Designing a sustainable-resilient humanitarian supply chain for post-disaster relief process, an earthquake case study in Haiti

Hossein Shakibaei and Seyyed Amirmohammad Moosavi
School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
Amir Aghsami
Department of Industrial Engineering, KN Toosi University of Technology, Tehran, Iran and
School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran, and
Masoud Rabbani
School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran

Abstract

Purpose – Throughout human history, the occurrence of disasters has been inevitable, leading to significant human, financial and emotional consequences. Therefore, it is crucial to establish a well-designed plan to efficiently manage such situations when disaster strikes. The purpose of this study is to develop a comprehensive program that encompasses multiple aspects of postdisaster relief.

Design/methodology/approach – A multiobjective model has been developed for postdisaster relief, with the aim of minimizing social dissatisfaction, economic costs and environmental damage. The model has been solved using exact methods for different scenarios. The objective is to achieve the most optimal outcomes in the context of postdisaster relief operations.

Findings – A real case study of an earthquake in Haiti has been conducted. The acquired results and subsequent management analysis have effectively assessed the logic of the model. As a result, the model's performance has been validated and deemed reliable based on the findings and insights obtained.

Originality/value – Ultimately, the model provides the optimal quantities of each product to be shipped and determines the appropriate mode of transportation. Additionally, the application of the epsilon constraint method results in a set of Pareto optimal solutions. Through a comprehensive examination of the presented solutions, valuable insights and analyses can be obtained, contributing to a better understanding of the model's effectiveness.

Keywords Humanitarian supply chain, Disruption, Relief operations, Multiobjective, Logistics, Disaster, Resilience

Paper type Research paper

1. Introduction

The term "disaster" encompasses events that inflict harm, devastation, environmental disruption, human suffering or damage to health and medical services. Such events necessitate immediate and extraordinary planning to address the impacted community or area (Mahmoodi *et al.*, 2022). Disasters are categorized into two main types: 1. Natural disasters, which include earthquakes, floods, volcanoes, droughts and more. 2. Human-made disasters, such as war, nuclear accidents, extreme poverty, disease outbreaks and others (Tofighi *et al.*, 2016). Based on documented statistics, there has been a significant rise in the frequency of natural disasters since 1980, and they usually give rise to damage to human life and their property (Bakhshi *et al.*, 2022). However, the impact of these disasters is not uniformly distributed across the globe, with underdeveloped nations experiencing the most severe devastation (Galanis *et al.*, 2021). The primary factors contributing to the rise in casualties from natural disasters are environmental changes (Naderi *et al.*, 2023a), the expansion of urban populations and the susceptibility of individuals residing in disaster-prone areas, making them more susceptible to events such as floods, typhoons and windstorms (Attia *et al.*, 2020).

The current issue and full text archive of this journal is available on Emerald Insight at: **https://www.emerald.com/insight/2042-6747.htm**

Journal of Humanitarian Logistics and Supply Chain Management
Emerald Publishing Limited [ISSN 2042-6747]
[DOI 10.1108/JHLSCM-08-2023-0071]

© Hossein Shakibaei, Seyyed Amirmohammad Moosavi, Amir Aghsami and Masoud Rabbani. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at http://creativecommons.org/licences/by/4.0/legalcode

Funding: This research work did not receive funding.

Compliance with ethical standards:

Ethical approval: This paper does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest: The authors declare that they have no conflict of interest.

Informed consent: Informed consent was not required as no humans or animals were involved.

Received 12 August 2023
Revised 31 January 2024
Accepted 18 February 2024

The recognition of the significance of coordination and meticulous planning in delivering aid to disaster victims has led to a departure from traditional approaches, which relied on external individuals providing essential items and shelter. This realization has prompted increased attention toward the establishment of a humanitarian supply chain (HSC), aiming to ensure a more effective and efficient response to the needs of those affected (Agarwal *et al.*, 2020). HSCs are consistently vulnerable to various risks, including facility damage, disruption of transportation routes, resource scarcity and political inefficiencies (Kovács and Spens, 2007). Flexibility in the components of the HSC has gained utmost importance, as it empowers supply chain managers to effectively respond to disruptions and unforeseen events (Das *et al.*, 2021). This study focuses on modeling a resilient HSC with the objective of providing optimal relief to disaster victims while minimizing casualties, damages and environmental pollution.

According to studies in the *International Journal of Disaster Risk Reduction*, from 2010 to 2019, more than 7,300 disasters occurred worldwide, causing the death of more than 1.2 million people. Also, the number and deaths due to disasters in that decade increased by 30% and 66%, respectively, compared to the previous decade (Bonaretti and Fischer-Preßler, 2021). Also, the Emergency Events Database recorded 432 natural disasters worldwide just in 2021 (Naderi *et al.*, 2023b). According to the statistics on deaths caused by earthquakes, there have been more casualties in recent years. According to the report, more than 2.5 million people have died as a result of earthquakes globally over the last century (Hayes *et al.*, 2015). Up until now, the most devastating disaster of the 21st century has been the coronavirus pandemic, resulting in a minimum of seven million fatalities (Kanecki *et al.*, 2021). Before 2017, more than 87% of disaster-related deaths in India were related to drought. Also, in this country, the most damage in disasters was related to floods, which caused more than 58bn dollars of damage to the country (Negi and Negi, 2021). During the span of 60 years, based on available statistics until 2019, Iran has experienced over 400 catastrophic events leading to considerable damage. Regrettably, these disasters have resulted in the loss of over 180,000 lives. Earthquakes contributed to more than 65% of these fatalities, while floods constituting approximately 10% of the overall casualties (Sharifian *et al.*, 2017).

HSCs play a crucial role in addressing the aftermath of disasters by providing vital resources and necessary equipment to victims. They should demonstrate swift and efficient action in the relief process to rescue and assist victims, ensuring the delivery of essential items and safely relocating them to secure locations (Bui *et al.*, 2021). The primary challenges faced during relief efforts include the destruction of communication routes and infrastructure, as well as difficulties in identifying and assessing vital items at various centers. This underscores the importance of well-planned relief projects. Humanitarian organizations can enhance their preparedness and response to supply chain disruptions by using resilience models. These models help ensure the uninterrupted provision of essential commodities and services to those in need. A resilient supply chain represents a constructive and responsible system that can deliver improved services to individuals requiring assistance (Wu *et al.*, 2019).

In the end, by reading this article, the following questions will be answered:

Q1. What is the optimal place to establish or choose a facility?

Q2. What effect can the uncertainty of the parameters have on our relief process?

Q3. How can resilience in the supply chain deal with disruptions and possible disruptions in the supply chain?

Q4. In addition to optimizing social satisfaction, how can an HSC effectively address multifaceted dimensions of sustainability, encompassing economic costs and environmental impacts, within the context of engineering solutions?

To address the aforementioned concerns, a model grounded in mixed-integer linear programing (MILP) has been proposed. This model seeks to determine the optimal locations of facilities, the most efficient transportation modes connecting these facilities and the appropriate quantity of relief item transfers between them.

The literature relevant to the subject matter is reviewed in Section 2. Section 3 provides an explanation of the problem and presents the proposed model. In Section 4, solution methods are introduced. Some numerical examples are presented in Section 5. Section 6 implements the proposed model on a case study, and derives the useful results. A comprehensive sensitivity analysis will be conducted in Section 7. Discussion and managerial insights are presented in Section 8. And in the last part, a conclusion of the article is presented.

2. Literature review

In recent years, numerous types of research have been presented on issues related to the HSC. The increase in disasters in recent decades has augmented attention to HSC. Therefore, in the following, the articles published in recent years addressing various aspects of sustainability, location problems, models with multiple objective functions and resilience in HSCs will be examined.

2.1 Sustainable humanitarian supply chain

In several papers, a mathematical model is used that considers all three aspects of sustainability. Haavisto and Kovács (2019) argued that other sustainability aspects such as pollution, sustainable development and social responsibility, have received less attention in HSCs. Oguntola and Ülkü (2023), conducted a study that examined the utilization of artificial intelligence (AI) in sustainable humanitarian logistics (SHL), taking into account the economic, environmental and social dimensions of sustainability. Their research concluded that the application of AI in SHL has the potential to significantly enhance life-saving efforts in humanitarian logistics. In a case study conducted in Mexico, Rodríguez-Espíndola *et al.* (2023) examined the simultaneous and effective consideration of both obtaining victims' consent and reducing carbon emissions in SHL. Their findings indicated that incorporating a diverse range of transportation modes can effectively contribute to reducing carbon emissions and optimizing victims' satisfaction during the relief process. Zarei *et al.* (2019) identified five key factors, namely, supply chain structure, transportation, suppliers, waste and the cultural aspects of people, as the primary components in the discourse on sustainability in the HSC. Praneetpholkrang and Kanjanawattana (2021) proposed a model that incorporates three objective functions for identifying the optimal locations of relief shelters in the aftermath of a disaster. Aghajani and Torabi (2020) developed a MILP model with dual objectives. The model aimed to minimize supply chain costs while also prioritizing relief time, taking into account the importance of various types of relief items. Their findings emphasized the crucial role of pre and postdisaster relief preparations in the overall disaster relief process. Jensen and Hertz (2016) conducted a comprehensive study on the sustainability of pharmaceutical waste in humanitarian aid across multiple regions in Africa. Their research revealed a significant lack of attention given to waste sustainability within the context of humanitarian aid, particularly in the medical sector. Additionally, their findings highlighted the increasing number of organizations involved in disaster relief and logistics. Cao *et al.* (2021) introduced a three-objective MILP model aimed at minimizing unmet demand, reducing biological damage during the relief process and minimizing supply chain costs. Their findings emphasized the importance of a central agency to oversee the supply chain components, ensuring comprehensive attention to sustainability throughout all activities:

> This article explores the dimensions of sustainability in the HSC with the goal of achieving overall satisfaction among all stakeholders and participants involved in the relief process across multiple facets.

2.2 Optimal facility location in the humanitarian supply chain

Given the potential for disruption during disasters, it becomes evident that maintaining uninterrupted relief operations is challenging. Therefore, strategically locating facilities before or after such events becomes crucial in minimizing the impact on the relief process. Since the 1950s, the importance of facility location in the HSC has significantly increased due to the escalating frequency of both natural and human-made disasters (Boonmee *et al.*, 2017). Erden *et al.* (2023), managed a study to determine the optimal location for building distribution centers in an HSC in the Saraka province of Turkey. They used criteria such as environmental factors, transportation infrastructure, proximity to airports and vulnerability to accidents. Using the best worst method, they evaluated and identified the most suitable location. Based on their findings, the Adaparazi region emerged as the optimal choice for establishing the distribution center in this area. Shavarani (2019) introduced a model with the objective of determining the optimal quantity and location of disaster relief centers and drone fueling centers. These centers play a crucial role in serving individuals involved in the HSC. Ak and Derya (2021) used multicriteria decision-making methods to prioritize criteria for identifying the optimal location for establishing a logistics warehouse within an HSC. Zhao and Liu (2018) developed a multiobjective model to enhance disaster response capabilities by determining the most suitable location for emergency rescue equipment on the ground. By presenting a range of Pareto solutions, they compared different approaches that took into account different facility locations. In their study, Loree and Aros-Vera (2018) introduced an innovative approach using a mixed-integer nonlinear programming model. The purpose of this model is to identify the most effective locations for distribution centers to provide humanitarian aid in postdisaster situations. The main goal of the model is to minimize human suffering and casualties. This approach demonstrates remarkable progress in terms of cost-effectiveness and overall satisfaction of the affected population, surpassing the capabilities of traditional disaster service models:

> This article discusses a comprehensive approach for determining the optimal locations of aid stations and refugee camps. It also explores alternative locations for each facility in the event of destruction or unavailability.

