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Classification of Cities Based on Land Use Land Cover Heterogeneity: A Case Study of Bangladesh

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Abstract

Urbanization is a complex phenomenon involving significant compositions and interactions in land use. Today not only identification but also the quantification of spatial patterns in the urban landscape is gaining its importance. Detailed information regarding urban land use characteristics has become imperative for urban planning and management. Where land use and its diversity play an essential part in determining how a city developed and distributed with heterogeneity landscapes.

This study examines 12 city corporations of Bangladesh through land use land cover classification and then landscape metrics were used to quantify the shapes and patterns of each city. Eight different metrics at landscape levels were calculated to see the shape, landscape, and distribution of land use patches, resulting from landscape metrics to determine the cities heterogeneity. Then cities were classified using a two-step clustering algorithm into four clusters that are named for their levels of landscape formation, which indicate simple, complex, or fragmented city forms.

This method investigates cities land-use patterns that facilitate the optimization of land-use and the allocation of land resources. The research sheds light on understanding land-use patterns configuration in the context of urbanization towards better planning.

Keywords: City classification, Cluster Analysis, Remote sensing, Land use Quantification, Landscape metrics.

1. Introduction

In recent, Land use composition and configuration are one of the frequent issues in urban planning and land use policy, specifically, describing the features of land use pattern (Hasan,2017:69; Gehrke and Clifton, 2017:52) Rapid urbanization has profoundly changed land use pattern in Bangladesh, which vice versa exerts influence on socio-economic development, population growth, city growth, etc. (Chakraborti et al. 2019,94). The empirical study suggests; as urbanization continued to increase, landcover become increasingly diverse in the pattern, fragmented in structure and more complex in shape (Qi et al., 2014:844), such as losses of fresh productive agricultural land, disturbance to rural economic stability (Wu et al., 2011:2; Hass et al., 2015:138).

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Urban areas represent heterogeneous featuring a high spectral diversity of various anthropogenic and natural materials make challenges for remote sensing data analysis (Heldens et al.,2013:476). However, the resolution of the imagery and the heterogeneity characteristic of urban landscapes make it difficult to automatically map detailed urban lands solely using optical remote sensing methods (Cockx et al., 2014:155).

An increase in the heterogeneity value of a city means that the compactness of a city is decreasing and the city is possibly sprawling which is consider as planning failure for the urban planner because sustainability has been incorporated in planning theory, through promoting the 'compact city' model for urban growth rather than 'unsustainable urban sprawl' (Arbury, 2006). Spatial metrics, that are commonly used to quantify the shapes and patterns of a city (Hargis et al., 1998:168) but a fixed set of suitable metrics for application in urban areas do not exist yet (Schwarz, 2010:30).

Individually urban heterogeneity was addressed at the city corporation level for this study and analyzed using landscape metrics. But the usual approach of city classification is on demographic characteristics of cities that neglect the spatial characteristics

This is why it is important to characterize urban areas by landscape diversity. Such as the ratio of built-up area to the total area of the city. For example, a city may have a large area but may have only a small built-up area compared to the city's size. In contrast, a city may have a small size, but most of the land is built-up. Therefore, researchers must acknowledge the spatial character of the landscape rather than the population size and revenue collection.

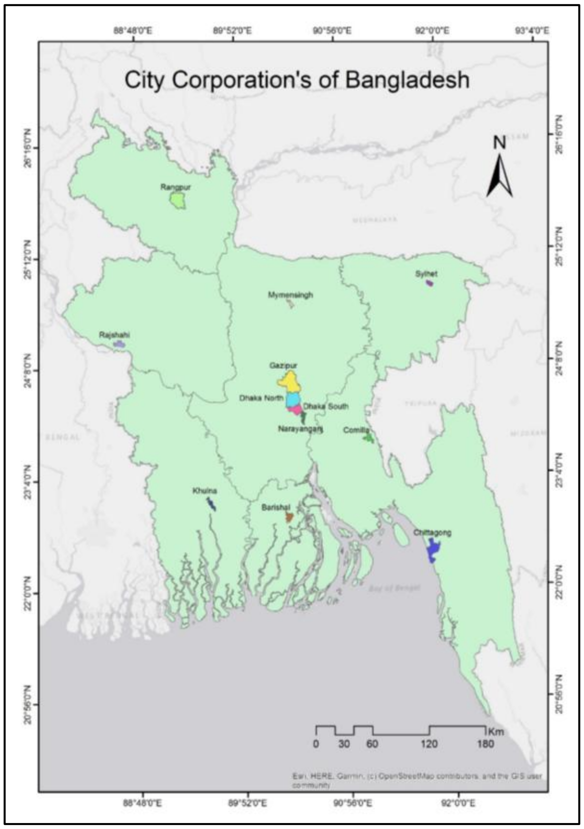
Therefore, the purpose of this study is to quantify the urban area across the city corporations from remote sensing imagery and classify cities based on land use land cover heterogeneity.

