Dynamic status of land surface temperature and spectral indices in Imphal city, India from 1991 to 2021

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ABSTRACT
The thermal status of northeast Indian cities has a great impact on the sustainability of these places. To meet the research gap in this area, a study is performed in Imphal city, India by investigating the relationship between land surface temperature (LST) and four spectral indices in the summer and winter seasons from 1991 to 2021. The mean LST of the city increases at \( >1\% \) rate per decade in both seasons. The urban heat island (UHI) develops mostly along the central Imphal. A considerable difference in the mean LST between UHI and non-UHI in summer (3.05 \(^\circ\)C in 1991, 2.46 \(^\circ\)C in 2001, 3.13 \(^\circ\)C in 2011, and 2.49 \(^\circ\)C in 2021) and winter (2.01 \(^\circ\)C in 1991, 2.63 \(^\circ\)C in 2001, 2.64 \(^\circ\)C in 2011, and 2.57 \(^\circ\)C in 2021) reflects the continuous warming status of the city. Some urban hot spots develop inside the UHI of the central and north Imphal. The dynamic nature of the relationships of spectral indices with LST (moderate negative for MNDWI and NDVI, strongly positive for NDBI, and moderate negative for NDBaI) will be helpful for proper sustainable urban planning. Urban thermal field variance index map shows that the south Imphal attains more ecological comfort than the rest of the parts.

1. Introduction
The process of urbanization enhances the thermal stress of an area by global or local warming (Grimm et al. 2008; Fu and Weng 2016). The continuous conversion process of land surface accelerates the warming status of today’s urban atmosphere (Zhou et al. 2018; Guha et al. 2020). Land surface temperature (LST) determined from various satellite sensors is considerably used in the demarcation of the heat islands and thermal stressed zones inside the urban area (Weng 2009; Tomlinson et al. 2011; Fu and Weng 2016; Hao et al. 2016; Tran et al. 2017). The variation of LST in the heterogeneous urban landscape is largely influenced by the land use/land cover (LULC) categories (Li et al. 2016; Estoque et al. 2017; Guha et al. 2020).
Satellite remote sensing techniques are applied to detect the changed land surface zones by using their visible to near-infrared (VNIR) and shortwave infrared (SWIR) bands (Chen et al. 2006). Moreover, thermal infrared (TIR) bands are also used to create some spectral indices (Kalnay and Cai 2003; Du et al. 2016; Berger et al. 2017; He et al. 2019). The most popular index for vegetation in LST estimation is the normalized difference vegetation index (NDVI) (Carlson and Ripley 1997; Sobrino et al. 2004). In mixed urban land, high LST is related to low vegetal covered area (Voogt and Oke 2003). Many studies are based on the LST-NDVI correlation (Gutman and Ignatov 1998; Guha and Govil 2021) to explore the pattern of LST. Modified normalized difference water index (MNDWI) is one of the most used water indices and it is considerably used in LST-related research works (Essa et al. 2012; Guha et al. 2017). Normalized difference built-up index (NDBI) is the most popular built-up index that is invariably used in LST-related studies (Zha et al. 2003; Guha et al. 2020). Normalized difference bareness index (NDBaI) is an index for bare land identification (Zhao and Chen 2005; Chen et al. 2006; Guha and Govil 2021).

Urban hot spots (UHS) develop mainly inside the urban heat island (UHI) due to heavy construction and manufacturing activities. These UHS are the most severely heated surface of the area (Chen et al. 2006; Coutts et al. 2016; Feyisa et al. 2016; Ren et al. 2016; Lopez et al. 2017; Pearsall 2017). The detection of UHS for prioritization is very significant to maintain the thermal status of a city.

Several research works introduced some ecological comfort indices (Matzarakis et al. 1999; Kakon et al. 2010; Willett and Sherwood 2012) among which urban thermal field variance index (UTFVI) is the most popular index for ecological evaluation as it is directly related to LST (Nichol 2005; Liu and Zhang 2011; Mackey et al. 2012; Guha et al. 2017).

