

Impact of Land Use Transformation on Urban Heat Island Phenomenon: A Case Study of Chennai Metropolitan Area, India

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Abstract This study investigates land use changes that influence the land surface temperature (LST) of the Land cover environment in the Chennai Metropolitan Area (CMA), India, over three decades (1991, 2001, 2011, and 2021). Landsat satellite imageries were used to classify this study area into six land use and land cover (LULC) types using the Support Vector Machine (SVM) classification technique. Similarly, LST was calculated using Thermal Infrared (TIR) bands through the conversion of radiation into temperature and estimated emissivity (e) through Normalized Difference Vegetation Index (NDVI) calculation. The result shows 1991 to 2021, LST increased from 35.6°C to 47.2°C. To evaluate the relationship between LST and LULC over the study period, Zonal Statistics Analysis (ZSA) was used. The findings show a steady rise in LST across all types of land use and land cover, with a built-up area-specific trend being particularly notable. Calculate the linear correlations between the mean sensitive LULC spectral indices and the mean LST. The results show a strong positive relationship ($R^2 = 0.5694$) between the mean LST and the mean Normalized Difference Built-Up Index (NDBI). These findings highlight the significant influence of land use changes, particularly Built-up land, on the increasing LST of the surrounding land cover.

Keywords: Support Vector Machine (SVM), Thermal infrared (TIR), Zonal Statistics Analysis (ZSA), Normalized Difference Built-Up Index (NDBI)

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1. Introduction

Changes in land use and cover contribute to global environmental changes, impacting climate, biodiversity, soil, water, air, and ecosystem services. The magnitude and rate of these changes vary globally due to geographical, climatic, and resource factors. The increasing expansion of impervious surfaces in urban areas has a significant environmental impact, leading to changes in surface properties and contributing to the urban heat island (UHI) effect. The UHI effect causes elevated temperatures in urban areas compared to suburban regions. Urbanization, characterized by horizontal and vertical development, is prominent in cities like Chennai, Mumbai, Delhi, and Kolkata in India. This study aims to investigate the complex relationship between land use changes, land surface temperature (LST), and the overall land cover environment in the Chennai Metropolitan City.

Understanding the intricate relationship between land use transformation, land surface temperature (LST), and the land cover environment in the Chennai region is

crucial for informed urban planning and effective adaptation to climate change. This study provides comprehensive insights into how urbanization influences temperature patterns and environmental conditions, offering valuable implications for sustainable development. The global significance of studying land use and land cover (LULC) changes and their impact on LST is evident in the substantial attention this subject has received from researchers worldwide. Numerous studies, employing diverse methodologies, have demonstrated a significant association between land use dynamics and LST variations [1]. Advanced algorithms like mono window (MWA) and split window (SWA) can be utilized for Exploring LST in major Indian metro cities, correlating their findings with NDVI and NDBI [2]. Mumbai exhibited the highest LST, while Kolkata recorded the lowest, showcasing diverse accuracy in coastal and interior cities between MWA and SWA. LULC and LST changes in Kolkata from 2005 to 2019, revealing reduced vegetation cover towards the city core and urban expansion towards the outskirts, resulting in a peak LST of 41°C in 2019 [3]. In South Karkheh Sub-basin, Iran, a negative correlation between LST and NDVI

was unveiled affirming vegetation's cooling effect. Higher LST was identified in four Nigerian cities due to LULC changes, using the ARIMA model to reveal a progressive increase in LST in built-up areas [4].

Previous studies extensively explored the relationship between land use changes and Land Surface Temperature (LST), utilizing remote sensing data, GIS techniques, statistical analysis, and predictive modeling. However, this study distinguishes itself by specifically investigating the influence of land-use changes on variations in LST and their subsequent impact on the temperatures of the surrounding land cover. Chennai Metropolitan Area (CMA), the capital of Tamil Nadu, has undergone rapid growth, leading to extensive infrastructure development and a substantial increase in its geographical extent. According to the 2022 report by the Chennai Metropolitan Development Authority, the CMA has expanded from 1189 km² to 5904 km². This expansion has resulted in the loss of natural landscapes, disruption of ecosystems, and alterations in hydrological patterns. In the current context, this study holds significant importance for urban planners, environmentalists, and academics. It provides valuable and reliable insights into the environmental conditions of the rapidly urbanizing CMA, offering relevance for understanding similar trends in other highly urbanized regions. Examining LST and LU changes in Chennai is vital for sustainable development amid urbanization. It identifies heat stress areas, aids urban comfort, and supports biodiversity preservation. Understanding changes is crucial for resilience and addressing urbanization

challenges. This study aims to address (1) examine LULC and LST changes, (2) explore the influence of land use changes on LST and land cover, and (3) determine the impact of mean LST on sensitive categories.

2. Study Area

Situated in southern India, the CMA is a significant metropolis covering 1,189 km² and positioned between latitudes 12°50'49"N and 13°17'24"N, and longitudes 79°59'53"E and 80°20'12"E. Experiencing a tropical wet and dry climate due to its coastal proximity and the thermal equator, the CMA sees scorching temperatures in May and June (35°C–40°C), while January represents the coldest period with temperatures around 19–25°C.

The city receives an average annual rainfall of approximately 1400 mm, with the highest during the Northeast monsoon season (October to December) according to the report of IMD. Chennai has evolved into a thriving information technology hub, transitioning from its commercial and manufacturing origins [5]. The CMA benefits from a well-developed transportation network connecting it efficiently to major Indian cities. Its flat terrain and coastal location along the Bay of Bengal contribute to its reputation as one of the most densely populated regions in the country. According to the 2011 census, Chennai's urban agglomeration accommodates around 8.65 million people, resulting in a population density of 2,109 persons per km².

