

Changes in Land Use Land Cover and its Resultant Impacts on Urban Thermal Environment of Chattogram City: A spatio-temporal analysis based on remote sensing and GIS techniques

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Abstract

The present study assessed the changes in land use and land cover to correlate the variations in the land surface temperature of Chattogram City. In order to analyze land use land cover (LULC) change and determine its effects on land surface temperature in the city area, temporal Landsat (5,7 ETM+ and 8,9 OLI) imageries from four time periods (2007, 2012, 2017 and 2022) were used. To assess the correctness of the picked random pixels, current ground truth data gathered from several sources was applied. Raster data has been utilized to identify the places that are influenced year-round in the green space (i.e. vegetation cover) and to examine the remote sensing image categorization for the green area using satellite images. These enable the study to explain the causes of the degradation and alteration of green space throughout time. The study identified that urbanization has resulted in a significant rise (about 2840 hectares, 16.74%) in urban land between 2007 and 2022, causing a loss of vegetative land (about 656 hectares, 3.85%). Additionally, the research concentrated on the actual affected area and attempted to forecast the cities' land use in 2037, which revealed a large loss of vegetation by that year. The research has the potential to be utilized as a reference in the future.

Key Words	Land Use and Land Cover (LULC), Landsat, Land surface temperature (LST), Probability matrix, Transition matrix, Urban Heat Island
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1. Introduction

The land is a crucial resource and a source of livelihood. It is an essential and limited resource for some most essential human activities including agriculture, manufacturing, forestry, energy generation, settlement, recreation, and water catchments and storage. Land is a key component of production, and for a large portion of human history, economic development has been closely correlated with it. It includes biophysical characteristics including terrain, geology, hydrology, biodiversity, soil, and topography (Gaonkar et al., 2024). Another definition of land includes socioeconomic elements like management and technology and land use refers to how and why people use the land and its resources (Meyer, 1995). In general, a piece of land is modified when its use changes. This shift is driven by needs, which need not just change the land cover but also its

intensity and management (Verburg et al., 2000). Agricultural expansion, propelled by population increase and technical progress, has profoundly transformed land cover, especially in developing nations, eclipsing other influences such as urbanisation and deforestation (Kirkpatrick, 2024). Social structure, attitudes, and values have all changed significantly in the same period. Urban regions are thought to be the most dynamic areas on the surface of the Earth, according to the history of urban growth. Urbanization has a significant negative influence on the local ecosystem (Pasha, Chowdhury, et al., n.d.) despite its relevance to the regional economy (Saraswat et al., 2024). Only 14% of the world's population lived in urban areas in 1900; by 2000, this percentage had risen to 47% which has recently touched 56% (Ritchie & Roser, 2018), (Long et al., 2007). Almost all nations around the globe experience urban expansion, however, the rate of growth varies. Urban environment and ecology are currently the main environmental issues that require rigorous analysis and monitoring in order to effectively regulate land use. Inventories of land usage and land cover are becoming more and more important in a variety of fields, including agricultural planning, urban planning, and infrastructure development (Kavitha et al., 2021). Other forms of land use turning into urban land can be characterized as the primary change in land use in these locations. Several elements, including both physical and human aspects, have an impact on the intricate process of land use change in major urban areas. On the one hand, socioeconomic reasons are typically linked to and responsible for accelerated urban growth; on the other, the process of urbanization has a significant impact on the local economy (TYAGI et al., 2023).

One way to learn about urban environments is through remote sensing, which is also a crucial tool for comprehending and addressing many issues that face cities and their suburbs. (Lillesand et al., 2015). Change detection is crucial because it enables the researcher to comprehend and track the pattern of land cover change in the study area (such as urbanization, deforestation, and agricultural land management) (Ahmed, 2011). The remote sensing technique is a great data source from which updated information and changes in land use and land cover (LULC) can be effectively extracted, examined, and simulated. A lot of pressure has been put on the nearby land and its biotic and abiotic resources in recent decades due to developing countries' rapid urbanization and population increase. (Singh & Singh, 2023). This pressure is also the cause of the urban areas accelerating rate of landscape change. Numerous studies have demonstrated that the land cover change brought on by urbanization has a significant impact on the radiative, thermodynamic, and hydrological processes that can modify the local climate (Qian et al., 2022). The quality of vegetation cover reduces its ability to moderate temperature patterns, resulting in a negative correlation between the vegetation and land surface temperature (Fatemi & Narangifard, 2019). One of the biggest issues of this century is the urban heat island (UHI), which is a product of human civilization's urbanization and industrialization (Jabbar et al., 2023). The rise in surface temperature caused by the human activity can be a major cause for the development of urban heat islands which is one of the most significant markers of urbanization. Urban heat island (UHI) is a problem that results from the unchecked urbanization of areas (Karakuş, 2019). Because of the significant amount of vegetation loss, urban growth and shifting of forest land to agricultural the, the land surface temperature increase which ultimately develops UHI (Thomas et al., 2024). After urbanization, it is impossible to restore the forest and vegetation to their pre-urban state (B. Mia et al., 2017). By the end of 2047, it is predicted that urban migration would account for 50% of all migration.

Bangladesh is one of the most populous nations in the world and is currently developing. It has recently experienced major environmental degradation and rapid, uncontrolled urban growth. However, because of rapid urbanization, the region has seen significant environmental degradation and several ecological issues, including deforestation, biodiversity loss, soil erosion, and modifications to the carbon sink in water-based ecosystems (Thomas et al., 2024). Chattogram is the second largest city of Bangladesh which is also experiencing land use and land cover changes because of urban development.

The local and microclimate of Chattogram City has changed as a result of anthropogenic activities and urban growth, which are driven by land use, such as built-up areas, impermeable structures, industrial activities, waste dumping, nucleated high buildings, and transportation activities (Pathirana et al., 2014). New urban development in the metropolis is destroying urban trees and plants, which are crucial for protecting the urban ecosystem and environment. With a population of 66% living in urban areas, Chattogram, Bangladesh's second-largest city and business hub, is currently one of the fastest-growing cities in the world. It accounts for 19.7% of the country's urban population and 30% of the GDP (Hassan & Nazem, 2016). The urban forests, water bodies, and vegetation in cities have all been gradually destroyed by the rapid rise of urbanization in Chattogram city (Gazi et al., 2021). It is important to take into account Chattogram, a developing city in Bangladesh when analysing LST in connection to land-use change. Therefore, it is essential to recognise how LST is changing in

Chattogram City. According to a (BBS, 2011) analysis, the country is losing 809 km² of agricultural land every year as a result of city growth, road construction, and infrastructure development. Due to migration from rural to urban areas, Chattogram City's average annual growth rate become 17.5% (M. A. Mia et al., 2015). Since rising urbanisation has a negative effect on LST (Hokao et al., 2012), it is critical to track changes in land use and land cover and how they relate to LST behaviour in Chattogram. Hence, the present study aimed to identify the rate of changes in land use and land cover in the study area. Moreover, the study investigated the multitemporal spatial dynamics of LULC change and its contribution to UHI generation for Chattogram City, additionally, it determined the mean LST for each LULC class, the dynamics of change, and the relation with the urban landscape. This study used open-source Landsat imageries with advanced remote sensing and GIS technology to trace the dynamics of urban growth, monitor geographical and temporal changes in land use and land cover, and evaluate Chattogram's environmental sustainability.

2. Materials and Methods

2.1 The study area: The city of Chattogram, which is part of the Chattogram district, is bordered by rivers and is made up of small hills and narrow valleys. In addition to being Bangladesh's busiest seaport, Chattogram is also renowned as the country's commercial centre. The second-largest city in Bangladesh is Chattogram, with a land area of 157 km² (M. A. Mia et al., 2015). The city is located between latitudes 21°54' and 22°59' north and 91°17' and 92°14' east. Its southern and eastern boundaries are formed by the Karnaphuli River, northern and eastern by the Halda River, and western by the Bay of Bengal. Chattogram City is the chosen research topic for this study because it has expanded its urban zone with time and become the second most important city after the capital. (Figure 1). About 2.5 million people live in the city, which is under the control of the City Corporation, and it covers an area of about 168 square kilometres (Statistics, 2011). Approximately 40% of the nation's large-scale enterprises are located in Chattogram, which also accounts for 85% of Bangladesh's imports and 80% of its exports in the country's seaborne trade (Hassan & Nazem, 2016), which makes it an important location for this study.

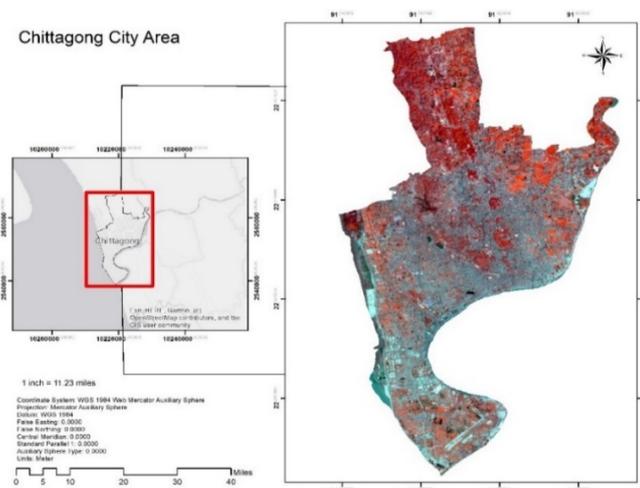


Figure 1: The location of Chattogram city selected for the present study.

