Long-run Homogeneity in Asian Countries Pertaining to Economic Development Indicators: A Study Based on Human Development Index

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Abstract: For sustainable development of any country, long-term economic development is essential. Developed countries over the world exhibits gradual economic development from decade to decade. This paper aims to group thirty-seven Asian countries based on long-term homogeneity of HDI (Human Development Index) trend from 1990 to 2018. The source of data is United Nations Development Program (UNDP). Out of forty-seven United Nations' (UN) listed Asian countries, thirty-seven Asian countries were selected due to missing data of the remaining ten countries. Hierarchical cluster analysis was conducted to visualize existing homogeneous groups and K-means cluster analysis was used to determine optimum number of clusters. The result of cluster analysis determines three distinguish clusters of Asian countries. Three clusters labeled as high HDI cluster (11 countries), medium HDI cluster (17 countries) and low HDI cluster (9 countries). Countries within clusters are found with similar economic development status and also geographically adjacent to each other. However, one-way ANOVA also indicates that, the average long-run HDI of three clusters were significantly different.

1. INTRODUCTION

Development is a dynamic term in economics. Economic development refers to the problems of underdeveloped countries (Jhingan M.L 2011). Before, the Second World War the main concentration towards economic development of most of the economists like Adam Smith to Keynes was solving problems which were essentially static in nature and vastly related to a Western European framework of social and cultural institutions. But, after the Second World War, economists tried to formulate and develop theories and models of development growth (Jhingan M.L, 2011). R. E Lucas (1988) said, "By the problem of economic development I mean simply the problem of accounting for the observed pattern, across countries and across time, in levels and rates of growth of per capita income" (Ray D. 1998). In general, economists define economic development as the problems of underdeveloped countries and economic growth of developed countries. Maddison (1970) distinguished these two terms as follows. According to him in rich countries economic growth refers to raising in income level; while it is referred as development in poor countries. Several measurements of economic development have been developed. But, Jhingan (2011) stated these four indicators of economic development- GNP, GNP per capita, Welfare, Social Indicators or Basic needs. Due to some limitations GNP per capita is better than GNP (for details, see G.M. Meier, *Leading Issues in Economic Development* 2005). Economic welfare is regarded as smooth flow of consumptions and services of individuals. "Economic development is a sustained, secular improvement in material well-being, which we may consider to be reflected in an increasing flow of goods and services"-stated by Okun and Richardson (1964). But development does not only refer to rise of income or flow of consumptions; but also, capability to fulfill basic human needs (health, education, food, water supply, sanitation and housing). The indicators of first five basic need are life expectancy at birth, literacy signifying primary school enrolment as per cent of population, calorie supply per head, infant mortality and percentage of population with access to potable water, infant mortality and percentage of population with access to sanitation (Hicks and Streeten 1979).

As a continuous effort of economists some human development indices as measures of economic development have been constructed. Two these are Physical Quality of Life Index (PQLI) of Morris and most widely used index Human Development Index (HDI) presented by United Nations Development Program (UNDP) in its annual *Human Development report*s, 1990. HDI is an index measuring socio-economic development on the basis of aggregating measures of education, health and adjusting real income per capita (Todaro M.P. et al, 2012). It ranges from 0 to 1. The calculation of HDI according to UNDP is described in details in methodology section. Generally, countries are divided into four groups based on HDI: low human development (0.0 to 0.499), medium human development (0.50 to 0.799), high human development (0.80 to 0.90) and very high human development (0.90 to 1.0).

Based on economic conditions, classification of countries could be in various ways. World Economic Situation and Prospects (2014)also classified countries as developed, transition economy and developing economy. Jovanović S. *et al.* (2014) also conducted a research to explore homogeneity according to tourism competitiveness performances among south-eastern European countries using cluster analysis. They were able to categorize south-eastern European countries into three clusters. Another study also classified 28 European countries into four clusters based on higher education competitiveness (Kabók J. *et al.*, 2016). An example was discussed on cluster analysis to classify 134 sovereign states into four cluster based on life expectancy data from the United Nations (2016) yearbook (V. Kimmo & Everitt B.S, 2019). Reiff M. et. al. (2018) characterize and classified European Union countries regarding world development indicators in the field of agriculture and food industry like agricultural raw materials exports, agricultural raw materials imports, crop production index, foodproduction index, livestock production index, cereal yield, agriculture value added and agriculture value added per worker. They classified 28 European countries into three clusters. Brauksa I. (2013) performed cluster analysis to identify distinct social and economic development bases exist in municipalities of Latvia.

The author used cluster analysis to group cities of Latvia based on similarities of growth rate of GDP per capita, illiteracy per capita and share of population employment in tertiary sector.

Ignoring economic classification, this study tries to classify 37 selected Asian countries based on long-run similarity of HDI trend from 1990 to 2018 using cluster analysis (discussed in methodology). This study is different from previous studies since grouping of Asian countries is conducted on the basis of long-term trend of HDI.

