Smart Disaster Risk Reduction and Emergency Management in the Built Environment

Xavier Romão and Fernando Lobo Pereira

Abstract Smart technologies such as artificial intelligence, the Internet of Things, and other cyber-physical systems are often associated to Industry 4.0 given their potential for transforming current manufacturing and industrial practices. In particular, the significant potential of these technologies for increasing automation, improving communication and self-monitoring, and optimizing production overall for industries is well known. However, the influential power of these technologies is not bounded by these applications and has significant potential for fields such as disaster risk reduction and emergency management. In this context, the proposed chapter discusses several applications of digital technologies and innovations from Industry 4.0 in these fields, such as big data, the Internet of Things and machine learning techniques for big data analytics. Additionally, research and governance needs in this context are highlighted, as well as certain challenges to widespread and mainstream the reliable use of these technologies in disaster management.

Keywords Disaster management · Risk assessment · Emergency response · Machine learning · Big data analytics · Internet of Things

1 Introduction

The occurrence of natural hazards such as cyclones, floods, tornadoes, droughts, earthquakes, or volcanoes is often synonymous of disasters, given their devastating impacts on human life, the economy or the environment. In 2019 alone, the

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Emergency Events Database (EM-DAT) recorded data about 396 disasters across the world, globally involving 11,755 deaths, 95 million people affected, and 103 billion US$ in economic losses [1]. While fully eliminating these negative impacts may be extremely difficult, efforts can nonetheless be undertaken to reduce their severity using adequate disaster management policies and practices.

Even though disaster impacts are often sourced in a natural process, they are seen to depend significantly on public policies addressing risk management, disaster preparedness, and emergency management. In this context, the 2030 Agenda for sustainable development [2] is seen as an important global policy step toward raising awareness about the importance of disaster and emergency management. In particular, the framework of 17 Sustainable Development Goals that it establishes includes four (Goals 1, 2, 11, and 13) that refer to the need of nations and communities to address the challenges related to natural hazards and disasters (see also chapter "Shaping the Future of Construction Professionals"). Simultaneously, disaster management practices also need to evolve by leveraging technological advancements and innovations that are being mainstreamed in the context of Industry 4.0. These advances, though originally targeting other objectives, create new possibilities to support disaster resilience and risk reduction actions [3].

Industry 4.0 is the overarching term that symbolizes the current technological trend underlying the Fourth Industrial Revolution (see chapter "Shaping the Future of Construction Professionals"), and several sectors are expected to benefit from its advancements. Disaster risk reduction and emergency management are among those, as can be seen from the growing number of applications appearing in these sectors that involve promising Industry 4.0 technological developments and innovations. To illustrate some of their potential, concepts such as big data (see chapter "Big Data and Cloud Computing for the Built Environment") and the Internet of Things (see chapter "Cyber-Physical Construction and Computational Manufacturing") are reviewed in the context of disaster management, and applications of machine learning techniques (see chapter "Artificial Intelligence for the Built Environment") for big data analytics and to emulate complex problems are discussed. In addition, research and governance needs in this context are also highlighted, as well as certain challenges to widespread and mainstream the use of these technologies in disaster management.

2 The Disaster Management Cycle and the Risk Management Cycle: A Brief Review

Several terminologies are available to define and describe the disaster management cycle. Even though different fields of disaster-related practice use alternative interpretations of this cycle, most of them are very close and differ in minor details only. Therefore, the definition of disaster management cycle that is considered herein is one that is simple, that incorporates all the main steps, and provides a clear

Fig. 1 Disaster management cycle

connection with the risk management cycle. As such, the disaster management cycle is considered to be a three-stage process, as presented in Fig. 1, that involves: mitigation and preparedness; response; recovery.

Even though mitigation and preparedness are usually seen as independent activities in several definitions of the disaster management cycle, they are in fact complementary and need to be carried out simultaneously. Therefore, they are considered to be in the same stage in the selected definition of the disaster management cycle. Mitigation involves actions attempting to prevent hazards from developing into disasters altogether or to minimize the damaging effects of disasters. Preparedness, on the other hand, is a continuous cycle of planning, organizing, training, evaluating, and improving activities to ensure the enhancement of capacities and an effective coordination to respond to and recover from the effects of a disaster. Mitigation and preparedness are a direct output of the risk management cycle that link with the disaster management cycle. The response stage includes all the emergency management actions taken during or immediately following an emergency, including efforts to save lives and to prevent further property damage. Ideally, disaster response involves putting into practice a pre-established disaster preparedness plan. Finally, the recovery stage involves actions to return the impacted area to its pre-disaster state or better by restoring, rebuilding, and/or reshaping it. This stage usually starts after damages have been assessed, and adequate response efforts are achieved and ongoing.

