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RESEARCH ARTICLE

Quantifying spatiotemporal changes of the urban impervious surface of Dhaka District using Remote sensing Technology

Mahzabin Abbasi[1], Samsunnahar Popy,[2]* Tan Yumin,[1]

[1] International School, Beihang University, Beijing, China;

[2] Department of environmental science and disaster management (ESD), Bangabandhu Sheikh Mujibur Rahman Science and Technology University (BSMRSTU), Bangladesh.

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Correspondent email:
popyesdm@gmail.com

Abstract. Dhaka, the capital of Bangladesh, is one of the world's fastest-growing cities where imperviousness expanding in tandem. Therefore, accurate estimation of impervious surfaces is essential for urban planning and management. This paper attempts to quantify the changes of urban impervious surfaces in Dhaka district from 1990 to 2020 using remote sensing technology. Satellite images of 1990, 1995, 2000, 2005, 2010, 2015, and 2020 have been taken from the Landsat TM, ETM+, OLI sensor. Unsupervised classification with k-means clustering and three different RS indices NDVI, NDBI, and BUI was used to delineate the actual impervious area of Dhaka city. This study reveals that due to urbanization a net increase of 67.30 sq. miles impervious area is added to the existing amount over the study period. In 2020 total 300.749 sq. miles which contain 51.02% of the total land were occupied by impervious surfaces compared to the 233.446 sq. miles in 1990. Instantaneously taking appropriate strategies is crucial for sustainable urban growth.

1. Introduction

About 55 percent of the world's population now resides in urban metropolitan areas. By 2050, the proportion of the global population living in cities is projected to reach 68 percent (UN, 2018). Dhaka, the Capital of Bangladesh has experienced the rapid growth of urban agglomerations. In 2014 The Urban Extent of Dhaka was 36,541 hectares, increasing at an average annual rate of 3.3% since 1999 (Atlas of Urban Expansion, 2016). The city of Dhaka has been struggling to breathe due to its large population and uncontrolled growth (Weng, 2001). As part of the urbanization process, the physical features of Dhaka City are gradually changing like plots and open spaces have been transformed into building areas, open squares into car parks, low land and water bodies into reclaimed built-up lands, etc. (Ahmed et al., 2009). As a result, a continuous increase in impervious surface (IS) cover has occurred here.

Impervious surface areas (ISA) that prevent water from infiltrating into the soil like Rooftops, bridges, sidewalks, parking lots, driveways, and other manmade concrete surfaces (Arnold & Gibbons, 1996). Impervious surfaces have a significant impact on the urban ecosystem by removing all vegetation that could serve as a habitat for a variety of animals (Mathew, Khandelwal & Kaul, 2016). ISA has also been identified as a measure of the strength of the urban environment (Zhou & Wang, 2008) as well as indicates the extent of urban growth and sprawl (Luo & Mountrakis, 2012). Increased urbanization has resulted in an increase in impervious surfaces as well as a decrease in the number of forested lands, wetlands, and other types of open space that absorb water in the natural system (Leopold 1968; Carter 1961). Increased impervious cover has various effects on land surface conditions of the urban area (Leopold 1968; Carter 1961; Brabec, Schulte & Richards, 2002). Imperviousness has a significant impact on the amount of runoff that enters streams and reservoirs, as well as non-point source contamination and the water quality of nearby lakes and streams (Bauer, Heinert, Doyle & Yuan, 2004).

Identification of urban expansion as well as accurate measurement of impervious surface area (ISA) is essential for urban and environmental planning and management (Schueler, 1994; USEPA, 2003; Yuan, Wu, & Bauer, 2008).). Traditional urban growth measurements are outperformed by impervious surface data. In addition, it has been utilized to assess adverse influences of urbanization on the environment (Dougherty, Dymond, Goetz, Jantz, & Goulet, 2004; Schueler, 1994; Weng, Lu & Schubring, 2004; Wu & Yuan., 2007).) Since impervious surface expansion always follows a nonlinear pattern with a lot of spatial and temporal heterogeneity, it's been difficult to track (Sexton et al., 2013; Liu et al., 2019).

Moreover, in developing countries like Bangladesh due to a shortage of resources and infrastructure, it becomes more challenging (Bramhe, Ghosh & Garg, 2018). Remote sensing technology provides a huge opportunity to detect and quantify impervious surfaces (Im, Lu, Rhee, & Quackenbush, 2012). Satellite imagery provides extensive geographic coverage and the temporal frequency of data collection at the same time reduces the cost, enhances the speed of ground survey, and eliminates the problems of surface access (Luo & Mountrakis, 2012). With the availability of the Landsat satellite archive (Bramhe, Ghosh & Garg, 2018). A range of satellite images with good spatial resolution has been utilized for impervious surface mapping (Im, Lu, Rhee, & Quackenbush, 2012).

Numerous methodologies have been constructed for the extraction of the ISA from remote sensing images (Yuan, Wu, & Bauer, 2008) with various spatial scales to map ISA and evaluate its dynamics. The manual interpretation was previously considered to be the most straightforward and reliable process. Classification and change detection methods can also be a useful source to research the changes in the ISA (Lefebvre, Sannier, & Corpetti, 2016). Mellino and Algiati used an integrated GIS approach to create a map of ISA which is called emergy (Mellino & Ulgiati, 2015). Per-Pixel Classification can also be a handy tool for monitoring ISA. Yuan (2006) presented a conference paper with two different kinds of ISA classification methods, object-based and per-pixel classification. There are some popular and important sub-pixel methods of extracting ISA, Spectral Mixture Analysis (SMA) which relate the class with Vegetation-Impervious- Soil endmember (Adams et al., 1995; Lu, Li, Kuang & Moran, 2014; Wu, 2004). Another method is the regression tree model which presents the ISA% and relates it to tassel cap greenness (Bauer, Heinert, Doyle & Yuan, 2004; Yuan,2005). And regression tree is also a widespread method (Qiu et al., 2019; Yang, Huang, Homer, Wylie, & Coan, 2003). However, it is time-consuming and difficult to carry out in a wide geographical area.

