

Fuzzy multimodal vehicle routing for last-mile flood relief: A scenario-based model for Chiang Mai

Kanyarat Phutthanawong¹⁾, Takashi Irohara²⁾, Israt Jahan Hridi³⁾ and Chawis Boonmee^{*4)}

¹⁾Program in Industrial Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai 50200, Thailand

²⁾Department of Information and Communication Sciences, Faculty of Science and Technology, Sophia University, Tokyo 102-8554, Japan

³⁾Program in Logistics Engineering and Supply Chain Management, Faculty of Engineering, Chiang Mai University, Chiang Mai 50200, Thailand

⁴⁾Humanitarian Logistics and Crisis Operations Research Unit, Department of Industrial Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai 50200, Thailand

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Abstract

This research addresses the logistical challenges of last-mile relief delivery during flood disasters in Chiang Mai, Thailand. We propose a scenario-based fuzzy multi-depot, multi-trip vehicle routing problem model with split deliveries and integrated multimodal accessibility across varying flood severity levels. The model incorporates fuzzy logic to handle uncertainty by transforming it into an equivalent auxiliary crisp model through triangular membership functions. The objective function aims to minimize total transportation time across five flood scenarios. Results demonstrate that community accessibility requirements vary significantly with flood severity: low water levels can be served entirely by trucks, while severe flooding necessitates intensive boat operations, significantly increasing response times and trip frequencies. Sensitivity analysis reveals that strategic boat-drone collaboration in Scenario 4 can reduce the number of trips by 2 and travel time by up to 3.7%, while significantly simplifying boat routing complexity. The study provides actionable insights for disaster management agencies, emphasizing the critical role of scenario-based planning, multimodal fleet deployment, and robust decision-making under uncertainty.

Keywords: Last-mile delivery, Fuzzy vehicle routing problem, Multimodal transportation, Humanitarian logistics, Thailand flood

1. Introduction

Thailand has long suffered from chronic flooding, and the effectiveness of disaster management has shown limited improvement. The country's vulnerability to extreme weather events is further exacerbated by climate change. The Climate Risk Index 2026 ranks Thailand 17th globally for climate-related impacts, with projections indicating escalating severity. However, Thailand's disaster management framework continues to lack clearly articulated operational protocols and sufficient efficiency to cope with the anticipated increase in severity. Despite the introduction of a broadcast-based early warning system in May 2025, the devastating floods of November 2025 exposed fundamental deficiencies in Thailand's disaster response capacity, including large-scale evacuation failures and fragmented coordination among responsible agencies. These inefficiencies stem from the absence of comprehensive operational protocols and inadequate decision support systems for last-mile logistics planning.

Chiang Mai Province presents a particularly compelling case study for last-mile flood relief optimization. In 2024, the province experienced its most severe flooding on historical record, with the low-lying economic zone of Chiang Mai Municipality being hardest hit. Data from the Chiang Mai Provincial Office of Social Development and Human Security revealed a stark disparity in evacuation outcomes: only 1,200 individuals reached government shelters, while a substantial number of residents remained stranded in high-risk zones throughout the flooded areas. Consequently, there is an urgent need for an effective logistics plan for delivering emergency relief kits to these non-evacuated households to minimize loss. Within this context, the vehicle routing problem (VRP) plays a pivotal role in humanitarian logistics for disaster management. However, a comprehensive literature review reveals significant research gaps. Li and Chung [1] introduced a robust optimization approach for the capacitated VRP (CVRP) with split deliveries under uncertainty, their study was limited to homogeneous fleets and lacked specific disaster scenarios or accessibility constraints. Giedelmann et al. [2] addressed routing for drought relief under cost minimization objectives but incorporated only capacity constraints without considering operational complexities inherent to disaster environments. Similarly, Li et al. [3] and Sabouhi et al. [4] addressed specific disasters, multi-depot multi-trip routing, and road accessibility frameworks aimed at minimizing response time; nevertheless, their models did not account for multimodal routing capabilities. Huang and Xu [5] and Nodoust et al. [6] developed earthquake-specific routing models but also lack multimodal and multi-trip considerations. In the context of flood disasters specifically, Insani et al. [7] proposed an integrated evacuation and relief model, their framework fails to incorporate accessibility constraints based on flood-induced road disruptions or multimodal transportation options which are critical factors given that vehicle accessibility varies substantially with

*Corresponding author.

Email address: Chawis.boonmee@cmu.ac.th

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water depth. Pujiana et al. [8] minimized routing costs but neglected varying flood scenarios, vehicle types, or accessibility limitations. Furthermore, studies incorporating dynamic road disruptions, such as Rojas Trejos et al. [9] and Toathom and Champrasert [10], introduced CVRP models that typically focus on single-depot models without multimodal considerations. Gong et al. [11] extended their analysis to include multimodal transportation but failed to address multiple flood scenario impacts comprehensively. Moreover, a critical gap identified across the literature concerns uncertainty modeling. Only Nodoust et al. [6] employed fuzzy parameter representation to capture uncertainty. This finding aligns with Maroof et al. [12], whose systematic review of humanitarian VRP research concluded that fuzzy-based and emerging uncertainty modeling techniques remain underexplored. Moreover, disaster-specific operational complexities such as road inaccessibility, flood-induced disruptions, heterogeneous vehicle fleets, and drone-assisted operations remain understudied, with only a few exceptions such as Gong et al. [11] and Weng et al. [13] explicitly considering drone operations. In summary, existing studies predominantly focus on homogeneous fleets or fixed modes, typically addressing only classical CVRP without extending to critical constraints such as accessibility. Furthermore, some studies incorporate a scenario-based approach to account for varying disaster intensities but incorporate with other remaining gaps. Additionally, while most humanitarian VRP research employs deterministic parameters, there is a notable lack of fuzzy optimization to address uncertainty models. Table 1 summarizes these literature findings.

To address these gaps, this research proposes a comprehensive decision-support model for last-mile delivery of emergency relief kits to non-evacuated households during flood disasters in Chiang Mai. The model introduces three key contributions to humanitarian logistics literature and practice. (I) This study develops an integrated scenario-based multimodal routing framework that explicitly accounts for the interplay between flood severity and road-mode accessibility. Our model incorporates five flood risk scenarios that dynamically capture whether communities can be served by modes appropriate to the water level in each specific area. This scenario-based approach enables disaster management agencies to prepare adaptive routing plans across different flood intensities, addressing a critical gap in last-mile flood relief planning. (II) The model addresses the remaining gaps by integrating a multi-depot, multi-modal, multi-trip, and split delivery framework. It incorporates not only capacity constraints but also accessibility constraints, prioritizing the minimization of transportation time. (III) We incorporate fuzzy uncertainty modeling through triangular fuzzy membership functions to systematically capture the inherent uncertainty of the situation. The model transforms fuzzy parameters from the classical VRP into an equivalent auxiliary crisp model. Through these contributions, the model selects the optimal number of depots and assigns appropriate multimodal routing based on flood depth in each community. Sensitivity analysis across different degrees of membership further demonstrates the robustness of decisions under varying uncertainty levels and evaluates boat-drone collaboration.

The remainder of this paper is structured as follows: Section 2 introduces the proposed mathematical model; Section 3 presents the solution methodology; Section 4 presents a case study; Section 5 presents the computational results and sensitivity analysis; Section 6 discusses the research; Section 7 provides managerial insights and practical implications for disaster management agencies; and Section 8 concludes with future research directions.

