COVID-19 lockdown effect on land surface temperature and normalized difference vegetation index

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ABSTRACT
Coronavirus disease (COVID-19) has changed the human lifestyle just like a disaster in 2020. Many people died throughout the world due to its severe attack. Lockdown is the most common term used in today’s life to prevent the adverse effect of COVID-19. However, during the lockdown period, a significant improvement in the urban environment was noticed in almost every part of the world. During the lockdown period, the decrease in the number of running vehicles and moving people on the road lowers the pollution level and it has a direct positive impact on the urban environment. The study examines the changes found in land surface temperature (LST) and normalized difference vegetation index (NDVI) during the lockdown period in Raipur city, India with the earlier periods (2013–19) to compare the environmental status. The results indicate that the LST is reduced and NDVI is increased significantly during the lockdown period, and the negativity of the LST-NDVI correlation is increased remarkably. The study also shows a better ecological status of the city during the lockdown period. The study is useful for environmental strategists and urban planners.

1. Introduction
COVID-19 has been spread by severe acute respiratory syndrome coronavirus-2 which has affected more than 219 countries and territories till 3 March 2021. Over 115.365 million total cases of COVID-19 patients were reported so far among whose 2.562 million people were died (https://www.worldometers.info/coronavirus). The most affected countries are the United States of America, India, Brazil, Russia, the United Kingdom, France, Spain, Italy, Turkey, Germany, Colombia, Argentina, Mexico, Poland, Iran, South Africa, Ukraine, Indonesia, Peru, Czechia, and the Netherlands. In each of these countries, at least 1 million people have been affected by the virus. The whole world is looking for its vaccine or suitable medicine for a long time which is still not available in the market. The World Health Organization
(WHO) and the government of individual countries have repeatedly presented several preventive methods to restrict the spreading of this disease. Lockdown is the most popular and effective method among them. As the common people of different countries did not maintain the basic steps to protect themselves from the severe effect of COVID-19, the lockdown was very necessary to stop the contamination process. In the lockdown process, people are compelled to stay at home without any emergency or medical purpose. Academic institutions, public and private offices, restaurants, banks, public and private transports, factories, shops, etc. are entirely closed at the time of proper lockdown.

The lockdown process slows down the environmental pollution and develops a less polluted ecologically rich society (Bashir et al. 2020; Chakraborty and Maity 2020; Garg et al. 2020; Gupta et al. 2020; Mandal and Pal 2020; Mollalo et al. 2020; Öcal et al. 2020; Pandey et al. 2020a, 2020b; Saadat et al. 2020; Şahin 2020; Sharma et al. 2020; Shi et al. 2020; Yunus et al. 2020; Zambrano-Monserrate et al. 2020). The restricted transportation system and industrial activities reduce the air pollution level and enhance air quality. The vegetation grows at a fast rate without any kind of interruption. The immediate positive effect of this lockdown on the environment was noticed in the reduction of air temperature and land surface temperature (LST) (Shi et al. 2020; Yunus et al. 2020). Some valuable studies were conducted in the Indian context to show the improvement of air quality during the lockdown period in India (Chauhan and Singh 2020a, 2020b; Garg et al. 2020; Singh and Chauhan 2020a, 2020b).

LST primarily depends on the land surface composition and solar radiation (Guha et al. 2018; Peng et al. 2016). The vegetation surface generates a low amount of LST, whereas the man-made concrete land surface reflects a high amount of LST (Li et al. 2017). Hence, LST has a broad impact on the planning and development of land utilization management systems (Guha and Govil 2020a, 2020b, 2020c). Normalized difference vegetation index (NDVI) is widely considered as the most significant remote sensing index that regulates the variation of LST (Chen et al. 2006). The LST and NDVI normally generate an inverse correlation (Chen et al. 2006). The improvement of air pollution and the increase of moisture in air predominantly increase the strength of the LST-NDVI correlation (Govil et al. 2019, 2020).