2.3 Enhancing resilience in humanitarian supply chain

Without a doubt, postdisaster scenarios often entail additional challenges that can further impact the relief supply chain. If the supply chain lacks the flexibility and resilience to cope with unforeseen disruptions, the relief efforts can suffer from significant delays, resulting in high costs and substantial losses. In their pioneering work, Modarresi and Maleki (2023) successfully integrated decision-making processes in an HSC both pre and postdisaster scenarios. Their study concluded that implementing strategies such as flexible long-term contracts and allocating dedicated budgets for unforeseen events and public assistance can significantly enhance the resilience of the HSC. These findings emphasize the importance of proactive measures and effective resource management in ensuring the preparedness and response capabilities of humanitarian operations. Kaur and Singh (2022) proposed a robust three-stage resilience framework combined with a mathematical model incorporating two objective functions aimed at mitigating disruptions in a global HSC. The framework consists of supplier selection as the initial step, followed by the application of a MILP model to minimize costs and reduce reliance on nonflexible suppliers. Finally, the focus shifts toward minimizing disruptions within the HSC. Xu *et al.* (2021) investigated key indicators for assessing the adaptability of the HSC during a 2020 flood in a specific region of China. Their findings emphasize the importance of establishing effective communication channels and information transfer mechanisms within the supply chain departments. This enables the formation of a flexible supply chain that can respond efficiently during flood-related disasters to ensure proper service delivery. In their research, Medel *et al.* (2020) explored the connection between collaboration in the private sector and public sector, and its influence on the resilience of HSCs. Their study demonstrated that when these two sectors collaborate by engaging in activities such as establishing reserves, enhancing capacities and sharing resources, it greatly improves the overall resilience of the aid supply chain. In their study, Foroughi *et al.* (2022) analyzed the potential risks of service delivery disruptions following natural disasters with the aim of identifying flexible parameters within the HSC. The parameters under investigation included the demand quantity, the probability of disruptions in different scenarios and the manufacturing cost for each product. The research findings revealed that incorporating flexible parameters into relief models brings them closer to real-world conditions, enhancing their practical applicability. Singh *et al.* (2018) examined the factors that impact the resilience of an HSC. Their research findings underscore the significance of several essential elements in bolstering supply chain resilience during disaster situations. These factors include the active support of government agencies, consistent monitoring of relief processes and strategic planning to align demand with the capacity of relief centers. The study emphasizes the critical role played by these factors in fostering resilience within the HSC. Reddy *et al.* (2016) conducted a comprehensive study to explore factors vital in strengthening the resilience of the food supply chain and agricultural industry during periods of disasters. Their research highlighted the importance of several key factors, such as establishing a parallel backup supply chain in conjunction with the primary supply chain, providing training sessions for supply chain agents prior to disasters and conducting disaster simulations. The study strongly indicated that proactive adoption of these measures before a disaster can significantly enhance the overall resilience of the supply chain, enabling more effective recovery in the aftermath of such events.

2.4 Multiobjective approach in humanitarian supply chain

Given the complexity of modeling HSCs, it is crucial to address multiple aspects simultaneously, including social satisfaction, economic costs, environmental concerns and more. In most cases, these models operate by optimizing multiple objective functions in parallel, understanding the interconnected nature of these factors and their collective impact on humanitarian operations. Ehsani *et al.* (2023) developed a scenario-based, multiobjective, multiperiod, internet of things-based, location-allocation-inventory model to respond phase of disasters in the epidemic outbreak. In their study, Akbari *et al.* (2023) proposed a three-objective function model for designing an HSC. The first objective function aimed to minimize the ratio of untreated wounded individuals to the total number of injured. The second objective function focused on minimizing the shortage of relief items, while the third objective function aimed at minimizing economic costs. Their research findings demonstrated that the sensitivity of the first objective function to cost-related parameters, such as transportation and facility construction costs, was greater compared to the second objective function. Bhuiyan *et al.* (2024) directed a study where they introduced a three-objective function model with the goal of reducing economic costs, relief time and the involvement of vehicles in humanitarian relief operations. The model was tested through a case study carried out in the Philippines. The research yielded compelling findings, indicating that this model significantly enhances the efficiency of HSCs, particularly in situations involving secondary accidents. Masoumi *et al.* (2022) discussed a multiobjective and multiperiod queueing-inventory-routing problem in which a queueing model has been considered to reduce the congestion in the borders of the affected areas (AA). In a study conducted by Jamali *et al.* (2021), the 2016 Kermanshah earthquake was examined using a multiobjective mixed-integer programming model. The objective was to assess and compare various aspects of the HSC, including social, economic and environmental factors. The results of the comparison highlighted that prioritizing and improving environmental aspects within the HSC does not always result in higher relief costs. However, it was noted that enhancing the environmental objective function could potentially hinder the improvement of the objective function tied to maximizing social satisfaction. This indicates the need for careful consideration and balance across the different objectives when optimizing the HSC in the context of its social, economic and environmental dimensions. In their study, Praneetpholkrang and Kanjanawattana (2021) proposed a comprehensive three-objective model to determine suitable housing locations for earthquake victims. The model aimed to minimize economic costs, decrease evacuation time for victims from AA and minimize the number of required shelters while ensuring accommodation for all victims. The results showcased the effectiveness of the model in reducing overall supply chain costs by optimizing the number of shelters needed, all while successfully providing housing for 100% of the victims. Mohammadi *et al.* (2021) proposed a three-objective model to address various factors involved in HSC design. These factors included determining the locations of relief centers, establishing evacuation routes for accident victims and optimizing truck routing. The primary objective of the model was to reduce economic costs across the supply chain, followed by the secondary objective of minimizing maximum truck overload. Additionally, the third objective function aimed to minimize human casualties during the relief process. The results demonstrated the model's effectiveness in designing a robust HSC under nondeterministic parameters, highlighting its practicality and usefulness in real-world applications. Jha *et al.* (2017) conducted a study where they introduced a multiobjective model specifically tailored for earthquake scenarios in service supply chains. The main goals of the model were to determine optimal locations for relief camps, optimize delivery routes from suppliers to relief centers and streamline transportation of victims from AA to shelters. The primary objective function focused on minimizing supply chain costs, while the secondary and tertiary objective functions aimed to reduce the gap between supply and demand, ensuring continuous service provision within the relief chain, and enabling efficient evacuation of victims. This multiobjective model encompasses various facets of the supply chain in emergency situations, facilitating effective coordination and resource allocation.

2.5 Gap analysis and research contribution

This article aims to address the gaps identified in previous articles within the field. These gaps can be summarized as follows:

- *Limited consideration of sustainability dimensions*: previous studies in philanthropic contexts have incorporated sustainability aspects into their quantitative supply chain models. However, the focus has primarily been on one or two dimensions of sustainability. This article seeks to broaden the scope by encompassing multiple sustainability dimensions in the model, providing a more comprehensive analysis.
- *Single criterion approach*: many articles in the field have focused on addressing only one criterion within each dimension of sustainability. For instance, when examining social satisfaction, they primarily consider factors such as the extent of demand coverage or the time taken for relief efforts. In contrast, this article acknowledges the need to assess multiple criteria within each dimension, allowing for a more nuanced evaluation of social satisfaction and other sustainability aspects.
- *Lack of consideration for resilience in supply chain disruptions*: most existing articles in the HSC domain overlook the

importance of resilience against future disruptions that may arise in various relief aspects. This article aims to address this gap by examining the impact of potential future disturbances on crucial criteria, such as relief time and victim demands. By incorporating resilience into the model, a more robust approach to HSC management can be achieved.

In this paper, a multiobjective HSC model is developed using a case study of the 2021 earthquake in Haiti. Through a review of existing literature, it has been observed that there is a lack of comprehensive models in the field of HSCs that consider all aspects of sustainability concurrently. This study comprehensively examines various factors, such as the emission of greenhouse gases resulting from the production and transportation of relief items, as well as the management and relocation of damaged goods during relief operations. Moreover, it encompasses economic costs, environmental considerations and social satisfaction, while also focusing on meeting demand requirements and ensuring timely delivery of relief aid. The proposed model is designed to incorporate resilience measures to effectively address potential disruptions caused by aftershocks. Additionally, the model's outcomes will generate a set of Pareto solutions, thereby equipping managers with invaluable insights for decision-making and control in the aftermath of a disaster.

This article offers several advantages over previous studies, including the following:

- In comparison to Boostani *et al.* (2021) article, this study includes an evaluation of victim satisfaction by considering the time it takes for relief processes. This additional aspect provides a superior approach to assessing the effectiveness of the relief efforts.
- In addition to addressing the sustainability aspect of the supply chain, this research specifically emphasizes the reduction of greenhouse gas emissions associated with the production and transportation of relief items, along with the effective management and relocation of damaged goods during relief operations. It is noteworthy that Shakibaei *et al.* (2023) study failed to consider these crucial factors, underscoring the valuable contribution of this article in integrating environmentally friendly practices within the humanitarian framework.
- The model presented in the article by Cao *et al.* (2021) was developed without considering secondary disasters and incorrectly assumed that survivors would need only one type of item, aid kits, without accounting for different quantities. Furthermore, the model did not consider capacity limits across various transportation modes. In contrast, our model takes into account different types of relief items with varying levels of importance and demand from the victims, as well as transportation capacity constraints.

3. Problem descriptions

This article introduces a comprehensive framework for disaster relief operations, focusing on the structure and methods used in providing aid to AA. A well-designed supply chain consisting of various facilities is proposed to facilitate the delivery of relief goods to distribution centers located in the affected regions. Consideration is given to the varying levels of importance assigned to different relief goods, and multiple transportation modes are used to ensure efficient movement between facilities. The primary objective of this study is to ensure timely and effective relief efforts while maximizing satisfaction in meeting the demands of disaster victims. Simultaneously, the article emphasizes the importance of minimizing environmental damage caused during the relief process and reducing overall economic costs. By integrating these three key objectives, the proposed framework aims to achieve a balanced and sustainable approach to disaster relief operations. By adopting this comprehensive approach, the article intends to contribute to the field of disaster management by providing a robust framework that optimizes resource allocation, enhances logistics efficiency and prioritizes the needs of affected communities. The holistic nature of the proposed model ensures that relief efforts are not only effective and efficient but also sensitive to environmental concerns and economically viable.

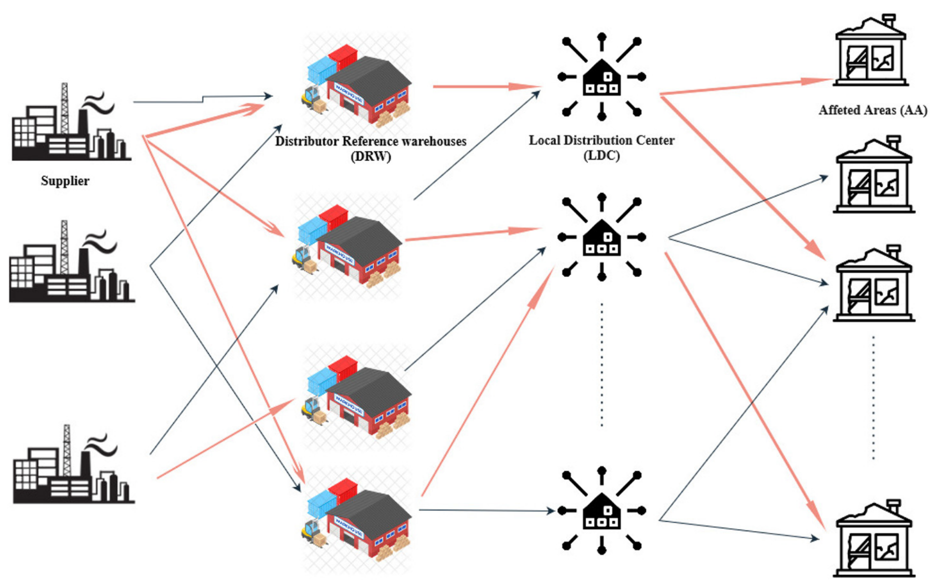
This study presents a three-objective mathematical model using MILP to address key considerations in a disaster relief supply chain. The supply chain comprises four levels of facilities, each serving a unique role. The first level involves established suppliers responsible for providing relief items. The second level consists of distributor reference warehouses (DRW) tasked with receiving large quantities of relief items from suppliers and distributing them to the third level: local distributors. Finally, the relief items are sent from the local distributors to the AA for distribution among the victims. The proposed model seeks to determine several factors, including the quantity of products transported between facilities, the selection of facilities to receive services, the choice of location for establishing these facilities, the type of transportation chosen for delivering goods, the inventory levels in each facility and the number of unused products based on transportation capacity limitations. Each facility and transportation mode has its own capacity limitations, leading to variable delivery times based on the type of vehicle used. Additionally, in the establishment of facilities, product manufacturing and transportation processes, various types of environmental damage are inevitably incurred. With this mathematical model, the article aims to optimize resource allocation, minimize transportation costs and enhance efficiency in the disaster relief supply chain while addressing environmental concerns. By considering these multiobjective factors, decision-makers can make informed choices to achieve an effective and sustainable relief operation (Figure 1).

