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Assessing the impact of Land Use/Land Cover Change on Land Surface Temperatures and SUHI: Case of Pune, India

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ABSTRACT:
The emergence of urban heat islands and rising land surface temperatures in developing countries like India is becoming a crucial concern for urban planners and policymakers. This study attempts to assess the impact of Land use and land cover (LULC) change on the Land Surface Temperature (LST) and Surface Urban Heat Islands (SUHI) in Pune, India, using remote sensing and Geographic information systems (GIS). A spatiotemporal analysis of the Landsat satellite imagery from 2000 – 2023 has been used to trace the LULC trends and compute LST variations across the years in land cover types. The thermal band, 10 of the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), is used for computing LST. Spatial indicators such as normalized difference vegetation index (NDVI) and normalized differentiated built index (NDBI) are also calculated. Results indicate that there has been a 30% decline in vegetation across the city over the years, alongside an increase of 16.64°C in LST due to urbanization-induced LULC changes. Furthermore, this study attempts to identify the thermal hotspots in the city. The results of this study can enable the assessment of urbanization and the formulation of informed climate-sensitive urban planning strategies.

Keywords: Land Surface Temperature, Pune, Remote Sensing, GIS, Local Climate Zone, SUHI

1. Introduction

Urban areas are rapidly becoming the primary choice for human habitat. With nearly half of the 8 billion people currently residing in cities, projections estimate a staggering increase by 2050 (UN Habitat, 2022). While cities offer opportunities and means of sustenance, they often need help to keep pace with the growing demands for resources and amenities. Despite occupying just 4% of the earth's land, urban areas are responsible for 70-80% of the carbon emissions (Santos et al., 2022). The challenges of urbanization and climate change make the urban population highly vulnerable. As cities expand due to urbanization, urban sprawl is evident alongside significantly changing land use and land cover patterns (Mohan et al., 2020). Vast stretches of natural land are being replaced by built areas, altering the vegetation cover and reflective properties of urban surfaces. These transformations disrupt the natural cooling mechanisms, exacerbate surface temperatures and give rise to the Urban Heat Islands (UHI) phenomenon (Cherif et al., 2024; Shimazaki et al., 2021; Zhang et al., 2022).

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The impacts of UHI occurrence have been seen to reverberate across various dimensions of sustainable development. In response, the United Nations (UN) proposed a 2030 Sustainable Development Agenda to address these global issues in 2015 (Uzzell et al., 2002). Previous research highlights the adverse impact of UHI on public health (Saha et al., 2021). SDG 3 on good health and well-being aims to counter these impacts on public health globally (Kim et al., 2022). Further, a direct impact of UHI was reported on decreased livability and restricted outdoor activities impacting the overall quality of life (Mulligan et al., 2004). This necessitates a comprehensive understanding of UHIs, which is crucial for SDG 11 on "Sustainable Cities and Communities" to be successful (De Neve & Sachs, 2020). Moreover, UHI leads towards increased energy consumption for cooling, impacting the local climate and calling for improved climate action globally.

Thus, it is crucial to address UHI and the influencing factors that contribute towards the formation and magnitude, including geographic location, morphology, terrain, population, land use and land cover, and anthropogenic heat emissions. UHI has been assessed by two methods - measuring the air temperature at a standard height of 2 meters above the ground level or by measuring LST. UHI measured using air temperature relies on a network of meteorological stations. Although it provides atmospheric UHI effects sensed by humans, the method is cost, manpower, resource and time-intensive. The procurement and maintenance of a network of weather stations pose a crucial challenge (Militino et al., 2018). Moreover, the data acquisition is limited to a smaller area, failing to capture the heterogeneity of the entire urban environment. Estimation of UHI based on LST obtained through remote sensing satellites is fast emerging as a reliable method to address the challenges posed by the first method. The use of high-resolution imagery allows researchers to estimate the land cover changes, and the use of thermal infrared sensors by the satellite allows the derivation of LST (Parmar et al., 2022). The study of the relationship between LST and LULC can reveal the thermal variations caused by the changes in the land cover and rapid urbanization over spatio-temporal dimensions (Kantakumar et al., 2016; Srivastava et al., 2022; Yadav & Singh, 2024).

The primary sources of dataset acquisition for satellite imagery by several researchers are LANDSAT and MODIS (Nayak et al., 2023). The Landsat legacy has provided researchers with consistent and accurate spatial imagery, with a resolution of up to 30 meters(Ajayi et al., 2023), while the MODIS provides a spatial resolution of 250 meters, which may fail to capture the details of the urban environment (Nayak et al., 2023). Temporally the Landsat has a low resolution of only 16 days, which may be suitable for long-term studies but fails to capture the short-term variations (Militino et al., 2018), whereas MODIS captures the data every day, which allows the frequent estimation of LST (Shiff et al., 2021). However, for studies requiring higher precision, sensors like Worldview and Sentinel-2 could be used for data acquisition since they provide a spatial resolution of up to 10 m (Salgueiro Romero et al., 2020). In addition to the data sources, researchers have used Light Detection and Ranging (LiDAR) and Object-based image analysis (OBIA) to assess urban morphology accurately. Previous studies have highlighted the need to conduct ground truth data verification for both the methods (Prince et al., 2020).

