Natural Hazards (2020) 103:2631–2689
https://doi.org/10.1007/s11069-020-04124-3

REVIEW ARTICLE



# Applications of artificial intelligence for disaster management

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Received: 1 February 2019 / Accepted: 16 June 2020 / Published online: 3 July 2020


**Abstract**
Natural hazards have the potential to cause catastrophic damage and significant socioeconomic loss. The actual damage and loss observed in the recent decades has shown an increasing trend. As a result, disaster managers need to take a growing responsibility to proactively protect their communities by developing efficient management strategies. A number of research studies apply artificial intelligence (AI) techniques to process disaster-related data for supporting informed disaster management. This study provides an overview of current applications of AI in disaster management during its four phases: mitigation, preparedness, response, and recovery. It presents example applications of different AI techniques and their benefits for supporting disaster management at different phases, as well as some practical AI-based decision support tools. We find that the majority of AI applications focus on the disaster response phase. This study also identifies challenges to inspire the professional community to advance AI techniques for addressing them in future research.

**Keywords** Disaster resilience · Disaster management · Artificial intelligence

## 1 Introduction

Natural hazards have caused catastrophic damage and significant socioeconomic loss, showing an increasing trend (Hoeppe 2016). Statistics for 2017 indicate economic losses from natural hazards in the USA exceed $300 billion; Hurricane Harvey alone has caused $125 billion in socioeconomic losses (Wilts 2018). These adverse impacts pose challenges

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to disaster response managers, who face increasingly tight resources and an exhausted workforce, and such challenges force local authorities to re-evaluate their policies for disaster management.

There are large volumes of data generated daily, including real data and simulation data. Both types of data can be used to support disaster management. The advancement of information communication technologies, such as social media, telecommunication data, and remote sensing, makes large volumes of real data available (Eguchi et al. 2008; Boccardo and Tonolo 2014; Rawat et al. 2015; Adeel et al. 2018; Novellino et al. 2018). Sometimes, real data are scarce. In research communities, many computational models are developed to generate simulation data for estimating the disaster-induced impact and identifying vulnerable structures, such as IN-CORE (Ellingwood et al. 2016) and PRAISys (The PRAISys Team 2018). Regardless of data type, acquiring, managing, and processing big data in a short time is essential to support efficient disaster management. Using AI to analyze the voluminous data to rapidly extract useful and reliable information becomes increasingly popular for supporting effective decision-making in disaster management (Eskandarpour and Khodaei 2017; Velev et al. 2018; Yu et al. 2018; Wang et al. 2018d; Barabadi and Ayele 2018).

Some published studies have reviewed AI applications in disaster management, with the topic targeted to certain types of hazard, infrastructure, and data. For example, Fotovatikhah et al. (2018) have discussed the status and challenges of applying computational intelligence methods to major flood control and disaster management. Zagorecki et al. (2013) have reviewed applications of data mining and machine learning to disaster management, but there is no discussion on any practical AI-based decision support tools. Other studies review how computer vision methods have been applied for disaster management by analyzing remote sensing data, such as target recognition with deep learning (Zhang et al. 2016b), fire detection with wavelet analysis and neural networks (Yuan et al. 2015), and estimating three-dimensional structures (Gomez and Purdie 2016). However, very few of them have explicitly discussed the progress and challenges of how AI has been applied in disaster management in different phases, by considering hazard and infrastructure as well as data in a general sense.

In what follows, we describe the research background of AI methods and disaster management first, followed by the state of research and practice of applications of AI in disaster management in four phases, and the challenges therein. In particular, practical decision support tools for disaster management based on AI methods have been reviewed. This study can facilitate new researchers to identify critical research gaps in this field and provide practitioners a comprehensive summary for selecting an appropriate AI model and practical decision support tool based on their community needs.

## 2 Background

### 2.1 AI methods

This study reviews the state of research and practice of applying AI in disaster management, by classifying AI methods in six categories: supervised models, unsupervised models, deep learning, reinforcement learning, and deep reinforcement learning, as well as optimization.

#### 2.1.1 Supervised models

Supervised models represent algorithms that are trained on pre-existing data with human input. Using labeled training data with known input and output pairs, supervised models infer a function from input to output using regression/classification methods to predict the value/category of the output variable (Russell and Norvig 2016). In general, supervised models have been used for information extraction, object recognition in computer vision, pattern recognition, and speech recognition, etc.

#### 2.1.2 Unsupervised models

Without human input, unsupervised models use statistical methods to extract hidden structure in unlabeled data based on inherent characteristics (Russell and Norvig 2016). Unsupervised models are suitable for detecting the abnormal data and reducing the data dimension, with wide applications to clustering and data aggregation problems. Clustering algorithms are used for pattern recognition by partitioning unlabeled data into multiple groups based on certain similarity features (Maulik and Bandyopadhyay 2002). Dimension reduction algorithms, such as principal component analysis (PCA), can reduce the complexity of data and avoid overfitting.

#### 2.1.3 Deep learning

Deep learning is a class of algorithms that use multiple layers to extract features from the input data progressively, with improved learning performance and broad application scopes (Deng and Yu 2014; Pouyanfar et al. 2018). Despite the drawback of requiring long training time, deep learning algorithms are particularly suitable to solve problems of damage assessment, motion detection, and facial recognition, transportation prediction, and natural language processing for supporting disaster management. For example, recursive neural networks (RvNN) and recurrent neural networks (RNN) have been successfully applied to natural language processing (NPL) (Socher et al. 2011; Graves et al. 2013). Convolutional neural networks (CNN) are suitable for image recognition (Simonyan and Zisserman 2014), computer vision (Krizhevsky et al. 2017), NPL (Zhao and Wu 2016), and speech processing (Dahl et al. 2012).

#### 2.1.4 Reinforcement learning

By learning from a series of reinforcements (using punishment and rewards as positive and negative signals), reinforcement learning algorithms are modeled in the form of Markov decision processes to address goal-oriented problems for making decisions in a sequential manner (Russell and Norvig 2016). Reinforcement learning is suitable for solving problems that need to make a sequence of decisions in an uncertain and complex environment, with successful applications in robotics, resource management, and traffic light control. The main challenge in reinforcement learning is preparing the suitable training environment that is closely related to tasks to be performed.

Typical reinforcement learning algorithms include Q-learning and SARSA (State-Action-Reward-State-Action), to name a few (Sutton and Barto 2018).

#### 2.1.5 Deep reinforcement learning

Deep reinforcement learning combines reinforcement learning with deep neural networks with the aim of creating software agents that can learn by themselves to establish successful policies for gaining the most long-term rewards. Deep reinforcement learning has superior performance for solving problems with complex sequential tasks, such as computer vision, robotics, finance, smart grids, etc. Requiring a large amount of training data and training time to reach reasonable performance, deep reinforcement learning sometimes becomes extremely computationally expensive.

#### 2.1.6 Optimization

While the focus of this study is how AI methods are applied for disaster management, optimization is an essential ingredient in most of AI methods to find the best model as measured by an objective function. For this reason, this study explicitly lists three optimization techniques as example methods and investigates their applications in disaster management.

### 2.2 Disaster management

#### 2.2.1 Four phases of disaster management

As shown in Fig. 1, disaster management involves four phases: mitigation, preparedness, response, and recovery. The mitigation phase refers to management activities for preventing or minimizing future emergencies and consequences with long-term benefits.

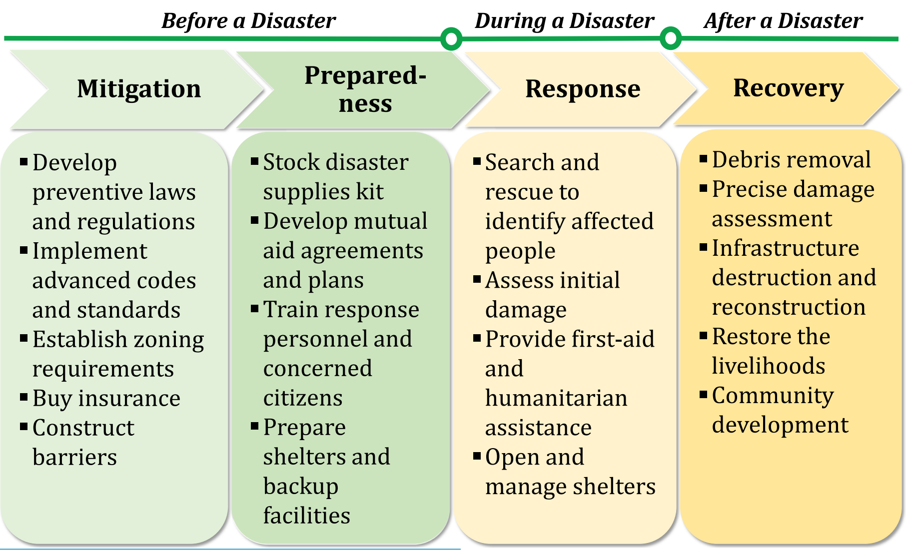


**Fig. 1** Four phases of disaster management

Examples of mitigation activities include enforcing advanced building codes and standards, retrofitting highway overpasses, hospitals, and shelters, informing and educating the general public and related stakeholders about hazards and potential mitigation strategies. The preparedness phase comes into place when an emergency or a disaster is likely to take place. It corresponds to preparatory activities prior to a disaster in order to save lives and help response and rescue operations, such as stocking food and water, posting emergency contacts, and preparing evacuations. With plans and strategies developed beforehand, the response phase mainly puts them into action. Response activities happen during a disaster, usually involving evacuating threatened areas, firefighting, search and rescue efforts, shelter management, and humanitarian assistance. After a disaster, the recovery phase refers to repair and reconstruction efforts to return to a normal or even better functionality level. Recovery actions usually include debris cleanup, precise damage assessment, and infrastructure reconstruction, as well as financial assistance from government agencies and insurance companies.

