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Optimal Site Selection for Post-Disaster Temporary Housing Using AHP and TOPSIS: A Case Study of Langarud City, Iran

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Abstract

Earthquakes are among the most destructive natural hazards, often causing extensive damage to residential buildings, infrastructure, and urban services and forcing large numbers of households to leave their homes. In such circumstances, providing safe and accessible temporary accommodation is one of the most immediate requirements of post-disaster response. The location of temporary housing is particularly important because an inappropriate site may increase the difficulty of emergency service delivery, restrict access to essential facilities, and expose displaced populations to additional environmental and social risks. Post-disaster temporary housing should therefore be considered not merely as the provision of physical shelter but as an integral component of disaster recovery and urban resilience. Previous research has demonstrated that the selection and arrangement of temporary housing sites involve multiple and sometimes conflicting criteria, including safety, accessibility, environmental conditions, proximity to essential services, land characteristics, social conditions, implementation costs, and the capacity of the site. Recent studies have further emphasized the importance of Geographic Information Systems (GIS)-based Multi-Criteria Decision-Making (MCDM), sustainability, flexibility, reuse, and rapid implementation in post-disaster shelter planning. This study aims to identify and prioritize suitable sites for temporary housing in Langarud City, Iran. Considering the city's environmental and urban characteristics and the need to address earthquake-related displacement as well as flood and waterlogging risks, the study adopts a descriptive-analytical research design. Relevant criteria for temporary housing site selection are identified through the literature and expert consultation. The Analytical Hierarchy Process (AHP) is employed to determine the relative weights of the criteria, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to prioritize candidate locations according to their overall suitability. The findings indicate that, among the investigated areas of Langarud, sections of the green space along Chamkhaleh Road and Fajr Park demonstrate comparatively higher suitability for temporary housing. These areas may therefore be considered potential sites for further technical assessment, infrastructure preparation, and pre-disaster planning. The study emphasizes that systematic pre-disaster site selection, supported by MCDM methods, can contribute to faster emergency response, more efficient allocation of resources, and improved conditions for displaced populations.

Keywords: Disaster management, Earthquake, Temporary housing, Temporary shelter, Site selection, Analytical hierarchy process, TOPSIS, Geographic information systems, Langarud.

1 | Introduction

Human settlements are continuously exposed to natural and human-induced hazards that can disrupt social, economic, physical, and environmental systems. Among natural hazards, earthquakes are particularly

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challenging because of their sudden occurrence, potentially extensive spatial impacts, and capacity to simultaneously affect residential buildings, transportation networks, utility systems, health facilities, and emergency services. Consequently, contemporary disaster management increasingly emphasizes preparedness and risk reduction before an event, in addition to emergency response and post-disaster recovery [1–3].

One of the most important components of preparedness is advance planning for the accommodation of populations whose homes may become damaged or uninhabitable. Temporary housing provides an immediate response to displacement and can bridge the period between the occurrence of a disaster and the restoration or reconstruction of permanent housing [4], [5]. However, temporary housing should not be understood simply as placing displaced households in any available open space. Previous studies have demonstrated that the location, organization, design, and management of temporary housing can substantially affect the effectiveness of disaster response and the subsequent recovery process [6], [7].

The selection of a temporary housing site is a complex spatial decision because several criteria must be considered simultaneously. A suitable site should provide an adequate level of safety while also allowing convenient access to roads, hospitals, emergency services, utilities, and other essential facilities. At the same time, physical characteristics such as slope, elevation, land use, distance from faults and waterways, environmental sensitivity, and population distribution can influence the suitability of a site [8], [9]. Recent Geographic Information Systems (GIS)-based studies have confirmed the value of combining spatial analysis with Multi-Criteria Decision-Making (MCDM) methods for identifying appropriate temporary shelter locations [10], [11].

The importance of pre-disaster planning has been repeatedly emphasized in the literature. Johnson [12], for example, found that temporary housing programs can experience excessive costs, delayed delivery, inappropriate locations, and unsuitable unit designs when planning is predominantly reactive rather than strategic. Similarly, Johnson et al. [9] demonstrated that temporary housing projects are complex systems in which organizational arrangements, technical decisions, and project management are closely interconnected. These findings indicate that decisions concerning temporary accommodation should be made, as far as possible, before disaster occurrence rather than under the severe time constraints of an emergency.

The physical characteristics of temporary accommodation are also important. Caia et al. [6] demonstrated that the characteristics of temporary housing can influence residents' satisfaction, attachment to their temporary homes, and psychological well-being. Their findings indicate that the quality of temporary accommodation should be considered alongside purely spatial and technical criteria. Similarly, Bonanno et al. [13] highlighted the importance of resilience in post-disaster populations and demonstrated that individuals can exhibit different psychological responses following traumatic events.

The broader recovery process also has important social dimensions. Aldrich [1] emphasized the role of social capital in post-disaster recovery, suggesting that social relationships and community networks can contribute to the capacity of communities to recover. Therefore, temporary housing sites should ideally be located and organized in ways that do not unnecessarily disrupt social networks and access to community resources.

The economic and managerial dimensions of post-disaster housing are equally significant. Freeman [14] examined the allocation of reconstruction financing and demonstrated the importance of resource allocation in post-disaster housing recovery. Comerio [5] also showed that housing recovery following disasters involves broader urban, social, and economic processes rather than simply replacing damaged buildings. Consequently, temporary housing site selection should consider not only physical suitability but also the costs and feasibility of providing services and infrastructure.

More recent research has strengthened the argument for systematic and technology-supported site selection. Ersayin [10] used GIS and the Best-Worst Method to identify post-disaster temporary shelter sites in Tokat, Türkiye, demonstrating the applicability of spatial multi-criteria methods to disaster planning. Similarly, de Albuquerque et al. [15] developed a multi-criteria decision model for locating and allocating urban shelters

against flood risk. Their findings illustrate the importance of integrating hazard exposure with spatial decision-making when planning emergency shelter systems.

The role of urban green spaces has also received increasing attention. A 2024 study in Türkiye assessed 240 urban parks in Uşak using GIS and Analytical Hierarchy Process (AHP) to determine their suitability for use as temporary shelter areas following disasters [16]. Such findings are particularly relevant to urban areas where the availability of open land is limited and existing public spaces may represent important components of emergency shelter capacity.

Recent studies have also expanded the range of criteria used in temporary shelter planning. Celik [17] examined shelter site selection criteria using the Best-Worst Method under interval type-2 fuzzy sets, highlighting the uncertainty inherent in disaster-related decision-making. Kızılkın and Birinci [18] subsequently integrated GIS and multi-criteria decision analysis with sensitivity analysis to identify post-earthquake temporary shelter areas. Their model considered geographical, geological, infrastructure, population, and health-service criteria and demonstrated the usefulness of sensitivity analysis in evaluating the robustness of site-selection results.

In addition to site selection, recent research has emphasized sustainability and the long-term implications of temporary housing. Kalak et al. [11] discussed flexibility, portability, and modularity in temporary housing design. Kahvecioğlu and Selçuk [19] reviewed sustainable temporary architecture and reuse strategies and emphasized the environmental, economic, and social dimensions of post-disaster temporary housing. Cho and Baek [20] investigated the potential use of public buildings as temporary housing facilities, demonstrating that existing public infrastructure may contribute to post-disaster accommodation capacity. Perrucci et al. [21] examined the time required for manufacturing and allocating temporary housing units and highlighted the importance of reducing delays in the transition from displacement to temporary accommodation.

Recent evidence also indicates that the implementation and governance of temporary housing programs can determine whether planned housing capacity is actually delivered. Kalak et al. [11], through a comparative analysis of temporary housing programs following the Lorca earthquake and La Palma volcanic eruption in Spain, identified governance, design, and implementation processes as important factors affecting the sustainability and effectiveness of temporary housing programs.

