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Impact of landuse change and urbanization on urban heat island effect in Narayanganj city, Bangladesh: A remote sensing-based estimation

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ABSTRACT

Urban development always had a significant influence on Land Surface Temperature (LST). The impacts of urbanization on the trend of temperature rise and the degradation of the ecological environment over a period of 8 years before and after the establishment of Narayanganj City Corporation have been studied in this paper. LST has been calculated by utilizing land-use change map and computation of vegetation coverage using the Normalized Difference Vegetation Index (NDVI), assessment of building coverage using the Normalized Difference Built-up Index (NDBI), and using the Urban Thermal Field Variance Index (UTFVI) for the evaluation of ecological index. The result indicates that the LST has been tremendously affected by the built-up areas, especially where the heavy industries had been established. The mean LST between 2011 and 2019 went upward by 1.86°C. A negative correlation has been found between the LST and NDVI, which suggests that the green coverage debilitates the effect on urban temperature. On the other hand, the positive correlation found between the LST and NDBI shows that the built-up or paved area intensifies the LST and gives rise to Urban Heat Island (UHI). The areas around vegetation and waterbody showed comparatively lower temperatures while the temperature of the built-up area exhibited an increasing trend. The study reveals that proper heat action plans and toolkits are necessary for urban heat management and ensuring sustainable city development.

Introduction

Socio-economic processes such as population growth, economic development, trade, and migration leads to land-use change; impacts of which can be observed and measured globally, regionally, and locally (IPCC, 2007; Goklany, 1996). Luke Howard first presented the evidence that city air temperatures are often higher than the surrounding countryside (Howard, 1833; Oke, 1982), while later validated this notion in 2001 Weng (2001), Martin et al. (2015). Land Surface Temperature (LST) is one of the key parameters used in this regard (Li et al., Apr. 2013). Studies have shown that industrialization along with other anthropogenic attributes generates massive heat flux, increasing LST around the urban centers of the world (Oke, 1982; Yao et al., 2021, Sultana and Satyanarayana, 2018, Voogt and Oke, 2003, Wang et al., 2007, Hamdi and Schayes, 2008, Zhang et al., 2010, Ayanlade, 2016, Mushore et al., 2017, Bai et al., 2020). Land cover and its changes are the major causes of environmental degradation and rapid urbanization exacerbates the situation (Singh et al., 2017, Deng et al., 2016, Ho et al., 2016, Kikon et al., 2016). The Urban Heat Island (UHI) is the phenomenon of higher atmospheric and surface temperature over the urban areas compared to the surrounding natural environments (Voogt and Oke, 2003; Sultana and Satyanarayana, 2020, Oke, 1995, Rotach et al., 2005, Roth, 2013). UHI intensity relates to the status of vegetation, water, and built-up areas and their changes over time (Chen et al., 2006). The natural or anthropogenic variations in the Land Use and Land Cover (LULC) pattern can increase the surface as well as the atmospheric temperature by several degrees compared to the undeveloped surroundings (Sultana and Satyanarayana, 2020; Sherafati et al., 2018).

Developing countries have seen a rapid increase in urbanization, with South Asia being one of the hotspots with nearly 15% of the urban population in the world, along with Latin America and sub-Saharan Africa due to land use change (Kotharkar et al., 2018;Hong et al., 2021). South Asian UHI-related publications have increased significantly with major concerns about the implications in the bigger cities like Dehli, Chennai, Dhaka, Chattogram, Khulna, and Kolkata (Kotharkar et al., 2018;Chaudhuri and Mishra, 2016). The increasing population density in the cities of Bangladesh is resulting in a reduction of surface water bodies, vegetation, and an increase in built-up areas, which is driving the acceleration in the rise of LST (Khan et al., 2019). In addition, hy-

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drological ecosystem services are also affected by the land use change with river discharge and sediment balance in the rivers being altered (Tuladhar et al., 2019;Yohannes et al., 2021). Dhaka city is one of the starkest examples as the built-up area was found to increase by 67% since 1990, replacing the lowlands, vegetations, and water bodies, with an increase in maximum LST by 4.62°C within the study period of 27 years (Imran et al., 2021;Dewan and Corner, 2012). The study also negatively correlated the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), while the Normalized Difference Built-up Index (NDBI) was positively correlated (Imran et al., 2021). The important role of land use change was also highlighted by Kalnay and Cai (2003) who estimated 0.27°C surface warming per century in continental America (Kalnay and Cai, 2003). In this respect, Ullah et al. (2019) suggested urban plantation and decentralization as possible mitigative measures which can be assessed using parameters such as NDVI and NDBI (Ullah et al., 2019). The NDVI values are taken as an indicator of the status of vegetation (Sultana and Satyanarayana, 2018). The NDVI process creates a single-band dataset mainly representing healthy biomass. NDVI values are between −1.0 and 1.0, where the negative values are mainly generated due to clouds, water, and snow. The values near zero are mainly generated from rocks and bare soil. The very low values of NDVI (0.1 and below) correspond to barren areas. The moderate values (0.2 to 0.3) represent parks, shrubs, and grassland, while the high values (0.6 to 0.8) indicate the forested area. Normalized Difference Built-up Index (NDBI) is also a useful parameter for studying the relationship between LST and built-up area (Zha et al., 2003).

Moreover, similar results have been found for the industrial megacity Chattogram, where the built-up area was found to increase at a rate of 3.55 km^2/yr, with the LST rising from 20.17°C in 1990 to 25.83°C in 2018 (Roy et al., 2020). NDBI was again positively correlated with LST, while the vegetated hilly areas, forest covers, and floodplain regions were negatively correlated (Roy et al., 2020, Islam and Ma, 2018, Al Kafy et al., 2021). Also, Raja et al. (2021) identified the seven most vulnerable wards in Chattogram City Corporation in this regard (Raja et al., 2021). Other major divisional cities of Bangladesh have also exhibited these trends in similar studies (Dewan et al., 2021). These results suggest a need to investigate the cities and towns undergoing rapid urbanization, and Narayanganj is one such city near the Dhaka Metropolitan (DMP) area which is undergoing rapid industrialization, similar to Chattogram. Assessment of spatio-temporal changes is important for different sectors like agriculture and industrial aspects (Belenok et al., 2021). It is essential to understand the trends of change in LST and other relevant parameters to effectively address the issues arising from UHI effects, while land use change related risks can be minimized through initiating proper measures like proper land use management (Noszczyk et al., 2020). Some studies on the impact of land use changes and urban heat islands are available to some extent, while the impact of land use change and urbanization on urban heat islands are not so common – specifically for peri-urban areas (Al Kafy et al., 2021; Dewan et al., 2021; Dewan and Yamaguchi, 2009; Al Kafy et al., 2020). Narayanganj city is one of the potential areas in Bangladesh for vast industrial development and already commercial and industrial areas are growing with improved road structures. Focusing on this background, this study aims to identify the UHI intensity of Narayanganj city by assessing the changes in LULC, LST, NDVI, NDBI, and UTFVI for the years 2011 and 2019. The findings of this study would be beneficial for the urban planners and policymakers to plan a sustainable urban environment for Narayanganj.

