

LAND SURFACE TEMPERATURE EXTRACTION USING LANDSAT DATA OVER DEHRADUN, INDIA: ASSESSMENT OF VARIOUS RETRIEVAL ALGORITHMS AND EMISSIVITY MODELS

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Abstract

Land Surface Temperature (LST) is an important parameter with widespread ecological implications due to its substantial influence on the dynamic interactions between the Earth's surface and its atmosphere. LST retrieval is helpful for the evaluation of urban environments; to identify the Urban Hot Spots (UHS) within a city and suggest mitigating plans to counteract the over-heating of urban areas. This study focuses on the extraction of LST data over Dehradun during the month of May (summer) for the years 1993, 2003, 2013, and 2023. The primary objective of this study is to calculate LST using satellite data using different LST retrieval models. LST retrieval methods: Radiative Transfer Equation (RTE), Mono Window Algorithm (MWA), and Single Channel Algorithm (SCA) were used and compared. To ensure validation of the estimated LST values, a comparison was conducted with weather station-based temperature measurements obtained from the Indian Meteorological Department (IMD). The results suggest that the land surface emissivity method to calculate LST, as proposed by Sobrino *et al.* (2008), provides the best performance among all LST methods. Although the approach proposed by Sobrino *et al.*'s (2008) LSE model achieved satisfying performance, MWA exhibited a marginally superior level of accuracy (0.052°C RMSE).

Keywords: Landsat; land surface emissivity; land surface temperature; mono window algorithm; radiative transfer equation; single channel algorithm

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Introduction

Climate change will most likely generate an abrupt increase in air temperatures as well as earth's skin temperature, thus demanding accurate analysis of Land Surface Temperature (LST). LST is one of the key indicators used to study climatic change trends. LST allows analysis of longwave radiation as well as heat fluxes between the earth and its atmosphere, allowing analysis of warming trends on the earth's surface and finding suitable urban planning solutions so as to mitigate associated effects (Almeida *et al.*, 2021). LST can further be used to retrieve related climate variables associated with the local micro climate, thermal discomfort and influences on public comfort.

Thermal remote sensing plays a prominent role in capturing radiation emitted from the Earth's surface, particularly for estimating LST. LST is defined as the earth's surface temperature obtained using infrared radiation measured using remote sensing data (Momo and Devi, 2022). LST represents the temperature of the top few millimeters (mm) of the Earth's surface, thus influencing several biophysical processes, including photosynthesis, plant respiration, as well as evapotranspiration (Kumar *et al.*, 2017). It is an important parameter affecting surface energy balance. Due to this, LST plays an important role in determining global and regional climate trends, which includes information about drought conditions and the vegetation water requirements (Jackson *et al.*, 1977; Mannstein, 1987; Feldhake *et al.*, 1996; Jaafar *et al.*, 2020; Momo and Devi, 2022). Urban hot spots (UHS) are the areas representing high heat stress because of various anthropogenic activities. Over the last decade, UHS derived with the help of LST has extensively been used for managing urban environments. Except for UHS, several other thermal comfort parameters, including urban thermal field variance index, temperature-humidity index as well as physiological equivalent temperature, have also been derived using LST. All these parameters can be used to study urban environments (Guha *et al.*, 2017).

Several researchers proposed different methodologies to determine LST using remote sensing data. Out of various methods proposed to determine LST, Single Channel Algorithm (SCA), Split Window Algorithm (SWA) Radiative Transfer Equation (RTE) and Mono Window Algorithm (MWA), which use thermal bands of Landsat images (Sekertekin and Bonafoni, 2020) have been extensively used. Mono-window methods use a single Landsat thermal infrared waveband whereas multiple thermal wavebands are utilised by split-

window or multi-channel method. Due to the availability of single thermal band, only single channel methods can be used for LST calculation using Landsat 5 and 7. On the other hand, availability of two thermal wavebands in Landsat 8, allows using SWA with Landsat 8. SWA methods can provide accurate land surface data (Salakkham and Piyatadsananon, 2023). In general, three methods are employed to determine LST values from satellite data: (1) the Temperature-based method (T-based), (2) the Radiance-based method (R-based), and (3) Cross-validation method (Li *et al.*, 2013). The T-based methods have been extensively used by various researchers and also considered in this study. This approach includes comparing satellite-based LST values with those obtained by ground-based measurements acquired at the time of acquiring satellite images. The advantage of the T-based method lies in the fact that they are able to assess the radiometric quality of the sensor and the efficacy of LST retrieval techniques concerning atmospheric and emissivity parameters (Sekertekin and Bonafoni, 2020).