Regarding the risk management cycle, several definitions and terminologies are also available to describe it. Although different fields of risk management practice also use alternative interpretations of the several steps involved, the risk management cycle definition considered herein incorporates the essential elements. The risk management cycle is considered to be a five-stage process, as represented in Fig. 2, that involves: risk assessment; risk communication; analysis and decision-making; risk mitigation and definition of emergency measures; control/monitoring and emergency training.

As can be seen from Fig. 2, the risk assessment component of the risk management cycle comprises three sub-stages. These correspond to hazard identification, assessing consequences, vulnerability and resilience, and risk evaluation. The output of this stage is a risk value or classification that is then conveyed to

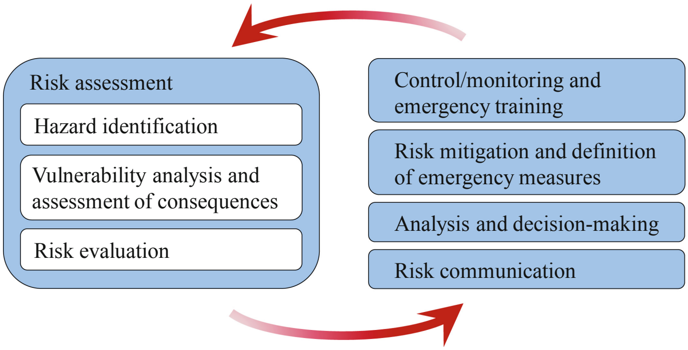

Fig. 2 Risk management cycle

stakeholders in the risk communication stage. Therefore, efficient risk communication needs to involve risk metrics that can be understood clearly by decision-makers. The analysis and decision-making stage is where the need for actions regarding a certain risk level is determined and where the type of action is gauged against potential losses using cost–benefit analyses and other criteria. The next stage has also two components: risk mitigation and definition of emergency measures. The first addresses the implementation of the risk mitigation actions that were selected in the previous stage (if any), and the second involves the development of emergency preparedness measures and processes to enhance the capacity to respond to and recover from a disaster. The final stage of the risk management cycle also comprises two components. The first is the control and monitoring of changes in the condition of the asset under analysis, including after the implementation of mitigation actions if such actions were defined. The second component involves the regular implementation of training activities addressing the emergency preparedness measures that were planned in the previous stage. Unlike the disaster management cycle that is only activated by the occurrence of a disastrous event, the risk management cycle needs to be regularly implemented to ensure an up-to-date risk assessment information and an adequate level of emergency preparedness. Moreover, it also becomes clear that the outputs of the stage that defines risk mitigation actions and emergency measures are the link between the risk management cycle and the disaster management cycle.

3 Current Needs and Challenges in Disaster Management

Understanding disaster risks plays a central role in disaster management activities. Research in this context has achieved significant developments, in particular over the past 20 years [4, 5], but it has traditionally been focused on advancing pre-event and post-event activities separately. Pre-event activities typically deal with the components of the risk management cycle previously described, thus focusing on preventing and reducing the frequency of disasters, i.e., reducing the frequency of cases in which the occurrence of a certain hazard turns into an event with negative impacts. Achieving this objective calls for adequate methodologies and tools capable of forecasting the potential loss of life or injuries, and the potential destruction or damage to tangible and intangible assets that could occur in a specific period of time, determined probabilistically as a function of hazard, exposure, and vulnerability. On the other hand, post-event activities are normally focused on developing adequate strategies to respond to, cope with and recover from disasters [6]. Research on post-disaster issues started later than research on risk management and other pre-disaster issues, but the outcomes of this multidisciplinary area can play an important role in reducing disaster losses, namely by integrating lessons learned in response and recovery from a given event into the development of enhanced risk reduction and disaster preparedness measures [7].

