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Research Paper

Detection of land use and land cover change and land surface temperature in English Bazar urban centre \ddagger

Swades Pal^a, Sk. Ziaul^{b,*}

^a Deptt. of Geography, University of Gour Banga, Mokdumpur, Malda 732103, West Bengal, India
^b University of Gour Banga, Mokdumpur, Malda 732103, West Bengal, India

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ABSTRACT

Present paper tends to capture the impact of land use land cover (LULC) on land surface temperature (LST) in English Bazar Municipality of Malda District using multi spectral and multi temporal satellite data. Seasonal and temporal LST is extracted in three phases e.g. in 1991, 2010 and 2014. Results show that LST increases 0.070 °C/year and 0.114 °C/year during winter and summer periods respectively and significant LST difference exist over different LULC units. Built up area retains maximum LST in all selected phases. Correlation coefficient among different deriving factors of LST with LST reveals that impervious land maximally control LST (r = 0.62) followed by water bodies and vegetation cover. Even a single land use unit like impervious land water body and vegetation also create differences in LST (R^2 of NDBI vs. LST ranges from 0.47 to 0.607; NDVI vs. LST ranges from 0.441 to 0.62). LST is almost co linear with aerial temperature as indicated by significant correlation value (0.44604 for January and 0.658 for April 2014) at 0.01 level of significance and the temperature gap between them ranges from 3.5 °C to 6.5 °C. Such co linearity validates the LST models. The estimated temperature gap is also strongly controlled by LULC. As the LULC pattern is getting changed, its imprint is reflected on LST and air temperature. So, immediate thinking about new urbanism should be adopted, started and implement to arrest the rising temperature and effect of urban heat island.

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1. Introduction

The most imperative problem in the earth especially urban halves is increasing surface temperature due to conversion of vegetated surfaces to impervious surfaces (Mallick et al., 2008), transformation of vegetated and wetland into agricultural land or bare waste land (Pal and Akoma, 2009). These changes affect the degree of absorption of solar radiation, albedo, surface temperature, evaporation rates, transmission of heat to the soil, storage of heat, wind turbulence, can drastically alter the conditions of the near-surface atmosphere over the cities (Mallick et al., 2008), modify energy and water balance processes (Oke, 1987) and also play vital role in many environmental processes (Weng et al., 2004). Along with other sorts of pollutants, land surface temperature will rise at rapid rate which will expose expectedly 69% world's population by 2050

* Corresponding author.

to this vulnerability (United Nations, 2010). This acceleration of urbanization is very high both in intensity and areal coverage in the developing country like India.

Urban temperature rise and formation of urban heat island (UHI) has long been a concern for more than 60 years. One of the earliest UHI studies was conducted in 1964 by Nieuwolt (1966) in the urban southern Singapore. Afterward, host of scientist (Zhong, 1996; Deosthali, 2000; Kim and Baik, 2002; Giridharan et al., 2004; Weng, 2009; Neteler, 2010; Ogashawara and Brum Bastos, 2012; Grover and Singh, 2015) have worked on this field emphasizing different cognitive issues. UHI intensity is related to patterns of land use/cover changes (LUCC), e.g. the composition of vegetation, water and built-up and their changes (Chen et al., 2006; Grover and Singh, 2015). Both horizontal and vertical urban expansion, spacing between building, building materials, location of public places, bus stoppage, railway station, major and minor industrial hubs etc. influence temperature concentration. Considering the importance of the work, many such scholarly works were done in the foreign nations. Cao et al. (2008) applied Fractal vegetation cover (FVC) change while detecting urban heat island and its shifting behaviour. Jiang and Tian (2010) used temperature-

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E-mail addresses: swadeshpal82@gmail.com (S. Pal), skziaul87@gmail.com (Sk. Ziaul).

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vegetation index (TVX) space for investigating the influence of land changes over LST. Hathway and Sharples (2012) investigated the role of the presence of river or water bodies on moderating urban heat island and thereby he suggested in making space for water bodies while designing of urban area for eco-climatic urban growth. Nichol and Hang (2012) investigated urban heat stress and heat island of Hong Kong city of China based on ASTER thermal imageries. Jongtanom et al. (2011) worked with thermal conditions of three cities of Thailand and reported that heat island intensity becomes very frequent during night and morning time. Neteler (2010) estimated land surface temperature of Alps mountainous environment by reconstructed MODIS LST data. Ogashawara and Brum Bastos (2012) investigated relationship between built up area and LST; water bodies and LST and vegetation density and LST of Brazilian urban centers and documented that built up area accelerates urban temperature: vegetation density and water presence moderate LST. Chandler (1965) and Lombardo (1985). explained urban heat island effect by three factors: (1) the effects of energy transformation in cities; (2) the decrease of evapotranspiration; and (3) the production of anthropogenic energy. Voogt (2004), depicted three types of UHIs: (1) Canopy Layer Heat Island (CLHI); (2) Boundary Layer Heat Island (BLHI); and (3) Surface Heat Island (SHI). Fabrizi et al. (2010) explained the differences among the types of UHI, characterizing the CLHI and BLHI as warming the urban atmosphere and the SHI as warming the urban surface. Lee et al. (2012) scaled urban heat island intensity of Phoenix and Arizona based on time dependent energy balance using ASTER and LANDSAT data. Siu and Hart (2013) did the same work on Hong Kong city.

In India only few studies were conducted by the scholars mainly for some metropolitan cities like Mumbai (Grover and Singh, 2015), Chennai (Lilly Rose and Devadas, 2009), Jaipur (Jalan and Sharma, 2014), Delhi (Mallick et al., 2008; Grover and Singh, 2015). But no such works have carried out for the small towns those are also started nucleating heating problem. Monitoring of those can help to provide early step for adopting suitable policies for either over come or minimize the problems. Keeping this concern in mind, present work is based on highly populated and rapidly growing English Bazar Municipality and its surrounding areas of Malda district of West Bengal. Moreover, In India average density of meteorological density in plain region it is 1/520 sq.km. which is too sparse and from this data it is difficult to conduct any high resolution work related to atmospheric or land surface temperature change. From land surface temperature one can roughly predict atmospheric temperature based on many of such works showing relation between land surface and atmospheric temperature. Kawashima et al. (2000) documented a relation between mean air temperature and mean surface temperature. Also they rightly mentioned that this relation varies in different altitudinal range. They recorded that mean air temperature is 7° to 9.6 °C greater than mean surface temperature and obviously it is high in the lower elevation. Adjusted R² ranges from 0.91 to 0.98 when regression is carried out between these two parameters.

Satellite image based analysis provides high resolution, consistent and repetitive coverage and capability of measurements of earth surface conditions (Owen et al., 1998). Remote sensing and geographical information system is considered as most responsive and effective tool for urban climate study and other decision support (AbdelRahman et al., 2016; Deep and Saklani, 2014). Main thrust of this present work is to detect change of land surface temperature in relation to land use land cover change and fractal vegetation cover (FVC) in some selected phases. This paper also investigates the temperature characters in different vegetation density zones, water depths, built up intensity zones over selected time periods.