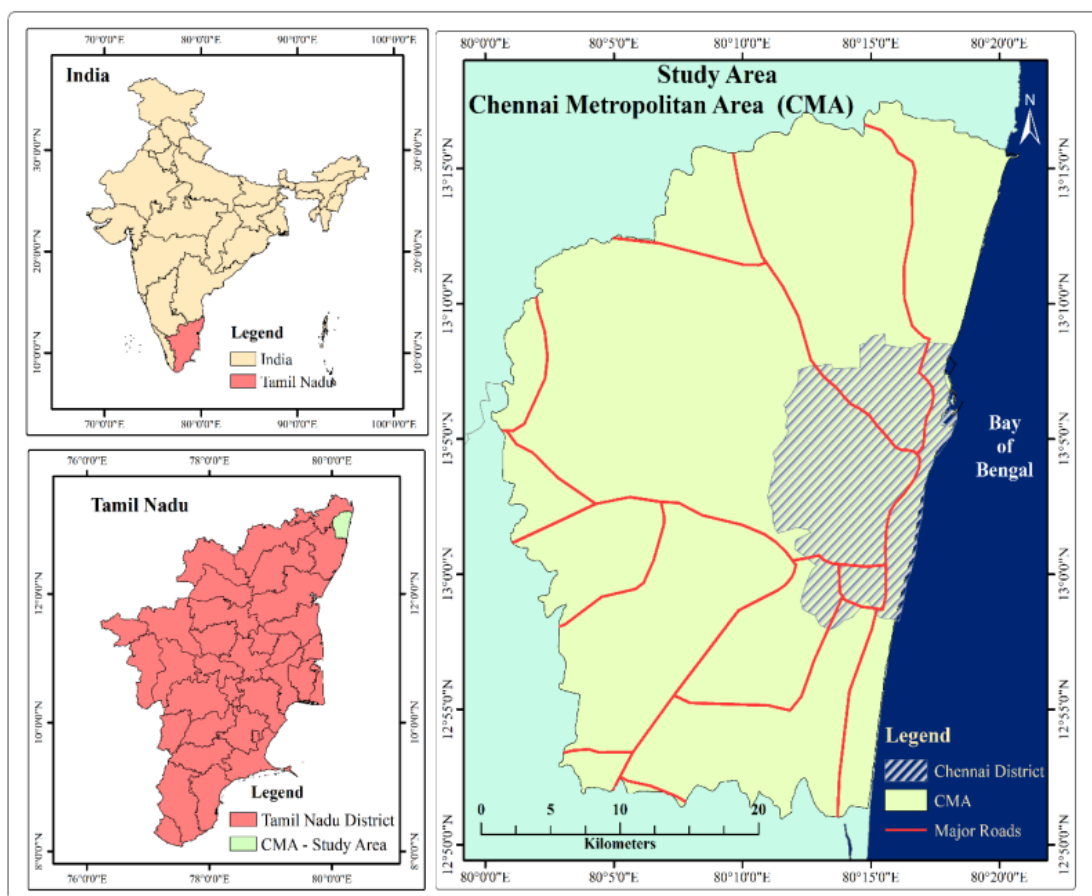


Figure 1. Study area

3. Dataset Used

Satellite data from Landsat 5 TM, 7 ETM+, and 8 OLI/TIRS sensors were obtained for 1991, 2001, 2011, and 2021 from the USGS website. Images closest to the vernal or autumnal equinox were prioritized for equal radiation, enhancing reliability for LST and LULC estimation. The acquired images correspond to Row 142 and Path 051 in the WRS, projected using the WGS 84 datum and UTM coordinate system (Zone 44 North). Pre-processing involved multiple steps. Layer stacking combined the Blue, Green, Red, and NIR bands, followed by histogram equalization to enhance contrast in all bands. The LULC classification was performed using the stacked images, and ancillary data from sources such as Survey of India (SOI) Toposheet (1: 50,000 scale) and Google Earth images were used to create training data for classification and evaluate result accuracy. For land surface temperature calculations, Thermal Infrared Sensor (TIRS) Band 6 was employed for Landsat-5 and Landsat-7, while Band 10 was used for Landsat-8. Normalized Difference Vegetation Index (NDVI) computation utilized the Near Infrared (NIR) and Red bands. Similarly, Short Wave Infrared (SWIR) and NIR bands were employed for Normalized Difference Built-Up Index (NDBI) calculation, and Green and Red bands were used for Normalized Difference Water Index (NDWI).

Table 1. Satellite data specifications

Sl. No.	Date	Landsat/Sensor	Scene ID
1	26.09.1991	5 TM	19910926_20170126_01_T1
2	21.03.2001	7 ETM +	20010321_20170206_01_T1
3	09.03.2011	5 TM	20110309_20161209_01_T1
4	20.03.2021	8 OLI/TIRS	20210320_20210328_02_T1

4. Methods

SVM Classification

For Land Use and Land Cover (LULC) classification, the study employed Support Vector Machine (SVM) algorithms through the ENVI 5.2 image processing software. Introduced by Vapnik in 1995, SVM has gained widespread acceptance in remote sensing due to its robust statistical basis and superior empirical performance. It outperforms traditional techniques such as neural networks and maximum likelihood classifiers, as evidenced by various studies [6]. SVM has higher accuracy in multi-class image classification compared to classifiers like discriminant analysis (DA), decision tree (DT), and feed forward neural network. The SVM classification utilized four kernels: linear, polynomial, Radial Basis Function (RBF), and sigmoid [7]. The study specifically applied the RBF kernel due to its low computational complexity and effectiveness in handling non-linear relationships between training data and the entire dataset. The RBF kernel function is represented by Equation 1. The classification threshold for the pyramid parameter was set to zero, allowing full spatial resolution analysis with no unclassified pixels [8].

