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## Article

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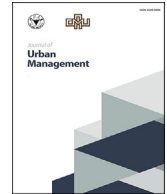
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## Research Article

# Spatial indices and SDG indicator-based urban environmental change detection of the major cities in Bangladesh

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## ABSTRACT

Understanding a city's urban growth trend and associated environmental change scenarios is necessary to ensure the quality of life of urban people by sustaining ecosystem health. We have performed urban environmental change detection for the major cities in Bangladesh based on the analysis of urban indices using remote sensing techniques. We have further correlated these indices-derived outcomes with Sustainable Development Goal (SDG) number 11 (sustainable cities and communities) by estimating the SDG indicator 11.3.1. This indicator deals with the urban land consumption rate ratio to the population growth rate. We calculated the Impervious Surface Area (ISA), Vegetation Fraction (VF), and Biotope Area Ratio (BAR) for Dhaka, Chittagong, Sylhet, and Khulna—the four major cities in Bangladesh. We have also estimated the Normalized Urban Area Composite Index (NAUCI) as NAUCI utilizes further information from other pertinent pre-established indices like NDVI, NDWI, and NDBI. These widely used indices are also essential to consider because these indicators are also directly related to land consumption and population growth. Here we find that each of the considered cities is expanding significantly faster. Therefore, the ecology of the urban environment is degrading as well as the cities' conditions are worsening in terms of SDG 11.3.1. Dhaka, Chittagong, and Sylhet exhibit a lowering trend of the SDG indicator, whereas Khulna city shows the opposite; however, we found Khulna's urban growth like the other cities under investigation is harming the ecology too.

## 1. Introduction

The role of urban areas in human activities is getting more vital in recent times. As of 2018, 55% of the world's population lived in urban areas, and the projected increase is up to 68% in 2050 (United Nations, 2018). The developing countries show a higher urbanization rate than the developed countries (Henderson, 2002). Urbanization enhances development, innovation, prosperity, wealth generation, and socioeconomic transformation (Baranov, 2016). According to the World Bank, urban areas generate more than 80% of the global GDP (World Bank, 2020). Urban areas and cities play a crucial role in achieving Sustainable Development Goals (SDG). The SDGs are UN adopted some specific targets to make the world more liveable, including indicators to assess progress towards those targets (United Nations, 2017). Among the 17 SDGs, goal 11 is “Sustainable cities and communities”. The mission statement of this goal is “Make cities and human settlements inclusive, safe, resilient, and sustainable”. Target 11.3 of the goal is “By 2030, enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management in all countries”, and the indicator 11.3.1 is the “ratio of land consumption rate to population growth rate” (<https://sdgs.un.org/goals/goal11>). The impact of urbanization reached local to global, immediate to long-term, and social to environmental dimensions (Marcotullio & McGranahan, 2006). Industrialization and housing sectors directly influence urban area formation, and significantly cause of

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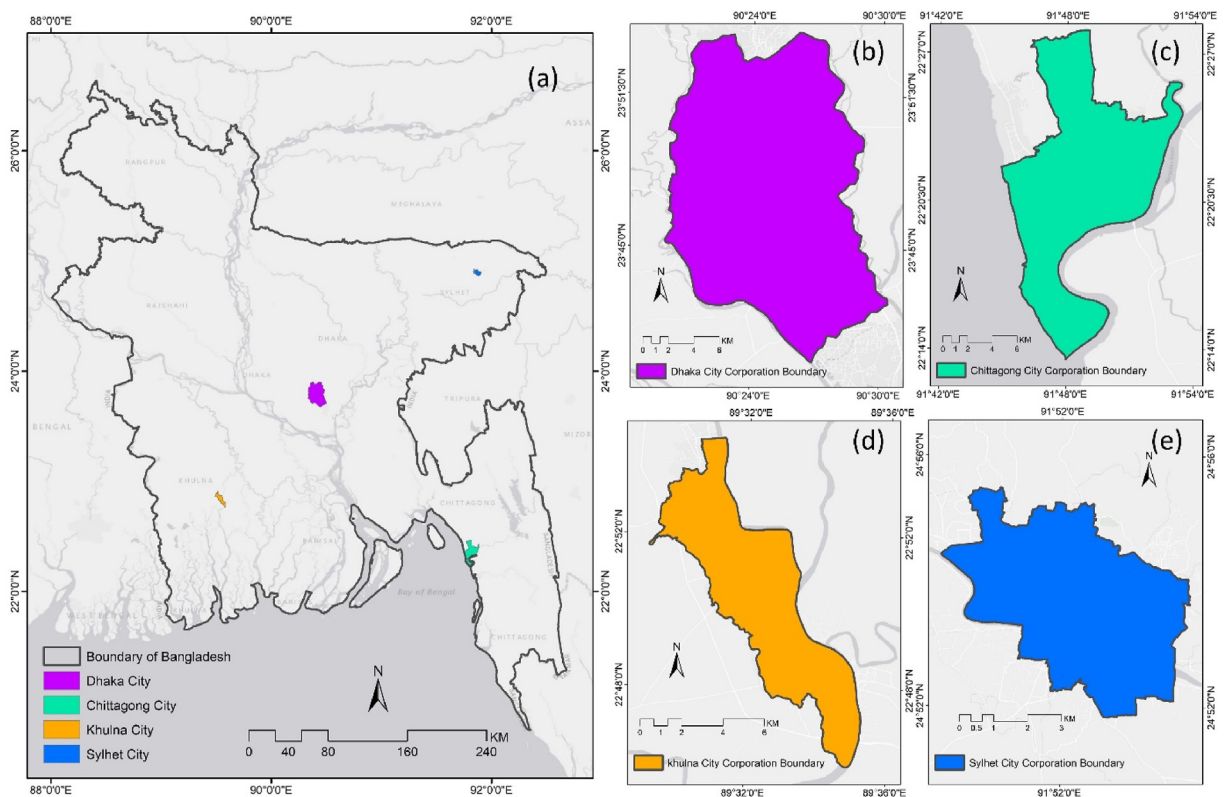
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unplanned urban growth, especially in developing regions (Dickson et al., 2012). Therefore, it's crucial to figure out how urbanization changes the natural environment and impacts the population.