Recently, there are some research materials available on the relationship between LST and different spectral indices in South Asia. Ramaiah et al. (2020) attempted to quantify the influence of urban factors on LST in the Panaji and Tumkur of India. Dissanayake (2020) investigated the spatiotemporal changes of LULC and its impact on LST in Galle City, Sri Lanka. Halder (2021) evaluated the impact of climate change on UHI based on LST and geospatial indicators in Kolkata, India. Shukla and Jain (2021) analyzed the impact of changing landscape patterns and dynamics on LST in Lucknow city, India. Dissanayake et al. (2019) assessed the changes in LULC and their impact on surface UHI in Kandy City, Sri Lanka. Ranagalage et al. (2018) showed the spatial changes of UHI formation in Colombo District, Sri Lanka for sustainable planning.

Imphal is an ecological smart city which is expanding rapidly in recent decades. It has agricultural fields, water bodies, wetlands, and green vegetation inside and outside the city area. The city can be representative of moderately populated Indian cities under humid subtropical climates. Kalota (2017) analyzed the LST of Manipur State with some selected built-up, vegetation, and topographical variables. The present study is perhaps the first significant attempt to evaluate the relationship built between LST and the spectral indices in Imphal city for the summer and winter seasons. The prime objectives of this study are: (1) to analyze the spatial, temporal, and seasonal changes of LST in UHI and non-UHI of Imphal city; (2) to identify the UHS inside the UHI; (3) to correlate
LST with the different spectral indices for the whole city and inside the UHI and UHS; and (4) to measure the ecological comfort level by UTFVI.

2. Study area and data

The present study was performed over Imphal, the capital city of Manipur, and its surrounding area. It is a humid subtropical landlocked mountainous city and is one of the important cities in northeast India. Imphal is the second round winner for the selection of Smart Cities Mission under the Ministry of Urban Development. The study area (Imphal city and its surroundings) extends from 24°53′47″N to 24°41′43″N and from 93°51′00″E to 94°01′00″E (Figure 1). The study area covers approximately 419.62 km² area. It has an average elevation of around 800 m. Imphal city is divided into Imphal West and Imphal East districts. Imphal, Kongba, and Iril are the main rivers of the city those are flowing from north to south direction. Nambul is another river that flows from west to east. The city h’s ” humid sub’ro”ical (Cwa) type of climate characterized by cool dry winter and warm wet summer. The summer season extends from April to August while December, January, and February are considered as the winter months. The average annual range of temperature is 14°C–27°C and the average annual precipitation is 145 cm. July is the rainiest month.

A total of eight (four from summer and four from winter season) multi-temporal cloud-free Landsat satellite imageries (http://earthexplorer.usgs.gov/) of Imphal from 1991 to 2021 were used in this study (Table 1). The simple description of four used remote sensing spectral indices in the current study have been shown in Table 2. Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) data of 23 September 2014 (http://earthexplorer.usgs.gov/) were also used to determine the elevation value of the study area. The spatial information of Imphal city was obtained from the Imphal Municipal Corporation (https://imc.mn.gov.in/). High-resolution Google Earth Image (https://earth.google.com/web/) was used for LULC identification.

3. Methodology

The entire methodology of the present study needs to determine the four mentioned spectral indices and to estimate the LST of the study area for each Landsat dataset. Apart from these, UHI, UHS, and UTFVI of the study area for different seasons have also been quantified. In below, these methods have been described briefly.

3.1. Description of NDVI, MNDWI, NDBI, and NDBaI

Many remote sensing indices are regularly used for the identification of different types of landscapes (Guha et al. 2017). Here, NDBaI (Zhao and Chen 2005), NDBI (Zha et al. 2003), NDVI (Tucker 1979), and MNDWI (Xu 2006) and were used for determining the relationship with LST. The band combinations of these spectral indices were given in Table 1. The value of any normalized difference spectral index is ranged between −1.0 and +1.0. Generally, the positive value of NDBaI, NDBI,
NDVI, and MNDWI indicate the bare land, built-up, vegetation, and water surface, respectively (Chen et al. 2006).