Table 1 Literature on mathematical programming for routing problems

Author	Objective	Multi-scenario	Multi-depot	Multi-trip	Multi-modal	Split delivery	Capacity constraints	Accessibility	Relief route	Disaster type	Fuzzy	Solution
Li and Chung [1]	Minimize time (multi)					✓	✓		✓	General		Heuristic
Sabouhi et al. [4]	Minimize time	✓	✓	✓		✓	✓	✓	✓	Earthquake		Metaheuristic
Giedelmann et al. [2]	Minimize cost						✓		✓	Drought		Metaheuristic
Huang and Xu [5]	Minimize time	✓	✓			✓	✓	✓	✓	Earthquake		Exact
Nodoust et al. [6]	Minimize cost	✓	✓				✓	✓	✓	Earthquake	✓	Exact
Insani et al. [7]	Minimize number of vehicles	✓		✓		✓	✓		✓	Flood		Metaheuristic
Pujiana et al. [8]	Minimize cost		✓				✓		✓	Flood		Exact
Toathom and Champrasert [10]	Minimize time	✓					✓	✓	✓	Flood		Metaheuristic
Weng et al. [13]	Minimize time		✓		✓		✓	✓	✓	General		Metaheuristic
Gong et al. [11]	Minimize time				✓		✓	✓	✓	Flood		Metaheuristic
Li et al. [3]	Minimize time and cost	✓	✓				✓	✓	✓	Hurricane, Epidemic		Metaheuristic
Rojas Trejos et al. [9]	Minimize time	✓					✓	✓	✓	Flood		Exact
This study	Minimize time	✓	✓	✓	✓	✓	✓	✓	✓	Flood	✓	Exact

2. Proposed model

2.1 Conceptual model

This study proposes a mathematical model for the multi-depot, multi-trip, multi-modal VRP, incorporating road and mode accessibility constraints. The model accounts for various scenarios corresponding to flood hazard risk levels, addressing transportation disruptions caused by river or road barriers and variable accessibility. Specific constraints include: (I) the impassability of river crossings during high flood conditions; (II) the necessity of traversing intermediate nodes for access or obstructions due to traffic conditions; and (III) the prohibition of cross-modal routing. Furthermore, the model optimizes the selection of depots. Figure 1 illustrates the proposed conceptual framework and a sample solution.

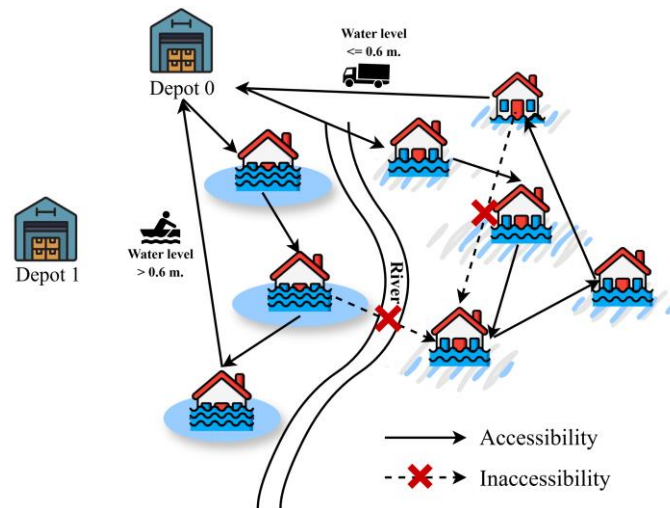


Figure 1 An illustration of sample solution

2.2 Mathematical formulation

The proposed mathematical model is formulated as a fuzzy mixed-integer linear programming model that extends the classical VRP by incorporating multi-depot, multi-trip capabilities, and multimodal transportation constraints to address dynamic flood accessibility. A single objective function is developed to minimize the total transportation time for delivering emergency relief kits to affected zones. The tilde symbol ($\sim$) denotes fuzzy parameters used to handle uncertainty. The model assumptions are as follows:

- Each affected zone node represents a community unit.
- Demand is calculated based on one emergency relief kit per non-evacuated household, which is derived by deducting the evacuated households from the total households based on the evacuation proportion.
- Capacity constraints are applied to both depots and the heterogeneous vehicle fleet, which varies by mode.
- Fuzzy parameters include transportation time, relief kit weight and volume, and the proportion of expected evacuation.
- Each community is served by a single depot using a single transportation mode, though split deliveries via multiple trips by the same vehicle are permitted to meet total demand.
- Each vehicle trip must start and end at the same depot.
- Service times for loading and unloading are excluded.

Indices:

I	Set of depots, $i = \{0,1\}$
J	Set of affected zones, $j = \{2,3, \dots, 26\}$
N	Set of total nodes, $N = I \cup J$
M	Set of transportation modes, $m = \{0,1,2\}$
K	Set of trip numbers, $k = \{0,1, \dots, K\}$

Parameters:

$Vcapacity_m$	Maximum capacity of vehicle or mode m (kg.)
$Scapacity_i$	Maximum capacity of depot i (m^3)
$\tilde{w}$	Weight of an emergency relief kit
$\tilde{v}$	Volume of an emergency relief kit
$\tilde{pe}$	Proportion of expected evacuation households
$\widetilde{TIME}_{ijm}$	Transportation time from node i to node j via mode m ; $i, j \in N$
fam_j	Total household in each affected zone j
a_{ijm}	1, if the route between node $i \in N$ and $j \in N$ is accessible by mode m ; 0, otherwise
b_{im}	1, if affected zone $i \in N$ is accessible by mode m ; 0, otherwise
α	Value of the feasibility degree

Decision variables:

X_{ijmk}	1, if there is transport from node i to j via mode m on trip k ; 0, otherwise
Q_{ijmk}	Delivery load from node i to j via mode m on trip k
Z_{ij}	1, if there is transport from node i to j ; 0, otherwise
$visit_{jmk}$	1, if there is a visit to affected zone j via mode m on trip k ; 0, otherwise
$demand_j$	Demand for emergency relief kits for non-evacuated households in each affected zone j
$delivered_{jmk}$	Amount of delivered demand for affected zone j via mode m on trip k
u_{jmk}	A sequence variable that ensures node j via mode m on trip k appears in the solution to eliminate subtours

Objective function:

$$\text{Min } Z = \sum_{i \in N, i \neq j} \sum_{j \in N} \sum_{m \in M} \sum_{k \in K} \widetilde{TIME}_{ijm} X_{ijmk} \quad (1)$$

Constraints:

$$X_{ijmk} \leq a_{ijm} * b_{im} \quad \forall i \in N, j \in N, m \in M, k \in K; i \neq j \quad (2)$$

$$\sum_{i \in N} X_{ijmk} = \text{visit}_{jmk} \quad \forall j \in J, m \in M, k \in K; i \neq j \quad (3)$$

$$\sum_{i \in I} Z_{ij} = 1 \quad \forall j \in J \quad (4)$$

$$\sum_{i \in I} \sum_{j \in J} X_{ijmk} \leq 1 \quad \forall m \in M, k \in K \quad (5)$$

$$\sum_{i \in I} \sum_{j \in J} X_{jimk} \leq 1 \quad \forall m \in M, k \in K \quad (6)$$

$$\sum_{j \in J} X_{ijmk} = \sum_{j \in J} X_{jimk} \quad \forall i \in I, m \in M, k \in K \quad (7)$$

$$\sum_{i \in N} \sum_{m \in M} \sum_{k \in K} X_{ijmk} \geq 1 \quad \forall j \in J; i \neq j \quad (8)$$

$$\sum_{m \in M} \sum_{k \in K} X_{ijmk} \leq |K| * Z_{ij} \quad \forall i \in I, j \in J \quad (9)$$

$$\sum_{i \in N} X_{ijmk} = \sum_{i \in N} X_{jimk} \quad \forall j \in N, m \in M, k \in K; i \neq j \quad (10)$$