Despite the significance of past advancements on these topics, many aspects remain to be addressed, in particular when considering that the nature and the scale of risks change continuously, often in a way that exceeds the risk management capabilities of institutions and approaches that are established. In this context, the systemic nature of certain events is a matter of increasing concern given its potential to generate different types of simultaneous damage and destruction, namely to different sectors of societies and economies [8]. The occurrence of this type of wide-reaching event can also be seen as an unfortunate byproduct of the current and unprecedented level of connectedness and complexity of societies due to globalization [9]. Events such as the 2010 Eyjafjallajökull volcanic eruption and its impacts on the airline industry [10], or the 2011 Thailand floods and their consequences for global supply chains [11] are just a few examples that demonstrate the reaches of systemic impacts. Given the growing interconnectedness of economic processes, systemic risks are therefore expected to increase, as can be seen by the ongoing impacts of the COVID-19 pandemic [12] and are also likely to be magnified by changes in the intensity and frequency of weather-related events as a result of climate change [13].

On the emergency response side, the more apparent challenges are often connected with the planning of disaster relief operations and their implementation in the response phase immediately after an event. Aside from the fact that planning these operations depends on the availability of robust and comprehensive risk assessment results, this planning needs to accommodate multiple scenarios and types of events whose complexity inevitably depends on the severity of the events (both in terms of intensity and geographical spread), on the number of entities that are involved, but also on unforeseen factors that may occur in real situations. Furthermore, as for the case of risk assessment, this complexity can also be amplified by the interconnectedness of society and its activities. In real events, the implementation of emergency response is, in general, information-driven [14], thus requiring that all the actors involved (governmental institutions, response operatives, etc.) interpret information and interact with each other to make rapid decisions. The quality and readiness of these decisions depend on several factors, but particularly on the speed at which adequate information is available for decision-making. In turn, the availability of this information depends significantly on the efficiency of the situational awareness of emergency operatives regarding the ongoing incidents, the available resources, and existing needs [15]. Accurate and timely assessment of the situation empowers decision-makers during an emergency by providing adequate support for decisions regarding appropriate response actions, ultimately facilitating the management of the overall response process.

Addressing the referred challenges, therefore, requires a robust and comprehensive understanding of disaster risks and emergency response. Disaster risk assessment is based on identifying the multidimensional characteristics of factors likely to cause or contribute to disasters, including exposure to hazards, vulnerability of people and property, land use, and environment. Therefore, robust risk predictions require detailed quantitative knowledge about hazard exposure and vulnerability of assets, including their dynamic evolution over time. In addition, given the relevance of multi-hazard risk scenarios in several situations [16, 17], this aspect also needs to be considered, which implies the need to align methodological approaches and data used for disaster risk assessment for different hazards. Moreover, in the context of data, the importance of having access to consolidated, detailed, and high-quality disaster loss data from past events cannot be overlooked, given its importance for validating risk model predictions, but also for identifying critical hazards, as well as disaster impact trends and spatial patterns [18, 19]. On the other hand, an efficient emergency response depends on having an adequate flow of information from the field-level operations to the decision-making process. This flow of information, in turn, depends also on operatives having a level of situational awareness that allows them to have an adequate perception and comprehension of the emergency and the ability to forecast its evolution [20].

4 Disaster Management Applications

Given the pervasiveness of big data, big data analytics based on machine learning techniques are expected to be central for producing meaningful information for disaster management from these large datasets. To illustrate the implementation of these techniques in certain disaster management research fields, recent reviews and developments on the topic are discussed in the following. The discussion addresses the ability to generate relevant and reliable information from big data, but also reports challenges that need to be overcome in each field and the corresponding opportunities for research, based on research case studies, as well as real applications. Prior to this analysis, big data sources relevant for disaster management are also briefly reviewed.

4.1 Big Data for Disaster Management

A brief and non-exhaustive review of existing literature dealing with disaster management issues was performed to identify sources of big data relevant for this topic. The following were found to be relevant either for risk assessment or emergency response and are briefly reviewed herein: satellite imagery; aerial imagery; wireless sensor networks; light detection and ranging (LiDAR) data; simulation data; spatial data; crowdsourced data; social media data; mobile-based global positioning system (GPS) data and call detail records.

Satellite imagery is a source of quantitative and qualitative data that can be useful for both risk assessment and emergency response [21–25]. Although satellite imagery can be seen to provide important and detailed information for risk assessments in terms of land use, it can also be used to develop building and infrastructure inventory maps. In terms of emergency response, the availability of satellite imagery has been used to identify disaster-affected areas and their characteristics, but combinations of two-dimensional data have also been used to produce three-dimensional data that help identifying the intensity of disaster damage. Such three-dimensional data are obtained by combining satellite stereo data and provide digital surface models that enable, for example, the identification of damaged/collapsed buildings by comparing the difference in their height by using pre- and post-event imagery. Reference is also made to the use of synthetic aperture radar (SAR) imagery since it can capture data during the day or night, regardless of weather conditions, thus overcoming several limitations of traditional optical satellite imagery.

