Use of Cellular Automata-Based Artificial Neural Networks For Detection and Prediction of Land Use Changes in North Eastern Dhaka City

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1 **Use of Cellular Automata-based Artificial Neural Networks for Detection and**
2 **Prediction of Land Use Changes in North Eastern Dhaka City**

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Abstract

The purpose of this study was to examine the pattern of change in Land Use Land Cover (LULC) and Land Surface Temperature (LST) in Mirpur and its surrounding area (north-eastern part of Dhaka) 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, five-year intervals of Landsat 4-5 TM and Landsat 8 OLI pictures were utilized to track the relationship between LULC changes and LST. Cellular Automata-based Artificial Neural Network (CA-ANN) algorithm was used to model the LULC and LST maps for the year 2039. Two environmental indices were analyzed to determine their link with LST: the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI). The link between LST and LULC types indicates that built-up area raises LST by substituting non-evaporating surfaces for natural vegetation. The average surface temperature has been increasing steadily for the previous 30 years. For the year 2019, it was determined that roughly 86 percent of total land area has been converted to built-up area and that 89 percent of land area has an LST greater than 28°C. According to the study, if the current trend continues, 72 percent 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

1. Introduction

Bangladesh is one of the heavily populated countries in South Asia, and over the past century, it has also experienced rapid population growth. The explosion of population growth mainly took place in the City areas. It is estimated that almost all other men, women, and children will be living in urban areas in the future (M. Rahman, A. S. Aldosary, & M. Mortoja, 2017). Dhaka, the capital of Bangladesh, is one of the world's fastest expanding megacities (M. Rahman, A. S. Aldosary, & M. Mortoja, 2017; Dewan & Yamaguchi, 2009; Meyer & Turner, 1992). Thus, while rising urbanization in Dhaka is likely to have a significant impact on land cover changes and, subsequently, on the urban microclimate, little is known about these developments. Additionally, it is home to almost 16 million people and covers an area of around 304.16 square kilometers. This city's population has expanded by nearly 11 million people during the last two decades (Dewan & Yamaguchi, 2009). Dhaka is spreading vertically and horizontally as a result of this population explosion driven primarily by rural-urban migration and partially by natural growth, and these expansions have been highlighted as a major contributor to the increase in Land Surface Temperature (LST) (Al-sharif & Pradhan, 2014).

Urbanization refers to the process of the change of country area to a City area, which is the result of population immigration, administrative services, construction of new infrastructure, and development of industry and service sector. Over the past few years, the Land Use Land Cover (LULC) change mechanism at the national and local level has also drawn the attention of researchers. It is reported that LULC's global spatial dynamics also reveal the connection between land-use change and human activity (Corner, Dewan, & Chakma, 2014; Dewan & Yamaguchi, 2009; Meyer & Turner, 1992; M. S. Rahman, Mohiuddin, Kafy, Sheel, & Di, 2018). Some scholars emphasized the effects on LULC changes by urbanization, believing that population growth and economic development contributed to urban expansion and a large number of water and agricultural land transformations into built-up areas. This transition also affects the local, regional and global ecosystems, including habitat quality, green areas, and destruction of the environment (Dewan, Kabir, Nahar, & Rahman, 2012; Dewan & Yamaguchi, 2009; IPCC, 2014; Lilly Rose, 2009). The mechanism of LULC transition is complex as the relationship depends on different scales of natural and socio-economic factors (Chen, Zhao, Li, & Yin, 2006; McKinney, 2002; Tran et al., 2017). The associated factors have an impact on the change in LULC due to the scale effect

and vulnerability of the land system dynamics and it is, therefore, vital to understand its relation. Meanwhile, accurate prediction for future land use is essentially required to avoid unexpected urbanization, which is necessary to plan and manage land use (Ahmed, 2011a; Balogun & Ishola, 2017; M. Rahman et al., 2017; M. S. Rahman et al., 2018).