2. Study area

Present study area consists of 29 wards of English Bazar Municipality (EBM). 16 surrounding mouzas from English Bazar block and 11 mouzas from Old Malda block covering an area of about 5465.43 ha. (100 ha. = 1 sq.km.). Entire study area comes under Diara tract of West Bengal with fertile fine grain silty clay carried out by river Ganga and its distributary Kalindri river and Mahananda river. Kalindri river and Mahananda rivers are located at northern and eastern margin of the study area. Average elevation of this region is 17 m from MSL. Present population in this study area is 2, 63,212 and growth rate of population are respectively 24.78% and 21.5% in between 1991-2001 and 2001-2011. Land use history of this area speaks that more than 25% vegetated area have been expunged in last 50 years. Chatra wetland (perennial) considered as lungs of the town is located at just proximate zone of this town. Over time this wetland area is captured by built up area. Climate of this region is characterized by sub tropical monsoon with seasonal wet and dry spell of rainfall, cold and hot spell of temperature. Entire year is sub divided by majorly four season viz. (1) winter season (January and February), (2) Pre monsoon season (March to May) with little rain and high temperature and evaporation, (3) Monsoon season (June to Mid October) with maximum (about 82% of total rain) rain and high temperature and (4) Post monsoon season (Mid October to Mid December) with steady declining of rain and temperature (Fig. 2). Average annual rainfall of this area as gauged by Malda meteorological station is 1444.432 mm. Average potential evaporation of this area since 1901-2014 is 73.45 mm./year which indicates one of the controlling factors of surface temperature.

This town possesses a good infrastructure and facilities. Two railway stations e.g. Gour Malda and Malda town are located at southern and northern part of this area. Railway line and National High way (NH) 34 perforate this town from south to north. Two main markets e.g. Netaji market/Rathbari market, Chittaranjan market is located at the heart of the town and considered as Central business district (CBD) of this commercially improved town (see Fig. 1). Hardware shop linearly arranged astride NH 34 from Rathbari major nodal point toward north.

3. Materials and methods

LANDSAT TM data for 1991 and 2010 and also LANDSAT 8 OLI 2014 have been obtained from the US Geological Survey (USGS) Global Visualization Viewer. The obtained Landsat data (Level 1 Terrain Corrected (L1T) product) were pre-geoRef. d to UTM zone 45 North projection using WGS-84 datum (see other details in Table 1). The other necessary corrections have been carried out in this study. Geometric correction of the images have done using 179 ground control points (GCP) collected through Global Positioning System (GPS), and ancillary data from topographic maps and Google Earth images. Arc GIS 10.1 and ERDAS IMAGINE 9.2 are used for the entire study.

For extracting surface temperature from thermal band of Landsat imageries, following steps have been followed.

3.1. LST extraction from thermal band

(Inverse of the Planck Function)

3.1.1. Conversion of the digital number (DN) to spectral radiance (L λ) Every object emits thermal electromagnetic energy as its temperature is above absolute zero (K). Following this principle, the signals received by the thermal sensors (ETM+) can be converted to at-sensor radiance. The spectral radiance (L λ) is calculated using the following equation (Landsat Project Science Office, 2002):





Fig. 1. Study area showing English Bazar Municipality (EBM) and its peripheral mouzas, majaor markets, rail line, national high way and Chatra wetland. All these features are draped over digital elevation model. Value within map indicates jurisdiction number (Jl. No.) of the mouzas (smallest revenue unit).

(1)

(2)

$$L\lambda =$$
 "gain" * QCAL + "offset"

where gain is the slope of the radiance/DN conversion function; DN is the digital number of a given pixel; bias is the intercept of the radiance/DN conversion function. This is also given as:

 $L\lambda = LMIN\lambda + [(LMAX\lambda - LMIN\lambda)/(QCALMAX - QCALMIN) * QCAL]$

where QCALMIN = 0, QCALMAX = 255 and QCAL = Digital Number (DN of each pixel).

The LMIN λ and LMAX λ are the spectral radiances for band 6 at digital numbers 0 and 255 respectively. These compute to 3.2 W. m^{-2} .sr and 12.65 W. m^{-2} .sr respectively.

Substitution of the respective values in Eq. (2) gives a simpler Eq. (3):



Fig. 2. Average rainfall and maximum and minimum temperature of the study area since 1991-2014

$$L\lambda = (0.037059 * DN) + 3.2 \tag{3}$$

3.1.2. Conversion of spectral radiance $(L\lambda)$ to At-satellite brightness temperatures (TB)

Corrections for emissivity (e) have applied to the radiant temperatures according to the nature of land cover. In general, vegetated areas have given a value of 0.95 and non-vegetated areas 0.92 (Nichol, 1994). The emissivity corrected surface temperature has been computed following Artis and Carnahan (1982).

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_2} + 1\right)} \tag{4}$$

where:

4

TB = At-satellite brightness temperature (K)

 $L\lambda$ = Spectral Radiance in W.m⁻².sr⁻¹. μ m⁻¹

 K_1 and K_2 = K2 and K1 are two pre-launch calibration constants. (For the Landsat 7 ETM+6.2 band, these compute to 1282.71 K and 666.09 W.m⁻².sr⁻¹.µm, respectively).

3.1.3. Land surface temperature (LST)

The obtained temperature values above are Ref. d to a black body. Therefore, corrections for spectral emissivity (ϵ) become necessary. These can be done according to the nature of land cover

Table 1

(Snyder et al., 1998) or by deriving corresponding emissivity values from the Normalized Differences Vegetation Index (NDVI) values for each pixel. The emissivity corrected land surface temperatures (St) have been computed following Artis and Carnahan (1982).

$$LST = T_B / [1 + \{(\lambda * TB/\rho) * \ln \epsilon\}]$$
(5)

where St = land surface temperature (LST) in Kelvin, λ = wavelength of emitted radiance in meters (for which the peak response and the average of the limiting wavelengths ($\lambda = 11.5 \,\mu m$) (Markham and Barker, 1985) is used, $\rho = h * c/\sigma$ (1.438 * 10⁻²m K), $\sigma =$ Boltzmann constant (1.38 * 10^{-23} J/K), h = Planck's constant (6.626 * 10^{-34} J s), and c = velocity of light (2.998 \times 10⁸ m/s) and ε = emissivity (ranges between 0.97 and 0.99) (see Eq. (6)).

Land surface emissivity (ϵ) = 0.004 * Pv + 0.986 (6)

where proportion of vegetation (Pv) can be calculated as Eq. (7).

$$P_{\nu} = \left(\frac{NDVI_{j_{r}} - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}}\right)^{2}$$
(7)

3.1.4. Conversion of LST from Kelvin to degree Celsius

For ease of comprehension, the above derived LSTs' unit was converted to degree Celsius using the relation of 0 °C equals 273.15 K.

3.2. Framing air temperature data layer

Air temperature of January and April (2014), on the same dates on which LST was derived from image, had been recorded directly from field from 137 sites of the study area and air temperature layers have been constructed. It is directly recorded from field because a good number of meteorological stations are not available there. Air temperature data from English Bazar substation of Indian Meteorological Department (IMD) was also collected. For detecting spatial pattern of air temperature and LST difference, LST layer is just deducted from air temperature of the respective periods.