Moreover, various spectral indices have been proposed such as Band Ration for Built-up Area (BRBA), Normalized Built-up Area Index (NBAI), New Built-up Index (NBI), Enhanced BuiltUp, and Bareness Index (EBBI), etc (Bramhe, Ghosh & Garg., 2018). (Yang et al., 2003) Developed a Sub-pixel Imperviousness Change Detection (SICD) approach to detect urban land-cover changes using Landsat and high-resolution imagery. (Liu et al., 2017) Proposed an approach to capture continuous impervious surface dynamics using spatial-temporal rules and dense time series stacks of Landsat data. (Lu et al., 2008) Explored extraction of impervious surface information from Landsat ETM+ data with the integration of fraction images from linear spectral mixture analysis based upon Ridd's vegetation-impervious surface-soil (V-I-S) model. (Wu & Yuan, 2007)Developed numerous approaches to quantify the distribution of impervious surfaces using remote sensing technologies. (Dewan & Yamaguchi, 2009) Evaluated land use/cover changes and urban expansion in Greater Dhaka, Bangladesh, between 1975 and 2003 using satellite images and socio-economic data.

This study attempts to quantify the impervious area along with other land use of Dhaka city classifying the Landsat satellite imagery using an unsupervised classification system. Furthermore, this study delineates the impervious area of study area applying the Built-up Index (BUI) previously proposed by Prasomsup et al. Where the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI) were intensively examined to present a BUI map correspondingly (Prasomsup, Piyatadsananon, Aunphoklang, & Boonrang, 2020).

2. Methods

Study Area

Dhaka District the capital of Bangladesh has been experienced urbanization from 19th century. Recently converting land type specially from agricultural land to impervious area have been increased in an alarming rate. Hence, it's attracted our concentration to quantifying the actual rate of impervious area of this district. The study area covers the whole Dhaka district with an area of 1463.60 sq. km. (565.00 sq. miles). Geographically it extends between 23º32' north to 24º02'north latitudes and between 90º01' east to 90º30' east longitudes (figure-1 represents the map of the study area) and it lies in the central part of Bangladesh. According to (BBS, 2011 ,2021) total population of this district is 12,043,977 and 13,798,000 in 2011 and 2021. The district consists of 6 subdistrict (Upazila in Bengali) Dhamrai, Dohar, Keraniganj, Nawabganj, Savar and Dhaka metro with 2 city corporations. The study area encompasses a diversity of land-cover classes with urban, suburban, and rural characteristics. Dhaka (city corporation), the capital of Bangladesh occupies only about one-fifth part of the study area where maximum land cover is occupied by impervious surfaces. The rest of the region Dhamrai, Dohar, Keraniganj, Nawabganj, and Savar thana which is mainly the periphery of urban are characterized by both urban and rural land use. The Buriganga, Turag, Tongi, and Balu are four significant river systems that run to the south, west, north, and east, respectively of the study area.

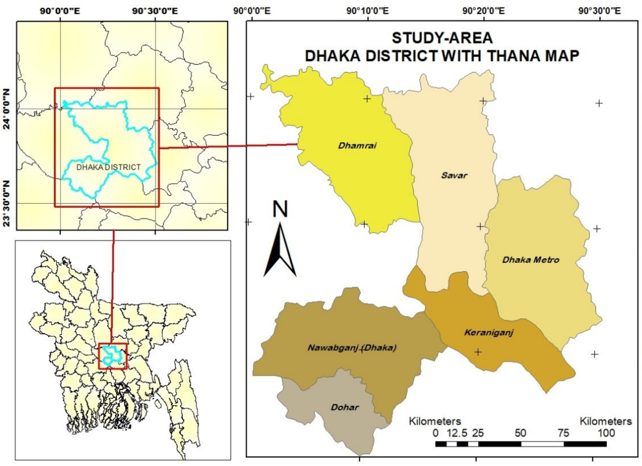

Figure 1. The location of the study Area

These rivers receive runoff from the much bigger Ganges, Brahmaputra, and Meghna rivers, and are mostly supplied by local rainfall. The city has a humid subtropical monsoon climate pg. 17 and receives approximately 2000 mm of rainfall annually, more than 80% of which falls during the monsoon season from June to September (Dewan & Yamaguchi, 2009)

Data

To achieve the objectives of the study, Landsat images were used to create chronological land cover maps in this research. Landsat satellite (TM and ETM+ and OLI) images years (1990, 1995, 2000, 2005, 2010, 2015, 2020) Path/Row 137/43 and 137/44 with a spatial resolution of 30 m were acquired from the United States Geological Survey (USGS) official website.

Table 1. Details of Acquired Landsat Satellite Images

Date	Path/Row	Cloud cover	Source (Landsat)
7/1/1990	137/43 & 137/44	<5%	TM
5/1/1995	137/43 & 137/44	<5%	TM
28/2/2000	137/43 &137/44	<5%	TM
8/1/ 2005	137/43 & 137/44	<5%	TM
22/1/2010	137/43 & 137/44	<3%	ETM+
30/12/2015	137/43 & 137/44	<3%	ETM+
20/2/2020	137/43 & 137/44	<3%	OLI

In Bangladesh winter lasts from December to February when temperature is pleasant, and cloud cover is lower than in other months. Hence, maximum imagery is downloaded in between December to February as well as maximum cloud cover was set less than 5% while downloading those data. Actual image acquisition dates and associated sensors used in the analysis are listed in the Landsat image properties in (tables 1).

Methodology

Pre-processing

Some radiometric corrections (image enhancement) are performed to improve the visual appearance of the imagery that helps better analysis. Histogram equalization has been performed to increase the tonal distinction between various features in an image. Therefore, to improve image quality, a haze reduction approach as well as a filtering option are performed. ERDAS Imagine 2014 and ArcGIS 10.3 were used to perform image processing tasks such as Layer Stack, Mosaicking, Subset, and Reprojection adjustments. After checking the geometric accuracy of multi-temporal Landsat images, image-to-image registration is performed using Universal Transverse Mercator (UTM) within Zone 46 N–Datum World Geodetic System (WGS) 84.

Land Use and Land cover classification

The land use and land cover were classified by an unsupervised classification method employing the k-means clustering algorithm. Total 36 subclasses were generated during the unsupervised classification. Then all the subclasses were recoded into five main classes, which is impervious area, Bare Land, Agricultural Land, Green Surface and Water Body (Table 2).

