5. BÖLÜM / CHAPTER 5

A DETERMINATION OF URBAN ATTRACTIVENESS BASED ON GLOBAL POWER CITY INDEX USING FUZZY CLUSTERING ANALYSIS

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ABSTRACT

In this paper, it is aimed to classify 44 global cities from 29 countries in different geographies of the world in terms of the economy, research and development, cultural interaction, livability, environment and accessibility indicators used in calculating the Global Power City Index. In the study using the fuzzy clustering analysis method, which is one of the multivariate statistical methods, firstly, the Silhouette Index, the Normalized Dunn Coefficient and the Normalized Kaufman Coefficient were calculated for each number of clusters (2, 3, 4, ...) and it was determined that the most appropriate cluster number is 4. Then, it was questioned statistically whether the averages of the variables used in the analysis differ significantly from each other. According to the findings, it has been observed that global cities are classified in clusters with different characteristics in terms of used index indicators.

Keywords: Global Power City Index, Cities, Fuzzy Clustering Analysis

1. Introduction

Long-term trends in nature and society lead to the emergence of new trends towards the 21st century sustainability transition. This transition is seen as a process in which the needs of a steadily increasing world population are met and the life support systems of the planet and the living resources are protected (Kates & Parris, 2003).

The increasing day-to-day urban population density offers a variety of opportunities for future sustainable development scenarios. This situation, on the one hand, constitutes possible economic scales for the development of the infrastructure of the cities, on the other hand, facilitates the adaptation of services to be offered in social services such as education, health services and effective management. Emerging demographic and social trends form an important part of the quantitative understanding of the social organization and dynamics of people living in urban areas, and the transition to sustainability (Helbing, Ku, West & Bettencourt, 2007).

There are numerous pieces of historical evidence showing that cities are the main centers of innovation and economic growth. Quantitative features need to be introduced to understand urban dynamics and to predict its future orbit and stability. Nevertheless, it is noteworthy that there are quantitative differences between small and large cities in terms of economic opportunities, the rate of innovation and the rate of life (Hall, 1998).

In the first half of the 20th century, industrialization revealed the "mass production metropolis" and transformed many of the city centers in the west into important, successful and wealthy cities within national economies. Along with globalization, in addition to the increased competition among economic centers, the interest and need for tools that allow researchers to compare cities in various dimensions and the changing faces of the cities worldwide is attracting the attention of researchers. In this direction, the need for the development of tools that are effective in comparing cities in various dimensions is increasing (Larsen, 2015).

Urban areas around the world are directly faced with competition as they are integrated with each other through progress in transportation and technology. People who want to get a career opportunity in cities or to get a better quality of life tend to relocate. However, factors such as air quality, the availability of parks, or ensuring the personal safety that environmental concerns reveal, may be equally attractive. Therefore, cities are also obliged to sell themselves and to identify the disadvantages that need to be further developed by providing advantages to residents or businesses living within them. This global competition for charm or magnetism is necessary to determine the city's future economic and overall developmental success. (Ichikawa, Yamato & Dustan, 2017).

The concept of the global city began to be widely used after Saskia Sassen's book "Global city: New York, Tokyo, London" was published in 1991. The global city, which is also called the world city, is a city regarded as central nodes in the economic system of global networks where information, capital and people are circulating. In addition, many governments have announced plans to work to make their cities a global city (Wang & Chi, 2016).

The Global Power City Index (GPCI) aims to assess the major world cities in terms of global competitiveness by collecting and comparing reliable and objective quantitative data. The GPCI, which provides data that can be used by policy makers, businesses and researchers, measures the functions of the cities related to economy, research and development, cultural interaction, accessibility, livability and environment (GPCI, 2017).

Cities that can determine their advantages in all functions will not only benefit their residents, but will also act as an index finger that attracts talent and investment for businesses and people (Ichikawa, Yamato & Dustan, 2017). In this context, the purpose of this study is to classify 44 global cities from almost every geographical area of the world by fuzzy clustering analysis with respect to six different indicators used to reveal the global power city index for 2017. In the second part of the study, the global power city index and six basic indicators of this index are introduced. In the third part, there is a literature review, in the fourth and fifth part, information about the method and data set to be used in the study is given. In the sixth and seventh part, empirical findings and conclusions are included.

2. The Global Power City Index (GPCI)

The GPC index created by the Mori Memorial Foundation Urban Strategies Institute, which is a Japanese research institute, has been publishing since 2008 (Lopez-Ruiz, Alfaro-Navarro & Nevado-Pena, 2014). In this decade-long period, financial crises, natural catastrophes, more than seven billion people and technological developments have emerged. However, the environments surrounding the cities have changed dramatically, and the world cities have been affected from such changes in a global context. The Institute has continued to follow this evolution of urban change over the past decade. The results of our 10-year research provide valuable information to researchers for understanding and exploring the challenges facing cities around the world (GPCI, 2017).