Human migration to Cities causes urban areas to grow every year and creates rapid changes to their ecosystems, biodiversity, natural landscapes, and the environment (McKinney, 2002). More than 70% of the world's population is anticipated to live in urban areas in the next 30 years (Celik, Kaya, Alganci, & Seker, 2019; Grimmond, 2007; Handayanto, Kim, & Tripathi, 2017; Kafy, Islam, Ferdous, Khan, & Hossain, 2019; M. Rahman et al., 2017; 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. Over the last decade, geographers, urban planners, and climate scientists have been paying considerable attention to elevated LST over urban areas (Al-sharif & Pradhan, 2014; Kafy et al., 2019; Maduako, Yun, & Patrick, 2016; M. Rahman, 2016; Zheng, Shen, Wang, & Hong, 2015; Zine El Abidine, Mohieldeen, Mohamed, Modawi, & Al-Sulaiti, 2014). 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 & Tripathi, 2014; Thapa & Murayama, 2009; Yu, Guo, & Wu, 2014). Increased LSTs and Urban Heat Island (UHI) impact have been associated with high energy consumption, air pollution, and health issues, including the deaths of children and elders from asthma and heat stroke (Ahmed, Kamruzzaman, Zhu, Rahman, & Choi, 2013; Maduako et al., 2016; M. T. Rahman, A. S. Aldosary, & M. Mortoja, 2017; M. T. Rahman & Rashed, 2015; Scarano & Sobrino, 2015; Zhi-hao, Wen-juan, Ming-hua, Karnieli, & Berliner, 2011; Zhou, Huang, & Cadenasso, 2011).

Bangladesh is one among the world's most populous countries, according to the "Bangladesh Delta Plan 2100." The overall population density, according to 2011 census statistics, is around 1,015 persons per square kilometer. Recent UN figures indicate that roughly 25% of Bangladesh's current population resides in urban areas. More than half of this urban population resides in four major cities: Dhaka, Chittagong, Khulna, and Rajshahi. The population density is currently estimated to be over 34,000 people per square kilometer, placing Dhaka among the world's most densely inhabited cities. In 1976, the rural settlement area was projected to be 885,637 hectares, accounting for 6.1 percent of the total land area of the nation. Rural settlement area rose at a quicker pace over

time, reaching 10% (1,458,031 ha) in 2000 and 12.1 percent (1,766,123 ha) in 2010. (van Scheltinga, Quadir, & Ludwig, 2015).

Examining LULC change in the last few decades has become an increasing concern because of biodiversity decreasing, habitat changing, and altering the regional and global climate patterns and composition (J. Li & Zhao, 2003; Lilly Rose, 2009; Mishra & Rai, 2016). It can be challenging, complicated, and likely to yield contradictory results to detect and tests changes in LULC through direct field visits (Meyer & Turner, 1992; M. Rahman, 2016; Zheng et al., 2015). Over the past few decades, developments and integration of Remote Sensing and Geographic Information System (GIS) technologies have overcome most of the constraints and are now powerful methods for assessing, monitoring changes in LST and LULCs (Corner et al., 2014; Fu & Weng, 2018; Hart & Sailor, 2009; Islam & Ahmed, 2011). Even since the early 1970s, the use of remote sensing techniques to measure LSTs and investigate the development and spatial distribution of UHIs has been quite successful. Research has identified that massive changes of various LULC components (water bodies, vegetation, and agricultural lands) contribute to the increase in LST which significantly stimulus the generation of UHI effect (Bahı, Rhinane, Bensalmia, Fehrenbach, & Scherer, 2016; Lambin, 1999; Maduako et al., 2016). LST is recognized as one of the main factors for urban microclimate warming. Several local issues are closely linked to the LST, such as biophysical hazards (e.g. heat stress), air pollution, and public health concerns (Amiri, Weng, Alimohammadi, & Alavipanah, 2009; Chander, Markham, & Helder, 2009; Gutman, Huang, Chander, Noojipady, & Masek, 2013; 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 to model possible LST so that policies can be implemented to mitigate the negative environmental impacts (Celik et al., 2019; M. Rahman et al., 2017; M. T. Rahman et al., 2017; M. T. Rahman & Rashed, 2015; Shatnawi & Abu Qdais, 2019; Weng, Lu, & Schubring, 2004).

As LST is largely dependent on LULC therefore, prediction of LULC for evaluating future change in LST is needed. 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. 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

129 impacts on future LST. Using a CA-ANN model, the simulation of future land cover can be
130 analysed. The CA-ANN model, together with the geographical information system, is widely
131 regarded as the most powerful tool for modelling the probabilities of the spatiotemporal shift in
132 LULC (Arsanjani, Helbich, Kainz, & Boloorani, 2013; Santé, García, Miranda, & Crecente, 2010).

133 Under these circumstances stated above, the research is primarily planned to investigate LULC
134 and LST shifts in the past two decades (1989-2019) through the use of recent and historically
135 archived Landsat satellite images in Mirpur and its surrounding area. Also, a simulation will be
136 done by using ANN-based CA algorithm to predict the future growth and surface temperature of
137 the Mirpur and its surrounding area for the year 2039.