Previous studies on UHI have focused on understanding the formation, intensity and mitigation strategies globally (Li & Zhou, 2019). Cities like Tokyo, London and New York have carried out extensive research on UHI occurrences (Brousse et al., 2022). The research on UHI has led to the implementation of new cooling strategies. On the other hand, the existing development plans and planning guidelines in the Indian context are yet to acknowledge the need to incorporate any type of spatiotemporal analysis to address the adverse impact of UHI (Tyagi & Sahoo, 2022).

UHI studies globally have also contributed towards developing early warning systems useful in detecting heatwaves. However, studies in the Indian context are in nascent stages and face unique challenges (Balas et al., 2023; Kulkarni & Vijaya, 2021). (Veena et al., 2020) highlighted that majority of the UHI studies have been conducted in the temperate regions with limited emphasis on the Indian context especially. The studies by Deosthali (2000), Mallick & Rahman (2012) and Yadav & Singh (2024) emphasize the influence of population growth and resource-intensive infrastructure development on the intensification of UHI effects. The research in the Indian context is currently focusing on the heat stress periods or a particular season (Mishra & Arya, 2023; P. Singh et al., 2024). Consequently, the influence of extreme weather events occurring throughout the year goes unnoticed. Furthermore, it is seen that the research on UHI in India is focused on major cities like Delhi, Mumbai, Hyderabad and Bengaluru, while smaller towns and medium-sized cities are under-explored (Jamei et al., 2019; Parmar et al., 2022; SINGH et al., 2013; Yadav & Singh, 2024).

Considering the critical gaps discussed above, this study focuses on Pune. The study employs a unique methodology for identifying and prioritizing thermally vulnerable zones in the city. This can facilitate planners and policymakers in the adoption of climate-sensitive policy measures.

The key objectives of the study are a) to investigate the spatiotemporal variations in the LST and evaluate land cover composition in Pune from 2000-2023; b) to examine and analyze the relationship between LST and land use indices like NDVI and NDBI; c) to identify the thermally vulnerable areas within Pune for developing climate-sensitive urban planning strategies.

2. Study Area

Pune has seen rapid urbanization in the last two decades and is expected to grow at 2.5% annually (Sonawane et al., 2021). This has led to the depletion of natural resources and the conversion of farmlands and bare lands to accommodate and provide infrastructure to the residents. The geographical context of Pune is shown in **Figure 1**.

3. Methodology

This study analyses the LST and LULC composition changes between 2000-2023 in Pune City, India, using Landsat imagery. The thermal band (band 10) data was processed to obtain TOA radiance, brightness temperature and emissivity to derive the LST. The LULC for this study was estimated using the supervised classification method. A detailed methodology is shown in **Figure 2.**

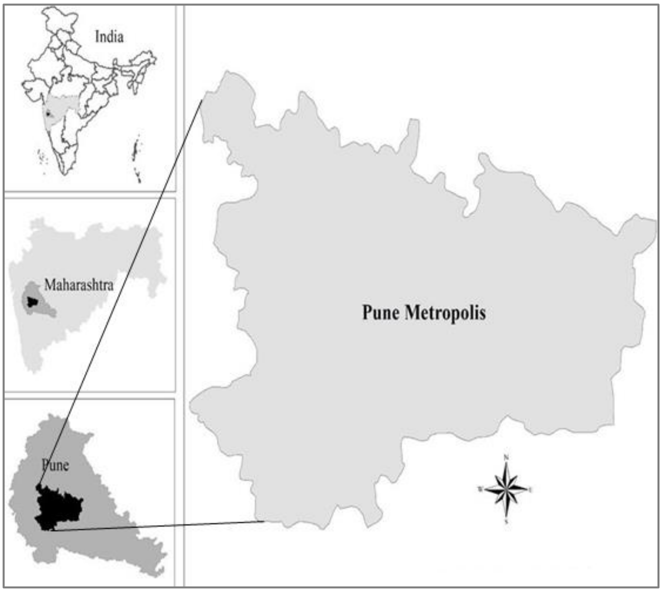

Figure 1 Study area - Pune and its Geographical Context

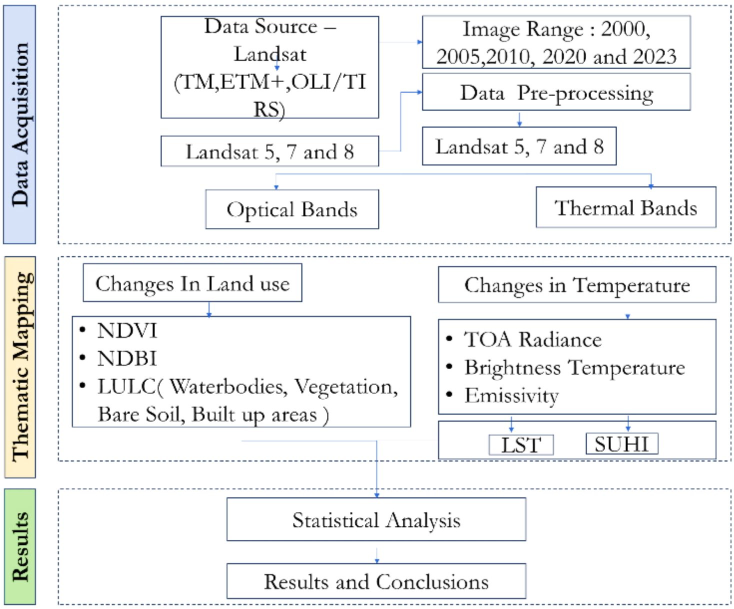

Figure 2 Detailed Methodology

For assessing the changes in the land cover the estimation of Normalized Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index (NDVI) was carried out using the optical bands (bands 4 and 5). The use of NDBI aids in identifying the built-up areas, while NDVI indicates vegetation cover. Further, the study uses statistical analysis of indices like NDVI and NDBI with LST to establish a correlation and map the influence of changes in land use over the LST variations.