Methodology

Study area

Narayanganj City Corporation (NCC) is the largest city in Narayanganj District, Bangladesh (Fig. 1). The city was formed into a City Corporation in 2011 by combining Narayanganj Sadar municipality, Siddirganj municipality, and Kadamrasul municipality following the Local Government Rules, 2010. NCC is located 17 km southeast of the capital Dhaka and is located between 23°33′ and 23°57′ north latitude and 90°26′ and 90°45′ east longitude (IPCC, 2011). Being at the bank of the Shitalakshya River and adjacent to the capital Dhaka, the city was historically a commercial and industrial hub that attracted both local and foreign investors. The city was historically known as 'The Dundee of East' due to its large jute markets and jute processing industries. Due to the ease of accessibility to nearby markets, raw materials, and availability of human resources, the city gradually established a large number of industries. These industrial units are mostly located on two banks of the Shitalakshya River and the east bank of the Buriganga River, providing employment opportunities in the city. With the steadily growing industrial and commercial activity over the last few years, the emerging city is experiencing rapid population growth. With a total area of 47.22 km^2 (NCC, 2016), Narayanganj City Corporation had a total population of 709,336 with a density of 15,021 per km^2 in 2011 (IPCC, 2011). According to the City Corporation, the current area under them is 72.43 km^2 and the total population is about 2 million (NCC, 2021). The summer season is hot and dry and lasts from mid-April to mid-June. The monsoon commences in early to mid-May and lasts till mid-October. Around 70-85% of yearly precipitation occurs within this period (Banglapedia, 2021). Annual rainfall averages 2004 mm in Narayanganj. The average temperature during summer is 29.4°C with a maximum of 34.7°C. In the calendar, the winter season spreads from mid-December to mid-February and the minimum temperature is recorded at 13.4°C during January. December is the driest month of the year with an average of 5 mm rainfall and the precipitation is maximum during July with an average of 374 mm (Climate-Data.org, 2021; NASA, 2021).

Table 1
Data used and their details.

Sensor	Path	Row	Data Acquisition Date
Landsat 7(ETM+)	137	44	14/03/2011
Landsat 7(ETM+)	137	44	21/04/2019

Data used

Two Landsat satellite images from the Landsat 7 of 2011 and 2019 had been collected from the USGS website. The cloud coverage of both sets of data was less than 10 percent. These Landsat data, mentioned in Table 1 were obtained to work on the characterization of LST, so the date was chosen to fall between March and May to avoid cloudy pixel problems. All these datasets had been converted to 30m cell size and brought into the same projection to perform spatial analysis. All the satellite images were pre-processed and the relevant tasks for the LULC classification and LST computation were performed in ArcGIS 10.4.

Image classification

Supervised classification was used for the image classification. Though there are many methods for supervised classification such as parallelepiped classification; K-nearest neighbor; minimum distance classification; maximum likelihood classification; Bayes's classification (Zhu et al., 2006), in this study, the Maximum Likelihood Classification (MLC) method was adopted. The MLC quantitatively evaluates the variance and covariance of the category spectral response patterns when classifying an unknown pixel. Being based on statistical parameters, it is considered to be one of the most accurate classifiers (Shalaby and Tateishi, 2007).

Training sets were selected for image classification through MLC. The images were classified into four categories – Waterbody (waterlogged area, pond, river, lakes), Built Up Area (buildings, roads, con-

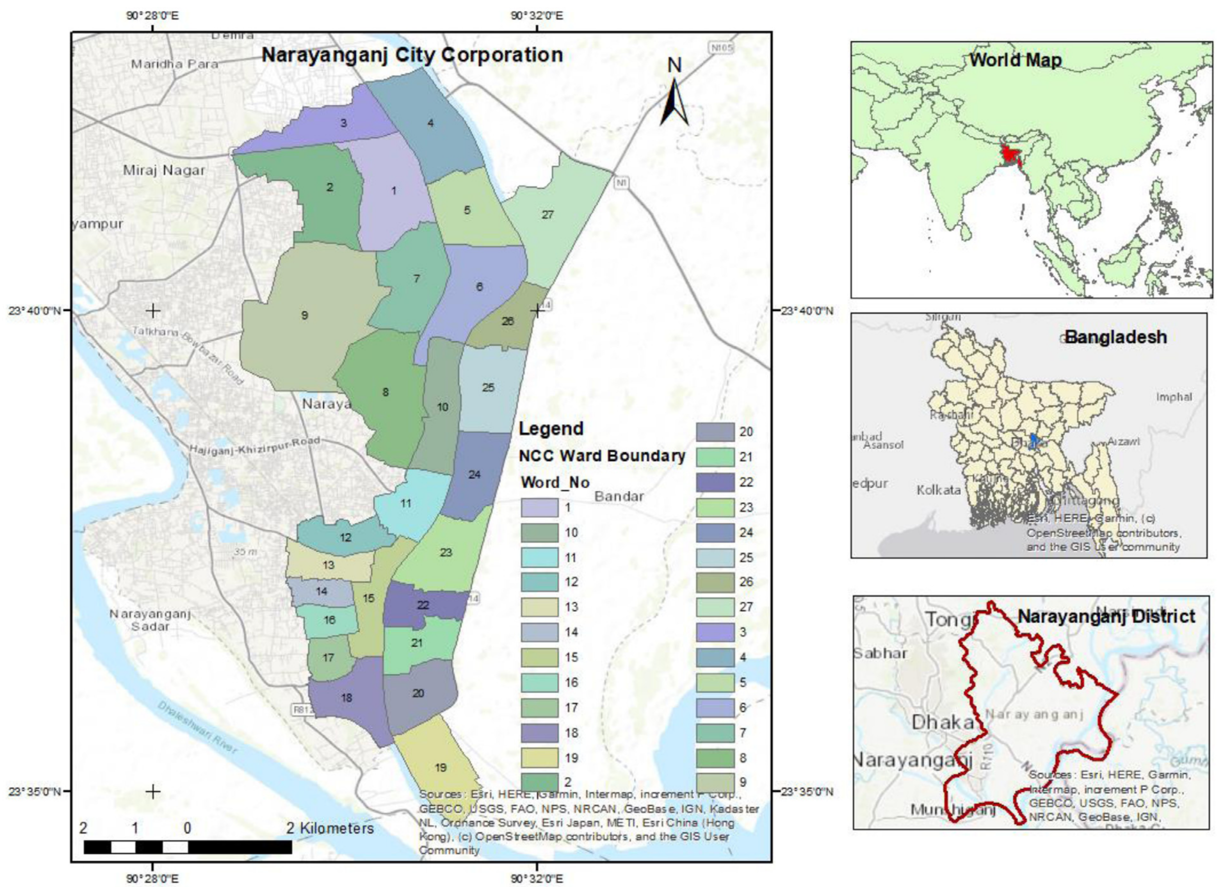

Fig. 1. Location of narayanganj city corporation, Bangladesh (Study area).

