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Review

Humanitarian facility location under uncertainty: Critical review and future prospects☆

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ABSTRACT

This paper provides a comprehensive review of the research done on facility location problems under uncertainty in a humanitarian context. The major goal is to summarize and help structuring this topic, which has increasingly attracted the attention of the scientific community. The literature is reviewed from different perspectives namely, in terms of the type of facilities involved, the decisions to make, the criteria to optimize, the paradigm used for capturing uncertainty, and the solution method adopted. The detailed analysis provided in the manuscript also contributes to identifying the distinguishing features of the problems in the topic. An outcome of the state-of-the-art presented is the identification of the current research trends, expectations and holes in the existing knowledge thus highlighting relevant research directions.

1. Introduction

Location Science is a well-established research area with a wide range of applications (Laporte et al. [70]). Since the 1960s, much work has been done in the topic, which is attested by the extensive literature of which we can mention a few review papers and books such as Daskin [28], Eiselt and Marianov [34], Melo et al. [82], ReVelle and Eiselt [116], ReVelle et al. [117], and Smith et al. [134].

Facility location problems can be classified according to different aspects such as the location space (continuous, on network, discrete), the type of objective functions (median, covering, center), the application (telecommunications, logistics, transportation, health care, etc.), the nature of the data (deterministic, robust, stochastic), etc.

Two important research streams are strongly intertwined: facility location under uncertainty and logistics network design. Although they have grown independently we have observed a clear increase in the work devoted to problems that merge them.

The role of facility location in logistics and supply chain management has been recognized a long time ago (see, e.g., the review article by Klose and Drexl [67]). Nevertheless, due to new challenges such as those emerging from a strong economic globalization, the Industry 4.0 and the Internet-of-Things, it keeps being a very fruitful research field (see, e.g., Dunke et al. [32] and the references therein). The relevance of capturing uncertainty in the context of facility location is also a research direction far from new. In the book chapter by Correia and Saldanha-da-Gama [25] the reader can get an overview and directions for specific research lines within this area. The topic has become more relevant than ever due to unpredictable aspects that may affect the decisions made (e.g., floods, terrorist attacks, pandemics etc.).

One particular area of logistics that has attracted much attention is that of humanitarian logistics, i.e., the efficient and cost-effective planning, implementation and control of the flow and storage of goods/materials and the related information from the point of origin to the point of destination for the purpose of alleviating the suffering of vulnerable people (Thomas and Kopczak [137]). The development of humanitarian logistics has led more recently to the concept of humanitarian supply chain (see, e.g., Kara and Rancourt [59]) and to that of humanitarian operations. It is within this context that, again, facility location in general and facility location under uncertainty in particular play a major role as we make clear in this paper.

Contrary to many concepts in facility location, those in the context of humanitarian operations are relatively new. Nevertheless, in the past 20 years, much work has been done. In fact, we can find several review papers summarizing this work. The interested

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reader can refer to Altay and Green [6], Leiras et al. [71], Minas et al. [84], Natarajarathinam et al. [90], Peres et al. [103], and Simpson and Hancock [133].

Narrowing our scope by considering the review papers that involve facility location decisions, we start by quoting the work by Caunhye et al. [20] which reviews the literature on disaster logistics by categorizing works according to the decisions to make, namely: (i) facility location, (ii) transportation (relief distribution or casualty transportation), and (iii) other operations. Existing work is also categorized according to the objectives and constraints, the nature of the data (deterministic versus uncertain), the nature of time (single- versus multi-period), the number of layers in the network (single- versus multi-layer) and the number of objectives (single versus multicriteria).

Anaya-Arenas et al [8] present a survey of the literature focusing on relief distribution networks. Again, location decisions are included in the categorization provided by the authors, who also detail the number of depots (single versus multiple), the nature of time (single- versus multi-period) and the number of depots (single versus multiple).

Habib et al. [42] published a survey on humanitarian supply chain management, in which they classify the existing models on facility location, relief distribution and mass evacuation according to objective function, constraints, the nature of data, the disaster phases and the solution techniques. Boonmee et al. [15] consider the existing work on facility location problems in disaster management applications including deterministic, dynamic, stochastic and robust facility location problems. The authors also analyze the articles according to facility type, data modeling type, disaster type, decisions, objectives, constraints, and solution methods.

The rich set of articles above quoted show much work done on humanitarian logistics under a deterministic setting. Nevertheless, uncertainty aspects have also captured the attention of the scientific community, although in a smaller scale. Specific reviews in the topic include Liberatore et al. [76] who cover the existing work on disaster logistics management under uncertainty. The literature is categorized according to the disaster phase, the nature of the uncertainty, the objective function, and the methodology used. Several sources of uncertainty are identified, namely: demand level, demand location, supply, affected areas, and transportation network. Methodologically, the distinction is made in terms of risk mapping as well as in terms of the modeling frameworks adopted: stochastic programming, robust optimization, simulation models, and fuzzy sets. Unfortunately, the existing literature at the time also shows that the studies mostly fail when it comes to the real-life applications.

Another paper relevant to mention here is that by Hoyos et al. [48], who focus on work published between 2006 and 2012 regarding disaster logistics under uncertainty. The authors emphasize the increasing interest in the field which they explain by the increasing number of disasters and their effects, which are also scaling up. They detail the models and methods employed such as mathematical programming, simulation, probability and statistical models, and decision theory. Facility location problems are examined in the section devoted to mathematical programming along with the resource allocation, relief distribution, casualty transportation and search & rescue operations. The authors also conclude that the probability of occurrence of a disaster and its magnitude are the sources of uncertainty that have been mostly accounted for.

The existing literature on humanitarian logistics show that facility location is one of the fundamental and most encountered problems in disaster management. Furthermore, as also discussed above, upon the occurrence of a disaster there are many sources of uncertainty. This gives much relevance to facility location under uncertainty in the context of humanitarian logistics. This has been somehow recognized in the literature looking into the significant work focusing specifically on such area. Nevertheless, the literature is rather scattered and has not been summarized so far.

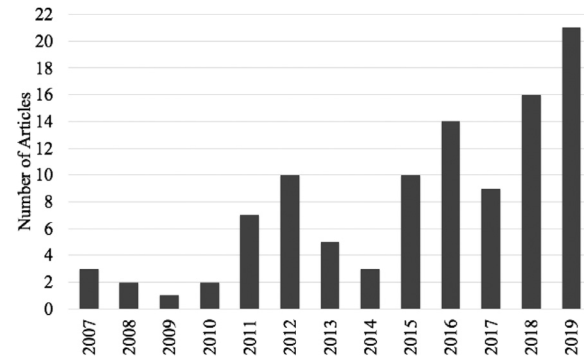

Fig. 1. Number of articles per year.

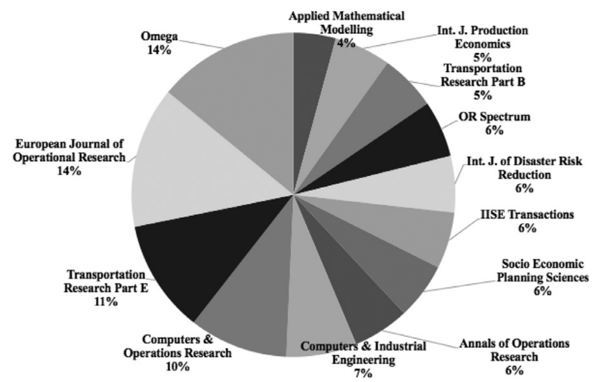

Fig. 2. Percentage of works per journal.

In the current paper we review the topic of facility location under uncertainty in the context of humanitarian logistics. We review the existing work published in 2007–2019, focusing on several aspects such as the type of facilities required, the decisions to make, the sources of uncertainty, the paradigm for capturing uncertainty, and the solution methods adopted. We also highlight the close relationship between some of these categories, i.e., the literature is analyzed in a multi-dimensional perspective. To the best of the authors' knowledge, this has never been done in the topic we are discussing.

The purpose of this review paper is to provide the reader with an overview of the topic and also to suggest several directions and trends for future work. We note that the perspective presented in this work is that of OR and its role in the development of quantitative approaches for better decision making support in humanitarian logistics. Therefore, our analysis focuses exclusively in OR models and methods that have been used in the literature.

We considered the literature available in the Web of Science. The keywords used in the search included: "facility location under uncertainty", "humanitarian logistics", "stochastic location", "facility location in disaster response", "disaster management under uncertainty". We restricted our search to the years 2007–2019 in the categories "Operations Research Management Science", "Engineering Industrial" and "Management". In total, we found 103 articles, 2 book chapters, 2 conference papers and 1 technical report of relevance to our analysis. Fig. 1 depicts the number of articles included in our search published per year in scientific journals with peer review. In Fig. 2 we present the distribution of the relevant works across the scientific journals where at least three papers involved in our analysis were published. We note that Omega—The International Journal of Management Science, European Journal of Operational Research, Transportation Research Part E—Logistics and

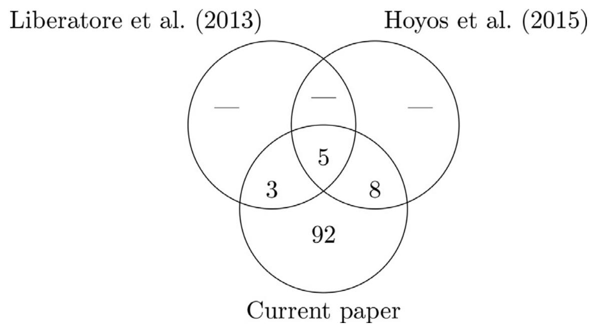

Fig. 3. Works involving location decisions and uncertainty in the context of humanitarian logistics.

Transportation Review, and Computers & Operations Research are the top four journals gathering in total approximately 50% of the work relevant to our review.

In Fig. 3 we provide a comparison between the current work and the other two review papers that cover uncertainty aspects in the context of disaster logistics management namely, Hoyos et al. [48] and Liberatore et al. [76]. In this figure we emphasize the overlapping (or its absence) in terms of the works that consider location decisions.

As we can observe, in our current paper, 92 works are reviewed that were not considered in the other two papers either because these works were still not published at the time or because they were out-of-scope.

The remainder of this paper is organized as follows: In Section 2 we detail the framework of our analysis. In Section 3 we discuss the type of facilities involved in the problems we are covering. Section 4 focuses on the sources of uncertainty that typically emerge in humanitarian logistics and that must be taken into account when making location decisions. The following section (Section 5) discusses all the aspects of relevance when considering an optimization model as well as the methodologies that have been proposed for tackling the models. Finally, we end the paper with some conclusions and insights driven from the analysis presented.

2. Framework of the analysis

As we have mentioned in the previous section, we are reviewing the existing work on facility location under uncertainty focusing on humanitarian settings. We categorize and synthesize that work. This is accomplished by identifying and classifying common modeling aspects and solution methods. In turn, this discloses areas that have been relatively overlooked, which leads to new research directions. In the proposed categorization we consider three major aspects: (i) sources of uncertainty, (iii) modeling framework(s) adopted, and (iii) solution technique(s) used.

Fig. 4 summarizes some aspects of relevance in our analysis namely, those related with the sources of uncertainty and the decisions made. We recall our focus: facility location under uncertainty. Hence, the need to make location decisions under an uncertainty setting is common to all the reviewed work. Nevertheless, it is important to identify the facility(ies) type(s) required by a specific context as well as the relevant sources of uncertainty. This triggers a major categorization that we discuss in depth in Sections 3 (facilities types) and 4 (sources of uncertainty).

Regarding the modeling framework adopted, we distinguish between the decisions to make and the objective(s) underlying the problem.