The resulting classes are compared with google earth for validation. Categorizing and recoding the features in Unsupervised Classification should be done very carefully with time. One wrong categorization can lead the whole process in vain. In this case, Google Earth Pro was linked up with Erdas Imagine for better visualization and interpretation. The overall accuracy, producer accuracy, and Kappa coefficient were determined.

Table 2: Description of LULC features

Extracted Features	Description
Impervious Area	Impervious surfaces are mainly artificial structures—such as pavements that are covered by water-resistant materials such as asphalt, concrete, brick, stone—and rooftops. Soils compacted by urban development are also extremely impermeable to water.
Bare Land	The Land with no more than 10% vegetation cover and other features like sand, rocks are classified as Bare Land
Agri. Land & others	All the cultivable lands and lands with no big trees and plants are classified in this category
Vegetation Cover	Reserved forestry and fields with wooded regions, as well as places where grasses predominate. They were placed here because it was difficult to discern between productive fields, sparsely located communities, and excavation roads.
Water Body	All the small Rivers like the Padma, Buriganga, Ichamati, Dhaleshwari, Turag and so many small canals, ponds and marshy land falls into this Category

Accuracy Assessment

Four kinds of accuracy, the Overall accuracy, Kappa Coefficient, User accuracy, and producer's accuracy have been conducted to validate the LULC classification for all image. For the accuracy calculation, a total of 36 points were taken for each class. The accuracy rate increased with the change of satellite sensors. The Landsat ETM+ and Landsat OLI have given more accurate results than Land MSS and TM sensors. The Accuracy assessment table are given below (Table 3,4,5):

Different Kind of RS indices analysis

NDVI

The Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index for observing greenery

Table 3. User's Accuracy Assessment

Classes	1990	1995	2000	2005	2010	2015	2020
Water Body	71.43%	100%	100%	100%	100%	100%	100%
Impervious Area	87.5%	90.91%	90.91%	88.9%	88.89%	90%	91.67%
Vegetation	83.34%	80%	100%	83.34%	83.34%	100%	1005
Bare Land	87.5%	83.34%	80%	100%	100%	83.34%	100%
Agri-Land	100%	85.71%	87.5%	100%	87.5%	100%	100%

Table 4. Producer's Accuracy assessment

Classes	1990	1995	2000	2005	2010	2015	2020
Water Body	100%	100%	100%	100%	100%	100%	100%
Impervious Area	87.5%	90.91%	90.91%	88.89%	88.89%	90%	100%
Vegetation	100%	80%	83.34%	83.34%	83.34%	100%	100%
Bare Land	70%	83.34%	80%	100%	80%	83.34%	83.34%
Agri-Land	100%	75%	100%	100%	87.5%	100%	100%

Table 5. Total Class Accuracy Assessment

Methods	1990	1995	2000	2005	2010	2015	2020
Over all Accuracy	85.72%	88.57%	91.43%	88.57%	88.57%	91.4%	91.29%
Kappa Coefficient	81.42%	85.28%	89.19%	89.06%	85.57%	89%	92.65%

globally. In general, Healthy vegetation is a good absorber of the electromagnetic spectrum for a visible reason. Chlorophyll in vegetation absorbs blue light quite well. (0.4 - 0.5 µm) and Red (0.6 - 0.7 µm) spectrum and reflects Green (0.5 – 0.6 µm) spectrum. Therefore, our eye perceives healthy vegetation as green. Healthy Plants with high reflectivity in the near-infrared (NIR) range of 0.7 to 1.3 µm. The interior structure of plant leaves is mostly responsible for this. High reflectance in NIR and high absorption in the red spectrum, these two bands are used to calculate NDVI. NDVI can be calculated by following formula (Bahadur, 2018).

NDVI = (NIR – Red) / (NIR + Red)
For Landsat 7 data, NDVI = (Band 4 – Band 3) / (Band 4 + Band 3)
For Landsat 8 data, NDVI = (Band 5 – Band 4) / (Band 5 + Band 4)

NDBI

The Normalized Difference Built-up Index (NDBI) is one of the popular indices for evaluating build up areas. Build up areas and barren land experience a drastic increment in the reflectance from band 4 to band 5. But vegetation has slightly larger or smaller DN value (not appreciable) on band 5 than on band 4. And this is the unique increment can be seen between these bands. This enables the build-up area to separate from remaining covers and hence NDBI. (Zha, Gao and Ni, 2001) These index takes advantage of the unique spectral characteristic of built-up areas and other land cover types, has been widely used to extract built-up areas from remote sensing imagery (Xu, Liu and Xu, 2018). The Normalize Difference Build-up Index calculation results between -1 to +1. Minus value of NDBI suggests water bodies and the higher value is carried by ISA. NDBI value for vegetation cover is the lowest.

NDBI can be calculated by following formula.

- NDBI = (SWIR – NIR) / (SWIR + NIR)

For Landsat 7 data, NDBI = (Band 5 – Band 4) / (Band 5 + Band 4)
For Landsat 8 data, NDBI = (Band 6 – Band 5) / (Band 6 + Band 5)

BUI

Build-Up area index (BUI) is the index for analyzing and monitoring urban infrastructure for variety of research. It can be obtained by NDVI and NDBI subtraction. the derived NDBI image was then recorded to create a binary image. The ratio is assigned a new value of 0 if input pixel had a negative index or 264 if its input index was larger than 0. According to the results of above table, subtraction of NDBI and NDVI will lead to only built-up area and barren pixels, while the rest of pixels with values of 0 or -264, allowing built-up area to be mapped automatically. The built-up index is the binary image with only a higher positive value indicates built-up and barren thus, allows to map the built-up area automatically using the following formula.

