Dynamic seasonal analysis on LST-NDVI relationship and ecological health of Raipur City, India

Subhanil Guha

Department of Applied Geology, National Institute of Technology, Raipur, India

ABSTRACT

Land surface temperature (LST) is a significant component of the ecological health of any city and the LST is closely related to the normalized difference vegetation index (NDVI). The present study evaluates the seasonal variability of the relationship of LST with NDVI by using a large dataset of Landsat sensors for different seasons from 1991–92 to 2018–19. Pearson’s correlation coefficient technique was used to obtain the LST-NDVI relationship. The study also compares the ecological and thermal status of the city by applying the urban thermal field variance index (UTFVI). The results found that the mean LST increased considerably. The post-monsoon season produces the best correlation (−0.59), followed by the monsoon season (−0.53), pre-monsoon season (−0.45), and winter season (−0.22). Apart from this relationship, the ecological status of the city has also been estimated. Almost an equal portion of lands are under the excellent and worst categories of ecological condition. This study is beneficial for future ecological planning in any tropical city.

Introduction

In the twenty-first century, urban expansion and growth is responsible to generate urban heat islands or high LST zones inside the city (Fu and Weng 2016; Liu, Peng, and Wang 2018; Peng et al. 2018a). Massive land conversion increases the LST (Zhou et al. 2019; Guha, Govil, and Diwan 2020). Different wavelength zones of the electromagnetic spectrum efficiently generate various spectral indices to detect the different categories of land surface materials (Guha and Govil 2021). VNIR, SWIR, and TIR bands efficiently detected the land surface characteristics (Das, Mondal, and Guha 2013; Govil et al. 2019). Various spectral indices can take an important role in extracting surface features. NDVI is a vegetation index frequently used in vegetation mapping, land use/land cover (LULC) mapping, town planning, LST monitoring, etc. (Mondal et al. 2011; Du et al. 2016; Peng et al. 2016; Berger et al. 2017; Peng et al. 2018b).

LST deals with the urban heat island effect and it changes significantly in an urban area (Hao, Li, and Deng 2016; Tran et al. 2017). Various land features influence LST differently (Shigeto 1994; Estoque, Murayama, and Myint 2017; Zhao et al. 2017; Mahato and Pal 2018; Mushore et al. 2019). Land conversion process changes the intensity of LST (Wen et al. 2017; Guha and Govil 2020). Seasonal analysis of LST is quite essential in urban ecological studies as vegetation changes with season.

The LST-NDVI correlation analysis influences LST related research work (Smith and Chowdhury 1990; Guha, Govil, and Diwan 2020). NDVI also classifies the LULC features by its optimum threshold limits in diverse physical environments (Chen et al. 2006). Seasonal variability changes LST, NDVI, and also LST-NDVI correlation analysis. The LST-NDVI correlation is quite fascinating in remote sensing studies (Gutman and Ignatov 1998; Goward, Xue, and Czajkowski 2002). This LST-NDVI correlation is mostly negative that is observed in many recent studies performed in the mixed urban areas (Alexander 2020; Chi et al. 2020; Neinavaz et al. 2020; Nse, Okoliea, and Nse 2020). However, the negativity varies with the change in LULC types.

Many LST-NDVI correlation-related research works are available in the tropics and sub-tropics (Kikon et al. 2016; Qu et al. 2018, 2020; Cui et al. 2019a, 2019b; Gui et al. 2019; Guha and Govil 2021). The correlation appears stronger in the wet season (Guha and Govil 2020). A long seasonal investigation between LST and NDVI is necessary for any sustainable town planning in tropical cities (Li et al. 2017). However, the LST-NDVI correlation on different LULC categories are not so much discussed for any Indian tropical city. The long-term ecological status of any Indian city was also need to evaluate.

The present study highlights the seasonal changes in the LST-NDVI correlation as a whole and on various types of land surface covers in Raipur using 64 Landsat satellite images. The primary focuses of the study are (1) to determine the seasonal variation of LST as a whole and on different land surface materials, (2) to...
investigate the seasonal variability of LST-NDVI correlation, and (3) to determine the long-term ecological and thermal status of the city.

