Use of cellular automata-based artificial neural networks for detection and prediction of land use changes in North-Western Dhaka City

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Abstract
The purpose of this study was to analyze the trend of change in land use land cover (LULC) and land surface temperature (LST) in Mirpur and its surrounding area over the last 30 years using Landsat satellite images and remote sensing indices, and to develop relationships between LULC types and LST, as well as to analyze their impact on local warming. Using this analyzed data, a further projection of LULC and LST change over the next two decades was made. From 1989 to 2019, 5-year intervals of Landsat 4–5 TM and Landsat 8 OLI images were utilized to track the relationship between LULC changes and LST. The modeled LST was validated with MODIS-derived LST within the study area. Cellular automata-based artificial neural network (CA-ANN) algorithm was used to model the LULC and LST maps for the year 2039. The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) were analyzed to determine their link with LST. The relation between LST and LULC types indicates that built-up area raises LST by substituting non-evaporating surfaces for natural vegetation. The average surface temperature was increasing steadily for the last 30 years. For the year 2019, it was determined that roughly 86% of total land area has been converted to built-up area and that 89% of land area had an LST greater than 28 °C. According to the study, if the current trend continues, 72% of the Mirpur area is predicted to see temperatures near 32 °C in 2039. Additionally, LST had a significant positive association with NDBI and a negative correlation with NDVI. The overall accuracy of LULC was greater than 90%, with a kappa coefficient of 0.83. The study may assist urban planners and environmental engineers in comprehending and recommending effective policy measures and plans to mitigate the consequences of LULC.

Keywords Urbanization · LST · UHI · NDVI · NDBI · CA-ANN

Introduction
In recent years, the mechanisms of the land use land cover (LULC) change, particularly in urban areas, have drawn special attention from researchers. LULC’s global spatial dynamics reveal the connection between land use change and human activities (Corner et al. 2014; Dewan and Yamaguchi 2009a, b; Meyer and Turner 1992; Rahman et al. 2017a; Rahman et al. 2018; Rahman and Esha 2022). In a developing country like Bangladesh, rapid population growth and economic development contributed much to the urban expansion. To facilitate such developments, a significant portion of water bodies and agricultural lands have transformed into built-up areas. This transformation of lands affects the local, regional ecosystems, and deteriorates the quality of living environment (Dewan et al. 2012; Dewan and Yamaguchi 2009a, b; IPCC 2014). Hence, the mechanism of LULC transformation is complex since it depends on numerous natural and socio-economic factors (Chen et al. 2006; McKinney 2002; Tran et al. 2017). Due to the scale effect and vulnerability of the land system dynamics, these factors have a significant impact on the change in LULC. Therefore, understanding the interrelationship among the driving factors of LULC change is essentially required. Moreover, prediction for future land use is also required to plan and manage sustainable future cities (Balogun and Ishola 2017; Rahman et al. 2017a, b; Rahman et al. 2018; Rahman and Esha 2022). Dhaka, the capital of Bangladesh, is one of the world’s fastest expanding megacities (Rahman et al. 2017a; Dewan...
and Yamaguchi 2009a, b; Meyer and Turner 1992). It is also one of the most densely populated cities where around 34,000 people reside per square kilometer (Population and Housing Census 2011 2011). The population of this city has expanded by nearly 11 million during the last two decades (Dewan and Yamaguchi 2009a, b). This rapid growth is primarily driven by rural–urban migration. Vertical and horizontal expansion, and the transformation of wetlands and greeneries into built-up areas are considered the major contributor to the increase in land surface temperature (LST) (Al-sharif and Pradhan 2014). However, very few researchers have explored the mechanism through which this urban expansion influences the changes in land cover and urban microclimate. There is a scope of scientific study in this field to measure the impacts of this massive urban population on land cover changes, biodiversity, and increase in average surface temperature. The study also aims at showing how the built-up area, reduction of surface water bodies and vegetation land, and negative consequence of unplanned rapid urbanization contribute to the increase in LST.

The same is the phenomenon at the macro level, as the increasing pace of exodus from villages to cities contributes to “rapid changes to the ecosystems, biodiversity, natural landscapes, and the environment of the cities” (McKinney 2002). Surprisingly, more than 70% of the world’s population is anticipated to live in urban areas in the next 30 years (Celik et al. 2019; Grimmond 2007; Handayanto et al. 2017; Kafy et al. 2019; Rahman et al. 2017a; Ullah et al. 2019). While this development is a sign of economic growth and economic stability in the region, it has several short- and long-term consequences. So, the importance of measuring the impacts on land cover changes and the urban microclimate becomes significantly important.

In fact, over the last decade, geographers, urban planners, and climate scientists have been paying considerable attention to elevated LST in urban areas (Al-sharif and Pradhan 2014; Kafy et al. 2019; Maduako et al. 2016; Rahman 2016; Zheng et al. 2015). Several studies suggest that population expansion appears to increase the average LST in urban environments by 2–4 °C in contrast with rural areas (Maimaitiyiming et al. 2014; Mozumder and Tripathi 2014; Thapa and Murayama 2009; Yu et al. 2014). Increased LSTs and urban heat island (UHI) impacts are associated with high energy consumption, air pollution, and health issues, including the deaths of children and elders from asthma and heat stroke (Ahmed et al. 2013; Maduako et al. 2016; Rahman et al. 2017a; Rahman and Rashed 2015; Scarano and Sobrino 2015; Zhi-hao et al. 2011; Zhou et al. 2011).

As LST is largely dependent on LULC therefore, prediction of LULC for evaluating future change in LST is required. Cellular automata-artificial neural network (CA-ANN) model provides a solid understanding of the complexities of the spatial system to evaluate and predict LULC changing patterns (Imran et al. 2021a, b; Kafy et al. 2021; Mortoja and Yigitcanlar 2020; Rahman et al. 2020; Rahman and Esha 2022). To monitor previous and existing LULC and determine the potential impacts of LULC on the city area, this study mainly focuses on predicting future changes of LULC and identifies its impacts on future LST. Using a CA-ANN model, the simulation of future land cover can be analyzed. The CA-ANN model, together with the geographical information system, is widely regarded as the most powerful tool for modeling the probabilities of the spatiotemporal shift in LULC (Arsanjani et al. 2013; Santé et al. 2010).

