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Final Report in Spatial Data Studio

On
**Land-use and Land-cover Change from 2016 to 2021 in Chittagong
Metropolitan Area, Bangladesh**

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1 Introduction

In recent years, increasing population growth and dramatic urban expansion have impacted the surrounded lands and biotic and abiotic components depending on it. Unprecedented landscape change has a tremendous influence on radiative, thermodynamic and hydrological processes that eventually alter temperature, rainfall and other climatic factors thereby increasing the vulnerabilities of local inhabitants to climatic stresses (Hassan and Nazem, 2016; McCarthy et al., 2010). Like numerous developing countries, Bangladesh also experienced tremendous growth in population and urbanization, resulting in enormous land-use change (Hassan and Nazem, 2016). Chittagong, the largest port city and second largest metropolitan city of Bangladesh has also experienced unprecedented land cover change hence expanding in all directions due to increasing population growth and job availability in recent decades. Serious environmental and ecological degradation like deforestation, hill cutting, soil and wetland degradation has amounted in the last few years which makes the city dwellers immensely vulnerable. Therefore, to track the degradation, it is crucial to understand and measure land-use change along with urban expansion in Chittagong city. Using remote sensing and GIS, this study aims to measure landuse and landcover change in Chittagong Metropolitan Area within the last five years (2016-2021). Specific objectives of the study include:

- To determine the land cover of each landcover class in 2016 & 2021 at Chittagong Metropolitan Area
- To measure the land-use change detection from 2016 to 2021 and area under each conversion class
- To generate ideas about how the city land-use has expanded from the city center to buffer areas

2 Data and methods

2.1 Study area

Chittagong is the commercial capital and biggest port city of Bangladesh, located in the south-eastern part of Bangladesh. The study area, Chittagong Metropolitan Area (CMA) is located within 22°13' to 22°27' North latitudes and 91°40' to 91°53' East longitude. CMA is surrounded by Karnafuli river to the south-east side, Bay of Bengal to the west, Halda river to the south-east and a hilly ranges to the northern part. The

total area of the CMA is 773.4 sq km with a population of more than 8 million (Ahmed, 2015). Core of the city is Chittagong City Corporation area (CCC) located inside the study area and the city centre is located at Panchlaish ($22^{\circ} 21' 32.93''\text{N}$, $91^{\circ} 50' 2.75''\text{E}$).