Study area and data

Raipur, the study area, is currently the capital of Chhattisgarh, and it ranks 45 in India by population. The total study area extends from 21°11′22″N to 21°20′02″N and from 81°32′20″E to 81°41′50″E with an average elevation of around 275 m. Figure 1(a), 1(b), 1(c), and 1(d) show the outline map of India, outline map of Chhattisgarh, false color composite (FCC) image of Raipur city, and contour map of Raipur City, respectively. The city covers an area of approximately 165 km². The climate of the city is considered as dry and wet savannah climate (https://www.mausam.imd.gov.in). Four types of seasons are observed in Raipur, i.e., monsoon, pre-monsoon, post-monsoon, and winter. The mean annual temperature ranges from 12°C (December) to 42°C (May). The pre-monsoon or summer months are usually hot and remain almost dry. The temperature often rises above 45°C in April and May. May is the hottest month (average temperature 35°C) followed by April (average temperature 33°C), June (average temperature 32°C), and March (average temperature 29°C). July is the rainiest month (average rainfall 327 mm) followed by August (average rainfall 300 mm), June (average rainfall 221 mm), and September (average rainfall 200 mm). October and November are the post-monsoon months that experience a pleasant weather condition with comparatively low temperature and high to the moderate moisture content in the air. The presence of a high density of green vegetation adds an extra flavor in Raipur during the monsoon and the post-monsoon seasons. December (the coldest month: average temperature 20°C), January (average temperature 21°C), and February (average temperature 24°C) come under the winter season. November to April remains almost dry (average rainfall <50 mm) compared to the June to September (average rainfall >200 mm). There are too many small patches of mixed sandy, loamy, and black soil formed in the study area. The south-eastern part of the city is mainly associated with dry bare soil with rocky weathered residuals that give a high amount of LST. The central part of the city has numerous small and medium-sized water areas.

Nine Landsat 5 data from 1991 to 1992, seven Landsat 5 data from 1995 to 1995, six Landsat 7 data from 1999 to 1900, eleven Landsat 5 data from 2004 to 2005, 13 Landsat 5 data from 2009 to 2010, nine Landsat 8 data from 2014 to 2015, and 10 Landsat 8 data from 2018 to 2019 were procured from the United States Geological Survey (USGS) Data Center (https://www.earthexplorer.usgs.gov). The present study used the band 10 of Landsat 8 data as it has a better calibration (Barsi et al. 2014). All the TIR bands from different Landsat sensors were resampled by the USGS data provider applying the cubic convolution method.

Methodology

Retrieving LST from landsat data

Mono-window algorithm (Qin, Karnieli, and Barliner 2001; García-Santos et al. 2018), single-channel algorithm (Jiménez-Muñoz and Sobrino 2003; Jiménez-Muñoz et al. 2009; Coll et al. 2010; Chatterjee et al. 2017), split-window algorithm (McMillin 1975;
Rozenstein et al. 2014), etc. are the main LST retrieval algorithm from Landsat thermal bands. In the present study, the reliable mono-window algorithm derives LST from three different Landsat sensors.

At first, the cubic convolution resampling process converts the original TIR bands (100 m resolution for Landsat 8 data, 120 m resolution for Landsat 5 data, and 60 m resolution for Landsat 7 data) into 30 m for further application. The entire procedure includes the following methods:

The TIR pixel values are firstly converted into radiance from digital number (DN) values. Radiance for TIR bands of Landsat 5 TM data and Landsat 7 ETM+ data are obtained using Eq. (1) (USGS):

$$L_{\lambda} = \frac{L_{\text{MAX}} - L_{\text{MIN}}}{Q_{\text{CAL MAX}} - Q_{\text{CAL MIN}}} \times (Q_{\text{CAL}} - Q_{\text{CAL MIN}}) + L_{\text{MIN}}$$  (1)

