Locating and deploying essential goods and equipment in disasters using AI-enabled approaches: A systematic literature review

Author

Farazmehr, Shima, Wu, Yong

Published

2023

Journal Title

Progress in Disaster Science

Version

Version of Record (VoR)

DOI

10.1016/j.pdisas.2023.100292

Rights statement

Downloaded from

Griffith Research Online

Progress in Disaster Science 19 (2023) 100292

Contents lists available at ScienceDirect

Progress in Disaster Science

journal homepage: www.elsevier.com/locate/pdisas

Review Article

Locating and deploying essential goods and equipment in disasters using AI-enabled approaches: A systematic literature review

Shima Farazmehr [a], Yong Wu [b,*]

[a] Research School of Management, College of Business and Economics, Australian National University, Canberra, ACT 2600, Australia
[b] Department of Business Strategy and Innovation, Griffith University, Gold Coast Campus, QLD 4222, Australia

ARTICLE INFO

Keywords:
Disaster management
Resilience
Artificial intelligence
Essential goods locating and deployment

ABSTRACT

Locating, routing and deploying essential goods and equipment are proactive disaster management strategies which received attention during recent decades. Many artificial intelligence (AI) based methods have been applied to respond to disasters in the past decade. However, there lacks a systematic review on these approaches. This paper reviews such papers published over the period of 2012–2022. These publications were examined according to their goal of using AI-based methods (e.g., for disaster management or for essential goods and equipment locating and deployment). We examined the approaches adopted and their specific application areas within the broad spectrum of disaster management. Based on our review, we recommend a few areas which could benefit from AI-based methods, especially for the less explored area of locating and routing problem during disasters. This research would be helpful for academics and practitioners alike in effectively adopting AI methods to improve the resilience and response in disastrous events.

1. Introduction

The governments worldwide have increasingly been concerned about the potential of natural disasters which could result in fundamental economic, social, and environmental impacts [98]. Most of these natural hazards are unpredictable, and are likely to cause serious damages, heavy casualties, and ecological, environment and property losses [30]. According to the yearly disaster statistical analysis 2015 [55], there were 376 natural calamities which resulted in mortality of 22,765 people, hurt 110.3 million individuals, and led to US$70.3 billion damage around the world in 2015 alone. In the 10 years to 2018, the annual cost of natural disasters worldwide averaged to US$212 billion [98]. Furthermore, climate change continues to exacerbate these challenges through a rise in the occurrence of extreme climatic events [132].

Due to the massive escalation of losses and harm in result of natural disasters, resilience has turned into a contemporary global principle for disaster decrease, preparation, response, and recovery activities [99]. Disaster management is defined as organizing and arranging resources and responsibilities to lessen the negative effects of a disastrous event [72]. One of the most fundamental principles to improve resilience for disaster management is locating and deploying the essential goods and equipment to the affected areas [110].

In fact, in the event of a disaster, the rapid deployment of emergency resources can be a critical factor in reducing losses [30]. The first 12 hours following the disaster are defined as the standard relief time (SRT). These hours are tremendously critical for disaster responses. Any delay in accomplishing the vital actions and delivering essential goods and equipment could result in more deaths and losses. In this situation, public and private organizations should investigate the circumstances swiftly and begin to send out and deliver the essential goods and equipment from local warehouses to the affected areas [131].

Therefore, locating essential goods such as medical equipment, water, food, and transportation, rescue and power supply equipment including fuel, generators, boats and other vehicles can be considered as one solution to counter the consequences of such disasters [110]. Once the inventory control plans are clear and warehouse positions are decided, disaster response teams endeavor to provide the best operations for aid distribution and reduce the duration and expense of the relief activities [131].

Large amounts of data would be generated from these natural disasters, consisting of real data and simulation data [128] which can be used to assist disaster management. In this regard, technologies such as remote sensing, information communication technologies, social media applications, and telecommunication have been increasingly deployed

* Corresponding author.
E-mail addresses: shima.farazmehr@anu.edu.au (S. Farazmehr), yong.wu@griffith.edu.au (Y. Wu).

https://doi.org/10.1016/j.pdisas.2023.100292
Received 26 September 2022; Received in revised form 9 May 2023; Accepted 4 July 2023
Available online 4 July 2023

and facilitated the collection of large volumes of real data [1,92]. Regardless of the data type, efficient disaster management necessitates gathering, arranging, and processing big data (BD) in a brief amount of time [128]. Recently, analyzing voluminous data using artificial intelligence (AI), with the aim of fast extraction of practical and reliable solutions has become more and more popular for efficient decision-making in managing disastrous situations and improving resilience (Z. N. [15,136]).

AI is a series of algorithms supported by data and is able to predict, comprehend, learn and act based on past observations, in a scientifically proven way [134]. Thus, AI-enabled methods, such as machine learning (ML), *k*-nearest neighbor (KNN), simulated annealing and neural networks (NN), are possible to process large amounts of data and achieve real-time solutions [137]. Consequently, disaster response teams can benefit from AI which can dramatically impact the development of disaster resilient strategies [75].

There are some published papers which have analyzed AI applications in disaster management, focusing on specific types of disaster, infrastructure, and data. For instance, A. T. Zagorecki et al. [150] investigated data mining and ML applications for disaster management; however their study lacks the investigation of pragmatic AI-based decision support tools. Fotovatikhah et al. [45] studied disaster management especially flood control and deliberated the obstacles and provocations of applying computational intelligence methods for this aim. Some other research papers investigated the way computer vision methods can be utilized for disaster management through examining the data gathered by remote sensing devices, including reckoning three-dimensional structures [53], detection of fire by wavelet analysis and NN [148], and target recognition through deep learning [151]. However, very limited number of these papers have specifically argued the advancement and problems with current AI applications in the field of disaster management in the phase of locating and deploying essential goods, along with considering the type of danger, infrastructure and data in a broad sense [128].

Despite the fact that the public is getting more and more engaged with activities involving AI-aided disaster management, only a few investigations and examinations exist about AI applications for managing hazards [91]. Furthermore, there is a paucity of studies concerning systematic literature review and categorization of the research on this topic.

Therefore, in this paper, we systematically explore the studies on the use of AI methods for hazard management focusing on locating and deploying essential goods and equipment. We rely on the following major questions to guide our search and discussion on these studies:

1. Which AI-enabled methods were used in the literature for disaster management?
2. Which AI-enabled methods and how they were applied for locating and deploying essential goods and equipment in disaster management?
3. What are the discovered research gaps related to the application of AI for locating and deploying essential goods and equipment?

The remainder of the paper is structured as follows. In Section 2, the research methodology and the keywords used for this systematic literature review are described. In Section 3, we investigate the papers focusing on disaster management using AI-based methods. Then in Section 4, we review the papers specifically on the issue of deploying and locating essential goods and equipment in disasters using AI-based approaches. Findings, challenges and opportunities in the investigated areas are discussed in Section 5 and finally, the conclusions are provided in Section 6.

2. Research methodology

The systematic literature review procedure, proposed by Tranfield et al. [133], is adopted to answer the above review questions. We started with collecting relevant literature through Google Scholar, IEEE, and Science Direct databases. For this aim, two sets of keywords, as described in Table 1, were considered.

The databases were thoroughly searched using these search terms and keywords to locate the most pertinent research papers for this topic [124]. The first set focused on disaster management using AI related approaches, while the second set paid special attention to locating and deploying essential goods and equipment with the assistance of AI. We limited the period for the literature search from 2012 to 2022 when we conducted the search in April 2022. This period was selected because there were several review articles on disaster management using AI published around 2012, such as A. Zagorecki et al. [149]. Moreover, AI-based approaches have received higher amount of attention in the last decade with many approaches proposed for disaster management [128].

A total of 258 articles were found using the mentioned keywords after removing duplicates and non-related papers. These articles were then either included or excluded based on the criteria presented in Table 2. Basically, we only selected papers which are research articles and are written in English. All other articles presented as comments, editorials, and letters were excluded.

We then assessed the articles for appropriateness of inclusion. This process involved examining and perusing the abstracts to discover the appropriateness of the study. This resulted in the exclusion of 131 articles. From the remaining 127 articles, 61 were thoroughly examined and included in the study, with 34 focusing on disaster management using AI-based methods and 27 related to locating and routing (deploying) essential goods and equipment through AI-enabled methods. In summary, articles must convey an application of AI to disaster management, preferably in the locating and routing of essential goods and equipment to be included. Fig. 1 presents an overview of this process.

3. Disaster management through AI methods

Emergency response and emergency logistics management fields are drastically attracting the attention of researchers [121]. AI models, due to their easy usage, high-velocity operation, and suitable accuracy [106], have been progressively implemented in various fields of natural disaster management, aiming to scale back the impact of disasters effectively [141]. These include searching and rescuing victims [78], recovering and incorporating catastrophe data [23], and carrying out post-disaster destruction analysis [13,130].

Furthermore, AI technologies are essential across quite a few disaster

Table 1
The used keywords for the literature review.

“Disaster management” literature				
Resilience OR Disaster OR Natural Disaster OR Hazard OR Pre-disaster	And	Management	And	AI OR Artificial Intelligence OR AI-based OR AI-enabled OR Machine Learning OR Random Forest OR Neural Network OR Genetic Algorithm OR Deep Learning
AI OR Artificial Intelligence OR AI-based OR AI-Enabled OR Machine Learning OR Random Forest OR Neural Network OR Genetic Algorithm OR Deep Learning	And	Locating goods OR Location Routing problem OR LRP problem OR Vehicle Routing Problem OR VRP problem OR Deploying Essential Equipment OR Relief Distribution OR Equipment Locating		

Table 2
The considered criteria for inclusion and exclusion of the identified papers.

Criteria	Inclusion	Exclusion
Full text	Full text is 'Available'.	Full text is 'Not Available'.
Language	English	Non-English papers
Type	Conference or Journal papers	Chapter from a book, Erratum, and Editorial

resilience dimensions including the environment, governance, economy, and society [145]. In this regard, with the advent of the notions of "smart city" or "sensor city", the usage of AI in the area of disaster resilience is quickly growing [38]. This in a way indicates that AI has turned into a fundamental subject for societies, due to the massive amount of data being created in the age of digital and the growing concerns about the importance of catastrophe early alarming and resilience [67,128]. Recently, deep learning-based methods have progressively been utilized for emergency response and disaster management issues. They have outperformed many traditional statistical approaches.