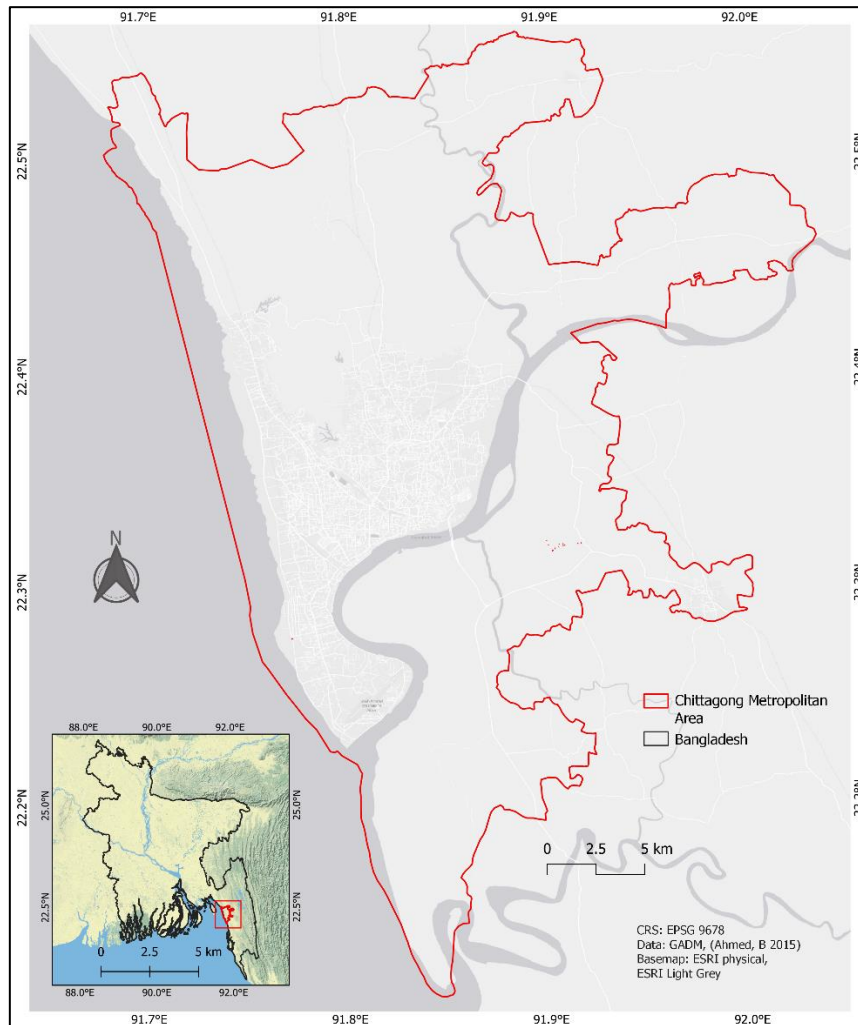


Figure 1: Study area Map

2.2 Data

For this study, secondary data sources were used. High resolution (10m) freely available sentinel imageries were used to detect surface landcover. For 2016, the Sentinel 2A images were acquired from US geological survey for the month of December and the Sentinel 2B images for 2021 were collected for the month of November from Copernicus Open Access Hub. Although the image sources were different, data from both sources are hosted by European Space Agency (ESSA) and both use Digital Number in their images. So, two images can be used for comparison and analysis. In order to reduce the seasonal variability, both images are collected from

the dry season. Chittagong Metropolitan area shapefile was obtained from the study of “Landslide susceptibility mapping using multi-criteria evaluation techniques in Chittagong Metropolitan Area, Bangladesh” (Ahmed, 2015). Country boundary was collected from GADM. In addition, ERSI physical and ERSI light grey base map were used for study area mapping.

2.3 Methods

Supervised classification was carried out in this study. At first, sentinel imageries with 10 m resolution were downloaded for the year 2016 and 2021. Collected images than geo-referenced to ‘Gulshan 303, Bangladesh Transverse Mercator – EPSG: 9678’ map projection system. From the reprojected dataset, 4,3,2 bands with 10m resolution were used to make a true colour band composite in QGIS (Annex 6.1).

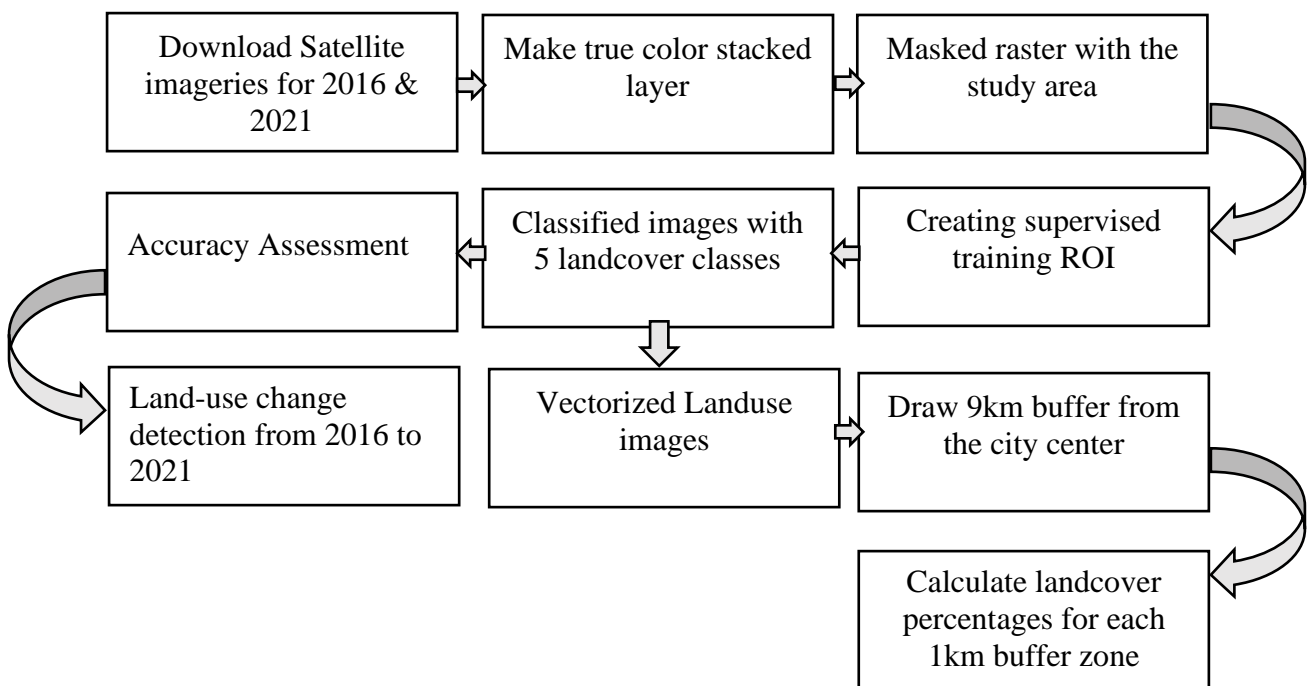


Figure 2: Process flow diagram

The stacked images were then masked with the study area shapefile which completes the pre-processing of satellite imageries. Around 150 (Region of Interest) ROIs were drawn for all landcover classes in each year to train the Maximum likelihood algorithm. After that, the images were classified into five specific classes: Waterbody, Vegetation, Agricultural land, Built area and Bare soil. Waterbody indicates sea (Bay of Bengal), all the rivers, canals, ponds and dighis (closed catchments bigger than ponds). Vegetation designates all the forested lands, hills, grasslands, plantations, coastal