2.2 Classification of images: Satellite imagery is detailed and essential for supplying geographic information. The complexity of field labour and study time is reduced by the quantitative and qualitative data provided by satellite and remote sensing imagery (Shahbaz et al., 2012). Image Classification is one of the most efficient methods which can provide both qualitative and quantitative data (Vaiphasa et al., 2011). Supervised image classification is the method (Figure 2) used here to identify and calculate the land cover amount of the study area. In this process researcher manually input some supervised samples in ArcGis software (Figure 2), later the software itself calculates the pixel of the image data and shows the output (Abburu & Golla, 2015). The amount of land cover used in an area can be calculated with the help of production. In this case, the land cover shows the amount of increase or decrease meant for a particular land cover category.

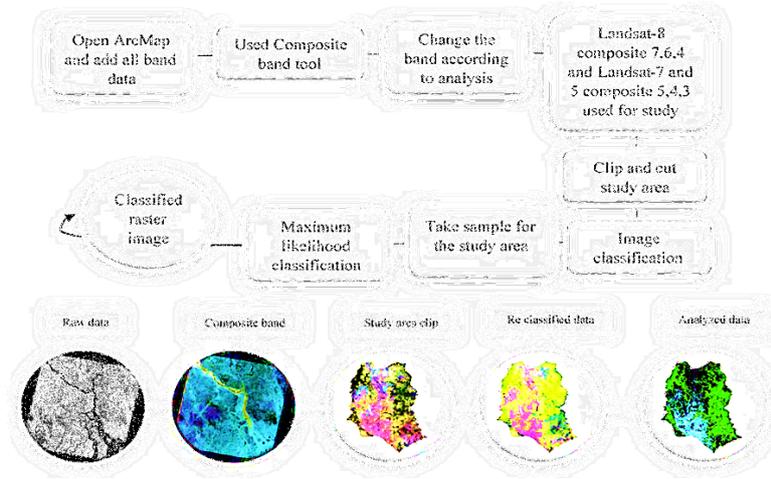


Figure 2: Representation of Data analysis process.

2.3 Markov modelling for probability matrix: A Markovian process is one that uses the current state of a system to predict its future state over time using the same design. Depending on the status right now, it is a random procedure. Markov chain is a discrete-time stochastic process (Winston & Goldberg, 2004). Here the condition of the future can be determined by analyzing the present state of that individual area (Ross, 2014). Markovian property can be described and stated with

$$i_0, i_1, \dots, i_{t-1}, i_t, i_{t+1}, \text{ and all } t \geq 0$$

$$\begin{aligned} P(x_{t+1} = i_{t+1} | x_t = i_t, x_{t-1} = i_{t-1}, \dots, x_1 = i_1, x_0 = i_0) \\ = P(x_{t+1} = i_{t+1} | x_t = i_t) \end{aligned} \quad (1)$$

According to the Markov chain, it assumes that the conditional probability does not change over time. for all States i and j and all t , $P(x_{t+1} = j | x_t = i)$ is independent of t , as expressed in Eq (1)

$$P(x_{t+1} = j | x_t = i) = p_{ij} \quad (2)$$

Where, P_{ij} = Transition probability that, given the system is in State i at time t , It will be in a state j at the time $(t + 1)$. The transition probabilities are expressed as a $[m \times m]$ Matrix and it is called the transition probability matrix or transition matrix, P . The characteristics of the transition probability matrix as p are given below

$$P = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1m} \\ p_{21} & p_{22} & \dots & p_{2m} \\ p_{m1} & p_{m2} & \dots & p_{mm} \end{bmatrix} \quad (3)$$

The estimation of transition probabilities in a Markov chain-based deterioration model requires data from the condition assessments of existing systems. (Baik et al., 2006).

2.4 Calculation of NDVI: The amount of vegetation or biomass present in the environment is measured by the Normalized Difference Vegetation Index (NDVI). Greater greenness and healthy vegetation are indicated by a higher NDVI (Curran, 1980). Data from Landsat MSS and TM can be used to calculate NDVI (Jensen, 1996). The reflectance data from the red (red) and near-infrared (nir) bands were utilized to calculate the NDVI values for the research area (Tan et al., 2010).

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red}) \quad (4)$$

2.5 Land surface temperature (LST) for Landsat 8/9 and 7/5 image: The temperature that is sensed while touching the ground in a region is known as the land surface temperature. It is distinct from the temperature of the air or the atmosphere.

Different Landsat data sets, including Landsat-9, 8, 7, and Landsat-5, were employed in this investigation (Pasha, Mozumder, et al., n.d.). Because the two Landsat data have different band values, calculating the land surface temperature for the two sets of data is different. There are eleven bands available for Landsat 8, and 9, and we used band 10 TIRS to calculate LST (Figure 3) (Avdan & Jovanovska, 2016). Thermal mapping is done using the Landsat 8 data band-10 TIRS, which specifies the thermal band with a 100-meter precision. Similar to this, Landsat 4-5 has a total of seven bands, each of which denotes a separate class. The thermal infrared band in Landsat 4-5 is band number 6, and it is frequently used to determine an area's thermal mapping (Figure 3) (Qin et al., 2001). Software named Arc GIS 10.4 has been used to perform the calculation. In order to obtain the LST, specific formulas were utilised in the raster calculator.

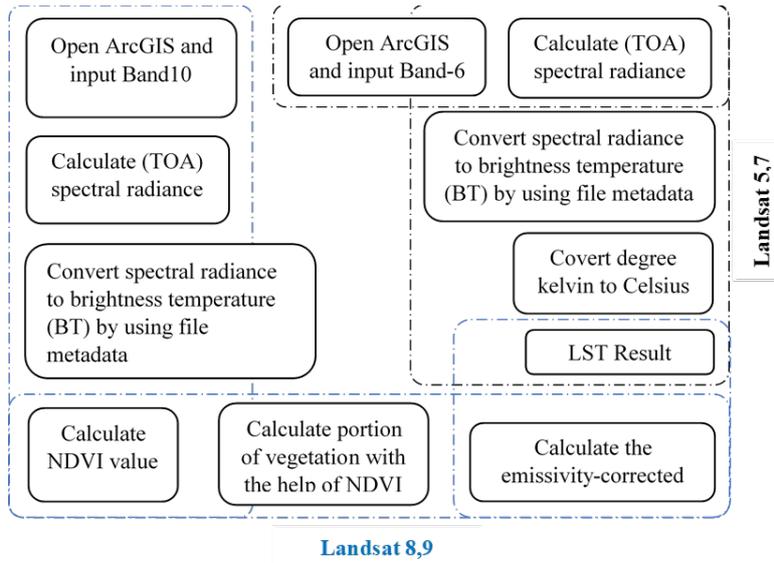


Figure 3: Graphical representation of the calculation of LST from Landsat 8,9 and 5,7 satellite image.

For Landsat 8/9, In order to recover the land surface temperature of various years from satellite photos, an image-based methodology has been used (Lo & Quattrochi, 2003). OLI images were converted using the USGS standard equation, and the DNs of the TIR bands of each year's ETM images were transformed to spectral radiance (Figure 3) using the method employed by Chander and Markham (Chander et al., 2009).

The algorithm's initial stage is the input of Band 10, which is used to calculate the atmospheric Spectral Radiance (Figure 3). The program retrieves the top of atmospheric (TOA) spectral radiance ($L\lambda$) once band 10 is inputted in the background using calculations from the USGS website.

$$L\lambda = M_L * Q_{cat} + A_L - O_i \quad (5)$$

Where ML stands for the band-specific multiplicative rescaling factor, Qcal for the Band 10 image, AL for the Band 10 additive rescaling factor, and Oi for the Band 10 correction (Barsi et al., 2014).

The next step is to calculate and covert spectral radiance to Brightness temperature (BT) by using metadata (Figure 3) where Using the thermal constants provided in the metadata file, the TIRS band data should be changed from spectral radiance to brightness temperature (BT) after being converted from digital numbers (DNs) to reflection. The tool's algorithm converts reflectance to BT using the equation shown below,

$$BT = \frac{K_2}{\ln \left[\left(\frac{K_1}{L\lambda} \right) + 1 \right]} - 273.15 \quad (6)$$

Where K1 and K2 refer to the metadata's band-specific thermal conversion constants. The radiant temperature is corrected by adding absolute zero (about -273.15 °C) to obtain the figures in Celsius (Xu & Chen, 2004). The Thermal constant for Landsat 9, Band 10 image is used in the method. Where the value of K_1 (Constant Band₁₀) is 799.0284 and the value of K_2 (Constant

Band₁₀) is 1329.2405. For the Rescaling factor for Landsat 9, Band 10 image, the value of M_L (Radiance Mult Band) is 0.000384 also the value of A_L (Radiance Add Band) is 0.10000 and the Correction value of Band 10 is $O_i = 0.29$.

In the third step NDVI value needed to be calculated following the procedure in section (2.5) then the portion of Vegetation P_v is calculated. The NDVI values for vegetation and soil ($NDVI_v = 0.5$ and $NDVI_s = 0.2$) are suggested to be used under global settings for computing P_v (Sobrino et al., 2004). Where,

$$P_v = \left(\frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \right)^2 \quad (7)$$

However, the figure for vegetated surfaces, 0.5, maybe too low because the NDVI values vary for each place. Since $NDVI_v$ and $NDVI_s$ will rely on atmospheric conditions, it would not be possible to establish global values in the case of an NDVI computed using TOA reflectivities (Figure 3). Global values from NDVI can be obtained from at-surface reflectivities (Jiménez-Muñoz et al., 2009).

