EARTHQUAKE VULNERABILITY EVALUATION OF ISTANBUL'S DISTRICTS USING DEA-BASED MODELS

(İSTANBUL'UN İLÇELERİNİN DEPREME DAYANIKLILIKLARININ VZA TEMELLİ MODELLER KULLANILARAK DEĞERLENDİRİLMESİ)

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I am committed to pursuing a life dedicated to academia. I pledge to continue my research endeavors for the benefit of humanity.

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Mehmet GÜDELEK

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LIST OF SYMBOLS

BCC : Banker, Charnes and Cooper
CCR : Charnes, Cooper and Rhodes
CRS : Constant Returns to Scale
DEA : Data Envelopment Analysis
DMU : Decision-Making Unit
MCDM : Multi-Criteria Decision-Making
GDP : Gross Domestic Product
MILP : Mixed Integer Linear Programming
MINLP : Mixed Integer Non-Linear Programming
MIP : Mixed Integer Programming
MOP : Multi-Objective Programming
MW : Magnitude
PGA : Peak Ground Acceleration
PGV : Peak Ground Velocity
SE-DEA : Super-Efficiency DEA
VRS : Variable Returns to Scale

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ABSTRACT

The recent earthquakes that hit the southeastern region of Türkiye have caused severe damage and casualties while also raising awareness about disaster management. According to scientists, it is likely that a strong earthquake hit Istanbul, which is the most populated city in Türkiye. Therefore, Istanbul needs to be well prepared for such a disaster that might occur. Data envelopment analysis (DEA) is a useful tool to evaluate the relative efficiency of decision-making units (DMUs) in various managerial areas including disaster management. There exist some studies in the context of disaster management based on DEA models. However, the input-output selection in the existing studies is not appropriate. Moreover, DEA models used in these studies are not proper for a complete and fair ranking of DMUs. Therefore, more robust studies in disaster management can be conducted by using common-weight DEA-based models which provide a practical ranking of DMUs disregarding excessive weight flexibility of the related factors. Thus, this thesis aims to evaluate the earthquake vulnerability of Istanbul's districts using common-weight DEA models, which enable incorporating interval data. Built-up area, building stock, and estimated ground motions are taken as inputs while expected disaster losses and damages are used as outputs. The analysis demonstrates that the most vulnerable district to earthquakes is Fatih while the least vulnerable district is Şile. Moreover, the findings indicate that the European side of Istanbul is more vulnerable to earthquakes than the Asian side of Istanbul.

ÖZET

Türkiye'nin güneydoğusunda meydana gelen son depremler, büyük hasar ve can kaybına yol açarken, afet yönetimi konusunda da farkındalık yarattı. Bilim insanlarına göre, Türkiye'nin en kalabalık şehri olan İstanbul'da şiddetli bir deprem yaşanması muhtemel görünüyor. Dolayısıyla, yaşanabilecek böyle bir felakete karşı İstanbul'un iyi hazırlanması geremektedir. Veri zarflama analizi (VZA), çeşitli yönetim alanlarındaki karar verme birimlerinin (KVB) göreceli etkinliğini değerlendirmek için yararlı bir araçtır. Afet yönetimi bağlamında VZA modellerine dayalı bazı çalışmalar mevcuttur. Ancak mevcut çalışmalarda girdi-çıktı seçimi uygun değildir. Ayrıca bu çalışmalarda kullanılan VZA modelleri, karar verme birimlerinin tam ve adil bir şekilde sıralanması için uygun değildir. Bu nedenle ilgili faktörlerin aşırı ağırlık esnekliğini göz ardı ederek KVB'lerin gerçekci bir şekilde sıralanmasını sağlayan ortak ağırlıklı VZA tabanlı modeller kullanılarak afet yönetiminde daha sağlıklı çalışmalar yapılabilir. Bundan ötürü bu tez, aralıkla ifade edilen verilerin dahil edilmesine olanak sağlayan ortak ağırlıklı VZA modelleri kullanılarak İstanbul ilçelerinin depreme dayanılıklarının değerlendirilmesini amaçlamaktadır. Yerleşik alan, yapı stoğu ve tahmini yer hareketleri girdi olarak alınırken, beklenen afet kayıpları ve hasarları çıktı olarak alınmıştır. Yapılan analiz sonuçları, depreme en dayanıksız ilçenin Fatih, en dayanıklı ilçenin ise Şile olduğunu göstermektedir. Ayrıca, elde edilen sonuçlar İstanbul'un Avrupa yakası, İstanbul'un Asya yakasına göre depreme karşı daha dayanıksız olduğuna işaret etmektedir.

1.INTRODUCTION

The recent earthquakes that occurred in the southeastern part of Türkiye resulted in over 48000 deaths and total damage of nearly 103.6 billion US dollars (T.C. Cumhurbaskanlığı Strateji ve Bütce Baskanliği, 2023). These figures related to loss and damages pose a question to the disaster management activities and possible earthquakes that might occur in the future. Many scientists and researchers warn the authorities in Türkiye due to the possible Istanbul earthquake with huge damage and casualties.

Istanbul is the most populated city in Türkiye and it generates forty percent of the gross domestic product (GDP) (Üstün, 2016). However, it has witnessed lots of strong earthquakes with huge losses due to these earthquakes. It is by virtue of the fact that one of the greatest fault lines which is called the North Anatolian fault is situated near Istanbul (Üstün, 2016).

It is anticipated that a strong earthquake hits in the near future according to scientists (Üstün, 2016). Türkiye will entirely be affected by such a strong earthquake considering the economic importance and population of Istanbul. Therefore, comprehensive studies need to be conducted to take precautions before possible earthquakes occur in Istanbul.

In this regard, the aim of this thesis is to evaluate the earthquake vulnerability of Istanbul's districts using common-weight data envelopment analysis (DEA). DEA is a widely used approach for efficiency analysis (Charnes et al., 1978). It is a mathematical programming technique that evaluates the efficiency of decision-making units (DMU) that use multiple inputs to generate multiple outputs. It is used in numerous managerial problems to compare the efficiency of DMUs (Ervural et al., 2018).

Conventional DEA models such as the CCR (the acronym for Charnes, Cooper and Rhodes) model and the BCC (the acronym for Banker, Charnes and Cooper) model have some drawbacks. Firstly, the computational burden of these models is relatively high since the models need to be solved *n* times which is the number of evaluated DMUs. Secondly, each unit is evaluated in the best-case scenario by using weighting vectors that maximise the weighted output to weighted input ratio. Due to this excessive weight flexibility, the model might provide a high weight to the criteria that perform exceptionally well and a negligible weight to the criteria that perform poorly to maximize the efficiency score. Another problem caused by the improper weight flexibility is that it may be inappropriate to evaluate the same component with different weights when the objective is to rank the alternatives or find the best performing alternative (Contreras, 2020). Thus, considering a common basis for the DMUs' evaluation appears more acceptable in the case of ranking alternatives.

Common-weight DEA models address the limitations of traditional DEA models by employing a common set of weights to evaluate the efficiency of all DMUs. These models exhibit a higher discriminating power than conventional models (Contreras, 2020).

There exist some studies that applied DEA models within the framework of disaster management. However, as far as we know, previous researches in disaster management have not employed DEA-based models that consider common weights despite the fact that they provide objective results and ranking, and ease in computation. Similarly, there is no study in the context of disaster vulnerability analysis based on DEA models in Istanbul. Thus, the aim of this thesis is to conduct a research on Earthquake Vulnerability Evaluation of Istanbul's Districts Using DEA-based Models.

The remaining part of this thesis is structured as follows. The literature review concerning the studies focused on DEA-based disaster management, recently proposed common weight DEA models with exact data and interval data are presented in Section 2. The methodology used throughout the analysis is given in Section 3. The selection of inputs and outputs, and implementation of the suggested methodology are detailed in Section 4. Section 5 presents the results of the analysis. The conclusion and directions for future research are provided in Section 6.

2.LITERATURE REVIEW

2.1 DEA Based Disaster Management Studies

There is a number of studies where the DEA method is applied in disaster management. Most of these studies tried to compare the disaster vulnerability, resilience, and disaster relief of some regions, cities, or provinces with the aid of the DEA method to provide some recommendations before any disaster occurs.

When the vulnerability is in question, a number of studies deployed DEA in numerous disasters. Wei et al. (2004) analyzed the vulnerability of each region in China with the help of the DEA model. They used two inputs, which are GDP and population of regions and affected people, and disaster loss as output. Similarly, Huang et al. (2013) calculated the regional vulnerability in China by deploying the CCR model. The results show that economic progress is negatively correlated with regional vulnerability. Another study evaluated the vulnerability of 31 Chinese provinces by DEA models that consist of three stages to overcome the shortcomings of traditional DEA models (Li et al., 2015). They used disaster frequency, population density, and GDP of each province as inputs, and economic losses and loss of life as outputs. Huang et al. (2019) tried to find the disaster vulnerabilities of 24 Chinese coastal cities by DEA models called friendly, neutral, and confrontation. They used exposure, hazard factors, disaster prevention, and disaster loss as input and output variables. Consequently, they found that each coastal city of China has regional characteristics in terms of disaster vulnerability. Recently, Wu et al. (2023) evaluated the regional vulnerability in China. They deployed some factors related to GDP and population, and total fixed investment in water conservation, environmental protection, and public facility management at the regional levels as inputs while taking affected persons and direct financial loss as outputs.

A few studies used DEA models within the framework of flood vulnerability. In the study conducted by Huang et al. (2012), they analyzed multidimensional flood vulnerability in terms of death, economy, agriculture, and population by employing the DEA model. Then, they gave some recommendations for flood prevention. Li et al. (2013) deployed DEA models to assess the vulnerability of floods in Hunan in terms of sensitivity, risk, and stability. Another study conducted in Shangai focused on the assessment of the agricultural vulnerability to floods by applying the CCR model and some recommendations were provided (Shi, 2018). Pathak et al. (2021) analyzed 21 districts of the Narmada River by employing the CCR model with the usage of the constant return to scale (CRS) technique in order to evaluate the flood vulnerability of districts. They found that the vulnerability of 16 districts is very high. Recently, Wang et al. (2022) evaluated the flood vulnerability of 8 Southeastern countries along the belt road. They employed DEA models to assess the vulnerabilities of each country. They took inputs as the number of deaths from total disasters, number of total disasters**,** economic losses caused by total disasters, and victims of total disasters. Outputs were determined as the number of deaths due to floods, the number of flood disasters, financial loss due to flood disasters, and victims of flood disasters**.**

For the assessment of vulnerability to other disasters there exist a restricted number of studies. For instance, Saein and Saen (2012) conducted research on earthquake vulnerability in Tehran. They employed the DEA model to evaluate earthquake vulnerability. In another study, the typhoon vulnerability of coastal regions in the Maritime Silk Road was estimated by using the super-efficiency DEA (SE-DEA) model (Yu et al., 2019). Inputs and outputs were determined concerning the economy, agriculture, and population factors. Ma et al. (2022) used SE-DEA and Tobit model to analyze the drought vulnerability of corn in Manchurian Plain. The inputs were taken as exposure and drought risk, and outputs were affected area and maize yield reduction. Recently, Gao et al. (2023) tried to assess the earthquake vulnerability of 69 earthquakes by deploying CCR and BCC models. They took the number of casualties and direct economic losses as the output variables, and energy released by earthquake, population density, and GDP density as input variables. Also, they found the technical and scale vulnerability.

