International Journal of Engineering and Geosciences
https://dergipark.org.tr/en/pub/ijeg
e-ISSN 2548-0960

Multi-dimensional optimization of nuclear emergency shelters: balancing capacity, evacuation efficiency, and supply accessibility

Maryna Batur *1, **Reha Metin Alkan** 2, **Himmet Karaman** 3, **Haluk Ozener** 4

1 Istanbul Technical University, Graduate School, Turkiye, baturm20@itu.edu.tr
2 Istanbul Technical University, Department of Geomatics Engineering, Turkiye, alkanr@itu.edu.tr
3 Istanbul Technical University, Department of Geomatics Engineering, Turkiye, karamanhi@itu.edu.tr
4 Bogazici University, Kandilli Observatory and Earthquake Research Institute, Department of Geodesy, Turkiye, ozener@bogazici.edu.tr

Cite this study: Batur, M., Alkan, R. M., Karaman, H., Ozener, H. (2025). Multi-dimensional optimization of nuclear emergency shelters: balancing capacity, evacuation efficiency, and supply accessibility. International Journal of Engineering and Geosciences, 10 (2), 244-261.

https://doi.org/10.26833/ijeg.1596244

Keywords
Nuclear Emergency
Road Network Analysis
Shelter Optimization
Evacuation Time
Urban Evacuation
GIS

Research/Review Article

Received:04.12.2024
Revised: 02.01.2025
Accepted:17.01.2025
Published:01.07.2025

Abstract

Effective shelter location-allocation is critical in nuclear emergencies to ensure rapid, safe evacuation and resource access for affected populations. This study presents a multi-dimensional optimization model for shelter allocation within humanitarian logistics, balancing evacuation time, supply accessibility, and shelter capacity. Using Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA), the model optimizes trade-offs among competing objectives. The first objective minimizes evacuation time, the second ensures adequate supply access, and the third prevents shelter overcrowding. Validated through k-fold cross-validation, the model reveals spatial biases: evacuees often cluster in nearby shelters, leading to overcrowding in dense areas and underuse in others. This analysis suggests adding flexible shelters in high-density zones to enhance response efficiency. Overall, the research supports more balanced shelter allocations in nuclear emergencies, improving both immediate and long-term disaster response strategies for affected populations.

1. Introduction

Nuclear Power Plant (NPP) accidents, though rare, can have catastrophic consequences for human life, infrastructure, and the environment. The Chernobyl (1986) and Fukushima Daiichi (2011) disasters, both of which led to the evacuation of hundreds of thousands of residents, underscore the critical importance of well-coordinated evacuation plans and sheltering strategies to minimize radiation exposure [1]. These disasters serve as stark reminders of the logistical complexities inherent in such emergencies and the need for effective planning.

The Chernobyl disaster in the then-Soviet Union (now Ukraine) resulted in release of vast amounts of radioactive material into the atmosphere, making it one of the worst nuclear accidents in history. This accident posed significant challenges in managing the evacuation and sheltering of thousands of people. Many residents were dispersed across multiple regions, often far from their homes, which made it difficult to maintain community cohesion and provide consistent support services. The scale of the disaster exposed severe weaknesses in evacuation and shelter planning, particularly in terms of resource allocation and long-term displacement management [2].

Similarly, the Fukushima Daiichi nuclear disaster, triggered by a massive earthquake and tsunami, led to release of radioactive materials and forced the evacuation of more than 150,000 people. Despite Japan's advanced infrastructure, the evacuation process was fraught with logistical challenges. In the immediate aftermath, many evacuees were housed in schools and community centers, which quickly became overcrowded, forcing people to stay in poor conditions. Furthermore, the rapid evacuation overwhelmed local resources, leading to shortages of essential supplies like food, water, and medical care, particularly in rural areas where supply chains were already weak. These issues further highlighted the challenges of coordinating emergency sheltering and resource distribution in a nuclear crisis [3].

In nuclear emergency situations, the timely evacuation and safe sheltering of affected populations are crucial to protect against radiation exposure and minimize health risks. Nuclear emergency shelters serve as critical, temporary refuges during such events, reducing the risk of acute radiation sickness and long-term health effects, such as cancer. These shelters are typically reinforced structures with controlled ventilation systems to prevent the infiltration of radioactive particles and are equipped with essential resources like food, water, and medical supplies to support evacuees over extended periods. However, effective shelter planning involves more than immediate protection – it requires careful consideration of multiple objectives, including minimizing evacuation time, ensuring efficient and continuous access to supplies, and preventing overcrowding, which can compromise safety, comfort, and access to resources [4]. To achieve this balance, shelters should be positioned close to population centers for quick access, strategically located near supply routes to streamline resource distribution, and sized appropriately to avoid overcrowding [5]. These objectives often conflict, as the most accessible shelters may not align with optimal supply routes or have sufficient capacity for large populations. Addressing these challenges requires a multi-dimensional optimization approach, integrating methodologies like Multi-Criteria Decision Analysis (MCDA), to evaluate trade-offs and prioritize objectives. This approach allows decision-makers to identify optimal shelter locations that enhance disaster resilience by providing both immediate safety and sustained support for affected populations.

This study addresses the multi-dimensional optimization challenges for nuclear emergency shelters, focusing on minimizing evacuation time, ensuring efficient supply access, and avoiding overcrowding. The novelty of our research lies in the integration of the above mentioned multiple critical aspects for nuclear emergency shelter planning that are rarely combined in existing studies. Here are the key points that highlight its unique contributions:

(1) Multi-dimensional optimization with practical constraints: While many studies focus on single objectives (e.g., minimizing evacuation time or maximizing shelter capacity), our research addresses a multi-dimensional optimization problem that balances evacuation time, supply access, and overcrowding prevention. The incorporation of real-world constraints like road networks, population density, and proximity to supply depots adds practicality to the model, making it more applicable to real-life emergency planning.

(2) GIS and MCDA integration: By combining Geographic Information Systems (GIS) with MCDA, the research goes beyond traditional optimization. This integration enables a spatially-informed, data-driven evaluation of shelter locations, which can dynamically accommodate changes in population and infrastructure, enhancing adaptability and robustness in shelter planning.

(3) Scalability for future planning: The methodology we propose is designed to be scalable, meaning it can be adapted for future nuclear emergencies in different regions. This scalability addresses a critical gap, as most existing studies focus on fixed or region-specific parameters without accounting for adaptability to future needs or varying scenarios.

(4) Comprehensive approach to immediate and long-term needs: By simultaneously addressing immediate evacuation logistics and long-term shelter needs (such as supply chain management and preventing overcrowding), this research contributes a more holistic view of nuclear disaster response. This dual focus ensures that evacuees' needs are met not only during the evacuation but throughout their stay, enhancing resilience in disaster response systems.

(5) Evaluation of trade-offs for optimal decision-making: Our model identifies optimal trade-offs between competing objectives, which is crucial for decision-makers who often have to prioritize conflicting goals under time constraints. This trade-off analysis provides actionable insights that can inform strategic planning and resource allocation, leading to more effective and balanced disaster response strategies.

2. Literature review

We considered three elements in the literature review: (1) nuclear evacuation planning, (2) shelter optimization, and (3) the integration of supply chain logistics.

2.1. Nuclear evacuation planning

Since the Chernobyl and Fukushima disasters, nuclear evacuation planning has been an area of extensive research, with much of the focus on radiological risk assessment and the development of predictive models for radioactive dispersion following an accident [6-8]. A key approach in this field involves atmospheric dispersion models, such as the Gaussian Plume Model [8], which is widely used to predict the spread of radioactive contaminants in the atmosphere. Based on these predictions, authorities delineate evacuation zones, typically within a 30 km radius of the nuclear site, to protect populations at the highest risk of exposure [10].

As research on nuclear evacuation planning has progressed, it has increasingly addressed the practical challenges of evacuating large populations during emergencies. [11] conducted a detailed exploration of strategies aimed at minimizing evacuation time during nuclear disasters. Their work highlighted the importance of traffic modeling to assess road capacity, potential bottlenecks, and travel times, particularly in densely populated urban areas where evacuation logistics are especially complex. Building on this, [12] introduced a cohort-based model for estimating evacuation times, which can significantly reduce the overall evacuation process. Other studies have evaluated specific factors affecting evacuation times, such as trip generation timing [13], road clearance time [14], and the impact of manual traffic controls [15].

Incorporating GIS has proven to be an essential advancement in nuclear evacuation planning. GIS technology allows researchers and emergency planners to simulate a variety of evacuation scenarios, model potential routes, identify choke points, and optimize evacuation strategies to reduce travel times and avoid congestion [16]. [17] demonstrated the effectiveness of GIS-based network simulations in improving evacuation planning. Similarly, [18] showed that by modeling different traffic patterns and route alternatives, authorities could better manage evacuation efforts, ensuring populations are moved away from danger zones as efficiently as possible. Moreover, the integration of GIS with agent-based models has further enhanced the ability to address complex evacuation challenges [19-20].

In addition to simulation technologies, recent research has underscored the importance of real-time data in optimizing nuclear evacuation plans. [21] proposed a dynamic path optimization algorithm that improves evacuation networks by adapting to evolving conditions. Similarly, [22] focused on solving dynamic optimization problems to reduce overall evacuation times, demonstrating the value of real-time data in enhancing evacuation efficiency.

Alongside these technological advancements, the social and behavioral aspects of nuclear evacuation have also gained increasing attention. Studies have shown that public response to evacuation orders is not always immediate or consistent, with individuals often delaying due to uncertainty, disbelief, or reluctance to leave their homes and possessions behind [23-24]. This highlights the need for effective communication strategies and public education campaigns to support nuclear emergency planning [1]. By ensuring the public understands the risks and rationale behind evacuation procedures, authorities can improve compliance and cooperation, leading to more successful evacuation efforts during a nuclear emergency.

2.2. Shelter location-allocation optimization

Shelter location modeling methods can be broadly categorized into three main approaches: GIS-based spatial analysis models, exact algorithms, and approximation algorithms [25-26]. Among these, GIS-based models are often faster and easier to implement for location-allocation problems compared to other methods. These models rely on key variables such as the destination points of evacuees, demand points (e.g., households, populations, or settlements), and the road network [27]. GIS-based location-allocation models are further classified into three groups: single-objective models, multi-objective models, and hierarchical models [26].

Single-objective models focus on solving the location problem with one primary objective. For example, the P-median problem aims to minimize the maximum distance between demand points and shelter locations, helping to find the optimal placement of shelters [28]. Another well-known model, the maximal covering location problem, seeks to maximize the coverage of demand points by shelters within a specified distance or time, known as the impedance cutoff value [29]. This value defines the maximum distance or time within which evacuees can access a shelter. These models are relatively straightforward and useful when a single optimization goal, such as minimizing distance, is paramount.

