure: horizontal axis progressing from prevention phase towards recovery phase of disaster management, while vertical axis detailing needs of each phase, corresponding assessments to address the needs and common technologies used in performed assessments. The proposed framework will help researchers in identifying gaps and proposing novel solutions to unaddressed disaster manage-

ment problems. Furthermore, to facilitate the process of requirement formulation, this article proposes a list of common constraints to be properly defined and incorporated in the development process. As a summary, the followings are the main contributions of this article:

1. Presents a systematic review of benchmark technological contributions across different phases of the disaster management cycle to demonstrate the trends of technology used over the last decade.
2. Proposes a process-driven and need-oriented framework for the analysis of literature to help contributors in a systematic classification of literature and identifying pinpoint gaps.
3. Proposes a list of disaster management related constraints and requirements with the idea of facilitating contributors in better addressing the problems and positioning their solutions in line with these requirements.
4. Explores the scope of computer vision in addressing disaster management related assessments and highlights the potential challenges.

The rest of the article is organized as follows. Section 2 presents contextual information about the modern disaster management cycle. Section 3 presents the methodology and protocols adopted to perform the presented review. Section 4 presents the review of technological advancements across different phases of the disaster management cycle. Section 5 proposes the process-driven and need-oriented framework and analyses the cited literature using the proposed framework. Section 6 lists disaster management related constraints and analyses the cited literature against the defined requirements. Section 7 presents the scope of computer vision for disaster management and highlights the potential challenges in this context. Section 8 concludes the study and reports important insights from the presented review.

## 2. Disaster management cycle

There are a variety of disaster management frameworks and procedures proposed in literature [90] to deal with disaster situations. The modern disaster management cycle is one of the most commonly and widely used frameworks, which consists of four phases; prevention and mitigation, preparedness, response and recovery [13, 16, 22, 90, 91, 92, 93, 94]. Each phase of the disaster management cycle is briefly described as follows:

- **Prevention and Mitigation** phase aims to minimize the impact of unavoidable future disasters in the long term. It involves the activities such as risk analysis, hazard zone mapping, resources allocation, climate forecasting and building warning codes.
- **Preparedness** phase involves the planning of responding to a near-future disaster. It involves the activities of disaster training, disaster exercises, and early warning systems.
- **Response** phase aims to reduce the impact and damages caused by the disaster after its immediate occurrence. It involves the activities of disaster mapping, damage estimations, search and rescue missions, and humanitarian assistance.
- **Recovery** phase aims to bring the community back to normal after a disaster occurrence. It involves the activities of reconstruction monitoring, debris clearance, and financial assistance.

Fig. 1 shows the functional block diagram of the modern disaster management cycle.

## 3. Review methodology and protocols

The presented review is performed using standard Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [95] guidelines with proposed process-driven and need-oriented analysis of literature. The protocol consisted of the following steps (a)

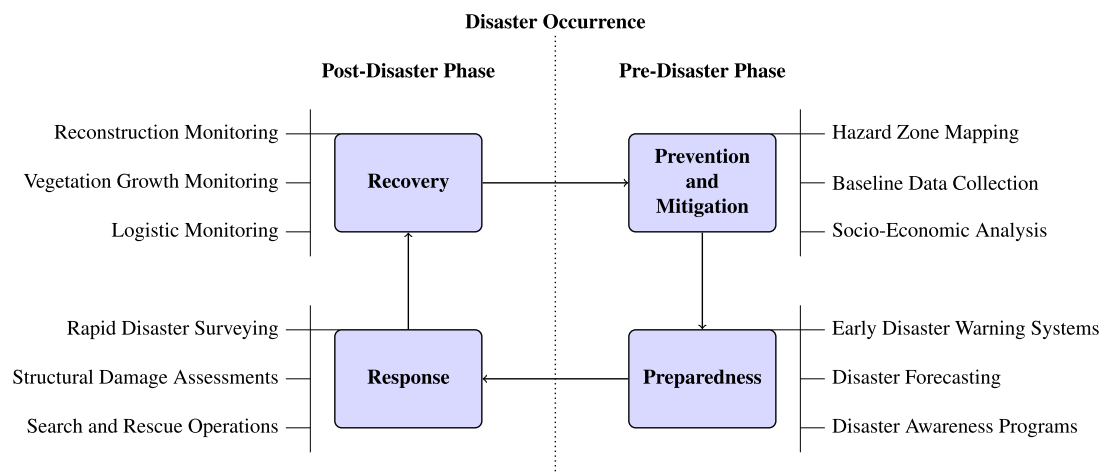


Fig. 1. Functional block diagram of modern disaster management cycle (reconstructed from [89, 90, 94]).

Table 1. List of search keywords.

“Disaster Management” AND “Phases”	“Disaster Management” AND “Cycle”
“Disaster Management” AND “Activities”	“Disaster Management” AND “Assessments”
“Disaster Management” AND “Requirements”	“Disaster Management” AND “Constraints”
“Disaster Management” AND “Technology”	“Disaster Management” AND “Solutions”

research questions formulation, (b) keywords selection, (c) academic databases selection, (d) inclusion/exclusion criteria, (e) descriptive analysis of selected literature, (f) evaluation of selected literature. To restrict the scope of the presented review, technological contributions are referred to literature entries where disruptive technologies (i.e., robotics, computer vision, machine learning, AI, Big Data, virtual reality, augmented reality, statistical/probabilistic modelling, remote sensing, UAVs, crowdsourcing, social media, ICT, Structure from Motion (SfM), Internet of Things (IoT), GIS) are deployed to address the disaster management related problems.

A number of research questions listed as follows were formulated to identify the needs involved, highlight a variety of assessments performed and explore technological contributions made across phases of the disaster management cycle.

- What are the different phases and needs involved at each phase of the disaster management cycle?
- What are different assessments and activities performed at each phase of the disaster management cycle to address the corresponding needs?
- What are different technological solutions proposed to facilitate disaster management related assessments?
- What are different disaster management related constraints and requirements associated with each phase?

A list of corresponding keywords presented in Table 1 was prepared to extract the relevant literature. Scopus, Web of Sciences (WoS) and IEEEXplore academic databases were searched against the defined keywords and literature was extracted. In total, 41946 records were extracted, 11769 from Scopus, 23905 from WoS and 6272 from IEEEXplore. Extracted literature was filtered using detailed and specific inclusion/exclusion criteria listed as follows to restrict the scope of performed review to the only benchmark studies.

- Only peer-reviewed literature (i.e., articles published in impact factor journals) published between 2010 and 2021 is considered for this review.
- Literature published only in the English language is considered.

- Literature involving only selected natural disasters (i.e., earthquake, avalanche, wildfire, drought, flood, tsunami, landslide, hurricane, heatwave, volcanic eruption, gully erosion) is included in the main review.

Duplicate entries were removed and the relevance of the article was assessed at stages, including title screening, abstract screening and full-text evaluations. It is inevitable to avoid the biasness and subjectivity in the process of screening the literature for inclusion in the final review despite having detailed inclusion/exclusion criteria as mentioned by Galindo and Batta [96]. A subjective test of “if the article proposes some technology-oriented solution to address one of disaster management related assessments” was applied during the full article screening process to determine the relevance. As a result, 111 articles were selected to be included in the presented review (i.e., 102 for the main review, 09 for framework support). The literature chosen for inclusion in this review is by no means near to the amount of research published in this domain; however, it can be considered as a representative sample of the most recent state-of-the-art literature. Fig. 2 presents the standard PRISMA flow diagram.

Exploratory analysis were performed on selected literature to highlight the year-wise and phase-wise trends. Fig. 3(a) presents the year-wise distribution of literature and indicates that the use of technology in disaster management has been increased significantly from 2017 onward. Fig. 3(b) shows the distribution of literature across phases of the disaster management cycle. Prevention and response phases were targeted the most from a technology perspective, while the recovery phase was least explored.

#### 4. Review of technological contributions to disaster management

This section presents the review of technology-oriented solutions proposed to address assessments at different phases of disaster management cycle. The review is presented in the chronological order to highlight the shift of technology over the years.

##### 4.1. Prevention and mitigation

In the year 2010, Bai et al. [24] proposed the use of GIS based logistic regression for landslide susceptibility mapping. Four different data

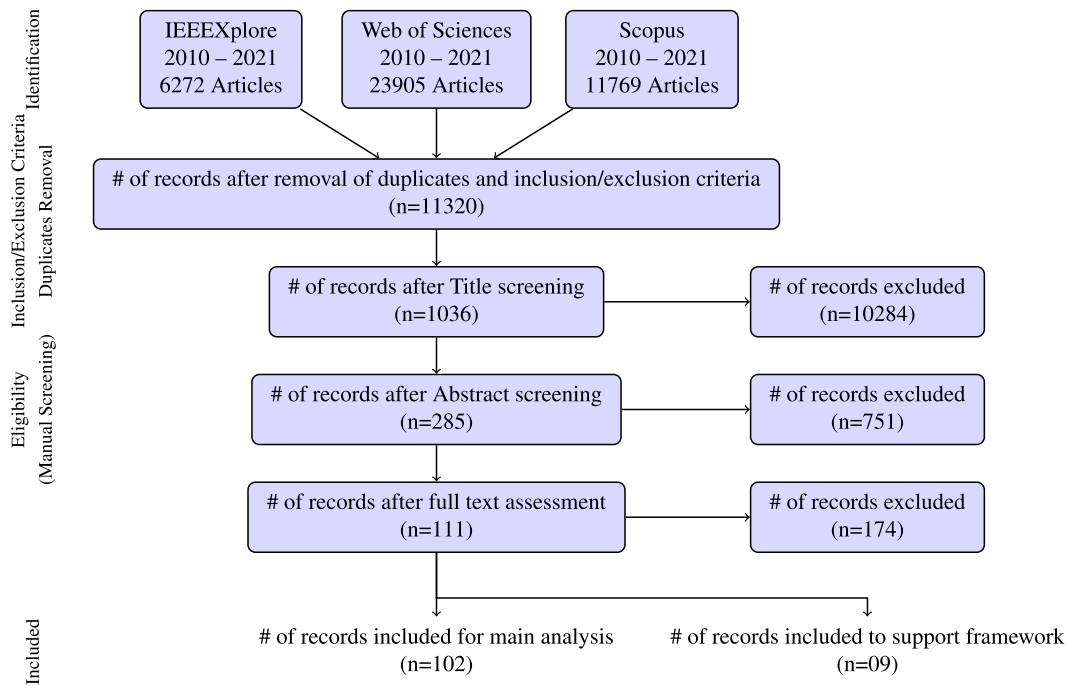


Fig. 2. PRISMA flow diagram for presented systematic review.