The cycle of disaster management contains four discrete phases, including "moderation", "readiness", "responses", and "recovery" [146]. Most concurrent disaster management practices have extensively utilized AI technology in order to amplify the efficiency of these approaches in pre, during, and post-disaster phases [60] which are respectively described below in chronological order.

3.1. Pre-disaster management

Estimating the probability of occurrence and forecasting disastrous situations have been widely under the investigation of practitioners. These probabilities would be pivotal in deciding the allocation of resources and making them available to the areas that are more likely to be hit by disasters. For example, Feng, Liu and Gong [43] used a Random Forest (RF) classifier, which was composed of 200 decision trees, to detect flooded areas and spectral-textural feature location mapping in China. Ansari, Firuzi and Etemadsaeed [11] combined fuzzy clustering examination and Monte Carlo simulation as an objective approach for probabilistically modeling and identifying of seismic sources. They described each seismic source's extent objectively by grouping its geographical positions and utilized a cluster quality measure to determine the ideal number of clusters.

In the case of pre-disaster occurrence probability estimation, Cheng and Hoang [34] have introduced a novel practice for slope collapse evaluation. Their method, consisting of the KNN density estimation and Bayesian framework integration, estimates the probabilistic slope stability and approximates the conditional probability density functions. K. Liu et al. [77] introduced a novel real-time updating method called KN2K that forecasts floods by combining the KNN technique with the Kalman Filter.

After that, Gauthier, Germain and Hétu [51] employed logistic regression (LR) to determine the likelihood of daily incidence of avalanches after analyzing the meteorological patterns that encourage the commencement of snow avalanches. In the meantime, Chapi et al. [26], presented a new AI approach by the combination of Logistic Model Tree (LMT) with bagging ensemble approach for calculating flood risk in Haraz watershed located in north of Iran. Furthermore, Bande and Shete [14] created a flood forecasting method using artificial neural networks (ANNs) as well as an IoT-based flood monitoring model. This system's primary objective was to track temperature, humidity, pressure, rainfall, and river water level in order to determine their temporal correlation data for flood prediction analysis. They deployed IoT for gathering the required data from the sensors and data transmission through Wi-Fi and then applied an ANN technique for data analysis in flood forecasting.

Then, Robertson et al. [109] compared machine-learned deep learning categorization techniques to human-coded pictures released after Hurricane Harvey in 2017. The VGG-16 convolutional NN is used in this framework for feature derivation. Their qualitative findings demonstrate that special disaster encounters are not always captured by machine learning techniques. Together, these techniques may sift

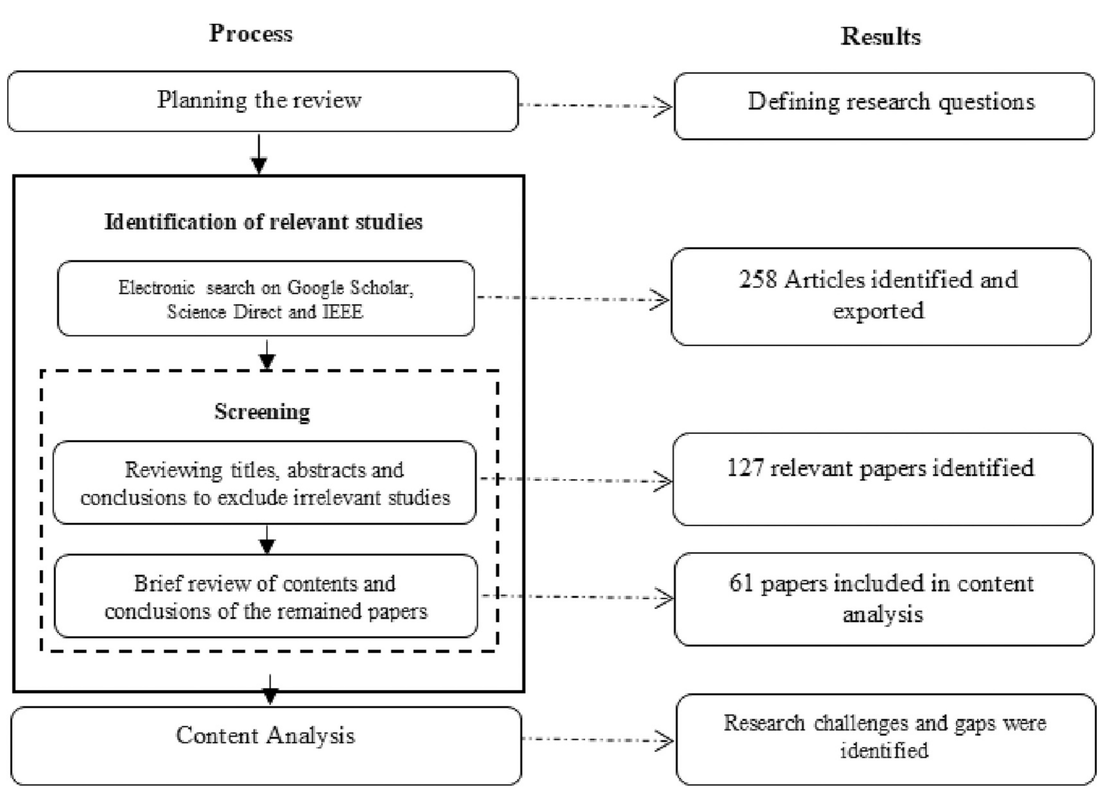

Fig. 1. The workflow of reviewing the locating and deploying essential goods and equipment.

through the volume of irrelevant material on social media to locate requests and content which are relevant. Yuan and Moayedi [147] assessed the outperformance of metaheuristic evolutionary techniques comparing to conventional ML classification methods for estimating the likelihood of landslides. In order to examine and contrast the practicality of these metaheuristic approaches, they also chose a real-world issue of landslide evaluation (i.e., containing 266 records and 15 landslide conditioning elements). On the other side, Anbarasan et al. [10] presented concepts and techniques for flood catastrophe detection based on IoT, BD, and convolutional deep NN to tackle the difficulties of previous used methods in disaster prediction.

Thereafter, Sankaranarayanan et al. [114] employed deep neural networks (DNN) for predicting flood occurrence considering the temperature and rainfall vehemence. In addition, they evaluated the accuracy and error of a deep learning model with those of other ML models (SVM, KNN, and Naive Bayes). Based only on monsoon factors, the findings indicated that DNN can be effectively employed for flood predicting with the maximum degree of accuracy.

Recently, Rathore, Jain and Parida [107] examined seven thoroughly studied ML algorithms for parameter forecasting, including linear discriminant analysis (LDA), RF, classification and regression tree (CART), convolutional neural networks (CNNs), KNN, SVM, and LR. In addition, while taking into account partial outsourcing, they suggested a routing approach in real-time for EMS vehicle routing in an emergency. The study's findings showed that, in regard to precision and F-1 score, the RF classifier beats the LDA, LR, CART, CNN, SVM, and Naive Bayes classifiers.

3.2. During-disaster management

There are several studies that have focused on during-disaster management. For instance, Restas [108] investigated the decision support systems and pragmatic drone utilization in disaster management through a time-scaled categorization of the application. After that, in order to allow information networks to be automatically organized to assist decision making and group activities during emergency scenarios, Ai, Comfort, Dong et al.)2016) designed a prototype of a GIS-SM-DDSS which stands for dynamic decision support system that is centered on geographic information systems and Twitter technology.

Okamoto et al. [93] then used Natural Language Processing (NLP) to efficiently detect objects and analyze data during disasters. Muhammad, Ahmad and Baik [88] proposed a beforehand fire detection framework through fine-tuned CNN which uses the closed-circuit television (CCTV) surveillance cameras' data. The framework was able to detect fire in various indoor and outdoor environments.

Choubin et al. [35] accomplished a snow-slide modeling applying two ML models, namely multivariate discriminant analysis (MDA) and SVM. Three key types of data, i.e., avalanche incidence sites, climatic parameters, and terrain features, were included to deal with the problem.

Kankanamge, Yigitcanlar, Goonetilleke, et al. (2020) investigated the engagement of social media channels which are related to hazard management. Their study adopted five attributes (i.e., approval, involvement, virality, participation, and utilization) and evaluated the degrees of participation in the community on various social media platforms. Meanwhile, Al Qundus, Dabbour, et al. [7] proposed a decision algorithm for wireless sensor networks. They used a SVM model which transmits binary judgments (flood or no flood) toward a cloud server linked to control rooms, where a choice on the response to a potential flood disaster may be made.

Besides, Chen, Li, Wang et al. [32] applied RF algorithm to scrutinize substantial factors of flood risks. They constructed a radial basis operation NN-based risk assessment model for examining the flood risk level.

On the other side, Imran, Ofli, Caragea, et al. [61] highlighted numerous applications and opportunities of social media multimodal data and social media image processing during hazards, crisis informatics and other related study topics, and elaborated on their most recent developments, present difficulties, and future goals.

M. A. Kumar and Laxmi [71] proposed a supervised ML approach based on classification learner for planned islanding of distributed energy supplies. They relied on real-time information gathered from a system called supervisory control and data acquisition (SCADA). Moreover, the effectiveness of the intentional islanding algorithm which is structured on ML was compared to previously proposed AI-based intentional islanding algorithms including artificial neural networks (ANN) and inference systems such as adaptive network-based inference systems using fuzzy inputs. The results indicated that the algorithm for intentional islanding based on ML outperforms all other algorithm in decision making regarding speed and accuracy.

Furthermore, Rahman, Hokugo and Ohtsu [105] developed an approach based on an RF algorithm concentrating on cyclones to forecast the time required for preparing for a house evacuation after inserting demographic and behavioral data. Additionally, to determine the major influencing elements that have a significant impact on household evacuation preparation time during catastrophes, they examined the variable significance and partial dependence plot. In the meantime, Elsotouhy, Jain, and Shrivastava [42] established a pandemic disaster arrangement strategy structured on BD text analytics, and highlighted the essential practicality and usefulness of BD in preventing pandemic disaster by showcasing the high-quality, thorough, and pertinent contextual information produced by BD.

