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Clustering Application and Evaluation of the Countries' Word Risk and Climate Risk Indices

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ABSTRACT

Societies take various initiatives to reduce the impact of natural disasters. Unfortunately, certain nations and regions are better suited than others to finding solutions to the problem, whether for political, cultural, economic, or other factors. This paper deals with the cluster analysis of 170 countries based on world risk index and climate risk index data. We use the k-means approach for clustering in sequential stages of this work. Specifically, we first carry out both the elbow method and silhouette scores to determine the number of clusters. Then clustering analysis is carried out, taking into account the World Risk Index, which includes risks of both exposure and vulnerability. Second, the Climate Risk Index is implemented into the first stage results by clustering countries after determining the number of clusters. Lastly, statistical analyses on the change of clusters for exposure, vulnerability, and climate risk are investigated and discussed in detail. Taken together, each of the risk elements like earthquake, tsunami, socioeconomic development, health care capability, etc. differs by nation. Clusters of countries with similar risks are reported. When the climate risk index is included in the evaluation, the number of clusters increases. The Climate Risk Index has been determined as a variable that cannot be ignored when countries are clustered according to their risk profiles.

1. Introduction

Humans have been damaged by natural disasters since the beginning of human history. Individuals and societies have made numerous attempts to reduce their exposure to the consequences of these disasters in response. Whatever approach is taken, all of these efforts have the same goal: disaster management [1]. However, the risk of a natural event becoming a disaster, whether an earthquake, storm, or flood, is determined only in part by the strength of the natural event itself. The structures in place for rapid response and assistance in emergencies is equally important with natural event [2]. Therefore, disaster management research is gaining more and more importance.

Digitalization has an impact on our daily activities such as, communicating, working, and consuming. It has become indispensable in disaster preparation and response, just as it is in everyday life. Digital elements have infiltrated all processes in disaster management, bringing new opportunities as well as new risks that must be examined and understood [2]. Taking into account digitalization, the risk assessment in the World Risk Report [2] is based on the idea that the likelihood of a disaster occurring is determined not only by how severely natural disasters affect society but also by how vulnerable that society is to their effects. Disaster risk is calculated using the interaction between the spheres of exposure and vulnerability. Furthermore, vulnerability is made up of susceptibility, a lack of coping abilities, and a lack of adaptive abilities. Earthquakes, tsunamis, cyclones, coastal floods, riverine floods, drought, and sea level rise are all categorized as "exposure." Socioeconomic development, social injustices, and population deterioration due to violence, natural disasters, and

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diseases all have an impact on "susceptibility." Social shocks, political stability, healthcare, infrastructure, and material security are all examples of "lack of coping capacities." "Lack of adaptive capacities" refers to educational and research advancements, disparity reduction, investments, and disaster preparedness. The structure of World Risk Index is summarized in Figure. 1.

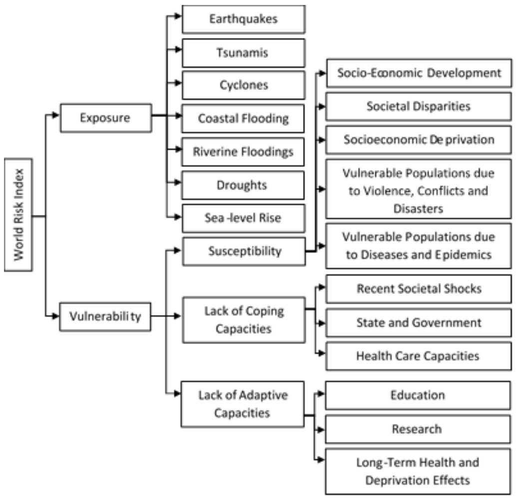

Figure 1. The structure of World Risk Index

The motivating concepts that guide disaster management and the reduction of damage to life, property, and the environment are largely consistent across the globe. The unfortunate reality is that some countries and regions are more capable than others of addressing the problem, whether for political, cultural, economic, or other reasons. Furthermore, the rise of the global economy makes it increasingly difficult to contain the consequences of any disaster within the borders of a single country [1]. Although the risks differ according to the countries of the world, they are similar in some common points. In order to cope with the risks, it is necessary to identify them first. Then, countries that show similar behaviour should exhibit approaches that take the other as an example.

