Multi-period model for disaster management in simultaneous disasters

Abstract: Relief activities are complicated when multiple disasters take place at different locations simultaneously. Designing effective relief networks for these instances involves managing the priorities among regions and products, developing the capacity to share limited resources and facilities, and engaging with multiple suppliers over several periods. Unfortunately, even after recent experiences in different countries, the management of simultaneous disasters is still understudied. This article introduces a two-stage dynamic formulation for logistics decisions in instances caused by simultaneous disasters. It guides supplier selection, facility location, stock pre-positioning, and resource allocation at the first stage, whereas relief distribution, post-disaster procurement, and inventory management are addressed at the second stage. The model minimizes cost and the maximum shortage. Results of numerical experiments show the way the model considers the characteristics of each situation to dispatch limited shared resources. The experiments show that planning for single disasters has a negative impact on performance when faced with situations caused by simultaneous disasters. That is confirmed by findings from the case study in Mexico, which also highlights the preference for prepositioning stock using a mix of different kind of suppliers, and the importance of developing a reliable network of facilities and suppliers to handle simultaneous disasters effectively.

Keywords: Humanitarian logistics; multi-objective programming; procurement; simultaneous disasters; disaster response.

Managerial relevance statement: The practical implications of the study include:

- Simultaneous disasters affect the quality of the response. Reacting to one disaster influences the resources and stakeholders available to respond to another disaster. Disregarding that can lead to sub-optimal solutions affecting the support given to victims.
- The nature and interconnectedness of the different disasters affects decision-making. As simultaneous disasters involve sharing resources available, the model enables authorities to allocate resources fairly among disasters based on their characteristics and impact.

- The model is valuable to test the real capabilities of the response system. The model can be used at the pre-disaster stage to test different scenarios to produce robust response plans using historical information, forecasts, or instances of interest. That includes the design of the relief network and potential strategies to handle different post-disaster conditions.
- The model can help develop plans for different seasons considering the potential damage over several time periods of recurrent disasters.
- The model allows evaluating suppliers. It investigates their participation in different scenarios, their contribution to response, and the performance of the supply network.

1. INTRODUCTION

The increasing frequency and impact of disasters over the last decades is alarming [1]. There is a sharp increase in the number of disasters, people affected and economic damage globally [2, 3]. The record of 432 catastrophes in 2021 is significantly higher than the average between 2000 and 2020 [4]. Those disasters caused over USD $252 billion in damages and affected around 101.8 million people [5]. The link between procurement and resource management affects the support given during disasters, as procurement represents up to 65% of the total expenses in disaster operations [6]. A reliable supply network prevents supply shortages, especially in simultaneous disasters. Unfortunately, examples of inefficient disaster procurement [7] show the limitations of the strategies used in research and in practice. The term compound disasters refers to disasters caused by different hazards occurring at the same time in the same community [8], whereas the term simultaneous disasters describes instances where natural hazards occur concurrently at different geographical locations [9]. Both involve handling multiple disasters, but this research is motivated by the extra complexity of supporting different communities in simultaneous disasters. These disasters involve supporting different regions with varying vulnerability levels that are affected by (potentially) different hazards. Hence, these events require modifying current response systems to facilitate the participation of different local, regional, or national organizations to overcome limitations of resources and geographical challenges [10]. These situations require balancing the needs of different areas [11] requiring swift and effective delivery of relief items. The current approach to manage simultaneous disasters involves adapting mechanisms designed for independent disasters [12] which only account for individual risks [11]. However, the cascading effects of one disaster on another, their varying magnitude, and the different level of vulnerability of the affected regions affect response [10, 13]. Planning is key in relief operations [14] as it promotes developing strategies to handle different conditions. Governments and NGOs need to plan for simultaneous disasters [15] given the expected increase of these hazards in the future [13]. This study targets two questions: (i) how can a plan for disaster response over multiple periods incorporate the occurrence of simultaneous disasters? (ii) what is the effect on performance of only planning for independent disasters when facing simultaneous disasters?

Following the call for multi-hazard rather than single-hazard management systems for disasters [16], this research uses optimization to support disaster management for multiple periods in instances caused by simultaneous disasters. The contribution of this study is threefold: i) it proposes a mathematical formulation for humanitarian logistics over multiple periods in situations caused by simultaneous disasters, ii) it provides an analysis about the importance of considering the different levels of priority of products across disasters, and iii) it provides evidence about the challenges of handling simultaneous disasters in systems designed for single independent disasters. The two-stage bi-objective dynamic stochastic formulation incorporates decisions about supplier selection, procurement, facility location, and resource allocation at the first stage, whereas the second stage supports procurement, inventory management, and relief distribution. It distinguishes between distinct areas with different levels of urgency for multiple products. The model is applied to numerical examples and to a case based on Mexico in 2013, where Hurricanes Ingrid, Manuel and major storms occurred at the same time in different regions. The article is structured as follows. Section 2 presents related literature; Section 3 introduces the development of the model and Section 4 elaborates on the numerical experiments. Section 5 describes the case study and the results from the implementation of the model, whereas Section 6 discusses the main findings and implications, and Section 7 provides the summary and conclusions of the article.

2. LITERATURE REVIEW

2.1. Procurement in humanitarian logistics

Supplier selection has been tackled using approaches such as action-based [17], multi-criteria decision-making [18], non-linear optimization [19], optimization based on focus groups [20], among others. These articles rely on the characteristics of the supplier, combining multiple stakeholders and multiple criteria.

Uncertainty in demand and the situation have been explored in the literature as well using game formulations and auction models. Shamsi, Torabi and Shakouri [21] propose a game formulation for vaccine procurement with option contracts considering a backup supplier. The aim of the buyer is to minimize cost and the objective of the supplier is to maximize profit. Considering the links between organizations and sustainability, Boostani, Jolai and Bozorgi-Amiri [22] propose a formulation minimizing cost, maximizing minimum satisfaction rate and minimizing environmental impact. The dimension of collaboration between different humanitarian organizations is taken forward by Nagurney and Qiang [23]. The article introduces a model based on the mean-variance approach to explore the impact of horizontal coordination in disaster scenarios. These articles provide valuable solutions for procurement for single stages, especially looking at response. However, it is important to consider the links between stages.

Two-stage or multi-stage approaches have been a common way to deal with uncertainty considering more than one stage in disaster management. Falasca and Zobel [6] develop a model to determine order quantities for immediate response at the first stage, whereas decisions are made at the second stage once there is more information. The model minimizes costs across all possible scenarios considering uncertainty in donations as well. Aghajani and Torabi [24] introduce a two-round decision model with information updates. The first-round model minimizes total cost, delivery time and the score of the suppliers selected. The second-round model minimizes cost and the total score of the suppliers selected.

There is a stream of procurement articles exploring contractual agreements using two-stage formulations. Considering the value added by quantity flexibility contracts (QFC), Balcik and Ak [25] propose a model to select suppliers based on cost minimization with uncertain demand. The model minimizes costs and includes in the constraints the need to satisfy quantity and lead time. Torabi, Shokr, Tofighi and Heydari [26] propose a fuzzy-stochastic model for prepositioning and procurement using QFC. The formulation minimizes cost, including penalty cost for unmet demand. First-stage decisions are focused on facility location and prepositioning, whereas second-stage decisions include post-disaster procurement and the distribution plan. Olanrewaju, Dong and Hu [27] consider the commitment quantity of the agency, the reserve capacity of the suppliers, and the quantity discount rate in their formulation exploring the impact of supplier agreements in supplier selection minimizing cost across stages. Although these articles account for two different stages and agreements with suppliers during disasters, the variation of the behavior of demand at different periods is not considered. The link between procurement, inventory, and relief distribution needs to consider the evolution of events to achieve efficient use of resources.

