LULC impacts onNDVI and LST: A case studyon Jashore District, Bangladesh

Abstract

Studies on land use and land cover (LULC) changes and subsequent effects on environmentare not satisfactory in Bangladesh because of the lack of geospatial data and time-series information. By using the open-source Landsat 7 and Landsat 8 imagery data coupled with GIS technology and other ancillary data, the main purpose of this study is to analyze the dynamic changes in LULCin Jashoredistrict of Bangladeshover a 20-year period between 2002 and 2022.Including pre-classification and post-classification identification scenarios, Normalized Difference Vegetation Index (NDVI) analysis was employed to examine the vegetation changes over the period. ArcGIS 10.8 software was employed for analyzing satellite images, and maximum likelihood classification was utilized to create supervised land cover category (water bodies, vegetation, built-up area, and bare soil). Microsoft Excel was used for data analysis and visualization. The findings of this present study indicate notable changes with an increase of 20.77% in urban areas and 14.53% in bare soil. Additionally, there has been a decline of 2.93% in water bodies and 32.37% in vegetation land cover including both natural and anthropogenically modified vegetation such as forests, croplands, grasslands and others. Accuracy evaluations on the land use classification's trustworthiness include Kappa statistics of 0.80 for the year 2022 and 0.65 for the year 2002. Adecrease in land surface temperature (LST) in Jashoredistrict over 20 years from 2002 to 2022has been reported in this study.Although the proportion of vegetation cover has been reduced in 2022, we found anegative correlation between LST and NDVI.Along with LULC, the LST is influenced by many atmospheric and ecological parameters. NDVI is dependent on vegetation canopy type, color and density, which could affect the relationship with LST. The findings of this study provide insightful information

to ecologists, environmentalists, urban planners, and lawmakers for developing sustainable land management plans and environmental conservation initiatives.

Keywords:LULC; Kappa statistics; LST; NDVI;Jashore district.

Introduction

The cities in Bangladesh experiencee one of the fastest urbanization rates in the world over the past few decades (Faisal et al. 2021). Rapid population growthand the migration of people to urban areas cause informal settlements, uncontrolled expansion of slums, pervasive urban poverty (Grant 2010), traffic jams(Islam and Ahmed 2011), waterlogging, environmental pollution and degradation (Kafy et al. 2020) and other socioeconomic issues(Gómez et al. 2020). Mostly the uncontrolled population growth and unplanned urbanization hinder sustainable development of the cities in Bangladesh (Kafy et al. 2021). For the sustainable land use, distribution and management of environmental and ecological resources,it is essential to consider the changes in urban land use and land cover (LULC). Land use refers to how humans utilize lands for purposes like agriculture, industry, or recreation (Rawat and Kumar 2015), whereas the land cover relates to the physical characteristics of the Earth's surface, such as agricultural lands, woodlands, water bodies, urban areas and natural vegetation(Audah et al. 2021; Mishaa et al. 2021). LULC is a critical component because of its potential environmental impact onnatural resource management(Munthali,et al. 2020). It may contribute to global environmental changes throughthe interaction with biodiversity, biogeochemical cycles, climatic systems, biological processes, and human activities (Khachoo et al. 2024). At local, regional, and global dimensions, the changes in LULC impact the equilibrium of energy, water, agricultural production, and geochemical exchanges. Thus, comprehensive knowledge onLULC changes is crucial for the sustainable management of land, allocation of resources, and preservation of the environment (Nedd et al. 2021).

Geospatial technology like satellite-based remote sensing (RS) and geographic information system (GIS) has revolutionized the research area on LULC by providing detailed qualitative and quantitative information toobserve and record LULC changes at a particular time and spatial location (Mamun 2013). Considering that the classification of LULC is an ongoing and dynamic process, it is essential to do continuous research on LULC changes and their impacts on both the society and the environment (Mondal et al. 2016; Munthali et al. 2020).All developed nations and majority of developing nations have access to current comprehensive LULC data, which enables them to monitor changes in their landforms. Hence, they are ready to face new environmental challenges and issues in advance. However, Bangladesh, as a developing nation, is not under continuous monitoring on LULC changes to overcome current challenges for the establishment of sustainable ecosystems. In the context of Bangladesh, various environmental challenges such as soil and water pollution, soil quality degradation, soil erosion, loss of minimum area of vegetation, and loss of biodiversity havebeen exacerbated mostly because of the rapid expansion of population and inadequate urban planning (Xu et al. 2020). Therefore, it is crucial to research the amount of farmed land,vegetation, water features, and wet/lowland areas that are lost to urban areas.

Land surface temperature (LST) is one of the most important parameters of surface–atmosphere interactions and climate change, which significantly alters seasonal vegetation phenology and in turns affectsthe energy balance at global and regional scale. Thermal RS techniques can measure the upward long-wave radiation from the land surface underclearsky and the data are used to retrieve the spatially distributed LSTs.LST is strongly influenced by landscape features as the features greatly change the thermal characteristics of the surface. The methods of anthropogenic heat discharge due to energy consumption cause increase inLST. In contrast, the vegetation and water surfaces in a landscape reduce the LST through evapotranspiration (Ding et al. 2023). Thus, the lowest LSTs are usually found in dense vegetative areas. However, the LST is dependent on time, place and types and distributions of vegetation (Ullah et al. 2023).As a victim of climate change, many cities in Bangladesh are expecting a gradual increase in LST (Imran et al. 2021). Multiple research projects have confirmed a significant correlation between LULC and LST. Researchers have found that the increase in LST is influenced by changes in LULC, particularly in metropolitan regions (Pal and Ziaul 2017; Imran et al. 2021; Ullah et al. 2024). RS and GIS technology are significant contemporary techniques used to identify LULC and extract LST (Choudhury et al. 2019).

For Bangladesh perspective, previous studies on LULC change and its impact on cities are available (e.g.,Haque and Basak 2017; Islam and Ma 2018; Kafy et al. 2020; Xu et al. 2020; Morshed et al. 2021; Morshed et al. 2023; Saha et al. 2024). However, the previously available studies on changes in LULC mostly cover the study sites as the capital city Dhaka (e.g., Imran et al. 2021; Hossain and Rahman 2022; Zarin and Zannat 2023; Huq et al. 2024), the most commercial city Chittagong (Abdullah et al. 2022; Imran et al. 2022) and other big cities like Rajshahi (Hassan 2017; Kafy et al. 2019), Sylhet, Rangpur, Barishal (Hassan 2017; Salman et al. 2021), Khulna (Ahmed 2011; Hassan 2017), and Sunamganj (Haque and Basak 2017). Having access to current and comprehensive LULC data allows many developing nations to keep track of changes to their landforms. This is not the case for developing nations like Bangladesh. The LULC structure is complicated and must be monitored periodically for better understanding of future urban growth pattern (Al-Darwish et al. 2018; Feng et al. 2018). Investigating the loss of farmed land that has been moved to urban areas as well as the alterations to vegetation, water bodies, and wet/lowlands is therefore imperative. A recent study has reported on future potential intra-urban LULC growth patterns of a developing city Jashore in Bangladesh up to the year 2050 (Morshed et al. 2023). However, as a first attempt, this present study is accomplished in Jashoredistrictfor analyzing the patterns of LULC changes and the effects of those changes on LST through the creation of the Normalized Difference Vegetation Index (NDVI) and spatiotemporal change maps by using GIS and RS technologies. It would be a great step towards strategic planning for sustainable urban development of that city (Maarseveen et al. 2018). NDVI is a metric which is employed to measure temporal variations in vegetative patterns. Therefore, the specific objectives of the present study areto identify (i) the significant changes in LULC, LST and NDVI over a period of 20 years by using 2002 as the reference year and (ii) the relationship analysis between LST and NDVI. The findings of this study are expected helping the national policymakers to set strategies for controlling urban growth and environmental changes in future.

Methodology

Study Area

Jashoredistrict, situated in the southwestern region of Bangladesh, has a tropical monsoon climate. Geographically, it is situated within the latitudes 23°0'N to 23°22'N and the longitudes 88°55'E to 89°15'E (Fig. 1). Geographically, the district is next to Narial in the northeast, Magura in the northwest, Khulna in the south, and the Republic of India, particularly the state of West Bengal, in the west. The district has a total land area of 2545.32 square kilometers. It is surrounded by a multitude of water bodies, including the Bhairab, Teka, Hari, Sree, Aparbhadra, Harihar, Haribhadra, Chitra, Betna, Kopotakkho, and Mukteshwari rivers.

