Seasonal evaluation of downscaled land surface temperature: A case study in a humid tropical city

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ABSTRACT

The present study evaluates the seasonal variation of estimated error in downscaled land surface temperatures (LST) over a heterogeneous urban land. Thermal sharpening (TsHARP) downscaling algorithm has been used with a separate combination of four selected remote sensing indices. This study assesses the capability of TsHARP technique over mixed land use/land covers (LULC) by analyzing the correlation between LST and remote sensing indices, namely, normalized difference built-up index (NDBI), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and normalized multi-band drought index (NMDI) and by determining the root mean square error (RMSE) and mean error (ME) produced by downscaled LST. Landsat 8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) images have been used for pre-monsoon, monsoon, post-monsoon, and winter seasons in 2014 covering the whole Raipur City, India. The RMSE of the downscaled LST decreases from 120 to 480 m spatial resolution in all the four seasons. It is concluded that NDBI is the most effective LULC index having the least error produced in TsHARP downscaling technique, irrespective of any season. Post-monsoon season reflects the most successful result followed by monsoon season. Even in the monsoon season of high vegetation coverage, NDBI presents a lower range of downscaled error compared to NDVI. This indicates better performance of NDBI in detecting the spatial and temporal distribution of mixed urban land.

1. Introduction

Land surface temperature (LST) is an important biophysical parameter in the processes of surface energy and water balance at regional and global scales (Anderson et al., 2008; Duan et al., 2014; Li et al., 2013; Wan and Li, 1997, 2008). LST is used in a large scale to determine soil moisture content (Voogt and Oke, 2003; Jeganathan et al., 2011; Zhan et al., 2013), to analyze the effect of urban heat island (Zaksek and Ostir, 2012; Sobrino et al., 2004; Guha et al., 2017, 2018, 2019; Zhou et al., 2019a,b), to evaluate diurnal temperature variation (Weng et al., 2004; Dennison et al., 2006; Agam et al., 2007a, 2007b; Stathopoulou and Cartalis, 2009) to calculate surface longwave radiation (Yang et al., 2011; Nichol, 2009), to compute different types of evapotranspiration (Sandholm et al., 2002; Nishii et al., 1996; Pardo-Iguzquiza et al., 2011; Gualtieri and Chettri, 2000), and to estimate surface albedo and thermal inertia (Mpixelsoka et al., 2001).

Current satellite imageries, such as the Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), can provide LST at different spatial, spectral, radiometric, and temporal resolutions (Moran, 1990; Kustas et al., 2003; Essa et al., 2012). Due to technical limitations, these current satellite thermal sensors reflect a balance between spatial and temporal resolutions; i.e., the high spatial resolution sensors generally have a low temporal resolution, and vice versa (Weng and Fu, 2014). In order to obtain LST at high spatial and high temporal resolutions downscaling technique is considered as an effective method (Duan and Li, 2016).

Various types of downscaling techniques have been developed to get high-resolution LST from a coarse resolution thermal infrared band (Wan and Dozier, 1996; Chen et al., 2010; Pardo-Iguzquiza and Atkinson, 2006; Zhang, 2015; Yang and Yao, 2009). Extended reviews on LST downscaling methods have been assessed so far (Zhan et al., 2013; Chen et al., 2014). The most frequently used algorithm is the DisTrad algorithm (Kustas, 2003) which was modified as the TsHARP algorithm.

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was the normalized difference vegetation index (NDVI) and the scale invariant relationship between the normalized difference vegetation index (NDVI) and LST is the foundation of this algorithm. The performance of these different algorithms was assessed on different land use/cover (LULC) categories, including cultivated land (Jeganathan et al., 2011) or mixed urban land (Essa et al., 2012). The main restriction of the TsHARP algorithm is that this relationship is not unique, and thus, provides an extensive range of LST for a single NDVI value. Merlin et al. (2010) further enhanced this TsHARP algorithm by considering the effect of photosynthetically and non-photosynthetically active cells of the green plants within the spatial variability of LST. Furthermore, Bindhu et al. (2013) developed a nonlinear DisTrad (NL-DisTrad) model where NDVI-LST polynomial relationship generates from the hot-edge pixels at a coarse resolution which is also valid at high-resolution pixels.