3.3. Post-disaster management

Estimation of loss, including human loss and fundamental costs and relief distribution, is the subject of the majority of studies focusing on post-disaster management. For instance, Aghamohammadi, Mesgari, Mansourian, et al. [2] developed a back-propagation NN method for investigating the intensity and spread of human mortality as a result of building destruction in an earthquake in Iran. Sahebjamnia, Torabi and Mansouri [111] created a hybrid decision support system which combines a rule-based deduction engine, a simulator and a knowledge-based system, to set up a three-stage humanitarian relief chain (HRC). The suggested approach enables the HRC managers to quickly and efficiently extract the best HRC configuration for the actual post-disaster scenario. Frank, Rebbapragada, Bialas, et al. [46] introduced a novel labeling tool to boost accuracy and picture coverage. Their findings indicated that autonomous damage categorization will guarantee quick post-disaster evaluation and help to reduce hazard risk. They also demonstrated the effect of object-based classifiers on geospatial label noise.

Kim and Hastak [70] explored patterns produced by the combined interactions of Facebook users during disaster reactions, which shed light on the crucial role that social media usage plays in the dissemination of emergency information. Wu and Cui [138] accomplished a hierarchical multi-scale study using many data sources, integrating information from social media, economic losses, and geographic locations and verified the crucial impact of social media before, in the middle, and after a natural disaster. In addition, their study investigates whether linking the social media to geo-location data might enhance early warning systems and cost assessments following hazards.

Sublime and Kalinicheva [127] introduced a cutting edge deep-learning technique for change discovery in satellite pictures captured before and after the Tohoku tsunami of 2011, to map the post disaster damage. Besides, Chemodanov et al. [29] applied deep learning in order to develop a novel AI-augmented geographic routing approach using satellite imagery and used this approach in different disaster response scenarios. At the same time, Shibuya and Tanaka [122], investigated the relationships between social media user sentiment and socioeconomic disaster recovery actions as seen in market data, and they discovered several connections between the two variables.

Afterwards, Pi, Nath and Behzadan [100] presented and evaluated a series of CNN models aiming at ground object detection from aerial views of disaster's aftermath. Chaudhuri and Bose [28] applied deep learning method for classification of geo-tagged pictures taken from regions affected by the earthquake and identification of survivors in debris. In this way, they proved the higher accuracy of the used methodology than conventionally used ML methods, as well as its significantly less required time and computational resources.

3.4. Summary of AI methods for disaster management

We summarize the methods used, together with their strengths and weaknesses, for the papers discussed in this section in Table 3. As it can be observed, several AI-enabled approached have been utilized in disaster management. However, the majority of these studies apply statistical data analytics, Social Media and GIS-based methods which could suffer from several shortcomings [54] as following:

Table 3
Summary of disaster management using AI-based methods.

Disaster management phase	Applications of AI	Authors & year of publication	Methods	Strengths of the method	Weaknesses of the method
Pre-disaster	Prediction and disastrous event detection	[34], [77]	KNN	Robust on large and noisy training data [125]	Space and time constraints; ineffective in scaling across high-dimensional multimedia datasets [125]
		[51]	Linear regression	Easy to understand and use in data analysis	Ineffective in dealing with complicated patterns; oversimplification of real-world phenomena [84]
		[147]	Metaheuristic & classification	Prudent randomization and effective data architectures [25]	Need to exploit the problem's structure, adapt to a specific instance problem, and avoid being stuck at local optima [25]
		[26]	Logistic Model Tree (LMT)	High accuracy and outperformance in comparison to Logistic regression and decision tree [74]	Complexity of the model interpretation and expertise requirement [74]
		[109], [14], [10], [114]	DNN	High accuracy and effective in working with huge amount of data [112]	Lack of transparency in computation and architectures [112]
		[43], [107]	RF	Easy to implement [85]	Extremely hard to interpret, expertise requirement [153]
		[11]	Fuzzy clustering	Scalable and simple [40]	Dependent on the user to determine the number of clusters; extremely sensitive to noise, outliers, and the initiation phase [40]
		[68]	Social media data analytics	Data availability [113]	Privacy issues, probable inaccuracy of data, potential data bias [113]
		[35], [7], [71]	SVM	Effective at handling non-separable training datasets which leads to strong generalization ability [35]	Expensive computation; the need of choosing suitable kernel function in advance; significant impact of kernel functions on the efficiency of SVM [50]
During-disaster	Situation recognition, evacuation & relief activities	[108], [4]	Decision Support System	Significant capability of processing large data sets and provision of support for decision making [123]	Expertise requirement to run the model; costly technological maintenance and outlay; inability to include external variables [94]
		[32], [105]	RF	Previously mentioned	
		[61]	Social media image processing	Flexibility, adaptability, and availability in disasters [80]	Lack of information validity; high potential transmission of noise [80]
		[42]	BD analytics	Possibility of implementation of several potential technologies such as GIS, satellite imagery, etc. [115]	Potential data inconsistency due to heterogeneous data collection from multiple sources; extreme tendency of data to be noise-prone [115]
		[88]	NN	Easy optimization; modeling of big data sets; predictive inference accuracy; facilitation of knowledge transmission [79]	Transparency issues in model interpretation; complexity of models [79]
		[93]	NLP	Ability to process large amount of data; objective and accurate analysis [65]	Very expensive and time-consuming; requirement of manual coding and labeled data sets for analysis; complex and difficult to understand [65]
Post-disaster	Response & Recovery	[100], [28,29,127], [2]	NN	Previously mentioned	
		[111]	Simulation	Effective prediction of hazards; ease of data verification, validation and improvement [115]	Expensive and time-consuming; difficult and complex operation [76]
		[122]	ML	Able to tackle complicated coordination while flexibly addressing the problem's stochastic and dynamic components [12]	Inherited lack of dimensionality [12]
		[46]	NLP	Previously mentioned	
		[70]	Network graph & data analytics	Precise comprehension of layers' interactions; highlighting the system dynamics [27]	Expertise requirement to run the model; difficult to interpret [27]
		[138]	Social media data analytics	Previously mentioned	

1. The approaches based on statistical analyses use post-disaster data in order to forecast the main disaster-related issues as well as the occurrence of events and their effects. These approaches could be insufficient and lack complete accuracy due to the frequency and form of disastrous events are transforming exponentially as time passes according to the climate condition [22].
2. Social Media could provide data about the prior and following the disaster to prevent losses and the location of resorts and rescue for the stakeholders. However, sometimes people post inaccurate information for the aim of attention. On the other hand, telecommunication networks might not be accessible for instant information posting on social media, in the middle or post disasters [135].
3. The data gathered using GIS-based systems are used during disasters to scrutinize the areas hit by hazards and the considerable damages in result of the disaster. Such information is highly comprehensive, so a huge challenge here would be data storage. Besides, these methods require high amount of computing to analyze the data as well as sophisticated experts to foretell the adverse effects of the disaster [104].

Furthermore, while AI-based methods often provide advantages such as increased efficiency and improved accuracy, they can suffer from demanding computational requirements, lack of empathy, lack of transparency and ethical concerns. Often, expertise is required for the preparation, running of the model, and interpretation its outputs.

On the other side, most current researches focus on issues related to resource allocation and relief distribution such as Ben-tal et al. [19] and facility location such as Sheu and Pan [120]. Although other problems regarding restoration or improvement tasks have been investigated by L. Chen and Miller-hooks [33] and Yan & Shih [143] and the previous mentioned researchers, the goal of many of previous studies is minimizing total costs (such as transportation expenses, shortfall expenses, flow expenses, and carry-over expenses), or unmet demand. Consequently, the subject of deploying and locating essential goods and equipment in severe situations using an accurate and efficient method has rarely received attention in the literature. Therefore, in the next section we investigate the few studies accomplished in the area of deploying and locating essential goods and equipment using AI-based approaches as a during-disaster management issue.

4. Deploying and locating essential goods using AI-based approaches

Having a plan and understanding the right way to react to disasters is crucial for crisis management [58]. This preparation involves creating a relief network with a two-level structure as a vital component: locating central warehouses and deploying essential goods and equipment to the affected people [131]. Any form of delay in taking the essential steps in the first 72 h following a tragedy might lead to further fatalities. Therefore, a humanitarian logistics system that works well and effectively would save expenses and reduce losses by sending supplies like nourishment, water, and medical supplies to the regions within the SRT [3,17,52].

Due to the high criticality of this stage in disaster response, various studies have applied AI-based approaches for disaster relief logistics. AI-based techniques have consistently demonstrated their capacity to address a wide range of real-world challenges. These methods integrate various learning techniques and adjust to rapidly changing circumstances, thereby assisting in overcoming some computational limitations and achieving quicker outcomes [6].

Disaster relief logistics subdues two fundamental subcategories: to strategically create the relief network, known as the facility (essential goods) location problem (FLP), also to define the operational pathways for the distribution of aid (deploying), known as the vehicle routing problem (VRP) [152]. These two subcategories have been investigated in literature both separately and simultaneously.

4.1. Facility location problem

A study on how to locate sites for stockpiling supplies in advance of disasters is accomplished by Akgün et al. [5]. They used optimization approach and considered the likelihood of the danger (e.g., earthquake), the demand point's susceptibility, as well as any potential value loss or damage brought on by threats, as the criteria for determination of the demand point. Also, An et al. [9] presented a mixed-integer non-linear program (MINLP) model with stochastic data based on different scenarios including facility destruction hazards, en-route traffic jams and in-facility queue delays and integrated them into a facility location problem.

After them, Hu & Dong [59] have applied a programming model with stochastic data in two stages to create plans that include facility placement and inventory, supplier selection, and distribution of relief goods. Their supplier selection criteria consisted of physical inventory, volume discounts on price, and the lead time.

4.2. Vehicle routing problem

Özdamar & Demir [96] applied hierarchical clustering and route procedure to coordinate vehicle routes for post-disaster essential goods delivery and evacuations. After that, Wu et al. [139] suggested an ant colony optimization technique structured on improved brainstorm optimization to resolve the vehicle routing problem with soft time windows. This approach includes updating the ant colony algorithm's results with a better brainstorming optimization technique as well as using the classification technique, to speed up the algorithm's convergence.