3.2. LST estimation using Landsat TIR band

LST is estimated from the TIR band of Landsat satellite sensor by Equation (1) (Artis and Carnahan 1982):

\[ L_k = \text{RadianceMultiBand} \times DN + \text{RadianceAddBand} \]  

\( L_k \) = the spectral radiance in Wm\(^{-2}\)sr\(^{-1}\)mm\(^{-1}\).
| Landsat scene ID       | Date of acquisition | Time (UTC)* | Path/Row | Sun elevation (°) | Sun azimuth (°) | Cloud cover (%) | Earth-Sun distance (astronomical unit) | Resolution of VNIR bands (m) | Resolution of TIR bands (m) |
|-----------------------|---------------------|-------------|----------|------------------|----------------|----------------|--------------------------------------|-------------------------------|----------------------------|
| **Summer season**     |                     |             |          |                  |                |                |                                      |                               |                            |
| LT51350431991108BKT00 | 18-Apr-91           | 03:34:00    | 135/043  | 56.09            | 108.42         | 7.00           | 1.00                                 | 30                            | 120                        |
| LT51350432001135BKT01 | 15-May-01           | 03:52:12    | 135/043  | 64.13            | 97.29          | 5.00           | 1.01                                 | 30                            | 120                        |
| LT51350432011099BKT01 | 09-Apr-11           | 04:01:51    | 135/043  | 59.68            | 119.96         | 0.00           | 1.00                                 | 30                            | 120                        |
| LC8135043202110LGN00  | 20-Apr-21           | 04:11:42    | 135/043  | 64.64            | 116.66         | 9.64           | 1.00                                 | 30                            | 100                        |
| **Winter season**     |                     |             |          |                  |                |                |                                      |                               |                            |
| LT51350431991028ISP00 | 28-Jan-91           | 03:32:37    | 135/043  | 34.42            | 137.09         | 1.00           | 0.98                                 | 30                            | 120                        |
| LT51350432001039BKT00 | 08-Feb-01           | 03:52:05    | 135/043  | 39.76            | 138.59         | 0.00           | 0.99                                 | 30                            | 120                        |
| LT51350432011035BKT00 | 04-Feb-11           | 04:02:01    | 135/043  | 40.21            | 142.28         | 0.00           | 0.99                                 | 30                            | 120                        |
| LC81350432021014LGN00 | 14-Jan-21           | 04:12:14    | 135/043  | 37.97            | 149.60         | 7.94           | 0.98                                 | 30                            | 100                        |

*IST = UTC + 05:30 (IST = Indian standard time, UTC = Coordinated universal time)
At-sensor brightness temperature is estimated by Equation (2).

\[ T_B = \frac{K_2}{\ln \left( \frac{K_1}{L_k} \right) + 1} \]  

(2)

Where, \( T_B \) = brightness temperature in Kelvin (K), \( L_k \) = spectral radiance in \( \text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1} \); \( K_2 \) and \( K_1 \) = calibration constants.

Fractional vegetation is calculated by Equation (3) (Carlson and Ripley 1997).

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

(3)

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

Land surface emissivity \( \varepsilon \), is calculated by Equation (4) (Sobrino et al. 2001, 2004):

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

(4)

Where, \( \varepsilon \) = surface emissivity.

Finally, LST is estimated by Equation (5) (Weng et al. 2004):

\[ LST = \frac{T_B}{1 + \left( \lambda \sigma T_B / (hc) \right) \ln \varepsilon} \]  

(5)

Where, \( \lambda \) = effective wavelength, \( \sigma \) = Boltzmann constant (1.38 \times 10^{-23} \text{ J/K}), \( h \) = Plank’s constant (6.626 \times 10^{-34} \text{ Js}), \( c \) = velocity of light in a vacuum (2.998 \times 10^{-8} \text{ m/sec}), \( \varepsilon \) = emissivity.

3.3. Mapping UHI

UHI and non-UHI zones are demarcated using the following equations (Guha et al. 2017):

\[ LST > \mu + 0.5 \times \sigma \]  

(6)

\[ 0 < LST \leq \mu + 0.5 \times \sigma \]  

(7)

Where, \( \mu \) and \( \sigma \) are the mean and standard deviation of LST in the study area, respectively.

3.4. Delineating the urban hot spots (UHS)

The UHS were delineated by the following equation (Guha et al. 2017):

\[ LST > \mu + 2 \times \sigma \]  

(8)
3.5. The urban thermal field variance index (UTFVI)

UTFVI was determined using the following equation (Liu and Zhang 2011):

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

(9)

Where, \(UTFVI\) = Urban Thermal Field Variance Index
\(T_s\) = LST (°C)
\(T_{mean}\) = Mean LST (°C)

This methodology used in Imphal city can also be used in similar types of the study area with Landsat data as the process of LST derivation and spectral indices determination remains the same. In different geographical locations, some methods may be modified to obtain a logical output.

