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Temporal and Spatial Variations in Surface Water and its Interrelations with Land Surface Temperature and Rainfall Patterns in Chattogram City, Bangladesh

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Abstract

The study focuses on the critical role of surface water as a strategic resource and ecological element in promoting sustainable communities. In Chattogram City, Bangladesh, rapid urbanization has led to the continuous destruction of surface water bodies, replaced by urban built-up areas. Simultaneously, climate change has disrupted rainfall patterns, resulting in water logging and urban flooding. The research aims to assess the status and degradation of surface water bodies and their connection with land surface temperature (LST) and rainfall patterns from 2001 to 2021. Remote sensing and GIS techniques were utilized for land use/land cover classification, LST analysis, Normalized Difference Water Index (NDWI), and rainfall data retrieval. Over the past two decades, approximately 20.51% of surface water bodies were lost, with 37% converted into urban areas, 28% into vegetation and agriculture, and 3% into bare land. This transformation has led to increased urban temperature, regular flash floods, and waterlogging. Preserving water bodies is crucial to improve drainage systems and mitigate unexpected water logging, urban flash flooding, and temperature rise, thus contributing to the city's sustainability in the future.

Keywords: *Surface water demolishment, Land cover changes, Urban flash flood, Land surface temperature, Sustainable city, Google Earth Engine.*

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গবেষণাটি টেকসই সম্প্রদায়ের প্রচারে একটি কৌশলগত সম্পদ এবং পরিবেশগত উপাদান হিসাবে ভূ-পৃষ্ঠের পানির গুরুত্বপূর্ণ ভূমিকার উপর দৃষ্টি নিবদ্ধ করে। বাংলাদেশের চট্টগ্রাম শহরে, দ্রুত নগরায়নের ফলে ভূ-পৃষ্ঠের জলাশয়গুলি ক্রমাগত ধ্বংস হয়ে যাচ্ছে, যার পরিবর্তে শহুরে বিল্ট-আপ এলাকা স্থান পেয়েছে। একই সাথে, জলবায়ু পরিবর্তন বৃষ্টিপাতের ধরণকে ব্যাহত করেছে, যার ফলে জলাবদ্ধতা এবং নগর বন্যা দেখা দিয়েছে। এই গবেষণার লক্ষ্য হল ভূ-পৃষ্ঠের জলাশয়ের অবস্থা ও অবক্ষয় এবং ২০০১ থেকে ২০২১ সাল পর্যন্ত ভূ-পৃষ্ঠের তাপমাত্রা এবং বৃষ্টিপাতের ধরণগুলির সাথে তাদের সংযোগ মূল্যায়ন করা। রিমোট সেন্সিং এবং জিআইএস কৌশলগুলি ভূমি ব্যবহার/ভূমি কভার শ্রেণীবিভাগ, ভূ-পৃষ্ঠের তাপমাত্রা বিশ্লেষণ, এবং স্বাভাবিক পার্থক্য পানি সূচক এর জন্য ব্যবহার করা হয়েছিল। গত দুই দশকে, ভূপৃষ্ঠের জলাশয়ের প্রায় ২০.৫০% হারিয়ে গেছে, যার ৩৭% শহরাঞ্চলে, ২৮% গাছপালা ও কৃষিতে এবং ৩% খালি জমিতে রূপান্তরিত হয়েছে। এই রূপান্তরের ফলে শহুরে তাপমাত্রা বৃদ্ধি, নিয়মিত আকস্মিক বন্যা এবং জলাবদ্ধতা বৃদ্ধি পেয়েছে। পানি নিষ্কাশন ব্যবস্থা উন্নত করতে এবং অপ্রত্যাশিত জলাবদ্ধতা, শহুরে আকস্মিক বন্যা এবং তাপমাত্রা বৃদ্ধি প্রশমিত করার জন্য জলাশয় সংরক্ষণ অত্যন্ত গুরুত্বপূর্ণ, এবং এটি আমাদের শহরকে অদূর ভবিষ্যতে আরও টেকসই করে তুলবে।

1. Introduction

Chattogram City Corporation (CCC) is a prominent metropolitan area in Bangladesh, playing a significant role in the country's economy by contributing 30% to the national GDP and accommodating 19.7% of the urban population [1]. Because of the rapid urban growth in the last two decades, this city experienced serious environmental degradation like; loss of biodiversity, deforestation, erosion of the soil, changes in the carbon sink, and degradation of ecosystems [2-4]. Here, surface water bodies have been converted into built-up areas [5] like; housing, commercial buildings, industrial buildings, roads, and other infrastructures**.** Through this process, urbanization declined the surface water bodies and increased the impervious built-up areas [6]. This haphazard urbanization surely harms the surface water bodies of the cities and environmental sustainability.

In recent years, Geographic Information Systems (GIS) with the integration of remote sensing (RS) have been used for the extraction and mapping of surface water bodies [7]. RS and GIS technique has been used to classify the LULC and to identify the changes and conversion of surface water bodies by other land uses [8]. The current study aims at an integration of RS imagery and the application of GIS techniques to identify and analyze the decadal changes in the surface water bodies of the CCC area. It also draws the significance of surface water bodies in establishing the CCC as more sustainable in near future. The application of the RS and GIS techniques for the extraction of water bodies will help to understand the extent and pattern of surface water bodies decreasing day by day. This supports decision-makers in taking the right decision and achieving a sustainable city in Bangladesh [8].

The availability of geospatial data on urban and city areas in Bangladesh is limited due to resource constraints and restrictions. In some cases, digital maps and spatial information regarding cities are unavailable or poor in quality [1 Bangladesh]. That is why the main aim of this study was to develop LULC maps and water indices of CCC for the last two decades (2001-2021) and to extract the changes in water bodies. The study also relates the change of surface water bodies to the rainfall and land surface temperature (LST) pattern of the study area.

