



## 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 (Zakšek and Oštir, 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 (Sandholt et al., 2002; Nishii et al., 1996; Pardo-Igúzquiza et al., 2011; Gualtieri and Chettri, 2000), and to estimate surface albedo and thermal inertia (Mpelasoka 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-Igúzquiza 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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(Agam et al., 2007b) and the scale invariant relationship between the normalized difference vegetation index (NDVI) and LST is the foundation of these algorithms. The performance of these different algorithms was assessed over different land use/land 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 the 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; Zaksek 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 Zhangye 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

was analyzed in agricultural field (Agam et al., 2007a,b). Here, the technique has been evaluated on Landsat 8 OLI and TIRS data for four different seasons (pre-monsoon, monsoon, post-monsoon, and winter) in the year of 2014. The main objectives of the research were (1) to estimate the accuracy of the downscaled LST in a heterogeneous urban landscape (Raipur City of India) of humid tropical region using TsHARP technique for separate LULC indices (normalized difference vegetation index (NDVI), normalized difference water index (NDWI), normalized difference built-up index (NDBI), and normalized multi-band drought index (NMDI)) and (2) to assess the seasonal variation of the result in 2014.

## 2. Materials & methods

The present study has been conducted in Raipur, a tropical city of India. Raipur is considered as a heterogeneous urban area characterized by dry tropical monsoon climate. Raipur has an average elevation of 298 m, is located between 21°11'22"N to 21°20'02"N and 81°32' 20"E to 81°41'50"E (Fig. 1). Average annual temperature varies between 34 °C (in summer), and 20 °C (in winter). The area receives 90% of annual rainfall of 130 cm during June to September. This urban area is characterized by four main LULC types, namely, vegetation, water bodies, bare land, and built-up area. A high rate of land conversion (other lands to the built-up area) has been taken place in the recent time periods.

Four separate cloud-free Landsat 8 OLI and TIRS images of 5 June 2014, 25 September 2014, 12 November 2014, and 30 December 2014 were used for the evaluation of the TsHARP downscaling technique. Green, red, near infrared, shortwave infrared 1, and shortwave infrared 2 bands of 30 m spatial resolution in OLI sensor were used in determining the LULC indices and thermal infrared band of 100 m spatial resolution in TIRS sensor was used for estimating the LST.

For the convenience of LST downscaling calculation, Landsat 8 TIRS data (100-m resolution) were resampled into 30 m by the nearest neighbor method by simple raster data aggregation to coincide with Landsat 8 OLI data (30-m resolution). These aggregated OLI and TIRS data were further resampled by aggregation into 960 m. The 960-m aggregated coarse-resolution data were used to build the relationship model, whereas the 30-m reflective data were used to downscale the LST at 30 m. The 30 m retrieved LST was used to validate the 30-m downscaled LST. Subsequently, the four indices (NDVI, NDWI, NDBI, and NMDI) with 30-m resolution were then estimated from the 30-m OLI images. The final available output is the downscaled LST of 30-m resolution. The overall accuracy of the entire downscaled LST in various LULC was compared and evaluated.

### 2.1. Retrieval of LST using Landsat 8 OLI and TIRS data

Retrieving LST from Landsat 8 OLI and TIRS data includes the brightness temperature calculation and the emissivity correction. The at-sensor brightness temperature assumes that the Earth's surface is a black body and includes atmospheric effects (along path absorption and emissions) (Chander et al., 2009). The conversion formula from the at-sensor spectral radiance  $L$  to the at-sensor brightness temperature  $T_B$  is shown in Eq. (1). LST is retrieved by Eq. (2):

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

$$LST = \frac{K_2}{1 + (\lambda\sigma T_B / (hc)) \ln e} \quad (2)$$

Where,  $T_B$  is the brightness temperature in Kelvin (K),  $L_\lambda$  is the spectral radiance in  $\text{Wm}^{-2}\text{sr}^{-1}\text{mm}^{-1}$ ,  $K_2$  and  $K_1$  are calibration constants. For Landsat 8 TIRS data,  $K_1$  is 774.89,  $K_2$  is 1321.08.  $\lambda$  is the effective wavelength (11.335  $\mu\text{m}$  for band 10 in Landsat 8 OLI data),  $\sigma$  is Boltzmann constant ( $1.38 \times 10^{-23}$  J/K),  $h$  is Planck's constant ( $6.626 \times 10^{-34}$

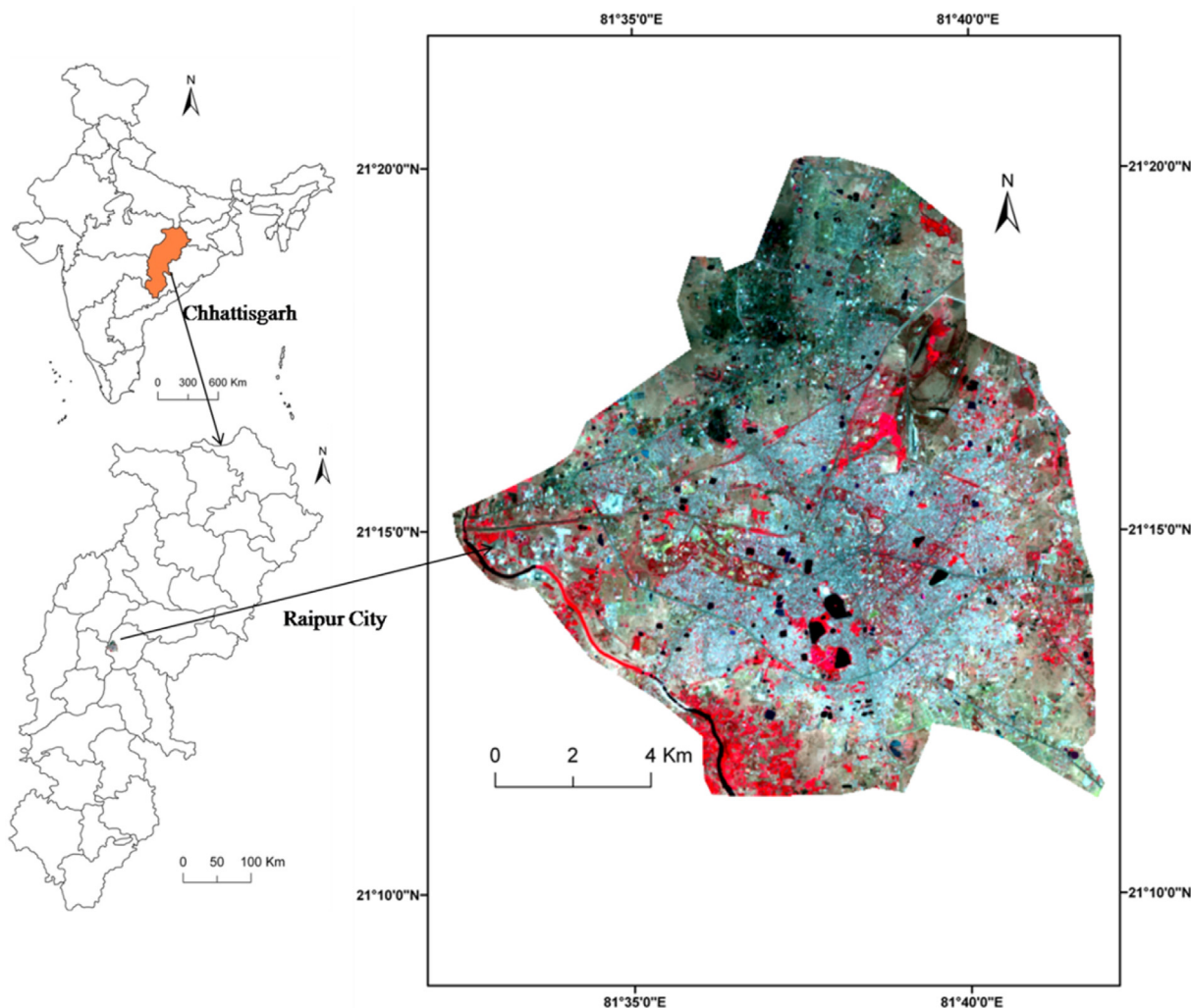


Fig. 1. Location of the study area with false colour composite image.