The GPCI evaluates and grades major cities with high attraction power around the world in the context of global competition among cities and the intense interest of major businesses in these cities. This index focuses on a wide variety of indicators to assess and rank a city's global potential and comprehensive power beyond limiting its ranking to specific research areas such as finance and livability (GPCI, 2017). In this index, the leading cities of the world have been evaluated in terms of six key indicators that represent the power of these cities (economy, research and development, cultural interaction, life cycle, environment and accessibility etc.) and have a total of 70 sub-indicators. At the same time, this index provides a comprehensive view of the city in terms of the perspective of the global actors who live, work, research, and visit or perform arts in the cities. As a result, the purpose of the GPCI is to provide an important tool for highlighting the strengths and weaknesses of cities and for creating future-oriented urban strategies by revealing the problems that must be overcome (Sudjic, Sarkis, Burdett & Nowak, 2009).

3. Related Literature Review

Today, the importance of national economies is declining, and the economic role of regions and cities is increasing day by day (Lengyel, 2009). In the last decade, cities have faced strong competition in terms of investors, tourists, qualified labor and international events (Begg, 1999). For this reason, assessing and comparing the strengths and weaknesses of cities and revealing future development strategies is an important guide for investors. In this direction, the cities with the strongest economies, the largest universities and richest cultures are considered as the most global cities in terms of the city indexes and rankings (Giffinger & Gudrun, 2010).

Environmental sustainability concerns are high in terms of many smart city policies. And it is also clear that there is a necessary interaction between environmental scores and population growth. Because urban size and mobility increase pollution problems, cities with very high populations and rapid population growth appear to perform worse on environmental indicators (Dahmann, 1983; Gursoy & Mc Cleary, 2004; Pike & Page, 2014).

A productivity increase, which is one of the key success factors, is crucial to gaining a strong competitive position in business life and expanding market share. This interpretation of entrepreneurial dynamics by Schumpeter is also valid for the lives of cities. Cities are born, and with the growing population, they can also grow in terms of attractiveness and wealth. Many cities in our world are growing in welfare with an increasing population. However, some cities continue to exist in a stable position and at a low welfare level, while others can gain an increasingly strong profile. But, regardless of urban economic welfare, population growth in most cities transforms large cities into metropolises and, especially in developing countries, into mega-cities (Sassen, 1991).

Kourtit et al. (2014), explained the performance of metropolitan areas around the world by using growth models, which is a larger variation of the multilevel model. Firstly, they analyzed comprehensive GPCI data for 35 world cities in R software. Later, using the fixed effect model in SAS software, it was tested which city function is statistically meaningful for global actors composed of managers, researchers, artists, and residents. Statistically, findings in the analysis show that the economic dimension of a city for managers, economy and research-development dimension for researchers, cultural interaction and viability dimension for artists, cultural interaction and viability dimension for artists are meaningful. In addition, the analysis shows that 91.21% of variance in any city score can be explained by the city's own characteristics.

The global city, which can affect the economy, culture and politics of the world, is an indispensable platform for businesses around the world with its ability to support and host the economy. These platform economy cities, which have become the driving force for the development of the economy, are the industrially leading cities that will accelerate urban development and transformation in the future. Chen & Chen (2016) determined that there is a high correlation between the frequency of major events in the city, the number of functional organizations and GPCI, but there is a weak correlation between the number of industrial establishments in international standards and GPCI, as a result of their correlation analysis applied to selected platform cities (London, New York, Paris, Singapore, Hong Kong, Seoul, Pekin, Shanghai, Saint Paul, Mumbai) in the context of the GPC index.

In order to reach a globally competitive position, it can be ensured that the efforts of city administrations are more effective by determining the strengths and weaknesses of the cities with the help of indicators that reveal the power of urban competitiveness. Research results on the GPCI can provide valuable information to researchers to understand the difficulties that cities face and to help formulate urban policies and institutional strategies. In the study of Ichikawa et. al. (2017) in this context, they analyzed the world's leading global cities and their causes, taking into account the 2015 GPCI data. London, New York, Paris and Tokyo have emerged as the four cities with the highest GPCI value. And according to the study, London have had the highest score because London hosted the 2012 Olympic and Paralympic Games.

Romão et. al. (2017) applied an econometric analysis that is based on the hidden growth curve model to the six functional dimensions that are the performance indicators of urban attraction in terms of resident population and international tourism demand using GPCI data in the period between 2012-2016. The analysis results of 40 global cities confirmed that urban functions have different effects on the behavior of visitors and residents. In the five-year observation period, the cities with the highest viability scores are Paris, Vienna, Vancouver, Berlin, Barcelona and Amsterdam. Cultural dynamics have emerged as an important factor in attracting new residents and supporting a strong international tourism industry. Accessibility has been found to be an attractive power for most visitors while it is observed that the economic power increases the attractiveness of a city in terms of residents. However, the results of latent growth curve models show that there is a reverse relationship between population growth and viability.

4. Fuzzy Clustering Analysis as a Method

Clustering analysis is one of the most frequently used multivariate statistical techniques to uncover data groups and classify observations according to their similarities. The method is used to identify homogeneous subgroups in a given set of data by gathering observations with similarities between different objects in a group. The fuzzy clustering analysis can assign each object to more than one cluster at a certain probability level while the classic clustering analysis tries to assign each object to only one cluster (group). Here, the possibilities that can be interpreted as the membership coefficients indicate the degree to which an object belongs to a cluster. Thus, it is considered that an object is more likely to belong to the cluster with the highest membership coefficient. Fuzzy clustering analysis was proposed by Dunn (1973) and was developed by Bezdek (1973).

