A long-term monthly analytical study on the relationship of LST with normalized difference spectral indices

Subhanil Guha and Himanshu Govil

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

Abstract

This study analyzes the long-term monthly variation of land surface temperature (LST) and its relationship with normalized difference spectral indices in the Raipur City of India using one hundred and 23 Landsat images from 1988 to 2020. In specific, the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), normalized difference built-up index (NDBI), and normalized difference bareness index (NDBal) were used to show the relationship between LST and land surface materials. In terms of LST, the warmest month is April (38.49°C) and the coldest month is January (23.04°C). The standard deviation in LST is noticed as 1.1022°C throughout the period. The growth pattern of LST is increasing in the earlier stage while it is steady and decreasing in the later stage. The linear regression method is used to correlate LST with the spectral indices. The mean regression coefficients for LST-NDVI is -0.42, LST-NDBI are 0.68, LST-NDWI is 0.27, and LST-NDBal is 0.32. It indicates that the high ratio of green vegetation and water bodies resist the raise of LST, whereas the bare rock surface and built-up land accelerate the LST. The value of the spectral indices and LST varies with the change of month due to the physical change of the land surface materials. Hence, the study will be an effective one for the town and country planners for their future estimation of land conversion.

Introduction

Urbanization accelerates the ecological stress by warming the local or global cities for a large extent (Foley et al., 2005; Fu & Weng, 2016; Grimm et al., 2008; Liu et al., 2018; Peng et al., 2018a). Presently, many urban areas are suffering with a huge land conversion and resultant new heat zones (Huang et al., 2009; Patz et al., 2005; Zhou et al., 2019). Remote sensing techniques are significantly effective in detecting the land use/land cover (LULC) change and its consequences (Guha et al., 2018). Apart from the conventional LULC classification algorithms, some spectral indices are used in detecting specific land features. Recently, thermal infrared (TIR) bands are used by generating some indices for different types of LULC extraction (Kalnay & Cai, 2003; Peng et al., 2018b; X-L. Chen et al., 2006). These remote sensing indices are used significantly in various application fields like rocks and mineral mapping, forest mapping, agricultural monitoring, LULC mapping, hazard mapping, urban heat island mapping, and monitoring (Berger et al., 2017; Chen et al., 2006; Du et al., 2016; He et al., 2019; Peng et al., 2016).

Land surface temperature (LST) retrieved from various remotely-sensed data is widely used in the detection of urban heat island and ecological comfort zone (Fu & Weng, 2015; Hao et al., 2016; Tomlinson et al., 2011; Tran et al., 2017; Weng, 2009). LST can be changed significantly in a vast homogeneous land surface or even inside a relatively small heterogeneous urban area (Hou et al., 2010; X-L. Chen et al., 2006). Different types of LULC response differently in TIR band and consequently LST largely varies in an urban environment (Estoque et al., 2017; Ghobadi et al., 2014; Li et al., 2016; Shigeto, 1994; Stroppiana et al., 2014; Yue et al., 2007). The LULC types are mainly changed by land conversion process. Thus, time is an important factor in LST monitoring. These spatial and temporal data of LST is also varied with the seasonal changes as sun elevation and sun azimuth are changed with seasons. Hence, the seasonal variation of LST is quite important in any LULC related study.

Most popular index for vegetation is normalized difference vegetation index (NDVI) that is invariably used in LST-related studies from the very beginning (Tucker, 1979; Smith & Choudhury, 1990; Hope & McDowell, 1992; Julien, ; Yuan et al., 2017). NDVI is directly used in the determination of land surface emissivity and thus is a significant factor for LST estimation (Carlson & Ripley, 1997; Sobrino et al., 2004). Generally, the nature of LST–NDVI relationship in a region is negative and is controlled by a number of factors, such as, dry or wet vegetation, greenness of vegetation, air pollution, moisture content in air, heterogeneous man-made materials, dry or wet soil, etc. (Ghobadi et al., 2014; Qu et al., 2014; Zhou et al., 2011). In mixed urban land, high LST is related to low vegetal
covered area (Voogt & Oke, 2003). NDVI depends on the method that computes LST (e.g., NDVI threshold method) (Goward et al., 2002) and many studies based on the LST-NDVI correlation (Gutman & Ignatov, 1998; Weng et al., 2004) are available to explore the pattern of LST. There are so many valuable research articles found on LST–NDVI relationships were conducted mainly in the Indian and Chinese landscape (Guha et al., 2020; Gui et al., 2019; Kikon et al., 2016; Kumar & Shekhar, 2015; Qu et al., 2020; Yuan et al., 2020). Normalized difference water index (NDWI) is the most popular index for extraction of water bodies and it is considerably used in LULC and LST related studies (Essa et al., 2012; McFeeters, 1996; X-L. Chen et al., 2006; Yuan et al., 2017). Generally, the nature of LST–NDWI relationship in an urban area is insignificant which is controlled by several factors, such as humidity, vegetation, wetland, bare land, air pollution, rock surface, dry or wet soil, heterogeneous man-made materials, etc. (Ghobadi et al., 2014; McFeeters, 1996, 2013). Normalized difference built-up index (NDBI) is the most popular built-up index which is invariably used in LST-related studies (Chen el al., 2013; Yuan et al., 2017; Zha et al., 2003). Generally, the nature of LST–NDBI relationship in a region is positive and is controlled by several factors, such as humidity, vegetation, air pollution, rock surface, dry or wet soil, heterogeneous man-made materials, etc. (Ghobadi et al., 2014). Normalized difference bareness index (NDBAI) is the most popular index for bare land extraction that is invariably used in LULC and LST related studies as it builds a positive relationship in tropical environment (Essa et al., 2012; L Chen et al., 2013; X-L. Chen et al., 2006; Weng & Quattrochi, 2006; Yuan et al., 2017; Zhao & Chen, 2005). Moreover, the dependence on LST of different land covers and the relation of LST with different indices has also been discussed together in some previous works (Bala et al., 2020, 2021).

However, these abovementioned research works mostly performed on temporal or seasonal analysis of the relationship. Number of research works conducted on monthly analysis of LST–spectral indices relationship is rare in any physical environment. Hence, it is a necessary task to build month-wise LST–spectral indices correlation for the sustainable development of town and country planning as the values of the LST and spectral indices change with the change of months due to the different climatic and biophysical factors. The study was conducted on Raipur City of India as it is a smart growing city with a moderate climatic condition. However, the strength of the LST-spectral indices relationship can change temporally, seasonally, and spatially. The relationship is changed with time as the land surface materials change with time. The relationship also depends on the LULC types as vegetation, soil, water, or built-up area change the values of spectral indices as well as LST. Different seasons also play a significant role in the LST–spectral indices relationship as the growth of vegetation and increase of LST primarily depend on seasonal change. However, no specific conclusion can be drawn on LST–spectral indices relationship for a small number of remotely-sensed data. Thus, long-term Landsat data sets are necessary to obtain a reliable result on this relationship. The present study analyzes the nature, strength, and trend of the effect of LST on NDVI, NDWI, NDBI, and NDBAI.

**Study area and data**

Raipur City is located in between 21°11′22″N to 21°20′02″N and 81°32′20″E to 81°41′50″E (Figure 1). Figure 1(a) presents the outline map of India where Chhattisgarh State is located in the middle part (Source: Survey of India). (Figure 1(b)) presents the outline map of Chhattisgarh State with districts (Source: Survey of India). (Figure 1(c)) represents the false colour composite (FCC) image of Raipur City from recent Landsat data. (Figure 1(d)) indicates the contour map of Raipur (Date: 11 October 2011) of Raipur City (Source: USGS). The total area covers around 165 km². The southern part of the city is covered by dense forests. The Mahanadi River flows along the western side of the city. The elevation is higher in the middle part of the city compared to the outer part. The climate of the city is considered as dry and wet savannah climate (source: India Meteorological Department (IMD)). Four types of seasons are observed in Raipur, i.e., monsoon (June–September), pre-monsoon (March–May), post-monsoon (October–November), and winter (December–February). The mean annual temperature ranges from 12°C (December) to 42°C (May). The temperature often rises above 45°C in April and May. November to April remains almost dry (average rainfall <50 mm) compared to the June to September (average rainfall >200 mm). The study area is also characterized by tropical mixed deciduous vegetation and mixed red soil. The city has a widely diverse population that migrated from the different parts of the country. The city is considered as one of the fastest-growing smart cities in India.

A total of 123 cloud-free (<10% cloud coverage) Landsat TM, ETM+, and OLI/TIRS data from 1988 to 2020 were freely downloaded from the USGS Data Centre to conduct the whole study (https://www.earthexplorer.usgs.gov). These satellite images were taken between 10th and 25th day of each and every month to obtain the minimum range of deviation in LST values. Moreover, only a single image can obtain between 10th and 25th day of any month due to the 16 days temporal resolution of Landsat satellite sensors. These satellite images have been radiometrically and geometrically corrected. All the TIR bands of OLI/TIRS, TM,
and ETM+ data were resampled to 30 m resolution by USGS data centre using cubic convolution resampling method.

Methodology

**LST estimation from Landsat satellite sensors**

Many LST retrieval methods are applicable for different satellite sensors. The mono-window algorithm (García-Santos et al., 2018; Gui et al., 2019; Qin et al., 2001; Sekertekin and Bonafoni, 2020; Yang et al., 2014), 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; Price, 1984; Becker and Li, 1990), and radiative transfer equation (C Qu et al., 2014) are the main well-known LST retrieval algorithms using Landsat thermal bands (Weng, 2001; Weng et al., 2004; Zhang et al., 2016). Despite giving a good result, the radiative transfer algorithm cannot be applicable without in situ parameters of atmospheric profile at the satellite pass. The actual measurement with infrared thermometer has not been applied to verify the results of the study due to some unavoidable circumstances. Although the split-window algorithm gives the accurate result, it was not used in the study as only band 10 of Landsat 8 OLI/TIRS data was selected for LST generation due to its better calibration (Barsi et al., 2014). The mono-window algorithm and single-channel algorithm also provide good results. In this study, the mono-window algorithm was applied to retrieve LST from multi-temporal Landsat satellite images. Ground emissivity, atmospheric transmittance, and effective mean atmospheric temperature – these three parameters are needed to derive the LST using the mono-window algorithm. At first, the original TIR bands (100 m resolution for Landsat 8 OLI/TIRS data, 120 m resolution for Landsat 5 TM data, and 60 m resolution for Landsat 7 ETM+ data) were resampled into 30 m by USGS data centre for further application.