Against this background, the present research focuses on the spatial identification and prioritization of suitable temporary housing sites in Langarud City. The study applies AHP to determine the relative importance of the selected criteria and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank candidate sites according to their overall suitability. The purpose is to provide a spatial decision-support framework that can assist disaster-management authorities in identifying potential temporary housing locations before a disaster occurs.

2 | Research Background and Literature Review

Research on post-disaster temporary housing has evolved from a primarily shelter-oriented perspective toward a broader framework incorporating spatial planning, social resilience, environmental sustainability, project management, and MCDM. The literature can generally be organized into four interconnected themes: Post-disaster recovery and social resilience; temporary housing planning and management; spatial site selection and decision-making; and sustainability and flexibility of temporary housing.

Aldrich [1] examined the role of social capital in post-disaster recovery and demonstrated that social relationships and community networks can contribute significantly to recovery processes. This perspective is relevant to temporary housing because the relocation of displaced populations can influence social networks, access to informal support, and community cohesion.

Barakat [3] examined housing reconstruction following conflict and disasters and emphasized the importance of planning reconstruction interventions, selecting appropriate implementation approaches, and coordinating different stages of housing recovery. His work illustrates that emergency shelter, temporary accommodation,

and permanent reconstruction should be considered as interconnected stages rather than isolated interventions.

Bonanno et al. [13] investigated psychological resilience following the September 11 attacks in New York City. Their study demonstrated substantial variation in psychological responses among affected populations and highlighted the importance of understanding resilience rather than assuming a uniform post-disaster psychological response.

Bonanno et al. [13] focused more specifically on temporary housing characteristics. Their comparison of container housing and wooden temporary dwellings following an earthquake demonstrated differences in satisfaction, attachment, discomfort, and psychological well-being. The findings suggest that the physical and environmental characteristics of temporary housing may influence residents' post-disaster experiences.

Comerio [5] examined urban housing recovery following major disasters and demonstrated that post-disaster housing problems extend beyond direct structural damage. Housing recovery may interact with urban restructuring, economic inequality, and social conditions. Therefore, temporary housing planning should be considered within the broader urban recovery process.

El-Anwar et al. [4] developed a multi-objective optimization model for temporary housing following the 1994 Northridge earthquake. Their model considered several potentially conflicting objectives, including reducing socioeconomic impacts on displaced households, improving safety, reducing environmental impacts, and minimizing public expenditures. This study established the importance of treating temporary housing as a multi-objective decision problem rather than a single-variable location problem.

El-Anwar et al. [22] subsequently developed an automated system for optimizing post-disaster temporary housing allocation. The system was designed to support decision-makers in identifying temporary housing arrangements for large numbers of displaced households. Their work demonstrated how computational tools can support emergency housing decisions.

A related study by El-Anwar et al. [7] addressed the optimization of large-scale temporary housing arrangements. The proposed model was designed to support emergency management agencies in developing temporary housing plans that balance social, economic, safety, environmental, and public-cost considerations.

Freeman [14] examined the allocation of post-disaster reconstruction financing to housing and discussed the economic implications of directing substantial resources toward housing reconstruction. The study highlights the importance of considering financial constraints and competing demands during post-disaster recovery.

Hayles [23] examined decision-making in post-disaster housing reconstruction and identified challenges related to hazard mitigation, stakeholder consultation, technological solutions, construction, and project financing. Her findings indicate that effective housing recovery depends not only on technical solutions but also on organizational and decision-making processes.

Johnson [12] examined six temporary housing programs following disasters in Turkey, Colombia, Japan, Greece, Mexico, and Italy. The study identified recurring problems including excessive costs, delayed delivery, poor location, and inappropriate unit design. Johnson [12] argued that strategic pre-disaster planning could reduce some of these problems.

Johnson et al. [9] adopted a systems perspective to examine temporary housing projects in Turkey and Colombia. Their study demonstrated that organizational structures and project-team design can substantially influence temporary housing outcomes. The research also emphasized the importance of maintaining a coherent relationship between immediate shelter, temporary housing, and permanent reconstruction.

Twigg [2] examined the relationship between post-disaster housing reconstruction and livelihood security. His work emphasized that housing reconstruction should not be considered independently of the livelihoods and vulnerability of affected households. This perspective reinforces the importance of selecting temporary

housing locations that allow displaced populations to maintain access to employment, services, and social networks.

The selection of temporary shelter sites is inherently a spatial decision involving multiple criteria. Earlier optimization studies established the need to consider several objectives simultaneously [7], [24], while more recent research has increasingly integrated GIS with MCDM techniques.

Ersayın [10] developed a GIS-based framework for post-disaster temporary shelter site selection in Tokat, Türkiye, using the Best-Worst Method. The study demonstrates how spatial criteria can be combined with expert-based weighting to identify suitable temporary shelter locations.

de Albuquerque et al. [15] developed a multi-criteria decision model for locating and allocating urban shelters against flood risk. Their approach incorporated risk and preparedness considerations into shelter-location decisions, demonstrating the applicability of multi-criteria analysis to hazards other than earthquakes.

A 2024 study on urban green spaces in Uşak, Türkiye, evaluated 240 parks using GIS and AHP to determine their suitability for temporary settlement after disasters [16]. The research illustrates the potential of existing urban open spaces to contribute to emergency shelter capacity.

Celik [17] analyzed disaster shelter site-selection criteria using the Best-Worst Method under interval type-2 fuzzy sets. The study is particularly relevant to disaster planning because it recognizes uncertainty in expert judgments and provides a framework for dealing with imprecise information during site selection.

Kızılkın and Birinci [18] further advanced this approach by integrating GIS, AHP, and multi-criteria decision analysis with sensitivity analysis for post-earthquake temporary shelter selection. Their model incorporated eleven criteria, including elevation, slope, distance to fault lines, lithology, distance to rivers and roads, land use, population density, sensitive areas, emergency facilities, and health facilities. The inclusion of sensitivity analysis strengthens the reliability assessment of the resulting suitability map.

These studies support the use of GIS and MCDM in the present research. However, the specific criteria and their relative importance should be adapted to the environmental, demographic, infrastructural, and hazard characteristics of the study area.

Recent research has increasingly emphasized that temporary housing should be assessed not only in terms of immediate shelter provision but also in relation to sustainability, adaptability, resource use, and long-term recovery.

Kalak et al. [11] examined flexible temporary housing models and emphasized the importance of portability, flexibility, and modularity in temporary housing design. Their study suggests that temporary housing systems should be capable of responding to changing spatial and functional requirements.

Kahvecioğlu and Selçuk [19] reviewed sustainable temporary housing and reuse strategies. Their findings highlight the growing importance of reuse, recycling, flexible planning, and reduction of environmental impacts in post-disaster temporary architecture.

Cho and Baek [20] examined the use of public buildings as post-disaster temporary housing in South Korea. Their study developed a framework for identifying suitable public buildings under a flood scenario. This research demonstrates that existing public infrastructure can potentially supplement conventional temporary housing solutions.

Perrucci et al. [21] investigated the critical path of manufacturing and allocating temporary housing units. Their findings demonstrate that production and logistical delays can prolong displacement and therefore should be incorporated into post-disaster housing planning.

Kalak et al. [11] examined temporary housing programs following the 2011 Lorca earthquake and the 2021 La Palma volcanic eruption. Their comparative study identified governance, housing design, and implementation processes as important factors influencing the effectiveness and sustainability of temporary housing programs.

Finally, Kızılkın and Birinci [18] demonstrated the growing sophistication of GIS-MCDM approaches by incorporating sensitivity analysis into earthquake shelter site selection. Their work is particularly relevant to the present research because it combines spatial analysis, AHP-based weighting, multiple geographical criteria, and robustness testing.