In this model, each product's importance level corresponds to the specific needs of the disaster victims, making its production crucial for ensuring their satisfaction. After a disaster, the importance of relief items needed by the victims varies significantly. Blood packs, therapeutic serums and play equipment for children in relief shelters each hold a different degree of importance in the relief model. The model incorporates different scenarios with varying aftershocks, resulting in disruptions across facilities, leading to the destruction of relief items and prolonging the relief timeline. Figure 2 provides an overview of the supply chain, with arrows indicating different modes of transportation between facilities. Each scenario considers rates for both time and disruption extent, illustrating the impact of each aftershock on relief time and disruptions. This article tackles the model by initially solving it precisely using general algebraic modeling system (GAMS) software. Some assumptions have been made to

Figure 1 Summary of the article structure

Source: Figure created by authors

Figure 2 Summary of the proposed methodology



Source: Figure created by authors

formulate this supply chain model accurately. By considering these various factors and using efficient algorithms, the aim is to optimize the relief process, minimize disruptions and achieve timely and effective aid delivery in disaster scenarios.

Figure 1 shows a simple summary of the article structure.

The model is developed under the following assumptions:

- Relief items are considered to be susceptible to damage only during the transit between facilities.
- Any relief items that sustain damage during transportation are discarded upon arrival at the destination facility.
- The capacity of each facility and transportation mode is defined in a general manner, without specifying individual

capacities for each type of relief item within each facility or vehicle.

- The inventory level within each facility is determined by the sum of items sent from that facility to other facilities, along with any remaining unused items within the facility due to capacity limitations in transportation and other facilities.
- There are predetermined options available for establishing facilities, and the selection is based on optimizing the overall performance of the supply chain.
- The transportation modes between facilities are predefined, and the choice of transportation is influenced by factors such as capacity and delivery time.
- The model considers different levels of importance for each product based on the needs and satisfaction of the disaster victims.
- The incorporation of different scenarios with varying aftershocks assumes that these scenarios can impact the facilities in the supply chain, resulting in disruptions and potentially damaging or destroying relief items.
- The environmental damage caused during the establishment of facilities, production of items and transportation processes is acknowledged as a significant factor.

Figure 2 shows an overview of the supply chain presented in this article.

3.1 Three-objective linear integer mathematical programming model

The article presents a formulated three-objective linear integer mathematical programming model to tackle the problem at hand. The epsilon constraint method has been used to generate a set of Pareto-optimal solutions for this multiobjective model. The primary goal of the model is to improve satisfaction levels among disaster victims through the minimization of relief time, unfulfilled demand, environmental damage and economic costs. The solution methodology section provides comprehensive details regarding the methodology and solution approach used in the study.

3.2 Mathematical modeling

This subsection focuses on presenting the mathematical modeling. Table 1 has listed the used notations of the proposed mathematical model.

The first objective function [equation (1)] aims to maximize social satisfaction in relief efforts. This objective function consists of two key components: the first component focuses on maximizing the fulfillment of victims' demands, while the second component focuses on minimizing the maximum relief time.

The second objective function [equation (2)] is centered on minimizing the economic costs associated with the HSC. These costs encompass various factors such as the establishment and utilization costs of supply chain facilities, production costs of relief items, transportation costs during the relief process, costs incurred due to unmet demands and costs attributed to unused items within the facilities. The objective is to optimize these economic factors and reduce overall expenses within the HSC.

The third objective function [equation (3)] focuses on minimizing the detrimental environmental impacts within the supply chain during the relief process. These impacts include factors such as the emission of greenhouse gases resulting from the production and transportation of relief items, as well as the disposal or evacuation of disrupted items during relief operations. The objective is to reduce the environmental footprint and promote sustainable practices throughout the supply chain, considering the ecological consequences of relief efforts.

$$MaxZ_1 = \left(\sum_l \sum_a \sum_k \sum_m \sum_s (\delta_k * P_s * x_{lamks} * \text{ч}_{aks})\right) - \text{л} * T^{max} \tag{1}$$

$$\begin{aligned} MinZ_2 = & \sum_j ED_j * jj_j + \sum_l EL_l * BL_l + \sum_a ER_a * BA_a \\ & + \sum_i \sum_j \sum_m \sum_k \sum_s TSD_{ijmk} * Q_{ijmks} \\ & + \sum_j \sum_l \sum_m \sum_k \sum_s TDL_{jlmk} * W_{jlmks} \\ & + \sum_l \sum_a \sum_m \sum_k \sum_s TLA_{lamk} * X_{lamks} \\ & + \sum_k (CSD_k * UU_{kas}) + \sum_i \sum_k \sum_s UIS_{ik} \\ & + ULS_{ikS} * P_S + \sum_j \sum_k \sum_s UID_{jk} * ULD_{jks} * P_S \\ & + \sum_l \sum_k \sum_s UIL_{lk} * ULL_{lks} * P_S \end{aligned} \tag{2}$$

$$\begin{aligned} MinZ_3 = & \sum_i \sum_k \sum_s ILI_{iks} * GP_{ik} \\ & + \sum_i \sum_j \sum_k \sum_m \sum_s GS_{ijkm} * Q_{ijkms} \\ & + \sum_j \sum_l \sum_k \sum_m \sum_s GS_{jlkm} * W_{jlkms} \\ & + \sum_l \sum_a \sum_k \sum_m \sum_s GS_{lakm} * X_{lakms} \\ & + \sum_s P_s \left(\sum_j \sum_k (1 - \delta_{jks}) * pc_{jk} * ILD_{jks} \right. \\ & + \sum_l \sum_k (1 - l_{lks}) * pc_{lk} * ILL_{lks} \\ & \left. + \sum_a \sum_k \sum_s (1 - \text{ч}_{aks}) * pc_{ak} * ILA_{aks} \right) \end{aligned} \tag{3}$$

Equations 4 to 21 represent the constraints within the model. These constraints play a crucial role in ensuring the accuracy and validity of the model's formulation.

Constraints 4 and 5 show the capacity limits for each local distribution center (LDC) and each DRW.

Constraint 6 states that the sum of unused items within each supplier and the items sent to DRWs must not exceed the supplier's capacity. This constraint ensures that the total inventory within a supplier remains within its specified limits, accounting for both unused items and those allocated to DRWs.

Constraint 7 shows that in each DRW, the sum of output items and unused items should not exceed the capacity of that DRW.

Constraint 8 shows that in each LDC, the sum of output items and unused items should not exceed the capacity of that LDC.

Constraint 9 shows the amount of unfulfilled demand for each relief item k in each AA.

Table 1 Notations

Sets	
I	Index of suppliers, i = 1,2, 3, . . ., I
J	Index of DRWs, j = 1,2, 3, . . ., J
L	Index of LDCs, l = 1,2, 3, ..., L
A	Index of AA, a = 1,2, 3, . . ., A
S	Index of scenarios, s = 1,2,3
F	Index of disasters that occur after the main disaster
K	Index of relief items, k = 1,2, 3, . . ., K
M	Index of modes of transportation, m = 1, 2, 3, . . ., M
Parameters	
W	A large number
CS_i	The capacity of the i-th supplier
CD_j	The capacity of the j-th DRW
CL_l	The capacity of the l-th LDC
CM_m	Transport capacity by mode m
Ck_i	The total cost of producing each unit of relief item K in supplier i
ED_j	The establishing cost of the *j*-th DRW
EL_l	Establishing the cost of the *l*-th LDC
ER_a	The total cost of shelter construction in the a-th affected area
TSD_{ijmk}	The cost of transporting each unit of product k from the i-th supplier to the j-th DRW by the m mode of transportation
TDL_{jlmk}	The cost of transporting each unit of product k from the j-th DRW to the l-th LDC by the m mode of transportation
TLA_{lamk}	The cost of transporting each unit of product k from the l-th LDC to the a-th AA by the m mode of transportation
SSD_{ijm}	The total transportation time from the i-th supplier to the j-th DRW by mode m
SDL_{jlm}	The total transportation time from the j-th DRW to the l-th LDC by mode m
SLA_{lam}	The total transportation time from the l-th LDC to the a-th AA by mode m
U_k	Capacity occupied by each unit of relief items k
CTS_{ijm}	Transport capacity between supplier i and DRW j in mode m
CDL_{jlm}	Transport capacity between DRW j and LDC l in mode m
CLA_{lam}	Transport capacity between LDC l and AA a in mode m
δ_k	The importance coefficient of the k-th relief item
Л	The coefficient of the importance of the maximum time compared to the obtained demand
UID_{jk}	The cost of each unit of unused k relief item in j-th DRW
UIL_{lk}	The cost of each unit of unused k relief item in l-th LDC
UIA_{Ak}	The cost of each unit of unused k relief item in a-th AA
UIS_{ik}	The cost of each unit of unused k relief item in i-th supplier
CSD_k	The cost of not fulfilling each unit of the demand for k-th relief items
D_{ak}	The amount of demand in the AA for the k-th relief item
P_s	The probability of scenario s
θ_{fs}	The rate of the impact that postdisaster f has on people’s demand in s scenario
R_{fs}	The impact rate of postdisaster f on relief time in scenario s
ɗ_{jks}	Usable (nondestroyed) inventory rate for relief item k in j-th DRW in scenario s
ɭ_{lks}	Usable (nondestroyed) inventory rate for relief item k in l-th LDC in scenario s
ч_{aks}	Usability rate for k-th relief items that have reached a-th affected area (AA) in scenario s
GP_{ki}	The amount of GHG released to produce each unit of relief item k in each supplier i
GS_{ijkm}	The amount of GHG released for shipping each unit of relief items k from supplier i to j-th DRW in mode m Transportation
GS_{jlkm}	The amount of GHG released for shipping each unit of relief items k from DRW j to l-th LDC in mode m Transportation
GS_{lakm}	The amount of GHG released for shipping each unit of relief items k from LDC l to a-th AA in mode m Transportation
Pc_{jk}	The amount of GHG caused by the disposal of the k-th relief items in DRW j
Pc_{lk}	The amount of GHG caused by the disposal of the k-th relief items in LDC l
Pc_{ak}	The amount of GHG caused by the disposal of the k-th relief items in a-th AA
Variables	
E_i	1 for whether the i-th supplier is selected, otherwise 0
JJ_j	1 for whether the j-th DRW is established, otherwise 0
BL_l	1 for whether the l-th LDC is established, otherwise 0
BA_a	1 for whether the a-th AA is established, otherwise 0
BI_{ijm}	1 if mode m transportation is used between the i-th supplier and the j-th DRW, otherwise 0 under scenario s