Moreover, Qi & Hu [103] used heuristic algorithm in order to optimize vehicle routing problem and resolve the scheduling problem related to urgent cold chain logistics. They considered "the destruction of the vehicle, the need for cooling, and the gradual degradation to the goods" as the modeling criteria.

4.3. Location routing problem

On the other side, some studies have simultaneously considered both routing and facility locating problems which is classified as the location routing problem (LRP). This problem contains both the operational and strategic decisions [152]. In regards to the operational side, Harks et al. [56] introduced an approximation solution for the capacitated location routing problem that is able to consider the expense of opening the depots where the vehicles are housed.

On the other hand, Mousavi & Tavakkoli-Moghaddam [87] applied a Tabu list to develop a hybrid simulated annealing model which combines quick to practical solutions to model the NP-hard scheduling for location and routing issues. Besides, particle swarm optimization algorithms have showed a great capability for route planning and delivery of emergency supplies, which were investigated by Marinakis, Iordanidou, and Marinaki, (2013). In the meantime, Prodhon & Prins [102] and then Drexl & Schneider [41] accomplished extensive examinations of the LRP.

Furthermore, Cadger et al. [24] utilized the ANN in order to solve location routing problem for disaster telemedicine. Following that, Lamos Díaz et al. [73] designed a memetic algorithm as an extension of Genetic Algorithm (GA) in order to solve LRPs in disasters and considered the expense of evacuating, including the time delay expense, the expense of opening shelters and routing as the criteria. They investigated the legitimacy of the suggested model in the city of Bucaramanga.

Then, Nadizadeh and Sabzevari Zadeh [89] applied Efficient GA for location-routing problem and proposes other applications for the model involving the delivery of specific products like cash, expansive metals, potentially dangerous materials, and even prisoners who would require security precautions. Also, Kamari and Ham [64] have recently applied deep learning method in order to identify the location of potential threat in hurricane disasters. The suggested framework aids practitioners in identifying probable wind-borne debris on building sites and comprehending the danger involved.

4.4. Summary of AI methods for locating and deploying essential goods and equipment

The studies mentioned above and other papers focusing on using AI-based methods for locating and routing, together with the methods' strengths and weaknesses, are summarized in Table 4. We can see that, due to the inherent intractability of these problems, heuristic and metaheuristic approaches are often used. These methods, when used by experts, are able to handle complex problems such as the LRP, are easy to parallelize which could be beneficial for large-scale problems and are adaptable to suit specific scenarios. That said, they typically need expertise support for tasks such as parameter tuning, checking for premature convergence and interpretation of model outputs.

5. Findings and discussion

In this paper, we analyzed 61 journal articles published in the period from 2012 to 2022. These articles tackled the disaster management and

Table 4
Literature review on locating and routing essential goods during disaster using AI-based methods.

AI-based method	Author & Year of publication	Application area	Country of origin	Strengths of the method	Weaknesses of the method
Ant-colony optimization	[49]	Routing problem in dynamic environments involving cyclic and incidental traffic factors	China	Automatic parallelism; high speed; adaptability to dynamic applications and changes [118]	Theoretical analysis can be challenging; iterative adjustments to the probability distribution; convergence will occur, although the timing is undetermined [118]
	[142]	Routing problem in dynamic environments	China		
	[139]	Vehicle routing problem	China		
	[44]	Disaster relief in the 2005 Niger dearth and 2010 Haiti earthquake	Spain		
	[140]	Routing problem	China		
GA	[16]	Determination of the place of relief distribution hubs and linking the destructed regions to relief distribution hubs in disaster	Iran	Incredibly powerful in parallel processing; provides large range of potential solutions; effectively handles noisy data; no requirement of advance domain knowledge [81]	Not always simple to locate a fitness function; long run time; selecting an ideal parameter is a difficult undertaking [81]
	[82]	Facility location problem	India		
	[73]	Location-Routing Problem based on Time Windows aiming to detect emergency refuges and discover evacuation routes	Colombia		
	[89]	Location-routing problem in maritime transportation	Iran		
Particle Swarm Optimization	[21]	Determination of relief distribution hub places and connecting the hit area to relief distribution places	Iran	Simplicity of calculation; capability of usage in wide variety of problems [118]	Highly susceptible to partial optimism; incapable of dealing with scattering problems [118]
	[83]	Vehicle routing problem with stochastic demands	Greece		
	[154]	Emergency supply distribution and route programming	China		
Approximation algorithm	[56]	Emergency locating routing problem	Netherland	Speed in computation	Near optimal solutions
Simulated Annealing	[87]	NP-hard location routing and place discovery scheduling problems.	Iran	Easy modification; ability of choosing the number of iterations to reach the desired quality; no entrapment into a local optimum [117]	Computationally unavailable stopping point; difficult verification of standard data [117]
Firefly Algorithm	[95]	Routing problem by time windows	Spain	Wide variety of application [8]	High potential for entrapment into local optima in complicated problems [8]
	[62]	Routing of relief distribution	Jordan		
	[97]	Routing problem by time windows	China		
Artificial Immune Systems	[86]	vehicle routing problem with multiple depots	Malaysia	Significantly adaptive; self-organizing in nature; ability to pattern recognition [39]	Use of numerical data only; single, unchanging depiction; requirement of standard affinity function [47]
	[69]	Emergency route planning (ERP)	Malaysia		
AI Metaheuristic	[36]	Multi-depot routing problem in disastrous situations	Canada	Adaptability to shifting circumstances and environments; ability to handle multimodal issues; parallel processing [18]	Potential entrapment into local optima; long computation time; requiring complex parameter tweaking [18]
	[126]	Multi-depot routing problem	Czech		
	[103]	vehicle routing problem and resolve the emergency cold chain logistics scheduling	China		
NN	[119]	emergency response and disaster relief location	India	Previously mentioned	
	[64]	detecting, locating, and evaluating the potential wind-borne derbies in building jobsites	USA		
	[24]	location-prediction in an ad-hoc network for relief telemedicine	United Kingdom		
	[90]	Emergency response in flood and flood mapping	Switzerland		
Clustering	[96]	Disaster relief locating and routing	Turkey	Previously mentioned	

locating and deploying of essential goods and equipment problems using AI-based approaches. Examination of these articles revealed that the utilization of AI-based approaches in disaster management has been concentrated on two broad areas: 1) preparedness through pre-positioning and vehicle routing in disaster, and 2) information extraction and classification for situational awareness. Consequently, during-disaster relief distribution and deployment of essential goods and equipment for disaster management have received less attention.

According to the studies listed in Table 4, we perceived that during-disaster evacuation planning is mostly investigated and modeled through clustering, GA and social media analysis, while more novel, fast and accurate AI methods such as graph neural network (GNN) and simulation have rarely been used for such problems. In addition, literature review revealed that CNNs have been increasingly implemented for locating and routing problems. One of the main limitations of these methods is that their normal convolutional operations can capture the spatial features of regular grid structures existing in images or videos, rather than the features of general graph forms [31]. Besides, there is an obvious research gap regarding to the application of approaches based on GNN in the field of disaster management considering massive volumes of data [28].

It is also clear that RF method has been rarely applied for locating and deploying essential goods and equipment specifically. This approach provides several advantages including its capability in solving both regression and classification issues and high speed of training and prediction processes. RF is able to be immediately applied to high-dimensional problems [48] and can be used for feature prioritizing, assigning weight coefficients to various classes, as well as for illustration and unsupervised learning [116].

Moreover, there are several untouched application areas which could benefit from AI-based approaches. For example, AI methods have seldom been applied for calamity training systems such as learning algorithms specifically reinforcement learning including SARSA and Q-learning, which require an environment that is suited for training and is closely connected to the activities to be accomplished [129]. This trend could be due to the shortage of available training data about human reactions in disastrous situations to create correct AI models for such aims [128]. Also, we can perceive that gradient-based algorithms for policy still have not been implemented in disaster management, specifically in hazard relief or disaster recovery, at all.

In addition, DNNs and recursive neural networks (RNN) are mostly used for predictions only, and rarely for disaster recovery and relief distribution, which could be a great opportunity and therefore attract future research attention for further exploration.

Furthermore, dynamic modeling in disaster response has seldom received attention, due to the unavailability of reliable information in emergency planning. Actually, in almost all urgent situations, acquiring the necessary information for preparation requires a huge amount of time, and some information may gradually display in the middle of disasters [144].

Indeed, a crucial challenge in this matter is that accurate and efficient predictions using AI techniques normally requires a lot of data to develop and train the model [57]. Such data are not always available. In fact, some data related to infrastructure are not easily accessible due to national security and competitiveness in the commercial realm.

Another issue in this regard could be data trustworthiness. As an example, raw data extracted from social networks, usually consists of different biases and inaccuracies which necessitate progressive filtering and validation. Moreover, social network data gathering requires collecting and analyzing personal data. This process could result in critical issues related to data ownership issues, responsibility, and human rights. Although the required data might be accessible, deficiency of these data could be a frequent problem in analyzing the data related to disasters. This is because the environmental circumstances of a disaster is dynamically changing [66,68].

Also, most of the investigated studies neglect the fact that there may not exist sufficient in-time training data which is human labeled due to the limited amount of manpower and increasing amount of data immediately after a calamity [101]. In this case, unsupervised methods can be practical and useful. Unsupervised AI models are able to identify patterns and relationships in the data without relying on pre-labeled examples, which can be particularly useful when dealing with new or unanticipated situations. For example, anomaly detection algorithms can be used to identify unusual patterns or events that may indicate an emergency or unusual situation, such as sudden changes in temperature, wind speed, or water levels. Using an earthquake as an example, RF could be applied to identify areas where the damage caused by the earthquake is particularly severe. GNNs can be used to identify communities or clusters that are most affected so that response efforts could be prioritized, and resources could be allocated more effectively.