The TIR pixel values are firstly converted into radiance from digital number (DN) values. Band 10 of Landsat 8 data was used as TIR band for its better calibration (Barsi et al., 2014). Radiance for TIR bands of Landsat 5 TM data and Landsat 7 ETM+ data are obtained using Eq. (1) (USGS):

\[
L_\lambda = \left( \frac{L_{\text{MAX}} - L_{\text{MIN}}}{Q_{\text{CALMAX}} - Q_{\text{CALMIN}}} \right) \times (Q_{\text{CAL}} - Q_{\text{CALMIN}}) + L_{\text{MIN}}
\]

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 \(Q_{\text{CALMIN}}\), \(L_{\text{MAX}}\) (Wm\(^{-2}\)sr\(^{-1}\)mm\(^{-1}\)) is the spectral radiance scaled to \(Q_{\text{CALMAX}}\), \(Q_{\text{CALMIN}}\) is the minimum quantized calibrated pixel value in DN and \(Q_{\text{CALMAX}}\) is the maximum quantized calibrated pixel value in DN. \(L_{\text{MIN}}\), \(L_{\text{MAX}}\), \(Q_{\text{CALMIN}}\), and \(Q_{\text{CALMAX}}\) 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):

\[
L_\lambda = M_\lambda Q_{\text{CAL}} + A_\lambda
\]
where \( L_\lambda \) is the TOA spectral radiance (W m\(^{-2}\) 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 radiances using Eq. (3) (USGS):

\[
\rho_\lambda = \frac{\pi L_\lambda d^2}{ESUN_\lambda \cos \theta_t} \tag{3}
\]

where \( \rho_\lambda \) is unitless planetary reflectance, \( L_\lambda \) is the TOA spectral radiance (W m\(^{-2}\) sr\(^{-1}\) µm\(^{-1}\)), \( d \) is Earth–Sun distance in astronomical units, \( ESUN_\lambda \) is the mean solar exo-atmospheric spectral irradiances (W m\(^{-2}\) µm\(^{-1}\)) and \( \theta_t \) is the solar zenith angle in degrees. \( ESUN_\lambda \) values for each band of Landsat 5 and Landsat 7 data can be obtained from the handbooks of the related mission. \( \theta_t \) and \( d \) values 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):

\[
\rho_\lambda = \frac{M_\rho Q_{\text{CAL}} + A_\rho}{\sin \theta_{\text{SE}}} \tag{4}
\]

where \( M_\rho \) is the band-specific multiplicative rescaling factor from the metadata, \( A_\rho \) is the band-specific additive rescaling factor from the metadata, \( Q_{\text{CAL}} \) is the quantized and calibrated standard product pixel values (DN) and \( \theta_{\text{SE}} \) 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; X-L. Chen et al., 2006):

\[
T_b = \frac{K_2}{\ln\left(\frac{K_1}{T_b} + 1\right)} \tag{5}
\]

where \( T_b \) is the brightness temperature in Kelvin (K), \( K_1 \) is the spectral radiance in W m\(^{-2}\) sr\(^{-1}\) mm\(^{-1}\); \( K_2 \) and \( K_3 \) are calibration constants. For Landsat 8 data, \( K_1 \) is 774.89, \( K_2 \) is 1321.08 (W m\(^{-2}\) sr\(^{-1}\) mm\(^{-1}\)). For Landsat 7 data, \( K_1 \) is 666.09, \( K_2 \) is 1282.71 (W m\(^{-2}\) sr\(^{-1}\) mm\(^{-1}\)). For Landsat 5 data, \( K_1 \) is 607.76, \( K_2 \) is 1260.56 (W m\(^{-2}\) sr\(^{-1}\) mm\(^{-1}\)).

The land surface emissivity, is estimated from Eq. (6) using the NDVI Thresholds Method (Sobrino et al., 2004, 2001).

\[
\varepsilon = \varepsilon_v F_v + \varepsilon_s (1 - F_v) + de \tag{6}
\]

where, \( \varepsilon \) is land surface emissivity, \( \varepsilon_v \) is vegetation emissivity, \( \varepsilon_s \) is soil emissivity, \( F_v \) is fractional vegetation, \( de \) is the effect of the geometrical distribution of the natural surfaces and internal reflections that can be expressed by Eq. (7):

\[
de = (1 - \varepsilon_v)(1 - F_v)F_v \tag{7}
\]

where \( \varepsilon_v \) 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 \( de \) maybe 2% for mixed land surfaces (Sobrino et al., 2004).

The fractional vegetation \( F_v \), of each pixel, is determined from the NDVI using Eq. (8) (Carlson & Ripley, 1997):

\[
F_v = \left( \frac{NDVI - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \right)^2 \tag{8}
\]

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 et al., 2004, 2001).

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

\[
\varepsilon = 0.004 * F_v + 0.986 \tag{9}
\]

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

Water vapour content is estimated by Eq. (10) (X-L. Chen et al., 2006; Yang & Qiu, 1996):

\[
w = 0.0981 + \left[ 10 + 0.6108 \exp \left( \frac{17.27(T_0 - 273.15)}{257.3 + (T_0 - 273.15)} \right) \right] RH \tag{10}
\]

where \( w \) is the water vapour content (g/cm\(^2\)), \( T_0 \) is the near-surface air temperature in Kelvin (K), \( RH \) is the relative humidity (%). These parameters of atmospheric profile are obtained from the Meteorological Centre, Raipur (http://www.imd raidspur.gov.in). Atmospheric transmittance is determined for Raipur City using Eq. (11) and Table 2 (Qin et al., 2001; Sun et al., 2010):

\[
\tau = 1.031412 - 0.11536w \tag{11}
\]

where \( \tau \) is the total atmospheric transmittance, \( w \) is the water vapour content (g/cm\(^2\)).

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

\[
T_a = 17.9769 + 0.91715T_0 \tag{12}
\]

LST is retrieved from Landsat 5 TM and Landsat 8 OLI/TIRS satellite data by using Eq. (13–15) (Qin et al., 2001):

\[
T_s = \frac{a(1-C-D)+(b(1-C-D)+C+D)T_b-DT_a}{C} \tag{13}
\]

\[
C = \varepsilon \tau \tag{14}
\]
where ε is the land surface emissivity, r is the total atmospheric transmittance, C and D are internal parameters based on atmospheric transmittance and land surface emissivity, \( T_a \) is the at-sensor brightness temperature, \( T_s \) is the mean atmospheric temperature, \( T_n \) is the near-surface air temperature, \( T_{LS} \) is the LST, \( a = -67.355351 \), \( b = 0.458606 \).

**Determination of NDVI, NDWI, NDBI, and NDBal**

In this study, special emphasis was given on NDVI (Ke et al., 2015; Purevdorj et al., 1998; Tucker, 1979), NDWI (McFeeters, 1996, 2013), NDBI (Zha et al., 2003), and NDBal (Zhao & Chen, 2005) for determining the relationship with LST. NDVI is a vegetation index used in LULC-related study and the determination of fractional vegetation. NDWI is a water index used to distinguish the water bodies from the wetland and moist soil. NDBI is a built-up index used in detecting the built-up areas and it is frequently used by the urban geographers in land use study. NDBal is a bareness index used to differentiate the bare lands from semi-bare lands and other LULC types. The band combinations of these spectral indices were given in Table 1. The value of any normalized difference spectral index is ranged between \(-1\) and \(+1\). Various types of LULC can be estimated by using the threshold limits of these normalized difference spectral indices (Table 1). Generally, in the tropical city, the positive value of NDVI, NDWI, NDBI, and NDBal indicates the vegetation surface, water surface, built-up surface, and bare land surface, respectively (X.-L. Chen et al., 2006).

**Results and discussion**

**Monthly variation in LST distribution**

Table 2 shows a clear observation of monthly change in the mean LST values. April (38.49°C) shows the highest mean monthly temperature while January (23.04°C) shows the lowest mean monthly temperature from 1988 to 2020.
(Figure 2–11) show the spatial distribution maps of Raipur City in different months from 1988 to 2020. It is seen from (Figure 2–11) that >90% area of the city was above 32°C mean LST in March–May of 1992, 2001–2002, 2004–2005, 2008–2011, 2013, 2016–2017, and 2019 (Figure 2–4). In June and September, 2005, 2006, and 2009 have mean LST values more than the earlier or later years (Figure 5–6). The scenario was completely different in October to February (Figure 7–11), where <10% area of the city was above 32°C LST. April (38.49°C mean LST), May (36.65°C mean LST), June (34.56°C mean LST), and March (31.80°C mean LST) – these four months have an average value of >30°C mean LST throughout the entire period of study. February (27.86°C mean LST), October (27.23°C mean LST), September (27.18°C mean LST), and November (25.83°C mean LST) – these four months have an average value of 25–28°C mean LST throughout the entire time. Only December (23.76°C mean LST) and January (23.04°C mean LST) months have an average value of <24°C mean LST for the entire period. The average value of the highest and the lowest mean LST from 1988 to 2020 is observed in April and January, respectively. The northwest and southeast parts of the study area exhibit high LST. These parts also have a low percentage of urban vegetation and a high percentage of built-up area and bare land. It shows that the proportion of vegetation was reduced significantly with time.

