Use of OR in earthquake operations management: A review of the literature and roadmap for future research

Betul Coban[a] **Maria Paola Scaparra**[ab] **Jesse R. O'Hanley**[ab*]

[a] Kent Business School, University of Kent, Canterbury, UK
[b] Centre for Logistics and Heuristic Optimisation, University of Kent, Canterbury, UK
[*] Correspondence email: j.ohanley@kent.ac.uk

Abstract

To reduce human losses and minimize social and economic disruption caused by large-scale earthquakes, effective planning and operational decisions need to be made by responsible agencies and institutions across all pre- and post-disaster stages. Operations Research (OR), which encompasses a broad array of quantitative and analytical methods for systematic decision making, has garnered a considerable amount of attention in the disaster operations management literature over the past few decades. The purpose of this review is to highlight and discuss main lines of research involving the use of OR techniques applied specifically to earthquakes disasters. As part of our review, we identify existing research gaps and propose a roadmap to guide future work and enhance the real-world applicability of OR to earthquake operations management. We emphasize the need for (i) developing models that are specifically tailored to earthquake operation management, including the need to contend with cascading effects and secondary disasters caused by aftershocks; (ii) greater stakeholder involvement in problem identification and methodological approach to enhance realism and adoption of OR models by practitioners; (iii) more holistic planning frameworks that combine decision making across multiple disaster stages; (iv) integration of OR methods with real- and near real-time information systems, while confronting the problem of dealing with missing and incomplete data; (v) greater use of use of multi-methodology and interdisciplinary approaches, including behavioral OR and Soft OR techniques as well as seismology and earthquake engineering expertise; and (vi) improved data generation defined at appropriate scales and better probability estimation of earthquake scenarios.

Keywords: disaster management; earthquakes; earthquake operations management; operations research; review

1. Introduction

Globally, geophysical disasters – primarily earthquakes – lead annually to the death of thousands of people, dislocate millions, and cause significant damage to buildings, roads, and other infrastructure. Between 2009 and 2020 (the timeframe of this review), there have been approximately 1800 large earthquakes (magnitude 6 or greater on the Richter scale) and nearly 366,000 fatalities caused by earthquakes across the globe (see Figure 1), more than all other natural disasters put together [1]. Information about the most devastating earthquakes during this period is presented in Table 1.

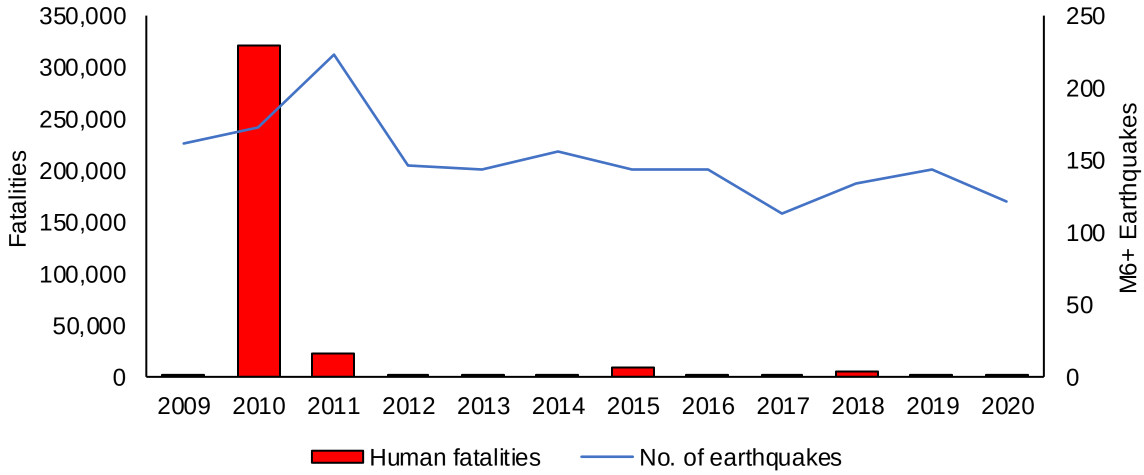

Figure 1. *High magnitude earthquake occurrence and human fatalities 2009 to 2020 based on data from the Centre for Research on the Epidemiology of Disasters [1].*

Recent earthquake disasters have affected many parts of the world from Asia to the Americas. Although a number of regions and countries are particularly prone to earthquakes, fatalities and other impacts can be highly variable depending on a range of factors such as geological conditions (e.g., presence of active faults and seismic vulnerability), earthquake characteristics (e.g., magnitude, focal depth, and epicentre location), area affected (e.g., city or region), level of development (e.g., physical conditions of building and transportation networks), and preparedness level (e.g., early warning system and risk management measures) [2–5].

Table 1. *Most devastating earthquakes 2009-2020.*

Event	Fatalities	Magnitude	Location
2010 Haiti earthquake	316,000	7.0	Haiti
2011 Tōhoku earthquake and tsunami	20,896	9.1	Japan
2015 Nepal earthquake	8,964	7.8	Nepal
2018 Sulawesi earthquake and tsunami	4,340	7.5	Indonesia

Strategic and systematic mitigation actions can significantly reduce vulnerabilities to earthquake damage. For example, two major earthquakes – the 2004 Indian Ocean tsunami and the 2010 Haiti earthquake – both lead to hundreds of thousands of deaths, while a similar scale earthquake in New Zealand in 2010 affected 300,000 people but killed no one due strict building codes and high level of preparedness [6]. Another example is the most recent disaster in September 2018, the 7.5 magnitude earthquake and subsequent tsunami that hit Palu and Donggala in central Sulawesi, Indonesia. While the number of deaths was comparatively small (4,340), the earthquake ended up displacing over 200,000 people and destroyed or damaged over 40,000 homes [7] as a result of power and communications lines being cut, which led to many residents not receiving tsunami warning messages. This disaster highlights the costs of not implementing a more sophisticated early warning system.

Along with pre-earthquake preparedness, an effective response strategy can also drastically reduce human end economic losses. Ineffectual management of the Haitian government enormously compounded the impact of the 2010 Haiti earthquake (magnitude 7). After 48-72 hours, chances of finding survivors rapidly decreases. The Haitian government, however, failed to take any decisive action during this crucial phase of the emergency. International organizations quickly mobilized in response, but even this was hampered by the availability of a single-runway airport with a limited capacity and sever damage to the maritime port. As a result, it took several days for the population to start receiving vital supplies [8]. By comparison, in the case of the much larger 2010 Chile earthquake (magnitude 8.8), the Chilean government had in place detailed plans for responding quickly to such an event. Because of the government's effective control over the situation, the impact of the disaster was greatly reduced (525 victims) and there was almost no need for international assistance [8].

In order to minimize loss of life and social/economic disruption caused by earthquakes, effective planning at all stages of disaster management (i.e., mitigation, preparedness, response, recovery) is required. One analytical approach is the use of operations research (OR) techniques, which can help government agencies and nongovernmental organizations (NGOs) to develop sound and effective procedures and optimize the use of limited resources. The Institute for Operations Research and the Management Sciences (INFORMS) defines OR as:

> "proven scientific, mathematical processes that enable organizations to turn complex challenges into substantial opportunities by transforming data into information, and information into insights that save lives, money and solve problems." [9]

OR encompasses a variety of quantitative and analytical methods for systematic decision making such as mathematical programing, simulation, and decision analysis. OR techniques have been successfully applied in various real-world application areas like supply chain management, logistics, transportation, healthcare, telecommunication, energy production and distribution, and disaster management. In the context of disaster management, a number of different OR based approaches have been proposed in the literature to find solutions to complex problems arising in different disaster management stages.

It is widely agreed that in order to enhance the realism OR methods for disaster operations management (DOM) and increase their uptake of by practitioners, models should be tailored to the key features of a given disaster type [10–14]. For instance, evacuation operations for disasters that strike with little or no warning, such as earthquakes and nuclear accidents, require different approaches to short-notice disasters, like hurricanes and floods, that typically provide lead times of 24-72 hours for evacuation to occur [15]. In earthquake evacuation, which begins immediately after, not before the disaster, one must typically contend with uncertainty both about the location and number of evacuees and route unavailability due to road damage and the presence of debris. Speaking more broadly, earthquakes typically stand apart from other types of disasters in terms of affecting a much a wider area, involving much larger numbers of causalities with more severe injuries (e.g., people with crushed limbs and spinal cord injuries requiring both emergency care and longer-term rehabilitation) and their potential to cause cascading effects and secondary disasters due to aftershocks. In this paper, we focus on how earthquake operations management (EOM) problems have been tackled using OR methodologies, exclusively reviewing papers that address EOM or those that rely on an earthquake case study to demonstrate the potential benefits of OR to disaster management.

The contribution of this paper is multi-fold. First, we present a general overview of the OR literature dealing with DOM. Second, we provide an in depth discussion the ways in which OR has been applied to enhance EOM and the common types of methodologies used. Third, we highlight some important research gaps of existing OR models and approaches in the context of EOM and a roadmap for future research. To this last point, it is our hope that this review will provide OR researcher working in EOM important insights on enhancing the realism and applicability of their models by moving away from generic problem definitions, imbedding wider use of coordinated decision making across multiple DOM stages when suitable, understanding the importance of involving stakeholders in model conceptualization and development, and adopting a more multi-methodology and interdisciplinary approach to EOM, including integration of other earthquake related disciplines, like seismology and earthquake engineering.

The remainder of this paper is organized as follows. Section 2 gives a general overview the role of OR in DOM by carrying out a meta-analysis of recent survey papers. In Section 3, we review how EOM is addressed in the OR literature. Section 4 provides a classification and analysis of reviewed papers. A roadmap for future research directions and some concluding remarks are outlined in Section 5 and 6, respectively.

2. Operations Research for Disaster Operations Management

'Disaster Management' is defined by The International Federation of Red Cross and Red Crescent Societies (IFRC) as:

> "the organization and management of resources and responsibilities for dealing with all humanitarian aspects of emergency situations under four stages: mitigation and preparedness for pre-disaster operations to decrease the negative influences as far as possible, and response and recovery for post-disaster activities in order to lessen the impact of disasters" [16].

In this section, we give a brief overview of the application areas and main operations of the disaster management stages.

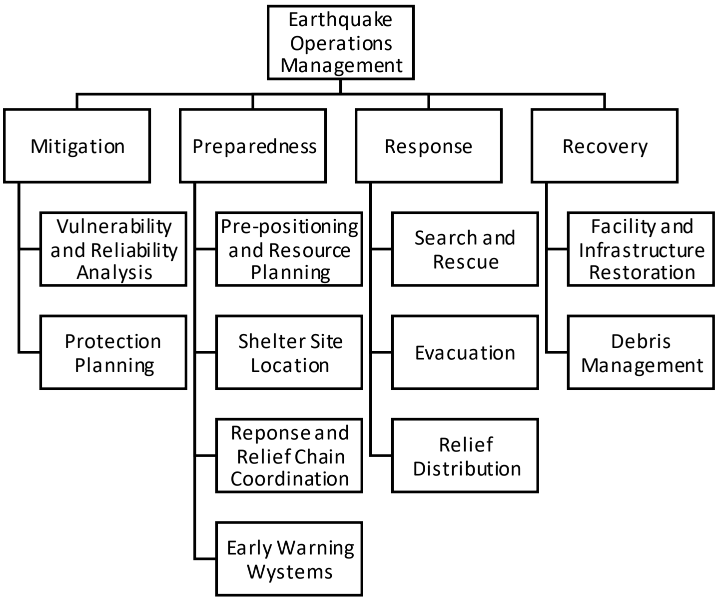

Figure 2. *Earthquake operations management stages and typical problems addressed in the OR literature.*

DOM involves four distinct stages. The first two focus on pre-disaster issues, the latter two deal with post-disaster measures [13]. *Mitigation* or prevention (stage 1) involves understanding what vulnerability to hazards exist along with protection measures to reduce risk and increase resilience. *Preparedness* (stage 2) assesses plans to save lives and organize response operations prior to a disaster occurring. The main aim is to reach a satisfactory level of readiness to respond to an emergency through development of programs that strengthen the technical and managerial capacity of governments, organizations, and communities (e.g., early warning systems and pre-position of supplies). *Response* operations (stage 3) aim to provide timely assistance to victims, relief, and evacuation of the affected population to a safe zone. *Recovery* (stage 4) takes place after an emergency and is primarily concerned with activities to remove debris, rebuild damaged buildings, and repair essential infrastructure. Figure 2 displays the four DOM stages and typical problems addressed in each stage.

OR techniques have been applied to deal with DOM problems since the early 1980s [13]. The OR literature on disaster operations and humanitarian supply chain management is considerable, as evidenced by the number of recent review papers published between 2015 and 2020 [10–12,14,15,17–28]. Published survey papers that we examined are summarized in Table 2.

A couple of survey papers consider the full breadth of OR and management science (MS) techniques applied to all disaster stage [25,28]. More commonly, reviews have focused on specific disaster stages, like recovery [27], response [11,17], or preparedness and response [22,23], and or specific features of DOM, like integration of information systems with OR methods [26], stochastic elements [12], humanitarian supply chain management [19,24], and shelter site location [17]. In a few cases, reviews have focused on particular methodologies, such as optimization [15,20,23] evolutionary algorithms [18]. Of note, none of the reviews listed in Table 2 look at a specific disaster type, like earthquakes, nor do they consider the ways OR methods have or should be tailored to a particular disaster type despite the observation in various studies [10–14] that this is critical to enhancing the realism and applicability of OR methods to DOM.

Table 2. *Summary of reviewed disaster operations management papers published in 2009-2020.*

Survey Article	Stage*	Focus†	Review Period
Galindo and Batta [25]	All	OR/MS literature related to DOM	2005-2010
Hoyos et al. [12]	All	OR techniques with stochastic components	2006-2012
Gupta et al. [28]	All	OR/MS literature related to DOM	1957-2014
Özdamar and Ertem [26]	Rs + Rc	Integration of OR with information systems and enabling technologies	1993-2014
Zheng et al. [18]	All	Evolutionary algorithms applied to disaster relief operations	1996–2014
Habib et al. [19]	All	Humanitarian supply chain management	2005-2015
Gutjahr and Nolz [20]	All	Multi-criteria optimization for disaster aid operations	2007-2015
Zhou et al. [21]	All	Emergency decision support systems	2000-2016
Çelik [27]	Rc	Network restoration and recovery operations	2000-2016
Balcik et al. [22]	P + Rs	Humanitarian inventory planning and management	2006–2016
Bayram [15]	Rs	Optimization models for evacuation planning	1952-2016
Boonmee et al. [23]	P + Rs	Optimization models for facility location planning	1964-2016
Behl and Dutta [24]	M + P + Rs	Humanitarian supply chain management	2011-2017
Sabbaghtorkan et al. [10]	P	Prepositioning of assets and supplies	2000-2018
Kovacs and Mosthtari [14]	All	Applied methodologies in humanitarian operations	2006-2018
Amideo et al. [17]	Rs	Shelter location and evacuation routing	2013-2018
Farahani et al. [11]	Rs	Casualty management	1977-2019

* M: Mitigation, P: Preparedness, Rs: Response, Rc: Recovery.
† OR: Operations Research, MS: Management Science.

3. Literature Review Methodology and Summary

In the remainder of this study, we review studies that apply OR methods to address problems in EOM. We use a broad definition of OR, which includes mathematical programing, heuristics and metaheuristics, decision analysis, machine learning and artificial intelligence (AI), Soft OR, and expert systems. "Mathematical programing" or optimization aims at finding the most efficient (i.e., guaranteed best) allocation of limited resources in order to maximize or minimize some objective (e.g., total cost) subject to a set of constrains that limit which actions can be taken [29]. "Heuristics and metaheuristics" (hereafter heuristics) are algorithms which apply a series of rules (typically iterative) to quickly find approximate solutions to large and/or complex optimization problems [30]. Heuristics are called for when an exact approach cannot be used or would require an excessive amount of time to solve. "Decision analysis" includes a number of quantitative and graphical methods for identifying the best option among a defined (usually small) set of alternatives for complex or risky decision problems based on one or more evaluation criteria [31]. "Simulation" involves representing a real-world system (normally over time) using logic, mathematics, and computers for the purposes of predicting system behavior (possibly stochastic) or evaluating performance of different plans for improving the system [9]. The main types of simulation include Monte Carlo simulation, discrete event simulation, system dynamics, and agent based modeling. "Stochastic modeling" is the application of probability theory to represent and predict the outcomes of stochastic processes [9]. "AI", in relation to OR, includes a broad class of approaches designed to enable computer systems to automatically perform tasks that would normally require human intelligence, such as information processing, pattern recognition, and decision making [32]. "Machine learning," a subclass of AI, include a wide range of mathematical models/algorithms which are trained to find patterns in data in order to make predictions or decisions [33]. "Soft OR" includes a variety of problem structuring and stakeholder facilitation methods to help frame messy, ill-defined, and complex problems in rigorous but non-mathematical way [34]. Soft OR primarily aims at promoting learning and shared understanding of a systems as opposed to specific 'solution.' Game theory studies situations involving conflict and cooperation "Game theory" is a branch of mathematics concerned with the analysis of strategies to competitive situations in which the payoff a participant receives depends on both his/her actions and the actions of other players [35]. Finally, "expert systems" are computer system that emulate the decision making ability of a human expert [36]. They are usually designed to solve complex problems by reasoning about facts and assertions, mainly with if-then rules rather than through procedural code.