The reviewed literature demonstrates that temporary housing site selection has increasingly moved toward integrated multi-criteria approaches. Nevertheless, several research gaps remain.

First, although numerous studies have investigated temporary shelter site selection in different geographical contexts, the appropriate criteria and their weights remain highly context-dependent. A criterion that is highly important in one city may have a different relative importance in another because of differences in topography, hazards, infrastructure, population distribution, land use, and urban morphology.

Second, a considerable part of the literature focuses either on the physical characteristics of temporary housing units or on large-scale optimization and logistics. Comparatively fewer studies integrate the spatial characteristics of urban land with accessibility to emergency services, environmental constraints, and local urban conditions within a single decision-making framework.

Third, recent research emphasizes sustainability, flexibility, and resilience, but these dimensions are not always incorporated into practical site-selection procedures. The integration of these considerations with conventional spatial criteria can improve the comprehensiveness of temporary housing planning [11], [18].

Accordingly, the present study addresses the site-selection problem in Langarud City by combining expert-based criterion weighting through AHP with alternative prioritization through TOPSIS. This approach allows multiple spatial and environmental criteria to be considered simultaneously and provides a systematic basis for identifying candidate areas for temporary housing.

3 | Research Methodology

In this study, after completing the questionnaire by experts and obtaining their opinions regarding the criteria for identifying safe sites, the AHP and pairwise comparison method are used to determine the relative weights of the criteria. Accordingly, the weight of each criterion is calculated based on the judgments and opinions of the experts.

Subsequently, the TOPSIS is used to rank the proposed safe sites. Expert Choice software is used to perform the AHP calculations and determine the relative importance of the criteria. The weights obtained from the AHP method are then incorporated into the TOPSIS procedure to rank the alternatives based on their relative closeness to the ideal solution.

3.1 | Analytic Hierarchy Process Method

The AHP is one of the well-known MCDM methods used when a decision-maker needs to select one alternative from a set of available alternatives or prioritize several alternatives. Among the various Multiple Attribute Decision-Making (MADM) methods, AHP has been widely applied in decision-making problems involving multiple criteria.

The AHP was developed by Saaty [25]. The method reflects the natural process of human judgment and thinking. It addresses complex decision-making problems by decomposing them into simpler components and examining the relationships among these components. AHP is particularly useful when a decision involves several competing alternatives and multiple decision criteria. The criteria may be either quantitative or qualitative.

The basic principle of AHP is based on pairwise comparisons. The decision-maker first develops a hierarchical structure of the decision problem. This hierarchy represents the overall objective, the criteria and sub-criteria, and the competing alternatives. Subsequently, pairwise comparisons are performed to determine the relative

importance of the criteria and the relative preference of the alternatives with respect to each criterion. Finally, the resulting priorities are synthesized to obtain the overall priority of the alternatives.

Saaty proposed four fundamental principles for the AHP:

- I. Reciprocal principle: If element A is preferred to element B by a value of n , then the preference of element B over element A is $1/n$.
- II. Homogeneity principle: The elements being compared should be homogeneous and comparable. In other words, the degree of preference between two elements should be within a meaningful and finite range.
- III. Dependency principle: Each element in a hierarchical level may depend on elements in the level immediately above it, and this dependency may continue hierarchically up to the highest level.
- IV. Expectations principle: If the structure of the hierarchy is changed, the evaluation process should be performed again.

The application of the AHP method generally consists of the following main stages: modeling the problem, making preference judgments through pairwise comparisons, calculating relative weights, and synthesizing the weights to determine the priorities of the alternatives.

3.1.1 | Modeling

At this stage, the decision problem and its objective are structured hierarchically into a set of interconnected decision elements. These elements include the decision criteria and the alternatives. The AHP method requires a complex problem involving several criteria to be decomposed into different hierarchical levels.

The highest level represents the main objective of the decision-making process. The intermediate level includes the main criteria, which may be further divided into sub-criteria, while the lowest level represents the decision alternatives.

In the present study, the main objective is to identify and prioritize suitable safe sites for temporary housing following a disaster. The identified criteria are placed at the criteria level, while the proposed sites for temporary housing are considered as the decision alternatives at the lower level of the hierarchy.

3.1.2 | Preference judgment and pairwise comparisons

After constructing the hierarchical structure, pairwise comparisons are conducted among the decision criteria. At this stage, experts determine the relative importance of each criterion compared with the others. The 1–9 Saaty scale is used for the pairwise comparisons.

The scale is defined as follows:

- I. 1: Equal importance; the two criteria have equal importance.
- II. 3: Moderate importance; one criterion is slightly more important than the other.
- III. 5: Strong importance; one criterion is clearly more important than the other.
- IV. 7: Very strong importance; one criterion has a significantly greater importance than the other.
- V. 9: Extreme importance; one criterion is absolutely more important than the other.
- VI. 2, 4, 6, and 8: Intermediate values used to represent judgments between the principal scale values.

After collecting the questionnaires, the pairwise comparison matrix is constructed based on the judgments of the experts, and the relative weights of the criteria are calculated.

3.1.3 | Calculation of relative weights

At this stage, the relative weights of the decision elements are determined through a series of numerical calculations. First, the values of each column of the pairwise comparison matrix are summed. Each element

of the matrix is then divided by the sum of its corresponding column. The resulting matrix is referred to as the normalized pairwise comparison matrix.

Next, the average of the elements in each row of the normalized matrix is calculated. This average represents the relative weight of the corresponding decision element. In this way, the relative importance of each criterion is determined.

3.1.4 | Synthesis of relative weights and prioritization

In this stage, the relative weight of each element is multiplied by the weight of the element at the higher hierarchical level in order to obtain its final weight. By applying this procedure to all criteria and alternatives, the final priorities of the alternatives can be determined.

Consistency of Judgments

Since the calculations in the AHP method are based on the initial judgments of decision-makers and the resulting pairwise comparison matrices, examining the consistency of these judgments is essential. For this purpose, the Consistency Ratio (CR) is used. The CR indicates the degree of consistency among the pairwise comparisons and provides an indication of the reliability of the resulting priorities.

The following steps are used to calculate the CR:

Step 1 (Calculation of the weighted sum vector). The pairwise comparison matrix is multiplied by the column vector of relative weights. The resulting vector is called the weighted sum vector.

Step 2 (Calculation of the consistency vector). Each element of the weighted sum vector is divided by the corresponding element of the relative priority vector.

Step 3 (Calculation of $\lambda_{\max}$). The average of the elements of the consistency vector is calculated to obtain $\lambda_{\max}$.

Step 4 (Calculation of the Consistency Index (CI)). The CI is calculated using the following equation:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \quad (1)$$

where n represents the number of elements being compared.

Step 5 (Calculation of the CR). The CR is calculated by dividing the CI by the Random Index (RI):

$$CR = \frac{CI}{RI}. \quad (2)$$

A CR of 0.10 or less is generally considered acceptable, indicating that the pairwise comparisons have an acceptable level of consistency. If the value exceeds 0.10, the pairwise comparisons should be reviewed and reconsidered.

3.2 | Technique for Order Preference by Similarity to Ideal Solution Method

The TOPSIS is one of the MCDM methods in which m alternatives are evaluated based on n criteria. The basic principle of this method is to identify a positive ideal solution and a negative ideal solution.

The positive ideal solution is defined as a solution that maximizes the benefit criteria and minimizes the cost criteria. Conversely, the negative ideal solution represents the least desirable condition. Accordingly, the optimal alternative is the one that has the shortest distance from the positive ideal solution and the greatest distance from the negative ideal solution.

In other words, in the TOPSIS method, alternatives that have greater similarity to the positive ideal solution obtain higher priorities. In the present study, after determining the weights of the criteria using AHP, TOPSIS is applied to rank the proposed safe sites.