The NDVI is not so appropriate for LST downscaling procedure performed in a heterogeneous urban land (Stathopoulou and Cartalis, 2009; Nichol, 2009; Dominguez et al., 2011; Zakisek and Ostir, 2012; Essa et al., 2012). Some recent research works reflected modern image classification techniques for detail LULC classification (Cheng et al. 2018a, 2018b; Zhou et al., 2019a,b). Different LULC types, found in a complex urban land, produce a unique emission rate. Emissivity (Stathopoulou and Cartalis, 2009; Nichol, 2009) has been used as one of the most significant environmental factors for highly heterogeneous urban landscapes. Small (2006) observed a close relationship between LST and surface albedo in urban areas. Dominguez et al. (2011) developed high-resolution urban thermal sharpener algorithm for downscaling LST in an urban area by integrating NDVI and surface albedo. Impervious surface percentage (Essa et al., 2012, 2013) and pure pixel index (Yang et al., 2010) have also been applied as basic parameters in urban areas. Impervious surface provides a better result than NDVI in LST downscaling in the mixed urban land by comparing 15 different parameters (Essa et al., 2012). Essa et al. (2012) and Yuan and Bauer (2007) also established a strong linear relationship between LST and impervious surface irrespective of the seasonal influence. Contrary to that, the LST-NDVI relationship changes with the seasonal variability (Kustas et al., 2003). For a complex urban area with mixed LULC types, multiple environmental parameters must be integrated to achieve a high downscaling precision. Although various types of LST downscaling methods have been suggested, they have also some limitations in the available remotely sensed data and LULC categories. Besides, selection of appropriate environmental predictors for LST downscaling in complex LULC surface is still considered as an important task.

Basically, the statistical downscaling of LST is based on the correlation between LST and other environmental factors or remote sensing based various LULC indices. Generally, most of the popular LST downscaling methods apply NDVI observed at a fine resolution (Kustas et al., 2003), but the NDVI alone cannot be able to explain all the variations in LST for a complex urban surface. Mukherjee et al. (2015) evaluated seasonal variation in downscaled LST in DisTrad, TsHARP, and local model using Landsat TM 5 data over a heterogeneous agricultural land in India. Bonafoni et al. (2016) attempted to retrieve LST using Landsat TM data for Florence city in Italy and proposed a traditional downscaling framework analyzing its performances using high-resolution LST airborne image. A combination of built-up and vegetation spectral indices was adopted for the LST downscaling methods using MODIS and Landsat TM data performed in Milan city, Italy (Bonafoni, 2016). A multiple regression-based LST downscaling technique using spectral mixture analysis over the heterogeneous urban area of Aprilia, Italy was also evaluated to examine the effectiveness of multiple environmental parameters (Bonafoni and Tosi, 2017). Another analytical research was performed in the Zhanqie oasis and Beijing city to assess the scale effect in LST downscaling from medium to high-resolution satellite data (Zhou et al., 2016).

In the present study, linear regression based TsHARP downscaling technique has been examined with some LULC indices along with NDVI. Basically, the TsHARP technique used fractional vegetation cover and it

\[ LST = \frac{K_1}{1 + \left(\frac{\alpha T_h/(hc)}{\ln(e)}\right) \ln(e)} \]
J), \( c \) is the velocity of light at a vacuum \((2.998 \times 10^{-8} \text{ m/s})\), \( \varepsilon \) is emissivity. Based on earlier studies, \( \varepsilon \) is determined as follows: if NDVI is \( \geq 0.157 \) and \( \leq 0.727 \), \( \varepsilon \) for that pixel is calculated by Eq. (3) (Van et al., 1993):

\[
\varepsilon = 1.0094 + 0.0047 \ln(\text{NDVI}) \tag{3}
\]

The land cover type should be vegetation if NDVI values \( \geq 0.727 \), and then a constant value of 0.99 is assumed (Sobrino et al., 2004) and \( \varepsilon \) is set to 0.995 for water bodies and 0.92 for the other land use and land cover types.

2.2. Determination of NDVI, NDWI, NDBI, and NMDI as LULC indices

NDVI (Purevdorj et al., 1998) is considered as one of the most frequently used vegetation indices in remote sensing study. It is also applied in deriving LST and normally shows a negative regression with LST. NDWI (Gao, 1996) is generally used for water body extraction. NDBI (Zha et al., 2003) is another spectral index which was applied in this study for built-up area extraction. NMDI (Yuan and Bauer, 2007) was also used to extract the dry soil or bare land. The formulation of these four indices was presented by Table 1.