2. Description of the study area, data source and methods

2.1 Study area

This study examined a total of 12 city corporations of Bangladesh (*Figure 1*), four of them are present in the capital Dhaka, Rangpur, Rajshahi, Mymensingh and Sylhet are located in the north, and Khulna, Barisal, Comilla and Chattogram are located in the south of the country.

The availability of data has influenced the selection of cities that the city corporations are the primate city that dominates the entire urban system of a division or region and larger than any others in the urban hierarchy. Also, it has enough urban parcels to characterize each city's land use pattern.



Source: Author

Figure 1: Study area map

2.2 Data Collection and Pre-processing

The majority of the data used in this study is remotely sensed data. Secondary data of City boundaries are collected from the LGED. The Sentinel-2A satellite data acquired on January 15, 2019, was used in this study. There are 13 spectral bands, four bands have 10m spatial resolution, six bands are at 20m resolution and the remaining three bands at 60m resolution (Yang et al., 2017:596). An image with the high spatial resolution is generally preferred for urban-related applications and sentinel dataset gives the finest resolution among all other freely available satellite images.

The steps of data pre-processing include adjusting, layer stacking, mosaicking, projection, resampling and clipping the study area and then the supervised classification of the image of land-use classes were conducted and projected in the same coordinate system.

2.3 Image Classification

Image Classification allows the identification of different land cover classes with various heterogeneous conditions that can be captured in image analysis (e.g. color, and roughness of the canopy layer). Once the images have been selected and refined, the land cover is grouped into relatively homogenous classes described in *Table 1*.

Table 1: Land use classes

Land-use classes	Description
Built-up	Areas containing artificial surfaces including residential, commercial, industrial areas, and transportation infrastructure.
Water	Lakes, rivers, ponds, marshlands, and other water bodies.
Vegetation	Cropland, forest, garden plots, and areas covered with dense and sparse vegetation.
Others	Bare land and other land cover not mentioned above.

Source: Hu et al., 2015:185

The maximum likelihood classification method was used to produce the land use map because a probability threshold is not selected in this case. This method is computationally intensive to classify each pixel especially when either a large number of spectral bands are involved or a large number of spectral classes must be differentiated, but modern multi-core computer processors process the classification fairly quickly (Proklamasi et al. 2015:38).

The classified image is compared with some ground truth to check the accuracy of the classification. It provides an example of how well a classification has categorized a representative subset of pixels used in the training process of supervised classification. For this study, 150 samples are sampled using an equalized stratified random sampling method for each city. The accuracy of classification is measured by Kappa statistics, where the higher Kappa value indicates higher classification accuracy of a classified image.

2.4 Selection of Metrics, the indicators of urban form:

Spatial metrics (indices) are numeric measurements that can quantify the spatial pattern of the urban landscape (Ji et al. 2006). It provides significant information about the composition and configuration of a landscape. The indicators of urban form in this research focuses on the spatial structure of an urban area, its form, character, arrangement, and composition to a certain extent.

