Analytical study of relation between Land surface temperature and Land Use/Land Cover using spectral indices: A case study of Chandigarh

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Abstract: Rapid urbanization is the major cause for Land Use and Land Cover changes globally. The urbanization alters the land surface dynamics and affects the surface temperature, which gives rise to urban heat island effect. In the present study, spatial correlation analysis has been done between Land Surface Temperature (LST) and Land Use and Land Cover (LULC) for the city of Chandigarh. The LST is retrieved from Landsat-8 thermal band using Mono-Window algorithm and shows 2.5°C increase of temperature from 2016 to 2022. The LULC has been derived using Maximum Likelihood Classifier (MLC) which shows an increase in built-up of 7.56% and decrease in forest cover by 32%. Spectral indices belonging to major LULC classes have been derived using Sentinel-2 optical bands and spatially correlated with LST using linear regression analysis. The results show a strong positive correlation (r=0.988) between built-up and LST and a negative correlation (r=-0.625) between urban vegetation cover and LST. The mean correlation coefficient for LST-NDVI for vegetation and forest cover, LST-NDWI for water bodies, LST-NDBI for built-up and LST-NBLI for bare land is -0.3, 0.116, 0.51 and 0.392 respectively. The results indicate that vegetation and water bodies mitigate the rise of LST, whereas built-up areas and bare lands sustain in the rise of LST. The statistical analysis will be helpful for policy makers and urban planners for prevention of further degradation of urban environment and surface dynamics.

Keywords: LST, LULC, spectral indices, change detection, correlation, regression, mono-window algorithm

1. Introduction

Chandigarh is a planned city in India with rapidly developing urbanisation. Urbanisation is caused by increase in demographic density in the suburbs of the cities (Nimish et. al, 2018) which causes the built-up regions to spread out. The modifications in the land use change the local climatic conditions like radiative and energy balance (Alexander and Mills 2014). Various studies conducted previously suggests that (Jiang et.al., 2015; Awuh et al. 2018) rapidly changing land use and land cover affects and contributes to increased land surface temperature (LST).
Urban sprawl leads to expansion of LULC, which further affects the air quality of the region, soil degrading (Nimish et al. 2018), which in turn makes the fertile land barren. The urban growth pattern of Chandigarh and its relation to Land surface temperature was studied by (Nimish et al. 2018). A time series analysis for monitoring the urban sprawl of Chandigarh was carried out by (Saini and Tiwari 2019) to see the changes in the land use pattern. (Awuh et al. 2019) established that a strong positive correlation exists between the built-up class and land surface temperature. Cooling effects of water bodies like on land surface temperature was carried out by (Gupta et.al., 2019). (Chang et.al., 2007) studied the effects of urban green spaces and local water bodies form urban cool island (UCI) which helps in mitigating the urban heat Island (UHI). Urban microclimate analysis and its effects on Land surface temperature for Chandigarh was assessed by (Gupta et.al., 2017). The study indicates that the heavy industrial areas exhibit highest LST followed by high-rise compact buildings. (Li et.al, 2017b) evaluated indices like EBBI (Enhanced built-up and Bareness Index), DBI (Dry Built-up index) and DBSI (Dry Bare Soil Index) for differentiating the dry areas and built-up regions. (Pandey and Joshi 2015) tried to model spatial patterns of urban growth by utilising a multi agent system.

Spectral indices provide an efficient alternative to the classical classification algorithms like supervised classification or neural nets to distinguish between different surface cover features (He et al. 2010; Li et al. 2015). (Li et. al., 2017b)] proposed a method to classify LULC using unsupervised classification by employing spectral indices as inputs to the classifier. (Faridatul and Wu 2018) proposed three new indices namely modified normalised difference bare- land index (MNDBI) for differentiating impervious surfaces and bare land, tasseled cap water and vegetation index (TCWVI) for enhanced separation of vegetation and water areas and shadow index (ShDI) to separate water from shadows. (Guha and Govil 2020) observed that normalized difference built-up index (NDBI) and normalized difference bareness index (NDBaI) are mixing the built-up and fallow or bare lands during dry climates, so they proposed new indices, namely the dry built-up index (DBI) and dry bare-soil index (DBSI) to distinguish between built-up areas and bare lands using Landsat-8 satellite imagery.

2. Study Area and Dataset

2.1 Study Area

Chandigarh is a city which is located in Northern India and works as a capital for the states of Punjab and Haryana. Being a planned city, it is located at 30.7333° N and 76.7794° E with an average elevation of 335 m above mean sea level (Nimish et al. 2018; Saini and Tiwari 2019) as shown in Figure 1. According to census of India, 2011, the population of city is 10.55 Lakhs, with a growth rate of 17.19%

2.2 Dataset Used

For correlation analysis of land surface temperature and Land use land cover, the month of May for the years 2016-2022 has been chosen as it represents the peak of summer season in Chandigarh. During this period, the weather is relatively stable with minimal rainfall and cloud cover. The description of datasets utilised in the study has been given below.

(a) Sentinel-2A optical data

Sentinel-2 Level-2A atmospherically corrected data with 10 m spatial resolution for Chandigarh city was used for processing and generating Land Use Land Cover maps. The details of the Sentinel dataset used for the current study are given in Table 1. Since there was unavailability of cloudless optical data for May 2016, the latest available cloudless data acquired on 4th June, 2016 was used for producing LULC map.

Table 1: Optical data acquisition from Sentinel-2

Satellite	Acquisition Date	Tile Number	Cloud cover
Sentinel-2A	04/06/2016	T43RFQ	0.24260
Sentinel-2A	20/05/2018	T43RFQ	0.00400
Sentinel-2A	07/05/2020	T43RFQ	0.02370
Sentinel-2A	14/05/2022	T43RFQ	0.00000

(b) Landsat-8 thermal data

Landsat-8 resampled 30 m spatial resolution thermal data (Band-10) acquired by the TIRS sensor was used for generating Land- surface temperature (LST) maps. The average/mean data for the month of May 2016, May 2018, May 2020 and May 2022 was acquired and downloaded from Google earth Engine (GEE) from the Landsat-8 Data collection.

3. Methodology:

The approach for this study is depicted in figure 2.

3.1 Mono-window algorithm for the retrieval of Land Surface Temperature

For LST retrieval, mono-window algorithm was first proposed by (Qin et. al, 2010). Three major variables are required for this algorithm: emissivity, transmittance, and mean ambient temperature. This algorithm utilizes Band 10 of TIRS sensor of Landsat-8 which records the radiation in the spectral range from 10.60 µm to 11.19 µm.

In order to retrieve LST, first, the DN values are converted into spectral radiance at the sensor aperture, otherwise known as Top of the Atmospheric (TOA) radiance (Equation 1).

$$L_\lambda = \frac{L_{max} - L_{min}}{QCAL_{max} - QCAL_{min}}(D - QCAL_{min}) + L_{min} \quad (1)$$

where L_λ is Top of the Atmospheric radiance at the sensor's aperture in W/ (m^2 sr µm), $QCAL_{max}$ (= 65535) and $QCAL_{min}$ (= 0) for Landsat-8. After calculating the radiance values, the brightness temperature values are obtained by applying the inverse of the Plank function.

