A GIS and remote sensing approach for measuring summer-winter variation of land use and land cover indices and surface temperature in Dhaka district, Bangladesh

Mizbah Ahmed Sresto, Sharmin Siddika, Md. Abdul Fattah*, Syed Riad Morshed, Md. Manjur Morshed

Department of Urban and Regional Planning, Khulna University of Engineering and Technology, Khulna, 9203, Bangladesh

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ABSTRACT

Rapid urbanization has induced land use and land cover change (LULC) that increases land surface temperature (LST). Analyzing seasonal variations of LULC and LST is a precondition for mitigating heat island effects and promoting a sustainable living environment. The objective of this study is to explore the association between the seasonal LST dynamics and LULC indices for the Dhaka district of Bangladesh. The LULC indices are comprised of the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Bareness Index (NDBAI), and Modified Normalized Difference Water Index (MNDWI). The results show that the LULC effect on LST in Dhaka is significant, with an increase in summer season LST from 34.58 °C to 37.66 °C and in winter season LST from 24.71 °C to 26.24 °C. Predictably, the highest and lowest LST values were observed in the built-up and vegetation-covered areas, respectively. Secondly, the correlation values indicate a significant inverse correlation \((R^2 > 0.50)\) between NDVI and LST, as well as MNDWI and LST. On the contrary, positive correlations were observed between NDBI and LST, and between NDBAI and LST for both the summer and winter seasons. Finally, subsequent vegetation decline (-69.34%) and increasing built-up area (+11.30%) between 2000 and 2020 in Dhaka district were found to be the most significant factors for the increasing trend and spatial heterogeneity of LST in Dhaka. The methodological approach of this study offers a low-cost efficient technique for monitoring LST hotspots, which can guide land use planners and urban managers for spatial intervention to ensure a livable environment.

1. Introduction

Climate and land use are interrelated with each other. Changes in land use and land cover (LULC) can affect and can be affected by climate. At various temporal and spatial dimensions, these changes interact; however, improper LULC change is the primary reason for climate change (Thakur et al., 2019; Mondal et al., 2021a, b; Fattah and Morshed 2022). The problem is most prominent in urban areas, especially in emerging cities. With the population growth and development of cities, city planning and management must confront an increasing number of challenges, including urban climatic effects. An increase in land surface temperature (LST) due to manmade and natural reasons is currently one of the most critical urban climate effects. Furthermore, the effects of rising LST have been linked to a variety of negative urban effects, including reduced comfort, deterioration of air and water quality, increased mortality rates, and indirect economic losses (Steeneveld et al., 2018; Kafy et al., 2022). The study of LULC and its impacts has become a research hotspot in urban planning as well as urban meteorology, ecology, and geography. Moreover, for adopting sustainable adaptation measures, more improved information and knowledge is required about the magnitude and extent of LST dynamics as well as seasonal LST dynamics caused by rapid urban expansion, especially in developing megacities like Dhaka.

LULC changes can occur as a result of both human and climate-related factors. Demand for additional settlements, for example, frequently results in the irreversible loss of working and natural land cover, which can lead to localized changes in weather patterns, precipitation, and temperature (Morshed et al., 2021; Mondal et al., 2021a, b, 2022; Thakur et al., 2020a, 2020b; Gazi and Mondal 2018). These changes have the ability to influence the Earth’s climate by modifying local, regional, and...
global circulation patterns, changing the reflectivity of the Earth’s surface, and increasing the CO2 in the atmosphere when they are accumulated over huge areas (Fattah et al., 2021a). An increase in built-up areas decreases the eco-friendly land cover types such as forest land, vegetation, and waterbodies, which affect the ecosystem and therefore carbon storage (Kumar et al., 2021; Thakur et al., 2019; Mondal et al., 2018, 2021a, b). The transformation of land cover to built-up areas in the urban areas accounted for the increased carbon emissions and the decline in carbon sequestration. This phenomenon is leading to global warming as well as increases in LST (Fattah et al., 2021b; Thakur et al., 2019; Mondal et al., 2021a, b). Though different regions across the world have been facing the adverse impacts of LULC change as well as LST growth, the impacts are more acute in the developed cities. The association between LULC and LST is attracting increasing attention from the scientific community, health authorities, urban planners, and environmental engineers because of its substantial impacts on human health, raised energy demand for cooling and altered vegetation phenology (Li et al., 2017; Lowe, 2016; Lemonsu et al., 2013).