Examining LULC change has become a matter of concern because of the decline in biodiversity, changes in habitats, and changes in the regional and global climate patterns and composition (Li and Zhao 2003; Mishra and Rai 2016). It can be challenging, complicated, and likely to yield contradictory results to detect and test changes in LULC through direct field visits (Meyer and Turner 1992; Rahman 2016; Zheng et al. 2015). The use of the remote sensing and geographic information system (GIS) technologies has overcome most of the constraints, enabling scientists to assess and monitor changes in LST and LULC trends easily (Corner et al. 2014; Fu and Weng 2018; Hart and Sailor 2009; Islam and Ahmed 2011). According to the research findings of many scientists, there are changes in various LULC components (water bodies, vegetation, and agricultural lands) that contributes to the increase in LST which significantly stimulates the generation of the UHI effect (Bahi et al. 2016; Lambin 1999; Maduako et al. 2016). LST is recognized as one of the main factors for warming the urban microclimate. Several local issues are closely linked to the LST, such as biophysical hazards (e.g., heat stress), air pollution, and public health concerns (Amiri et al. 2009; Chander et al. 2009; Streutker 2003). As the rise in surface temperature contributes significantly to the deterioration of the ecological balance, it is, therefore, important to obtain LST as a first and primary step. And then create models to predict LST so that findings can be implemented to mitigate the negative environmental impacts (Celik et al. 2019; Rahman et al. 2017a; Rahman and Rashed 2015; Shatnawi and Abu Qdais 2019; Weng et al. 2004).

Numerous studies have documented the changes in LULC and LST in Dhaka City, revealing that the city has been losing a substantial quantity of wetland in its north-western region (Mirpur and its surrounding area). These lands are being transformed into urban areas, and as a result, severe repercussions on the microclimate of this area have been posed (Dewan et al. 2021a, b; Imran et al. 2021a, b; Kafy et al. 2021; Mortoja and Yigitcanlar 2020; Rahman et al. 2020; Rahman and Szabó 2021; Trotter et al. 2017). The study can be a significant baseline to find out the area-specific microclimate change. For guiding the sustainable development of the area, it is necessary to safeguard the
unplanned urbanization of Dhaka’s north-western sector. Under these circumstances, the research, using ANN-based CA algorithm simulation and using the recent and historically archived Landsat satellite images of Mirpur and its surrounding areas, primarily investigates LULC and LST shifts in the past two decades (1989–2019) to predict the future growth and surface temperature of the study areas in 2039.

Materials and methods

Study area

Numerous studies show that Mirpur and its surrounding area face tremendous LULC change and so LST over the last 30 years (Imran et al. 2021a, b; Kafy et al. 2021; Mortoja and Yigitcanlar 2020; Rahman et al. 2020; Rahman and Szabó 2021). Therefore, to populate necessary relevant data for the analysis, Mirpur and its surrounding area (north-western part of Dhaka) have been selected as the main study area. The geographic location of the study area is located between 90°21′27.465″E and 23°44′46.334″N. The study area is a total of 48.834 km². The area of interest is situated in Dhaka Metropolitan (DMP) area. Eight (8) “Thana” boundaries such as Mirpur, Adabor, Mohammedpur, Pallabi, Darus Salam, Shah Ali, Kafrul, and Sher-e-Bangla Nagar cover the study region (Fig. 1).

Methodology

The primary approach of the study is based on satellite images. The satellite image spans a greater region and has several spectral bands that may be utilized for environmental study. On the other hand, satellite images may give historical data that can be useful for trend analysis from the past to the present. Futures may also be anticipated using this trend analysis and the development of an equation. Landsat images were collected from the United States Geological Survey (USGS) website. Before 2013, Landsat TM 4–5 data and after then Landsat OLI 8 data have been used for the study. The absolute calibration of the Landsat 8 Thermal Infrared Sensor (Band 11) has been impacted by out-of-field light since launch. This study makes an attempt to estimate LST using Landsat 8’s Band 10 in order to deal with this issue. Landsat 8’s estimated LST was cross-checked against temperature data from other sources, including the thermal band of Landsat 4–5, despite Band 10’s shorter wavelength. All the Landsat images are taken for November to get cloud-free images. After downloading the data, sequentially land cover, LST, NDVI, and NDBI were calculated. Using the data, LST and land cover were predicted for the next 30 years (till 2049). Meanwhile, the calculated data were validated using temperature data (following the same date when the image was taken) collected from Bangladesh Metrological Department (BMD) and Nasa Power Access Data. Afterwards, a correlation analysis was carried out among LST, NDVI, and NDBI. The whole methodological steps are given in the flow diagram (Fig. 2).

Land use land cover classification

To choose training samples and identify the various LULC classes, a true color composite (TCC) was created using appropriate band combinations for all images (d’Entremont and Thomason 1987; Good and Giordano 2019). Landsat images were categorized using the Maximum Likelihood Supervised Classification (MLSC) approach for the years 1989, 1994, 1999, 2004, 2014, and 2019. Mirpur is a versatile urban area; hence, to avoid complexity, the area has been classified into four major LULC classes (water body, built-up area, vegetation, and bare land). A total of around 25 samples were gathered to generate LULC maps for each LULC class. Each categorized map has been assessed for accuracy using the kappa index (Foody 2002; Pontius and Millones 2011; Story and Congalton 1986).

Estimation of land surface temperature (LST)

Estimating LST from Satellite imageries follows a simple methodological hierarchy. Firstly, atmospheric radiance has to be calculated from the raw data collected by the thermal band. Then, this atmospheric radiance has to be converted to sensor brightness temperature. Lastly, using this sensor brightness temperature, LST can be retrieved. A detailed description of the process has been given below.

a. Top of Atmospheric Spectral Radiance: Top of Atmospheric Spectral Radiance (TOA) was retrieved (Liu and Zhang 2011).

b. Sensor brightness temperature estimation (T_s): First and foremost, conversion from the spectral radiance of thermal infrared band to active radiance sensor brightness temperature was calculated (Liu and Zhang 2011; Maduako et al. 2016; Rahman et al. 2017a; Sholihah and Shibata 2019).