Several studies deployed DEA models in the evaluation of disaster resilience. Zou and Wei (2009) used the DEA model to examine the link between economic improvement and coastal hazard resilience for eight Southeast Asian nations. Data from these countries between 1995-2005 was used. As a result, it is seen that economic growth does not always increase a country's resilience to natural disasters. Zhou et al. (2020) analyzed the economic resilience and recovery of the post-earthquake in the Tibetan plateau. They applied improved variable returns to scale (VRS) DEA and the Malmquist Productivity Index. Furthermore, the economic resilience index after the Wenchuan Earthquake was calculated by the model of the autoregressive integrated moving average (ARIMA). Then, numerous suggestions were given about how the economic resilience of disaster-affected areas can be enhanced. Villano et al. (2020) conducted research on the assessment of the resilience of households in response to disasters caused by climates in the Philippines. They tried to estimate the resilience score by network DEA using the data acquired from the cross-sectional survey.

As for earthquake resilience, the evaluation of the earthquake resilience capacity of Istanbul's districts was analyzed by DEA and returns to scale analysis, and the districts were prioritized according to their disaster resilience (Üstün & Barbarosoğlu, 2016). In another study, Liu et al. (2018) evaluated moderate earthquakes whose magnitude can range from 5 to 7 in resilience in China. Then, 102 earthquakes in this category that have taken place between 2002 and 2014 were based throughout the study. The SE-DEA model which consists of three stages was deployed in the resilience evaluation of counties as traditional DEA models have some shortcomings. Results display that a vast number of counties in China are not efficient and their resilience is low. Therefore, these low-efficient counties should be improved with the required attention, effort, and fund.

Few studies in the field of disaster risk deployed DEA models. Cheng and Chang (2018) employed the CRR and BCC DEA models to analyze the efficiency of the disaster reduction risk policy in Yongkang City, Taiwan. Su et al. (2021) deployed a three-stage DEA model to analyze how the change in land use has affected disaster risk. The result shows that change in land use resulted in high disaster risk. Similarly, Li et al. (2022) analyzed the disaster risk reduction investment in China. They deployed the CCR DEA model based on the data from 2010 to 2020.

Previous studies focus on pre-disaster. They showed whether the cities and regions are resilient or vulnerable to possible disasters. In light of these studies, authorized organizations such as governments, municipalities, or nongovernmental organizations can make some inferences and take precautions to make the place more resilient or decrease the risk of disasters. However, some studies focused on the response time and post-disaster such as disaster relief or mitigation.

Relief logistics deals with the logistics activities after a disaster occurs. These activities can be the delivery of basic items to the victims or rescue activities. For instance, Barbarosoglu and Ustun (2015) estimated the efficiency of the relief organization that attended the relief operations during the Marmara earthquake that occurred in Türkiye. They divided relief and response into 4 categories. Then, they used unbounded DEA to find the efficiencies of each decision-making unit. However, some values of inputs and outputs were zero. To overcome this issue, they applied the bounded DEA model. The bounded model gave more accurate values. Liu and Wang (2019) used DEA model to evaluate disaster prevention and relief in Taiwan. For the location analysis of disaster relief warehouses, Wang et al. (2020) employed DEA models to evaluate the efficiencies of combinations of location sets. The combinations were done concerning risk, distance, and coverage. Li et al. (2021) analyzed disaster mitigation efficiency in China by employing modified DEA. Hong et al. (2022) integrated multi-objective programming (MOP) and some DEA models such as classical, cross-efficiency, and SE-DEA to evaluate a variety of disaster relief logistics network systems that provide the basic needs in the time of disaster to be delivered efficiently.

2.2 Common-Weight DEA Based Models

Several researchers tried to calculate efficiency by using DEA models that employs common weights due the limitations of traditional DEA models.

Jahanshahloo et al. (2005) presented a model on the basis of multi-objective fractional programming which maximizes the minimum efficiency scores. Subsequently, a numerical example was employed to demonstrate the effectiveness of the suggested model.

The aim of the model introduced by Kao and Hung (2005) is to generate a common set of weights for all DMUs using the compromise solution approach. The ideal solution for each DMU to achieve is the efficiency scores calculated from the standard DEA model; the compromise solution is the common set of weights that can produce a vector of efficiency scores that is closest to the ideal solution. The proposed model managed to create common weights and rank DMUs with the illustrative example from forest management.

Karsak and Ahiska (2007) introduced a minimax efficiency model to determine the best performing DMU in consideration of multiple inputs and outputs. Two numerical examples previously used in related studies were used to o show the discriminating power of the developed model. The results depicted that the model identified best performing DMU while achieving better weight dispersion for inputs and outputs.

Hatefi and Torabi (2010) introduced a common-weight DEA model based on multiple criteria decision-making (MCDM) to create composite indicators. The discriminating power of the proposed model which was improved by minimax objective is better than other studies in the literature. Two case studies were used for the validation of the proposed approach.

Chiang et al. (2011) presented a method based on multi objective fractional linear programming model. The decision variables were divided into numerator and denominator to construct a single objective linear programming. Then, common weights were obtained in order to determine the efficiency ratio of the DMU. Lastly, data from the most recent Beijing Olympic Games was analysed using the proposed approach.

Foroughi (2011) improved a mixed integer linear programming (MILP) model that generates only one efficient DMU. Also, he expanded the model to rank all extreme efficient DMUs. Using an actual data set of nineteen facility layout alternatives, the proposed model's efficacy was illustrated through the use of multiple numerical examples.

Wang and Jiang (2012) presented three new MILP models that alleviated the limitations of the model proposed by Foroughi (2011) to define the best performing DMU under VRS. Later, four numerical examples were used to show the performance of these proposed three models.

Sun et al. (2013) presented two models considering ideal and anti-ideal DMU to provide common-weight DEA models for evaluating and assessing performance. Then, the models were illustrated with two real-life applications.

Toloo (2014a) suggested a new basic integrated linear programming for identifying potential efficient units. Then, a new mixed integer programming (MIP) to find the most efficient DMU was proposed. The non-Archimedean epsilon was not considered in these models. Lastly, two numerical examples to demonstrate the diverse applications of these models in various important scenarios were presented. The proposed method was evaluated by numerical examples and the results showed that in terms of ranking DMU, it performed better than traditional models.

Toloo (2015) proposed a new method to find the most efficient DMU based on minimax MILP. Then, three case studies were used to compare the suggested method with proposed approaches in this context.

Lam (2016) proposed a two-stage model which consists of cross efficiency and MILP to rank DMUs by common weights.

A new MOP approach to rank the alternatives by common weights using the idea of distance from ideal was presented by Carillo and Jorge (2016). Through some numerical examples, the model performed well in ranking alternatives.

Toloo and Salahi (2018) proposed a new mixed integer nonlinear programming model (MINLP) that has a higher discriminating power compared to previous suggested models in the context of common weight DEA. Furthermore, linearization of the proposed approach and illustrative examples from previous studies were provided to show the applicability of the suggested model.

Karsak and Goker (2020) introduced a common-weight MCDM approach to determine the best-performing DMU. Two illustrative real-world applications were used and the results were compared with previous methods in this context to test the robustness of the proposed approach. The results demonstrated that the suggested approach guaranteed to determine the most efficient DMU and yielded enhanced distribution of weights assigned to each indicator.

Amiri et al. (2020) introduced a new algorithm based on the bootstrap establishing bounds for inputs and outputs. The common weights are determined by these bounded weights. The results demonstrated that this presented approach overcome the shortcomings of classical DEA models.

Ozsoy et al. (2021) presented a new method to find the most efficient DMU without epsilon based on the model introduced by Toloo and Salahi (2018). A real-life example generally used in the literature was used to test the proposed model. It was seen that the proposed approach was able to define the best performing DMU properly.

Mavi et al. (2022) introduced a common-weight model for the additive model in DEA using goal programming. The developed model was used to investigate the energy efficiency of OECD countries.

2.3 Common-Weight DEA-Based Models with Interval Data

The aforementioned models can easily handle precise data. However, it is impossible to have exact data in every case due to the uncertainty of life. For instance, the data can be obtained in the form of interval. To address this issue, there exist some studies that deal with interval data in the context of common weight DEA models.

Sun et al. (2014) presented three different methods from the extension of the models proposed by Wang et al. (2005) to determine the lower and upper efficiencies in the existence of interval data by common-weight DEA approach. These models were tested with two examples.

Toloo (2014b) presented a new MIP DEA model to find the most efficient suppliers and rank DMUs with the existence of imprecise data. The presented model was illustrated with some numerical examples from previous studies and the rankings were compared with the previous proposed models.

Aghayi et al. (2016) proposed a methodology by using goal programming approach. To fully rank DMUs, the model requires the decision maker to assign a confidence criterion. Then, the introduced model was applied to performance measurement in the banking sector to test its feasibility.

Salahi et al. (2016) developed a method to calculate robust solutions for a set of weights under interval uncertainties. They used robust efficiency scores of units considered ideal solutions. The method was tested with two numerical examples, and the results were compared to previous approaches.

Puri et al. (2017) proposed a two-level mathematical programming technique to calculate common weights for finding interval efficiencies with imprecise data. This proposed approach shows better discriminating power among DMUs while maintaining the linearity of the DEA. Then, they applied the proposed model by using the data among the significant bank categories in India.

Shirdel et al. (2017) introduced an MOP based on common weights in the existence of interval data. The model assesses the lower and upper bound efficiency according to the worst and the best state of inputs and outputs. Then, the average of these efficiencies is found to rank the DMUs. The models were illustrated with some numerical examples and the results were compared with previous studies.

Wen et al. (2018) suggested a modified MINLP with interval data to find the most efficient Six Sigma project. The model determines the most efficient DMU by solving one MINLP.

Tarkhoraini and Eini (2022) proposed a common-weight DEA model in the existence of flexible measures and interval data. The strategy aims to increase the decision maker's impact during the ranking process. Then, the methodology was illustrated with two numerical examples about bank branches.

3.METHODOLOGY

Data Envelopment Analysis (DEA) was given this name , due to the manner it "envelops" data to determine a "frontier" that is used to evaluate observations representing the performances of all the entities that generate outputs from inputs (Charnes et al., 1978).

It is a linear programming-based technique that is specifically developed to measure relative efficiency when employing multiple inputs and outputs without knowledge of which inputs and outputs will have the greatest impact on the efficiency score (Karsak & Dursun, 2014). DEA has been implemented in various sectors to assess the relative efficiency.