where $L_{\lambda}$ is Top of Atmosphere (TOA) spectral radiance (Wm$^{-2}$sr$^{-1}$mm$^{-1}$), $Q_{\text{CAL}}$ is the quantized calibrated pixel value in DN, $L_{\text{MIN}}$ (Wm$^{-2}$sr$^{-1}$mm$^{-1}$) is the spectral radiance scaled to $Q_{\text{CAL MIN}}$, $L_{\text{MAX}}$ (Wm$^{-2}$sr$^{-1}$mm$^{-1}$) is the spectral radiance scaled to $Q_{\text{CAL MAX}}$, $Q_{\text{CAL MIN}}$ is the minimum quantized calibrated pixel value in DN and $Q_{\text{CAL MAX}}$ is the maximum quantized calibrated pixel value in DN. $L_{\text{MIN}}$, $L_{\text{MAX}}$, $Q_{\text{CAL MIN}}$, and $Q_{\text{CAL MAX}}$ values are obtained from the metadata file of Landsat 5 TM data and Landsat 7 ETM+ data. Radiance for Landsat 8 TIR band is obtained from Eq. (2) (Zanter 2019):

$$L_{\lambda} = M_{\lambda} \cdot Q_{\text{CAL}} + A_{\lambda}$$  (2)

where $L_{\lambda}$ is the TOA spectral radiance (Wm$^{-2}$sr$^{-1}$mm$^{-1}$), $M_{\lambda}$ is the band-specific multiplicative rescaling factor from the metadata, $A_{\lambda}$ is the band-specific additive rescaling factor from the metadata, $Q_{\text{CAL}}$ is the quantized and calibrated standard product pixel values (DN). All of these variables can be retrieved from the metadata file of Landsat 8 data.

For Landsat 5 and Landsat 7 data, the reflectance value is obtained from radiance using Eq. (3) (USGS):

$$\rho_{\lambda} = \frac{\pi L_{\lambda} d^2}{E_{\text{SUR}} \cos \theta_{i}}$$  (3)

where $\rho_{\lambda}$ is unitless planetary reflectance, $L_{\lambda}$ is the TOA spectral radiance (Wm$^{-2}$sr$^{-1}$mm$^{-1}$), $d$ is Earth-Sun distance in astronomical units, $E_{\text{SUR}}$ is the mean solar exo-atmospheric spectral irradiances (Wm$^{-2}$sr$^{-1}$mm$^{-1}$) and $\theta_{i}$ is the solar zenith angle in degrees. $E_{\text{SUR}}$ values for each band of Landsat 5 and Landsat 7 data can be obtained from the handbooks of the related mission. $\theta_{i}$ and dvalues can be attained from the metadata file.

For Landsat 8 data, reflectance conversion can be applied to DN values directly as in Eq. (4) (Zanter 2019):

$$\rho_{\lambda} = \frac{M_{\lambda} \cdot Q_{\text{CAL}} + A_{\lambda}}{\sin \theta_{SE}}$$  (4)

where $M_{\lambda}$ is the band-specific multiplicative rescaling factor from the metadata, $A_{\lambda}$ is the band-specific additive rescaling factor from the metadata, $Q_{\text{CAL}}$ is the quantized and calibrated standard product pixel values (DN) and $\theta_{SE}$ is the local sun elevation angle from the metadata file.

Eq. (5) is used to convert the spectral radiance to at-sensor brightness temperature (Wukelic et al. 1989; Chen et al. 2006):

$$T_{b} = \frac{K_{2}}{\ln\left(\frac{K_{1}}{T_{\lambda}} + 1\right)}$$  (5)

where $T_{b}$ is the brightness temperature in Kelvin (K), $L_{\lambda}$ is the spectral radiance in Wm$^{-2}$sr$^{-1}$mm$^{-1}$; $K_{1}$ and $K_{2}$ are calibration constants. For Landsat 8 data, $K_{1}$ is 774.89, $K_{2}$ is 1321.08 (Wm$^{-2}$sr$^{-1}$mm$^{-1}$). For Landsat 7 data, $K_{1}$ is 666.09, $K_{2}$ is 1282.71 (Wm$^{-2}$sr$^{-1}$mm$^{-1}$). For Landsat 5 data, $K_{1}$ is 607.76, $K_{2}$ is 1260.56 (Wm$^{-2}$sr$^{-1}$mm$^{-1}$).