### 2.2.2 Disaster management and disaster resilience

The goals of disaster management are to implement operations and strategies to effectively prepare, rapidly respond and rescue, efficiently allocate resources, quickly correct damage and recover to full functionality, ultimately protect the community and minimize the adverse impact. That is to say that the efficient disaster management should strengthen the disaster resilience of a community. The term “disaster resilience” refers to the ability of an

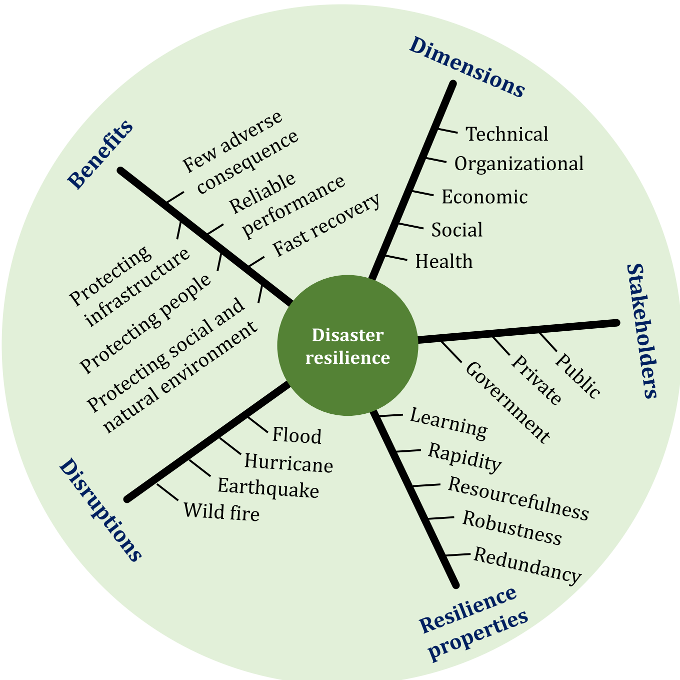


**Fig. 2** Features of disaster resilience

entity to anticipate, resist, absorb, adapt to, and rapidly recover from an unexpected disturbance (DHS 2010). Figure 2 displays features of disaster resilience in terms of dimensions, stakeholders, disruption types, properties of resilient entities, and benefits. In case of a disaster, such as a hurricane or an earthquake, a resilient community is expected to be able to protect people, infrastructure, and socioeconomic environment, with reliable performance and fast recovery capability, as well as minimal adverse consequence. The disaster resilience of a community can be enhanced by improving the rapidity, robustness, resourcefulness, and redundancy, as well as learning capability, in which learning refers to residents' changing expectations with respect to infrastructure performance and operational adaptations of infrastructures to new circumstances during and after a disaster (Sun et al. 2020b). From the disaster management perspective, governments and other stakeholders organize their operations in multiple aspects (technical, organizational, economic, social, and health), various management plans and strategies are developed and implemented.

A number of programs have been established to promote the research and practice of disaster resilience for supporting informed decision-making in disaster management. Some examples in the USA are described as follows. Since 2013, the Campus Resilience Program has yielded successful tools and guidelines for evaluating the vulnerability of the academic community nationwide. The Hazard Mitigation Grant Program (HMGP) supports communities in implementing cost-effective hazard mitigation measures, such as structure retrofit and reconstruction, to eliminate the risk of loss of life and property damage from future disasters (FEMA 2018). The Community Resilience Planning Guide presents a six-step process to help local community authorities identify gaps, create resilience plans, and implement strategies for better community resilience against future disasters (NIST 2018; Cauffman et al. 2018). In addition, local authorities and private organizations have been implementing practices for resilience enhancement. For example, Los Angeles County in California has developed a community resilience toolkit to support decision-making in disaster management (Eisenman et al. 2014; Bromley et al. 2017). The 100 Resilient Cities program supports city governments' efforts in fostering urban resilience and addressing climate change and equity (The Rockefeller Foundation 2019). In parallel, other countries have also been actively working in this direction. The Horizon 2020 Research and Innovation Programme has developed the European Resilience Management Guideline and tools for supporting effective disaster management and enhancing the resilience against disasters and climate change (EU-CIRCLE 2019). Under the Sendai Framework for Disaster Resilience Network, the Asia-Pacific region has been undertaking major reforms in developing disaster management policies with increasing applications of AI in disaster response (UN 2015; Renwick 2017; Pau et al. 2017; Izumi et al. 2019). All these guidelines and computational tools aim to support disaster management and enhance disaster resilience. AI has great potential to alleviate the burden of decision makers in disaster management by processing large amounts of disaster-related data more efficiently and effectively.

## 3 Applications of AI for disaster management

Figure 3 shows the increasing trend in the number of publications on WorldCat from 1991 to 2018 with regard to applying AI to disaster management. The greatest number of publication in disaster response among four phases indicates that applications of AI mainly focus on this phase. While AI will not replace the experience and wisdom of well-trained

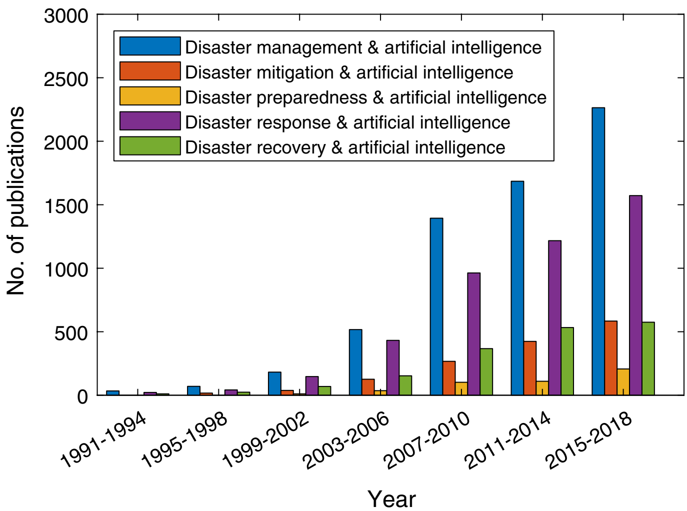


**Fig. 3** An increasing number of publications on artificial intelligence in disaster management. *Note* "Publications" refers to articles, books, and downloadable archive materials. The number of publications is determined by summing the number of publications every four years between 1991 and 2018 when searching with the keywords in the legend on WorldCat (http://www.worldcat.org/)

disaster professionals, at least in the foreseeable future, AI techniques can rapidly analyze big data and perform predictive analytics for supporting decision-making in disaster management.

To illustrate how different AI methods have been applied in disaster management, we have identified a total of 26 AI methods and 17 application areas as representative examples. By using every AI method and every application area as key words, we have searched for the related literature on the Web sites of Google Scholar and Web of Science, requiring joint presence of both keywords. Figure 4 presents our findings on AI applications to the four phases and their sub-areas. In this figure, every solid line demonstrates the presence of applications of an AI method in a certain area. More solid lines connecting to *Application Areas* 1–4 and 9–13 mean that there are more studies applying AI methods in mitigation and response phases. Detailed application examples are presented as citations in Tables 1, 2, 3 and 4. It is worth noting that only the most relevant/representative publications are presented in some cells in the tables due to space limits.

### 3.1 AI applications in disaster mitigation

In the disaster mitigation phase, decision makers need to identify hazard and risks (*Application Area* 1), predict possible impact (*Application Area* 2), assess vulnerability (*Application Area* 3), and develop mitigation strategies (*Application Area* 4), in order to create stronger, safer, and more resilient communities. AI methods have been widely applied to support disaster mitigation management in the four areas. In particular, supervised models and unsupervised models have been extensively used for *Application Area* 1, followed by *Areas* 2 and 3. Conversely, reinforcement learning and deep reinforcement learning are rarely used in the four areas.

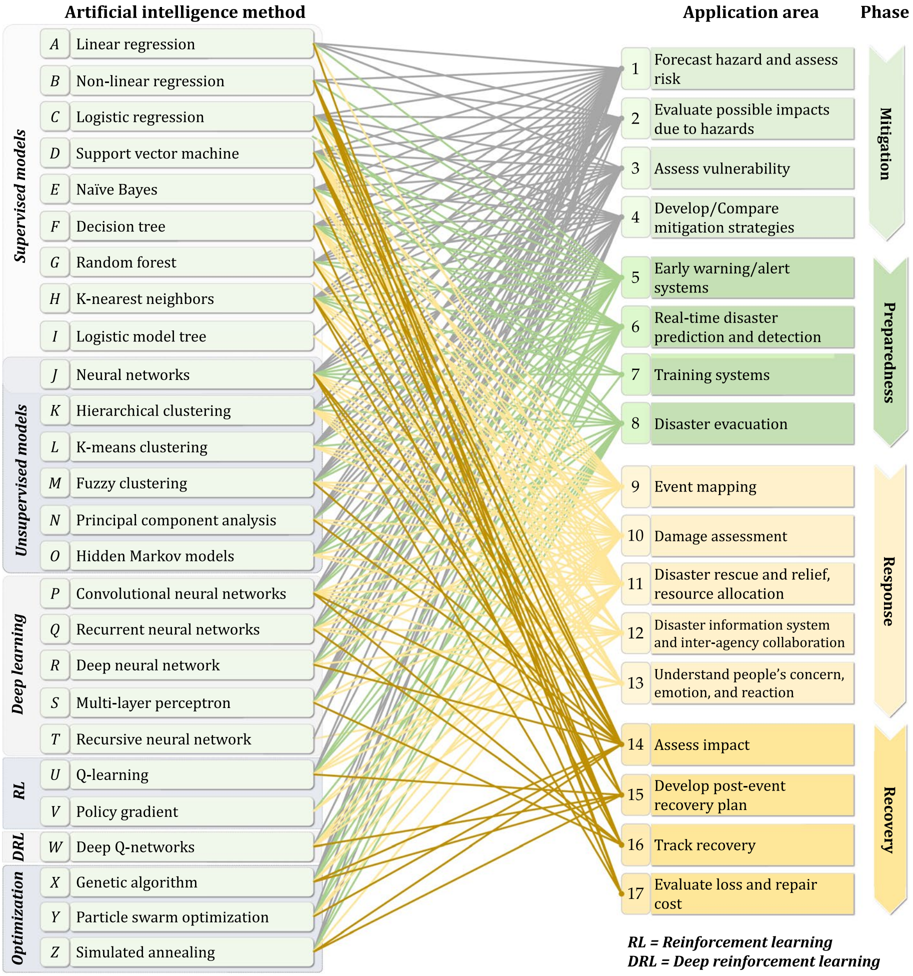


**Fig. 4** Applications of artificial intelligence in disaster management. *Note* A solid link between an AI method and an application area represents the fact that there are applications of the AI method to this area. Detailed application examples are presented in Tables 1, 2, 3 and 4