plantations etc. Agricultural lands are croplands, fallow lands, vegetable fields etc. Built area indicates all kind of settlements, industrial and commercial structures, seaports, bridges, road and railways, construction sites and water vessels in the rivers. Exposed soil, excavation sites, coastal char (barren) lands etc. are considered as Bare soil class. An accuracy assessment has been performed for classified landcover images to calculate the performance of the classification. For this, around 80 random polygons were drawn and identified in google earth for each date of satellite images. Then these polygons are compared with the classified images with the help of SCP (Semi-automated classification Plugin) in QGIS and a confusion matrix was generated as output. After accuracy assessment was done, land use and landcover change assessment was carried out by the same plugin, by inputting LU of 2016 as reference image and 2021's LU as the new image. Again, Land-use map of each year has been vectorized in order to perform urban expansion analysis from city center. Nine buffer zones, each of 1km diameter, were created. For every buffer zone, land cover area by each LU class was calculated. Then by comparing areas between 2016 and 2021 in each buffer zone, urban expansion was analyzed.

3 Results and Discussion

3.1 Land-use and Land-cover of 2016 and 2021

Figure 3 visualizes the LULC of 2016 and 2019 where Table 1 depicts the area covered by each land-use class in both years. In 2016, Land-use of Chittagong metropolitan areas was dominated by vegetation, around 29% of all land-use classes which has changed to Built areas (34% of all classes in 2021) within just 5 years. Total area covered by vegetation was 223 square kilometers in the starting year and significantly reduced to only 167 Km². Conversely, Built area has increased from 178 Km² to 265 Km² within the same duration. Initially Agricultural land contained 17% of all classes, changed to 25% in 2021, reflecting an increase in cropland from 130.5 Km² to 195 Km². A Significant change was noticeable in terms of bare soil, which covered around 120 Km² in 2016 and reduced to only 55 Km² in 2021. Similarly, Waterbody reduced by around 30 Km² between 2016 and 2021. In 2021, some new industrial and agricultural areas were formed by destroying vegetation and bare soil, which explains the reduction in vegetation and bare soil and increase in Built area and Agricultural

land. On the other hand, at north-west of the metropolis gained some sedimented areas by the interplay of erosion and accretion of Waterbody in the sea.