$$\sum_{i \in N} Q_{ijmk} - \sum_{i \in N} Q_{jimk} = \text{delivered}_{jmk} \quad \forall j \in J, m \in M, k \in K; i \neq j \quad (11)$$

$$\sum_{m \in M} \sum_{k \in K} \text{delivered}_{jmk} = \text{demand}_j \quad \forall j \in J \quad (12)$$

$$(1 - \widetilde{pe}) * f_{amj} \leq \text{demand}_j \quad \forall j \in J \quad (13)$$

$$\text{delivered}_{jmk} \geq \text{visit}_{jmk} \quad \forall j \in J, m \in M, k \in K \quad (14)$$

$$\sum_{j \in J} \sum_{m \in M} \sum_{k \in K} \widetilde{v} * \text{delivered}_{jmk} \leq \text{Scapacity}_i \quad \forall i \in I \quad (15)$$

$$\sum_{i \in N} \widetilde{w} * \text{delivered}_{imk} \leq \text{Vcapacity}_m \quad \forall m \in M, k \in K \quad (16)$$

$$\widetilde{w} * Q_{ijmk} \leq \text{Vcapacity}_m * X_{ijmk} \quad \forall i \in N, j \in J, m \in M, k \in K; i \neq j \quad (17)$$

$$u_{imk} - u_{jmk} + |J|(X_{ijmk}) \leq |J| - 1 \quad \forall i \in N, j \in J, m \in M, k \in K; i \neq j \quad (18)$$

$$X_{ijmk} \in \{0,1\} \quad \forall i \in N, j \in N, m \in M, k \in K \quad (19)$$

$$Z_{ij} \in \{0,1\} \quad \forall i \in I, j \in J \quad (20)$$

$$\text{visit}_{jmk} \in \{0,1\} \quad \forall j \in J, m \in M, k \in K \quad (21)$$

$$Q_{ijmk} \geq 0 \quad \forall i \in N, j \in N, m \in M, k \in K \quad (22)$$

$$\text{demand}_j \geq 0 \quad \forall j \in J \quad (23)$$

$$\text{delivered}_{jmk} \geq 0 \quad \forall j \in N, m \in M, k \in K \quad (24)$$

$$u_{jmk} \in \mathbb{Z} \quad \forall j \in J, m \in M, k \in K \quad (25)$$

The objective function (1) aims to minimize the total transportation time under ambiguous parameters, considering routing based on road and mode accessibility, capacity constraints, depot assignment, and multimodal transportation. To achieve this, the proposed model incorporates the following constraints: Eq. (2) ensures that travel adheres to accessibility constraints regarding both road conditions and transportation modes at each node. Eq. (3) ensures that there are transportation mode and trip assigned to each affected zone. Eq. (4) mandates that each community is served by exactly one depot. Eqs. (5)-(7) ensure that each trip enters and leaves the depot at most once and must return to the origin depot. Eq. (8) guarantees that each community is visited at least once. Eq. (9) restricts the number of trips originating from a depot to the maximum allowable limit, linking routing decisions to depot usage. Eq. (10) ensures that each mode and trip exits every node it enters. Eq. (11) determines the delivery quantity through flow conservation of the load entering and leaving nodes. Eq. (12) ensures that the delivered amount equals the demand in each affected zone. Eqs. (13)-(14) define demand based on the number of expected non-evacuated households and ensure that routing is established if demand exists. Eqs. (15)-(16) ensure that shipments do not exceed vehicle and depot capacity constraints. Eq. (17) tracks the load on each arc to strictly observe vehicle capacity limits. Eq. (18) represents the subtour elimination constraint. Eqs. (19)-(25) define binary, integer, and non-negativity constraints.

3. Proposed solution methodology: equivalent auxiliary crisp model

This research introduces equivalent auxiliary crisp models to transform imprecise parameters using triangular fuzzy numbers, as illustrated by the membership function in Figure 2. This study applies the transformation method proposed by Jiménez et al. [14]; the full detailed methodology can be referenced in Boonmee and Kasemset [15]. The reformulated proposed model is presented as follows.

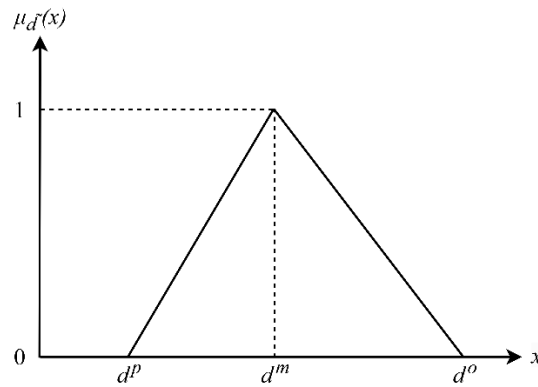


Figure 2 The membership function of a triangular fuzzy number

Notice that $\tilde{d}$ is a triangular fuzzy number, which is defined by three prominent points: the most pessimistic value (d^p), the most likely value (d^m), and the most optimistic value (d^o). This can be represented as $\tilde{d} = (d^p, d^m, d^o)$. The expected interval (EI) and expected value (EV) of the triangular fuzzy number $\tilde{d}$ can be defined as follows:

$$EI(\tilde{d}) = [E_1^d, E_2^d] = \left[\int_0^1 f_d^{-1}(x) dx, \int_0^1 g_d^{-1}(x) dx \right] = \left[\frac{1}{2}(d^p + d^m), \frac{1}{2}(d^m + d^o) \right]$$

$$EV(\tilde{d}) = \frac{(E_1^d + E_2^d)}{2} = \frac{(d^p + 2d^m + d^o)}{4}$$

According to the above description, the equivalent crisp model with an α -parameter, where a decision vector is feasible, can be represented as follows:

$$\begin{aligned} \text{Min } EV(\tilde{d})x \\ [(1 - \alpha)E_2^d + \alpha E_1^d]x \geq \alpha E_2^d + (1 - \alpha)E_1^d \end{aligned}$$

Thus, the proposed mathematical model can be reformulated as follows:

Objective function:

$$\text{Min } Z = \sum_{i \in N, i \neq j} \sum_{j \in N} \sum_{k \in K} \sum_{m \in M} \left[\frac{PTIME_{ijm} + 2MTIME_{ijm} + OTIME_{ijm}}{4} \right] X_{ijmk} \quad (26)$$

Constraints:

$$\left(1 - \left(\alpha \left(\frac{Mpe + Ope}{2} \right) + (1 - \alpha) \left(\frac{Mpe + Ppe}{2} \right) \right) \right) * fam_j \leq demand_j \quad \forall j \in J \quad (27)$$

$$\sum_{j \in J} \sum_{m \in M} \sum_{k \in K} \left(\alpha \left(\frac{Mv + Ov}{2} \right) + (1 - \alpha) \left(\frac{Mv + Pv}{2} \right) \right) * delivered_{jmk} \leq Scapacity_i \quad \forall i \in I \quad (28)$$

$$\sum_{i \in N} \left(\alpha \left(\frac{Mw + Ow}{2} \right) + (1 - \alpha) \left(\frac{Mw + Pw}{2} \right) \right) * delivered_{imk} \leq Vcapacity_m \quad \forall m \in M, k \in K \quad (29)$$

$$\left(\alpha \left(\frac{Mw + Ow}{2} \right) + (1 - \alpha) \left(\frac{Mw + Pw}{2} \right) \right) * Q_{ijmk} \leq Vcapacity_m * X_{ijmk} \quad (30)$$

$$\forall i \in N, j \in J, m \in M, k \in K; i \neq j$$

$$\text{Equations (2)-(12), (14), (18)-(25)}$$

4. Case study

This section presents a case study demonstrating the application of our proposed approach. The study area is categorized into flood risk levels 1 to 5, based on the Chiang Mai flood hazard map developed by CENDIM [16]. Following the major flood in October 2024, the water level at the Ping River's P.1 station reached an unprecedented historical peak of 5.30 m. This event was reported as the most severe flood observed in approximately the last 50 years [17], surpassing all previous major floods, such as the 1987 event (4.53 m), the 1994 event (4.43 m), the 2005 event (4.93 m), the 2011 event (4.95 m), and the 2022 event (4.75 m) [18]. By using the historical maximum water level of 5.30 m as a baseline for designing flood zones, the model inherently covers the severity of diverse past flooding events. It became evident that although relief centers were announced, there was no clearly established operational plan. Furthermore, government operations lacked sufficient efficiency, resulting in many families being unable to evacuate in time during the 2024 flood.

