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Multicriteria optimization approach to deploy humanitarian logistic operations integrally during floods

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Abstract

This paper addresses frequent and foreseeable floods in the short-term preparedness of an imminent event using a multicriteria optimization model integrated with a geographical information system to simulate flood levels, determine the best strategies, and update information. The proposed model takes into account the four main relief operations: location of emergency facilities (i.e., distribution centers, shelters, and meeting points), prepositioning of humanitarian aid, evacuation, and distribution of humanitarian aid. Three criteria are considered in the formulation to minimize: the maximum evacuation flow-time, the maximum distribution flow-time, and total cost of relief operations. The approximation to the efficient frontier is built using multiobjective programming through the use of commercial software. The usefulness and robustness of the model are verified using data from one of the worst Mexican floods considering various flood levels created from three key elements in humanitarian logistics. The strategies provided by the proposed methodology are compared with those implemented by the Mexican authorities during the studied disaster.

Keywords: multiple-objective programming; efficient solution; weighted-sum method; ε-constraint; humanitarian operations

1. Introduction

Natural disasters have impacted the world's population throughout the history of humanity with terrible consequences for inhabitants and their environment, as observed in several disasters over the past decade reported in Aon Benfield (2016). According to the International Database of

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Disasters EM-DAT (2016), the number of disasters affecting countries around the world is apparently increasing, as well as the number of people affected by them (approximately 4.8 billion people were affected by natural disasters between 1970 and 2003 compared to around two billion people in the last decade). However, the number of victims is decreasing, showing the ability of the community to protect itself and increase its resilience.

Among natural disasters, the maximum percentage increase is shown by hydrometeorological disasters, which constituted a share of 82% during the last decade (23% more than in the period 1970–2003) and affected almost one billion people. These disasters are closely related to seasonal weather events and can be accurately simulated in time, location, and magnitude, allowing for the growth of more effective plans to address their consequences (Díaz-Delgado and Gaytán, 2014).

Disaster management is related to planning, implementing, and controlling effective strategies to alleviate human suffering and reduce negative effects of disasters. The so-called disaster management cycle is divided into four phases (Tomasini and Van Wassenhove, 2009): mitigation, preparedness, response, and recovery/reconstruction. Despite the knowledge gained during the last two decades, disaster management remains a major challenge, creating important research opportunities in the analysis of integrated humanitarian operations and the application of multiple-criteria decision making (see Ortuño et al., 2013; Leiras et al., 2014; Gutjahr and Nolz, 2016).

Multiobjective optimization is a research field that has grown since the end of the last century and it is gaining more traction given the opportunities to analyze tradeoffs of multiple criteria in the same model (Ehrgott, 2005). In general, the related techniques provide a decision maker the opportunity to identify and evaluate various alternative high-quality approximations to optimal solutions (nondominated or Pareto optima) in order to support her final decision. This is particularly useful for decision makers in humanitarian contexts where there are diverse conflicting criteria in the operations. Furthermore, stakeholders assess the scarce resources or try to meet specific values, then they need to find the most suitable solution, and multicriteria optimization provides them this.

The aim of our approach is to introduce a methodology to make better decisions during the disaster preparedness phase, when the event is about to occur and becomes an emergency. This methodology involves two phases: (a) a geographical information system (GIS) that is used to simulate flood maps and evaluate damage in the available infrastructure (i.e., road network and potential emergency buildings) and (b) a multiobjective optimization model to determine the number and location of emergency facilities to be opened and the flow of evacuees and humanitarian aid through the available network using multiple vehicles, taking into account several criteria: evacuation and distribution flow-time, budget usage in various flood cases.

Therefore, the main contribution of this paper with regard to similar studies (e.g., Rodriguez-Espindola and Gaytan, 2015) is the formulation of a multicriteria optimization model that contemplates a novel approach in evacuation using a two-tiered strategy via meeting points, considers infrastructure saturation and availability of resources (i.e., vehicles, budget, facilities), and minimize the worst-case scenario to perform people evacuation and distribution of relief products under diverse circumstances in the short term after the disaster occurs. The paper is organized as follows. In Section 2, a brief literature review is presented. In Section 3, the framework of the proposed methodology is described together with the mathematical formulation of the problem under study. Once the methodology and the model are described, the results of a real Mexican case study related to a large flood in 2007 and a set of test instances are discussed in Section 4. Finally, Section 5 presents the study's conclusions and a number of suggestions for future work.

2. Literature review

In the last decade, a large number of studies has been published regarding humanitarian logistics and mathematical modeling. Among them, a number of review articles have been published in the last few years (see Ortuño et al., 2013; Leiras et al., 2014; Saafer et al., 2014; Özdamar and Ertem, 2015) underlining the importance of multicriteria optimization in the disasters relief field.

Humanitarian logistics is one important area of focus for multiple criteria. In this research field, cost is not a central criterion but rather other criteria, such as effectiveness, unmet demand, response time, flexibility, reliability, and equity have become more relevant to alleviate human suffering (see Balcik et al., 2008; Campbell et al., 2008; Ortuño et al., 2011; Vitoriano et al., 2011; Huang et al., 2012, 2015; Liberatore et al., 2014). The review of Gutjahr and Nolz (2016) is a complete work on relevant criteria and methodologies for multicriteria optimization in the field. Other authors have avoided addressing several criteria at the same time through the use of tradeoff functions as the deprivation cost (see Holguín-Veras et al., 2013).

Furthermore, important efforts have been made to create risk maps through GIS to feed mathematical models with updated information from natural disasters (Coutinho-Rodrigues et al., 2012; Esmaelian et al., 2015; Rodríguez-Espíndola and Gaytán, 2015), but there are still opportunities to be addressed in their combined use. On the other hand, research has focused on either addressing humanitarian operations such as evacuation and inventory management (see Beamon and Kotleba, 2006; Huang et al., 2012), distribution operations (see Barbarosoğlu and Arda, 2004; Özdamar et al., 2004; Chang et al., 2007; Tzeng et al., 2007; Vitoriano et al., 2011; Liberatore et al., 2014; Garrido et al., 2015), and location of emergency facilities separately or combining only a few of them:

- location of shelters and evacuation operations (see Barbarosoğlu et al., 2002; Sakakibara et al., 2004; Balcik et al., 2008; Coutinho-Rodrigues et al., 2012; Esmaelian et al., 2015).
- location of distribution centers and distribution operations (see Mete and Zabinsky, 2010; Nolz et al., 2010; Yushimito et al., 2012; Rodríguez-Espíndola and Gaytán, 2015).

In summary, there is a lack of an integrated formulation for humanitarian logistics operations to evaluate preparedness during emergencies taking into account future easily-updated operations to be used in the response phase in the following pair of critical days from the disaster aftermath. This gap has been overlooked due to the scarcity of countries that have a unique interagency decision maker for coordination and assignment of responsibilities regarding disaster management (see United Nations Development Programme, 2014). However, a few exceptions can be found (Chang et al., 2007; Huang et al., 2015; Rodríguez-Espíndola and Gaytán, 2015).

Chang et al. (2007) focused on simultaneous location of distribution and evacuation facilities, as well as in the intrazonal distribution and interzonal backup. Multiple locations, echelons, and levels in the network to ease the decision-making process in the preparedness and response phases of a flood are considered. Flood cases are forecasted/simulated via GIS. The model determines prepositioning of supplies and vehicles, as well as the flows of material over a transportation network to reach the affected areas at minimum time and cost.

Meanwhile, Huang et al. (2015) proposed a dynamic multiobjective optimization model that combines resource allocation with emergency distribution during the response phase. A time–space

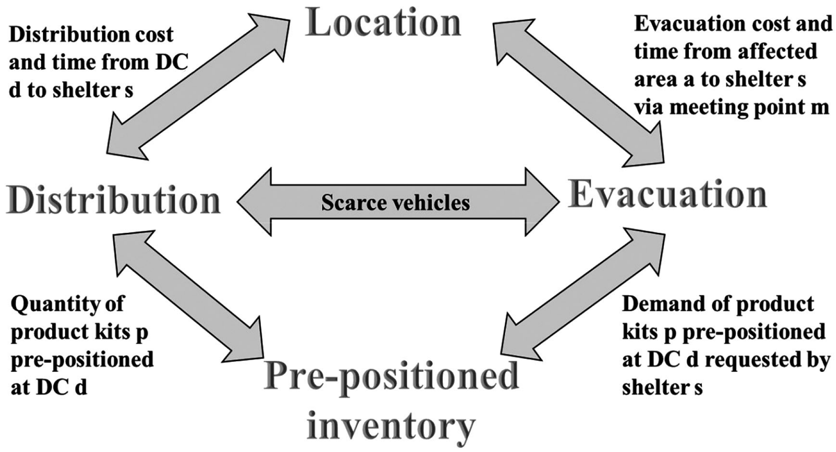

Fig. 1. Connections among humanitarian logistics operations and their resources.

network is used to incorporate information and decision updates in a rolling horizon approach. The authors used life-saving utility, delay cost, and fairness as criteria. Despite considering the dynamism of this complex decision (a feature of the scope of our research), the model does not integrate evacuation and distribution operations or takes advantage of GIS. Finally, Rodríguez-Espíndola and Gaytán (2015) proposed a multicommodity, multimodal, multicriteria model addressing the location of emergency facilities and prepositioned relief items focused on distribution operations.

