The British Academy

Journal of the British Academy, **9(s8)**, 23–53
DOI: https://doi.org/10.5871/jba/009s8.023
Posted 29 October 2021

Insights from vulnerability-driven optimisation for humanitarian logistics

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Abstract: Natural disasters and the vulnerability of a population go hand in hand. We cannot understand the level of a disaster without grasping the extent of people's vulnerability. But how can we ensure that humanitarian assistance is driven by people's vulnerability when the lack of resources makes it impossible to support all those that need it? This study thus contributes to this line of research by enhancing our understanding of how we can 'put the reality of the most vulnerable people first' (cf. Chambers 1995). For this purpose, we examine two experiences that have proposed to incorporate vulnerability concerns into the planning and optimisation of humanitarian logistics operations. The first experience relies on a very popular composite indicator called Social Vulnerability Index (SoVI) to build enhanced response capacity in more vulnerable areas. The second experience is built upon a poverty measure called Foster-Greer-Thorbecke (FGT) to identify the groups that potentially need the most relief aid supply and to help devising allocation plans in compliance with people's income. These two experiences reveal that in most cases targeting more vulnerable areas increases their level of access to relief aid goods without greatly compromising the relief service levels of less vulnerable areas.

Keywords: Social Vulnerability Index, FGT poverty measure, disaster management, humanitarian logistics, disaster relief optimisation.

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1 Introduction: disasters as social phenomena

In order to mitigate people's suffering in the aftermath of a disaster, humanitarian logisticians have to deal with complex decision-making processes that are nearly always complicated by socioeconomic conditions, severe uncertainty and lack of available resources, among others. These complicating factors can be even more pronounced in developing economies where higher levels of income concentration and social inequality create groups of people who are excluded in economic, social and political terms. When a natural hazard, such as floods or landslides, strike these groups of people, it is likely that they will experience more hardship in coping with its post-effects due to their *vulnerable* situation. This in turn may reduce their potential for recovery due to lack of insurance, savings/loans, relief aid, inefficient government and slow decision-making (Chang & Falit-Baiamonte 2002), thus intensifying previous economic stress and problems (Fothergill & Peek 2004).

The idea that disasters impacts and effects are the product of the socioeconomic and political processes that different groups of people are submitted to have been pointed out by academics and practitioners over the past decades. For example, Sapir & Lechat (1986) showed that disaster-induced mortality and morbidity are a function of physical and socioeconomic conditions of the affected people. Moreover, they suggested that poorer countries usually exhibit worse disaster-generated mortality rates than richer ones due to the inability of the former in reducing their overall vulnerability. For Cannon (1994), it is fundamental the understanding that hazards are natural, but disasters are not, as they depend on the people's vulnerability. For this reason, they claimed that differences in socioeconomic factors might result in hazards having an unequal degree of impact at distinct locations. For example, the 2010 Haiti earthquake of scale 7.0 caused 2 million victims, whereas the 2011 Japan earthquake of scale 9.0 resulted in 402,069 victims (da Costa *et al.* 2014). Such difference is usually explained by the economic development gap between these countries that lead to different coping capacities.

Although the precise meaning of vulnerability varies according disciplines, it is usually accepted that it represents 'the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards' (UNISDR 2008: 22). The vulnerability to natural hazards also evidences the capacity of a given community to 'anticipate, cope with, resist and recover from the impact of a natural hazard' (Wisner *et al.* 2003: 11), which is also aligned with the concept of vulnerability to climate hazards adopted by Gough *et al.* (2019) that is based on 'the level and duration of exposure of a receptor, the sensitivity of a receptor to harm, and the capacity of a receptor to adapt'. In this sense, there has been a great effort amongst scholars to quantify or measure vulnerability via indicators or scores, such that stakeholders and policymakers can use those indicators in a *predictive* fashion to help in the identification, proposal and evaluation of effective policies and actions, as well as the most useful coping responses (Smith 2013). However, the utilisation of vulnerability indicators in a *prescriptive* way to drive humanitarian logistics operations (HLO) towards benefiting vulnerable people and/or communities is rarely found in the literature.

Our aim is then to examine and analyse two experiences with a new emerging field of research, which we are calling *vulnerability-driven optimisation* for humanitarian logistics. In simple words, vulnerability-driven optimisation consists of: (1) an optimisation component designed to improve HLO decisions; and (2) a vulnerability-based criterion to drive such decisions in such a way as to prioritise the allocation of (scarce) resources and services to vulnerable people. The two experiences report the utilisation of vulnerability-driven optimisation in the Brazilian humanitarian supply chain. The motivation in pursuing this study for the Brazilian case is twofold: (1) Brazil is among the ten countries most affected by weather-related disasters in the last 20 years (Wahlstrom & Guha-Sapir 2015); (2) many recent disasters in Brazil are consequence of social processes whose primary characteristic is the unequal distribution of opportunities and social inequality that push more vulnerable people to risky areas (Carmo & Anazawa 2014). The two experiences are based on recent academic studies (Alem et al. 2021a; 2021b), and differ in the way the optimisation component is designed, as well as in the *proxy* for vulnerability that is adopted to prioritise the humanitarian assistance to disaster victims.

Following this introduction, the next section presents a brief background of optimisation and decision-making in humanitarian logistics, vulnerability approaches and measurements, as well as some context on the Brazilian humanitarian supply chain. The subsequent sections describe the two experiences with vulnerability-driven optimisation for humanitarian logistics. The first experience relies on a very popular composite indicator called Social Vulnerability Index (SoVI) to build enhanced response capacity in more vulnerable areas. The second experience is built upon a poverty measure called Foster-Greer-Thorbecke (FGT) to identify the groups that potentially need the most relief aid supply. The two experiences main goal is to help devise allocation plans in compliance with people's vulnerability. Insights into the two experiences are then reported. Finally, policy implications and limitations of the framework are discussed in the concluding remarks.

2 A potpourri of optimisation, vulnerability and the Brazilian humanitarian supply chain

The first part of this section briefly provides some background on optimisation and decision-making in humanitarian logistics, whereas the second part focuses on understanding vulnerability metrics and some approaches. Finally, the third part addresses the Brazilian humanitarian supply chain and some challenges that motivated the development of decision support models. It is important to mention that there is no intention to be exhaustive in the presentation of the definitions and concepts.

2.1 Optimisation and decision-making in humanitarian logistics

As we already mentioned, the vulnerability-driven optimisation approach consists of two components: an optimisation procedure and a vulnerability-based criterion. An optimisation procedure is simply a mathematical (thus quantitative) model that represents, through equations and inequalities, a given decision-making problem. This class of mathematical models belong to the so-called *mathematical programming* field; here, 'programming' is in the sense of 'planning', not 'computer programming'; see Williams (2013) for an introduction in this subject. The process of using mathematical programming to support decision-making usually encompasses the following phases: (1) identifying and formulating the problem; (2) building the model; (3) validating the model and performing the analyses; and (4) implementing the findings and updating the model. These phases and their corresponding overviews are illustrated in Figure 1.

In humanitarian logistics and disaster management, typical decision-making problems rely on the humanitarian logistics operations associated with the disaster life cycle, or disaster management cycle, which is a framework popularly utilised in disaster management to understand, visualise and delineate the distinct stages of a developing disaster event. 'Its main purpose is to tie the temporal dimension of an emergency with the appropriate functions for its successful management' (Young *et al.* 2020). Diverse authors summarise the disaster management cycle in two phases only (e.g. Tufekci & Wallace 1998): before disaster strikes (pre-event), whose main goal is to identify risks and take mitigating measures; and after disaster strikes (post-event), whose primarily objective is to manage the allocation of scarce resources.

The main activities commonly related to these two phases are described in Table 1. Both phases involve logistics planning and supply chain design, e.g. the construction of emergency operations centres (location), the maintenance of emergency supplies

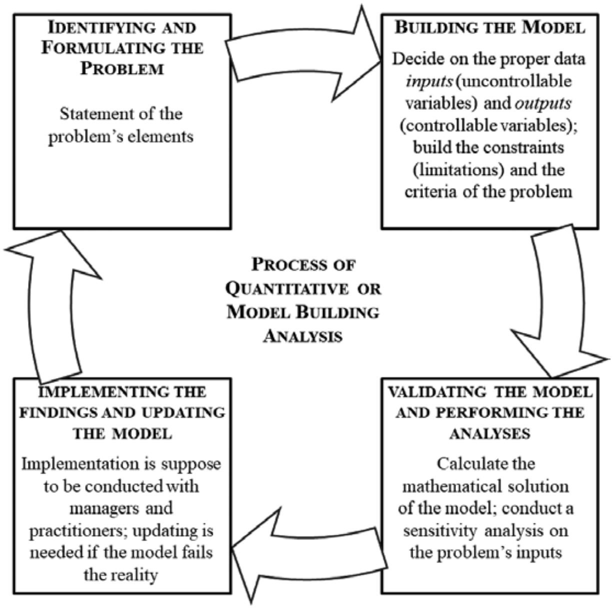

Figure 1. The process of quantitative or model building analysis (adapted from Wagner, 1975).

Table 1. Typical activities in preparedness and response of disaster operations management (adapted from Altay & Green 2006; Carter 2008).