In the next phase surface emissivity has to be calculated to estimate LST, the land surface emissivity (LSE) must be known because it is a proportionality factor that scales blackbody radiance (Planck's law) to forecast emitted radiance and measures how effectively thermal energy is transmitted from the surface to the atmosphere (Jiménez-Muñoz et al., 2006). The emissivity can be calculated with the following formula (Sobrino et al., 2004).

$$\varepsilon_\lambda = \varepsilon_{v\lambda} P_v + \varepsilon_{s\lambda} (1 - P_v) + C_\lambda \quad (8)$$

Where, C stands for surface roughness ($C = 0$ for homogeneous and flat surfaces) and is constant at 0.005 for vegetation and soil emissivities, respectively (Sobrino & Raissouni, 2000).

As a final step, the land surface temperature T_s , also known as the emissivity-corrected land surface temperature, is determined as follows.

$$T_s = \frac{BT}{\left\{ 1 + \left[\left(\frac{\lambda BT}{\rho} \right) \ln \varepsilon_\lambda \right] \right\}} \quad (9)$$

Where T_s is the LST in degrees Celsius (C), BT is the at-sensor BT (C), λ is the emission wavelength (for which the maximum response and the average of the limiting wavelength ($\lambda = 10.895$) will be used) and is the previously determined emissivity (Markham & Barker, 1985).

For Landsat 7 and 5 image L_λ have to be calculated with the following formula,

$$L_\lambda = L_{min} + \frac{L_{max} - L_{min}}{QCAL_{max} - QCAL_{min}} (DN - QCAL_{min}) \quad (10)$$

$Qcal$ is the DN of each image in the metadata of Landsat 7 and 5, $QCAL_{max}$ is the maximum DN (255), and $QCAL_{min}$ is the minimum DN (1). The top of the atmosphere (TOA) radiances, L_{max} and L_{min} , are scaled to $QCAL_{max}$ and $QCAL_{min}$ in $W/(m^2 \text{ srm})$, respectively. Using the following equation, the radiant images were transformed from the DNs to the spectral radiance to determine the blackbody temperature.

$$T_b = \frac{K_2}{\ln \left\{ \left(\frac{K_1}{L_\lambda} \right) + 1 \right\}} \quad (11)$$

Where K_1 and K_2 are prelaunch calibration constants in Kelvin units acquired from the image metadata file, T_b is the effective at-sensor brightness temperature in Kelvin units, L is spectral radiance in $W/(m^2 \text{ srm})$, For the Thermal constant for Landsat 7, Band 6 image is, K_1 (Constant Band 6) = 666.09 and the K_2 (Constant Band 6) = 1282.71. The Rescaling factor for Landsat 7 and 5, Band 6 image is, $QUANTIZE_{Cal \text{ Max Band}_6} = 255$ and $QUANTIZE_{Cal \text{ Min Band}_6} = 1$.

The calculated LST values were then translated to the standard Degree Celsius ($^{\circ}\text{C}$) unit by subtracting the absolute zero, which is roughly minus 273.5°C (Xu & Chen, 2004).

$$LST = T_b - 273.15 \quad (12)$$

2.6 Model Accuracy, Assumptions and Potential Errors: Rooted on the land use land cover changes data from 2007 to 2022, the Markov model anticipates land use changes depending upon the prior patterns in the future, which is likely to be a fallacy. It however does not out of consideration include the irregular events that can occur such as a change in policy, and natural catastrophes among others and simplifies changes to be linear which may not adequately portray the complexities related to urban growth. In this case, present conditions and the quality of data used for forecasting predictions, as well as the fact that the transition probabilities do not change, are major factors in determining the predictive power of these matrices. The span or the window of the data, which, in this instance is 15 years of history makes it difficult to trust the forecasting, for it is prone to future incongruence with present trends. The expected figures for urban encroachment and vegetation destruction relate to other fast-developing cities like Dhaka and Kolkata. These comparisons do enhance the forecasts made by the model, but their usage carries risks and should thus be moderated. The Markov modelling framework does not incorporate sudden land cover changes or any effects of land cover change on land use. This development could be even more beneficial for future projections by adding some innovative models with more dynamics like the CA-Markov model and integrating socio-economical and environmental factors in the modeling process.

3 Results

3.1 Changes in Land use and Land cover from 2007 to 2022: This study showed the land use and land cover of the Chattogram City Area. According to the analysis of land use and land cover, only 5901.21 hectares of urban area were found in 2007 (table 1). However, it expanded significantly from 5901.21 ha in 2007 to 6895.08 ha in 2012, rising from 34.77% to 40.63% of the total study area during those five years (figure 4). In 2017, the urban area's growth trends accounted for 8073.36 ha, or 47.57% of the total area (table 1). The Chattogram city has a huge population, and the urban area is growing swiftly. The urban area has grown even more, accounting for 8741.52 ha in 2022, or 51.51% of the city's total land area (table 1). But as the graph demonstrates, there has been a significant decline in the vegetation cover, with 0.4% (70 ha) between 2007 and 2012 and 2.15% (363.51 ha) between 2012 and 2017. 1.3% (220.95 acres) of vegetation was lost between 2017 and 2022. (figure 4). Over the course of 15 years, 654.39 ha less land was covered by vegetation. These trends in plant loss should worry city people because they portend an increase in urban heat, which is harmful to both the environment and human civilization. There was a discernible drop in bare land, agricultural land, and water body area. Agriculture occupied 3641.54 hectares (21.46%) of the total area in 2007, increased to 4686.03 ha (27.63%) in 2012, and again decreased to 2733.3 ha (16.11%) in 2017 (table 1). According to the study, the total amount of agricultural land decreased by 908.64 ha between 2007 and 2017, but in 2022, it climbed by roughly 5%, or 3661.74 ha, of the study region's total land cover (table 1). The area's bare land severely declined from 3215.07ha to 1793.07ha between 2007 and 2012 (a loss of 8.38%), but it dramatically increased from 2012 to 2017 (a gain of 8.15%) and became 3176.82 ha. The total land area in 2022 was 1574.1 ha, a 9.44% decrease in bare land area (table 1). Over the course of 15 years, bare land dropped by 1640.97 ha in total. The area occupied by inland water bodies shrunk between 2007 and 2012, from 1196.28 hectares in 2007 to 650.25 ha in 2012, and it also shrunk significantly between 2012 and 2017, between 650.25 hectares in 2012 and 404.46 hectares in 2017 (table 1). It did, however, grow in 2022, though still only by 3.72% of the overall area. Between 2007 and 2017, the water body shrunk by 791.82 ha, while between 2017 and 2022, it grew by 227.07 ha (table 1). Despite the fact that the total area by the years 2007, 2012, 2017, and 2022 was almost the same, the internal land use and landcover types have changed dramatically (figure 4). Urban lands produce more urban heat island zones than other types of land use. There was a noticeable change in the land use and land cover of the Chattogram region between 2007 and 2022. Analyses of change detection clearly demonstrated that several land use and land cover categories had undergone considerable changes. In 2007, urban land took up 34.77% of the research area's land area, followed by agricultural land (21.46% of the area), bare land (18.95% of the area), and vegetation (17.77%). Water bodies made up 7.05% of the study area's land area. The findings showed that the percentage of vegetation cover and bare land decreased to 3.85% and 9.67%, respectively. However Chattogram City's urban area drastically increased to 51.51% of the total area (table 1).

Table 1: Land cover change from 2007 to 2022.

Class	Hectors	P%	Hectors	P%	Hectors	P%	Hectors	P%
	2007		2012		2017		2022	
Vegetation	3015.9	17.77%	2945.97	17.36%	2582.46	15.22%	2361.51	13.92%
Agriculture	3641.94	21.46%	4686.03	27.61%	2733.3	16.11%	3661.74	21.58%
Urban	5901.21	34.77%	6895.08	40.63%	8073.36	47.57%	8741.52	51.51%
Bare land	3215.07	18.95%	1793.07	10.57%	3176.82	18.72%	1574.1	9.28%
Water body area	1196.28	7.05%	650.25	3.83%	404.46	2.38%	631.53	3.72%
Total	16970.4	100%	16970.4	100%	16970.4	100%	16970.4	100%

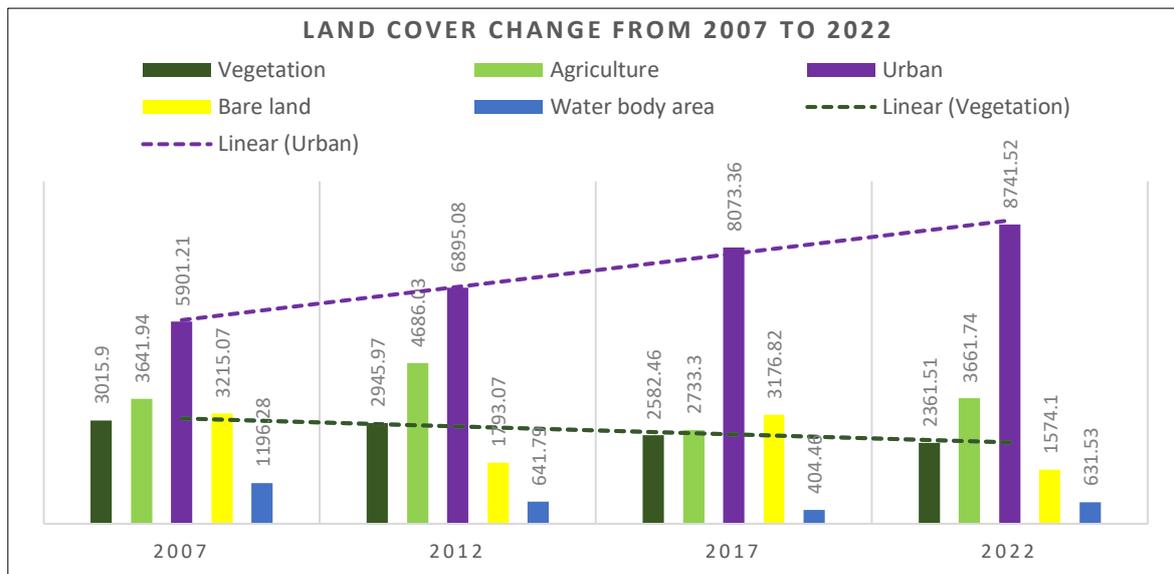


Figure 4: Land cover change including Vegetation and urban trend line.