138

2. Materials and Methods

2.1 Study Area

"Dhaka City," is known as "Dhaka Metropolitan Area (DMP)" situated on the eastern bank of the river Buriganga, near Bangladesh's geographical center at a latitude of 23°43' North and 90°24' East longitude (Fig. 1). DMP covers a total area of 306.04 sq. km (Ahmed, 2011b).

Fig. 1: Location of the study area

Historical data indicates that, Mirpur and its surrounding area faces tremendous LULC change and so LST from last 30 years. Therefore, to scrutinize the analysis, Mirpur and its surrounding area (north-eastern part of Dhaka) has been selected for the main study area of this analysis. Geographic location of the study area is located between 90°21'42.195"E to 90°21'27.465"E and 23°50'55.249"N to 23°44'46.334"N. The study area is total 48.834 sq. km. The area of interest is situated in DMP area. Eight (8) Thana boundaries such as Mirpur, Adabor, Mohammadpur, Pallabi, Darus Salam, Shah Ali, Kafrul and Sher-e-Bangla Nagar cover the study region.

2.2 Methodology

The main research methodology is focused primarily on satellite images. Satellite image covers larger area with significant spectral bands which can be used for several environmental analysis. On the other hand, satellite image can provide past data which can be significant for past to present trend analysis. Using this trend analysis, and building up an equation, future can also be predicted.

Landsat images can be 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. All the Landsat images are taken for the month of November to get cloud free images. Table 1 displays information regarding satellite images.

Table 1: Information of used satellite images

Satellite data	Date of acquisition	Sensor	Band No.	Spectral range (Wavelength μm)	Spatial resolution, m
Landsat 4-5	November 04, 1989;	TM	1	0.45–0.52	30
			2	0.52–0.60	30
	November 18, 1994;		3	0.63–0.69	30
			4	0.76–0.90	30
	November 16, 1999;		5	1.551.75	30
	November 13,		6	10.4012.50	120 resampled to 30

Satellite data	Date of acquisition	Sensor	Band No.	Spectral range (Wavelength μm)	Spatial resolution, m
	2004; November 11, 2009		7	2.082-3.5	30
Landsat 8	November 25, 2014; November 23, 2019	OLI	1	0.43–0.45	30
			2	0.45–0.51	30
			3	0.64–0.67	30
			4	0.53–0.59	30
			5	0.85–0.88	30
			6	1.57–1.65	30
			7	2.11–2.29	30
			8	1.36–1.38	15
			9	0.50–0.68	30
			TRIS 1	10	10.60–11.19
	TRIS 2	11	11.50–12.51	100 resampled to 30	

After downloading the data, sequentially landcover, LST, NDVI and NDBI were calculated. Using the data, LST and land cover were predicted for future 30 years. Meanwhile, the calculated data were validated using temperature data collected from Bangladesh Metrological Department (BMD). In addition, frequent field visits were taken place to validate the measured data by interviewing local respondents. Afterwards, a correlation analysis was carried out among LST, NDVI, and NDBI. The whole methodological steps are given by flow diagram (Fig. 2).

Fig. 2: Methodological flow diagram of the study

2.2.1 Land Use Land Cover Classification

ArcGIS 10.6.1 software was used to combine the satellite images obtained. 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 & Thomason, 1987; Good & Giordano, 2019). Landsat images were categorized using the Maximum Likelihood Supervised Classification (MLSC) approach into four major LULC classes (water body, built-up area, vegetation, and barren terrain) for the years 1989, 1994, 1999, 2004, 2014, and 2019. 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 Jr & Millones, 2011; Story & Congalton, 1986).

2.2.2 Estimation of Land Surface Temperature (LST)

a. Top of Atmospheric Spectral Radiance: Top of Atmospheric Spectral Radiance (TOA) was retrieved by using following equation 1 (Liu & Zhang, 2011).

$$L_{\lambda} = M_L \times Q_{cal} + A_L \quad \text{----- (1)}$$

184 Where M_L was represented as the band-specific multiplicative rescaling factor, Q_{cal} was the Band
 185 10, A_L is the band-specific additive rescaling factor.

186 **b. Sensor Brightness Temperature Estimation (T_i):** First and foremost, conversion from the
 187 spectral radiance of thermal infrared band to active radiance sensor brightness temperature was
 188 calculated by equation 2 (Liu & Zhang, 2011; Maduako et al., 2016; M. Rahman et al., 2017;
 189 Sholihah & Shibata, 2019).

