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ANALYSIS OF LULC AND LST CHANGES IN KANTH MORADABAD: ASSESSING SPATIAL AND TEMPORAL TRENDS

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ABSTRACT
Present study investigates the impact of urbanization on Land Use and Land Cover (LULC) and Land Surface Temperature (LST) in Kanth, a block in Moradabad District, Uttar Pradesh, India, over the last decade. Satellite data from Landsat, collected from from the United States Geological Survey (USGS), were used to study about LULC and LST dynamics for the years 2015 and 2024. The LULC classification was performed using supervised classification techniques, while LST was calculated using a mono-window algorithm. The analysis revealed a significant increase in built-up land within Kanth during the study period, accompanied by a noticeable decline in vegetation cover. The city's thermal landscape has changed significantly as a result of this transformation. The spatial distribution of LST showed higher temperatures concentrated in built-up areas, with decreasing values towards the periphery. The results highlight the growing trend of urban expansion and its thermal consequences in Moradabad. The increase in built-up surfaces has contributed to an elevated LST, approximately a rise of 4°C in the mean LST, with maximum temperatures rising significantly in urbanized zones. These findings underscore that there was a need for sustainable urban planning practices that incorporate green spaces to mitigate thermal stress and manage urban heat effectively.
Key Words - *Remote Sensing, GIS, LULC, LST, NDVI*

1. INTRODUCTION

Current estimates suggest that more than 45% of the global human population resides in urban areas, with projections exceeding 60% by 2030. Land use Land cover (LULC) change is a principal catalyst for environmental transformations that significantly impact ecosystems, biodiversity, and climate at local, regional, and global scales. The transformation of natural landscapes into urban, agricultural, and industrial zones significantly impacts Earth's surface processes, including modifications to land surface temperature (LST) (Jain et al., 2017b). LST, an essential parameter in climatology and environmental science, is profoundly influenced by alterations in LULC resulting from changes in surface albedo, emissivity, and thermal retention characteristics. These variations affect the quantity of solar energy absorbed by the Earth's surface and its capacity to emit heat, thereby influencing local and regional climate patterns (He et al., 2019). Comprehending the spatiotemporal dynamics of land use and land cover changes and their influence on land surface temperature is crucial for efficient land management, sustainable urban planning, and alleviating the effects of climate change (Thakur et al., 2020a). Through an in-depth analysis of the correlation between LULC and land surface temperature (LST), policymakers and environmental planners can formulate more efficacious strategies for managing urban expansion, preserving natural environments, and tackling climate-related issues.

In recent decades, population growth and industrialization have led to significant alterations in land use and land cover patterns globally (Thakur et al., 2020b). This phenomenon is the on-going process in developing countries, where urban expansion often occurs at the expense of agricultural land, forests, and water bodies. These transformations exert direct influences on the local microclimate and also contribute to the Urban Heat Island (UHI) phenomenon, characterized by elevated temperatures in urban regions relative to rural areas. The UHI effect is associated with various environmental and societal issues, including elevated energy consumption, increased air pollution, and negative health effects such as heat stress, respiratory disorders, and cardiovascular diseases. The increase in urban areas is anticipated to intensify the UHI effect, thereby complicating climate adaptation efforts. Consequently, comprehending the role of LULC changes in this phenomenon is essential for formulating strategies to mitigate its effects and bolster the resilience of urban populations against extreme heat events.

The emergence of RS technologies and GIS has transformed the monitoring and analysis of land use and land cover change studies (Kant et al., 2017). Satellite imagery from sources like Landsat, MODIS, and Sentinel offers high-resolution data that facilitates thorough monitoring of LULC and LST fluctuations over time. This data allows researchers to examine extensive geographic regions and evaluate changes across spatial and temporal dimensions, providing insights into the patterns of land use and their resultant environmental impacts. By integrating these tools, scientists can measure the magnitude and velocity of LULCC, pinpoint areas of temperature fluctuation, and assess the ecological, social, and various other consequences of these transformations. Such analyses are essential for pinpointing regions necessitating immediate intervention to alleviate the consequences of increasing temperatures (Solarin et al., 2017).