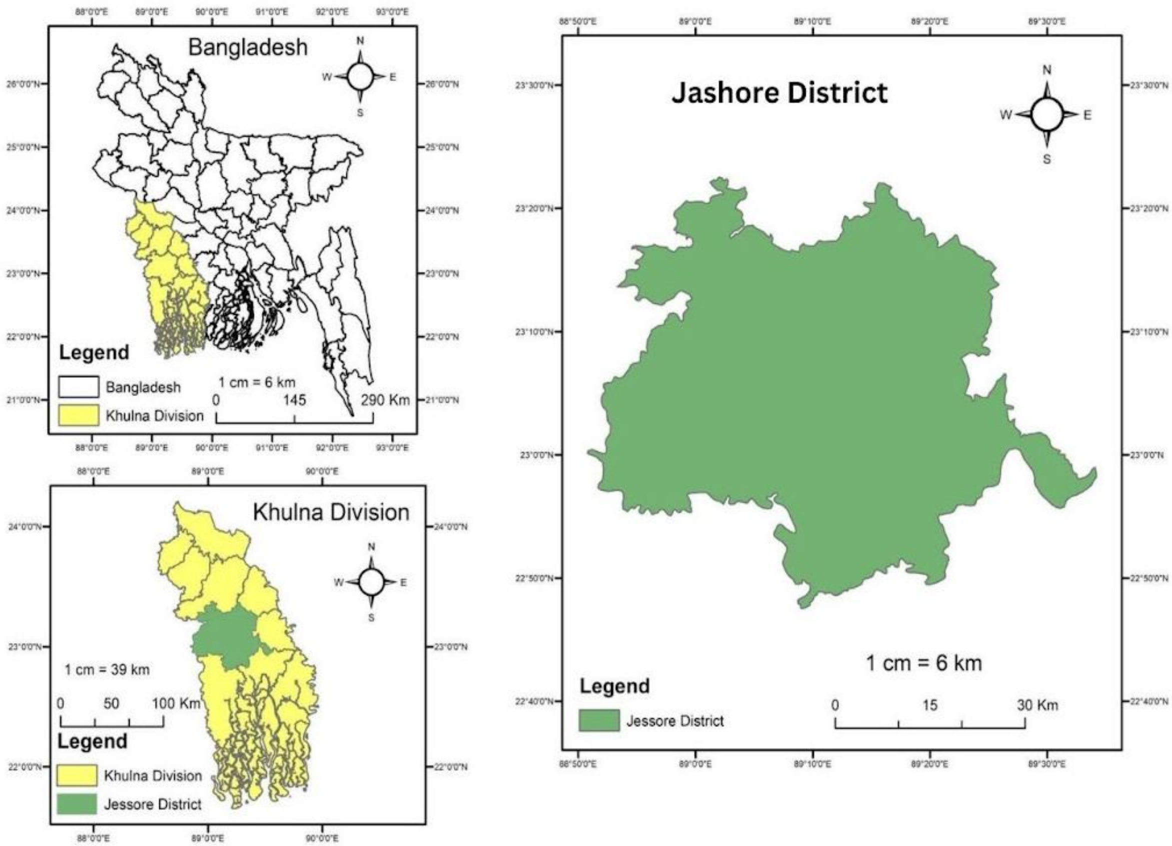

Figure 1 Study area, the Jashore district under Khulna division in Bangladesh.

Data Collection

The present analysis is dependent on secondary data and incorporates a diverse range of geographic and non-spatial data from several sources, including multiyear population census data and socioeconomic census data from city-level statistics yearbooks. The geographic and temporal data employed in this work were the latest high-resolution satellite pictures, namely Landsat ETM+ 30m (year 2002) and OLI-TIRS 30m (year 2022) (Audah et al. 2021), which have a row/path value of 44/138 with a resolution of 30 meters. The photos were obtained from the publicly accessible Landsat imaging services accessible at https://earthexplorer.usgs.gov. Table 1 presents the characteristics of Landsat data. Cloud-free and undesired shade-free photos were givenpriority during the image selection process. To avoid cloudsand expecting minimal variation in the period of capturing images, this study mostly used imagery data from the winter season (Uddin and Gurung 2008). The satellite images were georeferenced using the World Geodetic System (WGS) 84 coordinate system and the Universal Transverse Mercator (UTM) map projection in Zone 46 N datum. The shape file for the JashoreDistrictwas sourced from the Bangladesh Water Development Board (BWDB). The base maps of Jashore City were obtained from published papers by the Geological Survey of Bangladesh (GSB) for reference.

Table 1: Information on Landsat Satellite data used.

Satellite	Sensor	Row / Path	Date	Resolution	Image quality	Band information	Wavelength (µm)	Data source
Landsat-8	OLI-TIRS	44/138	2022-02-07	30m	9	B2 (Blue)	0.45- 0.51	https://earthexplorer.usgs.gov/
						B3 (Green)	0.53- 0.59	
						B4 (Red)	0.64- 0.67	
						B5 (NIR)	0.85-0.88	
						B8 ((Panchromatic)	0.50-0.68	
Landsat-7	ETM+	44/138	2002-02-24	30m	9	B1 (Blue)	0.45-0.51	https://earthexplorer.usgs.gov/
						B2 (Green)	0.52- 0.60	
						B3 (Red)	0.63- 0.69	
						B4 (NIR)	0.77- 0.90	
						B8 ((Panchromatic)	0.50-0.68	

Pre-processing of Data

The processes of stacking the Landsat imagery, combining them into multiband composite views, and focusing on the research region were imperative to optimize the quality and efficiency of the subsequent analyses. Using ArcGIS 10.8, the layer stacking process was carried out effectively, reducing the required bands into a small layer for the photos to be examined.To precisely align and synchronize the imageries used in this study, image registration was essential. In this case, the 2002 Landsat-7 imagery was registered against the Landsat-8 image from 2022 (path 138, row 44). After registration, the photos were put through several pre-processing steps to remove any possible distortions or irregularities.The most important procedure among the pre-processing steps was atmospheric adjustment.The atmospheric adjustment of the imageries was corrected following the methodology mentioned in Lopez-Serrano et al. (2016). Furthermore, radiometric adjustments were applied to account for any anomalies or atmospheric noise, specifically tackling cloud-related issues. The thorough pre-processing procedures established a strong basis for the ensuing picture analysis andensuringprecision and reliability in the results.

Method of classification and change detection inLULC

The LULC map was classified using the maximum likelihood method of the Image Classification tool in ArcGIS 10.8, which is a supervised classification procedure. The land use categorization has been based on the bands 1-4 and band-8 of the Landsat-7 ETM+ aerial photography. Furthermore, the classification of land use has been based on bands 2-4 and band-8 of the Landsat-8 OLI images (Audah et al. 2021). To generate the LULC maps, the image analyzer tool inside the ArcGIS 10.8 program was utilized to stack all the bands. The training sample management tool,with randomly chosen substantial quantity of training samples, was thereafter employed to determine the pixel signature. The flow chart in Figure 2 depicts the complete procedure of land use classification.

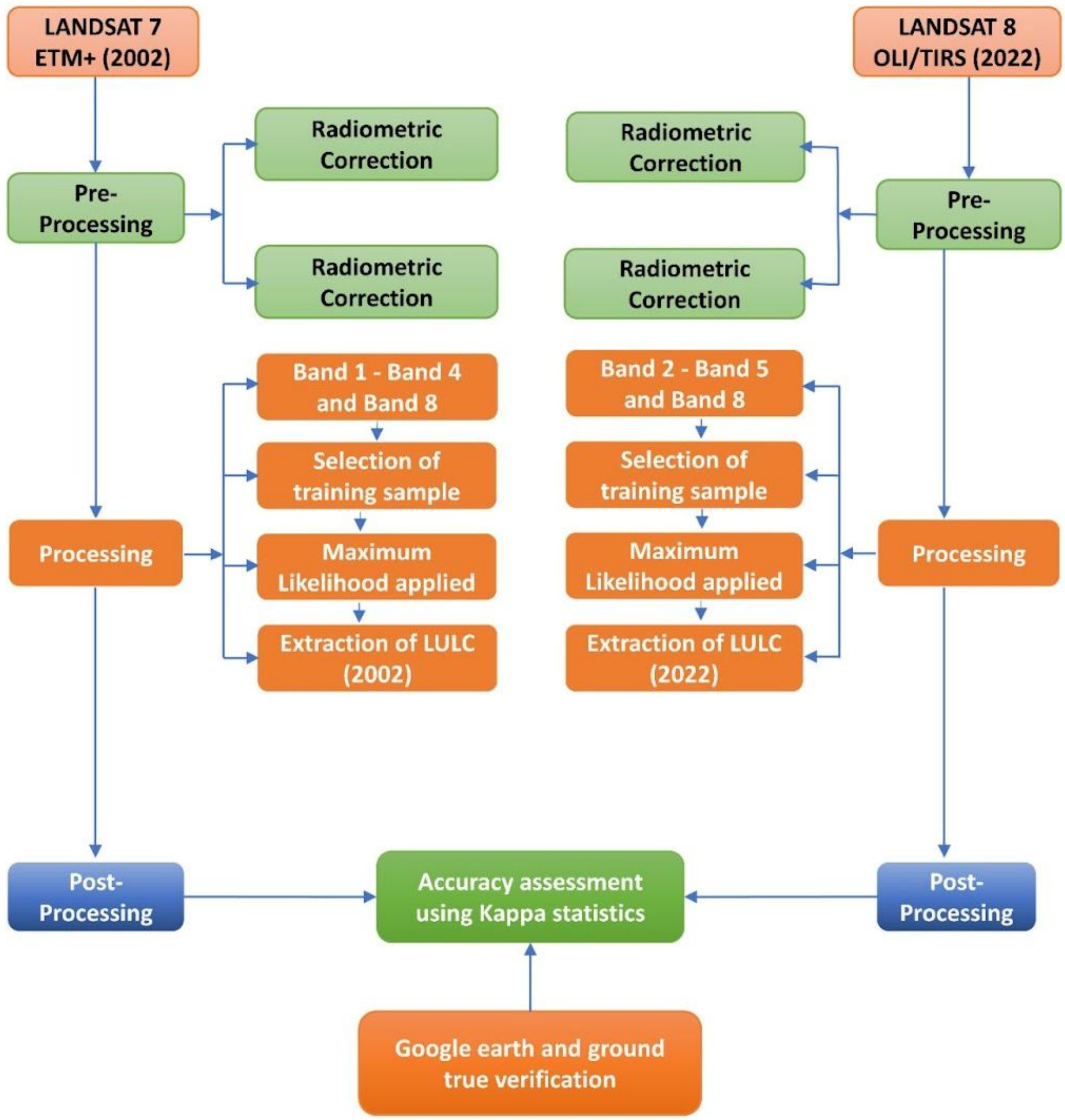

Figure 2 Procedures for LULC classification.