For this specific study, a group of eight metrics (*Table 2*) are selected based on the literature review and the potential of each metrics to best describe urban pattern (Buyantuyev et al., 2010:20; Dietzel; et al., 2005:233; Herold et al., 2005:371; Herold et al., 2003:994). Indicators are summarized below:

Table 2: Selected indicators for land use analysis

Sl. No	Name (units)	Description	Justification
1	Number of patches (NP)	The number of patches is an indication of the diversity or richness of the landscape. Range: NP $\geq$ 1, without limit. NP = 1 when the landscape contains only 1 patch. (McGarigal et al., 2015:149).	Fragmentation

Sl. No	Name (units)	Description	Justification
2	Patch density (per 100 ha) (PD)	Number of patches per unit area PD=N/A (10,000) * (100) Units: Number per 100 hectares Range: PD > 0, without limit. Description: PD equals the number of patches in the landscape divided by total landscape area, multiplied by 10,000 and 100 (to convert to 100 hectares) (McGarigal et al., 2015:149).	Fragmentation
3	Landscape shape index (LSI)	The landscape boundary and total edge within the landscape divided by the total area, adjusted by a constant for a square standard LSI= $\frac{.25\,E^*}{\sqrt{A}}$ Where E* = total length (m) of an edge in the landscape; A = total landscape area (m^2). *Range:* LSI ≥ 1, without limit. LSI = 1 (McGarigal et al., 2015:158).	Aggregation
4	Largest patch index (%) (LPI	Area of the largest patch in each class, represents the percent of the total landscape area, range 0 to 100 LPI = $\frac{\max_{j=1}^{n}(a_{ij})}{A}$ Where, a_{ij} = area (m^2) of patch ij. A = total landscape area (m^2). Units: Percent (%) Range: 0 < LPI ≤ 100 (McGarigal et al., 2015:96).	Dominance
5	Area-weighted mean patch fractal dimension (AWMPFD)	Shape complexity weighted by the area of patches AWMPFD = $\sum_{i=1}^{m}\sum_{j=1}^{n}[(\frac{2\ln(.25p_{ij})}{\ln a_{ij}})(\frac{a_{ij}}{A})]$ Units: None Range: 1 ≤ AWMPFD ≤ 2 AWMPFD approaches 1 for shapes with very simple perimeters such as circles or squares and approaches 2 for shapes with highly convoluted, plane-filling perimeters. (McGarigal et al., 2015:105).	Fragmentation
6	Interspersion and juxtaposition index (%) (IJI)	Intermixing of patches of different types, based on patch adjacencies. Increases to 100 as the patch type becomes increasingly interspersed with another patch type. IJI= $\frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right)\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln(0.5\,[m\,(m-1)])}(100)$ Where, e_{ik} = total length (m) of edge in the landscape between patch types (classes) i and k. E = total length (m) of edge in the landscape,	Fragmentation

Sl. No	Name (units)	Description	Justification
		m = number of patch types (classes) present in the landscape, including the landscape border, if present. *Units:* Percent (%) *Range: 0 < IJI ≤ 100* (McGarigal et al., 2015:154).	
7	Contagion Index (%) (CONTAG)	Approaches 0 when the patch types are disaggregated and interspersed. Approaches 100 when the landscape consists of a single patch. CONTAG= $1+\frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i\frac{g_{ik}}{\sum_{k=1}^{m}g_{ik}}\right]\left[\ln\left(P_i\frac{g_{ik}}{\sum_{k=1}^{m}g_{ik}}\right)\right]*100}{2\ln(m)}$ Where, P_i = proportion of the landscape occupied by patch type (class) i. g_{ik} = number of adjacencies (joins) between pixels of patch types (classes) i and k based on the double-count method. m = number of patch types (classes) *Units:* Percent *Range:* 0 < CONTAG ≤ 100 CONTAG approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. CONTAG = 100 when all patch types are equally adjacent to all other patch types. (McGarigal et al., 2015:153).	Fragmentation
8	Shannon's diversity index (SHDI)	SHDI equals minus the sum, measure of diversity. Approaches 0 when there is no diversity, increases with a number of patch types. SHDI= $-\sum_{i=1}^{m}(P_i \ln P_i)$ Where Pi = proportion of the landscape occupied by patch type (class) i. *Range:* SHDI ≥ 0, without limit SHDI increases as the number of different patch types increases and/or the proportional distribution of area among patch types becomes more equitable. (McGarigal et al., 2015:167).	Diversity

2.5 Classification of cities:

The procedure of classifying Bangladeshi cities according to the set of indicators is displayed in *Table 2* consists of cluster analysis. To compare cities according to their urban formation, two-step cluster analysis was conducted. This method is a scalable cluster analysis algorithm designed to handle very large data sets. It can deal with both continuous and categorical variables or attributes. It requires only one data pass.