Possible hazards and risks should be identified for the community of interest. For natural hazards, characteristics of terrain, lithology, meteorology, and even human activities should be analyzed, and hazard zone maps should be developed. Traditional methods, such as field monitoring, physics-based models, expert surveys, and multi-criteria decision-making methods, are applied to identify hazards and risk factors. Sometimes, these methods are labor intensive, possibly with high false alarm rate (Bellaire et al. 2017). In this case, AI techniques can rapidly analyze large volumes of data to assess hazard risks in a timely manner (Pradhan 2009; Yilmaz 2010). There are extensive studies applying different AI methods to developing susceptibility maps for different types of hazards. For instance, snow avalanche predictions have been made using logistic regression (LR) (Gauthier et al. 2017), support vector machine (SVM) (Choubin et al. 2019), and neural networks (Dekanová et al. 2018; Rauter and Winkler 2018). Landslide susceptibility can be assessed

**Table 1** Example AI applications for disaster mitigation

| AI Method | 1. Forecast hazard and risk | 2. Estimate impact | 3. Assess vulnerability | 4. Develop/Compare strategy |
|---|---|---|---|---|
| A. Linear regression and extensions | Reed (2008), Chang et al. (2010), Kim et al. (2019) | Kahn (2006), Simmons and Sutter (2008), Zahran et al. (2008), Peduzzi et al. (2009), Maliszewski et al. (2012) | Yang and Yu (2011), Geiß et al. (2014), Heß (2017), Wang et al. (2019g), Sun et al. (2019) | NA |
| B. Nonlinear regression | Pradhan (2009), Yilmaz (2010), Trafalis et al. (2014), Lin et al. (2017a), Goetz et al. (2015) | Zorn and Shamsedin (2015), Lee et al. (2016) | NA | NA |
| C. Logistic regression | Bai et al. (2010), Marjanović et al. (2011), Ozdemir and Altural (2013), Wang et al. (2013b) | Eskandarpour and Khodaei (2017), Rosellini et al. (2018), Yuan and Moayedi (2019) | Ettinger et al. (2016), Li et al. (2019b) | Khan and Sayem (2012), Rakgase and Norris (2014), Cavalcante et al. (2019) |
| D. Support vector machine | Yilmaz (2010), Marjanović et al. (2011), Xu et al. (2012), Lin et al. (2017a), Zhou et al. (2018a) | Galatzer-Levy et al. (2014), Li et al. (2014), Karstoft et al. (2015), Tinoco et al. (2018) | Geiß et al. (2014), Sun et al. (2019), Xiong et al. (2019) | Guo et al. (2009), Rudin et al. (2012), Dou et al. (2014), Pogrebnykov and Maldonado (2017) |
| E. Naïve Bayes | Shirzadi et al. (2017), Chen et al. (2019), Sankaranarayanan et al. (2019) | Bawono et al. (2020) | Geiß et al. (2014) | Sadiq et al. (2018) |
| F. Decision tree | Saito et al. (2009), Marjanović et al. (2011), Rhee and Im (2017) | Wanik et al. (2015), Yuan and Moayedi (2019) | Sriram et al. (2019) | Guo et al. (2009), Sadiq et al. (2015, 2018) |
| G. Random forest | McGovern et al. (2011), Goetz et al. (2015), Rhee and Im (2017), Chen et al. (2018) | Galatzer-Levy et al. (2014), Nateghi et al. (2014), Wanik et al. (2015), Cerrai et al. (2019) | Yoon and Jeong (2016), Sriram et al. (2019) | Rudin et al. (2012) |
| H. K-nearest neighbors | Liu et al. (2016), Sankaranarayanan et al. (2019) | Cheng and Hoang (2014) | Leon and Atanasiu (2006), Kusumawardani et al. (2016) | Sun et al. (2017), Sadiq et al. (2015, 2018) |
| I. Logistic model tree | Chen et al. (2018, 2019) | NA | Yang et al. (2019d) | NA |

**Table 1** (continued)

| AI Method | 1. Forecast hazard and risk | 2. Estimate impact | 3. Assess vulnerability | 4. Develop/Compare strategy |
|---|---|---|---|---|
| J. Neural networks | Melchiorre et al. (2008), Yilmaz (2010), Dou et al. (2015), Huang et al. (2018) | Karamouz et al. (2014), Tinoco et al. (2018), Oktarina et al. (2019), Tinoco et al. (2019) | Wu et al. (2008), Pilkington and Mahmoud (2016), Guo et al. (2018), Wahab and Ludin (2018) | Jones et al. (2008) |
| K. Hierarchical clustering | Leśniak and Isakow (2009), Trugman and Shearer (2017) | NA | Cavalieri et al. (2014), Su et al. (2015), Kim et al. (2017), Chang et al. (2018) | NA |
| L. K-means clustering | Iliadis (2005), Melchiorre et al. (2008), Leśniak and Isakow (2009), Jayaram and Baker (2010) | Lam et al. (2016) | Su et al. (2015), Fernandez et al. (2016) | Pua and Hariharan (2012) |
| M. Fuzzy clustering | Zhang (2004), Shi et al. (2010), Wang et al. (2013b), Ansari et al. (2015), Wang et al. (2018c) | da Silva et al. (2008), Wlwood and Corotis (2015) | Alam et al. (2000), Wu et al. (2013), Chen et al. (2014b) | Dou et al. (2014) |
| N. Principal component analysis | Chen and Hong (2012), Shi et al. (2015) | Li et al. (2014) | Chen et al. (2014a) Fernandez et al. (2016), Heß (2017), Uddin et al. (2019) | Moradi et al. (2019) |
| O. Hidden Markov models | Wang et al. (2010b), Khadr (2016), Wang et al. (2018a) | Song et al. (2014, 2016) | NA | Eicken et al. (2011) |
| P. Convolutional neural networks | DeVries et al. (2018), Padmawar et al. (2019) | NA | Crawford et al. (2018), Han et al. (2019) | Pogrebnykov and Maldonado (2017), Nguyen et al. (2019a) |
| Q. Recurrent neural networks | Ma et al. (2015b), Asim et al. (2017), Cortez et al. (2018), Wang et al. (2020b), Mutlu et al. (2019) | NA | NA | Canon et al. (2018), Pechenkin and Demidov (2018), Nguyen et al. (2019a), Yang et al. (2019b) |
| R. Deep neural network | Sankaranarayanan et al. (2019) | NA | Nabian and Meidani (2018b), Dogaru and Dumitrache (2019) | NA |

**Table 1** (continued)

| AI Method | 1. Forecast hazard and risk | 2. Estimate impact | 3. Assess vulnerability | 4. Develop/Compare strategy |
|---|---|---|---|---|
| S. Multilayer **perception** | Zare et al. (2013), Hernández et al. (2016), Pham et al. (2017) | Yuan and Moayedi (2019) | Wahab and Ludin (2018) | Sadiq et al. (2018) |
| T. Recursive neural network | Mishra and Desai (2006), Hosseini-Moghari and Araghinejad (2015) | NA | NA | NA |
| U. Q-learning | Lin et al. (2013) | NA | Yan et al. (2016), Otoum et al. (2019) | Zhang et al. (2019b) |
| V. Policy gradient | NA | NA | NA | NA |
| W. Deep Q-networks | NA | NA | NA | Elsayed and Erol-Kantarc (2018) |
| X. Genetic algorithm | Chang and Chien (2007), Terranova et al. (2015) | Tinoco et al. (2019) | NA | Tapia and Padgett (2015), Yan et al. (2017), Yang et al. (2019b) |
| Y. Particle swarm optimization | Romlay et al. (2016), Padmawar et al. (2019) | NA | NA | NA |
| Z. Simulated annealing | Zhu and Wu (2013), Hosseini et al. (2019) | NA | NA | Afandizadeh et al. (2013), Ma et al. (2015a), Gama et al. (2016) |

*NA* means that no literature was found on the application area (column) using the AI method (row)

**Table 2** Example AI applications for disaster preparedness

| AI Method | 5. Early warning system | 6. Real-time disaster prediction and detection | 7. Training systems | 8. Disaster evacuation |
|---|---|---|---|---|
| A. Linear regression | Uunk et al. (2010), Nolasco-Javier and Kumar (2018), Pillai et al. (2019) | NA | NA | NA |
| B. Nonlinear regression | Moon et al. (2018) | NA | NA | NA |
| C. Logistic regression | Wang et al. (2013a), Hoot and Aronsky (2006) | Agarwal et al. (2016), Kong et al. (2016b), Zhao et al. (2020) | NA | Riad et al. (2006), Nguyen et al. (2016) |
| D. Support vector machine | Sakaki et al. (2012), Chou and Thedja (2016), Rafiei and Adeli (2017), Wang et al. (2019c), Mori et al. (2013), Pogrebnykov and Maldonado (2017) | Arridha et al. (2017), de Morsier et al. (2013), Grasic et al. (2018), Jhong et al. (2017), Zhao et al. (2020) | NA | Mori et al. (2013), Higuchi et al. (2014), Jiang et al. (2017), Wang et al. (2019b) |
| E. Naïve Bayes | Mane and Mokashi (2015) | Muda et al. (2011), Kumar et al. (2014), Grasic et al. (2018) | NA | NA |
| F. Decision tree | Chen and Wang (2009), Zhou et al. (2017a) | Arridha et al. (2017) | NA | Burris et al. (2015), Wang et al. (2019b) |
| G. Random forest | Li et al. (2018b), Moon et al. (2018) | Grasic et al. (2018), Yu et al. (2017) | NA | NA |
| H. K-nearest neighbors | Pyayt et al. (2011), Cheng et al. (2013), Ali et al. (2019), Tomin et al. (2013) | Muda et al. (2011), Kumar et al. (2014) | NA | Rahman and Hasan (2018), Wang et al. (2019b) |
| I. Logistic model tree | NA | NA | NA | NA |
| J. Neural networks | Duncan et al. (2013), Kong et al. (2016a), Moon et al. (2018), Muhammad et al. (2018), Abdullahi et al. (2018), Tomin et al. (2013) | Ren et al. (2010), Bande and Shete (2017), Berkhahn et al. (2019), Zhao et al. (2020) | Djordjevich et al. (2008) | Sharma and Ogunlana (2015), Nguyen et al. (2016), Rahman and Hasan (2018), Peng et al. (2019), Wang et al. (2019b) |
| K. Hierarchical clustering | NA | Ifrim et al. (2014), Akhtar and Siddique (2017) | NA | Özdamar and Demir (2012) |