c. Retrieving LST: Thermal infrared wavelengths are used to determine Top of Atmosphere (TOA) brightness. Meanwhile, to get an accurate land surface brightness temperature, atmospheric influences such as upward emission and downward irradiance reflected from the surface should be adjusted. Calculating the land surface spectral emissivity (ε) enables the aforementioned adjustment to be made. Meanwhile, some elements such as water content, chemical composition, structure, and roughness all affect the emissivity of the surface (Zine
Numerous scholars have demonstrated that the surface emissivity is highly correlated with the NDVI, and so the emissivity can be calculated using the NDVI (Rouse et al. 1973). NDVI can be calculated using the reflectance values of the visible and near-infrared bands (Rouse et al. 1973). Using the NDVI value, the proportion of vegetation ($P_v$) can be calculated to measure land surface emissivity ($\varepsilon$) by using Eq. 4 (Liu and Zhang 2011). Using $P_v$, land surface emissivity ($\varepsilon$) can be measured by following Eq. 5 (d’Entremont and Thomason 1987; Good and Giordano 2019). The land surface temperatures corrected for spectral emissivity ($\varepsilon$) were computed (Avdan and Jovanovska 2016; Chaudhuri and Mishra 2016; Ullah et al. 2019; Xiong et al. 2012). LST represents land surface temperature (in Kelvin). To get values in Celsius, LST has to be modified by adding absolute zero ($-273.15 \degree C$); $T_s$ was the sensor’s brightness temperature. The emitted radiance’s
wavelength was indicated as \( \lambda \) and \( \varepsilon \) indicates the land surface spectral emissivity.

The Normalized Difference Built-up Index (NDBI) employs the near-infrared (NIR) and short-wave infrared (SWIR) bands to highlight manufactured built-up regions. It is ratio-based to account for changes in landscape lighting and atmospheric influences. NDBI is calculated as \((\text{SWIR} - \text{NIR}) / (\text{SWIR} + \text{NIR})\) (Zha et al. 2003).

**Simulation of land cover and LST**

The CA-ANN model is designed to simulate land use changes through a multiple output neuron. The network output layer decides the possibilities of multiple land uses with multiple output neurons. The appropriate parameters for the simulation are calculated automatically by the neural network training process. The CA-ANN model does not include specific transfer rules. The only function is to train the neural network to achieve empirical parameter values. Many factors can be added to the model to improve the precise simulation. A combination of cellular automata and ANN models will produce a better LULC and LST transition spatio-temporal pattern (Mondal et al. 2016; Parsa et al. 2016).

The LST and LULC for the year 2039 with the help of MOLUSCE Plugin in QGIS 2.18 are typically predicted with an ANN. ANN is an effective method that helps to forecast future LST and LULC using data sets from previous years (Civco 1993; Maduako et al. 2016; Shatnawi and Abu Qdais 2019). LST simulation was performed in this study using input parameters LULC images, NDVI, NDBI, latitude, and longitude as output parameters for LST (Gopal and Woodcock 1996; Maduako et al. 2016). Besides, the CA-ANN model for the future LULC was used in the prediction of input parameters of road layers, NDBI, NDVI, latitude, and longitude data. The pixel value data of the images were transformed in ArcGIS software 10.6.1 for the better performance of the model. The model was developed using the past 20 years’ data (1999–2019) as the input parameters for predicting the future year 2039 data.

**Field verification techniques of LULC**

Google Earth displays satellite and aerial imagery in a worldwide mosaic of varying resolutions, as well as additional data such as photos, addresses, and more. Additionally, it permits the creation of geometric primitives like points, lines, and polygons, as well as properties like vector format (KML). When zooming in on a specific area, different types of images are displayed depending on the level of detail desired. These images range from continental-scale SPOT5 and Landsat images to aerial orthophotos, IKONOS, and QuickBird images to GeoEye-1, Worldview-1, and Worldview-2 images for urbanized areas. When a user zooms in on a particular area, the name of the data source and the collection date are shown in the bottom portion of the window. In the latest version of Google Earth, you can now access archive pictures, which may be used to see how things have changed over time. Only by examining the dimensions of the features detected can the ground sample distance and picture resolution be calculated. There is no mismatch or seam with other pictures in terms of the spatial expansion of these images inside the Grande Raccordo Anulare.

The accuracy parameters include the overall accuracy, producer accuracy, user accuracy, and the kappa coefficients. The overall accuracy is determined by multiplying the error matrix by the total number of corrected samples. Historically, the term “producer accuracy” has been defined as the ratio of the total number of accurate sample units within a category to the total number of sample units within that category. This accuracy metric is based on the capability of accurately identifying a reference sample unit and is a
real indicator of omission error. When the total number of accurate category sample units is divided by the total number of row sample units on a map (e.g., the total number of row sample units), the result is a commission error measure. This is referred to as “user accuracy” or “reliability,” and it reflects the likelihood that a sample unit specified on the map is located on the ground. Following the calculation of all accuracy parameters, the kappa coefficient was determined (Congalton and Green 2008; Foody 2002; Pontius and Millones 2011; Story and Congalton 1986).

While this work makes a contribution to measuring UHI by the use of location-dependent meteorological, physiological, and environmental data, it has numerous drawbacks. Due to a lack of observed temperature data, this research relied on satellite-derived data. Landsat images were acquired in the early morning for this investigation (10:18 AM). However, the air temperature rises significantly throughout the afternoon and evening. Despite these shortcomings, this research provides a complete approach for estimating UHI. The technique used in this research, as well as the findings, will aid planners and policymakers in identifying variables related to UHI. The methodology offered in this research will help them to develop mitigation plans, policies, and strategies, as well as prioritize and sequence adaptation actions based on the degree of UHI.

Results

Land use land cover classification

The LULC map for 1989, 1994, 1999, 2004, 2009, and 2019 was generated using MLSC (Fig. 3a–f). The study’s entire area is roughly 48.830 km². The categorized picture from 1989 revealed a larger proportion of area for bare terrain, aquatic bodies, and vegetation, respectively, at 35.04%, 27.34%, and 24.9%. For 1989, the built-up area was just 12.56% (Fig. 3a). In 1994, bare ground had the most area (39.20%), followed by water bodies (24.63%) and vegetation (17.04%) (Fig. 3b). In 1994, built-up area increased by 7% over 1989 levels. The continuing upward trend in bare land (40.45%) and built-up area (31.85%) was accelerated in 1999, mostly due to growing urbanization. Water bodies (8.19%) and vegetative land (19.11%) have seen a decline in recent years due to the transfer of natural surfaces to bare ground and later to built-up land (Fig. 3c). In 2004, bare land (33.15%) continued to decline due to the conversion of bare land to urban built-up areas (43.76%). Filling up water bodies (4.77%) and vegetative land (18.32%) that were initially bare land and were eventually moved to built-up areas began to speed in 2004 (Fig. 3d).