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0 \quad (\text{Eq. 1})$$

Using Anderson's classification (1976) and NRSC's 2012 categorization, CMA was classified into six types: agriculture, fallow land, built-up land, vegetation, scrubland, and water bodies. This study focuses on agriculture, fallow land, and built-up land as land uses, and water bodies, scrubland, and natural vegetation cover as land cover. Training data, derived from satellite images, prior knowledge, topographic sheets, and Google Earth, fed into SVM classification. Rigorous documentation ensured quality classification.

Accuracy assessment

In this context, correctness refers to the extent of alignment between classified satellite images and the actual ground truth [9]. This assessment method gauges how accurately the classified map represents the real land cover and land use on the ground, utilizing reliable reference data such as GPS data, ground truth data, and high-resolution imagery [10]. To evaluate categorization accuracy, a total of 288 checkpoints were randomly selected through a robust sampling procedure. Various measures, including overall classification accuracy, producer accuracy, user accuracy and the Kappa coefficient [11] were calculated (Eq. 2).

$$K = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+})(x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+})(x_{+i})} \quad (\text{Eq. 2})$$

In the matrix, 'r' denotes the number of rows, and 'xii' signifies the count of observations in both column 'i' and row 'i' (diagonal elements). 'x+i' and 'xi+' represent the marginal totals in row 'r' and column 'i,' respectively, while 'N' stands for the total number of observations. User accuracy metrics and producer accuracy metrics address commissions and omissions. Subsequent to calculating the area and changes in land use and land cover (LULC), the computation of Land Surface Temperature (LST) was conducted through specific steps [12].

Retrieval of Land Surface Temperature (RLST)

Conversion of Digital Numbers to Sensor Radiance

The TIRS bands recorded by Landsat sensors are stored as digital numbers (DN), representing various brightness levels. The first step in calculating Land Surface Temperature (LST) is the conversion of DN values to radiance. Specifically, for Landsat-8, the DN is transformed into spectral radiance (Eq. 3).

$$L_\lambda = M_L * Q_{cal} + A_L - O_i \quad (\text{Eq. 3})$$

In the equation, L_λ represents spectral radiance ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$), M_L and A_L are rescaling factors, Q_{cal} denotes quantized and calibrated pixel value (DN), and O_i represents the calibration offset. For Landsat-8 TIRS band 10, the calibration factor is 0.29. DN was converted to radiance in Landsat-5 TM and Landsat-7 ETM+ using a spectral radiance rescaling equation (Eq. 4), which differed from Landsat-8 [13].

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{Q_{calmax} - Q_{calmin}} \right) (Q_{cal} - Q_{calmin}) + LMIN_\lambda \quad (\text{Eq. 4})$$

In the context of calculating LST, $L\lambda$ is the spectral radiance at the sensor (measured in $W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$). $LMAX\lambda$ is the spectral radiance scaled to the maximum quantized calibrated pixel value (Q_{calmax}), and $LMIN\lambda$ is the spectral radiance scaled to the minimum quantized calibrated pixel value (Q_{calmin}), both measured in $W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$. Q_{calmin} corresponds to the minimum quantized calibrated pixel value, and Q_{calmax} corresponds to the maximum value. All variables, except for Q_{cal} , are provided in the metadata file of a scene.

Computation of Brightness Temperature

After converting DN to radiance, the next step is to apply Eq. 5 to convert radiance to brightness temperature. This concept is based on the idea that a black body must reach a certain brightness temperature to emit or receive an equal amount of radiation per unit surface area [14].

$$T_{sen} = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.15 \quad (\text{Eq. 5})$$

T_{sen} represents the top of atmosphere brightness temperature, while $L\lambda$ denotes the top of atmosphere spectral radiance ($Watts\ m^{-2}\ srad^{-1}\ \mu m^{-1}$). K_1 and K_2 are band-specific thermal conversion constants obtained from the metadata. The resulting values were then converted from Kelvin to Celsius.

Determination of Land Surface Emissivity (LSE)

The NDVI, derived from the reflectance of Earth's features in the NIR and Red bands of the electromagnetic spectrum, is utilized to calculate emissivity (ϵ) and vegetation proportion (Pv) for determining LST [15]. Positive NDVI values indicate vegetated areas, while negative values show non-vegetated surfaces. For Landsat-5 TM and Landsat-7 ETM+, band 3 is red, and band 4 is NIR [16]. For Landsat 8 OLI/TIRS, band 4 is red, and band 5 is NIR (Eq. 6).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (\text{Eq. 6})$$

Calculation of surface emissivity using the NDVI threshold method

Surface emissivity, a crucial factor in LST inversion, accounts for the variance in heat radiation emitted by different LULC types. Emissivity (ϵ) is defined as the ratio of radiated light to blackbody emission at a given wavelength and temperature [17]. The NDVI threshold approach was employed to calculate surface-specific emissivity, relying on the strong linear correlation between NDVI and particular surface emissivity. The NDVI threshold approach was utilized for emissivity calculation as shown in Table 2.

Table 2. NDVI and emissivity threshold levels

NDVI Value	Land Surface Emissivity
$NDVI < -0.185$	0.995
$-0.185 < NDVI < 0.157$	0.970
$0.157 < NDVI < 0.727$	$1.0094 + 0.047 * \ln(NDVI)$
$NDVI > 0.727$	0.990

Calculation of Land surface temperature

The Landsat series data has been utilized to calculate the LST for each pixel (Eq. 7), where BT is the brightness temperature, λ is the wavelength of the radiance emitted in each band, σ is the Stefan-Boltzmann constant, and ϵ is the surface emissivity [18].

$$LST = \left[\frac{BT}{1 + \lambda * \frac{BT}{\rho * \ln(\epsilon)}} \right] \quad (\text{Eq. 7})$$

Zonal statistics (ZA)

Zonal Statistics is a tool employed for calculating statistics within specified zones in a dataset, offering insights into spatial patterns and relationships. It facilitates the analysis of variables like land cover, temperature, and other geospatial data within defined zones, allowing users to comprehend patterns and make informed decisions. Zonal-based spatial analysis provides a collection of more micro-sized observations [19]. A single output value is generated for each zone in the input zone dataset, revealing the association between LULC and LST. This approach proves effective in evaluating the relationship [20]. The Zonal Statistics results offer valuable insights into the actual trends of LST within each LULC type and how the LST of land cover features is influenced by the surrounding land use. Such analysis contributes to a deeper understanding of the thermal behavior of various land cover elements, shedding light on the dynamics and interactions between land use and LST across the research period.