To address more complex scenarios, multi-objective models have been developed. These models incorporate multiple objectives into the decision-making process [30]. For example, [31] developed a multi-objective model with the goals of maximizing population coverage while minimizing traffic costs. [32] and [33] focused on maximizing coverage of affected areas while minimizing human suffering. [28] proposed a multi-objective urban shelter location model that combining the maximum coverage and P-median models to address the diverse needs of urban shelter planning.

Hierarchical models, on the other hand, involve different levels of decision-making, with each level containing either a single or multiple objective. These models are particularly useful when decisions need to be coordinated across various organizational levels or when complex factors like population density, shelter capacity, and accessibility must be considered simultaneously [26].

Exact algorithms, commonly used for shelter placement, often address multiple objectives such as minimizing travel time, maximizing coverage, and ensuring equitable access to shelters. For instance, [34] developed an exact mixed-integer linear programming (MILP) model that optimized shelter locations under demand uncertainty. The model proposed by [35] also included capacity constraints to ensure shelters were not overburdened during large-scale evacuations, illustrating the precision and utility of exact algorithms for solving these complex problems.

However, as the scale of evacuation scenarios increases, the computational demands of exact algorithms become a challenge. In response, approximation algorithms have gained prominence, offering near-optimal solutions more quickly. For instance, [36] introduced a greedy approximation algorithm for shelter location optimization that balanced shelter proximity to population centers with capacity limits, providing a feasible solution in a fraction of the time required by exact methods. Similarly, [37] used particle swarm optimization (PSO) to reduce evacuation times while considering road network constraints, highlighting the effectiveness of approximation algorithms in solving large-scale, complex evacuation problems efficiently.

2.3. Supply chain logistics in emergency management

Humanitarian logistics plays a crucial role in disaster management by ensuring the evacuation of victims from affected areas to safe locations and facilitating the timely planning, storage, and distribution of relief supplies [38]. The primary goal of these efforts is to deliver aid to disaster victims at the right time, in the right place, and at an optimal cost [39]. To achieve this, numerous studies have proposed various optimization models aimed at enhancing the efficiency and effectiveness of humanitarian logistics. These models focus on key logistical operations, including the management of shelters, medical centers, warehouses, and distribution hubs [40]. Most of the models developed in these studies incorporate essential data, such as the locations of affected areas and potential facilities, the number of victims, relief supply requirements, and the availability of resources. A significant portion of the research has centered on single-objective optimization models that seek to improve either monetary or non-monetary outcomes [41]. For instance, [42] developed a model aimed at minimizing the number of shelters, which was solved using an Exact Algorithm. Similarly, [43] proposed a model that focuses on minimizing the total cost of shelter location-allocation, which was solved using a Genetic Algorithm. Other studies, such as that by [44], aimed to maximize decision-makers' satisfaction by employing Weighted Goal Programming.

While single-objective models have been common, multi-objective models, especially those that consider both monetary and non-monetary criteria, have been less prevalent. Most of the multi-objective models proposed tend to focus solely on non-monetary criteria. Examples include the works of [45] and [46], which prioritize factors such as service coverage and response times.

However, a growing number of studies have started integrating both monetary and non-monetary objectives into their optimization models, recognizing the importance of balancing cost efficiency with timely and effective disaster response. Research by [33, 47-48] among others, has demonstrated the potential of multi-objective approaches in improving overall logistics performance. These studies frequently employ weight-assigning methods such as Weighted Goal Programming (WGP) and the Weighted Sum Method (WSM) to address the multi-objective nature of humanitarian logistics.

Unlike natural disasters, nuclear disasters often require evacuees to remain in shelters for extended periods, possibly weeks or even months, due to the dangers posed by radiation [2]. As a result, shelters must be equipped not only for short-term emergencies but also for prolonged stays. This necessitates thorough planning to ensure that shelters can be continuously resupplied with food, water, medical supplies, and other essential items. A significant limitation in many existing shelter location optimization studies is the lack of focus on logistical concerns, such as resupply chains and the availability of services over time. The ability to sustain long-term shelter operations is crucial for maintaining the health and safety of evacuees, especially in large-scale nuclear disasters where external support may be delayed or restricted.

2.4. Discussions on literature review

The review of literature highlights significant advancements in nuclear evacuation planning, shelter location optimization, and supply chain logistics, particularly through the use of models that enhance the efficiency of disaster response. However, a notable research gap remains in integrating logistical concerns for prolonged shelter operations, especially in nuclear disaster scenarios. While many studies focus on optimizing shelter locations and minimizing evacuation times, few address the complexities of maintaining long-term operations in shelters where evacuees may need to remain for extended periods, such as in the aftermath of nuclear disasters.

Most shelter optimization models prioritize short-term objectives, like minimizing travel distances or maximizing coverage, but fail to account for the critical issue of shelter overcrowding, which can compromise safety and comfort during prolonged stays. This lack of integration between shelter location optimization and the management of population capacity poses a significant gap, particularly in scenarios where evacuees may need to stay for extended periods. Therefore, our research focuses on developing a model that accounts for both immediate evacuation logistics and the prevention of overcrowding, ensuring the well-being of evacuees throughout their stay.

3. Methodology

3.1. Model formulation and study framework

The proposed methodology in this study, illustrated in Figure 1, involves three key steps: (1) collection and preparation of input data, (2) model formulation, and (3) optimization process.

In the first step, raw data is gathered, including information about the road network, shelter and depot locations, population distribution, and shelter capacities. Using GIS network tools, two crucial analyses are performed: the calculation of the evacuation time matrix and the supply-access matrix. The evacuation time matrix represents the time required for residents to evacuate to various shelters, while the supply-access matrix measures the time needed for suppliers to reach each shelter. Both matrices serve as input data for the subsequent analysis. The second step involves the formulation of objective functions, aligned with the study's goals, which are combined into a weighted sum to balance the different objectives. In our study, we determined the weights by assigning logical priority to each objective based on the critical demands of a nuclear emergency. Recognizing that rapid evacuation is paramount, we assigned the highest weight of 0.40 to minimizing evacuation time. Although supply access and overcrowding are also essential considerations, we allocated them lower, yet meaningful, weights of 0.30 each. This weighting reflects our prioritization of quick evacuation, while still addressing the importance of timely supply delivery and preventing shelter

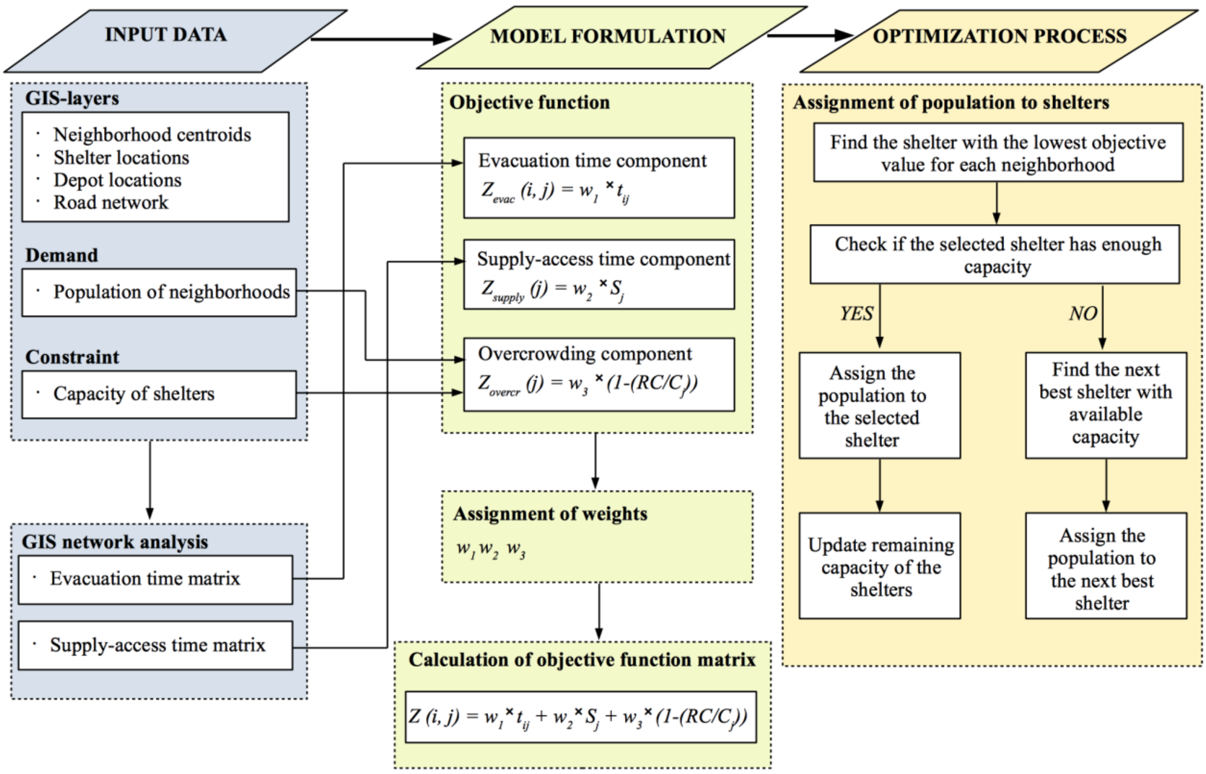


Figure 1. Flowchart of the proposed methodology.

overcrowding. The optimization process, as outlined in the final step, consists of four stages: (1) Populations are initially assigned to shelters based on the lowest objective function values; (2) Shelter capacity is checked to ensure it can accommodate the assigned population; (3) Shelter capacities are updated based on the number of evacuees; and (4) If a shelter is full, the remaining population is reassigned to the next available shelter.

The following sections provide a detailed explanation of the research methodology employed in this study.

3.2. Weighted sum method

The Weighted Sum Method (WSM) is a widely used decision-making technique in MCDA [49]. It allows for the evaluation and comparison of various alternatives based on multiple criteria, each assigned a specific level of importance through weights. When applied to a nuclear emergency scenario, WSM can help optimize three critical objectives: minimizing evacuation time, minimizing the time required to access supplies, and avoiding the overcrowding of shelters. In this context, the four key criteria are: evacuation time, the population of each neighborhood, the capacity of each shelter, and the supply access time.

The first objective is the minimization of evacuation time, where the evacuation time for residents of neighborhood *i* to shelter *j*, denoted as t_{ij}, is minimized. This component is weighted by w_1, representing the importance of evacuation time in the overall objective function (Eq. 1):

$$Z_{evac}(i,j) = w_1 \times t_{ij} \qquad \text{Eq. 1}$$

The second objective focuses on minimizing the supply accessibility time. The supply access time from a depot to shelter *j*, denoted as s_j, is minimized. This component is weighted by w_2, reflecting the relative importance of supply accessibility in the optimization (Eq. 2):

$$Z_{supply}(j) = w_2 \times s_j \qquad \text{Eq. 2}$$

To avoid shelter overcrowding, the model introduces a constraint based on the remaining capacity of each shelter. The remaining capacity of shelter *j* after population assignment is calculated as (Eq. 3):

$$remaining\_capacity_j = C_j - \sum_{i=1}^{m} A(i,j) \qquad \text{Eq. 3}$$

where C_j is the capacity of shelter *j*, and *A (i, j)* represent the assignment of population from neighborhood *i* to shelter *j*. The assignment *A (i, j)* is defined as (Eq. 4):

$$A(i,j) = \begin{cases} P_i, & if\ neighborhood\ i\ is\ assigned\ to\ shelter\ j \\ 0, & otherwise \end{cases} \qquad \text{Eq. 4}$$

where P_i is the population of neighborhood *i*. The penalty for overcrowding is captured through the term $\left(1 - \left(remaining\_capacity_j / C_j\right)\right)$, which is weighted by w_3, representing the importance of avoiding overcrowding.