struction sites, industries), Vegetation (forestland, shrubs, herbs, agricultural land, and other vegetative surfaces), and Barren Land (sands, exposed soils). Besides the literature review points out that there are significant works have been done to identify land use dynamics by following built-up area, vegetation, waterbody, and unused land. Many of the LULC studies work with 4 – 5 land use classes, namely agricultural, river, vegetation, built up area, and barren land/wasteland (Roy and Inamdar, 2019; Abdullah et al., 2019). As this study was carried out in the urban Narayanganj City Corporation (NCC) area, instead of separating agriculture, vegetation, forest, etc. they were grouped as “vegetation” class, along with “waterbody”, “built up area”, and “barren land”. Due to the low resolution of satellite images, the classification was performed by carefully comparing with google earth images of the respective dates. Mono-window algorithm might have been applied but the necessary data like humidity was not available.

Accuracy Assessment

As LULC classification generates some errors, the output needs to be tested for accuracy using statistical techniques. The error matrix approach is one of the methods widely used for this purpose (Foody, 2002). Without an error matrix, other important accuracy assessment elements, such as overall accuracy, omission error, commission error, and kappa coefficient, cannot be addressed (Lu and Weng, 2007). There were 62 ground truthing points for evaluating the accuracy of Land Cover classes. A greater number of truthing points were used to increase the robustness of the analysis and validate it (Chen et al., 2020). The points had been collected from the historical data of Google Earth. The overall accuracy ranged from 93 % and 87%, and the kappa coefficient ranged between 92% and 84%, which indicates better accuracy of classified images. A methodological framework is presented in Fig. 2.

Calculation of Land Surface Temperature

In this study, the LST of Narayanganj city was estimated using Thermal bands of Landsat TM 7 with a spectral range from 10.40 to 12.50. First, Digital Numbers (DN) of band 6 were converted into spectral radiance values by using the following equation which was derived from Landsat 7 Data Users Handbook (Ihlen and USGS, 2019).

$$L_\lambda = \frac{(LMAX_\lambda - LMIN_\lambda)}{(\mathrm{QCALMAX} - \mathrm{QCALMIN})} * (\mathrm{QCALMAX} - \mathrm{QCALMIN}) + LMIN_\lambda$$

Where L_λ= Sensor Radiance, $Lmax_\lambda$= maximum radiance of band 6, $Lmin_\lambda$= minimum radiance of band 6, QCALMAX= Maximum quantized calibrated pixel value in DN, QCALMIN = Minimum quantized calibrated pixel value in DN. All these data were obtained from MTL files of respective satellite images.

After converting DN to Radiance, the LST was computed using the following equations where K_1 = 666.09 and K_2 = 1282.71

$$LST = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}$$

Calculation UTFVI

Urban Thermal Field Variance Index (UTFVI) was calculated for Narayanganj city to delineate the effect of urban heat islands quantitatively. UTFVI was calculated through the following equation derived from (Yong et al., 2006).

$$UTFVI = \frac{(T_s - T_{mean})}{T_{mean}}$$

Where T_S= LST, T_{mean}= Mean temperature of the area

UTFVI was divided into six levels by six different ecological evaluation indices (Yong et al., 2006; Liu and Zhang, 2011). Thresholds in the six UTFVI levels are given in the following Table 3.

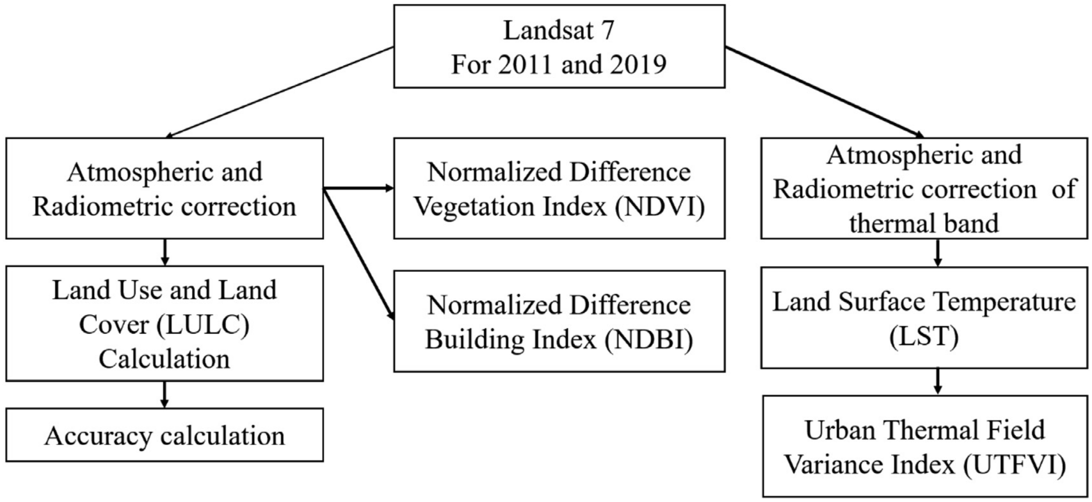

Fig. 2. Methodological framework of the study.

Calculation of NDVI and NDBI

Normalized Difference Vegetation Index (NDVI) has been extensively used across the world to enumerate vegetation cover (Jiang et al., 2006; Vani and Mandla, 2017). This index is determined by the difference in reflectance between the near-infrared band (NIR) and the red band (RED) of satellite images. The NDVI value ranges from -1.0 to +1.0, with the positive values indicating densely vegetated areas and the negative values indicating the non-vegetated areas. The following equation has been used to calculate the NDVI.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Normalized Difference Built-up Index (NDBI) is one of the popular methods to quantify built-up land in urban areas. The build-up areas and bare soil reflect through Short-Wave InfraRed (SWIR), and SWIR and NIR have been used for the calculation of NDBI. The value of NDBI is between -1 to +1 and the following equation has been followed to calculate NDBI (Kshetri, 2018).