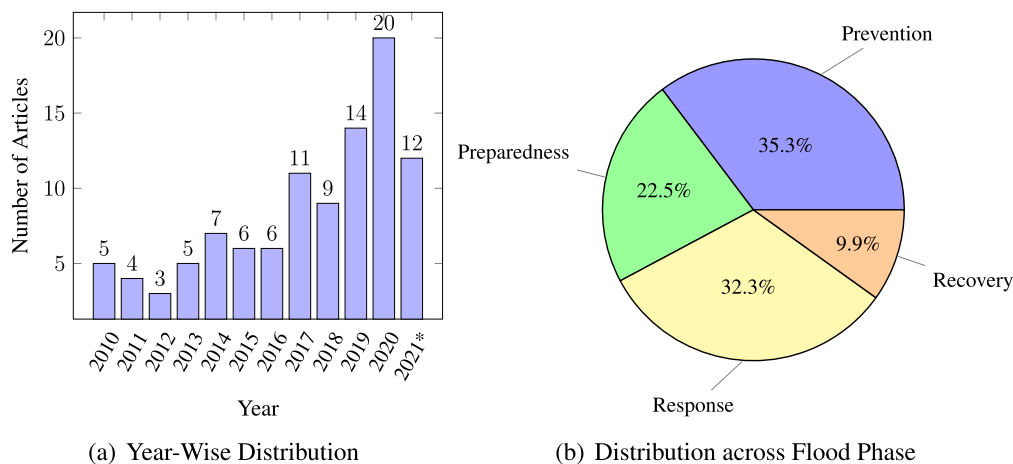


Fig. 3. Exploratory analysis of selected literature.

types including remote sensing, thematic maps, topographical maps, and geological maps were used for the investigation. Performance of regression model based mapping was measured using Root Mean Squared Error (RMSE) and classification accuracy. The proposed logistic regression model achieved an RMSE of 0.392 and an accuracy of 81.4%. Later in the same year, Martyr et al. [97] used high-resolution and unstructured mesh computational models (i.e., SWAN + ADCIRC SL16) of the Mississippi river to simulate the hurricane storm surge under varied flow conditions. To parameterize the effect of ripples from low to high flows, velocity variations were implemented. Model accuracy was assessed based on the quadratic fit estimates and  $R^2$  value of 0.93 was reported. Furthermore, it was reported that the implementation of boundary conditions improved the overall model performance.

In 2012, Aronica et al. [98] proposed the use of Monte Carlo simulation to generate flood hazard maps. The hydrodynamic model was used to derive the flood event characteristics in the performed simulation. In the same year, Sun et al. [72] discussed the non-structural measures for the mitigation of floods and landslide hazards. Eight non-

structural measures including safety zones, critical rainfalls, monitoring equipment, warning systems, GIS data, hierarchical responsibility system, guide, and training were discussed in this context. Campos et al. [99] proposed the use of transportation network to determine the independent paths from disaster struck area to safe locations by repeatedly applying an analytical heuristic function. Travelling time and capacity of transportation networks were used as the main parameters in the defined heuristic function. In 2014, Caballero and Rahman [100] deployed Monte Carlo stochastic simulation approach for design flood estimation. Data from two catchments in Australia was used as a case study. The advantage of simulation in selecting the appropriate input value for flood modelling was reported. Later in the same year, Radianti et al. [101] proposed a novel Spatio-temporal probabilistic model integrating crowd and hazard dynamics to simulate the crowd flow. Efficient crowd flow simulation can help in better evacuation planning during a disaster event. A Dynamic Bayesian Network (DBN) was used to simulate the flow.

In 2015, Liu et al. [102] proposed the use of a 1D-2D hydrodynamic model for flood simulation in detention basins. A novel approach was presented to link 1D and 2D models for flood simulation. Flood mapping was generation using GIS. Ramakrishnan et al. [103] in year 2016 proposed the use of phase change materials in the building fabrics towards reducing the risk during heatwave disaster events. A numerical simulation approach was adopted to investigate the potential of phase change material towards resisting heat stress risk. From the results, improved performance was reported when phase change material was used. In 2017, Zhu et al. [83] proposed the use of UAVs for efficient floods related baseline data collection. It was reported that UAV's captured images provided improved flooding related information when combined with geographic information. Chen et al. [25] in 2018 performed a comparative study using multiple machine learning regression approaches (i.e., Bayes' Net (BN), Radical Basis Function (RBF), Logistic Model Tree (LMT), Random Forest (RF)) for landslide susceptibility mapping. A landslide spatial dataset for a custom site was used in a 70:30 ratio for training and testing purposes. RF model was reported best with an accuracy of around 75%. In the same year, Tanaka et al. [104] proposed a requirement definition method to develop a global disaster database by incorporating data from multiple sources. Various critical issues and challenges were highlighted in developing a global database including data generality and validation. Zhang et al. [54] in the year 2018 proposed a novel Object-based Convolutional Neural Network (OCNN) for urban land use classification from Very Fine Spatial Resolution (VFSR) images. Instead of image pixels, segmented objects were used as functional units for CNN. Improved land use classification accuracy was reported when compared with existing literature.

In 2019, Bera et al. [73] proposed the use of a multi-criteria analysis approach with GIS for landslide hazard zone mapping. Multiple landslide related factors were integrated into the platform and risk scores were determined. The effectiveness of the proposed approach was validated using a case study. In the same year, Komolafe et al. [105] developed a loss function for flood risk assessment by incorporating multiple flood damage related features. The proposed models were validated using a case study and the effectiveness of loss function in precisely predicting the loss was reported. Later in 2019, Zhang et al. [55] proposed a novel joint deep learning framework for land use and land cover classification by making use of CNN and Multilayer Perceptron (MLP) approaches. Improved classification accuracy were reported for the proposed joint deep learning approach when applied to VFSR images. Furthermore, the advantage of using the iterative update method was highlighted.

Recently in 2020, Abdi [26] performed a comparative study using multiple machine learning algorithms (i.e., Support Vector Machine (SVM), RF, xgboost, deep learning) for land use and land cover classification. The sentinel-2 dataset was used for training the machine learning models. From the results, SVM was reported best in the classification of data. In the same year, Band et al. [27] proposed the use of hybrid and ensemble machine learning models for the prediction of flash flood prone areas and generating flood susceptibility maps. Fifteen features related to climate and geo-environment were used as input to models for training. Topographical and hydrological features were reported as the most significant in the final prediction. Chowdhuri et al. [28] in 2020 implemented state-of-the-art Artificial Intelligence ensemble models (i.e., Boosted Regression Tree (BRT), Bayesian Additive Regression Tree (BART), Support Vector Regression (SVR), Ensemble of SVR) for the gully erosion susceptibility mapping. From the results, the Ensemble approach was reported to achieve the highest accuracy.

In 2020, Harirchian and Lahmer [106] proposed a fuzzy logic model for seismic vulnerability assessment of buildings in the context of an earthquake disaster. A novel rapid visual screening framework was used for earthquake vulnerability assessment of buildings. The effectiveness of the proposed framework was demonstrated using two case studies. Later in the same year, Lestari et al. [107] tested a contingency

plan for volcanic eruption by finding a communication model through performing in-field training exercise simulations. Data was collected using in-field interviews, questionnaires, and surveys. The collected data were qualitatively analysed and interpreted for an efficient contingency plan. Mboga et al. [56] in the year 2020 proposed a fully connected CNN for land cover classification from historical aerial photographs. Two CNN architectures (i.e., atrous layers without downsampling, up-sampling layers with downsampling) were deployed and reported to achieve an accuracy of approximately 90% outperforming conventional machine learning approaches.

Mitsuahara and Shishibori [79] in the year 2020 developed a virtual reality and augmented reality based Simulated Tornado Experience (STE) for better preparation for future tornado events. Series of comparative experiments were performed and virtual reality based STE was reported better for controlling learner fear and system operations. In the same year, Pal et al. [108] used a similar approach to Chowdhuri et al. [28] and implemented ensemble machine learning approaches for gully erosion susceptibility mapping. From the results, Bagging ensemble was recommended for efficient gully erosion mapping. Pour et al. [109] proposed the use of Low Impact Development (LID) approaches along with conventional flood stormwater management to better mitigate the impacts of floods because of climate change. Advantages, limitations, challenges and potential future aspects of LIDs in context to mitigate the urban floods were investigated in detail.