The total objective function, *Z (i, j)*, for each neighborhood *i* and shelter *j*, is a weighted sum of the above components (Eq. 5):

$$Z(i,j) = w_1 \times t_{ij} + w_2 \times s_i + w_3 \times \left(1 - \frac{remaining\_capacity_j}{C_j}\right) \quad \text{Eq. 5}$$

where w_1, w_2, and w_3 are the weights corresponding to evacuation time, supply accessibility, and overcrowding, respectively.

The optimization problem is subject to two key constraints: capacity constraint and population assignment constraint, which are defined by the expressions (Eq. 6) – (Eq. 7).

The total population assigned to a shelter must not exceed its capacity:

$$\sum_{i=1}^{m} A(i,j) \leq C_j \quad \forall_j \quad \text{Eq. 6}$$

Each neighborhood must be assigned to exactly one shelter:

$$\sum_{i=1}^{n} A(i,j) = P_i \quad \forall_i \quad \text{Eq. 7}$$

The goal of the model is to minimize the total objective function across all neighborhoods and shelters, taking into account the weighted contributions of evacuation time, supply accessibility time, and overcrowding prevention (Eq. 8):

$$min \sum_{i=1}^{m} \sum_{j=1}^{n} Z(i,j) \times A(i,j) \quad \text{Eq. 8}$$

where *A (i, j)* is the decision variable indicating whether neighborhood *i* is assigned to shelter *j*.

By using the WSM, the optimization model finds a balance between minimizing evacuation time, minimizing supply accessibility time, and preventing shelter overcrowding. This approach ensures that shelters are utilized effectively while considering key criteria and respecting their capacities, providing a robust decision-making framework for emergency response planning in nuclear disaster scenarios.

3.3. Origin-Destination Cost Matrix analysis

Origin-Destination (OD) Cost Matrix analysis is a method used in emergency planning to evaluate the travel costs, typically in terms of time or distance, between multiple origin points (e.g., population centers) and destination points (e.g., shelters, hospitals) [50]. In the context of a nuclear emergency, this analysis helps identify the most efficient evacuation routes and estimate the time required to move people from affected areas to safer locations. The core formula for calculating travel time between an origin and a destination is as follows (Eq. 9):

$$T_{ij} = \frac{D_{ij}}{V_{avg}} \quad \text{Eq. 9}$$

where T_{ij} is the total travel time from origin *i* to destination *j*; D_{ij} is the distance between the origin and the destination; and V_{avg} is the average speed of travel (adjusted for road conditions), often derived from evacuation time estimates models (km/h).

Once the travel costs are calculated for each origin-destination pair, they can be organized into a matrix format. This matrix helps planners visualize and compare travel times for different routes, enabling better decision-making during an evacuation. The matrix is structures as follows (Table 1):

Table 1. OD cost matrix

Destination / Origin	D_1	D_2	D_3	…
O_1	T_{11}	T_{12}	T_{13}	…
O_2	T_{21}	T_{22}	T_{23}	…
O_3	T_{31}	T_{32}	T_{33}	…
…	…	…	…	…

where O_1, O_2, … represent the origins; D_1, D_2, … represent the destinations; and T_{ij} represent the travel cost (time) from origin O_i to destination D_j.

3.4. Evacuation time estimates

Evacuation Time Estimates (ETE) during a nuclear emergency depend on several key factors, such as the time it takes for people to mobilize, load vehicles, travel, and account for road conditions [51]. These elements can be combined into a total formula that represents the overall evacuation time (Eq. 10):

$$T_{evac} = T_{mob} + T_{load} + T_{travel} + T_{clear} \quad \text{Eq. 10}$$

where T_{mob} represents the time, it takes for the population to start evacuating; T_{load} is the time required for people to prepare for and load into vehicles; T_{travel} is the time taken to reach a safe area; and T_{clear} accounts for the time needed to clear the road during evacuation, including any delays caused by congestions or obstacles.

Mobilization time refers to the period between the issuance of an evacuation order and when people begin to act on it. This can be influenced by the population's preparedness, reaction speed, and the efficiency of the communication system in place. For practical purposes, mobilization time is often estimated as a constant based on prior emergency response data or pre-determined planning assumptions.

Loading time represents the time required for evacuees to prepare for evacuation and get into vehicles. This includes gathering belongings, organizing family members, and getting into cars. Like mobilization time, loading time is scenario-dependent and can vary but is often treated as a constant for simplicity in modeling evacuation scenarios.

Travel time represents the time required to drive from the evacuation starting point to a designated safe location. It depends on the distance, average speed, and any delays due to traffic congestion. Travel time can be calculated using the following equation (Eq. 11):

$$T_{travel} = \frac{D_{safe}}{V_{avg}} + T_{congestion} \quad \text{Eq. 11}$$

where D_{safe} is the distance to a safe location (km); V_{avg} is the average speed of travel, which considers the road conditions (km/h); and $T_{congestion}$ is the additional time due to traffic congestion, which increases as more people evacuate simultaneously.

Road clearness time accounts for delays caused by bottlenecks, obstacles, or other factors that slow the evacuation process. This can be modeled using flow rate equations that depend on the number of vehicles to be evacuated and the capacity of the evacuation routes. Road clearness time is given by (Eq. 12 – Eq. 14):

$$T_{clear} = \frac{N_v}{Q} \quad \text{Eq. 12}$$

$$N_v = \frac{N_p}{occupancy} \quad \text{Eq. 13}$$

$$Q = C \times L \quad \text{Eq. 14}$$

where N_v is the total number of vehicles to be evacuated with N_p being the total population and "occupancy" representing the average number of people per vehicle; Q is the flow rate of the road (vehicles per hour), determined by the road capacity C (vehicles per hour per lane) and the number of lanes L available for evacuation.

By combining all these components, the evacuation time estimate provides a comprehensive approach to evaluating how long an evacuation will take during a nuclear emergency, allowing for better preparedness and planning.

3.5. K-fold cross-validation

K-fold cross-validation is a statistical method used to evaluate the model's performance by dividing the dataset into k subsets (folds). Mathematically, the dataset $D = \{x_1, x_2, \dots, x_n\}$ is randomly partitioned into k approximately equal-sized subsets: $D_1, D_2, \dots D_k$. For each fold i, the model is trained on the data $D \backslash D_i$ (all data except fold i) and validated on the holdout set D_i [52].

The error for each fold i, denoted as L_i, is computed based on the model's performance on the validation set. The overall performance of the model is then calculated as the average of the objective values across all folds (Eq. 15):

$$L_{avg} = \frac{1}{k}\sum_{i=1}^{k} L_i \quad \text{Eq. 15}$$

This ensures that every data point is used for both training and validation, leading to a more generalized estimate of the model's performance. Additionally, the variance of the model's performance across folds can be calculated to assess its stability (Eq. 16):

$$\sigma^2 = \frac{1}{k}\sum_{i=1}^{k}\left(L_i - L_{avg}\right)^2 \quad \text{Eq. 16}$$

where σ^2 is the variance, L_i is the error for fold i, and L_{avg} is the mean error across all folds. This variance measures the consistency of the models' performance across different subsets of the data.

4. Case study

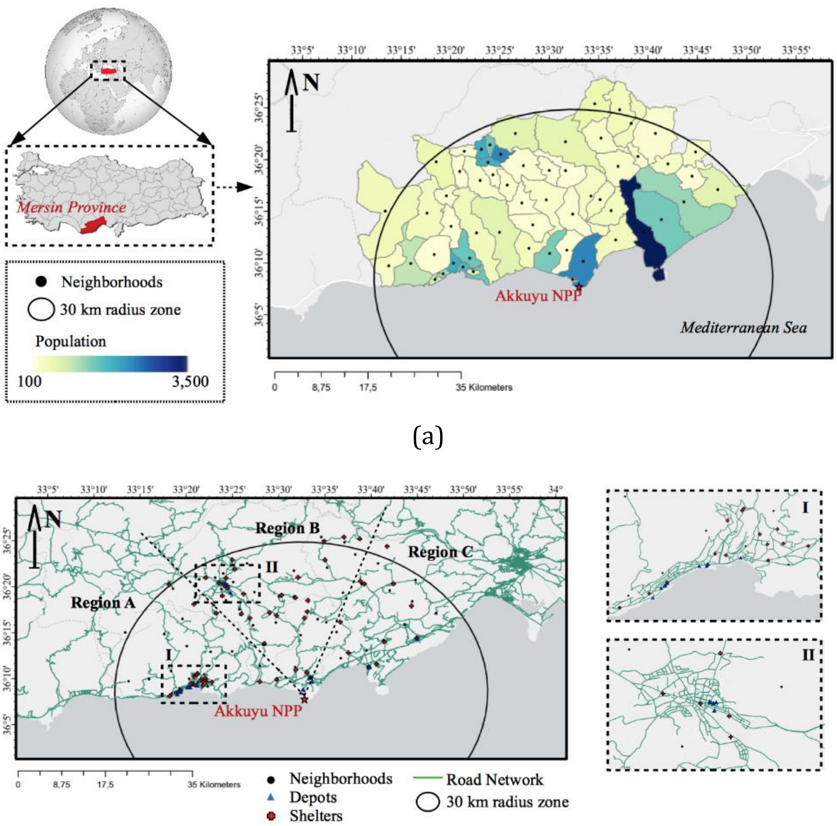
4.1. Study area and data sources

The study focuses on the Akkuyu Nuclear Power Plant (NPP), located in Mersin Province, Turkey, along the Mediterranean coast. As Turkey's first NPP, Akkuyu serves as a critical energy source for the region [53]. However, its proximity to densely populated areas underscores the need for comprehensive emergency preparedness, particularly in terms of efficient evacuation and shelter strategies in the event of a nuclear accident [54]. Moreover, Mersin is rich in agriculture, with fertile lands that play a vital role in regional food production and economic stability. Protecting this region from the impacts of a potential nuclear accident is crusial to safeguard its agricultural resources and environmental sustainability [55, 56].

