Innovative Applications of O.R.

Stochastic network models for logistics planning in disaster relief

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ABSTRACT

Emergency logistics in disasters is fraught with planning and operational challenges, such as uncertainty about the exact nature and magnitude of the disaster, a lack of reliable information about the location and needs of victims, possible random supplies and donations, precarious transport links, scarcity of resources, and so on. This paper develops a new two-stage stochastic network flow model to help decide how to rapidly supply humanitarian aid to victims of a disaster within this context. The model takes into account practical characteristics that have been neglected by the literature so far, such as budget allocation, fleet sizing of multiple types of vehicles, procurement, and varying lead times over a dynamic multiperiod horizon. Attempting to improve demand fulfillment policy, we present some extensions of the model via state-of-art risk measures, such as semideviation and conditional value-at-risk. A simple two-phase heuristic to solve the problem within a reasonable amount of computing time is also suggested. Numerical tests based on the floods and landslides in Rio de Janeiro state, Brazil, show that the model can help plan and organise relief to provide good service levels in most scenarios, and how this depends on the type of disaster and resources. Moreover, we demonstrate that our heuristic performs well for real and random instances.

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1. Introduction

Floods and landslides are just two of the various types of disaster that plague Brazil year after year, leaving a trail of huge destruction. According to Valencio (2014), the problem of disasters in Brazil should not be considered *residual*; it suffices to analyse the number of municipalities which declared an *emergency situation* or *state of public calamity* between the years 2003 and 2013 to confirm that disasters are, in fact, recurrent events. During this period, an average of 1368 municipalities, about 24 percent of Brazilian municipalities, had some sort of socioeconomic problem as a result of environmental disasters – from droughts in the northeast to flooding in the south region. In the same line, Yodmani (2001) argues that disasters should not be seen as simply extreme events caused only by natural forces, but also as symptoms of underdevelopment in countries.

In July 2013, the Civil Defense of Brazil and its Postal Service signed a contract for the prepositioning of strategic stocks for humanitarian assistance in certain regions of the country in an attempt to mitigate disaster impacts (Presidency of the Republic, Brazilian Government, 2013). The main idea behind such a policy is to provide a faster response, possibly by decreasing lead times between the request and arrival of supplies. For this purpose, though, an optimized system is needed to cross-check information about safety stocks (location, availability, etc.) with updated information about the disaster (e.g., affected areas, number and need of the victims, road damage) and to determine the quantity and sizes of existing vehicles required to deliver supplies. Such prepositioning, without mentioning the provision of emergency relief and supplies to disaster victims, is fraught with planning and operational challenges (Balcik, Beamon, Krejci, Muramatsu, & Ramirez, 2010) mostly due to the scarcity of overall resources and the inherent uncertainties of disasters.

Thus, in order to respond to disasters effectively, governments and humanitarian organisations need to consider these issues when designing effective relief supply chains. However, Gonçalves (2011) showed that humanitarian decision makers often make non-optimal decisions in the field by over-reliance on past experience, over-confidence in their own unaided decision-making abilities, and the use of simple decision heuristics. The resulting poor decisions motivate this paper to explore stochastic and dynamic models that can handle the urgent complexity and uncertainty faced by decisions makers. In particular, we propose an optimization model that could be used within a decision-aid tool by the Brazilian agencies that are currently responsible for providing rapid responses in disaster relief. Our model encompasses common decisions

regarding logistics planning, such as how to dispatch emergency aid from warehouses to affected areas over a number of time periods in order to alleviate suffering during relief operations, that is, to decide the most suitable routes, which vehicles should be used, in which periods and in which quantity, and so on.

The model also balances the immediate lack of external supplies by allowing (i) the procurement of emergency aid during a response; and (ii) the prepositioning of emergency aid before a disaster strikes. The first option is based on Brazilian humanitarian practices where procurement usually occurs some days or more after the start of the humanitarian operations in the same area where the disaster struck. However, only a few emergency aid items are likely to be available, in very limited amounts and at a very high cost, since local vendors often take advantage of the vulnerable situation. The second option may be seen as a global trend to overcome the suddenness of disasters (Davis, Samanlioglu, Qu, & Root, 2013; Duran, Gutierrez, & Keskinocak, 2011; Lodree, Ballard, & Song, 2012; Salmerón & Apte, 2010). Additional decisions supported by the proposed model concern defining appropriate inventory levels and budget allocation among the various operations. Backlogging is permitted at a very high cost, as we know that in practical problems there are not enough resources to meet the demand from all victims.

For Oztaysi, Behret, Kabak, Sari, and Kahraman (2013), uncertainty is a crucial challenge that must be overcome in disaster management. In fact, immediately after or during a natural disaster, the number of affected people (homeless, displaced, injured, deaths) may be only vaguely known and recipient demand will be difficult to predict in terms of timing, location, type, and size. Suddenly-occurring large demand and short lead times for a wide variety of supplies will contrast with periods of low demand (Kovács & Spens, 2009; Sarkis, Spens, & Kovács, 2010). In addition, since the situation is often unclear in the immediate aftermath of the disaster, some routes might be total or partially blocked, with uncertain information about any damage. In the megadisaster of the *Serrana* region of Rio de Janeiro (Brazil) in 2011, 14 state highways from 7 different cities suffered traffic blockages due to landslides and flooding, besides the countless number of urban and rural access roads that were also damaged. Although many emergency aid supplies can be strategically prepositioned, only some of them will remain usable, depending on the impact and location of the disaster.

Supplies and monetary funds may also be affected by the degree of the disaster. Recent studies suggest that donor behaviour may depend not only on measurable parameters – such as an aid agency's use of donated funds, fund-raising cost factors, and donors' unit utility of donations Toyasaki and Wakolbinger (2014) – but also on subjective factors that influence the decision to donate, such as how people perceive a certain disaster (Zagefka, Noor, Brown, de Moura, & Hopthrow, 2011), and the role of the media, social networks, etc. (Brito Junior, Leiras, & Yoshizaki, 2013). As supplies and monetary budgets usually come from a variety of organisations, they are considered to have uncertain values as well. This uncertainty is further complicated by the phenomenon of material convergence (Fritz & Mathewson, 1957; Holguín-Veras, Jaller, Van Wassenhove, Pérez, & Wachtendorf, 2012) whereby well-meaning non-professional donors supply huge quantities of unsolicited goods of doubtful usefulness that can (and often do) clog the supply chain, disrupting the flow of urgent aid to recipients in need.

In this paper, uncertainties are modelled via scenario-based two-stage stochastic programming. The first-stage plans the prepositioning of emergency aid and the overall capacity of each type of vehicle (fleet-sizing). The second-stage response makes operational decisions for transportation – including the detailed decision regarding the assignment of vehicles to routes – as well as inventory,

shortages, and procurement. The objective function is flexible, being able to minimise total expected costs or prioritize the meeting of recipient demand while avoiding excessive inventory. We also show how that the stochastic programming model can be straightforward extended to consider different risk-averse preferences to produce less risky or reliable solutions and/or to improve fairness.

As the mixed-integer stochastic programming models are huge and computationally challenging even for small-sized instances, we develop a two-phase heuristic that performs very well for real and random instances. The first phase solves a (smaller) simplified version of the model that overestimates the overall number of vehicles in the first-stage. The second phase then fixes the first-phase decisions regarding the operational distribution flow and re-solves the original model to determine the remaining decision variables.

Our overall numerical results have important implications in terms of roles within the humanitarian supply chain in efficiently managing both the preparedness and response phases of most sudden-onset disasters.

This paper is organised as follows. Section 2 reviews the most relevant literature. Section 3 develops the proposed stochastic optimization model. Section 4 shows how to extend the risk-neutral stochastic model to incorporate risk preferences. Section 5 presents a two-phase procedure to determine good-quality solutions within a reasonable amount of time. Section 6 implements the model on real data from the 2011 floods and landslides in Rio de Janeiro state, Brazil, and analyses the computational results. The paper concludes in Section 7 with a discussion of the model's value and flags remaining challenges and opportunities for future research.

2. Related literature

Possibly due to the increased frequency and severity of disasters around the world and to their greater visibility on television and social media in recent decades (Franks, 2014; Seib, 2014), these wrenching events have been the subject of growing public concern and research interest (Smith, Wasiak, Sen, Archer, & Burkle, 2009). This paper will not review all decision models for disaster management and emergencies, but rather will focus on the quantitative management of uncertainty in emergency logistics planning in disaster relief, considering only recent research on scenario-based stochastic programming approaches in transportation and distribution relief within network flows. The reader who is interested in wider surveys of the application of quantitative models and operational research to humanitarian logistics can consult Altay and Green (2006), Van Wassenhove (2006), Caunhye, Nie, and Pokharel (2012), De la Torre, Dolinskaya, and Smilowitz (2012), Holguín-Veras et al. (2012), Ortuño et al. (2013), Galindo and Batta (2013), Leiras, de Brito Jr, Queiroz Peres, Rejane Bertazzo, and Tsugunobu Yoshida Yoshizaki (2014) and Özdamar and Ertem (2015) amongst others.

Two-stage stochastic programming with recourse models have been successfully used in humanitarian logistics and disaster management as they allow the modeller to represent pre- and post-event phases together via first- and second-stage decision variables. Barbarosoğlu and Arda (2004) appears to be the pioneer paper that developed a two-stage stochastic model for both pre-event and post-event stages in disaster response, considering supply capacity and demand as random variables approximated by multiple scenarios. In addition, following a two-stage paradigm, but with different first- and second-stage decisions, Chang, Tseng, and Chen (2007) presented a scenario-based model adapted to represent a multi-echelon network in a flood disaster rescue system.

Relief resource allocation problems have also been researched in the following papers. Mete and Zabinsky (2010) designed a two-stage stochastic model to first locate possible medical storage centres and their stock levels before the disaster, then to deliver

medical supplies to hospitals for each disaster scenario. Salmerón and Apte (2010) used a two-stage stochastic optimisation model for the strategic positioning and sizing of a variety of relief resources, followed by scenario analysis to deploy the resources in the event of a disaster. Prepositioning decisions were also the focus of Rawls and Turnquist (2010), and are discussed in Rawls and Turnquist (2012), Noyan (2012), and Hong, Lejeune, and Noyan (2015). Rawls and Turnquist (2010) sought the pre-event prepositioning of relief supplies, using multiple scenarios to represent the huge amount of uncertainty regarding the date, location, and intensity of an eventual disaster and the difficulty of forecasting its impact on transport infrastructure. Noyan (2012) extended Rawls and Turnquist's model to include attitudes to risk by making use of the approach known as *conditional-value-at-risk* (CVaR), widely used in financial optimisation. Rawls and Turnquist (2012) developed a short-term planning model for pre-disaster use to meet uncertain needs in the first few days after the start of the disaster, requiring that a given high percentage of all scenarios (a type of $\alpha-$ reliable constraint) should fully meet needs. Hong et al. (2015) focused on location of distribution centers and positioning of emergency supplies in long-term pre-disaster planning in an attempt to improve network reliability. For this purpose, their paper developed a chance constrained model and proposed tractable reformulations to solve more efficiently problems with moderate-size networks and a large number of scenarios.

The last mile distribution in post-disasters was investigated by Noyan, Balcik, and Atakan (2015). The authors followed the two-stage paradigm to define the location of points of distribution in the first-stage and to determine the amount of supplies delivered to them in the second-stage in an attempt to maximise the expected accessibility to the distribution centers. Two-stage programming with recourse was adopted to plan relief shelters and then the allocation of evacuees to shelters in Li, Jin, and Zhang (2011) in which the authors adopted a two-echelon network to represent both evacuee and resource flows to permanent and temporary shelters. In contrast, Döyen, Aras, and Barbarosoğlu (2012) developed a two-echelon stochastic model for modelling flows between regional and local rescue centers, as well as locating them, prepositioning inventory, and then optimising cover and transport after the disaster, testing over many scenarios.

The integration between location and routing in emergency logistics is also tackled in Rennemo, Rø, Hvattum, and Tirado (2014) and Ahmadi, Seifi, and Tootooni (2015). The former authors have developed a first multi-stage stochastic programming model to deal with a facility routing model in humanitarian logistics. Their three-stage model incorporates the opening of local distribution facilities in the first-stage, the initial allocation of supplies in the second-stage, and the last mile distribution of emergency aid in the third-stage. The authors illustrated the outperformance of the model in comparison to deterministic approaches via the evaluation of both the expected value of perfect information and the value of stochastic solution. Ahmadi et al. (2015) proposed a location-routing model under network failure, multiple uses of vehicles, and standard relief time. Network failure is modelled via a two-stage stochastic program with random travel time and analysed using a case study in the San Francisco district.

A different stochastic approach to deal with the issue of the imbalance between supply and demand in post-disaster emergency logistics operations was suggested by Sheu and Pan (2015). Stochastic dynamic programming was used to determine the amount and the type of emergency resources to the affected areas. The authors pointed out the importance of collaboration among relief suppliers to alleviate the impact of an imbalanced relief supply chain through a number of numerical experiments.

To take advantage of the temporal nature of the disaster, Rottkemper, Fischer, and Blecken (2012) developed a rolling-horizon transshipment and inventory relocation model to reallocate goods as a disaster unfolds without prejudicing ongoing relief operations, resolving the model repeatedly for each time period, and updating as the situation changed over time.

Only a few authors have incorporated robustness issues within humanitarian operations. Bozorgi-Amiri, Jabalameli, and Mirzapour Al-e-Hashem (2013) considered multiple sources of uncertainty, including possible damage to prepositioned supplies, applied to earthquake scenarios in Iran. The authors used so-called robust optimization in the sense of Mulvey, Vanderbei, and Zenios (1995) to simultaneously reduce the variability of the second-stage costs and the infeasibility of the demand constraints. Kelle, Schneider, and Yi (2014) adapted a min–max regret model that results in good but wasteful cover in worst-case scenarios, so that it provides a range of cover-waste tradeoffs to choose from. The p-reliable regret criterion used by the authors resembles the $\alpha-$ reliable criterion in Rawls and Turnquist (2012).