The complete lockdown process in India was started on 25 March 2020 and ended on 31 May 2020. It was broken into four phases as follows:
First Phase: 25 March 2020 – 14 April 2020
Second Phase: 15 April 2020 – 3 May 2020
Third Phase: 4 May 2020 – 17 May 2020
Fourth Phase: 18 May 2020 – 31 May 2020

After the lockdown phases, unlock phases were started and it is still going. The unlock phases were broken into the following phases till 28 February 2021:
Unlock Phase 1.0: 1 June 2020 – 30 June 2020
Unlock Phase 2.0: 1 July 2020 – 31 July 2020
Unlock Phase 3.0: 1 August 2020 – 31 August 2020
Unlock Phase 4.0: 1 September 2020 – 30 September 2020
Unlock Phase 5.0: 1 October 2020 – 31 October 2020
Unlock Phase 6.0: 1 November 2020 – 30 November 2020
Unlock Phase 7.0: 1 December 2020 – 30 December 2020
Unlock Phase 8.0: 1 January 2021 – 31 January 2021
Unlock Phase 9.0: 1 February 2021 – 28 February 2021
Unlock Phase 10.0: 1 March 2021 – 31 March 2021 (ongoing)

The key objective of the case study is to examine the immediate effect during the lockdown period in Raipur city of India on the LST, NDVI, and LST-NDVI relationship. Another objective is to evaluate the effect of lockdown on the thermal comfort level of the city. The study can be appraised for future urban planners to develop better environmental planning and management system.

2. Study area

Figure 1 shows the geographical location of Raipur city of India which extends from 21°11’22'”N to 21°20’02’”N and from 81°32’20”E to 81°41’50”E. The city covers an area of around 165 km². Figure 1(a) presents the outline map of India where Chhattisgarh State is located in the middle part (http://www.surveyofindia.gov.in). Figure 1(b) presents the outline map of Chhattisgarh State with districts (http://www.surveyofindia.gov.in). Figure 1(c) represents the false colour composite (FCC) image of Raipur city (https://raipur.gov.in) from recent Landsat 8 OLI/TIRS data of 18 May 2020 (https://www.earthexplorer.usgs.gov). Figure 1(d) indicates the digital elevation map (DEM) of Raipur city produced by the ArcGIS software using the last available ASTER DEM data of 11 October 2011 (https://www.earthexplorer.usgs.gov). The city is characterised by the tropical dry and wet type of climate (http://www.imdraipur.gov.in). The mean monthly temperature ranges from 12 to 42 °C. May presents the
highest average temperature (35°C), while December presents the lowest average temperature (20°C). The highest average rainfall (327 mm) is observed in July. March, April, and May are considered as the summer or pre-monsoon months.

3. Materials and methods

In the study, level-1 eighteen Landsat 8 OLI/TIRS data for April and May from 2013 to 2020 were obtained from the United States Geological Survey (USGS) Data Centre (https://www.earthexplorer.usgs.gov). Red, NIR, and TIR bands were required for the research work. The spatial resolution of band 4, band 5, and band 10 of OLI/TIRS data are 30, 30, and 100 m, respectively. The original TIR band 10 was resampled into 30 m spatial resolution by the USGS data centre using the cubic convolution resampling method for further application. The entire research work was performed by using the ArcGIS 9.3 software (https://www.esri.com). The spatial analyst tools of ArcGIS software were used for the raster calculations, correlation analysis, and LST analysis. The following sub-sections are included in the whole methodology section: (1) estimation of LST, (2) determination of NDVI.

3.1. Estimation of LST

LST was estimated from OLI/TIRS sensor by using the mono-window algorithm (MWA) (Qin et al. 2001; Sekertekin and Bonafoni 2020; Wang et al. 2015, 2019). The MWA requires three essential parameters like surface emissivity, atmospheric transmittance, and effective mean atmospheric temperature for LST determination. Although OLI/TIRS data has two TIR bands, band 10 is appropriate for the LST retrieval method as band 11 has larger uncertainty (Barsi et al. 2014; Montanaro et al. 2014).

Equation (1) converts the pixel values of the TIR band into spectral radiance (Zanter 2019).

\[
L_\lambda = M_L Q_{CAL} + A_L
\]

where \( L_\lambda \) = TOA spectral radiance (Wm\(^{-2}\)sr\(^{-1}\)mm\(^{-1}\)), \( M_L \) = band-specific multiplicative rescaling factor, \( A_L \) = band-specific additive rescaling factor, \( Q_{CAL} \) = quantized and calibrated standard product pixel values.