(***continued***)

Table 1

Sets	
$\mathbf{Y}_{jlm}$	1 if mode m transportation is used between the j-th DRW and the l-th LDC, otherwise 0
η_{lam}	1 if mode m transportation is used between the l-th LDC supplier and the a-th AA, otherwise 0
Q_{ijkms}	The amount of relief item k that is sent from the i-th supplier to the j-th DRW by mode m transportation in scenario s
W_{jlkms}	The amount of relief item k that is sent from the j-th DRW to the l-th LDC by mode m transportation in scenario s
X_{lakms}	The amount of the k-th relief item delivered by the lth LDC to the a-th AA by mode m transportation in scenario s
UU_{kas}	The amount of unsatisfied demand for the k-th relief item in a-th AA in s scenarios
ILI_{iks}	The inventory level of k-th item in i-th supplier in scenario s
ILD_{jks}	The inventory level of k-th item in j-th DRW in scenario s
ILI_{lks}	The inventory level of k-th item in l-th LDC in scenario s
ILA_{aks}	The inventory level of k-th item in a-th AA in scenario s
ULD_{jks}	Amount of unused k-th relief item in the j-th DRW in scenario s
$\mathrm{ULL}_{\mathrm{lks}}$	Amount of unused k-th relief item in the l-th LDC in scenario s
ULS_{iks}	Amount of unused k-th relief item in the i-th supplier in scenario s
$\mathrm{T}^{\mathrm{max}}$	The maximum optimal time for relief items to reach AA

Source: Table created by authors

Constraints 10 to 12 specify the transportation constraints for each relief item (k) across different modes of transport (m).

Constraints 13 to 15 indicate the level of inventory in each facility of the supply chain.

Constraints 16 to 18 ensure transportation time between facilities in each mode remains below the maximum relief time.

Constraints 20 and 21 specify the loss percentage of goods during transportation between facilities:

$$\sum_k ILL_{lks} * u_k \le CL_l * BL_l \quad \forall l, \forall s \tag{4}$$

$$\sum_k ILD_{jks} * u_k \le CD_j * \mathfrak{JJ}_j \quad \forall j, \forall s \tag{5}$$

$$\sum_k \sum_j \sum_m Q_{ijkms} * u_k + \sum_k ULS_{iks} * u_k \le CS_i * E_i \quad \forall s, \forall i \tag{6}$$

$$\sum_k \sum_l \sum_m W_{jlkms} * u_k + \sum_k ULD_{jks} * u_k \le CD_j * \mathfrak{JJ}_j \ \forall s, \forall j \tag{7}$$

$$\sum_k \sum_a \sum_m X_{lakms} * u_k + \sum_k ULL_{lks} * u_k \le CL_l * BL_l \forall s, \forall l \tag{8}$$

$$\sum_l \sum_m (X_{lakms} * \text{ч}_{\mathrm{aks}}) + UU_{kas} = D_{ka}\left(1 + \sum_f (\theta_{fs})\right) \ \forall k, \forall a, \forall s \tag{9}$$

$$\sum_k Q_{ijkms} * u_k \le CTS_{ijm} * \mathrm{BI}_{\mathrm{ijm}} \quad \forall i, \forall j, \forall m, \forall s \tag{10}$$

$$\sum_k W_{jklms} * u_k \le CDL_{jlm} * \mathrm{Y}_{\mathrm{jlm}} \ \forall j, \ \forall l, \forall m, \forall s \tag{11}$$

$$\sum_k X_{lakms} * u_k \le CLA_{lam} * \eta_{\mathrm{lam}} \quad \forall l, \forall a, \forall m, \forall s \tag{12}$$

$$\sum_j \sum_m Q_{ijkms} + ULS_{iks} = ILI_{iks} * E_i \quad \forall i, \forall k, \forall s \tag{13}$$

$$\sum_l \sum_m W_{jlkms} + ULD_{jks} = ILD_{jks} * \mathfrak{JJ}_j * \delta_{\mathrm{jks}} \quad \forall j, \forall k, \forall s \tag{14}$$

$$\sum_a \sum_m X_{lakms} + ULL_{jks} = ILL_{lks} * BL_l * l_{\mathrm{ls}} \ \forall l, \forall k, \forall s \tag{15}$$

$$SSD_{ijm} * BI_{ijm} * \sum_f (1 + \mathrm{R}_{fs}) \le T^{max} \ \forall i, \forall j, \forall m, \forall s \tag{16}$$

$$SDL_{jlm} * \mathrm{Y}_{jlm} * \sum_f (1 + \mathrm{R}_{fs}) \le T^{max} \ \forall j, \forall l, \forall m, \forall s \tag{17}$$

$$SLA_{lam} * \eta_{lam} * \sum_f (1 + \mathrm{R}_{fs}) \le T^{max} \quad \forall l, \forall a, \forall m, \forall s \tag{18}$$

$$UFF_k = \sum_a \left(D_{ak} - \sum_s \sum_l \sum_m X_{lakms} * P_S\right) \quad \forall k \tag{19}$$

$$\sum_l W_{jlkms} \le \sum_i Q_{ijkms} * \delta_{jks} \quad \forall j, \forall k, \forall m, \forall s \tag{20}$$

$$\sum_a X_{lakms} \le \sum_j W_{jlkms} * l_{lks} \quad \forall l, \forall k, \forall m, \forall s \tag{21}$$

$$E_i, \ \mathfrak{JJ}_j, \ BL_l, \ BA_a, \ BA_a, \ BI_{ijm}, \ Y_{jlm}, \eta_{jlm} \in \ \{0, 1\}$$

Nonlinear constraints 13, 14 and 15 can be readily transformed into a set of linear constraints. To illustrate, constraint 13 can be expanded into four distinct linear constraints as illustrated below:

$$\sum_j \sum_m Q_{ijkms} + ULS_{iks} = EILI_{iks} \quad \forall i \ , \forall k, \forall s \tag{22}$$

$$EILI_{iks} \le ILI_{iks} \quad \forall i, \forall k, \forall s \tag{23}$$

$$EILI_{iks} \le E(i) * BigM \quad \forall i, \forall k, \forall s \tag{24}$$

$$EILI_{iks} \ge ILI_{iks} + (E(i) - 1) * BigM \quad \forall i, \forall k, \forall s \tag{25}$$

4. Solution methodology

This article demonstrates the validation of the proposed model through the presentation and solution of a small example. The results of this validation process are depicted in Figure 3 and Table 5. Following the successful validation, the implementation of the model in a case study concerning the 2021 earthquake in Haiti is discussed and the obtained results are comprehensively analyzed.

4.1 Multiobjective approach

In multiobjective mathematical programming models, multiple objectives with conflicting optimization goals exist. Achieving an optimal solution requires striking a balance between these objectives, which is facilitated by the set of Pareto solutions generated through multiobjective solving methods. In this article, the presented multiobjective model is solved using the epsilon constraint method to address this need for balancing the objectives and obtaining optimal solutions.

4.1.1 Epsilon – Constraint method

Different approaches to dealing with multiobjective mathematical models were considered in the pertinent literature (Lotfi *et al.*, 2023). One of this approach is epsilon-constraint method that is regarded as a conventional and extensively used technique for addressing multiobjective modeling issues. This approach is used in situations which is challenging to obtain a single optimal solution that be able to satisfy all objectives simultaneously (Eslamipirharati *et al.*, 2023). In this method, basic information about the decision-maker's preferences is needed. In this process, the decision-maker's priorities are conveyed to the analyzer, who then uses the epsilon-constraint method for solving. The key principle of this method is to optimize the objective function that holds the highest priority for the decision-maker, while treating the remaining objective functions as constraints within their respective limits (Mavrotas, 2009):

$$\begin{cases} Max\ Z(\mathrm{x}) = \ [\mathrm{z}_1(\mathrm{x}), z_2(\mathrm{x}), \ldots, \quad \mathrm{z}_k(\mathrm{x})] \\ \qquad\qquad s.t \\ \qquad g_i(x) \leq 0, \forall i = 1, 2, \ldots, m \end{cases} \tag{26}$$

After using the epsilon-constraint method, it becomes:

$$\begin{cases} \mathrm{Max} \quad \mathrm{Z_h(x)} \\ \mathrm{s.t} \\ \mathrm{g_i} \leq 0 \ \ \forall \mathrm{i} = 1, 2, \ldots, \mathrm{m} \\ \mathrm{Z_j(x)} \geq \mathrm{e}_j \ , \ \ \mathrm{j} = 1, 2, \ldots, \mathrm{h}-1, \mathrm{h}+1, \ldots, \mathrm{k} \end{cases} \tag{27}$$

The objective functions should be formulated as maximization type, and subsequently transformed into constraints with lower limits (e_j). By solving this transformed model iteratively, an efficient solution is obtained. After exploring different lower bounds for these objective functions, a set of Pareto solutions is generated. The epsilon-constraint method follows the solution algorithm outlined below:

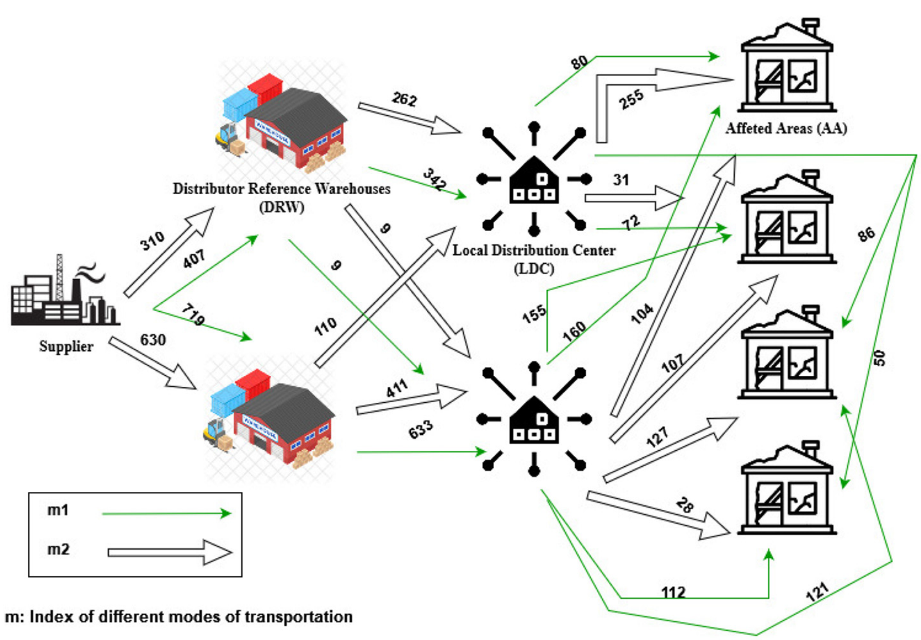
Step 1: Obtaining optimal solutions of all the objective functions individually.