A key area of concern is the 30-kilometer radius around the NPP, designated as the Emergency Planning Zone (EPZ). This zone is highly vulnerable to radioactive contamination in the event of an accident due to meteorological conditions such as frequent rainfall, which can accelerate the deposition of radioactive particles onto the ground [57]. The EPZ includes diverse communities, ranging from densely populated urban centers to sparsely populated rural districts. In total, the zone encompasses 56 neighborhoods with a combined population of approximately 38,000 people. Figure 2a illustrates the study area, highlighting the varying population across these communities. To mitigate potential risks in the EPZ, a network of [59] shelters and 25 depots has been established (Figure 2b). These shelters were selected from existing buildings, each meeting the requirement of having a wall thickness of at least 0.7 meters, which is essential for substantially reducing gamma radiation exposure during an emergency. Notably, most shelters and depots are concentrated in the southern part of the EPZ, where population density is highest, further emphasizing the importance of precise evacuation and resource distribution planning.

In Turkey, including Mersin Province, roads are classified into several categories based on their function and traffic capacity. Table 2 provides an overview of the main road types considered in this study. The classification of roads, ranging from state roads to local and urban roads, helps to inform evacuation routes and supply delivery strategies, particularly in areas where road capacity and speed limits vary significantly [58].

To enhance the accuracy and effectiveness of the multi-dimensional optimization process, the study area was divided into three distinct regions (Figure 2b). This division was based on several critical factors, including geographical and population diversity, evacuation and supply logistics, and shelter capacity management. The population is distributed relatively evenly across the three regions, with 32% residing in regions A and C each, and the remaining 36% in region B.



(a)

(b)

Figure 2. Study area: (a) Population within the 30 km radius zone (EPZ); (b) Location of shelters, depots, and neighborhoods' centroids, as well as road network

Table 2. Road description [59].

Type of road	Typical lane capacity (vehicles per hour per lane)	Speed limit (km per hour) for cars
State roads	1,800 – 2,200	90
Provincial roads	1,200 – 1,800	90
Local roads	500 – 1,000	50-90*
Highways	2,000 – 2,500	120
Urban roads	800 – 1,500	50

*Depending on the specific location and road conditions

Segmenting the EPZ allows the model to account for the unique characteristics of each region. For example, different areas of the EPZ have distinct road networks, infrastructure constraints, and shelter capacities. By analyzing smaller, more manageable segments, the model ensures that shelters in each sub-region are used efficiently, thereby reducing the risk of overcrowding. This approach also allows for more targeted optimization of evacuation times and supply delivery routes, avoiding the pitfalls of applying a uniform solution across a diverse and complex study area.

4.2. Results and analysis

4.2.1. OD analysis for evacuation route planning

Figure 3 illustrates the results of an OD Cost Matrix analysis, aimed at evaluating evacuation routes between residential neighborhoods and emergency shelters. The evacuation times were computed as outlined in Section 3.4, based on the road network and calculated for three-time thresholds: 75 minutes, 90 minutes, and 115 minutes. The dashed black lines represent the possible evacuation routes from each neighborhood to one or more shelters. While these lines are depicted as straight connections, they reflect real-time evacuation routes, accounting for the road network's curves and travel constraints.

The results demonstrate that the density and complexity of these routes increase as the time threshold is extended, allowing more feasible evacuation paths to emerge. In the 75-minute scenario, fewer routes are visible, meaning only neighborhoods in close proximity to shelters are accessible within this time frame. As the threshold increases to 90 and 115 minutes, a greater number of shelters become reachable, as indicated by the increasingly dense network of connections.

4.2.2. OD analysis of supply-access routes for emergency shelters

The results presented in Figure 4 illustrate an independent analysis of supply-access routes for shelters across three distinct regions. The analysis evaluates the availability of depots and their geographical distribution in relation to the shelters. In each of the graphs, the red dots represent supply depots, which serve as the starting points for emergency supply distribution, while the blue dots represent emergency shelters, the end points where

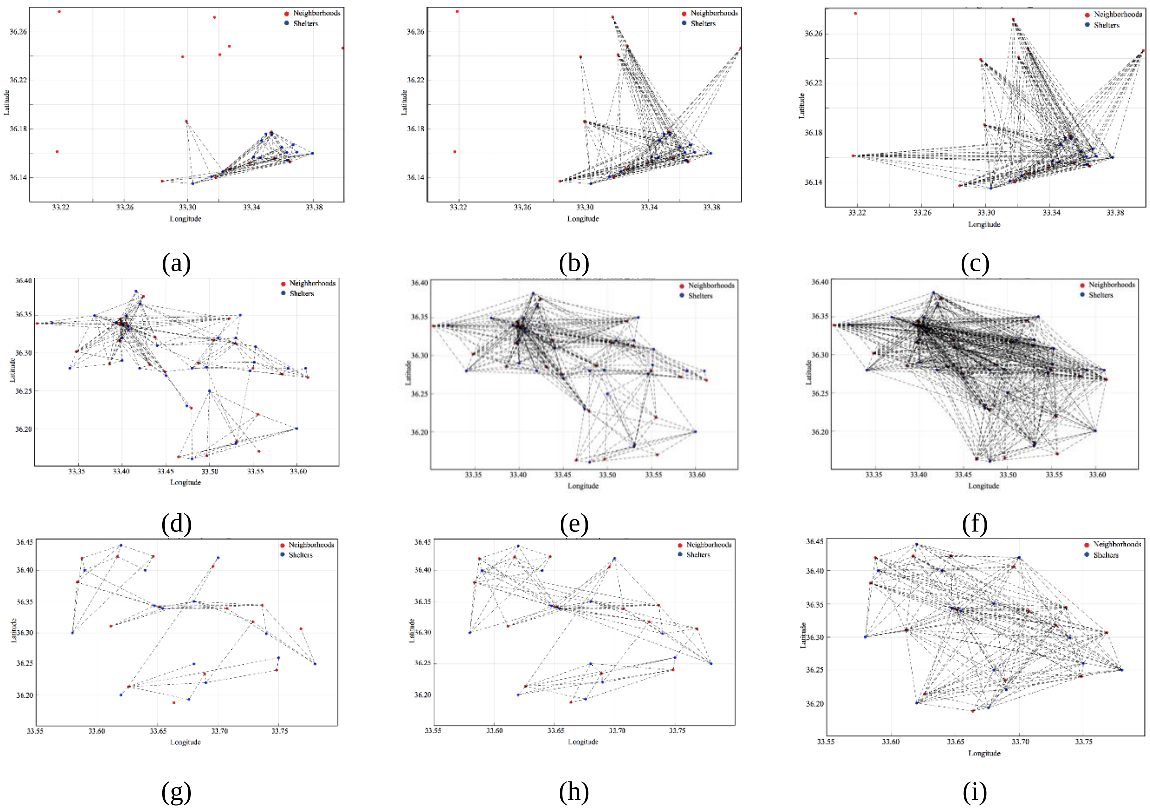


Figure 3. OD analysis of evacuation routes to emergency shelters: (a), (b), (c) Evacuation routes for Region A – thresholds 75 min, 90 min, and 115 min, respectively; (d), (e), (f) Evacuation routes for Region B – thresholds 75 min, 90 min, and 115 min, respectively; (g), (h), (i) Evacuation routes for Region C – thresholds 75 min, 90 min, and 115 min, respectively.

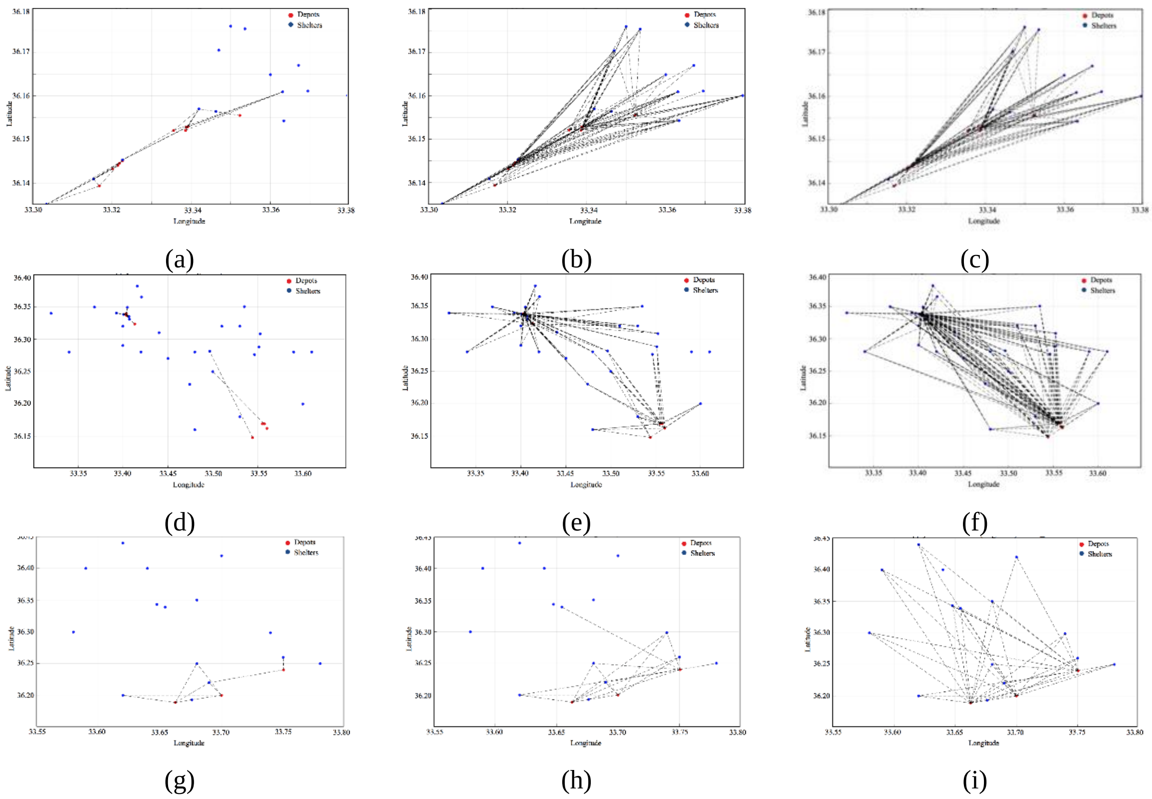


Figure 4. OD analysis of supply-access routes to emergency shelters: (a), (b), (c) Supply-access routes for Region A – thresholds 5 min, 15 min, and 20 min, respectively; (d), (e), (f) Supply-access routes for Region B – thresholds 5 min, 50 min, and 90 min, respectively; (g), (h), (i) Supply-access routes for Region C – thresholds 15 min, 50 min, and 90 min, respectively.

supplies must be delivered to support evacuees. The black lines connecting depots to shelters indicate the potential routes supplies may take. Similar to an OD analysis described in Section 4.2.1., these routes are evaluated based on factors such as distance, travel time, and potential road conditions during a nuclear emergency.

4.2.2. OD analysis of supply-access routes for emergency shelters

The results presented in Figure 4 illustrate an independent analysis of supply-access routes for shelters across three distinct regions. The analysis evaluates the availability of depots and their geographical distribution in relation to the shelters. In each of the graphs, the red dots represent supply depots, which serve as the starting points for emergency supply distribution, while the blue dots represent emergency shelters, the end points where supplies must be delivered to support evacuees. The black lines connecting depots to shelters indicate the potential routes supplies may take. Similar to an OD analysis described in Section 4.2.1., these routes are evaluated based on factors such as distance, travel time, and potential road conditions during a nuclear emergency.