Tackling procurement using multiple periods, there are formulations looking at the procurement of relief materials and vehicles. Hu, Han and Meng [28] propose a two-stage stochastic model to determine the number of suppliers, pre-disaster inventory levels, locations, and post-disaster procurement quantities. The formulation minimizes cost and includes lead time discount, return price and equity. Yan, Di and Zhang [29] present a multi-modal formulation for the distribution of relief materials minimizing response time and cost. The model allows for the expedite production of materials when there are disruptions in the supply chain. Alem, Bonilla-Londono, Barbosa-Povoa, Relvas, Ferreira and Moreno [30] adopt a social vulnerability index to prioritize victims and needs for procurement, facility location, prepositioning, and distribution at the pre-disaster stage. The model maximizes coverage using macro and micro time periods. Leveraging the idea of macro and micro periods but focused on vehicles, Moreno, Alem, Ferreira and Clark [31] propose a formulation for location and transportation minimizing logistics and deprivation costs. The first stage looks at facility location and fleet sizing, whilst the second stage is focused on relief distribution and inventory management. Alem, Clark and Moreno [32] introduce a model minimizing a weighted sum of cost and unmet demand. The first stage is focused on prepositioning and vehicle contracting, whereas the second stage looks at relief distribution and inventory management. Keshvari

Fard, Eftekhar and Papier [33] consider fleet sizing as well. They provide a stochastic dynamic programming model minimizing deprivation cost. The model considers mission criticality, budget-uncertainty, time-restricted budgets, and uncertainty in asset replacement. The inclusion of multiple periods in these models introduces the possibility of having pre-disaster and post-disaster procurement, the latter affected by the variations in demand. However, these models assume the occurrence of a single disaster affecting different areas in a region. The nature of any other disruptions is not considered, which would complicate the efficient use and the fair allocation of resources for regions with varying needs. In current models, the supply network is looking at a specific event of a single nature, which faced with more than one disaster can lead to insufficient capacity, supply delays, and shortages of critical items.

2.2. Humanitarian logistics in instances with multiple disasters

Some governments include simultaneous disasters in planning because of their potential damage [15]. Although the procurement literature is lagging in this area, there are some models to allocate resources. Zhang, Li and Liu [34] propose a resource assignment method minimizing travel time from supply points to the primary affected area and from the supply points to the secondary affected area considering the possibility of secondary disasters. Su, Zhang, Liu, Yue and Jiang [35] introduce a model to allocate rescue resources to multiple concurrent incidents happening simultaneously. It minimizes a weighted sum of travel time and total cost. Li, Zhao, Fan, Cao and Qu [36] propose a rescuer allocation model considering multiple rescue tasks and different departure places. The model maximizes the matching degrees between the rescuers and the rescue tasks to account for the preferences from the rescuers. Klibi, Ichoua and Martel [37] introduce a two-stage model focused on facility location and stock prepositioning. The article considers the possibility of multiple hazards affecting an area within the time horizon. Decisions in the first stage look at distribution center location and pre-disaster procurement, and second stage decisions focus on relief distribution. The model includes the inter-arrival time between two hazards and the objective is to maximize coverage and minimize cost using a weighted sum of both functions. Yu, Zhang, Yang and Miao [38] propose a model minimizing accessibility costs, deprivation costs, and penalty costs stemming from the allocation of critical relief. Wang, Bier and Sun [39] present a model for equitable allocation of emergency materials to multiple affected locations. The model minimizes the combination of the total disutility of shortfalls of materials, total transportation costs, and total allocation costs. Recently, Doan and Shaw [15] address resource allocation for simultaneous disasters with three optimization models: the first looking at risk of not reaching the desired level of service with resource constraints, the second one suggesting the resources needed to satisfy the emergencies and the third one combining both. Wang [40] addresses equitable allocation of resources to multiple disaster-stricken sites. The multi-objective formulation minimizes total delivery time, costs, and maximum coverage.

Although the formulations presented in this section show the importance of managing resources in instances with several concurrent disasters, the link to procurement is missing. There are a few articles exploring subsequent disasters accounting for procurement. Nezhadroshan, Fathollahi-Fard and Hajiaghaei-Keshteli [41] design a possibilistic-stochastic model minimizing logistics costs, maximum travel time, and maximizing resilience level. It considers the potential effects of subsequent disasters in demand and delivery time. Foroughi, Moghaddam, Behzadi and Sobhani [42] design a bi-objective formulation minimizing total cost and maximizes the resilience level of facilities including the effect of subsequent disasters on demand. These articles are a step forward to react to multiple disasters. However, subsequent disasters assume disasters are linked and affect a similar area. That facilitates preparing the supply network sharing basic needs and focusing on that region. Simultaneous disasters, however, require splitting resources across different regions with different needs. Current models would struggle to consider the varying needs of different regions and hazards.

2.3. Research gap

Table 1 shows a summary of the literature reviewed. There are different findings from this survey. Procurement is commonly associated with different logistics activities, but it is rarely linked to resource allocation. Only Boostani, Jolai and Bozorgi-Amiri [22] incorporate their link, but their model focuses on the allocation of relief rather than other resources such as vehicles or staff. Considering the interconnectedness between relief items and the resources needed to handle and deliver them, there is a need to design models integrating both with other humanitarian logistics activities.

None of the procurement articles consider simultaneous disasters. There are attempts from Nezhadroshan, Fathollahi-Fard and Hajiaghaei-Keshteli [41] and Foroughi, Moghaddam, Behzadi and Sobhani [42] with parameters to modify demand based on subsequent disasters, but looking at the impact on the same community. Having multiple events at similar times in different places stretches resources from authorities to the limit [15]. The expected increase of these situations [13] underscore the need to develop procurement strategies ensuring the continuous flow of relief to avoid sub-optimal policies.

The review shows that two-stage stochastic models are useful to integrate uncertainty to reflect the nature of disaster management. These models use possible occurrences of uncertain parameters to identify "good" strategies against any outcome with flexible decisions related to each outcome [43]. The user can define first stage pre-disaster decisions because these assume there is no precise value of the random variables, and second-stage post-disaster decisions once more information is available. These models are suitable to include multiple periods, which is promising for simultaneous disasters [See 15, 34].

The model considers the trade-off between reducing the maximum unmet demand and the operational cost given the importance of introducing more than one criterion in humanitarian operations [18, 44]. The first objective function reduces the maximum number of people without relief to reduce shortages and add fairness in the formulation by supporting equity per each region.

Overall, the review has shown an absence of articles considering the interconnectedness of procurement with resource allocation over multiple periods in instances caused by simultaneous disasters. That is problematic because the different requirements and priorities from each disaster affect their response and their attention to the other disasters. Using current models for independent disasters can lead to overestimation of the capacity of the response system or to a sub-optimal response network, as simultaneous disasters can make facilities or suppliers unsuitable or alter their preference [45]. In a context with multiple periods, that can affect the feasibility of the plan. This research is tackling that gap.

