An Elderly-Centered Location-Allocation Model for Multi-Scenarios Flood Relief Distribution in Mae Chan, Chiang Rai, Thailand

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Abstract
Flooding remains a major challenge in Thailand, severely impacting many regions and highlighting the need for efficient disaster logistics, particularly for elderly residents who often cannot evacuate. This study integrates logistics optimization and geoinformatics to identify optimal locations for temporary Relief Distribution Centers (RDCs) that can deliver aid effectively. Household-level survey data and Kernel Density Analysis were used to map areas with high concentrations of elderly populations. The Particle Swarm Optimization (PSO) algorithm was then applied to determine which RDCs should operate to maximize elderly coverage, minimize total travel time, and optimize resource allocation. Analysis across four flood scenarios revealed a pronounced disparity in workload distribution: a limited subset of RDCs consistently absorbed the majority of demand, with top-performing centers serving 27–230 households, 92–446 elderly, and 266–646 non-elderly individuals, while low-load centers managed fewer than 60 households and under 150 elderly. Overall, 30–40% of RDCs handled over 60% of the total assistance burden, highlighting systemic inequities in service allocation. These findings emphasize the need for scenario-specific, evidence-based resource prioritization, reinforced logistical capacity, and strategic staffing in high-demand centers to prevent service bottlenecks, ensure equitable coverage, and maintain effective flood response for vulnerable populations.

Keywords: Elderly Population Clustering, Flood Relief Distribution, Flood Vulnerability Mapping. Geoinformatics, Particle Swarm Optimization (PSO)

1. Introduction

Natural disasters are occurring with increasing frequency and severity worldwide due to climate change, posing significant challenges to human safety and environmental stability [1]. Research indicates that climate change alters rainfall patterns, leading to a rise in catastrophic events such as floods, landslides, and droughts [2]. These disasters profoundly impact communities, social systems, and economies, particularly in developing nations [3], where limited resources and inadequate preparedness exacerbate vulnerabilities. Key challenges include insufficient disaster response policies, infrastructure with low earthquakes resistant, inadequate medical resources, and poor emergency planning [4].

The Particle Swarm Optimization (PSO) tool has proven highly efficient for solving complex Location-Allocation (L-A) problems across diverse applications, including urban park placement, optimal business site selection, and multi-objective post-disaster relief planning [5][6] and [7]. PSO excels by significantly reducing computational complexity and finding timely optimal solutions, often outperforming algorithms like Simulated Annealing and Ant Colony in shelter location studies [8]. When compared to the Genetic Algorithm (GA), PSO is generally preferred for its fast convergence, though GA may offer a more exhaustive search for the absolute optimum in highly complex scenarios [9]. Furthermore, a modified PSO has demonstrated significantly superior results to GAMS in maximizing coverage for the Maximal Covering Location Problem [10]. Although some research suggests that other algorithms, such as GA, may achieve better accuracy in deeper processing layers [11], PSO's overall reliability, speed, and proven suitability for handling multi-objective conditions make it a strong choice. Consequently, PSO is deemed reliable and appropriate for application in this research to determine the optimal location for the flood relief distribution centers in Mae Chan District,

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Chiang Rai Province.

Previous Location-Allocation (L-A) research in disaster management has largely focused on Shelter Location studies, primarily addressing the optimal placement of shelters to minimize travel time for evacuees [12] and [13]. However, real-world deployment of shelter locations is often constrained by governmental mandates, leading to the designation of public facilities like schools, temples, or local administrative offices as official shelters. A critical gap emerges when these mandated locations are situated in flood-affected areas: they often fail to account for severe real-world constraints, such as mobility limitations among vulnerable populations [14] and [15]. Specifically, elderly residents frequently refuse or are unable to evacuate their homes [16] and [17], necessitating an alternative strategy of delivering aid directly to their residences. Therefore, this research shifts its focus to optimizing the placement of temporary flood relief distribution centers (RDCs). These centers are intended to serve as staging areas for storing relief goods and facilitating last-mile transport into flood zones. Typically, these RDCs are strategically positioned in non-inundated areas proximate to the flooded region. The literature reveals that while most location selection studies use decision-making, geographic, or mathematical tools separately, few combine these approaches. This research integrates geoinformation tools with optimization techniques to address complex flood scenarios. Among optimization methods, Particle Swarm Optimization (PSO) has proven effective for spatial problems. Therefore, this study differs from previous works in that the equations introduce variables specifically targeting the elderly and focus on the distribution of supplies rather than evacuation to shelters, while employing PSO as a tool to determine the optimal locations for establishing relief distribution centers (RDCs). The approach incorporates conditions to ensure coverage across multiple scenarios, prioritizing locations of elderly populations in the affected areas. By integrating geoinformation tools with optimization techniques, the study aims to develop actionable plans for disaster response during flooding events.

2. Methodology

2.1 Study Area

In this study, the selected research area is Chan Chawa Subdistrict, Mae Chan District, Chiang Rai Province, which is known for its recurrent flooding [18]. The subdistrict covers an area of approximately 128 square kilometers and is divided into two administrative areas: Chan Chawa Nuea (North) and Chan Chawa Tai (South), encompassing a total of 23 villages with a population of approximately 15,647 people. Historically, this area was a wetland, with the word 'Chawa' referring to the characteristic of water spreading out and dissipating in a wetland area. The key rivers in Chan Chawa are the Nam Kham River and the Nam Chan River, with 'Chan' referring to the latter. According to an interview with the former Mayor of Chan Chawa Subdistrict, flood problems have been officially reported in 2017, 2018, 2021, 2022, 2023, and 2024. In total, nine villages were affected. The Level 1 affected villages included Muang Muang Si, Mae Kham Fang Muen, Mae Kham Nam Lat, and Nong Bua Hua Fai. The Level 2 affected villages comprised Thi, Nong Khrok, Pa Bong, Pa Kuk, and San Na Nong Bua (Figure 1).