The categorized LULC findings for 2009, 2014, and 2019 were compared (Fig. 3e–f) by calculating the percentage change in each LULC class over time. Between 2009 and 2019, the quantity of bare and vegetated land decreased considerably (by roughly 10%). During the same time span, the built-up area expanded by a factor of two (21% of the study area). Finally, the water body declined by 1% of the studied area between 2009 and 2019.

Percent change analysis of different LULCs

During the 1989–2019 study period, LULC categories were converted into other categories and thus losses and gains of LULC categories were also examined (Table 1). The results indicate that built-up area was generally increasing and water bodies and vegetation land were decreasing significantly during the study period. For the years 1989 to 1994, built-up area and bare land area were gained 6.485% and 4.158% area, respectively, whereas vegetation and water bodies were lost by 7.930% and 2.713% of their area, respectively. Similar to the year 1994–1999, a significant increase in the built-up area and a very moderate increase in bare land and vegetation area were found and the percentages were shown by 12.717%, 1.653%, and 2.056%, respectively. Only dramatic loss in water bodies of 16.445% was recorded from 1994 to 1999. Moreover, from 1999 to 2004, except built-up area, other three LULC classes were facing decreasing trend. Built-up area gained 11.906% whereas bare land, water bodies, and vegetation land lost 7.686%, 3.421%, and 0.789% area respectively. From 1999, the percentage of built-up area has started to increase because of the conversion of large percentage of bare land to built-up area.

From 2004 to 2009, built-up area gained 23.281% area whereas bare land, vegetation, and water bodies were reduced to 17.748%, 4.228%, and 1.305% respectively. From 2009 to 2014, built-up area gained by 12.425% whereas bare land, vegetation, and water bodies reduced to 2.847%, 8.863%, and 0.715% respectively. Considering the year 2014–2019, built-up area gained by 7.499% whereas bare land, vegetation, and water bodies were lost 2.847%, 8.863%, and 0.715% respectively. Only the highest losses (bare land and vegetation) and gains (urban area) was observed in the 2004–2014 period. However, the water body expansively was lost its coverage from 1994 to 1999 (Table 1).

Field validation of LULC

Table 2 demonstrates the classification of overall accuracy, kappa coefficient, and validation of land use classification. For the year 2019, the overall accuracy was over 90% and the result of the kappa coefficient was 0.83. The accuracy level is classified as very strong when the kappa coefficient is greater than 0.75 (Congalton and Green 2008; Foody 2002; Pontius and Millones 2011; Story and Congalton 1986).
To validate the land use classification, 50 sampling points were compared with the corresponding point on Google Earth images over the same period. In conclusion, the overall classification accuracy, kappa coefficient statistics, and validation all show good accuracy which is suitable for LULC simulation.

**Estimation of land surface temperature (LST)**

Figure 4a–g indicate the spatial pattern of LST distribution. In all maps, bright yellow tone represents higher temperature and a greenish tone represents low surface temperature. LST concentration and spatial and temporal LST patterns display
rapid changes in LULC groups. The core built-up area is sensitive to high temperatures. As the images were taken in the month of November which is generally the winter season in Bangladesh, therefore, the displayed data will show the temperature of the corresponding winter season of the years.

Figure 4a and b focus on annual surface temperature conditions of 1989 and 1994 and LST varied within the range of less than 20–24 °C. From 1999 and 2004, temperature decreased slightly and the reason is Bangladesh went under massive flood during that period.

In that period, surface water existed for a long period. For that, temperature was comparatively lower than the previous year and LST varied 20–32 °C (Fig. 4c and d). In the year of 2009, the LST varied 20–32 °C (Fig. 4d). For 2014
and 2019, the LST was found at the highest peak because of the significant increase of built-up area and reduction of water bodies and vegetation land. From 2014 to 2019, LST varied from 24 °C to more than 34 °C (Fig. 4e–g). The north-western part of the study area exhibited a lowering in temperature due to higher vegetation and agricultural land whereas the southeastern part exhibits a rise in LST due to rapid urban expansion and decline of water bodies as well as vegetation land.

**Percent change in LST**

The percent change in LST will provide a better insight into the temperature variation at different ranges of LST. From 1989 to 1994, the highest percentage of the area (30.946%) was lost in having LST below 20 °C range. Also, 30.928% area increased within the range of 20–24 °C. Due to the abundance of vegetation and water bodies, the temperature range above 28 °C was found unavailable (Table 3). From 1989 to 1994, the highest percentage of the area (57.063%) was lost in having LST below 20 °C range. Also, 54.829% area increased within the range of 20–24 °C. Due to the abundance of vegetation and water bodies, the temperature range above 32 °C was found unavailable (Table 3).

Due to heavy floods in 2004, LST reduced to less than 20 °C from 1999 to 2004 (Table 3). But, from the year 2004 to 2009, the maximum percentage of the area increased to 89.09% within the LST range of 24–28 °C. During this period, significant increase in built-up area and a reduction of water bodies and vegetation area were noticed (Table 3).

The built-up area continued to increase from 2009 to 2014 and from 2014 to 2019 (Table 3) which resulted in the increase of LST by more than 32 °C. The maximum area of temperature was found within 28–32 °C (35.784% area) and it was 52.136% area from 2009 to 2014. Here, 1.273% and 0.238% area increased to more than 32 °C from the year 2009 to 2014. The increase of built-up area and reduction of water bodies and vegetation land were dominant from the year 2009 which contributed to an increase of LST by more than 32 °C from 2009.