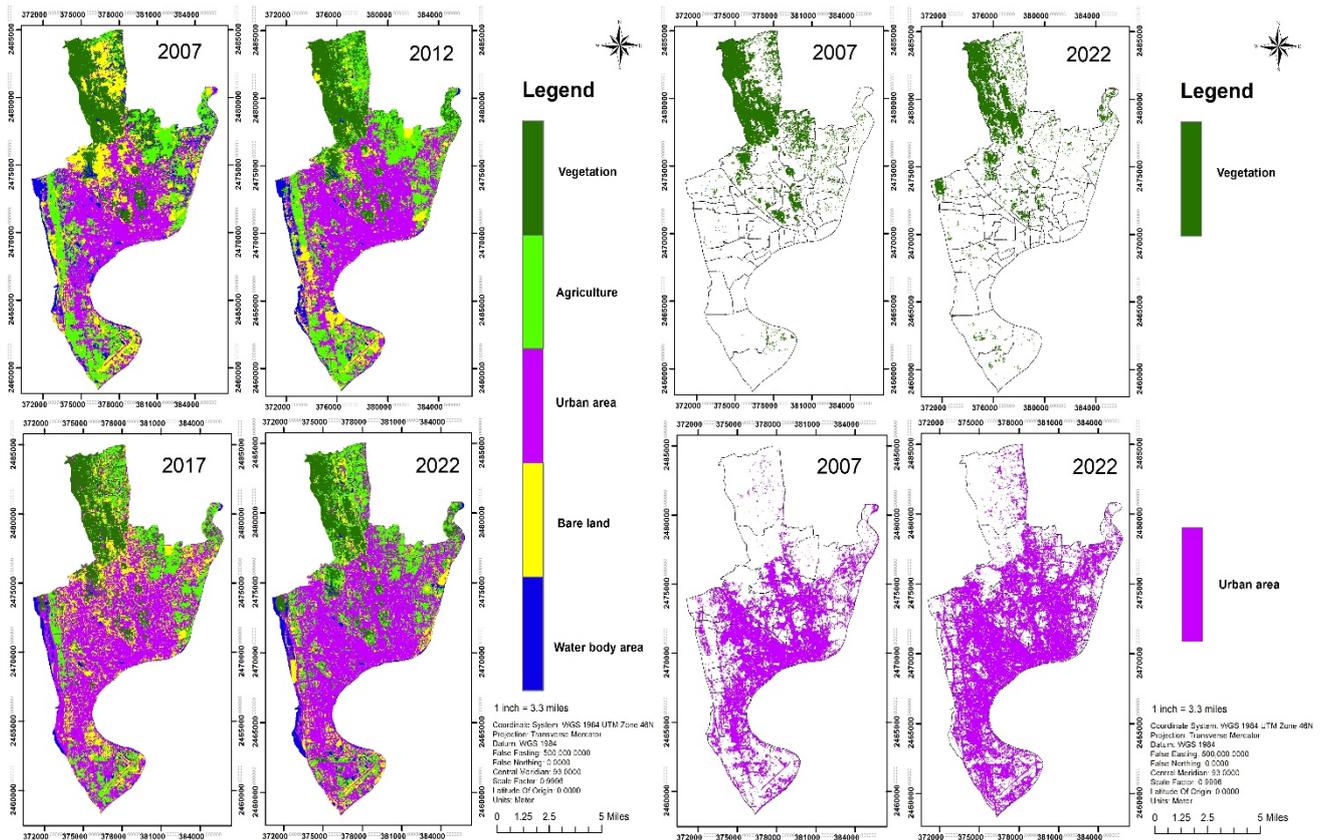


Figure 5: Land Use and Land Cover map from and the Changes in Vegetation and Urban area from 2007 to 2022.

3.2 Indicative changes in LULC by 2037: By examining two qualitative land uses from two distinct periods, Markov creates a transition matrix or a transition area matrix. For this study, 15 years of data from 2007 to 2022 (table 2) was used. More recent land cover usage is represented by the column, whereas older land cover use is represented by the rows. Agriculture, bare terrain, urban, vegetation, and water bodies are represented here in chronological order by the categories. Here, the Markov analysis used the matrix to forecast how the land cover will be used in 2037 (Islam & Ahmed, 2011).

Table 2: Probability of changes in the year 2037 land cover (prediction) using transition matrix.

Class	Agriculture	Bare land	Urban	Vegetation	Water Body	Grand Total
Agriculture	39.29%	11.19%	41.28%	5.97%	2.27%	100%
Bare land	28.20%	19.64%	41.20%	8.36%	2.59%	100%
Urban	5.15%	4.53%	86.28%	1.49%	2.56%	100%
Vegetation	25.57%	4.55%	15.56%	53.97%	0.35%	100%
Waterbody	16.64%	4.17%	41.54%	12.74%	24.91%	100%
Markov's prediction of land use change in the next 15 years						

According to the transition matrix, the probability of change for agricultural land is that 39.29% of the current agricultural area will remain the same in 2037. Of the current area, 11.19% may become bare land, 41.28% may become urban areas, 5.97% may become vegetation, and 2.27 per cent may become water body areas (table 2). 19.64 per cent of the current bare land area is likely to remain unchanged in 2037, which would represent no change in the bare land area. Currently, agriculture can occupy 28.20 per cent of the land, whereas urban uses can occupy 41.20 per cent, vegetation can occupy 8.36 per cent, and water bodies can occupy 2.59 per cent (table 2). Similar to this, in 2037, 86% of the currently developed urban land will still be there, with 4.53 % of it being bare land, 5.15 % being used for agriculture, 1.49 % being covered in vegetation, and 2.56 % being a body of water. In 2037, it is anticipated that 53.97 per cent of the area's vegetation cover will remain the same, while 15.56 per cent of it may become urban, 4.55 per cent could turn into bare ground, 25.57 per cent could be used for agriculture, and 0.35 per cent could turn into a body of water (table 2). In terms of the water body area, there will be no change of 24.91 per cent in 2037. However, 12.74 per cent may be covered by vegetation, 41.54 per cent by urban, 4.17 per cent by bare land, and 16.64 per cent by agriculture (table 2).

3.3 Relationship between NDVI and LST: Figure (6) shows the relationship between NDVI and LST. It has been demonstrated that the NDVI and surface temperature have a negative correlation. This is a blatant indication that the LST and NDVI have a high and unfavourable correlation. As a result, the land surface temperature is higher in areas with less vegetation. Figures (6) show that the area's temperature regime has been significantly impacted by changes in land use. However, compared to other locations, such as city areas, the vegetative area had a lower temperature. In comparison to urban green spaces such as parks, and agricultural fields, LST values were comparatively greater in urban areas with no vegetation cover. Because there is a negative association between NDVI and LST, areas with lower NDVI values have higher land surface temperatures, whereas areas with higher NDVI values have lower land surface temperatures (Gorgani et al., 2013). The value of the NDVI in 2007 ranged from +0.6 to -0.25, with a negative value indicating lesser vegetation cover (Table 3), which typically indicates places with water cover. By looking at the figure (6), it is clear that this range was true in 2007. The LST map for 2007 displays the same information, indicating that the maximum LST was 38⁰ C and the minimum LST was 24.5⁰ C (table 3). It is evident from the 2007 co-relationship diagram that NDVI value decreases with high LST value and increases with low LST value. The NDVI value was 0.289 in the trend line of correlation (Figure 6) when the LST value was close to 25⁰ C, but it constantly declined with higher LST values, as can be seen when the LST value was close to 38⁰ C and the NDVI value was negative at -0.075. That indicates that in 2007, the trend line is unmistakably demonstrating a negative association between NDVI and LST (Figure 6). With a slightly different NDVI and LST value for the year 2012, it was essentially a reflection of the year 2007. The trend line for 2012 shows a similar outcome to that of 2007, where the NDVI value is 0.237 while the LST is close to 22⁰ C but continuously decreases as the LST increases (Figure 6). The NDVI value is -0.221 when the LST value is near 35⁰ C. This clearly illustrates the conflict between the NDVI and LST. This

implies the tendency of inverse relationships between NDVI and LST where the increase of NDVI values fits to the decrease of LST values and vice versa. In the same way, in 2017 the relationship showed a negative trend line between NDVI and LST. In 2017 the highest NDVI was +0.56 and the lowest NDVI was -0.15, while the maximum LST and lowest LST values were 37.7⁰ C and 20.26⁰ C, respectively (table 3). The trend line indicated that less vegetation will be present if the LST has a higher value when the relationship between them is taken into account. When the LST was close to 37⁰ C, the NDVI value was negative (-0.086), indicating the absence of vegetation, as it was in 2017 when the NDVI value was 0.35 on the trendline (figure 6). In 2022 the result was quite similar as the correlation was negative. In 2022 the higher NDVI value was +0.60 and -0.17 was the lowest NDVI score. The highest LST and lowest LST in 2022 were 42.03⁰ C and 24.78⁰ C, respectively (figure 6). The trendline indicated that less vegetation will be present if the LST has a higher value when the relationship between them is taken into account. The NDVI had a low value of 0.02 when the LST was close to 41⁰ C, indicating very little vegetation, but it had a high value of +0.37 when the LST was close to 25⁰ C (figure 6).