**Table 2** (continued)

| AI Method | 5. Early warning system | 6. Real-time disaster prediction and detection | 7. Training systems | 8. Disaster evacuation |
|---|---|---|---|---|
| L. K-means clustering | Naidu et al. (2018), Tomin et al. (2013) | NA | NA | Andersson et al. (2012) |
| M. Fuzzy clustering | Saad et al. (2014), Tomin et al. (2013) | Ren et al. (2010) | NA | NA |
| N. Principal component analysis | Peiris et al. (2010), Wan and Mita (2010) | NA | NA | NA |
| O. Hidden Markov models | Holgado et al. (2017) | Benítez et al. (2007), Toreyin and Cetin (2009), Günay et al. (2010), Heck et al. (2010) | NA | Andersson et al. (2012), Raymond et al. (2012), Song et al. (2015) |
| P. Convolutional neural networks | Cheng et al. (2017), Lohumi and Roy (2018), Perol et al. (2018), Long et al. (2018), Giffard-Roisin et al. (2018), Muhammad et al. (2018), Pogrebnykov and Maldonado (2017) | Ali et al. (2019), Layek et al. (2019), Wang et al. (2019a), Muhammad et al. (2018) | NA | NA |
| Q. Recurrent neural networks | Hoot and Aronsky (2006), Cheng et al. (2017), Pogrebnykov and Maldonado (2017), Long et al. (2018) | Chen et al. (2013), Chang et al. (2014), Jaech et al. (2019) | NA | Rahman and Hasan (2018) |
| R. Deep neural network | Long et al. (2018) | NA | NA | Jiang et al. (2017) |
| S. Multilayer **perception** | Khan et al. (2018) | Tian and Chen (2017a), Wang et al. (2019a) | NA | NA |
| T. Recursive neural network | NA | NA | NA | NA |
| U. Q-learning | NA | Lingam et al. (2019) | Khouj et al. (2011) | Sarabakha and Kayacan (2016), Yao et al. (2019) |
| V. Policy gradient | NA | NA | NA | Zheng and Liu (2019) |
| W. Deep Q-networks | NA | NA | NA | Sharma et al. (2020) |

**Table 2** (continued)

| AI Method | 5. Early warning system | 6. Real-time disaster prediction and detection | 7. Training systems | 8. Disaster evacuation |
|---|---|---|---|---|
| X. Genetic algorithm | Shirzaei and Walter (2010), Terranova et al. (2015) | Ahmad et al. (2009) | NA | Pourrahmani et al. (2015), Sharma and Ogunlana (2015), Gao et al. (2019) |
| Y. Particle swarm optimization | Huang and Xiang (2018) | Lingam et al. (2019) | NA | Wang et al. (2010a), Zheng et al. (2013b) |
| Z. Simulated annealing | NA | Zhang et al. (2016a) | NA | Jahangiri et al. (2011) |

**Table 3** Example AI applications for disaster response

| AI Method | 9. Event mapping | 10. Damage assessment | 11. Disaster rescue and relief, resource allocation | 12 Disaster information system and collaboration | 13. Understanding people's concern, emotion and reaction |
|---|---|---|---|---|---|
| A. Linear regression | NA | NA | Bagloee et al. (2019) | NA | NA |
| B. Nonlinear regression | NA | NA | Liang et al. (2001), Luo et al. (2013), Robinson et al. (2014) | NA | NA |
| C. Logistic regression | Yang and Cervone (2019) | NA | Zhang et al. (2010), Jia and Zhang (2012), Hung et al. (2016), Reynard and Shirgaokar (2019) | NA | Gopnarayan and Deshpande (2019), Yu et al. (2019) |
| D. Support vector machine | Moskowitz et al. (2011), Ilyas (2014), Cresci et al. (2015), Ireland et al. (2015), Jiang and Friedland (2016), Yang and Cervone (2019) | Tan et al. (2010), Ashktorab et al. (2014), Izadi et al. (2017), Pogrebnykov and Maldonado (2017), Naito et al. (2018), Zhang et al. (2018a), Seydi and Rastiveis (2019) | Kiatpanont et al. (2016), Basu et al. (2019a), Chaudhuri and Bose (2020) | Maharjan et al. (2018) | Yu et al. (2019), Gopnarayan and Deshpande (2019), Ruz et al. (2020) |
| E. Naïve Bayes | Ilyas (2014), Li et al. (2018a) | Imran et al. (2013), Mangalathu et al. (2019) | Kiatpanont et al. (2016), Yoon et al. (2016), Basu et al. (2019a) | Neppalli et al. (2018) | Verma et al. (2011) |
| F. Decision tree | Bahrepour et al. (2010), Yang and Cervone (2019) | Mangalathu et al. (2019) | Kiatpanont et al. (2016), Berawi et al. (2019) | Barrientos and Sainz (2012) | NA |
| G. Random forest | Feng et al. (2019), Yang and Cervone (2019) | Conner et al. (2016), Mangalathu et al. (2019), Kellermann et al. (2020) | Acuna et al. (2017) | NA | Ruz et al. (2020) |
| H. K-nearest neighbor | Kim et al. (2016b), Zhao et al. (2019) | Mangalathu et al. (2019) | Kiatpanont et al. (2016), Liu et al. (2019a) | NA | Gopnarayan and Deshpande (2019) |
| I. Logistic model tree | NA | NA | Ahmad et al. (2017) | NA | NA |

**Table 3** (continued)

| AI Method | 9. Event mapping | 10. Damage assessment | 11. Disaster rescue and relief, resource allocation | 12 Disaster information system and collaboration | 13. Understanding people's concern, emotion and reaction |
|---|---|---|---|---|---|
| J. Neural networks | Yu et al. (2005), Kovordányi and Roy (2009), Yang and Cervone (2019) | Bandara et al. (2014), Conner et al. (2016), Rudner et al. (2019) | Bayerlein et al. (2018), Chaudhuri and Bose (2020) | Datt et al. (2015), Tian and Chen (2017b) | NA |
| K. Hierarchical clustering | Middleton et al. (2014) | Zhou et al. (2017b) | Guha et al. (1998), Kondaveti and Ganz (2009) | Zheng et al. (2011, 2013a), Li et al. (2016b) | Lodree and Davis (2016) |
| L. K-means clustering | Ganesan et al. (2016) | Atasever (2017), Hou et al. (2017) | ZIDI et al. (2019) | NA | NA |
| M. Fuzzy clustering | Wang et al. (2012), Ganesan et al. (2016) | Tan et al. (2010), Yu and Zhu (2014), Zeng et al. (2018) | Sheu (2007, 2010), Ruan et al. (2016) | NA | NA |
| N. Principal component analysis | NA | Hutchinson and Chen (2005), Bandara et al. (2014), Zhou et al. (2018b) | Basu et al. (2019b) | NA | NA |
| O. Hidden Markov models | Salmane et al. (2015) | NA | Suganya and Jayashree (2018) | Qiu et al. (2014) | NA |
| P. Convolutional neural networks | Kim et al. (2016c), Liu and Wu (2016), Bejiga et al. (2017), Kamilaris and Boldú (2017), Lee et al. (2017), Huang et al. (2019c, 2019b), Ahmad et al. (2019) | Alam et al. (2017), Kamilaris and Boldú (2017), Nguyen et al. (2017), Tian et al. (2018), Vetrivel et al. (2018), Xu et al. (2019a), Zhang et al. (2019a), Pogrebnykov and Maldonado (2017), Seydi and Rastiveis (2019) | Basu et al. (2019a), Hartawan et al. (2019), Robertson et al. (2019), Chaudhuri and Bose (2020) | Neppalli et al. (2018), Kumar et al. (2020) | Yu et al. (2019), Li et al. (2016a) |