Sansare and Mhaske [74] in the year 2020 proposed the use of a GIS software tool for flood and landslide hazard mapping. QGIS software tool helped in the identification of important flood and landslide related insights for future hazard mitigation. Shahri and Moud [29] proposed a novel Hybrid Block Based Neural Network (HBNN) model for landslide susceptibility mapping. The proposed model was the combination of the divide-and-conquer approach and genetic algorithm. The performance of the model was assessed using the Region of Convergence (ROC) curve and the area under the curve was reported as approximately 89%. Later in the 2020, Ziarh et al. [110] proposed a novel Multi-Criteria Decision Analysis (MCDA) based on the entropy and catastrophe theory for flood risk mapping. The functionality of the proposed approach was demonstrated using a case study. From the results, 93% accuracy in flood risk mapping was reported for the proposed approach.

Most recently in 2021, Arabameri et al. [30] proposed a novel ensemble of machine learning algorithms for predicting maps of gully erosion susceptibility. The genetic algorithm was combined with the xgboost machine learning model and deployed on a GIS database for gully erosion prediction. From the results, an accuracy of around 90% was reported for the proposed approach. In the same year, Ndehedehe et al. [31] assessed the variations in hydrological stores on drought intensities within Australia using machine learning regression approaches. Gaussian kernel based SVM was deployed as a regressor and Quantile Function Storage (QFS) for assessment. Very critical insights from analyses were reported to help drought resilience and efficient water resources management. Pal et al. [111] in 2021 proposed a spatial distribution based soil erosion map using empirical observations Revised Universal Soil Loss Equation (RUSLE) modelling. The importance of climate change and land cover variations was reported in controlling soil erosion. From the results, it was highlighted that if climate change and human activities are not controlled, by 2100, nearly 9.88% of land surface top soil will erode.

In one of the most recent studies, Rahman et al. [112] developed a machine learning and hydrodynamic modelling based flood hazard zone mapping system. The accuracy of the model was assessed using the ground truth values and was reported high with an  $R^2$  score of 0.83. Recently in 2021, Roy et al. [32] proposed the use of multiple machine learning algorithms (i.e., SVM, Biogeography Based Optimization (BBO), Extremely Randomised Trees (ERT)) for the mapping of flood prone regions in the Ajoy River basin of India. Climate change and land-use planning related features were used as input to the machine learning models. From the results, BBO performed best among



the three for flood susceptibility mapping. In the same year, Saha et al. [33] investigated the soil erosion and land degradation phenomena by making use of machine learning and optimisation models. Specifically, Gully Erosion Susceptibility (GES) mapping was investigated, and land use planning was optimized by deploying RF, BRT and EBO models. From the results, Ecogeography based Optimization (EBO) was reported as the best model for GES mapping. Saha et al. [34] in the year 2021 proposed the use of ensemble machine learning models for flood susceptibility mapping. The ensemble of hyperpipes and SVM was implemented on eight floods related variables to predict the susceptibility maps. From the experiments, the proposed ensemble approach was reported to achieve an accuracy of 93%. Most recently, Shahri et al. [113] developed a 3D topographical model using a geospatial and data-driven algorithm for generating accurate subsurface topography spatial variations. Accuracy of 82% was reported from the results. Furthermore, it was demonstrated that the proposed model was helpful in determining the hydrological properties of the structure.

It has been observed that technology has facilitate variety of assessments and activities at prevention and mitigation phase including landslide susceptibility mapping, disaster simulations, flood hazard mapping, evacuation planning, crowd flow simulation, structural design modifications, baseline data collection, flood risk assessment, land-use and land-cover classification, gully erosion susceptibility mapping, seismic assessment of buildings, contingency planning, drought prediction and subsurface topography mapping. To assist above-mentioned assessments, technology has evolved from the conventional approaches (i.e., Regression, Computational Modelling, Monte Carlo Simulation, Probabilistic Modelling, Hydrodynamic Modelling, Conventional Machine Learning Models, Empirical Modelling, 3D Modelling, Fuzzy Logic, Mathematical Modelling) towards learning based and AI oriented approaches (i.e., GIS, UAVs, CNN, Deep Learning, Ensemble Machine Learning, Artificial Intelligence, Augmented Reality, Neural Networks, Remote Sensing). Furthermore, it has been observed that most of the studies are performed under a limited scope for a specific region.

#### 4.2. Preparedness

In 2010, Chang et al. [35] proposed a clustering based hybrid inundation model using linear regression and Artificial Neural Networks (ANNs) for flood inundation forecasting. A simulated dataset using a two-dimensional non-inertial overland flow model was used for the training and testing of regression models. The proposed model was able to predict the flood inundation depths accurately 1 hour ahead. In the same year, Liao et al. [114] developed an early warning system for landslides by making use of geospatial and remote sensing data. The proposed system was capable of landslide susceptibility mapping, precipitation monitoring and landslide prediction. In 2011, Zhang et al. [115] developed a real-time landslide monitoring system using a wire-pulling trigger displacement meter and grid pluviometer. Software and hardware combination was used to acquire data from sensors and forecasting of landslide on the highway.

Lin et al. [36] in 2013 proposed a flood forecasting model using a two-stage support vector machine. The idea of forecasting the rainfall from typhoon characteristics along with observed rainfall at the first stage and using forecasted rainfall along with observed runoff to forecast the final runoff at the second stage was proposed. From the results, the proposed models were able to forecast accurately up to 6 hours ahead. In the same year, Devi et al. [116] developed a disaster prediction system based on the statistical analysis. SPSS data mining tool was used to interpret the spatial data for disaster prediction. The proposed approach was reported effective in analysing the data and predicting the future disaster event. In the year 2014, Chang et al. [37] proposed the use of multiple ANN models (i.e., static ANN, Elman NN, Nonlinear Autoregressive Network with Exogenous inputs (NARX)) towards forecasting the water levels from the rainfall data. From the results, the NARX model was reported to accurately forecast the water levels at the

selected station with 10-60 min ahead. Later in the same year, Dehghani et al. [38] deployed Neural Networks and Monte Carlo simulation approaches for drought forecasting. Streamflow discharge data was used and was indexed for being used in the simulations. From the analysis, forecasted results were reported within 95% of the confidence interval. Lucieer et al. [57] in the year 2014 proposed a cost-effective UAV based landslide monitoring system where structure from motion approach was used to map the landslide displacements using UAV captured imagery. The accuracy was validated using ground truth values and reported as 7 cm and 6 cm horizontal and vertical accuracy, respectively.

In 2015, Asharose et al. [117] proposed an education tool to conduct disaster awareness workshops to better prepare against hazards. Awareness workshops were reported helpful in enhancing the knowledge of people related to disasters and helped them in better dealing with disaster situations. Gong et al. [80] in year 2015 proposed the use of virtual reality technology for earthquake disaster awareness. A head mount hardware was used to simulate the disaster event in virtual to educate the community. From the results, the proposed technology proved effective in simulating earthquake events and improving disaster drills. In the same year, Moghari and Araghinejad [39] used multiple variants of neural networks for the forecasting of the monthly and seasonal drought. From the results, it was reported that forecasting accuracy increased with precipitation time-scale increase while decrease with an increase in lead time. In 2016, Hajian et al. [118] proposed a model to simulate wildfire propagation considering it a stochastic shortest path problem. Monte Carlo simulation approach was used to identify the distribution of fire travelling time. The proposed approach resulted in comparatively faster wildfire prediction with an acceptable effect on accuracy.

In 2017, Asim et al. [40] proposed the use of machine learning approaches (i.e., Recurrent Neural Network (RNN), NN, RF and Ensemble) to predict the magnitude of the earthquake in the Hindukush region. Models were trained using the mathematically calculated eight seismic indicators. From the analysis, encouraging results were reported. Later in the same year, Klise et al. [119] proposed Water Network Tool for Resilience (WNTR) software for water distribution resilience during an earthquake disaster event. Damage to the water distribution network was reported dependent on both the magnitude of the earthquake and the available resources to repair the network. In 2018, Hu et al. [81] proposed the use of virtual reality based simulations to help the community prepare for disasters. 3D reconstructed disaster situations were rendered using virtual reality in this context. From the analysis, it was reported that the proposed approach could help in better awareness of disaster situations. In year 2019, Seibert et al. [120] also proposed the use of citizen science for water level measurements by CrowdWater application. From the preliminary experiments, placement of virtual gauge size was found problematic.

In 2019, Berkahn et al. [41] developed an ensemble of neural networks to predict the water levels in real-time during a flooding event. A new network growing algorithm was proposed to select the topology of the ensemble network. The dataset used for training and testing of models was created using HE 2d hydrodynamic model. Acceptable forecasting accuracy with reduced computation time was reported for the proposed approach. In the same year, Wang et al. [58] proposed dilated casual CNN for the water level forecasting with a 1-hour to 6-hour lead time. The proposed approach was validated on a diversity of data collected from multiple typhoons and benchmarked against the conventional machine learning models. In the year 2020, De Vitry and Leitao [59] investigated the proxy water level measurements' impact on the pluvial flood forecasting models' performance. Image-based proxy water level measurements were used and multiple calibration tests were performed to study the impact. Pluvial flood forecasting model performance was reported enhanced when calibrated using proxy water level measurements; however, the presence of complex correlated errors was also reported, which may have a negative impact on model performance.