Aerial imagery captured by unmanned aerial vehicles (UAVs) is also becoming increasingly relevant for risk assessment and emergency response, despite the challenges that using UAVs still involve. Since UAVs can carry various types of sensors (e.g., cameras, video recorders, infrared and ultra-violet sensors, radiation sensors, weather sensors, LiDAR sensors, spectrum analyzers, etc.), imagery obtained using UAVs can be seen to have several advantages over satellite imagery, namely due to the versatility of the recording possibilities, but also due to the speed at which imagery can be captured and its spatial resolution. In post-disaster scenarios, imagery captured using UAVs can play a significant role given its ability to provide real-time high-resolution data that will enhance situational awareness. Furthermore, it can also be combined with other data sources such as satellite imagery or crowdsourced data to improve emergency response planning. Some of the technical challenges involved in the use of UAVs are seen to be related to their short battery life, which limits their coverage area, and to stability issues under certain atmospheric conditions. However, other non-technical challenges are also involved, namely those involving safety, security, and privacy issues [26].

Wireless sensor networks (WSNs) are self-configured and infrastructure-less wireless networks that can monitor physical or environmental conditions. The monitored data goes through the network down to a central location (or sink) that acts like an interface between users and the network and where data can be analyzed

[27]. A WSN can have thousands of sensor nodes that can communicate with each other using radio signals, often with multi-hop communication, and form a self-organized network infrastructure. The sensors of WSNs are also able to answer queries issued by the central location in order to perform specific actions or provide data samples. WSNs can work continuously or in an event-driven mode. Applications of WSNs relevant for disaster management are found in several fields. In the context of risk assessment and management, WSNs have been used, for example, to monitor certain environmental conditions relevant for forest fire detection [28], landslide detection [29], but also for the monitoring of specific built structures and infrastructures [30, 31]. In the context of emergency response, WSNs, often combined with other technologies such as UAVs, contribute to enhance situational awareness [32]. WSNs have also been used to improve communications in disaster scenarios, namely between the affected population and rescue services [33], or to extend the range of communications by combining the use of WSN with autonomous mobile robots [34]. Despite their popularity, WSNs have several limitations driven by memory, computing power, battery life, and bandwidth constraints, which can then have serious implications in terms of their security [35]. Since WSNs are seen as a major contributor to the Internet of Things, security concerns increase given the number of sensors and devices that are expected to be connected and the openness of the system. Aside from usual security concerns regarding privacy, authentication, and access control, the Internet of Things adds additional challenges regarding the capacity to be intrusion-tolerant and self-healing [36, 37].

LiDAR is an airborne or terrestrial remote sensing method that is capable of gathering detailed point cloud data that can provide high-quality distance measures of land topography and water conditions, as well as other features. Based on these measures, high-resolution digital elevation models can be developed, which can then be used for multiple risk assessment [38, 39] and emergency management purposes [40, 41]. LiDAR scanners are also able to gather information about the ground surface below the vegetation, which can be used for mapping or measuring geological features that can provide data for monitoring volcano growth and predicting eruption patterns [42].

Simulation using advanced predictive models is a central part of risk assessment, both for hazard and vulnerability modeling. Predicting natural events such as cyclones, heavy rain, storms, floods, or hurricanes requires huge meteorological data but also complex numerical models. The Hurricane Weather Research and Forecasting Model [43] for hurricane prediction and the Forecast Oriented Low Ocean Resolution [44] for cyclone prediction are examples of such models. Other advanced simulation environments are also being developed, such as those proposed for the multi-hazard risk assessment of network infrastructures [45], for the integrated dynamic flood risk assessment at regional scales [46], and those involved in several earthquake simulation and seismic resilience modeling initiatives and frameworks [47, 48]. Advances in modeling and simulating systemic risk scenarios [49] and cascading risk scenarios [50] are also likely to soon contribute with large datasets of simulation data. Aside from these modeling approaches, advances in the development of agent-based models for the simulation of human decisions [51] are being explored in the context of simulating emergency response situations. For example, these models are being used to simulate different types of crowd evacuation [52], disaster response coordination [53], or post-disaster recovery scenarios [54]. Given the large amounts of different types of observational data generated during a disaster, these are expected to be useful to validate the complex nature of agent-based models [55], if adequately curated and shared.