This approach is initially concerned with the preparedness phase because we address integrally the location of emergency facilities and prepositioning of humanitarian aid, taking into account the evacuated people and their immediate needs of humanitarian aid among demand–supply pairs in the humanitarian network (see Fig. 1). The latter guarantees providing the critical resources in less than 48 hours after a disaster occurs, and avoids causing chaos in the shelters and reduces human suffering. Diverse vehicle types are used to move people or humanitarian aid. Furthermore, additional replenishment operations of humanitarian aid will be repeatedly performed in the period after the first 48 hours.

Figure 2 illustrates our approach in terms of how multiple relief items are carried from open distribution centers to active shelters while the evacuation of the affected population is performed in a two-tiered process from affected areas to shelters (via meeting points). This chart is helpful to understand how humanitarian operations are deployed in the field by the stakeholders. This chart shows the relief operations that are typically performed in case of severe floods and provides a brief scheme of the problem description.

This study partially overlaps Rodríguez-Espíndola and Gaytan's (2015) work by considering the use of a GIS procedure, distribution of humanitarian aid, and location of facilities and a similar solution approach. However, our proposal integrates GIS as the basic tool to create different instances, not only based on different water levels, but also to gain flexibility on integrated evacuation and distribution strategies that a unique decision maker needs to perform in a coordinated way with its diverse active members during emergencies. This paper also extends previous approaches to (a) contemplate two-tiered evacuation operations via meeting points that allow gaining flexibility, efficiency in the evacuation of nearby affected areas, and the effective utilization of vehicles transfer-

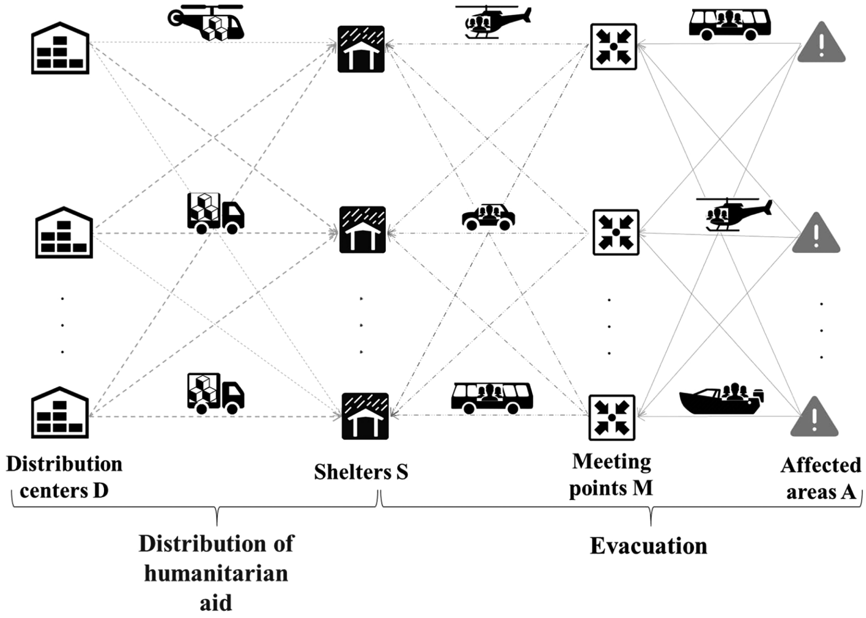

Fig. 2. Scheme of humanitarian operations activities included in the model.

ring evacuees to shelters; (b) consider road saturation under distinct flood cases to study the impact of road capacity using a congestion multiplier in the chosen humanitarian strategies; (c) take into account availability of vehicles for the humanitarian logistics operations to analyze how scarcity of resources affects both operations of a global humanitarian decision maker (interagency group); and (d) minimize a worst-case scenario to evacuate people and distribute relief products respecting evacuation and distribution flow-time under diverse circumstances.

3. Integrated methodology

This research combines the use of GIS with an optimization model for the analysis of frequent flood cases with short response time, underlining the integration of location of emergency facilities together with the allocation of humanitarian operations. The GIS procedure uses public data to simulate flood levels and define remaining road networks, nonisolated candidate facilities, and damage in the affected areas. The outcome is used to feed a mathematical programming model able to determine which facilities should be opened, how to evacuate people, and how to supply humanitarian aid to open shelters. The model includes time and cost, and a multiobjective programming approach is performed to obtain an approximation to the efficient frontier.

To develop this methodology, the following assumptions were made with the stakeholders:

(1) Affected areas are classified as in isolated (unreachable by ground transport) and nonisolated areas to let the stakeholders decide the type of vehicles to be used in the operations.

(2) The GIS procedure is able to determine locations of meeting points (i.e., transfer points) for different flood levels to link isolated areas with the connected network to facilitate evacuation under dynamic conditions (see Esmaelian et al., 2015).
(3) Available resources (i.e., emergency facilities and vehicles) and their capacities, locations, and costs are known in advance at every node of the proposed graph.
(4) Vehicles belong to different types (i.e., helicopters, buses, trucks, cars, and boats), are sufficient for the operations, or can be quickly allocated by the unique interagency decision maker, regardless if they belong to humanitarian organizations. They can work on specific humanitarian operations and within the chosen operation, these vehicles compete for the same space (i.e., ground vehicles compete for the same road infrastructure).
(5) Two types of available budget are considered and allocated in advance as part of an annual financial plan by authorities: Preparation budget is used for conditioning and preparation costs of facilities, while response budget is used for evacuation and distribution operations.
(6) Authorities recognize mainly the use of five types of relief kits: (a) food/water; (b) drugs; (c) personal hygiene items, such as toilet paper; (d) cleaning items; and (e) miscellaneous items, such as linens, fuel, and equipment (for further details, see Garrido et al., 2015).
(7) Facilities' construction costs are mainly considered as structural disaster risk reduction strategies in the mitigation phase of disasters. This stage is left out of the scope of this research, therefore, we do not model these costs. However, we consider that the decision maker must prepare existing buildings as shelters and distribution centers. Thus, we use fixed costs to adapt facilities. These costs rely on a cost of opportunity and a cost depending on the capacity of the facilities (i.e., number of evacuees per shelter, or volume of goods per distribution center).

3.1. GIS procedure

The topography must be addressed during the choice of potential facilities to reduce flood risk, and the possibility of locating facilities in isolated areas must be carefully considered (see Sakakibara et al., 2004; Chang et al., 2007; Díaz-Delgado and Gaytán, 2014). Therefore, an efficient tool, such as a GIS, is needed to perform sensitivity analysis for different highly probable water levels and quickly update information during the emergency.

After applying these steps for multiple flood analyses, decision makers can obtain input data for the mathematical formulation via flood maps (i.e., affected areas), undamaged infrastructure (i.e., roads and eligible facilities), connectivity among facilities, and travel time between the locations (see Figure 3). Further details can be found in Rodríguez-Espíndola and Gaytán (2015).

3.2. Mathematical programming model

The proposed formulation can be interpreted as a multicommodity, multimodal, multicriteria location–allocation model that considers, on one hand, the distribution of multiple products from distribution centers to shelters and, on the other hand, the evacuation of people in two tiers: first from affected areas to meeting points and then from meeting points to shelters (see Fig. 2). First, this model guarantees the flow of affected people and second, humanitarian aid to shelters to meet

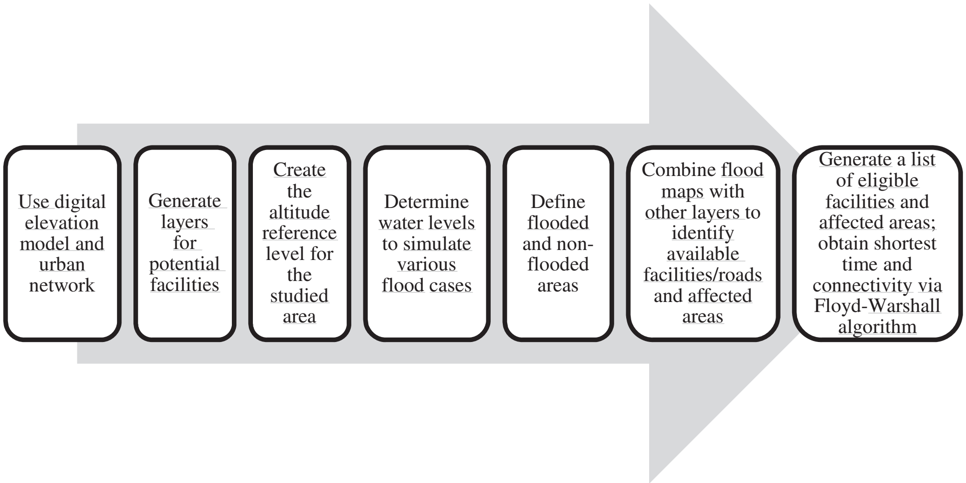

Fig. 3. Overview of the GIS procedure based on Rodríguez-Espíndola and Gaytán (2015).

demand using multiple vehicles, and respecting capacity and availability of resources. The mathematical model uses data from the GIS process to define eligible facilities to perform evacuation and distribution operations. In fact, distribution incorporates connectivity among locations via an adjacency-based matrix to represent the status of the road network.