Preparedness	*Response*
Construction of an emergency operations centre	Activating the emergency operations centre
Formulating and maintaining emergency planning	Implementing the emergency plans
Training programmes, including exercise and tests	Urban search and rescue
Maintaining emergency supplies	Providing emergency food, shelter, medical assistance, etc.
Public education and awareness	Emergency infrastructure protection and recovery of lifeline services
Budgeting for and acquiring vehicles and equipment	Managing donations
Emergency communications	Budgeting for activating response plans, e.g. transportation of commodities
Making safe boats and vehicles	

(prepositioning), the supply of emergency commodities (transportation), and so on. All these activities are included in the field of humanitarian logistics, defined as the process of planning, implementing and controlling the transport and storage of goods and materials from the point of origin to the point of consumption, in order to relieve the suffering of vulnerable people (Thomas & Kopczak 2005).

Alternatively, Figure 2 depicts an example of the disaster management cycle evidencing the four typical phases: (1) preparedness; (2) response; (3) recovery; and (4) mitigation. Each phase has distinct characteristics and activities to achieve the goals of the disaster relief operation. For example, one of the most popular strategies to supply victims' needs in the disaster aftermath is via *prepositioning* of goods in the preparedness phase (before the disaster strikes), whose underlying idea is to maintain a reasonable stockpiling of relief aid goods, such as water gallons and medicine at, or near the point of planned use in case the disaster really happens. This in turn reduces the transportation lead-times to the affected areas, thus increasing the chance of supplying the most vulnerable victims within the first few critical hours. No need to say that these activities can substantially vary depending on the disaster type and scale, geographical area and so forth. On this note, it is worth mentioning that although there is not a unique disaster classification system, most papers in the humanitarian logistics literature have been used a disaster classification based on three aspects of disaster events (Van Wassenhove 2006; Apte 2010): (1) the speed of onset, slow or sudden; (2) the location, localised or dispersed; and (3) the source of disaster, natural or man-made (also called as *technological*). L'Hermitte *et al.* (2014) proposed a logistics-focused classification for disasters based not only on time and geographic scope, but also five *situational factors* that reflect the impact of the external environment on the set of logistics operations and the corresponding performance of the humanitarian response, which were identified as: (1) the government situational factors;

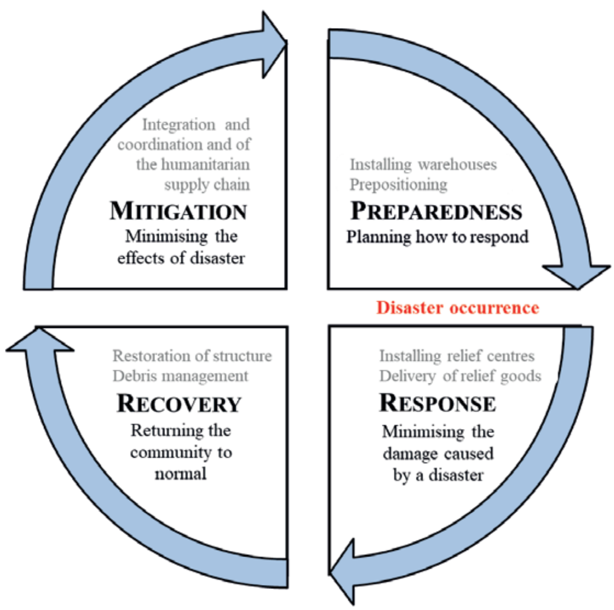

Figure 2. The disaster management cycle (adapted from Cozzolino, 2012; https://www.gdrc.org/uem/disasters/1-dm_cycle.html).

(2) the socioeconomic situational factors; (3) the infrastructure situational factors; (4) the physical situational factors; and (5) the security situational factors. A more recent classification focused on 'the impacted system and resulting interactions' correspondence to humanitarian-relief supply chain design' is developed in Mackay *et al.* (2019), where the authors acknowledged six disasters' factors that should be taken into account when proposing a disaster typology model: (1) speed of onset; (2) time horizon; (3) spatial considerations; (4) affected population needs; (5) perceived probability of occurrence; and (6) perceived magnitude of consequence. The International Disaster Database (EM-DAT)[1] also classifies natural disasters in five sub-groups: (1) geophysical (e.g. earthquake, volcano, mass movement—dry); (2) meteorological (e.g. storm); (3) hydrological (e.g. flood, mass movement—wet); (4) climatological (e.g. extreme temperature, drought, wildfire); and (5) biological (e.g. epidemic, insect infestation, animal stampede), covering 12 disaster types and more than 30 sub-types.

Although the practitioner's expertise is a key factor to conduct effective humanitarian logistics operations, Gonçalves (2011) showed that humanitarian decision-makers very often make use of non-optimal decisions in practice by over-reliance on past experience, over-confidence in their own unaided decision-making abilities, and the use of simple decision heuristics. These issues have motivated scholars to adopt mathematical programming tools to optimise humanitarian logistics activities over the past years, especially because 'emergency logistics in disasters is fraught with planning and operational challenges, such as uncertainty about the exact nature and magnitude of the disaster, a lack of reliable information about the location and needs of victims, possible random supplies and donations, precarious transport links, scarcity of resources, and so on' (Alem *et al.* 2016: 187). Mathematical programming models can help not only to circumvent the severe limitations of decision-making unsupported by prescriptive models, but also to capture, integrate and coordinate important decisions that must be made by policymakers effectively, efficiently, and equitably.

2.2 Vulnerability and its measurement in humanitarian logistics

The concept of vulnerability emerged from social sciences research, but its meaning substantially varies across disciplines (Janssen & Ostrom 2006; Fordham *et al.* 2013). There are several papers focused on exploiting and mapping vulnerability for both policy analysis and intervention purposes. For Adger (2006: 268), 'the concept of vulnerability has been a powerful analytical tool for describing states of susceptibility to harm, powerlessness, and marginality of both physical and social systems, and for guiding normative analysis of actions to enhance well-being through reduction of risk'. For Cutter *et al.* (2003: 6), 'vulnerability science helps us understand those

[1] See more in www.emdat.be/

circumstances that put people and places at risk and those conditions that reduce the ability of people and places to respond to environmental threats'. Various scholars understand that vulnerability to natural hazards is a combination of physical conditions and socioeconomic factors primarily derived from (income) class, gender and ethnicity (Cannon 1994; Bankoff 2003; Birkmann 2007).

Despite the fact that vulnerability can be seen through different lenses, it seems there is a general consensus within the social science community on the main drivers of vulnerability, or in other words, the factors that raise vulnerability levels. These include age, gender, disability, poverty, race, life expectancy, occupation, political system, education and food aid (Smith 2013). Cannon (1994) summarised the vulnerability types as degree of resilience (livelihood resilience), self-protection and social protection, as presented in Figure 3. Whereas the livelihood resilience is strongly determined by the aforementioned factors such as income (class), gender and ethnicity, self-protection is mainly seen as hazard-specific, thus return, period, intensity and magnitude are the main determinants. Finally, social protection is generally attributed to the level of scientific knowledge that enables state and other social/political bodies to protect people from a natural hazard.

It is not easy to objectively measure vulnerability in such a way that the assessment can be used for practical policy interventions (Smith, 2013). Mostly probably for this reason, scholars and practitioners continue to come up with novel vulnerability metrics and indices whose goals include the identification, assessment, visualisation and communication of diverse levels of vulnerability faced by local and global communities. Examples of vulnerability indexes include the so-called Social Vulnerability Index (SoVI), which is considered one of the most popular composite[2] indexes of overall social vulnerability, and it is employed in this article to prioritise more vulnerable people in disaster relief efforts. Despite of this effort in the development of new

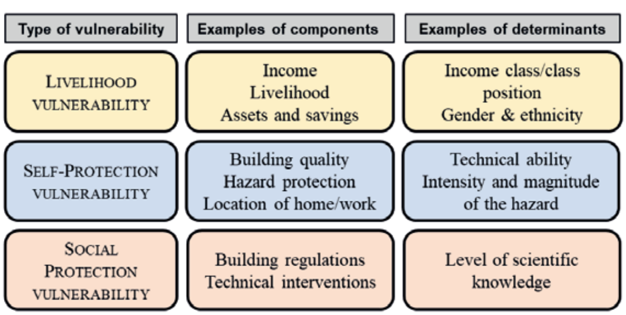

Figure 3. Vulnerability types, components and determinants (extracted and adapted from Cannon, 1994).

[2] Indicators are statistics that provide some sorts of measurement to a particular phenomenon of concern (Wong 2003). Composite indexes, such as SoVI, are statistics composed of more than one indicator.

vulnerability metrics and indicators, their utilisation within optimisation and decision-making in humanitarian logistics is still in its infancy. Most papers that somehow attempted to incorporate vulnerability issues within decision support tools used socioeconomic indicators instead of explicitly defining their vulnerability concept or criteria.