3.3. Method for land use land cover classification

3.3.1. LULC classifications

Earlier it is mentioned that LANDSAT TM data for 1991 and 2010 and also LANDSAT 8 OLI 2014 of USGS have been used for image classification. Supervised image classification technique

Satellite	Sensor	Path/Row	Year	Resolution (m)	Wavelength (µm)
Landsat-5	TM	139/43	1991	30	Band 1: 0.45–0.52
	(ThematicMapper)		2010		Band 2: 0.52–0.60
					Band 3: 0.63–0.69
					Band 4: 0.76–0.90
					Band 5: 1.55–1.75
					Band 7: 2.09–2.35
					Band 6: 10.40–12.50 (Thermal band)
Landsat- 8	OLI	139/43	2014	30	Band 1: 0.435–0.451
	(Operational Land Imager) and TIRS (Thermal InfraredSensor)			(For band 8 resolution is 15 m)	Band 2: 0.452-0.512
					Band 3: 0.533-0.590
					Band 4: 0.636-0.673
					Band 5: 0.851–0.879
					Band 6: 1.566–1.651
					Band 7: 2.107–2.294
					Band 8: 0.50–0.68
					Band 9: 1.363–1.384
					Band 10: 10.60–11.19 (Thermal band)
					Band 11: 11.50–12.51
					(Thermal band)

with Mahalanobis distance in parametric rule and parallelepiped method in non parametric rule has been used. ERDAS Imagine (version 9.2) software is used for image classification. For detecting each individual class properly, 92 signatures from all the images have collected and merged.

One issue that should be mentioned that the appropriate classification rules and method used may depend on the scale at which the classification is carried out. As described by Blaschke et al. (2008), the spectral variability or heterogeneity within a land class at fine scale may make the pixel-based approach less robust, causing it to generate the erroneous classification of pixels. It is found that the object-based classification method can overcome this spectral variability problem by utilizing not only the spectral information but also the topological relationships between image objects and obviously, resolution of image is one of the major concerns here. Bhaskaran et al. (2010), who used pixel and objectbased methods to detect urban features with VHR imagery, and Wang et al. (2004), who obtained higher classification accuracies. Flanders et al. (2003), Matinfar et al. (2007) and Yan et al. (2006) also suggested same approach for Landsat based image classification. Considering the goodness of fit of the approaches mentioned, here pixel and object based classification approach is adopted for image classification.

3.3.2. Method adopted for accuracy assessment

The accuracy assessment for supervised technique has been made through a confusion or error matrix. A confusion matrix contains information about actual and predicted classifications done by a classification system (Prisley and Smith, 1987; Hay,1988; Jupp, 1989; Czaplewski, 1992; Van Deusen, 1996; Yuan, 1997). The pixel that has been categorized from the image is compared to the same site in the field. The result of an accuracy assessment typically provides the users with an overall accuracy of the map and the accuracy for each class in the map. The percentage of overall accuracy was calculated using following formula:

Overall accuracy = Total number of correct samples

\times 100%Total number of samples

Total 179 sample sites from Google earth and ground verification are selected for accuracy assessment. Besides the overall accuracy, classification accuracy of individual classes is calculated in a similar manner. The two approaches are user's accuracy and producer's accuracy. The producer's accuracy is derived by dividing the number of correct pixels in one class divided by the total number of pixels as derived from Ref. data. Producer's accuracy measures how well a certain area has been classified. It includes the error of omission which refers to the proportion of observed features on the ground that is not classified in the map. Meanwhile, user's accuracy is computed by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (Story and Congalton, 1986). The user's accuracy measures the commission error and indicates the probability that a pixel classified into a given category actually represents that category on ground (Zhou et al., 1998; Congalton and Green, 1999; Khorram, 1999; Lunetta et al., 2001). Producer's and user's accuracy are derived from following formula:

 $Comission.Error = \frac{off.diagonal.row.elements}{total.of.row}$

 $Comission. Error = \frac{off. diagonal. column. elements}{total. of. column}$

Producer's accuracy (%) = 100% – error of omission (%) User's accuracy (%) = 100% – error of commission (%)

Kappa coefficient (K) is another measurement used in this study following Foody (1992), Ma and Redmond (1995). It is calculated by multiplying the total number of pixels in all the ground verification classes (N) by the sum of the confusion matrix diagonals (Xkk), subtracting the sum of the ground verification pixels in a class time the sum of the classified pixels in that class summed over all classes ($\Sigma X k \Sigma$ Yk Σ), where Xk Σ is row total and Yk Σ is column total, and dividing by the total number of pixels squared minus the sum of the ground verification pixels in that class times the sum of the classified pixels in that class summed over all classes. The value of Kappa lies between 0 and 1, where 0 represents agreement due to chance only. 1 represents complete agreement between the two data sets. Negative values can occur but they are spurious. It is usually expressed as a percentage (%). Kappa statistic (Cohen, 1960) can be a more sophisticated measurement to classifier agreement and thus gives better interclass discrimination than overall accuracy (Foody, 1992; Ma and Redmond, 1995). The calculation of Kappa statistic k is as follows:

$$k = \frac{N \sum_{i=1}^{r} xii - \sum_{i=1}^{r} (xi + *xi + i)}{N^{2} - \sum_{i=1}^{r} (xi + *xi + i)}$$

 $k = \frac{(Total \ Sum \ of \ correct) - Sum \ of \ the \ all \ the(row \ total \ column \ total)}{Total \ squared - Sum \ of \ the \ all \ the(row \ total \ column \ total)}$

Kappa is always less than or equal to 1. A value of 1 implies perfect agreement and values less than 1 imply less than perfect agreement. In rare situations, Kappa can be negative. This is a sign that the two observers agreed less than would be expected just by chance. It is rare that we get perfect agreement. Different people have different interpretations as to what is a good level of agreement.

Monserud and Leemans (1992) suggested that values lower than 0.4 represent poor or very poor agreement, values from 0.4 to 0.55 represent fair agreement, values from 0.55 to 0.7 represent good agreement, values from 0.7 to 0.85 represent very good agreement, and values higher than 0.85 represent excellent agreement between images.

3.3.3. Method for change detection

Classified image pairs of two different time phases are compared using cross-tabulation in order to determine qualitative and quantitative aspects of the changes for the periods from 1991 to 2010. A change matrix (Weng, 2001) is generated from this process. Quantitative areal data of the overall land use/cover changes as well as gains and losses in each category between 1991 and 2010 are then compiled.

3.4. Methods for framing used data layers

Here it is to be mentioned that what is the procedure to prepare NDVI, Normalized Differences Water Index (NDWI) and Normalized Differences Built up Index (NDBI) data layers used for intra land use LST change.