Given that the unique decision maker needs to identify various alternatives, we build an approximation to a Pareto frontier in order to support the final decision. Furthermore, this model is centered on the preparation phase but derives a plan to execute evacuation and distribution operations in the immediate disaster aftermath. Our argument to propose an integral plan is based on the fact that we performed operational planning to respond effectively to a specific forecasted scenario with meteorological and GIS data. As other papers, we gather data from the operations but our contribution stands out in how we treat them integrally to resemble the tasks that a unique, coordinated interagency develops on its decision-making process. This approach seeks to guarantee closely coordinated humanitarian logistics plans and implementations among various stakeholders (i.e., nongovernmental organizations—NGOs—army, public and private sector, society) who deploy strategies using their available resources in an efficient way.

Part of these resources includes how the national interagency group coordinates the availability of vehicles for diverse transportation modes. According to Pedraza-Martinez et al. (2011), the availability of vehicles becomes a critical factor for field vehicle performance, scheduling, and routing during the response phase of a disaster. Hence, it is crucial to understand the implications of limited vehicle fleet availability in various modes as we model in constraint (1). Additionally, due to rising flood levels and congestion, road saturation constrains the performance of humanitarian operations (Lambert et al., 2013), especially in highly affected areas and in analyzing a worst-case scenario. In our case, this is done for ground vehicles performing the same operation (evacuation first, second tier, or distribution).

The problem can be visualized as a graph with nodes and arcs denoted by $G = (\Omega, R)$, where Ω is the set of nodes and R is the set of arcs linking (i, j) nodes. Henceforth, the sets will be described

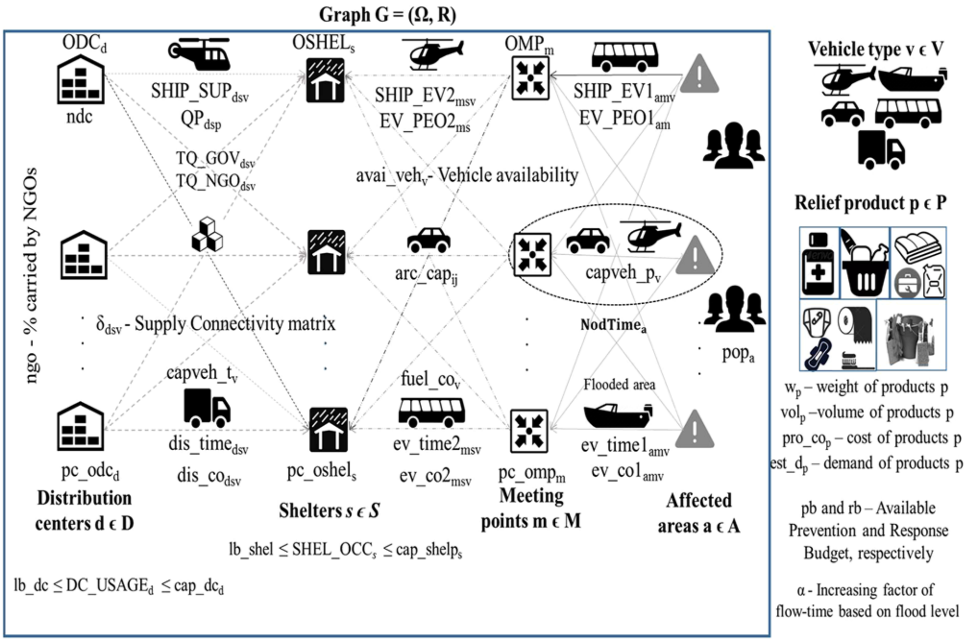

Fig. 4. Proposed multicriteria model with its elements. [Colour figure can be viewed at wileyonlinelibrary.com]

by bold letters, parameters (scalars, vectors, and matrices) by lowercase letters, and variables by uppercase letters. Figure 4 summarizes the main elements of the formulation.

3.2.1. Sets

According to the graph definition, the set of nodes is defined by $\Omega = D \cup S \cup M \cup A$, where $d \in D$ describes the set of candidate distribution centers, $s \in S$ the potential shelters, $m \in M$ the eligible meeting points that serve as transshipments points in the network, and $a \in A$ the affected areas. Other important sets of nodes are the vehicle types $v \in V$ and the relief products $p \in P$. Meanwhile, a subset R_v determines available arcs for every vehicle v, φ characterizes feasible distribution paths, and ϑ describes feasible evacuation paths from affected areas to shelters.

Finally, $\mathrm{NodTime}_a = \{m \in M, v \in V \,|\, \mathrm{evtime1}_{amv} \leq \mathrm{max\_time}\}$ is the set of meeting points that cover affected areas in at most a maximum time (defined by the authorities). These points are idle before a flood occurs, but are crucial for easing evacuation operations during the disaster.

3.2.2. Parameters

Parameters of the model, their brief description, units, and sources are given in Table 1.

3.2.3. Variables

Decision variables regarding humanitarian operations in the optimization model are given in Table 2.

Table 1
Parameters of the optimization model

Parameter	Description	Units	Source
arc_cap_{ij}	Maximum number of vehicles v that are able to traverse arc $(i, j) \in R_v$ before reaching road saturation	Vehicles/arc or road	Ministry of transport
α	Congestion multiplier for the different flood levels. A remaining capacity of 40% in the road network increases the saturation by 300%	–	Lambert et al. (2013) method
pop_a	Population to be evacuated from affected area a	Inhabitants	Census per zip code area
max_time	Maximum time to reach a meeting point from an affected area	Minutes	Defined by authorities
lb_shel	Minimum percentage of shelter occupancy to avoid additional costs (e.g., staff, equipment)	[0,1]	Defined by authorities
lb_dc	Minimum level of joint usage in distribution centers to avoid additional costs (e.g., staff, equipment)		
ngo	Percentage of vehicles owned by NGOs that supplement authorities' fleet to carry relief goods to shelters		
ndc	Number of distribution centers to be chosen (8–10 to guarantee feasibility in worst-case scenario)	Distribution centers	
$capveh\_p_v$	Maximum number of evacuees that can be transported by vehicle type v	People/vehicle	Databases and protocols
$capveh\_t_v$	Maximum number of relief tons that can be carried by vehicle type v	Tons/vehicle	
cap_shelp_s	Maximum number of evacuees assigned to shelter s	People/shelter	
cap_dc_d	Volumetric capacity to store humanitarian aid in distribution center d, which is critical due to the handling of goods such as toilet paper, blankets, and other voluminous items	m^3/distribution center	
$avai\_veh_v$	Availability of vehicles type v	Vehicles	
est_d_p	Estimated demand of how many evacuees are served by each kit containing relief products type p	Person/kit	Based on the number of affected people
w_p	Weight per kit of relief products p	Kilograms/kit	Databases and protocols

Continued

Table 1
Continued

Parameter	Description	Units	Source
vol_p	Volume per kit of relief products *p*	m^3/kit	
δ_{dsv}	Connectivity matrix to control trips from *d* to *s* with vehicle type *v* only if geographic paths connecting two points exist	-	GIS
ev_time1_{amv}	Expected evacuation time from affected area *a* to meeting point *m* for vehicle *v*	Minutes/vehicles	GIS via Floyd–Warshall distance and the average urban speed (km/h) and varied by congestion factor
ev_time2_{msv}	Predicted evacuation time from meeting point *m* to shelter *s* for vehicle *v*		
dis_time_{dsv}	Supply time estimated from distribution center *d* to shelter *s* for vehicle *v*		
ev_co1_{amv}	Evacuation cost from affected area *a* to meeting point *m* using vehicle *v*	\$MXP/vehicle	Databases and protocols
ev_co2_{msv}	Evacuation cost from meeting point *m* to shelter *s* using vehicle *v*		
dis_co_{dsv}	Transportation cost to supply shelter *s* from distribution center *d* using vehicle *v*		
$fuel\_co_v$	Fuel cost per time unit for the vehicle type *v*, computed multiplying energy consumption (l/km) by average urban speed (km/h)	\$MXP/Min-vehicle	Databases and protocols
pc_oshel_s	Preparation cost to open shelter *s* linked to the setup cost to receive people (not related to construction)	\$MXP/facility	Databases and protocols
pc_omp_m	Preparation cost to open meeting point *m* linked to protecting people during short time periods (not related to construction)		
pc_odc_d	Preparation cost to open distribution center *d* linked to handling goods (not related to construction)		
pro_co_p	Procurement cost for each kit of relief items *p*	\$MXP/kit	Databases and protocols
pb	Preparedness budget to locate facilities and preposition supplies in affected areas	\$MXP/year	Defined by authorities
rb	Response budget to evacuate people and distribute relief items		

Table 2
Decision variables related to humanitarian operations included in the model