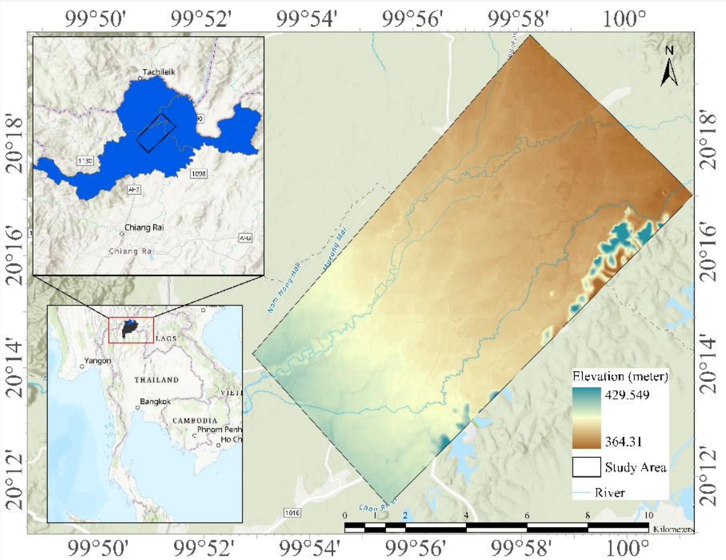

Figure 1: Chan Chawa subdistrict, Mae Chan district, Chiang Rai, Thailand

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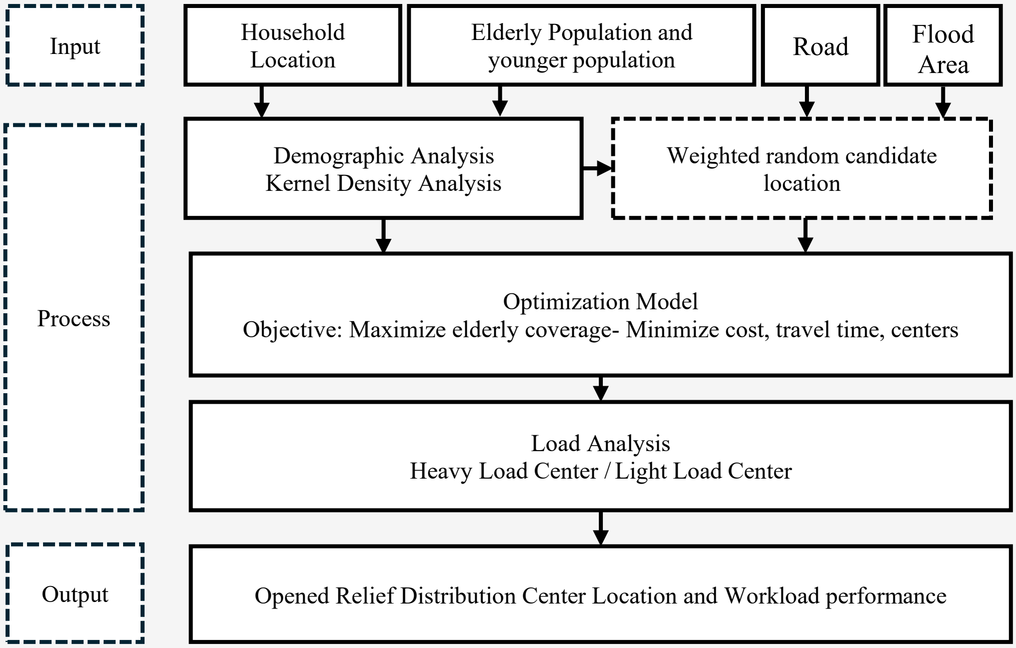

Figure 2: Opened relief distribution center location identification conceptual framework

2.2 Conceptual Framework

Figure 2 illustrates the conceptual framework guiding the data analysis in this study. The process starts with flood maps obtained from research [19] to identify flood-affected zones. Field surveys are conducted to collect household-level data, which are used to generate a map of affected populations. Prior to selecting relief distribution center (RDC) locations, a Kernel Density Analysis is performed to identify areas with high concentrations of elderly residents, ensuring that vulnerable populations are considered in the planning process. Unflooded roads are then extracted, and candidate locations for RDCs are systematically generated near the flood boundaries, ensuring they are in safe zones. These candidate points were evaluated using Particle Swarm Optimization (PSO) to determine the most suitable RDC locations for efficient relief delivery. Workload distribution among the selected RDCs is analyzed using statistical tools, including box plots, Welch's two-sample t-test, and the Wilcoxon rank-sum test, to ensure workload balance. The final output identifies the areas bearing the heaviest and lightest burdens, providing insights into effective disaster response planning.

2.3 Data Acquisition

The data collection methodology employed a combination of field surveys and structured interviews. Initially, flood-affected villages were identified through preliminary consultations with the subdistrict leader. This initial selection was subsequently validated using the authoritative flood map for Chan Chawa Subdistrict [20] developed by previous research [19] and further corroborated with Recurrent Flood Hazard Data from the Geoinformatics and Space Technology Development Agency (GISTDA), ensuring that only verified flood-impacted areas were included in the study. Following this, a comprehensive on-site survey was conducted at the village level to accurately document the geospatial coordinates of all households, thereby defining the demand points. Household-specific demographic data was conducted by a focus group with relevant stakeholders using satellite imagery from Google Earth to identify and discuss the locations of houses and residents related to the study. No personal names or identifiable information POI were collected or disclosed; only locations and counts were used, including community leaders and village health volunteers. This approach enabled precise quantification of both the general population and vulnerable subpopulations, particularly elderly residents with mobility limitations, at each demand point.

2.4 Sampling

In this study, the sample population is categorized into two distinct cases: the affected population groups (demand points) and potential distribution center locations (candidate points). The criteria for identifying the elderly group follow the definition of individuals aged over sixty years [21][22] and [23]. It was essential to obtain household population data from all nine villages to ensure that the assistance could comprehensively address the needs of the entire area. To identify candidate locations situated within flood-affected transportation corridors, a spatial overlay analysis was performed by ArcGIS Pro 3.3.2. Specifically, road networks were intersected with flood extent polygons using the Intersect tool to extract road segments located outside the flooded areas. Next, random point generation was applied along these flood free road features using the Create Random Points tool, constrained to the linear geometry of the flooded road segments.