Clustering countries with similar risks has been our approach in this regard. Clustering is a multivariate statistical analysis method that aids in the separation of units and variables into similar sub-clusters whose groups are unknown [3]. The primary goal of clustering is to group units based on their distinguishing characteristics. This method has the advantage of being the simplest to understand can be used in a variety of fields, such as financial risk analysis [4], pattern recognition [5], and biology [6].

The main aim of this study is to investigate clusters of countries. Data for this study is collected from World Risk Report 2022 [2] and Global Climate Risk Index 2021 [7]. By employing k-means algorithm of inquiry, we attempt to characterize different risk groups.

The paper is organized as follows: Section 2 summarizes the extant literature. Section 3 is concerned with the methodology of k-means clustering algorithm used for this study with results and discussions. It analyses the results in two subsections. The first part of the application pays regard to the World Risk Report. The last part of the application incorporates Climate Risk Index into the first stage. Obtained clusters are compared and distance between climate risk index and world risk index is discussed in detail. Section 4 concludes the study.

2. Literature Review

There is relatively small body of literature that is concerned with clustering the countries according to their risk scores. However, there is a large volume of published studies describing the role of clustering in disaster management. A selected sample is cited in this section.

Garschagen and Romero-Lankao [8] applied a clustering approach to identify country groups sharing similar patterns of urbanization and national income. Then they explored associations between these country groups. Merino et al. [9] searched the weather extremes by applying non-hierarchical k-means algorithm. Then they analyzed trends of extremes for clustered subareas. Lu et al. [10] used k-means clustering to predict areas of high climate risk.

Abbasi and Younis [11] presented the importance of clustering algorithms for wireless sensor networks which takes an important part of disaster management. Sheu [12] presented a fuzzy clustering-optimization approach for emergency logistic. The approach is conducted in a real earthquake area. First clustering is used to categorize subgroups affected from disaster, then relief is distributed. After this study, Sheu [13] extended the previous study with dynamic uncertainties. Xu et al. [14] employed k-means clustering to evaluate urban flood risk in China. They identified the risk zones for future use in urban flood management. Ali et al. [15] integrated clustering with device to device communications into cellular networks to maintain communication services in any disaster situation. Chu et al. [16] integrated clustering methods and kernel density estimation for identify typhoon regions and center of each region. Oktarina and Junita [17] clustered regions of Indeonesia as for risk profiles according to a disaster data. The results can be considered for construction of logistic warehouses for disaster management.

3. Methodology

This section uses the world risk index and the climate risk index values of many countries to illustrate how the K-means algorithm is implemented. The clustering analysis is conducted in two ways: Countries' exposure and vulnerability levels are taken into account in the initial analysis. Values from the climate risk index are added in the second analysis to track changes. The world risk index data set is gathered from World Risk Report [2] and the climate risk index data set is provided via the Global Climate Risk Index report [7]. In the proposed study, average data from the years 2000 to 2019 is used by considering both exposure, vulnerability, and the climate risk index. Data from 2020, 2021, and 2022 is not included. The reason for this is that data from the climate risk index could not be accessed after 2019. The analysis takes into account 170 countries. All data is standardized between 0 and 1 before the K-means algorithm is applied. Statistical analysis is done to demonstrate the quality of clusters after the integration of the climate risk index into clusters. These processes are conducted by using the Python Programming Language.

3.1. K-Means Clustering

K-means clustering is a type of grouping approach based on partitioning that iteratively moves data points between clusters. Depending on the characteristics discovered, it is used to separate either the instances or the variables of a dataset into non-overlapping groups, or clusters [18]. The number of clusters must be chosen before the K-means algorithm can be applied. It is determined by using Elbow method which is one of the common techniques for cluster optimization. To evaluate the consistency of the ideal number of clusters, this method examines the variance in the sum of square errors (SSE) of each cluster. The greatest difference determining the elbow angle creates the best cluster number [19]. The steps of K-means algorithm is demonstrated in Figure 2 [19].

