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Integrating CRITIC and Weighted K-Means for Humanitarian Relief Center Location Planning: Evidence from Gaziantep

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Abstract

The effective and successful management of post-disaster humanitarian relief logistics operations is directly related to the strategic and needs-based placement of aid distribution centers. In particular, improper placement of relief distribution facilities can result in issues such as service imbalances and delays in access. Therefore, this study aims to optimize the process by planning the needs-based determination of the centers' positioning. To take urban dynamics into consideration during the decision-making process, six important criteria were chosen. Park areas are being assessed as prospective relief centers due to their accessibility and function as open spaces in the aftermath of a disaster. A hybrid approach that integrates the CRITIC method with the machine learning-based weighted k-means algorithm is proposed. In the first stage, the priority score for each alternative location was determined using the CRITIC method. In the second stage, the scores were defined as weight coefficients, and scenario-based analysis was performed using the weighted k-means algorithm. Also, a correlation analysis was conducted to examine the structure of the data and the relationships among the criteria. Furthermore, the Kruskal-Wallis test was applied to determine whether the differences among the scenarios were statistically significant. In conclusion, this study provides an objective and flexible decision-support framework for decision-makers in post-disaster situations.

Keywords: CRITIC Method, Humanitarian Relief Logistics, Location-Allocation Problem, Weighted K-Means

1. Introduction

Disasters are crises that have sudden and destructive effects on society in various dimensions, including physical, social, and economic. These disasters are classified into two groups: natural disasters (earthquakes, floods, hurricanes) that occur spontaneously due to the dynamics of nature, and man-made disasters (terrorist attacks, chemical leakages) that occur as a result of direct or indirect human intervention (Sağdıç et al., 2025), (Caunhye et al., 2012). Natural or man-made disasters seriously threat to the functioning of society. In order to deal with the detrimental impacts of disasters, it is crucial to establish rapid and effective intervention procedures in disaster management.

Humanitarian relief logistics, one of the operations in the field of disaster management, is a process that involves planning, implementing, and controlling the evacuation of disaster victims to safe areas and the effective delivery of essential supplies and resources to them. This humanitarian relief logistics process, a critical component of the post-disaster response phase, is a discipline that aims to save lives and minimize suffering (Boonmee et al., 2017). The success of humanitarian relief logistics operations depends on the availability of critical resources, their effective distribution, and efficient coordination. However, post-disaster structural risks, such as network security and road accessibility, increase

logistical challenges and can directly impact the process (Zahari et al., 2025). In addition, the effective use of limited resources, the allocation of centers to enable distribution, and the coordination of the process also play an important role (Eligüzel, 2025). The strategic decisions made in this optimization process are based on location-allocation problems. This problem involves determining which facilities to open and strategically identifying the points to which they will be assigned. In this regard, the aim is to minimize the distance of a limited number of facilities from demand points while maximizing service capacity. However, location-allocation problems can be complicated by factors such as capacity and risk in real-life scenarios. In particular, during post-disaster relief operations, while some areas receive excessive amounts of aid beyond their needs, other areas are unable to secure sufficient resources. This situation can lead to the improper use of resources and logistical inefficiency. Consequently, the location of distribution centers must be planned not only based on geographical criteria but also by taking environmental factors into account.

In this context, this study proposes a hybrid approach for post-disaster site allocation problems that also accounts for urban dynamics and is presented in Fig. 1. This decision support framework, which is addressed in two stages of operational steps, encompasses the CRITIC method among multi-criteria decision-making (MCDM) methods, as well as machine learning-based weighted k-means techniques. In the implementation of this hybrid approach, 57 park points in the Şahinbey district were identified as alternative locations. The appropriateness of the designated park locations is directly contingent upon various parameters, including population density, building density, park area, proximity to facilities, proximity to fuel stations, and proximity to fault lines.

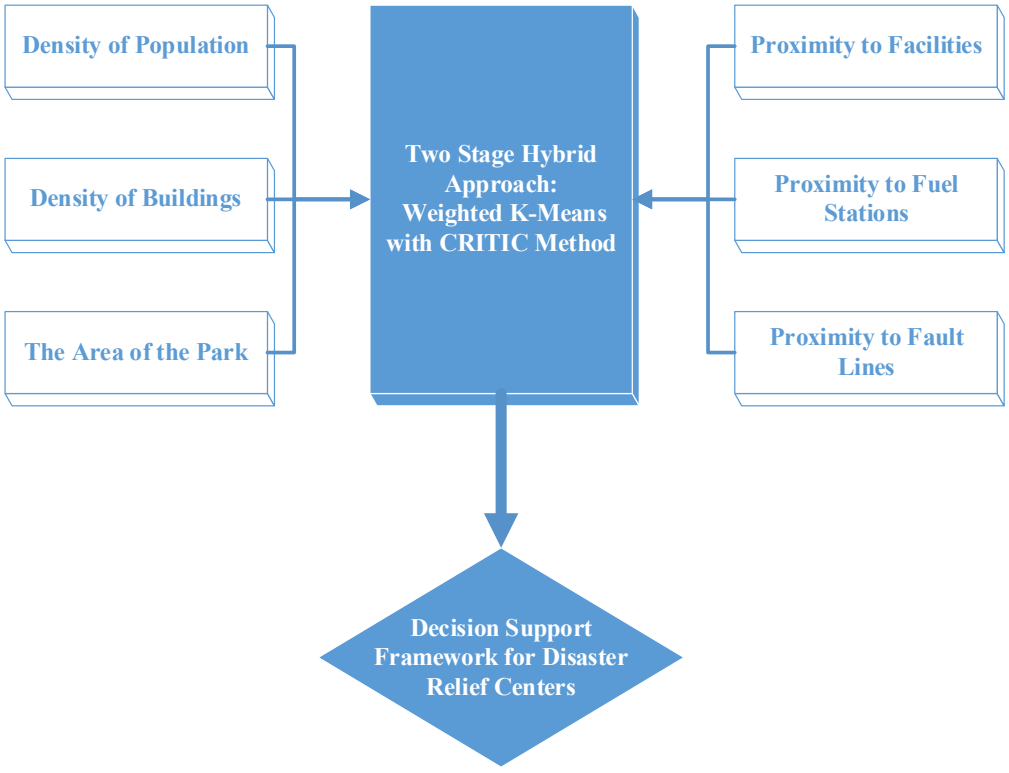


Fig. 1. Proposed Two-Stage Hybrid Decision Support Framework

The primary aim is to evaluate alternative locations according to relevant criteria utilizing CRITIC method and to include these evaluations into the Weighted K-Means algorithm to identify the most appropriate alternative centers depending on various circumstances. The contributions within this methodological framework are as follows:

- Determining the locations of post-disaster temporary relief distribution centers by taking urban dynamics into account.

- Identifying the importance levels of criteria using the CRITIC method, an objective weighting approach, and integrating a machine learning-based weighted k-means clustering approach

- Instead of offering decision-makers a single option, a comparative scenario-based decision support framework emphasizes the benefits and drawbacks of several situations

The study is structured into five chapters. The second chapter summarizes the relevant literature and highlights the contribution to the existing literature; the third chapter discusses the proposed hybrid approach in detail. The fourth chapter presents and discusses the findings and analysis results. Finally, the fifth chapter provides the conclusions.

2. Literature Review

Considering the literature on humanitarian logistics and disaster management, it is clear that the current studies can be divided into four main groups based on the main problems they address: (1) Choosing the best locations for warehouses and distribution centers, (2) planning temporary shelters and refugee camps, (3) emergency medical facilities and health-oriented interventions, and (4) smart city infrastructure and data-driven resource allocation (Roh et al., 2013), (Trivedi, 2018), (Mahajan et al., 2025), (Kaveh et al., 2024).