This study seeks to address a gap in prior research concerning the location of permanent and robust shelters. In contrast to established shelter location models, the actual sites utilized for relief distribution centers (RDCs) in real-world flood response are typically temporary structures, consisting merely of a sun-shelter tent, tables for storing relief goods, and chairs for monitoring personnel. Critically, these temporary RDCs are predominantly situated in non-inundated (dry) areas that are immediately proximate to the flood-affected zone, thus enabling the most rapid and efficient last-mile delivery of aid. This study considers 52 candidate locations for relief distribution centers (RDCs). These candidate points were generated using a two-stage randomization process. The first randomization applied a random seed strategy along feasible road segments unaffected by flood scenario 1, resulting in an initial set of candidate RDCs capable of operating under that specific flood condition. Subsequently, a second randomization was performed to select additional points, as the initial set proved insufficient due to the extensive inundation predicted by flood scenario 2. This sequential randomization, applied along unflooded road segments, ensured adequate spatial coverage while maintaining computational feasibility, with the total number of candidate points reaching 52. This approach guarantees that all candidate points are situated on accessible routes suitable for vehicles, boats, or pedestrian traffic, while also maximizing proximity to flood-affected areas and ensuring each point is located near villages impacted by flooding, as shown in Figure 3.

In this study, a sampling process was conducted by using the intersect tool in ArcGIS Pro 3.3.2 software on flood maps at two different levels along with road networks to exclude roads that are flooded. Then, the selected road lines were converted to points. Next, only points near the target areas within each flood level were filtered. These points were then randomly sampled as candidates, with additional criteria checked as follows:

1. Be in areas unaffected by all defined flood levels to ensure continuous operational capacity during disasters.
2. Maintain road access that remains usable throughout the emergency to enable efficient transport of relief on dry ground with direct logistical connectivity to flood-affected areas for timely aid distribution.
4. Fall within the administrative boundaries of the study area to align local governance and operational protocols.

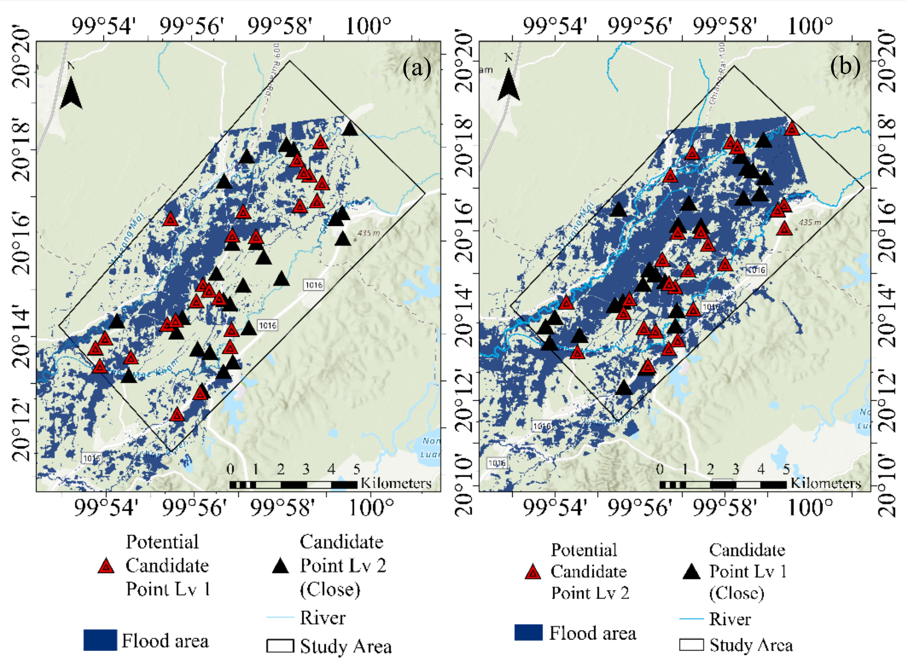

Figure 3: Structural random candidate points location and flood inundation: (a) flood level 1 (b) flood level 2

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2.5 Analysis Tools

In this research, Particle Swarm Optimization (PSO), a population-based metaheuristic algorithm inspired by the social behavior of birds and fish [24], was adopted to solve the location-allocation problem of flood relief distribution centers. PSO has demonstrated its effectiveness in solving complex multi-objective optimization problems [25] and [26] within certain limitations [27] and [28] and is suitable for the nature of this problem, which involves determining both the location of distribution centers and the allocation of demand points under multiple constraints.

Studies have shown that Particle Swarm Optimization (PSO) is widely used, particularly for analyzing areas during emergency situations [29]. It is often necessary to consider many locations, and PSO has the capability to search multiple options with high accuracy [30]. Research has demonstrated its potential to identify optimal areas according to predefined conditions [31]. However, studies also indicate that improvements are needed, particularly by creating hybrid approaches that incorporate Deep Learning or Machine Learning, which can enhance the model's accuracy and flexibility [32]. Nonetheless, since this study aims to integrate PSO with GIS, the focus is on testing the hypothesis that using PSO to identify suitable locations for relief distribution centers (RDCs) can provide valuable decision-support insights.

For the data analysis, the coordinates of affected households (demand points) and the numbers of elderly and younger individuals under Flood Level 1 were used as demand parameters, with Level 1 candidate point coordinates incorporated. Parameters were defined according to specific conditions, including prioritizing the elderly population, restricting transportation within operational distances, and limiting the load at each facility. The simulation was executed iteratively 100 times to identify the optimal solution. Subsequently, the analysis was repeated using Level 2 demand points, reflecting an increased number of affected individuals and deactivating Level 1 locations. As Flood Level 1 RDCs were fully utilized in Scenario 2, Level 2 candidate points were activated to continue the allocation process.

2.6 Particle Swarm Optimization Equation

The problem aims to optimize the selection of flood relief distribution centers (RDCs) to maximize coverage of the affected population, particularly the elderly, while minimizing operational costs, travel times, and resource usage. The study employs a customized Binary Particle Swarm Optimization (PSO) approach to solve this multi-objective Location-Allocation problem. The mathematical formulation of the problem is presented in Equations 1 and 2:

$$v_i^k = wv_i^k + c_1 r_1 \left(pbest_i^k - x_i^k \right) + c_2 r_2 \left(gbest^k - x_i^k \right)$$

Equation 1

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

Equation 2

Where:

i is the set of candidate RDCs locations

j is the set of affected demand points

v_i^k is the velocity of particle i at iteration k

w is the inertia weight

c_1 and c_2 are cognitive and social learning coefficients

r_1 and r_2 are random numbers in the range [0,1]

x_i^k is the current position of particle i at iteration k

$pbest_i^k$ is the personal best position of particle i up to iteration k

$gbest^k$ is the global best position found by the swarm up to iteration k

The updated velocity is then transformed into a probability using the sigmoid function as Equation 3 and transfer into a new position which is determined by comparing the probability with a random number as Equation 4:

$$S\left(v_i^{k+1}\right) = \frac{1}{1 + e^{-v_i^{k+1}}}$$

Equation 3

$$x_i^{k+1} = \begin{Bmatrix} 1 \; if \; rand() < S\left(v_i^{k+1}\right) \\ 0 \; otherwise \end{Bmatrix}$$