Evacuation	
$SHIP\_EV1_{amv}$	Number of vehicles type *v* going from affected area *a* to meeting point *m*
EV_PEO1_{am}	People transported from affected area *a* to meeting point *m*
$SHIP\_EV2_{msv}$	Quantity of vehicles type *v* moving people from meeting point *m* to shelter *s*
EV_PEO2_{ms}	People transported from meeting point *m* to shelter *s*
Distribution of humanitarian aid	
$SHIP\_SUP_{dsv}$	Number of freight vehicles type *v* going from distribution center *d* to shelter *s*
QP_{dsp}	Quantity of kits with relief product *p* shipped from distribution center *d* to shelter *s*
TQ_GOV_{dsv}	Tons of humanitarian aid transported by authorities and army in vehicle type *v* from distribution center *d* to shelter *s*
TQ_NGO_{dsv}	Tons of humanitarian aid moved by NGOs in vehicle type *v* from distribution center *d* to shelter *s*
Location of emergency facilities (binary variables)	
$OSHEL_s$	1 if shelter *s* is open, 0 otherwise
ODC_d	1 if distribution center *d* is open, 0 otherwise
OMP_m	1 if meeting point *m* is open, 0 otherwise

3.2.4. Constraints

Limit the availability of vehicles for the relief operations:

$$\sum_a \sum_m SHIP\_EV1_{amv} + \sum_m \sum_s SHIP\_EV2_{msv} + \sum_d \sum_s SHIP\_SUP_{dsv} \le avai\_veh_v \quad \forall\, v \in V. \tag{1}$$

Ensure capacity of vehicles for evacuation operations:

$$\sum_v capveh\_p_v \times SHIP\_EV1_{amv} \ge EV\_PEO1_{am} \quad \forall\, a \in A,\ m \in M \tag{2}$$

$$\sum_v capveh\_p_v \times SHIP\_EV2_{msv} \ge EV\_PEO2_{ms} \quad \forall m \in M,\ s \in S. \tag{3}$$

Guarantee arc capacity in a period only if the facility of origin or destination in the traversed arc is open:

$$\sum_v SHIP\_SUP_{dsv} \le arc\_cap_{ds} \times ODC_d \quad \forall\, d \in D,\ s \in S \tag{4}$$

$$\sum_v SHIP\_EV1_{amv} \le arc\_cap_{am} \times OMP_m \quad \forall\, a \in A,\ m \in M \tag{5}$$

$$\sum_v SHIP\_EV2_{msv} \le arc\_cap_{ms} \times OSHEL_s \quad \forall\, m \in M,\ s \in S. \tag{6}$$

Evacuate all the population from each affected area to the meeting points:

$$\sum_{\mathrm{m}} \mathrm{EV\_PEO1}_{\mathrm{am}} = \mathrm{pop}_{\mathrm{a}} \quad \forall\, a \in A. \tag{7}$$

Flow conservation of evacuees at the meeting points:

$$\sum_{\mathrm{s}} \mathrm{EV\_PEO2}_{\mathrm{ms}} - \sum_{\mathrm{a}} \mathrm{EV\_PEO1}_{\mathrm{am}} = 0 \quad \forall\, m \in M. \tag{8}$$

Consider maximum capacity and the number of evacuated people only if shelter s is open:

$$\sum_{\mathrm{m}} \mathrm{EV\_PEO2}_{\mathrm{ms}} \le \mathrm{cap\_shelp}_{\mathrm{s}} \times \mathrm{OSHEL}_{\mathrm{s}} \quad \forall\, s \in S. \tag{9}$$

Ensure a minimum occupancy level in the open shelters:

$$\mathrm{lb\_shel} \times \mathrm{cap\_shelp}_{\mathrm{s}} \times \mathrm{OSHEL}_{\mathrm{s}} \le \sum_{\mathrm{m}} \mathrm{EV\_PEO2}_{\mathrm{ms}} \quad \forall\, s \in S. \tag{10}$$

Guarantee that at least one meeting point is reachable from each lashed area:

$$\sum_{\mathrm{m} \in \mathrm{NodTime}_{\mathrm{a}}} \mathrm{OMP}_{\mathrm{m}} \ge 1 \quad \forall\, a \in A. \tag{11}$$

Meet the demand for kits with relief products for the evacuees:

$$\sum_{\mathrm{d}} \mathrm{QP}_{\mathrm{dsp}} \ge \mathrm{est\_d}_{\mathrm{p}} \times \sum_{\mathrm{m}} \mathrm{EV\_PEO2}_{\mathrm{ms}} \quad \forall\, s \in S, p \in P. \tag{12}$$

Determine the weight of relief products to be carried by NGOs and/or by authorities:

$$\mathrm{ngo} \times \sum_{\mathrm{p}} w_{\mathrm{p}} \times \mathrm{QP}_{\mathrm{dsp}} = 1000 \times \sum_{\mathrm{v}} \mathrm{TQ\_NGO}_{\mathrm{dsv}} \quad \forall\, d \in D, s \in S \tag{13}$$

$$(1 - \mathrm{ngo}) \times \sum_{\mathrm{p}} w_{\mathrm{p}} \times \mathrm{QP}_{\mathrm{dsp}} = 1000 \times \sum_{\mathrm{v}} \mathrm{TQ\_GOV}_{\mathrm{dsv}} \quad \forall\, d \in D, s \in S. \tag{14}$$

Guarantee that tons of relief products carried by all the actors respect the capacity of freight vehicles and transportation meets connection among origins and destinations via available modes:

$$\sum_{\mathrm{v}} \mathrm{capveh\_}t_{\mathrm{v}} \times \mathrm{SHIP\_SUP}_{\mathrm{dsv}} \ge \sum_{\mathrm{v}} \delta_{\mathrm{dsv}} \times \left(\mathrm{TQ\_NGO}_{\mathrm{dsv}} + \mathrm{TQ\_GOV}_{\mathrm{dsv}}\right) \quad \forall\, d \in D, s \in S. \tag{15}$$

Limit the volumetric capacity of distribution centers:

$$\sum_{\mathrm{p}} \sum_{\mathrm{s}} \mathrm{vol}_{\mathrm{p}} \times \mathrm{QP}_{\mathrm{dsp}} \le \mathrm{cap\_dc}_{\mathrm{d}} \times \mathrm{ODC}_{\mathrm{d}} \quad \forall\, d \in D. \tag{16}$$

Define the number of distribution centers to be opened:

$$\sum_{\mathrm{d}} \mathrm{ODC}_{\mathrm{d}} \le \mathrm{ndc}. \tag{17}$$

Minimum usage level of capacity in distribution centers:

$$\mathrm{lb\_dc} \times \sum_{\mathrm{d}} \mathrm{cap\_dc_d} \times \mathrm{ODC_d} \leq \sum_{\mathrm{d}} \sum_{\mathrm{s}} \sum_{\mathrm{p}} \mathrm{QP_{dsp}}. \tag{18}$$

Respect preparedness budget for the location of facilities and prepositioning relief goods:

$$\begin{aligned} &\sum_{\mathrm{d}} \mathrm{pc\_odc_d} \times \mathrm{ODC_d} + \sum_{\mathrm{s}} \mathrm{pc\_oshel_s} \times \mathrm{OSHEL_s} + \sum_{\mathrm{m}} \mathrm{pc\_omp_m} \times \mathrm{OMP_m} \\ &\quad + \sum_{\mathrm{d}} \sum_{\mathrm{s}} \sum_{\mathrm{p}} \mathrm{pro\_co_p} \times \mathrm{QP_{dsp}} \leq \mathrm{pb}. \end{aligned} \tag{19}$$

Consider response budget for evacuation and distribution of humanitarian aid:

$$\begin{aligned} &\sum_{\mathrm{a}} \sum_{\mathrm{m}} \sum_{\mathrm{v}} \left(\mathrm{ev\_co1_{amv}} + \mathrm{fuel\_c_v} \times \mathrm{ev\_time1_{amv}}\right) \times \mathrm{SHIP\_EV1_{amv}} \\ &\quad + \sum_{\mathrm{m}} \sum_{\mathrm{s}} \sum_{\mathrm{v}} \left(\mathrm{ev\_co2_{msv}} + \mathrm{fuel\_c_v} \times \mathrm{ev\_time2_{msv}}\right) \times \mathrm{SHIP\_EV2_{msv}} \\ &\quad + \sum_{\mathrm{d}} \sum_{\mathrm{s}} \sum_{\mathrm{v}} \left(\mathrm{dis\_co_{dsv}} + \mathrm{fuel\_c_v} \times \mathrm{dis\_time_{dsv}}\right) \times \mathrm{SHIP\_SUP_{dsv}} \leq \mathrm{rb}. \end{aligned} \tag{20}$$

Type of variables:

$$\mathrm{TQ\_GOV_{dsv}},\ \mathrm{TQ\_NGO_{dsv}} \geq 0 \quad \forall\, d \in D, s \in S, v \in V \tag{21}$$

$$\begin{aligned} &\mathrm{EV\_PEO1_{am}}, \mathrm{SHIP\_EV1_{amv}}, \mathrm{EV\_PEO2_{ms}}, \mathrm{SHIP\_EV2_{msv}}, \mathrm{SHIP\_SUP_{dsv}}, \mathrm{QP_{dsp}} \in \mathbb{Z}^{+} \\ &\qquad \forall\, a \in A, m \in M, s \in S, d \in D, p \in P, v \in V \end{aligned} \tag{22}$$

$$\mathrm{ODC_d}, \mathrm{OMP_m}, \mathrm{OSHEL_s} \in \{0, 1\} \quad \forall\, d \in D, m \in M, s \in S. \tag{23}$$

3.2.5. Criteria

Regarding the criteria, several authors have analyzed the importance of choosing accurate criteria to measure the performance of humanitarian operations. Beamon and Balcik (2008) analyze criteria based on the resource, output performance, and flexibility, while Huang et al. (2012) consider efficiency, efficacy, and equity. Based on various studies, we proposed the use of (a) maximum evacuation flow-time (output performance from Beamon and Balcik, 2008, and efficacy from Huang et al., 2012), (b) maximum distribution flow-time (output performance from Beamon and Balcik, 2008, and efficacy from Huang et al., 2012), and (c) total cost (resource performance from Beamon and Balcik, 2008, and efficiency from Huang et al., 2012).