To address this gap, routing plans for delivering relief kits should be established for the expected non-evacuated population across 25 communities within risk levels 1 to 5, defined as Scenario 1 to 5. Crucially, these routing decisions must account for the varying water levels in each community. The estimated maximum water level for each community under different scenarios was derived by interpolating the highest flood survey points from the Upper Northern Region Irrigation Hydrology Center [19] and CENDIM [16].

This interpolation was calculated relative to the historical 5.3 m peak at station P.1, corresponding to the maximum P.1 water levels of 4.4, 4.5, 4.6, 4.7, and 4.8 m for Scenarios 1 through 5, respectively. Flood scenarios can be simulated as shown in Figure 3 and Table 2, with colors in the figure illustrating the extent of the affected areas across different scenarios. Specifically, the blue areas represent zones where the water level is greater than or equal to 0.6 m, requiring boat routing, whereas the gray areas indicate zones with water levels lower than 0.6 m that can be accessed by truck. The water level threshold of 0.6 m was adopted from the Disaster Machinery Operations Manual published by the Department of Disaster Prevention and Mitigation [20]. The node placement for each affected zone was determined by calculating the centroid of the community using QGIS.

The total number of households in each affected zone (fam_j), as detailed in Table 3, was obtained from the Bureau of Registration Administration, Thailand. The population within the predicted flood extent was converted into household units by assuming an average of four persons per household. This total household value is then used in the mathematical model, from which the proportion of expected evacuated households ($\bar{p}\bar{e}$), specifically children under 12 and elderly individuals over 60 years old, is deducted to determine the relief kit demand required for the non-evacuated households.

Table 2 Estimated water level (m) at the highest P.1 level of 5.3 m

Scenario	Affected zone node (j)										
	2	3	4	5	6	7	8	9	10	...	26
1	0.26	0.25								...	
2	0.41	0.38	0.41	0.35	0.30					...	
3	0.55	0.51	0.55	0.48	0.41	0.35	0.35	0.46	0.41	...	
4	0.71	0.66	0.71	0.62	0.52	0.45	0.44	0.59	0.52	...	
5	0.86	0.81	0.86	0.76	0.64	0.55	0.54	0.72	0.64	...	0.88
P.1 (5.3 m.)	1.75	1.63	1.75	1.53	1.30	1.12	1.10	1.46	1.30	...	1.79

Table 3 Total household in each affected zone (fam_j)

Scenario	Affected zone node (j)										
	2	3	4	5	6	7	8	9	10	...	26
1	12	153								...	
2	16	572	13	477	152					...	
3	16	572	13	477	152	44	10	31	335	...	
4	16	572	13	477	152	119	373	63	335	...	
5	16	572	13	477	152	119	429	574	385	...	46

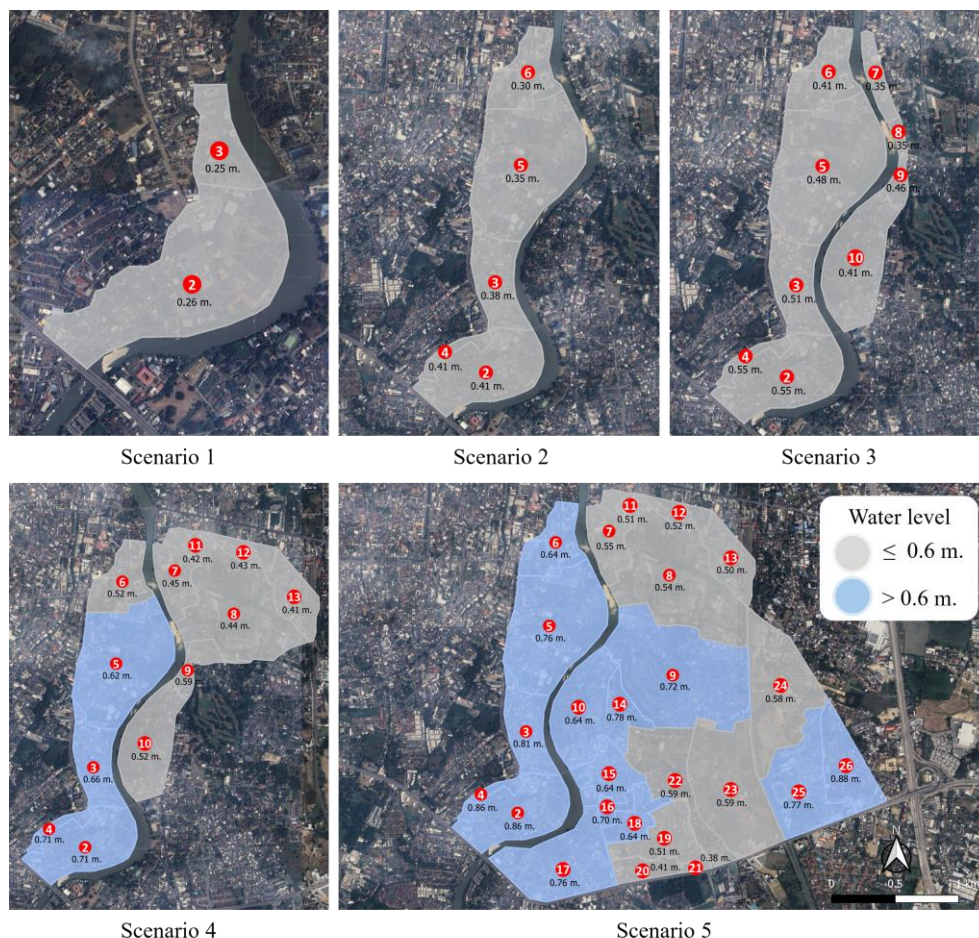


Figure 3 Geographical maps of affected areas with water level in each scenario

This research considers two candidate depots designated based on announcements from PR Chiangmai [21], with details provided in Table 4. While originally designated as evacuation centers, these locations were identified as suitable dual-purpose facilities—serving as both evacuation points and temporary distribution hubs—due to their substantial capacity for relief operations. This dual-function approach aligns with the strategy emphasized by Heng et al. [22]. Ultimately, the proposed model optimally selects the appropriate depot(s) for operation, without the necessity of utilizing all available locations.

Table 4 Depot capacity details

Node (<i>i</i>)	Name	Scapacity _{<i>i</i>} (m ³)
0	Chiang Mai Municipal Stadium	1,000
1	Chiang Mai University Convention Center	1,000

Transportation during disaster events is constrained by the availability of traffic routes. Some paths may be restricted by one-way road conditions, rendering certain communities directly inaccessible, while others may require traversing intermediate communities. As illustrated in the accessibility specifications in Figure 4, direct travel from node 0 to node 14 is inaccessible. Similarly, the return route from node 17 to node 2 is restricted because the main road is divided by a traffic barrier, allowing travel in only one direction.