4. Results and discussion

4.1. Spatial, temporal, and seasonal dynamics of different spectral indices

Figure 2 present the spatial distribution (1991–2021) of NDVI (Figure 2A) and MNDWI (Figure 2B) for the summer and winter seasons whereas Figure 3 shows the same for NDBI (Figure 3A) and NDBaI (Figure 3B) for both seasons. The maximum NDVI values gradually decrease in the region due to the loss of vegetation. North-western parts and south-eastern peripheries indicate a concentrated vegetal cover. Most of the water bodies are found in the southwest portions of the study area where MNDWI values are greater. High NDBI values are observed mainly along the outskirts of the central city. In the whole area, NDBI increases at an alarming rate that indicates a positive trend of LST. NDBaI values generally increase with time and the eastern part of the city is characterized by high NDBaI values compared to the western side because of the high proportion of bare lands.

Table 3 shows the dynamic nature of LST and these spectral indices. The mean NDVI values are gradually decreasing from 1991 to 2021 and the values of summer mean NDVI is slightly higher than winter mean NDVI. It indicates the exploitation of parks and green spaces inside the city. The summer and winter mean MNDWI values show a steady decrease throughout the periods that reflect an increase of water bodies and wetlands in the study area. The mean MNDWI values are a little bit more in the summer season due to wet conditions. Despite the increase of built-up surface,
The mean NDBI values show low variability due to the heterogeneity of built-up surface. The mean NDBI is continuously increasing and it always remains higher in the winter season due to dry weather. A steady increase in mean NDBI reflects the increase of bare land during the span. The mean NDBI of the summer season always reflects a higher value. These bare lands can enhance the ecological status of Imphal city through proper environmental planning. Mean LST increases considerably from 1991 to 2021 and the summer season always provides a high mean LST (more than 9°C) than the winter one.

Figure 2. Distribution of NDVI and MNDWI in summer and winter season in 1991, 2001, 2011, and 2021 in Imphal city (A = NDVI, B = MNDWI, Black line = city boundary).
4.2. Changing pattern of LST

A significant LST distribution trend was noticed during the last three decades (Figure 4A). A gradual increase of LST is noticed in the minimum, maximum, mean, and standard deviation values due to the change in LULC types. The green and water surfaces are decreased while the built-up surfaces are increased and this LULC change reflects in the LST distribution. North-eastern and central parts of the city receive more LST in every decade. Table 4 shows the temporal distribution of LST in Imphal.
city from 1991 to 2021. It is noticed that the minimum, maximum, and mean values of LST increase at a significant rate of 62.73%, 7.02%, and 14.39% in the summer season for the last three decades. In winter, the minimum, maximum, and mean values of LST increase at a rate of 42.19%, 8.63%, and 19.67% for the last 30 years.

Figure 4B shows the LST change over Imphal city. A little LST change is found in this span. The central part gets warmer than the cooler periphery regions. However, the picture changes in 2001–2011. In that time, the periphery receives more LST than the middle portions. In the next decade, the central parts become warmer than the previous decade and some outskirts of the city also experience a negative change in LST. Overall, the central and southern parts of Imphal city have significantly heated (>5 °C increase in mean LST) in the summer season of the last three decades. In the winter season, the whole city becomes warmer (>2-3 °C increase in mean LST) except in some patches of the northwest portions. The city is constantly heated due to rapid urbanization and land conversion.