Table 1 summarizes the literature review with respect to scenario-based stochastic programming network flow models in disaster relief and shows the main differences between the existing literature and this paper. Only a few papers consider dynamic or multiperiod settings, although most authors recognize a disaster as also being a temporal event. In fact, most papers that present dynamic models ignore their inherent uncertainties, e.g., Özdamar, Ekinci, and Küçükyazici (2004). Note too that some practical characteristics have been neglected by the literature so far, such as time-varying lead times and multiple modes of transportation. Regarding the decisions supported by the model, budget allocation, fleet sizing and procurement are rarely jointly considered in the current literature. Even though many papers account for random demands, networks and capacities, it seems that random supply has only recently been considered and random budgets have never been studied before. Most authors ignore the potential disadvantages of using risk-neutral approaches, i.e., very pessimistic worst-case solutions, or the high-variability of the second-stage decisions. In fact, the importance of analysing robust or risk-averse policies in stochastic network models for disaster relief has been pointed out only recently by Noyan (2012). Most papers develop solution procedures in order to obtain fast good-quality solutions. Exact and heuristic methods are usually based on decomposition schemes in an attempt to produce smaller and easier solvable problems. Finally, note that flooding and landslides are only rarely studied by the specialized literature as most papers deal with hurricane and earthquake disasters in USA.

Specifically, our contribution in this article can be summarised as follows. Firstly, we propose a new stochastic model that combines important characteristics in terms of network structure, decisions and stochastic treatment. Although some articles have already studied various sources of uncertainty in similar contexts, we combine them to analyse their relationship. Moreover, we use a scale system to categorize historical data from flooding and landslide disasters in Rio de Janeiro State to generate plausible scenarios. Secondly, we extend the traditional risk-neutral model to consider risk-averse attitudes via state-of-art risk measures, namely, so-called minimax-regret, semideviation and CVaR. Thirdly, we develop a solution procedure that exploits a simplified model to construct a feasible solution and demonstrate its good performance in different instances.

3. A two-stage stochastic network model for disaster relief

Our two-stage network flow model encompasses multiple types of emergency aid, multiple types of vehicles, multiple time periods, and multiple scenarios. The core of the model is the transport of emergency aid among nodes, but it is possible to adapt the model for the evacuation of people from affected areas to

Table 1

Literature review of scenario-based stochastic programming network-flow models for disaster relief featuring model characteristics, type of objective function, decisions supported by the model, stochastic treatment, solution method, and type of disaster addressed.

Reference	Characteristics						Objective function		
	Type of network	Multiperiod	Multicommodity	Multidepot	Multimodal	Leadtime[a]	Cost	Others	Multiobjective
This paper	Generic k-level	✓	✓	✓	✓	✓	✓	✓	
Barbarosoğlu and Arda (2004)	Transhipment		✓	✓	✓		✓		
Chang et al. (2007)	Multi-echelon		✓	✓			✓		
Salmerón and Apte (2010)	Transhipment		✓	✓	✓			✓	
Mete and Zabinsky (2010)	Single echelon		✓	✓	✓	✓	✓	✓	✓
Rawls and Turnquist (2010)	Single echelon		✓	✓			✓		
Li et al. (2011)	Two-echelon		✓	✓			✓		
Rawls and Turnquist (2012)	Single echelon	✓	✓	✓			✓		
Noyan (2012)	Single echelon		✓	✓			✓		
Döyen et al. (2012)	Two-echelon		✓	✓		✓			
Rottkemper et al. (2012)	Two-echelon	✓		✓	✓		✓		
Bozorgi-Amiri et al. (2013)	Two-echelon		✓	✓			✓	✓	✓
Rennemo et al. (2014)	Two-echelon		✓	✓	✓	✓		✓	
Ahmadi et al. (2015)	Two-echelon		✓	✓	✓	✓	✓	✓	
Hong et al. (2015)	Two-echelon			✓			✓		
Sheu and Pan (2015)	Single-echelon	✓	✓					✓	
Noyan et al. (2015)	Two-echelon			✓				✓	

Decisions									
Reference	Budgeting	Fleet	Inventory	Location	Prepositioning	Procurement	Shortage	Transportation	Others
This paper	✓	✓	✓		✓	✓	✓	✓	
Barbarosoğlu and Arda (2004)			✓				✓	✓	✓
Chang et al. (2007)			✓	✓	✓		✓	✓	
Salmerón and Apte (2010)	✓	✓		✓			✓	✓	✓
Mete and Zabinsky (2010)			✓	✓			✓	✓	✓
Rawls and Turnquist (2010)			✓	✓	✓		✓	✓	
Li et al. (2011)			✓	✓	✓		✓	✓	✓
Rawls and Turnquist (2012)			✓	✓	✓		✓	✓	
Noyan (2012)			✓	✓	✓		✓	✓	
Döyen et al. (2012)			✓	✓	✓		✓	✓	
Rottkemper et al. (2012)		✓	✓				✓	✓	✓
Bozorgi-Amiri et al. (2013)			✓	✓	✓	✓	✓	✓	
Kelle et al. (2014)			✓		✓		✓	✓	
Rennemo et al. (2014)	✓	✓		✓				✓	✓
Ahmadi et al. (2015)		✓		✓			✓	✓	✓
Hong et al. (2015)			✓	✓	✓		✓	✓	
Sheu and Pan (2015)			✓				✓		
Noyan et al. (2015)				✓			✓		✓

Table 1 (*continued*)

Reference	Characteristics						Objective function		
	Type of network	Multiperiod	Multicommodity	Multidepot	Multimodal	Leadtime[a]	Cost	Others	Multiobjective
	Stochastic treatment						**Solution procedure**	**Application**	
Reference	Demand	Supply	Network	Budget	Others	Risk/Robustness			
This paper	✓	✓	✓	✓	✓	✓	MIP-based heuristic	Flooding in Brazil	
Barbarosoğlu and Arda (2004)	✓	✓			✓			Earthquake Turkey	
Chang et al. (2007)	✓		✓		✓		SAA	Flooding	
Salmerón and Apte (2010)	✓		✓		✓			Hurricane	
Mete and Zabinsky (2010)	✓		✓		✓			Earthquake US	
Rawls and Turnquist (2010)	✓				✓		L-shaped	Hurricane US	
Li et al. (2011)	✓		✓		✓		L-shaped	Hurricane US	
Rawls and Turnquist (2012)	✓		✓		✓	✓		Hurricane US	
Noyan (2012)	✓				✓	✓	Benders-decomposition	Hurricane US	
Döyen et al. (2012)	✓						Lagrangean heuristic		
Rottkemper et al. (2012)	✓	✓			✓		Rolling horizon heuristic	Malaria Epidemic in Burundi	
Bozorgi-Amiri et al. (2013)	✓				✓	✓		Earthquake Iran	
Kelle et al. (2014)	✓				✓	✓	L-shaped	Storms and Hurricane US	
Rennemo et al. (2014)	✓		✓			✓			
Ahmadi et al. (2015)	✓						Metaheuristic VNS	Earthquake USA	
Hong et al. (2015)	✓		✓	✓		✓	Combinatorial patterns	Hurricane USA	
Sheu and Pan (2015)	✓	✓					SDP	Typhoon China	
Noyan et al. (2015)	✓						L-shaped	Earthquake Turkey	

[a] We also consider transportation time.

relief centers via simultaneous flows and counter-flows. Although the mathematical model is general enough to represent different disaster types, it is particularly suitable for help in logistics planning of sudden and localized onset disasters (Apte, 2009), due to its main characteristics in terms of parameters, uncertainty treatment, and decision variables. Thus, we believe that different institutions (the Red Cross, ONG's, etc.) can then flexibly use the model to represent their particular challenges.

3.1. Assumptions and limitation of the model

At first, nodes are partitioned only into two subsets: nodes with and without demand. We assume that nodes with demand represent relief center points and that nodes without demand represent warehouses points where emergency aid will be prepositioned. In addition, prepositioning is permitted only in the first time period, in an attempt to represent its strategic allocation well before a disaster strikes. Unused prepositioned emergency aid in the first time period becomes regular inventory afterwards. Procurement of emergency aid is allowed in all periods, but only at relief center points.

The optimal distribution of emergency aid among nodes is defined by their flow along each route (a network arc between two nodes) and by determining a suitable size of transport fleet, i.e., the quantity of each type of vehicle necessary to carry the emergency aid, considering both weight and volume loading capacities. The model is formulated assuming there is just one connection from one node to another for each type of vehicle − if not then dummy intermediate nodes can be inserted to represent different connections. There is a maximum amount of emergency aid that can be prepositioned and procured, and a maximum available number of each type of vehicles that can be hired in the first stage.

The model attempts to minimise clogging within the supply chain due to material convergence (Holguín-Veras et al., 2012) by pulling aid through as a function of specific recipient needs rather than pushing supplies into the chain. However, the elimination of unneeded donated goods at prepositioning warehouses remains a modeling challenge that is beyond the scope of this paper.

The monetary budget may be used for transportation and procurement of emergency aid; any unused budget in period t is passed to period $t + 1$ without interest.

To take uncertainty into account, we propose a scenario-based approach within a two-stage stochastic programming paradigm. We consider a probability space $(\Xi, \mathcal{F}, \Pi)$, where Ξ is the set of realizations, $\mathcal{F}$ is the set of events $\mathcal{F} \subseteq \Xi$, and Π is the probability measure. Associated with a particular realization $\xi \in \Xi$, there is a probability of occurrence π^ξ, such that $\pi^\xi > 0$ and $\sum_\xi \pi^\xi = 1$. In this paper, we also assume that the random variables become known only at a single moment after disaster strikes, thus not revealing themselves "by time". In addition, the random variables and decisions are not intertwined; our scenarios are independently sampled over the full horizon, justifying our choice for two-stage programming instead of a multistage version.

Before disaster strikes, we have to strategically define the quantity and location of prepositioned emergency aid, as well as determine the overall capacity of each type of vehicle to perform (in the "future") effective emergency logistics, since hiring a suitable fleet can be a very bureaucratic and time-consuming public bidding procedure. Thus both decisions are naturally considered as first-stage variables. After disaster strikes, we determine the second-stage decision variables based on the updated information on the quality of the routes, supplies, demands and donation. Those decisions include the flow of emergency aid among arcs, the number and type of vehicles necessary to perform distribution, procurement issues, inventory and backlogging. The first use of the second-stage model should be as soon as possible after the

start of the disaster. Its use thereafter will be on a rolling-horizon basis with updated information and scenarios as the impact of the disaster becomes clearer and fresh resources become available. An overview of the model's structure and usage is depicted in Fig. 1.

Although the location of relief centers and warehouses may have an important impact in certain relief supply network, we assume that they are well located beforehand so we focus on prepositioning, distribution, fleet decisions, etc. In our application, we consider all possibilities of location of both warehouses and relief centers, since we consider one relief center for each affected area and one warehouse for each big city. Other model's limitations include its data requirements, both deterministic and stochastic. The latter in particular are often guestimates for a given scenario, as acknowledged in the computational tests of Section 6. Moreover, the identification of a representative set of scenarios requires knowledge and experience of past or similar disasters, while climate change may cause new scenarios to occur, for example, flooding on a scale not seen before in many regions (Arnell & Lloyd-Hughes, 2014). In addition, the risk-aversion extensions developed in Section 4 take much longer to solve and tend to increase first-stage costs (but reduce the variability of second-stage costs) as shown and discussed in Section 6.

3.2. Model formulation

The full mathematical model uses the following notation.
Indices and sets

$\mathcal{I}$	set of types of emergency aid indexed by i (food, water, medicine kits, etc.)
$\mathcal{R}$	set of types of vehicles indexed by r (trucks, boats, helicopters, etc.)
$\mathcal{N}^{rc}$	subset of demand nodes, or relief center nodes, indexed by n and m
$\mathcal{N}^w$	subset of supply nodes, or warehouses, indexed by n and m
$\mathcal{N}$	set of all nodes, indexed by n and m ($\mathcal{N} = \mathcal{N}^{rc} \cup \mathcal{N}^w$)
$\mathcal{T}$	set of time periods, indexed by t
Ξ	set of scenarios, indexed by ξ

Deterministic input data

c_r^{max}	available number of vehicles of type r
c_i^w and c_i^v	weight and volume of emergency aid i, respectively
g_r^w and g_r^v	weight and volume capacities of vehicles of type r, respectively
ℓ_{rnmt}	Lead time to transport any emergency aid by vehicles of type r along arc $n \to m$ in period t
p_i^{max}	maximum amount of emergency aid i that can be prepositioned
o_{in}^{max}	maximum amount of emergency aid i that can be procured at node n
α_{rnm}	unit shipping cost by vehicles of type r through the arc $n \to m$
β_r	unit rental cost for using vehicles of type r
ι_{in}^+	unit holding cost for emergency aid i at node n
ι_{in}^-	unit penalty cost for the shortage of emergency aid i at node n
o_{in}	unit procurement cost of emergency aid i at node n
ρ_{in}	unit prepositioning cost for emergency aid i at node n (procurement plus opportunity cost)

Stochastic input data

|	
b_{int}^ξ	incoming supplies of emergency aid i at node n in period t in scenario ξ
d_{int}^ξ	demand for emergency aid i at node n in period t in scenario ξ
f_t^ξ	financial budget available in period t in scenario ξ (donations, federal funding, etc.)
q_{rnmt}^ξ	= 1 if a vehicles of type r can cross arc $n \to m$ in period t in scenario $\xi = 0$ if not
s_{in}^ξ	fraction of the prepositioned emergency aid i at node n that remains usable in the first period in scenario ξ
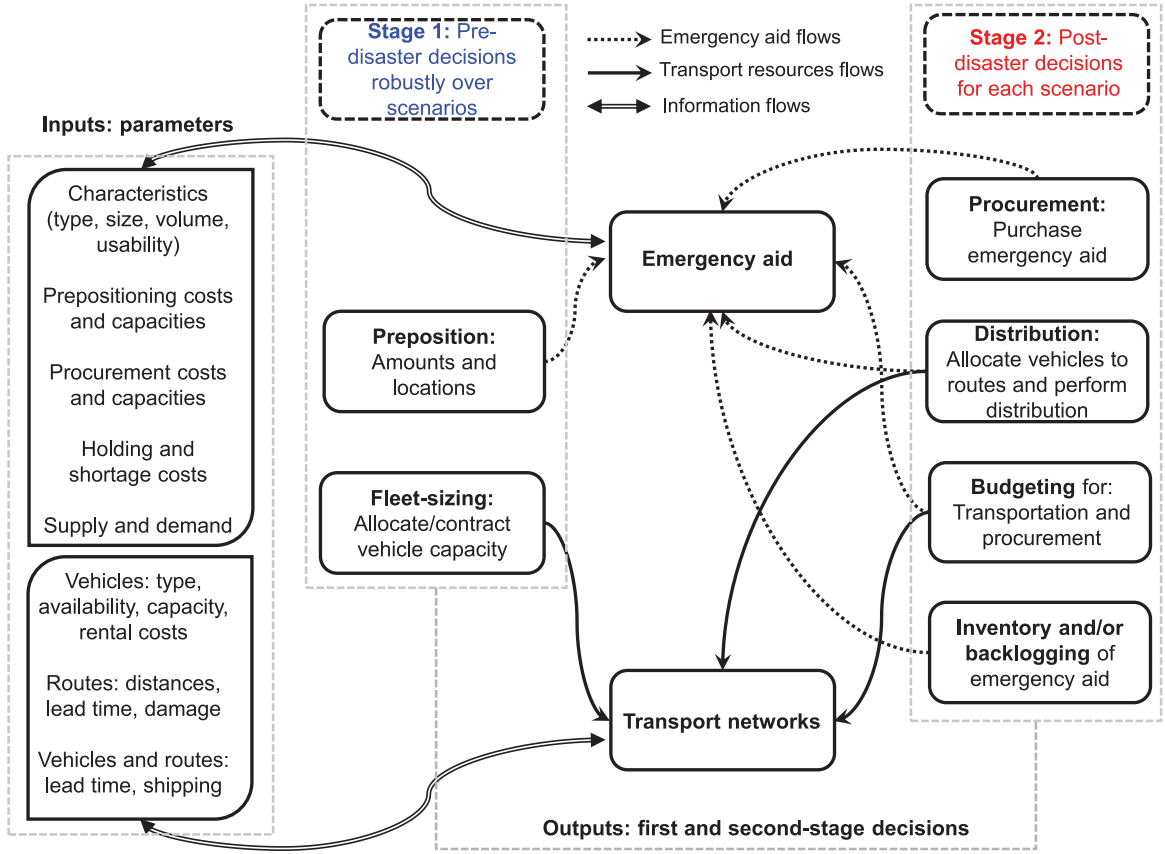
Fig. 1. Overview of the model's structure and usage.