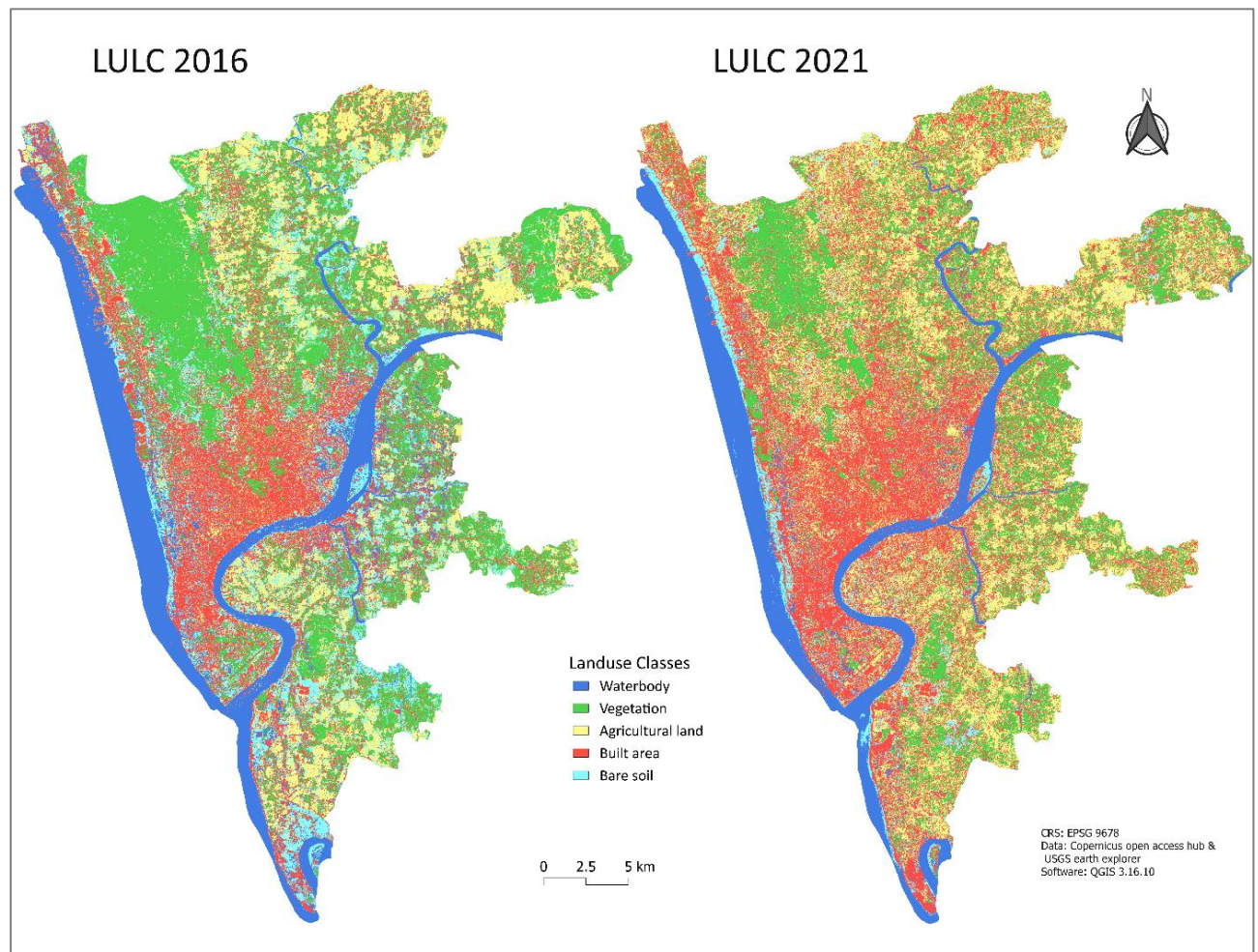


Figure 3: Land-use and Landcover Map of 2016 and 2021

Table 1: LULC area of 2016 and 2021

	2016	2021	2016	2021
Land cover class	Area (Km ²)	Area (Km ²)	Percentage %	Percentage %
Waterbody	122.71	90.30	15.86	11.67
Vegetation	223.17	167.64	28.85	21.67
Agricultural land	130.53	195.00	16.88	25.21
Built area	177.81	265.95	22.99	34.38
Bare soil	119.26	54.59	15.42	7.06

3.2 Accuracy Assessment

Accuracy assessment validates the classification according to ground truth data or another high-resolution imagery. For this study, accuracy assessment was carried out by google earth images, drawing about 100 polygons for each image and the confusion

matrix was generated by SCP plugin in QGIS. User accuracy refers to error of commission (inclusion) that is the performance of a classified image based on field data category whereas producer accuracy refers to error of omission (exclusion) that measures the performance of an analyst during the classification). Overall accuracy is measured by both user and producer accuracy and the suitability of the image for analysis is based on Kappa hat classification (Rana and Sarkar, 2021). Overall accuracy of the classification was 79% and 77% for 2016 and 2021 respectively. User accuracy of built area was lower, and vegetation was higher compared to other classes in both years. Kappa hat for every category was more than 90% except built area which means some built areas were not properly classified. However, overall kappa was 73% for 2016 and 70% for 2021 which is within the acceptable range. Several studies argue that, more than 70% accuracy is good while considering google earth for the accuracy assessment (Rwanga and Ndambuki, 2017; Tilahun and Zubairul, 2015). Therefore, this land use classification can be further used for change detection analysis.

Table 2: Confusion matrix of Accuracy Assessment

2016	Waterbody	Vegetation	Agricultural land	Built area	Bare soil
Standard Error	0.0022	0.001	0.0028	0.0051	0.0047
Producer Accuracy [%]	84.5207	98.4423	72.3733	99.0216	25.585
User Accuracy [%]	98.9105	99.8403	97.8849	58.6417	85.609
Kappa hat	0.9871	0.9979	0.975	0.4249	0.8241
Overall accuracy [%]	79.1828				
Kappa hat classification	0.7288				
2021					
Standard Error	0.0014	0.0048	0.0034	0.0053	0.0046
Producer Accuracy [%]	94.6899	67.4506	88.8625	98.5953	42.5808
User Accuracy [%]	95.3029	99.4719	89.828	41.9293	97.6164
Kappa hat	0.9468	0.9922	0.8635	0.3198	0.9716
Overall accuracy [%]	76.638				
Kappa hat classification	0.7047				

