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Earthquake risk prioritization via two-step cluster analysis and swara-electre methods

Ezgi GÜLER*[1,2], Selen AVCI[2], Zerrin ALADAĞ[2]

ABSTRACT

Earthquake is one of the most destructive disasters for people, both materially and morally. Some precautions to be taken before an earthquake reduce this harmful effect. Earthquake risk assessment is one of these precautions. Earthquake risk assessment, which is an interdisciplinary topic, is a problem suitable for clustering and multi-criteria decision-making (MCDM) techniques, as it includes more than one criterion and alternative. In this study, decision model was proposed for earthquake risk prioritization of twenty-nine provinces with high earthquake risk in Turkey. In the proposed model, provinces were clustered via Two-Step Cluster Analysis. Indicators determined in the Two-Step Cluster Analysis were defined as criteria, and criteria weighting was made via SWARA method. After weighing the criteria, the ELECTRE I method was used for earthquake risk ranking of the clustered provinces. In the proposed model for earthquake risk assessment, the similarity of provinces can be defined, and the impact of indicators can be examined. For this purpose, as the innovative aspect of this paper, while evaluating the clustering success, it was proposed to examine the coefficients of variation for continuous variables. In the Two-Step Cluster Analysis, clusters were formed in different ways and the risk rankings for provinces divided into six sub-clusters in total were presented. As a result of the Two-Step Cluster Analysis, two clusters consisting of six provinces, two clusters consisting of five provinces, one cluster consisting of four provinces and one cluster consisting of three provinces were obtained. The rankings of these provinces within clusters were obtained via ELECTRE I method. The aim of the study is to guide the decision makers working on earthquake risk assessment in the practical world by providing the hybridization of the specified clustering and multi-criteria decision-making methods.

Keywords: *Earthquake Risk Prioritization; ELECTRE; SWARA; Two-Step Cluster Analysis.*

INTRODUCTION

Disaster is any event that causes ecological deterioration, life, or economic damage in people's living spaces. Recently, the number and severity of disasters have increased, causing significant loss of life and great economic losses [1]. Earthquakes, mass movements, floods, tornadoes, volcanic eruptions, tsunamis, etc. are natural disasters that can cause many losses of life and damage property [2]. Especially, earthquakes are natural disasters with high destructive power and wide impact [3]. Since 1980, earthquakes accounted for 12.2% of all-natural disaster hazards worldwide and caused 56.2% of all disaster losses and 25.2% of total financial losses. The top five countries that have been most frequently affected by damaging earthquakes are China, Indonesia, Iran, Turkey, and Japan, respectively [4]. Many earthquakes occurred in Turkey, and Turkey is still under the threat of earthquakes. Marmara Earthquake (1999) is one of the most important earthquakes that have occurred in the recent past, causing loss of life and affecting the social, environmental, economic, and physical systems of the country. The result of this earthquake is not only limited to human deaths, but also has implications for the socioeconomic systems that directly affect the welfare of the country. Especially when Turkey's industrial production center is thought to be the largest share in the Marmara region and environmental destructiveness of the earthquake it has been more pronounced [5].

Awareness of the risks posed by seismic activity has heightened in the recent past because of the several significant earthquakes [6]. In this context, the concept of disaster management is important for the successful management of the disaster process and for the sustainability of physical, socioeconomic, and environmental systems [5]. Disaster management consists of four basic phases: a) reduction (mitigation) phase, b) preparation phase, c) intervention phase, d) improvement phase. Risk management is required in the mitigation phase. The loss mitigation process consists of activities such as determining

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[1] Bilecik Şeyh Edebali University, Department of Industrial Eng., Bilecik, Turkiye
[2] Kocaeli University, Department of Industrial Eng., Kocaeli, Turkiye
** E-mail address: ezgi.guler@bilecik.edu.tr*
Orcid id: https://orcid.org/ 0000-0001-8789-8244 Ezgi Güler, 0000-0001-7433-5696 Selen Avcı, 0000-0002-5986-7210 Zerrin Aladağ
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resources, identifying hazards, risk assessment, preparing mitigation plans, and improving existing mitigation measures. The paradigm shift from a disaster response-based approach to disaster mitigation and risk reduction approaches is necessary for disaster management. By taking necessary pre-disaster measures, including disaster mitigation and risk reduction actions, the unwanted consequences of disasters can be ignored or minimized [7]. Pre-disaster activities, including mitigation, have a special place in reducing the vulnerability of systems that sustain urban vitality [8]. The casualties and structural, social, economic, or environmental losses that may occur with a possible disaster are related to the fragility level of areas with higher vulnerability levels that are more prone to the negative effects of disasters [9].

Regional risk assessment in disaster management is of practical value for disaster prevention and mitigation phases [10]. It is possible to reduce the impact of earthquakes with appropriate disaster risk reduction strategies [11]. It is aimed to provide input to the disaster management process by determining the areas with earthquake risk and evaluating them according to various factors through risk assessment among the mitigation activities [5].

There are many different types of evaluation and ranking methods [12]. Hybrid techniques were used for earthquake risk assessment, ranking or prioritization in the literature. Shayannejad and Angerabı proposed a model for the 6th district of Tehran municipality in Iran. In their study, AHP method was used to obtain the importance degrees of criteria included in earthquake vulnerability and Fuzzy Logic was used for normalization. Integrating the two methods enriched the study, but not evaluating alternatives can be considered a limitation of the study. It is important to see the effect of the criteria weights on the results [13]. Peng proposed an approach that integrates the results of 6 MCDM methods for earthquake risk assessment of thirty-one Chinese regions. The weights of MCDM methods were obtained by calculating Spearman's Rank Correlation Coefficients. The fact that the coefficients of variation were not calculated for each criterion in the study. It was insufficient for the effectiveness of the study. Giving the results in a single rank is one of the advantages of this study. [14]. Delavar et al. examined the vulnerability of hospital buildings to earthquakes and made a risk assessment for buildings. Several criteria have been determined for risk assessment, such as building age, number of floors, material quality and earthquake intensity. The Sugeno integral, which can consider the interaction between criteria, was used to assess the degree of fragility of buildings. In this study, earthquake risk assessment was examined structurally (not regionally). The use of the Sugeno integral can be considered an innovation [15]. Alizadeh et al. developed a new hybrid framework using Analytical Network Process (ANP) and Artificial Neural Network (ANN) models to create a composite social, economic, environmental, and physical vulnerability index in earthquake risk assessment. Geographic Information Systems (GIS) analysis was used to make an earthquake vulnerability map and determine quantitative vulnerability indicators The use of GIS in this study was advantageous for mapping, but the ANP method used for weighting criteria should be expanded [16]. Nyimbili et al. used Analytical Hierarchical Process (AHP) integrated with GIS and Technique for Order Preference by Similarity to An Ideal Solution (TOPSIS) for earthquake disaster monitoring and risk analysis. Istanbul, Küçükçekmece in Turkey has been identified as a region in case study. AHP and TOPSIS are very classical and old methods, this is the limitation of the study. The use of GIS has created an advantageous situation [17]. Kumlu and Tudes used the GIS-based AHP and TOPSIS to determine the earthquake risk areas in Yalova City Center [5]. Chen et al. proposed a new MCDM model to assessment China's natural disaster risk at the regional scale. The model consists of twenty-eight criteria that reflect the natural disaster hazard and the vulnerability of the affected area, and it includes clustering, visualization, and ranking [10]. Yariyan et al. aimed to evaluate and analyze the scope of earthquake vulnerability according to demographic, environmental and physical criteria. An earthquake risk assessment (ERA) map was created using the Fuzzy AHP (FAHP) model combined with Artificial Neural Networks (ANN). Combining the FAHP-ANN application with GIS made it possible to assign weights to the layers of earthquake vulnerability criteria [18]. Jena et al. aimed to develop an integrated model by using the Artificial Neural Network-Analytical Hierarchy Process (ANN-AHP) model to create an earthquake risk map [19]. Jena et al. aimed to evaluate the Earthquake vulnerability assessment using AHP, VIKOR and GIS [20]. Jena et al (2021) proposed MCDM approach to estimate the weights of various input criteria such as slope, curvature, height, proximity to road, road density, proximity to land use, land use density, proximity to water bodies. They applied integrated Analytical Hierarchy Process (AHP) and Probabilistic Neural Network (PNN) for earthquake risk assessment. The PNN model was useful in terms of successfully investigating the relationship between the variables and weights obtained in the study. The research of criterion weights only with the AHP method can be considered as a direction that needs to be developed in the study [21]. Albulescu et al (2022) studied MCDM approaches to assess the systemic risk to earthquakes of urban centers in the Southeast region of Romania.