The source of data of this study is UNDP published in UNDP website (http://hdr.undp.org/en). Hence, reported HDI was calculated as per UNDP. In this study primarily 47 (except North Korea) Asian countries listed by United Nations' (UN) Statistics Division were considered. But due to unavailability of HDI data, 10 countries were excluded from analysis. The excluded countries are Azerbaijan, Bhutan, Georgia, Lebanon, Maldives, Oman, Palestine, Timor-Leste, Turkmenistan and Uzbekistan. Due to social, cultural, economic conditions and geographical position the HDI of these countries share some similarity as well as dissimilarity.

2. OBJECTIVES

Classification is necessary to group homogeneous items according to similarity of their several characteristics. It helps to distinguish different groups and thus implement development policy correctly. Among many scientific methods, cluster analysis is the most widely used method. Yim O.*etal*. (2015) stated that cluster analysis is a technique to classify items into groups that are relatively homogenous within themselves and relatively heterogeneous between each other (Landau & Chis Ster, 2010; Norusis 2010). The objectives of this study are:

a) To classify selected Asian countries into groups based on similarity of HDI trend from 1990 to 2018.

b) To visualize Asian countries under clusters.

c) To examine whether the overall distribution of HDI differs across clusters in long-run.

3. METHODOLOGY

This study tries to explore segmentation of 37 selected countries based on similarity measures through cluster analysis. So, this study is exploratory research in nature.

3.1 Data source, preparation, analysis and visualization

In this study secondary data of HDI (Human development index) from year 1990 to 2018 from the website of UNDP was used. The raw data contains 47 countries. Ten countries with missing values were excluded in analysis. Data preparation, cleaning and all statistical analysis and data visualization were conducted in R 3.6.1(R Core Team, 2019).

3.2 Description of Human Development Index (HDI)

In Human Development Report 2019 by UNDP, Human Development Index (HDI) is defined as a summarized measure of three dimension-long and healthy life, knowledge and a decent standard of living. Firstly, long and healthy life indicator is measured life expectancy at birth, knowledge is measured as expected years of schooling and mean years of schooling and decent standard of living is measured by GNI per capita (PPP[1] USD). Then, from each indicator, life expectancy index, education index and GNI index is calculated. Each dimension index is calculated as (UNDP 2019):

$$\textit{Dimension index} = \frac{\textit{actual value-minimum value}}{\textit{maximum value-minimum value}}$$

Finally, HDI is calculated as geometric mean of the three-dimensional indices as follows (UNDP 2019):

$$HDI = (I_{Health} \cdot I_{Education} \cdot I_{Income})^{1/3}$$

3.3 Statistical analysis

To classify 37 selected Asian countries into appropriate number of clusters, cluster analysis is conducted in two steps:

a) Applying Hierarchical cluster analysis to explore underlying groups/clusters

b) K-means cluster analysis to determine optimum number of clusters

3.3.1 Hierarchical clustering

In this method cases are grouped by hierarchy or treelike formation based on similarities. Hierarchical clustering techniques initiate by either a successive consolidation or a series of successive divisions (R. A Johnson, 2007). To measures similarity or dissimilarity between each pair of observation most common measure is distance. The most common measures of distance areEuclidean distance and Minkowskimetric.

Let, x' = $[x_1, x_2, \ldots\ldots, x_p]$and **y**'=$[y_1, y_2, \ldots\ldots, y_p]$are two *p*-dimensional observations.

Then the Euclidean distance between **x** and **y** is:

$$d(\mathbf{x},\mathbf{y}) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_1)^2 + \cdots + \left(x_p - y_p\right)^2} = \sqrt{(\mathbf{x}-\mathbf{y})'(\mathbf{x}-\mathbf{y})}$$

And Minkowski metric is :

$$d(\mathbf{x},\mathbf{y}) = \left[\sum_{i=1}^{p} |x_i - y_i|^m\right]^{1/m}$$

For, m=1, Minkowski metric also known as *Manhattan distance* (Kassambara A., 2017a).

In this study agglomerative hierarchical procedure is used. Agglomerative hierarchical process uses linkage method. There are three linkage methods:

a) Single linkage-based on minimum distance, also known as nearest neighbor rule. Everitt etal. (2011) mentioned that, it was first elucidated by Florek*et al*. (1951) and then by Sneath (1957) and Johnson (1967).

b) Complete linkage-based on maximum distance or furthest neighbor rule. It is opposite of single linkage method.

[1] *PPP=Purchasing power parity*

c) Average linkage-based on average of all pairs of distance not only the minimum or maximum distances, first introduced by Sokal and Michener (1958).

Since, average linkage method considers cluster structure and relatively robust, so, in this study average linkage method is used. The clustering algorithm for grouping *N* objects (here N=37) starts with *N* clusters, each containing a single entity and $N \times N$ symmetric matrix of distances (or similarities) $\boldsymbol{D} = \{d_{ij}\}$. Then using average linkage methods objects are grouped based on distances or similarities and after the algorithm terminates all objects will be in a single cluster (R. A Johnson 2007, p. 681).