Figure 12 shows the line graph of LST in different months from 1988 to 2019. October, November, and December present almost similar pattern of LST distribution. January and February show almost similar trend in their LST graph. A similarity also has been seen in the mean LST graph of March, April, and May. The LST graph of June shows a negative trend, while September shows a positive trend.

Figure 13 shows the mean monthly variation of LST (°C) during the study. The mean LST graph is sharply rising from January to April. After that, the graph is gently falling from April to June. A sharp fall is also noticed from June to September. One fact should be remembered that there was no data available for July and August; otherwise the falling trend might be gentle. From September to December the LST graph falls continuously.

Monthly analysis on LST–spectral indices relationship

Table 3 represents a monthly variation of Pearson’s linear correlation method between LST and NDVI. In average, October (~0.62), September (~0.55), April (~0.51), June (~0.47), May (~0.44), March (~0.44),
and November (−0.39) months have a moderate negative correlation. A weak negative correlation was found in February (−0.29), January (−0.24), and December (−0.21) months. The main reason behind the moderate LST–NDVI correlation in March–November is the presence of high intensity of moisture and chlorophyll content in green vegetation. Dry months reduce the strength of regression, while the wet months enhance the strength of the LST–NDVI regression.

Table 4 represents a monthly variation of Pearson’s linear correlation method between LST and NDBI. In average, October (0.49), September (0.40), June (0.33), and April (0.33) months build a moderate positive correlation. November (0.29), May (0.27), and March (0.23) months have a weak positive correlation. There is no such linear correlation found in February (0.09), December (0.04), and January (0.02). Here again, dryness of the season reflects low correlation.

Table 5 represents a monthly variation of Pearson’s linear correlation method between LST and NDWI. In average, October (0.48) and September (0.47) months build a moderate positive correlation. January (0.36), February (0.32), November (0.31), and March (0.30) months have a moderate to strong positive correlation. The strength of correlation increases with the increase of wetness.

Table 6 represents a monthly variation of Pearson’s linear correlation method between LST and NDBal. In average, October (0.48) and September (0.47) months build a moderate positive correlation. January (0.36), February (0.32), November (0.31), and March (0.30) months have a moderate to strong positive correlation. The strength of correlation increases with the increase of wetness.

Figure 3. Mean LST in February: (a) 24 February 1989 (b) 11 February 1990 (c) 14 February 1991 (d) 17 February 1992 (e) 19 February 1993 (f) 20 February 2002 (g) 18 February 2004 (h) 23 February 2006 (i) 15 February 2009 (j) 18 February 2010 (k) 16 February 2015 (l) 19 February 2016 (m) 21 February 2017 (n) 24 February 2018 (o) 11 February 2019 (p) 14 February 2020.
months have a moderate to weak positive correlation. A weak positive correlation is found in April (0.29), December (0.28), June (0.22), and May (0.21) months. Thus, the pre-monsoon and winter months indicate low correlation compared to the monsoon and post-monsoon months.

Figure 14 shows the line graphs for monthly variation of LST–spectral indices relationships. The LST–NDVI correlation is always negative, whereas the LST–NDBI correlation and the LST–NDBal correlation are always positive. From 1988 to 2000 a slightly falling trend is observed for LST–NDBI and LST–NDBal correlation. The trend of LST–NDWI correlation is slightly rising or neutral. There is also no such variation in LST–NDVI correlation and the trend is almost neutral. LST–spectral indices build a stronger correlation between March and November.

Figure 15 presents a comparison between LST and four aforesaid spectral indices. Average correlation coefficient was used to compare the monthly assessment of these relationships. LST builds the least correlation with NDVI, NDBI, and NDWI from November to February. Pre-monsoon months have the least correlation between LST and NDBal as the dry soil and open land absorbs a lot of heat in the summer months. Humidity accelerates the strength of the correlation while dry weather reduces the correlation coefficient values.

This LST–NDVI correlation tends to be more negative with the increase of surface moisture (Lambin &
Ehrlich, 1996; Moran et al., 1994; Sandholt et al., 2002). In high latitudes, positive LST–NDVI relationships have been observed (Karnieli et al., 2010) as the heat capacity of vegetation and water is more than the bare rock surface. Sun and Kafatos (2007) stated that the LST–NDVI correlation was positive in the winter season as vegetation retains temperature in winter; while it was negative in the summer season because presence of vegetation helps in cooling in summer. Yue et al. (2007) showed that the LST–NDVI relationship in Shanghai City, China was negative and was different in different LULC types. Liang et al. (2012) presented similar types of negative NDVI–LST correlation. This relationship was also negative in Mashhad, Iran (Gorgani et al., 2013). The relationship was strong negative in Berlin City for any season (Marzban et al., 2018). The present study also found the negative LST–NDVI correlation for all the months (average correlation coefficient value is −0.42 from 1988 to 2020). The value of the correlation coefficient is inversely related to the surface moisture content, i.e., the negativity of the relationship increases with the increase of surface moisture content.

The LST–NDBI correlation found in the present study is strong positive for each and every month. The strongest correlation was noticed in October (0.80) and September (0.76), whereas the least correlation was found in December (0.52) and January (0.61). Moist climate intensifies the strength of the correlation. The result of this study is comparable with the other LST-NDBI related studies conducted in the other cities. LST and NDBI built a strong correlation in Fuzhou City of China (Zhang et al., 2009). I, Chen et al. (2013) established a strong positive correlation between LST and NDBI in Wuhan City, China (0.639, 0.717, 0.807, and 0.762 in spring, summer, autumn, and winter, respectively). A strong positive LST–NDBI correlation was also observed in Kunming of China (Chen & Zhang, 2017). A strong positive correlation between LST and NDBI was noticed in Vila Velha, ES, Brazil (Dos Santos et al., 2017). In Melbourne City of Australia, LST and NDBI built a moderate to strong positive correlation (Jamei et al., 2019). Balew and Korme (2020) noticed a positive correlation in Bahir Dar City of Ethiopia. Using a long term Landsat series data in Chattogram Metropolitan Area of Bangladesh, Roy et al. (2020) showed that NDBI is positively correlated to LST. Son et al. (2020) showed that the LST–NDBI relationship was also strong positive (0.85) in San Salvador City of El Salvador in last 30 years. These

Figure 5. Mean LST in April: (a) 21 April 1992 (b) 16 April 1990 (c) 14 April 1995 (d) 22 April 2001 (e) 25 April 2002 (f) 12 April 2003 (g) 22 April 2004 (h) 20 April 2009 (i) 23 April 2010 (j) 23 April 2016 (k) 10 April 2017 (l) 18 April 2020.
Figure 6. Mean LST in May: (a) 21 May 1991 (b) 11 May 2002 (c) 24 May 2004 (d) 11 May 2005 (e) 14 May 2006 (f) 17 May 2007 (g) 19 May 2008 (h) 22 May 2009 (i) 25 May 2010 (j) 12 May 2011 (k) 17 May 2013 (l) 20 May 2014 (m) 23 May 2015 (n) 25 May 2016 (o) 12 May 2017 (p) 15 May 2018 (q) 18 May 2019.

Figure 7. Mean LST in June: (a) 12 June 2005 (b) 15 June 2006 (c) 23 June 2009 (d) 16 June 2018.
Figure 8. Mean LST in September: (a) 23 September 1996 (b) 21 September 2001 (c) 16 September 2002 (d) 25 September 2014.

Figure 9. Mean LST in October: (a) 19 October 1988 (b) 12 October 1991 (c) 14 October 1992 (d) 25 October 1996 (e) 15 October 2001 (f) 23 October 2001 (g) 15 October 2004 (h) 21 October 2006 (i) 13 October 2009 (j) 19 October 2011 (k) 14 October 2015 (l) 16 October 2016 (m) 22 October 2018.
Figure 10. Mean LST in November: (a) 20 November 1988 (b) 23 November 1989 (c) 13 November 1991 (d) 18 November 1993 (e) 10 November 1996 (f) 11 November 1999 (g) 16 November 2004 (h) 19 November 2005 (i) 22 November 2006 (j) 11 November 2008 (k) 25 November 2013 (l) 12 November 2014 (m) 17 November 2016 (n) 20 November 2017 (o) 10 November 2019.
Figure 11. Mean LST in December: (a) 22 December 1988 (b) 17 December 1992 (c) 23 December 1994 (d) 10 December 1995 (e) 15 December 2000 (f) 21 December 2002 (g) 18 December 2004 (h) 24 December 2006 (i) 13 December 2008 (j) 16 December 2009 (k) 19 December 2010 (l) 11 December 2013 (m) 19 December 2016 (n) 22 December 2017 (o) 25 December 2018 (p) 12 December 2019.
Figure 12. Monthly assessment of mean LST (°C) from 1988 to 2020: (a) January (b) February (c) March (d) April (e) May (f) June (g) September (h) October (i) November (j) December.
afaesaid examples of LST–NDBI positive correlations are simply based on the fact that the building and road construction materials like rock, cement, brick, concrete, tar, sand, stone chips, etc. produce high LST values. This result is very much similar to the result of the present study (mean correlation coefficients between LST and NDBI is 0.68 during the entire period).

The result is quite authentic with respect to the other LST–NDWI related studies in recent years. A study performed in Shenzhen City of China showed a significant negative LST–NDWI correlation on the water bodies (X-L. Chen et al., 2006). LST and NDWI built a negative correlation in desert landscape in Kuwait (Uddin et al., 2010). In Nanchang City of China, LST and NDWI develop a negative correlation on the water bodies (Zhang et al., 2017). In Asansol-Durgapur Development Region of India, a negative LST–NDWI correlation was found in the water bodies (Choudhury et al., 2019). Das (Choudhury et al., 2019) presented a dynamic negative LST–NDWI correlation in the dry bare land of Northwest India and the surrounding places of Pakistan, where different types of rock compositions influence the values of LST and NDWI. LST and NDWI built a negative linear correlation in Banda Aceh City of Indonesia in the last 30 years (Achmad & Zainuddin, 2019). An insignificant correlation was found in Wuhan City of China. The current analysis showed an insignificant and weak positive correlation (average value of 0.27 for all the months during the study period) between LST and NDWI. These results are based on the fact that LST reduces significantly in water bodies or wetland, but other surface materials have an insignificant relationship because different materials have different water or moisture content ratio.