Scientists often use indices to detect the condition of the urban area. Impervious surface area (ISA) is one of such indices. The worst side effect of the built environment is that it seals the soil through the construction of buildings, roads, etc. (Prokop et al., 2011). Such sealed areas are called impervious surface areas (ISA). ISA is often used to indicate the extent of urbanization and its environmental quality (Arnold & Gibbons, 2007; Elvidge et al., 2007; Mathew et al., 2016; Morse et al., 2003; Zhang et al., 2009). ISA is also responsible for influencing natural hazards. It influences the intensity of urban runoff in volume and duration, resulting in urban floods (Weng, 2001). It also brings a considerable decrease in groundwater recharge and base flow by covering watersheds, which is also responsible for increasing storm flow and flood frequency (Brun & Band, 2000). Imperviousness also affects the water quality of nearby surface water, for example, ponds, lakes, streams, etc., by carrying pathogens, toxic contaminants, nutrients, and sediment through runoffs (Hurd & Civco, 2004). Even the urban climate gets influenced by the impervious surface area as it facilitates altering heat flux and generating urban heat islands (Yang et al., 2003). The vegetation decrease due to urban expansion disrupts ecology, leading to declining local living conditions through poor air quality, heat island effect, etc. (Costanza et al., 1997; Manisalidis et al., 2020). Vegetation fraction (VF) spatial index is therefore inversely related to the impervious surface area (Weng, 2007). It specifies the amount of vegetation in the urban area. And biotope area ratio (BAR) determines the ecological value of sealed urban areas by calculating the ratio of the ecologically effective area to the total area (Boetticher & Fisch, 1988; Lakes & Kim, 2012). Our fourth considered spatial index is Normalized Urban Area Composite Index- NUACI adapted from (Liu et al., 2020), which determines the urban environmental scenarios, including the remote sensing indicators of water, vegetation, and built environment.

To obtain sustainable development goals, it is essential to monitor the condition of the cities. Cities are often viewed as living organisms because they are born, grow, adapt, transform, evolve, and die (Razzaghi-asl & Zarei, 2013). Therefore, it is necessary to understand how its components, like built-up area, population, etc., are growing to maintain the health of a city (Signoretta et al., 2009). Traditionally, urban growth is presented based on population growth (Black & Henderson, 1999) as cities grow spatially because of their population growth. The SDG indicator 11.3.1 introduced a new computation style that measures how cities grow spatially, considering the demographic and environmental dimensions. The SDG indicator 11.3.1 is a good indicator for measuring the land-use efficiency of a city (UN-Habitat, 2018).

Therefore, in this study, we observed the changes in the major cities of Bangladesh based on the urban indices and evaluated the urban changes according to the SDG indicator 11.3.1. To help reach that goal, we calculated ISA, VF, BAR, and NUACI as urban spatial indices. We depended on remote sensing products to assess the spatial indices and concerned SDG indicators for this study.



**Fig. 1.** Major cities of Bangladesh: (a) location of four major cities in Bangladesh, (b) Dhaka City Corporation, (c) Chittagong City Corporation, (d) Khulna City Corporation, and (e) Sylhet City Corporation.