User Accuracy = \frac{\text{correctly classified points in each category (diagonal)}}{\text{Total reference points in each category (row total)}} \times 100 \quad (3)

Producer Accuracy = \frac{\text{correctly classified points in each category (diagonal)}}{\text{Total reference points in each category (column total)}} \times 100 \quad (4)

Table 1. Details of the utilized Landsat images (https://earthexplorer.usgs.gov/).

| Years  | Acquisition date | Satellite | Sensor | Path/Row | Cloud coverage |
|--------|------------------|-----------|--------|----------|----------------|
| 2000 Summer | 2000-04-10 | Landsat 5 | TM | 137/44 | <10% |
| 2000 Winter | 2000-12-20 | Landsat 5 | TM | 137/44 | <10% |
| 2010 Summer | 2010-04-07 | Landsat 5 | TM | 137/44 | <10% |
| 2010 Winter | 2010-12-20 | Landsat 5 | TM | 137/44 | <10% |
| 2020 Summer | 2020-04-18 | Landsat 8 | OLI | 137/44 | <10% |
| 2020 Winter | 2020-12-27 | Landsat 8 | OLI | 137/44 | <10% |

Table 2. LULC classes and corresponding land use types.

| Classes       | Description                                                                 |
|---------------|-----------------------------------------------------------------------------|
| Waterbody     | Wetlands, gully, marshy land, low-lying lands and gully.                    |
| Built-up      | Residential, industrial, commercial areas, settlements, roads, mixed urban areas, impervious covers. |
| Bare land     | Open space, landfill sites, brickfields, barren soil, construction sites, abandoned land, uncultivated land. |
| Agriculture land | Crop fields, fruits and other cultivated lands, fallow lands.                |
| Vegetation    | Forest and trees, vegetative lands, mixed forest land, gardens.              |
Overall Accuracy = \frac{\text{Total correctly classified points (diagonal)}}{\text{Total reference points}} \times 100 \quad (5)

Kappa Coefficient = \frac{\text{Total Sample} \times \text{Total Correct Sample} - \sum (\text{column total} \times \text{row total})}{(\text{Total Sample})^2 - \sum (\text{column total} \times \text{row total})} \times 100 \quad (6)

Table 3. The NDVI value ranges indicates different LULC types, used for LST distribution (Akbar et al., 2019).

| Classes      | NDVI value ranges |
|--------------|-------------------|
| Waterbody    | -0.28 to -0.015   |
| Built-up     | -0.014 to +0.13   |
| Bare land    | +0.14 to +0.18    |
| Agriculture land | +0.19 to +0.27   |
| Vegetation   | +0.27 to +0.36    |
| Dense vegetation | +0.36 to +0.74  |

LST is a very important parameter for both local and global energy and water balances at the surface. Remote sensing sensors made it easier to study LULC and LST effects more precisely. Currently, many advanced and effective remote sensing technologies are used to estimate LST. The impact of LULC on LST has been widely studied in many prior studies, including Li et al. (2017); Steeneveld et al. (2018); Zhang et al. (2016); Al-Hameedi et al. (2021). Several researches also focused on the major cities of Bangladesh like Dhaka (Faisal et al., 2021); Chittagong (Gazi et al., 2021), Khulna (Fattah et al., 2021a, b), Sylhet (Kafy et al., 2022), Cumilla (Kafy et al., 2021). Although these studies focused on the LULC change effects on LST variations, there is a lack of research that comprehensively compares the seasonal effects. All these studies quantified the LST for only the summer season. In addition, most of the studies used only two common land use indices (NDVI—‘Normalized Difference Vegetation Index’ and NDBI—‘Normalized Difference Built-up Index’) and comprehended the impacts of vegetation cover loss and built-up cover increase on LST change. As a result, water bodies and bare land are frequently overlooked. A limited number of studies explored the influence of all LULC types on LST dynamics. The distribution of LST varies seasonally and responds differently to different LULC classes (Huang and Cadenasso, 2016).

Various land use indices (applied to the Landsat images to characterize different land cover classes) are used to characterize the specific land cover types. For example, NDVI is used to evaluate vegetation, NDBI for built-up cover, MNDWI—‘Modified Normalized Difference Water Index’ for soil moisture, and NDBaI—‘Normalized Difference Bareness Index’ for soil bareness related issues (Imran et al., 2021). However, in present studies, the use of all these land use indices is rarely explored comprehensively from the combined perspective of seasonal variations. Historical LULC and LST change identification, seasonality analysis, and determining the responses of LST to different land use indices have important application value and scientific research significance. To fill the previous study gap, the present study is designed to analyze the

Figure 2. Deprived LULC patterns of Dhaka during winter season of (a) 2000 (b) 2010 (c) 2020 and summer season of (d) 2000 (e) 2010 (f) 2020.
historical LULC and LST trends, seasonal (summer-winter) and spatial distribution of LULC, LST, NDVI, NDBAI, MNDWI, and NDBI from 2000 to 2020 over Dhaka City. Furthermore, the distribution and responses of seasonal LST change to all the land use indices were statistically analyzed. The outcomes of the present study can provide a scientific reference and guidance to urban planners and policy makers to adopt effective mitigation measures in urban development plans.