### 4.3. Dynamic scenario of UHI effect

A significant increase in the mean LST between UHI and non-UHI for summer (3.05 °C in 1991, 2.46 °C in 2001, 3.13 °C in 2011, and 2.49 °C in 2021) and winter (2.01 °C in 1991, 2.63 °C in 2001, 2.64 °C in 2011, and 2.57 °C in 2021) seasons of different decades is observed from the estimated LST (Table 5). For the UHI, A straight 12.14% and 19.35% mean LST is increased in summer and winter season respectively from 1991 to 2021. For the non-UHI, these temporal estimations are 16.05% and 18.2% for the summer and winter seasons, respectively. The standard deviation values of LST in the UHI zones for the summer and winter seasons are <0.98 and <1.07, respectively for each year indicate a very little variation in LST. The ranges of the

### Table 3. Descriptive statistics of MNDWI, NdaBI, NDBI, and NDVI (1991–2021).

|          | Summer       | Winter       |
|----------|--------------|--------------|
| **MNDWI**|              |              |
| Min      | –0.60        | –0.67        |
| Max      | 0.36         | 0.73         |
| Mean     | –0.34        | –0.35        |
| Std      | 0.09         | 0.12         |
| **NDBaI**|              |              |
| Min      | –0.70        | –0.91        |
| Max      | 0.33         | 0.22         |
| Mean     | –0.28        | –0.32        |
| Std      | 0.10         | 0.13         |
| **NDBI** |              |              |
| Min      | –0.34        | –0.74        |
| Max      | 0.46         | 0.52         |
| Mean     | 0.10         | 0.20         |
| Std      | 0.10         | 0.12         |
| **NDVI** |              |              |
| Min      | –0.60        | –0.68        |
| Max      | 0.41         | 0.44         |
| Mean     | 0.23         | 0.17         |
| Std      | 0.10         | 0.10         |

A. MONDAL ET AL.
standard deviation for UHI and non-UHI are 0.18 and 0.19 in the summer season while these ranges of standard deviation are 0.40 and 0.39 in the winter season. It reflects that the summer season has more consistent LST values in UHI and non-UHI compared to the winter season.

In Imphal, the UHI zones are consistently concentrated in the northern part in the first two decades and the central part in the last decade (Figure 5A). The northern
part is an area of the dry bare land surface while the central part of the city is mainly
the built-up area with commercial and residential blocks. The north-western and east-
ern portions are the area with high vegetal coverage space and come under the non-
UHI. Some urban vegetation has been planted in the north-western and eastern parts
of the city to reduce the pollution level. Most of the numerous water bodies are
found in the southwestern corner of the study area.

The UHI estimated from different satellite imageries occupies some common areas.
These common UHI experience a constant increase in LST (Figure 5B). Here, the
black colour shows the area under non-UHI. The analysis derived from Figures 5A
and 5B depicts that the highest LST values exist in the built-up and bare lands.
Change in mean LST for common UHI was represented in Figure 5B. UHI received
more surface temperature with time. During 1991–2021, 3–8 °C mean LST was
increased in most of the portions of common UHI.

Figure 6 presents some randomly selected points in Imphal city from the 20
April 2021 image. Points 1, 2, 3, 4, 5, and 6 falls inside the UHI whereas points 7,
8, 9, 10, 11, and 12 falls inside the non-UHI. Points 1–6 are mainly concentrated in
the central built-up area of the city where the high density of population and com-
mercial buildings is directly responsible for high LST generation. Point 1 is located
in the Lamlong Bazar area, point 2 is located in the Yengkhom Leirak area, point 3
is located near Manipur Rural Bank, point 4 is located in Kangjiabi Leirak locality,
point 5 is located near Leiningthow Khanglamba area, and point 6 is located in
Sanakhwa Yaima Kollup locality. Points 7 to 12 are mainly scattered along the area
outside the central built-up area that is a part of a vegetation-covered area or a
water body. Point 7 is located in a water body near NIT Manipur sports ground,
point 8 is located in dense vegetation near Cheirao Ching Garden, point 9 is
located in a zone surrounded by vegetation and water body near Imphal City
Sewage Treatment Plant, point 10 is located in a water body in Kakwa Pat area,
point 11 is located in RMS Equestrian Ground, and point 12 is located in a water
body near Khurai Lamlong Baptist Church in the north-eastern part of the city.
These particular areas have low LST values. The LST of the above location strongly
validates the results.