Recently in 2020, Mishra et al. [75] proposed the use of GIS technology for monitoring water levels and forecasting floods. A satellite altimetry derived approach was deployed for water level monitoring of large water bodies. Furthermore, a web based front-end was developed to visualize the flood maps. In 2020, Strobl et al. [121] proposed the use of citizen science base mobile application CrowdWater for water level measurements. The virtual-gauge functionality of the CrowdWater application was validated against the in-field surveys and from the analysis, application recorded water levels were reported comparatively accurately to field values. In 2021, Pillai et al. [122] developed a service-oriented IoT architecture for disaster forecasting and early warning by using machine learning algorithms over the cloud server. Acceptable absolute errors were reported when machine learning models were applied on three different sensors data on the cloud. In one of the most recent studies, Tamakloe et al. [123] developed an algorithm based on the topological features and Spatio-temporal traffic concentration within the network for better evacuation during disaster situations. From the experimental results, the proposed approach performed better in comparison to the conventional shortest passage approach.

From the cited literature in this section, it is observed that technology has been used to facilitate variety of activities at preparedness phase including flood inundation forecasting, early warning systems, landslide monitoring system, flood forecasting, water level forecasting, drought forecasting, disaster awareness workshops, earthquake magnitude prediction, water distribution network resilience and efficient evacuation planning. To assist above-mentioned activities, different solutions were proposed using technologies including ANNs, remote sensing, data acquisition, machine learning regression, Monte Carlo simulation, UAVs, ensemble of machine learning, virtual reality, citizen science, hydrodynamic modelling, and GIS.

### 4.3. Response

In 2010, Poser and Dransch [124] investigated the idea of using the Volunteered Geographic Information (VGI) as an efficient source to facilitate the activities within disaster response and recovery phases. A case study was presented where VGI was used for post flood rapid damage estimations and achieved comparable results to the conventional hydraulic modelling based estimates. In 2011, Barrington et al. [125] evaluated the use of crowdsourced satellite images for providing post-disaster damage assessments. Authors investigated the existing initiatives in this regard and highlighted the future aspects of how crowdsourced remote sensing can be used as a tool for quick damage assessments. Later in the same year, Bengtsson et al. [76] made use of mobile phone network data to track the post-earthquake movement of people for efficient response related decisions. A case study was presented to demonstrate the proposed idea and reported that population movement patterns could significantly help disaster management agencies in executing effective plans. Choi and Lee [84] in the year 2011 proposed the use of UAVs for real-time and effective monitoring of disasters. A system was developed using multiple sensors to acquire the disaster site data and transmit it to the ground station for analysis and effective decision making.

In 2013, Aghamohammadi et al. [42] proposed a neural network based approach for the estimation of human loss as a result of an earthquake event. The model was trained using the Bam 2003 earthquake data and reported the high estimation performance. In the same year Kao et al. [60] proposed a computer vision based monitoring and warning system for high risk flood debris flow. Optical flow and object based frame to frame comparison approaches were deployed for debris monitoring. Conventional image processing techniques including background subtraction, spatial filtering and entropy determination were also implemented. Lin et al. [36] in the year 2013 proposed a dual-camera setup (i.e., wide-angle, speed dome) for the high-resolution visual monitoring of disaster. Feature matching and stitching approaches were used to render high-resolution visuals for efficient disaster anal-

ysis. Houston et al. [47] in year 2014 proposed a framework to use social media in facilitating disaster management activities. The proposed framework connected all the actors involved within the disaster management domain and highlighted social media means to connect for efficient disaster response. In 2015, Albuquerque et al. [48] proposed the use of VGI extracted from social media and authoritative information from sensors to identify disaster related useful information. The effectiveness of the proposed approach was demonstrated for a flood case study and reported the usefulness of the proposed hybrid information combination. In the same year, Boccardo et al. [85] investigated the use of UAVs for post-disaster information gathering and mapping. The advantages and limitations of the UAV platforms were highlighted in this context. Furthermore, a framework was proposed for the efficient deployment of UAVs.

In 2016, Jiang and Friedland [126] proposed a mono-temporal image processing approach to classify the post-hurricane debris and non-debris satellite images. Multivariate texture features were reported helpful in the efficient classification of debris from non-debris regions for post-disaster damage assessment. In the same year, Kim et al. [82] proposed the use of mobile augmented reality to facilitate the process of post-disaster structural damage assessments and safety analysis. A framework was introduced to support the adaptability of virtual reality technology and a prototype system was developed to demonstrate its effectiveness. Later, Koyama et al. [61] proposed an advanced gradient based optical flow estimation approach to estimate the Tsunami debris from Synthetic Aperture Radar (SAR) images. The improved performance was reported for the image processing based approach with acceptable error. Kryvasheyev et al. [49] in the year 2016 proposed the use of social media activity as a tool to assess the damage caused by a disaster. The proposed approach was validated using a Hurricane case study and reported the strong relationship between Twitter activity in assessing the damage.

In 2017, Bejiga et al. [43] proposed the use of a UAV equipped with a camera to facilitate post avalanche search and rescue operations. CNN and SVM were used for classifying the objects of interest from UAV captured images. Pre-processing and post-processing steps helped in improving the detection rate and prediction performance, respectively. In the same year, Ghosh and Gosavi [127] proposed a semi-Markov model for post estimation of disaster restoration time and quantifying the disaster rate during the response phase. The use of dynamic programming was proposed for the determination of the response centre. Later, Kakooei and Baleghi [62] in 2017 proposed the use of images from multiple sources (i.e., satellite, airborne, UAV) for post-disaster damage assessment. Facade images captured by UAVs when fused with roof images from satellite provided better damage assessments. Conventional image processing approaches were implemented to process the images. Arnold et al. [86] in year 2018 proposed the use of autonomous flying robots for facilitating search and rescue operations during initial hours of a disaster event. Swarm of autonomous flying robots was simulated in this context and was reported effective in locating 90% of the disaster victims. The swarm was controlled by cooperative behaviour intelligence approach in the simulations. In the same year, Galbusera and Giannopoulos [128] investigated the role of different disaster modelling approaches in the context of input-output economic models for disaster impact assessments. Based on the equilibrium theory and economic production theory, input-output economic model variants are most commonly used for post-disaster impact assessments. In the same year, Vetrivel et al. [63] investigated the structural damage assessment using computer vision and deep learning approaches. 3D point cloud features in combination with multiple kernel learning were used to improve the generalization problem and effective post-disaster damage assessment of structures.

In 2019, Ahmad et al. [44] proposed novel deep learning approaches for the identification and detection of passable roads in satellite and social media images after a flooding disaster. A comprehensive dataset provided by MediaEval 18 was used and fusion techniques were de-

ployed to address the challenge. The improved performance was reported over the existing state-of-the-art approaches by the authors. In the same year, Aljehani and Inoue [77] proposed the use of UAVs to generate post-disaster safe maps based on the scanning of area and movement of population. Mobile network information was used to track the movement of the population, while UAV captured visuals were used to scan the area. Later, Bholra et al. [64] in the year 2019 proposed the use of computer vision based validation data for urban flood inundation forecasting. Computer vision algorithms were deployed to find the water depths mainly from the heights of reference objects in the images. From the results, it was reported that additional computer vision based validation data could help in significantly improving flood inundation forecasting. Bird et al. [50] discussed the potential of social media (i.e., Facebook) for flood related information sharing. The case of the 2011 Queensland floods event was specifically discussed to demonstrate how Facebook groups helped in sharing the community related information during the disaster event.

Huang et al. [51] in 2019 proposed the fusion of visual and textual features for automatic labelling of social media posts related to disaster for efficient response. Deep learning models were implemented for training on the fused features for automatic labelling. The addition of visual features improved the accuracy in comparison to only textual features case. Later in the same year, Liang [65] proposed the use of deep learning models with the Bayesian optimization approach for post-disaster structural inspection of concrete bridges. Deep learning classification, detection and segmentation approaches were deployed to extract the structural failure related information for making final “major failure” or “no failure” decision. An accuracy of over 90% was reported for structural integrity classification using the proposed approach. Madichetty and Sridevi [52] in the year 2019 proposed a Stacking-based Ensemble using Statistical features and Information Words (SESIW) for detection of social media tweets related the disaster damage assessments. The main features used in the model included hashtags frequency, URLs, and user mentions. The proposed approach, when validated on baseline Twitter datasets, outperformed the conventional machine learning models. Ogie et al. [53] in the year 2019 proposed the use of crowdsourced social media data for flood mapping. Results and important insights from the PetaJakarta project were presented where social media was effectively implemented for flood maps generation and other disaster management related activities.

In 2020, Arif et al. [66] performed a comparative investigation using multiple deep learning models for disaster detection from social media images. A custom visual dataset was developed, and existing CNN models were implemented. From the results, it was reported that the VGG model was able to successfully detect the type of disaster from social media visual content. In the same year, Hao et al. [45] proposed the use of multimodal social media data (i.e., text, images) for the post-disaster damage assessments using machine learning algorithms. From the investigation, it was reported that by use of both image and text analysis, the proposed approach was able to achieve accurate damage assessment and provided more useful information about the disaster. Later, Majumder et al. [129] proposed a post-earthquake debris management system by using a mathematical modelling approach. A mathematical model was proposed for the optimal cost of transportation of debris and the selection of suitable dumping locations. In a recent study, Zhai and Peng [67] proposed the use of Google Street View (GSV) for post-hurricane damage assessment by applying deep learning approaches. From the results, it was reported that GSV proved helpful in damage assessments when damage level was low, while remote sensing images provided better damage assessment for high damage levels. In one of the most recent studies, Tay et al. [68] proposed the use of SSAR images from satellite to assess the damage caused by the floods. Change detection approach and GIS technology were implemented for damage mapping.