In the first case—decisions to make—two major groups can be considered: decisions related with pre-positioning of commodities (holding the inventory of items to be distributed) and decisions related with the shipment of humanitarian services/commodities to those in need. Regarding the latter we distinguish between direct allocation— a customer is directly served by a facility— and routing—each customer is part of a service route to be defined.

Concerning the criteria that have been considered in the literature that we are reviewing we find three major categories: cost, equity, and reliability objectives. In Section 5 these categories are discussed in depth.

When it comes to capturing uncertainty in optimization problems, three paradigms have become much popular: Stochastic Programming, Robust Optimization and Chance-Constrained Programming. The first emerges when uncertainty can be “quantified” using some joint cumulative distribution function assumed to be known (for instance estimated using historical data). Robust Optimization is a possibility when no probabilistic information is available for the underlying uncertainty (or it is impossible/irrelevant to obtain). In this case, we seek for a decision that is feasible for all possible future scenarios. Finally, Chance-Constrained Programming is adequate when uncertainty can be quantified probabilistically and some constraints exist that do not need to be satisfied with probability 1. In this case, the goal is to find a solution satisfying the probabilistic constraints (jointly or independently—depending on the specific problem investigated). In Section 5.3 these three paradigms are discussed in the context of the literature we are reviewing. Using the observations in Sections 5.1–5.3, a comprehensive modeling framework is established in Section 5.4. Exact and approximate algorithms to solve such models are reviewed in Section 5.5.

3. Types of facilities to be located

In humanitarian logistics, it is the occurring disaster and its consequences in terms of the needs of the affected areas that determine the adequate facilities for providing support. Some examples include temporary health centers (when primary health is required), distribution centers (when it is necessary to distribute items to an affected area), or shelters (when temporary settlement is required).

Facilities supporting humanitarian operations can be classified according to their function. We distinguish among 6 categories: (i) suppliers, (ii) distribution centers, (iii) points of distribution, (iv) shelters, (v) field hospitals, and (vi) blood centers. Interestingly, when reviewing the literature we observe facilities with the same function being called differently. In the Appendix—Electronic Supplement, Table S-1—we provide detailed information including the different types of facilities that have been considered and the references making use of them.

A natural consequence of having facilities with different functions is the possibility of having several layers in the network. Suppliers appear at the upper one. In most of the existing literature, suppliers are assumed to be already located. Nevertheless, in some cases, selecting the suppliers is itself part of the decision making process. This can be seen as a location decision. This is the case considered by Balcik [10], Hu and Dong [49], Hu et al. [51], Safaei et al. [120], Sawik [128,129], Torabi et al. [139] and Yu et al. [149]. Suppliers send the relief items to the distribution centers which, in turn, define the next layer in the network.

In the context of humanitarian logistics, a facility is called a distribution center (DC) if it is used to ship relief items to the populations in need. In the literature, such facilities have been called local depots, transfer depots, warehouses, storages, relief/rescue bases, recovery centers, stockpile locations, emergency/response/supply facilities.

The choice of facility type also depends on the mode of transportation to be adopted. Often, trucks are used to transport relief items via roads. However, as new technologies emerge, additional dynamics and decisions are being associated to the transportation mode(s). For instance, recently, drones have started to be used in distribution systems. In this case, the facilities to locate should have the capability of operating drones (Kim et al. [62]).

When people in need can travel from the affected areas and receive relief directly from a facility, the latter is called a point of distribution (POD) (Kara and Rancourt [59]). In this case, direct allocation decisions would be enough to inform individuals where to go to receive relief items. However, mobility of the disaster-victims is a strong assumption, which does not hold in many disaster events. If the located facilities are close enough to all the affected regions, determining PODs can be a practical solution to the distribution challenges. PODs are also called emergency/supply points and relief centers, which can be misleading since these terms do not differentiate PODs from DCs.

Shelter sites are the temporary settlements for the people in need due to a disaster or due to a refugee movement. They are typically capacitated facilities that enable people to maintain their life by providing electricity, a proper infrastructure, clean water, food, tents, medicine, closeness to health centers etc. (Kınay et al. [63]). Shelter site location is a well studied subject in humanitarian facility location (see Kara and Rancourt [59]). In some studies, shelters are also called emergency tents. Moreover, shelter sites have been designated by accommodation centers or evacuation centers. Some existing literature on shelter site location have considered uncertainty in demand, which is naturally triggered by the occurrence of unexpected disastrous events. This aspect has been dealt with by Kınay et al. [63,64].

Some papers investigate the use of existing distribution centers to support the shelter sites (see Kamyabniya et al. [57]) while others focus on locating both distribution centers and shelters. In the latter, the transportation of relief items from DCs to shelters is a decision to make in addition to the evacuation plan of people from the affected areas to the shelter sites. This possibility is studied by Dalal and Üster [26], Fereiduni and Shahanaghi [39], Ghasemi et al. [41], Mohamadi et al. [85], Rodríguez-Espíndola et al. [119] and Yahyaei and Bozorgi-Amiri [148]. Finally, we quote the paper by Mohamadi et al. [85] in which shelter sites and telecommunication towers are looked at as an integrated facility to ensure an adequate and fast information flow during a disaster.

Another facility type of interest in many humanitarian logistics applications is field hospitals, which have also been called health/care centers, medical shelters, or casualty collection points by different authors. Central and regional hospitals or other existing health facilities can (and should) be used for providing health services after a disaster. However, often they are not close enough to every affected population or area. In addition to this, they can also be disrupted by the disastrous event. Therefore, temporary health centers are alternative facilities that can be located in the aftermath of a disaster to ensure adequate health services. The reader can refer to Alizadeh et al. [5], Habibi-Kouchaksaraei et al. [43], Haghi et al. [44], Kamyabniya et al. [58], Liu et al. [77] and Zarrinpoor et al. [150] for works exploring this possibility. Jenkins et al. [54] studied staging facilities for aeromedical helicopters which can be considered as temporary health centers as well.

Blood logistics is a crucial component of health care management in general and of disaster management in particular. It requires planning for operations such as collecting, processing and distributing blood (see, for instance, Pirabán et al. [104] for further details). Hence, it is not surprising that planning for the location of facilities for this commodity may be of relevance in the context of emergency supply chains. However, such facilities have more specific roles when compared to field hospitals since they perform only blood-related operations. Therefore, they are not categorized as field hospitals but define a different category.

Looking over the literature we conclude that DCs are the most considered facility type in location problems within the scope of this survey. Out of 108 papers, 74 consider DCs location. In the years 2007–2013, almost 80% of the papers consider only the location of DCs. Among the reviewed articles, we observe that location of field hospitals has been studied since 2017 which shows that it is a relatively new subject. Similarly, location of blood facilities is mostly studied after 2014 in the context of relief logistics. Overall, 28% of the papers include capacity decisions for the located facilities while 18% of them locate more than one facility type. Among 22 papers with multi-type facility location, 19 have been published since 2016. In the Appendix (Electronic Supplement) we provide Table S-1 with the details of the works considering each type of facility and the exact terminology used.

In some of the reviewed articles, capacity decisions are part of the decision making process. Typically, for each installed facility its operating level is also to be decided and the corresponding fixed cost paid. This particular situation is also marked in Table S-1.

As we mentioned above, the existence of multiple facility types may call for different but interconnected facility layers in the resulting humanitarian logistics network.

Dalal and Üster [26], Fereiduni and Shahanaghi [39], Irohara et al. [52], Mohamadi et al. [85], Rodríguez-Espíndola et al. [119] and Yahyaei and Bozorgi-Amiri [148], investigate the location of both shelter sites and DCs. Noyan and Kahvecioğlu [95] and Pradhananga et al. [105] seek for the best selection of PODs and DCs. Haghi et al. [44] study the simultaneous location of field hospitals and DCs. Ghasemi et al. [41] select shelter sites along with

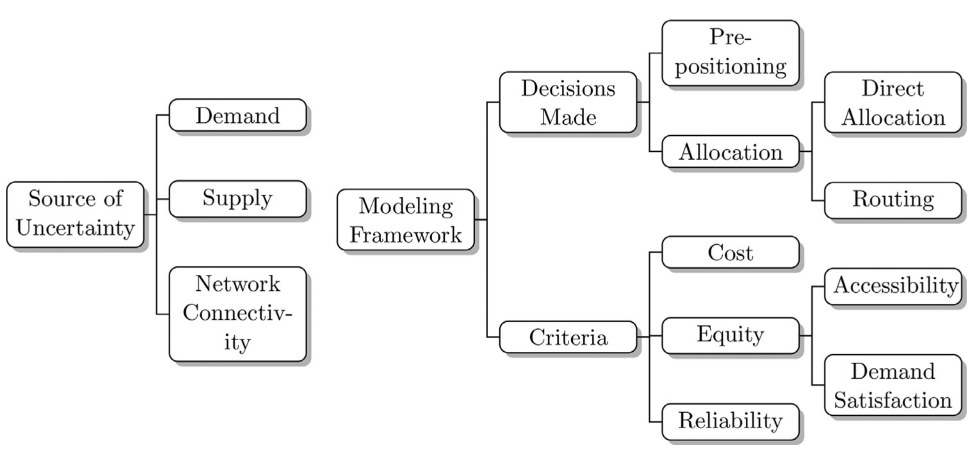

Fig. 4. Framework of the Analysis—sources of uncertainty and modeling framework.

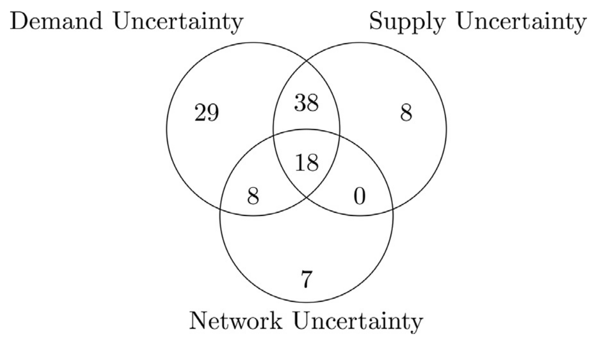

Fig. 5. Source of uncertainty: number of references reviewed.

the field hospitals. Finally, Habibi-Kouchaksaraei et al. [43] consider the location of both blood facilities and field hospitals.

To conclude this section, we emphasize the need for a more standardized terminology when it comes to refer to the functionality of the facilities supporting humanitarian operations. As we have made clear, this is currently not the case in the literature. Such standardization would allow a clearer definition of the problems and would help making a more structured analysis when it comes to the inclusion of other aspects such as those related with uncertainty.

4. Sources of uncertainty

As stated in Liberatore et al. [76], uncertainty is unavoidable when planning for a possible disaster. Compared to other applications of location analysis, uncertainty is intrinsic to many humanitarian facility location problems since disasters are inherently unpredictable events in terms of their timing, the affected areas and the magnitude. A challenge emerges from the need to cope simultaneously with unpredictable demand, short lead times, a very critical role of on time delivery with right amounts and limited resources (see, e.g., Balcik and Beamon [11]). One possibility for hedging against uncertainty is to capture it in the parameters underlying optimization models to support the decision making process. These parameters may appear on the receiver-side, on the provider-side or in the links in between (Álvarez-Miranda et al. [7]). Some examples include the location and amount of demand, the capacity of the suppliers, the connectivity of network, the transportation times (which likely impacts on the response time), and the costs.

In humanitarian logistics, coping with uncertainty becomes more challenging than in other applications due to the chaotic or unstructured setting typically associated with the post-disaster phase as well as the multiple stakeholder structure. Communication and transportation issues usually block information and material flow in the humanitarian network. Since facility location decisions are typically made at a strategic level (Owen and Daskin [97]), capturing uncertainty when making them may be decisive. Considering the above discussion we conclude that in context of humanitarian logistics we may face uncertainty: (i) from the demand side, (ii) from the supply side, and (iii) in terms of network connectivity. Next we discuss these three items in depth. In Fig. 5 we provide the global numbers in terms of the references reviewed. In the Appendix—Electronic Supplement, Table S-2—we specify the references falling in each category.