J),  $c$  is the velocity of light at a vacuum ( $2.998 \times 10^{-8}$  m/s),  $\epsilon$  is emissivity. Based on earlier studies,  $\epsilon$  is determined as follows: if NDVI is  $\geq 0.157$  and  $\leq 0.727$ ,  $\epsilon$  for that pixel is calculated by Eq. (3) (Van et al., 1993):

$$\epsilon = 1.0094 + 0.0047 \ln(\text{NDVI}) \tag{3}$$

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  $\epsilon$  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  
LULC indices used for LST downscaling.

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

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

resolution can be calculated by the predictors using such relationships. Table 1 shows the used LULC indices in the present study for estimating downscaled LST using TsHARP technique.

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 (Kustas 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, ( $LST_{fine}$ ) could be determined by the Eq. (4a–4d):

$$LST_{fine} = a_0 + a_1 \cdot NDVI_{fine} \tag{4a}$$

$$LST_{fine} = a_0 + a_1 \cdot NDWI_{fine} \tag{4b}$$

$$LST_{fine} = a_0 + a_1 \cdot NDBI_{fine} \tag{4c}$$

$$LST_{fine} = a_0 + a_1 \cdot NMDI_{fine} \tag{4d}$$

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

$$LST_{coarse} = a_0 + a_1 \cdot NDVI_{coarse} + \Delta T_{coarse} \tag{5a}$$

$$LST_{coarse} = a_0 + a_1 \cdot NDWI_{coarse} + \Delta T_{coarse} \tag{5b}$$

$$LST_{coarse} = a_0 + a_1 \cdot NDBI_{coarse} + \Delta T_{coarse} \tag{5c}$$

$$LST_{coarse} = a_0 + a_1 \cdot NMDI_{coarse} + \Delta T_{coarse} \tag{5d}$$

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

$$\Delta T_{coarse} = LST_{ref} - LST_{coarse} \tag{6}$$

The residual  $\Delta T_{coarse}$  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 ( $LST_{down}$ ) was estimated by the Eq. (7a–7d):

$$LST_{down} = a_0 + a_1 \cdot NDVI_{fine} + \Delta T_{coarse} \tag{7a}$$

$$LST_{down} = a_0 + a_1 \cdot NDWI_{fine} + \Delta T_{coarse} \tag{7b}$$

$$LST_{down} = a_0 + a_1 \cdot NDBI_{fine} + \Delta T_{coarse} \tag{7c}$$

$$LST_{down} = a_0 + a_1 \cdot NMDI_{fine} + \Delta T_{coarse} \tag{7d}$$

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 downscaling 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 downscaling has been applied at 30 m, 120 m, 240 m, and 480 m spatial resolutions.

#### 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 ( $LST_{ref}$ ). The aggregated 960-m resolution LST was downscaled ( $LST_{down}$ ) 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.

$$RMSE = \sqrt{\left[ n^{-1} \sum_{i=1}^n (LST_{down} - LST_{ref})^2 \right]} \tag{8}$$

$$ME = \sum_{i=1}^n (LST_{down} - LST_{ref}) \tag{9}$$

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.

### 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 downscaling 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 downscaling 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

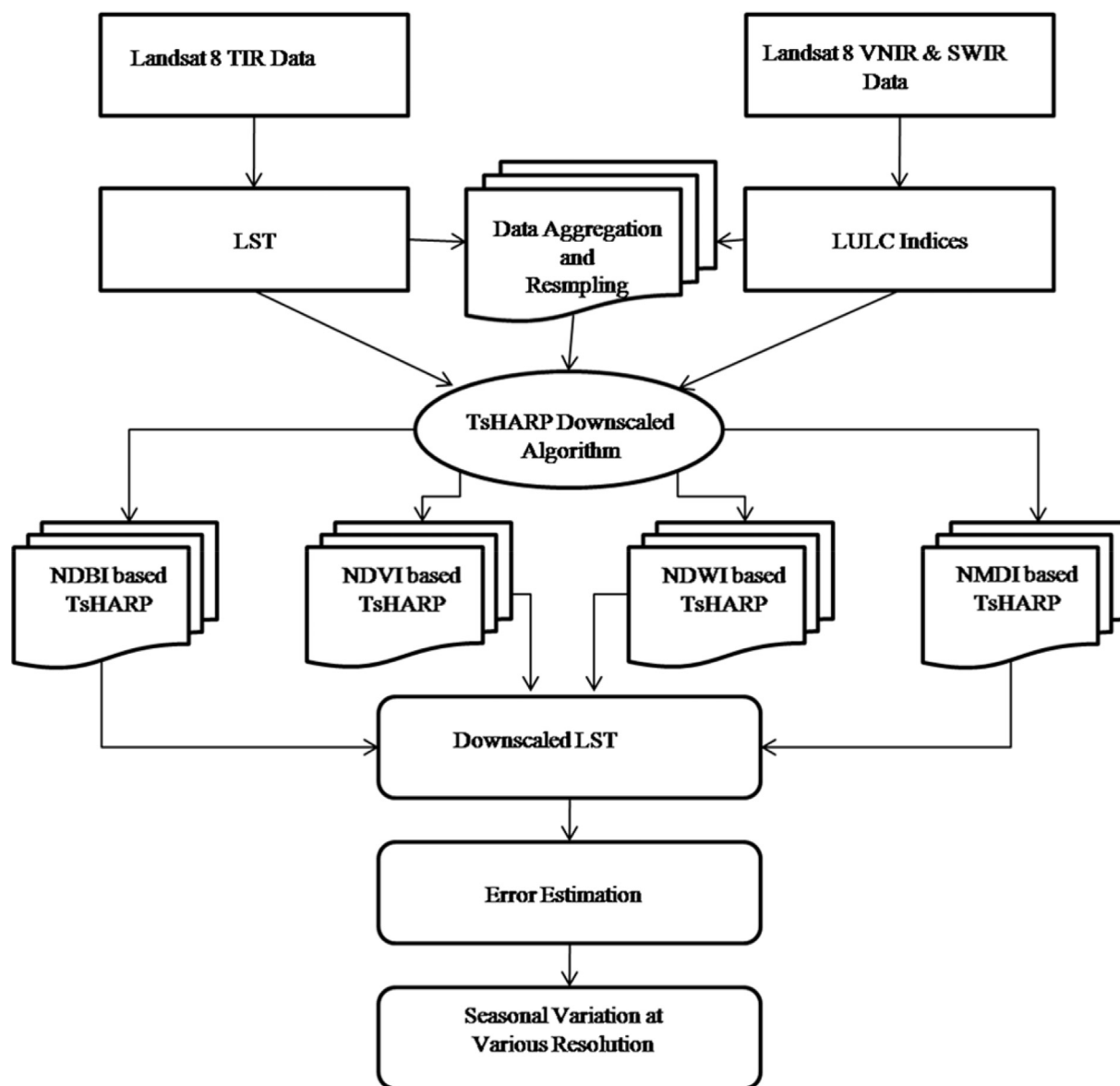


Fig. 2. Flowchart of methodology.