DEA was first introduced by Charnes, Cooper, and Rhodes in 1978 (1978). This model evaluates the efficiency of *n* DMUs that use varying amounts of *m* inputs to produce *s* outputs. Each DMU's efficiency is calculated as the ratio of its weighted outputs to its weighted inputs. The goal is to optimize this ratio for each DMU under evaluation, thereby maximizing their relative efficiency. Then, normalizing constraints that ensure that the output-to-input ratio of every DMU is less than or equal to unity are added. Hence, the mathematical model is as:

$$max E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

subject to (3.1)

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1, \qquad j = 1, \dots, n$$

$$u_r\ , v_i \geq 0; \quad r = 1, \dots, s\ ; i = 1, \dots, m$$

where the objective is to maximize E_{j_0} which denotes the efficiency score and is calculated by the ratio of total weighted output to total weighted input for the evaluated DMU. In here v_i and u_r are the weights assigned to input *i* and output *r* respectively. The x_{ij} and y_{rj} , represent the amount of input *i* and output *r* used by the *j*th DMU respectively. The subscript '*0*' refers to the evaluated DMU.

Since the fractional model above is nonlinear and nonconvex, it is not used in the computation of efficiency scores while it can be transformed to a linear program (Charnes et al., 1978). The linear model is as

$$maxE_{j_0} = \sum_{r=1}^{S} u_r y_{rj_0}$$

subject to

(3.2)

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \forall j,$$

$$u_r\ , v_i \geq \varepsilon, \forall r, i.$$

where ε stands for an infinitesimal positive number which is included to prevent zero weights. This model can be used in case of exact data. However, the data set might include interval data. To include interval data, the classical CCR model can be transformed as follows (Despotis & Smirlis, 2002):

$$maxE_{j_0} = \sum_{r=1}^{s}\left[u_r\, y_{rj0}^{L} + p_{rj0}(y_{rj0}^{U} - y_{rj0}^{L})\right]$$

subject to (3.3)

$$\sum_{i=1}^{m}\left[v_i\, x_{ij0}^{L} + q_{ij0}\left(x_{ij0}^{U} - x_{ij0}^{L}\right)\right] = 1$$

$$\sum_{r=1}^{s}\left[u_r\, y_{rj}^{L} + p_{rj}(y_{rj}^{U} - y_{rj}^{L})\right] - \sum_{i=1}^{m}\left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right)\right] \leq 0, \forall j,$$

$$p_{rj} - u_r \leq 0, \forall r, j,$$

$$q_{ij} - v_i \leq 0, \forall i, j,$$

$$\varepsilon \leq u_{r\,,} \forall r,$$

$$\varepsilon \leq v_i\,, \forall i,$$

$$0 \leq p_{rj\,,}\, \forall r, j,$$

$$0 \leq q_{ij}\,, \forall i, j,$$

To deal with the interval data, the model enables each DMU to select its own parameters respectively p_{rj} *and* q_{ij} to achieve the optimal efficiency score within the interval range.

Despotis and Smirlis (2002) have shown that the results of this model are equivalent to the results obtained from the following model:

$$maxE_{j_0} = \sum_{r=1}^{s} u_r \, y_{rj0}^{U}$$

subject to

$$\sum_{i=1}^{m} v_i \, x_{ij0}^{L} = 1 \qquad (3.4)$$

$$\sum_{r=1}^{s} u_r \, y_{rj0}^{U} - \sum_{i=1}^{m} v_i \, x_{ij0}^{L} \leq 0, \forall j \,,$$

$$\sum_{r=1}^{s} u_r \, y_{rj}^{L} - \sum_{i=1}^{m} v_i \, x_{ij}^{U} \leq 0, \qquad j = 1,..n; \; j \neq j_0$$

$$\varepsilon \leq u_{r\,,} v_i \;\; \forall r, i.$$

However, in these DEA models, the relative efficiencies can be determined by solving the formulations for each DMU. Thus, common performance attribute weights are not used to evaluate DMUs. Further, DMUs are classified into two categories such as "efficient" which are the DMUs that receive the efficiency score of one, and "inefficient" for which the efficiency score is less than one. Due to the fact that the efficiency scores of all efficient DMUs are 1, further discrimination among efficient DMUs is not possible.

Another issue is that the aforementioned DEA models have excessive weight flexibility that leads to poor discriminating power. The weights are assigned in a manner that the efficiency is to be maximized. Thus, the model can assign a high weight to the criteria that perform very well and a negligible weight to those that perform badly to maximize the efficiency score.

To overcome these deficiencies, some researchers have proposed common-weight DEA models with precise data. Karsak and Ahiska (2005) improved a common-weight DEA model which comprises of two stages that seeks to minimize the maximum deviation from efficiency based on multiple outputs and single input. The second stage is solved in the case of multiple efficient DMUs in the initial stage.

The first stage of the model is as follows:

$$\min \theta$$

subject to (3.5)

$$\theta \geq d_j, \forall j$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{x_j} + d_j = 1, \forall j$$

$$u_r \geq \varepsilon \ , \forall j$$

$$d_j \geq 0 \ , \forall j$$

where θ stands for the maximum deviation from the efficiency and d_j (that can be expressed as $d_j = 1 - E_j$) is the deviation from the *j*th DMU. When more than one DMUs are found to be efficient in the first stage, then the second stage is as:

$$\min \theta - k \sum_{j \epsilon EF} d_j$$

subject to (3.6)

$$\theta \geq d_j, \forall j$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{x_j} + d_j = 1, \forall j$$

$$u_r \geq \varepsilon \ , \forall j$$

$$d_j \geq 0 \ , \forall j$$

where $k \in (0,1]$ which is determined by the analyst denotes the discriminative parameter and the set of efficient DMUs determined in the first page are shown as EF.

Then, Karsak and Ahiska (2007) improved their previous model to solve the problems in case of multiple inputs and outputs.

The first stage of the model is as follows:

$$\min q$$

subject to (3.7)

$$q - d_j \geq 0, \forall j;$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \forall j,$$

$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1$$

$$u_r\ , v_i, d_j \geq 0, \forall j, i, j$$

The second stage is given as:

$$\min q - k \sum_{j \in \mathrm{EF}} d_j$$

subject to

(3.8)

$$q - d_j \geq 0, \forall j;$$

$$q - \sum_{j \in \mathrm{EF}} d_j \geq 0;$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \forall j,$$

$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1$$

$$u_r \ , v_i, d_j \geq 0, \forall j, i, j$$

Wang and Jiang (2012) proposed the following model to find the best performing DMU. The model is given as:

$$min \sum_{i=1}^{m} v_i \left(\sum_{j=1}^{n} x_{ij} \right) - \sum_{i=1}^{s} u_r \left(\sum_{j=1}^{n} y_{rj} \right)$$

subject to (3.9)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq I_j, \forall j,$$

$$\sum_{j \in 1} I_j = 1,$$

$$I_j \in \{0,1\}, \forall j,$$

$$u_r \geq \frac{1}{(m+s) max_j \left(y_{rj} \right)'} \quad \forall r,$$

$$v_i \geq \frac{1}{(m+s) max_j \left(x_{ij} \right)'} \quad \forall i,$$

The binary variable I_j takes the value of one for the best performing DMU.

Sun et al. (2013) presented the following model to rank alternatives properly. The model is as:

$$min \sum_{r=1}^{n}\left(\sum_{i=1}^{m} v_i x_{max} - \sum_{i=1}^{m} v_i x_{ij}\right) + \sum_{r=1}^{n}\left(\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} u_r y_{min}\right)$$

Subject to

(3.10)

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0, \forall j,$$

$$\sum_{i=1}^{m} v_i x_{max} = 1$$

$$\sum_{r=1}^{s} u_r y_{min} = 1$$

$$u_r\ , v_i \geq \varepsilon, \forall r, i$$

Similarly, Toloo (2015) proposed a common-weight DEA model that determines the most efficient DMU and can be shown as:

$$\min d_{max}$$

subject to

(3.11)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j - \beta_j = 0, \forall j,$$

$$d_{max} - d_j + \beta_j \geq 0, \forall j,$$

$$\sum_{j\in 1} d_j = n - 1,$$

$$d_j \in \{0,1\}, \forall j,$$

$$\beta_j \leq 1, \forall j,$$

$$u_r \geq \frac{1}{(m+s)max_j\left(y_{rj}\right)'} \quad \forall r,$$

$$v_i \geq \frac{1}{(m+s)max_j\left(x_{ij}\right)'} \quad \forall i,$$

The objective is to minimize maximum deviation which is represented by d_{max}. The deviation from the efficiency of *j*th DMU is denoted by the formula $d_j - \beta_j$. When $d_k^* = 0$, the most efficient DMU is DMU_k.

Karsak and Goker (2020) improved the model introduced by Karsak and Ahiska (2007). The difference is that a non- Archimedean infinitesimal ε is included to model and the discriminative parameter k is eliminated. The mathematical model is given as:

$$\min q$$

subject to (3.12)

$$q - d_j \geq 0, \forall j;$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \forall j,$$

$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1$$

$$u_r \, , v_i \geq \varepsilon, \forall r, i$$

$$d_j \geq 0, \forall j.$$

The maximum deviation from efficiency is tried to be minimized and ε denotes a small positive number. When there are multiple efficient DMUs, the second stage of the model is needed to be solved. The mathematical formulation of the second stage of the model is given as:

$$\min q$$

subject to (3.13)

$$q - d_j \geq 0, \forall j;$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \forall j,$$

$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1$$

$$d_j + Mz_j \geq \varepsilon \quad j \in \text{EF}$$

$$\sum_{j \in \text{EF}} z_j = 1,$$

$$z_j \in \{0,1\}, \qquad j \in \text{EF}$$

$$u_r\ , v_i \geq \varepsilon\ , \forall r, i$$

$$d_j \geq 0, \forall j.$$

The binary variable z_j is equal to one for the most efficient DMU, and M stands for a sufficiently large positive number.

Ozsoy et al. (2021) presented the following model.

$$h^* = \max h$$

subject to (3.14)

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq MI_j - h + z_j, \forall j,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \geq z_j - M(1 - I_j), \forall j,$$

$$\sum_{j \in 1} I_j = 1,$$

$$z_j \leq MI_j, \forall j,$$

$$z_j \leq h, \forall j,$$

$$h \leq z_j + M(1 - I_j), \forall j,$$

$$I_j \in \{0,1\}, \forall j,$$

$$u_r \geq \frac{1}{(m+s)max_j\left(y_{rj}\right)'} \quad \forall r,$$

$$v_i \geq \frac{1}{(m+s)max_j\left(x_{ij}\right)'} \quad \forall i,$$

$$z_j \geq 0, \forall j,$$

$$h \geq 0$$

where h is the difference between weighted sum of inputs and outputs, M is a sufficiently large positive number. The model guarantees a raking for all DMUs and one efficient DMU by variable z_j which takes the value of one for the most efficient DMU.

