

## Retrieval of Land Surface Temperature of Lahore Through Landsat-8 TIRS Data

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**Abstract:** Land surface temperature (LST) is an important parameter in global climate change and urban thermal environmental studies. The significance of land surface temperature is being acknowledged gradually and interest is increasing in developing methodologies for the retrieval of LST from Satellite Remote Sensing (SRS) data. Thermal Infrared Sensor (TIRS) of Landsat-8 is the newest TIR sensor for the Landsat Data Continuity Mission (LDCM), offering two adjacent thermal infrared bands (10, 11), having significant beneficiary for the land surface temperature inversion. The spectral radiance can be estimated through TIR bands 10 and 11 of Landsat-8 OLI\_TIRS satellite image. In the present study, the radiative transfer equation-based method has been employed in estimating LST of Lahore and the analysis demonstrated that estimated LST has the highest accuracy from the radiative transfer method through band 10. Land Surface Emissivity (LSE) was derived with the aid of the NDVI's threshold technique. The present study results show that as the built-up area increases and vegetation cover decreases in urban surface, they are linked to increase in urban land surface temperature and conversely larger vegetation cover associated with lower urban temperature. The output exposed that LST was high in built-up and barren land, whereas it was low in the area where there were more vegetation cover and water.

**Keywords:** Land surface temperature, Land surface emissivity, OLI, TIRS, NDVI, Landsat-8, Lahore.

### Introduction

Land Surface Temperature (LST) is an important parameter related to the process of surface energy and water exchange with the atmosphere, from local to global levels (Chapin et al., 2005; Yu et al., 2014) which plays a significant role in scientific studies with a wide range of application such as urban climate, climate change, ecology, vegetation monitoring and environmental and global change studies (Zhang and He, 2013; Sameen and Al Kubaisy, 2014). With the increasing recognition of importance of land surface temperature, techniques and methodologies for its assessment from space and time have constantly been developed (Li et al., 2013; Jimenez-Munoz et al., 2014). Surface temperature variations in space and time, retrieved by remote sensing (RS) data are utilized for the assessment of a multitude of geophysical key variables, such as soil moisture, thermal inertia, evapotranspiration, and vegetation water stress (Rozenstein et al., 2014). LST is the skin temperature of the land surface as the temperature felt when the ground is touched with the hands. Land surface temperature and the temperature emitted by the ground are measured in Kelvin. LST was mainly affected by the increasing built-up land and Greenhouse Gases (GHGs) in the atmosphere. Increase in land surface temperature influences the climatic condition leading to unpredictable rainfall in the monsoon region (Rajeshwari and Mani, 2014). Rapid urban expansion, economic growth and rural to urban migration have been indispensable drivers of change in LULC globally (Grimm, 2000). According to the estimate of United Nations (2014) 54% of the world population lives in urban areas. While, in 2030, over 60 percent of the

world's population will be living in towns and cities. Urban landscapes and urbanization have many significant influences on climate at a local, regional and global level. Anthropogenic and natural activities can ultimately change the land use in an area. Such land surface change can also affect the land surface temperature of that area (Goksel et al., 2004; 2006).

The amount of LST can be estimated by measuring the change of Land Use Land Cover (LULC) of an area (Balçık, 2014). Due to uncontrolled and haphazard growth of cities and conversion of rural land use, natural materials such as vegetation, water and soil have been substituted with urban artificial materials including metal, concrete, asphalt, and artificial surfaces (Xu, 2008). A number of studies show that a rapid increase in built-up areas is associated with intensifications in urban land surface temperatures and conversely vegetation cover and green spaces improve the climatic comfort and the city's ventilation. Consequently, the alteration of these surfaces has various negative impacts on the environment such as loss of agricultural land, change of urban climate, high demand of energy, quality of living, and human health in urban environments (Sanli et al., 2008; Santana, 2007; Balçık, 2014). Due to increasing atmospheric and environmental pollution by industrialization and urban expansion, global warming is increasing day by day. The changes recorded in the urban microclimate and regional heat islands are beyond global climatic change (Simsek and Sengezer, 2012). The UHI phenomenon is a significant effect of urbanization that obviously leads to the changes in surface, air temperature, and absorption of solar radiation, water vapor, evapotranspiration and concentration if the air