The study by Sekertekin and Bonafoni (2020) compared several methods of LST determination using Landsat 5, 7 and 8 images over a rural area. They suggested that out of various methods used for the comparison of LST determination, the method proposed by Sobrino *et al.* (2008) is found to perform best in terms of root mean square error (RMSE) using Landsat 5 and Landsat 7/8 data. In several other reported works, researchers have examined and validated various LST retrieval methods with Landsat data as well as in-situ LST measurements but found using only one LSE model for validation. In a study over India, Majumder *et al.* (2021) used Plank equation as well as MWA, SCA, and RTE methods with Landsat satellite data and validated results with those obtained using Moderate Resolution Imaging Spectroradiometer (MODIS) LST product. Another study by Momo and Devi (2022) obtained LST using images acquired at ten-year intervals and all three methods including MWA, RTE and SCA. They also compared the calculated LST values with MODIS and ground station data. Yu *et al.* (2014) used Landsat 8 data and developed NDVI-based LSE model to compare the RTE, SWA, and SCA approaches. Zhang *et al.* (2016) utilised the SCA approach and the LSE model developed by Sobrino *et al.* (2008) for LST extraction from Landsat 8 data.

Keeping in view the importance of LST for the urban environment, this study was carried out to evaluate the performance of different LST retrieval

algorithms and determine the most accurate method over the study area. For this study, Dehradun (Uttarakhand, India) was selected for day-time LST calculation using different methods. For this, Landsat images of different years (1993, 2003, 2013, and 2023) were downloaded from the USGS website for the month of May (summer). Ground temperature data collected from Indian Meteorological Department (IMD, 2023) were used to compare calculated LST values using different methods. Since the reliability of LST determination is based on LSE, the effect of various Normalized Difference Vegetation Index (NDVI) based LSE models was also compared in this study. In most of the earlier studies only one LSE model was taken into consideration in the validation of Landsat derived LST information using in-situ measurements. However, the validation of Landsat data using different LSE models still remains inadequately reported. Hence, along with various LST retrieval methods, this study aims to compare different LSE models using Landsat 5, 7, and 8 data. For researchers in other non-specialized domains, choosing the right algorithm for LST retrieval might be challenging due to the variety of retrieval techniques and the factors that go along with them. The findings of this study will provide a useful reference for the selection of LST retrieval algorithms for different periods.

The outcomes of this research would also be beneficial in determining the spatial and temporal patterns of LST for the period of 30 years over the study area. This research is unique in its examination of the pattern of LST variability using different algorithms in the area of a small yet rapidly urbanising city, Dehradun, where no such study has been reported yet. This study also provides information about the urban thermal environment of the city by identifying the most appropriate method to retrieve the LST.

Study Area

For this study, area lying with in Dehradun municipality, covering an area of about 60 Km² was used (Figure 1). Dehradun is the capital city of Uttarakhand (India) and located at an elevation of 674 m above mean sea level in the foothills of

Himalya. Its latitudinal and longitudinal extents lies within 30.26°N to 30.403°N and 77.985°E to 78.103°E respectively (Mishra and Garg, 2023). The region experiences humid sub-tropical climate with the average yearly temperatures range varying from 28°C to 15°C (IMD, 2023). Monsoon season in the study area starts from late June upto mid-August, bringing heavy to moderate rainfall with an annual average precipitation of about 1,800 mm (Dutta *et al.*, 2015). Dehradun, being an ecologically fragile region serves as an ideal location for investigating LST dynamics. Therefore, an evaluation of its timely temperature dynamics is needed to suggest mitigating plans to counteract the effect of urban heat islands in some areas.

Materials and Methods

Landsat 5, 7, and 8 images covering a period of 30 years over the study area were acquired (Table 1). Downloaded datasets were then corrected for atmospheric and radiometric errors. ArcGIS software was used for all image processing and LST estimation using different datasets acquired over the study area. For LST calculation using Landsat data, various methods as implemented by Sekertekin and Bonafoni (2020) in ArcGIS were used.

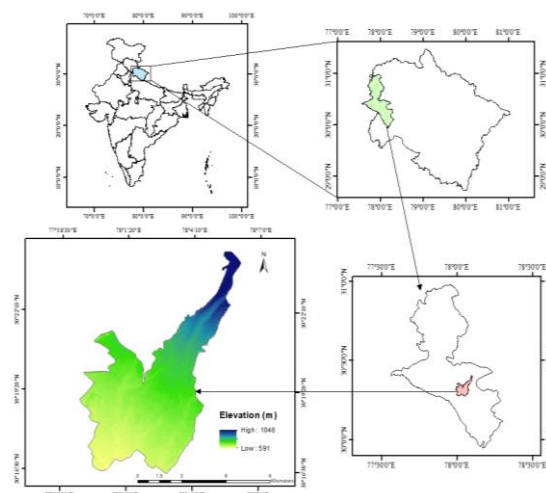


Figure 1. Location of the study area

Table 1. Description of satellite data

S. No.	Satellite	Image acquisition date	Path / row	Resolution (m)
1	Landsat 5 TM	1993-05-06	146 / 39	30
2	Landsat 7 ETM+	2003-05-10	146 / 39	30
3	Landsat 8 OLI/TIRS	2013-05-13	146 / 39	30
4	Landsat 8 OLI/TIRS	2023-05-09	146 / 39	30