This is the case of, for example, Horner and Downs (2008) that approached 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. El-Anwar *et al.* (2009) focused on the assignment of displaced families after a disaster to a number of alternative housing projects. For this purpose, they proposed to use socioeconomic indicators to build four indexes designed to address sustainable development, namely, environmental performance, social welfare, economic, and public safety. In particular, the welfare index took into account different indicators at the housing location, such as employment and educational opportunities, housing quality/delivery time, healthcare and overall essential services opportunities/access. El-Anwar *et al.* (2010) and El-Anwar (2013) also focused on housing arrangements problems using similar indicators. The work of Noyan *et al.* (2016) might be seen as an extension of Horner and Downs (2008) in which the authors characterised the concept of accessibility for a last-mile distribution network problem based on physical and socioeconomic factors, such as the proportion of vulnerable population, which was assumed to be composed by people with low mobility at the demand nodes, such as disabled people, people aged over 65 and females with children. Sutley *et al.* (2017) merged what they called an *engineering model* with specific socioeconomic metrics attempting to produce an improved framework to assess the allocation of mitigation funds for woodframe building stock. Their proposed decision support model balances the initial retrofit cost, the economic loss, the number of morbidities and the time to recovery. In particular, the number of morbidities were determined according to a set of socioeconomic data, such as income, household size, age, ethnicity/race, family structure, gender and socioeconomic status. Other papers, such as Chong *et al.* (2019) and Maharjan *et al.* (2020) and some references therein, focused on the physical vulnerability of their study areas to build decision support models aligned with the population needs/profile. In the first case, the main goal was to design a model to find the areas and facilities necessary for humanitarian logistics in sudden disaster response situations, whereas the second case analysed how to determine the best placement of mobile logistics hubs for emergency preparedness and response in Nepal. More recently, Kougkoulos *et al.* (2021) devised a multi-method approach combining satellite-based remote sensing tools for identifying informal migrant worker settlements, ground truthing inspections, and a Multi-Criteria Decision Analysis (MCDA) model. The main goal was to develop a decision support tool to be used by governments and humanitarian organisations that can assess labour exploitation risks in different settlements and to prioritise their interventions. For this reason, the authors collected several indicators that were used to understand the level of vulnerability of the informal settlements, such as hygiene conditions and safety measures, and thus to provide their ranking from highest to lowest risk of labour exploitation.

In the comparative analysis of disaster risk, vulnerability and resilience composite indexes, Beccari (2016) revealed that there may be important differences in the methodology used to construct them, such as type and number of variables. However, the agreement amongst scholars is that low income status (or poverty) increases social vulnerability. Hallegatte *et al.* (2016) indeed found that poverty is a major driver of people's vulnerability to natural hazards. The authors explain that poor people frequently have to settle in risky areas and benefit less from protection against natural hazards. Also, it was found that poor people are more often exposed to floods, droughts and extreme heat (Hallegatte & Rozenberg 2017). Moreover, those populations that were less successful in the recovery process are likely to be more vulnerable to the next hazard strike (Cannon, 1994). For the World Bank:

> *Disasters impact the poor much more than the rest of the population. The poor have much lower resilience capacities than other sectors of the population. We have seen recent studies by the World Bank indicating that disasters are pushing some 26 million people into poverty each year. This is because some live in high-risk areas and have little capacity to recover from disasters. It is something we are working on, but where much remains to be done. (World Bank 2017)*

Focused on the Brazilian reality, Valencio (2009) also affirms that poverty is indeed the most relevant variable to explain vulnerability in the context of rainfall in Brazilian cities.

Adger (2006) claims that several of the challenges involved in quantifying vulnerability have been tackled by assessing vulnerability using poverty measures. The author also proposes what is called a *generalised measure of vulnerability*, which is based on the popular class of poverty measures called Foster-Greer-Thorbecke (FGT) from Foster *et al.* (1984). Poverty measures are very popular in social sciences and economics, and aims at describing how poverty is distributed in a given population or groups of people. This assessment can help policymakers to devise proper anti-poverty policies and allocate scarce resources, amongst others. The literature concerning the proposition of poverty measures is rich and has shown a considerable number of different measures over the past years. However, as far as we know, there have not been academic efforts to use the FGT poverty measure within decision support models in humanitarian logistics to prioritise the poor. In this article, we show an example of how the FGT poverty measure can be useful for this purpose.

2.3 Because context matters: the Brazilian humanitarian supply chain and challenges

Brazil's National System for Protection and Civil Defence (SINPDEC) is responsible for the country's disaster management. SINPDEC comprises of diverse entities that together carry out the disaster operations management for the entire country. The National Department for Civil Protection and Defence (SEDEC) is the main body of SINPDEC. SEDEC is divided into four main departments that coordinate the planning, articulation and execution of civil defence and protection programmes, projects and actions. The National Centre for Risk and Disaster Management (CENAD) activities comprise of managing the strategic actions of preparedness and response in the Brazilian territory. The Department of Liaison and Management (DAG) supports, supervises and promotes programmes and plans guidelines related to the National Policy of Protection and Civil defence (PNPDEC), and for this reason, its action spans the entire disaster lifecycle. The Department of Disaster Mitigation (DMD) develops and implements preparedness programmes, including typical activities of mitigation, prevention and preparedness. The Department of Rehabilitation and Reconstruction (DRR) supports programmes in the response phases associated to rehabilitation and reconstruction (Alem *et al.* 2021a). The practices of all these entities are more complex and entail more responsibilities, but this discussion is beyond the focus of this article.

Currently, the Brazilian civil defence adopts a strategy for relief aid procurement, the so-called 'Price Registration System' (SRP in Portuguese abbreviation), attempting to complement the humanitarian assistance provided by states and municipalities faced with disasters. Basically, the suppliers that are able to provide and distribute a required product to a given geographic area are selected via a bidding process ('lower price strategy' or 'competition', Law no. 8.666) and registered in a 'Price Registration Form' (ARP in Portuguese abbreviation) that must contain information on their supply capacity, price and transportation lead-time. To request relief aid in either pre- or post-disaster phases, the applicant (state or municipality) must solicit it from SEDEC and SEDEC thus analyses the necessity of the applicant and authorises (or not) the requisition. If the solicitation is approved, the suppliers are ordered by SEDEC to transport the approved quantity of relief aid to the capital of the state where the applicant belongs.

The relief distribution from the capital to the municipalities is then performed with support of the state and municipal coordination bodies called CEDEC and COMDEC in the case of a disaster. The selected suppliers must transport the required quantity of relief aid to the capital of the corresponding municipality (applicant) within 192 hours for the North Region and 96 hours for the remaining Brazilian Regions. According to SEDEC, the federal government plays a secondary role in the relief distribution because it is presumed that the primary humanitarian assistance will be an initiative of the affected state or municipality (immediate response). However, if the affected municipality/state struggles to raise in-kind donations and funds to supply victims' needs immediately after disaster strikes, it is unlikely that relief assistance will arrive within the 48 critical hours, which might undermine the effectiveness of the overall humanitarian operation. To overcome this potential drawback, it is possible to adopt a prepositioning strategy attempting to maintain a reasonable stockpiling of relief goods at, or near the point of planned use. If on one hand prepositioning has the disadvantage of being sometimes prohibitively complicated and expensive (Balcik & Beamon 2008), on the other hand, this practice is also one of the most effective strategies to deal with several types of disasters (Apte & Yoho 2011; Alem *et al.* 2021a), such as sudden- and slow-onset ones.

In this context, the idea of both the decision support models to be described in the following sections is to help SINPDEC as well as other state/municipal bodies in charge of disaster management to plan, integrate and coordinate key HLOs that must be performed to meet victims' needs when resources are scarce. Our main assumption is that, regardless of which body will provide the first humanitarian assistance, taking forward the idea of enhancing/optimising the current status of their humanitarian logistics will allow policymakers to understand how to effectively allocate scarce humanitarian assistance to the people most in need, which are the most vulnerable. More specifically, under an effective prepositioning strategy, primary assistance such as relief aid goods can almost immediately be distributed to the most vulnerable communities, while secondary assistance towards less vulnerable communities is deployed, e.g. via in-kind donations, local procurement, amongst other strategies. It is worth noting that our vulnerability-driven approach resembles a type of 'rationing' in the sense that both are oriented to allocate scarce resources according to some objective rule. In particular, rationing of goods/services in health care have been debated throughout the history of medical ethics because it may be controversial from the equitable distribution point of view selecting one group over another to receive treatment (Annas 1985; Tragakes & Vienonen 1998).

To take into account some challenges faced by the Brazilian humanitarian supply chain, our decision support models are optimisation-based (see Section 2.1), and entail an objective function to be optimised (our criterion) and a group of constraints that reflect the problems' requirements. One of the main challenges, as already mentioned, is the scarcity of overall resources (money, relief aid goods, etc.) to perform humanitarian logistics operations. That is why our decision support models are both based on finding the most effective decision (allocation of humanitarian assistance/resources such as relief aid good), which can be understood as maximising the number of victims that will receive the appropriate humanitarian assistance considering their specific needs and vulnerability profiles. As a consequence of having scarce resources, planning how to satisfy victims' needs is a key concern to guarantee that humanitarian assistance will be impartially allocated and will be aligned with victims' needs and profiles. Other challenges refer to how many facilities (warehouses, relief centres, etc.) to establish, where to locate them, and at which capacity. Indeed, there might be a trade-off between the transportation costs advantage of decentralising (more but smaller) facilities near major disaster-prone areas and the operating costs advantage of consolidating (fewer but larger) facilities not necessarily near major disaster-prone areas. Particularly in continental-size countries like Brazil, finding the best trade-off is crucial to guarantee effective and efficient humanitarian logistics operations; clearly, this also encompasses the evaluation of the best transportation modes, such as trucks, small aircrafts and helicopters. All these challenges will be represented by a group of six main optimisation constraints in our decision support models. The main rationale of these constraints is discussed below.