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 NMDI reflect a smaller ME for pre-monsoon and winter seasons while NDVI and NDWI 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 downscaling 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 generate 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

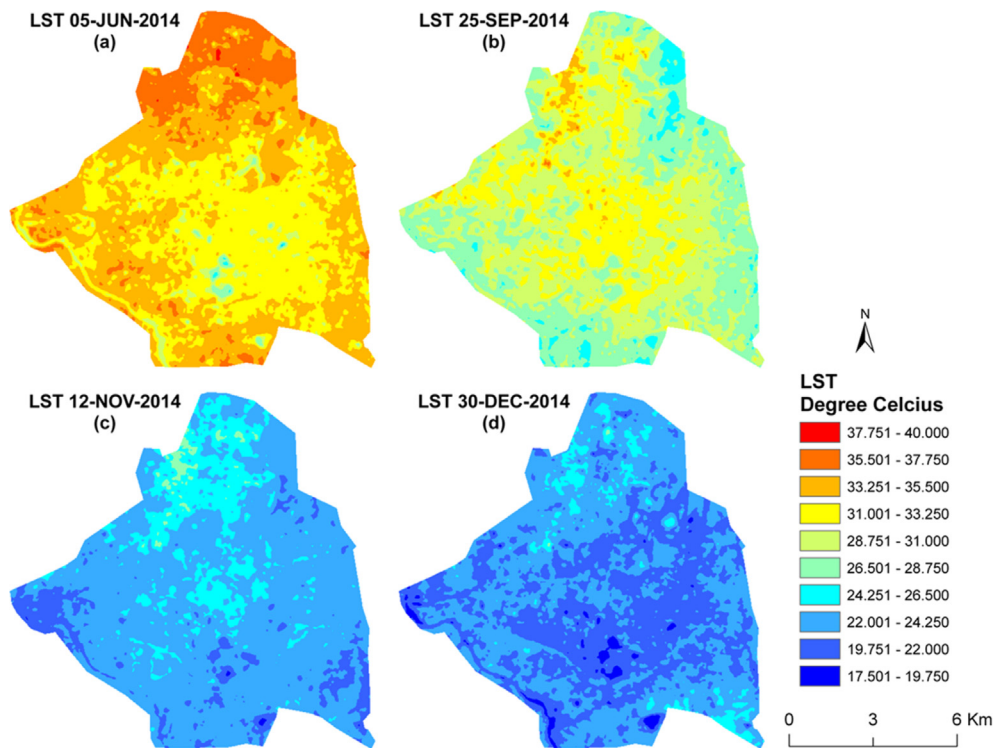


Fig. 3. Spatial distribution of reference LST at 30-m spatial resolution: (a) pre-monsoon; (b) monsoon; (c) post-monsoon; (d) winter.

**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

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.

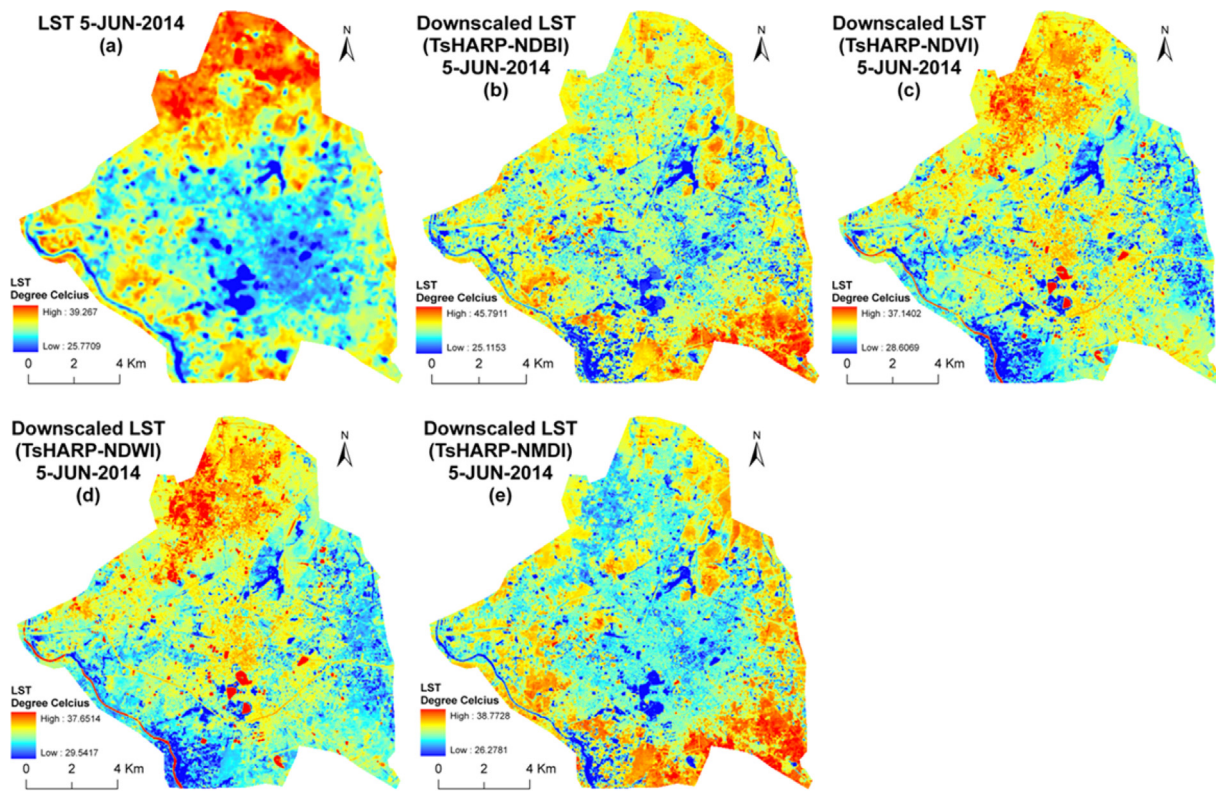


Fig. 4. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 5-JUN-14: (a)  $LST_{ref}$ ; (b) NDBI-based  $LST_{down}$ ; (c) NDVI-based  $LST_{down}$ ; (d) NDWI-based  $LST_{down}$ ; (e) NMDI-based  $LST_{down}$ .