Equation 4

This binary mechanism allows particles to move probabilistically through the solution space. After configuring the analytical tool, it is necessary to define its objectives by specifying the operational goals and incorporating constraints that are appropriate to the specific area. This study aims to reduce total impact by balancing key factors: it seeks to maximize benefits, such as efficiency or value, while minimizing costs, time, and the number of selected options. The weights determine how important each factor is in the decision-making process as follows:

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Objective Function:

$$Minimize\ Z = -\alpha_1 \sum_{i=1}^{n}\sum_{j=1}^{m} e_j y_{ij} - \alpha_2 \sum_{i=1}^{n}\sum_{j=1}^{m} d_1 y_{ij} + \beta_1 \sum_{i=1}^{n} c_i x_i + \beta_2 \sum_{i=1}^{n}\sum_{j=1}^{m} t_{ij} y_{ij} + \beta_3 \sum_{i=1}^{n} x_i$$

Equation 5

Where:

α_1 and α_2 are the weights of maximizing elderly and total population coverage respectively.
β_1, β_2, and β_3 are the weights of penalizing operational costs, travel time and number of open centers respectively.
c_i is the cost of opening RDC *i*.
t_{ij} is the travel time from RDC *i* to demand point *j*.
d_j is the total population at demand point *j*.
e_j is the elderly population at demand point *j*.
P_j is the younger population at demand point *j*.
T_{max} is the maximum allowable travel time (minutes).
Q is the maximum capacity of a distribution center (people).
N is the total number of candidate distribution centers.

Decision Variables:

From the PSO algorithms, each particle in the PSO algorithm represents a potential solution and is encoded using a binary vector that consists of two components:

x_i = 1 if the candidate RDC *i* is selected
0 if otherwise
y_{ij} = 1 if the demand point *j* is assigned to candidate RDC *i*
0 if otherwise

Velocity and Position Update Mechanism:

The algorithm iteratively updates each particle's velocity and position based on its own best-known solution and the global best solution found by the swarm. Next, the constraints ensure that each item is assigned only once, within time and capacity limits, meets performance requirements, and all decisions are binary, as expressed in Equations 6 to 10:

$$\sum_{i=1}^{n} y_{ij} \le 1$$

Equation 6

$$t_{ij} y_{ij} \le T_{\max}$$

Equation 7

$$\sum_{j=1}^{m} d_i y_{ij} \le Q x_i$$

Equation 8

$$\sum_{j=1}^{m} e_j y_{ij} \ge \sum_{j=1}^{m} p_j y_{ij}$$

Equation 9

$$x_i \in \{0,1\}, \quad y_{ij} \in \{0,1\}$$

Equation 10

The equation extracts the objective functions aims to minimizes costs, travel time, and the number of opened distribution centers while allowing each demand point to be served by at most one center within capacity and time constraints. It prioritizes elderly demand points to achieve an efficient and equitable flood relief operation. The constraints governing the optimization model ensure feasibility and alignment with the objectives. First, the Demand Point Assignment Constraint (Equation 6) ensures that each demand point is assigned to at most one open distribution center, avoiding overlapping assignments. The Travel Time Constraint (Equation 7) limits assignments to centers within a maximum allowable travel time (T_{max}), ensuring timely delivery of aid. The Capacity Constraint (Equation 8) ensures that the total population served by each open center does not exceed its maximum capacity, balancing demand and resource availability. The Elderly Prioritization Constraint (Equation 9) gives priority to demand points with elderly populations, ensuring that elderly populations are prioritized or served at least as much as the younger population. Finally, the Binary Constraints (Equation 10) specify that decision variables for opening centers (x_i) and assigned demand points (y_{ij}) are binary, indicating whether a center is opened, or a demand point is served by a particular center. These constraints collectively guide the model toward an efficient and equitable solution.

The analysis process was conducted using R Language through R-Studio on a computer equipped with Intel Core i7-14700HX central processing unit, an NVIDIA GeForce RTX 5060 graphics card, and 32GB of RAM. The priorities were assigned to focus on elderly and general population coverage, avoiding excessive center openings, preventing over coverage

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of the population and households, and minimizing distance from centers, in that order. A total of 100 particles were used in the Particle Swarm Optimization (PSO) process, with 200 iterations performed in total.

2.7 Load Analysis

The study aims to examine whether the placement of Relief Distribution Centers (RDCs) aligns with the spatial concentration of demand, thereby reflecting the distribution of workload across centers. Bar plots were utilized to depict the relative workload intensity among RDCs, enabling visual comparison between high-load and low-load centers. To further assess whether there were statistically significant differences in workload between RDCs, we applied both Welch's two-sample t-test and the Wilcoxon rank-sum test [33]. Welch's t-test was chosen due to its robustness against unequal variances and sample sizes, making it appropriate for comparing the mean workloads of two independent groups, those suspected of carrying heavier vs. lighter loads. In parallel, the Wilcoxon rank-sum test, a non-parametric alternative, was employed to compare the median workloads without assuming normality. The combination of these tests allowed for a more reliable classification of "heavy-load" and "light-load" RDCs. The results help pinpoint operational bottlenecks or underutilized centers. These findings are critical for optimizing resource allocation and improving future disaster response strategies by ensuring more balanced distribution planning [34] and [35].

2.8 Multi-Tier Scenarios and Assumptions

This study is based on realistic assumptions, requiring the research and collection of historical data related to the resources needed for operations. Four possible distribution plans are designed to reflect realistic flooding scenarios and corresponding relief distribution needs. The details of the multi-tier scenarios parameters are summarized in Table 1. And each scenario is defined as follows:

A1 refers to Level 1 flooding with a focus on distributing food and water boxes. In this scenario, each relief distribution center (RDC) can serve a maximum of 300 people and 120 households.

A2 refers to Level 2 flooding with food and water boxes as the relief items. Each RDC in this case can serve up to 400 people and 200 households.

B1 refers to Level 1 flooding with the distribution of relief bags. Each RDC can serve up to 120 households under this condition.

B2 refers to Level 2 flooding where relief bags are provided. Each RDC can support up to 200 households.