In support of human survival and social development, surface water is an irreplaceable resource [9], and public good has social and economic values [8]. It is also a vital element for the cultivation of food crops for humans, and ecosystems [10]. The monitoring of surface water dynamics is also essential for policy and decision-making [11]. Reliable information on the surface water bodies and their spatial distribution is certainly important for environmental monitoring and various scientific disciplines, such as flood mapping, surface water survey and management, watershed analysis, wetland inventory, agriculture suitability, river dynamics, climate models, and assessment of the present and future water resources availability [9, 12].

In recent years, monitoring of changes using remote sensing (RS) techniques with the integration of GIS is widely used for assessing forest and vegetation change, LULC change, disaster monitoring, urban sprawl, and hydrology [9, 13]. Moreover, RS technologies are excessively useful in the case of periodic assessment and monitoring of urban land covers [1 Bangladesh]. At present, there has been a great dearth of research work on the status and demolishment of the surface water bodies of this city. For sustainable development and policy-making in cities and communities, the findings of this investigation may be helpful. That's why the study uses the RS and GIS techniques to analyze the spatial and temporal changes in surface water bodies and their probable impact on the city communities. The primary objectives of the current study are mapping and visualizing the status of surface water and decadal changes in the CCC. The specific objective is as follows: 1) Mapping and visualizing the changes in CCC, LULC, and surface water using multi-temporal Landsat images for 2001, 2011, and 2021. 2) To visualize the rainfall pattern, LST, and Normalized Difference Water Index (NDWI) time series data for the last 20 years using the CHIRPS rainfall dataset and Landsat images. 3) Analyzing the potential effect of surface water degradation in sustainable city management.

2. Materials and Methods

2.1. Description of the study area

The research was carried out within Chattogram City Corporation (CCC) as depicted in Figure 1, encompassing the geographical coordinates between 22°14' to 22°22' N latitude and 91°46' to 91°51' E longitude. The region comprises 41 administrative divisions referred to as wards [14]. The Karnaphuli River is located on the southeastern side of this city [15]. Chattogram City in Bangladesh is bordered by Hathazari and Sitakunda Upazila to the north, Anowara Upazila and the Karnaphuli River to the south. To the east, it is surrounded by Raozan Upazila, Boalkhali Upazila, and the Karnaphuli River, while the western side is bounded by the Bay of Bengal and Sitakunda Upazila. According to Hussain et al. [5], the total area of this city is 158sq.km or 15800ha, but in our study, it was found the area as 16930 ha.

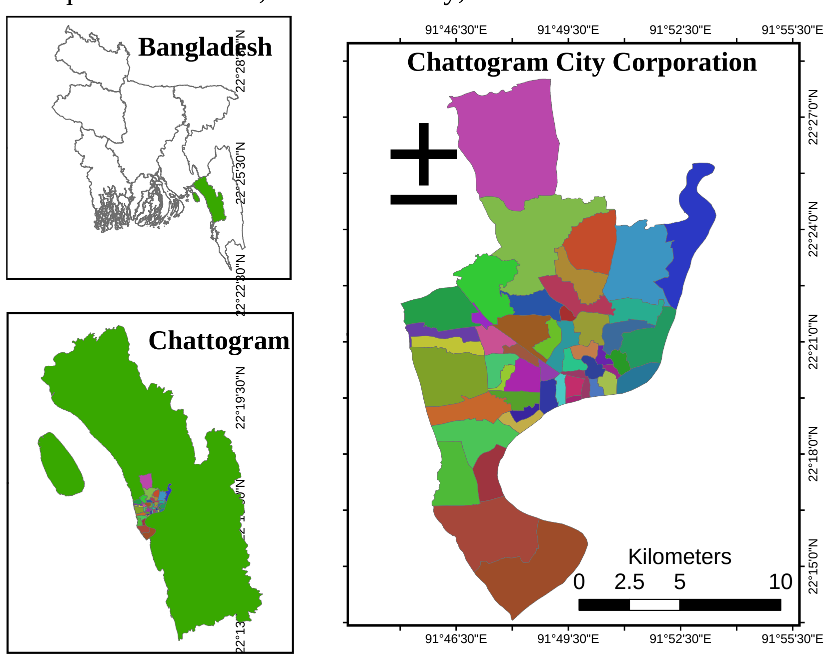


Figure 1. Map of the study area

2.2. Methodology of the study

To accomplish the study objectives, the researchers employed a series of methodologies, including delineating the study area, selecting suitable satellite imagery, preprocessing the images, comparing satellite-derived indexes with supervised classified LULC maps for surface water identification, post-processing the LULC map to extract surface area data from each image, change detection through conversion matrix analysis, calculating NDWI and LST, obtaining time series of NDWI and LST values, and extracting rainfall time series data. Figure 2 shows the overall methods followed by the current study to identify the changes in surface water area and to get the NDWI, LST, and rainfall time series data for 2001 to 2021.