For NDVI extraction, method of Townshend and Justice (1986) is used.

$$NDVI = \frac{(IR\,band - R\,band)}{(IR\,band + R\,band)}$$

where IR = near infrared band (band 4 of MSS and TM), R = red band (MSS band 2, TM band 3)

Values between 0 and 1 indicates vegetation coverage, value nearer to 1 means higher density. Threshold value for delineating

vegetation is 0.162 for Landsat TM, 1991 and it is 0.155 during 2014. Seasonally this value slightly differs to some extent. Values of the respective temporal resolution are also mentioned in the Fig. 15. These thresholds are determined from the theoretical range of value through the process of validation in reference to cadastral map of the concerned region and google image of the recent phase. For extracting NDWI, equation framed by McFeeters (1996) is used:

$$NDWI = \frac{(Green band - NIR band)}{(Green band + NIR band)}$$

where Green is the green band (MSS band 1, TM band 2) and NIR is the near infrared band (band 4 of MSS and TM).

Normalized differential built up index (NDBI) has been calculated following Zha et al. (2003). Threshold value of water presence area delineation is 0.066 in 1991 and 0.0111 in 2014.

$$NDBI = \frac{(MIR - NIR)}{(MIR + NIR)}$$

where MIR is the middle infrared band (TM band 5, OLI band 6) and NIR is the near infrared band (TM band 4, OLI band 5). In this work considered threshold value for built up 0.14 instead of 0 as delimited by Townshend and Justice (1986). In case of Landsat OLI, it is -0.038. All these things maps are validated in respect to cadastral map of the concerned region and google earth satellite image.

Land use data set has been prepared from Landsat 5 imageries as mentioned in Table 1. Supervised classification techniques (non parametric rule: maximum likelihood) has been used for land use land cover (LULC) classification. Accuracy assessment has been done cross checking 179 sites through GPS survey.

3.5. Deriving association ship between factors and LST

Six spatial continuous raster datasets have been prepared to find out their degree and directionality of association ship with LST condition in different periods. Spatial correlation in Arc GIS environment has been carried out and their respective 'r' value is derived.

Regression analysis is done for finding out how changes of land use intensity within a single land use unit varies over space and bring intra land use variation of LST. This type of analysis is carried out for NDVI, NDBI and NDWI.

4. Results and analysis

4.1. Land use land cover analysis

Considering the interest of the study and dominant LULC, six classes have been generated. Few other LULC classes can be generated but their proportion is too small is not even reflected clearly. For that those undefined pixels have been incorporated within neighbouring classes within the system. The ultimate classification products provide an impression of the major LULC features of English Bazar urban centre and its periphery for 1991 and 2014 (Fig. 3a–c). Tabulations and area calculations offer a comprehensive data set of area under different LULC, spatial and temporal transformation of LULC, transformation rate, increasing or declining pattern of LULC in terms of the overall landscape (Tables 2 and 4).

Total area = 5465.43 ha.; 1 ha = 2.47 acres.

The classified images were assessed for accuracy based on a random selection of 179 reference pixels for each time period, which were compared against the collected land use maps following Ahmed and Ahmed (2012). The overall accuracies of the classified images (1991, 2010, and 2014) were, respectively, found to be 86.67%, 90.21%, and 93.62%, with Kappa coefficients of 0.84, 0.92, and 0.94 (Table 3). Note that the Kappa coefficient is a measure of the proportional (or percentage) improvement by the classifier over a purely random assignment to classes (Ahmed et al., 2013). On the other hand, the user's accuracy measures the proportion of each land cover class, which is correct whereas producer's accuracy measures the proportion of the land base, which is correctly classified. It is observed that the accuracy of the land cover images is increasing over time. It is because of the fact of availability of more detailed and higher resolution Ref. maps in recent times. This sort of image classification and post classification is also done by a group of scholars e.g. Rawat et al. (2013), Sexton et al. (2013), Rawat and Kumar (2015), Ghebrezgabher et al. (2016) etc.

4.1.1. Area change and change rates of land cover types

The spatial distribution and patterns of land cover changes and persistence is shown in Fig. 3a–c. Over the entire study period, agriculture land was the predominant land use type (40.32%) during 1991, although it declined at an annual rate of 1.82%, and reached to only 12.63% in 2014. (Fig. 3 and Table 2). Forest (mango orchard) showed the significant increase (7.86% to 24.15%) since



Fig. 3. Land use land cover map of (a) 1991; (b) 2010; (c) 2014.

1991–2014 with an annual increase rate of 1.7% and such growing trend does exist mainly in the peripheral rural transition (north western part dominantly) of the urban centre. Within urban area, vegetation coverage has declined rapidly. Water body declined slightly at an annual rate of 0.73%, with around 6.75% to 5.21% since 1991–2014. Within main urban heartland, most of the water bodies are reclaimed and undergone into edifices. Large part of water bodies specifically Chatra wetland is majorly captured by water hyacinth. Urbanization trend enhanced the growth of urban area and in between 1991 and 2014 recorded areal expansion was 26.97% to 42.24% with an increasing rate of 1.51%. Steady urban

growth also captures fallow land and thereby its proportion reduced significantly (11.84% to 7.62%). Fig. 4 also clearly presents the land under change of different intensities. Values within parenthesis in legend of the Fig. 4 indicate percentage of area under change of different category. Within main urban area positive change of land in between 1991 and 2014 is highly detected indicating increasing intensity of built up area and extension of the same.

From Tables 2 and 4, it is cleared that most of the LULC units changed over three phases and changing rate is strong and positive in case of built up land (2.34% per year) followed by agricultural



Fig. 4. Detected LULC changes since 1991-2010.

Table 2

Percentage of Area under Different LULC in different periods.

LULC	1991 (Acres)	Area in percentage	2010 (Acres)	Area in Percentage	Change in percentage (2010–1991)	2014 (Acres)	Area in Percentage	Change in Percentage (2014–2010)
Water Bodies	912.709	6.76	779.717	5.77	-0.98	703.43	5.21	-0.56
Mango Orchard	1061.71	7.86	1672.63	12.39	4.52	3262	24.15	11.77
Impervious Area	3643.72	26.98	5350.38	39.62	12.64	5705.41	42.25	2.63
Water Hyacinth	841.32	6.23	868.675	6.43	0.20	1098.63	8.13	1.70
Agricultural Land	5446.23	40.33	3462.91	25.64	-14.69	1706	12.63	-13.01
Fallow Land	1599.69	11.84	1371.07	10.15	-1.69	1029.91	7.63	-2.53

Total area = 5465.43 ha.; 1 ha. = 2.47 acres.

Table 3

Accuracy assessments of the land cover types.

Year User's Accuracy (%)					Produce	Producer's Accuracy (%)						Карра		
	Water Bodies	Mango Orchard	Impervious area	Water hyacinth	Agricultural land	Fallow land	Water Bodies	Mango Orchard	Impervious area	Water hyacinth	Agricultural land	Fallow land	Accuracy Coefficien (%)	Coefficient
1991	87.13	86.61	85.44	86.12	87.46	88.37	85.67	86.39	86.05	85.88	84.34	88.21	86.67	0.84
2010	91.31	88.36	89.73	90.23	89.38	90.54	89.13	90.68	88.72	90.39	87.45	88.67	90.21	0.92
2014	93.37	94.58	93.66	94.43	91.09	92.44	94.75	95.44	93.58	92.86	87.96	89.32	93.62	0.94

Table 4

Land use land cover change matrix and transformation rate.