Primary main objective of present article was to analyze the spatiotemporal dynamics of LULC changes and their impact on LST in a rapidly urbanizing area. This research will utilize multi-temporal satellite data to (1) delineate historical and contemporary LULC patterns over a specified study period, (2) quantify the alterations in LST linked to different LULC types, and (3) evaluate the wider ramifications of these changes for local climate, land management, and urban planning. The research will yield essential insights into the influence of urbanization on climate change dynamics and propose recommendations for sustainable development (Sun et al., 2020). The results will be beneficial for policymakers, urban planners, and environmental scientists aiming to strengthen climate resilience, refine land use policies, and promote the establishment of climate-smart cities. These insights will inform future research and interventions focused on mitigating the challenges of climate change and advancing environmental sustainability (Modi et al., 2021).

2. STUDY AREA AND DATA

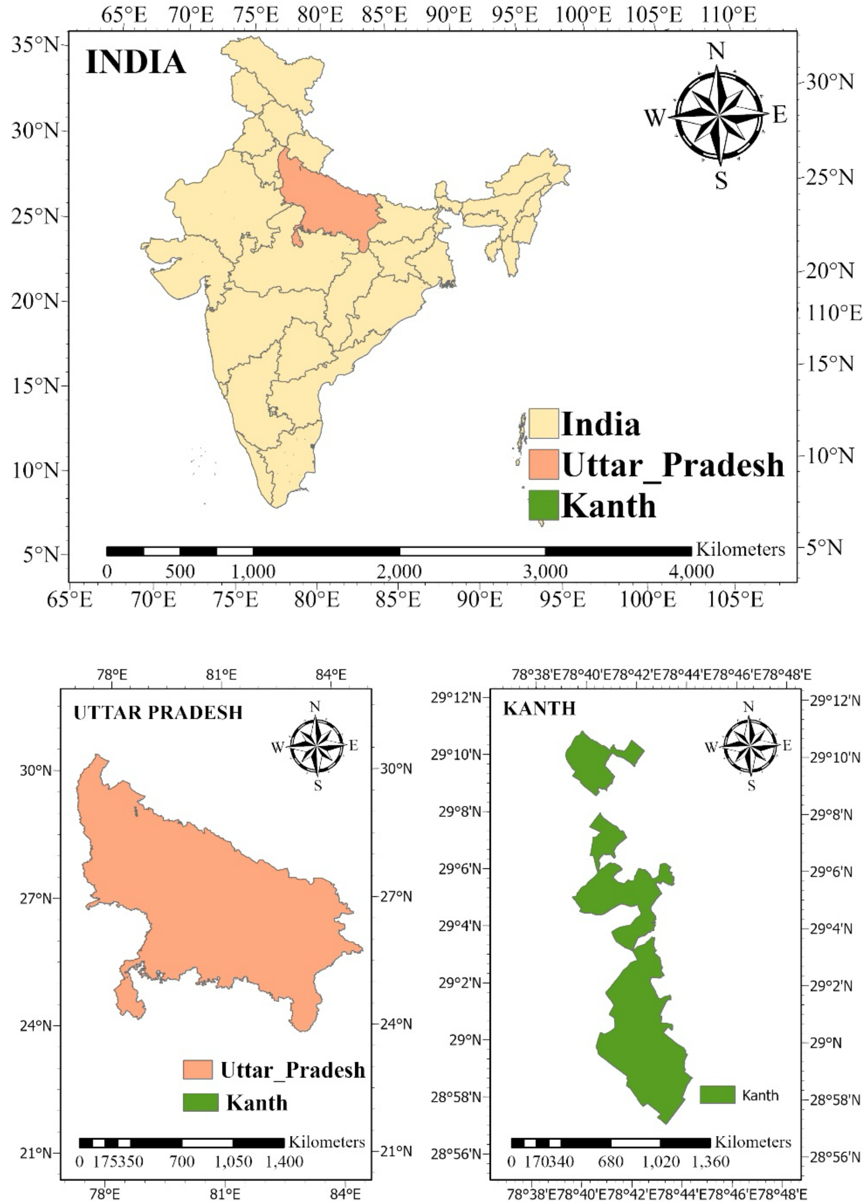


Fig. 1 Study area map

Kanth a block in Moradabad district of Uttar Pradesh, India, also famous as the 'Brass City,' is a significant industrial hub, mainly famous (Mohamed, 2021; Singh et al., 2022) for its large brass handicraft exports. Among the four tehsils of Moradabad, Kanth has emerged as a prominent industrial and rapidly developing area. Its growth is largely influenced by the economic expansion of nearby regions such as Kashipur and the state of Uttarakhand. Geographically, Kanth