BUI = NDBI – NDVI

3. Result and Discussion

Spatiotemporal Changes of LULC Features in study area

Our study area, Dhaka district encompasses urban, suburban, and some rural areas. Hence built-up area, agricultural land, green land, water body, and some bare lands are found there Which reflects the rural character of the urban periphery. Over the period Dhaka district has experienced significant change due to rapid urbanization. Figure.2 depicts five LULC categories, each of which is characterized by a distinctive color. By five years of interval, a total of 30 years of LULC was retrieved from 1990 to 2020. Land use and land cover (LULC) changes area from 1990 to 2020 of Dhaka district is shown by a map in figure-2 and by a line graph in figure-3. The impervious area changes were calculated using a total of 7 images. Landsat TM images from 1990 and 1995, Landsat ETM+ images from 2000, 2005, 2010, and 2015, and Landsat OLI and TIRS images from 2020 are among the photos. The ISA is indicated by the pink tint. The bare soil area is reddish-brown, whereas the dark green area is dark green. The colorful areas signify vegetation cover, whereas the light green tint indicates agricultural lands and other areas, while the water bodies are all blue. Spatial pattern of an impervious area which indicates urban growth are present in the figure 2. Impervious area is the dominant land-use type in the study area. Classifying the land use of the study area over the study period revealed that a considerable increase in the built -up areas has occurred. Green surface and waterbody are continuously declining and converted into the building, table-6 represent the summary of LULC Statistics between 1990 to 2020. The GIS analysis also revealed that the area occupied by water bodies decreased by becomes 54.0955 and 66.9516 sq. miles in the study area. Conversely, impervious area which is the dominant feature of the study area is continuously increasing. Atlas of Urban Expansion (2016) Between 1999 and 2014, a total of 12,15 hectares of the built-up area were added to the Dhaka urban area. Infill accounted for 41% of the additional built-up area, while Extension accounted for 41%, Leapfrog accounted for 0%, and Inclusion accounted for 11.and green surface by 8.60% between 1990 and 2020. In 1990 water bodies and green surfaces occupied 124.344 and 117.65 sq. miles area but in 2020 it decreases and 18%. likewise, the Average Road width in the Dhaka 1990-2014 expansion area was 4.28 meters, compared to 6.83 meters in its pre-1990 area. This study revel that Impervious area increased dramatically over the study period, from 233.446 sq. miles in 1990 to 300.749 sq. miles 2020, a net increase of 67.30 sq. miles. This corresponds to an average annual increase rate of .38%. In 1990 impervious area occupied a total of 39.6% area of the study area. Over time urbanization process is ongoing as a result waterbody, green surface, Agri land, and bare land are converted into impervious surfaces. Therefore in 2020 total of 51.02% area are occupied by impervious surfaces. The figure represents the gradual expansion of urbanization of the Dhaka district. Relative changes in all land use class of the study area from 1990 to 2020 are represented in figure-4. A slight increase in Agri land and bare land is observed here. In 1990 Agri land and bare land account for 18.49% and 0.86% area of the study area. In 2020 it increases and occupied 27.42% and 1.03% area of the study site.

Though the Agri land and bare land increases but it occupied a very negligible amount of the study area. Post 1990 Dhaka spread beyond the Buriganga River and Turag River in the north and south, respectively. The figure-2 indicated that impervious surface is being started to expand in all directions, specifically to north-east, south-east and southern trends by acquiring waterbody and green surface, bare land, Agri land. This expansion occurs in an unplanned and haphazard way. The majority of the increase in ISA occurred between 2004