We systematically reviewed the literature that included one or more of the following sets of keywords: 1) "earthquake'', ''disaster*'', "catastroph*, "humanitarian logistic*", or "emergency" and 2) "*modeling", "*programing", "optimization", "decision theory", "multi-criteria decision", "multi-criteria analysis", "problem structuring method", "system thinking", "Soft OR", "agent based simulation", "Monte Carlo simulation", "discrete event simulation", "system dynamics", "expert systems", "artificial intelligence", "neural network", "stochastic modeling", "stochastic model", "probabilistic model", "game theory", "heuristic" or "metaheuristic" and spelling variations (e.g., British English spellings). We limited the time interval for the review to 2009-20 and used Scopus databases covering various large publishers such as Elsevier, Springer, Taylor & Francis, and IEEE. Selection of articles was based on two main criteria; (i) whether a paper applied one or more OR techniques to DOM decision making and (ii) whether it specifically addressed EOM or did not necessarily focus on earthquakes but did have a case study involving earthquakes. After further manual processing, 211 papers, which satisfied these criteria, were finally selected.

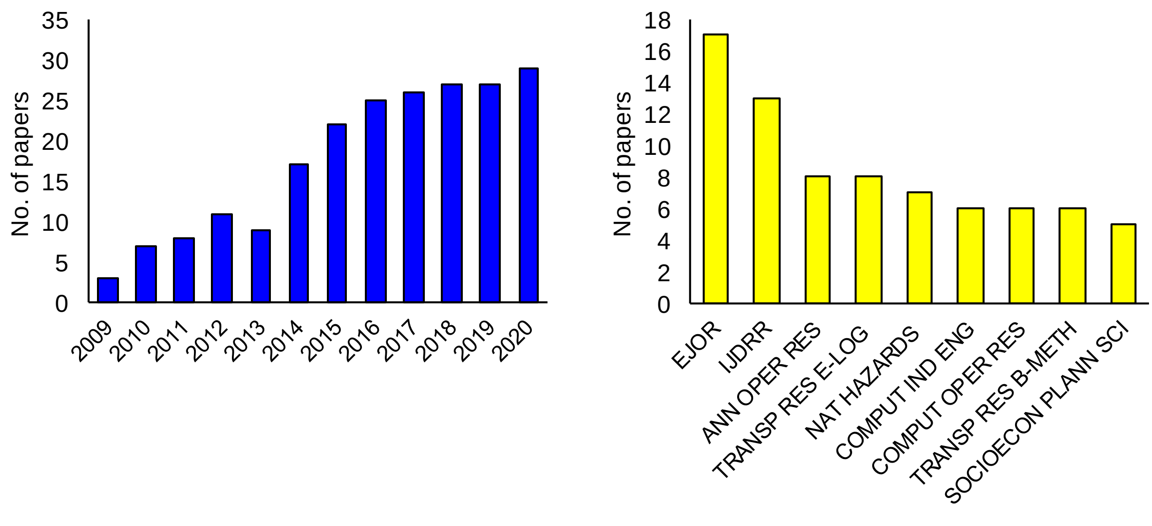

Figure 3. *Number of OR papers applied to EOM by year (a) and by journal with five or more such papers (b).*

Figure 3 shows the number of articles published between 2009 and 2020 on OR applied to EOM and the journals that published five or more such papers. The top two journals in terms of number of publications are European Journal of Operational Research (EJOR), which publishes both theoretical and applied research in OR, and International Journal of Disaster Risk Reduction, which covers a broad set of disciplines aimed at reducing the impact of natural, technological, and social disasters. A general observation is that many of the published EOM studies appear in OR focused journals (not unsurprising) and have bias towards transportation and other infrastructure related problems. Interestingly, more specialized journals in fields like seismology, engineering, and geography, which were included in our literature search, rarely publish OR based studies on EOM, hence why they do not appear in Figure 3b.

Table 3. Summary statistics of EOM disaster stages addressed in the literature.

Disaster Stage(s)	No. of papers	Proportion (%)
Mitigation	41	19.4
Preparedness	62	29.4
Response	66	31.3
Recovery	20	9.5
Integrated Stages	22	10.4
Mitigation & Preparedness	1	4.5
Mitigation & Response	2	9.1
Mitigation & Recovery	1	4.5
Mitigation, Preparedness & Response	1	4.5
Preparedness & Response	9	40.9
Preparedness, Response & Recovery	1	4.5
Response & Recovery	7	31.8

Statistics for reviewed papers are given in Tables 3 and 4. Of the 211 papers reviewed, the preparedness and response stages have received similar amounts of attention (29-31%), while mitigation has received comparatively less attention (19%), and recovery the least attention (9%). The vast majority of research (90%) has focused on a single disaster stage as opposed to the integration of operations from multiple stages (10%), which has generally appeared only more recently. Integration of either preparedness and response (41%) or response and recovery (32%) has received considerably more attention than any of the other combinations. In addition, not a single study addresses decision making in all four stages; usually only two stages are considered and only two studies consider three stages. As evident from Table 4, heuristics are the most frequently utilized OR method (33%), followed by mathematical programing (29%), simulation (11%), machine learning (10%), and decision analysis (3%). Few studies have involved the use of multiple methods (9%).

Table 4. Summary statistics of OR methodologies used in EOM.

Methodology	No. of papers	Proportion (%)
Heuristic	70	33.2
Mathematical programing	62	29.4
Simulation	24	11.4
Machine learning	21	10.0
Decision analysis	7	3.3
Soft OR	2	0.9
Expert system	2	0.9
AI	2	0.9
Game theory	1	0.5
Stochastic modeling	1	0.5
Multiple methods	19	9.0

4. Literature Review Classification and Analysis

In the following subsections, we provide an in-depth analysis of the literature using the categorization shown in Figure 2. Within each category, we discuss each disaster stage in turn and the methodologies used to address them. Studies that address the integration of two DOM stages are reviewed and categorized in the final subsection. For the most used OR methods in each category, tables and figures are provided to gather additional insights.

4.1. Mitigation Stage

The mitigation stage involves strategic decision making to enhance the condition of buildings and critical infrastructure networks (e.g., electricity generation and distribution, transportation, water supply, telecommunication, hospitals, and fire stations). Primary mitigation measures include earthquake-resistant construction, building retrofit, and upgrading components of critical infrastructure systems to make them resistant to seismic activity or/and ground motion. In comparison to other types of natural disasters, features specific to earthquake mitigation include the enormity of the challenge due to the extent of human habitation concentrated in seismically active areas, the relatively high cost to implement mitigation measures (to a large number structures spread over large areas), the typically long recurrence time (decades or more) between sizable quakes and, as a result, the greater amount of lead time to plan and take pre-emptive action.

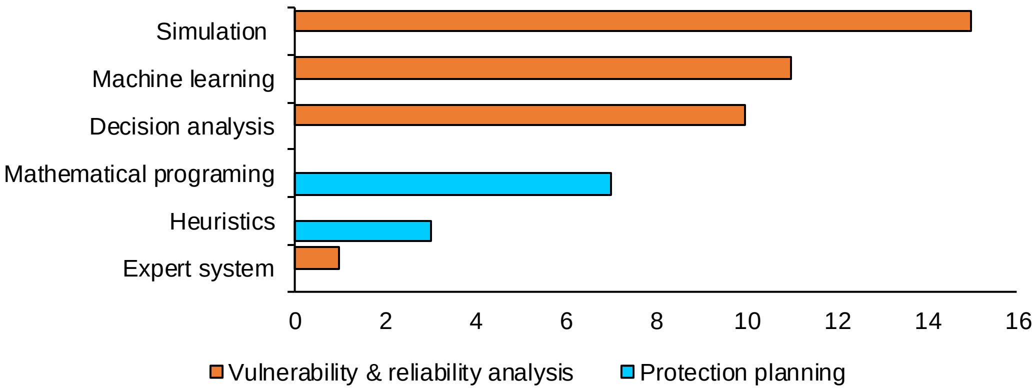

Figure 4. *Methodologies used in mitigation problems.*

Mitigation problems can be divided into two main categories: 1) reliability and vulnerability analysis, which involves, for instance, estimating damage levels of infrastructure components (e.g., whether a road segment is operational or not) and 2) protection planning to reduce vulnerabilities and risks to critical infrastructure. A summary of OR methodologies applied to solve mitigation problems is shown in Figure 4. Three methodologies – simulation, decision analysis, and machine learning – have been used the most (36 papers) among the 41 reviewed papers. Expert systems, mathematical programing, and heuristics, in contrast, have been applied far less (11 papers). Other methodologies, such as Soft OR, game theory, and stochastic modeling, appear not to have been used at all to address mitigation problems. As is clear from Figure 4, reliability and vulnerability analysis has drawn the most attention, while comparatively little has focused on protection planning. Table 5 provides a detailed breakdown of studies in each category by problem type and methodologies used.

Table 5. *Details of the types of problems addressed and methodologies used in the mitigation stage.*

Problem	**Method**	**References***
Vulnerability and reliability analysis		
Seismic reliability analysis	Simulation	[37–48]
	Machine learning	[49]
Seismic hazard mapping	Decision analysis	[50–55]
	Machine learning	[**55**]
Building vulnerability analysis	Simulation	[56,57]
	Machine learning	[58–63]
	Decision analysis	[**61**,**62**,64,65]
Fatality estimation	Simulation	[**57**]
	Machine learning	[66,67]
Earthquake characteristics prediction	Expert system	[68]
	Machine learning	[69]
Protection planning		
Fortification of infrastructure networks and buildings	Mathematical programing	[**43**,**46**,70–74]
	Heuristic	[75–77]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

4.1.1. *Vulnerability and Reliability Analysis*

Vulnerability and reliability are especially important when examining the operability of buildings and critical infrastructure. Murray and Grubesic [78] state: "*While reliability focuses on the possibility of maintaining the performance of critical infrastructure elements, vulnerability focuses on the potential for disrupting critical infrastructure elements or degrading them to a point when performance is diminished.*" Both vulnerability and reliability and are important for the continuity of critical infrastructure operations.

Seismic reliability analysis of critical infrastructure plays an essential role in the mitigation stage. The primary aim is to compute a measure of reliability given failure probabilities for an individual component of a system or for the system as a whole. Simulation is the most used OR method in this category. Details of simulation models reviewed are provided in Table 6. Simulation models have been used to estimate earthquake induced failure probabilities of system components, damage levels caused by interruptions to system operations, and reliability/vulnerability measures. Examples include reservoir storage of hydropower systems [48], substations in electric power grids [39], energy pipelines [47], water supply systems [37,45], and transportation networks [41,43,44,46]. In addition to specific types of infrastructure, simulation has been used to evaluate the susceptibility to landslides caused by earthquakes and heavy rainfall for regions of a large urban area [38,42]. Monte Carlo simulation appears to be the main simulation paradigm used for seismic reliability analysis, though there are a couple examples of system dynamics [37,48] and a very recent one using agent based modeling [40]. Besides simulation, Nabian and Meidani [49] investigate the use of deep neural networks, a machine learning method, for seismic reliability analysis. They use a case study of the California transportation network to demonstrate the effectiveness of the proposed method for accelerating earthquake reliability analysis.

Table 6. *Details of simulation models for reliability and vulnerability analysis.*

Reference	Model Type*	Outputs/Findings
Bagheri et al. [37]	SD	Failure probability for water supply systems
Sun and Chen [38], Sun et al. [42]	MCS	Failure probability of earthquake-induced landslides
Li et al. [39]	MCS	Failure probability of power systems
Feng et al. [40]	ABM	Traffic flow characteristics
Günneç & Salman [41]	MCS	Reliability measures for networks
Chang et al. [43]	MCS	Earthquake intensity at each bridge location
Gertsbakh & Shpungin [44]	MCS	Failure probabilities for links in a network
Jin & Wang [45]	MCS	Seismic risk of water supply systems
Mohaymany et al. [46]	MCS	Connectivity and reliability measures for networks
Dadfar et al. [47]	MCS	Vulnerability functions for energy pipelines
King et al. [48]	SD	System disturbances and failure states for hydropower systems
Ahmad et al. [56]	MCS	Damage levels of structures
Akpabot et al. [57]	MCS	Damage levels for buildings and casualty levels

* MCS: Monte Carlo simulation, SD: system dynamics, ABM: agent based model.

For studies on seismic hazard mapping the preferred approach is multi-criteria decision making (MCDM), a class of decision analysis techniques, implemented in a geographical information system (GIS). Examples of GIS-based MCDM include the generation of seismic physical vulnerability maps [38,39,45] and tsunami risk maps [52].

For building vulnerability analysis (i.e., analysis of individual buildings as opposed to infrastructure networks or urban/residential areas), machine learning is the most frequently used method for estimating risk/damage levels based on various independent variables like structure type, construction quality, built area, and occupancy level [58,66]. Neural networks have been developed to inform post-earthquake activity planning by evaluating building collapse ratios using optical and satellite data [60] and to construct a composite social, economic, environmental, and physical vulnerability index for seismically prone regions [61]. Simulation has also been used to estimate damage levels for bridges and buildings [56,57].

Another key strand of reliability and vulnerability analysis is estimating human fatalities and determining the distribution of casualties. One such study is Akpabot et al. [57], who address how to predict the post-earthquake status of buildings (collapsed or not) and casualty levels using Monte Carlo simulation. Another is Gul and Guneri [67], who apply a neural network to estimate casualty proportions based on earthquake occurrence time, earthquake magnitude, and population density. Aghamohammadi et al. [66] assume that damage levels for buildings are known in advance and apply a neural network to estimate casualty levels considering the same inputs as Gul and Guneri [67] along with damage levels.

Finally, earthquake characteristics prediction (e.g., magnitude, depth, location, probability of occurrence, seismic energy release) has been carried out using both machine learning techniques [69] and expert systems [68]. The study by Ikram and Qamar [68] is interesting for trying to predict subsequent earthquakes based on most recent earthquake attributes, such as a defined range, depth, and location, and for validating their approach using real-life earthquake data.

4.1.2. Protection Planning

This subsection covers studies on protection planning for strategic pre-earthquake mitigation. Note that all of the studies reviewed employ either mathematical programing or heuristics to decide which infrastructure to fortify or upgrade in order to minimize system vulnerability or maximize reliability/resilience. Details are provided in Table 7. The majority of work has focused on protection of links in transportation networks in order to optimize one or more objectives such as maximizing post-earthquake connectivity [70,75], minimizing travel cost [70,71,76], minimizing investment/retrofitting cost [46,71,72,76], minimizing unsatisfied demand [71,76], and maximizing evacuation capacity [43]. Only a few studies have additionally or exclusively looked at retrofitting buildings [72,73,76]. Liberatore et al. [73], for example, decide which hospitals to fortify in order to minimize maximum reduction in medical service capacity (i.e., unmet demand) and patient assignment costs in the presence of propagating failures.