The land surface emissivity, ε, is estimated from Eq. (6) using the NDVI Thresholds Method (Sobrino, Raissouni, and Li 2001; Sobrino, Jimenez-Munoz, and Paolini 2004).

$$\varepsilon = \varepsilon_{r} F_{v} + \varepsilon_{s}(1 - F_{v}) + d \varepsilon$$  (6)

where $\varepsilon$ is land surface emissivity, $\varepsilon_{r}$ is vegetation emissivity, $\varepsilon_{s}$ is soil emissivity, $F_{v}$ is fractional vegetation, $d\varepsilon$ is the effect of the geometrical distribution of the natural surfaces and internal reflections that can be expressed by Eq. (7):

$$d \varepsilon = (1 - \varepsilon_{s})(1 - F_{v}) F_{v}$$  (7)

where $\varepsilon_{s}$ is vegetation emissivity, $\varepsilon_{s}$ is soil emissivity, $F_{v}$ is fractional vegetation, $F_{v}$ is a shape factor whose mean is 0.55, the value of $d\varepsilon$ may be 2% for mixed land surfaces (Sobrino, Jimenez-Munoz, and Paolini 2004).

The fractional vegetation $F_{v}$, of each pixel, is determined from the NDVI using Eq. (8) (Carlson and Repley 1997):

$$F_{v} = \left(\frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}}\right)^{2}$$  (8)

where (a) NDVI < 0.2 for bare soil; (b) NDVI > 0.5 for vegetation; (c) 0.2 < NDVI < 0.5 for mixed land with bare soil and vegetation (Sobrino, Raissouni, and Li 2001; Sobrino, Jimenez-Munoz, and Paolini 2004).

Finally, the land surface emissivity $\varepsilon$ can be expressed by Eq. (9):

$$\varepsilon = 0.004 + F_{v} + 0.986$$  (9)

where $\varepsilon$ is land surface emissivity, $F_{v}$ is fractional vegetation.

Water vapor content is estimated by Eq. (10) (Yang and Que 1996):
\[ w = 0.0981 \\
\quad \times \left[ 10 \times 0.6108 \times \exp \left( \frac{17.27 \times (T_0 - 273.15)}{237.3 + (T_0 - 273.15)} \right) + RH \right] + 0.1697 \]

(10)

where \( w \) is the water vapor content (g/cm\(^3\)), \( T_0 \) is the near-surface air temperature in Kelvin (K), \( RH \) is the relative humidity (%). These parameters of atmospheric profile are obtained from the Meteorological Center, Raipur (http://www.imd-raipur.gov.in).

Atmospheric transmittance is determined for Raipur City using Eq. (11) (Qin, Karnieli, and Barliner 2001; Sun, Tan, and Xu 2010):

\[ \tau = 1.031412 - 0.11536w \]

(11)

where \( w \) is the total atmospheric transmittance, \( w \) is the water vapor content (g/cm\(^3\)).

Raipur City is located in the tropical region. Thus, Eq. (12) is applied to compute the effective mean atmospheric transmittance of Raipur (Qin, Karnieli, and Barliner 2001; Sun, Tan, and Xu 2010):

\[ T_a = 17.9769 + 0.91715T_0 \]

(12)

LST is retrieved from Landsat 5, 7, and 8 satellite data by using Eq. (13–15) (Qin, Karnieli, and Barliner 2001):

\[ T_s = \left[ \frac{\alpha(1 - C - D) + (b(1 - C - D) + C + D)T_0 - DT_a}{C} \right] \]

(13)

\[ C = \epsilon \tau \]

(14)

\[ D = (1 - \tau)(1 + (1 - \epsilon)\tau) \]

(15)

where \( \epsilon \) is the land surface emissivity, \( \tau \) is the total atmospheric transmittance, \( C \) and \( D \) are internal parameters based on atmospheric transmittance and land surface emissivity, \( T_0 \) is the at-sensor brightness temperature, \( T_s \) is the mean atmospheric temperature, \( T_0 \) is the near-surface air temperature, \( T_s \) is the land surface temperature, \( a = -67.355351 \), \( b = 0.458606 \).

