Analytical study on the relationship between land surface temperature and land use/land cover indices

Subhanil Guha, Himanshu Govil, Neetu Gill and Anindita Dey

*Department of Applied Geology, National Institute of Technology Raipur, Raipur, India; **Chhattisgarh Council of Science and Technology, Raipur, India; †Department of Geography, Nazrul Balika Vidyalaya, Guma, West Bengal, India

ABSTRACT
The present study focuses on the estimating land surface temperature (LST) of Raipur City in India emphasizing the urban heat island (UHI) and non-UHI inside the city boundary and their relationship with normalized difference vegetation index, normalized difference water index, normalized difference built-up index, and normalized multi-band drought index. The entire study has been performed on four multi-date Landsat 8 Operational Land Imager and Thermal Infrared Sensor images taken from four different seasons; pre-monsoon, monsoon, post-monsoon, and winter in the same year. The UHI has mainly been developed along the northern and southern periphery of the city. The range of LST in the common UHI for four different seasons varies between 25.72°C and 35.69°C. The results present the strongest correlation between LST and the land use/land cover indices in monsoon and post-monsoon images while winter and pre-monsoon images show a comparatively weak correlation.

1. Introduction
The concept of land surface temperature (LST) and urban heat island (UHI) is used to interpret the changing land use/land cover (LULC) pattern in heterogeneous urban area (Armfield 2003; Mirzaei 2015; Rizwan, Dennis, and Liu 2008; Rinner and Hussain 2011; Zhao et al. 2016). LST was determined in some major global cities (e.g., Beijing, Columbus, Shanghai, Baltimore, Chicago, etc.) to solve many environmental problems. Different types of LULC influence on the nature and distribution of LST (Chun and Guldmann 2014; Dai, Guldmann, and Hu 2018; Kim and Guldmann 2014; Zhang et al. 2013; Zhou, Huang, and Cadenasso 2011; Coseo and Larsen 2014). Some normalized difference LULC indices such as vegetation index, built-up index, bareness index, water index, etc. were frequently used in the recent LST related studies to estimate their impact on the changing environmental status of the urban areas (Li et al. 2011; Peng et al. 2016; Amiri et al. 2009; Song et al. 2014; Kuang et al. 2015). The linear correlation analyses between LST and LULC indices were discussed on the cities from different parts of the world like Some recent articles discussed the statistical linear correlation between LST and some selected LULC indices for separate study areas like Brisbane (Deilami and Kamruzzaman 2017), Raipur (Guha et al. 2017), Shanghai (Nie et al. 2016), Addis Ababa (Feyisa et al. 2016), Mexico (Lopez et al. 2017), Philadelphia (Pearsall 2017), Florence and Naples (Guha et al. 2018), etc.

Seasonal contrast in LST distribution depends on the composition of land surface and it was examined in some contemporary research works. Cui and de Foy (2012) clearly stated that the seasonal fluctuation of LST primarily depends on vegetation and weather elements. Zhou et al. (2014) was keen to build correlation between LST and LULC indices in Baltimore City of United State of America (USA), Haashemi et al. (2016) noticed a seasonal variation on LST-LULC indices relationship in a study performed in Tehran City of Iran.

A simple regression analysis was used to show the seasonal impacts of thermal conditions of Ohio City, USA (Chun and Guldmann 2018). An integration of statistical techniques were applied to estimate the seasonal changes in LST-LULC indices relationship (Peng et al. 2018). A seasonal study on LST-LULC indices relationship was conducted in Jaipur City, India (Mathew, Khandelwal, and Kaul 2017). A new model was applied to show the seasonal change of LST in Beijing, China (Quan et al. 2016). The annual and seasonal trends of LST in peninsular Spain were observed by using statistical model (Khorchani et al. 2018a, 2018b). Another analysis between LST and climatic elements were evaluated in...
the urban areas of China (Yao et al. 2018). A seasonal interpretation of LST with the weather elements was performed on the cities of China (Lai et al. 2018). The variation of LST and land connectivity was analyzed with a specific index applied in Beijing, China (Sun, Xie, and Chen 2018). Thus, the correlation analysis between LST and LULC indices was quite common in the UHI related study. The present paper also used a common linear regression method to show the seasonal variation of LST in UHI, non-UHI, and common UHI zones in a typical Indian city for a single year and the relationship of LST with different LULC indices. The main focus of the study was to determine the seasonal variation of LST-LULC indices relationship in the UHI, non-UHI, common UHI and the whole of Raipur City by using Landsat 8 satellite images.

2. Study area and data

Raipur, the capital of Chhattisgarh and a rapidly growing smart city in India was selected as the study area. Raipur extends from 21°11′22″ N to 21° 20′02″ N and from 81°32′20″ E to 81°41′50″ E (Figure 1). The range of elevation of the study area is approximately 300 m above mean sea level and it is located along the western part of the Mahanadi River (Figure 1). Overall the city is under a tropical savannah type of climate. According to India Meteorological Department, pre-monsoon, monsoon, post-monsoon, and winter occur in Raipur City. Pre-monsoon season (March-June) is hot and dry. Most of the heavy showers occur in July to September (Monsoon season). Temperature falls at a significant rate in the post-monsoon period (October-November). Winter season (December-February) is characterised by dry and cool weather. The average annual range of temperature is 21°C-34°C and the average annual precipitation is 120–150 cm.