is located between 29°05′90.00″ N latitude and 78°62′79.00″ E longitude, covering an area of approximately 64 km² (Fig. 1). Satellite imagery for the years 2015 and 2024 was acquired from the United States Geological Survey (USGS) portal. To ensure seasonal consistency, data for both years were selected from the summer season to facilitate accurate assessment of changes in land use and land cover patterns (refer to Table 1).

Table 1. Satellite data used in the present study

S.No	Satellite product	Image acquisition date	Path/Row	Resolution (m)
1.	Landsat 8 OLI/TIRS	10 April 2015	145/040	30
2.	Landsat 8 OLI/TIRS	28 May 2024	145/040	30

3. METHODOLOGY

This study aims to identify changes in LULC patterns using satellite imagery, employing a well-established supervised classification approach. In this method, an image analyst directs the classification process by defining LULC categories, which are then identified from satellite data through the application of specific classification algorithms. Classification schema is chosen as representative samples for each land cover type, and they help to create a numerical key that represents different land cover types based on their spectral attributes (Dutta et al., 2020; Gober-Meyers, 1978). Supervised image classification method i.e. Maximum Likelihood (ML) algorithm is applied, here authors assuming that the training data in each band for individual classes follows a normal distribution. The steps involved in finding LULC change were evaluated using the software ArcGIS Pro 2.9 as per the recommendation given by (Derdouri et al., 2021).

