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Building disaster preparedness and response capacity in humanitarian supply chains using the Social Vulnerability Index

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Abstract

We present a novel humanitarian supply chain approach to address disaster preparedness and build response capacity in humanitarian supply chains when people's vulnerability matters. Our primary motivation comes from the fact that disasters in Brazil are often associated with unequal distribution of opportunities and social inequalities that end up pushing more vulnerable people to risky areas or informal settlements. Moreover, investment in disaster management has dropped over the past few years in Brazil. In this way, we wonder: how to use the somewhat limited financial budget as effectively as possible towards meeting those that need the most while addressing disaster preparedness activities? To answer this question, we develop an optimization model to address location, capacity planning, prepositioning, local procurement, and relief aid flows' decisions. Differently from most existing research, we adopt the so-called Social Vulnerability Index (SoVI) in the objective function to build enhanced response capacity in more vulnerable areas when the lack of resources makes impassable to fulfil all victims' needs at once. Through a rich and real case-study based on the Brazilian Humanitarian Supply Chain, we come up with critical insights that can help to improve the humanitarian supply chain practices in the country. In particular, we show that the *social benefit* of using SoVI is as more significant as the vulnerability increases, which reveals the importance of considering this index to design more social-effective humanitarian supply chains.

Keywords. OR in Disaster Relief; humanitarian supply chain; disaster preparedness; social vulnerability index.

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1. Introduction

1.1. Context and Motivation

This paper addresses the design of a humanitarian supply chain to integrate logistics activities in an effective and efficient decision support system to cope with multiple disaster events over a dynamic time horizon. As the ultimate goal of humanitarian logistics is to mitigate human suffering, an effective response must be able to supply victim needs for those who need it most at the right time, in the right place, and in the right amount. When response involves procurement activities, goods and services should be procured according to the "Six Rights" i.e., right quality, right source, right cost, right quantities, right place, and right time (Logistics Cluster, 2015). In either case, long, medium, and short term decisions should be coordinated to ensure an efficient allocation of resources (Leiras et al., 2014), which means that there will be sufficient resources to assist logistics activities wherever necessary. However, many disaster management approaches focus only on short and medium-term decisions that span days and/or weeks to overcome the harmful consequences of a single event at a time. Consequently, such approaches usually fail in being protective and effective when multiple disasters occur repeatedly 'in the same space' and their effects span a longer horizon.

Our motivation in pursuing this work comes from the fact that Brazil is currently among the ten countries most affected by weather-related disasters in the last 20 years (UNISDR, 2015). In addition, the Brazilian experience in coping with multiple disaster events over the past years suggests that there is a lack of scientific reasoning in disaster management. Even though many Brazilian disasters are *recurrent* events that often strike the same areas, the current National System for Protection and Civil Defense (SINPDEC), which is in charge of the country's disaster management, still struggles nationwide to implement effective mitigation strategies across the Brazilian territory. In fact, from 1997 to 2017, the total number of affected people has exceeded 48 million and the corresponding economic damages were estimated to be 12 USD billion as a result of extreme events such as droughts, floods, landslides, and epidemics (EM-DAT, 2017). The year 2018 accounted for 372 confirmed occurrences of floods, flash foods, and landslides in which 110 events required Civil Defense action (Ramos et al., 2019). The continental dimension of Brazil, comprising distinct geology, geomorphology, and climate, associated with insufficient human and material resources, certainly poses unique humanitarian logistics challenges.

In addition, disasters in Brazil are often associated with unequal distribution of opportunities and social inequalities that end up pushing poorer people to risky areas or to informal settlements (Carmo and Anazawa, 2014), frequently located in slopes and floodplains that lack basic infrastructure, thus increasing the chance of being stricken by natural hazards. For Costa (2012), some priority actions that could contribute to disaster risk reduction in the country include identification of disaster risk areas, cooperation between the three government levels (country, state, and municipality), and "allocation of resources according to clear criteria and towards those most in need".

SINPDED currently supports “Program 2040” – Risk and Disaster Management, which in turn is part of the “Multiannual Plan 2016-2019”, whose main goal is to strengthen the coordination amongst the typical activities of the disaster life cycle, i.e., preparedness, response, recovery, and mitigation. This action plan is one of the first efforts towards a coordinated and integrated humanitarian supply chain that is able to mitigate human suffering and preserve their well-being in the long-term. Indeed, as remarkably pointed out in Valencio (2010), “Civil defense reaches its institutional maturity when the State envisages its attributions as essentially intersectoral and transversal coordinated, optimizing the use of material and human resources to promote a safer space”.

Based on the challenges faced by SINPDEC we develop in this paper a mathematical tool to support regional civil defenses to take forward the idea of enhancing/optimizing the current status of their humanitarian logistics. In particular, we seek to integrate and coordinate logistics activities in a longer time horizon than what is usually considered and through the prism of multiple natural hazards when people’s vulnerability matters. We introduce a new way to perceive effectiveness in humanitarian supply chains based on prioritizing allocation of scarce resources to more vulnerable areas. This prioritization is based on quantifying the overall social vulnerability of potential affected areas through the so-called Social Vulnerability Index or simply SoVI (Cutter et al., 2003) thus using it to encourage solutions that target the most vulnerable areas (effective) when there is no resources to meet all victims’ needs at once and, simultaneously, fall within the financial budget (efficient).

1.2. Related studies

This study is mainly related to humanitarian supply chain optimization with prioritization given by social vulnerability. Both academics and practitioners agreed that vulnerability ends up determining if a given natural hazard will be disastrous or not for a certain group of people (Chia-Chen Chen et al., 2007; Huafeng, 2016). Here, we rely on a broader concept of *vulnerability* that represents “*the propensity across different population segments to be affected by natural hazards and other shocks*” (Sodhi, 2016), which is usually determined by physical, social, economic, and environmental factors or processes (UNISDR, 2008, p. 22). Different disciplines measure/quantify vulnerability in different ways (Makoka and Kaplan, 2005) and, apparently, “the diversity and apparent lack of consistence in vulnerability research reflects the divergent objectives of the research and the phenomena being explained” (Adger, 2006). In this paper, we address vulnerability via the Social Vulnerability Index, which is a composite indicator that reflects several dimensions, such as socioeconomic status, gender, employment, and education. For many authors, SoVI can help to identify the most socially vulnerable communities (areas or regions), which in turn may enhance resource allocation policies during the disaster life cycle, e.g., providing an increased relief assistance for the most affected people during the course of a disaster (Flanagan et al., 2011). Our motivation in using SoVI as a proxy for the vulnerability is twofold: (i) it is widely accepted and used in different contexts and applications (Solangaarachchi et al., 2012; Arnette and Zobel, 2019); (ii) it is fairly robust and it can be easily replicated (De Loyola Hummell et al., 2016).

Despite its popularity across many disciplines, it seems that the only study that used SoVI in humanitarian logistics was carry out by Arnette and Zobel (2019), who developed a simple location model for asset prepositioning in the American Red Cross of Wyoming and Colorado (USA) that takes into account hazard, exposure, and vulnerability. Hazard is evaluated as the risk of occurrence of different natural hazards. Exposure is defined by population, displacement, and sheltering needs, while vulnerability data is quantified using SoVI. In terms of adopting other social indicators as proxy for vulnerability, our paper is related to Horner and Downs (2008), which was the first study to approach the interrelationships between socioeconomic status and relief distribution via the evaluation of people's needs based on the percentage of people living below the poverty line at Leon County in Florida, USA. The results revealed that the average response time increases when higher-income individuals are included in the demand for relief aid, as they generally live farther from central locations. This in turn encourages the establishment of more geographically disperses distribution points, which may reduce the poorest households' accessibility.

Also, El-Anwar et al. (2009) focused on the assignment of displaced families after a disaster to alternative housing projects, evaluated according to four indexes designed to address sustainable development, namely, environmental performance, social welfare, economic, and public safety. The welfare index considers different indicators at the housing location, such as employment and educational opportunities, housing quality/delivery time, health-care and basic services opportunities, and access. They derived a max-min utility function for each proposed index and then optimized all of them using scalarization. The proposed approach was illustrated with a potential hurricane event in the Gulf Coast of the USA. El-Anwar et al. (2010) and El-Anwar (2013) also focused on housing arrangements problems using a similar methodology.

Noyan et al. (2015) study might be seen as an extension of Horner and Downs (2008), in which the concepts of accessibility and equity were characterized for a last-mile distribution problem. Both concepts were incorporated into the optimisation model via the development of metrics based on a set of socioeconomic indicators. The accessibility metric was evaluated for the local distribution centres to points of distribution and for the demand locations to the points of distribution. The authors assumed that accessibility depends only on physical factors in the first case, whereas it depends on physical and socioeconomic factors in the second case. Accessibility is finally quantified via the evaluation of an accessibility *score* that allows for the updating of the post-disaster travel times based on the proportion of vulnerable population, which was assumed to be composed by people with low mobility at the demand nodes, such as disabled people, individuals older than 65, and women with children.

In terms of model contributions, our paper is mostly related to the work of Balcik and Beamon (2008), Salmerón and Apte (2010), Jahre et al. (2016), Charles et al. (2016), Torabi et al. (2018), and Rodríguez-Espíndola et al. (2018, 2020) which explicitly proposed how to capture critical strategic (long-term) aspects of supply chains in their approaches, in contrast to most papers that were essentially designed to cope with shorter-run goals and means for reaching them from operational and/or tactical decision points of view only. Although the importance of long-term planning in disaster management is well-recognized by the specialized literature, only a few studies have dedicated efforts in proposing analytical mathematical models with strategic components. In fact, for Balcik and Beamon (2008), critical decisions of disaster preparedness, such as facility location and relief prepositioning, indeed " $(\cdots)$ require long-term planning to achieve a high-performance disaster response". Salmerón and Apte (2010) also emphasized the necessary long-term commitments in relief chains to enable an efficient response through the capacity expansion of many assets including warehouses. Jahre et al. (2016) highlighted the importance of their pioneering work in integrating emergency relief and longer-term operations for relief prepositioning to reduce response time and overall costs. They introduced a warehouse location model for joint prepositioning and distribution model to represent a global humanitarian supply chain. Charles et al. (2016) proposed a warehouse location, pre-positioning and distributing relief problem at a strategic level whose main goal is to support logistics decisions for a broad range of humanitarian organizations. Torabi et al. (2018) presented a new framework to strategically integrate relief pre-positioning and procurement planning decisions in humanitarian supply chains. Rodríguez-Espíndola et al. (2018, 2020) developed a novel disaster flood-preparedness optimization model to take into account multiple actors and organizations in Acapulco, Mexico. In their model, relief shortage is minimized along with logistics costs.

With the exception of Charles et al. (2016), the remaining studies focused on static (single-period) settings and thus it is not clear how their proposed mathematical models could be adapted and operationalized in dynamic problems, e.g., when multiple disasters may occur simultaneously or successively over a finite number of time periods. Notice that one disaster clearly influences others – from the logistics standpoint at least – whether they imply an overlapping of logistics activities that usually share the same resources, such as financial budget, prepositioned items, and relief centers. In this case, a *multiple disaster management approach* that spans a relatively long-term horizon may suggest maintaining existing infrastructure in operation (e.g., warehouses and relief centers) from previous disasters to be deployed in future forthcoming events attempting to provide a faster response and save overall resources. It is also possible to take advantage of the unused safe stock in a given relief center to supply people's needs in future periods, reducing the probability of shortage and avoiding waste of relief items. Notice that these decisions can be conceived and implemented only in multiperiod settings. Although Charles et al. (2016) built their optimization framework on a multiperiod basis, they disregard several characteristics of strategic supply chain problems in disaster management, such as relief centers' location and capacity size of both types facilities. More importantly, all the aforementioned studies focus on either the minimization of logistics costs or maximization of the coverage without taking into account people's vulnerabilities.

In this paper, we address the problem of building disaster preparedness and response capacity via prepositioning networks driven by people's vulnerability. Our multiperiod framework allows us to represent several types of potential hazards that might hit a given geographical area over a time horizon spanning months or years. For this purpose, we consider a multi-commodity and multiperiod two-echelon network based on the disaster management structure of Brazil, which comprises regional warehouses (distributions centers), local relief centers (temporary shelters), and affected areas (where disasters are supposed to occur). In the optimization model, long-term preparedness decisions focus on the following logistics activities before disaster strikes: warehouses location, capacity planning, and prepositioning of relief aid at warehouses. Medium and short-term decisions take place post-disaster attempting to locate relief centers, perform local procurement if necessary, and define the flow amounts of relief items at both echelons. We use time scales of distinct lengths to coordinate the integration of strategic and tactical decisions that should naturally be taken/updated in different periods during the time horizon. For example, warehouse location and relief prepositioning span macrotime periods of months or years, whereas relief centers location and local procurement span microtime periods of months or weeks. Here we focus on a deterministic approach using past disasters from the last fourteen years to estimate the needs of potential victims. For Charles et al. (2016), not only can this type of approach "provide much clearer information on gaps than a stochastic or robust approach" but it can also make it easier to convince practitioners to use a simpler approach since they generally have little or no experience with optimization approaches. However, we also develop a scenario-based two-stage stochastic programming version to investigate if *here-and-now* decisions could bring useful insights to our humanitarian supply chain problem. For this purpose, each year of disaster data was treated as one scenario, long-term decisions were assumed first-stage variables, and medium/short-term decisions were considered second-stage variables.

Differently from most related papers in the humanitarian logistics field, our formulation explicitly considers capacity planning decisions to define 'when', 'where' and 'how much' warehouse capacity should be expanded/contracted so as to promote a fast recovery via relief assistance deployment wherever is needed, rather than providing the initial emergency needs (Liberatore et al., 2014). This is also in accordance with the idea stated by Apte and Yoho (2011) that "preparedness at an institutional level translates to the planning and preestablishment of adequate capacity and resources that will enable efficient relief operations". This way, we aim at building preparedness and response capacity for handling multiple hazards over multiple periods of time. Finally, the use of the Social Vulnerability Index drives the solution to prioritize areas that might have insufficient capacity to prepare for and to respond to eminent disasters. Our results are based on a real case-study of Brazilian disasters and they reveal that our approach is indeed more effective in providing an enhanced response to more vulnerable areas. Finally, it is worth mentioning that strategies to cope with the Brazilian case-study may benefit humanitarian operations in other countries and regions in different geographies but that share rather similar characteristics.

The remainder of the paper is structured as follows: Section 2 states the problem by giving an overview of the Humanitarian Supply Chain in Brazil. Section 3 introduces the supply chain optimization model. Section 4 characterizes the case-study area and presents a brief discussion on data gathering and estimation. Section 5 shows the main results and elaborates on some managerial insights. Finally, Section 6 summarizes the main contributions of the study and points out some future research directions.

2. Problem Description: The motivation case of Brazil

This section offers and overview of the Brazilian Institutional Framework of the National

System of Civil Protection and Defense to further present our problem description. Civil protection and defense in Brazil, legally established by law 12.608/2012, is organized into a system called *The National System of Civil Protection and Defense* (Portuguese acronym: SINPDEC), composed of a set of multisectoral bodies such as federal, state, and municipal agencies, as well as public and private entities in the area of civil protection and defense (Wang et al., 2020). SINPDEC may mobilize the civil society to act in an emergency or in a state of public calamity, mainly coordinating logistical support for the development of civil protection and defense actions.

SINPDEC is currently structured in diverse agencies and entities that are responsible to carry out all the activities involved in disaster management throughout the country. The National Department for Civil Protection and Defense (Portuguese acronym: SEDEC) is the main body that composes SINPDEC. In order to coordinate the planning, articulation, and execution of civil defense and protection programs, projects, and actions, SEDEC is further divided into four main departments/entities, as depicted in Figure 1. The activities of the National Center for Risk and Disaster Management (Portuguese acronym: CENAD) comprise managing the strategic actions of preparedness and response in the Brazilian territory and, eventually, in the international scope. The Department of Liaison and Management (Portuguese acronym: DAG) supports, supervises, and promotes programs and plans guidelines related to the National Policy of Protection and Civil Defense (Portuguese acronym: PNPDEC) and for this reason its action spans all the disaster life cycle. The Department of Disaster Mitigation (Portuguese acronym: DMD) is oriented to develop and implement pre-disaster programs, including typical activities of mitigation, prevention, and preparedness. Finally, the Department of Rehabilitation and Reconstruction (Portuguese acronym: DRR) supports programs in the post-disaster phase in terms of rehabilitation and reconstruction.

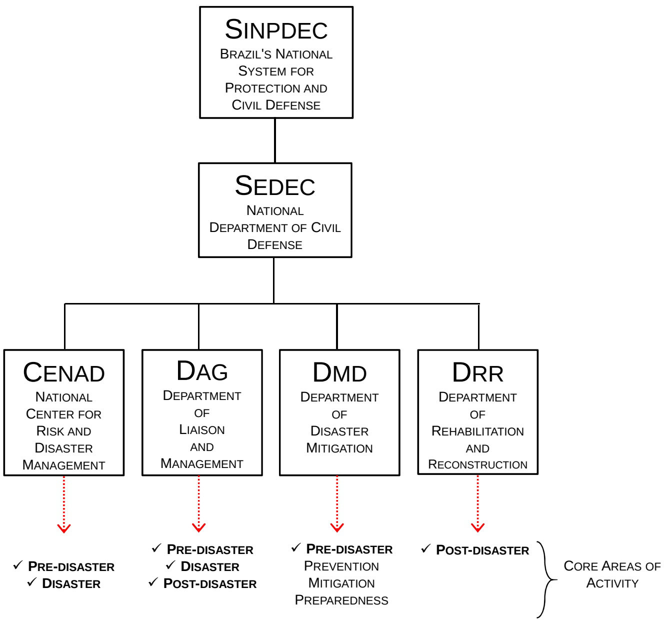


Figure 1: SINPDEC organization structure and main areas of activities of each department. Adapted from <http://www.mi.gov.br/web/guest/sedec/organograma>.

The Brazilian Civil Defense, represented by SEDEC, and the Brazilian Postal Office Service ('*Correios*') established an agreement in July 2013 to create strategic stocks of humanitarian assistance (food, water, medicine, among others) to fulfill victims needs in the aftermath of a disaster in Brazililian territory. Such agreement was part of a disaster response program devised by CENAD and coordinated by SEDEC. Initially stocks would be prepositioned in one municipality of each main region of Brazil, namely, Recife (PE), Manaus (AM), Porto Alegre (RS), Rio de Janeiro (RJ), and Brasília (DF) with the option to expand the stocks to other municipalities. The main objective of such prepositioning strategy conceived/realized by the Federal Instance (SEDEC) was to complement the initial emergency assistance provided by municipalities and states. The bureaucratic process to assess relief items is shown in Figure 2. First, the affected state or municipality requests relief assistance from SEDEC. Once SEDEC recognizes the real need of the applicant, relief items are deployed from warehouses and sent to the state/municipality which is responsible for performing the last-mile distribution.