They evaluated criteria such as proximity to hospitals and road types. The GIS supported approach has been beneficial in terms of visualization. The MCDM approaches used are AHP, TOPSIS and WPM. The fact that city centers are not clustered in terms of their different characteristics can be considered as the aspect of their study that needs to be developed [22].

Some studies in the literature were given in Table 1.

Table 1. Literature summary for earthquake risk assessment

Reference	Country	Methods
[13]	Iran	Fuzzy Logic, AHP
[14]	China	TOPSIS, VIKOR, ELECTRE III, PROMETHEE II, WSM
[15]	Iran	Group MCDM, Sugeno Integral
[16]	Iran	ANP, ANN, GIS
[17]	Turkey	AHP, TOPSIS, GIS
[5]	Turkey	AHP, TOPSIS, GIS
[10]	China	AHP, Self-Orginizing Map, Isometric Feature Mapping, TOPSIS
[18]	Iran	FAHP, ANN, GIS
[19]	Indonesia	ANN, AHP
[20]	Indonesia	AHP, VIKOR, GIS
[21]	India	AHP, PNN
[22]	Romania	AHP, TOPSIS, GIS, WPM

In this study, Two-Step Cluster Analysis was preferred because it is suitable for problem structures containing both categorical and continuous indicators. The SWARA method is an efficient method as it makes proportional evaluations while determining the criterion weights. For this reason, criterion weights were determined by the SWARA method in the study. It was preferred because it is a useful method for ranking, since each option is graded over the efficiency measures determined in the ELECTRE Method. The determined provinces in Turkey were divided into clusters via Two-Step Cluster Analysis according to earthquake risk indicators consisting of categorical and continuous variables. In Two-Step Cluster Analysis, the number of clusters can be determined by the formula of the number of clusters, as well as via SPSS package program. In this study, Two-Step Cluster Analysis was conducted twice to cluster the provinces with high similarity in terms of variables in detail. Clustering indicators were defined as criteria and opinions of Decision Makers (DMs) were used for criteria weights. The criteria data of the provinces were processed in the decision matrix in the ELECTRE method. The criterion weights obtained by the SWARA method were used in the ELECTRE method. According to the different clusters formed, the risk ranking of the provinces in each cluster was obtained separately. As far as is known this is the first study to integrate Two Step Cluster Analysis and MCDM methods for regional earthquake risk assessment. In this context, it is aimed that the study will contribute to the literature. Examining the provinces from a national perspective with such an analysis model will help decision makers for time and resource planning for earthquake study.

In the second part of the article, the methods used will be explained in detail. In the next section, an earthquake risk prioritization application will be made for the provinces in Turkey. In the last section, the findings will be discussed.

MATERIAL AND METHODS

In this study, the MCDM problem is defined as earthquake risk assessment. Afterwards, the criteria to be used for regional earthquake risk assessment will be determined by literature research. According to the AFAD Earthquake Hazard Map, provinces with high earthquake hazard in Turkey (provinces with the highest ground acceleration) will be assigned as alternatives to the decision problem. The data set for the criteria of the 29 provinces will be obtained from different sources. These provinces will be clustered with the Two-Step Cluster Analysis in terms of the determined criteria (indicators for the Two-Step Cluster Analysis). AIC and BIC values will be taken into account in the first clustering process. After the different clusters of the provinces are formed, the clustering analysis will be repeated with the cluster formulation. Then, the MCDM problem requirements will be defined, and the criteria will be weighted by taking DMs' opinions. The SWARA method will be applied in criterion weighting. The provinces in the final clusters will be listed by integrating the criterion weights into the ELECTRE method. The flowchart of the study was given in Figure 1.