Table 7. *Summary of protection planning studies.*

Reference	Decisions	Objective(s)	Case Study
Chang et al. [43]	Bridge retrofit standards	Maximize post-disaster evacuation capacity given a limited budget	Memphis, Tennessee, USA
Mohaymany et al. [46]	Transport links to invest in	Minimize investment cost to satisfy connectivity reliability and travel time reliability requirements	Sioux Falls, South Dakota, USA
Peeta et al. [70]	Road links to retrofit	Maximize post-disaster connectivity and minimize traversal cost between origin and destination nodes given a limited budget	Istanbul, Turkey
Lu et al. [71]	Bridge retrofit standards	Minimize retrofitting cost, expected transport cost, transport cost risk, and unsatisfied demand	Sioux Falls, South Dakota, USA
Zolfaghari & Peyghaleh [72]	Building retrofit standards	Minimize mitigation expenditures and future reconstruction expenditures	Tehran, Iran
Liberatore et al. [73]	Hospitals to retrofit	Minimize cost of assigning patients to hospitals and unmet demand	L’Aquila, Italy
Aydin [74]	Location of recycling and landfill areas for processing debris from end-of-life buildings	Minimize recycling and landfill area set-up cost, cost of debris transport and processing and maximize revenue of recovered materials	Istanbul, Turkey
Chu & Chen [75]	Road links to retrofit	Maximize connectivity reliability for highway networks	-
Döyen & Aras [76]	Building retrofit standards and road links to retrofit	Minimize building and road link retrofit costs, expected transport costs and unsatisfied demand for relief	Istanbul, Turkey
Edrisi & Askari [77]	Road links to expand and stabilize	Minimize travel time and expected fatalities	Sioux Falls, South Dakota, USA

As is typical with these studies, the authors first analyze the computational performance of their proposed model or solution approach and then apply it to a case study based on real-world data. The aim here is to show how the model is capable of capturing all crucial network information and how the solution methodology generates robust solutions in acceptable computation time. As seen in Table 7, some use case studies of transportation networks located in seismically active areas. In addition, there are multi-methodology approaches combining two methodologies, such as simulation for estimating parameters related to vulnerability and reliability (e.g., damage state scenarios based on structural characteristics) and a mathematical programing model for optimizing protection decisions [43,46].

4.2. Preparedness Stage

The preparedness stage, the most studied of the four disaster stages in EOM, includes plans and preparations made in advance of an earthquake, such as logistical readiness to deal with adverse impacts of earthquakes, the development of response mechanisms and procedures, rehearsals, the development of long-term and short-term strategies, public education, and the implementation of early warning systems. The problems associated with the preparedness stage can be categorized as: 1) relief pre-positioning and resource planning (i.e., locating distribution centers, stocking relief supplies, emergency medical care staffing); 2) shelter site location; 3) emergency response and relief chain coordination; and 4) early warning systems. While preparedness is crucial for any type of natural disaster, the severity of damage caused by earthquakes and, crucially, the often complete lack of advanced warning about when and where an earthquake will strike (i.e., essentially instantaneous for earthquakes and minutes for tsunamis versus days for hurricanes, wildfires, and volcanic activity), underscore the importance and benefits of preparedness.

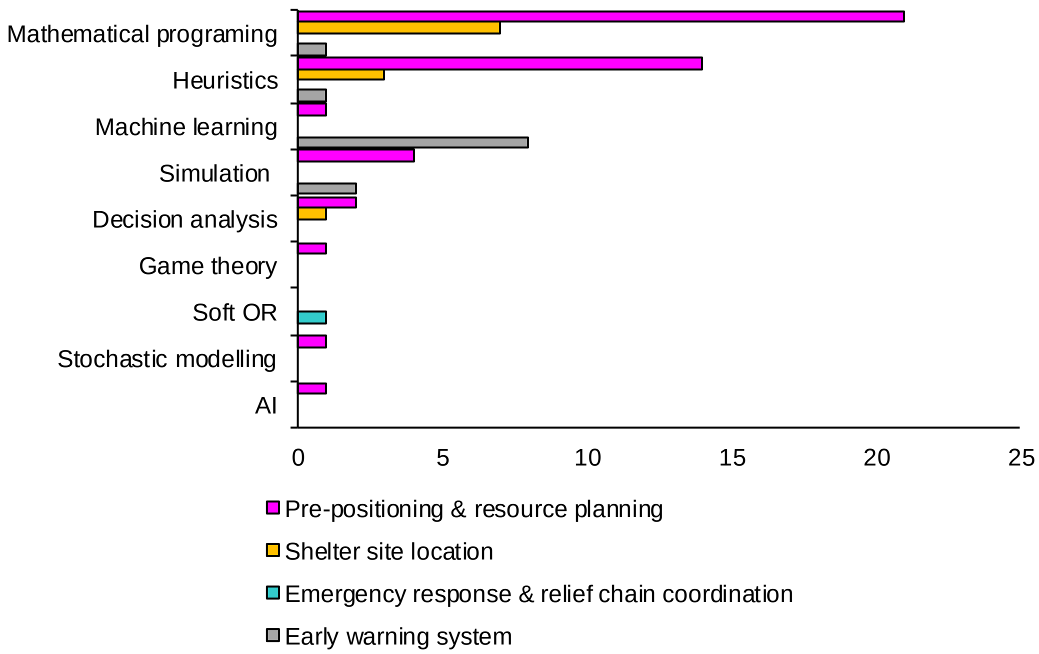

Figure 5. *Methodologies used in preparedness problems.*

A summary of problem types and the OR methodologies used is preparedness planning is shown in Figure 5. Relief pre-positioning and resource planning is the most addressed problem type, accounting for 40 of the 62 studies. The other three categories, shelter site location, relief chain coordination, and early warning systems, have received significantly less attention, with 11, 1, and 12 studies, respectively. In terms of methodologies, unlike with the mitigation stage, nearly all methodologies, apart from expert systems, have been used to analyze and solve problems in this stage. However, mathematical programing and heuristics are by far the dominate techniques, having been applied in 46 (74%) of the 62 studies. Table 8 gives a detailed breakdown of preparedness related studies based on problem type and methodology used.

Table 8. *Details of the types of problems addressed and methodologies used in the preparedness stage.*

Problem	Method	References*
Relief pre-positioning and resource planning		
Pre-positioning distribution centers	Mathematical programing	[79–95]
	Heuristic	[96–108]
	Decision analysis	[**85**,**102**]
	Game theory	[109]
	AI	[**86**]
Pre-positioning medical centers	Mathematical programing	[110]
Relief inventory management	Mathematical programing	[**81**–**87**,**91**–**95**,111–113]
	Heuristic	[**98**–**100**,**104**–**108**]
	AI	[**86**]
	Simulation	[**111**]
	Stochastic modeling	[114]
Staff planning	Simulation	[115–117]
	Machine learning	[**117**]
	Heuristic	[118]
Shelter site location		
	Mathematical programing	[**89**,119–124]
	Heuristic	[125–127]
	Decision analysis	[**122**]
Emergency response & relief chain coordination		
	Soft OR	[128]
Early warning system		
Earthquake/tsunami prediction and notification	Machine learning	[129–136]
	Simulation	[137,138]
Sensor location	Mathematical programing	[139]
	Heuristic	[140]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

4.2.1. Relief Pre-Positioning and Resource Planning

This category includes problems related to pre-positioning relief distribution centers (RDCs), medical centers, relief inventory management, and staff planning. RDCs play an indispensable role in relief logistics by receiving and consolidating relief supplies (e.g., food, water, clothing, temporary shelters, and medication) and then distributing them to affected populations. Strategic pre-positioning of RDCs prior to an earthquake can significantly affect the performance of the subsequent disaster response (e.g., in terms of response time, accessibility, and equity) [90]. Resource planning, meanwhile, plays a crucial role in the preparedness stage through effective stockpiling of supplies and determining staff requirements in order to avoid shortages, which could pose severe risks to human life if they were to occur. For clarity, most of the studies included here typically model aspects of the response stage (i.e., relief distribution), but do so only in a very simplified way for the purposes of determining where best to locate RDCs in order to satisfy anticipated demand for relief. Only if more complex decisions involving, for example, scheduling of rescue teams or loading and routing of relief, are the models considered integrated (i.e., preparedness and response, see Section 4.5).

Mathematical programing and heuristics are far and away the most commonly used approaches, comprising 35 (85%) of the 41 studies addressing relief pre-positioning and resource planning (see Table 8). Table 9 presents details of these studies, including the types of decisions and objectives considered. As can be seen, the most common objectives in pre-positioning RDCs and resource planning include the minimization of cost, transportation time, and demand shortages. In terms of cost components, some studies focus on fixed and variable operating costs (e.g., construction of facilities and the procurement and holding of supplies) and or transportation costs (e.g., [91,92,94,104]), while others separately or additionally consider social costs (e.g., fatalities and deprivation cost) [82,105]. Minimization of transport time usually refers to distances/travel time between RDCs and local distribution points (e.g., [79,95,101]). Most of the studies reviewed consider distribution of multiple commodities but do not give specifics. One study looks specifically at medical supply distribution to hospitals [81] and a couple at blood distribution [86,87].

Table 9. *Details of mathematical programing and heuristic approaches for relief pre-positioning and resource planning problems.*

Problem	Decisions	Objective(s)	References*
Pre-positioning distribution centers	Locations of distribution centers	Minimize cost	[86,87,89,94]
		Minimize distance	[96]
		Minimize transport time	[101–103]
		Maximize coverage	[97]
		Minimize cost and transport time	[79,104]
		Minimize cost and shortages	[80,85,91,93]
		Minimize transport time and shortages	[81,95]
		Minimize cost and shortages and maximize equity	[107]
		Minimize cost and maximize equity and reliability	[98]
	Locations and capacities of distribution centers	Maximize accessibility	[90]
		Minimize cost and shortages	[92,100]
		Minimize cost and victim travel time	[106]
		Minimize cost and fatalities	[82,105]
		Minimize cost and maximize equity	[84,99]
		Minimize cost, transport time and shortages	[108]
		Minimize cost, victim travel time and shortages	[88]
		Minimize cost, transport time and shortages and maximize equity	[83]
Pre-positioning medical centers	Location and capacity of medical centers	Minimize travel time, underachievement of target waiting time, unused capacity and set-up time	[110]
Relief inventory management	Inventory levels of relief supplies	Minimize cost	[**86**,**87**,**94**]
		Minimize cost and shortages	[**85**,**91**–**93**,**100**]
		Minimize cost and transport time	[**104**]
		Minimize cost and victim travel time	[**106**]
		Minimize cost and fatalities	[**82**,**105**]
		Minimize transport time and shortages	[**81**,**95**]
		Minimize cost and maximize equity	[**84**,**99**]
		Minimize cost and shortages and maximize equity	[**107**]
		Minimize cost, transport time and shortages	[**108**]
		Minimize cost and maximize equity and reliability	[**98**]
		Minimize cost, transport time and shortages and maximize equity	[**83**]
		Maximize probability of satisfied demand	[111]
		Maximize min. covered demand	[112]
		Minimize cost and shortages and maximize lives saved	[113]
Staff planning	Staffing levels	Maximize expected number of functional operating rooms and minimize expected travel distance	[118]

* References highlighted in bold address multiple problem types.

As highlighted by the Sphere Standards [141], RDCs should be established where they are safe and most convenient for affected populations. In addition, principles of equity should be considered to ensure every affected person receives equal opportunity to obtain relief. This highlights the importance of including accessibility and fairness as problem objectives. Some studies consider ease of access from affected areas to relief distribution points and accordingly maximize equitable access [90]. More recent studies consider equitable allocation of relief to affected areas and local distribution points, in other words, fair relief distribution [83,84,98].

It is worth noting that a majority of studies adopt a multi-faceted approach that considers multiple objectives and multiple types of decisions, including locating RDCs and determining their inventory levels. For example, Tofighi et al. [108] optimize four objectives: (i) minimization of fixed and variable costs associated with setting up central warehouses and RDCs and holding relief, (ii) minimization of total and (iii) minimization of maximum time to ship relief from central warehouses to affected areas via RDCs, and (iv) minimization of a weighted combination of relief shortages and unused relief. Paul and Wang [82], meanwhile, not only consider decisions about the locations, capacities, and inventory levels of RDCs but also the risk of damage to RDCs and how potential loss of supplies may impact relief allocation decisions.

In additional to mathematical programing and heuristic approaches, a few other methodologies have been applied to relief pre-positioning and resource planning. For instance, system dynamics was used by Wu et al. [111] to inform relief inventory planning, including stock holding and replenishment decisions, and by Xu et al. [115] to find best ratio of medical staff to rescue workers. Discrete event simulation has also been applied to assess the benefits of having an emergency plan in place as well as increasing staff and/or emergency room capacity [116]. A game theoretic approach is employed by Bell et al. [109] for locating RDCs in degradable road networks. Stochastic modeling has been used to find optimal reordering policies for relief goods given uncertainty about demand and lead-time [114]. Lastly, Bayesian belief networks (AI) was used by Chen and Wang [86] to model uncertainty about earthquake locations/intensity and number of injuries in need of blood when deciding about blood stocking levels.

4.2.2. Shelter Site Location

After a large earthquake, buildings may be damaged or destroyed and a large number (possibly hundreds of thousands) of people may become homeless. Affected residents will need to move to designated emergency housing termed shelters until the disaster recovery process is completed. Accordingly, pre-determined shelter areas should be strategically located, taking into account site suitability and access to relief supplies. Shelter areas must also be located within a reasonable distance from earthquake affected areas, accessible by safe travel routes, and provisioned with or close to essential services (e.g., medical care). It should be clear that identifying optimal locations for shelters is a complex problem. In all, we found ten studies on shelter site location specifically looking at earthquakes. All employ mathematical programing or heuristics.

A variety of factors have been considered when locating shelters. Bayram et al. [120], for example, focus on minimizing total evacuation time assuming evacuees travel to their nearest shelters via shortest or near shortest paths. Kınay et al. [124] instead locate shelters to maximize minimum site suitability based on criteria proposed by the Turkish Red Crescent, including distance to healthcare institutions, electrical infrastructure, and sanitary systems and terrain characteristics. Bayram and Yaman [121] apply a two-stage stochastic programing approach to incorporate uncertainty about evacuation demand and disruption to road and shelter site capacities. Hu et al. [126] employ particle swarm optimization, a metaheuristic approach, to locate shelters at minimum cost subject to capacity and distance constraints. Trivedi and Singh [122] propose a model for optimizing shelter sites based on victim travel distance, distance to relief and health centers, unmet demand, number of shelters, site risk (vulnerability to earthquakes, floods, landslides), and degree of public ownership. Other interesting aspects addressed in shelter location include risks associated with travelling to and remaining at shelters [119] and changes in both population size and spatial distribution [125] of those needing shelter.

4.2.3. Emergency Response and Relief Chain Coordination

Coordination and cooperation between emergency response and relief organizations (e.g., government agencies, emergency services, humanitarian organizations) is essential for responding in a timely and appropriate manner to earthquake disasters. Emergency response and relief chain coordination problems focus on the importance of effective and flexible structures that enhance interoperability, communication, and synchronized response of multiple EOM stakeholders to minimize human and economic losses in the aftermath of an earthquake.

Despite the importance of multi-agency coordination, we found only one study dealing with the topic. Specifically, Preece et al. [128] model the complex interactions involved with stakeholder communication. The authors examine how application of the viable system model (VSM), a Soft OR method, can help identify key shortcomings and opportunities in communication systems. Using a case study of the Great Hanshin-Awaji Earthquake in 1995, they demonstrate the utility of VSM structures to facilitate communication and coordination during a disaster.

4.2.4. Early Warning Systems

Earthquake early warning systems (EEWSs) form an essential part of the preparedness stage by providing timely and relevant information immediately following an earthquake. Effective EEWSs can help significantly to save lives and reduce damage. Two main problem types are discussed here: earthquake/tsunami prediction and notification and earthquake/tsunami sensor location.

Table 10. *Details of studies addressing early warning systems.*

Topic	Method	References
Earthquake location/magnitude prediction	Machine learning	[129,131]
Tsunami wave height prediction	Machine learning	[130,132]
Reduction of false alarm rates	Machine learning	[133–135]
Earthquake detection	Machine learning	[136]
Early warning lead time and reliability estimation	Simulation	[137]
Ground motion prediction	Simulation	[138]
Seismometer/tsunameter location	Mathematical programing	[139]
	Heuristic	[140]

As seen in Table 10, machine learning is the most commonly used approach in EEWS prediction and performance, comprising 8 (67%) of the 12 studies reviewed here. An example application of machine learning is to reduce false alarms by rapidly and reliably discriminating real earthquake signals from other signals [133–135]. This is critical to improving the performance of EEWSs, as excessive false alarm rates cant impose a heavy cost in terms of service loss, undue panic, and diminishing confidence in EEWSs [102]. Machine learning has also been used for initial detection of earthquakes from siesmic sensor data [133–135], advanced prediction of the location and magnitude of earthquakes [129,131], real-time classifcation of near- versus far-source earthquakes, and tsunami wave height estimation [130,132].

Somewhat surprisingly, only a couple examples of simulation being applied in EEWS were found in the literature. Wang et al. [138], for example, propose a Monte Carlo simulation approach to predict peak ground motion quickly and precisely given limited seismic data. Information about ground motion is crucial in early warning systems because a region’s peak ground motion provides an indication of the scale of the potential disaster in terms of building damage and threat to life. Meanwhile, Oliveria et al. [137] use Monte Carlo simulation to estimate amount “lead time” between when an early warning is received and the earthquake arrives and the potential costs of false alarms from an end-user standpoint.