A total of four (one from each season according to India Meteorological Department) Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) level-1 data (<10% cloud coverage) have been selected to determine the LST and to detect the UHI over the whole of the Raipur City for the following dates (Govil et al. 2019; Govil 2020; Guha et al. 2019): 5 June 2014 (pre-monsoon image), 25 September 2014 (monsoon image), 12 November 2014 (post-monsoon image), and
30 December 2014 (winter image). These four level-1 Landsat 8 OLI and TIRS images have been used as the representatives of four different seasons, separately. The Landsat 8 datasets have been freely downloaded from United States Geological Survey (http://earthexplorer.usgs.gov). The data specification has been shown in Table 1. Landsat 8 TIRS data have two bands (band 10 and band 11) having thermal characteristics. But, only TIR Band 10 data has been used for the LST retrieval process because TIR band 11 data faces some calibration uncertainty (Guha et al. 2018; Weng 2001; Weng and Yang 2004; Zhang et al. 2016). Optical bands 3, 4, 5, 6, and 7 datasets have been used in developing NDVI, NDWI, NDBI, and NMDI. ArcGIS 9.3 software was used for various types of image processing and mapping.

3. Methodology

3.1. Image pre-processing and atmospheric correction

The satellite data acquired from Landsat 8 sensor was subset to limit the data size. The thermal infrared band for Landsat 8 TIR image (band 10) has a spatial resolution of 100 m. This thermal band was resampled using the nearest neighbour algorithm with a pixel size of 30 m to match the optical bands. Atmospheric correction of the satellite data has been done by the following steps:

For band 1 to band 9 of Landsat 8 OLI data, the following equation is used to converting a digital number into spectral reflectance:

\[ \rho \lambda = M_p \times Q_{\text{cal}} + A_p \]  

(1)

where, \( \rho \lambda \) is the spectral reflectance at top-of-atmosphere (TOA) without correction for solar angle (Unitless), \( Q_{\text{cal}} \) is the Level 1 pixel value in Digital Number (DN), \( M_p \) is the reflectance multiplicative scaling factor for the band (REFLECTANCEW_MULT_BAND_n from the metadata), \( A_p \) is the reflectance additive scaling factor for the band (REFLECTANCE_ADD_BAND_N from the metadata). The \( \rho \lambda \) is corrected with local sun elevation angle \( \theta_s \) by the following equation:

\[ \rho' \lambda = \rho \lambda / \sin(\theta_s) \]  

(2)

For band 10 of Landsat 8 TIRS data, a similar calibration equation is used:

\[ L\lambda = M_L \times Q_{\text{cal}} + A_L \]  

(3)

where, \( L\lambda \) is the spectral radiance at TOA in Wm\(^{-2}\)sr\(^{-1}\)mm\(^{-1}\), \( Q_{\text{cal}} \) is the Level 1 pixel value in Digital Number (DN), \( M_L \) is the radiance multiplicative scaling factor for the band (RADIANCE_MULT_BAND_n from the metadata) and \( A_L \) is radiance additive scaling factor for the band (RADIANCE_ADD_BAND_n from the metadata).

3.2. Extraction of different LULC indices

Normalized difference vegetation index (NDVI) (Tucker 1979) is the most frequently used index for extracting vegetation. It is also applied in deriving LST and normally shows a negative correlation with LST. Normalized difference water index (NDWI) (McFeeters 1996) is generally used for water body extraction. Normalized difference built-up index (NDBI) (Zha, Gao, and Ni 2003) was applied in this study to detect the built-up area. Normalized multi-band drought index (NMDI) (Yuan and Bauer 2007) was used to identify the dry soil or bare land. These four indices can be applied to categorize different types of LULC (Table 2).

Table 1. Data specification of Landsat 8 OLI and TIRS satellite images for different seasons.

| Date of acquisition | Time (UTC) | Path/Row | Sun elevation (°) | Sun azimuth (°) | Cloud cover (%) | Earth-Sun distance (astronomical unit) | Resolution of VNIR bands (m) | Resolution of TIR bands (m) |
|---------------------|------------|----------|------------------|----------------|----------------|---------------------------------------|-----------------------------|-----------------------------|
| 05.06.2014          | 04:55:45   | 142/044  | 68.382           | 83.3089        | 0.02           | 1.0146                               | 30                          | 100                         |
| 25.09.2014          | 04:56:11   | 142/044  | 59.2100          | 134.1804       | 0.81           | 1.0030                               | 30                          | 100                         |
| 12.11.2014          | 04:56:21   | 142/044  | 46.2266          | 152.4664       | 7.59           | 0.9899                                | 30                          | 100                         |
| 30.12.2014          | 04:56:09   | 142/044  | 39.3441          | 150.8364       | 0.41           | 0.9834                                | 30                          | 100                         |

3.3. Retrieving LST from Landsat 8 thermal band

In this study, the mono-window algorithm (Qin et al. 2001; Guha and Govil 2020; Guha et al. 2017, 2018, 2019) has been applied to derive LST from Landsat 8 TIRS data where ground emissivity, atmospheric transmittance and effective mean atmospheric temperature are considered as the three required parameters. The entire procedure has the following steps:

Table 2. Description of four LULC indices.

| Acronym | Description                                   | Formulation | Reference          |
|---------|-----------------------------------------------|-------------|--------------------|
| NDVI    | Normalized difference vegetation index        | NDVI        | Tucker 1979        |
| NDWI    | Normalized difference water index             | NDWI        | McFeeters 1996     |
| NDBI    | Normalized difference built-up index          | NDBI        | Zha, Gao, and Ni et al. 2003 |
| NMDI    | Normalized multi-band drought index           | NMDI        | Yuan and Bauer 2007 |
where, $L_\lambda = 0.0003342 \times DN + 0.1$ (4)

where, $L_\lambda$ is the spectral radiance in $\text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1}$.

$T_b = \frac{K_2}{\ln(\frac{K_1}{\epsilon_s} + 1)}$ (5)

where, $T_b$ is the brightness temperature in Kelvin (K), is the spectral radiance in $\text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1}$; $K_2$ and $K_1$ are calibration constants. For Landsat 8 data, $K_2$ is 774.89, $K_1$ is 1321.08 ($\text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1}$).