Step 2: The optimal point of each objective function, denoted as $z_i(x^k)$, is substituted into the other objective functions. This process results in the creation of a payoff table (Table 2). Table 2 displays the values of each objective function when the model is optimized based on a single objective function. For instance, $Z_2(x^1)$ represents the value of the second objective function when the optimal solution of the model is determined by the first objective function:

$$\text{Also}: n_j \leq Z_j \leq m_j$$

Step 3: In the range of the objective function, we consider different values for $\mathrm{e_j}$ and solve the objective function according

Figure 3 Graphic representation of the solved model in the small scale of the supply chain



Source: Figure created by authors

Table 2 Payoff table

	$Z_1(x)$	$Z_2(x)$	...	$Z_k(x)$
x^1	$Z_1(x^1)$	$Z_2(x^1)$	...	$Z_k(x^1)$
x^2	$Z_1(x^2)$	$Z_2(x^2)$	...	$Z_k(x^2)$
...	...	...	...	...
x^k	$Z_1(x^k)$	$Z_2(x^k)$	...	$Z_k(x^k)$
Maximum	m_1	m_2	...	m_k
Minimum	n_1	n_2	...	n_k

Source: Table created by authors

to them. These values for e_j are calculated by the following equation:

$$e^j = n_j + \left[\frac{t}{r-1}\right](m_j - n_j) \quad t = 0, 1, \ldots, r-1 \tag{28}$$

r = The selection of points within the range of $n_j \le Z_j \le m_j$.

Some of the advantages of the epsilon-constraint method include:

- The method is computationally efficient and does not introduce additional variables to the problem.
- It generates a set of nondominant solutions, enhancing the understanding of the problem.
- Scaling the different objective functions is not required.
- The method allows for the control of the number of generated solutions based on the decision-maker's preferences (Teymoori *et al.*, 2022).

5. Numerical example

In this section, the model is validated through a small-scale numerical example solved using GAMS software. The computations were executed on a computer with a 2.3 GHz central processor and 8 GB of RAM, using the Baron solver for exact solutions. The results of solving this example are presented in Figure 3 as a graphical diagram.

5.1 Small size problem

In this subsection, an example on a small scale is presented to verify the logic of the model. The example involves one supplier, two DRWs, two LDCs and four AAs in the supply chain. Additionally, only transportation Modes 1 and 2 are taken into account for sending relief items between facilities.

Allocated capacities for each facility and costs of unused relief items are presented in Tables 3 and 4, respectively. Moreover, the values of other parameters remain consistent with those outlined in Section 6, ensuring accuracy and reliability across the analysis.

Table 3 Capacity allocated to the facility in the small-scale example

Facility	Facility number	Capacity
Supplier	1	5,000
DRW	1	2,400
	2	2,300
LDC	1	2,000
	2	2,000

Source: Table created by authors

Table 4 Cost of unused relief items in each facility

	Relief item index				
Facility	**1**	**2**	**3**	**4**	**5**
Supplier					
1	10	10	30	20	20
DRW					
1	1	1	3	2	2
2	1	1.5	2	2	2
LDC					
1	2	2	5	3.5	4
2	3	1.5	4	2	2.5
AA					
1	1	1	3	2	2
2	1	1.5	2	2	2
3	2	1	4	1.5	2
4	1	1	3	2	2

Source: Table created by authors

Based on the solutions obtained, Figure 3 illustrates the graphical representation of the total inflow and outflow of relief items for each facility. Also, in Table 5, the amount of unfulfilled demand in each AA (UU_{kas}) is shown.

5.2 Model validation

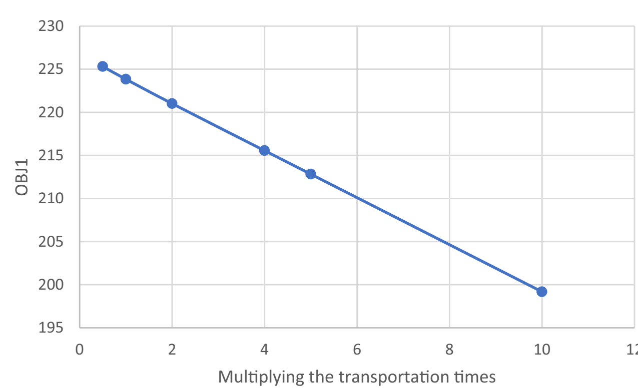
In this section, the validity of the model is evaluated from the results obtained by solving the model on a small scale. Figure 4

Table 5 Amount of shortage of each type of relief items in each affected area

	AA	a1	a2	a3	a4
Relief item	k1	335	366	303	257
	k2	69	66	61	240
	k3	0	0	0	32
	k4	127	388	356	295
	k5	9	0	0	0

Source: Table created by authors

Figure 4 First objective function based on transit time



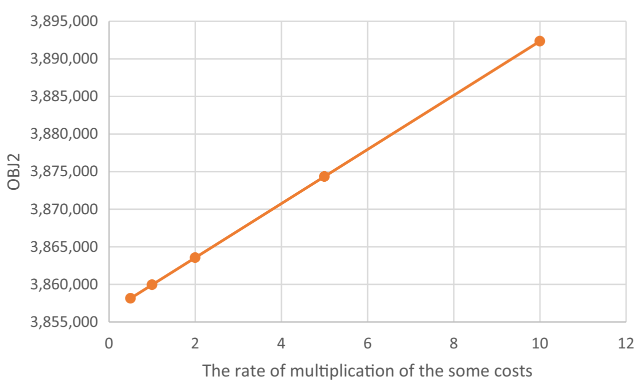
Source: Figure created by authors

shows the changes of the first objective function due to the increase in transportation time between facilities in the relief process. As anticipated, increasing transportation times during the relief process led to a decrease in the satisfaction level of disaster victims. In another study, Figure 5 illustrates the variations in the second objective function, which encompasses the total economic costs, including establishment costs of aid centers and marginal costs of unused items across each facility. The graph indicates that as costs increase, the second objective function also rises, as expected. Finally, in Figure 6 the impact on the third objective function, representing environmental damage, was examined concerning the escalation of greenhouse gas emissions during the transportation of goods between facilities. As predicted, an increase in pollutant emissions results in an increase in the third objective function.

6. Model implemented: a case study

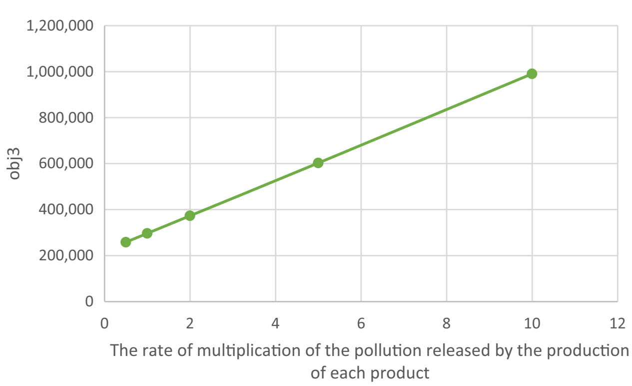
In the aftermath of a disaster, numerous individuals are directly or indirectly affected, often experiencing severe disruptions to their lives. Given the critical importance of swift action in relief planning, implementing the model in a case study and analyzing the results can significantly contribute to future disaster response planning efforts, mitigating potential damages. In this context, data has been collected from the 2021 earthquake in Haiti to inform the study and draw valuable lessons for more effective relief operations in the future. It should be noted that due to the fact that there is very little and contradictory information about the Haiti earthquake in 2021, there is very little data about this disaster and their values are often different from each other. For this reason, the values of some parameters are considered as an interval with a uniform distribution. Also, since this model was developed based on the implementation of possible future disasters, the only demand parameter is dependent on the data related to that earthquake and the values of other parameters such as parameters related to capacity, establishment costs and the parameters related to pollution have been determined according to field observations, environmental assessments and also past articles such as Nezhadroshan *et al.* (2021).

Figure 5 Sensitivity analysis of the second objective function based on some costs



Source: Figure created by authors

Figure 6 Sensitivity analysis of the third objective based on the produced pollutants



Source: Figure created by authors

6.1 Case study description

The model incorporates data from the 2021 earthquake in the Tibourn Peninsula of Haiti. This earthquake, registering a magnitude of 7.2 on the Richter scale, endured for over 30 s, tragically claiming the lives of at least 1,290 individuals and displacing more than 50,000 people (Sriram *et al.*, 2023). After the earthquake, the region experienced four significant aftershocks. The subsequent section presents the parameters derived from the data collected during the case study.

In the following, the values assigned to the parameters based on the data obtained from the case study are presented. In Table 6, the capacity of each facility that may be used in the supply chain is presented.

Table 7 provides a breakdown of the setup costs associated with each facility. These costs encompass the initial expenses

Table 6 Capacity of supply chain facilities

Facility	Facility number	Capacity
Supplier	1	9,500
	2	7,000
DRW	1	4,600
	2	4,500
	3	4,700
LDC	1	4,500
	2	3,400
	3	4,400
	4	2,000

Source: Table created by authors

Table 7 Cost of establishing or using the facility

Facility	Facility number	Establish cost
DRW	1	1,000
	2	1,200
	3	1,500
LDC	1	700
	2	700
	3	700
	4	500
Shelters in AA	All	1,000

Source: Table created by authors

for suppliers and DRWs, as well as the construction costs for LDCs and AAs.

Moving on to Table 8, it displays the quantity of demand for each AA categorized by different types of relief items. It is important to note that due to the inherent uncertainty in the demand quantities, this factor can contribute to generating varying outcomes within the model.

Table 8 Demand for relief items

Relief item index	Amount of demand for all AAs
1	Uniform (200,400)
2	Uniform (200,250)
3	Uniform (100,140)
4	Uniform (300,400)
5	Uniform (100,130)

Source: Table created by authors

Table 9 Cost per unit of unused relief items in the facility

	Relief item index				
Facility	1	2	3	4	5
Supplier					
1	10	10	30	20	20
2	10	15	20	20	20
DRW					
1	1	1	3	2	2
2	1	1.5	2	2	2
3	2	1	4	1.5	2
LDC					
1	2	2	5	3.5	4
2	3	1.5	4	2	2.5
3	2	2	3.5	3	3
4	2	2	3.5	3	3
AA					
1	1	1	3	2	2
2	1	1.5	2	2	2
3	2	1	4	1.5	2
4	1	1	3	2	2
5	1	1.5	2	2	2
6	2	1	4	1.5	2

Source: Table created by authors

As a result of capacity limitations in transportation modes and facilities at subsequent stages, certain items become unusable and are left in each facility. The disposal of these items incurs costs for the companies involved, which are detailed in Table 9.

Next, the values of other important parameters are shown in Table 10. These parameters encompass the expense associated with transferring each product between different types of facilities, the duration of transportation between said facilities, the capacity of each transportation mode, as well as variables related to the generation of environmental pollution.

6.2 Case study result

In this section, the optimal outcomes of the implemented model on a case study are showcased.

Table 11 presents a comprehensive overview of the quantity of each type of relief items received and dispatched to individual facilities. The transportation of these items is facilitated through various modes of transportation.

Furthermore, the entire process of providing relief and delivering relief items to the AA within this supply chain was successfully accomplished in a total timeframe of 292 h. Additionally, Table 12 provides the objective function values pertaining to each epsilon for all three objectives.

In Figures 7 and 8, a comparative analysis of the objective functions is presented, showcasing their behavior toward each other based on the set of Pareto solutions.

Figures 7 and 8 indicate that the third objective function exhibits an opposite relationship concerning desirability when compared to the two aforementioned objective functions. Improvements in this third objective function correspond to a decline in the objective function associated with social satisfaction and economic costs.

Figure 9 provides a concluding visual representation in the form of a scatter diagram, which effectively demonstrates the intricate interplay between the objective functions. It uses the set of Pareto solutions as a reference point, offering valuable insights into the relationships between these functions and fostering a deeper understanding of their dynamics.