pollutant is directly related to the issue concerning human health. The phenomenon of urban heat islands is usually referred to the higher radiation heat budget and thermal conductivity in urban centers, owing to the existent artificial surfaces when compared with rural areas (Tan et al., 2010; Landsberg, 1981).

Thermal infrared remote sensing offers a significant method to obtain land surface temperature at global and regional scales as the sensors detect energy directly in the spectral region. This is done by measuring heat emitted by the impervious surfaces (Jimenez-Munoz and Sobrino, 2008). During the past few decades, progressive initiatives have been taken to develop modern methods for retrieving LST from remote sensing (Li et al., 2014). The use of remote sensing thermal infrared (TIR) data were first demonstrated by Rao (1972) and it recognized areas by investigating thermal infrared (TIR) data. Several urban studies have shown a relationship between urban heat island and patterns of Land Use Land Cover (LULC) changes, with many indicating that the presence of water and vegetation cover reduced the intensity of urban heat islands while an increase in urban surfaces also increased the effect (Ganguly and Shankar, 2014). However, these land use and land cover changes were evaluated qualitatively keeping in view the relationship with the land surface temperature. To measure these LULC changes, indices such as the Normalized Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index (NDVI) have been used to represent land cover changes (Rinner and Hussain, 2011; Xiong et al., 2012). The aim of this study is to present a radiative transfer method for surface temperature assessment from the Landsat-8 OLI\_TIRS data. Quantitative remote sensing techniques have been adopted to examine temperature variation of Lahore.

### Study Area

Lahore is the second largest metropolitan city in Pakistan after Karachi with population of about 11 million (GoP, 2017). It lies between 31°15'—31°43' N and 74°10'—74°39' E, total area of is 1,772 km<sup>2</sup> (GoP, 2000). The city of Lahore has an extreme climate where summer begins in April and ends in September. The hottest weather during the year is recorded in May, June and July. The average minimum and maximum atmospheric temperatures for these months are 29.3°C and 45.4°C respectively. Winter commences from the month of November until March. The coldest weather is observed during the months from December to February (GoP, 2000). The mean minimum and maximum atmospheric temperatures for these months are 7.2°C and 21.1°C respectively. The average minimum and maximum atmospheric temperatures of Lahore are 17.8°C and 30.8°C respectively (GoP, 2000).

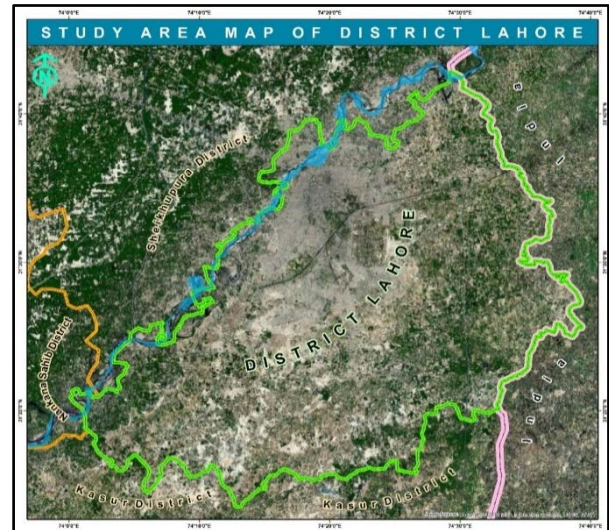


Fig. 1 Location of the study area (Lahore).