At first pre-cluster step uses a sequential clustering approach. It scans the data records one by one and decides if the current record should be merged with the previously formed clusters or starts a new cluster based on the distance criterion, the distance between two clusters is here defined by the Euclidean distance between the two cluster centers. A cluster center is defined as the vector of cluster means of each variable (Soukal et al.2012:819).

Then, the clustering step takes sub-clusters resulting from the pre-cluster step as input and then groups them into the desired number of clusters, uses an agglomerative hierarchical clustering method. All clusters are then compared, and the pair of clusters with the smallest distance between them is selected and merged into a single cluster. After merging, the new set of clusters is compared, the closest pair is merged, and the process repeats until all clusters have been merged (Kent et al., 2014:113).

3. Analysis & results

For land use land cover heterogeneity analysis, the first step is data preparation. Four types of land use categories are acquired by classifying satellite images shown in *Table 1*.

The spectral separability test was conducted where the variation number between the two classes represents the separability. Minimum and Average Separability values are presented in *Table 3*. As a general rule, if the result is greater than 1900 (TD) and 1300 (JM), then classes can be separated. Between 1700-1900 (TD)/ 1200-1300 (JM) the separation is fairly good. Below 1700 (TD)/ 1200 (JM), the separation is poor

Table 3: Spectral separability of training data

Minimum and average separability				
Bands	Transformed Divergence		Jefferies-Matusita Distance	
	AVE	MIN	AVE	MIN
13 Bands	1987	1957	1385	1354

Source: Author

For the accuracy assessment, overall kappa which is a statistical measure of overall agreement between two categorical items includes, the user's accuracy, producer's accuracy, and overall accuracy were calculated (*Table 4*).

This level of accuracy was found as satisfactory considering heterogeneity and image resolution of the study area, according to kappa agreement the accuracy was in a substantial level which means it can be used (Pontius, 2000:1103). The higher Kappa value indicates higher classification accuracy of a classified image. Therefore, the overall classification accuracy and kappa value indicate significant classification accuracy of the classified image with ground truth. However, the overall accuracy of all images was found to be greater than 85% (Table 4), which is considered as a good result for remote sensing image-based analysis (Herold et al., 2005:377).

Table 4: Accuracy assessment result for each city

City	Overall Classification Accuracy	Overall Kappa Statistics
Barishal City Corporation	86.00%	0.80
Chittagong City Corporation	86.60%	0.81
Comilla City Corporation	86.00%	0.80
Mymensingh City Corporation	89.33%	0.83
Dhaka North City Corporation	86.67%	0.80
Dhaka South City Corporation	88.67%	0.83
Gazipur City Corporation	86.00%	0.81
Khulna City Corporation	86.60%	0.87
Narayanganj City Corporation	85.33%	0.77
Rajshahi City Corporation	86.00%	0.80
Rangpur City Corporation	90.67%	0.87
Sylhet City Corporation	86.67%	0.73

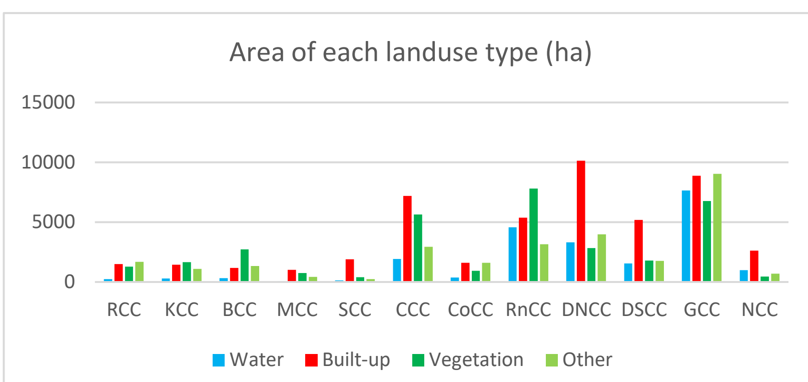
Source: Author

3.1 Quantification of Land use Pattern:

3.1.1 Class level Result:

Class metrics quantify the characteristics for the entire class such as the degree of aggregation and clumping and produce on a unique result for each class. *Figure 2* depicts each city corporation's Land use type composition. Where the built-up ratio is most in Sylhet city and comparatively high in Dhaka north, Dhaka south and Chattogram. It indicates that within the boundary of those cities most of the area is now built up.