**Table 3** (continued)

| AI Method | 9. Event mapping | 10. Damage assessment | 11. Disaster rescue and relief, resource allocation | 12 Disaster information system and collaboration | 13. Understanding people's concern, emotion and reaction |
|---|---|---|---|---|---|
| Q. Recurrent neural networks | Kundu et al. (2018), Mao et al. (2019), Rahnemoonfar et al. (2018) | Nguyen et al. (2019b), Moustapha and Selmic (2007), Verma et al. (2020), Biswas et al. (2019), Pogrebnykov and Maldonado (2017) | NA | Neppalli et al. (2018), Kumar et al. (2020) | Hernandez-Suarez et al. (2019) |
| R. Deep neural network | Khan et al. (2017), Bai et al. (2018) | Bai et al. (2018) | NA | Morito et al. (2016), Neppalli et al. (2018) | NA |
| S. Multilayer **perception** | NA | Seydi and Rastiveis (2019) | Robertson et al. (2019) | NA | NA |
| T. Recursive neural network | NA | NA | NA | NA | Dong et al. (2014) |
| U. Q-learning | NA | Zhao et al. (2017) | Su et al. (2011), Castellanos et al. (2018), Liu et al. (2019a), Hou et al. (2019) | Qiao and Luo (2012), Aydin and Fellows (2018) | NA |
| V. Policy gradient | NA | Mao et al. (2016), Wang et al. (2019e) | Rodriguez-Ramos et al. (2019), Silver et al. (2014) | NA | NA |
| W. Deep Q-networks | Baldazo et al. (2019), Maciel-Pearson et al. (2019) | Maciel-Pearson et al. (2019) | Wang et al. (2020a), Yang and Liu (2018), Guo et al. (2019) | Huang et al. (2017), Sun and Tan (2019), Liu et al. (2018) | NA |
| X. Genetic algorithm | NA | Izadi et al. (2017), Tian et al. (2018) | Pessin et al. (2009), Zhao et al. (2009), Wang (2018), Liu et al. (2019a), ZIDI et al. (2019) | NA | NA |

**Table 3** (continued)

| AI Method | 9. Event mapping | 10. Damage assessment | 11. Disaster rescue and relief, resource allocation | 12 Disaster information system and collaboration | 13. Understanding people's concern, emotion and reaction |
|---|---|---|---|---|---|
| Y. Particle swarm optimization | NA | Xu et al. (2019b) | Pugh and Martinoli (2007), Sánchez-García (2019), ZIDI et al. (2019) | NA | NA |
| Z. Simulated annealing | NA | NA | Fiedrich et al. (2000), Yadollahnejad et al. (2017), ZIDI et al. (2019) | NA | NA |

**Table 4** Example AI applications for disaster recovery

| AI Method | 14. Assess impact | 15. Develop recovery plan | 16. Track recovery | 17. Evaluate loss and repair cost |
|---|---|---|---|---|
| A. Linear regression | McCaslin et al. (2005), Zhang and Peacock (2009), Rosellini et al. (2018) | NA | Zobel (2014), Qiang et al. (2020) | Barthel and Neumayer (2012), Yu et al. (2014), Kim et al. (2016a), Kousky and Michel-Kerjan (2015) |
| B. Nonlinear regression | Haraoka et al. (2012), Mitsova et al. (2018), Rosellini et al. (2018), Cheng and Zhang (2020) | NA | Zobel (2014), Zhang (2016), Wang et al. (2018b), Jamali et al. (2019), Yabe and Ukkusuri (2019), Qiang et al. (2020) | Smith and Katz (2013), Kim et al. (2015, 2018b) |
| C. Logistic regression | Tunusluoglu et al. (2007), Nabian and Meidani (2018a), Mitsova et al. (2019) | NA | Gopnarayan and Deshpande (2019) | NA |
| D. Support vector machine | Gong et al. (2013), Nabian and Meidani (2018a), Moya et al. (2018), Rosellini et al. (2018), Sheykhmousa et al. (2019), Zhang and Burton (2019) | Oh et al. (2006) | Yabe and Ukkusuri (2019), Pogrebnykov and Maldonado (2017), Gopnarayan and Deshpande (2019) | NA |
| E. Naïve Bayes | NA | NA | Shibuya and Tanaka (2019) | NA |
| F. Decision tree | Merz et al. (2013), Rosellini et al. (2018) | NA | NA | Stojadinovic et al. (2017) |
| G. Random forest | Rosellini et al. (2018), Zhang et al. (2018b) | NA | NA | NA |
| H. K-nearest neighbors | Khaloo et al. (2017), Moya et al. (2018), Nabian and Meidani (2018a) | NA | Gopnarayan and Deshpande (2019) | NA |
| I. Logistic model tree | NA | NA | NA | NA |
| J. Neural networks | Mehrjoo et al. (2008), Khoshnoudian et al. (2017), Padil et al. (2017) | Asgary and Naini (2011) | NA | Chen and Huang (2006), Aghamohammadi et al. (2013) |
| K. Hierarchical clustering | NA | NA | NA | NA |

**Table 4** (continued)

| AI Method | 14. Assess impact | 15. Develop recovery plan | 16. Track recovery | 17. Evaluate loss and repair cost |
|---|---|---|---|---|
| L. K-means clustering | NA | NA | NA | NA |
| M. Fuzzy clustering | Yu et al. (2016) | NA | NA | NA |
| N. Principal component analysis | Yu et al. (2016), Cha and Buyukozturk (2015), Khoshnoudian et al. (2017), Yamaguchi and Shirota (2019) | NA | NA | NA |
| O. Hidden Markov models | NA | NA | NA | NA |
| P. Convolutional neural networks | Cha et al. (2017), Liang (2018), Ghaffarian et al. (2019) | NA | Yang et al. (2019c), Pogrebnykov and Maldonado (2017) | NA |
| Q. Recurrent neural networks | NA | NA | Pogrebnykov and Maldonado (2017) | NA |
| R. Deep neural network | Fallahian et al. (2018) | NA | NA | NA |
| S. Multilayer **perception** | NA | NA | Lin et al. (2008) | NA |
| T. Recursive neural network | NA | NA | NA | NA |
| U. Q-learning | NA | Memarzadeh and Pozzi (2019) | NA | NA |
| V. Policy gradient | NA | NA | NA | NA |
| W. Deep Q-networks | NA | Joo et al. (2019), Ning et al. (2019), Geng (2019) | NA | NA |
| X. Genetic algorithm | Alfaiate et al. (2007), Meruane and Heylen (2011), Gomes et al. (2019) | Xu et al. (2007), Bocchini and Frangopol (2012a, b), Tapia and Padgett (2015), Karamlou and Bocchini (2016), Eid and El-adaway (2017a, b), Li and Teo (2018) | NA | NA |
| Y. Particle swarm optimization | Huang et al. (2019a) | NA | NA | NA |
| Z. Simulated annealing | Strauss et al. (2009) | Hackl et al. (2018) | NA | NA |

by SVM (Xu et al. 2012; Goetz et al. 2015; Zhou et al. 2018a), LR (Goetz et al. 2015; Zhou et al. 2018a), random forest (RF) (Goetz et al. 2015), and neural networks (Dou et al. 2015; Zhou et al. 2018a). The aforementioned AI methods have also been applied to other types of hazards, such as mapping forest fire susceptibility (Sachdeva et al. 2018), predicting fire size (Mitsopoulos and Mallinis 2017), and forecasting precipitation (Huang et al. 2018).

AI techniques have been applied to estimate possible impacts and assess vulnerability. For instance, possible structural damage under natural hazard(s) can be predicted by using fragility curves, which were traditionally built from statistical analyses of historical and simulation data and now can be estimated from the application of AI methods, such as LR (Ghosh et al. 2013; Kameshwar and Padgett 2014; Mangalahtu et al. 2018), neural networks (Lagaros and Fragiadakis 2007; Mitropoulou and Papadrakakis 2011; Liu and Zhang 2018; Mangalathu et al. 2018), and SVM (Mahmoudi and Chouinard 2016). Infrastructure service disruptions due to hazards can be predicted based on historical data using generalized regression models (Reed 2008; Liu et al. 2008), RF (Nateghi et al. 2014; Cerrai et al. 2019; D'Amico et al. 2019), decision tree (DT) (Wanik et al. 2015), and Bayesian additive regression tree (BART) (Cerrai et al. 2019). Using data from physical sensors and social sensing, the vulnerability of structures and communities can be assessed with spatial regression models (Wang et al. 2019g), RF (Yoon and Jeong 2016), neural networks (Wu et al. 2008), deep neural networks (Nabian and Meidani 2018b), etc. In terms of the number of publications, there are fewer applications of AI methods to estimating hazard-induced impact and assessing community vulnerability (*Application Areas* 2 and 3), compared with those on hazard forecast and risk assessment (*Application Area* 1).

Based on the impact and vulnerability analyses, decision makers can gain better situation awareness with more confidence and develop effective mitigation strategies (Schwartz 2018), such as retrofitting vulnerable structures (Karamlou et al. 2016), elevating electric substations and using underground cables (Duffey 2019), and developing effective disaster-related policies (Sun et al. 2020a, 2021). In this process, AI techniques can support developing and comparing mitigation strategies. For instance, different AI methods have been applied to identifying management priorities (Canon et al. 2018), estimating people's needs during a disaster (Nguyen et al. 2019a), and recognizing human activities (Sadiq et al. 2018). Clustering algorithms are used for analyzing remote images and developing contingency plans (Dou et al. 2014), and optimization algorithms have been applied for developing effective plans of disaster response and restoration (Bocchini and Frangopol 2012a, b; Gama et al. 2016). So far, there are only a very small number of studies that apply AI to developing and comparing mitigation strategies (*Application Area* 4), as shown in Table 1.

### 3.2 AI applications in disaster preparedness

In the preparedness phase, decision-makers should send out early warnings and alert the public (*Application Area* 5) after identifying the disaster that is about to come (*Application Area* 6), utilize emergency training systems and tools (*Application Area* 7), and prepare for evacuations if needed (*Application Area* 8). Among the four areas, most AI methods have been applied to *Areas* 5, 6, and 8, with very limited applications to *Area* 7, as shown in Table 2.