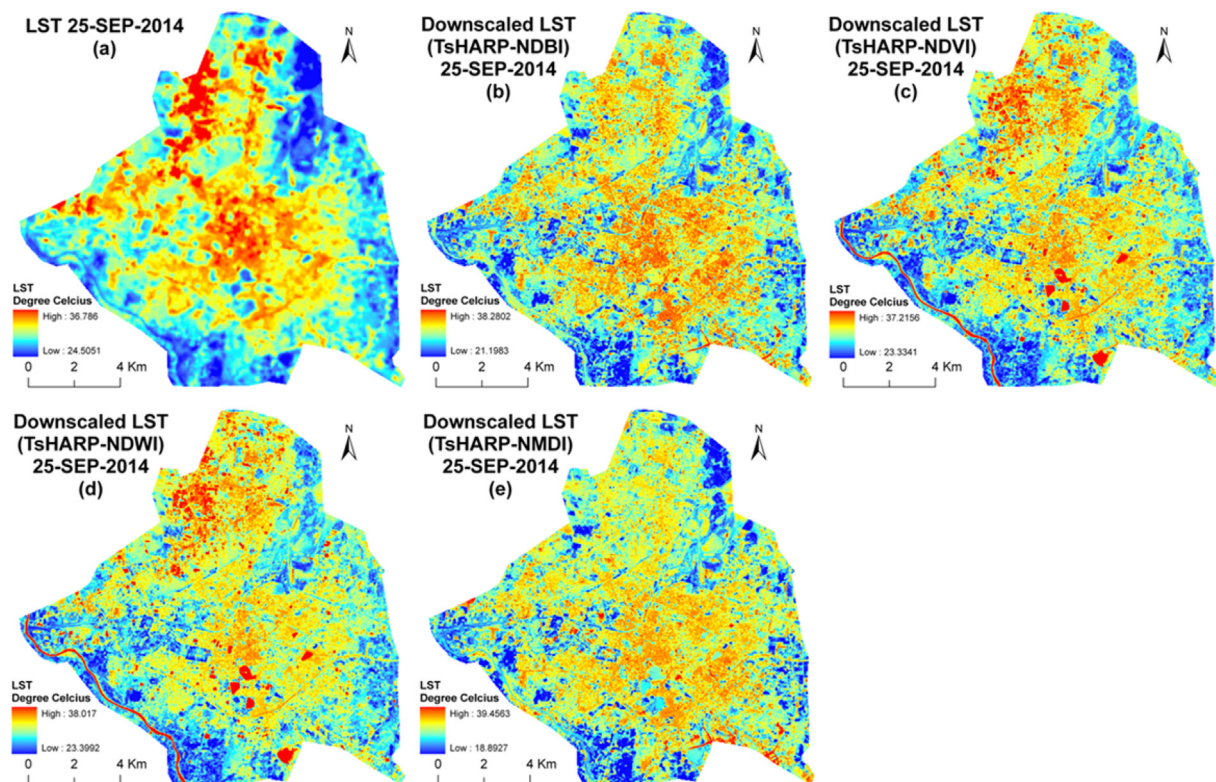


Fig. 5. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 25-SEP-14: (a)  $LST_{ref}$ ; (b) NDBI-based  $LST_{down}$ ; (c) NDVI-based  $LST_{down}$ ; (d) NDWI-based  $LST_{down}$ ; (e) NMDI-based  $LST_{down}$ .

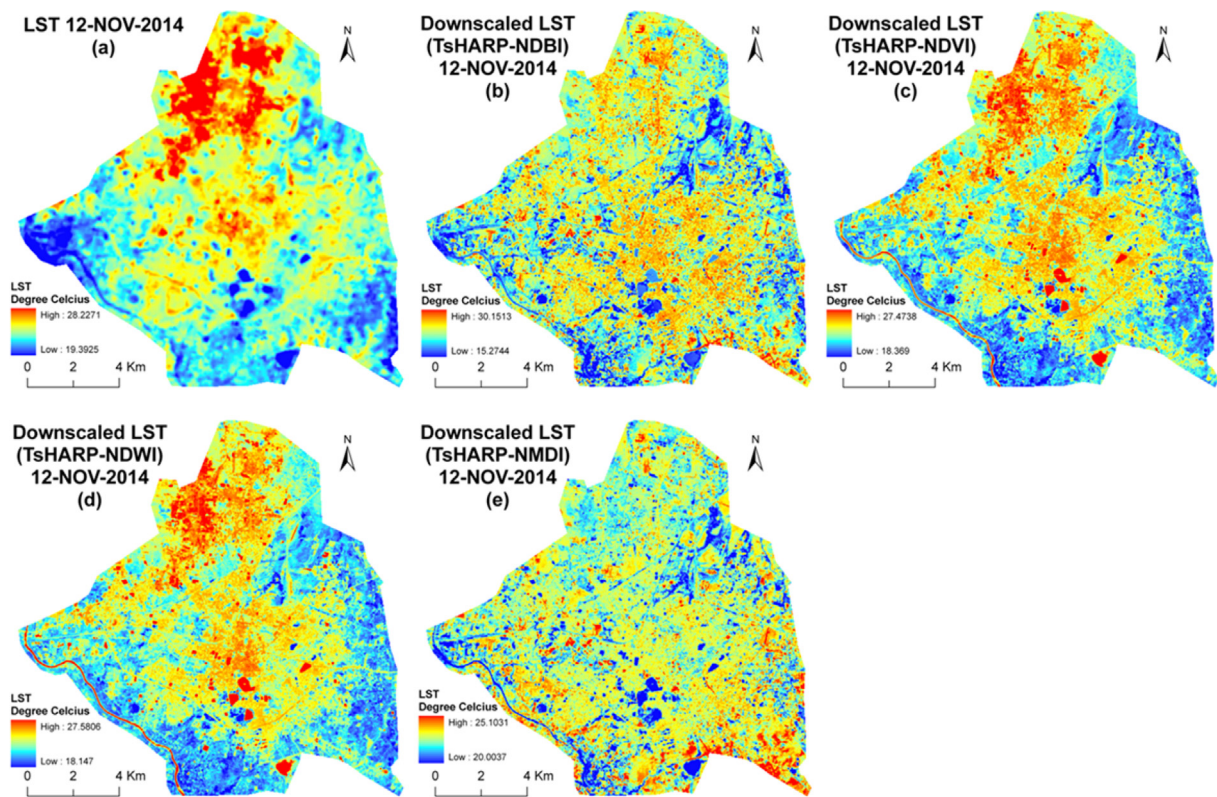


Fig. 6. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 12-NOV-14: (a) LST<sub>ref</sub>; (b) NDBI-based LST<sub>down</sub>; (c) NDVI-based LST<sub>down</sub>; (d) NDWI-based LST<sub>down</sub>; (e) NMDI-based LST<sub>down</sub>.