These common weight DEA models can be used with precise data. Nevertheless, the data can be in the form of intervals because of the imprecision and uncertainty regarding related inputs and outputs. Thus, the abovementioned common weight DEA models cannot be used in the existence of interval data. To overcome this, some researchers presented common-weight DEA models in the existence of interval data.

For instance, Shirdel et al. (2017) presented an MOP model based on common-weight DEA to calculate the efficiency when there exists interval data. The presented model is as follows:

$$\min \sum_{j=1}^{n} dj$$

(3.15)

subject to

$$u_r\, y_{rj}^U - v_i\, x_{ij}^L \leq 0, \forall j,$$

$$u_r\, y_{rj}^{L} - v_i\, x_{ij}^{U} + dj = 0\ , \forall j,$$

$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1$$

$$d_j \geq 0 \ \ \forall j,$$

$$u_r\ , v_i \geq \varepsilon, \forall r, i,$$

where U and L denote the upper and lower bound of inputs and outputs, $\mathcal{E}$ refers to the non-Archimedean infinitesimal.

The worst possible efficiency of DMU_j is calculated as

$$E_j^L = \frac{u_r{}^{*} y_{rj}^{L}}{v_i{}^{*} x_{ij}^{U}} \qquad (3.16)$$

The best possible efficiency of DMU_j is calculated as

$$E_j^U = \frac{u_r{}^{*} y_{rj}^{U}}{v_i{}^{*} x_{ij}^{L}} \qquad (3.17)$$

The average of these efficiencies to rank the DMUs is calculated as

$$\bar{E}_{j=} \frac{E_j^U + E_j^L}{2} \qquad (3.18)$$

Similarly, Wen et al. (2018) suggested the following modified MINLP minimax efficiency model based on common-weight DEA that considers interval data:

$$\min M$$

$$(3.19)$$

subject to

$$M - d_j \geq 0 \quad \forall j,$$

$$\sum_{r=1}^{s}\left[u_r\, y_{rj}^L + p_{rj}(y_{rj}^U - y_{rj}^L)\right] - \sum_{i=1}^{m}\left[v_i\, x_{ij}^L + q_{ij}\left(x_{ij}^U - x_{ij}^L\right)\right] + d_j = 0, \forall j,$$

$$\sum_{j\in 1} \varrho_j = n - 1,$$

$$\varrho_j - d_j\, \beta_j = 0\ \forall j,$$

$$p_{rj} - u_r \leq 0\ \forall r, j,$$
$$q_{ij} - v_i \leq 0\ \forall i, j,$$

$$\varepsilon \leq u_r \leq 1\ \forall r,$$

$$\varepsilon \leq v_i \leq 1\ \forall r,$$

$$p_{rj} \geq 0\ \forall r, j,$$
$$q_{ij} \geq 0\ \forall i, j,$$

$$\varrho_j = \{0,1\}\ \forall j,$$

$$\beta_j \geq 1\ \forall j,$$

$$d_j \geq 0 \quad \forall j,$$

where U and L stand for the upper and lower bound, ε denotes the non-Archimedean infinitesimal which avoids ignoring any indicator being 0. The binary ϱ_j and continuous variables are β_j introduced to create the nonlinear constraint. As for the interval data, the model enables each DMU to select its own parameters respectively p_{rj} *and* q_{ij} to achieve the optimal efficiency score within the interval range. Thus, the most favourable inputs and outputs are determined within the specified interval in this way. d_j denotes the deviation from ideal efficiency. The efficiency of DMUs is calculated as $E_j = 1 - d_j$. The model ensures the identification of the single efficient DMU where d_j = 0 by solving one MINLP. To prevent input and output weights from being zero, they are limited not to be less than ε. The value of ε is calculated by the following model:

$$\max \varepsilon \tag{3.20}$$

subject to

$$\sum_{r=1}^{s}\left[u_r\, y_{rj}^{L} + p_{rj}(y_{rj}^{U} - y_{rj}^{L})\right] - \sum_{i=1}^{m}\left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right)\right] + d_j = 0, \forall j,$$

$$\sum_{j\in 1} \varrho_j = n - 1,$$

$$\varrho_j - d_j\, \beta_j = 0\ \forall j,$$

$$p_{rj} - u_r \ \leq 0\ \forall r, j,$$
$$q_{ij} - v_i \ \leq 0\ \forall i, j,$$

$$\varepsilon \leq u_r \ \leq 1\ \forall r,$$

$$\varepsilon \leq v_i \ \leq 1\ \forall r,$$

$$p_{rj} \geq 0\ \forall r, j,$$
$$q_{ij} \geq 0\ \forall i, j,$$

$$\varrho_j = \{0,1\}\ \forall j,$$

$$\beta_j \geq 1\ \forall j,$$

$$d_j \geq 0\ \ \forall j,$$

Wen et al. (2018) proposed the above model and calculated the $E_j = 1 - d_j$ and this yielded *"0"* efficiency in their article. However, it is impossible to have "*0*" efficiency score as there is neither "*0*" output value nor "*0*" output weights in the illustrative example they have done in the article. This is probably due to the miscalculation of efficiency.

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} + d(j) = 1 \qquad (3.21)$$

The expression (3.21) is the main constraint in DEA models based on minimax efficiency. It can be converted into a constraint as follows:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + \left(d_j * \sum_{i=1}^{m} v_i x_{ij} \right) = 0 \qquad (3.22)$$

However, it is not possible to create a linear programming model with this constraint (Lotfi et al., 2013). Therefore, the model can be linearized by the following expression:

$$\frac{\sum_{r=1}^{s} \mathrm{u_r y_{rj}} + \mathrm{d(j)}}{\sum_{i=1}^{m} \mathrm{v_i x_{ij}}} = 1 \qquad (3.23)$$

This expression can be converted into the following linear constraint.

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0 \qquad (3.24)$$

Then, the efficiency scores of these kind of models can be obtained as :

$$1 - \frac{dj}{\sum_{i=1}^{m} v_i x_{ij}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \qquad (3.25)$$

As it can be seen, expression (3.24) is the constraint of the model proposed by Wen et al. (2018). However, they calculated the efficiency scores by $1 - d(j)$. This is the mistake of their proposed model. Therefore, the efficiency calculation of the proposed model by Wen et al. (2018) can be made by the following expressions:

$$\frac{\sum_{r=1}^{s}\left[u_r\, y_{rj}^{L} + p_{rj}(y_{rj}^{U} - y_{rj}^{L})\right]}{\sum_{i=1}^{m}\left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right)\right]} = 1 - \frac{dj}{\sum_{i=1}^{m}\left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right)\right]} \qquad (3.26)$$

4. INPUT-OUTPUT SELECTION AND DATA

Input-output selection is at the core of DEA studies. Inputs are considered as the factors to be minimized while outputs are to be maximized. However, the input-output selection in the context of disaster management based on DEA studies generally was not done appropriately. For example, outputs were chosen as losses such as economic loss, death toll, or affected people (Yang et al., 2021; Li et al., 2022; Wu et al., 2023). Nevertheless, these factors cannot be thought of as outputs but undesirable outputs in DEA studies considering the main logic of DEA. This is due to the fact that these studies tried to create vulnerability indexes instead of calculating the efficiency of DMUs. However, this contradicts the main idea of DEA. Therefore, the input and output selection of this study is very critical to evaluate the earthquake vulnerability in Istanbul's districts.

To evaluate the earthquake vulnerability, many factors can be considered as inputs. For example, the age of buildings and building types are important in the vulnerability analysis (Liu et al., 2018). Besides, it is important to understand the spatial variability of the surface response in a typical scenario earthquake (Saein & Saen, 2012). Also, the exposure of the socioeconomic system is important (Huang et al., 2013).

As for the output factors for the evaluation of earthquake vulnerability, most of the studies in the context of DEA-based vulnerability analysis used disaster losses, economic losses, and affected people (Yu et al., 2019; Su et al., 2021; Yang et al., 2021; Li et al., 2022; Gao et al., 2023; Wu et al., 2023). However, these factors should be considered as undesirable outputs considering the main logic of DEA.

The municipality of Istanbul published a report about Istanbul's Possible Earthquake Loss Estimates Update Project in 2019 (IBB Deprem ve Zemin Inceleme Sube Mudurlugu,2019). The possible earthquake loss for the 7.5 magnitudes (Mw) earthquake during the night scenario for each district was published as a report. Almost all inputs and outputs used in this study were chosen from this study. In addition, one input was taken from IBB Sehir Planlama (IBB Sehir Planlama,2019). The selected inputs and outputs are shown in Table 4.1.

For the age of buildings, the last huge earthquake that occurred in Istanbul was taken as a milestone. It is thought that the buildings that witnessed this huge earthquake are more vulnerable to earthquakes than the buildings constructed after this earthquake. Also, buildings with more than 5 flats are considered to be more vulnerable to earthquakes. Besides, it is important to add some ground motion movements when the vulnerability is in question. That is why built-up area, the number of buildings constructed before 2000,

Table 4.1 : Input-output indicators

	Inputs&Outputs	Factors
Input 1	Built-Up Area (Ha)	Exposure of the Socioeconomic System
Input 2	The Number of Buildings Constructed Before 2000	Age of Buildings
Input 3	The Number of Buildings with More than 5 Floors	Building Type
Input 4	Estimated PGA (Peak Ground Acceleration) for Possible 7.5 Mw Earthquake	Ground Motion
Input 5	Estimated PGV (Peak Ground Velocity) for Possible 7.5 Mw Earthquake	Ground Motion
Output 1	The Number of Expected Total Injured People in case of Possible 7.5 Mw Earthquake during the night	Disaster Loss
Output 2	The Number of Expected Extremely Damaged and Heavily Damaged Buildings in case of Possible 7.5 Mw Earthquake during the night	Disaster Loss
Output 3	The Number of Expected Loss of Life in case of Possible 7.5 Mw Earthquake during the night	Disaster Loss