### Table 1

| Acronym | Description                  | Formulation                                      | Reference          |
|---------|-------------------------------|--------------------------------------------------|--------------------|
| NDVI    | Normalized difference         | \( \text{NIR} - \text{Red} \)                  | Purevdorj et al. (1998) |
|         | vegetation index              |                                                 |                    |
| NDWI    | Normalized difference         | \( \text{Green} - \text{NIR} \)                  | Gao (1996)         |
|         | water index                   |                                                 |                    |
| NDBI    | Normalized difference         | \( \text{SWIR1} - \text{NIR} \)                  | Zha et al., (2003) |
|         | built-up index                | \( \text{SWIR2} - \text{NIR} \)                  |                    |
| NMDI    | Normalized multi-             | \( \frac{\text{NIR} - (\text{SWIR1 + SWIR2})}{\text{NIR}} \) | Yuan and Bauer (2007) |
|         | band difference index         |                                                 |                    |

2.3. TsHARP downscaling technique based on the regression of LST and LULC indices

LST can be derived using thermal infrared images with coarse spatial resolutions. Regression models between ancillary environmental predictors and LST have been widely established to enhance LST resolution. If the relationships between LST and the predictors do not change with the variation in the spatial resolution, a detailed LST with a high

Fig. 1. Location of the study area with false colour composite image.
The original TsHARP algorithm is primarily based on the regression model of LST and fractional vegetation cover. This technique was proposed by Agam et al. (2007a, b). Basically, it was a modification of the DisTrad algorithm (Rustas et al., 2003) and was evaluated on agricultural land of Central Iowa, USA. Jeganathan et al. (2011) showed that NDVI should be used as a covariate in TsHARP technique. The present study uses NDVI, NDWI, NDBI, and NMDI as the covariates with the LST. The TsHARP algorithm was outlined in Eq. (4a–4d) where \( a_0 \) is the intercept and \( a_1 \) is the slope of the regression equations. The Eq. 4a was followed by Eq. (4b–4d) by replacing the NDVI with NDWI, NDBI, and NMDI, respectively. The fine-resolution (30 m) LST, \( \text{LST}_{\text{fine}} \) could be determined by the Eq. (4a–4d):

\[
\text{LST}_{\text{fine}} = a_0 + a_1 \cdot \text{NDVI}_{\text{fine}}
\]

(4a)

\[
\text{LST}_{\text{fine}} = a_0 + a_1 \cdot \text{NDWI}_{\text{fine}}
\]

(4b)

\[
\text{LST}_{\text{fine}} = a_0 + a_1 \cdot \text{NDBI}_{\text{fine}}
\]

(4c)

\[
\text{LST}_{\text{fine}} = a_0 + a_1 \cdot \text{NMDI}_{\text{fine}}
\]

(4d)

Therefore, the coarse-resolution LST \( \text{LST}_{\text{coarse}} \) can be determined by the Eq. (5a–5d):

\[
\text{LST}_{\text{coarse}} = a_0 + a_1 \cdot \text{NDVI}_{\text{coarse}} + \Delta T_{\text{coarse}}
\]

(5a)

\[
\text{LST}_{\text{coarse}} = a_0 + a_1 \cdot \text{NDWI}_{\text{coarse}} + \Delta T_{\text{coarse}}
\]

(5b)

\[
\text{LST}_{\text{coarse}} = a_0 + a_1 \cdot \text{NDBI}_{\text{coarse}} + \Delta T_{\text{coarse}}
\]

(5c)

\[
\text{LST}_{\text{coarse}} = a_0 + a_1 \cdot \text{NMDI}_{\text{coarse}} + \Delta T_{\text{coarse}}
\]

(5d)

Then, a residual of LST \( \Delta T_{\text{coarse}} \) was computed as the difference between the retrieved LST \( \text{LST}_{\text{coarse}} \) and the corresponding observed LST \( \text{LST}_{\text{coarse}} \) by Eq. (6) (Kustas et al., 2003):

\[
\Delta T_{\text{coarse}} = \text{LST}_{\text{coarse}} - \text{LST}_{\text{coarse}}
\]

(6)

The residual \( \Delta T_{\text{coarse}} \) was introduced in the algorithm to take into account part of LST spatial variability that depends on the environmental factors other than the applied predictors, such as soil moisture, emissivity or other LULC indices. The \( a_0, a_1 \) and residual are different when different indices are used. Finally, downscaled fine-resolution (30 m) LST \( \text{LST}_{\text{down}} \) was estimated by the Eq. (7a–7d):

\[
\text{LST}_{\text{down}} = a_0 + a_1 \cdot \text{NDVI}_{\text{fine}} + \Delta T_{\text{coarse}}
\]

(7a)

\[
\text{LST}_{\text{down}} = a_0 + a_1 \cdot \text{NDWI}_{\text{fine}} + \Delta T_{\text{coarse}}
\]

(7b)

\[
\text{LST}_{\text{down}} = a_0 + a_1 \cdot \text{NDBI}_{\text{fine}} + \Delta T_{\text{coarse}}
\]

(7c)

\[
\text{LST}_{\text{down}} = a_0 + a_1 \cdot \text{NMDI}_{\text{fine}} + \Delta T_{\text{coarse}}
\]

(7d)

Where, the coarse-resolution regression coefficients were applied to fine-spatial resolution spectral indices, adding the residual error of the corresponding coarse-resolution image to increase the accuracy.