5. Results and Discussion

Accuracy Assessment

Table 3 summarizes LULC categorization accuracy, producer accuracy, and user accuracy. Water bodies consistently exhibit high accuracy, with producer accuracy ranging from 92.86% to 100%, and user accuracy from 86.67% to 92.86%, indicating reliable classification throughout the year. Built-up areas also demonstrate high accuracy, with producer accuracy ranging from 87.76% to 100% and user accuracy from 81.82% to 95.40%. Fallow Land maintains consistent accuracy, with producer accuracy between 87.93% and 94.44%, and user accuracy from 86.08% to 92.31%. Vegetation accuracy varies, with producer accuracy between 47.83% and 85.71%, and user accuracy from 61.54% to 100%, notably improving between 2011 and 2021. Scrubland accuracy ranges from 33.33% to 100%, with producer accuracy from 33.33% to 100%, and user accuracy from 20.00% to 100%, showing improvement between 2011 and 2021.

The accuracy of agricultural land is consistent, with producer accuracy ranging from 78.95% to 100%, and user accuracy from 75.00% to 88.24%.

Overall classification accuracy ranges from 86.06% to 93.04%, indicating an increasing trend over time. The categorization kappa in this study varies from 0.81 to 0.891, falling within an acceptable range.

Land Use and Land Cover Area

Table 4 and Figure 2 present the areas of different LULC classes in square kilometers and their corresponding percentages for 1991, 2001, 2011, and 2021. Agriculture remains relatively stable, accounting for around 122.5 km² in 1991 and slightly increasing to 123.6 km² in 2021. Fallow land experiences a downward trend, decreasing from 589.5 km² to 252.2 km² over the same period. Built-up land shows substantial growth, increasing from 144.8 km² to 620.3 km². Scrubland and vegetation exhibit minor fluctuations, with scrubland decreasing from 18 km² to 16.4 km², and vegetation decreasing from 118.3 km² to 61.8 km². Water bodies also show slight variations, decreasing from 195.2 km² to 114 km². This suggests that the expanding population drives the expansion of built-up areas. Consequently, urban development initiatives and shifts in economic activities

contribute to changes in land usage in CMA [21].

The agricultural land area has slightly decreased, potentially due to its concentration in the outer peripheral regions. A notable transformation is evident, where a significant portion of fallow land has been converted into built-up areas. Figure 2(a) to Figure 2(d) illustrate the CMA's expansion in built-up areas, particularly in the southern and western directions with Chennai as the focal center. Figure 2(a) shows sparsely developed territory in the southern and western directions, which has expanded in all directions over time, contributing to the observed built-up land cover in 2021. In 2021, there was a substantial increase in built-up land to approximately 620.3 km², while fallow land decreased to 252.2 km², indicating ongoing urbanization or development in the region. The expanded built-up land has encroached upon smaller-sized water bodies, especially in the central part of CMA.

Table 3. Accuracy assessment table for the years 1991, 2001, 2011, 2021

Class Name	1991		2001		2011		2021	
	Producers Accuracy (%)	Users Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)	Producer Accuracy (%)	User Accuracy (%)
Water bodies	93.33	93.33	92.86	86.67	100.00	92.86	87.50	87.50
Built-up	94.74	81.82	97.73	87.76	90.38	90.38	100.00	95.40
Fallow land	94.44	86.08	92.31	92.31	87.93	89.47	89.47	91.89
Vegetation	47.83	84.62	61.54	80.00	75.00	85.71	25.00	100.00
Scrubs	50.00	100.00	20.00	100.00	33.33	100.0	72.73	100.00
Agriculture	88.24	78.95	85.71	75.00	100.00	84.62	100.00	82.35
Classification Accuracy	86.06		88.82		89.02		93.04	
Kappa Statistics	0.8063		0.8323		0.8517		0.891	