In clustering analysis, it is aimed that objects in the same cluster are as similar as possible and objects in different clusters are not as similar as possible. In the solid or classical clustering process, the objects are divided into clusters so that each object belong exactly to one cluster. In the fuzzy clustering process, objects can belong to more than one cluster at different membership levels (Yang & Watada, 2012). That is, in fuzzy clustering analysis, the degree of dependence of an object on a cluster is quantified by the value of the probability that the object belongs to a particular cluster. Thus, more detailed information about the structure of the data is obtained when compared with the classical clustering.

In fuzzy analysis, there are n objects (countries e.g.) and p variables (features e.g.) in a data set with each object being denoted by a vector x_i. And each variable is standardized with a mean and so they have equal importance in determining the structure. The dissimilarity coefficient or distance $\|x_i - x_j\|$ between two objects can be defined as Euclidean distance[1] as follows (Artis & Zhang, 2002):

$$\|x_i - x_j\| = \sqrt{\sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2} \tag{1}$$

1 In this study, Euclidean distance is used to measure the dissimilarity between objects because it is the most common measure in clustering analysis.

The Fuzzy c-means method proposed by Dunn (1973) and Bezdek (1973) is based on the minimization of the following objective function (Artis & Zhang, 2002):

$$\sum_{k=1}^{m} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} u_{ik}^2 u_{jk}^2 \|x_i - x_j\|^2}{2 \sum_{j=1}^{n} u_{jk}^2} \tag{2}$$

subject to following constraints:

$$u_{ik} \geq 0,\ \Sigma_j\, u_{ij} = 1 \quad i=1,2, \ldots\ldots n;\ k= 1,2,\ldots\ldots m \tag{3}$$

Here, u_{ij} is the membership coefficient of the x object belonging to cluster j, n is the number of objects and k is the number of the cluster.

It is important to determine the number of clusters in order to produce a healthy result in clustering analysis. Although it is not possible to talk about a method that says exactly what the number of clusters will be, some basic methods are frequently used in the literature. The simplest method used to determine the number of clusters in the literature is formulated below:

$$k \cong (n/2)^{1/2} \tag{4}$$

In here, k is the number of sets and n is the number of observations. This method, which is recommended to be used especially in small-sample studies, may not yield healthy results in large sample studies (Dunn, 1973; Artis & Zhang, 2002; Wang, 2008).

In addition, fuzzy analysis has two more useful diagnostic statistics. These are Dunn's partition coefficient and average silhouette width. Dunn's partition coefficient is used to measure the degree of fuzziness, which is defined as the sum of squares of all the membership coefficient divided by the number of objects Dunn (1973):

$$D = \sum_{i=1}^{n} \sum_{k=1}^{m} u_{ik}{}^2 / n \tag{5}$$

Here, if objects have equal membership in all clusters, (1/k), then classifying is completely fuzzy. However, if each object belongs to only one cluster, then there is exact classifying, in other words no fuzziness. Therefore, the Dunn coefficient will always be between (1/k) and 1 (Alam, et al., 2000; Grubesic, 2006). On the other hand, Dunn's partition coefficient can be standardized as minimum 0 and maximum 1 as in the following formula (Dunn, 1973; Artis & Zhang, 2002):

$$D_n = \frac{m \sum_{i=1}^{n} \sum_{k=1}^{m} \frac{u_{ik}^2}{n} - 1}{m-1} \text{ or } D_n = \frac{D-(1/k)}{1-(1/k)} \tag{6}$$

In the normalized Dunn's partition coefficient, D_n varies from 0 to 1. And, a value close to 1 indicates no fuzziness (hard cluster) and a value close to 0 indicates complete fuzziness in the data set. Kaufman and Rousseeuw (1990) proposed a new partition coefficient and a normalized partition coefficient as an alternative to the Dunn coefficient. The Kaufman (K) and normalized Kaufman (K_n) coefficients are calculated as follows:

$$K = \sum_{k=1}^{m} \sum_{i=1}^{n} \frac{(u_{ik} - u_{jk})^2}{n} \tag{7}$$

$$K_n = \frac{K}{1-(1/k)} \tag{8}$$

Here, this coefficient ranges from 0 (hard clusters) to 1-1/K (completely fuzzy). In summary, D_n and K_n together give a good indication of an optimum number of clusters. We should choose k so that D and D_n are large and K and K_n are small.

Average silhouette width can be used to measure how well an object or a cluster is classified. In clustering analysis for the data partition, $\theta_m = [w_1,...,w_m]$ with m cluster, each cluster being indicated by $w_m = (k = 1,.., m)$, average dissimilarity of object x_i to all other objects in cluster w_k is defined as

$$d(x_i, w_k) = \frac{1}{|w_k|} \sum_{x_j \in w_k} \left| x_i - x_j \right| \tag{9}$$

where $|w_k|$ indicates the number of objects in the cluster. Here, if $x_j \in w_k$, then $d(x_i, w_k)$ indicates average dissimilarity of object x_i to all objects in its own cluster (intra-dissimilarity) but if $x_j \notin w_k$, then $d(x_i, w_k)$ indicates average dissimilarity of x_i to all objects in other clusters (inter-dissimilarity).