Data Used

Landsat products, which were used to calculate LST, were downloaded from the United States Geological Survey's Earth Explorer website (USGS, 2023). For LST calculation, only thermal bands of Landsat data were used. For proper comparison of results, Landsat imagery acquired in the same month of each year (May, summer season) for the years 1993, 2003, 2013, and 2023 were downloaded for analysis. The date of the downloaded data in the same month was decided based on the availability of cloud free images and availability of station-based temperature data (Table 1).

Landsat 5 and 7 acquire images in six wavebands, covering visible, near infrared, and short infrared regions of electromagnetic spectrum at spatial resolution of 30 m. Additionally, they acquire one image in Thermal Infrared (TIR) band (i.e. Band 6). The spatial resolution of thermal band of Landsat 5 and 7 are 120 m and 60 m respectively. In order to use these bands with other 30 m bands, USGS provides a resampled 30 m resolution images with both sensors. On the other hand, Landsat 8 uses Operational Land Imager (OLI) sensor having nine wavebands at a 30 m spatial resolution as well as carries two sensors for the thermal infrared imaging thus generating two bands in this region. These bands are designated as Bands 10 and 11. Both of these thermal wavebands are acquired at a spatial resolution of 100 m but are resampled to 30 m for final use. Temperature data were also obtained from the Indian Meteorological Department (IMD, 2023). The shape-files of India, Uttarakhand, Dehradun district and municipal region were taken from the Onlinemaps Portal provided by Survey of India (SOI, 2023).

LST Calculation using Landsat-5, 7, and 8

Thermal sensors in various Landsat satellites are designed to detect radiant energy emitted by different objects on earth surface. The operating range of these sensor include 3-5 μm and 8-14 μm , with the latter being more common for earth observation due to atmospheric considerations. For Land Surface Temperature (LST) calculation, an ArcGIS based toolbox encompassing various methods and models was used for this study (Sekertekin and Bonafoni, 2020). Various steps for LST calculation include: first of all the digital numbers (DN) were corrected to Top-of-Atmosphere (TOA) spectral radiance, followed by determination of brightness temperature. In next step, brightness temperature, which is an important intermediary step for temperature calculation is determined after obtaining TOA radiance using thermal sensors of different Landsat sensors.

Real surface temperature is derived by dividing brightness temperature by emissivity. Emissivity is influenced by surface characteristics and wavelength. In this study, three Normalized Difference Vegetation Index (NDVI)-based emissivity methods were employed to calculate Land Surface Emissivity (LSE). The choice of NDVI-based methods provides a comprehensive approach to considering surface and wavelength variations in emissivity calculations. Once radiance, brightness temperature, and LSE values are obtained, brightness temperature is corrected against LSE and atmospheric parameters. Among the different algorithms available for LST calculation, three algorithms, including MWA, RTE, and SCA, were used in this study (Qin *et al.*, 2001; Sekertekin and Bonafoni, 2020).

In spite of using all three methods for LST calculation, these methods differ in the way they use the atmospheric correction process. On the one hand, MWA uses two atmospheric parameters that include effective mean atmospheric temperature and atmospheric transmittance, as well as LSE, to estimate LST. On the other hand, RTE method uses three atmospheric parameters for all calculations that include upwelling radiance, downwelling radiance, and atmospheric transmittance, as well as radiance of the black body target of kinetic temperature for LST estimation. For calculation of atmospheric transmittance, upwelling radiance, and downwelling radiance, the Atmospheric Correction Parameter Calculator (ACPC, 2023) was used in this study (Barsi *et al.*, 2003; 2005). The three parameters mentioned above can be estimated with the help of this online calculator by entering some specified parameters which include latitude, longitude, time and date. However, for Landsat 5 in the year 1993, due to the unavailability of atmospheric data for dates before 2000 in the ACPC, LST was retrieved using the methodology outlined in the USGS, Landsat 5 (L5) Data Users Handbook. The Land Surface Emissivity (LSE) models and Land Surface Temperature (LST) retrieval algorithms are discussed in detail in further sections.

Land Surface Emissivity (LSE) Models

Land surface emissivity is defined as the ability of surface that transforms heat energy into radiant energy (Qin *et al.*, 2001). LSE (ϵ) is an important parameter for the determination of LST using remotely sensed data. Being easy to implement, NDVI-based methods are the most commonly used LSE retrieval approaches and achieve good results (Van de Griend and Owe, 1993; Sobrino *et al.*, 2008). Keeping this in view, present study considered three distinct Land Surface Emissivity (LSE) models as proposed by Van de

Griend and Owe (1993), Valor and Caselles (1996) and Sobrino *et al.* (2008) for Land Surface Temperature (LST) estimation using Landsat 7 and 8 data.