3.1. Spatial Data

Satellite imagery from the LANDSAT program was acquired for the following years: 2000, 2005,2010,2020 and 2023. The details of the acquired datasets are given in **Table 1.** The satellite imagery was downloaded from USGS Earth Explorer.

Table 1 - Details of the acquired datasets

Year	Dataset Date	Satellite	Sensor	Thermal Bands	Optical Bands	Row and Path	Cloud Cover
2000	04/05/2000	Landsat 7	ETM+	6	3,4	147/047	<20%
2005	04/05/2005	Landsat 7	ETM+	6	3,4	147/047	<20%
2010	10/05/2010	Landsat 4-5	TM	6	3,4	147/047	<20%
2015	10/05/2015	Landsat 8	TIRS, OLI	10	4,5	147/047	<20%
2020	07/05/2020	Landsat 8	TIRS, OLI	10	4,5	147/047	<20%
2023	05/05/2023	Landsat 8	TIRS, OLI	10	4,5	147/047	<20%

3.1.1. Land Surface Temperature (LST) retrieval

The acquired Landsat (4-5,7 and 8) imagery was used to estimate the LST. The study uses the surface reflectance provided by the USGS. The LST retrieval process involves converting the digital data to calculate the top of the atmosphere radiance (Keerthi et al., 2023), calculating the brightness temperature, converting the temperature to degrees Celsius and calculating the emissivity.

3.1.1.1. Top of Atmosphere (TOA) Radiance

The TIRS band pixels are converted to spectral radiance or Top of the atmosphere radiance using Eq. 1 (Saha et al., 2021).

$$L_\lambda = M_L X\, Q_{Cal} + A_L \qquad \text{Eq. 1}$$

Where L_λIs the spectral radiance in W/(m²*sr*µM); M_L represents the radiance multiplicative band indicated in the respective Landsat metadata file; Q_{Cal} ranges from 0 to 255, is the digital number of the band that ranges from 0 to 255, and A_L is the rescaling value of the image (Ghanbari et al., 2023).

3.1.1.2. TOA Brightness Temperature

The results obtained from Eq. 1 were further used to get the TOA brightness temperature (BT). The spectral radiance is converted to TOA brightness temperature using

Eq. 2 (Akomolafe & Rosazlina, 2022). The formula uses the constant data values provided by the Landsat programme.

$$BT = \frac{K2}{ln\left(\frac{k1}{L_\lambda}+1\right)} - 273.15 \quad \text{Eq. 2}$$

Where BT is the TOA brightness temperature (°C), L_λ is the spectral radiance (Ogunro & Owolabi, 2022), K1 and K2 band constants were extracted using the Landsat metadata.

3.1.1.3. Emissivity

The emissivity (ε)required for the LST retrieval was computed using Eq.3 and is based on the NDVI index along with the proportion of vegetation (Pv) (Gupta et al., 2020).

$$\varepsilon = 0.986 + 0.004\ x\ Pv \quad \text{Eq. 3}$$

3.1.1.4. LST Calculation

The LST was determined using Eq.4, and the values for BT and ε were obtained using Eq.2 and Eq.3, respectively.

$$LST = \left(\frac{BT}{1}\right) + (W * \left(\frac{BT}{14380}\right) * ln(\varepsilon) \quad \text{Eq. 4}$$

Where W is the wavelength of the emitted radiance mentioned in the metadata of the Landsat imagery (Helal & Zawawi, 2024).

3.1.2. Land Use Indices

3.1.2.1. Land Use and Land Cover Change (LULC)

Land use and land cover were measured over the study area between 2000 and 2023. The evolution of the NDVI, NDBI, and proportion of vegetation (PV) was carried out to map LULC. They used a supervised classification technique (Akomolafe & Rosazlina, 2022). For the study, the land cover was divided into vegetation, waterbodies, bare soil and built-up areas.

3.1.2.2. Normalized Difference Vegetation Index (NDVI)

NDVI is used to identify the healthy vegetation within the study area. NDVI uses red and near-infrared (NIR) radiance to isolate the healthy vegetation Eq.5 (García et al., 2023).

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad \text{Eq. 5}$$

NDVI values range from -1 to +1.

3.1.2.3. Normalized Difference Built-up Index (NDBI)

The built-up features from the selected satellite imagery are extracted using Eq.6 (García et al., 2023).

$$NDBI = \frac{NIR-SWIR}{NIR+SWIR} \quad \text{Eq. 6}$$

NDBI Quantifies built-up areas and bare land based on their distinct short-wave infrared and near-infrared reflectance (Guha et al., 2018).