The graphs depict varying levels of accessibility to shelters based on different time thresholds: 5, 15, and 20 minutes for Region A; 5, 50, and 90 minutes for Region B; and 15, 50, and 90 minutes for Region C. These time thresholds were selected based on the minimum, average, and maximum travel times from each depot to the shelters within the respective region. For instance, in Region A, the minimum, average, and maximum travel times were 5, 15, and 20 minutes, respectively, so there was no need to use extended thresholds (such as 90 minutes) in this case.

In Region A (Figure 4a, 4b, and 4c), there are 14 shelters and 12 depots. The results show that nearly all shelters can be reached by at least one depot within 15 to 20 minutes. This indicates a well-distributed network of depots, which ensures that most shelters can be supplied efficiently, provided there are no significant roadblocks or other disruptions.

Moving to Region B (Figure 4d, 4e, and 4f), there are 10 depots available for a total of 30 shelters. The analysis shows that shelters located further from depots experience significant delays in receiving supplies. This suggests the need for additional depots in remote areas or the optimization of transportation routes to minimize travel times and improve supply access.

Finally, in Region C (Figure 4g, 4h, and 4i), there are 3 depots and 15 shelters. Similar to Region B, the results indicate that the geographical distribution of depots is insufficient, and their remoteness from the shelters makes it challenging to achieve adequate supply access within the 15-minute window. In this case, the analysis highlights the importance of addressing logistical challenges, either by increasing the number of depots or developing alternative strategies to expedite supply distribution.

4.2.3. Optimization process

The optimization results for shelter allocation are presented in Figure 5, showing the population assignment across different regions. The map illustrates how residents from various neighborhoods are assigned to specific shelters.

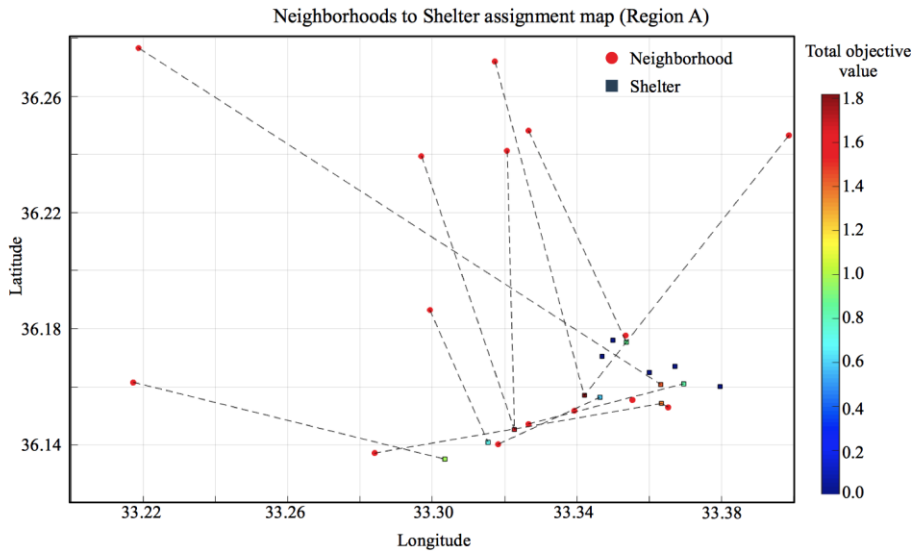
In Region A (Figure 5a), several neighborhoods have been assigned to only a few shelters, while others remain unallocated. Notably, neighborhoods 1, 3, and 6 are allocated to shelter S4, with total population assignments of 1,016, 1,231, and 604, respectively. In contrast, many other neighborhoods and shelters remain unused, suggesting that the optimization process led to a concentrated use of certain shelters. This uneven distribution is likely driven by the proximity of these neighborhoods to shelters that minimize evacuation time, the highest-priority objective in the model.

In Region B (Figure 5b), the results indicate substantial unused capacity in several shelters. For instance, shelter S2, with a capacity of 1,500, remains largely unutilized, while shelters S3 and S4 are almost at capacity, with only 17 and 14 remaining spaces, respectively. This points to an uneven distribution of evacuees across shelters, with some nearing full capacity while others remain underused. Despite this, shelter S5 emerges as the most optimal choice, with an objective value of 0.52, due to its favorable balance of short evacuation routes, proximity to resources, and minimal overcrowding. In contrast, shelters like S1 (objective value 0.796) and S16 (1.568) have higher objective values, indicating either longer evacuation times, higher congestion, or less accessible resources compared to the optimal shelter S5.

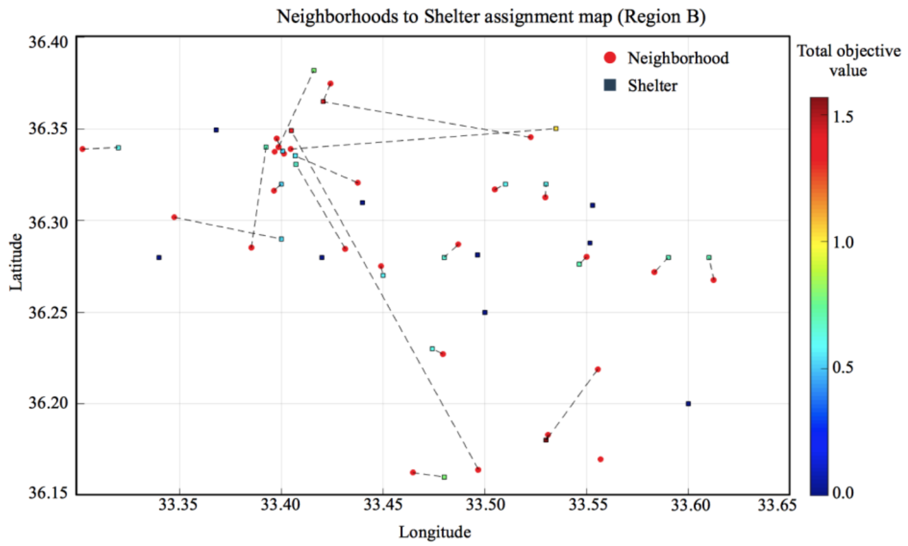
In Region C (Figure 5c), the population assignment shows a similar pattern, with some shelters heavily utilized and others underpopulated. Shelters S2 (1,532), S3 (1,268), and S5 (634) are assigned a large portion of the population, while shelters like S1, S6, and S7 are significantly underutilized. The remaining capacities of these shelters further highlight the uneven distribution, with some shelters, such as S12, having only 3 remaining spaces, while others, like S2, have 1,968 available spaces. The total objective values for shelters in Region C range from 0.580 to 1.834, with shelter S1 emerging as the optimal choice with the lowest objective value of 0.58. This suggests that shelter S1 is well-positioned in terms of evacuation time, resource access, and crowd control, despite its low utilization. Shelters S4 and S5, with higher objective values of 1.834 and 1.824, respectively, indicate inefficiencies in evacuation routes or overcrowding at these locations.

Figure 6 illustrates the population assignments and the remaining capacities of shelters.

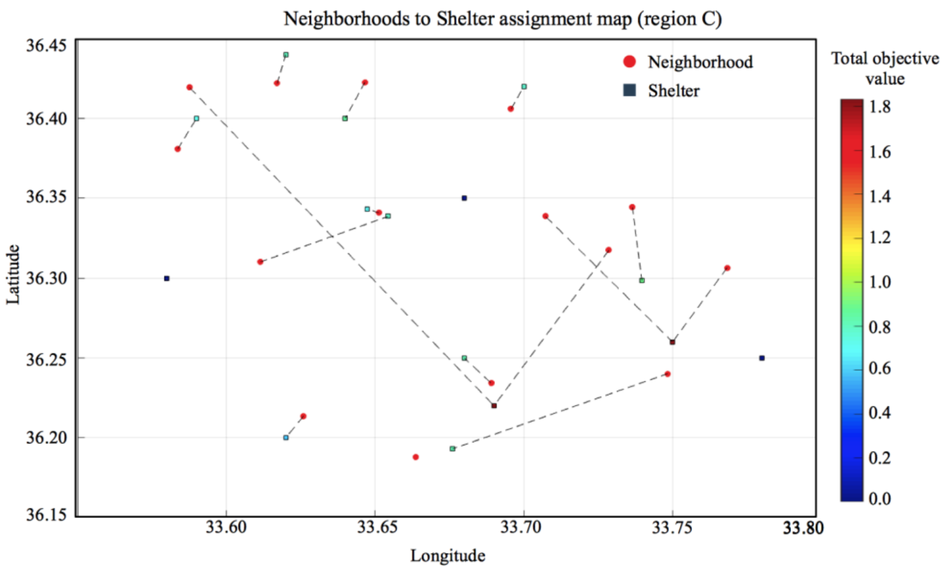
The fact that not all shelters were utilized in the population assignment process can be explained by several factors related to the objectives of the optimization model and the constraints of the study. The primary objective – minimizing evacuation time – leads to the assignment of evacuees to shelters closer to their neighborhoods, inherently reducing evacuation time.



(a)

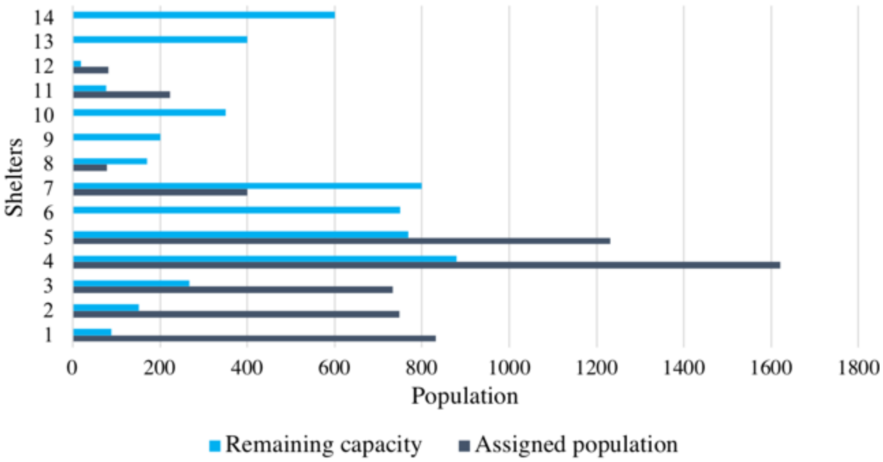


(b)