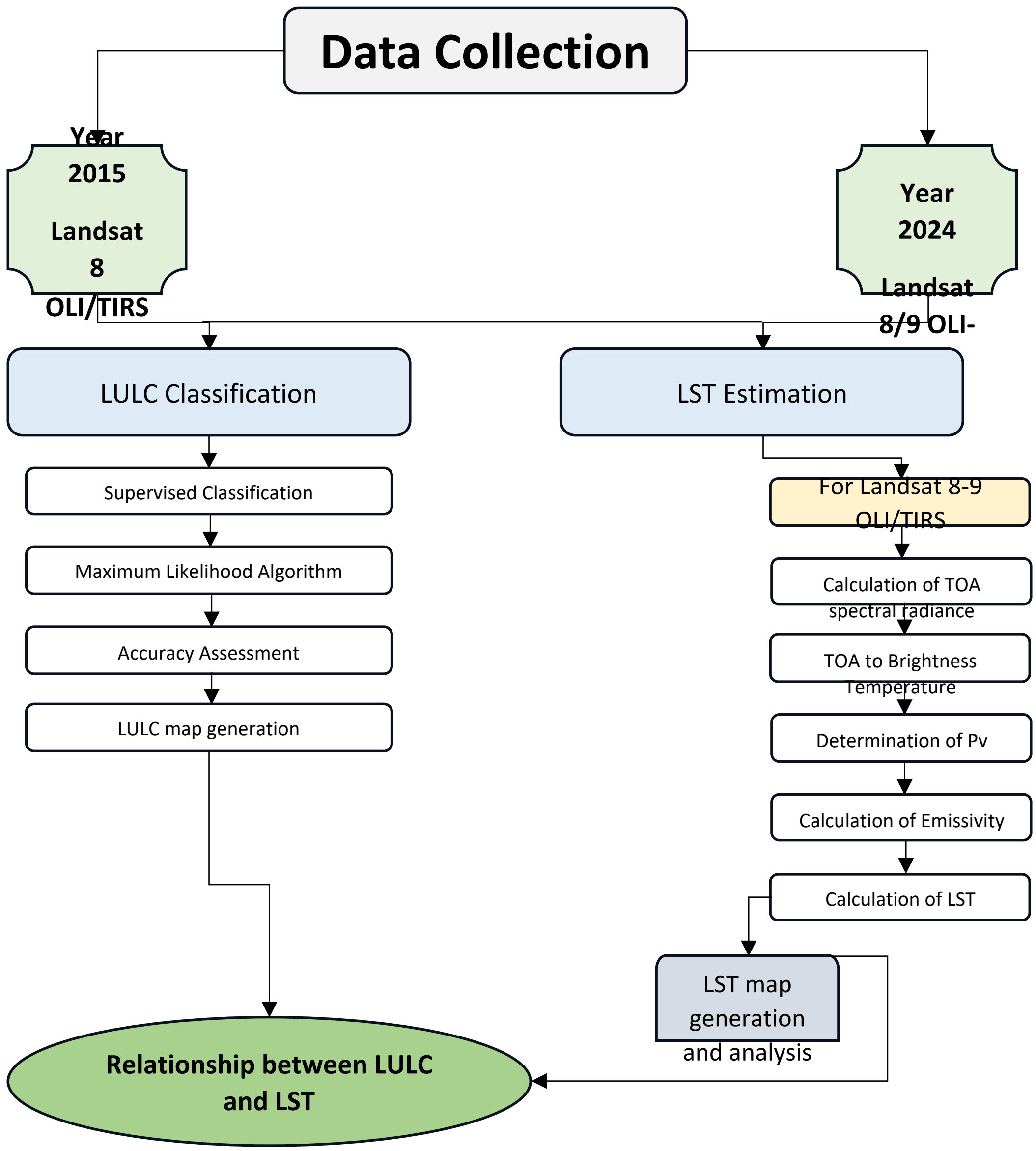


Fig. 2 Flow chart of methodology

For this study, freely accessible Landsat satellite images were downloaded from the USGS Earth Explorer for the years 2015 and 2024. Images acquired during April and May (Path 145, Row 040) were selected to maintain seasonal consistency. This period was chosen to account for phenological conditions while also improving the likelihood of obtaining cloud-free imagery suitable for accurate analysis. (*ArcGIS Pro Resources | Tutorials, Documentation, Videos & More*, n.d.). The LST was evaluated as per recommendation by (Ru et al., 2022) .The primary data was gathered through ground truthing points, while secondary data was sourced from Google Earth for the accuracy assessment. The detailed methodology adopted in present research was shown in the flowchart as shown in Fig. 2. Landsat 8 OLI/TIRS images for April 10, 2015, with a 30-meter resolution, and Landsat 8 OLI-TIRS data for May 28, 2024 were used in the current study, the mentioned group of bands were combined such as and bands 1, 2, 3, 4, 5, 6, 7, and 8 from Landsat 8-9 OLI into a single image using ArcGIS Pro 2.9.(Dutta et al., 2021)

3.1 *Image Classification*

In this research area, the approach classified satellite image pixels using per-pixel supervised classifiers based on their spectral reflectance properties. The supervised classification of Landsat imagery for the years 2015 and 2024 was carried out using the Maximum Likelihood Classification (MLC) algorithm implemented in ArcGIS Pro. This key was generated using representative sample sites or training regions, resulting in approximately 100 training samples for one class (Jain et al., 2017a). Each classified map consisted of a total of 300 reference samples. Following this, every pixel in the satellite imagery was categorized into the predefined land use/land cover classes according to its statistical similarity to the selected training samples.

3.2 *Accuracy Assessment*

For both the classified maps of the years 2015 and 2024 classified images, our supervised classifier's accuracy evaluation tool randomly generated 200 reference points through stratified random sampling (Chowdhury, 2024; *ELSE_2024_COMP*, n.d.; He et al., 2019). Each point had different color value and pixel value that was recognised by the software and will be cross checked on Google Earth Pro.