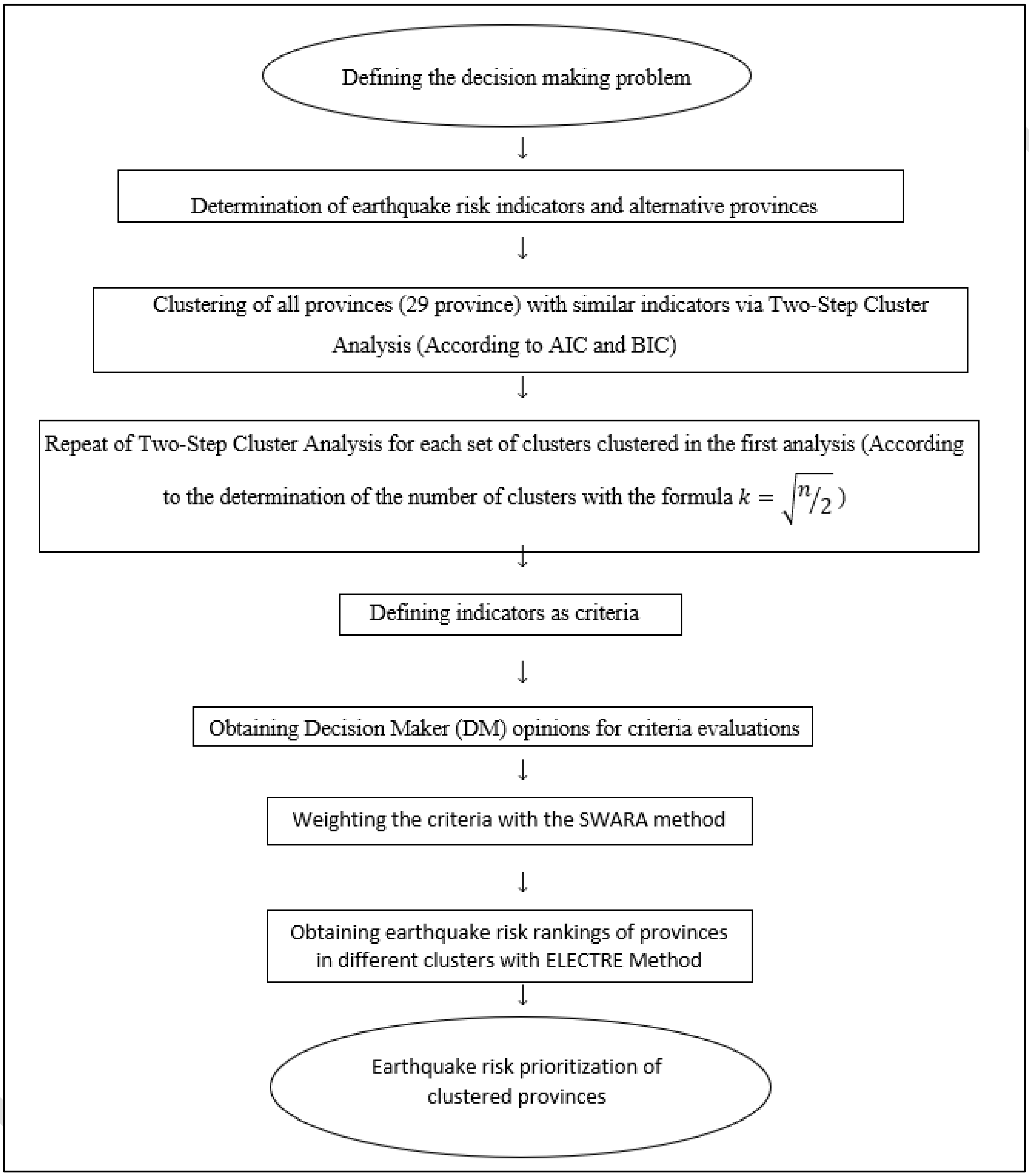

Figure 1. The flowchart for earthquake risk prioritization

TWO-STEP CLUSTER ANALYSIS

Clustering analysis is performed each based on different algorithms with the help of various statistical software packages by using hierarchical cluster, two-step cluster, K-Means cluster methods etc. [23]. While the last two of these methods are classical classification methods based on hierarchical and segmentation algorithms, the Two-Step cluster method is a method designed and applied in SPSS [24]. The most important features of Two-Step Cluster Analysis; it can be applied to large data sets, it can process categorical and continuous variables, it can automatically determine the most appropriate number of clusters, and it can be extracted from the data when required. The application steps of Two-Step Cluster Analysis are pre-clustering, detecting outliers and creating clusters [25]. In pre-clustering, the goal is to reduce the size of the distance matrix. The structure of the distance matrices varies according to whether the data is categorical or continuous. Distance matrices for continuous variables use Squared Euclidean Distance. Another distance matrix distance is the Log-Similarity Distance that can be used in both continuous and categorical data. The second phase of the Two-Step Cluster Analysis is the detection of outliers. In the last stage of the analysis, pre-sets form the new input matrix. With the new distance matrix, the desired number of clusters are created, and the analysis is completed [26].

The number of clusters can be determined in advance by the researcher, or in cases where the number of clusters is not known in advance, it can also be determined in accordance with Schwarz's Bayesian Information Criteria (BIC) or Akaike's Information Criteria (AIC) during analysis. The number of clusters with the smallest AIC or BIC criteria is considered the optimum number of clusters**.** The formulas of these values are given in Equation (1)-(3)**.**

$$BIC\ (J) = -2 \sum_{j=1}^{J} \xi_j + m_j \log (N) \tag{1}$$

$$AIC\ (J) = -2 \sum_{j=1}^{J} \xi_j + 2\, m_j \tag{2}$$

$$m_j = J \left\{ 2\, K^A + \sum_{k=1}^{K^B} (T_K - 1) \right\} \tag{3}$$

The distance between clusters *i* and *j* is calculated as in Equation (4). $\langle i,j \rangle$ represents the cluster created by combining clusters *i* and *j*.

$$d\ (i,j) = \xi_i + \xi_j - \xi_{\langle i,j \rangle} \tag{4}$$

The ξ_i given in Equation (5) is variance within the cluster i.

$$\xi_i = -N_r \left(\sum_{k=1}^{K^A} \frac{1}{2} \log(\sigma_k^2 + \sigma_{rk}^2) + \sum_{k=1}^{K^B} E_{rk} \right) \tag{5}$$

The E_{rk} is given in Equation (6).

$$E_{rk} = -\sum_{t=1}^{T_k} \frac{N_{rkt}}{N_r} \log \frac{N_{rkt}}{N_r} \tag{6}$$

where,
K^A: number of continuous variables
K^B: number of categorical variables
T_K: k. the number of categories of the categorical variable
N_r: r. number of observations in the cluster
N_{rkt}: Number of observations in categorical variable (k) with t categories
σ_k^2: estimated variance of continuous variable
σ_{rk}^2: Estimated variance of continuous variable k in cluster r

In Two-Step Cluster Analysis with strong results, the cluster size ratio (the ratio of the number of members in the largest cluster to the number of members in the smallest cluster) is less than 2.00 [26].

SWARA METHOD

SWARA method was proposed by Keršuliene et al [27]. It is called "Step-Wise Weight Assessment Ratio Analysis". This method was developed for weighting of criteria [28]. The simplicity of the SWARA method makes it easy for different DMs to work for one purpose at the same time. This situation enables DMs to save time [29]. In the SWARA method, the number of comparisons made between criteria for weighting is less than methods such as AHP and ANP. This situation decreases the transaction cost. In the method, the criteria to be used in the evaluation of alternatives are listed from important to unimportant, and unimportant criteria are eliminated by voting. While calculating the importance weights of the remaining criteria, the ranking formed by each DM is considered [30]. Final values are obtained by taking geometric averages for the evaluation of different DMs [31].

The steps of the SWARA method are summarized as follows:

Step 1. The criteria are listed in descending order of importance in accordance with DMs' opinions.

Step 2. Starting with the second criterion, relative importance levels are determined for each criterion. For this, criterion j is compared with previous criterion $(\mathrm{j}-1)$. Keršuliene et al. (2010) named this ratio as "the comparative importance of the mean value" and indicated it with the symbol "$\mathrm{s_j}$". The $\mathrm{s_j}$ values are assigned by DMs in multiples of five from 0 to 1 [32].

Step 3. Calculation of the "$\mathrm{k_j}$". The coefficient "$\mathrm{k_j}$" is determined as in Equation (7).

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases} \tag{7}$$

Step 4. Calculation of the "$\mathrm{q_j}$". The importance vector "$\mathrm{q_j}$" showing the corrected value is given in Equation (8).

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{q_{j-1}}{k_j} & j > 1 \end{cases} \tag{8}$$

Step 5. The relative weights of the criteria "$\mathrm{w_j}$" are calculated as in Equation (9).

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{9}$$

ELECTRE METHOD

The ELECTRE method was first introduced in 1966 by Benayoun et al. It is called "Elimination and Choice Translating Reality" [33]. This method is based on dual superiority comparisons between alternative decision points for each assessment factor. In this study, the risk ranking of the provinces with high earthquake risk was evaluated using the ELECTRE I method. ELECTRE I within the ELECTRE family developed by Roy can be expressed as a comparison method that reveals superiority relations (outranking relations) by comprehensively comparing each alternative [34].

The steps followed in the ELECTRE I method are summarized as follows [33, 35]

Step 1. Determine the decision matrix ($\mathrm{A_{ij}}$). It is supposed that the problem has m alternatives ($A_1, A_2, \ldots, A_m$) and n decision criteria ($C_1, C_2, \ldots, C_n$). The decision matrix is given in Equation (10).

$$A_{ij} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{10}$$

Step 2. Normalization of decision matrix ($\mathrm{X_{ij}}$). The normalized decision matrix is given in Equation (11).

$$\mathrm{x_{ij}} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \;; \qquad x_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{11}$$

Step 3. Creating of the weighted normalized decision matrix (V_{ij}). After the criteria weights are determined by the DMs, the V_{ij} matrix is formed by multiplying the relevant values of the elements in the X_{ij} matrix with the criteria weights (w_n). The weighted normalized decision matrix is given in Equation (12).

$$V_{ij} = \begin{bmatrix} w_1 x_{11} & \cdots & w_n x_{1n} \\ \vdots & \ddots & \vdots \\ w_1 x_{m1} & \cdots & w_n x_{mn} \end{bmatrix} \tag{12}$$