Similarly, mathematical programing and heuristics have found only limited used in EEWS design. Oth et al. [140] propose the use of a genetic algorithm to optimize the location and calibration (trigger thresholds) of seismic sensors for a regional EEWS. Mulia et al. [139] investigate the use of dimensionality reduction techniques to identify an initial set of sensor locations for detecting multiple large-magnitude tsunami sources and then apply optimization to minimize forecasting error by removing redundant measurement locations.

4.3. Response Stage

In the aftermath of an earthquake, the primary concerns in the response stage are providing first-aid and rescuing trapped survivals, determining temporary shelter site locations, evacuating the affected population to safe zones, shelters, and medical centers, and providing emergency relief to victims. What often makes response so critical in the case of earthquakes versus other natural disasters is the scale of the problem. Whereas other types of natural disasters tend to be more localized and affect a smaller population, earthquakes can cause damage over wide areas (hundreds of thousands of square miles), resulting in enormous damage to properties and infrastructure (tens of billions of dollars), and lead to enormous casualties both in terms of number (hundreds of thousands of dead and injured) and severity. With this in mind, we focus on three main problem types within the earthquake response stage: 1) search and rescue; 2) evacuation; and 3) relief distribution. A summary of the problem types and the OR methodologies used to solve response stage problems is provided in Figure 7 and Table 11.

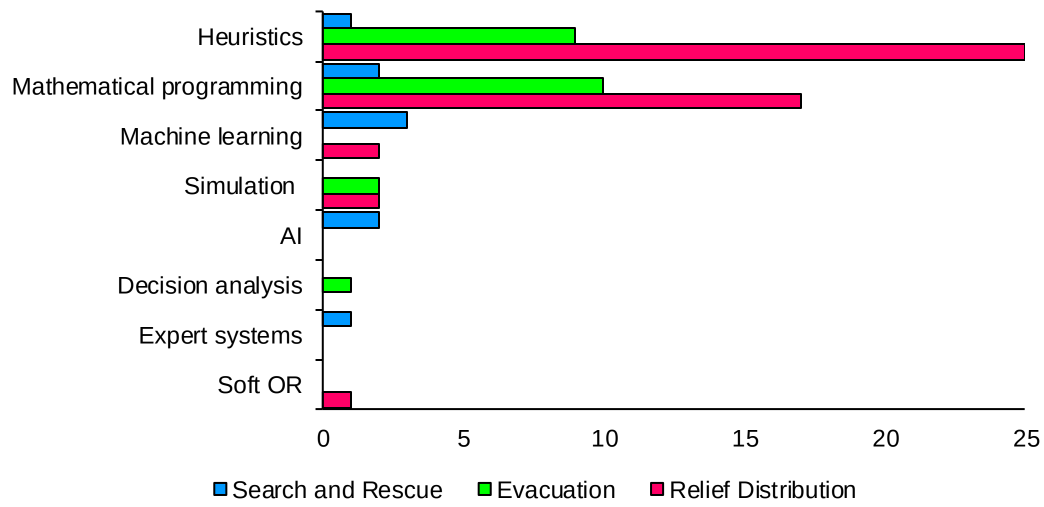

Figure 7. *Methodologies used in response problems.*

As can be seen, relief distribution problems have received the most interest among the three problem types. A handful of studies address the integration of relief distribution and evacuation. Two methodologies – mathematical programing and heuristics – dominate (used 56 times) among the 66 response stage studies. Interestingly, simulation, which is used frequently in pre-earthquake stages (mitigation and preparedness), has rarely been used in post-earthquake response problems.

Table 11. *Details of the types of problems addressed and methodologies used in the response stage.*

Problem	**Method**	**References***
Search and rescue		
Rapid damage assessment	Machine learning	[142,143]
	Expert system	[144]
	Heuristic	[145]
Rescue operations	Mathematical programing	[146,147]
	Machine learning	[148]
	Expert system	[**144**]
	AI	[149,150]
Evacuation		
Routing and allocation	Mathematical programing	[151–160]
	Heuristic	[**156**,161–168]
	Simulation	[**156**]
	Decision analysis	[**164**]
Human behavior	Simulation	[169]

Relief distribution		
Relief logistics	Mathematical programing	[**151**–**155**,170–182]
	Heuristic	[**167**,**168**,183–204]
	Simulation	[**171**,205]
	Machine learning	[**153**]
	Decision analysis	[**171**]
	Soft OR	[206]
Road damage assessment	Machine learning	[207]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

4.3.1. Search and Rescue

Search and rescue, the response stage category least examined in the literature, includes problems related to rapid damage assessment and rescue operations. Rapid damage assessment aims to inform first responders and other operations personnel about the damage status of buildings and infrastructure following an earthquake. Rescue operations involve the deployment of specially trained rescue teams to provide first-aid and free survivors from rubble. Table 12 provides details of studies in this category, including the systems/tools developed, their aims, OR methods used, and case study applications.

Table 12. *Details of studies addressing search and rescue problems.*

Reference	System/tool	Aim	Method	Case Study
Bai et al. [142]	Remote sensing	Building damage mapping	Machine learning	-
Kim et al. [143]	Seismic loss assessment	Sensor location for near real-time assessment of building damage	Machine learning	-
Schweier & Markus [144]	Information system	Support onsite search and rescue teams and building inspectors	Expert system	-
Chu et al. [145]	Participant selection	Selection of volunteers for collection of crowdsourcing data	Heuristic	2010 Haiti earthquake
Chu & Zhong [146]	Medical rescue team assignment	Maximize number of saved casualties	Mathematical programing	2008 Sichuan earthquake
Ahmadi et al. [147]	Scheduling/routing of rescue teams	Maximize min. demand coverage	Mathematical programing	Tehran, Iran
Chaudhuri & Bose [148]	Smart infrastructure image classifier	Identification of survivors in debris	Machine learning	2011 Tōhoku and 2012 Emilia earthquakes
Zheng et al. [149]	Rescue wings	Monitor and analyze the status of identified victims	AI	2013 Ya'an earthquake
Liu et al. [150]	Rescue team task assignment	Plan search and rescue operations given uncertain road damage	AI	2014 Ludian earthquake

Detecting the damage status of buildings quickly and accurately is vital to improving response times of rescue operations. Bai et al. [142] use a machine learning framework to compare the performance of using post-event remote sensing data versus multi-temporal images for estimating building damage ratios. Building damage ratio information is particularly useful for determining where damage is concentrated across a city or area and to efficiently concentrate response efforts. Schweier and Markus [144] develop two different integrated information systems involving the use of expert systems to inform both rescue operations and building damage assessment. The first generates advice for onsite search rescue teams about suitable procedures and equipment to use at a particular building collapse, while the second aids inspectors in determining whether a building is safe to use after an earthquake Accurate identification and classification of victims after an earthquake is crucial for improving rescue and evacuation efficiency. Chu and Zhong [146], meanwhile, propose a mathematical programing model for assigning medical rescue teams to affected areas in the very early stage after an earthquake to maximize the expected number of casualties that can be saved. Zheng et al. [149] describe a web-based system to classify potential earthquake victims according to priority of need based on profile data, vital signs, location, and environmental conditions. Finally, Chu et al. [145] propose a model and solution approach for making effective use of crowd sourcing information by selecting volunteers to explore earthquake affected areas given the benefits and cost of deploying them.

4.3.2. Evacuation

Evacuation normally takes place during initial phase of the response stage to transfer the injured to medical centers and those in immediate danger or made homeless due to an earthquake to safe zones and temporary shelters [15]. Evacuation is the second most addressed problem in the response stage, comprising 19 of the 67 studies. The main decision making issues include the allocation of evacuees to medical facilities, integration of evacuee planning and location of temporary shelters following an earthquake, and investigation of the role of human behavior on evacuation operations.

Among studies using mathematical programing and heuristics, two basic decision frameworks have been considered: routing and allocation of affected people to safe zones by minimizing travel distance or evacuation time [125,161,165], sometimes in combination post-disaster shelter site location [154,159,166], and recovery of injured and transfer to medical centers to minimize loss of life [152,153,156,158,164]. Forcael et al. [161], for example, find that optimized evacuation routes result in shorter evacuation times from tsunami prone areas based on validation from live evacuation drills. Chen et al. [162] investigate how GIS and global positioning system (GPS) technologies can be combined with heuristic methods to support evacuation decisions by identifying in real-time the location of people in need of evacuation and optimal paths (based on length and reliability) for emergency recuse teams to reach them. Rakes et al. [165] propose a model and solution approach for allocating individual families to temporary housing units. Unlike most other studies, they consider each family's educational and healthcare support needs when making assignments. Kilci et al. [159] consider jointly where to locate shelters and allocate victims to shelters taking into account accessibility to critical infrastructure, terrain characteristics, and public ownership of shelter sites. Ozbay et al. [166] present a multi-stage approach for (i) locating shelter sites after an earthquake but before demand is known; (ii) allocating evacuees to their nearest shelters once demand is known; (iii) the need to open additional shelters due aftershocks creating more demand for shelters. Meanwhile, Mills et al. [156] consider patient survival rates and service times for different types of traumatic injuries when making ambulance and medical facility allocation decisions in order to maximize the expected number of survivors. Both Oksuz and Satoglu [158] and Liu [164] look at where to locate temporary medical centers (aka field hospitals) to deal with the evacuation and treatment of mass casualties.

Among the few studies using simulation is Liu et al. [169], who develop an agent based model to examine how building damage and human behavior interact when people attempt to evacuate a building. A key aim of theirs is to understand how exit flow rates from buildings can be increased through better building design and the development of improved evacuation strategies. Mills et al. [156] also use a discrete event simulation approach but primarily as a way of assessing the performance of proposed heuristics that use limited up-to-date information when making dynamic ambulance assignments.

4.3.3. Relief Distribution

In the immediate aftermath of an earthquake, supply chains and logistics operations need to be rapidly organized to transport and distribute significant quantities of relief to affected areas taking into account an initial assessment of demand and post-disaster conditions (e.g., functionality of the transportation network). Logistics steps typically involve receiving and consolidating relief supplies from external suppliers (ESs) at large central warehouses (CWs) located outside the affected zone (aka "hot" zone"), distributing relief from CWs to RDCs located in the hot zone, and then redistributing relief from RDCs to local relief distribution points within affected areas (AAs), which may include shelters, spot recue areas, hospitals, and individual residential areas. Sometimes CWs do not constitute a distinct element of the logistics network (either because CWs are not required or CWs also serve as RDCs), in which case it is assumed that relief supplies move directly from ESs to RDCs.

As seen from Table 11, mathematical programing and heuristics stand out as the dominate methods for addressing relief distribution problems, making up 42 of the 45 studies in this category. An overview of these studies, including logistics activities, number of relief goods, and mode of transportation, is provided in Table 13 with further details provided in an Appendix A. A majority (27 out of 42) focus exclusively on distribution between RDCs and AAs; only a handful consider supply side logistics by including distribution from ESs (e.g., [152,167,179,196]) or CWs (e.g., [174,185,190,191]) to RDCs. A few recent papers have looked at even more complex multi-echelon relief supply chains involving (i) distribution among ESs, CWs, RDCs, and AAs [172] and (ii) blood donation at local collection centers (LCCs), transfer to testing laboratories or regional blood centers (~CWs), and on to local blood centers (~RDCs) and regional/local hospitals (~AAs) [153,177]. In addition, a majority of papers consider (i) multiple commodities (25 out of 42), as opposed to distribution of a single generic commodity, and (ii) multi-modal transport (27 out of 42) using a heterogeneous set of vehicles with different capacities and travel speeds, rather than with a fleet of identical vehicles. Vehicle types considered range from maritime ships [179] to road vehicles (e.g., [178,182,189,190]) and trains [199] through to helicopters [167,181,191]. In a few cases, submodels capture variants of vehicle routing problems in which capacitated vehicles complete tours to one or more AAs from a designated RDC (e.g., [186,190,191,204]) or travel to AAs while resupplying at different RDCs (e.g., [151,189]). Note that less than half (17 out of 42) simultaneously consider multiple commodities and multi-modal transport.

Table 13. *Summary of mathematical programing and heuristic approaches for relief distribution problems.*

Logistics activities	No. of Goods	Mode of transport	References
RDC-RDC	Multi	Multi	[175]
RDC-AA	Single	Single	[168,184,188,189,193,195,197]
		Multi	[178,182,192,198,200,201]
	Multi	Single	[183,186,187,203]
		Multi	[151,154,170,173,180,181,194,199,202,204]
CW-RDC-AA	Multi	Single	[174,185]
		Multi	[171,190]
ES-RDC-AA	Single	Multi	[152]
	Multi	Single	[155]
		Multi	[167,176,179,196]
ES-CW-RDC-AA	Multi	Single	[172]
LCC-CW-RDC-AA	Single	Multi	[153,177]

Further analysis reveals that nearly all mathematical programing and heuristic studies for relief distribution adopt a multi-objective framework to capture different, possibly conflicting logistics performance indicators. Typical objectives and variations thereof include: minimizing the cost of transporting relief (e.g., [167,181,198,201]), minimizing response time (e.g., [179,182,185,189]), minimizing unmet demand (e.g., [151,170,186,199]), and maximizing route reliability (e.g., [178,190,200,204]). Additionally, most of the studies, except five, apply their modeling framework to a case study, usually involving an historical earthquake. For example, Wang et al. [204] consider a multi-model transport fleet for distributing multiple commodities between RDCs and AAs to minimize both total cost and maximum time to distribute relief and maximize the minimum reliability of routes used by vehicles and then apply their approach to the 2008 Wenchuan earthquake. Vitoriano et al. [178], meanwhile, only consider a single commodity but optimize no less than six different objectives (minimization of transport cost, maximum time to deliver relief, unmet demand, and maximize unmet demand and maximization of route link reliability and security), using a case study of the 2010 Haiti earthquake as a demonstration. More recent work has combined relief distribution with evacuation to shelters and or transport of injured to medical facilities [152–154,168].

Four other methods besides mathematical programing and heuristics have been applied to relief distribution. This includes: (i) a system dynamic model to analyze a relief distribution system built for the Longmen Shan fault, China, where many destructive earthquakes have occurred [205]; (ii) Soft OR for developing a conceptual model of post-disaster survivor perception-attitude-resilience relationships to inform emergency logistics operations in a way that takes into account perspectives of both government planners and the psychology of affected populations; (iii) machine learning (neural networks) for designing an efficient blood supply chain [153] and predict the structural status of road links when deploying relief [207]; and (iv) decision analysis to assess performance of relief distribution based on demand coverage, logistics costs, and response time [171].

4.4. Recovery Stage

During recovery, the fourth stage of EOM, the overall aim is to return an affected community to normal after a major quake. Recovery begins right after the emergency. In the short-term, recovery is an extension of the response stage that deals with the restoration of basic services in the days and weeks after a disaster. In the long-term, recovery focuses on restoring economic activity and community wellbeing by rebuilding damaged facilities and housing, which can take years.

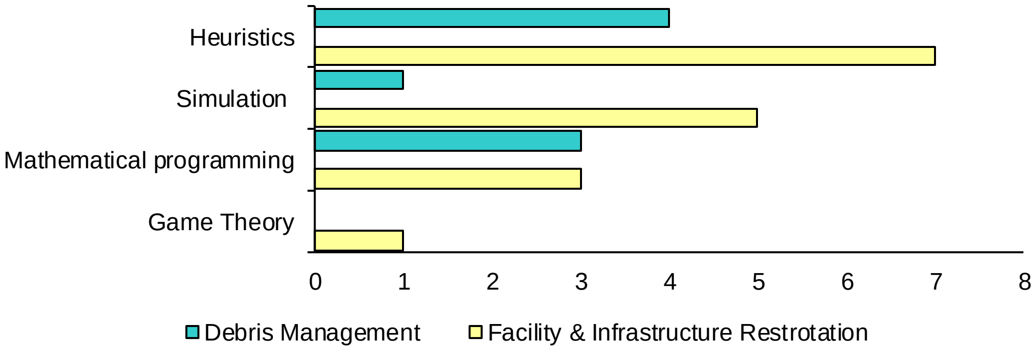

Figure 8. *Methodologies used in recovery problems.*

In view of this, we consider two basic types of recovery operations: 1) debris management and 2) facility and infrastructure restoration. Debris management is initially concerned with quickly clearing debris from impacted urban areas and roads, thereby allowing rescue, evacuation, and relief distribution operations to proceed more efficiently [208]. Later on, debris needs to be collected and processed. Debris removal management after large-scale earthquakes can be one of the most complicated and time consuming activities of post-disaster operations. Facility and infrastructure restoration focuses on planning operations involved with repair and rebuilding of damaged buildings and critical infrastructure networks like water, electricity, and road transportation. This includes prioritization of buildings and infrastructure components and scheduling of restoration work teams based on criticality and the need to provide maximum network functionality. Like with response stage problems, the sheer scale of both debris management and facility and infrastructure restoration operations involved with earthquakes sets them apart from other types of natural disasters.