190
$$T_i = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \text{-----} (2)$$

191 Here, K_1 and K_2 are the calibration constant; K_1 in $W/(m^2.sr. \mu m)$ and K_2 in kelvin respectively.
 192 The value of K_1 and K_2 for Landsat 4-5 and Landsat 8 are given as following Table 2 (Liu &
 193 Zhang, 2011).

194 Table 2: Landsat Thermal Bands Calibration Constants

Constant	Unit K_1 : $W/(m^2.sr. \mu m)$	Unit K_2 : Kelvin
Landsat 4-5 TM	607.76	1260.56
Landsat8 TIRS (band 10)	774.8853	1321.0789
Landsat8 TIRS (band 11)	480.8883	1201.1442

195 **c. Retrieving LST:** Thermal infrared wavelengths are used to determine Top of Atmosphere
 196 (TOA) brightness. Meanwhile, to get an accurate land surface brightness temperature, atmospheric
 197 influences such as upward emission and downward irradiance reflected from the surface should be
 198 adjusted. Calculating the land surface spectral emissivity (ϵ) enables the aforementioned
 199 adjustment to be made. Meanwhile, some elements such as water content, chemical composition,
 200 structure, and roughness all affect the emissivity of the surface (Zine El Abidine et al., 2014).
 201 Numerous scholars have demonstrated that the surface emissivity is highly correlated with the
 202 NDVI, and so the emissivity can be calculated using the NDVI (Ahmed et al., 2013).

203 NDVI can be calculated using the following equation 3 using the reflectance values of the Visible
 204 and Near Infrared bands (Ahmed et al., 2013).

$$NDVI = \frac{B_{NIR} - B_{RED}}{B_{NIR} + B_{RED}} \text{ ----- (3)}$$

Where, B_{NIR} , B_{RED} were the pixel values of near-infrared and red bands. Using the NDVI value the Proportion of Vegetation (P_v) can be calculated to measure land surface emissivity (ϵ) by using equation 4 (Liu & Zhang, 2011).

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \text{ ----- (4)}$$

Using P_v , land surface emissivity (ϵ) can be measured by following equation 5 (d'Entremont & Thomason, 1987; Good & Giordano, 2019).

$$\epsilon = 0.004 \times P_v + 0.986 \text{ ----- (5)}$$

The land surface temperatures corrected for spectral emissivity (ϵ) was computed by the following equation 6 (Avdan & Jovanovska, 2016; Chaudhuri & Mishra, 2016; Ullah et al., 2019; Xiong et al., 2012).

$$LST = \frac{T_i}{1 + \left(\lambda \times \frac{T_i}{\rho} \right) \times \ln(\epsilon)} \text{ ----- (6)}$$

Here, LST represents land surface temperature; T_i was the sensors brightness temperature. The emitted radiance's wavelength was indicated as λ and ϵ indicates the land surface spectral emissivity.

In addition,

$$\rho = h \frac{c}{\sigma} \text{ ----- (7)}$$

Here, the value of ρ is 1.438×10^{-2} mk (equation 7). Where h indicates Plank's constant which is equal to 6.626×10^{-34} Js, c indicates the velocity of light, which is equal to 2.998×10^8 ms⁻² and σ is the Boltzmann constant (5.67×10^{-8} Wm²k⁻⁴ = 1.38×10^{-23} JK⁻¹) (Zine El Abidine et al., 2014).

Daily temperature data collected from the Bangladesh Meteorological Department (BMD) located at Agargaon, Dhaka was used for validation of estimated LST.

2.2.3 Simulation of Landcover 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, Sharma, Garg, & Kappas, 2016; Parsa, Yavari, & Nejadi, 2016).

The LST and LULC for the year 2039 with the help of MOLUSCE plug-in in QGIS 2.18 is 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; Z.-L. Li et al., 2013; Maduako et al., 2016; Shatnawi & Abu Qdais, 2019). LST simulation was performed in this study using input parameters LULC images, NDVI, NDBI, latitude and longitude and as output parameters for LST (Gopal & 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 past 20 years data (1999-2019) as the input parameters for predicting the future year 2039 data. The LST prediction model architecture is shown in Fig. 3.