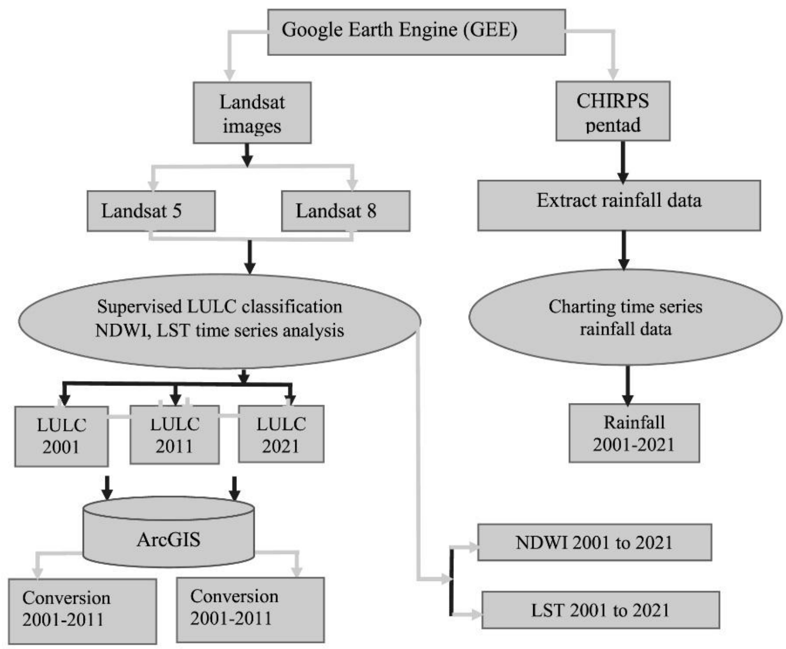


Figure 2. Methodological flow chart of the study.

2.3. Source of remote sensing data used for the study

The research utilized calibrated Top-Of-Atmosphere (TOA) reflectance data from Landsat-5 Thematic Mapper (TM) and Surface Reflectance (SR) data from Landsat-8 Operational Land Imager (OLI) (as shown in Table 1) for LULC classification, as well as time series analysis of NDWI and LST. Additionally, rainfall data was obtained from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) pentad precipitation dataset [16]. The spatial resolution of the Landsat 5 and Landsat 8 imagery is 30 meters, and the CHIRPS images are 5566 meters [16]. Current study used NDWI because it was found superior to other indexes to assess the spatiotemporal changes of the water body as evident by the study of Ashok et al. [17].

Table 1. Details of satellite imagery used for the study *(OLI= Operational Land Imager; TIRS= Thermal Infrared Sensor; TM= Thematic Mapper)*

Satellite	Sensor	Resolution (m)	Period use for image composite
Landsat 8	OLI-TIRS	30x30	01-12-2021 to 31-12-2021
Landsat 5	TM	30x30	01-12- 2011 to 31-12-2011
Landsat 5	TM	30x30	01-12-2001 to 31-01-2001

2.4 Processing of satellite imagery

The processing of the satellite imagery was performed by GEE JavaScript Application Programming Interface (API) and ArcGIS 10.8 interface. The processing activities are as follows.

2.4.1 Preprocessing of satellite imagery

This study used multi-temporal Landsat images (2001, 2011, and 2021) to extract and evaluate land cover changes in CCC of Bangladesh based on USGS free cloud Landsat satellite imagery and supervised classification using Random Forest (RF) classifiers. The Google Earth Engine (GEE) platform, accessible at (https://earthengine.google.com/) offers complimentary Landsat datasets sourced from the United States Geological Survey (USGS) available at (https://www.usgs.gov/) [18]. The dataset used in this study is an atmospherically corrected collection of Landsat 8 OLI surface reflectance (SR) and Landsat 5 TM top-of-atmosphere (TOA) reflectance [19 and EO-1 ALI sensors]. First of all, the study used a cloud and shadow bitmask of the Landsat (5 & 8) imagery, then used a median composition of the collection with a clipped study area. After that, it was used the required processing for the LULC supervised classification, NDWI, and LST time series analyses. For the CHIRPS pentad precipitation dataset, there has no preprocessing is required as it is a special collection only for the precipitation with in-situ station data [16].

2.4.2. The classification of the LULC

LULC classification of Landsat 5 TM and Landsat 8 OLI images was conducted on the GEE platform. The following steps were followed for this processing of images: (1) the selection of TOA reflectance data of December for each study year and using cloud cover sorting to get the cloud-free collection. The temporal filtering of December and January for all of the LULC were chosen for reducing the seasonal variation in surface water bodies. In December and January, CCC area mostly does not experience rainfall. (2) Mosaicking and clipping the cloud-free image collection and visualizing natural color images for interpretation of the LULC classes. (3) The study select a random forest (RF) classifier algorithm for supervised classification as it has more processing power than other algorithms for data noise and over-fitting [20]. Moreover, RF usually provides higher accuracy and can deal with complex datasets of large dimensions than other traditional algorithms [21]. (4) A confusion matrix is used for evaluating the accuracy of LULC classification by overall accuracy and kappa coefficient. The confusion matrix provides the correspondence between the LULC classification output and the validation data taken by the algorithm from the training samples. (5) After that, the areas of different land cover classes were calculated in GEE, and then the raster-classified data were exported for further processing in ArcGIS.

2.4.3. Land cover classes used for the classification

Based on the geographical characteristics and the purpose of the study, the study used four broad LULC classes (*viz.* water bodies, bare land, agricultural & vegetation, and urban area) for supervised classification. A LULC classification scheme with all classes and their description is shown in Table 2.

Table 2. Classification scheme for land use and land cover (lulc) in Chattogram city corporation.

LULC Classes	Description
Water bodies	This class includes permanent and seasonal open water bodies like; ponds and reservoirs, lakes, ditches, marshy land, wetlands, and aqua fishing.
Bare land	Bare land includes barren land, exposed soils, construction sites, excavation sites, landfill sites, and uncultivated open land.
Agriculture and Vegetation	This class includes all green vegetation like; hilly forest including herbs and shrubs, homestead forest, coastal mangrove vegetation, fruits orchards, vegetables, and paddy fields.
Urban area	Urban areas are considered the following residential and commercial areas, industrial areas, transportation, and other impervious areas.