Relief operations are modeled after real flood conditions, where rubber boats and plastic boats are primarily used and must be manually pulled by personnel. These types of boats were selected because they are commonly employed in actual flood situations and are suitable for shallow and narrow waterways. Based on field experiments conducted under real flood conditions, the movement of these manually pulled boats proved to be difficult and slow. When the water depth reached approximately knee level, the observed average travel speed was around 30 minutes per kilometer. Consequently, this value was adopted to represent the transport time for Level 2 flooding, while 20 minutes per kilometer was assigned for Level 1 flooding to reflect relatively lighter conditions.

Each boat can carry 40 relief bags or 100 sets of food and water per trip. Relief bags are distributed at a rate of one per household, while food and water boxes are distributed as one set per person, resulting in different calculation limits for the two distribution types. The maximum travel distances were set to no more than 3 kilometers for Level 1 flooding and no more than 5 kilometers for Level 2 flooding. These limits were established in accordance with the operational requirement that the first phase of relief operations must be completed within 24 hours.

Table 1: Multi-tier scenarios parameter

Scenario	Flood Level	Relief Item	Capacity (People)	Capacity (Households)	Transport Speed (min/km)	Max Distance (km)	Remarks
A1	Level 1	Food & Water boxes	300	120	20	3	Boat manually pulled
A2	Level 2	Food & Water boxes	400	200	30	5	Boat manually pulled
B1	Level 1	Relief bags	-	120	20	3	1 bag per household
B2	Level 2	Relief bags	-	200	30	5	1 bag per household

If transportation time is calculated to exceed 20 hours (excluding 3 hours allocated for setup and other operational activities), route or plan adjustments are required. The research declared 12 hours corresponds to the priority factor of the RDC's primary service area, 6 hours represent a secondary priority coefficient, and 3 hours indicate a high-priority factor without a specific deadline [36]. Under the assumed travel speeds, the chosen 3- and 5-kilometer limits ensure that round-trip transport times remain within approximately six hours, thereby satisfying the operational timeframe for the first response phase.

3. Result

3.1 Demographic Analysis

The analysis of the study results is divided into two main components: (1) the identification of elderly population clusters within Chan Chawa Subdistrict, Mae Chan District, Chiang Rai Province, and (2) the evaluation of optimal relief distribution center locations based on predefined assumptions. The findings were shown in Table 2. The demographic data from nine villages in Chan Chwa Subdistrict reveal clear differences in household size and elderly population distribution. Within the study area, nine villages were identified as being affected by flooding. Among these, Pa Bong Luang exhibited the largest number of households, totaling 273, whereas Ban Thi had the smallest, with 32 households. Analysis of the demographic structure indicates that the proportion of elderly residents is substantially high and statistically comparable to other population groups. Pa Bong Luang demonstrates a notably high aging rate, with more than 48% of its population aged 60 years and above. Moreover, the findings reveal that the average ratio of elderly individuals per household across all surveyed communities is approximately one elderly person per household, implying that a considerable share of households includes at least one older member. This pattern underscores the demographic significance of aging within these flood-affected communities and highlights the potential implications for community-based care and disaster response planning. Additionally, to provide a clearer visualization, the data were presented using Kernel Density to identify areas of concentration, which can later be compared with the load analysis. From Figure 4 the Kernel Density Estimation (KDE) using ArcGIS Pro 3.3.2 software to show the spatial distribution of elderly population density by using 1,000-meter radius distance.

Table 2: Population residence in the study area

Village_ID	Village_name	Number of houses	Ages		Elderly per household
			≥60	<60	
V1	Mae Kam Nam Lat	171	174	231	1.02
V2	Mae Kam Fang Min	195	228	309	1.17
V3	Muang Mu Si	73	52	131	0.71
V4	San Na Nong Bua	130	107	213	0.82
V5	Nong Bua Hua Fai	47	52	72	1.11
V6	Pa Kuk	47	37	72	0.79
V7	Pa Bong Luang	273	318	340	1.16
V8	Nong Khrok	204	227	279	1.11
V9	Thi	32	23	53	0.72

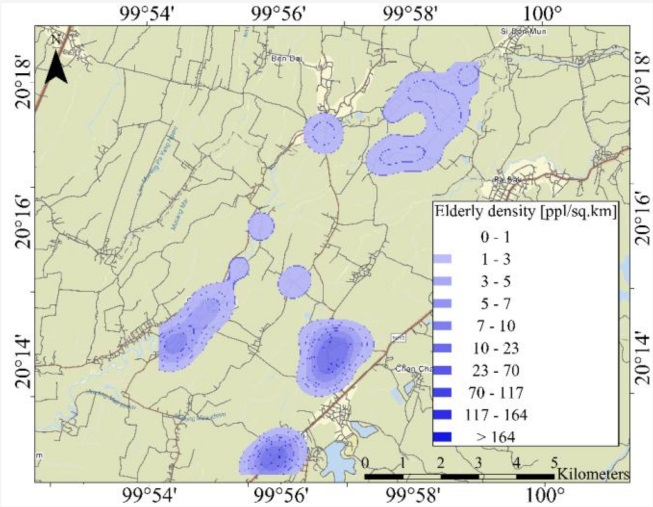

Figure 4: Kernel density analysis of elderly population

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For the elderly population density, the map clearly illustrates high elderly population areas of statistically significant high concentration, represented by the deep purple and dark blue shades (e.g., 70-117 and >164 person/km) indicating specific locales where the elderly density is highest. The highest density clusters are clearly observed in three villages: Nong Khrok Village, Pa Bong Luang Village, and Mae Kham Fang Min Village. The elderly distribution zone in the upper map, covering Mae Kam Nam Lat and San Na Nong Bua, is dispersed rather than clustered. This indicates that subsequent analyses should prioritize the high-density area and the upper zone, where the elderly population is substantial but dispersed, thus requiring a broader and more evenly distributed provision of assistance.