Table 4. Temporal distribution of LST (°C) in Imphal city.

| Year | LST(Min) | LST(Max) | LST(Mean) | LST(Std) | Threshold LST for UHI | Threshold LST for UHS |
|------|----------|----------|-----------|----------|----------------------|----------------------|
|      |          |          |           |          |                      |                      |
| Summer          |          |          |           |          |                      |                      |
| 1991 | 13.31    | 32.47    | 24.80     | 1.85     | 25.83                | 28.78                |
| 2001 | 17.02    | 32.05    | 25.59     | 1.55     | 26.67                | 28.76                |
| 2011 | 20.62    | 35.26    | 27.77     | 1.94     | 28.78                | 31.65                |
| 2021 | 21.66    | 34.75    | 28.37     | 1.64     | 29.19                | 31.65                |
| Winter          |          |          |           |          |                      |                      |
| 1991 | 8.01     | 27.95    | 15.71     | 1.44     | 16.58                | 18.85                |
| 2001 | 9.97     | 30.44    | 19.09     | 1.99     | 20.19                | 23.27                |
| 2011 | 9.39     | 27.08    | 17.80     | 1.78     | 18.76                | 21.43                |
| 2021 | 11.39    | 30.36    | 18.80     | 1.80     | 19.70                | 22.40                |
4.4. Delineation of UHS

In this study, UHS has been delineated for continuous monitoring of the most vulnerable heat zones. These small pockets are developed inside the UHI. UHS is more abundant over the bare land areas and the highly commercial and industrial zones. The UHS is mainly identified in the northern, eastern, and central parts of the city (Figure 7A). In 2021, the UHS is identified by a threshold value of 31.65 °C in summer and 22.40 °C in winter (Table 4). Bare earth surfaces, parking zones, metalled roads, metal roofs, and industrial factories are the most common places of UHS.

4.5. Relationship of LST with four spectral indices

Table 6 shows the dynamic analysis of the correlation of LST with MNDWI, NDVI, NDBI, and NDBaI for the whole Imphal city, for the UHI of Imphal city, and the UHS of Imphal city during the period. MNDWI gives a moderate negative correlation with LST for the entire study area in both seasons. However, for UHI, the LST-MNDWI relationship becomes weak negative in both seasons. For UHS, the correlation is weak negative in winter and insignificant in summer. NDVI also builds a moderate negative correlation with LST for the whole Imphal city in both seasons. For UHI, the strength of the relationship becomes weak negative in summer and insignificant in winter. For UHS, the correlation is insignificant in both seasons. The result indicates that areas with very high LST give a weak negative correlation with NDVI. In summer and winter, NDBI presents a strong positive correlation with LST for the whole Imphal city. However, in UHI, the value of the correlation coefficient becomes very weak positive in both seasons. UHS presents an insignificant correlation in summer and a weak positive correlation in winter. It is mainly due to the complex landscape composition. NDBaI reflects a moderate positive correlation with LST in the whole city in both the seasons which becomes insignificant for UHI and UHS. It indicates that a wide area with high LST values generates a moderate to a strong positive relationship with NDBI and NDBaI whereas the corresponding area builds a moderate negative correlation with NDVI and MNDWI. However, the strength tends to be weak with the increase of LST concentrated in a small area. It happens because

| Year | Min | Max | Mean | Std |
|------|-----|-----|------|-----|
|      | UHI | Non-UHI | UHI | Non-UHI | UHI | Non-UHI | UHI | Non-UHI |
| 1991 | 25.83 | 13.31 | 32.46 | 25.41 | 26.85 | 23.80 | 0.84 | 1.31 |
| 2001 | 26.66 | 17.01 | 32.04 | 26.24 | 27.36 | 24.90 | 0.79 | 1.18 |
| 2011 | 28.77 | 20.62 | 35.26 | 28.35 | 29.83 | 26.70 | 0.97 | 1.37 |
| 2021 | 29.19 | 21.65 | 34.75 | 29.19 | 30.11 | 27.62 | 0.82 | 1.30 |

Winter LST

| Year | Min | Max | Mean | Std |
|------|-----|-----|------|-----|
|      | UHI | Non-UHI | UHI | Non-UHI | UHI | Non-UHI | UHI | Non-UHI |
| 1991 | 16.57 | 8.01 | 27.94 | 16.11 | 17.21 | 15.20 | 1.06 | 1.17 |
| 2001 | 17.65 | 8.72 | 26.61 | 17.26 | 18.46 | 15.83 | 0.89 | 1.37 |
| 2011 | 18.76 | 9.39 | 30.35 | 18.31 | 19.53 | 16.89 | 0.82 | 1.45 |
| 2021 | 19.70 | 11.39 | 27.07 | 19.70 | 20.54 | 17.97 | 0.66 | 1.56 |
a small mixed land area does not generate a homogeneous surface that is very much responsible for the strong correlation between surface temperature and surface material.

