Optimizing localized humanitarian logistics: a stochastic programming approach for facility location, inventory and evacuation strategies

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Abstract

Purpose – Humanitarian logistics is vital for effective disaster response and preparedness, particularly in flood-prone regions where rapid and efficient relief operations can mitigate severe socioeconomic impacts. This paper aims to present a multi-objective two-stage stochastic optimization model designed to enhance humanitarian logistics and supply chain management by integrating facility location, inventory management, evacuation planning and vehicle logistics. The study aims to optimize response time, budget allocation and evacuation efficiency while addressing uncertainties in disaster scenarios.

Design/methodology/approach – The proposed model incorporates probabilistic disaster scenarios derived from flood hazard maps in Cambodia to simulate real-world uncertainties and improve decision-making. A stochastic programming approach balances multiple objectives to ensure efficient resource allocation. The weighted sum method is used to solve the multi-objective optimization problem, allowing decision-makers to analyze trade-offs between different performance metrics. A sensitivity analysis evaluates the impact of warehouse utilization rates on response times and costs, providing valuable insights for adaptive and cost-effective disaster planning strategies. In addition, trade-off analysis using the AUGMECON method provides decision-makers with a spectrum of Pareto-efficient solutions each offering different balances between speed, cost and reach.

Findings – The proposed model demonstrates significant improvements over traditional humanitarian logistics frameworks, achieving a 63.17% reduction in response time, 30.32% lower budget allocation and a 43.41% decrease in evacuation distances. The findings emphasize the importance of localized disaster management strategies, leveraging local markets, warehouses and shelters to enhance resilience and reduce dependence on external aid.

Originality/value – This research introduces a novel optimization framework that integrates local resource utilization into humanitarian logistics, improving sustainability and adaptability. The findings provide practical insights for policymakers and humanitarian organizations, supporting the development of cost-effective, scalable and adaptive disaster response strategies.

Keywords Humanitarian logistics, Disaster response optimization, Stochastic programming, Supply chain resilience, Emergency preparedness, Two-stage model

Paper type Research paper

1. Introduction

Natural disasters are intensifying in frequency and severity due to climate change and urbanization, creating substantial global challenges. According to the United Nations Office for Disaster Risk Reduction, approximately 328 million people were affected by natural disasters in 2022, resulting in damages exceeding $232 billion. In Southeast Asia, Cambodia is particularly vulnerable to floods, which annually

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
16/3 (2026) 225–250
Emerald Publishing Limited [ISSN 2042-6747]
[DOI 10.1108/JHLSCM-02-2025-0020]

Received 9 February 2025
Revised 31 May 2025
Accepted 3 July 2025

impact over 600,000 individuals, leading to widespread displacement, economic loss and logistical breakdowns. These figures highlight the urgent need for effective disaster response strategies to mitigate the adverse impacts of such events (NCDM, 2014). In 2023, United Nations International Children's Emergency Fund (UNICEF) collaborated with the Cambodian government to launch two cash transfer programs aimed at mitigating the impacts of flooding and global inflation. These programs benefited 355,658 households, totaling around 1.8 million individuals, including 689,658 children and 9,422 people with disabilities (UNICEF, 2023). Despite these efforts, Cambodia's disaster response system continues to face structural limitations due to constrained technical expertise, limited budgets and weak data analytics capacity.

One of the most persistent challenges is the lack of systematic coordination between facility location, inventory management, evacuation logistics and transportation planning. In past flood events, Cambodian relief operations often suffered from delays, fragmented evacuations and resource bottlenecks particularly in remote areas where aid relied heavily on centralized distribution from the capital. Shelters lacked prepositioned supplies, local warehouses were underused and evacuation plans were fragmented due to disconnected decision-making across facility, transport and inventory planning. These real-world challenges reveal a pressing need to shift from centralized models toward the decentralization of disaster logistics through localized disaster management strategies. Empowering local actors such as staging areas, non-governmental organizations (NGOs) and community markets can enable faster, more autonomous responses and reduce reliance on national coordination during the critical early stages of disaster onset. The current study is motivated by these practical gaps and aims to propose a robust, data-driven framework that captures the interdependent nature of humanitarian logistics under uncertainty.

In such contexts, humanitarian logistics plays a crucial role in disaster management by coordinating resources, personnel and information to deliver timely and effective assistance to affected populations. The efficiency of these logistics operations directly influences the survival and well-being of disaster victims (Kovács and Sigala, 2020). However, relief efforts face significant challenges, including unpredictable demand, damaged infrastructure and limited resources. These complexities necessitate a systematic and optimized approach to facility location, inventory management, evacuation planning and transportation logistics (Anaya-Arenas *et al.*, 2014).

This research introduces a multi-objective, two-stage stochastic optimization model designed to enhance localized disaster management strategies and resilience. The model integrates facility location planning, inventory management, evacuation procedures, and vehicle logistics, addressing the uncertainties inherent in disaster scenarios. By balancing key objectives such as minimizing response time, evacuation distance, and planning budget, the study provides a robust framework for effective and adaptive disaster response. Focused on flood-prone regions in Cambodia, the model leverages probabilistic disaster scenarios and flood hazard maps to develop realistic, actionable solutions that prioritize local resources and infrastructure.

While many studies treat facility location, inventory allocation and evacuation planning as separate problems, these decisions are deeply interconnected in real-world disaster response, especially in resource-constrained contexts. For instance, selecting a shelter site without considering the proximity of inventory supplies can delay relief distribution, while evacuation plans that ignore facility accessibility may result in longer travel times and inefficient resource use. Fragmented decision-making contributes to logistical bottlenecks and operational delays, particularly in remote or underserved regions. Therefore, integrating these elements into a unified optimization framework is essential to maximize efficiency and ensure coordinated, resource-aware responses. Our proposed model captures these interdependencies under uncertainty, enabling better preparedness and responsiveness even in low-resource humanitarian settings.

A core contribution of this study lies in its emphasis on the decentralization of disaster logistics through localized disaster management strategies. By leveraging existing community infrastructure such as local warehouses and markets, the model supports quicker mobilization of aid, reduces reliance on central authorities and enhances resilience during national-level supply chain disruptions. By predefining local roles and optimizing local flows, communities are better positioned to act autonomously and efficiently during emergencies. Prepositioned warehouses and local markets dramatically cut delivery delays. In practice, placing critical stock close to affected areas can totally or partially eliminate long procurement delays and make supplies available immediately after a disaster strikes (Bozkurt and Duran, 2012). Additionally, the study incorporates a Pareto frontier analysis using the Augmented ε-Constraint (AUGMECON) method to reveal how prioritizing one objective (e.g. time) can affect others (e.g. cost or distance). The framework is validated through extensive sensitivity testing, offering insights into how variations in resource availability and facility utilization influence the overall efficiency and feasibility of relief logistics.

Despite the growing body of research in humanitarian logistics, many studies address specific components, such as facility location or evacuation planning, in isolation, creating a gap in integrated approaches. For instance, Ghasemi *et al.* (2022) proposed a stochastic programming model optimizing costs, unmet demands and evacuation routes but neglected to integrate evacuation logistics with facility and transportation planning. Similarly, Caglayan and Satoglu (2021) developed a two-stage stochastic programming (TSSP) model optimizing casualty transportation during large-scale disasters, but it lacked a focus on inventory management and facility utilization. Haghi *et al.* (2017) introduced a robust multi-objective model for pre- and post-disaster logistics under uncertainty, emphasizing preparedness costs and resource allocation but overlooked dynamic evacuation strategies and adaptability to evolving disaster scenarios. This research addresses these gaps by seamlessly integrating facility location, inventory management, evacuation logistics and transportation planning into a unified framework.

The contributions of this study are both contextual and methodological. Contextually, the model is applied to flood-prone regions in Cambodia, a disaster-prone and underrepresented setting in the humanitarian logistics literature. The framework is designed to reflect the challenges of decentralized and resource-constrained environments, where aid delivery depends on local warehouses, community shelters local markets and limited transportation access. By emphasizing localized logistics planning, the model supports faster, more autonomous responses and reduces reliance on centralized infrastructure.

Methodologically, this study introduces a novel multi-objective TSSP model that simultaneously integrates facility location, inventory prepositioning, evacuation routing and transportation planning. Unlike existing models that often optimize these components separately, our framework captures their interdependencies under uncertainty. The model addresses three conflicting objectives response time, evacuation distance and planning budget and uses the weighted sum method to solve the multi-objective problem. This enables decision-makers to explore different strategic preferences by adjusting weights. Furthermore, we apply the AUGMECON method to generate a set of Pareto-efficient solutions, allowing for trade-off analysis across multiple operational criteria. A sensitivity analysis is also conducted to assess the impact of warehouse utilization levels on response time and cost, enhancing the model's adaptability to varying disaster severities and resource conditions.

The model is validated through a case study involving probabilistic flood scenarios and hazard maps in Cambodia, demonstrating its practical relevance and scalability. This study provides a comprehensive, context-aware and analytically robust decision-support tool for enhancing humanitarian logistics planning under uncertainty.

2. Literature review

2.1 Humanitarian logistics in disaster preparedness and response

Humanitarian logistics plays a vital role in managing disaster relief operations, encompassing the coordination of resources, personnel and information to support affected populations. It spans all phases of the disaster management cycle mitigation, preparedness, response and recovery each of which is interlinked through logistical decisions (Boonmee *et al.*, 2021). Among these, the preparedness and response phases are particularly critical, as they determine the efficiency and speed with which aid reaches those in need during and immediately after a disaster.

The preparedness phase involves proactive planning and resource allocation, akin to strategic planning in commercial supply chains (John *et al.*, 2012). It includes actions such as stockpiling essential goods, strengthening warehouse capacities, training personnel and identifying optimal locations for emergency facilities. Altay *et al.* (2018) emphasize that preparedness is essential for reducing delays in disaster response and for enhancing system resilience. Similarly, Ali Torabi *et al.* (2018) highlight the importance of facility readiness, supply availability and route optimization in shaping the effectiveness of response efforts.

Following the onset of a disaster, the response phase focuses on the immediate mobilization and delivery of aid to affected areas. This phase is characterized by high levels of uncertainty and urgency, where rapid access to shelters, medical services and food supplies is paramount. Scholten *et al.* (2014) argue that effective response logistics must be informed by long-term strategic planning, including preparedness drills and scenario-based exercises. The placement of key facilities such as shelters and distribution centers during this phase significantly affects both accessibility and scalability of relief operations (Ozbay *et al.*, 2019). Mpita *et al.* (2016) further stress the need to preposition essential supplies in appropriate quantities and locations to mitigate the impact of fragmented infrastructure and unpredictable demand.

Despite its recognized importance, humanitarian logistics during the preparedness and response phases faces persistent challenges, including damaged infrastructure, coordination breakdowns among stakeholders and limited availability of real-time data. These issues often delay aid delivery and reduce operational efficiency. As a result, there is an increasing need for integrated and data-driven logistics models that can enhance coordination, improve the speed and reach of aid delivery and support real-time decision-making under uncertainty.

This study responds to these challenges by building on existing knowledge in humanitarian logistics while addressing limitations in coordination and system integration. The proposed model aims to enhance decision-making across both preparedness and response phases by integrating key logistics components facility location, inventory allocation, evacuation planning and transportation planning within a stochastic, multi-objective framework tailored to real-world disaster scenarios.

2.2 Facility location and inventory management in humanitarian logistics

A fundamental strategy for enhancing responsiveness in humanitarian logistics is the optimal siting of warehouses and distribution hubs. Cotes and Cantillo (2019) developed a facility location model that incorporates both private (e.g. transportation, facility and inventory) and deprivation costs to provide a holistic view of logistical efficiency during the critical first hours of a disaster. Similarly, Balcik and Beamon (2008) introduced a scenario-based model to optimize relief distribution under capacity and budget constraints. These studies underscore the importance of strategic prepositioning but often address facility location and inventory decisions in isolation.

To better manage the dynamic and uncertain nature of disasters, more recent research has shifted toward robust and stochastic optimization approaches. Boostani *et al.* (2020) presented a two-stage robust model that integrates preparedness and response decisions to minimize total deployment and allocation costs. Yang *et al.* (2021) proposed a multi-period dynamic prepositioning model that considers demand uncertainty and emphasizes proactive supply chain planning. Charles *et al.* (2016) applied mixed-integer linear programming (MILP) to improve resource allocation based on predicted demand, enhancing response efficiency during crises. Meanwhile, Mahmoodi *et al.* (2022) highlighted the use of emerging technologies such as additive manufacturing to reduce response times and improve coverage in complex emergencies.

In addition, decision-support tools like the one developed by Taouktsis and Zikopoulos (2024) focus on rapidly identifying suitable distribution center locations, while Maghsoudi and

Moshtari (2020) emphasized the need for robust logistics systems capable of operating under extreme pressure. However, these models typically do not incorporate staging area coordination or evacuation logistics as part of their facility and inventory strategies.

Despite these valuable contributions, several gaps remain. Most existing models optimize a single component such as facility siting, inventory prepositioning or supply allocation without integrating evacuation planning or transportation planning. This fragmented approach limits their ability to capture the interdependencies between shelter access, transport efficiency and inventory availability, especially during the early response phase when time is critical. Models such as those by Boostani *et al.* (2020) and Yang *et al.* (2021) address uncertainty but focus primarily on supply-side planning, neglecting evacuation logistics and dynamic routing.

This study addresses these shortcomings by proposing a comprehensive multi-objective TSSP model that simultaneously optimizes warehouse location, inventory allocation, staging area selection and distribution strategies for both evacuation shelters and affected individuals. By integrating these key elements, the model provides a more realistic and coordinated decision-making framework that bridges both preparedness and response phases under uncertainty. This approach enhances logistical efficiency, supports localized operations and contributes a holistic planning tool for humanitarian relief in disaster-prone and resource-constrained settings.

2.3 Deterministic and stochastic programming in relief logistics

The growing scale, frequency and uncertainty of natural disasters have intensified the need for advanced decision-support tools in humanitarian logistics. Traditional deterministic models, which assume fixed inputs and predictable conditions, often fall short in dynamic disaster environments characterized by uncertain demand, infrastructure disruption and limited resource availability. In response, researchers have increasingly adopted stochastic and robust optimization approaches, particularly TSSP, to improve the preparedness and responsiveness of logistics systems under uncertainty (Boonmee *et al.*, 2023).

Stochastic models allow planners to consider multiple disaster scenarios by incorporating probabilistic variations in parameters such as supply, demand, transportation time and facility availability. For example, Ghasemi *et al.* (2022) developed a stochastic model using the ε-constraint method to minimize costs, unmet demand and evacuation inefficiencies. Although their model integrates shelter and distribution center siting, it emphasizes routing and demand satisfaction and does not fully capture inventory or transportation planning. Similarly, Meng *et al.* (2023) proposed a TSSP model enhanced with an evolutionary algorithm to optimize emergency logistics networks. While effective in handling uncertainty through linearization and heuristics, it lacks integration of evacuation logistics and real-time vehicle deployment.