Average silhouette width can also be showed as follows (Artis & Zang, 2002):

$$s(i) = \begin{Bmatrix} \text{if } a(i) < b(i) \text{ then } [1 - a(i)/b(i)] \\ \text{if } a(i) = b(i) \text{ then } 0 \\ \text{if } a(i) > b(i) \text{ then } [b(i)/a(i) - 1] \end{Bmatrix} \tag{10}$$

$$s(i) = \frac{b(i) - a(i)}{\max[a(i), b(i)]} \text{ and } -1 \leq s(i) \leq 1 \tag{11}$$

Here, a(i) indicates the intra-dissimilarity and b(i) indicates the smallest inter-dissimilarity.

Moving from here, the following evaluations can be made related with s(i):

- If s(i) is close to -1 then it means that the intra-dissimilarity is much larger than the smallest inter-dissimilarity and so that object i is misclassified.
- If s(i) is close to 0 then it means that a(i) and b(i) are approximately equal and it is not clear to which cluster object i should be assigned.
- If s(i) is close to 1 then it means that the intra-dissimilarity is much smaller than the smallest inter-dissimilarity and so that object i is well classified to an appropriate cluster.

Similarly, the average silhouette width of a cluster can be calculated as the average of s(i) for all objects in that cluster. And so, this indicator shows us how well a cluster is classified. The average silhouette width for all data set can be calculated as the average silhouette width, s(i), for all objects, and it can be used as an indicator to decide the optimal number of clusters in a data set (Rousseeuw, 1987; Artis & Zang, 2002).

Finally, it can be said that an easy way to select the appropriate number of clusters is to choose the number of clusters which maximizes the average silhouette. It is indicated that the maximum average silhouette across all values of k as s(i). Here, Rousseeuw (1987) recommended the following interpretations for silhouette width s(i):

Table 1
Reference Values for Silhouette Width

Silhouette Width	**Interpretation**
0.71-1.00	A strong structure has been found.
0.51-0.70	A reasonable structure has been found.
0.26-0.50	The structure is weak and could be artificial. Try other methods on this database.
-1.00-0.25	No substantial structure has been found.
Source: Rousseeuw (1987)	

5. Dataset Used in the Study

70 indicators are used in the calculation of the GPCI value. The selection criteria for the 44 cities included in the survey for 2017 are as follows (GPCI, 2017):

- Cities found in the top ten of existing, influential city rankings, such as the Global Financial Centers Index (GFCI, Z/Yen Group), Global Cities Index (GCI, A.T. Kearney), and Cities of Opportunity (PricewaterhouseCoopers).

- Major cities of countries that are in the top ten in terms of competition according to influential international competitiveness rankings, such as the Global Competitiveness Report (World Economic Forum) and IMD Competitiveness Ranking (Institute for Management Development).
- Cities which do not meet the above criteria but which are deemed appropriate for inclusion by the GPCI Executive Committee or its Working Committee members.

The cities included in the 2017 GPCI survey are listed in the Table 2 below (GPCI, 2017):

Table 2

Cities in the scope of the 2017 GPCI research

Region	**City**
Europe	Madrid, Barcelona, London, Paris, Brussels, Amsterdam, Geneva, Frankfurt, Berlin, Zurich, Milan, Copenhagen, Vienna, Stockholm, Moscow
Africa	Cairo, Johannesburg
Middle East	Istanbul, Dubai
Asia	Mumbai, Bangkok, Kuala Lumpur, Singapore, Jakarta, Hong Kong, Beijing, Shanghai, Taipei, Seoul, Fukuoka, Osaka, Tokyo
Oceania	Sydney
North America	Vancouver, San Francisco, Los Angeles, Chicago, Toronto, Washington, D.C., New York, Boston
Latin America	Mexico City, Sao Paulo, Buenos Aires
Source: GPCI (2017). http://mori-m-foundation.or.jp/pdf/GPCI2017_en.pdf	

The GPCI evaluates its target cities in six urban functions: Economy, Research and Development, Cultural Interaction, Livability, Environment, and Accessibility. Each of the functions comprises multiple indicator groups, which in turn consists of several indicators. A total of 70 indicators are used in the GPCI. The average indicator scores of the indicator groups are combined to create the function-specific rankings. The comprehensive ranking is created by the total scores of the function-specific rankings (GPCI, 2017). The indicator groups for the functions used in the study are listed in the following Table 3:

Table 3

Ranking Method: Flow of Function-Specific Ranking

Functions	**Indicator Groups**	**Indicators**
Economy	Market Size	1-Nominal GDP 2-GDP per Capita
	Market Attractiveness	3-GDP Growth Rate 4-Level of Economic Freedom
	Economic Vitality	5-Total Market Value of Listed Shares on Stock Exchanges 6-World's Top 500 Companies
	Human Capital	7-Total Employment 8-Number of Employees in Service Industry for Business Enterprises
	Business Environment	9-Wage Level 10-Ease of Securing Human Resources 11-Office Space per Desk
	Ease of Doing Business	12-Corporate Tax Rate 13-Level of Political, Economic and Business Risk
Research and Development	Academic Resources	14-Number of Researchers 15-World's Top 200 Universities
	Research Background	16-Academic Performance in Mathematics and Science 17-Readiness for Accepting Researchers 18-Research and Development Expenditure
	Research Achievement	19-Number of Registered Industrial Property Rights (Patents) 20-Number of Winners of Highly-Reputed Prizes (Science and Technology- Related Fields) 21-Interaction Opportunities Between Researchers
Cultural Interaction	Trendsetting Potential	22-Number of International Conferences Held 23-Number of World-Class Cultural Events Held 24-Trade Value of Audiovisual and Related Services
	Cultural Resources	25-Environment of Creative Activities 26-Number of World Heritage Sites (within 100 km Area) 27-Opportunities for Cultural, Historical and Traditional Interaction
	Facilities for Visitors	28-Number of Theaters and Concert Halls 29-Number of Museums 30-Number of Stadiums
	Attractiveness to Visitors	31-Number of Luxury Hotel Guest Rooms 32-Number of Hotels 33-Attractiveness of Shopping Options 34-Attractiveness of Dining Options
	International Interaction	35-Number of Foreign Residents 36-Number of Visitors from Abroad 37-Number of International Students