First-stage decisions

P_{in}^0 amount of emergency aid i prepositioned at node n at the start of the first period

Y_r^C number of vehicles of type r contracted in the first-stage to transport emergency aid over the periods

Second-stage decisions

$I_{int}^{\xi+}$ available inventory of emergency aid i at node n in period t in scenario ξ

$I_{int}^{\xi-}$ shortage (unmet demand) of emergency aid i at node n in period t in scenario ξ

$\mathcal{O}_{int}^{\xi}$ amount of procured emergency aid i at node n in period t in scenario ξ

V_{rnmt}^{ξ} number of vehicles of type r used on arc $n \to m$ in period t in scenario ξ

X_{irnmt}^{ξ} flow of emergency aid i shipped by vehicles of type r on arc $n \to m$ in period t in scenario ξ

Z_t^{ξ} unused budget at the end of period t in scenario ξ

The risk-neutral two-stage stochastic network model for emergency logistics planning is formulated as follows:

(F1: RiskNeutral)

$$\text{Min} \sum_{i\in\mathscr{I}}\sum_{n\in\mathscr{N}^w} \rho_{in} \cdot P_{in}^0$$

$$+ \sum_{r\in\mathscr{R}} \beta_r \cdot Y_r^C + \sum_{i\in\mathscr{I}}\sum_{n\in\mathscr{N}}\sum_{t\in\mathscr{T}}\sum_{\xi\in\Xi} \pi^\xi \cdot \left(\iota_{in}^+ \cdot I_{int}^{\xi+} + \iota_{in}^- \cdot I_{int}^{\xi-} \right) \quad (1)$$

s.t.: $$\sum_{n\in\mathscr{N}^w} P_{in}^0 \leq p_i^{\max}, \quad i\in\mathscr{I} \quad (2)$$

$$Y_r^C \leq c_r^{\max}, \quad r\in\mathscr{R} \quad (3)$$

$$\sum_{r\in\mathscr{R}}\sum_{m\in\mathscr{N}} \left[X_{irnmt}^{\xi} - X_{irmn(t-\ell_{rmnt})}^{\xi} \right]$$

$$= \begin{cases} I_{in(t-1)}^{\xi+} - I_{in(t-1)}^{\xi-} + I_{int}^{\xi-} - I_{int}^{\xi+} + \mathcal{O}_{int}^{\xi} + b_{int}^{\xi} - d_{int}^{\xi}, \\ \qquad i\in\mathscr{I}, \quad n\in\mathscr{N}^{rc}, \quad t\in\mathscr{T}, \quad \xi\in\Xi \\ I_{in(t-1)}^{\xi+} - I_{int}^{\xi+} + s_{in}^{\xi} \cdot P_{in}^0 + b_{int}^{\xi}, \\ \qquad i\in\mathscr{I}, \quad n\in\mathscr{N}^w, \quad t=1, \quad \xi\in\Xi \\ I_{in(t-1)}^{\xi+} - I_{int}^{\xi+} + b_{int}^{\xi}, \\ \qquad i\in\mathscr{I}, \quad n\in\mathscr{N}^w, \quad t\in\mathscr{T}-\{1\}, \quad \xi\in\Xi \end{cases} \quad (4)$$

$$\sum_{t\in\mathscr{T}} \mathcal{O}_{int}^{\xi} \leq o_{in}^{\max}, \quad i\in\mathscr{I}, \quad n\in\mathscr{N}^{rc}, \quad \xi\in\Xi \quad (5)$$

$$V_{rnmt}^{\xi} \geq \sum_{i\in\mathscr{I}} \frac{c_i^w}{g_r^w} \cdot X_{irnmt}^{\xi}, \quad r\in\mathscr{R}, (n,m)\in\mathscr{N}, \quad t\in\mathscr{T}, \quad \xi\in\Xi \quad (6)$$

$$V_{rnmt}^{\xi} \geq \sum_{i\in\mathscr{I}} \frac{c_i^v}{g_r^v} \cdot X_{irnmt}^{\xi}, \quad r\in\mathscr{R}, \quad (n,m)\in\mathscr{N}, \quad t\in\mathscr{T}, \quad \xi\in\Xi \quad (7)$$

$$\sum_{(n,m)\in\mathscr{N}}\sum_{t\in\mathscr{T}} V_{rnmt}^{\xi} \leq Y_r^C, \quad r\in\mathscr{R}, \quad r\in\mathscr{R}, \quad \xi\in\Xi \quad (8)$$

$$V_{rnmt}^{\xi} \leq q_{rnmt}^{\xi} \cdot Y_r^C, \quad r\in\mathscr{R}, \quad (n,m)\in\mathscr{N}, \quad t\in\mathscr{T}, \quad \xi\in\Xi \quad (9)$$

$$\sum_{r\in\mathscr{R}}\sum_{(n,m)\in\mathscr{N}} \alpha_{rnm} \cdot V_{rnmt}^{\xi} + \sum_{i\in\mathscr{I}}\sum_{n\in\mathscr{N}^{rc}} o_{in} \cdot \mathcal{O}_{int}^{\xi}$$

$$= f_t^{\xi} + Z_{(t-1)}^{\xi} - Z_t^{\xi}, \quad t\in\mathscr{T}, \quad \xi\in\Xi \quad (10)$$

$$Y_r^C \geq 0 \text{ and integer}, \quad r\in\mathscr{R} \quad (11)$$

$$V_{rnmt}^{\xi} \geq 0 \text{ and integer}, \quad r\in\mathscr{R}, \quad (n,m)\in\mathscr{N}, \quad t\in\mathscr{T}, \quad \xi\in\Xi \quad (12)$$

$P^0_{in|n \in \mathcal{N}^w}, X^{\xi}_{irnmt}, I^{\xi+}_{int}, I^{\xi-}_{int},$

$\mathcal{O}^{\xi}_{int|n \in \mathcal{N}^{rc}}, Z^{\xi}_t \geq 0, \quad i \in \mathcal{I}, \quad r \in \mathcal{R}, \quad (n,m) \in \mathcal{N}, \quad t \in \mathcal{T}, \quad \xi \in \Xi.$

$$\text{(13)}$$

The objective function (1) minimises a weighted sum of the first-stage cost of prepositioning stock, hiring vehicles, and the expected second-stage cost of inventory and unmet demand. Constraint (2) limits the amount of each emergency aid that can be prepositioned across the warehouse nodes and can be easily modified if a specific node has tight capacity. Constraint (3) limits the total quantity of each type of vehicle that can be contracted to transport emergency aid over the humanitarian operations.

The flow constraints (4) balance inventory, unmet demand, procurement and the prepositioning of emergency aid with demand and incoming supplies over consecutive time periods at each node in the network. The first equality in (4) represents the flow through nodes with demand (relief centers), where there could be supply and procurement. The second equality guarantees the flow of the available quantity of emergency aid (supplies and/or prepositioned goods) through nodes without demand (warehouses) in the first-period. In this case, prepositioning is possible, but shortages are not allowed. The last equality is similar, but it refers to the second time period onwards, in which case prepositioning is not a valid policy. Without loss of generality, initial inventory and unmet demand (in $t = 0$) are considered to be zero. Note that constraints (4) combined with the minimization of inventory and unmet demand in the objective function (1) means that material convergence clogging is lessened by not pushing unwanted donated supplies into the supply chain.

Constraint (5) limits the amount of emergency aid that can be procured across the relief center nodes. Constraints (6) and (7) determine the type and number of vehicles required to transport emergency aid through the network. A number of different vehicles, such as trucks, boats and helicopters, are likely to be used to reach precarious areas, such as flooded and collapsed regions. Both weight and volume loading are considered to determine the most suitable vehicles, as a particular emergency aid can be lightweight but bulky, or vice-versa. Constraint (8) guarantees that the total number of vehicles used to transport emergency aid after disaster strikes is not greater than the fleet of vehicles contracted in the first-stage. Constraint (9) links the number of vehicles required in each route, period and scenario to the available arcs. For example, depending on the disaster, q^{ξ}_{rnmt} might be zero for road transportation, but not necessarily for air transportation. If $q^{\xi}_{rnmt} = 1$, then the number of vehicles of type r used in the second-stage is limited by Y^C_r, which is a sufficiently large number in this case. Constraint (10) ensures that the total cost of using vehicles to ship emergency aid plus the procurement cost stays within the financial budget. Constraints (11)–(13) specify the domains of the decision variables.

4. Model extensions via risk management

Although the scope of this paper does not include a comprehensive analysis of possible extensions of the proposed stochastic model, we also analyse some models from the risk management viewpoint. The research question that motivates this discussion is: "Can risk-averse models improve humanitarian operations optimized by the risk-neutral model, by, for example, reducing a key variability measure or mitigating the risk of non-wanted scenarios?".

To answer, we investigated the classical minimax-regret approach (MinMax) and two state-of-art risk risk measures: semideviation (SD) and conditional value-at-risk (CVaR). The reasons behind the choice of those risk measures are as follows. Minimax is

well-known and used in the literature, and various authors claim that it can provide "robust" solutions from a worst-case scenario perspective (Kouvelis & Yu, 1997; Riis & Andersen, 2005; Shapiro & Ahmed, 2004). It means that optimal solutions present relatively good stability regarding perturbation of the underline distribution. This strategy can be particularly useful when the probability of the different scenarios is difficult to estimate accurately, or simply when we cannot assess the probability distribution due to a lack of historical data, for example. In this case, though, scenarios can be estimated based on statistical information on the random data. The motivation for adopting semideviation and CVaR as risk measures are their coherency, as well as their consistency with stochastic dominance principles – thus allowing us to search for stochastically non-dominated solutions (Ogryczak & Ruszczyński, 2001). Moreover, the corresponding optimization problems are computationally tractable (due to the convexity of the risk measures), which is an appealing feature when dealing with mixed-integer problems.

The minimax-with-regret aims to obtain the best worst-case deviation from optimality among all feasible decisions over the entire set of scenarios (Kouvelis & Yu, 1997). The regret is simply measured as the difference between the value of the recourse cost and the value of the corresponding scenario $W^{\star}(\xi)$. The resulting Minmax problem is as follows:

(F2: Minmax)

Min Φ

s.t. Constraints (2) − (13)

$\Phi \geq \sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}^w} \rho \cdot P^0_{in} + \sum_{r \in \mathcal{R}} \beta_r \cdot Y^C_r$

$\qquad + \sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \left[\iota^+_{in} \cdot I^{\xi+}_{int} + \iota^-_{in} \cdot I^{\xi-}_{int} \right] - W^{\star}(\xi), \quad \xi \in \Xi$

$\Phi \geq 0,$ (14)

where $W^{\star}(\xi)$ is the optimal value for the single scenario wait-and-see problem.

The CVaR risk measure accounts for the expected cost of exceeding VaR at confidence level u. VaR is the so-called value-at-risk, i.e., the loss that is expected to be exceeded with a small probability $(1 - u)$ during a certain time period. CVaR is defined as follows:

$$\text{CVaR}[Q(\mathcal{Y}, \xi)] = \inf_{\text{VaR} \in \mathbb{R}} \left\{ \eta + \frac{1}{1-u} \mathbb{E}[Q(\mathcal{Y}, \xi) - \text{VaR}]_+ \right\}, \quad \text{(15)}$$

where $\mathbb{E}(\cdot)$ is the expected value a random variable, $[Q(\mathcal{Y}, \xi) - \text{VaR}]_+ = \max\{0, Q(\mathcal{Y}, \xi) - \text{VaR}\}$, $u \in (0, 1)$, and $Q(\mathcal{Y}, \xi)$ is the random recourse that depends upon the first-stage decisions $\mathcal{Y}$. By assuming a finite support Ξ with probabilities $\pi^1, \pi^2, \ldots, \pi^{|\Xi|}$ associated to the instances $\xi^1, \xi^2, \ldots, \xi^{|\Xi|}$, then problem CVaR becomes:

(F3: CVaR)

Min $\sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}^w} \rho_{in} \cdot P_{in} + \sum_{r \in \mathcal{R}} \beta_r \cdot Y^C_r$

$\qquad + (1 - \phi) \cdot \sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \sum_{\xi \in \Xi} \pi^{\xi} \cdot \left[\iota^+_{in} \cdot I^{\xi+}_{int} + \iota^-_{in} \cdot I^{\xi-}_{int} \right]$

$\qquad + \phi \cdot \left(\text{VaR} + \frac{1}{1-u} \cdot \sum_{\xi \in \Xi} \pi^{\xi} \cdot \Theta^{\xi} \right)$ (16)

s.t. Constraints (2) − (13)

$\Theta^{\xi} \geq \sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \left[\iota^+_{in} \cdot I^{\xi+}_{int} + \iota^-_{in} \cdot I^{\xi-}_{int} \right] - \text{VaR}, \quad \xi \in \Xi$

$\Theta^{\xi} \geq 0, \quad \xi \in \Xi, \quad \text{VaR free},$

Table 2

Overview of the proposed risk-averse models in terms of necessary inputs and outputs.