Location constraints. The location constraints ensure that facilities such as warehouses, depots and relief centres can only be established in pre-approved sites that already have a basic infrastructure. These constraints can avoid that a facility is established 'too close' to another, and they also limit the maximum number of facilities that can be established. Finally, the location constraints can also be used to restrict the capacity of such facilities, e.g. warehouses cannot store any quantity of relief aid goods, as well as relief centres cannot accommodate any number of victims.

Prepositioning constraints. The prepositioning constraints guarantee that there will be a minimum quantity of prepositioned relief aid goods in warehouses/relief centres to be economically viable to install them. These constraints are necessary because it does not make sense to install a warehouse to store one gallon of water, for example. The prepositioning constraints also state that there is a maximum quantity of each type of relief aid good to be prepositioned over all the disaster-prone areas. This quantity is usually *a priori* agreed by private suppliers and public bodies or non-governmental organisations in charge of disaster relief operations.

Logical constraints. The so-called logical constraints help to link several constraints in attempt to avoid nonsensical decisions. For example, if a given warehouse, say '*n*', is *not* established at a disaster-prone area, say '*a*', then there is no way to prepositioning relief aid goods at disaster-prone area *a*. Analogously, if a given relief centre is not open, we cannot send victims to it.

Conservation flow (or victims' needs balance) *constraints*. The conservation flow constraints guarantee that victims' needs will be fulfilled; in case of insufficient resources to meet all victims' needs at once, these constraints also take into account the unfulfilled needs. The conservation flow constraints also help decide which facility (warehouse and/or relief centre) will be responsible for sending relief aid goods to which disaster-prone area.

Transportation/distribution constraints. The transportation/distribution constraints are fundamental to determine which transportation modes should be adopted to send relief aid goods from warehouses to relief centres (and/or to relief centres to disaster-prone areas), and to estimate how many of each type must be used (hired or subcontracted). These constraints are also necessary to visualise which routes can/ cannot be used to perform relief transportation, as some routes may be total or partially blocked[3] in the immediate disaster aftermath.

Budget constraints. The budget constraints define the pre-disaster and/or the post-disaster financial budgets for performing the humanitarian logistics operations. This way, they ensure that the total expenditure related to establishing facilities, prepositioning relief aid goods, relief transportation, as well as other activities' costs will fall within the values usually stipulated by government bodies or NGOs.

In Sections 3 and 4 we will refer to these groups of constraints when we describe the decision support models.

3 Experience 1: vulnerability-driven optimisation using the Social Vulnerability Index

The first experience is based on Alem *et al.* (2021a) and focuses on a disaster preparedness and capacity-building response problem in which SoVI is adopted as the vulnerability-based criterion whose conceptual framework is illustrated in Figure 4. The conceptual framework reads as follows: *There are key HLO decisions to be made, which are based on a number of input data, and whose main goal is to maximise the effectiveness of the response given SoVI as the vulnerability-based criterion*. The optimisation component is the mathematical programming model defined by the decisions, constraints and data, whereas the vulnerability-based criterion is solely defined by the way vulnerability is measured.

Roughly speaking, we are interested in devising a type of decision support model—as described in Figure 1—to help decide on a number of logistics operations that must be performed by the Brazilian National System for Protection and Civil Defence (SINPDEC), which is in charge of the country's disaster management. The key humanitarian logistics operations are categorised in either strategic (long-term) or tactical (mid- and short-term) decisions, which are mathematically represented via controllable outputs or variables. The long-term decisions span periods of years and mostly involve deciding on: (1) where (which Brazilian state) to establish warehouses and at what size/

[3] Indeed, a very popular problem in disaster response is the so-called *road restoration* problem whose main goal is to optimally plan how to restore damaged roads to evacuate victims and distribute relief aid goods to relief centres or disaster-prone areas; see Moreno *et al.* (2020) for more details about this problem, including computational approaches.

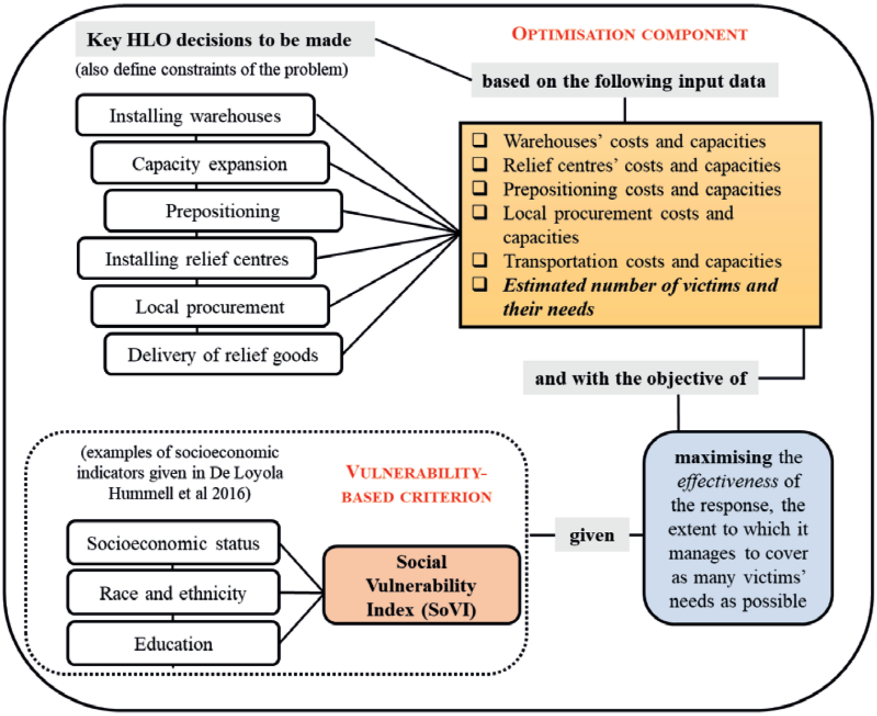

Figure 4. Conceptual framework underlying the first experience addressing the vulnerability-driven optimisation for disaster preparedness and capacity-building response in which the Social Vulnerability Index (SoVI) is adopted as the vulnerability-based criterion.

capacity they should be established; and (2) what relief aid goods should be acquired to be further propositioned at the established warehouses. Mid- and short-term decisions span shorter periods of time, such as months or even weeks, and primarily focus on: (1) setting up relief centres at disaster-prone areas; (2) performing local procurement; and (3) delivering relief aid good to disaster victims. The limitations (or constraints) of the decision support model take into account matters of network configuration for both warehouses and relief centres, expenditures, etc. The optimisation component, as shown in Figure 4, intends to find the best possible response policy (effectiveness of the response), understood here as the maximum fraction of people that will receive relief aid goods in the disaster aftermath, which is weighted by its corresponding vulnerability.

The objective of the optimisation component[4] is mathematically written as follows:

$$\max f(\mathbf{Z}) = \sum_{a \in A} \sum_{m \in M} \sum_{t \in T} \sum_{\tau \in \theta_t} \mathrm{V_a} \cdot \mathrm{v}_{\mathrm{a}\tau} \cdot \mathrm{Z}_{\mathrm{am}\tau}, \tag{1}$$

[4] We understand that it is beyond the scope of this article to discuss in details the optimisation component. The reader interested in familiarising with the full model is referred to Alem *et al.* (2021a).

where $f(Z)$ is the function to be optimised, V_a is the vulnerability-based criterion associated with disaster-prone area 'a', 'A' is the set of all disaster-prone areas, $v_{a\tau}$ is the percentage of the overall population living in area 'a' in time period 'τ', $Z_{am\tau}$ is our decision-to-be-made, representing the fraction of the population who lives in area 'a' that will receive relief aid goods from relief centre 'm' during time period 'τ', 'M' and 'T' represent the sets of all relief centres and time periods, respectively; finally, θ_t is the subset of time periods in time period t. The optimisation constraints, as discussed in the previous section, are related to location, prepositioning, logical constraints, conservation flow, transportation and budget. To illustrate an example of how these constraints work for this specific decision support model, Figure 5 shows the group of prepositioning constraints.