2. Methods and materials

2.1. Study area

Dhaka district is located between north latitudes 23°35’ and 24°06’ and the east longitudes between 90°01’ and 90°37’. Dhaka district includes Dhamrai, Savar, Dhaka city, Keraniganj, Dohar, and Nawabganj (Imran et al., 2021). The district shares borders with Tangail and Gazipur in the north, Munshiganj in the south, Rajbari and Manikganj districts on the west, and Narayanganj district on the east (Figure 1) (Moniruzzaman et al., 2021). Dhaka district is located between north latitudes 23°35’ and 24°06’ and the east longitudes between 90°01’ and 90°37’. Dhaka district includes Dhamrai, Savar, Dhaka city, Keraniganj, Dohar, and Nawabganj (Imran et al., 2021). The district shares borders with Tangail and Gazipur in the north, Munshiganj in the south, Rajbari and Manikganj districts on the west, and Narayanganj district on the east (Figure 1) (Moniruzzaman et al., 2021). The elevation of Dhaka district ranges from -49 (low) to 55 (high) (according to SRTM 30 m resolution dem) (USGS 200). The climate of Bangladesh can be divided into four distinct seasons: summer (March–May), monsoon (June September), post-monsoon (October–November) and winter (December–February). For being situated in a tropical region, the study area is mostly dry in winter and hot and humid in summer (Begum et al., 2021; BBS 2017).

Dhaka’s population is growing at a rate of about 4% per year, which is one of the fastest rates in Asian cities (Swapan et al., 2017). Over the last 50 years (1978–2018), the built-up area of Dhaka city and surrounding areas has increased from 1.7% to 23.8%. Dhaka is the most densely populated city in Bangladesh with 68,561 people per km² (Moniruzzaman et al., 2021).

There has been a lot of migration to the Dhaka region and the city’s boundaries have been expanded, which has led to a rise in the city’s population. In the 1980s, the city added more than a million people to its population (McGee, 2006). This led to rapid urban expansion towards upazilas (tertiary urban centers) around DMA, such as Dhamrai, Savar, Keraniganj, Dohar, and Nawabganj, which are under Dhaka district (Figure 1). To attract foreign investments and provide urban service facilities for people, various types of infrastructure, such as roads and highways, industry, commercial buildings, factories, and so on, were developed in these areas for economic development (Arefin et al., 2019). Though such initiatives will provide communities with economic possibilities and socio-economic benefits, they will result in urban expansions, LULC modifications, and accelerate urban heat islands (UHI) effects in the study area. In this regard, this study considered Dhaka district as the study area to assess the seasonal LST distributions and the influences of different land use factors.

2.2. Data collection

There are four seasons in Bangladesh, summer, pre monsoon, post monsoon and winter (Begum et al., 2021). To assess the seasonal diversity between summer and winter ten Landsat images were collected for analyzing the spatiotemporal changes. To identify the spatial and thermal variations in the summer and winter seasons, different Landsat images were collected as given in Table 1. For both Landsat 8 and 5, Landsat collection 1 level-1 images were assembled for this study. Geographical Information System (GIS) based remote sensing software ArcGIS 10.5 version was utilized to process and analyze the acquired data. Landsat imagery helped to extract the LST, LULC types, and land use indices from Landsat imagery. The shape files of the Dhaka District were collected from Rajdhani Unnayan Kartripakkha (RAJUK) (RAJUK, 2020). RAJUK is responsible for coordinating any development project in Dhaka, Bangladesh.

2.3. Radiometric correction of landsat images

First of all, the mosaic band tool was performed for attaching 2 different Landsat-5 images in order to cover the whole study area. On the other hand, one Landsat 8 image covered the whole study area. So, no preprocessing techniques were performed on the Landsat 8 image. All required bands were composited (bands 1 to 5 for the Landsat 5 image).

Table 4. Classified LULC statistics of Dhaka district Summer (S) and Winter (W) (area in %).

|          | 2000 W | 2000 S | 2010 W | 2010 S | 2020 W | 2020 S | Change during 2000 – 2020 (km²) |
|----------|--------|--------|--------|--------|--------|--------|-----------------------------|
| AL       | 23.37  | 24.19  | 20.95  | 21.31  | 17.01  | 17.6  | -93.45 –96.80              |
| BL       | 8.65   | 7.77   | 8.81   | 8.34   | 9.38   | 8.54  | 10.64 –11.30               |
| BU       | 14.55  | 14.48  | 18.03  | 17.87  | 23.19  | 23.08 | 126.97 –126.32             |
| VG       | 48.86  | 49.14  | 47.82  | 48.23  | 44.10  | 44.83 | -69.94 –63.20              |
| WB       | 4.57   | 4.43   | 4.39   | 4.25   | 6.32   | 5.96  | 25.78 –22.38               |
| Total    | 100    | 100    | 100    | 100    | 100    | 100   |                            |

VG = Vegetation, AL = Agricultural Land, BU = Built Up, WB = Water Body, BL = Bare Land.
Geometric, atmospheric and radiometric pre-processing techniques have been used by different researches like Adeyeri et al. (2017) and Nautiyal et al. (2021). The geometric adjustment was performed with the help of proper spatial referencing. FLAASH atmospheric correction was used to reduce noise caused by the atmospheric effect (Abir and Saha, 2021; Akram et al., 2018; Mondal et al., 2016).