Area (hectares)	Water bodies	Mango orchard (Ha.)	Impervious area	Water hyacinth	Agricultural land	Fallow land
Area change to	0	0	1706.66	610.92	0	27.355
Area converted from	132.992	228.62	0	0	1983.32	0
"Area changes	0	610.92	1706.66	610.92	0	27.355
TR	14.57% (0.73%)		46.83% (2.34%)	3.25% (0.16%)	36.41% (1.82%)	14.29% (0.71%)
IR	0	57.54% (2.87%/yr.)	46.83% (2.34%)	3.25% (0.16%)	0	0
DR	14.57% (0.73%)	0	0	0	36.41% (1.82%)	14.29% (0.71%)

* Area newly generated; TR = Transformation rate; IR = Increasing rate; DR = Decreasing rate.

land but it is negative (1.87%). Out of total area 57.2% area experienced positive, 7.2% area experienced negative and proportion of stable land is 36.5%. If it is categorized into positive and negative rate of growth, water body, agricultural land and fallow land experienced negative and mango orchard, impervious land and water hyacinth experienced positive growth. During the entire study period, we found that 48.56% of the study area was subject to change in all periods and only 36.5% of the pixels remained unchanged. The majority of the unchanged pixels (1991-2010) were impervious land (41.5%), wetland (21.25%), mango orchard (17.82%) and agriculture land (25.3%). The most intense change dynamics were located in the main urban contiguous area where unidirectional exchanges of other lands into impervious built up land happen steadily. Agriculture land and wetland adjacent to the urban area are highly susceptible to transformation either by building of land or expanding mango orchards. In high urban proximate areas agriculture land experienced urban growth and far away land is transformed into mango orchard. Some of the old mango orchard did not experience any change at any periods.

4.2. Fractal vegetation cover (FVC)

Vegetation distribution, intensity, continuity etc. play crucial role for regulating land surface temperature over space. FVC image can provide a clear picture showing spatial intensity of vegetation cover. FVC image (Fig. 5a-d) is represented in range from 0 to 1 having a mean value of 0.212 with standard deviation of 0.0851. It is observed that the dense vegetation (forest), sparse vegetation (grass/park) and agricultural cropland appears in bright tone, while waste land/bare soil appears in bright to gray tone. Residential (low and high dense built-up areas) and water bodies appear in dark tone. The lowest fractional vegetation value is over water bodies with the mean value of 0.068 (ranging from 0.011 to 0.087) and corresponding mean NDVI value of -0.042 (ranging from -0.123 to 0.096) as investigated from uncropped NDVI map. As obvious result of seasonal difference of vegetation cover area, upper end FVC value (0.67 in January and 0.60 in April) is lower in April due to excessive heat and bare agricultural land. Significant decrease of FVC value (0.67 to 0.26 during January and 0.60 to 0.31 during April) in both seasons (winter and pre monsoon) in between 1991 and 2014, reveal the coarsening of vegetation, reduce of agriculture crop area and qualitative degradation of vegetation.

Analysis between the NDVI and the FVC image shows a positive Pearson's correlation coefficient of 0.689 and correlation is significant at 0.01 level (1-tailed). These differences indicate not only distinct computation procedures for deriving NDVI and FVC, but also their relationship to their vegetation density or vegetation abundance. It is also noticed that the relationship between these two vegetation indicators are not linear for different land use/land cover categories as established by other scholars also like Mallick et al. (2008). However, this work is not so far interested to channelize it toward investigating the same, rather importance is provided on how different categories of vegetation intensity regulates temperature. It will empathetically prove the non co linearity between NDVI and FVC.

4.3. Land surface temperature change (LSTC)

Figs. 6-8 indicate spatial pattern of LST in three phases e.g. 1991, 2010 and 2014. This analysis is also carried out seasonally in all three phases (winter, pre monsoon and post monsoon). In all maps bright reddish tone highlights higher temperature and bluish tone low LST. These spatial patterns of LST concentration and temporal shift LST pattern actually highlights rapid change of LULCC. Fig. 6a-c focuses temperature conditions of January since 1991-2014. Usually, LST is confined within the range of 14.41-20.34 °C during January 1991 (Fig. 6a). Out of total area (5465.43 ha.), 32.83% area represents temperature from 16.18-16.77 °C followed by 24.8% area is represented by 16.77-17.37 °C temperature. More than 83% is characterized by the temperature ranges from 16.18 to 18.55 °C. Mean temperature of this study area in this time was 17.24 °C and CV was 4.04. Core urban area is sensitive to high temperature. In next two phases (2010 and 2014) both maximum and minimum LST patterns have up heaved. Minimum LST since 1991-2010 and 2010-2014 have raised from 14.40 °C to 16.72 °C and from 16.72 °C to 20.17 °C respectively. Similarly, maximum temperature has also raised up by 6 °C since 1991–2014 (see Fig. 6b and c). This growth is entirely arithmetic but more realistic temperature growth calculated using spatial average indicates that about 2.75 °C LST has increased since 1991–2014 and annual rate of increase is 0.114 °C/year.

April and May of this year show maximum air temperature near about 38 °C. LST in 2014 ranges from 23.99 °C to 34.64 °C which almost remains same in comparison to 1991 (see Fig. 7a and c). More than 81% area possesses temperature between 27.18 and





Fig. 5. (a) FVC of January 1991; (b) FVC of April 1991; (c) FVC of January 2014; (d) FVC of 2014.

32.5 °C. North western and south eastern part of the study area exhibit relatively low range of temperature due to Bagbari mango orchard and Chatra wetland. Only in April, wetland area is prominent due to its distinct oceanicity. It is observed that within 24 years of study period, minimum temperature level has raised about $2 \degree C$ with an average $0.083 \degree C$ /year. Since 1991–2014,

1.62 °C average LST has gained with an increasing rate of 0.070 °C/year.

In October month of post monsoon season, due to having tail ending rainfall and antecedent rainfall of the previous monsoon months, in spite of having high temperature potential, temperature is self regulated. In 2014 temperature ranges from 23.63 °C to

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Fig. 6. (a) LST of January 1991; (b) LST of January 2010; (c) LST of January, 2014.



Fig. 7. (a) LST of April 1991; (b) LST of April 2010 and (c) LST of April 2014 Rise of spatial temperature since 1991–2014 is 1.69 °C.



Fig. 8. (a) LST of October 1991; (b) LST of October 2010 and (c) LST of October, 2014.