Table 3: Retrieved statistics of LST (°C) and NDVI values from 2007-2022.

	LST				NDVI			
	2022	2017	2012	2007	2022	2017	2012	2007
Maximum	42.0361	37.755	37.2995	38.0009	0.608817	0.564	0.447368	0.6
Minimum	24.7868	20.2609	20.2609	24.5451	-0.17095	-0.15216	-0.28571	-0.25
Mean	33.41145	29.00795	28.7802	31.273	0.218932	0.205919	0.080827	0.175
Standard Deviation	12.1971	12.3702	12.04811	9.514687	0.551381	0.506403	0.518367	0.601040764

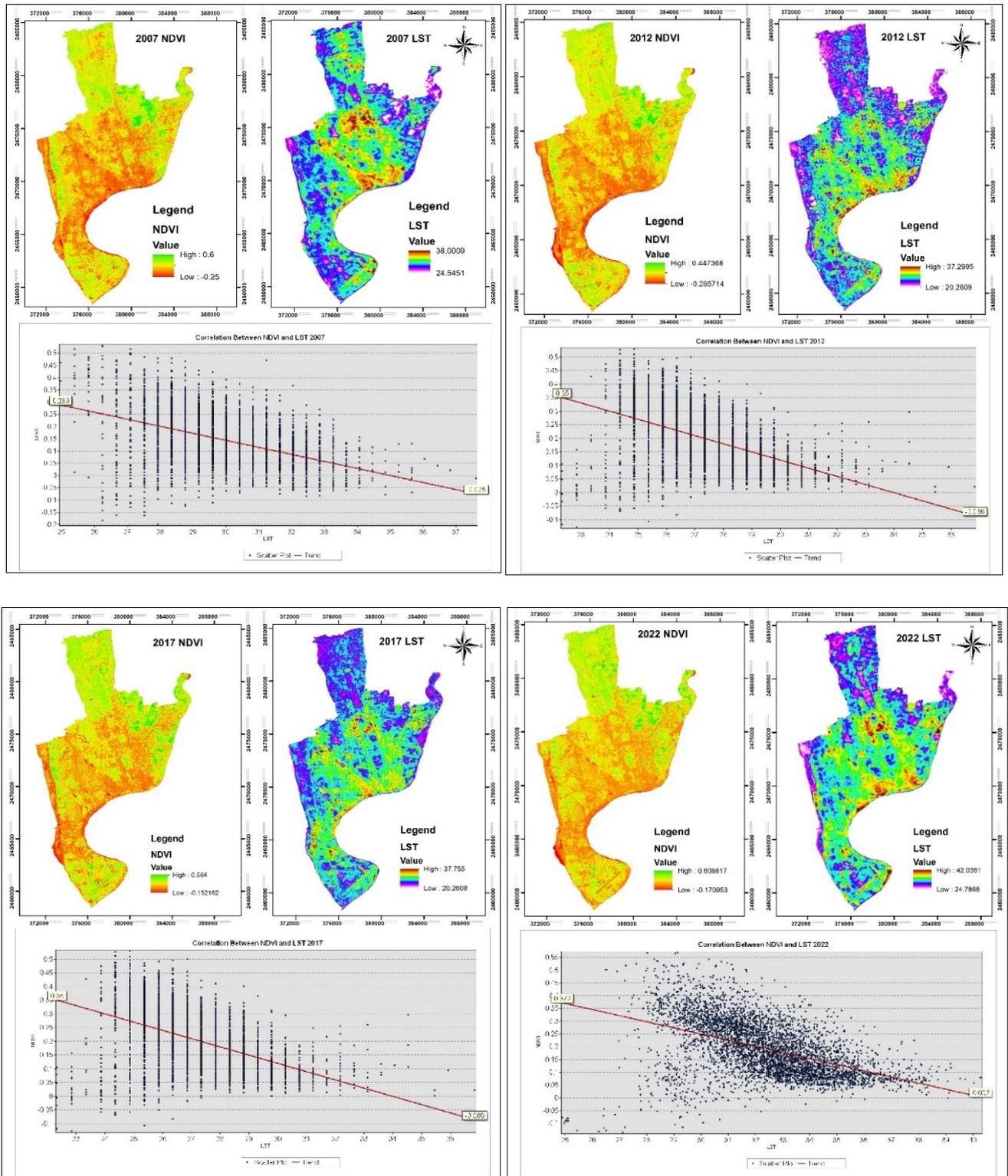


Figure 6: Correlation of LST and NDVI From the year 2007 to 2022.

4. Discussion

Gain-loss and net change estimation from the four temporal periods of 2007 to 2012, 2012 to 2017, 2017 to 2022 and 2007 to 2022 were detected using the continuous analysis of LULC. Nearly all of the land use land cover classes displayed gains and losses. Gain and loss graphs for various purposes (figure 7) were made per category to aid in understanding. From the transition matrix (table 4) it can be identified that lands from different categories have changed with time. The area which was covered by water in 2007, transformed into an urban area which is about 472 ha of land. Also, there is a significant change has been shown in the vegetation area which has been converted into an urban area in the last 15 years. About 470 ha of land has been converted from a vegetation area to an urban buildup area, also about 772 ha of land has been converted into agricultural land in the last 15 years in Chattogram city. The conversion of vegetation land to bare land is also alarming for the overall environment of Chattogram City. About 137 ha of land has been converted from vegetation to bare land. Because of the gain of urban area and loss of vegetation area, it is significantly impacting the thermal environment of the city. The Land Surface Temperature (LST) and NDVI both show their individual characteristics because of these changes (table 5). ArcGIS 10.4 image processing software is used to display the LST and NDVI images of Chattogram side by side in order to better comprehend the LST and NDVI pattern. The spatial distribution of the urban thermal environment and vegetation cover in Chattogram City is depicted in Figure (8) in an instructive manner. The urban area of Chattogram has a higher LST than the surrounding area of vegetation and agricultural land. It is evident that non-porous materials, such as metal, asphalt, and concrete, which are used to construct city structures and main transportation corridors, contribute to greater temperatures (Hoehne et al., 2022). Water bodies, agricultural areas, and vegetation, on the other hand, all have lower temperatures. In the NDVI image (Figure 8), the values are the exact opposite. Due to the lack of vegetation, built-up or core city regions have low NDVI values, as do water body locations. Because green biomass is present at relatively high levels, high values are found in agriculture, vegetation, and green land areas (Prashar et al., 2022). Regarding LST, the phenomenon that LST values are disproportionately greater in the built-up or core urban area than in the suburbs makes the impact of the urban thermal environment clear. With the exception of a few open spaces, NDVI values in the built-up or core city region are significantly lower than in the suburbs. When comparing LST and NDVI, one discovers that their respective changing trends are completely at odds (table 5). LST values are typically high where the main city area or buildup area is situated, while they are typically low where bodies of water and green space are present. The green space is where the NDVI peaks arise. LST and NDVI typically exhibit a clear inverse association. On the other hand, Chattogram's urban form and urban sprawl are intimately tied to the shifting trends of LST or NDVI.

Table 4: Land Use Land Cover Transition Matrix 2007-2022 in Hectors.

		Land cover class 2022						
		Land Class	Agriculture	Bare land	Urban	Vegetation	Water Body	Grand Total
Land cover class 2007	Agriculture		1431.744195	407.898234	1504.122069	217.562777	82.592654	3643.919929
	Bare land		893.989644	622.767495	1306.324578	265.116518	82.140167	3170.338402
	Urban		307.313042	270.381518	5153.086372	88.993963	152.719009	5972.493904
	Vegetation		772.824363	137.596243	470.26625	1631.57592	10.622077	3022.884852
	Waterbody		189.196549	47.430983	472.239674	144.855487	283.202797	1136.92549
	Grand Total		3595.067793	1486.074473	8906.038943	2348.10466	611.276704	16946.56258