Method of accuracy assessment of LULC maps

The accuracy assessment is necessary for both pre- and post-classified imagery. The confusion matrix or error matrix has been used to evaluate the study's reliability. The following equations were used to conduct the accuracy assessment in this study (Das et al. 2021):

$$Overall\ Accuracy = \frac{Total\ Number\ of\ Correctly\ Classified\ pixels(Diagonal)}{Total\ Number\ of\ Reference\ pixels} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$User\ Accuracy = \frac{Number\ of\ Correctly\ Classified\ pixels\ in\ each\ category}{Total\ Number\ of\ Classified\ Pixel\ in\ that\ catagory(The\ Row\ Total)} \times 100 \ldots\ldots\ldots ..(2)$$

$$Producer\ Accuracy = \frac{Number\ of\ Correctly\ Classified\ pixels\ in\ each\ category}{Total\ Number\ of\ Reference\ Pixels\ in\ that\ category(The\ Column\ Total)} \times 100 \ldots\ldots (3)$$

$$Kappa\ Coefficient\ (T) = \frac{((TSxTCS) - \Sigma(Column\ Total \times Row\ Total))}{(TS \wedge 2 - \Sigma(Column\ Total \times Row\ Total))} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Calculation of NDVI

The NDVI is a vegetation index that measures the variation in reflectance characteristics across wavelengths in the near-infrared and red ranges. The quantity is determined by dividing the total of these two reflectance values. The NDVI extraction has been successfully achieved using the methodology provided by Townshend and Justice (1986). The equation of NDVI calculation is as follows:

$$NDVI = \left(\frac{NIR - RED}{NIR + RED}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

where, the acronym NIR denotes the near Infrared band, while RED designates the red band. NDVI was extracted using Landsat ETM+ band-3 and band-5, along with Landsat OLI band-4 and band-5. Numerical NDVI values span from negative (-1) to positive (+1). Negative NDVI values provide evidence of water, whereas positive values suggest the existence of vegetation.

Calculation of LST from thermal band

The thermal bands of Landsat-7 ETM+ (band-6) and Landsat-8 OLI (band-10) were used to calculate the ground surface temperature for the month of February, which correspond to the winter season. Yet, the approach of obtaining LST from Landsat ETM+ and Landsat OLI varies somewhat in terms of computing spectral radiance (Lλ). The methodologies for obtaining LST have been well explained in previous research papers (e.g., Asgarian et al. 2015; Govind and Ramesh 2019). The sequential procedure of obtaining LST from Landsat ETM+ and Landsat OLI images is depicted in Figure 3. The detailed step-by-step technique for LST calculation is represented below:

Step-I: Conversion of the digital number (DN) to radiance or converting it to 'top of atmosphere' (TOA) radiance (Lk). The thermal band, band-6of Landsat-7 ETM+ imagery has been utilized to compute the spectral radiance (Lλ) by using the following equation.

$$L\lambda = LMIN\lambda \frac{(Lmax\lambda - Lmax\lambda)}{(QCALmax - QCALmin)} \times QCAL \ldots\ldots\ldots\ldots (6)$$

where, QCALmax and QCALmin are the maximum and minimum DN values (usually 255 and 1, respectively); QCAL isthe Digital Number of each pixel; Lmaxλ and Lminλ are the spectral radiances for the band-6 at digital number.The value of Lmaxλ = 17.040 and Lminλ = 0.The thermal band for Landsat-8 OLI imagery is band-10. To calculate the spectral radiance (Lλ), the following equation 7 is used,

$$L\lambda = ML \times (QCAL + AL - Oi) \ldots\ldots\ldots\ldots (7)$$

where,Lλ isthe spectral radiance of top of the atmosphere; ML is the band-specific multiplicative rescaling factor (0.0003342); AL is the band-specific additive rescaling factor (0.1); QCAL isthe Quantized and Calibrated Standard Product Pixel value (band-10 image); Oi is the Correction for band-10(0.29).

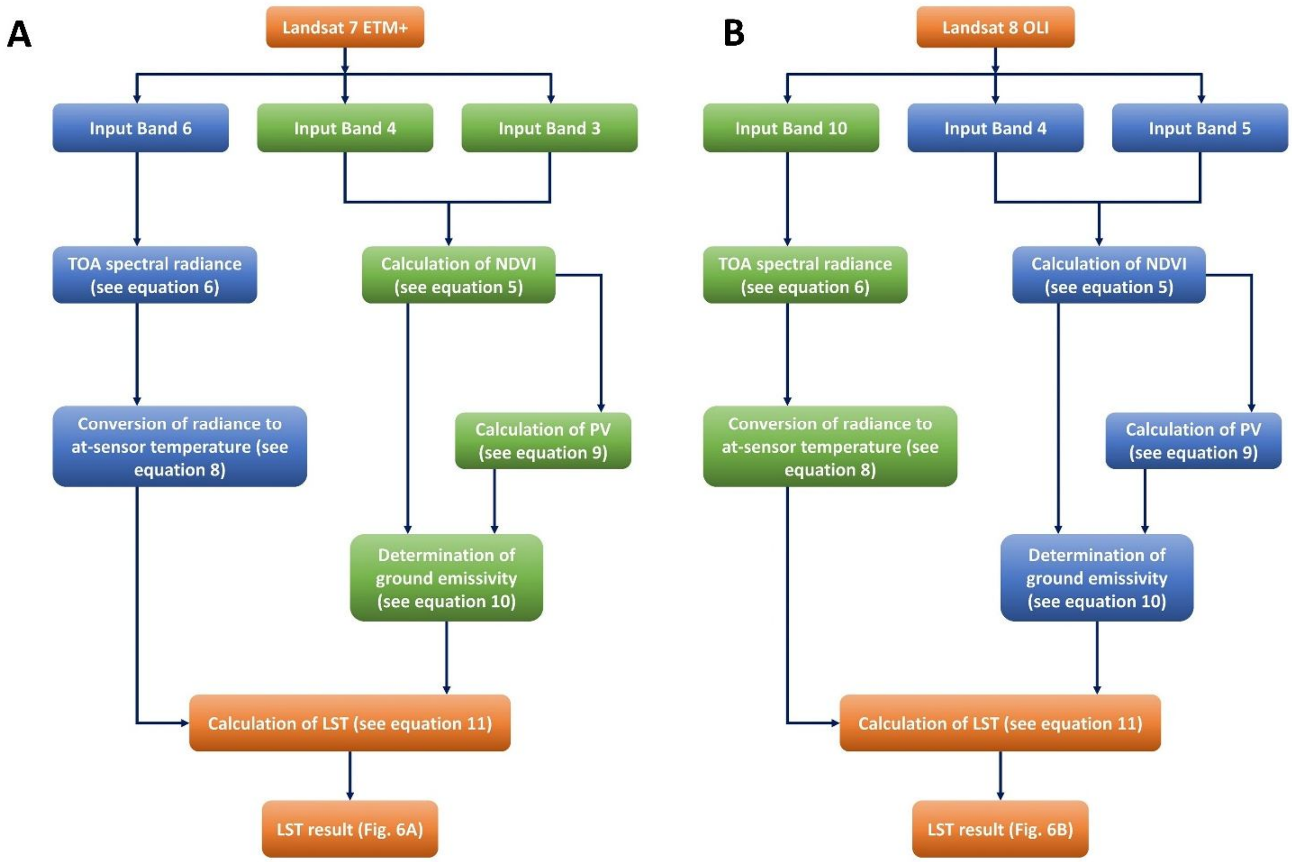

Figure 3 Procedures for LST calculation by using Landsat 7 ETM+ (A) and Landsat 8 OLI (B).

Step-II: Conversion of spectral radiation to satellite-derived brightness temperatures (BT). Upon converting the digital number into radiance, the data has been transformed into brightness temperature (BT) using the thermal constant provided in the metadata file. The tool's algorithm uses the following equation to convert reflectance to BT [equation 8].

$$BT = \left(\frac{K2}{In[(K1\ /\ L\lambda) + 1]}\right) - 273.15 \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

where,BT isthe satellite-derived brightness temperatures; Lλisthe TOA spectral radiance [equation (6)]; K1 and K2 arethe band constants (shown in Table 2), thosehelp to convert the temperature from Kelvin to Celsius.

Step III: Calculation of the proportion of vegetation (Pv). The NDVI is the primary metric used to determine the proportion of vegetation. The calculation was performed by using the followingequation -9.

$$Pv = (\frac{NDVI - NDVImin}{NDVImax - NDVImin})^2 \ldots\ldots\ldots (9)$$

where, NDVI is the Normalized difference vegetation index; NDVImin is the minimum value of NDVI; and NDVImax is the maximum value of NDVI.

Step IV: Emissivity adjustment (ε). The emissivity (ε) can be adjusted by using the equation provided in equation 10.

The land surface emissivity $\varepsilon = 0.004 \times PV + 0.986 \ldots\ldots\ldots (10)$

Step-V: Calculation Land surface temperature (LST).

$$LST = \frac{BT}{[1 + \{(\lambda \times \frac{BT}{\rho}) \times In\varepsilon\}]} \ldots\ldots\ldots (11)$$

where,λ isthe wavelength of emitted radiance in meters; ρ = h×c/σ, which value is 1.438×10^{-2} mK; σ isthe Boltzmann constant (1.38×10^{-23} J/K); h is the Planck's constant (6.626×10^{-34} Js); c is the velocity of light (2.998×10^{-8} m/s); andε is the emissivity ranging between 0.97 and 0.99.