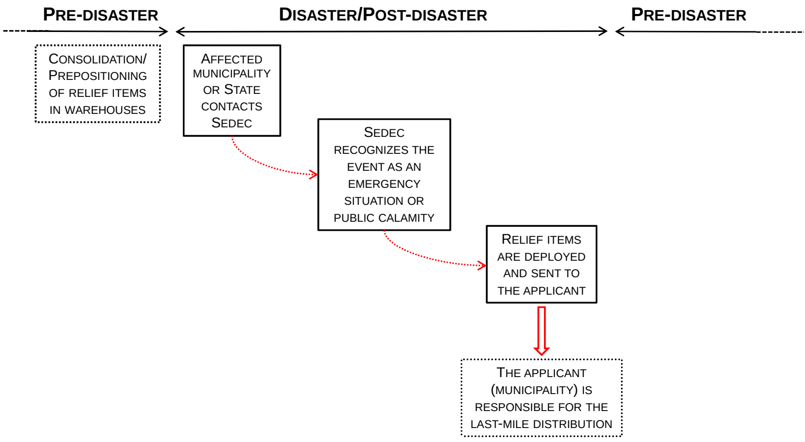


Figure 2: Main procedure to request the prepositioned relief items.

Apparently, the prepositioning agreement was canceled due to the inherent complexity of the logistics operations and their high costs. Instead, the Civil Defense has used a bidding procurement strategy in which suppliers are a priori selected to fulfill victims' needs within 192 hours for the North region and 96 hours for the remaining regions. However, most relief goods are required within the first 72 critical hours in the disaster aftermath (Van Wassenhove, 2006), which makes this strategy less effective in mitigating human suffering and, for this reason, potentially meaningless, especially if the affected municipality is socially vulnerable and struggles to act in defense of its victims in the first few hours of a disaster aftermath. If, on the one hand, prepositioning has the disadvantage of being sometimes prohibitively complicated and expensive (Balcik and Beamon, 2008), on the other hand, this practice is one of the most effective strategies to deal with both localized/dispersed slow and sudden-onset disasters. In fact, Figure 3 depicts a disaster classification based on time and location characteristics and provides examples of Brazilian disasters in each category. It also shows which logistics activities are more important (desirable) according to Apte and Yoho (2011). Basically, using the definition provided in previous studies (Heidtke, 2007; Apte and Yoho, 2011; Apte, 2014), we define *prepositioning* as the storage of relief aid in some moment in time *before* disaster strikes. *Proactive deployment* refers to moving relief aid into an area in advance of victims' needs requests to reduce lead time in response to a pre-existing event. *Phase deployment* is a "just in time" practice in which relief aid is pushed to a disaster area only when it is needed and in the required amount. Finally, *surge* (transportation or capacity) relies on "prepositioning" excess capacity rather than inventory attempting to be possible to mobilize resources in case of a disaster.

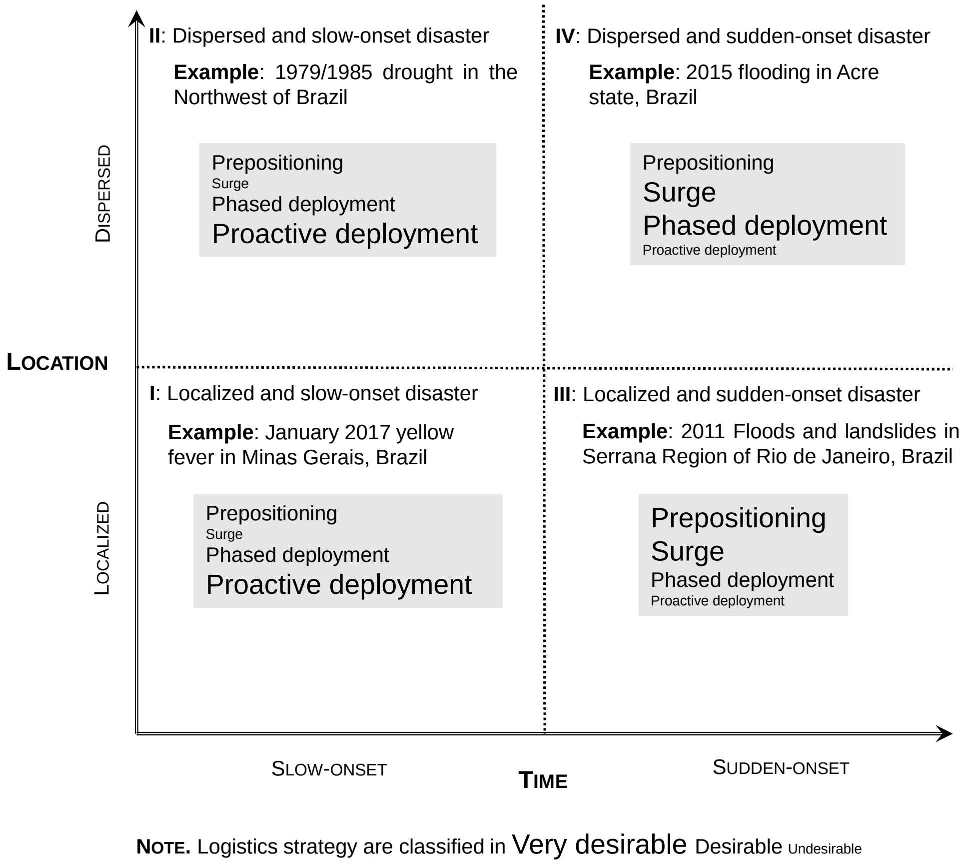


Figure 3: Classification of disasters and recommended logistics policies and examples of real Brazilian disasters.

The prepositioning policy is a 'very desirable' or a 'desirable' policy regardless of location and time. In addition, it might also stimulate other strategies in some sense, e.g., it is not possible to move relief aid before acquiring them in advance, thus making the proactive deployment strategy also dependent on a previous inventory of (prepositioned) goods. However, prepositioning must account for a number of challenging logistics decisions concerning warehouses and goods to be cost-effective, such as location and size of warehouses to store goods and types and quantity of goods that need to be stored. As the establishment of warehouses usually involves expensive long-term decisions (construction of buildings or rental contracts/agreements), it is not desirable to change its size or location in a medium or short-term horizon. At the same time, disasters timing, location, type, and impact/size might vary a lot and rapidly, specially in a continental-sized country that presents marked climatological differences among several regions and states like Brazil. This in turn also impacts the proper location, type, and quantity of relief goods that should be stored to be further deployed in the aftermath of a disaster. Determining a prepositioned strategy for one particular disaster independently from potential others, may result in an unnecessarily expensive warehousing network.

As a developing economy, Brazil struggles to raise sufficient resources to apply in preparedness and response activities. The Brazilian Government investment in disaster management has dropped over the past few years, and in 2018 Brazil has seen the lowest investment since 2008 (Ribeiro, 2018), making an effective use of the limited budget available for relief operations all the more relevant. Last but not least, Brazil is experiencing the longest period of increasing inequality and the proportion of the population in condition of poverty rose from 25.7% to 26.5% between 2016 and 2017 (IBGE, 2018; The World Bank, 2018). Poverty indeed increases vulnerability to disasters mainly by limiting coping and resistance strategies. However, there do not appear to be any prioritization schemes in place for more vulnerable areas or communities, even though past disasters have affected disproportionately more people who belonged to socially-vulnerable classes (Freitas et al., 2012).

In this paper, we thus develop a new approach to account for the aforementioned potential drawbacks of the previous papers and challenges of complex humanitarian supply chains, such as the Brazilian one. Our main assumptions are derived from the Brazilian case, but the model is sufficiently general to be applied in other similar contexts. Given a set of parameters, such as costs, capacities, and victims' needs, our main goal is to determine the best possible configuration of a network composed by two echelons, warehouses and relief centers, attempting to help as many victims as possible. The responsiveness of the humanitarian supply chain is increased with the possibility of purchasing relief aid items, in the *disaster aftermath*, via local procurement, assuming that there are local suppliers able to offer the items, and that the installed relief centers can manage the purchased items. However, local procurement exhibits some drawbacks, e.g., it generally faces quality problems, it might lead to supply shortages, and it can generate competition between organizations, resulting in high prices for the relief aid items (PAHO, 2001).

Considering that there is a budget constraint to perform all the logistics operations, we claim that it would be more effective to allocate the rather scarce resources to supply the needs of the areas that need the most, while other actors (NGOs) and strategies (in-kind donations) could be used to assist less vulnerable areas. In the end, our aim is to help more vulnerable areas to improve their response capacities seen here as the capacity of having its needs met in the disaster aftermath. With our approach, we show that even with an excessively scarce financial budget, it would be possible to provide a decent coverage to the most vulnerable areas.

3. A Humanitarian Supply Chain Design Model

Our model entails strategic (long-term) and tactical (mid- and short-term) decisions. We assume that the operational level are mostly related to the *very* short-term decisions made from day-to-day, such as last mile distribution/routing, which are not considered in this paper. Long-term decisions span longer periods of time (e.g., years) and are updated in the so-called macrotime periods. These decisions involve installing warehouses, determining the warehouses' capacity, expanding or uninstalling warehouses' capacities, performing propositioning of relief aid and determining their inventory levels at established warehouses, and deciding on the total logistics expenditures as well as the budget surplus at the end of each macrotime period. Mid- and short-term decisions usually span shorter periods of time (e.g., months). These decisions are updated in the so-called microtime periods. They entail setting up relief centers (where they should be installed and at what capacity), determining the quantity of relief aid to be purchased at relief centers via local procurement, the flow of relief aid from/to warehouses and relief centers, as well as inventory levels at operational relief centers; and finally deciding on how the victims' needs will be met. The objective is to maximize the overall number of supplied victims weighted by their corresponding social vulnerability index.

The assumptions invoked by the model are as follows. The same warehouse cannot be installed more than once during the timeline of the disaster. Once installed at a given initial capacity, the warehouses can be expanded or uninstalled from the second macrotime horizon onward. There is a maximum expansion capacity per macrotime period. It is possible to partly or totally reduce the capacity of a given warehouse from the second macrotime period onward. The same warehouse cannot be expanded and uninstalled at the same macrotime horizon. In this paper, we assume warehouses must be built to preposition relief aid goods and the warehouses' capacities are decisions that must be made based on an initial capacity (lower bound) and a maximum capacity (upper bound). For this reason, there is no fixed cost associated with the installation of a warehouse. Instead, all the costs of installing, operating, expanding, and uninstalling a warehouse are variables and depend linearly on its built capacity. All these capacities are given in square metres (m^2) to follow the construction unit cost (CUC), which is given in monetary units per square metres. On the other hand, relief centers represent current facilities that usually have different social functions (e.g., schools and gymnasiums and with an existing physical structure). Therefore, we assume that there is a fixed cost to adapt a given facility to serve as a relief center and a variable cost to operate it that depends linearly on its capacity. In order to maintain the same capacity unit for all types of facilities, relief centers' capacity is also given in square metres. The establishment of warehouses implies that a minimum amount of relief aid must be prepositioned. Prepositioning is limited according to its availability in units, which is based on the Brazilian bidding process mentioned in Section 3. The relief aid flows are allowed in any direction, i.e., between warehouses/relief centers, from warehouses to relief centers, and from relief centers to warehouses. All the relief aid flows are limited to the current capacity of warehouses and relief centers. Initial inventory in warehouses and relief centers is zero without loss of generality. The stock of relief aid is limited to the current capacity of warehouses and relief centers. There is also a maximum quantity of each type of relief aid that can be left in stock in warehouses and relief centers to reflect, e.g., limited cold storage capacity. Victims' needs can be met via prepositioned relief goods and/or local procurement at relief centers. Prepositioning is supposed to be performed before the disaster strikes, while local procurement is activated in the disaster aftermath. Deploying the stock of prepositioned relief aid at warehouses to fulfill victims' needs requires sending the goods to the installed relief centers first, thus paying shipping costs. In the end, relief centers can rely on relief goods that come from warehouses and relief goods that were purchased via local procurement. The total amount of relief aid in a given relief center can be allocated to one or more affected areas. One affected area can be assigned to one or more relief centers. There is a cost of assigning affected areas to relief centers that is linear with the distance between them. Relief aid goods purchased via local procurement are available in very limited quantities and their costs are higher than the purchase costs of the prepositioning strategy. The quantity of relief aid goods purchased at relief centers must also be within the current capacity of the relief center. All the aforementioned logistics activities incur costs. There is a per-macrotime-period financial budget to conduct these activities. Budget surpluses can be carried out from one macrotime period to another without any financial loss.

Our optimization model is based on the following indices and sets: $c \in \mathscr{C}$ for relief aid items; $n \in \mathscr{N}$ for candidate nodes for warehouses; $m \in \mathscr{M}$ for candidate nodes for relief centers; $k \in \mathscr{N} \cup \mathscr{M}$ for the set of all nodes; $a \in \mathscr{A}$ for affected areas; $t \in \mathscr{T}$ for macrotime periods; and $\tau \in \Theta_t$ for microtime periods in t. The parameters and decision variables are described next, followed by the optimization model. It is worth mentioning that all costs are given in Brazilian Reais (BRL).

Parameters

γ_{nt}^{w-new}	Cost of opening warehouse n at macrotime period t (BRL/m^2).
γ_{nt}^{w-o}	Cost of operating warehouse n at macrotime period t (BRL/m^2).
γ_{nt}^{w-e}	Cost of expanding warehouse n at macrotime period t (BRL/m^2).
γ_{nt}^{w-u}	Cost of uninstalling (part of) the capacity associated with warehouse n at macrotime period t (BRL/m^2).
$\gamma_{m\tau}^{rc-new}$	Fixed cost of opening relief center m at microtime period τ (BRL/m^2).
$\gamma_{m\tau}^{rc-o}$	Cost of operating relief center m at microtime period τ (BRL/m^2).
ι_{cnt}^{w}	Inventory cost of relief aid c at warehouse n at macrotime period t (BRL/unit).
$\iota_{cm\tau}^{rc}$	Inventory cost of relief aid c at relief center m at microtime period τ (BRL/unit).
$\mu_{cm\tau}$	Local procurement cost of relief aid c at relief center m at microtime period τ (BRL/unit).
ρ_{cnt}	Prepositioning cost of relief aid c at warehouse n at macrotime period t (BRL/unit).
$\chi_{ckk'\tau}$	Shipping cost of aid c between nodes k and k' at microtime period τ (BRL/unit).
$\zeta_{am\tau}$	Cost of fully assigning affected area a to relief center m at microtime period τ (BRL).
$v_{a\tau}$	Number of victims at affected area a at microtime period τ (people).
$v'_{a\tau}$	Relative number of victims at affected area a at microtime period τ evaluated as $\frac{v_{a\tau}}{\sum_{a'} v_{a'\tau}}$.
$d_{ca\tau}$	Victims' needs associated with relief aid c in affected area a at microtime period τ (units).

$h_{cn}^{w-\max}$ Inventory capacity for relief aid c at warehouse n (units).
$h_{cm}^{rc-\max}$ Inventory capacity for relief aid c at relief center m (units).
$p_{nt}^{\min}$ Minimum prepositioning level at warehouse n at macrotime period t (units).
$p_{ct}^{\max}$ Prepositioning capacity for relief aid c at macrotime period t (units).
q_n^0 Initial capacity for warehouse n (m^2).
$q_n^{w-\max}$ Maximum expansion capacity of warehouse n (m^2).
$q_n^{rc-\max}$ Maximum capacity of relief center m (m^2).
$q_n^{rc-\min}$ Minimum capacity of relief center m (m^2).
$u_{cm\tau}^{rc-\max}$ Maximum quantity of relief aid c that can be purchased via local procurement by relief center m at microtime period τ (units).
β_t Financial budget available during macrotime period t (BRL).
SoVI_a Social vulnerability index associated with affected area a.
f_c Conversion factor for relief aid c.

Continuous Variables

I_{cnt}^{w} Inventory of relief aid c at warehouse n at macrotime period t (units).
$I_{cm\tau}^{rc}$ Inventory of relief aid c at relief center m at microtime period τ (units).
P_{cnt} Amount of relief aid c prepositioned at warehouse n at macrotime period t (units).
Q_{nt}^{w} Capacity of warehouse n at macrotime period t (m^2)
Q_{nt}^{w-e} Expanded capacity for warehouse n at macrotime period t (m^2).
Q_{nt}^{w-u} Uninstalled capacity for warehouse n at macrotime period t (m^2).
$Q_{m\tau}^{rc}$ Capacity of relief center m at microtime period τ (m^2).
$U_{cm\tau}^{rc}$ Amount of relief aid c procured at relief center m at microtime period τ (units).
$X_{ckk'\tau}$ Flow of relief aid c between nodes k and k' at microtime period τ (units).
$Z_{am\tau}$ Fraction of the victims' needs associated with affected area a that is assigned to relief center m at microtime period τ.
G_t Total logistics expenditures in macrotime period t (BRL).
W_t Unused financial budget in macrotime period t (BRL).

Binary Variables

Y^{w}_{nt} $= 1$, if warehouse n is installed at macrotime period t;
$= 0$, otherwise.

Y^{w-e}_{nt} $= 1$, if warehouse n is expanded at macrotime period t;
$= 0$, otherwise.

Y^{w-u}_{nt} $= 1$, if (part of) warehouse n is uninstalled at macrotime period t;
$= 0$, otherwise.

$Y^{rc}_{m\tau}$ $= 1$, if relief center m is installed at microtime period t;
$= 0$, otherwise.

$Y^{rc-o}_{m\tau}$ $= 1$, if relief center m is operating at microtime period t;
$= 0$, otherwise.