Furthermore, a minimizing worst-case strategy (i.e., min–max functions) has been chosen to address the flow-time of the operations. According to Campbell et al. (2008), the combination of min–max and min-sum functions guarantees the equity. Therefore, this proposal considers a series of supplementary criteria that guarantee a better performance measurement of the operations for each flood level.

Minimizing the maximum evacuation flow-time:

$$\min\ z_1 = (1+\alpha) \times \max_{\vartheta}\Big(\sum\nolimits_{\mathrm{a}}\sum\nolimits_{\mathrm{m}}\sum\nolimits_{\mathrm{v}} \mathrm{ev\_time1}_{\mathrm{amv}} \times \mathrm{SHIP\_EV1}_{\mathrm{amv}} + \sum\nolimits_{\mathrm{m}}\sum\nolimits_{\mathrm{s}}\sum\nolimits_{\mathrm{v}} \mathrm{ev\_time2}_{\mathrm{msv}} \times \mathrm{SHIP\_EV2}_{\mathrm{msv}}\Big). \tag{24}$$

Minimizing the maximum flow-time of humanitarian aid distribution:

$$\min\ z_2 = (1+\alpha) \times \max_{\varphi}\Big(\sum\nolimits_{\mathrm{d}}\sum\nolimits_{\mathrm{s}}\sum\nolimits_{\mathrm{v}} \mathrm{dis\_time}_{\mathrm{dsv}} \times \mathrm{SHIP\_SUP}_{\mathrm{dsv}}\Big). \tag{25}$$

Minimizing the total cost related to location, prepositioning, evacuation, and distribution:

$$\begin{aligned}\min\ z_3 = {} & \sum\nolimits_{\mathrm{d}} \mathrm{pc\_odc}_{\mathrm{d}} \times \mathrm{ODC}_{\mathrm{d}} + \sum\nolimits_{\mathrm{s}} \mathrm{pc\_oshel}_{\mathrm{s}} \times \mathrm{OSHEL}_{\mathrm{s}} + \sum\nolimits_{\mathrm{m}} \mathrm{pc\_omp}_{\mathrm{m}} \times \mathrm{OMP}_{\mathrm{m}} \\ & + \sum\nolimits_{\mathrm{d}}\sum\nolimits_{\mathrm{s}}\sum\nolimits_{\mathrm{p}} \mathrm{pro\_co}_{\mathrm{p}} \times \mathrm{QP}_{\mathrm{dsp}} \\ & + \sum\nolimits_{\mathrm{a}}\sum\nolimits_{\mathrm{m}}\sum\nolimits_{\mathrm{v}} \left(\mathrm{ev\_co1}_{\mathrm{amv}} + \mathrm{fuel\_c}_{\mathrm{v}} \times \mathrm{ev\_time1}_{\mathrm{amv}}\right) \times \mathrm{SHIP\_EV1}_{\mathrm{amv}} \\ & + \sum\nolimits_{\mathrm{m}}\sum\nolimits_{\mathrm{s}}\sum\nolimits_{\mathrm{v}} \left(\mathrm{ev\_co2}_{\mathrm{msv}} + \mathrm{fuel\_c}_{\mathrm{v}} \times \mathrm{ev\_time2}_{\mathrm{msv}}\right) \times \mathrm{SHIP\_EV2}_{\mathrm{msv}} \\ & + \sum\nolimits_{\mathrm{d}}\sum\nolimits_{\mathrm{s}}\sum\nolimits_{\mathrm{v}} \left(\mathrm{dis\_co}_{\mathrm{dsv}} + \mathrm{fuel\_c}_{\mathrm{v}} \times \mathrm{dis\_time}_{\mathrm{dsv}}\right) \times \mathrm{SHIP\_SUP}_{\mathrm{dsv}}.\end{aligned} \tag{26}$$

Note that min-sum of flow-time is implicitly considered by the criterion (26) and together with min–max functions in the criteria (24) and (25), this model measures equity (Campbell et al., 2008; Huang et al., 2012). To ease the computation, min–max functions in the criteria (24) and (25) are linearized by defining $\min\ \theta,\ s.t.\ \theta \geq \mu_1, \ldots, \theta \geq \mu_n$, where θ is the value being minimized in the maximization functions $\mu_o\ \forall\ o = 1, \ldots, n$, where o refers to the vector of values acquired when evacuation paths in (24) and distribution paths in (25) are evaluated.

3.3. Multiobjective programming model

Addressing several criteria at the same time requires specific methodologies of multicriteria decision making. For humanitarian logistics, in addition to the different criteria that could be proposed, different approaches can be implemented (see Gutjahr and Nolz, 2016). In this case, the approach chosen to build the efficient frontier is multiobjective programming.

Definition 1. *Let Ψ be the feasible set of a multicriteria optimization problem in $\mathbb{R}^n$ and $f_i(x)$ the criterion i evaluated in solution x. Assuming minimization, a solution $\sigma^* \in \Psi$ is called Pareto optimum, if there is no $\sigma \in \Psi$ such that $f_i(\sigma) \leq f_i(\sigma^*) \forall i$, being one of the inequalities strict. If σ^* is Pareto optimum, then $\{f_1(\sigma^*), \ldots, f_n(\sigma^*)\}$ is called the efficient point. The set of all the efficient solutions is* *called Pareto/efficient frontier in the space of decisions. The set of all the efficient points is called the efficient set in the space of objectives.*

Because the disaster phase being addressed is preparedness, there is no time limit to compute efficient solutions; consequently, specialized algorithms were not applied (see Laummans et al., 2006; Mavrotas, 2009). However, two exact methods were used to build a better efficient frontier (i.e., solution space) and some prioritization of the criteria is possible using the first method.

In the first step, the weighted-sum method is applied to solve the proposed multicriteria model. This method builds an approximate efficient frontier using weighted linear convex combinations of the proposed criteria by formulating: min $\pi = \sum_u \omega_u f_u$, s.t. $\sum_u \omega_u = 1,\ \omega_u > 0$, where ω_u is the weight of criteria f_u and $u = 1, \ldots, 3$. These values are normalized by dividing them by their individual optimum, and weights are variated to obtain the efficient frontier. However, this technique does not guarantee finding all efficient solutions (Koski, 1985) because numerically it is solved for a limited set of weights.

Thus, in the second step, the application of ε-constraints allows finding other supplementary efficient solutions (Ehrgott, 2005) by defining: min $\mu' = f_h$, s.t. $f_u \leq \varepsilon_u \forall\, u = 1, \ldots, m;\ u \neq h$, where f_h is a primary objective function being minimized while other criteria are expressed as inequality constraints. After the approximation to the efficient frontier is obtained, it can be analyzed by the decision makers. They will use it for estimation purposes and to choose the efficient solution (that is also a comprehensive strategy) that best fits their expectations on the proposed criteria or that best responds to their available resources.

4. Results and discussion

In this section, a description of the case study based on the worst-case flood scenario (i.e., 4-m level) and additional analyses varying parameters, such as time, costs, and available resources, are introduced together with a discussion of the main findings. Results from a couple of additional flood levels are summarized to describe further insights. However, the worst-case scenario is particularly important for the unique decision maker who must perform effective strategies and avoid being surpassed by any disaster.

4.1. Mexican case study: floods in Villahermosa in 2007

According to the International Database of Disasters EM-DAT (2016), Mexico is considered one of the most affected countries by natural disasters, especially because hydrometeorological disasters that constitute 65% of the total natural disasters in Mexico and have the potential to affect at least 30% of the population that is currently living in areas exposed to this type of disaster. However, the Mexican authorities lack access to efficient mechanisms, such as the proposed in this research, to locate emergency facilities and protocols to supply humanitarian aid in a coordinated way (Rodríguez-Espíndola and Gaytán, 2015) and to evacuate people efficiently.