Remarkably most of the reviewed literature considers uncertainty in demand (either alone or combined with other sources of uncertainty). We observe that out of 35 reviewed articles that were published in 2007–2013, 19 (54%) consider a single uncertainty source while 12 (34%) capture two sources and others (12%) consider three sources. Combining at least two sources of uncertainty is a more recent research trend. In the period 2014–2019, 25 out of 73 papers (34%) consider a single source of uncertainty while 34 (46%) consider two sources and 14 consider three sources (20%). When it comes to combining the three major sources of uncertainty above identified we find 4 papers in the period 2007–2013 and 14 in 2014–2019.

4.1. Uncertainty in demand

Due to the unpredictable nature of disasters, the amount and location of people affected are likely to be unknown in advance. This is also the case with the exact amount of support per person that will be required, which is highly dependent on the type, magnitude and location of the epicenter of the disaster as well as on the vulnerability of the affected areas, just to mention a few factors.

Concerning the location and amount of the demand, the existing literature has often considered their prediction using geographic and demographic information along with forecasts on the disaster scale, epicenter, and timing. A specific location of demand can be predicted by calculating the distance between the area and the estimated epicenter of the disaster. This has been assumed by Li and Jin [73], Liu et al. [77], Mostajabdaveh et al. [88], Noyan [94], Noyan and Kahvecioğlu [95], Ozbay et al. [98], Paul and Zhang [102] and Rahafrooz and Alinaghian [106]. Regarding the amount of people affected by a disaster (and thus, the corresponding demand), it is usually assumed to be related (e.g. proportional) to the population area and to the scale of the disaster.

The vulnerability level of the potentially affected areas has also been taken into account by some authors for estimating the demand. This is the case in Bozorgi-Amiri and Khorsi [16], Bozorgi-Amiri et al. [18], Rahafrooz and Alinaghian [106], Safaei et al. [120] and Salehi et al. [122].

It is also worth noticing that the timing of the disaster can influence the demand at a certain location. For example, in working hours, the total population in some specific area or region may increase (e.g. in a business district). The estimation of demand level and location considering this aspect can be found in Mete and Zabinsky [83], Rezaei-Malek et al. [118] and Salehi et al. [122]. Other possibilities for estimating the location and amount of demand have been considered such as the use of experts' opinion (Habibi-Kouchaksaraei et al. [43], Kamyabniya et al. [58], Li et al. [74], Mohamadi et al. [85] and Torabi et al. [139]) or the use of historical data from previous disasters which is the case in Balcik and Beamon [11], Balcik et al. [12], Duran et al. [33], Hong et al. [47], Hu and Dong [49], Jabbarzadeh et al. [53], Kamyabniya et al. [58], Mohamadi et al. [85], Moreno et al. [87], Paul and Hariharan [99], Paul and Zhang [102], Pradhananga et al. [105], Rawls and Turnquist [109,110], Rodríguez-Espíndola et al. [119], Salehi et al. [122], Vargas Flores et al. [144] and Wand and Nie [147].

As far as the probabilistic behavior of the demand is concerned, in most of the existing work a uniform distribution is assumed: Aslan and Çelik [9], Balcik and Ak [10], Bozorgi-Amiri et al. [17], Dalal and Üster [26], Doodman et al. [29], Döyen et al. [30], Eskandari-Khanghahi et al. [37], Galindo and Batta [40], Kim et al. [62], Kınay et al. [63], Kulshrestha et al. [69], Moreno et al. [86], Noham and Tzur [92], Ozbay et al. [98], Samani et al. [125], Tricoire et al. [140], van Hentenryck et al. [143] and Zarrinpoor et al. [150]. Nevertheless, we also find other possibilities such as a log-normal distribution (Klibi et al. [65,66], Murali et al. [89] and Sanci and Daskin [126]) and the normal distribution (Campbell and Jones [19] and Sha and Huang [132]).

An alternative to considering a probability distribution (either because it is not possible to find it or because it is not relevant to get it) is to find a nominal value (e.g. a point estimate) and then consider some variability for generating other values that can be used in numerical applications. The reader can refer to Chang et al. [22], Kınay et al. [63], [64], Liu et al. [77], Paul and Wang [101], Yahyaei and Bozorgi-Amiri [148] and Zokaee et al. [153] for works exploring this possibility. Alizadeh et al. [5] used a simulation procedure to generate the demand data.

When it comes to estimate the specific demand locations after a potential disaster occurrence a GIS (geographic information system) emerges as an important tool that has been considered by some authors such as Chang et al. [22], Dalal and Üster [26] and Rodríguez-Espíndola et al. [119].

Nowadays, some sophisticated tools can be found. For instance, the US Federal Emergency Management Agency (FEMA) has developed a specific tool called *HAZUS* (https://www.fema.gov/HAZUS) which makes use of GIS to “estimate physical, economic, and social impacts of disasters” by identifying high risk areas in detail (w.r.t. different types of disaster). Several authors have made use of it in their works: Galindo and Batta [40], Li et al. [72], Paul and Hariharan [99], Paul and Wang [101] and Rawls and Turnquist [111].

4.2. Uncertainty in supply

Uncertainty in supply is possibly a major distinguishing feature of facility location problems in the context of humanitarian logistics. This is due to the nature of the facilities involved and to the types of commodities considered. The demand in humanitarian logistics problems often calls for storage facilities where a stock of relief commodities can be accumulated. Such facilities are often located close to the potentially affected areas. The drawback is that such premises can also be affected by the disaster, which may jeopardize the stored goods, turning pre-positioned supply materials partially or fully unusable.

Another factor explaining supply uncertainty is the nature of the commodities involved—relief items. In many cases, they strongly depend on donations. Some disaster management organizations manage donations by collecting, storing and delivering the items. However, they have no control over what, how much and when they will be obtained since that is decided by the donors. This particular reason for supply uncertainty has been considered by Condeixa et al. [24], Fahimnia et al. [38], Kohneh et al. [68], Moreno et al. [86], Salehi et al. [122], Samani et al. [125] and Sarma et al. [127]. A particular worrisome item is blood. Accounting for the effect of its inconsistent donation on a disaster management process is almost inevitable as it is highlighted in Fahimnia et al. [38], Kamyabniya et al. [58], Kohneh et al. [68], Salehi et al. [122] and Samani et al. [125].

In Kim et al. [62], flight range of drones is considered unknown due to the uncertainty in battery autonomy. Since distribution is done via drones, this represents a source of supply uncertainty.

As we can observe in Fig. 5, supply has been scarcely considered as the only source of uncertainty. In most of the references, this is jointly studied with demand uncertainty. Nonetheless, we observe an increasing interest in terms of investigating supply uncertainty in the context of humanitarian logistics. In the seven-year period 2007–2013, 51% of the reviewed papers (17 out of 35 articles) considered uncertainty in supply; this figure grows to 63% (46 out of 73 articles) when we look at the references published since 2014.

4.3. Uncertainty in network connectivity

In the aftermath of a disaster, the transportation of affected people and relief materials are crucial operations. Nevertheless, upon the occurrence of a disaster, the capacity for providing support to the affected populations may be severely affected simply because of partial or total disruption in the network connectivity (e.g. roads may become blocked.).

It is not possible to determine beforehand the extension of a network disruption (if some) since it very much depends on the type of disaster as well as on its magnitude and epicenter. Moreover, even after the event, the exact status of a transportation network may be unknown due to disrupted information flow caused by communication issues.

In Fig. 5 we can observe that some literature can be found considering this source of uncertainty (alone or combined with other sources). It is clear that uncertainty in the transportation network has been less studied compared to uncertainty in demand or supply. Nevertheless, this trend seems to be changing. In fact, we note that in the eight-year period 2007–2014, 20% of the reviewed articles (7 out of 35) consider this aspect whereas in the more recent years the number raises to 36% (26 out of 73 articles). Next we provide some details concerning the literature that has coped with this type of uncertainty.

Hong et al. [47] and Rawls and Turnquist [109] consider uncertainty in the capacity of the transportation network due to potential disruptions of the roads, which, in turn, depend on the distance to the disaster epicenter. The addition of new links to the network (e.g. air transportation connections) is a possibility for overcoming such disruption. Ukkusuri and Yushimito [141] assume independent link failures and look for the most reliable origin-destination paths. Yahyaei and Bozorgi-Amiri [148] consider the number of failing links as an uncertain parameter. Elçi and Noyan [35] investigate a set of scenarios where located facilities are assigned to a demand node, only if (i) the facility is available after the disaster, and (ii) the connection between the facility and the node is not disrupted. Road disruption is also taken into account by Aslan and Çelik [9], Paul and Wang [101], Rath et al. [108] and Tofighi et al. [138] who consider a threshold for the travel time which increases when the link gets damaged. Wang and Nie [147] study traffic congestion in disaster management assuming that the flow rate capacity of arcs can be affected.

Bayram and Yaman [13] consider the usable links under a disaster occurrence. The authors assume that a facility is available for serving an affected population if there is at least one link in this set connecting the facility and the affected population. Álvarez-Miranda et al. [7] study a setting in which they assume that such a link always exists. Salman and Yücel [124] investigate a problem such that the disruption of a link makes nearby links more likely to be disrupted as well. By comparing this setting with other possibilities (e.g. independent link failures), the authors conclude that capturing the dependency in link failures leads to a better expected coverage. They also conclude that overlooking network availability causes a lower demand satisfaction level. Mostajabdaveh et al. [88] also assume dependent link failures. Renkli and Duran [114] assign vulnerability levels to each link and aim at minimizing the weighted probability of total vulnerability levels of the used links. Noyan and Kahvecioğlu [95] assign so-called “accessibility scores” to each link depending on the damage of the road. Moreno et al. [86] consider a set of disruption scenarios and work with the availability of a link for a certain vehicle type under each scenario.

Other works can be found focusing on disruptions in the underlying network that make use of a GIS. This is the case in Ahmadi et al. [2] and Rodríguez-Espíndola et al. [119].

Some authors have considered uncertainty in terms of network connectivity by means of stochastic parameters representing the link capacities in the aftermath of a disaster. This has been done in Condeixa et al. [24], Mohamadi et al. [85], Noyan [94], Rawls and Turnquist [110,111] and Rennemo et al. [115]. In these cases, a partial link disruption is also a possibility. If not then binary stochastic parameters should be used to indicate whether a road is usable or

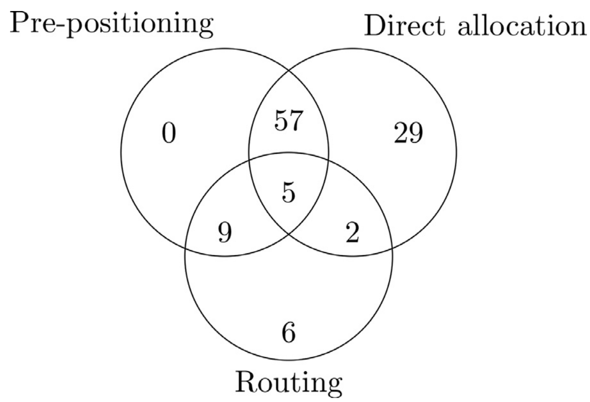

Fig. 6. Major decisions to make.

not. This possibility has been investigated by Manopiniwes and Irohara [80], Moreno et al. [87], Rodríguez-Espíndola et al. [119], Sanci and Daskin [126] and Zhan and Liu [152].