Spatial data are also known to be essential for the implementation of risk assessment at the regional or national scales, both for hazard and vulnerability modeling. Spatial data are important for mapping the physical and socioeconomic exposure of assets and society to different types of hazards and threats, but also for mapping hazards across territories. These include mapping land use and cover [56], population dynamics [57, 58], structure and infrastructure location data [59–61], georeferenced socioeconomic statistics and indicators [62], as well as hazard intensities [63, 64]. Spatial data come from a variety of sources, namely the previously referred data obtained from satellite imagery, areal imagery, LiDAR, or WSNs, but also from crowdsourcing and other collaborative initiatives. Despite the currently increasing volume and variability of formats of geospatially collected big data that present several challenges in storing, managing, processing, analyzing, visualizing, and verifying the quality of the data [65], important opportunities are being created for the disaster management sector from mixing these different data sources [66, 67].

The rise of Web 2.0 also led to the rise of the Internet as a means to outsource work to the crowd. This new form of dividing work among multiple participants to achieve a given outcome quickly led to the now ubiquitous *portmanteau* "crowdsourcing" [68]. The fact that crowdsourcing data became popular among the geospatial communities and that data are actively contributed by people also gave rise to the term Volunteered Geographic Information (VGI) [69], which signaled a new era where users became active providers of geospatial contents. Although there are a number of initiatives to collect different types of VGI data, the OpenStreetMap project [70] is perhaps the most popular example and one of the most relevant ones for disaster management. Other geospatial crowdsourcing initiatives include the Degree Confluence Project [71] and the Geo-Wiki initiative [72], which can both be used for land cover classification. There are also several map-based crowdsourcing platforms that can be used for creating crowdsourcing projects to collect data relevant for risk assessment or for emergency response. Examples of these platforms include Canvis.app, GIS Cloud, Greenmapper [73], Maptionnaire [73], Mapillary [74], and Ushahidi [75]. Although data collected through such collaborative initiatives are relevant to both risk assessment and emergency response, their potential to improve disaster response and resource allocation based on real-time reports from on-site responders and even affected people is particularly relevant [76, 77]. Despite the advantages of crowdsourcing, there are still issues and challenges regarding the integration of crowdsourced data into the decision-making processes. These are mostly related to concerns about the quality/reliability/credibility of the data [78, 79], although certain strategies can be adopted to improve the performance of data contributors [80]. Still, government-led crowdsourcing initiatives have been recently launched in order to interact with citizens during emergency situations to collect real-time information and improve disaster response efforts [81, 82].

Social media data are mostly passively contributed data since social media users are not creating data whose objective is to be collected by third-parties for additional purposes. There is currently a large number of social media platforms but not all are relevant to or have been used in activities related to disaster management. Among those, some of the more frequently used, in particular for emergency response situations, are Facebook and Facebook Disaster Map, Flickr, Instagram, and Twitter given their ability to provide geotagged data through the application programming interfaces (API) provided by the corresponding companies [83–85] or given the possibility of geolocating users of the platform. Despite the usefulness of social media data, they might be more effective for certain components of emergency management than for others, e.g., Twitter was found to be efficient for emergency detection and prediction but less relevant for response and recovery [86]. Given that social media are not only text-based data and also involve image and video data, these platforms have also been used for other purposes relevant to risk management such as land use and land cover classification [87], hazard analysis [88], risk assessment [89], risk communication [90], disaster recovery [91], or population and human mobility mapping [92]. Although the potential of social media for disaster management activities is becoming increasingly clear, challenges still need to be overcome before being able to ensure that only robust information is extracted. For example, automatic (unsupervised) recognition of relevant information based on individual messages or massive social media data need to be achieved in order to make these data sources truly usable in emergencies [93, 94]. Other relevant challenges are associated to organizational factors and policies of governmental institutions that may not be ready to embrace these new sources of data, namely due to credibility issues [95].