## 2. Study area

Bangladesh is a densely populated south-eastern country located between latitude 20°45' to 26°33' and longitude 88°14' to 92°22' (Fig. 1(a)) (Bangladesh Bureau of Statistics, 2021). In terms of population density, the country ranks 1st and in terms of the total population, it ranks 8th in the world (Banglapedia, 2021). The cities in Bangladesh are now growing faster than ever (Hasina, 2019). We have chosen the four major cities of Bangladesh: Dhaka, Chittagong, Khulna, and Sylhet, as our study area because of their high population density and areal extent (Bangladesh Bureau of Statistics, 2015). Dhaka is the largest city in Bangladesh and one of the megacities in the world (UN, 2018). As of 2018, at least 1418 people append to the total population of Dhaka city every day (Amin, 2018). Chittagong is the second-largest city and the largest port city in Bangladesh (ICBIID, 2019). Khulna and Sylhet position third and fourth respectively among the larger cities of Bangladesh (Bangladesh Bureau of Statistics, 2015). These four cities are our study areas of interest (AOI). All four cities share common problems due to urbanization, such as air pollution, traffic jams, noise pollution, water pollution, etc. (Hasan, 2022). However, the cities also have their unique issues depending on their unique setup (see Table 1).

## 3. Materials and methods

Our method includes geospatial analysis of the considered urban indices and SDG indicator evaluation. All the spatial indices were analyzed for 2014, 2017, and 2021. However, the SDG indicator covered 2000–2015 with a five-year interval. Therefore, the urban changes were observed based on values of the indices and indicator change over these periods.

We used the Google Earth Engine (GEE) JavaScript API (Gorelick et al., 2017) for the land cover mappings, Trends.Earth urban mapper (Trends.Earth) for SDG indicator and an additional software SNAP (ESA Sentinel Application Platform) (SNAP) for urban footprint analysis. The land cover maps were generated using Sentinel-2 and Landsat-8 images, and the urban footprints using Sentinel-1 (Product Type: SLC, Sensor mode: IW, and Polarization: VV). Sentinel-1 satellite has been providing Synthetic Aperture Radar (SAR) images since 2014 as an open-source. That's why we chose our time duration starting from 2014 for the spatial indices. Sentinel 2 and Landsat 8 satellite products are optical imagery having 10m and 30m spatial resolution respectively. Because of the higher resolution, we mostly used Sentinel-2 products and only for 2014, used Landsat 8 products. The detailed properties of remote sensing data and GEE filters have been provided in Table S:1.1 & S:1.2 of the supplementary document.

### 3.1. Urban spatial indices

#### 3.1.1. Impervious surface area (ISA)

ISA refers to the percentage or share of the impervious area within an urban area of interest. The value of ISA should lie between 0 and 1.

$$ISA = \frac{A_b + A_i}{A_{AOI}}$$

Where,  $A_b$  is the floor area covered by buildings within the AOI (area of interest),  $A_i$  is the area covered by sealed surfaces within AOI. In this study, we used urban footprints using radar images to calculate the ISA values. The urban footprints were the  $A_b$  and  $A_i$  combinedly. We utilized Sentinel-1 products for urban footprint analysis using amplitude and signal phase (Corbane et al., 2017). Two SAR images at the nearest date (Table S:1.1 in the supplementary document) were required for each urban footprint calculation. First, we assessed calibrated amplitude for the images and the interferometric coherence between the pair of images. The processing steps included applying precise orbits, calibration, debursting, multi-looking, terrain correction, back-geocoding, coherence estimation, and creating stacks of the amplitude and coherence images. Finally, we masked the urban footprint from the amplitude and coherence images. If the mean backscatter of the images were greater than  $-10$  and coherence was greater than 0.6, it was considered an urban area. Otherwise, it was the opposite.

**Table 1**

Basic information on the major cities of Bangladesh.

City	Latitude	Longitude	Population <sup>a</sup>	Surface Geology <sup>b</sup>	Common Natural Disaster <sup>c</sup>
Dhaka	23°40'25" to 23°54'25"	90°20'10" to 90°28'50"	21,741,000	Alluvial silt and clay, Madhupur clay residuum, and Marsh clay and peat	Waterlogging, Floods, etc.
Chittagong	22°13'55" to 22°27'50"	91°44'50" to 91°53'30"	5,133,000	Tipam sandstone, beach and dune sand, Boka bil formation, Valley alluvium and colluvium, and Dihing formation	Cyclones, Floods, Tidal surges, Landslides, etc.
Khulna	22°46'10" to 22°54'35"	89°29'20" to 89°34'50"	949,000	Deltaic silt, Tidal deltaic deposits, and Marsh clay and peat	Salinity, Tidal surges, Cyclone, Floods, etc.
Sylhet	24°52'5" to 24°55'25"	91°49'55" to 91°54'15"	890,000	Alluvial silt and clay, and Dihing and Dupitila formation undivided	Flash floods, Landslides, etc.

<sup>a</sup> Population data source: World Population Review.

<sup>b</sup> Geology data source: Persits et al., 2001.

<sup>c</sup> Common Natural Disaster: ADRA, 2019.