Finally, we quote the works by Nolz et al. [93] and Soltani-Sobh et al. [136]. In the former, the authors look for a risk value to assign to each link in the network and aim at minimizing the maximum risk level of links used for transportation. In the latter, the pre-positioning of supplies to restore damaged bridges after a disaster is studied. These bridges are previously identified as relevant to distribute relief items to the affected areas in a post-disaster phase; the goal is to find routes with least failure probability.

5. Modeling framework and solution methodologies

In this section we focus on two major aspects when it comes to building an optimization model: the decisions to make and the optimization criteria. The discussion is centered on the features relevant for building a facility location model capturing uncertainty in humanitarian logistics, which is the topic of this review paper. We also provide a general framework for such a model, considering the common dynamics used in the reviewed literature. Additionally, we briefly review the methodologies that have been used for tackling the models.

5.1. Decisions to make

In humanitarian logistics two major planning phases can be identified: preparedness (that includes preventive measures taken before a disaster occurs) and response (that includes the reaction to the consequences of the disaster). In the first phase we find location decisions (common to all articles reviewed in the current paper) and inventory decisions. In the second phase we usually find distribution decisions that often appear in the form of allocation decisions (demand nodes to facilities) or routing decisions.

Inventory decisions are implemented by pre-positioning relief items in the facilities (prior to the disaster). The above decisions (location and inventory) are looked at as strategic. After a disaster, operational decisions take place namely, direct allocation or routing, to ensure a proper help to the affected people. Next we categorize the existing literature according to the decisions above identified (excluding location decisions that are common to all works reviewed). In Fig. 6 we depict the global numbers in terms of the references reviewed and the corresponding categories. In the Appendix—Electronic Supplement, Table S-3—we provide the details.

5.1.1. Pre-positioning

In humanitarian logistics, the location of facilities often comes together with a pre-positioning of relief items. The latter results from the inventory decisions made to determine the quantity of each item to store in each facility.

Looking into the literature we conclude that location and inventory decisions are coupled in 71 out of the 108 articles analyzed (see Fig. 6). Since the allocation of demand nodes to facilities (direct or via routing) is always required, there is no paper that considers pre-positioning as the single decision to make (in addition to location decisions).

5.1.2. Allocation

Facility location problems are usually coupled with the allocation of the customers to the located facilities: direct allocation or routing.

Direct allocation of demand nodes to facilities means that the former are directly served by the latter without explicitly specifying the way the service is provided. A demand node can be supplied by more than one facility—multiple allocation. In the reviewed literature, multiple allocation is used significantly more than single allocation (see Table S-3 in the Electronic Supplement). This can be explained by the specific type of problems we are covering: in an emergency situation it makes sense to plan in a way that a disruption in a facility does not cause a full shortage at a demand point. In other words, multiple allocation is a way to increase reliability in humanitarian logistics. In some works both allocation patterns are considered. This holds, for instance, when a multi-layer network is considered (see Aslan and Çelik [9], Jabbarzadeh et al. [53] and Rahafrooz and Alinaghian [106]) or reallocation is performed due to a disruption of the facilities (see Irohara et al. [52]).

In humanitarian supply chain, we also see situations in which a facility is allocated to other facilities namely if a network with multiple layers of facilities is considered or if inventory balancing between facilities (in the same layer) is possible. Some works capturing this aspect are those by Alizadeh et al. [5], Aslan and Çelik [9], Bozorgi-Amiri et al. [17,18], Caunhye et al. [21], Doodman et al. [29], Ghasemi et al. [41], Haghi et al. [44], Kamyabniya et al. [57], Rahafrooz and Alinaghian [106] and Yahyaei and Bozorgi-Amiri [148]. Hu and Dong [49] consider both supplier selection and facility location decisions. Hence, they include the assignment decisions between suppliers and facilities.

Facility-facility allocation is much usual in blood supply chain management: blood units are collected in a facility and transferred to processing facilities or hospitals (see Salehi et al. [122]).

As mentioned above, an alternative to the direct allocation that we have been discussing in this section is to consider that the populations affected by a disaster are served as part of routes. This is accomplished by means of vehicle routing decisions, which include the number and type of vehicles to use as well as the corresponding routes. In this case the allocation decisions are implicit. Note also that vehicle routing decisions are usually implemented in the post-disaster phase (after uncertainty is disclosed).

Looking into the literature, three perspectives can be distinguished: (i) the routing decisions are jointly made with location decisions—a location-routing problem (LRP) is solved (Ahmadi et al. [2], Bozorgi-Amiri and Khorsi [16], Caunhye et al. [21], Eskandari-Khanghahi et al. [37], Kamyabniya et al. [57], Moreno et al. [86], Nolz et al. [93], Rennemo et al. [115], Tricoire et al. [140]), (ii) the location and routing decisions are made sequentially (van Hentenryck et al. [143]) and (iii) the routing decisions do not include the determination of the routes but just the assignment of vehicles to routes previously identified (Aslan and Çelik [9], Bayram and Yaman [13], Fereiduni and Shahanaghi [39], Kamyabniya et al. [58], Klibi et al. [65], Li et al. [72], Manopiniwes and Irohara [80], Mete and Zabinsky [83], Paul and Zhang [102], Tricoire et al. [140], Ukkusuri and Yushimito [141], Vahdani et al. [142] and Zhan and Liu [152]).

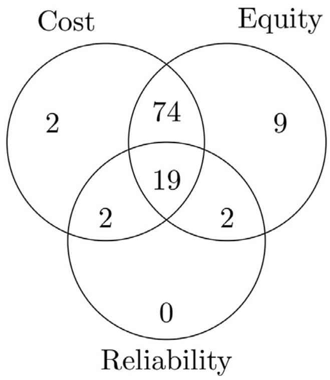

Fig. 7. Criteria categories.

The first possibility is widely accepted to be the most desirable one. It is well-known that when location and routing decisions are relevant in a problem, making them jointly can lead to significant cost reductions in the long term (see Salhi and Nagy [123]). The major difficulty in our case has to do with the inclusion of uncertainty, which makes a (combined) location-routing problem more challenging. As we can observe in Albareda-Sambola and Rodríguez-Pereira [4] most of the available LRP literature focuses on deterministic problems. This explains why we still find few works solving such problems in the context of humanitarian logistics. Observing again Fig. 6, we conclude that most of the literature considers direct allocation with pre-positioning: routing decisions are neglected in most of the papers. Out of 108 papers reviewed, only 22 investigate routing problems. Papers that include all three types of decisions (5 out of 108) are published after 2014.

5.2. Criteria

In humanitarian logistics like in many logistics applications, a common goal is to find cost-efficient solutions. However, emergency settings may call for the optimization of other performance measures such as fairness, travel time and thus response time, unmet demand, damage risk of facilities or roads. The above goals can be grouped into three criteria categories: cost, equity, and reliability. Fig. 7 depicts the global number of reviewed papers that fall in each category or combination of categories. In the Appendix—Electronic Supplement, Table S-4—we provide further details.

5.2.1. Cost

Even if the main purpose of a humanitarian network is to help people maintaining their life and providing them with the necessary relief items after a disaster, there is a cost involved in the activities that cannot be neglected when making decisions. Operations management should be cost-efficient to cover as many disaster victims as possible given the available resources. This aspect is often accounted for in optimization models by considering a cost-oriented objective function. In some cases a budget exists imposing financial limits for some operations. A cost objective has often been considered in the literature, as we can observe in Fig. 7. This is the case in 97 out of the 108 reviewed works. Nevertheless, we also observe that in almost all cases cost is considered along with additional humanitarian criteria.

There are different cost components (fixed and variable) that can be of relevance in humanitarian logistics network planning: (i) cost of establishing new facilities, (ii) operating cost for the facilities, (iii) transportation costs of people or materials, (iv) inventory holding costs, (v) shortage costs, (vi) surplus/waste costs, etc. Some components may be cast as penalties assigned to an undesired situation as it may be the case with shortages at demand points or surplus at the warehouses.

Besides considering fixed costs for opening the facilities, a fixed budget can be used to limit such expenses. The number of facilities can also be defined beforehand as a means to limit that cost component. In addition to transportation and operation costs, shortage, storage and surplus costs are the main variable costs found in the reviewed articles. In the Appendix—Electronic Supplement, Table S-5—we detail the references w.r.t the most common cost types used. We note that the majority of the reviewed papers—80%—consider a fixed setup cost for the facilities whereas 87% consider transportation/assignment variable costs. For this reason, in that table we do not detail these components.

Some authors consider facility relocation as a decision that can be made. This is the case in Fahimnia et al. [38], Jabbarzadeh et al. [53], Jenkins et al. [54], Samani et al. [125] and Sha and Huang [132]. A different perspective is investigated by Kamyabniya et al. [57], who assume that collaboration between facilities is possible with the corresponding cost incurred.

Holguín-Veras et al. [46] introduced the so-called "deprivation cost", which represents an economic value for human suffering due to being deprived of accessing some commodity or service. This concept has been explored by Condeixa et al. [24], Khayal et al. [61], Moreno et al. [87], Paul and Wang [101], Paul and Zhang [102], Pradhananga et al. [105] and Rahmani et al. [107].

Other types of cost considered in the reviewed papers are salvage cost (Galindo and Batta [40], Torabi et al. [139]), service disruption cost (Álvarez-Miranda et al. [7], Lu et al. [79]), unreliability costs for links (Soltani-Sobh et al. [136]), penalty cost for underage quantity of suppliers selected (Balcik and Ak [10]), recourse cost (Elçi and Noyan [35]), retrofitting/maintenance cost (Aslan and Çelik [9], Kim et al. [62], Rahafrooz and Alinaghian [106], testing cost of blood products (Habibi-Kouchaksaraei et al. [43]), capacity expansion cost (Mostajabdaveh et al. [88]).

5.2.2. Equity

Equity among demand nodes is a crucial aspect to consider when planning for facility location in humanitarian logistics. This is ensured by providing people in need with a fair service i.e. by distributing the resources in a fair manner. The difficulty lies in quantifying such a goal. What is considered as fair is very much context-dependent, yet a transparent assessment is crucial for the system to be accountable. Equity is typically ensured by providing people having similar needs with a similar service. However, under an uncertain setting, establishing a "fair" logistics system is even more challenging, which explains why 104 out of the reviewed 108 papers investigated equity criteria.

Matl et al. [81] define two key components to be determined for a fair allocation decision: an (in)equity metric and an (in)equity function. An equity metric refers to what is distributed while an equity function measures the equity level. For example, in a disaster, distance between affected areas and a set of shelter sites can be considered as an equity metric while the maximum of those distances can be seen as the equity function.

When checking the literature, we observe that equity has been accounted for using two main inequity metrics: accessibility and demand satisfaction (service level). The former can be defined as the capability—in terms of distance or traveling time (which may impact on the response time)—of the operating facilities to support the affected populations. This is an indirect way to avoid (or at least decrease) shortages. In fact, a long distance (or traveling time) between an affected area and its assigned facility(ies) jeopardizes an adequate demand satisfaction.

In some studies, all demand nodes are to be covered and full demand satisfaction is imposed as a means to establish a fair distribution system. Some works considering this type of fairness are those by Aslan and Çelik [9], Bayram and Yaman [13], Duran et al. [33], Fahimnia et al. [38], Irohara et al. [52], Jia et al. [55], Kim et al. [62], Kınay et al. [63], Kulshrestha et al. [69], Paul and Hariharan [99], Salehi et al. [122], Soltani-Sobh et al. [136], and Yahyaei and Bozorgi-Amiri [148].