To convert DN (a numerical value of each pixel, called a digital number) values into radiance while taking into account the gain and bias and radiometric adjustment has been carried out and increased by applying majority filter procedures for improved image quality (Thakur et al., 2019; Mondal et al., 2021a, b). The required bands (band 1 to 5 for Landsat 5 and band 2 to 7 for Landsat 8) were composited for LULC classification. A supervised image classification process was performed in this research to determine the LULC types, as recommended by the literature (Kafy et al., 2021; Georgiana and Uritescu, 2019). The LULC is separated into five different categories (Table 2) (built-up area-BU, bare land-BL, agricultural land-AL, waterbody-WB, and vegetation-VG) to recognize the change in land cover pattern (Georgiana and Uritescu, 2019; Faisal et al., 2021). The elevation data was collected from the United States Geological Survey (USGS) and the Arc map 10.5 platform was used to process the elevation data. For preparing the elevation map, SRTM 30m dem was first collected and then the area of interest was extracted by using the extract by mask tool. Following the authoring, new appropriate and quantitative image grouping precision estimate approaches known as Kappa statistics and confusion matrix were developed to verify the accuracy of the arrangement (Pal and Ziaul 2017; Morshed et al., 2022). An equalized stratified random sampling method was used to generate 160 points of reference for accuracy testing. With Google Earth photos as a reference point, overall accuracy, user accuracy, and Kappa Coefficient were examined. The following Eqs. (3), (4), (5), and (6) were used to determine accuracy. All the images achieved accuracy of more than 86%.

### 2.5. Land use indices calculation procedure

#### 2.5.1. Normalized difference built-up index (NDBI)

NDBI quantifies the concentration of built-up area by performing a function between the portion of near-infrared (NIR) (band 5 for Landsat 8 and band 4 for Landsat 5) and shortwave infrared (SWIR) (band 6 for Landsat 8 and band 5 for Landsat 5) retracted radiation accumulated by the Landsat Multi-spectral sensing element under the conditions (equation 7) (Zhang et al., 2013).

\[
\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}}
\]

NDBI values range from -1 to 1. The higher the value, the more developed area and construction land, metro area, or created territory exists. Consequently, the lower the value, the less built-up area, rural region, or undeveloped terrain exists (Kafy et al., 2021).

#### 2.5.2. Modified Normalized Difference Water Index (MNDWI)

The MNDWI is a spatial indicator that responds to changes in leaf moisture content (Das et al., 2021). NDWI is calculated using the following Eq. (8).

\[
\text{NDWI} = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}}
\]

However, MNDWI is a modified NDWI that has been used in this study. For the enhancement of open water features, the MNDWI employs pixel values from green (band 3 for Landsat 8 and band 2 for Landsat 5) and shortwave infrared (SWIR) bands (band 6 for Landsat 8 and band 5 for Landsat 5). It also reduces built-up area characteristics that are commonly linked to water in other indexes. The MNDWI estimation ranges from -1.0 to +1.0. Calculation of Modified MNDWI is calculated using Eq. (9).

\[
\text{MNDWI} = \frac{\text{Green} - \text{SWIR}}{\text{Green} + \text{SWIR}}
\]

#### 2.5.3. Normalized Difference Bareness Index (NDBaI)

NDBaI was suggested by Chen et al. (2006) to distinguish bare land from other land uses (NDBaI). NDBaI has already been used multiple times...
times in recent studies to estimate vegetation cover. The range of the NDBaI estimation is -1.0 to +1.0. The NDBaI is calculated using Eq. (10) following the research of (Imran et al., 2021).

\[
NDBaI = \frac{(\text{SWIR Band}1 - \text{TIRS Band}1)}{(\text{SWIR Band}1 + \text{TIRS Band}1)}
\] (10)

where, TIRS 1 (band 10 for Landsat 8 and band 6 for Landsat 5) is the Thermal Infrared Sensor band 1 and SWIR 1 is the Short-wave infrared band 1 (band 6 for Landsat 8 and band 5 for Landsat 5).

### 2.5.4. Normalized difference vegetation index (NDVI)

Pixel values from the Landsat Near-Infrared (band 5 for Landsat 8 and band 4 for Landsat 7) and Red (band 4 for Landsat 8 and band 3 for Landsat 5 image) spectral bands are employed to identify the NDVI (Georgiana and Uritšescu, 2019; Zhang et al., 2016). NDVI is calculated as given below (equation 11):

\[
\text{NDVI} = \frac{(\text{NIR Band} - \text{Red Band})}{(\text{NIR Band} + \text{Red Band})}
\] (11)

To identify the difference in land cover during the assessment period, the NDVI was analyzed in real time. The NDVI ranges from -1.0 (lowest) to +1.0 (highest). Low NDVI values are associated with rock land or metropolitan areas as well as developed areas. Table 3 represents the NDVI value ranges for different LULC types.