Table 2 Thermal Constants

Sensor	Year	Band	Band constant K1	Band constant K2
Landsat ETM+	2002	Band 6	666.09	1282.71
Landsat OLI	2022	Band 10	777.8853	1321.0789

The land use categories

The land uses within the research region were categorized into four unique classifications, such as (i) water Bodies, (ii) vegetation, (iii) build up area, (iv) bare soil (Table 3). After categorizing the photos based on the above land use categories, maps were generated with appropriate designs at a scale of 1cm = 5km (Figure 4).

Method for correlation analysis between LST and NDVI

The study used a quantitative technique to examine the correlation between LST and NDVI during the years 2002–2022. Microsoft Excel was utilized for data processing and visualization, regression analysis, and graphical representations of the LST-NDVI correlations. To assess the relationship between LST and NDVI, Pearson correlation analysis was used for yielding correlation coefficientsto measure the strength and direction of their association. In addition, regression analysis determined the slope of the linear connection and the rate of change in LST with changing NDVI values.

Result and discussion

Land cover dynamics in the Jashore District from the year 2002 to 2022

The land use pattern for the year 2002 and 2022, consisting of four categories, is presented in Table 3 and visually shown in Figure 4. The land area of Jashoredistrict in 2002 was estimated to be 2545.32 km^2 by supervised image classification using ArcGIS 10.8. The land use classification conducted in 2002 served as the basis for visual interpretation of the land use pattern in 2022. The sequence of highest areas of land use in 2002 was vegetation area > bare soil > water bodies > build-up area, whereas the sequence in 2022 was bare soil > build up area > vegetation > water bodies. Out of the four land use categories, two important categories i.e., bare soil and build up area had an increase of 15% and 20%, respectively in the year 2022 compared to the year 2002. In contrast, the areas of vegetation and water bodies decreased by 33% and 3%, respectively, in 2022.

Table 3 Change detection in LULC of Jashoredisctrictduring the years from 2002-2022.

Land type classifications	**Description land use feature**	**Land Use in 2002**		**Land Use in 2022**		**Changes of LULC over 20 years**		
		Area (km^2)	**Land area (%)**	**Area (km^2)**	**Land area (%)**	**Changed area (km^2)**	**% of change**	**Annual rate of change (%)**
Water Bodies	River, lake and pond	100.12	4	28.16	1	(-) 74.64	(-) 2.93	(-) 3.73
Vegetation	Fruit tree and bush	1347.36	53	520.84	20	(-) 823.89	(-) 32.37	(-) 41.19
Build Up Area	Building area including industry and commercial area	28.64	1	544.48	21	(+) 528.60	(+) 20.77	(+) 26.43
Bare Soil	Riverbank, landfill and barren land	1068.87	42	1451.67	57	(+) 369.93	(+) 14.53	(+) 18.50
	Total area	2545.32	100	2545.32	100			

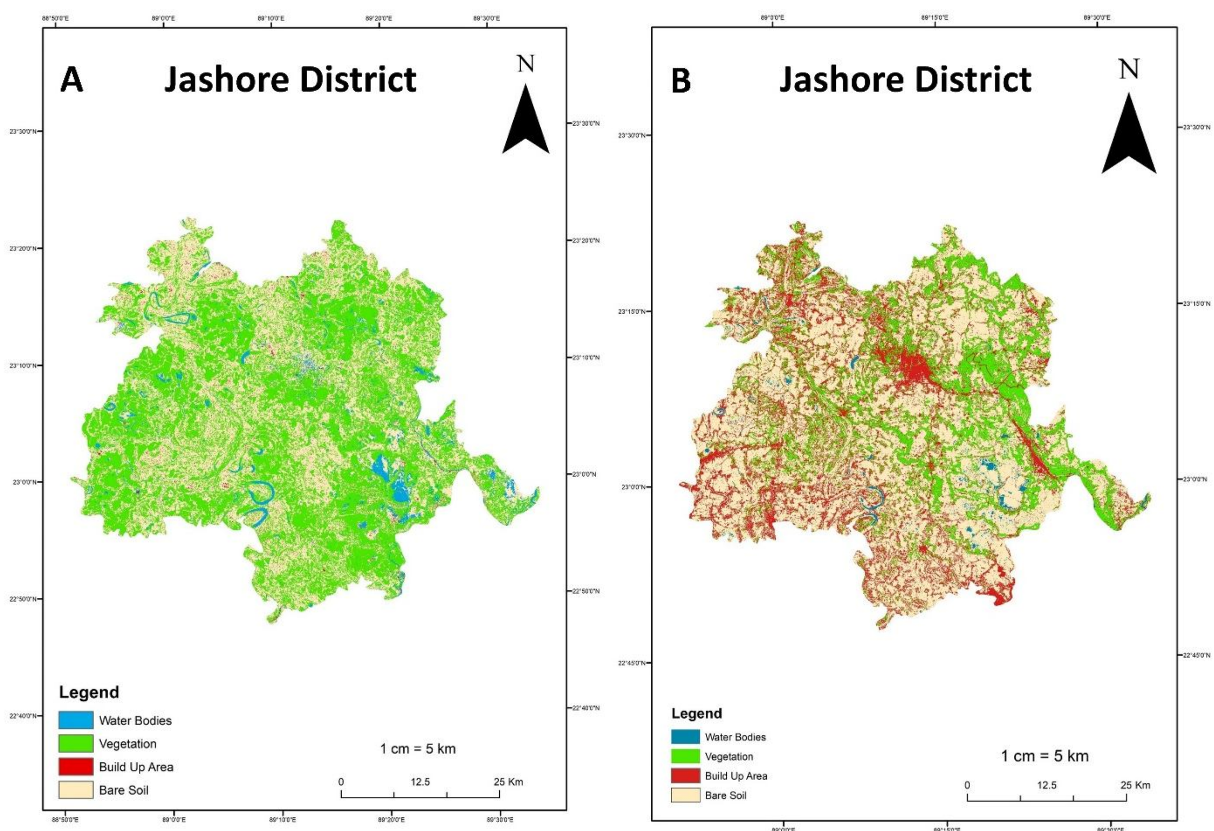

Figure 4 LULC map of Jeshoredistrict in the year 2002 (A) and in the year 2022 (B).

The assessment of the changes in land use categories between 2002 and 2022 revealed a combination of positive and negative changes across different classes, as shown in Table 3. A total of approximately 824km^2 of vegetation area had been reduced between the years 2002 and 2022 with anannual reduction of 41%. The area of water bodies exhibited a decrease of approximately 75 km^2 with a rate of 3.7% annually. During the period from 2002 to 2022, approximately 529 km^2 land was used for commercial and settlement purpose, with a change rate of approximately 26% annually.Several previous studies on LULC changes also revealed thatcropland andwaterbody areas in Bangladesh had been declining rapidly (Kafy et al. 2020; Morshed et al. 2021).This study illustrated that a large area of land cover under forests and vegetation in this study district has been used for widespread human settlement and development of commercial area over 20 years.To cope up with population pressure and modernization, urbanization is rapidly changing in LULC across the world during the last few decades(Kafy et al. 2021). The result coincides the future LULC modeling of Jashore city by Morshed et al. (2023), who compared LULC pattern of 2020 to that of 2050 and expected the urban area to be increased by 23.64%, whereas vegetation and water areas to be reduced by 5.47% and 7.73% respectively. However, the present study revealed an opposite trend in LULC change of bare soil category, as bare soil increased by approximately 15% in 2022 compared to 2002 (Table 3). Morshed et al. (2023) predicted a reduce of bare land by 9.55% by the year 2050 compared to 2020. He also reported that the urban areas would be increasing at the fastest rate during 2020–2030. Our study findings contribute to replan any decision about ecological and environmental development of the bare soil inJashoredistrict.

Accuracy evaluation and calculation of Kappa statistics

Accuracy assessment is crucial in the analysis of remotely sensed data as it allows for the evaluation of the heterogeneity and validation of the classified images (Elkington 1987). The supervised classification of images yielded different levels of accuracy,which was evaluated by Kappa statistics, a metric that quantifies the concordance between referred and user-observed categorized data. The results of Kappa coefficient were 0.80 for the 2022 classification and 0.65 for the 2002 classification. Thus, the image taken in 2022 by Landsat OLI had the maximum accuracy of 80%, while the image taken by Landsat ETM+ in 2002 showed the accuracy of 65%(Table 3). According toLandis and Koch (1977) Kappa coefficient values between 0.61 and 0.80 indicatedthat the supervised classification had a significant level of concurrence.The accuracy of a classification is highly dependent on the version of satellite dataset (Haque and Basak 2017). Advanced version of satellite can produce more accurate result.

Analysis of NDVI in Jashoredistrictbetweenthe years 2002 and 2022

The measurement of the vegetation area of Jashoredistrict was carried out with the Normalized Difference Vegetation Index (NDVI), classifying measurements into three distinct categories: low, moderate, and high. The value of NDVI ranges from +1 to -1. Values close to +1 indicates denser and greener vegetation, whereas those close to ‘0’ or less represents less green or other colored vegetation or dry leaf. The NDVI value ‘0’ characterizes no vegetation and ‘0 to 1’ means other land cover types (Haque and Basak 2017).In 2002, the NDVI analysis indicated that around 30% of the whole map consisted of areas with low values ranging from -0.06 to -0.15 (Figure 5A). After 20 years, in 2022, the low value -0.06 had risen to 36% as -0.11 (Figure 5B). This indicated a surge in the size of water bodies or areas devoid of vegetation throughout the time.The values close to zero are classified as mixed vegetation which might consist of settlement, water body, or any other land cover feature (Haque and Basak 2017). In 2002, approximately 53% of the land was covered by moderate NDVI values ranging from 0.16 to 0.22 (Figure 5A). Notably, the image taken in 2022 exhibited substantial alterations with moderate values ranging from 0.12 to 0.21 encompassing 30% of the Jashoredistrict (Figure 5B). This indicated a reduction in the amount of moderate vegetation.