The LST-NDBAI correlation is positive, irrespective of any season. The post-monsoon season reveals the best correlation among all the four seasons. The present study indicates that LST builds a stable strong to a moderate positive correlation with NDBAI in Raipur City, India from 1988 to 2020. Essa et al. (2012) presented a moderate positive LST–NDBAI correlation (0.39) in Greater Dublin region, Ireland. The LST and NDBAI have built a weak negative correlation (−0.11) in Guangzhou, China (Guo et al., 2015) as the bare earth surface was less. Sharma and Joshi (2016) showed the moderate positive nature of LSI–NDBAI correlation in the National Capital Region of India. A weak positive correlation between LST and NDBAI was presented in London (0.086) and Baghdad (0.469) by Ali et al. (2017). Chen and Zhang (2017) noticed the strong positive nature of the correlation coefficient of the LST–NDBAI relationship in a study performed in Kunming, China due to the presence of high bare land ratio. This correlation was weak positive (0.06) in Harare Metropolitan City, Zimbabwe (Mushore et al., 2017). This relationship was also positive (0.458) in Kolkata Metropolitan Area, India (Nimish et al., 2020). The present study shows that the average correlation coefficient between LST and NDBAI for all the months from 1988 to 2020 is moderate positive (0.32). LST will obviously be increased if the ratio of the bare rock surface, sand, or dry soil is high. However, in many modern cities, percentage of barren land is low that promotes a moderate positive LST–NDBAI relationship. From the above examples, it is clear that the relationship between LST and the four spectral indices is consistent and reliable with respect to the other previous similar types of research works.
Table 3. Monthly variation of LST-NDVI correlation coefficient (1988–2020).

| Month       | Correlation coefficient | Month       | Correlation coefficient | Month       | Correlation coefficient | Month       | Correlation coefficient |
|-------------|--------------------------|-------------|--------------------------|-------------|--------------------------|-------------|--------------------------|
| January     | Correlation coefficient  | February    | Correlation coefficient  | March       | Correlation coefficient  | April       | Correlation coefficient  |
| 1988-Jan-21 | −0.31                    | 1989-Feb-24 | −0.39                    | 1989-Mar-12 | −0.43                    | 1990-Apr-16 | −0.52                    |
| 1990-Jan-10 | −0.36                    | 1990-Feb-11 | −0.38                    | 1990-Mar-15 | −0.43                    | 1992-Apr-21 | −0.53                    |
| 1992-Jan-16 | −0.35                    | 1991-Feb-14 | −0.12                    | 1991-Mar-18 | −0.40                    | 1995-Apr-14 | −0.38                    |
| 1993-Jan-18 | −0.38                    | 1992-Feb-17 | −0.29                    | 1992-Mar-20 | −0.40                    | 2001-Apr-22 | −0.65                    |
| 2005-Jan-19 | −0.21                    | 1993-Feb-19 | −0.37                    | 2003-Mar-11 | −0.41                    | 2002-Apr-25 | −0.57                    |
| 2007-Jan-25 | −0.21                    | 2002-Feb-20 | −0.44                    | 2004-Mar-21 | −0.49                    | 2003-Apr-12 | −0.39                    |
| 2009-Jan-14 | −0.25                    | 2004-Feb-18 | −0.30                    | 2007-Mar-14 | −0.38                    | 2004-Apr-22 | −0.51                    |
| 2011-Jan-20 | −0.18                    | 2006-Feb-23 | −0.31                    | 2009-Mar-19 | −0.54                    | 2009-Apr-20 | −0.56                    |
| 2015-Jan-15 | −0.27                    | 2009-Feb-15 | −0.36                    | 2014-Mar-17 | −0.42                    | 2010-Apr-23 | −0.52                    |
| 2018-Jan-23 | −0.15                    | 2010-Feb-18 | −0.24                    | 2015-Mar-20 | −0.36                    | 2016-Apr-23 | −0.46                    |
| 2020-Jan-13 | −0.17                    | 2015-Feb-16 | −0.16                    | 2016-Mar-22 | −0.40                    | 2017-Apr-10 | −0.51                    |
|            | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient |
| June       | −0.27                    | September   | −0.30                    | October     | −0.44                    | November    | −0.51                    |
| 2005-Jun-12 | −0.51                    | 1996-Sep-23 | −0.54                    | 1988-Oct-19 | −0.69                    | 1988-Nov-20 | −0.54                    |
| 2006-Jun-15 | −0.46                    | 2001-Sep-21 | −0.58                    | 1991-Oct-12 | −0.63                    | 1989-Nov-23 | −0.29                    |
| 2009-Jun-23 | −0.42                    | 2002-Sep-16 | −0.56                    | 1992-Oct-14 | −0.68                    | 1991-Nov-13 | −0.38                    |
| 2018-Jun-16 | −0.46                    | 2014-Sep-25 | −0.53                    | 1996-Oct-25 | −0.64                    | 1993-Nov-18 | −0.19                    |
|            | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient |
|            | −0.47                    | Mean Correlation coefficient | −0.55                    | Mean Correlation coefficient | −0.62                    | Mean Correlation coefficient | −0.39                    |
|            | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient | Mean Correlation coefficient |
| Month       | Correlation Coefficient | Month       | Correlation Coefficient | Month       | Correlation Coefficient | Month       | Correlation Coefficient | Month       | Correlation Coefficient |
|-------------|--------------------------|-------------|--------------------------|-------------|--------------------------|-------------|--------------------------|-------------|--------------------------|
| January 1988-Jan 21 | 0.67 | February 1989-Feb 24 | 0.70 | March 1989-Mar 12 | 0.70 | April 1990-Apr 16 | 0.79 | May 1991-May 21 | 0.75 |
| January 1990-Jan 10 | 0.69 | February 1990-Feb 11 | 0.73 | March 1990-Mar 15 | 0.73 | April 1992-Apr 21 | 0.74 | May 2002-May 11 | 0.76 |
| January 1992-Jan 16 | 0.70 | February 1991-Feb 14 | 0.68 | March 1991-Mar 18 | 0.76 | April 1992-Apr 14 | 0.76 | May 2004-May 24 | 0.76 |
| January 1993-Jan 18 | 0.69 | February 1992-Feb 17 | 0.69 | March 1992-Mar 20 | 0.76 | April 2001-Apr 22 | 0.76 | May 2005-May 11 | 0.73 |
| January 2005-Jan 19 | 0.61 | February 1993-Feb 19 | 0.61 | March 2003-Mar 11 | 0.79 | April 2002-Apr 25 | 0.82 | May 2006-May 14 | 0.69 |
| January 2007-Jan 25 | 0.60 | February 2002-Feb 20 | 0.76 | March 2004-Mar 21 | 0.69 | April 2003-Apr 12 | 0.70 | May 2007-May 17 | 0.80 |
| January 2009-Jan 14 | 0.55 | February 2004-Feb 18 | 0.64 | March 2007-Mar 14 | 0.72 | April 2004-Apr 22 | 0.72 | May 2008-May 19 | 0.82 |
| January 2011-Jan 20 | 0.55 | February 2006-Feb 23 | 0.62 | March 2009-Mar 19 | 0.61 | April 2009-Apr 20 | 0.71 | May 2009-May 22 | 0.71 |
| January 2013-Jan 15 | 0.52 | February 2009-Feb 15 | 0.58 | March 2014-Mar 17 | 0.63 | April 2010-Apr 23 | 0.63 | May 2010-May 25 | 0.73 |
| January 2015-Jan 23 | 0.50 | February 2010-Feb 18 | 0.65 | March 2015-Mar 20 | 0.64 | April 2016-Apr 23 | 0.68 | May 2011-May 12 | 0.69 |
| January 2017-Jan 13 | 0.48 | February 2015-Feb 16 | 0.58 | March 2016-Mar 22 | 0.69 | April 2017-Apr 10 | 0.69 | May 2013-May 17 | 0.69 |
| July 2005-Jan 12 | 0.69 | September 1996-Sep 23 | 0.74 | October 1988-Oct 19 | 0.85 | November 1988-Nov 20 | 0.69 | December 1988-Dec 22 | 0.56 |
| July 2006-Jan 15 | 0.71 | September 2001-Sep 21 | 0.75 | October 1991-Oct 12 | 0.87 | November 1989-Nov 23 | 0.68 | December 1992-Dec 17 | 0.49 |
| July 2009-Jan 23 | 0.63 | September 2002-Sep 16 | 0.77 | October 1992-Oct 14 | 0.85 | November 1991-Nov 13 | 0.75 | December 1994-Dec 23 | 0.50 |
| July 2012-Jan 16 | 0.69 | September 2004-Sep 25 | 0.78 | October 1996-Oct 25 | 0.82 | November 1993-Nov 18 | 0.63 | December 1995-Dec 10 | 0.47 |
| July 2001-Oct 15 | 0.83 | September 1996-Nov 10 | 0.74 | October 1996-Oct 15 | 0.83 | November 1996-Nov 20 | 0.74 | December 2000-Dec 15 | 0.59 |
| July 2004-Oct 23 | 0.78 | September 1999-Nov 11 | 0.78 | October 2001-Oct 23 | 0.78 | November 1999-Nov 24 | 0.78 | December 2002-Dec 21 | 0.64 |
| July 2006-Oct 15 | 0.79 | September 2004-Nov 16 | 0.68 | October 2004-Oct 15 | 0.79 | November 2004-Nov 29 | 0.68 | December 2004-Dec 18 | 0.52 |
| July 2009-Oct 21 | 0.77 | September 2005-Nov 19 | 0.64 | October 2005-Oct 21 | 0.77 | November 2006-Nov 23 | 0.64 | December 2006-Dec 24 | 0.49 |
| July 2011-Oct 19 | 0.78 | September 2006-Nov 22 | 0.60 | October 2009-Oct 13 | 0.78 | November 2007-Nov 25 | 0.60 | December 2008-Dec 13 | 0.50 |
| July 2013-Oct 14 | 0.77 | September 2008-Nov 11 | 0.60 | October 2011-Oct 19 | 0.77 | November 2009-Nov 21 | 0.60 | December 2009-Dec 16 | 0.48 |
| July 2015-Oct 14 | 0.76 | September 2013-Nov 25 | 0.59 | October 2015-Oct 14 | 0.76 | November 2014-Nov 12 | 0.59 | December 2015-Dec 11 | 0.52 |
| July 2018-Oct 16 | 0.74 | September 2014-Nov 22 | 0.63 | October 2018-Oct 22 | 0.74 | November 2016-Nov 17 | 0.58 | December 2016-Dec 19 | 0.48 |
| July 2019-Nov 10 | 0.56 | September 2019-Nov 20 | 0.56 | October 2019-Nov 10 | 0.74 | November 2019-Nov 10 | 0.66 | December 2019-Dec 12 | 0.54 |