Model	Inputs				Outputs
	Probability of scenarios (π^ξ)	Wait-and-see solutions ($W^\star(\xi)$)	Risk parameter (ϕ)	Confidence level (u)	
F2: Minmax		✓			Maxium regret (Φ)
F3: CVaR	✓		✓	✓	VaR, CVaR, Θ^ξ
F4: SD	✓		✓		Semideviation (Δ^ξ)

where $\phi \in [0, 1]$ is a weight that serves to trade off expected value and risk and u is the confidence level. Variable Θ^ξ is 0 if scenario ξ has a total cost lower than the VaR, otherwise Θ^ξ is the difference between VaR and the corresponding cost for all ξ. Both ϕ and u reflect risk or robust preferences. As u increases, fewer worst-case scenarios are taken into account. Consequently, recourse costs are expected to be more stable across the different scenarios.

The semideviation measure of order p is defined as follows:

$$\mathbb{D}_p = \mathbb{E}[(Q(\mathscr{Y}, \xi) - \mathbb{E}Q(\mathscr{Y}, \xi))^p]^{1/p}, \quad \forall p \geq 1. \tag{17}$$

For $p = 1$, the semideviation of order 1 or the mean-semideviation measure (Krokhmal, Zabarankin, & Uryasev, 2011) can be stated as follows:

$$\mathbb{D}_p = \mathbb{E} \max[Q(\mathscr{Y}, \xi) - \mathbb{E}Q(\mathscr{Y}, \xi); \ 0]$$
$$= \mathbb{E} \max[Q(\mathscr{Y}, \xi); \ \mathbb{E}Q(\mathscr{Y}, \xi)]. \tag{18}$$

There are different ways to linearise expression (16). We use the straightforward linearisation proposed by Markert and Schultz (2005) who use an auxiliary variable, e.g. Δ^ξ, to account for the maximum value in Eq. (16). Under a finite number of scenarios, model SD is finally written as

(F4: SD)

$$\text{Min} \quad \sum_{i \in \mathscr{I}} \sum_{n \in \mathscr{N}} \rho_{in} \cdot P_{in} + \sum_{r \in \mathscr{R}} \beta_r \cdot Y_r^C + (1 - \phi)$$

$$\cdot \sum_{i \in \mathscr{I}} \sum_{n \in \mathscr{N}} \sum_{t \in \mathscr{T}} \sum_{\xi \in \Xi} \pi^\xi \cdot \left[\iota_{in}^+ \cdot I_{int}^{\xi+} + \iota_{in}^- \cdot I_{int}^{\xi-} \right] + \phi \cdot \sum_{\xi \in \Xi} \pi^\xi \cdot \Delta^\xi$$

s.t. Constraints $(2) - (13)$

$$\sum_{i \in \mathscr{I}} \sum_{n \in \mathscr{N}} \sum_{t \in \mathscr{T}} \left[\iota_{in}^+ \cdot I_{int}^{\xi+} + \iota_{in}^- \cdot I_{int}^{\xi-} \right] - \Delta^\xi \leq 0, \quad \xi \in \Xi \tag{19}$$

$$\sum_{i \in \mathscr{I}} \sum_{n \in \mathscr{N}} \sum_{t \in \mathscr{T}} \sum_{\xi' \in \Xi} \pi^{\xi'} \cdot \left[\iota_{in}^+ \cdot I_{int}^{\xi'+} + \iota_{in}^- \cdot I_{int}^{\xi'-} \right] - \Delta^\xi \leq 0, \quad \xi \in \Xi$$

$$\Delta^\xi \geq 0, \quad \xi \in \Xi$$

where the two new constraints in (19) together with the minimization of the risk term $\sum_{\xi \in \Xi} \pi^\xi \cdot \Delta^\xi$ define the semideviation risk measure represented by the second-stage decision variable Δ^ξ. Note that both CVaR and SD are mean-risk models with an objective function that is able to produce risk-neutral solutions for $\phi = 0$, solutions that are totally risk-averse for $\phi = 1$, or solutions that consider simultaneously both features for $\phi \in (0, 1)$.

Table 2 summarizes the structure of the proposed risk-averse models in terms of necessary inputs and outputs.

5. Solution procedure

Solving the proposed (risk neutral and risk-averse) two-stage stochastic mixed-integer programming model turns out to be computationally challenging. This is especially due to the number of integer decision variables, $|\mathscr{R}| + |\mathscr{R}||\mathscr{N}|^2|\mathscr{T}||\Xi|$, which can be large, even for small instances. Using the heuristic developed just below, this problem dimensionality is manageable for the real Brazilian network instance used in the computational tests in Section 6.
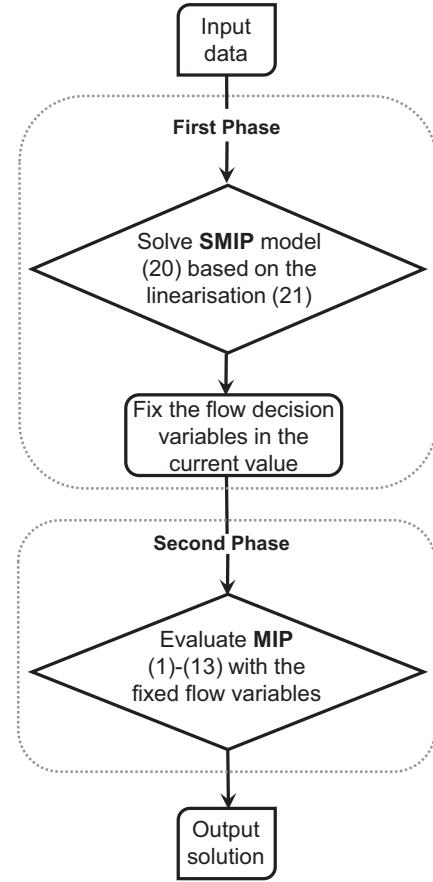

Fig. 2. Overview of the two-phase heuristic method.

However, it may well not be for some of the more complex and larger networks encountered in practice. Testing on larger instances will be required in future research.

In order to provide good-quality solutions within a reasonable amount of time, we propose a simple but effective two-phase heuristic. In the first phase, a simplified version of the mathematical model is solved in order to obtain transportation decisions (X_{irnmt}^ξ). In the second phase, the original formulation is solved with the information gathered from the first phase and the remaining decision variables are determined. The overall approach is illustrated in Fig. 2.

The simplified model SMIP (20) links the first-stage decisions Y_r^C directly with the second-stage flow variables X_{irnmt}^ξ via the parameters $\frac{c_r^w}{g_r^w}$ and/or $\frac{c_r^v}{g_r^v}$, without needing the integer decision variables V_{rnmt}^ξ.

$$\text{(SMIP)} \begin{cases} \text{Min Expression(1)} \\ \text{Constraints (2), (3), (4), (5), (11), (13)} \\ q_{rnmt}^\xi \cdot Y_r^C \geq \sum_{i \in \mathscr{I}} \frac{c_i^w}{g_r^w} \cdot X_{irnmt}^\xi, \quad r \in \mathscr{R}, \ (n,m) \in \mathscr{N}, \ t \in \mathscr{T}, \ \xi \in \Xi \\ q_{rnmt}^\xi \cdot Y_r^C \geq \sum_{i \in \mathscr{I}} \frac{c_i^v}{g_r^v} \cdot X_{irnmt}^\xi, \quad r \in \mathscr{R}, \ (n,m) \in \mathscr{N}, \ t \in \mathscr{T}, \ \xi \in \Xi \\ Y_r^C \geq \sum_{i \in \mathscr{I}} \sum_{(n,m) \in \mathscr{N}} \sum_{t \in \mathscr{T}} \frac{c_i^w}{g_r^w} \cdot X_{irnmt}^\xi, \quad r \in \mathscr{R}, \ \xi \in \Xi \\ Y_r^C \geq \sum_{i \in \mathscr{I}} \sum_{(n,m) \in \mathscr{N}} \sum_{t \in \mathscr{T}} \frac{c_i^v}{g_r^v} \cdot X_{irnmt}^\xi, \quad r \in \mathscr{R}, \ \xi \in \Xi \\ \sum_{i \in \mathscr{I}} \sum_{r \in \mathscr{R}} \sum_{(n,m) \in \mathscr{N}} \alpha_{rnm} \cdot \max \left\{ \sum_{i \in \mathscr{I}} \frac{c_i^w}{g_r^w} \cdot X_{irnmt}^\xi, \sum_{i \in \mathscr{I}} \frac{c_i^v}{g_r^v} \cdot X_{irnmt}^\xi \right\} \\ + \sum_{i \in \mathscr{I}} \sum_{n \in \mathscr{N}} rc \ o_{in} \cdot \mathcal{O}_{int}^\xi = f_t^\xi + Z_{(t-1)}^\xi - Z_t^\xi, \quad t \in \mathscr{T}, \ \xi \in \Xi. \end{cases}$$

$$\tag{20}$$

The non-linear budget constraint in (20) is then approximated by the linearisation (21) in which both the weight and volume of the emergency aid are taken into account to avoid infeasible solutions in the second phase. Section 6.6 shows that the differences between the exact and approximated solutions are negligible from the practical point of view, even though the number of vehicles in the first-stage is overestimated due to the linearisation:

$$\sum_{r \in \mathscr{R}} \sum_{(n,m) \in \mathscr{N}} \alpha_{rnm} \cdot \sum_{i \in \mathscr{I}} \left(\frac{c_i^w}{g_r^w} + \frac{c_i^v}{g_r^v} \right) \cdot X_{irnmt}^{\xi} + \sum_{i \in \mathscr{I}} \sum_{n \in \mathscr{N}^{rc}} o_{in} \cdot \mathcal{O}_{int}^{\xi}$$
$$= f_t^{\xi} + Z_{(t-1)}^{\xi} - Z_t^{\xi} \tag{21}$$

for all $t \in \mathscr{T}$ and $\xi \in \Xi$.

In the first phase, we still have a two-stage stochastic mixed-integer programming model, but with only $|\mathscr{R}|$ integer decisions. In practice, as the number of different types of vehicles (modes of transportation) is relatively small, we expect to obtain (sub)optimal solutions rapidly. Note that the simplified model only serves to provide the flow decisions for the original problem. Given the flow variables, V_{rnmt}^{ξ} is trivially determined, as well as the overall solution of the original problem. We also tested the two-phase procedure by varying the fixation criteria, but found that the most encouraging results are obtained by fixing the flow variables only. In the computational tests, we show that this procedure is indeed more efficient than solving the exact models directly via CPLEX. Note that the two-phase procedure is suitable for solving the risk-averse models as well.

6. Computational tests

The aim of this section is to analyse the performance of the proposed mathematical models and provide practical insights that can help decision-makers in the humanitarian logistics field. We also show the efficiency of the solution procedure in finding good-quality solutions within a reasonable amount of time. The mathematical model was tested and analysed using data from the flooding and landslide disaster in January 2011 in the *Serrana* region of *Rio de Janeiro* state, Brazil.

All the mathematical models were coded in the GAMS 24.0.2 modeling language and solved with the CPLEX 12.5 solver. Preliminary tuning experiments with GAMS/CPLEX led us to adopt the following nondefault options: do not solve the fixed problem ("solvefinal = 0"); use compressed node files on disk ("nodefileind = 3"); enable an opportunistic parallel search mode ("parallelmode = −1"); and use all but one core ("threads = −1"). The stopping criteria were either elapsed times exceeding 14,400 seconds or optimality gaps relative to the best lower bound smaller than 0.01. The experiments were performed on an Intel Core i7 computer with 16 gigabyte RAM and the Windows 7 operating system.

6.1. Brief description of the case-study

According to the state Geological Service (DRM, 2011), the disaster in January 2011 in the *Serrana* region of *Rio de Janeiro* state, Brazil, occurred due to three main factors: (*i*) predisposing factors, such as geology, geomorphology and the climate of the region; (*ii*) active factors, such as land use and occupation, previous rainfall, pre-storm rainwater and fluvial erosion; and (*iii*) the igniting factor, i.e., torrential rain that lasted 4 hours. The *Brazilian Yearbook of Natural Disasters* (Brasil, 2012) pointed out that the megadisaster caused hundreds of deaths and thousands of homeless and displaced people. It was the largest disaster ever recorded in Brazil in number of fatalities, causing *Serrana* to be the Brazilian region with the highest number of deaths caused by a natural disaster (40 percent of the national total between 1988 and 2012).

According to the categorization scheme proposed by Apte (2009), the megadisaster is a type III disaster, being a sudden onset from the temporal coverage viewpoint, and a localized onset from the spatial coverage standpoint. In fact, many floods and flash floods are sudden events. Despite the fact that the megadisaster reached several cities, it is still considered a geographically contained event, mainly in comparison to the 2004 Indian Ocean Tsunami that affected 14 dispersed countries. Fig. 4 depicts the complete categorization and provides some examples of disaster events for each category.

Basically, the idea behind this classification is to understand and analyse the level of difficulty that each type of disaster imposes for carrying out humanitarian operations in terms of geographical/spatial and temporal coverage. Higher uncertainty levels are also reflected in more difficult humanitarian operations. For example, prepositioning strategies can be more challenging in sudden onset and localized disasters than in sudden onset and dispersed (more uncertain) disasters as, in the second case, extra coordination mechanisms are needed among the players in the humanitarian supply chain in order to provide fast relief, even with decentralized stockpiles of emergency aid (Apte, 2009). Note too that a dispersed and slow onset disaster (type II), such as the 2015–16 Zica virus epidemic in Brazil and parts of Latin America, presents different levels of difficulty regarding humanitarian operations, but given that it is not a sudden event, humanitarian logisticians can benefit from time to prepare for relief operations.