The objective function (1) maximizes the *effectiveness of the response*, the extent to which it manages to cover as many victims' needs as possible. Differently from most papers in the existing literature, we employ the *Social Vulnerability Index*, SoVI, to *prioritize* supplying socially disadvantaged areas in case of insufficient resources to cover all victims' needs at once. The static nature of the index pushes the victims' needs coverage on an aggregate level, i.e., there will be an encouragement to fulfill victims' needs of more vulnerable affected areas over less vulnerable areas regardless of the microtime period when they arise. We thus say that a more *social-effective* response prioritizes supplying affected areas that exhibit worse SoVIs. The SoVI index for the Brazilian municipalities is a numerical value that falls within the interval $[-9.275, 27.673]$ (De Loyola Hummell et al., 2016), in which higher values mean higher vulnerability levels. The original SoVI values associated with the affected areas considered in our case-study were further standardized using a log-transformation procedure such that all the transformed values are strictly positive coefficients in the objective function. These details are discussed in Section 4. Notice that our 'coverage-maximization' is not greedily driven by the SoVI_a coefficient because the relative number of victims $v_{a\tau}$ is also weighted in the objective function.

$$\max \sum_{a\in\mathscr{A}} \sum_{m\in\mathscr{M}} \sum_{t\in\mathscr{T}} \sum_{\tau\in\theta_t} \text{SoVI}_a \cdot v'_{a\tau} \cdot Z_{am\tau}. \tag{1}$$

Constraint (2) guarantees that a warehouse cannot be installed more than once during the macrotime horizon. The constraints (3) and (4) ensure that warehouses cannot be expanded or uninstalled unless they were established in previous periods, respectively. The next constraint (5) guarantees that a warehouse cannot be simultaneously installed, expanded or uninstalled at the macrotime period t.

$$\sum_{t \in \mathscr{T}} Y_{nt}^{w} \leq 1, \ \forall n \in \mathscr{N}. \tag{2}$$

$$Y_{nt}^{w-e} \leq \sum_{t'=1}^{t} Y_{nt'}^{w}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{3}$$

$$Y_{nt}^{w-u} \leq \sum_{t'=1}^{t} Y_{nt'}^{w}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{4}$$

$$Y_{nt}^{w} + Y_{nt}^{w-e} + Y_{nt}^{w-u} \leq 1, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{5}$$

Constraint (6) states that it is necessary to guarantee a minimum amount of prepositioned stock in warehouse n to be economically viable to install it at macrotime period t, e.g., it does not make sense to install a warehouse to store a gallon of water. In addition, constraint (7) ensures that the overall prepositioned relief aid respects the actual capacity of the warehouse. The conversion factor f_c is used to compare different physical quantities. In constraint (7), for example, the prepositioned stock is given in *units* of relief aid, whereas the capacity of the warehouse is given in m^2. Therefore, f_c transforms the units of relief aid in m^2, since its dimension is exactly $[\frac{m^2}{units}]$. Constraint (8) states the prepositioning capacity per type of relief aid.

$$\sum_{c \in \mathscr{C}} P_{cnt} \geq p_{nt}^{\min} \cdot Y_{nt}^{w}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{6}$$

$$\sum_{c \in \mathscr{C}} f_c \cdot P_{cnt} \leq Q_{nt}^{w}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{7}$$

$$\sum_{n \in \mathscr{N}} P_{cnt} \leq p_{ct}^{\max}, \ t \in \mathscr{T} \wedge \forall c \in \mathscr{C}. \tag{8}$$

Constraint (9) defines the capacity level of warehouse n at macrotime period $t > 1$ as the capacity in the previous macrotime period $t-1$, plus the expanded capacity Q_{nt}^{w-e} and minus the uninstalled capacity Q_{nt}^{w-u}. Constraint (10) defines the capacity level for warehouses in the first macrotime period. Constraints (11) defines the upper bound for the warehouse capacity n at macrotime period t. The set of constraints (12) and (13) define the warehouse expanded and uninstalled capacity, respectively.

$$Q_{nt}^{w} = q_n^0 \cdot Y_{nt}^{w} + Q_{n(t-1)}^{w} + Q_{nt}^{w-e} - Q_{nt}^{w-u}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T} \backslash \{1\}. \tag{9}$$

$$Q_{nt}^{w} = q_n^0 \cdot Y_{nt}^{w}, \ \forall n \in \mathscr{N} \wedge t = 1. \tag{10}$$

$$Q_{nt}^{w} \leq \left(q_n^0 + (t-1) \cdot q_n^{w-\max} \right) \cdot \sum_{t'=1}^{t} Y_{nt'}^{w}, \ n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{11}$$

$$Q_{nt}^{w-e} \leq q_n^{w-\max} \cdot Y_{nt}^{w-e}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{12}$$

$$Q_{nt}^{w-u} \leq \left(q_n^0 + (t-1) \cdot q_n^{w-\max} \right) \cdot Y_{nt}^{w-u}, \ n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{13}$$

The set of constraints (14)−(15) force the flows either leaving or arriving at warehouse n to be within the warehouse capacity, respectively. These two constraints also force all flows to be zero if there is no warehouse installed, i.e., $Q^w_{nt} = 0$. Constraint (16) expresses the flow balance of the prepositioned relief aid c in warehouse n at macrotime period t. The LHS consists of (i) the amount of prepositioned stock; (ii) the stock of the immediate previous period; (iii) the amount of relief aid that comes from relief centers and other warehouses, respectively. The RHS entails, in this order, (i) the amount of relief aid that goes to either other warehouses or relief centers; and (ii) the amount of relief aid that remains in inventory. Without loss of generality, $I^w_{cn0} = 0$, for all c and n. The block of constraints (17) and (18) guarantee that the stock in warehouse n falls within its capacity and the maximum stock for each relief aid type and warehouse is not violated, respectively.

$$\sum_{c\in\mathscr{C}} \sum_{k\in\mathscr{N}\cup\mathscr{M}} \sum_{\tau\in\Theta_t} f_c \cdot X_{cnk\tau} \leq Q^w_{nt}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T} \tag{14}$$

$$\sum_{c\in\mathscr{C}} \sum_{k\in\mathscr{N}\cup\mathscr{M}} \sum_{\tau\in\Theta_t} f_c \cdot X_{ckn\tau} \leq Q^w_{nt}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{15}$$

$$P_{cnt} + I^w_{cn(t-1)} + \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq n}} \sum_{\tau\in\theta_t} X_{ckn\tau} = \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq n}} \sum_{\tau\in\theta_t} X_{cnk\tau} + I^w_{cnt}, \ \forall c \in \mathscr{C} \wedge n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{16}$$

$$\sum_{c\in\mathscr{C}} f_c \cdot I^w_{cnt} \leq Q^w_{nt}, \ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{17}$$

$$I^w_{cnt} \leq h^{w-\max}_{cn}, \ \forall c \in \mathscr{C} \wedge n \in \mathscr{N} \wedge t \in \mathscr{T}. \tag{18}$$

Constraint (19) expresses the conservation flow of the victims' needs at the relief centers' level over the microtime periods. The LHS consists of, in this order, (i) the amount of relief aid that remains in stock; (ii) the flow of relief aid that goes to warehouses and other relief centers; and (iii) the overall victims' needs fulfilled by the relief centers. The RHS entails, in this order, (i) the stock of the immediate previous period; (ii) the amount of relief aid that comes from warehouses and other relief centers; and (iii) the amount of relief aid purchased at the actual relief center via local procurement. Without loss of generality, $I^{rc}_{cm0} = 0$, for all c and m.

$$I^{rc}_{cm\tau} + \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq m}} X_{cmk\tau} + \sum_{a\in\mathscr{A}} [d_{ca\tau} \cdot Z_{am\tau}] = I^{rc}_{cm(\tau-1)} + \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq m}} X_{ckm\tau} + U^{rc}_{cm\tau}, \quad \forall c \in \mathscr{C} \wedge m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{19}$$

Constraint (20) guarantees that the relief centers do not cover more than the existing victims' needs. Notice that more than one relief center can be assigned to cover (full or part of) the needs of the same affected area. Constraint (21) states that relief centers could cover only a fraction of the needs of each affected area. Constraint (22) determines the capacity usage of the relief center m at microtime period τ. If $Q^{rc}_{m\tau} = 0$, then $Z_{am\tau} = 0$, i.e., the relief center m cannot meet victims' needs of the affected area a at this microtime period.

$$\sum_{m\in\mathscr{M}} Z_{am\tau} \leq 1,\ \forall a \in \mathscr{A} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \tag{20}$$

$$0 \leq Z_{am\tau} \leq 1,\ \forall a \in \mathscr{A} \wedge m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{21}$$

$$\sum_{c\in\mathscr{C}} \sum_{a\in\mathscr{A}} d_{ca\tau} \cdot f_c \cdot Z_{am\tau} \leq Q^{rc}_{m\tau},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{22}$$

Constraint (23) states that there is a minimum capacity to install the relief centers. Constraint (24) defines the maximum capacity for the relief center m if it is operating ($Y^{rc-o}_{m\tau} = 1$); otherwise ($Y^{rc-o}_{m\tau} = 0$), $Q^{rc}_{m\tau} = 0$. Constraint (25) defines the status of the relief centers.

$$Q^{rc}_{m\tau} \geq q^{rc-\min}_{m} \cdot Y^{rc-o}_{m\tau},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{23}$$

$$Q^{rc}_{m\tau} \leq q^{rc-\max}_{m} \cdot Y^{rc-o}_{m\tau},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{24}$$

$$Y^{rc}_{m\tau} \geq Y^{rc-o}_{m\tau} - Y^{rc-o}_{m(\tau-1)},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{25}$$

The block of constraints (26) and (27) force the flows either arriving or leaving at relief center m to be within the relief center capacity, respectively. These two constraints also force all flows to be zero if $Q^{rc}_{mr} = 0$.

$$\sum_{c\in\mathscr{C}} \sum_{k\in\mathscr{N}\cup\mathscr{M}} f_c \cdot X_{ckm\tau} \leq Q^{rc}_{mr},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}, \tag{26}$$

$$\sum_{c\in\mathscr{C}} \sum_{k\in\mathscr{N}\cup\mathscr{M}} f_c \cdot X_{cmk\tau} \leq Q^{rc}_{mr},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{27}$$

Constraint (28) defines the upper bound for the inventory levels in the relief centers. Note that this constraint ensures that it is not possible to carry on relief aid from one microtime period to another unless the relief center is operating in these successive microtime periods. Constraint (29) guarantees that the stock plus the amount of purchased relief aid via local procurement falls within the capacity of the relief center. Similarly, constraint (30) limits the maximum amount of relief aid that can be purchased in the disaster aftermath via local procurement.

$$I^{rc}_{cm\tau} \leq h^{rc-\max}_{cm} \cdot Y^{rc-o}_{m\tau},\ \forall c \in \mathscr{C} \wedge m \in \mathscr{M} \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{28}$$

$$\sum_{c\in\mathscr{C}} (f_c \cdot I^{rc}_{cm\tau} + f_c \cdot U^{rc}_{cm\tau}) \leq Q^{rc}_{m\tau},\ \forall m \in \mathscr{M} \wedge t \in \mathscr{T}. \tag{29}$$

$$U^{rc}_{cm\tau} \leq u^{rc-\max}_{cm\tau} \cdot Y^{rc-o}_{m\tau},\ \forall c \in \mathscr{C} \wedge m \in \mathscr{M} \tau \in \theta_t \wedge t \in \mathscr{T}. \tag{30}$$

Constraint (31) states the financial budget to perform the logistics operations. If it is not possible to use any budget surplus, decision variable W_t can be set to zero for all $t \in \mathscr{T}$. Another possibility would be to simply state $G_t \leq \beta_t,\ \forall t \in \mathscr{T}$.

$$\beta_t + W_{t-1} - W_t = G_t, \ \forall t \in \mathscr{T} \tag{31}$$

in which the overall logistics costs are defined as follows:

$$G_t = \sum_{n \in \mathscr{N}} \gamma_{nt}^{w-new} \cdot q_n^0 \cdot Y_{nt}^w + \sum_{n \in \mathscr{N}} \gamma_{nt}^{w-o} \cdot Q_{nt}^w + \sum_{n \in \mathscr{N}} \gamma_{nt}^{w-e} \cdot Q_{nt}^{w-e} + \sum_{n \in \mathscr{N}} \gamma_{nt}^{w-u} \cdot Q_{nt}^{w-u} + \tag{32}$$

$$+ \sum_{c \in \mathscr{C}} \sum_{n \in \mathscr{N}} \iota_{cnt}^w \cdot I_{cnt}^w + \sum_{c \in \mathscr{C}} \sum_{n \in \mathscr{N}} \rho_{cnt} \cdot P_{cnt} + \tag{33}$$

$$+ \sum_{m \in \mathscr{M}} \sum_{\tau \in \Theta_t} \gamma_{m\tau}^{rc-new} \cdot Y_{m\tau}^{rc} + \sum_{m \in \mathscr{M}} \sum_{\tau \in \Theta_t} \gamma_{m\tau}^{rc-o} \cdot Q_{m\tau}^{rc} + \sum_{c \in \mathscr{C}} \sum_{m \in \mathscr{M}} \sum_{\tau \in \Theta_t} \mu_{cm\tau} \cdot U_{cm\tau}^{rc} + \tag{34}$$

$$+ \sum_{a \in \mathscr{A}} \sum_{m \in \mathscr{M}} \sum_{\tau \in \Theta_t} \zeta_{am\tau} \cdot Z_{am\tau} + \sum_{c \in \mathscr{C}} \sum_{m \in \mathscr{M}} \sum_{\tau \in \Theta_t} \iota_{cm\tau}^{rc} \cdot I_{cm\tau}^{rc} + \tag{35}$$

$$+ \sum_{c \in \mathscr{C}} \sum_{k \in \mathscr{N} \cup \mathscr{M}} \sum_{\substack{k' \in \mathscr{N} \cup \mathscr{M} \\ k' \neq k}} \sum_{\tau \in \Theta_t} \chi_{ckk'\tau} \cdot X_{ckk'\tau} \tag{36}$$

Term (32) refers to the cost of installing, operating, expanding, and uninstalling a warehouse, respectively. Term (33) evaluates, in this order, the costs due to the inventory left in warehouses and the prepositioning of relief aid in the established warehouses. Term (34) assesses the cost of opening a relief center, operating it, and performing local procurement. Term (35) determines the cost of assigning the needs of an affected area to a relief center, and inventory left in relief centers, respectively. It is worth mentioning that the cost of assigning an affected area to a relief centre simply encourages the establishment of relief centers as close as possible to the affected areas, thus improving victims' accessibility to humanitarian assistance. Finally, shipping costs are determined by expression (36).

4. Case-Study and Overview of Data Collection

Brazil is the fifth country in territorial extension on the planet, with a surface of 8,515 767,049 square kilometers. It occupies almost half of the South American continent and has a vast border region with all the nations of South America, with the exception of Chile and Ecuador (de Figueiredo, 2016). Brazil is a Federative Republic and it is divided into 26 states, 1 federal district and and 5,570 municipalities. It has six well-defined regions divided according to geographical and cultural aspects (Ribeiro, N.d.), named North: Acre (AC), Amapá (AP), Amazonas (AM), Pará (PA), Rondônia (RO), Roraima (RR), and Tocantins (TO); Northeast: Alagoas (AL), Bahia (BA), Ceará (CE), Maranhão (MA), Paraíba (PB), Pernambuco (PE), Piauí (PI), Rio Grande do Norte (RN), and Sergipe (SE); South: Paraná (PR), Rio Grande do Sul (RS), and Santa Catarina (SC); Southeast: Espírito Santo (ES), Minas Gerais (MG), Rio de Janeiro (RJ), and São Paulo (SP); Central-West: Goiás (GO), Mato Grosso (MT), and Mato Grosso do Sul (MS).

Typical Brazilian natural hazards are considered the 'extensive risk' type, i.e., most of them present low-severity risk but they are very frequent, and they can be highly localized events, although not exclusively (UNISDR, 2017). In this study, we consider the most relevant types of natural hazards (in terms of overall affected people) that hit the Brazilian territory in the period 2003-2016, as follows: floods, runoff, flash floods, heavy rainfall, gales, hailstorm, landslides, drought, seasonal drought, and tornado (Anuario, 2012; CENAD, 2014). This information was collected from the Integrated System of Disasters Information (SEDEC-CEPED/UFSC, 2018), whose aim is to computerize various data sources from SEDEC and make them available. Afterwards, the data was consolidated and analyzed by the authors towards building a realistic case, which is acknowledged to be a missing aspect of several research papers (Sabbaghtorkan et al., 2019). Figure 4 shows the front page (left) and the page for assessing the data on the number of victims, in which we can select a given time range of the realized disaster, the type of disaster and the Brazilian state.

Figure 4: The figure shows (right) the "Integrated System of Disasters Information" web page, also called "S2iD" (*Sistema Integrado de Informacoes sobre Desastres* in Portuguese), and (left) the web page for the selection of the data on the number of victims of a realized disaster for a given time range and state (left). Source: `https://s2id.mi.gov.br/`. Accessed in July 2019.

With these data in hands, we first analyzed the cumulative number of homeless and displaced people as a consequence of the aforementioned eleven types of disasters from 01/01/2003 to 31/12/2016 for all the 26 states plus the Federal District, as depicted in Figure 5. In our numerical study, we took into account all those states whose corresponding number of victims is greater or equal to 1% of the total number of homeless and displaced people, which means that AL, RO, MS, MT, SE, GO, AP, TO, RR, and DF were not considered in the analyses. The capital of the remaining 17 states were treated as potential candidates to allocate warehouses, as depicted in Figure 6.

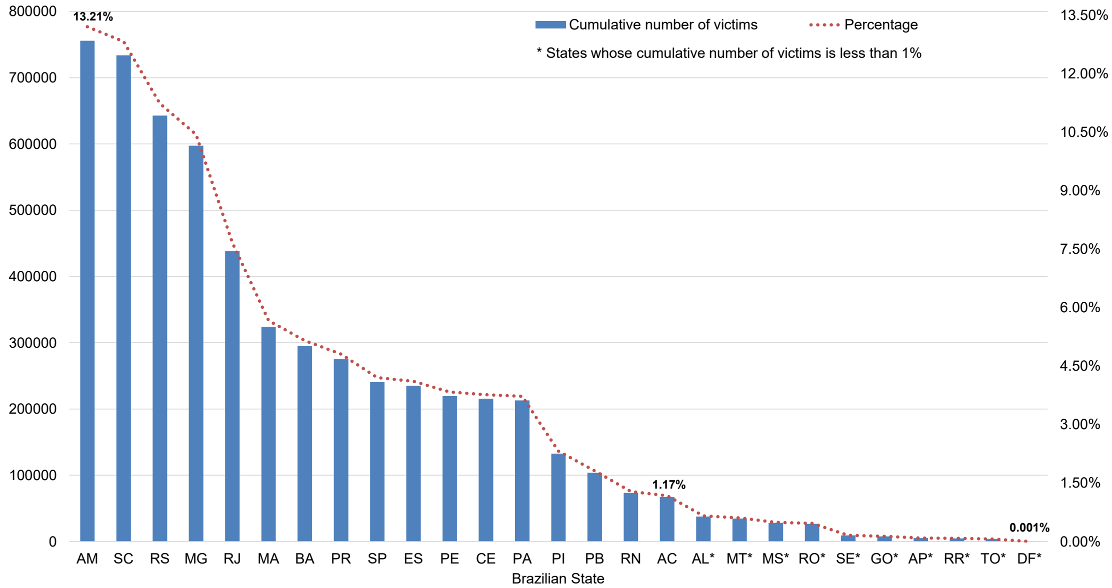


Figure 5: Absolute and relative *cumulative* number of homeless and displaced victims in the 26 Brazilian states and in the Federal District from 01/01/2003 to 31/12/2016.