$F_v = \left( \frac{\text{NDVI} - \text{NDVI}_{min}}{\text{NDVI}_{max} - \text{NDVI}_{min}} \right)^2$ (6)

where, $\text{NDVI}_{min}$ is the minimum NDVI value (0.2) where pixels are considered as bare soil and $\text{NDVI}_{max}$ is the maximum NDVI value (0.5) where pixels are considered as healthy vegetation.

$d\varepsilon$ is the effect of the geometrical distribution of natural surfaces and internal reflections. For heterogeneous and undulating surfaces, the value of $d\varepsilon$ may be 2%.

$d\varepsilon = (1 - \varepsilon_s)(1 - F_v)\varepsilon_v$ (7)

where, $\varepsilon_v$ is vegetation emissivity, $\varepsilon_s$ is soil emissivity, $F_v$ is fractional vegetation, $F$ is a shape factor whose mean is 0.55.

$\varepsilon = \varepsilon_v F_v + \varepsilon_s (1 - F_v) + d\varepsilon$ (8)
where, $\varepsilon$ is the land surface emissivity. The value of $\varepsilon$ may be determined by the following equation:

$$
\varepsilon = 0.004 \times F_v + 0.986
$$

(9)

Water vapour content is determined by the following equation:

$$
w = 0.0981 \times \left[ 10 \times 0.6108 \times \exp \left( \frac{17.27 \times (T_0 - 273.15)}{273.3 + (T_0 - 273.15)} \right) \times RH \right] + 0.1697
$$

(10)

where, $w$ is the water vapour content (g/cm$^2$), $T_0$ is the near-surface air temperature in Kelvin (K), $RH$ is the relative humidity (%). These parameters of the atmospheric profile are the average values of 14 stations around Raipur which have been obtained from the Meteorological Centre, Raipur and the Regional Meteorological Centre, Nagpur.

$$
\tau = 1.031412 - 0.11536w
$$

(11)

where, $\tau$ is the total atmospheric transmittance, $\varepsilon$ is the land surface emissivity.

Raipur City is located in the tropical region. Thus, the following equation may be applied to compute the effective mean atmospheric transmittance of Raipur:

$$
T_a = 17.9769 + 0.91715T_0
$$

(12)

$$
T_s = \frac{a(1 - C - D) + (b(1 - C - D) + C + D)T_b - DT_a}{C}
$$

(13)

$$
C = \varepsilon \tau
$$

(14)

$$
D = (1 - \tau)(1 + (1 - \varepsilon)\tau)
$$

(15)

where, $\varepsilon$ is the land surface emissivity, $\tau$ is the total atmospheric transmittance, $T_a$ is the mean atmospheric temperature, $T_0$ is the near-surface air temperature, $T_s$ is the land surface temperature, $a = -67.355351, b = 0.458606$.

### 3.4. Mapping UHI, non-UHI, and common UHI

UHI and non-UHI zones were identified using the following methods (Guha et al. 2017, 2018):

$$
LST > \mu + 0.5 \times \sigma
$$

(16)

$$
0 < LST \leq \mu + 0.5 \times \sigma
$$

(17)
where, $\mu$ and $\sigma$ are the mean and standard deviation of LST in the study area respectively. Equation 16 has been used to derive UHI zones as the zones having LST more than the combined value of mean LST and half standard deviation. These zones are the most heated zones of the city. Apart from the UHI, the rest of the city area is considered as the non-UHI (Equation 17). The ratio of vegetation and water bodies is higher in the non-UHI, whereas in the UHI, the main LULC types are built-up areas and bare land. Moreover, the common UHI areas for four Landsat 8 images have also been determined. The common UHI is that specific area that is found inside the UHI for all the images and it is the most heated zone of the study area. This common UHI zone always remains severely heated, irrespective of any season. It is the most stable thermal zone with a high temperature compared to its surrounding zones. It is important due to its temporal or seasonal stability as a thermal stressed area.

4. Results and discussion

4.1. Seasonal variation in the distribution of NDVI, NDWI, NDBI, and NMDI

The descriptive statistics (Table 3) presents the minimum, maximum, mean, and standard deviation values of NDVI, NDWI, NDBI, and NMDI (Figure 2) for the whole of Raipur City.

4.2. Seasonal variation of LST distribution

The LST maps retrieved from satellite images have been shown in Figure 3. The seasonal variation in the LST distribution shows a specific thermal pattern. The mean LST values in pre-monsoon, monsoon, post-monsoon, and winter images are 33.59°C, 29.56°C, 23.40°C, and 22.26°C, respectively. The ranges of LST (maximum LST - minimum LST) are found as 13.50°C in pre-monsoon image, 12.28°C in monsoon image, 8.83°C in the post-monsoon image, and 10.12°C in the winter image, respectively. Basically, this type of heterogeneity in LST has been observed due to the change in vegetation abundance and soil moisture content. Monsoon and post-monsoon images are characterized by healthy vegetation and wet soil. The winter image reflects the least standard deviation value of LST (Table 4).