Table 1. Summary of the literature review

	Decisions			**Characteristics**				
Authors	*Procurement*	*Facility location*	*Resource allocation*	*Modelling approach*	*Multiple disasters*	*Multi-commodity*	*Multiple suppliers*	*Multi-period*
Falasca and Zobel (2012)	✓			Two-stage stochastic		✓		
Balcik and Ak (2013)	✓			Two-stage stochastic			✓	✓
Alem et al. (2016)	✓			Two-stage stochastic		✓		✓
Hu et al. (2017)	✓	✓		Two-stage stochastic			✓	✓
Moreno et al. (2018)	✓	✓		Two-stage stochastic		✓		✓
Shamsi et al. (2018)	✓			Stochastic model			✓	
Torabi et al. (2018)	✓	✓		Two-stage stochastic		✓	✓	
Keshvari et al. (2019)	✓			Dynamic				✓
Nagurney and Qiang (2020)	✓			Multiproduct network		✓	✓	
Aghajani and Torabi (2020)	✓			Stochastic model		✓	✓	
Boostani et al. (2020)	✓	✓	✓	Stochastic model		✓	✓	
Olanrewaju et al. (2020)	✓			Multi-stage stochastic			✓	

Nezhadroshan et al. (2021)	✓	✓		Possibilistic-stochastic	✓	✓	✓	
Yan et al. (2021)	✓			Deterministic				✓
Alem et al. (2021)	✓	✓		Deterministic		✓		✓
Foroughi et al. (2022)	✓	✓		Stochastic model	✓	✓	✓	
Klibi et al. (2018)	✓	✓		Deterministic	✓	✓	✓	
Zhang et al. (2012)			✓	Two-stage stochastic	✓	✓		
Su et al. (2016)			✓	Deterministic	✓	✓		
Yu et al. (2018)			✓	Dynamic				✓
Wang et al. (2019)			✓	Deterministic		✓		✓
Li et al. (2019)			✓	Deterministic	✓			
Doan and Shaw (2019)			✓	Two-stage stochastic	✓	✓		✓
Wang (2021)			✓	Deterministic		✓		✓
This article	✓	✓	✓	*Two-stage stochastic*	✓	✓	✓	✓

3. MODEL

3.1. Context of the situation

The relief network is prepared ahead of the disaster (first stage) to allow the system to react quickly and efficiently. Decisions at this stage include the selection of suppliers, location of critical facilities, and allocation of personnel to relief delivery activities. Critical facilities are managed by staff and are selected based on their distance to the affected regions, their capacity, opening cost, and number of employees required. A set of suppliers is selected to deliver relief to be prepositioned in regional distribution centers. Relief items are procured based on the price, the availability of stock, and their distance to the affected regions. Because of donation uncertainty, only items procured by the decision-maker are considered.

A set of scenarios are used in the second stage of the model to manage the uncertainty of demand. These scenarios must be based on reliable forecasts or historical information about the different events to leverage the formulation. Having that information in advance allows the model to explore the different combinations of variables to provide meaningful results. Prepositioned items from the first stage are supplemented by post-disaster procurement to deliver swift support [46]. Post-disaster procurement is undertaken every period to balance available stock and the demand from affected regions. Delivery trips are defined based on the distribution vehicles, staff available, and stock inventory at facilities per period. The scarcity of resources is reflected in the second objective function, which minimizes facility, procurement, staff, and delivery costs. Evidence about limitations in the resources available for immediate disaster response highlights the need to incorporate this dimension to support victims. This objective function shows the impact of different levels of investment, the type of resources required, and the extra level of investment needed for added resources beyond their current plan to decision-makers.

The inclusion of simultaneous disasters is a prominent feature of the model. Although resource allocation has been studied in these instances, there is an absence of research connecting procurement decisions with resource allocation, which affects the management of simultaneous disasters because of the existence of resource-dependent decisions [15]. The model proposed supports procurement, facility location, and distribution in the context of simultaneous disasters. Its impact is twofold; it incorporates equity among areas affected by the same disaster, and it prioritizes products among regions based on the nature of the disaster. The formulation can be easily modified to support compound or subsequent disasters by defining the quantity and type of demand at different periods in the same region. Hence, the model introduces a degree of flexibility to ensure every region is served appropriately. The priority level reflects the urgency of an affected area to allow optimal resource allocation [47]. Sabbaghtorkan, Batta and He [48] identify the priority of relief as a major gap in current studies in humanitarian logistics using the example of earthquakes and draughts, where medical supplies are crucial for the first whereas food and water are of the foremost importance in the second. Hence, the priorities stemming from the type of disaster come into play here, which are a distinctive characteristic of the model proposed as opposed to other contributions in the literature. The model tackles the need to consider the resources required based on the type of disasters [See 15]. That affects supplier selection, which relies on their characteristics and supply capacity, along with the capacity of the facilities selected, to ensure a quick and efficient response. The formulation proposed works in instances where disasters of the same type occur in different regions as well. Although the disasters would require the same products, the magnitude of the disasters can be considered to adjust the priorities to guide allocation. For instance, when there are two simultaneous earthquakes occurring in different parts of a country, the magnitude of the earthquake and the vulnerability of the affected areas can be used to define the priorities of delivery of relief. Simultaneous disasters occur at the same time or at similar times, so depending on the length of the time periods, this model can handle multiple disasters overlapping. Because of these reasons, the model adds flexibility to disaster management. Having a reliable forecast about the different events and their evolution over time, it can consider single disasters, multiple simultaneous disasters with different characteristics, disasters separated by one or more time periods, and hazards of different nature (e.g., sudden onset and slow onset). The reason is that the supply network defined by the model based on the probability profile can support all the different regions potentially affected, either individually or in conjunction.

3.2. Model notation

The model notation and definitions are presented in Table 2.

Table 2. Model notation and definitions

Sets		*Sets*	
i	Distribution center, i = [1, 2, …, |I|]	l	Regions affected by disasters, l = [1, 2, …, |L|]
j	Demand areas, j = [1, 2, …, |J|]	s	Scenario, s = [1, 2, …, |S|]
k	Potential suppliers, k = [1, 2, …, |K|]	t	Time periods, t = [1, 2, …, |T|]
n	Type of products, n = [1, 2, …, |N|]		

Parameters	
$\alpha_{k,n}$	Cost of product *n* from supplier *k* at stage the second stage
$\beta_{k,n}$	Supply capacity of product *n* from supplier *k*
γ_i	Cost of opening supply facility *i*
$\delta_{j,n,l,s}$	Demand of product *n* in area *j* at region *l* on scenario *s*
ε	Employees available
$\zeta_{i,j,l}$	Cost of each trip from supply facility *i* to demand point *j* at region *l*
η	Weight capacity of each vehicle
$\theta_{n,l}$	Priority of product *n* at region *l*
κ_k	Cost of the partnership with supplier *k*
λ_i	Personnel required per facility *i*
μ	Wage per employee
$\xi_{i,j,l}$	Coverage from facility *i* to area *j* in region *l*
π_s	Probability of scenario *s*
σ	Personnel required for distribution
ς	Number of periods for prepositioning

τ_i	Volumetric capacity of the distribution center *i*
Φ_n	Volume of product *n*
ψ	Number of periods
$\Omega_{k,n}$	Cost of buying product type *n* from supplier *k* at stage 1
First-stage decision variables	
A_k	Selection of supplier *k*; 1 if the supplier is chosen, 0 otherwise
X_i	Activation of distribution center *i*; 1 if the facility is opened, 0 otherwise
$Y_{i,k,n}$	Products type *n* bought from supplier *k* for distribution center *i* at stage 1
D	Number of warehouse employees allocated at the first stage
E_l	Number of employees allocated to distribution at the first stage in region *l*
Second-stage decision variables	
$INV_{i,n,t,s}$	Number of products *n* stored on facility *i* at period *t* at scenario *s*
$TT_{i,k,n,t,s}$	Product type *n* bought from supplier *k* for DC *i* at stage 2 at period *t* at scenario *s*
$G_{i,j,l,t,s}$	Trips from facility *i* to zone *j* at region *l* at period *t* at scenario *s*
$U_{j,n,l,t,s}$	Unmet demand of product *n* at area *j* in region *l* at period *t* at scenario *s*
$P_{n,l,t,s}$	Maximum unmet demand of product *n* in region *l* at period *t* at scenario *s*
$Q_{i,j,n,l,t,s}$	Products type *n* sent from *i* to *j* in region *l* at period *t* at scenario *s*

3.3. Model formulation

The model uses a single shared network of suppliers and facilities to avoid competition for resources among jurisdictions and achieving the optimal assignment of human and material resources [49].

