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Earthquake Vulnerability Evaluation of Istanbul's Districts Using DEA-Based Models

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Abstract - Recent earthquakes in southeastern Türkiye have highlighted the need for disaster preparedness in the country's most populous city, Istanbul. Scientists believe that a huge earthquake is likely to strike Istanbul. Data envelopment analysis (DEA) is a valuable tool for evaluating the efficiency of decision-making units (DMU) in various managerial areas, including disaster management. This study employs common-weight DEA-based models, which enable incorporating interval data, to evaluate the earthquake vulnerability of Istanbul’s districts. Building stock, and estimated ground motions are taken as inputs while expected disaster losses and damages are used as outputs for assessing the earthquake vulnerability. The results depict that the most vulnerable district of Istanbul to earthquakes is Fatih while the least vulnerable one is Sile. The proposed earthquake vulnerability evaluation approach can be a practical guide for authorities for disaster risk reduction projects.

Keywords**:** Data Envelopment Analysis (DEA), disaster management, common-weight DEA, vulnerability analysis, interval data

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 [1].These figures related to loss and damages resulted in concerns about possible earthquakes that might occur soon, especially in Istanbul. It is foreseen that Istanbul might be struck by a huge earthquake and its consequences will affect all across Türkiye since Istanbul generates forty percent of gross domestic product (GDP) [2]. Thus, it is important to be prepared for such a huge earthquake before it occurs.

In this sense, the aim of this study is to assess the earthquake vulnerability of Istanbul’s districts using common-weight data envelopment analysis (DEA). DEA is a widely used approach for efficiency analysis [3]. It is a mathematical programming technique that evaluates the relative efficiency of decision-making units (DMUs) that use multiple inputs to generate multiple outputs. It is used in numerous managerial problems to compare the efficiency of DMUs [4].

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 shortcomings. 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, these models have excessive weight flexibility since each DMU is allowed to choose its own input and output weights to maximize the weighted output to weighted input ratio. 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 [5]. It is possible to avoid these drawbacks by deploying common-weight DEA models. The efficiency scores for DMUs are measured by a common set of weights in these models. The discriminating power of these models are better than conventional DEA models.

As far as we are aware, no study employed common weight DEA-based models in the context of disaster management even though these models provide a more practical approach and facilitate the ranking of all DMUs. Hence, this paper aims to evaluate the earthquake vulnerability of Istanbul’s districts using common-weight DEA models.

The rest of this study is structured as follows. The literature review regarding the studies deploying DEA models within the framework of disaster management is given in Section 2. The proposed methodology is provided in Section 3 while

Section 4 presents the earthquake vulnerability evaluation of Istanbul's districts using common-weight DEA-based models incorporating interval data. Lastly, conclusion and directions for future research are given in Section 5.

2. Literature Review

Numerous studies have deployed DEA models in disaster management. These studies primarily focus on comparing disaster vulnerability, resilience, and relief efforts across different regions, cities, or provinces. By employing the DEA method, researchers aim to identify areas that require improvement and provide recommendations to enhance disaster preparedness and response before the occurrence of a disaster.

Various studies used DEA to evaluate vulnerability to a variety of disasters such as earthquakes, typhoons, droughts floods, etc. For instance, Wei et al. [6] analyzed the vulnerability of Chinese regions by using the DEA model. Similarly, Huang et al. [7] employed the CCR model to evaluate regional vulnerability in China. The results show that economic progress is negatively correlated with regional vulnerability. Saein and Saen [8] used the DEA model to assess earthquake vulnerability in Tehran. Li et al. [9] used DEA models to estimate the vulnerability of floods in Hunan in terms of sensitivity, risk, and stability. Li et al. [10] analyzed the vulnerability of 31 Chinese provinces by using GDP, death toll, population density, economic loss, and disaster frequency. They deployed three-stage DEA to overcome the drawbacks of conventional DEA models. Yu et al. [11] used Super-Efficiency DEA (SE-DEA) to estimate the typhoon vulnerability of coastal regions in the Maritime Silk Road. Inputs and outputs were determined concerning the economy, agriculture, and population factors. Pathak et al. [12] used CCR DEA model with constant returns to scale technique to analyze the flood vulnerability of 21 districts of the Narmada River. Ma et al. [13] used SE-DEA and Tobit model to analyze the drought vulnerability of corn in Manchurian Plain. Recently, Gao et al. [14] tried to assess the earthquake vulnerability of 69 earthquakes by deploying CCR and BCC models.