Table 4.2 : Input-output values for Istanbul's districts

Districts	Input 1	Input 2	Input 3	Input 4 Lower Bound	Input 4 Upper Bound	Input 5 Lower Bound	Input 5 Upper Bound	Output 1	Output 2	Output 3
Adalar	458	5325	238	0,2	0,45	20,1	40	656	1156	76
Arnavutköy	6506	19299	2984	0,075	0,2	5,3	25	213	284	0
Ataşehir	2519	18032	8809	0,12	0,28	10,1	25	1132	594	89
Avcılar	2414	16883	10249	0,15	0,45	10,1	46,6	4423	1494	465
Bağcılar	2229	34618	24298	0,15	0,45	10,1	35	9669	2621	1179
Bahçelievler	1661	19375	17912	0,2	0,45	25,1	40	12739	2286	1633
Bakırköy	2024	9961	5578	0,2	0,45	30,1	46,6	7892	2088	1046
Başakşehir	4774	14434	4615	0,12	0,28	10,1	30	1002	690	71
Bayrampaşa	948	18535	10295	0,15	0,28	10,1	30	4263	1796	520
Beşiktaş	1575	12467	6328	0,09	0,28	5,3	25	353	251	26
Beykoz	5110	34333	2511	0,046	0,2	5,3	20	412	556	25
Beylikdüzü	3778	6262	4699	0,2	0,45	25,1	46,6	4387	1271	527
Beyoğlu	882	24992	11371	0,15	0,28	10,1	35	1900	1251	217
Büyükçekmece	5799	14925	3972	0,12	0,45	10,1	35	2793	2074	288
Çatalca	4302	11129	684	0,046	0,28	5,3	30	94	364	4
Çekmeköy	2358	14342	5781	0,046	0,2	5,3	20	127	129	1
Esenler	1842	18320	15620	0,12	0,28	10,1	35	5172	1204	638
Esenyurt	4258	23801	20380	0,15	0,45	15,1	35	8773	2331	1003
Eyüpsultan	3232	22137	9661	0,075	0,28	5,3	35	1715	1141	168
Fatih	1608	39786	21072	0,2	0,28	15,1	35	11649	5579	1484
Gaziosmanpaşa	1176	21161	14365	0,12	0,28	10,1	30	1399	532	140
Güngören	720	9800	8712	0,2	0,45	25,1	35	5876	953	754
Kadıköy	2481	18427	15787	0,15	0,28	10,1	30	1820	714	190
Kâğıthane	1435	23690	14935	0,12	0,28	10,1	25	920	369	84
Kartal	2883	23702	12730	0,12	0,45	10,1	30	1788	792	176
Küçükçekmece	3691	28156	17565	0,15	0,45	15,1	46,6	12417	3856	1515
Maltepe	2919	24685	12096	0,12	0,45	10,1	35	2274	927	234
Pendik	5443	34592	16668	0,075	0,28	5,3	30	2374	1315	195
Sancaktepe	3598	16333	9664	0,075	0,28	5,3	25	814	500	48
Sarıyer	4938	33068	4525	0,075	0,2	5,3	25	503	469	33
Silivri	8054	26630	2553	0,046	0,28	5,3	30	839	2151	58
Sultanbeyli	2220	23275	3593	0,12	0,28	10,1	25	1094	757	73
Sultangazi	1741	22923	17130	0,105	0,2	10,1	25	800	306	57
Şile	2656	18685	348	0,046	0,2	5,3	20	1	128	0
Şişli	1065	19088	13452	0,12	0,28	10,1	25	567	275	55
Tuzla	5014	14021	5221	0,12	0,45	10,1	46,6	2542	1816	268
Ümraniye	4037	33727	16713	0,12	0,2	10,1	20	971	639	42
Üsküdar	3414	35353	16196	0,12	0,28	10,1	25	1256	639	95
Zeytinburnu	1146	12697	10022	0,2	0,45	25,1	40	5347	1535	668

the number of buildings with more than 5 floors, the estimated Peak Ground Acceleration (PGA) for a possible 7.5 Mw earthquake, and the estimated Peak Ground Velocity (PGV) for a possible 7.5 Mw earthquake are taken as inputs. Lastly, the number of expected total injured people, the number of expected extremely damaged and heavily damaged buildings, and the number of expected loss of life in case of a possible 7.5 Mw earthquake are taken as outputs but these losses are taken as undesirable outputs. The Table 4.2 shows the data set.

The undesirable outputs which are output 1, output 2, and output 3 are transformed into desirable output by an exponential transformation since they contain "*0*" output values. The transformation is done by the following expression (Zhou et al., 2019):

$$y_{rj}^{\gamma} = (1 - \varepsilon_r)^{y_{rj}} \tag{4.1}$$

The value of ε can be determined by trial and error but it is better to define it by a specific approach. Zhou et al. (2019) determined the value of ε in a way that the standard deviation of the data after the transformation is maximized. Similarly, the value of ε for the undesirable outputs in this study is calculated in this way which is shown by the following formula:

$$\max \sqrt{\frac{\sum_{j=1}^{n}\left[(1-\varepsilon_r)^{y_{rj}} - \left(\frac{\sum_{j=1}^{n}(1-\varepsilon_r)^{y_{rj}}}{j}\right)\right]^2}{n}} \tag{4.2}$$

The exact inputs which are input 1, input 2, and input 3 are normalized via $\frac{x_{ij}}{max_j(x_{ij})}$ and transformed outputs are normalized by $\frac{y_{rj}^{\gamma}}{max_j(y_{rj}^{\gamma})}$ (Karsak & Ahiska, 2007).

Also, the lower and upper bounds of input 4 and input 5 are normalized by the following linear normalization (Tarkhorani & Eini, 2022) :

$$\left[\frac{x_{ij}^{l}}{max_j(x_{ij}^{u})}, \frac{x_{ij}^{u}}{max_j(x_{ij}^{u})}\right] \tag{4.3}$$

5.RESULTS

Firstly, the data transformation and normalization are provided in this section. The data arrangements were done by Excel and Excel solver. Then, DEA models with interval data mentioned in the methodology were applied to the data set after the required transformations were done.

The DEA models were solved using GAMS software. The BARON solver was used since it is a very powerful software for solving MINLP problems. The option decimal was taken as 6 in all models.

The undesirable outputs were converted into desirable outputs by the formula (4.1) explained in the previous section. The з values were found to be $4.48\, x\, 10^{-4}$, $1.025x\ 10^{-3}$ and $4.707\ x\ 10^{-3}$ for output 1, output 2 and output 3 respectively by the formula (4.2). The Table 5.1 shows the transformed version of undesirable outputs.

Then, inputs and outputs were normalized by linear normalization explained in previous section. Normalized data are demonstrated in Table 5.2.

After data adjustments, the model (3.4) proposed by Despotis and Smirlis (2002), (3.15) proposed by Shirdel et al. (2017), and (3.19) proposed by Wen et al. (2018) which were explained in detail in the methodology section were applied to normalized data.

The epsilon values for models (3.4) and (3.15) are taken as 10^{-6} while for the model (3.19), it was calculated by the model (3.20).

Table 5.1 : Transformed output values

Districts	ε_1=0.000448 Output 1	ε_2=0.001025 Output 2	ε_3=0.004707 Output 3
Adalar	0.745524	0.305445	0.698646
Arnavutköy	0.909052	0.747242	1.000000
Ataşehir	0.602447	0.543673	0.657078
Avcılar	0.138067	0.215940	0.111455
Bağcılar	0.013188	0.067950	0.003837
Bahçelievler	0.003337	0.095819	0.000450
Bakırköy	0.029218	0.117401	0.007186
Başakşehir	0.638547	0.492679	0.715325
Bayrampaşa	0.148319	0.158407	0.085979
Beşiktaş	0.853828	0.772973	0.884544
Beykoz	0.831572	0.565287	0.888728
Beylikdüzü	0.140310	0.271452	0.083185
Beyoğlu	0.427175	0.277080	0.359181
Büyükçekmece	0.286411	0.119099	0.256931
Çatalca	0.958793	0.688361	0.981303
Çekmeköy	0.944733	0.876038	0.995293
Esenler	0.098735	0.290768	0.049270
Esenyurt	0.019696	0.091496	0.008802
Eyüpsultan	0.464059	0.310182	0.452612
Fatih	0.005435	0.003268	0.000910
Gaziosmanpaşa	0.534576	0.579378	0.516542
Güngören	0.072044	0.376168	0.028501
Kadıköy	0.442751	0.480696	0.407984
Kâğıthane	0.662423	0.684839	0.672765
Kartal	0.449139	0.443728	0.435845
Küçükçekmece	0.003854	0.019139	0.000786
Maltepe	0.361321	0.386337	0.331494
Pendik	0.345503	0.259471	0.398471
Sancaktepe	0.694614	0.598715	0.797326
Sarıyer	0.798376	0.618063	0.855805
Silivri	0.686884	0.110053	0.760578
Sultanbeyli	0.612783	0.459951	0.708606
Sultangazi	0.698981	0.730565	0.764175
Şile	0.999552	0.876937	1.000000
Şişli	0.775827	0.754173	0.771421
Tuzla	0.320471	0.155190	0.282359
Ümraniye	0.647471	0.519143	0.820222
Üsküdar	0.569916	0.519143	0.638736
Zeytinburnu	0.091295	0.207046	0.042766