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

Results

Relationship between LULC change with LST

LULC change and urbanization induce an increase in LST. During the eight years from 2011 to 2019, Narayanganj experienced rapid urbanization, which had a dramatic shift in the overall LULC of the city. In 2011, only 10.74 km^2 or 23% of the city area was built up, which has increased substantially to 26.29 km^2 in 2019, which is almost 56% of the total city area. Nearly 33% increase of built-up area in 8 years has caused 33% conversion of other land-uses. For instance, LULC of vegetation and agricultural lands have been reduced, respectively, to 5.89 and 6.75 km^2 in 2019 from 15.60 and 10.95 km^2 in 2011. These two types of lands have suffered the most alteration during this period, which has been reduced by 21%. Furthermore, both barren land and water bodies declined by 9% and 4% respectively. These changes in the LULC have greatly affected the LST of the city. From Figs. 3 and 4, it can be observed and ascertained that the areas with higher temperatures are mostly in the built-up areas. Around 10/20 points with the highest temperature were taken from LST of 2019 and it was identified that most of these highest temperature spots are in the industrial establishments. The minimum LST to be found in 2011 was 22.84°C which increased by 0.51°C in eight years and reached 23.35°C in 2019. Whereas, there has been a radical change in the highest temperature which was 34.06°C in 2011, and went upward to 35.92°C in 2019. The city witnessed an almost 1.86°C rise in the highest temperature during this period.

Moreover, Bangladesh Meteorological Department (BMD) recorded a maximum temperature of 33.5°C and a minimum of 21.8°C at Narayanganj in 2011. This agrees with the data in this study, as a maximum of 34.06°C and a minimum of 22.84°C were found. This implies a variation of 0.017% in the case of the maximum temperature and a 0.048% variation in the case of the minimum temperature in 2011. Similarly, BMD recorded 33.4°C and 22°C, respectively, as the maximum and minimum temperature in the year 2019, while in this study it has been found to be 35.92°C and 23.35°C, implying a variation of 0.08% and 0.06% for the maximum and minimum temperature. This indicates fairly good agreement and gives a good account of the accuracy of this study.

Relationship between LST, NDVI, and NDBI

Vegetation has a major impact on the LST. Usually, the higher density of vegetation reduces the LST. The NDVI value of NCC in 2011 ranged between (-0.41) - 0.2 and the majority of the area had a negative value, which indicates the presence of water bodies, barren land, and built-up areas. Only 0.8 km^2 area indicated values between 0 - 0.2, which indicates a little vegetation. Although some areas had dense vegetation in 2011, the presence of water bodies or built-up space nearby has reduced the pixel value. For 2019, the NDVI values ranged between (-0.2) - 0.5, and 65% of the area has a value between (-0.2) - 0.1, which indicates waterbodies, barren land, and built-up area. Despite most of the areas having been converted into built-up spaces, some areas were found to have increased and denser vegetation. On the other hand, some large waterbodies reflected a high NDVI value (0.4 - 0.5) due to dense moss concentration in the water (May et al., 2018).

A significant relationship has been created with a simple linear regression model between LST and NDVI as well as LST and NDBI. This relationship justifies the effect of rising temperature due to the change in land use. Moreover, for a simple linear regression model, LST has been selected as a dependent variable, and NDVI and NDBI have been selected as independent variables. Fig. 8 represents a downward trend where the temperature decreases with a high density of vegetation and increases when there is a low density of vegetation. Whereas for NDBI, the correlation with LST is very strong: the R^2 for 2011 and 2019 are 0.65 and 0.68, respectively. Their relation is visible such that the higher the built-up area the higher the temperature escalates and vice-versa. The negative coefficient between LST and NDVI indicates that the green area can contribute to reducing the UHI.

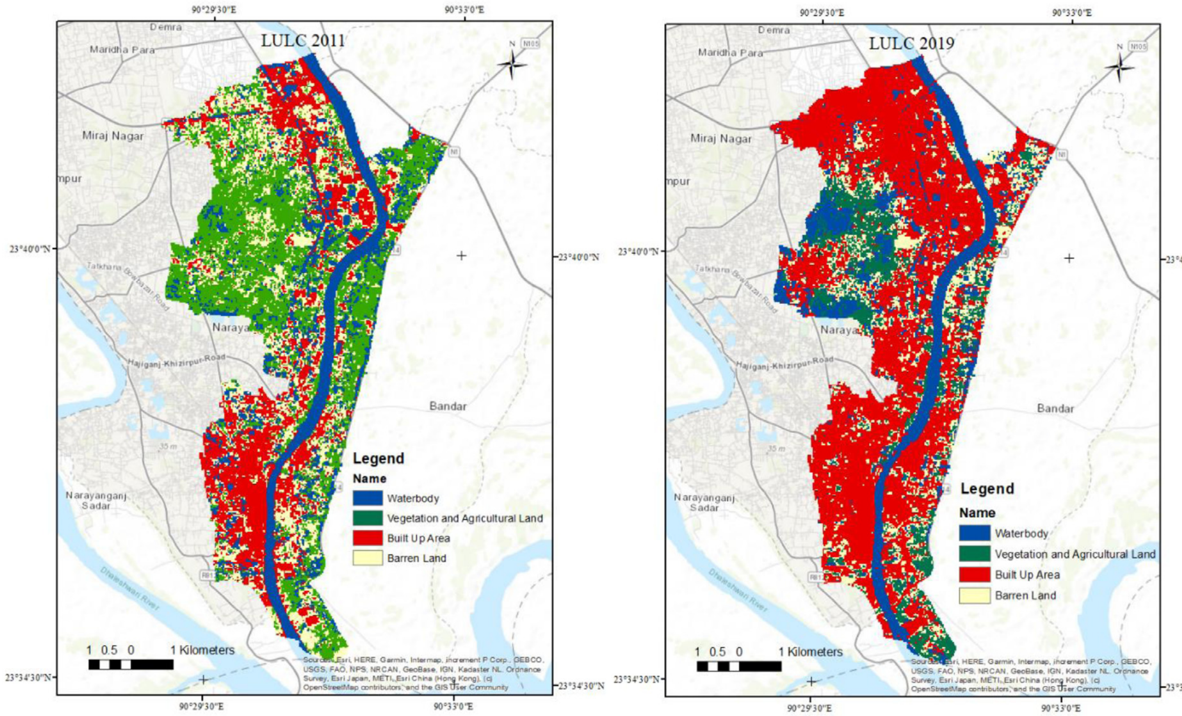

Fig. 3. Land use and land cover (LULC) of Narayanganj city in (a) 2011 and (b) 2019.

