Research Article

Monitoring LST-NDVI Relationship Using Premonsoon Landsat Datasets

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Received 23 December 2019; Revised 5 February 2020; Accepted 7 February 2020; Published 9 June 2020

Academic Editor: Haydee Salmun

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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.

FIGURE 1: Location of the study area.

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

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 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.

TABLE 3: Temporal variations in the distribution of LST (oC) (2002–2018).

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

FIGURE 3: Distribution of mean LST (°C): (a) 2002 (b) 2006 (c) 2010 (d) 2014 (e) 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

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

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:

$$\rho\lambda = M\rho \times Q_{cal} + A\rho, \quad (1)$$

where $\rho\lambda$ 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), $M\rho$ is the reflectance multiplicative scaling factor for the band (REFLECTANCE_MULT_BAND_n from the metadata), and $A\rho$ 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 θ_s by the following equation:

$$\rho'\lambda = \frac{\rho\lambda}{\sin(\theta_s)}. \quad (2)$$

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

$$L\lambda = ML \times Q_{cal} + AL, \quad (3)$$

where $L\lambda$ is the spectral radiance at TOA in $Wm^{-2}sr^{-1}mm^{-1}$, Q_{cal} is the Level 1 pixel value in Digital Number (DN), ML is the radiance multiplicative scaling factor for the band (RADIANCE_MULT_BAND_n from the metadata), and AL 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 monowindow 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:

$$L_\lambda = \text{RadianceMultiBand} \times \text{DN} + \text{RadianceAddBand}, \quad (4)$$

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

$$T_b = \frac{K_2}{\ln((K_1/L_\lambda) + 1)}, \quad (5)$$

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

FIGURE 4: Variation in the distribution of NDVI: (a1-a2) 2002 (b1-b2) 2006 (c1-c3) 2010 (d1-d4) 2014 (e1-e4) 2018.

FIGURE 5: Distribution of mean NDVI: (a) 2002, (b) 2006, (c) 2010, (d) 2014, and (e) 2018.

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

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

$d\epsilon$ is the geometric distribution effect for the natural surface and internal reflection. The value of $d\epsilon$ may be 2% for mixed and elevated land surfaces.

$$d\epsilon = (1 - \epsilon_s)(1 - F_v)F\epsilon_v, \quad (7)$$

where ϵ_s is soil emissivity; F_v is fractional vegetation; F is a shape factor (0.55); and ϵ_v is vegetation emissivity.

$$\epsilon = \epsilon_v F_v + \epsilon_s (1 - F_v) + d\epsilon, \quad (8)$$

where ϵ is land surface emissivity. The value of ϵ is calculated by the formula given below:

$$\epsilon = 0.004 \times F_v + 0.986. \quad (9)$$

Water vapour content is determined by the following equation:

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

where w is water vapour content (g/cm^2); 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 τ is the total atmospheric transmittance.

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

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.

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

$$T_a = 17.9769 + 0.91715T_0,$$

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

$$C = \varepsilon\tau,$$

$$D = (1 - \tau)[1 + (1 - \varepsilon)\tau],$$

(12)

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 used to estimate 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

[56]. After performing the downscaling process, a significant correlation 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. 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

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.

TABLE 7: Temporal variations of NDVI in the area below mean LST (2002–2018).

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

FIGURE 9: Temporal variation of mean NDVI for each satellite image.

FIGURE 10: Year-wise analysis of NDVI.

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 ($0.851\text{--}0.879\text{ }\mu\text{m}$ wavelength) is different from the NIR band of Landsat 5 data ($0.760\text{--}0.900\text{ }\mu\text{m}$ wavelength) or Landsat 7 data ($0.770\text{--}0.900\text{ }\mu\text{m}$ 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

FIGURE 11: Date-wise LST-NDVI correlation analysis.

FIGURE 12: Year-wise LST-NDVI correlation analysis.

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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