The NDVI-LST relationship always tends to be varied over the mixed urban landscape. In order to overcome the problem, some remote sensing indices may be tested along with NDVI to obtain higher accuracy in the downscaled LST. The multiple least-squares linear regression downsampling method with a number of predictors was applied in some recent studies (Bonafoni, 2016; Bonafoni et al., 2016). A number of remote sensing indices have also been tested individually to obtain a better downscaled LST (Essa et al., 2012). In the present study, NDVI, NDWI, NDBI, and NMDI have been examined separately in four different dates for the downscaling method. Finally, the overall procedure of downsampling has been applied at 30 m, 120 m, 240 m, and 480 m spatial resolutions.

### 3. Results & discussion

Fig. 3 represented the spatial distribution of reference LST at 30 m resolution and Table 2 showed the statistical information of LST at 30-m resolution in four multi-date images. Seasonal variation in the LST distribution shows a specific thermal pattern. The mean LST values in pre-monsoon, monsoon, post-monsoon, and winter season are 33.59 °C, 29.56 °C, 23.40 °C, and 22.26 °C respectively. The range of temperature is found as 13.50 °C in pre-monsoon, 12.28 °C in monsoon, 8.83 °C in post-monsoon, and 10.12 °C in the winter season, respectively. Basically, this type of heterogeneity in LST was observed due to the changes in vegetation abundance and soil moisture content. Monsoon and post-monsoon seasons are characterized by healthy vegetation and wet soil. Winter remains comparatively dry and having least standard deviation value in LST (Table 2).

Figs. 4, 5, 6, and 7 and Table 3 presents the downscaled LST using various LULC indices based TsHARP algorithm along with the retrieved reference LST in four different seasons (pre-monsoon, monsoon, post-monsoon, and winter). It is observed that the first panel (LST reference) has a smoothed pattern since the 30-m LST resolution is not an actual measurement but a resampling, and that the downsampling improve the detail at this spatial scale. It is clearly revealed that NDBI and NMDI based TsHARP algorithm generates almost similar nature in the downscaled LST while NDVI and NDWI based TsHARP algorithm has almost identical spatial distribution of downscaled LST. This particular type of spatial pattern is reflected in each and every season. The spatial pattern of downscaled LST generates from NDBI and NMDI based TsHARP technique has a similarity with retrieved reference LST where the study area achieves a higher temperature. Monsoon season indicates most identical scenario when reference LST compares with the downscaled LST, irrespective of any LULC indices based TsHARP technique.

Table 4 presents the seasonal variation of the estimated errors (RMSE and ME) produced in downscaled LST by various types of LULC indices based TsHARP algorithm. Downscaled LST at lower spatial resolution generates a greater error than downscaled LST at higher spatial resolution. It is a common phenomenon observed in each and every season and it remains constant for any LULC indices based TsHARP downsampling technique. NDBI-based TsHARP algorithm showed the best result among all the LULC indices-based TsHARP algorithm for all the season and at every resolution level as the values of RMSE of downscaled LST lie.

### 2.4. Accuracy assessment and validation

The LST of 100-m resolution is aggregated to 960, 480, 240, and 120-m resolution and these new aggregated data are known as reference data \( \text{LST}_{\text{ref}} \). The aggregated 960-m resolution LST was downscaled \( \text{LST}_{\text{down}} \) to 480, 240, 120, and 30-m resolution. Root mean square error (RMSE) and mean error (ME) statistics were applied to estimate the error in downscaled LST with respect to the reference LST. RMSE and ME have been calculated by the following Eq. (8) and Eq. (9), respectively.

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\text{LST}_{\text{down}} - \text{LST}_{\text{ref}})^2}
\]

(8)

\[
\text{ME} = \frac{1}{n} \sum_{i=1}^{n} (\text{LST}_{\text{down}} - \text{LST}_{\text{ref}})
\]

(9)

A complete flowchart of the entire study has been shown in Fig. 2. The computation cost of the proposed method was small as it required less time and storage space for the entire computation process.
significantly below the standard deviation for the corresponding actual native LST reference images at 100 m spatial resolution in each and every occasion. NDBI proves as the most successful parameter for LST downscaling in almost every season. Since it is an urban area having so many mixed landscapes built-up area has the most dominant land use in controlling LST. Previously, NDVI-LST relationship based TsHARP algorithm proved as one of the most effective downscaling methods for single LULC dominated region (Agam et al., 2007a,b; Jeganathan et al., 2011). In the present study, NDVI also proves as an important indicator in determining the downscaled LST values in a heterogeneous urban landscape. Along with NDBI and NDVI, two more remote sensing indices (NDWI and NMDI) were also examined to compare the accuracy level in downscaled LST. Post-monsoon and winter season shows a better accuracy in terms RMSE and ME for any of the indices based downscaled LST. NDBI and NDVI reflect a smaller ME for post-monsoon and winter seasons while NDWI and NMDI indicates a smaller ME in monsoon and post-monsoon seasons as an indicator used to develop TsHARP downscaling technique. Figs. 8, 9, 10, and 11 and Figs. 12, 13, 14, and 15 show the spatial distribution of RMSE and ME, respectively.