LSE Model of Van de Griend and Owe (1993)

This model was used across Landsat series, encompassing Landsat 7 ETM+, and 8 OLI/TIRS. Van de Griend and Owe (1993) introduced this approach for Land Surface Emissivity (LSE) retrieval using Normalized Difference Vegetation Index (NDVI) values lying within the range of 0.157 to 0.727. NDVI is calculated using the Near-Infrared (NIR) and Red (R) bands of different Landsat sensors (Sekertekin and Bonafoni 2020). The formulated model for LSE calculation as proposed by this approach is expressed as follows:

$$\varepsilon = 1.0094 + 0.047 \ln(NDVI) \quad (1)$$

LSE Model of Valor and Caselles (1996)

This model was utilized for Land Surface Temperature (LST) retrieval processes across Landsat 7 and 8 data. This model establishes a relation between emissivity and the NDVI of a particular surface. The model is expressed as follows:

$$\varepsilon = \varepsilon_v P_v + \varepsilon_s (1 - P_v) + 4(d\varepsilon) + (1 - P_v) \quad (2)$$

where ε_v and ε_s denote the emissivity of vegetation and soil, respectively. ($d\varepsilon$) is a term representing the cavity effect and depends on the surface geometry (Valor and Caselles, 1996). P_v represents proportion of the vegetation (Carlson and Ripley, 1997):

$$P_v = \left[\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \right]^2 \quad (3)$$

LSE Model of Sobrino *et al.* (2008)

Sobrino *et al.* (2008), Skoković *et al.* (2014), Yu *et al.* (2014) and Li and Jiang (2018) used NDVI threshold values considering the following three cases as shown in Equations (4), (5), and (6) below to estimate LSE:

$$\varepsilon = a_i \rho_R + b_i \quad NDVI < 0.2 \quad (4)$$

$$\varepsilon = \varepsilon_v + \varepsilon_s (1 - P_v) + d\varepsilon \quad 0.2 \leq NDVI \leq 0.5 \quad (5)$$

$$\varepsilon = \varepsilon_v + d\varepsilon \quad NDVI > 0.5 \quad (6)$$

In the above equations: $d\varepsilon = (1 - \varepsilon_s)(1 - P_v) F_{\varepsilon_v} \rightarrow a_i$ and b_i are estimated from an empirical relationship depending on the red band reflectance and emissivity values. ε_v and ε_s are the soil and vegetation emissivity, respectively. $d\varepsilon$ is the cavity effect due to surface roughness. F is a geometrical shape factor assumed as the mean value of 0.55. Final version of the LSE model, as proposed by Sobrino *et al.* (2008) and Skoković *et al.* (2014) was used to obtain the LSE value in this study.

LST Retrieval Methods

For the determination of LST over the study area, three methods: (1) The Mono-window algorithm (MWA), (2) Radiative Transfer Equation (RTE), and (3) Single-channel algorithm (SCA) are used.

Mono-Window Algorithm (MWA)

The Mono Window Algorithm used three parameters, i.e., emissivity, atmospheric transmittance, and effective mean atmospheric temperature with Landsat TM data (Qin *et al.*, 2001). To determine LST values using the MWA algorithm following equation is used:

$$T_s = \frac{a(1 - C - D) + (b(1 - C - D) + C + D)T_b - DT_a}{C} \quad (7)$$

where, $C = \varepsilon * \tau$; $D = (1 - \tau) [1 + (1 - \varepsilon) \tau]$ and ε represents LSE, τ atmospheric transmittance; T_s LST (°K). a and b are constants whose values during summer are $a = -67.355351$ and $b = 0.458606$. T_b and T_a represent at-sensor brightness temperature and effective mean atmospheric temperature respectively. T_o represents near-surface air temperature (°K) and obtained from the weather website (NASA, 2023). As T_o and T_a are linearly related under different conditions, the effective mean atmospheric temperature at mid-latitude regions in summer can be calculated by $T_a = 16.011 + 0.9262 * T_o$. Detailed description of the values of the T_o , T_a and τ parameters adopted in this work are provided in Table 2.