4. RESULTS

4.1 *LULC analysis*

(LULC) maps of Kanth presented in Fig. 3(a) and 3(b) were generated using imagery from Landsat 8 for the years 2015 and 2024, respectively.

The 2015 classification results indicate that vegetation covered 24 sq. km (37.5%) of the total study area. Built-up land occupied 6 sq. km (9.37%), while water bodies extended over 9 sq. km (14.06%). Barren land accounted for 13 sq. km (20.31%), and dense vegetation covered 12 sq. km (18.75%) of the area (Fig. 3).

Similarly, the 2024 LULC map (Fig. 3(b)) was prepared using the same satellite dataset. The analysis shows that vegetation decreased to 16 sq. km (25%), whereas built-up land expanded significantly to 15 sq. km (23.43%). Water bodies declined to 6 sq. km (9.37%). In contrast, barren land increased to 19 sq. km (29.68%), and dense vegetation reduced to 8 sq. km (12.5%), as detailed in Table 2.

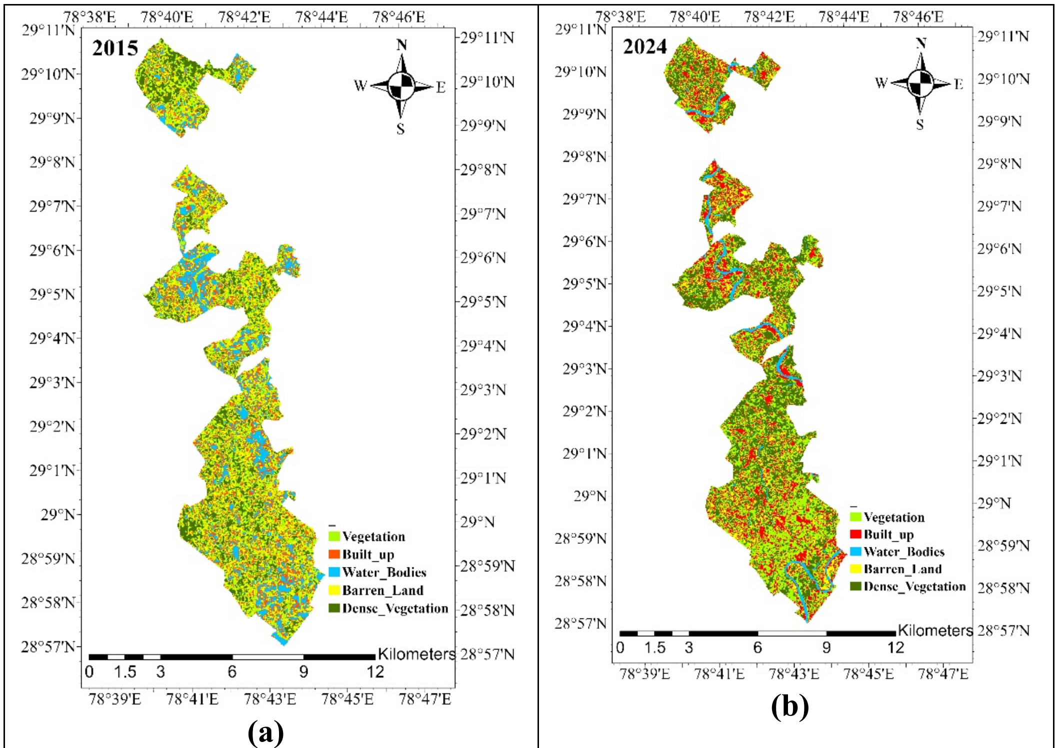


Fig. 3. LULC classification maps for the years **(a)** 2015 and **(b)** 2024

A substantial shift in LULC characteristics was observed between 2015 and 2024. The 2024 classified map (Fig. 3) clearly indicates large-scale conversion of pervious surfaces into impervious surfaces, especially in the northern part of the study area. This change is primarily associated with the expansion of residential and commercial infrastructure, which explains the nearly 2.5-fold increase in built-up land during the study period.