4.3. Validation of derived LST with respect to MODIS data

Before performing any kind of application, validation of derived LST is necessary with in situ measurement or with any other satellite sensor. In the present study, MODIS datasets have been applied for the validation of LST values as a reference image. For any particular date, MODIS and Landsat sensors do not provide imageries for the same study area. Thus, MOD11A1 data (1 km spatial resolution) of 4 June 2014 (pre-monsoon image), 24 September 2014 (monsoon image), 13 November 2014 (post-monsoon image), and 29 December 2014 (winter image) have

| Date of acquisition | LST (Minimum) | LST (Maximum) | LST (Mean) | LST (Standard deviation) | Threshold LST value for UHI |
|---------------------|---------------|---------------|------------|--------------------------|---------------------------|
| 5 June 2014         | 25.77         | 39.27         | 33.59      | 1.61                     | 34.40                     |
| 25 September 2014   | 29.56         | 36.79         | 30.42      | 1.73                     | 30.42                     |
| 12 November 2014    | 22.26         | 28.23         | 24.00      | 1.12                     | 24.00                     |
| 30 December 2014    | 22.82         | 27.76         | 22.26      | 1.11                     | 22.82                     |
been taken for the validation of estimated LST. No precipitation or atmospheric disturbances are observed in between the acquisition date of both Landsat 8 and MOD11A1 imageries for each aforementioned season. For MODIS and Landsat 8 data, the spatial resolution of retrieved LST is 1000 m and 100 m, respectively. In spite of not performing any upsampling or downscaling procedure, a moderate to strong positive regional correlation has been found between the mean derived LST from Landsat 8 data and MODIS data (Table 5).

4.4. Relationship of LST with wind speed, humidity, air temperature, air pressure, and elevation

The relationship between LST and some weather and terrain characteristics has been analysed in the present study. Elevation and some weather components like wind speed, humidity, air temperature, air pressure, etc. (obtained from the observation stations) correlate with LST differently. These relationships have been presented in Table 6. Air temperature has a very strong positive relationship with LST for the whole area, UHI, non-UHI, and common UHI, whereas air pressure builds a very strong negative relationship with LST. LST and wind speed correlate moderately negative for different heated areas of the city. Humidity and LST has a weak negative relationship. There is no such linear correlation found in the LST-elevation relationship.

4.5. Seasonal variation of UHI, non-UHI, and common UHI

The intensity of UHI has been determined by the difference between the mean values of LST in UHI and non-UHI (Table 7). In pre-monsoon and winter images, the UHI zones are mainly generated in the north, west, and south-east periphery (Figure 4). But, in monsoon and post-monsoon images, the northern and central parts (the main built-up areas and bare lands within the city boundary) have been considered as the UHI zones. The difference between the mean LST values in UHI and non-UHI of Raipur City is 2.66°C, 2.91°C, 1.89°C, and 1.88°C in pre-monsoon, monsoon, post-monsoon, and winter images, respectively. The mean LST values of the common UHI of the city for all the four images have been ranged between 24.08°C (winter image) and 35.69°C (pre-monsoon image). Regardless of any particular date, the common UHI zones have been developed mainly in the north-west portion (bare lands and built-up areas) of the city (Figure 5).

4.6. Relationship of LST and NDVI, NDWI, NDBI, and NMDI for the Whole area, UHI, non-UHI, and common UHI of Raipur City

Generally, LST presents a negative relationship with NDVI and NMDI, whereas it shows a positive relationship with NDBI. There is no such significant relationship formed between LST and NDWI. This particular pattern has been seen in the whole of Raipur City, irrespective of dates (Table 8).

---

Table 5. Validation of LST (°C) retrieved from Landsat 8 OLI and TIRS data with MODIS data (significant at 0.05 level).

| Landsat 8 (5 June 2014) & MODIS (4 June 2014) | Landsat 8 (25 September 2014) & MODIS (24 September 2014) | Landsat 8 (12 November 2014) & MODIS (13 November 2014) | Landsat 8 (30 December 2014) & MODIS (29 December 2014) |
|------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Correlation coefficient | 0.61479                     | 0.62433                     | 0.62009                     | 0.55437                     |

Table 6. Relationship of LST with wind speed, humidity, air temperature, air pressure, and elevation (significant at 0.05 level).

| Correlation coefficient | LST-wind speed | LST-humidity | LST-air temperature | LST-air pressure | LST-elevation |
|-------------------------|----------------|--------------|---------------------|-----------------|---------------|
| Whole city              | −0.48          | −0.28        | 0.94                | −0.92           | 0.02          |
| UHI                     | −0.49          | −0.26        | 0.94                | −0.91           | −0.09         |
| Non-UHI                 | −0.46          | −0.29        | 0.94                | −0.93           | 0.19          |
| Common UHI              | −0.52          | −0.23        | 0.94                | −0.90           | −0.07         |

Table 7. Seasonal variations of LST (°C) in UHI, non-UHI, and common UHI in Raipur City.

| Date of Acquisition | LST (Minimum) | LST (Maximum) | LST (Mean) | LST (Standard deviation) |
|---------------------|---------------|---------------|------------|--------------------------|
|                     | UHI | Non-UHI | Common UHI | UHI | Non-UHI | Common UHI | UHI | Non-UHI | Common UHI |
| 5 June 2014         | 34.40| 25.78   | 34.40      | 39.27| 34.40   | 38.45      | 35.42| 32.76   | 35.69      | 0.73 | 1.16   | 0.73 |
| 25 September 2014   | 30.42| 24.51   | 30.42      | 36.79| 30.42   | 36.78      | 31.50| 28.59   | 32.09      | 0.85 | 1.14   | 1.16 |
| 12 November 2014    | 24.00| 19.39   | 24.00      | 28.23| 24.00   | 28.22      | 24.81| 22.92   | 25.72      | 0.78 | 0.76   | 0.74 |
| 30 December 2014    | 22.82| 17.64   | 22.81      | 27.76| 22.82   | 27.75      | 23.63| 21.75   | 24.08      | 0.68 | 0.75   | 0.69 |
Correlation coefficient values are significant at 0.05 level. NDBI shows the strongest correlation with LST among the four LULC indices for four multi-date images. But, these relationships tend to be changed within the UHI of the city, whereas NDVI and NDWI reflect a stronger correlation with LST for each and every image. Again, the scenario became different within the non-UHI portions of the city where NDBI and NMDI presented a stronger correlation with LST compare to the other two LULC indices. In the common UHI (using the mean value of single season or the mean value of four seasons) region, NDVI and NDWI have a much better correlation with LST, but these relationships become gradually weak with the increase of the heterogeneous surface features. Monsoon and post-monsoon images reveal a better correlation between LST and LULC indices. Common UHI (Figure 6) using the mean value of four seasons indicate a stronger correlation for LST and LULC indices.