Identifying the coming disasters in real time and sending out early warnings are practical solutions for disaster preparations. These tasks usually rely on experts' analyses and judgments of sensor measurements in the field, and AI techniques can serve as an alternative in a cost-effective manner to forecasting the coming events (Ko and Kwak 2012), such as impending hurricane trajectories and storms (Ghosh and Krishnamurti 2018), earthquakes (Mousavi et al. 2019), ice jams (Zhao et al. 2012), floods (Yaseen et al. 2015), volcano eruptions (Parra et al. 2016), and fires (Muhammad et al. 2018). For instance, the Urban-Flood project in Europe has established an internet-based platform for early flood warnings, in which an AI component has been developed for detecting abnormal dike behaviors based on the analysis of thousands of sensor streams (Noymanee et al. 2017). Sakaki et al. (2012) performed semantic analysis of Japanese tweets with a tweet crawler, estimated the earthquake location, and developed a reporting system named Toretter that was faster than broadcast announcements by Japan Meteorological Agency. Based on the real-time analysis of smartphone accelerometer measurements of tilting motions, earthquake early warnings can also be sent out (Reilly et al. 2013). Prior to a disaster event, utility companies can use AI-based tools to estimate likely damage locations and service outage duration and get prepared beforehand. For example, Hydro One, a large utility company in Ontario, Canada, has successfully used such real-time predictive analyses in April 2018 and then positioned crews in key areas and effectively restored the power service within four days, significantly reducing the restoration time (McConnon 2018). With the implementation of IoT, cloud network services can also rapidly and accurately share information on disaster situations for early warnings (Chung and Park 2016).

With respect to disaster evacuations, some situations may give people a day or two to prepare while others might call for immediate actions. To prepare for evacuations, possible problems should be carefully considered and countermeasures should be developed. For example, contraflow operations can be implemented for hurricane evacuations in coastal areas to move the most traffic toward inland safety, and AI methods can help practical implementations by determining when to activate contraflow lane reversals (Burris et al. 2015). While large crowds move in different routes during evacuations, it is necessary to estimate crowd dynamics (Jiang et al. 2017; Wang et al. 2019b; Zheng and Liu 2019), identify the best evacuation paths (Peng et al. 2019), and develop evacuation support systems (Higuchi et al. 2014). The most popular AI methods applied for evacuations (*Application Area* 8) include SVM, DT, neural networks, and reinforcement learning, as well as optimization algorithms.

### 3.3 AI applications in disaster response

Timely disaster responses are a matter of life and death. Decision-makers need to make best efforts to understand the situation and improve the efficiency of response efforts. This naturally requires situation awareness for effective decision-making (*Application Areas* 9 and 10) and user-friendly disaster information systems for effective coordination (*Application Area* 12) to ensure disaster relief and address people's urgent needs and concerns (*Application Areas* 11 and 13). AI methods can be applied to facilitate relief and response efforts. In general, supervised and unsupervised models, and deep learning have been extensively applied to *Areas* 9 and 10, while other AI methods are rarely adopted for the two areas. Most AI methods have been applied to *Area* 11. Mainly supervised models and deep learning algorithms have been applied to *Areas* 12 and 13, as shown in Table 3.

Developing maps of the impact area(s) is essential for situation awareness, supporting efficient disaster response efforts (Ramchurn et al. 2015, 2016). Event maps and damage information that are generated from different AI methods can provide vital information for planning search and rescue operations, staging and deploying resources, and understanding short-term housing needs (Vieweg 2012; Lin 2015; Kim et al. 2018c; Rizk et al. 2019). Huge volumes of disaster-related data are continuously generated from satellites (Eguchi et al. 2008), unmanned aerial vehicles (Aljehani and Inoue 2018), robots (Park et al. 2019), and social media (Cervone et al. 2016), based on which disaster event maps can be generated. For instance, satellite images have been used to generate maps of infrastructure inventory models (Eguchi et al. 2008), damaged buildings and bridges (Adams et al. 2002; Hutchinson and Chen 2005; Balz and Liao 2010), and disaster-impacted regions (Casagli et al. 2017; Rosser et al. 2017). By rapidly analyzing these data with computer vision methods, "live maps" are generated to represent disaster situations (Lucieer et al. 2014; Middleton et al. 2014; Fohringer et al. 2015; Valkaniotis et al. 2018; Xiao et al. 2018). When analyzing maps and images, classifier algorithms are often used (Vetrivel et al. 2016). By comparing maps and images pre-event and post-event, feature discrepancies can be extracted to assess damage of structures and infrastructures for prioritizing response efforts (van Aardt et al. 2011; German et al. 2013; Bevington et al. 2015; Koch et al. 2016; Axel and van Aardt 2017; Cresci et al. 2015; Cervone et al. 2016; Nguyen et al. 2017). Different databases have been established for supporting damage assessment for different structures and hazards, such as xBD for building damage assessment (Gupta et al. 2019), and HOWAS21 (Kellermann et al. 2020) and FIMA NFIP Redacted Claims Data Set (FEMA 2019) for flood damage assessment. Crowdsourced information becomes increasing popular in supporting disaster response. Many volunteer efforts focus on speeding up the data analysis process to rapidly generate maps and provide invaluable crowdsourced information for situation awareness and damage assessment (Barrington et al. 2011; Ghosh et al. 2011; Butler 2013). By harnessing "crowds" of over 1000 experts from 82 countries, for example, the Humanitarian OpenStreetMap Team generated devastation maps of the affected areas in the Philippines shortly after typhoon Haiyan, enabling rapid damage assessment and efficient response efforts (Butler 2013).

In disaster rescue and relief, utilizing social media and robotics as well as mobile phone data often support timely and effective decision-making. Social media platforms are powerful communication tools for individuals and local communities to seek help and for governments and organizations to disseminate disaster relief information (Li and Rao 2010; Tatsubori et al. 2012; Takahashi et al. 2015). Social media data embed time and geo-location information as well as disaster-related information, serving as good information sources for building disaster information systems (Goodchild and Glennon 2010; Srivastava et al. 2012; Laylavi et al. 2017). This ultimately supports decision-making for disaster relief and resource allocations (Castellanos et al. 2018) and for building disaster information systems (Aydin and Fellows 2018). To analyze social media data, popular AI methods include classifiers, reinforcement learning, deep reinforcement learning, and other sentiment analysis techniques. However, there are concerns of using social media data as information sources due to issues of credibility, reliability, and difficulties in verifying information and processing big data into actionable knowledge (Acar and Muraki 2011; MacEachren et al. 2011; Tapia et al. 2011).

In the aftermath of a disaster, the harsh environment hinders human efforts of disaster rescue. Disaster robots allow responders and stakeholders to sense and act at a distance from the impacted areas (Murphy 2014). Robots can serve as remote sensing platforms for mapping and interacting with the destroyed environment (Adams et al. 2014; Kochersberger et al. 2014; Stefanov and Evans 2014), fight fires in dangerous conditions (Schneider and Wildermuth 2017; Ando et al. 2018), search and rescue (Murphy and Stover 2007; Murphy et al. 2009; Steimle et al. 2009; Zhang et al. 2014; Bakhshipour et al. 2017; Hu et al. 2019), and inspect damage (Devault 2000; Murphy et al. 2011; Torok et al. 2014;

Ellenberg et al. 2015; Lattanzi and Miller 2015, 2017). Machine learning has been widely used for robotics to acquire new skills and adapt to the surrounding environment (Lenz 2016). For example, deep learning has been applied to visual detection (Socher et al. 2008; Giusti et al. 2015), handling multiple input data (Ngiam et al. 2011; Noda et al. 2014), and robotic manipulation (Saxena et al. 2008; Gemici and Savena 2014; Lenz 2016). In addition, optimization algorithms are often used for dynamic path planning and multi-robot communication and coordination (Liu et al. 2013; Takeda et al. 2014).

One of the first things people commonly do during a disaster is to contact emergency services (and loved ones). Therefore, telecommunications volume sharply increases, usually following the jump-delay pattern (Bagrow et al. 2011). In disaster response, disaster management agencies need to rapidly classify information from such calls and share urgent needs of the public to relevant agencies and utility companies. Machine listening can help to automatically recognize voices to identify key words with a high priority and rapidly process voice data from different regions (Ramchurn et al. 2016). With natural language processing algorithms, sentiment mining can help disaster managers perform crisis management and enable efficient disaster relief with better awareness of the situation, such as where to send first responders and distribute resources. Based on the location information of the nearby communication network mast, mobile phone data have also been used to estimate population movements and track population displacement in the immediate aftermath of disasters (Gonzalez et al. 2009; Tatem et al. 2009; Bengtsson et al. 2011). Oftentimes, disasters may completely destroy the base stations of the mobile communication network, and so alternative base stations should be rapidly established and allocated to support emergency communication, with different countermeasures proposed (Suriya and Sumithra 2019; Wang et al. 2019d; Samir et al. 2019).

Information sharing and coordination is often the bottleneck in multi-agency response due to the unpredictable and dynamic nature of the disaster environment (Chen et al. 2008a, b). As the disaster unfolds, the information of the disaster event and its impact, victims, and resources may become outdated with large uncertainty and unpredictability by the time of sharing, making life-and-death decision-making very challenging (Holguín-Veras et al. 2012). Disaster information systems with shared access across agencies and organizations can help address these issues, such as collaborative geographic information systems (Sun and Li 2016; Abdalla and Esmall 2018; Li et al. 2019c), shared information management platforms (Bunker et al. 2015; Rasouli 2018) and decision tools (Moskowitz et al. 2011). With the shared data, collaborative data analytics can be implemented to learn about the disaster situation and identify relief needs (Tucker et al. 2017). Disaster information systems with automatic data-sharing capacity can help decision-makers from different organizations coordinate response efforts in a timely manner. Such ideas have been implemented in the forms of various prototypes (Bartoli et al. 2013; Lin and Liaw 2015; Foresti et al. 2015; Kim et al. 2018a; Hochgraf et al. 2018). There are multiple applications for disaster information systems by using supervised models and deep learning to extract information from social media data (Neppalli et al. 2018), mobile phone data (Sun and Tan 2019), remote sensing data and aerial images (Morito et al. 2016; Tian and Chen 2017b). Example disaster information systems include MADIS (Yang et al. 2012), Sahana (Careem et al. 2006), SPIDER (Šubik et al. 2010), CrowdHelp (Besaleva and Weaver 2013), and DMCsim (Hashemipour et al. 2017).