2.1. Site Selection for Logistics, Warehouses, and Distribution Centers

One of the most addressed problems in the literature is how to choose warehouses for storing aid items and distribution stations after a disaster. Roh et al. investigated the challenge of pre-positioned storage site selection at regional and local levels for humanitarian aid organizations by employing AHP and Fuzzy-TOPSIS methodologies (Roh et al., 2013), (Roh et al., 2015). He et al. (He et al., 2017) suggested a new multi-criteria decision-making (MCDM) model based on stochastic ELECTRE to deal with the fact that data and decision-maker preferences are not always clear when choosing a site for emergency warehouses. In addition, Yılmaz and Kabak (Yılmaz and Kabak, 2020) created multiple standards for main and local distribution centers and used the Type-2 Fuzzy AHP and TOPSIS methodologies to develop a priority model for the Istanbul area. Considering the planning temporary shelters and refugee camps several studies are conducted in literature. One of them is implemented by Carnero Quispe et al. (Carnero Quispe et al., 2025) and they used the "p-median" formulation and the SMART technique to figure out which temporary distribution points to turn on first in a disaster when resources are limited. Also, Mittal and Obaid (Mittal and Obaid, 2023) proposed a tripartite framework (economic, environmental, and social) for sustainable warehouse site selection in the humanitarian supply chain, utilizing the Best-Worst Method (BWM) and TOPSIS techniques, in the context of the sustainability of logistics networks. It is also required to conduct a robust methodology for locating temporary shelters and refugee camps. In that aspect, Munyaka and Yadavalli (Munyaka and Yadavalli, 2021) have employed hybrid decision support systems that amalgamate AHP with linear programming (LP) in previous research that integrate facility location with demand planning.

2.2. Temporary Shelter Areas and Refuge Planning

Locating the right places for disaster victims who have lost their homes to evacuate to and stay temporarily involves particular criteria that are oriented on people (Trivedi, 2018), (Nappi and Souza, 2015). Using the AHP technique, Nappi and Souza (Nappi and Souza, 2015) have put the basic criteria for choosing temporary shelters in order of importance. These criteria include location, safety, urban infrastructure, and cultural relevance. By employing the DEMATEL technique to look at the cause-and-effect correlations and interactions between these factors, Trivedi has given policymakers a strategic framework (Trivedi, 2018). To solve the challenges of choosing sites and allocating resources for shelters, Praneetpholkrang et al. suggested using multi-objective optimization models that use Epsilon Constraints (EC) and Goal Programming (GP) methods to balance different goals (Praneetpholkrang et al., 2021). Geng et al. (Geng et al., 2020) effectively amalgamated Fuzzy AHP, TOPSIS, and multi-

objective optimization techniques for emergency shelters. In post-disaster relocation situations, Bhakuni et al. (Bhakuni et al., 2025) established the "Multi-Objective Solid Transportation Model" (MOSTM), which takes into account the safety of the people who were impacted and the costs. They also looked at the stability of six other MCDM techniques, including COCOSO and MABAC. Batur et al. (Batur et al., 2025) have suggested GIS-supported multidimensional optimization models for certain disasters, like nuclear emergencies, that find a compromise between capacity, evacuation speed, and resource availability. Tak and Akay (Tak and Akay, 2026) have created a generative design framework that improves the internal layout of temporary shelter spaces by turning SPHERE, UNHCR, and national criteria into computational parameters. This is a step above typical site selection methods.

2.3. Emergency Medical Facility Site Selection and Health-Focused Interventions

In medical procedures when time is essential the combination of modern technologies and analytical methods is becoming increasingly relevant (Mahajan et al., 2025), (Khosravi and Rabbani, 2026). Mahajan et al. (Mahajan et al., 2025) created a new group decision-making model that uses T-global fuzzy logic, SWARA, MEREC, and CoCoSo approaches to find the best places for emergency medical facilities to be during drone-supported disaster response operations. Khosravi and Rabbani, (Khosravi and Rabbani, 2026) conversely, introduced a telemedicine-centric disaster management framework; they employed Machine Learning (ML) algorithms for the triage of the injured, guaranteed the prioritization of impacted regions through the OPA method, and combined the allocation of health resources with a mathematical optimization model.

2.4. Smart City, Crowdsourcing, and Resource Allocation

Research concentrating on real-time data acquisition and smart city integrations to mitigate pre- and post-disaster uncertainty has gained traction (Kaveh et al., 2024), (Sarma et al., 2022). Kaveh et al. (Kaveh et al., 2024) proposed a nonlinear model that uses the SWARA and WASPAS methodologies to find the best warehouse site by combining concepts of sustainability, resilience, and smart cities during the pre-disaster preparedness phase through the use of IoT cameras and sensors. Sarma et al. (Sarma et al., 2022) utilized "crowdsourced" data from disaster locations to ascertain the priority level of demands and developed a three-tier model grounded in TOPSIS and Genetic Algorithm to achieve cost reduction. The literature summarized above provides a comprehensive analytical foundation on disaster logistics and temporary facility site selection, but it also contains some significant gaps.

The majority of existing MCDM research employs subjective methods based on expert opinions (AHP, BWM, SWARA, etc.) in determining criterion weights. This situation can lead to the reflection of decision-makers' biases in the results and the neglect of rapidly changing urban dynamics in the models after a disaster. In addition, there is a need for the site selection and allocation studies conducted at the strategic level to be supported by operational data; however, hybrid approaches that combine MCDM methods with data-driven innovative algorithms such as Machine Learning and focus directly on operational improvements are quite limited in the literature. The research we have developed aims to directly address the subjectivity and operational integration deficiencies identified in the literature, filling the existing gaps.

This study focuses on the location-allocation problem, specifically the identification of temporary centers for post-disaster humanitarian relief logistics. It sets itself apart from other research through setting proposed an objective weighting framework based on CRITIC method that incorporates urban dynamics into consideration in order to remove the biases of decision-makers. Additionally, a hybrid approach combining MCDM methods with machine learning techniques is proposed to achieve operational-level improvements.

3. Proposed Methodology

A hybrid decision support framework based on the CRITIC-based weighted k-means algorithm proposed to address the location-allocation problem in post-disaster humanitarian relief logistics. In this decision support framework, the proposed approach incorporates urban dynamics into the system. This proposed structure is designed to provide decision support based on risk and need. This section details the hybrid methodological approach applied in the study and presented Fig. 2.