3.2.1 | Steps of the technique for order preference by similarity to ideal solution method

Step 1 (Formation of the decision matrix). In the TOPSIS method, m alternatives are evaluated according to n criteria. Therefore, each alternative is assigned a score for each criterion. These scores may be based on quantitative and actual data or qualitative evaluations and expert judgments. Finally, an $m \times n$ decision matrix is constructed.

Step 2 (Normalization of the decision matrix). In order to eliminate differences in the scales of measurement among the criteria, the decision matrix is normalized. In the present study, the vector normalization method is used. In this method, each value is divided by the square root of the sum of the squared values of the corresponding criterion:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}, \quad (3)$$

where x_{ij} represents the performance value of alternative i with respect to criterion j , and r_{ij} represents the normalized value.

Step 3 (Formation of the weighted normalized decision matrix). In the next step, the normalized decision matrix is weighted according to the weights of the criteria. In the present study, the weights of the criteria are obtained using the AHP method. To construct the weighted normalized matrix, each normalized value is multiplied by the weight of its corresponding criterion:

$$v_{ij} = w_j r_{ij}, \quad (4)$$

where w_j represents the weight of criterion j , and v_{ij} represents the weighted normalized value of alternative i with respect to criterion j .

Step 4 (Determination of the positive and negative ideal solutions). At this stage, the positive ideal solution A^+ and the negative ideal solution A^- are determined for each criterion.

For criteria with a benefit (positive) orientation:

- I. The positive ideal solution is the largest value of the criterion.
- II. The negative ideal solution is the smallest value of the criterion.

For criteria with a cost (negative) orientation:

- I. The positive ideal solution is the smallest value of the criterion.
- II. The negative ideal solution is the largest value of the criterion.

Thus, the positive and negative ideal solutions are determined for all criteria.

Step 5 (Calculation of the distance from the positive and negative ideal solutions). At this stage, the distance of each alternative from the positive and negative ideal solutions is calculated. The Euclidean distance is used for this purpose:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad (5)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, \quad (6)$$

where S_i^+ represents the distance of alternative i from the positive ideal solution, and S_i^- represents its distance from the negative ideal solution.

Step 6 (Calculation of the relative closeness coefficient and ranking of alternatives). In the final step, the relative closeness coefficient of each alternative to the ideal solution is calculated using the following equation:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (7)$$

The value of C_i ranges between zero and one. The closer this value is to one, the closer the alternative is to the positive ideal solution and the farther it is from the negative ideal solution. Therefore, the alternatives are ranked in descending order based on the value of C_i . The alternative with the higher coefficient receives a higher rank.

In the present study, after determining the weights of the criteria using AHP and constructing the decision matrix for the proposed safe sites, the TOPSIS procedure is applied. Finally, the study sites are ranked according to their relative closeness to the ideal solution.

4 | Data Analysis

The data analysis stage is a critical component of the research process, as the collected information must be systematically analyzed in accordance with the research objectives, research questions, and analytical framework. In studies concerned with post-disaster temporary housing and shelter site selection, the decision-making process commonly involves multiple criteria, spatial constraints, and potentially conflicting objectives. Therefore, MCDM methods provide an appropriate framework for evaluating and prioritizing alternative locations based on a set of predefined criteria [4], [7], [10], [15], [17], [18], [22].

In post-disaster housing and shelter planning, the selection and allocation of temporary accommodation sites cannot be determined based on a single criterion. Factors such as accessibility, population characteristics, available area, proximity to hazards, accessibility to essential services, and the relationship between the selected site and the surrounding urban infrastructure may simultaneously influence the suitability of a location [7], [9], [12], [15], [17], [22]. Previous studies have also emphasized the importance of systematic planning and multi-criteria approaches in post-disaster temporary housing and shelter allocation [4], [7], [10], [15], [18], [22].

MCDM methods enable several criteria to be considered simultaneously and provide a structured basis for comparing alternative solutions. In the context of disaster shelter site selection, these methods have increasingly been combined with spatial analysis and GIS to identify suitable locations and establish priorities among candidate sites [15], [17], [18], [22]. Such approaches are particularly relevant to temporary shelter planning because they allow decision-makers to incorporate both spatial and non-spatial criteria into the decision-making process.

Among the various MCDM techniques, the AHP provides a hierarchical framework for structuring a decision problem into different levels, including the overall objective, evaluation criteria, and alternatives. The method enables the relative importance of criteria to be determined through pairwise comparisons and provides a systematic procedure for assigning weights to the criteria. AHP and other MCDM approaches have been widely applied in disaster management, temporary housing, and shelter site selection studies [7], [10], [15], [18], [22].

In the present study, an MCDM framework based on the AHP was employed to determine the relative importance of the criteria affecting the selection of temporary accommodation sites in Langanud. The AHP model was implemented using Expert Choice software. Subsequently, the TOPSIS technique was employed to prioritize the candidate sites based on their performance with respect to the selected criteria. The

combination of weighting and ranking procedures provides a structured approach for comparing the candidate locations and identifying their relative priorities.

The analytical framework adopted in this study is consistent with recent research that has employed MCDM, fuzzy decision-making, and GIS-based approaches for disaster shelter site selection and temporary housing planning [15], [17], [18], [22]. In particular, previous studies have demonstrated the applicability of multi-criteria frameworks for evaluating alternative shelter locations while simultaneously considering several environmental, spatial, accessibility, and infrastructural factors [15], [17], [18], [22].

4.1 | Descriptive Statistics of the Sample Demographic Characteristics

The demographic characteristics of the respondents were examined using descriptive statistics. The frequency and percentage distribution of the respondents according to their educational attainment are presented in *Table 1*.

Table 1. Frequency and percentage distribution of the sample by educational attainment.

Number	Educational Attainment	Frequency	Percentage
1	Associate degree	2	9.1%
2	Bachelor's degree	6	27.5%
3	Master's degree	11	50.0%
4	Doctoral degree	3	13.65%

The results indicate that respondents with a master's degree constitute the largest proportion of the sample, accounting for 50% of the respondents. Bachelor's degree holders represent 27.5% of the sample, followed by doctoral degree holders at 13.65% and associate degree holders at 9.1%.

4.2 | Ranking of the Criteria Affecting the Selection of Temporary Accommodation Sites

In this section, the AHP is used to determine the relative importance and weights of the criteria affecting the selection of temporary accommodation sites. The use of MCDM techniques for shelter site selection allows several criteria to be evaluated simultaneously and provides a systematic framework for comparing candidate locations [15], [17], [18], [22].

In the AHP framework, the decision problem is structured hierarchically into three main levels. The first level represents the overall objective of the decision-making process. The second level consists of the evaluation criteria, while the third level contains the alternatives under consideration. Pairwise comparisons are then performed between the elements at each level with respect to the elements at the higher level. This procedure makes it possible to determine the relative importance of the criteria and subsequently calculate their weights.

The AHP methodology is particularly suitable for the present study because the selection of temporary accommodation sites involves multiple criteria that may differ considerably in terms of their importance and spatial characteristics. Similar multi-criteria approaches have been applied in recent studies addressing post-disaster shelter site selection and temporary housing planning [15], [17], [18], [22].

For the selection of temporary accommodation sites in Langarud, ten criteria were identified based on the research framework and the characteristics of the study area. These criteria include population density, area, distance from faults, distance from mountains, distance from water bodies, distance from gas stations, distance from medical centers, distance from police and security centers, distance from fire stations, and distance from major roads.

The criteria were coded as C1 to C10 in the analytical model. The candidate locations were coded as A1 to A22. This coding system was adopted to facilitate the construction of the decision matrix, the implementation of the AHP model, and the subsequent ranking of alternatives using TOPSIS.