On the other hand, Barisal, Rangpur, Rajshahi and Khulna cities built-up area is less than the non-built up area. It can generate fragment city pattern because of the scope of urban sprawling is high as their non-built area can attract population.

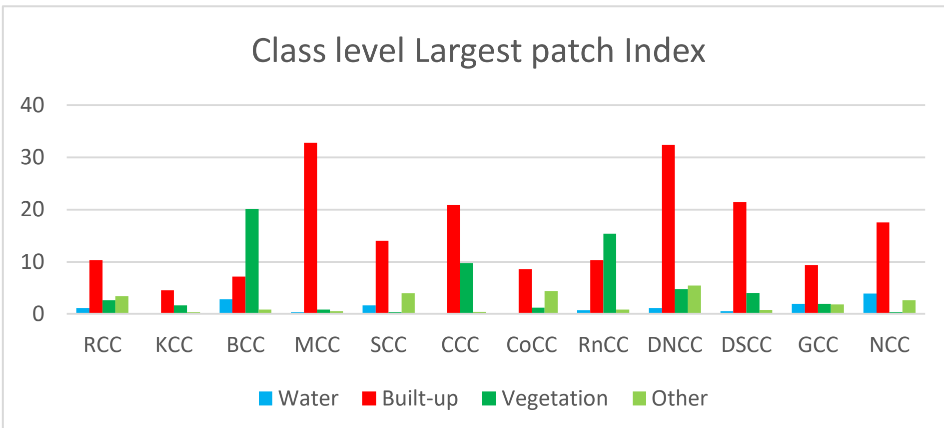


Source: Author

Figure 2: Class area of Land use types (ha)

LPI quantifies landscape composition through the percent of landscape occupied by the largest patch. LPI across the cities found variation in terms of the built-up area. It gives a better understanding of the land use type when the areas become more aggregated and integrated with the urban cores.

According to *Figure 3* except Rangpur and Barisal all other city corporations core area is defined as the build-up area. Also, show the percent of built-up patches are aggregated in the city boundary. Where Mymensingh and Dhaka North built-up areas are mostly aggerated with over 30% built-up patches are associated. Rangpur and Barisal city's largest patch being in vegetation land-use types, also indicates most of the area is not developed within the city corporation's jurisdiction. The examination of LPI for each class allows a better understanding of the behavior of this metric than when analyzed for the entire landscape.



Source: Author

Figure 3: Largest patch index of Land use types

3.1.2 Landscape-level result

Landscape-level metrics result showed the integration of overall patch types or classes over the entire landscape. Most of the landscape-level metrics can be interpreted broadly as landscape heterogeneity indices because they measure the overall landscape pattern, according to *Table 5* each city can be characterized using landscape metrics.

Gazipur city corporation showed the highest fragmentation in terms of Number of patches, also its landscape shape index, Built-up area is highest among other cities. Its built-up area is 27% only and most of the area is non built-up. From the classified image, we see the Built-up area is concentrated and expands along with the major road. So, it shows aggregation in built-up patch also shows compactness for its vegetation area.

Dhaka South and **North City** corporation has similar LPI, NP, LSI indicates the compactness of the cities. It also shows less shape complexity because of its high built-up ratio those became interspersed with another patch type.

Barishal, Rajshahi, Khulna city shows complexity in patch shape indicates more fragmentation, also patch density in high gives us the information that land use classes are not interconnected with each other.

Narayanganj Cumilla and **Rangpur** land use classes are adjacent to each other indicate the compactness of urban formation. Rangpur shows compactness more in vegetation type other than built-up area because vegetation patch was counted most in city boundary.

On the other hand, **Mymensingh City** corporation found compactness in terms of landscape shape index, SHDI, and Build-up area, but the built-up ratio of **Sylhet city** corporation is highest from the other cities because the built-up patch was counted most in city boundary.