### 2.6. Land surface temperature (LST) calculation process

LST is the radioactive temperature of earth surface which is critical for understanding the basic science of the land surface via the energy cycle and aquatic exchange with the environment (Zhang et al., 2013; Ahmed et al., 2013). LST analysis using satellite thermal data entails a variety of procedures, including sensor radiometric alignment, correction of air and surface reflectance and spatial variation of LULC. For calculating LST thermal band 11 (for Landsat 8) and thermal band 6 (for Landsat 5) were utilized. The process of calculating LST is explained below by following the method of Thakur et al. (2020a, b) and Kafy et al. (2021) (Eqs. (12), (13), (14), (15), and (16)):

\[
L_\lambda = A_L + M_L \times QCAL
\] (12)

where, \(L_\lambda\) = TOA Spectral Radiance (W/(m² × sr × μm)); \(M_L\) = Radiance multiplicative scaling factor for the band; \(A_L\) = Band’s Radiance additive scaling factor; QCAL = Digital Numbers (DN) of band 10.

After that, TOA spectral radiance (\(L_\lambda\)) values are converted into At-Satellite Brightness Temperature (TB).

\[
TB = \frac{\sum(K_j)}{(ln(K1 / KB + 1))}
\] (13)

where, TB = At-Satellite Brightness Temperature, in Kelvin (K); K1, K2 = Thermal conversion constants for the band.
Then, Proportion of vegetation cover (PV) and surface emissivity (ε) is calculated according to equation as below

\[
PV = \frac{(\text{NDVI} - \text{NDVImin})^2}{(\text{NDVImax} - \text{NDVImin})^2}
\]  
(14)

\[
ε = (0.004 \times PV) + 0.986
\]  
(15)

Figure 5. NDBAI profile of the study area during winter season of (a) 2000 (b) 2010 (c) 2020 and summer season of (d) 2000 (e) 2010 (f) 2020.

Figure 6. MNDWI profile of the study area during winter season of (a) 2000 (b) 2010 (c) 2020 and summer season of (d) 2000 (e) 2010 (f) 2020.
Figure 7. NDBI profile of the study area during winter season of (a) 2000 (b) 2010 (c) 2020 and summer season of (d) 2000 (e) 2010 (f) 2020.

Figure 8. NDVI profile of the study area during winter season of (a) 2000 (b) 2010 (c) 2020 and summer season of (d) 2000 (e) 2010 (f) 2020.
Lastly, the TOA Brightness Temperature was converted to LST values in Kelvin (K).

\[
LST = \frac{TB}{1 + \left(\frac{287}{\lambda}\right) \ln e}
\]  

(16)

where

\[\lambda = \text{the wavelength of emitted radiance}\]
\[\alpha = \frac{hc}{k} \left(1.438 \times 10^{-2} \text{ mK}\right)\]
\[h = \text{Planck constant} \left(6.626 \times 10^{-34} \text{ J s}^{-1}\right)\]
\[c = \text{velocity of light} \left(2.998 \times 10^{8} \text{ m s}^{-1}\right)\]
\[k = \text{Boltzmann constant} \left(1.38 \times 10^{-23} \text{ J/K}\right)\]

2.7. Correlation analysis

To determine the interlinkage between two different variables or variable of interest correlation analysis is very effective (Obilor and Amadi, 2018; Sedgwick, 2014). So, for assessing the nexus between land use indices and LST, regression models namely linear regression, Pearson's correlation coefficient \((Pr)\) was calculated using:

\[
Pr = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}
\]  

(17)

Spearman's rank correlation coefficient \((SC)\) (Sedgwick, 2014) was also calculated for all the seasons and years. Where \(d_i\) = difference between the two ranks of each observation, \(n = \) number of observations (equation 18).

\[
SC = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}
\]  

(18)

3. Results

3.1. Seasonal variability of LULC distribution between 2000 and 2020

The outcome of the supervised image classifications is presented in Figure 2 and the statistics of the classified LULC types for both the summer and winter seasons (area in %) and change (in km²) are presented in Table 4. Figure 3 shows the LULC variation ranges (standard deviations) for summer and winter season. The LULC analysis shows that, in 2000, the vegetation (VG) covered the largest areas, accounting for 48.14% in winter and 49.14% in summer.
The second largest, the agricultural land (AL), covered 23.37% of areas in winter and 24.19% in summer. Water body (WB) cover was the lowest (4.57% in winter and 4.43% in summer). Rapid population growth, higher urbanization and migration rates, and the transformation of other LULC types into built-up areas have all increased over the last two decades. In 2020, the built up (BU) cover was the second largest, increasing by 126.97 km² (59.40%) during 2000–2020. About 27.24% (95.13 km²) of agricultural AG covers declined, while VG covers decreased by 66.57 km² (8.76%) (Table 5).