3.1.2.4. Surface Urban Heat Islands (SUHI)

SUHI is retrieved using Eq. 7 (Saha et al., 2021) with the help of calculated LST. The SUHIs were obtained by the difference in each pixel of the land surface temperature within the urban area and the average LST in a 10 km zone of influence outside the urban area, obtaining a positive SUHI where the Surface Temperature has increased inside the cities.

$$\boldsymbol{SUHI = LSTi(°C) - LSTo(°C)} \quad \text{Eq. 7}$$

3.1.2.5. Urban Hot Spots (UHS)

Identifying urban hotspots for the study area is an interesting take on spatial analysis as it will help identify the areas that display significantly higher temperatures than the surroundings. Urban Hotspots for the study area are mapped using the retrieved LST using Eq. 8

$$\boldsymbol{UHS = LST > \mu + (2 * \sigma)} \quad \text{Eq. 8}$$

Where μ equals the mean LST, and σ explains the standard deviation in LST (Keerthi Naidu & Chundeli, 2023).

4. Results

4.1. Spatiotemporal changes (2000-2023)

4.1.1. LULC changes

Land use and land cover (LULC) change maps for 2000,2005,2010,2015, 2020 and 2023 were prepared using the supervised classification technique (**Figure 3**). According to the LULC statistics presented in **Table 2,** the most significant change was seen in the vegetation class. The area under vegetation decreased from 100.04 sq. km. in 2000 to 21.05 sq. km. in 2023, thus reducing to only 8% of the total urban area. On the other hand, the city witnessed a significant transformation with the change in the built-up area from 105.268 sq. km. in 2000 to 213.84 sq. km. in 2023. The rise in the built-up area suggests the expansion of the city's extent spatially.

Table 2 - Statistics of LULC changes from 2000- 2023

Year	Bare Soil		Built-Up Area		Vegetation		Waterbodies		Total
	Area (Sq.Km.)	(%age)	Area (Sq.Km.)	(%age)	Area	(%age)	Area	(%age)	
2000	44.73	17	105.268	40	100.04	38	13.15	6	100
2005	101.55	45	106.89	36	31.41	15	23.36	4	100
2010	61.19	23	147.45	56	47.00	18	7.54	3	100
2015	46.45	18	172.67	66	24.45	9	19.61	7	100
2020	77.21	29	152.83	57	30.97	12	4.58	2	100
2023	23.68	9	213.84	80	21.05	8	2.18	2	100

This increase indicates a rapid pace of urbanization within the city, which aligns with the result of similar studies in Delhi (Kumari et al., 2021), Hyderabad (Pattanayak & Diwakar, 2018) and Bengaluru (Sussman et al., 2021). From 2000-2023, the area under bare soil classification decreased significantly to 23.68 sq. km. in 2023. This area has been converted into a built-up area in the past two decades to accommodate the growing population within the city. Lastly, the area under the waterbodies classification has consistently decreased from 13.15 sq. km. to 2.18 sq. km. in 2023, highlighting the alarming decrease in the spread of the two rivers flowing through the city.

Table 3 -Accuracy Assessment of the LULC changes

LULC Classification	**2000**		**2005**		**2010**		**2015**		**2020**		**2023**	
	U.A. (%)	P.A. (%)	U.A. (%)	P.A. (%)	U.A. (%)	P.A. (%)	U.A. (%)	P.A. (%)	U.A. (%)	P.A. (%)	U.A. (%)	P.A. (%)
Vegetation	89.5	86.5	97.3	95.0	98.5	88..5	84.7	82.7	90.4	89.2	96.8	95.7
Built-up area	95.8	92.8	94.4	96.4	94.5	96.5	95.8	94.6	97.5	94.7	94.5	92.1
Bare Soil	94.3	91.8	98.4	96.7	97.6	91.5	97.8	96.2	97.0	89.4	92.1	91.2
Waterbodies	100	98	98.7	97.4	100	99.4	98.2	95.3	89.8	90.2	94.7	94.1
Overall accuracy	93.54%		96.2%		97.62%		93.14%		92.45%		93.25%	
Kappa Score	0.911		0.953		0.949		0.918		0.898		0.911	

Where U.A. is the User's Accuracy, and P.A. denotes the Producer's Accuracy.

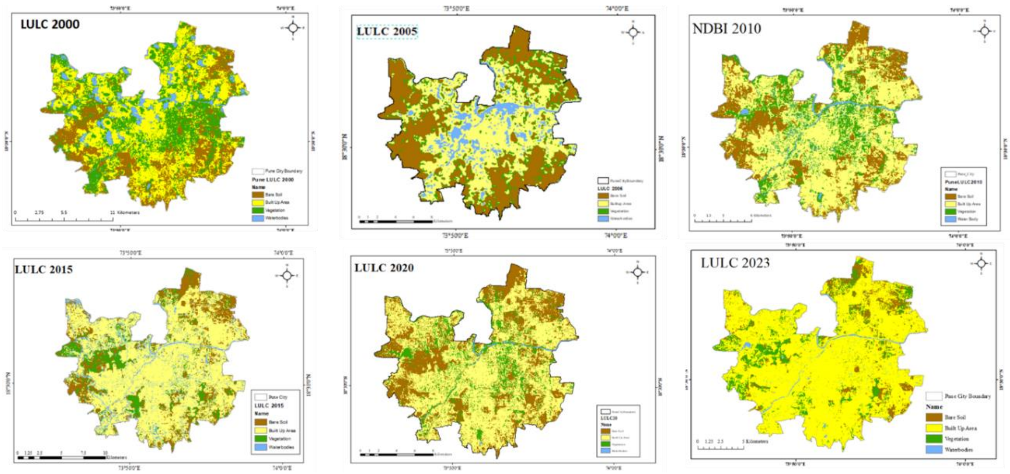

Figure 3 LULC changes from 2000-2023

The accuracy of the LULC was verified for all the years using the kappa coefficient and has been reported in **Table 3**. Manual corrections were carried out for the points lying outside the original selection.