**Determination of ecological status by urban thermal field variance index (UTFVI)**

The study has applied the UTFVI (Nichol 2005) for determining the ecological status of Raipur City in different seasons during the study span. The Eq. 16 computes the UTFVI.

\[ UTFVI = \frac{T_s - T_{mean}}{T_{mean}} \]

(16) where \( UTFVI \) = Urban Thermal Field Variance Index

\( T_s \) = LST (°C)

\( T_{mean} \) = Mean LST (°C)

**Various categories of LULC extraction using NDVI threshold method**

NDVI, the most popular vegetation index (Tucker 1979) was used in the present research for determining the seasonal correlation with LST. The value of NDVI ranges from −1.0 to +1.0. Positive NDVI indicates the presence of green vegetation. Greenness increases with the increase of the positive NDVI. But, this threshold limit of NDVI varies according to different climatic conditions. NDVI is used to extract various LULC categories (Chen et al. 2006). Generally, the wet season has more NDVI values compared to the dry season. Here, the post-monsoon images generate LULC maps as it maintains the ratio of wetness and dryness. In the present study, various threshold limits of NDVI present various categories of LULC (Table 1). The estimated threshold limit of NDVI depends on the physical environment of any region. NDVI > 0.2 shows vegetation, NDVI < 0 shows water and 0 < NDVI < 0.2 shows built-up and bare surface. The maximum likelihood classification method validates the NDVI threshold-based classified LULC categories.

**LST-NDVI correlation on various categories of LULC**

The present study used Pearson’s correlation coefficient method to analyze the relationship between LST and NDVI. The value of the correlation coefficient (\( r \)) ranges from −1 to +1. The −1 value of \( r \) represents a perfect negative correlation whereas the +1 value of \( r \) represents a perfect positive correlation. The 0 value of \( r \) represents neutral correlation. The LST-NDVI correlation develops on various LULC categories. Each LULC category generates a separate correlation coefficient value for LST-NDVI relationship. The study also evaluates the seasonal variability of the LST-NDVI correlation.

**Results and discussion**

**Accuracy assessment for the classification of various land surface materials**

The maximum likelihood classification algorithm classifies Raipur City into various land surface materials for

| Table 1. Description and threshold values of NDVI in LULC classification. | Threshold limits of NDVI for extracting different LULC types |
|---|---|
| Acronym | Description | Formulation | References | Vegetation | Water bodies | Built-up area and bare land |
| NDVI | Normalized difference vegetation index | \( \frac{NIR - Red}{NIR + Red} \) | Tucker 1979 | > 0.2 | < 0 | 0–0.2 |
1991–92, 1995–96, 1999–00, 2004–05, 2009–10, 2014–15, and 2018–19. The NDVI threshold method-based extracted LULC data is used as the reference data. The values of overall accuracy are 95.00%, 92.50%, 97.50%, 85.00%, 92.50%, 95.00%, and 87.50% in 1991–92, 1995–96, 1999–00, 2004–05, 2009–10, 2014–15, and 2018–19, respectively. The Kappa coefficient values are 0.91, 0.88, 0.96, 0.76, 0.89, 0.92, and 0.78 in 1991–92, 1995–96, 1999–00, 2004–05, 2009–10, 2014–15, and 2018–19, respectively. According to Nigatu, Øb, and Tveite (2014), the classification is satisfied if Kappa coefficient is > 0.75. The average overall accuracy is 92.14% and the average Kappa coefficient is 0.87. Thus, the maximum likelihood classification method significantly validates the NDVI threshold method-based LULC classification.