Table 2. Values of atmospheric parameters

Date_Acquired	Time (GMT)	τ	L^+	L_-	T_o (°K)	T_a (°K)
2003-05-10	05:07	0.87	1.00	1.72	297.39	291.45
2013-05-13	05:20	0.80	1.70	2.84	295.16	289.38
2013-05-09	05:17	0.87	1.08	1.85	292.34	286.77

Radiative Transfer Equation

The Radiative Transfer Equation (RTE) works by subtracting the atmospheric influence on surface radiation from the total observed thermal radiation by satellite sensors. The equation is derived by inverting Planck's law and represented as follows:

$$T_s = \frac{K_2}{\ln[1 + K_1/B(T_s)]} \quad (8)$$

In the formula, $B(T_s)$ represents radiation brightness received by the sensor for a blackbody with temperature T_s and defined by equation $[L_\lambda - L^+ - \tau(1 - \varepsilon)L_-]/\tau\varepsilon$ where L_λ is the spectral radiance received by the sensor ($\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$). L^+ and L_- are defined as upwelling and downwelling radiance in the atmosphere, τ represents average atmospheric transmittance in the thermal infrared band. The atmospheric parameters τ , L^+ and L_- used in this study are reported in Table 2. These values are computed using online atmospheric correction parameter calculator (ACPC, 2023). K_1 and K_2 and are the constant coefficients that can be obtained from the Landsat MTL file.

Single-Channel Algorithm

The Single-Channel Algorithm (SCA; Sobrino *et al.* 2008)) is a widely used approach to determine LST using Landsat data. Its usefulness comes from the facts that it requires only few real-time atmospheric parameters except LSE and atmospheric water vapor contents. It is calculated using following equation:

$$T_s = \gamma \frac{1}{\varepsilon} (\psi_1 L_{sen} + \psi_2) + \psi_3 + \delta \quad (9)$$

where, T_s represent the LST ($^{\circ}\text{K}$), ε is LSE; L^+ and L_- represent upwelling and downwelling atmospheric radiance, ψ_1 , ψ_2 , ψ_3 are called as atmospheric function parameters ($\psi_1 = 1/\tau$; $\psi_2 = -L_- - L^+/\tau$; $\psi_3 = L_-$). Finally, τ is the atmospheric transmittance with γ and δ are the intermediate parameters for LST calculation ($\gamma \approx T_2 / b_\gamma L_{sen}$; $\delta \approx T_{sen} - T_2 / b_\gamma$). L_{sen} is referred as at-sensor radiance ($\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$) which can be determined through radiometric calibration. The value of b_γ for band 10 is considered as 1,324 $^{\circ}\text{K}$. The parameters τ , L^+ and L_- used for calculation of ψ_1 , ψ_2 , and ψ_3 in this study is provided in Table 2.

Results and Discussion

LST derived for the Years 1993, 2003, 2013 and 2023

Maximum, minimum and mean values of satellite derived LST and air temperature ($^{\circ}\text{C}$) values, collected from weather station of Indian Meteorological Department at Dehradun-Karanpur, are compared. The weather station is located at an elevation of 620 m at 30 $^{\circ}$ 19' N latitude 78 $^{\circ}$ 2' E longitude. The LST values obtained using different LST retrieval methods in this study are provided in Tables 3 and 4. Figure 2 shows the comparison



Figure 2. Comparison of LST determined using satellite data of the years - (a) 2003, (b) 2013 and (c) 2023 respectively with weather station data by using different LSE models

Table 3. Maximum, minimum and mean values of satellite derived LST and weather station-based air temperature ($^{\circ}\text{C}$) for the year 1993

Year	Generated data ($^{\circ}\text{C}$)			Station-based data ($^{\circ}\text{C}$)		
	Max LST	Min LST	Mean LST	Max LST	Min LST	Mean LST
1993	38.00	27.10	32.16	39.40	22.10	31.56

between the derived LST results and Weather station data.

Validation of Retrieved LST

A comparison of results from Table 4 indicates a positive correlation between LST and air temperature, especially during summer nights, but their cool and hot spots may not always overlap in space (Cao *et al.*, 2021). The pronounced sensitivity of LST to spatio-temporal variations often pose à challenge in assessing the accuracy and validation of satellite derived data (Jiang and Lin, 2021). In this study, the temperature-based (T-based) validation method was employed to validate the retrieval results and evaluate the accuracy of the three algorithms.

Given that actual spatial resolution of Landsat thermal channels ranges from 60 to 120 m, even after resampling at 30 m by USGS, the effective diameter of the field-of-view of the weather station aligns roughly well with the Landsat pixel size. Thus, the Landsat image pixel that covers the IMD weather station was selected for the comparison test. This approach is consistent with many LST studies reported in the literature.

The comparison between Satellite-based LST and Weather station-based temperature utilized the

Root Mean Square Error (RMSE) and average *bias* as statistical criteria, as followed in the next section. The formulas for these two matrices are as follows:

$$RMSE = \sqrt{\frac{T_{SAT}-T_{IMD}}{n}} \quad (10)$$

$$bias = \sqrt{\frac{\sum(T_{SAT}-T_{IMD})}{n}} \quad (11)$$

where *n* represents a number of pixels and T_{SAT} and T_{IMD} represent satellite-based and Weather station-based LST, respectively. The *RMSE* and *bias* serve as a widely adopted statistical metric for assessing the effectiveness of models.