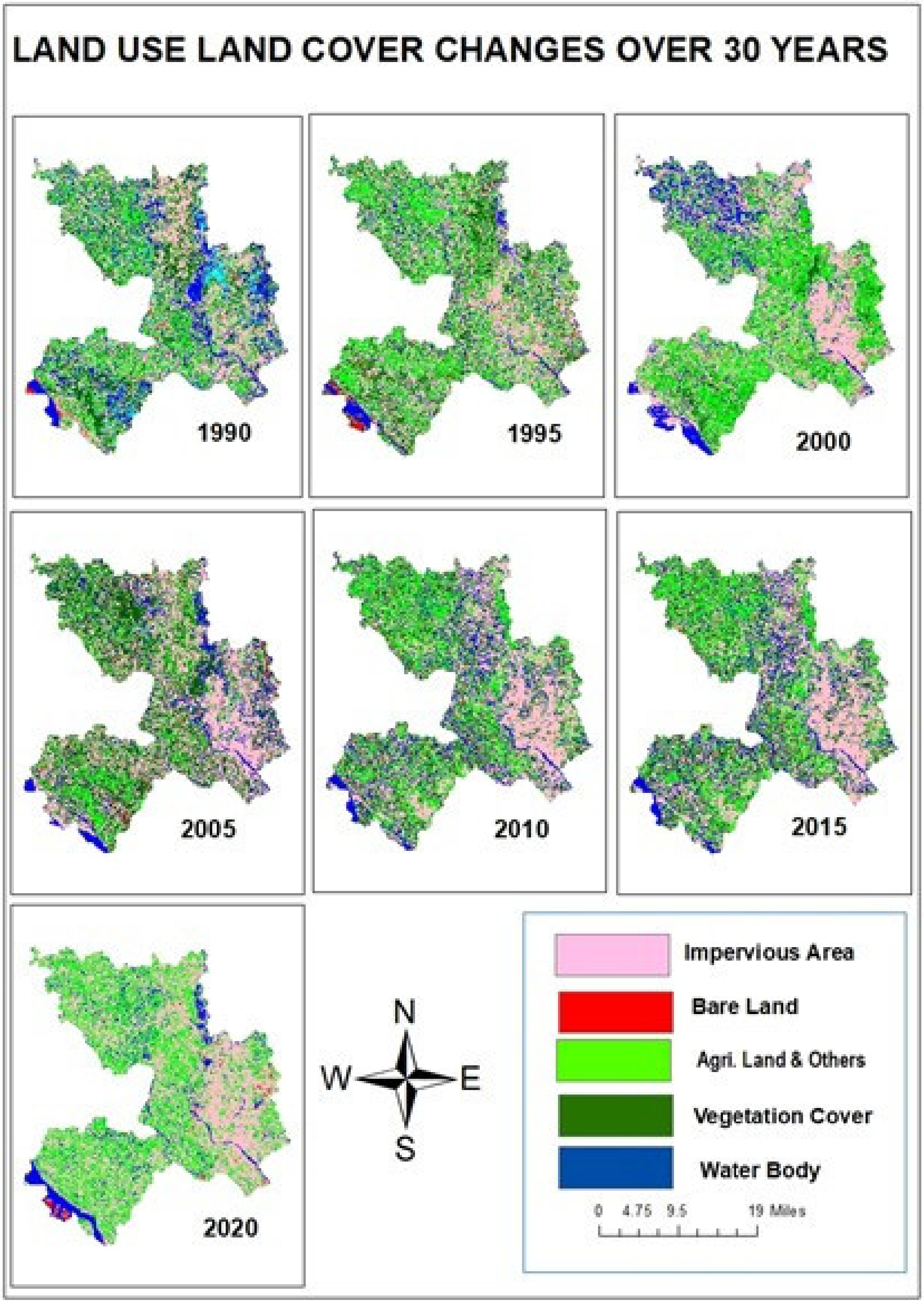

Figure 2. Spatial changes of LULC over 30 years of Dhaka District

Table 6. Summary of LULC Statistics between 1990 to 2020

Feature's name	1990		1995		2000		2005		2010		2015		2020	
	Area (sq. miles)	%	Area (sq. miles)	%	Area (sq. miles)	%	Area (sq. miles)	%	Area (sq. miles)	%	Area (sq. miles)	%	Area (sq. miles)	%
1.Impervious Area	233.45	40	234.14	42	249.59	42	260.77	44	274.95	47	288.76	49	300.75	51
2. Bare Land	5.09	.85	8.51	2	13.41	2	9.96	2	14.06	2	15.22	3	6.06	1
3. Agri. Land	108.98	18.15	175.19	31	201.15	34	186.47	32	130.82	22	153.48	25	161.66	28
4.Vegetation Cover	117.65	20	95.00	18	51.06	9	72.98	12	92.77	16	88.07	15	66.95	11
5.Water Body	124.34	21	51.72	9	74.30	13	59.37	10	76.92	13	43.92	8	54.10	9

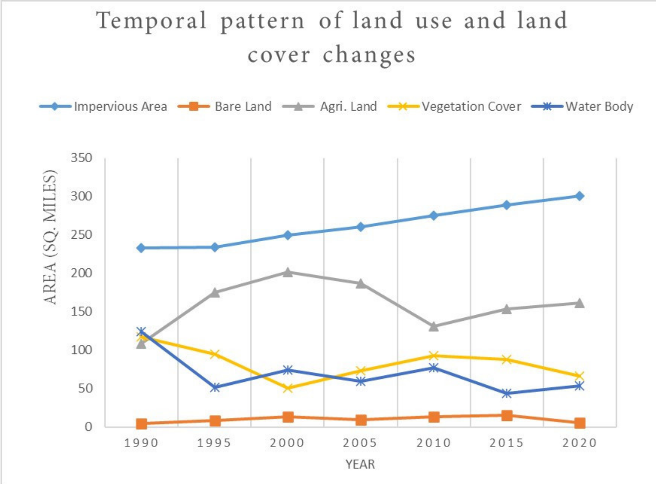

Figure 3. Temporal pattern of LULC of Dhaka District

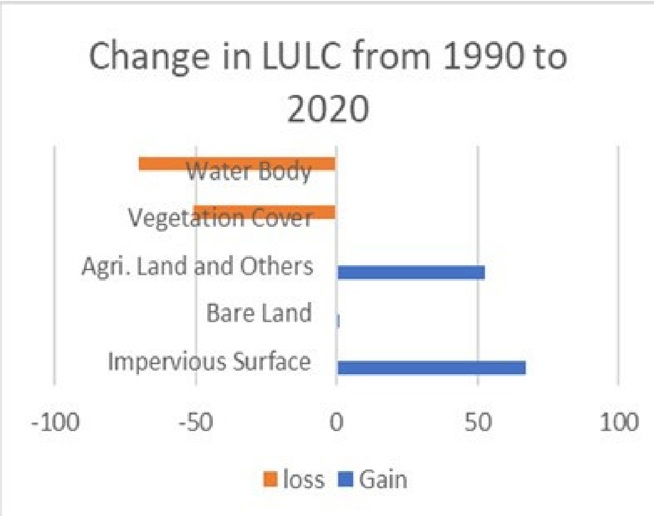

Figure 4. Relative changes in LULC features from 1990 to 2020

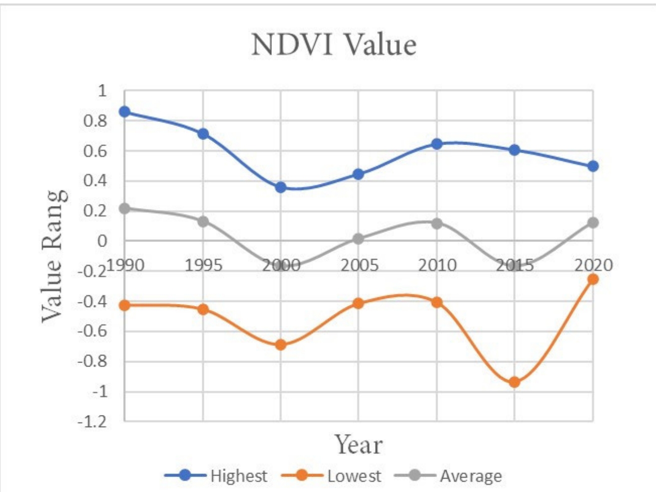

Figure 5.NDVI values from 1990 to 2020

and 2016 when the ISA grew by 238.11 km2. The increase in ISA was mostly concentrated in northeast Utara, Badda, tongi, savar, and in southeast Demra, Keraniganj.

Changes in Impervious and Non-impervious regions from1990-2020

The growth in infrastructure development in Dhaka in the last three decades has played a key role in urban expansion, exhibiting a lack of appropriate planning strategies. This research aimed to determine and explore the spatial extents of Impervious areas throughout the study period (Figure.2). To accomplish this, a reclassification was performed to produce land use and land cover maps of built-up and non-built-up areas, as seen in (Table.7). In 1990, where ISA was covering only 39.06 percent of the study area, it increased to 51.02% in 30 years.