Livability	Working Environment	38-Total Unemployment Rate 39-Total Working Hours 40-Level of Satisfaction of Employees with Their Lives
	Cost of Living	41-Average Housing Rent 42-Price Level
	Security and Safety	43-Number of Murders per Million People 44-Economic Risk of Natural Disaster
	Well-Being	45-Life Expectancy 46-Degree of Social Freedom, Fairness, and Equality 47-Risk to Mental Health
	Ease of Living	48-Number of Medical Doctors per Million People 49-ICT Readiness 50-Variety of Retail Shops 51-Variety of Restaurants
Environment	Ecology	52-Number of Companies with ISO 14001 Certification 53-Percentage of Renewable Energy Used 54-Percentage of Waste Recycled
	Air Quality	55-CO2 Emissions 56-Density of Suspended Particulate Matter (SPM) 57-Density of Sulfur Dioxide (SO2), Density of Nitrogen Dioxide (NO2)
	Natural Environment	58-Water Quality of Rivers 59-Level of Green Coverage 60-Comfort Level of Temperature
Accessibility	International Transportation Network	61-Number of Cities with Direct International Flights 62-International Freight Flows
	Transportation Infrastructure	63-Number of Arriving / Departing Passengers on Domestic and International Flights 64-Number of Runways
	Inner-City Transportation Services	65-Density of Railway Stations 66-Punctuality and Coverage of Public Transportation 67-Travel Time between Inner-City Areas and International Airports
	Traffic Convenience	68-Commuting Convenience 69-Transportation Fatalities per Million People 70-Taxi Fare
Source: GPCI (2017). http://mori-m-foundation.or.jp/pdf/GPCI2017_en.pdf		

Istanbul was included in the scope of the research in 2012, although the GPCI has been calculated regularly every year since 2008. In this study, the GPCI values for 2017 were used for 43 cities. According to the function-based evaluation, Istanbul ranks 30^{th} among 44 cities. Looking at the 6 different functions that the data compiled, Istanbul ranks 26^{th} in terms of economic power, 26^{th} in terms of research and development, 16^{th} in terms of cultural interaction, 37^{th} in terms of livability, 40^{th} in terms of environment, and 11^{th} in terms of accessibility (GPCI, 2017).

Table 4
Data Set: Function-Specific Ranking Scores Alphabetically

Cities	Economy	R&D	Cultural Interaction	Livability	Environment	Accessibility
Amsterdam	195.5	65.2	131.7	363.7	172.2	201.6
Bangkok	154.2	44.5	132.1	292.2	137.3	148.5
Barcelona	121.9	41.8	133.9	352.6	158.5	158.4
Beijing	295.6	77.9	155.0	284.8	79.40	158.9
Berlin	192.3	79.7	158.1	369.3	172.8	135.7
Boston	185.1	119.5	84.0	283.9	148.7	143.6
Brussels	152.4	59.3	131.5	320.7	157.9	156.6
Buenos Aires	70.8	19.7	93.6	293.4	134.0	116.9
Cairo	80.6	5.5	49.8	269.1	88.5	110.4
Chicago	181.0	113.6	107.4	268.9	136.7	168.0
Copenhagen	195.4	39.6	74.1	342.0	187.7	145.3
Dubai	216.5	43.2	141.9	287.4	103.7	177.0
Frankfurt	198.8	32.0	69.4	358.4	200.1	201.2
Fukuoka	147.7	44.0	38.8	334.0	162.4	114.0
Geneva	204.8	54.5	35.9	316.0	191.3	99.3
Hong Kong	242.7	96.4	105.9	275.6	162.8	206.7
Istanbul	183.8	46.4	127.7	273.7	103.5	191.1
Jakarta	130.0	12.4	36.6	289.4	107.4	99.9
Johannesburg	118.0	7.5	49.2	214.6	122.8	80.9
Kuala Lumpur	190.9	33.1	78.4	327.5	154.7	134.7
London	301.6	165.1	333.1	328.3	188.0	244.0
Los Angeles	190.7	148.9	123.6	302.5	161.3	146.5
Madrid	128.9	31.4	117.8	348.3	162.4	156.8
Mexico City	139.8	11.5	109.1	277.4	122.3	123.6
Milan	141.7	26.4	101.7	338.9	162.4	142.3
Moscow	145.4	57.8	98.3	299.7	75.10	181.5
Mumbai	115.4	8.1	59.8	268.3	121.2	94.4
New York	323.2	183.7	233.1	280.0	145.2	221.1
Osaka	169.5	87.2	101.3	321.7	142.9	136.1
Paris	211.9	104.4	217.3	350.5	152.7	245.3
San Francisco	210.4	112.1	93.5	298.1	164.4	127.3
Sao Paulo	118.5	15.7	89.4	289.8	172.0	91.8
Seoul	227.9	126.5	134.0	308.7	153.6	192.8
Shanghai	256.0	61.7	124.0	273.6	93.6	224.0
Singapore	239.3	125.4	180.9	290.1	191.4	197.5
Stockholm	209.8	53.6	80.6	359.2	190.5	133.7
Sydney	231.5	73.2	135.2	329.1	177.4	131.6
Taipei	174.8	54.1	35.7	264.7	167.9	150.8
Tokyo	294.3	162.9	186.3	332.8	172.4	206.1
Toronto	198.5	60.4	93.3	342.0	153.9	144.2
Vancouver	190.2	43.6	79.3	344.7	174.3	112.6
Vienna	163.2	45.0	148.9	358.6	189.6	140.6
Washington	202.8	75.5	95.2	239.8	166.6	148.4
Zurich	243.7	52.9	48.6	329.2	197.5	125.1