Lahore has light to moderate rainfall during the months of January and February which is succeeded by a spell of pleasant weather during the spring season. In the months of May and June, the maximum temperature rises to 40.4°C. During the winter, the season's minimum temperature goes down to zero degree centigrade (GoP, 2000). The urban expansion of Lahore has been increasing rapidly since 1951 which led to an increase in surface and air temperatures. The factors responsible for increasing temperature include conversion of land from vegetation cover to impervious surface housing schemes, industrial and commercial activities, deforestation, emission of GHGS and exhausts of vehicles.

### Materials and Methods

The Landsat-8 imagery of Lahore used in present research was acquired on 26<sup>th</sup> March 2017, which is a level 1 product that was downloaded from the Earth Explorer website (*glovis.usgs.gov*). In order to get the retrieval of LST the thermal infrared (TIR) bands 10 and 11 were utilized to estimate brightness temperature and OLI optical bands 2, 3, 4, and 5 were utilized to produce NDVI of the study area (Fig. 1, Table 1). Thermal constant and rescaling factor values of thermal bands have been provided by the Landsat-8 satellite as mentioned in Table 2 which can be utilized for computing LST algorithms. The data-sets in the study comprises of the Universal Transverse Mercator (UTM) projection along with WGS84 datum and zone 43North. The data type and the file format provided by USGS of Landsat 8 image were Tagged Image File Format (TIFF) and integer. The vector layer (administrative boundary) of district Lahore is utilized as masks to subset image for clipping the area of interest (AOI) from the complete scene. No atmospheric corrections were executed as mentioned by Bhatti and Tripathi (2014) since the Landsat imagery was cloud-free (Deng and Wu, 2013).

Table 1. Landsat 8 OLI\_TIRS image description

| Date of Acquisition | Sensor | Bands   | Spatial Resolution | Thermal Resolution | Path/ Row |
|---------------------|--------|---------|--------------------|--------------------|-----------|
| 26-03-2017          | OLI    | 1-7 & 9 | 30 m               | -                  | 149/38    |
|                     |        | Pan (8) | 15 m               | -                  |           |
|                     | TIR    | 10 & 11 | -                  | 100 m              |           |

Source: <http://earthexplorer.usgs.gov>.

A number of algorithms have been recognized to measure LST from Landsat TIRS bands data such as the single-channel method, mono-window algorithm and radiative transfer method (Jiménez-Muñoz and Sobrino, 2003; Qin et al., 2001). In the present study the radiative transfer equation-based method is used to calculate the LST of Lahore.

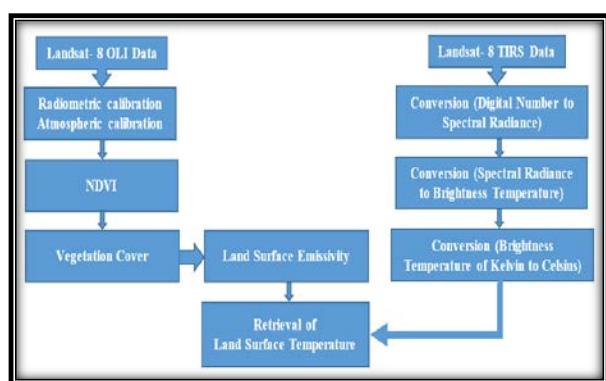


Fig. 2 Flow chart for the retrieval of land surface temperature.

**Retrieval of Brightness Temperature**

To estimate the brightness temperature the thermal infrared bands (10, 11) of Landsat 8, OLI\_TIRS were used in order to make the LST map and recognize the urban thermal environment of Lahore on 26<sup>th</sup> March, 2017. The TIRS bands of Landsat satellite were used to convert the raw value into the black body temperature in Celsius Degree (Joshi and Bhatt, 2012). Hashim et al., (2007) have given three steps in order to measure brightness of surface temperature.