Thus, it is obvious that lots of challenges regarding to pragmatic AI utilization in disaster management are related to data issues, including data inconvenience, data unavailability, security and ethical issues, completeness, and privacy [20,37]. These data issues all pose challenges in disaster response and will require disaster response teams and agencies to address. For example, data inconvenience and data unavailability could be addressed by using alternative sources of data, triangulating various data sources, and leveraging existing data networks and partnerships to facilitate data sharing and collaboration. Security and ethical issues could be dealt with by upholding high data security and ethical standards, establishing data sharing and access protocols, and using encryption to protect sensitive information. Data completeness can be addressed by implementing quality control measures and closely working with data providers to improve data quality. Privacy issues can be protected by using data anonymization techniques to protect individuals' privacy, and working with legal and ethical experts to ensure that data use is consistent with applicable laws and regulations.

6. Conclusion

Resilience and efficient disaster responses play an ever-increasing role in disaster management, because of the significant cost and danger of recent natural disasters such as the Australian bushfire in 2019, Indonesian flash floods in 2020, Assam floods in India in 2020, and Iran's earthquake in 2020. AI models have steadily been implemented in various aspects of natural hazard management, aiming to reduce the impact of the disasters effectively [141], due to their quick functioning, comprehensible correctness, and simplicity of usage [106]. These applications include detecting and rescuing victims [78], recovering and combining the disaster data [23], and accomplishing loss estimation following a disaster [13,130]. However, there lacks a systematic review on these methods implemented in natural disaster management, especially in locating and deploying essential goods and equipment.

Therefore, in this paper, we have reviewed 61 papers in the area of disaster management using AI-based approaches, with 34 focusing on general disaster management and 27 focusing specifically on locating and routing of essential goods and equipment or relief distribution. Review of the published papers revealed that, in recent years, deep learning based methods have been increasingly applied to emergency response and disaster management issues and have outperformed many traditional statistical approaches e.g., KNN [119] and SVM [71] in various prediction tasks related to this topic [31]. However, these methods undertake considerable challenges regarding to the lack of data or the incapability of their normal convolutional operations in capturing the features of general graph forms.

On the other hand, there are lots of untouched applications areas by some AI-based approaches, as well as the rare usage of applying some efficient AI-based approaches such as RF and GNNs.

Thus, for further research in the field of locating and deploying of essential goods and equipment, it is suggested to take advantage of unsupervised approaches and increase the usage of less applied AI-based methods such as GNN, RF and simulation-based methods for the problem. Ultimately, the choice of AI model will depend on the specific context and needs of the disaster response operation, and a combination of supervised and unsupervised techniques may be necessary. It is also suggested to focus on during disaster emergency response, including locating the shelters, essential goods warehouses and finding the best routes to them, during critical hours of disaster and urgent need.

CRediT authorship contribution statement

Shima Farazmehr: Methodology, Investigation, Formal analysis, Writing – original draft. **Yong Wu:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

Data availability

Review article

References

[1] Adeel A, Gogate M, Farooq S, Ieracitano C, Dashtipour K, Larijani H, et al. A survey on the role of wireless sensor networks and IoT in disaster management. In: Geological disaster monitoring based on sensor networks. Singapore: Springer; 2019. p. 57–66. https://doi.org/10.1007/978-981-13-0992-2_5.
[2] Aghamohammadi H, Mesgari MS, Mansourian A, Molaei D. Seismic human loss estimation for an earthquake disaster using neural network. Int J Environ Sci Technol 2013;10(5):931–9. https://doi.org/10.1007/s13762-013-0281-5.
[3] Ahmadi M, Seifi A, Tootooni B. A humanitarian logistics model for disaster relief operation considering network failure and standard relief time: a case study on San Francisco district. Transp Res Part E: Log Transp Rev 2015;75:145–63. https://doi.org/10.1016/j.tre.2015.01.008.
[4] Ai F, Comfort LK, Dong Y, Znati T. A dynamic decision support system based on geographical information and mobile social networks: a model for tsunami risk mitigation in Padang, Indonesia. Safety Sci 2016;90:62–74. https://doi.org/10.1016/j.ssci.2015.09.022.
[5] Akgün I, Gümüşbuğa F, Tansel B. Risk based facility location by using fault tree analysis in disaster management. Omega (United Kingdom) 2015;52:168–79. https://doi.org/10.1016/j.omega.2014.04.003.
[6] Akwafuo SE, Mikler AR, Irany FA. Optimization models for emergency response and post-disaster delivery logistics: a review of current approaches. Int J Eng Technol Manag Res 2020;7(8):35–49. https://doi.org/10.29121/ijetmr.v7.i8.2020.738.
[7] Al Qundus J, Dabbour K, Gupta S, Meissonier R, Paschke A. Wireless sensor network for AI-based flood disaster detection. Ann Operat Res 2020;0123456789:1–23. https://doi.org/10.1007/s10479-020-03754-x.
[8] Ali N, Othman MA, Husain MN, Misran MH. A review of firefly algorithm. ARPN J Eng Appl Sci 2014;9(10):1732–6.
[9] An S, Cui N, Bai Y, Xie W, Chen M, Ouyang Y. Reliable emergency service facility location under facility disruption, en-route congestion and in-facility queuing. Transp Res Part E: Log Transp Rev 2015;82:199–216. https://doi.org/10.1016/j.tre.2015.07.006.
[10] Anbarasan M, Muthu BA, Sivaparthipan CB, Sundarasekar R, Kadry S, Krishnamoorthy S, et al. Detection of flood disaster system based on IoT, big data and convolutional deep neural network. Comp Commun 2020;150(August 2019):150–7. https://doi.org/10.1016/j.comcom.2019.11.022.
[11] Ansari A, Firuzi E, Etemadsaeed L. Delineation of seismic sources in probabilistic seismic-hazard analysis using fuzzy cluster analysis and Monte Carlo simulation. Bull Seismol Soc Am 2015;105(4):2174–91. https://doi.org/10.1785/0120140256.
[12] Anuar WK, Lee LS, Pickl S, Seow HV. Vehicle routing optimisation in humanitarian operations: a survey on modelling and optimisation approaches. Appl Sci (Switzerland) 2021;11(2):1–70. https://doi.org/10.3390/app11020667.
[13] Bai Y, Mas E, Koshimura S. Towards operational satellite-based damage-mapping using U-net convolutional network: a case study of 2011 Tohoku. Remote Sens (Basel) 2018;10(1626). https://doi.org/10.3390/rs10101626.
[14] Bande S, Shete VV. Smart flood disaster prediction system using IoT & neural networks. In: Proceedings of the 2017 international conference on smart technology for Smart Nation, SmartTechCon 2017. IEEE; 2018. p. 189–94. https://doi.org/10.1109/SmartTechCon.2017.8358367.
[15] Barabadi A, Ayele YZ. Post-disaster infrastructure recovery: prediction of recovery rate using historical data. Reliab Eng Syst Safety 2018;169:209–23. https://doi.org/10.1016/j.ress.2017.08.018.
[16] Barzinpour F, Saffarian M, Makoui A, Teimoury E. Metaheuristic algorithm for solving biobjective possibility planning model of location-allocation in disaster relief logistics. J Appl Math 2014;2014:1–17. https://doi.org/10.1155/2014/239868.
[17] Baskaya S, Ertem MA, Duran S. Pre-positioning of relief items in humanitarian logistics considering lateral transhipment opportunities. Socioecon Plann Sci 2017;57:50–60. https://doi.org/10.1016/j.seps.2016.09.001.
[18] Beheshti Z, Mariyam S, Shamsuddin H. A review of population-based meta-heuristic algorithm. Int J Adv Soft Comput 2013;5(1):1–35.
[19] Ben-tal A, Do Chung B, Reddy Mandala S, Yao T. Robust optimization for emergency logistics planning: risk mitigation in humanitarian relief supply chains robust optimization for emergency logistics planning: risk mitigation in humanitarian relief supply chains. Transp Res Part B: Methodol 2011;45(8):1177–89. https://doi.org/10.1016/j.trb.2010.09.002.
[20] Boyd D, Crawford K. Critical questions for big data - provocations for a cultural, technological, and scholarly phenomenon. Inf Commun Soc 2012;15(5):662–79. https://doi.org/10.1080/1369118X.2012.678878.
[21] Bozorgi-Amiri A, Jabalameli MS, Alinaghian M, Heydari M. A modified particle swarm optimization for disaster relief logistics under uncertain environment. Int J Adv Manuf Technol 2012;60(1–4):357–71. https://doi.org/10.1007/s00170-011-3596-8.
[22] Brennan M, O'Neill E, Brereton F, Dreoni I, Shahumyan H. Exploring the spatial dimension of community-level flood risk perception: a cognitive mapping approach. Environ Hazards 2016;15(4):279–310. https://doi.org/10.1080/17477891.2016.1202807.
[23] Budiharto W. Intelligent surveillance robot with obstacle avoidance. Comput Intell Neurosci 2015;2015:5. https://doi.org/10.1155/2015/745823.
[24] Cadger F, Curran K, Santos J, Moffett S. Location and mobility-aware routing for multimedia streaming in disaster telemedicine. Ad Hoc Networks 2016;36:332–48. https://doi.org/10.1016/j.adhoc.2015.08.016.
[25] Calvet L, De Armas J, Masip D, Juan AA. Learnheuristics: hybridizing metaheuristics with machine learning for optimization with dynamic inputs. Open Math 2017;15(1):261–80. https://doi.org/10.1515/math-2017-0029.
[26] Chapi K, Singh VP, Shirzadi A, Shahabi H, Bui DT, Pham BT, et al. A novel hybrid artificial intelligence approach for flood susceptibility assessment. Environ Model Software 2017;95:229–45. https://doi.org/10.1016/j.envsoft.2017.06.012.
[27] Charles A, Bouleux G, Cherifi C. Understanding the situation at a glance: the powerful value added of complex networks to analyse humanitarian operations. Int J Disaster Risk Reduct 2022;75(February). https://doi.org/10.1016/j.ijdrr.2022.102932.
[28] Chaudhuri N, Bose I. Exploring the role of deep neural networks for post-disaster decision support. Decision Supp Syst 2020;130(July 2019):113234. https://doi.org/10.1016/j.dss.2019.113234.
[29] Chemodanov D, Esposito F, Sukhov A, Calyam P, Trinh H, Oraibi Z. AGRA: AI-augmented geographic routing approach for IoT-based incident-supporting applications. Future Generat Comp Syst 2019;92:1051–65. https://doi.org/10.1016/j.future.2017.08.009.
[30] Chen B, Yuan Q, Jing J, Yi Z, Zhou Y. Advanced engineering informatics the optimization of warehouse location and resources distribution for emergency rescue under uncertainty. Adv Eng Inform 2021;48(February):101278. https://doi.org/10.1016/j.aei.2021.101278.
[31] Chen C, Li K, Teo SG, Zou X, Wang K, Wang J, et al. Gated residual recurrent graph neural networks for traffic prediction. In: Proceedings of the AAAI conference on artificial intelligence. Vol. 33; 2019. p. 485–92.
[32] Chen J, Li Q, Wang H, Deng M. A machine learning ensemble approach based on random forest and radial basis function neural network for risk evaluation of regional flood disaster: a case study of the yangtze river delta, China. Int J Environ Res Public Health 2020;17(1):1–21. https://doi.org/10.3390/ijerph17010049.
[33] Chen L, Miller-hooks E. Resilience: An Indicator of recovery capability i intermodal freight transport. Transp Sci 2012;46(1):109–23. Retrieved from https://www.jstor.org/stable/41432828.
[34] Cheng M-Y, Hoang N-D. Slope collapse prediction using Bayesian framework with K-nearest neighbor density estimation: case study in Taiwan. J Comp Civil Engi 2016;30(1):04014116. https://doi.org/10.1061/(asce)cp.1943-5487.0000456.
[35] Choubin B, Borji M, Mosavi A, Sajedi-Hosseini F, Singh VP, Shamshirband S. Snow avalanche hazard prediction using machine learning methods. J Hydrol 2019;577(March):123929. https://doi.org/10.1016/j.jhydrol.2019.123929.
[36] Contardo C, Martinelli R. A new exact algorithm for the multi-depot vehicle routing problem under capacity and route length constraints. Discrete Optimiz 2014;12(1):129–46. https://doi.org/10.1016/j.disopt.2014.03.001.
[37] Crawford K, Finn M. The limits of crisis data: analytical and ethical challenges of using social and mobile data to understand disasters. GeoJournal 2015;80(4):491–502. https://doi.org/10.1007/s10708-014-9597-z.
[38] D'Amico G, L'Abbate P, Liao W, Yigitcanlar T, Ioppolo G. Understanding sensor cities: insights from technology giant company driven smart urbanism practices. Sensors (Switzerland) 2020;20(16):4391. https://doi.org/10.3390/s20164391.
[39] Dasgupta D, Yu S, Nino F. Recent advances in artificial immune systems: models and applications. Appl Soft Comp J 2011;11(2):1574–87. https://doi.org/10.1016/j.asoc.2010.08.024.
[40] Deepti S, Lokesh S, Sisodia S, Saxena Khushboo. Clustering techniques : a brief survey of different clustering algorithms. Int J Latest Trends Eng Technol (IJLTET) 2015;1(3):82–7.