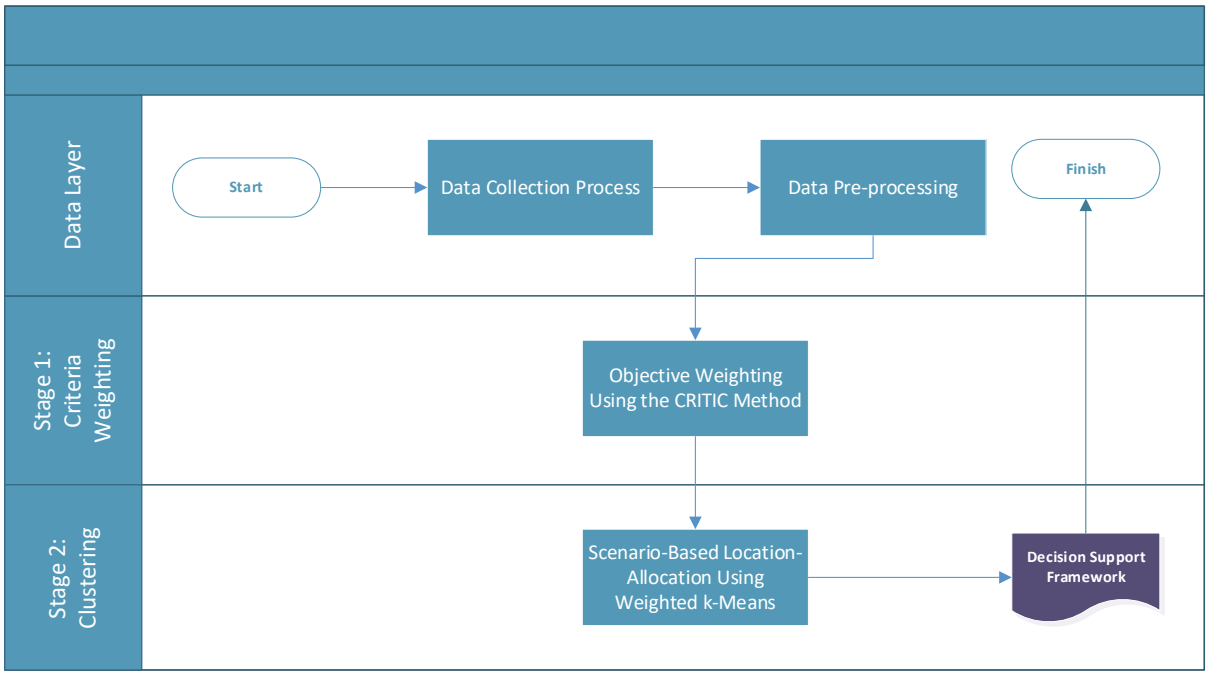


Fig. 2. Flowchart of the Proposed Hybrid Methodological Framework

3.1. Study Area, Data Collection and Pre-Processing

The selection of relief centers and their strategic placement, which takes into account urban characteristics like the concentration of demands and available capacity, are crucial to the successful execution of activities during the post-disaster period. Accordingly, the problem of selecting locations for relief centers must be evaluated using a data-driven approach.

The criteria were selected based on literature regarding post-disaster humanitarian relief logistics. Information on population density is required to identify needs and ensure the proper implementation of plans within the scope of emergency response (Tenerelli et al., 2015). Furthermore, Bakhshi Lomer et al. (Bakhshi Lomer et al., 2023) emphasizes that population density is one of the important factors in selecting facility locations following a disaster. For this reason, neighborhood-level population density has been identified as a criterion representing areas where demand may be concentrated. In addition, green spaces are considered a criterion because they serve as locations where temporary facilities can be set up and relief operations can be carried out following a disaster (Chen et al., 2018) (Bakhshi Lomer et al., 2023) (Kara and Yavruoğlu, 2025). Thus, park areas are also considered as criteria. Moreover, building density which is used in the literature as an important component in the selection of emergency facility sites is also included among the criteria (Wang et al., 2024). Additionally, proximity to fault lines and fuel stations must also be taken into account to ensure effective safety. Fuel stations and other potentially dangerous locations should be kept far from aid centers (Bakhshi Lomer et al., 2023). Finally, the criterion of proximity to hospitals, schools, social facilities, and similar establishments was chosen because it provides essential infrastructure, ensures sufficient capacity, and offers accessible areas for temporary use and service delivery. After the criteria were established, the data were compiled from open data sources.

In this study, the Şahinbey district of Gaziantep as shown in Fig. 3, was used as a case study. The study area is restricted to the five neighborhoods with the highest populations in the Şahinbey district, according to 2024 data from the Turkish Statistical Institute (TÜİK). Because park areas feature open spaces, they hold potential for temporary use following a disaster. For this reason, the park areas in the selected neighborhoods have been included in the dataset as candidate sites.

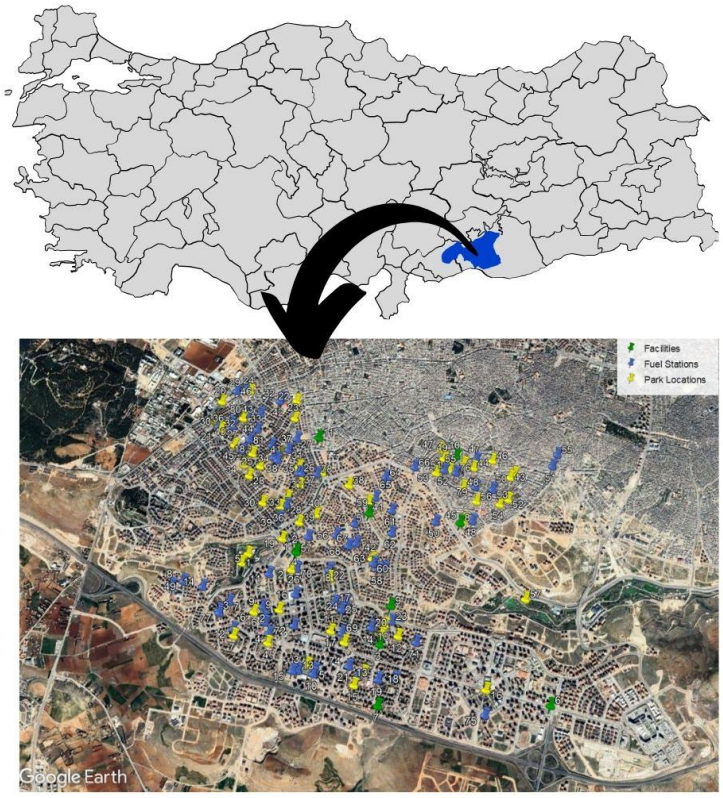


Fig. 3. Case Study Area

The Turkish Statistical Institute's Portal provided the study area's neighborhood-level population density (“Veri Portalı - TÜİK,” n.d.). Furthermore, data regarding building density, park areas, proximity to facilities (hospitals, schools, social facilities), and the locations of fueling stations were acquired from Google Earth Pro program. Additionally, proximity to fault lines was acquired using data supplied by the General Directorate of Mineral Research and Exploration (Ö. et al., 2013). The closest distances to active faults, faults, and surface fractures for each alternative location within the study area, as determined using the Earth Sciences Map Viewer, are presented in Fig. 4.

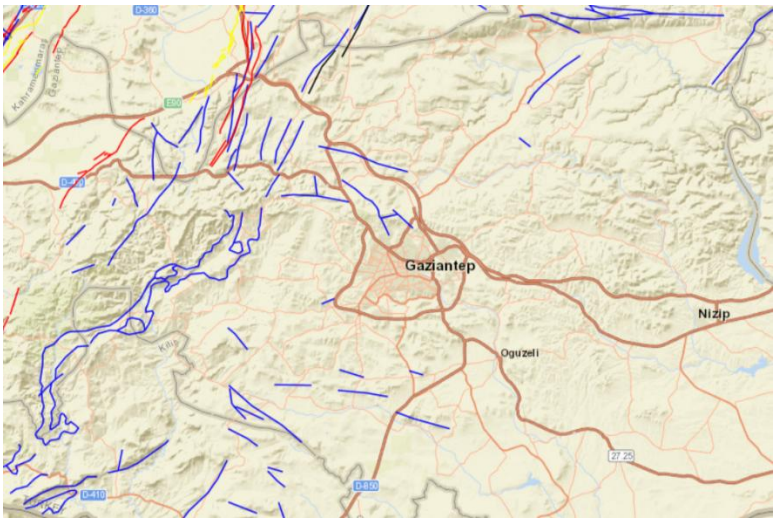


Fig. 4. The Distribution of Fault Lines within The Study Area and Its Adjacent Regions *(Ö. et al., 2013)*

During the assessment process, population density, park areas, and proximity to facilities were examined to evaluate the region's capacity in the event of a disaster. In particular, the criterion of proximity to facilities was included in the assessment because such facilities provide essential infrastructure services. However, proximity to fuel stations was included as a negative criterion due to the risk of explosion. Similarly, proximity to a fault line was included as a negative factor due to the risk of earthquakes and aftershocks. In addition to these, to guarantee that the relief center is situated in a secure location and to mitigate transportation challenges caused by debris from structural failures, the building densities within a 3 km radius of the alternative sites were incorporated into the assessment as detrimental factors.