Table 5: Landscape metrics of each city

City	NP	PD	LPI	LSI	AWMPFD	CONTAG	IJI	SHDI	Built-up Ratio
RCC	22761	198.16	17.15	68.91	1.42	48.93	55.25	1.32	0.31
KCC	34069	208.32	40.45	57.92	1.40	62.56	75.11	0.94	0.31
BCC	22380	210.93	29.58	57.27	1.37	47.55	66.47	1.32	0.21
MCC	5584	68.83	45.67	21.5	1.37	66.46	67.5	0.91	0.45
SCC	8282	152.02	50.71	29.95	1.38	55.79	74.05	1.14	0.71
CCC	27402	70.43	28.44	83.91	1.44	52.14	52.98	1.27	0.39
CoCC	13780	99.7	67	35.43	1.19	60.25	83.17	1.05	0.36
RpCC	56352	172.27	19.45	105.38	1.28	40.71	69.8	1.5	0.26
DNCC	38214	133.54	32.4	75.14	1.29	43.32	72.52	1.48	0.40
DSCC	22496	99.83	34.95	49.35	1.20	53.32	76.04	1.25	0.51
GCC	107618	171.65	33.68	127.78	1.23	45.05	76.71	1.4	0.28
NCC	16627	164.45	22.23	45.9	1.19	51.63	76.89	1.23	0.55

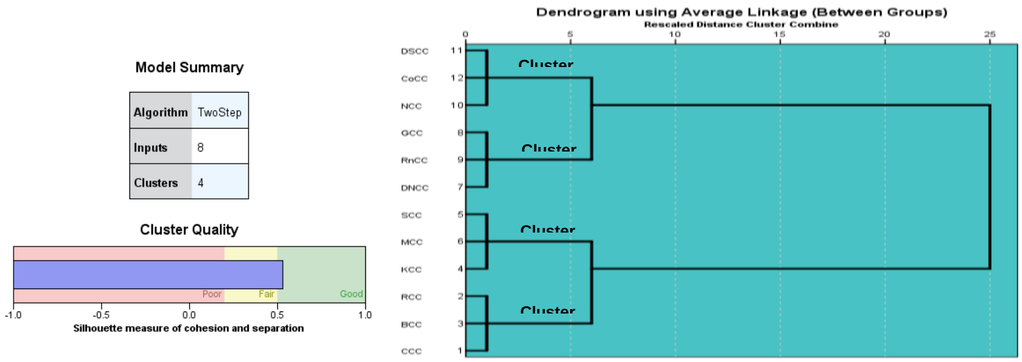
Low	High

Source: Author

3.2 Classification of cities:

Two-step cluster analysis: Firstly, cluster quality was observed to perform pre-clustering and according to predictor importance in gives 4 clusters of cities and it gives us an idea of the cluster quality and the cluster quality is good *Figure 4*. The predictor importance chart displayed in a model that indicates AWMPFD/ Frac_AM gives the most influence on determining that 4 clusters.

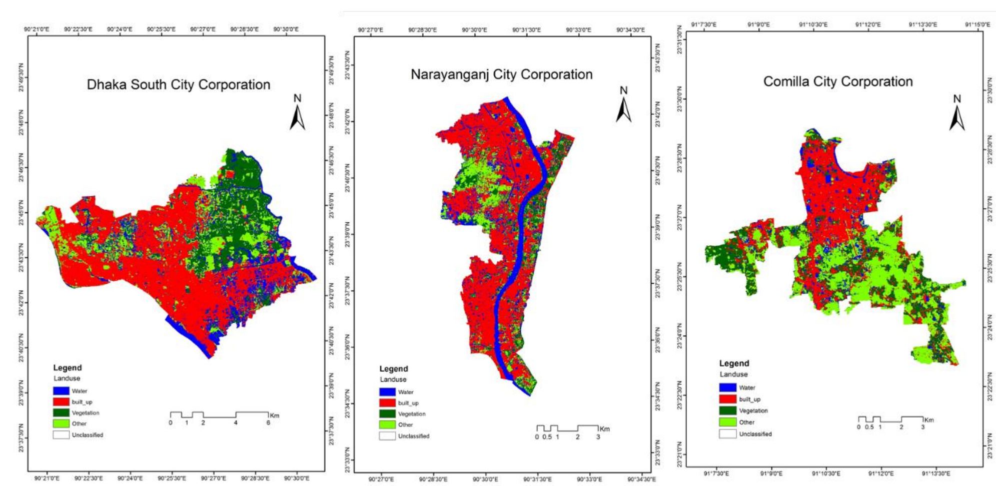
Secondly, the Hierarchy of cities was generated to show the cluster of cities, shown in dendrogram Figure 4