[41] Drexl M, Schneider M. A survey of variants and extensions of the location-routing problem. Eur J Operat Res 2015;241(2):283–308. https://doi.org/10.1016/j.ejor.2014.08.030.
[42] Elsotouhy M, Jain G, Shrivastava A. Disaster management during pandemic: a big data-centric approach. Int J Innov Technol Manag 2021;18(4):1–24. https://doi.org/10.1142/S0219877021400034.
[43] Feng Q, Liu J, Gong J. Urban flood mapping based on unmanned aerial vehicle remote sensing and random forest classifier-A case of Yuyao, China. Water (Switzerland) 2015;7(4):1437–55. https://doi.org/10.3390/w7041437.
[44] Ferrer JM, Ortuño MT, Tirado G. A new ant colony-based methodology for disaster relief. Mathematics 2020;8(4):1–23. https://doi.org/10.3390/math8040518.
[45] Fotovatikhah F, Herrera M, Shamshirband S, Chau KW, Faizollahzadeh Ardabili S, Piran MJ. Survey of computational intelligence as basis to big flood management: challenges, research directions and future work. Eng Appl Comp Fluid Mech 2018;12(1):411–37. https://doi.org/10.1080/19942060.2018.1448896.
[46] Frank J, Rebbapragada U, Bialas J, Oommen T, Havens TC. Effect of label noise on the machine-learned classification of earthquake damage. Remote Sens (Basel) 2017;9(8):1–18. https://doi.org/10.3390/rs9080803.
[47] Freitas AA, Timmis J. Revisiting the foundations of artificial immune systems for data mining. IEEE Trans Evolut Comp 2007;11(4):521–40. https://doi.org/10.1109/TEVC.2006.884042.
[48] Galicia A, Talavera-Llames R, Troncoso A, Koprinska I, Martínez-Álvarez F. Multi-step forecasting for big data time series based on ensemble learning. Knowledge-Based Syst 2019;163:830–41. https://doi.org/10.1016/j.knosys.2018.10.009.
[49] Gao S, Wang Y, Cheng J, Inazumi Y, Tang Z. Ant colony optimization with clustering for solving the dynamic location routing problem. Appl Math Comput 2016;285:149–73. https://doi.org/10.1016/j.amc.2016.03.035.
[50] Gao Z, Fang SC, Luo J, Medhin N. A kernel-free double well potential support vector machine with applications. Eur J Operat Res 2021;290(1):248–62. https://doi.org/10.1016/j.ejor.2020.10.040.
[51] Gauthier F, Germain D, Hétu B. Logistic models as a forecasting tool for snow avalanches in a cold maritime climate: northern Gaspésie, Québec. Canada Nat Hazards 2017;89(1):201–32. https://doi.org/10.1007/s11069-017-2959-3.
[52] Ghasemian Sahebi I, Arab A, Sadeghi Moghadam MR. Analyzing the barriers to humanitarian supply chain management: a case study of the Tehran Red Crescent Societies. Int J Disaster Risk Reduct 2017;24:232–41. https://doi.org/10.1016/j.ijdrr.2017.05.017.
[53] Gomez C, Purdie H. UAV- based photogrammetry and geocomputing for hazards and disaster risk monitoring – a review. Geoenviron Disasters 2016;3(1):1–11. https://doi.org/10.1186/s40677-016-0060-y.
[54] Goyal HR, Ghanshala KK, Sharma S. Post flood management system based on smart IoT devices using AI approach. In: Materials today: proceedings. Vol. 46; 2021. p. 10411–7. Selection and peer-review under responsibility of the scientific committee of the international conference on technological advancements in materials science and manufacturing, https://doi.org/10.1016/j.matpr.2020.12.947. Selection and peer-review under responsibility of the scientific committee of the international conference on technological advancements in materials science and manufacturing.
[55] Guha-sapir D, Hoyois P, Below R, Ponserre S. Annual disaster statistical review 2015 the numbers and trends. 2015.
[56] Harks T, König FG, Matuschke J. Approximation algorithms for capacitated location routing. Transp Sci 2013;47(1):3–22.
[57] Heidary Dahooie J, Razavi Hajiagha SH, Farazmehr S, Zavadskas EK, Antucheviciene J. A novel dynamic credit risk evaluation method using data envelopment analysis with common weights and combination of multi-attribute decision-making methods. Comp Operat Res 2021;129:105223. https://doi.org/10.1016/j.cor.2021.105223.
[58] Holguín-veras, J., Jaller, M., Wassenhove, L. N. Van, Pérez, N., & Wachtendorf, T. (2012). On the unique features of post-disaster humanitarian logistics. J Operat Manag, 30(7–8), 494–506. doi: https://doi.org/10.1016/j.jom.2012.08.003.
[59] Hu S, Dong ZS. Supplier selection and pre-positioning strategy in humanitarian relief. Omega (United Kingdom) 2019;83:287–98. https://doi.org/10.1016/j.omega.2018.10.011.
[60] Huang D, Wang S, Liu Z. A systematic review of prediction methods for emergency management. Int J Disaster Risk Reduct 2021;62(November 2020):102412. https://doi.org/10.1016/j.ijdrr.2021.102412.
[61] Imran M, Ofli F, Caragea D, Torralba A. Using AI and social media multimodal content for disaster response and management: opportunities, challenges, and future directions. Inf Process Manag 2020;57(5):1–9. https://doi.org/10.1016/j.ipm.2020.102261.
[62] Jaradat A, Diabat W. Solving traveling salesman problem using firefly algorithm and K-means clustering. In: In 2019 IEEE Jordan international joint conference on electrical engineering and information technology, JEEIT 2019 - proceedings; 2019. p. 586–9. https://doi.org/10.1109/JEEIT.2019.8717463.
[64] Kamari M, Ham Y. AI-based risk assessment for construction site disaster preparedness through deep learning-based digital twinning. Automat Const 2022;134(July 2021):104091. https://doi.org/10.1016/j.autcon.2021.104091.
[65] Kang Y, Cai Z, Tan CW, Huang Q, Liu H. Natural language processing (NLP) in management research: a literature review. J Manag Anal 2020;7(2):139–72. https://doi.org/10.1080/23270012.2020.1756939.
[66] Kankanamge N, Yigitcanlar T, Goonetilleke A. How engaging are disaster management related social media channels? The case of Australian state emergency organisations. Int J Disaster Risk Reduct 2020;48(March):101571. https://doi.org/10.1016/j.ijdrr.2020.101571.
[67] Kankanamge N, Yigitcanlar T, Goonetilleke A. Public perceptions on artificial intelligence driven disaster management: evidence from Sydney, Melbourne and Brisbane. Telemat Inform 2021;65(October):101729. https://doi.org/10.1016/j.tele.2021.101729.
[68] Kankanamge N, Yigitcanlar T, Goonetilleke A, Kamruzzaman M. Determining disaster severity through social media analysis: testing the methodology with South East Queensland Flood tweets. Int J Disaster Risk Reduct 2020;42(October):101360. https://doi.org/10.1016/j.ijdrr.2019.101360.
[69] Khalid MNA, Yusof UK. An artificial immune approach for optimizing crowd emergency evacuation route planning problem. In: In ICAART 2015 - 7th international conference on agents and artificial intelligence, proceedings. Vol. 2; 2015. p. 503–8. https://doi.org/10.5220/0005275305030508.
[70] Kim J, Hastak M. Social network analysis: characteristics of online social networks after a disaster. Int J Inform Manag 2018;38(1):86–96. https://doi.org/10.1016/j.ijinfomgt.2017.08.003.
[71] Kumar MA, Laxmi AJ. Machine learning based intentional islanding algorithm for DERs in disaster management. IEEE Access 2021;9:85300–9. https://doi.org/10.1109/ACCESS.2021.3087914.
[72] Kumar TV, Sud K. AI and robotics in disaster studies. 1st ed. Singapore: Palgrave Macmillan, Singapore; 2020. p. 93–101. https://doi.org/10.1007/978-981-15-4291-6_7.
[73] Lamos Díaz H, Aguilar Imitola K, Barreto Robles M, Niño Niño P, Martínez Quezada DO. A memetic algorithm for location-routing problem with time windows for the attention of seismic disasters: a case study from Bucaramanga, Colombia. INGE CUC 2018;14(1):75–86. https://doi.org/10.17981/ingecuc.14.1.2018.7.
[74] Landwehr N, Hall M, Frank E. Logistic model trees. Machine Learn 2005;59(1–2):161–205. https://doi.org/10.1007/s10994-005-0466-3.
[75] Li M, Porter AL, Suominen A. Insights into relationships between disruptive technology/innovation and emerging technology: a bibliometric perspective. Technol Forecast Social Change 2018;129:285–96. https://doi.org/10.1016/j.techfore.2017.09.032.
[76] Li N, Sun N, Cao C, Hou S, Gong Y. Review on visualization technology in simulation training system for major natural disasters. Nat Hazards (Dordrecht, Netherlands) 2022;112(3):1851–82. https://doi.org/10.1007/s11069-022-05277-z.
[77] Liu K, Li Z, Yao C, Chen J, Zhang K, Saifullah M. Coupling the k-nearest neighbor procedure with the Kalman filter for real-time updating of the hydraulic model in flood forecasting. Int J Sediment Res 2016;31(2):149–58. https://doi.org/10.1016/j.ijsrc.2016.02.002.
[78] Liu Y, Nejat G. Multirobot cooperative learning for semiautonomous control in urban search and rescue applications. J Field Robot 2016;33(4):512–36. https://doi.org/10.1002/rob.
[79] Lisboa PJ, Taktak AFG. The use of artificial neural networks in decision support in cancer: a systematic review. Neural Netw 2006;19(4):408–15. https://doi.org/10.1016/j.neunet.2005.10.007.
[80] Luna S, Pennock MJ. Social media applications and emergency management: a literature review and research agenda. Int J Disaster Risk Reduct 2018;28(January):565–77. https://doi.org/10.1016/j.ijdrr.2018.01.006.
[81] Majeed PG, Kumar S. Genetic algorithms in intrusion detection systems: a survey. Int J Innov Appl Stud 2014;5(3):233–40. http://www.issr-journals.org/ijias/.
[82] Mangla M, Akhare R, Ambarkar S, Mumbai N. Implementing genetic algorithm to solve facility location problem. Int Res J Eng Technol 2015;2(5):781–4.
[83] Marinakis Y, Iordanidou GR, Marinaki M. Particle swarm optimization for the vehicle routing problem with stochastic demands. Appl Soft Comp J 2013;13(4):1693–704. https://doi.org/10.1016/j.asoc.2013.01.007.
[84] Maulud D, Abdulazeez AM. A review on linear regression comprehensive in machine learning. J Appl Sci Technol Trends 2020;1(4):140–7. https://doi.org/10.38094/jastt1457.
[85] Montesinos López OA, Montesinos López A, Crossa J. Multivariate statistical machine learning methods for genomic prediction. In: In Multivariate statistical machine learning methods for genomic prediction; 2022. https://doi.org/10.1007/978-3-030-89010-0.
[86] Montoya-Torres JR, Franco JL, Isaza SN, Jiménez HF, Herazo-Padilla N. A literature review on the vehicle routing problem with multiple depots. Comp Indust Eng 2015;79:115–29. https://doi.org/10.1016/j.cie.2014.10.029.
[87] Mousavi SM, Tavakkoli-Moghaddam R. A hybrid simulated annealing algorithm for location and routing scheduling problems with cross-docking in the supply chain. J Manufact Syst 2013;32(2):335–47. https://doi.org/10.1016/j.jmsy.2012.12.002.
[88] Muhammad K, Ahmad J, Baik SW. Early fire detection using convolutional neural networks during surveillance for effective disaster management. Neurocomputing 2018;288:30–42. https://doi.org/10.1016/j.neucom.2017.04.083.
[89] Nadizadeh A, Sabzevari Zadeh A. A bi-level model and memetic algorithm for arc interdiction location-routing problem. Comp Appl Math 2021;40(3):1–44. https://doi.org/10.1007/s40314-021-01453-2.
[90] Nemni E, Bullock J, Belabbes S, Bromley L. Fully convolutional neural network for rapid flood segmentation in synthetic aperture radar imagery. Remote Sens (Basel) 2020;12(16):1–30. https://doi.org/10.3390/RS12162532.
[91] Neri H, Cozman F. The role of experts in the public perception of risk of artificial intelligence. AI Soc 2020;35(3):663–73. https://doi.org/10.1007/s00146-019-00924-9.
[92] Novellino, A., Jordan, C., Ager, G., Bateson, L., Fleming, C., & Confuorto, P. (2019). Remote sensing for natural or man-made disasters and environmental changes. In Geological disaster monitoring based on sensor networks (pp. 23–31). Springer, Singapore, 2019. doi: https://doi.org/10.1007/978-981-13-0992-2_3.