The most common way to define a fair allocation consists of using a so-called Rawlsian approach: the worst-off element in the allocation vector is controlled (Rawls [112]). For instance, a coverage radius can be imposed as a constraint to ensure an acceptable distance for coverage or traveling time between facilities and the affected areas—a threshold is set for the maximum distance (or traveling time) which defines a minimum accessibility level accepted. This threshold is sometimes called the "survivability time" indicating the time limit for reaching a person depending on the severity level of the patient (see Paul and Hariharan [99] and Paul and MacDonald [100]). Liu et al. [77] aim to maximize the survival rate of the disaster victims.

Similarly, the shortage at a demand node can be limited by means of a pre-specified threshold or, equivalently, by defining a minimum demand satisfaction level.

As an alternative to setting the above thresholds, the equity measures just discussed can be considered as goals in an optimization problem: in this case we look for the minimization of the maximum shortage across the demand nodes or the minimization of the maximum travel time between facilities and affected areas.

In the Appendix—Electronic Supplement, Table S-6—we provide further details namely, the studies that consider these approaches to ensure equity.

Penalizing shortage of relief times at the demand nodes can be included in the objective function of an optimization model by assigning a cost value to unmet demand. This penalty can be considered in different ways. For instance, shortage may lead to an infeasible solution, to which a cost can be associated. On the other hand, outsourcing as a means to overcome shortage can also be considered. Nevertheless, the most common situation is the one in which some demand points may not be satisfied, which incurs a penalty.

Mostajabdaveh et al. [88] combines efficiency and equity by using a linear combination of mean distance between a set of shelters and the affected areas and Gini's Mean (Absolute) Difference of these distances. Klibi et al. [65] uses mean standard deviation of distances from demand nodes to assigned facilities as an evaluation metric.

5.2.3. Reliability

In addition to the areas affected by a disaster, several elements in a humanitarian logistics network can also be disrupted namely, facilities, suppliers, and links (e.g. roads). The literature has considered this aspect by assigning a risk level to these elements, that is, a measure of their reliability in case of a disaster. Two works of relevance in the broader context of logistics and supply chain management under uncertainty are those by Nickel et al. [91] and Heckmann et al. [45]. A reliability criterion is a distinguishing feature of humanitarian logistics planning under uncertainty for minimizing the risk of failures in the network. In fact, such a criterion makes no sense when perfect information about the future is available. In this section we consider the literature that explicitly focuses on reliability aiming at improving/maximizing it. We note that in 23 out of 108 reviewed articles some type of reliability is accounted for.

Safaei et al. [120,121], assume that suppliers can also be affected by the potential disaster and allocate different risk levels to them for each commodity they can provide. Hu and Dong [49] also consider the reliability of suppliers by ensuring minimum quantity amounts provided by them. Yu et al. [149] study single and dual sourcing strategies to increase reliability while Sawik [128,129] consider back-up suppliers to mitigate the disruption risk.

Akgün et al. [3] introduced a reliability model to minimize the maximum risk level of chosen facilities which depends on vulnerability of the point and the scale of the disaster. Lu et al. [79] assume disruption for all facilities that are more vulnerable than an already disrupted facility. Yahyaei and Bozorgi-Amiri [148] consider the reliability of the facilities in their analysis by eliminating some of the candidate locations namely, the most vulnerable ones. They conclude that if the disruption risk gets higher, a reliable network design provides better results in terms of expected cost. Ghasemi et al. [41], Mohamadi et al. [85] and Rahmani et al. [107] consider the use of backup facilities for overcoming disruptions. Paul and Zhang [102] consider an additional capacity option for disrupted facilities.

Another element whose reliability may be of relevance in humanitarian logistics planning concerns the connections between different geographical points (e.g. roads). Mohamadi et al. [85], Salman and Yücel [124] and Ukkusuri and Yushimito [141] study the reliability of the selected routes under the risk of facility and road disruption. Vahdani et al. [142] introduce reliability of a path as an uncertain parameter. Noyan and Kahvecioğlu [95] introduce a multi-echelon network model where they optimize a risk level for the whole network.

Nolz et al. [93] consider several possibilities for maximizing reliability: (i) minimizing total risk, (ii) using alternative paths considering unreachability occurring between two nodes when all the links between them become unusable, and (iii) establishing a threshold on the risk levels of the links used. Soltani-Sobh et al. [136] associate a cost to the unreliability emerging in a route when a primary facility is destroyed by the disaster. In such a case, a backup facility is used, which is reached by less reliable paths. Restoration of damaged roads is another way of increasing reliability of the arcs (see Aslan and Çelik [9] and Sanci and Daskin [126]). Finally, we mention the work by Renkli and Duran [114], in which the authors assume that each item requires a different reliability level.

Reliability of facilities/suppliers or reliability of the network links can be maximized. The first is usually considered for tackling supply uncertainty whereas the latter is usually adopted to diminish the effect of uncertainty on network connectivity.

Only 11% of the reviewed work that was published between 2007 and 2013 (4 out of 35) consider reliability while 25% of the papers published in the period 2014–2019 (19 out of 73) capture that aspect. Hence, we observe that reliability concerns is a more recent trend.

5.2.4. Multiple criteria approaches

The nature of the problems in humanitarian logistics often calls for the use of several objectives. In this case, a multicriteria decision making process emerges as a possibility for handling such problems. In Table 7 we detail the articles that consider a single criterion or several criteria but separately.

The works considering a multicriteria decision making process are detailed in Table 8: 34 out of the 108 reviewed papers, of which 28 were published since 2014.

Goal programming is a well-known paradigm for formulating multicriteria optimization problems. In preemptive goal programming a hierarchy exists between the objectives: each objective is optimized restricted to the (multiple) optimal solution(s) for the objectives higher in the hierarchy. Moreover, each objective is a function of the desired goals set by the decision maker. This paradigm has been considered by some authors in the context of the current review, namely: Habibi-Kouchaksaraei et al. [43], Safaei et al. [121] and Zhan and Liu [152].

Table 1
Potential Decision Variables.

Location	$Y_i = \begin{cases} 1 \text{ if facility } i \text{ is used;} \\ 0 \text{ otherwise} \end{cases}$	$(i \in I)$
Pre-positioning	$H_i =$ amount stored at location i.	$(i \in I)$
Allocation/Shipment	$X_{ij} = \begin{cases} 1 \text{ if beneficiary } j \text{ is assigned to facility located at } i \\ 0 \text{ otherwise} \end{cases}$	$(i \in I, j \in J \mid (i, j) \in A)$
	$F_{ij} =$ amount shipped from facility i to beneficiary j.	$(i \in I, j \in J \mid (i, j) \in A)$
	$Z_{\ell\ell' k} = \begin{cases} 1 \text{ if } \ell \text{ preceedes } \ell' \text{ in the route of vehicle } k \\ 0 \text{ otherwise} \end{cases}$	$((\ell, \ell') \in A, k \in K)$

Kınay et al. [64] also explore the use of goal programming in addition to another possible paradigm namely, vectorial optimization. The latter emerges when no hierarchy exists between the objectives. In this case, several possibilities emerge for tackling the problems. One consists of using compromise programming (see Zeleny [151]) that consists of finding the solution “closest” to the ideal point. This has been done by Bozorgi-Amiri et al. [18] and Sarma et al. [127]. The latter compares this method with a global criterion and a weighted sum criterion.

The ε-constraint method is a well-known solution procedure for multicriteria optimization. In this case, the ultimate goal is to obtain exact Pareto solutions. This is accomplished by considering a single objective model using one of the objective functions and setting a threshold constraint for the others. This procedure is used in Ahmadi et al. [2], Eskandari-Khanghahi et al. [37], Fahimnia et al. [38], Ghasemi et al. [41], Haghi et al. [44], Jenkins et al. [54], Kamyabniya et al. [57], Liu et al. [77], Rahafrooz and Alinaghian [106], Rath et al. [108], Rodríguez-Espíndola et al. [119] and Tricoire et al. [140]. Rahafrooz and Alinaghian [106] used the so-called ℓ_p-metric method (Soltani et al. [135]) together with an improved augmented ε-constraint method to solve a three-criteria robust model. Mohamadi et al. [85] also utilized ℓ_p-metric method using weights for the objective functions determined by the decision-maker. Haghi et al. [44] considered the ε-constraint method and used a multi-objective optimization procedure using genetic and simulated annealing algorithms (MOGASA) and a non-dominated sorting genetic algorithm II (NSGA-II) for tackling large instances.

Ghasemi et al. [41] and Vahdani et al. [142] also proposed a NSGA-II algorithm that they compare with a multi-objective particle swarm optimization (MOPSO) procedure.

In some articles, priority-based weights are assigned to the objective functions and weighted sum/average approaches are considered. This is the case in Dalal and Üster [26], Manopiniwes and Irohara [80] and Sawik [128].

Rezaei-Malek et al. [118] investigate the use of the reservation level Tchebycheff procedure (RLTP) (Reeves and Macleod [113]) to solve a bi-objective problem. Nolz et al. [93] proposed a two-phase procedure: a memetic algorithm is used in the first phase to generate approximate Pareto optimal solutions while an enrichment process is applied in the second phase to improve the solutions.

Fuzzy solution methods have also been considered for dealing with multicriteria optimization problems in the context of this review. This is done by Doodman et al. [29], Kohneh et al. [68] and Samani et al. [125].

Finally, we refer to bi-level programming as another possibility for handling conflicting objectives. Safaei et al. [120] investigate a leader-follower game assuming that the upper level consists of location decisions minimizing the total cost and the proportion of unmet demand. The lower level decisions concern the selection of the suppliers with the lowest risk. Since bi-level programming models are often non-convex they are more challenging to solve. In the above paper, the authors use a standard technique and model the problem as a single level problem using the KKT conditions. Safaei et al. [121] make use of Goal Programming to deal with a bi-objective model that is considered at the upper level. Kamyabniya et al. [58] and Moreno et al. [87] also used bi-level programming. Finally, we refer to Liberatore et al. [75] who use tri-level programming to evaluate the criteria by different decision makers.

5.3. Paradigm for capturing uncertainty

Acknowledging the inevitable uncertainty in a humanitarian setting is crucial to successfully devise a quantitative analysis for solving real problems. Different possibilities have been considered for capturing uncertainty in an optimization problem. The most used ones are Stochastic Programming (SP), Robust Optimization (RO), and Chance-Constrained Programming (CCP). Fig. 8 provides a global analysis of the reviewed literature in terms of the number of articles that fall in each such category or combinations of categories. In the Appendix—Electronic Supplement, Table S-7—we provide all details.

The adequate modeling framework depends on the available information regarding uncertainty and the type of constraints to be included in the model. A first distinguishing feature concerns the knowledge on the probability distribution of the underlying random vector. If such distribution is known (e.g. can be estimated using historical data) then we can resort to a SP model. In this case we typically consider two- or multi-stage models. The here-and-now decisions (decisions to implement before any uncertainty is revealed) are defined as first-stage decisions. For the subsequent stages, a discrete number of scenarios is usually used for capturing the uncertainty and decisions are made that adapt to the occurring scenario. In the context of humanitarian facility location, the location and the inventory pre-positioning decisions are usually assumed as first-stage decisions. The allocation, routing and demand satisfaction decisions have been mostly assumed as second-stage decisions.

If the information on the probability distribution of the underlying random vector is not known (or it is irrelevant to take it into account), then RO is a good framework in many cases. In this case, an uncertainty set is assumed for each unknown parameter and a solution is sought that is feasible no matter the value of the parameters. In some of the works, SP and RO are used together. This is the case in Alizadeh et al. [5], Dalal and Üster [26], Das and Hanaoka [27], Fereiduni and Shahanaghi [39], Rezaei-Malek et al. [118], Salehi et al. [122] and Vargas Florez et al. [144].

