Monitoring LST-NDVI Relationship Using Premonsoon Landsat Datasets

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The present study monitors the interrelationship of land surface temperature (LST) with normalized difference vegetation index (NDVI) in Raipur City of India using premonsoon Landsat satellite sensor for the season of 2002, 2006, 2010, 2014, and 2018. The results describe that the mean LST of Raipur City is gradually increased with time. The value of mean NDVI is higher in the area below mean LST compared to the area above mean LST. The value of mean NDVI is also higher in Landsat 8 data than Landsat 5 and Landsat 7 data. A strong negative LST-NDVI correlation is observed throughout the period. The correlation coefficient is higher in the area above mean LST and lower in the area below mean LST. The value of the correlation coefficient is decreased with time. The mixed urban landscape of the city is closely related to the changes of LST-NDVI relationship. These results provide systematic planning of the urban environment.

1. Introduction

Thermal infrared (TIR) bands of satellite images often regulate the biogeochemical actions of the Earth surface features [1–4]. Land surface temperature (LST) determination from TIR bands is very important as it depends on the land surface material and varies from time to time [5]. Fast urbanization rapidly changes the characteristics of the surface components [6]. Natural vegetation is one of the most significant features that control the variation of LST distribution [7]. The most commonly used vegetation index is normalized difference vegetation index (NDVI) which is significantly applied in the computation of LST [8–11]. There are so many factors like climate, types of vegetation, land use, urbanization, etc., that influence the LST-NDVI correlation [12–14].

A number of research scholars recently attempted to build the LST-NDVI correlation [12, 15–17]. Some previous attempts were spatiotemporal in nature and were mainly conducted on the big cities like Tokyo, Shanghai, Chongqing, Shijiazhuang, Rome, Shiraz, Melbourne, Bangkok, Monte Hermoso, Beijing, Islamabad [18–27], etc. But, the discussion based on the LST-NDVI correlation in an Indian city in premonsoon season was rare.

The surface configurations naturally control the spatial and temporal resolution of any satellite sensor [28]. Generally, LST builds an inverse relationship with vegetation [29]. NDVI acts as a determining factor of LST [30], and some studies used the LST-NDVI correlation to evaluate the distributional pattern of LST [31–36]. A lot of recent studies assess the LST-NDVI correlation in multidimensional approach [2, 32, 37–48].

Many recent research works conducted on the Indian context describe the LST-NDVI correlation [49–54]. To discuss the spatial-temporal variation of LST-NDVI correlation in the premonsoon season, Raipur, a smart and rapidly growing Indian city, was selected. The study reflects the following specific objectives:

1. Describe the spatiotemporal distribution of LST and NDVI in the premonsoon months.
2. Analyze the LST-NDVI correlation in the premonsoon months.
2. Study Area and Data

Raipur, the capital and the largest city of Chhattisgarh, India, was selected as the study area which extends between 21°11′22″N to 21°20′02″N and 81°32′20″E to 81°41′50″E with an elevation of 280–310 m (Figure 1). The average annual temperature of the city is around 27–30°C. The entire work conducted on the hot and dry premonsoon months...

Table 1: Description of Landsat data from different sensors.

| Date of acquisition | Satellite sensor | Time   | Path/row | Cloud cover (%) |
|---------------------|-----------------|--------|----------|-----------------|
| 25-Apr-2002         | Landsat 7 ETM+  | 04:44:54 | 142/044  | 0.00            |
| 11-May-2002         | Landsat 7 ETM+  | 04:44:54 | 142/044  | 5.00            |
| 28-Apr-2006         | Landsat 5 TM    | 04:48:00 | 142/044  | 2.00            |
| 15-Jun-2006         | Landsat 5 TM    | 04:48:12 | 142/044  | 4.00            |
| 07-Apr-2010         | Landsat 5 TM    | 04:47:02 | 142/044  | 0.00            |
| 23-Apr-2010         | Landsat 5 TM    | 04:46:59 | 142/044  | 0.00            |
| 25-May-2010         | Landsat 5 TM    | 04:46:51 | 142/044  | 0.00            |
| 17-Mar-2014         | Landsat 8 OLI_TIRS | 04:26:36 | 142/044  | 0.00            |
| 02-Apr-2014         | Landsat 8 OLI_TIRS | 04:26:19 | 142/044  | 0.00            |
| 20-May-2014         | Landsat 8 OLI_TIRS | 04:25:38 | 142/044  | 5.46            |
| 05-Jun-2014         | Landsat 8 OLI_TIRS | 04:25:45 | 142/044  | 0.02            |
| 12-Mar-2018         | Landsat 8 OLI_TIRS | 04:55:43 | 142/044  | 2.10            |
| 28-Mar-2018         | Landsat 8 OLI_TIRS | 04:55:36 | 142/044  | 0.01            |
| 15-May-2018         | Landsat 8 OLI_TIRS | 04:55:08 | 142/044  | 0.30            |
| 16-Jun-2018         | Landsat 8 OLI_TIRS | 04:55:01 | 142/044  | 2.31            |
Table 2: Derivation of normalized difference vegetation index (NDVI).