[93] Okamoto K, Mochida T, Nozaki D, Wen Z, Qi X, Sato T. Content-oriented surveillance system based on ICN in disaster scenarios. In: International symposium on wireless personal multimedia communications, WPMC. Vol. 2018-Novem. IEEE; 2018. p. 484–9. https://doi.org/10.1109/WPMC.2018.8712852.
[94] Ong HT. The applications of expert system among the top corporations in metro Manila and its perceived advantages and disadvantages. Rev Integrat Bus Econ Res 2018;3(2):169–78. http://buscompress.com/journal-home.html.
[95] Osaba E, Carballedo R, Yang XS, Diaz F. An evolutionary discrete firefly algorithm with novel operators for solving the vehicle routing problem with time windows. In: Nature-inspired computation in engineering. vol. 637. Cham: Springer; 2016. p. 21–41. https://doi.org/10.1007/978-3-319-30235-5_2.
[96] Özdamar L, Demir O. A hierarchical clustering and routing procedure for large scale disaster relief logistics planning. Transp Res Part E: Log Transp Rev 2012;48 (3):591–602. https://doi.org/10.1016/j.tre.2011.11.003.
[97] Pan F, Ye C, Wang K, Cao J. Research on the vehicle routing problem with time windows using firefly algorithm. J Comp (Finland) 2013;8(9):2256–61. https://doi.org/10.4304/jcp.8.9.2256-2261.
[98] Parsons M, Reeve I, McGregor J, Hastings P, Marshall GR, McNeill J, et al. Disaster resilience in Australia: a geographic assessment using an index of coping and adaptive capacity. Int J Disaster Risk Reduct 2021;62:102422. https://doi.org/10.1016/j.ijdrr.2021.102422.
[99] Parsons M, Thoms MC. From academic to applied: Operationalising resilience in river systems. Geomorphology 2018;305:242–51. https://doi.org/10.1016/j.geomorph.2017.08.040.
[100] Pi Y, Nath ND, Behzadan AH. Convolutional neural networks for object detection in aerial imagery for disaster response and recovery. Adv Eng Inform 2020;43(October 2019):101009. https://doi.org/10.1016/j.aei.2019.101009.
[101] Pouyanfar S, Sadiq S, Yan Y, Tian H, Tao Y, Reyes MP, et al. A survey on deep learning: algorithms, techniques, and applications. ACM Comp Surveys 2018;51 (5):1–36. https://doi.org/10.1145/3234150.
[102] Prodhon C, Prins C. A survey of recent research on location-routing problems. Eur J Operat Res 2014;238(1):1–17. https://doi.org/10.1016/j.ejor.2014.01.005.
[103] Qi C, Hu L. Optimization of vehicle routing problem for emergency cold chain logistics based on minimum loss. Phys Commun 2020;40:101085. https://doi.org/10.1016/j.phycom.2020.101085.
[104] Qi H, Altinakar MS. A GIS-based decision support system for integrated flood management under uncertainty with two dimensional numerical simulations. Environ Model Software 2011;26(6):817–21. https://doi.org/10.1016/j.envsoft.2010.11.006.
[105] Rahman MA, Hokugo A, Ohtsu N. Household evacuation preparation time during a cyclone: random Forest algorithm and variable degree analysis. Progr Disaster Sci 2021;12:100209. https://doi.org/10.1016/j.pdisas.2021.100209.
[106] Rajaee T, Ebrahimi H, Nourani V. A review of the artificial intelligence methods in groundwater level modeling Qom- Iran. J Hydrol 2019;572(May 2019): 336–51. https://doi.org/10.1016/j.jhydrol.2018.12.037.
[107] Rathore N, Jain PK, Parida M. A sustainable model for emergency medical services in developing countries: a novel approach using partial outsourcing and machine learning. Risk Manag Healthc Policy 2022;15(February):193–218. https://doi.org/10.2147/RMHP.S338186.
[108] Restas A. Drone applications for supporting disaster management. World J Eng Technol 2015;3(03):316–21. https://doi.org/10.4236/wjet.2015.33c047.
[109] Robertson BW, Johnson M, Murthy D, Smith WR, Stephens KK. Using a combination of human insights and 'deep learning' for real-time disaster communication. Progr Disaster Sci 2019;2:100030. https://doi.org/10.1016/j.pdisas.2019.100030.
[110] Sabbaghtorkan M, Batta R, He Q. Prepositioning of assets and supplies in disaster operations management : review and research gap identification. Eur J Operat Res 2020;284(1):1–19. https://doi.org/10.1016/j.ejor.2019.06.029.
[111] Sahebjamnia N, Torabi SA, Mansouri SA. A hybrid decision support system for managing humanitarian relief chains. Decision Supp Syst 2017;95(November): 12–26. https://doi.org/10.1016/j.dss.2016.11.006.
[112] Saleem R, Yuan B, Kurugollu F, Anjum A, Liu L. Explaining deep neural networks: a survey on the global interpretation methods. Neurocomputing 2022;513: 165–80. https://doi.org/10.1016/j.neucom.2022.09.129.
[113] Salim S, Turnbull B, Moustafa N. Data analytics of social media 3.0: privacy protection perspectives for integrating social media and internet of things (SM-IoT) systems. Ad Hoc Networks 2022;128(November 2021):102786. https://doi.org/10.1016/j.adhoc.2022.102786.
[114] Sankaranarayanan S, Prabhakar M, Satish S, Jain P, Ramprasad A, Krishnan A. Flood prediction based on weather parameters using deep learning. J Water Clim Change 2020;11(4):1766–83. https://doi.org/10.2166/wcc.2019.321.
[115] Sarker MNI, Peng Y, Yiran C, Shouse RC. Disaster resilience through big data: way to environmental sustainability. Int J Disaster Risk Reduct 2020;51(July):101769. https://doi.org/10.1016/j.ijdrr.2020.101769.
[116] Savargiv M, Masoumi B, Keyvanpour MR. A new random forest algorithm based on learning automata. Comput Intell Neurosci 2021;5572781. https://doi.org/10.1155/2021/5572781. 19 pags.
[117] Selim SZ, Alsultan K. A simulated annealing algorithm for the clustering problem. Pattern Recognition 1991;24(10):1003–8. https://doi.org/10.1016/0031-3203(91)90097-O.
[118] Selvi V, Umarani R. Comparative analysis of ant Colony and particle swarm optimization algorithms for distance optimization. Int J Comp Appl 2010;5(4): 245–53. https://doi.org/10.1016/j.procs.2020.06.029.
[119] Shalini R, Jayapratha K, Ayeshabanu S, Selvi GC. Spatial big data for disaster management. In: IOP conference series: Materials science and engineering. vol. 263, No. 4. IOP Publishing; 2017. p. 042008. https://doi.org/10.1088/1757-899X/263/4/042008.
[120] Sheu JB, Pan C. A method for designing centralized emergency supply network to respond to large-scale natural disasters. Transp Res Part B: Methodol 2014;67: 284–305. https://doi.org/10.1016/j.trb.2014.05.011.
[121] Sheu JB, Pan C. Relief supply collaboration for emergency logistics responses to large- scale disasters. Transportmet A: Transp Sci 2015;11(3):210–42. https://doi.org/10.1080/23249935.2014.951886.
[122] Shibuya Y, Tanaka H. Using social media to detect socio-economic disaster recovery. IEEE Intell Syst 2019;34(3):29–37. https://doi.org/10.1109/MIS.2019.2918245.
[123] Shyshatskyi A, Zvieriev O, Salnikova O, Trotsko O. Complex methods of processing different data in intellectual systems for decision support system. Int J Adv Trends Comp Sci Eng 2020;9(4):5583–90. https://doi.org/10.30534/ijatcse/2020/206942020.
[124] Sivanpillai R, Jones BK, Lamb RM. Accessing satellite imagery for disaster response through the international charter: lessons learned from the 2011 US Midwestern floods. Space Policy 2017;42:54–61. https://doi.org/10.1016/j.spacepol.2017.08.003.
[125] Soofi AA, Awan A. Classification techniques in machine learning: applications and issues. J Basic Appl Sci 2017;13:459–65.
[126] Stodola P. Using metaheuristics on the multi-depot vehicle routing problem with modified optimization criterion. Algorithms 2018;11(5):74. https://doi.org/10.3390/a11050074.
[127] Sublime J, Kalinicheva E. Automatic post-disaster damage mapping using deep-learning techniques for change detection: case study of the Tohoku tsunami. Remote Sens (Basel) 2019;11(9):1123. https://doi.org/10.3390/rs11091123.
[128] Sun W, Bocchini P, Davison BD. Applications of artificial intelligence for disaster management. Nat Hazards 2020;103(3):2631–89. https://doi.org/10.1007/s11069-020-04124-3.
[129] Sutton RS, Barto AG. Reinforcement learning: An introduction. 2nd ed.vol. 3. MIT press; 2018. p. 1–13.
[130] Tan L, Guo J, Mohanarajah S, Zhou K. Can we detect trends in natural disaster management with artificial intelligence ? A review of modeling practices. Nat Hazards 2021;107(3):2389–417. https://doi.org/10.1007/s11069-020-04429-3.
[131] Tavana M, Abtahi A, Di Caprio D, Hashemi R, Yousefi-Zenouz R. An integrated location-inventory-routing humanitarian supply chain network with pre- and post-disaster management considerations. Socioecon Plann Sci 2018;64 (December 2017):21–37. https://doi.org/10.1016/j.seps.2017.12.004.
[132] Tolulope Busayo E, Mukalazi Kalumba A, Abayomi Afuye G, Adeyemi Ololade O, Oluwayemisi Ololade O, Ropo Orimoloye I. Rediscovering South Africa: flood disaster risk management through ecosystem-based adaptation. Environ Sustain Indicat 2022;14(February):100175. https://doi.org/10.1016/j.indic.2022.100175.
[133] Tranfield D, Denyer D, Smart P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British J Manag 2003;14(3):207–22. https://doi.org/10.1016/j.intman.2013.03.011.
[134] United Nations activities on artificial intelligence (AI) 2019. 2019.
[135] Velev D, Zlateva P. Use of social media in natural disaster management. In: In International proceedings of economics development and research. Vol. 39; 2012. p. 41–5. https://doi.org/10.7763/IPEDR.
[136] Wang ZN, Chen J, Cheng WC, Arulrajah A, Horpibulsuk S. Investigation into the tempo-spatial distribution of recent fire hazards in China. Nat Hazards 2018;92 (3):1889–907. https://doi.org/10.1007/s11069-018-3264-5.
[137] Wong YK. Dealing crisis management using AI. Int J Eng Trends Appl (IJETA) 2021;8(5):95–102. https://doi.org/10.5121/csit.2021.111409.
[138] Wu D, Cui Y. Disaster early warning and damage assessment analysis using social media data and geo-location information. Decision Supp Syst 2018;111(April): 48–59. https://doi.org/10.1016/j.dss.2018.04.005.
[139] Wu L, He Z, Chen Y, Wu D, Cui J. Brainstorming-based ant colony optimization for vehicle routing with soft time windows. IEEE Access 2019;7:19643–52. https://doi.org/10.1109/ACCESS.2019.2894681.
[140] Xiang X, Qiu J, Xiao J, Zhang X. Demand coverage diversity based ant colony optimization for dynamic vehicle routing problems. Eng Appl Artif Intel 2020;91 (August 2019):103582. https://doi.org/10.1016/j.engappai.2020.103582.
[141] Xie J, Tang H, Huang T, Yu FR, Xie R, Liu J, et al. A survey of blockchain technology applied to smart cities: research issues and challenges blockchain-based. IEEE Commun Surv Tutorials 2019;21(3):2794–830. https://doi.org/10.1109/COMST.2019.2899617.
[142] Xu H, Pu P, Duan F. Dynamic vehicle routing problems with enhanced ant colony optimization. Discrete Dynam Nat Soc 2018;2018:1–13. https://doi.org/10.1155/2018/1295485.
[143] Yan S, Shih Y. Optimal scheduling of emergency roadway repair and subsequent relief distribution. Comp Operat Res 2009;36(6):2049–65. https://doi.org/10.1016/j.cor.2008.07.002.
[144] Yazdani M, Mojtahedi M, Loosemore M, Sanderson D, Dixit V. Hospital evacuation modelling: a critical literature review on current knowledge and research gaps. Int J Disaster Risk Reduct 2021;66(December):102627. https://doi.org/10.1016/j.ijdrr.2021.102627.
[145] Yigitcanlar T, Kankanamge N, Vella K. How are smart city concepts and technologies perceived and utilized? A systematic geo-twitter analysis of smart cities in Australia. J Urban Technol 2021;28(1–2):135–54. https://doi.org/10.1080/10630732.2020.1753483.
[146] Yu M, Yang C, Li Y. Big data in natural disaster management: A review. Geosciences (Switzerland) 2018;8(5):165. https://doi.org/10.3390/geosciences8050165.