**Validation of LST**

Aside from the stray light issue, the computed LST using just Landsat 8 Band 10 cannot be accepted until cross-validation because of the band’s short wave length. The simulation of future LST patterns was estimated on the basis of 1989 to 2019 data at 5-year interval period and BMD Agargaon station’s data was available. Estimated LST data has a minimum and maximum LST value and BMD data also had minimum and maximum temperature data. Therefore, the percentage of error was calculated in two ways considering maximum and minimum LST and temperature values (Table 4). After validating both source data,

| Table 1 | Percentage change of LULCs in the study area from 1989 to 2019 |
|---------|---------------------------------------------------------------|
| LULC    | Area in km²          | Change in %          | 1994–1989 | 1999–1994 | 2004–1999 | 2009–2004 | 2014–2009 | 2019–2014 |
| Water body       | 13.4 12.03 4.00 2.33 1.69 1.34 1.13 | –2.713 –16.445 –3.421 –1.305 –0.715 –0.440 |
| Urban area       | 6.2 9.34 15.55 21.37 32.74 38.81 42.47 | 6.485 12.717 11.906 23.281 12.425 7.499 |
| Vegetation       | 12.2 8.32 9.33 8.95 6.88 2.56 2.37 | –7.930 2.075 –0.789 –4.228 –8.863 –0.380 |
| Bare land        | 17.1 19.14 19.95 16.19 7.52 6.13 2.87 | 4.158 1.653 –7.696 –17.748 –2.847 –6.679 |
| Total            | 48.83 48.83 48.83 48.83 48.83 48.83 48.83 |

| Table 2 | Accuracy Assessment for 2019 LULC |
|---------|----------------------------------|
| Year    | Classified Class | Validation points for different LULC classes | Water Body | Urban Area | Vegetation Cover | Bare Land | Total | User Accuracy |
| 2019    | Water          | 10 0 1 0 | 0 | 11 | 90.91 |
|         | Built up Area  | 0 15 0 1 | 1 | 16 | 93.75 |
|         | Vegetation     | 0 2 11 1 | 1 | 12 | 91.67 |
|         | Bare Land      | 1 1 0 9 | 11 | 81.82 |
|         | Total          | 11 16 12 11 | 50 |
|         | Producer Accuracy | 90.91 93.75 91.67 | 81.82 | Overall Accuracy 90% | Kappa Coefficient 83.85 |
the minimum and maximum temperature errors for the year 2014 were estimated as 3.678% and 4.982%, respectively. However, BMD only have one station for the entire Dhaka City that too does not lie inside the study area. Hence, further and more accurate validation is necessary. MODIS Land Surface Temperature (LST) and Emissivity daily data (1 km pixels) offers geospatially enabled LST. Therefore, MODIS Land Surface Temperature/Emissivity Daily L3 Global 1 km (MOD11A1) data has been chosen to test the accuracy of the predicted LST derived.
from Landsat 8’s Band 10 image (Leya et al. 2022). These MOD11A1 data obtains spatio-temporal validation as they are of the same date and falls in the research region. Mean and standard variation of the MOD11A1 data indicated that there is a non-significant small difference between MODIS and Landsat means and therefore the estimation of LST was acceptable for further processing (Table 5).

**Association of LST and LULC**

**Cross-sectional profile of LULC vs LST**

The most effective method for determining the effect of LULC on LST is to study the relationships between thermal signatures and land cover types. The thermal infrared
radiation emitted from the ground’s surface, including roofs, pavements, plants, bare soil, and water bodies, was measured and stored as LST using remotely sensed sensors. Two cross-sections were taken over the research region to represent the LST for each LULC type, and the average LST for each LULC type is presented in Fig. 5a−g. Two cross-sections were investigated, one from northwest to southeast (AB) and one from northeast to southwest (CD).

From the profile, it was found that congested built-up area experienced average LST more than 24 °C in 1989 (Fig. 5a), > 27 °C in 1994 (Fig. 5b), > 28 °C in 1999 (Fig. 5c), 29 °C in 2004 (Fig. 5d), > 30 °C in 2009 (Fig. 5e), > 32 °C in 2014 (Fig. 5f), and > 34 °C in 2019 (Fig. 5g). Also, the highest LST was recorded as 22 °C in 1989, > 25 °C in 1994, > 27 °C in 1999, 28 °C in 2004, > 30 °C in 2009, > 31 °C in 2014, and > 33 °C in 2019 for bare land in seven different years’ cross-sections. Besides, the other two LULCs (water bodies and vegetation) were recorded as having the lowest temperature ranging from 16 to 27 °C. The findings signify that built-up area increases LST by replacing natural vegetation with non-evaporating and non-transpiring surfaces.

**LULC wise LST distribution**

The distribution of LST in different LULC classes in various ranges demonstrates the LULC wise LST concentration in the study area. Considering the LST distribution in different LULC classes for the year 1989, most of the area was experienced below 20 °C in every LULC class and the covered area under 20 °C was 15.40 km² in water bodies, 12.27 km² in bare land, 3.24 km² in built-up area, and 12.20 km² in vegetation cover (Table 6). In 1994, most of the area experienced below 20 °C for all LULC and the dominated LULC was bare land (14.08 km²), water bodies (10.35 km²), and vegetation (2.91 km²). At LST range 20–24 °C, 7.97 km², 5.41 km², and 5.06 km² areas were recorded as built-up area, vegetation land, and bare land respectively (Table 6). For the year 1999, the highest range was 20–24 °C and the maximum coverage of LULC class was bare land (19.11 km²), followed by built-up area (14.08 km²) and vegetation (5.30 km²). In the year 2004, the highest range of temperature was 24–28 °C and the maximum coverage of LULC class was in the urban area (14.08 km²), followed by bare land area (12.13 km²). The lowest LST was found at water bodies (1.42 km²) that were below 20 °C (Table 6). In the year 2009, the highest range of temperature was 24–28 °C and the maximum coverage of LULC class was in the urban area (31.90 km²), followed by bare land area (6.75 km²). The lowest temperature was recorded in an urban area (0.02 km²) under 20–24 °C temperature (Table 6).

As the built-up area is continuously increasing, therefore, LST values got momentum from 2014 to 2019. In 2014, the highest percentage of built-up areas was found in the

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**Table 3** Percentage change of LSTs in the study area from 1989 to 2019 (km²)

| LST range | 1989 | 1994 | 1999 | 2004 | 2009 | 2014 | 2019 | Change in % |
|-----------|------|------|------|------|------|------|------|-------------|
| <20 °C    | 43.11| 28.00| 12.01| 0    | 0    | 0    | 0    | −30.95      |
| 20–24 °C  | 5.02 | 20.12| 46.89| 34.93| 3.30 | 0    | 0    | −24.33      |
| 24–28 °C  | 0.70 | 0.71 | 1.12 | 1.20 | 44.71| 21.93| 4.46 | 0.02        |
| 28–32 °C  | 0   | 0   | 0.69 | 0.69 | 0.82 | 26.28| 43.64| 0           |
| >32 °C    | 0   | 0   | 0    | 0    | 0.62 | 0.74 | 0    | 0           |
| Total     | 48.83| 48.83| 48.83| 48.83| 48.83| 48.83| 48.83|             |