6.2. Data of the base case

The base case was designed to be as realistic as possible through interviews with governmental organisations, and by extracting information from a variety of technical reports, websites, and existing literature (Brasil, 2016; Lin, Batta, Rogerson, Blatt, & Flanigan, 2012; da Costa Peixoto Filho, 2013; Rawls & Turnquist, 2010; dos Santos, 2013). Due to the limited availability of information on Brazilian disasters, some parameters were estimated from previous papers, so the example should be treated as illustrative. For the sake of brevity, we present the main data here, but the detailed description of the remaining parameters are presented in the online supplementary content (Appendix A.1; see Tables A–E).

The requirement is to provide humanitarian aid to fulfill daily demand over a horizon of 7 periods of 1 day each by supplying emergency aid across a network structure composed of 9 relief centers (demand nodes) and 4 depots (non-demand nodes). Motivated by real-life cases, the examples assume that prepositioning and incoming supplies occur only at depot nodes and procurement only at demand nodes from the first time period onwards. However, it is possible to transport emergency aid across any arc $n \to m$ (n and m being relief centers and/or depots) as long as it is available. Initially, all arcs are assumed to be available for any type of vehicle ($q_{rnmt}^{\xi} = 1$) and that both the capacities $c_{rnm}^{\max}$ and $c_r^{\max}$ are sufficiently large.

The following nine affected areas (demand nodes) were considered: Teresópolis (TRS), Petrópolis (PTP), Nova Friburgo (NFB), São José do Vale do Rio Preto (SVRP), Bom Jardim (BJD), Sumidouro (SMD), Areal-Sapucaia-Três Rios (AST), Santa Maria Madalena (SMM) and São Sebastião do Alto (SSA). There are four depots (non-demand nodes) located in Teresópolis (TRS-D), Petrópolis (PTP-D), Nova Friburgo (NFR-D) and Rio de Janeiro city (RJ-D). Fig. 3 shows the district map of Rio de Janeiro state where Serrana is the inland central region.

We consider six emergency aid items that are commonly distributed among disaster victims: food, water, hygiene, cleaning products, medical products, and mattress. A kit of food represents a basic food basket covering the nutritional requirements of a five-person family. Each unit of water represents a container with
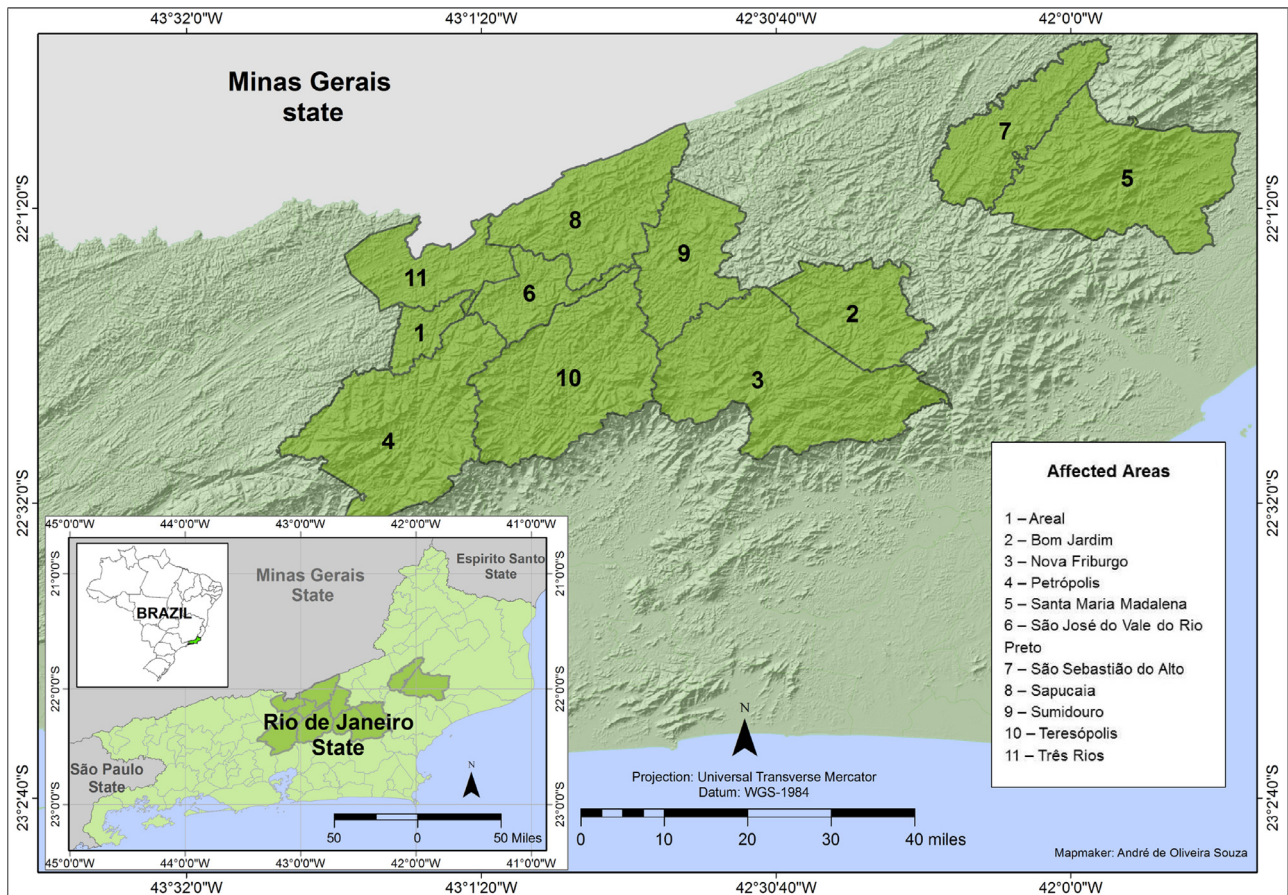
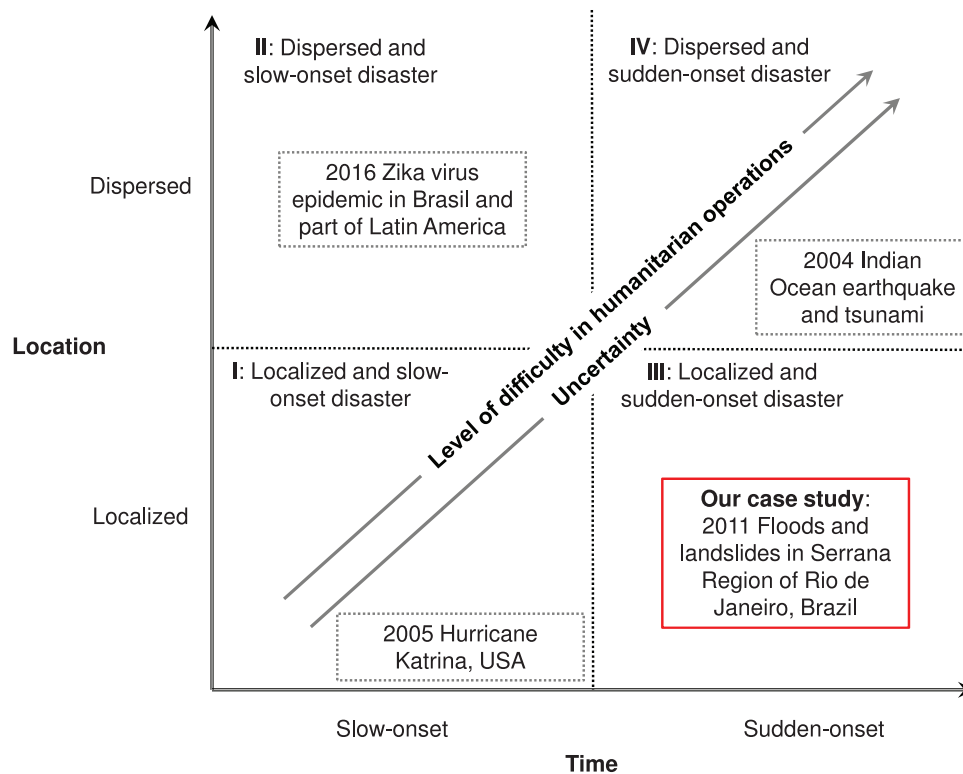**Fig. 3.** Map showing the *Serrana* region of Rio de Janeiro state.

Fig. 4. Disaster categorisation proposed by Apte (2009). Adapted from Apte and Yoho (2011) and Apte (2009).

Table 3
Required emergency aid for survivors of a disaster and the characteristics of each type of emergency aid.

Emergency aid type	Weight (kilogram)	Volume (litre)	Quantity per day per victim	Procurement price[a]	Prepositioning capacity in units
Food	23	30	1/5 kit	86.18	20,000
Water	20	20	5 l	7.50	19,000
Hygiene	3	10	1 kit	27.03	10,328
Cleaning	7	16	1/5 kit	60.27	1000
Mattress	2	103	1 unit	29.90	30,611
Medicine	14	11	1/90 kit	85.20	0

[a] All costs are given in Brazilian Real (BRL).

20 litres. A kit of personal hygiene products serves only one person. A unit of cleaning products (or one kit) serves a five-person family. On the other hand, a kit of medical products serves 90 people. A mattress serves one person. A summary of these requirements, the characteristics of the emergency aid (weight c_i^w, volume c_i^v, the prepositioning cost per emergency aid ρ_{in}, and the maximum amount of each emergency aid that can be prepositioned (p_i^{max}) is shown in Table 3. Prepositioning costs correspond to the procurement price of emergency aid before a disaster strikes; the penalty for unmet demand of each emergency aid item (ι_{in}^-) is 100 times greater than the procurement price, and holding costs (ι_{in}^+) are 25 percent of the procurement price. Procurement costs after a disaster strikes (o_{in}) are 5 times those before the disaster. The procurement capacity for each emergency aid and node (o_{in}^{max}) is limited to 20 percent of the corresponding prepositioning capacity.

We consider three types of vehicle: trucks, boats and helicopters, whose capacities and costs are summarized in Table E in Appendix A.1. Shipping costs were evaluated as follows:

$$\alpha_{rnm} = \frac{\text{fuel}(r)}{\text{consumption}(r)} \cdot \text{dist}(n, m), \qquad (22)$$

where dist(n, m) is the distance (in km) between two nodes. In the absence of the exact address of the relief center or depot, the distance was approximated via the centroid of each area.

Finally, the total monetary donation (f_t) was estimated to be 25 million Brazilian Reais (BRL) in the first period only. Lead times were assumed to be 1 day only for the first time period and for truck vehicles. The remaining lead times were considered to be zero.

6.3. Scenario generation

To draw up plausible scenarios, historical data from previous disasters was investigated and classified according to the scaling system proposed by Eshghi and Larson (2008), who categorised any disaster in one of six magnitude classes: emergency situation, crisis situation, minor disaster, moderate disaster, major disaster and catastrophe. Through extensive data sourced from the *Emergency Events Database* EM-DAT (Centre for Research on the Epidemiology of Disasters, 2014) of the last 105 years of disasters around the world, the distribution of disasters was analysed for different values of fatal and affected victims. The output of this analysis consists of (a) six ranges or intervals for the number of *fatal* victims and the corresponding proportion of disasters that fall within each interval; and (b) six ranges or intervals for the number of *affected* victims and the corresponding proportion of disasters that fall within each interval. For example, it was concluded that 78.1 percent of all disasters cause the number of fatal victims to be in the interval (10; 100]. We now present the main data for the scenario generation procedure. Additional data are presented in the online supplementary content (Appendix A.2; see Tables F–I).

The magnitude class of a particular disaster is calculated from the number of fatal (μ^+) and affected victims (μ) using a mathematical expression to represent the impact of the disaster, as follows:

$$\psi = \max\left\{\frac{\mu^+ - L_{\mu^+}}{U_{\mu^+}} + \log L_{\mu^+}, \quad \frac{\mu - L_{\mu}}{U_{\mu}} + \log L_{\mu} - 1\right\}, \qquad (23)$$

where L_{μ^+} (L_{μ}) and U_{μ^+} (U_{μ}) are the lower (L) and upper (U) bounds of the intervals that contain the exact number of fatal (affected) victims. We then analysed the value of ψ to further classify the type of the disaster; see Table F in Appendix A.2 for the detailed intervals proposed for the number of fatal and affected victims, as well as the value of the magnitude ψ of each disaster and its corresponding classification.

Based on this methodology, we determined the magnitude ψ and classified the disasters in the state of Rio de Janeiro from 1966 to 2013, as depicted in Table G in Appendix A.2. For example, consider the last recorded disaster that caused 67 fatal victims and 2300 affected people for which $\mu^+ = 67$ and $\mu = 2300$. The number of victims lies in the interval (10; 100] and the number of affected people in (1000; 10, 000], so that $L_{\mu^+} = 10$, $U_{\mu^+} = 100$, $L_{\mu} = 1, 000$, $U_{\mu} = 10, 000$. Thus the magnitude ψ is evaluated as follows:

$$\psi = \max\left\{\frac{67 - 10}{100} + \log 10; \quad \frac{2300 - 1000}{10, 000} + \log 1000 - 1\right\}$$
$$= \max\{1.57; 2.13\} = 2.13,$$

which lies on the interval [2, 3] and corresponds to an *emergency situation* (as classified in Table G).

We used the frequency Table H in Appendix A.2 to estimate the probability of occurrence of all types of disasters in the state of Rio de Janeiro. The transition probabilities among different types of disasters are shown in Table I in Appendix A.2. Note that, although there are only 21 recorded events, they cover a period of 47 years of analysis. For this reason, we assume that the relative frequency of each disaster event can be used as a reasonable approximation for the underlying probability distribution.

The number of affected people (column 3 in Table G) corresponds not only to the displaced and homeless, but also to anyone who was directly or indirectly affected. Thus only some of these victims need emergency supplies. The actual number of victims requiring aid is estimated via the percentage of displaced, homeless and fatal victims from the overall number of affected people in the disaster of 2011, being 10.96 percent (33,370 victims from 304,562 total affected). Thus we use this percentage to estimate the amount of needed emergency aid for all scenarios. The daily number of victims was generated using a random-based generator that we devised for this paper. Basically, the random generator assumes that large amounts of demand occur abruptly over short lead times (Sarkis et al., 2010), contrasting with periods of low demand.