Figure 7-10 represent the seasonal variation of LST distribution maps and their corresponding NDVI, NDWI, NDBI, and NMDI maps for the UHI, non-UHI, common UHI using the mean value of single season, and common UHI using the mean value of four seasons, respectively. Due to the presence of more moisture content in soil and air, the relationships between LST and LULC indices are more consistent in the monsoon and post-monsoon images.

Figure 4. UHI and non-UHI of Raipur City: (a) Pre-monsoon, (b) Monsoon, (c) Post-monsoon, and (d) Winter season.
NDWI, NDBI, and NMDI maps for the UHI of Raipur City for four multi-date images. The black coloured portion of the map represents the non-UHI area of Raipur City. The post-monsoon image reveals the most consistent relationship. The northwest portion of the study area shows a stronger spatial relationship between LST and all the LULC indices. In the pre-monsoon season, the high LST values are

**Figure 5.** Common UHI (using the mean value of each season) of Raipur City: (a) Pre-monsoon, (b) Monsoon, (c) Post-monsoon, and (d) Winter season. The black colour portions of the images represent the area outside the common UHI for different seasons.

**Table 8.** Correlation coefficient values of LST with different LULC indices (significant at 0.05 level).

| LULC Indices | 5 June 2014 | 25 September 2014 | 12 November 2014 | 30 December 2014 |
|--------------|-------------|-------------------|------------------|-----------------|
| NDVI         | -0.3201     | -0.5942           | -0.5337          | -0.0982         |
| NDWI         | 0.2300      | 0.5065            | 0.4906           | 0.0005          |
| NDBI         | 0.5764      | 0.7235            | 0.5384           | 0.4950          |
| NMDI         | -0.5030     | -0.6467           | -0.2829          | -0.4026         |
| NDVI         | -0.4634     | -0.4069           | -0.4833          | -0.3333         |
| NDWI         | 0.4708      | 0.4497            | 0.5177           | 0.2706          |
| NDBI         | -0.0465     | 0.2621            | 0.1150           | 0.1703          |
| NMDI         | 0.2456      | -0.0935           | 0.1963           | 0.0675          |
| NDVI         | -0.1017     | -0.3640           | -0.2613          | 0.1520          |
| NDWI         | -0.0501     | 0.2699            | 0.1798           | -0.2702         |
| NDBI         | 0.5732      | 0.5955            | 0.4966           | 0.5045          |
| NMDI         | -0.6234     | -0.5828           | -0.4078          | -0.5737         |
| NDVI         | -0.3714     | -0.4313           | -0.5126          | -0.2924         |
| NDWI         | 0.3739      | 0.4463            | 0.5068           | 0.2538          |
| NDBI         | -0.0073     | 0.3319            | 0.1768           | 0.0425          |
| NMDI         | 0.1621      | -0.1024           | 0.1616           | 0.1448          |
| NDVI         | -0.5566     | -0.5244           | -0.3731          | -0.5356         |
| NDWI         | 0.6139      | 0.5465            | 0.4182           | 0.5159          |
| NDBI         | -0.2039     | 0.1263            | 0.1819           | -0.1213         |
| NMDI         | 0.3899      | 0.2354            | 0.0089           | 0.3571          |
corresponding to moderate NDVI, moderate NDWI, high NDBI, and moderate NMDI values. The monsoon season shows that the high LST values are found in the area of low NDVI, moderate NDWI, low NDBI, and low NMDI. In the post-monsoon season, low NDVI, moderate NDWI, high NDBI, and moderate NMDI zones represent the high LST values. In the winter season, low NDVI, high NDWI, high NDBI, and low NMDI zones represent the high LST values.

Figure 8 shows the variation of LST distribution maps and their corresponding NDVI, NDWI, NDBI, and NMDI maps for the non-UHI of Raipur City for four multi-date images. The black coloured portion of the map represents the area outside the common UHI area of Raipur City. The post-monsoon image reflects the most significant relationship. In the southern portion of the non-UHI, the relationship is more reliable. In the pre-monsoon season, the high LST values are corresponding to moderate NDVI, low NDWI, moderate NDBI, and low NMDI values. The monsoon season shows that the high LST values are found in the area of high NDVI, low NDWI, low NDBI, and high NMDI. In the post-monsoon season, moderate NDVI, low NDWI, moderate NDBI, and low NMDI zones represent the high LST values. In the winter season, moderate NDVI, moderate NDWI, high NDBI, and low NMDI zones represent the high LST values.

LST distribution maps and their corresponding NDVI, NDWI, NDBI, and NMDI maps for the common UHI of Raipur City using mean value of single season are presented by Figure 9. The black coloured portion of the map represents the area outside the common UHI of the city. Post-monsoon and monsoon images indicate the most significant relationship of LST with LULC indices. In the pre-monsoon season, the high LST values are corresponding to moderate NDVI, moderate NDWI, high NDBI, and moderate NMDI values. The monsoon season shows that the high LST values are found in the area of low NDVI, moderate NDWI, high NDBI, and low NMDI. In the post-monsoon season, low NDVI, moderate NDWI, high NDBI, and moderate NMDI zones represent the high LST values. In the winter season, low NDVI, high NDWI, high NDBI, and low NMDI zones represent the high LST values.