The ten criteria considered in the analysis are as follows:

- I. C1: Population density (persons per hectare).
- II. C2: Area (m²).
- III. C3: Distance from faults (m).
- IV. C4: Distance from mountains (m).
- V. C5: Distance from water bodies (m).
- VI. C6: Distance from gas stations (m).
- VII. C7: Distance from medical centers (m).
- VIII. C8: Distance from police and security centers (m).
- IX. C9: Distance from fire stations (m).
- X. C10: Distance from major roads (m).

The selection of these criteria is consistent with the broader literature on post-disaster temporary shelter and housing site selection, where hazard exposure, accessibility, land availability, population characteristics, and access to essential services are among the factors considered in evaluating potential sites [12], [15], [17], [18], [22].

To demonstrate the application of the AHP method, the data-processing procedure implemented in Expert Choice is presented step by step in the following sections.

4.3 | Determining the Priority of the Model Elements Using the Analytical Hierarchy Process Technique

In the first step of the AHP procedure, the main evaluation criteria were established. The criteria represent the principal spatial and demographic factors affecting the suitability of potential temporary accommodation sites.

The main criteria considered in this research are population density (persons per hectare), area (m²), distance from faults (m), distance from mountains (m), distance from water bodies (m), distance from gas stations (m), distance from medical centers (m), distance from police and security centers (m), distance from fire stations (m), and distance from major roads (m).

A total of 22 candidate sites were identified in the study area. These alternatives were evaluated according to the ten criteria and subsequently ranked using the TOPSIS technique. The use of a separate numerical code for each alternative and criterion facilitates the organization of the decision matrix and enables the alternatives to be systematically traced throughout the analytical process.

The hierarchical structure of the proposed decision model consists of three levels: the first level represents the overall objective, namely the selection of a suitable temporary accommodation site; the second level contains the ten evaluation criteria; and the third level consists of the 22 candidate sites. The weights of the criteria were determined using the AHP technique, after which the weighted criteria were incorporated into the TOPSIS procedure to obtain the final ranking of the alternatives.

The hierarchical structure of the proposed AHP model is presented in *Fig. 1*.

Table 2. Research criteria and alternatives.

Symbol	Alternative	Symbol	Main Criterion
A1	Langarud Football Field	C1	Population (persons per hectare)
A2	Takhti Sports Field, Langarud	C2	Area (m ²)
A3	Langarud Bazaar Park Area	C3	Distance from faults (m)

Table 2. Continued.

Symbol	Alternative	Symbol	Main Criterion
A4	Green Space along Chamkhaleh Road	C4	Distance from mountains (m)
A5	Fajr Park, Langarud	C5	Distance from water bodies (m)
A6	Islamic Azad University Campus, Langarud	C6	Distance from gas stations (m)
A7	Ghadir University, Langarud	C7	Distance from medical centers (m)
A8	Azadi Park	C8	Distance from police and security centers (m)
A9	Parking Area Adjacent to Saderat Bank	C9	Distance from fire stations (m)
A10	Kolidbar Mosque Area	C10	Distance from major roads (m)
A11	Green Space Adjacent to Agha Seyyed Mohammad		
A12	Passenger Terminal		
A13	Kalantari High School and Adjacent Areas		
A14	Noorani High School		
A15	Anzali Neighborhood Green Space		
A16	Modarres High School, Kolidbar		
A17	Shahid Rajaei High School		
A18	Shahed Middle School (Adjacent to the IRGC)		
A19	Taleghani School (Adjacent to Taleghani Sports Club)		
A20	Municipality		
A21	Noghan Administration Office		
A22	Mehr Housing Project		

The criteria and alternatives presented in *Table 2* constitute the basic elements of the decision model. The criteria are subsequently weighted through the AHP pairwise comparison procedure, while the performance of the 22 alternatives with respect to each criterion is incorporated into the TOPSIS model for the final prioritization.

This analytical framework provides a systematic basis for evaluating potential temporary accommodation sites by simultaneously considering demographic, environmental, hazard-related, accessibility, and infrastructure-related characteristics. Such an integrated approach is consistent with recent research emphasizing the importance of combining multiple criteria and spatial information in post-disaster shelter site selection [15], [17], [18], [22].



Fig. 1. Research criteria in expert choice software.

4.3.1 | Prioritization of the main criteria based on the objective

To perform the AHP, the main criteria were first compared pairwise with respect to the overall objective. The AHP technique is a ranking method in which prioritization is performed based on pairwise comparisons. Pairwise comparison is a straightforward procedure in which all elements within each cluster are compared with one another in pairs. Therefore, if a cluster contains n elements, the number of pairwise comparisons is calculated as:

$$\frac{n(n-1)}{2}.$$

Since there are three criteria, the number of pairwise comparisons performed is:

$$\frac{3(3-1)}{2} = 3.$$

Therefore, pairwise comparisons were conducted by a group of 22 experts, and the judgments of the experts were aggregated using the geometric mean method. The resulting pairwise comparison matrix obtained from the aggregation of the experts' judgments is presented in *Table 3*.

Table 3. Pairwise comparison matrix of the main criteria.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
c1		2.3	1.23	1.87	1.9	1.45	1.11	2.18	2.97	2.03
c2		—	1.5	1.45	1.28	1.66	1.27	2.15	2.25	1.03
c3			—	1.45	1.48	1.69	1.52	1.16	1.19	2.1
c4				—	1.47	1.49	2.44	1.37	1.112	1.65
c5					—	1.5	2.58	1.47	1.17	1.65
c6						—	1.22	1.26	1.34	2.07
c7							—	1.19	1.08	1.05
c8								—	1.5	1.14
c9									—	1.41
c10	Incon. = 0.03									

The next step is to calculate the geometric mean of each row in order to determine the weights of the criteria.

The geometric mean is calculated in the same manner for the remaining rows.

Next, the sum of the geometric means of all rows is calculated.

By dividing the geometric mean of each row by the sum of the geometric means of all rows, the normalized weight is obtained, which is also referred to as the priority vector or eigenvector.

In this study, the geometric mean values are entered into Expert Choice software to assign weights to the criteria and generate the criteria prioritization chart. The resulting priority eigenvector of the main criteria is denoted by W_1 .

$$W_1 = \begin{pmatrix} 0.166 \\ 0.125 \\ 0.125 \\ 0.118 \\ 0.105 \\ 0.100 \\ 0.088 \\ 0.077 \\ 0.075 \\ 0.072 \\ 0.073 \end{pmatrix}.$$

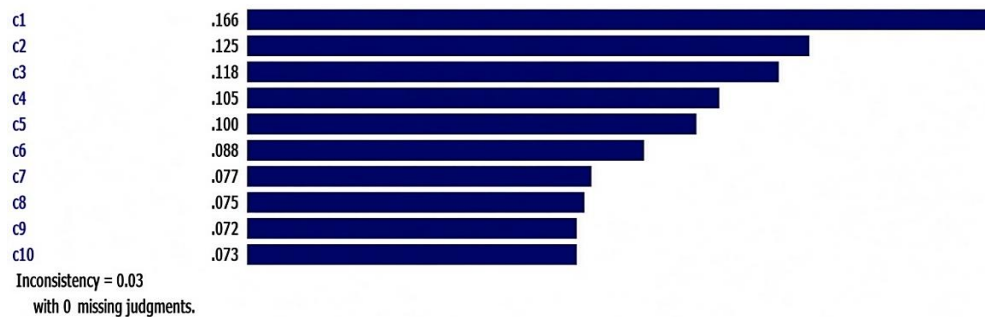


Fig. 2. Graphical representation of the priorities of the main criteria.