| Acronym | Description                  | Formulation                        | Reference |
|---------|------------------------------|------------------------------------|-----------|
| NDVI    | Normalized difference vegetation index | \((\text{NIR} - \text{Red})/(\text{NIR} + \text{Red})\) | [60]      |

Figure 2: Variation in the distribution of LST (°C): (a1-a2) 2002, (b1-b2) 2006, (c1–c3) 2010, (d1–d4) 2014, and (e1-e4) 2018.
(March, April, May, and June). The range of the maximum temperature of the premonsoon months lies between 40–45°C. The total population of Raipur is 1,010,087. Literacy rate and sex ratio are 86.45% and 945, respectively.

Five Landsat 5 Thematic Mapper (TM), two Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and eight Landsat 8 Operational Land Imager (OLI)/Thermal Infrared Sensors (TIRS) data of premonsoon seasons with four years interval were freely downloaded from the United States Geological Survey website (https://earthexplorer.usgs.gov) to use in the present study (Table 1). Different types of Landsat satellite sensors overpass the Raipur City of India between 04:25 and 04:56 Greenwich Mean Time (09:55 to 10:26 AM Indian Standard Time). The data were obtained with maximum illumination which is needed in LST related study. ArcGIS 9.3 software was used to conduct the entire computation.

### 3. Methodology

Geometric correction, radiometric correction, and resampling are the required preprocessing steps for using the

| Date      | LST (minimum) | LST (maximum) | LST (mean) | LST (standard deviation) |
|-----------|---------------|---------------|------------|--------------------------|
| Mean 2002 | 22.08         | 36.56         | 31.91      | 1.82                     |
| Mean 2006 | 25.83         | 41.83         | 35.62      | 2.06                     |
| Mean 2010 | 25.82         | 43.35         | 37.42      | 2.22                     |
| Mean 2014 | 31.26         | 47.27         | 40.49      | 2.03                     |
| Mean 2018 | 33.98         | 50.40         | 43.53      | 2.11                     |

Table 3: Temporal variations in the distribution of LST (°C) (2002–2018).

Figure 3: Distribution of mean LST (°C): (a) 2002 (b) 2006 (c) 2010 (d) 2014 (e) 2018.
Landsat images. LST was determined by using the TIR bands (band 6 for TM and ETM+ data, and band 10 for OLI and TIRS data).

### 3.1. Image Preprocessing and Atmospheric Correction

The satellite data acquired from Landsat sensors were subset to limit the data size. The thermal infrared bands of Landsat sensors were resampled at 30 m resolution using the nearest neighbour algorithm to match the optical bands. Atmospheric correction of the satellite data was performed by the following steps.

For optical bands of Landsat data, the following equation is used to converting a Digital Number into spectral reflectance:

\[
ρ_λ = M_ρ × Q_{cal} + A_ρ, \quad (1)
\]

where \(ρ_λ\) is the spectral reflectance at top-of-atmosphere (TOA) without correction for solar angle (Unitless), \(Q_{cal}\) is the Level 1 pixel value in Digital Number (DN), \(M_ρ\) is the reflectance multiplicative scaling factor for the band (REFLECTANCE_MULT_BAND_n from the metadata), and \(A_ρ\) is the reflectance additive scaling factor for the band (REFLECTANCE_ADD_BAND_n from the metadata). The \(ρ_λ\) is corrected with local sun elevation angle \(θ_s\) by the following equation:

\[
ρ′_λ = \frac{ρ_λ}{\sin(θ_s)} \quad (2)
\]

For TIR band of Landsat data, a similar calibration equation is used:

\[
L_λ = M_L × Q_{cal} + A_L, \quad (3)
\]

where \(L_λ\) is the spectral radiance at TOA in \(\text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1}\), \(Q_{cal}\) 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. LST Estimation Using Landsat Satellite Sensors

In the present study, the LST was determined by using the monomodel algorithm [55] in which the three necessary elements are atmospheric transmittance, ground emissivity, and effective mean atmospheric temperature.