The best correlation between LST and the four above-mentioned LULC indices is found for the whole of Raipur City, irrespective of any date. The relationship is weaker with the increase of heterogeneity in an urban landscape. Common UHI of all seasons simply indicates the built-up area and semi-bare lands which are more heterogeneous. Thus, the least correlation has been found in the common UHI of the city area. UHI and non-UHI of the city reflect the moderate values of the correlation coefficient.

5. Conclusion

In this paper, Landsat 8 OLI and TIRS data of four different dates selected from four different seasons in a single year have been used to investigate the UHI intensity effect in Raipur City of India and to interpret the dynamic relationship between LST with NDVI, NDWI, NDBI, and NMDI. The above relationships have been examined using the whole area, UHI, non-UHI, and common UHI of Raipur City. UHIs have
been identified through the spatial distribution of LST which are mainly existed in the northern and southern parts of the city. Bare land and built-up area are mostly responsible for generating high LST values. LST level is reduced significantly due to the presence of vegetation and water bodies.

Furthermore, the relationships of LST to NDVI, NDWI, NDBI, and NMDI have been interpreted quantitatively by linear regression analysis (using Pearson’s product moment correlation coefficient) at the pixel level. For the whole of Raipur City, LST shows a strong positive correlation with NDBI; and a moderate to strong negative correlation with NMDI, irrespective of dates. Inside the UHI, NDVI and NDWI show a stronger correlation (NDVI-negative, NDWI-positive) with LST in comparison with the other indices. Conversely, inside the non-UHI zone, NDBI and NMDI present a stronger correlation (NDBI-positive, NMDI-negative). Besides, NDVI-LST and NDWI-LST relationships are stronger inside the common UHI in all seasons.

One of the main objectives of the present study is to estimate the variation in the correlation analysis for the

Figure 7. LST-NDVI, LST-NDWI, LST-NDBI, and LST-NMDI relationship in UHI of Raipur City: (a)-(d) Pre-monsoon season; (e)-(h) Monsoon season; (i)-(l) Post-monsoon season; (m)-(p) Winter season. The black colour portions of the images represent the non-UHI for different seasons.
Satellite images of four different dates. Monsoon and post-monsoon images are more prominent in showing the relationship between LST and LULC indices due to the presence of green healthy vegetation and high moisture content in the soil. Pre-monsoon image is less dominant compared to the above two images, whereas these relationships show the lowest correlation coefficient values in the winter image.

In the future, many additional research works may be included. Firstly, the entire research work can be performed with other satellite data of different spatial resolution (e.g., IKONOS (1 m), Quickbird (0.6 m), ASTER (15 m), Sentinel-2A (10 m), MODIS (1000 m), etc.). Secondly, seasonal variation in the correlation values between LST and LULC indices may be monitored with ten years or more time period. Thirdly, other LULC indices (e.g., Enhanced vegetation index, Soil adjusted vegetation index, Modified normalized difference water index, Normalized difference mud index, Burn area index, etc.) may be examined to find the better correlation with LST. Fourthly, the present study may be examined in

Figure 8. LST-NDVI, LST-NDWI, LST-NDBI, and LST-NMDI relationship in non-UHI of Raipur City: (a)-(d) Pre-monsoon season; (e)-(h) Monsoon season; (i)-(l) Post-monsoon season; (m)-(p) Winter season. The black colour portions of the images represent the UHI for different seasons.
different environments with large physical varieties. Finally, other statistical methods and algorithms (Spearman Rank Correlation Coefficient, Kendall correlation coefficient, etc.) may also be applied to estimate the correlation between LST and different LULC indices.

**Acknowledgements**

The authors are indebted to United States Geological Survey and National Institute of Technology Raipur, India.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

**ORCID**

Subhanil Guha [http://orcid.org/0000-0002-2967-7248](http://orcid.org/0000-0002-2967-7248)
Himanshu Govil [http://orcid.org/0000-0002-3433-8355](http://orcid.org/0000-0002-3433-8355)
Neetu Gill [http://orcid.org/0000-0001-7392-2178](http://orcid.org/0000-0001-7392-2178)
Anindita Dey [http://orcid.org/0000-0002-6400-4284](http://orcid.org/0000-0002-6400-4284)
References

Amiri, R., Q. Weng, A. Alimohammadi, and S. K. Alavipanah. 2009. “Spatial-temporal Dynamics of Land Surface Temperature in Relation to Fractional Vegetation Cover and Land Use/cover in the Tabriz Urban Area, Iran.” Remote Sensing of Environment 113:2606–2617. doi:10.1016/j.rse.2009.07.021.

Arnfield, J. 2003. “Two Decades of Urban Climate Research: A Review of Turbulence, Exchanges of Energy and Water, and the Urban Heat Island.” International Journal of Climatology 23: 1–26. doi:10.1002/joc.859.

Chun, B., and J.-M. Guldmann. 2014. “Spatial Statistical Analysis and Simulation of the Urban Heat Island in High-density Central Cities.” Landscape and Urban Planning 125: 76–88. doi:10.1016/j.landurbplan.2014.01.016.

Coseo, P., and L. Larsen. 2014. “How Factors of Land Use/land Cover, Building Configuration, and Adjacent Heat Sources and Sinks Explain Urban Heat Islands in Chicago.” Landscape and Urban Planning 125: 117–129. doi:10.1016/j.landurbplan.2014.02.019.

Cui, Y. Y., and B. de Foy. 2012. “Seasonal Variations of the Urban Heat Island at the Surface and the Near-surface and Reductions Due to Urban Vegetation in Mexico City.” Journal of Applied Meteorology and Climatology 51: 855–868. doi:10.1175/JAMC-D-11-0104.1.
Dai, Z., J.-M. Guldmann, and Y. Hu. 2018. “Spatial Regression Models of Park and Land-use Impacts on the Urban Heat Island in Central Beijing.” Science of the Total Environment 626:1136–1147. doi:10.1016/j.scitotenv.2018.01.165.