### 3.1.2. Vegetation fraction

Vegetation Fraction (VF) refers to the percentage or fraction of vegetation or green coverage within an area of interest. The amount of urban greenery, the portion of high-rise buildings, and the distance between buildings influence VF (Schöpfer et al., 2005). The value of VF ranges from 0 to 1, like ISA. But VF is inversely related to ISA.

$$VF = \frac{A_t + A_g}{A_{AOI}}$$

Where,  $A_t$  is the area covered by trees within AOI,  $A_g$  is the area covered by grass/shrubs within AOI, and,  $A_{AOI}$  is the total area of AOI. The shrubland and vegetation were considered for vegetation fraction calculation from the land cover maps created in GEE using Landsat 8 and Sentinel 2 images.

### 3.1.3. Biotope area ratio

BAR is a simple quantitative ecological parameter that designates the amount of ecologically effective surface area compared to the total area (Planen et al., 1990). Since the impervious surface area hinders the natural process of habitat, air filtration, runoff, and groundwater recharge, the surface land cover type and area were distinguished first by land cover mapping. To get the ecologically effective area, the surface type was then multiplied by their corresponding "ecological significance scale" value (Lakes & Kim, 2012). We determined these corresponding values or weights by reviewing the literature and analyzing the unique conditions of the cities so that they can genuinely present ecological significance. The summations of those areas were later divided by the total area for BAR calculation as follows:

$$BAR = \frac{\text{Ecologically effective area}}{\text{Total area}}$$

or,

$$BAR = \frac{\sum(\text{Landcover type} * \text{Weight})}{\text{Total area}}$$

We used GEE for land cover mapping because the remote sensing data were available, and no high-volume satellite data download or no high-definition computer was needed for these heavy tasks. We found that the Random Forest classifier produced the best result after some trial-and-error cycles. We considered five land cover classes: built-up area, bare land, shrubland, vegetation, and water. Then we validated them through the error matrix method using Google Earth's high-resolution images and the different band compositions of optical images. Though shrubs and other vegetation look similar to the naked eye in the true color composition (B4, B3, B2), their reflectance differs in the false-color composition (B8, B4, B3). We took the training samples by observing these color compositions and cross-checked them with very high-resolution Google Earth imagery to ensure accuracy. Therefore, the number of training samples varied for each landcover mapping. GEE also helped to analyze the producers' and users' accuracy for validation. 20 validation samples for each class and 100 for each map were taken through stratified random sampling using the same approach of training sample. The details of the land cover mapping and accuracy assessment have been provided in Table S:2 of the supplementary document. Land cover mapping was also used for VF calculation.

### 3.1.4. Normalized Urban Area Composite Index (NUACI)

NUACI was first introduced by Liu et al. (2015). Then, Liu et al., (2020) updated the index, as shown in the following equation. This index integrated Normalized Difference Vegetation Index (NDVI) to determine the presence of vegetation, the Normalized Difference Water Index (NDWI) to determine the presence of water bodies, and the Normalized Difference Built-up Index (NDBI) to include the presence of the built environment.

$$NUACI = U_{\text{mask}} * \left( 1 - \sqrt{(NDWI - a_{NDWI})^2 + (NDVI - a_{NDVI})^2 + (NDBI - a_{NDBI})^2} \right)$$

here,  $U_{\text{mask}}$  is extant of urban area within the city boundary (Urban = 1, Non-urban = 0), and a-based indices are the average of that particular index within the city boundary. We took the urban footprints calculated from Sentinel-1 images as  $U_{\text{mask}}$  here. The normalized difference indices were calculated in Google Earth Engine. The NUACI was then calculated, and one single value of the mean NUACI of the considered years and cities was taken to compare the growth.

## 3.2. Urban change observation with SDG indicator 11.3.1

Land consumption is the consumption of land through urban development and urbanized open spaces. The land consumption rate shows the compactness which means the progressive spatial expansion of the city. On the other hand, the population growth rate is the rate by which the population of a particular area changes over a specific time. Both land consumption rate and population growth rate have been calculated through the logarithm of the ratio of the value in the initial year and in the final year with respect to the number of years between the initial and final year. Therefore, the equation of the population growth rate and the land consumption rate is as follows:

$$\text{Population Growth Rate} = \frac{\text{LN}(\text{Pop}_{t+n}/\text{Pop}_t)}{y}$$

Here,  $\text{Pop}_t$  = Total population within the urban extant in the past or initial year;  $\text{Pop}_{t+n}$  = Total population in the urban extant in the current or final year;  $y$  = Number of the years between the two measurement periods.

$$\text{Land Consumption Rate} = \frac{\text{LN}(\text{Urb}_{t+n}/\text{Urb}_t)}{y}$$

Here,  $\text{Urb}_t$  = Total area of urban extant in the  $\text{km}^2$  for the past or initial year;  $\text{Urb}_{t+n}$  = Total area of urban extent in  $\text{km}^2$  for the current or final year;  $y$  = Number of years between the two measurement periods.

Therefore, SDG indicator 11.3.1: “Ratio of land consumption rate to population growth rate” remains as

$$\text{SDG indicator 11.3.1} = \frac{\text{Annual Land Consumption Rate}}{\text{Annual Population Growth Rate}}$$

We used Trends. Earth, a google earth engine app for this analysis. The temporal coverage of the tool is 2000–2015 with five years intervals. This tool provides a precomputed 30m resolution impervious surface, night time, and water frequency index layer for the land consumption rate calculation and gridded world population version 4 (GPW v4) for population growth rate calculation (<https://trends.earth/docs/en/>).