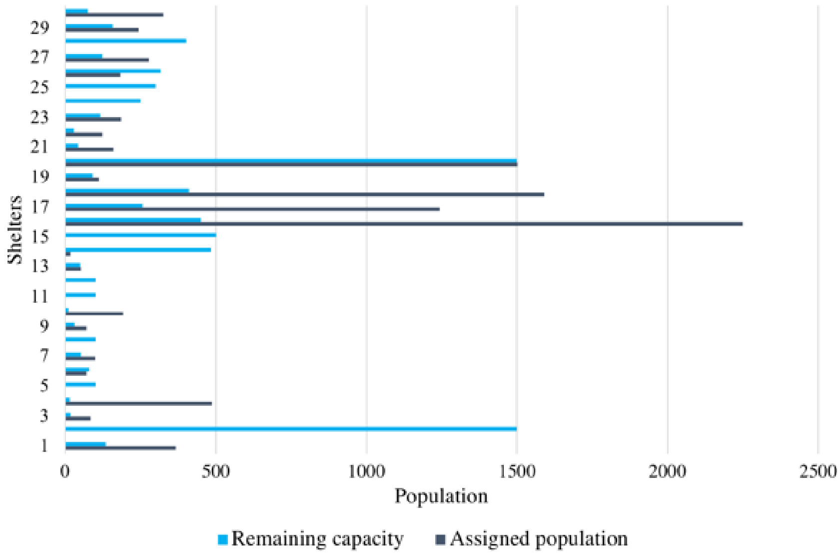


(c)

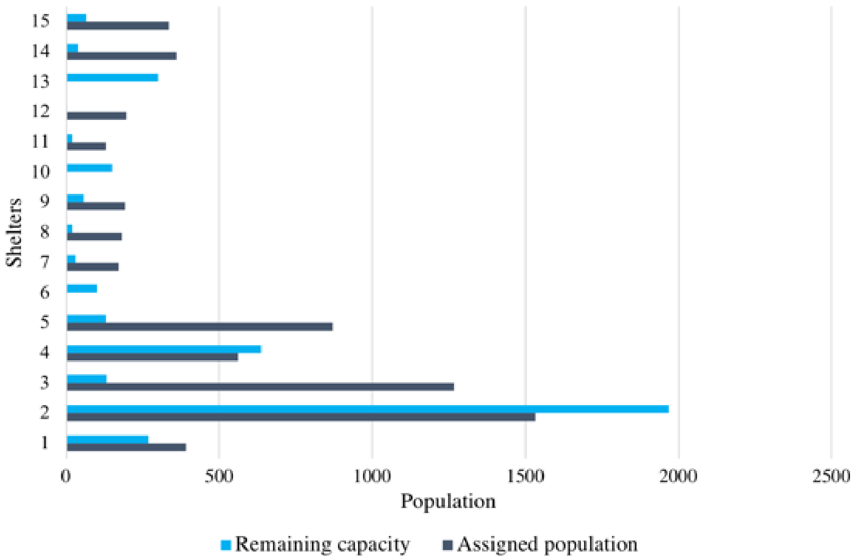
Figure 5. Neighborhoods to shelter assignment map with shelter ranking: (a) Region A; (b) Region B; (c) Region C.



(a)



(b)



(c)

Figure 6. Population assignment and remaining capacity in shelters: (a) Region A; (b) Region B; (c) Region C.

Consequently, shelters located farther from population centers may remain unused, despite having available capacity, as they do not contribute to minimizing evacuation time as effectively as others. Additionally, the optimization process incorporates capacity constraints, ensuring that no shelter becomes overcrowded. If a shelter's capacity is fully utilized by nearby neighborhoods, it cannot accommodate more evacuees, even if it is geographically close to other population centers. This constraint further limits the number of shelters actively used in the population assignment.

The geographic distribution of shelters also plays a role. The southern part of the study area, where population density is higher, contains a greater concentration of shelters. Conversely, areas with lower population density have fewer shelters, and those shelters may not be filled to capacity due to the smaller population in need of evacuation. This uneven population and shelter distribution results in the underutilization of some shelters, particularly in less densely populated areas.

While minimizing evacuation time is the primary goal, other factors, such as supply access time and overcrowding prevention, are also considered. The selected shelters represent a balance between these objectives. Some shelters, despite being available, may not significantly improve the overall objective score and are therefore left unused in the optimization process. This outcome highlights the complex trade-offs in optimizing shelter allocation during an emergency evacuation, where proximity, capacity, and resource accessibility must all be balanced.

4.2.4. Model assessment

In this study, we employed k-fold cross-validation to evaluate the performance of our neighborhood-to-shelter assignment model. Specifically, we conducted a 3-fold cross-validation, where the dataset was randomly divided into three equal subsets. In each iteration, two subsets were used for training, while the remaining subset served as the validation set. This process was repeated three times, ensuring that each subset was used as the validation set exactly once. The final model performance was determined by averaging the objective function values across all subsets, providing a robust estimate of the model's effectiveness and reducing the risk of overfitting. The results for each region are presented in Figure 7.

For Region A, the mean objective value across the 3 folds is 4.14, with a standard deviation of 0.35. This indicates that, on average, the model achieves an objective score of 4.14 during validation. The standard deviation of 0.35 suggests a moderate level of variability in the model's performance across different folds. While a lower standard deviation would imply greater consistency, this value shows that the model's performance is reasonably stable across the different data subsets.

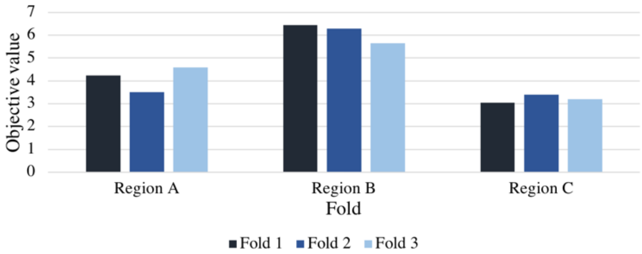


Figure 7. Objective value across folds.

In contrast, for Region B, the mean objective value is 6.22, with a standard deviation of 0.46. The higher mean objective value indicates that the model performs worse compared to Region A, as lower objective values are typically preferred in optimization tasks. Additionally, the larger standard deviation of 0.46 reflects higher variability in the model's performance across the folds, suggesting less stability in this region compared to the others.

For Region C, the model performs the best, with a mean objective value of 3.20 and a standard deviation of 0.30. The lower mean objective value shows that the model achieves the lowest error or cost in the optimization task for this region. Furthermore, the smaller standard deviation of 0.30 suggests that the model's performance is the most consistent across the different data folds, with the least variability among the three regions.

In summary, Region C shows the best overall performance, followed by Region A, while Region B demonstrates the highest error and variability.

4.2.5. Sensitivity analysis

Sensitivity analysis is a systematic approach used to evaluate how changes in input parameters influence the outcomes of a model [60]. By varying key variables within defined ranges, this analysis helps identify which parameters have the most significant impact on the results. it is widely applied in decision-making, optimization, and risk assessment to ensure the robustness and reliability of models. Sensitivity analysis provides critical insights into the trade-offs and interdependencies among variables, enabling informed adjustments to improve performance and achieve desired objectives under varying conditions.

Figure 8 illustrates a sensitivity analysis of a multi-dimensional optimization problem involving three weighted criteria: evacuation time (α), supply-access time (β), and overcrowding prevention (γ). The horizontal axis represents the weight assigned to evacuation time (α), while the vertical axis shows the corresponding total objective value. The plot includes annotations identifying the weights for supply-access time (β) and overcrowding prevention (γ) for each point. This analysis reveals how varying weight combinations influence the total objective value, highlighting the trade-offs among the criteria. For instance, increasing α generally corresponds to higher total objective values, which indicates a prioritization of minimizing evacuation time. Conversely, higher weights for β and γ lead to lower

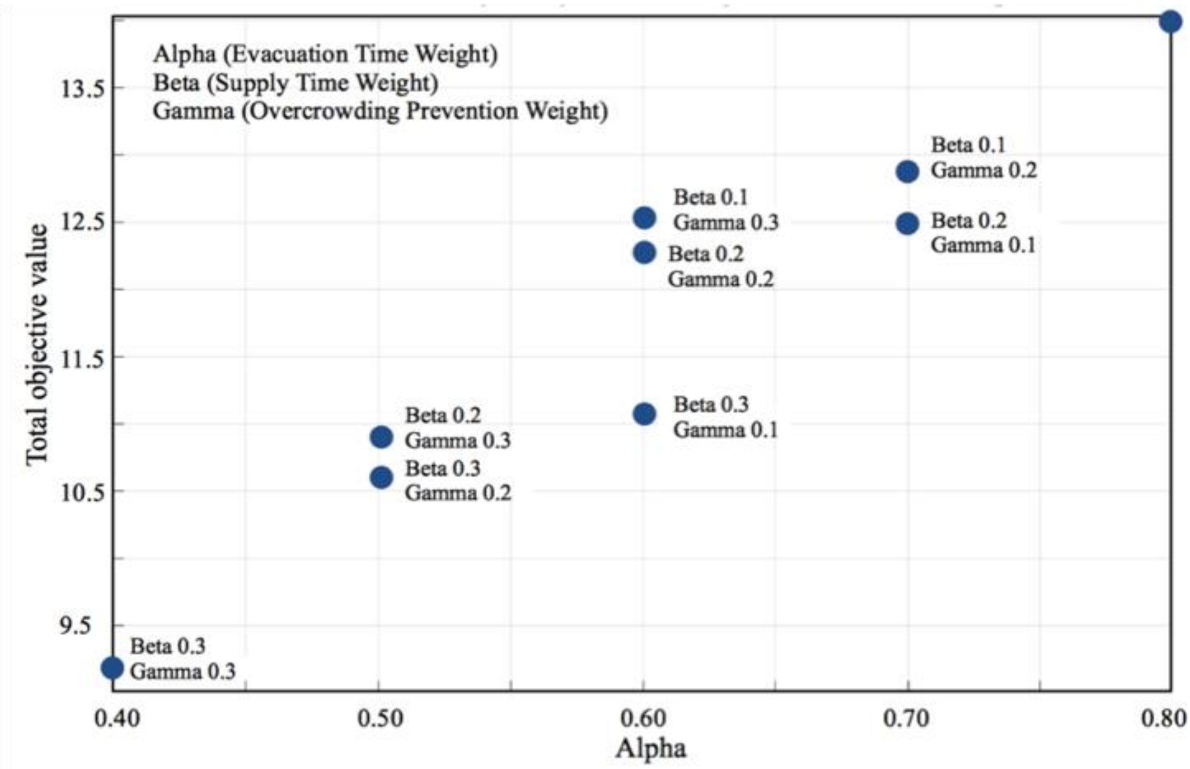


Figure 8. Sensitivity analysis: total objective value vs. weights.

total objective values, underscoring their impact on overall optimization. The clustering of points shows interdependencies between weights and the overall performance of the solution.

In conclusion, the sensitivity analysis provided a comprehensive understanding of how variations in the weights assigned to evacuation time, supply-access time, and overcrowding prevention influenced the total objective value of the model. By systematically evaluating the trade-offs and interdependencies among these criteria, the analysis highlighted the optimal balance necessary to achieve the most effective outcomes. Consequently, the weights in the model were selected based on these results, ensuring a well-informed and robust decision-making process tailored to the specific priorities and constraints of the scenario.