In 2002, approximately 17% of the area was covered by high vegetation, identified by NDVI values ranging from 0.23 to 0.39 (Figure 5A). However, in 2022, the high value of NDVI ranged from 0.22 to 0.5 (Figure 5B), which indicated anincreasein high vegetation comprised of 34% of the land area. An incline in positive values, indicating forested high land vegetation, represented a notable increase in plant growth over 20 years. NDVI is the most effective indicator for categorizing native forests, especially for places with medium to high vegetation density (Piyoosh and Ghosh 2022). Since NDVI is less affected by soil and atmosphere, it might be affected by the vegetation type andgrowth phase (Muradyan et al. 2019).NDVI is a useful metric to show a significant increase with a clear upwards trend, vegetation and canopy cover (Roy and Bari 2022).

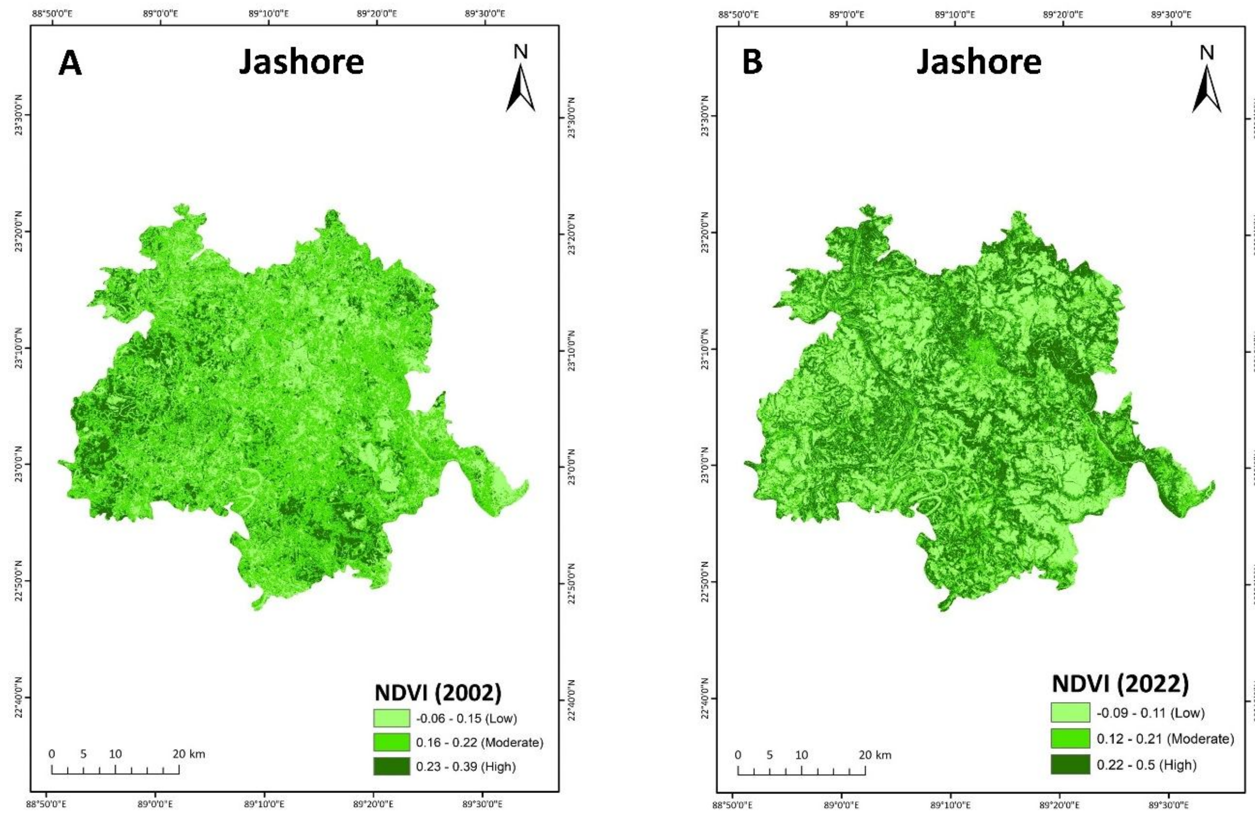

Figure 5. Normalized Difference Vegetation Index (NDVI) of Jashoredistrict in 2002 (A) and in 2022 (B).

Thus, the present finding of the higher NDVI values of denser and greener vegetation area expanding by two times of its original size demonstrated major alterations of land use between 2002 and 2022, which might be due to high growth of planted vegetation with large volume of dense canopy cover. Now a days farmers throughout the country are following high yielding crop variety cultivation with huge number of chemical fertilizers. However, Bangladesh exhibited a small change in net national tree cover with significantly variable forest types (Islam and Ma 2018).

Change detection in LST and validation of LST data

A significant change in LSTin the month of February has been documented over20 years from 2002 to 2022, as presented in Table 4 and Figure 6. Despite using an accurate and well-established technology to extract the spatiotemporal distribution of LST, the procedure has several small drawbacks. To get entirely accurate LST values for the research region, good weather and cloudless satellite photos are required. While the cloud cover was less than 10%, it was not completely absent, resulting in minor differences from the field-acquired data (Chen et al., 2006; Neteler, 2010; Dar et al., 2019). Such problems may lead to a biassed assessment of the LST distribution in any location. To validate the predicted LST, maximum and minimum temperature data were gathered from weather station in the study region under Bangladesh Meteorological Department (BMD) between the years 2002 and 2022, and deviations were computed (Table 4). There are both positive and negative deviations of minimum, maximum and mean Land Surface Temperature, while comparing the BMD and Landsat data in both years 2002 and 2022. Despite the constraints of the RS-derived LST data, the variances indicated a fair result between the estimated and recorded LST and was considered acceptable for future examination in the study region.

Table 4Change in LST over 20 years from 2002 to 2022 in Jashoredistrict, Bangladesh recorded by Landsat and weather station of Bangladesh Meteorological Department (BMD).

Land Surface Temperature (LST, □) in the month of February	**Recorded by Landsat and Bangladesh Meteorological Department (BMD) weather station**			
	2002		2022	
	Landsat	BMD recorded LST	Landsat 2022	BMD recorded LST
Minimum Temp.	20.78	18.38	13.66	12.01
Maximum Temp.	32.18	33.50	23.36	24.00
Mean Temp.	24.53	24.8	17.24	16.9

The trend of LST changes in this investigation signifies a discernible decline in the highest and lowest temperatures over 20 years. Differential composition of urban and rural LULC (Bala et al. 2021; Roy and Bari 2022), natural vegetation cover (Yuan et al. 2017; Bari et al. 2021; Roy 2021), vegetation types (Deng et al. 2018), heat conductivities of urban surfaces, anthropogenic discharges, and density of built-up areas are the contributors to LST intensity (Mathew et al. 2016). Due to the roughness of different LULC and the surface reflectance, the LST of different surface areas varies prominently (Guanglei et al. 2009) in the studied years. Both water and vegetation areas contribute negatively to the urban heat island, whereas the built-up areas and barren grounds contribute positively to LST (Bala et al. 2021). However, built-up areas will show greater temperatures than barren grounds since they reflect more heat than the Earth's surface (Aslam et al. 2021). Although LST is a good indicator of heat-retaining or heat-reflecting surfaces, it is also strongly affected by air surface temperature, (Roy and Bari 2022), water body, altitude (Deng et al. 2018) and season (Sun and Kafatos 2007).