Source: (GPCI, 2017) **http://mori-m-foundation.or.jp/pdf/GPCI2017_en.pdf**

6. Empirical Findings

In the fuzzy clustering analysis in this study, average Silhouette width (S), Dunn's partition coefficient (D), normalized Dunn's partition coefficient (D_n), Kaufman partition coefficient (K) and normalized Kaufman partition coefficient (K_n) are used to determine the appropriate number of clusters. The specific Silhouette amount value is obtained as zero for Jakarta and this city breaks the clustering structure. For this reason, the clustering analysis was conducted for 43 cities. The results of the indexes are given below at Table 5:

Table 5
Appropriate Number of Cluster

Cluster Number	S	D	D_n	K	K_n
2	0.5782	0.8453	0.6906	0.0838	0.1676
3	0.6155	0.7965	0.6947	0.1068	0.1602
4	0.6155	0.7796	0.7061	0.1314	0.1752
5	0.4256	0.8422	0.8027	0.0767	0.0959
6	0.1468	0.8037	0.7644	0.0926	0.1111
S: Average Silhouette Width, D: Dunn partition coefficient Dn: Normalized Dunn partition coefficient, K: Kaufman partition coefficient Kn: Normalized Kaufman partition coefficient.					

When examining Table 5, the Silhouette width and the other partition coefficients obtained for the different cluster numbers (k = 2, 3, 4 ...) show that the number of the appropriate cluster can be taken as 4.

Table 6 shows the cluster membership possibilities concerning what degree global cities belong to each cluster for 4 clusters which are obtained by fuzzy clustering using Euclid as a distance measure. As an example, it can be said that Amsterdam is located in the fourth cluster with 65% probability.

Table 6
The Possibilities of Belonging to 4 Clusters for 43 Cities

Cities	Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Amsterdam	4	0.3404	0.0000	0.0000	**0.6596**
Bangkok	1	**0.5206**	0.1693	0.1692	0.1409
Barcelona	4	0.3404	0.0000	0.0000	**0.6596**
Beijing	1	**1.0000**	0.0000	0.0000	0.0000
Berlin	4	0.0000	0.0000	0.0000	**1.0000**
Boston	2	0.2481	**0.2737**	0.2736	0.2046
Brussels	4	0.3404	0.0000	0.0000	**0.6596**

Buenos Aires	3	0.1485	0.3527	**0.3529**	0.1460
Cairo	3	0.1485	0.3522	**0.3534**	0.1460
Chicago	1	**0.8793**	0.0414	0.0414	0.0380
Copenhagen	4	0.0000	0.0000	0.0000	**1.0000**
Dubai	1	**1.0000**	0.0000	0.0000	0.0000
Frankfurt	4	0.0000	0.0000	0.0000	**1.0000**
Fukuoka	4	0.0000	0.0000	0.0000	**1.0000**
Geneva	4	0.0000	0.0000	0.0000	**1.0000**
Hong Kong	4	0.0000	0.0000	0.0000	**1.0000**
Istanbul	1	**1.0000**	0.0000	0.0000	0.0000
Johannesburg	3	0.1485	0.3525	**0.3531**	0.1460
Kuala Lumpur	4	0.0000	0.0000	0.0000	**1.0000**
London	4	0.2453	0.0000	0.0000	**0.7547**
Los Angeles	4	0.0000	0.0000	0.0000	**1.0000**
Madrid	4	0.3411	0.0000	0.0000	**0.6589**
Mexico City	2	0.1485	**0.3531**	0.3524	0.1460
Milan	4	0.0000	0.0000	0.0000	**1.0000**
Moscow	1	**0.8734**	0.0455	0.0455	0.0355
Mumbai	2	0.1485	**0.3533**	0.3523	0.1460
New York	1	**1.0000**	0.0000	0.0000	0.0000
Osaka	4	0.1054	0.1041	0.1040	**0.6865**
Paris	1	**1.0000**	0.0000	0.0000	0.0000
San Francisco	4	0.0000	0.0000	0.0000	**1.0000**
Sao Paulo	4	0.0202	0.0315	0.0315	**0.9167**
Seoul	4	0.2448	0.0000	0.0000	**0.7552**
Shanghai	1	**1.0000**	0.0000	0.0000	0.0000
Singapore	4	0.2453	0.0000	0.0000	**0.7547**
Stockholm	4	0.0000	0.0000	0.0000	**1.0000**
Sydney	4	0.0000	0.0000	0.0000	**1.0000**
Taipei	4	0.0202	0.0315	0.0315	**0.9167**
Tokyo	4	0.2454	0.0000	0.0000	**0.7546**
Toronto	4	0.0000	0.0000	0.0000	**1.0000**
Vancouver	4	0.0000	0.0000	0.0000	**1.0000**
Vienna	4	0.0000	0.0000	0.0000	**1.0000**
Washington	4	0.0000	0.0000	0.0000	**1.0000**
Zurich	4	0.0000	0.0000	0.0000	**1.0000**