5. Discussions

The optimization results for shelter allocation in this study reveal important insights into the challenges and trade-offs involved in emergency evacuation planning, particularly in a nuclear emergency scenario. The analysis of population assignments across different regions demonstrates that while the optimization process effectively minimized evacuation time, it also led to an uneven distribution of evacuees and shelter utilization. These results underscore the complexities of balancing multiple objectives (evacuation time, shelter capacity, and supply access time) within the constraints of a real-world scenario.

In Region A, the results show that neighborhoods 1, 3, and 6 were heavily assigned to shelter S4, while many other shelters and neighborhoods remained underutilized. This concentration can be attributed to the proximity of these neighborhoods to shelter S4, which minimized evacuation time, the highest-priority objective in the model. However, the underutilization of other shelters suggests that geographic location and proximity play a dominant role in the optimization process, potentially leading to congestion in a few shelters while others go unused.

Similarly, in Region B, shelters such as S2 had significant unused capacity, while others like S3 and S4 were almost at full capacity. Shelter S5 emerged as the most optimal due to its proximity and accessibility, with a low objective value of 0.52. In contrast, shelters like S1 and S16 had higher objective values, reflecting longer evacuation times or less accessible resources. These findings suggest that, although the optimization process effectively minimizes evacuation time, it may benefit from additional constraints or adjustments to ensure a more even distribution of evacuees across shelters.

Region C exhibits the same trends, with some shelters (S2, S3, and S5) being heavily utilized while others, like S1, S6, and S7, remain underpopulated. This highlights the same geographic bias in shelter selection observed in Regions A and B, where shelters minimizing travel time are favored, potentially leading to inefficient resource utilization. Shelter S1 in Region C, with the lowest objective value (0.58), was well-positioned to balance evacuation time, supply access, and crowd control, but the high values of shelters like S4 and S5 point to similar inefficiencies seen across all regions.

The underutilization of many shelters can be explained by several factors inherent to the optimization model. The primary objective (minimizing evacuation time) drives the assignment of evacuees to the closest shelters. As a result, shelters located farther from population centers, even if they have available capacity, may remain unused. This tendency to prioritize proximity over capacity leads to the concentration of evacuees in certain shelters and the underuse of others. While this approach is efficient from an evacuation time perspective, it raises concerns about resource utilization and the potential for overcrowding in the most optimal shelters.

The geographic distribution of shelters is another key factor influencing the optimization results. The southern part of the study area, where population density is higher, contains a greater concentration of shelters. In contrast, areas with lower population density have fewer shelters, and those shelters may not be filled to capacity due to the smaller population in need of evacuation. This geographic disparity leads to the underutilization of shelters in less populated areas and the concentration of evacuees in more densely populated regions. This uneven distribution highlights the need for a more balanced approach to shelter placement and utilization, particularly in areas with varying population densities. In densely populated regions, additional shelters may be necessary to prevent overcrowding and ensure that evacuees have sufficient access to resources. In less populated areas, flexible or mobile shelters could be deployed to supplement existing resources and ensure that all evacuees have access to safe, well-equipped shelters.

The findings of this study have important implications for emergency planning, particularly in scenarios involving nuclear accidents or other large-scale disasters. While proximity and evacuation time are critical factors in determining shelter assignment, the results suggest that additional constraints or criteria may be needed to ensure more balanced utilization of shelter resources. Incorporating dynamic factors, such as real-time traffic conditions or shelter occupancy levels, could help refine the optimization process and ensure that all available shelters are used effectively. Moreover, the geographic distribution of shelters should be reconsidered to address disparities in population density and resource availability. In densely populated areas, additional shelters or enhanced capacity may be required to prevent overcrowding, while in less populated areas, flexible or mobile shelters could be deployed to ensure comprehensive coverage.

6. Conclusion

This study provides a comprehensive analysis of the multi-dimensional optimization challenges involved in nuclear emergency shelter allocation, focusing on minimizing evacuation time, ensuring efficient supply access, and preventing overcrowding. By integrating GIS and MCDA, we evaluated existing shelter locations to identify trade-offs between these competing objectives. The results demonstrate the complexities inherent in emergency evacuation planning, particularly in balancing proximity, capacity, and supply accessibility.

The findings reveal a strong geographic bias in shelter allocation, with evacuees being concentrated in shelters that minimize evacuation time, often leading to the underutilization of other available shelters. This trend was observed across all regions in the study, where certain shelters were heavily utilized while others remained underpopulated. The primary objective of minimizing evacuation time, while crucial, often overshadowed other considerations such as shelter capacity and even distribution, resulting in inefficiencies in resource utilization.

These insights underscore the need for a more balanced approach to shelter allocation, particularly in areas with high population density. The current geographic distribution of shelters, coupled with the focus on proximity, highlights the importance of re-evaluating shelter locations and incorporating additional constraints to prevent overcrowding. In densely populated regions, the provision of additional shelters or enhanced capacities may be necessary, while in less populated areas, flexible or mobile shelters could be deployed to ensure comprehensive coverage and effective use of resources.

Future models could benefit from incorporating dynamic factors such as real-time traffic conditions, shelter occupancy rates, and updated supply accessibility data to refine the optimization process. Additionally, the results suggest that a more flexible, scenario-based approach to shelter allocation may be needed to adapt to varying population densities and resource availability. Overall, the findings of this study contribute to the ongoing discourse on optimizing disaster response strategies and provide actionable insights for future nuclear emergency planning.

Acknowledgment
This research was conducted as part of the first author's Ph.D. study at Istanbul Technical University, Istanbul, Turkiye.

Author contributions

Maryna Batur (Ph.D. Candidate): Conceptualization, methodology, software and analysis, writing-original draft. **Reha Metin Alkan (Prof. Dr.):** Data curation, supervision, verification of results, writing-review and editing. **Himmet Karaman (Prof. Dr.):** Data curation, resources and data acquisition, verification of results, writing-review and editing. **Haluk Ozener (Prof. Dr.):** Final verification, review, and editing.

Conflict of interest

The authors declare no conflict of interest. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Ohba, T., Tanigawa, K., Liutsko, L. (2021). Evacuation after a nuclear accident: Critical reviews of past nuclear accidents and proposal for future planning. Environment international, (148), 106379. https://doi.org/10.1016/j.envint.2021.106379
2. Batur, M., Alkan, R. M. (2023). What can we learn from past nuclear accidents? A comparative assessment of emergency response to accidents at the Three Mile

Island, Chernobyl, and Fukushima Nuclear Power Plants. Advanced Land Management, 3(2), 76-89. https://publish.mersin.edu.tr/index.php/alm/article/view/1075

3. Hasegawa, A., Ohira, T., Maeda, M., Yasumura, S., Tanigawa, K. (2016). Emergency responses and health consequences after the Fukushima accident; evacuation and relocation. Clinical Oncology, 28(4), 237-244. https://doi.org/10.1016/j.clon.2016.01.002
4. Oka, Y. (2022). Risks and benefits of evacuation in TEPCO's Fukushima Daiichi nuclear power station accident. Progress in Nuclear Energy, 148, 104222. https://doi.org/10.1016/j.pnucene.2022.104222
5. Sarı, S. & Türk, T. (2021). An investigation of urban development with geographical information systems: 100-year change of Sivas City, Turkey. International Journal of Engineering and Geosciences, 6(1), 51-63.
6. Sohrabi, M., Ghasemi, M., Amrollahi, R., Khamooshi, C., Parsouzi, Z. (2013). Assessment of environmental public exposure from a hypothetical nuclear accident for Unit-1 Bushehr nuclear power plant. Radiation and environmental biophysics, 52, 235-244. https://doi.org/10.1007/s00411-013-0456-y
7. Zhu, Y., Guo, J., Nie, C., Zhou, Y. (2014). Simulation and dose analysis of a hypothetical accident in Sanmen nuclear power plant. Annals of Nuclear Energy, 65, 207-213. https://doi.org/10.1016/j.anucene.2013.11.016
8. Ramana, M. V., Nayyar, A. H., Schoeppner, M. (2016). Nuclear High-level Waste Tank Explosions: Potential Causes and Impacts of a Hypothetical Accident at India's Kalpakkam Reprocessing Plant. Science & Global Security, 24(3), 174-203. https://doi.org/10.1080/08929882.2016.1237661
9. Batur, M., Alkan, R. M., Karaman, H., Ozener, H. (2024). Recommendations for Protective Actions Based on Projected Public Health Risks Following a Postulated Nuclear Power Plant Accident. Malaysian Journal of Fundamental and Applied Sciences, 20(4), 923-938. https://doi.org/10.11113/mjfas.v20n4.3561
10. Mohammed Saeed, I. M., Saleh, M. A. M., Hashim, S., Hama, Y. M. S., Hamza, K., Al-Shatri, S. H. (2020). The radiological assessment, hazard evaluation, and spatial distribution for a hypothetical nuclear power plant accident at Baiji potential site. Environmental Sciences Europe, 32, 1-12. https://doi.org/10.1186/s12302-020-0288-8
11. Murray-Tuite, P., Wolshon, B. (2013). Evacuation transportation modeling: An overview of research, development, and practice. Transportation Research Part C: Emerging Technologies, 27, 25-45. https://doi.org/10.1016/j.trc.2012.11.005
12. Park, S., Sohn, S., Jae, M. (2021). Cohort-based evacuation time estimation using TSIS-CORSIM. Nuclear Engineering and Technology, 53(6), 1979-1990. https://doi.org/10.1016/j.net.2020.11.028
13. Herrera, N., Smith, T., Parr, S. A., Wolshon, B. (2019). Effect of trip generation time on evacuation time estimates. Transportation research record, 2673(11), 101-113. https://doi.org/10.1177/0361198119850793
14. Hsu, Y. T., Peeta, S. (2015). Clearance time estimation for incorporating evacuation risk in routing strategies for evacuation operations. Networks and Spatial Economics, 15, 743-764. https://doi.org/10.1007/s11067-013-9195-5
15. Parr, S. A., Herrera, N., Wolshon, B., Smith, T. (2020). Effect of manual traffic control on evacuation time estimates. Transportation research record, 2674(9), 809-819. https://doi.org/10.1177/0361198120932165
16. Howard, E. E., Pasquini, L., Arbib, C., Di Marco, A., Clementini, E. (2021). Definition of an Enriched GIS Network for Evacuation Planning. In GISTAM, 241-252. https://doi.org/10.5220/0010452302410252
17. Manfré, L. A., Cruz, B. B., Quintanilha, J. A. (2020). Urban settlements and road network analysis on the surrounding area of the Almirante Alvaro Alberto Nuclear Complex, Angra dos Reis, Brazil. Applied spatial analysis and policy, 13, 209-221. https://doi.org/10.1007/s12061-019-09299-2
18. Hasnat, M. M., Islam, M. R., Hadiuzzaman, M. (2018). Emergency response during disastrous situation in densely populated urban areas: a gis based approach. Geographia Technica, 13(2), https://doi.org/10.21163/GT_2018.132.06
19. Maqbool, A., Usmani, Z., Afzal, F., Razia, A. (2020). Disaster mitigation in Urban Pakistan using agent based modeling with GIS. ISPRS International Journal of Geo-Information, 9(4), 203. https://doi.org/10.3390/ijgi9040203
20. Hwang, Y., Heo, G. (2021). Development of a radiological emergency evacuation model using agent-based modeling. Nuclear Engineering and Technology, 53(7), 2195-2206. https://doi.org/10.1016/j.net.2021.01.007
21. Zhang, H., Zhao, Q., Cheng, Z., Liu, L., Su, Y. (2021). Dynamic path optimization with real-time information for emergency evacuation. Mathematical Problems in Engineering, 2021(1), 3017607. https://doi.org/10.1155/2021/3017607
22. Zeng, M. H., Wang, M., Chen, Y., Yang, Z. (2021). Dynamic evacuation optimization model based on conflict-eliminating cell transmission and split delivery vehicle routing. Safety science, 137, 105166. https://doi.org/10.1016/j.ssci.2021.105166
23. Turcanu, C., Sala, R., Perko, T., Abelshausen, B., Oltra, C., Tomkiv, Y., Zeleznik, N. (2021). How would citizens react to official advice in a nuclear emergency? Insights from research in three European countries. Journal of Contingencies and Crisis Management, 29(2), 143-169. https://doi.org/10.1111/1468-5973.12327
24. Fei, L., Chunhua, C., Fang, R., Yuan, C., Jingxian, Z., Jianye, W. (2023). Influence of human factors on emergency evacuation efficiency of nuclear power plant accident. Journal of Radiation Research and Radiation Processing, 41(4), 40602. 10.11889/j.1000-3436.2022-0128
25. Ma, Y., Xu, W., Qin, L., Zhao, X. (2019). Site selection models in natural disaster shelters: A review. Sustainability, 11(2), 399. https://doi.org/10.3390/su11020399