The high values of RMSE (positive) and ME (positive or negative) have mostly been found in the areas where LST is very high or abnormally low. Due to the presence of mineral-based industrial agglomeration or thermal power plants in the northwest portions of the study area, LST generally remains high. This portion has come under one of the most erroneous zones regarding the downscaled LST. It happens mainly due to the anthropogenic activities and no such hypothetical relationship is built to support the particular behaviour.

Table 5 presents the percentage of RMSE in downscaled LST at 30 m spatial resolution for different seasons. In pre-monsoon season, NMDI and NDBI based TsHARP downscaling technique provide almost 73% of the total pixels in the study area having less than 1.5 °C RMSE in downscaled LST. NDBI again proves as the best parameter for TsHARP downsampling algorithm in monsoon season as 72.7% pixels having less than 1.5 °C RMSE. Post-monsoon season reflects the best result regarding RMSE in downscaled LST. In post-monsoon season, NDVI and NDWI based TsHARP algorithm have proved as the best output at 30 m resolution irrespective of any season as they generates downscaled LST with more than 90% pixels having less than 1.5 °C RMSE. In winter season, NDVI and NMDI based TsHARP techniques give the best result (>86% pixels have less than 1.5 °C RMSE).

Seasonal variation in the percentage of mean error (ME) in downscaled LST at 30 m resolution has been shown in Table 6. It is very clear
from Table 6 that all the LULC indices are almost equally suitable for TsHARP downscaling technique. Post-monsoon season simply generates the best result for downscaled LST due to low pollution level, high vegetation coverage and high moisture content. NDWI and NDVI based TsHARP downscaling algorithm generates lowest level of mean error (>75% pixels have a ME from 0 °C to 1 °C (positive/negative)).

The study was evaluated the downscaling LST in a humid tropical city of India and reflected a good result. The similar types of studies were also performed successfully in the cities of other climatic zones, e.g., humid subtropical zone (Pan et al., 2018), temperate zone (Bechtel et al., 2012; Bonafoni et al., 2016).

The proposed work also have some limitations. The 30 m LST resolution is not an actual measurement but a resampling, and the downscaling improve the detail at this spatial scale. Only one date of a particular season may not be appropriate for seasonal assessment of downscaling technique. The other relevant LULC indices may also be incorporated to improve the downscaling results.

4. Conclusion

The aim of this research is to estimate remote sensing indices (NDBI, NDVI, NDWI, and NMDI) based downscaled LST at 30, 120, 240, and 480 m resolution and compare the results in different seasons (pre-monsoon, monsoon, post-monsoon, and winter) over a heterogeneous urban area like Raipur city. The NDVI-LST linear relationship is the primary basis of TsHARP downscaling technique. NDBI, NDWI, and NMDI are tested separately in place of NDVI to form new linear relationships, i.e., NDBI-LST, NDWI-LST, and NMDI-LST. The downscaled LST based on NDBI-LST, NDVI-LST, NDWI-LST, and NMDI-LST was finally evaluated through error estimation. The seasonal variation of the results was also determined. The results were examined at various spatial resolutions. It is clear from the various results that NDBI based TsHARP technique provides the lowest RMSE in downscaled LST at 30 m spatial resolution, irrespective of all seasons. In pre-monsoon, monsoon, and winter seasons, NDBI and NMDI based TsHARP technique have a smaller range of ME, but, in post-monsoon season, NDVI and NDWI indicate small ME due to the presence of a higher percentage of chlorophyll and moisture content. The RMSE and ME became gradually smaller with the increase of spatial resolution in downscaled LST. The LULC based TsHARP models may also be examined in determining the downscaled LST for daytime and nighttime thermal data. Different satellite sensors may also be used to assess the capability of this technique in a separate study area. Any further modification in the present TsHARP algorithm will be expected by the future researchers.