Mean 0.68 | Mean 0.76 | Mean 0.80 | Mean 0.66 | Mean 0.52
### Table 5. Monthly variation of LST-NDWI correlation coefficient (1988–2020).

| Month       | Correlation coefficient | Month       | Correlation coefficient | Month       | Correlation coefficient | Month       | Correlation coefficient |
|-------------|-------------------------|-------------|-------------------------|-------------|-------------------------|-------------|-------------------------|
| January 1988-Jan-21 | 0.03                    | February 1989-Feb-24 | 0.03 | March 1990-Mar-12 | 0.12 | April 1990-Apr-16 | 0.28 | May 1991-May-21 | 0.15 |
| January 1990-Jan-10 | 0.08                    | February 1990-Feb-11 | 0.07 | March 1991-Mar-18 | 0.21 | April 1992-Apr-21 | 0.27 | May 1992-May-11 | 0.34 |
| January 1992-Jan-16 | 0.10                    | February 1991-Feb-14 | −0.04 | March 1992-Mar-20 | 0.13 | April 1993-Apr-14 | 0.11 | May 1994-May-24 | 0.24 |
| January 1993-Jan-18 | 0.10                    | February 1992-Feb-17 | 0.01 | March 1993-Mar-21 | 0.07 | April 1994-Apr-24 | 0.46 | May 1995-May-11 | 0.36 |
| January 2005-Jan-19 | −0.03                   | February 1993-Feb-19 | 0.05 | March 2005-Mar-11 | 0.13 | April 2005-Apr-22 | 0.31 | May 2005-May-14 | 0.34 |
| January 2007-Jan-25 | 0.01                    | February 2002-Feb-20 | 0.19 | March 2007-Mar-21 | 0.30 | April 2007-Apr-12 | 0.23 | May 2007-May-17 | 0.05 |
| January 2009-Jan-14 | 0.10                    | February 2004-Feb-18 | −0.09 | March 2009-Mar-21 | 0.15 | April 2009-Apr-22 | 0.31 | May 2008-May-19 | 0.29 |
| January 2011-Jan-20 | 0.06                    | February 2006-Feb-23 | 0.06 | March 2011-Mar-19 | 0.22 | April 2011-Apr-20 | 0.39 | May 2009-May-22 | 0.22 |
| January 2013-Jan-15 | 0.01                    | February 2009-Feb-15 | 0.17 | March 2013-Mar-21 | 0.30 | April 2013-Apr-23 | 0.38 | May 2001-May-25 | 0.31 |
| January 2018-Jan-23 | −0.28                   | February 2010-Feb-18 | 0.08 | March 2015-Mar-20 | 0.23 | April 2015-Apr-23 | 0.31 | May 2011-May-12 | 0.45 |
| January 2020-Jan-13 | 0.08                    | February 2015-Feb-16 | 0.02 | March 2016-Mar-22 | 0.26 | April 2016-Apr-10 | 0.38 | May 2013-May-17 | 0.29 |
| June         | 0.02                    | September     | 0.09                    | October     | 0.23                    | November    | 0.33                    | December    | 0.27                    |
| 2005-Jun-12  | 0.34                    | 1996-Sep-23   | 0.36                    | 1998-Oct-19 | 0.47                    | 1988-Nov-20 | 0.22                    | 1988-Dec-22 | −0.16                    |
| 2006-Jun-15  | 0.31                    | 2001-Sep-21   | 0.44                    | 1991-Oct-12 | 0.43                    | 1989-Nov-23 | 0.09                    | 1992-Dec-17 | −0.02                    |
| 2009-Jun-23  | 0.31                    | 2002-Sep-16   | 0.35                    | 1992-Oct-14 | 0.49                    | 1991-Nov-13 | 0.28                    | 1994-Dec-23 | 0.051                    |
| 2018-Jun-16  | 0.35                    | 2014-Sep-25   | 0.44                    | 1996-Oct-25 | 0.50                    | 1993-Nov-18 | 0.32                    | 1995-Dec-10 | −0.08                    |
| June         | 0.33                    | Mean         | 0.40                    | Mean         | 0.49                    | Mean         | 0.29                    | Mean         | 0.04                    |
Table 6. Monthly variation of LST-NDBal correlation coefficient (1988–2020).

| January       | Correlation coefficient | February       | Correlation coefficient | March          | Correlation coefficient | April          | Correlation coefficient | May            | Correlation coefficient |
|---------------|-------------------------|----------------|-------------------------|----------------|-------------------------|----------------|-------------------------|-----------------|-------------------------|
| 1988-Jan-21   | 0.54                    | 1989-Feb-24    | 0.44                    | 1989-Mar-12    | 0.47                    | 1990-Apr-16    | 0.42                    | 1991-May-21    | 0.44                    |
| 1990-Jan-10   | 0.53                    | 1990-Feb-11    | 0.57                    | 1990-Mar-15    | 0.47                    | 1992-Apr-21    | 0.38                    | 2002-May-11    | 0.34                    |
| 1992-Jan-16   | 0.53                    | 1991-Feb-14    | 0.12                    | 1991-Mar-18    | 0.52                    | 1995-Apr-14    | 0.47                    | 2004-May-24    | 0.32                    |
| 1993-Jan-18   | 0.49                    | 1992-Feb-17    | 0.49                    | 1992-Mar-20    | 0.51                    | 2001-Apr-22    | 0.46                    | 2005-May-11    | 0.28                    |
| 2005-Jan-19   | 0.42                    | 1993-Feb-19    | 0.48                    | 2003-Mar-11    | 0.56                    | 2002-Apr-25    | 0.51                    | 2006-May-14    | 0.19                    |
| 2007-Jan-25   | 0.21                    | 2002-Feb-20    | 0.51                    | 2004-Mar-21    | 0.32                    | 2003-Apr-12    | 0.19                    | 2007-May-17    | 0.45                    |
| 2009-Jan-14   | 0.14                    | 2004-Feb-18    | 0.37                    | 2007-Mar-14    | 0.41                    | 2004-Apr-22    | 0.29                    | 2008-May-19    | 0.17                    |
| 2011-Jan-20   | 0.14                    | 2006-Feb-23    | 0.30                    | 2009-Mar-19    | 0.12                    | 2009-Apr-20    | 0.17                    | 2009-May-22    | 0.20                    |
| 2015-Jan-15   | 0.11                    | 2009-Feb-15    | 0.09                    | 2014-Mar-17    | 0.11                    | 2010-Apr-23    | 0.15                    | 2010-May-25    | 0.17                    |
| 2018-Jan-23   | 0.34                    | 2010-Feb-18    | 0.34                    | 2015-Mar-20    | 0.09                    | 2016-Apr-23    | 0.16                    | 2011-May-12    | 0.11                    |
| 2020-Jan-13   | 0.22                    | 2015-Feb-16    | 0.19                    | 2016-Mar-22    | 0.17                    | 2017-Apr-10    | 0.14                    | 2013-May-17    | 0.10                    |
| 2016-Feb-19   | 0.25                    | 2017-Feb-21    | 0.23                    | 2018-Mar-12    | 0.15                    | 2019-May-23    | 0.10                    | 2015-May-23    | 0.10                    |
| 2018-Feb-24   | 0.24                    | 2020-Mar-17    | 0.17                    | 2019-Feb-11    | 0.21                    | 2017-May-12    | 0.15                    | 2018-May-15    | 0.11                    |
| 1989-Feb-24   | 0.14                    | 2019-Feb-14    | 0.44                    | 2020-Feb-14    | 0.18                    | 2019-May-18    | 0.10                    | 2019-May-18    | 0.10                    |
| Mean          | 0.36                    | Mean           | 0.32                    | Mean          | 0.30                    | Mean          | 0.29                    | Mean          | 0.27                    |
| 2005-Jun-12   | 0.13                    | 1996-Sep-23    | 0.54                    | 1988-Oct-19    | 0.67                    | 1988-Nov-20    | 0.41                    | 1988-Dec-22    | 0.51                    |
| 2006-Jun-15   | 0.23                    | 2001-Sep-21    | 0.53                    | 1991-Oct-12    | 0.81                    | 1989-Nov-23    | 0.34                    | 1992-Dec-17    | 0.35                    |
| 2009-Jun-23   | 0.25                    | 2002-Sep-16    | 0.56                    | 1992-Oct-14    | 0.66                    | 1991-Nov-13    | 0.42                    | 1994-Dec-23    | 0.26                    |
| 2018-Jun-16   | 0.24                    | 2014-Sep-25    | 0.21                    | 1996-Oct-25    | 0.60                    | 1993-Nov-18    | 0.32                    | 1995-Dec-10    | 0.38                    |
| Mean          | 0.22                    | Mean           | 0.47                    | Mean          | 0.48                    | Mean          | 0.31                    | Mean          | 0.28                    |
Figure 14. Monthly assessment of LST-spectral indices relationship (1988–2020): (a) January (b) February (c) March (d) April (e) May (f) June (g) September (h) October (i) November (j) December (significant at 0.05 level).
The study reflects the relationship between LST and normalized difference spectral indices to take new action in environmental planning and management of any city. The area has a positive correlation promotes the LST whereas the area with a negative correlation reduces the LST. Hence, the environmental planners should take special attention in conversion of the barren or fallow lands into vegetation, water bodies, and wetland to control the rising trend of LST. In this way, the fallow or barren lands can be converted into parks, wetlands, or artificial water bodies. Forest or dense vegetation must be protected and social forestry can be introduced at a large scale. Most of the industrial and commercial activities must be restrained in particular areas located far away from the dense residential places. A specific area of the city should be allotted as wasteland. Thus, the correlation between LST and the spectral indices significantly determines the vulnerable area of the city and the ecological health of the city could be improved by converting these vulnerable places into vegetation and water bodies.