Spatial distribution of different types of LULC
Figure 2(a) presents the spatiotemporal changes of LULC of Raipur City from 1991–92 to 2018–19. Green vegetation decreases in a very high proportion while the settlement and barren land increase at a very high rate due to rapid land conversion. Figure 2(b) shows the percentage of changed LULC during the study period. The annual rate of conversion for waterbodies and vegetation from 1991–92 to 2018–19 is 2.08% and 1.85%, respectively. However, in the same period, the settlement and barren land expands at a high percentage of the annual rate (13.23%). An alarming annual growth of bare land/built-up (49.95% between 1991–92 and 1995–96, 40.57% between 1995–96 and 1999–00, 11.42% between 1999–00 and 2004–05, 44.10% between 2004–05 and 2009–10, 13.53% between 2009–10 and 2014–15, and 19.99% between 2014–15 and 2018–19) was observed during the whole span. This rapid conversion of urban land is mainly due to the massive pressure for population growth and migration (Parvaze and Nasser 2012; Guha, Govil, and Mukherjee 2017; Ray et al. 2020).

LST and NDVI distribution
There is a prominent seasonal variation occurred in the mean LST values (Table 2). The lowest and highest values of the mean LST are noticed in the winter and pre-monsoon season, respectively.

Figure 3(a-d) shows the seasonal change in the minimum, maximum, and mean values of LST for the entire study period. The pre-monsoon season shows the highest LST and winter season has the lowest LST. Before 2009–2010, the trend of LST is increasing. However, 2009–2010 onwards, the LST is slightly

Figure 2. Change in LULC (191–92 to 2018–19): (a) area under different types of LULC (b) percentage of changed LULC.
Table 2. Seasonal variability of LST and the LST-NDVI correlation coefficient.

| Season | Year of acquisition | Min. | Max. | Mean | Std. | Correlation coefficient for LST-NDVI |
|--------|---------------------|------|------|------|------|--------------------------------------|
| Pre-1991–92 | 24.25 | 35.22 | 31.54 | 1.30 | -0.38 |
|         | 1995–96 | 24.34 | 41.07 | 34.64 | 1.89 | -0.38 |
|         | 1999–00 | 26.36 | 41.57 | 36.38 | 1.89 | -0.58 |
|         | 2004–05 | 27.37 | 43.32 | 38.01 | 2.05 | -0.49 |
|         | 2009–10 | 25.39 | 41.84 | 36.67 | 2.25 | -0.47 |
|         | 2014–15 | 26.97 | 39.68 | 34.40 | 1.65 | -0.43 |
|         | 2018–19 | 25.50 | 38.70 | 33.14 | 1.68 | -0.43 |
| Average | 25.76 | 40.20 | 34.96 | 1.81 | -0.45 |
| Monsoon | 1991–92 | 22.38 | 30.83 | 25.74 | 1.41 | -0.48 |
|         | 1995–96 | 19.26 | 30.01 | 24.09 | 1.33 | -0.55 |
|         | 1999–00 | 17.62 | 31.23 | 24.18 | 1.34 | -0.64 |
|         | 2004–05 | 22.16 | 29.97 | 26.11 | 0.96 | -0.55 |
|         | 2009–10 | 21.94 | 38.38 | 33.06 | 2.40 | -0.52 |
|         | 2014–15 | 26.43 | 36.63 | 31.70 | 1.16 | -0.48 |
|         | 2016–19 | 25.49 | 34.98 | 31.08 | 1.13 | -0.47 |
| Average | 22.18 | 33.14 | 27.99 | 1.39 | -0.53 |
| Post-1991–92 | 20.17 | 29.38 | 24.32 | 1.65 | -0.59 |
|         | 1995–96 | 19.85 | 28.20 | 23.70 | 1.30 | -0.59 |
|         | 1999–00 | 24.36 | 36.38 | 29.17 | 1.91 | -0.69 |
|         | 2004–05 | 23.46 | 34.46 | 28.01 | 1.58 | -0.59 |
|         | 2009–10 | 22.59 | 34.45 | 27.51 | 1.54 | -0.58 |
|         | 2014–15 | 19.44 | 28.31 | 23.47 | 1.12 | -0.53 |
|         | 2018–19 | 24.31 | 34.09 | 28.08 | 1.30 | -0.62 |
| Average | 22.02 | 32.18 | 26.32 | 1.48 | -0.59 |
| Winter | 1991–92 | 18.37 | 28.33 | 23.29 | 1.15 | -0.24 |
|         | 1995–96 | 18.38 | 25.61 | 21.79 | 0.98 | -0.20 |
|         | 1999–00 | 19.74 | 34.30 | 26.54 | 1.71 | -0.29 |
|         | 2004–05 | 19.27 | 29.27 | 24.07 | 1.15 | -0.17 |
|         | 2009–10 | 18.82 | 27.79 | 23.31 | 1.15 | -0.22 |
|         | 2014–15 | 19.95 | 30.62 | 25.13 | 1.35 | -0.14 |
|         | 2018–19 | 20.33 | 30.14 | 24.37 | 1.18 | -0.25 |
| Average | 19.26 | 29.43 | 24.07 | 1.23 | -0.22 |