4.1.2. NDVI and NDBI

The evaluation of the urban environment and pace of development can be done using several indices. Indices like NDVI and NDBI help categorize the concentration of healthy vegetation and growing built-up areas and are used as measures to map LULC changes. **Figure 4** shows the computed NDVI for the selected period over Pune. Highest values of NDVI are consistently seen in the city's core areas ranging from 0.55 in 2000 to 0.47 in 2023.

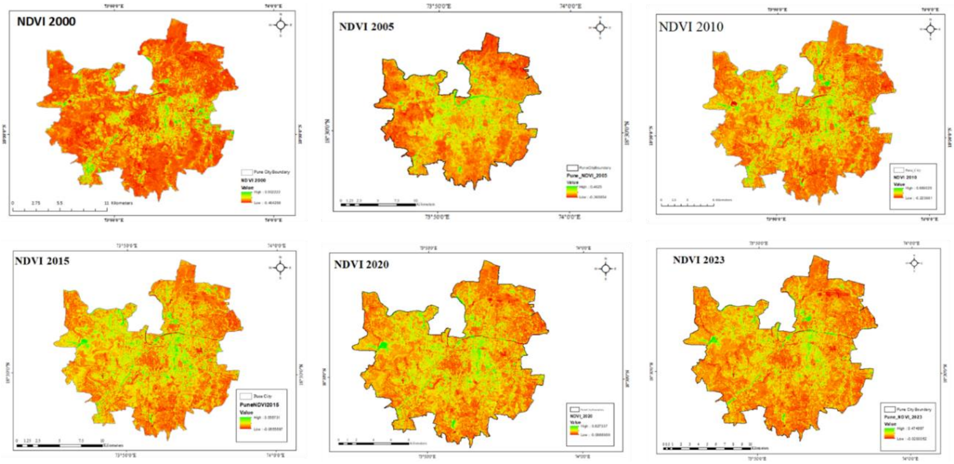

Figure 4 NDVI index investigated

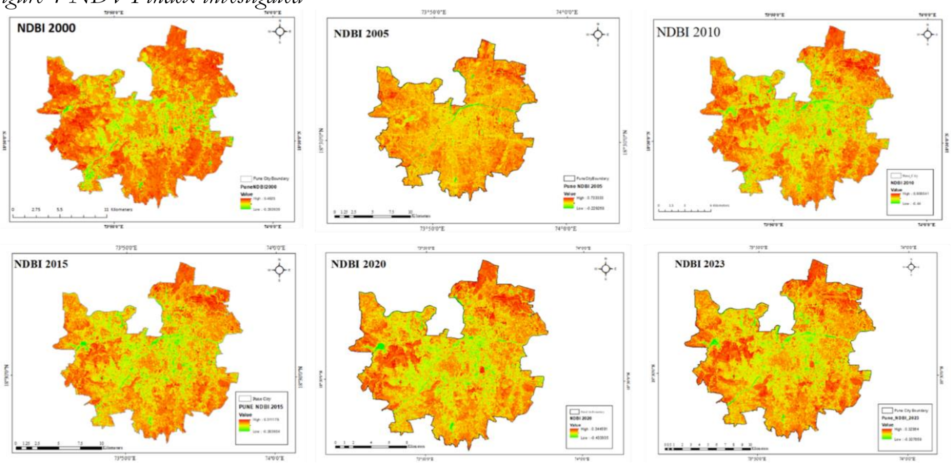

Figure 5 NDBI Index Investigated

However, around the year 2015, higher values of NDVI were also observed towards the city's western periphery. The calculated NDBI for 2000-2023. **Figure 5** shows that the central core maintains a dense built-up area. The changes in NDBI over the years highlight the outward expansion of the built-up areas within the city, concentrating towards the western periphery in 2023.