The original TIR bands of Landsat datasets were resampled into 30 m. The equations are as follows:

\[
L_λ = \text{RadianceMultiBand} × \text{DN} + \text{RadianceAddBand}, \quad (4)
\]

where \(L_λ\) is spectral radiance (\(\text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1}\)).

\[
T_b = \frac{K_2}{\ln((K_1/L_λ) + 1)}, \quad (5)
\]

where \(T_b\) is the at-sensor brightness temperature (Kelvin); \(K_2\) and \(K_1\) are calibration constants for Landsat datasets.

### Table 4: Correlation coefficients between Landsat and MODIS sensors derived mean LST.

| Acquisition date (Landsat data) | Acquisition date (MODIS data) | Correlation coefficient |
|---------------------------------|-------------------------------|------------------------|
| 25-Apr-2002                     | 25-Apr-2002                   | 0.72                   |
| 11-May-2002                     | 11-May-2002                   | 0.68                   |
| 28-Apr-2006                     | 29-Apr-2006                   | 0.75                   |
| 15-Jun-2006                     | 17-Jun-2006                   | 0.79                   |
| 07-Apr-2010                     | 06-Apr-2010                   | 0.71                   |
| 23-Apr-2010                     | 22-Apr-2010                   | 0.78                   |
| 25-May-2010                     | 24-May-2010                   | 0.67                   |
| 17-Mar-2014                     | 16-Mar-2014                   | 0.79                   |
| 02-Apr-2014                     | 01-Apr-2014                   | 0.76                   |
| 20-May-2014                     | 19-May-2014                   | 0.64                   |
| 05-Jun-2014                     | 04-Jun-2014                   | 0.72                   |
| 12-Mar-2018                     | 13-Mar-2018                   | 0.62                   |
| 28-Mar-2018                     | 27-Mar-2018                   | 0.68                   |
| 15-May-2018                     | 12-May-2018                   | 0.70                   |
| 16-Jun-2018                     | 15-Jun-2018                   | 0.73                   |

### Table 5: Temporal variations in the distribution of NDVI for whole Raipur City (2002–2018).

| Date of acquisition | NDVI (minimum) | NDVI (maximum) | NDVI (mean) | NDVI (standard deviation) |
|---------------------|----------------|----------------|-------------|---------------------------|
| Mean                | -0.23          | 0.56           | 0.00        | 0.07                      |
| Mean                | -0.19          | 0.52           | 0.09        | 0.08                      |
| Mean                | -0.21          | 0.50           | 0.02        | 0.06                      |
| Mean                | -0.11          | 0.48           | 0.14        | 0.07                      |
| Mean                | -0.12          | 0.44           | 0.12        | 0.06                      |
Figure 4: Variation in the distribution of NDVI: (a1-a2) 2002 (b1-b2) 2006 (c1-c3) 2010 (d1-d4) 2014 (e1-e4) 2018.
F_{v} = \left( \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2, \quad (6)

where \( NDVI_{min} \) is the minimum value (0.2) of NDVI for bare soil pixel and \( NDVI_{max} \) is the maximum value (0.5) of NDVI for healthy vegetation pixel.

\( d_{e} \) is the geometric distribution effect for the natural surface and internal reflection. The value of \( d_{e} \) may be 2% for mixed and elevated land surfaces.

\[ d_{e} = (1 - \varepsilon_s)(1 - F_v)F, \quad (7) \]

where \( \varepsilon_s \) is soil emissivity; \( F_v \) is fractional vegetation; \( F \) is a shape factor (0.55); and \( \varepsilon_v \) is vegetation emissivity.

\[ \varepsilon = \varepsilon_s F_v + \varepsilon_v (1 - F_v) + d_{e}, \quad (8) \]

where \( \varepsilon \) is land surface emissivity. The value of \( \varepsilon \) is calculated by the formula given below:

\[ \varepsilon = 0.004 \times F_v + 0.986. \quad (9) \]