Mobile GPS has emerged as an effective means of inferring data relevant to risk assessment or emergency response related to human mobility and behavior through the geolocation of mobile phones. These data can be relevant for both the real-time analysis of human evacuation [96] and the post-disaster analysis of human behavior during emergencies in order to enhance response in future events [97]. When mobile emergency notification applications are present in the mobile device, mobile GPS can complement them and provide additional information to the emergency response centers gathering these emergency notification data [98, 99]. In a post-disaster scenario, mobile GPS can also be combined with other mobile apps to speed the damage assessment process of structures and infrastructures and facilitate the analysis of their usability [100]. Call detail records are another data source relevant for detecting human mobility and behavior by placing mobile phone users in a geographical location based on the tower used by the mobile phones to send or receive a phone call, text message, or Internet data connection. The ability to monitor human population dynamics daily, seasonally, or annually can provide relevant data for risk assessment and management. In low-income countries where population distribution data may be scarce, outdated or unreliable, mobile positioning data are able to fill this gap [101]. In countries where detailed human population census data are available at high resolution, the added value of using mobile data lies in the ability to estimate changes in population distributions through time, i.e., along the week days or a season, or due to other events that may affect population over large spatial extents [102]. While mapping the exposure of people to risks is facilitated by having information on their mobility patterns, it can also provide useful information for developing risk prevention and mitigation programs focusing on transport infrastructures that are more frequently used [103, 104]. In addition, the potential for using near real-time call detail records to assist in emergency response has also been analyzed [105] and, as for mobile GPS, call detail records generated during emergencies can also be used in post-disaster analysis of human behavior, either alone or in combination with other data [106, 107]. Despite the increasing usefulness of call detail records when analyzing human mobility, their validity must be carefully examined using robust methodologies [108, 109] to avoid biased conclusions [110].

4.2 Outlook of Applications in Particular Fields of Disaster Management

Recent reviews addressing the impact of machine learning techniques for flood risk modeling and related aspects highlighted several applications where significant changes are ongoing or are likely to occur due to the increasing use of these techniques [111, 112]. Among other aspects, the use of data-driven machine learning models for hazard prediction is increasing given their ability to provide results faster than hydrologic and hydraulic models describing the physical processes, which usually require large computational overheads. Still, this preference comes at a cost since a trained machine learning model is unable to account for changes to the hydraulic system it represents (e.g., when a certain protection structure is introduced in the system) and may not perform well in predicting scenarios far outside the training domain. Among the several machine learning techniques that are being used, reference is made to the increasing popularity of hybrid models where the hazard process simulation integrates machine learning to perform certain tasks in the modeling process [113, 114]. Another popular approach involves the use of an ensemble of methods, which increases the generalization capabilities of the models and decreases the uncertainty of the predictions [115, 116]. In addition, it is also referred that advanced machine learning techniques are being developed for applications in grid-based modeling and forecasting [117, 118]. In the domain of flood damage and loss modeling, the most common current trend involves the development of multivariable flood impact models with the help of machine learning techniques [119, 120], although developments in the field of flood index insurance [121] are also exploring the use of machine learning-based methodologies. The reliability of these applications, however, is often limited by the unavailability of high-quality data (especially data related to more extreme and thus rare events) to train and build robust machine learning models. Overcoming the challenges regarding the availability of representative high-quality data requires changes in the current practice of post-event data collection and sharing, data standardization and data quality protocols [18, 19], as well as the collaboration between relevant organizations and stakeholders [112]. In this context, it is noted that machine learning techniques developed for automatic damage identification/classification based on remote-sensed data may offer limited advantages given that, in many cases, the damage occurs inside built structures and infrastructures and cannot be identified using the referred remote sensing technologies.

A recent review addressing the use of machine learning techniques in earthquake engineering topics related to risk assessment, among others, emphasizes that machine learning provides the ability to tackle certain problems that are difficult to solve using traditional methods [122]. These include mostly the development of data-driven or hybrid models simulating processes for which structural, geotechnical, or physics-based models are difficult to derive or costly to use, e.g., ground motion prediction and generation [123, 124], seismic response of structural components or systems [125, 126], fast and large-scale post-earthquake damage assessment in built structures and infrastructures [127–129], and seismic fragility assessment [130, 131]. Still, there are challenges to progressing the use of machine learning in these topics. In particular, it is noted that large amounts of high-quality data are necessary for machine learning outputs to be reliable, which is often difficult to achieve since creating such large datasets may require high-fidelity numerical analyses with large computational overheads or large-scale experimental tests that can involve prohibitive financial costs. To address this issue, the review refers that more transparent, accessible, and high-quality data should be shared among the worldwide research community, namely by using dedicated online platforms supporting research in these fields [48], but also that efforts should also target the development of more simulation-based data based on high-quality modeling approaches. Moreover, to overcome the limitations of purely data-driven machine learning applications, which may lead to inadequate results outside their training domain, it also suggests that machine learning algorithms incorporating the physical understanding of the underlying process should be developed. In this context, research addressing the development of more interpretable machine learning models can be seen as a progress toward that goal [132, 133], as well as the development of hybrid simulation approaches mixing physics-based simulations and experimental data [134].