The other stochastic parameters were taken into account as follows: a first scenario is constructed with the same magnitude as the demand; a second scenario with magnitude one demand level lower; and a third scenario with magnitude one level higher. For example, a moderate demand scenario splits into 3 supply-donation pair scenarios corresponding to a minor

disaster (one level below), a moderate disaster (same level), and a major disaster (one level above). This $(-1, 0, +1)$ split assumes that the amount of collected supplies and donations will not follow exactly the magnitude of the disaster, but could be somewhat lower or higher. It also assumes that the route damage is partially proportional to the number of victims in the sense that worse disasters provoke more damage, but major disasters could cause slightly less damage (as in minor disasters), or slightly worse damage (as in catastrophic situations). The conditional probabilities among states $(-1, 0, +1)$ are assumed to be those in Table J of the supplementary material. Thus, for example, scenario 23 has

π[demand is moderate] = 0.1429
π[supply-donation is minor-minor | demand is moderate]
  = 0.25
π[damage is minor | demand is moderate] = 0.25

so that the corresponding probability of scenario 1 [moderate, minor-minor, minor] = 0.1429 × 0.25 × 0.25 = 0.0089.

The resulting set of scenarios is the combination of the four stochastic parameters, totalling 40 scenarios, as depicted in Fig. 5. Statistical independence among the parameters is assumed so that the probability of each scenario is determined by the product of the probabilities of each stochastic parameter. It is worth noting that our proposed scenarios are not time-dependent. Thus we simply independently generate a number of instances over the full horizon and combined them in the proposed scenario-tree.

Note that the categorisation based on temporal and spatial coverage (Apte, 2009) previously discussed could be used in conjunction with this current scale system to generate alternative scenarios in an attempt to analyse, for example, the effectiveness of both preparation and response operations when localized and dispersed disasters occur at the same time in Brazilian territory. Testing via alternative scenario use is left for future research.

6.4. Presentation of the test cases

Based on the nominal data (base case), we construct 16 additional cases, totalling 17 instances. The motivation in proposing extra instances is to obtain insights into the performance of the model over a spectrum of practical situations commonly observed in humanitarian contexts. These cases were designed with the same parameters as the base case (A0), but by considering different assumptions, as follows. (A1) without prepositioning; (A2) prepositioning in all nodes is allowed; (A3) 25 percent of stockpiling is lost; (A4) procurement is not allowed; (A5) doubled supply; (A6) doubled donations; (A7) doubled supply and donations; (A8) without damaged arcs; (A9) with more damaged arcs; (A10) without trucks; (A11) without helicopters; (A12) without trucks and boats; (A13) truck capacity is 5 times larger; (A14) without lead time; (A15) objective function prioritises medicine kits; (A16) scenarios are equiprobable. These 16 variants from the base case overlap to some extent and are not exhaustive, but do provide an interesting range of representative cases against which to test the model.

6.5. Numerical results and managerial insights

This section presents the numerical results and discusses the managerial insights. Additional material to support our insights is presented in the online supplementary content (Appendix A.3; see Tables J–P, and Fig. A).

In stochastic programming, it is common to (i) evaluate the impact of randomness in the problem, and (ii) analyse if simpler approaches (e.g., replacing all random variables by their expected

values and solving the resulting problem) are sufficient to take uncertainty into account. These two issues can be addressed by analysing the *Expected Value of Perfect Information* (EVPI) and the *Value of Stochastic Programming* (VSS) (Birge & Louveaux, 1997). EVPI compares stochastic with wait-and-see approaches and provides an idea of how a solution would be under perfect information. It is computed as the difference between the objective function (RP) of the stochastic programming model (the recourse problem) and the expected wait-and-see solution (WS), i.e., EVPI = RP − WS, where WS = $\sum_{\xi \in \Xi} \pi^\xi W^\star(\xi)$ and $W^\star(\xi)$ is the single-scenario deterministic problem associated with scenario ξ. VSS compares stochastic with expected value (EV) approaches by quantifying the possible gain in solving the stochastic problem instead of simpler EV approaches (whose corresponding random variables are replaced by their expected values). To evaluate VSS, we have to solve the EEV problem, which exhibits the same structure as the stochastic programming model, but the corresponding first-stage decision variables are fixed according to the EV solution. Then VSS = EEV − RP.

The main results in terms of costs and decision variables for the stochastic problem (RP) associated with the 16 cases are provided in Table 4. Table 5 summarises the key values involved in EVPI and VSS.

Consistent with theoretical results, we found that WS $\leq$ RP $\leq$ EEV. Moreover, EVPI ranged from 356,542 (0.5374 percent) to 148,153,582 (18.97 percent), with a corresponding average value of 23,435,039 (3.341 percent). Note that the average value is far from negligible, corresponding to 94 percent of the financial budget provided by the government. On the other hand, the VSS values are high in most cases; the average value found of 404,351,193 (66.28 percent) indicates that it is possible to achieve significant gains by solving RP instead of EV, which also justifies the use of the stochastic programming model.

The importance of prepositioning is evident. Without it (A1) EVPI and VSS decreases due to the high increase in backlogging costs compared to the base case (A0) that affects WS, RP and mostly EV. In this case, gathering perfect and accurate information about the random parameters would be more attractive than solving the stochastic model, since randomness plays a minor role in the problem. The stochastic solution without prepositioning presents a service level almost 4 percent worse with an increase of 22 percent in the objective function. Case A2 shows that prepositioning in all nodes has a negligible effect on EVPI and VSS values, since the WS, EEV and RP problems do not benefit much from prepositioning at RC nodes when prepositioning capacity is tight.

If some facilities were struck by a disaster so that 25 percent of depot inventory were lost (A3), then backlogging costs would increase, but without leading to deteriorated service levels. The result could be much worse if prepositioning in all nodes were permitted (A2). As the impact of the lost inventory is more pronounced in both RP and WS, but less evident in EEV, we found that EVPI slightly increases and VSS decreases accordingly.

Interestingly, EVPI increases dramatically without procurement (A4), but VSS drops more than 30 percent. In fact, procurement does not improve the distribution of emergency aid under perfect information, so WS does not vary significantly with or without procurement. However, this strategy is an important contingency decision for the stochastic problem. When it is not possible to purchase emergency aid in disaster areas, it is necessary to travel more among depots and warehouse in order to supply more demands. This in turn increases the first-stage costs of the fleet and the second-stage costs of the shipments. Due to the limited budget, the service level is then 3.45 percent worse. RP increases up to 21 percent in this case, approaching the upper bound value given by EEV. Thus RP-WS increases and EEV-RP decreases.
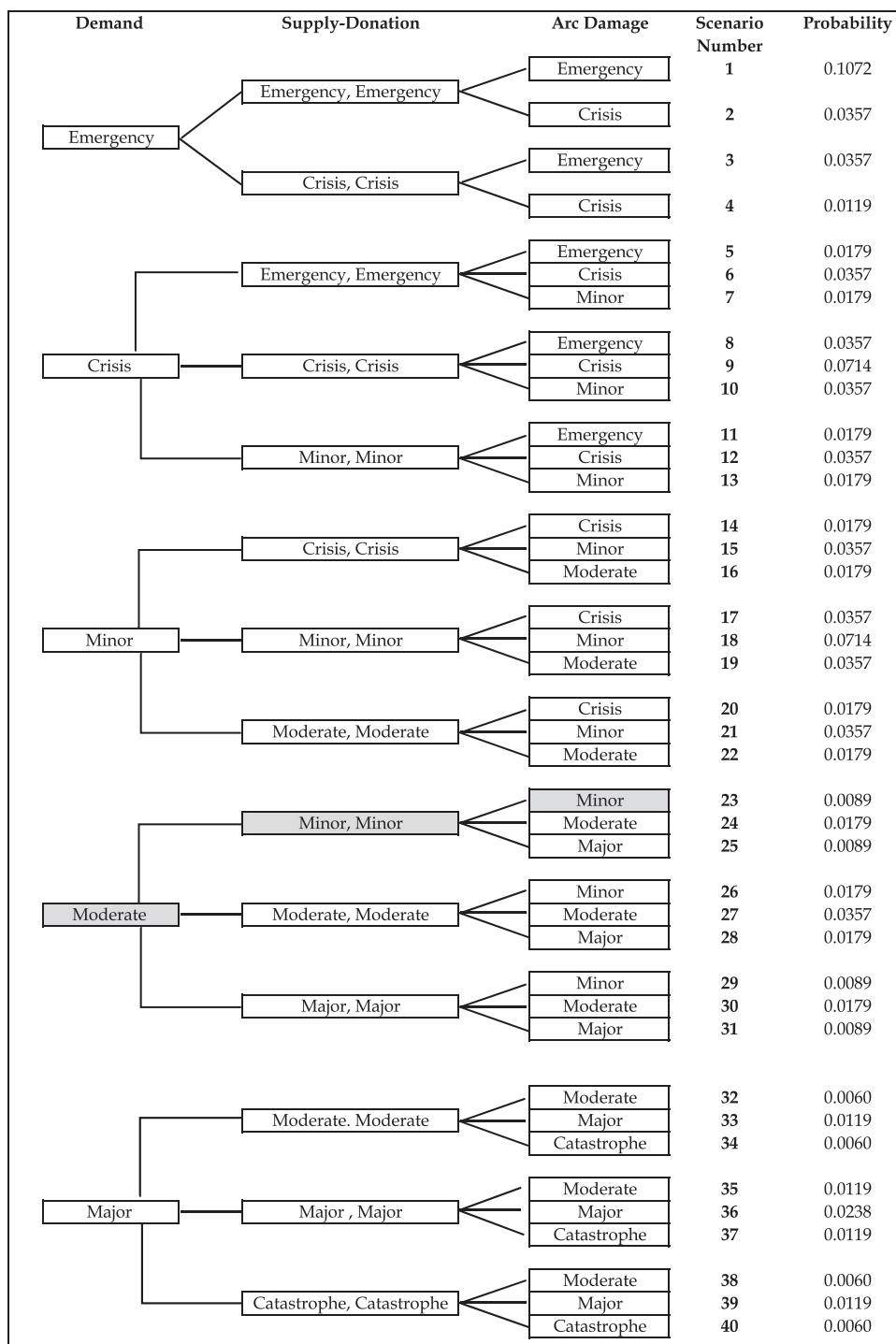
Demand	Supply-Donation	Arc Damage	Scenario Number	Probability
Emergency	Emergency, Emergency	Emergency	1	0.1072
		Crisis	2	0.0357
	Crisis, Crisis	Emergency	3	0.0357
		Crisis	4	0.0119
Crisis	Emergency, Emergency	Emergency	5	0.0179
		Crisis	6	0.0357
		Minor	7	0.0179
	Crisis, Crisis	Emergency	8	0.0357
		Crisis	9	0.0714
		Minor	10	0.0357
	Minor, Minor	Emergency	11	0.0179
		Crisis	12	0.0357
		Minor	13	0.0179
Minor	Crisis, Crisis	Crisis	14	0.0179
		Minor	15	0.0357
		Moderate	16	0.0179
	Minor, Minor	Crisis	17	0.0357
		Minor	18	0.0714
		Moderate	19	0.0357
	Moderate, Moderate	Crisis	20	0.0179
		Minor	21	0.0357
		Moderate	22	0.0179
Moderate	Minor, Minor	Minor	23	0.0089
		Moderate	24	0.0179
		Major	25	0.0089
	Moderate, Moderate	Minor	26	0.0179
		Moderate	27	0.0357
		Major	28	0.0179
	Major, Major	Minor	29	0.0089
		Moderate	30	0.0179
		Major	31	0.0089
Major	Moderate. Moderate	Moderate	32	0.0060
		Major	33	0.0119
		Catastrophe	34	0.0060
	Major , Major	Moderate	35	0.0119
		Major	36	0.0238
		Catastrophe	37	0.0119
	Catastrophe, Catastrophe	Moderate	38	0.0060
		Major	39	0.0119
		Catastrophe	40	0.0060

Fig. 5. Set of scenarios as the combination of the four stochastic parameters, totaling 40 scenarios.

The effect of increasing supply and/or financial donations (A5, A6 and A7) in both EVPI and VSS is not clear due to the complex inter-relationship between these two random variables. A further increase in supply (A5) yields higher EVPI and VSS, but by assuming that an increase in budget that is sufficient to supply most demands (A6) decreases EVPI and VSS; similar results were found in Rennemo et al. (2014). In the latter case (A6), uncertainty is reduced by increasing the investment in procurement by 30 percent and by improving fleet usage, instead of hiring a larger (possibly more expensive) fleet. Finally, EVPI and VSS experience a cross-effect when supply and donation increase simultaneously

(A7): on the one hand, the improvement of service levels by almost 2.5 percent indicate that it is more likely to satisfy demand (the EVPI decreases); on the other hand, the EV solution leads to an underestimated fleet of vehicles that in turn increases substantially the backlogging costs of the EEV problem, thus increasing VSS.

When all arcs/routes are available (A8), the decision maker can contract a smaller fleet of vehicles to ship emergency aid, with fewer trucks and helicopters. This in turn helps to decrease perfect information. Conversely, with more damaged arcs (A9), more vehicles are required, mainly those that depend less on existing

Table 4
Summary of the results for the test cases.