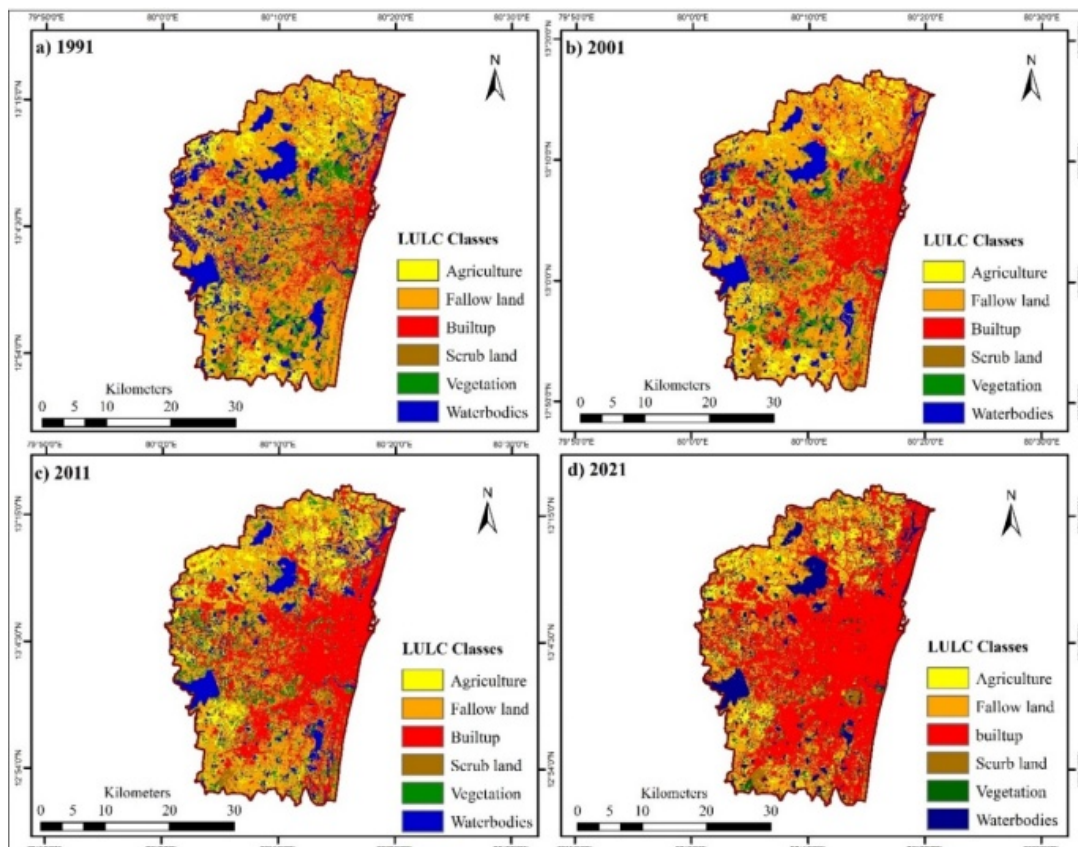


Figure 2. Land Use and Land Cover map a) 1991 b) 2001 c) 2011 and d) 2021

Table 4. Area Calculation of LULC

Class Name	Area in (km ²)				Area (%)			
	1991	2001	2011	2021	1991	2001	2011	2021
Agriculture	122.5	122.7	140.6	123.6	10.3	10.3	11.8	10.4
Fallow Land	589.5	534.7	400.6	252.2	49.6	45	33.7	21.2
Built-up	144.8	277.4	395.3	620.3	12.2	23.3	33.3	52.2
Scrubs	18	17.4	14.5	16.4	1.5	1.5	1.2	1.4
Vegetation	118.3	91.7	105.5	61.8	10	7.7	8.9	5.2
Water bodies	195.2	144.5	131.8	114	16.4	12.2	11.1	9.6
Total	1188.4				100			

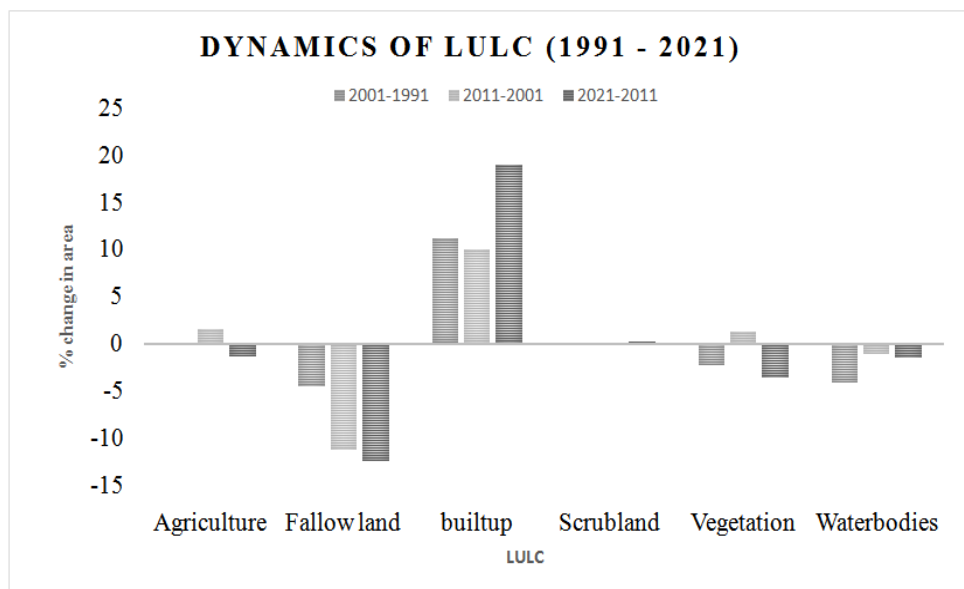


Figure 3. Dynamics of LULC indicating the changes from 1991-2021

Table 5. LULC Changes

Class Name	Changes in km ²			Changes in Percentage		
	1991-2001	2001-2011	2011-2021	1991-2001	2001-2011	2011-2021
Agriculture	0	17.9	-17	0	1.5	-1.4
Fallow land	-4.6	-134.1	-148.4	-4.6	-11.3	-12.5
built-up	11.1	117.9	225	11.1	10	18.9
Scrubland	0	-2.9	1.9	0	-0.3	0.2
Vegetation	-2.3	13.8	-43.7	-2.3	1.2	-3.7
Water bodies	-17.8	-12.7	-4.2	-1.5	-1.1	-4.2

Significant LULC changes have occurred over the years. Agricultural land remained relatively stable from 1991 to 2001, increased slightly from 2001 to 2011, and then decreased from 2011 to 2021. Fallow land consistently decreased, notably dropping by 134.1 km² from 2001 to 2011 and 148.4 km² from 2011 to 2021. In contrast, built-up areas consistently increased, with significant gains of 117.9 km² from 2001 to 2011 and 225 km² from 2011 to 2021. Scrubland and vegetation exhibited fluctuations, with scrubland increasing slightly and vegetation decreasing notably between 2011 and 2021. The dominance of built-up land (impervious surface) is evident, as indicated by the varying growth trends in LULC.