The Trends.Earth did global testing for the built-up area extraction and assessed the quality between 0 and 5 scale. (0: No Data, 1: Unusable, 2: Problematic, 3: Some issues, 4: Minor Issues, and 5: High Quality). Dhaka city lies in the 5: High-Quality category. They found cities in the high-quality data category showing high confidence in calculating SDG 11.3.1 and perfect agreement between the built-up areas from Trends.Earth and high-resolution imagery in Google Earth. As Bangladesh is a small country containing similar climatic conditions, it can be assumed that the rest of the cities: Chittagong, Khulna, and Sylhet also contain high-quality built-up data with high confidence in SDG 11.3.1 estimation. Therefore, we did not evaluate the accuracy of the built-up area data, as it is already assessed by the Trends.Earth team.

We utilized the default GPWv4 population data despite other population data like Global Human Settlement (GHS Pop), WorldPop, census data, etc. We could not evaluate the GHS Pop and census population data for our study area, because they have a low temporal resolution. The GHS Pop data is available only for 2000 and 2015, and the census data is available for only 2001 and 2011. But evaluated the gridded WorldPop data along with the default GPWv4 population data. However, we had to reject the WorldPop data as it showed a population decrease with time in Khulna city which is impossible.

## 4. Findings and interpretation

### 4.1. Urban environmental change scenarios

For the four cities, the land cover mapping was done for 2014, 2017, and 2021. Each of the cities showed a similar result that urban area is growing over this short period. However, the other classes occasionally fluctuate because of activities like tree plantation, annual rainfall increase or decrease, etc. The accuracy of the land cover maps varied from 99% to 86%, where Dhaka city showed very high accuracy, but Khulna city showed comparatively low accuracy (Table S:2 in the supplementary document). As Dhaka is one of the megacities of planet Earth (UN, 2018), the region is extremely urbanized, which lacks vegetation in between the buildings which makes the machine learning to create landcover maps more precisely. On the other hand, in Khulna city the built-up areas are mixed up with vegetation and waterbodies, therefore, from the satellite image band information, the machine learning sometimes resulted in distorted outcomes for some pixels of the land cover maps. Again, in all of the maps, the class “bare soil” showed comparatively low accuracy, because the satellite band information of bare soil is often similar to built-up areas. Table 2 shows how land cover classes’ area changes over time. The visual representation of the land cover maps is added in Appendix 01.

**Table 2**

Land cover class area (square kilometer) 2021, 2017, and 2014 respectively.

	Year	BUILT-UP	BARE LAND	SHRUB LAND	VEGETATION	WATER
Dhaka	2021	207.5	12.1	14.7	46.8	17.8
	2017	188.1	10.2	21.5	59.5	19.7
	2014	130.9	17.1	43.1	84.5	23.3
Chittagong	2021	83.3	13.0	12.8	55.5	5.2
	2017	79.2	9.3	15.1	59.2	7.0
	2014	75.4	14.4	26.5	45.7	7.8
Khulna	2021	27.3	1.3	1.4	13.3	7.5
	2017	26.2	2.0	2.9	11.1	8.8
	2014	19.9	2.0	1.8	17.6	9.6
Sylhet	2021	17.0	0.7	1.1	7.4	1.1
	2017	15.0	1.7	1.2	8.2	1.1
	2014	11.1	0.7	1.7	11.5	2.2

Despite the countless benefits of remote sensing, there exist limitations. For example, bad weather conditions, clouds, air pollution, etc. can limit the optical image quality. Therefore, we used images from the winter season to avoid the distortion of the images by bad weather.

4.1.1. Spatial indices

4.1.1.1. ISA, VF, and BAR. Sentinel-1 image produced the amount of urban area but with much higher accuracy than the land cover maps because of its image properties. It also shows that urban areas are increasing rapidly in every city. The spatial changes can be seen in Appendix 02. Using radar images in urban footprint analysis addresses such limitations.

Table 3 shows their values and their changing trends. ISA is increasing for every city. Sylhet showed the highest increase in ISA. Chittagong increased comparatively less than the other cities. The decrease in VF and BAR curves was also less steep for Chittagong city but higher for Sylhet city.

As the impervious surface area presents the built-up area for the total area, several changes can happen in that environment with the increase of ISA, from human health to the underground environment. In 2021, the ISA of Sylhet crossed Dhaka city. Sylhet is an area full of natural beauty and tourism potential. This congested urbanization can destroy its ecological balance and cause groundwater depletion, air and surface water pollution, etc. However, the other three cities are not free from the risk of these problems. Especially in Dhaka and Chittagong, it is observed from the urban footprints that some places are way more congested than others. Those over-crowded places can cause more problems than cities like Sylhet, with higher urbanization rate.