3.2 Location Allocation Analysis

From the population density is used as a key factor in the analysis, the most suitable approach is to locate relief distribution centers (RDCs) near areas with a high concentration of elderly people. In this study, the Particle Swarm Optimization (PSO) method was applied to identify the optimal locations for these centers. The analysis was based on conditions that prioritize minimum distance to target areas, complete coverage, minimal number of centers, and non-overlapping locations. Therefore, the results of the study under four different scenarios are as follows:

From the scenarios A1 and B1, where the RDCs were established in areas with a high concentration of elderly populations, it can be observed that the model performed effectively. In Scenario A1, the relief distribution centers (RDCs) must operate at all eight locations. Collectively, these centers are required to serve a total of 1,250 people, including 506 elderly individuals and 744 younger population members, by providing food and water supply sets. The distribution of assistance load in Scenario A1 shows that Centers 1, 4, and 22 carry the greatest responsibility, as they support the largest numbers of both elderly and non-elderly individuals. Center 1 has the highest coverage, followed closely by Center 4, while Center 22 also manages a substantial population. In contrast, Centers 24, 23, 15, and 7 support much smaller groups, indicating an uneven allocation of service demands. Overall, the assistance load is concentrated in a few key centers, highlighting the need for resource prioritization to support these high-demand areas effectively (Figure 5(a)). In Scenario B1, the assistance load is heavily concentrated in Centers 8 and 5, which support the largest numbers of elderly and non-elderly individuals, making them the primary high-demand locations. Center 22 also manages a considerable population, though to a lesser degree. Meanwhile, Centers 24, 23, 15, and 7 handle relatively smaller groups, indicating a more modest service burden. Overall, the distribution reflects a clear imbalance, with only a few centers absorbing most of the assistance responsibilities and therefore requiring greater resource support to maintain effective service provision (Figure 5(b)).

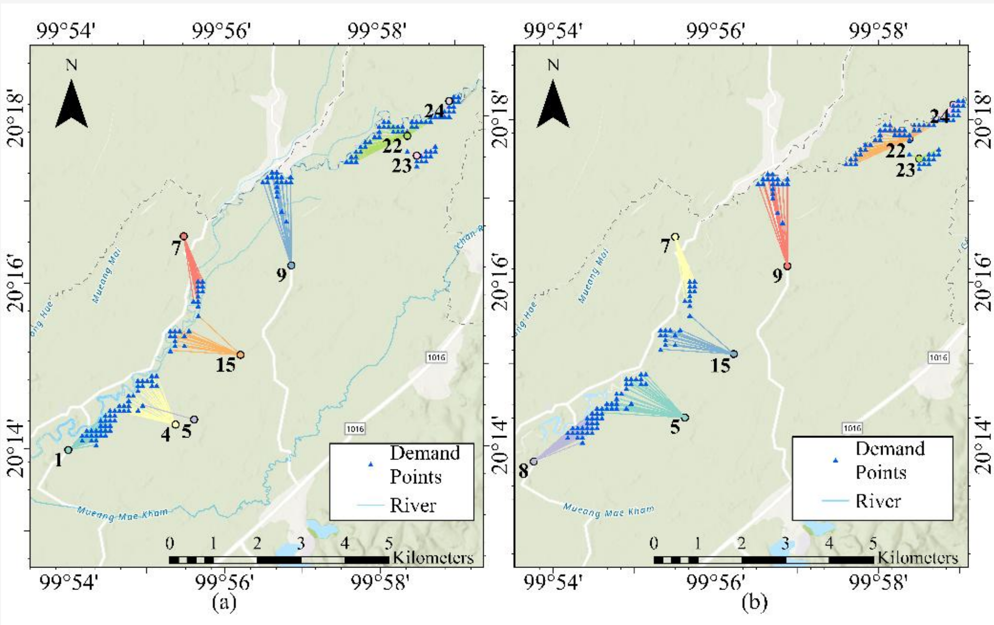

Figure 5: Relief distribution centers (RDC) coverage map scenarios (a) A1 (b) B1

Across both scenarios, the distribution of service load is clearly concentrated in only a few centers, with Centers 1 and 4 in Scenario A1 and Centers 8 and 5 in Scenario B1 absorbing the largest share of households and elderly populations. These centers consistently carry substantially higher burdens than the others, while centers such as 22, 24, 23, 15, and 7 handle relatively low and stable loads. This pattern indicates a structural imbalance in demand, suggesting that the high-load centers function as primary hubs and will require greater resource allocation and operational support to maintain effective delivery service.

In scenarios A2 and B2, it is clearly demonstrated that the model can effectively respond to the high demand of the elderly population while satisfying the condition of achieving the fastest possible transportation, by establishing locations within the areas of elderly population concentration as identified through the kernel density analysis. In Scenario A2, the relief distribution centers (RDCs) can serve up to 2,918 people, consisting of 1,218 elderly individuals and 1,700 younger population. This first scenario requires the operation of 12 RDCs (Figure 6(a)). In Scenario A2, the assistance load is highly concentrated in a few centers, particularly Centers 27, 49, and 28, which support the largest elderly and non-elderly populations and therefore function as the primary high-demand hubs. Center 27 carries the greatest burden, followed closely by Centers 49 and 28, indicating significant clustering of service needs in these areas. Centers such as 44, 43, 34, and 51 also manage moderate loads, while others including Centers 35, 41, 48, 30, and 47 handle comparatively smaller populations. In Scenario B2, the assistance load is concentrated in several key centers, with Centers 52, 28, 34, and 51 supporting the largest numbers of elderly and non-elderly individuals, making them the primary high-demand locations. Center 52 carries the heaviest burden, followed closely by Center 28, while Centers 34 and 51 handle substantial but slightly lower loads. Other centers, including 41, 26, 40, 47, 44, and 43, manage moderate populations, and Center 30 supports the smallest group. Overall, the distribution highlights an uneven allocation of service responsibilities, emphasizing the need to prioritize resources and operational capacity for the centers with the highest demand (Figure 6(b)). This situation representing an alternative RDC configuration, achieves a more equitable load balance and significant risk mitigation by reducing the maximum single-center burden as 488 individuals at RDC 28, which is a superior strategic outcome for managing large-scale disasters. While B2 offers enhanced resilience, both scenarios underscore a fundamental structural limitation requiring consistent reliance on a limited number of core RDCs, compelling planners to prioritize resource fortification and strategic redundancy in these consistently high-demand centers to ensure a flexible and effective humanitarian response.