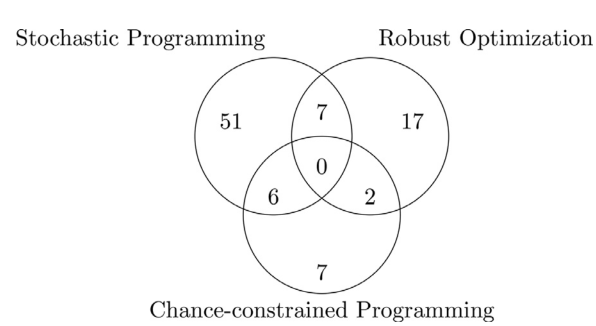

Fig. 8. Modeling framework adopted for capturing uncertainty.

Chance constraints are a means to capture constraints that should hold with some pre-specified probability. This is particularly relevant when facing uncertainty because hard constraints may impose solutions much influenced by extreme cases that may occur with a small probability. Chance constraints have been used alone, along with SP or combined with RO. In general, the aim of using such constraints is to ensure a high probability of satisfying demands, i.e. to ensure a minimum service level. This is done in Elçi and Noyan [35], Elçi et al. [36], Hong et al. [47], Kınay et al. [63,64], Murali et al. [89], Rahafrooz and Alinaghian [106], Renkli and Duran [114], Torabi et al. [139], Zarrinpoor et al. [150], Zhan and Liu [152].

Kınay et al. [63] introduce a chance-constrained model to ensure that the probability of achieving a minimum utilization rate is high for the shelters to be located in their study. The authors conclude that performance measures associated with accessibility, equity, and efficiency improve when a chance-constrained model is used.

Ozbay et al. [98] consider the conditional value at risk (CVaR) for the over-utilization of shelter sites—a risk averse decision maker is assumed. Other works consider specially tailored attitudes of the decision maker towards risk by means of using chance constraints to handle extreme scenarios. This is done in Balcik et al. [12], Bozorgi-Amiri et al. [17,18], Condeixa et al. [24], Elçi and Noyan [35], Hong et al. [47], Hu et al. [51], Jabbarzadeh et al. [53], Noyan [94], Ozbay et al. [98] and Paul and Zhang [102].

Kamyabniya et al. [57] suggest the use of a so-called "soft worst case model" to avoid infeasible worst-case solutions while minimizing the worst-case cost. The use of chance constraints to "control" feasibility is also considered by Elçi and Noyan [35], Elçi et al. [36], Hong et al. [47] and Yahyaei and Bozorgi-Amiri [148].

Mostajabdaveh et al. [88] embed chance constraints within a stochastic programming framework to ensure that an existing budget is not exceeded with a certain probability since this situation may cause shortage. Kim et al. [62] use chance constraints to ensure that the drones with random flight distances return to the facilities with a predetermined probability. Eskandari-Khanghahi et al. [37] investigate the use of fuzzy possibilistic programming combined with chance constraints. Possibilistic programmming is also investigated by Doodman et al. [29] for dealing with imprecise parameters. Tofighi et al. [138] use fuzzy chance-constrained programming to use crisp parametric counterparts of the stochastic models.

In addition to the three major paradigms above discussed for capturing and modeling uncertainty, we can find other methods in the reviewed literature. Rodríguez-Espíndola et al. [119] handle uncertain network conditions by using GIS data to acknowledge the effects of geographical factors as well as the vulnerability levels. In some articles, risk levels and failure probabilities are used to capture uncertain parameters. Fault tree analysis is applied by Akgün et al. [3] to account for vulnerability levels. In particular, risk levels for each demand node are estimated considering the magnitude of the disaster and expected damage as a result of the magnitude. Campbell and Jones [19] assume a normally distributed demand and present an analytical analysis aiming at finding the best solution in terms of quantity and location for pre-positioning emergency commodities. A normal distribution is also assumed by Galindo and Batta [40]. The authors use the concept of "demand buffer" to deal with the uncertainty. Balcik et al. [12] consider risk pooling among different countries to mitigate the effect of disaster uncertainty. The corresponding investment cost is distributed among countries based on the expectation and the variance of demands. Irohara et al. [52] apply an interdiction framework to handle uncertainty (the reader can refer to Scaparra and Church [130] for an overview of facility location problems with interdiction). Kamyabniya et al. [58] and Mohamadi et al. [85] use fuzzy numbers to capture uncertainty. In the former work, the authors consider the coordination between different levels and "demand and capacity sharing mechanisms" to handle the uncertain demand parameters. Sarma et al. [127] use a defuzzification method to deal with uncertain parameters, which are considered as triangular neutrosophic numbers (Abdel-Basset et al. [1]). Jenkins et al. [54] use a multi-stage model to capture different possibilities for demand whereas Yu et al. [149] obtain closed form solutions using expectation calculations. Finally, Dufour et al. [31] use a simulation-based heuristic to account for demand uncertainty.

To end this section we observe that out of 108 reviewed papers, 64, 26 and 15 consider SP, RO and CCP, respectively. In the first seven years of our scope, i.e., 2007–2013, 20 out of 35 articles (57%) considered a SP approach, 6 (17%) used RO and 2 (6%) used a CCP model. However, in the more recent years we observe that 44 out of 73 articles (60%) included a SP based approach, 20 (27%) consider RO and 13 (18%) use chance constraints. These figures show an increasing trend in the use of RO and CCP.

5.4. A General Modeling framework

In this section we aim at illustrating the discussion presented in the previous sections by presenting generic modeling aspects that may become of interest when dealing with the problems focused in this paper.

Three sets are of major relevance: the facilities to operate (they can be existing/new suppliers or facilities to install), the beneficiaries (e.g. potential affected populations), and the existing connections between facilities and beneficiaries (e.g. a single link or a sequence of links):

- I, set of facilities (existing and potential).
- J, set of beneficiaries.
- K, set of vehicles (when beneficiaries are to be satisfied as part of routes).

From the above sets and given the underlying network we can also consider:

$A = \{(\ell, \ell') \mid \ell, \ell' \in I \cup J \text{ and } \ell' \text{ is reachable from } \ell\}$

In terms of the decisions to make and following the discussion presented in Section 5.1 we may need to consider (among others) different sets of decision variables to build an optimization model as shown in Table 1.

A multi-commodity extension of the above decisions is straightforward, albeit may increase the computational effort. In terms of the assignment and routing decisions, various extensions can also be considered: (i) facility-facility allocation, (ii) supplier selection, (iii) supplier-facility assignment decisions (as another layer to the network), (iv) variable number and type of the vehicles to use, etc.

Regarding the parameters underlying the problem, Table 2 summarizes several possibilities of relevance.

The constraints to be considered depend of course on the exact problem. Nevertheless, we can devise several types of constraints that will be often encountered as can be seen in Table 3.

Depending upon the criteria category, different sets of decision variables may play a role. A generic structure is provided in Table 4.

Table 5 presents possible criteria in the form of an objective function or a constraint. Cost objective functions are typically minimization objectives involving monetary values. The specific form of the objective function depends on the problem. For example, equation (7) shows a location-allocation setting with facility-related costs (setup, operating and inventory) and allocation cost whereas equation (10) shows a location-routing setting where facility and routing costs are used. Equation (9) represents a shortage cost. Some or all the monetary amount that can be spent may be

Table 2
Potential Parameters.

For all $i \in I,\ j \in J,\ (\ell, \ell') \in A$;		
Demand related	d_j	demand of beneficiary j[a]
	c^s_j	unit shortage cost at beneficiary j[b]
Supply related	β_i	a risk (vulnerability) factor associated with facility i[c]
	s_i	supply at facility i by donation (type, amount and timing can be uncertain)
	c^f_i	fixed cost of establishing a new facility i
	c^o_i	operating cost of facility i
	c^h_i	unit inventory holding cost at facility i
Shipment related	$r_{\ell\ell'}$	vulnerability factor associated with link (ℓ, ℓ')
	$c_{\ell\ell'}$	cost for traveling between ℓ to ℓ'
	$t_{\ell\ell'}$	time for traveling between ℓ and ℓ'
	θ	link reliability threshold
	γ	accessibility threshold in terms of distance or time
	α	service level[d]

[a] This quantity is typically uncertain since it depends on the intensity and magnitude of the disaster.
[b] In some papers deprivation cost is used instead.
[c] The value of this parameter may render some or all the pre-positioned goods unusable.
[d] Depending on the problem α can be a ratio, a probability, etc.

Table 3
Potential Constraints.

For all $i \in I,\ j \in J,\ k \in K$;		
Location-allocation (routing) related	$X_{ij} \le Y_i$	(1)
	$\sum_{k\in K} \sum_{\ell:(j,\ell)\in A} Z_{j\ell k} = 1$	(2)
	$\sum_{(i,j)\in A} Z_{ijk} \le 1$	(3)
	$\sum_{\ell\in I\cup J} \left(Z_{i\ell k} + Z_{\ell jk}\right) \le 1 + X_{ij}$	(4)
Inventory pre-positioning and supply related	$\sum_{j\in J} F_{ij} \le (1-\beta_i)H_i + s_i,$	(5)
Demand related	$F_{ij} \le d_j X_{ij}$	(6)

Table 4
Objective functions—General structure.

Cost	Equity		Reliability
	demand satisfaction	accessibility	
$\min f^C(Y, X, F, Z, H)$	$\min f^S(F)$	$\min f^A(X)$	$\min f^R(Y, X, F, Z, H)$

Table 5
Potential Criteria.

		as Objective Function		as Constraint	
Cost		$f^C(.) \equiv \sum_{i\in I}(c^f_i + c^o_i)Y_i + \sum_{i\in I} c^h_i H_i + \sum_{i\in I}\sum_{j\in J} c_{ij}X_{ij}$	(7)	$\sum_{i\in I} c^f_i Y_i \le B$	(8)
		$f^C(.) \equiv \sum_{j\in J} c^s_j\left(d_j - \sum_{i\in I} F_{ij}\right)$	(9)		
		$f^C(.) \equiv \sum_{i\in I}(c^f_i + c^o_i)Y_i + \sum_{i\in I} c^h_i H_i + \sum_{(\ell,\ell')\in A} (c_{\ell\ell'} \sum_{k\in K} Z_{\ell\ell' k})$	(10)		
Equity	*Demand Satisfaction*	$f^S(.) \equiv \max_{j\in J}\{d_j - \sum_i F_{ij}\}$	(11)	$\frac{\sum_{i\in I} F_{ij}}{d_j} \ge \alpha \quad \forall i \in I$	(12)
	Accessibility	$f^A(.) \equiv \max_{i\in I,\ j\in J} \left\{t_{ij}X_{ij}\right\}$	(13)	$\sum_{i:t_{ij}\le\gamma} X_{ij} \ge 1 \quad \forall j \in J$	(14)

bounded by some pre-defined budget. A budget constraint is given in (8). Similarly, equity in accessibility can be incorporated as an objective function, according to equation (11) or can be imposed in the form of a coverage constraint (14). If full demand satisfaction is not imposed, a minimum demand satisfaction level can be used so as to incorporate fairness as in constraint (12). By adopting demand satisfaction as a metric we can consider the objective function (13). Reliability objectives make more sense under supply and network uncertainty since satisfying them in the deterministic setting is trivial: it reduces to eliminating (unreliable) facilities or links.

We discuss now different possibilities for capturing uncertainty in an optimization model. We analyze separately the different paradigms for capturing uncertainty. Some possibilities in the context of stochastic programming and chance-constrained programming are summarized in Table 6.