Several other studies focus on specialized aspects of postdisaster logistics. Caglayan and Satoglu (2021) introduced a multi-objective two-stage stochastic model to minimize casualties, ambulance shortages and transportation time using mobile phone data, but their work centers on casualty transport rather than comprehensive relief distribution. Wang *et al.* (2021) and Jamali *et al.* (2021) addressed supply allocation and sustainability, including lateral transhipment and environmental objectives (e.g. CO_2 emissions and deprivation costs), yet evacuation and shelter logistics were not within their scope.

Metaheuristic and hybrid approaches have also been explored to improve solution scalability. Turkeš *et al.* (2021) combined iterated local search with exact methods to solve a stochastic facility location problem that considers unmet demand and response time. Cavdur *et al.* (2021) presented a two-stage stochastic model where the first stage determines facility locations and the second manages service distribution postdisaster. Manopiniwes and Irohara (2016) proposed a stochastic model focused on preparedness and response but initially restricted transport to a single mode, limiting flexibility in dynamic logistics environments.

Some models incorporate multi-objective optimization to address equity, cost and satisfaction. For example, Seraji *et al.* (2021) used vibration damping optimization and NSGA-II to improve shelter placement and transportation planning. Haghi *et al.* (2017) designed a robust two-stage stochastic model for locating distribution centers and minimizing preparedness costs. Wang *et al.* (2022) used particle swarm optimization (PSO) and CPLEX to optimize the distribution of rescue teams and medical resources, while Pouraliakbari-Mamaghani *et al.* (2023) proposed a stochastic-robust model to minimize access and waiting times under disrupted conditions. Finally, Gan (2024) developed a bi-objective logistics center siting model that balances transportation, construction and inventory costs using deterministic and robust techniques.

Despite these valuable contributions, several gaps remain. Many models address individual aspects of relief logistics such as facility location, supply allocation or casualty transport but do not provide a unified framework that integrates facility siting, inventory allocation, evacuation planning and transportation planning. Moreover, trade-off analysis among competing objectives such as cost, response time and evacuation distance are often absent or underdeveloped, limiting decision-makers' ability to explore strategic alternatives. Finally, there is limited attention to resource-constrained, decentralized environments especially in low-income or disaster-prone countries where logistics planning must rely heavily on local assets and infrastructure.

To address these gaps, this study proposes a multi-objective two-stage stochastic optimization model that integrates all critical components of humanitarian logistics. The model is applied to realistic flood scenarios in Cambodia, using hazard maps to simulate uncertainty and inform decision-making. Through the use of weighted sum trade-off analysis and AUGMECON-based Pareto frontier construction, the model provides decision-makers with a deeper understanding of how planning priorities affect outcomes across cost, time and distance dimensions. This integrated and context-sensitive approach advances the practical and theoretical development of humanitarian logistics under uncertainty.

2.4 Summary of literature and research gaps

To synthesize the key insights from the reviewed literature in sub-Sections 2.1–2.3, Table 1 presents a structured comparison of optimization models applied in humanitarian logistics and disaster management. The table highlights various dimensions, including objective functions, problem scope (deterministic or stochastic), model characteristics, constraints considered and solution methodologies.

As shown in Table 1, the majority of existing studies focus on specific elements of the humanitarian logistics chain most commonly facility location, cost minimization and supply allocation. While models such as those by Caglayan and Satoglu (2021) and Meng *et al.* (2023) incorporate stochastic elements and address uncertainty, their primary focus remains on postdisaster response or routing. Models by Jamali *et al.* (2021) explores environmental and construction-related objectives but do not comprehensively address evacuation planning or transportation planning. Similarly, studies like Haghi *et al.* (2017) focus on facility planning and preparedness but fall short in integrating evacuation strategies or trade-off analysis.

Furthermore, while several models use multi-objective approaches, relatively few explicitly evaluate the trade-offs between response time, evacuation distance and total planning cost critical criteria in disaster response planning. Only a limited number of studies integrate all three elements concurrently. Most models also neglect localized and decentralized logistics structures, which are essential for disaster-prone, low-resource regions such as Cambodia. Moreover, sensitivity analysis and behavioral modeling factors critical for operational adaptability and decision-maker preference incorporation are rarely addressed.

In contrast, this study contributes a multi-objective TSSP model that simultaneously considers facility and stock location, evacuation distance, relief transportation and budget constraints. It further incorporates Pareto trade-off analysis using the AUGMECON method and applies the model to a real-world case study with probabilistic flood scenarios in Cambodia. As summarized in Table 1, this work uniquely integrates all critical components facility siting, inventory allocation, evacuation logistics and transportation planning within a single, adaptable framework.

3. Multi-objective two stage stochastic programming model

3.1 Conceptual model

The conceptual model addresses the problem by reflecting a realistic humanitarian supply chain flow, as illustrated in Figure 1. Effective disaster management depends on the collaboration of governments and organizations to ensure the timely relief items and an effective response to urgent and diverse needs arising from unpredictable needs.

This proposed in this study introduces a novel humanitarian logistics network that integrates key decisions across facility location, inventory management, evacuation logistics and transportation coordination under uncertainty. As illustrated in Figure 1, the network is structured around a two-stage disaster management cycle preparedness and response and includes diverse facility types: main warehouses, local warehouses, local markets, NGOs, staging areas and shelters, along with affected zones.

A core novelty of the proposed network lies in its joint selection of multiple facility types. Unlike most existing models, which treat warehouses, shelters and staging areas as independent decision problems (Caglayan and Satoglu, 2021; Jamali *et al.*, 2021), this study simultaneously optimizes all facility types within one unified framework.

Another distinct feature is the dual functionality of shelters, which may also serve as staging areas. While traditional humanitarian logistic models often assign rigid, single-use roles to facilities (Ghasemi *et al.*, 2022), our model introduces flexible nodes that can simultaneously house evacuees and serve as temporary storage. This dual-role capacity significantly enhances network flexibility, especially in space-constrained or time-critical environments.

Moreover, the model challenges conventional logistics assumptions by allowing relief items to originate not only from centralized warehouses but also directly from shelters and staging areas. This localized supply strategy reduces response time and reflects practical realities in remote or fragmented infrastructures where centralized aid might be delayed (e.g. in flood-affected provinces far from the capital).

The network also incorporates scenario-based planning through a TSSP framework. It models three levels of disaster severity, each with unique logistical demands and dynamically adjusts the flow of resources according to scenario-specific disruptions. Unlike static or deterministic models (Balcik and Beamon, 2008; Boostani *et al.*, 2020), this model adapts facility activation, inventory allocation and transportation routing to probabilistic.

3.2 Proposed mathematical model

The proposed mathematical model integrates decisions related to facility location, distribution, evacuation and inventory management under parameter uncertainties. It focuses on optimizing time performance, budget planning and total evacuation distance while ensuring that each location satisfies demand within capacity constraints and prioritizes evacuation based on predefined vulnerabilities. The objective functions and constraints are formulated using mixed-integer programming (MIP) within a TSSP framework. Based on the covering problem, the objective function seeks to minimize total response time, the overall budget plan and total evacuation distance.

The model operates under the following key assumptions:

- The operational cost of vehicles varies depending on the transportation mode and their load capacity in each scenario.
- Staging areas and shelters are designed to serve all affected zones.
- Each affected zone is represented by the number of households impacted.
- Local warehouses, staging areas and shelters have limited storage capacities for relief items, which are received from facilities such as the main warehouse, local markets and NGOs and subsequently dispatched to affected zones.
- The evacuation process involves moving victims to designated shelters, where evacuees from each affected area are relocated as family units to a single shelter, without assigning them to multiple locations.

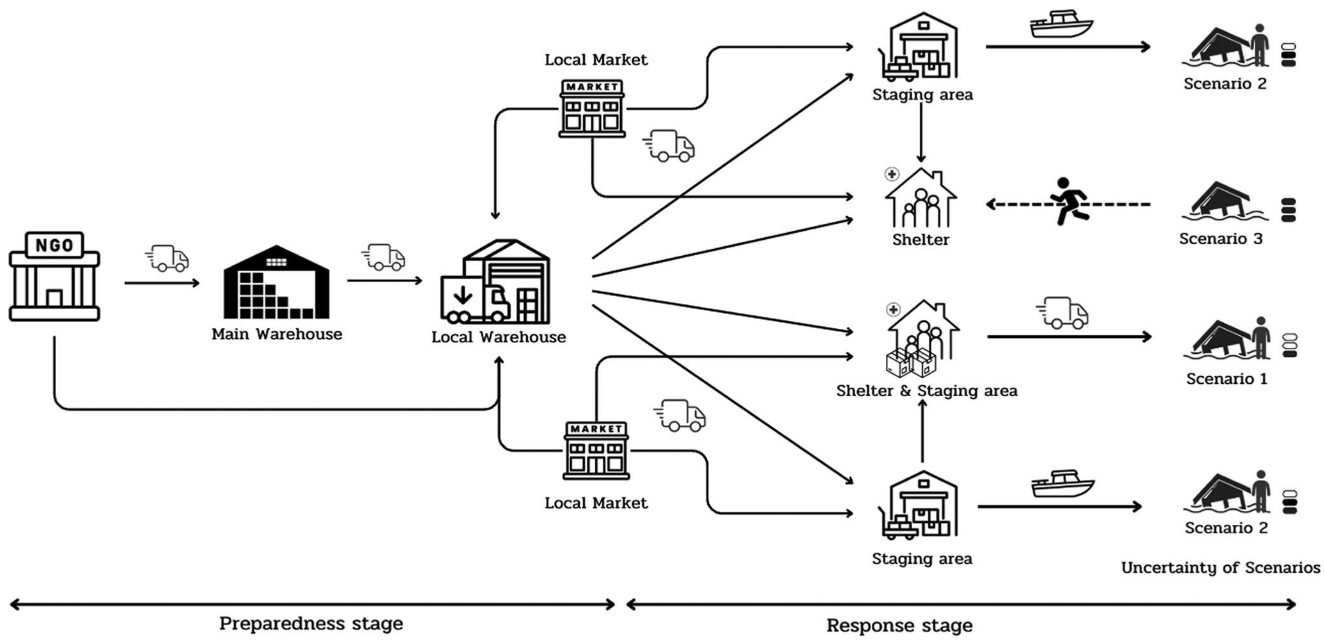
The proposed model serves as a decision-support tool for designing an effective humanitarian logistics supply chain under uncertainty.

Table 1 Review study of the optimization model for humanitarian logistic in disaster management

Authors	Objective function: Cost	Time	Evacuation of distance	Other objective	Fs	E	RT	D/S	Multi /single objective	Constraint: Capacity	Budget	Limit site	Transportation mode	Items	Demand	Math model	Exact approach	Solution algorithm
(Caglayan and Satoglu, 2021)		✓				✓	✓	S	Multi	✓		✓			✓	MILP	CPLEX	Augmencon epsilon-constraint
(Jamali *et al.*, 2021)	✓			✓	✓	✓		S	Multi	✓	✓	✓	✓		✓	MILP	GAMS	GP
(Cavdur *et al.*, 2021)	✓				✓			S	Single		✓	✓				MILP	–	Heuristic
(Gan, 2024)	✓	✓				✓		D	Multi	✓	✓	✓			✓	MILP	MATLAB	HFHA
(Ghasemi *et al.*, 2022)	✓		✓		✓	✓	✓	S	Multi		✓				✓	Nonlinear	MATLAB	Metaheuristic/epsilon-constraint
(Haghi *et al.*, 2017)	✓				✓		✓	S	Multi		✓					MILP	ILOG CPLEX	Exact method
(Manopiniwes and Irohara, 2016)	✓	✓			✓	✓	✓	S	Multi	✓	✓	✓	✓			Nonlinear	GUROBI	Exact method
(Meng *et al.*, 2023)	✓	✓				✓	✓	S	Multi	✓	✓		✓		✓	Nonlinear	CPLEX	Heuristic/evolutionary
(Pouraliakbari-Mamaghani *et al.*, 2023)		✓			✓			S	Single	✓					✓	Nonlinear	GUROBI	Heuristic
(Seraji *et al.*, 2021)	✓	✓	✓		✓	✓	✓	D	Multi		✓	✓	✓		✓	MILP	GAM / CPLEX	GA
Wang *et al.* (2021)	✓				✓			S	Single	✓	✓				✓	MILP	CPLEX	Exact method
(Turkeš *et al.*, 2021)		✓			✓			S	Single	✓	✓	✓			✓	MILP	CPLEX	Metaheuristic/heuristic
(Wang *et al.*, 2022)	✓				✓			S	Single	✓		✓				Nonlinear	CPLEX	PSO
This work	✓	✓	✓		✓	✓		S	Multi	✓	✓	✓	✓	✓	✓	MILP	LINGO	Exact method

Note(s): Fs = facility & stock location; E = evacuation; RT = relief transportation; D = deterministic problem; S = stochastic problem; LP = linear programming; MILP = mixed integer linear programming; GA = genetic algorithm; GP = goal programming; PSO = particle swarm optimization; HFHA = hybrid frog hopping algorithm
Source(s): Authors' own work

Figure 1 Framework of proposed model



Source: Authors' own work

It identifies the optimal locations and allocations of key resources to support relief distribution, balancing objectives such as response time, cost efficiency and evacuation coverage across multiple disaster scenarios. The model selects appropriate sites for staging area, shelter and local warehouse, which function as stockpiling hubs for relief supplies sourced from NGOs and local markets. It also designates local warehouses and markets to serve as staging areas and emergency shelters. In this framework, shelters play a dual role providing temporary accommodations for evacuees while also acting as distribution points for essential supplies. Finally, the model determines the flow of resources by assigning each facility to specific demand points, including evacuation destinations, to ensure timely and equitable delivery of aid.

Notations

Sets

N = Set of affected zweones ($n = 1, 2\ldots, N$);
I = set of the main warehouses ($i = 1, 2\ldots, I$);
$\mathcal{J}$ = set of candidate local warehouses ($j = 1, 2\ldots, \mathcal{J}$);
K = set of candidate local markets ($k = 1, 2\ldots, K$);
L = set of candidate staging area ($l = 1, 2\ldots, L$);
M = set of candidate shelters ($m = 1, 2\ldots, M$);
O = set of item types, indexed by ($o = 1, 2\ldots, O$);
P = set of candidate non-profit organizations (NGO) ($p = 1, 2\ldots, P$);
R = set of vehicle modes ($r = 1, 2\ldots, R$); and
U = set of scenarios ($u = 1, 2\ldots, U$).