This case study is based on one of the most severe floods that took place in Villahermosa in 2007 due to intense rain and problems with the "Peñitas" local dam. Villahermosa is a city that belongs to the municipality Centro in the State of Tabasco, Mexico. It has approximately 347,000 inhabitants spread over 62 km^2 and with a median age of 27 years. Villahermosa has been continually hit by floods; however, the flood of 2007 affected 65% of the territory, with water levels reaching 4 m, challenging authorities by the magnitude of the humanitarian logistics required in the first couple of days. This disaster affected 1.6 million people and caused economic losses of three billion dollars (CENAPRED, 2009; EM-DAT, 2016).

Given the magnitude, stakeholders' local capacity was surpassed to manage the emergency; thus the Mexican interagency forum for coordination and allocation of responsibilities regarding disaster management, called the National Civil Protection System (SINAPROC), was convened to reach agreements on how to attend the disaster (United Nations Development Programme, 2014) using highly trained armed forces (i.e., the army and navy) and special staff (e.g., Red Cross). Decision making and deployment of humanitarian strategies from stakeholders in Villahermosa's flood are compared with our multicriteria optimization solutions that are built from similar data.

4.1.1. Data gathering

The developed model is strongly supported by gathered data via interviews, surveys, and access to databases and protocols, or they were computable through our GIS procedure. The data were available beforehand to the authorities but spread over various specialized sources (e.g. Defense Department, Interior Department, Coast and Seas Department, SINAPROC, as well as humanitarian organizations such as the UN, International Red Cross, Caritas, and OXFAM). Therefore, the authorities were able to use data regarding facilities' and vehicles' capacities, forecasted demand for different kits with products that must be located rapidly into the shelters to respond to immediate needs and avoid robbery and chaos, expected number of evacuees, and proxy cost functions. Unfortunately, authorities did not know how to integrate these elements to make better decisions at that time.

Most of the parameters are obtained from the GIS procedure (evacuation and distribution time, connectivity matrix and capacity of emergency facilities). Other parameters are provided by the decision makers (minimum levels of occupancy are fixed at 20%; number of facilities to open; maximum coverage time per meeting point—20 minutes; congestion multiplier depending on the water level; percentage of humanitarian aid carried by NGO vehicles—22%; preparedness budget—\$135.7 million Mexican Pesos (M MXP) = US\$8 million; response budget—426.2 M MXP = US\$25.1 million; and road capacity—630 vehicles per hour). Others are collected via the inventory of available vehicles (acquired from media, databases and protocols and validated through interviews), the census of immediately affected population (in total 160,352 people from Villahermosa were evacuated), and the physical limitations defined by SINAPROC (vehicle capacity, weight and volume occupied by kits). All the eligible facilities respect international standards and welfare in infrastructure and services (CENAPRED, 2009; Sphere Project, 2012).

Other estimations, such as the demand for products per evacuee, are computed by the government, which creates kits to fulfill the needs of an average family of four. The case of drug kits differs because their content (e.g., vaccines, drugs) is computed by the Ministry of Health for every 100 inhabitants considering the age range and number of people.

To conclude, the preparation costs were calculated depending on the number of people or kits in each facility, while the procurement costs for products are defined as market price; evacuation and distribution costs are calculated depending on the opportunity cost to use the vehicle in other activities. Thus, decision makers are "renting" vehicles, and setup and overhead costs (e.g., maintenance, spare parts) are considered when carrying products or moving people; but no construction costs are linked to the any of the parameters.

Furthermore, all the parameters are reliable since they were taken from protocols and databases that documented the real disaster and they were also validated by stakeholders. The data used for this research were provided by the research group *Modelación de la Cadena de Suministro y Sistemas de Transporte (MOSILTRA)*. The values and estimations used for the parameters in the instances are available upon request to ease the replicability of the tests.

4.1.2. Results of the case study for the worst-case scenario

Flood cases are chosen by Mexican authorities based on critical moments to perform humanitarian operations (CENAPRED, 2009). We test our model taking into account a network of 504 nodes, 45,849 arcs (without considering multiple transport modes), and collected information for the case study. For the sake of space, we only present in detail the results from the worst-case flood corresponding to a 4-m level scenario, but our methodology can consider other cases. The network for this scenario is composed of 109 affected areas, 270 shelters (from 549 eligible locations, such as public buildings, and schools), 111 meeting points (from 150 eligible locations, such as intersections, small spots and temporary stations), and 14 distribution centers (from 22 locations, such as warehouses and public buildings) that are opened. The numbers of affected areas and shelters differ from Rodríguez-Espíndola and Gaytán (2015) due to a higher level of resolution in the areas. This higher resolution procedure let the authors propose 111 meeting points in locations nearby affected areas to leverage the evacuation, eliminate more than 50% of the shelters and around 40% of the eligible distribution centers due to the water level in the flood simulation, and maintain a low level of road connectivity.

In this study, GIS IDRISI^{TM} from Clark Labs was used for the GIS procedure. Moreover, the weighted-sum and ε-constraint methods were programmed in GAMS^{TM} v22.6 and solved via CPLEX^{TM} v11.0 on an Intel Xeon CPU with 9.75GB of RAM. We obtain an approximate efficient frontier for the case study and another 10 test instances that were used for sensitivity analyses. Approximation to the Pareto frontier was obtained using a standard step-size of 1% (that is normalized by dividing every value by its individual optimum) in the weighted-sum method for the three criteria and only use strictly positive weights (e.g., $\omega_1 = 0.01, \omega_2 = 0.01, \omega_3 = 0.98$; $\omega_1 = 0.02, \omega_2 = 0.01, \omega_3 = 0.97$; and so on). This strategy avoids getting weakly efficient solutions, which might be an extreme case if we include the zero as part of the evaluated weights for the criteria.

After constructing a set of nondominated solutions with the latter method, the ε-constraint method is added to seek other nondominated solutions and to obtain a better approximation of the efficient frontier. The payoff matrix of this problem is shown in Table 3, where rows correspond to the achieved solutions for the considered objective functions from monocriterion optimization, with the main diagonal the ideal point (unreachable) for this problem. The difference in the cost regarding Rodríguez-Espíndola and Gaytán (2015) is mainly derived from the inclusion of preparation costs for the meeting points.

A set of nondominated points is obtained for the 4-m water level flood (Table 4).

Table 3
Payoff matrix for the 4-m water level in the case study

	Max. evacuation flow-time	Max. distribution flow-time	Cost
Max. evacuation flow-time	48,860 flow-minutes	9617 flow-minutes	$85.643
Max. distribution flow-time	49,212 flow-minutes	9219 flow-minutes	$82.586
Total cost ($million pesos)	250,656 flow-minutes	37,121 flow-minutes	$65.947

Table 4
Set of efficient points obtained for the 4-m water level in the case study

Efficient solution	Max. evacuation flow-time (flow-minutes)	Max. distribution flow-time (flow-minutes)	Total cost ($M MXP)	Efficient solution	Max. evacuation flow-time (flow-minutes)	Max. distribution flow-time (flow-minutes)	Total cost ($M MXP)
1	48,860	9617	85.643	33	57,256	13,590	66.001
2	49,212	9219	82.586	34	57,720	13,905	66
3	49,560	9869	80.706	35	57,740	14,049	65.999
4	49,812	10,044	78.337	36	57,912	14,220	65.998
5	49,960	10,498	75.099	37	58,216	14,590	65.9973
6	50,280	10,624	74.441	38	58,272	14,695	65.9971
7	50,528	10,676	74.21	39	58,312	14,909	65.996
8	50,912	10,757	69.538	40	58,488	15,697	65.995
9	51,048	10,790	67.942	41	58,804	15,992	65.994
10	53,212	10,825	66.131	42	59,420	16,132	65.991
11	53,524	10,861	66.125	43	59,544	16,208	65.9905
12	53,856	10,920	66.108	44	59,612	16,441	65.9904
13	53,860	11,077	66.1	45	59,760	16,711	65.9903
14	53,928	11,133	66.096	46	59,944	16,830	65.9902
15	54,048	11,180	66.092	47	60,064	17,123	65.9901
16	54,712	11,183	66.079	48	60,676	18,062	65.988
17	54,864	11,269	66.064	49	60,892	18,467	65.9873
18	55,152	11,495	66.063	50	62,316	18,578	65.9872
19	55,440	11,743	66.055	51	62,572	18,899	65.984
20	55,448	11,768	66.021	52	63,312	19,438	65.983
21	56,124	11,987	66.015	53	63,856	21,033	65.9814
22	56,184	12,006	66.0146	54	63,916	23,706	65.9812
23	56,188	12,417	66.0145	55	63,996	23,890	65.977
24	56,200	12,728	66.0143	56	64,192	25,906	65.975
25	56,384	12,835	66.0094	57	64,380	26,906	65.973
26	56,416	12,862	66.0093	58	65,004	28,848	65.971
27	56,536	12,886	66.0092	59	65,580	29,160	65.968
28	56,652	13,053	66.005	60	66,044	29,346	65.966
29	56,672	13,354	66.004	61	66,496	29,769	65.965
30	56,768	13,378	66.0034	62	66,668	31,438	65.958
31	56,952	13,427	66.0032	63	250,656	37,121	65.947
32	57,204	13,456	66.0031				
Record of facts	63,491	24,982	69.574				

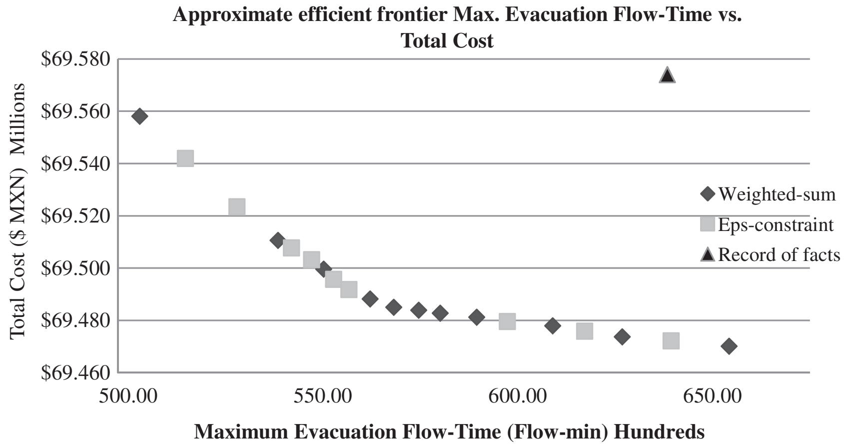

Fig. 5. Approximate efficient frontier for criteria 1 and 3 in the worst-case scenario.