Table 14. *Details of the types of problems addressed and methodologies used in the recovery stage.*

Problem	**Method**	**References***
Debris management		
Debris clearance, collection and processing	Mathematical programing	[208–210]
	Heuristic	[**208**,211–213]
	Simulation	[214]
Facility and infrastructure restoration		
Planning repair work	Mathematical programing	[215–217]
	Heuristic	[218–224]
	Simulation	[**214**,**215**,225–227]
	Game theory	[**217**]

* References highlighted in bold incorporate more than one methodology and/or address multiple problem types.

Recovery problems have received significantly less attention than the other stages with only 20 studies reviewed. A summary of OR methodologies used for both problem types is shown in Figure 8. As can be seen, only four OR methods have been applied in recovery stage problems. Similar to the preparedness and response stages, mathematical programing and heuristics are the most frequently used OR methods. A limited number use simulation alone or in combination with mathematical programing and heuristics, while one study combines mathematical programing with game theory. Additional details about recovery problems are given in Table 14.

4.4.1. Debris Management

Given limited resources, efficient and effective planning of debris clearance to improve connectivity between relief demand and supply is vital during disaster response. There are a few studies addressing debris clearance and relief distribution problems in an integrated manner, but details of these studies are given in Section 4.5. In this section, we only discuss studies that deal exclusively with debris clearance, collection, and processing operations.

Mathematical programing and heuristic methods for debris management have considered a number of different objectives, such as maximizing road network accessibility by minimizing the time to reopen a predefined set of travel paths [209], minimizing the time to clear debris from a road network and restore full connectivity [208], minimizing the time to clear debris from a road network while maximizing connectivity between all origin and destination pairs over time [211], and minimizing a combination of logistics costs involved with processing debris (i.e., transporting, sorting, storage, and disposal of debris), environmental and operational risks from exposure to contaminated debris, and the psychological costs imposed on victims and residents from the waiting time to remove debris [210]. Apart from these, a system dynamics model was used by Hwang et al. [214] to adopt a more holistic perspective to recovery operations, including debris removal. A key finding is that consideration of the interdependencies among multiple recovery operations can lead to better understanding of the overall recover process and development of more effective recovery strategies.

4.4.2. Facility and Infrastructure Restoration

Problems dealing with the repair and rebuilding of facilities and critical infrastructure networks (e.g., road transportation, water, gas, and electricity networks) damaged by earthquakes mainly focus on resource allocation and scheduling/routing of emergency repair crews. Here, typical aims are to restore full functionality of infrastructure networks as quickly as possible following an earthquake, minimizing the number of people without service during repair, and minimizing reconstruction costs. A variety of different aspects of this basic problem have been considered, mostly involving the use of mathematical programing and heuristics (10 out of 13).

For example, González et al. [215] consider a set of interdependent water, gas, and power networks and apply both mathematical programing and simulation to minimize repair and supply shortage costs by coordinating repair of multiple, different network elements collocated in the same area. Meanwhile, Nozhati et al. [218] employ approximate dynamic programing (a hybrid mathematical programing and heuristic approach) to minimize the time to restore electricity to a specified fraction of the population, while maximizing the number of people with electricity service over time. In a series of papers, Yan, Shih, and colleagues explore the application of time-space network flow models and heuristic solution methodologies for scheduling the deployment of road repair crews in order to minimize the time of road repair operations [219,220] and distribution of essential supplies (e.g., fuel, machines, food) to repair crews at least cost [221,222]. Different problem variants include the need to adjust original schedules following demand and supply perturbations (e.g., aftershocks causing additional damage and additional repair crews being mobilized) and consideration of multiple vehicle types combined with stochastic travel times. Luna et al. [226] examine the use discrete event simulation to model the restoration time of a water distribution network under different seismic scenarios and help inform resource allocation planning. Besides repair of critical infrastructure networks, Gosavi et al. [227] address damage containment and restoration of urban areas using discrete even simulation. Longman and Miles [225] also use discrete event simulation to predict timelines for rebuilding damaged housing and inform resource requirements (e.g., inspectors and construction workers) following the 2015 Nepal earthquake.

4.5. Integrated Stages

Given interdependencies among EOM stages, greater effectiveness and efficiencies can often be achieved through integrated planning of various pre- and post-disaster activities. The majority of research, however, has focused on a single EOM stage. Relatively few studies (22 out of 211) have combined problems from different EOM stages in an integrative fashion. Integrated disaster management is clearly recognized as a key gap in the literature that needs be addressed moving forward. Figure 9 shows the different methods used in the integration of different EOM stages. As with most single stage studies, mathematical programing and heuristics are the most frequently used OR methods, accounting for no less than 19 (86%) of the 22 studies.

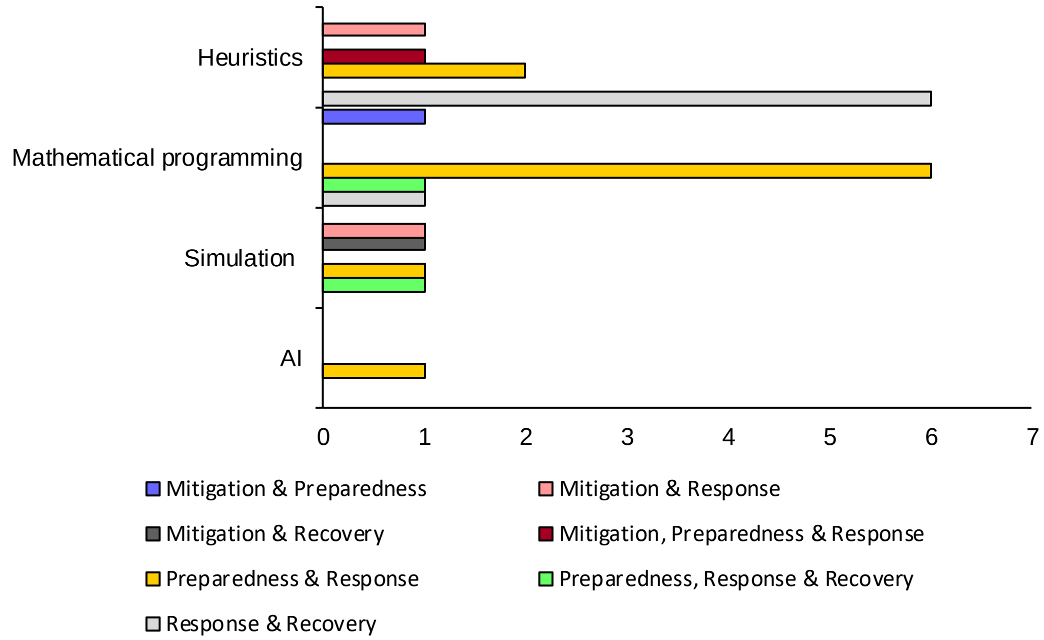

Figure 9. *Methodologies used in integrated stages of EOM.*

Table 15 provides a breakdown of the problems addressed and methodologies used in the integration of EOM stages. The two most frequent combination of stages are preparedness and response (9 out of 22) and response and recovery (7 out of 23). Only two studies combine three stages, namely (i) mitigation, preparedness, and response and (ii) preparedness, response, and recovery. As can be seen from Table 15, studies combining preparedness and response have looked at relief pre-positioning and resource planning problems together with either evacuation of victims or the distribution of relief to affected areas. Integrated response and recovery planning, meanwhile, has focused mainly on how facility and infrastructure restoration (e.g., road networks) can more effectively support relief distribution operations. Table 16 present further details of integrated EOM studies involving the application of mathematical programing and heuristic methods, including the types of decisions and objectives considered.

A total of 11 studies have looked specifically at how preparedness positively impacts on response. A general observation is that many of the papers reviewed investigate inherent trade-offs between greater investment in locating RDCs and or stockpiling relief and lower penalties as measured by demand shortages, response time, number of people evacuated, etc. Typically, multi-objective frameworks are adopted to capture the multitude of planning goals that often at play. Salman and Gül [228], for instance, propose a model for locating field hospitals and determining the number of ambulances needed to minimize travel and waiting times of casualties. Regarding relief distribution, Mete and Zabinsky [229] optimize the location, capacity, and inventory levels of RDCs at minimum cost in order to reduce the transport time of and unmet demand for medical supplies. Of note, they incorporate operational level decisions about vehicle loading and routing when devising an optimal relief distribution plan. Sitting of RDCs and relief distribution combined with vehicle routing has been considered by other authors as well [230–232]. In a few cases, studies RDC location has also been combined with evacuation [99,233,234]. Apart from mathematical programing and heuristic methods, Sahebjamnia et al. [235] develop a sophisticated hybrid simulation and AI decision support system for prepositioning RDCs and managing the allocation and distribution of relief by a humanitarian relief chain. Three main performance indicators – set-up/transport cost, relief shortages/excess, and response time – are used to evaluate tradeoffs of alternative relief chain configurations under different disaster scenarios, make iterative improvements, and finally make recommendations about the best configuration for any given post-disaster state.

Table 15. *Details of the types of problems addressed and methodologies used in integrated stages of EOM.*

Stages	Problems*	Method(s)	References
Mitigation & Preparedness	PP & P/RP	Mathematical programing	[236]
Mitigation & Response	PP & RD	Heuristic	[237]
	RVA & SR	Simulation	[238]
Mitigation & Recovery	RVA & FIR	Simulation	[239]
Mitigation, Preparedness & Response	PP, P/RP & RD	Heuristic	[240]
Preparedness & Response	P/RP & E	Mathematical programing	[228,234]
	P/RP & RD	Mathematical programing	[229,230,241]
		Heuristic	[231,232]
		Simulation & AI	[235]
	P/RP, E & RD	Mathematical programing	[233]
Preparedness, Response & Recovery	P/RP, RD & FIR	Mathematical programming & simulation	[242]
Response & Recovery	RD & DM	Heuristic	[243]
	RD & FIR	Mathematical programing	[244]
		Heuristic	[245–249]

* PP: Protection Planning, P/RP: Pre-positioning and/or Resource Planning, RD: Relief Distribution, RVA: Reliability and Vulnerability Analysis, SR: Search and Rescue, FIR: Facility and Infrastructure Restoration, E: Evacuation, DM: Debris Management.

Relatively fewer studies have looked at combining both pre-disaster stages (1 study) or both post-disaster stages (8 studies). All have employed mathematical programing or heuristic methods. Hu et al. [236] examine the problem of reinforcing RDCs and roads (mitigation) as well as setting relief inventory levels (preparedness) in order to minimize total cost (protection plus relief procurement, holding, and transport), deaths, and demand shortages. Integration of response and recovery has been considered by a number of authors. For example, Çelik et al. [243] develop a heuristic for optimizing the clearance of road debris (recovery) and the distribution of relief from RDCs to AAs (response) over time. Meanwhile, various studies, including Liberatore et al. [244], Yan and Shih [246], and Li and Teo [248], have looked at variations of how repair of damaged road links (recovery) can better support relief distribution (response) by reducing response time and increasing demand satisfaction, among other goals.

Table 16. *Details of mathematical programing and heuristic approaches for integrated stages of EOM.*

Stages*	Decision(s)	Objective(s)	References
M+P	Reinforcement of buildings, reinforcement of the road network and relief inventory levels	Minimize building reinforcement, road network reinforcement, procurement, and expected transport/holding costs, transport time, shortages and deaths	[236]
M+Rs	Road link protection and distribution of relief items	Minimize expected weighted average distances between supply and demand points	[237]
M+P+Rs	Building retrofits, road link protection, capacity of emergency aid and distribution of relief items	Minimize lives at risk and maximize number of people saved	[240]
P+Rs	Location of field hospitals, number and allocation of ambulances and transport of casualties by ambulances	Minimize casualty travel and waiting times	[228]
	Location of medical supply centers and transfer points, allocation of medical supplies and transport of injured to hospitals via transfer points	Minimize transportation time of injured and supplies and minimize set-up, transport and response time violation costs	[234]

	Location and inventory levels of distribution centers and distribution of relief through a network	Minimize set-up, procurement and transport costs, unused inventory and unmet demand	[241]
	Location, capacity and inventory levels of distribution centers and distribution of relief by vehicle routing	Minimize set-up costs, transport time and unmet demand	[229]
	Location, capacity and inventory levels of distribution centers and distribution of relief by vehicle routing	Minimize max. weighted unmet demand, transport time and set-up, procurement, transportation, inventory holding shortage costs	[230]
	Location of distribution centers and distribution of relief by vehicle routing	Minimize transport time, unmet demand and set-up costs	[231]
	Location of distribution centers and distribution of relief by UAV trip assignments	Minimize transport time of UAVs and travel time of people	[232]
	Location and inventory levels of distribution centers, allocation of rescue vehicles and relief and transport of injured to medical facilities by vehicle trip assignment	Minimized set-up, operational, transport and holding costs, cost variability, unmet demand and unrecovered injuries	[233]
P+Rs+Rc	Location and capacity of distribution centers, restoration equipment inventory levels, distribution of relief through a network and repair of damaged road links	Minimize set-up, restoration equipment procurement and expected transport costs and unmet demand	[242]
Rs+Rc	Debris clearance from roads and distribution of relief	Maximize satisfied demand for relief	[243]
	Repair of damaged road links and distribution of relief through a network	Maximize satisfied demand, security and reliability and minimize max. delivery time	[244]
		Minimize delivery time	[245]
		Minimize delivery time and time to repair	[246]
	Repair of damaged road links and accessibility of affected areas from distribution centers	Minimize time to reach affected areas	[247]
	Repair of damaged road points and distribution of relief through a network	Maximize cumulative accessibility and min. satisfied demand	[248]
	Repair of damaged road links and distribution of relief by vehicle routing	Minimize set-up, transport and road repair costs and response time and maximize route reliability	[249]

* M: Mitigation, P: Preparedness, Rs: Response, Rc: Recovery.

5. Roadmap for Future Research

As should be clear from our review, OR provides a powerful array of tools for effective and efficient decision making in EOM. However, despite the volume and variety of EOM studies employing OR methods, the development of widely applicable modeling frameworks emerges as a key shortcoming in need of greater attention. As noted in previous surveys, applicability is critical in the field EOM owing to how any real world decisions ultimately translate into direct impacts on communities and individuals. Below we examine some important considerations relating to realism, comprehensiveness, practicality, and user-friendliness that have been taken from the various problem definitions and solution methodologies described in the literature. Figure 10 summarizes these features as they relate to the development of applicable EOM planning frameworks. Our hope is that this will prove useful to informing future lines of research and continued advancement of the field.

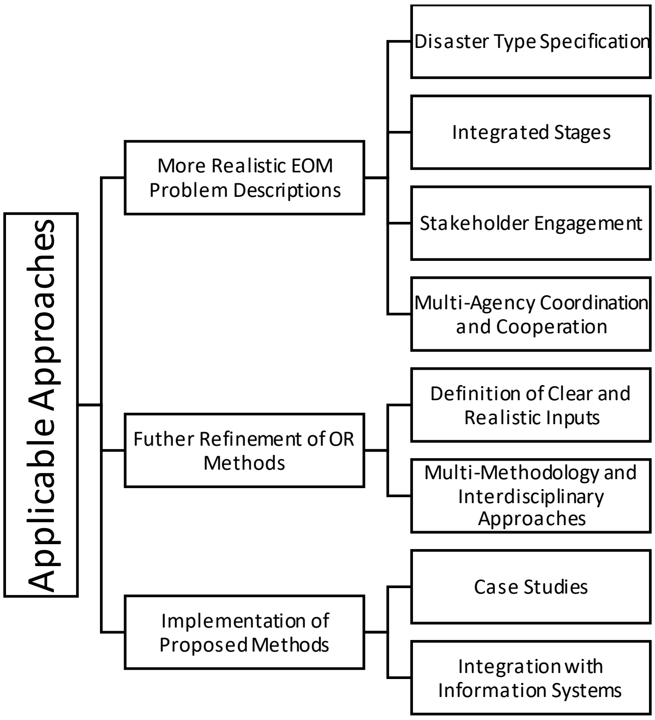

Figure 10. *Key features for developing more applicable EOM methods.*

5.1. More Realistic EOM Problem Descriptions

As evident from our literature review and previous reviews [12,15,17,25], a vast amount of research has been carried out in the past decades on the use of OR methods for EOM. We point out, however, that most studies have analyzed problem from a methodological and or theoretical perspective as opposed to real-world applicability and use. Frequently, studies fail to develop problem representations that are familiar to practitioners, instead opting to define novel problem formulations that differ greatly from practical and realistic ways of doings things. For OR methods to achieve greater applicability in EOM, it is essential that problem definitions be well-grounded in reality and context. To this end, we provide some recommendations that may serve to enhance the realism and, therefore, applicability of OR methods in EOM through better problem identification and specification, greater stakeholder involvement, further integration of different disaster stages, and enhancement of multi-agency coordination and cooperation.