The data collected was prepared for application subsequent to the data preparation phase. In order to prepare them for Stage 1, the density of buildings, proximity to fuel stations, and proximity to fault lines criteria were also evaluated from a cost viewpoint, whereas the population density, park area, and proximity to facilities criteria were treated from a benefit perspective.

3.2. Objective Weighting Using the CRITIC Method

In the first stage of the study, the CRITIC method was used to determine the importance levels of the criteria in the decision-making process and to perform objective weighting. This method, developed by Diakoulaki and colleagues in 1995, aims to determine the importance weights of the criteria by calculating their standard deviations and the correlation coefficients between columns (Nandi et al., 2025).

The steps of the CRITIC method, an analytical method that uses correlation analysis, are as follows (Abdullah et al., 2024):

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{1}$$

The first step in applying the CRITIC method is to normalize the initial decision matrix using constraint (1).

$$w_j = \frac{c_j}{\sum_{i=1}^{m} c_i} \tag{2}$$

The weight of the criterion (w_j) is calculated using the formula specified in constraint (2) for standard deviation and correlation among criteria.

$$c_j = \sigma_j \sum_{i=1}^{m} (1 - r_{ij}) \tag{3}$$

Constraint (3) is used to determine c_j, i.e., the amount of data in the jth criterion. In this constraint, σ represents the standard deviation and r represents the correlation coefficient. In this case, a high c value indicates that more information is available and, therefore, a higher level of importance in the decision-making process.

3.3. Weighted K-Means Clustering

In the second stage of the proposed hybrid approach, the objective weights obtained from the CRITIC method were integrated into the weighted k-means algorithm for clustering.

Clustering is the process of dividing a data set or any sample into clusters based on specified characteristics. It is one of the fundamental building blocks of data analysis. Clustering analysis, this important building block, is one of the analysis methods that ensures minimum variance within clusters and maximum variance between clusters (Qi et al., 2016). The mathematical model is presented below:

The objective function (4) aims to minimize the total cost.

$$min \sum_{i=1}^{n} \sum_{j=1}^{k} w_i \, z_{ij} \, \|x_i \, \mu_i\|^2 \tag{4}$$

Constraint (5) is an assignment constraint that ensures each point is assigned to only one center.

$$\sum_{j=1}^{k} z_{ij} = 1 \quad \forall i \in \{1,2,3, \dots n\} \tag{5}$$

Constraint (6) is a constraint that updates the coordinates of the centers based on the criteria.

$$\mu_j = \frac{\sum_{i=1}^{n} w_i \; z_{ij} \; x_i}{\sum_{i=1}^{n} w_i \; z_{ij}} \tag{6}$$

Constraint (7) represents a binary variable.

$$z_{ij} \in \{0,1\} \quad \forall i, j \tag{7}$$

4. Findings and Discussion

This section presents and discusses results based on the methodology employed to identify post-disaster temporary relief locations. First, the relationships among the criteria data are revealed through correlation analysis. Subsequently, the results obtained from applying the CRITIC method, which involves objective weighting and weighted k-means clustering based on the identified criteria, are summarized. Finally, the results of the scenario-based clustering approach are tested using the Kruskal-Wallis test to comprehensively examine the impact of each criterion on the results and to demonstrate their suitability.

4.1 Objective Weighting of Criteria Using the CRITIC Method

The importance level of the criteria used in the evaluation of alternative park locations was calculated using the CRITIC method. In the normalization process of the criteria, density of buildings and proximity to fuel stations and fault lines were treated as negative (cost) because they represent risk, while the others were treated as positive (benefit).

A correlation analysis was conducted to examine the relationship among the criteria used in the study. The normalized values of the criteria, ranging from 0 to 1, are shown in the box plot in Fig. 5. Upon

examining this figure, it becomes clear that the criteria do not reflect the same structure and exhibit different distributions.

Building density exhibits a wide range of variation. This indicates that the level of development around alternative temporary aid center locations varies. Similarly, population density and proximity to fault lines also show a wide range of variation. This non-homogeneous distribution of population density highlights the need to plan by considering areas where demand may concentrate. Furthermore, the variability in the proximity to fault lines criterion indicates that some candidate sites are in geologically risky locations, while other areas are more suitable for establishing temporary relief centers. Additionally, there is a wide variance in the proximity to fuel station criterion, which must be assessed in terms of safety. This signifies that candidate sites vary in safety and risk levels. Furthermore, a diminished central tendency and the presence of outliers are noted in the proximity to facilities criterion. Finally, the park area criterion has a relatively narrow range compared to the other criteria. This indicates that some park areas offer capacity advantages over others. Moreover, the upper-end outliers indicate that, although most park areas are comparable in size, a few are substantially larger.

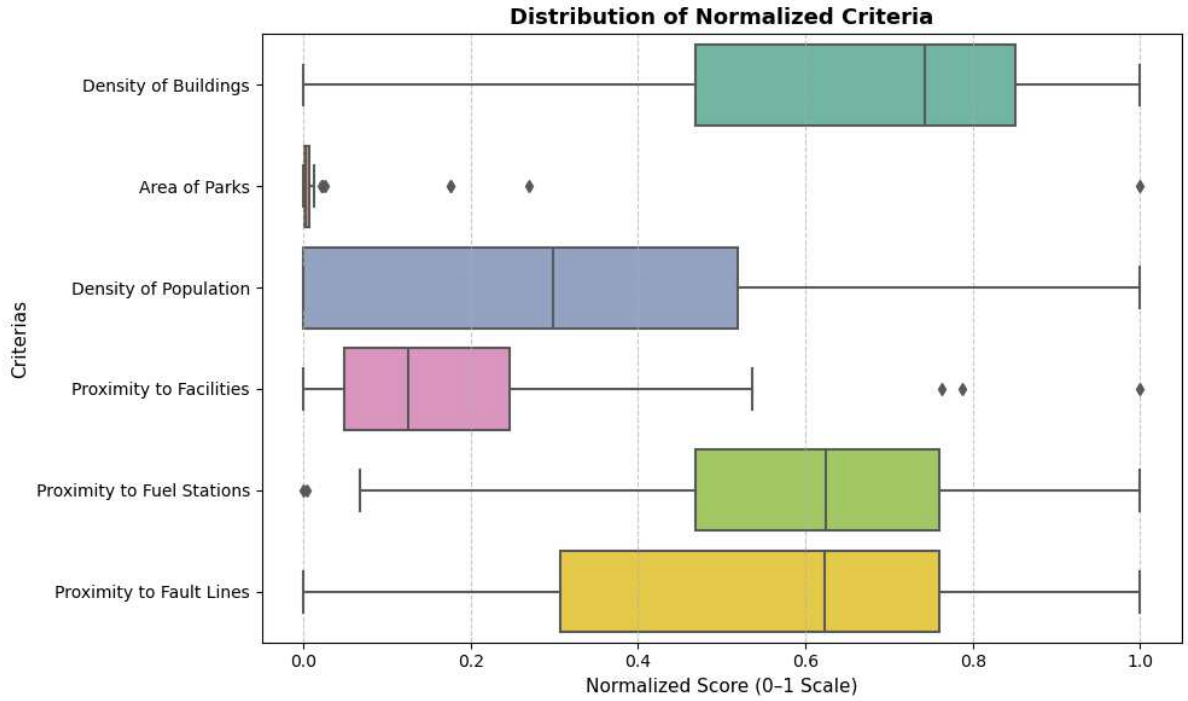


Fig. 5. Distribution of Normalized Criteria

Fig. 6 presents the correlation matrix showing the bivariate relationships among the criteria. The findings indicate that there are positive relationships between some criteria and negative relationships between others. For example, there is a strong relationship between population density and building density ($r = 0.75$). This suggests that demand for post-disaster assistance may be concentrated in areas with high building density and population density. Consequently, these two criteria stand out as indicators representing potential basic needs. Conversely, these two criteria have a negative relationship with proximity to facilities. The negative correlation between building density and proximity to facilities ($r = -0.35$), as well as between population density and proximity to facilities ($r = -0.32$), demonstrates that a favorable situation does not exist under all conditions. Similarly, there is a negative relationship between proximity to fuel stations and proximity to fault lines ($r = -0.53$). This signifies that different risk factors must be considered when determining the locations of aid centers. In conclusion, the

correlation findings demonstrate that the criteria contribute to the problem of determining temporary relief centers in various dimensions.