Step 4. Calculation of concordance set (C_{kl}) and discordance set (D_{kl}). The V_{ij} matrix is used to determine these sets. Alternatives are compared in terms of criteria and sets are created. Concordance set and discordance set are given Equation (13) and Equation (14), respectively.

$$C_{kl} = \{j, v_{kj} \geq v_{lj}\} \tag{13}$$

$$D_{kl} = \{j, v_{kj} < v_{lj}\} \tag{14}$$

Step 5. Creating concordance (C) and discordance matrix (D). The concordance set is used to create the concordance matrix. Matrix C is of mxm size and takes no value for k = 1 . The elements of matrix C are calculated as in Equation (15). The elements of the discordance matrix (D) are calculated by Equation (16). Like matrix C, matrix D is of mxm size and takes no value for k = 1.

$$c_{kl} = \sum_{j \epsilon C_{kl}} w_j$$
$$C = \begin{bmatrix} - & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & - \end{bmatrix} \tag{15}$$

$$d_{kl} = \frac{max\left|v_{kj} - v_{lj}\right|_{j \epsilon D_{kl}}}{max\left|v_{kj} - v_{lj}\right|_{j}}$$
$$D = \begin{bmatrix} - & \cdots & d_{1m} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & - \end{bmatrix} \tag{16}$$

Step 6. Concordance (F)and discordance (G) superiority matrices are calculated as in Equation (17) and Equation (18), respectively. The elements of the ($m \times m$) dimensional superiority matrices can also take only 1 and 0 values.

$$\underline{c} = \frac{1}{m(m-1)} \sum_{k=1}^{m} \sum_{l=1}^{m} c_{kl} \tag{17}$$
$$if\ c_{kl} \geq \underline{c} \rightarrow f_{kl}=1,\ otherwise,\ f_{kl}=0$$

$$\underline{d} = \frac{1}{m(m-1)} \sum_{k=1}^{m} \sum_{l=1}^{m} d_{kl} \tag{18}$$
$$\text{if } d_{kl} \leq \underline{d} \rightarrow g_{kl}=1, \text{ otherwise, } g_{kl}=0$$

Step 7. Net Superior Values (C_p) and Net Inferior Values (D_p) are calculated: C_p's are ordered in descending order and D_p's are ordered in increasing order. The values are given in Equation (19) and Equation (20). They obtained are used for the final ranking.

$$C_p = \sum_{k=1}^{m} C_{lk} - \sum_{k=1}^{m} C_{kl} \quad , \ k \neq l \tag{19}$$

$$D_p = \sum_{k=1}^{m} D_{lk} - \sum_{k=1}^{m} D_{kl} \quad , \ k \neq l \tag{20}$$

Step 8. Creating the Total Superiority Matrix (E). The elements of the total superiority matrix are equal to the mutual product of the elements of the matrices F and G. The matrix E is of mxm size. It consists of "1" and "0" values. The decision point that takes the value "1" in the matrix is considered superior to the other decision point (alternative).

Step 9. Determining the rank of importance of alternatives: The rows and columns of the E matrix and ranking of C_p and D_p values show the decision points.

THE RESEARCH FRAMEWORK AND FINDINGS

Research Framework

Alpine mountain ranges were formed by the effect of compressive forces created by the relative movements of the Asian and European continents. Similarly, the Himalayas were formed because of the merger of India and the Asian continent. Turkey, which is one of the most active earthquake zones, is in the Himalayan seismic belt. Turkey's earthquake hazard map based on the highest ground acceleration values were prepared by Disaster and Emergency Management Authority (AFAD in Turkish) [36].

Turkey between 36-42° northern latitude and 26-45° east meridians, being part of the Asian and European continent. Turkey covers 783.562 Km^2 area. In this study, the provinces of Turkey determined were “Aydın, Balıkesir, Bartın, Bilecik, Bolu, Bingöl, Burdur, Bursa, Çanakkale, Çankırı, Denizli, Düzce, Erzincan, Hatay, Isparta, İzmir, Karabük, Kırıkkale, Kırşehir, Kocaeli, Manisa, Muğla, Muş, Osmaniye, Sakarya, Siirt, Tokat, Tunceli, Yalova”. Twenty-nine provinces selected for evaluation were those with the highest ground acceleration values in the earthquake hazard map prepared by Disaster and Emergency Management Authority (AFAD) and were known to have high earthquake hazards [36].

The indicators that were decisive in earthquake risk prioritization were defined. The indicators determined for earthquake risk prioritization were given in Table 2. As indicated in Figure 1, indicators defined for Two-Step Cluster Analysis were defined as sub-criteria for SWARA-ELECTRE methods. In other words, each indicator used in clustering the provinces is a sub-criterion for earthquake risk prioritization.

Table 2. Criteria for earthquake risk assessment

Main Indicator (Criteria)	Indicators (Sub-Criteria)	Units or Categories of Sub-Criteria in this study	Data Type	Source of Data	References
A. Geotechnical	A1. Lithology	Alluvial Fan Deposits	Categorical	(AFAD, 2019)	[5, 19]
		Volcanics			
		Limestone			
		Undifferentiated Quaternary Deposits			
		Continental Deposits			
	A2. EuroCode8 (EC8) class	B class	Categorical	(AFAD, 2019)	[42]
		C class			

	A3. Elevation	Meter (m)	Continuous	(AFAD, 2019)	[18, 19, 37, 38]
B. Structural	B1. Total number of houses	Number	Continuous	(DASK, 2019)	[19, 37]
	B2. Total number of organized industrial zone and R&D centers	Number	Continuous	(Republic of Turkey Ministry of Industry and Technology, 2019)	[19, 20]
C. Socioeconomic	C1. Population density	Population/Km^2	Continuous	(TURKSTAT,2019)	[18, 19, 38, 39, 40]
	C2. Average household size	Total household population/ Total number of households	Continuous	(TURKSTAT,2019)	[18, 20]
	C3.GDP per capita	Turkish lira (₺)	Continuous	(TURKSTAT,2019)	[14, 41]

Indicator/ Criteria explanations are defined in the following sections.

A1. Lithology: Alluvial Fan Deposits, Volcanic, Limestone, Undifferentiated Quaternary Deposits and Continental Deposits are certain lithological characteristics of Turkey. Lithology types are the indicators of earthquake hazard and risk. Different provinces or regions of Turkey have different lithological characteristics [5].

A2. EC8 class: The subject of Eurocode8, the European standard for earthquake zones, is to apply earthquake engineering criteria and requirements to building construction and design in earthquake zones. There are different soil types according to the undrained shear strength of the floor. Shear wave velocity is a parameter that reflects the strength of the ground. If the value of Vs (30) is less than 180 m / s, it reflects weak grounds, if it is greater than 760 or 800m / s, it reflects rock environments. In this study, ground classification was used according to EC8 regulation. According to CEN, 2004, the range of "360 <Vs <= 800" for Vs (30) values is called class B, and the range "180 <Vs <= 360" is class C. Class B soils cover very dense sand, gravel, or extremely hard clays, while Class C soils cover firm or medium-tight sand, gravel, or hard clays [42].

A3. Elevation: Elevation is altitude relative to a known level. Usually this known level is the average sea level. The same landforms can be located at different heights, and different landforms can be at the same heights. The earthquake risk is high in low elevation areas [37].

B1. Total number of houses: With an efficient development plan, it is possible to reduce the number of building constructions, to improve old houses with urban transformations instead of building excess and to ensure an even distribution of houses in terms of density. The excess of the total number of housings is a risk factor [19].

B2. Total number of organized industrial zone and R&D centers: In the event of a possible earthquake in an area with many organized industrial zones and R&D centers, the risk is high [20].