At response stage of disaster management cycle, technological solutions were proposed in abundant involving both conventional and

state-of-the-art approaches to address the variety of assessments including disaster response, damage assessments, victims tracking, disaster monitoring, disaster loss estimation, debris management, disaster information gathering, search and rescue operations, determining clear transport routes and flood inundation mapping. Some significant technologies used at this stage included VGI, crowdsourcing, remote sensing, mobile phone, UAVs, NN, conventional computer vision, social media, SAR, CNN, conventional machine learning, semi-Markov modelling, deep learning, ensemble of machine learning, and mathematical modelling.

#### 4.4. Recovery

In 2014, Hoshi et al. [69] explored the use of satellite images for post-earthquake recovery monitoring. Satellite images were visually interpreted and validated against the results of field surveys to demonstrate the effectiveness of satellite imagery in assessing the recovery. In 2017, Baytiyeh [78] investigated the role of ICT in post-earthquake education delivery. The effectiveness of online learning and the use of technology was highlighted in reinstating education after a disaster event. In 2017, Chowdhury et al. [87] proposed a Continuous Approximation (CA) model to explore the potential of drones in providing logistics to disaster-struck areas. The proposed model was able to identify optimal locations for distribution and estimate the overall operational costs.

In 2017, Hashemi-Parast et al. [130] used information from multiple resources (i.e., statistics, images from field surveys, satellite images) for the assessment of post-earthquake urban reconstruction monitoring in Bam, Iran. From the results, it was reported that satellite images and photographs helped in better assessment of reconstruction monitoring. However, the interpretation of visuals was made manually. In the same year, Shiraki et al. [131] proposed a resilience engineering approach for road network recovery after an earthquake. Mathematical heuristics and analytical rule formation approaches were used in the proposed framework for effective reinstatement of the road network. Later, Yang and Qi [70] proposed a system for spatial-temporal dynamic vegetation monitoring after an earthquake event. Normalized vegetation index time series data was used for the analysis and cross-correlogram and spectral matching approaches were implemented. From the results, it was reported that the proposed approach was able to efficiently monitor the vegetation growth in the region.

In 2018, Barabadi and Ayele [132] proposed the use of different statistical and machine learning models for the prediction of infrastructure recovery rates after disasters. Historical data was used for the analysis. The proposed framework was divided into three scenarios based on the availability and type of data (i.e., missing data, heterogeneous data, homogeneous data). The proposed approach helped in selecting the correct model for recovery rate monitoring based on the scenario. In the same year, Contreras et al. [133] assessed the recovery process after the 2009 L'Aquila earthquake event by using a recovery index based on spatial indicators. From the results, it was reported that the recovery index was helpful in highlighting the spatial pattern in the recovery process and can be used to quantify the recovery progress. In a most recent study performed in 2020, Soulakellis et al. [71] used the Unmanned Aerial System (UAS) captured data for post-earthquake recovery monitoring. High-resolution images and geo-information approach were used for efficient structural recovery mapping. The SfM approach was used for creating 3D point clouds of structures. The proposed approach proved 97% accurate in demolish detection. In 2021, Fan et al. [46] proposed the idea of Disaster City Digital Twin by incorporating ICT and AI into the process of facilitating disaster management activities. Data collection, data analysis, decision making and networking were reported as the four main components of the proposed paradigm.

It has been observed from cited literature that recovery phase been least addressed from technology perspective. Assessments addressed at recovery phase included recovery monitoring, restoration of education,



logistics restoration, reconstruction monitoring, restoration of transport routes and vegetation growth monitoring. Some highlighted technologies used in literature to address these activities included remote sensing, ICT, Continuous Approximation (CA) modelling, mathematical heuristics, machine learning, statistical modelling, UAS, AI, SFM and UAVs.

## 5. Process-driven and need-oriented framework based analysis

This section presents the proposed process-driven and need-oriented framework based analysis of cited technological contributions to disaster management. The proposed process-driven and need-oriented framework is designed to orient the literature in a two-dimensional structure to better align it against the respective phase of disaster management and corresponding assessment it aims to address. The horizontal axis of the framework represents different phases of disaster management progressing from prevention towards recovery. On the other hand, the vertical axis lists the needs/tasks involved at each phase, respective assessments/activities performed to address the needs and common technologies used to assist the assessments in addressing the disaster needs. Functional illustration of the proposed process-driven and need-oriented framework deployed for the cited literature is given in Fig. 4. Some literature entries (i.e., [134, 135, 136, 137, 138, 139, 140, 141]) were included to support the framework and were not part of the main review as mentioned in Section 3.

From the framework, it can be interpreted that at the prevention phase, the most addressed need is “Disaster Risk Analysis and Management”, and the most addressed assessment is the “Disaster Hazard Zone and Susceptibility mapping”. Machine learning and deep learning were observed to be most deployed technologies at the prevention phase. At the preparedness phase, “Disaster Forecasting and Prediction” was the most addressed need in literature and corresponding “Disaster Pre-Warning Systems and Prediction Models” was the most explored assessment. Similar to the prevention phase, machine learning, deep learning and computer vision were the most used technologies. At the response phase, “Disaster Damage Analysis” was the most addressed need while “Structural Damage Assessment” was the most investigated assessment. Computer vision, social media and remote sensing were observed as the leading technologies used at this phase. Finally, at the recovery phase, “Restoration to Normal” was the most addressed need while corresponding “Reconstruction Monitoring” assessment was most explored from a research perspective. Computer vision, remote sensing, and UAVs were observed as the highlighted technologies used at this phase. Overall, it can be observed that the recovery phase has been least explored from a technological point of view and offers a huge potential to technology providers for deploying technological solutions to assist the assessments.

Tables 2 to 5 present the detailed process-driven and need-oriented analysis of cited literature for prevention, preparedness, recovery and response phases, respectively. Each literature entry is investigated for addressed disaster need, addressed disaster assessment, disaster type and technology used to address the corresponding assessment.

## 6. Constraints and set of requirements

Each phase of disaster management involves a number of constraints and a set of basic requirements associated with specific needs and problems. For a proposed solution to be effective, it must minimally address these requirements; however, from cited literature, proper requirement formulation is found lacking. Carter [16] mentioned some basic requirements to be addressed for effective disaster management performance. Building on the idea of Carter [16] and bringing it together with the proposed need-oriented review; this article proposes a list of basic constraints and a set of requirements to help the contributors propose efficient solutions to disaster management related problems. Proposed

constraints are generalized and applicable in the scope of all common disasters; however, more comprehensive and assessment related constraints are recommended to be defined depending on the type of disaster and phase of the disaster management cycle. Listed are the proposed constraints:

- **Responsiveness** is referred to the speed of the proposed solution and is often measured by analyzing the processing times in providing the desired output. This constraint is closely related to the real-time functionality of the proposed approach and varies across different phases. In general, any proposed solution should process information as quickly as possible; however, it is not always the priority. Other than the assessments which require real-time operational functionality (e.g., flood monitoring, early warning systems, rapid flood mapping, search and rescue), responsiveness is not the priority in disaster management. Having said that, a problem-specific formulation of required response time is recommended.
- **Accuracy** is referred to the correctness of the proposed solution and is measured by validating against ground truth samples. In general, any proposed solution should be as accurate as possible; however, not always the priority. For the assessments where quick results are required (e.g., early disaster mapping, search and rescue, early visual inspections), accuracy is not as important as responsiveness. On the other hand, assessments where relaxed time constraints are involved (e.g., structural damage assessment, prevention measures, risk assessment, hazard zone mapping) should be highly accurate. For the assessment like early disaster warning systems, both accuracy and responsiveness are equally important, which makes it a challenging task for contributors to achieve. A specific formulation of accuracy requirement for the addressed problem is recommended for efficient outcome.
- **Generalization** is referred to the implementation diversity of the proposed solution and is assessed by validating the proposed method for comprehensive data containing multiple scenarios. In general, any proposed solution should be capable of performing under variable disaster situations without major changes. Having said that, it is not practical for most disaster management related assessments to have a highly generalized single solution applicable to all disasters. Therefore, it is highly recommended to properly formulate the generalization requirement specific to disaster type and assessment for efficient results.
- **Cost and Hardware Implementation** is referred to the overall cost and hardware implementation related constraints for the proposed solution. A feasibility study of the required budget, availability of hardware components, availability of power on-site, and communication network is highly recommended but often ignored by contributors. Logistic requirements vary significantly based on the type of disaster and assessment; therefore, an assessment-specific formulation of cost and implementation related requirements is recommended.
- **User-Friendliness** is referred to the ease by which a non-technical person can deploy, supervise and monitor a technological solution. It is highly desirable for a proposed system to be easy to operate by a non-technical individual with little knowledge. In practice, it is recommended to have a system that can be operated by anyone after a quick training session.

The cited literature has been evaluated against the proposed set of requirements to highlight the trends of addressed requirements. For this article, subjective evaluation criteria are defined and listed as follows:

- Responsiveness (✓): If processing times for the proposed technological solution are minimally discussed.
- Accuracy (✓): If the performance of the proposed model is quantified by at least one measure.