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Table 5	
Coefficient variation Co-efficient of variation of temperature in selected time per	ods

Month	Year	minimum Temperature	Maximum Temperature	Mean Temperature	Standard Deviation	Co efficient of Variation (%)
January	1991	14.41	20.34	17.24	0.70	4.04
	2010	16.72	22.98	19.97	0.82	4.11
	2014	20.17	27.30	23.39	1.01	4.33
April	1991	23.99	34.64	29.67	1.94	6.53
	2010	26.83	36.98	31.47	1.67	5.32
	2014	25.22	34.60	30.36	1.64	5.40
October	1991	21.66	28.09	23.40	0.79	3.36
	2010	22.98	30.58	25.37	1.19	4.70
	2014	23.63	33.66	28.70	1.28	4.47



Fig. 9. Seasonal rise of LST in different selected years (1991, 2010 and 2014).

33.66 °C (Fig. 8C). About 89% spatial extent is characterized by 22.30 °C to 24.87 °C. Spatial character of moisture availability regulates temperature over space. Within main town variation of temperature is 27.64% which is about 64.25% in the peripheral area. It does mean within main urban area also possesses variation of temperature but it is quite less in comparison to peripheral land with multifarious LULC. Rise of spatial temperature since 1991–2014 is 1.62 °C with an increasing rate of 0.067 °C/year.

Table 5 clearly describes the descriptive statistics of LST of the selected years. Intra urban variation for all the selected years ranges from 4.04% to 6.53% which is relatively high during April. Fig. 9 depicts seasonal rise of LST over different phases. It is observed that in all seasons LST increased and the rate is quite alarming.

Fig. 10a and b represent the shifting nature of seasonal LST in between 1991 and 2014. Both the figures show that proportion of area under temperature classes. Results highlight that in later phases proportion of area concentration has been aggravated toward higher temperature classes. It does mean greater proportion of area has been gaining enhanced temperature. Fig. 10b shows that during January, this increasing rate is significantly high in compare to the previous phase.

4.4. Temperature Variations for different land cover types

Remotely sensed LST records the radiative energy emitted from the ground surface, including building roofs, paved surfaces, vegetation, bare ground, and water (Arnfield, 2003; Voogt and Oke, 2003). To represent the LULC wise LST, three cross sections has been made across the study area (Fig. 11) and average LST of each LULC types have been illustrated in Figs. 11. It is found from the cross profile that urban core with dominant built up land experienced LST > 31.5 °C, mango orchard recorded LST about 30 °C and mixed LULC spatial unit measured LST is about 30.46 °C.

Fig. 12a and b respectively summarize the average values of radiant surface temperatures (°C) during January and April by land-use types in three phases 1991, 2010 and 2014. To understand the impact of LULCC on surface radiant temperature, first of all must it is to be studied LST of each land-use type. For selected years, urban or built-up land exhibits highest surface radiant temperature (31.42 °C in 1991 and 33.14 °C in 2010, 34.06 °C in 2014), followed by fallow land (30.92 °C in 1991 and 31.78 °C in 2010 and 33.10 °C in 2014). This implies that urban development does carry up surface radiant temperature by replacing other less radiant surfaces with non evaporating surfaces such as stone, metal and concrete. The coefficient of variation (CV) of the radiant temperature values are small for both Built-up Land (2.37% in 1991 and 2.23% in 2010 and 2.05% in 2014), indicating that an urban surface does not experience a wide variation in surface radiant temperature. The lowest radiant temperature in 1991 is observed in water bodies (24.21 °C), followed by mango orchard (25.34 °C) (see Fig. 12a). This pattern is analogous with that in 2010, when the low radiant temperature is found in water (27.23 °C), followed by mango orchard (27.46 °C). Vegetation shows a considerably low radiant temperature in all years, because the amount of heat stored within vegetation is reduced through transpiration. Vegetation land-use type is denser and the soil is not exposed. However, vegetation



Fig. 10. (a) Changing pattern of heat zone (intensity) during April (b) during January in between 1991 and 2014.

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Fig. 11. LST profiles (A-B; C-D; E-F) drawn over LST of April, 2014.



Fig. 12. Temporal rise of temperature in different land use over time (a) January and (b) April.

show a relatively large CV in radiant temperature values (3.18% in 1991 and 3.92% in 2010 and 4.13% in 2014) compared with other land-cover types, indicating the heterogeneous nature of vegetation covers. Only within mango orchard area, CV is arrested within 1% although over time it is increased slightly. Water bodies has also gained temperature due to increasing level of TDS within water bodies and shallowing of water bodies. Although intensity of LST is quite lower during January buy identical trend of LULC specific temperature is also observed (Fig. 12b).

4.5. Land surface temperature change in newly grown LULC units

Table 6 tries to capture how newly grown lands after transformation reacts on radiant energy. It is captured that newly grown built up land has gained more temperature but its nature is quite diversified. For example, built up land transformed from agriculture land has increased temperature by 1.40 °C; built up land from water bodies by 1.45 °C, built up land from fallow land by 1.41 °C. Built up land converted from fallow land accumulated maximum LST and it reached to 32.33 °C as recorded from April 2014. Newly generated mango orchard exhibits 1.07 °C less temperature than its previous land use.

4.6. Association of different LULC with LST

Six local factors (LULC, built up land, water bodies, vegetation canopy intensity, major road and rail line) have been considered to correlate with LST conditions. For such work, water bodies is extracted using normalized differences vegetation index (NDVI), built up land is extracted using normalized difference built up index (NDBI) and water bodies is extracted using normalized differences water index (NDWI). From the selected driving factors of temperature in local scale, it is being identified that association of NDBI strongly controls surface temperature followed by land use and major roads. Correlation value between NDBI and surface temperature ranges from 0.42 to 0.80 and mean value for all season is 0.66 (Table 7) and these values are significant at 0.01 significance level. Such association is also documented by Mallick et al. (2008), Lilly Rose and Devadas (2009), Ogashawara and Brum Bastos (2012) and Zhang and Huang (2015). Impact of NDVI is prominent during pre monsoon season but its impact is less observed during monsoon caused by monotonization of surface in regard to high moisture availability. Major road specifically highly trafficked NH34 enhanced temperature level along its axis

Table 6	
Temperature change in different detected LULC change categories (April).	

Newly grown land	LST 1991	LST 2014
Agriculture to Built up Area	30.53 °C	31.93 °C
Water Body to Built up Area	29.15 °C	31.06 °C
Fallow Land to Built up Area	31.91 °C	32.33 °C
Mango Orchard to Built up	30.06 °C	31.55 °C
Agriculture to Mango Orchard	29.35 °C	28.22 °C

and it is imprinted in extracted LST models created for different seasons. Other roads also contribute in same trend but with slightly less intensity as also reported by Lilly Rose and Devadas (2009). Brick kiln factories (25) in the north western part (Bagbari region) of the study area highly enhance temperature. Actually this layer is not separately taken into consideration because of it identical emissivity with built up area. Impact of water bodies on lowering temperature is reflected on temperature. Chatra wetland (>4 sq.km.) located at south western part of the study area not only lower down temperature of its own but also helps to reduce temperature in its surroundings. In this regard it could be mentioned that in last 20 years more than 50% of the total wetland area is converted into built up land or being captured for the same (Kar and Pal, 2012). Railway station carries role for modifying temperature in very isolated manner, mainly in the station premises.

N.B.: Bold digits show significant at 0.01 level.