4.3.2 | Prioritization of the main criteria based on the objective

Based on the obtained priority vector:

- I. The population density (persons per hectare) criterion, with a normalized weight of 0.166, has the highest priority.
- II. The area (m^2) criterion, with a normalized weight of 0.125, ranks second.
- III. The distance from faults (m) criterion, with a normalized weight of 0.118, ranks third.
- IV. The distance from mountains (m) criterion, with a normalized weight of 0.105, ranks fourth.
- V. The distance from water bodies (m) criterion, with a normalized weight of 0.100, ranks fifth.
- VI. The distance from gas stations (m) criterion, with a normalized weight of 0.088, ranks sixth.
- VII. The distance from medical centers (m) criterion, with a normalized weight of 0.077, ranks seventh.
- VIII. The distance from police/security centers (m) criterion, with a normalized weight of 0.075, ranks eighth.
- IX. The distance from fire stations (m) criterion, with a normalized weight of 0.073, ranks ninth.
- X. The distance from major roads (m) criterion, with a normalized weight of 0.072, ranks tenth.

The inconsistency ratio of the comparisons was calculated as 0.03, which is lower than 0.10. Therefore, the pairwise comparisons can be considered sufficiently consistent and reliable.

4.4 | Selection of the Best Alternative Using the Technique for Order Preference by Similarity to Ideal Solution Technique

In this study, the TOPSIS technique was employed to select the best alternative. The TOPSIS method was proposed by Hwang and Yoon [26] and is one of the widely used MCDM methods for selecting the most suitable alternative. The preferred alternative is the one that has the shortest distance from the positive ideal solution and the greatest distance from the negative ideal solution.

In the present study, 10 criteria were used for decision-making, and 22 alternatives were ranked based on the criteria under investigation.

Following the preliminary assessment, 22 potential locations were identified, as presented in the following table, and each location was evaluated with respect to the selected criteria. The identified locations and their characteristics are presented below.

Table 4. Identified locations for temporary accommodation.

Number	Location	Number	Location
1	Langarud Football Field	12	Passenger Terminal
2	Takhti Sports Field, Langarud	13	Kalantari High School and Adjacent Areas
3	Langarud Bazaar Park Area	14	Noorani High School
4	Green Space along Chamkhaleh Road	15	Anzali Neighborhood Green Space
5	Fajr Park, Langarud	16	Modarres High School, Kolidbar
6	Islamic Azad University Campus, Langarud	17	Shahid Rajaei High School
7	Ghadir University, Langarud	18	Shahed Middle School (Adjacent to the IRGC)
8	Azadi Park	19	Taleghani School (Adjacent to Taleghani Sports Club)
9	Parking Area Adjacent to Saderat Bank	20	Municipality
10	Kolidbar Mosque Area	21	Noghan Administration Office
11	Green Space Adjacent to Agha Seyyed Mohammad	22	Mehr Housing Project

Table 5. Characteristics of the alternatives based on the effective criteria.

Number	Location	Population (persons/ha)	Area (m ²)	Distance from Fault (m)	Distance from Mountain (m)	Distance from Water Body (m)	Distance from Gas Station (m)	Distance from Medical Centers (m)	Distance from Police/Sec urity Centers (m)	Distance from Fire Station (m)	Distance from Major Road (m)
1	Langarud Football Field	184	19290	671	1436	2810	937	1718	2304	3235	133
2	Takhti Sports Field, Langarud	162	9202	957	2232	1691	2031	464	1060	1994	55
3	Langarud Bazaar Park Area	155	12450	1104	2270	622	835	1120	1132	1126	544
4	Green Space along Chamkhaleh Road	187	5800	4184	5233	3044	3920	4211	4206	3363	10
5	Fajr Park, Langarud	154	45340	1407	2500	512	498	783	760	790	160
6	Islamic Azad University Campus, Langarud	135	20400	270	930	1610	1557	3786	2854	3793	676
7	Ghadir University, Langarud	97	7260	280	838	2533	1464	2210	2820	3757	380
8	Azadi Park	204	3500	2025	3195	1680	863	576	1688	1727	10
9	Parking Area Adjacent to Saderat Bank	235	800	1780	2932	1658	1090	826	1922	1938	57
10	Kolidbar Mosque Area	156	2100	1847	2730	1164	812	2220	2180	1050	10

Table 5. Continued.

Number	Location	Population (persons/ha)	Area (m ²)	Distance from Fault (m)	Distance from Mountain (m)	Distance from Water Body (m)	Distance from Gas Station (m)	Distance from Medical Centers (m)	Distance from Police/Sec urity Centers (m)	Distance from Fire Station (m)	Distance from Major Road (m)
11	Green Space Adjacent to Agha Seyyed Mohammad	183	4800	1600	2658	473	731	1054	1036	124	5
12	Passenger Terminal	163	1800	785	1846	2500	1235	1354	1984	2914	97
13	Kalantari High School and Adjacent Areas	165	6700	50	1298	2025	1000	1480	2078	3032	20
14	Noorani High School	147	1300	2156	3214	2694	2265	1974	2634	3544	618
15	Anzali Neighborho od Green Space	184	1800	2536	3812	2419	1926	1612	2770	2775	788
16	Modarres High School, Kolidbar	162	1740	1860	2740	1562	1233	2443	2734	2748	117
17	Shahid Rajaei High School	202	1200	1657	2826	1400	584	292	1405	1470	89
18	Shahed Middle School (Adjacent to the IRGC)	227	940	1930	3105	1340	633	350	1453	1351	365
19	Taleghani School (Adjacent to Taleghani Sports Club)	278	830	1936	3114	1264	593	314	1427	1467	317
20	Municipality	225	1060	1520	2709	1070	393	153	1246	1270	132
21	Noghan Administrati on Office	197	6300	1584	2808	828	190	493	773	770	40
22	Mehr Housing Project	146	26400	1322	2360	297	1252	1534	1563	335	360

Step 1 (Construction of the decision matrix: Matrix N (identification of criteria and alternatives)).

The main indicators (criteria) and alternatives were identified based on the literature review. Accordingly, a decision matrix was constructed by scoring the alternatives with respect to the selected criteria. The alternatives were evaluated according to each criterion. In this study, the decision matrix was developed and applied based on the available numerical data. The decision matrix is presented in *Table 6*.

Table 6. Decision matrix.

Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	184	19290	671	1436	2810	937	1718	2304	3235	133
A2	162	9202	957	2232	1691	2031	464	1060	1994	55
A3	155	12450	1104	2270	622	835	1120	1132	1126	544
A4	187	5800	4184	5233	3044	3920	4211	4206	3363	10
A5	154	45340	1407	2500	512	498	783	760	790	160
A6	135	20400	270	930	1610	1557	3786	2854	3793	676

Table 6. Continued.

Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A7	97	7260	280	838	2533	1464	2210	2820	3757	380
A8	204	3500	2025	3195	1680	863	576	1688	1727	10
A9	235	800	1780	2932	1658	1090	826	1922	1938	57
A10	156	2100	1847	2730	1164	812	2220	2180	1050	10
A11	183	4800	1600	2658	473	731	1054	1036	124	5
A12	163	1800	785	1846	2500	1235	1354	1984	2914	97
A13	165	6700	50	1298	2025	1000	1480	2078	3032	20
A14	147	1300	2156	3214	2694	2265	1974	2634	3544	618
A15	184	1800	2536	3812	2419	1926	1612	2770	2775	788
A16	162	1740	1860	2740	1562	1233	2443	2734	2748	117
A17	202	1200	1657	2826	1400	584	292	1405	1470	89
A18	227	940	1930	3105	1340	633	350	1453	1351	365
A19	278	830	1936	3114	1264	593	314	1427	1467	317
A20	225	1060	1520	2709	1070	393	153	1246	1270	132
A21	197	6300	1584	2808	828	190	493	773	770	40
A22	146	26400	1322	2360	297	1252	1534	1563	335	360

Step 2 (Normalization of the decision matrix — matrix N). In the second step, the decision matrix was normalized using the vector normalization method. If each element of the normalized matrix is denoted by n_{ij} , each normalized value is calculated by dividing the corresponding element of the original matrix by the square root of the sum of the squared elements in the corresponding column, as follows:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}$$

Accordingly, the output of the TOPSIS software for the normalized decision matrix N is presented below.