C1. Population density: Population density is the amount of the population per unit area or the amount of population per Km2 with widespread use. It is an important criterion in terms of determining the aggregation degree of the population in any area and making comparisons. Higher the population density is higher the risk [37].

C2. Average household size: Average household size is defined as the average number of people in a household that is found by the ratio of the household population to the number of households. High average household size increases the risk [18].

C3.GDP per capita: GDP per capita is obtained when the gross domestic product of a country or region is divided by the population. Earthquake risk results for all periods are based on the same population and GDP exposure estimates [41]. When GDP per capita is high, it is important that the relevant region is affected by the consequences of a possible earthquake.

In this study, earthquake risk ranking was obtained for 29 provinces with hazard of earthquakes in Turkey. For this purpose, provinces were clustered according to indicators/criteria via Two-Step Cluster Analysis. Earthquake risk/vulnerability assessment has been handled as a decision problem. Opinions of three DMs have been taken for proportional comparison of the determined criteria. Criteria were weighted using the SWARA method. The obtained criteria weights were used in the ELECTRE method and the risk ranking of the provinces was obtained. As indicated in Figure 1, the 'indicators' determined for Two-Step Cluster Analysis and required to cluster the provinces were defined 'sub-criteria' for the SWARA and ELECTRE methods. Input data set (criteria) for provinces in decision matrix were obtained from different sources [43-46]. This information was given in Table 2. Since there must be quantitative and continuous variables in the decision matrix for the ELECTRE method, the variables considered categorically in the Two-Step Cluster Analysis were graded and expressed as numbers through DMs' opinions. Categorical data for "A1. Lithology" and "A2. EC8 Class" were numbered and expressed numerically. The categorical variables in the decision matrix were given as follows:

A1. Lithology

Alluvial Fan Deposits:1; Volcanics: 2; Limestone: 3; Undifferentiated Quaternary Deposits; 4; Continental Deposits: 5.

A2. EC8 Class

B:2; C:3.

The decision matrix was given in Table 3.

Table 3. Decision matrix

	A			B		C		
Provinces/Criteria	A1	A2	A3	B1	B2	C1	C2	C3
Aydın	1	3	65	284970	17	136.887	2.89	37889
Balıkesir	2	2	158	335710	20	84.250	2.71	44302
Bilecik	3	2	532	51200	13	52.507	2.95	57069
Bolu	4	3	746	58660	7	38.028	3	54156
Bingöl	5	2	1133	30780	1	34.959	3.75	27322
Burdur	4	3	874	63030	4	37.741	2.76	42289
Bursa	4	3	132	670750	147	282.634	3.26	58957
Çanakkale	5	2	128	126590	5	55.226	2.63	53680
Çankırı	4	2	726	50150	7	25.960	2.79	37589
Denizli	5	3	395	251500	18	85.479	2.98	46529
Düzce	4	3	160	68470	15	157.370	3.34	43749
Erzincan	4	3	1198	45870	4	19.868	3	47288
Tunceli	4	2	1732	16220	1	11.164	2.72	47830
Hatay	4	2	85	274470	10	294.876	3.8	31899
Isparta	5	2	992	121580	4	49.733	2.86	41229
İzmir	4	3	68	1120220	107	367.274	2.95	60554
Karabük	5	2	302	56630	3	59.985	2.83	38715
Kırşehir	5	2	754	60690	3	36.898	3.1	33772
Kocaeli	4	3	70	421370	139	574.929	3.43	81228
Manisa	4	3	106	309460	40	107.999	3.07	49467
Muğla	4	3	615	241650	2	77.694	2.82	56463
Muş	4	2	1303	31410	1	47.261	5.23	23327
Osmaniye	1	2	122	89670	5	162.277	3.8	29967
Sakarya	4	3	45	194190	32	213.443	3.43	49757
Siirt	5	2	890	33410	1	57.771	5.03	26592

Tokat	4	3	590	127320	5	61.018	3.18	26902
Kırıkkale	5	2	754	75150	3	59.072	2.98	39246
Bartın	4	3	17	30620	1	85.085	2.99	32190
Yalova	5	2	219	79590	11	339.569	3.03	55029

CLUSTERING OF PROVINCES VIA TWO-STEP CLUSTER ANALYSIS

It was aimed to cluster the provinces determined for detailed analyses. Two-Step Cluster Analysis method, which can evaluate categorical and continuous variables or indicators simultaneously, and allows data size and diversity, was used. The number of clusters can be determined in advance by the researcher, or in cases where the number of clusters is not known in advance, it can also be calculated during the SPSS analysis in accordance with BIC or AIC [26].

In this study,

(i) Assuming that the number of clusters was not known, the number of clusters was determined by using AIC and BIC values.

The data belonging to BIC and AIC criteria obtained because of clustering were given in Table 4. The number of clusters that minimized the AIC and BIC criteria was determined as “2”. For the 2 clusters, the AIC value was calculated as “224.752” and the BIC value was calculated as “271.240”. These values were the minimum values calculated within the group (application in SPSS). Therefore, the number of clusters that minimized the AIC and BIC criteria was determined as “2”.

Table 4. BIC and AIC values for first Two-Step Cluster Analysis

Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change[a]	Akaike's Information Criterion (AIC)	AIC Change[a]
1	279.251		256.007	
2	271.240	-8.011	224.752	-31.255
3	296.786	25.545	227.054	2.301
4	330.200	33.415	237.224	10.171
5	369.879	39.679	253.659	16.434
6	413.186	43.307	273.722	20.063
7	458.838	45.652	296.130	22.408
8	507.603	48.765	321.651	25.521
9	559.027	51.424	349.831	28.180
10	611.128	52.101	378.688	28.857
11	663.448	52.320	407.764	29.076
12	715.843	52.394	436.914	29.150
13	768.821	52.978	466.648	29.734
14	822.079	53.258	496.662	30.014
15	875.782	53.704	527.122	30.460

A summary view of the clusters formed via the Two-Step Cluster Analysis was given in Figure 2. The provinces were divided into 2 clusters. The Average Silhoutte Index value was obtained as 30 %. It can be said that clustering success was at a “good” level in terms of the ratio of the number of members and “fair” level in terms of Average Silhoutte Index. The fulfilment of one of the two conditions at a good level and the emergence of a medium-level result in the other condition show that the clustering success was relatively significant. The size ratio calculated in this analysis is 1.42. Cluster-1 consists of 17 provinces, and Cluster-2 consists of 12 provinces.