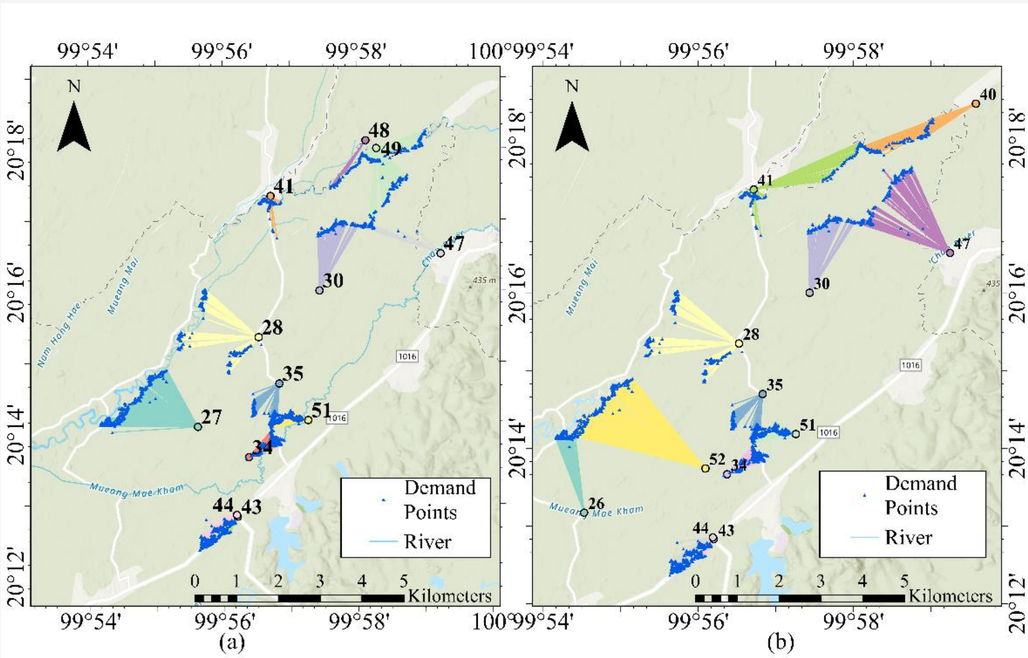

Figure 6: Relief distribution centers (RDC) coverage map scenarios: (a) A2 and (b) B2

3.3 Loading Analysis

In summary, the four scenarios (A1, A2, B1, B2) illustrate different relief strategies under varying flood levels. A1 and B1 use the seven and eight RDCs but differ in what they distribute. A1 provides food and water to 1,250 people, while B1 delivers relief bags to 498 households. This setup works well in early-stage floods when roads are still passable but may lack scalability for more severe events. In A2 and B2 (Level 2 floods), distribution expands. A2 uses 12 RDCs to serve 2,918 people with food and water, while B2 uses only 9 RDCs to serve 1,176 households with relief kits, offering broader coverage and greater efficiency. Eight RDCs are shared between A2 and B2, showing an overlap in key locations. Overall, A1/B1 suits moderate floods with quick local response. A2 handles larger operations but needs more resources, whereas B2 offers the most efficient and flexible response for severe floods (Figure 7). The analysis of service demand across the four scenarios demonstrates a significant and escalating disparity in workload distribution among Relief Distribution Centers (RDCs), across all four scenarios, the spatial distribution of assistance load exhibits a pronounced and systemic concentration in a limited subset of centers, with the top-performing centers in each scenario Centers 1, 4, and 22 in A1; Centers 8 and 5 in B1; Centers 27, 49, and 28 in A2; and Centers 52, 28, 34, and 51 in B2 accounting for the overwhelming majority of demand. Quantitatively, these high-load centers serve between 27 and 230 households, covering 92–446 elderly and 266–646 non-elderly individuals, whereas low-load centers consistently manage fewer than 60 households and under 150 elderly, highlighting a stark inequity in service allocation. Cumulatively, approximately 30–40% of centers absorb over 60% of the total assistance burden, revealing a highly skewed distribution that has critical operational implications. This imbalance underscores the imperative for scenario-specific, evidence-based resource prioritization, reinforced logistical capacity, and strategic staffing in high-demand centers, as failure to address these disparities risks service bottlenecks, compromised coverage, and inequitable assistance provision, particularly for vulnerable elderly populations.

To assess the difference in workload between the groups of distribution centers categorized as heavy load and light load we conducted both parametric and non-parametric statistical tests to ensure robustness of the results [37] and [38]. The classification of centers into heavy and light load groups was based on the upper 25th percentile and lower 25th percentile of total demand, respectively. This grouping allowed us to compare the distribution of the elderly and younger populations; each center serves under different workload scenarios. Given the sample sizes and potential differences in variance between groups, Welch's Two Sample t-test was employed to compare the mean number of elderly and younger individuals served by heavy and light load centers.

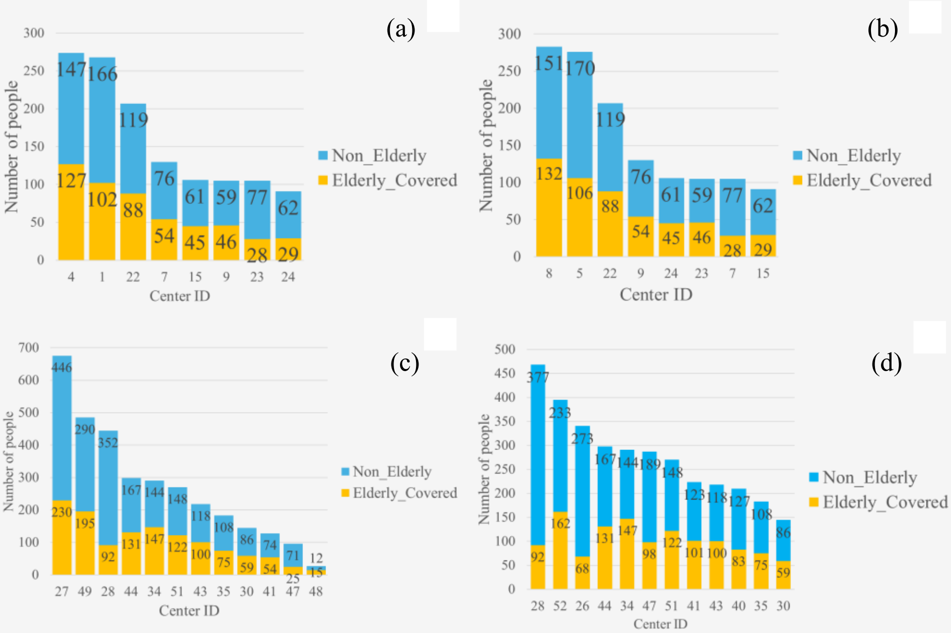

Figure 7: Comparison of workload distribution across RDCs in different scenarios: (a) A1 (b) B1 (c) A2 (d) B2