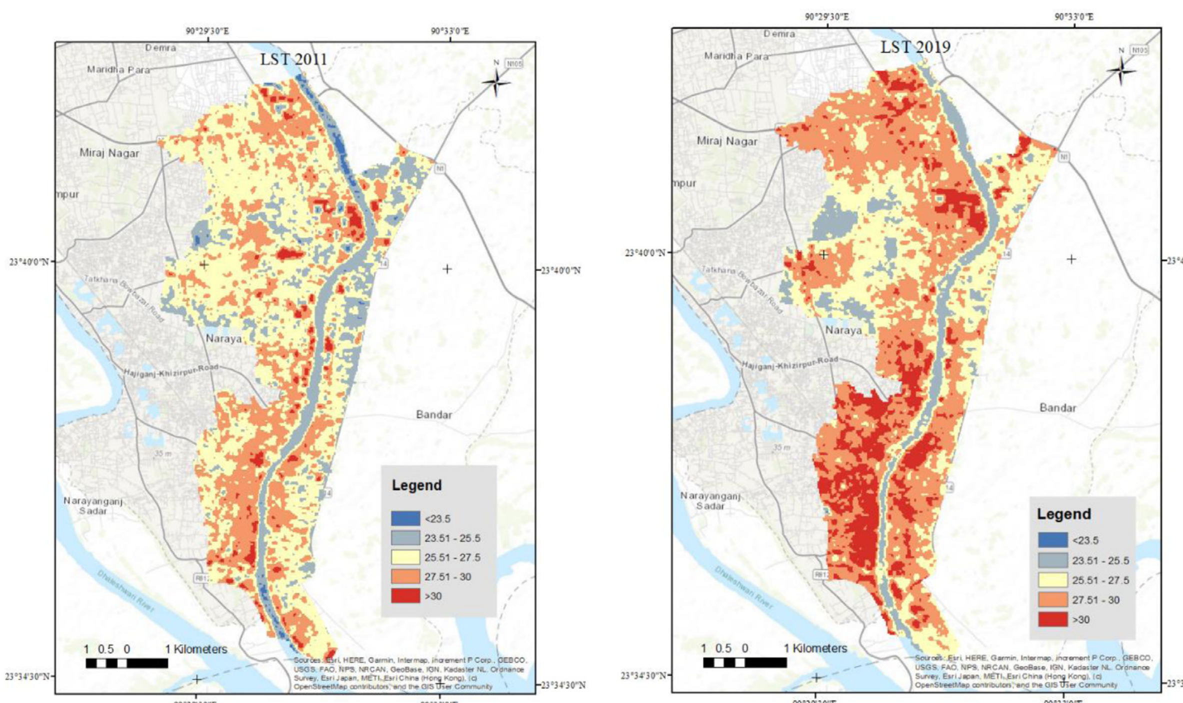

Fig. 4. Land surface temperature (LST) of Narayanganj in (a) 2011 and (b) 2019.

Ecological evaluation index

Urban Thermal Field Variance Index (UTFVI) is used for quantitative elucidation of UHI effects on ecological degradation. UTFVI has been classified into six levels to define the effect of each level. From Table 7 and Fig. 9, it is noticeable that the total area of both the No-heat-island effect and the Weak-heat-island effect has reduced by a small margin in 2019, compared to 2011. However, the areas with middle, strong, stronger, and strongest heat island effects have almost doubled in 2019. In 2011, the area of stronger heat island phenomenon was noticed at only 0.21 km^2 area. Over the years, more areas have experienced worse ecological alteration and imbalance, thus increasing the area of the strong heat island phenomenon to 0.41 km^2 in 2019. Similarly, the strongest heat island effects in 2011 were noticed in only 0.02 km^2 area

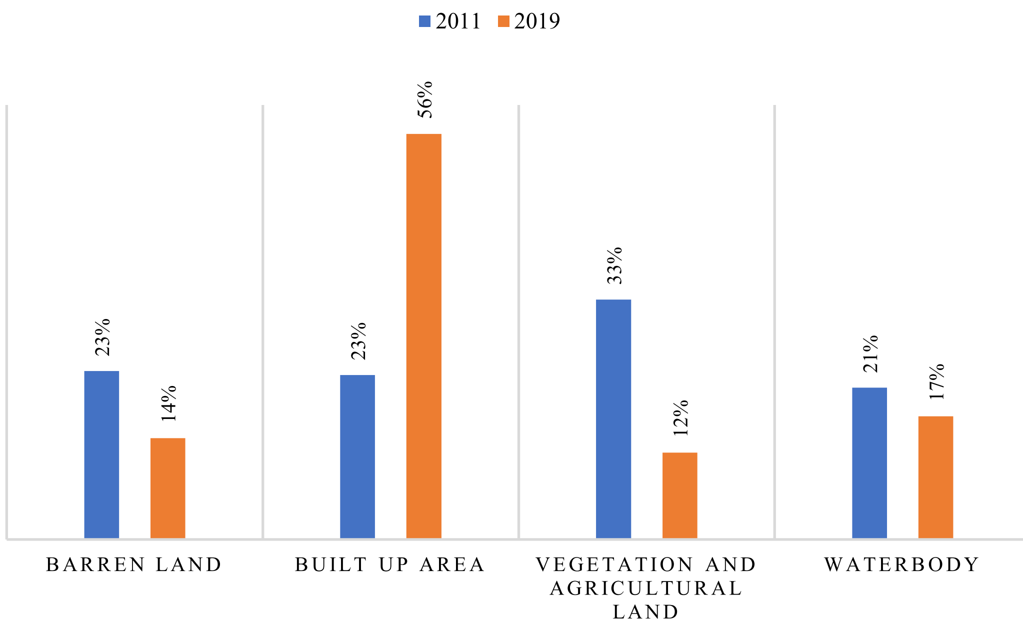

Fig. 5. Land surface temperature (LST) percentage of total area in (a) 2011 and (b) 2019.