2.5. Accuracy assessment

The accuracy assessment of LULC classification is essential because it assesses the effectiveness of the correctness of the classified pixels [22]. In this study, to obtain the overall accuracy (OA) of the supervised classification the GEE-based error matrix was used. OA is one of the most popular agreements for the measurement of the accuracy of supervised classification. For validation of the classification, 30% of the samples were used by splitting the whole samples. In this study, equation (1) was used for the calculation of the OA based on the error matrix [23].

$$OA = \frac{\sum_{i=1}^{q} n_{ii}}{n} \times 100 \quad (1)$$

Here,

OA = overall accuracy; **n=** total number of pixels; **i =** each single class; **q =** number of the classes; $\mathbf{n_{ii}}$ **=** diagonal elements

2.6. NDWI time series analysis

At the first, McFeeters [24] introduce the Normalized Difference Water Index (NDWI) for the detection and measurement of surface water bodies and their spatial extent. The NDWI values greater than zero are considered water surfaces and less than zero or equal to zero are considered non-water surfaces [25]. NDWI is an open water feature delineation method by using remotely sensed satellite images. The NDWI used the reflection of visible green and near-infrared radiation light to detect the water surface water bodies by eliminating the reflection of vegetation and soil [24]. In this study, the NDWI raster was generated using the following formula (2).

NDWI = ((Green-NIR) / (Green+NIR)) [24] (2)

For NDWI time series analysis, the study used preprocessed satellite imageries which were similar processes to LULC classification. Then, the current study used equation (1) over a map GEE JavaScript function to calculate the NDWI value of the study area over a period. After that, it was used GEE charting algorithm (UI.Chart.image.series) to visualize the time series chart of NDWI by using a mean reducer (ee.Reducer.mean()) to get the mean of NDWI for the whole study area. Finally, the study export the CSV file for data cleaning, visualization, and further analysis. In this study, NDWI has been estimated for 20 years of January 2001 to December 2021.

2.7. LST time series analysis

There have been so many ways to derive Land Surface Temperature (LST) from satellite-based remotely sensed images. In this study, Land surface emissivity (Ɛ) and the Normalized Difference Vegetation Index (NDVI) based LST derivation methods was used. After preprocessing the Landsat 5 and Landsat 8 images, the study used the following steps to derive LST time series data.

Step-1: The Red and NIR spectral bands of the satellite images were used to calculate the NDVI of Landsat-5 and Landsat-8 images. For Landsat-8, spectral images of band 4 (Red) and band 5 (NIR) and for Landsat-5, band 3 (Red) and band 4 (NIR) were used for calculating NDVI by using equation (3).

$$NDVI = ((Red-NIR) / (Red+NIR) \ [26] \qquad (3)$$

Step-2: Fractional vegetation (FV) is the proportion of vegetation calculated by using equation (4) [27, 28], where NDVI is obtained from step-1 and $NDVI_{min}$ are obtained from NDVI values using a GEE reducer (reduceRegion) algorithm.

$$FV = ((NDVI-NDVI_{min}) / (NDVI_{max}-NDVI_{min}))^2 \qquad (4)$$

Step-3: Land Surface Emissivity (LSE) is a proportionality factor which an essential parameter for estimating the LST and scaling the black body radiance (Plank's law) which is used to measure emitted radiance [29]. The study used equation (5) [27, 28] for calculating the emissivity (ε) of the land surface area by using the Landsat 5 and Landsat 8 images.

$$\varepsilon = 0.004FV + 0.986 \qquad (5)$$

Here,

0.004 - Standard deviation of soil bands,

0.986 - Emissivity of the soil and vegetation

Step-4: The final step of calculating LST is the use of the brightness temperature (BT) of (Landsat 8, Band 10) and (Landsat 5, Band 6), and LSE derived from FV and NDVI. For retrieving LST, the study used equation (6) [28, 30].

$$LST = (BT/ (1 + (W * (BT / \rho))*\log (\varepsilon))) - 273.15 \qquad (6)$$

Here,

LST - LST in Celsius (°C)

BT- Brightness temperature bands (Band 6 for Landsat 5 & Band 10 for Landsat 8)

W – The average wavelength of the emitted radiance of BT (11.45 µm for Landsat 5 & 10.895µm for Landsat 8)

$\rho = h \times c/\sigma = 1.438 \times 10^{-2}$mK ($\sigma$=Boltzmann constant=$1.38 \times 10^{-23}$J/K, h=Planck's constant=6.626×10^{-34}Js, c = the velocity of light = 2.998×10^{8} m/s)

Ɛ - Land surface emissivity

Step-5: Finally, the study used a GEE JavaScript function (step-1 to step-4) over the map to get a time series LST value for each of the images over the study period. Then, it used a median reducer over the study area to get the mean LST value for the whole area and make a chart to export the value in a CSV file for further analysis. In this study, LST has been estimated for 20 years of January 2001 to December 2021.

2.8. Rainfall time series data extraction

In the case of rainfall data, the study used the CHIRPS pentad precipitation dataset which was freely available on the GEE platform. This dataset has more than 40 years of quasi-global rainfall data ranging from 1981 to near-present. However, the study select this dataset not only as a free dataset but also it is a collaborative dataset having the in-situ rain gauge data gridded with satellite-derived data. So, it is free from the biases of satellite terrain complexity and fewer rain-gauge station in rural regions [16].

First of all, the study load the dataset in GEE by this link (ee.ImageCollection('UCSB-CHG/CHIRPS/PENTAD')). After that, it filter this dataset according to our required time series and study area. Then, it used a mean reducer to get the mean rainfall for the whole study area. Finally, the study used a chart to visualize the final output before exporting the CSV file of the rainfall dataset.