4.1.3. LST Changes and SUHI occurrences (2000-2023)

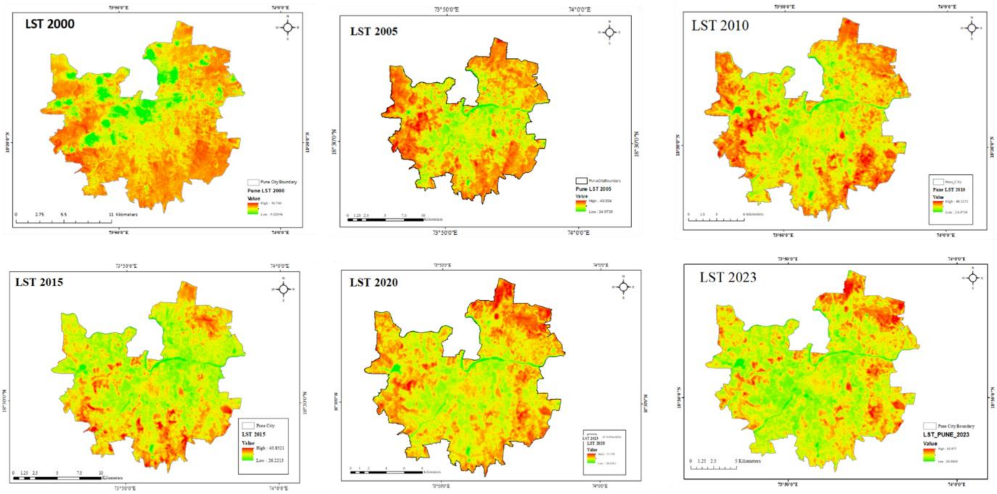

Figure 6 Land Surface Temperature (LST) from 2000-2023

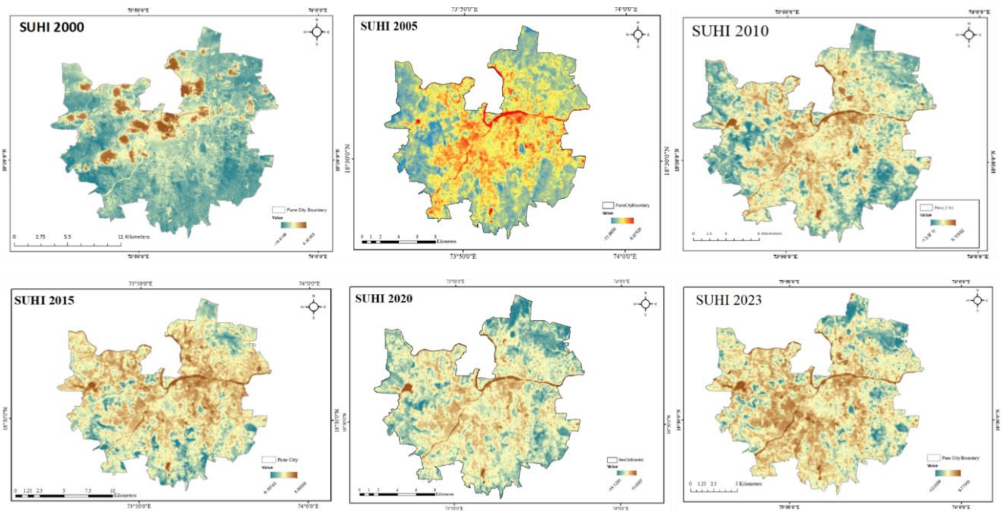

Figure 7 SUHI From 2000-2023

The variability of the LST from 2000-2023 is shown in **Figure 6**. The maximum and minimum values of LST were calculated for each selected year. The data for the same is given in Table 4. The lowest maximum of LST was estimated in 2000 at 36.06 °C and the highest maximum in 2020 at 53.18 °C. The lowest minimum LST was experienced in 2000 at 9.02 °C, and the highest minimum was observed in 2020 at 28.02 °C.

The spatiotemporal variation of the SUHI from 2000-2023 has been mapped using Eq. 7. The SUHI minimum and maximum values have been tabulated in **Table 4.** The spatial distribution of SUHI suggests higher intensities towards the northern part of the city in 2000. However, the SUHI is scattered throughout the city. The northeastern part of the city has consistently experienced the lowest SUHI from 2000-2023.

The lowest possible extreme value of SUHI in °C was observed for 2000 at 8.82 and the highest maximum in 2020 at 11.00. The lowest minimum SUHI was experienced in 2000 at -18.91, and the highest minimum was observed in 2015 at 8-8.76.

Table 4 - LST and SUHI results for 2000 - 2023

Year	**LST Min. (°C)**	**LST Max (°C)**	SUHI Min(**°C)**	SUHI Max (**°C)**
2000	9.02	36.06	-18.91	8.82
2005	24.97	45.934	-11.98	8.97
2010	24.97	48.12	-13.97	9.17
2015	26.22	43.85	-8.76	8.86
2020	28.02	53.158	-14.12	11.00
2023	26.33	45.677	-12.00	8.77

4.1.4. Urban hotspots (UHS)

The study used Eq. 8 to plot the variability of urban hotspots within the city over a time period of 2000-2023. **Figure 8** shows the variability of UHS and the increase in the area of urban hotspots from 2000-2023. The area in Figure 8 is divided into the No UHS and UHs categories to identify the area under urban hotspots. This increase in thermal hotspots within the city can be attributed to unplanned rapid urbanization.