Parameters

BM = The large number;
$f_s^{\,l}$ = opening cost for staging area l;
$f_{sh}^{\,m}$ = opening cost for shelter m;
$f_{lw}^{\,j}$ = opening cost for local warehouse j;
$h_{lw}^{\,jo}$ = holding cost of item type o at local warehouses j;
S_u^{or} = distributing cost of item type o transportation mode r in scenario u;
v^o = the volume or weight of item type o;
$c_s^{\,l}$ = storage capacity at staging area l;
$c_{sh}^{\,m}$ = storage capacity at shelter m;
$c_{lw}^{\,j}$ = storage capacity at local warehouse j;
$c_{ev}^{\,m}$ = evacuation capacity at shelter m;
d_u^{no} = demand of item type o at zone n in scenario u;
$need^o$ = an amount of demand for item type o;
fam_u^n = the number of households affected by flooding in zone n under scenario u;
p_{eu} = proportion of households expected to be evacuated in scenario u;
β = threshold value for minimum storing utilization of local warehouse;
$prob_u$ = probability of each scenario u;
rln^{ln} = distance between staging area l to affected zone n;
rlm^{lm} = distance between staging area l to shelter m;
rmn^{mn} = distance between shelter m to affected zone n;
rjl^{jl} = distance between local warehouse j to staging area l;
rjm^{jm} = distance between local warehouse j to shelter m;
rij^{ij} = distance between main warehouse i to local warehouse j;
rkj^{kj} = distance between local market k to local warehouse j;

rkl^{kl} = distance between local market k to staging area l;
rkm^{km} = distance between local market k to shelter m;
rpi^{pi} = distance between NGO p to main warehouse i;
rpj^{pj} = distance between NGO p to local warehouse j;
tln^{ln}_{ru} = response time transported items from staging area l to affected zone n with transportation mode r in scenario u;
tlm^{lm}_{ru} = response time transported items from staging area l to shelter m with transportation mode r in scenario u;
tjl^{jl}_{ru} = response time transported items from local warehouse j to staging area l with transportation mode r in scenario u;
tjm^{jm}_{ru} = response time transported items from local warehouse j to shelter m with transportation mode r in scenario u;
tij^{ij}_{ru} = response time from main warehouse i to local warehouse j with transportation mode r in scenario u;
tkj^{kj}_{ru} = response time from local market k to local warehouse j with transportation mode r in scenario u;
tkl^{kl}_{ru} = response time from local market k to staging area l with transportation mode r in scenario u;
tkm^{km}_{ru} = response time from local market k to shelter m with transportation mode r inscenario u;
tpi^{pi}_{ru} = response time from NGO p to main warehouse i with transportation mode r in scenario u;
tpj^{pj}_{ru} = response time from NGO p to local warehouse j with transportation mode r in scenario u;
$Max_{MWarehouse}{}^{io}$ = maximum capacity of main warehouse i to storage item type o;
$Max_{LMarket}{}^{ko}$ = maximum capacity of local warehouse k to storage item type o;
$Max_{NGO}{}^{po}$ = maximum capacity of NGO p to storage item type o;
$Total_{Time\,u}$ = total time in each scenario u;
$Total_{Transport_{Cost}\,u}$ = total transport cost in each scenario u;
$Total_{Evacuation_{Distance}\,u}$ = total evacuation distance for each family in scenario u;
$Total_{Demand\_ev^{o}_{u}}$ = total demand for item type o required by evacuee households in scenario u; and
$Total_{Demand^{o}_{u}}$ = total demand in eanch item type o in each scenario u.

First stage decision variables

$$x_s{}^{l} = \begin{cases} 1, & \text{if local staging area } l \text{ is opened} \\ 0, & \text{otherwise;} \end{cases}$$

$$x_{sh}{}^{m} = \begin{cases} 1, & \text{if local shelter } m \text{ is opened} \\ 0, & \text{otherwise;} \end{cases}$$

$$x_{lw}{}^{j} = \begin{cases} 1, & \text{if local warehouse } j \text{ is opened} \\ 0, & \text{otherwise; and} \end{cases}$$

$q_{lw}{}^{jo}$ = Quantities of items type o to be stored at local warehouse j.

Second stage decision variables

$$\mathrm{yln}^{ln}_{ru} = \begin{cases} 1, & \text{if items are transported from staging area } l \text{ to affected zone } n \text{ withtransportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{ylm}^{lm}_{ru} = \begin{cases} 1, & \text{if items are transported from staging area } l \text{ to shelter } m \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{ymn}^{mn}_{ru} = \begin{cases} 1, & \text{if items are transported from shelter } m \text{ to affected zone } n \text{ withtransportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{yjl}^{jl}_{ru} = \begin{cases} 1, & \text{if items are transported from local warehouse } j \text{ to stagging area } l \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{yjm}^{jm}_{ru} = \begin{cases} 1, & \text{if items are transported from local warehouse } j \text{ to shelter } m \text{ withtransportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{yij}^{ij}_{ru} = \begin{cases} 1, & \text{if items are transported from main warehouse } i \text{ to local warehouse } j \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{ykj}^{kj}_{ru} = \begin{cases} 1, & \text{if items are transported from local market } k \text{ to local warehouse } j \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\mathrm{ykl}^{kl}_{ru} = \begin{cases} 1, & \text{if items are transported from local market } k \text{ to staging area } l \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\text{ykm}_{ru}^{km} = \begin{cases} 1, & \text{if items are transported from local market } k \text{ to shelter } m \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\text{ypi}_{ru}^{pi} = \begin{cases} 1, & \text{if items are transported from NGO } p \text{ to main warehouse } i \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

$$\text{ypj}_{ru}^{pj} = \begin{cases} 1, & \text{if items are transported from NGO } p \text{ to local warehouse } j \text{ with transportation mode } r \text{ in scenario } u \\ 0, & \text{otherwise;} \end{cases}$$

zln_{ru}^{lno} = Quantities of item type o that is transported from staging l to affected zone n with transportation mode r in scenario u;
zlm_{ru}^{lmo} = quantities of item type o that is transported from staging l to shelter m with transportation mode r in scenario u;
zmn_{ru}^{mno} = quantities of item type o that is transported from staging area m to affected zone n with transportation mode r in scenario u;
zjl_{ru}^{jlo} = quantities of item type o that is transported from local warehouse j to staging area l with transportation mode r in scenario u;
zjm_{ru}^{jmo} = quantities of item type o that is transported from local warehouse j to shelter m with transportation mode r in scenario u;
zij_{ru}^{ijo} = quantities of item type o that is transported from main warehouse i to local warehouse j with transportation mode r in scenario u;
zkj_{ru}^{kjo} = quantities of item type o that is transported from local market k to local warehouse j with transportation mode r in scenario u;
zkl_{ru}^{klo} = quantities of item type o that is transported from local market k to staging area l with transportation mode r in scenario u;
zkm_{ru}^{kmo} = quantities of item type o that is transported from local market k to shelter m with transportation mode r in scenario u;
zpj_{ru}^{pjo} = quantities of item type o that is transported from NGO p to local warehouse j with transportation mode r in scenario u;
zpi_{ru}^{pio} = quantities of item type o that is transported from NGO p to main warehouse i with transportation mode r in scenario u; and
ev_{u}^{mn} = number of households evacuated from affected zone n to shelter m in scenario u.

As outlined earlier, the proposed model uses a MIP approach to address the complexities of disaster logistics. The model's objectives are designed to optimize critical aspects of relief operations as follows:

1. *Objective 1:* Minimize the total response time for relief supplies and evacuees across all scenarios. This involves optimizing facility activation, transportation routes and allocation decisions, as expressed in equation (1):

$$Min\,Z1 = \sum_{u} prob_u Total_{Time(u)} \tag{1}$$

2. *Objective 2:* Minimize the total planning budget to ensure efficient allocation of limited resources. This includes facility opening costs, holding costs and transportation costs, as shown in equation (2):

$$Min\,Z2 = \sum_{l} f_s{}^l x_s{}^l + \sum_{m} f_{sh}^{m} x_{sh}^{m} : \; + \sum_{j} f_{lw}^{j} x_{lw}^{j} + \sum_{j}\sum_{o} h_{lw}^{jo} q_{lw}^{jo} + \sum_{u} prob_u Total_{Transport\,cost(u)} \tag{2}$$

3. *Objective 3:* Minimize the total evacuation distance to ensure efficient relocation of affected individuals. This is formulated in equation (3):

$$Min\,Z3 = \sum_{u} prob_u Total_{Evacuation\,Distance\,(u)} \tag{3}$$

3.2.1 Constraints

The constraints of the model are subdivided according to their functional roles.

The minimizes the total response time from supply points (main warehouse, NGOs and local markets) to distribution points (local warehouses, staging areas and shelters) and then to the affected zones, under each disaster scenario, as presented in (4):

$$\begin{aligned} Total_{Time(u)} = {} & \sum_{l}\sum_{m}\sum_{r} tlm_{ru}^{lm} ylm_{ru}^{lm} + \sum_{l}\sum_{n}\sum_{r} tln_{ru}^{ln} yln_{ru}^{ln} \\ & + \sum_{m}\sum_{n}\sum_{r} tmn_{ru}^{mn} ymn_{ru}^{mn} + \sum_{j}\sum_{l}\sum_{r} tjl_{ru}^{jl} yjl_{ru}^{jl} \\ & + \sum_{j}\sum_{m}\sum_{r} tjm_{ru}^{jm} yjm_{ru}^{jm} + \sum_{i}\sum_{j}\sum_{r} tij_{ru}^{ij} yij_{ru}^{ij} \\ & + \sum_{k}\sum_{j}\sum_{r} tkj_{ru}^{kj} ykj_{ru}^{kj} + \sum_{k}\sum_{l}\sum_{r} tkl_{ru}^{kl} ykl_{ru}^{kl} \\ & + \sum_{k}\sum_{m}\sum_{r} tkm_{ru}^{km} ykm_{ru}^{km} + \sum_{p}\sum_{i}\sum_{r} tpi_{ru}^{pi} ypi_{ru}^{pi} \\ & + \sum_{p}\sum_{j}\sum_{r} tpj_{ru}^{pj} ypj_{ru}^{pj};\ \forall u \end{aligned} \tag{4}$$

The Constraint (5) focuses on reducing the cost of total transportation and response costs across all activated links in the supply chain network under scenario u, reflecting the second objective:

$$\begin{aligned} Total_{Transport_{Cost(u)}} = {} & \sum_{l}\sum_{m}\sum_{o}\sum_{r} S_u^{or} rlm^{lm} zlm_{ru}^{lmo} \\ & + \sum_{l}\sum_{n}\sum_{o}\sum_{r} S_u^{or} rln^{ln} zln_{ru}^{lno} \\ & + \sum_{m}\sum_{n}\sum_{o}\sum_{r} S_u^{or} rmn^{mn} zmn_{ru}^{mno} \\ & + \sum_{k}\sum_{l}\sum_{o}\sum_{r} S_u^{or} rkl^{kl} zkl_{ru}^{klo} \end{aligned}$$

$$+\sum_{k}\sum_{m}\sum_{o}\sum_{r} S_{u}^{or} rkm^{km} zkm_{ru}^{kmo}$$
$$+\sum_{k}\sum_{j}\sum_{o}\sum_{r} S_{u}^{or} rkj^{kj} zkj_{ru}^{kjo}$$
$$+\sum_{i}\sum_{j}\sum_{o}\sum_{r} S_{u}^{or} rij^{ij} zij_{ru}^{ijo}$$
$$+\sum_{j}\sum_{m}\sum_{o}\sum_{r} S_{u}^{or} rjm^{jm} zjm_{ru}^{jmo}$$
$$+\sum_{j}\sum_{l}\sum_{o}\sum_{r} S_{u}^{or} rjl^{jl} zjl_{ru}^{jlo};\ \forall u \tag{5}$$

The Constraint (6) captures the cumulative distance for evacuating households from affected zones to shelters and is minimized as the third objective.

$$Total_{Evacuation_{Distance(u)}} = \sum_{m}\sum_{n} rmn^{mn} ev_{u}^{mn};\ \forall u \tag{6}$$

To ensure storage and handling feasibility, Constraints (7)–(9) ensure that the volume of items assigned to each location (staging areas, shelters and local warehouses) does not exceed their maximum capacities.

$$\sum_{n}\sum_{o}\sum_{r} v^{o} zln_{ru}^{lno} \le c_{s}{}^{l} x_{s}{}^{l};\ \forall l \tag{7}$$

$$\sum_{n}\sum_{o}\sum_{r} v^{o} zmn_{ru}^{mno} \le c_{sh}{}^{m} x_{sh}{}^{m};\ \forall m, u \tag{8}$$

$$\sum_{o} v^{o} q_{lw}{}^{jo} + \sum_{i}\sum_{o}\sum_{r} v^{o} zij_{ru}^{ijo} + \sum_{k}\sum_{o}\sum_{r} v^{o} zkj_{ru}^{kjo} + \sum_{p}\sum_{o}\sum_{r} v^{o} zpj_{ru}^{pjo} \le c_{lw}{}^{j} x_{lw}{}^{j};\ \forall j, u \tag{9}$$

Additionally, Constraint (10) a minimum utilization threshold is imposed on local warehouses to ensure that selected warehouses maintain a predetermined level of usage when opened:

$$\frac{1}{c_{lw}{}^{j}}\left(\sum_{o} v^{o} q_{lw}{}^{jo} + \sum_{i}\sum_{o}\sum_{r} v^{o} zij_{ru}^{ijo} + \sum_{k}\sum_{o}\sum_{r} v^{o} zkj_{ru}^{kjo} + \sum_{p}\sum_{o}\sum_{r} v^{o} zpj_{ru}^{pjo}\right) \ge \beta x_{lw}^{j};\ \forall j, u \tag{10}$$

Constraint (11) ensures that the total quantity of relief items delivered from both staging areas and shelters satisfies or exceeds the demand in each affected zone n, for every item o and under all disaster scenarios u:

$$\sum_{l}\sum_{r} zln_{ru}^{lno} + \sum_{m}\sum_{r} zmn_{ru}^{mno} \ge d_{u}^{no}\ \forall n, o, u \tag{11}$$

This Constraint (12) calculates the total demand for relief items among evacuated households, ensures that relief items adequately support households during evacuation:

$$\sum_{n} pe_{u} fam_{u}^{n} need^{o} = Total_{Demand\_ev_{u}^{o}};\ \forall o, u \tag{12}$$