The model is formulated using a two-stage stochastic approach. The pre-disaster phase is addressed at the first-stage and the second-stage is focused on the post-disaster phase [See 26]. Parameter $\xi_{i,j,l}$ represents the difficulty to reach the demand areas from facilities and it is determined based on road connectivity, maximum response distance, and path vulnerability. The model is structured as follows:

$$\min UD = \sum_n \sum_l \sum_t \sum_s P_{n,l,t,s} * \pi_s \quad (1)$$

$$\min cost = \sum_i X_i * \gamma_i + (\sum_l E_l + D) * \mu * \psi + \sum_i \sum_k \sum_n Y_{i,k,n} * \omega_{k,n} + \quad (2)$$

$$\sum_k \kappa_k * A_k + \sum_s \pi_s * (\sum_i \sum_k \sum_n \sum_t TT_{i,k,n,s,t} * \alpha_{k,n} + \sum_i \sum_j \sum_l \sum_t G_{i,j,l,t,s} * \zeta_{i,j,l}$$

Subject to:

$$U_{j,n,l,t,s} = \delta_{j,n,l,t,s} - \sum_i Q_{i,j,n,l,t,s} * \xi_{i,j,l} \qquad \forall\, j,n,l,t,s \quad (3)$$

$$P_{n,l,t,s} \geq U_{j,n,l,t,s} * \theta_{n,l} \qquad \forall\, j,n,l,t,s \quad (4)$$

$$INV_{i,n,t+1,s} = INV_{i,n,t,s} + \sum_k TT_{i,k,n,t,s} - \sum_j \sum_l Q_{i,j,n,l,t,s} \qquad \forall\, i,n,t,s \quad (5)$$

$$INV_{i,n,0,s} = \sum_k Y_{i,k,n} \qquad \forall\, i,n,s \quad (6)$$

$$\sum_n INV_{i,n,t,s} * VOL_n + \sum_n \sum_k TT_{i,k,n,t,s} * \Phi_n \leq X_i * \tau_i \qquad \forall\, i,t,s \quad (7)$$

$$\sum_i Y_{i,k,n} \leq A_k * \beta_{k,n} * \varsigma \qquad \forall\, k,n \quad (8)$$

$$\sum_i TT_{i,k,n,t,s} \leq A_k * \beta_{k,n} \qquad \forall\, k,n,t,s \quad (9)$$

$$G_{i,j,l,t,s} * \eta \geq \sum_n Q_{i,j,n,l,t,s} * \Phi_n \qquad \forall\, i,j,l,t,s \quad (10)$$

$$E_l \geq \sigma * \sum_i \sum_j \sum_l G_{i,j,l,t,s} \qquad \forall\, l,t,s \quad (11)$$

$$D = \sum_i X_i * \lambda_i \quad (12)$$

$$\sum_l E_l + D \leq \varepsilon \quad (13)$$

$$X_i, A_k \in [0,1]; \qquad D, E_l, Y_{i,k,n}, TT_{i,k,n,t,s}, G_{i,j,l,t,s}, U_{j,n,l,t,s}, P_{j,l,t,s}, Q_{i,j,n,l,t,s}, INV_{i,n,t,s} \in \mathrm{Z}$$

Objective function (1) minimizes the sum of the maximum number of unmet demand per disaster. Objective function (2) minimizes the total cost of first stage and second stage activities. Equation (3) calculates the number of people not served by the relief delivered at each demand area per disaster, whereas expression (4) determines the maximum unsatisfied demand considering the priority of each product per disaster. Equation (5) determines the inventory held per facility per period based on the items procured and delivered, whereas expression (6) determines the prepositioned stock of relief and constraint (7) ensures inventory is held in open facilities only. Expressions (8) and (9) constrain the maximum number of products that can be bought using the maximum capacity of selected suppliers at the first and second stage, respectively. Constraint (10) calculates the number of trips required and expression (11) determines the number of distribution employees needed. Equation (12) determines the number of warehouse employees required and expression (13) ensures the number of employees needed does not exceed the number of staff available. Finally, the declaration of variables is presented.

3.4. Model solution approach

Optimizing the two objective functions do not produce a unique solution, but a set of efficient solutions reflecting the trade-off between objectives and forming the Pareto front [50]. The problem has the form:

$Min\ \mathrm{F(x)} = (f_1(x), f_2(x))$ s.t. $g_i(x) \leq 0\ ;\ (i = 1,2, \dots, q);\quad h_j(x) = 0\quad (j = 1,2, \dots, p)$

In this kind of problem, one dimension can only be further improved by worsening the value of the other variable. This article uses the traditional ε-constraint method for solution [See 43]. The payoff table of both objective functions is obtained to create discrete ranges. One of the objective functions becomes a constraint and its range is used to solve a discrete number of experiments, turning the problem into:

$Min\ \mathrm{F(x)} = f_1(x)$ s.t. $g_i(x) \leq 0\quad (i = 1,2, \dots, q);\qquad h_j(x) = 0\quad (j = 1,2, \dots, p)$

with the additional constraint: $f_2(x) \leq \varepsilon_n$

The epsilon values are obtained from the payoff table depending on the number of iterations. The objective function is optimized for a number of iterations to create the Pareto front.

4. EXPERIMENTATION

Different disasters may require different products at different levels of priority. Even similar disasters requiring similar products respond based on the magnitude of the event and the vulnerability of the region. That makes the adjustment of priorities a crucial part of the model to guide decision-making. Sections 4.1 and 4.2 examine the performance of the model using disasters with different impact and needs.

The availability of different resources over time affects operations as well. Section 4.3 investigates the impact of facing multiple disasters over several time periods on prepositioning and post-procurement strategies. The randomly generated network for analysis is exemplified in Figure 1.

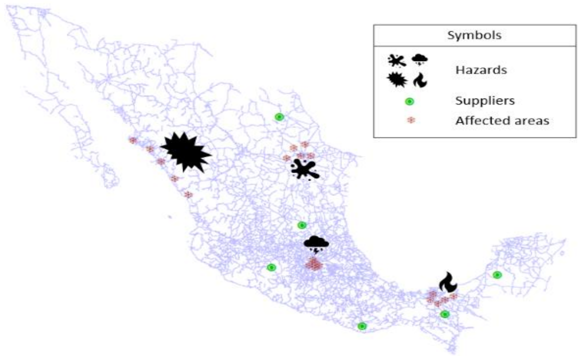

Fig. 1. Test case

It includes six candidate supply facilities serving 20 affected areas over 5 periods across four disasters (5 areas per region). Disasters are assumed to occur at the same time. Food, medicine, and cleaning kits are the products purchased from ten candidate suppliers. The demand of these items has been randomly generated using the standardized relief products defined by the Ministry of Interior [51]. These units simplify procuring, handling, and delivering disaster relief. The experiments have 9 potential scenarios with varying demand. The system has lower supply than immediate demand to reflect real conditions.

4.1. Analysis of disasters

The level of urgency per region depends on the damage caused by the disaster, the level of vulnerability of the area, the impact on economic activities, and media attention. The first set of experiments assume the same priority of products, but disasters of different magnitude. Four disasters with low priority (0.25) and high priority (0.75) produced 16 experiments (2^4). The UD was used as objective function and the COST objective function as constraint in the e-constraint method for 100 iterations using GAMS 33.

Table 3 shows the maximum unmet demand of each one of the areas in the non-dominated solutions. Results suggest that disasters with higher priorities (green) are consistently delivered a higher percentage of the total number of items shipped based on the relative priorities of other disasters. Consequently, the average number of unsatisfied people per region is considerably lower in disasters with higher priorities.