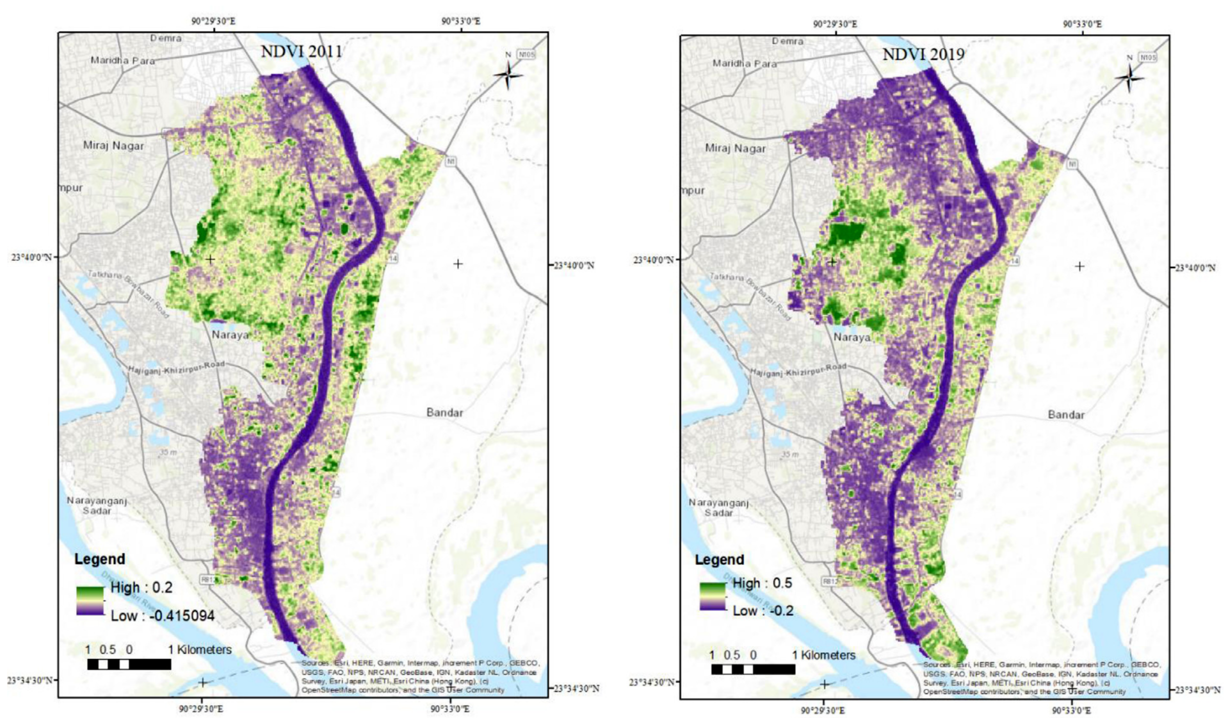

Fig. 6. Normalized difference vegetation index (NDVI) of Narayanganj city in (a) 2011 and (b) 2019.

which also increased to 0.054 km^2 in 2019. This worsening trend of the ecological evaluation index reflects the existing condition of environmental degradation and UHI intensity elevation. From Figs. 1 and 9, it can be clearly defined that due to the high concentration of the built-up area the temperature has been increasing in the central part of the city.

Discussion

The population of Narayanganj city has increased exponentially since it was established as a City Corporation in 2011. Since then, the city has experienced a massive industrial and business expansion, which has resulted in a significant alteration in land use. Before 2011, most of the lands in Siddirganj and Kadamrasul municipality were agricultural, vegetation, and waterbodies. After 2011, land use of most of these areas was converted to establish industries and residential areas for the incoming workforce. In addition, the Adamjee Export Processing Zone (AEPZ) was established in the Siddirganj area covering 245 acres of land in 2006. Since then, 229 industrial establishments have been built and it employed nearly 62000 workers in 2018-19 which is 5 times higher than the number of workers in 2011 (BEPZ, 2020). This sudden but rapid surge in population and simultaneous expansion of industrial, commercial, and residential establishments had a major impact on the solar ra-

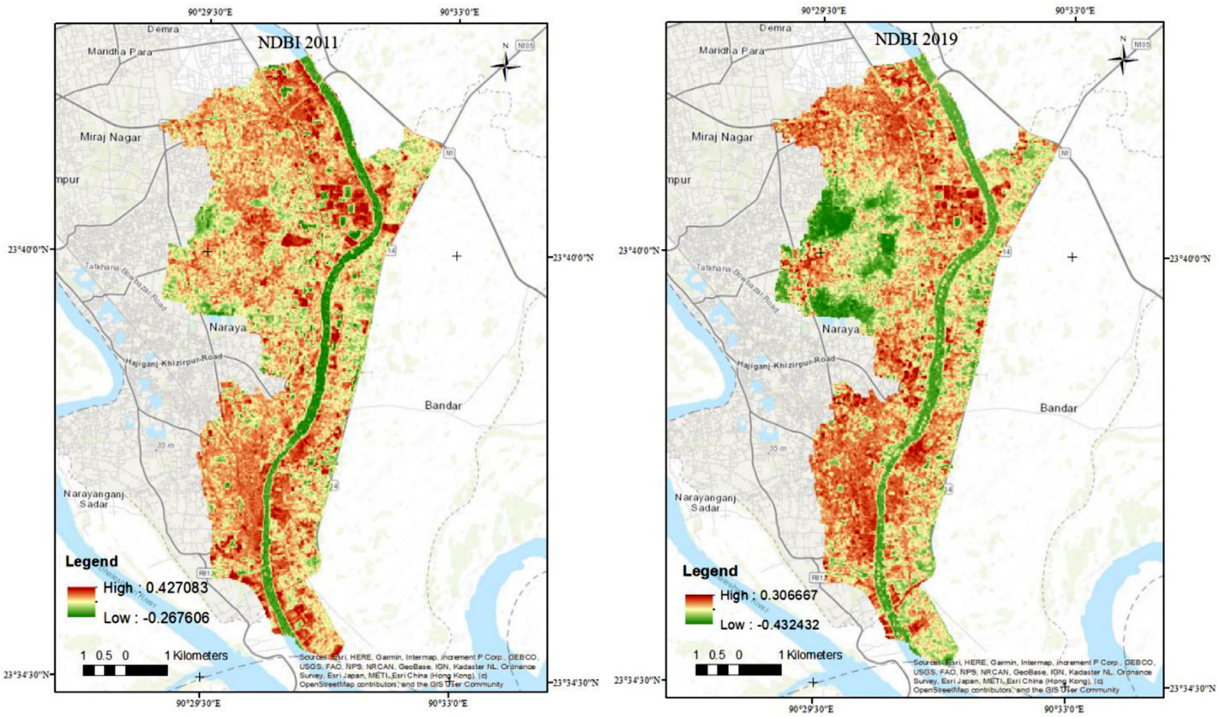

Fig. 7. Normalized difference built-up index (NDBI) of Narayanganj city in (a) 2011 and (b) 2019.