Table 2
Spatial distribution of LST (°C) for four multi-date reference images at 30 m resolution.

| Date of Acquisition | Time   | Path/Row | LST (Minimum) | LST (Maximum) | LST (Mean) | LST (Standard deviation) |
|---------------------|--------|----------|---------------|---------------|------------|--------------------------|
| 05-JUN-2014         | 04:55:45 | 142/044  | 25.77         | 39.27         | 33.59      | 1.61                     |
| 25-SEP-2014         | 04:56:11 | 142/044  | 24.51         | 36.79         | 29.56      | 1.73                     |
| 12-NOV-2014         | 04:56:21 | 142/044  | 19.39         | 28.23         | 23.40      | 1.12                     |
| 30-DEC-2014         | 04:56:09 | 142/044  | 17.64         | 27.76         | 22.26      | 1.11                     |

Fig. 3. Spatial distribution of reference LST at 30-m spatial resolution: (a) pre-monsoon; (b) monsoon; (c) post-monsoon; (d) winter.
Fig. 4. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 5-JUN-14: (a) LST$_{ref}$; (b) NDBI-based LST$_{down}$; (c) NDVI-based LST$_{down}$; (d) NDWI-based LST$_{down}$; (e) NMDI-based LST$_{down}$.

Fig. 5. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 25-SEP-14: (a) LST$_{ref}$; (b) NDBI-based LST$_{down}$; (c) NDVI-based LST$_{down}$; (d) NDWI-based LST$_{down}$; (e) NMI-based LST$_{down}$.
Fig. 6. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 12-NOV-14: (a) LST_{ref}; (b) NDBI-based LST_{down}; (c) NDVI-based LST_{down}; (d) NDWI-based LST_{down}; (e) NMDI-based LST_{down}.

Fig. 7. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 30-DEC-14: (a) LST_{ref}; (b) NDBI-based LST_{down}; (c) NDVI-based LST_{down}; (d) NDWI-based LST_{down}; (e) NMDI-based LST_{down}.
Table 3
Seasonal variation in different LULC indices based downscaled LST (°C) at various resolutions.

| LULC Indices-based downscaled LST (°C) | at 30 m | at 120 m | at 240 m | at 480 m |
|----------------------------------------|---------|----------|----------|----------|
|                                        | Min     | Max      | μ         | σ         | Min     | Max      | μ         | σ         | Min     | Max      | μ         | σ         | Min     | Max      | μ         | σ         |
| NDBI-based                             | 25.77   | 39.27    | 33.59    | 1.61      | 26.33   | 38.14    | 33.62    | 1.58      | 27.01   | 38.06    | 33.64    | 1.52      | 27.98   | 37.09    | 33.70    | 1.42      |
| NDVI-based                             | 25.12   | 45.79    | 33.64    | 1.34      | 25.69   | 38.41    | 33.66    | 1.12      | 28.87   | 36.52    | 33.67    | 0.98      | 30.26   | 36.29    | 33.70    | 0.88      |
| NDWI-based                             | 28.61   | 37.74    | 33.74    | 0.91      | 29.00   | 36.61    | 33.74    | 0.77      | 30.55   | 35.87    | 33.74    | 0.69      | 31.41   | 35.57    | 33.74    | 0.62      |
| NMDI-based                             | 29.54   | 37.65    | 33.74    | 0.83      | 29.82   | 37.29    | 33.74    | 0.72      | 31.31   | 36.51    | 33.74    | 0.64      | 31.90   | 35.68    | 33.74    | 0.58      |
| NDBI-based                             | 26.28   | 38.77    | 33.64    | 0.93      | 26.28   | 38.78    | 33.64    | 0.93      | 30.96   | 35.98    | 33.67    | 0.72      | 31.39   | 35.64    | 33.69    | 0.66      |

Table 4
Seasonal variation in mean RMSE and mean ME for downscaled LST (°C) at various resolution.

| LULC Indices-based downscaled LST (°C) | at 30 m | at 120 m | at 240 m | at 480 m |
|----------------------------------------|---------|----------|----------|----------|
|                                        | Min     | Max      | μ         | σ         | Min     | Max      | μ         | σ         | Min     | Max      | μ         | σ         | Min     | Max      | μ         | σ         |
| NDBI-based                             | 19.39   | 28.23    | 23.40    | 1.12      | 19.53   | 27.92    | 23.39    | 1.11      | 19.66   | 27.37    | 23.38    | 1.07      | 20.26   | 26.96    | 23.36    | 1.02      |
| NDVI-based                             | 15.27   | 30.15    | 23.34    | 1.28      | 15.59   | 27.58    | 23.33    | 1.03      | 19.81   | 26.16    | 23.33    | 0.88      | 19.81   | 25.26    | 23.32    | 0.74      |
| NDWI-based                             | 18.37   | 27.47    | 23.38    | 1.05      | 19.38   | 26.41    | 23.37    | 0.93      | 20.52   | 26.08    | 23.36    | 0.86      | 21.48   | 25.59    | 23.34    | 0.79      |
| NMDI-based                             | 18.15   | 27.58    | 23.38    | 1.02      | 19.64   | 26.84    | 23.37    | 0.91      | 20.77   | 26.80    | 23.36    | 0.84      | 21.59   | 25.95    | 23.34    | 0.78      |
| NDBI-based                             | 20.00   | 25.10    | 23.30    | 0.28      | 21.31   | 24.59    | 23.31    | 0.22      | 22.45   | 24.67    | 23.31    | 0.19      | 22.48   | 22.97    | 23.31    | 0.15      |