Fig. 3: CA-ANN model architecture

2.2.4 Field Verification Techniques of LULC

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 (equation 8). 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 (equation 9). 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 actually located on the ground (equation 10). Following the calculation of all accuracy parameters, the Kappa coefficient was determined using equation 11. (Congalton & Green, 2008; Foody, 2002; Pontius Jr & Millones, 2011; Story & Congalton, 1986).

$$\text{Overall Accuracy} = \frac{\text{Total number of corrected classified pixels (diagonal)}}{\text{total number of reference pixels}} * 100 \quad (8)$$

$$\text{Producer Accuracy} = \frac{\text{number of correctly classified pixels in each category (diagonal)}}{\text{total number of reference pixels in each category (column total)}} * 100 \quad (9)$$

$$\text{User Accuracy} = \frac{\text{number of correctly classified pixels in each category (diagonal)}}{\text{total number of reference pixels in each category (row total)}} * 100 \quad (10)$$

$$\text{Kappa Coefficient (T)} = \frac{\text{Total number of Sample} * \text{Total Number of Corrected Sample} - \sum(\text{col.tot} * \text{row tot})}{(\text{Total number of Sample})^2 - \sum(\text{col.tot} * \text{row tot})} * 100 \quad (11)$$

3. Results and Discussions

3.1 Land Use Land Cover Classification

The LULC map for 1989, 1994, 1999, 2004, 2009, 2014, and 2019 was generated using MLSC (Fig. 4a to 4f). The study's entire area is roughly 48.830 square kilometers. The categorized picture

273 from 1989 revealed a larger proportion of area for bare terrain, aquatic bodies, and vegetation,
 274 respectively, at 35.04 percent, 27.34 percent, and 24.9 percent. For 1989, the built-up area was just
 275 12.56 percent (Fig. 4a). In 1994, bare ground had the most area (39.20 percent), followed by water
 276 bodies (24.63 percent) and vegetation (17.04 percent) (Fig. 4b). In 1994, built-up area increased
 277 by 7% over 1989 levels. The continuing upward trend in bare land (40.45 percent) and built-up
 278 area (31.85 percent) was accelerated in 1999, mostly due to growing urbanization. Water bodies
 279 (8.19%) and vegetative land (19.11%) have saw a decline in recent years due to the transfer of
 280 natural surfaces to bare ground and later to built-up land (Fig. 4c). In 2004, bare land (33.15
 281 percent) continued to decline due to the conversion of bare land to urban built-up areas (43.76
 282 percent). Filling up water bodies (4.77 percent) and vegetative land (18.32 percent) that were
 283 initially bare land and were eventually moved to built-up areas began to speed in 2004. (Fig. 4d).
 284 The categorized LULC findings for 2009, 2014, and 2019 were compared (Fig. 4e to 4f) by
 285 calculating the percentage change in each LULC class over time. Between 2009 and 2019, the
 286 quantity of bare and vegetated land decreased considerably (by roughly 10%). During the same
 287 time span, the built-up area expanded by a factor of two (21 percent of the study area). Finally, the
 288 water body declined by 1% of the studied area between 2009 and 2019.

Fig. 4: Classified land use land cover map of the study area in (a) 1989, (b) 1994, (c) 1999, (d) 2004, (e) 2009, (f) 2014, (g) 2019

3.1.1 Percent Change Analysis of Different LULC

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 3). 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 year 1989 to 1994, built up area and bare land area were gained 6.485% and 4.158% area, respectively, where vegetation and water bodies were lost by 7.930% and 2.713% of its area, respectively. Similar for 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 showed by 12.717%, 1.653% and 2.056%, respectively. Only dramatic loss in water bodies by 16.445% was recorded from 1994-1999. Moreover, from 1999-2004, except built-up area other three LULC classes were facing decreasing trend. Built up area gained by 11.906% where 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.

Table 3: Percentage Change of LULCs in the Study Area from 1989-2019

LULC	Area in Km ²							Change in %					
	1989	1994	1999	2004	2009	2014	2019	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						

From 2004 to 2009, significantly built-up area gained 23.281 % area where 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 reduced to 6.679 %, 0.383 % and 0.440 % respectively. Overall, the highest losses (bare land and vegetation) and gains (urban area) were observed in the 2004–2014 period. However, the water body expansively was lost its coverage from 1994 to 1999 (Table 3).

3.1.2 Field validation of LULC

Table 4 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 & Green, 2008; Foody, 2002; Pontius Jr & Millones, 2011; Story & Congalton, 1986). In order 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.

Table 4: Accuracy Assessment for 2019 LULC

Classified Class	Ground Truth					User Accuracy
	Water body	Urban	Vegetation	Bare Land	Total	
Water	10	0	1	0	11	90.91
Built up Area	0	15	0	1	16	93.75
Vegetation	0	0	11	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	Kappa Statistics
					90	83.85

3.2 Estimation of Land Surface Temperature (LST)

Fig. (5a to 5g) indicates the spatial pattern of LST distribution. In all maps bright yellow tone represents higher temperature and 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 winter season in Bangladesh, therefore, displayed data will show the temperature of corresponding winter season of the years.