All these results can provide a wide variety of strategies to the interagency decision maker, and their tradeoffs should be analyzed carefully to acquire advantages from any criteria regarding available resources and most suitable strategies during the emergency. For example, an increase of 0.9% in the total cost can provide savings of approximately 1.2% for the worst-case scenario in the distribution flow-time and savings of 0.6% for the worst-case scenario in evacuation flow-time when comparing the fifth and the sixth efficient solutions.

In general terms from these efficient solutions, the number of shelters maintained by the authorities was 256 with a median occupancy of 85%, while the open meeting points varied from 44 to 103 and the distribution centers varied from 8 to 14 open locations with a median usage of 50%. Evacuation operations consume on average 70% of the available budget, while distribution of humanitarian aid consumes only 10%. Procurement costs constitute on average 5%, and the preparation costs of the facilities consume the remaining 15%.

Comparing these efficient solutions results in Table 4 with the actions taken by the authorities during the 2007 Villahermosa floods, it is clear that the set of efficient points dominate this solution in any of the criteria. This finding is not surprising because the authorities were not prepared in advance for a disaster of this magnitude. However, this comparison is useful to show the benefits of using any of the nondominated solutions. It is worth mentioning that authorities agree that solutions achieved with the integrated methodology are creditable.

Because efficient solutions are difficult to visualize in a three-dimensional chart, an analysis of every pair of criteria is performed. Due to space constraints, only the approximate efficient frontiers for maximum evacuation flow-time versus total cost and maximum evacuation flow-time versus maximum distribution flow-time are presented in Figs. 5 and 6, respectively.

Table 5 shows an example of the partial strategy of the fourth nondominated solution corresponding to pair (53,928 maximum evacuation flow-minutes, $69.511 M MXP) in the space of decisions from Fig. 5. This solution uses 256 shelters, 101 meeting points and eight distribution centers.

From the first part of Table 5, the average shelters' occupation is 89% and the utilization rate of distribution centers is 73%. In the case of evacuation, the solutions also fulfill the predefined authorities' evacuation time window during floods (less than or equal to 30 minutes). Furthermore,

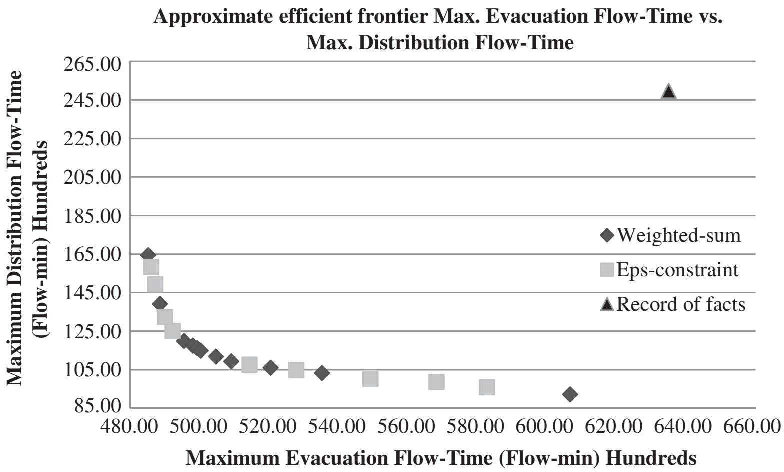

Fig. 6. Approximate efficient frontier for criteria 1 and 2 in the worst-case scenario.

Table 5
Partial humanitarian logistics strategy for an efficient solution (worst-case scenario)

Shelter ID	1	2	3–5	6	7–18	19	20	21	22–41
% Occupancy	22%	20%	100%	91%	100%	97%	63%	84%	100%
Shelter ID	116	117	118–119	120	121–126	127	128–131	132	133–134
% Occupancy	98%	97%	100%	20%	100%	93%	100%	99%	100%
Shelter ID	210	211	212	213	214	215–217	218–219	220	221–222
% Occupancy	20%	21%	20%	99%	20%	21%	100%	20%	100%
Shelter ID	241	242	243	244	245	246	247	248	249
% Occupancy	100%	100%	99%	100%	100%	74%	90%	100%	68%

Product kits	A—foods/water	B—drugs	C—hygiene items	D—cleaning items	E—miscellaneous
Quantity	40,169	2448	40,786	40,140	40,175

	Helicopter	Truck/bus	Car	Boat
Share of vehicles in distribution: distribution center–shelter	30%	6%	1%	NA
Share of vehicles in evacuation 1st tier: affected area–meeting point	70%	39%	49%	95%
Share of vehicles in evacuation 2nd tier: meeting point–shelter	0%	50%	39%	NA

evacuation flow-time presents some savings, due to the flexibility to relocate evacuees in various shelters, although the benefits obtained are small (between 2% and 6%). Finally, the maximum distribution flow-time is also improved, giving the opportunity to easily reach larger quantity of shelters via the eight opened distribution centers.

Regarding the computational time, efficient solutions are on average acquired in 1.5 hours with a gap (computed regarding the best possible bound) of 5%, and the worst computational time is nine hours due to the combinations and the competitive tradeoff between the first two criteria.

Table 6
Partial humanitarian logistics strategy deployed by authorities in the record of facts

Shelter ID	1	2	3–5	6	7–18	19	20	21	22–41
% Occupancy	0%	100%	80%	75%	100%	90%	89%	20%	100%
Shelter ID	116	117	118–119	120	121–126	127	128–131	132	133–134
% Occupancy	90%	100%	100%	50%	100%	0%	100%	100%	100%
Shelter ID	210	211	212	213	214	215–217	218–219	220	221–222
% Occupancy	20%	40%	20%	80%	20%	20%	20%	20%	100%
Shelter ID	241	242	243	244	245	246	247	248	249
% Occupancy	80%	100%	100%	100%	100%	80%	100%	100%	40%

Product kits	A—foods/water	B—drugs	C—hygiene items	D—cleaning items	E— miscellaneous
Quantity	38,312	1623	38,312	38,312	38,312

	Helicopter	Truck/bus	Car	Boat
Share of vehicles in distribution: distribution center–shelter	25%	15%	0%	NA
Share of vehicles in evacuation 1st tier: affected area–safer location or shelter	75%	85%	52%	100%

4.2. Validation of efficient solutions: worst-case instance

The configuration of the humanitarian operations used by the authorities in the record of facts should be compared with the proposed efficient solutions (see Table 6). Thus, this subsection shows how the authorities attended Villahermosa's flood in 2007 and presents a brief discussion about the validation of results compared with Table 5 from the fourth nondominated solution of Fig. 5.

Regarding occupation of shelters, it shows that the median of occupation of our approach is around 90%, while the occupation during the disaster was 76% considering the complete set of shelters. Furthermore, authorities originally used 370 shelters compared with about 250 shelters used by our approach. This fact helps to explain why in Figs. 5 and 6 the total cost of any of our efficient solutions is more distant to the record of facts (i.e., implemented solution). The latter also makes evident the improved usage of resources brought by our solutions and the change of the humanitarian network given the fewer number of used facilities.

With regard to the humanitarian kits, on average there is a 14% more of the different product types in our approach, particularly in the case of drugs, showing 50% more supply than in the real case. This increase in our analyzed solution is explained by the known large quantity of people (i.e., known demand) who were affected during the disaster. Authorities might not have predicted this huge impact. Furthermore, their lack of resources and centralized data to respond in advance to the disaster cause them to have huge shortage of drugs and food during the disaster response.

Also, 200 helicopter trips delivered around 150 tons of humanitarian aid and a few evacuation trips were made to move sick people directly from flooded area to shelters. The difference in the analyzed solution arises because of the use of the land transportation and the existence of meeting points that had not been used by the authorities before this proposal. During the disaster in 2007, authorities sought safer places (e.g., streets) to leave evacuees and continue performing evacuation operations.