A disaster causes not only physical damage to structures and infrastructure but also mental damage to people. Different types of feelings will make human focus their attention on very different information and lead to completely different decisions and actions (Watson and Clark 1994; Greifeneder et al. 2011). Understanding feelings and psychological needs of victims would be helpful for effective disaster relief (Lin et al. 2017b; Li et al. 2019a). AI methods can help in this regard by analyzing social media data to track feelings and reactions of the public. Social media data embed emotional text and images, time and geo-location information, which as useful to identify the spatial and temporal evolution of public behaviors and population mobility, as well as psychological and healthcare needs (Bengtsson et al. 2011; Caragea et al. 2014; Ukkusuri et al. 2014; Wilson et al. 2016; Kuang and Davison 2017). Previous studies show that there are human activity abnormalities in the physical proximity of the disaster event with obvious spatial and temporal disparities (Chae et al. 2014; Shelton et al. 2014; Kryvasheyeu et al. 2016; Neppalli et al. 2017; Liu et al. 2019b; Zou et al. 2019). There are many research efforts working on this area (*Area* 13), such as developing metrics with sentiment analyses to quantify people's reaction/emotion in response to response efforts (Neppalli et al. 2017; Bhavaraju et al. 2019; Singh et al. 2019; Chen et al. 2020).

### 3.4 AI applications in disaster recovery

Disaster recovery is a multifaceted process, involving governments and public authorities, as well as private organizations. This requires comprehensive decision-making to quickly understand the complexity of the situation, identify operational needs and recovery plans, and perform rehabilitation and reconstruction activities. As disaster recovery usually takes a long time, including precise damage assessment, budgeting, planning, permitting, design and construction, AI can be an important module for supporting disaster recovery management in less time. AI methods have been applied to disaster recovery management, by assessing the disaster induced impact in detail (*Application Area* 14), developing recovery plans (*Application Area* 15), tracking the recovery process (*Application Area* 16), and estimating loss and repair cost (*Application Area* 17). The increasing number of publications in recent years, shown in Table 4, indicates increasing attention to applying AI for disaster recovery management. Among them, more attention has been paid to *Application Area* 14 than others (*Application Areas* 15, 16 and 17).

Quick and accurate assessment of the disaster-induced impact is critical for rapid recovery. In addition to physical damage, a disaster causes psychological distress and economic disturbance. When assessing physical damage, visual inspection is a primary method adopted in current practice for buildings (Pham et al. 2014; Choi et al. 2018; Lenjani et al. 2019), bridges (Yeum and Dyke 2015), tunnels (Victores et al. 2011), storage tanks (Schempf et al. 1995), etc. However, the visual inspection method is often tedious and labor intensive. AI methods can help eliminate such human efforts based on aerial images, social media imagery data, and sensor measurement data (Khaloo et al. 2017; Khoshnoudian et al. 2017). When assessing the disaster-induced impact on human, sentiment analyses of social media data can track human activity pattern throughout the recovery (Caragea et al. 2014; Hasan and Ukkusuri 2014; Shelton et al. 2014; Resch et al. 2018; Liu et al. 2019b). When investigating psychological distress following a disaster, the use of surveys is a primary method adopted in current practice. Both supervised and unsupervised models, particularly regression methods, dimension reduction methods, and neural networks, are often adopted to analyze survey results to identify risk factors and assess the effectiveness of preventive interventions (Gao et al. 2006; Kim et al. 2008; Huang et al. 2010; Gong et al. 2013; Rosellini et al. 2018). In addition, AI methods have been applied to estimate the economic impacts of a hazard, in which supervised models are often used to establish quantitative relations between critical factors and the economy and identify possible stimulus for economic growth (Zhang and Peacock 2009; Yamaguchi and Shirota 2019; Cheng and Zhang 2020; Qiang et al. 2020).

After precisely assessing the disaster induced impact, establishing post-event recovery plans is essential for effectively conducting recovery and renewal activities. While pre-event planning allows participation members to spend significant time and resources for fostering cooperative plans, post-event planning is often carried out in a relatively hostile environment with less time and resources at hand. In current research, optimization techniques are often adopted to identify efficient plans of restoration, or to estimate human decisions of recovery planning (Sun et al. 2021), including genetic algorithms (Xu et al. 2007; Orabi et al. 2010; Bocchini and Frangopol 2012b; Karamlou and Bocchini 2016), and simulated annealing (Hackl et al. 2018), and other methods (Sarkale et al. 2018; Zhong et al. 2018). Additionally, there are few studies applying reinforcement learning and deep reinforcement learning to planning post-event recovery strategies (Joo et al. 2019; Ning et al. 2019).

During the recovery process, practitioners need metrics and tools to measure and monitor how well a community recovers from a disaster over time as a means of building community resilience (Curtis et al. 2007). Supervised models and deep learning algorithms are often used in this aspect by analyzing data from various sources. As social media data are attached with geotags or hashtags, using sentiment analysis methods and image classification techniques to analyze social media data can be very helpful for disaster recovery tracking (Eckle et al. 2017; Pogrebnykov and Maldonado 2017; Jamali et al. 2019; Malawani et al. 2020; Mihunov et al. 2020). By comparing nighttime light data at different time, established regression relations between economic indicators and spatial variations in light intensity can provide valuable insights about how the regional economy recovers in a quantitative manner (Wang et al. 2018b; Qiang et al. 2020). Using Google Street View to remotely track disaster recovery has also become increasingly popular (Curtis et al. 2010; Mabon 2016).

In the aftermath of a disaster, governments need to provide timely assistance to reconstruct homes and rebuild lives; there are urgent demands for a rapid assessment of loss estimate and repair cost (Eguchi et al. 1998; Ladds et al. 2017; Deryugina 2017). AI methods can help estimate disaster losses and repair costs. In particular, supervised models, such as regression and neural network, have been used to rapidly process imagery for detecting structural damage, identifying repair needs, and estimating repair cost; they have also been used to analyze historical dispersion data of disaster recovery funds for budget allocations, and process insurance claims in less time (Chen and Huang 2006; Barthel and Neumayer 2012; Zagorecki et al. 2013; Stojadinovic et al. 2017). The existence of only a small number of publications in this field indicates that AI applications to *Area* 17 are still in their infancy. In current practice, the disaster loss and repair cost are usually estimated based on real data from different sources, such as insurance claims, post-disaster assessment, and assistance grants and personal loans to victims (Eguchi et al. 1998; Kim et al. 2015). The availability of big data and the rapid development of data analytics offer an unprecedented opportunity to promote AI applications in rapid estimation of disaster loss and repair cost in the near future. However, the lack of standardized methods for collecting and recording data may lead to very different estimates of economic impacts (Ladds et al. 2017). Therefore, establishing policies and standards for data collection is an urgent need.

After a disaster, disaster related rumors and fraud may appear, requiring the awareness and alertness of both disaster victims and governments. Data mining can help to identify potential fraud (Bagde and Chaudhari 2016; Dutta et al. 2017) and rumors (Mendoza et al. 2010; Liu et al. 2015; Wu et al. 2015; Zubiaga et al. 2016, 2018), as well as track trends of information flow (Hong et al. 2011; Badmus 2020). For example, insurance companies and law enforcement agencies can use machine learning to quickly examine the truthfulness of a claim for a flooded house by making a before-and-after comparison of high-resolution satellite images (Gilmour 2019).

## 4 Practical AI-based decision support tools

To ultimately facilitate informed disaster management in practice, many AI-based decision support tools have been developed by research institutes and industrial companies in the past few decades. By searching on Web sites of Google Scholar and Web of Science with keywords of “disaster management,” “decision support tool,” and “artificial intelligence,” we have found related AI-based tools for decision-making in disaster management. Table 5 presents example tools that apply various AI techniques in disaster management. These tools make use of various data as input to extract useful information, including social media data, mobile phone data, sensor measurements, on-site reports from first responders, and crowdsourced information from volunteers. These tools cover different infrastructures and different types of hazards, contributing to the advancement of AI applications to fostering informed disaster management at different phases. A general trend is that there are more tools applicable for the disaster response phase than other phases. Most tools use social media data as input; a small portion of tools use sensor measurements, remote sensing data, or mobile phone data as input.

Some tools focus on predicting possible consequences under a hazard scenario for developing management plans of retrofit and evacuation in the disaster mitigation and preparedness phases. For instance, Optima Predict™ software simulates and predicts emergent medical service demand and ambulance availability changes in the wake of a disaster, helping dispatchers and operations personnel find possible optimal ways of preparing for unexpected emergencies (Mason 2013). Other tools provide comprehensive platforms for efficient communications with text, audio, and location services for professional response teams in the disaster response phase, as saving life is typically the most critical issue in the first few days after a disaster and requires communication and situational awareness (Yin et al. 2012b). For example, Blueline Grid analyzes real-time mobile phone data for efficient disaster responses. One Concern predicts possible infrastructure damages and consequences based on infrastructure data and historical disaster data. Artificial Intelligence for Disaster Response (AIDR) automatically classifies crisis-related tweets along with crowdsourced information of aerial images to identify victims’ needs and infrastructure damage for efficient disaster response management (Imran et al. 2014; Ofli et al. 2016). SensePlace3 is a geo-visual interface that can visualize time, location, and relationships of events, by applying data mining tools available in Solr to process real-time Twitter data (Tomaszewski et al. 2011; Pezanowski et al. 2018). DeepMob simulates human behavior and mobility during natural disasters by learning from millions of users’ GPS records with deep belief networks (Song et al. 2017). GeoQ is an open-source tool for assessing damage by crowdsourcing geo-tagged photographs of the disaster-affected areas, developed in coordination with the National Geospatial-Intelligence Agency, the Presidential Innovation Fellow Program, the Federal Emergency Management Agency (FEMA), and other analysts.