Constraint (13) ensures that the required amount of relief items for families in an affected zone, adjusted for nonevacuated populations, does not exceed the demand in each scenario:

$$need^{o} fam_{u}^{n} * (1 - pe_{u}) = d_{u}^{no};\ \forall n, o, u \tag{13}$$

This Constraint (14) guarantees that the number of evacuees accommodated in shelter m does not exceed its capacity for each scenario:

$$\sum_{n} ev_{u}^{mn} \le c_{ev}{}^{m};\ \forall m, u \tag{14}$$

While Constraint (15) ensures that the actual number of evacuated households matches the expected evacuation proportion in each scenario:

$$\sum_{m} ev_{u}^{mn} = pe_{u} fam_{u}^{n};\ \forall n, u \tag{15}$$

Constraint (16) ensures that the total demand for each item is met in every scenario:

$$\sum_{n} d_{u}^{no} = Total\_Demand_{u}^{o};\ \forall o, u \tag{16}$$

To enforce logical flow continuity, Constraints (17)–(19) govern item inflows and outflows across facilities that ensure the distribution of relief items adheres to the capacity constraints of storage facilities and satisfies demand in affected zones:

$$\sum_{l}\sum_{r} zjl_{ru}^{jlo} + \sum_{m}\sum_{r} zjm_{ru}^{jmo} \le q_{lw}{}^{jo} + \sum_{i}\sum_{r} zij_{ru}^{ijo} + \sum_{k}\sum_{r} zkj_{ru}^{kjo} + \sum_{p}\sum_{r} zpj_{ru}^{pjo};\ \forall j, o, u \tag{17}$$

$$\sum_{j}\sum_{r} zjl_{ru}^{jlo} + \sum_{k}\sum_{r} zkl_{ru}^{klo} = \sum_{n}\sum_{r} zln_{ru}^{lno} + \sum_{m}\sum_{r} zlm_{ru}^{lmo};\ \forall l, o, u \tag{18}$$

$$\sum_{j}\sum_{r} zjm_{ru}^{jmo} + \sum_{l}\sum_{r} zlm_{ru}^{lmo} + \sum_{k}\sum_{r} zkm_{ru}^{kmo} = \sum_{n}\sum_{r} zmn_{ru}^{mno} + \sum_{n} need^{o} ev_{u}^{mn};\ \forall m, o, u \tag{19}$$

To avoid exceeding supply center capacities, Constraints (20)–(22) these constraints prevent exceeding the capacity limits of the main warehouse, local markets and NGO supply centers respectively:

$$\sum_{j}\sum_{r} zij_{ru}^{ijo} \le Max_{MWarehouse}{}^{io} + \sum_{p}\sum_{r} zpi_{ru}^{pio};\ \forall i, o, u \tag{20}$$

$$\sum_j \sum_r zkj_{ru}^{kjo} + \sum_l \sum_r zkl_{ru}^{klo} + \sum_m \sum_r zkm_{ru}^{kmo} \le Max_{LMarket}{}^{ko};\ \forall k, o, u \tag{21}$$

$$\sum_i \sum_r zpi_{ru}^{pio} + \sum_j \sum_r zpj_{ru}^{pjo} \le Max_{NGO}{}^{po};\ \forall p, o, u \tag{22}$$

The model uses a Big-M formulations (23)–(28) to enforce that flow variables are only positive when the corresponding binary variable indicates an active transportation link:

$$zln_{ru}^{lno} \le BMyln_{ru}^{ln},\ zlm_{ru}^{lmo} \le BMylm_{ru}^{lm};\ \forall l, n, m, o, r, u \tag{23}$$

$$zmn_{ru}^{mno} \le BMymn_{ru}^{mn};\ \forall m, n, o, r, u \tag{24}$$

$$zjl_{ru}^{jlo} \le BMyjl_{ru}^{jl},\ zjm_{ru}^{jmo} \le BMyjm_{ru}^{jm};\ \forall j, l, m, o, r, u \tag{25}$$

$$zij_{ru}^{ijo} \le BMyij_{ru}^{ij},\ zkj_{ru}^{kjo} \le BMykj_{ru}^{kj};\ \forall i, k, j, o, r, u \tag{26}$$

$$zkl_{ru}^{klo} \le BMykl_{ru}^{kl},\ zkm_{ru}^{kmo} \le BMykm_{ru}^{km};\ \forall k, l, m, o, r, u \tag{27}$$

$$zpi_{ru}^{pio} \le BMypi_{ru}^{pi},\ zpj_{ru}^{pjo} \le BMypj_{ru}^{pj};\ \forall p, i, j, o, r, u \tag{28}$$

Binary variables are defined in Constraint (29) to represent transportation routes between different locations and facilities under various disaster scenarios:

$$yln_{ru}^{ln}, ylm_{ru}^{lm}, ymn_{ru}^{mn}, yjl_{ru}^{jl}, yjm_{ru}^{jm}, yij_{ru}^{ij}, ykj_{ru}^{kj}, ykl_{ru}^{kl}, ykm_{ru}^{km}, ypi_{ru}^{pi}, ypj_{ru}^{pj}, x_s{}^l, x_{sh}{}^m, x_{lw}{}^j \in \{1, 0\};\ \forall i, j, k, l, m, n, p, r, u \tag{29}$$

All flow variables are continuous and nonnegative as presented in Constraint (30):

$$q_{lw}{}^{jo}, zln_{ru}^{lno}, zlm_{ru}^{lmo}, zmn_{ru}^{mno}, zjl_{ru}^{jlo}, zjm_{ru}^{jmo}, zij_{ru}^{ijo}, zkj_{ru}^{kjo}, zkl_{ru}^{klo}, zkm_{ru}^{kmo}, zpi_{ru}^{pio}, zpj_{ru}^{pjo}, ev_u^{mn} \ge 0;\ \forall i, j, k, l, m, n, o, p, r, u \tag{30}$$

3.3 Solution method

The formulation of the multi-objective model presents a challenge as multi-objective problems are inherently more complex than single objective, particularly when the objectives involve different units. In multi-objective optimization, the goal is not fine a single global optimal solution but rather a set of Pareto optimal solution representing trade-offs among conflicting objectives. A solution $x^* \in X$ is Pareto optimal if there is no other solution $x \in X$ such that $F_i(x) \le F_i(x)$ for all objectives, and strictly $F_j(x) < F_j(x)$ for at least one objective (Marler and Arora, 2004). All pareto optimal point lie on the boundary of the feasible criterion space.

Consequently, Manopiniwes and Irohara (2016) solving multi-objective problems requires identifying a range of solutions that satisfy the defined optimality criteria. To address these problems, several approaches can be used, including the weighted sum method, epsilon constraint method, LP-matrix technique and nonpreemptive goal programming. Among the various techniques for solving multi-objective optimization problems, the weighted sum method is one of the most commonly used approaches. The method transforms the multi-objective problem into a single-objective problem by constructing a linear combination of the individual objective functions $f_i(x)$, each weighted by a coefficient α_i. The weighted sum method is given by:

$$\sum_{i=1}^{k} \alpha_i f_i(x) \quad \text{Where } \alpha_i \ge 0, \quad \forall i = 1, \ldots, k \text{ And } \quad \sum_{i=1}^{k} \alpha_i = 1 \tag{31}$$

However, this method is only effective when all objective functions are homogeneous and expressed in the same units, so when the objectives have different units or magnitudes, normalization is essential to make them comparable on a common scale, which is achieved through a linear normalization technique based on the Utopia and Nadir points.

The Utopia point Z_i^U is defined as the best possible value for the i_{th} objective, typically obtained by minimizing the objective function independently. On the other hand, the Nadir point Z_i^U is the worst possible value, generally obtained by maximizing the objective function independently. Normalizing the objective functions ensures they are bounded between 0 and 1, making them suitable for aggregation in the weighted sum method. The normalization equations are defined as follows:

$$Minz = w_1\left(\frac{Z_1 - Z_1^U}{Z_1^N - Z_1^U}\right) + w_2\left(\frac{Z_2 - Z_2^U}{Z_2^N - Z_2^U}\right) + w_3\left(\frac{Z_3 - Z_3^U}{Z_3^N - Z_3^U}\right) \tag{32}$$

subject to:

Z_i^U is a Utopia point with $Min f_i(x)$ for the cost criteria;
Z_i^N is a Nadia point with $Max f_i(x)$ for the cost criteria; and
$0 < \frac{f_i(x) - Z_i^U}{Z_i^N - Z_i^U} < 1$ for the cost criteria.

4. Computation study

The case study examines Banteay Meanchey Province in Cambodia, which is highly vulnerable to annual flooding with a population of approximately 677,872 and 7 districts and 2 municipalities. Based on the total area affected by flooding is 721.9 km^2 (QuickworldFactoid, 2025), which focuses on 46 affected locations during floods listed in Table 2 and a logistics network comprising 4 local warehouses, 1 local market, 9 shelters and 9 staging areas, with supplies directed from the main warehouse and 4 NGO locations as illustrated in the Figure 2. Additionally, the facilities were selected based on specific criteria:

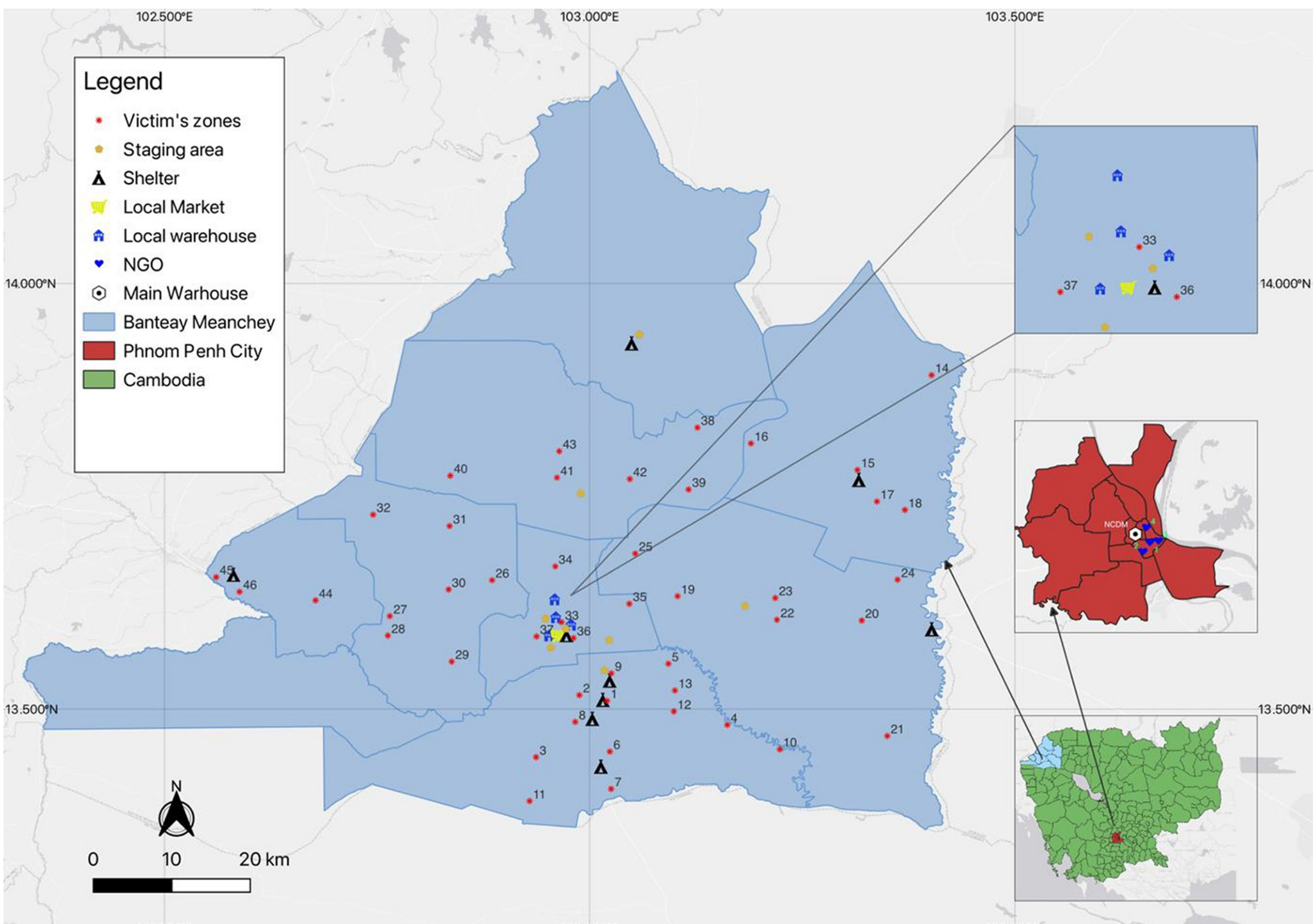
- *Main warehouse:* Managed by the National Disaster Committee (NCDM);
- *Local warehouses:* Situated in government facilities including Hall Center, Cambodian; Red Cross, Department of Rural Development and UYFC Banteay Meanchey;

Table 2 Amount of family affected zone during flood occurs

	The number of victims during the flooding										
		Scenario				Scenario				Scenario	
No.	**u = 1**	**u = 2**	**u = 3**	**No.**	**u = 1**	**u = 2**	**u = 3**	**No.**	**u = 1**	**u = 2**	**u = 3**
1	82	143	493	**16**	63	110	380	**31**	21	37	129
2	29	50	174	**17**	31	55	189	**32**	31	55	190
3	74	129	445	**18**	40	70	241	**33**	99	174	600
4	26	45	154	**19**	31	55	190	**34**	37	65	225
5	29	52	178	**20**	75	132	455	**35**	26	46	158
6	62	108	374	**21**	35	61	209	**36**	61	107	369
7	54	94	324	**22**	70	122	421	**37**	66	115	397
8	52	90	312	**23**	50	87	300	**38**	57	100	346
9	89	156	536	**24**	58	102	352	**39**	24	42	145
10	32	56	194	**25**	57	100	345	**40**	57	100	345
11	59	104	358	**26**	56	98	337	**41**	22	39	135
12	32	57	196	**27**	32	57	195	**42**	36	64	220
13	33	59	202	**28**	39	69	238	**43**	19	33	113
14	57	101	347	**29**	26	46	159	**44**	72	126	433
15	50	87	300	**30**	38	67	230	**45**	192	337	1,161
								46	118	208	716

Source(s): Authors' own work

Figure 2 Current situation of facility during flood occurs



Source: Authors' own work

- *Staging areas:* Serve as locations for sorting and distributing donated supplies before they are dispatched to affected zones or shelters; and
- *Shelters:* Positioned along main routes, flood-safe areas for better accessibility and safety.

Based on these criteria, geographic data from sources like Google Maps identified key facilities including the main warehouse, local warehouses, NGOs, markets, staging areas, shelters and affected zones. The capacity of each facility was specified according to its ability to store donated items. As shown in Table 3, the storage capacity of each facility was then determined based on its physical dimensions and internal layout a task complicated by the absence of standardized warehouse capacity data in Cambodia, the distribution of supplies from the main warehouse to local warehouses with capacities ranging from 1,500 to 3,000 units was mapped, along with shelters having capacities ranging from 9,052 to 15,068 units (300–500 families) and staging areas holding 3,448–4,310 units. Additionally, the assessment by the humanitarian response forum (HRF) and the National Committee for Disaster Management (NCDM) outlines the number of victims affected by the floods. According to Phy *et al.* (2022), the results of a scenario-based analysis using flood probability data (0.5714, 0.2857 and 0.1429 for three scenarios). As reported by CFE-DM (2024), flood data from 2019, 2021 and 2022 revealed evacuation rates of 0.061, 0.104 and 0.17, respectively. To summary this probability of occurrence for each scenario shown in Table 4.

5. Result

5.1 Experimental results

The proposed multi-objective two-stage stochastic optimization model was implemented using LINGO software and evaluated on a computer equipped with an Intel® Core^{TM} i7-6700 CPU (3.40 GHz) and 16 GB of RAM. The model's performance was assessed by solving each objective individually, treating others as constraints, to determine Utopia and Nadir points. These points provide valuable insights into the trade-offs inherent in single-objective optimization.