Figure 3 shows the map of spatiotemporal and seasonal distributions of mean LST throughout the study. The high LST zones are formed in the northwest and southeast sections where vegetation is less compared to the bare land/built-up area. Throughout the time, more than 85% of the area was above 27°C LST in the pre-monsoon period.

Figure 5 reflects the map of seasonal distribution of NDVI. The spatial relationship of LST with NDVI is easy to understand in Figures 5 and 6. The high NDVI is related to the healthy and green plants that reduce the intensity of LST. The NDVI value was found higher in the earlier images. In the middle period, the NDVI value decreased due to tree felling and land conversion. The NDVI value develops a significant rising trend in recent years. After taking some initiation of social forestry by the government and many non-government sectors, the city becomes ecologically rich, and the NDVI values increase gradually. Consequently, some governmental activities control the rising trend of LST in many parts of the city, which promotes even a reverse tendency of LST in the last few years. It can be a remarkable achievement for the city planners.

**Relationship of land surface materials with LST**

The temporal changes of LST depend on various categories of land surface materials. Green area and water area decrease the LST, while bare land/built-up surface increases LST. Consequently, the built-up/bare land surfaces increase, while vegetation and water surface decrease in a significant amount. Land conversion is the main responsible factor for the seasonal change of mean LST. As a result, the mean LST significantly increased (1.60°C).
Figure 4. Spatiotemporal and seasonal distribution map of LST.
Figure 5. Spatiotemporal and seasonal distribution map of NDVI.
in pre-monsoon, 5.34°C in monsoon, 4.76°C in post-monsoon, and 1.08°C in winter season) from 1991–92 to 2018–19.

**Seasonal fluctuation on LST-NDVI correlation**

Figure 6 represents a negative correlation between LST and NDVI. The correlation is weak negative (minimum, maximum, and mean correlation coefficients are −0.14, −0.29, and −0.22, respectively) in winter due to the dryness of the weather. The pre-monsoon season has a moderate negative (minimum, maximum, and mean correlation coefficients are −0.36, −0.58, and −0.45, respectively) LST-NDVI correlation because of the moderate humidity in air and plant. The correlation is moderate to strong negative (minimum, maximum, and mean correlation coefficients are −0.47, −0.64, and −0.53, respectively) in monsoon because of the wet weather condition. The correlation is strong negative (minimum, maximum, and mean correlation coefficients are −0.51, −0.69, and −0.59, respectively) in post-monsoon season throughout the study period because the percentage of water vapor also remains high in the post-monsoon season and plants look healthy due to high ratio of chlorophyll content. Thus, the post-monsoon and monsoon seasons generate a more stable and stronger correlation compared to the winter season. The results show that the wetness of the season enhances the strength of the LST-NDVI correlation.