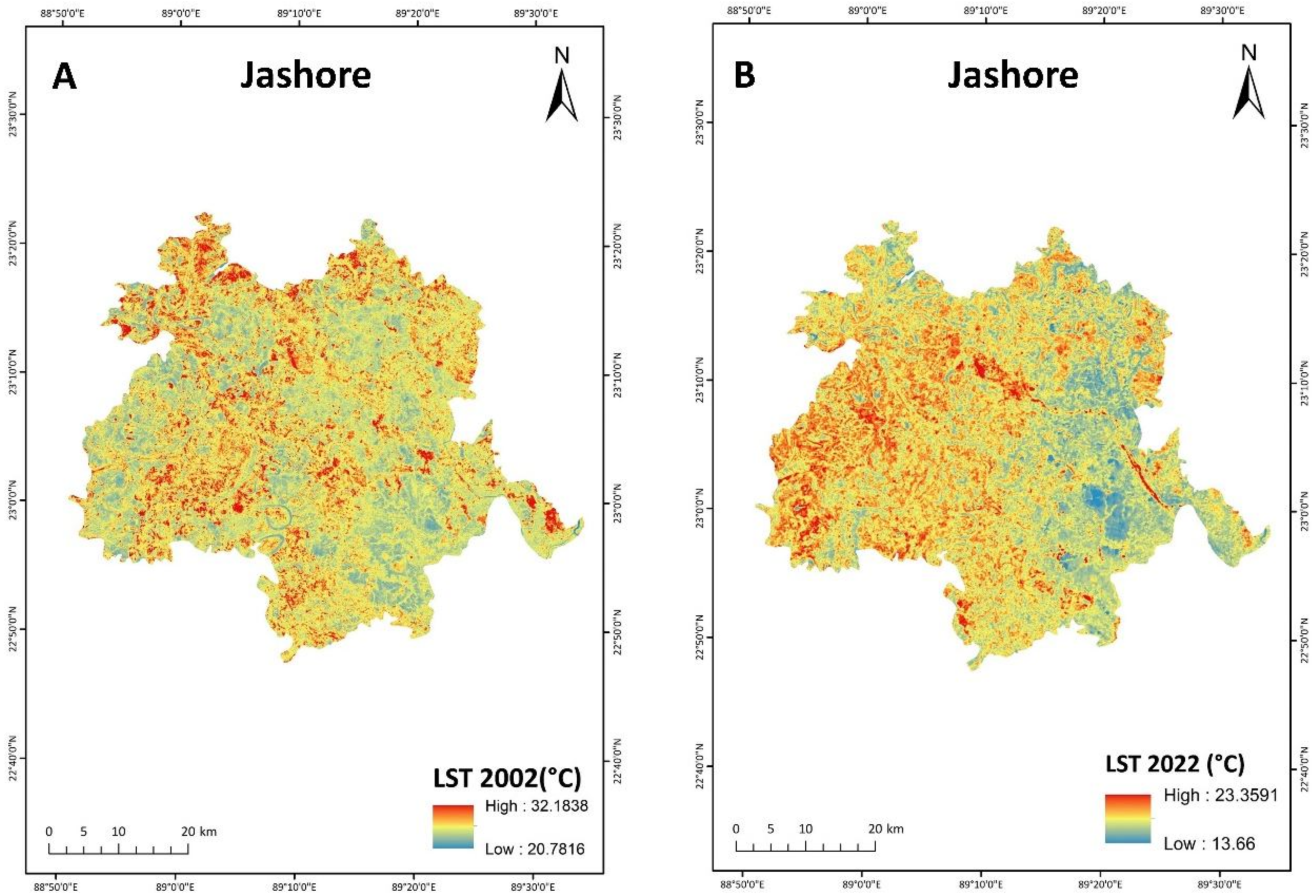

Figure 6. Land surface temperature (LST) showing the minimum and maximum temperature (□) on 7th Februaryin 2002 (A) and in 2022 (B).

The decline of the minimum, maximum and mean temperature of land surface in this investigation over a 20-years period (Table 4), associated with a decrease in areas of vegetation and water body, as well as an increase in areas of build-up and bare soil, reflected an integrated effects of different land cover types and their characteristics. Different types of vegetation such as woodland, grassland, and cultivated land are shown to affect LST in different ways (Deng et al. 2018; Ismal and Ma 2018). The order of high LST showed by different land use types is construction land > unused land > cultivated land > water body > grassland > woodland/forest land (Deng et al. 2018). To explore the effects of specific vegetation type on LST might better explain the reason of declining LST in the year 2022 than in 2002.

Relationship betweenLST andNDVI

To understand the variations in LST during the study years, whether the vegetation area affected on LST, the correlation between LST and NDVI was used (Guha and Govil 2021). In a previous study by Deng et al. (2018), the relation between LST and NDVI showed an obtuse-angled triangle shape but a negative linear correlation after excluding the water body data. Das et al. (2021) observed a negative relationship between NDVI and LST, as dense vegetation reduces the amount of heat absorbed by the Earth's surface.In this study, a negative correlation was observed between NDVI and LST values for both the years2002 and 2022, as shown in Figure 7.

The correlation between greater LST and lower vegetation densities pointed to a pattern in which warmer climates are linked to less robust or decreased vegetation cover. The Pearson correlation analysis showed that the correlation coefficient between LST (2002) and NDVI (2002) was -0.3934, showing a significant negative link, whilst the correlation value between LST (2022) and NDVI (2022) was -0.1824, indicating a weak negative relationship. The negative correlation coefficients indicate an increase in the driving parameter is associated with lower LST values. Additionally, the regression analysis showed that the slope of the linear line for the year 2002 is -0.0154 (Figure 7A), which is greater than -0.0286 for the year 2022 (Figure 7B). Thus, a sharper decline of LST values with rising NDVI was observed in 2002 (R^2 = 0.1548, Figure 7A) than 2022 (R^2 = 0.0333, Figure 7B). A reduction in one unit of LST required a higher value of NDVI in case of the year 2022 (intercept value is 0.6558; Figure 7B) than the year 2002 (intercept value is 0.5498; Figure 7A).

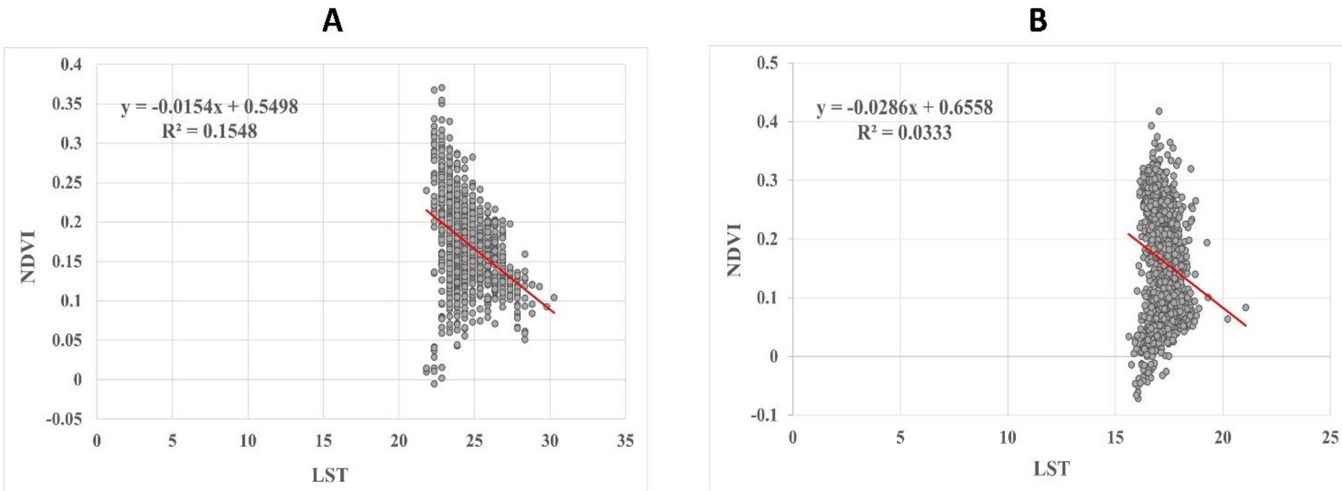

Figure 7. Relationship between LST and NDVI in the years 2002 (A) and 2022 (B).

The negative values of NDVI wereincreased in 2022 from 2002, which indicated the loss of vegetation and an increase in areas other than vegetation in recent times. Similarly, the NDVI values close to zero wereenhanced in 2022 indicating loss of moderately dense vegetation. However, the positive value of NDVI was increased in 2022 representing larger area of denser and healthy greener vegetation than those found in 2002. The reason might be the development of agriculture technology, more use of agrochemicals, as well as usage of hybrid variety of crop resulting in dense and healthy greener growth of vegetation. However, the results indicated that the relationship between LST and NDVI was stronger in erlier year (2002), but weaker in recent year (2022) (Guha and Govil, 2021). Thismight be due tothe combined effects of all atmospheric parameters, land type factors and types of vegetation,whichgenerally influenced the LST.

Limitations and future concern

Due to its temporal and spatial variability, LST goes through rapid changes across the widespread geographical regions, which makes it an apt indicator of global warming (Guha and Govil, 2023). Therefore, LST is critical in understanding global climate changes (El-Magd et al., 2024). Globally rising LST as aftereffect of global warming profoundly affects ecological processes on Earth. LST is influenced by properties like vegetation density, type of vegetation cover, albedo, precipitation, and land use (Guan et al. 2009; Li et al. 2018; Ismal and Ma 2018;). Many studies reported that the LST is critical for reclaiming significant climate variables like relative humidity, air temperature (Kuang, 2020), water studies (Zare et al., 2020) and soil moisture (Weng et al., 2004).According to the Global Climate Risk Index (NAPB 2022), Bangladesh ranked seventh in the world for countries most affected by climate change in 2021.Therefore, an in-depth study for clear understanding of LSTexploring combined effects of all driving forces, those can influence LST, isessential.

The present study showed remarkable changes in LULC and LST over a period of 20 years from 2002 to 2022 in Jashoredistrict in Bangladesh.To validate the accuracy of the findings through Kappa coefficient, it would be helpful to include accuracy assessment for intermediate year and provide a clearer picture of how LULC has changed over time. However, the Landsat image of 2012 was not clear and there were some lines error in the image file which limited us to observe the LULC and LST changes in the middle of the study period. Future studies, including time-span multi-year atmospheric variables, includingair temperature, soil moistureand vegetation type is required for better understanding in LST changes in relation to LULC. Such a study is crucial for elucidating the interaction with regional and global effects of climate changes (Eleftheriou et al. 2018) and with other ecological parameters.

Conclusion

This study provides insightful information about the dynamic changes in land use and land cover in Jashoredistrict of Bangladesh over a 20-year period from 2002 to 2022 using remote sensing and GIS based data obtained from Landsat satellites. The land use classification analysis showed notable increase in bare soil and built-up areas and decrease in water bodies and vegetation cover. The reliability of the classification process is validated by the accuracy evaluation through Kappa statistics, which validates the interpretation of land cover patterns. The examination of land surface temperature (LST) has revealed significant temperature changes during the research period, mainly due to changes in types of vegetation and area of vegetation cover.The analysis of the interaction between LST and NDVI further justified the assessmentof health and density of vegetationin the studied area and substantial impacts on LST.

Vegetation is one of the fundamental components in combating climate change by providing numerous ecosystem services like carbon sequestration. The current study could helpBangladeshi policymakers, urban planners, and environmental conservationists for understanding aftereffects of the changes in ecology and environment and evaluating on the effectiveness of ecological restoration initiatives. Continuous studying and monitoring on LULC and LST changes is essential for the evaluation on local, regional as well as national upgradation to sustainable development goals (SDGs) such as significant effects of climate action (SDG 13), sustainable land use (SDG 15), and biodiversity conservation (SDG 14).