$$BT = \frac{K_2}{\ln(\frac{K_1}{L}+1)} - 273.15 \quad (2)$$

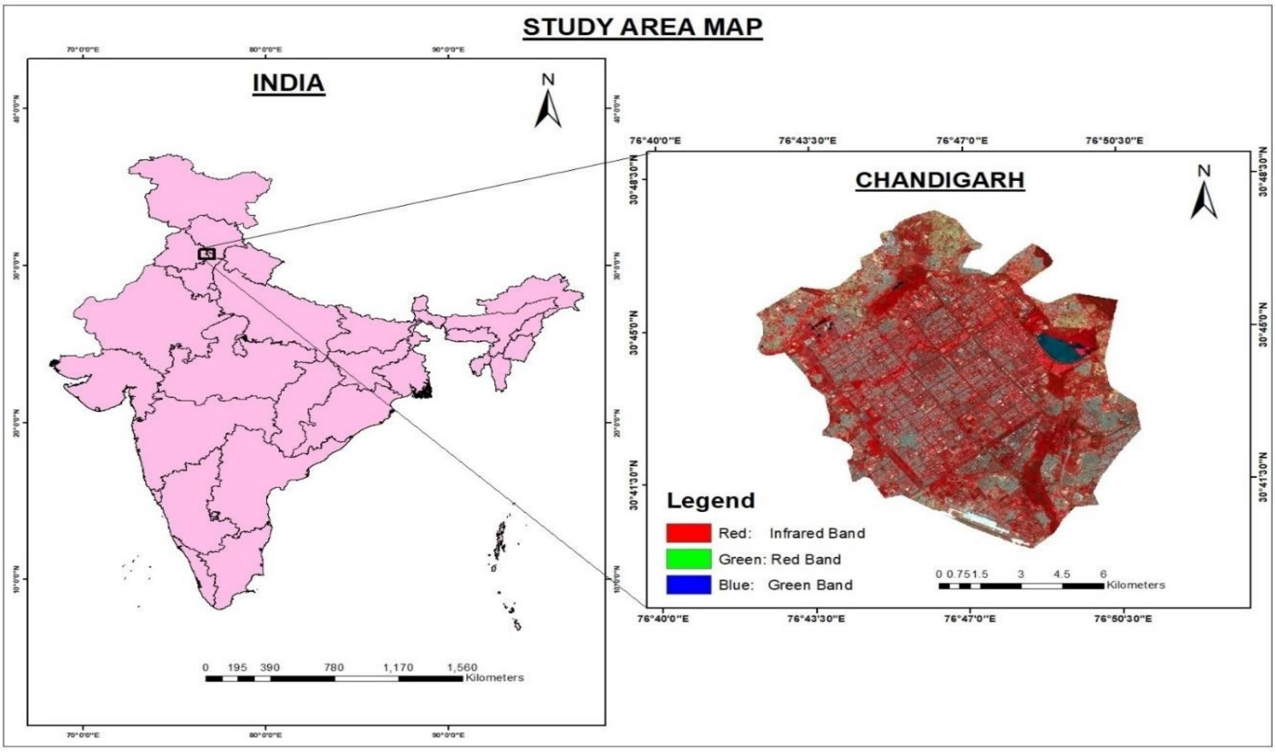

Figure 1. Study area map of Chandigarh represented by FCC (Sentinel-2)

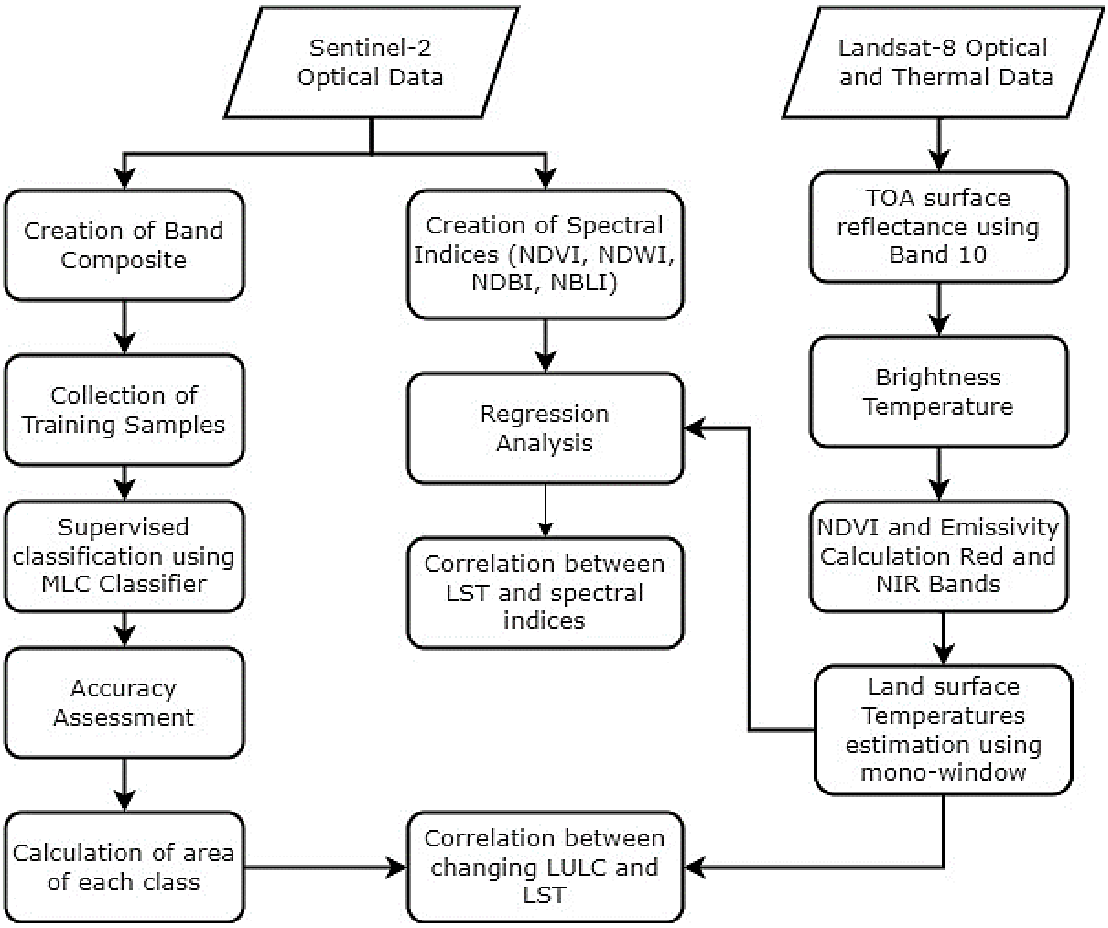

Figure 2. Flowchart depicting the methodology

Where BT is the temperature in Celcius (°C), K_1 is the pre-launch calibration constant in W/(m^2 sr µm) and K_2 is the pre-launch calibration constant in Kelvin. for Landsat 8 ETM+, K_1 = 774.89 W/(m^2 sr µm) and K_2 = 1321.08 K. The next step was to correct the BT from the effects of atmosphere and ground emissions. For this, Normalized Difference Vegetation Index (NDVI), Proportion of Vegetation (P_v) and Emissivity (ε) are derived.

$$NDVI = \frac{NIR-Red}{NIR+Red} \tag{3}$$

$$P_v = (\frac{NDVI-NDVI_{min}}{NDVI_{max}-NDVI_{min}})^2 \tag{4}$$

$$\varepsilon = 0.004 * P_v + 0.986 \tag{5}$$

$$LST = \frac{BT}{1+(\frac{\lambda \times BT}{P_v} \times \ln \varepsilon)} \tag{6}$$

Where, LST is in Celsius (°C), BT is the brightness temperature in (°C), λ is the average wavelength (m).

3.2 Maximum-Likelihood Classification for Land Use Land Cover Map

Maximum-Likelihood classifier (MLC) for LULC classification is a parametric algorithm based on Bayesian theory of probability. MLC assumes that each class in every band is normally distributed. It is a supervised classification algorithm which is an extension of Bayes theorem (Norovsuren et al. 2019). In MLC, probability for each pixel belonging to *m* classes is calculated. Maximum likelihood classifier assigns every pixel *i* to a class w_i if the probability for the class w_i is maximum for that pixel (Shivakumar and Rajashekararadhya 2018). The probability density function for each class is calculated using:

$$P(x|w_i) = \frac{1}{\sigma_i\sqrt{2\pi}}\, e^{-(\frac{x-\mu_i}{2\sigma_i})^2} \tag{7}$$

The MLC algorithm required a homogenous collection of training samples for the classes to be mapped, that is, Water, Bare Land, Healthy Vegetation, Forest and Built-Up. It assigns each cell to one of the classes of the signature file. With the help of mean vector and covariance matrix, membership of each cell to all the classes was calculated and each cell was assigned a class which has maximum likelihood of being a member of that class.

3.3 Retrieval of Land Surface Parameters

Normalized Difference Vegetation Index (NDVI) for vegetation and forested areas was proposed by (Tucker 1979). It takes reflectance values for near-infrared and red band in consideration. For water bodies surface retrieval, Normalized Difference Water Index (NDWI) was proposed by (McFeeters 1996) which uses spectral reflectance of near infrared and green bands. Normalised Difference Built-Up Index (NDBI) for retrieval of settlements and concrete structures was proposed by (Zha et al. 2003) which uses short-wave infrared and near infrared bands. For bare and fallow land retrieval, Normalised Bare Land Index (NBLI) was proposed by (Li et.al., 2017a) which uses reflectance values of thermal infrared and red bands. The spectral indices used in the study are summarized in Table 2.