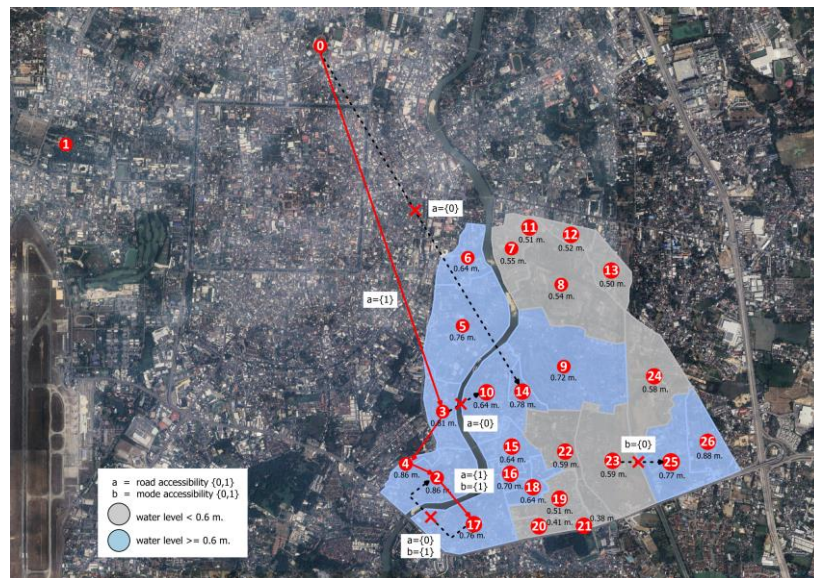


Figure 4 Determination of accessibility parameters and predicted flood levels

Additionally, high floodwaters prevent crossing the bridge from node 17 back to node 2. In such situations, the road accessibility parameter is set to $a = \{0\}$, indicating that the route cannot be accessed. Furthermore, each scenario presents different predicted maximum water levels, imposing constraints on vehicle accessibility. For example, routing between node 23 and node 25 is inaccessibility, denoted by the mode accessibility parameter $b = \{0\}$, which indicates that cross-modal traversal between truck and boat networks is not allowed.

Based on the detailed flood-scenario definitions and input parameters in Table 5, if the water level of the Ping River at station P.1 exceeds 4.2 m, it is considered an overflow event. Scenarios are classified according to the overflow levels shown in the table, which result in varying numbers of affected communities and different proportions of expected evacuation. Transportation times are based on distance and vehicle speed, considered as fuzzy parameters, and the coefficients of response time for each scenario are adopted from Manopiniwes and Irohara [23].

Table 5 Detailed parameter configuration for each scenario

Scenario	1	2	3	4	5
Flood stage of Ping River at station P.1 (+4.20 m.)	4.2-4.4	4.4-4.5	4.5-4.6	4.6-4.7	4.7-4.8
Coefficient of response time	1.20	1.44	1.72	2.01	2.42
Number of affected communities	2	5	9	12	25
Proportion of expected evacuation ($\bar{p}_e$)	(0.0485, 0.0909, 0.1333)	(0.0902, 0.1789, 0.2675)	(0.0903, 0.1782, 0.2661)	(0.0950, 0.1877, 0.2807)	(0.0813, 0.1610, 0.2404)
Emergency relief kit	Weight: $\tilde{w}$ (kg.) Volume: $\tilde{v}$ (m ³)	(7.25,14.83,21.25) (0.03,0.05,0.09)			
Transportation Mode	Speed (km/hr.) $V_{capacity_m}$ (kg.)	Mode 0 (truck): (35,40,45) Mode 1 (boat): (25,30,35) Mode 0 (truck): 12,000 Mode 1 (boat): 1,000			
Mode accessibility	0: Truck 1: Boat	Water level ≤ 0.6 m. Water level > 0.6 m.			

The weight and volume of emergency relief kits are treated as fuzzy parameters. The maximum values correspond to standard Red Cross relief kits that every household receives, while the minimum values correspond to essential survival items procured during extreme emergencies for initial relief. Delivery is conducted by trucks with a capacity of 12,000 kg, which is comparable to government 10-wheel trucks, when water levels are below 0.6 m, and by boats with a maximum capacity of 1,000 kg when water levels exceed 0.6 m.

5. Result

5.1 Solution finding from the proposed mathematical model

The proposed mathematical model was solved using the Gurobi optimizer, with computational experiments conducted on an Intel(R) Xeon(R) CPU E5-2630 v3 (2.40GHz) with 32 GB of RAM, and the feasibility degree of the α -parameter was set to 0.5 to represent a normal situation. The computational results are categorized into five scenarios with varying flood risk levels. The model determines the optimal depot activation and delivery quantities for each arc, adhering to practical capacity and accessibility constraints. For instance, the geographical routing results for Scenario 3, illustrated in Figure 5, demonstrate adherence to traffic patterns; specifically, the route from node 2 to node 10 follows a one-way restriction, ensuring the load does not exceed truck capacity.

The complete results for all scenarios are presented in Table 6. The total transportation times for each scenario are as follows: Scenario 1 (serving 2 communities) requires 37.87 min, Scenario 2 requires 53.11 min, Scenario 3 requires 69.55 min, Scenario 4 requires 495.34 min, and Scenario 5 requires 2,888.98 min. It is observed that in Scenarios 1 to 3, only mode 0 (truck) is utilized, as the maximum predicted water level in each area does not exceed 0.6 m. Conversely, mode 1 (boat) is deployed from Scenario 4 onwards, with certain communities, such as node 3, requiring multiple delivery trips. Additionally, for Scenario 5, the computation was interrupted at 36,000 s (10 h). This limitation was necessary because the exact method required excessive computational time as the problem dataset size increased. Furthermore, with limited relief vehicles, the response time in Scenario 5 could reach 2,888.98 min, requiring up to 47 boat trips, whereas truck operations consistently require only 2 trips across Scenarios 1 to 5. Therefore, alternative relief modes should be considered to supplement operations, specifically to reduce the duration of boat deployment.

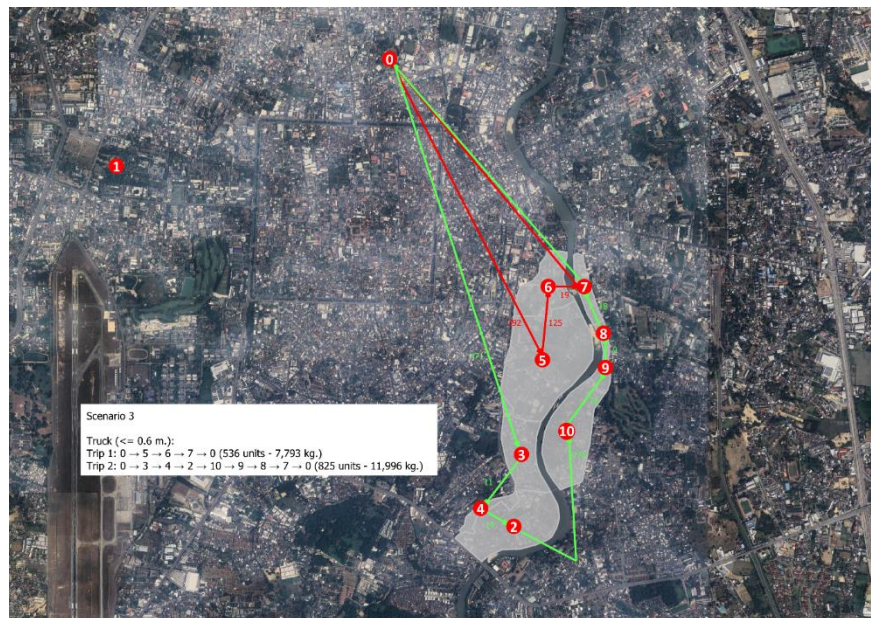


Figure 5 Solution finding of routing in scenario 3

Table 6 Results from the mathematical model with $\alpha = 0.5$

Scenario	Mode	Route	Total number of trips	Total amount (unit)	Total scenario time (min)	Solver runtime (s)
1	0	0-3-2-0	1	151	37.87	0.15
2	0	0-3-2-4-0	1	495	53.11	2.43
		0-6-5-0	1	517		
3	0	0-5-6-7-0	1	536	69.55	10.33
		0-3-4-2-10-9-8-7-0	1	825		
	0	0-6-11-12-13-0	1	403		
		0-7-8-9-10-0	1	725		
4	0	0-3-0	6	401	495.34	124.58
	1	0-5-0	5	340		
		0-5-3-0	1	68		
		0-3-2-4-0	1	68		