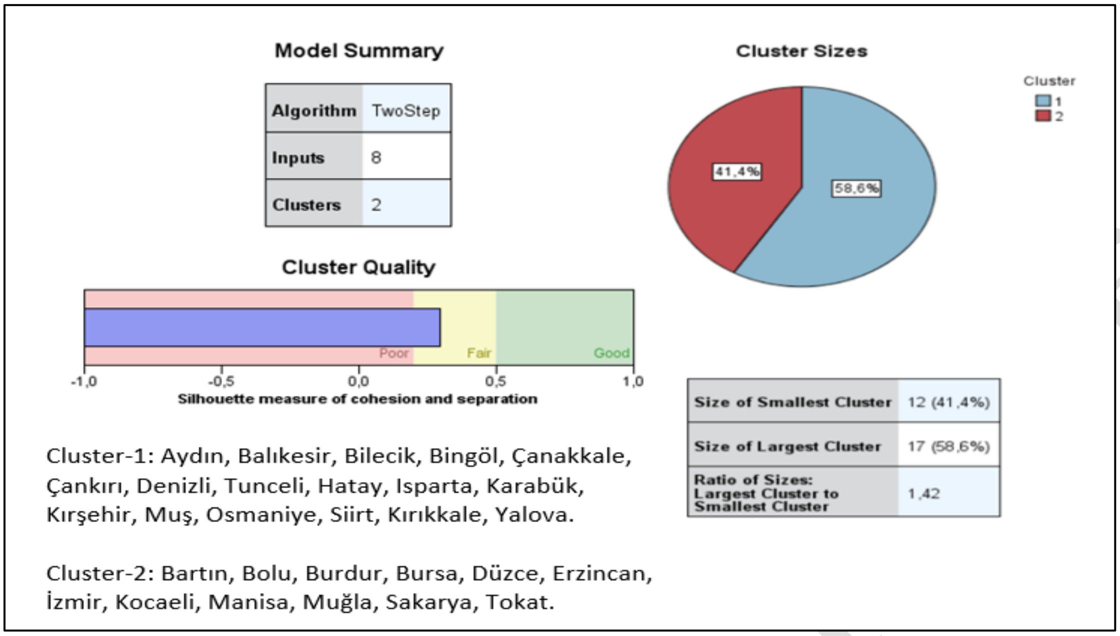

Figure 2. Model Summary for First Two-Step Cluster Analysis

The clusters formed by the Two-Step Cluster Analysis were given as follows:
Cluster-1: Aydın, Balıkesir, Bilecik, Bingöl, Çanakkale, Çankırı, Denizli, Tunceli, Hatay, Isparta, Karabük,
Cluster-2: Bolu, Burdur, Bursa, Düzce, Erzincan, İzmir, Kocaeli, Manisa, Muğla, Sakarya, Tokat, Bartın.

(ii) Sub-clusters were obtained with the formula for finding the number of clusters for the clusters determined later $\left(k = \sqrt{n/2}, k: number\ of\ sub - cluster; n = number\ of\ provinces\ at\ clusters\right)$.

After the Two-Step Cluster Analysis results were obtained according to AIC and BIC, the provinces in the Cluster-1 and Cluster-2 were clustered again via Two-Step Cluster Analysis for detailed analysis. In the second Two-Step Cluster Analysis, the number of clusters was decided with the $k = \sqrt{n/2}$ formula [47]. It was concluded that provinces in Cluster-1 and Cluster-2 should be divided into "3" clusters. As a result of the second Two-Step Cluster Analysis for Cluster-1 and Cluster-2, model summaries and cluster sizes were given in Figure 3 and Figure 4, respectively.