3.3.2 K-means clustering

The term K-means suggested by MacQueen, 1967; describing an algorithm such that each item is assigned to the cluster having the nearest centroid(mean) (R. A Johnson 2007, p.694). Most of the cases number of clusters (K) is specified by the researcher. There are many algorithms; of them standard algorithm is the Hartigan-Wong algorithm (1979). In this algorithm total within-cluster variation is measured as the sum of squared distances between items and the corresponding centroid (KassambaraA.,2017b):

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

Where, x_i is a data point belonging to the cluster C_k and μ_k is the average of the points assigned to the cluster C_k. The algorithm tries to minimize sum of squared distance by assigning each observation (x_i) to their assigned cluster centers μ_k. Optimum number of cluster (k) determined so that the *total within-cluster sum of square is minimized*.

$$Total\ within - cluster\ sum\ of\ square = \sum_{k=1}^{k} W(C_k) = \sum_{k=1}^{k} \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

Elbow plot is used to visualize the total within-cluster sum of square for different cluster size(k). The location of bend in this plot indicates an appropriate number of clusters.

Silhouette analysis also very useful to find optimum cluster number. Silhouette width *s*(*i*) is calculated as follows (Kaufman *et al.*,2005):

Suppose, *a (i) = average within cluster distance of data point i*

And *b(i)= average closest neighbor distance of data point i*

$$\text{Then, } s(i) = \begin{cases} 1 - \frac{a(i)}{b(i)};\ if\ a(i) < b(i) \\ 0;\ if\ a(i) = b(i) \\ \frac{b(i)}{a(i)};\ if\ a(i) > b(i) \end{cases}$$

It is clear that, $-1 \le s(i) \le 1$. Observations with large s(i) (close to 1) very well matched to cluster, close to -1 indicates that observations better fit in neighboring cluster and small *s(i)* means that observation lies on border between two clusters. For each cluster the average silhouette width has been calculated. The average silhouette width will be maximum for optimum number of clusters *(k)*.

3.3.3 Visualizing clusters

Since, this study working with 29 years' data (each year considered as feature or variable), hence to construct two-dimensions scatter plot; principal component analysis (PCA) techniques has been used as dimension reduction method. Principal components come from the fact that they partition the total variations in original set of variables by first finding the linear combination of the variables that extract maximum amount of variance (Keenan A. Pituch *et al*., 2016).The first component is:

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p.$$

Where, coefficients are scaled such that $a_1'a_1 = 1\ [where\, a'_1 = (a_{11}, a_{12}, \dots, a_{1p})]$ which produce the variance of y_1 equal to the largest eigenvalue of the sample covariance matrix of x_is (Morrison, 1967). The coefficients of the principal component are obtained from the corresponding largest eigen value of the eigen vector. Then the procedure attains a second linear combination such that, it accounts for the next largest amount of variance. The second component is:

$$y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2p}x_p;\ \ such\ that\ a_2'a_2 = 1$$

Point to be noted that y_1 and y_2 are uncorrelated. The third component is uncorrelated with the first two, and accounts for the third largest amount of variation of the original variables and so on. In cluster analysis cases are grouped on the basis of similarity of two or more than two features. Hence, since first two principal components extract majority percentage of variation, so to visualize cases(individuals) within their assigned clusters in two-dimensional scatter plot principal component analysis is a great technique.

3.3.4 Data standardization

Since HDI ranges from 0 to 1 and this is similar for all countries; so, data standardization was not needed to perform cluster analysis.

4. RESULT ANALYSIS AND DISCUSSION

In this study data were analyzed in two in segment. Firstly, trend of HDI of 37 Asian countries had been visualized and HDI in year 2018 of selected Asian countries were presented in descending order. Secondly, cluster analysis had been conducted to classify countries based on long term homogeneity of HDI. All data visualization and analysis were carried out using R-programming language.

4.1 HDI trend in Asian countries

Time series plot of HDI was constructed to show trend of HDI of 37 selected Asian countries from 1990 to 2018. **Figure 1** presents the HDI trend of selected Asian countries. It is clear that the trend of HDIs are almost increasing and linear across all countries except Syria and Yemen from 1990 to 2018. In 1990 top three countries were Japan, Israel and Brunei with HDI 0.816,0.792 and 0.768 respectively; while Afghanistan, Myanmar and Nepal had lower HDI (0.298, 0.350, 0.380 respectively).

In 1990 HDI of Bangladesh was 0.388 with 33rd position (as per UNDP, 2019 report Bangladesh was a country of low human development). The HDI of Bangladesh showed increasing linear trend. It indicates promising economic development for almost three decades.

The HDI of Syria showed on average upward trend from 1990 to 2007; but started to go downward from 2008 to 2016 (the lowest HDI, 0.539) and slightly increased in 2017 and 2018. Ye-men also experienced similar trend of HDI; but not so severe as Syria. There are many reasons behind the decreasing trend of HDI of countries like Syria and Yemen. Some of them are political unrest, civil-war as well as ongoing international conflicts.