Table 5.2 : Normalized data for inputs and outputs

Districts	input 1	input 2	input 3	input 4 lower bound	input 4 upper bound	input 5 lower bound	input 5 upper bound	output 1	output 2	output 3
Adalar	0.056866	0.133841	0.009795	0.444444	1.000000	0.431330	0.858369	0.745858	0.348309	0.698646
Arnavutköy	0.807797	0.485070	0.122808	0.166667	0.444444	0.113734	0.536481	0.909460	0.852104	1.000000
Ataşehir	0.312764	0.453225	0.362540	0.266667	0.622222	0.216738	0.536481	0.602717	0.619968	0.657078
Avcılar	0.299727	0.424345	0.421804	0.333333	1.000000	0.216738	1.000000	0.138128	0.246244	0.111455
Bağcılar	0.276757	0.870105	1.000000	0.333333	1.000000	0.216738	0.751073	0.013194	0.077485	0.003837
Bahçelievler	0.206233	0.486980	0.737180	0.444444	1.000000	0.538627	0.858369	0.003338	0.109265	0.000450
Bakırköy	0.251304	0.250364	0.229566	0.444444	1.000000	0.645923	1.000000	0.029231	0.133876	0.007186
Başakşehir	0.592749	0.362791	0.189933	0.266667	0.622222	0.216738	0.643777	0.638833	0.561818	0.715325
Bayrampaşa	0.117705	0.465867	0.423697	0.333333	0.622222	0.216738	0.643777	0.148385	0.180637	0.085979
Beşiktaş	0.195555	0.313351	0.260433	0.200000	0.622222	0.113734	0.536481	0.854210	0.881447	0.884544
Beykoz	0.634467	0.862942	0.103342	0.102222	0.444444	0.113734	0.429185	0.831944	0.644615	0.888728
Beylikdüzü	0.469084	0.157392	0.193390	0.444444	1.000000	0.538627	1.000000	0.140373	0.309546	0.083185
Beyoğlu	0.109511	0.628161	0.467981	0.333333	0.622222	0.216738	0.751073	0.427366	0.315963	0.359181
Büyükçekmece	0.720015	0.375132	0.163470	0.266667	1.000000	0.216738	0.751073	0.286540	0.135813	0.256931
Çatalca	0.534145	0.279722	0.028150	0.102222	0.622222	0.113734	0.643777	0.959222	0.784961	0.981303
Çekmeköy	0.292774	0.360479	0.237921	0.102222	0.444444	0.113734	0.429185	0.945156	0.998975	0.995293
Esenler	0.228706	0.460463	0.642851	0.266667	0.622222	0.216738	0.751073	0.098779	0.331572	0.049270
Esenyurt	0.528681	0.598226	0.838752	0.333333	1.000000	0.324034	0.751073	0.019704	0.104335	0.008802
Eyüpsultan	0.401291	0.556402	0.397605	0.166667	0.622222	0.113734	0.751073	0.464267	0.353711	0.452612
Fatih	0.199652	1.000000	0.867232	0.444444	0.622222	0.324034	0.751073	0.005438	0.003726	0.000910
Gaziosmanpaşa	0.146014	0.531871	0.591201	0.266667	0.622222	0.216738	0.643777	0.534815	0.660684	0.516542
Güngören	0.089397	0.246318	0.358548	0.444444	1.000000	0.538627	0.751073	0.072077	0.428956	0.028501
Kadıköy	0.308046	0.463153	0.649724	0.333333	0.622222	0.216738	0.643777	0.442949	0.548153	0.407984
Kâğıthane	0.178172	0.595436	0.614660	0.266667	0.622222	0.216738	0.536481	0.662720	0.780944	0.672765
Kartal	0.357959	0.595737	0.523911	0.266667	1.000000	0.216738	0.643777	0.449340	0.505997	0.435845
Küçükçekmece	0.458282	0.707686	0.722899	0.333333	1.000000	0.324034	1.000000	0.003856	0.021825	0.000786
Maltepe	0.362429	0.620444	0.497819	0.266667	1.000000	0.216738	0.751073	0.361483	0.440553	0.331494
Pendik	0.675813	0.869452	0.685982	0.166667	0.622222	0.113734	0.643777	0.345657	0.295883	0.398471
Sancaktepe	0.446735	0.410521	0.397728	0.166667	0.622222	0.113734	0.536481	0.694925	0.682734	0.797326
Sarıyer	0.613111	0.831147	0.186229	0.166667	0.444444	0.113734	0.536481	0.798734	0.704797	0.855805
Silivri	1.000000	0.669331	0.105070	0.102222	0.622222	0.113734	0.643777	0.687191	0.125497	0.760578
Sultanbeyli	0.275639	0.585005	0.147872	0.266667	0.622222	0.216738	0.536481	0.613057	0.524497	0.708606
Sultangazi	0.216166	0.576157	0.704996	0.233333	0.444444	0.216738	0.536481	0.699294	0.833087	0.764175
Şile	0.329774	0.469638	0.014322	0.102222	0.444444	0.113734	0.429185	1.000000	1.000000	1.000000
Şişli	0.132232	0.479767	0.553626	0.266667	0.622222	0.216738	0.536481	0.776175	0.860008	0.771421
Tuzla	0.622548	0.352410	0.214874	0.266667	1.000000	0.216738	1.000000	0.320615	0.176968	0.282359
Ümraniye	0.501242	0.847710	0.687834	0.266667	0.444444	0.216738	0.429185	0.647761	0.591996	0.820222
Üsküdar	0.423889	0.888579	0.666557	0.266667	0.622222	0.216738	0.536481	0.570171	0.591996	0.638736
Zeytinburnu	0.142290	0.319132	0.412462	0.444444	1.000000	0.538627	0.858369	0.091336	0.236101	0.042766

The results of the models are depicted in Table 5.4. Through the application of the modified CCR model proposed by Despotis and Smirlis (2002) in the existence of interval data, twenty-four DMUs were identified as efficient while the remaining DMUs were identified as inefficient. However, it is not suitable to rank DMUs with the results of this model due to the explained shortcomings of CCR models shown in previous sections. Therefore, common-weight DEA models with interval data were used to rank DMUs.

Table 5.3 : Weights assigned to each input and output

Weights	Shirdel et al. (2017)	Wen et al. (2018)
v1	0.584937	0.535956
v2	0.185500	0.265527
v3	0.000001	0.265527
v4	0.027585	0.265527
v5	0.000001	0.869836
u1	0.000001	0.265527
u2	0.201974	0.265527
u3	0.000001	0.265527

The model (3.15) proposed by Shirdel et al. (2017) provided a full ranking of DMUs. According to the results of this model, Şişli is the best district in terms of earthquake vulnerability. Meaning that it is the least vulnerable DMU. However, this model did not yield appropriate results since the ground motion factors which are shown in the Table 5.3 as the weights v4 and v5 were not taken into consideration as needed. Therefore, some risky districts were ranked as less vulnerable. For example, Adalar district is claimed to be very vulnerable in terms of earthquakes by experts considering its geographic position. Nevertheless, Adalar was ranked as 3^{rd}. Similarly, Güngören district has the same contradiction. It is one of the riskiest districts in Istanbul according to scientists. However, it was ranked as 5^{th}. Conversely, Silivri is claimed to be moderately vulnerable. However, it was ranked as 37^{th} which means it is one of the most vulnerable districts.

Table 5.4 : Efficiency scores and rankings

	Despotis and Smirlis (2022)		Shirdel et al. (2017)				Wen et al. (2018)	
Districts	Score	Rank	E_j^L	E_j^U	$\bar{E}_j$	Rank	Score	Rank
Adalar	1.000000	1	0.821125	1.000000	0.910563	3	0.440458	16
Arnavutköy	1.000000	1	0.299443	0.303489	0.301466	17	0.621935	6
Ataşehir	1.000000	1	0.440624	0.456375	0.448499	10	0.491218	15
Avcılar	0.487612	31	0.176602	0.188940	0.182771	29	0.116339	31
Bağcılar	0.153436	35	0.044603	0.047070	0.045836	36	0.027183	37
Bahçelievler	0.131468	37	0.092510	0.098861	0.095686	32	0.029144	36
Bakırköy	0.190884	34	0.122337	0.131451	0.126894	30	0.046534	34
Başakşehir	1.000000	1	0.263169	0.269295	0.266232	22	0.427642	17
Bayrampaşa	0.397574	32	0.211585	0.221837	0.216711	26	0.191202	26
Beşiktaş	1.000000	1	0.938594	1.000000	0.969297	2	0.782576	3
Beykoz	1.000000	1	0.239571	0.243807	0.241689	25	0.577275	9
Beylikdüzü	0.699160	27	0.188789	0.197949	0.193369	28	0.131199	30
Beyoğlu	1.000000	1	0.322723	0.336275	0.329499	15	0.268189	24
Büyükçekmece	0.567406	30	0.052922	0.055071	0.053996	34	0.171997	27
Çatalca	1.000000	1	0.415587	0.431824	0.423705	11	0.661978	4
Çekmeköy	1.000000	1	0.805840	0.837413	0.821626	4	0.966993	2
Esenler	0.656578	28	0.283336	0.295602	0.289469	19	0.11562	32
Esenyurt	0.139113	36	0.047059	0.049074	0.048066	35	0.034071	35
Eyüpsultan	1.000000	1	0.201183	0.208563	0.204873	27	0.274896	23
Fatih	0.008038	39	0.002356	0.002393	0.002374	39	0.002668	39
Gaziosmanpaşa	1.000000	1	0.663112	0.697088	0.680100	9	0.412644	18
Güngören	0.841503	26	0.689962	0.785873	0.737917	5	0.149173	29
Kadıköy	1.000000	1	0.390845	0.402159	0.396502	12	0.334956	21
Kâğıthane	1.000000	1	0.680354	0.710409	0.695382	7	0.535886	10
Kartal	1.000000	1	0.294117	0.312298	0.303207	16	0.33582	20
Küçükçekmece	0.029100	38	0.010325	0.010790	0.010558	38	0.007046	38
Maltepe	0.872383	25	0.250879	0.266054	0.258467	24	0.280001	22
Pendik	1.000000	1	0.104158	0.106491	0.105324	31	0.246286	25
Sancaktepe	1.000000	1	0.388847	0.403133	0.395990	13	0.531828	11
Sarıyer	1.000000	1	0.271112	0.275127	0.273119	21	0.529378	13
Silivri	1.000000	1	0.034903	0.035606	0.035254	37	0.359651	19
Sultanbeyli	1.000000	1	0.369226	0.382294	0.375760	14	0.50319	14
Sultangazi	1.000000	1	0.685163	0.701806	0.693484	8	0.585951	7
Şile	1.000000	1	0.691048	0.714114	0.702581	6	1.000000	1
Şişli	1.000000	1	0.946552	1.000000	0.973276	1	0.654246	5
Tuzla	0.634882	29	0.078195	0.081816	0.080005	33	0.171565	28
Ümraniye	1.000000	1	0.258413	0.261181	0.259797	23	0.584564	8
Üsküdar	1.000000	1	0.278103	0.284596	0.281350	20	0.531645	12
Zeytinburnu	0.341840	33	0.280483	0.308270	0.294376	18	0.101656	33

The model (3.19) proposed by Wen et al. (2018) managed to provide a full ranking of DMUs. Firstly, the epsilon value was calculated by model (3.20) and it was found as 0.265527. Then, it was integrated into the model (3.19). Besides, the q_{ij} weights assigned to each interval value are demonstrated in Table 5.5. If the $q_{ij} = v_i$, then it means that the model considers the upper bound value. Conversely, If the $q_{ij} = 0$, the model considers the lower bound value.

The model (3.19) yielded only one efficient DMU which is Şile. Şile, Çekmeköy, Çatalca and Beşiktaş are the least vulnerable districts according to the results of this model. The model assigned more importance to the ground motions and no factors were neglected. All factors were taken into consideration as it can be seen in Table 5.3.

The results obtained from the model (3.19) are very logical. Looking at the least vulnerable districts such as Şile, Çekmeköy, Çatalca, and Beşiktaş, the expected losses and estimated ground motions are very low in these districts compared to others. Hence, these districts are thought to be very safe in terms of earthquake vulnerability. On the contrary, Fatih, Küçükçekmece, Bağcılar, Bahçelievler, and Esenyurt are the most vulnerable districts. This is due to the fact that these districts are the most populated and urbanized ones which means that their input levels are very high. Also, the ground motions in these districts are high compared to other districts. Moreover, the expected losses are the most in these districts. Thus, it can be claimed that the results are very plausible.

As a conclusion, the outcomes of the model (3.19) proposed by Wen et al. (2018) yielded more plausible results compared to other models applied in this study. Nevertheless, input 1 which is built-up area might not be a good indicator and distort the results. Therefore, all the models were solved again after excluding input 1.

The results after excluding the built-up area are depicted in Table 5.9. After excluding built-up area, the modified CCR revealed that twenty-three DMUs are efficient, while the remaining DMUs are inefficient. Again, common weight DEA-based models were used to rank DMUs because of the limitations of the CCR model explained in former sections.