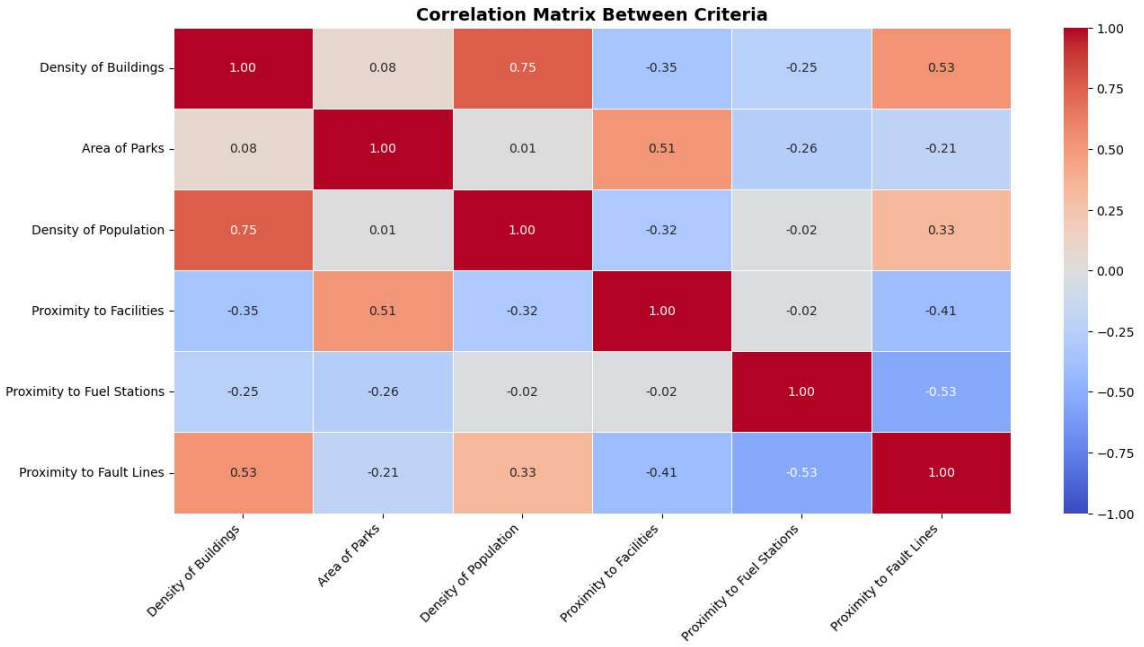


Fig. 6. Correlation Matrix Between Criteria

The findings from the CRITIC method analysis indicate that the importance levels of the criteria vary, and the results are presented in Table 1. Upon examining the results, it is observed that the criteria of proximity to fuel stations (0.2040) and proximity to fault lines (0.1900) have the highest weights. This situation highlights that criteria addressing the risk dimension take precedence in determining temporary relief centers and that selecting a safe location is a priority. In contrast, the fact that building density (0.0918) has the lowest weight indicates that it has a more limited impact compared to other criteria. Additionally, the weights for proximity to facilities, park area, and population density are 0.1547, 0.1759, and 0.1836, respectively. The fact that these values are similar indicates that their levels of importance are close to one another.

Table 1 Objective Weighting Coefficients for Criteria Determined using the CRITIC Method

Criteria	Weight of Criteria
Density of Population	0.1836
Density of Buildings	0.0918
The Area of the Park	0.1759
Proximity to Facilities	0.1547
Proximity to Fuel Stations	0.2040
Proximity to Fault Lines	0.1900

4.2 Scenario-Based Weighted Clustering Analysis

Strategic decisions in location-allocation problems applied in disaster logistics are directly related to resources. In this context, four different alternative scenarios with 3, 4, 5, and 6 centers (k=3, 4, 5, 6) were presented to provide decision-makers with operational flexibility.

Table 2 demonstrates the results for the scenario where the number of clusters is 3 (k=3). The clusters are allocated 11, 31, and 15 nodes, respectively. This indicates that the distribution is not uniform across the clusters and that Cluster 2, in particular, covers a more concentrated service area. Thus, it is

anticipated that an increased number of vehicles, staff, and additional resources will be required at center node 2, which possesses the greatest allocation of nodes and the longest cumulative distance. The findings from this scenario indicate that, for k=3, the service load is not distributed evenly across the clusters. This is significant because it has the potential to cause delays in the delivery of relief supplies and imbalances in service capacity during post-disaster operations. Thus, this scenario can be assessed as inadequate in terms of accessibility and service balance.

Additionally, a graphical representation of the results for this scenario is illustrated in Fig. 7. The points illustrated in various colors in the graphic signify the cluster membership of each demand point, whereas the red cross symbols denote the relief centers designated to serve the corresponding cluster. The sizes of the park locations representing each demand point within the clusters vary depending on the priority scores obtained from the CRITIC method. As seen in the Fig. 7, due to the limited number of distribution centers in this scenario, the service area is extensive. This situation results in increased distances between points. This is important as it may extend service access durations for post-disaster operating procedures.

Table 2 Weighted K-Means Algorithm (k=3) Site Selection and Allocation Results

Clusters	Location of Center Node	Temporary Center Node	Nodes within The Cluster	Total Distance within The Cluster
1	37.017096, 37.351975	14	[3, 8, 10, 11, 12, 13, 14, 15, 16, 17, 42]	0.070249
2	37.027680, 37.331258	30	[1, 2, 4, 5, 6, 7, 9, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41]	0.251211
3	37.034230, 37.359668	56	[43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57]	0.079243

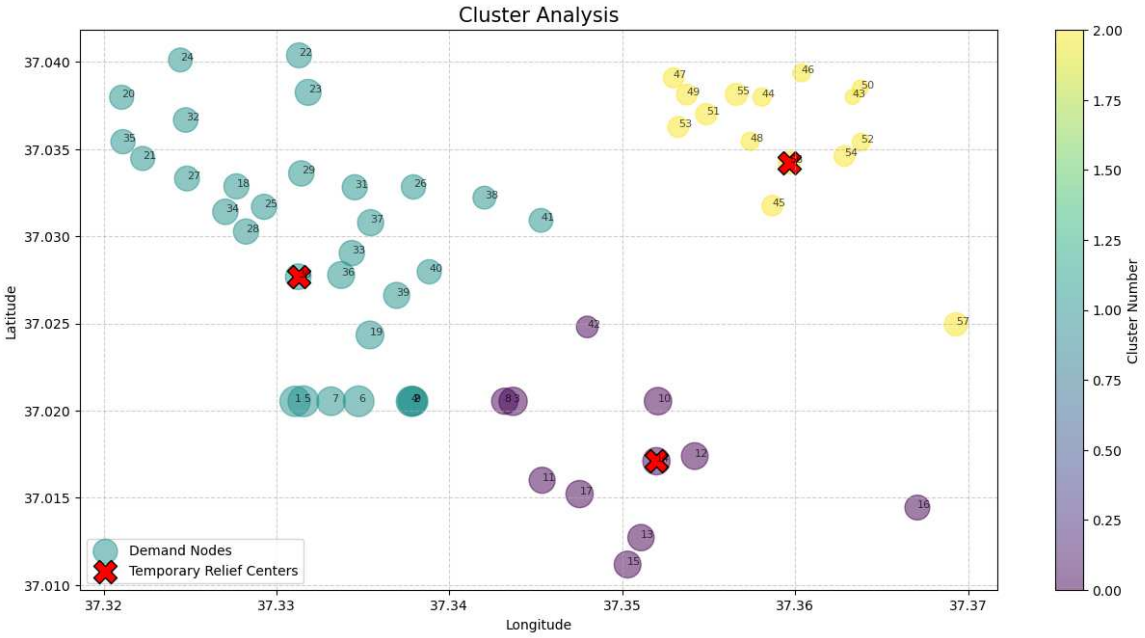


Fig. 7. Location–Allocation Results for Temporary Relief Centers under the k = 3 Scenario