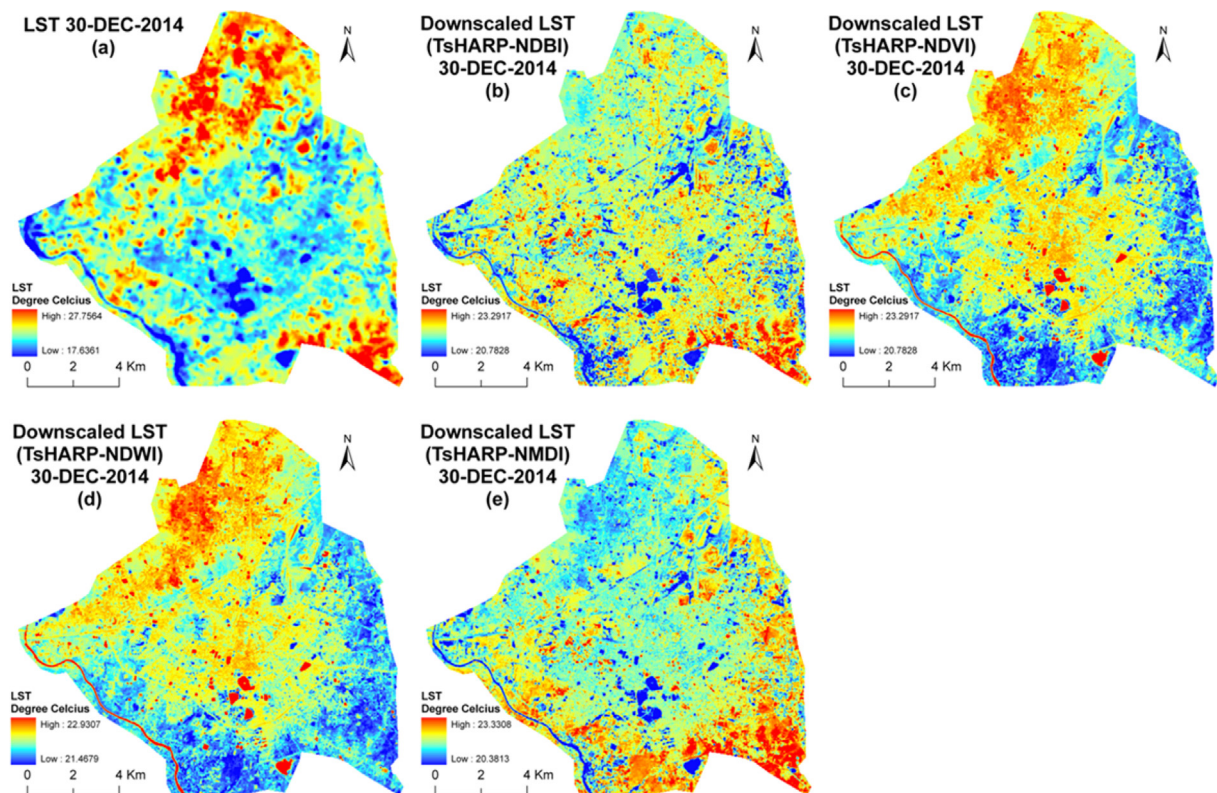


Fig. 7. Spatial distribution of retrieved LST and downscaled LST at 30-m resolution for 30-DEC-14: (a) LST<sub>ref</sub>; (b) NDBI-based LST<sub>down</sub>; (c) NDVI-based LST<sub>down</sub>; (d) NDWI-based LST<sub>down</sub>; (e) NMDI-based LST<sub>down</sub>.



**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			
<b>June-05-2014</b>																
	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$
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	33.69	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	37.14	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	36.08	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
<b>September-25-2014</b>																
	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$
NDBI-based	24.51	36.79	29.56	1.73	24.59	35.89	29.54	1.71	24.67	34.76	29.52	1.65	25.26	34.49	29.46	1.57
NDVI-based	21.20	38.28	29.50	2.02	23.38	34.77	29.49	1.73	23.68	33.06	29.47	1.51	24.96	32.29	29.44	1.40
NDWI-based	23.33	37.22	29.49	2.00	24.06	35.38	29.47	1.70	24.38	34.87	29.46	1.51	25.49	33.19	29.43	1.34
NMDI-based	23.40	31.02	29.47	1.90	24.37	36.57	29.46	1.61	24.72	36.51	29.45	1.42	25.59	34.07	29.42	1.25
NDBI-based	18.89	39.46	29.47	1.87	22.38	35.56	29.45	1.58	22.75	33.44	29.44	1.41	24.54	33.22	29.42	1.26
<b>November-12-2014</b>																
	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$
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	24.39	23.31	0.22	22.45	24.07	23.31	0.19	22.48	23.97	23.31	0.15
<b>December-30-2014</b>																
	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$	Min	Max	$\mu$	$\sigma$
NDBI-based	17.63	27.76	22.26	1.11	17.68	26.86	22.27	1.08	17.78	25.79	22.28	1.03	19.08	25.41	22.29	0.94
NDVI-based	13.48	28.56	22.29	1.06	15.07	26.26	22.29	0.84	18.71	25.29	22.30	0.70	19.71	25.29	22.30	0.60
NDWI-based	20.78	23.29	22.31	0.25	21.03	23.14	22.31	0.22	21.56	23.07	22.31	0.20	21.83	22.80	22.31	0.19
NMDI-based	21.47	22.93	22.31	0.14	21.68	22.90	22.31	0.13	21.95	22.86	22.31	0.12	22.02	22.64	22.30	0.11
NDBI-based	20.38	23.33	22.29	0.17	21.30	22.93	22.29	0.14	21.79	22.79	22.29	0.13	21.89	22.75	22.30	0.11

$\mu$  = mean, and  $\sigma$  = standard deviation.

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

LULC indices based LST <sub>down</sub>	at 30 m		at 120 m		at 240 m		at 480 m	
<b>June-05-2014 (the standard deviation of the native LST reference image at 30 m spatial resolution is 1.61)</b>								
	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME
NDBI-based	1.09	0.05	0.96	0.04	0.91	0.03	0.87	0.01
NDVI-based	1.22	0.14	1.17	0.12	1.13	0.09	1.05	0.05
NDWI-based	1.23	0.15	1.19	0.13	1.15	0.10	1.07	0.05
NMDI-based	1.09	0.05	1.03	0.04	0.99	0.02	0.96	0.01
<b>September-25-2014 (the standard deviation of the native LST reference image at 30 m spatial resolution is 1.73)</b>								
	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME
NDBI-based	1.11	-0.05	0.81	-0.05	0.69	-0.05	0.61	-0.03
NDVI-based	1.21	-0.07	0.97	-0.06	0.86	-0.06	0.75	-0.04
NDWI-based	1.25	-0.08	1.08	-0.08	0.98	-0.07	0.86	-0.04
NMDI-based	1.18	-0.09	0.92	-0.08	0.82	-0.07	0.75	-0.05
<b>November-12-2014 (the standard deviation of the native LST reference image at 30 m spatial resolution is 1.12)</b>								
	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME
NDBI-based	0.91	-0.06	0.72	-0.05	0.65	-0.05	0.60	-0.05
NDVI-based	0.75	-0.01	0.66	-0.02	0.60	-0.02	0.55	-0.03
NDWI-based	0.74	-0.01	0.66	-0.02	0.60	-0.02	0.55	-0.02
NMDI-based	0.81	-0.09	0.79	-0.08	0.78	-0.07	0.76	-0.06
<b>December-30-2014 (the standard deviation of the native LST reference image at 30 m spatial resolution is 1.11)</b>								
	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME
NDBI-based	0.85	0.03	0.71	0.03	0.65	0.02	0.59	0.01
NDVI-based	0.86	0.05	0.84	0.05	0.79	0.04	0.73	0.01
NDWI-based	0.86	0.05	0.84	0.04	0.80	0.03	0.72	0.01
NMDI-based	0.81	0.03	0.79	0.03	0.76	0.02	0.69	0.01