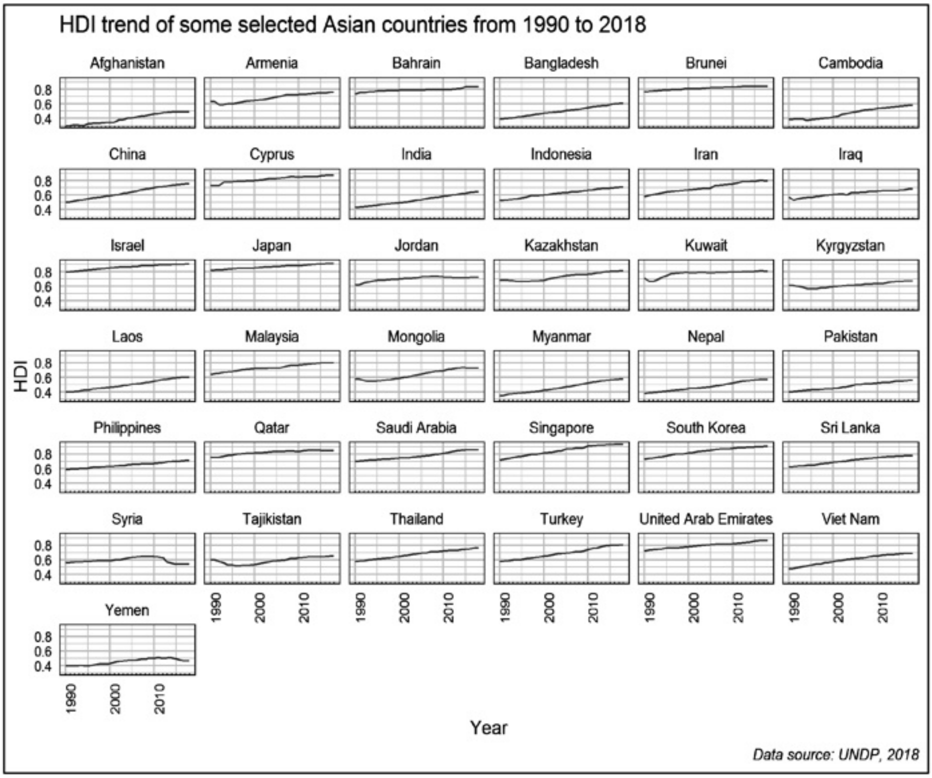

Figure 1: HDI Trend in Asian Countries

4.2 Classification of Asian countries based on cluster analysis

As stated earlier the main goal of this study is to classify Asian countries based on long term similarity of HDI scores among countries from 1990 to 2018 beyond classification of UNDP or others. On the basis of distance matrix computed from HDI score of 29 years (1990 to 2018) cluster dendrogram had been constructed **(Figure 2.A)** using hierarchical clustering with average linkage method. From dendrogram, based on height it is understood that, it would be appropriate to extract 3 or 4 clusters. To determine optimum number of clusters, elbow plot and silhouette analysis was conducted by K-means clustering method.

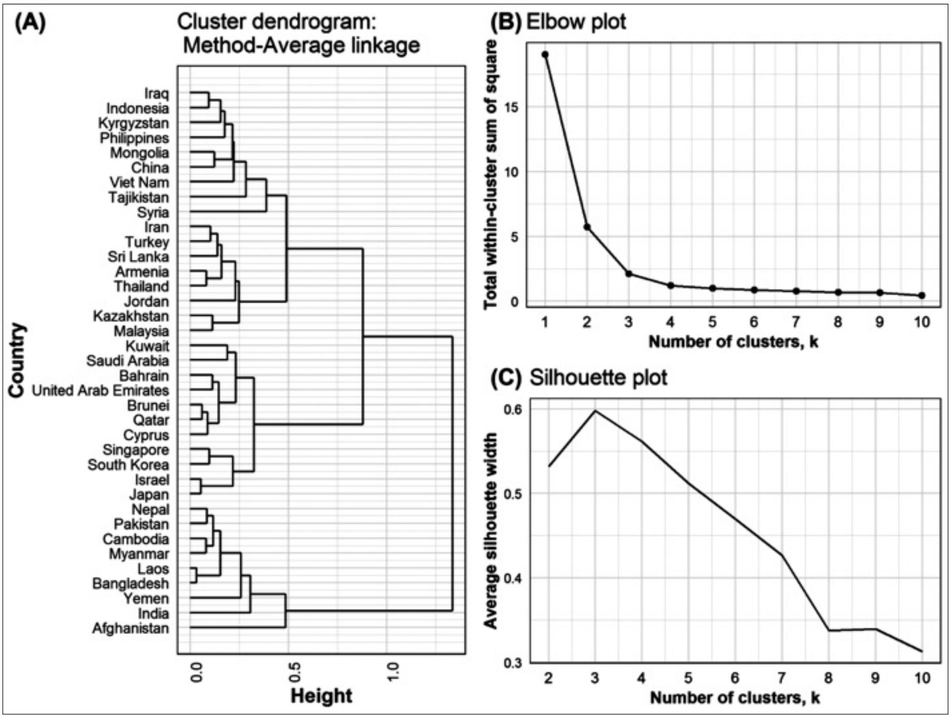

Figure 2: Cluster Dendrogram and Elbow Plot

Elbow plot in Figure **2.B** shows that, after k equal 3, the total within-cluster sum of squares starts decreasing with a linear trend; suggesting 3 clusters. Silhouette plot clearly indicates that optimum number of clusters is 3 as average silhouette width was the highest for k equal to 3 **(Figure 2.C)**. So, both elbow plot and silhouette plot suggested that three clusters would be optimum to assign 37 Asian countries in three clusters.