Table 3 indicates the results for the case in which the number of clusters is four (k=4). Upon examination of these results, the nodes allocated to each cluster are 19, 15, 14, and 9, respectively, indicating a more equitable allocation of the service demand in comparison to k=3. This is further supported by the reduction of the maximum overload from 31 to 19 in comparison to the k=3 scenario. Moreover, the

highest total distance is 0.251211 for k=3, which diminishes to 0.109989 in the k=4 scenario, indicating enhancement and underscoring its efficacy in reinforcing resistance.

In this scenario, it is observed that by dividing the service areas into smaller and more homogeneous units, excessive load on a single center is prevented, thereby enabling more effective management. In other words, the reduction in the region's size has enabled the temporary center to serve a smaller area, thereby reducing intra-cluster distances. This has contributed to increasing the speed of aid distribution and transforming the distribution network into a more flexible structure. Since this structure offers significant opportunities, particularly in situations where access time is critical, this scenario presents a viable alternative for decision-makers.

As a result of the analysis, the demand points were grouped into four distinct clusters, and a temporary relief distribution center was identified for each cluster, as shown in Fig. 8. Upon examining this figure, it is observed that the park locations representing points 14 and 56 were designated as centers in both scenarios (k=3 and k=4). Furthermore, it is apparent that an increase in the number of centers allows for a greater differentiation of the demand structure compared to the k=3 scenario. Consequently, it is observed that the center-demand relationship evolves into a more balanced structure. Thus, in this scenario, a more balanced distribution network proposal is observed in terms of both coverage and access efficiency, due to improved access compared to the k=3 scenario. This situation provides a more advantageous structure for access and coordination in the distribution of relief supplies following a disaster.

Table 3 Weighted K-Means Algorithm (k=4) Site Selection and Allocation Results

Clusters	Location of Center Node	Temporary Center Node	Nodes within The Cluster	Total Distance within The Cluster
1	37.024339, 37.335409	19	[1, 2, 3, 4, 5, 6, 7, 8, 9, 19, 26, 30, 33, 36, 37, 38, 39, 40, 41]	0.109989
2	37.034230, 37.359668	56	[43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57]	0.079243
3	37.032865, 37.327683	18	[18, 20, 21, 22, 23, 24, 25, 27, 28, 29, 31, 32, 34, 35]	0.068772
4	37.017096, 37.351975	14	[10, 11, 12, 13, 14, 15, 16, 17, 42]	0.051849

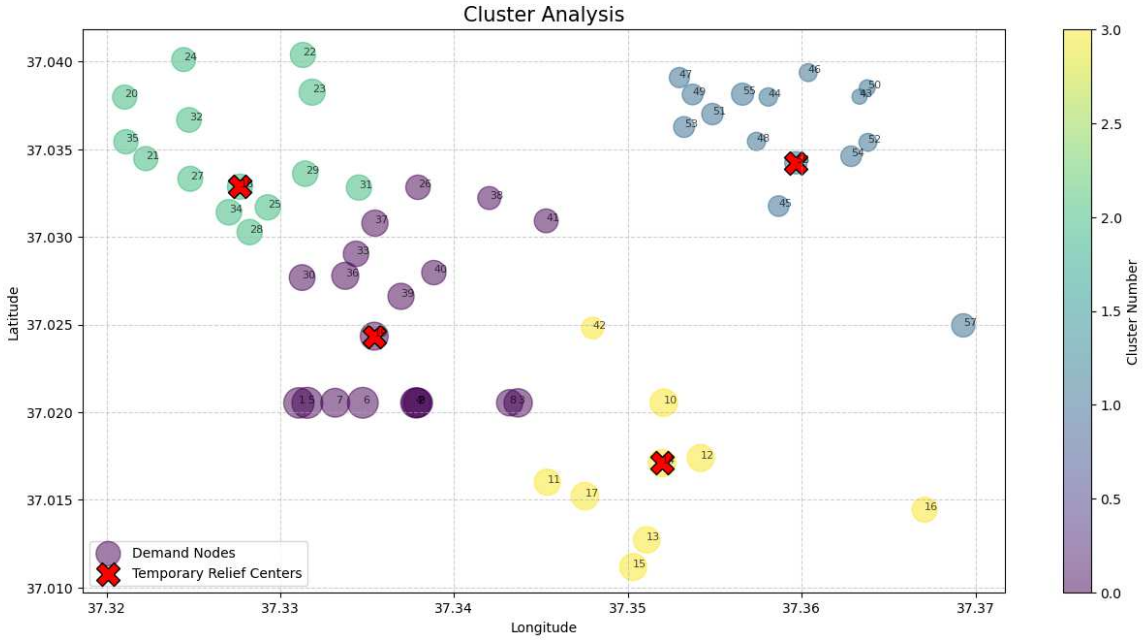


Fig. 8. Location–Allocation Results for Temporary Relief Centers under the k = 4 Scenario

Table 4 summarises the results of the scenario where the number of clusters is five (k=5). In this scenario, the number of points assigned to the clusters is 10, 14, 2, 14, and 17. This distribution indicates that a balanced structure has not been formed among the clusters. Especially, it shows that the service area of center 3 is very limited. The total intra-cluster distances were calculated as 0.053423, 0.068772, 0.010752, 0.059792, and 0.092211, respectively. In conclusion, although this scenario offers an advantage in terms of reducing the intra-cluster distance and improving access to service points for disaster victims, it should also be evaluated in terms of service balance and resource utilisation efficiency.

For the k=5 case, the analysis findings are shown graphically in Fig. 9. When the figure is examined, a denser and more compact structure is observed in some areas, while a more fragmented distribution structure is observed in other areas. This situation indicates that each region does not possess equal characteristics in post-disaster processes.