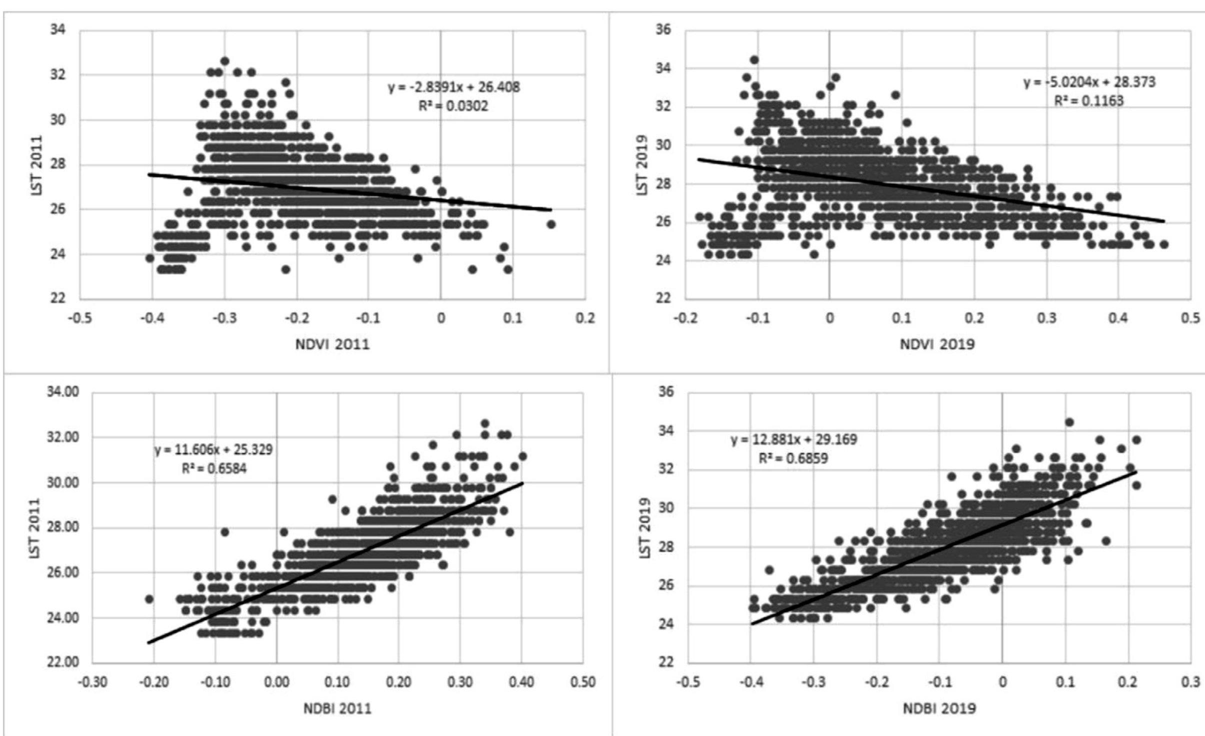

Fig. 8. Correlation of LST vs NDVI and LST vs NDBI.

diance and LST of the city. This is in agreement with the findings of a study by Yao et al. (2019), where it was revealed that the urban can increase more rapidly than the rural LST.

A major increase in temperature was noticed over the built-up areas in both of the analyzed years. The densely developed CBD of Narayanganj in the Chasara area and on both sides of BB road has many industrial (mostly ready-made garments and knitting industries) and commercial buildings. This area also has the least quantity of vegetation and water bodies, and as a result, most of the heat islands and higher LST values are found in this area. Bandar area of Kadamrasul municipality and AEPZ of Siddirganj municipality also has a higher concentration of industries and hence have a higher LST value. While the heat island spots were found mostly over the industrial establishments, the lowest LST values were found on the Shitalakshya River and other water bodies.

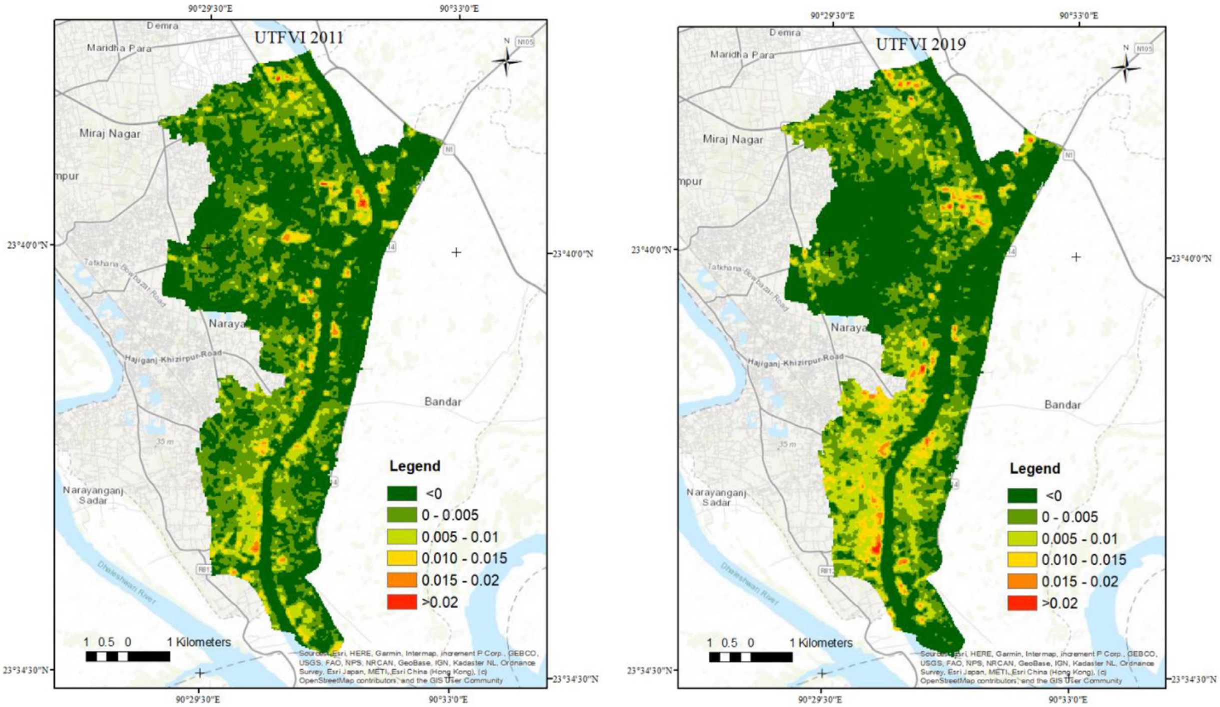

Fig. 9. Urban thermal field variance index (UTFVI) of Narayanganj city in (a) 2011 and (b) 2019.

This increasing trend of temperature found in this study matches with the findings of ICLEI (2020), which shows that the average temperatures in Narayajganj are increasing, with a higher degree of increase in the annual minimum temperatures.

The overall trend in UHI has been found to be directly related to LST values, while LST is associated with LULC types. On the other hand, there is an inverse relationship between LST and NDVI for all types of LULC in the study area. The LST of industrial areas is observed to be the highest among all LULC types and it is highly affected by NDVI compared to other areas. This implies that an increase in vegetation cover in Narayanganj city will be the most effective way to reduce temperature. Thus, increasing vegetation coverage in built-up areas, especially in the industrial areas and surrounding residential areas may be particularly significant in improving the urban thermal characteristics of the study area.