Fig. (5a and 5b) focuses on annual surface temperature conditions of 1989 and 1994 and LST varied within the range of less than 20 – 24⁰C. From 1999 and 2004 temperature decreased slightly and the reason is Bangladesh went under massive flood during that period.

Fig. 5: Land surface temperature distribution in the year (a) 1989, (b) 1994, (c) 1999, (d) 2004, (e) 2009, (f) 2014 and (g) 2019

In that period, surface water existed for a long period. For that temperature was comparatively lower than the previous year and LST varied 20 – 32⁰C (Fig. 5c and 5d). In the year of 2009 the LST varied 20 – 32⁰C (Fig. 5d). For 2014 and 2019, the LST were 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 24⁰C to more than 34⁰C (Fig. 5e to 5g). The north-

western part of the study area exhibited lowering in temperature due to higher vegetation and agricultural land whereas the south eastern part exhibits the rise in LST due to rapid urban expansion and declining of water bodies as well as vegetation land.

3.2.1 Percent Change in LST

The Percent Change in LST will provide a better insight about the temperature variation at different ranges of LST. From 1989 to 1994, the highest percentage of area (30.946%) was lost in having LST below 20⁰C range. Also, 30.928% area increased within the range of 20-24⁰C. Due to abundance of vegetation and water bodies, temperature range above 28⁰C found unavailable (Table 5). From 1989 to 1994, the highest percentage of area (57.063%) was lost in having LST below 20⁰C range. Also, 54.829% area increased within the range of 20-24⁰C. Due to abundance of vegetation and water bodies, temperature range above 32⁰C found unavailable (Table 5).

Due to heavy flood in 2004, LST reduced to less than 20⁰C from 1999 to 2004 (Table 5). But, from the year 2004 to 2009, maximum percentage of area increased to 89.09% within the LST range of 24-28⁰C. During this period significant increase of built-up area, reduction of water bodies and vegetation area were noticed (Table 3).

Table 5: Percentage Change of LSTs in the Study Area from 1989-2019 (km²)

LST Range	Area in Km ²							Change in %					
	1989	1994	1999	2004	2009	2014	2019	1994- 1989	1999- 1994	2004- 1999	2009- 2004	2014- 2009	2019- 2014
< 20 ⁰ C	43.11	28	0.13	12.01	0	0	0	-30.95	-57.06	24.33	-24.60	0	0
20-24 ⁰ C	5.02	20.12	46.89	34.93	3.30	0	0	30.93	54.83	-24.51	-64.76	-6.76	0
24-28 ⁰ C	0.70	0.71	1.12	1.20	44.71	21.93	4.46	0.02	0.83	0.17	89.10	-46.65	-35.78
28-32 ⁰ C	0	0	0.69	0.69	0.82	26.28	43.64	0	1.41	0.009	0.27	52.14	35.55
> 32 ⁰ C	0	0	0	0	0	0.62	0.74	0	0	0	0	1.27	0.24
Total	48.83	48.83	48.83	48.83	48.83	48.83	48.83						

Built-up area continued to increase from 2009 to 2014 and from 2014 to 2019 (Table 3) which resulted in the increase of LST more than 32⁰C. Maximum area of temperature found within 28-32⁰C (35.784% area) and it was 52.136% area in 2009 to 2014. Here, 1.273% and 0.238% area increased to more than 32⁰C from the year 2009 to 2014. The increase of built-up area, reduction

of water bodies and vegetation land were dominant from the year 2009 which contributed to increase of LST more than 32⁰C from 2009.

3.2.1 Validation of LST using BMD data

As the simulation of future LST pattern was estimated on the basis of 1989 to 2019 data at 5 years interval period and BMD Agargaon station's data was available from 2013 to 2018 therefore only LST data of 2014 could be validated. Estimated LST data has 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. After validating both source data, the minimum and maximum temperature error was estimated as 3.678% and 4.982%, respectively. The percentage of error was negligible and therefore the estimation of LST was acceptable for further processing by considering a little limitation (Table 6).