Table 3. Maximum unmet demand of each disaster region per scenario

Exp	R1	R2	R3	R4	Exp	R1	R2	R3	R4
E1	12,390	14,314	12,687	13,280	*E9*	4,137	17,648	15,730	17,335

E2	16,736	19,313	15,707	4,147	*E10*	7,206	20,756	20,422	6,144
E3	15,466	17,719	3,529	15,177	*E11*	6,491	21,172	5,766	20,285
E4	19,271	21,632	5,677	6,313	*E12*	9,844	24,693	8,634	10,046
E5	15,579	4,879	16,637	16,983	*E13*	6,106	8,163	19,548	20,787
E6	19,668	7,627	21,381	6,497	*E14*	8,359	10,071	24,179	9,490
E7	19,763	7,798	6,512	20,185	*E15*	9,100	10,412	8,298	23,140
E8	23,162	10,963	8,743	8,873	*E16*	11,358	13,366	11,810	12,899

4.2. Analysis of products

Simultaneous disasters can face different needs across areas, as the importance of certain products can be different depending on the type of hazard. That means disaster victims can require different products with distinct levels of urgency [52]. This section investigates the importance of these variations. A set of experiments has been prepared using the same network but with three types of hazards with the following priorities: (i) D1 – High priority of medicines and cleaning kits, low priority of food, (ii) D2 – High priority of food and medicines, low priority of cleaning kits, (iii) D3 – High priority of food and cleaning kits, low priority of medicine. The experiments include nine combinations of these occurring at different regions. The e-constraint method was programmed in GAMS 33 with 100 iterations per experiment. Table 4 shows the maximum unsatisfied demand across all scenarios. Instances with low priority of food, medicine, or cleaning kits (yellow) showed higher levels of unmet demand, whereas instances where any of the products was critical (green) showed a smaller portion of people without the products. The result suggests the model can dispatch the most important products where these are more critically needed, splitting them fairly, at the same time as human and material resources are used efficiently and effectively.

Table 4. Average maximum unmet demand

Exp	**Product**	**R1**	**R2**	**R3**	**R4**	**Exp**	**Product**	**R1**	**R2**	**R3**	**R4**
E1	*FOOD*	6,765	2,902	1,002	6,755	*E6*	*FOOD*	6,006	2,116	6,495	6,026
	MEDI	5,089	5,651	9,471	5,531		*MEDI*	6,018	6,458	6,317	6,244

	CLEA	1,666	5,372	856	1,973		*CLEA*	1,299	5,256	1,171	1,896
	FOOD	2,630	2,989	1,038	7,726		*FOOD*	6,711	2,259	1,359	6,763
	MEDI	5,562	6,097	9,501	5,962		*MEDI*	6,007	6,551	6,259	6,184
E2	*CLEA*	4,786	5,072	863	1,524	*E7*	*CLEA*	910	4,421	4,347	1,512
	FOOD	1,526	3,476	1,523	7,287		*FOOD*	7,815	2,816	1,144	2,533
	MEDI	8,411	5,274	8,922	5,253		*MEDI*	5,455	6,023	9,499	5,928
E3	*CLEA*	1,291	5,780	1,233	2,396	*E8*	*CLEA*	1,557	5,060	1,051	4,531
	FOOD	6,425	2,007	1,415	6,150		*FOOD*	7,258	3,078	1,488	1,322
	MEDI	4,359	8,568	8,700	4,703		*MEDI*	4,648	5,180	8,889	8,541
E4	*CLEA*	2,448	2,087	1,327	3,026	*E9*	*CLEA*	1,906	5,526	1,148	1,092
	FOOD	6,220	6,702	1,049	6,257						
	MEDI	5,168	5,788	9,615	5,687						
E5	*CLEA*	2,358	2,835	1,178	2,684						

4.3. Analysis of resources

This part provides insights about the impact on resources of having multiple disasters and multiple periods. The experiments include 25 instances varying from 1 to 5 simultaneous disasters with the need to support victims from 1 to 5 periods. Table 5 shows the solutions with the lowest level of unmet demand of the experiments. Situations with a single disaster or short duration (i.e., one or two periods) are completely served with the resources available. However, increasing the number of periods or the number of disasters adds significant pressure on the system. Neglecting any of those aspects can lead to overestimating the capacity of the response system. Disaster management plans need to consider the possibility of simultaneous disasters occurring over multiple periods to support victims effectively.

Table 5. Level of shortage of the different experiments

	One period	**Two periods**	**Three periods**	**Four periods**	**Five periods**
One disaster	0	0	0	0	0

Two disasters	0	0	0	0	0
Three disasters	0	0	10.01	25.21	38.14
Four disasters	0	71.83	461.28	717.01	847.21
Five disasters	0	587.33	1,715.80	2,223.17	2,533.15

Delivering relief requires buying products before and after the disaster. Figure 2 shows the percentage of capacity of prepositioned products and of the maximum number of products purchased at the second stage. These suggest that prepositioning inventory is an efficient way to react to disasters, even in instances with multiple periods. The complete prepositioning capacity was depleted in several instances, whereas the percentage of items purchased after the event was more sensible to the number of periods.

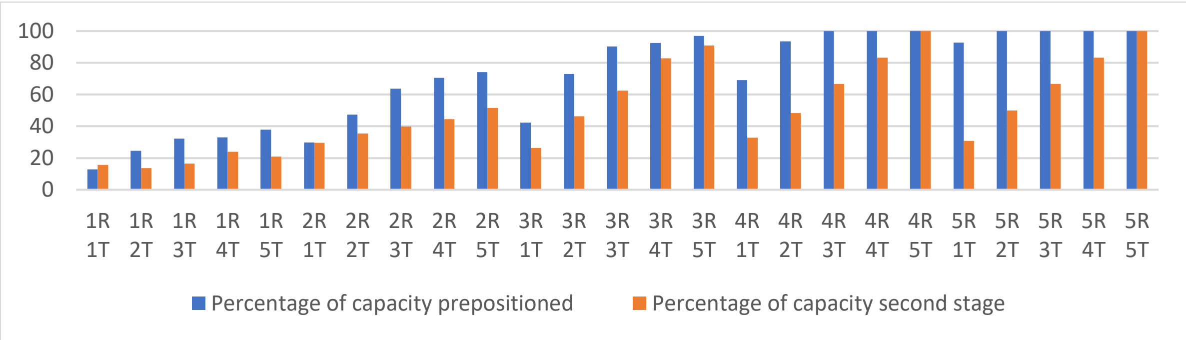

Fig. 2. Percentage use of prepositioning and post-disaster procurement

Thus, a good prepositioning strategy can be key to deal with simultaneous disasters over multiple periods.

5. CASE STUDY

5.1. Region of study

Mexico has been the second worst affected country by disasters in the Americas since 1950, behind the United States [53]. Hurricanes represent a large portion of those disasters [54]. These situations are even more problematic when different threats affect the country at the same time. As Mexico is vulnerable to the occurrence of multiple hazards [55], several disasters in the country have occurred simultaneously before [54]. The most notable example is recent years has been Hurricane Ingrid and Hurricane Manuel in September 2013, affecting the Gulf of Mexico and the Pacific coast at the same time. Around 155,000 people were affected by these disasters [54]. This research uses that case study for analysis.

5.2. Data collection

Official emergency declarations between September 16th and September 30th of 2013 issued by the Ministry of Interior (SEGOB) have been used to create the different regions as shown in Table 6.