Table 4. Weighted K-Means Algorithm (k=5) Site Selection and Allocation Results

Clusters	Location of Center Node	Temporary Center Node	Nodes within The Cluster	Total Distance within The Cluster
1	37.015209, 37.347532	17	[3, 8, 10, 11, 12, 13, 14, 15, 17, 42]	0.053423
2	37.032865, 37.327683	18	[18, 20, 21, 22, 23, 24, 25, 27, 28, 29, 31, 32, 34, 35]	0.068772
3	37.014435, 37.367068	16	[16, 57]	0.010752
4	37.035452, 37.357402	48	[43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56]	0.059792
5	37.024339, 37.335409	19	[1, 2, 4, 5, 6, 7, 9, 19, 26, 30, 33, 36, 37, 38, 39, 40, 41]	0.092211

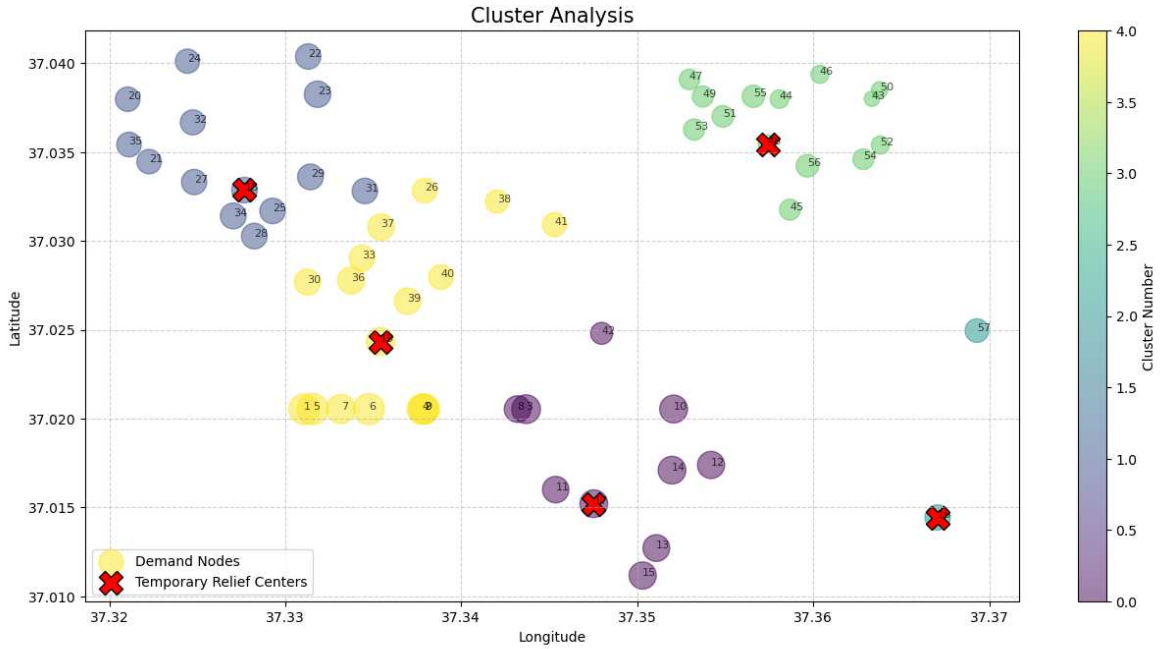


Fig. 9. Location–Allocation Results for Temporary Relief Centers under the k = 5 Scenario

The results for the scenario where there are six clusters (k=6) are given in Table 5. In comparison to Scenario 4, it is noted that the four cluster centers, specifically 17, 18, 16, and 48, remain unchanged. The decrease in overall intra-cluster distance is crucial for enhancing logistical operations during the initial intervention. The demand points in the region have been allocated to the clusters as 10, 10, 2, 14, 8, and 13. This scenario demonstrates a predominantly homogeneous distribution.

The outcomes of the k=6 scenario is demonstrated in Fig. 10. In contrast to other cases, service regions are segmented into smaller parts and distinctly demarcated. As service areas diminish, each center is located nearer to the demand points within its respective cluster. This circumstance enhances access efficiency and establishes a more localized distribution network; yet, it necessitates additional needs, including the establishment of more facilities (resulting in increased costs), enhanced inventory management, and improved coordination. Consequently, decision-makers ought to evaluate this scenario for both its efficacy and practicality.

Table 5 Weighted K-Means Algorithm (k=6) Site Selection and Allocation Results

Clusters	Location of Center Node	Temporary Center Node	Nodes within The Cluster	Total Distance within The Cluster
1	37.015209, 37.347532	17	[3, 8, 10, 11, 12, 13, 14, 15, 17, 42]	0.053423
2	37.030783, 37.335445	37	[26, 30, 31, 33, 36, 37, 38, 39, 40, 41]	0.041604
3	37.014435, 37.367068	16	[16, 57]	0.010752
4	37.035452, 37.357402	48	[43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56]	0.059792
5	37.020534, 37.334753	6	[1, 2, 4, 5, 6, 7, 9, 19]	0.021649
6	37.032865, 37.327683	18	[18, 20, 21, 22, 23, 24, 25, 27, 28, 29, 32, 34, 35]	0.061927

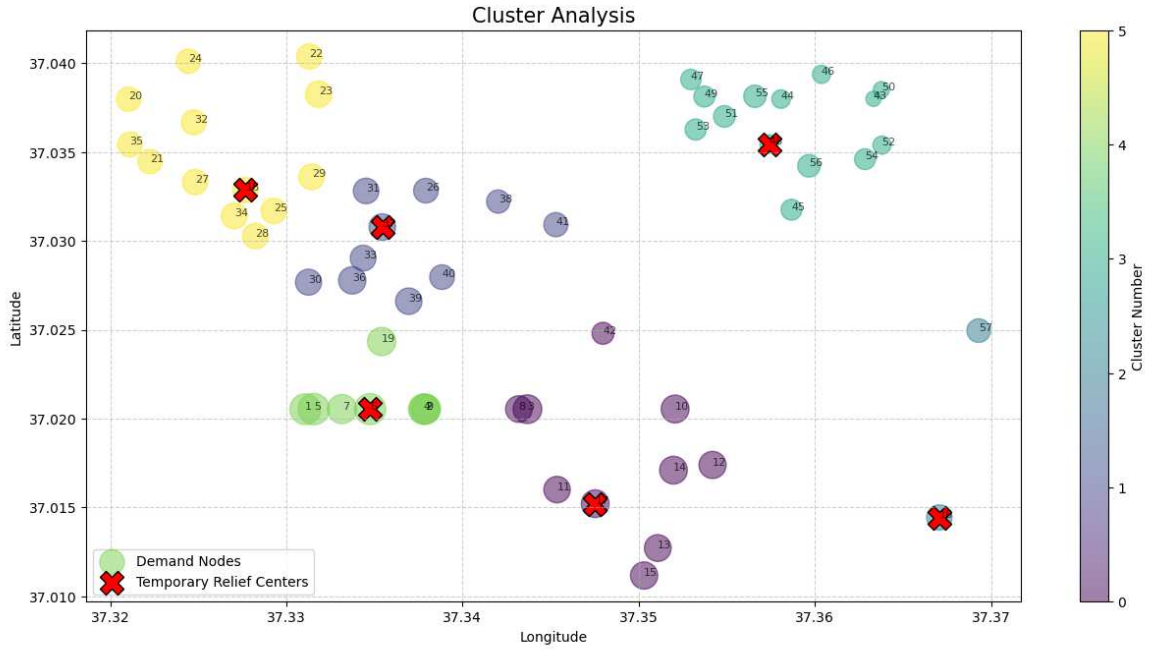


Fig. 10. Location–Allocation Results for Temporary Relief Centers under the k = 6 Scenario

The outcomes of the scenario-based methodology are displayed in Table 6. The given points for each cluster, total distance, objective function value, and percentage improvement are provided. Analysis of the data reveals that an increase in the number of centers, or k value, results in a substantial reduction in both the total distance within the system and the objective function value. A 42.31% enhancement is specifically noted between k=3 and k=4. This can be elucidated by the equitable distribution in the k=3 scenario and the reality that, in the k=4 situation, service areas are partitioned into smaller regions, providing a benefit for accessibility. The two-node clusters identified in the k=5 and k=6 scenarios suggest restricted service areas. In this context, even with enhanced accessibility, these scenarios must be assessed regarding resource consumption efficiency and operational equilibrium.