Deilami, K., and M. Kamruzzaman. 2017. “Modelling the Urban Heat Island Effect of Smart Growth Policy Scenarios in Brisbane.” Land Use Policy 64:38–55. doi:10.1016/j.landusepol.2017.02.027.

Feyisa, G. L., H. Meilby, G. Darrel Jenerette, and S. Pauleit. 2016. “Locally Optimized Separability Enhancement Indices for Urban Land Cover Mapping: Exploring Thermal Environmental Consequences of Rapid Urbanization in Addis Ababa, Ethiopia.” Remote Sensing of Environment 175:14–31. doi:10.1016/j.rse.2015.12.026.

Govil, H., S. Guha, A. Dey, and N. Gill. 2019. “Seasonal Evaluation of Downscaled Land Surface Temperature: A Case Study in a Humid Tropical City.” Heliyon 5 (6): e01923. doi:10.1016/j.helyion.2019.e01923.

Govil H., Guha S., Diwan P., Gill N., Dey A. 2020. “Analyzing Linear Relationships of LST with NDVI and MNDISI Using Various Resolution Levels of Landsat 8 OLI and TIRS Data.” In Data Management, Analytics and Innovation. Advances in Intelligent Systems and Computing. Vol. 1042. pp. 171-184. edited by N. Sharma, A. Chakrabarti, V. Balas, et al.  Singapore: Springer. doi:10.1007/978-981-32-9949-8_13.

Guha, S., H. Govil, and S. Mukherjee. 2017. “Dynamic Analysis and Ecological Evaluation of Urban Heat Islands in Raipur City, India.” Journal of Applied Remote Sensing 11 (3): 036020. doi:10.1117/1.JRS.10.036020.

Guha, S., H. Govil, and P. Diwan. 2019. “Analytical Study of Seasonal Variability in Land Surface Temperature with Normalized Difference Vegetation Index, Normalized Difference Water Index, Normalized Difference Built-up Index, and Normalized Multiband Drought Index.” Journal of Applied Remote Sensing 13 (2): 024518. doi:10.1117/1.JRS.10.024518.

Guha, S., and H. Govil. 2020. “An Assessment on the Relationship between Land Surface Temperature and Normalized Difference Vegetation Index.” Environment, Development and Sustainability doi:10.1007/s10668-020-00657-6.

Guha, S., H. Govil, A. Dey, and N. Gill. 2018. “Analytical Study of Land Surface Temperature with NDVI and NDBI Using Landsat 8 OLI and TIRS Data in Florence and Naples City, Italy.” European Journal of Remote Sensing 51 (1): 667–678. doi:10.1080/22797254.2018.1474494.

Haashemi, S., Q. Weng, A. Darvishi, and S. Alavipanah. 2016. “Seasonal Variations of the Surface Urban Heat Island in a Semi-arid City.” Remote Sensing 8 (352). doi:10.3390/rs8040352.

Khorchani, M., M. Martin-Hernandez, S. M. Vicente-Serrano, C. Azorin-Molina, M. Garcia, M. A. Domínguez-Durán, and F. Reig. 2018b. “Average Annual and Seasonal Land Surface Temperature, Spanish Peninsular.” Journal of Maps 14 (2): 465–475. doi:10.1080/17445647.2018.1500316.

Khorchani, M., M. S. Vicente-Serrano, C. Azorin-Molina, M. Garcia, N. Martin-Hernandez, M. Peña-Gallardo, and A. El Kenawy. 2018a. “Trends in LST over the Peninsular Spain as Derived from the AVHRR Imagery Data.” Global and Planetary Change 166:75–93. doi:10.1016/j.gloplacha.2018.04.006.

Kim, J.-P., and J.-M. Guldmann. 2014. “Land-use Planning and the Urban Heat Island.” Environment and Planning B 41:1077–1099. doi:10.1068/B130091P.

Kuang, W., Y. Liu, Y. Dou, W. Chi, G. Chen, C. Gao, and T. Yang. 2015. “What are Hot and What are Not in an Urban Landscape: Quantifying and Explaining the Land Surface Temperature Pattern in Beijing, China.” Landscape Ecology 30:357–373. doi:10.1007/s10980-014-0128-6.

Lai, J., W. Zhan, F. Huang, J. Quan, L. Hu, L. Gao, and W. Ju. 2018. “Does Quality Control Matter? Surface Urban Heat Island Intensity Variations Estimated by Satellite-derived Land Surface Temperature Products.” ISPRS Journal of photogrammetry and Remote Sensing 139:212–227. doi:10.1016/j.isprsjprs.2018.03.012.

Li, J., C. Song, L. Cao, F. Zhu, X. Meng, and J. Wu. 2011. “Impacts of Landscape Structure on Surface Urban Heat Islands: A Case Study of Shanghai, China.” Remote Sensing of Environment 115:3249–3263. doi:10.1016/j.rse.2011.07.008.

Lopez, J. M. R. 2017. “Frontiers of Urbanization: Identifying and Explaining Urbanization Hot Spots in the South of Mexico City Using Human and Remote Sensing.” Applied Geography 79 (1–10). doi:10.1016/j.apgeog.2016.12.001.

Mathew, A., S. Khandelwal, and N. Kaul. 2017. “Investigating Spatial and Seasonal Variations of Urban Heat Island Effect over Jaipur City and Its Relationship with Vegetation, Urbanization and Elevation Parameters.” Sustainable Cities and Society 35:157–177. doi:10.1016/j.scs.2017.07.013.

McFeeters, S. K. 1996. “The Use of the Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features.” International Journal of Remote Sensing 17 (7):1425–1432. doi:10.1080/01431169608948714.