Table 5 represent the seasonal LULC transformation matrix of the study area during 2000–2020. The data in Table 5 shows the considerable increase in built-up areas (103.21 km² from VG, 15.14 km² from WB, 49.63 km² from BL and 93.66 km² from AL). Again, a large portion of VG (195.46 km²) was transformed into AL. The conversion of VG, AL and WB to BL was also significant (Figure 4). Dhaka is the capital city and the most advanced city in Bangladesh with the most employment and service facilities. Factors like migration from better living standards, unplanned urbanization, higher population density and increasing rates and unplanned urban expansions are responsible for the notable transformation of VG and AL in Dhaka. Such increase in built-up area is responsible for unplanned LULC transformation which led to an increase in LST and decrease in the environmental sustainability of Dhaka district.

The results of the LULC types evaluated in Table 4 show that the overall percentage and total area of the water body have increased over time. But previous research findings, for example, Imran et al. (2021), Kafy et al. (2021), and Moniruzzaman et al. (2021) suggest that water bodies have decreased and small water bodies have turned into built-up areas or other types of land cover over time in Dhaka city and surrounding areas. The analysis results of the present study show such results because the study area is on the bank of the Padma River, which is one of the largest rivers in Bangladesh. Over the past few decades, the Padma River has changed its tidal flow, resulting in river erosion and several river training works taking place (CEGIS, 2005; Neill et al., 2010; Hassan and Akhtaruzzaman, 2010; Ophra et al., 2018). However, the transformation of water bodies into built-up land or other land cover types (vegetation, agricultural, bare land) can be better understood by observing the LULC transition matrix (Table 5).

### 3.2. Seasonal variability and intensity of land use index analysis, 2000–2020

For both the winter and summer season, the health status of built-up areas, bare land, soil moisture and vegetation in the study area were measured using the NDBAI, MNDWI, NDBI, and NDVI indices, respectively. The outcomes of these indices are presented in Figures 5, 6, 7, and 8. The value range of each index is divided into five groups, and the area of each group (area in %) of all the indices is presented in Table 6. The details seasonal statistics of the land-use indices are presented in Figure 9.

### 3.3. Seasonal variability of LST, 2000–2020

Table 7. Observed seasonal LST variations during the study period.

| LST ranges | 2000 | 2010 | 2020 |
|------------|------|------|------|
| Winter     | Summer | Winter | Summer | Winter | Summer |
| 15–20 °C   |       | 61.48 | 0      | 30.21  | 0      | 42.60  | 0      |
| 20–25 °C   |       | 38.02 | 7.85 | 68.50 | 6.40 | 52.85 | 9.35 |
| 25–30 °C   |       | 0.50  | 51.15 | 1.29 | 33.35 | 4.55 | 33.65 |
| 30–35 °C   |       | 0     | 28.50 | 0    | 41.00 | 0    | 20.50 |
| 35–40 °C   |       | 0     | 12.50 | 0    | 19.25 | 0    | 36.50 |

Figure 10 represents the (a–c) winter season and (d–f) summer season LST of the study area during 2000–2020. Table 7 shows the areas (in percentage) witnessed different LST values over the study period. The seasonal outcomes of the LST analysis shows a huge variation in summer and winter. Figure 10 shows the land covers of the study area witnessed...
an increasing trend of LST over the study period (2000–2020). The
winter season LST range was observed between 11.81 °C–24.71 °C in
2000, 12.62 °C–26.89 °C in 2010 and 13.31 °C–26.24 °C in 2020. The
mean winter season LST was observed 17.30 °C, 18.64 °C and 19.91 °C,
respectively in 2000, 2010 and 2020. The mean LST for summer season
was found to be more than 10 °C than the mean LST in winter season
(27.74 °C, 28.81 °C and 30.74 °C in three distinct years). The summer
season LST ranged from 27.56 °C to 34.59 °C in 2000, 21.62 °C–32.65 °C
in 2010, and 23.66 °C–37.66 °C in 2020.

The statistics of spatial distributions of the LST are presented in
Table 7. Analysis shows that 61.48% of areas LST was between 15
°C–20 °C during winter in 2000, whereas it decreased to 42.60% in
winter 2020. In winter 2000, about 0.50 of total areas LST was above
25 °C, and in winter 2020, about 4.55% of areas LST was observed
above 25 °C. Substantial change in LST was also observed for the
summer season also. In summer 2000, about 12.50% of areas exhibited
LST above 35 °C, this percentage increased to 19.25% in summer 2010
and to 36.50% in summer 2020. Figure 10 shows that the increasing
trend of LST was scattered throughout the district, but increased mostly
in Dhaka Metropolitan area. The regions that exhibited LST between 25
°C–30 °C were distributed mostly in the suburban regions of Dhaka
district, with areas of 51.15% in 2000, 33.35% in 2010, and 33.65% in
2020.