As shown in Table 5, upon solving the reformulated model, the optimal solution for minimizing total response time was 682.69 min, the total budget was $193,547.83 and the total evacuation distance was 7,040.23 km to attain the Utopia point for each objective. Conversely, maximum total response time resulted in 104,920.50 min of response time, $1,411,933.07 for the budget and 42,279.78 km for evacuation distance. These results demonstrate the inherent conflicts in multi-objective optimization, whereby improvements in one objective are often made at the expense of another. The Utopia points indicate ideal scenarios, while the Nadir points represent the worst scenarios that can happen when an objective is deprioritized. These results represent the complexity of objective balancing in disaster management and provide an insight for decision-makers in adapting various strategies according to their needs, such as prioritizing rapid responses for critical emergencies or cost efficiency during constrained scenarios.

To apply the proposed solution method outlined in sub-Section 3.3, the Utopia and Nadir points were used as reference

Table 3 Capacity of each facility

		Local warehouse		Staging area		Shelter/staging area	
Index	**Shelter**	**Capacity**	**Fixed cost**	**Capacity**	**Fixed cost**	**Capacity**	**Fixed cost**
1	1,100	3,000	6,000	4,310	1,000	9,052	2,100
2	700	1,500	3,000	3,448	800	15,086	3,500
3	500	3,000	6,000	4,310	1,000	9,052	2,100
4	700	1,500	3,000	3,448	800	9,052	2,100
5	500			4,310	1,000	15,086	3,500
6	1,100			3,448	800	15,086	3,500
7	500			3,448	800	15,086	3,500
8	1,100			3,448	800	9,052	2,100
9	500			3,448	800	9,052	2,100

Source(s): Authors' own work

Table 4 Probability of occurrence for each scenario

	Scenario 1		Scenario 2		Scenario 3	
Index	**Item 1**	**Item 2**	**Item 1**	**Item 2**	**Item 1**	**Item 2**
Transportation cost mode 1	0.65	0.65	0.73	0.73	0.91	0.91
Transportation cost mode 2	0.59	0.59	0.70	0.70	0.97	0.97
Probability flooding occur	0.57		0.29		0.14	
Properties of evacuation	0.06		0.10		0.17	
Number of victims	82		143		493	

Source(s): Authors' own work

Table 5 Ideal values for the single objective programming model

Objective function value	Single objective model Z1	Z2	Z3	Utopia point	Nadir point
Min Z1	682.69	104,920.5	104,920.5	682.69	104,920.50
Min Z2	1,049,521	193,547.8	1,411,933	193,547.83	1,411,933.07
Min Z3	42,279.78	18,127.58	7,040.232	7,040.23	42,279.78

Source(s): Authors' own work

values, with a warehouse utilization threshold (β) set to 0.5. Equal weights of 0.33 were assigned to each objective for balanced optimization. As the shown in the Table 6, the optimal solution achieved an objective value of 0.01, a total distribution time of 1,794.73 min, a total cost of $219,383.60 (including holding, opening, staging, shelter, local warehouse and transportation) and a total evacuation distance of 7,065.42 km.

The scenario-based study offers insights into system performance under varying disaster intensities. In Scenario 1 (low severity), response time was 1,738.12 min, transportation costs were $81,988.56 and evacuation distance was 1,831.06 km. Moreover, shelter demand for Items 1 and 2 was 132 units, indicating manageable logistics. Moving on to Scenario 2 (moderately severe), transportation costs rose to $169,289.90, evacuation distance increased to 5,273.47 km and response time slightly increased to 1,808.61 min. Shelter demand for each item increased to 379 units, requiring more resources due to the wider geographical impact of the disaster which increased the need for supplies to be distributed over a larger area. As the logistical demands grew, it became clear that a more flexible and responsive system was needed to handle the increased scale of operations effectively. In Scenario 3 (high severity), response time jumped to 1,993.36 min, transportation costs surged to $769,364.90 and evacuation distance soared to 31,578.17 km. Additionally, shelter demand for Items 1 and 2 reached 2,260 units each, reflecting the significant logistical strain of a severe disaster.

Overall, the proposed model clearly illustrates its adaptability and scalability across a variety of crisis scenarios. It provides a realistic strategy for balancing numerous objectives in disaster logistics, particularly during severe disasters when resource demands and operational complexity are at their highest. These results significant the value of having flexible strategies to manage the challenges that arise in large-scale disaster situations. By assigning equal weight to all objectives, the model achieves a balanced approach. This enables decision-makers to assign priorities to each objective, such as reducing budget planning in resource-limited situations or enhancing response time in emergencies.

In Figure 3 shows the geographical map of the selected distribution zone sites. The model identifies one local warehouse, one local market, five staging areas and one shelter acting as staging areas, along with nine shelters. This setup ensures the efficient distribution of supplies to both evacuees and nonevacuated individuals. The model improves on existing supply chain strategies by reducing the reliance on the main warehouse and NGOs, promoting a more localized approach to disaster management. Conversely, minimizing costs can result in longer response times. Despite moderate flooding scenarios, the model optimizes for NGO involvement in higher-severity flooding. In these severe conditions, NGOs are crucial for bridging supply chain gaps when local networks are overwhelmed. It provides critical support by facilitating the flow of essential goods to affected areas to ensure that resources are allocated where victims are most needed. This involvement becomes even more crucial when demand exceeds the capacity of local warehouses and local market, helping to maintain supply continuity and optimize distribution efficiency despite resource constraints.

5.2 Analysis of transportation and supply dynamics

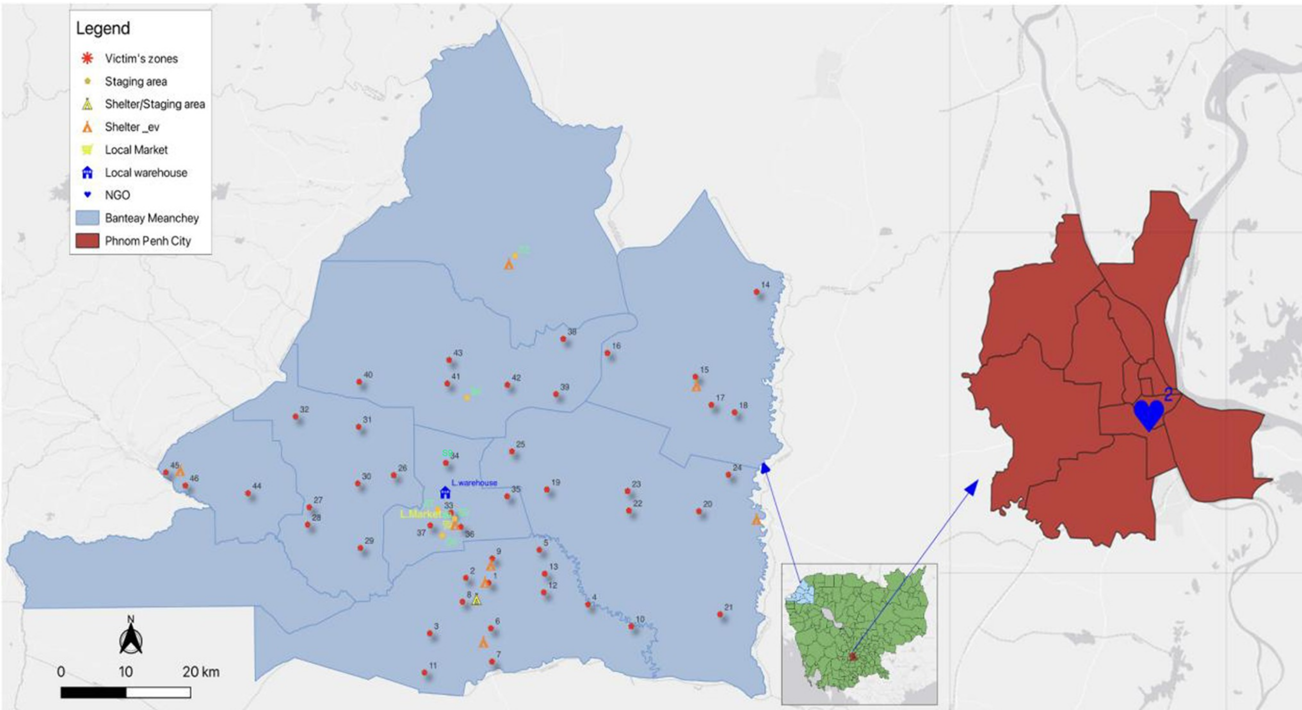
Regulating transportation flows is crucial for maintaining supply chain balance by ensuring proportional allocation of

Table 6 Optimal result with $\beta = 0.5$

Optimal solution Total factor	Z1 (minutes) 1,794.73 Scenario 1	Z2 ($) 219,383.60 Scenario 2	Z3 (kilometers) 7,065.42 Scenario 3
Total time (minutes)	1,738.12	1,808.61	1,993.36
Total transportation cost ($)	81,988.56	169,289.90	769,364.90
Total evacuation distance (kilometers)	1,831.06	5,273.47	31,578.17
Total demand			
Item 1	2,267	3,830	12,252
Item 2	2,267	3,830	12,252
Total demand at shelters			
Item 1	132	379	2,260
Item 2	132	379	2,260

Source(s): Authors' own work

Figure 3 Geographical mapping selection



Source: Authors' own work

supplies to meet demand without overwhelming specific locations like staging areas or shelters which helps reduce congestion and stockouts. By integrating local markets warehouses and shelters the model prioritizes resource allocation based on capacity and fluctuating demand creating an efficient and adaptive disaster response system that ensures flexibility and resilience under varying conditions. As shown in the Table 7, at Staging Area L6 substantial demand is observed in Scenario 3 with 4,293 units of supplies needed compared to only 225 and 195 units in Scenarios 1 and 2. However Transportation 1 is prioritized due to its faster response time especially in severe scenarios while Transportation 2 with its longer response time is avoided when quick action is essential. At Staging Area 2 supplies are directed to shelters instead of affected zones to prioritize shelter operations ensure quick distribution minimize delays optimize resource use and consolidate evacuation and distribution functions to improve efficiency and reduce the need for multiple locations.

5.3 Victim allocation across scenarios to evacuation

The model was developed to evaluate evacuation needs and resource distribution across different scenarios while ensuring evacuee numbers stay within shelter capacities and meet the needs of affected populations. As shown in Table 8, in the evacuation plan N2 is supplied by three shelters M9, M3 and M2 across various scenarios. The allocation is based on the capacity and needs of each shelter. Smaller groups of evacuees are handled by M9, medium-sized groups by M3 and the largest numbers by M2. This ensures that shelters operate within their capacities and the evacuation process is optimized.

As the number of evacuees rises the responsibility for supplying N26 initially handled by M8 gradually shifts to M1 to accommodate the increasing demand, maintaining an efficient evacuation process during higher flood scenarios, as these shelters are better equipped to manage a larger influx of evacuees due to their locations and available resources. M1, serving areas with high concentrations of evacuees like N19, N28 and N40, shelters up to 500 evacuees in Scenario 3. This distribution highlights the importance of having flexible shelter capacities and evacuation plans that can adjust to the changing number of evacuees in different disaster situations. Proper management of resources and shelters are essential to avoid overcrowding and ensure that evacuations happen quickly and effectively.

5.4 Pareto frontier with weight normalization method

Under the same computational settings, the model produces a set of nondominated solutions outlining feasible performance. The findings show the Pareto optimal front relating Z1–Z2, Z1–Z3 and Z2–Z3, with weight adjustments ranging from 0 to 1 (11 iterations for each bi-objective). These trade-offs, which are critical for decision-makers in choosing the best balance between conflicting objectives, are illustrated in Figure 4.

Figure 4(a) plots the full Pareto frontier relating total response time (Z1) to the overall planning budget (Z2). A clear inverse relationship is observed as the budget increases, the total response time declines. Notably, dramatic improvements in response time can be achieved with relatively modest increases in budget up to a certain threshold. For example, reducing Z1 from over 100,000 min to approximately

Table 7 Transport types and items need at staging areas under three scenarios

Staging area	Transportation 1			Both items need		
	u1	u2	u3	u1	u2	u3
L2	M3, M5			4 / 0	0	0
L6	N33, N34, N37–N39, N41, N43, M5	N37–N39, N41, M5	N14, N23, N25, N26, N28, N29, N31, N33, N34, N37–N39, N40, N41, N42, N43, M5, M8	225	195	4,293
L7	N24, N32, N36	N21, N24, N32	N16, N17, N19, N21, N24, N32, N36, N46	142	198	2,191
L8	N5, M8	N2, N9, N16, N22, M8	N45	31	408	980
L9	N14, N19, N26, N27, N28–N31, N35, N37–N39, N42	N14, N15, N18, N19, N23, N26, N27–N31, N35, N37–N39, N43	N15, N18, N20, N22, N27, N30, N37–N39, N44	483	1,009	1,921
Staging area	**Transportation 2**			**Both items need**		
	u1	u2	u3	u1	u2	u3
L2	M6	M6	–	15/11	15	0
L6	N33, N40	N40, N42	–	54	324	134
L7	N16, N17	N17	–	89	50	0
L8	N9, N45	N36, N45, M9	–	265	432	0
L9	N15, N18, N20–N23, N44, N46, M8, M9	M8	–	510	507	0

Note(s): N = affected zone; L = staging area; M = shelter; u = scenario
Source(s): Authors' own work

Table 8 Evacuation shelter allocation and evacuee distribution across scenarios

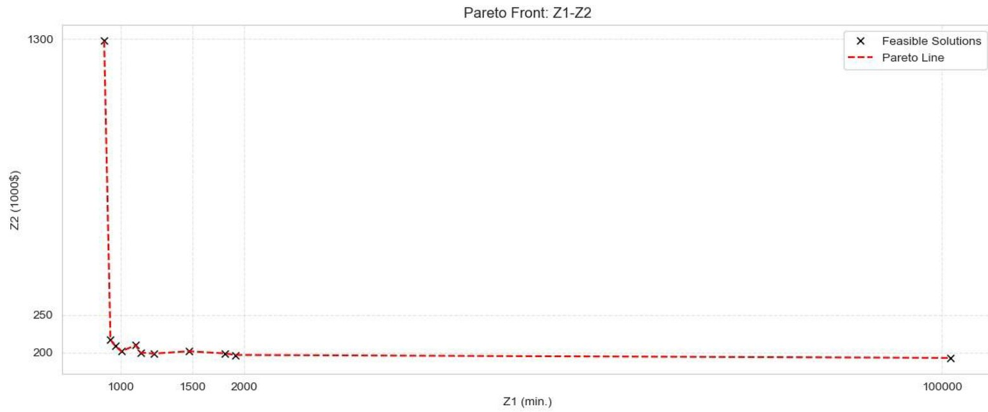
Shelter	Location affected zone			Evacuee's numbers		
	u1	u2	u3	u1	u2	u3
M1→	N19, N28, N29, N32–N37, N40	N19, N28, N29, N32–N37, N40	N19, N26, N28, N29, N32–N37, N40	26	75	500
M2→	N1, N4, N12	N1, N4, N12	N1, N2, N4, N12	8	22	158
M3→	N3, N8	N2, N3, N8	N3, N8	7	24	118
M4→	N6, N7, N11	N6, N7, N11	N6, N7, N11	10	28	164
M5→	N38, N39, N41–N43	N38, N39, N41–N43	N38, N39, N41–N43	9	25	149
M6→	N5, N9, N13, N22, N25	N5, N9, N13, N22, N25	N5, N9, N13, N22, N25	15	44	262
M7→	N10, N20, N21, N23, N24	N10, N20, N21, N23, N24	N10, N20, N21, N23, N24	14	39	235
M8→	N26, N27, N30, N31, N44–N46	N26, N27, N30, N31, N44–N46	N27, N30, N31, N44–N46	29	84	446
M9→	N2, N14–N18	N14–N18	N14–N18	15	38	227

Note(s): N = affected zone; M = shelter; u = scenario
Source(s): Authors' own work

1,100 min requires only a around 3% budget increase (from around \$193,656 to \$200,000). However, as the frontier progresses toward lower response times, the cost of marginal improvement escalates significantly. Achieving response times below 1,000 min demands disproportionate increases in expenditure, with the final point on the frontier (Z1 = 912.74 min) requiring over \$1.28 million, representing diminishing returns. This frontier reflects a convex shape, indicating the existence of a "knee point" where an optimal balance is achieved between rapid disaster response and acceptable cost. Beyond this point, further reductions in time may no longer be economically justified, especially in constrained-budget environments.