2.9. Post-processing of LULC raster data

Based on the LULC classified raster, a conversion matrix of different land cover from 2001 to 2021 was prepared to show the internal change of the different land-cover classes. For this purpose, the study used the spatial analysis and geo-processing tools of ArcGIS desktop 10.8 interface and the pivot table of MS Excel. The study also produces a conversion map of the surface water bodies to show the spatial and temporal changes. For validation of the surface water bodies, the author utilized 150 randomly generated points using Google Earth Pro high resolution satellite images. It was chosen as it provided temporal coverage of high resolution satellite imageries for the study period. The validation supported the results of LULC classification.

3. Results and Discussion

3.1. Land use land cover (LULC) changes

In this study, the classification of LULC of CCC was used to analyze the decadal changes in land use and land cover, especially the surface water bodies. The current study use four categories including water bodies, bare land, agricultural and vegetation land, and urban areas for LULC classification. The land cover change of CCC in Figure 3, shows that the surface water bodies of the north and northeastern are continuously demolished by other land uses, especially urban areas and bare land.

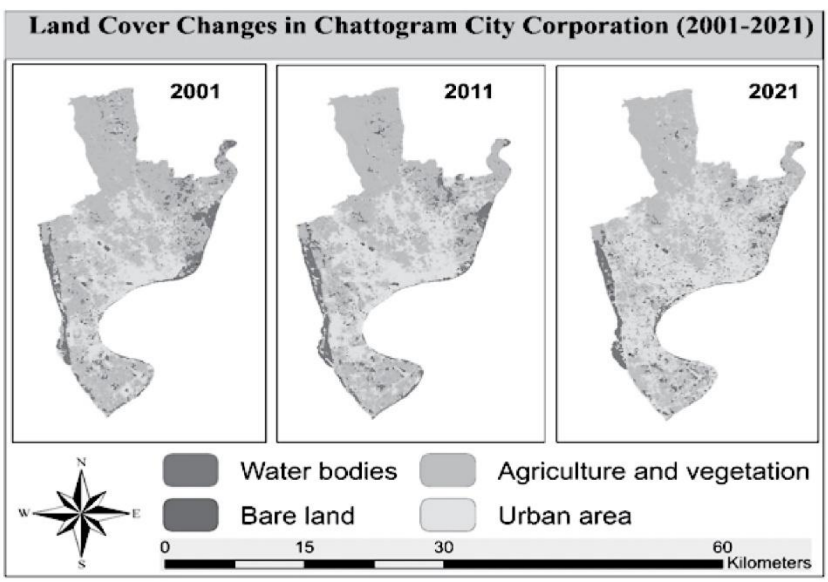


Figure 3. Land use and land cover classification map of Chattogram City Corporation, Bangladesh.

3.2 Deviation in land use of CCC

In 2001, the total amount of surface water bodies in CCC was 3123 ha, and the urban area was 5278.34 ha, whereas, in 2011, little change in the water bodies was noticed. Here, the water bodies were reduced to 2853 ha, and as a result, the urban area increased from 5278 ha to 6106 ha. A significant change in surface water was noticed in the last decade. Increasing population and settlement pressure by humans were forced upon the water bodies and decreased to 2482 ha.

Noticeably, the urban area increased to 7671 ha, which was 6106 ha in 2011. In Table 3, it is also noticeable that agricultural and vegetation land somewhat decreases with water bodies. Whereas, bare soil somewhat increases accompanied by urban areas. In the LULC of 2021, the significant increases of bare land due to new landfill in the Anandabazar coastline at the left side and another new landfill in the Bangabandhu Sheikh Mujibur Rahman Maritime University at the right side (Figure 3). It was confirmed by using Google Earth Pro high resolution time series satellite imageries and physical observation. The most important finding of this study was that, in the last decade, the demolishment of surface water bodies in urban areas was about double in comparison with the previous decade.

Table 3. Decadal land use land cover changes of Chattogram City Corporation from 2001-2021.

Land use	2001(ha)	2011(ha)	2021(ha)
Water bodies	3122.96	2853.21	2482.08
Bare Soil	42.55	58.44	193.27
Agricultural & Vegetation land	8486.06	7912.08	6583.28
Urban Area	5278.34	6106.20	7671.29
Total Area	16929.91	16929.93	16929.92

3.3. Accuracy of LULC classification

Based on the confusion matrix and validation data of GEE, the maximum overall accuracy and kappa were found for the LULC of 2021 as 0.99 and 0.98. Where the minimum was found for 2001 as 0.95 and 0.93. In the case of 2001, it was found as 0.97 and 0.96, respectively (Table 4).

Table 4. Overall accuracy and kappa statistics of land use land cover classification.

LULC year	2001	LULC	2021
Overall accuracy	0.95	0.97	0.99
Kappa value	0.93	0.96	0.98

3.4. Conversion of different land cover classes from 2001-2021

In the case of surface water bodies, which was 2957 ha in 2001 reduced to 2309 ha in 2021 by the overall demolishment of 648 ha. At this time, 1082 ha of the surface water bodies were converted into urban areas and the rest of the area was converted into agricultural and vegetation 836 ha and bare land 79 ha (Table 5). In the Table 5, it was shown that 780 ha of land which was under agricultural and vegetation in 2001 was converted to water bodies in 2021. The urban area was also converted into surface water bodies by 568 in 2021, this may be the mixed urban area that was previously covered by the urban structure like culverts, urban wastage, and others. Or, it is the effect of seasonal changes of surface water up-down in the low land urban areas.

Table 5. Land cover changes in Chattogram City Corporation (2001 to 2021), Bangladesh.