The study presents a good output regarding the relationship. Halder et al. (2021) showed that LST builds a negative relation with NDVI and SAVI ($R^2$ values are 0.20 and 0.15, respectively), positive relation with NDBI and UI ($R^2$ values are 0.61 and
0.27, respectively), and an insignificant relation with MNDWI and NDBaI ($R^2$ values are 0.0003 and 0.04, respectively) in Kolkata, India. Ramaiah et al. (2020) also presented the fact that LST is positively correlated to EBBI and negatively correlated to SAVI and MNDWI in a study performed in Panaji and Tumkur City of India and these relationships become weak in the UHI zones as the heterogeneity of land surface is increased. Guha and Govil (2021) also observed that LST builds a positive correlation with NDBI, NDBaI, and NDWI (0.65, 0.30, and 0.19, respectively), and a negative correlation with NMDI, MNDWI, and NDVI (0.54, 0.38, and 0.38, respectively) in a 30 years long study conducted on Raipur City, India. These results support the output of the present study.

### 4.6. Ecological evaluation of Imphal city using UTFVI

Table 7 shows the six different ecological evaluation indices for Imphal city based on the UTFVI values in both seasons from 1991-2021. Figure 7B presents the spatial distribution maps of UTFVI of the city during the entire study period.
It is clear from Figure 7B and Table 7 that most of the areas of Imphal (>44% in summer and >39% in winter throughout the entire time) having excellent thermal conditions (i.e., UTFVI < 0). The percentage of the area under this excellent category is gradually decreasing from 1991 to 2021. Here the concentration of water bodies and vegetation is more. Mainly the southern portions experience such thermal conditions. However, the worst category (i.e., UTFVI > 0.020) of the ecological evaluation index also exists in a large portion (>37% in summer and >42% in winter throughout the entire time) of the city. The northern and some of the central parts fall under
the worst category where most of the lands are impervious. The good (0 < UTFVI < 0.005) and normal (0.005 < UTFVI < 0.010) thermal conditions are found in some small patches surrounding the areas under excellent condition while the bad (0.010 < UTFVI < 0.015) and worse (0.015 < UTFVI < 0.020) conditions exist around the areas of the worst condition. The area under the excellent category slightly decreases from 50.05% in 1991 to 44.53% in 2021 (summer) and from 52.69% in 1991 to 43.33% in 2021 (winter) due to loss of vegetation and increase of built-up area. Some eco-environmental strategies like social forestry or wetland preservation can reduce the severe UHI effects.

Table 8 shows the correlation matrix of the UTFVI values among the summer and winter seasons of 1991, 2001, 2011, and 2021. The results show a strong positive correlation in the winter season while it is moderate positive in the summer season. In summer, the UTFVI of 1991 and 2001 has a correlation coefficient value of 0.52 which becomes 0.45 between the UTFVI of 2001 and 2011. This value remains almost similar (0.48) for the 2011 and 2021 UTFVI values. In winter, the correlation becomes stronger. The correlation coefficient values are 0.76, 0.81, and 0.82 between 1991-2001, 2001-2011, and 2011-2021, respectively. The correlation matrix of UTFVI indicates that the effect of UHI is more consistent in the winter season while it is much variable in the summer. This correlation matrix validates the result that comes from the UTFVI analysis.

The specific strengths of this research work are the LST-spectral indices relationship. It clearly describes the nature of the thermal status of the city and also helps to delineate the ecologically most vulnerable zones of the city. The UHSs are the most severely heated surface of the study area where special attention must be paid to developing better environmental condition. However, there are also some specific weaknesses of the study. LST also depends on wind speed, surface moisture,
humidity, and intensity of solar radiation which have not been considered in the present study. Further, the analysis might be more authentic if it assessed the nighttime LST data. However, Landsat data does not provide nighttime LST. Furthermore, the results may be validated with a high-resolution LST product but it is a costly and time-taking task. Thus, the results should be considered in light of these limitations.