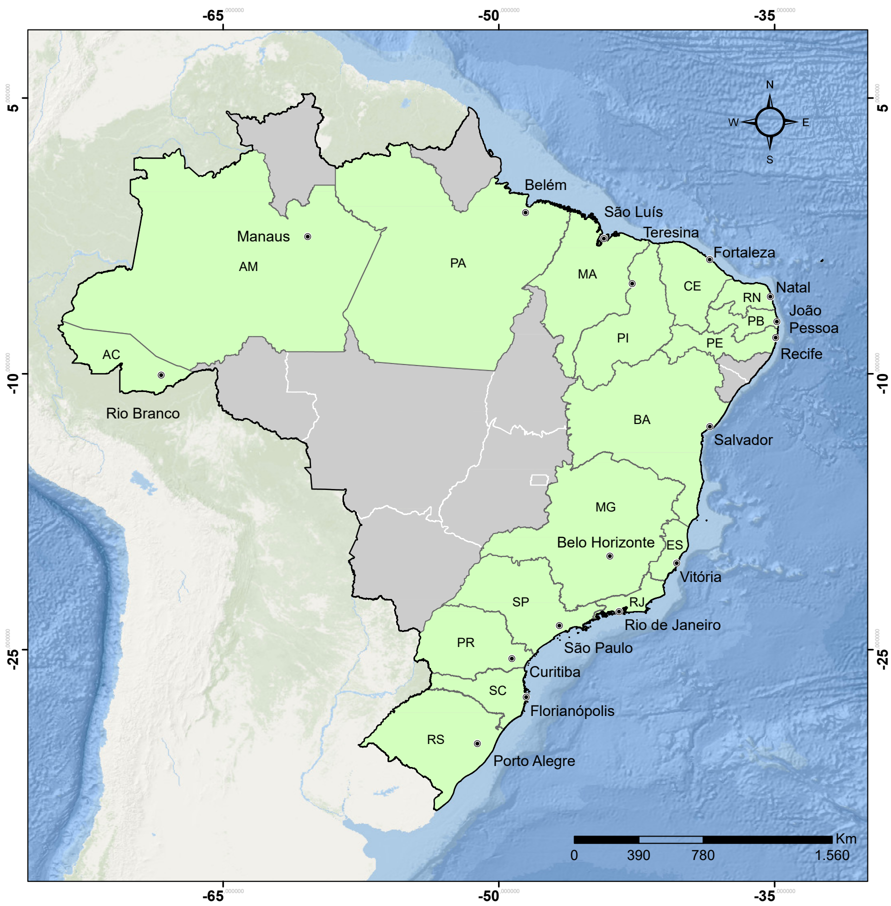
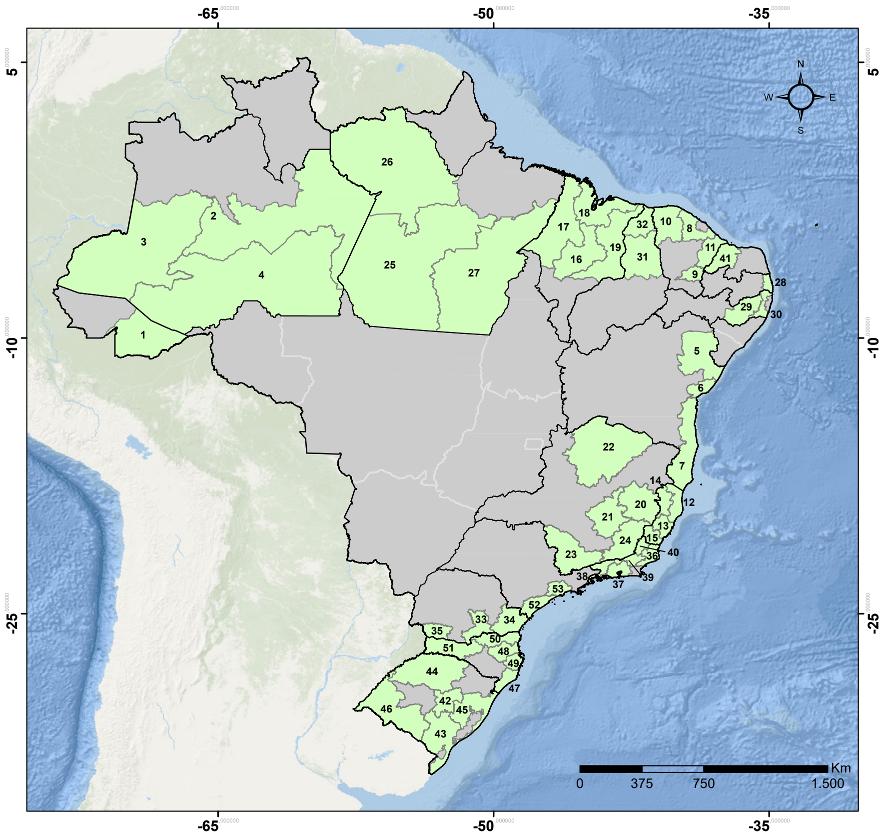


Figure 6: Brazil's map and candidates to warehouses (capital of the 17 states considered in the analysis).

We then identified all the affected areas for each one of the 17 states and considered only those whose corresponding number of victims is greater or equal to 0.5% of the total number of homeless and displaced people in the period under analysis. It is worth noting that the affected areas correspond to Brazilian *mesoregions* or *intermediary geographic regions*, which is a group of several municipalities in geographical proximity that share common characteristics (see details in Appendix A). A total of 53 areas were then selected and treated as affected areas and candidates to locate relief centers, as illustrated in Figure 7. The cut-off at 0.5% was also based on the trade-off between model tractability and realism. In total, we considered 4,955,748 victims out of 5,720,819, which represents almost 87% of the historical number. We thus consolidated the number of homeless and displaced victims for each affected area and month (January to December) for the 14 years of data (2003-2016). Finally, to determine the number of victims of our instance composed of 2 macrotime periods (years) and 6 microtime periods (blocks of two months, January/February, March/April, May/June, July/August, September/October, and November/December), we proceeded as follows: we took the average of the monthly number of victims over 2003-2009 (7 years of data) for all affected areas and added the corresponding average number of victims for the first six blocks of two months to obtain the bimonthly number of victims of macrotime period 1 (year 1). Analogously, we took the average of the monthly number of victims over 2010-2016 (7 years of data) for all affected areas and added the corresponding average number of victims for the second six blocks of two months to have the bimonthly number of victims of macrotime period 2 (year 2). Figure 8 depicts the bimonthly average number of victims per affected area.



1 Vale do Acre	19 Leste Maranhense	37 Metropolitana do Rio de Janeiro
2 Centro Amazonense	20 Vale do Rio Doce	38 Sul Fluminense
3 Sudoeste Amazonense	21 Metropolitana de Belo Horizonte	39 Centro Fluminense
4 Sul Amazonense	22 Norte de Minas	40 Noroeste Fluminense
5 Nordeste Baiano	23 Sul/Sudoeste de Minas	41 Oeste Potiguar
6 Metropolitana de Salvador	24 Zona da Mata	42 Centro Oriental Rio-Grandense
7 Sul Baiano	25 Sudoeste Paraense	43 Sudeste Rio-Grandense
8 Norte Cearense	26 Baixo Amazonas	44 Noroeste Rio-Grandense
9 Centro-Sul Cearense	27 Sudeste Paraense	45 Metropolitana de Porto Alegre
10 Noroeste Cearense	28 Mata Paraíbana	46 Sudoeste Rio-Grandense
11 Jaguaribe	29 Agreste Pernambucano	47 Sul Catarinense
12 Litoral Norte Espirítio-Santense	30 Mata Pernambucana	48 Vale do Itajaí
13 Central Espírito-Santense	31 Centro-Norte Piauiense	49 Grande Florianópolis
14 Noroestel Espírito-Santense	32 Norte Piauiense	50 Norte Catarinense
15 Sul Espírito-Santense	33 Sudeste Paranaense	51 Oeste Catarinense
16 Centro Maranhense	34 Metropolitana de Curitiba	52 Litoral Sul Paulista
17 Oeste Maranhense	35 Sudoeste Paranaense	53 Metropolitana de São Paulo
18 Norte Maranhense	36 Norte Fluminense	

Figure 7: Brazil territory and the selected 53 affected areas. Notice that the names of the affected areas were kept in their original language (Portuguese).

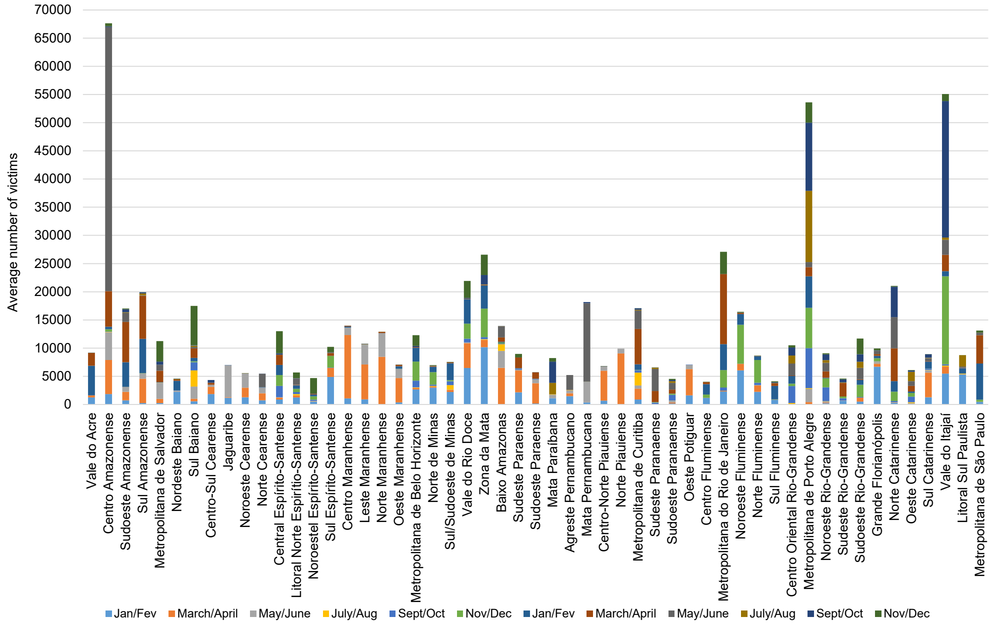


Figure 8: Average number of victims over the period ranging from 01/01/2003 to 31/12/2016 for each microtime period in 53 affected areas.

Insight 1. *Historical data on the number of homeless and displaced victims reveals its large dispersion over the bi-month-periods of each year, suggesting that a single-period approach could fail to accurately represent the problem.*

Given the number of homeless and displaced people in Figure 7, we determined their needs for water, food, hygiene kits, cleaning kits, dormitory kits, and mattresses. Each unit of water represents a container with 5 litres for one person. A food, hygiene and cleaning kit covers a four-person family. A kit of dormitory products serves only one person and a mattress serves one person (ATA, 2016).

The Social Vulnerability Index (SoVI) for each affected area is shown in Figure 9. These figures were obtained by using a log-transformation to only have positive values, as follows: $\text{SoVI} = \log(\text{SoVI}_o + 1.1 - \min[\text{SoVI}_o])$, in which SoVI_o is the original SoVI value, and $\min[\text{SoVI}_o]$ is the minimum SoVI among the 53 affected areas. Logarithmic transformation is one of the most used data transformation procedures, especially when the data vary a lot on the relative scale, which is our case. In fact, the original SoVI values vary from -0.14 to 21.02 and the coefficient of variation (standard deviation/mean value) is 54.43%. After the log transformation, our SoVI data vary from 0.04 to 1.35 and the coefficient of variation is 28.39%. With this gain in terms of variance reduction, our data is more fairly comparable.

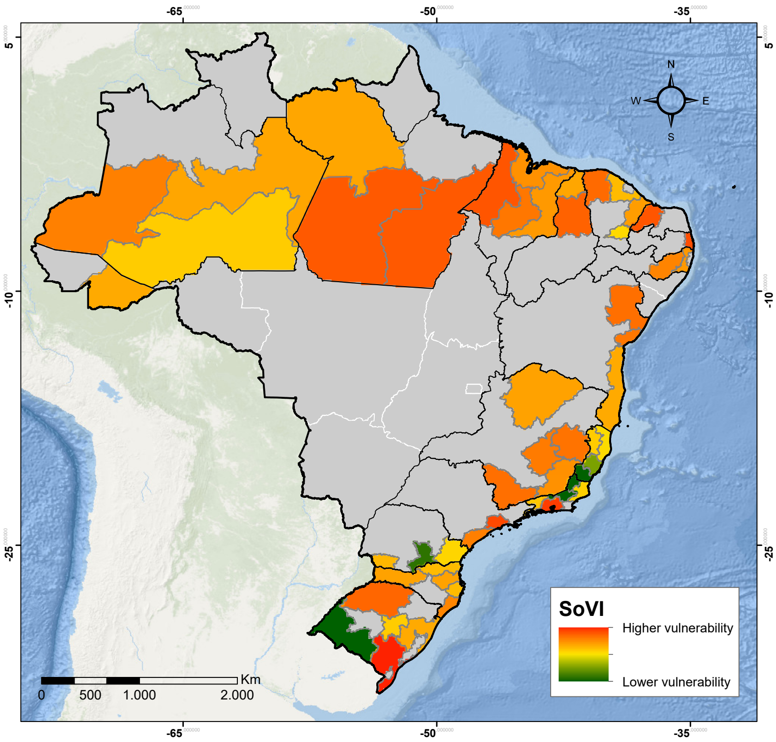


Figure 9: Social Vulnerability Index (SoVI) after transformation of the 53 affected areas.

Insight 2. *The SoVI associated with the fifty three most affected municipalities show that most of them exhibit a worrying level of social vulnerability.*

The details on the evaluation of the other parameters of the optimization models can be obtained by emailing the authors.

5. Case-study results

This section presents the case-study results whose main goal is to evaluate the performance of the proposed model based on real Brazilian disasters described in the previous section. We also provide managerial insights that could be useful to (re)think some current disaster management strategies/policies. For this purpose, we first focus on the detailed analysis of our case-study solutions (Subsection 5.1). Afterwards, we analyze the relief service levels for different budget levels (see Definition 1) and, consequently, the role of the SoVI index in driving these decisions (Subsection 5.2). Finally, we assess the value of the here-and-now solutions by solving a scenario-based two-stage stochastic programming model (Subsection 5.2). Throughout this section, we assume that the financial budget of our *base-case* problem is the *reference budget* reduced by 40%, with is aligned with our motivation in using SoVI to prioritize the allocation of resources with rather limited financial budgets (see Appendix B for details).

Definition 1. *The relief service level of affected area 'a' in microtime period 'τ' is evaluated as follows:*

$$\alpha_{a\tau} = 100\% \times \sum_{m} Z_{am\tau}. \tag{37}$$

We used GAMS 25.1.1 to code the optimization model and CPLEX 12.8 to solve the instances on a computer Intel core i7 processor with 16 GB RAM under Windows 10 operating system. The stopping criterion was either the elapsed time exceeding 14,400 seconds or the relative optimality gap smaller than 0.01. The average (resp., largest) solution time across the all our proposed instances was 3,213 (resp. 7,926) seconds. The scenario-based model was solved by a heuristic procedure implemented in the same language (Appendix F shows the details).

5.1. Results and Discussion

The base-case solution resulted in the establishment of only 5 warehouses to preposition relief aid (see Table 1 and Figure 10); four of them are located in the Northeast region, specifically at São Luís (Maranhão state), João Pessoa (Paraíba state), Teresina (Piauí state), and Natal (Rio Grande do Norte state), while one warehouse is located at Belo Horizonte (Minas Gerais state), which belongs to the Southeast region. Not coincidentally, the installation costs in all these states are less expensive than in the remaining locations, suggesting that the centralization of the prepositioning strategy in the Northeast region is consequence of the high cost of establishing and operating warehouses in the other regions. Similar results were found for different budget levels; in particular, it is worth mentioning that João Pessoa was selected to host a warehouse for budget reductions from 20% to 90% because it is the least expensive location across all the 17 candidates. All the warehouses of our base-case instance operate with their maximum capacity during the entire horizon of two years; also, the warehouses at São Luís and João Pessoa expand their capacities by 76% and 100%, respectively. Because of the few number of operational warehouses, most of them end up serving several relief centers; this is particularly true for the warehouse at São Luís that sends relief aid to 35 different RCs in year two. The amount of relief aid delivered (last column of Table 1) gives an idea of the capacity of the relief centers to meet the needs of their corresponding affected areas; e.g., for the relief centers served by the warehouse at Belo Horizonte, this figure would be 43.42%.

Table 1: Established warehouses, capacities, and utilization.

Established warehouses	Macrotime period	Warehouse capacity (m^2)	Warehouse utilization* (%)	Expansion** (m^2)	Number of relief centers served	Number of relief centers served*** (%)	Amount of relief aid delivered**** (%)
São Luís	1	71,901	100	0	27	50.94	14.56
Belo Horizonte	1	51,469	100	0	29	54.72	34.52
João Pessoa	1	22,579	100	0	2	3.770	234.7
Teresina	1	22,579	100	0	14	26.42	14.18
Natal	1	22,579	100	0	20	37.74	10.98
São Luís	2	126,688	100	54,788	35	66.04	19.10
Belo Horizonte	2	51,469	100	0	29	54.72	43.42
João Pessoa	2	45,158	100	22,579	18	33.96	17.14
Teresina	2	22,579	100	0	16	30.19	15.93
Natal	2	22,579	100	0	19	35.85	7.780

* Based on the total prepositioned capacity in m^2.
** All the expansion capacities were performed in the second macrotime period.
*** According to the total number of RCs installed.
**** According to the overall victims' needs of the RCs served.

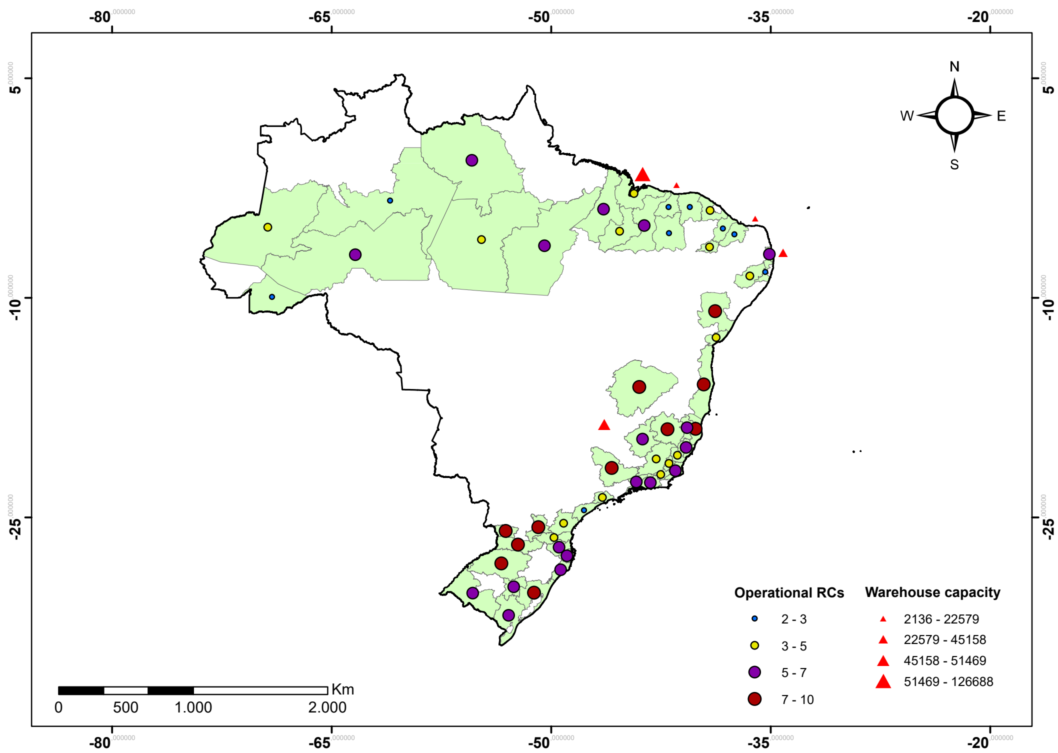


Figure 10: Spatial distribution of warehouses and relief centers.