				2021 (ha)		
Land Cover Classes		Agriculture and vegetation	Bare land	Urban area	Water bodies	Grand Total
2001 (ha)	Agriculture and vegetation	**5054.71**	41.93	2770.62	779.80	8647.04
	Bare land	10.74	**1.32**	23.58	2.45	38.09
	Urban area	726.69	55.22	**3938.00**	567.52	5287.42
	Water bodies	835.98	79.41	1082.26	**959.71**	2957.37
	Grand Total	6628.11	177.88	7814.45	2309.47	16929.92

3.5. Demolishment of surface water bodies

Figure 4 shows the direct impact of urbanization on the demolishment of surface water bodies. Suspended sediments released from construction activities enter into surface water bodies by urban runoff [8]. The water bodies and wetlands of CCC have been filled in an increasing trend in the last 20 years. In this investigation, current study found that almost 37% of the water surface was converted into an urban area and 28% into vegetation and agriculture. Where 3% water surface was converted into bare land.

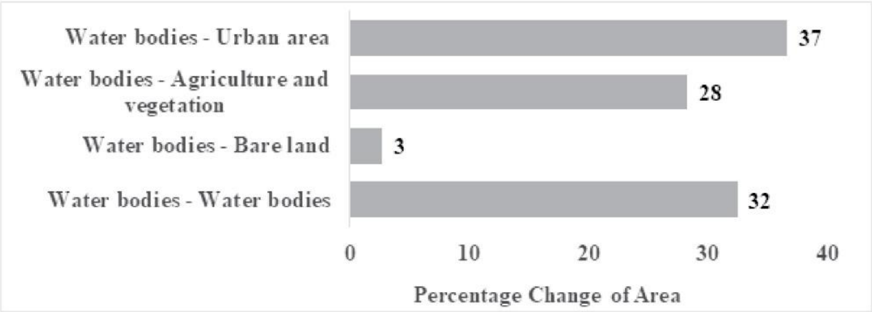


Figure 4. Surface water bodies filled up by urbanization in Chattogram City Corporation (2001-2021).

The percentage degradation of the surface water bodies of Chattogram city in the last decade, 13.01% was almost double that of the previous decade 8.63% (Table 6). The main waterway becomes bottleneck compressed because of the development of urban residential areas in the water bodies and river basins. It reduces the width of the water channel and watercourses, resulting in the insufficient movement of rainwater and causing urban flash floods [31].

Figure 5 shows the direct association of urbanization with the surface water body filling up or demolishment. In Figure 4, the blue area indicates an unchanged water body from 2001 to 2021 and the red area indicates a conversion of the water body to an urban area, whereas the yellow and green area indicates the change of the water body to bare land and vegetation agriculture from 2001 to 2021. It shows that the north and north-eastern parts of Chattogram city tend to demolish its surface water bodies in a continuous process from 2001 to 2021, and most of the converted land was urban constructions.

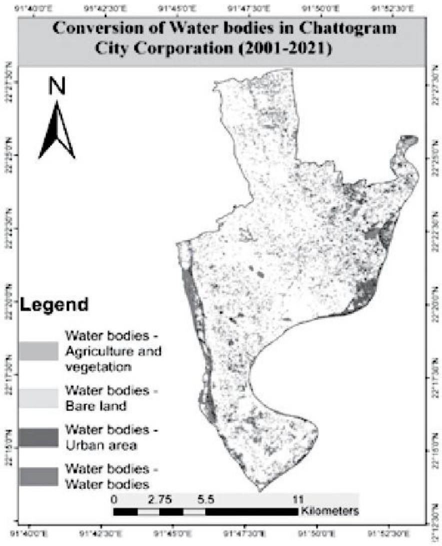


Figure 5 Demolishment of surface water bodies.

Table 6. Loss of water bodies in Chattogram city, Bangladesh during the last 20 years.

Year	Total surface water bodies (ha)	Area loss (ha)	Percentages of loss
2001-2011	3122.96	269.75	8.63
2011-2021	2482.08	371.13	13.01

Table 6 shows the destruction of the surface water bodies in 2001-2011 and 2011 - 2021. The rate of demolishment of water bodies shows an increasing trend in the recent decade. About 8.63% of the water bodies were filled up in the years 2001 to 2011. The parentage loss of water bodies almost doubled by 13.01% from 2011 to 2021, which indicated a very alarming situation for surface water in the Chattogram city area. Because of the haphazard and unplanned urbanization of the CCC area, water bodies were continuously demolished at an increasing rate. A properly planned urbanization might be reduced this alarming destruction by meeting the present demands of the increasing population [8].

3.6. The conversion of water bodies to the urban area from 2001 to 2021

In the case of water bodies, the conversion of the urban area has a great role. In Figure 6, it is shown that most of the administrative unit shows water body demolishment to a great extent, in that case, the urban area shows a great increase. The linear trend line of urban area change and water body demolishment shows an inverse relationship. So it is clear that surface water bodies in CCC are converted into urban areas to a great extent. Research by Rahman in 2022 also found that urban areas of Chattogram city showed a substantial prolongation during 2000–2010 and 2010–2020 by 2.76% to 14.98% respectively [32].