Water vapour content is determined by the following equation:

\[ w = 0.0981 \times \left[ 10 \times 0.6108 \times \exp \left( \frac{17.27 \times (T_0 - 273.15)}{237.3 + (T_0 - 273.15)} \right) \right] \times RH + 0.1697, \quad (10) \]

where \( w \) is water vapour content (g/cm²); \( T_0 \) is near-surface air temperature (Kelvin); RH is relative humidity (%). The information on these parameters was provided by the Meteorological Centre, Raipur.

\[ \tau = 1.031412 - 0.11536w, \quad (11) \]

where \( \tau \) is the total atmospheric transmittance.

The effective mean atmospheric transmittance of Raipur City was determined as follows [33]:

Figure 5: Distribution of mean NDVI: (a) 2002, (b) 2006, (c) 2010, (d) 2014, and (e) 2018.
Figure 6: The area above mean LST (pink portion) and the area below mean LST (black portion): (a1-a2) 2002, (b1-b2) 2006, (c1-c3) 2010, (d1-d4) 2014, and (e1-e4) 2018.
Figure 7: NDVI in the area above mean LST: (a-b) 2002, (c-d) 2006, (e-g) 2010, (h-k) 2014, and (l-o) 2018. The black portion of the maps shows the area below mean LST.
resampling method, and different passing time of the sensors
different value of LST due to water vapour content,
respectively). Landsat and MODIS sensors provide a slightly
(120 m, 120 m, and 100 m for Landsat 5, 7, and 8 sensors,
TIR bands of MODIS sensor (1 km) and Landsat sensors
dates were free from any cloud coverage or precipitation.
were used to validate for the resulting LST. (These particular
solution—1 km) of the following particular dates (Table 4)
region in a particular date, MOD11A1 data (resolution—1 km)
of the city, because of the
land, experience higher LST values. (The lower values of LST
southwest parts of the study area, which are under open bare
vegetation [33, 57–60]. Red and NIR bands of Landsat data
extract various land use classes [8, 18, 23, 24, 33, 34, 49, 56].
research works applied various remote sensing indices to
to correlate with LST. NDVI
NDVI for the Landsat satellite images during the study
period. Figure 4 presents the spatial and temporal status of
NDVI for the whole study area, date-wise and year-wise.
Southwest and northeast portions of the city reflect higher
NDVI values due to high percentage of green vegetation.
The average values of maximum NDVI were gradually
decreased (0.56 in 2002, 0.52 in 2006, 0.50 in 2010, 0.48 in
2014, and 0.44 in 2018) since the beginning of the study. It
means that vegetation was lost at a substantial rate. The
spatial distribution of LST and NDVI exhibits an opposite
direction (Figure 5).

4.4. Spatiotemporal Distribution of NDVI during the Entire
Period. Figure 6 shows the area above mean LST (pink part)
and the area below mean LST (black part) for every single
image during the period of study. Figure 7 and Table 6
represent the temporal variation in the NDVI distribution
values for the area has more than mean LST during the entire
period. The black portion of the maps shows the area below
mean LST (Figure 7). Generally, it seems to have an increase
in NDVI values with time. But, there is no such particular
pattern of increase of NDVI. 2014 and 2018 have greater
NDVI values (maximum and mean NDVI) than the earlier
years.

Figure 8 and Table 7 represent the temporal variation in
the spatial distribution of NDVI values in the area below
mean LST. The black portion of the maps shows the area
above mean LST (Figure 8). A steady decreasing trend has
been observed in the values of mean NDVI. The value of
maximum NDVI is much higher in the area below mean LST
than in the area above mean LST.

Figure 9 shows the graphical presentation of the spatial
and temporal change of mean NDVI for the area having less
than mean LST, the area having more than mean LST, and
the whole area of the city. The overall trend is increasing
in nature. In 2006, the mean NDVI values were more than
in 2002. The values were reduced again in 2010. From 2010
to 2014, a high slope was found in mean NDVI values. In 2014
and 2018, the trend line was quite stable. It is clear from
Figure 9 that mean NDVI values are higher for Landsat 8

$$T_a = 17.9769 + 0.91715T_0,$$
$$T_s = \left[\frac{a(1 - C - D) + (b(1 - C - D) + C + D)T_b - DT_a}{C}\right],$$
$$C = \epsilon\tau,$$
$$D = (1 - \tau)(1 + (1 - \epsilon)\tau),$$

where $T_a$ is mean atmospheric temperature and $T_s$ is
land surface temperature; $a = -67.355351$ and $b = 0.458606$.