NDVI Analysis Results

The NDVI is a method for detecting vegetation cover that is widely applied. However, distinct land cover types using the re-cored technique in various GIS and RS tools can be detected by NDVI. Our study area Dhaka is the most important and influential center of all economic, administrative, academic, political as well as trade and commerce. With the rise of population pressure the city has experienced a huge transformation. Vegetation cover, agricultural land, garden, natural forest is converted to multistoried building in an alarming rate. Hence, detecting vegetation cover status is very much significant by NDVI indices. NDVI status of the study area through the study period is shown in Figure.6, where the green color denotes a higher value, while the purple color denotes a lower value of NDVI. Here lower value reflects the impervious surface. The presence of a lot of vegetation and little impervious area is indicated by a high NDVI value. Circle drew on the map to represent the impervious surface area for easier interpretation and visualization. The NDVI was at its maximum in 1990 (0.859155), indicating that the impervious surface was at its lowest at that time (Figure-5). Then, from 1995 to 2005, the numbers gradually fell (0.714286, -0.42342), (0.358491, -0.68807), (0.714286, -0.42342) respectively, After, it increased somewhat in 2010 (0.64557, -0.93751) and 2015 (0.60656, -0.25399), before falling again in 2020. (0.49664, -0.25399). The average NDVI (figure-5) kept decreasing from the year 1990 to 2000, then it increases a bit in 2010 (-0.1655) then again it decreases. The NDVI was highest in 1995 and lowest in 2020, which is Environmentally adverse. It is very clear as showing on the Map that the Vegetation cover of the study area is decreasing with the incensement of Impervious area over time.

The built-up area can be extracted using the Normalize Difference Built-Up index. The highest NDBI values indicate a greater quantity of built-up area, while the majority of the urban built-up area is impervious surface, and a greater quantity of impervious area indicates a densely built-up region, vice versa. The green color in the Figure. 8 indicates

Table 7. Relative changes in Impervious Vs others Features

Features Name and area (sq. miles)	1990	1995	2000	2005	2010	2015	2020
Impervious Surface	233.45	234.14	249.59	260.77	274.95	288.76	300.75
Non-Impervious Surface	356.06	355.37	339.92	328.74	314.56	300.75	288.76
ISA Percentage	39.60	39.72	42.34	44.24	46.64	48.98	51.02

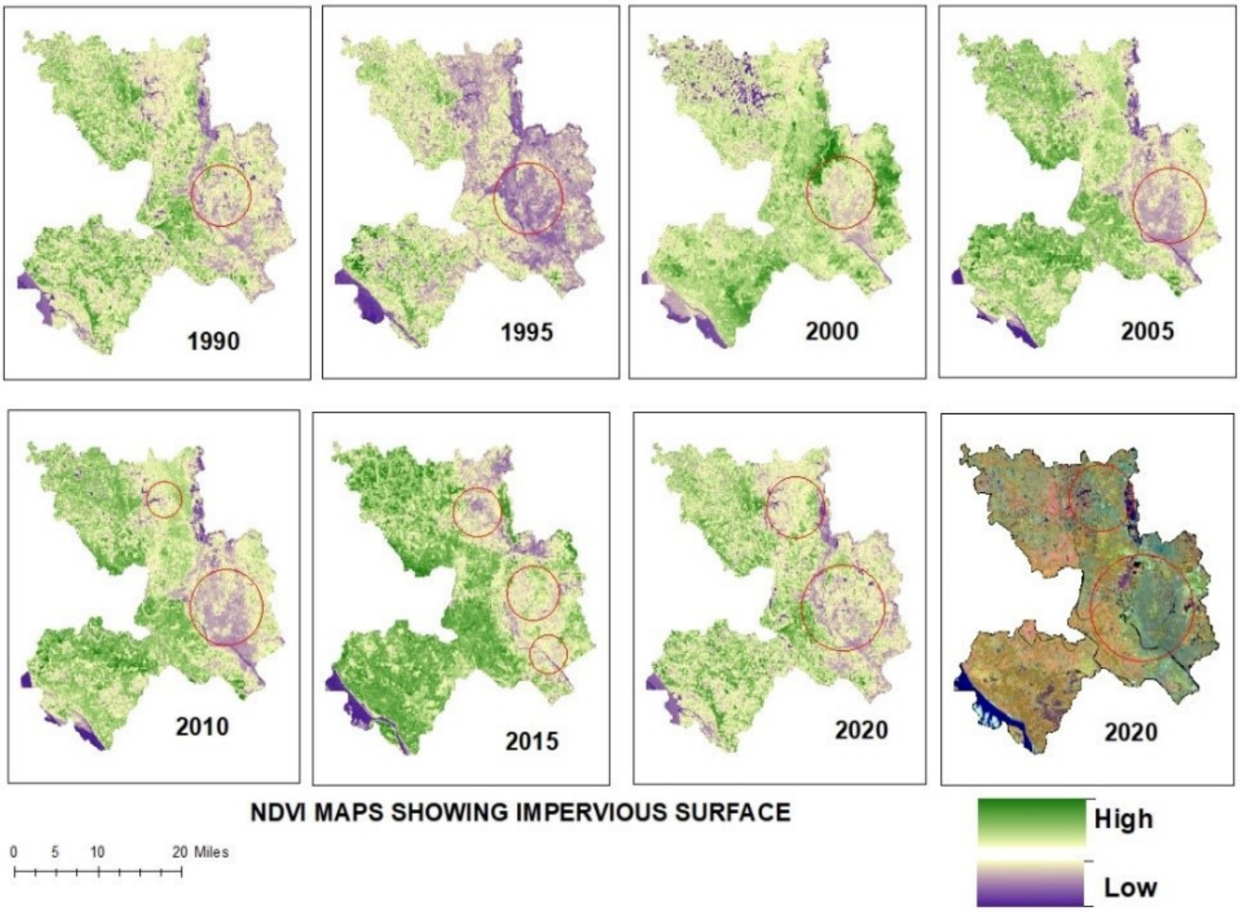

Figure 6. Normalized Difference Vegetation Index (NDVI) Maps of the Study area**3.4. NDBI Analysis Result**