Table 6: Validation of LST simulation based to the estimate LST for the year 2014

Year	Temperature from Satellite Image	BMD Data	Percentage of Error
2014	Minimum Temperature		
	24.883	24.000	3.678
	Maximum Temperature		
	32.545	31.000	4.982

3.3 Association of LST and LULC

3.3.1 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 radiative radiation radiated 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. 6. (a-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. 6a), > 27°C in 1994 (Fig. 6b), > 28°C in 1999 (Fig. 6c), 29°C in 2004 (Fig. 6d), > 30°C in 2009 (Fig. 6e), > 32°C in 2014 (Fig. 6f) and > 34°C in 2019 (Fig. 6g). Also, 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, other two LULC (water bodies and vegetation) were recorded as the lowest temperature ranging from 16°C to 27°C. The findings signify that built-up area increases LST by replacing natural vegetation with non-evaporating and non-transpiring surfaces.

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Fig. 6: 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

3.3.2 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 sq. km in water bodies, 12.27 sq. km in bare land, 3.24 sq. km in built-up area and 12.20 sq. km in vegetation cover (Table 7). In 1994 most of the area experienced below 20°C for all LULC and the dominated LULC was bare land (14.08 sq. km),

water bodies (10.35 sq. km), and vegetation (2.91 sq. km). At LST range 20-24⁰C, 7.97 sq. km, 5.41 sq. km and 5.06 sq. km area were recorded as built-up area, vegetation land and bare land respectively (Table 7).

For the year 1999, the highest range was 20-24⁰C and the maximum coverage of LULC class was bare land (19.11 sq. km), followed by built-up area (15.75 sq. km) and vegetation land (5.30 sq. km) (Table 7).

Table 7: LULC Wise LST Distribution from 1989 to 2019

Temperature	< 20 ⁰ C	20-24 ⁰ C	24-28 ⁰ C	28-32 ⁰ C	> 32 ⁰ C
Land cover	1989 (area in km ²)				
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	-	-	-
Landover	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	-	-	-
Landover	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				

Temperature	< 20⁰C	20-24⁰C	24-28⁰C	28-32⁰C	> 32⁰C
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

In 2004, the highest range of LST was 20-24⁰C and the maximum LULC classes were built-up area (18.05 sq. km), followed by bare land area (12.13 sq. km). The lowest LST found at water bodies (1.42 sq. km) which was below 20⁰C (Table 7). In year 2009, the highest range of temperature was 24-28⁰C and the maximum coverage of LULC class was in urban area (31.90 sq. km), followed by bare land area (6.75 sq. km). The lowest temperature was recorded urban area (0.02 sq. km) under 20-24⁰C temperature (Table 7).

As the built-up area is continuously increasing, therefore, LST values got a momentum from 2014 to 2019. In 2014, highest percentage of built-up areas were found in the range of 28-32⁰C and 24-28⁰C with corresponding areas of 23.04 sq. km and 15.15 sq. km respectively. In 2019, 0.61 sq. km and 40.94 sq. km of built-up areas were found having more than 32⁰C and 28-32⁰C respectively (Table 7).

3.4 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 shrub 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 correlation reveal that LST has a significant and positive connection with NDBI and a strong and negative correlation with NDVI (Fig. 7a to 7g). In all correlation analyses, the R² 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 (Figure 7a–7g).

(c)

(d)

(e)

(f)

(g)

436 **Fig. 7: Correlation between LST vs NDVI & NDBI in the year (a) 1989, (b) 1994, (c) 1999,**
 437 **(d) 2004, (e) 2009, (f) 2014 and (g) 2019**

3.5 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 value were 84 percent (Table 8), which is an acceptable degree of accuracy for LULC modeling. The model validation result shown in Figure 8a was obtained using the QGIS program.

Table 8: ANN Model Validation for LULC in QGIS MOLUSCE Plugin

Prediction Year	ANN model validation for LULC prediction			
2039	QGIS-MOLUSCE Plugin module			
	%-correctness	Overall Kappa Value	Kappa- location	Kappa- histo
	84.56%	0.84508	0.8529	0.8852

Simulation results showed that approximately 92% of the area will be converted into built-up area in 2039 (Fig. 8b). Predicted LULC change in future could adversely affect the environment altering both climate and biodiversity of the area.

457 Fig. 8: (a) LULC Prediction Model Validation Result for the Year 2039 and (b) Simulated LULC
 458 Map for the year 2039

459 Table 9: Percentage Change of LULCs in the Study Area from 2019-2039

LULC	Area km ² (2019)	Area in %	Area km ² (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	

460 The percentage of change indicates that in 2039, built-up area would increase about 5.5% higher
 461 than the 2019 if this pattern continues. Moreover 92.42% of Mirpur and surrounding area would
 462 convert in to built-up area and there will be drastic reduction of other LULC such as vegetation,
 463 bare land and water bodies (Table 9).