Equation (2) converts the pixel values directly into spectral reflectance (Zanter 2019).

\[
\rho_\lambda = \frac{M_\rho Q_{CAL} + A_\rho}{\sin \theta_{SE}}
\]

where \( \rho_\lambda \) = spectral reflectance, \( M_\rho \) = band-specific multiplicative rescaling factor, \( A_\rho \) = band-specific additive rescaling factor, \( Q_{CAL} \) = quantized and calibrated standard product pixel values, \( \theta_{SE} \) = local sun elevation angle.

Equation (3) converts the spectral radiance into at-sensor brightness temperature (Wukelic et al. 1989):
where \( T_b \) = brightness temperature (Kelvin), \( L_k \) = spectral radiance \((\text{Wm}^{-2} \text{sr}^{-1} \text{mm}^{-1})\), \( K_1 \) and \( K_2 \) are calibration constants. For OLI/TIRS data, \( K_1 = 774.89 \), \( K_2 = 1321.08 \) \((\text{Wm}^{-2} \text{sr}^{-1} \text{mm}^{-1})\).

Equation (4) determines the fractional vegetation of each pixel (Carlson and Ripley 1997):

\[
F_v = \left( \frac{NDVI - NDVI_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \right)^2
\]

where \( F_v \) = fractional vegetation, \( \text{NDVI}_{\text{min}} \) = minimum NDVI value, \( \text{NDVI}_{\text{max}} \) = maximum NDVI value.

Equations (5–6) show the relationship among \( \varepsilon, \varepsilon_v, \varepsilon_s, F_v \), and \( d\varepsilon \) (Sobrino et al. 2004).

\[
d\varepsilon = (1-\varepsilon_s)(1-F_v)\varepsilon_v
\]

\[
\varepsilon = \varepsilon_v F_v + \varepsilon_s (1-F_v) + d\varepsilon
\]

where \( \varepsilon = \) land surface emissivity, \( d\varepsilon = \) effect of the geometrical distribution of the natural surfaces and internal reflections, \( \varepsilon_v = \) vegetation emissivity, \( \varepsilon_s = \) soil emissivity, \( F_v = \) fractional vegetation.

Equation (7) calculates the land surface emissivity (Sobrino et al. 2004).

\[
\varepsilon = 0.004 \times F_v + 0.986
\]

where \( \varepsilon = \) land surface emissivity, \( F_v = \) fractional vegetation.

Equation (8) calculates the water vapour content (Yang and Qiu 1996):

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

where \( w = \) water vapour content \((\text{g/cm}^2)\), \( T_0 = \) near-surface air temperature (Kelvin), \( RH = \) relative humidity (%). These atmospheric parameters were provided by the Meteorological Centre, Raipur.

Equation (9) estimates the atmospheric transmittance of Raipur (Qin et al. 2001):

\[
\tau = 1.031412 - 0.11536w
\]

where \( \tau = \) total atmospheric transmittance, \( w = \) water vapour content \((\text{g/cm}^2)\).

Equation (10) estimates the effective mean atmospheric transmittance of Raipur (Qin et al. 2001):
where \( T_a \) = mean atmospheric temperature, \( T_0 \) = near-surface air temperature.

Equations (11–12) computes the internal parameters \( C \) and \( D \) and Eq. (13) retrieves LST from OLI/TIRS data (Qin et al. 2001):

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

where \( \varepsilon \) = land surface emissivity, \( \tau \) = total atmospheric transmittance, \( C \) and \( D \) are internal parameters based on atmospheric transmittance and land surface emissivity, \( T_s \) = land surface temperature, \( T_a \) = mean atmospheric temperature, \( T_b \) = at-sensor brightness temperature, \( a = -67.355351 \), \( b = 0.458606 \).

**3.2. Determination of NDVI**

The study used NDVI (Tucker 1979) as a significant remote sensing index to estimate the impact of the changing environment on LST.