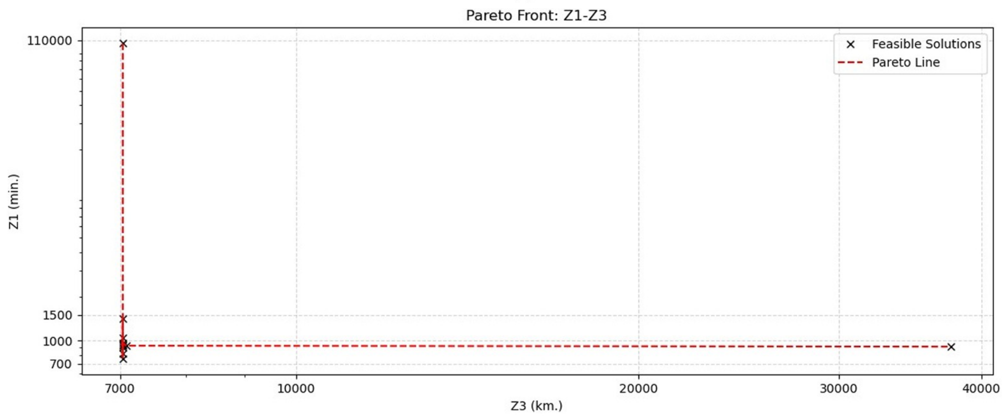
Figure 4(b) visualizes the Pareto frontier between total response time (Z1) and total evacuation distance (Z3). In contrast to typical trade-offs in multi-objective optimization, most solutions along this frontier exhibit a consistent and stable evacuation distance around 7,040.23 km, even as response time varies significantly from 755.82 to 1,417.58 min. This flat pattern suggests that many configurations are capable of maintaining evacuation distance performance regardless of response time, implying a decoupling between these two objectives under certain logistics setups. However, one outlier solution demonstrates a deviation from this trend. Although this configuration achieves the fastest response time of 925.52 min, it results in an excessive evacuation distance

Figure 4 (a) Pareto frontier of response time and budget planning, (b) pareto frontier of response time and evacuation distance, (c) pareto frontier of budget planning and evacuation distance



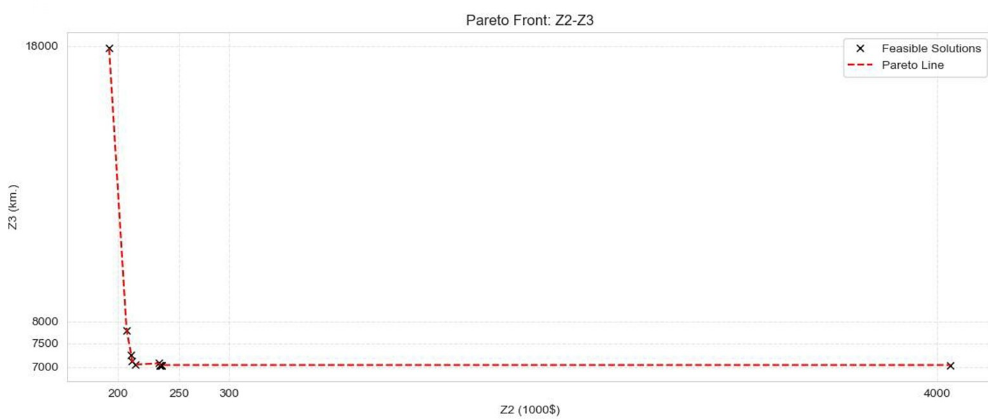
Weight (Z1,Z2)	(1.0,0.0)	(0.9,0.1)	(0.8,0.2)	(0.6,0.4)	(0.7,0.3)	(0.5,0.5)	(0.4,0.6)	(0.2,0.8)	(0.3,0.7)	(0.1,0.9)	(0.0,1.0)
Z1 (min.)	912.74	945.53	971.05	1,004.68	1,089.63	1,118.43	1,207.22	1,465.10	1,799.50	1,905.76	104,920.50
Z2 (1000$)	1,283.90	215.86	207.76	201.47	208.84	199.85	198.72	201.51	198.89	197.11	193.66

(a)



Weight (Z1,Z3)	(0.0,1.0)	(0.1,0.9)	(0.2,0.8)	(0.3,0.7)	(0.4,0.6)	(0.5,0.5)	(0.6,0.4)	(0.7,0.3)	(0.8,0.2)	(0.9,0.1)	(1.0,0.0)
Z1 (min.)	104,920.50	755.82	1,041.69	925.61	942.08	1,417.58	816.64	897.59	964.20	925.52	912.74
Z3 (km.)	7,040.23	7,040.23	7,040.23	7,040.23	7,040.23	7,040.23	7,040.23	7,040.23	7,040.23	7,089.49	37,615.91

(b)



Weight (Z1,Z3)	(1.0,0.0)	(0.9,0.1)	(0.8,0.2)	(0.7,0.3)	(0.5,0.5)	(0.6,0.4)	(0.3,0.7)	(0.4,0.6)	(0.2,0.8)	(0.1,0.9)	(0.0,1.0)
Z2 (1000$)	193.55	206.33	209.85	210.32	213.09	232.06	233.32	233.32	234.09	234.36	4,201.46
Z3 (km.)	17,876.95	7,799.00	7,259.36	7,131.10	7,050.43	7,077.39	7,040.23	7,040.23	7,040.23	7,040.23	7,040.23

(c)

Source: Authors' own work

7,089.49 km, likely caused by an imbalanced allocation of resources (e.g. fewer shelters selected in remote areas). While these differences are modest, they highlight that even in generally stable systems, minor imbalances in resource allocation can lead to measurable logistical strain. Overall, this analysis underscores that while minimizing response time is critical, careful coordination is necessary to avoid inadvertently increasing evacuation burdens. Solutions achieving response times below 1,200 min (20 h) can still maintain near-optimal evacuation distances when facilities are strategically activated and supply flows are efficiently balanced.

Figure 4(c) displays the Pareto frontier between budget (Z2) and evacuation distance (Z3). The most striking observation is the plateau in evacuation distance performance across a wide range of budget values. From $234,000 to over $4.2 million, the evacuation distance remains nearly constant (around 7,040 km), indicating that a broad set of budget allocations can deliver equivalent evacuation outcomes. The implication is that additional funding beyond a certain threshold does not yield tangible gains in evacuation efficiency. However, this stability breaks down when budgets fall below $234,000. At $213,094.92, evacuation distance begins to rise slightly to 7,050.43 km, and continues to increase with lower budgets reaching 7,799.00 kilometers at $206,330.17, and sharply peaking at 17,876.95 km with a minimum budget of $193,547.83. This trend underscores the existence of a minimum budgetary threshold below which evacuation logistics deteriorate significantly. Overall, the Pareto frontier derived through the weight normalization approach underscores the necessity of incorporating multiple objectives in humanitarian logistics planning. While this method often emphasizes extreme solutions, these outcomes tend to reflect practical and actionable decisions. The results demonstrate the utility of the Pareto front in revealing trade-offs among conflicting goals and in guiding decision-makers toward assigning more balanced weights. This ultimately enhances the robustness and adaptability of multi-objective optimization in complex disaster response scenarios.

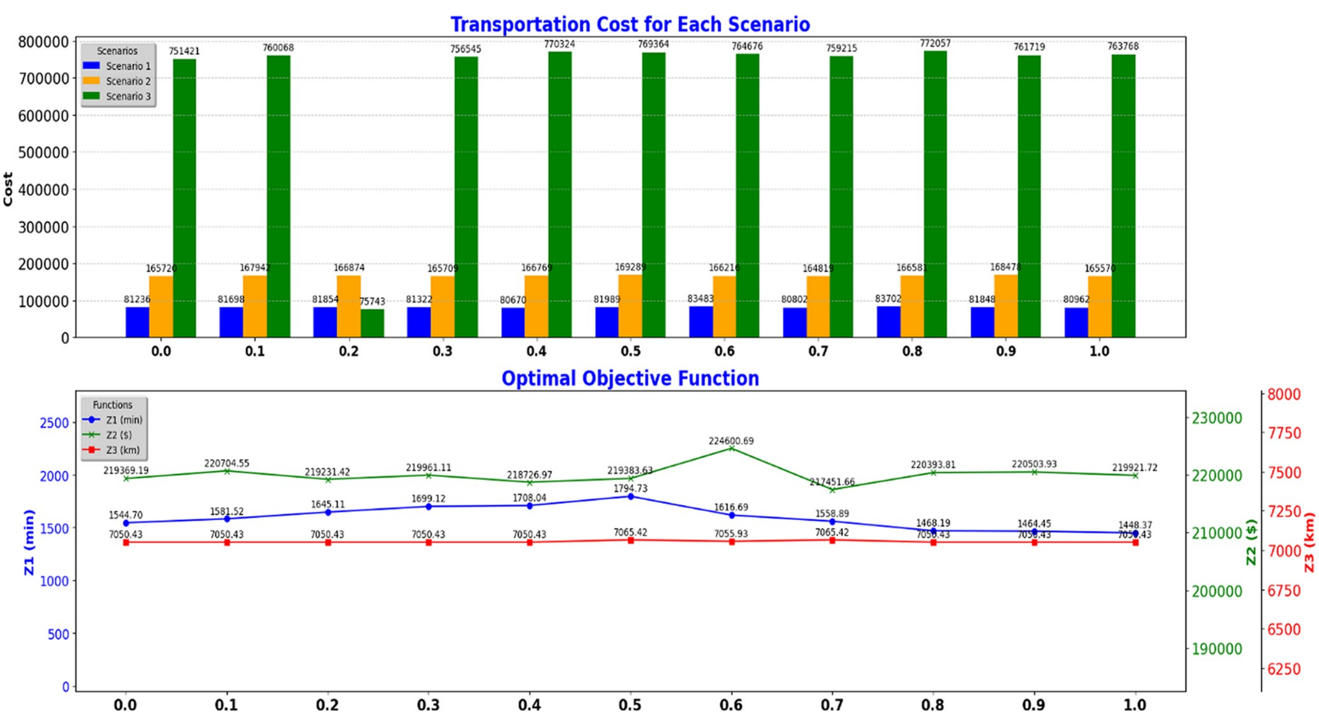
5.5 Sensitive analysis for utilization facility

The sensitivity analysis shows how changes in warehouse utilization (β) affect disaster logistics. As shown in Figure 5, β increases meaning higher stock levels and more warehouses use response time peaks at $\beta = 0.5$ and drops at $\beta = 1$ which indicates that medium stock levels cause delays while higher stock levels speed up operations. The budget fluctuates slightly as different stock levels are tested showing that decisions about using more or fewer facilities affect the budget. Transportation costs rise as stock levels increase particularly in Scenario 3 which sees the highest transportation costs. This increase in transportation costs happens because the model reduces the number of staging areas or excludes NGOs leading to longer travel distances. In summary the analysis highlights the trade-offs between stock levels response times transportation costs and budgets and shows how adjusting warehouse utilization can help decision-makers balance these factors more effectively ensuring that disaster response remains efficient even when conditions change.

5.6 Sensitivity analysis of weight normalizes method

A sensitivity analysis was conducted to examine how alternative weight allocations among the three objectives (Z1, Z2 and Z3) affect the solution. The weighted-sum approach is a common

Figure 5 Sensitivity analysis of utilization warehouse



Source: Authors' own work

scalarization method in multi-objective optimization, and different weight combinations can yield different Pareto-optimal outcomes. The model tested seven weight patterns reflecting equal and biased importance on each objective (Table 9). Patterns 2–4 each emphasize one objective (time, distance or cost, respectively), while Patterns 5–7 impose moderate weight shifts. The results show that emphasizing an objective indeed lowers its value at the expense of others (e.g. Pattern 2 achieves the lowest Z1 at 1,187.90 min but increases Z2, whereas Pattern 3 yields the lowest Z2 at $211,865.15 with higher Z1). However, the objective values remain on the same order of magnitude; notably, Z3 varies by only about 4% across all patterns. This indicates that the trade-offs behave as expected and that no extreme or erratic changes occur under reasonable weight variations. Overall, the sensitivity analysis shows that although the solutions adjust sensibly to different priorities, none of the objective values change dramatically. In particular, the cost objective Z3 remains nearly constant below 4% variation and the other objectives trade off in a predictable way. These results confirm that the model's performance remains robust across the tested range of weightings.

5.7 Sensitivity analysis of the proportion of households expected to be evacuated

To investigate the sensitivity of the proposed model with respect to variations in proposition of household need to evacuate (*Pe*), a series of simulations were conducted under five scenarios. Each scenario corresponds to a unique *Pe* triplet: (0.07, 0.11 and 0.18), (0.09, 0.13 and 0.20), (0.11, 0.15 and 0.22), (0.13, 0.17 and 0.24) and (0.15, 0.18 and 0.26). For each case, the model was solved, and the resulting objective values were Total response time (Z1), total budget (Z2) and evacuation distance (Z3) as shown in Table 10.

The evacuation distance (Z3) exhibits a near-monotonic increase as *Pe* rises, reflecting the intuitive outcome that higher evacuation probabilities result in more evacuees and increases total travel distances. Specifically, Z3 increases steadily from 8,393.0562 to 13,549.64 km, representing an overall increase of approximately 61.4%. In contrast, the total budget (Z2) demonstrates a nonmonotonic response. It rises from $219,967.85 to a peak of $222,143.81, before slightly declining to $220,348.91 in the high proportion evaluated to shelter. Additionally, the response time (Z1) follows a distinctly nonlinear trajectory. It initially increases from 1,693.34 min to 1,786.87 min, then declines to a minimum of 1,492.56 min, before rising again to 1,612.01 min.