Table 5.5 : q values for model (3.19)

Districts	*q* values for PGA	*q values* for PGV
Adalar	0.265527	0.869836
Arnavutköy	0.265527	0.869836
Ataşehir	0.265527	0.869836
Avcılar	0.265527	0.373163
Bağcılar	0.001988	0
Bahçelievler	0.014236	0
Bakırköy	0.053517	0
Başakşehir	0.265527	0.869836
Bayrampaşa	0	0
Beşiktaş	0.265527	0.869836
Beykoz	0.265527	0.869836
Beylikdüzü	0.265527	0.000709
Beyoğlu	0	0.869836
Büyükçekmece	0.253054	0.140084
Çatalca	0.265527	0.869836
Çekmeköy	0.265527	0.869836
Esenler	0.008395	0.792791
Esenyurt	0	0
Eyüpsultan	0.206636	0.818370
Fatih	0	0
Gaziosmanpaşa	0.265527	0.869836
Güngören	0.265527	0
Kadıköy	0	0.869836
Kâğıthane	0.265527	0.869836
Kartal	0.265527	0.367143
Küçükçekmece	0.001142	0.001158
Maltepe	0.207355	0.322583
Pendik	0	0.382725
Sancaktepe	0.265527	0.869836
Sarıyer	0.265527	0.869836
Silivri	0.207355	0.351009
Sultanbeyli	0.265527	0.869836
Sultangazi	0.265527	0.869836
Şile	0.265527	0.869836
Şişli	0.265527	0.869836
Tuzla	0.265527	0.343121
Ümraniye	0	0
Üsküdar	0	0
Zeytinburnu	0.197864	0

Table 5.6 : Weights assigned to each input and output after excluding built-up area

Weights	Shirdel et al.(2017)	Wen et al.(2018)
v1	0.735422	0.249523
v2	0.002421	0.249523
v3	0.000001	0.574869
v4	0.000001	0.867488
u1	0.000001	0.249523
u2	0.262153	0.249523
u3	0.000001	0.249523

The weights assigned to each input and output and Table 5.6. The model (3.15) proposed by Shirdel et al. (2017) again assigned negligible weights to the ground motion factors. Therefore, some risky districts were ranked as less vulnerable. For instance, Adalar, Bayrampaşa, Beylikdüzü which are very risky districts according to experts are ranked at the top which means that they are less vulnerable. Hence, the model again yielded implausible results due to the fact that the model did not take into consideration the ground motions.

Excluding built-up area did not change the most efficient DMU in the model (3.19) proposed by Wen et al. (2018). Firstly, the model (3.20) was deployed to find the epsilon value. It was found 0.249523. Then, it was used in model (3.19). Besides, the q_{ij} weights assigned to each interval values are demonstrated in Table 5.7.

In both cases, Şile is found to be the most efficient district. Looking at the least efficient DMUs, the results did not change extremely. Fatih, Küçükçekmece, Bağcılar, Bahçelievler and Esenyurt are the least efficient districts in both cases.

It is possible that the rankings of some DMUs change after excluding built-up area. However, this change is not enormous. To test and show this, Spearman's Rank Correlation was done.

Table 5.7 : q values for model (3.19) after excluding built-up area

Districts	*q* values for PGA	*q* values for PGV
Adalar	0.371109	0.859912
Arnavutköy	0.574869	0.867488
Ataşehir	0.574869	0.867488
Avcılar	0.574869	0.191119
Bağcılar	0.083943	0.067280
Bahçelievler	0	0
Bakırköy	0.052673	0
Başakşehir	0.574869	0.867488
Bayrampaşa	0.569904	0.391136
Beşiktaş	0.574869	0.867488
Beykoz	0.574869	0.867488
Beylikdüzü	0.574869	0
Beyoğlu	0.073010	0.867488
Büyükçekmece	0.574869	0.256378
Çatalca	0.574869	0.867488
Çekmeköy	0.574869	0.867488
Esenler	0.001881	0.865808
Esenyurt	0.124342	0
Eyüpsultan	0.212313	0.312848
Fatih	0	0
Gaziosmanpaşa	0.536598	0.660631
Güngören	0.177747	0
Kadıköy	0.228269	0.867488
Kâğıthane	0.558123	0.831767
Kartal	0.374367	0.867488
Küçükçekmece	0.071632	0.072631
Maltepe	0.574869	0.231607
Pendik	0.190474	0.867488
Sancaktepe	0.574869	0.867488
Sarıyer	0.574869	0.867488
Silivri	0.574869	0.867488
Sultanbeyli	0.574869	0.867488
Sultangazi	0.574869	0.867488
Şile	0.574869	0.867488
Şişli	0.574869	0.867488
Tuzla	0.209243	0.659083
Ümraniye	0.574869	0.867488
Üsküdar	0.553596	0.532471
Zeytinburnu	0.114034	0

The hypothesis of the correlation analysis is as follows:

H_0: There is no correlation between the rankings before and after excluding built-up area for the model (3.19)

H_1: There is a correlation between the rankings before and after excluding built-up area for the model (3.19)

Table 5.8 : The results of the correlation analysis

			Rankings of the model (3.19) built-up area included	Rankings of the model (3.19) built-up area excluded
Spearman's rho	Rankings of the model (3.26) built-up area included	Correlation Coefficient	1,000	,978**
		Sig. (1-tailed)	.	,000
		N	39	39
	Rankings of the model (3.26) built-up area excluded	Correlation Coefficient	,978**	1,000
		Sig. (1-tailed)	,000	.
		N	39	39

**. Correlation is significant at the 0.01 level (1-tailed).

The SPSS statistical tool was used. The analysis was done as one-tailed. The results are depicted in Table 5.8. The p-value was found to be 0. Then, the null hypothesis is rejected. The correlation analysis shows that excluding the built-up area does not change the rankings enormously since the correlation is significant. The correlation coefficient is 0.978 which is approximately 1. This means that there is approximately a perfect correlation between the results of these sets of rankings.

Table 5.9 : Efficiency scores and rankings after excluding built-up area

	Despotis and Smirlis (2002)		Shirdel et al. (2017)				Wen et al. (2018)	
Districts	Score	Rank	E_j^L	E_j^U	$\bar{E}_j$	Rank	Score	Rank
Adalar	1.000000	1	0.927445	0.927455	0.927450	4	0.361085	19
Arnavutköy	1.000000	1	0.625673	0.625675	0.625674	8	0.789708	3
Ataşehir	1.000000	1	0.486333	0.486334	0.486334	13	0.456874	14
Avcılar	0.487612	31	0.206180	0.206180	0.206180	27	0.110099	32
Bağcılar	0.153436	35	0.031625	0.031625	0.031625	37	0.025138	37
Bahçelievler	0.109265	37	0.079584	0.079585	0.079584	34	0.027435	36
Bakırköy	0.190884	34	0.190036	0.190037	0.190037	28	0.044040	34
Başakşehir	1.000000	1	0.551077	0.551078	0.551077	11	0.453551	15
Bayrampaşa	0.357697	32	0.137805	0.137806	0.137805	31	0.110956	30
Beşiktaş	1.000000	1	0.999996	1.000000	0.999998	1	0.676630	6
Beykoz	1.000000	1	0.266177	0.266177	0.266177	20	0.679227	5
Beylikdüzü	0.699161	26	0.698236	0.698242	0.698239	6	0.117755	29
Beyoğlu	0.846270	25	0.178864	0.178864	0.178864	29	0.241789	24
Büyükçekmece	0.567407	30	0.128872	0.128872	0.128872	32	0.163881	27
Çatalca	1.000000	1	0.999995	1.000000	0.999997	2	0.684875	4
Çekmeköy	1.000000	1	0.985718	0.985720	0.985719	3	0.943805	2
Esenler	0.656578	27	0.255511	0.255512	0.255511	22	0.110820	31
Esenyurt	0.139113	36	0.061885	0.061885	0.061885	36	0.036259	35
Eyüpsultan	1.000000	1	0.226079	0.226080	0.226080	26	0.435119	16
Fatih	0.007203	39	0.001324	0.001324	0.001324	39	0.002507	39
Gaziosmanpaşa	1.000000	1	0.441186	0.441186	0.441186	15	0.390326	18
Güngören	0.621306	29	0.617811	0.617814	0.617812	9	0.135878	28
Kadıköy	1.000000	1	0.419949	0.419950	0.419949	16	0.319188	21
Kâğıthane	1.000000	1	0.465942	0.465943	0.465942	14	0.476770	12
Kartal	1.000000	1	0.301896	0.301897	0.301897	19	0.274265	22
Küçükçekmece	0.029100	38	0.010957	0.010957	0.010957	38	0.007128	38
Maltepe	0.872383	24	0.252447	0.252447	0.252447	23	0.242642	23
Pendik	1.000000	1	0.120996	0.120996	0.120996	33	0.229821	25
Sancaktepe	1.000000	1	0.590954	0.590956	0.590955	10	0.529594	10
Sarıyer	1.000000	1	0.302056	0.302057	0.302057	18	0.603960	7
Silivri	1.000000	1	0.066804	0.066805	0.066804	35	0.353856	20
Sultanbeyli	1.000000	1	0.319333	0.319334	0.319333	17	0.457932	13
Sultangazi	1.000000	1	0.513363	0.513363	0.513363	12	0.550705	9
Şile	1.000000	1	0.758952	0.758953	0.758952	5	1.000000	1
Şişli	1.000000	1	0.636570	0.636571	0.636570	7	0.555768	8
Tuzla	0.634882	28	0.178647	0.178648	0.178648	30	0.168855	26
Ümraniye	1.000000	1	0.248276	0.248276	0.248276	24	0.508438	11
Üsküdar	1.000000	1	0.236904	0.236905	0.236904	25	0.409839	17
Zeytinburnu	0.261163	33	0.262603	0.262604	0.262604	21	0.095364	33

As it was stated before, the model proposed by Wen et al. (2018) yielded more plausible results than the model proposed by Shirdel et al. (2017) due to the weights assigned to ground motion factors. Also, excluding built-up area did not cause grand changes in the results for the model proposed by Wen et al. (2018) as this was proven by Correlation Analysis. Therefore, the vulnerability map of Istanbul is created by the model proposed by Wen et al. (2018). The maps are created for both cases, including and excluding built-up area.

To create vulnerability maps, K-Means Cluster Analysis was deployed on SPSS. The efficiency scores were used to create maps. The number of clusters was determined as 3 to classify the districts as highly vulnerable, medium vulnerable, and low vulnerable.