Various researchers used DEA-based models to assess the resilience of communities and systems in the face of disasters. Zou and Wei [15] used the DEA model to analyze the relationship between economic improvement and coastal hazard resilience for eight Southeast Asian nations. Ustun [2] evaluated the earthquake resilience capacity of Istanbul's districts by DEA and returns to scale analysis. Then, he ranked the districts based on their disaster resilience. Villano et al. [16] tried to assess the resilience of households in response to disasters caused by climates in the Philippines. Using data from a cross-sectional survey, they tried to calculate the resilience score through network DEA.

Some studies employed DEA models in the framework of disaster risk or relief. Cheng and Chang [17] employed the CRR and BCC DEA models to analyze the efficiency of the disaster reduction risk policy in Yongkang City, Taiwan. Barbarosoglu and Ustun [18] calculated the efficiency of the relief organization that attended the relief operations during the Marmara earthquake that occurred in Türkiye. Li et al. [19] analyzed the disaster risk reduction investment in China. They deployed the CCR DEA model based on the data from 2010 to 2020.

3. Methodology

Data Envelopment Analysis (DEA) 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. DEA has been implemented in various sectors to assess the relative efficiency of homogenous DMUs. DEA was first introduced by Charnes, Cooper, and Rhodes in 1978 [3]. 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

$$max E_{j_0} = \frac{\sum_r u_r y_{r j_0}}{\sum_i v_i x_{i j_0}} \tag{3.1}$$

subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1, \qquad j = 1, \ldots, n \tag{3.2}$$

$$u_r\ , v_i \geq 0; \quad r = 1, \ldots, s\ ; i = 1, \ldots, m \tag{3.3}$$

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* used and output *r* produced by the *j*th DMU, respectively. The subscript '*0*' refers to the evaluated DMU.

Since the fractional programming model above is nonlinear and nonconvex, it is not used in the computation of efficiency scores while it can be converted into a linear program [3]. The linear model is as

$$maxE_{j_0} = \sum_{r=1}^{S} u_r y_{r j_0} \tag{3.4}$$

subject to

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1, \tag{3.5}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \forall j, \tag{3.6}$$

$$u_r\ , v_i \geq \varepsilon, \forall r, i. \tag{3.7}$$

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 also include interval data. To incorporate interval data, the classical CCR model can be transformed as follows [20] :

$$maxE_{j_0} = \sum_{r=1}^{s} \left[u_r\, y_{rj0}^{L} + p_{rj0}\left(y_{rj0}^{U} - y_{rj0}^{L}\right) \right] \tag{3.8}$$

subject to

$$\sum_{i=1}^{m} \left[v_i\, x_{ij0}^{L} + q_{ij0}\left(x_{ij0}^{U} - x_{ij0}^{L}\right) \right] = 1 \tag{3.9}$$

$$\sum_{r=1}^{s} \left[u_r\, y_{rj}^{L} + p_{rj}(y_{rj}^{U} - y_{rj}^{L}) \right] - \sum_{i=1}^{m} \left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right) \right] \leq 0, \forall j\ , \tag{3.10}$$

$$p_{rj} - u_r\ \leq 0, \forall r, j \tag{3.11}$$

$$q_{ij}\ \ - v_i\ \leq 0, \forall i, j \tag{3.12}$$

$$\varepsilon \leq u_{r\ ,} v_i\ \forall r, i \tag{3.13}$$

$$0 \leq p_{rj\ ,}\, q_{ij}\ \ \forall r, i\ \ , j. \tag{3.14}$$

To deal with the interval data, the model enables each DMU to select its own parameters $p_{rj}\ and\ q_{ij}$, respectively, to achieve the optimal efficiency score within the interval range. Despotis and Smirlis [20] have shown that the results of this model are equal to the results of the following model:

$$maxE_{j_0} = \sum_{r=1}^{s} u_r\, y_{rj0}^{U} \tag{3.15}$$

subject to

$$\sum_{i=1}^{m} v_i\, x_{ij0}^{L} = 1 \tag{3.16}$$

$$\sum_{r=1}^{s} u_r\, y_{rj0}^{U} - \sum_{i=1}^{m} v_i\, x_{ij0}^{L} \leq 0, \forall j\,, \tag{3.17}$$

$$\sum_{r=1}^{s} u_r\, y_{rj}^{L} - \sum_{i=1}^{m} v_i\, x_{ij}^{U} \leq 0, \qquad j = 1, .. n;\ j \neq j_0 \tag{3.18}$$

$$u_{r\,,} v_i \;\geq\; \varepsilon \;\; \forall r, i. \tag{3.19}$$

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 excessively high weights to the factors with superior performance and negligible weights to those with poor performance to maximize the efficiency score for the evaluated DMU.

To overcome these deficiencies, some researchers have proposed common weight DEA models in the existence of interval data. For instance, Shirdel et al. [21] presented a Multi-Objective Programming (MOP) model based on common-weight DEA to calculate the efficiency scores when there exists interval data.

Similarly, Wen et al. [22] suggested a modified Mixed Integer Nonlinear Programming (MINLP) minimax efficiency model based on common-weight DEA that considers interval data. The model determines the most efficient DMU by solving one MINLP.

Wen et al. [22] 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 provided in the article. This is probably due to a miscalculation as the efficiency scores in these kind of models can be obtained as

$$\frac{\sum_{r=1}^{s}\left[u_r\, y_{rj}^{L} + p_{rj}\left(y_{rj}^{U} - y_{rj}^{L}\right)\right]}{\sum_{i=1}^{m}\left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right)\right]} = 1 - \frac{dj}{\sum_{i=1}^{m}\left[v_i\, x_{ij}^{L} + q_{ij}\left(x_{ij}^{U} - x_{ij}^{L}\right)\right]} \tag{3.20}$$

4. Earthquake Vulnerability Evaluation

Input-output selection is very important in DEA studies. Inputs are regarded as the factors that should be minimized while outputs are the factors that should be maximized. Numerous variables can be taken into account as inputs when evaluating earthquake vulnerability. For example, the age of buildings and building types are important in the vulnerability analysis [23]. Besides, it is important to understand the spatial variability of the surface response in a typical scenario earthquake [8] . Also, the exposure of the socioeconomic system is important [24].

The majority of research in the framework of DEA-based vulnerability analysis used disaster losses, economic losses, and affected people as the output factors for the evaluation of earthquake vulnerability [11, 25, 26, 19, 14, 27]. 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 [28]. 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 is taken from IBB Sehir Planlama [29]. The selected inputs and outputs are shown in Table 4.1.

The undesirable outputs which are output 1, output 2, and output 3 are transformed into desirable outputs by an exponential transformation as follows [30]

$$y_{rj}^{\Upsilon} = (1 - \text{з}_r)^{y_{rj}} \tag{4.1}$$

The value of з can be determined by trial and error but it is better to define it by a specific approach. Zhou et al.[30] determined the value of з in a way that the standard deviation of the data after the transformation is maximized. Similarly, the value of з for the undesirable outputs in this study is calculated in this way which is shown by the following formula:

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

Then, linear normalization is applied to data. The exact inputs which are input 1, input 2, and input 3 are normalized via $x_{ij}/max_j(x_{ij})$ and transformed outputs are normalized by $y_{rj}^{\Upsilon}/max_j(y_{rj}^{\Upsilon})$ [31]. The lower bound data of input 4 and input 5 are normalized by $x_{ij}^{l}/max_j(x_{ij}^{u})$ and upper bound data are $x_{ij}^{u}/max_j(x_{ij}^{u})$ [32].