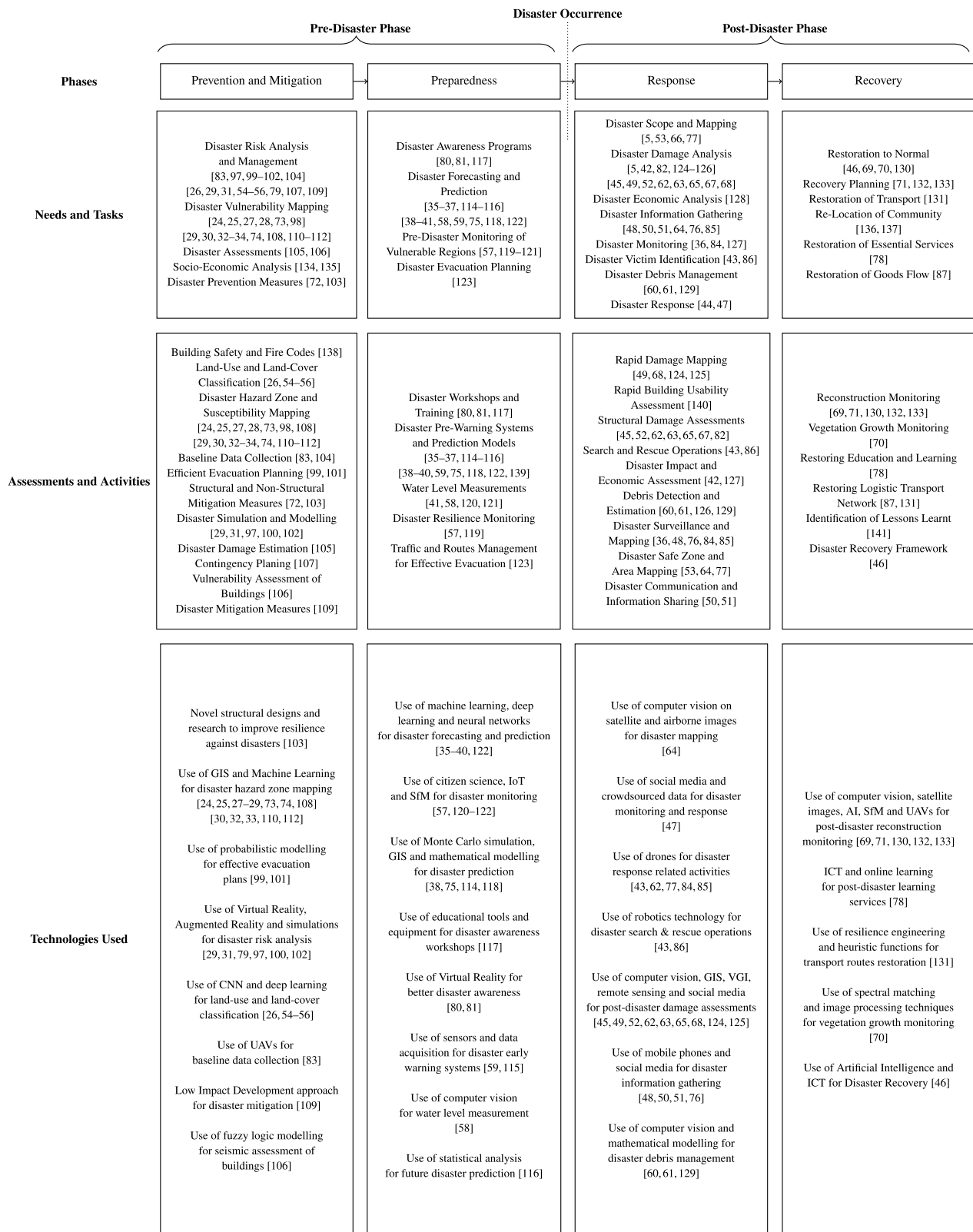


Fig. 4. Functional illustration of the proposed process-driven and need-oriented review framework.

- Cost and Hardware Implementation (✓): If hardware requirements and/or cost of deploying the proposed solution in practice is minimally addressed.
- Generalization (✓): If the proposed solution is validated against diversity of scenarios/data.

- User-Friendliness (✓): If operational information and user interface for the proposed solution are minimally addressed.

Tables 6 to 9 present the proposed constraint based analysis of the cited literature from the prevention, preparedness, recovery and re-

**Table 2.** The proposed process-driven and need-oriented analysis of cited literature from prevention and mitigation phase.

Author/s	Year	Need and Tasks	Assessments and Activities	Disaster	Technology Used
Bai et al. [24]	2010	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Landslide	Conventional Machine Learning
Martyr et al. [97]	2010	Disaster Risk Analysis and Management	Disaster Simulation and Modelling	Hurricane	Computational Mathematical Models
Aronica et al. [98]	2012	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Monte Carlo Simulation
Sun et al. [72]	2012	Disaster Prevention Measures	Structural and Non-Structural Measures	Flood and Landslide	GIS and Equipment
Campos et al. [99]	2012	Disaster Risk Analysis and Management	Effective Evacuation Plans	All/Common	Analytical Heuristic
Caballero and Rahman [100]	2014	Disaster Risk Analysis and Management	Disaster Simulation and Modelling	Flood	Monte Carlo Simulation
Radianti et al. [101]	2014	Disaster Risk Analysis and Management	Effective Evacuation Plans	All/Common	Spatio-Temporal Probabilistic Model
Liu et al. [102]	2015	Disaster Risk Analysis and Management	Disaster Simulation and Modelling	Flood	1D-2D Hydrodynamic Models
Ramakrishnan et al. [103]	2016	Disaster Prevention Measures	Structural and Non-Structural Measures	Extreme Heat Wave	Phase Change Material, Simulations
Zhu et al. [83]	2017	Disaster Risk Analysis and Management	Baseline Data Collection	Flood	Unmanned Aerial Vehicles (UAVs)
Chen et al. [25]	2018	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Landslide	Conventional Machine Learning
Tanaka et al. [104]	2018	Disaster Risk Analysis and Management	Baseline Data Collection	All/Common	Database Development
Zhang et al. [54]	2018	Disaster Risk Analysis and Management	Land-Use and Land-Cover Classification	All/Common	Object-Based CNN (OCNN)
Bera et al. [73]	2019	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Landslide	GIS and Multi-Criteria Analysis
Komolafe et al. [105]	2019	Disaster Assessments	Disaster Damage Estimation	Flood	Mathematical Modelling
Zhang et al. [55]	2019	Disaster Risk Analysis and Management	Land-Use and Land-Cover Classification	All/Common	CNN and MLP
Abdi [26]	2020	Disaster Risk Analysis and Management	Land-Use and Land-Cover Classification	All/Common	Conventional Machine Learning
Band et al. [27]	2020	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Hybrid and Ensemble Machine Learning
Chowdhuri et al. [28]	2020	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Gully Erosion	Conventional Machine Learning
Harirchian and Lahmer [106]	2020	Disaster Assessments	Vulnerability Assessment of Buildings	Earthquake	Fuzzy Logic Model
Lestari et al. [107]	2020	Disaster Risk Analysis and Management	Contingency Planing	Volcanic Eruption	Communication Model and Training
Mboga et al. [56]	2020	Disaster Risk Analysis and Management	Land-Use and Land-Cover Classification	All/Common	Fully Connected CNN
Mitsuhara and Shishibori [79]	2020	Disaster Risk Analysis and Management	Disaster Simulation and Modelling	Tornado	Virtual Reality and Augmented Reality
Pal et al. [108]	2020	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Gully Erosion	Ensemble of Machine Learning
Pour et al. [109]	2020	Disaster Risk Analysis and Management	Disaster Mitigation Measures	Flood	Low Impact Development (LID) Approach
Sansare and Mhaske [74]	2020	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Geographic Information System (GIS)
Shahri and Moud [29]	2020	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Landslid	Novel Hybrid Neural Networks
Ziarh et al. [110]	2020	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Multi-Criteria Decision Analysis
Arabameri et al. [30]	2021	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Gully Erosion	Ensemble of Machine Learning
Ndehedehe et al. [31]	2021	Disaster Risk Analysis and Management	Disaster Simulations and Modelling	Drought	Conventional Machine Learning
Pal et al. [111]	2021	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Soil Erosion	Empirical Modelling
Rahman et al. [112]	2021	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Hydrodynamic Models and Machine Learning
Roy et al. [32]	2021	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Machine Learning Models
Saha et al. [33]	2021	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Soil Erosion	Machine Learning and Optimization Models
Saha et al. [34]	2021	Disaster Vulnerability Mapping	Disaster Hazard Zone and Susceptibility Mapping	Flood	Ensemble of Machine Learning
Shahri et al. [113]	2021	Disaster Risk Analysis and Management	Disaster Simulations and Modelling	Flood	3D Topographical Models

**Table 3.** The proposed process-driven and need-oriented analysis of cited literature from preparedness phase.

Author/s	Year	Need and Tasks	Assessments and Activities	Disaster	Technology Used
Chang et al. [35]	2010	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Flood	Conventional Machine Learning
Liao et al. [114]	2010	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Landslide	Geospatial and Satellite Data Modelling
Zhang et al. [115]	2011	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Landslide	Conventional Sensory Equipment
Lin et al. [36]	2013	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Flood	Machine Learning SVM
Devi et al. [116]	2013	Disaster Forecasting	Disaster Pre-Warning System and Prediction	All/Common	Statistical Analysis and Data Mining
Chang et al. [37]	2014	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Flood	Artificial Neural Networks
Dehghani et al. [38]	2014	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Drought	NN and Monte Carlo
Lucieer et al. [57]	2014	Disaster Monitoring	Disaster Resilience Monitoring	Landslide	SfM and UAVs
Asharose et al. [117]	2015	Disaster Awareness	Disaster Workshops and Training	All/Common	Workshops and Educational Tools
Gong et al. [80]	2015	Disaster Awareness	Disaster Workshops and Training	Earthquake	Virtual Reality and Simulations
Moghari and Araghinejad [39]	2015	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Drought	Neural Networks
Hajian et al. [118]	2016	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Wildfire	Monte Carlo Simulation
Asim et al. [40]	2017	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Earthquake	Conventional Machine Learning
Klise et al. [119]	2017	Disaster Monitoring	Disaster Resilience Monitoring	Earthquake	Modelling and Software Package
Hu et al. [81]	2018	Disaster Awareness	Disaster Workshops and Trainings	Flood	Virtual Reality
Seibert et al. [120]	2019	Disaster Monitoring	Water Level Measurements	Flood	Citizen Science
Berkhahn et al. [41]	2019	Disaster Forecasting	Water Level Measurements	Flood	Ensemble Neural Networks
Wang et al. [58]	2019	Disaster Forecasting	Water Level Measurements	Flood	Dilated Casual CNN
De Vitry and Leitao [59]	2020	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Flood	Image Processing and Sensors for Calibration
Mishra et al. [75]	2020	Disaster Forecasting	Disaster Pre-Warning System and Prediction	Flood	Geographic Information System (GIS)
Strobl et al. [121]	2020	Disaster Monitoring	Water Level Measurements	Flood	Citizen Science
Pillai et al. [122]	2021	Disaster Forecasting	Disaster Pre-Warning System and Prediction	All/Common	IoT and Machine Learning
Tamakloe et al. [123]	2021	Disaster Evacuation	Traffic and Routes Management for Effective Evacuation	All/Common	Traffic Network Features based Algorithm