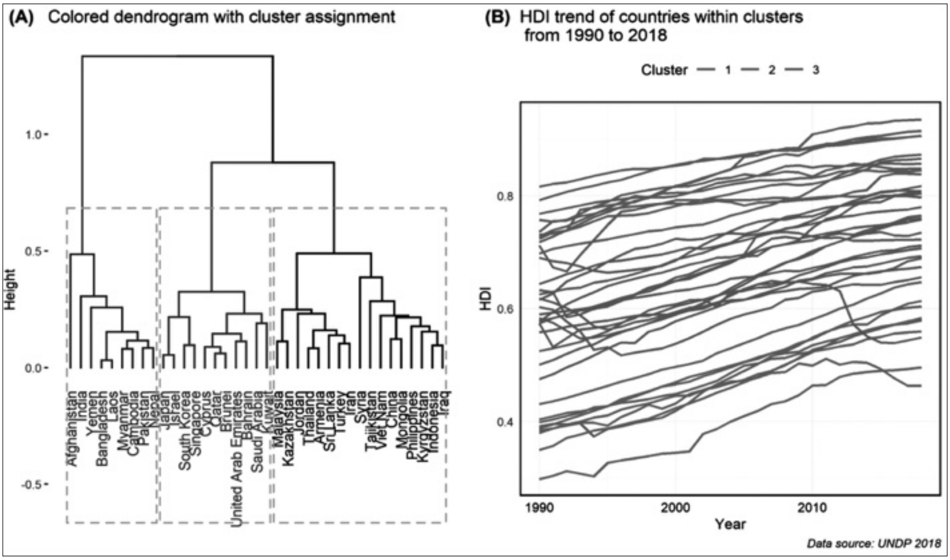

Figure 3: HDI Trend

Figure 3.A presents the colored dendrogram of three clusters showing the countries within these clusters. HDI trend of Asian countries from 1990 to 2018 also distinguished by three clusters **(Figure 3.B)**.

4.3 Visualising clusters

The data contained 29 years HDI of 37 Asian countries. In cluster analysis, years were conducted as features of each country. So, the multidimensional data could not be visualized in 2-dimensional (2D) scatter plot with labels (countries). Principal component analysis (PCA) helps to reduce higher dimensions into lower dimensions. In this study, 29 features (dimensions) were reduced into two dimensions. In a 2D scatter plot (dimension-1 in x-axis and dimension-2 in y-axis) countries were shown within three clusters in **Figure 4**. PCA technique is not discussed briefly because this is not the main concentration of this study. It is seen from **Figure 4** is that, dimension-1 and dimension-2 explained in total 97.6% variation of 29 features. So, after reducing dimensions only 1.7% information was lost. In third cluster, Yemen and Afghanistan were in the farthest countries from cluster centroid; while Cambodia, Nepal and Myanmar were close to the centroid. In second cluster, Syria was located very far from cluster centroid; indicating largest dissimilarity with other countries of same cluster. Countries of first cluster were relatively close to each other compare to other clusters **(Figure 4)**.