Disclaimer (Artificial intelligence)

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Reference

Abdullah, S., Barua, D., and Abdullah, S.M.A. et al. (2022). Investigating the impact of land use/land cover change on present and future land surface temperature (LST) of Chittagong, Bangladesh. *Earth Syst Environ,* 6, 221–235. https://doi.org/10.1007/s41748-021-00291-w

Ahmed, B. (2011). Modelling spatio-temporal urban land cover growth dynamics using remote sensing and GIS techniques: A case study of Khulna City. *Journal of Bangladesh Institute of Planners,* 4, 15–32.http://www.bip.org.bd/SharingFiles/journal_book/20130724135944.pdf.

Al-Darwish, Y., Ayad, H., Taha, D., and Saadallah, D. (2018). Predicting the future urban growth and it's impacts on the surrounding environment using urban simulation models: Case study of Ibb city – Yemen. *Alexandria Engineering Journal*, 57(4), 2887–2895. https://doi.org/10.1016/j.aej. 2017.10.009.

Asgarian, A., Amiri, B.J., and Sakieh, Y. (2015). Assessing the effect of green cover spatial patterns on urban land surface temperature using landscape metrics approach. *Urban Ecosystems*, 18, 209-222.

Aslam, B., Maqsoom, A., Khalid, N., Ullah, F., and Sepasgozar, S. (2021). Urban overheating assessment through prediction of surface temperatures: a case study of karachi, Pakistan. *ISPRS Int. J. Geo-Inf.*, 10(8), 539.

Audah, S., Rizky, M.M., and Lindawati. (2021). Making of classification land cover through result of visual data satellite image analysis landsat 8 OLI: Case study in Tapaktuan District, South Aceh District. *JurnalInotera*, 6(1), 59–65. https://doi.org/10.31572/inotera.vol6.iss1.2021.id139

Bala, R., Prasad, R., and Yadav, V.P. (2021). Quantification of urban heat intensity with land use/land cover changes using Landsat satellite data over urban landscapes. *Theor. Appl. Climatol.*, 145(1–2), 1–12.

Bari, E., Nipa, N.J., and Roy, B. (2021). Association of vegetation indices with atmospheric and biological factors using MODIS time series products. *Environ. Challeng*e, 5, 100376.

Chen, X. L., Zhao, H. M., Li, P. X., and Yin, Z. Y. (2006). Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. Remote sensing of environment, 104(2), 133-146.

Choudhury, D., Das, K., and Das, A. (2019). Assessment of land use land cover changes and its impact on variations of land surface temperature in Asansol-Durgapur Development Region. *The Egyptian Journal of Remote Sensing and Space Science*, 22(2), 203-218.

Dar, I., Qadir, J., and Shukla, A. (2019). Estimation of LST from multi-sensor thermal remote sensing data and evaluating the influence of sensor characteristics. Annals of GIS, 25(3), 263-281.

Das, N., Mondal, P., Sutradhar, S., and Ghosh, R. (2021). Assessment of variation of land use/land cover and its impact on land surface temperature of Asansol subdivision. *The Egyptian Journal of Remote Sensing and Space Science*, 24(1), 131-149.

Deng, Y., Wang, S., Bai, X., Tian, Y., Wu, L., Xiao, J. et al. (2018). Relationship among land surface temperature and LUCC, NDVI in typical karst area. *Sci. Rep.*, 8(1), 641.

Ding, N., Zhang, Y., Wang, Y., Chen, L., Qin, K., and Yang, X. (2023). Effect of landscape pattern of urban surface evapotranspiration on land surface temperature. *Urban Climate*, 49, 101540. https://www.sciencedirect.com/journal/urban-climate

Eleftheriou, D., Kiachidis, K., Kalmintzis, G., Kalea, A., Bantasis, C., Koumadoraki, P., Spathara, M.E., Tsolaki, A., Tzampazidou, M.I., and Gemitzi, A. (2018). Determination of annual and seasonal daytime and nighttime trends of MODIS LST over Greece - climate change implications. Sci. Total Environ. 616, 937–947. https://doi.org/ 10.1016/j.scitotenv.2017.10.226. –617.

Elkington, M.D. (1987). A review of: "Remote Sensing Digital Image Analysis: An Introduction" by J. A. Richards. *International Journal of Remote Sensing*, 8(7), 1075. https://doi.org/10.1080/01431168708954750.

El-Magd, S.A.A., Masoud, A.M., Hassan, H.S., Nguyen, N.M., Pham, Q.B., Haneklaus, N.H., Hlawitschka, M.W., and Maged, A. (2024). Towards understanding climate change: Impact of land use indices and drainage on land surface temperature for valley drainage and non-drainage areas. Journal of Environmental Management, 350, 119636.https://doi.org/10.1016/j.jenvman.2023.119636

Faisal, A.-A., Kafy, A.-A., Rakib, A.A., et al. (2021). Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area. *Environ., Chall.* 4, 100192.

Feng, Y., Li, H., Tong, X., Chen, L., and Liu, Y. (2018). Projection of land surface temperature considering the effects of future land change in the Taihu Lake Basin of China. Glob. Planet. *Change*, 167, 24–34. doi: 10.1016/j.gloplacha.2018.05.007.

Gómez, J., Patiño, J., Duque, J., and Passos, S. (2020). Spatiotemporal modeling of urban growth using machine learning. Remote Sensing, 12(1), 109. https://doi.org/10. 3390/rs12010109

Govind, N.R., and Ramesh, H. (2019). The impact of spatiotemporal patterns of land use land cover and land surface temperature on an urban cool island: a case study of Bengaluru. *Environmental monitoring and assessment*, 191, 1-20.

Grant, U. (2010). Spatial inequality and urban poverty traps. London, UK: Overseas Development Institute. Retrieved from https://www.odi.org/publications/4526-spatial-inequality-andurban-poverty-traps

Guan, X., Huang, J., Guo, N., Bi, J., and Wang, G. (2009). Variability of soil moisture and its relationship with surface albedo and soil thermal parameters over the loess plateau. *Adv. Atmos. Sci.*, 26, 692–700.

Guanglei, H., Hongyan, Z., Yeqiao, W., Zhihe, Q., and Zhengxiang, Z. (2009). Retrieval and spatial distribution of land surface temperature in the middle part of jilin province based on MODIS data. *Sci. Geogr. Sin*. 30(3), 421–427. Accessed: Aug. 16, 2021. [Online]. Available: https://en.cnki.com.cn/Article_en/CJFDTotal-DLKX2010030 17.htm.

Guha, S., and Govil, H. (2021). An assessment on the relationship between land surface temperature and normalized difference vegetation index. *Environ. Dev. Sustain.*, 23(2), 1944–1963.

Haque, M.I., and Basak, R. (2017). Land cover change detection using GIS and remote sensing techniques: A spatio-temporal study on Tanguar Haor, Sunamganj, Bangladesh. *The Egyptian Journal of Remote Sensing and Space Sciences*, 20, 251–263. http://dx.doi.org/10.1016/j.ejrs.2016.12.003

Hassan, M.M. (2017). Monitoring land use/land cover change, urban growth dynamics and landscape pattern analysis in five fastest urbanized cities in Bangladesh. *Remote Sensing Applications: Society and Environment*, 7, 69-83. https://doi.org/10.1016/j.rsase.2017.07.001

Hossain, M.S., and Rahman, M. (2022). Assessment of Land Use/Land Cover (LULC) changes and urban growth dynamics using remote sensing in Dhaka City, Bangladesh. In: Dissanayake, R., Mendis, P., Weerasekera, K., De Silva, S., Fernando, S. (eds) ICSBE 2020. Lecture Notes in Civil Engineering, vol 174. Springer, Singapore. https://doi.org/10.1007/978-981-16-4412-2_48.

Huq, M.H., Rahman, M.M., and Hasan, G.M.J. (2024). Temporal land-use change of a reclaimed land in greater Dhaka and its impact on natural water cycle. MIST International Journal of *Science and Technology*, 12(1), 35–49. Retrieved from https://www.banglajol.info/index.php/MIJST/article/view/74626

Imran, H.M., Hossain, A., Islam, A.K.M.S., Rahman, A., Bhuiyan, M.A.E., Paul, S., and Alam, A. (2021).Impact of land cover changes on land surface temperature and human thermal comfort in Dhaka city of Bangladesh. *Earth Syst Environ*, 5, 667–693. https://doi.org/10.1007/s41748-021-00243-4

Imran, H.M., Hossain, A., Shammas, M.I., Das, M.K., Islam, M.R., Rahman, K., and Almazroui. M. (2022). Land surface temperature and human thermal comfort responses to land use dynamics in Chittagong city of Bangladesh.*Geomatics, Natural Hazards and Risk*, 13(1), 2283–2312.https://doi.org/10.1080/19475705.2022.2114384

Islam, M.S., and Ahmed, R. (2011). Land Use Change Prediction In Dhaka City Using Gis Aided Markov Chain Modeling. *J. Life Earth Sci.*, 6, 81-89. http://banglajol.info.index.php/JLES.

Islam, S., and Ma, M. (2018). Geospatial monitoring of land surface temperature effects on vegetation dynamics in the southeastern region of Bangladesh from 2001 to 2016. *ISPRS Int. J. Geo-Inf.*, 7, 486. doi:10.3390/ijgi7120486

Khachoo, Y.H., Cutugno, M., Robustelli, U., and Pugliano, G. (2024). Impact of land use and land cover (LULC) changes on carbon stocks and economic implications in Calabria using Google Earth Engine (GEE). *Sensors*, 24, 5836. https:// doi.org/10.3390/s24175836

Kafy, A., Faisal, A., Hasan, M.M., Sikdar, M.S., Khan, M.H.H., Rahman, M., and Islam, R. (2019). Impact of LULC Changes on LST in Rajshahi District of Bangladesh: A Remote Sensing Approach. *J. Geographical Studies*, 3 (1), 11-23. https://dx.doi.org/10.21523/gcj5.19030102.