- *Stochastic programming*: In the simplest setting—a two-stage modeling framework for a risk neutral decision maker—we consider a set of here-and-now decisions (to implemented before uncertainty is revealed), e.g. facility location, pre-positioning and allocation of beneficiaries to facilities. The other decisions (recourse decisions—to be implemented after uncertainty is disclosed) adapt to the values observed for the uncertain parameters.
  We denote the underlying random vector by $\boldsymbol{\xi} = (\mathbf{d}, \mathbf{s}, \boldsymbol{\beta}, \mathbf{r})$ although not all components of $\boldsymbol{\xi}$ need to be uncertain (in this case we can use the same notation but assuming a single value occurring with probability 1 for the deterministic component(s)).
  A cost criterion would become (15), where the first term represents a here-and-now cost (to be paid independently from how uncertainty is revealed) and $Q^C(Y, X, Z, H; \boldsymbol{\xi})$ is the opti-

Table 6
SP and CCP for Dealing with Uncertainty.

Stochastic Programming	*Cost*		$\min f^C(Y,X,Z,H)+\mathbb{E}_{\boldsymbol{\xi}}(Q^C(Y,X,Z,H;\boldsymbol{\xi}))$	(15)
	Equity	*Demand Satisfaction*	$\min \mathbb{E}_{\boldsymbol{\xi}}[f^S(F)]$	(16)
		Accesibility	$\min \mathbb{E}_{\boldsymbol{\xi}}[f^A(X)]$	(17)
	Reliability		$\min f^R(Y,X,Z,H)+\mathbb{E}_{\boldsymbol{\xi}}(Q^R(Y,X,Z,H;\boldsymbol{\xi}))$	(18)
Chance-Constrained Programming	*Cost*		$\mathbb{P}\big(f^C(.)\geq B\big)\leq\delta$	(19)
	Equity	*Demand Satisfaction*	$\mathbb{P}\big(\sum_i F_{ij}\geq d_j\big)\geq\alpha$	(20)
			$\mathbb{P}\big(\sum_{j\in J} F_{ij}\leq\beta_i H_i+s_i\big)\geq\alpha$	(21)
		Accessibility	$\mathbb{P}\big(\sum_{i:t_{ij}\leq\gamma}(1-r_{ij})X_{ij}\geq 1\big)\geq\theta$	(22)
	Reliability		$\mathbb{P}\big(\sum_{(\ell,\ell')\in A}(1-r_{\ell\ell'})\sum_{k\in K}Z_{\ell\ell'k}\geq 1\big)\geq\theta$	(23)
			$\mathbb{P}(\sum_{i\in I}(1-\beta_i)Y_i\geq 1)\geq\theta$	(24)

Table 7
Synthesis of the literature—single-objective problems: Sources of Uncertainty (D: demand; S: supply; NC: network connectivity), Criteria (C: cost; E: equity; R: reliability), and Decisions (Pre-positioning, location-allocation, location-routing).

Source of	Type of	No Pre-positioning		Pre-positioning	
uncertainty	criteria	Location-Allocation	Location-Routing	Location-Allocation	Location-Routing
D	**C, E**	Balcik and Ak [10] Sha and Huang [132] Kulshrestha et al. [69]	Klibi et al. [65]	Balcik and Beamon [11] Chang et al. [22] Döyen et al. [30] Hu et al. [50] Li et al. [74] Torabi et al. [139] Rawls and Turnquist [111] Khayal et al. [61] Li and Jin [73]	Caunhye et al. [21] van Hentenryck et al. [143]
	C			Dufour et al. [31]	
	E	Kınay et al. [63] Lu [78] Noham and Tzur [92] Jia et al. [56]		Murali et al. [89] Duran et al. [33]	
S	**C, E, R**	Lu et al. [79] Sawik [129]			
	C, E	Kim et al. [62]		Irohara et al. [52]	
	E, R	Akgün et al. [3]			
NC	**C, E, R**			Renkli and Duran [114]	
	C, E		Ahmadi et al. [2]		
	E, R	Salman and Yücel [124]			
D, S	**C, E, R**			Rahmani et al. [107] Ghasemi et al. [41] Hu and Dong [49]	Paul and Zhang [102]
	C, E	Zarrinpoor et al.[150] Verma and Gaukler [146] Alizadeh et al. [5]	Li et al. [72]	Balcik et al. [12], Bozorgi-Amiri et al. [17], Das and Hanaoka [27] Galindo and Batta [40], Jabbarzadeh et al. [53] Klibi et al. [66], Pradhananga et al. [105] Paul and Hariharan [99], Paul and MacDonald [100] Salehi et al. [122], Samani et al. [125], Zokaee et al. [153]	Fereiduni and Shahanaghi [39]
	C, R	Yu et al. [149]			
	C	Verma and Gaukler [145]		Campbell and Jones [19]	
D, NC	**C, E, R**	Yahyaei and Bozorgi-Amiri [148]		Noyan and Kahvecioğlu [95]	
	C, E	Mostajabdaveh et al. [88]		Hong et al. [47]	Rennemo et al. [115]
S, NC	**C, R**		Ukkusuri and Yushimito [141]		
D, S, NC	**C,E,R**	Mohamadi et al. [85]		Sanci and Daskin [126]	Aslan and Çelik [9]
	C, E	Álvarez-Miranda et al. [7]		Elçi and Noyan [35] Noyan [94], Paul and Wang [101] Rawls and Turnquist [109,110] Vargas Florez et al. [144], Wang and Nie [147]	Moreno et al. [86]
	E		Bayram and Yaman [13]		

Table 8
Synthesis of the literature—multicriteria problems: Sources of Uncertainty (D: demand; S: supply; NC: network connectivity), Criteria (C: cost; E: equity; R: reliability), and Decisions (Pre-positioning, location-allocation, location-routing).

Source of	Type of	No Pre-positioning		Pre-positioning	
uncertainty	criteria	Location-Allocation	Location-Routing	Location-Allocation	Location-Routing
D	**C**, **E**	Dalal and Üster [26] Kınay et al. [64]	Tricoire et al. [140]	Mete and Zabinsky [83] Kamyabniya et al. [57] Liu et al. [77]	
	E			Jenkins et al. [54]	
S	**C**, **E**, **R**			Safaei et al. [121] Sawik [128]	
	C, **E**	Liberatore et al. [75]			
NC	**C**, **E**, **R**	Soltani-Sobh et al. [136]	Nolz et al. [93]		
	C, **E**			Rath et al. [108]	
D, **S**	**C**, **E**, **R**			Safaei et al. [120]	
	C, **E**	Jia et al. [55] Kohneh et al. [68] Habibi-Kouchaksaraei et al. [43] Rahafrooz and Alinaghian [106] Samani et al. [125] Fahimnia et al. [38]	Eskandari-Khanghahi et al. [37]	Bozorgi-Amiri et al. [18] Haghi et al. [44] Rezaei-Malek et al. [118] Sarma et al. [127] Doodman et al. [29]	Bozorgi-Amiri et al. [18]
D, **NC**	**C**, **E**			Rodríguez-Espíndola et al. [119]	Manopiniwes and Irohara [80]
D, **S**, **NC**	**C**, **E**, **R**				Vahdani et al. [142]
	C, **E**		Zhan and Liu [152]	Tofighi et al. [138]	

mal value of a second-stage optimization problem, which is a problem defined for every feasible here-and-now solution (satisfying e.g. (1)–(4)) and for every possible observation of the random vector. In this case, constraints such as (5) or (12) must be part of this second-stage problem as well as the cost (9) that if relevant in our problem should be part of $Q^C(Y, X, Z, H; \boldsymbol{\xi})$—it depends on how uncertainty is revealed.
The existence of a budget constraint involving second-stage decisions (adaptable to how uncertainty is revealed) can be easily accommodated by moving those constraints to the second-stage optimization problem.
An equity criterion in terms of demand satisfaction would be (16). In fact, the shipment amounts will depend on how uncertainty is revealed (e.g. demand and supply).
An equity criterion in terms of accessibility would not change w.r.t. what was shown before if the allocation of beneficiaries to the facilities is assumed as a non-adaptative decision (it is the same no matter how uncertainty is revealed). If this is not the case, then the allocation decisions X_{ij} should go to the second stage problem and the appropriate criterion becomes (17).
As far as reliability is concerned, several possibilities emerge. If we focus on the facility vulnerability then we can consider objectives such as (18) with $f^R(Y, X, Z, H) = \max_{i \in I}\{\beta_i Y_i\}$ or $f^R(Y, X, Z, H) = \sum_{(\ell,\ell') \in A}((r_{\ell\ell'}) \sum_{k \in K} Z_{\ell\ell' k})$, to mention a few possibilities of relevance.
All the above discussion in the context of stochastic programming can be extended to other attitudes towards risk namely, for a risk-averse decision maker which may turn out to be more appropriate in the context of humanitarian logistics. In this case we can consider an expectation not for the entire range of the underlying random vector but for the observations leading to some percentage of the worst possible outcomes in terms of the criterion considered.

- *Chance-Constrained Programming*: In this case, instead of considering a two- or multi-stage stochastic programming model, one considers a model in which some constraints should hold with at least some probability defined beforehand. This is particularly relevant when all decisions are non-adaptative. Chance constraints (19) may be used to indicate that the probability of exceeding budget cannot exceed a predetermined threshold δ. Constraints that are often candidates for this treatment are service level constraints that can be written as (20) i.e., the probability that the amount planned to satisfy the beneficiaries is enough should be at least some value α.
In our case, the probabilistic version of constraints (5) would be (21). In this case, we would be ensuring a high probability of being able to ship as planned.
Equity in terms of accessibility can be ensured by (22): with some (typically high) probability, there will be an available channel to satisfy every beneficiary.
For reliability, chance constraints may have the form indicated in (23) and (24). Note that (23) ensures the reliability of links used whereas (24) ensures the reliability of the facilities located.
- *Robust Optimization*:
In this case we assume an uncertainty set for every uncertain parameter and we look for a solution that is feasible for every possible observation of the parameters.
This paradigm can be easily illustrated considering the demands, d_j. If we know that $d_j \in \mathcal{D}_j$ $j \in J$ ($\mathcal{D}_j$ is the uncertainty set for d_j), then we can use this information to ensure that a feasible solution is found in terms of (non-adaptative) shipment for every possible occurrence of the uncertain parameters:

$$\sum_{i \in I} F_{ij} \geq \max_{d \in \mathcal{D}_j}\{d\}.$$

An objective function such as $f^S(F) = \max_{j \in J}\left\{d_j - \sum_{i \in I} F_{ij}\right\}$ would need to be handled as a constraint:
min $\quad \nu$
s.t. $\quad \nu \geq d_j - \sum_{i \in I} F_{ij}, \quad j \in J$
Now, a robust counterpart can be derived as follows:
$\nu \geq \max_{d \in \mathcal{D}_j}\{d\} - \sum_{i \in I} F_{ij}, \quad j \in J.$
The reader can refer to Ben-Tal et al. [14], Cheng et al. [23], Correia and Saldanha-da-Gama [25] and to the references therein

for additional insights on how to consider and tackle robust optimization models in problems involving location decisions.