Table 2. Indices derived using remote sensing for each major class

Surface Feature type	Index	Description	Formula	Reference
Vegetation	NDVI	Normalised Difference Vegetation Index	NIR-Red/NIR + Red	(Tucker 1979)
Water bodies	NDWI	Normalised Difference Water Index	Green-NIR/Green + NIR	(McFeeters 1996)
Built-Up	NDBI	Normalised Difference Built-Up Index	SWIR1-NIR/SWIR1+NIR	(Zha et al. 2003)
Bare/Fallow Land	NBLI	Normalised Bare Land Index	Red-TIR/Red + TIR	(Li et.al., 2017a)

4. Results and Discussion

The spatial-temporal assessment of LST, LULC and various spectral indices conducted for the study area are discussed below.

4.1 Spatial-Temporal Analysis of LST

Land surface temperature of Chandigarh city was derived using mono-window algorithm as shown in Figure (3). The statistical parameters including minimum and maximum temperatures, mean and standard deviation are summarized in Table (3). The mean temperature of the city varies between 34-36 °C in the month of May. There has been a slight rise in the minimum and maximum temperatures from 2016 to 2022.

The built -up has risen by almost 8% from 2016 to 2022 (Table 3) which can be accounted for the increase in the ranges of temperature. Though the vegetation area has increased by almost 8%, but the mean temperature of the area has been increased by almost 2.5 °C.

The highest temperature can be observed in the outskirts of the city where the concentration of bare and open land is highest. Sukhna lake and Dhanas lake shows least temperature (around 25- 27 °C). The Patiali Roa reserved forest and the Sukhna lake reserved forest shows less temperature compared to surrounding areas.

4.2 Spatial-Temporal Analysis of LULC

Multitemporal LULC mapping was done using MLC classifier as shown in Figure (4) and the results are summarized in Figure (5). Built-up and vegetation class have shown an increase of 7.56% and 8.19% respectively from 2016 to 2022. The forest cover has reduced by almost 32% and bare land has seen an overall decrease of about 16% as more urbanisation has covered the bare land. The net water content doesn’t show much variation over the years. The increase in vegetation cover can be accounted by plantation activities. The outskirt of the city has seen major urban densification in the last few years due to urban sprawl.

The analysis shows that there is a high positive correlation (0.9886) between built up class and LST, which suggests that increased urbanisation strongly affect the land surface temperature.

Table 3. Multi-temporal LST changes and statistical summary for Chandigarh

Time Period	Minimum Temperature °C	Maximum Temperature °C	Mean °C	Standard Deviation
May 2016	25.74	40.48	34.21	1.641
May 2017	24.98	39.64	34.06	1.42
May 2018	25.11	40.96	35.22	1.22
May 2019	25.25	40.76	35.56	1.54
May 2020	25.84	41.56	35.88	1.915
May 2021	26.19	41.24	36.41	1.56
May 2022	27.04	41.60	36.94	1.641

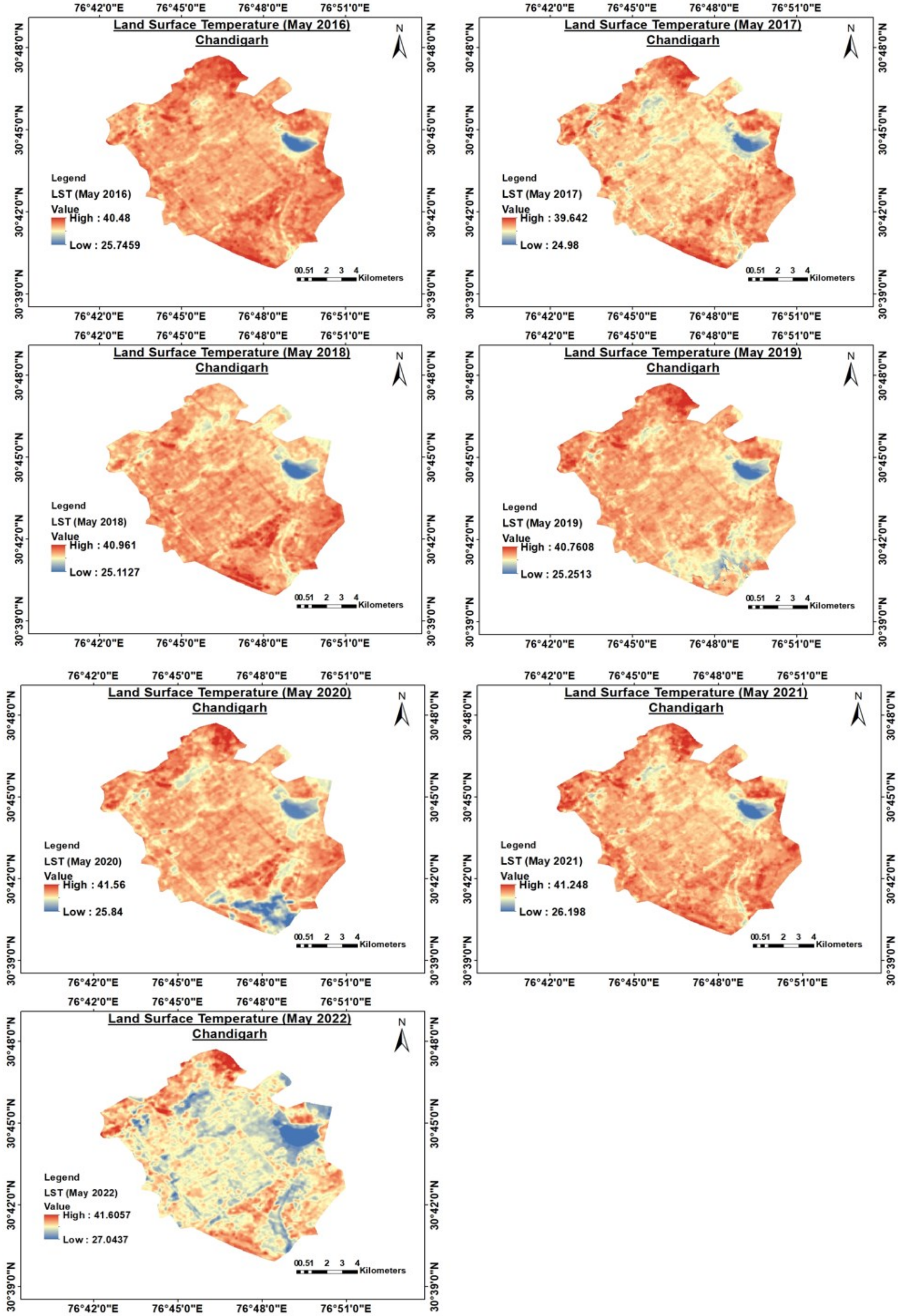

Figure 3. Land-surface temperature estimation using mono-window method for May 2016, May 2017, May 2018, May 2019, May 2020, May 2021 and May 2022