5. Conclusion

In this article, multi-temporal Landsat satellite images of the summer and winter seasons in 1991, 2001, 2011, and 2021 are used to evaluate the dynamic correlation between LST and different LULC indices in Imphal city and surroundings, India. UHI zones are identified through LST which are mainly distributed in the north-eastern and south-central parts of Imphal. LST of the specified UHI has been significantly increased from 1991 to 2021. During the study period, the LST of the city increases at 14.39% and 19.67% rates in summer and winter, respectively. The southern part of the city is less warm compared to the rest of the parts due to the concentration of vegetation and water bodies. Some UHS were also delineated inside the zone of UHI, characterized by high concentrated LST.

Furthermore, the relationship of LST to NDVI, MNDWI, NDBI, and NDBaI was quantitatively interpreted by Pearson’s correlation coefficient method. For the whole Imphal city, LST shows a moderate negative correlation with NDVI and MNDWI, a strong positive correlation with NDBI, and a moderate positive correlation with NDBaI. The winter season indicates a more consistent relationship. The relationship becomes weaker or even tends to be an inverse for UHI zones and urban hot spots. It may be due to the heterogeneous landscape in the urban area.

In addition, the spatial, temporal, and seasonal dynamics of the ecological evaluation index of Imphal were measured by the UTFVI. Most of the lands (44–50% in summer and 39–52% in winter) are under excellent condition although the percentage is declined. A high proportion of land (37–42% in summer and 42–47% in winter) also comes under the worst category. It indicates that the non-UHI zones remain almost unchanged. The ecological condition of the city can be developed by converting the bad category lands into the good category.

It can be recommended from the present study that a proper arrangement of LULC features is the most essential part of sustainable urban management planning. Urban land is always built over a small area and therefore a space-saving modern

| UTFVI | UHI phenomenon | Ecological evaluation index | Summer season | Winter season |
|-------|----------------|-----------------------------|---------------|--------------|
|       |                |                             | 1991 | 2001 | 2011 | 2021 | 1991 | 2001 | 2011 | 2021 |
| <0.000| None           | Excellent                   | 50.05 | 49.53 | 48.70 | 44.53 | 52.69 | 46.60 | 39.72 | 43.33 |
| 0.000-0.005 | Weak        | Good                        | ——   | ——   | ——   | 3.59  | 4.72  | ——   | 12.52 | 2.72  |
| 0.005-0.010 | Middle      | Normal                      | 10.00 | 11.07 | 9.09  | 4.99  | ——   | ——   | 10.69 | 2.67  |
| 0.010-0.015 | Strong      | Bad                         | ——   | ——   | ——   | 4.64  | ——   | ——   | 10.69 | 2.66  |
| 0.015-0.020 | Stronger    | Worse                       | ——   | ——   | ——   | 4.59  | ——   | ——   | ——   | 2.62  |
| >0.020  | Strongest     | Worst                       | 39.95 | 39.40 | 42.19 | 37.66 | 47.31 | 42.71 | 47.76 | 46.00 |
planning and management system is required. The built-up area should be expanded without reducing the concentration of green areas, water bodies, and wetlands.

The study was an attempt to simply correlate LST with four spectral indices in a humid subtropical landlocked mountainous urban area using Landsat data for summer and winter seasons. There are some limitations of the study. Such as, the results should be compared with other satellite data of different spatial resolutions (e.g., IKONOS (1 m), Quickbird (0.6 m), ASTER (15 m), Sentinel-2A (10 m), MODIS (1000 m), etc.). Besides, the seasonal variation of the correlation coefficients can be monitored for one or two years. Moreover, some other spectral indices (e.g., urban index, built-up index, soil and vegetation index, normalized difference mud index, normalized multi-band drought index, etc.) can be investigated to find a better correlation with LST. Apart from these, the results can be examined in different environments with large physical varieties. In addition to these, some other statistical methods and algorithms (Spearman rank correlation coefficient, Kendall correlation coefficient, etc.) can also be applied to estimate the correlation between LST and different spectral indices.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The data that support the findings of this study are openly available in the earth explorer website of USGS at https://earthexplorer.usgs.gov/.

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