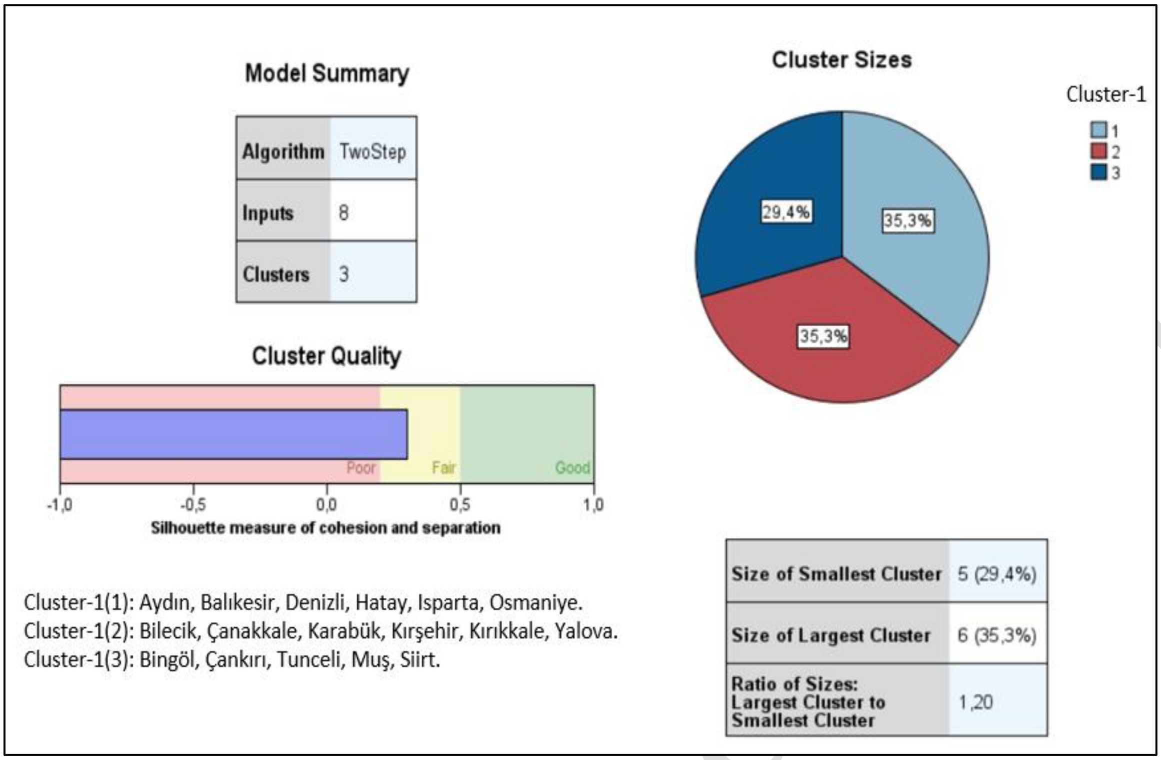

Figure 3. Model Summary for "Cluster-1" in Second Two-Step Cluster Analysis

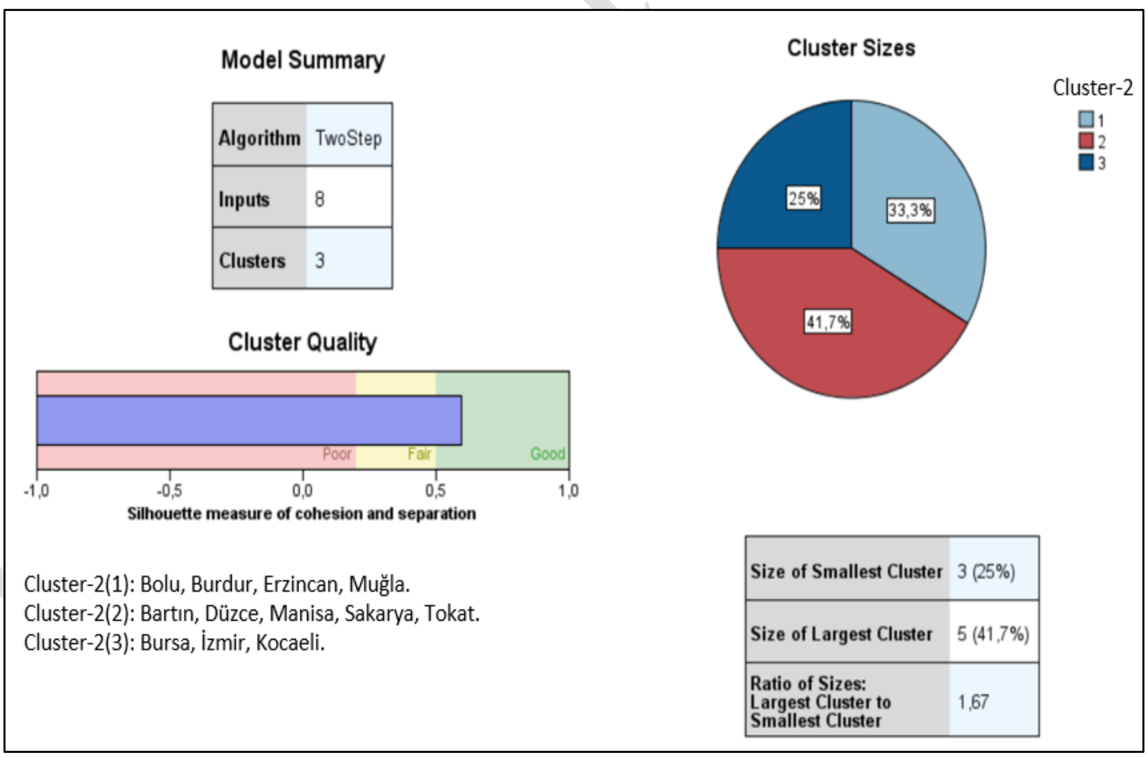

Figure 4. Model Summary for "Cluster-2" in Second Two-Step Cluster Analysis

For the second Two-Step Cluster Analysis, the cluster quality in Cluster-1 and Cluster-2 can also be evaluated. In the second Two-Step Cluster Analysis for Cluster-1, Average Silhouette Index value was obtained as 0.40. The ratio of size value was 1.20 as given in Figure 3. The success of clustering of Cluster-1 was evaluated as positive. Likewise, in the second Two-Step Cluster Analysis for Cluster-2, Average Silhouette Index value was obtained as 0.60. The ratio of size value was 1.67 as given in Figure 4. Clustering success in Cluster-2 was also positive.

To evaluate the clustering success from a different perspective, the mean and standard deviation values of the determined continuous criteria were used. In a way, this additional assessment and proposal reflects the original and innovative value of this study and its overall purpose. The coefficient of variation is obtained by dividing the standard deviation by the mean in criteria data set. The general formula for the coefficient of variation is $C_v = \frac{S}{M}$ (C_v: $Coefficient\ of\ variation$; S: $Standart\ Deviation$; M: $Mean$) In the study, the first Two-Step Cluster Analysis results and the second Two-Step Cluster Analysis results were evaluated. The coefficients of variation were calculated by obtaining the mean and standard deviations of the continuous variables for provinces included in clusters and the sub-clusters. The expected situation is that the coefficient of variation decreases as a set of clusters are divided into sub-clusters. This situation will be an indication that the similarity has increased and therefore a good clustering has been made. Thus, clustering provinces with similar characteristics and making risk rankings will allow detailed analysis. The calculated coefficients of variation were given in Table 5.

Table 5. Average coefficient of variation values calculated for continuous indicators in each cluster formed as a result of the first and second Two-Step Cluster Analysis

For first Two-Step Cluster Analysis	For second Two-Step Cluster Analysis
$C_{vCluster\text{-}1} = 0.678$	$C_{vCluster\text{-}1(1)} = 0.521$
	$C_{vCluster\text{-}1(2)} = 0.522$
	$C_{vCluster\text{-}1(3)} = 0.521$
$C_{vCluster\text{-}2} = 0.814$	$C_{vCluster\text{-}2(1)} = 0.404$
	$C_{vCluster\text{-}2(2)} = 0.623$
	$C_{vCluster\text{-}2(3)} = 0.279$

As seen in Table 5, when Cluster-1 and Cluster-2 were divided into sub-clusters, the coefficients of variability for the sub-clusters decreased. For example, while the average coefficient of variation of continuous variables for provinces in Cluster-1 formed because of the first Two-Step Cluster Analysis was 0.678, the coefficient of variation in Cluster-1 (1), Cluster-1 (2) and Cluster-1 (3) was calculated as 0.521, 0.522 and 0.521, respectively. Likewise, while the average coefficient of variation of the continuous variables for the provinces in Cluster-2 formed because of the first Two-Step Cluster Analysis was 0.814, the coefficient of variation in Cluster-2 (1), Cluster-2 (2) and Cluster-2 (3) was calculated 0.404, 0.623 and 0.279, respectively. As Cluster-1 and Cluster-2 were divided into sub-clusters, the coefficients of variability for the sub-clusters decreased. These evaluations indicated that Two-Step Cluster Analysis applications can gather provinces with high similarity into a cluster.

After dividing the provinces into clusters in detail, each cluster was evaluated separately. In the post-clustering phase, common sub-criteria weights required to evaluate all cluster sets were calculated via SWARA method. Then, the cluster sets were evaluated via ELECTRE method.

The sub-clusters formed by the Two-Step Cluster the provinces were given as follows:

Cluster-1(1): Aydın, Balıkesir, Denizli, Hatay, Isparta, Osmaniye,

Cluster-1(2): Bilecik, Çanakkale, Karabük, Kırşehir, Kırıkkale, Yalova,

Cluster-1(3): Bingöl, Çankırı, Tunceli, Muş, Siirt.

Cluster-2(1): Bolu, Burdur, Erzincan, Muğla.

Cluster-2(2): Düzce, Manisa, Sakarya, Tokat, Bartın.

Cluster-2(3): Bursa, İzmir, Kocaeli.

After dividing the provinces into clusters in detail, each cluster was evaluated separately. In the post-clustering phase, common sub-criteria weights required to evaluate all cluster sets were calculated.

WEIGHTING THE CRITERIA VIA SWARA METHOD

After clustering the provinces in terms of earthquake hazard, common sub-criteria weights required to evaluate all cluster sets of Cluster-2 were calculated. Each of the variables considered as "indicators" in the Two-Step Cluster Analysis was considered as a decision “criterion”. Opinions of the DMs (DM_1: industrial engineer, DM_2: geological engineer and DM_3: geophysical engineer) were used for weighting the earthquake risk criteria. DMs work within AFAD. Since the effect of the DMs on the decision process is equivalent, the DM weights are also considered equal. No DM has dominance over other DMs.

Evaluations were made for all the remaining main criteria and sub-criteria. After evaluating the three DMs’ criteria, common evaluations were obtained by taking the geometric mean. As a result of all evaluations, the general weights of the sub-criteria were given in Table 6.

Table 6. Weights of criteria

Main criteria	Weights of main criteria	Sub-criteria	Weights of the sub-criteria	General Weights
A. Geotechnical	0.380	A1. Lithology	0.344	0.131
		A2. EC8 Class	0.328	0.125
		A3. Elevation	0.329	0.125
B. Structural	0.304	B1. Total Number of Houses	0.527	0.160
		B2. Total Number of Organized Industrial Zone and R&D Centers	0.473	0.144
C. Socioeconomic	0.316	C1. Population density	0.364	0.115
		C2. Average Household Size	0.373	0.118
		C3.GDP Per Capita	0.263	0.083

The calculated criteria weights were integrated for Equation 12 in the 3rd step of the ELECTRE method, which was used to obtain earthquake risk rankings for sub-clusters.

RANKING THE PROVINCES VIA ELECTRE METHOD

The ELECTRE method was used for the earthquake risk ranking of the provinces in the cluster sets. To create the “Decision Matrix in Table 2”, which is the first step of the ELECTRE method, continuous and categorical values of the criteria on provincial basis were used.

While creating the weighted normalized decision matrices for each sub-cluster in the ELECTRE method, the criteria weights obtained from the SWARA method were used.

Net Superior Values (C_p) and Net Inferior Values (D_p) in Equation 19 and Equation 20 were calculated for each set of clusters, and the Total Superiority Matrix (E)in the 8th step of the ELECTRE method were calculated for each sub-cluster set. Net Superior Values (Cp) and Net Inferior Values (Dp) in Equation 19 and Equation 20 were calculated for each sub-cluster. These values were given in Table 7.