As this study calculated vegetation fractions from the land cover classes produced by optical images, apart from urbanization and deforestation, the value of vegetation fraction can also fluctuate based on the annual weather condition of that area. For example, the VF value of Chittagong city in 2014 and Khulna city in 2017 didn't follow the trend. At that time, the cities lacked roadside vegetation, park maintenance, and rainfall deviated.

Land cover class-based ecological effectiveness assessment was the aim of the BAR index. Therefore, the limitations in land cover classification also limit the values. But, our weight-determination tactics reduced such limitations. This approach results ideally in getting an overall ecological scenario of a city. For example, the values of Chittagong city seem not to change as rapidly as the others. A significant portion of the city is covered with hilly vegetated areas. The urban area is congested at the bank of the Karnafuly river. Whereas in other cities, BAR value is changing rapidly with the increase in the urban regions.

As Dhaka is the capital city of Bangladesh, its' urban growth has kept increasing since the birth of the country (1971). Morshed et al. (2017) assessed land use and land cover classifications from 1989 to 2014. They observed 81.54% of total urban growth along with a steep decline in the natural vegetation cover of the city area. We observed that between 2014 and 2021 the ISA of Dhaka city increased 75% which means the urban area of the city kept following the trend of increasing. For Chittagong city, Hassan & Nazem, (2016) examined the land cover changes from 1977 to 2013 and found that within the 36 years period the built-up area expanded by 618% whereas we found a 38.1% increase in ISA of the city only from 2014 to 2021. Molla et al. (2021) found a decreasing trend in the urban

**Table 3**  
Spatial indices of the major cities.

Table 3:		Spatial indices of the major cities			
Dhaka	Year	ISA	VF	BAR	
	2014	0.20	0.43	0.39	
	2017	0.25	0.27	0.27	
	2021	0.35	0.21	0.22	
Chittagong	Year	ISA	VF	BAR	
	2014	0.21	0.43	0.37	
	2017	0.22	0.44	0.36	
	2021	0.29	0.40	0.33	
Khulna	Year	ISA	VF	BAR	
	2014	0.21	0.38	0.47	
	2017	0.25	0.28	0.38	
	2021	0.35	0.29	0.36	
Sylhet	Year	ISA	VF	BAR	
	2014	0.18	0.48	0.43	
	2017	0.27	0.35	0.30	
	2021	0.37	0.31	0.26	

water bodies of the city from 1989 to 2015, which also supports our findings of the declining amount of water from 2014 to 2021 (Table 2). For Khulna and Sylhet city, there were no significant previous studies to compare with that detected urban changes. Also, no previous studies had been done to estimate BAR for any of the cities to compare with. However, following trends of urban land cover changes in Dhaka and Chittagong cities provides support to validate our result.

**4.1.1.2. NUACI.** The result of the NUACI value shows a gradual growth over the period from 2014 to 2021 for all cities. Fig. 2 shows how the mean value of NUACI is changing for our study areas. The maps of the cities look similar to the urban footprints because when the rest of the equation was multiplied with urban masks where the urban = 1 and non-urban = 0, the non-urban are excluded.

The value of NUACI increases with the increase of urban areas within a city. As the average values of the indices are the average of the whole city, the NUACI equation calculates how the indices differentiate from the average within the urban mask. The higher the difference, the lower the NUACI value is. When the urban area grows within the city, the average indices within the city become closer to the values of the indices within the urban mask. Therefore, the NUACI value increases with time as the urban/built-up area grows within the city boundary. From our results, it is clear that the NUACI of every city is increasing significantly within a brief time interval, which means that within the city, NDWI, and NDVI are dropping, and NDBI is increasing rapidly. The calculation of NUACI also validates the results of the other indices by showing an upward trend.

#### 4.2. Alignment of urban growth with SDG indicator 11.3.1

The analysis of this portion indicated that most of the cities are dropping in SDG 11.3.1 values except Khulna city; the value was 1.56 in 2000. It became 2.77 in 2015 because the city population growth rate was lower than the land consumption rate, whereas the rest of the cities showed the opposite condition. Among the four cities, SDG 11.3.1 increased most in Dhaka, from 1.21 to 0.37. Chittagong city became second in increase, and Sylhet city was third. But except for Sylhet city, the rest of the cities' value was more than 1 in 2000, which means there was a higher land consumption rate than the population growth rate. In Sylhet city, there was always a higher population growth rate within our considered time. However, from 2005-to 2010, the land consumption rate in Khulna city doubled compared to the population growth rate.

It may seem that the more SDG 11.3.1, the more it is suitable for sustainable development. However, in reality, the situation is not that simple. If people live in a congested way, it is not sustainable. Similarly, if people consume more land from nature than the population increases, it is not sustainable either. Therefore, the increase in values in Khulna city isn't sustainable. The land consumption rate doubled the population growth rate in 2005–2010 and continued to increase in 2010–2015, which is also alarming.