In this experience, the vulnerability-based criterion V_a in expression (1) is the popular Social Vulnerability Index, which is a composite indicator that has been extensively investigated over the past years within particular applications in disaster management since the seminal paper of Cutter *et al.* (2003). For many authors, SoVI can help to identify the most socially vulnerable communities (areas or regions), which can indicate the areas that need the most during the course of a disaster. In the work of De Loyola Hummell *et al.* (2016), the authors developed a SoVI index to natural hazards in Brazil to understand the differences in terms of human capacity to prepare for, respond to and recover from disasters. SoVI was evaluated based on several dimensions, such as socioeconomic status, gender, race and ethnicity, and education. Each dimension may be composed of a number of variables. For example, socioeconomic status includes three variables: the percentage of extremely poor people, the percentage of families living in households with more than one family, and the percentage of households with no phone. In Alem *et al.* (2021a), the authors claim that the adoption of SoVI in expression (1) helps prioritise supplying more vulnerable areas, i.e. those with higher (worse) SoVI values, to the detriment of less vulnerable

$$\sum_{c\in\mathscr{C}} P_{cnt} \;\geq\; p^{\min}_{nt} \cdot Y^{w}_{nt},\ \forall n \in \mathscr{N} \wedge t \in \mathscr{T}.$$

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

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

Figure 5. Prepositioning constraints of the optimisation model. The first constraint ensures that there must be a minimum prepositioned quantity of relief aid goods at warehouse n if this warehouse is indeed established. The second constraint states that all the prepositioned goods must respect the capacity of the warehouse. And finally the last constraint guarantees that there is a maximum quantity of relief aid goods that can be deployed (prepositioned).

areas in the event of not having the resources (relief aid goods and/or money) to fulfil all victims' needs at once.

This experience relies on a number of different data types, including costs (warehouse costs, relief centre costs, transportation costs and procurement costs), capacities (prepositioning capacity, inventory capacity and transportation capacity), number of affected people (victims), victims' needs, and SoVI of the disaster-prone areas. All data was extracted from diverse sources and consolidated by the author. In this experience, the capital of 17 Brazilian states were considered as potential candidates to receive a warehouse where relief aid good should be prepositioned until their deployment in the disaster aftermath. Fifty-three disaster-prone areas of Brazil were considered as the potential affected areas to be hit by natural hazards such as floods and landslides. To evaluate the number of potential victims, we analysed the number of homeless and displaced people as a consequence of 11 types of disasters (including floods, heavy rainfalls, landslides and drought) from 1 January 2003 to 31 December 2016, which is available in the website of the 'Integrated System of Disasters Information' (https://s2id.mi.gov.br/). Based on the disaster classification models discussed in Section 2.1, our disaster dataset encompasses: (1) both slow- and sudden-onset disasters; (2) both localised and dispersed disasters; and (3) natural disasters of three main types, hydrological, meteorological and climatological.

Figure 6 shows the disaster-prone areas and the cumulative number of affected people in the past disasters. Notice that the North and South regions present some areas with very high number of victims in the period under analysis. As for the relief aid goods, we assumed that disaster victims need water, food, mattresses, dormitory items, hygiene items and cleaning items. The SoVI values[5] for the considered disaster-prone areas are exhibited in descending order in Figure 7, where we can see that 'Sudeste Rio-Grandense' is the most socially vulnerable disaster-prone area, whereas 'Centro Fluminense' is the least socially vulnerable disaster-prone area.

4 Experience 2: disaster preparedness and designing of prepositioning strategies using the FGT poverty measure

The second experience is based on Alem *et al.* (2021b) and focuses on disaster preparedness and designing of prepositioning strategies problem in which the FGT poverty measure was adopted as the vulnerability-based criterion whose conceptual

[5] These values are based on the original SoVI values evaluated in De Loyola Hummell *et al.* (2016). However, we further applied *log-transformation* to the original data in order to have positive values only and help decrease the variance of the data and, therefore, having more fairly comparable SoVI values.

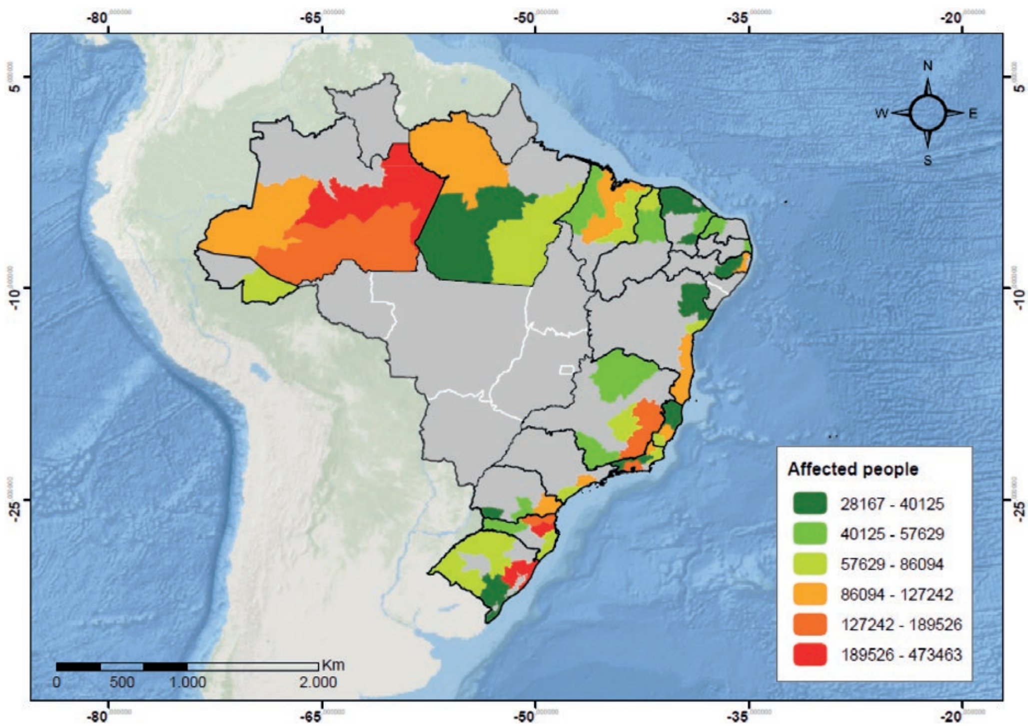

Figure 6. Number of affected people (homeless and displaced people) as a consequence of the aforementioned 11 types of disasters (including floods, heavy rainfalls, landslides, and drought) from 1 January 2003 to 31 December 2016 in all the 53 disaster-prone (affected) areas considered in the study.

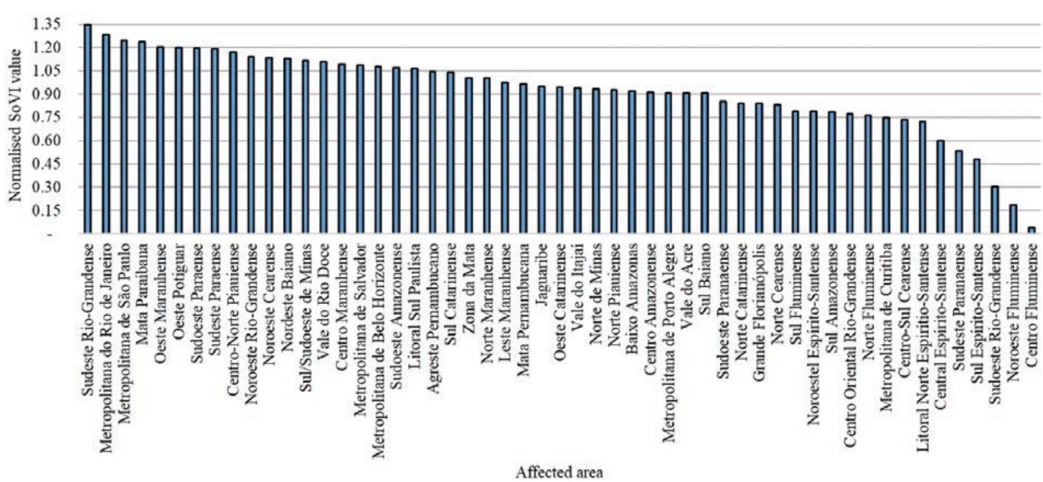

Figure 7. Normalised SoVI values for all the 53 affected areas considered in the study.

framework is illustrated in Figure 8. The conceptual framework reads as follows: *There are key HLO decisions to be made, which are based on a number of input data, and whose main goal is to maximise the effectiveness of the response given FGT poverty measure as the vulnerability-based criterion*. The optimisation component is also the mathematical programming model defined by the decisions, constraints and data, whereas the vulnerability-based criterion is solely defined by the way vulnerability is measured. Different from the first experience, now we are interested in devising a type of decision support model in which the core contribution is to evaluate whether disaster-prone areas should be prioritised or not, considering that a prioritised disaster-prone area would, ideally, satisfy the following condition. A *prioritised* disaster-prone area should satisfy three conditions: (1) it has a relief centre facility; (2) its quantity of prepositioned relief aid goods is greater than its overall needs, and it is used to cover its own needs first; (3) there is no relief aid shortage at prioritised disaster-prone areas. The aforementioned conditions intend to avoid logistics disruptions at prioritised disaster-prone areas, assuming that those areas are supposed to be more socially vulnerable and, therefore, deserve more attention. Considering that both the amount of relief aid available to be prepositioned and the financial budget to carry out the logistics