Decreasing vegetative canopy cover and increasing concrete impervious surface modifies thermal processes in urban regions, thus creating 2°-3.5 °C warmer temperature regimes relative to rural areas (known as urban heat island effect) (Slonenecker et al., 2001; Ogashawara and Brum Bastos, 2012). Alteration of the hydrologic cycle represents the most significant urban water quality issue at hand now-a-days (Slonenecker et al., 2001; DeBusk et al., 2010) because storm water runoff from impervious surfaces creates water quality problems including higher water temperatures and elevated levels of contaminants in surface waters (Slonenecker et al., 2001; Davis et al., 2010). This effect can immediately influence the nearby Chatra wetland which is considered as lungs of this town (Kar and Pal, 2012). Such sort of result is also found in the findings of Weng et al. (2004). The modification of LULC associated with urbanization has altered the thermal properties of land, thereby changing the energy budget, creating the UHI as also reported by Xiong et al. (2012) in his work.

4.7. Intra LULC specific LST association

From the above discussion, it is cleared that each LULC has its own character assemblage of LST pattern and its seasonal responses are also so different. In the later section it is to be investigated that how a single LULC with different intensity can create variant LST surface. For example, built up land retains maximum temperature but within built up land radiant surface is diversified as the intensities of built up land varies in different parts of urban area (Mallick et al., 2008). This association is also valid in case of depth and quality of water bodies and intensity and canopy cover area of the vegetated land. Keeping this fact in mind, LULC specific temperature analysis is also carried out. Three land cover indices (e.g., NDVI, NDWI and NDBI) have derived in order to establish quantifiable relationships between LST and the indices.

4.7.1. Temperature change in built up areas

Xiong et al. (2012) found that high temperature anomalies are closely associated with built-up land, densely populated zones, and heavily industrialized districts. They analyzed Landsat

Table 1	7
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Pearson's correlation between LST and several land use type individually. (Bold correlation values indicate correlation significant at 0.01 level of significance.)

Parameters	January 1991	April 1991	October 1991	January 2010	April 2010	October 2010	January 2014	April 2014	October 2014
LULC	0.0677	0.4095	0.0316	0.4974	0.3332	0.0734	0.5910	0.2275	0.1059
Built up land (NDBI)	0.6168	0.7940	0.6364	0.6828	0.8068	0.7422	0.6706	0.4239	0.6266
Vegetation density (NDVI)	0.1192	0.3442	0.2293	0.1726	0.6522	0.4097	0.0736	0.2534	0.2320
Water bodies (NDWI)	0.3741	0.2921	0.2743	0.0492	0.4887	0.2743	0.1126	0.1617	0.1678
Major Road	0.1763	0.2664	0.3925	0.2280	0.3069	0.4465	0.2709	0.2637	0.4117
Railway Station	0.1332	0.059	0.1289	0.0597	0.2157	0.3901	0.0386	0.0706	0.3162

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TM/ETM + images, NDVI and NDBI indices for UHI analysis of Guangzhou in South China. Xiao et al. (2007) reported that impervious surface is positively correlated with LST in Beijing, China.

Weng and Yang (2004) argued that low vegetation coverage is one of the main reasons for UHI effect. Fig. 13a-c depicts the extracted NDBI classes indicating intensity and spatial pattern of built up area and impervious land for 1991, 2010 and 2014. Spatial extension and intensity have increased over selected phases. Fig. 14a and b exhibit the relationship between NDBI and LST of winter period in 1991 and 2014 and 14c and 14d indicate the same relation in pre monsoon or summer period (April) of the same time phases. As documented by previous literatures, present result does not show any exception. Linear regression model fitted in all four cases and coefficient of determination value generated for January 1991 is 0.546 which is increased in 2014 and becomes 0.607. Both the values strongly show that NDBI score positively control LST ($R^2 = 0.469$ in April 1991 and 0.540 in April 2014). Similar fact and trend is found for summer month. Such increasing trend of R^2 value establishes the fact that high intensity impervious land retains maximum LST.

4.7.2. Temperature change in vegetated land

Fig. 15a–c show the spatial pattern of NDVI classes extracted from the multi temporal satellite images as mentioned in Section 3. This classification is done for making a relation between NDVI of different intensity levels and LST. Changing cropping pattern,



Fig. 13. NDBI classes of (a) 1991; (b) 2010; (c) 2014.



Fig. 14. Changing control of NDBI on LST in (a) January 1991; (b) January 2014; (c) April 1991 and (d) April, 2014.

squeezing of agricultural land, spatial relocation of water hyacinth and growth of mango orchard are the principal regulating factors behind such dynamism of NDVI.

As documented in the literature, a higher level of LST is found to be associated with a lower NDVI in this research (Fig. 15a–d). In 1991, the NDVI ranged between 0.22 and 0.345, which gradually increased to between 0.27 and 0.48, in

2014. Therefore, it can be said that the NDVI decreased in urban heartland over time. As per the documented results of the previous work, the relation between NDVI and LST is negative and R^2 value for January 1991 is 0.44 and it is raised to 0.632 in 2014. In summer month same nature of control (R^2 = 0.45 in 1991 and 0.57 in 2014) is observed in between 1991 and 2014 (Fig. 16a–d).





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Fig. 16. Changing control of NDVI on LST in (a) January 1991; (b) January 2014; (c) April 1991 and (d) April, 2014.

4.7.3. LST change in water bodies

The temperature of water is usually lower than other kinds of land uses (Hathway and Sharples, 2012; Zhang and Huang, 2015). For bringing this relation more explicit, following Yang et al. (2015) 11 matrices have been calculated and correlated with LST. The proportion of water body, average water body size, the isolation and fragmentation of water body, and other eight metrics have obvious correlation with the LST, whose Pearson's correlation coefficient with temperature is higher than -0.428 (Table 8). Among the 11 metrics, CA, TCA, and LPI are of very high correlation with LST and all these are significant at 0.01 level. The proportion of water body, the higher the mean LST. Meanwhile, the mean size of water body, the proportion of the total landscape which is made up by the lar-

Table 8

Landscape metrics of water and their corresponding meaning, according to the Patch Analyst Help of ArcGIS.

Landscape metrics	Meaning	r
Class proportion	The proportion of class	-0.517**
MPI	Measure of the degree of isolation and fragmentation	-0.532**
CA	Sum areas of all patches belonging to a given class	-0.612**
MPS	Average patch size	-0.543**
PSSD	Patch size standard deviation	-0.551**
TCA	The total size of disjunct core patches	-0.631**
MCA	The average size of disjunct core patches	-0.517**
CASD	Measure of variability in core area size	-0.521**
TCAI	Measure of amount of core area in the landscape	-0.428*
LPI	The LPI is equal to the percent of the total landscape that is made up by the largest patch	-0.616**
MCAI	The average core area per patch	-0.509**
* Correlation is sign	nificant at 0.05 level.	