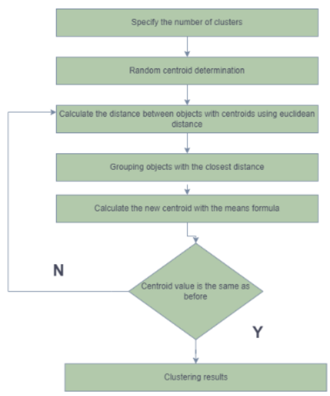

Figure 2. General process of the K-means algorithm

3.2. Results and Discussions

In the first step, the clustering analysis is conducted by using exposure and vulnerability values under the world risk index for the 170 countries. Both elbow method and silhouette scores are utilized in order to decide number of the clusters. From the Figure 3, the ideal value of K (the number of the clusters) = 2, when the elbow point is seen. In addition, one of the most well-liked and useful internal measures for assessing the validity of clustering is silhouette [20]. To support the elbow method, silhouette scores are also taken into consideration. In Table 1, average silhouette scores are given considering the number of clusters from 1 to 10.

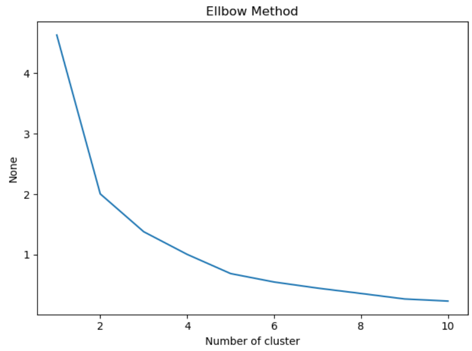

Figure 3. Elbow method for the first analysis

Table 1. Silhouette Scores for the First Analysis

For n_clusters = 2 The average silhouette_score is :0.858331028
For n_clusters = 3 The average silhouette_score is :0.853275129
For n_clusters = 4 The average silhouette_score is :0.535263593
For n_clusters = 5 The average silhouette_score is :0.575796348
For n_clusters = 6 The average silhouette_score is :0.581834638
For n_clusters = 7 The average silhouette_score is :0.416457082
For n_clusters = 8 The average silhouette_score is :0.584584266
For n_clusters = 9 The average silhouette_score is :0.423241403
For n_clusters = 10 The average silhouette_scoreis:0.40663563

Silhouette value similarly runs from -1 to 1, with -1 indicating extremely poor clustering and 1 indicating ideal clustering [20]. As can be seen from Table 1, two clusters provide the highest silhouette score. The elbow approach likewise yields 2 as the ideal number of clusters. Analysis is therefore carried out in accordance with two clusters. In Figure 4, silhouette analysis for K-means clustering on sample data with two clusters is demonstrated.

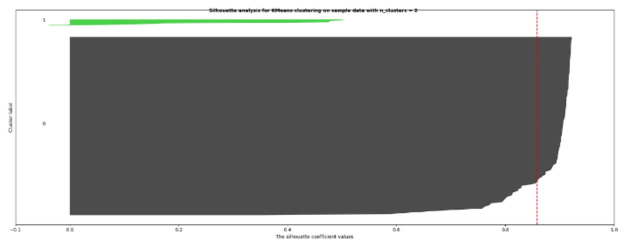

Figure 4. Silhouette analysis for the first step

The cluster size can also be seen from the silhouette plot's thickness. It is seen that from Figure 4, the number of clusters equal to 2, the silhouette plot for cluster 0 is larger. In particular, the cluster sizes vary greatly from one another. The names of the countries that make up the same cluster are listed in Table 2.

Table 2. Results of the Clustering for the First Stage

Cluster 0	Cluster 1
Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize Benin, Bhutan, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic Chad, Chile, China, Colombia, Comoros, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Democratic People's Republic of Korea, Democratic Republic of Congo, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Eswatini, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran (Islamic Republic of), Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyzstan, Lao People's Democratic Republic, Latvia, Lebanon, Lesotho, Liberia, Libyan Arab Jamahiriya, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall, Islands, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Republic of Congo, Republic of Korea, Republic of Moldova, Romania, Russian Federation, Rwanda, Samoa, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, South Africa, South Sudan, Spain, Sri Lanka, Sudan, Suriname, Sweden, Switzerland, Tajikistan, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom of Great Britain and Northern Ireland	Uruguay Uzbekistan Vanuatu VietNam Zambia Zimbabwe

It is seen that most of the countries are in the first cluster. There are only 6 countries in the second cluster which are Uruguay, Uzbekistan, Vanuatu, VietNam, Zambia, Zimbabwe.