**i) Conversion of the Digital Number (DN) to Spectral Radiance (L<sub>λ</sub>)**

Thermal infrared band is converted to Top of Atmospheric (TOP) spectral radiance through rescaling factors as mentioned in the metadata as shown in Table 2.

$$L_{\lambda} = M_L \times Q_{CAL} + AL \dots \dots \dots 1$$

Where

- L<sub>λ</sub> = TOA spectral radiance
- M<sub>L</sub> = Band-specific multiplicative rescaling factor
- Q<sub>CAL</sub> = Q<sub>CAL</sub> calibrated and quantized standard pixel values (DN),

AL = Band-specific additive rescaling factor as shown in Table 2.

Table 2. Rescaling Factor of Landsat 8-TIRS

| Rescaling Factor         | Band 10   | Band 11   |
|--------------------------|-----------|-----------|
| Radiance Multiplier (ML) | 0.0003342 | 0.0003342 |
| Radiance Add (AL)        | 0.1       | 0.1       |

Source: <https://landsat.usgs.gov/landsat-8-data-users-handbook>.

**ii) Conversion of Spectral Radiance to Brightness Temperature in Kelvin**

At the second step thermal infrared data can be obtained from spectral radiance to measure brightness temperature in Kelvin using the Planck curve equation 2 (Chander and Markham, 2003) and the thermal constant's value as presented in Table 3.

$$T_k = K_2 / \ln (K_1 / L_{\lambda} + 1) \dots \dots \dots 2$$

Where T<sub>k</sub> refers to brightness temperature in Kelvin and L<sub>λ</sub> = TOA spectral radiance (Watts/ (m<sup>2</sup> \* srad \* μm)). On the other hand, K<sub>1</sub> and K<sub>2</sub> refer to constant 1 and constant 2 in Kelvin of prelaunch calibration as presented in Table 3.

Table 3. Thermal Constant of Landsat 8-TIRS.

| Thermal Constant | Band 10 | Band 11 |
|------------------|---------|---------|
| K1               | 774.89  | 480.89  |
| K2               | 1321.08 | 1201.14 |

Source: <https://landsat.usgs.gov/landsat-8-data-users-handbook>.

At the final stage brightness temperature in Kelvin can be converted to degree Celsius (°C) by utilizing the given equation 3:

**iii) Conversion of Kelvin to Celsius**

$$T_B = T_K - 272.15 \dots \dots \dots 3$$

Where T<sub>B</sub> is considered to be brightness temperature in Celsius degree (°C) and T<sub>k</sub> is reckoned as the brightness temperature in Kelvin (K).

**Derivation of NDVI**

In this study, the Normalized Difference Vegetation Index is used to recognize the correlation between vegetation cover and LST. The NDVI is used by a number of scholars in their research such as Gao, (1996); Purevdorj et al., (1998) and Myneni et al., (2001) in order to differentiate the type of land use. It facilitates the analyst to recognize relationship between land use type and estimate surface temperature quantitatively (Schmidt and Karnieli, 2000). The Normalized Difference Vegetation Index (NDVI) is derived by equation number 4, given by Purevdorj et al., (1998); Peijun et al., (2010), in order to accomplish the vegetation cover thickness of the study area.

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \dots\dots\dots 4$$

Calculation of the NDVI pixel values ranges from -1 to +1; showing a value close to 0 relate to barren land and reflects the absence of vegetation on the other hand -1 means water, while a value touching +1 shows healthy and thick vegetation cover (Weier and Herring, 2011). The NDVI is used to classify different land use types for instance, built-up area, bare land, water body and vegetation cover. The NDVI value ranges for all these land use types are unpredictable, which show variations in different regions and diverse environments.