7. Sensitivity analysis

The key parameters of the presented model are primarily the facility capacity-related parameters (CL_l, CD_j, CS_i), the transportation mode capacities (CTS_{ijm}, CDL_{jlm}, CLA_{lam}) and the AA demand (D_{ak}). Also, the importance rate of total time

Table 10 Values of other important parameters

Parameter	Distribution function	Parameter	Distribution function
TSD_{ijmk}	Uniform (1,3)	Pc_{jk}	Uniform (11,15)
TDL_{jlmk}	Uniform (1,3)	Pc_{lk}	Uniform (10,15)
TLA_{lamk}	Uniform (1,3)	Pc_{ak}	Uniform (25,35)
SSD_{ijm}	Uniform (40,60)	PI	0.01
SDL_{jlm}	Uniform (40,60)	GP_{ki}	Uniform (5,15)
SLA_{lam}	Uniform (40,60)	GS_{ijkm}	Uniform (5,15)
CTS_{ijm}	Uniform (10,000,14,000)	GP_{jlkm}	Uniform (5,15)
CDL_{jlm}	Uniform (10,000,14,000)	GS_{lakm}	Uniform (5,15)
CLA_{lam}	Uniform (10,000,14,000)		

Source: Table created by authors

Table 11 Amount of relief items received to or sent from each facility

The shipment amount of type k relief items from supplier i to DRW j (Q_{ijkms})					
Q_{111}	237	Q_{124}	380	Q_{223}	159
Q_{112}	73	Q_{132}	94	Q_{224}	517
Q_{113}	114	Q_{133}	698	Q_{232}	1273
Q_{114}	36	Q_{212}	35	Q_{233}	25
Q_{115}	425	Q_{214}	1,063	Q_{234}	494
Q_{121}	1,780	Q_{215}	432	Q_{235}	34
Q_{122}	168	Q_{222}	59		
The shipment amount of type k relief items from DRW j to LDC l (W_{jlk})					
W_{111}	171	W_{145}	564	W_{244}	31
W_{115}	87	W_{211}	1,340	W_{314}	344
W_{121}	51	W_{214}	82	W_{315}	18
W_{122}	33	W_{223}	54	W_{322}	976
W_{123}	84	W_{231}	43	W_{323}	468
W_{124}	51	W_{232}	33	W_{333}	37
W_{125}	48	W_{233}	74	W_{334}	80
W_{134}	895	W_{234}	650	W_{342}	88
W_{135}	40	W_{241}	124	W_{343}	116
W_{142}	70	W_{242}	155	W_{345}	14
The shipment amount of type k relief items from l-th LDC to a-th AA (X_{lak})					
X_{111}	144	X_{234}	46	X_{353}	17
X_{114}	110	X_{242}	143	X_{354}	173
X_{115}	16	X_{243}	88	X_{363}	16
X_{121}	224	X_{245}	5	X_{364}	240
X_{124}	49	X_{252}	144	X_{411}	68
X_{131}	172	X_{253}	17	X_{412}	63
X_{135}	18	X_{255}	14	X_{415}	35
X_{141}	282	X_{262}	153	X_{421}	87
X_{145}	10	X_{263}	91	X_{422}	31
X_{151}	184	X_{313}	20	X_{425}	87
X_{154}	122	X_{314}	255	X_{432}	35
X_{155}	19	X_{323}	17	X_{435}	87
X_{161}	297	X_{324}	279	X_{442}	31
X_{164}	85	X_{325}	18	X_{443}	26
X_{165}	16	X_{332}	35	X_{444}	28
X_{212}	149	X_{333}	20	X_{445}	86
X_{213}	114	X_{334}	218	X_{451}	40
X_{221}	48	X_{335}	19	X_{452}	43
X_{222}	149	X_{342}	30	X_{453}	77
X_{223}	97	X_{343}	20	X_{455}	77
X_{225}	19	X_{344}	253	X_{461}	5
X_{232}	164	X_{351}	40	X_{462}	31
X_{233}	115	X_{352}	19	X_{465}	91

Source: Table created by authors

(Л) can play an important role. In this section, the impact of the variation of the key parameters within the model on the resulting values of the decision variables and objective functions is examined.

The sensitivity of the ratio of total shortages to the ratio of total demands $\frac{UU_{ka}}{D_{ak}}$ as influenced by the Л rate is illustrated in Figure 10. It is widely recognized that an increase in the coverage rate of demands occurs when less significance is placed on time.

Figures 11 to 18 illustrate the behavior of the objective functions in response to changes in variables. Figure 11 demonstrates that there is no distinct relationship between increasing or decreasing demand and the first objective function. However, Figure 12 reveals a notable impact of increased demand on the rise of economic costs in the second objective function.

Figures 13 to 15 illustrate how the objective functions are affected by the capacities of various transportation modes. It is evident that a decrease in transportation capacity has a significant and adverse impact on the objective function related to social satisfaction and economic costs. Conversely, once the desired capacity level of a transportation mode is attained, further increases in capacity do not significantly affect the objective functions.

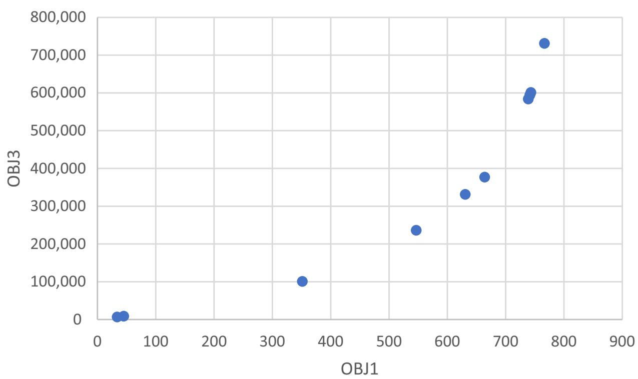
In Figures 16, 17 and 18, the impact of increasing or decreasing facility capacities on the objective functions is

Table 12 Set of objective function values for different epsilons

	obj1	obj2	obj3
1	725.112	1,222,577	532,731.2
2	765.327	550,692.9	717,731.9
3	741.384	999,985.1	592,369.1
4	741.384	999,985.1	592,369.1
5	459.734	502,3991	163,370.8
6	520.32	4,110,701	220,301.9
7	591.172	3,041,932	282,874.3
8	649.045	2,383,913	354,898.3
9	676.782	1,965,076	400,347.9

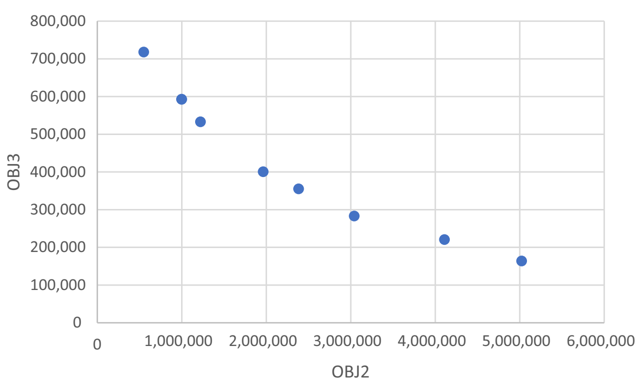
Source: Table created by authors

Figure 7 Comparative analysis of the first and third objective functions based on the set of Pareto solutions



Source: Figure created by authors

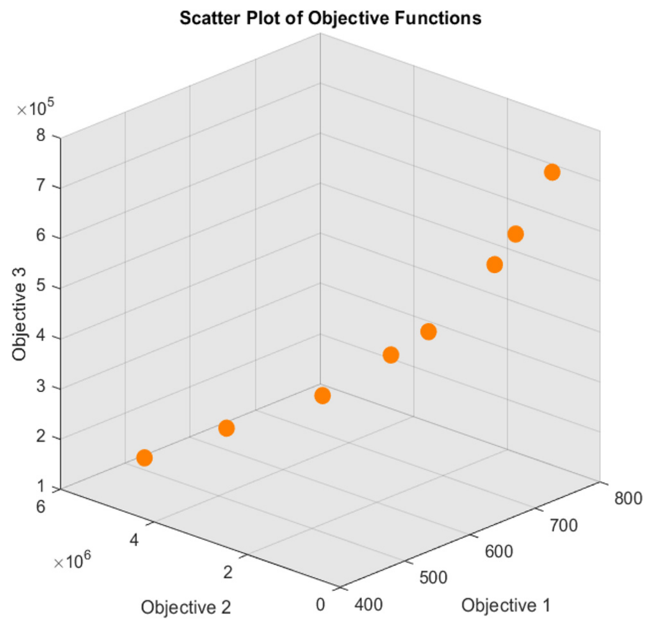
Figure 8 Comparison of the behavior between the 1st and 3rd objective function based on the set of Pareto solutions



Source: Figure created by authors

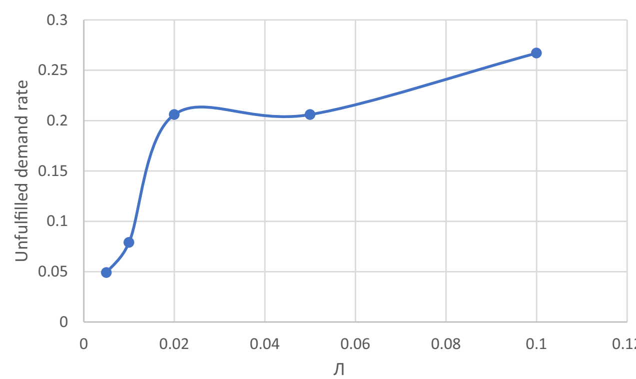
demonstrated. It is widely recognized that reducing facility capacity from an optimal level can significantly detriment the satisfaction of disaster victims during the relief process while increasing supply chain costs due to inadequate support. Conversely, enhancing facility capacities improves the performance of the first and second objectives, as depicted in Figure 16. However, as shown, increasing facility capacities ultimately results in greater environmental damage.

Figure 9 Scatter diagram based on pareto model solutions



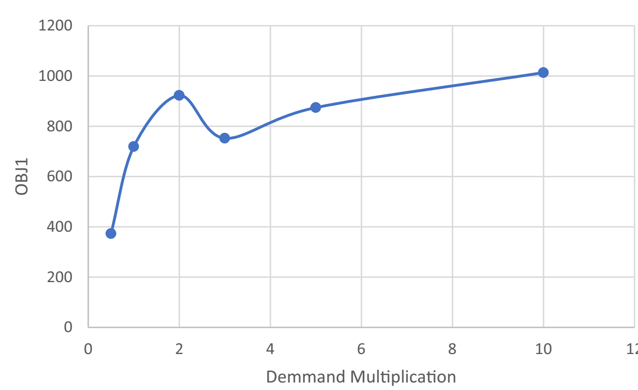
Source: Figure created by authors

Figure 10 Sensitivity analysis of demand rate based on the importance of time



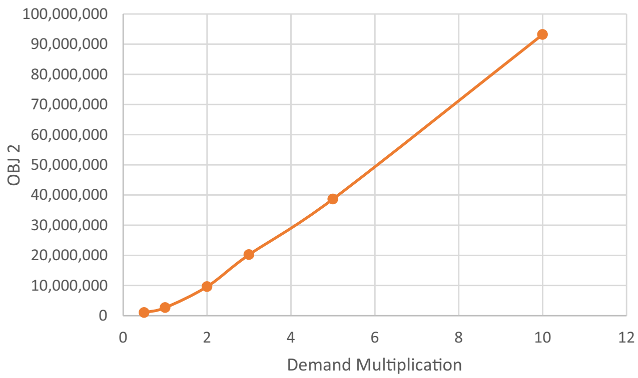
Source: Figure created by authors

Figure 11 Sensitivity of the first objective function to the multiplication of demand in AAs



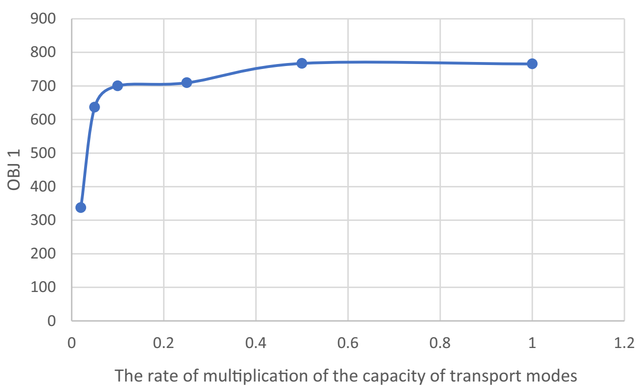
Source: Figure created by authors

Figure 12 Sensitivity of the second objective function to the multiplication of demand in AAs