Conclusion

The present study estimates the monthly variation of LST distribution in Raipur City, India using 123 Landsat images from 1988 to 2020. April May, June, and March present higher LST value than the rest of the months. The present study also assesses the monthly correlation of LST and spectral indices in Raipur City. The results show that LST is inversely related to NDVI, and positively related to NDBI and NDBaI, irrespective of any month. NDWI does not generate significant correlation with LST. LST builds strong to moderate correlation with NDVI, NDBI, and NDWI between March and November, whereas it is found weak negative in the winter months (December to February). For LST–NDBaI correlation, the strength is reduced in the summer and winter months. The growth of vegetation depends on the climatic component and soil condition those are largely changed in different months. The LST is directly controlled by the ratio of green vegetation in a city. The value of the spectral indices and LST varies with the change of month. Thus, the study is useful for the environmentalist and urban planner for the future ecological planning.

There is obviously some limitations and future scope of the present study. First, LST can be derived by using other algorithms or from other satellite sensors to compare with the present result. Downscaling technique can be applied to get the LST with high pixel values. Secondly, the in situ measurement can be used to validate the result significantly. Third, some new spectral indices can be used for different land surface features to compare the result with the existing indices. Fourth, some other robust statistical techniques and diagrams can be applied to present these relationships. Finally, the entire method may be applied in other study areas with different climatic and physiographic regions.
Acknowledgments

The authors are indebted to the United States Geological Survey (USGS). This study was supported by National Institute of Technology Raipur, Government of India, Grant No./NITRR/Dean(R&C)/2017/8301.

Data availability statement

All the used data sets are freely downloadable from the official website of earth explorer (http://earthexplorer.usgs.gov).

Disclosure statement

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

ORCID

Subhanil Guha http://orcid.org/0000-0002-2967-7248
Himanshu Govil http://orcid.org/0000-0002-3433-8355

References

Achmad, A., & Zainuddin, M. M. (2019). The relationship between land surface temperature and water index in the urban area of a tropical city. IOP Conference Series: Earth and Environmental Science, 365, 012013. https://doi.org/10.1088/1755-1315/365/1/012013
Ali, J. M., Marsh, S. H., & Smith, M. J. (2017). A comparison between London and Baghdad surface urban heat islands and possible engineering mitigation solutions. Sustain Cities Soc, 29, 159–168. https://doi.org/10.1016/j.scs.2016.12.010
Bala, R., Prasad, R., & Yadav, V. P. (2020). A comparative analysis of day and night land surface temperature in two semi-arid cities using satellite images sampled in different seasons. Advances in Space Research, 66(2), 412–425. https://doi.org/10.1016/j.asr.2020.04.009
Bala, R., Prasad, R., & Yadav, V. P. (2021). Quantification of urban heat intensity with land use/land cover changes using Landsat satellite data over urban landscapes. Theoretical and Applied Climatology, 145(1–2), 1–12. https://doi.org/10.1007/s00704-021-03610-3
Balew, A., & Korme, T. (2020). Monitoring land surface temperature in Bahir Dar city and its surrounding using Landsat images. Egypt J Remote Sens Space Sci. https://doi.org/10.1016/j.ejrs.2020.02.001
Barsi, J., Schott, J., Hook, S., Raqueno, N., Markham, B., Rodocinski, R. (2014). Landsat-8 thermal infrared sensor (TIRS) vicarious radiometric calibration. Remote Sens, 6 (11), 11607–11626. https://doi.org/10.3390/rs61111607
Becker, F and Li, ZL. (1990). Towards a local split window method over land surfaces. Int J Remote Sens 11(3), 369-393. https://doi.org/10.1080/014316908955028
Berger, C., Rosentretre, J., Voltersen, M., Baumgart, C., Schmullius, C., & Hese, S. (2017). Spatio-Temporal analysis of the relationship between 2D/3D Urban Site characteristics and land surface temperature. Remote Sensing of Environment, 193, 225–243. https://doi.org/10.1016/j.rse.2017.02.020
Carlson, T. N., & Ripley, D. A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of Environment, 62(3), 241–252. https://doi.org/10.1016/S0034-4257(97)00104-1
Chatterjee RS, Singh N, Thapa S, Sharma D, Kumar D. (2017). Retrieval of land surface temperature (LST) from landsat TM6 and TIRS data by single channel radiative transfer algorithm using satellite and ground-based inputs. Int J Appl Earth Obs Geoinf, 58, 264–277. https://doi.org/10.1016/j.jag.2017.02.017
Chen, L., Li, M., Huang, F., & Xu, S. (2013). Relationships of LST to NDBI and NDVI in Wuhan City based on Landsat ETM+ image. 2013 6th International Congress on Image and Signal Processing (CISP), Hangzhou, pp. 840–845. https://doi.org/10.1109/CISP.2013.6745282
Chen, X., & Zhang, Y. (2017). Impacts of urban surface characteristics on spatiotemporal pattern of land surface temperature in Kunming of China. Sustain Cities Soc, 32, 87–99. https://doi.org/10.1016/j.scs.2017.03.013
Chen, X.-L., Zhao, H.-M., Li, P.-X., & Yi, Z.-Y. (2006). Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. Remote Sensing of Environment, 104(2), 133–146. https://doi.org/10.1016/j.rse.2005.11.016
Choudhury, D., Das, K., & Das, A. (2019). Assessment of land use land cover changes and its impact on variations of land surface temperature in Asansol-Durgapur development region. Egypt J Remote Sens Space Sci, 22(2), 203–218. https://doi.org/10.1016/j.jers.2018.05.004
Coll C, Galve JM, Sanchez JM, Casselles V (2010) Validation of Landsat-7/ETM+ thermal-band calibration and atmospheric correction with ground-based measurements. IEEE Trans Geosci Remote Sens 48(1), 547–555. https://doi.org/10.1109/TGRS.2009.2024934
Dos Santos, A. R., de Oliveira, F. S., Da Silva, A. G., Gleriani, J. L., Goncalves, W., Moreira, G. L, Silva, F. G., Branco, E. R. F., Moura, M. M., Da Silva, R. G., Juvalnhol, R. S., de Souza, K. B., Rebeiro, C. A. A. S., de Queiroz, V. T., Costa, A. V., Lorenzon, A. S., Domingues, G. F., Marcatti, G. E., De Castro, N. L. M., Resende, R. T., … PHS, M. (2017). Spatial and temporal distribution of urban heat islands. The Science of the Total Environment, 605-606, 946–956. https://doi.org/10.1016/j.scitotenv.2017.05.275
Du, S., Xiong, Z., Wang, Y., & Guo, L. (2016). Quantifying the multilevel effects of landscape composition and configuration on land surface temperature. Remote Sensing of Environment, 178, 84–92. https://doi.org/10.1016/j.rse.2016.02.063
Essa, W., Verbeiren, B., Van der Kwast, J., Van de Voorde, T., & Batelaan, O. (2012). Evaluation of the DisTrad thermal sharpening methodology for urban areas. International Journal of Applied Earth Observation and Geoinformation : ITC Journal, 19, 163–172. https://doi.org/10.1016/j.jag.2012.05.010
Estoque, R. C., Murayama, Y., & Myint, S. W. (2017). Effects of landscape composition and pattern on land surface temperature: An urban heat island study in the megacities of Southeast Asia. The Science of the Total Environment, 577, 349–359. https://doi.org/10.1016/j.scitotenv.2016.10.195
Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., et al. (2005). Global Consequences of Land
Hao, X., Li, W., & Deng, H. (2016). The oasis effect and summer temperature rise in arid regions-case study in Tarim Basin. *Scientific Reports*, 6(1), 35418. https://doi.org/10.1038/srep35418

He, B. J., Zhao, Z. Q., Shen, L. D., Wang, H. B., Li, L. G., & He, B. I. (2019). An approach to examining performances of cool/hot sources in mitigating/enhancing land surface temperature under different temperature backgrounds based on landSat 8 image. *Sustain Cities Soc*, 44, 416–427. https://doi.org/10.1016/j.scs.2018.10.049

Hope, A. S., & McDowell, T. P. (1992). The relationship between surface temperature and a spectral vegetation index of a tall grass prairie: Effects of burning and other landscape controls. *International Journal of Remote Sensing*, 13(15), 2849–2863. https://doi.org/10.1080/01431169208904086

Hou, G. L., Zhang, H. Y., Wang, Y. Q., Qiao, Z. H., & Zhang, Z. X. (2010). Retrieval and spatial distribution of land surface temperature in the middle part of Jilin Province based on MODIS data. *Sci Geogr Sin*, 30, 421–427. http://cn.cnki.com.cn/Article_en/CJFDOTAL-DLKX201003017.htm

Huang, S., Taniguchi, M., Yamano, M., & Wang, C. H. (2009). Detecting urbanization effects on surface and subsurface thermal environment — A case study of Osaka. *The Science of the Total Environment*, 407(9), 3142–3152. https://doi.org/10.1016/j.scitotenv.2008.04.019

Jamei, Y., Rajagopalani, P., & Sun, Q. C. (2019). Spatial structure of urban heat island and its relationship with vegetation and built-up areas in Melbourne, Australia. *The Science of the Total Environment*, 659, 1335–1351. https://doi.org/10.1016/j.scitotenv.2018.12.308

Jiménez-Muñoz JC, Cristóba J, Sobrino JA, Soria G, Ninyerola M, Pons X (2009) Revision of the single-channel algorithm for land surface temperature retrieval from Landsat thermal-infrared data. *Photogram Eng Remote Sens* 47(1), 339–349. http://dx.doi.org/10.1109/TGRS.2008.2007125

Jiménez-Muñoz JC, Sobrino JA (2003) A generalized single channel method for retrieving land surface temperature from remote sensing data. *J Geophys Res*, 108(D22), 4688. http://dx.doi.org/10.1029/2003JD003480

Julien, Y. Sobrino JA Verhoef W (2006) Changes in land surface temperatures and NDVI values over Europe between 1982 and 1999. *Remote Sensing of Environment*, 103(1), 43–55. https://doi.org/10.1016/j.rse.2006.03.011

Kalnay, E., & Cai, M. (2003). Impact of urbanization and land-use change on climate. *Nat Cell Biol*, 423, 528–531.