3.3 Landuse and Landcover Change detection

LULC of Chittagong Metropolitan area has been changing rapidly within short period of time as it is the biggest port city and second largest city in Bangladesh. According to Table 3, significant land use change has been observed in Vegetation, Agricultural land and Built area. Around 119.11 Km² forest land was preserved where 55.76 Km² of forest areas has been converted to built area and almost 39 Km² converted to agricultural land. In the northern part of the change detection map (Figure 4), small hillock area has

been destroyed and new industrial zone has shown up in 2021. Besides, throughout the study area hills, plantation, even reserve forest has been cleared for agricultural purposes. From 2016 to 2021, there was a conversion of 41.44 Km² croplands to built area. Human settlement in addition to new industrial establishment in the sub-urban region explains the situation which were formerly crop fields and fallow lands. Around 11 Km² agricultural land has converted to Vegetation in 2021 where farmers start plantation of commercial species in their fellow lands. In terms of built-up areas, 104 Km² remained unchanged from 2016 to 2021 where around 37 Km² and 20 Km² have been converted to agricultural land and vegetation respectively. Indeed, there was some classification inaccuracies that produced the high value for agriculture and vegetation. However, in recent years, rooftop plantation in Chittagong city has been increasingly popular. Also, some beautification of industrial zones with ornamental tree species was carried out as per Department of Environment's guideline that explains how some of built area's pixel has converted to vegetation. In case of bare soil, almost same amount of bare soil (45 Km²) has changed to agricultural and built areas. In order to feed the huge population and their settlement some empty areas were no longer empty in 2021. Near about 10 Km² of bare soil is replaced by public and private plantation. About 78 Km² waterbody remain unchanged, however 18 Km² and 11.74 Km² transformed to built area and bare soil. Over the period, some inland waterbody has changed to human settlement, mostly in suburban areas. Some waterbodies have also converted to accreted land along the coast from 2016 to 2021. Furthermore, water vessels in seaport and ship breaking yard in Vatiary has increased which also represented the area of waterbody transformed to built areas.

Table 3: LULC change detection

2021/ 201q. km)	Waterbody (2021)	Vegetation (2021)	Agricultural land (2021)	Built area (2021)	Bare soil (2021)	Total
Waterbody (2016)	78.63	7.46	6.52	18.36	11.74	122.71
Vegetation (2016)	1.77	119.11	38.99	55.76	7.53	223.17
Agricultural land (2016)	2.32	10.88	66.76	41.44	9.14	130.53
Built area (2016)	2.85	19.71	37.69	104.05	13.51	177.81
Bare soil (2016)	4.74	10.48	45.04	46.33	12.67	119.26
Total	90.30	167.64	195.00	265.95	54.59	1814.97