The values of the 170 countries' climate risk indices are also taken into account in the second stage. With the values of the exposure, vulnerability, and climate risk indices, clustering analysis is carried out. Similar to the initial analysis, the number of the ideal clusters is calculated using the elbow approach and silhouette scores. In Figure 5, the elbow point for climate risk index is shown.

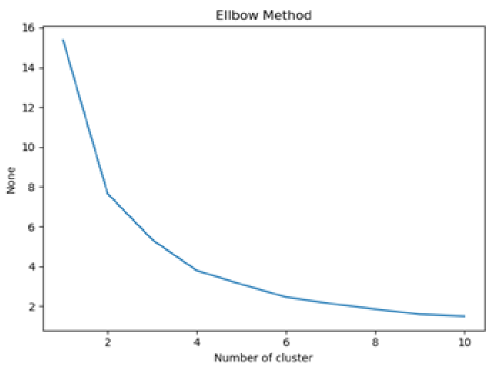

Figure. 5 Elbow method for the second analysis with climate risk index

In Figure 5, the optimal value of K (the number of the clusters) is equal to 2. However, three clusters seem ideal when we consider the silhouette scores from Table 3.

Table 3. Silhouette Scores for the Second Analysis with Climate Risk Index

For n_clusters = 2 The average silhouette_score is :0.481217885552
For n_clusters = 3 The average silhouette_score is :0.511190595896
For n_clusters = 4 The average silhouette_score is :0.427435769361
For n_clusters = 5 The average silhouette_score is :0.432454483900
For n_clusters = 6 The average silhouette_score is :0.387870180168
For n_clusters = 7 The average silhouette_score is :0.388132940572
For n_clusters = 8 The average silhouette_score is : 0.341829290629
For n_clusters = 9 The average silhouette_score is : 0.347752842380
For n_clusters = 10 The average silhouette_score is :0.35508796163

The highest silhouette score is produced by three clusters. Silhouette scores for K- means clustering on sample data with 3 clusters are given in Figure 6.

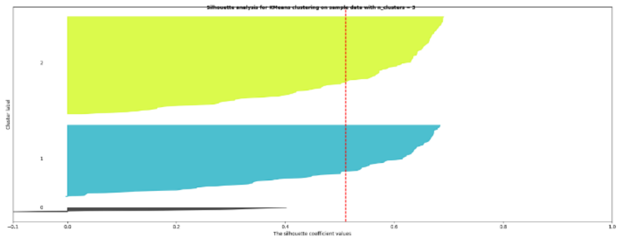

Figure. 6 Silhouette analysis for the second step (with climate risk index)

Clusters 1 and 2 have sizes that are relatively close to one another when there are exactly 3 clusters. More data are present in these clusters. However, Cluster 0 is smaller and contains fewer data due to its modest size. Table 4 is a list of the names of the countries that make up the same cluster.

When climate risk index values are taken into account in the study, there are 3 clusters. Six countries make up the first cluster, 70 countries make up the second cluster, and 95 countries make up the third cluster.

The second phase involves the application of statistical analysis by taking into account the mean, standard deviation, quartiles, lowest and maximum values of each input, such as exposure, vulnerability, and climate risk index. In Table 5 and Figure 7, statistical values and box plot analysis are given, respectively for the exposure values.