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**Table 4** Validation of LST simulation based on the estimated LST for the year 2014

| Year | Temperature from satellite image | BMD data | Percentage of error |
|------|---------------------------------|----------|---------------------|
| 2014 | Minimum temperature            | 24.00    | 3.678               |
|      | Maximum temperature             | 31.00    | 4.982               |

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**Table 5** Validation of LST simulation based on the estimated LST using MODIS

| Satellite | Maximum value | Minimum value |
|-----------|---------------|---------------|
| MODIS     | MODIS Landsat | MODIS Landsat |
| Year      | 1989          | 1989          |
|           | 29.7          | 28.3          |
|           | 27.3          | 26.9          |
|           | 26.66         | 27.65         |
|           | 31.73         | 31.25         |
|           | 28.25         | 29.3          |
|           | 30.15         | 31.19         |
|           | 31.73         | 32.73         |
| Mean      | 29.36         | 29.61         |
| SD        | 2.03          | 2.16          |
Fig. 5 Cross-sectional profile of LULC vs LST for the year (a) 1989, (b) 1994, (c) 1999, (d) 2004, (e) 2009, (f) 2014, and (g) 2019
range of 28–32 °C and 24–28 °C with corresponding areas of 23.04 km² and 15.15 km² respectively. In 2019, 0.61 km² and 40.94 km² of built-up areas were found to have more than 32 °C and 28–32 °C respectively (Table 6).

Relationship among LST, NDVI, and NDBI

Two land cover indices, the NDVI and the NDBI, were developed in order to quantify the link between LST and the indices. The lower NDVI value was associated with a greater LST level in this study. Additionally, the NDVI score in the studied region decreased from −0.1 to −0.3 between 1989 and 2019. The lower NDVI value corresponds to paved ground, bare soil, and rock, all of which result in elevated surface temperatures. Low NDVI values (0.2 to 0.3) correspond to shrubs and grassland, whereas high values correspond to green surfaces.

On the contrary, the NDBI value increased steadily, resulting in greater LST levels. From 1989 to 2019, the results of linear regression and multiple correlations reveal that LST has a significant and positive connection with NDBI and a strong and negative correlation with NDVI (Fig. 6a−g). In all correlation analyses, the $R^2$ value was greater than 0.75, indicating that the variables were highly linked. By entering the value of an independent variable such as LST for each year, the resulting linear regression formula developed an equation for forecasting the dependent variable NDVI or NDBI. The equation fluctuates year to year and may be used to model more complex relationships between LST, NDBI, and NDVI. Additionally, the correlation coefficient for each equation with a complicated relationship between variables may be addressed in greater detail in future research (Fig. 6a−g).

LULC prediction for the year 2039

LULC classes in the research region changed considerably throughout the study period (1989−2019). It was necessary to predict future LULC dynamics because, if historical trends continue, LST would change, affecting both biodiversity and microclimate in the research region. Additionally, the future LULC forecast is critical because it establishes a foundation for sustainable urban design. Additionally, the variance in LST analysis from 1999 to 2019 demonstrated a noticeable shift. As a result, it was critical to forecast future LST trends. The CA-ANN model was used to forecast future LULC and LST for the year 2039 by analyzing the research area’s historical LULC and LST trends. The prediction’s accuracy was confirmed using the proportion of right predictions, the overall kappa value, the kappa location value, and the kappa history value for the predicted variables. The model validation findings for transition potential modeling indicated that the total kappa index and percent-correctness

| Table 6 | LULC wise LST distribution from 1989 to 2019 |
|---------|------------------------------------------|
| Temperature | < 20 °C | 20–24 °C | 24–28 °C | 28–32 °C | > 32 °C |
| Land cover 1989 (area in km²) | | | | | |
| Water body | 15.40 | 0.00 | - | - | - |
| Built-up area | 3.24 | 2.89 | 0.70 | - | - |
| Vegetation land | 12.20 | 0.00 | - | - | - |
| Bare land | 12.27 | 2.12 | - | - | - |
| Land cover 1994 | | | | | |
| Water body | 10.35 | 1.68 | - | - | - |
| Built-up area | 0.66 | 7.97 | 0.71 | - | - |
| Vegetation land | 2.91 | 5.41 | - | - | - |
| Bare land | 14.08 | 5.06 | - | - | - |
| Land cover 1999 | | | | | |
| Water body | 0.09 | 3.91 | 0.00 | 0.00 | - |
| Built-up area | 0.00 | 14.54 | 0.32 | 0.69 | - |
| Vegetation land | 0.04 | 9.33 | 0.00 | 0.00 | - |
| Bare land | 0.00 | 19.11 | 0.84 | 0.00 | - |
| Land cover 2004 | | | | | |
| Water body | 1.42 | 0.39 | 0.00 | 0.00 | - |
| Built-up area | 1.94 | 18.05 | 1.20 | 0.69 | - |
| Vegetation land | 4.59 | 4.36 | 0.00 | 0.00 | - |
| Bare land | 4.06 | 12.13 | 0.00 | 0.00 | - |
| Land cover 2009 | | | | | |
| Water body | - | 1.32 | 0.37 | 0 | - |
| Built-up area | - | 0.02 | 31.90 | 0.82 | - |
| Vegetation land | - | 1.45 | 5.43 | 0 | - |
| Bare land | - | 0.51 | 6.75 | 0 | - |
| Land cover 2014 | | | | | |
| Water body | - | - | 1.33 | 0.01 | 0.00 |
| Built-up area | - | - | 15.18 | 23.04 | 0.59 |
| Vegetation land | - | - | 1.23 | 1.33 | 0.00 |
| Bare land | - | - | 4.19 | 1.89 | 0.03 |
| Land cover 2019 | | | | | |
| Water body | - | - | 0.92 | 0.21 | 0.00 |
| Built-up area | - | - | 0.92 | 40.94 | 0.61 |
| Vegetation land | - | - | 1.84 | 0.53 | 0.00 |
| Bare land | - | - | 0.78 | 1.95 | 0.14 |
Fig. 6 Correlation between LST vs NDVI and NDBI in the year (a) 1989, (b) 1994, (c) 1999, (d) 2004, (e) 2009, (f) 2014, and (g) 2019.
value were 84% (Table 7), which is an acceptable degree of accuracy for LULC modeling. The model validation result shown in Fig. 8a was obtained using the QGIS program.