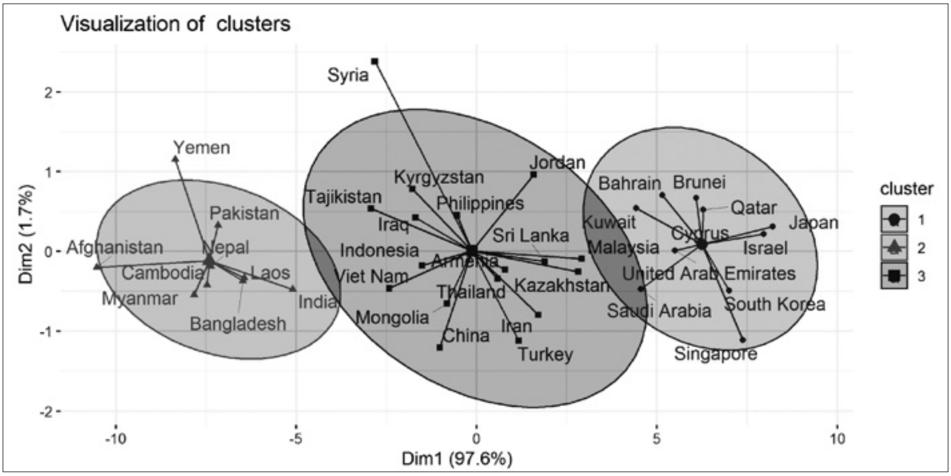

Figure 4: Visualisation of Cluster

4.4 Summarising clusters

Well classification of clusters will indicate significant difference in their features. **TABLE II** shows comparative summary statistics of overall HDI across three clusters. HDI of cluster 2 ranges from 0.298 to 0.647 with lowest mean (M=0.476, SD=0.073); while HDI of cluster ranges from 0.666 to 0.935with the highest mean (M=0.819, SD=0.052). HDI of cluster 1 is found with moderate HDI (ranges from 0.475 to 0.817) with mean 0.659 (M=0.659, SD=0.072). ANOVA (Analysis of variance) test also implies that long term mean HDI of 3 clusters differed significantly from each other, $F(2,1070)=1860$, p-value<0.000 **(TABLE III)**. Both cluster-wise density plot of HDI (scaled or standardized) **(Figure 5.A)** and boxplot **(Figure 5.B)** visually reflects that, location of distribution of HDI of three clusters differ from each other with great extent.

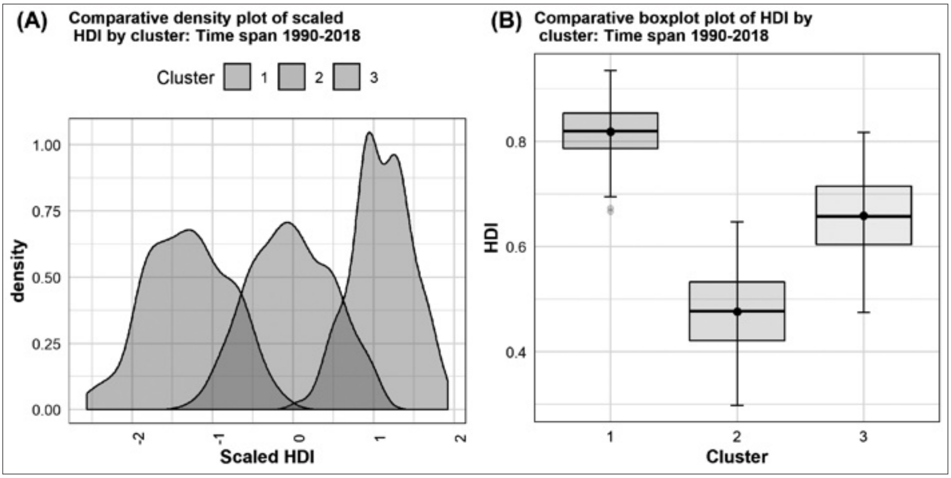

Figure 5: Comparative Density Plot and Boxplot

TABLE II

Cluster wise summary statistics of HDI in Asian Countries

Cluster	Minimum	Maximum	Mean	Median	SD
1	0.666	0.935	0.819	0.819	0.052
2	0.298	0.647	0.476	0.477	0.073
3	0.475	0.817	0.659	0.657	0.072

TABLE III

ANOVA Table for Test of Equality of HDI Means of Clusters

Source of variation	df	Sum of Square (SS)	Mean SS	F-statistic	p.value
Cluster	2	16.824526	8.4122629	1860.061	0.000
Residuals	1070	4.839154	0.0045226		

4.5 List of countries within clusters

On the basis of result from cluster analysis, 37 Asian countries are grouped into three clusters presented in **TABLE IV**. It is easy to perceive that the first cluster includes 11 developed and graduating to developed countries Japan, South Korea, United Arab Emirates, Israel, Singapore, Qatar, Cyprus, Saudi Arabia, Kuwait, Bahrain and Brunei with HDI ranges from 0.666 to 0.935. Developing countries like China, Indonesia, Philippines, Viet Nam, Turkey, Iran, Thailand, Iraq, Malaysia, Sri Lanka, Syria, Jordan, Mongolia and countries with transition economies, Kazakhstan, Tajikistan, Kyrgyzstan, Armenia fall in third cluster with HDI ranges from 0.475 to 0.817 (Source: World Investment Report, 2019). Total number of countries in this cluster is 17. Second cluster consists of 9 countries, India, Pakistan, Bangladesh, Myanmar, Afghanistan, Yemen, Nepal, Cambodia, Laos; which all are developing countries reported by United Nations Conference on Trade and Development, 2019. The HDI ranges from 0.298 to 0.647 of countries in third cluster. Thus, first cluster can be labeled as countries with high HDI, countries in third cluster as medium HDI and countries in second cluster as low HDI.