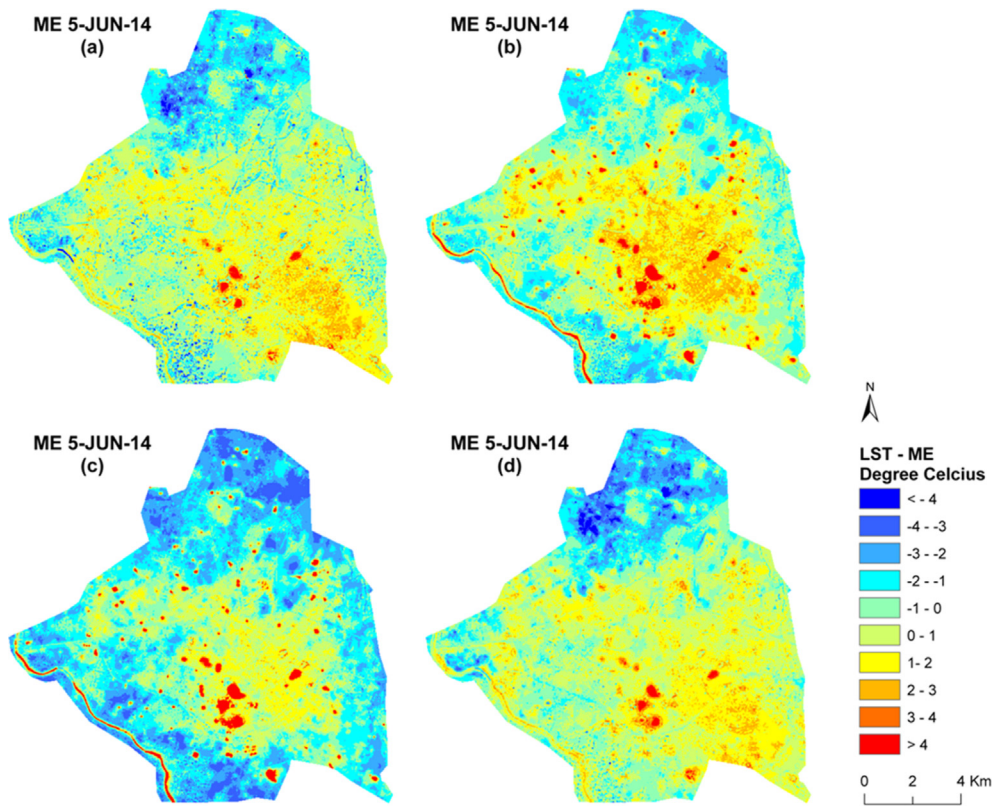


Fig. 8. Spatial distribution of ME at 30-m resolution for 5-JUN-14: (a) NDBI-based  $LST_{down}$ ; (b) NDVI-based  $LST_{down}$ ; (c) NDWI-based  $LST_{down}$ ; (d) NMDI-based  $LST_{down}$ .

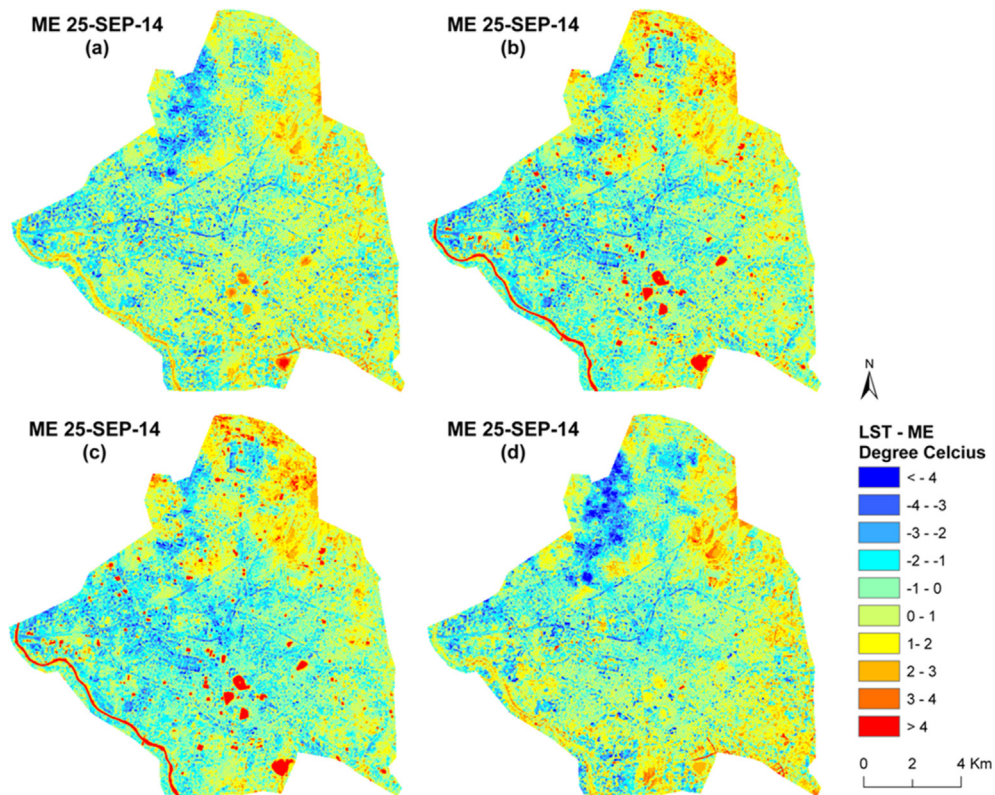


Fig. 9. Spatial distribution of ME at 30-m resolution for 25-SEP-14: (a) NDBI-based  $LST_{down}$ ; (b) NDVI-based  $LST_{down}$ ; (c) NDWI-based  $LST_{down}$ ; (d) NMDI-based  $LST_{down}$ .

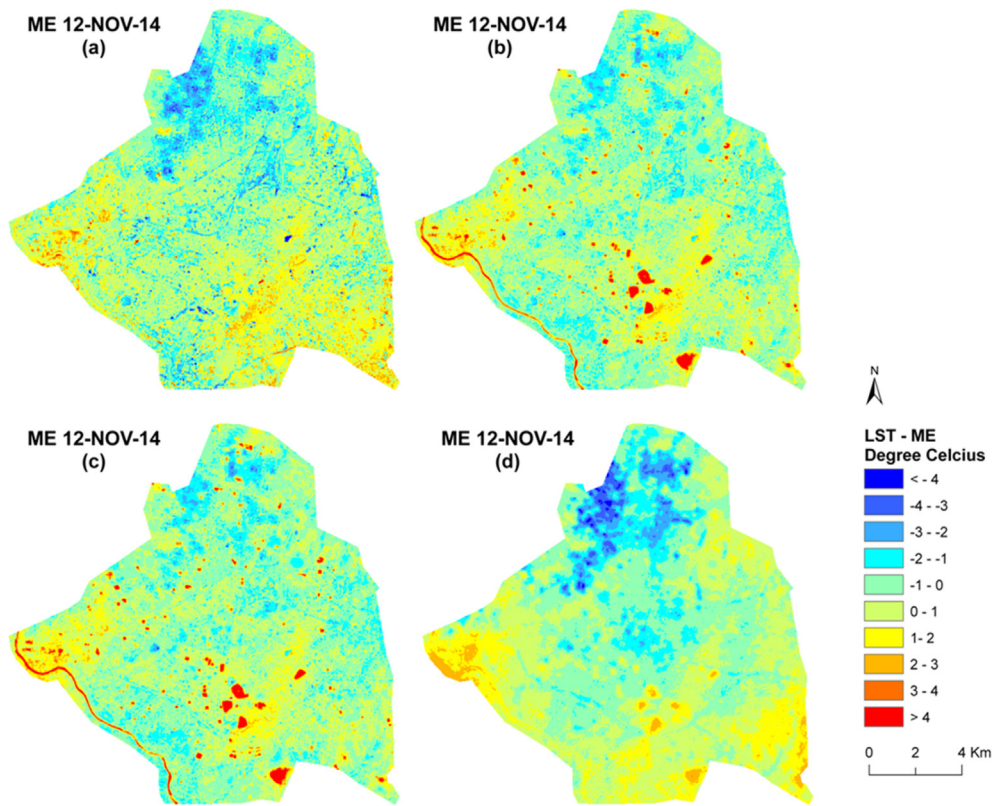


Fig. 10. Spatial distribution of ME at 30-m resolution for 12-NOV-14: (a) NDBI-based  $LST_{down}$ ; (b) NDVI-based  $LST_{down}$ ; (c) NDWI-based  $LST_{down}$ ; (d) NMDI-based  $LST_{down}$ .