3.4. Nexus between LULC and LST

3.4.1. Distribution of LST under different LULC types

To assess the dynamics of LST in different LULC classes, we
randomly selected 1250 points, and extracted the LST, NDVI,
NDBAI, NDBI, and MNDWI values of these points. Figure 11 represents
the distributions of LST in different LULC classes, which were classi-
ﬁed based on the NDVI value ranges. Table 8 shows the observed
mean LST in different LULC classes over the study period. In accor-
dance with Table 8, in summer 2000, the highest mean LST was
observed 33.73 °C in BU, and lowest in VG cover. The BU cover areas
had the highest average LST in both seasons, followed by WB, BL, AL
and VG. The highest mean LST was observed 35.49 °C in summer
2020, followed by 34.95 °C in summer 2010 and 33.73 °C in summer
2000.

Figure 11 shows that the LST in some VG covers was also high in 2000
(in both seasons) and in winter 2010, and we also observed high LST in
BL and AL in all the seasons. The average LST in all the LULC has
increased over the course of the investigation. Analysis shows that the
minimum average LST was observed in VG cover in both seasons over the
study period. This is because vegetation cover provides shade and helps
evapotranspiration, which lowers the temperature. Also, sequestrition
of CO₂ by vegetation reduces temperature. Although the mean differences
between the LST in BU and WB are small, between BU and other three
land covers were very high in both seasons, especially between the BU
and VG was more than 9 °C.

3.5. Regression analysis

In this section, we assessed the nexus between the seasonal LST and
land use indices by using the linear regression model, Pearson’s corre-
lation model, and Spearman’s rank correlation method. Figure 12 and
Figure 13 represent the outcomes of the regression analysis for the
summer season and winter season, respectively.
Among the land use indices, MNDWI (Fig. 12a–c, Fig. 13a–c) and NDVI (Fig. 12j–l, Fig. 13j–l) showed inverse correlations, while NDBI (Fig. 12g–i, Fig. 13g–i) and NDBAI (Fig. 12d–f, Fig. 13d–f) showed positive correlations. Among the land use indices, the NDVI had the maximum correlation value in both seasons.

The R² value for NDVI vs LST is 0.7435, 0.7821 and 0.82774, respectively; and Pearson’s r were -0.8623, -0.8844 and -0.9098, respectively in the years 2000, 2010 and 2020 indicates the strong negative correlation between the LST and vegetation health dynamics. The Pearson’s correlation coefficient values of -0.6837, -0.6302 and -0.7130 indicate strong negative correlation between LST and water health during the summer season. For NDBI vs LST, the summer season LST value was calculated 0.60132, 0.64243 and 0.7764, respectively, which indicates strong positive correlations between built-up expansion and LST. The linear regression, Spearman correlation coefficients and Pearson’s coefficients demonstrate that the increase in LST in Dhaka district was mostly influenced by the decline of vegetation and increase in built-up areas.

Figure 13 shows that all the land cover dynamics have significant influences on the LST dynamics during the winter season. The Spearman coefficient values -0.5005, -0.4540 and -0.4640 (Pearson’s r = -0.5196, -0.450, -0.4944) for the years 2000, 2010 and 2020 indicate moderate negative correlations between MNDWI and LST dynamics. The correlation coefficient between NDVI and LST also indicates strong negative influences on LST dynamics. Previous studies have confirmed the significant inverse influences of water and vegetation dynamics on surface temperature (Zhi et al., 2020). The positive correlations between the NDBAI and LST (Pearson’s r = +0.4643, +0.4899 and +0.47701) indicate that the increase of bare lands has been accelerating the surface temperature of Dhaka. Transformations of AL and VG to bare lands decrease the soil’s heat absorption capacity and thus increase the surface temperature. On the other hand, increase of the built-up areas helped to accelerate the average LST of Dhaka district significantly. This is reflected in the association between NDBI and LST. The R² value between both seasons’ NDBI and LST shows the positive significant influences of the built-up expansions on the rise of LST in the study area. Imran et al. (2021) found that the NDBI and NDBI are positively correlated with LST dynamics of Dhaka Metropolitan area, while NDVI is negatively correlated.