3.3. NDVI Estimation Using Landsat Sensors. Many previous
research works applied various remote sensing indices to
extract various land use classes [8, 18, 23, 24, 33, 34, 49, 56].
Here, only NDVI was applied to correlate with LST. NDVI
can be estimated using other LULC types along with green
vegetation [33, 57–60]. Red and NIR bands of Landsat data
are used to determine NDVI (Table 2).

4. Results and Discussion

4.1. Spatiotemporal Contrast in the Distribution of LST.
Figure 2 presents the distribution of LST in the premonsoon
months from 2002 to 2018 with a four years interval (Table
3). The average of annual mean LST value lies between
31.91°C (2002) and 43.53°C (2018). The north-west and the
southeast parts of the study area, which are under open bare
land, experience higher LST values. The lower values of LST
are observed in central regions of the city because of the
presence of park, scattered trees, wetlands, and water bodies
(Figure 3).

4.2. Validation of the Result by Using Other Satellite Data.
Any satellite retrieved LST needs a proper validation with an
in situ measurement or other satellite retrieved LST [2].
Here, MODIS data were used to validate the values of LST.
As MODIS and Landsat sensors cannot pass over the same
region in a particular date, MOD11A1 data (resolution—1 km)
of the following particular dates (Table 4) were used to validate for the resulting LST. These particular
dates were free from any cloud coverage or precipitation.
TIR bands of MODIS sensor (1 km) and Landsat sensors
(120 m, 120 m, and 100 m for Landsat 5, 7, and 8 sensors,
respectively). Landsat and MODIS sensors provide a slightly
different value of LST due to water vapour content, resampling method, and different passing time of the sensors

| Year   | NDVI (minimum) | NDVI (maximum) | NDVI (mean) | NDVI (standard deviation) |
|--------|----------------|----------------|-------------|---------------------------|
| Mean 2002 | -0.14          | 0.21           | -0.02       | 0.03                      |
| Mean 2006 | -0.09          | 0.34           | 0.06        | 0.05                      |
| Mean 2010 | -0.18          | 0.30           | 0.01        | 0.04                      |
| Mean 2014 | -0.03          | 0.39           | 0.12        | 0.05                      |
| Mean 2018 | -0.08          | 0.34           | 0.11        | 0.04                      |

After performing the downscaling process, a significant
relationship coefficient was found between the Landsat
derived mean LST and corresponding MODIS derived mean
downscaled LST (Table 4).

4.3. Variation in NDVI Distribution for Multitemporal
Landsat Data. Red and NIR bands are required to derive
the formula of NDVI [60]. Table 5 represents the value
of NDVI for the Landsat satellite images during the study
period. Figure 4 presents the spatial and temporal status of
NDVI for the whole study area, date-wise and year-wise.
NDVI values due to high percentage of green vegetation.
The average values of maximum NDVI were gradually
decreased (0.56 in 2002, 0.52 in 2006, 0.50 in 2010, 0.48 in
2014, and 0.44 in 2018) since the beginning of the study. It
means that vegetation was lost at a substantial rate. The
spatial distribution of LST and NDVI exhibits an opposite
direction (Figure 5).

4.4. Spatiotemporal Distribution of NDVI during the Entire
Period. Figure 6 shows the area above mean LST (pink part)
and the area below mean LST (black part) for every single
image during the period of study. Figure 7 and Table 6
represent the temporal variation in the NDVI distribution
values for the area has more than mean LST during the entire
period. The black portion of the maps shows the area below
mean LST (Figure 7). Generally, it seems to have an increase
in NDVI values with time. But, there is no such particular
pattern of increase of NDVI. 2014 and 2018 have greater
NDVI values (maximum and mean NDVI) than the earlier
years.

Figure 8 and Table 7 represent the temporal variation in
the spatial distribution of NDVI values in the area below
mean LST. The black portion of the maps shows the area
above mean LST (Figure 8). A steady decreasing trend has
been observed in the values of mean NDVI. The value of
maximum NDVI is much higher in the area below mean LST
than in the area above mean LST.