The LST-NDVI correlation was negative in several recent studies performed in Shanghai, China (Yue et al. 2007); in Mashhad, Iran (Gorgani, Panahi, and Rezaie 2013); in Berlin, Germany (Marzban, Sodoudi, and

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### Table 3. The threshold of ecological evaluation index.

| UTFVI   | UHI phenomenon | Ecological evaluation index |
|---------|----------------|----------------------------|
| <0.000  | None           | Excellent                  |
| 0.000–0.005 | Weak         | Good                       |
| 0.005–0.010 | Middle      | Normal                     |
| 0.010–0.015 | Strong      | Bad                        |
| 0.015–0.020 | Stronger    | Worse                      |
| >0.020  | Strongest      | Worst                      |

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Figure 7. Thermal status of Raipur City in pre-monsoon season using UTFVI: (a) 1991–92 (b) 1995–96 (c) 1999–00 (d) 2004–05 (e) 2009–10 (f) 2014–15 (g) 2018–19.
Preusker (2018); in Aarhus, Denmark (Alexander 2020); in Uyo, Nigeria (Nse, Okoliea, and Nse 2020); in Yellow River Delta, China (Chi et al. 2020); in Bavarian Forest National Park, Germany (Neinavaza, Skidmorea, and Darvishzadeha 2020). The presence of surface moisture reduces the intensity of LST (Lambin and Ehrlich 1996).

The present research also shows a negative correlation.

**Ecological and thermal status of Raipur City**

One additional aim of the study was to estimate the thermal and ecological status of Raipur City. The thermal status of Raipur City was based on the values of UTFVI those are categorized into six ecological evaluation indices (Table 3). The areas with high UTFVI values show low NDVI and vice-versa.

Figures 7, 8, 9, and 10 indicate that Raipur City has two extreme categories for ecological and thermal status: the excellent category (UTFVI < 0) and the worst category (UTFVI > 0.020) for each and every season. Almost half of the areas of Raipur City (approximately 40–45% during the entire periods) have an excellent thermal condition (i.e., UTFVI < 0). These areas have abundant green fields and waterbodies. Mainly, the central and southwest portions experience such thermal condition. However, the worst category (i.e., UTFVI > 0.020) of the ecological evaluation index also exists in a large portion (approximately 35–45% for all of the satellite data) of the city. The northwest and southeast parts fall under the worst category. Here, most of the lands are impervious (bare land with exposed rock surface or built-up areas). The good and normal categories of ecological condition (0.000 < UTFVI < 0.020) are also common in various parts of the city.

**Figure 8.** Thermal status of Raipur City in monsoon season using UTFVI: (a) 1991–92 (b) 1995–96 (c) 1999–00 (d) 2004–05 (e) 2009–10 (f) 2014–15 (g) 2018–19.

**Figure 9.** Thermal status of Raipur City in post-monsoon season using UTFVI: (a) 1991–92 (b) 1995–96 (c) 1999–00 (d) 2004–05 (e) 2009–10 (f) 2014–15 (g) 2018–19.
< 0.010) are found with some small patches surrounding the areas with excellent condition while the bad and worse categories (0.010 < UTFVI < 0.020) exist around the areas of the built-up class. The pre-monsoon season shows the highest worst categorized area while the monsoon and post-monsoon seasons show the lowest percentage of area having excellent condition. The area under the excellent category has slightly increased from 1991–92 to 2018–19 due to proper ecological planning and environmental management.

**Conclusion**

The present research concludes that the LST is negatively correlated to NDVI for all four seasons. The correlation is strong to moderate in post-monsoon (−0.59) and monsoon (−0.53), moderate in pre-monsoon (−0.45), and weak to moderate in winter (−0.22). Wet season shows a strong correlation, while dry season shows a weak correlation. The mean LST of the city significantly increased during the research period (1.60°C in the pre-monsoon, 5.34°C in monsoon, 4.76°C in post-monsoon, and 1.08°C in winter). The result appreciably shows the influence of LULC change and climate change. Moreover, the thermal status of the city is quite interesting. Almost an equal portion of lands are under the excellent and worst categories of ecological condition. A stable ecological healthy status can be achieved through a suitable environmental planning and management system.

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No potential conflict of interest was reported by the author(s).

**ORCID**

Subhanil Guha [http://orcid.org/0000-0002-2967-7248](http://orcid.org/0000-0002-2967-7248)

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