Karnieli A, Agam N, Pinker RT, Anderson M, Imhoff ML, Gutman GG, Panov N, Goldberg A (2010) Use of NDVI and land surface temperature for drought assessment: Merits and limitations. *J Clim* 23(3), 618–633. doi:10.1175/2009JCLI2900.1

Ke, Y. H., Im, J., Lee, J., Gong, H. L., & Ryu, Y. (2015). Characteristics of landSat 8 oli-derived NDVI by comparison with multiple satellite sensors and in-situ observations. *Remote Sensing of Environment*, 164, 298–313. https://doi.org/10.1016/j.rse.2015.04.004

Kikon, N., Singh, P., Singh, S. K., & Vyas, A. (2016). Assessment of urban heat islands (UHI) of Noida City, India using multi-temporal satellite data. *Sustain Use, Science*, 309(5734), 570–574. https://doi.org/10.1126/science.1111772

Fu, P., & Weng, Q. (2015). Temporal dynamics of land surface temperature from landsat TIR time series images. *IEEE Geosci Sens Lett*, 12, 1–5.

Fu, P., & Weng, Q. (2016). A time series analysis of urbanization induced land use and land cover change and its impact on land surface temperature with landsat imagery. *Remote Sensing of Environment*, 175, 205–214. https://doi.org/10.1016/j.rse.2015.12.040

García-Santos V, Cuxart J, Martinez-Villagrasa D, Jiménez MA, Simó G (2018) Comparison of Three Methods for Estimating Land Surface Temperature from Landsat 8-TIRS Sensor Data. *Remote Sens* 10(9), 1450. https://doi.org/10.3390/rs10091450

Ghobadi, Y., Pradhan, B., Shafri, H. Z. M., & Kabiri, K. (2014). Assessment of spatial relationship between land surface temperature and land use/cover retrieval from multi-temporal remote sensing data in South Karkheh Sub-basin, Iran. *Arab J Geosci*, 8(1), 525–537. https://doi.org/10.1007/s12517-013-1244-3

Gorgani, S. A., Panahi, M., & Rezaie, F. (2013). The relationship between NDVI and LST in the Urban area of Mashhad, Iran. *International Conference on Civil Engineering Architecture and Urban Sustainable Development. November, Tabriz, Iran.

Goward, S. N., Xue, Y. K., & Czajkowski, K. P. (2002). Evaluating land surface moisture conditions from the remotely sensed temperature/vegetation index measurements: An exploration with the simplified simple biosphere model. *Remote Sensing of Environment*, 79(2–3), 225–242. https://doi.org/10.1016/S0034-4257(01)00275-9

Grimm, N. B., Faeth, S. H., Golubiewski, N. E., Redman, C. L., Wu, J., Bai, X., Briggs, J. M., & Grimm, N. (2008). Global change and the ecology of cities. *Science*, 319(5864), 756–760. https://doi.org/10.1126/science.1150195

Guha, S., Govil, H., Dey, A., & Gill, N. (2018). Analytical study of land surface temperature with NDVI and NDBI using Landsat 8 OLI/TIRS data in Florence and Naples city, Italy. *Eur J Remote Sens*, 51(1), 667–678. https://doi.org/10.1080/22797254.2018.1474944

Guha, S., Govil, H., Dey, A., & Gill, N. (2020). A case study on the relationship between land surface temperature and land surface indices in Raipur City, India. *Geografisk Tidsskrift / udgivet af Bestyrelsen for Det Kongelige danske geografiske selskab*, 120(1), 35–50. https://doi.org/10.1080/00167223.2020.1752272

Gui, X., Wang, L., Yao, R., Yu, D., & Li, C. (2019). Investigating the urbanization process and its impact on vegetation change and urban heat island in Wuhan, China. *Environ Sci Pollut Res*, 26(30), 30808–30825. https://doi.org/10.1007/s11356-019-06273-w

Guo, G., WuGuo, G., Wu, Z., Xiao, R., Chen, Y., Liu, X., & Zhang, X. (2015). Impacts of urban biophysical composition on land surface temperature in urban heat island clusters. *Landscapde and Urban Planning*, 135, 1–10. https://doi.org/10.1016/j.landurbplan.2014.11.007

Gutman, G., & Ignatov, A. (1998). The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models. *International Journal of Remote Sensing*, 19(8), 1533–1543. https://doi.org/10.1080/014311698215333
Cities Soc, 22, 19–28. https://doi.org/10.1016/j.scs.2016.01.005
Kumar, D., & Shekhar, S. (2015). Statistical analysis of land surface temperature-vegetation indexes relationship through thermal remote sensing. Ecotax Environ Safe, 121, 39–44. https://doi.org/10.1016/j.ecoenv.2015.07.004
Lambin, E. F., & Ehrlich, D. (1996). The surface temperature-vegetation index space for land use and land cover change analysis. International Journal of Remote Sensing, 17(3), 463–487. https://doi.org/10.1080/01431169608949021
Li ZN, Duan SB, Tang BH, Wu H, Ren HG, Yan GJ. (2016). Review of methods for land surface temperature derived from thermal infrared remotely sensed data. J Remote Sens, 20, 899–920.
Liang, B. P., Li, Y., & Chen, K. Z. (2012). A research on land features and correlation between NDVI and land surface temperature in Guilin City. Remote Sens Tech Appl, 27, 429–435.
Liu, Y., Peng, J., & Wang, Y. (2018). Efficiency of landscape metrics characterizing urban land surface temperature. Landscape and Urban Planning, 180, 36–53. https://doi.org/10.1016/j.landurbplan.2018.08.006
Marzban, F., Soudodi, S., & Preusker, R. (2018). The influence of land-cover type on the relationship between LST-NDVI and LST-Tair. International Journal of Remote Sensing, 39(5), 1377–1398. https://doi.org/10.1080/01431161.2017.1462366
McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. International Journal of Remote Sensing, 17(7), 1425–1432. https://doi.org/10.1080/01431169608948714
McFeeters, S. K. (2013). Using the Normalized Difference Water Index (NDWI) within a geographic information system to detect swimming pools for mosquito abatement: A practical approach. Remote Sens, 5(7), 3544–3561. https://doi.org/10.3390/rs5073544
McMillin, LM. (1975). Estimation of sea surface temperatures from two infrared window measurements with different absorption. J Geophys Res 80, 80–82. https://doi.org/10.1029/JC080i03p00513
Moran, M. S., Clarke, T. R., Inouie, Y., & Vidal, A. (1994). Estianting crop water-deficit using the relation between surface air-temperature and spectral vegetation index. Remote Sensing of Environment, 49(3), 246–263. https://doi.org/10.1016/0034-4257(94)90020-5
Mushore, T. D., Odindi, J., Dube, T., & Mutanga, O. (2017). Prediction of future urban surface temperatures using medium resolution satellite data in Harare metropolitan city, Zimbabwe. Building and Environment, 122, 397–410. https://doi.org/10.1016/j.buildenv.2017.06.033
Nimish, G., Bharath, H. A., & Lalitha, A. (2020). Exploring temperature indices by deriving relationship between land surface temperature and urban landscape. Remote Sens Appl Soc Environ, 18, 100299. https://doi.org/10.1016/j.rse.2020.100299
Patz, J. A., Campbell-Lendrum, D., Holloway, T., & Foley, J. A. (2005). Impact of regional climate change on human health. Nat Cell Boll, 438, 310–317. https://doi.org/10.1038/nature04188
Peng, J., Jia, J., Liu, Y., Li, H., & Wu, J. (2018a). Seasonal contrast of the dominant factors for spatial distribution of land surface temperature in urban areas. Remote Sensing of Environment, 215, 255–267. https://doi.org/10.1016/j.rse.2018.06.010
Peng, J., Ma, J., Liu, Q., Liu, Y., Hu, Y., Li, Y., & Yue, Y. (2018b). Spatial-temporal change of land surface temperature across 285 cities in china: An urban-rural contrast perspective. The Science of the Total Environment, 635, 487–497. https://doi.org/10.1016/j.scitotenv.2018.04.105
Peng, J., Xie, P., Liu, Y., & Ma, J. (2016). Urban thermal environment dynamics and associated landscape pattern factors: a case study in the Beijing metropolitan region. Remote Sensing of Environment, 173, 145–155. https://doi.org/10.1016/j.rse.2015.11.027
Price, JC. (1984). Land surface temperature measurements from the split window channels of the NOAA 7 Advanced Very High Resolution Radiometer. J Geophys Res Atmos 89, 231–237. https://doi.org/10.1029/JD089iD05p02731
Purevдорж, Т. С., Tätelishi, R., Ishiyama, T., & Honda, Y. (1998). Relationships between percent vegetation cover and vegetation indices. International Journal of Remote Sensing, 19(18), 3519–3535. https://doi.org/10.1080/014311698213797
Qin, Z., Karnieli, A., & Barliner, P. (2001). A mono-window algorithm for retrieving land surface temperature from landsat TM data and its application to the Israel-Egypt border region. International Journal of Remote Sensing, 22(18), 3719–3746. https://doi.org/10.1080/01431169008955164
Qu, C., Ma, J. H., Xia, Y. Q., & Fei, T. (2014). Spatial distribution of land surface temperature retrieved from MODIS data in Shiyang River Basin. Arid Land Geogr, 37, 125–133.
Qu, S., Wang, L., Lin, A., Yu, D., Yuan, M., & Li, C. (2020). What drives the vegetation restoration in Yangtze River basin, China: Climate change or anthropogenic factors? Ecological Indicators, 108, 105724. https://doi.org/10.1016/j.ecolind.2019.105724
Roy, S., Pandit, S., Eva, E. A., Bagmar, M. S. H., Papia, M., Banik, L., Dube, T., Rahman, F., & Razi, M. A. (2020). Examining the nexus between land surface temperature and urban growth in Chattogram Metropolitan Area of Bangladesh using long term Landsat series data. Urban Clim, 32, 100593. https://doi.org/10.1016/j.uclim.2020.100593
Sandholt, I., Rasmussen, K., & Andersen, J. (2002). A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. Remote Sensing of Environment, 79(2–3), 213–224. https://doi.org/10.1016/s0034-4257(01)00274-7
Sekertekin, A and Bonafoni, S. (2020). Land surface temperature retrieval from landsat 5, 7, and 8 over rural areas: assessment of different retrieval algorithms and emissivity models and toolbox implementation. Remote Sens 12 (2): 294. https://doi.org/10.3390/rs12020294
Shigeto, K. (1994). Relation between vegetation, surface temperature, and surface composition in the Tokyo region during winter. Remote Sensing of Environment, 50(1), 52–60. https://doi.org/10.1016/0034-4257(94)90094-9
Smith, R. C. G., & Choudhury, B. J. (1990). On the correlation of indices of vegetation and surface temperature over south-eastern Australia. International Journal of Remote Sensing, 11(11), 2113–2120. https://doi.org/10.1080/01431169008955164
Sobrino, J. A., Jimenez-Munoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from Landsat TM5. *Remote Sensing of Environment*, 90(4), 434–440. https://doi.org/10.1016/j.rse.2004.02.003