Table 4. Results of the Clustering for the Second Stage

Cluster 0	Cluster 1	Cluster 2
Uruguay Vanuatu VietNam Zambia Zimbabwe	Albania, Armenia, Azerbaijan, Bahrain, Barbados, Belarus, Benin, Botswana, Brunei Darussalam, Burkina Faso, Cameroon, Cape Verde, Central African Republic, Chad, Cote d'Ivoire, Cyprus, Democratic People's Republic of Korea, Democratic Republic of Congo, Denmark, Egypt, Equatorial Guinea, Eritrea, Estonia, Finland, Gabon, Ghana, Guinea, Guinea-Bissau, Guyana, Iceland, Iraq, Ireland, Israel, Jordan, Kazakhstan, Kiribati, Kuwait, Kyrgyzstan, Lebanon, Lesotho, Liberia, Libyan Arab Jamahiriya, Lithuania, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritius, Nigeria, North Macedonia, Norway, Panama, Qatar, Republic of Congo, Rwanda, Saudi Arabia, Senegal, Seychelles, Singapore, Slovakia, Suriname, Sweden, Togo, Trinidad and Tobago, Tunisia, Turkey, Tuvalu, United Arab Emirates, Uzbekistan	Afghanistan, Algeria, Angola, Antigua and Barbuda, Argentina, Australia, Austria, Bahamas, Bangladesh, Belgium, Belize, Bhutan, Bosnia and Herzegovina, Brazil, Bulgaria, Burundi, Cambodia, Canada, Chile, China, Colombia, Comoros, Costa Rica, Croatia, Czech Republic, Djibouti, Dominica, Dominican Republic, Ecuador, El Salvador, Eswatini, Ethiopia, Fiji, France, Gambia, Georgia, Germany, Greece, Grenada, Guatemala, Haiti, Honduras, Hungary, India Indonesia, Iran (Islamic Republic of), Italy, Jamaica, Japan, Kenya, Lao People's Democratic Republic, Latvia, Luxembourg, Madagascar, Malawi, Mauritania, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Pakistan, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Republic of Korea, Republic of Moldova, Romania, Russian Federation, Samoa, Serbia, Sierra Leone, Slovenia, Solomon Islands, South Africa, South Sudan, Spain, Sri Lanka, Sudan,Switzerland, Tajikistan, Thailand, Tonga, Uganda, Ukraine,United Kingdom of Great Britain and Northern Ireland

Table 5. Statistical Analysis for 3 Clusters by Considering Exposure Values

Exposure			
	Cluster 0	Cluster 1	Cluster 2
The number of country	5	70	95
Mean	0.265743	0.422152	0.426655
Standart deviation	0.406686	0.066648	0.072358
Minimum score	0.000000	0.128341	0.053902
Lower quartile	0.023053	0.394299	0.396909
Median	0.091966	0.416897	0.423779
Upper quartile	0.240003	0.445191	0.449877
Maximum score	0.973694	0.572847	0.604154

While the lowest score, excluding outliers, is called the minimum score, the line dividing the box into two pieces, which indicates the median and serves as the midpoint of the data. Half of the scores are higher than or equal to this number, while the other half are lower, 75% of the results are lower than the upper quartile value, and the highest score after removing outliers is called the maximum score [21].

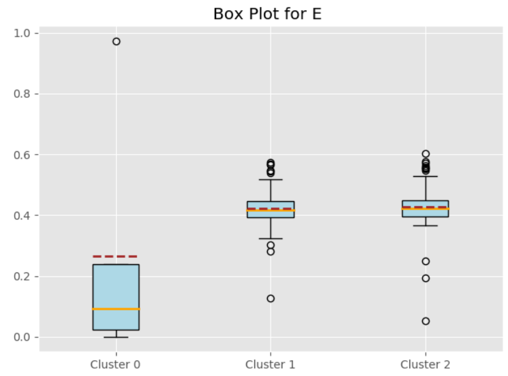

Figure. 7 Box plot analysis for 3 clusters by considering Exposure values

Figure 7 demonstrates the considered data in box plot. Each of the cluster is indicated separately. From the Figure 7, it can be seen that mean values for cluster 1 and 2 are almost same. However, cluster 0 has significantly lower value from the rest of the clusters. Therefore, it can be deducted that countries in cluster 0 have lower exposure rates than clusters 1 and 2. Specifically, clusters 1 and 2 are where disasters like earthquakes, tsunamis, floods, etc. most frequently occur. We may say that the countries in cluster 0 are less risky in terms of exposure. In addition, median values of each cluster shows almost same characteristics like in mean values. Another important point that Figure 7 shows is whiskers and sizes of the boxes. Cluster 1 and 2 have smaller whiskers and boxes compared to cluster 0, which indicates that countries in cluster 1 and 2 have more homogenous values than countries in cluster 0. Lastly, outliers are represented by “o”. Figure 8 and Table 6 demonstrates the statistical analysis for vulnerability values.