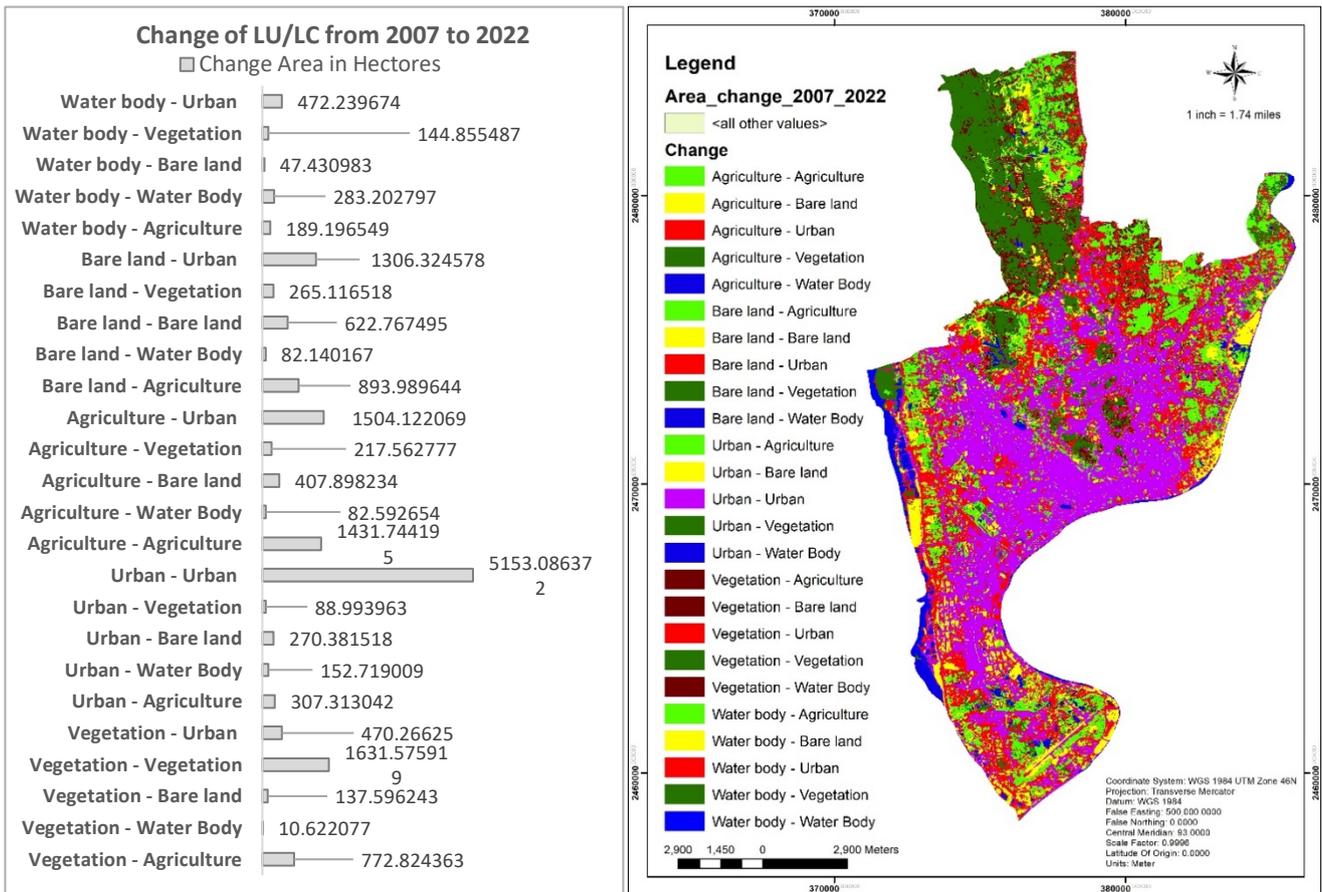


Figure 7: Changes in Land cover in each category from 2007 to 2022.

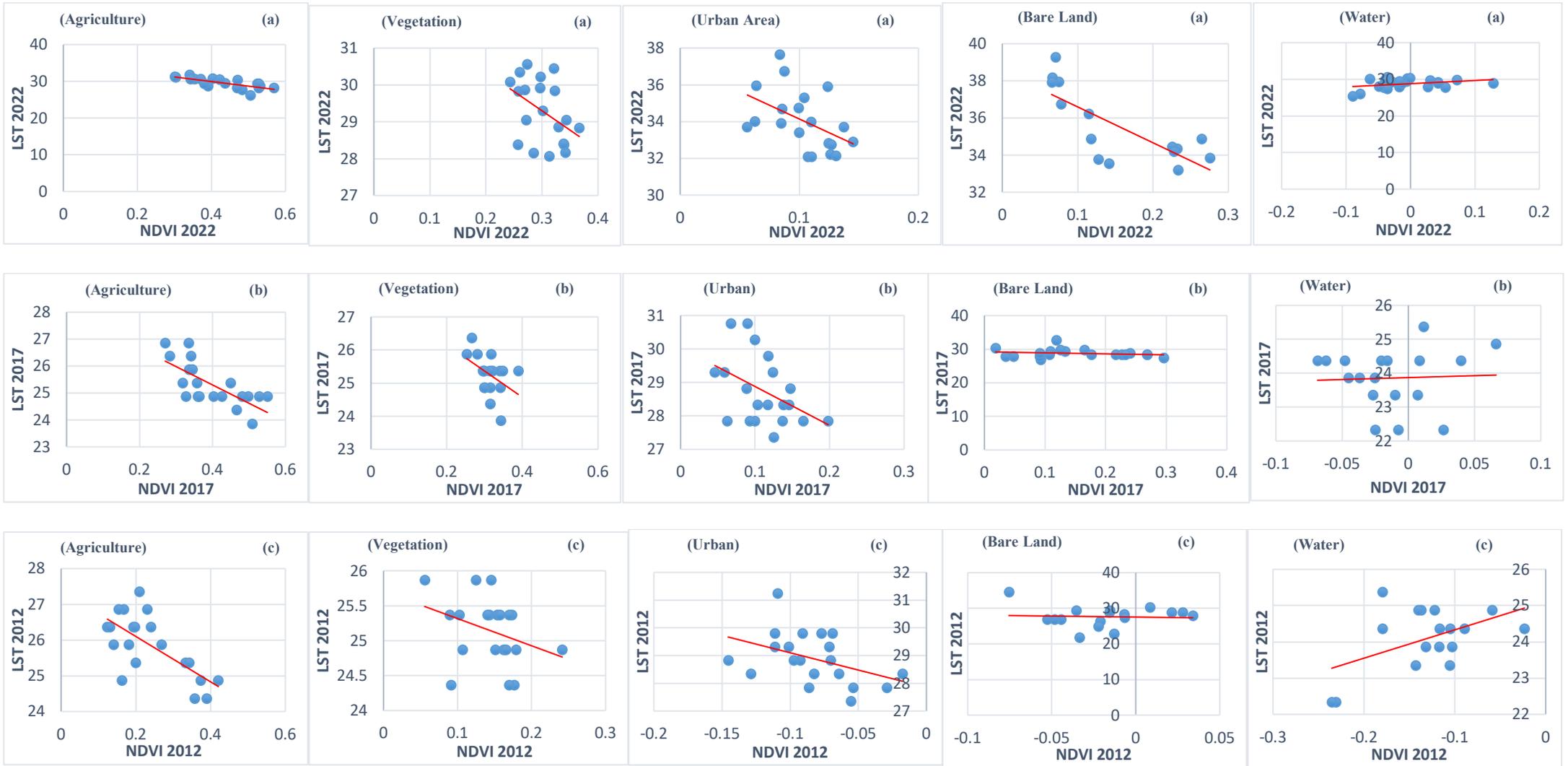
Table 5 presents the regression functions and correlation coefficient (R^2), which gauges the potency of linear regression, to show the relationship between LST and NDVI for each LULC type. NDVI and LST of all LULC categories, with the exception of water bodies, showed a substantial inverse association. For every year the greatest negative regression slope was indicated by "Urban area," while the shallowest negative regression slope was revealed by "Vegetation area." Figure 8 illustrates that the NDVI and LST association was consistently negative except water body area. The NDVI reduced as LST grew at all-time intervals due to having a negative connection, and this association demonstrated that when a lower Vegetation Level was present, the LST increased (Table 5). In other words, higher Vegetation Levels caused lower LST while lower vegetation levels caused higher LST (Figure 8). So if the vegetation decreases with time in Chattogram region the, with time a significant amount of LST will increase which is usually responsible for creating an Urban heat island that also has a direct impact on the overall temperature of the city (Roy et al., 2020). According to (Farzana et al., 2022) a city's heat island can also have an impact on precipitation, which is a problem for Chattogram City.

Table 5: LST and NDVI Relationship by LULC Type.

Class	2022	2017	2012	2007
(2007-2022)	Regression function and (R ²)			
Vegetation	$y = -10.502x + 32.449$ R ² = 0.1912	$y = -7.9417x + 27.748$ R ² = 0.1925	$y = -3.8895x + 25.705$ R ² = 0.1143	$y = -5.1192x + 29.643$ R ² = 0.1151
Agriculture	$y = -12.517x + 34.941$ R ² = 0.5495	$y = -6.8163x + 28.026$ R ² = 0.5096	$y = -6.3522x + 27.371$ R ² = 0.4693	$y = -11.12x + 31.164$ R ² = 0.4159
Urban	$y = -29.924x + 37.13$ R ² = 0.2255	$y = -11.624x + 30.041$ R ² = 0.1868	$y = -12.469x + 27.854$ R ² = 0.1794	$y = -15.409x + 32.227$ R ² = 0.229
Bare land	$y = -19.346x + 38.531$ R ² = 0.5969	$y = -2.9813x + 29.199$ R ² = 0.0397	$y = -5.6523x + 27.541$ R ² = 0.0034	$y = -12.806x + 33.853$ R ² = 0.314
Water area	$y = 8.6653x + 28.799$ R ² = 0.1108	$y = 1.1331x + 23.87$ R ² = 0.0021	$y = 7.8215x + 25.113$ R ² = 0.2422	$y = 5.4723x + 27.463$ R ² = 0.0552

The swift growth of the population in the urban area of Chattogram City and its changing patterns of land use and land cover (LULC) has brought about tremendous changes in the urban thermal environment, –that is, the urban heat islands (UHI) phenomenon is becoming increasingly prevalent. With the growth of the built-up areas, especially those where trees and farms are cleared, the UHI intensity increases, which in turn has far-reaching consequences on health, diversity, and energy usage. Citing previous studies, it can be said these increasing UHI effects worsen heat stress and the associated health risks, especially during heat waves which are very dangerous to certain people such as the aged and those with underlying illnesses (Liu et al., 2021; Wang et al., 2021). With the growing infrastructure in Chattogram City, for example, there is loss of vegetation and enhancement of pavements. As a result, the capacity of the land to cool down by means of an efficient natural process known as evapotranspiration reduces. There is a body of literature that supports the view that such a process is very important in controlling surface temperatures in other cities which have undergone similar transformations (Atasoy, 2020; Zhou et al., 2022). Extreme weather conditions attributed to urban surfaces not only mean hotter temperatures but also prolonged hot days and warm nights (Wang et al., 2021).