Another recent review analyzed the application of machine learning methods in wildfire disaster management to address a manifold of problems such as fuels characterization, fire detection, fire mapping, fire susceptibility, fire behavior prediction, fire effects, and fire management [135]. As for the applications in the earthquake engineering field, the lack of interpretability of machine learning models is also seen as a major obstacle for the adoption of machine learning techniques in these fire research domains. It can be seen that the development of machine learning models with greater interpretability is starting to address this limitation, e.g., by analyzing the importance of certain variables from machine learning models [136, 137] or by using different model interpretation and visualization techniques [138]. Still, the review also refers that expertise in wildfire science will always be necessary to ensure realistic modeling of wildfire processes using machine learning techniques. Moreover, as in other domains, the availability of sufficient high-quality data for developing reliable machine learning models is also an issue in wildfire disaster management. For fire management problems, data are needed at large spatial and temporal scales, while for fire spread and behavior modeling data are needed at very fine spatiotemporal scales (including high-resolution fuel maps and surface weather variables). To overcome this issue, the review highlights that wildfire research and management communities should start sharing free high-quality wildfire data that can be used by practitioners developing machine learning models, e.g., see [139, 140]. Given the impact of the response phase on the overall financial expenditure of wildfire management, the review also suggests that further research involving machine learning techniques should target fire occurrence prediction and fire behavior prediction, namely by using machine learning in time-series forecasting applications. Recent research on these topics is consistent with this suggestion [141, 142].

Regarding landslide risk management, recent reviews highlight that most of the existing machine learning applications in this domain are related to landslide identification and susceptibility mapping by applying machine learning techniques to remote-sensed data [143, 144]. The performance of several machine learning techniques for landslide identification and susceptibility mapping has been analyzed [144–146], but none can be claimed to be the most efficient overall. Still, deep leaning-based machine learning algorithms have started to be favored in this domain since they require less supervision than traditional methods [144, 147]. Nevertheless, the use of ensemble-based approaches is recommended to improve the reliability of the model predictions [148, 149], as well as the use of hybrid models [150, 151]. Given that the reliability of the machine learning models developed in this domain depends on the accurate detection of landslide features across large labeled training datasets, data augmentation techniques have been used to artificially extend an existing dataset. These techniques can involve a translation or a rotation of an image, a mirroring of an image or window shifting [144, 152]. Nevertheless, it is expected that remote-sensed big data may provide solutions to overcome some of these issues [153], and applications are currently being developed on this front [154]. Another field related to landslide risk management with increasing applications of machine learning addresses the monitoring of landslide displacements and volume for developing early warning systems [155, 156]. In this context, remote-sensed big data and the Internet of Things are both expected to play relevant roles in the near future [157, 158].

Despite the large sub-domains of emergency management and disaster response in which the application of machine learning techniques combined with multiple big data sources can provide important advantages [159, 160], the following only briefly reviews aspects related to situational awareness in emergency situations and demand forecasting of emergency resources in disasters. These sub-domains were selected given some of the challenges they encompass. Regarding the former, machine learning techniques have been applied in several situations to extract relevant information for disaster response from text, image, or video data coming from social media [161, 162]. Despite the increasing number of machine learning applications addressing this topic, there are still several important challenges that need to be overcome. For example, the identification of small-scale events remains a challenge given that small events do not stand out across social media data that are usually extremely noisy. Advances in machine learning techniques based on multi-label learning have been used to address this issue [163, 164]. Another challenge lies in the fact that the geolocalization of events that may be identified from social media content is often difficult since only 1–3% of that is geotagged. Machine learning applications dedicated to geoparsing based on classification and semantic annotation, probabilistic language models, and representations of structured information contained in knowledge graphs are being developed to address this issue [165, 166]. Another challenge is connected to the fact that crowdsourced data often contains more than the credible data (e.g., ambiguity, opinions, comments) and also to the concerns related to the trustworthiness of social media data since it may contain fake news, rumors, misinformation, and disinformation. Several advances are also being made on this front with the use of multiple machine learning approaches [167, 168]. A further challenge related to social media data analysis in emergency management situations refers to the risk of multimodal data overload when a disaster occurs. Since manual analysis of these data is often impossible, efficient data processing pipelines based on machine learning techniques are being proposed [169]. Despite the availability of the referred machine learning models, their reliability depends on the availability of large datasets for the successful training and validation of the referred models. To achieve this, governmental and non-governmental organizations need to collaborate with research initiatives on this topic to curate such datasets [170, 171]. Finally, with respect to the topic of demand forecasting of emergency resources in disasters, research involving machine learning applications is scarcer [172]. A few studies have addressed the issue of predicting the number of casualties in disasters using different types of machine learning techniques [173–175] but applications in other fields of disaster emergency demand forecasting are even fewer [176–179]. According to [172], the lack of research in these fields is due to lack of data describing the management of past emergency events. As such, governments and emergency management agencies should start sharing relevant data about past events in order to promote research in the multiple fields related to the prediction of the necessary emergency resources in disasters.