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Table 3: Statistical comparison of elderly and younger populations served by heavy and light load RDCs

Variable	Group Comparison	Test Type	Test Statistic	Degrees of Freedom	p-value	Confidence Interval	Mean Heavy Group	Mean Light Group
Elderly Count	Heavy vs Light Load	Welch two Sample t-test	7.15	9.73	3.60×10^{-5}	87.39 to 167.01	163.2	36
Elderly Count	Heavy vs Light Load	Wilcoxon rank-sum test	100	NA	1.08×10^{-5}	NA	NA	NA
Younger Count	Heavy vs Light Load	Welch two Sample t-test	6.95	9.94	4.05×10^{-5}	113.37 to 220.43	228	61.1
Younger Count	Heavy vs Light Load	Wilcoxon rank-sum test	100	NA	1.08×10^{-5}	NA	NA	NA

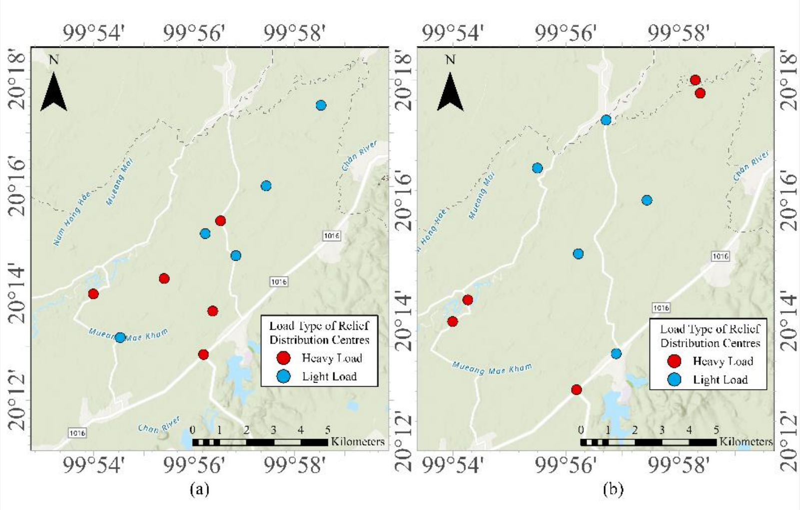

Figure 8: Load type of RDCs location for scenarios
(a) food and water, and (b) relief box

Welch's t-test is appropriate here as it does not assume equal variances between groups. To complement the parametric analysis and address any concerns regarding non-normality or outliers, we also applied the Wilcoxon rank-sum test, a non-parametric alternative that compares median differences between the groups [33] and [34] and [35]. From Table 3, the statistical analysis using Welch's two-sample t-test revealed striking differences in how many elderly individuals were served by relief centers depending on their workload classification. Centers operating under "heavy load" conditions served significantly more elderly residents than those in the "light load" category ($t(9.73) = 7.15$, $p < 0.0001$). The numbers tell a compelling story: heavy load centers averaged 163.2 elderly individuals compared to just 36.0 in light load centers. This represents a substantial difference, with the 95% confidence interval showing the true mean difference between 87.39 and 167.01 elderly individuals. To ensure the reliability of these findings, we confirmed the results using the non-parametric Wilcoxon rank-sum test ($W = 100$, $p < 0.00001$). This additional test strengthens the confidence that the observed differences between heavy and light load centers are genuine and not simply due to random variation in the data. The pattern held true when we examined younger populations as well. Heavy load centers consistently served much larger numbers of younger individuals, averaging 228.0 people compared to 61.1 in light load centers. The statistical testing confirmed this difference as highly significant (Welch's t-test: $t(9.94) = 6.95$, $p < 0.0001$), with the 95% confidence interval ranging from 113.37 to 220.43 individuals. Again, the Wilcoxon test provided additional confirmation of this finding ($W = 100$, $p < 0.00001$).

These results provide compelling evidence that centers we classified as "heavy load" face substantially greater demand from both elderly and younger populations compared to their "light load" counterparts. The consistency of the findings across both parametric and non-parametric statistical tests gives us confidence in concluding that these workload differences are statistically significant and practically meaningful for emergency planning purposes. By using both types of statistical tests, we gain a more complete and robust understanding of the

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true differences in service demands between these two types of relief centers. The spatial distribution of heavy and light load centers across all scenarios (A1, A2, B1, B2) is visualized in Figure 8. This map reveals a consistent pattern: most heavy-load centers are clustered in areas with high elderly population density. This concentration appears to be a direct consequence of the PSO algorithm's objective to prioritize proximity to elderly residents. As a result, relief centers in these zones are frequently selected and tasked with serving disproportionately higher numbers of people, especially elderly individuals across all flood scenarios.

4. Conclusion

This study presents a data-driven framework that integrates geoinformatics and Particle Swarm Optimization (PSO) to address the Location-Allocation problem of flood relief distribution with a specific focus on elderly populations. By incorporating household-level demographic data and spatial clustering of elderly residents, the framework identifies optimal Relief Distribution Center (RDC) locations under multiple flood scenarios, ensuring that vulnerable groups are explicitly prioritized in disaster logistics planning. The findings reveal a significant imbalance in service workloads, where a small number of RDCs consistently bear a disproportionate share of relief demand, particularly for elderly households. This highlights a critical operational challenge in flood response and emphasizes the need for scenario-based resource prioritization, reinforced logistical capacity, and strategic staffing at high-demand centers to prevent service bottlenecks and ensure equitable assistance delivery.

Despite its contributions, the study has several important limitations. The model assumes static population distributions and consistent infrastructure accessibility throughout the disaster, which does not fully reflect evacuation dynamics, temporary relocation, or rapidly changing road conditions. In addition, reliance on flood extent maps and census-based demographic data introduces uncertainty, as outdated or low-resolution spatial data can affect the accuracy of demand estimation and the identification of safe RDC locations. The optimization process also does not incorporate real-time system feedback or dynamic load balancing, potentially limiting responsiveness under evolving flood conditions. Furthermore, the absence of comparative performance evaluation against benchmark algorithms constrains the assessment of PSO's relative efficiency and solution quality.

Future research should therefore move toward dynamic and adaptive allocation models that integrate real-time environmental data, updated population information, and accessibility monitoring. Incorporating participatory inputs from local communities and conducting comparative analyses with alternative optimization techniques would further enhance the robustness, equity, and operational relevance of Location-Allocation models for disaster response.

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