Comparison of Different LST Retrieval Methods and LSE Models

To facilitate a comprehensive comparison of LST retrieval methods, all four images used in this study (Landsat 5, 7, and 8) were employed, with one image corresponding to each year under consideration. The MWA, RTE, and SCA methods were used with Landsat 7 and 8 satellite data. The results highlight the impact of different LSE models on the accuracy of the LST retrieval methods.

Table 4. Maximum, minimum and mean values of satellite derived LST and weather station-based air temperature (°C) for the years 2003, 2013 and 2023

Year	Emissivity method	LST Retrieval method	Generated data (°C)			Station-based data (°C)		
			Max LST	Min LST	Mean LST	Max LST	Min LST	Mean LST
2003	[a]	[1]	45.57	22.46	29.85	34.78	17.28	26.83
		[2]	43.00	22.99	30.06			
		[3]	44.85	23.05	30.26			
	[b]	[1]	35.41	23.69	28.72			
		[2]	35.64	24.10	29.06			
		[3]	35.82	24.20	29.19			
	[c]	[1]	34.24	21.82	27.19			
		[2]	34.76	22.42	27.75			
		[3]	34.72	22.46	27.76			
2013	[a]	[1]	49.99	27.78	39.37	33.44	16.28	25.44
		[2]	48.98	26.94	37.74			
		[3]	47.47	26.99	37.98			
	[b]	[1]	45.50	27.42	37.97			
		[2]	43.79	26.58	36.63			
		[3]	46.95	26.62	36.80			
	[c]	[1]	43.17	25.44	34.81			
		[2]	44.67	26.60	35.71			
		[3]	44.91	26.64	35.83			
2023	[a]	[1]	47.02	27.31	38.02	33.61	19.00	25.22
		[2]	47.50	27.35	38.22			
		[3]	48.86	28.65	37.91			
	[b]	[1]	45.35	27.92	36.80			
		[2]	46.90	27.96	36.94			
		[3]	42.71	26.93	34.69			
	[c]	[1]	43.55	27.22	35.78			
		[2]	43.70	27.25	35.87			
		[3]	47.02	27.31	38.02			

Results for the year 1993

Validation results for Landsat 5 TM data for Satellite-based LST and Weather station-based temperature revealed that the LST retrieved using standard procedure had an *RMSE* value of 2.638°C. The average *bias* (satellite LST-station temperature) is 1.638°C. Moreover, the Mean Absolute error (MAE) is equal to 2.638°C.

Results for the year 2003

Table 5 provides results using different LST retrieval methods in terms of *RMSE* values using Landsat 7 data. Results indicate the best performance by Sobrino *et al.*'s (2008) model with all three LST retrieval methods. Valor and Caselles (1996) and Van de Griend and Owe (1993) models are found to achieve inferior performance than Sobrino *et al.*'s (2008). Results in terms of *RMSE* and *bias* values also suggest better performance by the MWA method than RTE and SCA for the area used in this study.

Results for the year 2013

Table 6 provides results in terms of *RMSE* values using Landsat 8 OLI/TIRS data. Results again indicate better performance by Sobrino *et al.*'s (2008) model, in comparison to both Valor and Caselles' (1996) and Van De Griend and Owe's (1993) models. Although all LST retrieval approaches utilizing Sobrino *et al.*'s (2008) LSE model perform well with Landsat 8 OLI/TIRS data, results suggest improved performance by RTE approach (values of *RMSE* and *bias* equal to 0.932°C and 0.574°C respectively).

Results for the year 2023

Table 7 provides results by different LST methods using Landsat 8 OLI/TIRS data. Similar to Landsat 7 and 5 data, Sobrino *et al.* (2008) model is found to outperformed other two models with Landsat 8 data also. Results (*RMSE* value of 0.885°C and *bias* value of 0.559°C) also suggest the improved performance of RTE approach by Sobrino *et al.*'s (2008) LSE model in comparison to MWA and SCA.