Although the cities of Buenos Aires, Cairo, and Johannesburg are located in the third cluster, the membership probability values are quite close to the second cluster. However, the cities of Boston, Mexico City and Mumbai, which are in the second cluster with a very low probability difference, are quite close to the third cluster probability value. This proximity in the probability values shows that these cities have a fuzzy structure in terms of clustering. It can be said that these cities remained at the intersection of two relatively different clusters.

As a result of the fuzzy clustering analysis, the four clusters obtained from the data of 6 indicators used in the calculation of GPCI index and the placement of 43 global cities in clusters are given in Table 7.

Table 7
The Summary Clusters for 43 Cities

Cluster 1	Bangkok, Beijing, Chicago, Dubai, İstanbul, Moscow, New York, Paris, Shanghai
Cluster 2	Boston, Mexico City, Mumbai
Cluster 3	Johannesburg, Buenos Aires, Cairo
Cluster 4	Amsterdam, Barcelona, Berlin, Brussels, Copenhagen, Frankfurt, Fukuoka, Geneva, Hong Kong, Kuala Lumpur, London, Los Angeles, Madrid, Milan, Osaka, San Francisco, Sao Paulo, Seoul, Singapore, Stockholm, Sydney, Taipei, Tokyo, Toronto, Vancouver, Vienna, Washington, Zurich

According to these results, Beijing, Dubai, Istanbul, New York, Paris and Shanghai are placed in the same cluster. The second cluster consists of three cities: Boston, Mexico City and Mumbai. The third cluster also consists of three cities: Johannesburg, Buenos Aires and Cairo. In the fourth cluster, there are 28 cities, mostly Asian and European cities.

The Shapiro-Wilk normality test was used to determine whether the data used in the study was normal. When Table 8 is examined, it is observed that the normality assumption is generally achieved at 5% significance level.

Table 8
Shapiro Wilk Normality Test (p values)

Variable/Cluster No.	**1**	**2**	**3**	**4**
Economy	.435	.673	.378	.323
R&D	.054	.051	.249	.012
Cultural Interaction	.049	.980	.022	.003
Livability	.845	.817	.584	.066
Environment	.271	.067	.455	.149
Accessibility	.499	.795	.325	.028

Note: When the p value for the Shapiro Wilk statistic is greater than 0.05, then it can be accepted the variable (indicator) in the cluster has a normal distribution.

Table 9, which shows the cluster averages of each indicator group, is given below:

Table 9
Cluster Averages for Variables

Cluster No.	Economy	R&D	Cultural Interaction	Livability	Environment	Accessibility
1	219.46	78.60	139.94	282.54	109.31	183.76
2	146.77	46.37	84.30	276.50	130.73	120.53
3	89.80	10.90	64.20	259.03	115.10	102.73
4	196.26	72.76	115.64	325.41	171.09	156.10

The first cluster, which includes Bangkok, Beijing, Chicago, Dubai, Istanbul, Moscow, New York, Paris and Shanghai global cities, is located first in terms of economy (219.46), R&D (78,6), cultural interaction (139.94), and accessibility (183.76) indicators and is located second in terms of livability (282.54). In contrast, it has the worst performance compared to other clusters in terms of environment (109.31) indicators.

The second cluster, consisting of Boston, Mexico City and Mumbai, is located third in terms of economy (146.77), R&D (46.37), cultural interaction (84.3), livability (276.5) and accessibility (120.53) indicators. However, it is located in the second place in terms of environment (130.73) indicators.

The third cluster, which includes Johannesburg, Buenos Aires and Cairo, is located last in terms of economy (89.8), R&D (10.9), cultural interaction (64.2), livability (259.03) and accessibility (102.73) indicators. However, it is in the third place in terms of environment (115.1) indicators.

The fourth cluster, which includes European and Asian cities such as Amsterdam, Barcelona, Tokyo and Hong Kong, has the highest average of livability (325.41) and environment (171.09) variables. But, it is in the second place in terms of economy (196.26), R&D (72.76), cultural interaction (115.64) and accessibility (156.1) indicators.

ANOVA testing can be used to determine whether clusters are statistically different from each other on the basis of cluster means of variable groups. However, before the ANOVA test is applied to the data from the normal distribution, it should be tested whether the variance of the data of the variables is homogeneous. Table 10 shows the results of the homogeneity test of the variances which is the basic assumption of one-way ANOVA.