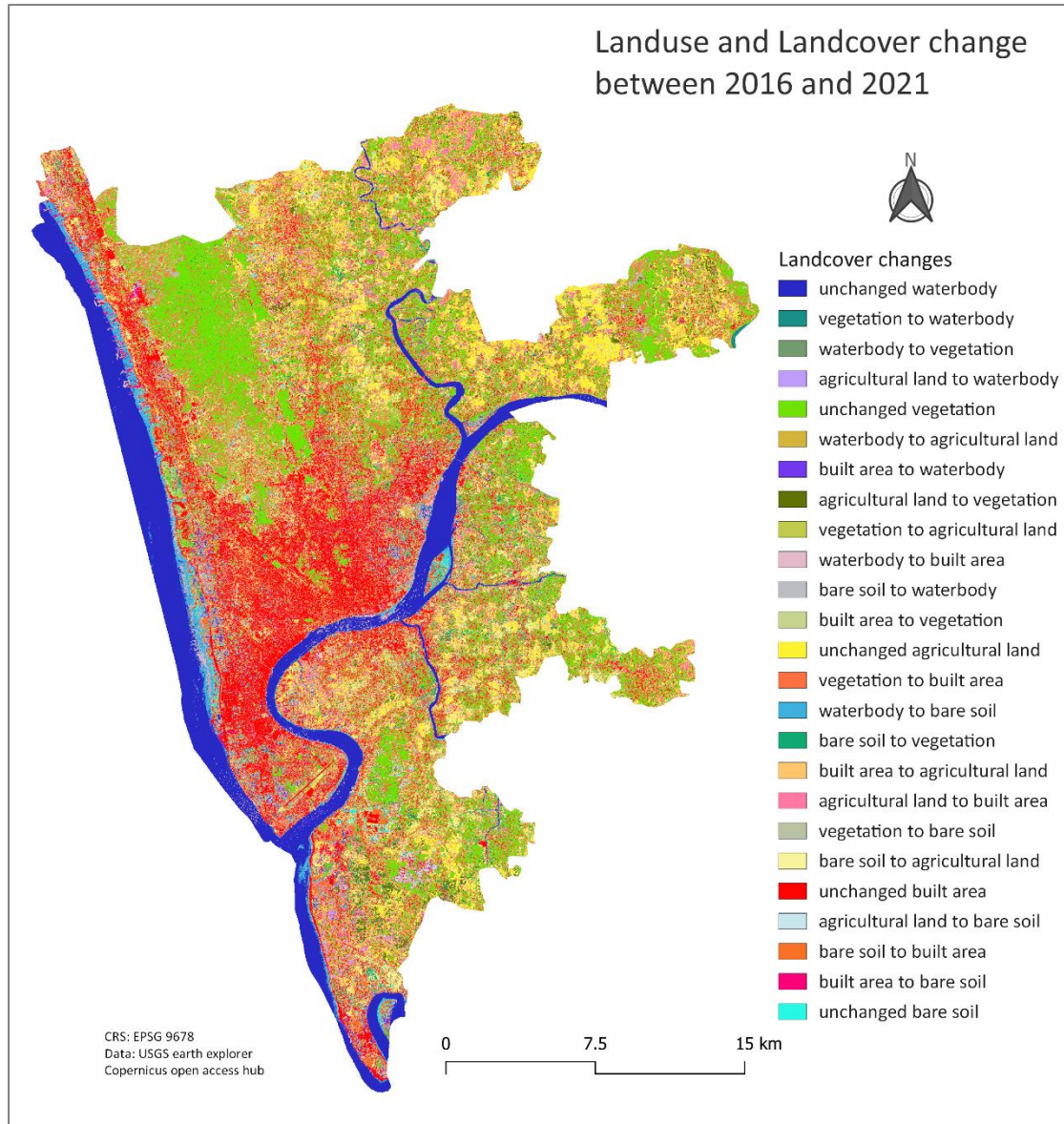


Figure 4: Landuse and Landcover Change Detection from 2016 to 2021

3.4 Urban Expansion Analysis

In order to visualize the distribution of landcover classes nine buffer zones were drawn each with 1km diameter (Annex 6.2). Then to calculate share of each LU in buffer zones, raster images were vectorized. Figure 5 and 6 visualizes the share of each landcover class in every buffer zone where it is observed that, built area decreases with an increase in buffer zone whereas agricultural lands, vegetation and bare soil increase. According to Table 4, in both years, the first 1km diameter from city center was dominated by built area (68.5% in 2016 and 73% in 2021). In 2016, proportion of built area was high on all the buffer zone except the last two (8 km and 9 km), which were dominated by vegetation. But in 2021, built area covers most of the share in every buffer

zone, although it reduced from 73% to 36%. Highest vegetation proportion was shown in 8km buffer in both years.

Table 4: Share of LU class in buffer zones

2016									
LU class %	1000m	2000m	3000m	4000m	5000m	6000m	7000m	8000m	9000m
Waterbody	3.38	5.84	6.43	29.11	23.04	13.24	9.52	10.45	13.77
Vegetation	8.34	6.14	11.20	8.42	10.01	19.85	29.69	30.03	27.88
Agriculture	9.93	10.15	10.10	8.33	8.21	13.06	12.62	13.67	13.91
Built area	68.45	66.54	57.67	41.16	41.88	37.31	30.90	25.61	23.13
Bare soil	9.90	11.33	14.59	12.98	16.86	16.54	17.28	20.23	21.31
2021									
Waterbody	1.90	2.71	2.71	21.41	17.56	7.79	4.84	5.70	5.76
Vegetation	6.26	4.97	7.93	4.23	6.66	16.30	20.65	22.43	21.62
Agriculture	11.45	10.89	14.91	14.18	16.22	22.46	25.08	26.47	26.79
Built area	73.08	74.00	67.05	52.42	50.63	47.26	43.05	38.61	36.58
Bare soil	7.31	7.43	7.40	7.76	8.93	6.19	6.38	6.78	9.24

In 2016, vegetation covered only 8.34% in the first buffer, with some fluctuation reached to around 28% in the last buffer. But in 2021, a significant amount of vegetation has lost, from only 6% in 1km buffer to 21% in the 9km buffer. In addition, agricultural land has also increased while going further from the city center. In comparison between two years, built area has increased in 2021 in every buffer. In the last buffer, it rose from 23% in 2016 to 36% in 2021 representing a significant urban expansion even in the sub-urban regions. In 2016, vegetation covers only 8.34% in the first buffer, with some fluctuation reached to around 28% in the last buffer. But in 2021, significant amount of vegetation has lost, from only 6% in 1km buffer to 21% in the 9km buffer.