The NDVI analysis of 2011 showed the existing vegetation scenario, but the NDVI of 2019 could not properly represent the condition of the city. This was because the water bodies in most of the locations were covered with moss which showed up in the analysis as dense vegetation, and indicated a higher value when in reality the amount and density of vegetation has decreased. The encroachment of existing water bodies and filling up ponds for infrastructure development projects are resulting in a loss of water bodies which could have contributed to keeping the LST lower. This also leads to drainage congestion and pollution that further exacerbate the situation in Narayanganj (ICLEI, 2020).

One of the major drivers of the increase in temperature in Narayanganj is the emission of greenhouse gas. According to the study of the ICLEI South Asia-Urban LEDS project, 1,070,132 tonnes of CO_2 emissions took place in the year 2018-19. Furthermore, the highest amount of emission has been contributed by the manufacturing sector, which is 57.07% (ICLEI, 2020). The rapidly increasing manufacturing activities in Narayanganj are further exacerbating this scenario (Table 2, Tables 4–6).

Considering Narayanganj is an industrial city, low carbon emissions should be given the highest priority. The local government should take initiatives to encourage the industries for reducing emissions and introduce green initiatives. In May 2017, BBC Media Action initiated a 16-day campaign to raise awareness among the youth of Bangladesh regarding extreme heat risks. The campaign was focused on heat risks and heat-risk reduction strategies by preparing short videos with messages in the local language. This provided platform to engage youth and policymakers (Arrighi et al., 2017). This type of initiative can be taken by the local government to raise awareness. Additionally, green-roof top and micro forest initiatives can be good steps to reduce the heat effects around the city following the correlation of high NDVI values with lower LST (Figs. 5–7).

Table 2
Accuracy of MLC of 2011 and 2019.

Year	Classes	User accuracy (%)	Producer accuracy (%)
2011	Water	100	87
	Built-up	100	87
	Barren Land	85.71	100
	Vegetation	90	100
	Overall Accuracy	93	
	Kappa Coefficient	92	
2019	Water	100	100
	Built-up	80	100
	Barren Land	75	75
	Vegetation	87	70
	Overall Accuracy	87	
	Kappa Coefficient	84	

Table 3
Threshold of ecological evaluation index.

UTFVI	UHI phenomenon	Ecological Evaluation Index
<0	None	Excellent
0.000-0.005	Weak	Good
0.005-0.010	Middle	Normal
0.010-0.015	Strong	Bad
0.015-0.015	Stronger	Worse
>0.020	Strongest	Worst

Table 4
Land use and land cover of Narayanganj city during 2011 and 2019.

LULC Category	2011 (km^2)	Percentage	2019 (km^2)	Percentage	Change over the period of 2011-2019
Waterbody	9.87	21%	8.19	17%	-4%
Built-Up area	10.74	23%	26.29	56%	33%
Vegetation and Agricultural Land	15.60	33%	5.89	12%	-21%
Barren Land	10.95	23%	6.75	14%	-9%

Table 5
LST Percentage of total area in 2011 and 2019.

Temperature		0 - 23.5°C	23.5 - 25.5°C	25.5 - 27.5°C	27.5 - 30°C	>30°C
Area	2011 (km^2)	0.4293	7.89	23.66	13.89	1.28
	2019 (km^2)	0	4.92	13.99	21.28	6.97

Table 6
Something of Narayanganj city during 2011 and 2019.

Year	Mean	SD	Max	Min
2011	300.1287	1.5063	307.2167	295.9917
2019	301.2446	1.8362	309.0734	296.5013

Table 7
UTFVI of NCC for 2011 and 2019.

Threshold Values	2011	2019
<0	25.5582	23.4441
0.000-0.005	15.4548	13.2984
0.005-0.010	4.8789	7.8552
0.010-0.015	1.0467	2.0682
0.015-0.015	0.2151	0.4563
>0.020	0.0225	0.054

Though the local government has access to limited resources and budget, they can play a vital role to reduce the LST and UHI effects by promoting early warning or robust forecast systems, spray parks for cooling, urban forest, cooling centers for communities, removing vehicles that emit black smoke, cooling the roofing by painting, etc. Additionally, the National government should come forward to support the local government to prepare a heat action plan considering different geographic locations have different drivers and intensities of heat. This will help with identifying the hotspots of the city and take necessary interventions to reduce the UHI effects.

Conclusion

Urban Heat Island has been a major concern all over the world for over a century. With the rapid urbanization in developing countries, UHI assessment has become a useful tool for urban and environmental planners in monitoring and managing urban growth. It is now evident that urbanization and environmental alteration have a direct impact on the increased surface temperature of urban areas. When the vegetation and water bodies are replaced by concrete and asphalt, and agricultural lands are turned into barren lands, these surfaces absorb solar radiance rather than reflecting and thus increase both surface and ambient temperature.

This study was conducted to identify the urban heat island effect in Narayanganj city as a result of LULC changes in the years 2011 and 2019 using satellite imagery and remote sensing techniques. Landsat TM and ETM data were used to assess LULC, NDVI, NDBI, and UTFVI changes and their impacts on LST. The result shows that urbanization has increased the overall surface temperature of the city where the Central Business District (CBD) of Narayanganj (Chasara and both sides of BB road), Bandar, AEPZ area, and Chittagong Road area have experienced the most LST increase over the years. These areas also went through the most LULC alteration since Narayanganj was declared as a city corporation. Comparatively lower temperatures were observed mostly in the surrounding areas and city periphery, but it was still higher than that of 2011.

Vegetation and waterbodies seemed to play a significant role in lowering the overall surface temperature. Both the vegetation and water bodies experienced a serious declination in eight years which in return raised the temperature of those areas. Although the NDVI assessment displayed better value for 2019 than in 2011, it was mostly due to the increase in moss coverage in waterbodies. Apart from the overall declination in total vegetation, agricultural land, and water bodies, recent canal restoration and tree plantation initiatives in some areas of NCC have helped in reducing the surface temperature to some degree.

Although the analysis of LULC change, NDVI, NDBI, and LST from satellite images like Landsat 7 is not accurate at the micro-level due to the low resolution of the images, the macro-level results can be very helpful for urban and environmental planners in formulating suitable strategies and policies. For more accurate assessment at the micro-level, satellite images with higher resolution and ground-truthing are required. Besides, lack of cloud-free data for computing LST, difficulties to get data on humidity as the city corporation had no records of it, and absence of weather data in the city corporation is considered as some of the limitations of this study. This study will help other researchers, Narayanganj city, and local environment authorities to take initiatives to reduce overall LST and urban heat island effects in Narayanganj.

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Declaration of Competing Interest

Authors declare no conflict of interest.

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