Table 10

Homogeneity Test of Variances

Variable	**Levene Stat.**	**Sig.**
Economy	1.645	.195
R&D	1.663	.191
Cultural Interaction	.926	.437
Livability	2.850	.051
Environment	2.885	.049
Accessibility	1.060	.377
Note: When the p value for the Levene statistic is greater than 0.05, then it can be accepted the variances of indicators in the cluster are equal.		

Since the p values of the 6 indicator groups in the 4 clusters obtained from the clustering analysis are mostly greater than 0.05 significance level, it can be said that the variances are homogeneous. Thus, it can be said that the results obtained from the analysis of variance will be healthier since the basic assumption of variance analysis is provided.

The results of the ANOVA test to determine whether there is a significant difference between the clusters in terms of indicator variables is given in Table 11. When Table 11 is examined, it is seen that the four variable groups used in the study are effective in clustering. According to this result, it is determined that the data of global cities on the economy, livability, environment, and accessibility indicator groups differed significantly from cluster to cluster ($p<0.05$). However, clustering is meaningless in terms of R&D and cultural interaction data. In addition, it is seen that the most effective variable that constitutes the difference in clustering analysis is the environment indicator group ($F=29.85$).

Table 11

Variance Analysis (F Test)

Variable	**F**	**Sig.**
Economy	6.337	0.001
R&D	2.275	0.095
Cultural Interaction	1.689	0.185
Livability	9.858	0.000
Environment	29.849	0.000
Accessibility	4.678	0.007
Note: When the p value for the F test statistic is greater than 0.05, then it can be accepted that there is no significant difference between the clusters according to the indicators.		

7. Result and Discussion

In this study, 44 global cities in 29 countries were classified by fuzzy c-means clustering analysis in terms of the economy, research-development, cultural interaction, livability, environment, and accessibility indicators used in the calculation of the GPC index. In clustering analysis based on Euclidean distance, firstly, for each cluster number, the Silhouette index, the normalized Dunn coefficient and the normalized Kaufman coefficient are determined. According to this, it is determined that the most suitable cluster number is 4. In the analysis, the city numbers in the 1st, 2nd, 3rd and 4th clusters are 8, 3, 3, 29 respectively. In addition, the statistical significance of the mean values of the variables used in the study was questioned by homogeneity test and ANOVA test. According to this, global cities have a statistically significant difference in terms of economy, livability, environment, and accessibility indicators.

The countries in the first cluster are located in Asia, Europe and the America. These cities, especially US cities, have a high academic level in science and technology, and a significant number of the world's best universities are located in these cities. Moreover, these cities have the highest average values regarding the economy, R&D, cultural interaction, and accessibility indicators. For example, Shanghai is a very strong city in terms of the total market value of public shares in the world's top 300 companies. Additionally, New York is a well-known international financial center, and Paris and Istanbul are well known international tourism centers. However, these global cities, which have the worst performance compared to other global cities in terms of environmental indicators, need to make significant improvements. In this sense, the main issues to be reviewed and developed are: Percentage of Renewable Energy Used, Percentage of Waste Recycled, CO_2 Emissions, Density of Suspended Particulate Matter (SPM), Density of Sulfur Dioxide (SO_2), Density of Nitrogen Dioxide (NO_2), Water Quality of Rivers, and Level of Green Coverage.

The second cluster includes the cities of Boston, Mexico City and Mumbai, which are far behind the cities in the first and fourth clusters in terms of economy, livability, environment and accessibility. In this respect, first of all, necessary arrangements should be made in terms of accessibility, environment and livability indicators. Furthermore, the cities of Boston and Mexico City are in the middle ranks of research and cultural interaction indicators.

In the third cluster, the global cities of Cairo, Buenos Aires and Johannesburg were identified as cities with the lowest scores in terms of all indicative variables. These cities need to become competitive cities by renewing themselves within the framework of all the variable groups dealt with and making new arrangements.

The fourth cluster includes the cities of Frankfurt, Zurich, Singapore, Geneva and Stockholm which are the top five cities in the environment indicators, and ranks first in terms of environmental and livability indicators. At the same time, this cluster includes European cities that are at the top of the list for indicators such as life expectancy, degree of social freedom, green area, CO_2 emission and percentage of renewable energy. For example, Singapore is a pioneering city in terms of high recyclable waste. Moreover, cities in this cluster have developed economies. For example, Zürich is among the leading cities in terms of GDP per capita, wage level and production efficiency indicators. Additionally, this cluster contains global cities such as Paris, London, Shanghai and Hong Kong, which are high in the accessibility category. These cities are the leading cities in terms of number of passengers on international flights, international transportation network and transportation infrastructure. Finally, the cities of Amsterdam, Barcelona, London, Tokyo, Singapore, Sydney and Vienna, which are on the front lines for cultural interaction indicators such as visitors, museums and visitors from abroad, are also in this cluster.

As a result, the 10-year results obtained from the GPC index, which has been calculated since 2008, will allow us to understand the challenges facing the world's leading global cities. In addition, these results also provide some important data that will contribute to exhibiting the features that make these cities attractive. The GPCI can be a road map in the development of corporate strategies by providing urban policy recommendations to countries and communities. It is hoped that this study will be an example of the studies to be carried out using GPCI data from 2018 and the following period and will give a perspective to the decision makers.

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