**Table 4.** The proposed process-driven and need-oriented analysis of cited literature from recovery phase.

Author/s	Year	Need and Tasks	Assessments and Activities	Disaster	Technology Used
Hoshi et al. [69]	2014	Restoration to Normal	Reconstruction Monitoring	Earthquake	Satellite Image Processing and Field Surveys
Baytiyeh [78]	2017	Restoration of Essential Services	Restoring Education and Learning	Earthquake	ICT and Online Learning
Chowdhury et al. [87]	2017	Restoration of Goods Flow	Restoring Logistic Transport Network	All/Common	Drones
Hashemi-Parast et al. [130]	2017	Restoration to Normal	Reconstruction Monitoring	Earthquake	Statistics and Images
Shiraki et al. [131]	2017	Restoration of Transport	Restoring Logistic Transport Network	Earthquake	Resilience Engineering, Heuristic Functions
Yang and Qi [70]	2017	Restoration to Normal	Vegetation Growth Monitoring	Earthquake	Spectral Matching and Cross-Correlogram
Barabadi and Ayele [132]	2018	Recovery Planning	Reconstruction Monitoring	All/Common	Statistical Models and Machine Learning
Contreras et al. [133]	2018	Recovery Planning	Reconstruction Monitoring	Earthquake	Recovery Index based on Spatial Features.
Soulakellis et al. [71]	2020	Recovery Planning	Reconstruction Monitoring	Earthquake	SfM and UAS
Fan et al. [46]	2021	Restoration to Normal	Disaster Recovery Framework	All/Common	Artificial Intelligence and ICT



**Table 5.** The proposed process-driven and need-oriented analysis of cited literature from response phase.

Author/s	Year	Need and Tasks	Assessments and Activities	Disaster	Technology Used
Poser and Dransch [124]	2010	Disaster Damage Analysis	Rapid Damage Mapping	Flood	VGI
Barrington et al. [125]	2011	Disaster Damage Analysis	Rapid Damage Mapping	Earthquake	Crowdsourced Remote Sensing
Bengtsson et al. [76]	2011	Disaster Information Gathering	Disaster Surveillance and Mapping	Earthquake	Mobile Phone
Choi and Lee [84]	2011	Disaster Monitoring	Disaster Surveillance and Mapping	All/Common	UAVs and Sensors
Aghamohammadi et al. [42]	2013	Disaster Damage Analysis	Disaster Impact and Economic Assessment	Earthquake	Neural Networks
Kao et al. [60]	2013	Disaster Debris Management	Debris Detection and Estimation	Flood	Conventional Image Processing
Lin et al. [36]	2013	Disaster Monitoring	Disaster Surveillance and Mapping	All/Common	Dual-Camera Setup
Houston et al. [47]	2014	Disaster Response	Multiple Assessments	All/Common	Social Media based Framework
Albuquerque et al. [48]	2015	Disaster Information Gathering	Disaster Surveillance and Mapping	Flood	Social Media and VGI
Boccardo et al. [85]	2015	Disaster Information Gathering	Disaster Surveillance and Mapping	All/Common	Unmanned Aerial Vehicles (UAVs)
Jiang and Friedland [126]	2016	Disaster Damage Analysis	Debris Detection and Estimation	Hurricane	Mono-Temporal Image Processing
Kim et al. [82]	2016	Disaster Damage Analysis	Structural Damage Assessment	All/Common	Mobile Virtual Reality
Koyama et al. [61]	2016	Disaster Debris Management	Debris Detection and Estimation	Tsunami	Gradient-Based Optical Flow
Krycasheyev et al. [49]	2016	Disaster Damage Analysis	Rapid Damage Mapping	Hurricane	Social Media Activity
Bejiga et al. [43]	2017	Disaster Victims Identification	Search and Rescue Operations	Avalanche	CNN, SVM, UAV
Ghosh and Gosavi [127]	2017	Disaster Monitoring	Disaster Impact and Economic Assessment	Earthquake	Semi-Markov Model
Kakooei and Baleghi [62]	2017	Disaster Damage Analysis	Structural Damage Assessment	All/Common	Conventional Image Processing and UAVs
Arnold et al. [86]	2018	Disaster Victims Identification	Search and Rescue Operations	All/Common	Autonomous Aerial Robots and SWARM Intelligence
Galbusera and Giannopoulos [128]	2018	Disaster Economic Analysis	Disaster Impact and Economic Assessment	All/Common	Input-output Economic models
Vettrivel et al. [63]	2018	Disaster Damage Analysis	Structural Damage Assessment	Earthquake	3D Point Cloud with Deep Learning
Ahmad et al. [44]	2019	Disaster Response	Effective Evacuation Planning	Flood	Deep Learning Models
Aljehani and Inoue [77]	2019	Disaster Scope and Mapping	Disaster Safe Zone and Area Mapping	All/Common	UAVs, and Mobile Phone
Bhola et al. [64]	2019	Disaster Information Gathering	Disaster Safe Zone and Area Mapping	Flood	Computer Vision Approaches
Bird et al. [50]	2019	Disaster Information Gathering	Disaster Communication and Information Sharing	Flood	Social Media
Huang et al. [51]	2019	Disaster Information Gathering	Disaster Communication and Information Sharing	All/Common	Social Media and Deep Learning
Liang [65]	2019	Disaster Damage Analysis	Structural Damage Assessments	All/Common	Deep Learning and Bayesian Optimization
Madichetty and Sridevi [52]	2019	Disaster Damage Analysis	Structural Damage Assessments	All/Common	Social Media Data Mining
Ogie et al. [53]	2019	Disaster Scope and Mapping	Disaster Safe Zone and Area Mapping	Flood	Crowdsourced Social Media
Arif et al. [66]	2020	Disaster Scope and Mapping	Disaster Identification	All/Common	Deep Learning Models
Hao et al. [45]	2020	Disaster Damage Analysis	Structural Damage Assessments	Hurricane	Social Media and Machine Learning
Majumder et al. [129]	2020	Disaster Debris Management	Debris Detection and Estimation	Earthquake	Mathematical Model
Zhai and Peng [67]	2020	Disaster Damage Analysis	Structural Damage Assessments	Hurricane	Google Street View and Deep Learning
Tay et al. [68]	2021	Disaster Damage Analysis	Rapid Damage Mapping	Flood	SAR Images and GIS

**Table 6.** The proposed disaster constraints based analysis of cited literature from prevention and mitigation phase.

Case	Responsiveness	Accuracy	Cost and Hardware Implementation	Generalization	User Friendliness
Bai et al. [24]	×	✓	×	×	×
Martyr et al. [97]	×	✓	×	×	×
Aronica et al. [98]	×	✓	×	×	×
Campos et al. [99]	×	×	×	×	×
Sun et al. [72]	×	×	×	×	✓
Cballero and Rahman [100]	×	✓	×	×	×
Radianti et al. [101]	×	✓	×	✓	×
Liu et al. [102]	×	✓	×	×	×
Ramakrishnan et al. [103]	×	✓	×	✓	×
Zhu et al. [83]	×	✓	×	×	×
Chen et al. [25]	×	✓	×	✓	×
Tanaka et al. [104]	NA	NA	×	×	×
Zhang et al. [54]	×	✓	×	✓	×
Bera et al. [73]	×	✓	×	×	×
Komolafe et al. [105]	×	✓	×	×	×
Zhang et al. [55]	✓	✓	×	✓	×
Abdi [26]	×	✓	×	✓	×
Band et al. [27]	×	✓	×	✓	×
Chowdhuri et al. [28]	×	✓	×	✓	×
Harirchian and Lahmer [106]	×	✓	×	×	×
Lestari et al. [107]	NA	NA	NA	NA	×
Mboga et al. [56]	×	✓	×	×	×
Mitsuhara and Shishibori [79]	×	✓	×	×	×
Pal et al. [108]	×	✓	×	×	×
Pour et al. [109]	NA	NA	×	NA	×
Sansare and Mhaske [74]	×	×	×	×	✓
Shahri and Moud [29]	×	✓	×	×	×
Ziarh et al. [110]	×	✓	×	×	×
Arabameri et al. [30]	×	✓	×	✓	×
Ndehedehe et al. [31]	×	✓	×	×	×
Pal et al. [111]	×	✓	×	✓	×
Rahman et al. [112]	×	✓	×	×	×
Roy et al. [32]	×	✓	×	×	×
Saha et al. [33]	×	✓	×	✓	×
Saha et al. [34]	×	✓	×	✓	×
Shahri et al. [113]	×	✓	×	✓	×

sponse phase. From the analysis, it can be observed that “Accuracy” is the most addressed need for the proposed technological solutions; however, all other constraints are least addressed by a significant margin in comparison to “Accuracy”. This suggested the lack of collaboration between technology providers and disaster management officials and the lack of proper requirement formulation for the problem to be addressed from a disaster management perspective. A qualitative case study to bring the opinion of disaster management officials into the development process is a potential activity that can be performed in the future.