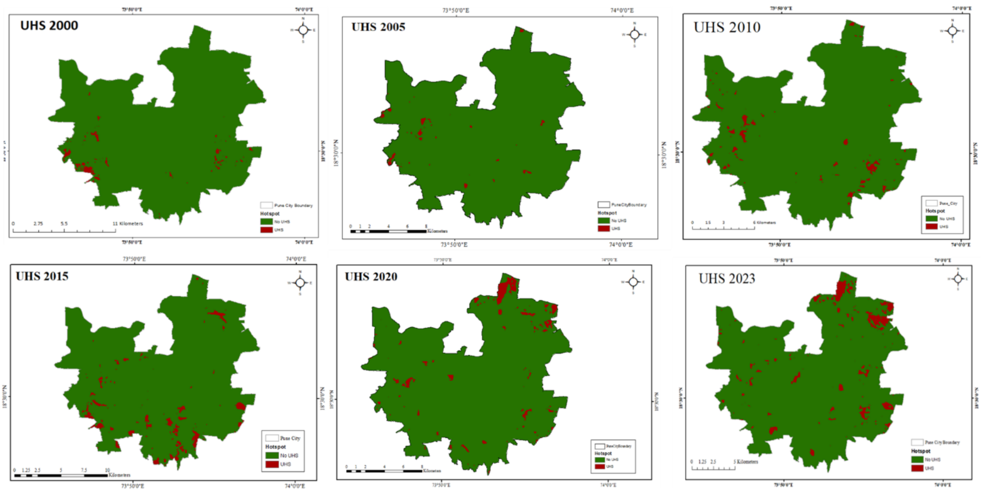

Figure 8 Urban Hotspot (UHS) variability from 2000-2023

The significant increase in the hotspots is seen from the year 2010, intensifying in 2023. In 2000, only 2.368 sq. km. (0.91% of the total area) was under the urban hotspots. However, this has increased to 25.61 sq. km. (11.98% of the total area). In 2000, the area classified as UHS was mainly towards the city's peripheral southwestern and northeastern sides. The results showcase that the city's core did not experience UHS from 2000 to 2010. However, the changes in the LULC have directly contributed to the occurrence of UHS in the city core. Contrastingly, the area on the northeastern side of the city has substantially converted to UHS from 2020 to 2023.

4.2. Correlation analysis

To determine the correlation, linear plots were generated to assess the impact of land cover changes on the LST from 2000 to 2023. The correlation between NDVI and LST is shown in **Figure 9**, and the correlation between NDBI and LST is shown in **Figure 10**. The analysis indicates a negative correlation between NDVI and LST. The areas with higher NDVI values exhibit healthier and denser vegetation. A consistently negative correlation is observed between NDVI and LST over 2000-2023.

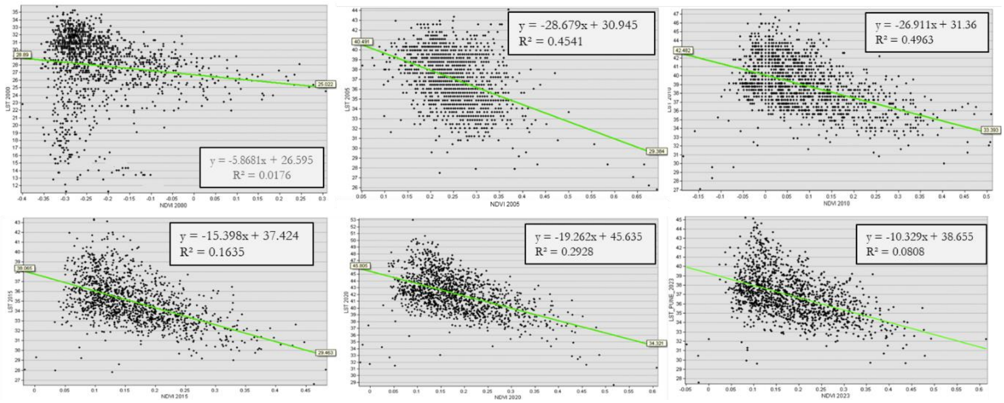

Figure 9 Correlation Analysis between NDVI and LST (2000-2023)

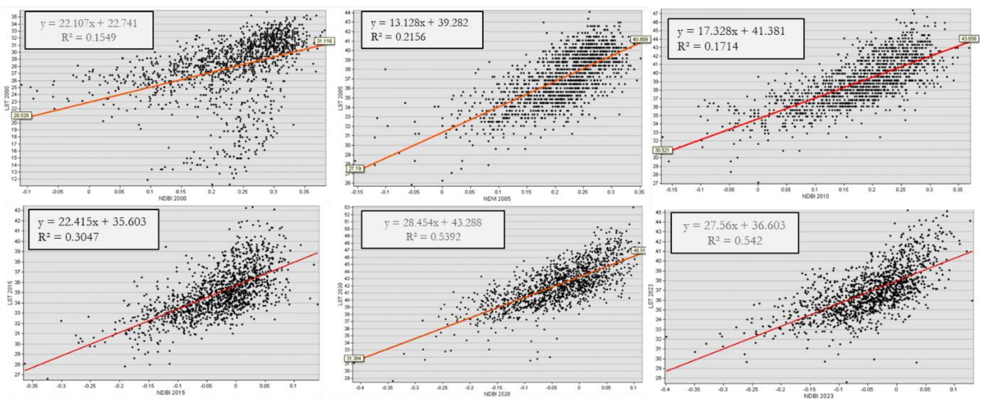

Figure 10 Correlation Analysis between NDBI and LST (2000-2023)

However, the fluctuations within the correlation values indicate a dynamic relationship between the vegetation and the surface temperatures. The year 2000 data shows a weak negative correlation ($R^2 = 0.01$), suggesting minimal influence of NDVI on LST. However, the data from 2005 highlights a strong negative correlation emerging, indicating an inversely proportional relationship between NDVI and LST. The overall analysis highlights an increase of 4.46°C from 2000-2023 in areas with declining vegetation. However, the strength of this relationship varies across years, suggesting that factors besides vegetation cover influence the variations in LST in specific locations.