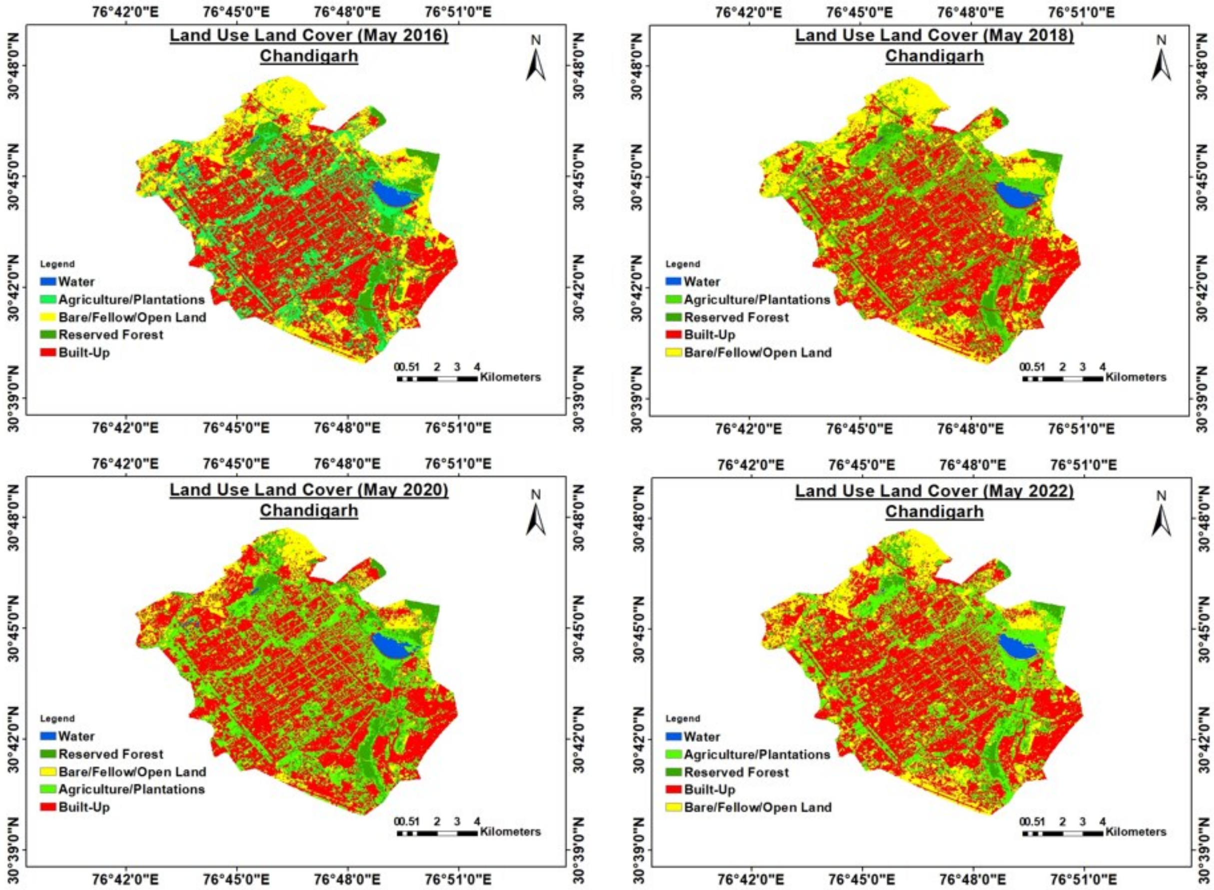

Figure 4. LULC changes for Chandigarh over May 2016, May 2018, May 2020 and May 2022.

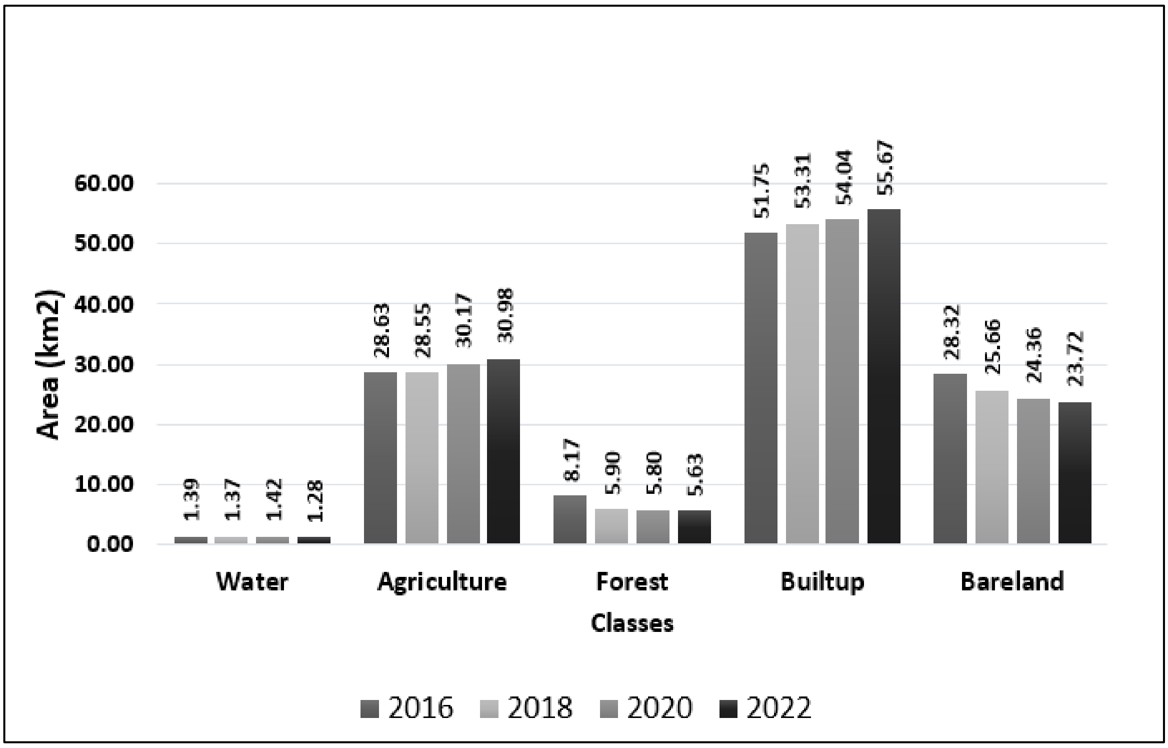

Figure 5. Statistical Analysis of changes in each class of LULC

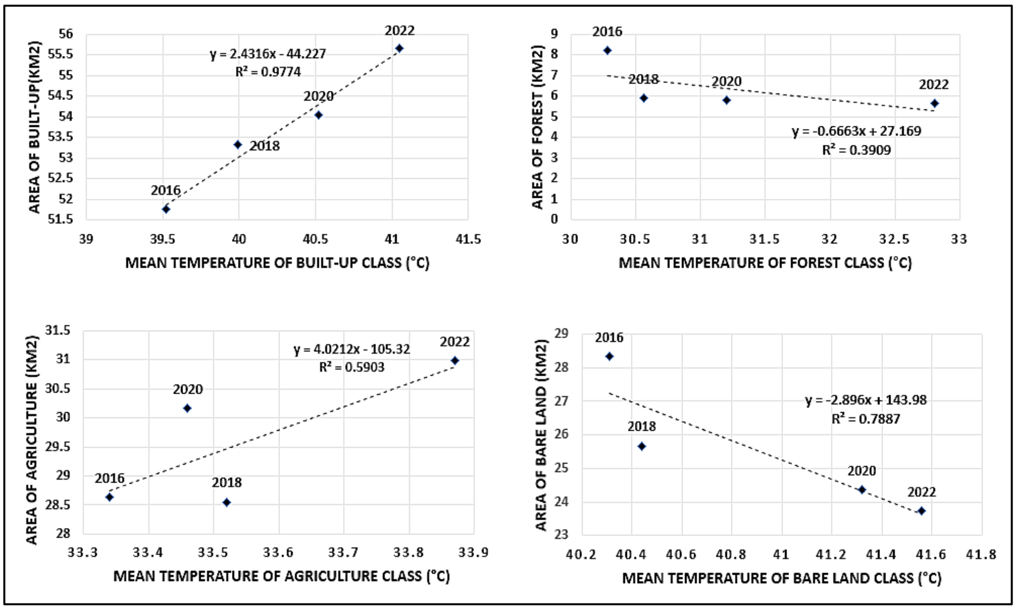

Figure 6. Relation between changes in LULC and LST

Table 4. User Accuracy (UA) and Producer Accuracy (PA) for LULC classification using MLC

Class	UA	PA	UA	PA	UA	PA	UA	PA
	2016		2018		2020		2022	
Water	100%	100%	100%	100%	100%	100%	100%	83.33%
Agriculture/Plantation	82.35%	75%	73.68%	82.35%	82.6%	76%	87.5%	77.77%
Reserved Forest	90%	81.81%	100%	76.925	90%	66.25%	100%	83.33%
Built-Up	87.09%	90%	97.5%	90.32%	78.57%	100%	82.14%	88.46%
Bare Land	81.25%	100%	86.66%	86.67%	80%	100%	79.23%	100%