Simulation results showed that approximately 92% of the area will be converted into built-up area in 2039 (Fig. 7b). Predicted LULC change in future could adversely affect the environment altering both climate and biodiversity of the area.

The percentage of change indicates that in 2039, built-up area would increase about 5.5% higher than 2019 if this pattern continues. Moreover, 92.42% of Mirpur and the surrounding area would convert into built-up area and there will be a drastic reduction of other LULC such as vegetation, bare land, and water bodies (Table 8).

**LST prediction for 2039**

The simulated result showed a strong agreement that confirmed the accuracy of the ANN model’s prediction for 2039 with 91.856% correctness and 0.9362 overall kappa value (Table 9). Based on the ANN model validation in other research, the percentage of correctness value over 80% demonstrates strong agreement of accuracy.

The validation provided an excellent accuracy with more than 90% of correctness for the simulated LST map in 2039 (Fig. 8a). Similar to the LULC for the study period from 1989 to 2019, LST also shows a substantial amount of change. Accordingly, LST is simulated for 2039. The past trends of estimated LST data are used in the ANN model to predict the future LST trends of the study area.

The prediction exhibited that approximately 23.69% of the Mirpur area is likely to have LST greater than 32 °C and 72.62% area is likely to remain 28–32 °C LST range. There may not be any temperature area that might experience below 28 °C LST. The change of percentage of area is around 22.18% which will fall within the range of LST greater than 32 °C in 2039 (Table 10). The prediction results demonstrate that most of the LST remain below 32 °C. Figure 8b shows the rising trend of LST in the study area for the year 2039.

This effect of high LST is going to be a worrying problem for the study area. The temperature effect depends on the city geometry and Dhaka City’s unexpected growth triggers this devastating impact of the increase of LST.

**Discussion**

The impact of LULC fluctuations on the LST in Dhaka’s northwest region (Mirpur and the surrounding area) was measured during a 5-year period between 1989 and 2019, with forecasts extending to 2039. Prior research on LULC alterations and LST was useful for conducting this study and comparing its results with those of other studies. This study indicated an increase in the amount of developed and barren land and a decrease in the amount of vegetation and water bodies, which is in line with prior findings (Ahmed et al. 2013; Dewan and Yamaguchi 2009a, b; Mia et al. 2017). Ahmed et al. (2013) observed that the urban area in Dhaka City rose from 15.68 to 36.91% between 1989 and 2009, while vegetation declined from 19.97 to 8.53%. For the Mirpur region alone, this study found that waterbodies, vegetation, and barren ground dropped by 27.44% to 2.3%, 24.98% to 4.85%, and 35.02 percentage points, respectively. On the other hand, the built-up area has expanded from 12.6 to 86.98%, a 585% increase in the measured time period. Ahmed et al. (2013) predicted that Dhaka’s built-up area will grow to 49% by 2019. And this study found that increased urbanization has mostly affected the city’s northwestern suburbs. Butt et al. (2011) stated that built-up area expanded from 18.22 to 27.86% and thick forest/mixed vegetation declined from 34.07 to 27.33% from 1972 to 2009 in Islamabad, Pakistan. In the instance of the north-western region of Dhaka, land cover underwent a dramatic transformation across the whole research period. The lowland of the research area was filled with sand and transformed to bare land. Imran et al. (2021a, b) observed that housing, settlement, and industry had caused a loss of wet and vegetation land in Dhaka’s northeast and northwest suburbs, which verifies the study’s finding of a rising tendency. Most of the bare lands in 1989 turned into the built-up area in Mirpur region. Most of the vegetation cover, water bodies, and low-lying land also converted to the built-up area, which affected environmental biodiversity and natural habitat (Alphan 2003).

Population increases in Dhaka City because of a greater birth rate and migration from rural to urban areas, as well as the city’s social and economic development, which led to urbanization (Dewan and Yamaguchi 2009a, b). Migration from rural to urban areas accounted for the majority of Dhaka’s rapid population rise. Substantial urbanization has already happened to meet the needs of a larger population, and it has had a negative influence on the limited natural resources because of ongoing overexploitation. The extension of the urban area of Dhaka City was not evenly
distributed in all directions; rather, urban expansion was concentrated on the city’s outskirts. The northern region of the city of Dhaka saw rapid urbanization. Lowland, bare soil, vegetation, and water body all contributed to a net change in the built-up area, although the contribution of built-up area to other land cover was minimal. LST heat zones migrated to a higher temperature zone with the growth of built-up area and bare land, and the probable cause was an increase

Fig. 7  a LULC prediction model validation result for the year 2039 and (b) simulated LULC map for the year 2039
in impervious surface, which stored solar heat throughout the day and caused greater LST. Pal and Ziaul (2017) discovered a similar tendency of heat zone changing in the urban center of English Bazar, West Bengal, India, but the change of LULC and the movement of the heat zone from a low to a high rate in the Mirpur region was dramatic.

According to the findings of this study, a large part of the UHI impact in Mirpur can be attributed to man-made structures, such as buildings and paved surfaces. Evapotranspiration from plants may reduce LST, thereby reducing the UHI impact (Li et al. 2012; Myint et al. 2013). In the Mirpur region, however, increasing green plant cover may not be the best technique for mitigating urban heat island effects (UHI). Green vegetation provides cooling benefits and minimizes the impacts of paved surfaces; hence, optimizing land cover

| LULC | Area km² (2019) | Area in % | Area km² (2039) | Area in % | Change in % (2039–2019) |
|------|----------------|-----------|----------------|-----------|-------------------------|
| Water body | 1.1259 | 2.31 | 1.12 | 2.29 | −0.012 |
| Built-up area | 42.4674 | 86.96 | 45.13 | 92.42 | 5.459 |
| Vegetation | 2.3697 | 4.85 | 2.05 | 4.19 | −0.664 |
| Bare land | 2.871 | 5.88 | 0.53 | 1.09 | −4.788 |
| Total | 48.83 | 100.00 | 48.83 | 100.00 | 0.000 |

### Table 9 ANN model validation for LST in QGIS MOLUSCE Plugin

| Prediction year | ANN model validation for LST prediction QGIS-MOLUSCE Plugin module | %-correct- | Overall | Kappa location | Kappa histo |
|----------------|--------------------------------------------------------------------|-----------|---------|----------------|------------|
| 2039 | 91.856 | 0.9362 | 0.9037 | 0.92582 |

**Fig. 8**  (a) LST prediction model validation result for the year 2039 and (b) simulated LST map for the year 2039
spatial layout is one option to optimize cooling and decrease warming effects. It was determined that big, continuous clusters of greenery had a greater cooling impact than fragmented, dispersed greenery (Li et al. 2012; Maimaitiyiming et al. 2014; Zhang et al. 2009).