Comparison of method-based LST with station-based temperature

The results in terms of *RMSE* indicate better performance by Sobrino *et al.*'s (2008) model, in comparison to Valor and Caselles' (1996) and Van De Griend and Owe's (1993) models. The LSE model developed by Sobrino *et al.* (2008) considers various landcover classes (such as bare soil, vegetation, etc.) while calculating the emissivity values from the NDVI. It takes into account the impact of interior reflections and the geometric

Table 5. Results of different LST retrieval methods for the year 2003 using all three LSE models (The optimal result is highlighted in bold)

Methods	LST Retrieval method	<i>RMSE</i> (°C)	<i>Bias</i> (°C)
[a]	[1]	1.224	0.639
	[2]	1.345	0.690
	[3]	1.426	0.710
[b]	[1]	0.657	0.482
	[2]	0.778	0.524
	[3]	0.778	0.524
[c]	[1]	0.052	0.136
	[2]	0.237	0.289
	[3]	0.261	0.304

Table 6. Results for LST retrieval methods for the year 2013 using all three LSE models (The optimal result is highlighted in bold)

Methods	LST Retrieval method	<i>RMSE</i> (°C)	<i>Bias</i> (°C)
[a]	[1]	3.091	1.015
	[2]	2.427	0.926
	[3]	2.577	0.955
[b]	[1]	1.478	0.723
	[2]	1.023	0.602
	[3]	1.078	0.617
[c]	[1]	1.363	0.694
	[2]	0.932	0.574
	[3]	0.982	0.589

Table 7. Results for LST retrieval methods for the year 2023 using all three LSE models (The optimal result is highlighted in bold)

Methods	LST Retrieval method	<i>RMSE</i> (°C)	<i>Bias</i> (°C)
[a]	[1]	2.261	0.868
	[2]	1.849	0.809
	[3]	1.940	0.828
[b]	[1]	1.578	0.747
	[2]	1.167	0.642
	[3]	1.219	0.656
[c]	[1]	1.242	0.663
	[2]	0.885	0.559
	[3]	0.923	0.571

distribution of natural surfaces. The model also considers the proportion of vegetation as well as the emissivities of the soil and vegetation, making it relevant to locations with multiple types of soil and vegetation as well as where the vegetation cover varies. Its superior performance over the other two approaches may be attributed to these characteristics.

A comparison of the plots (Figure 3) indicates that in spite of all methods overestimating LST, the MWA values are on the higher side. The average

bias (satellite LST-station temperature) for MWA, RTE, and SCA is 0.663°C, 0.624°C, and 0.639°C, respectively. Moreover, the Mean absolute errors (MAE) are 3.609°C, 3.555°C and 3.713°C for MWA, RTE, and SCA, respectively. The *bias* and MAE values are minimum for RTE. The results, especially the *bias* value, can be attributed to the input parameter accuracy as reported earlier. RTE and SCA use the same input parameters, whereas MWA uses T_a instead of L^+ and L_- . Annotations a, b, and c in Figure 3 referred to the by Van de Griend and Owe (1993), Valor and Caselles (1996) and Sobrino *et al.*'s (2008) LSE models.

Analysis of Spatio-Temporal Variations

Results from previous sections indicate best performance for LST calculation is achieved by Sobrino *et al.*'s (2008) LSE model. Keeping this in view, spatio-temporal variation of LST derived using different Sobrino *et al.*'s (2008) LSE model with all Landsat data were obtained (Figure 4). Figure 4 shows the Landsat LST image over the Dehradun, acquired in 1993, 2003, 2013, and 2023, respectively, and the spatial variation derived using the best LST retrieval method. Over the span of 30 years, it is evident that there is a real increase

temperature as represented by higher LST values. In the years 1993 and 2023, the higher temperature regions are located in the southern part of the city which may be attributed to presence of barren land. From the year 1993 to 2023, the regions with higher LST values tend to shift towards the central region of the city. This shift can be attributed to urban expansion and subsequent alterations in land cover.

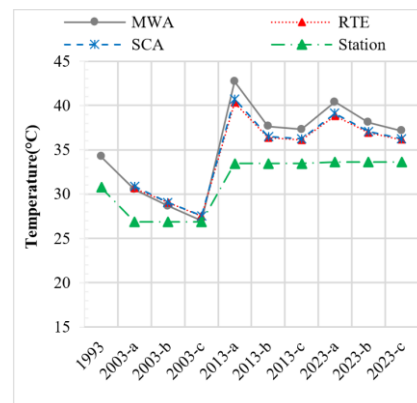


Figure 3. Comparison of LST values of different years derived using all three LSE methods with weather station data