Table 6. Groups of regions affected by each hurricane and rainfall

States (S / C)	Affected	States (E)	Affected	States (NW)	Affected
Guerrero	238,028	San Luis P.	46,926	Colima	15,523
Oaxaca	13,618	Nuevo León	3,663	Jalisco	31,598
Chiapas	15,746	Quintana Roo	14,263	Zacatecas	11,001
Morelos	4,014	Tamaulipas	29,958	Chihuahua	60,250
Michoacán	49,368	Veracruz	7,555	Nayarit	9,762
				Sinaloa	18,497

Source: Compiled by authors with information from SEGOB

Human and material resources available for disaster response were collected using freedom of information requests, transparency websites and reports. Human resources were aggregated from the different agencies involved, whereas the vehicles included were assumed to have a capacity of 4 tons, according to governmental reports about small trucks with capacities between 3.5 and 5 tons [56-58]. The capacity was set considering the use of small trucks accessible for relief agencies. A total of 22 suppliers involved in previous disasters were considered. Records from those purchases were used to identify pre-disaster procurement cost, supplier capacity, minimum order size (assumed at 1% of capacity), cost at the post-disaster stage (assumed to be 20% more expensive) and partnering cost. The Mexican food kit delivered to victims including coffee, chocolate, canned beans, fluor, powdered milk, rice, instant soup, chilies, tuna can, chilorio package, and oatmeal cookies was adopted. These items and their consumption have been standardized to satisfy the dietary requirements of victims for their survival according to Mexican regulations [51]. Kits are used to facilitate the process of delivery and ensure the different needs from the victims are satisfied [50]. The supply facilities used were obtained from Diconsa, which handles the distribution of products for social programs and disaster management [59]. These were geo-referenced using Google Earth® and located using ArcGIS®. The geographical layers for network analysis are publicly available from the Mexican Institute of Statistics and Geography (INEGI) [60]. These layers were imported into TransCAD® for multiple path analysis. The results were used to determine road connectivity and cost calculations. The network can be seen in Figure 3.

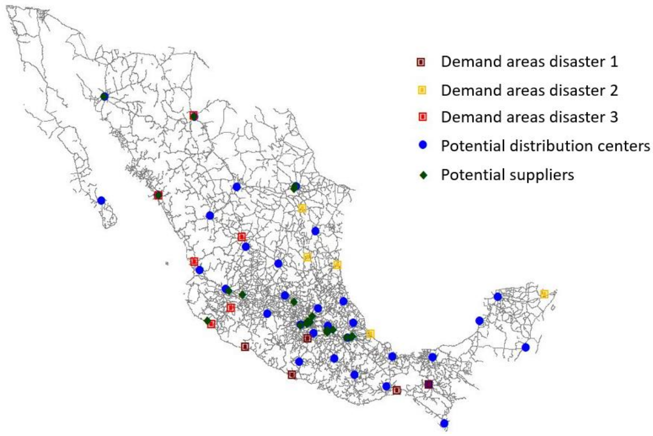

Fig. 3. Case study network

Information about the impact of Hurricanes Ingrid, Manuel, and heavy rainfall was found in the emergency declarations. Two situations were considered for scenario development: the real conditions (R), and an increase of 50% of the affected population (I). That led to 8 scenarios (2^3). As there was no information about decision-maker priorities, the priorities were considered similar. However, that can be easily adjusted by the user. Demand was obtained from authorities based on the real events from the Mexican Disaster Prevention Centre (CENAPRED), which led to the probability profiles presented in Table 7.

Table 7. Scenarios used

Scenario	**R1**	**R2**	**R3**	**Prob**	**Scenario**	**R1**	**R2**	**R3**	**Prob**
S1	I	I	I	0.04	S5	R	I	I	0.07
S2	I	I	R	0.07	S6	R	I	R	0.15
S3	I	R	I	0.07	S7	R	R	I	0.15
S4	I	R	R	0.15	S8	R	R	R	0.30

Source: Compiled by authors with information from CENAPRED [61]

5.3. Results of the case study

The e-constraint method was programmed in GAMS using the solver CPLEX to obtain the non-dominated solutions. Each one of them represents a non-dominated point, which is not improved in both, cost, and shortage, by any other point. The summary results can be seen in Table 8. Each result contains a set of decisions for first and second stage variables which are made based on the information from all the scenarios. The first stage variables are scenario independent, meaning that their value does not change depending on the scenario. Second stage variables are scenario dependent, and each decision has a value per scenario. The table shows the maximum value per scenario per period for the second stage variables (trips and post-disaster procurement). The trade-off between both objective functions is evident with variations in cost/benefit. For instance, the cost of ND13 is more than twice of the cost of ND12, but that affects less than 10% of the maximum shortage. More steep investments are required to ensure that all the people affected receive relief. Solutions ND15 and ND16 are interesting for service-oriented users. To move from ND15 to ND16 there is a need to access considerably more resources, which makes a significant difference in demand met. Given the priorities and constraints from authorities, the results can be the basis to explore the most acceptable trade-offs for them and identify a suitable solution.

Table 8. Summary of the results of the case study

ID	Cost	Shortage	Sup	Fac	Staff	Max trips	Pre-positioned	Max procured 2nd
ND1	0	2,605,981	0	0	0	0	0	0
ND2	800,000	2,421,180	2	1	60	19	171,547	39,182
ND3	1,600,000	2,276,763	2	1	144	40	327,556	74,479
ND4	2,400,000	2,163,042	3	1	166	44	444,993	71,534
ND5	3,199,999	2,047,740	3	1	177	63	571,690	74,480
ND6	4,000,000	1,937,711	4	1	210	67	679,903	123,123
ND7	4,799,996	1,837,654	4	1	265	83	767,148	147,336
ND8	5,599,996	1,750,616	5	1	309	100	855,584	174,261

ND9	6,400,000	1,668,476	5	1	375	150	928,606	235,119
ND10	8,000,000	1,645,178	5	3	749	166	629,731	566,261
ND11	8,799,999	1,520,708	5	2	677	206	889,396	461,448
ND12	16,800,000	1,319,758	6	9	2,391	312	711,425	1,174,592
ND13	34,400,000	1,208,073	14	14	4,389	606	161,634	2,925,030
ND14	36,800,000	965,004	14	14	4,621	634	1,057,474	2,289,522
ND15	40,000,000	363,735	9	7	2,966	743	1,924,683	1,749,956
ND16	76,799,999	3,251	10	5	5,706	2,000	3,157,735	1,527,558
ND17	78,398,271	3,108	10	9	6,387	1,579	3,127,818	1,549,301
ND18	79,199,993	2,471	10	9	6,563	1,411	3,147,209	1,568,778
ND19	80,799,998	2,467	10	9	6,942	1,385	3,136,679	1,560,048
ND20	81,600,000	333	14	9	6,606	1,526	2,724,866	2,032,422
ND21	82,400,000	0	17	6	6,423	1,472	2,844,972	1,912,318

According to the results, current agreements with suppliers provide enough capacity to support disaster management. All the areas affected can be served by tapping into the current pool of suppliers from authorities. However, three of them have not been selected by any of the non-dominated solutions.

The number of facilities, employees, relief items and trips increase in solutions focused on reducing shortage of relief. However, using more suppliers or more facilities does not necessarily reduce shortage. In solutions ND13 and ND14 for instance, the model activates more facilities and suppliers than several solutions, but the shortage is not the lowest. That is because in those points second-stage procurement is preferred over stock prepositioning, making more facilities and suppliers necessary to outweigh second-stage uncertainty. This balance between pre-positioned stock and procurement is seen across all solutions, with victim-oriented solutions slightly preferring stock prepositioning to reduce uncertainty.

The capacity of the model to handle simultaneous disasters is reflected in this part. Table 9 shows the details about the minimum, maximum, and average values of the maximum unmet demand in each region. The focus on balancing product dispatch among regions is noticeable. Based on the needs and resources available, the requirements of disasters 1 and 2 are completely covered since ND20, whereas disaster 3 requires an extra investment of MXN $800,000 to be completely served. This information can help inform decision-makers about the different investments needed to satisfy vulnerable regions.