Land Surface Temperature

From 1991 to 2021, the CMA exhibits a distinct pattern of

rising LST. The maximum temperature increased from 35.6°C in 1991 to 47.2°C in 2021, and the minimum temperature grew from 22.3°C to 25.9°C (Table 6, Figure 5).

Table 6. LST statistics from 1991 – 2021

Year	Land surface Temperature			
	Maximum	Minimum	Mean	STD
1991	35.6	22.3	28.95	1.89
2001	37.2	21.9	28.15	1.81
2011	43.3	24.5	32.63	2.63
2021	47.2	25.9	37.49	2.43

From 1991 to 2021, the CMA exhibited a consistent increase in LST. The mean temperature rose steadily from 28.95°C in 1991 to 37.49°C in 2021, indicating a positive correlation with time. The standard deviation also increased significantly from 1.89°C in 1991 to 2.43°C in 2021, highlighting growing unpredictability. These trends emphasize the presence of urban heat island effects and the need to address the impact of rising LST on the urban environment and human health in CMA.

Zonal Statistics

Over three decades, zonal statistics were utilized to generate LST statistics, including maximum, minimum, mean, and standard deviation over different LULC classes [22]. Table 7 presents the results. The maximum LST for Built-up areas increased steadily from 35.68°C in 1991 to 47.06°C in 2021, indicating a consistent rise in surface temperatures in CMA. Similarly, LST in fallow land increased from 35.29°C in 1991 to 47.17°C in 2021,

suggesting an overall warming trend in fallow land areas. Agriculture also experienced rising LST values, increasing from 32.93°C in 1991 to 46.22°C in 2021, indicating a considerable rise in surface temperatures in agricultural regions. The mean LST of Built-up areas exhibited a significant upward trend, while Fallow land remained relatively stable, and Agriculture showed a clear upward trend. From 1991 to 2001, the built-up deviation of LST ranged from 1.45°C to 1.85°C, demonstrating moderate changes in surface temperature variability within the CMA, along with a slight variance in SD values (1.56°C to 2.05°C) for fallow land. Temperature variability in agriculture increased from 1.67°C in 1991 to 2.4°C in 2021.

Water bodies displayed an increase in maximum LST from 35.29°C to 47.23°C, while scrubland and vegetation experienced growth in LST values. The mean LST for water bodies consistently rose from 26.17°C in 1991 to 35.73°C in 2021. Scrubland showed stable readings between 27.16°C and 35.82°C, and vegetation demonstrated a significant temperature rise from 27.22°C in 1991 to 37.26°C in 2021. The standard deviation of LST for water bodies increased from 1.94°C in 1991 to 4.08°C in 2021, indicating greater temperature variability. Scrubland exhibited relatively stable readings, ranging from 1.17 to 1.8 degrees Celsius, while vegetation showed varying temperature changes from 1.58°C to 2.44°C. These findings highlight the diverse thermal characteristics of different land cover types and their potential impact on

ecosystem dynamics and climate observations.

Relation between Land Surface Temperature, Land Use & Land Cover Environment

The zonal statistical analysis in Figure 5 and Table 7 reveals a consistent trend of increasing surface temperatures over time in different land use and land cover types. Built-up areas, fallow land, and agriculture all show rising LST values, indicating a warming trend. Similarly, water bodies, scrubland, and vegetation exhibit an upward trend in LST levels, with vegetation experiencing a particularly significant temperature increase. These findings highlight a potential correlation between land use and land cover types, emphasizing the distinct thermal characteristics of each category and their potential impact on ecosystem dynamics and climate monitoring. Further research could explore a finer-grained linear correlation between land use LST and land cover LST to strengthen this connection.

Correlation between LST & sensible Land use and Land cover

In this study, a statistical analysis is performed to establish a linear relationship between different spectral indices, including the mean Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and the mean Land Surface Temperature (LST).