Equation (14) expresses the formula of NDVI:

\[
NDVI = \frac{NIR - Red}{NIR + Red}
\]

For OLI/TIRS data, NIR and red bands are bands 5 and 4, respectively. The value of NDVI lies between \(-1\) (the extreme negative value) and \(+1\) (the extreme positive value). The negative NDVI values generally indicate water bodies, whereas high positive NDVI values correspond to green and healthy vegetation covers. Values near to 0 or slightly positive indicate sealed areas or barren lands.
Table 1. Comparison of LST and LST-NDVI correlation (significant at 0.05 level) in April and May from 2013 to 2020 using Landsat 8 OLI/TIRS data [Data during the lockdown period have been shown as bold italic font].

| Date of acquisition | Time (UTC) | Cloud cover (%) | LST (°C) | NDVI | Correlation coefficients for LST-NDVI relationship |
|---------------------|------------|-----------------|----------|------|-----------------------------------------------------|
|                     |            |                 | Min.     | Max.  | Mean  | SD | Min. | Max.  | Mean  | SD |                    |
| April               |            |                 |          |       |       |    |      |       |       |    |                     |
| 2013-Apr-08         | 04:59      | 0               | 29        | 47    | 41    | 2.58 | -0.17 | 0.55 | 0.11 | 0.61 | -0.46 |
| 2014-Apr-02         | 04:56      | 0               | 28        | 43    | 36    | 1.99 | -0.13 | 0.52 | 0.14 | 0.07 | -0.45 |
| 2015-Apr-05         | 04:55      | 0               | 27        | 43    | 37    | 2.08 | -0.13 | 0.49 | 0.12 | 0.06 | -0.45 |
| 2016-Apr-23         | 04:55      | 0               | 30        | 49    | 43    | 2.27 | -0.16 | 0.55 | 0.13 | 0.07 | -0.47 |
| 2017-Apr-10         | 04:55      | 0               | 27        | 44    | 38    | 2.18 | -0.14 | 0.48 | 0.11 | 0.06 | -0.47 |
| 2017-Apr-26         | 04:55      | 2               | 29        | 49    | 42    | 2.57 | -0.19 | 0.59 | 0.12 | 0.07 | -0.51 |
| 2020-Apr-02         | 04:55      | 0               | 26        | 43    | 35    | 2.09 | -0.12 | 0.55 | 0.19 | 0.09 | -0.57 |
| 2020-Apr-18         | 04:55      | 1               | 27        | 38    | 33    | 1.48 | -0.09 | 0.52 | 0.17 | 0.07 | -0.53 |
| May                 |            |                 |          |       |       |    |      |       |       |    |                     |
| 2013-May-01         | 04:57      | 0               | 28        | 42    | 37    | 1.72 | -0.13 | 0.56 | 0.13 | 0.06 | -0.48 |
| 2013-May-17         | 04:58      | 2               | 28        | 46    | 40    | 2.22 | -0.12 | 0.52 | 0.12 | 0.06 | -0.44 |
| 2014-May-20         | 04:55      | 5               | 26        | 39    | 35    | 1.72 | -0.07 | 0.45 | 0.12 | 0.05 | -0.41 |
| 2015-May-07         | 04:55      | 0               | 27        | 40    | 35    | 1.81 | -0.09 | 0.49 | 0.14 | 0.05 | -0.42 |
| 2015-May-23         | 04:55      | 9               | 25        | 42    | 36    | 2.26 | -0.07 | 0.43 | 0.12 | 0.05 | -0.35 |
| 2016-May-25         | 04:55      | 0               | 28        | 41    | 37    | 1.65 | -0.07 | 0.47 | 0.12 | 0.05 | -0.38 |
| 2017-May-12         | 04:55      | 0               | 29        | 43    | 38    | 1.89 | -0.17 | 0.55 | 0.14 | 0.06 | -0.29 |
| 2018-May-15         | 04:55      | 0               | 30        | 44    | 37    | 1.92 | -0.09 | 0.40 | 0.13 | 0.05 | -0.46 |
| 2019-May-18         | 04:55      | 0               | 29        | 45    | 40    | 2.12 | -0.18 | 0.51 | 0.12 | 0.06 | -0.44 |
| 2020-May-04         | 04:55      | 3               | 29        | 41    | 35    | 1.67 | -0.16 | 0.57 | 0.18 | 0.08 | -0.53 |

*IST = UTC + 0530 (IST = Indian standard time, UTC = coordinated universal time).