Table 6 (continued) Results from the mathematical model with $\alpha = 0.5$

Scenario	Mode	Route	Total number of trips	Total amount (unit)	Total scenario time (min)	Solver runtime (s)
5	0	0-24-23-22-19-20-21-7-0	1	449	2,888.98	36,000.72
		0-11-12-13-8-7-0	1	649		
	1	0-3-0	7	476		
		0-5-0	6	408		
		0-6-0	2	136		
		0-25-0	1	61		
		0-9-26-0	7	476		
		0-9-10-18-26-0	5	340		
		0-9-14-18-26-0	5	340		
		0-17-16-15-18-26-0	4	272		
		0-17-26-0	5	340		
		0-3-15-18-26-0	3	204		
		0-4-2-15-18-26-0	1	68		
		0-17-15-18-26-0	1	68		

5.2. Sensitivity analysis of collaborative with drone

Based on the results from Section 5.1, we identified the importance of integrating drones with boat transportation. Boats have small capacity and pose high operational risks, particularly during flash floods or strong currents. Furthermore, future climate conditions are likely to increase the severity of such events. Consequently, a test was conducted to evaluate collaborative operations where drones work in parallel with boats, using Scenario 4 as an illustrative example. The test imposes the condition that the total drone transportation time across all trips must not exceed 300 min. The drone launch point is designated as an open area located as close as possible to the affected zones requiring boat access, ensuring that all communities fall within a coverage radius of 2 to 5 km. The drone has a maximum payload capacity of 25 kg and a travel speed of (35,40,45) km/hr. The test results at $\alpha = 0.5$ indicate that only one demand unit can be transported per trip. These results are presented in Table 7. Specifically, deliveries to Node 3 are split between both boat and drone modes. Furthermore, boat routing is streamlined to minimize the necessity of traversing multiple communities within a single trip. Noted that the proposed model focuses on optimizing transportation time and does not account for additional delays, particularly those associated with water transport. Consequently, a comparison reveals that collaborative drone operations reduced the boat operation time in the affected area by 15.62 min or 3.7%, resulting in a total time of 410.56 min. The key assumptions are as follows:

- A single drone is considered capable of performing multiple trips.
- Drone transportation time runs parallel to boat transportation time.
- The total drone transportation time does not exceed the time limit.
- The drone payload capacity is limited to one unit per trip.

The results illustrated in Figure 6 prior to before drone collaboration and Figure 7 after drone collaboration demonstrate a shift in routing patterns following the integration of drones. This integration mitigates the need for relief operations to traverse multiple high-risk communities, specifically nodes 2, 3, and 4. These nodes are prone to high flood levels and are among the first areas to be inundated. Notably, during the 2024 flood, these three communities experienced water levels reaching 1.63 to 1.75 m when the situation exceeded level 5.

Table 7 A comparison of boat-drone routing operation

Scenario	Mode	Route	Total number of trips	Total amount (unit)	Total time (min)
Without drone					
4	1: Boat	0-3-0	6	401	426.18
		0-5-0	5	340	
		0-5-3-0	1	68	
		0-3-2-4-0	1	68	
With drone					
4	1: Boat	0-3-0	7	443	410.56
		0-5-0	6	388	
	2: Drone	D-2-D	13	13	184.00
		D-3-D	22	22	
		D-4-D	11	11	

D: Drone lunch point

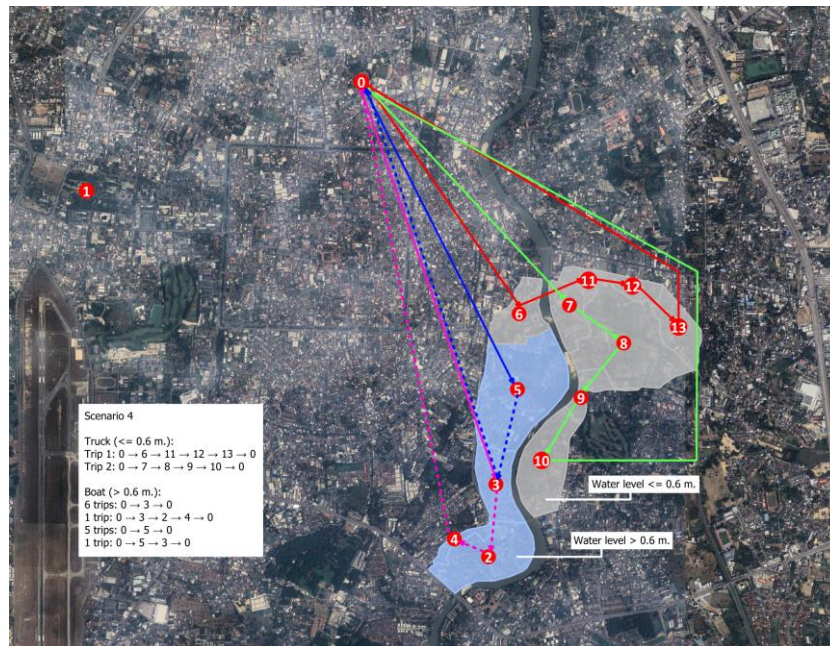


Figure 6 Solution finding of routing in scenario 4

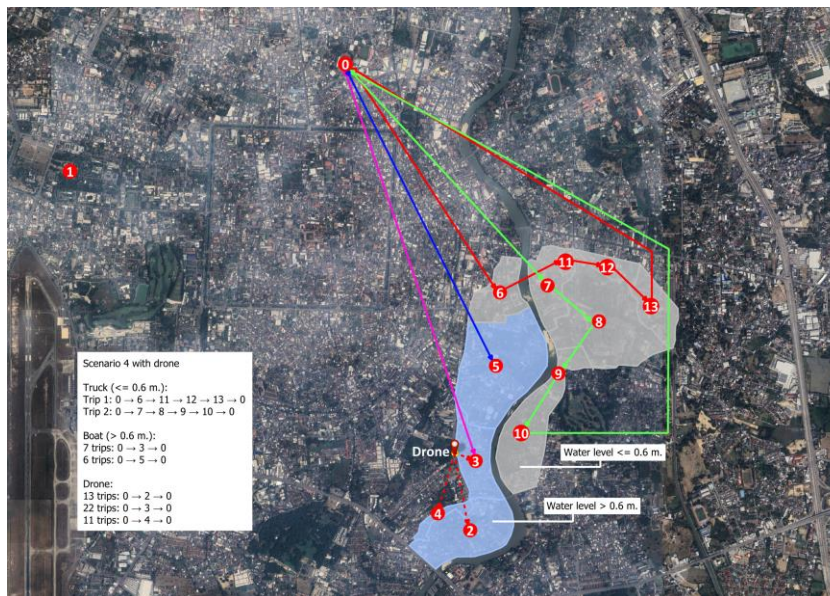


Figure 7 Solution finding of routing with drone in scenario 4

5.3 Sensitivity analysis of boat-drone collaboration in the worst-case scenario

As demonstrated in Section 5.2, drone integration can effectively reduce boat dependency and simplify routing operations in highly flooded areas. Building upon these advantages, this section simulates a worst-case scenario to ensure that the model is capable of handling the most severe conditions in the case study area.