In the meantime, there are some challenging issues of using these AI-based decision support tools in practice. First, these tools typically require large amounts of data as input,

**Table 5** AI-based decision support tools for disaster management

| Example tool | Owner | Input data | Hazard | Applicable phase | Web site/Reference |
|---|---|---|---|---|---|
| Optima Predict™ | Intermedix | Mobile phone data, clinical data, and others | General | Mitigation | https://www.r1rcm.com/optima |
| One Concern | One Concern, Inc. | Public and private infrastructure data-sets | Seismic, flood | Mitigation, and response | https://www.oneconcern.com |
| The Geospiza Solution | Geospiza Inc. | Data of hazard modeling, community, and live event | General | Mitigation, and response | https://geospiza.us/solution |
| TweetTracker | Arizona State University | Tweet | General | Preparedness, and response | http://tweettracker.fulton.asu.edu/ |
| EARS | National Research Council, Italy | Twitter | Earthquake | Preparedness | Avvenuti et al. (2014) |
| EAIMS | University of Glasgow | Twitter | General | Preparedness | McCreadie et al. (2016) |
| Ground Truth | Sandia National Laboratories | Human decision input via video games | General | Preparedness | Djordjevich et al. (2008) |
| Argus | Rutgers University | Smartphone data | General | Preparedness, and response | Sadhu et al. (2017) |
| CrisisMappers | Crisis Mappers Net | Social media data | General | Preparedness, and response | https://crisismapping.ning.com/ |
| Dataminr | Dataminr | Social media data | General | Preparedness, and response | https://www.dataminr.com/ |
| Disaster Management Coordination simulation (DMCsim) system | George Washington University | Infrastructure data, GIS data, and organization capabilities | General | Preparedness, and response | Hashemipour et al. (2017) |
| Artificial Intelligence for Digital Response (AIDR) | Qatar Computing Research Institute | Tweets | General | Response | http://aidr.qcri.org |
| Blueline Grid | WorldAware, Inc | Mobile phone calls | General | Response | https://www.bluelinegrid.com |
| Blueworx | Blueworx | Emergency calls | General | Response | https://www.blueworx.com |
| CRED | Stanford University | Seismogram data | Earthquake | Response | Mousavi et al. (2019) |

**Table 5** (continued)

| Example tool | Owner | Input data | Hazard | Applicable phase | Web site/Reference |
|---|---|---|---|---|---|
| DeepMob | Multi-government-industry collaborations | Disaster data, human mobility data, earthquake records, transportation network data | Earthquake | Response | Song et al. (2017) |
| ESA | Information Engineering Laboratory | Information management system | General | Response | Yin et al. (2012a) |
| HAC-ER | University of Southampton, University of Nottingham, and University of Oxford | Social media data and first responder reports | General | Response | Ramchurn et al. (2015, 2016) |
| SensePlace3 | Pennsylvania State University | Tweets | General | Response | Pezanowski et al. (2018) |
| Sahana | Sahana Foundation | Information management system | General | Response | Careem et al. (2006) |
| Disaster Intelligence product | Disaster Intelligence | Images, data of hazard, infrastructure, and community | General | Mitigation, preparedness, response, and recovery | https://www.disaster-ai.com |
| Disaster City Digital Twin | Texas A&M University | Remote sensing data and crowdsourced data | General | Mitigation, preparedness, response, and recovery | Fan et al. (2019) |
| Disaster Reporter | Federal Emergency Management Agency | Photographs and descriptive text | General | Response, and recovery | https://www.fema.gov/disaster-reporter |
| FIU-Miner | Florida International University | Geospatial data | General | Preparedness, response, and recovery | Zheng et al. (2013a), Li et al. (2017a, b) |
| GeoQ | National Geospatial-Intelligence Agency | Geo-tagged photographs | General | Response, and recovery | https://github.com/ngageoint |
| Tweet Earthquake Dispatch | United States Geological Survey | Tweets | Earthquake | Response, and recovery | https://github.com/usgs/earthquake-ted |
| Tractable | Tractable | Images | Flood, fire, hurricane | Recovery | https://tractable.ai |

and data-related issues are a practical challenge. Input data might be available in different types and formats for different communities, or available for some communities but not available for others due to various reasons, such as legal ramifications and commercial competitiveness. For example, big cities and urban areas usually have documented data detailed enough and sufficient in size to make AI predictions accurate, which may not be the case for small cities and rural areas. Even if all input data are available, some of it may be inaccurate, and there may be data ownership issues involved when using some of these tools. Therefore, policies and regulations need to be established for appropriate data collection, cleaning, protection, and management. Second, communities are exposed to different types of hazards and have different socioeconomic backgrounds. The AI-based decision support tools that are developed based on data from one community might not be suitable for another community. This naturally poses a challenge to the application generalization of AI-based decision support tools for a diverse set of communities. Third, some tools may require a high level of competence in deployment, making them less user friendly for practitioners. Many tools require advanced software and high-performance computers to conduct big data analytics, which may not be available for many local governments and emergency agencies in economically disadvantaged regions.

## 5 Discussion

As shown in Tables 1, 2, 3 and 4, all AI methods have been applied to disaster management. However, there are many untouched application areas by some AI methods. For instance, very few AI methods have been used for disaster training systems (*Application Area* 7); that is probably because there is very little training data of human responses in disasters available to build appropriate AI models for such purposes. Deep neural networks (*method R*) and recursive neural networks (*method T*) are rarely applied for disaster preparedness and disaster recovery (*Application Areas* 5–8 and 14–17). Policy gradient-based algorithms have not been applied in disaster mitigation and disaster recovery (*Application Areas* 1–4 and 14–17). The absence of AI applications to untouched areas may attract future research attention for exploration.

Many challenges of practical AI applications to disaster management are due to data-related issues, such accessibility, completeness, security, privacy, and ethical issues (Boyd and Crawford 2012; Crawford and Finn 2015). Making accurate predictions with AI techniques typically requires a large amount of good data for building the model. Such data are not always available. For example, some infrastructure data cannot be easily accessible due to reasons of national security and commercial competitiveness. Data trustworthiness is another issue. For instance, raw data from social networks often contain various inaccuracies and biases, requiring advanced information filtering and verification. One step further, collecting and analyzing personal data poses significant issues related to fairness, responsibility, and human rights. Even if the required data are available, data incompleteness is a common problem in disaster-related data analyses due to the dynamically changing environment of a disaster. To deal with the aforementioned issues, there have been various platforms and databases built to collect and share disaster-related data in a relatively standardized form. Some examples include ShakeMap and ShakeCast (USGS 2016b, a), GeoPlatform (GeoPlatform 2016), I-WASTE (EPA 2016), Lantern Live (DOE 2014), and Disaster Response Program (ESRI 2016), DesignSafe (NHERI 2019), xBD (Gupta et al. 2019), etc.

There are three computation-related challenging issues. First, there may not be enough human labeled training data in time considering the increasing amount of data and the limited amount of manpower in the wake of a disaster (Pouyanfar et al. 2018). In this regard, applying and improving unsupervised learning approaches may be the way out for handling real-world data without manual human labels (Ranzato et al. 2013). Second, the computational complexity sharply increases with the size, variety, and update rate of data, which challenges the capacity of processing, managing, and learning data within a reasonable response time in the disaster scenario. Efficiently managing, storing, and processing big data is essential for disaster management, particularly disaster response. Using cloud platforms to efficiently query and store big data is helpful to address this challenge. Developing more efficient AI methods would naturally be helpful. There have been efforts made to address this challenge, including reservoir computing (Tanaka et al. 2019) and using GPUs and AI accelerators (Wang et al. 2019f). Using crowdsourcing with real-time AI analyses can help to complete the necessary computation within the time limit and eliminate the amount of necessary but tedious work that traditionally needs effort on-site (Bevington et al. 2015). Third, building user-friendly tools for disaster management is essential for practitioners. This means building AI-based tools with interfaces that require minimal technical expertise for practical use.

Analysis results from AI models should be explainable and repeatable for supporting practical disaster management. To address this issue, there have been research efforts made to improve the interpretability and explainability of AI models, such as explainable artificial intelligence (Arrieta et al. 2020; Gunning et al. 2019). On the other hand, as AI solutions are developed for disaster management, we recognize that there are often challenges in reproducibility of new results. For disaster related data, the non-reproducibility issue is a particular challenge, because disasters happen irregularly with various impacts in different regions (Wang et al. 2016). Replication of experimental results is essential for trustworthy advancement in science generally and for AI models specifically. To address this issue, there have been research efforts such as IBM's AI OpenScale and OpenML (Vanschoren et al. 2014; Rossi 2019; Yang et al. 2019a). These efforts work toward making AI transparent and trustworthy by capturing the processes, data, and parameters for experiments to become repeatable.

## 6 Concluding remarks

This study focuses on AI applications in assisting in efficient disaster management during four disaster management phases: mitigation, preparedness, response, and recovery. In particular, this study reviews applications of a total of 26 AI methods in 17 Application Areas in disaster management in all four phases. Both research and practice show that analysis results from AI models are very useful for supporting disaster management. In the current stage, the general trend is that most applications focus on disaster response, followed by disaster mitigation.

AI is better than humans in terms of data analysis speed and thus the volume of analyzable data. It can make acceptable forecasts when the scope is within the range of the training data, but predictions when the scope is beyond the range may be unacceptable. This is especially true as both the hazard and the society are constantly evolving, which might fundamentally change the utility of attributes used to train the original model. Even if AI algorithms can make reasonably good predictions with the available data, a further concern is whether we should completely rely on the predictions and suggestions from AI algorithms to deploy resources and develop disaster plans. This question has no simple answer.

For practical AI applications in disaster management, there are a number of challenging issues related to data and computation, as well as inseparability and replicability of analysis results. This study also identifies many untouched application areas of different AI methods. How to develop more powerful and cost-effective AI-based tools to support decision-making in practical disaster management with improved analysis accuracy and speed is an urgent problem for the research community. Despite these challenges and untouched areas, AI methods provide numerous opportunities and easy solutions for various successful applications in disaster management. By discussing the application status of AI methods in disaster management, this study aims to inspire future research to tackle the identified challenging issues and advance disaster management with AI for improving community disaster resilience.

**Acknowledgements** This work is part of the Probabilistic Resilience Assessment of Interdependent Systems (PRAISys) project (www.praisys.org). Support from the National Science Foundation through grant CMMI-1541177 is gratefully acknowledged.

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