Table 6. Statistical Analysis for 3 Clusters by Considering Vulnerability Values

Vulnerability			
	Cluster 0	Cluster 1	Cluster 2
The number of country	5	70	95
Mean	0.793855	0.107233	0.108802
Standart deviation	0.219848	0.070585	0.049349
Minimum score	0.436936	0.030639	0.000000
Lower quartile	0.784829	0.075964	0.079854
Median	0.800968	0.096525	0.099040
Upper quartile	0.946544	0.119918	0.131029
Maximum score	1.000000	0.602176	0.301713

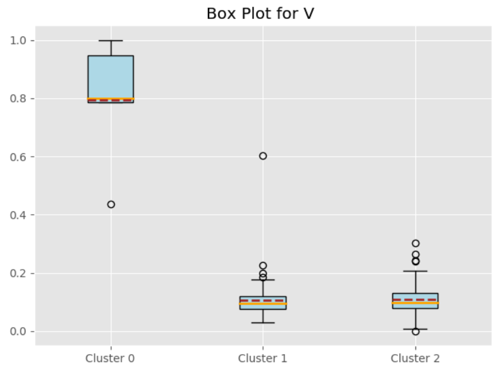

Figure. 8 Box plot analysis for 3 clusters by considering Vulnerability values

From the both Figure 8 and Table 6, it can be easily said that mean values for cluster 1 and cluster 2 are close to each other. However, mean of cluster 0 is almost seven times bigger than others. In that aspect, it can be concluded that countries in cluster 1 and cluster 2 more preferable compared to countries in cluster 0 in that aspect. Also, standard deviation is considerably higher for cluster 0, which indicates that countries in this cluster have varying values. Therefore, boxplot for cluster 0 has bigger size from the other two clusters. All in all, cluster 1 and 2 have more preferable and dependable values unlike the cluster 0. Results of statistical analysis by considering climate risk index values are given in Table 7 and Figure 9, respectively.

Table 7. Statistical Analysis for 3 Clusters by Considering Climate Risk Index

Climate Rısk Index			
	Cluster 0	**Cluster 1**	**Cluster 2**
The number of country	5	70	95
Mean	0.340307	0.753645	0.322569
Standart deviation	0.206242	0.138194	0.131701
Minimum score	0.156840	0.539684	0.000000
Lower quartile	0.166982	0.638984	0.224537
Median	0.267795	0.747938	0.336042
Upper quartile	0.487750	0.874473	0.433800
Maximum score	0.622167	1.000000	0.533574

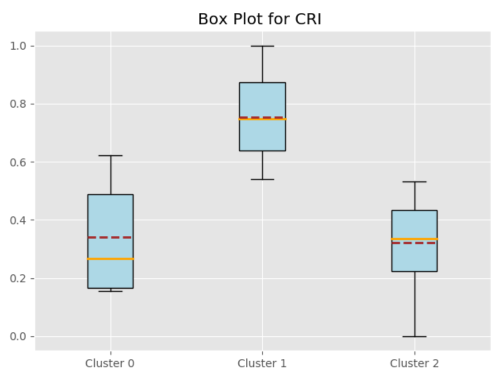

Figure. 9 Box plot analysis for 3 clusters by considering climate risk index

Cluster 0 and cluster 2 mean values lower that cluster 1. Also, mean value of cluster 1 is almost doubled the rest of the clusters. In that aspect, one can conclude that countries in cluster 1 are more riskier than other cluster with respect to climate risk index. When it comes to median values, it can be said that same trend in mean values is observed. From the box plots, variation of data in cluster 1 and cluster 2 is almost same and data in cluster 0 are more varied. It means that countries in cluster 1 and 2 are close the each other compare to cluster 0 considering climate risk index.

4. Conclusion

Risks associated with a globalized society must be managed by people in numerous nations. The risk profiles of many countries and regions have also been proven to have grown more diverse and complex over time through annual assessments. The proposed study is divided into two stages: The World Risk Index Report is taken into account as the initial step of a clustering analysis. Following the inquiry, numerous risk indices, such as exposure and vulnerability, are taken into consideration in order to identify the clusters to which the countries belong. The aforementioned risk indices are made up of numerous sub-risk indices, including risk elements like earthquakes, tsunamis, socioeconomic development, societal inequities, health care capabilities, susceptibility, and a lack of coping and adaptation skills. Each of these risk elements differs by nation. The climate risk index is also included in the second stage analyses of the first stage, where a comparison is made and a statistical analysis of how the clusters are changed is done. The cluster number increased from 2 to 3 with the addition of the climate risk index. Some of the countries' world risk index are decreased relatively. All in all, in the proposed study, countries are evaluated by risk indexes and clustered in accordance. Therefore, systematic approach for evaluating countries with respect to world risk index is provided.

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