In English Bazar urban center, West Bengal, India, Pal and Ziaul (2017) observed an LST rise of 0.114 °C/year during the summer season. In contrast, the Mirpur region had an LST increase of 0.21 °C/year during the summer season across the whole research period. Although these two cities have comparable meteorological circumstances, the urban growth scenarios were distinct; hence, urbanization had a significant impact in the increase of LST in the urban region. The spatial distribution of LST indicates that Mirpur area was influenced by higher temperature zones as the time progressed, and that regions of higher temperature heat zones extended as the built-up area and bareness increased. The growth of LST in newly developed built-up and undeveloped land was greater than that of all other land use types. Consequently, the primary finding of this research is that LST increased with LULC modification owing to an increase in imperviousness.

Albedo analysis by Ejiagha et al. (2020) revealed that industrial and residential regions have greater and weaker albedo values, respectively, indicating the importance of rooftop materials in influencing LST. However, the influence of LULC on LST varies depending on the land cover composition of the area. After a certain percentage of land is covered by buildings, the cooling benefits of such structures begin to diminish, according to Zheng et al. (2014). There were also higher connections between the spatial patterns of paved surfaces and LST in regions with more than 50% of paved surfaces and more than 90% of the combined proportion of paved surfaces and soils (Zheng et al. 2014). The impervious layers of Mirpur and the adjacent region are more thickly formed, including several high-rise structures in the vicinity.

The influence of land cover change on the LST has previously been described; nevertheless, there was also an effect of climate change. Climate change has led to a rise in temperature in Bangladesh, according to several past research. When it comes to average annual maximum and minimum temperatures, Khan et al. (2019) found that between 1981 and 2010, they rose by 0.3 and 0.4 °C every decade, respectively. According to the findings of Mullick et al. (2018), throughout the years 1966–2015, the average yearly temperature increased by 0.4 °C. There was a 1.38 °C rise in the minimum, mean, and maximum temperatures during the previous 49 years, while the temperature ranges were 21.05 to 23.41 °C, 25.35 to 26.99 °C, and 30.13 to 31.70 °C. Because of this, land use change was not the only factor contributing to an overall rise in LST throughout the course of the research period; the climatic change was also a significant factor. Based on these findings, land use and climate change have had a significant role in the greater rise in LST in the area.

The results in this article imply that high-density structures are unsuitable for urban environments. According to Zheng et al. (2019), taller residential structures have negligible LST impacts in a neighborhood-scale residential area with sufficient greenery and residential buildings, resulting in a strong cool island effect. Urban sprawl must be restricted in this setting to enhance the microclimate environment of Mirpur and the surrounding region. It is concluded that the lack of attention given by city planning officials to building construction, as well as the city’s unplanned and chaotic spatial expansion, may be the driving causes of LST in Mirpur and thus across Dhaka City. However, without appropriate planning tools such as decentralization, green belts, increasing open/green space in the core city through redevelopment/land readjustment techniques, public awareness of city planning rules/regulations, and increased responsibility on the part of the responsible authorities, it will be difficult to halt the negative effects of spatial growth. On the other side, in highly populated places, building upgrades using green construction materials and rooftop plants may assist minimize LST.

### Conclusions and recommendations

The study area faced a tremendous increase in built-up area. Increase in impervious layers’ trend will reflect more heat and generate higher surface temperature. Considering
the year 2014–2019, built-up area gained 7.499% area whereas bare land, vegetation, and water bodies were lost 6.679%, 0.383%, and 0.440% area, respectively. The maximum losses (bare land and vegetation) and gains (built-up area) were observed in the 2004–2014 period. However, the water body expensively lost its coverage in the 1994–1999 periods.

The average surface temperature increasing rate is high in 5-year interval period. In 1989, 88.284% of the area was covered under 20 °C temperature. Later, the maximum area of temperature was increased to the range of 28–32 °C at 52.136% from the year 2009 to 2014. Here, 1.273% and 0.238% area were increased to more than 32 °C from the year 2009 to 2014 and from 2014 to 2019, respectively. The increase of built-up area and reduction of surface water bodies and vegetation land were dominant from the year 2009 which contribute to the increase in the LST up to more than 32 °C from the year 2009. Validation of LST estimated data with BMD data and MODIS LST guided the way forward in estimating the future LST.

Prediction indicates that in the year 2039, approximately 92.42% of Mirpur and its surrounding areas will be covered by built-up area and the corresponding predicted LST range will be greater than 32 °C. The prediction exhibited that approximately 23.69% of the Mirpur area is likely to have LST greater than 32 °C and 72.62% area is likely to remain 28–32 °C LST range. There may not be any area that might experience a temperature below 28 °C LST, even in the winter season. The change of percentage of area is around 22.18% which will fall within the range of LST greater than 32 °C in 2039. The prediction results demonstrate that most of the LST remain below 32 °C.

The cross-section profile of LULC vs LST shows higher temperature existed in built-up areas in all time periods. In the year 2019, 0.61 km² of the urban area was fallen more than 32 °C temperature range followed by 40.94 km² in the range of 28–32 °C. LST has a strong and positive correlation with NDBI. LST has a strong and negative correlation with NDVI. In all the correlation analysis, the $R^2$ was found more than 0.9 which means the variables are strongly correlated with each other. The study shows a clear past and present situation of the negative consequence of unplanned rapid urbanization as well as predicts the future scenario of the study region.

The overall result shows a high LST change in the study area. Mirpur area is located in the DMP area which is the most economically productive area of this country. Therefore, preparation steps to reduce LST, as well as UHI effects, are important. The seasonal change of LST in the study area, which in a tropical country is very uncertain, needs cloud-free satellite images. In summer region, cloud contains the whole study region. If summer images could be collected, then actual LST effects can easily be realized. In addition, to understand the magnitude, it is necessary to evaluate UHI locally and nationwide.

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Data availability Not applicable

Declarations

Ethics approval Not applicable

Consent to participate Agree to participate

Consent to publication Agree to publish

Competing interests The author declares that this research work is his original work and has written it in its entirety. He has duly acknowledged all the sources of information that have been used in the paper.

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