Case #	Objective function value	Contracted fleet size	Used fleet size	Fleet usage[a]	Service level[b]	Rental cost	Prepositioning cost	Shipping cost	Procurement cost	Inventory cost	Backlogging cost
A0	642,242,178	9466	7,232	0.7640	0.9393	6,483,655	3,061,430	889,165	2,286,845	3,273,052	629,424,041
A1	784,082,756	9433	4499	0.4769	0.9025	6,527,875	–	651,142	2,398,419	3,045,975	774,508,906
A2	642,228,026	9471	5876	0.6204	0.9393	6,485,850	3,061,430	760,071	2,293,095	3,275,108	629,405,638
A3	670,123,563	9629	5735	0.5956	0.9386	6,540,775	3,061,430	865,658	2,263,633	3,223,419	657,297,939
A4	780,931,218	9934	7146	0.7193	0.9069	6,769,525	3,061,430	1,069,675	–	3,300,554	767,799,709
A5	379,802,565	10,035	7542	0.7516	0.9599	6,851,135	3,061,430	1,018,326	2,120,400	7,881,098	362,008,903
A6	618,274,260	9527	8246	0.8655	0.9401	6,445,245	3,061,430	1,130,392	3,068,234	3,255,779	605,511,806
A7	364,364,564	9677	8152	0.8424	0.9604	6,562,945	3,000,350	1,183,104	2,844,050	7,977,302	346,823,967
A8	640,868,261	7845	6469	0.8246	0.9394	5,526,790	3,061,430	903,040	2,283,873	3,271,501	629,008,540
A9	642,634,767	9658	6573	0.6806	0.9393	6,616,555	3,061,430	774,238	2,287,958	3,271,147	629,685,635
A10	666,707,502	35,479	30,457	0.8584	0.9326	17,864,500	3,061,430	4,380,324	1,421,307	8,108,816	637,672,757
A11	642,369,032	9603	5788	0.6028	0.9393	6,433,555	3,061,430	681,381	2,285,816	3,274,987	629,599,060
A12	733,871,342	6597	1669	0.2529	0.9373	85,761,000	3,061,430	232,647	1,646,981	8,151,378	636,897,534
A13	636,268,566	1909	671.5	0.3518	0.9393	1,318,350	3,061,430	75,849	2,298,884	3,294,893	628,593,894
A14	644,450,981	6111	6011	0.9836	0.9394	4,919,355	3,061,430	493,538	1,667,210	8,138,822	628,331,374
A15	66,343,615	300,000	7686	0.0256	0.9394	1,430,500,000	3,061,430	1,265,852	2,298,402	3,228,043	627,933,603
A16	1,536,012,315	9542	6176	0.6472	0.8922	6,602,140	3,061,430	878,159	4,458,637	4,616,752	1,521,731,993
Average	652,445,618	27,289	7407	0.6390	0.9344	95,188,779	2,877,753	1,014,857	2,230,809	4,740,507	667,190,312

[a] Fleet usage $= \frac{\sum_{r,n,m,t,\xi} \pi^{\xi} \cdot V_{rnmt}^{\xi}}{\sum_r Y_r^C}$.

[b] Service level $= 1 - \frac{\sum_{i,n,\xi} \pi^{\xi} \cdot I_{int|t=T}^{\xi-}}{\sum_{i,n,t,\xi} \pi^{\xi} \cdot d_{int}^{\xi}}$.

Table 5
Summary of the results involving in EVPI and VSS values.

Case #	RP	WS	EV	EEV	EVPI	$\frac{EVPI}{RP}$ (percent)	VSS	$\frac{VSS}{RP}$ (percent)
A0	642,242,178	632,395,696	7,579,952	1,078,540,884	9,846,481	1.533	436,298,706	67.93
A1	784,082,756	777,135,050	70,133,016	1,092,386,604	6,947,706	0.8861	308,303,848	39.32
A2	642,228,026	632,391,214	7,579,952	1,078,540,045	9,836,812	1.532	436,312,018	67.94
A3	670,123,563	659,962,987	10,896,606	1,080,205,676	10,160,576	1.516	410,082,113	61.19
A4	780,931,218	632,777,636	7,579,952	1,078,540,045	148,153,582	18.97	297,608,826	38.11
A5	379,802,565	369,585,610	12,439,072	913,724,812	10,216,955	2.690	533,922,247	140.6
A6	618,274,260	608,772,255	7,563,980	1,021,531,730	9,502,005	1.537	403,257,471	65.22
A7	364,364,564	354,866,792	12,445,368	859,014,217	9,497,772	2.607	494,649,652	135.8
A8	640,868,261	631,913,077	7,569,218	1,079,277,126	8,955,184	1.397	438,408,865	68.41
A9	642,634,767	632,302,345	7,599,441	1,080,185,474	10,332,421	1.608	437,550,707	68.09
A10	666,707,502	637,758,138	8,813,827	1,117,665,213	28,949,365	4.342	450,957,711	67.64
A11	642,369,032	632,764,751	7,614,811	1,078,719,785	9,604,280	1.495	436,350,753	67.93
A12	733,871,342	642,298,497	17,893,955	1,101,513,177	91,572,845	12.48	367,641,834	50.10
A13	636,268,566	633,417,835	7,008,684	1,065,540,943	2,850,731	0.4480	429,272,377	67.47
A14	644,450,981	631,642,898	7,671,256	1,095,340,858	12,808,083	1.987	450,889,877	69.96
A15	66,343,615	65,987,073	507,255	77,354,522	356,542	0.537	11,010,907	16.60
A16	1,536,012,315	1,517,207,990	139,865,011	2,067,464,674	18,804,325	1.224	531,452,358	34.60
Average	652,445,618	629,010,579	20,044,786	1,056,796,811	23,435,039	3.341	404,351,193	66.28

infrastructure; as a result, the EVPI increases. The availability of arcs has a minor impact on VSS. In both cases, service levels are only marginally affected.

Cases A10–A13 suggest that it becomes more difficult to meet demand without one or more types of vehicle (A10–A12), particularly if trucks are not available in which case boats are the most used vehicle. Reducing the capacity of the trucks (A10) leads to a less efficient distribution of emergency aid, mostly in the RP, EV and EEV problems, since trucks present the best capacity/cost ratio among the vehicles. The result is a large increase in the value of perfect information, but a minor increase in the VSS. On the contrary, far fewer transport resources are used when truck capacity is larger (A13). This in turn decreases rental, shipping and backlogging costs. Using the same rationale as in case A10, we have smaller EVPI and VSS values. Without trucks and boats (A12), perfect information increases substantially more than in case A10, thus being impractical and adopting wait-and-see solutions instead of using stochastic ones. On the other hand, the stochastic solution value decreases up to 15 percent. All the aforementioned behaviors are due to the great impact of a less diversified fleet on rental and backlogging costs, particularly in the RP problems.

Finally, case A11 suggests that without using helicopters, backlogging slightly increases, but this effect has a minor impact on EVPI and VSS.

In the absence of lead times (A14), only trucks are used to ship emergency aid, since the one-day lead time for trucks in the first period enforced the utilization of the remaining modes of transportation. As a consequence, rental, shipping, procurement, and backlogging costs were reduced significantly, but inventory costs increased 150 percent in comparison to the base case. Most extra inventory in relief centers results from extra shipments due to efforts to increase transportation efficiency (fleet usage is about 98 percent). The consequence is an increase in EVPI and VSS, thus indicating that the cost of uncertainty cannot be ignored.

Prioritising the delivery of the medical kits (A15) improves the service level for this emergency aid up to 8 percent, but this provides a very low fleet efficiency. In this case, the objective values of all of problems WS, RP, EV and EEV may represent the "cost of urgency" of the medical kits. The relative EVPI and VSS values indicate not only the low impact of randomness in the problem, but also that a stochastic solution is less justified than in most of the remaining cases.
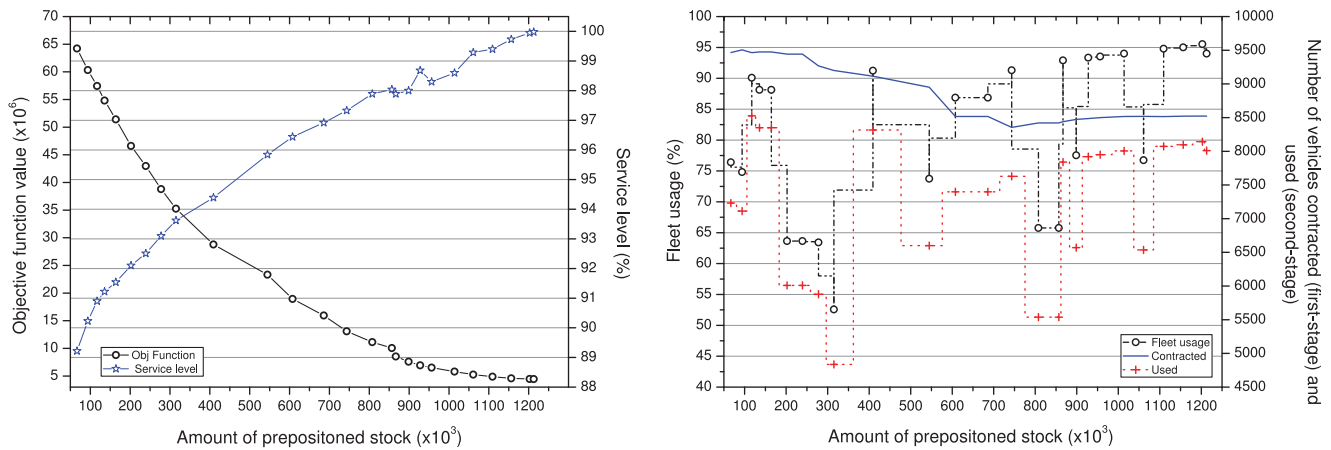
Fig. 6. Effect of increasing the prepositined stock in the objective value and in the fleet of vehicles.

Finally, (A16) shows that, even though the probabilities do not change substantially the structure of the solution, the objective function is much worse for equiprobable scenarios, as the probability of the more pessimistic and expensive scenarios (moderate and major) increases from 0.24 to 0.45. As a result, both EVPI and VSS increase.

Cases A1, A3, A4, A9, A10, and A12 suggest that in a situation of scarce resources, there is a trend of increasing EVPI and/or decreasing VSS values. This apparent behaviour is particularly pronounced in the cases where prepositioning and procurement are not allowed (A1 and A4), without trucks (A10), and without both trucks and boats (A12). Considering that decision-making is often more complex (and expensive) in the presence of uncertainty, it is natural that scarcity impacts more in these situations than in situations under perfect information. Mathematically, we have an increase in RP greater than in WS, which intensifies EVPI. Due to the pre-determined first-stage decisions based on average values, the EEV problem is not as sensitive to resource shortages as RP, and the VSS tends to decrease.

Since the prepositioning capacity can be viewed as a strategic decision, specially useful in sudden/localised onset disasters (Apte & Yoho, 2011), and decision-makers may have few bases on which to decide its value in practical contexts, we perform a sensitivity analysis to show the impact of increasing it with respect to the main decision variables of the model. Table J in Appendix A.3 shows the detailed results. As expected, the objective value decreases as the amount of prepositioned stock increases due to the great reduction experienced by the level of overall unmet demand. However, the increase in prepositioning capacity has only a marginal effect in service levels, e.g., the double amount of prepositioned stock improves service levels in less than 1.7 percent. In practice, it is not desirable to manage high amounts of prepositioned stock, as it may involve extra coordination among the different players of the humanitarian chain.

Increasing the prepositioned capacity also helps to improve the fleet usage via contracting a smaller fleet of vehicles in the first-stage, but using the overall vehicle capacity more efficiently in the second-stage. This strategy is partially responsible for the increase in the holding costs. Fig. 6 illustrates these behaviours. Shipping and procurement costs do not present any particular trend as prepositioning stock increases.

6.6. Risk-averse results

The proposed risk-averse models were analysed for $\phi = 0.7$ and $u = 0.9$ (CVaR), and $\phi = 0.4$ (SD), by considering all the proposed instances A0-A16. Tables K and L in Appendix A.3 summarize the performance of the models. The results of all instances were enhanced by at least one risk approach in either unmet demand or

second-stage costs at the expense of a minor "price" of risk aversion. In fact, with exception of the minimax approach that incurs a high price for less risky solutions in case A4 (when procurement is not allowed), the average price varies from 0.5 percent (SD) to almost 3 percent (minimax).

The semideviation model presents the lowest price of risk aversion, but the overall results are not very encouraging. In fact, its average and best performances across all the instances are clearly dominated by the CVaR model in terms of unmet demand and second-stage costs. On the other hand, CVaR provides the best improvement in unmet demand and second-stage costs in most instances. With CVaR, the distribution-aid plan is able to fulfill promptly 56,351 more emergency aid units than in the risk-neutral approach, approximately 1400 more emergency aid units per scenario. Although this number sounds negligible in a commercial supply chain, since it represents less than 1 percent of total demand, it is sufficient to supply overall demand in affected areas with a lower number of victims, which is in accordance with the attitude of humanitarian logistics. CVaR also mitigates unmet demand in the worst-case scenario in 12 cases. On average, almost 5000 more emergency aid units are delivered right-on-time in the most pessimistic scenario. This gain is substantially better in case A10 (without trucks), where the corresponding improvement is 52,000 emergency aid units. As a consequence of this better policy for demand fulfillment, overall costs associated with worst-case scenarios reduce accordingly, as well as the standard deviation of second-stage costs.

The minimax-regret model is the most conservative approach to deal with risk aversion. Besides the higher increase in objective values, the model still fails more often in improving both unmet demand and costs, and provides the worst overall performance. On average, expected service levels deteriorate 6 percent, and unmet demand worsens in the worst-case scenario. However, in the instances where minimax succeed in improving unmet demand in the worst-case scenario, it achieves the best average performance and the best overall result: up to 91,000 extra emergency aid units are delivered in the worst-case scenario of instance A1.

Compared to the risk-neutral results, the overall trend of the risk-averse models is twofold: (i) increasing first-stage costs; and (ii) decreasing the standard deviation of the second-stage costs. In the first case, the increase is consequence of a larger fleet of vehicles, or a more expensive fleet composed of bulky vehicles, that in turn helps to decrease second-stage costs, as more emergency aid is promptly delivered, avoiding as much as possible shortage and holding costs. Given that shortages are much higher than holding costs, the consequence of enforcing risk aversion is decreasing unmet demand. This behavior is more pronounced when resources are very limited, e.g., without prepositioning, trucks and/or boats,
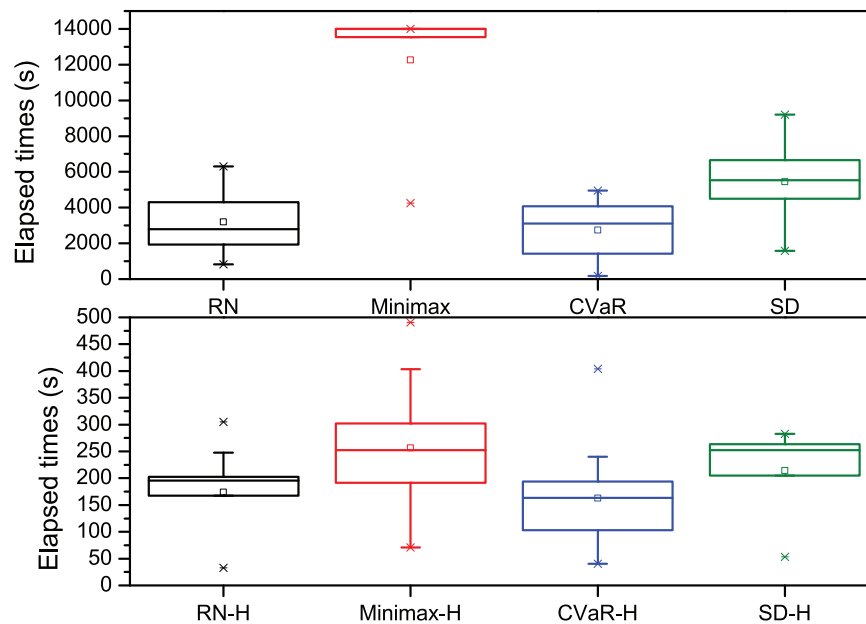
Fig. 7. Elapsed times of all instances regarding the exact approach (above) and the two-phase heuristic approach (below). Box-plots represent, in this order, maximum values, 95th percentiles, 75th percentiles, medians, means, 25th percentiles, 5th percentiles, and minimum values.

and less evident with excess of resources. Decreasing the cost standard deviation over the scenarios leads to more equity regarding unmet demands over scenarios and affected areas. The concept of equity or fairness in humanitarian operations is important because all affected areas (or a set of emergency aid) need to be fulfilled as equitably as possible.