Although minor exchanges between other land use/land cover categories were identified, they were not examined in detail due to their limited extent and scattered spatial distribution. The observed transformations are also shaped by multiple interacting factors, including socioeconomic growth, technological advancement, and environmental influences. Additionally, the geographic setting of the area and its proximity to the Delhi NCR region have played a significant role in driving these land cover changes.

Table 1. Area distribution of each LULC class in Kanth in Moradabad District

LULC classes	**Area (km^2) in 2015**	**Area (km^2) in 2024**
Vegetation	24	16
Built Up	06	15
Water Bodies	09	06
Barren_Land	13	19

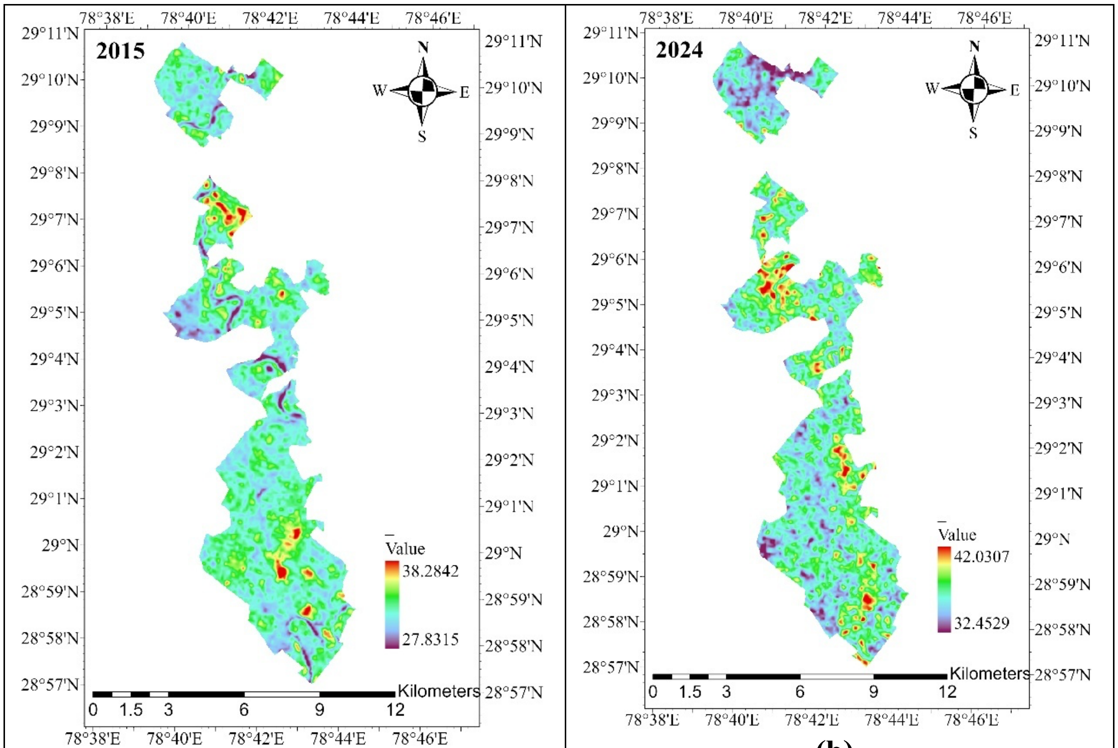
Dense Vegetation	12	08

Economic expansion and the availability of employment opportunities are primary factors influencing human migration. As people relocate in search of better livelihoods, the demand for land increases significantly. This population influx leads to the conversion of natural and agricultural landscapes into various land use categories, particularly residential settlements, commercial zones, and industrial infrastructure. Consequently, migration not only reshapes demographic patterns but also accelerates urban growth and transforms the spatial structure of regions over time.

4.2 *Seasonal LST changes*

Thermal bands from Landsat imagery were utilized to assess variations in Land Surface Temperature (LST) during the summer seasons of 2015 and 2024 in Kanth, as illustrated in Fig. 4(a) and 4(b). The temperature distribution is represented through a color gradient ranging from purple (lower temperatures) to red (higher temperatures).