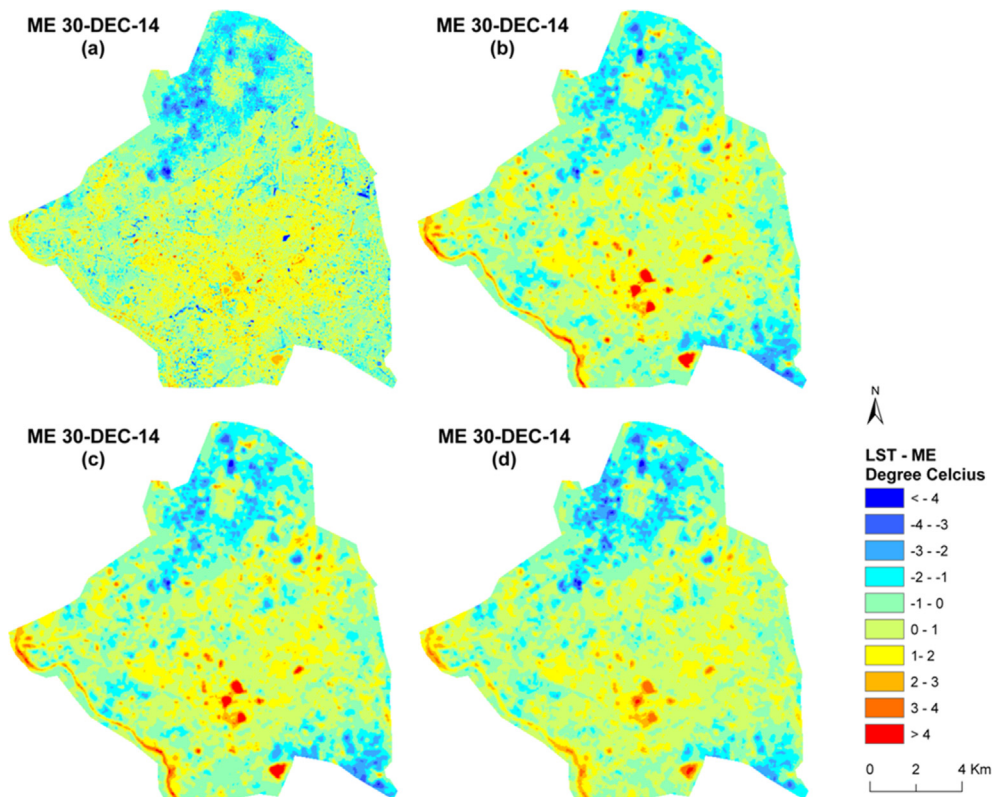


Fig. 11. Spatial distribution of ME at 30-m resolution for 30-DEC-14: (a) NDBI-based  $LST_{down}$ ; (b) NDVI-based  $LST_{down}$ ; (c) NDWI-based  $LST_{down}$ ; (d) NMDI-based  $LST_{down}$ .

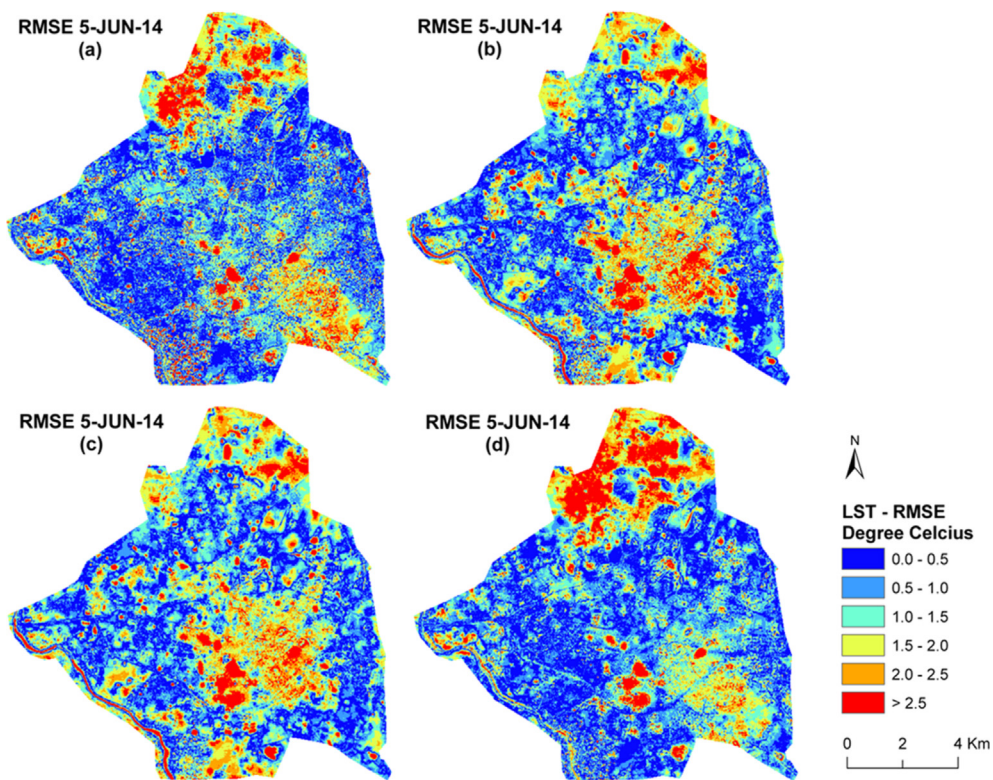


Fig. 12. Spatial distribution of RMSE at 30-m resolution for 5-JUN-14: (a) NDBI-based LST<sub>down</sub>; (b) NDVI-based LST<sub>down</sub>; (c) NDWI-based LST<sub>down</sub>; (d) NMDI-based LST<sub>down</sub>.

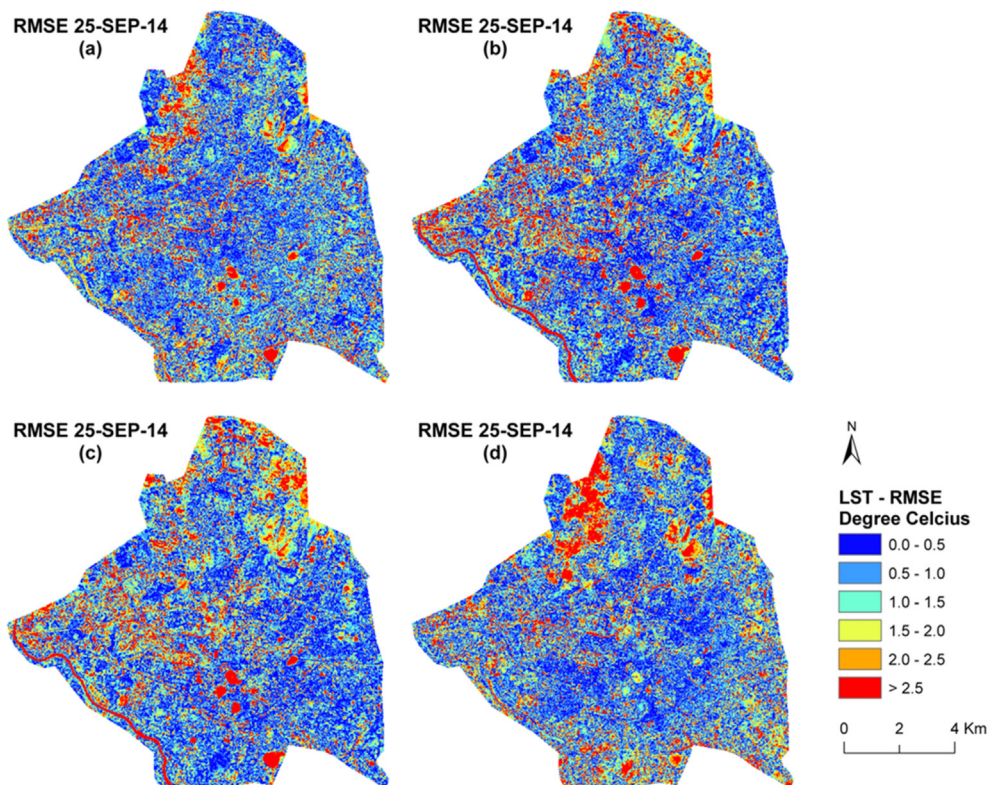


Fig. 13. Spatial distribution of RMSE at 30-m resolution for 25-SEP-14: (a) NDBI-based LST<sub>down</sub>; (b) NDVI-based LST<sub>down</sub>; (c) NDWI-based LST<sub>down</sub>; (d) NMDI-based LST<sub>down</sub>.