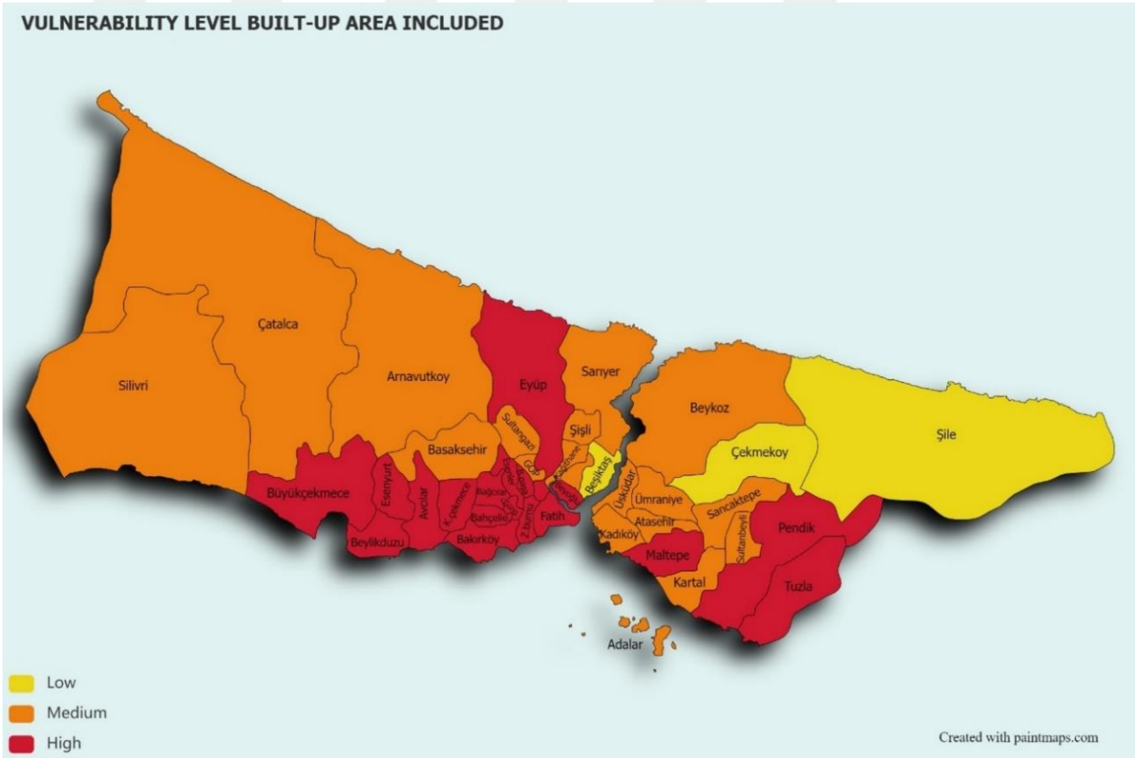

Figure 5.1 : Vulnerability map of Istanbul

The Figure 5.1 shows the vulnerability map of Istanbul in case of built-up area included. The highly vulnerable districts are generally the districts close to the Marmara Sea, more urbanized and populated districts. Moreover, it can be easily noticed that the number of highly vulnerable districts in the European sides of Istanbul is greater than the number of highly vulnerable districts on Asian side of Istanbul. The average efficiency score of the Asian side of Istanbul is 0.499700 while the average efficiency score of the European side of Istanbul is 0.289552. Similarly, the average ranking of the Asian side is 14.57 while it is 23.04 in the European side. Thus, it can be inferred that the European side of Istanbul is more vulnerable to earthquakes than the Asian side.

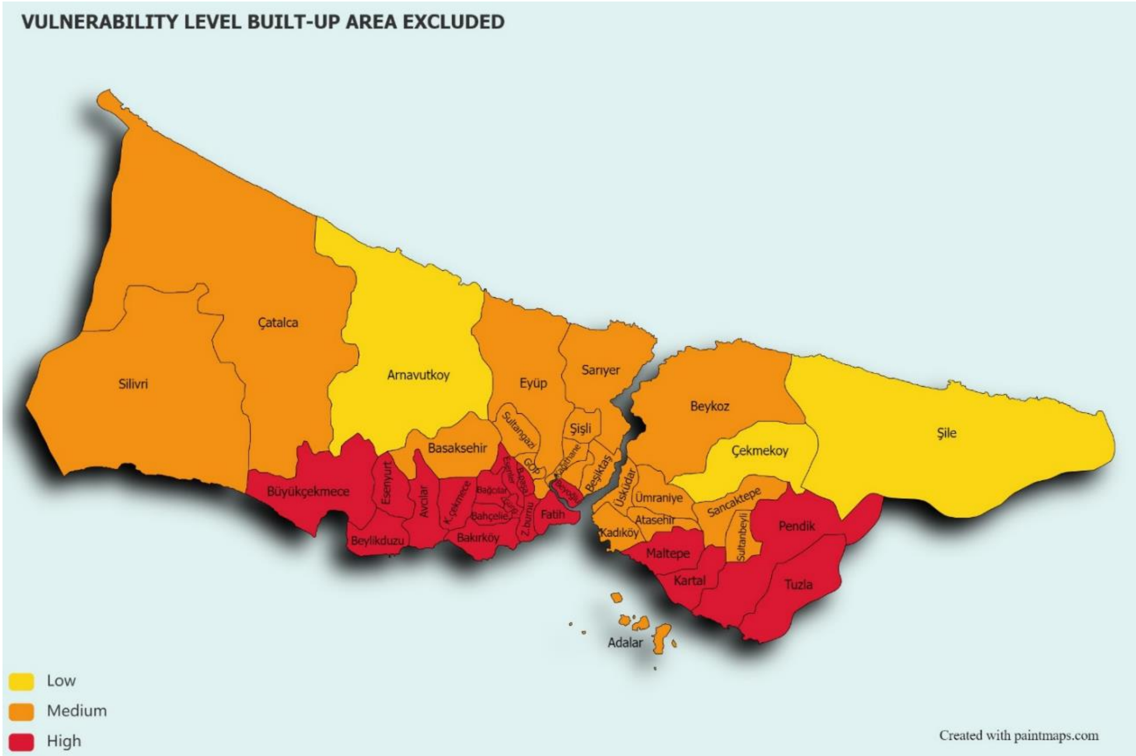

Figure 5.2 : Vulnerability map of Istanbul after excluding built-up area

The Figure 5.2 shows the vulnerability map of Istanbul in case of built-up area excluded. Similar to the case built-up area included, the highly vulnerable districts are generally the districts close to the Marmara Sea, more urbanized and populated districts. Again, it can be easily noticed that the number of highly vulnerable districts in European sides of Istanbul is greater than the number of highly vulnerable districts in Asian sides of Istanbul. The average efficiency score of Asian side of Istanbul is 0.470112 while the average efficiency score of European side of Istanbul is 0.288013. Similarly, the average ranking of Asian side is 14.93 while it is 22.84 in European side. Thus, it can be inferred that the European side of Istanbul is more vulnerable to earthquakes than the Asian side.

6.CONCLUSION

The recent earthquakes in southeastern Türkiye resulted in significant casualties and economic damage. Scientists are warning of a potential devastating earthquake in Istanbul due to its location near a major fault line. Given the city's economic importance and population, preparations need to be made to mitigate the impact of a potential earthquake in the future. Thus, there is a huge need for studies in the context of disaster management in Istanbul.

DEA is a mathematical programming technique used to evaluate the efficiency of DMUs that use multiple inputs to generate multiple outputs. Conventional DEA models such as the CCR model and the BCC model have limitations, including high computational burden and excessive weight flexibility issues. Common-weight DEA models address these drawbacks by using a common set of weights to evaluate DMUs, resulting in higher discriminating power. These models are effective for ranking alternatives and identifying the best performing DMUs.

There exist some studies in the context of disaster management studies. The vulnerability, resilience, or disaster risk reduction efficiency of districts, cities, or countries was made by DEA. However, existing disaster management studies have not employed common-weight DEA-based models. Furthermore, there exist only two DEA-based disaster management studies in Turkey.

Recently, Istanbul Municipality published a report about the estimation of disaster losses in case of a possible earthquake with a magnitude of 7.5 MW occurring during nighttime. This report was released for the 39 districts of Istanbul. Besides, this report includes some information about building types, age of buildings, estimated ground motions, possible death toll, injured people, and damaged buildings.

In this sense, this thesis evaluates the earthquake vulnerability of Istanbul's districts using common-weight DEA-based models with the data from this report. In assessing the vulnerability of districts in Istanbul to earthquakes, factors such as age, size, and seismic activity are considered. Inputs include the built-up area, number of buildings constructed before 2000, number of buildings with more than 5 floors, and estimated seismic activity such as PGA and PGV. Outputs include the expected number of injured people, heavily damaged buildings, and loss of life in the event of a major earthquake. These losses are considered undesirable outputs in the earthquake vulnerability assessment of Istanbul.

The input factors also include interval values. Therefore, common-weight DEA-based models in the existence of interval data are used to assess the earthquake vulnerability analysis of Istanbul. There exist few studies within common-weight DEA-based models with interval data in the literature. From these studies, the models proposed by Shirdel et al. (2017) and Wen et al. (2018) are used. However, the model proposed by Shirdel et al. (2017) does not yield plausible results due to the fact that it assigned poor weights to the ground motion factors which are very critical in vulnerability analysis. Inversely, none of the factors were neglected in the model proposed by Wen et al. (2018). Therefore,it yielded more plausible results. Despite all these results, it is possible that the built-up area might not be a good indicator and cause some distortion in results. Therefore, it is excluded and all models are solved again. Still, the model proposed by Shirdel et al. (2017) again assigns poor weights to the ground motion factors. Therefore, this model yields implausible results.

The model proposed by Wen et al. (2018) is used as the main model for vulnerability assessment since its results are plausible. By the results of the model proposed by Wen et al. (2018), the earthquake vulnerability maps are created for both cases, built-up area included and excluded. The maps reveal that the European side of Istanbul is more vulnerable to earthquakes than the Asian side of Istanbul. Moreover, the districts close to the Marmara Sea, more urbanized and populated districts are more vulnerable.

The results of this earthquake vulnerability evaluation can be a practical guideline for the authorities to prepare Istanbul for a possible earthquake. For instance, urban transformation projects can be prioritized district by district according to the results of this thesis. Similarly, the most vulnerable districts according to this study can be given more importance to be well prepared for a possible earthquake.

Consequently, this thesis evaluates the earthquake vulnerability of Istanbul's districts using common-weight DEA based models. This thesis is, as far as we are aware, the first to apply common-weight DEA-based models to vulnerability assessment and disaster management. Moreover, this is the first study that evaluates the earthquake vulnerability of Istanbul's districts using common-weight DEA-based models.

During the implementation of the analysis, the main problem was unavailability of data. The earthquake vulnerability evaluation of Istanbul's districts can be improved by reaching more data. The study can be enhanced with more input and output factors. Besides, the report published by Istanbul Municipality was published in 2019. This is the recent study in this context that is available publicly. Since we are in 2024, some input factors might have decreased or increased. Therefore, the analysis can be improved with up-to-date data. Moreover, the data is available for each district. Detailed studies can be conducted with the availability of the data for each neighbor. Thus, the earthquake vulnerability evaluation can be done for each neighbor. Likewise, this analysis can be done for the whole country with the availability of data. In addition, Turkey is prone to other disasters such as floods, erosion, forest fires, etc. Vulnerability evaluation to these disasters can be also done in case of data availability.

The common-weight DEA models with interval data are limited. The more the models exist, the better the analysis can be conducted. Besides, the main model used in this study is a MINLP model. It is really hard to solve MINLP problems due to the issues of global and local optimums. Therefore, it would be more computationally efficient to use common-weight DEA models with interval data within the LP framework. However, there are very limited studies in the scope of common-weight DEA based models with interval DEA.

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