In 2015, elevated temperatures were mainly concentrated in the southern region of the study area. By 2024, these high-temperature zones had expanded toward the northwest (Fig. 4(b)), reflecting a noticeable spatial shift in LST patterns. The minimum LST increased from 27.83 °C in 2015 to 32.45 °C in 2024, indicating a rise of nearly 4 °C. Similarly, the maximum temperature increased from 38.28 °C to 42.08 °C during the same period, also showing an approximate 4 °C rise (Table 3). This overall increase in temperature is likely linked to ongoing land use and land cover modifications. Furthermore, Fig. 5 presents the comparative changes in mean LST and LULC between 2015 and 2024, highlighting significant transformations over the nine-year period.



(a) (b)

Fig. 4. LST maps for the years **(a)** 2015 and **(b)** 2024

Table 3. Descriptive statistics of LST from 2015 to 2024 in Degree Celsius (°C)

YEAR	2015	2024
Min (°C)	27.83	32.45
Max (°C)	28.28	42.03
Mean	32.16	36.58
STD	1.25	1.42

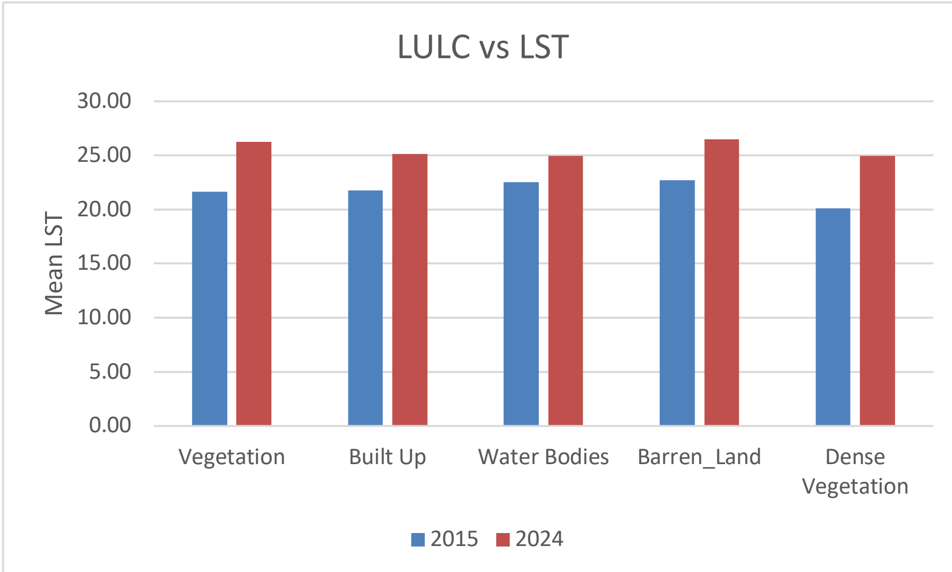


Fig. 5 Graphical representation of mean LST and various LULC classes for years 1998, 2013 and 2023

The study suggests that between 2015 and 2024, temperatures could rise significantly due to the expansion of built-up areas and the decline in vegetated land and water bodies.

5. CONCLUSION

This research was conducted in Kanth, a rapidly developing area in the Moradabad district of Uttar Pradesh. To investigate spatial and temporal variations, multitemporal satellite imagery was employed, enabling efficient assessment of landscape changes over a relatively short duration. The findings reveal that pervious surfaces—comprising vegetation, barren land, and water bodies—constitute the dominant land cover within the study area. Between 2015 and 2024, impervious surfaces (built-up land) expanded markedly, showing an increase of 224.16%. In contrast, pervious land categories experienced a substantial decline during the same period. Additionally, the mean Land Surface Temperature (LST) rose by approximately 4 °C, which may be associated with the growth of built-up areas. The pronounced land transformation in Kanth is largely attributed to the expansion of impervious surfaces, driven by population growth and intensified industrial development over the past two decades. Overall, the study emphasizes the need to inform policymakers and relevant stakeholders about the rapid urban expansion and evolving land use dynamics in Kanth to support sustainable planning and management strategies.

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