5.1.1. Disaster Type Specification

DOM reviews thus far have not really touched on which specific disaster types may be more or less favorable to real-world application of OR methodologies. This is somewhat surprising, since in practice, disaster risk assessment and planning is usually performed separately (e.g., using software like Hazus [250]) for tsunamis, earthquakes, floods, hurricanes, and other disaster types. Contrary to this, we observed that only 138 of 211 studies in our review present a problem definition expressly focused on earthquakes and EOM decision making (see Appendix B). In only a few studies were emergency operations and stakeholder roles defined by field experts [122,205]. Interestingly, studies addressing reliability and vulnerability analysis and integrated disaster management have gone the furthest in terms of using earthquake-oriented problem specifications. Other EOM problem areas, however, tend to be more generic and theory-oriented and potentially less useful in real-world planning. We would argue that specifying which disaster type is being addressed would translate into greater transparency and precision in terms the problem that is being addressed and, in turn, lead to the development of more realistic and applicable models.

With regard to EOM, the frequent neglect to identify a specific disaster type is perhaps one reason why problem descriptions usually ignore two key features of large earthquakes, namely the potential for and need to contend with 1) cascading or secondary effects [251] and 2) subsequent disasters caused by aftershocks [152,181]. Cascading events can occur as an indirect result of a major quake. For instance, an earthquake that ruptures gas supply pipelines can result in fires and explosions that dramatically increase urban damage and risk to life [252]. Other examples of secondary effects from earthquakes include landslides that occur long after the event following heavy rainfall, flooding caused by breached dams and levees, and even the triggering of volcanic eruptions. In the case of earthquakes, which normally strike with no warning and affect a large area, the potential for cascading effects is often magnified in comparison other types of disasters. Aftershocks, meanwhile, are common following a large quake and not only can cause significant damage days or even weeks later, but can seriously hamper response and recovery operations. The 2011 Tōhoku (aka Great East Japan Earthquake), for example, caused extensive damage and left over 20,000 people dead. This was in large part because it was a compound disaster involving earthquakes, a tsunami, and a nuclear accident that widely impacted the whole nation [253]. As noted by Marano et al. [254], over 20% of deaths attributed to earthquakes over the past 40 years were a result of secondary causes (e.g., landslide, liquefaction, tsunami, and fire).

In spite of their importance, only a small handful of papers we reviewed explicitly consider cascading effects and or the potential of subsequent aftershock damage. Liberatore et al. [73] for one develop an multi-level optimization model for deciding which hospitals to reinforce given the presence of propagating damage across a network. Work by Ozbay et al. [166] on shelter site location, Liu et al. [181] on evacuation planning, and Yan et al. [220] on road infrastructure restoration is notable for incorporating uncertain damage from aftershocks to improve the robustness of proposed solutions. Clearly, there is need for future EOM research to treat and analyze earthquakes more holistically, both in the mitigation and preparedness stages by hedging against cascading and secondary effects and in the response and recovery stages by recognizing the importance of aftershocks the need for adaptive planning.

5.1.2. Integrated Stages

Besides a lack of disaster type specification, realism of EOM studies is often constrained by proper consideration of how different DOM stages interact with one another. Like other reviews, we found that the vast majority of OR based EOM studies (189 out of 211) published in the previous 11 years focus on only one disaster stage as opposed to the integration of multiple stages. The latter group has mostly appeared in the literature fairly recently. In this subsection, we identify a number of aspects of EOM that could be aptly addressed through integration of different DOM stages.

Tasks associated with recovery and mitigation partially overlap. Better understanding of the connections between protection strategies and damage states that result in lower recovery costs of a system is a key research theme that warrants greater consideration in decision modeling frameworks. Conversely, recovery can also be catalyst for mitigation. The motto ‘Build Back Better’, often heard in recent years, advocates the adoption of integrated disaster risk reduction measures into physical infrastructure restoration work following a disaster in order to enhance resilience of and minimize future risks to people, livelihoods, and the environment [253]. Despite the clear links between mitigation and recovery, we found only one study by Cho and Park [239] addressing this combination of DOM stages. Analysis of the trade-offs between investing in infrastructure protection and the associated economic and social costs of disruption and recovery is a clear gap in the literature.

Notably, recent work has examined problems that intersect with the mitigation and response stages. This includes the use of heuristics to optimize building/road link protection and post-disaster relief distribution [237,240] and simulation to assess vulnerabilities to urban infrastructure and search and rescue effectiveness [238]. Invariably, simplifications need to be made with any model. Nonetheless, identified drawbacks with existing mitigation and response studies include lack of consideration regarding post-earthquake resource availability (e.g., personnel, vehicles, relief supplies) and potential reduction of resources due to earthquake damage, as well as overly simplistic assumptions about infrastructure damage (e.g., facilities and road links can be in one of two states: either fully operational or not) and the effectiveness of protection (e.g., protection entirely prevents all damage to facilities/road links). From a modeling perspective, incorporating protection-damage functions, in particular, is no easy task. However, future work on this aspect might take inspiration from Chang et al. [43], among others, who looked at using Monte Carlo simulation to better understand how for various bridge retrofit standards, uncertainty about earthquake intensity and bridge structural damage affected bridge traffic-carrying capacity based on established bridge fragility and damage-functionality relationships.

Although relief pre-positioning and resource planning (preparedness) combined with relief distribution (response) has received relatively more attention than other types of integrated planning (see Table 15), additional lines of research within this area remain. Most researchers have concentrated on the impact of locating RDCs, while sometimes also considering decisions about capacity and inventory levels, on relief distribution effectiveness. However, to our knowledge, no studies have looked at simultaneously positioning RDCs, setting relief inventory levels, and locating shelter sites with relief distribution. Further research might address this gap as well as factor in the interplay between shelter site location and evacuation time/distance.

Blocked roads and paths to affected areas are frequent in the aftermath of an earthquake. While some research has dealt with debris clearance to reestablish relief supply lines (see Table 15), there is an evident lack of research focused on how debris removal allows for evacuation from affected areas. Additionally, none have incorporated stochastic elements related to debris amount or resource requirements for clearance/repair. Finally, no research that we are aware of has combined preparedness and recovery, for example RDC location and resource planning considering likely road infrastructure damage and speed of debris clearance on relief distribution performance.

We acknowledge that from a modeling standpoint, development of integrated models often involves much a higher degree of complexity that can pose a serious challenge in terms of substantially increased computational time requirements. Nevertheless, greater use of integrated modeling can provide clear benefits (i.e., greater realism, enhanced coordination, more efficient use of limited resources) and issues related to solution time can at least partially be addressed by developing multiple inter-linked models and solving them in stages or using heuristics and approximation methods to solve realistically sized problem instances in reasonable computational time.

5.1.3. Stakeholder Engagement

There is broad recognition that in order to achieve buy-in and a measurable improvement in EOM performance, all key stakeholders need to be involved both in implementation and problem identification and modeling (not necessarily fine-grain details but at least general structure) [144,157,176,205]. Lack of stakeholder involvement in model conceptualization and development often leads to more theoretical and less realistic problem definitions, case studies that provide limited insights, and ultimately low likelihood of proposed methods ever being implemented [17].

To help understand the prevalence of stakeholder involvement in academic studies, the articles we reviewed were assigned one of three categories: 1) no involvement; 2) partial involvement (e.g., providing data and or general advice for case studies, including review and verification of model inputs); and 3) significant involvement (e.g., direct participation of an agency, NGO, or institution in the conceptualization and development of the modeling approach). Findings are detailed in Appendix B. Regrettably, despite the large body of EOM research reviewed, we found that only 19 (8%) of the 211 studies had significant stakeholder involvement and just 64 (25%) had even partial stakeholder involvement.

Focusing on studies that had “significant” stakeholder involvement, these can be further subdivided into various distinct groups. One group worked in close collaboration and co-design of the study through use of participatory approaches (e.g., interviews and workshops) to inform model conceptualization from the very beginning [79,201]. A second group engaged with stakeholders, mainly through interviews with emergency department personnel and EOM planners, to seek advice about specific issues relating to emergency response operations [116] or as part of defining qualitative or quantitative evaluation criteria (a.k.a. key performance indicators) of their decision support models [61,64,65,122]. Finally, a third group mainly looked at post-disaster psychological metrics of local residents directly impacted by large-scale earthquakes based on interviews and questionnaires [205,206]. Only one study addressed a problem proposed by EOM practitioners themselves [107]. Although the level of stakeholder involvement does vary somewhat, a general observation about the afore mentioned studies (in comparison to those with no or partial stakeholder involvement) is that their assumptions and model features tend to show a greater degree of realism aimed at meeting the specific needs of EOM practitioners.

To sum up, our analysis reveals that stakeholder involvement is for the most part an important but neglected aspect of OR studies applied to EOM, especially in the initial problem identification stage. Failure to identify earthquakes as the key focus of DOM research and involve EOM stakeholders from the start has resulted in modeling approaches that lack realism and real-world application by practitioners. Greater use of problem structuring (e.g., hierarchical process modelling) and other Soft OR methods as part of facilitated workshops involving one or more stakeholders, we would suggest, would go a long way toward addressing this shortcoming. Such approaches are commonly used in healthcare settings [255,256] when dealing with complex and unstructured problems and or where they may be multiple groups of stakeholders with potentially conflicting views about a problem. EOM shares much in common with healthcare and would likely benefit by adopting Soft OR conceptual frameworks. This is not to say that Soft OR should be the preferred or only approach to EOM, but simply that it should be used much more frequently as the starting point for subsequent Hard OR approaches (e.g., mathematical programming and heuristics) to ensure that they are well-grounded within a stakeholder perspective.

5.1.4. Multi-Agency Coordination and Cooperation

As noted by various authors, cooperation and coordination among multiple outside relief agencies and local and national government agencies is crucial to efficient EOM [12,257]. For example, in the case of the Indonesia Tsunami in 2018, foreign and local humanitarian organizations, including the Red Cross, other NGOs, and the United Nations (UN), were all in close communication with the Indonesian government to provide rapid support to the affected area of Sulawesi [258]. Foreign militaries actively participated in relief aid distribution with an average of 15-20 flights per day to the city of Palu. Supporting this effort was the UN Office for the Coordination of Humanitarian Affairs (OCHA), which assisted with information sharing and coordination of relief aid shipments. Similar to OCHA, the EU's Emergency Response Coordination Centre is responsible for collecting and analyses real-time information, devising response plans, and coordinating the EU's disaster response efforts by matching offers of assistance to the needs of the disaster-stricken country [259].

In spite of the importance of multi-agency coordination and cooperation in real-world planning, surprisingly little research involving OR methods has been devoted to this subject. We found only one study focused specifically on emergency response and relief chain coordination [128] (preparedness) and a second that applies a sophisticated bi-level optimization framework to the problem of coordinating multiple, independent countries and aid agencies in relief distribution (response) [179]. Clearly, future research needs redress this gap in the literature.

5.2. Further Refinement of OR Methods

After defining a realistic and holistic problem description, ideally supported by stakeholder involvement, the next step should be the development of modeling frameworks and solution methodologies based on clearly defined model inputs (i.e., data, decision variables, and objectives or performance criteria). Depending on the specific problem and needs of decision makers, multi-methodology and interdisciplinary approaches may be called for. Below, we elaborate on these points.

5.2.1. Definition of Clear and Realistic Inputs

Lack of a clear problem description and assumptions has been highlighted by other DOM reviews [12,17]. Here we delve into this topic for the specific case of earthquake disasters, emphasizing the need to define clear and realistic inputs for various EOM problems.

While reliability and vulnerability analysis has been successfully applied to a wide range of different types of infrastructure (see Table 6), including electricity grids [39], energy pipelines [47], water supply systems [37,45], and transportation networks [41,43], protection planning models have mainly focused on transportation networks (e.g., road links and bridges) [70,71] and occasionally buildings [72,73] (see Table 7). Often times, in the case of road network protection, rather abstract representations of the transport infrastructure have been applied without going into detail regarding the individual components of the network that can suffer damage (e.g., nodes, links, and pathways), the possibility some component are composed of multiple elements, the type of damage that can be sustained by different components, the degree of susceptibility to damage of each component, and what specific options are available to mitigate against damage. For instance, the literature is rather vague about what constitutes a road link. If a particular section of road has an intervening bridge or tunnel, then by any normal standard it should be decomposed into three links even if there are no road junctions along the way. Further, little or no consideration is given to the causes and likelihood of link failures; is it due to say landslide blockage versus fracture, buckling, or subsidence? Finally, in most models there is no explicit consideration of what a protection action constitutes or its effectiveness in preventing damage [76,237].

Based on the above assessment, we offer two recommendations. The first is that there is a clear need to address protection of critical infrastructure networks besides just transport. Different infrastructure networks face unique risks from earthquakes and have very different types of protection strategies that can be practically implemented. It would be worthwhile to elucidate these differences and develop bespoke models for different infrastructure types. The second recommendation, regardless of the type of infrastructure network being considered, is that protection models should be combined more frequently with a preliminary reliability and vulnerability analysis, especially when it comes to case studies. We envision that reliability and vulnerability assessment models could form the basis for producing inputs to a protection model, including a detailed assessment of failure modes and probabilities and development of concrete protection strategies that are properly costed out and understood in terms of their physical/operational effects of damage prevention.

Turning now to the preparedness stage, while there is a fair amount of research on relief pre-positioning and resource planning, various limitations are evident based on our review of existing models. For one, a fair number of studies considered stocking of multiple commodities but do not give any specifics. It is not at all clear if non-perishable or perishable goods are involved or some combination thereof. For perishable goods, holding time (which is not usually considered) as well as transport time (which often is considered) becomes a key factor. Only a few studies on relief pre-positioning and resource planning have looked at inventory holding and stock replenishment policies [94,111,114], which directly influence holding time. Additionally, with few exceptions (e.g., [83,91]), RDC location and inventory planning problems focus exclusively on relief distribution between RDCs and AAs, without considering supply from external suppliers or central warehouses. What is more, little or no mention of transport mode and vehicle availability is made in the literature on relief pre-positioning and resource planning.

A similar set of critiques apply to relief distribution models (response stage), except that multi-modal transport and vehicle resources are often considered. Looking specifically at provision of emergency medical services, only limited work has dealt with duty allocation and scheduling [146,188], even though this is crucial factor in determining the number of earthquake victims that can be saved. Further research could also look at medical team composition (e.g., number of nurses, doctors, and first aid workers) depending on estimated casualty amounts.

Evacuation planning, another response stage problem, has usually been based on defining routes to predetermined safe zones [119,161]. In practice, however, safe areas may need to be designated after an earthquake occurs, depending on the location of the epicenter, its magnitude, and damage to roads and buildings. Future work in this area needs to address the stochastic nature of earthquakes and the imperative of having contingent evacuation plans based on a range of different scenarios. Amideo et al. [17] emphasize paying greater attention to mass-transit-based evacuation and multi-modal evacuation approaches in DOM, which also applies to EOM.

5.2.2. Multi-Methodology and Interdisciplinary Approaches

A number of authors have pointed out the need for using interdisciplinary approaches in DOM. Amideo et al. [17], for example, suggest that use of techniques and concepts from different relevant disciplines would provide a more realistic frameworks for shelter location and evacuation routing. Hoyos et al. [12] provide some general recommendations about combining optimization with probabilistic or stochastic methods. Here, we aim to highlight how a multi-methodology approach, in particular handling of information using multiple techniques and different disciplines, would help facilitate a more open and systematic decision making process.