Source: Author

Figure 4: Cluster Quality and Dendrogram of classified cities

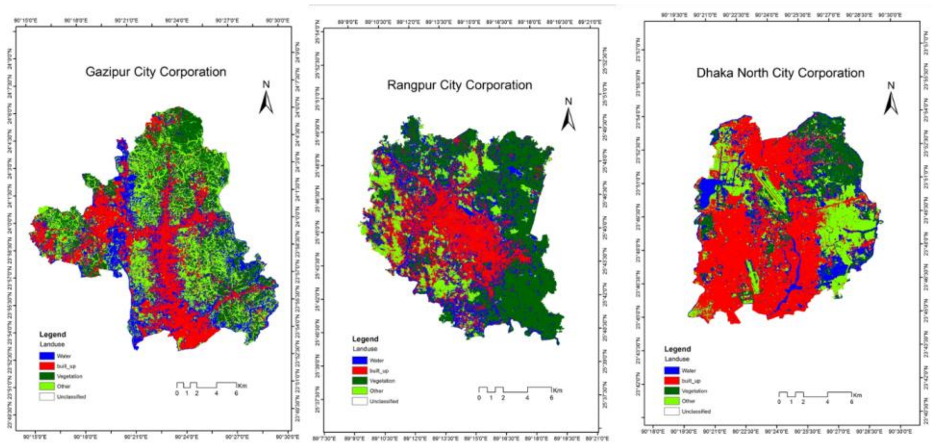
Cluster 1 indicates simple urban forms *Figure 5*, Narayangonj and Dhaka South city's density in terms of built-up area entitles the most compact city in this cluster. But Comilla considered a compact city in terms of both vegetation and built-up index, also shows compactness in terms of Largest patch and Interspersion & juxtaposition index. But Comilla considered



Source: Author

Figure 5: Cluster 1 and the most Compact cities

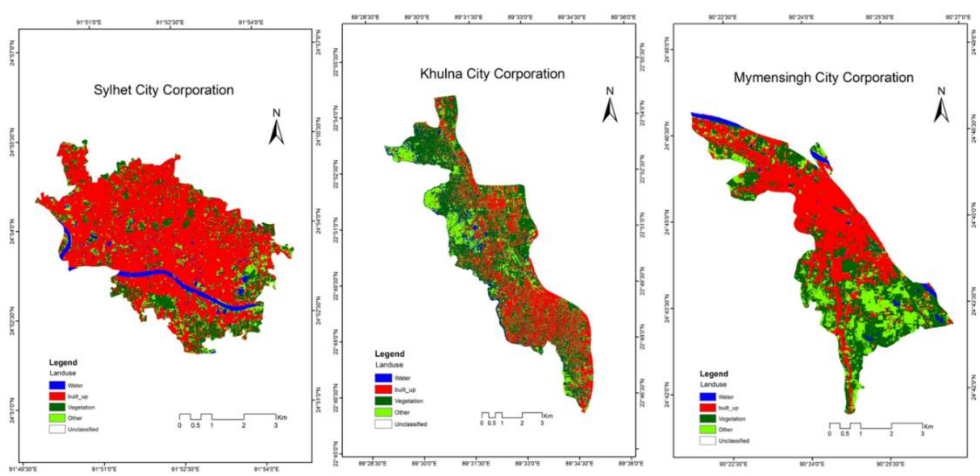
Cluster 2 indicates Compactness with moderate juxtaposition *Figure 6*, but shows disaggregated land use pattern in Gazipur, the Largest shape of vegetation in Rangpur city defines its compactness.