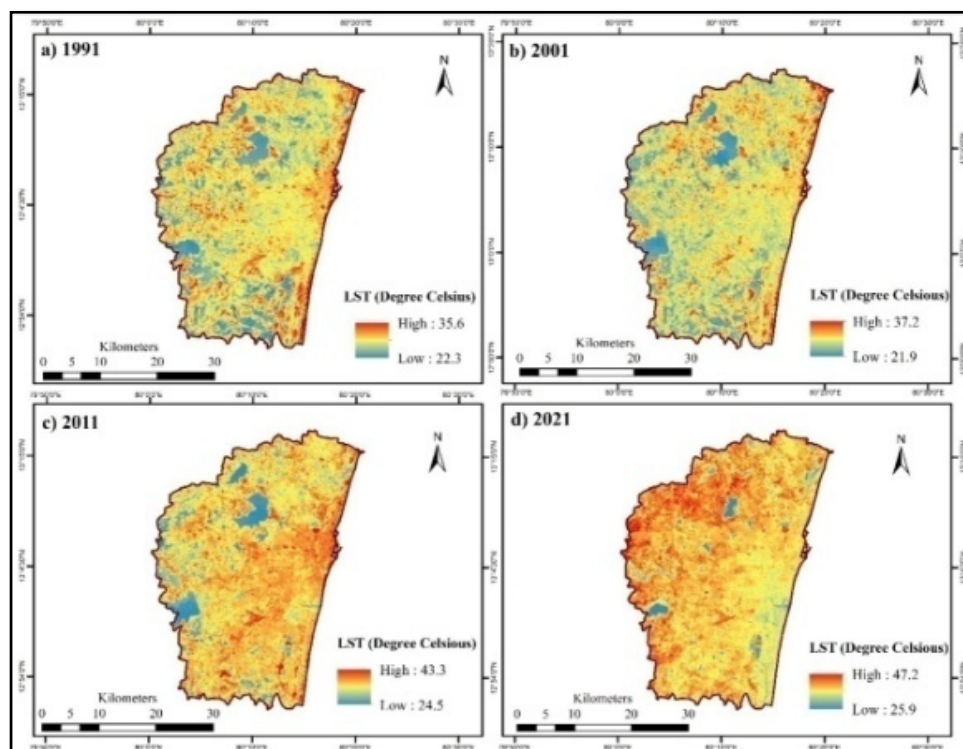


Figure 4. Land Surface Temperature map a) 1991 b) 2001 c) 2011 d) 2021

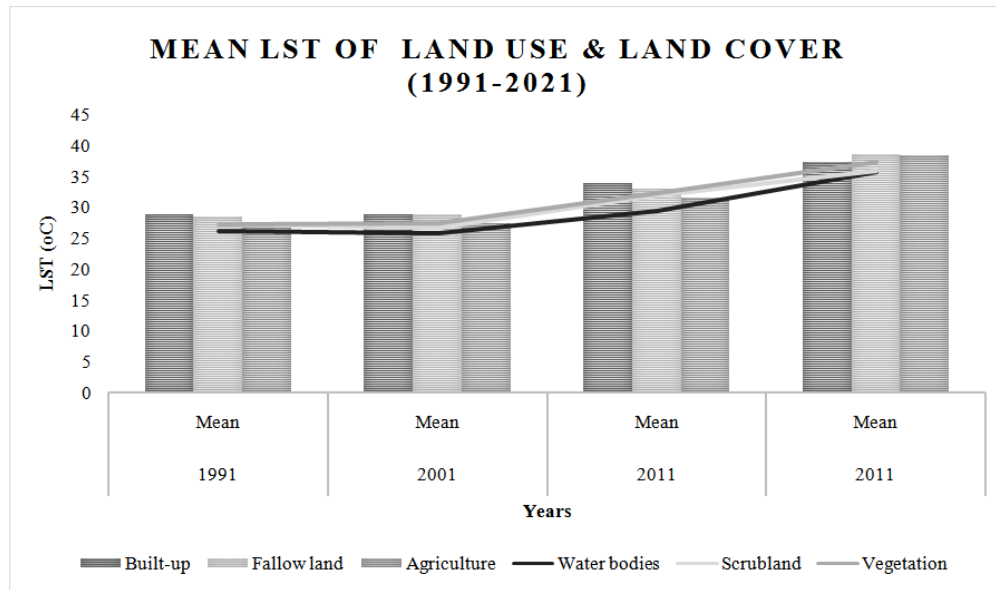


Figure 5. Mean LST of Land use & land cover

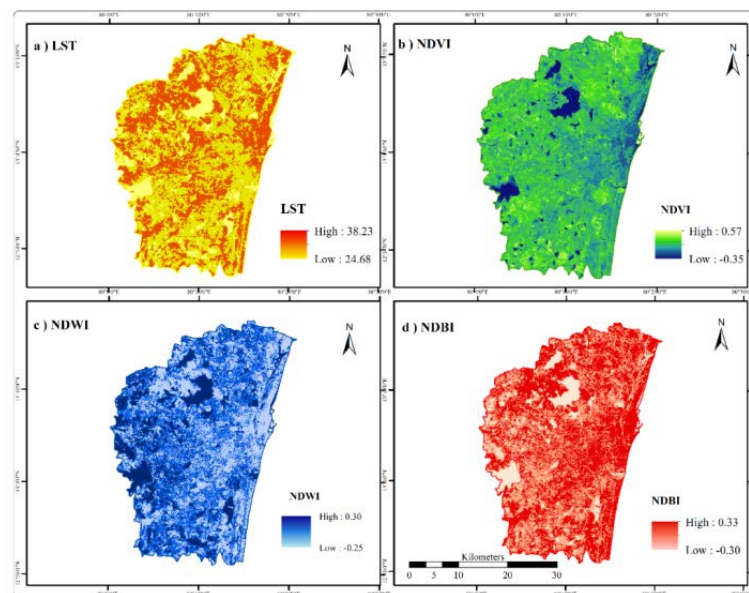
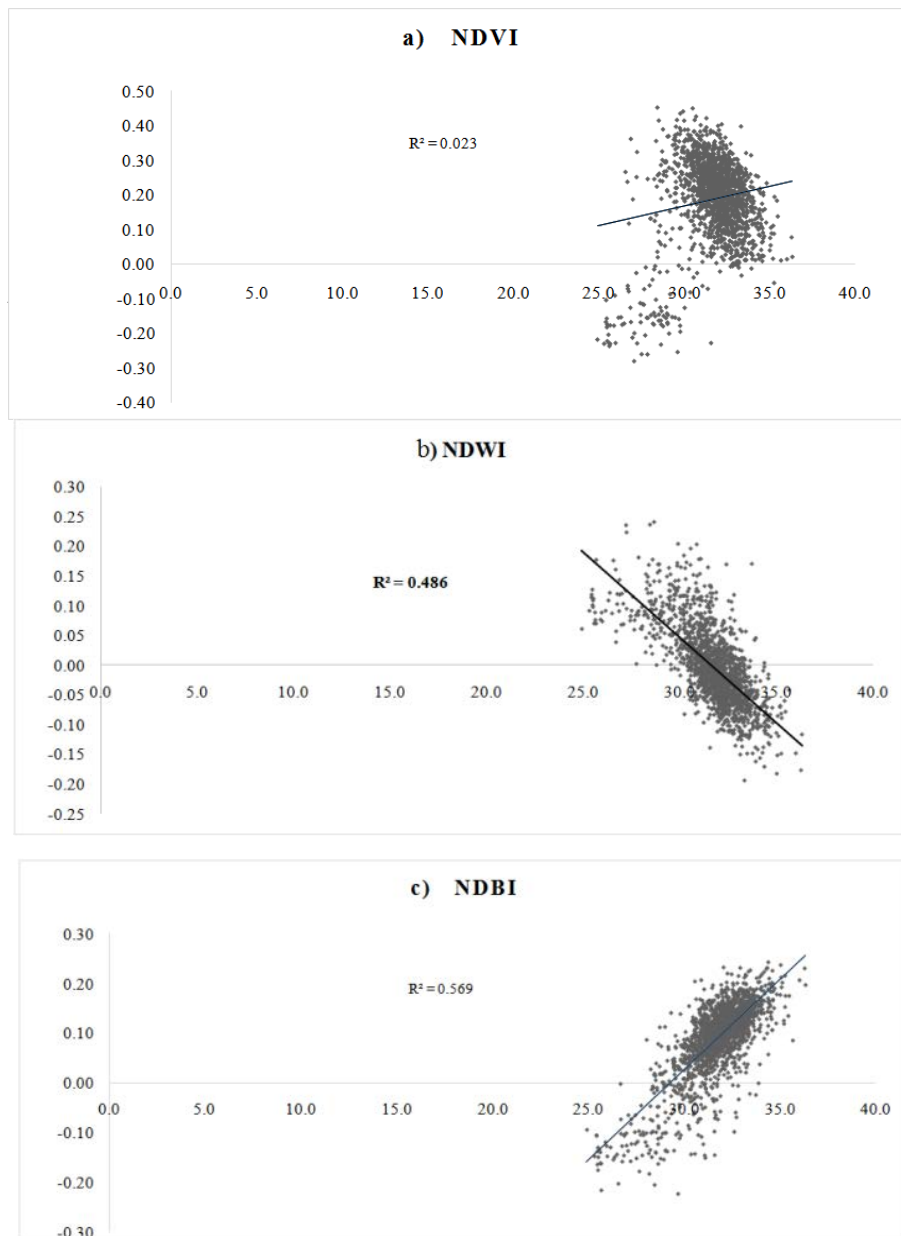