**Retrieval of Land Surface Emissivity (LSE)**

In order to find Land Surface Temperature, it is required to estimate the LSE of Lahore. LSE is an important constraint in the retrieval of LST Model. Natural surfaces are heterogeneous in terms of variation in surface emissivity at the pixel scale. In addition, the surface emissivity mainly depends on the range of wavelength sensor and surface structure, nature of vegetation cover and surface roughness (Mallick, Kantand and Bharath, 2008). LSE is a key measure of the capability of a land surface to release energy by emission which has a great impact on the assessment of LST (Yang et al., 2014). In this research, an attempt has been made to estimate LSE by compelling the vegetation proportion per pixel in combination with NDVI (Caselles and Sobrino, 1989; Valor and Caselles, 1996). In the present research, the process of derivation of surface emissivity calculation from the Normalized Difference Vegetation Index given by Caselles and Sobrino, (1989); Sobrino et al., (2008) has been applied. Land surface emissivity ( $\epsilon$ ) can be estimated through NDVI by acknowledging three dissimilar classes as following;

- a) Bare land surface
- b) Massive vegetation cover
- c) Mixture of bare land and vegetation cover

$$\epsilon = \begin{cases} 0.979 - 0.035P_v & \text{NDVI} < 0.2 \\ 0.986 + 0.004P_v & 0.2 < \text{NDVI} < 0.5 \\ 0.99 & \text{NDVI} > 0.5 \end{cases}$$

The pixels values were distributed under this procedure into three different categories according to the NDVI values. In the case of  $\text{NDVI} < 0.2$ , the pixel is measured as bare land and the surface emissivity is acquired from the values of reflectivity. On the other hand, in case of  $\text{NDVI} > 0.5$ , NDVI pixel values higher than 0.5 are reflected as abundant vegetation cover, and then a constant value for the emissivity is supposed typically of 0.99 is consigned to them. If the Normalized Difference Vegetation Index is from 0.2 to

0.5 in pixels values, the  $P_v$  (Proportional Vegetation) is measured by utilizing the given equation 5.

$$P_v = [(\text{NDVI} - \text{NDVI}_{\text{min}}) / (\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}})]^2 \dots\dots 5$$

Where  $P_v$  is the proportion of vegetation (Carlson and Ripley 1997). Finally, the surface emissive ( $\epsilon$ ) was obtained from equation 6 by using the  $P_v$  values of equation 5.

$$\text{LSE} (\epsilon) = 0.004 \times P_v + 0.986 \dots\dots\dots 6$$

**1.1.1. Retrieval of Land Surface Temperature**

If the surface emissive values are recognized, LST can be estimated by utilizing the given equation 7.

$$\text{LST} = (T_B / 1 + \lambda * (T_B / \rho) * \ln(\epsilon)) \dots\dots\dots 7$$

Where

- $T_B$  = brightness surface temperature
- $\lambda$  = 11.5  $\mu\text{m}$  (Wavelength of emitted radiance)
- $\rho$  = 14380
- $\epsilon$  = Land surface emissivity

**Results and Discussion**

**Spatial Variation of NDVI**

Spatial patterns of NDVI are not only subject to the impact of vegetation amount but also to solar radiation availability, topography, slope, and other factors. NDVI is generally utilized as an indicator of land surface greenness (LSG) based on the assumption that NDVI value is positively proportional to the amount of surface vegetation in an image pixel area (Olaide et al., 2013). This was proved by Fig. 3 which shows the variation of NDVI over Lahore, the NDVI values for the vegetated areas were positive values, on the other hand, other features namely, built-up, bare and open area and water bodies had negative values. To observe the spatial distribution of the vegetation cover, NDVI map was produced for the study area and a classification assigned to denote the distribution. In this study NDVI was considered to provide estimates of the abundance of actively photosynthesizing vegetation. Large NDVI values denoted large fractions of vegetation cover per pixel. The NDVI map revealed that the NDVI value ranged between -0.14 to 0.58. The eastern, southern and south-western parts of Lahore had the highest positive NDVI values, whereas area under water bodies, built-up and open land had negative NDVI values.