TABLE IV

Membership of selected Asian Countries within clusters			
Cluster	**HDI range**	**Members**	**Number of countries**
1 (High)	(0.666-0.935)	Japan, South Korea, Saudi Arabia, United Arab Emirates, Israel, Singapore, Kuwait, Qatar, Bahrain, Cyprus, Brunei	11
2 (Low)	(0.298-0.647)	India, Pakistan, Bangladesh, Myanmar, Afghanistan, Yemen, Nepal, Cambodia, Laos	9
3(Medium)	(0.475-0.817)	China, Indonesia, Philippines, Viet Nam, Turkey, Iran, Thailand, Iraq, Malaysia, Sri Lanka, Kazakhstan, Syria, Jordan, Tajikistan, Kyrgyzstan, Mongolia, Armenia	17

4.6 Mapping selected Asian countries grouped by clusters

Finally, thirty-seven countries are shown in geographic map constructed in R **(Figure 6)**. The map of these countries is grouped by three clusters with different colors. From map, it is very clear that, countries share same cluster are geographically adjacent to each other. For, example, consider the countries of second cluster. Except Yemen, Afghanistan, Pakistan, India, Nepal, Bangladesh, Myanmar, Laos, and Cambodia are adjacent to other. Similarly, in third cluster Kazakhstan, Kyrgyzstan, Tajikistan, Mongolia, China are located in east Asia; Armenia, Turkey, Syria, Jordan, Iraq, Iran located in west Asia. Other countries (Viet Nam, Thailand, Singapore, Malaysia, Indonesia, Philippines) of third cluster located in South-East Asian region. Based on similarity of high HDI, Japan and south Korea of third cluster are located east Asia; while Israel, Kuwait, Bahrain, Qatar, United Arab Emirates and Saudi Arabia located in west Asia. Only Brunei of third cluster is located in South-east Asia.

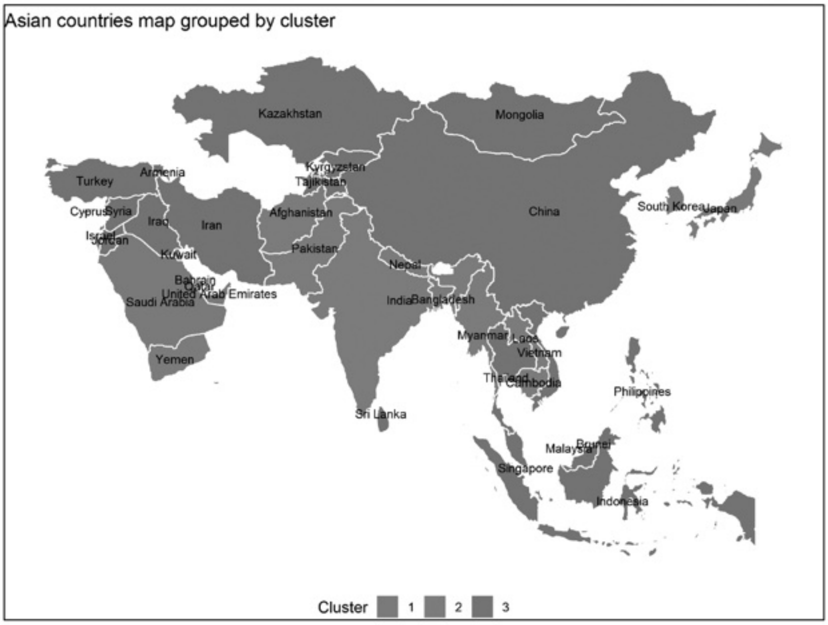

Figure 6: Map of Asian countries

5. CONCLUSIONS

This research indicates different HDI trends in selected Asian countries. Asia is the largest continent in the world. Despite in same continent Asian countries' socio-economic and cultural development differ with great extent. This study investigates that homogenous countries within cluster showed on average consistent trend from 1990 to 2018. But exceptional feature also found for those countries which were war toned and still facing several conflicts. For example, in 1990 Syria, Iraq and Yemen were at 25th, 24th and 32nd position respectively based on HDI. While, in 2018, the positions of these countries were 35th, 25th and 37th based on HDI. Running geopolitical conflicts and civil war affect greatly economic development of middle east counties in Asia. A notable finding of the study is that countries grouped as clusters were located geographically with each other except some exceptional.

Taking under consideration of this finding, development plan can be implemented to increase per capita income, life expectancy, quality of education, literacy rate and other economic development indicators of Asian countries with long term low HDI. Though Bangladesh was grouped in a low HDI cluster; but she was in better position compare to her neighboring countries like Myanmar, Nepal, Pakistan and Afghanistan in 2018.

This study could be linked to Sustainable Development Goals (SDG) 2030 by UN (https://sustainabledevelopment.un.org/). There are seventeen goals of SDG. First goal is to end poverty in all its forms everywhere, second goal is to end hunger, third is to ensure healthy lives and promote well-being for all at all ages, fourth goal is to ensure quality education and tenth goal is to reduce inequality within and among countries. Since HDI is an index of consisting GDP per capita, life expectancy and education; so, increase in HDI could be an indicator of fulfilling some important SDGs as mentioned above. For example, rise in GDP per capita directly or indirectly indicates poverty alleviation and hunger; extended life expectancy indicates healthy living and quality education ensures knowledgeable manpower which is very much needed to acquire sustainable development. All these features are aggregated in HDI. This study found that, eleven Asian countries are grouped as a cluster with the highest HDI (0.935) in 2018. Countries with medium HDI are in the cluster with the highest HDI value 0.817 and in 2018 the highest HDI was 0.647 of low clustered countries. So, in the journey of attaining SDGs within 2030, nine Asian countries with low HDI can try to achieve HDI of 0.80 and seventeen Asian countries with medium HDI can try to score HDI 0.90 at least. Finally, in the question inequality in economic development we expect less than three cluster within 2030.