In order to further analyse which risk approach provides fewer changes in the operational results, i.e., which one is the most "stable" from the relief operations standpoint, we evaluated the standard deviation (StDev), the coefficient of variation (CV), and the quartile coefficient of variation (QCV) for each type of cost (first-stage, second-stage, and expected total) obtained for each risk-averse approach in the 17 proposed cases. CV was determined as (standard deviation/mean), whereas QCV was calculated as $(Q75 - Q25)/(Q75 + Q25)$, where $Q25$ and $Q75$ are the corresponding first and third quartiles of the sample. Fig. 8 suggests that CVaR not only leads to overall lower statistics (StDev, CV, QCV), but also that it is not the worst approach in any of the cases analysed. These results indicate that CVaR is indeed the most stable method. On the other hand, minimax presents the least stable behaviour over the proposed instances. Interestingly, semideviation is particularly efficient to reduce the quartile coefficient of variation of the first-stage decisions. Basically, more stable solutions are also more reliable. It means that, for example, the fleet of vehicles provided by the CVaR framework has a higher chance to be feasible (or it is easier to make that decision feasible) under disruptions compared to the same decision provided by the other approaches.

6.7. Computational efficiency of the two-phase approach

The computational efficiency improvement of the two-phase procedure compared to the exact method over the 17 proposed cases for RN, minimax, CVaR and SD approaches is now discussed. Here, the exact method means solving the original model directly via CPLEX 12.5. Averages, medians, upper and lower quartiles and extreme points of the elapsed times (in seconds) for all approaches are shown in Fig. 7. Table 6 summarizes the results of two metrics that analyse the overall quality of the heuristic procedure: (i) the relative difference between the objective value of the two-phase procedure and the (sub)optimal objective value (gap); (ii) the ratio

between elapsed times (ratio). Tables M and N in Appendix A.3 present the detailed results.

It is clear from the plots that, as expected, minimax was the most time consuming risk-averse framework: over the 17 cases, elapsed times of the exact approach varied from a minimum of 4000 seconds to a maximum of 14,000 seconds. The risk-averse model SD exhibited the second worst performance. Despite presenting more variation in performance, the CVaR instances were solved 14 percent faster than the corresponding RN instances, on average. The results show that the computational efficiency resulting from the two-phase procedure is much better than when solving the original model directly. In fact, most heuristic solutions are very near to the optimal, and their corresponding elapsed times are at least 17 times faster than solving the original model directly. The plots reveal that the elapsed time of the heuristic is at most 500 seconds, against 14,400 seconds for the exact method. The heuristic procedure also exhibits less variation in performance than the exact approach. In some instances, the two-phase approach improved the solution of the original model, which is possible because of the 1 percent relative gap at termination, meaning that exact solutions had not been verified as optimal. The improvement is particularly noticeable in the minimax results regarding instances A3, A7 and A13. In many minimax instances, though, the two-phase procedure fails to provide solutions with tighter gaps.

As expected, heuristic and exact solutions are similar in structure, since both optimization models (approximate and exact) exhibit basically the same set of constraints. The overestimation of the number of vehicles by using the sum of weight and volume of emergency aid, though, generated an average of 12 percent more vehicles contracted in the first-stage in comparison to the exact solution (over the 17 cases of the risk neutral model), in which 4.5 percent are trucks, 60 percent are boats, and 1 percent are helicopters. In terms of fleet usage, the results showed that the heuristic solution is 55 percent worse than the exact method. On the other hand, in terms of service levels, the difference between both solutions is less than 0.1 percent in favour of the heuristic ones. The results for the risk-averse models are similar, and for this reason, we omitted them. Table O and Fig. 1 in Appendix A.3 present the detailed results regarding this comparison.
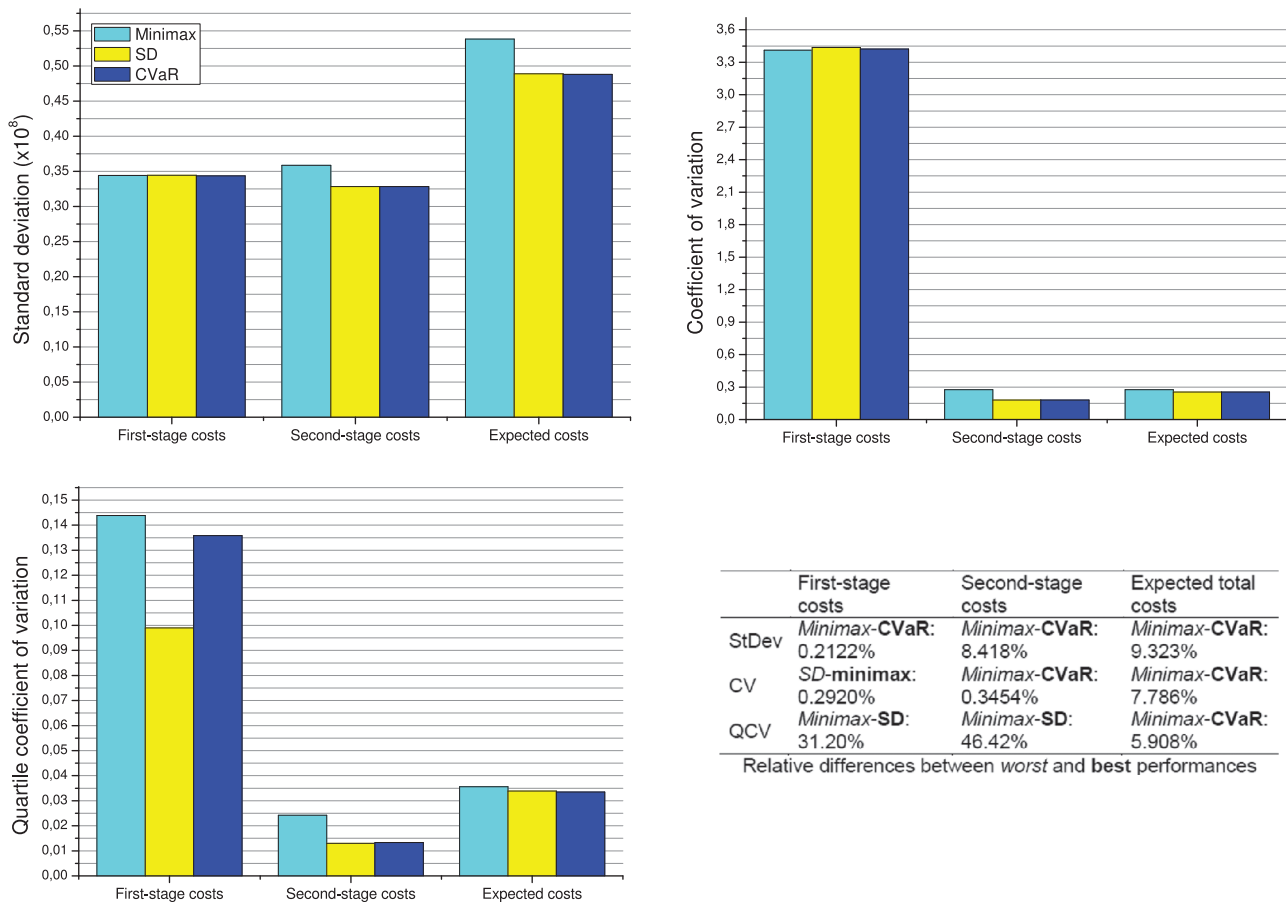
Fig. 8. Stability analysis of the costs over the 17 proposed instances according to each risk-averse approach. The bars illustrate the following statistics: standard deviation, coefficient of variation evaluated as standard deviation/mean, and quartile coefficient of variation, evaluated as (Q75−Q25)/(Q75+Q25), where Q25 and Q75 are the corresponding first and third quartiles of the sample.

Table 6
Comparison between computational efficiency of the exact and the two-phase approach over the propose instances.

Case	RN		MinMax		CVaR		SD	
	Gap (percent)	Ratio	Gap (percent)	Ratio	Gap (percent)	Ratio	Gap (percent)	Ratio
A0	0.2987	29.14	36.99	44.80	0.0126	24.26	0.2065	26.11
A1	0.1198	9.535	29.61	70.06	0.0216	4.454	0.0900	19.81
A2	0.3009	21.77	34.30	50.03	0.0127	24.95	0.1866	35.35
A3	0.3457	9.856	−6.003	64.04	0.0330	10.00	0.2180	16.76
A4	0.2543	22.60	0.1925	37.16	0.0323	28.61	0.4757	23.09
A5	0.4982	19.91	11.35	34.70	0.0518	20.44	0.3996	20.97
A6	0.3372	20.30	12.59	37.15	0.0171	16.49	0.2690	29.18
A7	0.4792	11.60	−20.93	28.53	0.0403	14.11	0.4508	16.50
A8	0.0931	32.36	10.09	46.96	0.0452	8.214	0.0495	19.57
A9	0.3888	19.98	29.92	55.47	−0.0081	23.84	0.2466	19.10
A10	2.074	10.29	10.26	67.43	0.0852	8.384	0.5322	21.62
A11	0.1109	43.66	122.9	146.4	0.0568	21.92	0.2067	50.46
A12	0.2925	36.15	2.297	59.99	−0.0021	4.483	0.2611	29.75
A13	−0.0365	12.83	−67.52	41.38	−0.2581	21.29	−0.4524	23.36
A14	0.5014	9.150	25.94	57.57	−0.0076	11.91	0.2016	27.12
A15	−0.0683	61.90	100.0	39.68	−0.0107	39.32	−0.0403	44.99
A16	0.1514	7.808	9.304	47.86	0.0067	9.101	0.0258	39.82
Average	0.3613	22.28	20.07	54.66	0.0076	17.16	0.1957	27.27

$\text{Gap} = \frac{Z^H - Z^{MIP}}{Z^{MIP}}$, where Z^H refers to the objective value of the two-phase procedure, and Z^{MIP} is the objective value of the exact approach.

$\text{Ratio} = \frac{\text{elapsed}^{MIP}}{\text{elapsed}^H}$, where elapsed^H is the elapsed time of the two-phase procedure, and elapsed^{MIP} is the elapsed time of the exact approach.

Further tests based on larger networks with 30 nodes and/or 100 scenarios evidence the strong performance of the heuristic procedure. Indeed, the exact method provides in 14,400 seconds an average gap of 85 percent, whereas the heuristic procedure yields in 4500 seconds an average gap of only 5.6 percent.

These figures were evaluated over a set of 15 randomly generated instances, whose details are provided in Table P in Appendix A.3. Even though the elapsed times of the heuristic method increase substantially for larger instances, this solution procedure succeeded in finding a feasible solution even when the exact

method failed. Those results encourage the study of alternative heuristic methods to solve more efficiently the simplified model, perhaps without solving it directly via commercial optimization packages.

Remark. The wait-and-see problems were solved in 767.5 seconds (±960.8 seconds) on average; best and worst elapsed times were 43.10 and 3426 seconds, respectively. For the EEV problems, we have an average of 315.3 seconds (±944.8 seconds), and best/worst elapsed times of 50.60 seconds and 3980 seconds, respectively. All EV problems were solved in less than 40 seconds.

7. Conclusions and future challenges

Despite a growing concern to improve the distribution of aid in relief activities, it is still challenging to deal with all the particularities of the humanitarian supply chain. This paper thus aimed to contribute to the existing literature by developing a new two-stage stochastic network flow model under practical assumptions that are rarely considered in previous similar papers, such as the dynamic multiperiod nature of disaster relief operations, limited budgets, fleet sizing, and a variety of uncertain data. A set of scenarios was generated by combining a recent classification of the magnitudes of general disasters and historical data from the 2011 Brazilian megadisaster in the Serrana region in Rio de Janeiro state. We also devised a solution procedure to provide good-quality solutions within plausible elapsed times and found encouraging results. The model demonstrated that it can help plan and organise relief to provide good service levels in most scenarios, and how this depends on the type of disaster and resources. Tests on 16 variants of the base case scenario provided further insights and pointers to the impact of single-factor changes, for example, levels of prepositioning. Additional results suggested that it might be possible to improve equity (fairness) in distribution by enforcing risk aversion. We demonstrated that our heuristic has a good performance for both real and random instances.

As disasters are complex events, the solutions provided by the mathematical models are not meant to be implemented arbitrarily, but with the involvement, input and supervision of agency experts and local people, as well as, for example, geographic information systems (GIS). Thus, it would be useful to contact some Brazilian agencies to get feedback from experts regarding the usefulness of the proposed approach in terms of mathematical models and solutions. Such feedback would be used to refine the models and better understand the applicability of our framework. Our findings also bring up new open and challenging questions, for example, how to solve more efficiently the proposed mathematical models, and the impact of incorporating additional equity-based objectives in the stochastic model, and a social profit for meeting demands promptly. Also, the management of disaster relief fleets could be an interesting future work, for example, we could analyse the impact of the heterogeneity of the fleet of each type vehicle (e.g. trucks with different capacities). These sub-types would be interchangeable amongst themselves, which would change the structure of the problem (Van Wassenhove & Pedraza Martinez, 2012). Lastly, extensions to multistage stochastic models deserve further efforts.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.ejor.2016.04.041.

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