Source: Author

Figure 6: Cluster 2 and less Compact cities

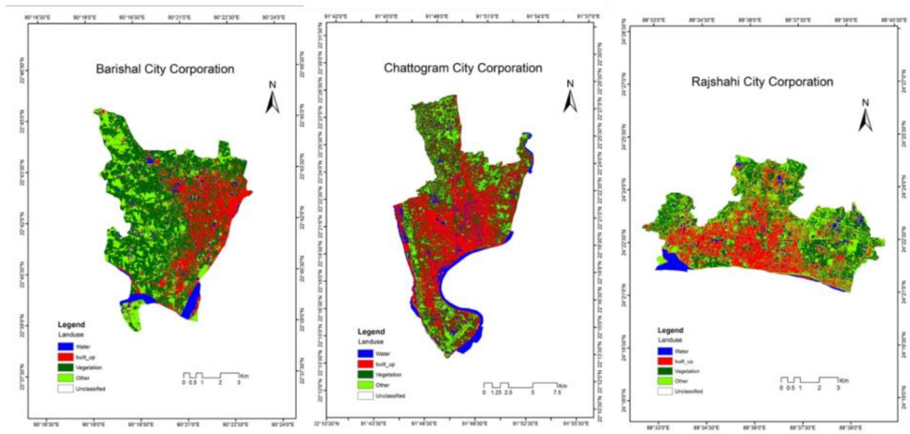
Cluster 3 Sylhet and Mymensingh city comprises with moderate largest built-up shape but the complex form *Figure 7*, Khulna shows high patch density and diversity in land use pattern.



Source: Author

Figure 7: Cluster 3 represent fragmented cities

Cluster 4 indicates complex urban forms *Figure 7*, In Chattogram is the most fragmented city in this cluster, also the Number of patches per unit area is high in Barishal and Rajshahi illustrate fragmentation.



Source: Author

Figure 8: Cluster 4 represents the least fragmented cities

A city ranking was developed using classical George Zipf's 'rank-size' (*Table 6*). So, considering the largest built-up area of Gazipur, second and subsequently smaller cities represent the proportion of the largest city. similarly considering the population density city ranking was generated.

Table 6: City Ranking through the built-up area and Population density

Rank	Built-up	Population density
1	Gazipur	Dhaka south
2	Dhaka North	Dhaka North
3	Chittagong	Chattogram
4	Rangpur	Khulna
5	Dhaka south	Narayanganj
6	Narayanganj	Sylhet
7	Sylhet	Barisal
8	Cumilla	Cumilla
9	Rajshahi	Gazipur
10	Khulna	Mymensingh
11	Barisal	Rajshahi
12	Mymensingh	Rangpur

Source: Author

The results show that Gazipur city is placed in the top by built-up area but the population density is highest in Dhaka and Chattogram. Also, the result gives us an understanding of the inequal distribution and variation in terms of built-up area and population density.

4. Conclusion

The classification result and spatial characteristics of cities indicate that Sylhet city got the highest built-up ration (70.9%) and the lowest in Barishal city (21.4%). Also, cities like Gazipur with the largest area and compact development in built-up areas and the cities with less built-up areas like Barishal, Rangpur, Rajshahi Comilla city authorities have the opportunity for optimum resource allocation and balanced development.

The cluster analysis result shows, the minimum indicator set for urban form. In Cluster 1 it includes Dhaka South, Narayanganj and Cumilla. Cluster 2 considers Dhaka North, Gazipur and Rangpur. Cluster 3 formed with Sylhet, Khulna, and Mymensingh. Cluster 4 contains Rajshahi, Chattogram, and Barishal. Where cluster 1 represents compact cities and cluster 4 represents Fragmented cities.

The proposed classification system has a practical implication for policymaking on the country level and for urban planners in single city regions who seek to compare their cities with those in other countries. On the other hand, comparisons regarding urban form among Bangladeshi cities can focus on very few indicators, thereby reducing the efforts of data gathering and data analysis. However, comparisons among Bangladeshi cities should be pursued very carefully because they are very diverse. Comparative research regarding the influence of governance structure on the urban form could inform policymakers on helpful governance structures to reach their goal of a compact city.

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