Table 9. Maximum unmet demand

Sol	**Dis**	Min	Max	Average	**Sol**	**Dis**	Min	Max	Average
ND 1	*R1*	2,024,154	3,036,242	2,530,198	*ND 12*	*R1*	1,022,786	1,692,517	1,362,063
	R2	315,876	473,836	394,856		*R2*	198,550	353,019	263,501
	R3	817,916	1,226,885	1,022,401		*R3*	589,549	942,685	771,680
ND 2	*R1*	1,851,706	2,827,011	2,339,102	*ND 13*	*R1*	928,834	1,268,026	1,085,885
	R2	315,876	473,836	394,856		*R2*	91,760	256,678	181,896
	R3	817,916	1,226,885	1,022,401		*R3*	315,662	647,039	500,300
ND 3	*R1*	1,762,783	2,724,592	2,244,273	*ND 14*	*R1*	655,514	1,181,196	837,625
	R2	300,408	457,305	378,483		*R2*	99,650	241,735	168,471
	R3	764,714	1,158,239	961,062		*R3*	312,685	603,986	469,410
ND 4	*R1*	1,661,962	2,613,896	2,138,392	*ND 15*	*R1*	251,586	563,453	396,275
	R2	295,878	457,864	377,663		*R2*	50,716	123,345	87,797
	R3	747,966	1,157,972	951,465		*R3*	176,428	387,758	287,543
ND 5	*R1*	1,556,495	2,523,673	2,033,269	*ND 16*	*R1*	1	2,743	722
	R2	294,217	446,614	370,479		*R2*	16	6,155	1,090
	R3	730,374	1,135,683	932,418		*R3*	183	50,731	24,982
ND 6	*R1*	1,477,758	2,438,216	1,948,749	*ND 17*	*R1*	0	11,081	1,823
	R2	261,041	416,341	339,198		*R2*	0	5,955	1,878
	R3	728,844	1,138,075	929,902		*R3*	0	50,553	23,253

ND 7	*R1*	1,408,499	2,291,696	1,847,684	*ND 18*	*R1*	0	238	36
	R2	261,045	418,303	340,580		*R2*	0	2,184	508
	R3	715,712	1,112,749	913,839		*R3*	1,896	28,562	13,909
ND 8	*R1*	1,337,432	2,202,147	1,771,086	*ND 19*	*R1*	0	1,410	199
	R2	259,975	418,473	339,695		*R2*	0	2,400	309
	R3	694,581	1,090,371	892,139		*R3*	0	48,190	21,212
ND 9	*R1*	1,286,306	2,098,957	1,691,660	*ND 20*	*R1*	0	0	0
	R2	256,245	418,153	338,766		*R2*	0	0	0
	R3	674,088	1,063,655	872,408		*R3*	0	12,696	1,587
ND 10	*R1*	1,214,548	2,034,663	1,647,279	*ND 21*	*R1*	0	0	0
	R2	258,497	417,201	338,370		*R2*	0	0	0
	R3	715,036	1,106,112	906,320		*R3*	0	0	0
ND 11	*R1*	1,145,512	1,964,897	1,551,250					
	R2	241,042	403,033	320,572					
	R3	663,153	1,076,621	867,590					

5.4. Analysis of independent disasters

This section contrasts the results of considering and disregarding simultaneous disasters using the case study. A set of experiments has been prepared assuming each disaster is tackled independently. The ε-constraint method was used to run 25 iterations of each model. The results of each region were combined to identify the non-dominated solutions. The comparison between these results and Table 8 can be seen in Figure 4. There is an important effect on cost and shortage, as the aggregated results are dominated by the solutions of the model. That means similar investment incurs higher levels of unmet demand. Considering isolated disasters delivers solutions that work well for the local disaster, but not necessarily for the whole system. The number of facilities and the network of suppliers required for handling the three disasters as independent events is usually higher than the number required by the model. The three most service-oriented solutions require 22 suppliers and 15 facilities, which is higher than the ones used in ND21. The reason is that some facilities and suppliers beneficial for one region are not necessarily used by others. That is also reflected in an increasing number of employees (over 1,916 more staff required) and higher cost. The major drawback is feasibility. The two most service-oriented solutions exceeded the capacity of suppliers. Although disasters are assumed to be independent, they share the same network of suppliers and their constraints. Neglecting the effect of other disasters leads to overestimating supplier capacity, which means activating/looking for new suppliers, which delay delivery and increase cost.

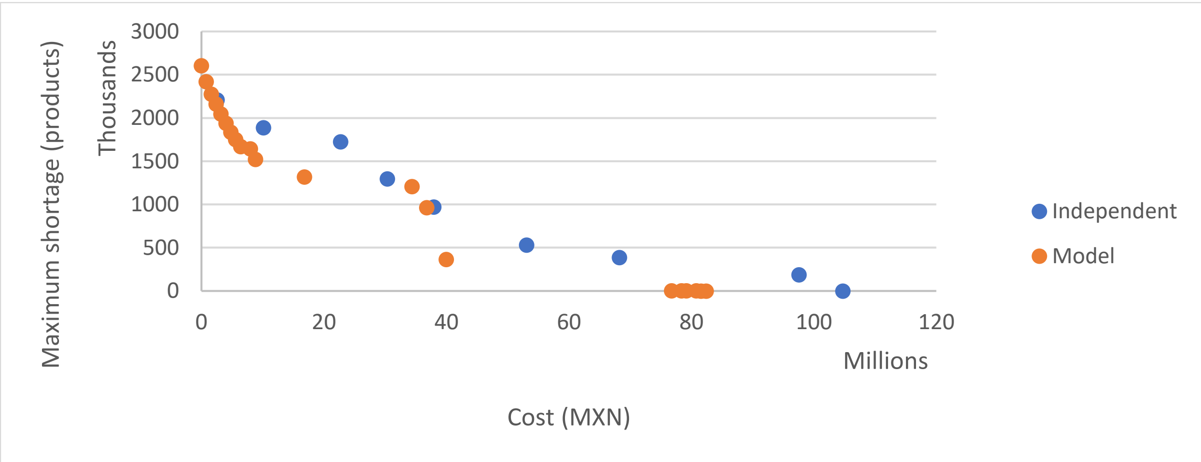

Fig. 4. Comparison between the results of the model and the Pareto front of independent disasters

Clearly, it is very complicated to assume every disaster will be completely independent. Therefore, another comparison assumed that each situation was allocated a third of the resources available at the beginning (based on the same priorities). The problem found with this approach is that deciding on the split of resources can disadvantage some instances. Table 10 shows the comparison of the most service-oriented solutions obtained by the model, the experiments assuming independent response, and the experiments splitting resources equally. The solution splitting resources is the only one where all demand cannot be covered. The reason is because two areas were given more resources than needed to tackle the situation, whilst one instance had insufficient resources to satisfy the needs of the community. Interestingly, the model favors a pre-positioning strategy, whereas the experiments assuming independent disasters focused on post-disaster procurement. That can be linked to the balance between uncertainty of the situation and supplier capacity. For instances with independent disasters, uncertainty is associated with a single region, whereas with simultaneous disasters there is demand uncertainty in several regions. The constraint of capacity of suppliers requires a reliable amount of stock prepositioned.

Table 10. Comparison of results between the experiments and the model

Solution	Cost	Shortage	Sup	Fac	Staff	Max trips	Pre-positioned	Max post-procured
Model	82,400,000	0	6	17	6,423	1,472	2,844,972	1,912,318
Independent	104,748,866	0	15	22	8,339	1,557	1,360,496	3,453,700
Split	102,609,337	2,752	22	14	10,627	1,560	2,013,963	2,698,085

The analysis in this part has shown the problems of using standard models for independent decision-making in situations with simultaneous disasters. The results suggest that overestimation of resources, more expensive solutions, the use of more complex networks of facilities and suppliers, and increased level of shortage are drawbacks of neglecting simultaneous disasters in humanitarian logistics models.

6. DISCUSSION

6.1. Discussion of the numerical experiments

Simultaneous disasters share a common set of resources needed to provide support in the different areas [15]. The results show the capacity of the model to support procurement, facility location, resource allocation, relief distribution, and inventory management over several periods in simultaneous disasters. As disasters vary in magnitude and affect communities with different levels of vulnerability, authorities tend to allocate more resources to the most affected communities [62]. The model introduces this logic using a weighting factor. In the first set of experiments, the results showed negligible variation in the overall number of people served but a significant variation in the number of items distributed per disaster. The model achieved the highest level of overall support at the same time as most urgent areas were given priority. Current formulations neglecting multiple disasters fail to consider these priorities.