Insight 3. *The strategic decision on where to locate the warehouses is heavily driven by their installation and operational costs. Therefore, less expensive locations are generally selected to host this type of facility.*

Relief centers play different roles in the humanitarian supply chain. They can provide humanitarian assistance to the victims either via prepositioned goods that are sent to them, or via local procurement to complement the assistance not covered by the prepositioned goods. All the affected areas that will be covered by humanitarian assistance must necessarily be assigned to an established relief center after the disaster has occurred. These facilities can serve as transshipment points from where emergency goods can travel to warehouses and other relief centers. Also, decentralizing RCs helps to reduce the distance (time) that victims must travel (wait) to receive humanitarian assistance. For all these reasons, it is not surprising that all the 53 relief centers are operational in at least two microtime periods, as can be seen in the penultimate column of Table 2 and in Figure 10. The results also reveal that 48% of the RCs are operational over the horizon on average; 55% of the RCs operate during 6 or more microtime periods; up to 70% of the RCs are operational at microtime periods 1 (January/February of macrotime period 1) and 7 (January/February of macrotime period 2), which is the period of the year in which rainfalls and landslides are more frequent in the South and Southeast regions. The so-called Megadisaster of at the Serrana region of Rio de Janeiro in January 2011 is an example; it was the largest disaster ever recorded in Brazil in number of fatalities, and among the ten worst landslides worldwide caused by a natural disaster since 1900 (Alem et al., 2016). Finally, the last column of Table 2 reveals that most installed RCs end up serving several affected areas. In particular, Sul Baiano, Litoral Norte Espírito-Santense, and Metropolitana de Curitiba serve, in this order, 13, 13, and 15 affected areas, being operational for 8, 9, and 10 microtime periods, respectively, suggesting that the more affected areas are served by a given RC, the higher the chance of this RC being operational.

Table 2: Relief centers' status over the microtime periods.

Relief center location	Microtime periods (bimonthly)											# of op. micro-time periods*	# of affected areas**
	1	2	3	4	5	6	7	8	9	10	11	12		
Vale do Acre	$\odot$						$\odot$	$\otimes$					3	2
Centro Amazonense			$\odot$					$\odot$	$\otimes$				3	6
Sudoeste Amazonense	$\odot$		$\odot$				$\odot$	$\otimes$			$\odot$		5	6
Sul Amazonense		$\odot$	$\otimes$				$\odot$	$\otimes$		$\odot$	$\otimes$		6	9
Metropolitana de Salvador			$\odot$				$\odot$	$\otimes$			$\odot$	$\otimes$	5	3
Nordeste Baiano	$\odot$		$\odot$			$\odot$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$	8	6
Sul Baiano			$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$		$\odot$		$\odot$	8	13
Centro-Sul Cearense	$\odot$	$\otimes$	$\otimes$					$\odot$			$\odot$		5	7
Jaguaribe	$\odot$		$\odot$										2	3
Noroeste Cearense	$\odot$	$\otimes$	$\otimes$										3	1
Norte Cearense	$\odot$	$\otimes$	$\otimes$				$\odot$		$\odot$				5	10
Central Espírito-Santense	$\odot$				$\odot$	$\otimes$	$\otimes$	$\otimes$			$\odot$	$\otimes$	7	8
Litoral Norte Espírito-Santense	$\odot$			$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$		$\odot$	$\otimes$	9	13
Noroeste Espírito-Santense	$\odot$				$\odot$	$\otimes$	$\otimes$	$\otimes$				$\odot$	6	5
Sul Espírito-Santense	$\odot$	$\otimes$				$\odot$		$\odot$				$\odot$	5	5
Centro Maranhense	$\odot$	$\otimes$	$\otimes$				$\odot$				$\odot$		5	5
Leste Maranhense	$\odot$	$\otimes$	$\otimes$			$\odot$					$\odot$	$\otimes$	6	10
Norte Maranhense		$\odot$	$\otimes$				$\odot$	$\otimes$		$\odot$			5	12
Oeste Maranhense	$\odot$	$\otimes$	$\otimes$			$\odot$	$\otimes$	$\otimes$			$\odot$		7	5
Metropolitana de Belo Horizonte	$\odot$				$\odot$	$\otimes$	$\otimes$				$\odot$	$\otimes$	6	3
Norte de Minas	$\odot$			$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$			$\odot$	$\otimes$	8	8
Sul/Sudoeste de Minas	$\odot$		$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$				$\odot$	8	8
Vale do Rio doce	$\odot$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$				$\odot$	$\otimes$	8	11
Zona da Mata	$\odot$					$\odot$	$\otimes$				$\odot$	$\otimes$	5	5
Baixo Amazonas		$\odot$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$					6	8
Sudeste Paraense	$\odot$	$\otimes$	$\otimes$		$\odot$		$\odot$	$\otimes$				$\odot$	7	10
Sudoeste Paraense		$\odot$	$\otimes$				$\odot$	$\otimes$					4	2
Mata Paraibana	$\odot$		$\odot$	$\otimes$		$\odot$				$\odot$	$\otimes$	$\otimes$	7	11
Agreste Pernambucano	$\odot$	$\otimes$	$\otimes$	$\otimes$					$\odot$				5	6
Mata Pernambucana			$\odot$						$\odot$		$\odot$		3	4
Centro-Norte Piauiense	$\odot$	$\otimes$	$\otimes$										3	2
Norte Piauiense		$\odot$	$\otimes$										2	4
Metropolitana de Curitiba	$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$		10	15
Sudeste Paranaense					$\odot$	$\otimes$		$\odot$	$\otimes$	$\otimes$			5	6
Sudoeste Paranaense			$\odot$		$\odot$	$\otimes$		$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	8	7
Oeste Potiguar	$\odot$	$\otimes$	$\otimes$										3	2
Centro Fluminense	$\odot$					$\odot$	$\otimes$	$\otimes$				$\odot$	5	4
Metropolitana do Rio de Janeiro	$\odot$				$\odot$	$\otimes$	$\otimes$	$\otimes$				$\odot$	6	4
Noroeste Fluminense	$\odot$					$\odot$	$\otimes$	$\otimes$				$\odot$	5	6
Norte Fluminense	$\odot$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$						6	8
Sul Fluminense	$\odot$					$\odot$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$	7	8
Centro Oriental Rio-Grandense					$\odot$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$	$\otimes$	7	7
Metropolitana de Porto Alegre			$\odot$		$\odot$	$\otimes$	$\otimes$	$\otimes$		$\odot$	$\otimes$	$\otimes$	8	8
Noroeste Rio-Grandense			$\odot$		$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	9	6
Sudeste Rio-Grandense	$\odot$				$\odot$	$\otimes$		$\odot$		$\odot$	$\otimes$	$\otimes$	7	4
Sudoeste Rio-Grandense	$\odot$					$\odot$	$\otimes$		$\odot$	$\otimes$	$\otimes$	$\otimes$	7	9
Grande Florianópolis	$\odot$		$\odot$			$\odot$	$\otimes$	$\otimes$				$\odot$	6	7
Norte Catarinense						$\odot$	$\otimes$	$\otimes$	$\otimes$		$\odot$		5	6
Oeste Catarinense			$\odot$	$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$		$\odot$	$\otimes$		8	9
Sul Catarinense	$\odot$	$\otimes$	$\otimes$		$\odot$		$\odot$				$\odot$		6	8
Vale do Itajaí	$\odot$					$\odot$	$\otimes$	$\otimes$			$\odot$	$\otimes$	6	12
Litoral Sul Paulista	$\odot$						$\odot$			$\odot$			3	3
Metropolitana de São Paulo						$\odot$	$\otimes$	$\otimes$				$\odot$	4	4
Total number of operational RCs	36	20	33	9	2	32	38	34	12	16	28	28	–	–

Note: Symbol $\odot$ indicates that RC was installed and is *already operational*; symbol $\otimes$ indicates that RC is operational because it was installed in a microtime period before.
* Number of microtime periods for which RCs are operational.
** Number of affected areas (totally or partially) served by operational RCs.

Table 3 shows that average RCs' utilization is higher in the South and Southeast regions of the country, which is due to two main factors: (i) the representativeness of these regions in the total number of disaster victims during the period considered in the analysis; and (ii) the high levels of social vulnerability of some of its affected areas. In fact, about 58% of the total amount of victims' needs are due to the South (30.9%) and the Southeast (27%) regions, while the North and the Northeast regions account for 20.1% and 22%, respectively. Regarding the spatial distribution of SoVI, note that although the North and the Northeast regions have a greater social vulnerability on average, the South and the Southeast regions have the three most vulnerable affected areas, namely Sudeste Rio-Grandense (SoVI = 1.3475), Metropolitana do Rio de Janeiro (SoVI = 1.2845), and Metropolitana de São Paulo (SoVI = 1.2474).

Table 3: Utilization of relief centers for each Brazilian region as the ratio (in %) between the number of operational RCs and the total number of RCs candidates.

	Relief	Microtime periods												Average
	centers*	1	2	3	4	5	6	7	8	9	10	11	12	
North	7	42.86	57.14	85.71	14.29	14.29	14.29	85.71	100.0**	14.29	14.29	28.57	14.29	40.48
Northeast	17	70.59	64.71	100.0	17.65	5.88	29.41	41.18	35.29	17.65	23.53	47.06	29.41	40.20
South	13	46.15	15.38	53.85	15.38	69.23	84.62	76.92	76.92	53.85	69.23	84.62	61.54	58.97
Southeast	16	93.75	18.75	18.75	18.75	56.25	93.75	93.75	68.75	6.250	12.50	43.75	87.50	51.04
Average	–	63.34	39.00	64.58	16.52	36.41	55.52	74.39	70.24	23.01	29.89	51.00	48.18	47.67

* Total number of RCs candidates per region.
** In this case all the 7 RCs candidates were operational.

Insight 4. *It would be useful to evaluate the possibility of keeping the RCs that serve a significant number of affected areas operational throughout the year, or at least in the period of the year in which the probability of having more disasters is greater, which may depend on the region. This could reduce the response time associated with their establishment in the post-disaster, thus speeding up the deployment of humanitarian assistance.*

Table 4 shows that victims' needs are fulfilled via a hybrid strategy entailing prepositioning (71.63%) and local procurement (28.37%). Although the unit local procurement cost of all emergency goods is 50% higher than their unit cost of prepositioning in our base-case, the latter strategy incurs in higher opening/operational costs and, in addition, transportation costs from warehouses to relief centers must be taken into account. The procurement of emergency products in the post-disaster, on the other hand, considers only their purchasing cost. Therefore, for some relief goods, it is worth to adopt local procurement. Note that, for example, the needs for single mattresses are 44.34% satisfied via procurement. In fact, as this relief aid occupies the largest area per square meter (1.44 m^2/unit), prepositioning would imply the need of establishing more and/or larger warehouses, which could increase logistics costs substantially. In order to more thoroughly analyze the role of local procurement, we ran additional tests considering different local procurement costs and/or availability of relief goods. As expected, when the local procurement costs increase, yet slightly, this strategy is an even less appealing option to meet victims' needs. In particular, increasing these costs beyond 16% implies a steep decrease in the percentage of needs satisfied by means of local procurement ($\approx$ 47%). In such a case, relief service levels are marginally deteriorated ($\approx$ 1.8%) because prepositioning is 15.78% incremented. In most cases, mattresses are still locally procured even with a further increase in the local procurement costs, which confirms our previous findings and highlights the importance of this strategy to help meeting the needs of this bulky relief aid (see Appendix C for details). As the local procurement strategy is strongly driven by its costs and availability, and considering that costs can be very high and goods are not necessarily available in a disaster aftermath, relying on this strategy can disrupt the effectiveness of the humanitarian assistance.

Insight 5. *One strategy to improve the effectiveness of the humanitarian assistance in case of scarce resources should be encouraging to raise in-kind donations of relief goods that are generally local procured, such as water, mattress, and dormitory kits in the disaster aftermath, thus the disaster budget could prioritize the prepositioning of other emergency goods and/or in a greater quantity in the preparedness phase, thus helping to reduce the dependency of local procurement.*

Table 4: Quantity of relief aid units prepositioned at warehouses and local procured at relief centers.

Relief aid	Victims' needs	Victims' needs met	Prepositioned relief aid	Prepositioned relief aid* (%)	Local procured relief aid	Local procured relief aid* (%)
Water	708,170	451,743	254,211	56.27	197,532	43.73
Food	177,043	112,936	112,936	100.0	–	–
Mattress	708,170	451,743	251,419	55.66	200,324	44.34
Dormitory	708,170	451,743	369,065	81.70	82,678	18.30
Hygiene	177,043	112,936	112,936	100.0	–	–
Cleaning	177,043	112,936	112,936	100.0	–	–
Total	2,655,638	1,694,035	1,213,502	71.63	480,533	28.37

* Both values were evaluated according to the overall victims' needs met.

The base-case results also show that the warehouse in Belo Horizonte centralizes 49.94% of the relief aid flow that are shipped to the operational relief centers, followed by the warehouses located in São Luis (22.68%), João Pessoa (11.06%), Teresina (10.02%), and Natal (6.30%). In particular, the warehouse in Belo Horizonte ships relief aid to 29 different relief centers; 16 of which in the Southeast region, altogether corresponding to 53% of the overall flow. Overall, only a few arcs are necessary to shipping relief aid from warehouses to relief centers. In our base-case results, this figure represents less than 15% of the feasible arcs. This makes the problem more robust to potential transportation disruptions. We confirmed this result by conducting a sensitivity analysis on both transportation costs and network, in which up to 20% of the arcs were considered damaged or blocked, and transportation costs were 25% higher. Results reveal that the optimal solution of our base-case problem is indeed only marginally affected by worsening these two transportation conditions (costs and network). In fact, in all cases, the same five warehouses were established and the configuration of relief centers was quite similar. Moreover, the strategy adopted to supply victims' needs did not present any significant variation and/or trend (see Appendix D for details).

Figure 11 shows an example of how the various logistics activities (prepositioning, local procurement and distribution) relate to supply victims' needs from the Belo Horizonte warehouse and the Sul/Sudoeste de Minas relief center. 606,070 units of relief aid goods are prepositioned at Belo Horizonte warehouse. 45,191 (7.5%) are then shipped to the Sul/Sudoeste de Minas relief center, 5,454 units are locally procured, and 4,499 units are received from other warehouses, totaling 55,144 items at this RC. 22,673 units (41.1%) are used to cover the victims' needs associated with 8 affected areas, such as Metropolitana de Belo Horizonte, Leste Maranhense, and Metropolitana de São Paulo. The remaining 32,471 units (58.9%) are distributed to 5 relief centers, e.g. Metropolitana de Curitiba, Sudeste Paranaense, Grande Florianópolis, Norte Catarinense and Vale do Itajaí. These relief centers, in turn, are responsible for serving many other affected areas. For instance, Sudeste Paranaense (partially) satisfies the needs of Sudoeste

Amazonense, Mata Pernambucana, Sudoeste Paranaense, Oeste Catarinense, Vale do Itajaí besides its own. Metropolitana de Curitiba helps meeting the needs of 15 affected areas, and so forth.

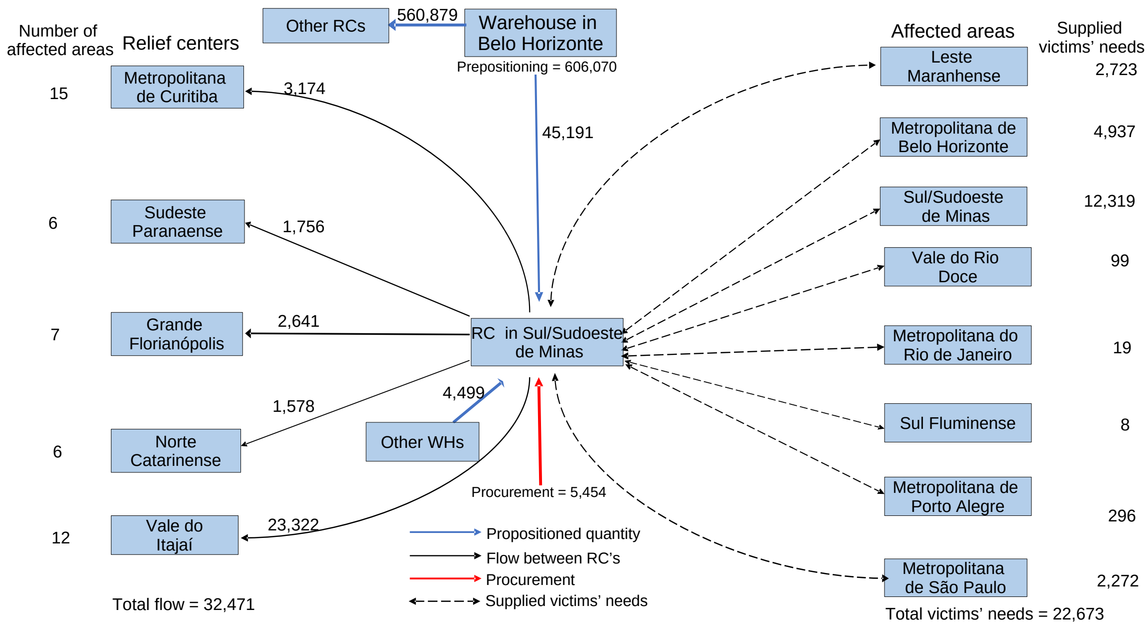


Figure 11: Example of how the various logistics activities (prepositioning, procurement and distribution) relate to supply victims' needs focusing on the warehouse located in Belo Horizonte.

5.2. Implications of reduced budget levels

Figure 12 portrays the relief service levels of all the 53 affected areas in decreasing order of vulnerability for budget levels 20%, 40%, 60%, 80%, and 90% reduced. For comparison purposes, the relief service level without considering the priority given by SoVI, which is equivalent to set SoVI = 1 in the objective function (1), is also plotted. Afterwards, we assess the *social benefit of using* SoVI within our humanitarian supply chain, which is based on Definition 2.

Definition 2. *The social benefit of using SoVI for affected area 'a' in microtime period 'τ' is the relative difference between the relief service level with and without using SoVI, i.e.,*

$$\beta_{a\tau} = 100\% \times \frac{(\alpha_{a\tau} - \alpha'_{a\tau})}{\alpha'_{a\tau}}, \tag{38}$$

in which $\alpha_{a\tau}$ ($\alpha'_{a\tau}$) is the relief service level with (without) using SoVI.

Notice that the social benefit of using SoVI is precisely the distance between the blue line and the red line depicted in Figure 12. Also, it is worth noting that some affected areas will have a positive benefit while others will experience a negative social benefit, meaning that, in this case, using SoVI leads to worsened relief service levels. Here, it is important to make sure that more vulnerable areas will have a positive benefit on average, though. Therefore, we evaluated the average social benefit for the areas belonging to the following categories: 'top 5', 'top 10', 'top 15', 'top 20', 'top 30', and 'top 40' most vulnerable affected ares, understanding 'more vulnerable' areas as having higher SoVIs. We also present the global or average relief service level over all the 53 affected areas. All these figures are summarized in Table 5.