As discussed before, exposure refers to the spatial characteristics of people and assets that can be affected by hazards. Aside from the possibility of crowdsourcing exposure data, as previously referred, machine learning techniques are also expected to cause significant changes in exposure mapping by classifying and labeling remote-sensed data. Applications in these fields involve mapping built-up areas based on night-time light data [180, 181] or satellite imagery [182, 183]. Furthermore, machine learning algorithms are also being used to automatically label buildings [184, 185], determine their height [186, 187], and map roads [188, 189] using aerial/satellite imagery. These imagery sources can also be combined with others such as street view images in order to enhance the identification of building characteristics [190, 191] or extract other land use features [192]. Aside from exposure mapping, machine learning algorithms can also be used to predict the future evolution of exposure. In this context, machine learning algorithms have been used on their own to model urban growth and land use change [193, 194] or by integrating them with cellular automata which have been increasingly used to model the evolution of urban systems. Given the complexity of defining the transition rules needed for cellular automata, due to the nonlinear evolution of urban expansion, hybrid models combining cellular automata and machine learning algorithms are being increasingly used to overcome these difficulties [195, 196].

5 Conclusion

This chapter reviewed the risk and disaster management cycles and discussed how they can benefit from integrating certain technologies of Industry 4.0. Moreover, applications of machine learning for big data analytics and emulation of complex problems were also discussed in light of certain challenges identified in the risk assessment and emergency response domains. In addition, challenges and research opportunities for progressing the use of machine learning techniques in several disaster management domains were also examined.

Several of these challenges were seen to be common to all domains. Among those, the unavailability of large representative high-quality datasets to train machine learning algorithms is at the top. To overcome this, real data collection and experimental/simulated data generation need to advance significantly, while dedicated systems and protocols also need to be developed among research, practice, and governmental organizations to make those data available. The lack of interpretability of machine learning models was also seen as a challenge common to most domains. This issue is a major obstacle for the wider adoption of machine learning models and is also a gateway to the dangerous path of reducing the role of human judgment in the modeling processes. A possible solution for this issue involves the development of hybrid machine learning algorithms incorporating the physical understanding of the processes being emulated. Finally, concerns related to the reliability of machine learning models and the uncertainty of their outputs are also challenges that need to be addressed. A promising solution in this context involves generalizing the use of ensemble-based approaches.

These challenges are in line with those identified in other domains related to the bias, ethics, and fairness of machine learning models and artificial intelligence technology in general [197, 198]. Although the disaster management sector does not appear to be engaged in this global debate yet, the potential to generate negative impacts in this sector with the use of machine learning approaches is not negligible. Bias-related issues in machine learning can occur due to the previously referred unavailability of representative high-quality datasets. This may include lack of important data that cannot be easily measured or identified and are, therefore, left out of the modeling process. These issues are particularly common when developing large-scale regional- or country-level risk assessment studies for which collecting all the relevant data in detail is often impossible [199]. Furthermore, since economic exposure values are central for developing risk mitigation strategies based on risk assessments, decisions for risk mitigation can be mostly driven by the economic values that need to be protected [200], potentially leaving out other relevant factors to consider. In addition, given that social media users are not representative of all the demographics of a region [201, 202], bias-related issues may also occur when deriving models from social media data only (i.e., certain vulnerable parts of the true demographics will not be represented) [203]. As such, these and other challenges that may be intensified by the widespread use of big data, machine learning techniques, and artificial intelligence technology in general (e.g., data privacy concerns, lack of public participation in disaster management decisions) need to be carefully addressed by adequate governance actions from multiple sectors [204] if objectives such as those of the AI for Social Good movement [205] are to be achieved in the future.

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