The total methodology of the present study is shown by a simple flowchart in Figure 2.

4. Results and discussion

Table 1 represents the values of LST, NDVI, and the LST-NDVI correlation coefficients before 2020 and during the lockdown period of 2020 due to COVID-19. The effects have been discussed separately as follows:

4.1. Effect of lockdown on LST

The minimum LST values in the earlier images of April month (28.64, 27.92, 27.30, 30.22, 27.35, and 29.47 °C) were quite higher compared to the minimum LST values in the lockdown images of April month (26.21 and 27.08 °C). The maximum LST values also show similar result (47.38, 43.52, 43.34, 49.45, 44.58, 49.39 °C LST in the earlier images and 43.30, 38.38 °C LST during the lockdown period). The mean LST values during the lockdown period of April month (35.10 and 33.47 °C) were quite lower compared to the mean LST values in the lockdown images of April month (40.88, 36.61, 36.79, 42.97, 38.37, and 42.06 °C). The average value of the mean LST of April during the lockdown period (34.29 °C) is 5.3 °C lower than the earlier years (39.61 °C). Like April, a similar type of result regarding LST is found in May also. The average value of the mean LST of May during the lockdown period (35.49 °C) is 2.30 °C lower than the earlier years (37.59 °C). The result indicates a positive change during the lockdown phase. It is mainly because of the low concentration of the population and various types of vehicles on the road. The reduction of transport and
industrial pollutants performs a crucial role in the reduction of mean LST during the lockdown period in Raipur City.

Figures 3 and 4 shows the spatial distribution of LST of Raipur city of April and May from 2013 to 2020. During the lockdown period, LST was reduced throughout the area. In 2020, LST reduced significantly spatially from west to east and from south to north. It shows a nice result for our environment. The health status of vegetation covers increased prominently and pollution levels decreased at a significant rate. It helps to decrease the LST directly.

4.2. Effect of lockdown on NDVI

Figures 5 and 6 present the NDVI distribution map for April and May from 2013 to 2020. The lockdown phases had a great effect on NDVI. The three dates (2 April 2020, 18 April 2020, and 4 May 2020) of the lockdown phase show a higher value of mean NDVI (0.19, 0.17, and 0.18 on 2 April 2020, 18 April 2020, and 4 May 2020,
respectively) than the images of earlier years (Table 1). The low level of pollution and the health status of vegetation not impacted by anthropic disturbance (emission, traffic, industrial activities, etc.) reflect an increase in NDVI. It is very clear from Figures 4(g, h), and 5(j) that overall NDVI values were enhanced in the southwest and northeast portions of the area during the lockdown period. It is a positive sign of the lockdown period.
4.3. Effect of lockdown on LST-NDVI relationship

The LST–NDVI relationship was analyzed by applying Karl Pearson’s linear correlation coefficient method. These correlation coefficients were negative throughout the research period (2013–2020). A two-tailed test was performed at a significance level of 0.05 for the correlation analysis. Table 1 shows a clear picture of the correlation analysis in both April and May. In April 2020 (lockdown period), the correlation coefficients were $-0.57$ (2 April 2020) and $-0.53$ (18 April 2020). These numerical figures are quite higher than the earlier years, e.g. $-0.46$ in 8 April 2013, $-0.45$ in 2 April 2014, $-0.45$ in 5 April 2015, $-0.47$ in 23 April 2016, $-0.51$ in 10 April 2017, $-0.47$ in 26 April 2017. The average LST-NDVI correlation coefficient of the lockdown period for April month was $-0.55$ that was higher than the average of the earlier years ($-0.47$).