5.5. Solution methodologies

Discrete facility location problems are known to be NP-hard in general. Therefore, in the context of humanitarian facility location under uncertainty we should also expect the same level of complexity. For this reason, the literature is prone to algorithms for solving problems in this area. We can easily distinguish between exact procedures (typically for small or medium-sized instances) and heuristics. Among the exact methods that have been attempted to solve problems in the context of this review, we can highlight Benders Decomposition (Álvarez-Miranda et al. [7], Bayram and Yaman [13], Dalal and Üster [26], Elçi and Noyan [35], Noyan [94], Tricoire et al. [140], Verma and Gaukler [146], Wang and Nie [147] and Zarrinpoor et al. [150]), Lagrangian relaxation based algorithms (Fahimnia et al. [38] and Rahmani et al. [107]), branch-and-cut methods (Álvarez-Miranda et al. [7], Elçi and Noyan[35], Noyan and Kahvecioğlu [95] and Salehi et al. [122]), procedures based upon the Gale-Hoffman inequalities (Hong et al. [47]), cutting plane algorithms (Kulshrestha et al. 2011 [69]), Karush-Kuhn-Tucker (KKT) optimality conditions reformulations (Safaei et al. [121]), the L-shaped method (Li and Jin [73] and Li et al. [74]) and, a so-called fuzzy K^{th}-Best algorithm (Kamyabniya et al. [58]).

Much work has also been done on approximate algorithms. To start with, we mention the use of sample average approximation which is an elaborated sampling technique for approximating the optimal solution to a stochastic programming problem. This has been attempted by Alizadeh et al. [5], Aslan and Çelik [9], Chang et al. [22] and Sanci and Daskin [126].

When it comes to the use of heuristics, we observe a rich literature. Some of the most used methods are variable neighborhood search (Ahmadi et al. [2]), large neighborhood search (van Hentenryck et al. [143]), tabu search (Noham and Tzur [92]), binary tree search (Liberatore et al. [75]), particle swarm optimization (Bozorgi-Amiri et al. [17]), Lagrangean based heuristics (Döyen et al. [30], Li et al. [72], Rawls and Turnquist [109] and Sha and Huang [132]), simulated annealing (Eskandari-Khanghahi et al. [37] and Lu [78]), genetic algorithms (Jia et al. [56], Mostajabdaveh et al. [88] and Murali et al. [89]), MOSAGA and NSGA-II procedures (Ghasemi et al. [41], Haghi et al. [44] and Vahdani et al. [142]), "relax-and-fix" and "fix-and-optimize" heuristics (Moreno et al. [86,87]), evolutionary optimization based heuristics (Paul and MacDonald [100]), a branch-and-cut epsilon-constraint based heuristic (Salman and Yücel [124]), differential evolution (Tofighi et al. [138] and Torabi et al. [139]), nested tabu search (Klibi et al. [65]), sample-average based branch-and-cut algorithms (Tricoire et al. [140]), cut generation heuristics (Irohara et al. [52]), aggregation schemes (Galindo and Batta [40]), and Benders decomposition based heuristics (Kim et al. [62]).

6. Conclusions and insights

The main purpose of the current paper is to provide a major understanding of the role of facility location under uncertainty in humanitarian logistics planning. In addition to the categorization provided in the previous sections in terms of several major aspects, it is also relevant to look into the main trends in the literature as well as into the challenges yet-to-be addressed in the topic.

In order to obtain a deeper insight, we summarize the above mentioned aspects using two tables. Table 7 focuses on papers dealing with single-criterion problems whereas Table 8 presents a synthesis of the papers dealing with a multicriteria problem. These tables help highlighting the gaps in the literature. For instance, in Table 7, we observe that no article considers only demand as the source of uncertainty together with the three types of criteria identified (cost, reliability and equity). We also note that for instance, no paper investigating a multicriteria problem considers simultaneously supply and network connectivity together as sources of uncertainty. Observing these tables we can draw several other conclusions as we detail next.

Looking at the most populated cells we see where the major effort has been put so far. This is the case with location-allocation models with pre-positioning decisions under demand uncertainty considering cost and equity. In addition to demand uncertainty, most of the reviewed articles also acknowledge supply as an uncertainty source. Overall, the most populated cells in the tables correspond to work considering demand uncertainty with an equity type criterion and pre-positioning of the commodities. Only occasionally have routing decisions been considered in this large majority of the papers.

Other interesting conclusions can be drawn from these tables. First, rarely is demand uncertainty combined with a reliability criterion. Second, all multicriteria works consider both cost and equity as the type of criteria to optimize. In other words, reliability criteria have scarcely been considered together with other criteria. Third, most of the papers investigating reliability consider uncertainty in network connectivity. Finally, uncertainty in terms of network connectivity is rarely studied together with routing decisions, which is a little unexpected.

Two important aspects in humanitarian logistics concern the multi-commodity and multi-period nature of many problems. In 44% of the papers reviewed, the model proposed includes multiple commodities. However, it is not that common to categorize the commodities based on their attributes.

Some relevant attributes that could be important in modeling are shelf–life and demand frequency (consumable, non-consumable, perishable, non-perishable). Some papers distinguish commodities according to their shelf–life (see Mete and Zabinsky [83] and Rezaei-Malek et al. [118]). Other than this, blood is the most studied perishable item in the context of humanitarian facility location problems under uncertainty (see Eskandari-Khanghahi et al. [37], Kamyabniya et al. [57,58] and Samani et al. [125]).

Another characteristic is the demand frequency of the item(s). For some goods, demand occur only once at the beginning of the relief distribution process (such as tents, blankets, kitchen kits etc.) while some commodities must be delivered to the disaster-victims more than once since they are consumable items (food, water, hygiene products etc.). Consumable items can be further classified according to their perishability, which already affect the inventory decisions for these items. The ones that are not highly perishable, can be distributed beforehand to the demand areas and stored to be consumed later (bottled water, canned food etc.). For others, distribution should be performed before the item deteriorates (e.g. milk). In the context of humanitarian logistics, consumable and quickly perishable items are not preferable. Instead, whenever possible, items that can be stored are used as relief goods since it allows to hold inventory, which adds more flexibility to the logistics operations. Categorization of items based on their demand frequency is considered in Ahmadi et al. [2], Bozorgi-Amiri and Khorsi [16], Khayal et al. [61] and Rawls and Turnquist [111].

In some papers, time is a dimension included in the analysis. This is done by means of a multi-period model, which helps making decisions in a dynamic basis. Most of the existing work capturing this aspect conceives a plan for the location decisions to be made in the beginning of the planning horizon and then the allocation decisions are made on a multi-period basis. Using multiple stages to make location decisions, i.e. adopting a multi-

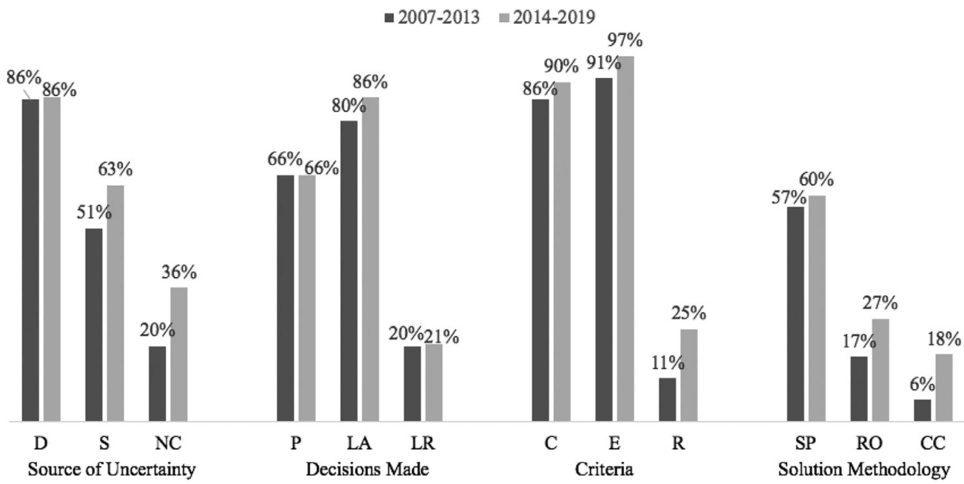

Fig. 9. Percentage of articles that study main sources of uncertainty (D: demand; S: supply; NC: network connectivity), decisions made (P: pre-positioning, LA: location-allocation, LR: location-routing), criteria (C: cost; E: equity; R: reliability) and solution methodology for uncertainty (SP: stochastic programming, RO: robust optimization, CC: chance constraints) in the years 2007–2013 and 2014–2019.

stage facility location plan, has not been frequently observed. If the setup cost of the facilities is not high compared to the operational cost, re-locating can be used to perform deliveries more quickly. In relief distribution, temporary/mobile facilities with low setup costs can be used to meet the demand from different locations as much as possible. Such mobile facilities are re-located or moved in using a multi-period model in Eskandari-Khanghahi et al. [37], Kamyabniya et al. [57,58], Moreno et al. [86] and Vahdani et al. [142].

In Fig. 9, we show the frequencies of the papers categorized with respect to (i) the main sources of uncertainty, (ii) the main decisions to make, (iii) the main criteria to optimize, and (iv) the modeling framework adopted for capturing uncertainty.

We report the frequencies separately for the first (2007–2013) and the second half (2014–2019) of the scope of this survey. From this figure, we observe some trends in the research area. It can be seen that supply uncertainty and network connectivity have been studied more recently. Concerning the decisions to make, location-allocation problems are the most studied ones and they become even more popular in recent years. When we look at the criteria, we see that reliability has drawn more attention recently. One can also observe that equity is a key criterion, which is justified by the fact that it is considered in almost all studies. While handling uncertain parameters, robust optimization and chance constraints have been used more frequently in the second half of our scope (2014–2019).

The above insights together with other aspects already observed in the previous sections allows us to devise some research directions of interest in the context of humanitarian facility location under uncertainty:

- Coping with network disruptions is still much unexplored. For instance, the use of helicopters or aircrafts and their role in overcoming network disruptions is mostly neglected in the reviewed literature. Especially, drones can be incorporated to provide a faster and undisrupted distribution.
- The role of unmanned vehicles in the humanitarian logistics context has been mostly neglected.
- Although we can observe some work focusing on routing decisions, there are unavoidable aspects in humanitarian logistics that have not been considered: the first has to do with the need to make multiple trips using the same vehicle; the second is the need to consider multi-echelon vehicle routing problems arising when the humanitarian network has several layers of supporting facilities.
- One aspect that has also been neglected to a large extent in the literature is the demonstration of the quantitative gain resulting from capturing uncertainty in facility location problems emerging in the context of humanitarian logistics. Although our intuition tells that this makes sense, the existing literature mostly ignores this fact. Measures such as the value of the stochastic solution (in the case of stochastic programming) or the expected value of perfect information have not been considered in general although they are important to indicate (i) how relevant is to capture uncertainty, and (ii) how relevant it is to consider a more elaborate model for capturing uncertainty compared to using a simplified (e.g. deterministic) one.
- Acknowledging the effect of commodity types on the problem structure is quite crucial. Consumable/non-consumable or perishable/non-perishable items require different delivery frequency and storage conditions. These commodity attributes and their effects are not studied sufficiently in the literature.
- In terms of solution techniques we still observe a major distinction between exact and approximate algorithms. It would be interesting to start thinking of algorithms such as matheuristics that combine both perspectives thus taking advantage from both.
- Most of the works incorporating equity adopt a *minimax* objective. While this is better than a “do-nothing” approach it fails to capture (distinguish among) alternative solutions that perform the same with respect to a minimax function since it satisfies the Pigou-Dalton principle of transfers only in the weak sense (Karsu and Morton [60], Sen [131]). To see why, consider two scenarios in which the delivery amounts of a good to three demand nodes are (90,89,10) and (90,10,10). Both have the same minimum value while the first distribution actually outperforms the second one in terms of the total amount distributed. More sophisticated functions should be used to ensure that the solutions are as fair as possible. Of course, this need brings further new design challenges on how to choose the metrics and the functions. One can borrow from the Robust Optimization literature so as to obtain good solutions over a range of possible choices for such functions. Another direction worth exploring is the idea of the lexicographic minimax approach (e.g., Ogryczak [96]), which could resolve issues like the three-node example above given.

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Supplementary material

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