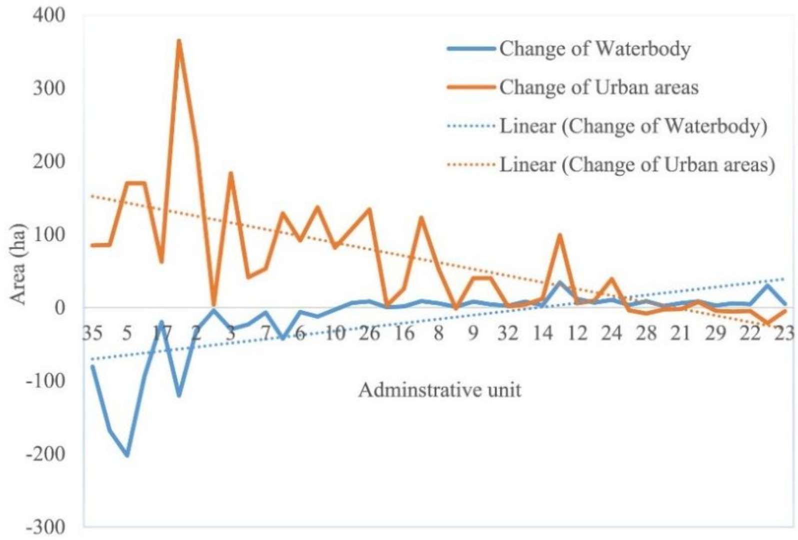


Figure 6. Conversion of water bodies to the urban area from 2001 to 2021 at different administrative units of Chattogram City Corporation, Bangladesh (*Here, positive values of the area indicate the increase in area, and the negative values indicate the decrease in the area*).

3.7. Effect of demolishment of surface water bodies on urban areas

From the time series analysis of the NDWI, LST, and rainfall data of the CCC area, it was found that the NDWI and rainfall in Figure 9, show somewhat positive slope (increasing trend). Whereas the LST in Figure 7, shows a higher positive slope (increasing trend) with time. Since the study area shows the degradation of the surface water bodies and the increment of the urban built-up areas, the increasing trend line of LST is an obvious process with the increased urbanization. The rapid growth of unplanned urbanization with impermeable surfaces like roads, buildings, and metallic roofs associated with increased population results in the increase of the temperature in the local climate [32-34]. The increasing trend of bare land with urban expansion also increased the urban LST [32] of this city. Research by Ali in 2019, revealed that a rise in urban surface water bodies contributes to cooling the urban environment, whereas a decline in such water bodies leads to an increase in urban temperatures [35].

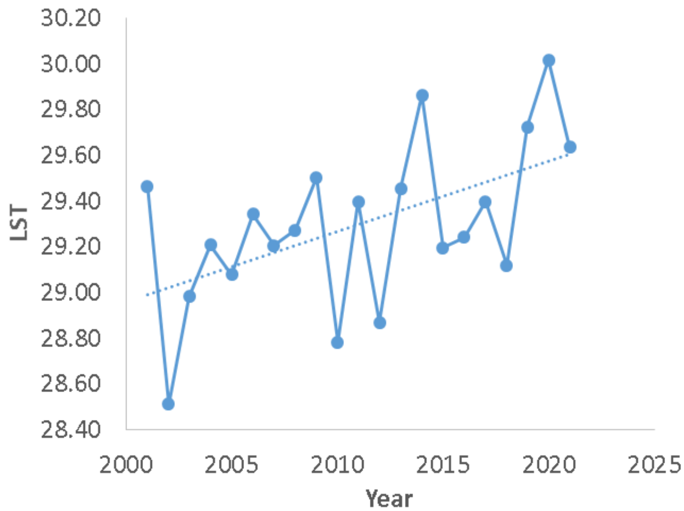


Figure 7. Time series chart of the land surface temperature of Chattogram City Corporation from 2001 to 2021.

On the other hand, in Figure 9 the increasing trend of rainfall and NDWI indicate the increasing trend of heavy rainfall, and a higher mean value of water index (NDWI) indicates a higher area of surface water bodies. This is probably the indication of the urban flash flood or urban water logging situation due to unplanned urbanization. In Figure 8 the rainfall pattern throughout the years 2001, 2011, and 2021 shows an increase in the average rainfall, especially from June to October of the year.

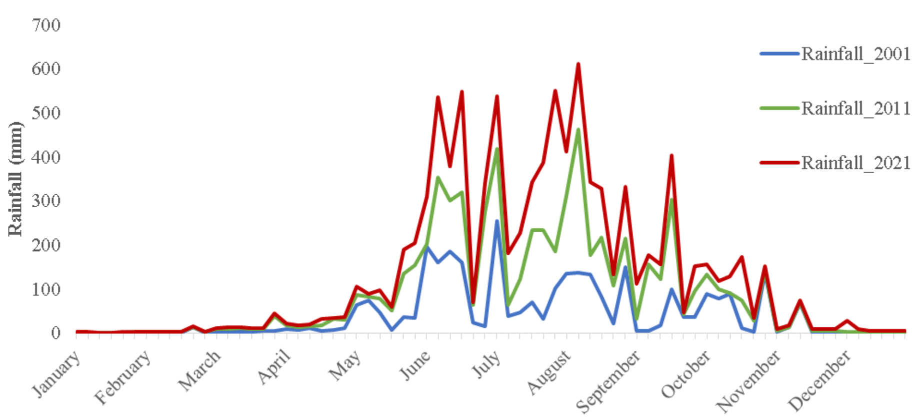
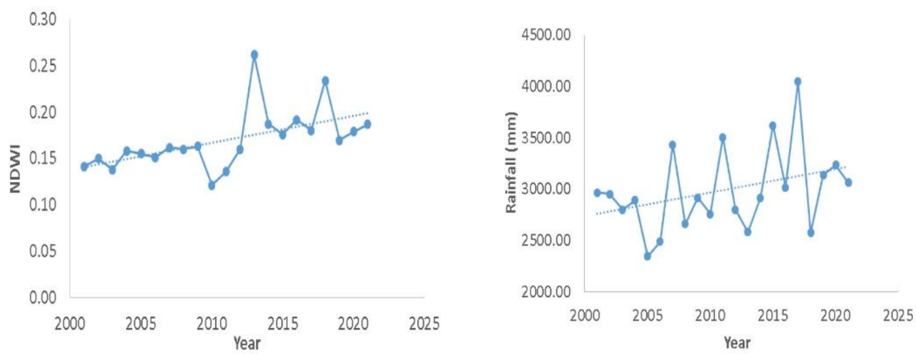


Figure 8. Variation of the rainfall pattern throughout the different years.