The ISA values of Khulna city showed a gradual increase like the other cities, but the SDG indicator says it differently. Because the SDG indication calculation did not consider the administrative boundary, it measured the land consumption rate by detecting the growth of built-up areas in and from the city center. For Khulna city, the urban sprawl consumed land faster than the population growth (Table 4). Therefore, the SDG 11.3.1 value was increasing differently from other cities, but the ISA trend of Khulna city followed the rest of the cities.

The limitation of this portion of the analysis is the temporal extent. We could only calculate up to 2015 because of the app Trends.Earth was programmed for it. However, from the growth trends of the cities, it can be concluded that there is a tendency that the

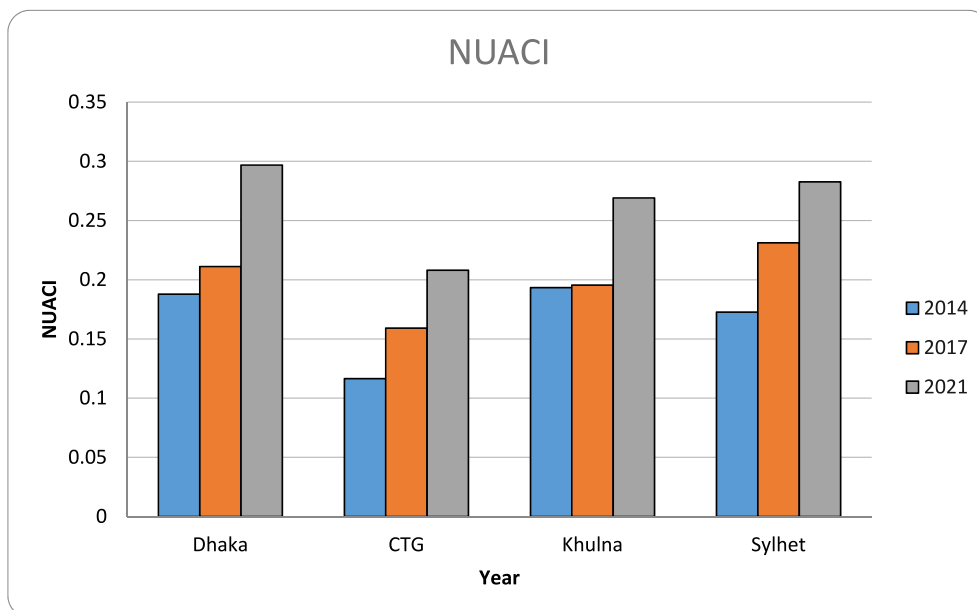


Fig. 2. Temporal change of NUACI values for the major cities of Bangladesh.



**Table 4**  
Analysis result of SDG indicator 11.3.1

Period	City Population change	City Population growth rate	City area change (hectares)	Land consumption rate	SDG 11.3.1
<b>Dhaka City</b>					
2000–2005	1,346,955	0.048	12,815.16	0.058	1.21
2005–2010	1,217,523	0.035	9026.61	0.032	0.92
2010–2015	898,068	0.022	2533.14	0.008	0.37
<b>Chittagong City</b>					
2000–2005	256,863	0.035	2658.03	0.046	1.33
2005–2010	184,086	0.022	1892.49	0.027	1.27
2010–2015	149,496	0.016	1080.65	0.014	0.88
<b>Khulna City</b>					
2000–2005	89,582	0.038	904.24	0.059	1.56
2005–2010	18,821	0.007	309.39	0.017	2.36
2010–2015	7870	0.003	157.52	0.008	2.77
<b>Sylhet City</b>					
2000–2005	13,329	0.066	433.48	0.042	0.63
2005–2010	19,746	0.070	551.04	0.043	0.62
2010–2015	13,825	0.037	117.68	0.008	0.22

scenario of cities in 2020 and afterward may follow the trend because the cities kept lessening or increasing the SDG values from 2000 to 2015. As we calculated the spatial indices since 2014 for SAR image scarcity, calculating the SDG indicator since 2000 also helped to see through the condition of the cities for a wide range of time. We also tried to evaluate our study with pertinent research findings. Arifeen et al. (2021) have considered change detection of land cover using optical image data in Gazipur, Bangladesh for its' SDG 11. However, they did not consider any SDG indicator for it. In this study, we tried to contribute to the SDG through indicator 11.3.1 which was not previously addressed in the context of Bangladesh.

## 5. Conclusion

Developing cities in a sustainable manner require proper knowledge of the urban-environmental conditions of the city. Our considered indices can observe urban environmental conditions very efficiently and require minimal time, money, and resources. We estimated the changes in the ISA, VF, BAR, and NUACI values of the four major cities in recent times and observed how they are altering the environment. This is the core focus of SDG's goal 11 and, more specifically, SDG's indicator 11.3.1. The urban area of Dhaka, Chittagong, Khulna, and Sylhet is increasing rapidly with continuous environmental degradation. The combined index NUACI of every city is increasing significantly within a brief time interval, which means that within the city, NDWI, and NDVI are dropping, and NDBI is increasing rapidly. Among the four cities, SDG 11.3.1 increased most in Dhaka, from 1.21 to 0.37. Chittagong city became second in increase, and Sylhet city was third. The analysis indicated that most of the cities are dropping in SDG 11.3.1 values except Khulna city because the city population growth rate was lower than the land consumption rate. The research findings will provide useful information for city planners and policy-making bodies about the most recent changing scenarios in the urban-environmental conditions of the major cities in Bangladesh.