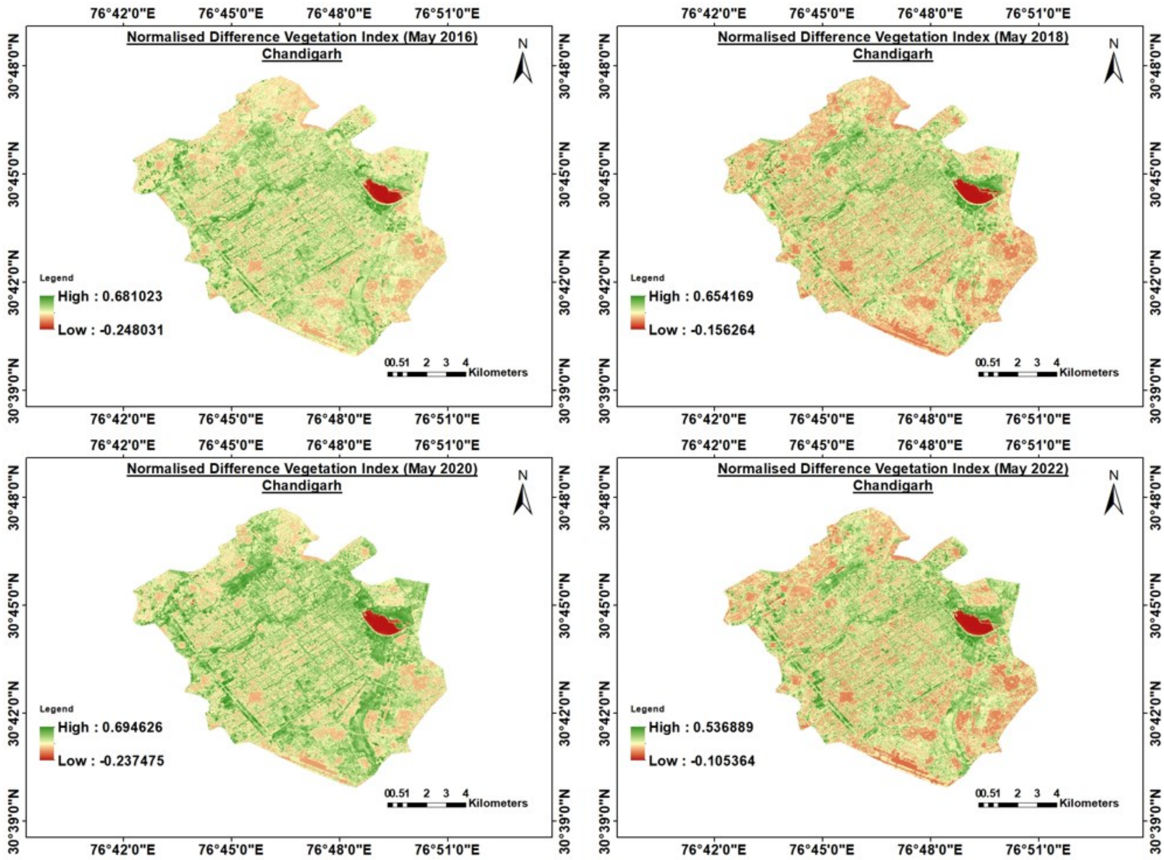

Figure 7. NDVI extraction for May 2016, May 2018, May 2020 and May 2022

Table 5. Overall Accuracy and Kappa coefficient for LULC classification

Year	Overall Accuracy	Kappa coefficient
2016	86.71%	0.795
2018	88.2%	0.82
2020	84.95%	0.78
2022	86.9%	0.799

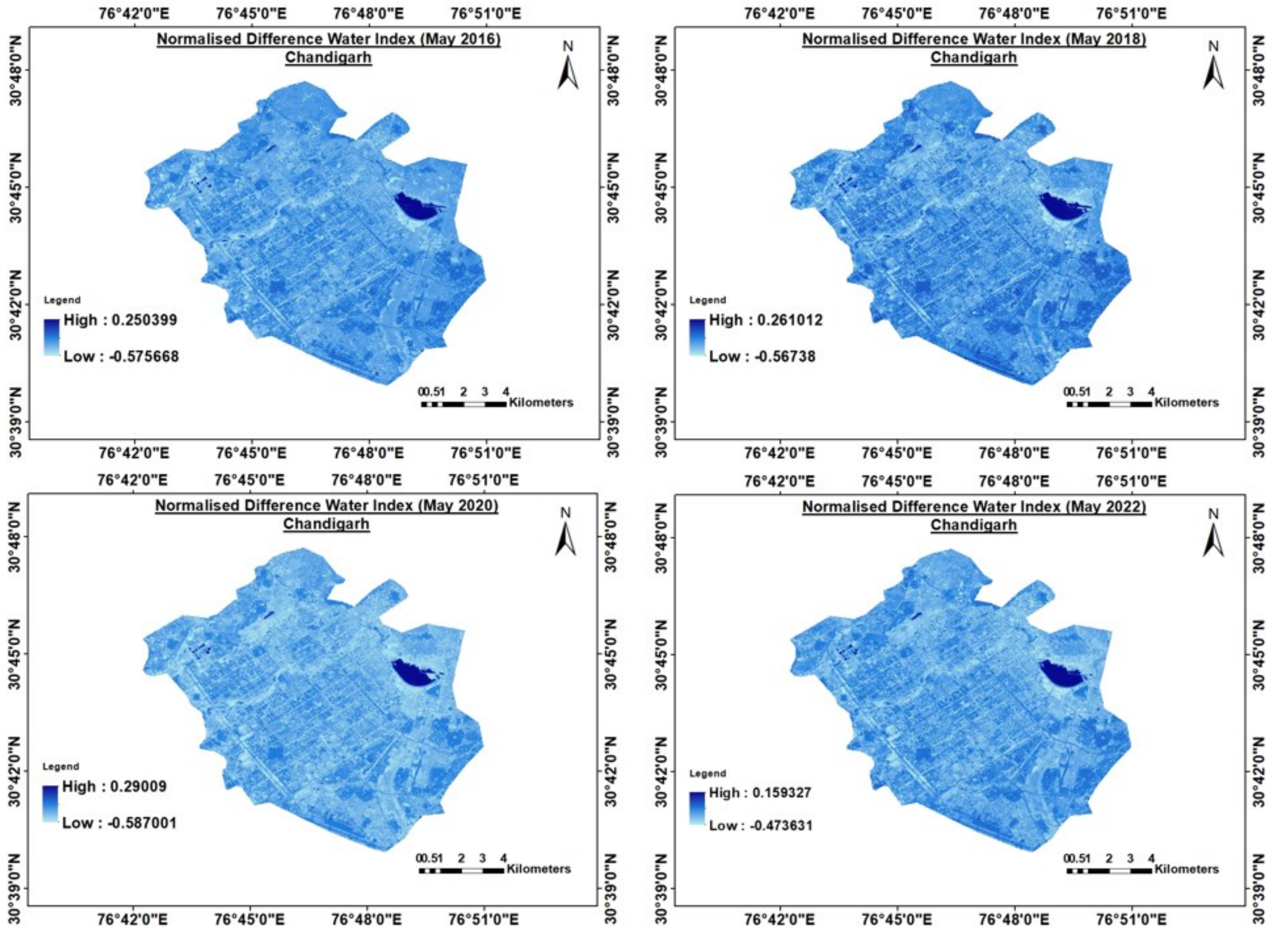

Figure 8. NDWI extraction for May 2016, May 2018, May 2020 and May 2022.

4.3 Accuracy Assessment

Error matrix or confusion matrix was computed to derive accuracy for the above classification. Stratified random sampling approach was used to select sample for each class. Highest overall accuracy of 88.20% was observed for the year 2018 with kappa coefficient of 0.82. The lowest accuracy for the year 2020 could be accounted for the misclassification of pixel points between vegetation and reserved forest class. The accuracy assessment has been summarised in Table (4) and Table (5).

4.4 Spatial-Temporal Analysis of Spectral Indices

Indices for four major classes, that is, NDVI for vegetation, NDWI for open water, NDBI for built-up and NBLI for bare lands have been considered and regression analysis along with correlation has been carried out. As can be observed from figure (7), NDVI is high (>0.3) for agricultural and forested areas. NDVI is a significant factor to consider with respect to LST as NDVI is directly employed for determination of LST. Correspondingly, LST in low in these areas.