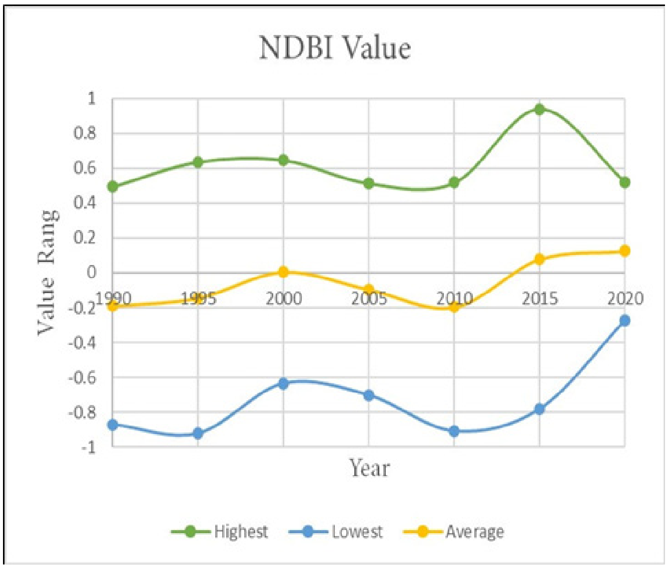

Figure 7. Range of NDBI values from 1990 to 2020

a slighter extent of infrastructure, while the blue color indicates a region with a high percentage of Built-Up area as in impervious surface. Therefore, the maps of NDBI from 1990-2010 indicating that the built-up areas are increasing slowly but efficiently. The most concentration of Built-Up Index is seen in the Dhaka Metropolitan area and areas beside the city. NDBI is calculated by the Short-Wave Infrared and Near Infrared band. Higher values are indicated as the highest amount of ISA. As the Figure. 7 is showing, in the year 2015, the NDBI value was at its pick which is 0.9375, The reason behind it could not be determined but it can be related to either seasonal variation or satellite sensor. But in the Year 1990, the built-up area was the lowest (0.492958 and -0.87097). The value of 2000(0.6458, -0.6364) ,2005(0.5138, -0.9091) and 2010(0.5172, -0.9091) was not fluctuated much as follows the year of 2020 (0.5221, -0.2728).

BUI Analysis Results

The landscape of Dhaka city gone through rapid alteration along with the social, structural and economic change. The urban growth rate in Bangladesh is affected mainly by rural to urban migration. Different type of employment opportunity, improved medical treatment, quality education and urban facility attract people to migrate here from different area of Bangladesh. Due to this high urban growth rate the city has been faced with the conquest problem. To meet this population pressure large number of residential, administrative, academic, commercial, industrial, cultural and political structure is being constructing continuously. For example, Dhaka city alone has 80% of the garment factories that are in Bangladesh. Dhaka's district has changed dramatically over time as a result of growing urbanization. The following (Figure.10) shows a spatial pattern of impervious areas that demonstrate urban expansion. The dominant land use type in the study area is impervious surface. The BU index is determined by subtracting the NDVI and NDBI values by presenting raster values. The vegetation cover of the research region is removed by removing the NDVI values. In the following map, the blue-colored area is the highest concentrated Built-Up region as follows the green-colored area is the lowest. Because, the NDVI values are eliminated during the calculation procedure, the vegetation

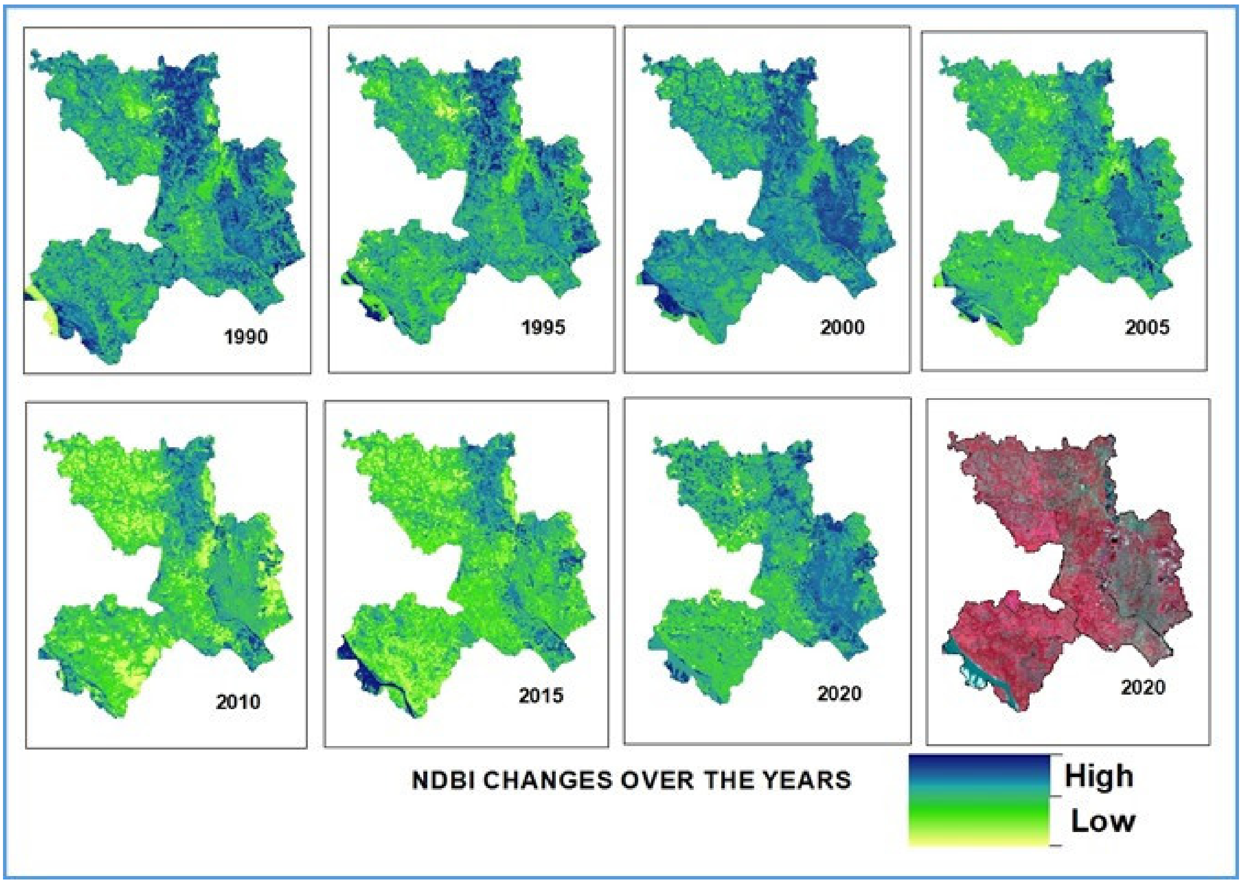

Figure 8. Normalized Figure Difference Vegetation Index (NDVI) Maps of the Study area