In the wider mitigation planning literature, the survival and damage levels of road networks and other infrastructure is typically determined by distance from epicenters or fault lines. In OR studies, however, few attempts have been made to accurately estimate post-disaster network failures as part of protection planning. Based on our review, Monte Carlo simulation is the most frequently used method to estimate infrastructure failure probabilities [43,46], though other techniques like Bayesian networks have also been applied [237]. In many cases, however, it not clear how these probabilities relate to the geophysical properties of quakes (including epicenter distance, magnitude, and wave type) and infrastructure vulnerabilities. Further research on infrastructure fortification would benefit from a multi-methodology approach combining optimization with seismic risk assessment and engineering in addition to simulation. Here, various techniques used in the field of seismology, including machine learning, might prove particularly useful in estimating damage levels [58,66] and human losses [67] based on key variables like structure type, construction quality, built area, and occupancy level. Subsequent application of simulation to assess key uncertainties combined with earthquake engineering to specify feasible fortification/retrofit alternatives [260,261] could form the basis for developing more holistic and realistic mathematical programing or heuristic methods to efficiently allocate limited protection resources. Similar to protection planning type studies, greater use of forecasting methods from the seismology (e.g., for estimating the intensity and frequency of quakes) would significantly enhance the rigor of relief pre-positioning and resource planning models. A good example is a study by Battarra et al. [112]. While the mathematical programing model they present is fairly simplistic, their work is notable for adopting a multi-disciplinary approach to disaster preparedness, specifically the allocation of relief supplies among RDCs.

Finally, better understanding of human behavioral responses would also greatly improve the realism of OR models, especially as part of response operations. Amideo et al. [17], for example, categorize evacuee behavior based on five different dimensions that have an impact on evacuation effectiveness during an emergency: time of day, route diversions, demographics, route preference, and warning signals. One of their key findings is that time of day and demographics play a critical role in route diversion choice and, in turn, potential delays during an evacuation. In the case of EOM, however, only one study by Liu et al. [169] explicitly address aspects of human behavior during evacuation. Similar to Amideo et al. [17], they find that mean evacuation time from buildings can be underestimated by at least 20% if social behaviors are not accounted for. We highlight this gap in EOM and suggest that future research should incorporate behavioral OR [262] and Soft OR [34] techniques to analyze individual and group responses as part of multi-methodology response planning.

5.3. Implementation of Proposed Methods

In the final stage of developing EOM methods applicable to real-world problems, it is important to consider: 1) validation via the use of case studies and 2) the frequently need to integrate information systems to support real-time data acquisition and multi-agency coordination. Below we discuss these two key point in further detail.

5.3.1. Case Studies

Most studies we looked applied their modeling and solution framework to a real or semi-realistic case study (see Appendix C) to demonstrate the utility of their proposed approach and derive new insights to support policy making and planning. This was typically carried out in two steps – first the generation of inputs to highlight data requirements and show how the proposed framework can be applied in practice and second a set of computational experiments to generate baseline results and carry out further what-if or sensitivity analysis. Here, we focus on the data generation phase and the common limitations of earthquake scenario development.

The generation of problem data can sometimes be laborious and require the use of specialized GIS software, like ArcGIS and GoogleMaps. For other types of data, discussions and interviews with expert stakeholders (discussed in Section 5.1.2) are sometimes required. More often than not, simplified versions of infrastructure systems (e.g., transport networks and water supply systems) are developed from secondary data sources or based on randomly generated data (see Appendix C). Consequently, even when GIS tools are used to develop a network representation, they may not involve a high degree of detail (e.g., individual road segments and buildings). In addition, demand nodes are typically represented by whole cities or even provinces with level of demand proportional to population size (e.g., [103,181,237]). Resources, however, are sometimes defined in aggregate terms (e.g., total supply), instead of being distributed among individual locations with defined distances to demand nodes (e.g., [209,247]). Based on this we make a few seemingly obvious recommendations. These are particularly pertinent to protection planning, relief pre-positioning, shelter site location, evacuation, relief distribution, and recovery stage problems. Where possible, real network data of sufficient detail for planning purposed should be used. Linked to this, demand should generally be defined at district or neighborhood level for large cities and by towns/communities when working at the scale of provinces. Finally, supply nodes and supply amounts should nearly always be included, ideally based on information provided by local authorities, to give a more realistic picture of how resources can be most effectively allocated.

Besides basic network configuration and resource availability data, case studies must also invariably incorporate information about the anticipated impacts of an earthquake (e.g., casualties, infrastructure damage, traffic conditions). Our analysis shows that disaster scenario development is mainly informed by two sources: 1) government and NGO technical reports and 2) software platforms (see Appendix B). Reports from agencies like the Japan International Cooperation Agency [263,264] often provide detailed analysis of likely earthquake occurrences and post-earthquake conditions, including predicted magnitudes, rupture locations and lengths [97,237], classification of at risk highway components [208], and casualty rates and associated evacuation demand [121]. Software like Hazus [250] are also useful in forecasting the number of displaced households [186], the number of critically injured [156,186], and infrastructure damage levels [243]. Depending on the disaster stage and type of model, either the most probable scenario is examined [64,120,212] or multiple scenarios (that vary in terms of earthquake position/magnitude, time of occurrence, etc.) are considered in an effort to find sufficiently robust solutions [79,121,232]. We do not have any major critiques about how disaster scenarios are developed in the case studies we reviewed except to say that greater attention should be paid to properly assigning probabilities to each scenario when multiple scenarios are included. This mainly applies to mitigation and preparedness stage problems. Not infrequently, scenarios are given equal chance of occurrence. Clearly, more scientific approaches are needed, perhaps involving interdisciplinary methods.

5.3.2. Integration with Information Systems

In the context of EOM, information systems are invaluable for providing accurate data to all relevant actors and area experts involved in both pre-disaster mitigation and preparedness planning and post-disaster response and recovery activities. Usually, information systems are implemented using a combination of GIS software, remote sensing data, government databases, and other modern information technology systems. Such systems greatly enhance the decision making-process of EOM, including but not limited to relief chain coordination, search and rescue, evacuation, relief distribution, and debris clearance through better knowledge of where damage to buildings and infrastructure and location and needs of affected people. As with other reviews [12,17,26], we affirm the critical need for the development and deployment of user-friendly information systems in EOM, as well as the potential of OR methods to enhance the capabilities of such systems.

Especially important to enhancing the efficiency of humanitarian relief operations and guiding investment in preemptive measures to reduce earthquake risks is the availability of accurate real- and near real-time data. In more developed areas of the world, national- or regional-level earthquake information systems have been created, which provide access to real- and near real-time data for various types of analyses. An example of a near real-time system is Hazus, developed and maintained by the US Federal Emergency Management Agency (FEMA). Hazus integrates geographic and other types of data into a GIS-based software platform to estimate direct and indirect losses from hazards, including earthquakes [265]. A notable real-time data information system is Turkey's Rapid Earthquake Response System, which can estimate damage to facilities and the highway network across Istanbul following an earthquake through collection of data from pre-installed seismic sensors [208]. In the absence of centrally managed earthquake information systems, as is common in many least economically developed countries, open-source, online platforms that make use of Volunteered Geographic Information (VGI) have sometimes been relied up by government agencies and NGOs. Following the 2010 Haiti earthquake, for example, OpenStreetMap volunteers from around the world used satellite images to map the outlines of streets and buildings in the Port-au-Prince area. This effort was further supported by on-the-ground volunteers in Haiti who upload additional information using portable GPS devices [266]. We note that decentralized online and VGI systems like one used in Haiti are, in comparison to a centralized information system, less prone to being knocked out as a result of a large quake.

We observe that a number of OR studies in the EOM literature have made use of outputs from near real-time information systems as part of case studies, typically when defining earthquake scenarios and estimating damage and casualty levels (e.g., [156,186,243]). A key difficulty potentially inhibiting wider integration of real- and near real-time data into OR based decision support tools may be the considerable amount of data processing required to translate data contained in an information system into a format that can be readily inputted into an OR model. More importantly, vital pieces of information needed by OR models are often missing or incomplete (e.g., due to inability to assess on-the-ground conditions), which invariably impacts the quality and usefulness of OR model outputs. In the worst case, data gaps can render solutions infeasible (e.g., when a bridge is shown to be intact from satellite images but no longer capable of bearing vehicles above a critical weight). This is especially concerning when deriving solutions for early stage response. There have been some attempts to address this. Yagci Sokat et al. [207], for example, propose a framework to estimate incomplete information on the status of a network following a disaster. Although promising, a significant amount of time for manual collection and data transformation is still needed. Future studies could consider automating these processes to quickly provide essential data in an appropriate format that can be used by OR planning tools. Additionally, future research might look at new approaches for incorporating real-time data provided by UAVs, as well as social media or other user-generated data. Great use of UAVs in EOM would help to eliminate uncertainties about post-earthquake states by providing information to first responders and relief organization about which structures have been affected, the extent of damage, estimated numbers of people affected, the passability of roads, and so on, thus improving damage assessment, search and rescue, evacuation, relief distribution, and restoration activities. Similarly, social media data may be useful for quickly identifying the needs of victims and improving situational awareness of emergency response and relief efforts. However, given obvious concerns about the accuracy of such data, there is a clear need for formal frameworks to determine the best way of integrating social-media with more conventional data sources [197]. Finally, future research might look to move beyond the traditional paradigm of having a separate information system that subsequently feeds into standalone OR models for carrying out analyses. We believe there is enormous potential for greater integration of OR methods into real- and near real-time earthquake data information systems, either directly through collaboration with government agencies and NGOs or possibly by developing add-on modules for more widely used systems (e.g., OpenStreetMap).

6. Conclusions

To the best of our knowledge, this review is the first attempt at investigating the use of OR techniques specifically for EOM. Given that we limited our review to studies dealing with earthquake-oriented problem definitions or those involving the use of earthquake disaster case studies, our review stands apart from past and recent DOM review papers. Throughout, we have taken care to precisely categorize studies based on the disaster stage(s) being dealt with, methodology(ies) applied, and specific planning/operational problem type. We also provide details about the extent of stakeholder involvement and information relating to case studies (i.e., type of infrastructure network examined, if any, and whether real or randomly generated data were used). Basic findings are that most research has focused on a single EOM disaster stage, with preparedness and response problems receiving by far the most attention. More recent work has begun to look at the integration of two or more disaster stages. In terms of modeling and solution methodology, mathematical programing and heuristics are by far the most widely used for most problem types, though there are exceptions. Finally, most studies have little or no stakeholder involvement.

Based on our extensive analysis, we have identified current gaps in the field and outlined a roadmap for future research to enhance the real-world applicability of OR methods applied to EOM in particular and potentially to DOM more generally. Some of these reaffirm findings and recommendations derived in previous surveys on OR applied to DOM, like the need for (i) more integrated planning that involves decision making across multiple disaster stages, such as shelter site location and RDC pre-positioning and inventory management (preparedness) combined with evacuation and relief distribution (response) or infrastructure protection planning (mitigation) combined with infrastructure restoration (recovery); (ii) more emphasis on and enabling of stakeholder and multi-agency coordination; (iii) integration of OR methods with information systems that provide real- and near real-time data, including the use of data provided by UAVs and social media; (iv) defining clear and realistic model inputs/assumptions; and (v) greater use of multi-methodology and interdisciplinary approaches, including behavioral OR to more accurately represent human behavioral responses.

Other recommendations we provide, however, are new or much less emphasized in previous reviews. Speaking broadly, we observe that in many studies, problem specifications are framed in terms of generic disasters as opposed to being specifically focused on earthquakes. This has resulted in a general failure to address the importance of cascading effects and secondary disasters caused by aftershocks. We also highlight the frequent lack of stakeholder involvement in problem identification and methodological approach, leading to less realistic problem definitions and uptake by practitioners. We argue that stakeholder involvement from the beginning and the use of Soft OR for problem structuring and conceptual modeling would help ensure that any Hard OR methods being developed are well-grounded within a stakeholder perspective. While the value of integrating OR methods with real- and near real-time information systems has been highlighted previously, we point out the challenges of this vis-à-vis the significant amount of data processing involved and, more critically, the problem of dealing with missing and incomplete data. We also observe that case studies could be improved by better data generation and earthquake scenario development, for example defining data inputs appropriate to the spatial scale being analyzed and more precisely assigning probabilities to earthquake scenarios.

Finally, looking at a few specific EOM problems, additional observations and recommendations include: (i) the overly narrow focus on transport systems in the context of critical infrastructure protection and the need for better integration with reliability and vulnerability assessment as well as adopting a more multi-methodological approach involving the use of seismic risk assessment and earthquake engineering; (ii) the need for further investigation of inventory holding and stock replenishment policies as part of relief pre-positioning, including the importance of distinguishing between perishable and non-perishable goods; (iii) the general lack of consideration regarding external suppliers as part of RDC location and inventory planning, and (iv) the very limited amount of research looking at medical services allocation and scheduling as part of the response phase to minimize fatalities.

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APPENDICES

Appendix A. Details of mathematical programing and heuristic approaches for relief distribution problems.

Reference	Decision(s)			Objective(s)	Case Study
	Logistics activities	Goods	Mode of transport		
Najafi et al. [151]	RDC-AA	Multi	Multi	Minimize unserved injured people, unmet demand, and number of vehicles required	-
Mohammadi et al. [152]	ES-RDC-AA	Single	Multi	Minimize set-up and transport costs of relief, transport cost of injured, variability in transport cost (both) and transport time (both)	2017 Iran-Iraq earthquake
Khalilpourazari et al. [153]	LCC-CW-RDC-AA	Single	Multi	Minimize set-up, procurement, transport and holding costs and transport time of blood and transport cost and time of injured	2017 Iran-Iraq earthquake
Mansoori et al. [154]	RDC-AA	Multi	Multi	Minimize unmet demand for relief and number of people not evacuated to shelters or hospitals	Tehran, Iran
Fereiduni et al. [155]	ES-RDC-AA	Multi	Single	Minimize transport, operation, holding and evacuation costs	Tehran, Iran
Liu & Guo [167]	ES-RDC-AA	Multi	Multi	Maximize min. fill rate, fill rate difference and set-up, procurement and transport costs	2008 Wenchuan earthquake
Sabouhi et al. [168]	RDC-AA	Single	Single	Minimize transport time of relief and evacuees to shelters	Tehran, Iran
Liu et al. [170]	RDC-AA	Multi	Multi	Minimize total weighted unmet demand	2008 Wenchuan earthquake
Baharmand et al. [171]	CW-RDC-AA	Multi	Multi	Minimize operating, staff and transport costs, response time and unmet demand	2015 Nepal earthquake
Safaei et al. [172]	ES-CW-RDC-AA	Multi	Single	Minimize set-up, procurement, holding and transport costs, unmet demand and supply risk	Mazandaran, Iran
Khare et al. [173]	RDC-AA	Multi	Multi	Minimize transport cost and unmet demand	2015 Nepal earthquake
Hosseini-Motlagh et al. [174]	CW-RDC-AA	Multi	Single	Minimize procurement, holding and wastage costs of blood, set-up cost of emergency shelters and expected unmet demand for blood	Kermanshah, Iran
Gao [175]	RDC-RDC	Multi	Multi	Minimize supply shortages and transport time	2008 Sichuan earthquake
Baharmand et al. [176]	ES-RDC-AA	Multi	Multi	Minimize transport and staff/non-staff operating costs	2015 Nepal earthquake
Fazli-Khalaf et al. [177]	LCC-CW-RDC-AA	Single	Multi	Minimize set-up, blood collection/testing and fixed/variable transport costs and transport time and maximize reliability of testing	2003 Bam earthquake
Vitoriano et al. [178]	RDC-AA	Single	Multi	Minimize transport cost, max. response time, unmet demand and max. unmet demand and maximize route link reliability & security	2010 Haiti earthquake
Camacho-Vallejo et al. [179]	ES-RDC-AA	Multi	Multi	Minimize response time and transport cost	2010 Chile earthquake
Cao et al. [180]	RDC-AA	Multi	Multi	Minimize set-up and processing costs, task completion time and carbon emissions	-
Zhang et al. [181]	RDC-AA	Multi	Multi	Minimize expected response time, transport cost and unmet demand	2008 Wenchuan earthquake

Ferrer et al. [182]	RDC-AA	Single	Multi	Minimize transport cost, max. response time, unmet demand and max. unmet demand and maximize route link reliability & security	2010 Haiti earthquake
Hu et al. [183]	RDC-AA	Multi	Single	Maximize overall utility of relief and min. utility satisfaction rate	2008 Wenchuan earthquake
Balcik [184]	RDC-AA	Single	Single	Maximize min. coverage ratio	2011 Van earthquakes
Cao et al. [185]	CW-RDC-AA	Multi	Single	Maximize min. satisfaction at each response substage and minimize max. deviation in satisfaction at each substage and across substages	2008 Wenchuan earthquake
Lin et al. [186]	RDC-AA	Multi	Single	Minimize unmet demand, response time, transport cost and maximize equity	1994 Northridge earthquake
Wang & Sun [187]	RDC-AA	Multi	Single	Minimize fixed/variable transport costs and unmet demand	2013 Ya'an earthquake
Lei et al. [188]	RDC-AA	Single	Single	Minimize tardiness of medical operations	2011 Tōhoku earthquake
Nedjati et al. [189]	RDC-AA	Single	Single	Minimize unmet demand and response time	-
Vahdani et al. [190]	CW-RDC-AA	Multi	Multi	Minimize set-up, holding, unused inventory and transport costs, vehicle travel time and route reliability	-
Xiong et al. [191]	CW-RDC-AA	Single	Multi	Minimize response time and max. response time	-
Rezaei et al. [192]	RDC-AA	Single	Multi	Minimize unmet demand and variability in unmet demand	Yazd City, Iran
Nolz et al. [193]	RDC-AA	Single	Single	Minimize victim travel distance, unmet demand, transport cost and max. response time	Manabí, Ecuador
Zahedi et al. [194]	RDC-AA	Multi	Multi	Minimize procurement and transport costs and unmet demand	2017 Iran-Iraq earthquake
Bruni et al. [195]	RDC-AA	Single	Single	Minimize waiting time and variability in waiting time	2010 Haiti earthquake
Hu et al. [196]	ES-RDC-AA	Multi	Multi	Minimize vehicle rental, transport and handling costs and unmet demand	2013 Ya'an earthquake
Kirac & Bennett [197]	RDC-AA	Single	Single	Maximize accurate satisfied demand	2010 Haiti earthquake
Chang et al. [198]	RDC-AA	Single	Multi	Minimize unmet demand, response time and transport cost	1999 Chi-Chi earthquake
Zheng et al. [199]	RDC-AA	Multi	Multi	Minimize response time and unmet demand	2013 Dingxi earthquake
Ferrer et al. [200]	RDC-AA	Single	Multi	Minimize fixed/variable transport costs, response time and unmet demand and maximize equity and route link reliability & security	2010 Haiti earthquake
Penna et al. [201]	RDC-AA	Single	Multi	Minimize transport cost	2010 Haiti earthquake
Liu et al. [202]	RDC-AA	Multi	Multi	Maximize expected fill rate and minimize set-up, procurement and transport costs	2008 Wenchuan earthquake
Ma et al. [203]	RDC-AA	Multi	Single	Minimize unmet demand for blood products	2008 Wenchuan earthquake
Wang et al. [204]	RDC-AA	Multi	Multi	Minimize set-up and transport costs and max. response time and maximize min. route reliability	2008 Wenchuan earthquake

Appendix B: List of studies which are either focus on earthquakes in their problem description or have partial or significant stakeholder involvement.