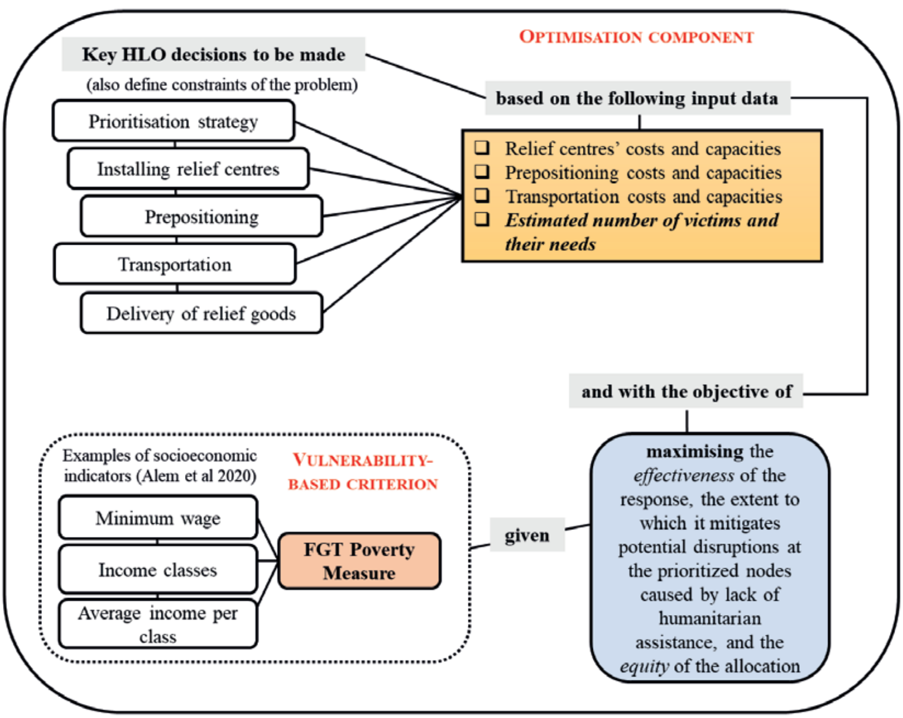

Figure 8. Conceptual framework underlying the second experience addressing the vulnerability-driven optimisation for disaster preparedness and designing of prepositioning strategies in which the FGT poverty measure was adopted as the vulnerability-based criterion.

activities are rather limited, our approach allows policymakers to select a number 'p' of potential disaster-prone areas to prioritise. The selection of which nodes should be prioritised may also be determined *a priori* by experts and given as an input of our proposed optimisation approach; in this case, the model could help assess the effectiveness of different prioritisation strategies.

The optimisation component, as shown in Figure 8, intends to find the best possible prioritisation policy (or effectiveness of the response), understood here as the extent to which it mitigates potential disruptions at the prioritised disaster-prone areas, given a set of logistics (capacity, financial, etc.) constraints. The objective of the optimisation component[6] is mathematically written as follows:

$$\max f(Z) = \alpha_1 \sum_{a \in A} V_a \cdot W_a + \alpha_2 \sum_{a \in A} P_a \cdot W_a - \alpha_3 \sum_{a \in A} U'_a \cdot W_a - \alpha_4 \sum_{a \in A} U_a / d_a, \tag{2}$$

in which $f(Z)$ is the function to be optimised, V_a is the vulnerability-based criterion associated with disaster-prone area 'a', W_a is a binary or Boolean decision variable that represents whether disaster-prone area 'a' should be prioritised ($W_a = 1$) or not ($W_a = 0$) in disaster relief efforts, P_a is also a biny decision variable that indicates whether the quantity of relief aid goods in disaster-prone area 'a' is greater than its own needs ($P_a = 1$) or not ($P_a = 0$), U'_a is another binary decision variable that shows whether there is relief aid shortage in disaster-prone area 'a' ($U'_a = 1$) or not ($U'_a = 0$), U_a is a decision variable that measures the absolute quantity of relief aid shortage in disaster-prone area 'a', d_a is the input data that represents all victims' needs in disaster-prone area 'a', and finally α_1, α_2, α_3, and α_4 are 'weights' (numerical value usually between 0 and 1) that may reflect the policymaker's perspective on the importance of each decision in expression (2). For example, if policymakers are only interested in prioritising disaster-prone areas based on their vulnerability levels, then a plausible choice for these input data would be $\alpha_1 = 1$, $\alpha_2 = 0$, $\alpha_3 = 0$, and $\alpha_4 = 0$. However, if it is important to make sure that the prioritised disaster-prone areas will receive their necessary quantity of relief aid goods, then both α_1 and α_2 must be greater than zero, and so forth. The optimisation constraints, as discussed in the Section 2.3, are related to location, prepositioning, logical constraints, conservation flow, transportation, and budget. Differently from the previous experience, we have an extra group of constraints related to prioritisation requirements. For example, we have a maximum number of disaster-prone areas that can be prioritised, and this number must aligned with the availability of resources and the capacity of public bodies in managing prioritised sites, which may require extra staff and deployment of resources. Also, if a given disaster-prone area is prioritised,

[6] We understand that it is beyond the scope of this article to discuss in detail the optimisation component. The reader interested in familiarising with the full model is referred to Alem *et al.* (2021b).

then we have to ensure that its existing relief aid goods are allocated to meet its own needs first before covering the needs of other disaster-prone areas.

The vulnerability-based criterion V_a in expression (2) is an adaptation of the Foster-Greer-Thorbecke (FGT) poverty measure developed in Foster *et al.* (1984) and aims at finding a numerical value (score) associated with the poverty of disaster-prone area '*a*'. The FGT class of poverty measures is based on powers of normalised (poverty) shortfalls, it is considered simple, thus facilitating the communication with policy-makers, and satisfies desirable axiomatic properties, such as additive decomposability and sub-group consistency (Foster *et al.* 2010), which allow us to evaluate poverty across population sub-groups in a coherent way. It is worth noting that we assume that the population of disaster-prone area '*a*' can be divided into extremely poor, very poor or poor, based on their average incomes. In what follows, we provide some definitions to understand how our FGT poverty measure is calculated.

Definition 1 (adapted from Alem *et al.* 2021b): The income classes represented by *extremely* poor, *very* poor and poor people have a per capita household income equal to or less than thresholds given by EP_a, VP_a, and P_a, per month, respectively. The average income of these groups are given by IEP_a, IVP_a, and IP_a, respectively.

Definition 2 (adapted from UNDP 2014): The group of people defined by the income classes designated as extremely poor, very poor and poor constitute the most socially vulnerable group.

Definition 3 (adapted from Alem *et al.* 2021b): The FGT poverty measure or poverty gap for disaster-prone area '*a*' is defined as follows:

$$\mathrm{FGT}_a = \frac{H_a^{EP}}{H_a}\left(\frac{t - \mathrm{IEP}_a}{t}\right) + \frac{H_a^{VP}}{H_a}\left(\frac{t - \mathrm{IVP}_a}{t}\right) + \frac{H_a^{P}}{H_a}\left(\frac{t - \mathrm{P}_a}{t}\right), \tag{3}$$

in which

1 't' is a poverty line or given threshold for income;
2 H_a^{EP} is the number of *extremely* poor people in disaster-prone area '*a*';
3 H_a^{VP} is the number of *very* poor people in disaster-prone area '*a*';
4 H_a^{P} is the number of poor people in disaster-prone area '*a*';
5 H_a is the total number of people in disaster-prone area '*a*'.

This experience strongly relies on historical data[7] on the number of homeless and displaced people due to natural hazards, such as floods and landslides, to estimate the potential number of victims for each Brazilian state,[8] which is available on the

[7] In the period 2007–2016.

[8] The capital of each state was considered a disaster-prone area. More information about how data was consolidated and generated can be found in Alem *et al.* (2021b).

website of the 'Integrated System of Disasters Information' (https://s2id.mi.gov.br/). Socioeconomic data on the number and income of extremely poor, very poor and poor people were extracted from the Human Development Atlas (http://atlasbrasil.org.br). The FGT poverty measure of the potential disaster-prone areas is depicted in Figure 9. Notice that 'SC' (Santa Catarina) exhibits the best FGT (0.082), while 'MA' (Maranhao) state exhibits the worst FGT (0.495). This difference is primarily explained by the number of extremely poor, very poor and poor people of these two states. For example, 22.5 per cent of people in 'MA' are considered extremely poor, but only 1.01 per cent of people in 'SC' live in extreme poverty. Overall, the coefficient of variation[9] of the FGTs given in Figure 7 is 42 per cent, confirming that poverty gap levels are very dispersed around the mean value of 0.296.