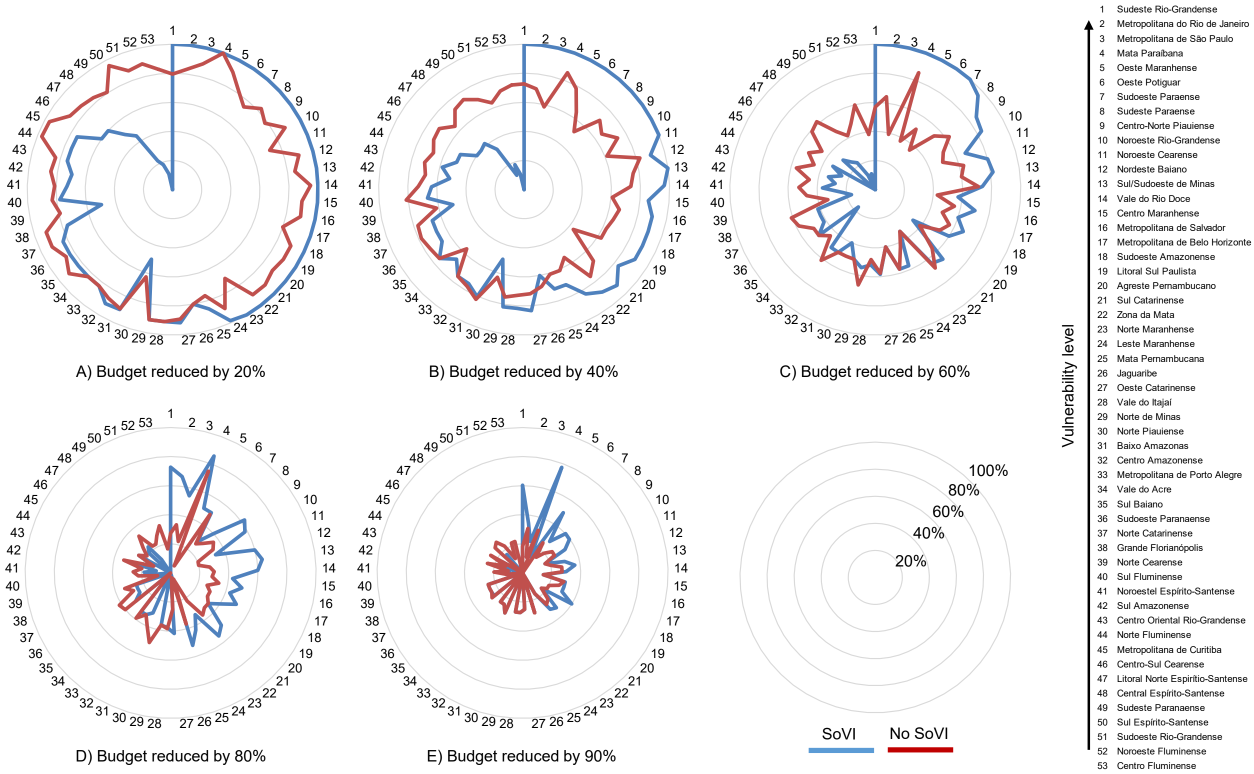


Figure 12: Relief service levels of the 53 affected areas when budgets are 20%, 40%, 60%, 80%, and 90% reduced. The exact values are depicted in Table E of Appendix E.

Table 5: Average relief service levels ($\boldsymbol{\alpha}$ in %) and average social benefit ($\boldsymbol{\beta}$ in %) according to each vulnerability category for varying budget levels.

Budget level	Metric	Top 5	Top 10	Top 15	Top 20	Top 30	Top 40	Global relief service level
No reduction	SoVI	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	No SoVI	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Social Benefit	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20% reduction	SoVI	100.0	100.0	100.0	100.0	96.26	92.24	81.57
	No SoVI	88.46	84.77	85.26	85.86	84.99	85.40	85.85
	Social Benefit	17.18	31.75	30.54	27.35	22.22	14.26	0.4425
40% reduction	SoVI	100.0	100.0	98.14	95.77	89.30	84.19	72.39
	No SoVI	72.97	69.12	69.68	67.26	67.15	68.88	69.14
	Social Benefit	38.87	59.87	53.22	52.46	36.77	25.35	8.847
60% reduction	SoVI	100.0	96.45	88.26	80.70	71.56	62.94	52.32
	No SoVI	56.70	54.00	55.12	53.95	53.29	52.60	52.04
	Social Benefit	60.89	52.98	43.41	34.41	22.98	12.61	−0.5822
80% reduction	SoVI	65.93	56.90	55.26	52.26	46.45	40.18	33.07
	No SoVI	32.56	33.74	30.91	30.86	30.12	29.77	28.45
	Social Benefit	45.69	29.38	31.59	27.75	21.34	13.54	6.867
90% reduction	SoVI	41.35	39.83	35.04	33.61	28.73	26.32	21.36
	No SoVI	18.25	20.05	20.40	20.91	19.84	19.71	19.08
	Social Benefit	37.59	28.06	20.23	17.00	11.91	8.727	3.439

The radar charts show that, as expected, the relief service levels gradually shrink to the center as budget levels decrease, as it is not possible to fulfill all the victims' needs with reduced budgets. However, there are significant differences between the charts with/without considering the priority given by the index SoVI. While the red line chart (without SoVI) contracts in almost all directions equally, the left side of the blue line chart (with SoVI) clearly shrinks first, indicating that relief service levels are better in more vulnerable affected areas. This is particularly evident in the top 5 most vulnerable areas, i.e., Sudeste Rio-Grandense, Metropolitana do Rio de Janeiro, Metropolitana de São Paulo, Mata Paraíbana, and Oeste Maranhense, respectively. These areas maintain the maximum relief service level even when the budget is 60% reduced. On the other hand, when SoVI is disregarded, the average relief service level of these municipalities is only 56.70%, confirming that the social-effectiveness of the humanitarian assistance substantially improves with the incorporation of SoVI as a prioritization weight. In the situation of extreme scarcity of resources, e.g., when there is no more than 10% of the budget, the inclusion of SoVI as a prioritization measure enhances the social benefit by an average of 37.59%, 28.06%, and 20.23% for the top 5, top 10, and top 25 most vulnerable areas. This comes with a price, though, since the average social benefit of the 15 least vulnerable areas is -11.12%.

Figure 13 illustrates the spatiality of the relief service levels of the top 20 most vulnerable affected areas for budget levels reduced by 40% (map A), 60% (map B), 80% (map C), and 90% (map D). In general, our SoVI approach provides a decent coverage for those affected areas when resources are limited. Most areas indeed display relatively good relief service levels; around $80\% - 100\%$ for budget reductions up to 60%, around $60\% - 40\%$ for budget levels 80% reduced; and around $20\% - 40\%$ in the extreme case of 90% reduction. Even with little budget, some areas exhibit surprisingly good relief service levels, e.g., Sudeste Rio-Grandense (60.27%), Mata Paraibana (77.40%), and Oeste Potiguar (50%), as shown in map D. Although the SoVI approach provides better relief service levels for more vulnerable communities on average, there are some exceptions. For example, Central Espírito-Santense, the sixth least vulnerable area, has a service level 33.33% better than Oeste Maranhense, the fifth most vulnerable area. One explanation for this behavior, for this particular case, is the fact that our objective function also encourages the fulfillment of municipalities with greater needs; therefore, as Central Espírito-Santense has 13,015 victims over the two macrotime periods and Oeste Maranhense has 7,088, priority was given to the former.

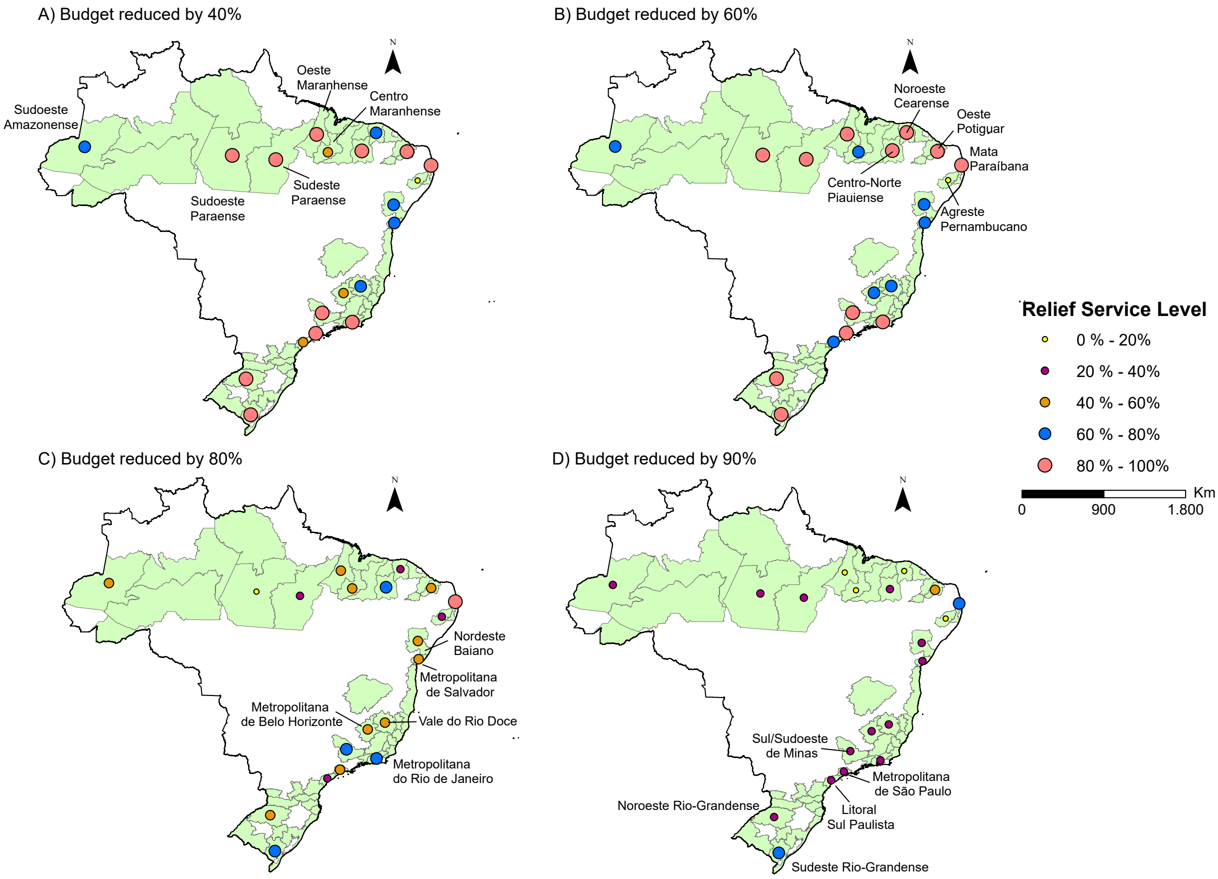


Figure 13: Relief service levels for different budgets.

Insight 6. *The overall great social benefit of using SoVI reveals the importance of considering this index in designing more social-effective humanitarian supply chains. In particular, the SoVI strategy: (a) becomes more effective as the budget level is reduced; however, after a given threshold (reduction above 80% in our case), the social benefit of using SoVI is less pronounced; (b) improves the average relief service-level of most affected areas at the expense of a marginal deterioration of that of the remaining ones; (c) is very effective in improving the worst-case relief service-levels of the top 5 most vulnerable areas.*

5.3. Wait-and-see versus here-and-now solutions based on historical information

Our deterministic approach and the solutions analyzed so far are based on the premise that the number of victims (and their needs) is known before making any decision. More precisely, this number is supposed to be accurately represented by the average values obtained from 14 years of disaster data. This deterministic modelling paradigm in which (disaster) data is first observed and decisions can only be made afterwards in hindsight is called *wait-and-see*. Another modelling paradigm, hereafter called *here-and-now*, would be assuming that we do not know the exact number of victims, but we have to make strategic decisions such as warehouse location and prepositioning without it. Therefore, these decisions must be *robust* for any particular outcomes and optimal on average over all possible realizations. After observing the disaster data, short-term decisions such as local procurement and service levels can be adjusted to accommodate any disaster data optimally. One question that may arise in this context is whether there is a significant difference between the solutions given by these two approaches. To answer this question we perform a comparison analysis amongst (i) the solution of our deterministic base-case instance (our benchmark solution), (ii) the wait-and-see solutions, and (iii) the here-and-now solutions, focusing on long-term decisions concerning warehouse location and prepositioning, and short-term decisions of local procurement and relief service levels. The wait-and-see solutions are computed by solving deterministic one-macrotime-period problems, each one associated with a given year, say ξ, of disaster data, for $\xi = 2003, 2004, \cdots, 2016$, totalling 14 problems (and solutions). The here-and-now solution is obtained via solving a *scenario-based two-stage stochastic programming* problem in which the disaster data for each year is treated as one scenario. In this case, all the macrotime decision variables are defined as first-stage ones, whereas the microtime decision variables are treated as second-stage ones. We also run a here-and-now problem with 5 scenarios as a combination of the 14 original scenarios to obtain better-quality solutions since the instance with 14 scenarios is difficult to solve. Further details are given in Appendix F.

Table 6 shows the warehouse location decisions of the base-case, wait-and-see, and here-and-now approaches. Observations on Tables 6 and 7 are summarized as follows. Although the overall number of installed warehouses of the wait-and-see solutions varies from 3 (years 2003, 2006, and 2016) to 7 (years 2004 and 2008), the average number is 5, which coincides with the optimal number given by the base-case instance. Clearly, the warehouse location follows the same rationale in all approaches: less expensive locations are generally selected to host this type of facility, as already inferred in Insight 3. Interestingly, the solutions of the worst-case (the highest number of victims) and best-case (the lowest number of victims) scenarios are quite similar. Notice that João Pessoa and Teresina show up in all cases, and São Luís and Natal show up in 88.24% of the instances, indicating that this aspect of the solution is not supposed to change substantially regardless at which stage this decision has to be made or how much information is available at that stage. Although both the prepositioning and local procurement levels vary a lot amongst all the strategies, it is clear that the latter strategy is preferred in most cases. One remarkable exception is the wait-and-see years 2006 and 2016, and the here-and-now solution with all the 14 scenarios. In the first case, notice that because local procurement was preferred, only 3 warehouses were needed. In the second case, the favoritism towards the local procurement strategy is attributed to its poor solution quality, mainly reflected by the relief service levels of only 50.08%. The overall analysis of the relief service levels reveals that our SoVI approach is deemed important for serving more vulnerable areas in pessimistic situations. For example, the global relief service level of the wait-and-see year 2009 (worst-case scenario) is 30.90%, against 83.28% attributed to the top 5 more vulnerable areas; the years 2008 and 2013 (second and third worst years in terms of overall victims) exhibit a similar behavior.

Insight 7. *The warehouse location decision does not vary much across the different approaches. This decision is robust even when the flexibility of the wait-and-see paradigm is allowed. Although the prepositioning and local procurement solutions considerably vary amongst the approaches, their qualitative behavior mostly follows the same rationale of favoring prepositioning to obtain better relief service levels. Last, the relief service levels of the top 5 most vulnerable areas are rather stable across wait-and-see and here-and-now approaches. Therefore, even under uncertainty, the deterministic solutions, particularly our base-case one, would work well to guide the policy makers on where to locate the warehouses and how to serve the most vulnerable areas.*

Table 6: Warehouse location decisions of the base-case, wait-and-see, and here-and-now approaches.

	Rio Branco	Fortaleza	São Luís	Belo Horizonte	João Pessoa	Recife	Teresina	Natal	São Paulo	Total
Base-case (benchmark)	–	–	1	1	1	–	1	1	–	5
Wait-and-see year 2003	–	–	1	–	1	–	1	–	–	3
Wait-and-see year 2004	1	1	1	1	1	–	1	1	–	7
Wait-and-see year 2005	–	–	1	–	1	–	1	1	1	5
Wait-and-see year 2006	–	–	–	–	1	–	1	1	–	3
Wait-and-see year 2007	–	1	1	–	1	–	1	–	–	4
Wait-and-see year 2008	–	1	1	1	1	1	1	1	–	7
Wait-and-see year 2009	–	–	1	1	1	–	1	1	–	5
Wait-and-see year 2010	–	1	1	1	1	–	1	1	–	6
Wait-and-see year 2011	–	1	1	1	1	–	1	1	–	6
Wait-and-see year 2012	–	1	1	1	1	–	1	1	–	6
Wait-and-see year 2013	–	1	1	1	1	–	1	1	–	6
Wait-and-see year 2014	–	1	1	1	1	–	1	1	–	6
Wait-and-see year 2015	–	1	1	1	1	–	1	1	–	6
Wait-and-see year 2016	–	–	–	–	1	–	1	1	–	3
Here-and-now* (5 scenarios)	–	1	1	1	1	–	1	1		6
Here-and-now** (14 scenarios)	–	–	1	–	1	–	1	1	–	4
Frequency*** (%)	5.882	58.82	88.24	64.71	100.0	5.882	100.0	88.24	5.882	–

Worst-case scenario; *Best-case* scenario.

* Solved using a Fix-and-Optimize heuristic as the exact Branch-and-Cut (default CPLEX method) was unable to provide a feasible solution after 36 hours of computation. The elapsed time was 12,300 seconds. See the details of the heuristic method in Appendix F.

** Solved using a Fix-and-Optimize heuristic as the exact Branch-and-Cut (default CPLEX method) was unable to provide a feasible solution after 36 hours of computation. The elapsed time was 36 hours. See the details of the heuristic method in Appendix F.

*** The frequency (in %) in which a given warehouse is installed over the 17 analyzed instances (base-case, 14 wait-and-see, and 2 here-and-now instances).

Table 7: Prepositioning, local procurement, and relief service levels given by the base-case, wait-and-see, and here-and-now approaches.

	Prepositioned relief aid	Prepositioned* relief aid (%)	Local procured relief aid	Local procured* relief aid (%)	Global relief service level (%)	Top 5 (%)	Top 10 (%)	Top 15 (%)	Top 20 (%)
Base-case	606,751	71.64	240,267	28.36	72.39	100.0	100.0	98.14	95.77
Wait-and-see year 2003	285,411	56.72	217,742	43.28	100.0	100.0	100.0	100.0	100.0
Wait-and-see year 2004	564,115	70.75	233,254	29.25	90.23	100.0	100.0	100.0	100.0
Wait-and-see year 2005	398,501	56.29	309,436	43.71	100.0	100.0	100.0	100.0	100.0
Wait-and-see year 2006	163,961	34.72	308,340	65.28	100.0	100.0	100.0	100.0	100.0
Wait-and-see year 2007	307,920	48.10	332,283	51.90	99.62	100.0	100.0	100.0	100.0
Wait-and-see year 2008	576,496	71.05	234,886	28.95	54.25	83.33	76.94	62.00	65.45
Wait-and-see year 2009	460,435	59.79	309,606	40.21	30.90	83.28	59.97	49.54	43.08
Wait-and-see year 2010	478,557	57.56	352,794	42.44	50.12	67.60	55.30	51.10	54.92
Wait-and-see year 2011	472,876	57.53	349,025	42.47	73.53	100.0	100.0	100.0	100.0
Wait-and-see year 2012	471,922	57.75	345,321	42.25	66.80	100.0	100.0	100.0	93.91
Wait-and-see year 2013	471,922	57.16	353,622	42.84	56.61	100.0	94.69	93.78	83.06
Wait-and-see year 2014	471,922	57.37	350,648	42.63	90.38	100.0	100.0	100.0	100.0
Wait-and-see year 2015	472,468	56.96	357,062	43.04	76.54	100.0	100.0	97.50	98.08
Wait-and-see year 2016	121,867	30.97	271,595	69.03	100.0	100.0	100.0	100.0	100.0
Wait-and-see** (average)	408,455	55.19	308,972	44.81	77.78	95.30	91.92	89.57	88.46
Here-and-now*** (5 scenarios)	488,971	67.34	237,138	32.66	75.81	99.33	98.20	96.34	93.19
Here-and-now**** (14 scenarios)	88,204	23.39	288,838	76.61	50.08	72.11	63.77	60.26	60.19

Worst-case scenario; *Best-case* scenario.