[147] Yuan C, Moayedi H. Evaluation and comparison of the advanced metaheuristic and conventional machine learning methods for the prediction of landslide occurrence. Eng Comp 2020;36(4):1801–11. https://doi.org/10.1007/s00366-019-00798-x.

[148] Yuan C, Zhang Y, Liu Z. A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques. Can J For Res 2015;45(7):783–92. https://doi.org/10.1139/cjfr-2014-0347.

[149] Zagorecki A, Ristvej J, Johnson D. Automated data analysis in the context of crisis and disaster management. In: Proceedings Riešenie krízových situácií v špecifickom prostredí, Žilina: Žilinská univerzita. Vol. 44; 2012. p. 61–7.

[150] Zagorecki AT, Johnson DEA, Ristvej J. Data mining and machine learning in the context of disaster and crisis management. Int J Emerg Manag 2013;9(4):351–65. https://doi.org/10.1504/IJEM.2013.059879.

[151] Zhang L, Zhang L, Du B. Deep learning for remote sensing data: a technical tutorial on the state of the art. IEEE Geosci Remote Sens Mag 2016;4(2):22–40. https://doi.org/10.1109/MGRS.2016.2540798.

[152] Zhong S, Cheng R, Jiang Y, Wang Z, Larsen A, Nielsen OA. Risk-averse optimization of disaster relief facility location and vehicle routing under stochastic demand. Transp Res Part E: Log Transp Rev 2020;141(March):102015. https://doi.org/10.1016/j.tre.2020.102015.

[153] Ziegler A, König IR. Mining data with random forests: current options for real-world applications. Wiley Interdiscip Rev Data Min Knowledge Disc 2014;4(1):55–63. https://doi.org/10.1002/widm.1114.

[154] Rong XX, Lu Y, Yin RR, Zhang JH. A robust optimization approach to emergency vehicle scheduling. Mathematical Prob Eng 2013:848312. https://doi.org/10.1155/2013/848312.