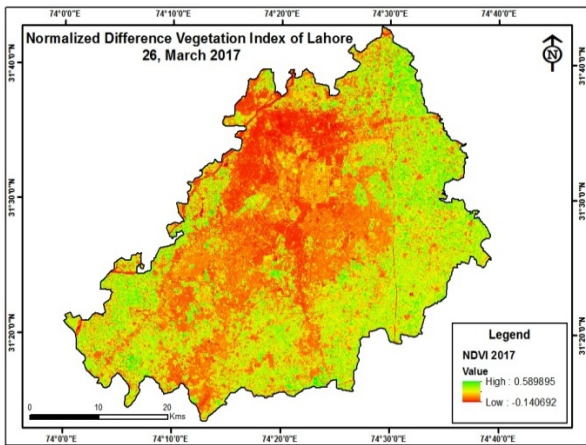


Fig. 3 Spatial distribution of NDVI of Lahore.

### Spatial Variation of LSE

To examine the spatial variation of LST and accurate temperature estimation in Lahore, it is required to measure the LSE. Land surface emissivity is a significant parameter in the appraisal of the LST Model. Land surface emissivity (Fig. 5) was produced using the NDVI threshold method. The LSE of Lahore ranged between 0.98 to 0.99. Eastern and south-western parts of Lahore had a more vegetative cover, and thus, LSE was high in these regions. Whereas, low LSE was observed in northern, southern and central parts of Lahore. Figure 4 shows the Land Surface Emissivity range for the different land use over Lahore. While, Figure 5 shows the extent of LSE for different features. The result reflects that vegetation over Lahore has the highest emissivity value (0.996), closely followed by built-up area, open land and water bodies with 0.991, 0.990 and 0.989 respectively. The high surface emissivity values noted for vegetation cover over Lahore can be recognized to the fact that fully vegetated areas are estimated black bodies.

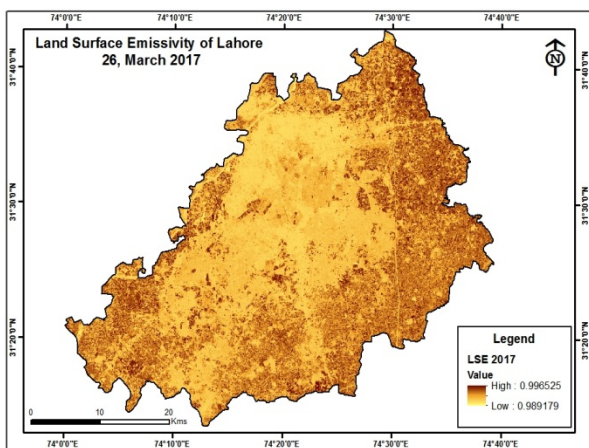


Fig. 4 Spatial variation of LSE of Lahore.

### Spatial Distribution of LST

The spatial variation of LST is one of the most important parameters in climate change studies. Figure 5 displays the spatial patterns of LST of Lahore and

some hotspots of surface temperature were observed. A Land Surface Temperature map has been derived utilizing LSE (Fig. 4), emissivity and surface brightness temperature difference between LSE of band 10 and 11 of Landsat TIR. The LST map revealed that temperature varied from 22°C to 39°C. From the visual interpretation of the LST map (Fig. 5). It is clear that an area covered by vegetation comprises the lowest surface temperature value. In comparison, built-up area and open land have the highest surface temperatures. The lower surface temperature was observed in an area covered by green vegetation since the amount and nature of vegetation governs the surface temperature through latent heat flux from the land to atmosphere via the process of evapotranspiration. The relationship between LST and NDVI has been presented to be valuable for urban climate change studies. The present study used NDVI to recognize the correlation between the LST and vegetation cover. The spatial-temporal distribution of vegetation and the NDVI can best be described from the Figure 3. High green vegetation areas have the highest values of NDVI as compared to urban built-up area. Open land and water bodies had the lowest values of NDVI.