Kafy, A.-A., Hasan, M.M., Faisal, A.-A., Islam, M., and Rahman, M.S. (2020). Modelling future land use land cover changes and their impacts on land surface temperatures in Rajshahi, Bangladesh. *Remote Sensing Applications: Society and Environment*, 18(2).

Kafy, A.-A., Faisal, A.-A., Rahman, A.S., Islam, M., Rakib, A.-A., Islam, M.A., et al. (2021). Prediction of seasonal urban thermal field variance index using machine learning algorithms in Cumilla, Bangladesh. *Sustainable Cities and Society*, 64, 102542. https://doi.org/10.1016/j.scs.2020.102542.

Kuang, W. (2020). Seasonal variation in air temperature and relative humidity on building areas and in green spaces in Beijing, China. Chin. Geogr. Sci. 30, 75–88. https://doi. org/10.1007/s11769-020-1097-0.

Landis, J.R., and Koch, G.G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 159-174.

Li, Q., Ma, M., Wu, X., and Yang, H. (2018). Snow cover and vegetation-induced decrease in global albedo from 2002 to 2016. *J. Geophys. Res. Atmos.*, 123.

López-Serrano, P.M., Corral-Rivas, J.J., Díaz-Varela, R.A., Álvarez-González, J.G., and López-Sánchez, C.A., 2016. Evaluation of radiometric and atmospheric correction algorithms for aboveground forest biomass estimation using landsat 5 TM data. *Remote Sens.*, 8, Pp. 1–19. http://dx.doi.org/10.3390/rs8050369.

Maarseveen, M., Martinez, J., and Flacke, J. (2018). GIS in sustainable urban planning and management: A global perspective (1st Edn). CRC Press. https://doi.org/10.1201/9781315146638

Mamun, A.A., Mahmood, A., and Rahman, M. (2013). Identification and monitoring the change of land use pattern using remote sensing and GIS: A case study of Dhaka City. *IOSR Journal of Mechanical and Civil Engineering*, 6(2), 20-28.

Mathew, A., Khandelwal, S., and Kaul, N. (2016). Spatial and temporal variations of urban heat island effect and the effect of percentage impervious surface area and elevation on land surface temperature: study of Chandigarh city, India. Sustain. *Cities Soc.*, 26, 264–277.

Mishaa, M., Manikandan, A.D., and Neebha, T.M. (2021). Image based land cover classification for remote sensing applications: A review. 2021 3rd International Conference on Signal Processing and Communication (ICPSC). IEEE. http://dx.doi.org/10.1109/icspc51351.2021.9451755

Mondal, M.S., Sharma, N., Garg, P.K., and Kappas, M. (2016). Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results. *Egypt. J. Remote Sens. Space Sci.*, 19 (2), 259–272. http://dx.doi.org/10.1016/j.ejrs.2016.08.001.

Morshed, S.R., Fattah, M.A., Haque, M.N., and Morshed, S.Y. (2021). Future ecosystem service value modeling with land cover dynamics by using machine learning based Artificial Neural Network model for Jashore city, Bangladesh. *Physics and Chemistry of the Earth, Parts a/b/c*. https://doi.org/10.1016/j.pce.2021.103021.

Morshed, S.R., Fattah, M.A., Hoque, M.M., Islam, M.R. Sultana, F., Fatema, K. et al. (2023). Simulating future intra□urban land use patterns of a developing city: a case study of Jashore, Bangladesh. *GeoJournal*, 88, 425–448. https://doi.org/10.1007/s10708-022-10609-4

Munthali, M.G., Davis, N., Adeola, A.M., and Botai, J.O. (2020). The impacts of land use and land cover dynamics on natural resources and rural livelihoods in Dedza District, Malawi. *Geocarto International*, 37(6), 1529–1546. https://doi.org/10.1080/10106049.2020.1791978

Muradyan, V., Tepanosyan, G., Asmaryan, S., Saghatelyan, A., and Dell'Acqua, F. (2019). Relationships between NDVI and climatic factors in mountain ecosystems: a case study of Armenia. *Remote Sens. Appl. Soc. Environ.*, 14, 158–169. http://refhub.elsevier.com/S2405-8440(22)01956-9/sref63

NAPB (National Adaptation Plan of Bangladesh, 2023-2050). Report published in 2022. Ministry of Environment, Forest and Climate Change, Government of the People's Republic of Bangladesh. Available online: https://moef.portal.gov.bd/sites/default/files/files/moef.portal.gov.bd/npfblock/903c6d55_

3fa3_4d24_a4e1_0611eaa3cb69/National%20Adaptation%20Plan%20of%20Bangladesh %20%282023-2050%29%20%281%29.pdf

Nedd, R., Light, K., Owens, M., James, N., Johnson, E., and Anandhi, A. (2021). A synthesis of land use/land cover studies: definitions, classification systems, meta-studies, challenges and knowledge gaps on a global landscape. *Land*, 10, 994. https://doi.org/10.3390/land10090994

Neteler, M. (2010). Estimating daily land surface temperatures in mountainous environments by reconstructed MODIS LST data. Remote sensing, 2(1), 333-351.

Pal, S., and Ziaul, S.K. (2017). Detection of land use and land cover change and land surface temperature in English Bazar urban center. *The Egyptian Journal of Remote Sensing and Space Science*, 20(1), 125-145.

Piyoosh, A.K., and Ghosh, S.K. (2022). Analysis of land use land cover change using a new and existing spectral index and its impact on normalized land surface temperature. *Geocarto Int.*, 37(8), 2137–2159. http://refhub.elsevier.com/S2405-8440(22)01956-9/sref62

Rawat, J.S., and Kumar, M. (2015). Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Science*, 18(1), 77-84.

Roy B., and Bari E. (2022). Examining the relationship between land surface temperature and landscape features using spectral indices with Google Earth Engine. *Heliyon* 8, e10668. https://doi.org/10.1016/j.heliyon.2022.e10668.

Roy, B. (2021). A machine learning approach to monitoring and forecasting spatio-temporal dynamics of land cover in Cox's Bazar district, Bangladesh from 2001 to 2019. *Environ. Challenges*, 5, 100237.

Salman, M.A., Nomaan, M.S.S., Sayed, S., Saha, A., and Rafiq, M.R. (2021).Land use and land cover change detection by using remote sensing and GIS technology in Barishal District, Bangladesh.*Earth Sciences Malaysia* (ESMY), 5(1), 33-40.doi: http://doi.org/10.26480/esmy.01.2021.33.40.

Saha, J., Ria, S.S., Sultana, J., Shima, U.A., Seyam, M.M.H., and Rahman, M.M. (2024). Assessing seasonal dynamics of land surface temperature (LST) and land use land cover (LULC) in Bhairab, Kishoreganj, Bangladesh: A geospatial analysis from 2008 to 2023.*Case Studies in Chemical and Environmental Engineering,* 9, 100560.https://doi.org/10.1016/j.cscee.2023.100560

Sun, D., and Kafatos, M. (2007). Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America. Geophysical Research Letters, 34, 1-4. https://doi.org/10.1029/2007GL031485

Townshend, J.R.G., and Justice, C.O. (1986). Analysis of the dynamics of African vegetation using the normalized difference vegetation index. *International Journal of Remote Sensing*, 7(11), 1435–1445. https://doi.org/10.1080/01431168608948946.

Uddin, K., and Gurung, D. (2008). Land cover change in Bangladesh- a knowledge-based classification approach. In Proceedings of the 10th International Symposium on High Mountain Remote Sensing Cartography ICIMOD, Kathmandu, Nepal, 8–11 September; 41–46.

Ullah, W., Ahmad, K., Ullah, S., Tahir, A.A., Javed, M.F., and Nazir, A., et al. (2023).Analysis of the relationship among land surface temperature (LST), land use land cover (LULC), and normalized difference vegetation index (NDVI) with topographic elements in the lower Himalayan region. *Heliyon,* 9(2), e13322. https://www.sciencedirect.com/journal/heliyon/vol/9/issue/2

Ullah, S., Qiao, X., and Abbas, M. (2024). Addressing the impact of land use land cover changes on land surface temperature using machine learning algorithms. *Sci Rep*., 14, 18746. https://doi.org/10.1038/s41598-024-68492-7

Weng, Q., Lu, D., and Schubring, J. (2004). Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment,* 89(4), 467-483.

Xu, X., Shrestha, S., Gilani, H., Gumma, M.K., Siddiqui, B.N., and Jain, A.K. (2020). Dynamics and drivers of land use and land cover changes in Bangladesh. *Regional Environmental Change*, 20, 54. https://doi.org/10.1007/s10113-020-01650-5

Yuan, X., Wang, W., Cui, J., Meng, F., Kurban, A., and De Maeyer, P. (2017). Vegetation changes and land surface feedbacks drive shifts in local temperatures over Central Asia. *Sci. Rep.*, 7(1), 3287.

Zare, M., Drastig, K., and Zude-Sasse, M. (2020). Tree water status in apple orchards measured by means of land surface temperature and vegetation index (LST-NDVI) trapezoidal space derived from landsat 8 satellite images. Sustain. Times 12, 1–19. https://doi. org/10.3390/SU12010070.

Zarin, T., and Zannat, M.E.U. (2023). Assessing the potential impacts of LULC change on urban air quality in Dhaka city. *Ecological Indicators,* 154, 110746.https://doi.org/10.1016/j.ecolind.2023.110746