4. Discussion

This research quantifies the nexus between seasonal diversity of LULC indices and LST in Dhaka district of Bangladesh for the period...
between 2000 and 2020. The population of Dhaka district increased from 10.285 million to 12.04 million between 2000 and 2011. In 2011, the population density of Dhaka district was 8229 people per sq. km., whereas it was 30551 per km² in the Dhaka Metropolitan area (Faisal et al., 2021). This higher population increase in Dhaka witnessed a substantial decline of AL and VG in the study area. A large portion of the AL and VG covers have slightly disappeared and transformed into built-up covers. The outputs show that LST increased over the last 20 years significantly; in the summer of 2000, around 12.50 percent of places had LSTs exceeding 350 degrees Celsius. This number grew to 19.25 % in the summer of 2010 and to 36.50 % in the summer of 2020. Similar seasonal variation was observed by (Mallick, 2021) in India. A comparable result was also reported by Kafy et al. (2021) in Comilla, Bangladesh. However, the mean LST of WB was observed relatively high in this study, the direct disposal of industrial wastes into river water is the possible reason behind this higher mean LST of WB (Bashar and Fung, 2020). Akter et al. (2021) observed the lowest LST in the vegetation covers and highest in the built-up areas and river side areas across the northwestern region of Bangladesh during 1990–2018.

Previous research findings suggest that water bodies have diminished and water bodies have transformed into built-up areas or other types of land cover through time in Dhaka city and neighboring areas, according to Imran et al. (2021), Kafy et al. (2021), and Moniruzzaman et al. (2021). Similarly, the present study suggests that small water bodies have decreased due to excessive urbanization (Figure 4 & Table 5). But this study shows the overall percentage of water bodies has increased over the past few decades (Table 4). The reason behind such findings is the Padma River, alongside Dhaka district, and the river's tidal flow has shifted, resulting in river erosion and river training projects (CEGIS, 2005; Neill et al., 2010; Hassan and Akhtaruzzaman, 2010; Ophra et al., 2018). The study area for this research includes the Padma River, which was hardly considered by other researchers. So, the findings explain that water bodies inside Dhaka city and surrounding areas have decreased, but due to the shift in the tidal flow of the Padma River, the overall percentage of water bodies has increased a little over time.

The results of this research indicated a substantial negative association between the LST and vegetation health trends. On the other hand, positive correlation was observed between NDBI and LST. The regression results were strong enough to justify the correlations and researchers

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**Figure 13.** Correlation between the winter season land use indices and LST during 2000–2020.
such as Kafy et al. (2020) and Zhang et al. (2022) also evaluated such correlation results. Figure 2 and figure 10 clearly explains that build up area and bare land is producing more LST than other types of land cover. Urban expansion, centralization, decrease of vegetation and water bodies are particularly responsible for the increasing trend of LST. In the study of Fu and Weng (2016), Trenberth (2011) and Hassan and Southworth (2018) explained how mega urbanization, vegetation and agglomeration influences the dynamics of surface temperature. Despite the fact that the aforementioned findings are informative, they should be interpreted with caution because they were obtained from satellite images taken at various times. More in-situ data needs to be incorporated to confirm and validate the findings of this study.

5. Conclusion

LULC through increasing built-up and decreasing vegetation area is one of the most important contributors to the rising LST. Knowledge of seasonal LULC and LST dynamics has the potential to be used for mitigating LST hotspots and ensuring ecological balance for the living environment. This study explored the impacts of seasonal dynamics of land use indices on the LST between 2000 and 2020. Four land use indices – MNDWI, NDVI, NDBAI, and NDBDI – were used to measure the spatial and seasonal variation of LULC and LSC in the Dhaka District of Bangladesh. The findings of this paper are as follows: First, about 126.32 km² of built-up area was increased in Dhaka district by replacing 96.80 km² of agricultural land and 63.20 km² of vegetation cover. The built-up areas increased rapidly in the sub-urban areas in comparison to the Dhaka city area. Second, the spatial distribution of mean summer and winter season LST in Dhaka district showed an increase of 3.07 °C and 1.89 °C, respectively. Besides, areas of higher LST (summer season) between 35°C–40 °C increased from 12.50% to 36.50%, whereas areas of the lowest LST ranges between 15°C–20 °C decreased from 61.48% to 42.60% over the study period. Finally, the MNDWI and NDVI indices were inversely correlated with LST dynamics, while the NDBI and NDBAI indices were positively correlated. Furthermore, the decline of vegetation cover has been identified as the most influential factor for the rise of LST in the study area.

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The study has several limitations. First, freely available low-resolution images were used for the study. Secondly, remote sensing techniques on low-resolution images covering vast areas result in limited accuracy. Therefore, we have very little justification for the increase in waterbody area over the study period. However, the methodological approach of this study proposes a low-cost and efficient method for continuous monitoring of LULC and LST. Therefore, land use planners and urban managers can continuously monitor the LULC and LST change patterns and employ subsequent mitigating as well as policy measures for guiding land development.

Declarations

Author contribution statement

Mizbah Ahmed Sresto; Sharmin Siddika: Conceived and designed the experiments; Performed the experiments; Md. Abdul Fattah; Syed Riad Morshed: Analyzed and interpreted the data; Wrote the paper.

Md. Manjur Morshed: Contributed reagents, materials, analysis tools or data; Wrote the paper.

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No data was used for the research described in the article.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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