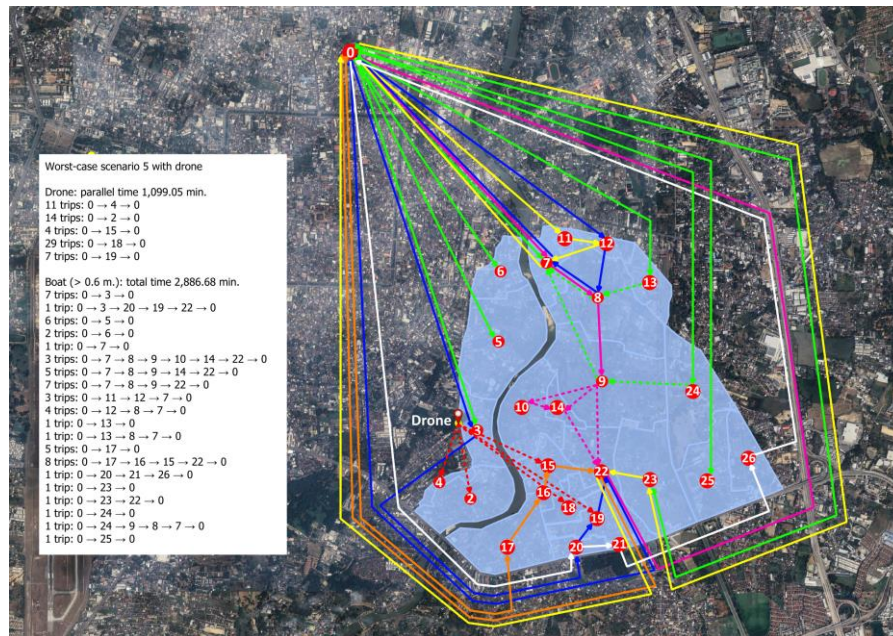
In this simulation, we assume that all affected zones in Scenario 5 experience flood levels exceeding 0.6 m. In other words, the water level surpasses the baseline predicted levels for Scenario 5, rendering the entire area accessible exclusively by boat, as depicted in Figure 8. To manage this extreme condition, the collaborative boat-drone operation is applied, restricting the total drone transportation time to a maximum of 1,200 min. The computational results demonstrate a solver runtime of 36,001.85 s, yielding an optimality gap of 2.81% at $\alpha = 0.5$.

As shown in the comparative results in Table 8 and the routing layout in Figure 8, this extreme condition significantly shifts routing patterns. Boats are now required to serve the areas that were previously accessible by trucks under the baseline Scenario 5 (based on the historical peak of 5.3 m at the P.1 station)—specifically, nodes 7, 8, 11, 12, 13, 19, 20, 21, 22, 23, and 24. However, the integration of drones effectively mitigates this intensified workload. Nodes 2, 4, and 18 are exclusively served by drones, covering a total demand of 54 units, while nodes 15 and 19 receive split deliveries via both boats and drones.

Ultimately, the findings reveal that deploying drones in parallel with boats ensures that, even in a worst-case scenario, the total makespan time—defined as the total transportation time of surface modes (trucks and boats)—is successfully contained at 2,886.68 min, which remains highly comparable to the makespan time in the baseline Scenario 5. This outcome maintains systemic stability and time-efficiency even when confronted with extreme crisis conditions where truck operations are completely halted.

Table 8 A comparison of worst-case scenario with drone operation

Scenario	Mode	Total trips	Total time (min)	Makespan time (min)
Based on the historical peak of 5.3 m at the P.1 station				
5	0: Truck	2	108.84	2,888.98
	1: Boat	47	2,780.14	
Worst-case scenario				
5	1: Boat	60	2,886.68	2,886.68
	2: Drone	200	1,099.05	

**Figure 8** Solution finding of routing with drone in the worst-case scenario

5.4 Sensitivity analysis of α -parameter

This section examines the fuzziness value α ranging from 0 to 1 with increments of 0.2, under set K of 18 trips in Scenario 4. Each increasing level of α implies a higher rate of evacuation, resulting in a decrease in the quantity of relief kits dispatched from the depot. Concurrently, the weight of individual relief kits increases. This necessitates multiple delivery trips due to the increased load per unit, subsequently leading to longer response times. The results in Table 9 indicate that as α increases, the total amount of relief kits transported from the depot tends to decrease. For instance, at $\alpha = 0$, a total of 2,121 units are utilized, whereas at $\alpha = 1$, this decreases to 1,893 units. This reduction aligns with the increased load per trip; due to the larger delivery size per unit, transportation must be divided into multiple trips, resulting in a corresponding increase in total response time.

The sensitivity analysis suggests that if operators anticipate a high trend in evacuation, a high α value should be selected to accommodate uncertainty and ensure confidence in travel time estimates. Conversely, in scenarios where the number of evacuees is expected to be low, a lower α value is more appropriate. Notably, based on the results from Scenario 4, the maximum travel time observed is 582.45 min, largely attributable to boat transportation to support the requirement to transport relief kits weighing up to 21.25 kg necessitates the maximum number of trips, reaching 18. However, across all iterations, mode 0 (truck) consistently required only 2 trips.

Table 9 Sensitivity of α -parameter

α	Z1 (min.)	Mode time (min.)	Total trips	Depot (unit)	Solver runtime (sec.)
0	423.54	[0: 66.42, 1: 357.12]	13	[0: 2,121]	18.698
0.2	460.26	[0: 67.20, 1: 393.06]	14	[0: 2,072]	24.907
0.4	489.18	[0: 69.16, 1: 420.02]	15	[0: 2,067]	41.703
0.5	495.34	[0: 69.16, 1: 426.18]	15	[0: 2,005]	124.578
0.6	522.31	[0: 69.16, 1: 453.15]	16	[0: 1,989]	30.328
0.8	552.09	[0: 69.16, 1: 482.93]	17	[0: 1,982]	25.457
1	582.45	[0: 70.02, 1: 512.43]	18	[0: 1,893]	113.485

6. Discussion

This study addresses the multi-depot, multi-trip, multi-modal, and split deliveries across five flood scenarios under uncertainty regarding transportation time, weight and volume of emergency kits, and the proportion of household evacuation. The model operates under vehicle and depot capacity constraints while considering route accessibility across different flood risk scenarios. These scenarios account for the interplay between flood severity and obstructions such as traffic blockages and indirect access requirements where

transit through intermediate communities is necessary. Furthermore, flood levels vary across communities due to topographical differences, with some areas situated in low-lying zones. Moreover, the lack of a publicly announced operational management plan for the case study area underscores the significance of this research. By establishing a clear relief plan, the government can decentralize authority, fostering public participation and autonomous coping mechanisms. Data from the 2024 event reveals that only 1,200 individuals, or approximately 300 households, evacuated. Consequently, this routing plan is critical for mitigating the impact on the remaining population. Additionally, based on officially announced government shelter data, we evaluated the feasibility of utilizing these locations as temporary distribution depots. These sites were deemed suitable due to their adequate capacity and proximity to flooded areas. This approach aligns with the findings of Heng et al. [22], who proposed the implementation of shelters with dual functionality to reduce operational complexity and maximize space utilization.