* Both values were evaluated according to the overall victims' needs served.

** The average wait-and-see (WS) over 14 wait-and-see solutions.

*** Solved using a Fix-and-Optimize heuristic as the exact Branch-and-Cut (default CPLEX method) was unable to provide a feasible solution after 36 hours of computation. The elapsed time was 12,300 seconds. See the details of the heuristic method in Appendix F.

**** Solved using a Fix-and-Optimize heuristic as the exact Branch-and-Cut (default CPLEX method) was unable to provide a feasible solution after 36 hours of computation. The elapsed time was 36 hours. See the details of the heuristic method in Appendix F.

6. Conclusions and Future research

We have presented a novel optimization framework to build disaster preparedness and response capacity via prepositioning networks when people's vulnerability matters. To this aim, our model entails typical long- and medium-term disaster management decisions, such as location of warehouses and relief centers, capacity expansion, and relief aid flow. In the absence of sufficient resources to supply all victims' needs, our approach encourages the prioritization of more vulnerable areas, which is aligned with the well-established idea that the more vulnerable populations have both a reduced capacity for and a decrease ability to cope with disasters. Our approach was applied to real-data from Brazilian disasters ranging from 2003-2016, encompassing eleven recurrent events that hit Brazil year after year. Our results brought about key insights that can be useful to re-think the humanitarian supply chain in the country. In particular, we have showed that the *social benefit* of using SoVI is particular significant for decreased budget levels and the top 5 most vulnerable areas, which reinforces the importance of considering this index to design more social-effective humanitarian supply chains. Moreover, SoVI might also help to improve worst-case relief service levels at the expense of a marginal deterioration of that of the remaining areas. Future research includes developing other objective functions to take into account different vulnerability dimensions other than the social, as well as other challenging aspects of humanitarian operations (Ferrer et al., 2018). The resulting optimization model will naturally be a multi-objective one, for which specialized methods should be developed to find the efficient frontier (Gutjahr and Nolz, 2016). The integration of our proposed disaster preparedness framework to allocation of resources in other contexts (Moreno et al., 2019, 2020;

Doan and Shaw, 2019), or from a multi-agency coordination perspective (Rodríguez-Espíndola et al., 2020) is another promising topic of investigation.

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Appendix A

The affected areas (mesoregions) for each one of the 17 states in descending order of the relative figures over the total number of victims is showed in Table A. We then consider all those affected areas whose corresponding relative number of victims is greater or equal to 0.5%.All the remaining 53 areas were treated as affected areas and thus candidates to locate relief centers.

Table A: Brazilian *affected areas* and respective number of victims in 2003-2016.

Affected area	Victims*	%
Centro Amazonense	473463	8.510
Vale do Itajaí	385660	6.932
Metropolitana de Porto Alegre	375316	6.746
Metropolitana do Rio de Janeiro	189526	3.407
Zona da Mata	186023	3.344
Vale do Rio Doce	153465	2.758
Norte Catarinense	147269	2.647
Sul Amazonense	139383	2.505
Mata Pernambucana	127242	2.287
Sul Baiano	122465	2.201
Metropolitana de Curitiba	119697	2.152
Sudoeste Amazonense	119244	2.143
Noroeste Fluminense	115090	2.069
Centro Maranhense	97766	1.757
Baixo Amazonas	97385	1.750
Metropolitana de São Paulo	91882	1.652
Central Espírito-Santense	91064	1.637
Norte Maranhense	90490	1.627
Metropolitana de Belo Horizonte	86094	1.548
Sudoeste Rio-Grandense	81859	1.471
Metropolitana de Salvador	78730	1.415
Leste Maranhense	75361	1.355
Centro Oriental Rio-Grandense	73489	1.321
Sul Espírito-Santense	71511	1.285
Grande Florianópolis	69470	1.249
Norte Piauiense	69384	1.247
Vale do Acre	64047	1.151
Noroeste Rio-Grandense	63571	1.143
Sudeste Paraense	62783	1.128
Sul Catarinense	62499	1.123
Litoral Sul Paulista	61381	1.103
Norte Fluminense	60707	1.091
Mata Paraíbana	57629	1.036
Sul/Sudoeste de Minas	52752	0.9482
Oeste Potiguar	49602	0.8916
Oeste Maranhense	49462	0.8891
Norte de Minas	48957	0.8800
Jaguaribe	48801	0.8772
Centro-Norte Piauiense	47576	0.8552
Sudeste Paranaense	45872	0.8245
Oeste Catarinense	42624	0.7661
Sudoeste Paraense	40125	0.7212
Litoral Norte Espirítio-Santense	39676	0.7132
Noroeste Cearense	38708	0.6958
Norte Cearense	38053	0.6840
Agreste Pernambucano	36506	0.6562
Noroestel Espírito-Santense	32840	0.5903
Nordeste Baiano	32166	0.5782
Sudeste Rio-Grandense	32113	0.5772
Sudoeste Paranaense	31755	0.5708
Centro-Sul Cearense	30306	0.5447
Sul Fluminense	28742	0.5166
Centro Fluminense	28167	0.5063
Metropolitana de Recife**	27216	0.4892
Serrana**	26439	0.4752
Oeste Paranaense**	25661	0.4612
Norte Amazonense**	23612	0.4244
Vale do Mucuri**	23301	0.4188
Sertões Cearenses**	22225	0.3995
Centro Sul Baiano**	21590	0.3881
Sul Cearense**	20708	0.3722
Sertão Paraibano**	20217	0.3634
Agreste Paraibano**	18691	0.3360
Centro-Sul Paranaense**	18395	0.3306
Vale São-Franciscano da Bahia**	18110	0.3255
Campinas**	17758	0.3192
Metropolitana de Fortaleza**	16758	0.3012
Vale do Paraiba Paulista**	16383	0.2945
Baixadas**	16285	0.2927
Centro Norte Baiano**	16276	0.2926
São Francisco Pernambucano**	15834	0.2846
Macro Metropolitana Paulista**	15443	0.2776
Sertão Pernambucano**	12648	0.2273
Leste Potiguar**	12436	0.2235
Jequitinhonha**	12338	0.2218
Oeste de Minas**	11862	0.2132
Sul Maranhense**	11112	0.1997
Sudoeste Piauiense**	10688	0.1921
Noroeste de Minas**	9315	0.1674
Norte Pioneiro Paranaense**	9215	0.1656
Centro Ocidental Rio-Grandense**	8787	0.1579
Noroeste Paranaense**	8300	0.1492
Centro Oriental Paranaense**	7705	0.1385
Nordeste Rio-Grandense**	7658	0.1376
Itapetininga**	7346	0.1320
Borborema**	7194	0.1293
Bauru**	7107	0.1277
Norte Central Paranaense**	6973	0.1253
Marajó**	6656	0.1196
Central Potiguar**	6287	0.1130
Presidente Prudente**	6112	0.1099
Nordeste Paraense**	5643	0.1014
Ribeirão Preto**	5517	0.0992
Extremo Oeste Baiano**	5507	0.0990
Campo das Vertentes**	5327	0.0958
Piracaia**	5271	0.0947
Agreste Potiguar**	5091	0.0915
Sudeste Piauiense**	4994	0.0898
Triângulo Mineiro/Alto Paranaíba**	4940	0.0888
Assis**	4477	0.0805
Central Mineira**	3089	0.0555
Vale do Juruá**	3060	0.0550
Centro Ocidental Paranaense**	1502	0.0270
São José do Rio Preto**	1194	0.0215
Metropolitana de Belém**	517	0.0093
Marília**	381	0.0068
Araçatuba**	293	0.0053
Araraquara**	144	0.0026
Lagoa dos Patos**	76	0.0014
Total	5,563,412	100

*Cumulative number of affected people in 2003-2016.
**Affected areas that were not considered in the analyses.

Appendix B

In order to establish a reference budget, we have solved the corresponding cost-minimization problem subjected to full satisfaction of victims' needs, replacing the 'less-than or equal to' constraints (20) by its 'equal to' version, as follow:

$$
\begin{aligned}
\min \sum_{t\in\mathscr{T}} \Bigg(& \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-new} \cdot q_n^0 \cdot Y_{nt}^w + \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-o} \cdot Q_{nt}^w + \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-e} \cdot Q_{nt}^{w-e} + \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-u} \cdot Q_{nt}^{w-u} + \\
& + \sum_{c\in\mathscr{C}} \sum_{n\in\mathscr{N}} \iota_{cnt}^w \cdot I_{cnt}^w + \sum_{c\in\mathscr{C}} \sum_{n\in\mathscr{N}} \rho_{cnt} \cdot P_{cnt} + \\
& + \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \gamma_{m\tau}^{rc-new} \cdot Y_{m\tau}^{rc} + \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \gamma_{m\tau}^{rc-o} \cdot Q_{m\tau}^{rc} + \sum_{c\in\mathscr{C}} \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \mu_{cm\tau} \cdot U_{cm\tau}^{rc} + \\
& + \sum_{a\in\mathscr{A}} \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \zeta_{am\tau} \cdot Z_{am\tau} + \sum_{c\in\mathscr{C}} \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \iota_{cm\tau}^{rc} \cdot I_{cm\tau}^{rc} + \\
& + \sum_{c\in\mathscr{C}} \sum_{k\in\mathscr{N}\cup\mathscr{M}} \sum_{\substack{k'\in\mathscr{N}\cup\mathscr{M} \\ k'\neq k}} \sum_{\tau\in\Theta_t} \chi_{ckk'\tau} \cdot X_{ckk'\tau} \Bigg)
\end{aligned}
$$

$$
\text{s.t.:} \sum_{m\in\mathscr{M}} Z_{am\tau} = 1, \ \forall a \in \mathscr{A} \wedge \tau \in \theta_t \wedge t \in \mathscr{T}
$$

$$
\text{Constraints } (2) - (19), (21) - (30).
$$

The solution for this problem gives a budget of 592,764,070 BRL for the first macrotime period and 362,524,615 for the second macrotime period.

Appendix C

Table B shows the sensitivity analysis of the local procurement costs (parameter $\mu_{cm\tau}$), and availability of relief aid for local procurement (parameter $u_{cm\tau}^{rc-\max}$). Cases $1-7$ refer to the instances in which the local procurement costs increase from 1.75 to 3.25 times the corresponding prepositioning cost. Cases $7-14$ refer to the instances in which the local procurement costs increase from 1.75 to 3.25 times the corresponding prepositioning cost and, simultaneously, the availability of relief aid for local procurement increases from 0.4 to 1.0 times the corresponding victims' needs.

Table B: Sensitivity analysis of the local procurement costs.

	Local procu- -rement cost ($\mu_{cm\tau}$)	Availa- bility ($u_{cm\tau}^{rc-\max}$)	Prep. cost (%)	Proc. covered via prep. (%)	Victims' needs covered via local proc. (%)	Victims' needs service level (%)	Global relief service level (%)	Top 5 relief service level (%)	Top 10 relief service level (%)	Top 15 relief service level (%)	Top 20 relief service level (%)
Base-case	$1.5 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	32.04	16.39	45.70	18.09	72.39	100.0	100.0	98.14	95.77
Case 1	$1.75 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	33.72	14.71	52.91	9.621	71.11	100.0	100.0	97.92	95.61
Case 2	$2.0 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	33.18	16.30	53.97	7.393	71.39	100.0	100.0	97.81	95.52
Case 3	$2.25 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	32.61	17.69	52.94	7.129	70.66	100.0	100.0	97.81	95.52
Case 4	$2.5 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	32.21	18.50	52.08	6.710	69.63	100.0	100.0	97.81	94.72
Case 5	$2.75 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	31.65	19.94	51.18	6.574	68.81	100.0	100.0	96.56	93.33
Case 6	$3.0 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	31.27	20.81	50.43	6.292	67.66	98.18	98.26	94.84	90.60
Case 7	$3.25 \cdot \rho_{cnt}$	$0.3 \cdot d_{ca\tau}$	31.81	18.81	50.57	5.248	65.84	94.29	90.45	88.52	85.72
Case 8	$1.75 \cdot \rho_{cnt}$	$0.4 \cdot d_{ca\tau}$	32.70	19.07	54.62	10.10	72.20	100.0	100.0	99.40	96.72
Case 9	$2.00 \cdot \rho_{cnt}$	$0.5 \cdot d_{ca\tau}$	29.80	27.86	48.77	16.14	70.74	100.0	100.0	99.68	96.43
Case 10	$2.25 \cdot \rho_{cnt}$	$0.6 \cdot d_{ca\tau}$	28.01	33.38	50.14	13.46	71.61	100.0	100.0	99.99	96.66
Case 11	$2.5 \cdot \rho_{cnt}$	$0.7 \cdot d_{ca\tau}$	26.44	38.99	48.26	14.14	71.36	98.18	97.84	98.21	95.32
Case 12	$2.75 \cdot \rho_{cnt}$	$0.8 \cdot d_{ca\tau}$	25.11	42.37	46.18	13.97	68.19	94.29	91.80	90.03	86.86
Case 13	$3.00 \cdot \rho_{cnt}$	$0.9 \cdot d_{ca\tau}$	25.42	40.78	45.59	12.33	67.23	94.29	92.63	91.09	87.65
Case 14	$3.25 \cdot \rho_{cnt}$	$d_{ca\tau}$	24.42	43.31	43.94	12.08	65.75	94.29	90.02	88.24	85.51

Appendix D

We have conducted a sensitivity analysis on the transportation cost and network. To that end, we have analyzed 7 new instances for varying transportation costs and network damaged levels, as presented in Table C. The first three instances (Case 1 – Case 3) have the same transportation costs, but the transportation network is 5%, 10%, and 20% damaged, respectively. This means there are fewer arcs to perform transportation. The last three instances (Case 4 – Case 7) have a 25% increase in transportation costs and the transportation network is 0%, 5%, 10%, and 20% damaged, respectively.

Table C: Sensitivity analysis of the transportation costs and transportation network.

	Transp. cost ($\chi_{ckk'\tau}$)	Damage* (%)	Transp. cost** increase (%)	Prep. cost (%)	Local proc. cost (%)	Transp. cost (%)	Needs covered via prep. (%)	Needs covered via local proc. (%)
Base-case	$\chi_{ckk'\tau}$	0%	–	32.04	16.39	0.5840	45.70	18.09
Case 1	$\chi_{ckk'\tau}$	5%	0.0984	32.12	16.27	0.5846	45.82	17.97
Case 2	$\chi_{ckk'\tau}$	10%	4.023	32.23	16.12	0.6075	45.95	17.84
Case 3	$\chi_{ckk'\tau}$	20%	16.67	32.09	16.22	0.6814	45.79	17.90
Case 4	$1.25 \cdot \chi_{ckk'\tau}$	0%	21.97	32.07	16.27	0.7124	45.74	17.97
Case 5	$1.25 \cdot \chi_{ckk'\tau}$	5%	23.12	32.07	16.27	0.7191	45.75	17.96
Case 6	$1.25 \cdot \chi_{ckk'\tau}$	10%	26.72	32.02	16.32	0.7401	45.67	18.02
Case 7	$1.25 \cdot \chi_{ckk'\tau}$	20%	45.56	32.32	15.79	0.8501	46.16	17.45

* Randomly generated.
** In comparison to the base-case.

Appendix E

Tables D and E summarize the optimal solutions for different budget levels.

Table D: Warehouse location for different budget levels.

Warehouse	State	No reduction	20% reduction	40% reduction	60% reduction	80% reduction	90% reduction
Rio Branco	AC	1	-	-	-	-	-
Salvador	BA	1	-	-	-	-	-
Fortaleza	CE	1	1	-	-	1	-
São Luís	MA	1	1	1	1	-	-
Belo Horizonte	MG	1	1	1	-	-	-
Belém	PA	1	1	-	-	-	-
João Pessoa	PB	1	1	1	1	1	1
Recife	PE	1	-	-	-	-	-
Teresina	PI	1	1	1	1	-	-
Natal	RN	1	1	1	-	1	-
Porto Alegre	RS	1	-	-	-	-	-
Total		11	7	5	3	3	1

Table E: Global relief service levels of the affected areas for different budget levels.