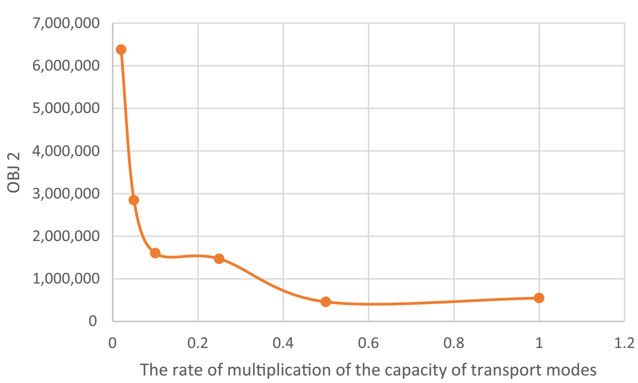
Source: Figure created by authors

Figure 13 Sensitivity analysis of the first objective function based on the multiplication of capacity of transportation modes



Source: Figure created by authors

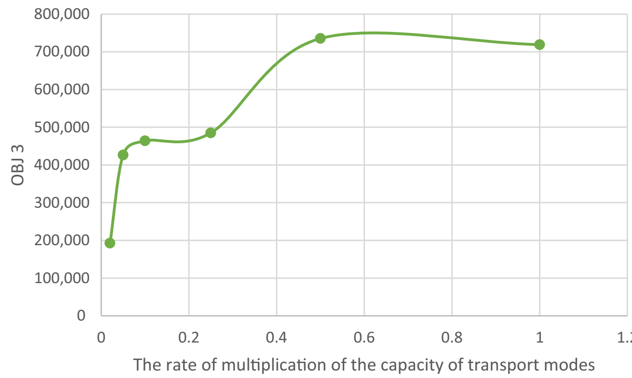
Figure 14 Sensitivity analysis of the second objective function based on the multiplication of capacity of transportation modes



Source: Figure created by authors

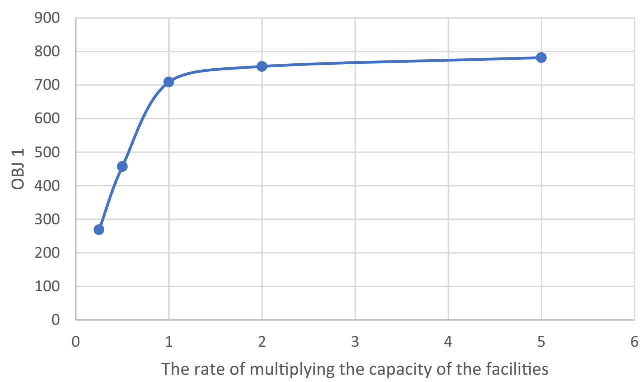
Based on the aforementioned sensitivity analysis of the parameters, it can be deduced that the most crucial factors affecting the satisfaction of disaster victims and the costs of the entire supply chain are the parameters associated with facility

Figure 15 Sensitivity analysis of the third objective function based on the multiplication of capacity of transportation modes



Source: Figure created by authors

Figure 16 Sensitivity analysis of the first objective function based on facility capacity



Source: Figure created by authors

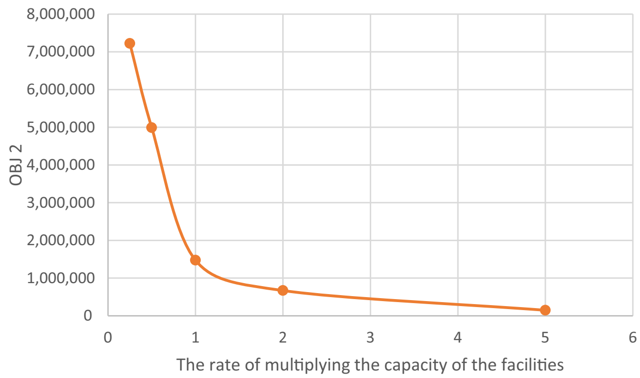
capacity and transportation capacity. Hence, during the initial setup and equipment allocation stages, it is advisable for managers to prioritize the establishment of facilities with high capacities. This approach will contribute to achieving satisfactory outcomes in the relief process.

8. Discussion and managerial insights

Shakibaei *et al.* (2023) neglected to address the environmental aspects in their research. Considering the imperative of combating global warming and escalating environmental pollution, it is essential to prioritize environmental considerations in real-life scenarios to proactively prevent man-made disasters. Moreover, Boostani *et al.* (2021) focused solely on fulfilled demand when evaluating the objective function pertaining to social satisfaction in their study. In contrast, this article acknowledges the pivotal role of relief time as a crucial criterion, among other factors.

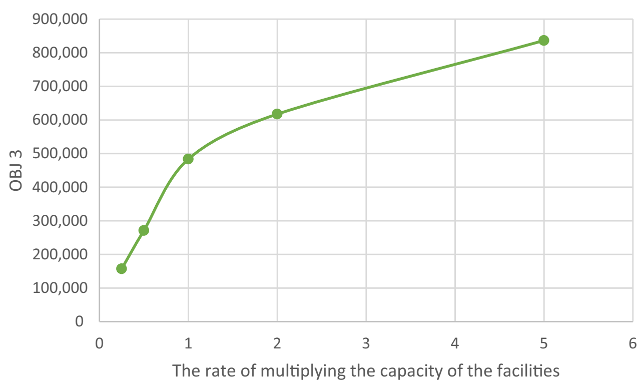
From the results of the sensitivity analysis of different parameters of the model, various managerial insights are obtained, which will be expressed in two sections: theoretical managerial insights and practical managerial insights:

Figure 17 Sensitivity analysis of the second objective function based on facility capacity



Source: Figure created by authors

Figure 18 Sensitivity analysis of the third objective function based on facility capacity



Source: Figure created by authors

8.1 Theoretical managerial insights

- Based on the results obtained from Figures 13 to 18, it is recommended that the HSC management prioritize the construction of facilities with high capacities because it greatly improves the first and second objective function.
- Based on the results obtained from Figure 10 and considering the high importance of both unfulfilled demand and relief time factors, the management is expected to be able to achieve a balance between the two. Because neglecting each one to pay attention to the other can have irreparable consequences.
- According to Figures 13 and 14, the shortage of capacity in different modes of transportation has a very unfavorable effect on the economic and social objective functions. On the other hand, excessive increase in their capacity leads to deterioration of economic and environmental objective functions.

8.2 Practical managerial insights

- Figures 13 and 14 show the key impact of the capacity of different modes of transportation. In reality, the capacity of a mode of transportation can be increased to a certain extent. So, the management should increase the number of means of transportation in any mode.
- To guarantee relative success in the relief process, it is recommended that government and management officials build prefabricated facilities and warehouses in the vicinity of disaster-prone areas. This action will put the speed of relief in the event of a disaster at a much higher level.
- Based on their expertise and experience and according to Figures 17 and 18, managers may pay less attention to environmental consequences in times of crisis. This approach happens due to speeding up the relief process and paying attention to the needs of the victims. Addressing the environmental aspect of sustainability needs to be planned proactively to prepare for potential natural incidents, as attempting to plan and implement environmental measures at the time of an incident is impractical. This article explained how to approach this issue.
- Managers have the opportunity to seek financial assistance from the public, government or private sector to protect against financial constraints that could disrupt the critical aid process. This proactive approach ensures that relief efforts can proceed unhindered. These aids can be in the form of creating a public aid fund, government aid or requesting a loan from international organizations or other governments.
- Using nonfossil fuels like electricity for emergency vehicles, establishing recycling facilities in safe zones and consciously choosing the most efficient transportation routes are some of the measures that can help reduce environmental pollution in areas affected by disasters.

9. Conclusion and future study

In conclusion, this article addresses the critical need for an efficient HSC to effectively provide postdisaster relief. By developing an MILP model with three interconnected objectives, the study optimizes the supply chain's performance across social satisfaction, economic costs and environmental impact. The research combines both available data from the 2021 earthquake in Haiti's Hispaniola Island and newly generated data to enhance the model's accuracy. To begin the solution process, the model is first implemented and solved using a small-scale example. Following validation, it is then implemented on a master case. Through a sensitivity analysis on key parameters, valuable management decisions are presented to support supply chain supervisors in making informed decisions. The model's strength lies in its comprehensive consideration of all dimensions of sustainability, with linear constraints and objective functions facilitating efficient problem-solving time.

Ultimately, the model provides comprehensive insights into the optimal allocation of relief items, determining the necessary transfers between facilities, appropriate vehicles for transportation, timing of relief provision, remaining unused items in each facility and identification of item shortages across AA. By integrating these findings, the HSC can better serve disaster victims in every impacted region.

In future studies, there is an opportunity to expand the scope of the model proposed in this article to incorporate risk management strategies. This would involve considering potential risks within the facilities and fluctuations in key parameters such as demand. Additionally, protocols can be developed to monitor the implementation of social justice principles in the fair distribution of relief services. This can be achieved by incorporating indicators such as the criticality of the victim's condition, age group, gender and other relevant factors. Including these aspects in the model would further enhance the effectiveness and equity of HSC operations.

Several suggestions for future studies can be made, including:

- Developing protocols to monitor the implementation of social justice principles in the fair distribution of relief services.
- Integration of real-time data and advanced technologies.
- Evaluation of risk in HSCs.
- Investigating the impact of social and cultural factors on HSC operations.
- Exploring effective collaboration models and coordination mechanisms among various stakeholders, including government agencies, non governmental organizations, private entities and local communities.
- Designing training programs and capacity-building initiatives for humanitarian logisticians and supply chain managers.

References

Agarwal, S., Kant, R. and Shankar, R. (2020), "Humanitarian supply chain management: a systematic literature review and directions for future research", *International Journal of Emergency Management*, Vol. 16 No. 2, pp. 111-151.

Aghajani, M. and Torabi, S.A. (2020), "A mixed procurement model for humanitarian relief chains", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 10 No. 1, pp. 45-74.

Ak, M.F. and Derya, A. (2021), "Selection of humanitarian supply chain warehouse location: a case study based on the MCDM methodology", *Avrupa Bilim ve Teknoloji Dergisi*, Vol. 22, pp. 400-409.

Akbari, H., Mohtashami, A. and Yazdani, M. (2023), "Designing a cross docking-based humanitarian supply chain network using a meta-heuristic algorithm", *Journal of Industrial and Systems Engineering*, Vol. 15 No. 1, pp. 26-53.

Attia, P.M., Grover, A., Jin, N., Severson, K.A., Markov, T. M., Liao, Y.-H., Chen, M.H., Cheong, B., Perkins, N. and Yang, Z. (2020), "Closed-loop optimization of fast-charging protocols for batteries with machine learning", *Nature*, Vol. 578 No. 7795, pp. 397-402.

Bakhshi, A., Aghsami, A. and Rabbani, M. (2022), "A scenario-based collaborative problem for a relief supply chain during post-disaster under uncertain parameters: a real case study in dorud", *Journal of Modelling in Management*, Vol. 18 No. 3, pp. 906-941.

Bhuiyan, M.Z.H., Chowdhury, M.R.H. and Ghosh, S. (2024), "Multi-objective resources scheduling model in humanitarian logistics considering secondary disaster".

Bonaretti, D. and Fischer-Preßler, D. (2021), "The problem with SMS campus warning systems: an evaluation based on recipients' spatial awareness", *International Journal of Disaster Risk Reduction*, Vol. 54, p. 102031.