Table 7. Normalized decision matrix.

N	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.214	0.305	0.082	0.111	0.363	0.140	0.208	0.236	0.298	0.087
A2	0.188	0.145	0.117	0.173	0.202	0.304	0.056	0.108	0.184	0.036
A3	0.180	0.197	0.134	0.176	0.074	0.125	0.135	0.116	0.104	0.354
A4	0.217	0.092	0.510	0.406	0.364	0.586	0.509	0.430	0.310	0.007
A5	0.179	0.716	0.171	0.194	0.061	0.074	0.095	0.078	0.073	0.104
A6	0.157	0.322	0.033	0.072	0.192	0.233	0.458	0.292	0.349	0.440
A7	0.113	0.115	0.034	0.065	0.303	0.219	0.267	0.289	0.346	0.247
A8	0.237	0.055	0.247	0.248	0.201	0.129	0.070	0.173	0.159	0.007
A9	0.273	0.013	0.217	0.227	0.198	0.163	0.100	0.197	0.178	0.037
A10	0.181	0.033	0.225	0.212	0.139	0.121	0.268	0.223	0.097	0.007
A11	0.213	0.076	0.195	0.206	0.057	0.109	0.127	0.106	0.011	0.003
A12	0.189	0.028	0.096	0.143	0.299	0.185	0.164	0.203	0.268	0.063
A13	0.192	0.106	0.006	0.101	0.242	0.149	0.179	0.213	0.279	0.013
A14	0.171	0.021	0.263	0.249	0.322	0.339	0.239	0.270	0.326	0.402
A15	0.214	0.028	0.309	0.296	0.289	0.288	0.195	0.283	0.256	0.513
A16	0.188	0.027	0.227	0.212	0.187	0.184	0.295	0.280	0.253	0.076
A17	0.235	0.019	0.202	0.219	0.167	0.087	0.035	0.144	0.135	0.058
A18	0.264	0.015	0.235	0.241	0.160	0.095	0.042	0.149	0.124	0.237
A19	0.323	0.013	0.236	0.241	0.151	0.089	0.038	0.146	0.135	0.206
A20	0.261	0.017	0.185	0.210	0.128	0.059	0.018	0.127	0.117	0.086
A21	0.229	0.100	0.193	0.218	0.099	0.028	0.060	0.079	0.071	0.026
A22	0.170	0.417	0.161	0.183	0.035	0.187	0.185	0.160	0.031	0.234

Step 3 (Construction of the weighted normalized decision matrix — matrix V). In the third step, the normalized decision matrix N is transformed into the weighted normalized decision matrix V. To obtain the weighted normalized matrix, the weights of the criteria are required. The weight of each criterion was calculated using the AHP technique, as shown in Fig. 2.

For this purpose, the normalized matrix is multiplied by a square diagonal matrix $W_{n \times n}$, whose diagonal elements represent the criterion weights and whose off-diagonal elements are zero. The resulting matrix is referred to as the weighted normalized decision matrix and is denoted by V.

$$V = N \times W_{n \times n}.$$

The results of this calculation are summarized in Table 8.

Table 8. Weighted normalized decision matrix.

V	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.0355	0.0381	0.0096	0.0117	0.0336	0.0123	0.0160	0.0177	0.0214	0.0063
A2	0.0312	0.0182	0.0138	0.0182	0.0202	0.0267	0.0043	0.0081	0.0132	0.0026
A3	0.0299	0.0246	0.0159	0.0185	0.0074	0.0110	0.0104	0.0087	0.0075	0.0258
A4	0.0361	0.0115	0.0601	0.0426	0.0364	0.0516	0.0392	0.0323	0.0223	0.0005
A5	0.0297	0.0895	0.0202	0.0204	0.0061	0.0066	0.0073	0.0058	0.0052	0.0076
A6	0.0260	0.0403	0.0039	0.0076	0.0192	0.0205	0.0352	0.0219	0.0251	0.0321
A7	0.0187	0.0143	0.0040	0.0068	0.0303	0.0193	0.0206	0.0216	0.0249	0.0180
A8	0.0393	0.0069	0.0291	0.0260	0.0201	0.0114	0.0054	0.0130	0.0114	0.0005
A9	0.0453	0.0016	0.0256	0.0239	0.0198	0.0143	0.0077	0.0148	0.0128	0.0027
A10	0.0301	0.0041	0.0265	0.0222	0.0139	0.0107	0.0207	0.0167	0.0070	0.0005
A11	0.0353	0.0095	0.0230	0.0216	0.0057	0.0096	0.0098	0.0080	0.0008	0.0002
A12	0.0313	0.0036	0.0113	0.0150	0.0299	0.0162	0.0126	0.0152	0.0193	0.0064
A13	0.0318	0.0132	0.0007	0.0106	0.0242	0.0132	0.0138	0.0159	0.0201	0.0009
A14	0.0283	0.0026	0.0310	0.0262	0.0322	0.0298	0.0184	0.0202	0.0235	0.0293
A15	0.0355	0.0036	0.0364	0.0310	0.0289	0.0253	0.0150	0.0213	0.0184	0.0374
A16	0.0312	0.0034	0.0267	0.0223	0.0187	0.0162	0.0227	0.0210	0.0182	0.0056
A17	0.0390	0.0024	0.0238	0.0230	0.0167	0.0077	0.0027	0.0108	0.0097	0.0042
A18	0.0438	0.0019	0.0277	0.0253	0.0160	0.0083	0.0033	0.0112	0.0090	0.0173
A19	0.0536	0.0016	0.0278	0.0254	0.0151	0.0078	0.0029	0.0110	0.0097	0.0151
A20	0.0434	0.0021	0.0218	0.0221	0.0128	0.0052	0.0014	0.0096	0.0084	0.0063
A21	0.0380	0.0124	0.0228	0.0229	0.0099	0.0025	0.0046	0.0059	0.0051	0.0019
A22	0.0282	0.0521	0.0190	0.0192	0.0035	0.0615	0.0143	0.0120	0.0022	0.0171

Step 4 (Calculation of the positive and negative ideal solutions A^+ and A^-). In this step, a positive ideal solution (A^+) and a negative ideal solution (A^-) are determined for each criterion. In the present decision-making problem, two criteria are classified as cost-type (negative) criteria, whereas the remaining criteria are classified as benefit-type (positive) criteria. Accordingly, the positive and negative ideal solutions are determined for each criterion.

The resulting positive and negative ideal values for the present decision-making problem are as follows.

Table 9. Positive and negative ideal solutions.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
V^+	0.054	0.090	0.060	0.043	0.036	0.052	0.039	0.032	0.025	0.037
V^-	0.0187	0.0016	0.0007	0.0068	0.0035	0.0025	0.0014	0.0058	0.0008	0.0002

Step 5 (Calculation of the distance of each alternative from the positive and negative ideal solutions).

The output of the TOPSIS software for these calculations is presented in *Table 10*.

Table 10. Calculations of d^+ and d^- .

Alternative	D^+	D^-
A1	0.0988	0.0594
A2	0.1112	0.0421
A3	0.1079	0.0435
A4	0.0882	0.1062
A5	0.0928	0.0925
A6	0.0948	0.0717
A7	0.1150	0.0518
A8	0.1150	0.0465
A9	0.1169	0.0479
A10	0.1177	0.0417
A11	0.1212	0.0344
A12	0.1201	0.0424
A13	0.1214	0.0386
A14	0.1023	0.0693
A15	0.0996	0.0737
A16	0.1116	0.0501
A17	0.1223	0.0391
A18	0.1176	0.0477
A19	0.1181	0.0528
A20	0.1247	0.0386
A21	0.1210	0.0361
A22	0.0926	0.0618

Step 6 (Calculation of the ideal solution). In this step, the relative closeness of each alternative to the ideal solution is calculated using the following equation:

$$CL_i^* = \frac{d_i^-}{d_i^- + d_i^+}.$$

The value of CL ranges between zero and one. A higher CL value indicates greater relative closeness to the ideal solution. The calculated values are presented in *Table 11*.