The impact on the environment goes further than just human wellbeing. Urban biodiversity is especially sensitive to the higher temperatures resulting from the urban heat island effect. Species twice as rapid as climate-adjusting species pose a risk of extinction or decline in numbers in (Kong et al., 2021). The intensified UHI effect also increases the energy consumption demand for buildings especially air conditioning. Also, this may lead to high-energy use and emissions which contribute to the problem of combating urban ecological pollution (Dudorova & Belan, 2022; Liu et al., 2021). Overall, the results from Chattogram City are consistent with worldwide observations, where uncontrolled urban development contributes significantly to increased UHI effects, which presents great threats to human health, the environment as well as energy utilization. Addressing these negative effects requires strategic urban development and active measures to mitigate the effects including increasing urban vegetation as well as the use of energy effective technologies (Jusuf et al., 2019; Kong et al., 2021).



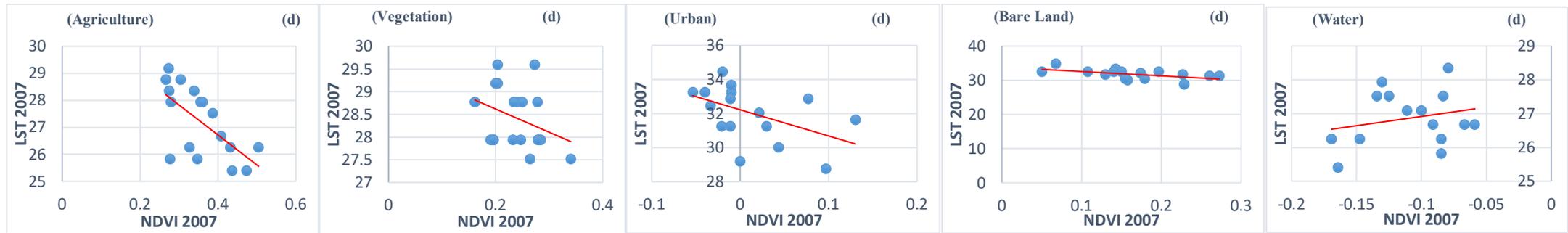


Figure 8: LST and NDVI Relationship by LULC Type for the year 2022 (a), 2017 (b), 2012 (c), 2007 (d).

5. Conclusion: The analysis shows that there have been significant changes in land use and land cover in the Chattogram City region during the past 15 years. This study also illustrates how the study area's urban heat island is distributed spatially and how land surface temperature fluctuates over time. For four separate years 2007, 2012, 2017, and 2022 the study has determined the land surface temperature and the urban heat island zone. Due to changes in land use and land cover, there have been observed variations in land surface temperature and urban heat islands, which have altered radiant surface temperatures and ultimately produced urban heat island zones. In the Chattogram City Area, the urban area had the largest land cover (34.77 per cent of the entire study area) in 2007, and it rapidly rose in 2012, 2017 and 2022. In 2022, the urban area became the CMA's main and significant land cover, accounting for 51.51 per cent of the entire study area, while the covering of dominating vegetation declined by 654.39 ha. The land surface temperature in Chattogram City significantly increased between 2007 and 2022 as a result of the shift in land usage. Rooftop gardening and plantations might help restore some of the lost green space that has been lost over the previous few decades, which may help to regulate the current level of UHI. Additionally, rooftop gardening and tree planting can lower the temperature of the city of Chattogram's surface as well. Both of the mayors of the city corporations in Dhaka, the capital of Bangladesh, have promised a 10% holding tax discussion to promote rooftop gardening. Even if only half of the structures in Chattogram allowed for rooftop gardening, it would still be good for the city's ecosystem. The rooftop tree plantation and gardening plan in Chattogram City may be difficult to accomplish due to a lack of awareness, policy, and management. However, action must be taken in the Chattogram City area for a safe and environmentally friendly future.

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References

- Abburu, S., & Golla, S. B. (2015). Satellite image classification methods and techniques: A review. *International Journal of Computer Applications*, 119(8).
- Ahmed, B. (2011). *Urban land cover change detection analysis and modeling spatio-temporal Growth dynamics using Remote Sensing and GIS Techniques: A case study of Dhaka, Bangladesh*.
- Assessment of Urban Heat Island and Spatiotemporal Landscape Transformation In Three Cities Of Sindh, Pakistan. (2022). *SINDH UNIVERSITY RESEARCH JOURNAL -SCIENCE SERIES*, 54(1).
<https://doi.org/10.26692/surj.v54i1.4494>
- Atasoy, M. (2020). Assessing the impacts of land-use/land-cover change on the development of urban heat island effects. *Environment, Development and Sustainability*, 22(8), 7547–7557.
<https://doi.org/10.1007/s10668-019-00535-w>
- Avdan, U., & Jovanovska, G. (2016). Algorithm for automated mapping of land surface temperature using LANDSAT 8 satellite data. *Journal of Sensors*, 2016.
- Baik, H.-S., Jeong, H. S., & Abraham, D. M. (2006). Estimating transition probabilities in Markov chain-based deterioration models for management of wastewater systems. *Journal of Water Resources Planning and Management*, 132(1), 15–24.
- Barsi, J. A., Schott, J. R., Hook, S. J., Raqueno, N. G., Markham, B. L., & Radocinski, R. G. (2014). Landsat-8 thermal infrared sensor (TIRS) vicarious radiometric calibration. *Remote Sensing*, 6(11), 11607–11626.

- BBS, S. Y. (2011). Bangladesh Bureau of Statistics, Ministry of Planning. *Govt. of Bangladesh, Dhaka*.
- Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, 113(5), 893–903.
- Curran, P. (1980). Multispectral remote sensing of vegetation amount. *Progress in Physical Geography*, 4(3), 315–341.
- Dudorova, N. V., & Belan, B. D. (2022). The Energy Model of Urban Heat Island. *Atmosphere*, 13(3). <https://doi.org/10.3390/atmos13030457>
- Farzana, R., Tabassum, A., Mannan, Md. A., & Karunatilake, S. (2022). Assessment of Uhi and its Long-Term Impact on Temperature, Precipitation, and Evapotranspiration for the Major Cities in Bangladesh. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4127959>
- Fatemi, M., & Narangifard, M. (2019). Monitoring LULC changes and its impact on the LST and NDVI in District 1 of Shiraz City. *Arabian Journal of Geosciences*, 12(4), 1–12.
- Gaonkar, V. G., Nadaf, F. M., & Kapale, V. (2024). Mapping and Quantifying Integrated Land Degradation Status of Goa Using Geostatistical Approach and Remote Sensing Data. *Nature Environment & Pollution Technology*, 23(1).
- Gazi, M., Rahman, M., Uddin, M., & Rahman, F. M. (2021). Spatio-temporal dynamic land cover changes and their impacts on the urban thermal environment in the Chittagong metropolitan area, Bangladesh. *GeoJournal*, 86(5), 2119–2134.
- Gorgani, S. A., Panahi, M., & Rezaie, F. (2013). The Relationship between NDVI and LST in the urban area of Mashhad, Iran. *International Conference on Civil Engineering Architecture & Urban Sustainable Development 27&28 November*, 51.
- Hassan, M. M., & Nazem, M. N. I. (2016). Examination of land use/land cover changes, urban growth dynamics, and environmental sustainability in Chittagong city, Bangladesh. *Environment, Development and Sustainability*, 18(3), 697–716.
- Hoehne, C. G., Chester, M. V., Sailor, D. J., & King, D. A. (2022). Urban Heat Implications from Parking, Roads, and Cars: a Case Study of Metro Phoenix. *Sustainable and Resilient Infrastructure*, 7(4), 272–290. <https://doi.org/10.1080/23789689.2020.1773013>
- Hokao, K., Phonekeo, V., & Srivanit, M. (2012). Assessing the impact of urbanization on urban thermal environment: A case study of Bangkok Metropolitan. *International Journal of Applied*, 2(7).
- Islam, M. S., & Ahmed, R. (2011). Land use change prediction in Dhaka city using GIS aided Markov chain modeling. *Journal of Life and Earth Science*, 6, 81–89.
- Jabbar, H. K., Hamoodi, M. N., & Al-Hameedawi, A. N. (2023). Urban heat islands: a review of contributing factors, effects and data. *IOP Conference Series: Earth and Environmental Science*, 1129(1), 012038. <https://doi.org/10.1088/1755-1315/1129/1/012038>
- Jensen, J. R. (1996). *Introductory digital image processing: a remote sensing perspective*. (Issue Ed. 2). Prentice-Hall Inc.