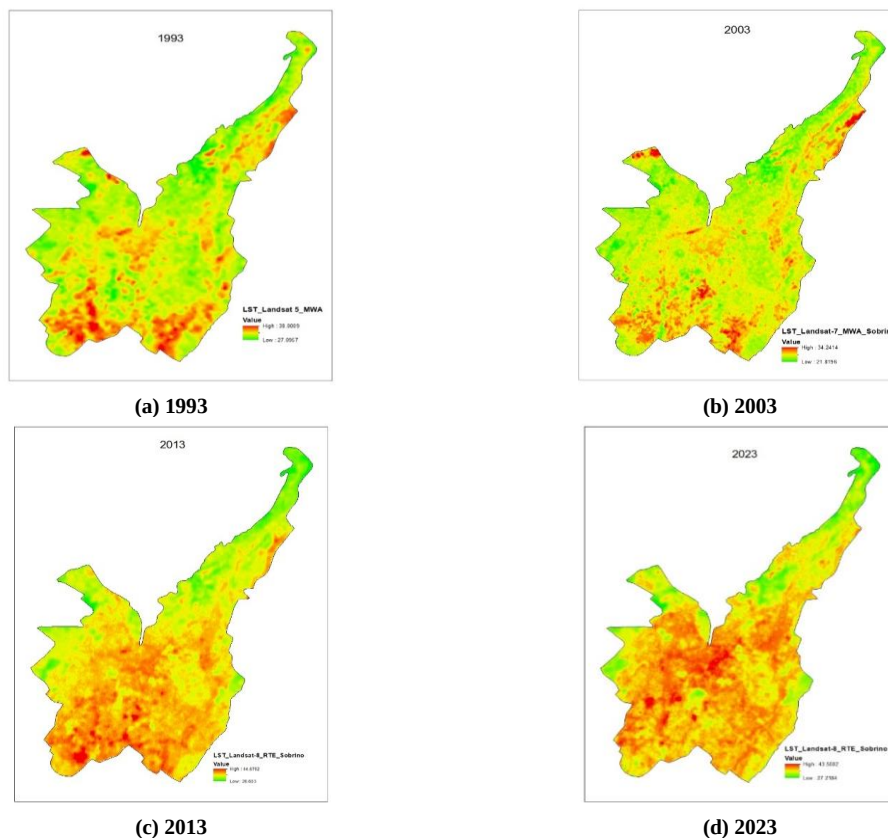


Figure 4. Spatio-temporal variations of LST for the years - (a) 1993, (b) 2003, (c) 2013 and (d) 2023

It can be noted that the high LST zones are generally concentrated in densely built regions (Mishra and Garg, 2023). The city's temperature rises as the densely inhabited structures substantially impede air circulation, have high rate of solar radiation absorption and are not conducive to heat exchange. The regions with lesser LST values indicate presence of vegetation.

A comparison of Figure 4 indicates improved performance by MWA with 2003 data, whereas RTE perform well for 2013 and 2023 data.

The differences in the performance of three algorithms as proposed in Sobrino *et al.*'s (2008) LSE model were compared in Table 8. It can be seen that the overall trends of the surface temperature retrieval result over different periods were relatively similar but with some differences. The two algorithms with the largest difference in average values for the year 2003 were MWA and SCA (difference of 0.59°C between them), followed by 0.52°C between RTE and MWA. The smallest difference of 0.07°C was achieved between SCA and RTE. The maximum difference in average values of 2013 was 1.22°C between RTE and MWA, and only 0.14°C between RTE and SCA. The largest difference between the mean values on 2023 was 1.01°C for RTE and MWA whereas the smallest difference of 0.11°C was between SCA and RTE. Overall, results suggest that LST values obtained by RTE and SCA were the closest to each other. The reason for this comparable performance by both RTE and SCA algorithms may be attributed to the fact of using the same atmospheric parameters. The largest average temperature difference of 0.92°C was observed between MWA and RTE, followed by 0.86°C between MWA and SCA. This may be attributed to the reason for the introduction of average atmospheric temperature MWA while approximating upwelling and downwelling radiation in the atmosphere.

Conclusions

The study primarily, focusses on the retrieval of accurate LST for the region as well as underscores the substantial influence of LSE models on the accuracy of satellite-based LST retrieval methods. The findings from this study indicate that Sobrino *et al.*'s (2008) LSE model performed best among all compared methods used for LST extraction using different Landsat data. Although all LST retrieval methods using Sobrino *et al.*'s (2008) LSE model provided satisfactory and similar results, MWA achieved the highest accuracy. Comparison of LST value with ground temperature measurements with all three algorithms' results generally displays

a similar overall trend, with minor differences. Across all Landsat missions, RTE offered superior accuracy compared to MWA and SCA. Notably, RTE and SCA, utilizing identical atmospheric parameters, yielded results with the least disparity.

Satellite-based LST retrieval still remains a difficult process due to the extreme variability of Earth's surface and the requirement for prior knowledge of various parameters, including the atmosphere, weather, and sensor specifications (spectral responses, signal to noise ratio, spectral resolution, spatial resolution, and viewing angle). Furthermore, no single technique can guarantee correct LST determination from all satellite TIR data, and determining which algorithm is better than another is a challenging task (Li *et al.*, 2013). Error analysis is not included in the LST toolbox that was used for this investigation. Further, to improve the accuracy of the LST retrieval, users should perform accuracy and sensitivity analysis after acquiring LST images. The accuracy of similar works can be improved by using higher-resolution imageries, field observations, observed weather station data, and thermal sensors.

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