	20% reduction			40% reduction			60% reduction			80% reduction			90% reduction		
	SoVI	No SoVI	Social benefit	SoVI	No SoVI	Social benefit	SoVI	No SoVI	Social benefit	SoVI	No SoVI	Social benefit	SoVI	No SoVI	Social benefit
Sudeste Rio-Grandense	100.0	79.39	21.50	100.0	72.73	27.27	100.0	56.86	63.01	72.73	27.27	45.45	60.27	18.18	45.45
Metropolitana do Rio de Janeiro	100.0	83.33	16.67	100.0	69.76	39.10	100.0	64.34	56.42	66.67	33.33	33.33	34.34	30.76	12.06
Metropolitana de São Paulo	100.0	88.89	11.11	100.0	58.47	64.58	100.0	39.08	108.25	54.53	22.22	44.44	22.22	11.11	11.11
Mata Paraíbana	100.0	100.0	0.0000	100.0	85.71	14.29	100.0	85.71	14.29	85.71	74.54	51.33	77.40	31.18	106.8
Oeste Maranhense	100.0	90.68	36.63	100.0	78.18	49.13	100.0	37.50	62.50	50.00	5.409	53.89	12.50	0.0000	12.50
Oeste Potiguar	100.0	81.39	72.79	100.0	64.22	127.7	100.0	50.00	50.00	50.00	48.53	1.559	50.00	25.00	25.00
Sudoeste Paraense	100.0	75.06	56.15	100.0	52.47	117.3	100.0	35.90	70.71	28.57	26.51	2.404	28.57	14.29	14.29
Sudeste Paraense	100.0	82.54	39.31	100.0	70.49	70.78	95.76	54.73	42.17	40.00	30.00	10.00	40.00	20.00	20.00
Centro-Norte Piauiense	100.0	78.18	49.13	100.0	65.68	61.63	85.40	62.50	25.00	62.50	36.26	26.38	39.67	25.00	25.00
Noroeste Rio-Grandense	100.0	88.22	14.20	100.0	73.45	26.90	83.33	53.33	37.51	58.33	33.33	25.00	33.33	25.00	8.333
Noroeste Cearense	100.0	72.01	52.01	100.0	61.45	80.79	66.67	50.00	16.67	33.33	20.32	59.42	16.67	16.67	0.0000
Nordeste Baiano	100.0	90.00	10.00	90.00	82.54	29.31	80.00	63.00	33.33	60.00	20.00	40.00	30.00	20.00	10.00
Sul/Sudoeste de Minas	100.0	84.93	26.54	100.0	75.84	35.63	81.82	59.97	53.18	63.64	27.27	36.36	36.36	27.27	9.091
Vale do Rio Doce	100.0	94.96	10.15	96.43	73.39	39.49	73.73	70.98	3.861	60.00	30.00	30.00	30.00	27.25	3.796
Centro Maranhense	100.0	89.35	41.87	85.71	60.79	14.29	57.14	42.86	14.29	42.86	28.57	14.29	14.29	14.29	0.0000
Metropolitana de Salvador	100.0	90.00	10.00	90.00	66.84	24.62	70.00	55.57	10.00	50.00	33.92	25.54	30.00	29.06	1.033
Metropolitana de Belo Horizonte	100.0	80.00	20.00	90.00	64.60	31.73	60.00	48.63	27.51	42.94	26.45	25.52	30.00	26.45	5.515
Sudoeste Amazonense	100.0	90.00	10.00	90.00	62.54	49.31	66.90	56.44	15.67	50.00	30.00	20.00	30.00	20.00	10.00
Litoral Sul Paulista	100.0	90.00	10.00	90.00	62.54	49.31	60.00	52.39	0.4525	40.00	30.00	10.00	40.00	20.00	20.00
Agreste Pernambucano	100.0	88.33	38.89	83.33	43.46	96.02	33.33	39.22	-16.67	33.33	33.33	0.0000	16.67	16.67	0.0000
Sul Catarinense	100.0	91.30	27.97	91.67	68.37	16.67	66.67	56.11	11.37	50.00	33.33	16.67	33.33	25.00	8.333
Zona da Mata	100.0	90.91	9.091	88.60	75.10	25.95	63.78	67.88	-9.744	54.55	36.36	18.18	31.42	27.27	9.091
Norte Maranhense	100.0	70.91	65.51	83.33	54.24	16.67	33.33	33.33	0.0000	33.33	22.40	31.77	16.67	16.67	0.0000
Leste Maranhense	98.50	89.35	35.98	71.43	60.78	0.0000	57.14	42.86	14.29	42.86	4.531	59.33	0.0000	0.0000	0.0000
Mata Pernambucana	85.71	76.29	27.71	71.43	60.78	41.87	57.14	57.14	0.0000	52.06	36.70	16.18	28.57	28.57	0.0000
Jaguaribe	80.00	80.00	0.0000	60.00	67.70	-20.00	40.00	40.00	0.0000	0.0000	3.145	-20.00	0.0000	0.0000	0.0000
Oeste Catarinense	91.67	89.19	3.525	83.33	71.78	13.58	58.33	57.61	0.7892	41.67	25.00	16.67	25.00	25.00	0.0000
Vale do Itajaí	90.91	90.91	0.0000	81.82	72.73	9.091	51.84	48.25	11.69	37.64	38.43	-3.486	27.27	27.27	0.0000
Norte de Minas	90.91	90.91	0.0000	81.82	75.04	0.0000	54.55	66.52	-27.27	36.36	36.36	0.0000	27.27	27.27	0.0000
Norte Piauiense	50.00	62.72	-50.00	50.00	62.93	-50.00	50.00	50.00	0.0000	0.00	50.00	-50.00	0.0000	0.0000	0.0000
Baixo Amazonas	90.00	89.47	-5.571	80.36	82.40	0.000	40.00	50.00	-10.00	30.00	40.00	-10.00	30.00	30.00	0.0000
Centro Amazonense	90.99	86.70	10.60	75.00	77.12	-8.333	50.00	50.00	0.0000	33.33	33.33	0.0000	25.00	25.00	0.0000
Metropolitana de Porto Alegre	83.33	83.33	0.000	75.00	75.00	0.0000	50.00	61.25	-16.67	33.33	39.11	-16.67	25.00	25.00	0.0000
Vale do Acre	83.33	83.33	0.000	66.67	56.71	24.76	16.67	44.28	-50.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sul Baiano	83.33	91.67	-8.333	75.00	75.00	0.0000	50.00	50.00	0.0000	30.90	40.08	-10.77	25.00	27.08	-8.333
Sudoeste Paranaense	83.33	86.46	-8.333	66.67	76.17	-16.67	41.67	50.00	-8.333	25.00	41.67	-16.67	25.00	25.00	0.0000
Norte Catarinense	83.33	91.67	-8.333	66.67	78.19	-16.67	41.67	58.17	-25.00	25.00	28.24	-8.33	25.00	25.00	0.0000
Grande Florianópolis	76.30	91.67	-15.37	66.67	77.12	-16.67	41.67	60.83	-25.00	25.00	33.33	-8.33	25.00	25.00	0.0000
Norte Cearense	50.00	78.94	-50.00	50.00	61.51	-33.33	16.67	33.33	-16.67	0.0000	9.214	-16.67	0.0000	0.0000	0.0000
Sul Fluminense	77.78	83.18	-11.11	66.67	81.36	-22.22	22.22	47.27	-33.33	11.11	22.22	-11.11	11.11	11.11	0.0000
Noroestel Espírito-Santense	72.73	81.10	-9.091	63.64	72.73	-9.091	36.36	52.52	-18.18	18.18	25.82	-9.09	9.091	19.72	-18.18
Sul Amazonense	70.00	84.60	-20.00	51.74	68.65	-28.26	27.88	45.89	-32.12	10.00	20.00	-10.00	10.00	10.00	0.0000
Centro Oriental Rio-Grandense	75.00	83.33	-8.333	58.33	70.87	-16.67	33.33	56.31	-25.00	25.00	33.33	-8.333	16.67	25.00	-8.333
Norte Fluminense	75.00	97.09	-25.00	50.00	67.32	-25.00	25.00	45.50	-37.50	12.50	12.50	0.0000	0.0000	12.50	-12.50
Metropolitana de Curitiba	75.00	96.72	-25.00	50.00	71.02	-25.00	33.33	52.27	-25.00	25.00	25.00	0.0000	16.67	25.00	-8.333
Centro-Sul Cearense	60.00	86.78	-40.00	40.00	71.87	-60.00	0.0000	45.15	-60.00	0.0000	20.00	-20.00	0.0000	0.0000	0.0000
Litoral Norte Espirítio-Santense	60.00	85.14	-30.00	40.00	64.50	-30.00	30.00	59.06	-30.00	20.00	25.55	-10.00	10.00	25.55	-20.00
Central Espírito-Santense	50.00	83.33	-33.33	41.67	72.73	-33.33	25.00	61.68	-41.67	23.63	33.33	-9.703	16.67	27.76	-16.67
Sudeste Paranaense	44.44	80.60	-44.44	33.33	74.58	-55.56	22.22	48.17	-33.33	11.11	22.22	-11.11	0.0000	22.22	-22.22
Sul Espírito-Santense	22.22	95.81	-77.78	11.11	69.49	-66.67	11.11	41.65	-44.44	0.0000	22.22	-22.22	0.0000	11.11	-11.11
Sudoeste Rio-Grandense	18.18	87.05	-72.73	18.18	63.64	-45.45	0.0000	48.18	-54.55	0.0000	27.27	-27.27	0.0000	21.99	-27.27
Noroeste Fluminense	11.11	88.89	-77.78	11.11	69.69	-66.67	11.11	59.89	-66.67	0.0000	33.33	-33.33	0.0000	22.22	-22.22
Centro Fluminense	0.0000	83.33	-83.33	0.0000	72.34	-83.33	0.0000	38.24	-66.67	0.0000	16.67	-16.67	0.0000	0.0000	0.0000

Appendix F

This appendix presents the two-stage stochastic approach developed to analyze alternative here-and-now solutions when a set of scenarios, say $\xi \in \Xi$, is used to represent the victims' needs. The parameters dependent on ξ are as follows. $v_{a\tau\xi}$ is the number of victims in affected area a at microtime period τ (people) in scenario ξ; $v'_{a\tau\xi}$ is the relative number of victims in affected area a at microtime period τ in scenario ξ, which is evaluated as $\frac{v_{a\tau\xi}}{\sum_{a'} v_{a'\tau\xi}}$; $d_{ca\tau\xi}$ is the victims' needs associated with relief aid c in affected area a at microtime period τ (units) in scenario ξ; and π_ξ is the probability of occurrence of scenario ξ. The first-stage decision variables are P_{cnt}, Q^{w}_{nt}, Q^{w-e}_{nt}, Q^{w-u}_{nt}, I^{w}_{cnt}, G_t, W_t, Y^{w}_{nt}, Y^{w-e}_{nt}, and Y^{w-u}_{nt}. The second-stage decision variables are $I^{rc}_{cm\tau\xi}$, $Q^{rc}_{m\tau\xi}$, $U^{rc}_{cm\tau\xi}$, $X_{ckk'\tau\xi}$, $Z_{am\tau\xi}$, $Y^{rc}_{m\tau\xi}$, and $Y^{rc-o}_{m\tau\xi}$, which all depend on scenario $\xi \in \Xi$. The scenario-based two-stage stochastic programming version is posed as follows.

$$\max \sum_{\xi\in\Xi}\sum_{a\in\mathscr{A}}\sum_{m\in\mathscr{M}}\sum_{t\in\mathscr{T}}\sum_{\tau\in\theta_t} \mathrm{SoVI}_a \cdot \pi_\xi \cdot v'_{a\tau\xi} \cdot Z_{am\tau\xi}. \tag{39}$$

s.t. Constraints $(2)-(13), (17)-(18), (31)$

$$\sum_{c\in\mathscr{C}}\sum_{k\in\mathscr{N}\cup\mathscr{M}}\sum_{\tau\in\Theta_t} f_c \cdot X_{cnk\tau\xi} \leq Q^{w}_{nt},\ \forall n \in \mathscr{N} \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{40}$$

$$\sum_{c\in\mathscr{C}}\sum_{k\in\mathscr{N}\cup\mathscr{M}}\sum_{\tau\in\Theta_t} f_c \cdot X_{ckn\tau\xi} \leq Q^{w}_{nt},\ \forall n \in \mathscr{N} \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{41}$$

$$P_{cnt} + I^{w}_{cn(t-1)} + \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq n}}\sum_{\tau\in\theta_t} X_{ckn\tau\xi} = \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq n}}\sum_{\tau\in\theta_t} X_{cnk\tau\xi} + I^{w}_{cnt},$$

$$\forall c \in \mathscr{C} \wedge n \in \mathscr{N} \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{42}$$

$$I^{rc}_{cm\tau\xi} + \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq m}} X_{cmk\tau\xi} + \sum_{a\in\mathscr{A}} \left[d_{ca\tau\xi} \cdot Z_{am\tau\xi}\right] = I^{rc}_{cm(\tau-1)\xi} + \sum_{\substack{k\in\mathscr{N}\cup\mathscr{M}\\ k\neq m}} X_{ckm\tau\xi} + U^{rc}_{cm\tau\xi},$$

$$\forall c \in \mathscr{C} \wedge m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{43}$$

$$\sum_{m\in\mathscr{M}} Z_{am\tau\xi} \leq 1,\ \forall a \in \mathscr{A} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{44}$$

$$0 \leq Z_{am\tau\xi} \leq 1,\ \forall a \in \mathscr{A} \wedge m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{45}$$

$$\sum_{c\in\mathscr{C}}\sum_{a\in\mathscr{A}} d_{ca\tau\xi} \cdot f_c \cdot Z_{am\tau\xi} \leq Q^{rc}_{m\tau\xi},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{46}$$

$$Q^{rc}_{m\tau\xi} \geq q^{rc-\min}_{m\xi} \cdot Y^{rc-o}_{m\tau\xi},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{47}$$

$$Q^{rc}_{m\tau\xi} \leq q^{rc-\max}_{m\xi} \cdot Y^{rc-o}_{m\tau\xi},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{48}$$

$$Y^{rc}_{m\tau\xi} \geq Y^{rc-o}_{m\tau\xi} - Y^{rc-o}_{m(\tau-1)\xi},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{49}$$

$$\sum_{c\in\mathscr{C}}\sum_{k\in\mathscr{N}\cup\mathscr{M}} f_c \cdot X_{ckm\tau\xi} \leq Q^{rc}_{m\tau\xi},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{50}$$

$$\sum_{c\in\mathscr{C}}\sum_{k\in\mathscr{N}\cup\mathscr{M}} f_c \cdot X_{cmk\tau\xi} \leq Q^{rc}_{m\tau\xi},\ \forall m \in \mathscr{M} \wedge \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{51}$$

$$I^{rc}_{cm\tau\xi} \leq h^{rc-\max}_{cm\xi} \cdot Y^{rc-o}_{m\tau\xi},\ \forall c \in \mathscr{C} \wedge m \in \mathscr{M} \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{52}$$

$$\sum_{c\in\mathscr{C}} \left(f_c \cdot I^{rc}_{cm\tau\xi} + f_c \cdot U^{rc}_{cm\tau\xi}\right) \leq Q^{rc}_{m\tau\xi},\ \forall m \in \mathscr{M} \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{53}$$

$$U^{rc}_{cm\tau\xi} \leq u^{rc-\max}_{cm\tau\xi} \cdot Y^{rc-o}_{m\tau\xi},\ \forall c \in \mathscr{C} \wedge m \in \mathscr{M} \tau \in \theta_t \wedge t \in \mathscr{T} \wedge \xi \in \Xi. \tag{54}$$

$$
\begin{aligned}
G_t \geq & \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-new} \cdot q_n^0 \cdot Y_{nt}^w + \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-o} \cdot Q_{nt}^w + \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-e} \cdot Q_{nt}^{w-e} + \sum_{n\in\mathscr{N}} \gamma_{nt}^{w-u} \cdot Q_{nt}^{w-u} \\
& + \sum_{c\in\mathscr{C}} \sum_{n\in\mathscr{N}} \iota_{cnt}^w \cdot I_{cnt}^w + \sum_{c\in\mathscr{C}} \sum_{n\in\mathscr{N}} \rho_{cnt} \cdot P_{cnt} \\
& + \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \gamma_{m\tau}^{rc-new} \cdot Y_{m\tau\xi}^{rc} + \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \gamma_{m\tau}^{rc-o} \cdot Q_{m\tau\xi}^{rc} + \sum_{c\in\mathscr{C}} \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \mu_{cm\tau} \cdot U_{cm\tau\xi}^{rc} \\
& + \sum_{a\in\mathscr{A}} \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \zeta_{am\tau} \cdot Z_{am\tau\xi} + \sum_{c\in\mathscr{C}} \sum_{m\in\mathscr{M}} \sum_{\tau\in\Theta_t} \iota_{cm\tau}^{rc} \cdot I_{cm\tau\xi}^{rc} \\
& + \sum_{c\in\mathscr{C}} \sum_{k\in\mathscr{N}\cup\mathscr{M}} \sum_{\substack{k'\in\mathscr{N}\cup\mathscr{M} \\ k'\neq k}} \sum_{\tau\in\Theta_t} \chi_{ckk'\tau} \cdot X_{ckk'\tau\xi}, \ \forall t \in \mathscr{T} \wedge \forall \xi \in \Xi. \qquad (55)
\end{aligned}
$$

The objective function (39) maximizes the *expected* effectiveness of the response. The block of constraints (40)−(55) is similar to its deterministic version developed in Section 3, but it must now be valid for all $\xi \in \Xi$.

Solution method. The scenario-based version was first solved by the default Branch-and-Cut (CPLEX) method during 36 hours without returning any feasible solution when the number of scenarios was greater than 3. This is due to the *random recourse structure* of the two-stage model. In fact, it is well-known that this class of problems is indeed more challenging to solve (Hanasusanto et al., 2016) than fixed recourse formulations. Therefore, we developed a Fix-and-Optimize (FXO) heuristic strategy to take advantage of the model's structure that involves multiple scenarios. The motivation was to be able to solve smaller (possibly easier) subproblems by decomposing the problem into scenarios, considering that the deterministic version had been well-solved. FXO starts with an initial feasible solution and tries to improve it iteratively by solving the subproblems generated by a defined partition criteria. The considered partition criteria was by scenario. The pseudo-code of our FXO heuristic is outlined in Algorithm 1. Note that since the partition is by scenario we do not fix the binary variables related to warehouse location and thus we only need to provide an initial solution for the binary variables $Y_{m\tau\xi}^{rc}$ and $Y_{m\tau\xi}^{rc-o}$. Such variables were initially set to 0.

Algorithm 1 Fix-and-Optimize algorithm.

`Initialization`: Generate an initial solution. Fix all the variables in their current values. Define the partition $\mathscr{P}_\xi$ for the discrete variables $Y^{rc}_{m\tau\xi}$ and $Y^{rc-o}_{m\tau\xi}$ by scenario.
Incumbent solution := initial solution; OF_incumbent := objective function of the initial solution; iter := 0; time := 0; IterLimit := 100; timeLimit := 36 hours.
LastImprovement:=0; $\xi' := 1$.
while iter < IterLimit **and** time < timeLimit **do**
  for $\xi = 1$ **to** $|\Xi|$ **do**
    if $\xi = \xi'$ and LastImprovement=1 **then**
      Stop.
    else
      Unfix variables from set P_ξ.
      Solve the resulting subproblem.
      if OF_MIP < OF_incumbent **then**
        LastImprovement := 0; $\xi' := \xi$.
        Incumbent solution := MIP solution.
        OF_incumbent:= OF_MIP.
      end if
      Fix all variables according to the incumbent solution.
    end if
  end for
  LastImprovement:=1;
  time := current elapsed time;
end while

Note. OF_MIP: objective function of the subproblem; OF_incumbent: objective function of the incumbent solution; IterLimit: maximum number of iterations; timeLimit: maximum elapsed time.

Here-and-now instance. Two here-and-now instances were considered. The first instance considered 1 macrotime period and 14 scenarios. The number of victims associated with those scenarios was generated according to the consolidated number of homeless and displaced victims for each affected area over the past 14 years of disaster data (2003-2016). In the second instance, a scenario reduction was performed to have a smaller set of scenarios and, hopefully, an easier optimization problem to solve. The scenario reduction technique is based on the similarity of the optimal structure of the wait-and-see solutions related to the warehouse location. Therefore, we ran all the 14 wait-and-see problems and analyzed their corresponding solutions, as shown in Table 6. We then identified five distinct groups of scenarios, whose optimal structure is quite similar amongst themselves: (1) 2003, 2006, and 2009; (2) 2004 and 2008; (3) 2005 and 2009; (4) 2010−2015; and (5) 2007. The scenarios were then evaluated as the average number of victims within each group, totalling 5 scenarios. The two here-and-now instances, '14-sce' and '5-sce', assume the scenarios are equiprobable. Both instances were solved using the compact two-stage formulation and the FXO heuristic. However, the compact formulation did not even provide a feasible solution within a time limit of 36 hours. On the other hand, FXO provided a feasible solution in both cases within the same time limit. The instance of 5 scenarios stopped after 12,300 seconds, while the instance of 14 scenarios stopped after 14 hours of processing. Although it is not possible to determine the optimality gap of both instances, the objective function values makes it possible to infer that the solution quality of 5-sce is very good because it is very close to the solution of the wait-and-see approach (4.72 versus 4.74, respectively). From the stochastic programming theory, we know that the wait-and-see objective function value (WS) can be seen as an upper bound on the stochastic programming objective function value (RP), i.e., RP $\leq$ WS (maximization problem). Therefore, the best possible objective function value for RP would be 4.74. On the other hand, the objective function value of 14-sce is 3.53, which is 25% worse than WS. In addition, the global relief service level of 14-sce is only 50.08, whereas the global service level of 5-sce is 72.81%, indicating that the victims' needs coverage might be further improved in the first case.