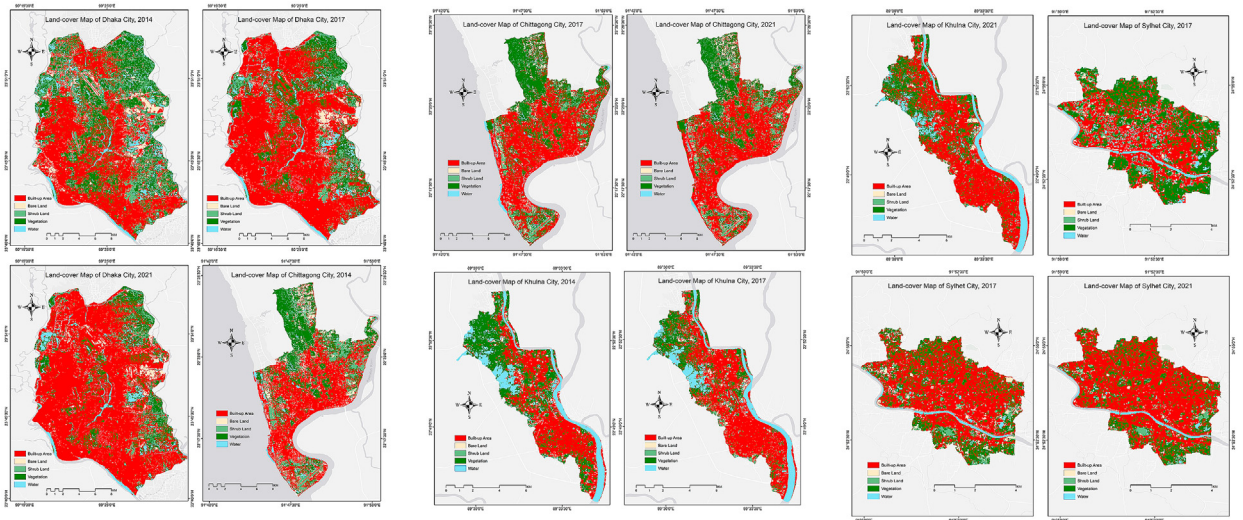
## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

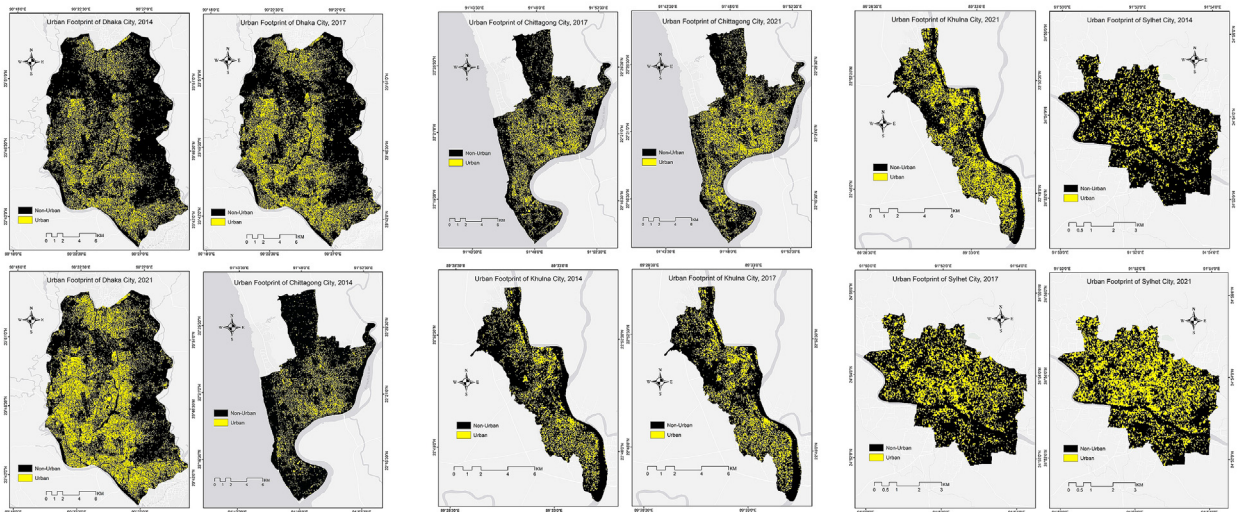
## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jum.2022.09.004>.

Appendix 01



Appendix 02



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