Table 7. C_p and D_p values for sub-clusters of Cluster-1 and Cluster-2

Cluster-1								
Cluster-1(1)			Cluster-1(2)			Cluster-1(3)		
Province	C_p	D_p	Province	C_p	D_p	Province	C_p	D_p
Aydın	-0.111	0.584	Bilecik	-0.658	-1.468	Bingöl	0.396	0.936
Balıkesir	0.447	0.758	Çanakkale	-0.172	0.318	Çankırı	1.146	-1.927
Denizli	2.089	-1.330	Karabük	-1.164	4.147	Tunceli	1.622	-1.060
Hatay	0.320	-1.744	Kırşehir	-0.361	1.030	Muş	-0.580	-1.871
Isparta	-1.147	-1.863	Kırıkkale	0.509	-0.437	Siirt	-2.584	3.921
Osmaniye	-1.598	3.594	Yalova	1.846	-3.589			
Cluster-2								
Cluster-2(1)			Cluster-2(2)			Cluster-2(3)		
Province	C_p	D_p	Province	C_p	D_p	Province	C_p	D_p
Bolu	0.581	-0.821	Düzce	0.396	0.936	Bursa	0.142	0.034
Burdur	-0.433	1.591	Manisa	1.146	-1.927	İzmir	-0.454	-0.673
Erzincan	-0.297	0.908	Sakarya	1.622	-1.060	Kocaeli	0.312	0.639
Muğla	0.149	-1.678	Tokat	-0.580	-1.871			
			Bartın	-2.584	3.921			

Following the evaluations, the risk rankings using ELECTRE of the provinces included in the sub-clusters were given in Table 8.

Table 8. Earthquake risk ranking in sub-clusters

Cluster-1						Cluster-2					
Cluster-1(1)		Cluster-1(2)		Cluster-1(3)		Cluster-2(1)		Cluster-2(2)		Cluster-2(3)	
Province	Rank	Province	Rank	Province	Rank	Provinces	Rank	Provinces	Rank	Provinces	Rank
Denizli	1	Yalova	1	Siirt	1	Muğla	1	Sakarya	1	Kocaeli	1
Balıkesir	2	Kırıkkale	2	Çankırı	2	Bolu	2	Manisa	2	Bursa	2
Hatay	3	Çanakkale	3	Muş	3	Erzincan	3	Düzce	3	İzmir	3
Aydın	4	Kırşehir	4	Bingöl	4	Burdur	4	Tokat	4		
Isparta	5	Bilecik	5	Tunceli	5			Bartın	5		
Osmaniye	6	Karabük	6								

DISCUSSION

In this study, the earthquake risk in some provinces of Turkey were prioritized. In many studies in the literature, a single region or a province is evaluated for earthquake risk prioritization (Peng, 2015; Nyimbili *et al.*, 2018; Yariyan *et al.*, 2020). The innovative aspect of this study is the clustering of provinces with similar characteristics via Two-Step Clustering Analysis. When the first Two-Step Cluster Analysis results were examined, the statistical data of continuous and categorical indicators were important. Different inferences or interpretations can be made from the cluster sequences formed because of the analysis:

According to Table 8, Denizli is the first province in terms of earthquake risk ranking in Cluster-1(1). Osmaniye is the last province in terms of earthquake risk in Cluster-1(1). Osmaniye is a province with low earthquake risk, especially in terms of lithological features and the amount of GDP per capita.

Among the provinces clustered in Cluster-1(2), Yalova is the first province in terms of earthquake risk ranking. Yalova was one of the important provinces affected by the 1999 Marmara earthquake. It is at the highest risk of earthquakes in its provincial cluster. In addition, the population density in Yalova is significantly higher. Karabük was the last province in the risk ranking in Cluster-1(2). It can be said that Karabük has advantageous in terms of lithological features, household size and total number of houses criteria.

Siirt is the first province in terms of earthquake risk ranking in Cluster-1(3). The first striking situation in Siirt is the high average household size with the effect of cultural conditions. This situation may have put the province at high risk in terms of earthquake risk. Tunceli in Cluster-1(3) is at a low risk due to the favorable elevation and the low economic impacts that may affect the industry.

When the sub-clusters in Cluster-2 are examined, Muğla is the first province in terms of earthquake risk ranking in Cluster-2(1). When Muğla is examined in terms of earthquake risk criteria, it is a province with a high number of built-in houses. It can be said that the excess of buildings stands out as a factor that increases the earthquake risk. Burdur has the lower household density compared to the provinces in the same cluster can be evaluated as factor that reduce the risk of earthquakes.

Among the provinces clustered in Cluster-2(2), Sakarya is the first province in terms of earthquake risk ranking. It can be said that low elevation, excessive total number of houses, and unfavorable lithology structure in Sakarya are important for earthquake risk. In Bartın, it can be said that low total number of houses and low population density reduce the risk.

In Cluster-2(3), Kocaeli is the province with the highest risk in earthquake risk prioritization. Elevation is extremely low in Kocaeli. According to socioeconomic features, Kocaeli has many centers in terms of industry and population density of Kocaeli is extremely high. A possible earthquake event may cause serious damage in the region unless precautions are taken. İzmir ranks last in the Cluster-2(3) in terms of earthquake risk ranking.

CONCLUSION

Earthquake risk assessment is one of the important damage reduction activities necessary to minimize the loss of life and property that may occur after an earthquake. Earthquake vulnerability and risk assessments support improvement and preparedness at sites or structures. In this study, earthquake risk prioritization within the scope of earthquake risk assessment is handled with a hybrid decision-making approach. In proposed decision model, 29 provinces were clustered via Two-Step Cluster Analysis using the determined indicator data. In the first cluster analysis, the number of clusters was determined according to AIC and BIC values. In the first cluster analysis, two cluster were formed as Cluster-1 and Cluster-2. For the second Two-Step Cluster Analysis, the numbers of clusters were determined according to the clusters number determination formula $k = \sqrt{n/2}$ based on the number of units (n) in the cluster. The main purpose of doing Two-Step Cluster Analysis for the second time with the formula for determining the number of clusters was to obtain the earthquake risk ranking of provinces clustered according to similar indicator values in micro scale and in detail. After, three DMs have proportionally evaluated the main criteria and sub-criteria. Criteria weights for each criterion were calculated by applying the SWARA method steps. The criteria weights obtained were used in the ELECTRE method. The data in the decision matrix was used for all sub-clusters (Cluster-1(1); Cluster-1(2); Cluster-1(3); Cluster-2(1); Cluster-2(2); Cluster-2(3)) obtained from the Two-Step Cluster Analysis and risk ranking was made with the ELECTRE method. As a result, earthquake risk rankings were obtained separately for the provinces in sub-clusters. In line with the results, policy makers will be able to take more comprehensive and region-appropriate measures. The difference and novelty of this study from the studies in the literature is the detailed analysis for wide areas. Obtained earthquake risk rankings are important in terms of determining priority study areas for priority provinces. Among the clusters formed in the first Two-Step Cluster Analysis, detailed analyses, evaluations can be made for the provinces in Cluster-1 and Cluster-2. Analyses can be expanded by integrating the GIS into the decision-making methods. One of the limitations of this study is that it is limited to the spatial evaluation. Structural or building-scale studies can be done with additional analyzes, and the proposed model structure can be supported by these studies. Another limitation of the study is that the fuzzy decision-making approach is not used in the decision-making process. Fuzzy logic integrated forms of MCDM methods used in weighting of earthquake risk criteria and ranking of provinces can be used in future studies. In addition, the effect of changes in criterion weights on the results can be examined for future studies. Criterion weights can be obtained by different methods other than SWARA. Sensitivity analysis may be included in the study. With the sensitivity analysis, the effect of the criterion weights on the process can be examined by changing the criterion weights. In literature, no study has been found that recommends cluster analysis and MCDM approaches together. In terms of the originality of the study, the effectiveness of the methods can be examined by comparing the results of similar studies to be conducted in future studies.

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