The result was almost similar in May. In May 2020 (lockdown period), the correlation coefficient was $-0.53$ (4 May 2020). It is higher than the earlier years, e.g. $-0.48$ in 1 May 2013, $-0.44$ in 17 May 2013, $-0.41$ in 20 May 2014, $-0.42$ in 7 May.
The LST-NDVI correlation coefficient of the lockdown period for May month was 0.53 that was much higher than the average of the earlier years (-0.41). This analysis presents a positive impact of COVID-19 on our natural environment as the lockdown period enhances the LST-NDVI correlation coefficient. It was the combined result of a decrease in LST and an increase in NDVI.

Figure 6. Spatial distribution of NDVI in May: (a–i) 2013–19 (earlier period); (j) 2020 (lockdown period).

2015, −0.35 in 23 May 2015, −0.38 in 25 May 2016, −0.29 in 12 May 2017, −0.46 in 15 May 2018, −0.44 in 18 May 2019. The LST-NDVI correlation coefficient of the lockdown period for May month was −0.53 that was much higher than the average of the earlier years (-0.41). This analysis presents a positive impact of COVID-19 on our natural environment as the lockdown period enhances the LST-NDVI correlation coefficient. It was the combined result of a decrease in LST and an increase in NDVI.
It can be considered that if the pollution level is controlled like the lockdown period, the negativity of the LST-NDVI correlation must be increased and a better environmental system can be achieved.

Figure 7 shows the comparison between the LST and NDVI values and their correlation between the lockdown period of 2020 and the earlier years since 2013. In the lockdown period, LST decreases at a high percentage than the previous years (up to 22% in April and up to 12% in May) (Figure 7(a1–a3)). It is clear that the value of NDVI increases up to 73% in April and up to 50% in May in the lockdown period compared to the previous years due to the interrupted growth of green vegetation (Figure 7(b1–b3)). Thus, a negative LST-NDVI correlation was observed throughout the entire period. But, the strength of this negative correlation or the negativity of the correlation was increased at a high percentage, e.g. up to 27% in April and up to 83% in May (Figure 7(c1–c3)). It was a great achievement of the lockdown period in the natural environment.

4.4. Effect of lockdown on the thermal comfort level of the city

Some thermal comfort indices are available for evaluating the ecological quality of urban life. In this study, the urban thermal field variance index (UTFVI) was used for the evaluation of the thermal comfort level of Raipur city during the lockdown period. UTFVI is calculated using the Eq. 15 (Guha et al. 2017):

$$UTFVI = \frac{T_s - T_{mean}}{T_{mean}}$$

(15)

Where, $UTFVI = \text{Urban Thermal Field Variance Index}$
The UTFVI values of Raipur city were divided into six following categories (Table 2).

Figures 8 and 9 present the spatial distribution map of UTFVI for April and May, respectively. Table 3 shows the percentage of area under different UTFVI categories for each image. The city has two extreme categories for ecological evaluation: the

| 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                      |

Figure 8. Spatial distribution of UTFVI in April: (a–f) 2013–17 (earlier period); (g–h) 2020 (lockdown period).

\[ T_s = LST \ (°C) \]
\[ T_{mean} = \text{Mean LST} \ (°C) \]

The UTFVI values of Raipur city were divided into six following categories (Table 2).

Figures 8 and 9 present the spatial distribution map of UTFVI for April and May, respectively. Table 3 shows the percentage of area under different UTFVI categories for each image. The city has two extreme categories for ecological evaluation: the
excellent category (UTFVI < 0) and the worst category (UTFVI > 0.020). Most of
the areas of Raipur (> 45% during the entire period) having an excellent thermal
condition (UTFVI < 0) where vegetation and water bodies are present in a high
ratio. The central and southwest portions experience excellent thermal conditions.
However, the worst category (UTFVI > 0.020) of the ecological evaluation index also
exists in a large portion (>31% during the entire period) in the northwest, north,
east, and southeast parts. Here, most of the lands are impervious (either bare land with exposed rock surface or under built-up areas). The normal thermal condition ($0.005 < \text{UTFVI} < 0.010$) is found in some small patches surrounding the vegetation and water areas while the worse condition ($0.015 < \text{UTFVI} < 0.020$) exists around the areas of the built-up class.