Table 11. Calculated CLV alues.

Alternative	D^+	D^-	CL
A1	0.0988	0.0594	0.3756
A2	0.1112	0.0421	0.2743
A3	0.1079	0.0435	0.2875
A4	0.0882	0.1062	0.5464
A5	0.0928	0.0925	0.4992
A6	0.0948	0.0717	0.4306
A7	0.1150	0.0518	0.3106
A8	0.1150	0.0465	0.2878
A9	0.1169	0.0479	0.2905
A10	0.1177	0.0417	0.2618
A11	0.1212	0.0344	0.2210
A12	0.1201	0.0424	0.2611

Table 11. Continued.

Alternative	D ⁺	D ⁻	CL
A13	0.1214	0.0386	0.2411
A14	0.1023	0.0693	0.4040
A15	0.0996	0.0737	0.4253
A16	0.1116	0.0501	0.3097
A17	0.1223	0.0391	0.2422
A18	0.1176	0.0477	0.2888
A19	0.1181	0.0528	0.3089
A20	0.1247	0.0386	0.2363
A21	0.1210	0.0361	0.2299
A22	0.0926	0.0618	0.4003

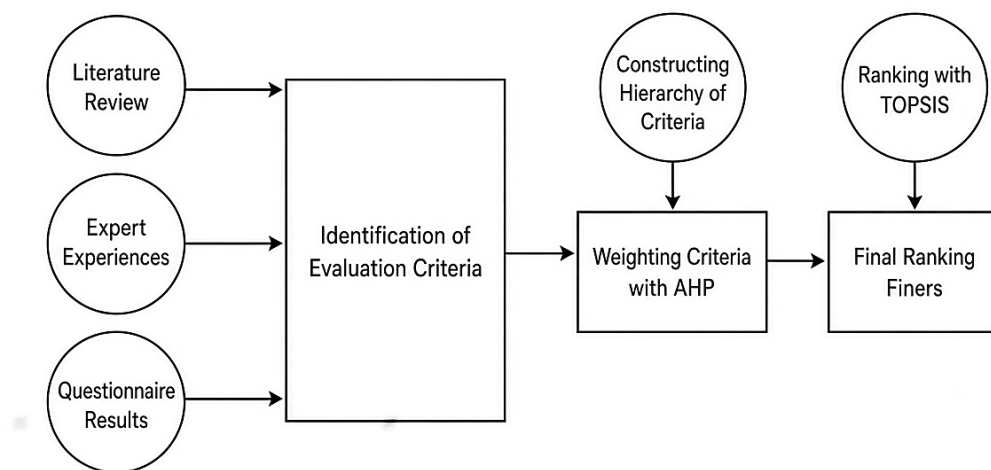


Fig. 3. Conceptual model of the research methodology.



Fig. 4. Location of Area 1 (Langarud Football Field).



Fig. 5. Location of Area 2 (Takhti Sports Field, Langarud).



Fig. 6. Location of Area 2 (Takhti Sports Field, Langarud).

Based on the results of the TOPSIS analysis, the priority status of the areas according to their fulfillment of the criteria considered in the selection of temporary accommodation sites is presented in the following table.

Based on Fig. 3, the ranking of the alternatives is presented in the following table:

Table 12. Final ranking of alternatives.

Symbol	Alternative	Weight	Rank
A4	Green Space along Chamkhaleh Road	0.5464	1
A5	Fajr Park, Langarud	0.4992	2
A6	Islamic Azad University Campus, Langarud	0.4306	3
A15	Anzali Neighborhood Green Space	0.4253	4
A14	Noorani High School	0.4040	5
A22	Mehr Housing Project	0.4003	6
A1	Langarud Football Field	0.3760	7
A7	Ghadir University, Langarud	0.3106	8
A16	Modarres High School, Kolidbar	0.3097	9
A19	Taleghani School (Adjacent to Taleghani Sports Club)	0.3089	10
A9	Parking Area Adjacent to Saderat Bank	0.2905	11
A18	Shahed Middle School (Adjacent to the IRGC)	0.2888	12

Table 2. Continued.

Symbol	Alternative	Weight	Rank
A8	Azadi Park	0.2878	13
A3	Fajr Park Area	0.2875	14
A2	Takhti Sports Field	0.2740	15
A10	Kolidbar Mosque Area	0.2618	16
A12	Passenger Terminal	0.2611	17
A17	Shahid Rajaei High School	0.2422	18
A13	Kalantari High School and Adjacent Areas	0.2411	19
A20	Municipality	0.2363	20
A21	Noghan Administration Office	0.2299	21
A11	Green Space Adjacent to Agha Seyyed Mohammad	0.2210	22

5 | Conclusion

Despite the advances achieved by humanity in the present era, people remain vulnerable to unexpected natural hazards such as earthquakes, floods, and other disasters, which continue to cause significant loss of life, injuries, and financial damage. Among natural hazards and disasters, earthquakes receive particular attention because of the extensive destruction they can cause. In quantitative terms, since 1900, approximately 20 earthquakes with a magnitude greater than 7 on the Richter scale have occurred annually.

Given Iran's location within the Alpine–Himalayan seismic belt, the country is also considered one of the earthquake-prone countries in the world. In Iran, over the past several years, an earthquake with a magnitude greater than 6 on the Richter scale has occurred, on average, approximately once per year. Although preventing the occurrence of earthquakes is, at least at present, beyond human capability, preparedness for confronting such disasters or crises is feasible. The absence of sound and fundamental planning, inadequate planning for urban development and expansion, and non-standard construction practices have intensified this threat. The need for unified management and coordination among different organizations and agencies, particularly in the moments following an earthquake, highlights the importance of effective disaster management.

Based on past experiences, disaster management in Iran has often faced weaknesses due to inadequate management, resulting in confusion during times of crisis. To address this problem, the preparation of pre-designed plans and the implementation of advance studies can make a significant contribution to resolving the problems and crises that arise. Temporary accommodation of affected populations is regarded as one of the essential stages of post-disaster management, and success in providing temporary accommodation can contribute to successful implementation of the subsequent stages of disaster management. Temporary accommodation is one of the issues that consumes considerable time and energy of managers during crises.

Accordingly, given the importance of temporary accommodation, anticipating and identifying suitable locations for temporarily accommodating people who have lost their homes as a result of a disaster, particularly an earthquake, is essential.

Following preliminary investigations and a review of the literature, 10 criteria were identified as factors affecting the selection of temporary accommodation sites. After distributing the questionnaire using a fuzzy approach, the criteria were ranked and prioritized using Expert Choice software. Based on the weights of the influential criteria and the scores obtained by each of the 22 areas in terms of satisfying these criteria, the TOPSIS method was used to identify and rank the most suitable areas.

Among the influential criteria, population density, with a weight of 0.166, and area, with a weight of 0.125, have the greatest influence on the selection of temporary accommodation sites. These are followed by distance

from faults and distance from mountains. The criteria with the least influence are distance from major roads and distance from fire stations.

The TOPSIS results indicate that Areas 4 and 5 are the most suitable areas for temporary accommodation within the study area. Areas 6 and 15 are subsequently identified as suitable alternatives. Based on the calculations, Areas 11 and 21 have the lowest weights among the 22 areas.

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All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

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Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflict of Interest

The author declares that they do not have any conflict of interest.

Consent for Publication

The author confirms consent for the publication of this work.

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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