The near-linear rise in Z3 with *Pe* reflects the fact that more evacuees travel longer total distance, a direct effect of demand on travel requirements. By contrast, Z1 and Z2 do not simply scale linearly. The peak in Z2 at medium *Pe* (and subsequent slight decline) suggests that after a certain point, reallocating resources or opening additional facilities allows the solution to handle more evacuees with only modest extra cost. Similarly, the U-shaped behavior of Z1 implies that initial increases in evacuation compliance slow down response but beyond a threshold the system adapts perhaps by deploying resources differently. These outcomes illustrate classic multi-objective trade-offs: for example, minimizing travel time or distance generally reduces risk exposure, but as proportion of households rises, the system may favor shorter (timewise) routes at the expense of longer distance or higher cost. In fact, the lowest response time (Z1 = 1,492.5624 min) coincides with an intermediate proportion of households setting where Z3 and Z2 are already large, highlighting a cost time trade-off. High value forces the evacuation of more people, thereby extending distances as noted in evacuation literature.

Table 9 Objective outcomes (Z1, Z2, Z3) under seven weighting scenarios

	Weight				Solution		
Pattern	**Z1**	**Z2**	**Z3**	**Meaning**	**Z1 (minutes)**	**Z2 ($)**	**Z3 (kilometers)**
1	0.33	0.33	0.34	Equal importance	1,792.11	219,700.80	7,050.42
2	0.7	0.15	0.15	Emphasize time	1,187.89	239,774.34	7,119.29
3	0.15	0.7	0.15	Emphasize distance	2,668.67	211,865.14	7,317.11
4	0.15	0.15	0.7	Emphasize cost	1,689.96	228,551.96	7,093.87
5	0.5	0.3	0.2	Moderate time priority	1,397.45	220,729.46	7,081.33
6	0.2	0.5	0.3	Moderate distance priority	1,966.38	217,367.51	7,097.50
7	0.2	0.3	0.5	Moderate cost priority	1,881.83	229,967.96	7,108.45

Source(s): Authors' own work

Table 10 Proportion of households expected to be evacuated

Pe				Objective function		
Scenario 1	**Scenario 2**	**Scenario 3**		**Z1**	**Z2**	**Z3**
0.07	0.11	0.18	→	1,693.34	219,967.85	8,393.05
0.09	0.13	0.2	→	1,786.86	220,610.96	9,668.60
0.11	0.15	0.22	→	1,527.24	222,143.81	10,962.28
0.13	0.17	0.24	→	1,492.56	220,543.89	12,255.96
0.15	0.18	0.26	→	1,612.01	220,348.91	13,549.64

Source(s): Authors' own work

5.8 Sensitivity analysis of the households affected by flooding

As shown in Figure 6, the total budget (Z2) increases steadily from \$220,655 at 1% to \$242,156 at 10%, while evacuation distance (Z3) rises from 7,140.98 to 7,760.81 km [Figures 6(b) and 6(c)]. In contrast, response time (Z1) exhibits a nonlinear trend [Figure 6(a)], with fluctuations ranging from a low of 1,511.08 min to a peak of 1,744.17 min, followed by a slight decline at 10%. The nearly monotonic growth in Z2 and Z3 increased demand more affected households require the need, leading to proportional increases in cost and distance.

The nearly linear increases in Z2 and Z3 indicate predictable scaling with evacuation demand. However, fluctuations in Z1 suggest that system efficiency varies with demand levels. At lower expected evacuation percentages, resources may be underused, leading to longer travel times due to fixed overhead. As demand increases, resource saturation and route congestion may lead to delays, temporarily increasing response time before adjustments in deployment improve efficiency again. This underscores the importance of adaptive resource management under varying evacuation scales.

5.9 The AUGMENCON method application

This study presents a practical way to navigate the competing priorities of total planning budget, response time and evacuation distance by generating a well-structured Pareto frontier of feasible solutions. While the primary optimization is performed using the weighted sum method which requires predefined weights and may miss nonconvex regions of the solution space the AUGMECON method is used to systematically explore a broader range of trade-offs and identify nondominated solutions. This Mavrotas (2009) approach ensures that decision-makers are not constrained by a single weight configuration and can assess how prioritizing one objective impacts the others. In this framework, the model prioritizes budget minimization while incrementally varying ε-constraints on the secondary objectives to construct the Pareto front. The method is implemented using LINGO software and the procedure proceeds as follows:

1 Step 1. Identify the primary objective by second objective (Z2) which is total budget planning as the first priority.

2 Step 2. Construct the payoff table by independently optimizing the remaining objectives Z1 and Z3, as shown in Table 11.

However, the results for Z1 and Z3 were found to be unrealistic based on discussions with decision-makers. Therefore, we decided to constrain the solution space by setting the bounds for Z1 between 682.69 and 2,500 (range $r_1 = 1{,}817.31$), and for Z3 between 7,040.23 and 20,000 (range $r_3 = 12{,}959.77$).

1 Step 3. Divide each range r_k into q_k equal intervals. Here, $q_1 = q_3 = 10$, yielding 11 grid points per objective of each Z1 and Z3.

2 Step 4. Compute the right-hand-side value to represent a set of planning decisions. Noted that ε_k^g is right hand side of Z2 and Z3, where k is number of secondary objective K= {1,} and g is $q+1$ grid points. The formulation as follows:

$$\varepsilon_k^g = Z_k^{min} + \frac{(i_k \times r_k)}{q_k};\ g = \{0,, \ldots, q_k\},\ k = \{1,\}$$

The varying value of ε_k^i provides different Pareto-optimal solutions. The equation can be rewritten as follows:

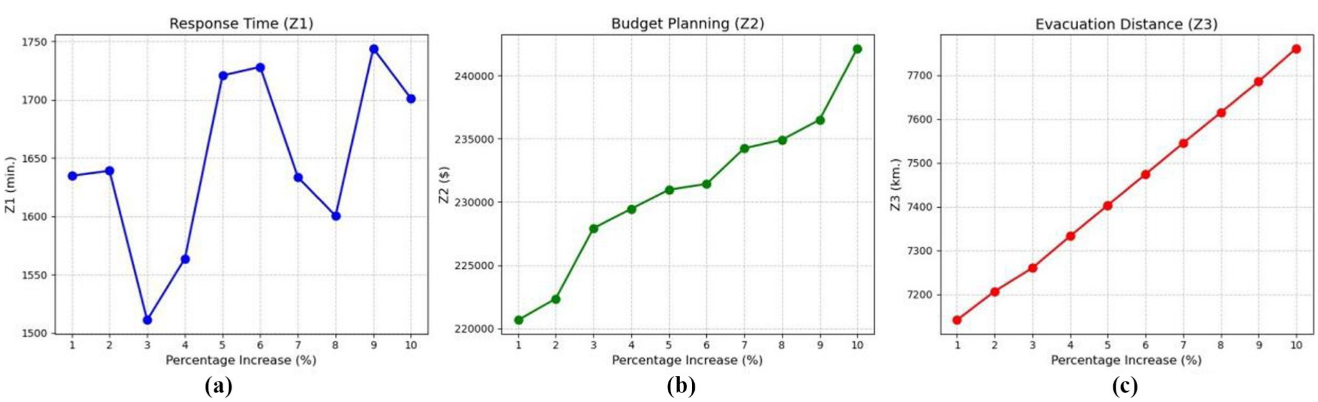
$$\varepsilon_1^g = Z_1^{min} + \frac{(i_1 \times r_1)}{q_1}$$

$$\varepsilon_3^g = Z_3^{min} + \frac{(i_3 \times r_3)}{q_3}$$

1 Step 5. Reformulate the original multi-objective problem into a single-objective model according to AUGMECON.

Additional parameters:
g set of grid points; $g = \{0,,.,q_k + 1\}$
ε_1^g = the altered to generate the set of Pareto-optimal solutions of Z1
ε_3^g = the altered to generate the set of Pareto-optimal solutions of Z3
s_1 and s_3= nonnegative surplus variables of Z1 and Z3, respectively.

Figure 6 Increasing proportion of affected households



Source: Authors' own work

Table 11. Payoff table analysis

Pay off table	Z1	Z3
Min Z1	682.69	104,920.50
Min Z3	42,279.78	7,040.23

Source(s): Authors' own work

r_1 and r_3 = range of objective function Z1 and Z3, respectively.

eps = a very small number (10^{-3} to 10^{-6})

AUGMECON objective:

$$\min Z = Z2 + eps\left(\frac{s_1}{r_1} + \frac{s_3}{r_3}\right)$$

AUGMECON contraints:

$$Z1 + s_1 = \varepsilon_1^g$$

$$Z3 + s_3 = \varepsilon_3^g$$

$$s_1,\ s_3 \geq 0$$

Equations (4)–(30).

As shown in Figure 7, the results obtained using the AUGMECON method offer critical insights into the feasibility boundaries of evacuation planning scenarios. Specifically, the model indicates infeasibility for evacuation distances (Z3) below 8,336.21 kilometers, as evidenced by the absence of feasible solutions for Z1 values ranging from 682.69 min to 1,046.15 min. This infeasibility suggests that attempting to achieve shorter evacuation distances under the given constraints may not be viable. Conversely, feasible solutions emerge when Z3 is set at or above 8,336.21 km, with associated costs decreasing as Z1 increases. For instance, at Z1 = 1,227.88 min and Z3 = 8,336.21 km, the cost is approximately $218,311.83, which gradually reduces to around $193,447.83 at Z1 = 2,500 min and Z3 = 20,000 kilometers.

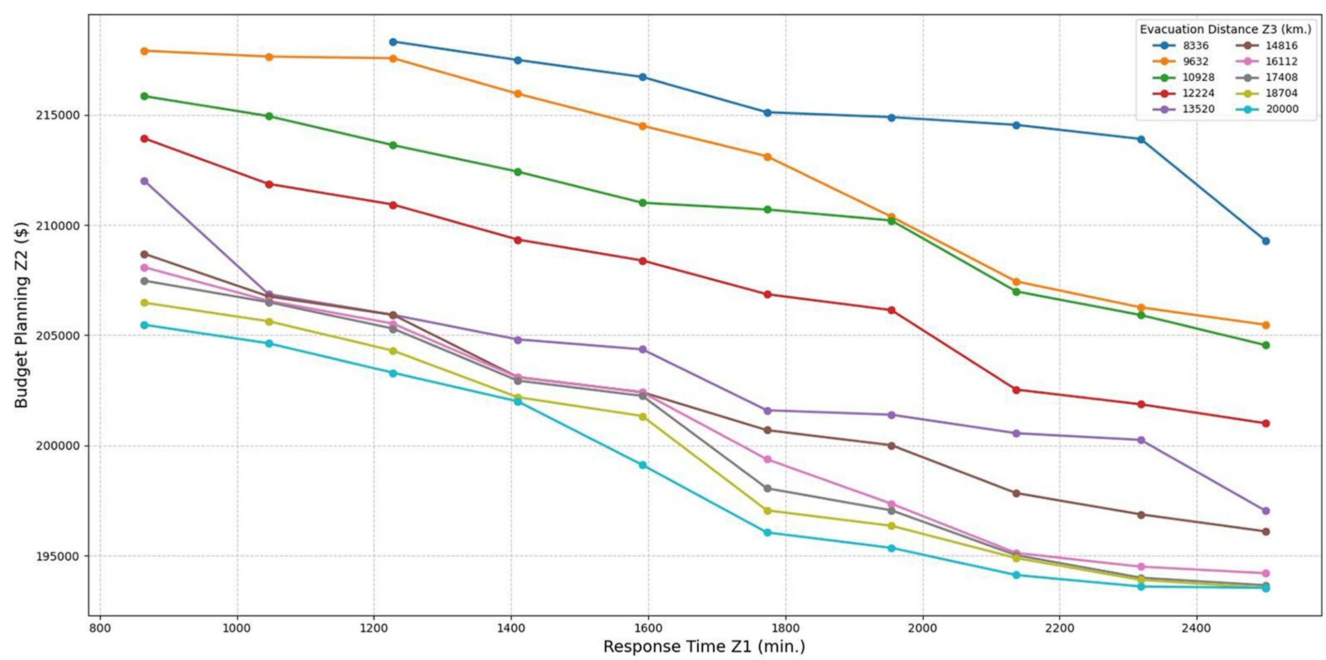
In the comparative analysis of evacuation strategies, the AUGMECON method demonstrates a notable balance between response time and evacuation distance. Specifically, at Z1 = 1,773.076 min, Z2 = $215,000.40, and Z3 = 8,336.21 km, AUGMECON achieves a shorter response time compared to the weighted sum method, which records Z1 = 1,794.73 min, Z2 = $219,383.60, and Z3 = 7,065.42 km. While the this offers a reduced evacuation distance, it does so at the expense of a longer response time and higher cost. This trade-off underscores the importance of prioritizing response time in emergency scenarios, where rapid evacuation is critical. The AUGMECON approach, therefore, provides a more balanced and feasible solution by ensuring a shorter response time while maintaining a reasonable evacuation distance and cost.

6. Discussion and practical implications

6.1 Discussion

The findings of this research underscore the effectiveness of a multi-objective two-stage stochastic optimization model in enhancing localized disaster management. By integrating probabilistic disaster scenarios and balancing key objectives:

Figure 7 Impact on budget across varying Z1 – Z3 using AUGMENCON method



Source: Authors' own work

response time, total budget and evacuation distance, the model provides a robust framework for efficient disaster logistics.

In low-severity disasters, response times and transportation costs remain manageable, but in high-severity events, response times escalate to 1,993.36 min, transportation costs rise to $769,364.90, and evacuation distances extend to 31,578.17 km, which emphasizing importance of prepositioning strategies and adaptive logistics to handle increased demand and complexity. The equal weighting of objectives enables a balanced approach, though decision-makers can adjust priorities such as rapid response or cost reduction based on their operational goals. This trade-off is further explored through the Pareto frontier analysis between Z1–Z2, Z1–Z3 and Z2–Z3 (sub-Section 5.5), providing clearer decision support on how favoring one objective may compromise others. Although the model relies on synthetic data calibrated from historical patterns and expert consultations, it reflects realistic disaster conditions in Cambodia. Due to limitations in public data availability, empirical field validation remains a future priority. However, the model architecture is designed to be easily adaptable to real input data once such information becomes available. On the other hand, sensitivity analysis validates the model's robustness, demonstrating how variations in warehouse utilization thresholds (β) impact key metrics response time and transportation costs, thereby aiding strategic decision. While a normalized weighted sum method was applied in this study for its simplicity, it may not fully capture the complexity of trade-offs in nonconvex spaces.