During the lockdown period, the area under the worst ecological condition ($<33\%$ of the total area) has been decreased at a significant rate than the previous years. However, all the satellite images of the previous periods include areas belonging to the worst ecological condition and exceeding $>35\%$. The climatic conditions remain almost unchanged throughout the period and no precipitation has occurred during this time. Only the percentage of relative humidity is increased during the lockdown period due to reduced air pollution (Table 4). Besides, Figure 10 and Table 5 show that the built-up area is increased (27.42%) and the area covered by vegetation is decreased (26.73%) during this total period of study. Hence, it may be stated that the city has experienced a better ecological and thermal condition during the lockdown period.

### 5. Conclusion

The study examines the value of LST, NDVI, and LST-NDVI correlation coefficient to compare the environmental condition of Raipur city in the lockdown period and the earlier times. A total of eighteen Landsat 8 OLI/TIRS data of April (eight) and May (ten) months from 2013 to 2020 were used for this investigation. The results show that the value of LST reduced and the value of NDVI increased in the lockdown period (25 March 2020 – 31 May 2020) due to the sudden stop of industrial and transport activities in Raipur. The negativity of the LST-NDVI correlation was also increased significantly during the lockdown period. It shows that the natural
environment becomes less polluted and ecologically more comfortable compared to the previous years and before the lockdown period.

The study is very much useful for urban planners as the results depict the positive impact of the lockdown period on the land surface of Raipur city and surrounding areas. As green areas and water bodies are the main responsible land covers for the generation of low LST zones, city planners should focus more on the land conversion process. The urban planners should convert the existing bare lands into vegetation and water surface. To conserve the ecological condition, tree plantation is quite necessary along the roads, commercial buildings, and residential apartments.

Table 4. Description of some meteorological components [Data during the lockdown period have been shown in bold italic font].

| Date of acquisition | Rainfall (mm) | Air temperature (°C) | Air pressure (mbar) | Relative humidity (%) | Wind speed (km/h) |
|---------------------|---------------|----------------------|---------------------|----------------------|-------------------|
| April               |               |                      |                     |                      |                   |
| 2013-Apr-08         | 0             | 34                   | 1007                | 24                   | 0                 |
| 2014-Apr-02         | 0             | 33                   | 1007                | 28                   | 4                 |
| 2015-Apr-05         | 0             | 33                   | 1006                | 27                   | 6                 |
| 2016-Apr-23         | 0             | 36                   | 1003                | 22                   | 6                 |
| 2017-Apr-10         | 0             | 34                   | 1010                | 12                   | 5                 |
| 2017-Apr-26         | 0             | 36                   | 1006                | 20                   | 5                 |
| 2020-Apr-02         | 0             | 34                   | 1009                | 57                   | 2                 |
| 2020-Apr-18         | 0             | 32                   | 1008                | 44                   | 4                 |
| May                 |               |                      |                     |                      |                   |
| 2013-May-01         | 0             | 36                   | 1004                | 40                   | 12                |
| 2013-May-17         | 0             | 39                   | 1000                | 20                   | 6                 |
| 2014-May-20         | 0             | 33                   | 1006                | 31                   | 10                |
| 2015-May-07         | 0             | 32                   | 1008                | 38                   | 12                |
| 2015-May-23         | 0             | 35                   | 1000                | 18                   | 12                |
| 2016-May-25         | 0             | 36                   | 1000                | 30                   | 7                 |
| 2017-May-12         | 0             | 35                   | 1009                | 41                   | 4                 |
| 2018-May-15         | 0             | 34                   | 1007                | 49                   | 6                 |
| 2019-May-18         | 0             | 38                   | 1005                | 26                   | 6                 |
| 2020-May-04         | 0             | 32                   | 1007                | 46                   | 4                 |

Table 5. Total area (km²) under different types of LULC in 2013 and 2020.

| Date of acquisition | Green vegetation | Built-up area and bare land | Water bodies |
|---------------------|------------------|-----------------------------|--------------|
| 08 April 2013       | 82.13            | 80.78                       | 1.32         |
| 18 April 2020       | 60.18            | 102.93                      | 1.12         |

Figure 10. LULC map of Raipur city: (a) 2013, (b) 2020.
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Disclosure statement

No potential conflict of interest was reported by the authors.

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