Since the surface water bodies or rainwater reservoirs, and the natural waterways decreased in amount, the water holding capacity of that area also decreased. Eventually, unexpected water logging in household and agricultural areas and urban flash floods become a common fact in this city [31].



a b

Figure 9. Time series chart of normalized difference water index (a) and Rainfall (b) of the Chattogram City Corporation, Bangladesh from 2001 to 2021.

3.8 Interrelation between different land uses and LST

The current study utilized regression analysis to examine the relationships between different factors and land surface temperature (LST). The results revealed a strong positive relationship between bare soil and LST, with an R-square value of 0.87. Additionally, urban areas exhibited a moderate positive relationship with LST, with an R-square value of 0.67. On the other hand, water bodies and agricultural/vegetation areas showed moderate negative relationships with LST, with R-square values of 0.57 and 0.70, respectively.

The study noted that the continuous degradation of water bodies and agricultural/vegetation areas, as well as the ongoing expansion of urban areas, contribute to an evident increase in the LST of the city, as observed in Figure 10. Moreover, Figure 7 demonstrates a consistent upward trend in LST from 2000 to 2020, which is consistent with other studies conducted in Bangladesh, including Chittagong city. For instance, Akter et al. [34] found a temperature increase of 5.5 °C within 28-year period (1990-2018) in north-western regions of the country. Similarly, Imran et al. [36] observed LST increases of 4.04°C and 6.45°C during winter and summer seasons, respectively, between 1993 and 2020.

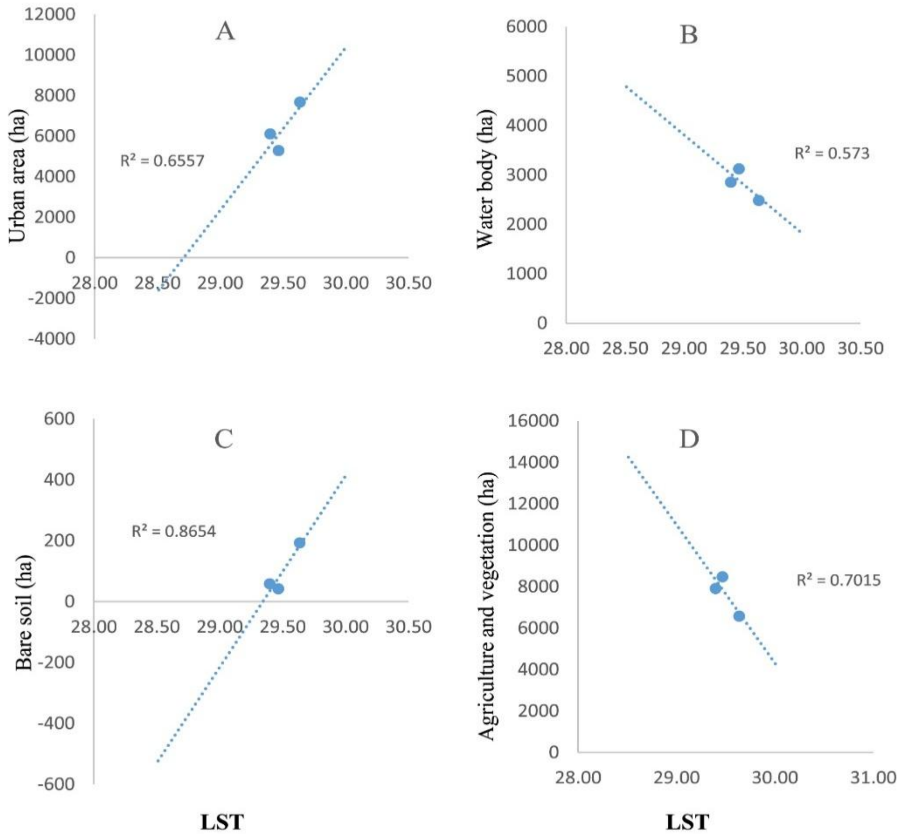


Figure 10. Impact of land use changes on the land surface temperature at Chattogram City, Bangladesh.

4. Conclusion

The preservation of surface water bodies is essential as climate change and global warming change the rainfall pattern and cause unexpected water logging and urban flash flooding. The conservation of surface water bodies increases the functionality of the drainage system and helps to reduce flash floods and unexpected water logging in the urban area. It also reduces the urban microclimatic temperature and makes the city sustainable. The conservation of surface water also helps the potential users of this water, especially the poor and marginalized people who depend on this water for their daily water demands. Reversely the continuous destruction of these resources becomes a threat to the dependent communities. The current study suggested controlling the haphazard and unplanned growth of urban areas since it is one of the key factors of surface water demolishment. Planned urbanization may reduce this destruction and can reduce the raising urban temperature and urban flash floods and unexpected waterlogging. The authorities should take vital activities to hinder further deterioration of the surface water body by executing a further investigation and taking necessary steps on time for sustainable use of surface water bodies.

Limitations of the study

The major restriction of this consideration is the inaccessibility of high-resolution satellite images. Since the current study is based on the land use and land cover classification yield of satellite images of Landsat-8 and Landsat-5 having spatial resolution 30m x 30m. The surface water bodies inside an area less than 900 sq.m. seem not to be found throughout this study. That's why the exactness of this result essentially depends on the image resolution. The study utilized TOA of Landsat 5 due to the unavailability of good quality SR for this study area during December and January for the year 2001 and 2011. However, the result of supervised classification could reduce the error due to the sensor's limitation.

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Conflict of Interest: The authors declare that they have no conflict of interest.

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