26. Şentürk, E. & Erener, A. (2017). Determination of temporary shelter areas in natural disasters by gis: A case study, Gölcük/Turkey. International Journal of Engineering and Geosciences, 2(3), 84-90.
27. Wigati, S. S., Sopha, B. M., Asih, A. M. S., Sutanta, H. (2023). Geographic information system based suitable temporary shelter location for Mount Merapi eruption. Sustainability, 15(3), 2073. https://doi.org/10.3390/su15032073
28. Bera, S., Gnyawali, K., Dahal, K., Melo, R., Li-Juan, M., Guru, B., Ramana, G. V. (2023). Assessment of shelter location-allocation for multi-hazard emergency evacuation. International Journal of Disaster Risk Reduction, 84, 103435. https://doi.org/10.1016/j.ijdrr.2022.103435
29. Ozkan, B., Mete, S., Çelik, E., Özceylan, E. (2019). GIS-based maximum covering location model in times of disasters: the case of tunceli. Beykoz Akademi Dergisi, 100-111. https://doi.org/10.14514/BYK.m.26515393.2019.sp/100-111
30. Sotelo-Salas, C., Monardes-Concha, C. A., Perez-Galarce, F., Santa Gonzales, R. (2024). A multi-objective optimization model for planning emergency shelters after a tsunami. Socio-Economic Planning Sciences, 93, 101909. https://doi.org/10.1016/j.seps.2024.101909
31. Zhang, P., Zhang, H., Guo, D. (2015, November). Evacuation shelter and route selection based on multi-objective optimization approach. In Proceedings of the 1st ACM SIGSPATIAL International Workshop on the Use of GIS in Emergency Management, 1-5. https://doi.org/10.1145/2835596.2835598
32. Hallak, J., Koyuncu, M., Miç, P. (2019). Determining shelter locations in conflict areas by multiobjective modeling: A case study in northern Syria. International journal of disaster risk reduction, 38, 101202. https://doi.org/10.1016/j.ijdrr.2019.101202
33. Perez-Galarce, F., Canales, L. J., Vergara, C., Candia-Vejar, A. (2017). An optimization model for the location of disaster refuges. Socio-Economic Planning Sciences, 59, 56-66. https://doi.org/10.1016/j.seps.2016.12.001
34. Kınay, O. B., Kara, B. Y., Saldanha-da-Gama, F., Correia, I. (2018). Modeling the shelter site location problem using chance constraints: A case study for Istanbul. European Journal of Operational Research, 270(1), 132-145. https://doi.org/10.1016/j.ejor.2018.03.006
35. Eriskin, L., Karatas, M. (2022). Applying robust optimization to the shelter location–allocation problem: a case study for Istanbul. Annals of Operations Research, 339, 1589-1635. https://doi.org/10.1007/s10479-022-04627-1
36. Gu, J., Zhou, Y., Das, A., Moon, I., Lee, G. M. (2018). Medical relief shelter location problem with patient severity under a limited relief budget. Computers & Industrial Engineering, 125, 720-728. https://doi.org/10.1016/j.cie.2018.03.027
37. Zhu, J., Li, W., Li, H., Wu, Q., Zhang, L. (2017). A novel swarm intelligence algorithm for the evacuation routing optimization problem. Computational complexity, 1(1), 2.
38. Salam, M. A., Khan, S. A. (2020). Lessons from the humanitarian disaster logistics management: A case study of the earthquake in Haiti. Benchmarking: An International Journal, 27(4), 1455-1473. https://doi.org/10.1108/BIJ-04-2019-0165
39. Caunhye, A. M., Nie, X., Pokharel, S. (2012). Optimization models in emergency logistics: a literature review. Socio-Economic Planning Sciences, 46(1), 4-13. https://doi.org/10.1016/j.seps.2011.04.004
40. Boonmee, C., Arimura, M., Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. International journal of disaster risk reduction, 24, 485-498. https://doi.org/10.1016/j.ijdrr.2017.01.017
41. Yang, W., Caunhye, A. M., Zhuo, M., Wang, Q. (2024). Integrated planning of emergency supply pre-positioning and victim evacuation. Socio-Economic Planning Sciences, 95, 101965. https://doi.org/10.1016/j.seps.2024.101965
42. Ozbay, E., Çavuş, Ö., Kara, B. Y. (2019). Shelter site location under multi-hazard scenarios. Computers & operations research, 106, 102-118. https://doi.org/10.1016/j.cor.2019.02.008
43. Praneetpholkrang, P., Huynh, V. N. (2020). Shelter site selection and allocation model for efficient response to humanitarian relief logistics. In Dynamics in Logistics: Proceedings of the 7th International Conference LDIC 2020, Bremen, Germany, 309-318. Springer International Publishing. https://doi.org/10.1007/978-3-030-44783-0_30
44. Kanoun, I., Chabchoub, H., Aouni, B. (2010). Goal programming model for fire and emergency service facilities site selection. INFOR: Information Systems and Operational Research, 48(3), 143-153. https://doi.org/10.3138/infor.48.3.143
45. Gormez, N., Koksalan, M., Salman, F. S. (2011). Locating disaster response facilities in Istanbul. Journal of the operational research society, 62(7), 1239-1252. https://doi.org/10.1057/jors.2010.67
46. Xu, W., Zhao, X., Ma, Y., Li, Y., Qin, L., Wang, Y., Du, J. (2018). A multi-objective optimization based method for evaluating earthquake shelter location–allocation. Geomatics, Natural Hazards and Risk, 9(1), 662-677. https://doi.org/10.1080/19475705.2018.1470114
47. Barzinpour, F., Esmaeili, V. (2014). A multi-objective relief chain location distribution model for urban disaster management. The International Journal of Advanced Manufacturing Technology, 70, 1291-1302. https://doi.org/10.1007/s00170-013-5379-x
48. Burkart, C., Nolz, P. C., Gutjahr, W. J. (2017). Modelling beneficiaries' choice in disaster relief logistics. Annals of Operations Research, 256, 41-61. https://doi.org/10.1007/s10479-015-2097-9
49. Marler, R. T., Arora, J. S. (2010). The weighted sum method for multi-objective optimization: new insights. Structural and multidisciplinary

optimization, 41, 853-862. https://doi.org/10.1007/s00158-009-0460-7

50. Mamei, M., Bicocchi, N., Lippi, M., Mariani, S., Zambonelli, F. (2019). Evaluating origin–destination matrices obtained from CDR data. Sensors, 19(20), 4470. https://doi.org/10.3390/s19204470
51. Urbanik, II. T. (2000). Evacuation time estimates for nuclear power plants. Journal of Hazardous Materials, 75(2-3), 165-180. https://doi.org/10.1016/S0304-3894(00)00178-3
52. Zhang, X., Liu, C. A. (2023). Model averaging prediction by K-fold cross-validation. Journal of Econometrics, 235(1), 280-301. https://doi.org/10.1016/j.jeconom.2022.04.007
53. Kyriakides, K. A. (2023). The Akkuyu Nuclear Power Plant in Turkey: Some Causes for Concern. Journal of Balkan and Near Eastern Studies, 25(3), 340-377. https://doi.org/10.1080/19448953.2022.2143855
54. Unel, F. B., Kusak, L., & Yakar, M. (2023). GeoValueIndex map of public property assets generating via Analytic Hierarchy Process and Geographic Information System for Mass Appraisal: GeoValueIndex. *Aestimum*, *82*, 51-69
55. Güven, O., Yıldırım, Ümit ., Güler, C., & Kurt, M. A. (2024). Land use and land cover classes affected by the possible sea level rise in Mersin city center (Türkiye). Advanced GIS, 4(1), 15–23. Retrieved from https://publish.mersin.edu.tr/index.php/agis/article/view/1348
56. Topaloglu, R. H. (2022). Investigation of Land Use/Land Cover change in Mersin using geographical object-based image analysis (GEOBIA). Advanced Remote Sensing, 2(2), 40–46. Retrieved from https://publish.mersin.edu.tr/index.php/arsej/article/view/247
57. Yilmaz, C. B., Sevimli, M. F., Demir, F., Yakar, M. (2021). Trend analysis of temperature and precipitation in Mediterranean region. Advanced GIS, 1(1), 15-21. Retrieved from https://publish.merisn.edu.tr/index.php/agis/article/view/60
58. Balcı, D. (2022). Researching the use of infrastructure in land management. Advanced GIS, 2(1), 18–23. Retrieved from https://publish.mersin.edu.tr/index.php/agis/article/view/250
59. General Directorate of Highways. The Republic of Turkey General Directorate of Highways. Republic of Turkey, www.kgm.gov.tr. Accessed on September 2024.
60. Bijaber, N., Rochdi, A., Yessef, M., El Yacoubi, H. (2024). Mapping the structural vulnerability to drought in Morocco. International Journal of Engineering and Geosciences, 9(2), 264-280. https://doi.org/10.26833/ijeg.1404507