Boonmee, C., Arimura, M. and Asada, T. (2017), "Facility location optimization model for emergency humanitarian logistics", *International Journal of Disaster Risk Reduction*, Vol. 24, pp. 485-498.

Boostani, A., Jolai, F. and Bozorgi-Amiri, A. (2021), "Designing a sustainable humanitarian relief logistics model in pre-and postdisaster management", *International Journal of Sustainable Transportation*, Vol. 15 No. 8, pp. 604-620.

Bui, T.-D., Tsai, F.M., Tseng, M.-L., Tan, R.R., Yu, K.D.S. and Lim, M.K. (2021), "Sustainable supply chain management towards disruption and organizational ambidexterity: a data driven analysis", *Sustainable Production and Consumption*, Vol. 26, pp. 373-410.

Cao, C., Liu, Y., Tang, O. and Gao, X. (2021), "A fuzzy bi-level optimization model for multi-period post-disaster relief distribution in sustainable humanitarian supply chains", *International Journal of Production Economics*, Vol. 235, p. 108081.

Das, D., Datta, A., Kumar, P., Kazancoglu, Y. and Ram, M. (2021), "Building supply chain resilience in the era of COVID-19: an AHP-DEMATEL approach", *Operations Management Research*, Vol. 15 Nos 1/2, pp. 1-19.

Ehsani, B., Karimi, H., Bakhshi, A., Aghsami, A. and Rabbani, M. (2023), "Designing humanitarian logistics network for managing epidemic outbreaks in disasters using Internet-of-Things. A case study: an earthquake in salas-e-Babajani city", *Computers & Industrial Engineering*, Vol. 175, p. 108821.

Erden, C., Ateş, Ç. and Esen, S. (2023), "Distribution center location selection in humanitarian logistics using hybrid BWM–ARAS: a case study in türkiye", *Journal of Homeland Security and Emergency Management*.

Eslamipirharati, M., Jolai, F. and Aghsami, A. (2023), "A Bi-objective two-stage stochastic optimization model for sustainable reverse supply chain network design under carbon tax policy and government subsidy considering product quality", *Journal of Industrial and Production Engineering*, Vol. 40 No. 6, pp. 1-21.

Foroughi, A., Moghaddam, B.F., Behzadi, M.H. and Sobhani, F.M. (2022), "Developing a bi-objective resilience relief logistic considering operational and disruption risks: a post-earthquake case study in Iran", *Environmental Science and Pollution Research*, Vol. 29 No. 37, pp. 56323-56340.

Galanis, M., Rao, K., Yao, X., Tsai, Y.-L., Ventura, J. and Fricker, G.A. (2021), "DamageMap: a post-wildfire damaged buildings classifier", *International Journal of Disaster Risk Reduction*, Vol. 65, p. 102540.

Haavisto, I. and Kovács, G. (2019), "Sustainability in humanitarian supply chains", *Handbook on the Sustainable Supply Chain*, Edward Elgar Publishing, Cheltenham, pp. 500-512.

Hayes, G.P., Briggs, R.W., Barnhart, W.D., Yeck, W.L., McNamara, D.E., Wald, D.J., Nealy, J.L., Benz, H.M., Gold, R.D. and Jaiswal, K.S. (2015), "Rapid characterization of the 2015 M w 7.8 gorkha, Nepal, earthquake sequence and its seismotectonic context", *Seismological Research Letters*, Vol. 86 No. 6, pp. 1557-1567.

Jamali, A., Ranjbar, A., Heydari, J. and Nayeri, S. (2021), "A multi-objective stochastic programming model to configure a sustainable humanitarian logistics considering deprivation cost and patient severity", *Annals of Operations Research*, Vol. 319 No. 1, pp. 1-36.

Jensen, L.-M. and Hertz, S. (2016), "The coordination roles of relief organisations in humanitarian logistics", *International Journal of Logistics Research and Applications*, Vol. 19 No. 5, pp. 465-485.

Jha, A., Acharya, D. and Tiwari, M. (2017), "Humanitarian relief supply chain: a multi-objective model and solution", *Sādhanā*, Vol. 42 No. 7, pp. 1167-1174.

Kanecki, K., Nitsch-Osuch, A., Goryński, P., Wojtyniak, B., Juszczyk, G., Magdalena, B., Kosińska, I. and Tyszko, P. (2021), "Hospitalizations for COVID-19 in Poland: a study based on data from a national hospital register", *Polish Archives of Internal Medicine*, Vol. 131, pp. 535-540.

Kaur, H. and Singh, S.P. (2022), "Disaster resilient proactive and reactive procurement models for humanitarian supply chain", *Production Planning & Control*, Vol. 33 Nos 6/7, pp. 576-589.

Kovács, G. and Spens, K.M. (2007), "Humanitarian logistics in disaster relief operations", *International Journal of Physical Distribution & Logistics Management*, Vol. 37 No. 2, pp. 99-114.

Loree, N. and Aros-Vera, F. (2018), "Points of distribution location and inventory management model for post-disaster humanitarian logistics", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 116, pp. 1-24.

Lotfi, A., Shakouri, M., Abazari, S.R., Aghsami, A. and Rabbani, M. (2023), "A multi-objective optimization for a closed-loop sustainable pharmaceutical supply chain network design: a case study", *Journal of Advances in Management Research*, Vol. 20 No. 4.

Mahmoodi, A., Zergani, M.J., Hashemi, L. and Millar, R. (2022), "Analysis of optimized response time in a new disaster management model by applying metaheuristic and exact methods", *Smart and Resilient Transportation*, Vol. 4 No. 1, pp. 22-42.

Masoumi, M., Aghsami, A., Alipour-Vaezi, M., Jolai, F. and Esmailifar, B. (2022), "An M/M/C/K queueing system in an inventory routing problem considering congestion and response time for post-disaster humanitarian relief: a case study", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 12 No. 2, pp. 182-219.

Mavrotas, G. (2009), "Effective implementation of the ε-constraint method in multi-objective mathematical programming problems", *Applied Mathematics and Computation*, Vol. 213 No. 2, pp. 455-465.

Medel, K., Kousar, R. and Masood, T. (2020), "A collaboration–resilience framework for disaster management supply networks: a case study of the Philippines", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 10 No. 4, pp. 509-553.

Modarresi, S.A. and Maleki, M.R. (2023), "Integrating pre and post-disaster activities for designing an equitable humanitarian relief supply chain", *Computers & Industrial Engineering*, Vol. 181, p. 109342.

Mohammadi, S., Avakh Darestani, S., Vahdani, B. and Alinezhad, A. (2021), "Multi-objective optimization model for designing a humanitarian logistics network under service sharing and accident risk concerns under uncertainty", *Journal of Quality Engineering and Production Optimization*, Vol. 6 No. 1, pp. 105-126.

Naderi, M., Khoshdel, A.R., Sharififar, S., Moghaddam, A.D. and Zareiyan, A. (2023a), "Components of health surveillance system in natural disasters that affect military health services: a systematic review", *Iranian Journal of Public Health*, Vol. 52 No. 9, p. 1788.

Naderi, M., Khoshdel, A.R., Sharififar, S., Moghaddam, A.D. and Zareiyan, A. (2023b), "Respond quickly and effectively! Components of the military health surveillance system in natural disasters: a qualitative study", *Journal of Education and Health Promotion*, Vol. 12 No. 1, p. 383.

Negi, S. and Negi, G. (2021), "Framework to manage humanitarian logistics in disaster relief supply chain management in India", *International Journal of Emergency Services*, Vol. 10 No. 1, pp. 40-76.

Nezhadroshan, A.M., Fathollahi-Fard, A.M. and Hajiaghaei-Keshteli, M. (2021), "A scenario-based possibilistic-stochastic programming approach to address resilient humanitarian logistics considering travel time and resilience levels of facilities", *International Journal of Systems Science: Operations & Logistics*, Vol. 8 No. 4, pp. 321-347.

Oguntola, I.O. and Ülkü, M.A. (2023), "Artificial intelligence for sustainable humanitarian logistics", *Encyclopedia of Data Science and Machine Learning*, IGI Global, Hershey, PA, pp. 2970-2983.

Praneetpholkrang, P. and Kanjanawattana, S. (2021), "A multi-objective optimization model for shelter location-allocation in response to humanitarian relief logistics", *The Asian Journal of Shipping and Logistics*, Vol. 37 No. 2, pp. 149-156.

Reddy, V.R., Singh, S.K. and Anbumozhi, V. (2016), "Food supply chain disruption due to natural disasters: entities, risks, and strategies for resilience", *ERIA Discussion Paper, 18.*

Rodríguez-Espíndola, O., Dey, P., Albores, P. and Chowdhury, S. (2023), "Sustainability and intermodality in humanitarian logistics: a two-stage multi-objective programming formulation", *Annals of Operations Research*, pp. 1-30.

Shakibaei, H., Farhadi-Ramin, M.R., Alipour-Vaezi, M., Aghsami, A. and Rabbani, M. (2023), "Designing a post-disaster humanitarian supply chain using machine learning and multi-criteria decision-making techniques", *Kybernetes*.

Sharifian, S., Ghomian, Z., Khodadadizadeh, A. and Jahangiri, K. (2017), "Assessment of disaster mitigation and preparedness", *Trauma Monthly*, Vol. 22 No. 2.

Shavarani, S.M. (2019), "Multi-level facility location-allocation problem for post-disaster humanitarian relief distribution: a case study", *Journal of Humanitarian Logistics and Supply Chain Management*, Vol. 9 No. 1, pp. 70-81.

Singh, R.K., Gupta, A. and Gunasekaran, A. (2018), "Analysing the interaction of factors for resilient humanitarian supply chain", *International Journal of Production Research*, Vol. 56 No. 21, pp. 6809-6827.

Sriram, S., Vishwas, U., Geetha Priya, M. and Deva Jefflin, A. (2023), "Earthquake deformation assessment of tiburon peninsula, Haiti—an application of image processing", *Computational Vision and Bio-Inspired Computing: Proceedings of ICCVBIC 2022*, Springer, Cham, pp. 757-764.

Teymoori, F., Safari, A. and Kamalinasab, M. (2022), "Augmented ε-constraint algorithm applied to multi-objective optimization programs of residential Micro-CHP systems", *Process Integration and Optimization for Sustainability*, Vol. 6 No. 4, pp. 1143-1161.

Tofighi, S., Torabi, S.A. and Mansouri, S.A. (2016), "Humanitarian logistics network design under mixed uncertainty", *European Journal of Operational Research*, Vol. 250 No. 1, pp. 239-250.

Wu, S., Deng, S., Zhu, J., Bashir, M.A. and Izuno, F. (2019), "Optimization of a novel liquid-phase plasma discharge process for continuous production of biodiesel", *Journal of Cleaner Production*, Vol. 228, pp. 405-417.

Xu, W., Xiong, S., Proverbs, D. and Zhong, Z. (2021), "Evaluation of humanitarian supply chain resilience in flood disaster", *Water*, Vol. 13 No. 16, p. 2158.

Zarei, M.H., Carrasco-Gallego, R. and Ronchi, S. (2019), "On the role of regional hubs in the environmental sustainability of humanitarian supply chains", *Sustainable Development*, Vol. 27 No. 5, pp. 846-859.

Zhao, M. and Liu, X. (2018), "Development of decision support tool for optimizing urban emergency rescue facility locations to improve humanitarian logistics management", *Safety Science*, Vol. 102, pp. 110-117.

Corresponding author

Masoud Rabbani can be contacted at: mrabani@ut.ac.ir

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgrouppublishing.com/licensing/reprints.htm
Or contact us for further details: **permissions@emeraldinsight.com**