The solution obtained at $\alpha = 0.5$ indicates that for Scenarios 1 to 5, only depot $i = [0]$ (Chiang Mai Municipal Stadium) is selected. In areas where flood levels remain below 0.6 m, mode 0 (12-ton truck) is utilized for only 2 trips per scenario. However, in Scenarios 4 and 5, mode 1 (boat) operations are introduced, requiring between 13 and 47 trips, with total travel times reaching 495.34 min in Scenario 4 and 2,888.98 min in Scenario 5. These substantial increases in travel time are attributed to extensive boat usage necessitated by high flood levels spreading across a wider area, requiring boat access for 14 communities. Furthermore, practical boat operations may face significant challenges when traversing multiple communities due to strong currents or other route obstructions, potentially hindering efficient and equitable aid distribution. Consequently, we emphasize the importance of integrating drone operations with boats. This is demonstrated in the sensitivity analysis for Scenario 4, where drone operations run in parallel with boats, utilizing launch points situated near the affected areas. The results in Section 5.2 highlight the critical role of drone assistance, which reduced boat travel time by 3.7% and eliminated the need for boats to traverse potentially hazardous communities, specifically nodes 2, 3, and 4, which are prone to early inundation. Additionally, sensitivity analysis of the α -parameter indicates that if actual evacuation rates are high, a higher α -value should be selected; conversely, a lower α -value is appropriate for low evacuation rates. This analysis further estimates that the maximum relief time in Scenario 4 could reach 582.45 min, with the majority of this duration attributable to boat travel. Therefore, collaborative drone operations should be implemented for relief delivery, particularly where boat operations pose risks to personnel due to environment conditions. The integration of drones simplifies routing by bypassing high-risk communities. This necessity is underscored by the recent major flood in Chiang Mai, where one vulnerable individual tragically lost their life during a boat evacuation.

A review of the literature reinforces that the majority of studies on humanitarian VRP fail to consider heterogeneous transportation modes. Within the context of disaster management, only Gong et al. [11] and Weng et al. [13] have incorporated drones. Similarly, in flood management, only Gong et al. [11] have addressed the truck-speedboat-drone combination proposed in this study. This research significantly extends the model previously developed by Phutthanawong and Boonmee [24]. While their earlier work successfully addressed heterogeneous fleets and scenario-based accessibility, it was limited by deterministic parameters and lacked drone integration. Our proposed model overcomes these limitations by integrating fuzzy uncertainty and multimodal boat-drone collaboration. Another significant limitation in existing research is the lack of defined route accessibility during disasters and the absence of scenario-based testing across varying severity levels. In the context of flooding, addressing these factors is crucial for configuring transportation modes appropriate for the specific problem and ensuring accessibility to every household. Regarding data management, few studies account for data uncertainty, with only Nodoust et al. [6] addressing ambiguity using fuzzy membership functions. In terms of computation, Scenario 5 involves 25 communities and approximately 130,000 constraints, constituting a large-scale problem for the Gurobi optimizer. Due to the extensive computational time required, a feasible solution was accepted by interrupting the process at 10 hours, resulting in a gap of 1.91%. Future research should employ metaheuristic approaches to efficiently address these large-scale and complex problems.

7. Managerial insights

This section provides actionable guidance for government agencies, policymakers, and logistics coordinators in disaster management:

- Agencies should evaluate the feasibility of shelters serving as temporary distribution centers. This dual functionality maximizes space utilization, allowing facilities to operate as both evacuation centers and cross-docking hubs. This approach facilitates rapid aid distribution to nearby non-evacuated households without relying solely on transport from the main warehouse. Facilities performing these dual functions are referred to as shelters that also serve as staging areas.
- Relief delivery operations should avoid empty backhauls. Logistics planning must incorporate the evacuation of residents, particularly vulnerable groups, to shelters during the return trip from relief kit delivery.
- Agencies should prioritize the evacuation of residents in high-risk zones to the maximum extent possible, without waiting for the onset of Scenario 4 or 5. Furthermore, if extreme severity is anticipated, a robust vehicle pre-positioning strategy should be implemented. Specifically, rescue boats and transport drones should be stationed at access points for communities 2, 3, and 4 as soon as the water level at station P.1 reaches the 4.5 to 4.6 m range.
- During the initial phase of a disaster when information remains ambiguous, decision-makers are advised to allocate resources above average levels by selecting an α -value lower than 0.5. This approach accommodates potential surges in demand from non-evacuated populations, thereby mitigating shortages and ensuring equitable distribution.
- Based on the routing results, operational zoning should be assigned to different agencies according to their available vehicle resources. Assignments should align as closely as possible with the calculated number of trips. This strategy aims to prevent operational bottlenecks and the duplication of relief efforts in specific areas while ensuring that other regions are not neglected, thus facilitating rapid response.
- Regarding future directions for delivery drones, their integration should be coordinated with government aid-request platforms, such as the *Jitasa* platform and the *Phonphai* application. This integration aims to assist high-priority non-evacuated households, particularly vulnerable groups or those with medical conditions, by delivering emergency relief items. This is especially critical for communities at nodes 9, 10, 14, 15, 16, and 18 in Scenario 5, which are only accessible by traversing intermediate communities. The deployment of drones in these contexts would significantly accelerate aid delivery and reduce operational risks.

8. Conclusions

This study proposes a scenario-based fuzzy multimodal vehicle routing model for last-mile flood relief delivery in Chiang Mai Municipality, addressing the critical challenge of emergency relief kit distribution to non-evacuated households. The model integrates multi-depot, multi-trip operations with split-delivery capabilities under fuzzy uncertainty across five distinct flood risk scenarios. The scenario-based framework explicitly captures the interplay between flood severity and multimodal accessibility requirements. High-flood scenarios, specifically Scenarios 4 and 5, necessitate multimodal operations combining trucks and boats. Predicted flood levels for each community are derived from the Ping River level at station P.1, peaking at 5.3 m, based on the 2024 flood event—the most severe disaster recorded in the study area. The model incorporates dynamic road-mode accessibility constraints based on water depth levels, along with factors such as indirect community access and traffic limitations, including road barriers, to ensure practically feasible last-mile routing solutions appropriate to actual flood conditions. The results at $\alpha = 0.5$ demonstrate that only one depot can operate with minimized transportation time. For low water level scenarios, truck-based delivery within 2 trips is sufficient to serve all affected communities. However, severe flood scenarios at levels 4 and 5 require intensive boat operations, necessitating up to 47 trips, which significantly increases total last-mile transportation time and operational complexity. A key finding is that collaborative boat-drone routing substantially reduces last-mile delivery time while alleviating the burden on low-capacity boats and mitigating operational risks. Test results from Scenario 4 indicate that drone integration simplifies boat routes, reducing travel time by 3.7%. Furthermore, sensitivity analysis of the fuzzy α -parameter reveals that lower and higher ambiguity levels imply varying evacuation rates and illustrate potential demand ranges. This analysis enables assessment of probable trip frequencies to ensure adequate fleet capacity and provides actionable guidance for resource allocation to disaster management decision-makers. Although this study provides a framework that advances both theoretical understanding and practical application, research gaps remain. Specifically, future research should apply metaheuristic algorithms to solve large-scale problems and extend the framework. Additionally, future studies should consider prioritizing deliveries based on community vulnerability indices to ensure immediate assistance for the most fragile populations, or exploring multi-objective formulations that balance time minimization with equity considerations. Furthermore, the framework should be extended to integrate relief facility location decisions within location-routing problems and incorporate simultaneous pickup and delivery capabilities for more comprehensive last-mile logistics planning.

9. Acknowledgements

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