3.6 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 10). Based on the ANN model validation in other researches, the percentage of correctness value over 80% demonstrates strong agreement of accuracy.

Table 10: ANN Model Validation for LST in QGIS MOLUSCE Plugin

Prediction Year	ANN model validation for LST prediction			
	QGIS-MOLUSCE Plugin module			
2039	%-correctness	Overall Kappa Value	Kappa- location	Kappa- histo
	91.856	0.9362	0.9037	0.92582

The validation provided an excellent accuracy with more than 90% of correctness for simulated LST map in 2039 (Fig. 9a). Similar to the LULC for the study period from 1989–2019, 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 Mirpur area 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. Change of percentage of area is around 22.18% which will fall within the range of LST greater than 32°C in 2039 (Table 11). The prediction results demonstrate that most of the LST remains below 32°C. Fig. 9b shows the rising trend of LST in the study area for the year 2039.

Table 11: Percentage Change of LSTs in the Study Area from 2019-2039

Range	Area km ² (2019)	Area in Percentage	Area km ² (2039)	Area in Percentage	Change in Percentage (2039-2019)
< 20°C	-	-	-	-	-
20-24°C	-	-	-	-	-
24-28°C	4.46	9.13	1.80	3.69	-5.44

28-32°C	43.64	89.36	35.46	72.62	-16.74
> 32°C	0.74	1.51	11.57	23.69	22.18
Total	48.83	100	48.83	100	

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

484 Fig. 9: (a) LST Prediction Model Validation Result for the Year 2039 and (b) Simulated LST
485 Map for the year 2039

486 4. Conclusions and Recommendations

487 The study area faced tremendous increase of built-up area. Increasing impervious layers trend to
488 reflect and generate higher surface temperature. Considering the year 2014-2019, built-up area
489 gained 7.499 % area where bare land, vegetation and water bodies were lost 6.679%, 0.383% and
490 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 expansively was lost its coverage in the 1994–1999 periods.

The average surface temperature increasing rate is high in 5 years interval period. In 1989, 88.284% of area was covered under 20⁰C temperature. Later, maximum area of temperature was increased to the range of 28-32⁰C at 52.136% from the year 2009 to 2014. Here, 1.273% and 0.238% area were increased to more than 32⁰C from the year 2009 to 2014 and from 2014 to 2019, respectively. The increase of built-up area, 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 32⁰C from the year 2009. Validation of LST estimated data with BMD data was pretty much impressive and the percentage of error is 3 to 4%.

Prediction indicates that in the year 2039 approximately 92.42% of Mirpur and surrounding areas will be covered by built-up area and corresponding predicted LST range will be greater than 32°C. The prediction exhibited that approximately 23.69% of Mirpur area 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. 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 remains below 32°C.

Cross section profile of LULC vs LST shows higher temperature existed in built-up area in all time periods. In the year 2019, 0.61 sq. km of urban area was fallen more than 32⁰C temperature range followed by 40.94 sq. km in the range of 28-32⁰C. LST has strong and positive correlation with NDBI. LST has strong and negative correlation with NDVI. In all the correlation analysis, the R² found more than 0.9 that 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 is 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.

To the Author's knowledge, this is the first research to provide a method for estimating future LST of metropolitan areas from observable connections between land cover and LST changes in the study region. Since a result, future city planning should place a greater emphasis on urban greening, as the research region increasingly shifts towards the highest temperature zone owing to urbanization. If current trends continue, by 2039, nearly the whole study region will be a UHI. A compact-town-style decentralization of metropolitan regions (satellite-towns) is therefore a viable path ahead for preventing the future creation of large-scale UHI effects. The work derived future LST using LULC indices (NDVI and NDBI) and a simple regression equation. It is feasible to combine the various land cover indices as independent variables in a multiple regression equation model in order to calculate the LST in a more robust manner, potentially using factor analysis. Future research should integrate these elements and strive to improve upon the model given here.

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Contributions

A N M Foyezur Rahman: methodology, software, data curation, writing—original draft preparation.

M Tauhid Ur Rahman: conceptualization, methodology, writing—review & editing.

Ethics approval

Not applicable

Consent to participate

545 Agree to participate

546 **Consent for publication**

547 Agree to publish

548 **Competing interests**

549 The author declares that this research work is his original work and has written it in its entirety.

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554 The datasets used and analysed during the current study are available from the corresponding

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