The yearly variation of NDWI for the month of May is shown in Figure (8). NDWI is highest for Sukhna lake and Dhanas lake (>0.25) and LST for these regions is lowest. The yearly variation of NDBI for the month of May is shown in Figure (9). Highest NDBI can be observed for the central city and outskirts of the city (>0.5). Figure (10) shows yearly variations for the month of May for Chandigarh. Significant NBLI s observed in outskirts of the city.

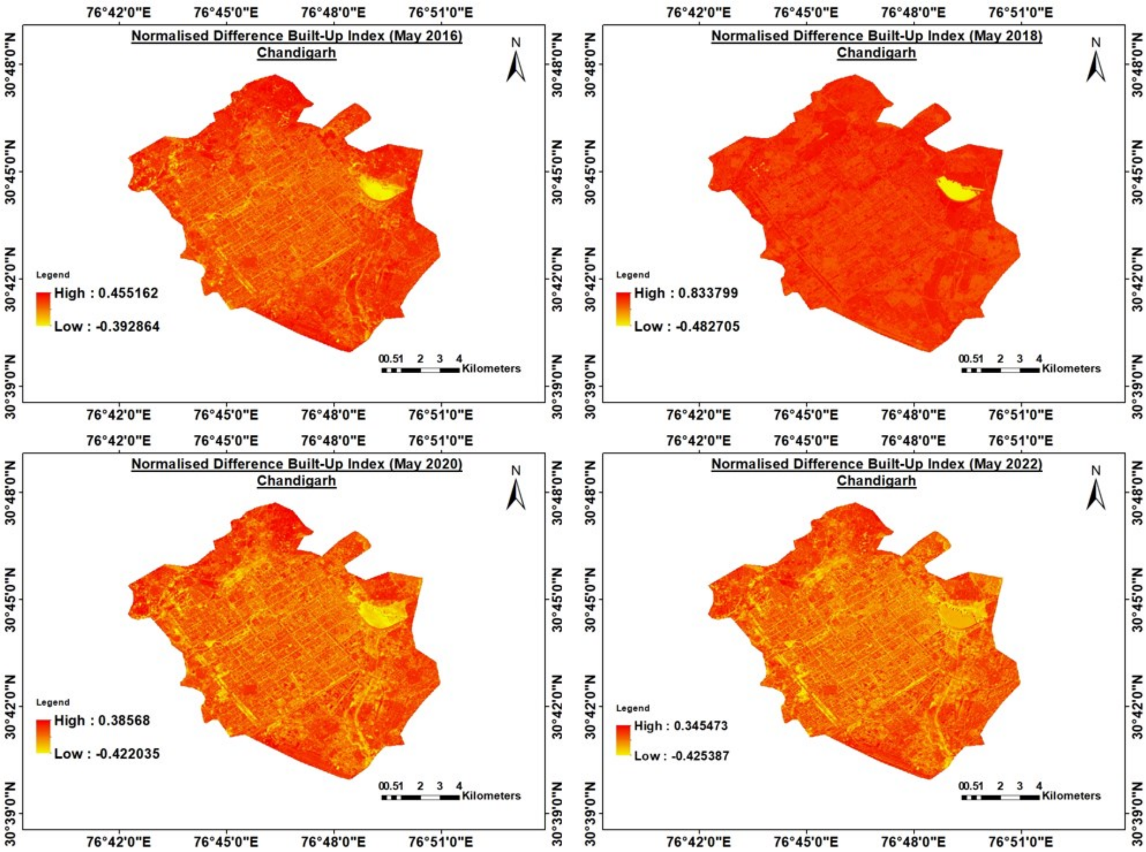

Figure 9. NDBI extraction for May 2016, May 2018, May 2020 and May 2022

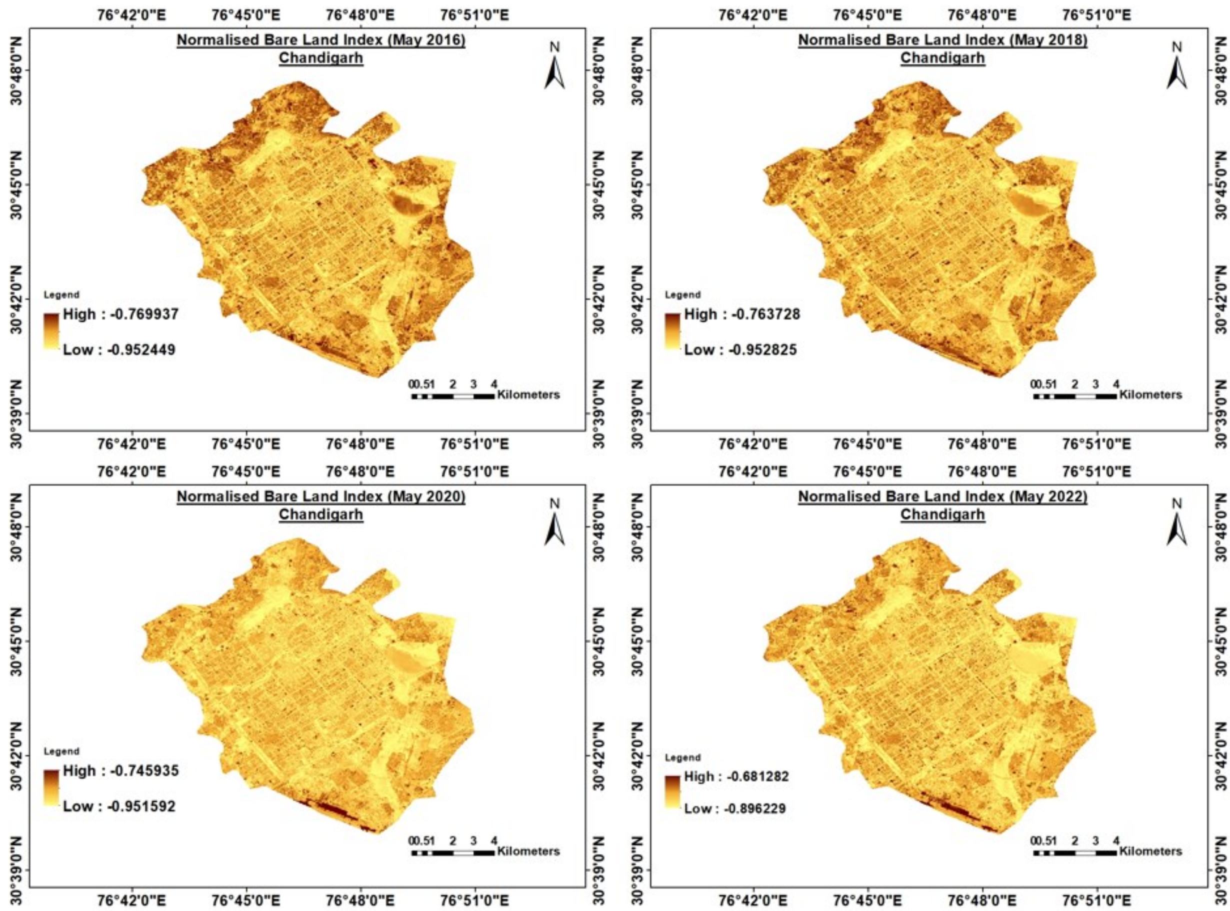

Figure 10. NBLI extraction for May 2016, May 2018, May 2020 and May 2022

4.5 Pearson's Correlation

A correlation analysis to establish relationship between surface temperature and spectral indices done and the results are summarised in Table (6). The Pearson correlation coefficient (r) measures the strength and direction of the linear relationship between two variables. A positive value of r (r>0) indicates an increasing trend between the two variables, whereas a negative value of r (r<0) indicates that when one variable is increasing, the other is decreasing. If r=0, it indicates little to no correlation between the variables. Indices for four major classes, that is, NDVI for vegetation, NDWI for open water, NDBI for built-up and NBLI for bare lands have been considered and regression analysis along with correlation has been carried out. A total of 2048 sample points each for NDVI, NDWI, NDBI and NBLI were utilised to establish the correlation with LST.As can be observed from figure (11), NDVI is high (>0.3) for agricultural and forested areas. NDVI is a significant factor to consider with respect to LST as NDVI is directly employed for determination of LST. Correspondingly, LST in low in these areas. This establishes the fact that there is a negative correlation between NDVI and LST. LST and NDVI shows a significantly negative correlation for May 2016 (-0.25), May 2018 (-0.29), May 2020 (-0.31) and May 2022 (- 0.352). In May 2022, there is a stronger negative relationship between NDVI and LST compared to all the previous years. This indicates that areas with more vegetation have a significant cooling effect on land surface temperatures during this period. Higher vegetation levels are associated with lower land surface temperatures. A weak negative correlation between NDVI and LST can be accounted for the dry month of May as the dry months tend to reduce the strength of regression (Guha and Govil 2021).