μ = mean, and σ = standard deviation.
Fig. 8. Spatial distribution of ME at 30-m resolution for 5-JUN-14: (a) NDBI-based LST$_{down}$; (b) NDVI-based LST$_{down}$; (c) NDWI-based LST$_{down}$; (d) NMDI-based LST$_{down}$.

Fig. 9. Spatial distribution of ME at 30-m resolution for 25-SEP-14: (a) NDBI-based LST$_{down}$; (b) NDVI-based LST$_{down}$; (c) NDWI-based LST$_{down}$; (d) NMDI-based LST$_{down}$.
Fig. 10. Spatial distribution of ME at 30-m resolution for 12-NOV-14: (a) NDBI-based LST\textsubscript{down}; (b) NDVI-based LST\textsubscript{down}; (c) NDWI-based LST\textsubscript{down}; (d) NMDI-based LST\textsubscript{down}.

Fig. 11. Spatial distribution of ME at 30-m resolution for 30-DEC-14: (a) NDBI-based LST\textsubscript{down}; (b) NDVI-based LST\textsubscript{down}; (c) NDWI-based LST\textsubscript{down}; (d) NMDI-based LST\textsubscript{down}.
Fig. 12. Spatial distribution of RMSE at 30-m resolution for 5-JUN-14: (a) NDBI-based $\text{LST}_{\text{down}}$; (b) NDVI-based $\text{LST}_{\text{down}}$; (c) NDWI-based $\text{LST}_{\text{down}}$; (d) NMDI-based $\text{LST}_{\text{down}}$.

Fig. 13. Spatial distribution of RMSE at 30-m resolution for 25-SEP-14: (a) NDBI-based $\text{LST}_{\text{down}}$; (b) NDVI-based $\text{LST}_{\text{down}}$; (c) NDWI-based $\text{LST}_{\text{down}}$; (d) NMDI-based $\text{LST}_{\text{down}}$. 
Fig. 14. Spatial distribution of RMSE at 30-m resolution for 12-NOV-14: (a) NDBI-based \( \text{LST}_{down} \); (b) NDVI-based \( \text{LST}_{down} \); (c) NDWI-based \( \text{LST}_{down} \); (d) NMDI-based \( \text{LST}_{down} \).

Fig. 15. Spatial distribution of RMSE at 30-m resolution for 30-DEC-14: (a) NDBI-based \( \text{LST}_{down} \); (b) NDVI-based \( \text{LST}_{down} \); (c) NDWI-based \( \text{LST}_{down} \); (d) NMDI-based \( \text{LST}_{down} \).
Declarations

Author contribution statement

Guha, S. Govil, H. Dey, A. Gill, N.: Conceived and designed the analysis; Performed the experiments; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

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Competing interest statement

The authors declare no conflict of interest.