Study	Focus on Earthquakes	Stakeholder Involvement		
		No involvement	Partial involvement	Significant involvement
Mitigation Stage				
Bagheri et al. [37]	✓	✓		
Sun & Chen [38]	✓	✓		
Li et al. [39]	✓	✓		
Feng et al. [40]	✓	✓		
Sun et al. [42]	✓	✓		
Chang et al. [43]	✓		✓	
Gertsbakh & Shpungin [44]	✓	✓		
Jin & Wang [45]	✓	✓		
Dadfar et al. [47]	✓	✓		
King et al. [48]	✓		✓	
Nabian & Meidani [49]	✓	✓		
Sinaga et al. [50]	✓	✓		
Akin et al. [51]	✓	✓		
Cankaya et al. [52]	✓		✓	
Moradi et al. [53]	✓		✓	
Kumlu & Tudes [54]	✓		✓	
Yariyan et al. [55]	✓			✓
Ahmad et al. [56]	✓	✓		
Akpabot et al. [57]	✓	✓		
Carreño et al. [58]	✓		✓	
Tayfur & Bektas [59]	✓	✓		
Piscini et al. [60]	✓	✓		
Alizadeh et al. [61]	✓			✓
Janalipour & Taleai [62]	✓	✓		
Mangalathu et al. [63]	✓	✓		
Sadrykia et al. [64]	✓			✓
Ranjbar & Nekooie [65]	✓			✓
Aghamohammadi et al. [66]	✓	✓		
Gul & Guneri [67]	✓		✓	
Ikram & Qamar [68]	✓	✓		
Asim et al. [69]	✓	✓		
Zolfaghari & Peyghaleh [72]	✓	✓		
Aydin [74]	✓		✓	
Chu & Chen [75]	✓		✓	
Döyen & Aras [76]	✓	✓		
Edrissi et al. [77]	✓	✓		
Preparedness Stage				
Görmez et al. [79]	✓			✓
Khojasteh & Macit [81]	✓	✓		
Paul & Wang [82]	✓	✓		
Boostani et al. [84]	✓		✓	
Rezaei et al. [85]	✓		✓	
Chen & Wang [86]	✓	✓		
Salehi et al. [87]	✓		✓	
Cavdur et al. [88]	✓		✓	
Noyan et al. [90]	✓	✓		
Charles & Lauras [91]			✓	
Bozorgi-Amiri et al. [92]			✓	
Mahootchi & Golmohammadi [93]	✓		✓	
Lejeune [94]			✓	

Saeidian et al. [96]	✓				✓		
Salman & Yucel [97]				✓			
Molladavoodi et al. [98]	✓			✓			
Haghi et al. [99]	✓		✓				
Ghasemi et al. [100]	✓	✓					
Saeidian et al. [102]	✓				✓		
Verma and Gaukler [103]	✓		✓				
Xing [104]	✓					✓	
Paul & MacDonald [105]	✓		✓				
Javadian et al. [106]				✓			
Mohammadi et al. [107]	✓					✓	
Tofighi et al. [108]	✓		✓				
Bell et al. [109]	✓		✓				
Acar et al. [110]	✓		✓				
Battarra et al. [112]	✓					✓	
Yang et al. [113]	✓			✓			
Das & Hanoka [114]	✓		✓				
Xu et al. [115]				✓			
Cimellaro et al. [116]	✓					✓	
Gul et al. [117]	✓			✓			
Shavarani et al. [118]	✓		✓				
Bayram et al. [120]				✓			
Bayram & Yaman [121]				✓			
Trivedi & Singh [122]	✓					✓	
Zhao et al. [125]	✓			✓			
Hu et al. [126]	✓	✓					
Xu et al. [127]	✓				✓		
Preece et al. [128]	✓						✓
Rafiei et al. [129]	✓		✓				
Srivichai et al. [130]	✓		✓				
Kuyuk et al. [131]	✓		✓				
Mase et al. [132]	✓		✓				
Li et al. [133]	✓		✓				
Mousavi et al. [134]	✓		✓				
Chin et al. [135]	✓				✓		
Lee at al. [136]	✓		✓				
Oliveira et al. [137]	✓				✓		
Wang et al. [138]	✓		✓				
Mulia et al. [139]	✓				✓		
Oth et al. [140]	✓		✓				
Response Stage							
Bai et al. [142]	✓	✓					
Kim et al. [143]	✓	✓					
Schweier & Markus [144]	✓					✓	
Chu & Zhong [146]	✓		✓				
Ahmadi et al. [147]	✓		✓				
Chaudhuri & Bose [148]	✓			✓			
Zheng et al. [149]	✓		✓				
Najafi et al. [151]	✓		✓				
Mohammadi et al. [152]	✓		✓				
Khalilpourazari et al. [153]	✓			✓			
Mansoori et al. [154]	✓			✓			
Mills et al. [156]				✓			
Caunhye & Xie [157]	✓					✓	
Oksuz & Satoglu [158]				✓			

Kilci et al. [159]	✓			✓		
Pérez-Galarce et al. [160]	✓		✓			
Forcael et al. [161]	✓		✓			
Chen et al. [162]	✓		✓			
Liu [164]	✓		✓			
Ozbay et al. [166]	✓		✓			
Liu & Guo [167]	✓		✓			
Liu et al. [169]	✓					✓
Liu et al. [170]	✓			✓		
Baharmand et al. [171]	✓					✓
Safaei et al. [172]	✓			✓		
Hosseini-Motlagh et al. [174]	✓			✓		
Baharmand et al. [176]	✓					✓
Fazli Khalaf et al. [177]	✓			✓		
Camacho -Vallejo et al. [179]				✓		
Zhang et al. [181]				✓		
Ferrer et al. [182]				✓		
Balcik [184]				✓		
Lin et al. [186]	✓			✓		
Nedjati et al. [189]	✓		✓			
Vahdani et al. [190]	✓		✓			
Xiong et al. [191]	✓		✓			
Rezaei et al. [192]	✓		✓			
Zahedi et al. [194]	✓			✓		
Penna et al. [201]	✓					✓
Liu et al. [202]	✓		✓			
Wang et al. [204]	✓		✓			
Xu et al. [205]	✓					✓
Sheu [206]	✓		✓			
Yagci et al. [207]	✓					✓
Recovery Stage						
Kasaei & Salman [208]	✓	✓				
Hu & Sheu [210]	✓			✓		
Onan et al. [212]				✓		
Hwang et al. [214]				✓		
González et al. [215]	✓		✓			
Caunhye et al. [216]	✓		✓			
Nozhati et al. [218]	✓		✓			
Yan et al. [220]	✓		✓			
Yan et al. [221]				✓		
Yan et al. [222]				✓		
Longman & Miles [225]				✓		
Luna et al. [226]	✓			✓		
Gosavi et al. [227]	✓			✓		
Integrated Stages						
Hu et al. [236]	✓		✓			
Yucel et al. [237]					✓	
Edrissi et al. [240]	✓		✓			
Salman & Gul [228]					✓	
Mohamadi & Yaghoubi [234]	✓				✓	
Ni et al. [241]	✓		✓			
Mete & Zabinsky [229]	✓				✓	
Bozorgi et al. [230]					✓	
Ahmadi et al. [231]	✓		✓			

Golabi et al. [232]			✓
Sahebjamnia et al. [235]			✓
Fereiduni et al. [233]	✓	✓	
Xu et al. [245]	✓		✓
Yan & Shih [246]	✓	✓	
Sakuraba et al. [247]	✓	✓	
Li & Teo [248]	✓	✓	

Appendix C. Details of applied case studies involving the use of infrastructure network data.

Study	Earthquake Scenario	Infrastructure Type		
		Transportation	Electricity	Water
Mitigation Stage				
Bagheri et al. [37]	W/ERS			Real
Li et al. [39]	Random		Real	
Günneç & Salman [41]	W/ERS	Real		
Jin & Wang [45]	W/ERS			Real
Mohaymany et al. [46]	Random	Random		
Dadfar et al. [47]	W/ERS			Real
King et al. [48]	W/ERS			Real
Nabian & Meidani [49]	W/ERS	Real		
Peeta et al. [70]	W/ERS	Real		
Lu et al. [71]	Random	Random		
Liberatore et al. [73]	W/ERS	Real		
Aydin [74]	W/ERS	Real		
Chu & Chen [75]	W/ERS	Real		
Döyen & Aras [76]	Random	Random		
Edrissi et al. [77]	W/ERS	Random		
Preparedness Stage				
Görmez et al. [79]	W/ERS	Real		
Zokaee et al. [80]	Random	Real		
Khojasteh & Macit [81]	W/ERS	Real		
Paul & Wang [82]	W/ERS	Real		
Rahafrooz & Alinaghian [83]	Random	Random		
Boostani et al. [84]	Random	Real		
Rezai et al. [85]	W/ERS	Real		
Chen & Wang [86]	Random	Real		
Salehi et al. [87]	W/ERS	Real		
Cavdur et al. [88]	W/ERS	Real		
Yahyaei & Bozorgi-Amiri [89]	W/ERS	Real		
Noyan et al. [90]	W/ERS	Real		
Bozorgi-Amiri et al. [92]	W/ERS	Real		
Mahootchi & Golmohammadi [93]	W/ERS	Real		
Renkli & Duran [95]	W/ERS	Real		
Salman & Yucel [97]	W/ERS	Real		
Molladavoodi et al. [98]	W/ERS	Real		
Ghasemi et al. [100]	W/ERS	Real		
Lu [101]	Random	Random		
Saeidian et al. [102]	W/ERS	Real		
Verma & Gaukler [103]	Random	Real		
Paul & MacDonald [105]	W/ERS	Real		
Mohammadi et al. [107]	W/ERS	Real		
Tofighi et al. [108]	W/ERS	Real		
Bell et al. [109]	Random	Real		
Acar et al. [110]	W/ERS	Real		
Yang et al. [113]	W/ERS	Real		
Xu et al. [115]	W/ERS	Real		
Shavarani et al. [118]	W/ERS	Real		
Coutinho-Rodrigues et al. [119]	Random	Real		
Bayram et al. [120]	W/ERS	Real		
Bayram & Yaman [121]	W/ERS	Real		
Trivedi & Singh [122]	W/ERS	Real		
Kınay et al. [123]	W/ERS	Real		
Kınay et al. [124]	W/ERS	Real		
Xu et al. [127]	W/ERS	Real		
Response Stage				
Ahmadi et al. [147]	W/ERS	Real		
Najafi et al. [151]	Random	Random		
Mohammadi et al. [152]	W/ERS	Real		
Khalilpourazari et al. [153]	W/ERS	Real		
Mansoori et al. [154]	Random	Real		
Caunhye & Nie [157]	W/ERS	Real		
Oksuz & Satoglu [158]	W/ERS	Real		
Kilci et al. [159]	Random	Real		

Pérez-Galarce et al. [160]	Random	Real		
Forcael et al. [161]	Random	Real		
Liu [164]	W/ERS	Real		
Liu & Guo [167]	Random	Real		
Sabouhi et al. [168]	Random	Real		
Liu et al. [170]	W/ERS	Real		
Baharmand et al. [171]	W/ERS	Real		
Safaei et al. [172]	W/ERS	Real		
Khare et al. [173]	W/ERS	Real		
Hosseini-Motlagh et al. [174]	W/ERS	Real		
Gao [175]	Random	Real		
Baharmand et al. [176]	W/ERS	Real		
Fazli Khalaf et al. [177]	Random	Real		
Vitoriano et al. [178]	W/ERS	Real		
Camacho -Vallejo et al. [179]	W/ERS	Real		
Cao et al. [180]	W/ERS	Real		
Zhang et al. [181]	Random	Real		
Ferrer et al. [182]	W/ERS	Real		
Hu et al. [183]	W/ERS	Real		
Balcik [184]	W/ERS	Real		
Cao et al. [185]	W/ERS	Real		
Lin et al. [186]	W/ERS	Real		
Wang & Sun [187]	W/ERS	Real		
Lei et al. [188]	W/ERS	Real		
Nedjati et al. [189]	Random	Random		
Vahdani et al. [190]	Random	Random		
Xiong et al. [191]	Random	Real		
Rezaei et al. [192]	W/ERS	Real		
Zahedi et al. [194]	W/ERS	Real		
Bruni et al. [195]	W/ERS	Real		
Hu et al. [196]	W/ERS	Real		
Chang et al. [198]	W/ERS	Real		
Zheng et al. [199]	W/ERS	Real		
Penna et al. [201]	W/ERS	Real		
Liu et al. [202]	Random	Real		
Wang et al. [204]	W/ERS	Real		
Xu et al. [205]	Random	Real		
Yagci et al. [207]	W/ERS	Real		
Recovery Stage				
Kasaei & Salman [208]	W/ERS	Real		
Tüzün Aksu & Özdamar [209]	Random	Real		
Hu & Sheu [210]	W/ERS	Real		
Özdamar et al. [211]	Random	Real		
Ajam et al. [213]	W/ERS	Real		
González et al. [215]	W/ERS		Real	Real
Caunhye et al. [216]	Random	Real		
Smith et al. [217]	Random		Real	Real
Nozhati et al. [218]	W/ERS		Real	
Yan et al. [220]	Random	Real		
Yan et al. [221]	Random	Real		
Yan et al. [222]	Random	Real		
Rey & Bar-Gera [223]	Random	Real		
Luna et al. [226]	W/ERS			Real
Gosavi et al. [227]	Random	Real		
Integrated Stages				
Hu et al. [236]	W/ERS	Real		
Yucel et al. [237]	W/ERS	Real		
Edrissi et al. [240]	Random	Random		
Salman & Gul [228]	W/ERS	Real		
Mohamadi & Yaghoubi [234]	W/ERS	Real		
Ni et al. [241]	W/ERS	Real		
Mete & Zabinsky [229]	W/ERS	Real		
Bozorgi et al. [230]	W/ERS	Real		
Ahmadi et al. [231]	Random	Real		
Golabi et al. [232]	W/ERS	Real		
Sahebjamnia et al. [235]	Random	Real		
Fereiduni et al. [233]	Random	Real		

Çelik et al. [243]	W/ERS	Real
Liberatore et al. [244]	W/ERS	Real
Xu & Song [245]	Random	Real
Yan & Shih [246]	Random	Real
Sakuraba et al. [247]	W/ERS	Real
Li & Teo [248]	Random	Real

* W/ERS: With external resource support based on expertise advice or technical reports.