Figure 9 shows the graphical presentation of the spatial
and temporal change of mean NDVI for the area having less
than mean LST, the area having more than mean LST, and
the whole area of the city. The overall trend is increasing
in nature. In 2006, the mean NDVI values were more than
in 2002. The values were reduced again in 2010. From 2010
to 2014, a high slope was found in mean NDVI values. In 2014
and 2018, the trend line was quite stable. It is clear from
Figure 9 that mean NDVI values are higher for Landsat 8

Table 6: Temporal variations of NDVI in the area above mean LST (2002–2018).

| Year   | NDVI (minimum) | NDVI (maximum) | NDVI (mean) | NDVI (standard deviation) |
|--------|----------------|----------------|-------------|---------------------------|
| Mean 2002 | -0.14          | 0.21           | -0.02       | 0.03                      |
| Mean 2006 | -0.09          | 0.34           | 0.06        | 0.05                      |
| Mean 2010 | -0.18          | 0.30           | 0.01        | 0.04                      |
| Mean 2014 | -0.03          | 0.39           | 0.12        | 0.05                      |
| Mean 2018 | -0.08          | 0.34           | 0.11        | 0.04                      |
Figure 8: NDVI in the area below mean LST: (a-b) 2002, (c-d) 2006, (e-g) 2010, (h-k) 2014, and (l-o) 2018. The black portion of the maps shows the area above mean LST.
data, whereas these values were lower for Landsat 5 or Landsat 7 data. This variation of mean NDVI in different Landsat sensors is mainly due to the configuration of the sensors as the spectral resolution of NIR band of Landsat 8 data (0.851–0.879 μm wavelength) is different from the NIR band of Landsat 5 data (0.760–0.900 μm wavelength) or Landsat 7 data (0.770–0.900 μm wavelength). Further, the year-wise analysis of NDVI has been shown in Figure 10. The diagram shows that the values of maximum NDVI are gradually decreasing with time, whereas the values of minimum NDVI and mean NDVI are increasing. The result is quite significant as it reflects the loss of urban vegetation within the entire time period.

4.5. LST-NDVI Correlation in the Whole City, Above Mean LST Areas, and Below Mean LST Area. LST builds a strong to moderate stable negative correlation with NDVI in the whole Raipur City during the study period. Figure 11 shows a date-wise correlation. The LST-NDVI correlation is moderate to strong negative for the whole area, whereas the correlation does not show any specific pattern for below mean LST zones and above mean LST zones, separately. Figure 12 shows a year-wise correlation. The negativity was almost gradually decreased with time. In the area above mean LST, this correlation is moderately negative and it is stable as these regions mainly cover a high proportion of urban vegetation. In the area below mean LST, LST builds a

| Date of acquisition | NDVI (minimum) | NDVI (maximum) | NDVI (mean) | NDVI (standard deviation) |
|---------------------|----------------|----------------|-------------|---------------------------|
| Mean                | −0.23          | 0.57           | 0.04        | 0.10                      |
| Mean                | −0.19          | 0.52           | 0.11        | 0.09                      |
| Mean                | −0.21          | 0.50           | 0.04        | 0.08                      |
| Mean                | −0.11          | 0.48           | 0.17        | 0.07                      |
| Mean                | −0.12          | 0.44           | 0.14        | 0.06                      |

**Table 7: Temporal variations of NDVI in the area below mean LST (2002–2018).**
moderate to weak correlation with NDVI and some fluctuations are present in this relationship due to the different land compositions.

5. Conclusion

The present study monitors the LST-NDVI correlation using different Landsat satellite sensors of the premonsoon season for a specific time interval. Mean LST was a significant measurement for the study as it performs in the area above mean LST as well as in the area below mean LST along with the whole Raipur City. From 2002 to 2018 premonsoon months, the LST was increased by 11.62°C. The LST-NDVI correlation was negative for the study area throughout the period. For Landsat 8 data, mean NDVI values are higher than the other Landsat sensors and thus, the mean NDVI values become higher in recent times. The area below mean LST has a weaker correlation than the area above mean LST. The strength of the correlation was reduced gradually with time. Future urban and environmental planning in the premonsoon season can be implemented using the spatio-temporal variation of LST-NDVI relationship.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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