Table 6. Correlation between LST and spectral indices

LST	NDVI	NDWI	NDBI	NBLI
May 2016	-0.25	-0.015	0.44	0.324
May 2018	-0.29	0.212	0.51	0.348
May 2020	-0.31	0.159	0.53	0.421
May 2022	-0.352	0.110	0.59	0.477

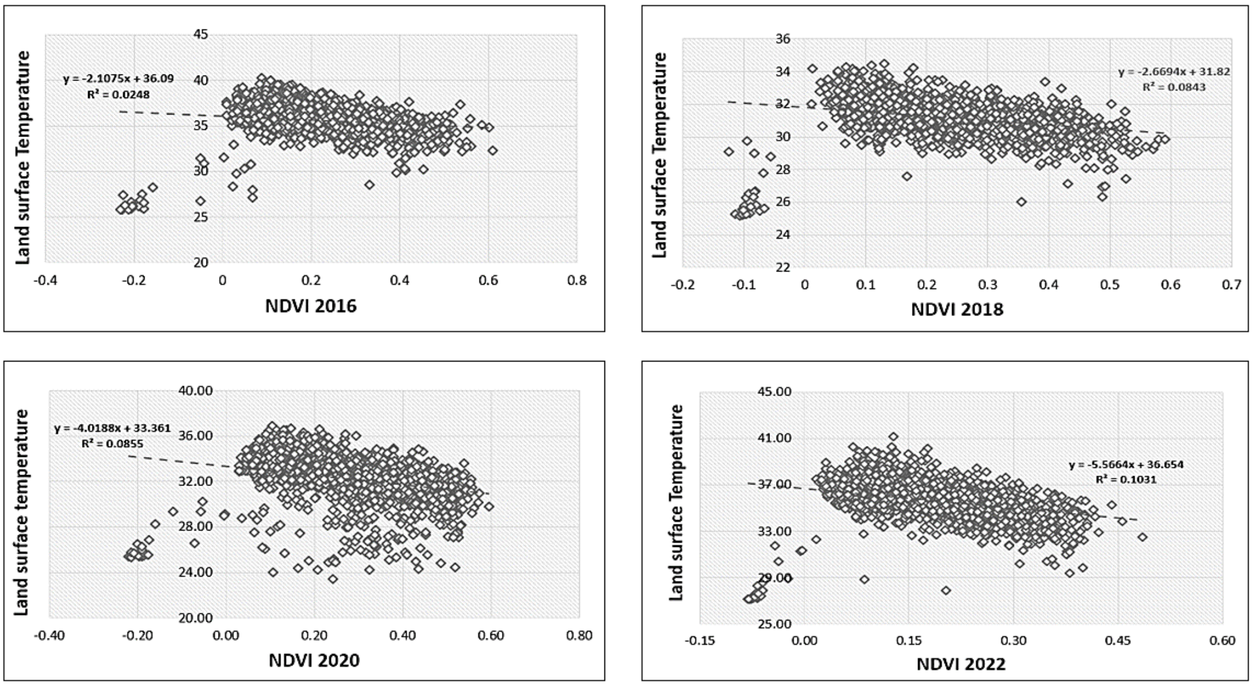

Figure 11. Correlation between NDVI and LST

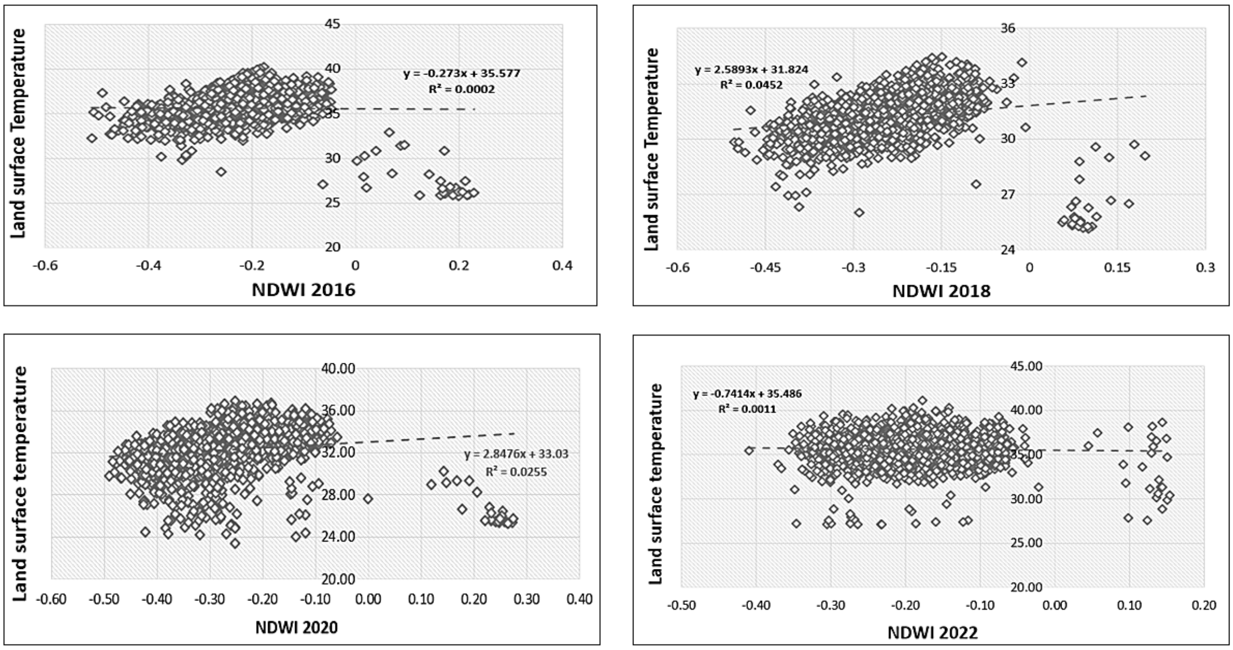

Figure 12. Correlation between NDWI and LST

Figure (12) shows correlation of LST and NDWI. The best LST-NDWI correlation can be observed for May 2018 (0.212), followed by May 2020 (0.159), May 2022 (0.11) and May 2016 (-0.015). From the analysis, it can be established that LST and NDWI build an insignificant correlation and can be considered as neutral.

Figure (13) shows correlation of LST and NDBI. The best LST-NDBI correlation can be observed for May 2022 (0.59), followed by May 2020 (0.53), May 2018 (0.51) and May 2016 (0.44). From the analysis, it can be established that LST and NDBI has a strong positive correlation and are highly correlated to each other. The correlation coefficients consistently indicate a positive correlation between NDBI (built-up areas) and LST across all the time periods. This suggests that urbanization and built-up areas have a substantial impact on increasing land surface temperatures during this period. The strength of this positive relationship varies but becomes notably stronger in more recent years for Chandigarh. This corresponds to building materials like asphalt and concrete which have low albedo and contribute to higher temperatures. One disadvantage of NDBI is that the tonal differences between built-up and bare land is unclear as one is not able to distinguish between bare land and built-up in the outskirts of the city. For this, another index called NBLI is considered.