Sobrino, J. A., Raissouni, N., & Li, Z. (2001). A comparative study of land surface emissivity retrieval from NOAA data. *Remote Sensing of Environment*, 75(2), 256–266. https://doi.org/10.1016/S0034-4257(00)00171-1

Son, N. T., Chen, C. F., & Chen, C. R. (2020). Urban expansion and its impacts on local temperature in San Salvador, El Salvador. *Urban Clim*, 32, 100617. https://doi.org/10.1016/j.uclim.2020.100617

Stroppiana, D., Antoninetti, M., & Brivio, P. A. (2014). Seasonality of MODIS LST over Southern Italy and correlation with land cover, topography and solar radiation. *Eur J Remote Sens*, 47(1), 133–152. https://doi.org/10.5721/EurJRS20144709

Sun, D., & Kafatos, M. (2007). Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America. *Geophysical Research Letters*, 34. http://doi.org/10.1029/2007GL031485

Sun, Q., Tan, J., & Xu, Y. (2010). An ERDAS image processing method for retrieving LST and describing urban heat evolution: A case study in the Pearl River Delta region in South China. *Environ Earth Sci*, 59(5), 1047–1055. https://doi.org/10.1007/s12665-009-0096-3

Tomlinson, C. J., Chapman, L., Trones, J. E., & Baker, C. (2011). Remote sensing land surface temperature for meteorology and climatology: A review. *Meteorol Appl*, 18(3), 296–306. https://doi.org/10.1002/met.287

Tran, D. X., Pla, F., Latorre-Carmona, P., Miyint, S. W., Caetano, M., & Kieu, H. V. (2017). Characterizing the relationship between land use land cover change and land surface temperature. *ISPRS J Photogramm Remote Sens*, 124, 119–132. https://doi.org/10.1016/j.isprsjprs.2017.01.001

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0

Uddin, S., Al Ghadbani AN, Al Dousari A, Al Murad, M. Al Shamroukh D (2010) A Remote Sensing Classification for Land-Cover Changes and Micro-Climate in Kuwait. *Int J Sustain Dev Plann*, 5, 367–377. https://doi.org/10.2495/SDP-V5-N4-367-377

Voogt, J. A., & Oke, T. R. (2003). Thermal remote sensing of urban climates. *Remote Sensing of Environment*, 86(3), 370–384. https://doi.org/10.1016/S0034-4257(03)00079-8

Weng, Q. (2001). A remote sensing-GIS evaluation of urban expansion and its impact on surface temperature in Zhujiang Delta, China. *Int J Remote Sens*, 22(10), 1999–2014. https://doi.org/10.1080/713860788

Weng, Q. H. (2009). Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. *ISPRS J Photogramm Remote Sens*, 64(4), 335–344. https://doi.org/10.1016/j.isprsjprs.2009.03.007

Weng, Q. H., Lu, D. S., & Schubring, J. (2004). Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment*, 89(4), 467–483. https://doi.org/10.1016/j.rse.2003.11.005

Weng, Q. H., & Quattrochi, D. A. (2006). Thermal remote sensing of urban areas: An introduction to the special issue. *Remote Sensing of Environment*, 104(2), 119–122. https://doi.org/10.1016/j.rse.2006.05.002

Wukelich, G. E., Gibbons, D. E., Martucci, L. M., & Foote, H. P. (1989). Radiometric calibration of landsat thematic mapper thermal band. *Remote Sensing of Environment*, 28, 339–347. https://doi.org/10.1016/0034-4257(89)90125-9

Yang, J., & Qiu, J. (1996). The empirical expressions of the relation between precipitable water and ground water vapor pressure for some areas in China. *Sci Atmos Sinica*, 20, 620–626.

Yang L., Cao YG, Zhu XH, Zeng SH, Yang GJ, He JY, Yang XC (2014). Land surface temperature retrieval for arid regions based on Landsat-8 TIRS data: a case study in Shihhezi, Northwest China. *J Arid Land*. 6, 704–716. https://doi.org/10.1007/s40333-014-0071-2

Yuan, F., & Bauer, M. E. (2007). Comparison of impervious surface area and normalized difference index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment*, 106(3), 375–386. https://doi.org/10.1016/j.rse.2006.09.003

Yuan, M., Wang, L., Lin, A., Liu, Z., & Qu, S. (2020). Vegetation green up under the influence of daily minimum temperature and urbanization in the Yellow River Basin, China. *Ecological Indicators*, 108, 105760. https://doi.org/10.1016/j.ecolind.2019.105760

Yuan X., Wang W., Cui J., Meng F., Kurban A., De Maeyer P. (2017). Vegetation changes and land surface feedbacks drive shifts in local temperatures over Central Asia. *Sci Rep*, 7(1), 3287. https://doi.org/10.1038/s41598017034322

Yue, W., Xu, J., Tan, W., & Xu, L. (2007). The relationship between land surface temperature and NDVI with remote sensing, application to Shanghai Landsat 7 ETM+ data. *International Journal of Remote Sensing*, 28(15), 3205–3226. https://doi.org/10.1080/0143116050036906

Zanter, K. (2019). Landsat 8 (L8) Data Users Handbook; EROS: Sioux Falls, SD, USA.

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, 24(3), 583–594. https://doi.org/10.1080/01431160304987

Zhang X., Estoque RC, Murayama Y. (2017). An urban heat island study in Nanchang City, China based on land surface temperature and social-ecological variables. *Sustain Cities Soc*, 32, 557–568. https://doi.org/10.1016/j.scs.2017.05.005

Zhang, Y., Odeh, I. O. A., & Han, C. (2009). Bi-temporal characterization of land surface temperature in relation to impervious surface area, NDVI and NDBI, using a sub-pixel image analysis. *International Journal of Applied Earth Observation and Geoinformatics : ITC Journal*, 11(4), 256–264. https://doi.org/10.1016/j.jag.2009.03.001

Zhang Z., He G., Wang M., Long T., Wang G., Zhang X., Jiao W. (2016). Towards an operational method for land surface temperature retrieval from Landsat 8 data. *Remote Sens Lett*, 7(3), 279–288. http://doi.org/10.1080/2150704X.2015.1130877

Zhao, H. M., & Chen, X. L. (2005). Use of normalized difference bareness index in quickly mapping bare areas from TM/ETM+. *Geoscience and Remote Sensing Symposium*, 3(25–29), 1666–1668. https://doi.org/10.1109/IGARSS.2005.1526319
Zhou, D., Xiao, J., Bonafoni, S., Berger, C., Deilami, K., Zhou, Y., Frolking, S., Yao, R., Qiao, Z., & Sobrino, J. A. (2019). Satellite remote sensing of surface urban heat Islands: Progress, challenges, and perspectives. Remote Sens, 11(1), 48. https://doi.org/10.3390/rs11010048

Zhou, Y., Shi, T. M., Hu, Y. M., & Liu, M. (2011). Relationships between land surface temperature and normalized difference vegetation index based on urban land use type. Chin J Ecol, 30, 1504–1512.

Sharma, R., Joshi, P. K. (2016). Mapping environmental impacts of rapid urbanization in the National Capital Region of India using remote sensing inputs. Urban Clim 15, 70-82. https://doi.org/10.1016/j.uclim.2016.01.004