5 Insights and discussion

In order to understand how the vulnerability-driven optimisation approaches work, we conducted several computational simulations, which correspond to numerically solving through an optimisation method the models presented in the previous sections. The computational analysis of our two vulnerability-driven optimisation approaches was delineated to answer the following research questions: (1) Do the proposed approaches really improve the allocation of scarce resources of more vulnerable areas? If so, how? (2) How do the proposed approaches trade-off important

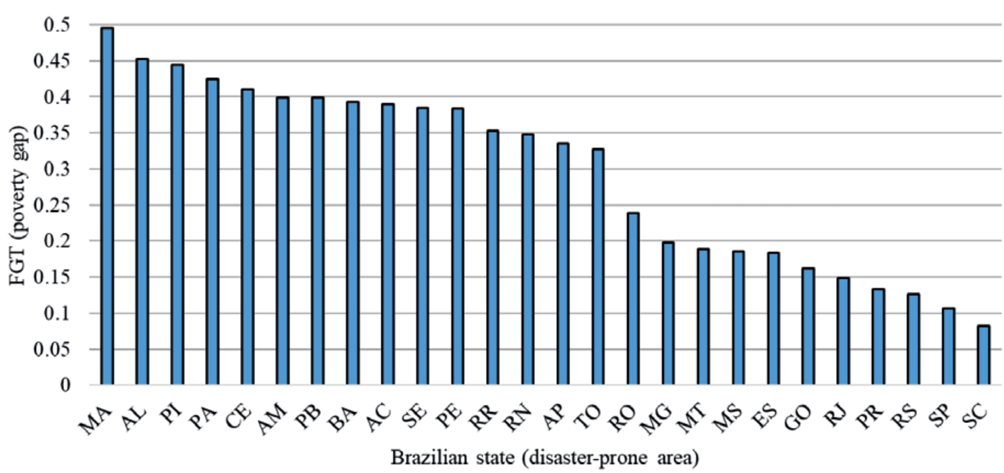

Figure 9. FGT poverty measure (poverty gap) of the 26 Brazilian states whose capitals were considered as potential disaster-prone areas.

[9] The *coefficient of variation* is the *ratio* between the population standard deviation and the population mean. Higher coefficients of variation reveal more dispersed data around the mean.

metrics, such as effectiveness and equity? For this purpose, all models were vis-à-vis compared to their versions with no vulnerability-based criterion using the performance metric called *relief service-level*, which is the percentage of needs that is actually delivered (served) within the time frame of the humanitarian logistics operation.

Figures 10 and 11 show the relief service-levels that can be obtained through the optimisation of our disaster preparedness and capacity-building response problem (i.e. 'Experience 1' illustrated in Figure 4) considering both approaches 'SoVI' (vulnerability-driven approach) and 'No SoVI' (without the vulnerability-driven component).[10] We optimised our problem assuming that there was either a 60 per cent budget cut to perform the HLOs (Figure 10) or an 80 per cent budget cut to perform the HLOs (Figure 10). This assumption is aligned with the motivation of using the vulnerability-driven approach to prioritising the allocation of humanitarian assistance when resources are rather limited.[11] Both figures exhibit the disaster-prone areas (horizontal axis) in descending order of vulnerability: from the most vulnerable ('Sudeste Rio-Grandense') to the least vulnerable ('Centro Fluminense'). The

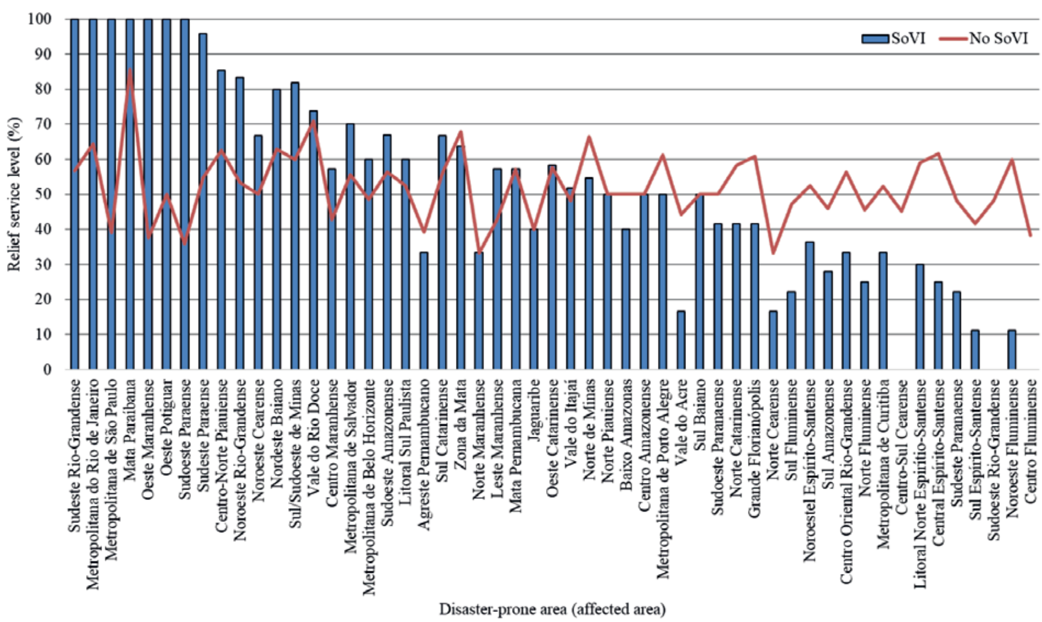

Figure 10. Relief service-level of 'Experience 1' assuming budget cuts up to 60 per cent.

[10] In this case, we set V_a to 1 in expression (1) for all disaster-prone areas.

[11] Indeed, if 'disaster resources' necessary to perform HLOs are widely available, one can claim our approach is unnecessary. Ultimately, it suffices to serve all disaster-prone areas, from the most to the least vulnerable.

results reveal that the then most vulnerable disaster-prone areas would be able to receive most of their needs for relief aid goods; in particular, the seven most vulnerable areas have 100 per cent of their needs served by humanitarian assistance (Figure 10). It is important to mention that this remarkable result is achieved at expense of the drop in the service levels of the least vulnerable areas, as the right-side of the figures suggests. As expected, when the vulnerability is neglected, relief service-levels are not driven by SoVI, and therefore, we cannot expect that more vulnerable areas present higher relief service-levels.

Indeed, the relief service-levels of 'Sudeste Rio-Grandense' are 100 per cent (SoVI) and 57 per cent (No SoVI) when budget cuts are up to 60 per cent (Figure 10), and 72 per cent (SoVI) and 27 per cent (No SoVI) when budget cuts are up to 80 per cent (Figure 11). On the other hand, 'Central Espírito-Santense' exhibits relief service-levels of 25 per cent (SoVI) and 62 per cent (No SoVI) when budget cuts are up to 60 per cent (Figure 10), and 24 per cent (SoVI) and 33 per cent (No SoVI) when budget cuts are up to 80 per cent (Figure 11). When vulnerability is not part of the decision-making process for allocation of relief aid goods, we might have allocation strategies that end up prioritising much less vulnerable disaster-prone areas as our figures reveal: the 'Non SoVI' approach allocated 9 per cent (resp. 22 per cent) more relief aid goods for 'Central Espírito-Santense' for budget cuts up to 60 per cent (resp. 80 per cent). Obviously the practice of decision-making in disaster management settings is more complex and may entail other components overlooked by our optimisation models, which could change the way allocation of relief aid goods is done. The moral of the story, though, is that our vulnerability-driven approach shows that it is possible to

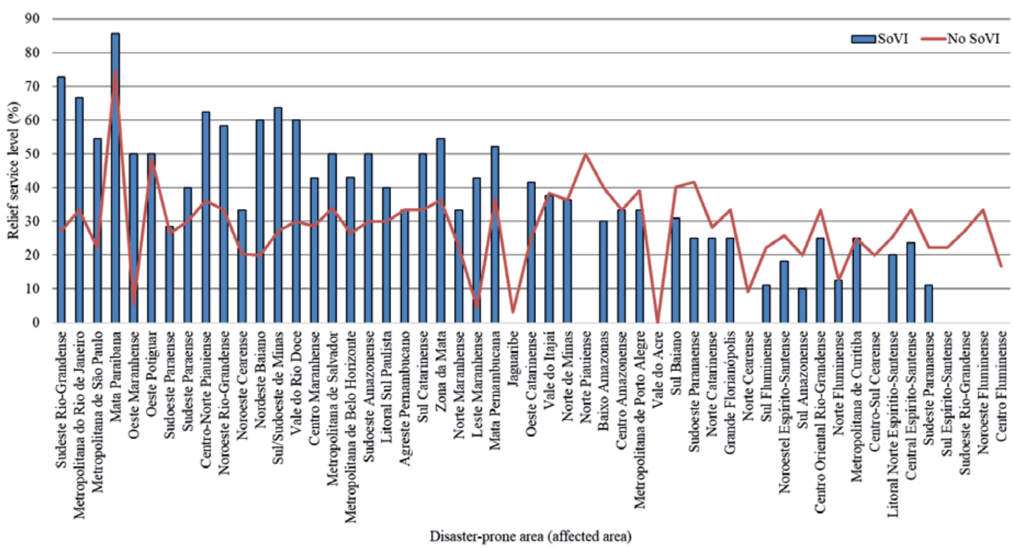

Figure 11. Relief service-level of 'Experience 1' assuming budget cuts up to 80 per cent.

factor social vulnerability into decision-making of distribution humanitarian aid, for example, thus somehow favouring more vulnerable areas in receiving aid when it is impossible to serve all disaster-prone areas due to the lack of overall resources.

Figure 12 depicts the frequency in which disaster-prone areas were prioritised over ten simulation runs[12] of our disaster preparedness and designing of prepositioning strategies (i.e. 'Experience 2' illustrated in Figure 8), starting (clockwise) from the most vulnerable disaster-prone area ('MA') to the least one ('SC').