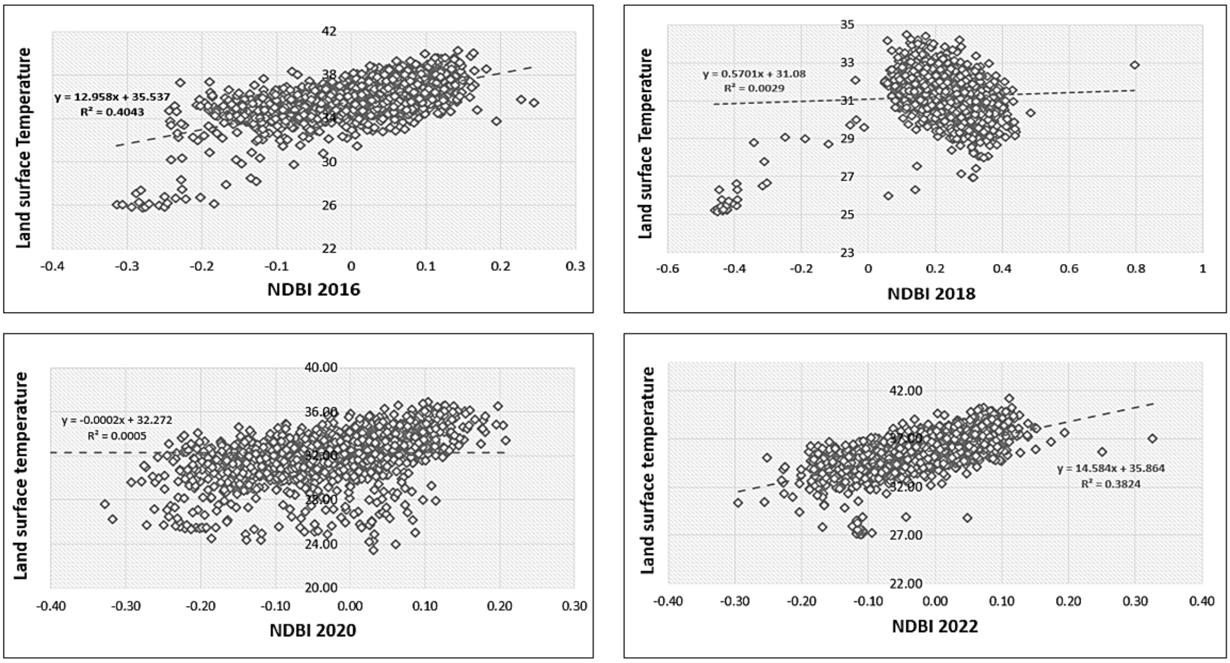

Figure 13. Correlation between NDBI and LST

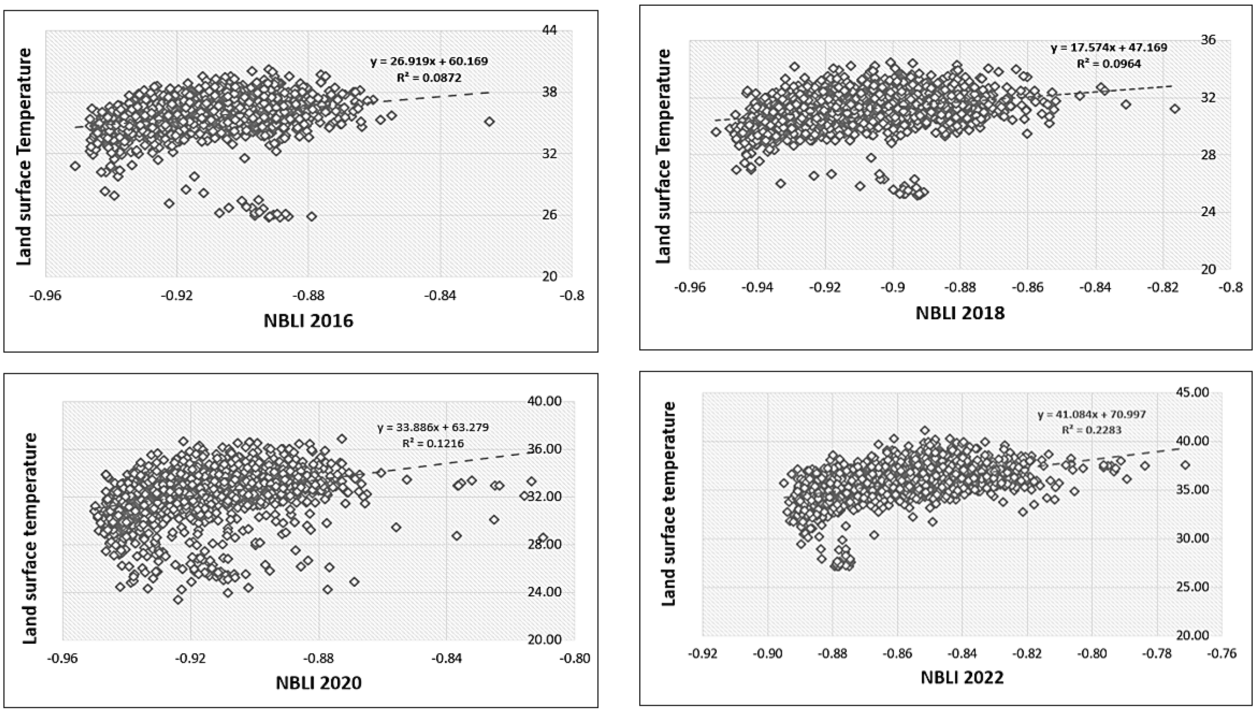

Figure 14. Correlation between NBLI and LST

The relation between LST and NBLI is shown in Figure (14). The best LST-NBLII correlation can be observed for May 2022 (0.477), followed by May 2020 (0.421), May 2018 (0.348) and May 2016 (0.324). The correlation coefficients consistently indicate a positive correlation between NBLI (bare lands) and LST across all the time periods. This suggests that areas with a high proportion of bare land experience a substantial increase in land surface temperatures during this period. The moisture present in the soil also plays a significant role in influencing the local temperature. Due to low moisture content of soil in the dry month of May, it is likely that sand absorbs more heat thus increasing the local surface temperature. The strength of this positive relationship varies but becomes notably stronger in more recent years, especially in 2022. This underscores the significant impact of bare land and the absence of vegetation on local land surface temperatures in Chandigarh during the study period.

The results obtained using correlation analysis indicate that in urban areas with high building density (as indicated by NDBI) and limited vegetation (low NDVI), there tends to be a positive correlation between LST and indices like NDBI and NBLI. Urban areas typically have higher temperatures due to the absorption and retention of heat by buildings and pavement, leading to increased LST, a phenomenon commonly referred to as Urban Heat Island Effect.

5. Conclusion

In this study, a comprehensive statistical analysis was conducted to examine the intricate relationship between Land Surface Temperature (LST) and Land-Use Land Cover (LULC) patterns within the urban context of Chandigarh city. LST was derived from Landsat-8 thermal and optical data using the mono-window method. Notably, our findings revealed a discernible increasing trend in LST, particularly within the categories of built-up and bare land, over the period spanning from 2016 to 2022. The mean LST exhibited a notable increment of approximately 2.5°C during this time frame. The utilization of Sentinel-2 Level 2A data was instrumental in enabling comprehensive analysis and investigation for LULC analysis. LULC classification was performed utilizing the Maximum Likelihood Classifier (MLC), which indicated an expansion of the built-up area within the city from 2016 to 2022, accompanied by a reduction in forest cover and bare land. Conversely, the water bodies and plantations remained relatively stable in terms of their spatial extent. A strong positive correlation can be seen between increase in built-up and LST, whereas a negative correlation can be seen for decreased forest cover and LST. Spectral indices have been derived using Sentinel 2 optical data. Analysis has been done to correlate LST with different spectral indices like NDVI, NDWI, NBLI and NDBI. A moderate negative correlation was discerned between LST and NDVI, underscoring the cooling effect of vegetation on local land surface temperatures. Conversely, the correlation between NDWI and LST was found to be insignificant for the Chandigarh region. Notably, NDBI exhibited a robust positive correlation with LST, further substantiating the heightened land surface temperatures in areas with increased urbanization and built-up structures. Additionally, a moderately positive correlation was observed between LST and NBLI, affirming the influence of bare land on elevating land surface temperatures. Furthermore, it was observed that the presence of water bodies, as indicated by NDWI, consistently led to negative correlations, underlining the cooling influence of water bodies in mitigating LST. These findings are influenced by a multitude of factors including the local climate, geographic characteristics, and topographical attributes. Urban canyons, characteristic of a city like Chandigarh, may experience positive correlations owing to heattrapping phenomena. While correlations provide valuable insights into relationships between variables, they do not indicate a direct cause-and-effect relationship. Consequently, these findings hold substantial utility in guiding informed environmental planning and policymaking for urban areas. Chandigarh, as a meticulously planned city, has shown a notable surge in plantation efforts in recent years. Transforming barren lands into eco-parks or wetlands represents a constructive avenue for urban planners and policymakers to mitigate the Urban Heat Island (UHI) effect and contribute positively to climate change mitigation efforts.

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