**7. Scope of computer vision in disaster management**

A review of technological advancements in disaster management presented in Section 4 has highlighted computer vision as an emerging technology used to facilitate a variety of assessments. From the cited literature, computer vision technology has been used mainly for land-use and land-cover classification [26, 54, 55, 56], water level measurements [58], disaster mapping [64], disaster damage assessments [45, 49, 52, 62, 63, 65, 68, 124, 125], disaster debris management [60] and disaster reconstruction monitoring [69, 71, 130, 132, 133]. However, the technological advancements in edge computing hardware have opened new horizons for computer vision and deep learning technologies towards addressing complex disaster management related problems. The application of computer vision technologies to disaster management related assessments and corresponding potential challenges are discussed under this section.

State-of-the-art CNN models have already proven their utility for land-use and land-cover classification on satellite images with high ac-

curacy; however, on-demand and real-time local mapping is still an unexplored area where UAVs equipped with computer vision algorithms can play their part. From the analysis of literature, machine learning approaches have been abundantly used for disaster hazard zone mapping; however, the scope of computer vision technologies on satellite and airborne images has not been explored to its potential. Monitoring disaster prevention structures such as Dams is another domain where computer vision can be deployed for real-time damage detection and water-level measurements. At the preparedness phase, disaster monitoring and early warning systems can make use of computer vision based approaches for disaster detection. Real-time water level measurement at disaster vulnerable points using computer vision is one typical example where computer vision has already been used to issue early warnings for flood disasters. However, most of the studies were performed on a local scale and using conventional image processing techniques. For disaster forecasting, incorporation of visual data and respective computer vision analysis into existing time-series numerical data based models is one potential domain that can be explored.

At the response phase, on-demand quick mapping of disaster to identify the scope and extent of disaster using a UAV equipped with computer vision algorithms is a potential domain to explore. As of now, disaster mapping is done either by manned helicopters, ground communications, or satellite images. However, UAVs and computer vision have the potential to make this process cost economical, quick and more accurate to facilitate post-disaster response activities. In a similar scope, disaster victims identification is another assessment that can be facilitated by UAVs and computer vision algorithms (i.e., object detection, object segmentation). Post-disaster structural damage estimation is the assessment where computer vision has been deployed the most using

**Table 7.** The proposed disaster constraints based analysis of cited literature from preparedness phase.

Case	Responsiveness	Accuracy	Cost and Hardware Implementation	Generalization	User Friendliness
Chang et al. [35]	×	✓	×	✓	×
Liao et al. [114]	×	✓	×	×	×
Zhang et al. [115]	×	✓	✓	×	×
Lin et al. [36]	×	✓	×	✓	×
Devi et al. [116]	×	×	×	✓	✓
Chang et al. [37]	×	✓	×	×	×
Dehghani et al. [38]	×	✓	×	✓	×
Lucieer et al. [57]	×	✓	×	×	×
Asharose et al. [117]	NA	NA	NA	NA	✓
Gong et al. [80]	×	×	×	✓	✓
Moghari and Araghinejad [39]	×	✓	×	✓	×
Hajian et al. [118]	×	✓	×	×	×
Asim et al. [40]	×	✓	×	×	×
Klise et al. [119]	×	✓	×	✓	✓
Hu et al. [81]	×	✓	×	×	✓
Seibert et al. [120]	×	✓	×	×	✓
Berkhahn et al. [41]	✓	✓	×	×	×
Wang et al. [58]	×	✓	×	✓	×
De Vitry and Leitao [59]	×	✓	×	×	×
Mishra et al. [75]	×	×	×	×	✓
Strobl et al. [121]	×	✓	×	×	✓
Pillai et al. [122]	×	✓	✓	×	✓
Tamakloe et al. [123]	✓	✓	×	×	×

**Table 8.** The proposed disaster constraints based analysis of cited literature from recovery phase.

Case	Responsiveness	Accuracy	Cost and Hardware Implementation	Generalization	User Friendliness
Hoshi et al. [69]	×	✓	×	×	×
Baytiyeh [78]	NA	NA	NA	NA	NA
Chowdhury et al. [87]	×	✓	✓	×	×
Hashemi-Parast et al. [130]	×	✓	×	×	×
Shiraki et al. [131]	×	×	×	×	×
Yang and Qi [70]	×	✓	×	✓	×
Barabadi and Ayele [132]	×	✓	×	×	×
Contreras et al. [133]	×	✓	×	×	×
Soulakellis et al. [71]	×	✓	×	×	×
Fan et al. [46]	NA	NA	×	NA	×

satellite images and UAV captured images. State-of-the-art technologies such as SfM and 3D reconstruction based on point clouds have already been efficiently used. However, detailed structural damage assessments and building re-usability assessments at a local scale are least explored from a computer vision perspective and can be benefited. Disaster debris detection and estimation is an important assessment where computer vision technologies are least applied. For example, assessment of blockage at culverts using computer vision algorithms to avoid floods is one potential domain [142]. At the recovery phase, reconstruction monitoring from satellite images is the most explored assessment where computer vision is deployed. However, on-demand reconstruction monitoring at the local scale is still unexplored. Vegetation growth monitoring is another assessment where computer vision can be used in the same scope as reconstruction monitoring.

One of the highlighted challenges observed from cited literature is the availability of comprehensive benchmark visual datasets to address the disaster management related assessments from a computer vision perspective. It was observed that for the assessments where benchmark datasets were available, state-of-the-art computer vision algorithms are already deployed (e.g., land-use classification, structural damage mapping). Otherwise, most of the studies were performed using custom datasets with limited scope. In addition, dealing with diverse weather conditions, variable lighting conditions, and camera viewpoint problems are some highlighted challenges in deploying computer vision based solutions for addressing disaster management assessments.

### 8. Conclusion

A review of benchmark studies was presented using a proposed process-driven and need-oriented framework to highlight the technological trends in disaster management. The proposed framework helped in better classification of literature and finding potential research gaps. Machine learning, UAVs, AI, ICT, robotics, Big Data, virtual reality, augmented reality, social media and computer vision were reported as the highlighted technologies deployed to address disaster management assessments. Disaster hazard zone mapping, land-use classification, disaster forecasting, water level measurement, disaster damage assessments, and reconstruction monitoring were the reported assessments where most technological solutions were proposed. A list of disaster related constraints was formulated to align the solutions against the disaster management requirements. Accuracy was reported as the most fulfilled disaster requirement in literature, while responsiveness, generalization, cost and hardware implementation, and user-friendliness were rarely discussed. Proper requirement formulation related to addressed disaster management assessment for effective outcome was found consistently lacking. Overall, the availability of comprehensive benchmark datasets was found missing and most of the studies were performed for a local utility. Finally, the scope of computer vision in facilitating different disaster management related assessments was explored and potential challenges were highlighted as future research directions. Land-use and land-cover classification, water level measurements, disaster mapping, disaster damage assessments, disaster debris management and disas-

**Table 9.** The proposed disaster constraints based analysis of cited literature from response phase.

Case	Responsiveness	Accuracy	Cost and Hardware Implementation	Generalization	User Friendliness
Poser and Dransch [124]	×	✓	×	×	×
Barrington et al. [125]	NA	NA	NA	NA	✓
Bengtsson et al. [76]	×	✓	×	✓	×
Choi and Lee [84]	×	×	✓	×	✓
Aghamohammadi et al. [42]	×	✓	×	×	×
Kao et al. [60]	✓	✓	×	×	×
Lin et al. [36]	×	×	×	×	×
Houston et al. [47]	NA	NA	NA	NA	✓
Albuquerque et al. [48]	×	✓	×	×	×
Boccardo et al. [85]	×	✓	✓	×	✓
Jiang and Friedland [126]	✓	✓	×	×	×
Kim et al. [82]	×	✓	×	✓	✓
Koyama et al. [61]	×	✓	×	×	×
Krycasheyu et al. [49]	×	✓	×	×	×
Bejiga et al. [43]	✓	✓	×	✓	×
Ghosh and Gosavi [127]	×	✓	×	×	×
Kakooei and Baleghi [62]	×	✓	×	×	×
Arnold et al. [86]	×	✓	×	✓	×
Galbusera and Giannopoulos [128]	NA	NA	NA	NA	×
Vetriver et al. [63]	✓	✓	×	✓	×
Ahmad et al. [44]	×	✓	×	✓	×
Aljehani and Inoue [77]	×	✓	✓	✓	✓
Bhola et al. [64]	×	✓	×	✓	×
Bird et al. [50]	NA	NA	NA	NA	✓
Huang et al. [51]	×	✓	×	✓	×
Liang [65]	×	✓	×	×	×
Madichetty and Sridevi [52]	×	✓	×	✓	×
Ogie et al. [53]	×	✓	×	✓	×
Arif et al. [66]	×	✓	×	✓	×
Hao et al. [45]	×	✓	×	×	×
Majumder et al. [129]	×	×	×	×	✓
Zhai and Peng [67]	×	✓	×	×	×
Tay et al. [68]	×	×	×	×	×

ter reconstruction monitoring were reported as highlighted assessments where computer vision can potentially be used in the future.

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