In the proposed model, while a centralized main warehouse (I1) is included, the operational emphasis is on local facilities. The model strategically activates local warehouses (J1 and J2), shelters (M1, M4, M5 and M9), and a local market, with minimal dependence on the central warehouse and NGOs. The model's effectiveness was tested under three flood severity scenarios to assess whether local facilities alone could meet relief demands. In the low and moderate scenarios, all needs were fulfilled using only local warehouses, shelters and markets, with no activation of the main warehouse or NGOs. Even in the high-severity scenario, minimal NGO support was sufficient, demonstrating that localized infrastructure can effectively absorb most disaster response needs, reserving external assistance for only extreme conditions. Table 12 illustrates this shift: NGOs only contribute to Scenario 3 (highest severity), where only one location (P4) contributes to relief distribution. In contrast, local infrastructure plays a central role across all scenarios, managing both supply delivery and evacuation logistics. Importantly, several shelters (e.g. M1, M4, M5 and M9) function as dual-purpose nodes, simultaneously serving as evacuation centers and temporary storage hubs, thereby enhancing responsiveness and reducing reliance on centralized facilities. Furthermore, when the local market is not used, operations become congested, leading to prolonged response times 22,070.43 min, high costs $350,998.80 and excessive evacuation distances 26,293.44 km. In contrast, the optimized stochastic solution eliminates the main warehouse to improve agility and focuses on a single streamlined local warehouse (J2). Instead of overloading shelters with storage duties, five dedicated staging areas (L2, L6–L9) are strategically positioned to facilitate efficient material flow and minimize congestion at shelters. The shelter network is restructured, with M2 serving as a designated evacuation point to ensure a clear separation between supply distribution and evacuation operations. A local market (K1) is integrated to use existing store networks for faster, cheaper distribution without the need to stockpile everything. The involvement of NGOs is optimized, with P2 replacing P4 to enhance coordination. These improvements result in reductions of 63.17% in response time (Z1), 30.32% in budget plan (Z2) and 43.41% in evacuation distance (Z3), as summarized in Table 13.

This research addresses critical gaps in the literature by offering an integrated approach to disaster logistics, optimizing facility location, evacuation planning and other components simultaneously (Ghasemi *et al.*, 2022; Meng *et al.*, 2023), this model simultaneously optimizes interdependent objectives. Incorporating stochastic programming to handle probabilistic scenarios enhances its capacity to address uncertainties, overcoming the limitations of deterministic models (Haghi *et al.*, 2017; Seraji *et al.*, 2021). Additionally, the model promotes localized disaster management by prioritizing local warehouses and staging areas over external aid, aligning with Kovács and Sigala (2020) emphasis on community resilience and reduced reliance on NGOs. The results also provide actionable for facility utilization include prioritizing local warehouses and staging areas during high-severity scenarios to minimize reliance on main warehouses and external

Table 12 Compares the current logistics location with the optimized stochastic location

Solution	Facility types	Facility location								
Current situation	Main warehouse	I1	–	–	–	–	–	–	–	–
	Local warehouse	J1	J2	–	–	–	–	–	–	–
	Local market	–	–	–	–	–	–	–	–	–
	Staging area	–	–	–	–	–	–	–	–	–
	Shelter	M1	–	–	M4	M5	–	–	–	M9
	NGO	–	–	–	P4	–	–	–	–	–
Optimized stochastic solution	Main warehouse	–	–	–	–	–	–	–	–	–
	Local warehouse	–	J2	–	–	–	–	–	–	–
	Local market	K1	–	–	–	–	–	–	–	–
	Staging area	–	L2	–	–	–	L6	L7	L8	L9
	Shelter	–	M2	–	–	–	–	–	–	–
	NGO	–	P2	–	–	–	–	–	–	–

Source(s): Authors' own work

Table 13 Logistics model performance comparison

Objective	Z1	Z2	Z3
Current situation	4,872.36	314,858.22	12,485.02
Stochastic solution	1,794.73	219,383.60	7,065.42
% of reduction	63.17%	30.32%	43.41%

Source(s): Authors' own work

organizations, improving operational efficiency (Balcik and Beamon, 2008; Mahmoodi *et al.*, 2022).

A key feature of the proposed model is its decentralized structure, which reflects the realities of humanitarian operations in resource-constrained and disaster-prone settings. Rather than assuming centralized command over all logistics layers, the model enables the use of distributed facilities, including local warehouses, community shelters and nearby markets, each of which can operate semi-independently. This design allows decision-makers to predefine roles for local actors such as NGOs, community leaders or local governments who may have varying levels of authority or logistical capacity. In doing so, the model supports partial control and localized decision-making, which are more realistic in complex disaster scenarios where central oversight is limited or delayed. Additionally, by optimizing resource flows based on availability and proximity, the model helps reduce dependence on centralized infrastructure and promotes resilient, adaptive logistics networks. These decentralized strategies are particularly important in regions like Cambodia, where remote communities often face delayed aid due to geographic and infrastructural barriers. The framework thus not only aligns with practical field conditions but also provides a flexible tool that humanitarian agencies can adapt to diverse operational constraints and governance structures.

It is important to acknowledge that the results of this study are based on synthetic data generated from probabilistic flood scenarios, hazard maps, and operational assumptions specific to the Cambodian context. While these inputs were carefully constructed to reflect realistic disaster conditions—including road accessibility, shelter capacity, and vehicle limitations—the absence of real operational data presents a limitation in terms of external validity. This constraint is not uncommon in humanitarian logistics research, where access to empirical data is often restricted due to privacy concerns, fragmented record-keeping, and the unpredictable nature of disaster events. Nonetheless, the model provides a computationally robust and conceptually integrated framework that supports decision-making in the predisaster planning phase. To enhance practical applicability, future research will focus on validating the model through partnerships with local NGOs, disaster management agencies, and government bodies. Field-level application using empirical data will help test the model under actual constraints and improve its adaptability for real-world deployment. This step is essential for transforming the proposed framework from a theoretical tool into an operational support system for humanitarian response planning.

6.2 The advantage of integrated decision-making

Integrated decision-making is pivotal in localized disaster management, offering a unified strategy that enhances efficiency, timeliness and effectiveness in disaster response efforts. In the context of complex logistical challenges, integrating critical elements such as shelter capacities, transportation logistics and local resource utilization ensures cohesive planning. This approach aligns resources effectively, minimizes delays and reduces waste, making it a cornerstone of resilient disaster management (Kovács and Sigala, 2020).

A holistic strategy in disaster logistics streamlines resource flows by harmonizing interdependent components, such as facility locations, inventory management and evacuation plans. For instance, aligning shelter capacities with transportation plans prevents bottlenecks and overstocking, issues that frequently arise during relief operations (Ghasemi *et al.*, 2022). Additionally, this integration enhances adaptability to dynamic scenarios, such as sudden increases in demand or adverse weather, enabling rapid and efficient responses (Seraji *et al.*, 2021).

Localized approaches to disaster management emphasize leveraging community resources, such as local warehouses and staging areas, to reduce dependency on external aid. This not only enhances operational efficiency but also builds long-term resilience by fostering self-reliance and strengthening local infrastructure (Manopiniwes and Irohara, 2016). Moreover, the approach encourages collaboration among government agencies, NGOs, and local communities, minimizing redundancy and optimizing resource utilization, as demonstrated in successful case studies (Balcik and Beamon, 2008).

Integrated decision-making addresses both immediate relief and long-term recovery, ensuring sustainable outcomes for affected populations. By embedding resilience into disaster strategies, this approach positions communities for more effective and proactive responses to future crises.

6.3 The managerial insight

This research delivers concrete managerial insights for improving disaster logistics strategy through data-driven planning and optimization. The proposed multi-objective two-stage stochastic optimization model enables decision-makers such as government planners, NGO coordinators and logistics managers to improve operational efficiency, responsiveness and adaptability in disaster response. While maintaining balanced stock levels, minimizing costs and alignment of resource allocation, the model allows budget planning and identification of opportunities to save costs and further operational efficiency.

Numerical results from the model show a 63.17% reduction in response time, a 30.32% decrease in total budget and a 43.41% reduction in evacuation distance compared to the existing logistics plan. These improvements highlight the model's potential to not only save lives through faster aid delivery but also enhance cost efficiency and coverage. Decision-maker can use these gains to strategically reallocate saved resources, improve local capacity (e.g. community-based warehouses or suppliers) and better match supply to forecasted demand and manpower estimates.

The model also supports contingency planning by incorporating probabilistic disaster scenarios, allowing for prepositioned assets and flexible routing strategies across varying disaster intensities. Sensitivity analysis reveals how warehouse locations, transportation modes and inventory levels affect performance, enabling better decisions around facility sitting and resource deployment. Importantly, by reducing dependence on centralized aid and encouraging multistakeholder collaboration, the model strengthens resilience through localized response capabilities. Key managerial implications as described below:

- *Maximize warehouse throughput:* high utilization of storage facilities minimizes waste and delay. In our scenarios, running the local warehouse at least 80% capacity sharply reduced per-unit costs and lead times, whereas underused space created inefficiency.
- *Invest up to the critical threshold:* a modest budget increase around 3% in our model yields a steep improvement in speed, but further funding brings much smaller gains. In other words, we observe clearly diminishing returns to aid spending. For decision-makers, this means funding just above the critical level is most effective – extra dollars beyond that point do not proportionately accelerate response. Decision-makers should re-evaluate budget targets: aim for the level that sharply reduces delays and recognize that adding more budget beyond that threshold gives only marginal benefit.
- *Recognize system limits and concentrate under pressure:* based on the AUGMECON results, evacuation distances below 8,336.21 km consistently result in infeasible solutions across nearly all response time configurations. This indicates a practical lower bound on evacuation distance, suggesting that, under current infrastructure and conditions any plan targeting evacuation distances shorter than 8.3 km is unviable. In high-intensity disaster scenarios, results also confirm that a single, well-resourced NGO node (e.g. P2) can effectively meet demand without requiring additional distribution points. This supports a strategy of concentrated resource deployment, rather than dispersing supplies across multiple nodes, which may dilute impact and increase coordination overhead without substantial benefit. Additionally, relief agencies or decision-makers should plan around these constraints reinforcing one primary hub in high-intensity situations and avoiding overly ambitious distance or time targets.
- *Leverage proven logistics hubs:* our model shows that concentrating resources at key facilities yields outsized benefits. Activating one local warehouse (J2) and five specific staging areas (L2, L6–L9) dramatically improves performance: response time drops around 63.17%, and evacuation distance around 43.41%. This highlights the value of prepositioning and pooling relief assets. In practice, decision-makers should prioritize established nodes, since concentrating aid through trusted hubs can deliver help fast and at lower cost to donors and the environment.

Overall, the insights empower humanitarian managers to design logistics systems that are not only cost-effective and responsive but also scalable and equitable ensuring timely aid delivery even in high-risk or resource-constrained environments.

6.4 Practical applicability in humanitarian operations

While the proposed model is mathematically robust, we acknowledge that its computational complexity and data requirements may pose challenges for humanitarian agencies, particularly those with limited analytical resources. To address this, the model can be adapted for practical field use through two main strategies. First, a simplified version of the model can be embedded into a user-friendly decision-support tool such as an MS Excel-based interface or mobile application allowing field personnel to input key parameters and receive actionable recommendations without needing in-depth technical expertise. Second, a modular or phased approach can be adopted, where agencies initially apply the model using essential, readily available data and incrementally incorporate more detailed components as additional data and capacity become available. Moreover, partnerships with academic institutions or technical experts can provide valuable support in configuring and interpreting the model, especially during disaster preparedness and recovery planning. These adaptations aim to bridge the gap between theoretical rigor and operational feasibility, ensuring that the model can be realistically applied in field conditions.

To further support practical application, we provide guidance on how critical parameters can be estimated and how the framework can be applied in operational settings. Demand estimates may be derived from national census data, past disaster records, satellite data or humanitarian agency estimates. In the absence of high-resolution data, planners can use affected population ratios based on flood zones and local settlement patterns. Facility capacities are often obtained through municipal records, field assessments or historical usage during previous disasters. Transportation distances can be measured using Geographic Information System (GIS) tools such as OpenStreetMap or QGIS, calculated manually through distance matrices or shortest-path algorithms. Information about vehicle availability and capacity can be sourced from transportation departments, NGO vehicle records, or logistics operators and generalized truck capacities can be used where specific data are lacking. Disaster scenario probabilities are typically estimated from historical flood maps, hydrological models or national disaster risk platforms, while cost parameters such as fuel, labor and warehousing costs can be drawn from local procurement data or previous relief operations.

For users in data-limited environments, we recommend practical techniques such as expert elicitation through structured interviews or Delphi methods, the use of proxy data from comparable regions and constructing best-case to worst-case scenario ranges for critical variables. Sensitivity analysis can be used to identify the most influential parameters and guide targeted data collection. The model is implemented using MILP and solved with LINGO, while input data can be prepared in common formats such as MS Excel or CSV. GIS platforms are used for spatial visualization of shelters and flood zones. Though the case study focuses on flood scenarios in Cambodia, the model can be adapted for other disaster types such as earthquakes or typhoons by modifying the scenario parameters and infrastructure inputs. This practical guidance ensures the model is not only academically rigorous but also operationally relevant for NGOs, local governments and international relief agencies seeking to optimize disaster logistics under uncertainty.

7. Conclusion and future research

This research introduces a multi-objective stochastic linear MIP model to optimize integrated decision-making in disaster management, with a focus on response and preparedness. The model incorporates key components of relief logistics, including facility and inventory management, evacuation planning, and vehicle logistics coordination. By using a normalized weighted sum method, it balances objectives such as budget efficiency, response time, and evacuation requirements. Probabilistic disaster scenarios based on flood hazard maps simulate real-world conditions in Cambodia, addressing the uncertainties inherent in disaster scenarios. The findings emphasize the importance of localized disaster management by prioritizing local markets and warehouses over reliance on NGOs. This approach enhances resource availability and operational efficiency, fostering resilience in affected communities. Decision-makers gain practical insights for optimizing the placement and utilization of local warehouses, staging areas, and shelters, adapting strategies based on disaster severity and resource constraints.

Despite its strengths, the proposed model has several limitations that present opportunities for future research. First, it excludes important operational parameters such as boats and emergency vehicles, which are often essential in disaster-prone and geographically challenging regions. Incorporating these elements would enhance the model's realism and applicability. Second, the model does not currently account for human behavioral factors, such as decision-makers' risk aversion or the preferences of local communities. These factors are especially critical in humanitarian contexts, where logistics decisions are shaped by subjective judgments, cultural dynamics, and community trust. While the model focuses on quantitative optimization and system-level efficiency, it does not fully capture these human dimensions. Future work could address this by integrating behavioral modeling and participatory decision-making frameworks to better reflect real-world decision processes and improve model acceptance. Third, the reliance on deterministic decision rules limits the model's flexibility in uncertain environments. Introducing fuzzy logic and real-time data integration would enhance its adaptability and responsiveness during rapidly evolving disaster scenarios. Additionally, the use of more advanced metaheuristic algorithms could improve the model's scalability and computational efficiency, particularly in large-scale applications. Overall, this research contributes a robust and practical framework for advancing disaster logistics planning, offering valuable tools for improving resilience and efficiency in humanitarian response operations.

Acknowledgements

This research work was partially supported by Chiang Mai University.

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