The usage of helicopters and boats was the most demanded and it was due to the scarce availability of those vehicles. Trucks and buses were completely used and cars helping evacuees were quantified around 52% of the total available quantity. Comparing with the analyzed solution in Table 5, the difference in the usage of cars arises due to the assumed control of authorities to use any kind of vehicle in case of a disaster, the small decrease in the usage of boats is given by the opportunity that population has to evacuate a future affected area before the flood level increases and, consequently the use of other vehicle types as trucks/buses is impacted to move the evacuees to the assigned shelter.

Finally, the eight opened distribution centers of analyzed solution save on average 50% of the maximum flow-time criterion (20,200 vs. 51,000 flow- minutes from the record of facts) and sometimes more than 75% due to their greater proximity and coverage (Yushimito et al., 2012). Despite the lower utilization rate of 73% compared to 91% of the only distribution center used by authorities in 2007, the new distribution network let user minimize undesired effects on lack of equality and reduce worst case. On average 20% of the worst-case distribution flow-time is saved by any of the efficient solutions in relation to the implemented solution by the authorities.

4.3. Other flood cases with respect to the worst-case scenario

Previous results are based on the worst-case flood scenario, but our multiobjective model might be applied to optimize other flood cases. By reducing flood level to 1 m, an increase of 18% in the traveling time is expected in the network due to the congestion caused by road and focal areas' damage, while by reducing the flood level to 2 m worsens the traveling time to 83%. Both cases enable larger number of candidate facilities due to lesser damage.

The 1-m flood enables 458 candidate shelters, 185 meeting points, and 22 distribution centers to attend 72 affected areas. This case resembles a case with higher availability of infrastructure and resources (i.e., facilities, resources) to evacuate around 72,000 people. On the other hand, the 2-m flood enables 352 candidate shelters, 140 meeting points, and 18 distribution centers to evacuate 96 affected areas. Naturally, this case resembles the worst case to evacuate around 133,000 people but having a few more available resources. Table 7 shows the results for the studied cases. In summary, lower the flood level carries higher availability of resources, higher dispersion of facilities, and preference for longer, consolidated routes, as well as higher utilization of cars to traverse the less-damaged roads. This table allows understanding how strategies vary depending on the flood level in terms of usage and availability of resources (i.e., vehicles, facilities) and performance (i.e., cost, time).

4.4. Factor analyses and sensitivity results

The case study has been adapted to evaluate the model performance when its variables or assumptions are altered. The consideration of additional instances enables to determine better strategies. Such instances are generated depending on three critical elements:

- Geographical dispersion of the facilities (Apte, 2010; Esmaelian et al., 2015) because it impacts the quantity of resources, coverage of the facilities, and total cost.

Table 7
Summary of results for diverse flood levels

Features/flood level	1 m	2 m	4 m
Availability and dispersion of facilities	Higher	Intermediate	Lower
Average evacuation and distribution times	Higher	Intermediate	Lower
Maximum evacuation time	Lower due to higher dispersion and availability	Higher due to lower dispersion and availability	
Maximum distribution time	Higher due to more decentralization in the road network	Intermediate	Lower due to more centralization in the road network
Transportation costs	Higher due to few longer routes (more consolidation)	Higher due to bigger number of shorter routes and vehicles in the system	
Type of strategy for humanitarian operations (evacuation and distribution)	Longer routes, high consolidation for a few facilities due to dispersion	Intermediate routes	Shorter routes, high consolidation for multiple facilities due to centralization
Utilization of distribution centers	Intermediate due to larger number of DCs		High
Utilization of shelters	Intermediate	High	Extremely high due to decreasing number of shelters
Use of meeting points (MP)	Intermediate	Intermediate	High to guarantee higher utilization of larger vehicles from MP to shelters
Use of boats	Low	Intermediate	Extremely high
Use of cars	High due to infrastructure availability	Low between affected areas and MP, intermediate between MP and shelters	Extremely low between affected areas, intermediate between MP and shelters
Use of helicopters	Intermediate (distribution)	Intermediate (distribution and evacuation)	Extremely high (distribution and evacuation)
Use of buses and trucks	Intermediate	High	Extremely high

- The quantity of available resources, since it strongly determines the actions that can be taken in humanitarian logistics and it is related to shortage situations (van Wassenhove, 2006).
- Variations in cost structure since logistics costs are based on local economic conditions and budget, causing dramatic differences in humanitarian operations (van Wassenhove, 2006).

With the aim of creating a set of test instances from the previous elements and determining the ability of the model to define useful solutions and operate successfully (i.e., robustness), factor-analysis combinations from scattered or scarce resources, cost variations, and other changes in the humanitarian network are considered. Table 8 shows the procedure to create these instances.

Table 8
Main characteristics of the analyzed instances

	Geographical dispersion	Availability of resources	Variations in cost
Facilities	20% facilities keep original location + 80% facilities change their location, randomly increasing their distribution and evacuation time in the range [50%, 300%] for shelters, [10%, 150%] for meeting points and [30%, 500%] for distribution centers	Available shelters are [180, 210] to reduce idle capacity to only 0.5% guaranteeing feasibilityAvailable distribution centers [8, 12] because a solution with fewer than eight distribution centers is not feasible Available meeting points [60, 70] to guarantee enough coverage of flooded areas	Remove advantages of economies of scale in larger facilities, increasing costs randomly in [10%, 500%]Vary the procurement costs of the products to be prepositioned in the facilities [10%, 500%]
Vehicles	Location of vehicles in *Ciudad Deportiva* Stadium, as well as active shelters and distribution centers	Restrict number of cars to remove 40% excess capacity and limit the number of available buses: buses/trucks [6200, 10,000], cars [1200, 6634], helicopters [2, 5] and boats [100, 300]	Remove advantages of economies of scale in buses/trucks, increasing costs randomly in [10%, 500%]

From our analyses some general insights can be derived to be used in other floods. Our proposed model shows that the geographical proximity of the distribution centers to the shelters strongly determines the frequency and probability of opening the facilities, since there is a strong link between the use of facilities and vehicles in evacuation and distribution operations. Consequently, any change in the vehicles will have an impact on the facilities' use. We summarized the main results in Table 9.

From Table 9 budget is a key parameter determining a balance in the deployment of humanitarian logistics operations and to choose the best strategies regarding variation of the criteria and covered population (Garrido et al., 2015). It is clear that budget variations generate a tradeoff among the strategies to prepare for and respond to the flood considering the supplementary costs of these strategies. This tradeoff compares strategies locating few emergency facilities closer to large affected areas with strategies with more dispersed facilities leading to longer evacuation and distribution routes.

5. Conclusions

This research presents a methodology for effectively addressing integrated humanitarian logistic operations in short-term disaster preparedness. The proposed methodology includes a model that considers the location of emergency facilities (e.g., distribution centers, shelters, and meeting points), prepositioning of humanitarian aid, and evacuation and distribution allocation during frequent and predictable floods.

The model is supported by GIS and demographic information to develop flood simulation and understand damage in the studied area. These data are used to feed a multicriteria

Table 9
Main insights and tradeoffs from the factor analyses in the worst-case flood

	Utilization rates	Cost	Time	Well-being of the affected people
Scarce vehicles and facilities	Higher	Lower	Shorter	Guaranteed
Dispersed facilities	Higher	Higher	Longer	Guaranteed
Variation in procurement cost	–	Higher	–	Threatened
Variation in transportation costs	Higher	Higher	Longer	Threatened
Use of helicopters and cars	Higher	Higher	Shorter	Quickly guaranteed
Use of buses and trucks	Higher (with huge demand variation)	Lower	Longer	Guaranteed
Prepositioning stock	Higher (especially in distribution centers)	Higher	Shorter	Guaranteed
Lower minimum occupancy level	Lower	Higher	Shorter	Guaranteed
Limited (preparedness and response) budget	Higher	Lower	Longer	Threatened

location–allocation model that guarantees the flow of people from vulnerable areas to shelters and of multiple humanitarian aid kits from distribution centers to shelters using multiple vehicles and taking into account capacity, demand, availability of resources (e.g., vehicles, budget, roads and buildings), and other side constraints. The optimization model is composed of three criteria to minimize (a) maximum evacuation flow-time, (b) maximum supply flow-time, and (c) total cost. This formulation is solved to build the approximate efficient frontier via weighted-sum method and ε-constraint techniques.

With the adoption of these techniques, the unique Mexican interagency decision maker is able to identify nondominated solutions in a reasonable time during the preparedness phase of the second worst Mexican flood. Any of the efficient solutions obtained surpass the authorities' performance during the real case study, generating average savings of approximately 20% due to better resources' utilization and more effective strategies. Furthermore, sensitivity analyses for the three key elements—(a) spatial distribution of emergency facilities, (b) the number of resources, and (c) variations in cost structure—are studied to prove the usefulness and robustness of the model's performance. Flood cases show how to plan and execute humanitarian operations considering fleet management, usage of resources, and allocation/routing strategies to guarantee high performance. However, since we focus on solving the case study and related instances using an exact approach, it is possible to extend this study in order to (a) get efficient strategies via heuristic algorithms, (b) address uncertainty, and (c) incorporate location-routing formulations.

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