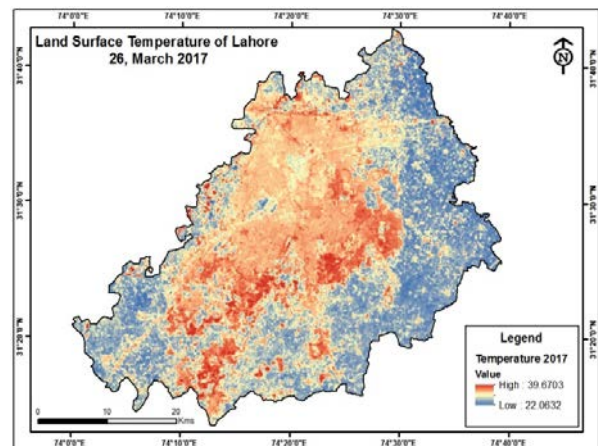


Fig. 5 Spatial distribution of LST of Lahore.

In order to observe the spatial variation of urban surface temperature in Lahore thermal signatures of different land use were studied. The present study revealed highest and lowest values of surface temperature for each of these land use type (Fig. 5). The LST map clearly shows that a gradual temperature change from the urban area (39°C) out into the peripheral area (22°C) (Fig. 5). This indicates that the urban area is mainly dominated by impervious surfaces such as metals, concrete, and asphalt, which are non-transpiring and non-evaporating. Impervious surfaces which display a high potential for absorption and radiation of heat alike with black bodies are found the highest land surface temperature. High rate of conversion of land from agricultural to built-up area, emission of plumes from industrial activities and motor vehicles, high rate of energy consumption, air-conditioning system and emission of GHGs are the major factors responsible for the higher temperature in

urban areas. From Figure 5 that the heat island and higher surface temperature are not generally found in the downtown of the city. Yet in some cases, it is found in the peripheries of the city. This was due to the urbanization and developing sites that are constantly created in the periphery areas. The new developing sites, housing colonies and industrial areas in the outskirts of the city demolished the natural vegetation cover and increased surface temperature.

## Conclusion

Present study conducted that the RS technique which is used to investigate variation in temperature in the city of Lahore. The estimation of LST distribution with the help of Landsat-8, OLI and TIRS', sensor bands are free of cost as provided by USGS. Landsat 8-TIRS bands (10 and 11) are considered to be the most efficient thermal infrared sensors along with high spatial resolutions. The information acquired is enough for getting thermal infrared spectral bands of 10.90 and 12.0um. LST measurement can provide better information on the basis of the Radiative Transfer Method. In this paper, the calculation of LST from TIRS is acquired from the Radiative Transfer Method. Results show that the land surface temperature estimated from the Radiative Transfer Method through band 10 has the highest accuracy. The radiation of heat energy on the surface of the earth determines the factors including vegetation cover, land use type and soil in the area under study, revealed variation in temperature according to different land surface patterns. The surface heat along with water exchange with the atmosphere is controlled by the variations in surface temperature ultimately exercising changes in the climatic patterns in the region. The major role resulting in the temperature variation can be attributed to land conversion due to rapid urban expansion, combustion from domestic kitchens, generators and an ever-increasing number of automobiles emitting carbon. Other prominent factors include removal of agricultural land replaced by residential colonies, industrial and commercial areas, whereas a minor role is played by climatic phenomena in temperature variation. Remote Sensing data and technology such as Landsat-8, proved to be significant in estimating urban temperature. The analysis helps us in estimating microclimatic change, the maximum temperature in vulnerable areas and heat pockets in Lahore. It also helps us in making decisions like the restoration of forests, checking of vehicles to reduce pollution and reducing plastic incineration to reduce temperature increase. Owing to the deficiency in synchronous ground measured land surface temperature during transit time of the Landsat satellite measurement, accurate estimation of the surface temperature change cannot be made. Present study is an initial attempt from the perception of quantitative presentation using Landsat-8 thermal data. Furthermore, investigation and studies are needed to acquire an efficient application of Landsat-8's thermal infrared data to inquire about urban heat islands and their impact on human health.

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