Figure 6. Mean LST and mean LULC a) Mean LST b) Mean NDVI c) mean NDWI d) Mean NDBI

Table 7. Zonal Statistic Analysis (ZSA) of LULC and LST

Year	Statistic	Land Use			Land Cover Temperature		
		Built-up	Fallow land	Agriculture	Water bodies	Scrubland	Vegetation
1991	Min	22.39	22.39	22.38	22.82	22.82	22.82
	Max	35.68	35.29	32.93	35.29	34.09	35.68
	Mean	28.78	28.48	26.93	26.17	27.16	27.22
	SD	1.45	1.57	1.67	1.94	1.74	1.58
2001	Min	23.69	23.25	24.12	21.95	23.26	22.85
	Max	37.26	36.47	33.69	35.68	34.89	34.89
	Mean	28.81	28.83	27.38	25.76	26.7	27.41
	SD	1.48	1.56	1.35	1.28	1.17	1.34
2011	Min	25	25	24.5	25	25.4	25
	Max	43.4	42.6	41.9	42.6	39.3	41.9
	Mean	33.9	33	31.5	29.4	31.9	32.2
	SD	1.8	2.1	2.3	3.2	1.8	2.3
2021	Min	25.99	28.2	28.58	27.22	29.02	28.96
	Max	47.06	47.17	46.22	47.23	45.79	46.53
	Mean	37.28	38.54	38.41	35.73	35.82	37.26
	SD	1.85	2.05	2.4	4.08	1.75	2.44



a) Mean NDVI and Mean LST b) Mean NDWI and LST c) Mean NDBI and Mean LST

Figure 7. Linear correlation between LST and various mean Sensible LULC

The correlation between mean LST and NDVI is weak ($R^2 = 0.0235$), suggesting a minimal linear relationship. Other LULC factors may have a stronger influence on LST.

The correlation between mean LST and NDWI is moderate ($R^2 = 0.4863$), indicating a moderate linear relationship, with NDWI explaining 48.63% of the LST variation. Similarly, the correlation between mean LST and NDBI is relatively strong ($R^2 = 0.5694$), with NDBI explaining around 56.94% of the LST variation.

6. Conclusion

In this study, the impact of three decades of land use changes on Land Surface Temperature (LST) in the Chennai Metropolitan Area (CMA) (1991, 2001, 2011, and 2021) was examined using Landsat satellite imagery

and Support Vector Machine (SVM) techniques. The CMA was categorized into six Land Use and Land Cover (LULC) types, with LST determined from Thermal Infrared (TIR) bands and emissivity (ϵ) assessed using the Normalized Difference Vegetation Index (NDVI). The results underscore the significant impact of land use changes, particularly in urban areas, on the rising LST in adjacent land cover. LST increased significantly from 35.6°C in 1991 to 47.2°C in 2021; with a consistent rise across all land use and land cover types, notably in built-up regions. The mean LST and overall mean NDBI exhibited a substantial positive correlation, reflecting their linear associations with mean sensitive LULC spectral indices.

The urban heat island (UHI) effect in Chennai, driven by rapid urbanization and increased impermeable surfaces, leads to higher temperatures in the metropolitan area compared to suburban regions. This study sheds light on the relationship between land use changes, Land Surface

Temperature (LST), and the broader land cover environment in Chennai. The findings contribute valuable insights for informed urban planning and climate change adaptation measures in this rapidly urbanizing area.

The significant growth and expansion of the Chennai Metropolitan Area (CMA) have resulted in ecological disruptions and changes in hydrological patterns. This study, using remote sensing data, GIS methods, and statistical analysis, identifies urban hotspots and supports sustainable development efforts, ecological balance, and biodiversity preservation. The methodologies can be applied globally to address urbanization challenges. Understanding the impact of changing land use on rising temperatures emphasizes the need for proactive urban planning and sustainable development to mitigate environmental consequences and build resilient cities. Policymakers, urban planners, and environmentalists can benefit from informed solutions based on research and analysis.

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