Table 4.1 Input-output indicators and related factors

Inputs&Outputs		Related 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 Results of the models

	Despotis and Smirlis [20]		Shirdel et al. [21]				Wen et al. [22]	
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
Arnavutkoy	1.000000	1	0.299443	0.303489	0.301466	17	0.621935	6
Atasehir	1.000000	1	0.440624	0.456375	0.448499	10	0.491218	15
Avcilar	0.487612	31	0.176602	0.188940	0.182771	29	0.116339	31
Bagcilar	0.153436	35	0.044603	0.047070	0.045836	36	0.027183	37
Bahcelievler	0.131468	37	0.092510	0.098861	0.095686	32	0.029144	36
Bakirkoy	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
Bayrampasa	0.397574	32	0.211585	0.221837	0.216711	26	0.191202	26
Besiktaş	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
Beylikduzu	0.699160	27	0.188789	0.197949	0.193369	28	0.131199	30
Beyoglu	1.000000	1	0.322723	0.336275	0.329499	15	0.268189	24
Buyukcekmece	0.567406	30	0.052922	0.055071	0.053996	34	0.171997	27
Catalca	1.000000	1	0.415587	0.431824	0.423705	11	0.661978	4
Cekmekoy	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
Eyupsultan	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
Gaziosmanpasa	1.000000	1	0.663112	0.697088	0.680100	9	0.412644	18
Gungoren	0.841503	26	0.689962	0.785873	0.737917	5	0.149173	29
Kadıkoy	1.000000	1	0.390845	0.402159	0.396502	12	0.334956	21
Kagithane	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
Kucukçekmece	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
Sariyer	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
Sile	1.000000	1	0.691048	0.714114	0.702581	6	1.000000	1
Sisli	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
Umraniye	1.000000	1	0.258413	0.261181	0.259797	23	0.584564	8
Uskudar	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 models were solved using GAMS software. Table 4.2 demonstrates the results of the proposed models. The modified CCR model proposed by Despotis and Smirlis [20] yielded twenty-four efficient DMUs. As it was explained in previous sections, the CCR model is not able to provide a complete ranking and robust evaluation. Therefore, common-weight DEA models with interval data are employed to rank the DMUs.

Table 4.3 Input-output weights

Weights	Shirdel et al. [21]	Wen et al. [22]
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 proposed by Shirdel et al. [21] provided a full ranking of DMUs. The results show that Sisli is the best district in terms of earthquake vulnerability. However, the ground motion factors were not taken into consideration in this model shown in Table 4.3. Therefore, this model did not yield plausible results.

The model proposed by Wen et al. [22] managed to provide a full ranking of DMUs and yielded only one efficient DMU which is Sile. The model assigned more importance to the ground motions and none of the factors were neglected. All factors were taken into account as it can be seen in Table 4.3. Thus, it can be claimed that this model provided more appropriate results than the model provided by Shirdel et al. [21].

The results show that Sile, Cekmekoy, Besiktas,and Catalca are the least vulnerable districts where the expected losses and estimated ground motions are very low in comparison to other DMUs while Fatih, Kucukçekmece, Bagcilar, Bahcelievler, and Esenyurt are the most vulnerable districts where the ground motion, the population and urbanization level in these districts are very high compared to other districts.

5. Conclusion

The recent earthquakes in southeastern Türkiye have shown the critical need for disaster management preparedness in Istanbul due to an expected possible earthquake. To mitigate the potential impact of a likely earthquake in Istanbul, extensive research and planning are crucial in the field of disaster management.

This study evaluates the earthquake vulnerability of Istanbul’s districts using common weight DEA-based models since conventional DEA models such as the CCR model and the BCC model have limitations such as high computational burden and excessive weight flexibility issues. 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 a few studies addressing common-weight DEA-based models with interval data in the literature. The models proposed by Shirdel et.al [21] and Wen et al. [22] are used from the existing literature. The model proposed by Wen et al. [22] yields more plausible results than the model proposed by Shirdel et al. [21] due to the fact that the ground motion factors were neglected in the model proposed by Shirdel et al. [21] .

Consequently, this study 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. The results of this earthquake vulnerability evaluation can be a 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 work. Similarly, the most vulnerable districts according to this study can be given more importance to be well prepared for a possible earthquake.

During the implementation of the analysis, the main problem was unavailability of data. The earthquake vulnerability evaluation of Istanbul’s districts can be improved through obtaining more data, and thus, the study can be enhanced with more input and output factors. Besides, the common-weight DEA models with interval data are limited. The more the models exist, the better the analysis can be conducted.

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