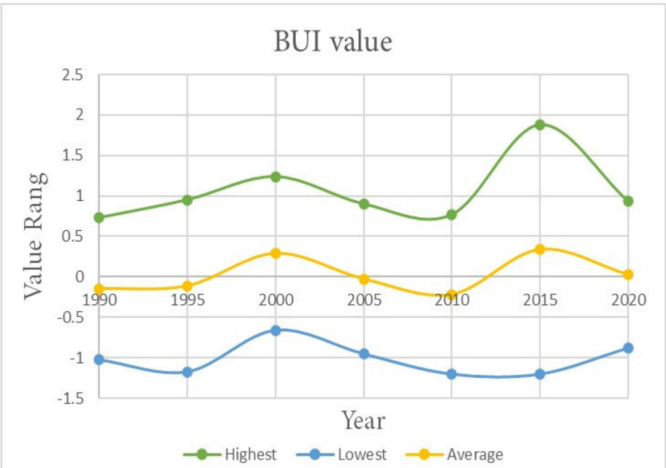

Figure 9. Range of BUI values from 1990 to 2020

cover is no more a problem. But the water area is still a problem if it needs to use for Urban Land Cover classification. The Build-up Index is an NDBI and NDVI-based index for analyzing urban patterns. The built-up index is a binary picture in which a larger positive value indicates built-up and a lower positive value indicates barren, allowing BU to automatically map the built-up area. Though BUI is a very efficient tool for extracting the urban land cover, it is not much useful with low-resolution imagery.

Figure 9 is showing average fluctuation over the 30 years and highest and lowest value of BUI. Here the positive value which indicates impervious area going upward from 1990 to 2015. In 1990 BUI value was its lowest range and in 2015 we found highest BUI value through the study period. In 2020 we found little bit less BUI value then 2015, it happens due to different type of sensor of different type of satellite.

4. Conclusion

Therefore, monitoring and assessing impervious earth is critical to a range of challenges and concerns in environmental technology, particularly in regards to global environmental issues and human-environment interactions. Excessive imperviousness of the Earth's surface has negative consequences for both the natural and human environment. Dhaka, the study location, has been dealing with unhealthily growing human structures for decades. To maintain the uncontrolled growth of Imperviousness in the urban setting, sustainable environment-friendly infrastructure and public services, such as municipal infrastructure, piped water, sanitation, and waste recycling management, are considerably more pleasant, easy, and cost-effective to create, operate, and maintain, should be available. In addition, urbanization allows more individuals to have affordable access to environmentally friendly infrastructure and services. This study suggests some appropriate strategies for achieving sustainable Impervious growth and resolving environmental difficulties based on the urban difficulties. Furthermore, a great deal of good quality research on urban environment management should take into account. In future this research can help to introduce a new phase by developing environment friendly policy. In Dhaka city, the local administration can encourage citizen participation in sustainable development for ISA growth. By providing training on public involvement and facilitation for urban research, policymakers may develop a strategy for urbanization expansion and environmental protection.

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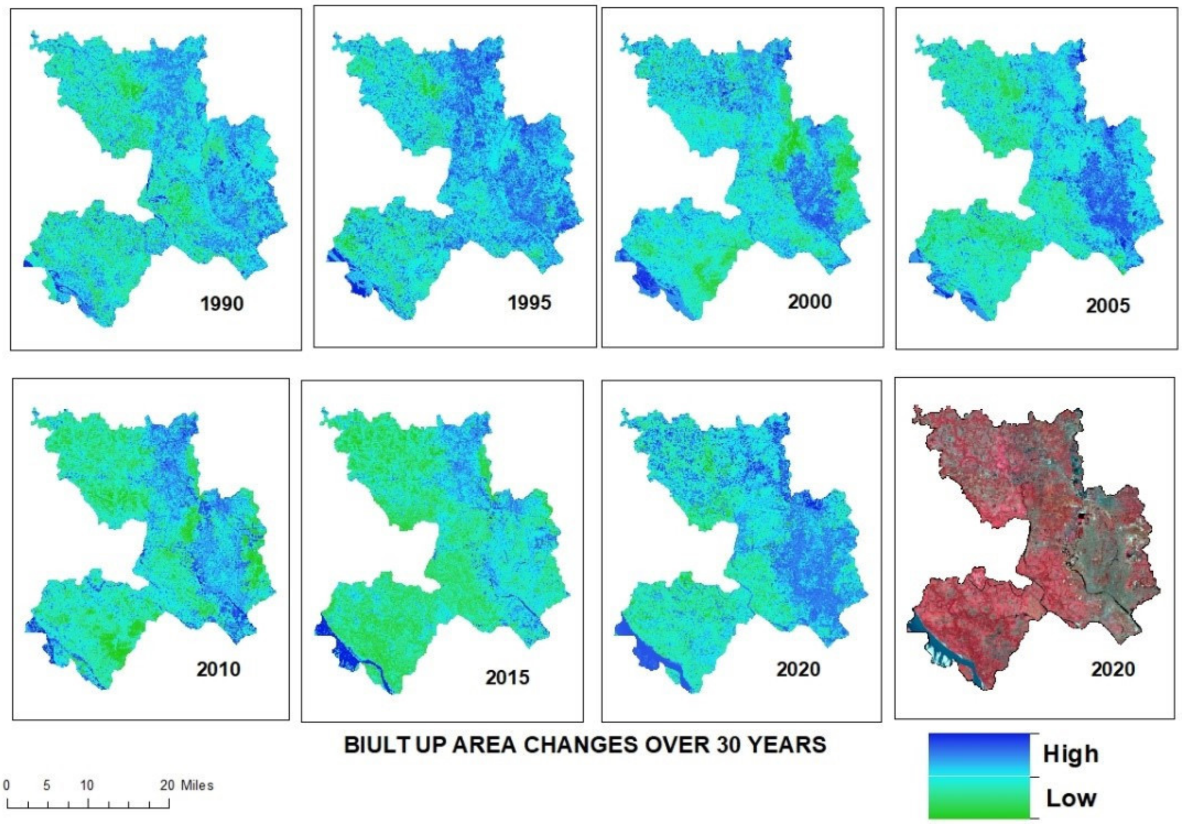

Figure 10. Build-Up Index (BUI) Maps of the Study Area

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