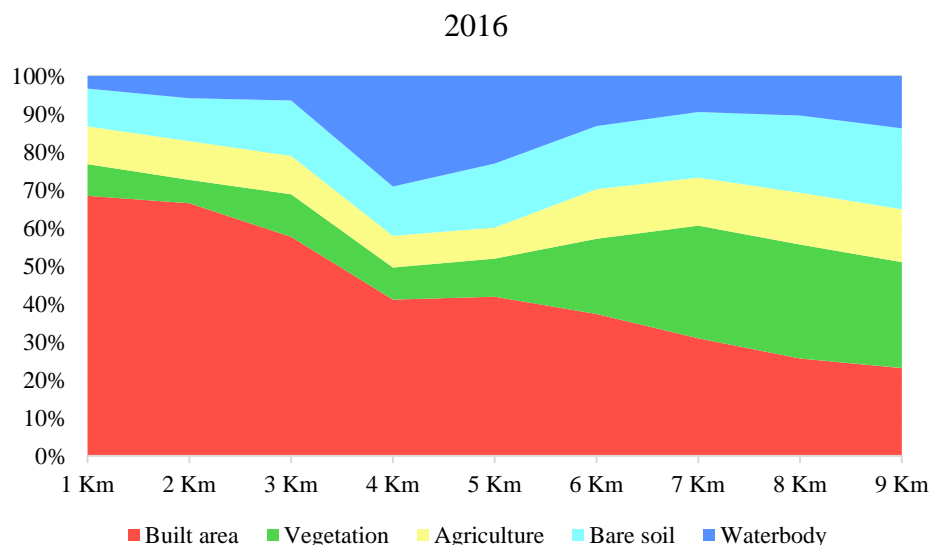


Figure 5: Landuse share by each buffer zone in 2016

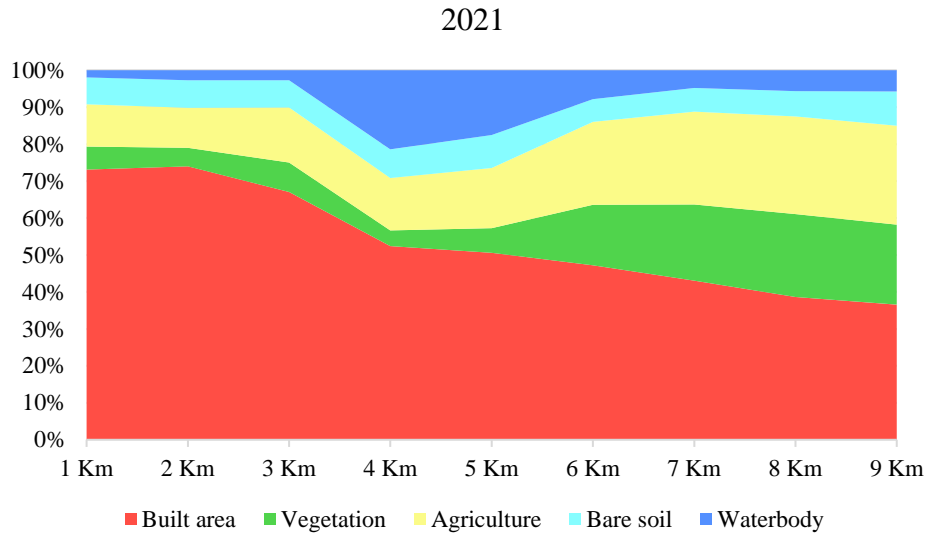


Figure 6: Land-use share by each buffer zone in 2021

In addition, agricultural land has also increased while going further from the city center. In comparison between two years, built area has increased in 2021 in every buffer. In the last buffer, it rose from 23% in 2016 to 36% in 2021 representing a significant urban expansion even in the sub-urban regions.

4 Conclusion

In this study, landuse and landcover change within the last five years in Chittagong metropolitan area has been quantitatively identified. The findings indicate that, Chittagong has been experiencing dramatic landcover change where green areas like forests, hills, hillocks, coastal plantation etc. are cleared and replaced by agricultural lands, human settlements, industries and commercial activities. In addition, some portion of waterbody and a huge amount of bare soil has converted to agricultural land and built-up areas. Areas near the city center was always dominated by built area, where the 9th buffer circle was dominated by vegetation in 2016 but replaced by built area in 2021. City growth has also been observed in the suburban region of the metropolitan converting cropland and vegetation to built area. All these represent an unsustainable growth of urbanization which possess the city at a great risk of environmental degradation, biodiversity loss, socio-economic vulnerability and overall vibrancy of the city. This study can help policymakers, urban planners and Chittagong Development Authority (CDA) by indicating the most vulnerable sites and undertake necessary steps for sustainable city planning.