The analysis of the correlation between NDBI and LST across the years 2000-2023 highlights the increasing influence of built-up areas on the thermal environment and LST within the city. The initial years (2000 and 2005) show a relatively weaker positive correlation (R^2=0.15); however, from 2015-2023, a stronger positive correlation (R^2=0.542) is exhibited.

5. Discussion

This study assessed the relationship between LULC and their impact on the LST and SUHI in Pune, India, from 2000 to 2023. The results of this study are consistent with the previous studies exemplifying the impact of LULC changes on the thermal environment (Kulkarni & Vijaya, 2021; Parmar et al., 2022). The analysis revealed significant correlations between LULC changes and LST. Several researchers have reported a substantial increase in LST associated with the growing built-up area, as identified through the LULC mapping (Mishra & Arya, 2023; Rajesh & Pande, 2023; P. Singh et al., 2024). A decline in the vegetative cover over Indian cities has been reported by authors between the years 2000-2023 (Pattanayak & Diwakar, 2018; Shahfahad et al., 2020; P. Singh et al., 2024). Our study reports a 30% decline in the vegetation, aligning with the results reported for NDVI by (Jagtap et al., 2024). Interestingly, a growing body of research in the South Asian and Indian context related to the LULC changes and SUHI reinforces the theory of significant influence on the rising temperatures due to spatiotemporal transformation in LULC (Mohan et al., 2020; Nayak et al., 2023; Yadav & Singh, 2024). A significant increase in the areas under UHS has been observed between the evaluated years from 2000-2023. This phenomenon is primarily influenced by increased LST and SUHI and a drastic decrease in vegetation (García et al., 2023).
To understand the critical determinants of LST variations comprehensively, Mallick & Rahman (2012) correlated the high population density with increased LST due to rising vehicular emissions and anthropogenic heat release in Delhi. In a similar case, one of the root causes of the increasing LST was attributed to the industrial areas in Hyderabad, where the consumption and emissions were concentrated and higher (Suthar et al., 2024). Another contributing factor to the rising temperature is the extensive use of asphalt and concrete to create impervious surfaces, which has led to reduced evapotranspiration and changes within the natural cooling processes (G. Singh & Singh, 2023). In addition to the developmental changes, the unique topography across India is also attributed to the LST Variations; Fahad et al. (2022) observed the role of sea and prevailing winds over the LST characteristics contrary to the influence of higher altitude on the lower Himalayan region as observed by Ullah et al. (2023).
Similarly, a study conducted in Thiruvananthapuram, Kerala, reported a 3.76°C rise in LST on account of urbanization. The study suggested mitigation measures- green spaces, rooftop gardens, etc. for alleviating the adverse effects of UHI (Jibitha et al., 2024). In other cases, policymakers have leveraged the results from UHI studies in cities like

Hyderabad and Ahmedabad for furthering sustainable urban planning strategies like changes in bye-laws, energy-efficient building regulations and increased vegetation(Mohammad et al., 2022; Sussman et al., 2021; Suthar et al., 2024). Similar strategies could be adopted in Pune to address and mitigate the adverse effects of the SUHI and elevated LST.

6. Conclusions

In the present study, it was observed that LULC has a significant influence on LST, particularly in rapidly urbanizing cities. This investigation assessed the relationship between LULC transformations and LST in Pune, Maharashtra, India. The correlation between LST and LULC was analyzed, and subsequently, its effect on the thermal was determined from 2000-2023 using Landsat satellite images. The key findings of the study include:

- The area under vegetation decreased by 30% from 2000- 2023, indicating a possible land degradation and changes in land use over the study timeframe.
- Buit-up neighborhoods dramatically doubled from 40% to 80% of the city area.
- The transformation of natural landscapes to urbanized areas is reflected by an 8% decrease in the regions under bare soil classification.
- The correlation analysis suggests that LULC changes is one of the crucial determinants in increasing LST.
- UHS hotspots have consistently increased to 11.07% of the total city area, highlighting the intense thermal dynamics due to the LULC transformations.

The analysis confirms the changes in converting the natural landscape and bare soil to built-up areas, significantly contributing to the rising LST and exacerbating SUHI. While the Landsat imagery has contributed the most to the computation of LST and LULC changes, the moderate- -spatial resolution presents a challenge. Acquiring higher-resolution imagery from sensors such as Sentinel-2, Worldview, and Rapid Eye may allow greater precision in representing urban transformations. Considering these limitations, the future scope of the study may include exploring LiDAR data for identifying UHI coupled with microclimatic assessments. This would allow a strong analysis of the thermal environment within the urban spaces for informed mitigation strategies. This study adds to the understanding of the SUHI in developing nations. This methodology may be applied to other urban areas experiencing rapid urbanization.

Lastly, this study critically highlights the need for sustainable urban planning strategies to address the challenges due to urbanization, LULC changes and LST variations and the results of this study can be used to develop effective heat mitigation strategies for Pune.

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