We can clearly see that the prioritisation policy is heavily driven by the vulnerability of the disaster-prone areas, which is given by the FGT poverty measure captured by the first term of expression (2). The 15 most vulnerable areas were prioritised at least once, and seven out of the ten most vulnerable areas 'MA', 'AL', 'PI', 'PA', 'PB', 'AC' and 'SE' were prioritised in the ten simulation runs, i.e., regardless the budget cut level. Here, we assume that the types of natural hazards we want to protect people from are relatively *predictable*,[13] which is the case of several water-related natural

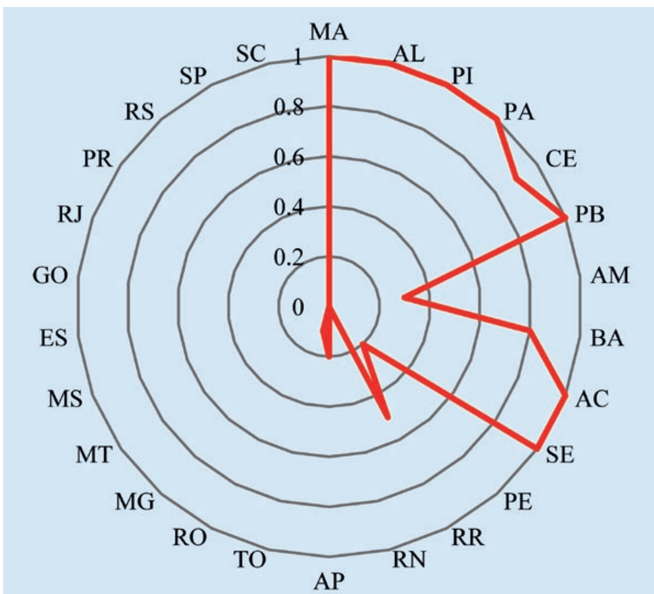

Figure 12. Frequency in which disaster-prone areas were prioritised over ten simulations ('Experience 2').

[12] Each simulation run corresponds to solving the optimisation model described in Figure 7 for a given level of budget cut. This way, in simulation run 1, no budget cut is imposed; simulation run 2 corresponds to a 10 per cent budget cut, and so forth.

[13] Assuming predictable natural hazards, it makes sense to define a disaster *timeline* to position logistics activities that must be performed in anticipation of the hazard (or *before disaster strikes* in accordance with the humanitarian logistics literature) and in its aftermath. This helps social and political bodies involved in the country's disaster management to better action towards disaster threats and risks.

hazards in Brazil, the so-called *recurrent events*.[14] Therefore, in terms of practical interventions, our results mean that the prioritisation could be done any moment during the preparedness phase even with partial (or no) information about the potential recurrent hazard *per se* and overall resources that could be destined to mitigate it because the disaster-prone areas that deserve especial attention are relatively *robust* in the face of context variation. This would allow policymakers to focus their attention and resources to those areas and the deployment of humanitarian assistance to more vulnerable communities within the critical hours of the disaster aftermath could be eased and more effective. Interestingly, Hallegatte *et al.* (2016) found out that poor people are more severely affected by *recurrent* events, and described three case studies showing this alarming result:

> *Large-scale events make the news, but repeated small adverse events such as regular floods often have serious implications for poor people, even though little data exist on them and their consequences. And although poor and nonpoor people may decide to live in places that are sometimes affected by natural hazards—to enjoy other benefits—only poor people live in dwellings that are frequently flooded or in areas in which landslides are common. (p. 40)*

If recurrent hazards affect (more often) poor people (in a given geographical area), and data can help us to identify who is (more) at-risk in the imminence of natural hazards, our vulnerability-driven approach can help not only the formulation and implementation of other preparedness and response activities (as shown in Table 1), such as public education and awareness campaigns, but also contribute to more strategic goals of 'building the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters', 'creating sound policy frameworks at the national, regional and international levels, based on pro-poor and gender-sensitive development strategies, to support accelerated investment in poverty eradication actions', 'significantly reducing the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including water-related disasters, with a focus on protecting the poor and people in vulnerable situations', which are all part of Sustainable Development Goals defined by the United Nations.[15]

[14] Recurrent events may repeat themselves year after year and are mostly associated to certain climatological triggering circumstances that often occur in specific seasons. For example, the analysis of past data on natural hazards occurred in Rio de Janeiro State from to 2003 to 2016 show that many types of hazards, such as floods and landslides, occur more often during warmer months, from November to April.

[15] The 2030 Agenda for Sustainable Development was adopted by all United Nations Member States in 2015; see more at www.un.org/sustainabledevelopment/

6 Concluding remarks

Approaching the optimisation of humanitarian logistics operations from the social vulnerability viewpoint, putting the reality of the most vulnerable first in humanitarian logistics efforts, has the main purpose of giving visibility to the invisibilised population that is by far more affected by natural hazards and suffer the most with its consequences. This article has examined two experiences on decision-making in humanitarian logistics that have developed vulnerability-driven optimisation approaches whose underlying idea is to have a vulnerability-based criterion embedded in a mathematical programming model in which the ultimate goal is the allocation of scarce humanitarian assistance. Differently from the mainstream literature in which overall logistics decisions are somehow monetary-based,[16] or disregard the population's vulnerability, in the vulnerability-driven approach, resource allocation is strongly based on the vulnerability profile of the population of a given disaster-prone area. The first experience focuses on disaster preparedness and capacity-building response problem using the Social Vulnerability Index, or SoVI, whose corresponding objective encourages fulfil victims' needs of more vulnerable disaster-prone areas over less vulnerable ones, aligned with several scholars who show that SoVI can help identify the most vulnerable, which in turn may enhance resource allocation policies during the disaster lifecycle. SoVI is widely accepted and used in different contexts and applications; and it is fairly robust and can be 'easily' replicated. The second experience relies on a disaster preparedness and designing of prepositioning problem in which the FGT poverty measure is used as the main vulnerability proxy. For this purpose, several aspects of the sociology of disasters were brought together, specifically those that make the claim that poverty contributes to vulnerability through narrowing of coping and resistance strategies, the loss of diversification and the restriction of entitlements, and the lack of empowerment. Vulnerability, in turn, weakens the ability to overcome poverty, thereby creating a vicious cycle. FGT is adapted from the popular class of poverty measures called Foster-Greer-Thorbecke, which is considered simple and satisfies desirable axiomatic properties.

The most striking aspect of the findings reported in this article is in the difference between the relief service-levels of vulnerable communities with and without the vulnerability-based criterion (SoVI and FGT) driving the logistics decisions. In this regard, the results revealed that the SoVI strategy improves the relief service-level of most disaster-prone areas at the expense of a *certain* deterioration of that of the remaining ones. FGT helps to prioritise the poorest areas and this decision is

[16] By *monetary-based* we mean optimisation models for humanitarian logistics in which the main objective relies on minimising overall costs, such as location-allocation costs or even *deprivation* costs when human life is somehow monetarised.

relatively robust in the face of context variation. Remarkably, when there is very little humanitarian assistance to be allocated to several affected areas, both SoVI and FGT help us to 'make the most' out of the resources and this generally means targeting the top (5 or 10) most vulnerable areas in the injection of relief aid goods. Although both metrics, SoVI and FGT, are crucial to the understanding of how vulnerability to natural hazards are spread across the Brazilian territory, and yield similar results concerning the behaviour of the allocation strategy, FGT may be easier to understand and interpret. In addition, FGT requires fewer data to be evaluated and, therefore, it can be more appealing in low-income countries where a comprehensively updated population census is impractical. Moreover, both metrics might be used for diverse purposes, including social monitoring, programme evaluation, and goal-setting or prioritisation. Future academic research includes analysing other vulnerability-based criteria, such as the Disaster Risk Index (DRI), as well as creating specific metrics that can be more generalisable for other optimisation problems or contexts. In addition, the implication of prioritising certain disaster-prone areas to poverty reduction and alleviation is a promising research agenda area that deserves further attention.

Acknowledgements

I am grateful for the grant NRCP1516/1/54 from the Royal Academy of Engineering, London, for their support via Newton Research Collaboration. My foremost thanks goes to the team of this project (in alphabetical order): Professor Ana Paula Barbosa-Povoa (CEG-IST, Instituto Superior Técnico, University of Lisbon, Portugal), Dr Alfredo Moreno (HEC Montréal, Canada), Professor Deisemara Ferreira (Department of Physics, Chemistry and Mathematics, Federal University of Sao Carlos, Brazil), Ms Hector F. Bonilla-Londono (Department of Civil and Industrial Engineering, Pontificia Universidad Javeriana de Cali, Colombia), Luciana R. Londe (Brazilian Centre for Monitoring and Warnings of Disasters, Cemaden, Brazil), Rafaela Veloso (Universidade Federal de São Paulo, UNIFESP, Brazil), Professor Susana Relvas (CEG-IST, Instituto Superior Técnico, University of Lisbon, Portugal) and Professor Tolga Bektaş (University of Liverpool Management School, United Kingdom).

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To cite the article: Douglas Alem (2021), 'Insights from vulnerability-driven optimisation for humanitarian logistics', *Journal of the British Academy*, 9(s8): 23–53.
DOI https://doi.org/10.5871/jba/009s8.023

Journal of the British Academy (ISSN 2052–7217) is published by
The British Academy, 10–11 Carlton House Terrace, London, SW1Y 5AH
www.thebritishacademy.ac.uk