Table 6 Performance Metrics for Different Number of Clusters (k) Scenarios

Number of Clusters	Node Allocation for Each Cluster	Total Distance of the Overall System	Objective Value	Percentage Improvement Values
3	[11, 31, 15]	2.316781	0.001501	-
4	[19, 15, 14, 9]	2.217398	0.000866	%42.31
5	[10, 14, 2, 14, 17]	1.919770	0.000668	%22.86
6	[10, 10, 2, 14, 8, 13]	1.516572	0.000482	%27.84

When the results of the scenarios are evaluated together, it is observed that an increase in the k-value or the number of centers has a direct effect on the service area, intra-cluster distance, and travel time. Conversely, when the k-value is low, the service areas of the centers expand. However, the expansion of the service area may lead to delays in logistics operations. In summary, this highlights the need to evaluate the determination of temporary aid centers after a disaster not only based on distance or objective criteria but also in terms of resource allocation, service load balance, and central management.

4.3 Statistical Evaluation of Scenario Results Using the Kruskal–Wallis Test

The Kruskal–Wallis test was applied to statistically evaluate the results of scenario-based clustering, and the results are presented in Table 7. When the findings are examined, the p-value being less than

0.05 indicates statistically significant differences for all scenarios and all criteria. In other words, the scenarios exhibit distinct characteristics.

In particular, the criteria of population density, park area, and proximity to fault lines have very low p-values in all scenarios. This indicates that factors such as demand density, safety, and risk actually play a decisive role in the process of determining temporary disaster response points. Along with this, there are also significant differences in building density across all scenarios. However, with values of 0.0134, 0.0196, 0.0025, and 0.0028, it is higher than some other criteria. Additionally, the p-values for the proximity to fuel stations criterion decrease as the number of cluster centers increases. These findings are consistent with the CRITIC results. For instance, this is supported by the fact that building density has the lowest weight, while the weights for population density, park area, and proximity to a fault line are similar to each other.

Table 7 Kruskal–Wallis Test Results for Scenario-Based Analysis

Scenarios	Density of Population	Density of Buildings	The Area of the Park	Proximity to Facilities	Proximity to Fuel Stations	Proximity to Fault Lines
k=3	p=0.0000	p=0.0134	p=0.0000	p=0.0078	p=0.0270	p=0.0000
k=4	p=0.0000	p=0.0196	p=0.0000	p=0.0008	p=0.0005	p=0.0000
k=5	p=0.0000	p=0.0025	p=0.0000	p=0.0008	p=0.0001	p=0.0000
k=6	p=0.0000	p=0.0028	p=0.0000	p=0.0050	p=0.0001	p=0.0000

The graph showing the results of the scenario-based analysis is presented in Figure 11. It is observed that all criteria exhibit statistically significant differences across all scenarios considered. However, changes in the number of clusters result in variations specific to each criterion. In this regard, it is noted that the criterion of building density and proximity to fuel stations vary according to alterations in the number of clusters. In particular, increasing the number of clusters from k=3 to k=4 produces an inverse effect on the building density and proximity to gas stations criteria. In contrast, it is observed that the proximity to fault lines criterion is not affected by changes in the number of clusters.

Overall, the results of the Kruskal–Wallis test demonstrate that the proposed approach has a robust structure not only in terms of performance but also in terms of statistical validity.

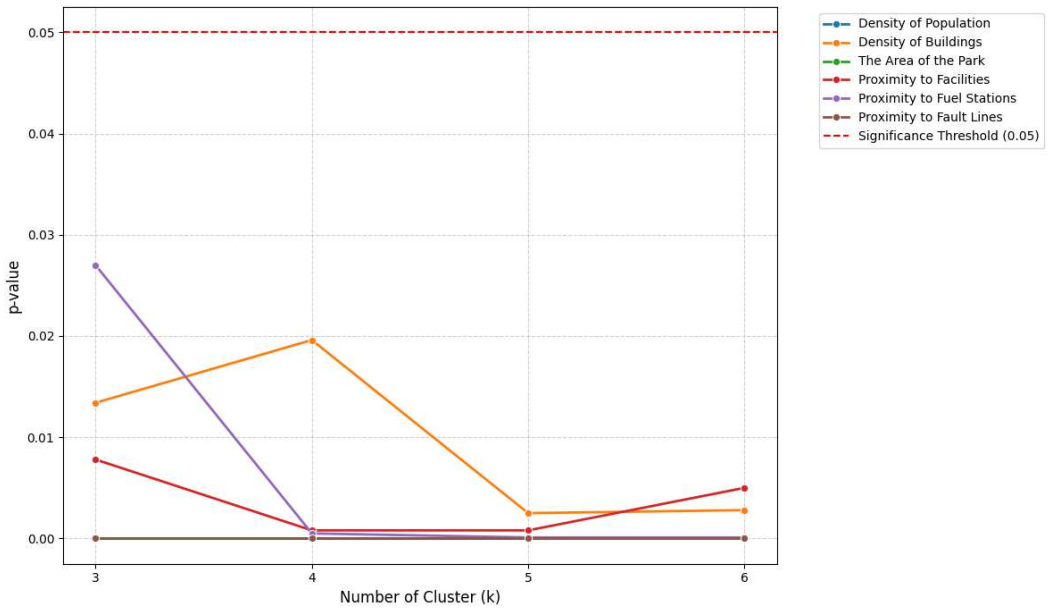


Fig. 11. Comparison of P Values based on the k Value of The Criteria

5. Conclusion

In the event of a potential disaster, it is essential not only to assess the region's capacity to meet its needs but also to address logistical gaps that could pose risks due to debris. In such a situation, it is important to identify strategic locations that focus on ensuring operational safety and maximizing access speed. In this context, park areas located in districts can serve as potential sites for relief distribution centers because they are not affected by hazards such as destruction that may occur during disasters. However, the functionality of this center is not solely dependent on location. It also involves various criteria that are inversely proportional to one another. For instance, while a large park area increases operational capacity, high building density in the surrounding area carries the risk of disrupting the logistics process. Therefore, to ensure the effective and rapid distribution of aid, a hybrid approach to post-earthquake humanitarian aid logistics is recommended.

In this context, a hybrid approach combining MCDM and machine learning techniques was applied to site selection and allocation problems. After implementing an objective weighting mechanism utilizing the CRITIC method, weighted k-means clustering was employed. This study takes into account the balance between needs and risks. While population density, proximity to parks, and proximity to facilities are evaluated positively as advantageous criteria, building density, proximity to fuel stations, and proximity to fault lines are evaluated negatively as detrimental criteria that could hinder logistics processes. Thus, the site selection and allocation problem for a temporary relief center in the post-disaster process is examined from a multidimensional perspective. In this regard, it contributes by taking urban dynamics into account in the decision-making process, adopting an objective weighting methodological approach, and offering a scenario-based approach tailored to the dynamic and varied conditions of a disaster.

The findings indicate that a multi-criteria evaluation is necessary for determining the locations of critical facilities following a disaster. In particular, it has been established that risk-related criteria such as proximity to fault lines and proximity to gas stations are key determining factors. Furthermore, the high weight assigned to population density and park areas highlights the need to evaluate demand and capacity together. Furthermore, the results of the correlation analysis and the Kruskal-Wallis test reveal that both the sets of criteria and the cluster-based scenarios possess a meaningful structure.

In summary, it has been determined that a lower k value should be preferred to establish a simple distribution network when resources are limited; however, a higher k value should be preferred for an access-oriented and more sophisticated service structure. Nevertheless, it has been demonstrated that an increase in the k value can directly influence components such as capacity, resources, and coordination; hence, decisions should not rely exclusively on access-related concerns but must also be assessed in terms of operational load and cost. Thus, the scenario analysis provides decision-makers with the opportunity to comparatively assess the advantages and limitations under different scenarios. In future studies, more comprehensive results specific to different types of disasters can be obtained by incorporating additional criteria such as road accessibility and infrastructure capacity. Additionally, adapting the model to address man-made disasters, such as industrial accidents and chemical spills, could be considered as a potential area of research. Furthermore, the development of optimization-based dynamic models could enhance the sensitivity of the decision-making process.

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Data Availability Statement

The datasets generated and analysed during the current study are included in this article

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Declarations

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