REFERENCES

Everitt B.S., Landau S., Leese M. &Stahl.D. (2011). *Cluster Analysis* (5th edition). John Wiley & Sons Ltd., United Kingdom.

Florek, K., Lukaszewiez, L., Perkal, L. et al. (1951). Sur la liaison et la division des points d'un ensemble fini. *Colloquium Mathematicum*, 2, 282–285.

http://hdr.undp.org/en/data (accessed December 03, 2019).

https://sustainabledevelopment.un.org/post2015/transformingourworld (accessed February 02,2020). https://sustainabledevelopment.un.org/sdgs (accessed on February 02, 2020).

https://unstats.un.org/unsd/demographic-social/products/dyb/ (accessed January 13, 2020).

Jhingan M.L.(2011). T*he Economics of Development and Planning* (40th edition).Vrinda Publications (P) Ltd.Delhi, India.

Jovanović S., Milić V.J.&Krstić B. (2014). Homogeneity analysis of south-eastern European countries according to tourism competitiveness performances. *Economic Research*, Vol. 27, No. 1, 207–220.

Johnson, S. C. (1967). Hierarchical clustering schemes. Psychometrika, 32, 241–254.

KabókaJ., Radišićb S.&Kuzmanović B. 2016. Cluster analysis of higher- education competitiveness in selected European countries. *Economic Research*, voL. 30, no. 1, 845–857.

Kassambara A. (2017). *Practical Guide to Cluster Analysis in R.* Published by STHDA. (http://www.sthda.com).

Kaufman L. &Rousseeuw P.J. (2005).*Findings Groups in Data-An introduction to Cluster Analysis.* John Wiley & Sons, Inc. Hoboken, New Jersey.

Keenan A. Pituch and James P. Stevens (2016). *Applied Multivariate Statistics For The Social Sciences (6th edition).* New York: Routledge.

Landau, S. & Chis Ster, I. (2010). Cluster Analysis: Overview. In P. Peterson, E. Baker, & B. McGaw (Eds.), *International Encyclopedia of Education, 3rd edition* (pp. 72-83). Oxford, UK: Elsevier Ltd.

Lucas, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics, 22*, 3–42.

Maddison, A. (1970). Economic Progress and Policy in Developing Countries. *The Economic Journal*,Volume 80, Issue 320, 1 December 1970, pp. 958-960, https://doi.org/10.2307/2229921.

Meier, G.M. 2005. *Leading Issues in Economic Development* (8th ed.). Oxford University Press.

Reiff M., Ivanicova Z., Surmanova K. (2018): Cluster analysis of selected world development indicators in the fields of agriculture and the food industry in European Union countries. *Agricultural Economics – Czech, 64*: 197-205.

Morrison, D.F. (1967). *Multivariate statistical methods.* New York, NY: McGraw-Hill.

Norman L. Hicks and Paul P. Streeten.(1979). Indicators of Development: The Search for a BasicNeedsYardstick.*World Development*, Vol. 7.

Okun, O. and Richardson, R.W. (1964). *Studies in Economic Development*. p.230. New York, Holt, Rinehart & Winston.

R. A Johnson.(2007). *Applied Multivariate Statistical Analysis* (6th edition). Pearson Education, Inc.

Ray D. (1998). *Development Economics.* Princeton University Press.

R Core Team. (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org.

Sokal, R. R. and Michener, C. D. (1958). A statistical method for evaluating systematic relationships. *University of Kansas Science Bulletin,* 38, 1409–1438.

Todaro, M.P. &Smith, S.C. 2012. *Economic Development* (11th edition). Harlow: Pearson Education Limited.

UNDP. (1990).*Human Development Report 1990.*

UNDP. (2014).*Human Development Report 2014.*

UNDP.(2019).*Human Development Report 2019.*

United Nations.(2016). *Demographic Yearbook.* United Nations, New York.

United Nations.(2014). *World Economic Situation and Prospects.* United Nations, New York.

V. Kimmo & Everitt B.S. (2019). *Multivariate Analysis for the Behavioral Sciences* (2nd edition). CRC Press Taylor & Francis Group.

YihuiXie. 2019. knitr: A General-Purpose Package for Dynamic Report Generation in R. R package version 1.25.

Yim, O., &Ramdeen, K. T. 2015. Hierarchical Cluster Analysis: Comparison of Three Linkage Measures and Application to Psychological Data. *The Quantitative Methods for Psychology*, 11 (1), 8-21.

IevaBrauksa. 2013.Use of Cluster Analysis in Exploring Economic Indicator Differences among Regions: The Case of Latvia.J*ournal of Economics, Business and Management*, vol. 1, no. 1, pp. 42-45, 2013.

Rezanková, H. (2014). Cluster Analysis of Economic Data. *Statistika*, 94 (1).