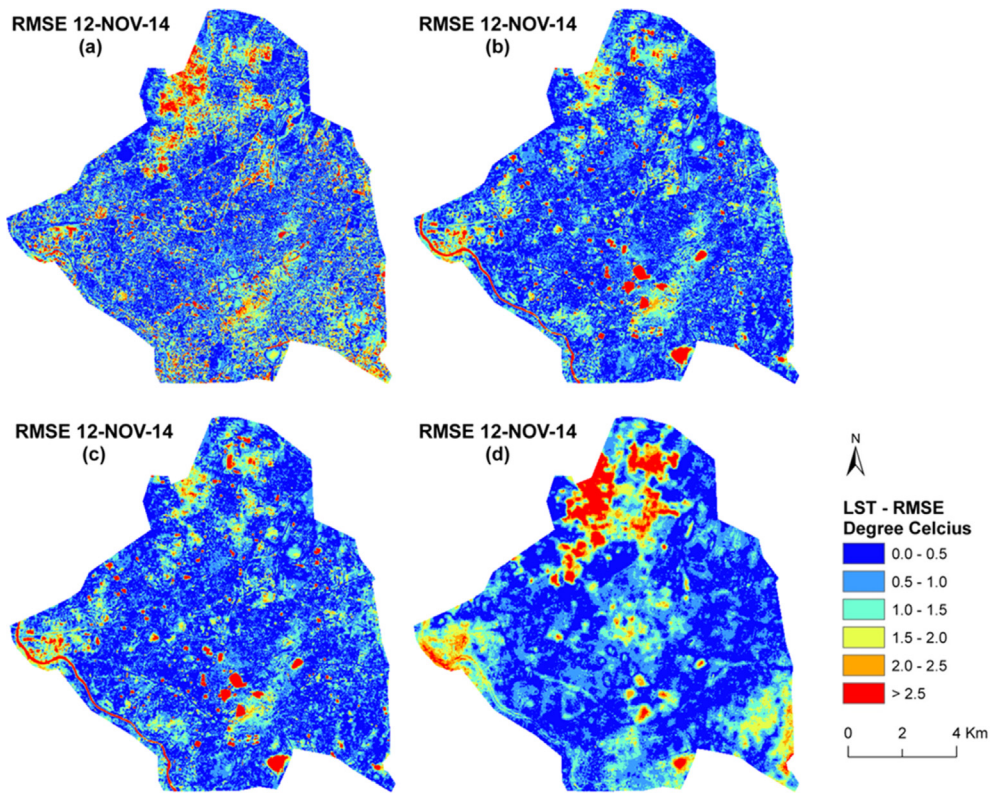


Fig. 14. Spatial distribution of RMSE at 30-m resolution for 12-NOV-14: (a) NDBI-based LST<sub>down</sub>; (b) NDVI-based LST<sub>down</sub>; (c) NDWI-based LST<sub>down</sub>; (d) NMDI-based LST<sub>down</sub>.

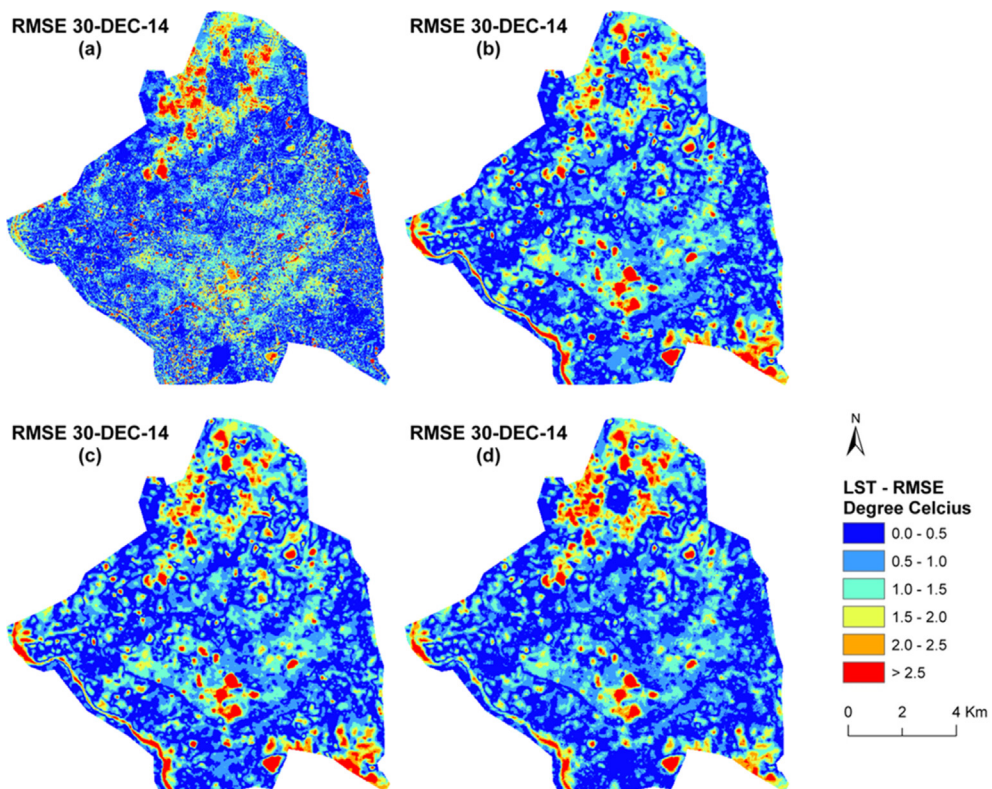


Fig. 15. Spatial distribution of RMSE at 30-m resolution for 30-DEC-14: (a) NDBI-based LST<sub>down</sub>; (b) NDVI-based LST<sub>down</sub>; (c) NDWI-based LST<sub>down</sub>; (d) NMDI-based LST<sub>down</sub>.

**Table 5**  
Percentage of root mean square error (RMSE) in downscaled LST (°C) at 30 m resolution.

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%	2.61%
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%	2.70%
NDVI-based	35.47%	31.16%	19.47%	7.30%	3.29%	3.35%
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**  
Percentage of mean error (ME) in downscaled LST (°C) at 30 m resolution.

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	0.01%	0.29%	5.00%	19.48%	25.89%	21.25%	17.53%	7.89%	1.06%	1.63%
NDWI-based	0.01%	0.32%	5.47%	19.18%	25.36%	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%	1.01%	0.20%
NDVI-based	0.62%	2.29%	6.99%	16.35%	27.62%	26.13%	12.65%	4.06%	1.09%	2.20%
NDWI-based	0.47%	2.06%	7.22%	18.24%	29.85%	22.90%	11.41%	4.00%	1.23%	2.62%
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%	0.78%	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%

**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.

*Additional information*

No additional information is available for this paper.

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