Mirzaei, P. A. 2015. “Recent Challenges in Modeling of Urban Heat Island.” Sustainable Cities and Society 19:200–206. doi:10.1016/j.scs.2015.04.001.

Nie, Q., W. Man, Z. Li, and Y. Huang. 2016. “Spatiotemporal Impact of Urban Impervious Surface on Land Surface Temperature in Shanghai, China.” Canadian Journal Remote Sensing 42 (6): 680–689. doi:10.1007/003992.2016.1217484.

Pearsall, H. 2017. “Staying Cool in the Compact City: Vacant Land and Urban Heating in Philadelphia, Pennsylvania.” Applied Geography 79:84–92. doi:10.1016/j.apgeo.2016.12.010.

Peng, J. 2018. “Seasonal Contrast of the Dominant Factors for Spatial Distribution of Land Surface Temperature in Urban Areas.” Remote Sensing of Environment 215:255–267. doi:10.1016/j.rse.2018.06.010.

Peng, J., P. Xie, Y. Liu, and J. Ma. 2016. “Urban Thermal Environment Dynamics and Associated Landscape Pattern Factors: A Case Study in the Beijing Metropolitan Region.” Remote Sensing of Environment 173:145–155. doi:10.1016/j.rse.2015.11.027.

Qin, Z. 2001. “A Mono-window Algorithm for Retrieving Land Surface Temperature from Landsat TM Data and Its Application to the Israel–Egypt Border Region.” International Journal of Remote Sensing 22 (18): 3719–3746. doi:10.1080/0143116001006971.
Quan, J., W. Zhan, Y. Chen, M. Wang, and J. Wang. 2016. “Time Series Decomposition of Remotely Sensed Land Surface Temperature and Investigation of Trends and Seasonal Variations in Surface Urban Heat Islands.” Journal of Geophysical Research-Atmospheres 121 (6): 2638–2657. doi:10.1002/2015JD024354.

Rinner, C., and M. Hussain. 2011. “Toronto’s Urban Heat Island: Exploring the Relationship between Land Use and Surface Temperature.” Remote Sensing 3: 1251–1265. doi:10.3390/rs3061251.

Rizwan, A. M., L. Y. C. Dennis, and C. LIU. 2008. "A Review on the Generation, Determination and Mitigation of the Urban Heat Island.” Journal of Environmental Sciences 20 (1): 120–128. doi:10.1002/2017EF000569.

Song, J., S. Du, X. Feng, and L. Guo. 2014. “The Relationships between Landscape Compositions and Land Surface Temperature: Quantifying Their Resolution Sensitivity with Spatial Regression Models.” Landscape and Urban Planning 123 :145–157. doi:10.1016/j.landurbplan.2013.11.014.

Sun, R., W. Xie, and L. Chen. 2018. “A Landscape Connectivity Model to Quantify Contributions of Heat Sources and Sinks in Urban Regions.” Landscape and Urban Planning 178 :43–50. doi:10.1016/j.landurbplan.2018.05.015.

Weng, Q. 2001. “A Remote Sensing-GIS Evaluation of Urban Expansion and Its Impact on Surface Temperature in Zhujiang Delta, China.” International Journal of Remote Sensing 22 (10): 1999–2014. doi:10.1080/713860788.

Weng, Q., and S. Yang. 2004. “Managing the Adverse Thermal Effects of Urban Development in a Densely Populated Chinese City.” Journal of Environmental Management 70 (2): 145–156. doi:10.1016/j.jenvman.2003.11.006.

Yao, R., L. Wang, X. Huang, W. Zhang, J. Li, and Z. Niu 2018. “Interannual Variations in Surface Urban Heat Island Intensity and Associated Drivers in China.” Journal of Environmental Management 222: 86–94. doi:10.1016/j.jenvman.2018.05.024.

Yuan, F., and M. E. Bauer. 2007. “Comparison of Impervious Surface Area and Normalized Difference Index as Indicators of Surface Urban Heat Island Effects in Landsat Imagery.” Remote Sensing of Environment 106: 375–386. doi:10.1016/j.rse.2006.09.003.

Zha, Y., J. Gao, and S. Ni. 2003. “Use of Normalized Difference Built-up Index in Automatically Mapping Urban Areas from TM Imagery.” International Journal of Remote Sensing 24 (3): 583–594. doi:10.1080/01431160304987.

Zhang, H., Z.-F. Qi, X.-Y. Ye, Y.-B. Cai, W.-C. Ma, and M.-N. Chen. 2013. “Analysis of Land Use/Land Cover Change, Population Shift, and Their Effects on Spatiotemporal Patterns of Urban Heat Islands in Metropolitan Shanghai, China.” Applied Geography 44 :121–133. doi:10.1016/j.apgeog.2013.07.021.

Zhang, Z., G. He, M. Wang, T. Long, G. Wang, X. Zhang, and W. Jiao 2016. “Towards an Operational Method for Land Surface Temperature Retrieval from Landsat 8 Data.” Remote Sensing Letters 7 (3): 279–288. DOI:10.1080/2150704X.2015.1130877.

Zhao, M., H. Cai, Z. Qiao, and X. Xu. 2016. “Influence of Urban Expansion on the Urban Heat Island Effect in Shanghai.” International Journal of Geographical Information Science 30 (12): 2421–2441. doi:10.1080/13658816.2016.1178389.

Zhou, W. Q., G. Huang, and M. L. Cadenasso. 2011. “Does Spatial Configuration Matter? Understanding the Effects of Land Cover Pattern on Land Surface Temperature in Urban Landscapes.” Landscape and Urban Planning 102 (1): 54–63. doi:10.1016/j.landurbplan.2011.03.009.