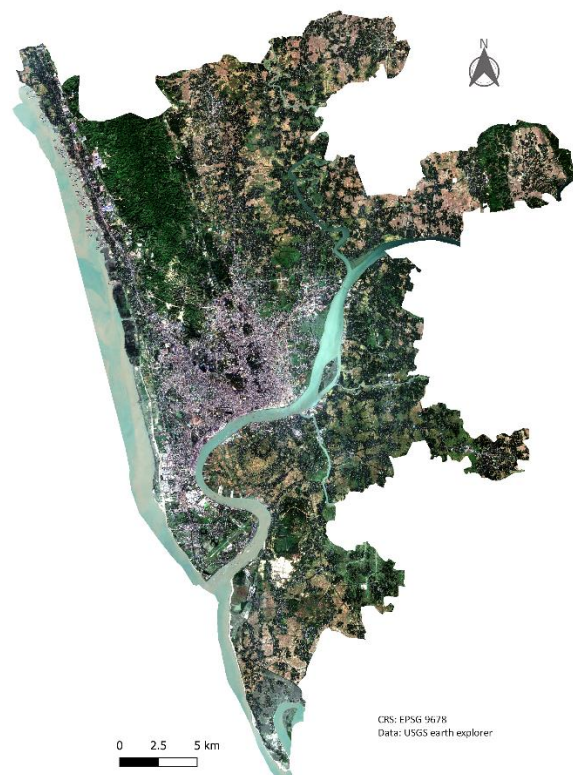
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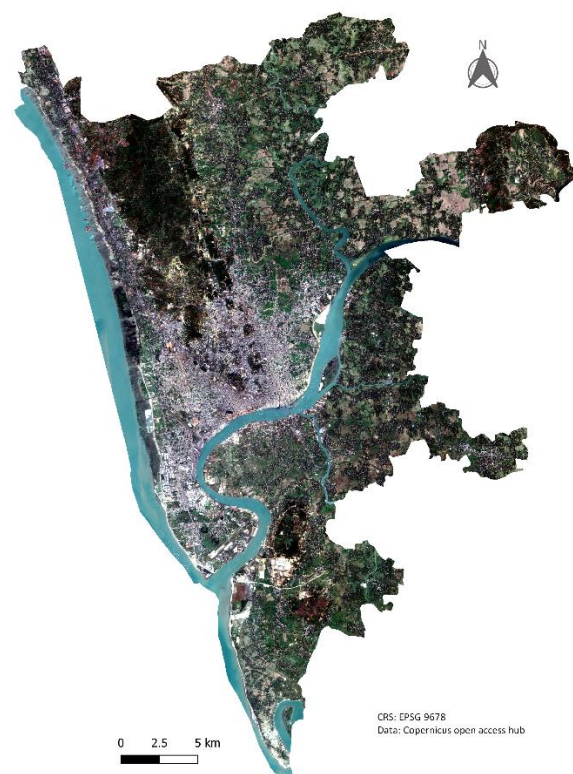
6 Annexes

6.1 Annex 1: True colour composites

2016

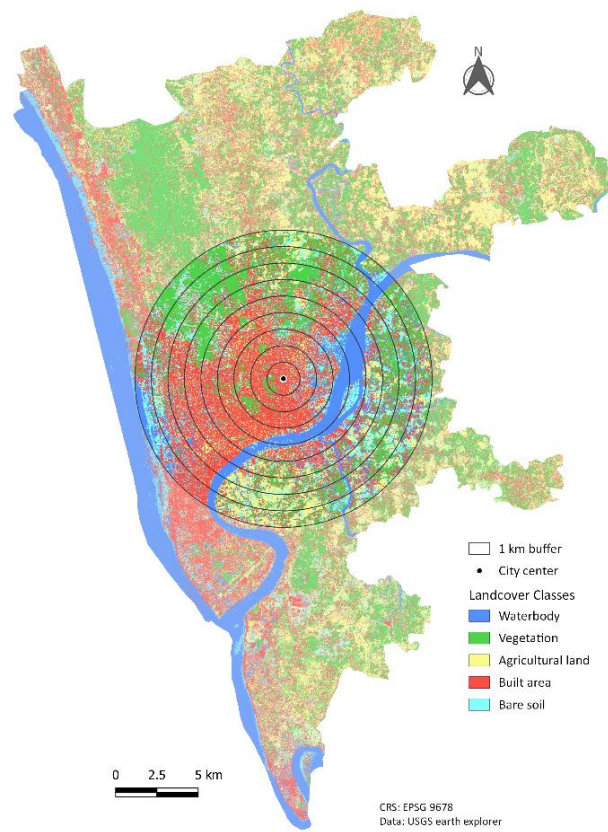


2021



6.2 Annex 2: Nine buffer zones and land-use share by each

2016



2021