Table 5

| RMSE in downscaled LST (°C) | 0.0–0.5 | 0.5–1.0 | 1.0–1.5 | 1.5–2.0 | 2.0–2.5 | >2.5 |
|-----------------------------|---------|---------|---------|---------|---------|------|
| June-05-2014                |         |         |         |         |         |      |
| NDBI-based                  | 28.70%  | 24.43%  | 19.52%  | 13.66%  | 7.34%   | 6.35% |
| NDVI-based                  | 24.00%  | 23.13%  | 19.00%  | 16.33%  | 9.43%   | 6.46% |
| NDWI-based                  | 23.94%  | 23.10%  | 20.60%  | 16.46%  | 9.54%   | 6.36% |
| NMDI-based                  | 29.46%  | 25.80%  | 18.61%  | 11.86%  | 6.86%   | 7.41% |
| September-25-2014           |         |         |         |         |         |      |
| NDBI-based                  | 28.82%  | 25.27%  | 18.61%  | 11.91%  | 7.28%   | 8.13% |
| NDVI-based                  | 29.49%  | 24.26%  | 17.51%  | 11.49%  | 7.03%   | 10.22%|
| NDWI-based                  | 28.66%  | 24.09%  | 17.78%  | 11.87%  | 7.06%   | 10.54%|
| NMDI-based                  | 28.29%  | 23.80%  | 17.92%  | 12.29%  | 7.72%   | 9.98% |
| November-12-2014            |         |         |         |         |         |      |
| NDBI-based                  | 30.07%  | 27.52%  | 17.58%  | 9.91%   | 5.19%   | 3.74% |
| NDVI-based                  | 43.58%  | 31.52%  | 14.98%  | 5.50%   | 1.81%   | 3.35% |
| NDWI-based                  | 46.43%  | 30.42%  | 13.77%  | 4.91%   | 1.60%   | 2.87% |
| NMDI-based                  | 41.28%  | 30.01%  | 14.26%  | 7.18%   | 3.47%   | 3.80% |
| December-30-2014            |         |         |         |         |         |      |
| NDBI-based                  | 36.98%  | 28.71%  | 18.75%  | 9.13%   | 3.74%   | 2.79% |
| NDVI-based                  | 35.47%  | 31.16%  | 19.47%  | 7.30%   | 3.29%   | 3.58% |
| NDWI-based                  | 36.28%  | 30.67%  | 18.31%  | 7.54%   | 3.62%   | 3.58% |
| NMDI-based                  | 39.58%  | 30.55%  | 16.15%  | 7.14%   | 3.64%   | 2.94% |

Table 6

| ME in downscaled LST (°C) | < -4 | -4–3 | -3–2 | -2–1 | -1–0 | 0–1 | 1–2 | 2–3 | 3–4 | >4 |
|---------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|----|
| June-05-2014              |     |     |     |     |     |     |     |     |     |    |
| NDBI-based                | 0.40% | 1.61% | 5.90% | 13.79% | 23.35% | 29.78% | 19.39% | 4.80% | 0.61% | 0.36% |
| NDVI-based                | 0.00% | 0.29% | 5.00% | 19.48% | 25.57% | 21.25% | 17.53% | 7.89% | 1.06% | 1.63% |
| NDWI-based                | 0.00% | 0.06% | 4.71% | 19.18% | 25.86% | 21.67% | 17.88% | 7.18% | 1.01% | 1.92% |
| NMDI-based                | 0.57% | 2.26% | 6.93% | 10.70% | 21.39% | 33.86% | 19.77% | 3.59% | 0.58% | 0.35% |
| September-25-2014         |     |     |     |     |     |     |     |     |     |    |
| NDBI-based                | 0.61% | 2.15% | 6.65% | 14.35% | 24.53% | 29.56% | 16.16% | 4.77% | 0.43% | 0.39% |
| NDVI-based                | 0.62% | 2.29% | 6.99% | 14.35% | 27.62% | 26.13% | 12.65% | 4.08% | 0.71% | 0.88% |
| NDWI-based                | 0.47% | 2.06% | 7.22% | 18.24% | 29.85% | 22.90% | 11.41% | 4.00% | 1.33% | 2.26% |
| NMDI-based                | 1.11% | 2.68% | 6.79% | 14.37% | 25.42% | 26.68% | 15.84% | 5.47% | 1.36% | 0.29% |
| November-12-2014          |     |     |     |     |     |     |     |     |     |    |
| NDBI-based                | 0.14% | 0.85% | 4.57% | 13.97% | 30.98% | 32.6% | 13.52% | 2.88% | 0.41% | 0.06% |
| NDVI-based                | 0.01% | 0.04% | 1.03% | 12.45% | 41.24% | 33.86% | 8.03% | 1.52% | 0.73% | 1.04% |
| NDWI-based                | 0.01% | 0.04% | 0.95% | 11.73% | 43.41% | 33.49% | 6.95% | 1.33% | 0.74% | 1.41% |
| NMDI-based                | 0.18% | 1.55% | 3.80% | 10.12% | 34.98% | 36.31% | 11.32% | 1.73% | 0.01% | 0.01% |
| December-30-2014          |     |     |     |     |     |     |     |     |     |    |
| NDBI-based                | 0.19% | 0.80% | 3.68% | 11.13% | 29.75% | 35.93% | 16.75% | 1.62% | 0.12% | 0.03% |
| NDVI-based                | 0.03% | 0.37% | 3.11% | 12.55% | 30.79% | 35.84% | 14.17% | 1.86% | 0.74% | 0.54% |
| NDWI-based                | 0.04% | 0.48% | 3.43% | 12.30% | 30.19% | 36.76% | 13.55% | 2.02% | 0.75% | 0.46% |
| NMDI-based                | 0.07% | 0.65% | 3.62% | 11.19% | 28.49% | 41.64% | 12.10% | 1.68% | 0.51% | 0.05% |

Additional information

No additional information is available for this paper.

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