As each disaster can be different, the products required can also be different [52]. The relief used for an earthquake can be different from the relief needed for a nuclear incident or a flood. When a single disaster occurs, it is possible to adjust the level of demand of each product and even their priority to guide decision-making. In the case of simultaneous disasters, however, that is complicated if the disasters are not disaggregated. Even if the demand is adjusted to only include the products required by the disaster, it will have common resources used in different disasters with different priorities [15]. For instance, first aid kits can be used in earthquakes and floods. These are crucial in the former to save lives, whereas in the latter these are used to treat less urgent victims. As most resources are finite, it is necessary to reflect their relative importance to manage simultaneous disasters successfully. The second set of experiments showed the capability of the system to increase the flow of the products accounting for their importance to each one of the different disasters. That result suggests that the model can help regulate the allocation of resources in different disasters considering their relative importance and different community needs.

The third set of experiments showed the importance of considering multiple disasters and multiple periods in planning. Even if the disaster response system can handle situations for few periods or single disasters, there is a significant pressure added by multiple periods and disasters. When information is available about the potential impact of disasters and the evolution of the events, the model provides guidance to maximize the service for victims. These factors are essential to design useful strategies in practice. Aligned to the comments from Sabbaghtorkan, Batta and He [48], the model incorporates priorities among disasters and products. Current models struggle to disaggregate the different types of disasters and needs through time, which is one of the contributions of the model. As shown by the results, systems tackling single independent disasters, or considering a short time horizon, would be overwhelmed by the occurrence of multiple disasters of long duration. This article is filling the need to combine interconnected logistics decisions (i.e., facility location, procurement, resource allocation, and relief distribution) considering the occurrence of different disasters and maintaining fairness among the different events.

6.2. Discussion of the case study results

The case study showed the performance of the model in a real-world instance. The findings show the way the number of suppliers, facilities, employees, relief procured, and number of trips adapts to decision-maker preferences considering the trade-off between both objective functions. The model uses different strategies to support logistics decisions, which shows the relevance of having an integrated formulation. The analysis shows that the supplier base and the number of facilities available have enough capacity to handle all the scenarios tested. In fact, it is possible to identify the key strategic suppliers that represent the basis for most of the solutions. Over 95% of the solutions included suppliers 1 and 23, which are the largest suppliers (4 and 3 different types of products supplied, respectively). These two suppliers were the cornerstone of the non-dominated solutions and were just complemented by smaller suppliers for specific products. That suggests the need to have very clear agreements with them and the possibility to strengthen those links for future planning. Conversely, the analysis shows that three suppliers were not included in any of the non-dominated solutions, which suggests a need to reflect on the agreements with them. The results show that the model looks for a mix of different types of suppliers that can help satisfy the requirements from the different areas considering the peak in demand whilst reducing cost.

The findings suggest the value of considering the evolution of the event [50]. The results provide a detailed account of when and how many products need to be procured, the number of trips and deliveries per period, when and where to allocate human resources for transportation, and the levels of inventory per period. The solutions suggest that the model can adjust to varying demand profiles across periods.

The comparison with models for independent decision-making shows the value of the proposed formulation. The unfeasible solutions reached when the interconnectedness of the disasters is neglected, and the sub-optimal solutions obtained from splitting resources beforehand show the need to have a formulation that can consider multiple concurrent disasters. Particularly, the overestimation of supply, the difficulty sharing overlapping resources, and the localized supply networks worsen performance.

Commonly, authorities use a common set of finite resources [10], both human and material, to handle simultaneous disasters. The model can consider the impact of one disaster on the availability of resources for other disasters of using shared resources in each contingency, unlike current formulations. That provides a more concrete and realistic view of the situation and the limitations of the response system.

Overall, the results presented provide evidence of the value of the formulation. Although simultaneous disasters are increasing and there are several benefits for decision-makers of considering this dimension, it is a understudied area currently [15]. This article contributes to the literature by formulating a novel bi-objective stochastic multi-period model to support decision-making about procurement, facility location, inventory management, relief distribution, and resource allocation over time in instances caused by simultaneous disasters. The model can deal with different types and magnitudes of disasters. It balances resources considering the urgency of the different areas and the relative importance of the products required. It can help decision-makers to have more clarity about their capabilities to handle these situations and to identify critical infrastructure and suppliers required to strengthen the response system.

6.3. Limitations

The model has several benefits for decision-makers, but it is important to be mindful of its limitations. A two-stage approach is based on average values, but the uncertainty of disaster situations is always challenging. The model requires reliable information about all disasters from forecasts, historical data or expected impact to account for the impact and evolution of the event, as it cannot adapt to new conditions or account for unforeseen disasters without having to run the model again. That must be supported by reliable probability profiles, which can include the occurrence of single and multiple disasters to have a realistic view of potential situations. In that sense, the damage to the road network, evacuee behavior, and the behavior of first responders depend on the context and conditions of the disaster, which require an analysis at the granular level. Those limitations of the model open opportunities for further work to adapt its ideas to more specific conditions based on historical information (recurrent disasters) and the priorities of the civil protection system. Additionally, there is an opportunity to introduce a heterogeneous fleet of vehicles to provide more alternatives for distribution and to adapt to the participant organizations. The model considers consistent supply before and after the disaster. The reason is because suppliers are assumed to be located outside of vulnerable regions. However, it is possible that suppliers can be affected by the disaster, which would require new models including uncertainty of supply or variations in the supply capacity from suppliers. This study tackles the effect of those aspects by using information about the capacity of suppliers at the time of disaster, which would be lower than in normal conditions.

One of the complex features of simultaneous disasters is the possibility of having local authorities in different regions that need to cooperate under the constraints of jurisdictions. The model assumes that all organizations have the attributions to help on the different regions because it assumes that is a sensible approach in large-scale disasters, but smaller instances would have to be very mindful of the response system and governance. Finally, the model does not include the impact of donations on the operations. Although donations make a significant difference, even experienced NGOs struggle to know how much relief they will receive [63]. This study focuses on the use of resources obtained by the decision-maker directly, but further studies can investigate the inclusion of donations to support response.

7. CONCLUSION

Simultaneous disasters are a global threat. This paper introduces a novel bi-objective dynamic two-stage stochastic model for humanitarian logistics to deal with situations caused by them. The novel formulation supports decisions about procurement, facility location, inventory management, relief distribution, and resource allocation for multiple periods. It considers multiple distinct regions affected by concurrent hazards with different magnitude and needs. The model includes the differences in priorities and requirements between disasters and it promotes fairness in the areas affected. The performance of the model has been shown with numerical experiments and a case study in Mexico in 2013.

The numerical examples presented show the importance of accounting for the level of urgency in different regions and the priority of products required based on the nature of the crisis. Models focused on supporting a single crisis can struggle to balance the allocation of scarce resources among distinct areas effected by different hazards. As different disasters can require the same resources with a different degree of urgency, models need to consider different requirements to support informed decision-making about the use of resources. The ability to consider the requirements and priorities of different disasters over different periods is a distinctive feature of the model, as these can affect the performance of the response system. The results consistently showed how the model can split resources based on the characteristics of the different areas and disasters without worsening the global response.

The results of the case confirmed the capacity of the relief supply chain in Mexico to cope with simultaneous disasters. The model handled the large instance effectively and highlighted key suppliers using scenarios. It showed the importance of considering simultaneous disasters to avoid overestimating the response capacity of civil protection systems, as the comparison with models focused on independent disasters showed the potential for unfeasible solutions and sub-optimal global performance.

The study also opens different opportunities for future research. The design of a heuristic algorithm to solve the formulation and select the best solution from the Pareto front based on the priorities of decision-makers would expedite response. The development of a multi-agency formulation for simultaneous disasters would prevent the convergence of human resources. Finally, considering uncertainty in supply and a heterogeneous fleet would give decision-makers more confidence to foster implementation.

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