** Completion is significant at the 0.01 loss

** Correlation is significant at the 0.01 level.

gest water patch, and the isolation and fragmentation of water body all have negative correlation with the mean LST as documented by Huang et al. (2008), Yang et al. (2015) in their works. The result of multiple stepwise regression analysis indicated that the gross size and amount of core water patches have a larger effect on the LST except for the variable of surrounding temperature calculated through weight matrix. The core water patches represent the interior water body with small external influence.

Fig. 17a-d describes the water body depth classes over space. 17a and 17b show the nature of NDWI condition in January 1991 and April 1991 and 17c and 17d represent NDWI condition in January 2014 and April 2014. From these maps it is noticed that (a) extension of water body reduces in every summer month (b) overall spatial spread of water is also reduced by 22.92% in between 1991 and 2014. Shallowing of water body is also indicated by lowering of NDWI score (maximum NDWI, January-1991 was 0.422 and it is 0.143 in 2014) (see Fig. 17a and c).

Fig. 18 presents the degree of control of NDWI on LST for different periods. All the cases it is observed that NDWI negatively controls LST. In between 1991 and 2014, R^2 value increased (R^2 = 0.437 in 1991 and 0.635 in 2014) in January indicating growing controlling power of water bodies on LST. Not so acute but inverse case is noticed in summer period (R^2 = 0.605 in 1991 and 0.577 in 2014). Penetration of radiation to the greatest depth of the water bodies due its shallowing is one of the major reasons behind such inversion. Certainly, if such water body modification continues, very soon this trend will rise up.

4.8. Spatial aerial temperature pattern

Spatial air temperature surface has been created from directly collected data collected from the study area on 13th April 2014. In the one hand this model will help to validate the LST model of that period and help to calculate the relationship between aerial temperature and LST over different LULC units. Fig. 19a and b present the aerial temperature surfaces for January 2014 and April 2014 respectively. Maximum aerial temperature in January varies from 24.21 °C to 30.58 °C while it ranges from 30.12 °C to





Fig. 17. NDWI classes of (a) January 1991; (b) April 1991; (c) January 2014; (d) April, 2014.

38.45 °C in April. It is detected that air temperature is maximum (>35 °C) in the built up land and impervious land while lowest value is detected over water bodies (<28 °C) in summer month (Fig. 19b). Table 9 depicts the temperature differential between air temperature and LST in different LULC units.

Arnfield (2003), Frey et al. (2011) clearly mentioned that there is a sharp difference between air temperature and LST for depicting spatial pattern of urban heat island, heat patches etc. Kawashima et al. (2000) documented a relation between mean air temperature and mean surface temperature. Also they rightly mentioned that this relation varies in different altitudinal range. They recorded that mean air temperature is 7° to 9.6 °C greater than mean surface temperature and obviously it is high in the lower elevation. Adjusted R² ranges from 0.91 to 0.98 when regression is carried out between these two parameters. Fig. 20a and b presents the temperature gap between aerial temperature and LST both in





NDWI, Jan, 2014;

NDWI, April, 2014

Fig. 18. Changing control of NDWI on LST in (a) January 1991; (b) January 2014; (c) April 1991 and (d) April, 2014.



Fig. 19. Spatial pattern of air temperature in (a) January 2014 and (b) April, 2014.

winter and summer periods. Deduced temperature surfaces in both the periods indicate that maximum temperature deviation (>5 °C) is observed in the urban core area whereas in the peripheral urban area it ranges between 4 and 5 °C in April (Fig. 20b). Usually, water body reacts inversely i.e. during summer period water body shows little temperature difference (<4 °C) and winter period shows maximum temperature differences (>5 °C). Actually, during winter

period water body retains more temperature than non water body and thereby inflates temperature differential. Few patches of vegetated area account high temperature differences caused by heterogeneity of vegetation coverage and seasonal biological cycle of wearing off and on of foliage.

For validating aerial temperature and LST Pearson's correlation coefficient has been calculated and tested 't' at 0.01 level of

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Table 9 Temperature gap in different LULC categories for the period of January 2014 and April 2014.

	Month of January			Month of April				
LULC	Average Air temp (in $^\circ$ C)	Average LST (in °C)	Difference (in °C)	Average Air temp (in °C)	Average LST (in °C)	Difference (in °C)		
Water bodies	25.826	21.14	4.686	32.07	27.164	4.906		
Mango orchard	26.794	22.73	4.064	33.92	29.34	4.58		
Impervious area	28.132	23.768	4.364	36.614	32.014	4.6		
Agricultural land	27.49	23.748	3.742	33.784	28.956	4.828		
Water hyacinth	26.57	22.748	3.822	32.922	28.502	4.42		
Fallow land	27.22	24.102	3.118	33.538	29.282	4.256		



Fig. 20. Air temperature and LST gap in (a) January since 1991-2014 (b) April since 1991-2014.

significance. Correlation value between air temperature and LST for Jan 2014 is 0.44604 and for April 2014 it is 0.658. Both these values are significant at 0.01 level. So, from this significant correlation, it can be inferred that LST extracted from thermal band is valid.

5. Conclusion

In fine, it can be said that surface temperature has been rising over advancing phases in all seasons and LST surface is diversified due to positional influence of the existing LULC. Distinct difference is identified in different LULC unit and temperature is gaining over time. Temperature variation is also detected within a single LULC unit. Land use change in terms of installing brick kiln industries, transforming of wetland into urban land, exchange of land between mango orchard and agricultural land etc. are some vital causes behind surface temperature change in the urban fringe area. Considering this trend, immediate land transformation policies should be reviewed specially regarding transforming mango orchard and wetland. Note worthy to mention is that, urbanization is the main driving process of land cover changes and consequently rise of LST. However, unless a radical decentralization policy is undertaken, it is difficult to stop or reverse the urbanization process even to the medium and small cities because it is a facility hub. Steady growth of LST can disturb the ambient habitat for the man and other ecosystem members.

Considering this soaring alarm, growth management policies (e.g., green belt) can be implemented that would contain the growth and consequently help reducing UHI effect as suggested by Park (1986) in case of Dhaka municipality of Bangladesh. In addition, policies must not be limited to horizontal growth management only. Additional consideration to implement the new urbanism (e.g., green building) concepts in the planning permission (or development assessment) stage of development would also help reducing the LST as reported by Kibert (2012). This small town is so congested in its core part, that it is pretty difficult make any more space for greening and reducing land surface temperature. But further growth should be associated with new urbanism concepts. Existing roof top areas can be surfaced with horticulture based plants. Presently, municipal rules regarding keeping space between two buildings is only 1 foot which is indeed too small. So, this policy of vacant space should be rectified. One of the valuable environmental limbs is Chatra wetland located in the south western part of this city that should be conserved with deep attention. Unfortunately, this wetland is rapidly reclaimed by built up area through urban sprawl. It ought to be stopped at any cost, as association of such wetland can to some extent decelerate rise of temperature. Dispersion of urban population through expanding urban structure toward peripheral areas can also reduce temperature. Keeping free earthen space with less concrete structure can help to minimize rising temperature effect. So it is inferred that

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there is an ought need for continuous monitoring of city's land use land cover dynamics and to devise rational, scientific and sustainable urban land use policies so as to check the phenomenon of intensification of UHI.

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