- Jiménez-Muñoz, J. C., Sobrino, J. A., Gillespie, A., Sabol, D., & Gustafson, W. T. (2006). Improved land surface emissivities over agricultural areas using ASTER NDVI. *Remote Sensing of Environment*, 103(4), 474–487.
- Jiménez-Muñoz, J. C., Sobrino, J. A., Plaza, A., Guanter, L., Moreno, J., & Martínez, P. (2009). Comparison between fractional vegetation cover retrievals from vegetation indices and spectral mixture analysis: Case study of PROBA/CHRIS data over an agricultural area. *Sensors*, 9(02), 768–793.
- Jusuf, S. K., Ignatius, M., Hien, W. N., & Akbari, H. (2019). Editorial: Urban Heat Island (UHI) and its Mitigation through Urban Planning, Design, and Landscaping. *Architectural Science Review*, 62(1), 1–2. <https://doi.org/10.1080/00038628.2019.1548095>
- Karakuş, C. B. (2019). The impact of land use/land cover (LULC) changes on land surface temperature in Sivas City Center and its surroundings and assessment of Urban Heat Island. *Asia-Pacific Journal of Atmospheric Sciences*, 55(4), 669–684.
- Kavitha, A. V., Srikrishna, A., & Satyanarayana, Ch. (2021). A Review on Detection of Land Use and Land Cover from an Optical Remote Sensing Image. *IOP Conference Series: Materials Science and Engineering*, 1074(1), 012002. <https://doi.org/10.1088/1757-899X/1074/1/012002>
- Kirkpatrick, J. (2024). A Big History of Land Clearance and Deforestation. *Journal of Big History*, 7(3), 1–18. <https://doi.org/10.22339/jbh.v7i3.7301>
- Kong, J., Zhao, Y., Carmeliet, J., & Lei, C. (2021). Urban heat island and its interaction with heatwaves: A review of studies on mesoscale. *Sustainability (Switzerland)*, 13(19). <https://doi.org/10.3390/su131910923>
- Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). *Remote sensing and image interpretation*. John Wiley & Sons.
- Liu, B., Xie, Z., Qin, P., Liu, S., Li, R., Wang, L., Wang, Y., Jia, B., Chen, S., Xie, J., & Shi, C. (2021). Increases in Anthropogenic Heat Release from Energy Consumption Lead to More Frequent Extreme Heat Events in Urban Cities. *Advances in Atmospheric Sciences*, 38(3), 430–445. <https://doi.org/10.1007/s00376-020-0139-y>
- Lo, C. P., & Quattrochi, D. A. (2003). Land-use and land-cover change, urban heat island phenomenon, and health implications. *Photogrammetric Engineering & Remote Sensing*, 69(9), 1053–1063.
- Long, H., Tang, G., Li, X., & Heilig, G. K. (2007). Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. *Journal of Environmental Management*, 83(3), 351–364.
- Markham, B. L., & Barker, J. L. (1985). Spectral characterization of the Landsat Thematic Mapper sensors. *International Journal of Remote Sensing*, 6(5), 697–716.
- Meyer, W. B. (1995). Past and Present Land Use and Land Cover in the U. S. A. *Consequences: The Nature and Implications of Environmental Change*, 1(1).
- Mia, B., Bhattacharya, R., & Woobaidullah, A. S. M. (2017). Correlation and monitoring of land surface temperature, urban heat island with land use-land cover of Dhaka City using satellite imageries. *Int. J. Res. Geogr*, 3, 10–20.

- Mia, M. A., Nasrin, S., Zhang, M., & Rasiah, R. (2015). Chittagong, Bangladesh. *Cities*, 48, 31–41.
- Pasha, A. B. M. K., Chowdhury, A. H., Hussain, A., Rahman, M., Mozumder, S., & Fuente, J. A. Dela. (n.d.). *Identification of the ecosystem services and plant diversity in Ramna Park Dhaka*.
- Pasha, A. B. M. K., Mozumder, S., Bhuiyan, M. A. H., & Parveen, M. (n.d.). *MONITORING LAND USE AND LAND COVER CHANGES OF DHAKA CITY: A REMOTE SENSING AND GIS-BASED ANALYSIS*.
- Pathirana, A., Deneke, H. B., Veerbeek, W., Zevenbergen, C., & Banda, A. T. (2014). Impact of urban growth-driven land use change on microclimate and extreme precipitation—A sensitivity study. *Atmospheric Research*, 138, 59–72.
- Prashar, Y., Sharma, R., Kumar, S., Hassan, S. S., & Pateriya, B. (2022). ANALYZING THE IMPACT OF BUILT UP AND GREEN SPACES ON LANDSURFACE TEMPERATURE WITH SATELLITE IMAGES IN JALANDHAR SMART CITY. *International Journal on Environmental Sciences*, 13(02), 99–106. <https://doi.org/10.53390/ijes.v13i2.6>
- Qian, Y., Chakraborty, T. C., Li, J., Li, D., He, C., Sarangi, C., Chen, F., Yang, X., & Leung, L. R. (2022). Urbanization Impact on Regional Climate and Extreme Weather: Current Understanding, Uncertainties, and Future Research Directions. *Advances in Atmospheric Sciences*, 39(6), 819–860. <https://doi.org/10.1007/s00376-021-1371-9>
- Qin, Z., Karnieli, A., & Berliner, P. (2001). A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region. *International Journal of Remote Sensing*, 22(18), 3719–3746.
- Ritchie, H., & Roser, M. (2018). Urbanization. *Our World in Data*.
- Ross, S. M. (2014). *Introduction to probability models*. Academic press.
- Roy, S., Pandit, S., Eva, E. A., Bagmar, Md. S. H., Papia, M., Banik, L., Dube, T., Rahman, F., & Razi, M. A. (2020). Examining the nexus between land surface temperature and urban growth in Chattogram Metropolitan Area of Bangladesh using long term Landsat series data. *Urban Climate*, 32, 100593. <https://doi.org/10.1016/j.uclim.2020.100593>
- Saraswat, A., Pipralia, S., & Kumar, A. (2024). Exploring the Application of Ecosystems Approach to Urban Planning: *International Review for Spatial Planning and Sustainable Development*, 12(2), 2. https://doi.org/10.14246/irspsd.12.2_28
- Shahbaz, M., Guergachi, A., Noreen, A., & Shaheen, M. (2012). Classification by object recognition in satellite images by using data mining. *Proceedings of the World Congress on Engineering*, 1, 4–6.
- Singh, G., & Singh, S. K. (2023). Evapotranspiration Over the Indian Region: Implications of Climate Change and Land Use/Land Cover Change. *Nature Environment and Pollution Technology*, 22(1), 211–219.
- Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from LANDSAT TM 5. *Remote Sensing of Environment*, 90(4), 434–440.
- Sobrino, J. A., & Raissouni, N. (2000). Toward remote sensing methods for land cover dynamic monitoring: Application to Morocco. *International Journal of Remote Sensing*, 21(2), 353–366.

- Statistics, B. B. S. D. (2011). *Chittagong. Bangladesh Bureau of Statistics; Statistics and Informatics Division (SID), Ministry of Planning, Parishankhan Bhaban. E-27/A, Agargaon, Dhaka-1207.*
- Tan, K. C., Lim, H. S., MatJafri, M. Z., & Abdullah, K. (2010). Landsat data to evaluate urban expansion and determine land use/land cover changes in Penang Island, Malaysia. *Environmental Earth Sciences, 60*(7), 1509–1521.
- Thomas, G. S., Liu, Y., & Mwanga, N. (2024). Exploring the Environmental Effects of Urbanization in Monrovia. *European Journal of Theoretical and Applied Sciences, 2*(3), 1117–1130. [https://doi.org/10.59324/ejtas.2024.2\(3\).89](https://doi.org/10.59324/ejtas.2024.2(3).89)
- TYAGI, S. K., KUMAR, V., KUMAR, K., & KUMAR, D. (2023). ENVIRONMENTAL HEALTH QUALITY AND THE CONSEQUENCES OF URBANIZATION: A REVIEW. *International Journal of Advances in Agricultural Science and Technology, 10*(5), 13–23. <https://doi.org/10.47856/ijaast.2023.v10i05.003>
- Vaiphasa, C., Piamduaytham, S., Vaiphasa, T., & Skidmore, A. K. (2011). A Normalized Difference Vegetation index (NDVI) Time-series of idle agriculture lands: A preliminary study. *Engineering Journal, 15*(1), 9–16.
- Verburg, P. H., Chen, Y., Soepboer, W., & Veldkamp, A. (2000). GIS-based modeling of human-environment interactions for natural resource management. *Proceeding of the 4th International Conference on Integrating GIS and Environmental Modeling: Problems, Prospects En Research Needs, Canada 2000*, 1–13.
- Wang, J., Chen, Y., Liao, W., He, G., Tett, S. F. B., Yan, Z., Zhai, P., Feng, J., Ma, W., Huang, C., & Hu, Y. (2021). Anthropogenic emissions and urbanization increase risk of compound hot extremes in cities. *Nature Climate Change, 11*(12), 1084–1089. <https://doi.org/10.1038/s41558-021-01196-2>
- Winston, W. L., & Goldberg, J. B. (2004). *Operations research: applications and algorithms* (Vol. 3). Thomson Brooks/Cole Belmont.
- Xu, H., & Chen, B. (2004). Remote sensing of the urban heat island and its changes in Xiamen City of SE China. *Journal of Environmental Sciences, 16*(2), 276–281.
- Zhou, D., Xiao, J., Frohking, S., Zhang, L., & Zhou, G. (2022). Urbanization Contributes Little to Global Warming but Substantially Intensifies Local and Regional Land Surface Warming. *Earth's Future, 10*(5), 1–19. <https://doi.org/10.1029/2021EF002401>